Modelling participatory modelling

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0.1 FOREWORD

This is the thesis for my integrated double degree master thesis on Science communication and Complex systems engineering and management. My CoSEM supervisors were Igor Nikolic and Gerdien de Vries. My SeC supervisors were Maarten van der Sanden and Steven Flipse.

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CONTENTS

0.1 Foreword 2
0.2 Executive summary 5

1 INTRODUCTION 9

2 THEORETICAL CONTEXT 14
2.1 Social learning foundations and issues 14
2.1.1 Social learning in practice and complications 15
2.2 Social learning and participatory modelling 16
2.3 Research questions 17

3 RESEARCH METHODOLOGY 19

4 THEORETICAL FRAMEWORK 20
4.1 Context and problem definition 20
4.2 Basic actions in participatory modelling processes 21
4.3 Theories of interest 23

5 CONCEPTUAL MODEL NARRATIVE 28
5.1 Conceptual model 28
5.1.1 System identification and decomposition 28
5.1.2 General model 30
5.1.3 The information sharing model 31
5.1.4 Information processing model 32

6 LEARNING AND KNOWLEDGE CONCEPTUALISATION 34
6.1 Conceptualising knowledge 35
6.1.1 Personal knowledge and group knowledge 36
6.1.2 Knowledge basis, social worlds and communities of practice 37
6.2 Conceptualisation learning 38
6.2.1 Sharing of information 38
6.2.2 Energy & learning 40
6.2.3 Learning energy and attitude 41
6.3 Decision making on the boundary object 43
6.4 Theory synthesis 44

7 MODEL FORMALISATION 46
7.1 Programming ABM introduction 46
7.2 Simplifications regarding the conceptualisations 47
7.3 Set-up 48
7.4 Behaviour 49
7.4.1 information sharing 50
7.4.2 Information processing 51
7.5 Interface 52
7.6 Summary 55

8 MODEL EXPLORATION 56
8.1 LHS and random forests introduction 56
8.1.1 Random forests and extremely randomized forests 56
8.2 Experimental set-up 57
8.3 Experimental output 58

8.3.1 Exploratory descriptive analysis 60
8.4 Discussion 65

9 EXPERIMENTATION 67
9.1 Case layout 67
9.1.1 Windmasters 67
9.2 Dutch blockhain 68
9.3 Experimentation 69
9.3.1 Learning mean differences between experiments 70
9.3.2 Discussion 76

10 DISCUSSION AND CONCLUSIONS 78
10.1 Run-down, discussion on the thesis and researh question 78
10.2 Results discussion and conclusions on a theoretical perspective 80
10.2.1 Theoretical implication of the ABM 82
10.2.2 Theoretical implications CoSEM 82
10.3 Conclusions from a practical perspective 83
10.4 Future work 85
10.5 Issues and loopholes to look out for 86
References 88

A SCATTERPLOTS EXPLORATORY ANALYSIS 95
A.0.1 Number of individuals and information items 96
A.0.2 Processing and sharing costs 99

B PRELIMINARY EXPERIMENT PLOTS 101
B.0.1 Energy decay vs learning over different agenda topic durations 101
B.0.2 Number of items per topic and connectivity of topics 104
B.0.3 Processing and Sharing energy vs learning over different agenda topic durations 106
B.0.4 Relevance vs learning over different agenda topic durations 109
B.0.5 Attitudes vs Learning 111

0.2 EXECUTIVE SUMMARY

To deal with increasing complexity and connectivity of socio-technical systems it becomes unlikely for individuals to be able to oversee all possible changes. These systems are riddled with a plurality of actors with differing interests, disciplines, institutions and ecological limitations. Examples of systems like these are energy and gas grids. If one wants to tackle problems on these systems one would ideally understand possible results of changing things in these systems as a change in one part of the system can lead to results in other subsystems. If a tree falls down on an energy pole, for example, chemical plants can stop functioning. This in turn can cause orders to be late, influencing a whole production chain.

To this end one would ideally one would ideally apply systems thinking: "Systems thinking is a set of synergistic analytic skills used to improve the capability of identifying and understanding systems, predicting their behaviors, and devising modifications to them in order to produce desired effects. These skills work together as a system."

However, because the earlier pluralities it unlikely for a single individual or organisation to have all the required information for this. Processes are required where information is collected and co-created with multiple parties in such as system to enable the creation of comprehensive solutions for these problems. What is required is social learning. Social learning (SL)is learning that happens by people participating in so called communities of practice. A community of practice can be seen as a group of people with converging interests and skills. An example would be a grid operator, which have their own sub-communities (E.G. cable technician or systems manager). They can be smaller groups, E.G. a family, and participation is often not mutually exclusive. Rather than being part of a community of practice one could be seen as being part of the landscape of practice, consisting out of multiple communities. By partaking in these communities people gain experiences by both learning and expanding on a communities' knowledge.

