Instructional Designs of Machine Learning

Ji Darwish*
Supervisor(s): Gosia Migut, Marcus Specht†
EEMCS, Delft University of Technology, The Netherlands

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*j.darwish@student.tudelft.nl
†m.a.migut@tudelft.nl, m.m.specht@tudelft.nl

Abstract

Instructional Design is a discipline and a science that has existed for decades. There has been research done into the most effective instructional designs for different study disciplines, the same cannot be said about machine learning. As ML is a relatively young discipline, no research has been done into instructional designs and teaching methods of machine learning. This paper investigates the existing instructional designs of ML by analysing various bachelor ML courses at different universities, the compare the results with the existing instructional designs at the TU Delft using the help of interviews with the education experts at TU Delft in order to draw conclusions regarding the differences and how to improve on the course at the TU Delft.

Keywords: Machine Learning, Instructional Designs, Educational Methods, Technical University of Delft.

1 Introduction

Machine Learning (ML) is considered to be a subset of the methodology of Artificial Intelligence (AI). It nowadays has a wide range of applications [1]. The most broadly used one is making predictions regarding real world events, such as predicting the buying behaviour of customers or estimating the price in real estate to name a few.

With all that in mind, today's society has plenty of benefits from the rise of this field. Machine Learning has been a hot topic in the world of Computer Science and Engineering for a reasonable amount of time. Given the importance machine learning has, it is no question that a certain level of proficiency in the work field is necessary. However, despite the hot seat position of this field, we can see from statistics [2] that a high level of deep understanding of the fundamentals of this topic is very rare, this in turn leads to scarcity in skill despite the high demand. This is a clear problem that will only become more prominent the longer it goes on. Tracing back the root of the problem, it can be assumed that education is one of the possible causes of this problem. The way the fundamental concepts of machine learning are taught is yielding a relatively lower number of highly proficient practitioners of machine learning in the industry [2]. This brings us to reminisce about a quote from Amy J. Ko from her blog post "We need to learn how to teach Machine Learning" [3] which outlines this problem perfectly. One can then only ask the question, how can we improve the quality if the education if it is indeed one of the causes of this problem? This is still quite a broad question, which is why this research paper will attempt to analysing the different instructional designs that are being used or are missing from the teaching of machine learning.

1.1 Research Question

The research question of this paper is: **What are the existing Instructional Designs for Machine Learning in the Computer Science (and Engineering) bachelor degrees curricula and what can we learn from them for the Machine Learning course at the TU Delft?** which encapsulates many questions that need to be answered in order to draw conclusions:

1. What is instructional design? [4]

2. What instructional designs exist in introductory machine learning curricula (Using existing literature and different universities and educational entities as base)?

3. What instructional designs from different universities are missing from the TU Delft machine learning course?

4. What conclusions can be drawn from the results to improve the ML course at the TU Delft?

The conclusions/hypothesis of this paper, which you can read further into the research, will be a list of instructional designs that are missing from the TU Delft Machine Learning course. Along side this conclusions about the differences in instructional designs will be drawn after interviewing the TU Delft ML teaching staff.

2 Methodology

This research will require data to describe the characteristics of different instructional designs/strategies and gain more in depth understanding of how ML curricula are built in terms of topics covered. Thus, the type of data needed is qualitative as we need to explain the instructional designs used by different universities and institutional entities. There are no papers which attempt to answer related question to the one this paper attempts to answer. For this reason primary data will be collected by doing own research using a taxonomy and categorization strategy to identify the characteristics of different curricula and categorize them in different groups in order to be able to make comparisons.

This research will look at curricula of different universities and institutional entities, for this to be possible, a selection of what universities are included in the research needs to be done. This is done with two categories in mind:

- Including multiple universities in the Netherlands as they are influential to/influenced by the choices of the Instructional Designs at the TU Delft.

- Universities that are ranked highly in the department of Computer Science (and Engineering) around the world. (Even though university rankings is not a perfect measure [5] it will suffice for the purposes of this research paper).

This paper will also make two important distinctions:

- Distinction between Technical and non-technical universities as this fact might have an effect on the content of various curricula.

