MOOC Analytics

Learner Modeling and Content Generation

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MOOC Analytics: Learner Modeling and Content Generation

Guanliang Chen

MOOC Analytics: Learner Modeling and Content Generation

Dissertation

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Guanliang Chen
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Contents

Chapter 1

Introduction

1.1 Motivation and Objectives

Lifelong learning has been widely recognized as an important social issue. As indicated by UNESCO, one objective stated in the Education 2030 Framework for Action is to "promote lifelong learning as the leading educational paradigm for achieving inclusive and sustainable learning societies" [153]. Learning used to be largely restricted to formal education in schools. With the development of technology, people now have more options to receive education and learn. *Massive Open Online Courses* (MOOCs), as one of the available options, are endowed with the mission to *educate the world* [121]. MOOCs refer to online courses that are designed for an unlimited number of participants. In MOOCs, the learning materials are distributed over the Web, which can be accessed by learners with internet connections anytime and anywhere [112]. There are two types of MOOC platforms: *topic-agnostic* and *topic-specific*. Topic-agnostic platforms (e.g., `edX`[1] and `Coursera`[2]) provide courses covering a wide range of topics, while *topic-specific* MOOC platforms (e.g., `Duolingo`[3] and `Codeacademy`[4]) focus on courses in one specific topic. UNESCO regards MOOCs as an essential tool to "promote lifelong learning opportunities for all" [121]. In fact, MOOCs are becoming increasingly popular. According to Class Central [141], by the end of 2017, there have been more than 81 million learners enrolled in 9,400 MOOCs in 33 MOOC platforms including `edX`, `Coursera`, etc.

[1] https://www.edx.org/
[2] https://www.coursera.org/
[3] https://www.duolingo.com/
[4] https://www.codecademy.com/

To better support MOOC learners, there have been many works on investigating MOOC learning. Typically, these works employed the data traces generated by learners *within* MOOC platforms to investigate their behavior *during* the running of a course, such as course navigation patterns of learners of various demographics [63], the impact of different video types on learner engagement [66], the sentiment expressed by learners in forum posts [163], the effect of instructor involvement [149]. Still, there are many other aspects of MOOC learning to be explored.

In this thesis, we focus on (i) *learner modeling* and (ii) *generation of educational material* for both topic-agnostic and topic-specific MOOC platforms. For *learner modeling* in the topic-agnostic platforms, as there have been a lot of works utilizing the learner traces generated within the MOOC platforms, we hypothesize that we can better understand learners by moving *beyond* the MOOC platforms and exploring other data sources on the wider Web, especially the `Social Web`. Nowadays, hundreds of millions of users are heavily using `Social Web` platforms with different purposes, such as microblogging (`Twitter`[5]), professional networking (`LinkedIn`[6]), Q&A (`StackExchange`[7]) and collaborative programming (`GitHub`[8]). Previous research demonstrated that abundant data traces in the `Social Web` platforms can be used to reveal detailed information about users such as age [113], occupation [127], language proficiency [159] and professional experience [26]. Therefore, we investigate what attributes can be revealed for modeling MOOC learners with the aid of the `Social Web`, not only *during* a MOOC but also *before* and *after* the MOOC. With regard to the topic-specific MOOC platforms, given that there are only a few works on modeling learners [63, 66, 163], we investigate what approaches can be used to enable a better understanding of learners in these platforms.

For *generation of educational material*, previous research demonstrated that certain `Social Web` data (e.g., code snippets in `GitHub`, Q&A pairs in `StackExchange`) can be reused by users of similar interests and needs [41, 130]. Therefore, we investigate what `Social Web` data can be used to generate educational material and potentially benefit MOOC learners.

[5] https://twitter.com/
[6] https://www.linkedin.com/
[7] https://stackexchange.com/
[8] https://github.com/

1.2 Research Questions and Contributions

In the following, we present the research questions investigated in Chapters 2-6. Each chapter explores different data sources (MOOC platforms and `Social Web` platforms), and focuses on different MOOC stages (*before*, *during* and *after* a MOOC), which are summarized in Figure 1.1. In total, we consider two MOOC platforms and eight `Social Web` platforms in our thesis, and most of our works focus on the stage of *during* a MOOC.

Data Sources \ MOOC Stages		Before	During	After
MOOC Platforms	edX		2 3 5	
	duolingo		4	
Social Web Platforms	Gravatar	2		
	twitter	2		
	LinkedIn			2
	StackExchange	2	2	2
	GitHub			2 3
	Upwork		5	
	KHAN ACADEMY		6	
	TEDEd		6	

Figure 1.1: An overview of the MOOC stages and data sources investigated in Chapters 2-6. The number in a cell represents the corresponding chapter, which focuses on the MOOC stage specified in the column and the MOOC platform or the `Social Web` platform specified in the row.

To explore whether the `Social Web` can be used to enable learner modeling beyond the topic-agnostic MOOC platforms, in **Chapter 2** we first verify whether MOOC learners are active on `Social Web` platforms and investigate how to reliably identify these learners. As people tend to be attracted by different `Social Web` platforms and correspondingly leave various data traces in those platforms, it is a non-trivial task to identify MOOC learners across multiple platforms and further gather information relevant to their learning activities in MOOCs. Specifically, we investigate the following research questions:

RQ 1.1 On what `Social Web` platforms can a significant fraction of MOOC learners be identified?

RQ 1.2 Are learners who demonstrate specific sets of traits on the `Social Web` drawn to certain types of MOOCs?

RQ 1.3 To what extent do `Social Web` platforms enable us to observe (specific) user attributes that are highly relevant to the online learning experience?

To answer those questions, we consider over 320,000 learners from eighteen MOOCs in `edX` and propose a systematic methodology to reliably identify these learners across five popular `Social Web` platforms, i.e., `Gravatar`[9], `Twitter`, `LinkedIn`, `StackExchange` and `GitHub`. Furthermore, we explore what valuable data traces can be gathered from the considered platforms and used to investigate MOOC learning. In particular, we find that over one-third of learners from a MOOC teaching functional programming are actively engaged with `GitHub`, the most popular social coding platform in the world to date, and have left abundant coding traces in the specific platform. More importantly, this enables a first investigation on *learning transfer*, which refers to the application of knowledge or skills gained in the learning environment to another context [10].

Based on the observation of the active engagement of learners from a programming MOOC in `GitHub` in Chapter 2, in **Chapter 3**, we zoom in on the coding traces of these learners in `GitHub` and continue the investigation of their *learning transfer*, as a perspective to examine the influence of the course on the learners. Concretely, we investigate the following research questions:

RQ 2.1 To what extent do learners from a programming MOOC transfer the newly gained knowledge to practice?

RQ 2.2 What type of learners are most likely to make the transfer?

RQ 2.3 How does the transfer manifest itself over time?

To answer those questions, we conduct a longitudinal analysis on both the MOOC platform data and the `GitHub` data. We find that only a small fraction of engaged learners (about 8%) display transfer. To our knowledge, this analysis has been the first to introduce the use of the `Social Web` to model learners' knowledge application beyond the learning platform.

[9] https://gravatar.com/

As indicated before, only a few works attempted to model learners in topic-specific MOOC platforms like `Duolingo` and `Codeacademy`. The main reason for this is the lack of public available datasets from these platforms to enable further research. In the Second Language Acquisition Modeling challenge [140] organized by `Duolingo`, which is the largest language-learning MOOC platform in the world, three large-scale datasets collected from its learners over the first 30 days of language learning were released. With the datasets, we are able to gain more insights about learners in topic-specific MOOC platforms.

In **Chapter 4**, we use the three released datasets to analyze learners' behavior in `Duolingo` and model their mastery of the taught knowledge over time (i.e., *knowledge tracing* [125]). Concretely, we investigate the following research question:

RQ 3.1 What factors are correlated with learners' language learning performance?

To answer the question, we analyze the three `Duolingo` datasets to identify a range of features that are correlated with learners' performance and further investigate their effectiveness in predicting learners' future performance. We demonstrate that the learning performance, which is measured by learners' accuracy in solving exercises and the amount of vocabulary learned, is correlated with not only learners' engagement with a course but also contextual factors like the devices being used.

In Chapter 3, we have shown that learners transfer the acquired knowledge to practice. In **Chapter 5**, we investigate whether learners could apply the acquired knowledge to solve real-world tasks, i.e., paid tasks which are retrieved from online marketplaces and can be solved by applying the knowledge taught in a course. If learners are able to solve such tasks, ultimately, we envision a recommender system that presents learners with paid relevant tasks from online marketplaces. By solving these tasks, learners, who cannot spend a large amount of time in learning because of the need to work and earn a living, could earn money and thus gain more time for learning with the MOOC. To investigate the feasibility of the proposed recommender system, we investigate the following questions:

RQ 4.1 Are MOOC learners able to solve real-world (paid) tasks from an online work platform with sufficient accuracy and quality?

RQ 4.2 How applicable is the knowledge gained from MOOCs to paid tasks offered by online work platforms?

RQ 4.3 To what extent can an online work platform support MOOC learners (i.e., are there enough tasks available for everyone)?

RQ 4.4 What role do real-world (paid) tasks play in the engagement of MOOC learners?

To answer those questions, we consider a MOOC teaching data analysis in `edX` and manually select a set of paid tasks from `Upwork`[10], one of the most popular freelancing marketplaces in the world, and present the selected tasks to learners and observe how learners interact with these real-world tasks. We find that these tasks can be solved by MOOC learners with high accuracy and quality. This demonstrates the potential of using freelancing paid tasks to enrich MOOC content.

Questions are recognized as essential not only for assessment but also for learning because questions allow learners to not only assess their understanding of concepts but also to reflect on their knowledge state and then better direct their learning efforts [8, 128]. However, designing a suitably large question bank to meet the needs of MOOC learners is a time-consuming and cognitively demanding task for course instructors. To ease the burden of the instructors, *automatic question generation* has been proposed and investigated by researchers to automate the question creation process with the aid of machine learning techniques [69, 110, 136]. Ideally, we can construct a question generator, which takes an article of any learning topic as input and generates a set of questions that are relevant to the article and useful for assessment or discussion. To this end, two challenges need to be overcome. Firstly, a large-scale dataset covering questions of various cognitive levels from a set of diverse learning topics should be collected. With the collected dataset, we are able to discover common question-asking patterns and inform the construction of the question generator. Secondly, given that an article often contains a limited number of sentences that are worth asking questions about, i.e., those carrying important concepts, we need to develop effective strategies to identify question-worthy sentences from the article before using them as input to the question generator. To deal with the challenges, we turn to education-oriented `Social Web` platforms (e.g., `TED-Ed`[11], `Khan Academy`[12], `Codecademy`) because these platforms typically have accumulated a substantial amount of high-quality questions generated by instructors and learners. Therefore, in Chapter **Chapter 6**, we investigate whether we can

[10]https://www.upwork.com/
[11]https://ed.ted.com/
[12]https://www.khanacademy.org/

use the education-oriented `Social Web` platforms to collect a large-scale educational question dataset and further use the dataset to develop effective strategies to identify question-worth sentences from an article. Correspondingly, we investigate the following research questions:

RQ 5.1 Can a large-scale and high-quality educational question dataset be collected from the `Social Web`?

RQ 5.2 What are effective strategies in identifying question-worthy sentences from an article?

To answer those questions, we rely on `TED-Ed` and `Khan Academy` to retrieve an educational question dataset, *LearningQ*, which contains over 230K document-question pairs generated by both instructors and learners. To the best of our knowledge, *LearningQ* is the largest dataset that can be used for educational question generation. We demonstrate that *LearningQ* consists of high-quality questions covering not only all cognitive levels in the Bloom's Revised Taxonomy [104] but also various learning topics. We show that it is a challenging task to automatically generate educational questions, even with sufficient training data and state-of-the-art question generation techniques. Besides, we develop and compare a total of nine strategies to select question-worthy sentences from an article and demonstrate that questions in learning contexts usually are based on source sentences that are informative, important, or contain novel information.

In summary, this thesis makes the following research contributions.

- We contribute a systematic methodology to reliably identify learners across five popular `Social Web` platforms and derive a set of valuable learner attributes to investigate MOOC learning.
- We contribute a novel approach to use `GitHub` to complement data traces within MOOC platforms as a means to investigate learner behavior (i.e., *learning transfer*) beyond the MOOC platform.
- We contribute an analysis to identify factors (e.g., learners' engagement with a course, the learning devices being used) that are related to learners' performance in second language acquisition.
- We contribute a study to demonstrate that learners can apply the knowledge acquired from a MOOC to solve real-world tasks with high accuracy and quality.

- We contribute a large educational dataset (*LearningQ*) for automatic question generation and investigate nine strategies in selecting question-worthy sentences from an article.

1.3 Thesis Outline and Origin of Chapters

This thesis consists of seven chapters. The current chapter describes the motivation, objectives, and research questions as well as contributions. All the main chapters (Chapter 2-6) are based on full research papers published in conferences or journals, except for Chapter 4, which is published as a workshop paper.

- **Chapter 2** is based on the paper published at the ACM Conference on Web Science [31].
- **Chapter 3** is based on the paper published at the ACM Conference on Learning at Scale [30], where the paper received the *Honorable Mention Award*.
- **Chapter 4** is based on the paper published at the Workshop on Innovative Use of NLP for Building Educational Applications [32].
- **Chapter 5** is based on the paper published at the IEEE Transactions on Learning Technologies [28].
- **Chapter 6** is based on the paper published at the International AAAI Conference on Web and Social Media [33] and includes new research work.

Lastly, **Chapter 7** concludes this thesis by summarizing the main findings and contributions. Furthermore, we provide an outlook on future research directions in relevant fields.

Chapter 2

Learner Identification across Social Web Platforms

In this chapter, we first conduct an exploratory study to verify whether MOOC learners are active in the `Social Web` and how to reliably identify their accounts across various `Social Web` platforms. This study is intended to serve as a foundation to collect learner traces beyond the MOOC platform and investigate questions that cannot be answered by solely utilizing the data traces learners leave within the MOOC platform. To this end, we consider over 320,000 learners from eighteen MOOCs in `edX`. Notice that not every `Social Web` platform attracts a large number of learners and is open for user identification and data retrieval, we eventually consider five popular `Social Web` platforms in our study, i.e., `Gravatar`, `Twitter`, `LinkedIn`, `StackExchange` and `GitHub`. Furthermore, we investigate what data traces can be collected from these platforms and used to derive learner attributes that are relevant to their learning activities in the MOOC setting. The contributions of this chapter have been published in [31].

2.1 Introduction

Online education recently entered a new era of large-scale, free and open-access which has revolutionised existing practices. This new era dates from 2011, when the University of Stanford released its initial three MOOCs. Today, a wide range of courses in the humanities, business and natural sciences are offered for free with millions of learners taking advantage of them.

At the same time, however, the initial predictions of the "MOOC revolution" (universities will become obsolete) have not come to pass. On the contrary, MOOCs today generally suffer from a lack of retention [82, 95] — many learners sign up, but on average less than 7% complete a course.

Examining the current nature of MOOCs reveals an important clue as to why they, as yet, fail to realize their full potential. Although the "MOOC revolution" changed online education with respect to scale and openness, it did not involve any truly novel pedagogical approaches or education technologies. Currently, many MOOCs revolve around a set of videos, a set of quizzes and little else (the so-called "xMOOCs"). Instead, new approaches are necessary that support learning under the unique conditions of MOOCs: (i) the extreme diversity among learners (who come from diverse cultural, educational and socio-economic backgrounds [64]), and, (ii) the enormous learner-staff ratio, which often exceeds 20,000:1.

In order to improve the learning experience and retention, MOOC data traces (i.e. learners' clicks, views, assignment submissions and forum entries) are being employed to investigate various aspects of MOOC learning, such as the effect of lecture video types on learner engagement [66], the introduction of gamification [37], the impact of instructor involvement [149] and the significance of peer learning [38].

Few data-driven research works go beyond the data learners generate *within* a MOOC platform. We argue that we can potentially learn much more about MOOC learners if we move beyond this limitation and explore the learners' traces on the wider Web, in particular the Social Web, to gain a deeper understanding of learner behavior in a distributed learning ecosystem. Hundreds of millions of users are active on the larger Social Web platforms such as `Twitter` and existing research has shown that detailed user profiles can be built from those traces, covering dimensions such as age [113], interests [1], personality [7], location [68] and occupation [127].

While MOOC learners are usually invited to participate in pre-course surveys that include inquiries about their demographics and motivations, not

all of them do (and those who do may fill in non-credible or false information), with return rates hovering around 10%[1]. In addition, these surveys can only provide a very limited view of the learners as the return rate drops with every question that is added to the questionnaire and, finally, questionnaires offer us only a snapshot-based perspective as learners cannot be polled continuously across a period of time.

We hypothesize that the Social Web can provide us with a source of diverse, fine-grained and longitudinal learner traces we can exploit in order to (i) derive more extensive learner profiles for a larger learner population than is possible through pre/post-MOOC surveys, and, (ii) investigate questions that cannot be investigated solely based on the traces learners leave within MOOC environments (e.g. the uptake of learned concepts in practice).

In this work we provide a first exploratory analysis of more than 329,000 MOOC learners and the Social Web platforms they are active on, guided by the following three **R**esearch **Q**uestions:

RQ 1.1 On what `Social Web` platforms can a significant fraction of MOOC learners be identified?

RQ 1.2 Are learners who demonstrate specific sets of traits on the `Social Web` drawn to certain types of MOOCs?

RQ 1.3 To what extent do `Social Web` platforms enable us to observe (specific) user attributes that are highly relevant to the online learning experience?

Our contributions can be summarized as follows:

- We provide a methodology to reliably identify a subset of learners from a set of five Social Web platforms and eighteen MOOCs. Depending on the MOOC/platform combination, between 1% and 42% of the learners could reliably be identified.
- We show that it is indeed possible to derive valuable learner attributes from the Social Web which can be used to investigate learner experience in MOOCs.

[1] An estimate we derived based on the MOOCs we consider in this work. This percentage drops to 1% or less when considering post-course surveys, i.e. questionnaires conducted at the end of a MOOC.

- We show that the tracking of learners over time (in the case of `GitHub` we consider three years of data traces) enables us to investigate the impact of MOOCs in the long-term.

2.2 Social Web & MOOCs

The wider Web is starting to be viewed as a source of useful information in MOOC *learning analytics* — the field concerned with the understanding and optimization of learning in massive open online courses. Existing works focus on the analysis of Social Web platforms *during* the running of a MOOC in order to learn more about the interactions and processes occurring within a MOOC. These analyses are not conducted on the individual learner level, but on the aggregated group level, without the explicit matching of MOOC learners to Social Web profiles.

Alario et al. [5] investigate the learners' engagement with two built-in MOOC platform components (Q&A and forum) and three external Social Web portals (Facebook, `Twitter` and MentorMob) during the running of a single MOOC. Learners' MOOC and Social Web identities are not matched directly, instead, learners are asked to join a specific Facebook group and use a course-specific `Twitter` hashtag. The authors find that despite the active encouragement of the platforms' usage to exchange ideas and course materials, after the initial phase of excitement, participation quickly dropped off. Similarly, van Treeck & Ebner [156] also rely on `Twitter` hashtags to identify the microblog activities surrounding two MOOCs. They (qualitatively) analyse the tweet topics, their emotions and the extent of actual interactions among learners on `Twitter` and find a small group of MOOC participants (6%) to have generated more than half of all microblog content.

Garcia et al. [59] analysed the concurrent `Twitter` activities of students taking a "Social Networking and Learning" MOOC to track their engagement and discussion beyond the MOOC environment by designating and tracking hashtagged conversation threads. In the same MOOC, [42] presented a generalisable method to extend the MOOC ecosystem to the Social Web (in this case Google+ and `Twitter`) to both facilitate and track students' collaborations and discussions outside of the immediate context of the course.

[80] tracked `Twitter` interactions among MOOC students to understand the dynamics of social capital within a connectivist [142] MOOC environment, which is inherently decentralised and distributed across platforms. This work was primarily concerned with learner-learner relationships in the

context of a MOOC—not individual learner traits. And, more broadly, [81] explored the types and topics of conversations that happen in the Social Web concurrent to a MOOC.

Four observations can be made based on these studies: existing works (i) analyze one or two Social Web platforms only, (ii) are usually based on experiments within a single MOOC, (iii) do not require a learner identification step (as an intermediary such as a `Twitter` hashtag is employed), and (iv) focus on learner activities exhibited during the running of a MOOC that are topically related to the MOOC content (e.g. ensured through the use of moderated Facebook group).

In contrast, we present a first exploratory analysis across eighteen MOOCs and five Social Web platforms exploring the learners' behaviours, activities and created content over a considerably longer period of time.

2.3 Approach

In this section, we first describe our three-step approach to locate a given set of MOOC learners on Social Web platforms, before going into more detail about the analyses performed on the learners' Social Web traces.

2.3.1 Locating Learners on the Social Web

On the `edX` platform, a registered learner l_i is identified through a username, his or her full name and email address (as required by the platform), i.e. $l_i = (login_i, name_i, email_i)$. On a Social Web platform P_j, the publicly available information about a user u^j usually consists of (a subset of) username, full name, email address and profile description. The profile description is often semi-structured and may also contain links to user accounts on other Social Web Platforms $P_x, ..P_z$. A common assumption in this case (that we employ as well) is that those accounts belong to the same user u.

For each Social Web platform P_j we attempt to locate l_i through a three-step procedure:

Explicit If P_j enables the discovery of users via their email address, we use $email_i$ to determine l_i's account u_i^j on P_j. If available, we also crawl the profile description of u_i^j, the profile image (i.e. the user avatar) and extract all user account links to other Social Web platforms under the assumption stated before.

Direct This step is only applied to the combination of learners and Social Web platforms (l_i, P_j) for which no match was found in the **Explicit** step. We now iterate over all extracted account links from the **Direct** step and consider l_i's account on P_j to be found if it is in this list.

Fuzzy Finally, for pairs (l_i, P_j) not matched in the **Direct** step, we employ fuzzy matching: we rely on l_i's $name_i$ & $login_i$ and search for those terms on P_j. Based on the user (list) returned, we consider a user account a match for l_i, if one of the following three conditions holds:

> **(i)** the profile description of the user contains a hyperlink to a profile that was discovered in the **Explicit** or **Direct** step,
>
> **(ii)** the avatar picture of the user in P_j is highly similar to one of l_i's avatar images discovered in the **Explicit** or **Direct** step (we measure the image similarity based on image hashing [143] and use a similarity threshold of 0.9), or,
>
> **(iii)** the username and the full name of the user on P_j and l_i are a perfect match.

2.3.2 Social Web Platforms

Our initial investigation focused on ten globally popular Social Web platforms, ranging from `Facebook` and `Twitter` to `GitHub` and `WordPress`. We eventually settled on five platforms, after having considered the feasibility of data gathering and the coverage of our learners among them. Concretely, we investigate the following platforms:

`Gravatar`[2] is a service for providing unique avatars to users that can be employed across a wide range of sites. During our pilot investigation, we found `Gravatar` to be employed by quite a number of learners in our dataset. Given that `Gravatar` allows the discovery of users based on their email address, we employ it as one of our primary sources for **Explicit** matching. We crawled the data in November 2015. We were able to match 25,702 `edX` learners on `Gravatar`.

`StackExchange`[3] is a highly popular community-driven question & answering site covering a wide range of topics. The most popular sub-site on this platform is `StackOverflow`, a community for computer programming related questions. `StackExchange` regularly releases a full "data dump" of their content that can be employed for research purposes. We employed the data

release from September 2015 for our experiments. We were able to match 15,135 edX learners on StackExchange.

LinkedIn[4] is a business-oriented social network users rely on to find jobs, advertise their skill set and create & maintain professional contacts. The public profiles of its users can be crawled, containing information about their education, professional lives, professional skills and (non-professional) interests. We crawled the data in November 2015. We were able to match 19,405 edX learners on LinkedIn.

Twitter[5] is one of the most popular microblogging portals to date, used by hundreds of millions of users across the globe. Twitter allows the crawling of the most recent 3,200 tweets per user. We crawled the data in December 2015 and January 2016. We were able to match 25,620 edX learners on Twitter.

GitHub[6] is one of the most popular social coding platforms, allowing users to create, maintain and collaborate on open-source software projects. The GitHub platform creates a large amount of data traces, which are captured and made available for research through two large initiatives: *GitHub Archive*[7] and *GHTorrent*[8]. For our work, we rely on all data traces published between January 1, 2013 and December 31, 2015. We were able to match 31,478 edX learners on GitHub。

In addition, we are interested in how many learners are observed across more one platform. The numbers of learners that can be matched across 2, 3, 4, 5 platforms are 14824, 6980, 3129, 1125, respectively.

2.3.3 Social Web Data Analysis

As our work is exploratory in nature, we employ a range of data analysis approaches that enable us to explore our gathered data traces from various angles.

t-SNE. Many of our user profiles are high-dimensional: a LinkedIn user may be represented through a vector of his or her skills[9] and a Twitter user profile may be encoded as a vector of the entities or hyperlinks mentioned in his or her tweets. If we are interested to what extent those user profiles

[7] https://www.githubarchive.org/

[8] http://ghtorrent.org/

[9] The dimension of the vector space depends on the number of unique skills in the dataset, with a single skill being encoded in binary form.

are similar or dissimilar for users (learners) that are taking different kinds of MOOCs, we can visualize these similarities using t-SNE (t-Distributed Stochastic Neighbor Embedding [154]), a visualization approach for high-dimensional data that computes for each datapoint a location on a 2D (or 3D) map. t-SNE[10] creates visualizations that reveal the structure of the high-dimensional data at different scales and has been shown to be superior to related non-parametric visualizations such as Isomaps [9].

Age and gender prediction. Predicting certain user attributes based on a user's Social Web activities is an active area of research. It has been shown that attributes such as age [113], gender [11], personality [79], home location [106] and political sentiments [14] (to name just a few) can be predicted with high accuracy from Social Web data sources.

In our work we focus on the prediction of age and gender, as those two attributes can be inferred of Social Web users with high accuracy. We also have intuitions concerning the age and gender (in contrast to, for instance, their personalities) of the learners that take our MOOCs (e.g. a computer science MOOC is likely to have a larger pool of male participants), enabling us to judge the sensibility of the results.

The main challenge in this area of work is the collection of sufficient and high-quality training data (that is, Social Web users with known age, gender, location, etc.). Once sufficient training data has been obtained, standard machine learning approaches are usually employed for training and testing.

In our work, we make age and gender predictions based on tweets and employ the models provided by [139][11], who utilized the English language Facebook messages of more than 72,000 users (who collectively had written more than 300 million words) to create unigram-based age & gender predictors based on Ridge regression [77]. The age model M_{age} contains 10,797 terms and their weights w_i. To estimate the age of a user u, we extract all his English language tweets (excluding retweets), concatenate them to create a document D_u and then employ the following formulation:

$$age_u = w_0 + \sum_{t \in M_{age}} w_t \times \frac{freq(t, D_u)}{|D_u|}. \tag{2.1}$$

[10] In this work, we utilize t-SNE's `scikit-learn` implementation: http://scikit-learn.org/.

[11] The models are available at http://www.wwbp.org/data.html

Here, $|D_u|$ is the number of tokens in D_u, w_0 is the model intercept and $freq(t, D_u)$ is the term frequency of t in D_u. Only terms in D_u that appear in M_{age} have a direct effect on the age estimate. The model is intuitively understandable; the five terms with the largest positive weights (indicative of high age) are {*grandson*, *daughter*, *daughters*, *son*, *folks*}. Conversely, the five terms with the largest negative weights (indicative of a young user) are {*parents*, *exams*, *pregnant*, *youth*, *mommy*}.

The gender prediction is derived in an analogous fashion based on model M_{gender}, which consists of $7,137$ terms and their weights. In contrast to the age estimation (which provides us with a continuous estimate), we are interested in a binary outcome. Thus, after the regression stage, classification is performed: if the estimation is ≥ 0, the user is classified as *female* and otherwise as *male*. Once more, the model is intuitive; the largest negative weights (indicating maleness) are {*boxers*, *shaved*, *ha3ircut*, *shave*, *girlfriend*}.

Learning Transfer. Existing investigations into student learning *within* MOOC environments are commonly based on pre- & post-course surveys and log traces generated within those environments by the individual learners [74]. With a crude, binary measure of learning, the success (pass/no-pass) of the learner could be labeled. While learning is an important success measure, we also believe that the amount of *learning transfer* [94] that is taking place should be considered: do learners actually utilize the newly gained knowledge in practice? Are learners expanding their knowledge in the area over time or do they eventually move back to their pre-course knowledge levels and behaviours? While most Social Web platforms do not offer us insights into this question, for MOOCs (partially) concerned with the teaching of programming languages (such as *Functional Programming*) we can rely on the `GitHub` platform to perform an initial exploration of this question.

`GitHub` provides extensive access to data traces associated with *public* coding repositories, i.e. repositories visible to everyone[12]. `GitHub` is built around the `git` distributed revision control system, which enables efficient distributed and collaborative code development. `GitHub` not only provides relevant repository metadata (including information on how popular a repository is, how many developers collaborate, etc.), but also the actual code that was altered. As the *GitHub Archive*[13] makes all historic `GitHub` data traces easily accessible, we relied on it for data collection and extracted all `GitHub`

[12]Data traces about private repositories are only available to the respective repository owner.

[13]https://www.githubarchive.org/

data traces available between January 1, 2013 and June 30, 2015 (five months after the end of the programming MOOC in our dataset). We then filtered out all traces that were *not* created by the 31,478 learners we identified on the `GitHub` platform. Of the more than 20 `GitHub` *event types*[14], we only consider the `PushEvent` as vital for our analysis.

Every time code is being updated ("pushed" to a repository), a `PushEvent` is triggered. Figure 2.1 contains an excerpt of the data contained in each `PushEvent`. The most important attributes of the event are the `created_at` timestamp (which allows us to classify events as before/during/after the running of the programming MOOC), the `actor` (the user doing the "push") and the `url`, which contains the URL to the actual *diff file*. While the `git` protocol also allows a user to "push" changes by another user to a repository (which is not evident from inspecting the *diff file* alone), this is a rare occurrence among our learners: manually inspecting a random sample of 200 `PushEvents` showed 10 such cases.

```
{
  "_id" : ObjectId("55b6005de4b07ff432432dfe1"),
  "created_at" : "2013-03-03T18:36:09-08:00",
  "url" : "https://github.com/john/
           RMS/compare/1c55c4cb04...420e112334",
  "actor" : "john",
  "actor_attributes" : {
        "name" : "John Doe",
        "email" : "john@doe.com"
  },
  "repository" : {
        "id" : 2.37202e+06,
        "name" : "RMS",
        "forks" : 0,
        "open_issues" : 0,
        "created_at" : "2011-09-12T08:28:27-07:00",
        "master_branch" : "master"
    }
}
```

Figure 2.1: Excerpt of a `GitHub` PushEvent log trace.

A *diff file* shows the difference between the last version of the repository and the new one (after the push) in terms of added and deleted code. For each of the identified `PushEvents` by our learners, we crawled the corresponding *diff file*, as they allow us to conduct a more fine-grained code analysis. As a first step in this direction, we identified the number of additions and deletions a user conducts in each programming language based on the filename extensions found in the corresponding *diff file*.

[14] https://developer.github.com/v3/activity/events/types/

2.4 MOOC Learners & the Social Web

As a starting point for our investigation we utilize eighteen MOOCs that have run between 2013 and 2015 on the `edX` platform — the largest MOOCs conducted by the Delft University of Technology (situated in the Netherlands) to date; the courses cover a range of subjects in the natural sciences, computer science and the humanities and were all taught in English. An overview of the MOOCs can be found in Table 2.1; we deemed the MOOC titles not to be self-explanatory, so we also added the MOOC's "tag line". Apart from the *Pre-universiy Calculus* (specifically geared towards pre-university learners) and the *Topology in Condensed Matter* (aimed at MSc and PhD physics students) courses, the MOOCs were created with a wide variety of learners in mind. All courses follow the familiar MOOC recipe of weekly lecture videos in combination with quizzes and automatically (or peer-) graded assignments.

The MOOCs vary significantly in size. The largest MOOC (*Solar Energy* 2013) attracted nearly 70,000 learners, while the smallest one (*Topology in Condensed Matter* 2015) was conducted with approximately 4,200 learners. While the majority of learners register for a single MOOC only, a sizable minority of learners engage with several MOOCs and thus the overall number of unique learners included in our analysis is 329,200.

To answer **RQ 1.1**, Table 2.1 summarizes to what extent we were able to identify learners across the five Social Web platforms, employing the three-step procedure described in Section 2.3.1. Note that the numbers reported treat each course independently, i.e. if a learner has registered to several courses, it will count towards the numbers of each course.

The percentage of learners we identify per platform varies widely across the courses between 4-24% (`Gravatar`), 1-22% (`StackExchange`), 3-42% (`GitHub`), 4-11% (`LinkedIn`) and 5-18% (`Twitter`) respectively. *Functional Programming* is the only MOOC we are able to identify more than 10% of the registered learners across *all* five Social Web platforms. While this finding by itself is not particularly surprising — two of the five Social Web platforms are highly popular with users interested in IT topics (i.e. `GitHub` and `StackExchange`) and those users also tend to be quite active on Social Web platforms overall — it can be considered as an upper bound to the fraction of learners that are active on those five platforms and identifiable through robust and highly accurate means.

In Table 2.2 we split up the matches found according to the type of matching performed (Explicit, Direct or Fuzzy). On `Gravatar`, we relied exclusively on Explicit matching, while the vast majority of learners on `GitHub`

MOOC	Year	#Learners	Gravatar	StackExchange	GitHub	LinkedIn	Twitter
Solar Energy	2013	67,143	†3,510	1,570	†3,677	2,997	†3,828
Solar Energy	2014	34,524	†1,923	874	†2,229	1,625	†2,152
Solar Energy	2015	26,178	1,147	435	1,184	1,181	†1,557
Introduction to Water Treatment	2013	34,897	1,559	508	1,198	1,362	1,741
Introduction to Drinking Water Treatment	2014	10,458	457	129	430	427	†548
Introduction to Water and Climate	2014	9,267	†561	154	†510	452	†558
Technology for Biobased Products	2014	9,811	†545	149	†511	452	†547
Next Generation Infrastructures[1]	2014	20,531	†1,438	583	†1,451	†1,155	†1,447
Functional Programming[2]	2014	38,682	‡9,087	‡8,477	‡16,220	‡4,274	‡6,801
Data Analysis[3]	2015	33,547	†2,392	1,165	‡4,432	†2,469	†2,800
Pre-university Calculus	2015	28,015	†1,928	960	†2,477	†1,406	†2,064
Introduction to Aeronautical Engineering	2014	20,481	†1,134	605	†1,373	921	†1,192
Introduction to Aeronautical Engineering	2014	13,197	†699	318	†837	609	†788
Topology in Condensed Matter[4]	2015	4,231	†277	†292	†600	201	†302
Framing[5]	2015	34,018	†2,838	1,034	†2,597	†2,211	†2,657
Solving Complex Problems[6]	2014	32,673	†2,803	1,620	‡3,928	†1,934	†2,647
Delft Design Approach[7]	2014	13,543	†1,319	514	‡1,376	†1,085	†1,124
Responsible Innovation[8]	2014	10,735	†877	274	†800	†713	†753
Unique Users		329,200	25,702	15,135	31,478	19,405	25,620

[1] Explores the challenges of global & local infras-tructure (ICT, energy, water and transportation).
[2] Teaches the foundations of functional programming & how to apply them in practice.
[3] Teaches data analysis skills using spreadsheets and data visualization.
[4] Provides an overview of topological insulators, Majoranas, and other topological phenomena.
[5] Analyzes how politicians debate and what the underlying patterns are framing and reframing.
[6] How to solve complex problems with analytics based decision-making & solution designs.
[7] How to design meaningful products & services.
[8] How to deal with risks and ethical questions raised by the development of new technologies.

Table 2.1: Overview of the edX MOOCs under investigation, the number of learners registered to those MOOCs and the number of learners that could be matched (with either Explicit/Direct or Fuzzy matching) to our five Social Web platforms. Marked with † (‡) are those course/platform combinations where we were able to locate $> 5\%$ ($> 10\%$) of the registered learners. The final row contains the unique number of users/learners (a learner may have taken several MOOCs) identified on each platform.

and StackExchange were also identified in this manner, with Direct and Fuzzy matching contributing little. On these platforms, users' email addresses are either directly accessible (Gravatar and GitHub) or indirectly accessible (StackExchange provides the MD5 hash of its users' email ad-

dresses[15]). In contrast, the LinkedIn and Twitter platforms do not publish this type of user information and thus the majority of matches are fuzzy matches. Overall, the Direct approach has the least impact on the number of matches found.

To verify the quality of our matchings, for each platform, we sampled 50 users identified through any matching strategy and manually determined whether the correct linkage between the learner's edX profile and the Social Web platform was found (based on the inspection of user profile information and content). We found our matching to be robust: of the 100 samples, we correctly linked 93 (StackExchange), 87 (GitHub), 97 (Twitter) and 95 (LinkedIn) respectively.

	Explicit	**Direct**	**Fuzzy**	**Overall**
Gravatar	7.81%	—	—	7.81%
StackExchange	4.32%	0.01%	0.25%	4.58%
GitHub	9.04%	0.02%	1.23%	10.29%
LinkedIn	—	0.48%	5.41%	5.89%
Twitter	—	0.67%	7.12%	7.78%

Table 2.2: Overview of the percentage of MOOC learners (329,200 overall) identified through the different matching strategies on the five selected Social Web platforms. A dash (—) indicates that for this specific platform/strategy combination, no matching was performed.

2.5 Results

In this section, we present an overview of our findings. As we collected different types of data (tweets vs. skills vs. source code) from different Social Web platforms, we describe the analysis conducted on each platform's data traces independently in the following subsections.

2.5.1 Learners on Twitter

Our Twitter dataset consists of 25,620 unique users having written 12,314,067 tweets in more than 60 languages, which offers many insights into **RQ 1.2**. The majority language is English (68.3% of all tweets), followed by Spanish

[15]Note that StackExchange stopped the release of MD5 hashes in September 2013, thus we use the 2013 data dump for email matching and the September 2015 data dump for our content analysis.

(7.3%), Dutch (3.1%), Portuguese (3.1%) and Russian (2.2%)[16]. The popularity of the Dutch language among our Twitter users can be explained by the fact that all MOOCs we consider in this analysis are offered by a Dutch university.

For each Twitter user with at least 100 English language tweets we estimated their age according to the approach described in Section 2.3.3. The results for our Twitter user set overall and three exemplary MOOCs (that is, we only consider users that participated in a particular MOOC) are shown in Figure 2.2: we have binned the estimations into six age brackets[17]. The average MOOC learner is between 20 and 30 years of age, though we do observe that different types of courses attract slightly different audiences: In the *Functional Programming* MOOC, the 20-40 year old learners are overrepresented (compared to the "Overall" user set — computed across all eighteen MOOCs), while *Framing* and *Responsible Innovation* engage older learners to a larger than average degree.