So called boundary object may be used for SL processes. A boundary object or process is a thing that allows for coordination between different groups without requiring consensus. It does this by being fluid enough to garner group activities and several interpretations by each group, while being standardized enough to make local use relatively clear.

For solving problems sustainability problems a boundary object that may be particularly useful is the idea of participatory (simulation) modelling (PM). PM is the act of conceptualising and (sometimes) building a model of a situation with group of people it is defined as: "a purposeful learning process for action that engages the implicit and explicit knowledge of stakeholders to create formalized and shared representations of reality". They are particularly useful as they require participants to explain themselves explicitly and concretely as badly defined ideas and concepts can not be modelled well. Furthermore they are intensive processes enforcing involvement and the resulting model can be assumed to have a certain degree of mutual acceptance behind them. This means that the eventually built model may be used in later processes with these people for things like decision making. Participatory simulation modelling may be especially useful as one can test and experiment with their 'shared representation of reality', helping with anticipation of behaviour of these systems when things are changed. It can be assumed that participant will agree with these results as well as they are party responsible for them. PM has been used.

Insights regarding the workings of social learning processes are still lacking and there are no clear design criteria. Measurements regarding social learning are often lacking or confused with things that are required or assumed results of social learning. If one would want to measure or design such processes it would be useful to understand why and how these processes work from the perspective of individuals rather than the process of a whole. Knowing when and how individuals learn and interact would, additionally, be useful for knowing what one can measure and what one could influence for experiments. These insights will also help practitioners of PM or SL to reflect on their own way of working, creating new theoretical insights. Such a look at the participatory modelling process as a collection of individual actions, reflecting on participatory modelling, has not been done yet.

The aim of this thesis is to gain insights into:

1. mechanics shaping and steering social learning
2. how to measure social learning processes for in vivo experimentation
3. design mechanics for participatory modelling processes and Social learning in general to improve development of such processes

To do this a theory has been made on the mechanics and behaviour of individuals in a SL process. This has been done in chapters 4, 5 and 6. To do this a PM perspective has been used as this give a structure on the actions someone can take and requires shared information to be structured. Additionally it is seen as a useful tool for tackling socio-technical problems.

The theory thus focussed on the main action of PM, namely sending information, receiving and processing information and deciding upon the model. To develop the theory knowledge from multiple disciplines is needed. To this end a theory has been developed using supersynthesis. This is a research method where multiple theories are combined to make a new on to explain something. The aim is not to supersed the combined theories, but to explain something new. The fields that have been the focus are communication science, helping understand how information is processed and sent, and social psychology, helping understand why and when individuals take certain actions. The theories have been synthesised in two rounds of conceptualisation, with the first focussing on conceptualising every possible action and mechanic. The ones that were deemed most interesting or useful have been conceptualised more in depth. To this an additional conceptualisation of knowledge and information is made. The final theory is as follows:

Knowledge takes the shape of a knowledge graph. In this graph fields of expertise are called topics. One can think about the weather as such a topic. These topics consist out of information items, think cloudiness or temperature, and links between these items indicating their relation, think cloudiness leads to lower temperatures. These items may have links to items from other topics. For example cloudiness is related to sun hours and yields of Photovoltaics from th topic of Photovoltaics.

It is assumed that a complete knowledge graph exists. Each individual knows part of this graph, signifying knowledge or expertise in the topic. The larger part of a topic they know the more expertise they have in that topic. This includes both information items as their links (relationships). All these items, links and topics also have a perceived relevance for people. This is based on interests or affiliation. Affiliation means relationship with a group of people, for example, meteorologists. Something is also seen as more relevant if it is discussed often, attributed to common knowledge effects. In a social learning process there are several individuals. Each round they are able to share information. Information is seen as information items and/or their links. A topic as a whole can also be discussed, but this is not seen as actual information for learning. What they share is based on the amount of energy they have and are willing to spend on sharing information. This is dependent on perceived relevance of the item they are considering to share, their expertise on the related topic and their tiredness. It is assumed that the energy one has decays over rounds.