- Whether the title of the bachelor degree is Computer Science or Computer Science and Engineering. This might indicate that while the courses might attempt to teach the same topics,the focus of the courses might be slightly different)

The method for collecting and analysing the data was the following. Making a selection of universities the curricula of which will be investigated. Developing a taxonomy and a categorization strategy that aid analysing data that are of importance for this research, Looking both on the Instructional Designs used and the range of topics covered while taking in mind the previous distinctions between universities. Based on the taxonomy, the categorization strategy and the selected universities characterize different curricula and place them in a table accordingly in order to facilitate comparison for experts. Present the findings to the teaching staff at the TU Delft and make comparisons with the current curriculum's Instructional Designs used at the TU Delft course. Attempt to draw conclusions (hypothesis of this paper) based on the feedback from the TU Delft teaching staff.

With the resulting analysed data this paper will attempt to get answers to the research questions

3 Literacy analysis

A challenge that poses in teaching machine learning to software engineering and computer science students consists of changing the methodology from a constructive design-first perspective to an empirical one, focusing on proper experimental work [6]. This is currently being done in a limited manner at universities due to the lack of research supporting the effectiveness of adopting different instructional designs for the discipline of machine learning than is being done for general computer science fields.

The topic this research paper investigates has not been well researched, there are no studies that look at the instructional designs in teaching machine learning specifically, nor are there comparisons drawn between the different teaching strategies/topics as this paper attempts to do by analysing the curriculum of the TU Delft.

A first step into this study involves having clear definition of terms such as instructional design, a list of instructional designs to observe in universities educational curricula of machine learning and, most importantly, a target group of universities the curricula and teaching methods of which will be investigated.

3.1 Target Researched Universities

In order to analyse the instructional designs of different universities, a selection of target research universities needed to be made. To achieve this, the QS World University Rankings [7] was used. A constraint that needed to be taken into account was the availability of the teaching material for research and how transparent the teaching material was, which was inspected by visiting various universities machine learning course teaching websites. Whilst choosing the universities, it was of interest that the Computer Science bachelor study selected group is diverse and expressive, for this reason it was taken into account whether it is a Computer Science or Computer Science and Engineering bachelor. The following is the selected group based on the criteria.

University	Bachelor
Stanford	Computer Science
Vrije Universiteit	Computer Science
Berkeley	Computer Science
Oxford	Computer Science
University of virginia	Computer Science
Massachusetts Institute of Technology	Computer Science and Engineering
Technical University of Delft	Computer Science and Engineering

Figure 1: Selected Universities for the study

3.2 Instructional Designs

Instruction is described by Gagne [8] as an action of arranging the conditions of learning that are external to the learner. Instructional Design can be defined in many ways, it is the practical application of this knowledge to create a situation where learning is most likely to effectively occur. It advocates making use of the available research on how people think, how people learn, the technologies available for communication. It is a discipline that constantly looks to the findings of other disciplines (e.g., cognitive psychology, communication) to study and improve methods of developing, delivering, and evaluating instruction and instructional practices [9].

Instructional design is also defined as a process, most commonly known as ADDIE (figure 2), an acronym that describes the process of creating Instructional Designs: analyze, design, develop, implement, and evaluate[10]. This method is used by instructional designers around the world to create, analyse and assess teaching methods for specific disciplines.

Figure 2: the ADDIE process [11]

Based on this definition of instructional design, it was important to have a clear set of definitions for various instructional designs of interest to this study. This was done in order to observe certain characteristic of curricula in order to derive the instructional design used [4] [12] [13] [14] (figure 3).