We conduct an analogous analysis of our users' gender distribution; the results are shown in Figure 2.3[18]. The majority of MOOCs we investigate are anchored in engineering or the natural sciences, which traditionally attract a much larger percentage of male learners (in most parts of the world). This is reflected strongly in our Twitter sample: across all users with 100 or more English speaking tweets, 89% were identified as male. The MOOC with the highest skew in the distribution is *Functional Programming* with more than 96% of users identified as male. In contrast, the *Framing* and *Robust Innovation* exhibit the lowest amount of skewness: in both MOOCs, more than 20% of the users in our sample are classified as female.

The results we have presented provide us with confidence that microblog-based user profiling in the context of massive open online learning yields reliable outcomes. Future work will investigate the derivation of more complex and high-level attributes (such as personalities and learner type) from microblog data and their impact on online learning.

[16]We generated these numbers based on Twitter's language auto-detect feature.

[17]Based on the ground truth data provided by 20,311 `edX` learners, the prediction precision is 36.5%.

[18]The prediction precision is 78.3% based on the ground truth provided by 20,739 `edX` learners.

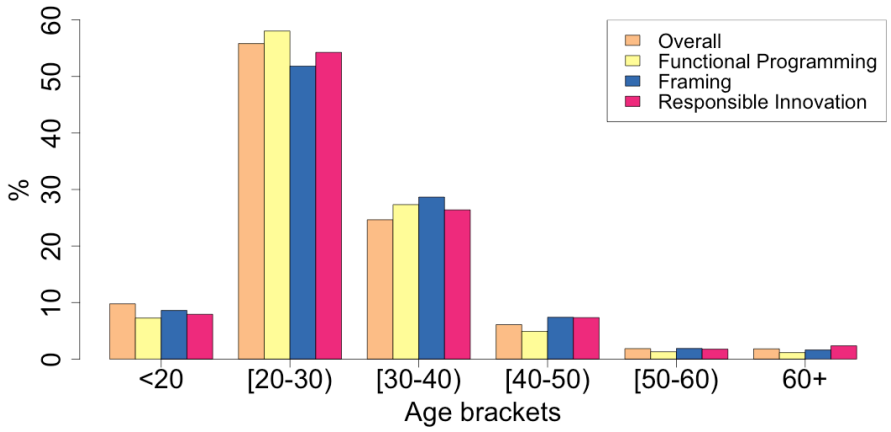


Figure 2.2: Percentage of our Twitter users across eight age brackets. The "Overall" user set contains all users independent of the specific MOOC(s) taken, the remaining three user sets are MOOC-specific.

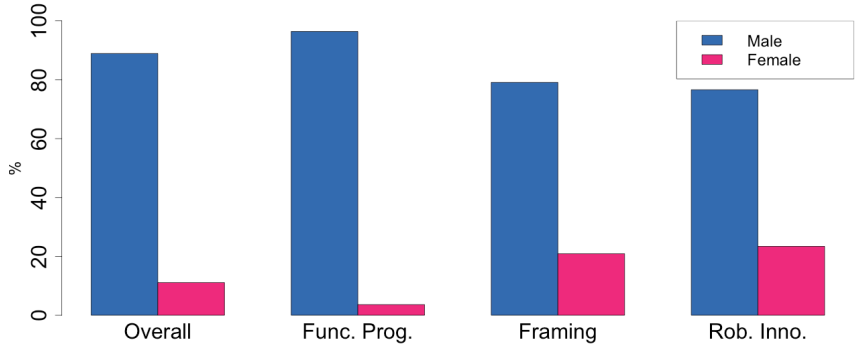


Figure 2.3: Percentage of our Twitter users of each gender. The "Overall" user set contains all users independent of the specific MOOC(s) taken, the remaining three user sets are MOOC-specific.

2.5.2 Learners on LinkedIn

`LinkedIn` user profiles are often publicly accessible, containing information about a user's education, past and current jobs as well as their interests and skills. As shown in Table 2.1, for each of the MOOCs we were able to identify between 200 (*Topology in Condensed Matter*) and 2,997 (*Solar Energy* 2013) learners on the `LinkedIn` platform. To explore **RQ 1.2** we focus on two types

of information in those profiles: job titles and skills. In our dataset, among the 19,405 collected `LinkedIn` profiles, 17,566 contain a job title (with on average 5.89 number of terms) and 16,934 contain one or more skills (37.42 skills on average).

Figure 2.4: Overview of the most frequent job title bigrams among the learners of the *Data Analysis* (top), *Delft Design Approach* (middle), and *Responsible Innovation* (bottom) MOOCs.

In Figure 2.4, exemplary for three MOOCs (*Data Analysis*, *Responsible Innovation*, and *Delft Design Approach*), we present the most frequently occurring bigrams among the job titles of our learners. Interestingly, the *Data Analysis* MOOC attracts a large number of self-proclaimed "software engineers" and "business analysts," despite the fact that it covers elementary material (it is an introduction to spreadsheet-based data analysis & Python) which we consider users in this area to be already familiar with. In contrast, the *Delft Design Approach* and *Responsible Innovation* job title bigram distributions are more in line with our expectations — the most frequent bigrams are "project manager" and "co founder" respectively, positions for which knowledge about the risks and ethical questions of new technologies (*Responsible Innovation*) and the design of new products (*Delft Design Approach*) are very relevant to.

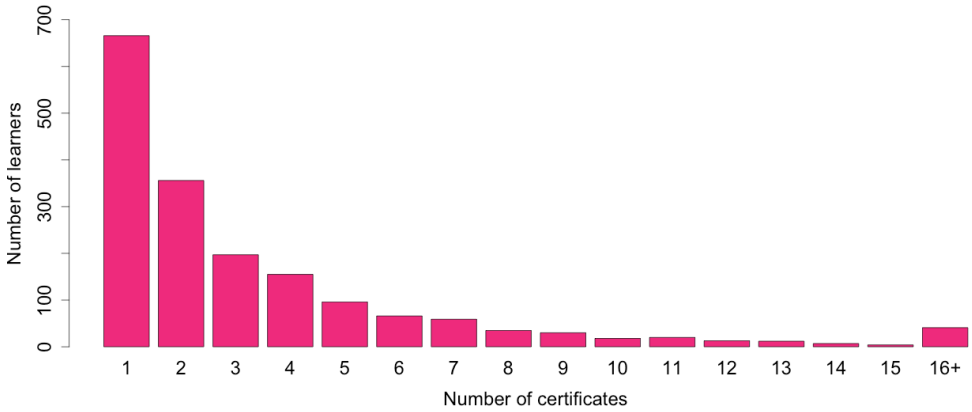


Figure 2.5: Fraction of learners displaying n numbers of MOOC certificate.

As prior works [176] have indicated extrinsic factors such as recognition-by-others to play an important motivating role for MOOC learners, an explanation for the observed discrepancy between expected learners and actual MOOC participants, we also investigate to what extent our learners on `LinkedIn` present their MOOC achievements to the outside world. In Figure 2.5 we present a distribution of the number of MOOC certificates our users in the `LinkedIn` dataset list on their profile page. Each certificate represents a successfully completed MOOC. We limit our investigation to any certificate issued by the `edX` or Coursera platforms, as they offer a verifiable certificate interface to `LinkedIn`. We manually checked a random sample of 100 DelftX `edX` certificates listed by `LinkedIn` users to check whether each was actually issued to this specific user via `edX`. This was indeed the case for all sampled certificates. Overall, 9% of our users list one or more MOOC

certificates on their public profile with the majority of users (57%) having achieved one or two certificates only. A small fraction of learners (2%) is highly active in the MOOC learning community, having collected more than 15 certificates over time. Future work will investigate the impact of MOOC certificates on professional development through the lense of `LinkedIn`.

Lastly, we investigate to what extent the users' listed skills on their `LinkedIn` profiles can be considered indicative of their course preferences (to enable course recommendations for instance). A user can list up to 50 skill on his profile — skills are not restricted to a pre-defined set, any keyword or short phrase can be added as a skill. Across all `LinkedIn` users in our dataset (19,405 users in total), the five most frequently mentioned skills are *management* (5,847 times), *project management* (4,894 times), *java* (4,087 times), *microsoft office* (4,073 times) and *leadership* (3,971 times). Thus, most of the users in our dataset present skills of themselves that are required for higher positions. We created a skill vocabulary by considering all skills mentioned at least once by a user in our dataset and then filtering out the fifty most frequent skills overall, leaving us with $28,816$ unique skills. We create a user-skill matrix, where each cell represents the presence or absence of a skill in a user's profile. We then applied truncated SVD [52] to reduce the dimensions of the matrix to 50 and then employed t-SNE (described in Section 2.3.3) to visualize the structure of the data in a two dimensional space.

In Figure 2.6 we present the t-SNE based clustering of user skills exemplary for three pairs of MOOCs: *Delft Design Approach* vs. *Topology of Condensed Matter*, *Data Analysis* vs. *Solar Energy* 2015, and, *Functional Programming* vs. *Framing*. Recall, that a point in a plot represents a skill vector; t-SNE visually clusters data points together that are similar in the original (high-dimensional) skill space. The most distinct clustering can be observed for the final course pairing — users interested in functional programming are similar to each other, but different in their skill set from users interested in the analyses of political debates. This is a sensible result, which highlights the suitability of t-SNE for this type of data exploration. For the other two course pairings, the plots show less separation. In particular, for the *Data Analysis* vs. *Solar Energy* 2015 pairing, we observe a complete overlap between the two sets of users, i.e. there is no distinct set of skills that separates their interests. The pairing *Delft Design Approach* vs. *Topology of Condensed Matter* shows that the users of the design course have a larger spread of skills than those taking the physics MOOC. Still, the overlap in the skill set is considerable.

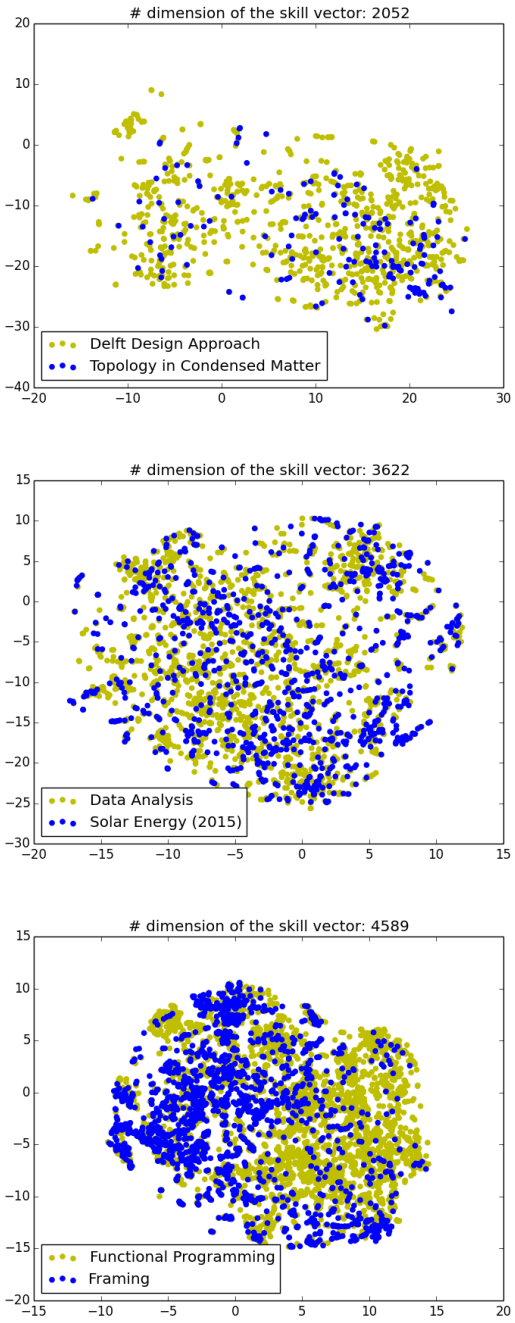


Figure 2.6: t-SNE based visualization of `LinkedIn` skill vectors for pairs of MOOCs. Each data point represents one skill vector (i.e. one user).

2.5.3 Learners on StackExchange

Our `StackExchange` dataset consists of 86,672 questions (1% of all `StackExchange` questions posted), 197,504 answers (1.2% of all answers) and 418,633 comments, which were contributed by the 31,478 unique users we identified as MOOC learners among our courses. Given that 51.5% of the identified users registered for the *Functional Programming* MOOC, we focus our attention on the `StackOverflow` site within `StackExchange` (the Q&A site for programming-related questions), where our learners contributed 71,344 questions, 177,780 answers and 358,521 comments.

Driven by **RQ 1.3**, we first explored to what extent (if at all) MOOC learners change their question/answering behaviour during and after a MOOC. We restricted this analysis to the learners of the *Functional Programming* MOOC as those were by far the most active on `StackOverflow`. Among the 38,682 learners that registered for that MOOC, 8,068 could be matched to `StackExchange`. Of those users, 849 attempted to answer at least one question related to functional programming.

In Figure 2.7 (top) we plot month-by-month (starting in January 2014) the number of questions and answers by our learners that are tagged with "Haskell", the functional language taught in the MOOC. Two observations can be made: (i) a subset of learners was already using Haskell before the start of the MOOC (which ran between 10/2014 and 12/2014), and, (ii) the number of Haskell questions posed by MOOC learners after the end of the MOOC decreased considerably (from an average of 32 questions per month before the MOOC to 19 per months afterwards), while the number of answers provided remained relatively stable. Figure 2.7 (bottom) shows that this trend is specific to the subset of MOOC learners: here we plot the frquency of "Haskell"-tagged questions and answers across all `StackExchange` users and observe no significant changes in the ratio between questions and answers. Finally, in Figure 2.7 (middle) we consider our learners' uptake of functional programming in general, approximated by the frequency of questions and answers tagged with any of the nine major functional language names[19]. We again find that over time, the ratio between questions & answers becomes more skewed (i.e. our learners turn more and more into answerers).

Finally, we also explored whether our MOOC learners have a similar expertise-dispensing behaviour as the general `StackOverflow` user population. To this end, we make use of the two expertise use types proposed in [169]: *sparrows* and *owls*. In short, sparrows are highly active users that

[19]Scala, Haskell, Common Lisp, Scheme, Coljure, Racket, Erlang, Ocaml, F#

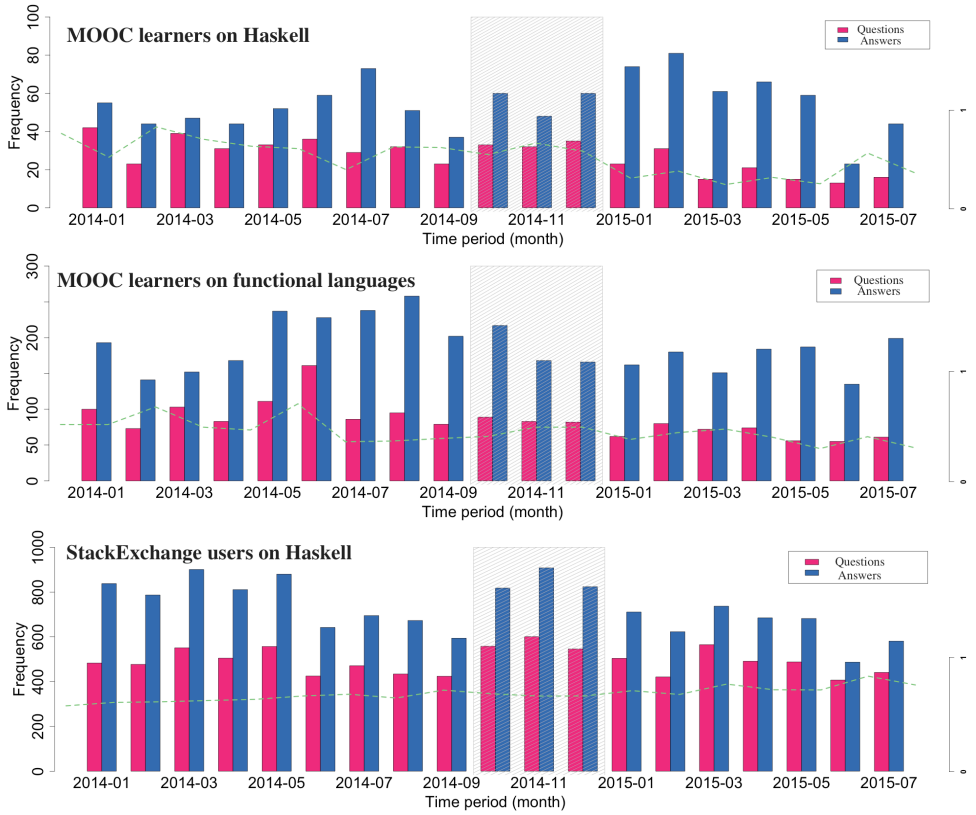


Figure 2.7: Overview of the number of `StackOverflow` questions and answers posted on a monthly basis between January 2014 and July 2015 by (i) our MOOC learners [top and middle], and (ii) all `StackExchange` users [bottom] for Haskell [top, bottom] and the nine major functional languages [middle]. Marked in gray is the time period of the *Functional Programming* MOOC. The dashed green line indicates the ratio of $\frac{Questions}{Answers}$ in each month.

contribute a lot but do not necessarily increase the community's knowledge. Their answers, while relevant, might be of low quality or low utility as they are motivated by reputation scores, and gamification elements of the platform. Owls on the other hand are users that are motivated to increase the overall knowledge contained in the platform. Owls are experts in the discussed topic, and they prove their expertise by providing useful answers to important and difficult questions. [169] proposed the *mean expertise contribution* (MEC) metric to capture measure expertise, based on answering quality, question debatableness and user activeness. Based on this metric, they determined 10.0% of the `StackOverflow` users to be owls. We derived MEC for our set of *Functional Programming* MOOC learners that are active on `StackOverflow` and found 21.0% of them to be owls. Thus, the

average MOOC learner is not only interested in gathering knowledge, but also in distributing knowledge to others, on a deeper level than the average `StackExchange` user.

2.5.4 Learners on GitHub

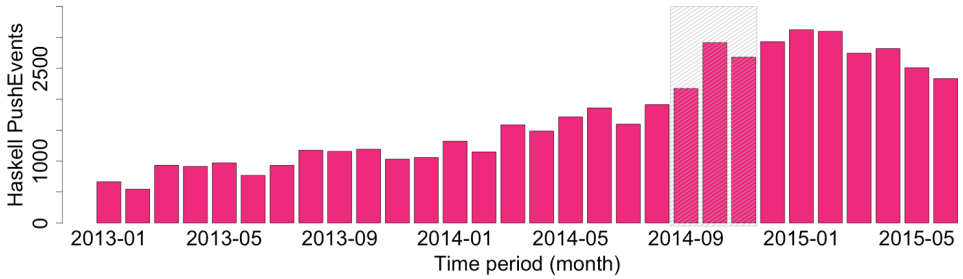


Figure 2.8: Month-by-month `GitHub` contributions in the Haskell language by the *Functional Programming* MOOC learners identified on `GitHub`.

Finally, with respect to **RQ 1.3**, we consider the concept of learning transfer, introduced in Section 2.3.3. As a social coding platform, `GitHub` is most suitable to explore programming-heavy MOOCs, thus we restrict our analysis (as in the previous section) to the *Functional Programming* MOOC. We are particularly interested in the extent of the learners' functional programming after the end of the MOOC — our MOOC learners ask fewer topic-related questions (on `StackExchange`) over time, but does it also mean they program less in the language? To his end, we explored th $6,371,518$ `PushEvents` we extracted from our MOOC learners between January 1, 2013 and June 30, 2015. Figure 2.8 provides a first answer to this question. The amount of Haskell programming by our learners was increasing slowly over time even before the start of the MOOC. A spike is visible in November 2014 (weeks 3-6 of the *Functional Programming* MOOC) and immediately after the end of the MOOC the contributions increase. However, by March 2015, i.e. three months after the end of the MOOC, the contributions are beginning to decline again towards nearly pre-MOOC levels.

In contrast to Haskell, we observe a sharp rise in "Scala" (the main functional language in industry) activities after the end of the MOOC which peak in November 2015. These functional activities are not evenly spread across all users though, only 32% of the users we identified on `GitHub` exhibited any type of functional language activities after the end of the *Functional Language* MOOC.

In the future, we will not only consider the addition of lines of codes in a particular language, but also perform fine-grained code analyses to investigate which specific concepts the learners picked up on in the MOOC and later employed in their own works.

2.6 Conclusion

In this chapter, we have provided a first exploratory analysis of learners' Social Web traces across eighteen MOOCs and five globally popular Social Web platforms. We argue that MOOC-based learning analytics has much to gain from looking beyond the MOOC platform and accounting for the fact that learning events frequently happen beyond the immediate course environment. This study embraces the data traces learners leave on various Social Web platforms as integral parts of the distributed, connected, and open online learning ecosystem.

Focusing on **RQ 1.1**, we have found that on average 5% of learners can be identified on globally popular Social Web platforms. We observed a significant variance in the percentage of identified learners; in the most extreme positive case (*Functional Programming*/`GitHub`) we were able to match 42% of learners. We also found that learners with specific traits prefer different types of MOOCS (**RQ 1.2**) and we were able to present a first investigation into user behaviours (such as learning transfer over time) that are paramount in the push to make MOOCs more engaging and inclusive (**RQ 1.3**).

In this work we were only able to explore the possible contributions of each Social Web platform to enhance massive open online learning on a broad level. In future work, we will zoom in on each of the identified platforms and explore in greater detail how learners' behaviours and activities can be explored to positively impact our understanding of massive open online learning and improve the learning experience.

Chapter 3

Learning Transfer

In this chapter, we follow Chapter 2, in which we have observed that over one-third of learners from a *Functional Programming* MOOC used `GitHub` to maintain their programming activities. While course completion is indeed an important measure of learning, we argue that another key measure is *learning transfer*: do learners actually use the newly acquired knowledge and skills to solve problems in practice? To answer the question, we combine the data traces from both `edX` and `GitHub` for analysis. The contributions of this chapter have been published in [30].

3.1 Introduction

The rising number of MOOCs enable people to learn & advance their knowledge and competencies in a wide range of fields. *Learning*, though, is only the first step; the *application* of the taught concepts is equally important, as knowledge that is learned but not frequently applied or activated is quickly unlearned [166, 18, 148].

Existing investigations into student learning *within* MOOC environments are commonly based on pre- & post-course surveys and log traces generated within those environments by the individual learners [74]. While student learning is indeed an important measure of success, we argue that another key measure is the amount of **learning transfer** [94] that is taking place: do learners actually utilize the newly gained knowledge in practice? Are learners expanding their knowledge in the area over time or do they eventually move back to their pre-course knowledge levels and behaviours? These are important questions to address in the learning sciences, and their answers will enable us to shape the MOOCs of the future based on empirical evidence.

The main challenge researchers face in answering these questions is the lack of *accessible*, *large-scale*, *relevant* and *longitudinal* data traces outside of MOOC environments. While learners can be uniquely identified within a MOOC platform, at this point in time we have no general manner of capturing their behavioural traces outside of these boundaries.

Not all is lost though. Social Web platforms (Twitter being the prime example) have become a mainstay of the Web. They are used by hundreds of millions of users around the world and often provide open access to some — if not all — of the data generated within them. While most of these platforms are geared towards people's private lives, in the past few years social Web platforms have also begun to enter our professional lives.

One such work-related social Web platform is `GitHub`[1]; it is one of the most popular *social coding* platforms world-wide with more than 10 million registered users. Hobbyists and professional programmers alike use `GitHub` to collaborate on programming projects, host their source code, and organize their programming activities. As `GitHub` was founded in 2007, we have potential access to log traces reaching several years into the past; moreover, its continuously increasing popularity will enable us to observe our learners over years to come. The potential of `GitHub` for behavioural mining has long been recognized by the software engineering research community where `GitHub` is

[1] https://github.com/

one of the most popular data sources to investigate how (groups of) people code.

Thus, for MOOCs with a strong focus on programming concepts, we consider `GitHub` to be one of the most detailed and openly accessible sources of learners' relevant behavioral traces outside of the MOOC environment itself. Concretely, we analyze *FP101x*[2], an `edX` MOOC covering basic functional programming concepts. Of the 37,485 learners that registered for *FP101x* we matched 12,415 (33.1%) to their respective `GitHub` accounts, enabling a first large-scale analysis of the uptake of taught programming concepts in practice.

Here, we are foremost interested in exploring to what extent the course affects learners *after it has ended*. We are guided by the following three **R**esearch **Q**uestions:

RQ 2.1 To what extent do learners from a programming MOOC transfer the newly gained knowledge to practice?

RQ 2.2 What type of learners are most likely to make the transfer?

RQ 2.3 How does the transfer manifest itself over time?

Based on these guiding questions we have formulated seven research hypotheses which build on previous research efforts in work-place and classroom learning. In contrast to our work though, in these settings, the investigations are mostly based on questionnaires and interviews instead of behavioural traces. To the best of our knowledge, learning transfer has not yet been investigated in the context of MOOCs. Gaining deeper insights about the (lack of) learning transfer in MOOCs will lead to more informed discussions on the practical purposes and benefits of MOOCs. The main contributions of our work can be summarized as follows:

- We investigate to what extent learning transfer insights gained in work-place and classroom settings hold in the MOOC context. We find that the majority of findings are also applicable in the case of MOOCs.
- We introduce the use of *external* social Web-based data sources to complement learner traces within MOOC environments as a means to capture much more information about MOOC learners.

[2]https://www.edx.org/course/introduction-functional-programming-delftx-fp101x

- We introduce `GitHub` as a specific large-scale data source to mine relevant longitudinal behavioural traces about learners before, during and after a programming-oriented MOOC.

3.2 Background

Meaningful, robust educational experiences transcend rote memorization of facts and leave the learner empowered to take on new problems and practice novel ways of thinking. In tracking student activity from the learning context (`edX`) to a real-world, practical one (`GitHub`) over a period of three years, the present study observes the first two of the three criteria of *robust learning* as outlined in [94]: (i) application in new situations different from the learning context, (ii) retained over the long-term, and (iii) prepares for future learning. Gaining a better understanding of how students apply what they learn in online learning environments over an extended time frame enables instructors to design future courses that induce more robust learning.

Some researchers [162, 158] have begun to look beyond traces generated in online learning environments, by utilizing post-course surveys or conducting post-course interviews with MOOC students.

Although the early studies of transfer stemmed from educational issues, the majority of recent learning transfer research literature is concerned with work-place training in Human Resource Development (HRD) [19]. With the recent influx of student activity data generated from digital learning environments, we can now empirically measure not only the rate of transfer, but other contributing factors as well. That, in tandem with the established surveying strategies used by HRD, promises to fundamentally change the way we think about measurable learning outcomes.

Learning transfer is the application of knowledge or skills gained in a learning environment to another context [10]. While training situations in professional environments have a clear target context (the job), this is not the case with most academic learning situations. Students are generally taught a broad set of skills and knowledge which they may apply in countless ways. This deliberately broad definition encapsulates both *near transfer* (to similar contexts) and *far transfer* (to dissimilar contexts) [13] and avoids the subjective question of *how* similar or different the learning context is from the target context, as we are only concerned with whether the student transferred the learned skills or knowledge beyond the learning context.

Due to their rising popularity as a professional development tool and their roots as an educational resource, MOOCs serve as an ideal source of information to gain new insights on learning transfer. Studies have begun to discuss the learners' intention to apply what they've learned in MOOCs but do not continue to track student activity beyond the learning platform [55]. The present research aims to reoperationalize [45] the understanding of learning transfer given the emerging possibilities of user modeling and learning analytics from the current standard of *reported* learning transfer towards *observed* learning transfer.

Yelon & Ford [173] offer a key distinction in transfer that differentiates *open* and *closed* skills. Open skill training programs include "leadership and interpersonal skills training," and typical closed skill trainings include "various technical training and computer software training." This emerges as an important distinction. In a study in which Blume et al. [19] found post-training knowledge (PTK) and post-training self-efficacy (PTSE) to have similar correlations with learning transfer, PTK and PTSE for closed skills resulted in lower correlation coefficients than for open skills. Independent of performance, self-efficacy is a person's self-reported ability to successfully complete a future task [12]. Knowledge is measured as a result of a task—answering a quiz question correctly indicates possession of that knowledge [19].

Regarding the maintenance and persistence of learning transfer over time, Blume et al. [19] analyzed how the *amount of time* (the "lag") between the end of training and the beginning of the transfer study affects learning transfer. They found that in studies with at least some lag time between training and testing, learners exhibited significantly lower post-training knowledge and post-training self-efficacy than those that tested students immediately following training.

In their survey of training professionals from 150 organizations, [138] report that 62% of employees in their organization *"effectively apply what they learned in training"* to their job immediately, 42% after six months, and 34% after one year. Other studies directly survey students in gathering self-reported data about learning transfer [99]. Another manner by which researchers have measured transfer is through assessment questions following instruction that, in order for students to answer correctly, would have to apply what they learned to a new context or problem [101, 2]. The present study examines transfer as a more naturally occurring, un-elicited phenomenon that the learners undertake and exhibit on their own accord.

3.3 FP101x

Introduction to Functional Programming (or short *FP101x*) is a MOOC offered on the `edX` platform. The course introduces learners to various functional programming concepts; all programming is performed in the functional language *Haskell*.

The first iteration of the course ran between October 15, 2014 and December 31, 2014. As is common in MOOCs today, learners were invited to participate in a pre-course and a post-course survey containing questions on the motivation of the learners, the perceived quality of the course, etc. In August 2015 we approached a subset of learners for an additional post-course survey.

The course was set up as an xMOOC [134]: lecture videos were distributed throughout the 8 teaching weeks. Apart from lectures each week, exercises ("homeworks" and "labs") were distributed in the form of multiple choice (MC) questions. While homework questions evaluated learners on their understanding of high-level concepts and code snippets (e.g., *"What is the result of executing [...]?"*), labs required learners to implement programs themselves. To enable fully automatic evaluations, all lab work was also assessed through MC questions. Each of the 288 MC questions was worth 1 point & could be attempted once. Answers were due 2 weeks after the release of the assignment. To pass the course, $\geq 60\%$ of all MC questions had to be answered correctly.

Overall, 37,485 users registered for the course. Fewer than half (41%) engaged with the course, watching at least one lecture video. The completion rate was 5.25%, in line with similar MOOC offerings [95]. Over 75% of the learners were male and more than 60% had at least a Bachelors degree.

3.4 Methodology

We first outline and justify the seven research hypotheses upon which we ground our work. Next, we describe in detail how to verify them empirically based on course questionnaire data, `edX` logs and `GitHub` data traces.

3.4.1 Research Hypotheses

Based on prior work we can make the following hypothesis associated with **RQ 2.1**:

H1 *Only a small fraction of engaged learners is likely to exhibit learning transfer.*
While previous works, e.g. [138], note transfer rates of up to 60%, we hypothesize our rate to be much lower, due to the natural setting we investigate, the difficulty of the topic (closed skills) and the generally low retention rate of MOOCs.

A large part of existing literature has focused on the different dimensions of a learner that may be indicative of a high or low transfer rate. Thus, the following research hypotheses are all related to **RQ 2.2**, which focuses on the *type* of learner exhibiting transfer.

H2 *Intrinsically motivated learners with mastery goals are more likely to exhibit learning transfer than extrinsically motivated learners.*

[129] found that, in academic settings, mastery goals are more consistently linked to transfer success than performance goals. This was measured by instructors guiding students through either mastery- or performance-oriented experimental conditions and comparing their assessment scores. In line with intrinsic motivation, mastery goals are characterized by a learner's intention to understand and develop new knowledge and abilities. Performance goals, extrinsically motivated, are those sought after in order to obtain positive judgements from others [43].

H3 *Learners expressing high self-efficacy are more likely to actively apply their trained tasks in new contexts.*
In other words, in both academic and professional settings, if you believe that you are able to do something, you are more likely to try it [56, 73, 78, 129].

H4 *Experienced learners (high ability levels) are more likely to transfer trained skills and knowledge in order to maintain and improve performance levels* [56].

H5 *Learners reporting a high personal capacity (time, energy and mental space) for transfer are more likely to actually exhibit learning transfer* [78].

H6 *Learners exhibiting a high-spacing learning routine are more likely to exhibit learning transfer than learners with a low-spacing learning routine.*

Here, high-spacing refers to a larger number of discrete learning sessions than low-spacing with few learning sessions each lasting a long time (i.e. "cramming") [111, 49, 17].

Finally, for **RQ 2.3** we investigate the following hypothesis:

H7 *The amount of exhibited transfer decreases over time* [138].

3.4.2 From Hypotheses To Measurements

Table 3.1 shows an overview of the data sources used to investigate each research hypothesis.

	Pre CS	Post CS	edX Logs	GitHub Logs
H1			✓	✓
H2	✓	✓		✓
H3		✓		✓
H4	✓			✓
H5		✓		✓
H6			✓	✓
H7				✓

Table 3.1: Overview of the different data sources used to investigate each research hypothesis. *CS* refers to the conducted Course Surveys (before and after the course).

To explore **H1** we relate learners' performance during the course (as found in the `edX` logs) to their development activities on `GitHub`.

To determine the impact of learners' motivation on learning transfer (**H2**), we distinguish learners based on their answers to several pre/post-course survey questions we manually established as being motivation-related. To determine *intrinsic motivation* we identified six question-answer pairs including the following two[3]:

- What describes your interest for registering for this course?; Answer: My curiosity (in the topic) was the reason for me to sign up for this course [Pre CS, 5-point Likert]

[3]Due to space constraints, only a subset of the identified question/answer pairs are shown.

- Express your level of agreement with the following statement.; Answer: Course activities piqued my curiosity. [Post CS, 5-point Likert]

Similarly, for *extrinsic motivation* we determined nine appropriate question-answer pairs, including:

- What describes your interest for registering for this course? Choose the one that applies to you the most; Answer: My current occupation motivated me to enroll in the course. [Pre CS, 5-point Likert]
- Considering your experience in this, how much do you agree with the following statement?; Answer: The course was compulsory for me [Post CS, Multiple choice]

Learners' belief in their ability to complete a task (**H3**), can be inferred based on a question asking the learners to express their level of agreement with a set of statements from the validated General Self-Efficacy Scale [29]:

- I can describe ways to test and apply the knowledge created in this course. [Post CS, 5-point Likert]
- I have developed solutions to course problems that can be applied in practice. [Post CS, 5-point Likert]
- I can apply the knowledge created in the course to my work or other non-class related activities. [Post CS, 5-point Likert]

The prior expertise of learners (**H4**) can both be inferred from survey questions as well as from the `GitHub` logs. The questions utilized are:

- Is your educational background related to (Functional) Programming? [Pre CS, 5-point Likert]
- Do you have professional experience in this field? [Pre CS, 5-point Likert]

The personal capacity (**H5**) of a learner is inferred based on two questions:

- Did any of the following negatively affect your participation in the course? [Post CS, 5-point Likert]
- Considering your experience in this course, how much did each of the technical issues affect your participation? [Post CS, 5-point Likert]

Responses to these questions allow learners to share which factors inhibited and distracted them from engaging with the course. Examples of responses to these questions range from personal problems, such as family obligations and medical issues, to technical trouble, such as slow Internet or hardware problems.

H6 considers the manner in which learners learn and can be inferred solely based on `edX` log traces which will be explained in more detail in the section below. Finally, **H7**, the extent to which functional programming is employed and applied by the learners over time can be inferred from `GitHub` logs alone.

`edX` Logs

For each learner, we collect all available traces (between October 1 and December 31, 2014), such as the learner's clicks & views, provided answers to MC questions as well as forum interactions. Using the `MOOCdb` toolkit[4] we translate these low-level log traces into a data schema that is easily queryable.

To investigate **H6**, for each learner the learning routine is determined based on their `edX` logs. We partition the learners into low-spacing and high-spacing types following [111]. Initially, all learners are sorted in ascending order according to their total time on-site. Subsequently they are binned into ten equally-sized groups. Within each group, the learners are sorted according to the number of distinct sessions on the site and based on this ordering divided into two equally-sized subgroups: learners with few sessions (low-spacing) and learners with many sessions (high-spacing). In this manner, learners spending similar amounts of time (in total) on the course site can be compared with each other.

GitHub Logs

We identify `edX` learners on `GitHub` through the email identifiers attached to each `edX` and `GitHub` account. A third of all learners that registered to *FP101x* are also active on GitHub: 12,415 learners in total[5]. This is likely to be an underestimate of the true number of `GitHub` users (people generally have multiple email accounts), as we did not attempt to match accounts based on additional user profile information.

`GitHub` provides extensive access to data traces associated with *public* coding repositories, i.e. repositories visible to everyone[6]. `GitHub` is built

[4] http://moocdb.csail.mit.edu/

[5] Note that the number is different from the one (16,220) we presented in Table 2.1 in Chapter 2. This is because: (i) we only consider learners registered before the end of the MOOC; (ii) Chapter 2 used *GitHub Archive* to match learners and we use *GHTorrent* here as it provides a more fine-grained record about users' coding traces.

[6] Data traces about private repositories are only available to the respective repository owner.

around the `git` distributed revision control system, which enables efficient distributed and collaborative code development. `GitHub` not only provides relevant repository metadata (including information on how popular a repository is, how many developers collaborate, etc.), but also the actual code that was altered. As the *GitHub Archive*[7] makes all historic `GitHub` data traces easily accessible, we relied on it for data collection and extracted all `GitHub` data traces available between January 1, 2013 and July 21, 2015. We then filtered out all traces that were *not* created by our `edX` learners, leaving us with traces from 10,944 learners. Of the more than 20 `GitHub` *event types*[8], we only consider the `PushEvent` as vital for our analysis.

```
{
  "_id" : ObjectId("55b6005de4b07ff432432dfe1"),
  "created_at" : "2013-03-03T18:36:09-08:00",
  "url" : "https://github.com/john/
           RMS/compare/1c55c4cb04...420e112334",
  "actor" : "john",
  "actor_attributes" : {
        "name" : "John Doe",
        "email" : "john@doe.com"
  },
  "repository" : {
        "id" : 2.37202e+06,
        "name" : "RMS",
        "forks" : 0,
        "open_issues" : 0,
        "created_at" : "2011-09-12T08:28:27-07:00",
        "master_branch" : "master"
    }
}
```

Figure 3.1: Excerpt of a `GitHub` PushEvent log trace.