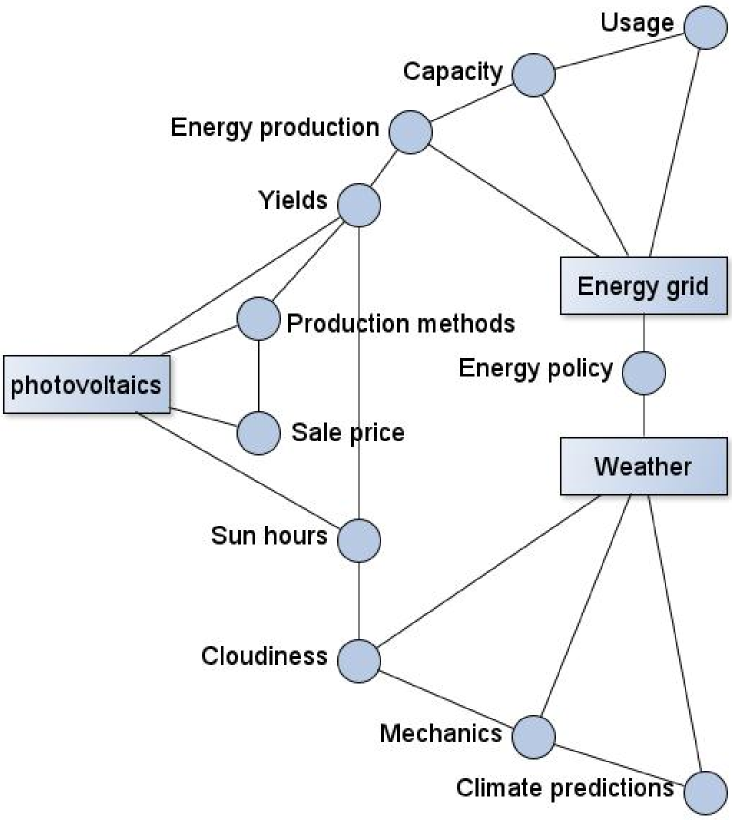


Figure 1: Theoretical 'complete' knowledge set

Shared energy is received by others and they start to process it. Here something is integrated or learned if they are able or willing to invest enough energy in the processing. This is dependent on their expertise of the related topic, their perceived relevance of what is shared and their attitude with regards to the sender. If expertise, relevance and attitudes are high enough someone will process and integrate information. Processing energy is also assumed to decay each round.

In addition to information on knowledge, individuals can also share relational information. These are details like hobbies and other personal details. These are processed as either positive or negative and influence attitudes.

Processing of shared information may also happen during breaks or downtime. Here one has more energy to spend and attitudes are less relevant. Total recall of information is assumed in the whole model (I.E. people do not forget anything).

To allow for further reflection on the theory and to act as a proof of concept of the theory the theory has been translated into an agent based simulation model. This model has been analysed in a sensitivity experiment using LHS and extremely randomised forest in addition to a variety of plotting techniques in R.

Additionally two experiments are designed, inspired by real cases. These are used to reflect on the theory and find less noticeable quirks from the ABM.

Based on the theory and ABM the following things have been concluded:

- While communication science theories and social psychology theories have been used for theory development, they are not a be all end all. One can apply other fields if one wants. This specific combination, however works especially well for an individual perspective
- The theory can be used to reflect on SL by practitioners as it tells why and how people can act. Furthermore the idea of the knowledge graph can be

connected to landscapes of practice, with topics relating to a community and links between items of these topics to those of other relating places where boundaries interact

- Matters like conflict and increasing conflict, coalitions, personal inhibitions and norms are some of the values that would make sense to include in the theory. This would make the theory less usable for simulation modelling, however and would add a lot of behaviour that is not directly related to the learning process. To implement these additional behaviour could be conceptualised and added, making the theory more complete but less comprehensive. The most important addition that could be made according to me would be an extension on the actions influencing attitudes and the actual definition of a process result (a participatory built model or a plan).
- This new theory is valuable as this individual based perspective has not been taken before, inviting to reflection on practice
- The knowledge graph could be used as a means for building new theories that are comparable. Additionally it is a way to explicitly learning.
- The combination between social learning and Participatory modelling has not been made this explicit before. It would allow participatory modellers to reflect on their practice
- The ideas of energy for sharing and processing are quite influential in the ABM. They are interesting as they give clear reasons why learning may not happen or happen suboptimally. For learning to happen information need to be shared. If people lack the energy or the willingness to spend energy sharing will not happen. If they do not have the energy to process this they will also fail to learn. This highlights the need for keeping energy levels in mind when designing these processes. It is assumed that these energy levels decay linearly. While arguably too simplistic still it does show how intensive processes or boring processes can fail.