Instructional Design Approach	Instructional Design	Definition/What students do
Teacher Centered	Lecture	Instructor presenting material and answering student questions that arise. Students receive, take in and respond
	Directed Discussion	Class discussion that follows a pre-determined set of questions to lead students to certain realizations or conclusions, or to help them meet a specific learning outcome
	Guided Instruction	Direct and structure instruction that includes extensive instructor modeling and student practice time
	Just-in-Time Teaching	Instructor adjusts class activities and lectures to respond to the misconceptions revealed by assessing students' prior knowledge
	Interactive Lecture	A lecture that includes 2-15 minute breaks for student activities every 12-20 minutes.
	Direct Instruction	Lecturing, but includes time for guided and independent practice
	Modelled teaching	involves the teacher 'showing' students how to do a task. The teacher shows the task while also breaking it down into small steps.
Student Centered	Scaffolding	involves providing support to students while they cannot complete a task alone, when the student can complete the task alone, the teacher withdraws their support
	Flipped Instruction	Events that have traditionally taken place inside the classroom now take place outside the classroom and vice versa.
	Case-based Learning	Students apply course knowledge to devise one or more solutions or resolutions to problems or dilemmas presented in a realistic story or situation. uses a guided inquiry method and provides more structure during small-group sessions
	Inquiry-based	Students learning or applying material in order to meet a challenge, answer a question, conduct an experiment, or interpret data
	Problem-based Learning	Student groups conducting outside research on student-identified learning issues (unknowns) to devise one or more solutions or resolutions to problems or dilemmas presented in a realistic story or situation
	Project-based Learning	Students applying course knowledge to produce something; often paired with cooperative learning
	Role Plays and Simulations	Students acting out roles or improvising scripts, in a realistic and problematic social or interpersonal situation. Students playing out, either in person, or virtually, a hypothetical social situation that abstracts key elements from reality
	Fieldwork and Clinicals	Students learning how to conduct research and make sound professional judgements in real-world situations
	Prior Knowledge Assessment	Entails assessing students' knowledge at the beginning of a unit of work in order to teach students at an appropriate level
	Peer Assisted Learning	Has the teacher step aside and allows students to take charge of the learning environment
	Cooperative Learning	A teaching strategy that involves having students work together rather than in competition. Usually, this takes place in small groups where the success of the group is dependant on the students working together to achieve a common goal

Figure 3: Definition of various instructional designs

Based on the table of definitions of instructional design methods observed in this study, it is notable that instructional designs can be divided into two main overarching categories. Namely, student-centered and teacher-centered instructional designs. Theses are completely different techniques of instructional designs with different focus, approach and manner of assessment. The main difference is that in teacher centered approach, students' focus is completely on the teacher, whereas in learner-centred classroom, both students and educators have equal focus. Below is a table that shows compares the two in greater detail (figure 4).

Teacher–Centered	Person–Centered
Teacher is the sole leader	Leadership is shared
Management is a form of oversight	Management is a form of guidance
Teacher takes responsibility for all the paperwork and organization	Students are facilitators for the operations of the classroom
Discipline comes from the teacher	Discipline comes from the self
A few students are the teacher's helpers	All students have the opportunity to become an integral part of the management of the classroom
Teacher makes the rules and posts them for all students	Rules are developed by the teacher and students in the form of a constitution or compact
Consequences are fixed for all students	Consequences reflect individual differences
Rewards are mostly extrinsic	Rewards are mostly intrinsic
Students are allowed limited responsibilities	Students share in classroom responsibilities
Few members of the community enter the classroom	Partnerships are formed with business and community groups to enrich and broaden the learning opportunities for students

Figure 4: Student-Centered vs Teacher-Centered instructional designs [15] [16]

Using the instructional designs defined by the research paper, along side the grouping criteria created by the overarching teacher- and student-centered approaches, we can categorize the instructional designs as shown below (figure 5)

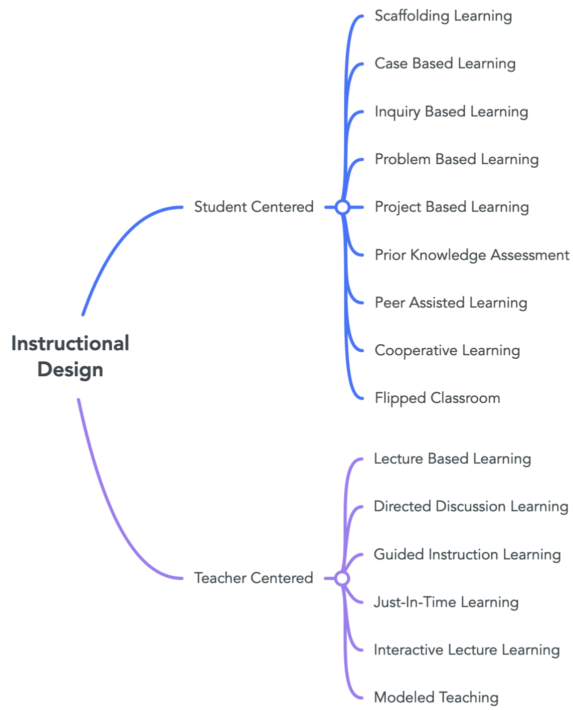

Figure 5: Instructional Designs Categories [12]

3.3 Literature Study Results

Now that this paper has defined the terminology needed to conduct research, the curricula of the chosen universities was researched and instructional designs were observed. This was done through examining the course catalogues of the introductory machine learning courses, the method of assessment and the material used to teach the topics. The resulting data is shown in the tables below (figures 6 7).