Every time code is being updated ("pushed" to a repository), a `PushEvent` is triggered. Figure 3.1 contains an excerpt of the data contained in each `PushEvent`. The most important attributes of the event are the `created_at` timestamp (which allows us to classify events as before/during/after the running of *FP101x*), the `actor` (the user doing the "push") and the `url`, which contains the URL to the actual *diff file*. While the `git` protocol also allows a user to "push" changes by another user to a repository (which is not evident from inspecting the *diff file* alone), this is a rare occurrence among our learners: manually inspecting a random sample of 200 `PushEvents` showed 10 such cases. A *diff file* shows the difference between the last version of the repository and the new one (after the push) in terms of added and deleted code. An example excerpt is shown in Figure 3.2. For each of the identified 1,185,549 `PushEvents` by our learners, we crawled the corresponding *diff*

[7] https://www.githubarchive.org/
[8] https://developer.github.com/v3/activity/events/types/

file, as they allow us to conduct a fine-grained code analysis. As a first step, we identified the additions and deletions a user conducts in each programming language based on the filename extensions found in the corresponding *diff file*. We consider code updates in the following nine functional languages as clear evidence for functional programming: *Common Lisp, Scheme, Clojure, Racket, Erlang, Ocaml, Haskell, F#* and *Scala*. We also log changes made in any of the other 20 most popular programming languages found on `GitHub` in the same manner. Any filename extension not recognized is first checked against a blacklist (which includes common filename extensions for images, compressed archives, audio files, etc.) and if not found, the change is classified as *Other*.

```
diff --git a/viewsA.rb b/viewsA.rb
index e37bca1..3ad75e4 100644
--- a/viewsA.rb
+++ b/viewsA.rb
@@ -26,6 +26,16 @@ def new
@shift = Shift.new
end
...
diff --git a/config/routes.rb b/config/routes.rb
index e576929..27ce68f 100644
--- a/config/routes.rb
+++ b/config/routes.rb
@@ -29,6 +29,7 @@
put 'secondary'
...
```

Figure 3.2: Excerpt of a *diff file*. Two files were changed (*viewsA.rb* and *routes.rb*). The extension `*.rb` indicates code written in Ruby.

3.5 Results

We first present some basic characteristics of *FP101x*, before delving into the analyses of our research questions and hypotheses.

3.5.1 FP101x Overview

We partition our set of all *registered FP101x* learners according to two dimensions: (i) learners with and without a `GitHub` account, and (ii) learners with and without prior expertise in functional programming. In the latter case, we consider only those learners that could be identified on `GitHub`. We define **Expert learners** as those who used any of our nine identified functional programming languages before the start of the course to a meaningful degree

(i.e. more than 25 lines of functional code being added). The characteristics of these learner cohorts are listed in Tables 3.2 and 3.3.

When considering the `GitHub` vs. non-`GitHub` learners, we observe significant differences along the dimensions of engagement and knowledge:

- `GitHub` learners are on average **more engaged** with the course material (significantly more time spent on watching lecture videos and significantly more questions attempted).
- `GitHub` learners exhibit **higher levels of knowledge** (significantly more questions answered correctly).

Zooming in on the `GitHub` learners and their functional programming expertise, we find the differences to be enlarged: Expert learners have a higher completion rate (more than double that of non-Expert learners), attempt to solve significantly more problems and are significantly more accurate in answering. Experts are also more engaged in terms of forum usage - 8% post at least once compared to 4% of the non-Expert learners.

Finally, we note that we repeated this analysis on the subset of *engaged* learners only, where we consider all learners that attempted to solve at least one MC question or watched at least one video. While the absolute numbers vary, the trends we observe for the different partitions of learners in Tables 3.2 and 3.3 remain exactly the same.

3.5.2 Learning Transfer

Let us first consider the general uptake of functional programming languages. We can split each learner's `GitHub` traces into three distinct sequences according to their timestamp: traces generated *before*, *during* and *after FP101x*. We are interested in comparing the before & after and will mostly ignore the activities generated during *FP101x*.

Expert Learners.

Overall, 1,721 of all `GitHub` learners have prior functional programming experience (our **Expert learners**). 1,165 of those are also *engaged* with *FP101x* (the remainder registered, but did not engage), leading to nearly a third (29.4%) of all engaged `GitHub` learners having pre-*FP101x* functional programming experience.

Most of our `GitHub` learners though are not continuously coding functionally: Figure 3.3 shows for each month of `GitHub` logs (January 2013 to

	All Learners	GH Learners	Non-GH Learners
#Enrolled learners	37,485	12,415	25,070
Completion rate	5.25%	7.71%	4.03%
%Learners who watched at least one video	40.84%	50.58%	36.02%
Avg. time watching video material (in min.) †	31.87	44.56	25.59
%Learners who tried at least one question	23.28%	31.94%	18.99%
Avg. #questions learners attempted to solve †	22.07	31.29	17.51
Avg. #questions answered correctly †	18.30	26.54	14.22
Avg. accuracy of learners' answers †	16.36%	23.41%	12.86%
#Forum posts	8,157	3,726	4,431
%Learners who posted at least once	2.84%	4.27%	2.13%
Avg. #posts per learner †	0.22	0.30	0.18

Table 3.2: Basic characteristics across all learners and their partitioning into GitHub (GH) and non-GitHub learners. Significant differences (according to Mann-Whitney) between GH and non-GH learners are marked with †($p < 0.001$).

July 2015) the *unique* number of `GitHub` learners programming functionally - while in 2013 less than 250 of our `GitHub` learners were active per month, by 2015 this number has increased to nearly unique 600 active users a month. Thus, the trend to functional programming is generally increasing. Most learners though are not actively using functional languages on a monthly basis.

How much functional code do our engaged Expert learners produce over time? An answer to this question delivers Figure 3.4: here, for each month, the functional coding activities (calculated as the additions made in functional languages as a fraction of all additions made in recognized programming languages) are averaged across all engaged Expert learners. Again we observe that over the years functional programming has become more popular. By September 2014 (right before the start of *FP101x*), on average more than 36% of coding activities are functional. What is surprising (and somewhat counter-intuitive) is the steady decline of functional activities af-

	Expert Learners	Non-Expert Learners
#Enrolled learners	1,721	10,694
Completion rate	15.05%	6.53%
%Learners who watched at least one video	64.44%	48.35%
Avg. time watching video material (in min.) †	69.61	40.53
%Learners who tried at least one question	48.69%	29.24%
Avg. #questions learners attempted to solve †	57.86	27.02
Avg. #questions answered correctly †	50.24	22.73
Avg. accuracy of learners' answers †	37.96%	21.06%
#Forum posts	1,612	2,114
%Learners who posted at least once ‡	7.55%	3.74%
Avg. #posts per learners	0.94	0.20

Table 3.3: Basic characteristics when partitioning the GitHub learners according to prior functional programming expertise. Significant differences (according to Mann-Whitney) between Expert and Non-Expert learners are marked with †($p < 0.001$) and ‡($p < 0.01$).

ter the end of *FP101x*. If we restrict our engaged Expert Learners to those 542 learners with functional traces before *and* after *FP101x* (Figure 3.5), the results are more in line with our expectations: functional programming is continuously gaining in popularity and a peak in activities is observed in the two months following *FP101x*[9]. Thus, 46.5% of engaged Expert learners did continue to program functionally after the end of *FP101x*.

Novice Learners.

Most interesting to use are the **Novice Learners**: to what extent do learners that did not program (meaningfully) in functional languages before *FP101x* take it up afterwards? We find 522 such learners — 4.3% of all `GitHub` learners. If we restrict ourselves to engaged `GitHub` learners, we are left with 336 Novice learners (8.5% of all engaged `GitHub` learners). Fig-

[9]The drop in July 2015 is explained by the non-complete log coverage of July (the log ends on July 21, 2015).

ure 3.6 shows the evolution of their functional programming usage over time: the uptake after the end of *FP101x* is substantial, on average more than 35% of all activities are conducted subsequently in functional languages! While there is no substantial increase after the initial uptake over time, there is also no significant drop. Since the average can only provide limited insights, we drill down to the individual user level in Figure 3.7: the usage of functional programming is highly varied; 50% of the Novice Learners use it for less than 10% of their programming activities, while some learners almost exclusively code in functional languages. Finally, we also consider which functional languages these Novice learners code in. Figure 3.8 shows that a month after *FP101x* ended (January 2015), Haskell contributions made up 48% of all contributions, but continued dropping to a low of 14.5% in June 2015. Scala on the other hand (the most popular functional language in industrial settings) slowly rises in popularity over time and by June 2015 makes up roughly half of the functional contributions. Other functional languages play less of a role. Conducting a similar analysis on our engaged Expert learners (not shown here), we find that on average across all months, 47% ($\sigma = 7.4$) of all functional activities are in Scala, whereas 24.0% ($\sigma = 5.5$) are in Haskell. The distribution of functional languages is stable over time. The only outliers can be found in the three months of *FP101x*, where Haskell contributions rise significantly.

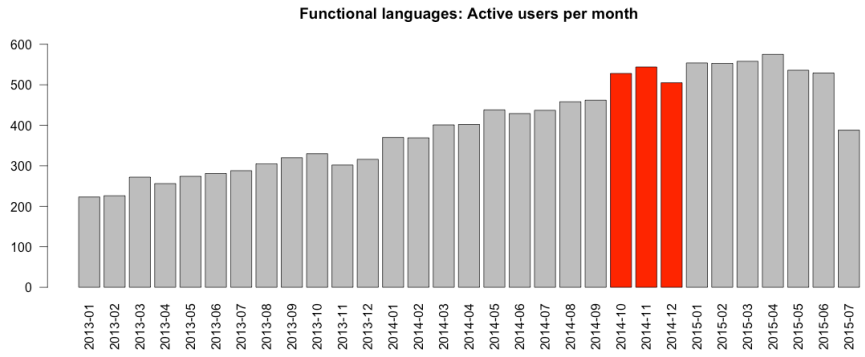


Figure 3.3: Number of unique users actively using a functional language. *FP101x* ran during the highlighted region.

Transfer Learning Hypotheses

On which learners should (or can) we investigate our seven research hypotheses? Ideally, we rely on all learners that engaged with the course and for whom `GitHub` traces are available. However, for Expert learners we are unable to determine the amount of transfer: since our analysis of functional

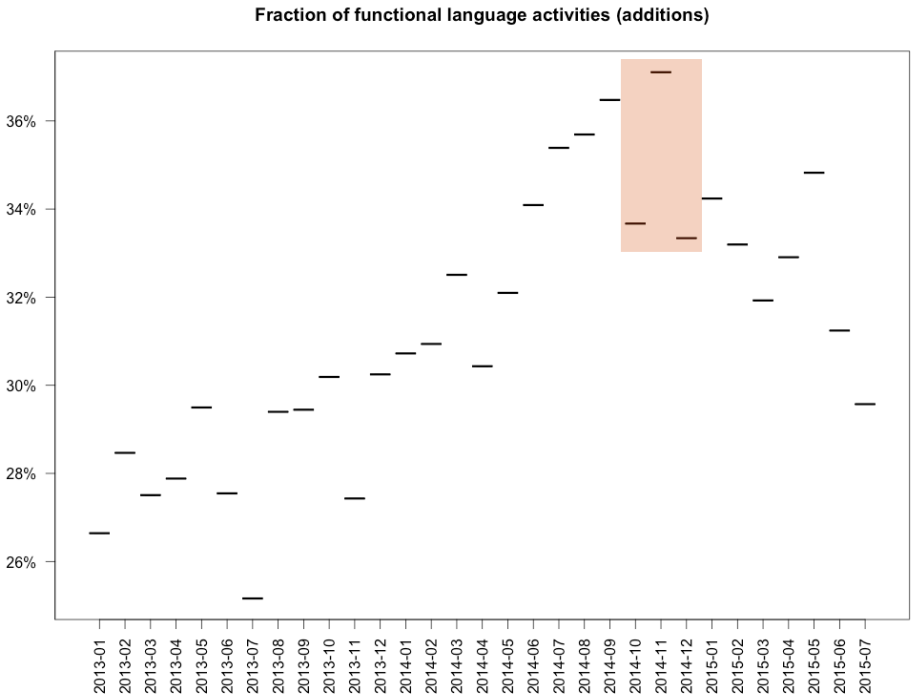


Figure 3.4: Fraction of functional programming activities among the 1,165 engaged Expert Learners. *FP101x* ran during the highlighted region.

coding is based on activities in functional languages (instead of a more fine-grained analysis of the type of functional concepts employed), we are not able to determine whether learners that programmed functionally before acquired knowledge in *FP101x* and applied it in practice (a direction of future work). Only for the engaged Novice learners can we be confident that *FP101x* actually impacted their programming practice and that the observed transfer is likely a result of *FP101x*.

Considering **H1**, we observe a **transfer rate of at least 8.5%** (i.e. among the 3,965 engaged `GitHub` learners we found 336 Novice learners that began programming functionally after *FP101x*). This percentage can be considered as a lower bound, as we (due to the reasons listed above) do not consider engaged Expert learners here. Only a minority (70) of the 336 engaged Novice learners did pass *FP101x*, indicating that transfer and pass rate are related but not synonymous. In fact, while the 70 Novice learners that successfully completed the course remained mostly active until the final

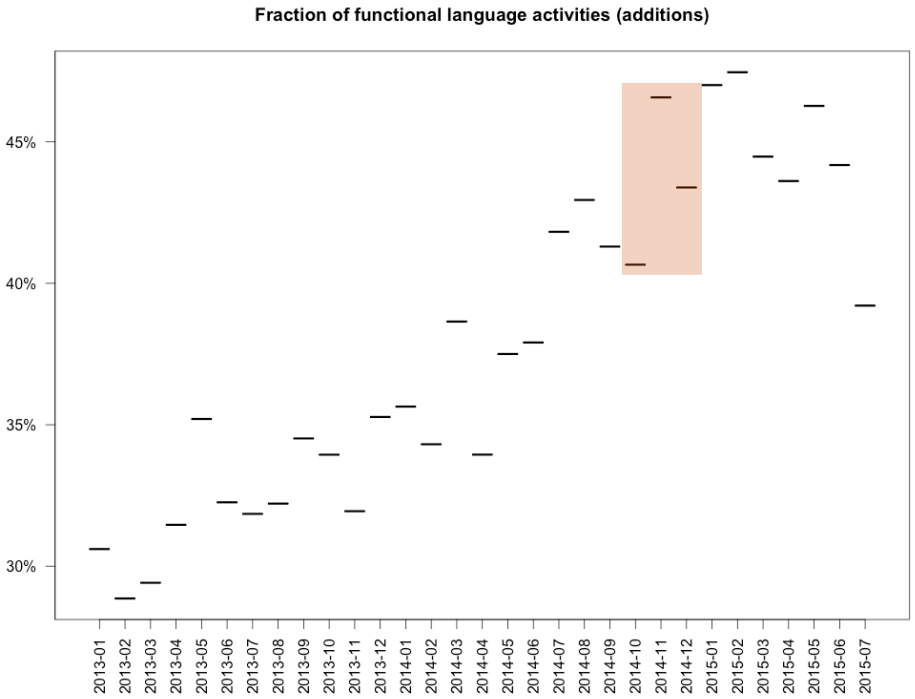


Figure 3.5: Fraction of functional programming activities among the 542 engaged Expert Learners with functional activities before & after *FP101x*. *FP101x* ran during the highlighted region.

course week (Figure 3.9), nearly 40% of all engaged Novice learners became inactive after week 1.

To investigate **H2, H3, H4, H5** and **H6**, for each hypothesis, we partition our 336 engaged Novice Learners who made the transfer according to the investigated dimensions (e.g. intrinsic vs. extrinsic motivation). Recall that the partitioning of the learners relies on their self-reported abilities in the pre- and post-course surveys. Similar to the retention rate, the return rate for such questionnaires is very low and many learners do not participate in these surveys for a variety of reasons. Table 3.4 shows the partitioning of our engaged Novice learners based on their survey data. The majority of learners cannot be assigned to a dimension due to a lack of data. Despite the low numbers, we do observe that the transfer learning hypotheses seem to hold in *FP101x* (for those learners for which it is possible to measure their effect): learners are more likely to make the transfer if (i) they are intrinsically motivated, (ii) have high self-efficacy, (iii) are more experienced programmers, and (iv) report a high personal capacity. Even though the number of learners

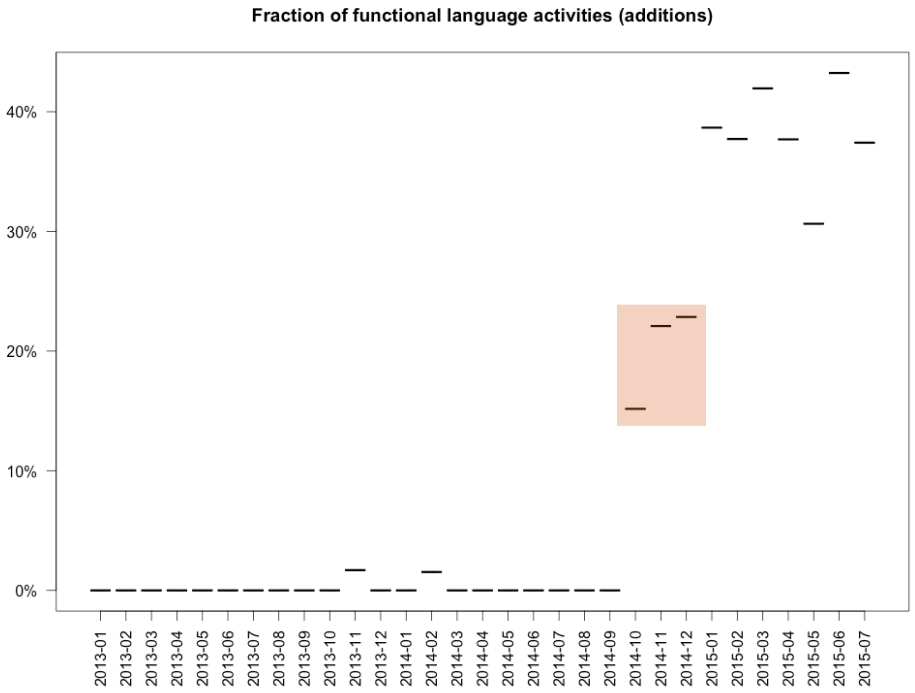


Figure 3.6: Fraction of functional programming activities among the 336 engaged Novice Learners with functional activities after *FP101x*. *FP101x* ran during the highlighted region.

we were able to investigate are small, we consider this as first evidence that transfer learning hypotheses also hold in the MOOC setting.

	Dimensions		**N/A**
H2 Motivation	Extr.: 12	Intr.: 28	296
H3 Self-efficacy	High: 23	Low: 5	308
H4 Experience	A lot: 42	Little: 25	269
H5 Personal capacity	High: 22	Low: 10	304

Table 3.4: Partitioning of the 336 Novice learners according to several dimensions. The last column shows the number of learners that could not be assigned (N/A) to a dimension.

To answer **H6** (high-spaced learners are more likely to transfer), we binned all `GitHub` learners according to their total time and number of distinct sessions in the *FP101x* `edX` environment, as outlined earlier. This creates 10 groups, with learners in *Group 0* spending the least amount of time

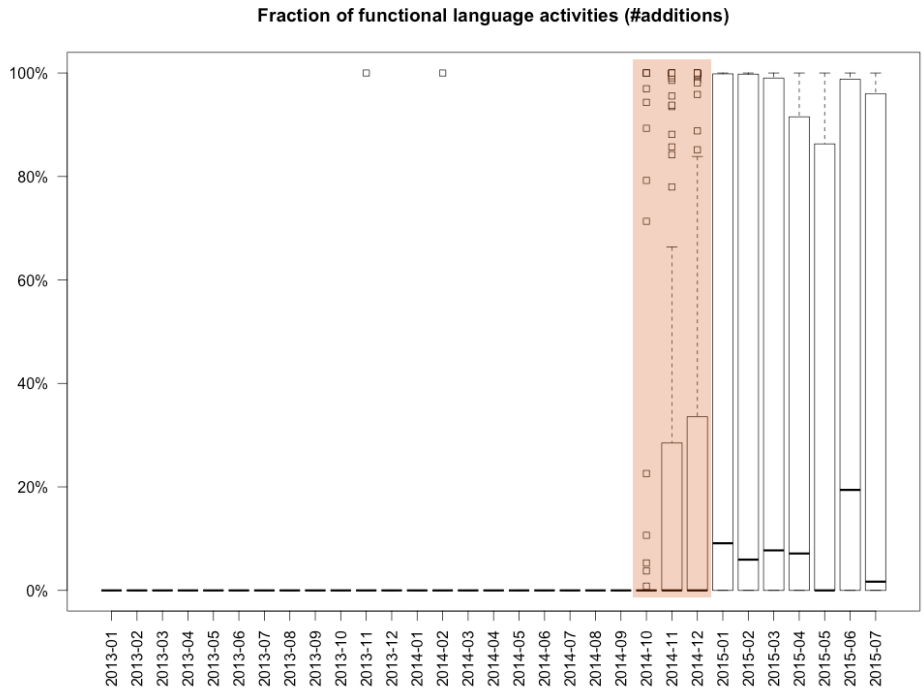


Figure 3.7: Distribution of functional programming activities among the 336 engaged Novice Learners with functional activities after *FP101x*. *FP101x* ran during the highlighted region.

Groups	Low spacing	High spacing
0	2	2
1	9	9
2	6	16
3	10	20
4	21	21
5	19	16
6	19	22
7	20	22
8	16	29
9	27	30

Table 3.5: The number of Novice Learners falling into spacing groups.

and learners in *Group 9* spending the most amount of time on the course site. Thus, each group contains those learners that roughly spent the same

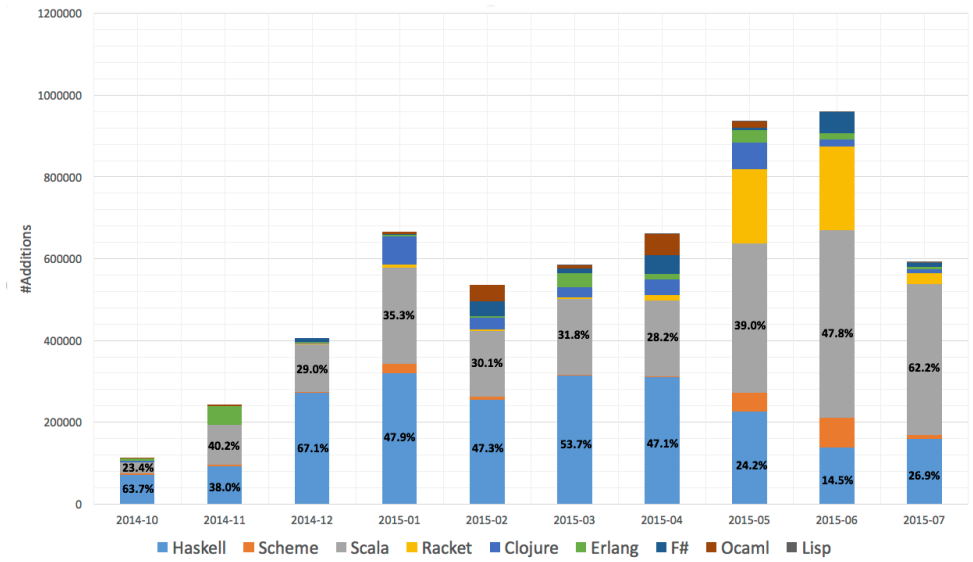


Figure 3.8: Functional languages used by the 336 engaged Novice Learners during and after *FP101x*. Best viewed in color.

amount of time on the site. Further, within each group, learners are divided according to the number of distinct sessions. In Table 3.5 we report how many engaged Novice learners fell into each group and which part of the group — the high-spacing or the low-spacing one. While 187 engaged Novice learners are classified as high-spacing, 149 are classified as low-spacing. Thus, there is some indication that **H6** holds. However, the observed difference is rather small.

To conclude this section, we lastly consider **H7**. In contrast to the hypothesis (transfer decreases over time), we neither observe a significant decrease nor increase after the initial uptake as evident in Figures 3.6 and 3.7.

3.5.3 A Qualitative Analysis

We have found similarities and differences between transfer in classroom learning and our MOOC. Instead of speculating about the reasons for these differences, we designed a follow-up survey (containing 10 questions about learners' functional programming experiences before and after *FP101x*) and distributed it to subsets of `GitHub` learners in August 2015[10]. A second purpose of this questionnaire is to verify whether `GitHub` logs offer a good

[10] All contacted learners had consented to additional contact.

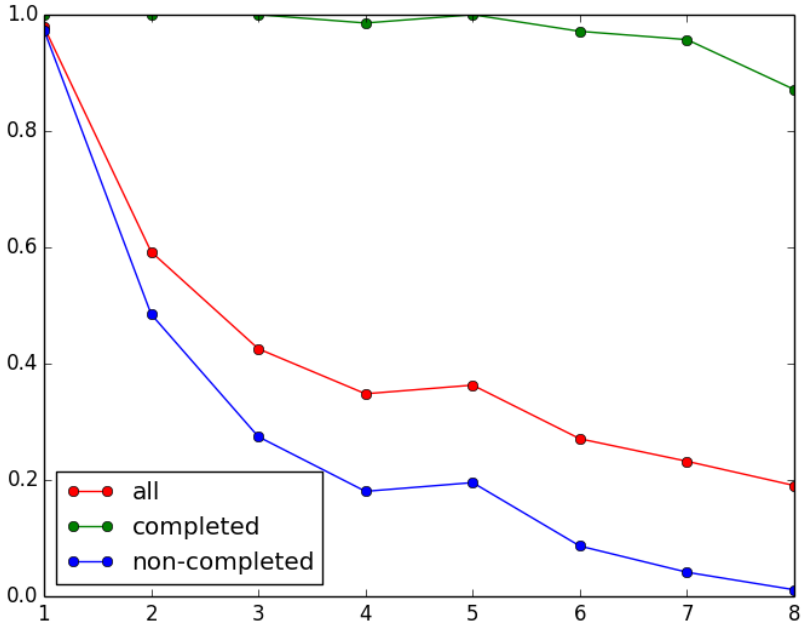


Figure 3.9: Fraction of the 336 engaged Novice learners remaining active in each course week. 70 Novice learners completed *FP101x* successfully, 266 did not complete it.

approximation of our learners' true behaviour. We partitioned the *engaged* `GitHub` learners into eight categories:

A **Novice** learners that **completed** the course but did **not transfer** (i.e. we did not observe functional `GitHub` traces after *FP101x*). #Survey responses: 131 (32% return rate).

B **Expert** learners that **completed** the course but did **not transfer**. #Survey responses: 15 (39%).

C **Novice** learners that **completed** the course and **transferred** (i.e. we observed functional `GitHub` traces after *FP101x*). #Survey responses: 11 (61%).

D **Novice** learners that **did not complete** the course, but **transferred**. #Survey responses: 1 (3%).

E **Expert** learners that **completed** the course and **continued programming functionally** (did they transfer?). #Survey responses: 20 (56%).

F **Expert** learners that did **not complete** the course but did **program functionally** after *FP101x*. #Survey responses: 8 (16%).

G **Novice** learners that were engaged in the course (but not completed) and did **not transfer**. #Survey responses: 93 (6%).

H **Expert** learners that were engaged in the course (but not completed) and did **not transfer**. #Survey responses: 4 (7% return rate).

How accurate are `GitHub` traces as approximation of learners' functional programming activities? Of those learners we had identified as Novices, 63% also self-reported as such. Of the learners we estimated to have some prior functional programming experience, 77% self-reported prior experience. In particular, the latter number is intriguing: based on our stringent methodology, we can be confident that all of our identified Expert learners did indeed functionally program before *FP101x*, though about a quarter self-reports otherwise. Of the learners we identified as having demonstrated learning transfer, 88% also self-reported as doing so. Of those we identified as not having demonstrated learning transfer, only 37% self-reported of not having applied anything they had learnt. An explanation for this discrepancy is based on the non-exclusive use of `GitHub`: while 73% indicated that they use `GitHub` for either work or personal coding projects, 65% use a Private/Employer's repository service, and 39% use BitBucket. While 73% is promising in that it accounts for nearly three quarters of all learners, we could only detect users who use the same email address for both their `edX` and `GitHub` account.

What are the main reasons for learners not to transfer their acquired functional programming skills? 80% of learners reporting a reason for not transferring their acquired skills report a lack of opportunities. Many learners go on to explain that the programming language standards in their work-place do not allow them to practice what they have learned. Another common sentiment is that it is difficult for some experienced programmers to suddenly change their ways. For example, when asked why they did not apply what they learned in *FP101x* to either work or personal projects, one respondent shared, "It takes time and effort to change old programming habits." And another shared a similar sentiment: "[It's] hard to think functionally after 25 years of imperative [programming] experience."

3.6 Conclusion

We have investigated the extent of learning transfer in the MOOC setting and introduced the use of a social-Web based data source (i.e. `GitHub`) to complement the learner traces collected within MOOC environments. Focus-

ing on one-third of *FP101x* learners we were able to link to `GitHub`, we made several important findings:

(1) Most transfer learning findings from the classroom setting translate into the MOOC setup; large discrepancies were only found for **H1**: the amount of observed transfer and **H7**: the development of transfer over time.

(2) The observed transfer rate in MOOCs is low. We found that 8.5% of engaged learners were indeed exhibiting transfer to varying degrees in our `GitHub` traces. We acknowledge that a substantial amount of programming occurs outside of `GitHub` (e.g. in private employer repositories). While the traces we gather offer many new insights by following learners beyond the MOOC platform for an extended period of time, considering one external data source alone is a limiting factor.

(3) The amount of transfer, operationalized as the fraction of functional coding is varying highly: about 50% of the learners transferring code less than 10% of the time functionally, while a small minority almost exclusively turns to functional languages.

(4) After the end of *FP101x*, learners making the transfer quickly identified the most industrially-relevant functional language at this moment (Scala). Over time their activities in Scala increased significantly, while their activities in Haskell (the language of *FP101x*) decreased. Overall though, after the initial uptake of functional programming, the fraction of functional activities (between 35%-40%) of all coding activities remained constant.

The limitations of the current study (only 33% of learners could be coupled to a `GitHub` account and our exploratory analysis has been conducted on the programming language type level) naturally lead to three directions for future work: (i) instead of focusing on the amount of code added per language, a more detailed analysis will determine the particular functional concepts employed and match them with the course material, (ii) programming languages are taught in a variety of MOOCs, it is an open question whether the same methodology is applicable across a variety of courses, and lastly, (iii) we will move beyond the `GitHub` platform and consider alternative external data sources.

Chapter 4

Second Language Acquisition Modeling

In this chapter, we focus on investigating the problem of *knowledge tracing* in the setting of topic-specific MOOC platforms. Knowledge tracing, which uses computational algorithms to model learners' mastery of knowledge being taught over time, is a well-established problem in computer-supported education. However, due to the lack of available datasets, this problem remains largely unexplored in the topic-specific MOOC platforms. With the three large-scale language learning datasets released by `Duolingo` [140], now we can gain a better understanding of learners in the topic-specific MOOC platforms. In particular, we investigate factors that are correlated with learners' performance and then apply a machine learning technique to predict learners' future performance. The contributions of this chapter have been published in [32].

4.1 Introduction

Knowledge tracing plays a crucial role in providing adaptive learning to learners [123]: by estimating a learner's current knowledge state and predicting her performance in future interactions, learners can receive personalized learning materials (e.g. on the topics the learner is estimated to know the least about).

Over the years, various knowledge tracing techniques have been proposed and studied, including Bayesian Knowledge Tracing [40], Performance Factor Analysis [122], Learning Factors Analysis [27] and Deep Knowledge Tracing [125]. Notable is that most of the existing works focus on learning performance within mathematics in elementary school and high school due to the availability of sufficiently large datasets in this domain, e.g. ASSISTment and OLI [125, 168, 175, 86]. The generalization to other learning scenarios and domains remains under-explored.

Particularly, there are few studies attempted to explore knowledge tracing in the setting of Second Language Acquisition (SLA) [15]. Recent studies showed that SLA is becoming increasingly important in people's daily lives and should gain more research attention to facilitate their learning process [97]. It remains an open question whether the existing knowledge tracing techniques can be directly applied to SLA modeling—the release of the Duolingo challenge datasets now enables us to investigate this very question.

Thus, our work is guided by the following research question: **RQ 3.1 What factors are correlated with learners' language learning performance?**

To answer the question, we first formulate six research hypotheses which are built on previous studies in SLA. We perform extensive analyses on the three SLA Duolingo datasets [140] to determine to what extent they hold. Subsequently, we engineer a set of 23 features informed by the analyses and use them as input for a state-of-the-art machine learning model, *Gradient Tree Boosting* [172, 34], to estimate the likelihood of whether a learner will correctly solve an exercise.

We contribute the following major findings: (i) learners who are heavily engaged with the learning platform are more likely to solve words correctly; (ii) contextual factors like the device being used and learning format are correlated with learners' performance considerably; (iii) repetitive practice is a necessary step for learners towards mastery; (iv) Gradient Tree Boosting

is demonstrated to be an effective method for predicting learners' future performance in SLA.

4.2 Data Analysis

Before describing the six hypotheses we ground our work in as well as their empirical validation, we first introduce the Duolingo datasets.

4.2.1 Data Description

To advance knowledge modeling in SLA, Duolingo released three datasets[1], collected from learners of English who already speak Spanish (EN-ES), learners of Spanish who already speak English (ES-EN), and learners of French who already speak English (FR-EN), respectively, over their first 30 days of language learning on the Duolingo platform [140]. The task is to predict what mistakes a learner will make in the future. Table 4.1 shows basic statistics about each dataset. Interesting are in particular the last two rows of the table which indicate the unbalanced nature of the data: across all languages correctly solving an exercise is far more likely than incorrectly solving it. Note that the datasets contain rich information not only on learners, words and exercises[2] but also on learners' learning process, e.g., the amount of time a learner required to solve an exercise, the device being used to access the learning platform and the countries from which a learner accessed the Duolingo platform.

	FR-EN	**ES-EN**	**EN-ES**
#Unique learners	1,213	2,643	2,593
#Unique words	2,178	2,915	2,226
#Exercises	326,792	731,896	824,012
#Words in all exercises	926,657	1,973,558	2,622,958
#Avg. words / exercise	2.84	2.7	3.18
%Correctly solved words	84%	86%	87%
%Incorrectly solved words	16%	14%	13%

Table 4.1: Statistics of the datasets.

[1] http://sharedtask.duolingo.com/#task-definition-data
[2] An exercise usually contains multiple words.

In our work, we use *learning session* to denote the period from a learner's login to the platform until the time she leaves the platform. We use *learning type* to refer to the "session" information in the original released datasets, whose value can be *lesson*, *practice* or *test*.

4.2.2 Research Hypotheses

Grounded in prior works we explore the following hypotheses:

H1 A learner's *living community* correlates with her language acquisition performance.
Previous works, e.g., [48] demonstrated that the surrounding living community is a non-negligible factor in SLA. For instance, a learner learning English whilst living in an English-speaking country is more likely to practice more often and thus more likely to achieve a higher learning gain than a learner not living in one.

H2 The more *engaged* a learner is, the more words she can master.
Educational studies, e.g., [24], have shown that a learner's engagement can be regarded as a useful indicator to predict her learning gain, which is the number of mastered words in our case.

H3 The *more time* a learner spends on *solving an exercise*, the more likely she will get it wrong.

H4 *Contextual factors* such as the device being used (e.g. iOS or Android), learning type (lesson, practice or test) and exercise format (such as transcribing an utterance from scratch or formulating an answer by selecting from a set of candidate words) are correlated with a learner's mastery of a word.
We hypothesize that, under specific contexts, a learner can achieve a higher learning gain due to the different difficulty level of exercises. For instance, compared to transcribing an utterance from scratch, a learner is likely to solve more exercises correctly when being provided with a small set of candidate words.

H5 *Repetition* is useful and necessary for a learner to master a word [174, 62, 98].

H6 Learners with a high-spacing learning routine are more likely to learn more words than those with a low-spacing learning routine.
Here, high-spacing refers to a larger number of discrete learning sessions. Correspondingly, low-spacing refers to relatively few learning sessions, which

usually last a relatively long time. In other words, learners with a low-spacing routine tend to acquire words in a "cramming" manner [111, 49, 17].

4.2.3 Performance Metrics

We now define four metrics we use to measure a learner's exercise performance.

Learner-level Accuracy (Lear-Acc) measures the overall accuracy of a learner across all completed exercises. It is calculated as the ratio between the number of words correctly solved by a learner and the total number of words she attempted.

Exercise-level Accuracy (Exer-Acc) measures to what extent a learner answers a particular exercise correctly. It is computed as the number of correctly solved words divided by the total number of words in the exercise.

Word-level Accuracy (Word-Acc) measures the percentage of times of a word being answered correctly by learners. For a word, it is calculated as the number of times learners provided correct answers divided by the total number of attempts.

Mastered Words (Mast-Word) measures how many words have been mastered by a learner. As suggested in [174], it takes about 17 exposures for a learner to learn a new word. Thus, we define a word being mastered by a learner only if (i) it has been exposed to the learner at least 17 times and (ii) the learner answered the word accurately in the remaining exposures.

4.2.4 From Hypotheses To Validation

To verify **H1**, we use the location (country) from where a learner accessed the Duolingo platform as an indicator of the learner' living community. We first bin learners into groups according to their locations. Next, we calculate the average learner-level accuracy and the number of mastered words of learners in each group. We report the results in Table 4.2. Here we only consider locations with more than 50 learners. If a learner accessed the platform from more than one location, the learner would be assigned to all of the identified location groups. In contrast to our hypothesis, we do not observe the anticipated relationship between living community and language learning (e.g. Spanish-speaking English-learners living in the US do not perform better than other learners).

Datasets	Locations	Lear-Acc	Mast-Word
FR-EN	Avg.	83.57	3.37
	CA	84.12	3.13
	US	83.01	3.40
	GB	83.66	3.46
	AU	85.69	3.70
ES-EN	Avg.	85.91	2.74
	CA	84.89	3.26
	US	86.22	2.58
	AU	85.82	3.50
	GB	83.94 *	3.30
	NL	87.15	2.86
EN-ES	Avg.	87.62	4.39
	CO	87.49	4.14
	US	87.98	5.02
	ES	87.85	5.66 *
	MX	86.92 *	3.71 *
	CL	88.95	4.42
	DO	87.26	4.40
	AR	89.58	4.75
	VE	89.47 *	4.99
	PE	88.83	4.37

Table 4.2: Avg. learner-level accuracy (%) and the number of mastered words of learners living in different locations (approximated by the countries from which learners have finished the exercises). Significant differences (compared to *Avg.*, according to Mann-Whitney) are marked with $*$ ($p < 0.001$).

	Lear-Acc			Mast-Word		
	FR-EN	**ES-EN**	**EN-ES**	**FR-EN**	**ES-EN**	**EN-ES**
# Exercises Attempted	-0.05 *	-0.09 *	-0.08 *	0.85 *	0.87 *	0.79 *
# Words Attempted	-0.06 *	-0.08 *	-0.08 *	0.85 *	0.86 *	0.80 *
Time Spent	-0.13 *	-0.14 *	-0.22 *	0.73 *	0.79 *	0.61 *

Table 4.3: Pearson Correlation between learner engagement (measured by # attempted exercises/words and the amount of time spent in learning) and learner-level accuracy as well as # mastered words. Significant differences are marked with $*$ ($p < 0.001$).