The following design mechanics are proposed:

1. Usage of a knowledge graph to keep track of what is learned by researchers
2. Usage of knowledge graph to steer the process order that makes learning more likely (topics that closely relate to all participants first and expand that towards specific participants later down the line).
3. Use set structures, conceptual modelling, drawings and other tools to make information sharing and processing easier and less intensive. This would make the process spend less energy if the used tools are chosen well (I.E. a conceptual drawing of what is said or what someone wants to explain using causal diagramming is probably better to explain ideas than doing so via live programming of a simulation model).
4. Use actions like summarizing what has been said to slow down the process if it becomes to quick, leading to a processing energy deficit.
5. Use means like using an agenda to ensure the speed of the process does not become to slow, leading to boredom and potential energy decays

1 INTRODUCTION

Nearly all facets of human life are becoming increasingly interconnected, meaning that change in one system has results in others. Not only are humans becoming more and more interconnected via social media, technical systems are as well. Additionally society depends on these systems to function well with things ranging from subsidies and taxes to acquiring matters like electricity or even pencils. Changing these systems or parts of them needs to happen with care. One of these changes is the drive towards becoming more sustainable because of climate change. This topic will be used as the focal point for this thesis as it is 1) a topic that I find important and interesting; and 2) it is a topic that is often discussed in the literature that inspired the combination of Social learning with modelling, the basis for this thesis. The specific perspective here is one that focusses on the changing of large energy systems like grids or industries, rather than smaller things like greener stoves. Note that many other socio-technical systems could have been used, leading to the same conclusions. The perspective on sustainability is there to help frame a context for examples and to highlight the kinds of issues where the ideas of the thesis can be applied.

Becoming more sustainable requires systematic change over a plethora of systems, concerning problems that are riddled with differing perceptions, interests, institutions and ecological limitations (Steyaert & Jiggins, 2007; Blackmore, 2007). Furthermore these systems are often path dependent and interconnected in physical or digital ways. They are grown over time, leading to changes leading to unpredictable and non-linear outcomes for the system as a whole. This path dependency and interdependency of systems is required for functioning as a whole and the convergence of the expectations of participants, but hampers required change (Pahl-Wostl, 2009). For example, going from a fuel based economy to an electricity based one requires large changes in the chemical industry as one would need to find other sources of heat or resources required to produce their products. These products are used in other production chains which may require social and technical changes because of this and so on. The energy produced needs to handle demand while not hampering operations of related systems. This nestedness of systems leads to the people operating in these systems having different viewpoints, competences, interests and resources; and small changes caused by any of them in one sub-system may lead to ripple effects in others.

In other words future sustainability requires changes in complex systems where system behaviour is emergent and hard to predict based on different sub systems. In these subsystems disciplines are different and people may have private information regarding these systems. These systems have both technical and social components that can self organise, leading to feedback loops in other parts of the system of systems and that are hard to predict. To tackle these kinds of issues a system thinking approach could be useful, that allows us to identify these systems and, to a degree, gain insights into its behaviour allowing for modifications or policy interventions (Ryan, 2008; Arnold & Wade, 2015). A system thinking approach is defined as follows (Arnold & Wade, 2015):

> Systems thinking is a set of synergistic analytic skills used to improve the capability of identifying and understanding systems, predicting their behaviors, and devising modifications to them in order to produce desired effects. These skills work together as a system.

However, as these systems pertain to highly diverse disciplines, it is unlikely that a single person or even a group of people has enough knowledge to oversee results of changes and requirements of the system as a whole. Furthermore, these systems can consists out of multiple parts where a single individual has no influence over. Collective actions or governance spread over multiple parts of these systems is required as highlighted, for example, by Pahl-Wostl (2009), Cundill e.a (2012) and Collins (2009). Where a meteorologist may know the physics behind sun-hours they will not know how Photovoltaics (PVs) generate power using the sun, and the inverse is likely true for the PV designer. Additionally certain parties may have needs that are unbeknownst to others that are directly influenced by these others. E.G. a chemical factory may require an amount of heat for its processes that can only be cheaply provided via fossil fuels. A combination and elicitation of knowledge like this is required to understand the larger systems, allowing for interventions to be designed and implemented.