University	Stanford	Vrije Universiteit	Berkeley	Oxford
Bachelor Title	Computer Science	Computer Science	Computer Science	Computer Science
University Type	University	University	University	University
Prerequisites	- Computer Science principles and skills - Probability Theory - Multivariable Calculus - Linear Algebra	- Linear Algebra - Calculus - Probability - Programming Experience	- Multivariable calculus - Linear algebra - Discrete mathematics and probability theory	- Continuous Mathematics - Linear Algebra - Probability - Design and Analysis of Algorithms
Topics extent (Beyond what TUD ML course offers)	- Neural Networks - Deep Learning - Self-Supervised learning - Reinforcement Learning - Decision Trees - Model-based RL - Learning Theory	- Neural Networks - Deep Learning - Tree models, Decision trees - Models for sequential data - Recommender Systems - Reinforcement learning - Deep q-learning	- Neural Networks - Decision Trees - Learning Theory - CNN - Decision Trees	- Neural Networks - CNN - Recurrent neural networks and LSTMs - Reinforcement learning
Assessment	- 40% Assignments (Theory + Programming) - 40% Final Project (In groups) - 20% Midterm	- 50% Written Exam - 50% practical assignment (made in groups of 5)	- 40% homework - 20% midterm - 20% final exam - 20% project	- Final Exam - Weekly Practicals (Theory + programming with Lua)
Teaching Material	- (Pre)recorded lectures on Mondays - 1 Lab session on Wednesdays - 1 Homework friday (on campus) - Optional weekly discussion sections led by TAs (interactive/small groups) - Lecture notes	- Deep learning book (https://www.deeplearningbook.org/) - Slides (twice aweek) - Optional homework - Pre-recorded videos of the slides	- 3 hours of lectures - 1 hour of discussion - Textbooks - An introduction to statistical analysis with applications in R - The elements of statistical learning: Data Mining	- (pre)recorded lectures - Textbooks: - C. M. Bishop. Pattern Recognition and Machine Learning. Springer 2006. - Kevin P. Murphy. Machine Learning: A Probabilistic Perspective. MIT Press 2012. - Ian Goodfellow, Yoshua Bengio and Aaron Courville. Deep Learning. MIT Press 2016.
Observed Instructional Designs	**(Teacher-centered/Dirct instruction) Lecture-based:** Weekly lectures introduce the main material	**(Teacher-centered/Dirct instruction) Lecture-based:** Weekly lectures introduce the main material	**(Teacher-centered/Dirct instruction) Lecture-based:** Weekly lectures introduce the main material	**(Teacher-centered/Dirct instruction) Lecture-based:** Weekly lectures introduce the main material
	Project-based/Problem-based/Cooperative-Learning/Field-work: Project is 40% of the final grade	**Case-based/Inquiry-based:** Weekly homework	**Project-based/Problem-based/Cooperative-Learning/Field-Work:** Project is 20% of the final grade	**Case-based/Inquiry-based:** Weekly assignements
	Case-based/Inquiry-based: Weekly assignements		**Directed Discussion:** 1 hour a week of discussions	**Flipped Instruction**: The learning material is intentionally pre-recorded and dives deeper during the lectures
	Scaffolding (Student-based): Lab sessions where TA's provide help if needed			
	Directed Discussion: Discussions in small groups led by TAs			
	Flipped Instruction: The learning material is intentionally pre-recorded and dives deeper during the lectures			