For **H2** (learner engagement), we consider three ways to measure engagement with the platform: (i) number of attempted exercises, (ii) number of

attempted words and (iii) amount of time spent learning. To quantify the relationship between learners' engagement and their learning gain, we report the Pearson correlation coefficient between the three engagement metrics and Lear-Acc as well as Mast-Word (Table 4.3). We note a consistent negative correlation between accuracy and our engagement metrics. This is not surprising, as more engagement also means more exposure to novel vocabulary items. When examining the number of mastered words, we can conclude that—as stated in **H2**—higher engagement does indeed lead to a higher learning gain. This motivates us to design engagement related features for knowledge tracing models.

	FR-EN	**ES-EN**	**EN-ES**
Correlation	-0.16 *	-0.18 *	-0.18 *

Table 4.4: Pearson Correlation between the amount of time spent in solving each exercise and exercise-level accuracy. Significant differences are marked with $*$ ($p < 0.001$).

To determine the validity of **H3**, in Table 4.4 we report the Pearson correlation coefficient between the amount of time spent in solving each exercise and the corresponding exercise-level accuracy. The moderate negative correlation values indicate that the hypothesis holds to some extent.

For **H4**, we investigate three types of contextual factors: (i) device used (i.e., Web, iOS, Android); (ii) learning type (i.e., Lesson, Practice, Test) and (iii) exercise format (i.e., Reverse Translate, Listen, Reverse Tap). To verify whether these contextual factors are correlated with learners' exercise performance, we partition exercises into different groups according to the contextual condition in which they were completed and calculate the average of their exercise-level accuracy within each group. Table 4.5 shows the results. Interestingly, learners with *iOS* devices perform better than those using *Web* or *Android*. Learners' learning accuracy is highest in the *Lesson* type. Learning formats are also likely to have a positive effect: *Reverse Tap* achieves the highest accuracy followed by *Reverse Translate* and then *Listen*. This result is not surprising as active recall of words is more difficult than recognition. Finally, we note for English learners who speak Spanish (EN-ES) and Spanish learners who speak English (ES-EN), the accuracy of *Reverse Translate* is considerably higher than *Listen*, which is not the case in FR-EN (where both are comparable). These results suggest that contextual factors should be taken into account in SLA modeling.

	FR-EN	ES-EN	EN-ES
Avg.	84.29	86.31	87.96
Client			
Web	80.64 *	85.44 *	85.68 *
iOS	86.45 *	87.90 *	88.10 *
Android	83.92 *	84.88 *	88.92 *
Session			
Lesson	85.43 *	87.23 *	88.76 *
Practice	80.94 *	83.92 *	84.19 *
Test	82.19 *	84.34 *	84.66 *
Format			
Reverse Translate	77.92 *	85.88 *	85.42 *
Listen	78.30 *	77.01	82.78 *
Reverse Tap	92.51 *	94.84 *	95.48 *

Table 4.5: Average exercise-level accuracy (%) in different contextual conditions. Significant differences (compared to *Avg.*, according to Mann-Whitney) are marked with $*(p < 0.001)$.

We investigate **H5** from two angles. Firstly, we investigate whether words with very different exposure amounts will differ from each other in terms of word-level accuracy as they are practiced by learners to different degrees. For this purpose, we only retain words with more than n exposures (with n being ≥ 1, ≥ 10, ≥ 20, ≥ 50, ≥ 100) and calculate Pearson correlation coefficient between the word-level accuracy and their number of exposures (Table 4.6). As expected, the more low-exposure words we filter out, the higher the average word-level accuracy and the stronger the correlation scores (albeit at best these are moderate correlations).

Secondly, we believe that whether a learner will solve a word correctly (0 mean solving correctly and 1 incorrectly) is correlated with two factors that are related to word repetition. One factor is the number of previous attempts that a learner has for a word, and the other is the amount of time elapsed since her last attempt at the word. Therefore, we compute Pearson correlation coefficient between learners' performance on exercises and the two repetition related factors (Table 4.7). The resulting correlations are even weaker than in our preceding analysis, though they do point towards a (very) weak relationship: if a learner gets more exposed to a word or practices the

	# Words	Word-Acc	Correlation
FR-EN			
≥ 1	2,178	72.30	-0.08 *
≥ 10	1,007	75.01	0.13 *
≥ 20	756	75.78	0.15 *
≥ 50	756	76.41	0.19 *
≥ 100	580	77.47	0.25 *
ES-EN			
≥ 1	2,915	75.33	-0.10 *
≥ 10	1,798	77.10	0.12 *
≥ 20	1,511	77.29	0.19 *
≥ 50	1,163	77.92	0.25 *
≥ 100	900	78.67	0.31 *
EN-ES			
≥ 1	2,226	75.58	0.00
≥ 10	1,587	77.12	0.25 *
≥ 20	1,401	77.88	0.28 *
≥ 50	1,171	78.90	0.28 *
≥ 100	963	79.57	0.34 *

Table 4.6: Avg. word-level accuracy (%) of words with different number of exposures.

	FR-EN	ES-EN	EN-ES
# Previous attempts	-0.05 *	-0.04 *	-0.07 *
Time elapsed	0.05 *	0.06 *	0.07 *

Table 4.7: Pearson Correlation between learner performance and the number of previous attempts and the amount of time elapsed since the last attempt for a word.

word more frequently, she is more likely to get it correct. Clearly, the results indicate that other factors at play here too.

Lastly, to study **H6**, we partition all learners into low-spacing and high-spacing groups according to [111]. Initially, all learners are sorted in ascending order according to their total time spent in learning words. Subsequently, these learners are binned into ten equally-sized groups labeled from 0 (spending the least amount of time) to 9 (spending the most amount of time). Therefore, we can regard learners from the same group as learning roughly the same amount of time. Next, within each group, the learners

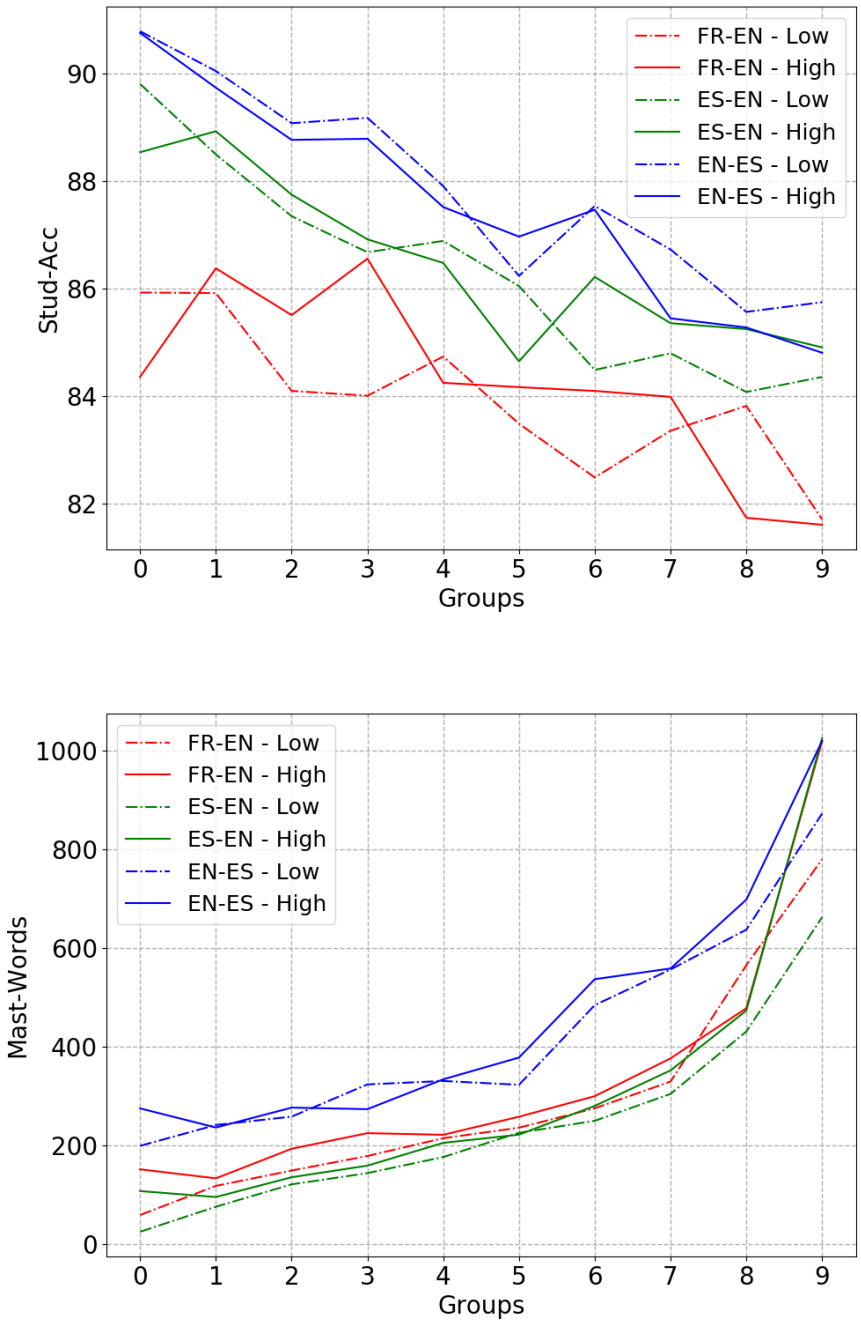


Figure 4.1: The average learner-level accuracy, i.e., Lear-Acc (Top), and the average number of mastered words, i.e., Mast-Word (Bottom), of learners in high-spacing and low-spacing groups.

are sorted based on their number of distinct learning sessions[3], and we further divide them into two equally-sized subgroups: learners with few sessions (low-spacing) and learners with many sessions (high-spacing). In this way, learners spending similar total amounts of time can be compared with each other. We plot the average learner-level accuracy as well as the number of mastered words within each low-spacing and high-spacing subgroup in Figure 4.1. We do not observe consistent differences between low-spacing and high-spacing groups. Therefore, we conclude **H6** to not hold.

4.3 Knowledge Tracing Model

We now describe the machine learning model we adopt for knowledge tracing and then introduce our features.

4.3.1 Gradient Tree Boosting

Various approaches have been proposed for modeling learner learning. Two representatives are Bayesian Knowledge tracing [40] and Performance Factor Analysis [122], both of which have been studied for years. Inspired by the recent wave of deep learning research in different domains, deep neural nets were also recently applied to track the knowledge state of learners [125, 168, 175]. In principal, all of these methods can be adapted to predict learners' performance in SLA. As our major goal is to investigate the usefulness of the designed features, we selected a robust model that is able to take various types of features as input and works well with skewed data. Gradient Tree Boosting (GTB) is a machine learning technique which can be used for both regression and classification problems [172]. It is currently one of the most robust machine learning approaches that is employed for a wide range of problems [34]. It can deal with various types of feature data and has reliable predictive power when dealing with unbalanced data (as in our case). We selected it over a deep learning approach as we aim to built an interpretable model.

4.3.2 Feature Engineering

Based on the results in Section 4.2, we designed 23 features. The features are categorized into two groups: features directly available in the datasets (7

[3]Here we consider all learning activities occurring within 60 minutes as belonging to the same learning session.

given features) and features derived from the datasets (16 *derived features*). Note that the features differ in their granularity—they are computed per learner, or per word, per exercise or a combination of them, as summarized in Table 4.8.

Features	**Granularity Level**		
	User	**Word**	**Exercise**
Learner ID	√		
Word		√	
Countries	√		
Format			√
Type			√
Device			√
Time spent (exercise)			√
# Exercises attempted	√		
# Words attempted	√		
# Unique words attempted	√		
# sessions	√		
Time spent (learning)	√		
# Previous attempts	√	√	
# Correct times	√	√	
# Incorrect times	√	√	
Time elapsed	√	√	
Word-Acc	√	√	
Std. timestamps (exercise)	√		√
Std. timestamps (word)	√	√	
Std. timestamps (session)	√		
Std. timestamps (word-session)	√	√	
Std. timestamps (word-correct)	√	√	
Std. timestamps (word-incorrect)	√	√	

Table 4.8: Granularity levels on which each feature is retrieved or computed. Features marked with *b* are used as input in the baseline provided by the benchmark organizers.

Given features:

- *Learner ID*[b]: the 8-digit, anonymized, unique string for each learner;
- *Word*[b]: the word to be learnt by a learner;

- *Countries*: a vector of dimension N (N denotes the total number of countries) with binary values indicating whether a learner complete an exercise in one or multiple countries;
- *Format*[b]: the exercise format in which a learner completed an exercise, i.e., Reverse Translate, Reverse Tap and Listen;
- *Type*: the learning type in which a learner completed an exercise, i.e., Lesson, Practice and Test;
- *Device*: the device platform which is used by a learner to complete an exercise, i.e., iOS, Web and Android;
- *Time spent (exercise)*: the amount of time a learner spent in solving an exercise, measured in seconds;

Derived features:

- *# Exercises attempted*: the number of exercises that a learner has attempted in the past;
- *# Words attempted*: the number of words that a learner has attempted in the past;
- *# Unique Words attempted*: the number of unique words a learner has attempted in the past;
- *# Sessions*: the number of learning sessions a learner completed;
- *Time spent (learning)*: the total amount of time a learner spent learning, measured in minutes;
- *# Previous attempts*: a learner's number of previous attempts at a specific word;
- *# Correct times*: the number of times that a learner correctly solved a word;
- *# Incorrect times*: the number of times that a learner incorrectly solved a word;
- *Time elapsed*: the amount of time that elapsed since the last exposure of a word to a learner;
- *Word-Acc*: the word-level accuracy that a learner gained for a word in the training dataset;

- *Std. timestamps (exercise)*: the standard deviation of the timestamps that a learner solved exercises;
- *Std. timestamps (word)*: the standard deviation of the timestamps that a learner solved a word;
- *Std. timestamps (session)*: the standard deviation of timestamps that a learner logged in to start a learning session;
- *Std. timestamps (word-session)*: the standard deviation of session starting timestamps that a learner solved a word;
- *Std. timestamps (word-correct)*: the standard deviation of timestamps that a learner answered a word correctly;
- *Std. timestamps (word-incorrect)*: the standard deviation of timestamps that a learner answered a word incorrectly.

Finally, we note that none of the features in our feature set make use of external data sources. We leave the inclusion of additional data sources to future work.

4.4 Experiments

In this section, we first describe our experimental setup and then present the results.

4.4.1 Experimental Setup

Each of the three Duolingo datasets consists of three parts: TRAIN and DEV sets for offline experimentations and one TEST set for the final evaluation. We use the TRAIN and DEV sets to explore features that are useful in predicting a learner's exercise performance and then combine TRAIN and DEV sets to train the GTB model; we report the model's performance on the TEST set.

We trained the GTB model using XGBoost, a scalable machine learning system for tree boosting [34]. All model parameters[4] were optimized through grid search and are reported in Table 4.9.

[4]For a detailed explanation of the parameters, please refer to https://github.com/dmlc/xgboost/blob/v0.71/doc/parameter.md.

We also report the official baseline provided by the benchmark organizers as comparison. The baseline is a logistic regression model which takes six features as input, which include learner ID, word, format and three morpho-syntactic features of the word (e.g., Part of Speech). As suggested by the benchmark organizers, we use the AUC and F1 scores as our evaluation metrics.

	FR-EN	**ES-EN**	**EN-ES**
learning_rate	0.4	0.5	0.6
n_estimatorss	800	1100	1550
max_depth	6	6	5
min_child_weight	7	8	13
gamma	0.0	0.0	0.1
subsample	1.0	1.0	1.0
colsample_bytree	0.7	0.7	0.85
reg_alpha	4	6	5

Table 4.9: Model parameters of the GTB model; determined by using grid search per dataset.

4.4.2 Results

In order to investigate the features described in Section 4.3.2, we report in Table 4.10 different versions of GTB training, starting with three features (Learner ID, Word, Format) and adding additional features one at a time. We incrementally added features according to the order presented in Section 4.3.2 and only kept features that boost the prediction performance (i.e. the AUC score improves on the DEV set). Among all 23 evaluated features, seven are thus useful for SLA modeling. Here, we only report the results in the ES-EN dataset; we make similar observations in the other two datasets. In contrast to our expectations, a large number of the designed features did not boost the prediction accuracy. This implies that further analyses of the data and further feature engineering efforts are necessary. The extraction of features from external data sources (which may provide insights in the difficulty of words, the relationship between language families and so on) is also left for future work.

In our final prediction for the TEST set, we combine the TRAIN and DEV data to train the GTB model with the nine features listed in Table 4.10 and learner ID as well as the word as input. The results are shown in Table 4.11.

	TRAIN	DEV
Learner ID & Word & Format	0.8095	0.7758
Mode	0.8111	0.7780
Client	0.8137	0.7790
Time spent (exercise)	0.8270	0.7828
# Previous attempts	0.8323	0.7835
# Wrong times	0.8348	0.7871
Std. time (word-session)	0.8348	0.7871

Table 4.10: Experimental results reported in AUC on ES-EN. Each row indicates a feature added to the GBT feature space; the model of row 1 has three features.

Compared to the logistic regression baseline, GTB is more effective with a 6% improvement in AUC and 83% improvement in F1 on average.

	Methods	AUC	F1
FR-EN	Baseline	0.7707	0.2814
	GTB	0.8153 *	0.4145 *
ES-EN	Baseline	0.7456	0.1753
	GTB	0.8013 *	0.3436 *
EN-ES	Baseline	0.7737	0.1899
	GTB	0.8210 *	0.3889 *

Table 4.11: Final prediction results on the TEST data. Significant differences (compared to Baseline, according to paired t-test) are marked with $*$ ($p < 0.001$).

4.5 Conclusion

Knowledge tracing is a vital element in personalized and adaptive educational systems. In order to investigate the peculiarities of SLA and explore the applicability of existing knowledge tracing techniques for SLA modeling, we conducted extensive data analyses on three newly released Duolingo datasets. We identified a number of factors relating to learners' learning performance in SLA. We extracted a set of 23 features from learner trace data and used them as input for the GTB model to predict learners' knowledge state. Our experimental results showed that (i) a learner's engagement plays an important role in achieving good exercise performance; (ii) contextual factors like the device being used and learning format should be taken into

account for SLA modeling; (iii) repetitive practice of words and exercises are related to learners' performance considerably; (iv) GTB can effectively use some of the designed features for SLA modeling and there is a need for further investigation on feature engineering. Apart from the future work already outlined in previous sections, we also plan to investigate deep knowledge tracing approaches and the inclusion of some of our rich features into deep models, inspired by [175]. Also, instead of developing a one-size-fits-all prediction model, it will be interesting to explore subsets of learners that behave similarly and develop customized models for different learner groups.

Chapter 5

Enabling MOOC Learners to Solve Real-world Paid Tasks

In this chapter, we focus on investigating whether learners can apply the knowledge acquired from a MOOC to solve real-world tasks, e.g., freelancing tasks collected from online marketplaces like `Upwork` or `witmart`[1], which can be solved with the knowledge taught in the MOOC. If learners are capable of solving such tasks, it becomes possible that learners can learn with a MOOC and apply the newly acquired knowledge to earn money at the same time. Ultimately, we envision a recommender system that automatically retrieves paid tasks relevant to a MOOC from online marketplaces and presents these tasks to learners to solve, as a possible means to help learners, who do not have a large amount of time for learning because of the need to work and earn a living, to benefit from MOOCs. To investigate the potential of the proposed vision, we consider the specific case of *Data Analysis: Take It to the MAX()* (a MOOC teaching data analysis in `edX`). We manually select a set of relevant tasks from `Upwork` and offer them to learners in the MOOC as bonus exercises to solve. Based on our experimental design, we also investigate the impact of real-world tasks on the MOOC learners. The contributions of this chapter have been published in [28].

[1] http://www.witmart.com

5.1 Introduction

In 2011, the first MOOCs started out with the promise of educating the world. To this day, this promise remains largely unfulfilled, as MOOCs struggle with student engagement and retention rates — on average, only 6.5% of MOOC learners complete a course and those who do often already have a higher degree [82]. At the same time though, the potential reach of MOOCs was visible from the very beginning: learners from 162 different countries engaged with the very first MOOC (*Circuits and Electronics*) offered on the `edX` platform [21].

Among the many reasons for learners' disengagement from a course are also financial ones: learning is superseded by the need to work and earn a living. Our ultimate vision is to *pay* learners to take a MOOC, thus enabling learners from all financial backgrounds to educate themselves. But how can we achieve this *at scale*? We believe that online work platforms such as `Upwork` and `witmart` can be an important part of the solution; if we were able to automatically recommend paid online work tasks to MOOC learners which are related and relevant to the MOOC content, the financial incentive would enable more learners to remain engaged in the MOOC and continue learning.

Figure 5.1 shows a high-level overview of our vision: online work task platforms are continuously monitored for newly published work tasks; a recommender system maintains an up-to-date course model of every ongoing MOOC and determines how suitable each work task is for every ongoing course and course week. At any given moment, the suitable open work tasks are shown alongside the course material on the MOOC platform, together with the possible financial gain and their level of difficulty.

While we do not claim this vision as *the* solution for MOOCs to single-handedly "lift ... people out of poverty," [57], we strongly believe this to be a step in the right direction and something to build upon.

To lay the groundwork, we investigate the *feasibility* of letting MOOC students solve real world tasks from an online work market place. In a pilot study presented here, we manually selected a number of paid tasks from `Upwork` and offered them to learners of the *EX101x* MOOC (*Data Analysis: Take It to the MAX()*, offered on `edX`) as bonus exercises. We illustrate that it is indeed feasible to expect students to be able to earn money while taking a MOOC.

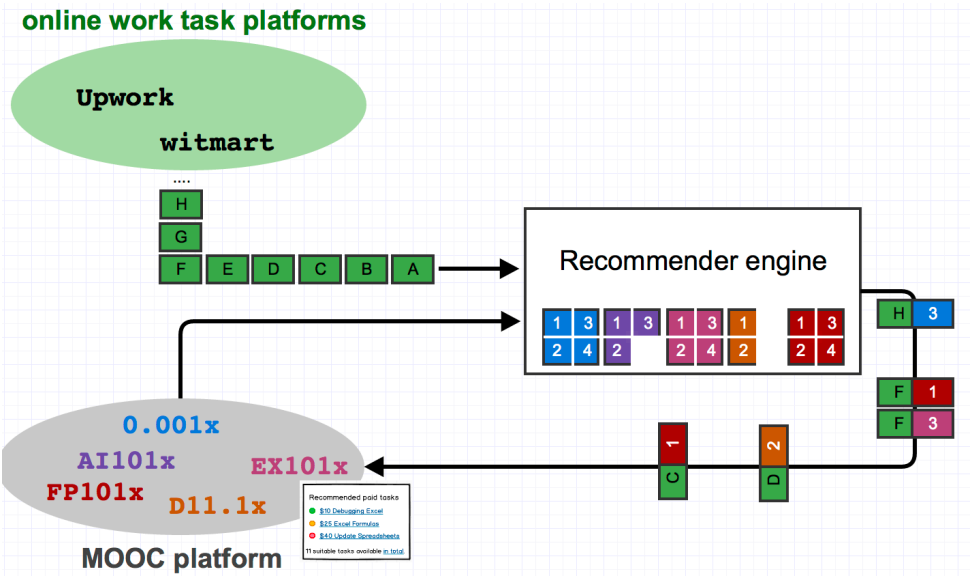


Figure 5.1: Paying MOOC learners — a vision.

Based on these encouraging initial results we then expand our investigation and analyse the realm of online work platforms and their suitability for our vision along a number of dimensions including payments, topical coverage and task time.

Lastly, it is worth nothing that our experimental setup not only allows us to investigate **learning enabling** methods (i.e. paying learners), but also **learner motivations**: we expect that real-world tasks (as shown in the bonus exercises) engage learners more than artificially created course tasks.

The work we present in this chapter is guided by the following four **R**esearch **Q**uestions:

RQ 4.1 Are MOOC learners able to solve real-world (paid) tasks from an online work platform with sufficient accuracy and quality?

RQ 4.2 How applicable is the knowledge gained from MOOCs to paid tasks offered by online work platforms?

RQ 4.3 To what extent can an online work platform support MOOC learners (i.e., are there enough tasks available for everyone)?

RQ 4.4 What role do real-world (paid) tasks play in the engagement of MOOC learners?

By answering these questions, we expect to provide solid evidence to the feasibility of the proposed design, i.e., automatically retrieving relevant tasks from online marketplaces and recommend them to learners, we expect to financially enhance MOOC learners and help them achieve professional development in the long run.

5.2 Background

This study represents a movement towards MOOCs truly living up to their name with respect to their openness. The current demographic of MOOC participants is predominantly educated males from developed countries [36, 44, 74, 132, 90]. Simply putting the content out there on the Web may not be enough to justify calling it "open". Although it is available, it is not readily accessible to everyone. Based on both survey and student activity data, Kizilcec and Halawa found that "the primary obstacle for most [MOOC] learners was finding time for the course" [90]. By conducting post-course surveys, [90] found that 66% of students struggled to keep up with course deadlines and 46% reported that the course required too much time.

Self-regulated learning

Providing income to students in exchange for real-world tasks can serve as a support mechanism in encouraging students to better self-regulate their study and engagement habits. The study of Self-Regulated Learning (SRL) has a rich history in the traditional classroom setting [126, 179], but now the new challenge arises of how to support and enable non-traditional and disadvantaged students to practice effective SRL habits in online/distance learning endeavors. SRL is defined as a student's proactive engagement with his or her learning process by which various personal organization and management strategies are used in order to control and monitor one's cognitive and behavioral process towards a learning outcome [157, 178]. Many SRL tactics hinge on effective time management skills [22, 117]. Although, with proper coaching, many students can be taught to find and make time for studies [105, 117], this is simply not plausible for others who do not have enough time in a day to introduce a new challenge–no matter how well they manage their time. These learners are the primary target of our vision. By introducing these opportunities to earn money while completing a course, we hope that they can essentially "buy time."

For the group of students who complete the paid tasks in order to make "extra" money, the compensation can be viewed as a reward mechanism and

an incentive to prioritize the MOOC over other less important tasks [54, 90]. For the other group, the money earned from the extra tasks is a required means for them to commit time. Whereas reward-seeking students would no longer have a reason to complete the extra tasks if the monetary prize was removed, the other group of students would no longer have the time or the ability.

Using rewards to motivate learning

One of the leading critiques of reward programs in traditional education settings is that their prize pool is finite, and once that is exhausted, student motivation will dwindle [165]. In our setup, however, this is not an issue, as online work platforms are consistently replenished with new tasks to recommend to our MOOC learners. This model thus shows the potential for sustainability at scale.

The existing literature on paying or rewarding students with material goods is concerned with young students in traditional classroom settings [46, 58, 67, 165], however the people who stand to benefit the most from the inclusion of freelance projects and tasks into the MOOC environment are predominantly non-traditional students.

[58] approaches the dilemma of incentivising student performance with money through an economic lens. In order to test how financial incentives impact student performance in historically-disadvantaged and under-performing school districts in the United States, this study compared the effectiveness of input-driven versus output-driven reward systems. It was found that incentives based on student input, such as completing assignments or reading books, are more effective than those based on output, such as test scores and grades [6, 46, 58]. In line with the concept of instructional scaffolding, this finding suggests that incentivising and rewarding intermediate tasks along the path to a larger learning goal or objective is more effective than rewarding only the goal itself. Likewise, one of these intermediate tasks especially challenging to open learning is that of allocating and committing time, and we hope the potential to get paid for this time will support learners in doing so.

Incentives for underprivileged learners

We also see the introduction of opportunities for learners to contribute to online work market places while taking a MOOC as a potential manner by which we can mitigate belonging uncertainty for under-privileged learners [87, 160]. This is characterized by stigmatized or minority group members feeling uncertain and discouraged by their social bonds in a given environment [160].

If a student sees his or her participation in the course with an immediately clear and relevant purpose—learning the necessary skills to complete this real-world task—then it should thus mitigate any uncertainty or doubt about the students belonging. Walton and Cohen found that interventions designed to reduce/remove feelings of belonging uncertainty can have great effects on students' subjective experiences in academic settings which can therefore boost academic performance. Learners of low socio-economic status are not the only ones who stand to benefit from this. Other major demographics, such as women (particularly in STEM courses), are currently outnumbered, and often outperformed [74], by their male student counterparts [44, 132, 90].

Using extra credit to motivate learning

Many studies have examined the effect that offering extra credit assignments to students can have on overall class performance. [25] found that extra credit assignments can be used to motivate students to read journal articles; [20] found extra credit, in the form of an in-class token economy, to increase course participation; [164] saw increases in course attendance stemming form the offering of extra credit assignments; and [116] found that extra credit assignments can facilitate mastery of course material and strongly predict final exam performance.

Similarly, in a study that specifically targeted students on the verge of failing a college course, researchers found that an intervention in the form of a skills-based extra credit assignment increased these students' final exam grades, increased and diversified their engagement, and decreased their dropout/incompletion rate [84].

In December 2015, `edX`, one of the most popular MOOC platforms announced a new policy which rescinds the free honor code course completion certificates previously made available to any student who earned a passing grade in the course. Instead, according to the announcement on the `edX` blog [4], "all of edX's high-quality educational content, assessments and forums will continue to be offered for free, but those learners who want to earn a certificate upon successful completion of the course will pay a modest fee for a verified certificate." While both `edX` and its partner institutions will offer various levels of financial aid to students who apply, the design introduced in this work has the potential to reduce the burden of supporting students. Simply by completing one task from an online marketplace (of high enough value), a student can offset the cost of the verified course certificate.

To the best of our knowledge, this effort to pay students in an open learning environment in order to encourage and enable student engagement

is the first of its kind. Research findings in this area promise to help narrow the established achievement gap we currently observe among MOOC learners.

5.3 EX101x

To investigate our research questions, we inserted bonus exercises, drawn from paid tasks posted on `Upwork`, into the MOOC *Data Analysis: Take It to the `MAX()`*, or in short: *EX101x*. *EX101x* is a MOOC offered on the `edX` platform; its first edition (the one we deployed this study in) ran between March 31, 2015 and June 18, 2015. The core objective of *EX101x* is to learn to conduct data analysis using spreadsheets. Throughout the first six course weeks, the following set of skills are taught (using Excel as specific spreadsheet instance): string manipulation and conditional statements (Week 1), lookup and search functions (Week 2), pivot tables (Week 3), named ranges (Week 4), array formulas (Week 5) and testing in spreadsheets (Week 6). Week 7 is dedicated to the programming language Python and its use within spreadsheets, while the final week (Week 8) introduces the graph database `Neo4j`.

As is common in MOOCs today, learners were invited to participate in a pre-course and a post-course survey containing questions on the motivation of the learners, the perceived quality of the course, etc. In September 2015 we approached a selected subset of all learners for an additional post-course survey.

The course was set up as an xMOOC [134]: lecture videos were distributed throughout the 8 teaching weeks. Apart from lectures, each week exercises were distributed in the form of multiple choice and numerical input questions. Each of the 136 questions was worth 1 point and could be attempted twice. Answers were due 3 weeks after the release of the respective assignment. To pass the course, $\geq 60\%$ of the questions had to be answered correctly. Each week, alongside the usual assignments, we posted one additional bonus exercise.

Overall, 33,515 users registered for the course. Less than half of all learners (45%) engaged with the course, watching at least one lecture video. The completion rate was 6.53% in line with similar MOOC offerings [95]. Over 65% of the learners were male and more than 76% had at least a Bachelor degree.

5.4 Approach

The design of our experiments was guided by our research questions. As we aim to determine whether learners can solve real-world tasks that are related to the course material with high accuracy and high quality (**RQ 4.1**), for the six weeks of *EX101x* that cover data analysis topics in spreadsheets, we *manually* selected appropriate paid tasks from the `Upwork` platform — one task per course week. No bonus exercises were posted in weeks 6 and 8 due to the topics covered that week: testing in spreadsheets and the graph database Neo4J. We chose `Upwork` (which at that time was still called `oDesk`) as it is one of the largest online work platforms in the English speaking world (cf. Table 5.4); for each course week, we chose an `Upwork` task that was strongly related to that week's course content by extensively scanning the currently active `Upwork` tasks worth up to $50. We chose this price limit to provide tasks that can be solved in a reasonable amount of time. We kept the task description intact, and added a short introduction to provide the necessary context to our learners (i.e. a clear disclaimer that this is a real-world task). A concrete example of a bonus exercise derived in this manner is shown in Figure 5.2; it was posted in week 4 of *EX101x*.

To answer **RQ 4.2** and **RQ 4.3**, we explored the suitability of `Upwork` as a source of paid tasks along several dimensions including the covered topics, the task longevity, and the financial gain. In order to investigate **RQ 4.1** and **RQ 4.4** we require exact definitions of a number of metrics (i.e. accuracy, coverage, quality and engagement). In the following section, we describe them in detail.

5.4.1 Measurements

Accuracy. For each bonus exercise, we developed a gold standard solution in collaboration with the course instructor and verified whether the submitted learner solutions matched the gold standard solution, thus measuring their *accuracy*. We considered a submitted spreadsheet a match to our gold standard if it contained the required solution columns with the correct cell content; additional columns were ignored; slight deviations from the gold standard (e.g. an empty string or "N/A" instead of an empty cell in the gold standard) were allowed. We iteratively refined our automated grading script by randomly sampling 20 submission in each iteration (and manually verifying the correctness of the grading script) until all samples were classified correctly.

Have you ever sold anything on Amazon.com? For this real-world task (again derived from an actual oDesk task), we put you in the shoes of an Amazon seller who is selling accessories for pets. The seller himself buys these accessories from a supplier. The seller currently has a five star feedback rating on Amazon. To keep it this way, only items that the seller can immediately ship should appear in the seller' s Amazon storefront (i.e., those items that the supplier has in stock).
The seller has this Excel sheet which stores the ID of all products to be posted on his Amazon.com storefront and the number of units available, as illustrated in the example below.

ID	Stock
08357EDA-DF5C-392E-F7CC-A27E3AB768DF	?
08357EDA-DF5C-392E-F7CC-DD445453DDEF	?

File 1: Excel sheet of the seller

It is your job to update the **Stock** column based on the information the seller receives from the supplier.
Every day, the seller receives an Excel sheet from his supplier, which contains the supplier' s inventory. An example is provided below. Note that the supplier' s column **Product** corresponds to the seller' s column **ID**.

Product	Inventory
08357EDA-DF5C-392E-F7CC-A27E3AB768DF	7
08357EDA-DF5C-392E-F7CC-DD445453DDEF	188

File 2: Excel sheet of the supplier

To keep his customers satisfied, the seller uses the following two rules to set the Stock column:

- If the supplier' s inventory of a product is less than 30, Stock should be set to 0;
- If the supplier' s inventory of a product is more than or equal to 30, Stock should be set to 20.

Applying these two rules to our example files above, yields the following result:

ID	Stock
08357EDA-DF5C-392E-F7CC-A27E3AB768DF	0
08357EDA-DF5C-392E-F7CC-DD445453DDEF	20

File 3: Result sheet of the seller

Please send your solutions to ...

Figure 5.2: Bonus exercise posted in week 4 of *EX101x*. The original task was posted with a price of $35 to `Upwork` (note that at the time of posting this exercise, `Upwork` was still called oDesk).

Coverage. Besides accuracy, we also measured the coverage of learner solutions. We operationalize *coverage* as the percentage of cells that the learner

solution *shares* with the gold standard. As for *accuracy*, we ignored additional columns and allowed minor deviations in the cells such as additional white spaces or minimal numeric differences to account for floating point inaccuracy on different computers. Coverage can be seen as an indicator of how close the solution is to the gold standard solution.

Quality. To investigate the *quality* of the submissions, we turned to the concept of *code smells* [155], an established measure of quality in the field of Software Engineering: code smells are specific to particular programming languages; spreadsheets code smells include standard errors (e.g., `#N/A!`, `#NAME?`), high conditional complexity (e.g., involving too many nested `IF` operations), hidden rows/columns/worksheets, etc. We adopted the code smells for spreadsheets proposed in [71] and rank the solutions by the number of smells they exhibit - the fewer smells a solution has, the higher its quality.

Engagement. Finally, based on our experimental setup, we are also able to investigate the effect of real-world tasks on student engagement (**RQ 4.4**). We hypothesize that learners who *view* the bonus exercises and realize that those are real-world tasks that could earn them money, will become more engaged with the course material than learners who did not *view* the bonus material. To this end, we only consider the subset of active learners $L_{noBonus}$ that did *not* submit any solutions to the bonus exercises.

We group learners together that are similarly engaged in the course up to the point of either viewing a bonus exercise or not. If our hypothesis holds, then after that point in time, those learners that viewed the bonus exercise should, on average, exhibit higher engagement than those that did not.

We operationalize this experiment as follows: we measure a learner's engagement through his or her amount of video watching. In week 1, we partition the learners in $L_{noBonus}$ in two groups: we sort the learners in video watching time order and then split them in two equally sized groups - the lower half is the *low* engagement, and the upper half is the *high* engagement group. We then compute for each learner the amount of video watching in all following weeks and determine for the low and high engagement groups separately whether there is a statistically significant difference between those learners that did view and those that did not view the bonus exercise. In week 2, we repeat this analysis by taking as starting point only the subset of learners in $L_{noBonus}$ that viewed the bonus exercise in 1. We repeat those steps until week 7 (in each week resorting the remaining learners into the low and high engagement groups). While we expect significant differences based on bonus exercise viewing in the early weeks of the course, we should

not observe significant differences towards the end of the course — in week n we only include learners that up to that point in time have viewed all $n-1$ bonus exercises. At some point, bonus exercises should not provide additional engagement anymore.

5.5 Results

Before we discuss our results for each of the four research questions in turn, we provide a first global view of our learner population in *EX101x*.

	All Engaged Learners	**BE Learners**	**Non-BE Learners**
#Learners	15,074	2,020	13,054
Completion rate	14.02%	44.11%	9.36%
Avg. time watching video material (in min.) ‡	58.78	133.48	47.21
%Learners who tried at least one question	59.89%	98.56%	53.91%
Avg. #questions learners attempted to solve ‡	24.06	67.41	17.36
Avg. #questions answered correctly ‡	19.56	*55.60*	13.98
Avg. accuracy of learners' answers ‡	53.40%	90.09%	47.73%
#Forum posts	10,106	4,341	5,765
%Learners who posted at least once	16.20%	43.61%	11.96%
Avg. #posts per learner ‡	0.67	2.15	0.44

Table 5.1: Basic characteristics across all learners and their partitioning into those who attempted to solve at least one Bonus Exercise (BE) and those who did not (Non-BE). Where suitable, significance tests between the BE/Non-BE groups were performed according to Mann-Whitney. All performed tests exhibited significant differences - indicated with ‡ (significant difference with $p < 0.001$).