Figure 6: University curricula results 1

University	University of virginia	Massachusetts Institute of Technology	Technical University of Delft
Bachelor Title	Computer Science	Computer Science and Engineering	Computer Science and Engineering
University Type	University	Institute of Technology	Technical University
Prerequisites	- Calculus and Linear Algebra - Probability and Statistics - Proficiency in Python	- Introduction to Algorithms - Linear algebra - Multivariate Calculus	- OOP - ADS - Calculus - Linear Algebra - Probability Theory and Statistics
Topics extent (Beyond what TUD ML course offers)	- Neural networks - deep learning - CNNs and RNNs	- Neural networks - CNNs - State machines and MDP's	
Assessment	- 72% four Homeworks - 25% Project - 3% Class participation	- 5% Excersises - 20% Homework - 5% lab attendence - 20% lab checkoffs - 20% quizzes - 30% final	- 100% Final exam - 0% labs
Teaching Material	- Slides - Understanding Machine Learning: From Theory to Algorithms (https://www.cs.huji.ac.il/w~shais/UnderstandingMachineLearning/understanding-machine-learning-theory-algorithms.pdf)	- 2 lectures a week - Monday small lecture and working through homework - Wednesday quiz followed by lab assignments with a student partner	- 2 weekly lectures - 1 TA labs (4 hours) - prtools python library - Weekly exercises - Books - Goodfellow, Bengio, Courville (2016). Deep Learning - Bishop (2006). Pattern Recognition and Machine Learning - lecture notes by Andrew Ng (course CS229, Standford University)
Observed Instructional Designs	**(Teacher-centered/Dirct instruction) Lecture-based:** Weekly lectures introduce the main material	**(Teacher-centered/Dirct instruction) Lecture-based:** Weekly lectures introduce the main material	**(Teacher-centered/Dirct instruction) Lecture-based:** Weekly lectures introduce the main material
	Case-based/Inquiry-based: Weekly Homework	**Case-based/Inquiry-based:** Weekly Homework	**Case-based/Inquiry-based:** Weekly Labs/exercises
	Interactive Lecture: Class participation nature of the lectures	**Scaffolding (Student-based):** Lab sessions where TA's provide help if needed	**Scaffolding (Student-based):** Lab sessions where TA's provide help if needed
	Project-based/Problem-based/Cooperative-Learning/Fieldwork: Project is 25% of the final grade	**Prior Knowledge Assessment**: Through the use of weekly quizzes	
		Modelled Teaching: Monday sessions go through the homework	
		Peer Assissted Learning: Lab assignment done with a partner	

Figure 7: University curricula results 2

Upon analysing the results, a few observations can be made:

- The prerequisites of all machine learning courses is similar to identical, having them include: probability and statistics, multi-variable calculus and linear algebra. An interesting observation however, is that machine learning courses of Computer Science and Engineering bachelors contain algorithmic knowledge as a prerequisites while Computer Science bachelors do not.

- All the machine learning courses with the exception of TU Delft dive into deeper topics of machine learning, such as neural networks and reinforcement learning.

- All the machine learning courses with the exception of TU Delft have various methods of assessing students knowledge as oppose to the course of TU Delft which only uses a final exam for 100% of the students' grade.

Upon analysing the results, this paper created an overview of instructional designs used at different universities (figure 8):

Figure 8: Instructional Designs used at different universities

Based on the definitions of the instructional designs, the existence of certain instructional designs can be observered. It is observed that the course at the TU Delft uses straight-forward classical instructional designs:

- **Teacher based**: The material of the course is taught weekly through 2 classical lectures (Lecture based learning).
- **Student based**: To practice the material of the course, assignments are given to students and made at labs with the presence of teaching assistants, who provide help when the student needs it (Scaffolding). Using these assignments, other instructional designs can be deduced, namely inquiry based and case based learning.

It can be noted from the table (figure 8) that other universities apply more instructional designs than is done at the TU Delft. For example analysing the instructional designs Stanford universities applies we can see:

- **Teacher based**: The material of the course is taught in class in classical lecture manner (Lecture based learning). An optional discussion session is led weekly by teaching assistants in an interactive manner (Directed discussion learning)
- **Student based**: Multiple Student based instructional designs can be observed:
  - Students have to complete a project throughout the course, this utilizes multiple instructional designs (Project based learning, problem based learning, cooperative learning).
  - Students have to complete mandatory weekly assignments which utilizes the (case based learning and inquiry based learning) instructional designs.
  - Weekly labs are held where teaching assistants only offer their help to students in case it is needed which utilizes the (Scaffolding) instructional design.
  - Before the lecture on Mondays, students are asked to watch pre-recorded lecture sessions, which will be expended upon during the lectures on Monday. This clearly utilizes the flipped instruction instructional design.

As can be seen from the breakdown above, Stanford universities has a more diverse set of instructional designs applied in the course of machine learning. This variation has proven to provide students with a better learning experience, that is due to the fact that certain instructional designs and teaching methods can cover the other methods or techniques shortcomings and make teaching enriched and more effective[17].

In order to draw conclusions and find points of interest in this data, a similar breakdown of the various university machine learning courses has been made. Using this data, unstructured interviews were held with 3 of the head teaching staff of the introductory course of machine learning at the TU Delft. In the following section the paper discussed the results of these interviews.

3.4 Unstructured interviews with the TU Delft machine learning teaching staff

Unstructured Interviews are interviews where neither the question nor the answer categories are predefined; instead they rely on social interaction between the researcher and the interviewee[18]. This interviewing technique was used as the aim of this interview is to get an in-depth understanding of the instructional designs used in the context of teaching machine learning at the TU Delft. Furthermore, on the basis on the assumptions / interesting points observed during research, this paper wanted to understand the phenomenon of interest from the perspective of the people who are involved with it[18].

Unstructured interviews were conducted with the 3 head teaching staff of the course machine learning at the TU Delft. Throughout this section, these teachers will be referred to as teacher1, teacher2 and teacher3 in order to preserve their anonymity as per requested. Below is an overview of the findings in the following structure: Each list item was an interesting topic of discussion to the teachers, below each list item, the opinions of the teachers is stated.