We classified our set of *engaged* learners, i.e., those who watched at least one video[2] (a definition also employed for instance in [65]), according to two

[2]We note, that we also evaluated two alternative definitions of engagement: (1) learners that watched at least 15 minutes of video material (i.e. at least two videos), and (2) learners that submitted at least five quiz questions. While the absolute values reported in Tables 1

dimensions: (i) whether learners attempted to solve at least one bonus exercise (**BE**) or not (**Non-BE**) and (ii) the number of bonus exercises learners attempted to solve. In the latter case, we consider only the **BE** learners. We mark learners as dedicated bonus exercise solvers (**DBE**) if they attempted to solve more than two bonus exercises, the remaining learners are non-dedicated (**Non-DBE**). The basic statistics of both learner cohorts are presented in Tables 5.1 and 5.2. It is evident that learners who solved at least one bonus exercise are more engaged than learners who did not - across all important characteristics (average time spent watching videos, average number of questions answered, accuracy of answers) the BE learners perform significantly better than the Non-BE learners. Among the cohort of BE learners, this trend continues with the dedicated learner group being significantly more engaged and successful than the non-dedicated learner group.

We note that these results are not surprising — they are dictated by common sense and our manner of classifying learners. Importantly, we do not claim a causal relationship between bonus exercise presence and learner engagement based on *these* results (in Section 5.5.3 we explore the relationship between engagement and bonus exercises in greater detail).

As our goal is to improve the ability of learners from the developing world to engage and successfully complete the course, we also investigate to what extent they are already capable of doing so now. For each country, we computed the percentage of learners that completed the course (based on all registered learners). Shown in Figure 5.3 is the completion rate of *EX101x* across countries, split into developed countries according to the OECD (in blue) and developing countries (in red). We observe, that in general, the completion rate of learners from developed countries is higher than those of developing countries (with the exception of Russia and Malaysia). This confirms one of our assumptions that learners from developing countries are facing issues that learners in developed countries do not face. This result is in line with previous findings in [36].

5.5.1 RQ 4.1: Can learners solve real-world tasks well?

Across all weeks, we received a total of 3,812 bonus exercise solutions from 2,418 learners. Since the `edX` platform has very limited solution uploading capabilities, we asked learners to email us their solutions and then matched the email addresses of the learners to their `edX` accounts. 352 of the learners

& 2 change depending on the definition employed, we did observe the same trends and the same significant differences for all three engagement definitions and thus only report one.

	DBE Learners	Non-DBE Learners
#Enrolled learners	314	1,706
Completion rate	86.31%	36.34%
Avg. time watching video material (in min.) ‡	189.45	123.18
%Learners who tried at least one question	100.00%	98.30%
Avg. #questions learners attempted to solve ‡	110.52	59.47
Avg. #questions answered correctly ‡	93.99	48.53
Avg. accuracy of learners' answers ‡	94.83%	89.22%
#Forum posts	1,626	2,715
%Learners who posted at least once	59.87%	40.62%
Avg. #posts per learners ‡	5.18	1.59

Table 5.2: Basic characteristics of BE learners partitioned into dedicated BE learners (DBE) solving 3+ bonus exercises and non-dedicated BE learners. Where suitable, significance tests between the DBE/Non-DBE groups were performed according to Mann-Whitney. All performed tests exhibited significant differences - indicated with ‡ (significant difference with $p < 0.001$).

could not be matched to an `edX` account (i.e. these learners used a different email when signing up for `edX`) and had to be excluded from the subsequent analyses of `edX` log traces (they are included though in all results analyzing the accuracy/quality of the solutions).

Table 5.3 lists the main results of our accuracy and quality analyses. Between 1% (in week 7) and 15% (in week 1) of active learners participated in the bonus tasks each week. The percentage of *accurate* solutions varies widely between tasks and is not correlated with the amount of pay for a task. In fact, the two tasks with the lowest pay ($20 in weeks 3 & 5) resulted in the lowest percentage of accurate solutions (11% and 17% respectively). The low accuracy for the seemingly simple (as cheaply priced task) is intriguing. We sampled 50 of the incorrect solutions and found most of them to miss a required final step in the task. Both tasks require students to carefully read and understand the assignment to be successful. In week 3, learners needed to implement an equation containing an *absolute* value. As the equation

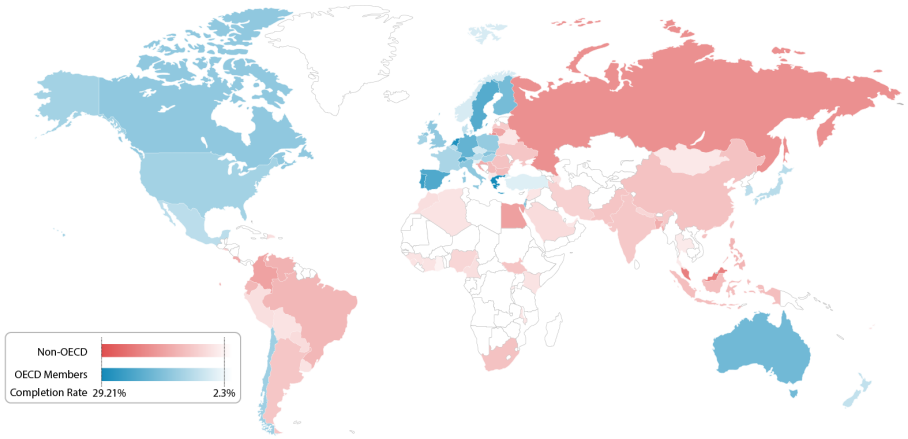


Figure 5.3: Developed countries according to the OECD are shown in blue, developing countries are shown in red. The color shade indicates the overall completion rate of learners from that country. A darker shade indicates a higher completion rate.

text is fairly long, students tended to miss this vital piece of information; 78% of all wrong answers that week show this misconception. In week 5, the solutions had a similar issue, often missing a final re-ranking step of the result columns as required in the task description.

An alternative view of submission accuracy is presented through the average *coverage* of all submissions, that is the fraction of gold standard result cells, that were also present in the submissions. Coverage is 1.0 for the correct submissions, but usually lower for incorrect ones (note that it is possible for an incorrect solution to reach a coverage of 1.0 if it contains all gold standard result cells as well as additional result cells - this happens rarely though). In Table 5.3 we observe that the coverage across all submitted solutions is rather high (with the exception of week 3), thus even solutions that are not correct are at least sensible.

Having considered accuracy and coverage, we now turn to the *quality* of the solutions. Among the correct solutions, a large fraction (between 38% and 96%) are of high quality, that is they exhibit zero code smells as shown in Table 5.3. Again, we do not observe a correlation between the price of a task and the quality of the solutions. The quality of the accurate and inaccurate solutions (as measured in code smells) is comparable. Across all weeks and submitted solutions, the median number of code smells is less than 10, indicating that most learners were able to code high-quality solutions.

The vast majority of solutions across all weeks have less than 50 reported code smells.

Overall, we can positively answer **RQ 4.1**: it is indeed possible for MOOC learners to provide correct and high-quality solutions to selected real-world tasks from an online work platform.

Week	# Active learners	# Bonus (% from active)	Task payment	# Accurate (% of active)	# High quality (% of accurate)	Coverage (SD)
1	13,719	2,145 (15.64%)	$ 25	1,731 (80.70%)	1,230 (71.06%)	0.88 (0.32)
2	8,228	594 (7.22%)	$ 50	227 (38.22%)	87 (38.33%)	0.91 (0.27)
3	5,825	390 (6.70%)	$ 20	44 (11.28%)	28 (63.64%)	0.54 (0.32)
4	4,270	414 (9.70%)	$ 35	354 (85.51%)	296 (83.62%)	0.95 (0.22)
5	3,709	231 (6.23%)	$ 20	39 (16.88%)	16 (41.03%)	0.69 (0.24)
7	3,059	38 (1.24%)	$ 35	26 (68.42%)	25 (96.15%)	0.73 (0.68)

Table 5.3: Learners' performance on real-world tasks. The second column shows the number of active learners. The third column shows the number of students taking the bonus exercise. The fourth column shows the task payment offered at UpWork. Accurate submissions are those matching our gold standard (with the additional requirement of the correct order for tasks 3 and 5). High-quality submissions are those correct submissions without code smells. The coverage column reports the average (and standard deviation) fraction of cells covered by all of a week's submissions.

5.5.2 RQ 4.2 & RQ 4.3: An exploratory analysis of UpWork

We first note that `Upwork` is only one of multiple large online work platforms in the English speaking world as shown in Table 5.4. Together those companies facilitated more than 2.5 billion dollars in worker payments. Important for us, some of these platforms (including `Upwork`) provide API access to their content, thus enabling a recommender system as we envision.

For our analysis, we took a snapshot of all available tasks on `Upwork` on September 15, 2015 leading to a total of 56,308 open tasks. Each task is assigned to one or more topical categories, e.g. *Translation* or *IT & Networking*. Additionally, tasks can be tagged with particular required skills such as *excel* or *python*. Tasks either pay per hour or have a fixed budget. We focus on the latter, as the budget is a direct indicator for the amount of work required. A task pays on average $726 (SD: $3,417) and stays 27 days on the platform (SD: 34 days) before being solved or canceled. Among all tasks, we found 574 spreadsheet tasks (potentially relevant for *EX101x*) in the budget range from $1 - $50. A task in this (*budget*) subset stayed 25 days on the platform on average (SD: 40 days).

To estimate the proportion of tasks that may be suitable recommendations for *EX101x* learners, we analysed a random sample of 80 tasks of the *budget* set. An expert classified these tasks into three categories:

1. *lecturable* are tasks that would make them suitable as course material for a specific lecture (e.g. a task that requires knowledge of a spreadsheet's `VLookUp` function);

2. *relevant* are tasks that fit the topic yet do not fit into a specific lecture (e.g. a task that requires the use of spreadsheets but otherwise does not rely on knowledge taught in the course);

3. *unrelated* are all other tasks that do not fit in the courseware in general.

Among the 80 tasks we found 34 *unrelated* tasks, 39 *relevant* tasks and 7 *lecturable* tasks. Based on these numbers and the average time a task stays online we can estimate how many tasks are added every day to `Upwork` that fit our criteria (i.e. have a price between $1 and $50 and require spreadsheet knowledge): 10 *unrelated* tasks, 11 *relevant* tasks, and 2 *lecturable* tasks. These numbers indicate that there are not yet enough budget tasks available to provide individual MOOC learners with weekly opportunities to earn money whilst learning — at least for the *EX101x* MOOC.

Company	**Paid worker fees**	**API**
Upwork	$ 1,000 M	yes
witmart	$ 1,000 M	no
freelance	$ 462 M	no
Guru	$ 200 M	yes
Envato	$ 200 M	yes
Topcoder	$ 72 M	yes

Table 5.4: Paid total worker fees by company in Million US Dollar. These numbers are self reported by the companies and are not given for a specific year.

One limiting factor in our design is the budget limit we set ourselves ($50). The majority of tasks have a higher budget as shown in Figure 5.4 and future experiments will investigate the question up to which budget level learners are able to solve tasks in a reasonable amount of time, with high accuracy and high quality.

Tasks that have a higher budget (on the topic of spreadsheets) are usually more intricate and instead of solving one specific problem in a spreadsheet

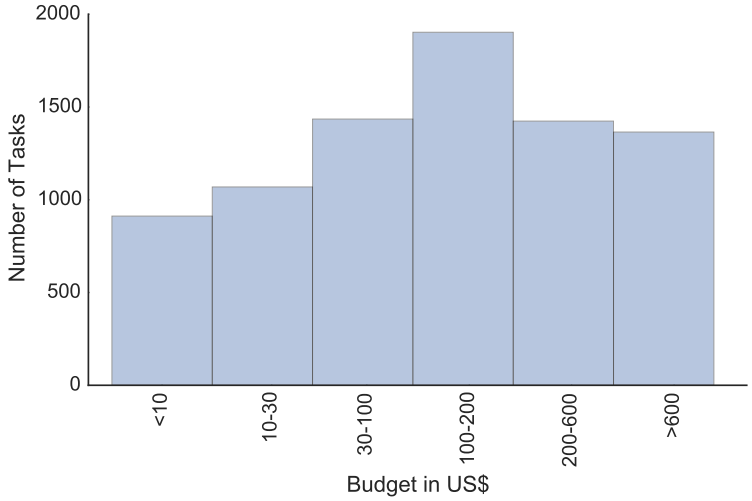


Figure 5.4: From the 56,308 `Upwork` tasks available on 15/09/2015 a total of 8,153 have a fixed budget (the remaining tasks are paid by the hour). Budgeted tasks are binned according to the budget they have.

(as less pricey tasks, cf. Figure 5.2) they often require the development of a complete solution as exemplified in the three task examples priced between $100 and $500 at `Upwork`:

$500 *"We are commercial real estate brokers and are looking for an expert in Microsoft Excel to create an interactive Excel worksheet(s) for rental comparison purposes."*

$250 *"I need to have financial calculations for a customer equity/lifetime value model integrated into an excel workbook. (...)"*

$100 *"I currently plot support and resistance zones manually on a chart like the attached image. (...) I need to calculate these support and resistance levels within MS Excel programmatically or using some sort of algorithm. (...)"*

In contrast to the budget, the longevity of tasks on `Upwork` is beneficial for our vision. Figure 5.5 shows that many tasks remain available for at least 20 days, which is beneficial in the MOOC setting where assignments also commonly have a grace period of 2-3 weeks.

Recall, that additionally to a general category each task is tagged with a set of required skills. Table 5.5 shows *Excel* (the comon tag for spreadsheet

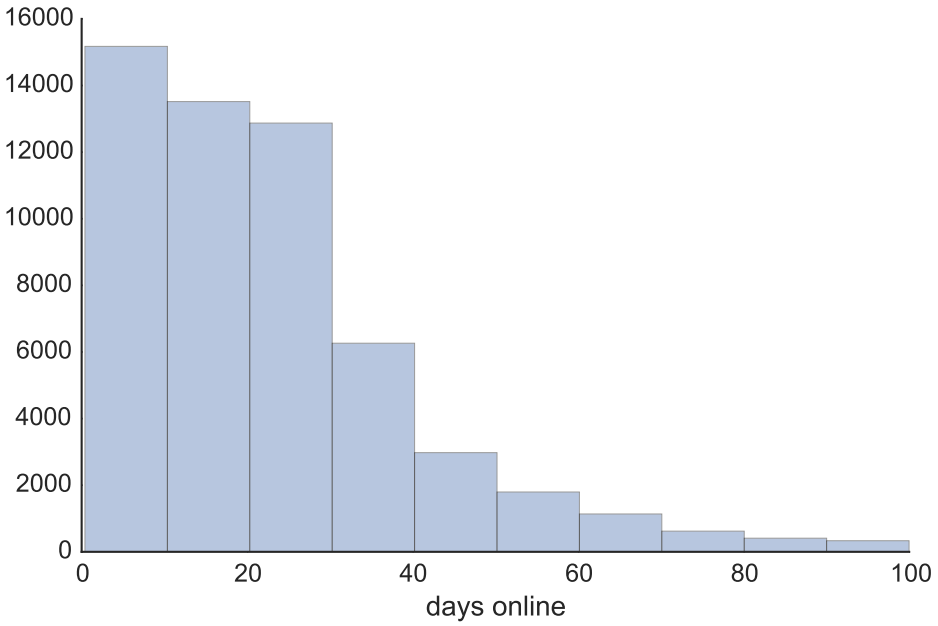


Figure 5.5: The 56,308 `Upwork` tasks available on 15/09/2015 are binned according to the number of days they have been "online" (i.e. the task is open).

tasks) to be a relatively popular task. More general skills such as proficiency in *HTML* and *CSS* occur more often than specific skills such as proficiency in *R*. Overall, programming tasks only make up a small percentage of all available tasks, as shown in Table 5.6. Indeed, the breadth of tasks offered on `Upwork` indicates the tremendous potential of online work platforms for suggesting paid tasks to learners across a range of MOOCs.

To conclude, we observe that, indeed, the knowledge gained during *EX101x* can be used to solve paid tasks (**RQ 4.2**), though the number of tasks posted per day that fit our criteria is rather low: we estimate that, an average, 13 tasks a day are posted in the $1-$50 category, requiring spreadsheet knowledge fitting the course topic of *EX101x*.

This result also provides an answer to **RQ 4.3** in the context of *EX101x*: as per day, on average, only 13 MOOC students stand to benefit from these paid tasks (i.e., can earn money from them), there are not sufficient tasks available to sustain a standard MOOC population of learners throughout an entire run of *EX101x* — at least at the current rate of online work tasks being posted to `Upwork`.

#Tasks	Skill Tag
5,443	HTML5 & HTML
5,034	PHP
3,928	Javascript
2,731	Excel
616	Python
559	Ruby & Ruby-on-Rails
537	Objective-c
450	Java
26	Perl
34	R

Table 5.5: Overview of programming tasks among our crawl of 56,308 `Upwork` tasks on 15/09/2015.

Category	#Tasks	Days Online (SD)	Payment (SD)
Customer Service	986	74.76 (83.24)	$1,817 ($6,692)
Engineering & Architecture	1,432	53.70 (61.50)	$1,699 ($6,640)
Translation	2,109	53.02 (74.64)	$1,156 ($3,710)
Admin Support	5,961	50.33 (89.14)	$ 982 ($4,855)
Accounting & Consulting	1,095	49.37 (77.77)	$ 997 ($4,642)
IT & Networking	2,182	39.60 (52.38)	$ 854 ($4,356)
Data Science & Analytics	1,156	37.29 (45.94)	$ 777 ($3,308)
Writing	8,448	32.31 (58.54)	$ 418 ($ 832)
Legal	333	27.97 (33.67)	$ 377 ($2,055)
Web, Mobile & Software Dev	16,328	25.39 (46.02)	$ 376 ($2,028)
Design & Creative	9,667	24.60 (45.70)	$ 274 ($ 710)
Sales & Marketing	6,724	21.54 (34.31)	$ 263 ($2,124)

Table 5.6: The 56,308 `Upwork` tasks available on 15/09/2015 are partitioned according to their category. Shown are the number of tasks per category, the average number of days online and the average task payment (for the subset of 8,153 tasks with a fixed budget).

5.5.3 RQ 4.4: Learner engagement

We hypothesize that our bonus exercises, in particular the realization that those are real-world tasks with which money could be earned, are beneficial for learner engagement.

In Figure 5.6 we present the results of our experiment, comparing the amount of video watching between learners who did view and did not view

the bonus exercises (computed separately for low and high engagement learners). Let's consider week 1: in the low engagement group, the learners that did not view the bonus exercise spent on average 0.08 hours (5 minutes) in subsequent weeks on video watching, while the learners that did view the bonus exercise spent 1.3 hours in subsequent weeks on videos. This difference is statistically significant ($p < 0.001$, Mann-Whitney test). Similarly, in the high engagement group, learners that did not view the bonus exercise continued to spend 0.4 hours (24 minutes) on video watching, while learners that did view the bonus exercise spent 1.7 hours on the course. Across both engagement groups, the low amount of overall time spent in watching videos can be explained by the fact that over time, more and more learners drop out of a course. In week two, we only consider the subset of learners that viewed the bonus exercise in week 1, and again we observe significant differences in engagement between those that viewed the second bonus exercise and those that did not. As the weeks go on, the difference in video watching time between learners viewing and not viewing the bonus exercise of the week tends to decrease—also evident in the fact that in weeks 5 and 7, we find no significant differences in engagement for the high engagement learners. We consider these results as a first confirmation of **RQ 4.4**: our bonus exercises (real-world tasks) are likely to have a positive effect on engagement. We realize that this experiment can only be considered as first evidence: we observed that similarly engaged learners diverge in their behavior after having (not) viewed our real-world bonus tasks. We assume that this divergent behavior is caused by the action of (not) viewing the task, but this assumption cannot be directly verified. We attempt to verify it (among others) through a post-course survey, outlined next.

5.5.4 Post-course survey

We sent a follow-up survey with 11 questions (about success & engagement in *EX101x*, financial incentives in MOOC learning and the bonus tasks in *EX101x*) to a subset of learners who expressed their willingness to be contacted after the course had completed. An overview of all questions can be found in Table 5.7.

We partitioned the set of contacted learners into four groups according to their origin (developed vs. developing country) and their engagement with the bonus exercises (submitted vs. not submitted):

- from developed nations & submitted at least one bonus exercise (126 learners contacted, 26 replied);

Success & engagement							
1.	How engaged were you in EX101x?	Completed successfully 75|87|67|45%	Stopped midway 14|10|16|23%	Stopped in weeks 1 or 2 11|0|14|27%	Registered, but nthg. else 0|3|3|5%	- -	- -
2.	To what extent did you engage with the bonus exercises?	Submitted 3+ exercises 48|52|8|0%	Submitted 1-2 exercises 41|38|25|32%	Attempted 1+ exercises, but not submitted 11|3|20|45%	Looked at 1+ exercises, but not attempted 0|7|20|9%	Knew about exercises, did not look at any 0|0|19|9%	No knowledge of exercises 0|0|8|5%
3.	In case you did not complete EX101x successfully, were financial reasons a major factor?	Not applicable 74|71|62|35%	No 26|18|32|50%	Yes, a minor factor 0|11|0|10%	Yes, a major factor 0|0|6|5%	- -	- -
Financial incentives in general							
4.	If you require financial incentives to complete a MOOC, how much (in US dollar) would you need to earn per week via real-world freelance tasks in order to complete a MOOC?	No financial incentive required 80|52|77|64%	$0-$9 0|7|0|5%	$10-$29 0|10|6|9%	$30-$49 8|7|11|13%	$50-$99 4|14|3|9%	$100+ 8|10|3|0%
5.	If earning that much money per week, how many hours per week would you commit to a MOOC?	*Open-answer form*					
6.	Would you consider this income essential to your well-being or more like extra spending money?	Not applicable 80|48|66|55%	1 (Essential) 4|10|3|9%	2 0|4|9|5%	3 8|17|6|23%	4 0|14|8|9%	5 (Extra) 8|7|8|0%
Bonus exercises in *EX101x*							
7.	How many hours per week did you actually commit to EX101x?	*Open-answer form*					
8.	Did the bonus exercises increase your motivation to engage with the course (beyond the standard course material)?	1 (Not at all) 8|7|33|11%	2 12|0|23|21%	3 28|24|17|31%	4 32|41|20|26%	5 (Very much) 20|28|7|10%	- -
9.	How difficult did you find the bonus exercises?	1 (Too easy) 0|0|7|0%	2 4|4|7|6%	3 56|31|61|50%	4 36|62|21|31%	5 (Too difficult) 4|3|4|13%	- -
10.	Why did you begin attempting the bonus exercises?	*Open-answer form*					
11.	Why did you stop?	*Open-answer form*					

Table 5.7: Overview of the 11 questions in our post-course survey. For presentation purposes, some questions and answers appear slighlty condensed. For all closed-form questions, we provide the distribution of answers (in %) across the four learner partitions in the form A | B | C | D%: (A) from developed nations + at least one bonus exercise submitted, (B) from developing nations + at least one bonus exercise submitted, (C) from developed nations + no bonus exercise submitted, and, (D) from developing nations + no bonus exercise submitted.

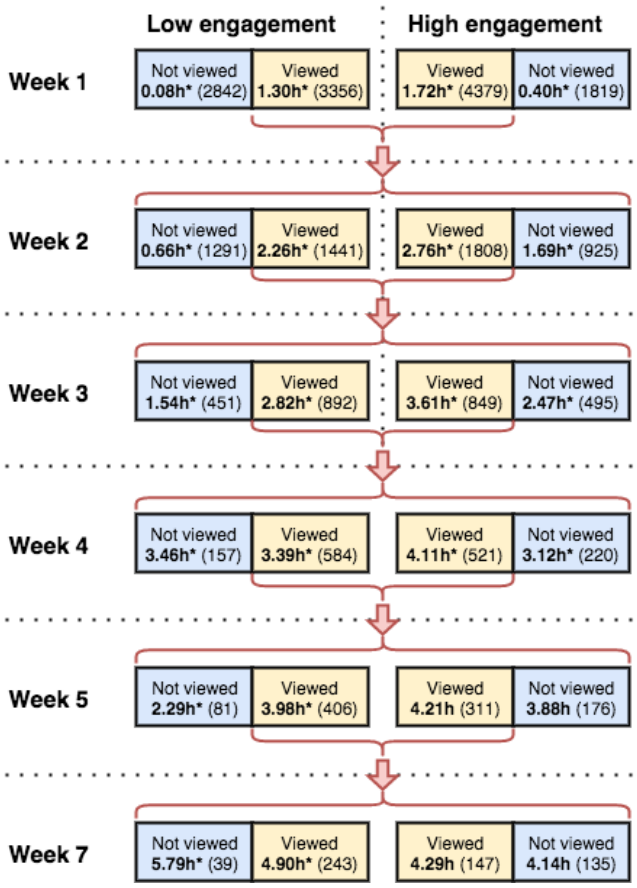


Figure 5.6: The average amount of time (in hours) that learners spent in watching video after viewing (but not submitting) the bonus exercises. The numbers of learners within each group are given in brackets. Results marked with * ($p < 0.001$) are significantly different (*Viewed* vs. *Not viewed*) according to the Mann-Whitney U-test.

- from developing nations & submitted at least one bonus exercise (114 learners contacted, 29 replied);
- from developed nations & did not submit a bonus exercise (357 learners contacted, 34 replied);
- from developing nations & did not submit a bonus exercise (271 learners contacted, 22 replied);

Besides the questions and answer options, in Table 5.7 we also report the distribution of given answers for all closed-form questions and each learner partition. We note that a small number of learners who we classified as not

having submitted a bonus solution self-reported having done so. The converse is also true: a small number of learners that we have received bonus exercise submissions from reported not having submitted any. These self-reporting errors could be explained by the amount of time (12 weeks) passed between the end of *EX101x* and the release of the survey. Overall though, the vast majority of learners were remembering their (lack of) submissions for our bonus exercises correctly.

Students from developing nations who did not attempt any of the bonus exercises report that if they could earn somewhere between $10 and $100 per week through such online work platform tasks, they would commit up to six more hours to the course per week. In this same group, 45% of respondents attempted one or more bonus exercises but did not submit it to the course instructor. In contrast, of the survey respondents from developed nations who did not submit a bonus exercise to the instructor, only 20% reported having attempted to solve any. This difference suggests that learners from developing nations are more motivated and eager to engage with course material, but there seems to be a barrier stopping them from fully engaging as much as they would like. Providing an opportunity for them to gain income in the process could be a key factor in enabling them to fully commit to a MOOC.

In question 9 we asked students how difficult they found the bonus exercises to be on a five-point Likert scale—"1" being too easy and "5" being too difficult. Of the entire group of learners (across all partitions) that responded, the average score was 3.48. As bonus exercises, they are expected to be slightly more difficult than the rest of the course material, and the students seem to generally view them as such—slightly more difficult, yet accessible. This sentiment is also echoed in the students' comments in the survey when asked why they chose to engage with the bonus exercises in the first place; the three most common words to appear in the responses, in order, are "challenge," "real," and "test." To synthesize, students generally see these activities as an added challenge in which they test their ability to apply what they learned in the course to a real-world problem.

Also interesting is that learners from developing countries perceived the bonus exercises as being more difficult than learners in developed countries (Mann-Whitney U-test with $U = 781$, $Z = -2.13$ and $p < 0.05$). This discrepancy underlines the importance for learners in developing countries to be able to commit the necessary time for these types of tasks, as a higher perceived difficulty would require more time from the learner to understand and/or master the content.

Finally, we also explored the effect of the bonus exercises on learners' motivation to engage with the course (survey question 8). These responses, also on a five-point Likert scale, ranged from "Not at all" (1) to "Very much" (5). A difference emerged in the way learners from different backgrounds are affected by the presence of the bonus exercises. Learners from developing nations report that bonus exercises increased their motivation to engage with the course significantly more than learners from developing countries (Mann-Whitney U-test with $U = 617.5$, $Z = 2.61$ and $p < 0.05$).

5.6 Freelance Recommender System Design

Based on our analyses presented in the previous sections, we have to take the following two requirements into account when designing our freelance task recommender:

- The recommender should support multiple task platforms, as we have found `Upwork` (at this point in time) to only offer a very limited number of tasks in our specified price range and on our specific MOOC's topic each day.
- Once we recommend learners tasks on `Upwork` and other similar platforms, we need to continuously track the tasks' status (are they still available?) as well as the number of times we have recommended them to different learners (to avoid hundreds of learners trying to "bid" for the same task — only one of them can get the job and be paid).

Figure 5.7 shows our designed recommender system, which — for any given MOOC — will automatically retrieve real-world tasks relevant to the topics covered in the MOOC and recommend them to our learners. We briefly discuss the different layers in turn:

- **MOOC**. The MOOC layer serves as the playground for learners to interact with course components and our freelance task recommender system.
- **Data layer**. This layer is responsible for collecting learners' activity data and gathering real-world tasks from freelance platforms. To be specific, the component *MOOC data collector* collects data of learners' interactions with course components (e.g., watching lecture videos, viewing forum posts, submitting quiz answers) and the recommender

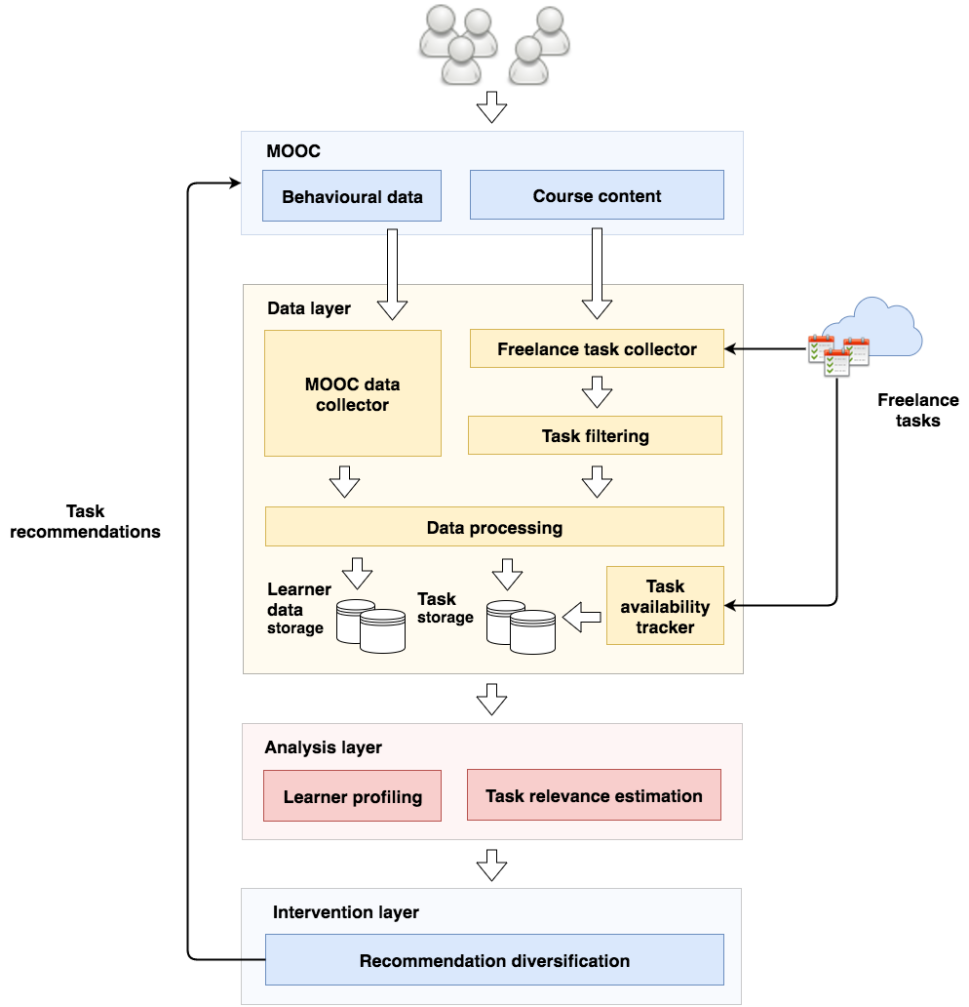


Figure 5.7: Overview of the freelance work task recommender system's design.

system (e.g., viewing recommended freelance tasks, dwell time). On the other side, the component *Freelance task collector* retrieves course-relevant tasks from multiple freelance platforms including `Upwork`, `witmart`, `Guru` and `Envato`. As some of the discovered freelance tasks may not be suitable for our setting of "earning whilst learning" (high budget tasks often require deep knowledge of several fields), the *Task filtering* component filters out unsuitable tasks by applying rule-based strategies (e.g., by setting the maximun budget). In addition, the *Task availability tracker* component regularly checks whether the recommended

freelance tasks are still open & available before generating the recommendations for our learners.

- **Analysis layer**. In this layer, the *Learner profiling* component analyzes learners' interaction patterns with the recommender system and how/whether learners' course engagement can be influenced by freelance task recommendations. The *Task relevance estimation* component computes the relevance of the discovered tasks with respect to the specific MOOC as well as (potentially) the learner profile.
- **Intervention layer**. At last, the intervention layer makes task recommendations to our learners. The *Recommendation diversification* component is responsible for presenting a diverse selection of recommendations (to avoid hundreds or thousands of learners competing for the same freelance tasks).

In future work we will implement this design and test its influence in various MOOCs by exploring its effect on MOOC learners.

5.7 Conclusion

Can MOOC learners be paid to learn? We set out to provide a first answer to this question in the context of the *EX101x* MOOC. We found that indeed, work tasks of up to $50 can be solved accurately and in high quality by a considerable percentage of learners that attempt it. We also explored the suitability of the online work platform `Upwork` in providing tasks to MOOC learners - while there are many budget tasks available (between $1 and $50), those specific to *EX101x* are rather low in number; at the moment we expect no more than 13 suitable tasks (i.e. specific to taught course material) to be posted per day. Finally, we investigated the matter of engagement: does knowing that real-world tasks may be solved with course knowledge increase learners' engagement? Our evidence suggests that this is may indeed be the case. We note that while we did observe correlational relationships between learners' bonus exercise engagement and in-course behavior, the present research cannot yet claim any causality.

Based on the work presented here, we will explore several promising directions (beyond the development and deployment of the presented recommender design) in the future. We will investigate (i) experimental setups that allow us to further investigate the causal relationship between real-world tasks and learner engagement, (ii) the suitability of more complex tasks (i.e.

tasks with a budget greater than $50) for MOOC learners, (iii) the acceptance of the "learners can be earners" paradigm in different populations, and (iv) setups that aid MOOC learners to take the first steps in the paid freelance task world, inspired by [146].

Chapter 6

LearningQ for Educational Question Generation

In this chapter, we focus on the collection of a large-scale and high-quality educational question dataset, as the first step to construct an automatic question generator to ease the burden of instructors in manually creating a suitably large question bank. To this end, we examine the learning material accumulated in two mainstream education-oriented `Social Web` platforms, i.e., `TED-Ed` and `Khan Academy`, and present *LearningQ*, which consists of a total of 230K document-question paris, whose questions are of all cognitive levels in the Bloom's Revised Taxonomy [104] and covering various learning subjects. To show the research challenges in generating educational questions, we use *LearningQ* as a testbed to examine the performance of two state-of-the-art approaches in automatic question generation and investigate possible strategies to select question-worthy sentences from an article. The contributions of this chapter have been published in [33].

6.1 Introduction

In educational settings, questions are recognized as one of the most important tools not only for assessment but also for learning [128]. Questions allow learners to apply their knowledge, to test their understanding of concepts and ultimately, to reflect on their state of knowledge. This, in turn, enables learners to better direct their learning effort and improve their learning outcomes. Previous research has shown that the number of questions learners receive about a knowledge concept is positively correlated with the effectiveness of knowledge retention [8]. It is thus desirable to have large-scale question banks for every taught concept to better support learners.

Designing a suitably large set of high-quality questions is a time-consuming and cognitively demanding task. Instructors need to create questions of varying types (e.g., open-ended, multiple choice, fill-in-the-blank), varying cognitive skill levels (e.g., applying, creating) and varying knowledge dimensions (e.g., factual, conceptual, procedural) that are preferably syntactically different yet semantically similar in order to enable repeated testing of a knowledge concept. To ease instructors' burden, *automatic question generation* has been proposed and investigated by both computer scientists and learning scientists to automate the question creation process through computational techniques [110, 136, 137, 69].

Typically, automatic question generation has been tackled in a rule-based manner, where experienced teachers and course instructors are recruited to carefully define a set of rules to transform declarative sentences into interrogative questions [161, 3, 69]. The success of these rule-based methods is heavily dependent on the quality and quantity of the handcrafted rules, which rely on instructors' linguistic knowledge, domain knowledge and the amount of time they invest. This inevitably hinders these methods' ability to scale up to a large and diverse question bank.

Data-driven methods, deep neural network based methods, in particular, have recently emerged as a promising approach for various natural language processing tasks, such as machine translation, named entity recognition and sentiment classification. Inspired by the success of these works, Du et al. [51] treated question generation processes as a sequence-to-sequence learning problem, which directly maps a piece of text (usually a sentence) to a question. In contrast to rule-based methods, these methods can capture complex question generation patterns from data without handcrafted rules, thus being much more scalable than rule-based methods. As with most data-driven ap-

proaches, the success of neural network based methods is largely dependent on the *size* of the dataset as well as its *quality* [131].

Source	***Doc*ument-*Q*uestion pairs**
SQuAD	*Doc:* ... after Heine's German birthplace of Düsseldorf had rejected, allegedly for anti-Semitic motives ... *Q:* Where was Heine born?
RACE	*Doc:* ... There is a big supermarket near Mrs. Green's home. She usually ... *Q:*: Where is the supermarket?
LearningQ	*Doc:* ... gases have energy that is proportional to the temperature. The higher the temperature, the higher the energy the gases have. The crazy thing is that at the same temperature, all gases have the same energy ... *Q:* If you were given oxygen (molecular mass = 18 AMU) and hydrogen (molecular mass = 1 AMU) at the same temperature and pressure, which has more energy?

Table 6.1: Examples of document-question pairs.

Exiting datasets, such as SQuAD [131] and RACE [96], though containing a large number of questions (e.g., 97K questions in SQuAD), are not suitable for question generation in the learning context. Instead of being aimed at educational question generation, these datasets were originally collected for reading comprehension tasks. They are often limited in their coverage of topics—the questions in SQuAD for example, were generated by crowdworkers based on a limited number (536) of Wikipedia articles. More importantly, these questions seek factual details, and the answer to each question can be found as a piece of text in the source passages; they do not require higher-level cognitive skills to answer them, as exemplified by the SQuAD and RACE example questions in Table 6.1. We speculate, as a consequence, question generators built on these datasets cannot generate questions of varying cognitive skill levels and knowledge dimensions that require a substantial amount of cognitive efforts to answer, which unavoidably limits the applicability of the trained question generators for educational purpose.

To address these problems, we investigate the research question: **RQ 5.1 can a large-scale and high-quality educational question dataset**

be collected from the `Social Web`? Specifically, we present *LearningQ*, which consists of more than 230K document-question pairs collected from mainstream online learning platforms. *LearningQ* does not only contain questions designed by instructors (7K) but also questions generated by students (223K) during their learning processes, e.g., watching videos and reading recommended materials. It covers a diverse set of educational topics ranging from computing, science, business, humanities, to math. Through both quantitative and qualitative analyses, we show that, compared to existing datasets, *LearningQ* contains more diverse and complex source documents; moreover, solving the questions requires higher-order cognitive skills (e.g., *applying*, *analyzing*). Specifically, we show that most questions in *LearningQ* are relevant to multiple source sentences in the corresponding document, suggesting that effective question generation requires reasoning over the relationships between document sentences, as shown by the *LearningQ* question example in Table 6.1. Besides, we evaluate both rule-based and state-of-the-art deep neural network based question generation methods on *LearningQ*. Our results show that methods which perform well on existing datasets cannot generate high-quality educational questions, suggesting that *LearningQ* is a challenging dataset worth of significant further study.

Have you ever dropped your swimming goggles in the deepest part of the pool and tried to swim down to get them? It can be frustrating because the water tries to push you back up to the surface as you're swimming downward. **The name of this upward force exerted on objects submerged in fluids is called the buoyant force.**

Table 6.2: Question-worthy sentence in a paragraph.

After presenting *LearningQ*, we further investigate the problem of identifying question-worthy content (i.e., sentences used as input for the question generator) from an article, which is largely ignored by existing studies [51, 69]. Formally, we direct our efforts in answering the research question: **RQ 5.2 what are effective strategies in identifying question-worthy sentences from an article?** To be specific, given a paragraph or an article, often there are only a limited number of sentences that are worth asking questions about, i.e., those carrying important concepts. An example is shown in Table 6.2, where the last sentence defines the most important concept "buoyant force". We, therefore, argue that selecting question-worthy sentences is of critical importance to the generation of high-quality educational questions.

To this end, we aim at achieving a better understanding of the effectiveness of different textual features in identifying question-worthy sentences from an article and proposing a total of nine strategies for question-worthy sentence selection, which cover a wide range of possible question-asking patterns inspired by both low-level and high-level textural features. For instance, we represent our assumption that *informative* sentences are more likely to be asked about by leveraging low-level features such as sentence length and the number of concepts as informativeness metrics; our assumption that *important* sentences are more worth asking about is represented by leveraging semantic relevance between sentences, which can be measured by using summative sentence identification techniques [53, 23]. To evaluate the effectiveness of the proposed strategies, we apply them to identify question-worthy sentences on five question generation datasets, i.e., *SQuAD* [131], *TriviaQA* [83], *MCTest* [133], *RACE* [96] and *LearningQ* presented in this chapter. We use the sentences identified by the proposed strategies as input for a well-trained question generator and evaluate the effectiveness of sentence selection strategies by comparing the quality of the generated questions.

To the best of our knowledge, *LearningQ* is the first large-scale dataset for educational question generation. It provides a valuable data source for studying cross-domain question generation patterns. The distinct features of *LearningQ* make it a challenging dataset for driving the advances of automatic question generation methods. Also, our work is the first to systematically study question-worthy sentence selection strategies across multiple datasets. Through extensive experiments, we find that the most question-worthy sentences in Wikipedia articles are often the beginning ones. In contrast, questions collected for learning purposes usually feature a more diverse set of sentences, including those that are most informative, important, or contain the largest amount of novel information. We further demonstrate that *LexRank*, which identifies important sentences by calculating their eigenvector centrality in the graph representation of sentence similarities, gives the most robust performance across different datasets among the nine selection strategies.

6.2 Related Work

6.2.1 Question Generation

Automatic question generation has been envisioned since the late 1960s [135]. It is generally believed by learning scientists that the generation of high-

quality learning questions should be based on the foundations of linguistic knowledge and domain knowledge, and thus they typically approach the task in a rule-based manner [161, 3, 69, 109]. Such rules mainly employ syntactic transformations to turn declarative sentences into interrogative questions [35]. For instance, Mitkov and Ha [109] generated multiple-choice questions from documents by employing rules of term extraction. Based on a set of manually-defined rules, Heilman and Smith [69] produced questions in a overgenerate-and-rank manner where questions are ranked based on their linguistic features. These methods, however, are intrinsically limited in scalability: rules developed in certain subjects (e.g., introductory linguistics, English learning) cannot be easily adapted to other domains; the process of defining rules requires considerable efforts from experienced teachers or domain experts. More importantly, manually designed rules are often incomplete and do not cover all possible document-question transformation patterns, thus limiting rule-based generators to produce high-quality questions.

Entering the era of large-scale online learning, e.g., Massive Open Online Courses [119], the demand for automatic question generation has been increasing rapidly along with the largely increased number of learners and online courses accessible to them. To meet the need, more advanced computational techniques, e.g., deep neural network based methods, have been proposed by computer scientists [51, 50]. In the pioneering work by Du et al. [51], an encoder-decoder sequence learning framework [144] incorporated with the global attention mechanism [103] was used for question generation. The proposed model can automatically capture question-asking patterns from the data, without relying on any hand-crafted rules, thus has achieved superior performance to rule-based methods regarding both scalability and the quality of the generated questions.

These methods, however, have only been tested on datasets that were originally collected for machine reading comprehension tasks. Noticeably, these datasets contain a very limited number of useful questions for learning, as we will show in the following sections. Therefore, it remains an open question how deep neural network methods perform in processing complex learning documents and generating desirable educational questions.

6.2.2 Datasets for Question Generation

Several large-scale datasets have been collected to fuel the development of machine reading comprehension models, including SQuAD [131], RACE [96], NewsQA [150], TriviaQA [83], NarrativeQA [93], etc. Though containing

questions, all of these datasets are not suitable for educational question generation due to either the limited number of topics [131, 96] or the loose dependency between documents and questions, i.e., a document might not contain the content necessary to generate a question and further answer the question. More importantly, most questions in these datasets are not specifically designed for learning activities. For example, SQuAD questions were generated by online crowdworkers and are used to seek factual details in source documents; TriviaQA questions were retrieved from online trivia websites. An exception is RACE, which was collected from English examinations designed for middle school and high school students in China. Though collected in a learning context, RACE questions are mainly used to assess students' knowledge level of English, instead of other skills or knowledge of diverse learning subjects.

Depending on different teaching activities and learning goals, educational questions are expected to vary in cognitive complexity, i.e., requiring different levels of cognitive efforts from learners to solve. Ideally, an educational question generator should be able to generate questions of all cognitive complexity levels, e.g., from low-order recalling factual details to high-order judging the value of a new idea. This requires the dataset for training educational question generators to contain questions of different cognitive levels. As will be presented in our analysis, *LearningQ* covers a wide spectrum of learning subjects as well as cognitive complexity levels and is therefore expected to drive forward the research on automatic question generation.

6.2.3 Question-worthy Sentence Selection

Existing studies, however, pay little attention to the selection of question-worthy sentences: they either assume that the question-worthy sentences have been identified already [51] or simply take every sentence in an article as input for the question generator. For instance, [69] assume that all sentences in an article are question-worthy and thus generate one question for each sentence and select high-quality ones based on their linguistic features. To our knowledge, [50] is the only study that explicitly tackles the question-worthy sentence selection problem. It uses a bidirectional LSTM network [75] to simultaneously encode a paragraph and calculate the question-worthiness of a sentence in the paragraph. However, training such a network relies on a large amount of ground-truth labels of question-worthy sentences (e.g., tens of thousands). Obtaining these labels is a long, laborious, and usually costly process. Furthermore, the proposed deep neural network was only validated in short paragraphs instead of the whole article. Considering that reading

materials can be much longer and deep neural networks can fail at processing long sequence data due to the vanishing gradient problem [76], it remains an open question whether the proposed method can handle long articles.

Instead of developing a novel neural network architecture that simultaneously does sentence selection and question generation (like [50] does), we take one step back and focus extensively on question-worthy sentence selection. We propose heuristic strategies which exploit different textual features in selecting question-worthy sentences from an article, so as to clarify the main criteria in the selection process, and to adequately inform educational question generator design.

6.3 Data Collection

6.3.1 Data Sources

To gather large amounts of useful learning questions, we initially explored several mainstream online learning platforms and finally settled on two after having considered the data accessibility and the quantity of the available questions as well as the corresponding source documents. Concretely, we gathered *LearningQ* data from the following two platforms:

`TED-Ed`[1] is an education initiative supported by TED which aims to spread the ideas and knowledge of teachers and students around the world. In TED-Ed, teachers can create their own interactive lessons, which usually involve lecture videos along with a set of carefully crafted questions to assess students' knowledge. Lesson topics range from humanity subjects like arts, language, and philosophy to science subjects like business, economics and computer technology. Typically, a lesson, covering a single topic, includes one lecture video, and lasts from 5 to 15 minutes. Due to the subscription-free availability, TED-Ed has grown into one of the most popular educational communities and served millions of teachers and students every week. As questions in `TED-Ed` are created by instructors, we consider them to be high-quality representations of testing cognitive skills at various levels (e.g., the LearningQ question in Table 6.1 is from `TED-Ed`). We use TED-Ed as the major data source to collect instructor-crafted learning questions.

`Khan Academy`[2] is another popular online learning platform. Similar to `TED-Ed`, `Khan Academy` also offers lessons to students around the world. Compared to

[1] https://ed.ted.com/
[2] https://www.khanacademy.org/

TED-Ed, the lessons are targeted at a wider audience. For example, the math subjects in Khan Academy cover topics from kindergarten to high school. In addition, the lessons are organized in alignment with typical school curriculum (from the easier to the more advanced) instead of being an independent collection of videos as is the case in TED-Ed. Another distinction between the two platforms is that Khan Academy allows learners to leave posts and ask questions about the learning materials (i.e., lecture videos and reading materials) during their learning. For instance, the chemistry course *Quantum numbers and orbitals*[3] includes one article (titled *The quantum mechanical model of the atom*) and three lecture videos (titled *Heisenberg uncertainty principle*, *Quantum numbers* and *Quantum numbers for the first four shells*) and learners can ask questions about any of them. More often than not, learners' questions express their confusion about the learning material—e.g., "How do you convert Celsius to Calvin?"—and thus are an expression of learners' knowledge gaps that need to be overcome to master the learning material. We argue that these questions can promote in-depth thinking and discussion among learners, thus complementing instructor-designed questions. We use those learner-generated questions as part of *LearningQ*.

We implemented site-specific crawlers for both Khan Academy and TED-Ed and collected all available questions and posts in English as well as their source documents at both platforms that were posted on or before December 31, 2017, resulting in a total of 1,146,299 questions and posts.

6.3.2 Question Classification for Khan Academy

Compared to instructor-designed questions collected from TED-Ed, learner-generated posts in Khan Academy can be of relatively low quality for our purposes since they are not guaranteed to contain a question (a learner may for example simply express her appreciation for the video), or the contained question can be off-topic, lack the proper context, or be too generic. Examples of high- and low-quality questions are shown in Table 6.3.

Originally, we gathered a total of 953,998 posts related to lecture videos and 192,301 posts related to articles from Khan Academy. To distill useful learning questions from the collected posts, we first extracted sentences ending with a question mark from all of the posts, which resulted in 407,723 such sentences from posts on lecture videos and 66,100 on reading material. To further discriminate useful questions for learning from non-useful ones, we ran-

[3] https://www.khanacademy.org/science/chemistry/electronic-structure-of-atoms/orbitals-and-electrons/

domly sampled 5,600 of these questions and recruited two education experts to annotate the questions: each expert labeled 3,100 questions (600 questions were labeled by both experts to determine the inter-annotator agreement) in a binary fashion: useful for learning or not. Based on the labeled data, we trained a convolutional neural network [88] on top of pre-trained word embeddings [108] to classify the remaining `Khan Academy` questions. In the following, we describe the labeling process in more details.

ID	Questions	Topic	Label
a)	What is the direction of current in a circuit?	S	√
b)	Why can't voltage-gated channels be placed on the surface of Myelin?	S	√
c)	Is there a badge for finishing this course?	E	
d)	Have you looked on your badges page to see if it is one of the available badges?	T	
e)	Why do each of them have navels?	H	
f)	Does it represent phase difference between resistance and reactance?	S	
g)	What should the graph look like for higher voltages?	S	√
h)	What if some of the ideas come from different historical perspectives, giving inaccurate information?	H	
i)	What if the information is wrong ?	M	
j)	Can someone please help me?	C	
k)	Could you be more specific ?	T	
l)	Are you asking what geometric means?	M	
m)	Are you talking about the frequency?	E	
n)	What programming language or how much of coding I need to know to start learning algorithms here?	C	
o)	Can I do algorithms or should I do programming first?	C	

Table 6.3: Examples of useful (marked with √) and non-useful questions from `Khan Academy`. S/H/M/C/E/T denote Science, Humanities, Math, Computing, Economics and Test Preparation, respectively.

Question Annotation. We consider a user-generated question to be as useful for learning when all of the following conditions hold: (i) the question is *concept-relevant*, i.e., it seeks for information on knowledge concepts taught in lecture videos or articles; (ii) the question is *context-complete*, which means sufficient context information is provided to enable other learners to answer the question; and (iii) the question is not generic (e.g., a question asks for learning advice). To exemplify this, two concept-relevant learning questions are shown in Table 6.3 (a and b), accompanied by two concept-irrelevant ones (c and d). Question e and f in the same table are also concept-relevant. However, as they don't provide enough context information, e.g., lack of references for "they" and "it", we consider them as non-useful. As a counter-example, we consider question g in the table as useful since the reference for "the graph" can be easily inferred. This comes in contrast to question h and i, where the references for "the idea" and "the information" are too vague thus failed to to provide sufficient context information. Finally, generic questions expressing the need for help (j and k), asking for clarification (l and m) or general learning advice (as exemplified by n and o), are not useful for learning the specific knowledge concepts.

Annotation & Classification Results. Of the 5,600 annotated questions, we found 3,465 (61.9%) to be useful questions for learning. The inter-annotator agreement reached a Cohen's Kappa of 0.82, which suggests a substantially coherent perception of question usefulness by the two annotators. To understand the performance of the classifier trained on this labeled dataset, we randomly split the dataset into a training set of size 5,000, a validation set of size 300, and a test set of size 300. We iterated the training and evaluation process 20 times to obtain a reliable estimation of classification performance. Results show that the model reaches an accuracy of 80.5% on average (SD=1.8%), suggesting that the classifier can be confidently applied for useful/non-useful question classification. With this classifier, we retain about 223K unique useful questions in `Khan Academy`, which will be used for our following analysis.

6.3.3 Final Statistics of *LearningQ*

An overall description of *LearningQ* is shown in Table 6.4 (rows 1—4). As a means of comparison, we also provide the same statistics for the popular question generation datasets (though not necessarily useful for education and learning) SQuAD and RACE. Compared to these two datasets, *LearningQ* (i) consists of about 230K questions (versus 97K in SQuAD and 72K in RACE) on nearly 11K source documents; (ii) contains not only useful educational

Row	Feature Type	Features	SQuAD	RACE	TED-Ed	Khan Academy	
						Video	Article
1.	Basic statistics	Creator	Crowdworker	Instructor	Instructor	Learner	Learner
2.		# Unique documents	20,958	27,933	1,102	7,924	1,815
3.		# Unique questions	97,888	72,547	7,612	201,273	22,585
4.		# Avg. questions / document	4.67	2.60	6.91	25.40	12.44
5.	Document & question length	# Avg. words / document	134.84	322.88	847.64	1370.83	1306.55
6.		# Avg. sentence / document	4.96	17.63	42.89	73.51	49.85
7.		# Avg. words / sentence of documents	27.17	18.31	19.76	18.65	26.21
8.		# Avg. words / question	11.31	11.51	20.07	16.72	17.11
9.		# Avg. sentence / question	1.00	1.03	1.41	1.00	1.00
10.	Entities	# Avg. entities /document	10.24	9.75	17.66	14.55	47.38
11.		# Avg. entities /question	0.92	0.53	0.66	0.29	0.44
12.		% Entity words in question	8.10	4.58	3.29	1.72	2.54
13.	Readability	Document readability	45.82	73.49	64.08	76.54	55.15
14.		Question readability	67.23	51.00	66.32	72.15	69.04

Table 6.4: Descriptive features and statistics of *LearningQ* and the datasets in comparison.

questions carefully designed by instructors but also those generated by learners for in-depth understanding and further discussion of the learning subject; (iii) covers a wide range of educational subjects from two mainstream online learning platforms. To highlight the characteristics of *LearningQ*, we also include SQuAD and RACE in the data analysis presented next.

6.4 Sentence Selection Strategies

In the following, we describe in detail our proposed sentence selection strategies based on different question-asking assumptions and sentence properties measured by different textual features.

- **Random sentence (Random).** As the baseline, we randomly select a sentence and use it as input for the question generator.
- **Longest sentence (Longest).** This strategy selects the longest sentence in an article. The assumption is that people tend to ask questions about sentences containing a large amount of information, which, intuitively, can be measured by their lengths.
- **Concept-rich sentence (Concept).** Different from *Longest*, this strategy assumes that the amount of information can be better measured by the total number of entities in a sentence. The more entities a sentence contains, the richer information it has.
- **Concept-type-rich sentence (ConceptType).** This strategy is a variant of *Concept*. It calculates the total number of entity types in a sentence to measure the informativeness of a sentence.

The above three strategies approximate question-worthiness of a sentence by *informativeness*, which is further measured by different textual features. In contrast, the following two strategies approximate question-worthiness of a sentence by *difficulty* and *novelty*, respectively.

- **Most difficult sentence (Hardest).** This strategy is built on the assumption that difficult sentences can sometimes bring the most important messages that should be questioned and assessed. Therefore, it chooses the most difficult sentence in an article as the question-worthy sentence. We calculate the Flesch Reading Ease Score [39] of sentences as their difficulty indicators.

- **Novel sentence (Novel).** Unlike *Hardest*, this strategy believes that sentences with novel information that people do not know before are more question-worthy. We calculate the number of words that never appear in previous sentences as a sentence's novelty score [151] and select the most novel one.

Finally, we introduce three strategies that approximate question-worthiness of a sentence by the relative *importance* of the sentence concerning the remaining ones in an article. The importance is either measured by the relative position of a sentence or its centrality represented by semantic relevance with other sentences.

- **Beginning sentence (Beginning).** In the research of text summarization, one common hypothesis about sentence positions is the importance of a sentence decreases with its distance from the beginning of the document [115], and therefore less question-worthy. This strategy selects the first sentence in an article as the most question-worthy sentence.
- **Centroid based important sentence (LexRank).** In line with *Beginning*, this strategy also believes that question-worthy sentences should be selected from those of greater importance. The difference here is that the sentence importance is measured by the centroid-based method, *LexRank* [53], which calculates sentence importance based on eigenvector centrality in a graph of sentence similarities.
- **Maximum marginal relevance based important sentence (MMR).** Different from *LexRank*, this strategy computes sentence importance by considering a linear trade-off between relevance and redundancy [23], i.e., selecting the sentence that is most relevant but shares least similarity with the other sentences as the most important sentence.

6.5 Data Analysis on LearningQ

The complexity of questions concerning the required cognitive skill levels and knowledge dimensions is a crucial property that can significantly influence the quality of questions for learning [104]. We thus believe that this factor should be studied when building efficient question generators. However, to

our knowledge, there is no work attempting to characterize this property of questions in datasets for question generation.

In this section, we characterize the cognitive complexity of questions in *LearningQ* and other existing question generation datasets (i.e., SQuAD and RACE as two representatives) along several dimensions: *(i)* low-level document and question attributes related to cognitive complexity [167, 170], e.g., the number of sentences or words per document or per question; *(ii)* document and question properties that can affect human perception of cognitive complexity, which include topical diversity, document and question readability [39, 147], etc.; and *(iii)* cognitive skill levels in accordance with Bloom's Revised Taxonomy [104].

6.5.1 Document & Question Lengths

Table 6.4 (rows 5—9) presents statistics on document and question lengths. It can be observed that while, on average, the number of words per sentence in the documents of *LearningQ* are not larger than in SQuAD/RACE, documents from both `TED-Ed` and `Khan Academy` are more than twice as longer than those from SQuAD and RACE. In particular, SQuAD documents are on average nearly ten times shorter than `Khan Academy` documents. The same observation holds for the questions in *LearningQ*, where question length is twice as long as that of SQuAD and RACE. Compared with those in `Khan Academy`, documents in `TED-Ed` are shorter. This is mainly due to the fact that `TED-Ed` encourages shorter videos on a single topic.

6.5.2 Topics, Interrogative Words, and Readability

To gain an overview of the topics, we applied Named Entity Recognition to obtain statistics on the entities. The results are shown in rows 10 and 11 of Table 6.4. To gain more insights into the semantics of the documents and questions, we report the most frequent terms (after stopword removal) in Table 6.5 across both documents and questions. To gain insights into the type of questions, we separately consider interrogative terms (such as who or why) in the rightmost part of Table 6.5 by keeping most stopwords but filtering out prepositions and definite articles.

We observe in Table 6.4 that documents in *LearningQ* on average contains 160% more entities than SQuAD and RACE, which is expected because *LearningQ* documents are longer. Yet, the number of entities in *LearningQ* questions are not significantly larger than SQuAD and RACE. In particular,

Top Words in Documents				Top Words in Questions				Top Starting Words of Questions			
SQuAD	RACE	TED-Ed	KA	SQuAD	RACE	TED-Ed	KA	SQuAD	RACE	TED-Ed	KA
new	people	like	**going**	year	**passage**	think	**number**	what	what	what	what
city	say	people	**let**	**type**	according	following	know	who	which	which	how
time	time	time	right	use	following	people	**Sal**	how	according	how	why
world	like	know	time	new	**author**	**explain**	**mean**	when	why	why	**is**
use	**day**	make	**equal**	**city**	**writer**	use	use	which	how	if	if
state	new	**way**	say	people	people	time	like	where	when	when	**can**
century	**school**	call	**plus**	call	know	like	right	why	if	who	**do**
united	make	world	**negative**	time	text	make	difference	according	who	according	when
war	year	think	**minus**	**war**	**learn**	different	**negative**	whose	where	**explain**	**are**
know	world	different	think	**located**	**probably**	world	**equation**	if	list	where	**would**

Table 6.5: Top words in documents and questions and top interrogative words of quiestions in LearningQ and the datasets in comparison. Words pertinent to a specific data source platforms are in bold. KA represents Khan Academy.

questions in SQuAD contain 40% more entities than those in *LearningQ*. This is despite the fact that SQuAD documents are shortest overall, as we showed earlier. To eliminate the influence of question lengths and refine the analysis, we further observe that the percentage of entities among all the words (row 12) in SQuAD questions is higher than that in *LearningQ* questions. The same observation holds when comparing RACE with *LearningQ*. These observations imply that, on the one hand, documents in *LearningQ* are more complex concerning the number of involved entities; on the other hand, fewer questions related to entities, i.e., fewer factual questions, exist in *LearningQ* than the other datasets.

This interpretation is also supported by the top-k words shown in Table 6.5. We observe that while both documents and questions in SQuAD favor topics related to time and location (e.g., *time*, *year*, *century*, *city*, *state*), all data sources in *LearningQ* have fewer questions on these topics; more often in *LearningQ* questions, we find abstract words such as *mean*, *difference*, *function*, which are indicative of higher level cognitive skills being required. In line with this observation, we note that more interrogative words seeking factual details such as *who* and *when* rank high in the list of starting words of questions in SQuAD, while questions in *LearningQ* sources start much more frequently with *why*. This suggests that answering *LearningQ* questions often requires a deeper understanding of learning materials. Interestingly, one can observe in `TED-Ed` questions (in the middle part of the table) frequent words such as *think* and *explain*, which explicitly ask learners to process learning materials in a specific way. These required actions are directly related to learning objectives defined by Bloom's Revised Taxonomy, as we will analyze later. In addition to the above, another interesting observation from Table 6.5 is that learners frequently ask questions for the clarification of videos using words such as *know*, *Sal* (the name of the instructor who initially created most videos at `Khan Academy` in the early stage of the platform), and *mean*.

Readability. Readability is an important document and question property related to learning performance. Table 6.4 (rows 13—14) reports the Flesch readability scores of documents and questions in the compared datasets [39]. A piece of text with larger a Flesch readability score indicates it is easier to understand. Questions found alongside both `Khan Academy` videos and article possess similar readability scores, despite the different sources. This confirms our previous finding on the similarity between the two subsets of Khan Academy data. We, therefore, do not distinguish these two subsets in the following analyses focused on questions.

6.5.3 Cognitive Skill Levels

It is generally accepted in educational research that a good performance on assessment questions usually translates into "good learning" [72]. We first use Bloom's Revised Taxonomy to categorize the questions according to the required cognitive efforts behind them [104]. The taxonomy provides guidelines for educators to write learning objectives, design the curriculum and create assessment items aligned with the learning objectives. It consists of six learning objectives (requiring different cognitive skill levels from lower order to higher order):

- **Remembering**: questions that are designed for retrieving relevant knowledge from long-term memory.
- **Understanding**: questions that require constructing meaning from instructional messages, including oral, written and graphic communication.
- **Applying**: questions that ask for carrying out or using a procedure in a given situation.
- **Analyzing**: questions that require learners to break material into constituent parts and determine how parts relate to one another and to an overall structure or purpose.
- **Evaluating**: questions that ask for make judgments based on criteria and standards.
- **Creating**: questions that require learners to put elements together to form a coherent whole or to re-organize into a new pattern or structure.

To exemplify, we select one question example for each category that we collected from `TED-Ed` and `Khan Academy`, as shown in Table 6.6. Among the different learning objectives defined by Bloom's Revised Taxonomy, *analyzing* is an objective closely related to the task of automatic question generation. *analyzing* questions require the learner to understand the relationships between different parts of the learning material. Existing question generation methods [51], however, can usually only take one sentence as input. To cope with *analyzing* questions, state-of-the-art methods first need to determine the most relevant sentence in the learning material, which is then used as input to the question generator. This inevitably limits the ability of trained question generators to deliver meaningful *analyzing* questions covering multiple

Taxonomy	TED-Ed Examples	Khan Academy Examples
Remembering	How big is an atom?	What is a negative and a positive feedback in homeostasis?
Understanding	Why do some plankton migrate vertically?	Why can't voltage-gated channels be placed on the surface of myelin?
Applying	What kind of invention would you make with shape memory materials if you could get it in any form you wanted?	If i double the area and take the half of the fraction, do I get the same result?
Analyzing	Why are cities like London, Tokyo, and New York facing shortages in burial ground space?	Why did sea levels drop during the ice age?
Evaluating	Mansa Musa is one of many African monarchs throughout the continent's rich history. Yet, the narratives of only a few kings and queens are featured in television and movies. Analyze and evaluate why you think that this is the case, then create two ideas for how we can work to bring more positive awareness of the history of Africa's ancient and contemporary kings and queens to students today.	Will all the cultures merge into one big culture, due to the fading genetic distinctions?
Creating		Can somebody please explain to me what marginal benefits is and give me some examples?

Table 6.6: Question Examples of Different Bloom' Revised Taxonomy Level in `TED-Ed` and `Khan Academy`.

knowledge concepts scattered in the source documents. To understand the complexity of the *LearningQ* questions specifically from the point of view of training question generators, we also include in our analyses an exploration of the proportion of questions at various Bloom levels that require knowledge from multiple source document sentences.

Data Annotation. To facilitate our analysis, we recruited two experienced instructors to label 200 randomly sampled questions from each of the compared datasets according to Bloom's Revised Taxonomy. The Cohen's Kappa agreement score between the two annotators reached 0.73, which is a substantial agreement. In a second labeling step, we labeled the selected questions with their sentence(s) based on which they are generated.

Comparative Results. Table 6.7 shows the results of question classification according to Bloom's Revised Taxonomy. SQuAD only contains *remembering* questions, suggesting that it is the least complex dataset among all compared datasets regarding required cognitive skill levels. In general, we note a trend of decreasing percent of *remembering* questions (and increasing percentage of *understanding* questions) from SQuAD, RACE, to `TED-Ed` and `Khan Academy`. We can conclude that questions in *LearningQ* demand higher cognitive skills than those in SQuAD and RACE. Interestingly, among the two different *LearningQ* sources, we can observe that there are more *understanding* and *applying* questions in `Khan Academy` than in in `TED-Ed`, while there are more *evaluating* and *creating* questions in `TED-Ed` than in `Khan Academy`. This shows the inherent differences related to the corresponding learning activities between instructor-designed questions and learner-generated questions. The former is mainly used for assessment purpose and thus contains more questions of higher-order cognitive skill levels; the latter is generated during students' learning process (e.g., watching lecture videos and reading recommended materials) and is usually used to seek for a better understanding of the learning material. Note that 26.42% `Khan Academy` questions were labeled as either irrelevant or unknown due to being not useful for learning or missing enough context information for the labeler to assign a Bloom category. This aligns with the accuracy of the useful question classifier we reported in the data collection section.

In Table 6.8 we report the results of our source sentence(s) labeling efforts. From the statistics of # words in source sentences, we can observe an increasing requirement for reasoning over multiple sentences from SQuAD and RACE to `TED-Ed` and `Khan Academy`. Compared to the 98.5% of single sentence related questions in SQuAD, questions in `TED-Ed` (`Khan Academy`) are related to 3.53 (6.65) sentences on average in source documents. In par-

	SQuAD	RACE	TED-Ed	Khan Academy
Remembering	100	82.19	61.86	18.24
Understanding	0	18.26	38.66	55.97
Applying	0	0.46	9.79	12.58
Analyzing	0	8.22	14.95	15.09
Evaluating	0	1.37	4.12	1.89
Creating	0	0	1.55	0.63
Unknown/ Irrelevant	0	3.20	0	26.42

Table 6.7: Distribution of Bloom's Revised Taxonomy Labels.

	SQuAD	RACE	TED-Ed	KA
# Words	32.39	46.02	76.57	128.23
# Sent.	1.01	2.87	3.53	6.65
% ONE	98.53	37.10	28.63	9.43
% MULTIPLE	1.47	62.90	52.42	23.27
% EXTERNAL	0	0	18.95	38.99

Table 6.8: Results of Source Sentence Labelling. # Words/Sent. denote the average words/sentences in the labelled source sentences. % ONE/MULTIPLE/EXTERNAL refer to the percentage of questions related to ONE single sentence, MULTIPLE sentences or require EXTERNAL knowledge to generate, respectively. KA denotes Khan Academy.

ticular, Table 6.8 (the last row) further shows that a large portion of the questions in *LearningQ*, especially in `Khan Academy`, cannot be answered by simply relying on the source document, as exemplied by the *evaluating/creating* question from `TED-Ed` in Table 6.6 and thus require external knowledge to generate.

6.6 Experiments and Results

In this section, we first conduct experiments to evaluate the performance of rule-based and deep neural network based methods in question generation using *LearningQ*. We aim to answer the following questions: 1) how effective are these methods at generating high-quality educational questions; 2) to what extent is their performance influenced by the learning topics; and 3) to

what extent does the source sentence(s) length affect the question generation performance.

Then, we evaluate the performance of the strategies for question-worthy sentence selection as proposed in Section 6.4 across the five datasets.

6.6.1 Experimental Setup

Comparison Methods for *LearningQ* Evaluation. We investigate a representative rule-based baseline and two state-of-the-art deep neural networks in question generation:

- **H&S** is a rule-based system which can be used to generate questions from source text for educational assessment and practice [69]. The system produces questions in a overgenerate-and-rank manner. We only evaluate the top-ranked question.
- **Seq2Seq** is a representative encoder-decoder sequence learning framework proposed for machine translation [144]. It automatically learns the patterns of transforming an input sentence into an output sentence based on training data.
- **Attention Seq2Seq** is the state-of-the-art method proposed in [51], which incorporates the global attention mechanism [103] into the encoder-decoder sequence learning framework during the decoding process. The attention mechanism allows the model to mimic humans problem-solving process by focusing on relevant information in the source text and using this information to generate a question.

We implemented the two neural network based methods on top of the OpenNMT system [92]. In accordance with the original work [144, 51], Bi-LSTM is used for the encoder and LSTM for the decoder. We tune all hyper-parameters using the held-out validation set and select the parameters that achieve the lowest perplexity on the validation set. The number of LSTM layers is set to 2, and its number of hidden units is set to 600. The dimension of input word embedding is set to 300 and we use the pre-trained embeddings *glove.840B.300d* for initialization [124]. Model optimization is performed by applying Adam [89]; we set the learning rate to 0.001 and the dropout rate to 0.3. The gradient is clipped if it exceeds 5. We train the models for 15 epochs in mini-batches of 64. When generating a question, beam search with a beam size of 3 is used, and the generation stops when every beam in the stack produces the `<EOS>` (end-of-sentence) token.

***LearningQ* Preparation.** We use the NLTK tool [16] to pre-process *LearningQ*: lower-casing, tokenization and sentence splitting. To account for the fact that existing methods can only process a small number of sentences as input, we need to decide the source sentences that each question corresponds to before the evaluation. Instead of applying the nine sentence selection strategies we propose in Section 6.4, which are evaluated and compared in Section 6.6.3, here for each question, we use the following strategy inspired by approaches for text similarity [60] to locate the source sentences in the corresponding document most relevant to the question. If the target question contains a timestamp—e.g., "in 10:32, what does the Sal mean ..."—indicating the source sentence(s) location from which the target question is generated, we then choose that sentence as the starting sentence and compute the cosine similarity with the target question. We then go forwards and backwards in turns to determine whether including a nearby sentence would increase the cosine similarity between the target question and the source sentences. If yes, the nearby sentence is added. Otherwise, the search process stops. If a target question does not contain timestamp information, we select the sentence with the largest cosine similarity to the question to start our search the same way as described above to locate the source sentences. Due to the vanishing gradient problem in recurrent neural networks [76], we only keep data with source sentences containing no more than 100 words.

Notice that deep neural network based methods usually require a substantial amount of training data. The quantity of instructor-crafted questions in `TED-Ed` is not sufficient (7K). We, therefore, train the selected methods only on learner-generated questions. Concretely, we first merge all of the questions posted by `Khan Academy` learners on both lecture videos and reading materials, then randomly select 80% for training, 10% for validation and 10% for testing. At the same time, we also use all of the instructor-crafted questions as a second test set to investigate how effective the models built on learner-generated questions are in delivering instructor-crafted questions.

Unified Question Generator for Sentence Selection Evaluation. We also use *Attention Seq2Seq* as our testbed to evaluate the effectiveness of the proposed sentence selection strategies. To our knowledge, SQuAD is the only reading comprehension dataset with ground-truth labels of question-worthy sentence labels. Therefore, we use the labeled input sentences and the corresponding questions in SQuAD for training the question generator. We set the hyper-parameters as suggested in [51].

Notice that articles can be of different lengths and thus possibly contain different numbers of question-worthy sentences. During experiments, we be-

lieve the number of selected sentences should be dependent on the number of ground-truth questions gathered about an article: different ground-truth questions are seeking for different details about the article, i.e., based on different question-worthy sentences. We, therefore, evaluate the each of the questions generated by different selected sentences against all the ground-truth questions of the article and consider the result with the best performance as an indication of the selected sentence matched with the ground-truth question.

Datasets for Sentence Selection Evaluation. Generally, all reading comprehension datasets, i.e., those with questions and the corresponding documents which the questions are about, can be used to evaluate the selection strategies. We expect that the generated questions should be useful for learning purposes. Therefore, we select experimental datasets that contain natural questions designed by humans instead of search queries [114] or cloze-style questions [70]. With such consideration, we include five datasets for experiments: *SQuAD* [131], *TriviaQA* [83], *MCTest* [133], *RACE* [96], and *LearningQ* [33]. TriviaQA contains questions from trivia and quiz-league websites and evidence documents gathered from web search and Wikipedia. Here we only consider questions with evidence documents collected from Wikipedia, which results in 138K question-document pairs. MCTest consists of 660 stories written by crowd-workers and 2K associated questions about the stories. Recall that LearningQ contains both instructor-designed questions gathered from `TED-Ed` and learner-generated questions gathered from `Khan Academy`. As the learner-generated questions can be redundant about the same knowledge concepts (i.e., same sentences), to avoid concept bias, we only include the 7K instructor-designed questions for experiments on sentence selection.

Questions in SQuAD and TriviaQA mainly seek for factual details and the answers can be found as a piece of text in the source paragraph/article from Wikipedia. Questions in MCTest are designed for young children. RACE and LearningQ are collected in learning contexts: RACE questions are mainly used to assess students' knowledge level of English, whereas LearningQ covers a diverse set of educational topics, more complex articles, and the questions require higher-order cognitive skills to solve.

Evaluation Metrics. Similar to [51], we adopt Bleu 1, Bleu 2, Bleu 3, Bleu 4, Meteor and $Rouge_L$ for evaluation. Bleu-n scores rely on the maximum n-grams for counting the co-occurrences between a generated question and a set of reference questions; the average of Bleu is employed as final score [118]. Meteor computes the similarity between the generated question and the reference questions by taking synonyms, stemming and paraphrases into account

[47]. $Rouge_L$ reports the recall rate of the generated question concerning the reference questions based on the longest common sub-sequence [100].

	Methods	Bleu 1	Bleu 2	Bleu 3	Bleu 4	Meteor	Rouge_L
Khan Academy	H&S	0.28	0.17	0.13	0.10	3.24	6.61
	Seq2Seq	19.84	7.68	4.02	2.29	6.44	23.11
	Attn. Seq2Seq	24.70	11.68	6.36	3.63	8.73	27.36
TED-Ed	H&S	0.38	0.22	0.17	0.15	3.00	6.52
	Seq2Seq	12.96	3.95	1.82	0.73	4.34	16.09
	Attn. Seq2Seq	15.83	5.63	2.63	1.15	5.32	17.69

Table 6.9: Performance of rule-based and deep neural network based methods on *LearningQ*.

6.6.2 Evaluation on LearningQ

Results. Table 6.9 reports the performance of the selected methods on learner-generated questions from `Khan Academy` and instructor-designed questions from `TED-Ed`. We can observe that across all different evaluation metrics, the rule-based method H&S is outperformed by both deep neural network based methods. This confirms previous findings in the new context of learning that data-driven methods are a better approach for question generation. Among the two deep neural network based methods, Attention Seq2Seq consistently outperform Seq2Seq (p-value $< .001$, Paired t-test). This verifies that the attention mechanism is an effective approach for boosting the performance of educational question generation.