Interesting Finding	Instructional Design	Opinion Type	Teacher 1	Teacher 2	Teacher 3
3% of the grade is class participation at the University of Virginia	Interactive Lecture	Pros	We try to include this in our lectures, sadly sometimes the explanations the teacher has to do run out so there is little time for this. I think this needs to be planned more carefully so there is enough time for it to add value.	If you remove the grade associated with this I would love it, designing our lectures in a way that we focus more on interactivity and having students be more active through the lecture rather than passively listening to what I am saying.	We try to do this during the lecture, sadly not very successfully. Removing the grade from the equation, I am in full support of doing this more often during lectures. I do note that this should be planned better during the lecture so that it gets enough time and focus during the lecture and that it is not rushed through. This allows students to reflect on ideas before revealing the correct answer which could help students understand the ideas better.
		Cons / difficulties	I think having this be a part of the grading is not something we would benefit from, as the ultimate goal we want to have is that students are motivated themselves to take part at learning activities such as this one.	I detest using grades as motivation for students in this way. A student would feel like they are being led into doing this which contradicts the work ethic we want our students to have.	I do not like the fact that students receive a grade for this, I would like it more for students to develop an intrinsic motivation where they are in control of their own learning process
MIT has weekly quizzes to test the knowledge of students about previous weeks material, the results of these quizzes form 20% of the final grade	Prior Knowledge Assessment	Pros	This ties in very well with the research to reduce the misconceptions students get when being introduced to ML.	I do not have good experience with this to think what kind of questions to ask. I do find this very helpful to keep students engaged and up to date with the material. I still think this all depends on the quality of questions.	I like this approach, we are at the TU Delft introducing weekly multiple choice questions where students can test their knowledge of the previous weeks. I like the direct feedback that after doing these questions I as a student can immediately see how I did.
		Cons / difficulties	None	Making up the questions is a very tricky part.	I do not like the fact that it is used as a structural part of the course with grades, I think students should be motivated to do these without them being associated with a grade. It is important at some point during your bachelor to learn more and more that you are in charge of your progress.
Students of Stanford university go through pre-recorded lecture upon which the physical lecture builds	Flipped Instruction	Pros	I think this is extremely valuable, either you explain concepts and let students play around in the labs which is limited. Or you do it the other way around like it is being done here where you delve deeper with the students	We do this for the more advanced machine learning course where the lecture is already recorded and then you check throughout the lecture where students are stuck and expand from there. This works out very well for students in combination with interactivity in lectures.	I would be interested in knowing whether this is something students like, in that case this could make teaching certain difficult topics easier by breaking them into digestable pieces.
		Cons / difficulties	This could be tricky as some students might not take it seriously and watch the pre-recorded sessions. This is something that teachers need to prepare for from the first year.	Doing this in the first few years of the university career of students, they are not mature enough to follow the instructions by actually watching the material they are intended to watch pre lecture.	This could be difficult to do with a large group of students. From the prespective of students, it feels like the lecture is saying, you have to spend twice the amount of time for the lecture, being a session at home and a session at universities.
MIT dedicates a session a week where teachers show students, in relatively small groups, how to go on about solving the homework assignments of the previous week	Modelled Teaching	Pros	If we would have a larger teaching staff this would be an interesting strategy to experiment with.	It would work if you are with a small groups of students and you can hold eye contact and semi personal level of communication. For example to spot out people who are spaced out.	I think we try to do this to some extent in the lecture, showing a process that I hope students will mimic. The difference being I do not expect students to be able to do what I do during the lecture. This is also interesting for the implementation aspects of the assignments.
		Cons / difficulties	This would be very resource intensive as we would need to split the students in smaller groups. This is accompanied by the need for more teachers which we do not have at the moment	This has the same issue with the size of students as doing a project. There will also be more overhead with some students wanting it to be recorded or wanting the answers to go on brightspace. Eventually very few people will show up and actually benefit from these sessions in my opinion.	None
40% of the final grade at Stanford university is a group project	Project based learning Cooperative learning Problem based learning Inquiry based learning	Pros	The project is currently a bonus so it is available for the students to do it but it is not obligatory. This is because for me it does have added value.	I love this approach, we used to have this for the previous machine learning course and I think students can learn a great deal while collaborating on such a project.	I think the project could be a good idea in case we had more time during the course which we do not.
		Cons / difficulties	I believe as labs are being done weekly, it involves cooperative learning and I think it is more effective than the project. We can also that not all students want to do labs or a project and I believe it is the students choice what their learning process is. Thus some students would rather do labs, some want to do the project and other do not need any. The important thing is that the learning goals are being met by the final exam	Due to the high increase of student numbers previous years this idea becomes more resource intensive and infeasible with our current teaching staff capacities. On the other hand, with the current number of students, even if we had more teachers it would still be difficult to apply as teachers need to be guided and also need to learn how to assess students doing this kind of projects. So this brings a lot of new overhead	Our course is currently more focussed on the concepts than on the applications. Looking at this learning goal, spending multiple weeks on this project is a mismatch. We could change the project for it to be more conceptual, this would feasability concerns (checking the projects with the current number of teacher and student assistants)

Figure 9: Interviews with TU Delft ML teaching staff

4 Responsible Research

For this research paper ethical choices are of essence importance, be it in the selection of university courses to evaluate or in the methods according to which to evaluate those. In order to achieve that this paper ensures the use of academic honesty and proper citation styles.

The steps that were taken to collect the data (see Methodology), the parameters chosen to be of interest and the taxonomy according to which the data was categorized and analyzed (see Methodology) were documented in detail such that the research results are reproducible and repeatable. The data used in this research is available online for reproducibility purposes hereby following the guidelines recommended by the Netherlands Code of Conduct for Research Integrity[19]. However, for drawing the conclusions of this paper, the expertise of 3 of the TU Delft Machine Learning teaching staff were consulted through unstructured interviews. As the target group is relatively small for such a research, it could be the case that different experts might have different opinions than the conclusions drawn here. This paper uses interviews with TU Delft teaching staff to draw conclusions. Before the interviews all teachers participating in the study have signed a consent form to be recorded, dictated, and so what is said could be used anonymously throughout this study.