By comparing the performance of the selected methods on `Khan Academy` and on `TED-Ed`, we find that the performance of rule-based method H&S varies across different evaluation metrics. The performance measured by Bleu scores are higher on learner-generated questions than on instructor-designed questions, while it is low as measured by Meteor and $Rouge_L$. On the other hand, deep neural network based methods consistently reach a higher performance on learner-generated questions than on instructor-designed questions. Considering the fact that recurrent networks are less effective in handling long sentences, this could be due to two reasons: 1) the majority of questions in `TED-Ed` are related to multiple sentences as we found (Table 6.8); and 2) the questions generated by learners are generally shorter than those designed by instructors (Table 6.4). In later analysis, we further describe how the length of source sentences would affect question generation performance.

The performance of the state-of-the-art methods is much lower on *LearningQ* than on existing datatsets. Attention Seq2Seq achieves a Bleu 4 score > 12 and a Meteor score > 16 on SQuAD, while on *LearningQ* it only achieves Bleu 4 scores of $< 4/< 2$ and Meteor scores of $< 9/< 6$ on learner-generated questions/instructor-designed questions, respectively. Similar results also hold for the other metrics.

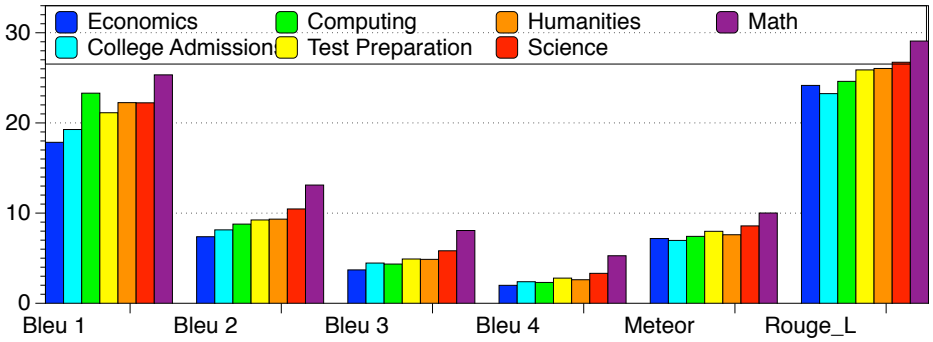


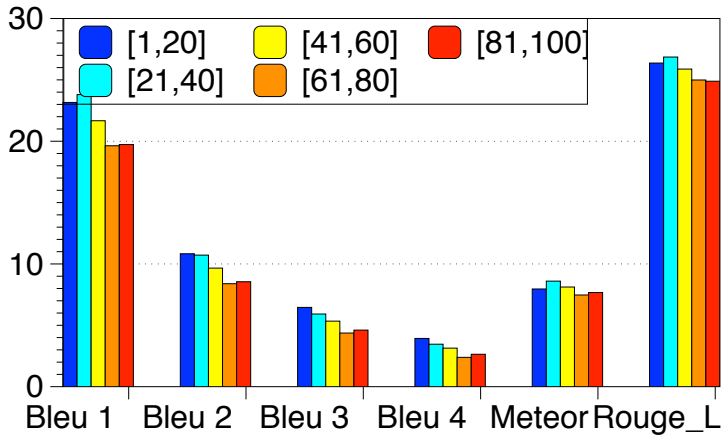
Figure 6.1: Results of question generation on different learning subjects in `Khan Academy`.

Impacts of Subjects and Source Sentence Lengths. We now investigate the performance of Attention Seq2Seq in generating educational questions as affected by different subjects and different lengths of input source sentences.

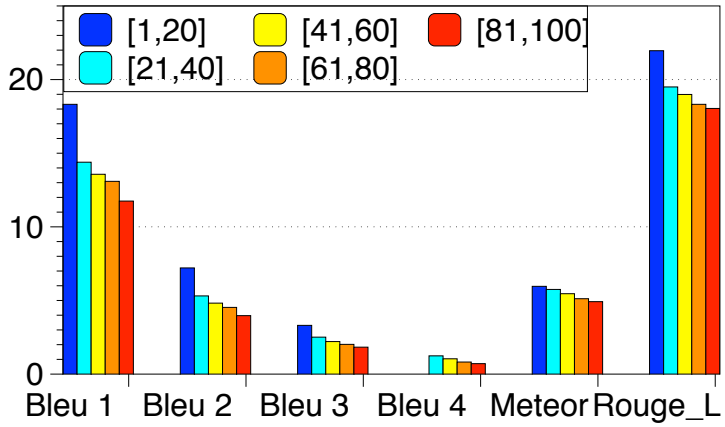
The impact of the source document topic on question generation performance is shown for `Khan Academy` in Figure 6.1. We observe that question generation performance varies across subjects. In particular, Bleu 4 varies from < 2 to > 5 for learner-generated questions and from 0.38 to 0.92 for instructor-designed questions. Compared to Economics and College Admissions, question generation for Math and Science can usually achieve higher performance. A similar variation is also observed on `TED-Ed`. These results indicate that topics can affect question generation performance. Fully understanding the co-influence of topics and other document properties (e.g., difficulty) however requires more studies, which we leave to future work.

As we showed before (Table 6.8), educational questions are related to multiple source sentences in the documents. However, existing neural network methods usually take only one or two source sentences as input to generate questions. To further investigate the effectiveness of existing methods when taking source sentences of different lengths as input, we divide the testing set according to the length of their source sentences. The results are shown in Figure 6.2. In general, question generation performance decreases when the length of source sentences increases across all metrics for both `Khan Academy`

and TED-Ed. This strongly suggests that the performance of the state-of-the-art method is significantly limited by long source sentences.



(a) Khan Academy



(b) TED-Ed

Figure 6.2: Results of question generation with different source sentence lengths.

6.6.3 Evaluation on Sentence Selection Strategies

Table 6.10 reports the results of the proposed sentence selection strategies on four datasets. We do not show results on the SQuAD dataset, as we found that the performance of different sentence selection strategies on SQuAD shows little variance, owing to the small number of sentences in the SQuAD documents (Wikipedia paragraphs, with five sentences on average). For the

Metrics	**Blue 1**	**Blue 2**	**Blue 3**	**Blue 4**	**Meteor**	**Rouge$_L$**	**Blue 1**	**Blue 2**	**Blue 3**	**Blue 4**	**Meteor**	**Rouge$_L$**
Dataset	TriviaQA						RACE					
Random	6.69	2.07	0.70	0.31	**6.21**	8.29	4.24	1.28	0.45	0.20	5.74	11.47
Beginning	**9.42**	**3.67**	**1.51**	**0.74**	**6.66**	**10.70**	4.50	1.33	0.43	0.18	5.95	11.82
Longest	3.37	1.21	0.45	0.21	3.57	8.67	**6.48**	**2.08**	**0.74**	**0.33**	**7.83**	**12.84**
Hardest	1.99	0.66	0.23	0.11	2.37	6.84	4.36	1.35	0.47	0.21	5.51	11.60
Concept	0.73	0.19	0.06	0.02	1.63	4.04	2.74	0.86	0.34	0.16	3.41	10.69
ConceptType	1.94	0.57	0.19	0.08	2.94	6.02	2.78	0.88	0.35	0.17	3.45	10.71
LexRank	**8.79**	**3.11**	**1.14**	**0.52**	**5.54**	**9.81**	**5.47**	**1.73**	**0.63**	**0.29**	**6.79**	**12.59**
MMR	**7.13**	**2.44**	**0.92**	**0.42**	5.06	**8.93**	4.45	1.39	0.51	0.24	5.78	11.75
Novel	3.25	1.12	0.42	0.20	3.47	8.28	**5.89**	**1.80**	**0.61**	**0.26**	**7.59**	**12.32**
Dataset	LearningQ						MCTest					
Random	5.66	1.48	0.43	0.14	5.55	14.83	4.18	1.41	0.55	0.21	7.04	16.46
Beginning	5.02	1.29	0.37	0.13	5.13	14.53	4.69	1.56	**0.63**	**0.27**	7.93	**17.36**
Longest	**6.34**	**1.81**	**0.57**	**0.22**	**9.10**	**16.86**	**5.75**	**1.99**	**0.79**	**0.29**	**9.95**	**17.96**
Hardest	5.92	1.60	**0.52**	**0.21**	5.77	15.48	4.41	1.42	0.51	0.18	7.53	16.73
Concept	4.57	1.25	0.40	0.16	4.77	14.20	3.92	1.48	0.60	**0.27**	5.72	16.71
ConceptType	4.75	1.29	0.41	0.16	4.91	14.24	4.01	1.49	0.60	**0.28**	5.89	16.66
LexRank	**6.74**	**1.91**	**0.62**	**0.26**	**7.44**	**16.40**	**5.24**	**1.85**	**0.70**	0.22	**8.55**	**18.13**
MMR	5.86	1.53	0.47	0.17	5.72	15.12	4.53	1.53	0.57	0.22	7.52	17.20
Novel	**6.00**	**1.64**	0.50	0.17	**8.93**	**16.28**	**4.92**	**1.58**	0.57	0.20	**9.15**	17.14

Table 6.10: Experimental results on TriviaQA, RACE, LearningQ and MCTest. The top three results in each metric are in bold.

other datasets, we highlight the top-3 strategies for each dataset. Based on these results, several interesting findings are observed as follows.

For the TriviaQA dataset, *Beginning* achieves the best performance, indicating that most questions in TriviaQA are about the first sentence in the source document. Considering that the articles of TriviaQA are collected from Wikipedia, such a result can be interpreted by the fact that the first sentences of Wikipedia paragraphs/articles often contain the most important information worth asking about [171]. This observation can be further verified by the well-performing results given by *LexRank* and *MRR* – ranking at the 2nd and 3rd position, respectively – which also identifies important sentences but uses a different method. Overall, these results show that importance based strategies are more effective than informativeness based (e.g., *Longest, Concept*), difficulty based (i.e., *Hardest*), or novelty based ones (i.e., *Novel*).

For the two datasets collected in learning contexts, namely RACE and LearningQ, *Longest*, *LexRank*, and *Novel* generally show better performance than the other strategies. Such a result suggests that questions in learning related datasets are relevant to a more diverse set of sentences, i.e., those informative, important, or contain novel information, a result we believe is due to the diverse learning goals related to the questions. We further observe big gaps between these three strategies and the remaining ones. For example, *Longest*, *LexRank*, and *Novel* are the only strategies achieving Blue 1 scores greater than 5 and Meteor scores greater than six on RACE. This observation reveals that sentence selection strategies based on similar sentence properties however measured through different textual features (e.g., *Longest* vs. *Concept* and *LexRank* vs. *Beginning*) can have big variance in terms of performance. This highlights the importance of selecting appropriate textual features in question-worthy sentence selection.

Similar results also hold on the MCTest dataset: *Longest*, *LexRank*, and *Novel* generally achieve good performance, which suggests that questions in MCTest are also relevant to a diverse set of sentences. On the other hand, strategies such as *Beginning* and *ConceptMax* also perform well on several metrics, signifying that different measures of sentence properties (e.g., informativeness using *Longest* and *ConceptMax*) do not necessarily lead to highly different sentence selection results on MCTest. Despite this, we can observe that *LexRank* is the only sentence selection strategy consistently ranking in top-3 across all the five considered datasets, demonstrating its superior robustness against all the other compared strategies.

6.7 Conclusion

In this chapter, we present *LearningQ*, a large-scale dataset for automatically generating educational questions by applying the state-of-the-art deep neural network approaches. It consists of 230K document-question pairs produced by both instructors and learners. To our knowledge, *LearningQ* is the first dataset that covers a wide range of educational topics, and the questions require a full spectrum of cognitive skills to solve. Extensive evaluation of state-of-the-art question generation methods on *LearningQ* shows that *LearningQ* is a challenging dataset that deserves significant future investigation. Moreover, we propose nine sentence selection strategies inspired by different question-asking heuristics and experiments on multiple datasets show that the beginning sentence is often worth questioning about for Wikipedia articles, while questions in learning contexts feature source sentences that are informative, important, or contain novel information.

As an implication for future research on question generation, deep neural network based methods can be further enhanced by considering the relationships among multiple source sentences and combining different strategies for selecting question-worthy sentences in question generation.

Chapter 7

Conclusion

MOOCs have been recognized as an important tool to achieve inclusive and equitable quality education and promote lifelong learning opportunities for people all over the world [121]. Typically, there are two types of MOOC platforms: *topic-agnostic* MOOC platforms like `edX` and `Coursera` provide courses covering various topics, while *topic-specific* MOOC platforms like `Duolingo` and `Codeacademy` focus on courses in one single topic. Existing research on MOOCs mainly used learner traces (e.g., video clicks, quiz submissions, forum entries) generated *within* the *topic-agnostic* MOOC platforms to investigate MOOC learning [37, 38, 66, 149]. In this thesis, we focused on (i) *learner modeling* and (ii) *generation of educational material* for both of the *topic-agnostic* and *topic-specific* MOOC platforms. In this chapter, we summarize the main contributions made in this thesis and provide an outlook on future research directions.

7.1 Summary of Contributions

To employ the Social Web to model learners from the topic-agnostic MOOC platforms, we investigated whether MOOC learners are active in Social Web platforms and how to reliably identify these learners across multiple platforms. Concretely, in **Chapter 2** we answered the following research questions:

RQ 1.1 On what Social Web platforms can a significant fraction of MOOC learners be identified?

RQ 1.2 Are learners who demonstrate specific sets of traits on the Social Web drawn to certain types of MOOCs?

RQ 1.3 To what extent do Social Web platforms enable us to observe (specific) user attributes that are highly relevant to the online learning experience?

To answer those questions, we investigated to what extent learners from eighteen MOOCs in edX could be discovered across five popular Social Web platforms (i.e., Gravatar, Twitter, LinkedIn, StackExchange and GitHub) and further derived a set of learner attributes from these platforms to investigate learners' behaviors in MOOCs. Depending on the MOOC-platform combination, we identified between 1% and 42% of learners (5% on average) in the five considered platforms (**RQ 1.1**). In the most extreme case, 42% of learners from a *Functional Programming* MOOC could be identified in GitHub. We also showed that learners with specific traits were attracted to different types of MOOCs (**RQ 1.2**). In particular, we presented a first investigation into the knowledge application behavior of learners, i.e., *learning transfer*, beyond the MOOC platform over time (**RQ 1.3**). We provided a reliable methodology to gather information about learners by moving from the MOOC platform to the wider Social Web. More importantly, we demonstrated that a set of valuable learner attributes relevant to MOOC learning can be derived from the Social Web. The data-driven approaches used in our work can be applied in not only the MOOC setting but also other educational settings like e-learning courses as well as campus-based courses, as long as the learners can be identified in the Social Web.

After observing that learners of programming courses actively engaged with GitHub, we considered the Functional Programming MOOC as a specific case and continued the investigation of learning transfer. Concretely, in **Chapter 3** we answered the following research questions:

RQ 2.1 To what extent do learners from a programming MOOC transfer the newly gained knowledge to practice?

RQ 2.2 What type of learners are most likely to make the transfer?

RQ 2.3 How does the transfer manifest itself over time?

To answer those questions, we conducted a large-scale longitudinal analysis, in which both the learning traces generated within the MOOC platform and the coding traces collected from `GitHub` were used. We observed that about 8% of engaged learners, who had no prior knowledge in functional programming, began programming functionally after the MOOC (**RQ 2.1**). In addition, learners were more likely to make the transfer if they had (i) intrinsical motivation, (ii) high self-efficacy, (iii) prior experience in programming, and (iv) a high personal capacity (**RQ 2.2**). Lastly, neither a significant transfer increase nor decrease was observed over half a year after the course (**RQ 2.3**). By examining programming learners' uptake of knowledge after the MOOC, instructors can not only gain a better understanding of the course influence on learners but also evaluate the current course and design future courses to induce more knowledge transfer.

Most existing research focused on investigating learner behaviors in topic-agnostic MOOC platforms. We used the three large-scale language learning datasets, which were released by `Duolingo` in the Second Language Acquisition Modeling challenge, to enable a better understanding of learners in the topic-specific MOOC platforms. Concretely, in **Chapter 4** we answered the following research question:

RQ 3.1 What factors are correlated with learners' language learning performance?

To answer the question, we conducted an analysis on the three `Duolingo` datasets and demonstrated that factors like the amount of time spent in learning and the devices being used were related to learners' accuracy in solving exercises and the amount of vocabulary learned. Furthermore, based on the results, we designed a set of features and examined their effectiveness in predicting learners' future performance in the setting of second language acquisition.

As demonstrated in Chapter 3, learners indeed transferred the knowledge acquired from a MOOC to practice. We further investigated whether learners could apply the acquired knowledge to solve real-world tasks, i.e., paid tasks

collected from online marketplaces which can be solved by learning with the course. If learners are capable of solving such tasks, ultimately, we envision to construct a recommender system to suggest learners solve paid freelancing tasks relevant to the course, as a possible means to earn money when learning with the course. Concretely, in **Chapter 5** we answered the following research questions:

RQ 4.1 Are MOOC learners able to solve real-world (paid) tasks from an online work platform with sufficient accuracy and quality?

RQ 4.2 How applicable is the knowledge gained from MOOCs to paid tasks offered by online work platforms?

RQ 4.3 To what extent can an online work platform support MOOC learners (i.e., are there enough tasks available for everyone)?

RQ 4.4 What role do real-world (paid) tasks play in the engagement of MOOC learners?

To answer those questions, we designed a study, in which we manually selected a set of tasks from `Upwork` and deployed them into a MOOC teaching data analysis as bonus exercises for learners to solve. We demonstrated that learners could solve the paid tasks with the knowledge gained from the course with high accuracy and quality (**RQ 4.1** & **RQ 4.2**). However, there were not sufficient tasks available on `Upwork` to sustain the learner population throughout the entire run of the course (**RQ 4.3**). We also observed that real-world tasks were likely to have a positive effect on learners' course engagement (**RQ 4.4**). Our study contributed the first step to develop a paid task recommender systems that we envisioned to help learners earn money when learning with a MOOC. With more online marketplace platforms considered and a larger number of paid tasks retrieved, we hypothesize the proposed system can truly help learners, especially learners who suffer from poor financial situations and consequently have a limited amount of time for learning because of the need to work and earn a living, to gain more time to learn with MOOCs.

Driven by the importance of questions in learning and the need of easing instructors' burden in manually creating a large question bank to meet the needs of various learners, we explored the `Social Web` to collect a large-scale educational question dataset. With the collected dataset, we investigated whether an educational question generator could be constructed and how to effectively select question-worthy sentences from an article. Concretely, in **Chapter 6** we answered the following research questions:

RQ 5.1 Can a large-scale and high-quality educational question dataset be collected from the `Social Web`?

RQ 5.2 What are effective strategies in identifying question-worthy sentences from an article?

To answer those questions, we turned to education-oriented `Social Web` platforms. Specifically, we targeted `TED-Ed` and `Khan Academy` as our main data sources and collected a large-scale educational question dataset (*LearningQ*), which consists of over 230K document-question pairs generated by both instructors and learners (**RQ 5.1**). In particular, the questions contained in *LearningQ* vary in all cognitive levels in the Bloom's Revised Taxonomy and cover a wide range of learning topics. With *LearningQ* as a testbed, we demonstrated the research challenges in constructing an educational question generator and examined the effectiveness of nine strategies in selecting question-worthy sentences from an article for educational question generation (**RQ 5.2**).

7.2 Future Work

This thesis has contributed novel technical approaches to model learners and generate educational material for both topic-agnostic and topic-specific MOOC platforms. However, there is still space for improvements. In this section, we provide an outlook on interesting research directions in MOOCs opened up by the research conducted in this thesis.

7.2.1 Adaptive Learning in MOOCs

Adaptive learning is an educational approach which employs computational algorithms to decide what learning materials should be presented to a learner so as to address the unique needs of the learner [85, 107, 120, 152]. Though being recognized as essential by instructors, adaptive learning has not been fully supported and investigated in MOOCs yet. One key step before enabling effective adaptive learning is to construct learner models, which are built based on learner data. However, there is no data about learners available in the learning platform at the beginning of a course unless they have been active in the platform before and, even then, the learners' knowledge on the course topic might still be unknown to the instructors.

Our works presented in Chapters 2-3 have demonstrated that it is possible to enhance the construction of a learner model by mining the `Social Web`. To further the learner model construction in MOOCs, in addition to the eight `Social Web` platforms investigated in this thesis, it will be valuable to explore other `Social Web` platforms (e.g., `YouTube`, `Instagram`, `Quora`) to reveal a more diverse set of learner attributes in the future. These attributes could be learners' interests, prior knowledge, learning preferences, personal goals, social relations, and so on. Building upon the enhanced learner models, future work can also focus on developing effective adaptive algorithms to personalize learner experiences in MOOCs. For instance, what learner attributes should be considered to generate a personalized learning path for a MOOC learner? What are the influences of prior knowledge on learners' learning paths? How can personalized learning strategies (e.g., tips in time management [91]) be generated based on the learner models? How can the temporal dynamics of learner behaviors be captured and used to provide adaptive learning supports (e.g., recommended learning paths, personalized learning strategies)?

7.2.2 Interactive Learning in MOOCs

Interactive learning is a pedagogical model which encourages learners to interact with each other instead of passively absorbing the knowledge taught in the course [102]. In the classroom setting, interactive learning occurs in a variety of forms such as hands-on group projects and class discussions. However, in the MOOC setting, learning takes place in an asynchronous manner, and learners' interaction with instructors and peers are mostly limited to the discussion forum. Thus, learners cannot gain a wealth of experience in interactive learning.

Future research on developing interactive tools for MOOC learners can be built on the works presented in this thesis. Specifically, with the data collected from the `Social Web`, e.g., the *LearningQ* in Chapter 6, an intelligent personal assistant can be constructed and used to help MOOC learners by providing the support they need. The support could be: discussing questions, scheduling time for learning, providing emotional support, and so on. Future research can first work on investigating what learning support is needed in the MOOC setting. For each kind of support, it will be valuable to explore what data and techniques can be used to enable the support. Furthermore, how should the interface of the assistant be designed so as to engage learners? What are effective strategies to allow the assistant to interact with learners?

7.2.3 Content Enrichment in MOOCs

Most existing MOOCs in the major topic-agnostic platforms adopt the one-size-fits-all approach, i.e., providing the same set of learning materials to all learners in a MOOC. However, these learners are often of high diversity (e.g., their demographics [36, 74, 177]) and likely to have different learning needs, which demand the MOOC to contain a larger and more diverse set of learning materials instead of only a limited number of videos and quizzes to meet their needs. To enrich MOOC content, there have been several studies working on *Learnersourcing* [61], i.e., employing the intelligence of learners enrolled in a MOOC to gather or create more content for the MOOC. However, Learnersourcing faces the problem of lacking enough responses from learners as such content gathering and creation process is very cognitively demanding and time-consuming.

Our works presented in Chapters 5-6 demonstrated the potential of the `Social Web` in enriching MOOCs. Building on the work presented in Chapter 5, future research can focus on developing techniques to automatically retrieve relevant freelancing tasks and determine their relevance and suitability to a course. Considering that a large number of freelancing tasks are with high payment and more challenging to solve, it will be interesting to investigate how to enable the partition of a high-payment task across several learners. Ideally, such partition can motivate the learners to learn and solve the task together and then the learners can share the payment. In Chapter 6, we focused on generating text-based questions with the aid of *LearningQ*. In addition to text-based questions, future research can also work on the generation of questions consisting of not only text but also plots and images, which are necessary for course topics like math and physics. Furthermore, how can the answers provided by learners to the generated questions be automatically assessed? As demonstrated in Chapter 6, educational content creation is a cognitively demanding task, which we believe cannot be achieved by simply exploiting the power of machines in the near future. We hypothesize that MOOC content enrichment can be greatly enhanced by combining the power of humans and machines, e.g., using human intelligence as a means to refine low-quality questions generated by the algorithms. How can learners effectively assist machines to create course content? What are the effects on learning by enabling learners to create course content? How can the usefulness of the created content be measured? How can the feedback provided by learners in the process of content creation be effectively utilized (e.g., by applying reinforcement learning [145]) to further improve the performance of algorithms?

Bibliography

[1] Fabian Abel, Qi Gao, Geert-Jan Houben, and Ke Tao. Semantic enrichment of twitter posts for user profile construction on the social web. In *The Semanic Web: Research and Applications*, pages 375–389. 2011.

[2] Lea T. Adams, Jane E. Kasserman, Alison Yearwood, Greg A. Perfetto, John D. Bransford, and Jeffery J. Franks. Memory access: The effects of fact-oriented versus problem-oriented acquisition. *Memory & Cognition*, 16(2):167–175, 1988.

[3] David Adamson, Divyanshu Bhartiya, Biman Gujral, Radhika Kedia, Ashudeep Singh, and Carolyn P Rosé. Automatically generating discussion questions. In *AIED*, 2013.

[4] Anant Agarwal. News About edX Certificates, 2015.

[5] Carlos Alario-Hoyos, Mar Pérez-Sanagustín, Carlos Delgado-Kloos, Mario Muñoz-Organero, Antonio Rodríguez-de-las Heras, et al. Analysing the impact of built-in and external social tools in a mooc on educational technologies. In *European Conference on Technology Enhanced Learning*, pages 5–18. Springer, 2013.

[6] Bradley M Allan and Roland G Fryer. *The power and pitfalls of education incentives*. Brookings Institution, Hamilton Project, 2011.

[7] Yoram Bachrach, Michal Kosinski, Thore Graepel, Pushmeet Kohli, and David Stillwell. Personality and patterns of facebook usage. In *Web Science '12*, pages 24–32, 2012.

[8] Harry P. Bahrick, Lorraine E. Bahrick, Audrey S. Bahrick, and Phyllis E. Bahrick. Maintenance of foreign language vocabulary and the spacing effect. *Psychological Science*, 4(5):316–321, 1993. doi: 10.1111/j.1467-9280.1993.tb00571.x. URL http://dx.doi.org/10.1111/j.1467-9280.1993.tb00571.x.

[9] Mukund Balasubramanian and Eric L Schwartz. The isomap algorithm and topological stability. *Science*, 295:7–7, 2002.

[10] Timothy T. Baldwin and Kevin J. Ford. Transfer of training: A review and directions for future research. *Personnel Psychology*, 41(1):63–105, 1988.

[11] David Bamman, Jacob Eisenstein, and Tyler Schnoebelen. Gender identity and lexical variation in social media. *Journal of Sociolinguistics*, 18(2):135–160, 2014.

[12] Albert Bandura. Self-efficacy: toward a unifying theory of behavioral change. *Psychological review*, 84(2):191–215, 1977.

[13] Susan M. Barnett and Stephen J. Ceci. When and where do we apply what we learn? a taxonomy for far transfer. *Psychological bulletin*, 128 (4):612–637, 2002.

[14] Adam Bermingham and Alan F Smeaton. On using twitter to monitor political sentiment and predict election results. *IJCNLP 2011 Workshop*, pages 2–10, 2011.

[15] Ellen Bialystok. A theoretical model of second language learning. *Language learning*, 28(1):69–83, 1978.

[16] Steven Bird and Edward Loper. NLTK: the natural language toolkit. In *ACL*, 2004.

[17] Robert A. Bjork. Memory and metamemory considerations in the training of human beings. *Metacognition: Knowing about knowing*, pages 185–205, 1994.

[18] Robert A. Bjork and Elizabeth L. Bjork. A new theory of disuse and an old theory of stimulus fluctuation. *From learning processes to cognitive processes: Essays in honor of William K. Estes*, 2:35–67, 1992.

[19] Brian D Blume, J Kevin Ford, Timothy T Baldwin, and Jason L Huang. Transfer of training: A meta-analytic review. *Journal of management*, 36(4):1065–1105, 2010.

[20] Kurt A Boniecki and Stacy Moore. Breaking the silence: Using a token economy to reinforce classroom participation. *Teaching of Psychology*, 30(3):224–227, 2003.

[21] Lori Breslow, David E Pritchard, Jennifer DeBoer, Glenda S Stump, Andrew D Ho, and Daniel T Seaton. Studying learning in the worldwide classroom: Research into edx' s first mooc. *Research & Practice in Assessment*, 8(1):13–25, 2013.

[22] Bruce K Britton and Abraham Tesser. Effects of time-management practices on college grades. *Journal of Educational Psychology*, 83(3): 405–410, 1991.

[23] Jaime Carbonell and Jade Goldstein. The use of mmr, diversity-based reranking for reordering documents and producing summaries. In *SIGIR*, pages 335–336, 1998.

[24] Robert M. Carini, George D. Kuh, and Stephen P. Klein. Student engagement and student learning: Testing the linkages*. *Research in Higher Education*, 47(1):1–32, Feb 2006. ISSN 1573-188X. doi: 10.1007/s11162-005-8150-9. URL https://doi.org/10.1007/s11162-005-8150-9.

[25] David M Carkenord. Motivating students to read journal articles. *Teaching of Psychology*, 21(3):162–164, 1994.

[26] Casey Casalnuovo, Bogdan Vasilescu, Premkumar Devanbu, and Vladimir Filkov. Developer onboarding in github: the role of prior social links and language experience. In *Proceedings of the 2015 10th Joint Meeting on Foundations of Software Engineering*, pages 817–828. ACM, 2015.

[27] Hao Cen, Kenneth Koedinger, and Brian Junker. Learning factors analysis–a general method for cognitive model evaluation and improvement. In *International Conference on Intelligent Tutoring Systems*, pages 164–175. Springer, 2006.

[28] G. Chen, D. Davis, M. Krause, E. Aivaloglou, C. Hauff, and G. Houben. From learners to earners: Enabling mooc learners to apply their skills and earn money in an online market place. *IEEE Transactions on Learning Technologies*, 11(2):264–274, April 2018. ISSN 1939-1382. doi: 10.1109/TLT.2016.2614302.

[29] Gilad Chen, Stanley M. Gully, and Dov Eden. Validation of a new general self-efficacy scale. *Organizational research methods*, 4(1):62–83, 2001.

[30] Guanliang Chen, Dan Davis, Claudia Hauff, and Geert-Jan Houben. Learning transfer: Does it take place in moocs? an investigation into the uptake of functional programming in practice. In *Proceedings of the Third (2016) ACM Conference on Learning @ Scale*, L@S '16, pages 409–418, New York, NY, USA, 2016. ACM. ISBN 978-1-4503-3726-7. doi: 10.1145/2876034.2876035. URL http://doi.acm.org/10.1145/2876034.2876035.

[31] Guanliang Chen, Dan Davis, Jun Lin, Claudia Hauff, and Geert-Jan Houben. Beyond the mooc platform: Gaining insights about learners from the social web. In *Proceedings of the 8th ACM Conference on Web Science*, WebSci '16, pages 15–24, New York, NY, USA, 2016. ACM. ISBN 978-1-4503-4208-7. doi: 10.1145/2908131.2908145. URL http://doi.acm.org/10.1145/2908131.2908145.

[32] Guanliang Chen, Claudia Hauff, and Geert-Jan Houben. Feature engineering for second language acquisition modeling. In *Proceedings of the Thirteenth Workshop on Innovative Use of NLP for Building Educational Applications*, pages 356–364, 2018.

[33] Guanliang Chen, Jie Yang, Claudia Hauff, and Geert-Jan Houben. Learningq: A large-scale dataset for educational question generation. In *ICWSM*, 2018.

[34] Tianqi Chen and Carlos Guestrin. Xgboost: A scalable tree boosting system. In *Proceedings of the 22nd acm sigkdd international conference on knowledge discovery and data mining*, pages 785–794. ACM, 2016.

[35] Noam Chomsky. Conditions on transformations, 1973.

[36] Gayle Christensen, Andrew Steinmetz, Brandon Alcorn, Amy Bennett, Deirdre Woods, and Ezekiel J Emanuel. The mooc phenomenon: who takes massive open online courses and why? *Available at SSRN 2350964*, 2013.

[37] Derrick Coetzee, Armando Fox, Marti A Hearst, and Björn Hartmann. Should your mooc forum use a reputation system? In *CSCW '14*, pages 1176–1187, 2014.

[38] Derrick Coetzee, Seongtaek Lim, Armando Fox, Bjorn Hartmann, and Marti A Hearst. Structuring interactions for large-scale synchronous peer learning. In *CSCW '15*, pages 1139–1152, 2015.

[39] Kevyn Collins-Thompson. Computational assessment of text readability: A survey of current and future research. *ITL-International Journal of Applied Linguistics*, 165(2):97–135, 2014.

[40] Albert T Corbett and John R Anderson. Knowledge tracing: Modeling the acquisition of procedural knowledge. *User modeling and user-adapted interaction*, 4(4):253–278, 1994.

[41] D. Correa and A. Sureka. Integrating issue tracking systems with community-based question and answering websites. In *2013 22nd Australian Software Engineering Conference*, pages 88–96, June 2013. doi: 10.1109/ASWEC.2013.20.

[42] Juan Cruz-Benito, Oriol Borrás-Gené, Francisco J García-Peñalvo, Ángel Fidalgo Blanco, and Roberto Therón. Extending mooc ecosystems using web services and software architectures. In *Interacción '15*, pages 52:1–52:7, 2015.

[43] Céline Darnon, Fabrizio Butera, and Judith M. Harackiewicz. Achievement goals in social interactions: Learning with mastery vs. performance goals. *Motivation and Emotion*, 31(1):61–70, 2007.

[44] Peter de Vries and Thieme Hennis. Tu delft online learning research working paper #6, 2014.

[45] Jennifer DeBoer, Andrew D. Ho, Glenda S. Stump, and Lori Breslow. Changing "course": Reconceptualizing educational variables for massive open online courses. *Educational Researcher*, 43(2):74–84, 2014.

[46] Edward L Deci, Richard Koestner, and Richard M Ryan. A meta-analytic review of experiments examining the effects of extrinsic rewards on intrinsic motivation. *Psychological bulletin*, 125(6):627–668, 1999.

[47] Michael Denkowski and Alon Lavie. Meteor universal: Language specific translation evaluation for any target language. In *SMT*, 2014.

[48] L Quentin Dixon, Jing Zhao, Blanca G Quiroz, and Jee-Young Shin. Home and community factors influencing bilingual children' s ethnic language vocabulary development. *International Journal of Bilingualism*, 16(4):541–565, 2012.

[49] John J. Donovan and David J. Radosevich. A meta-analytic review of the distribution of practice effect: Now you see it, now you don't. *Journal of Applied Psychology*, 84(5):795–805, 1999.

[50] Xinya Du and Claire Cardie. Identifying where to focus in reading comprehension for neural question generation. In *EMNLP*, 2017.

[51] Xinya Du, Junru Shao, and Claire Cardie. Learning to ask: Neural question generation for reading comprehension. In *ACL*, 2017.

[52] Lars Eldén. *Matrix methods in data mining and pattern recognition*, volume 4. SIAM, 2007.

[53] Günes Erkan and Dragomir R Radev. Lexrank: Graph-based lexical centrality as salience in text summarization. *Journal of Artificial Intelligence Research*, 22:457–479, 2004.

[54] George Farkas, Robert P Grobe, Daniel Sheehan, and Yuan Shuan. Cultural resources and school success: Gender, ethnicity, and poverty groups within an urban school district. *American Sociological Review*, pages 127–142, 1990.

[55] Ángel Fidalgo-Blanco, María Luisa Sein-Echaluce, Francisco J. García-Peñalvo, and Javier Esteban Escaño. Improving the mooc learning outcomes throughout informal learning activities. In *TEEM '14*, pages 611–617, 2014.

[56] Kevin J. Ford, Miguel A. Quinones, Douglas J. Sego, and Joann S. Sorra. Factors affecting the opportunity to perform trained tasks on the job. *Personnel Psychology*, 45(3):511–527, 1992.

[57] Thomas Friedman. Revolution hits the universities. *The New York Times*, January 26, 2013.

[58] Roland G Fryer Jr. Financial incentives and student achievement: Evidence from randomized trials. Technical Report 15898, National Bureau of Economic Research, 2010.

[59] Francisco J García-Peñalvo, Juan Cruz-Benito, Oriol Borrás-Gené, and Ángel Fidalgo Blanco. Evolution of the conversation and knowledge acquisition in social networks related to a mooc course. In *Learning and Collaboration Technologies*, pages 470–481. 2015.

[60] Wael H Gomaa and Aly A Fahmy. A survey of text similarity approaches. *International Journal of Computer Applications*, 68(13), 2013.

[61] Paul Grau, Oisin Daly Kiaer, and Yoo Jin Lim. Verbivore: Learner-sourcing vocabulary flashcards. 2016.

[62] Yongqi Gu and Robert Keith Johnson. Vocabulary learning strategies and language learning outcomes. *Language learning*, 46(4):643–679, 1996.

[63] Philip J. Guo and Katharina Reinecke. Demographic differences in how students navigate through moocs. In *Proceedings of the First ACM Conference on Learning @ Scale Conference*, L@S '14, pages 21–30, New York, NY, USA, 2014. ACM. ISBN 978-1-4503-2669-8. doi: 10.1145/2556325.2566247. URL http://doi.acm.org/10.1145/2556325.2566247.

[64] Philip J Guo and Katharina Reinecke. Demographic differences in how students navigate through moocs. In *L@S '14*, pages 21–30, 2014.

[65] Philip J. Guo, Juho Kim, and Rob Rubin. How video production affects student engagement: an empirical study of mooc videos. In *Proceedings of the First ACM Conference on Learning at Scale*, pages 41–50, 2014.

[66] Philip J Guo, Juho Kim, and Rob Rubin. How video production affects student engagement: An empirical study of mooc videos. In *L@S '14*, pages 41–50, 2014.

[67] DD Guttenplan. Motivating students with cash-for-grades incentive. *The New York Times*, November 20, 2011.

[68] Bo Han, Paul Cook, and Timothy Baldwin. Text-based twitter user geolocation prediction. *Journal of Artificial Intelligence Research*, pages 451–500, 2014.

[69] Michael Heilman and Noah A. Smith. Good question! statistical ranking for question generation. In *HLT-NAACL*, 2010.

[70] Karl Moritz Hermann, Tomas Kocisky, Edward Grefenstette, Lasse Espeholt, Will Kay, Mustafa Suleyman, and Phil Blunsom. Teaching machines to read and comprehend. In *NIPS*, pages 1693–1701, 2015.

[71] F. Hermans, M. Pinzger, and A. van Deursen. Detecting code smells in spreadsheet formulas. In *Proceedings of the 28th IEEE Software Maintenance Conference*, pages 409–418, 2012.

[72] K Michael Hibbard et al. *Performance-Based Learning and Assessment. A Teacher's Guide.* 1996.

[73] Thomas Hill, Nancy D. Smith, and Millard F. Mann. Role of efficacy expectations in predicting the decision to use advanced technologies:

The case of computers. *Journal of Applied Psychology*, 72(2):307–313, 1987.

[74] Andrew D. Ho, Isaac Chuang, Justin Reich, and Cody A. Coleman *et al.* Harvardx and mitx: Two years of open online courses fall 2012-summer 2014. *SSRN 2586847*, 2015.

[75] Sepp Hochreiter and Jürgen Schmidhuber. Long short-term memory. *Neural computation*, 9(8):1735–1780, 1997.

[76] Sepp Hochreiter, Yoshua Bengio, Paolo Frasconi, Jürgen Schmidhuber, et al. Gradient flow in recurrent nets: the difficulty of learning long-term dependencies, 2001.

[77] Arthur E Hoerl and Robert W Kennard. Ridge regression: Biased estimation for nonorthogonal problems. *Technometrics*, 12(1):55–67, 1970.

[78] Elwood F. Holton III, Reid A. Bates, and Wendy E.A. Ruona. Development of a generalized learning transfer system inventory. *Human resource development quarterly*, 11(4):333–360, 2000.

[79] David John Hughes, Moss Rowe, Mark Batey, and Andrew Lee. A tale of two sites: Twitter vs. facebook and the personality predictors of social media usage. *Computers in Human Behavior*, 28(2):561–569, 2012.

[80] Srećko Joksimović, Nia Dowell, Oleksandra Skrypnyk, Vitomir Kovanović, Dragan Gašević, Shane Dawson, and Arthur C Graesser. How do you connect?: Analysis of social capital accumulation in connectivist moocs. In *LAK '15*, pages 64–68, 2015.

[81] Srećko Joksimović, Vitomir Kovanović, Jelena Jovanović, Amal Zouaq, Dragan Gašević, and Marek Hatala. What do cmooc participants talk about in social media?: A topic analysis of discourse in a cmooc. In *LAK '15*, pages 156–165, 2015.

[82] Katy Jordan. Initial trends in enrolment and completion of massive open online courses. *The International Review of Research in Open and Distributed Learning*, 15(1), 2014.

[83] Mandar Joshi, Eunsol Choi, Daniel S. Weld, and Luke Zettlemoyer. Triviaqa: A large scale distantly supervised challenge dataset for reading comprehension. In *ACL*, July 2017.

[84] Ellen N Junn. Empowering the marginal student: A skills-based extra-credit assignment. *Teaching of Psychology*, 22(3):189–192, 1995.

[85] Pythagoras Karampiperis and Demetrios Sampson. Adaptive learning resources sequencing in educational hypermedia systems. *Journal of Educational Technology & Society*, 8(4), 2005.

[86] Mohammad Khajah, Robert V. Lindsey, and Michael C. Mozer. How deep is knowledge tracing? *CoRR*, abs/1604.02416, 2016. URL http://arxiv.org/abs/1604.02416.

[87] JaMee Kim and WonGyu Lee. Assistance and possibilities: Analysis of learning-related factors affecting the online learning satisfaction of underprivileged students. *Computers & Education*, 57(4):2395–2405, 2011.

[88] Yoon Kim. Convolutional neural networks for sentence classification. *arXiv preprint arXiv:1408.5882*, 2014.

[89] Diederik P. Kingma and Jimmy Ba. Adam: A method for stochastic optimization. *CoRR*, abs/1412.6980, 2014. URL http://arxiv.org/abs/1412.6980.

[90] René F Kizilcec and Sherif Halawa. Attrition and achievement gaps in online learning. In *Proceedings of the Second ACM Conference on Learning at Scale*, pages 57–66, 2015.

[91] René F. Kizilcec, Mar Pérez-Sanagustín, and Jorge J. Maldonado. Recommending self-regulated learning strategies does not improve performance in a mooc. In *Proceedings of the Third (2016) ACM Conference on Learning @ Scale*, L@S '16, pages 101–104, New York, NY, USA, 2016. ACM. ISBN 978-1-4503-3726-7. doi: 10.1145/2876034.2893378. URL http://doi.acm.org/10.1145/2876034.2893378.

[92] Guillaume Klein, Yoon Kim, Yuntian Deng, Jean Senellart, and Alexander M Rush. Opennmt: Open-source toolkit for neural machine translation. *arXiv preprint arXiv:1701.02810*, 2017.

[93] Tomáš Kočiskỳ, Jonathan Schwarz, Phil Blunsom, Chris Dyer, Karl Moritz Hermann, Gábor Melis, and Edward Grefenstette. The narrativeqa reading comprehension challenge. *TACL*, 2017.

[94] Kenneth R Koedinger, Albert T Corbett, and Charles Perfetti. The knowledge-learning-instruction framework: Bridging the science-

practice chasm to enhance robust student learning. *Cognitive science*, 36(5):757–798, 2012.

[95] Daphne Koller, Andrew Ng, Chuong Do, and Zhenghao Chen. Retention and intention in massive open online courses. *Educause Review*, 48(3):62–63, 2013.

[96] Guokun Lai, Qizhe Xie, Hanxiao Liu, Yiming Yang, and Eduard Hovy. Race: Large-scale reading comprehension dataset from examinations. *arXiv preprint arXiv:1704.04683*, 2017.

[97] Diane Larsen-Freeman and Michael H Long. *An introduction to second language acquisition research*. Routledge, 2014.

[98] Michael J Lawson and Donald Hogben. The vocabulary-learning strategies of foreign-language students. *Language learning*, 46(1):101–135, 1996.

[99] Doo H. Lim and Scott D. Johnson. Trainee perceptions of factors that influence learning transfer. *International journal of training and development*, 6:36–48, 2002.

[100] Chin-Yew Lin. Rouge: A package for automatic evaluation of summaries. In *ACL*, 2004.

[101] Robert S Lockhart, Mary Lamon, and Mary L Gick. Conceptual transfer insimple insight problems. *Memory & Cognition*, 16(1):36–44, 1988.

[102] Bengt-Åke Lundvall. *National systems of innovation: Toward a theory of innovation and interactive learning*, volume 2. Anthem press, 2010.

[103] Minh-Thang Luong, Hieu Pham, and Christopher D Manning. Effective approaches to attention-based neural machine translation. *arXiv preprint arXiv:1508.04025*, 2015.

[104] Anderson LW, Krathwohl DR, Airasian PW, Cruikshank KA, Richard Mayer, Pintrich PR, J D. Raths, and Wittrock MC. *A Taxonomy for Learning, Teaching, and Assessing: A Revision of Bloom's Taxonomy of Educational Objectives*. 01 2001. ISBN ISBN: 080131903X.

[105] Therese H Macan, Comila Shahani, Robert L Dipboye, and Amanda P Phillips. College students' time management: Correlations with academic performance and stress. *Journal of Educational Psychology*, 82 (4):760–768, 1990.

[106] Jalal Mahmud, Jeffrey Nichols, and Clemens Drews. Where is this tweet from? inferring home locations of twitter users. *ICWSM*, 12: 511–514, 2012.

[107] Carol Midgley. *Goals, goal structures, and patterns of adaptive learning*. Routledge, 2014.

[108] Tomas Mikolov, Ilya Sutskever, Kai Chen, Greg S Corrado, and Jeff Dean. Distributed representations of words and phrases and their compositionality. In *NIPS*. 2013. URL http://papers.nips.cc/paper/5021-distributed-representations-of-words-and-phra.

[109] Ruslan Mitkov and Le An Ha. Computer-aided generation of multiple-choice tests. In *HLT-NAACL*, 2003.

[110] Ruslan Mitkov, Le An Ha, and Nikiforos Karamanis. A computer-aided environment for generating multiple-choice test items. *Natural Language Engineering*, 12(2):177–194, June 2006. ISSN 1351-3249. doi: 10.1017/S1351324906004177. URL http://dx.doi.org/10.1017/S1351324906004177.

[111] Yohsuke R. Miyamoto, Cody A. Coleman, Joseph J. Williams, Jacob Whitehill, Sergiy O. Nesterko, and Justin Reich. Beyond time-on-task: The relationship between spaced study and certification in moocs. *SSRN 2547799*, 2015.

[112] Almedina Music and Stéphan Vincent-Lancrin. Massive open online courses (moocs): Trends and future perspectives. *EDU/CERI/CD/RD*, 2016(5), 2016.

[113] Dong-Phuong Nguyen, Rilana Gravel, RB Trieschnigg, and Theo Meder. " how old do you think i am?" a study of language and age in twitter. *ICWSM '13*, pages 439–448, 2013.

[114] Tri Nguyen, Mir Rosenberg, Xia Song, Jianfeng Gao, Saurabh Tiwary, Rangan Majumder, and Li Deng. Ms marco: A human generated machine reading comprehension dataset. *arXiv preprint arXiv:1611.09268*, 2016.

[115] You Ouyang, Wenjie Li, Qin Lu, and Renxian Zhang. A study on position information in document summarization. In *COLING*, pages 919–927, 2010.

[116] Laura M Padilla-Walker. The impact of daily extra credit quizzes on exam performance. *Teaching of Psychology*, 33(4):236–239, 2006.

[117] Viktoria Pammer, Marina Bratic, Sandra Feyertag, and Nils Faltin. The value of self-tracking and the added value of coaching in the case of improving time management. In *Design for Teaching and Learning in a Networked World*, pages 467–472. Springer, 2015.

[118] Kishore Papineni, Salim Roukos, Todd Ward, and Wei-Jing Zhu. Bleu: a method for automatic evaluation of machine translation. In *ACL*, 2002.

[119] Laura Pappano. The year of the mooc. *The New York Times*, 2(12): 2012, 2012.

[120] Alexandros Paramythis and Susanne Loidl-Reisinger. Adaptive learning environments and e-learning standards. In *Second european conference on e-learning*, volume 1, pages 369–379, 2003.

[121] Mariana Patru and Venkataraman Balaji. Making sense of moocs: A guide for policy-makers in developing countries, 2016.

[122] Philip I Pavlik Jr, Hao Cen, and Kenneth R Koedinger. Performance factors analysis–a new alternative to knowledge tracing. *Online Submission*, 2009.

[123] Radek Pelánek. Bayesian knowledge tracing, logistic models, and beyond: an overview of learner modeling techniques. *User Modeling and User-Adapted Interaction*, 27(3):313–350, Dec 2017. ISSN 1573-1391. doi: 10.1007/s11257-017-9193-2. URL https://doi.org/10.1007/s11257-017-9193-2.

[124] Jeffrey Pennington, Richard Socher, and Christopher Manning. Glove: Global vectors for word representation. In *EMNLP*, 2014.

[125] Chris Piech, Jonathan Bassen, Jonathan Huang, Surya Ganguli, Mehran Sahami, Leonidas J Guibas, and Jascha Sohl-Dickstein. Deep knowledge tracing. In *Advances in Neural Information Processing Systems*, pages 505–513, 2015.

[126] Paul R Pintrich and Elisabeth V De Groot. Motivational and self-regulated learning components of classroom academic performance. *Journal of Educational Psychology*, 82(1):33–40, 1990.

[127] Daniel Preoţiuc-Pietro, Vasileios Lampos, and Nikolaos Aletras. An analysis of the user occupational class through twitter content. pages 1754–1764. The Association for Computational Linguistics, 2015.

[128] Michael Prince. Does active learning work? a review of the research. *Journal of engineering education*, 93(3):223–231, 2004.

[129] Kevin J. Pugh and David A. Bergin. Motivational influences on transfer. *Educational Psychologist*, 41(3):147–160, 2006.

[130] M. M. Rahman and C. K. Roy. On the use of context in recommending exception handling code examples. In *2014 IEEE 14th International Working Conference on Source Code Analysis and Manipulation (SCAM)*, volume 00, pages 285–294, Sept. 2014. doi: 10.1109/SCAM.2014.15. URL doi.ieeecomputersociety.org/10.1109/SCAM.2014.15.

[131] Pranav Rajpurkar, Jian Zhang, Konstantin Lopyrev, and Percy Liang. Squad: 100, 000+ questions for machine comprehension of text. In *EMNLP*, 2016.

[132] Saif Rayyan, Daniel T Seaton, John Belcher, David E Pritchard, and Isaac Chuang. Participation and performance in 8.02x electricity and magnetism: The first physics mooc from mitx. *arXiv preprint arXiv:1310.3173*, 2013.

[133] Matthew Richardson, Christopher JC Burges, and Erin Renshaw. Mctest: A challenge dataset for the open-domain machine comprehension of text. In *EMNLP*, pages 193–203, 2013.

[134] Osvaldo Rodriguez. The concept of openness behind c and x-moocs (massive open online courses). *Open Praxis*, 5(1):67–73, 2013.

[135] John Robert Ross. Constraints on variables in syntax. 1967.

[136] Vasile Rus and C Graesser Arthur. The question generation shared task and evaluation challenge. In *The University of Memphis. National Science Foundation*, 2009.

[137] Vasile Rus and James Lester. The 2nd workshop on question generation. In *AIED*, 2009. ISBN 978-1-60750-028-5. URL http://dl.acm.org/citation.cfm?id=1659450.1659629.

[138] Alan M Saks and Monica Belcourt. An investigation of training activities and transfer of training in organizations. *Human Resource Management: Published in Cooperation with the School of Business Administration, The University of Michigan and in alliance with the Society of Human Resources Management*, 45(4):629–648, 2006.

[139] Maarten Sap, Gregory Park, Johannes C Eichstaedt, Margaret L Kern, David Stillwell, Michal Kosinski, Lyle H Ungar, and H Andrew Schwartz. Developing age and gender predictive lexica over social media. *EMNLP '14*, pages 1146–1151, 2014.

[140] B. Settles, C. Brust, E. Gustafson, M. Hagiwara, and N. Madnani. Second language acquisition modeling. In *Proceedings of the NAACL-HLT Workshop on Innovative Use of NLP for Building Educational Applications (BEA)*. ACL, 2018.

[141] Dhawal Shah. By the numbers: Moocs in 2017, 2018.

[142] George Siemens. Connectivism: A learning theory for the digital age. 2014.

[143] Giuseppe Silvestri, Jie Yang, Alessandro Bozzon, and Andrea Tagarelli. Linking accounts across social networks: the case of stackoverflow, github and twitter. In *International Workshop on Knowledge Discovery on the WEB*, pages 41–52, 2015.

[144] Ilya Sutskever, Oriol Vinyals, and Quoc V Le. Sequence to sequence learning with neural networks. In *NIPS*, 2014.

[145] Richard S Sutton and Andrew G Barto. *Introduction to reinforcement learning*, volume 135. MIT press Cambridge, 1998.

[146] Ryo Suzuki, Niloufar Salehi, Michelle S. Lam, Juan C. Marroquin, and Michael S. Bernstein. Atelier: Repurposing expert crowdsourcing tasks as micro-internships. In *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems*.

[147] John Sweller and Paul Chandler. Why some material is difficult to learn. *Cognition and instruction*, 12(3):185–233, 1994.

[148] Edward L. Thorndike. *The psychology of learning*. Educational Psychology. Teachers College, Columbia University, 1913.

[149] Jonathan H Tomkin and Donna Charlevoix. Do professors matter?: Using an a/b test to evaluate the impact of instructor involvement on mooc student outcomes. In *L@S '14*, pages 71–78, 2014.

[150] Adam Trischler, Tong Wang, Xingdi Yuan, Justin Harris, Alessandro Sordoni, Philip Bachman, and Kaheer Suleman. Newsqa: A machine comprehension dataset. *CoRR*, abs/1611.09830, 2016. URL http://arxiv.org/abs/1611.09830.

[151] Flora S Tsai, Wenyin Tang, and Kap Luk Chan. Evaluation of novelty metrics for sentence-level novelty mining. *Information Sciences*, 180 (12):2359–2374, 2010.

[152] Judy CR Tseng, Hui-Chun Chu, Gwo-Jen Hwang, and Chin-Chung Tsai. Development of an adaptive learning system with two sources of personalization information. *Computers & Education*, 51(2):776–786, 2008.

[153] UNESCO. Unesco institute for lifelong learning: Annual report 2017, 2017.

[154] Laurens Van der Maaten and Geoffrey Hinton. Visualizing data using t-sne. *Journal of Machine Learning Research*, 9(2579-2605):85, 2008.

[155] Eva Van Emden and Leon Moonen. Java quality assurance by detecting code smells. In *Proceedings of the Ninth Working Conference on Reverse Engineering*, pages 97–106. IEEE, 2002.

[156] Timo van Treeck and Martin Ebner. How useful is twitter for learning in massive communities? an analysis of two moocs. *Twitter & Society*, pages 411–424, 2013.

[157] Stephen Vassallo. Implications of institutionalizing self-regulated learning: An analysis from four sociological perspectives. *Educational Studies*, 47(1):26–49, 2011.

[158] George Veletsianos, Amy Collier, and Emily Schneider. Digging deeper into learners' experiences in moocs: Participation in social networks outside of moocs, notetaking and contexts surrounding content consumption. *British Journal of Educational Technology*, 46(3):570–587, 2015.

[159] Svitlana Volkova, Stephen Ranshous, and Lawrence Phillips. Predicting foreign language usage from english-only social media posts. In *Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 2 (Short Papers)*, volume 2, pages 608–614, 2018.

[160] Gregory M Walton and Geoffrey L Cohen. A question of belonging: race, social fit, and achievement. *Journal of Personality and Social Psychology*, 92(1):82–96, 2007.

[161] Weiming Wang, Tianyong Hao, and Wenyin Liu. Automatic question generation for learning evaluation in medicine. In *ICWL*, 2007.

[162] Yuan Wang, Luc Paquette, and Ryan Baker. A longitudinal study on learner career advancement in moocs. *Journal of Learning Analytics*, 1(3):203–206, 2014.

[163] Miaomiao Wen, Diyi Yang, and Carolyn Penstein Rosé. Sentiment analysis in mooc discussion forums: What does it tell us? In *EDM*, 2014.

[164] David A Wilder, William A Flood, and Wibecke Stromsnes. The use of random extra credit quizzes to increase student attendance. *Journal of Instructional Psychology*, 28(2), 2001.

[165] Daniel T Willingham. Should learning be its own reward? *American Educator*, 31(4):29–35, 2007.

[166] Daniel T. Willingham. What will improve a student's memory? *American Educator*, 32(4):17–25, 2008.

[167] Robert E Wood. Task complexity: Definition of the construct. *Organizational Behavior and Human Decision Processes*, 37(1):60 – 82, 1986. ISSN 0749-5978. doi: http://dx.doi.org/10.1016/0749-5978(86)90044-0. URL http://www.sciencedirect.com/science/article/pii/0749597886900440.

[168] Xiaolu Xiong, Siyuan Zhao, Eric Van Inwegen, and Joseph Beck. Going deeper with deep knowledge tracing. In *EDM*, pages 545–550, 2016.

[169] Jie Yang, Ke Tao, Alessandro Bozzon, and Geert-Jan Houben. Sparrows and owls: Characterisation of expert behaviour in stackoverflow. In *UMAP'14*, pages 266–277. 2014.

[170] Jie Yang, Judith Redi, Gianluca Demartini, and Alessandro Bozzon. Modeling task complexity in crowdsourcing. In *HCOMP*, 2016.

[171] Yi Yang, Wen-tau Yih, and Christopher Meek. Wikiqa: A challenge dataset for open-domain question answering. In *EMNLP*, pages 2013–2018, 2015.

[172] Jerry Ye, Jyh-Herng Chow, Jiang Chen, and Zhaohui Zheng. Stochastic gradient boosted distributed decision trees. In *Proceedings of the 18th ACM Conference on Information and Knowledge Management*, CIKM '09, pages 2061–2064, New York, NY, USA, 2009. ACM. ISBN 978-1-60558-512-3. doi: 10.1145/1645953.1646301. URL http://doi.acm.org/10.1145/1645953.1646301.

[173] Stephen L Yelon and J Kevin Ford. Pursuing a multidimensional view of transfer. *Performance Improvement Quarterly*, 12(3):58–78, 1999.

[174] Belinda Young-Davy. Explicit vocabulary instruction. *ORTESOL Journal*, 31:26, 2014.

[175] Liang Zhang, Xiaolu Xiong, Siyuan Zhao, Anthony Botelho, and Neil T. Heffernan. Incorporating rich features into deep knowledge tracing. In *Proceedings of the Fourth (2017) ACM Conference on Learning @ Scale*, L@S '17, pages 169–172, New York, NY, USA, 2017. ACM. ISBN 978-1-4503-4450-0. doi: 10.1145/3051457.3053976. URL http://doi.acm.org/10.1145/3051457.3053976.

[176] Saijing Zheng, Mary Beth Rosson, Patrick C. Shih, and John M. Carroll. Understanding student motivation, behaviors and perceptions in moocs. In *CSCW '15*, pages 1882–1895, 2015.

[177] Chen Zhenghao, Brandon Alcorn, Gayle Christensen, Nicholas Eriksson, Ezekiel J. Emanuel, and Daphne Koller. Who's benefiting from moocs, and why. *Harvard Business Review*, 09/2015 2015. URL https://hbr.org/2015/09/whos-benefiting-from-moocs-and-why.

[178] Barry J Zimmerman. A social cognitive view of self-regulated academic learning. *Journal of Educational Psychology*, 81(3):329–339, 1989.

[179] Barry J Zimmerman and Manuel Martinez-Pons. Student differences in self-regulated learning: Relating grade, sex, and giftedness to self-efficacy and strategy use. *Journal of Educational Psychology*, 82(1): 51–59, 1990.

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Summary

MOOC Analytics: Learner Modeling and Content Generation

Massive Open Online Courses (MOOCs), as one of the popular options for people to receive education and learn, are endowed with the mission to educate the world. Typically, there are two types of MOOC platforms: *topic-agnostic* and *topic-specific*. Topic-agnostic platforms such as `edX` and `Coursera` provide courses covering a wide range of topics, while *topic-specific* MOOC platforms such as `Duolingo` and `Codeacademy` focus on courses in one specific topic. To better support MOOC learners, many works have been proposed to investigate MOOC learning in the past decade. Still, there are many other aspects of MOOC learning to be explored.

In this thesis, we focused on (i) *learner modeling* and (ii) *generation of educational material* for both topic-agnostic and topic-specific MOOC platforms.

For *learner modeling* in the topic-agnostic platforms, as there have been a lot of works utilizing the learner traces generated within the MOOC platforms, we proposed that we can better understand learners by moving beyond the MOOC platforms and exploring other data sources on the wider Web, especially the `Social Web`. As an exploratory but necessary step, in Chapter 2, we first investigated whether MOOC learners are active in the `Social Web` and how to reliably identify their accounts across various `Social Web` platforms. To this end, we considered over 320,000 learners from eighteen MOOCs in `edX` and made efforts to identify their accounts across five popular `Social Web` platforms, i.e., `Gravatar`, `Twitter`, `LinkedIn`, `StackExchange` and `GitHub`. Furthermore, we investigated what data traces could be collected from these platforms and used to derive learner attributes that are relevant to their learning activities in the MOOC setting. We found that on av-

erage 5% of learners could be identified on globally popular Social Web platforms and learners with specific traits preferred different types of MOOCs. Based on the observations we had in Chapter 2, in which we have observed that over one-third of learners from a *Functional Programming* MOOC used `GitHub` to maintain their programming activities, we further combined the data traces generated by those learners in both `edX` and `GitHub` to investigate *learning transfer* in Chapter 3: do learners actually use the newly acquired knowledge and skills to solve problems in practice? Our analyses revealed that (i) more than 8% of engaged learners transferred the acquired knowledge to practice, and (ii) most existing transfer learning findings from the classroom setting are indeed applicable in the MOOC setting as well. For *learner modeling* in the topic-specific platforms, in Chapter 4, we focused on investigating the problem of knowledge tracing, which remained largely unexplored in previous studies due to the lack of available datasets from such platforms. With three large-scale language learning datasets released by `Duolingo`, we investigated factors that are correlated with learners' performance and then applied a machine learning technique (i.e., Gradient Tree Boosting) to predict learners' future performance. We demonstrated that the learning performance was correlated with not only learners' engagement with a course but also contextual factors like the devices being used. In Chapter 5, we further investigated whether learners could apply the acquired knowledge to solve real-world tasks, i.e., paid tasks which are retrieved from online marketplaces and can be solved by applying the knowledge taught in a course. For this purpose, we considered a MOOC teaching data analysis in `edX` and manually selected a set of paid tasks from `Upwork`, one of the most popular freelancing marketplaces in the world, and presented the selected tasks to learners and observed how learners interacted with these real-world tasks. We observed that these tasks could be solved by MOOC learners with high accuracy and quality.

For *generation of educational material*, in Chapter 6, we focused on the generation of educational questions, as they are widely recognized as essential for learning. To build an effective automatic question generator, two challenges need to be overcome. Firstly, a large-scale dataset covering questions of various cognitive levels from a set of diverse learning topics should be collected. Secondly, effective strategies for identifying question-worthy sentences (i.e., those carrying important concepts) from an article, should be developed before using those sentences as input to the question generator. To deal with these challenges, we relied on `TED-Ed` and `Khan Academy` to retrieve an educational question dataset, *LearningQ*, which contains over 230K document-question pairs generated by both instructors and learners. We

showed that *LearningQ* consists of high-quality questions covering not only all cognitive levels in the Bloom' s Revised Taxonomy but also various learning topics. We showed that it is a challenging task to automatically generate educational questions, even with sufficient training data and state-of-the-art question generation techniques. Besides, we developed and compared a total of nine strategies to select question-worthy sentences from an article and demonstrated that questions in learning contexts usually are based on source sentences that are informative, important, or contain novel information.

Samenvatting

MOOC Analyse: Modelleren van studenten en genereren van content

Massive Open Online Courses (MOOC' s) zijn, als een van de populaire manieren waarop mensen onderwijs krijgen en leren, verbonden met de missie om de wereld te onderwijzen. Karakteristiek zijn er twee typen van MOOC-platforms: *onderwerp-onafhankelijk* en *onderwerp-specifiek*. Onderwerp-onafhankelijke platforms zoals `edX` en `Coursera` bieden cursussen aan over een breed spectrum van onderwerpen, terwijl *onderwerp-specifieke* MOOC-platforms zoals `Duolingo` en `Codeacademy` zich richten op cursussen in een specifiek onderwerp. Om MOOC-studenten beter te ondersteunen is er in het afgelopen decennium veel onderzoek gedaan naar het leren in MOOC' s. Desondanks zijn er nog veel aspecten van het leren in MOOC' s die nog moeten worden onderzocht.

In dit proefschrift richten we ons op (i) *modelleren van studenten* en (ii) *genereren van educatieve content* voor zowel onderwerp-onafhankelijke als onderwerp-specifieke MOOC-platforms.

Voor het *modelleren van studenten* in de onderwerp-onafhankelijke platforms, hebben we voorgesteld dat we studenten beter kunnen begrijpen door verder te kijken dan de MOOC-platforms en andere databronnen op het wijdere Web te verkennen, speciaal het `Social Web`; dit omdat een heleboel onderzoek al de student-logs hebben benut die door de MOOC-platforms zelf worden gegenereerd. Als een verkennende maar noodzakelijke stap, hebben we in hoofdstuk 2 eerst onderzocht of MOOC-studenten actief zijn in het `Social Web` en hoe we betrouwbaar hun accounts op verschillende `Social Web` platforms kunnen identificeren. Hiertoe hebben we meer dan 320.000 studenten van achttien MOOC's in `edX` onderzocht en gekeken hoe we hun accounts op vijf populaire `Social Web` platforms kunnen identificeren, i.c.,

`Gravatar`, `Twitter`, `LinkedIn`, `StackExchange` en `GitHub`. Verder hebben we onderzocht welke logs van deze platforms kunnen worden verzameld en benut om student-attributen af te leiden die relevant zijn voor hun leeractiviteiten in de MOOC-context. We stelden vast dat gemiddeld 5% van de studenten konden worden geïdentificeerd op globaal populaire Social Web platforms en dat studenten met specifieke eigenschappen voorkeur hebben voor verschillende typen van MOOC's. Gebaseerd op de observaties van Hoofdstuk 2, waar we observeerden dat meer dan een derde van de studenten van een *Functional Programming* MOOC `GitHub` gebruikten voor hun programmeer-activiteiten, combineerden we de logs gegenereerd door die studenten in zowel `edX` als `GitHub` om zogenoemde *learning transfer* te onderzoeken in Hoofdstuk 3: gebruiken studenten daadwerkelijk de nieuw verworven kennis en vaardigheden voor problemen in de praktijk? Onze analyses toonden aan dat (i) meer dan 8% van betrokken studenten inderdaad de verworven kennis benutten in de praktijk, en (ii) de meeste bestaande inzichten over transfer van de klassieke klas-context inderdaad ook van toepassing zijn in de MOOC-context. Voor het *modelleren van studenten* in onderwerpspecifieke platforms, hebben we ons in Hoofdstuk 4 gericht op het onderzoeken van het probleem van kennis-herleiding, dat grotendeels niet is onderzocht in eerdere onderzoeken vanwege het gebrek aan beschikbare datasets van zulke platforms. Met drie grootschalige datasets rond taalverwerving beschikbaar gesteld door `Duolingo` hebben we factoren onderzocht die gecorreleerd zijn met de performance van studenten en dan een machine learningtechniek toegepast (namelijk Gradient Tree Boosting) om de toekomstige performance van studenten te voorspellen. We hebben aangetoond dat de performance van de studenten was gecorreleerd met niet alleen de betrokkenheid van de student met de cursus maar ook met contextuele factoren zoals de apparaten die werden gebruikt. In Hoofdstuk 5 hebben we verder onderzocht of studenten de verkregen kennis zouden kunnen toepassen in echte realistische taken, i.c. betaalde taken verkregen van online marktplaatsen die kunnen worden volbracht door de kennis toe te passen uit de cursus. Voor dit doel hebben we een data-analyse van MOOC-onderwijs in `edX` beschouwd en handmatig een set van betaalde taken geselecteerd van `Upwork`, een van de populairste freelance marktplaatsen ter wereld, en de geselecteerde taken aan studenten aangeboden en gezien hoe de studenten met deze echte realistische taken omgaan. We hebben geconstateerd dat deze taken konden worden volbracht door MOOC-studenten met hoge accuratesse en kwaliteit.

Voor het *genereren van educatieve content* hebben we ons in Hoofdstuk 6 gericht op het genereren van educatieve vragen, aangezien die algemeen als essentieel worden beschouwd voor leren. Om een effectieve automatische

vraag-generator te bouwen, moeten twee uitdagingen worden overwonnen. Ten eerste moet er een grootschalige dataset worden verzameld van vragen van verschillende kennisniveau' s voor verschillende onderwerpen. Ten tweede moeten effectieve strategieën worden ontwikkeld voor het identificeren van zinnen in een artikel die een vraag waard zijn (i.c. zinnen die belangrijke concepten bevatten), voordat deze zinnen worden gebruikt als input voor een vraag-generator. Om met deze uitdagingen om te gaan, hebben we ons gebaseerd op `TED-Ed` en `Khan Academy` om een educatieve dataset van vragen te verkrijgen, *LearningQ*, met meer dan 230K document-vraag-paren gegenereerd door zowel docenten als studenten. We hebben aangetoond dat *LearningQ* bestaat uit vragen van hoge kwaliteit die niet alleen alle kennisniveau' s van Bloom' s Revised Taxonomy beslaan maar ook verschillende onderwerpen. We hebben laten zien dat het een uitdagende taak is om automatisch educatieve vragen te genereren, zelfs met voldoende trainingsdata en state-of-the-art technieken voor vraag-generatie. Daarnaast hebben we in totaal negen strategieën ontwikkeld en vergeleken om uit een artikel zinnen te selecteren die een vraag waard zijn en aangetoond dat vragen in leercontexten doorgaans gebaseerd zijn op bronzinnen die informatief zijn, belangrijk zijn en nieuwe informatie bevatten.

Curriculum Vitae

Guanliang Chen was born in Zhanjiang, China on February 24, 1988. He received his master degree with an outstanding thesis award from South China University of Technology, China. His master thesis was completed when he served as an exchange research student at Hong Kong Baptist University, China, where he worked on developing effective context-aware recommender systems. Prior to that, he received his bachelor degree from South China University of Technology, China.

From March 2015 to December 2018, Guanliang Chen was a PhD student in the Web Information Systems group at Delft University of Technology, supervised by Geert-Jan Houben and Claudia Hauff. His PhD work focused on developing data-driven approaches for better modeling MOOC learners and generating useful educational content through external sources, in particular, the Social Web. Guanliang's research has been published in leading conferences and journals on relevant fields such as ICWSM, WebScience, UMAP, L@S, LAK, EDM, EC-TEL, IEEE Transactions on Learning Technologies, and Computers & Education. He received Best Student Paper Award from EC-TEL 2016 and Best Student Paper Nominee Award from both L@S 2016 and UMAP 2014. Guanliang co-organized the Workshop on Integrated Learning Analytics of MOOC Post-Course Development at LAK 2017 and the 15th Dutch-Belgian Information Retrieval Workshop in 2016. He was invited as a keynote speaker in the 2017 Doctoral Student Forum on MOOC Research in Peking University, China. He has also served as a program committee member and reviewer for several conferences and journals, such as LAK, ICWL, IEEE Transactions on Learning Technologies, Computers & Education, ACM Computing Surveys, etc.

Publications

1. **Guanliang Chen**, Jie Yang, Claudia Hauff, Geert-Jan Houben. *LearningQ: A Large-scale Dataset for Educational Question Generation.* In Proceedings of the 12th International AAAI Conference on Web and Social Media, California, US. ICWSM'18. (Full conference paper)

2. Dan Davis, **Guanliang Chen**, Claudia Hauff, Geert-Jan Houben (2018). Activating Learning at Scale: A Review of Innovations in Online Learning Strategies. Computers & Education, Vol. 125: 327-344. (Journal paper)

3. Sepideh Mesbah, **Guanliang Chen**, Manuel Valle Torre, Alessandro Bozzon, Christoph Lofi, Geert-Jan Houben. *Towards User-Centric Online Learning Meta-Data:Concept Focus for MOOCs.* In Proceedings of the 13th European Conference on Technology Enhanced Learning, Leeds, UK. EC-TEL'18. (Full conference paper)

4. **Guanliang Chen**, Claudia Hauff, Geert-Jan Houben. *Feature Engineering for Second Language Acquisition Modeling.* In Proceedings of the 13th Workshop on Innovative Use of NLP for Building Educational Applications, New Orleans, US. BEA'13. (Workshop paper)

5. Yue Zhao, Dan Davis, **Guanliang Chen**, Christoph Lofi, Claudia Hauff, Geert-Jan Houben. *Certificate Achievement Unlocked: Exploring MOOC Learners' Behaviour Before & After Passing.* In Proceedings of the 24th ACM International Conference on User Modeling, Adaptation and Personalization, Bratislava, Slovakia. UMAP'17, ACM. (Late-breaking results paper).

6. Yingying Bao, **Guanliang Chen**, Claudia Hauff. *On the Prevalence of Multiple-Account Cheating in Massive Open Online Learning.* In Proceedings of the 10th International Conference on Educational Data Mining, Wuhan, China. EDM'17. (Short conference paper)

7. **Guanliang Chen**, Dan Davis, Markus Krause, Claudia Hauff, Geert-Jan Houben. *Buying Time: Enabling Learners to become Earners with a Real-World Paid Task Recommender System.* In Proceedings of the 7th International Conference on Learning Analytics and Knowledge, Vancouver, Canada. LAK'17. (Poster paper)

8. Dan Davis, Ioana Jivet, René F. Kizilcec, **Guanliang Chen**, Claudia Hauff, Geert-Jan Houben. *Follow the Successful Crowd: Raising*

MOOC Completion Rates through Social Comparison at Scale. In Proceedings of the 7th International Conference on Learning Analytics and Knowledge, Vancouver, Canada. LAK'17. (Full conference paper)

9. Elle Wang, Dan Davis, **Guanliang Chen**, Luc Paquette. *Workshop on Integrated Learning Analytics of MOOC Post-Course Development.* In Proceedings of the 7th International Conference on Learning Analytics and Knowledge, Vancouver, Canada. LAK'17. (Workshop summary paper)

10. **Guanliang Chen**, Dan Davis, Markus Krause, Efthimia Aivaloglou, Claudia Hauff, Geert-Jan Houben (2016). *From Learners to Earners: Enabling MOOC Learners to Apply Their Skills and Earn Money in an Online Market Place.* IEEE Transactions on Learning Technologies, Vol. 11(2): 264-274. (Journal paper)

11. Dan Davis, **Guanliang Chen**, Tim van der Zee, Claudia Hauff, Geert-Jan Houben. *Retrieval Practice and Study Planning in MOOCs: Exploring Classroom-Based Self-Regulated Learning Strategies at Scale.* In Proceedings of the 11th European Conference on Technology-Enhanced Learning, Lyon, France. EC-TEL'16. (Full conference paper, Best student paper award)

12. **Guanliang Chen**, Dan Davis, Claudia Hauff, Geert-Jan Houben. *On the Impact of Personality in Massive Open Online Learning.* In Proceedings of the 24th ACM International Conference on User Modeling, Adaptation and Personalization, Halifax, Canada. UMAP'16. (Full conference paper)

13. Dan Davis, **Guanliang Chen**, Claudia Hauff, Geert-Jan Houben. *Gauging MOOC Learners' Adherence to the Designed Learning Path.* In Proceedings of the 9th International Conference on Educational Data Mining, Raleigh, USA. EDM'16. (Full conference paper)

14. **Guanliang Chen**, Dan Davis, Jun Lin, Claudia Hauff, Geert-Jan Houben. *Beyond the MOOC platform: Gaining Insights about Learners from the Social Web.* In Proceedings of the 8th ACM Conference on Web Science, Hannover, Germany. WebSci'16. (Full conference paper)

15. **Guanliang Chen**, Dan Davis, Claudia Hauff,Geert-Jan Houben. *Learning Transfer: Does It Take Place in MOOCs? An Investigation into the Uptake of Functional Programming in Practice.* In Proceedings of the 3rd ACM Conference on Learning @ Scale, Edinburgh, UK. L@S'16. (Full conference paper, Best student paper nominee)

16. Dan Davis, **Guanliang Chen**, Ioana Jivet, Claudia Hauff, Geert-Jan Houben. *Encouraging Metacognition & Self-Regulation in MOOCs through Increased Learner Feedback.* In Proceedings of the LAK 2016 Workshop on Learning Analytics for Learners, Edinburgh, UK. (Workshop paper)

17. **Guanliang Chen**, Li Chen (2015). *Augmenting service recommender systems by incorporating contextual opinions from user reviews.* User Modeling and User-Adapted Interaction Journal (UMUAI), Vol. 25(3):295-329. (Journal paper)

18. Li Chen, **Guanliang Chen**, Feng Wang (2015). *Recommender systems based on user reviews: the state of the art.* User Modeling and User-Adapted Interaction Journal (UMUAI), Vol. 25(2):99-154. (Journal paper)

19. **Guanliang Chen**, Li Chen. *Recommendation Based on Contextual Opinions.* In Proceedings of 22nd International Conference on User Modelling, Adaption and Personalization, Aalborg, Denmark. UMAP'14. (Best student paper nominee)

20. Jian Chen, **Guanliang Chen**, Haolan Zhang, Jin Huang, Gansen Zhao. *Social Recommendation Based on Multi-relational Analysis.* In IEEE/WIC/ACM International Conferences on Web Intelligence and Intelligent Agent Technology, Macau, China. WI-IAT'12. (Special session paper)

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