5 Conclusions

This study looked at the instructional designs used in teaching introductory machine learning courses in bachelor Compute Science studies. Firstly, it discussed various definitions of the term Instructional Design (1), being an action of arranging the conditions of learning that are external to the learner in order to provide an efficient and enjoyable learning experience [8]. Then, the study looked at the existent instructional designs that are existent in introductory ML courses at a group of university selected based on university rankings [5], in figures (figure 1) and (figure 5) respectively (2). The TU Delft was also considered as a part of the study in order to discover any differences in the choices of instructional designs used. As for such, many new instructional designs were observed by looking at the curricula of the universities, the most important of which were documented in (figure 9) (3). Those findings are only interesting in the right context, for that reason unstructured interviews were conducted with 3 teachers of the head teaching staff of ML at the TU Delft. The analysis of this research is found in the latter figure. Based on the data collected and analysed and the interviews conducted with the teaching staff, a few instructional designs rise in popularity among the teaching staff, which are implementable at the TU Delft and remain to be tested for effectiveness and efficiency (4). The list is as follows:

- **Interactive Lecture**: By including interactive participation of the students during lectures.
- **Prior Knowledge Assessment**: Using quizzes to test students knowledge of the material after every module/topic.
- **Flipped Instruction**: Providing pre-recorded teaching material to students before the lecture and using this knowledge to further expand upon ideas during the lecture, or to help digest difficult topics.

These results deem interesting based on the research collected, the universities applying them and the opinion of the teaching staff at the TU Delft. The following section discusses possibilities and suggestions for further research in future studies.

6 future work

This research topic proved to be one yielding many interesting results which, unfortunately, cannot be handled in this single research paper. The results of the research raises questions that could be further researched which, due to the nature of this broad research, could not have been answered here:

- This paper compares introductory courses of machine learning in bachelor studies, how does that compare to those courses of master studies? Or more advanced courses during the bachelor.
- It could be further research how, based on the results of this paper, one can design and evaluate a new skill circuit model to teach machine learning at TU Delft.
- The results of this research were based on interviews with teaching staff of machine learning at the TU Delft, which is a small target group and a slightly biased one at that. It could be researched what the results would be according to students as a target group by creating a learning activity and having students as the target group to compare the effectiveness of applying the new findings in the learning activity.

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A Appendix

A.1 Machine Learning Topics Categorized

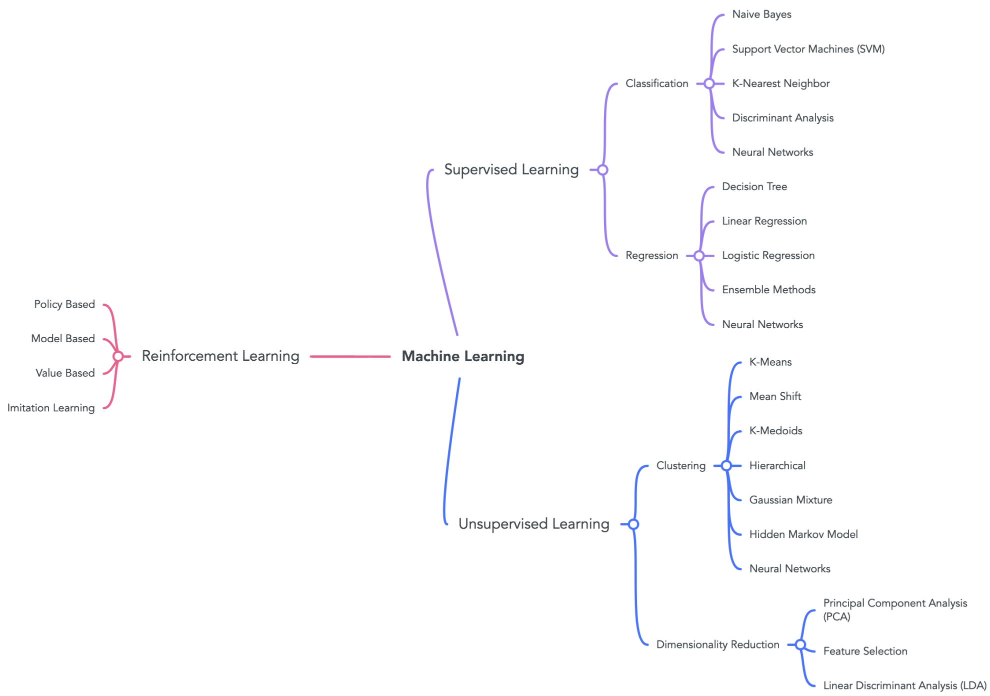

Figure 10: Machine learning topics

Figure 11: University covered topics