What is required is transformative change where knowledge is co-created in application within a wide, inclusive, set of communities and practices as change requires knowledge that does not exist yet or is scattered between these communities (Steyaert & Jiggins, 2007). What is required is social learning, enabling concerted action between stakeholders (Steyaert & Jiggins, 2007; Bouwen & Taillieu, 2004; Blackmore, 2007; Collins, Blackmore, Morris, & Watson, 2007). Social learning (SL)is learning that happens by people participating in so called communities of practice. A community of practice can be seen as a group of people with converging interests and skills. An example would be a grid operator, which have their own sub-communities (E.G. cable technician or systems manager). They can be smaller groups, E.G. a family, and participation is often not mutually exclusive. Rather than being part of a community of practice one could be seen as being part of the landscape of practice, consisting out of multiple communities. By partaking in these communities people gain experiences by both learning and expanding on a communities' knowledge. By crossing and intersecting boundaries between communities social learning happens (Wenger, 2000; Wenger-Trayner, Fenton-O'Creevy, Hutchinson, Kubiak, & Wenger-Trayner, 2014).

When garnered in policy problems it should lead to (Blackmore, 2007):

1. Convergence of goals, criteria and knowledge, leading to more accurate mutual expectations, and the building of relations of trust and respect. This should lead to the emergence of agreement on concerted action.
2. Co-creation of knowledge needed to understand issues and practices.
3. A change in behaviours, norms and procedures arising from development of mutual understanding of issues as a result of shared actions such as physical experiments, joint fact

   finding and participatory interpretation.

While social learning has gained traction in the world of natural resource management (Cundill & Rodela, 2012; Steyaert & Jiggins, 2007; Collins et al., 2007), which climate and sustainability problems are, this is not always without issue. If SL processes are incoherent for its participants or if they are deemed as unfair due to matters like power imbalances there may be backlash (Muro & Jeffrey, 2008) as procedural fairness is one of the most important factors for acceptance of decisions (Visschers & Siegrist, 2012). Concerted actions are based on agreements based of a shared understanding.

To garner social learning in a way that fosters understanding between participants so called boundary objects and processes (BO) are helpful as they help communities of practice cross boundaries with other communities, by mediating an understanding into each other's world and terminologies (Wenger, 2000; Star, 2010). A boundary object or process is a thing that allows for coordination between different groups without requiring consensus. It does this by being fluid enough to garner group activities and several interpretations by each group, while being standardized enough to make local use relatively clear (Star, 2010). An example of simple boundary objects would be a map to coordinate a disaster response, allowing non-professionals help aid efforts coordinated by professional aid organisations.

With regards to unpredictable sustainability problems a boundary object or process should help cross boundaries between, for example, NGO's, laypeople, stakeholders like farmers, chemical companies or fishermen; scientists, network operators and policy makers. Next to support mutual understanding it also needs to help coordination and knowledge for concerted actions; and actually help change of related systems by changing norms and behaviours and enabling system thinking (Blackmore, 2007). To this end participatory modelling (PM) could be particularly helpful.

Participatory modelling can be defined as "a purposeful learning process for action that engages the implicit and explicit knowledge of stakeholders to create formalized and shared representations of reality" (Voinov et al., 2018). The formalizations and shared representations of reality in this definition are the models. It is a process where people create a (simulation) model with others to investigate problems, knowledge gaps or possible interventions. Within this process people share information regarding an issue or field to first create an inventory of concepts and mechanics. The shared information needs to be unambiguous and highly explicit to actually derive mechanics for a model, which should help different participants understand each other's world/systems with relation to their own. Based on this information conceptual models are created and even simulation models could be developed. These models can then be used a basis for decision making or further exploration of an issue. This involved learning process is expected to lead to improved system and awareness (Voinov et al., 2018).

With relation to boundary objects and processes and SL one could say that PM is a boundary process used to create a boundary object. During the PM process the unfinished model also serves as a boundary object for mediating meanings between participants garnering social learning for the group that is developing the model (Voinov et al., 2018).

Participatory simulation modelling can be particularly useful for sustainability issues as its support the formulation and testing of policy pathways for change by not only bridging societal gaps between groups, but also by giving new insights through simulations (van Bruggen, Nikolic, & Kwakkel, 2019).

However, insights regarding the workings of such social learning processes are still lacking and there are no clear design criteria. Measurements regarding social learning are often lacking or confused with things that are required or assumed results of social learning (E.G. improved participation, convergence of goals rather than what is learnt) (Reed et al., 2010; Muro & Jeffrey, 2008). If one would want to measure or design such processes it would be useful to understand why and how these processes work from the perspective of individuals rather than the process of a whole. Knowing when and how individuals learn and interact would, additionally, be useful for knowing what one can measure and what one could influence for experimentation. These insights will also help practitioners of PM or SL to reflect on their own way of working, creating new theoretical insights. Such a look at the participatory modelling process as a collection of individual actions, reflecting on participatory modelling, has not been done yet according to discussions with PM practitioners during the 10th IEMSS (International Environmental Modelling and Software Society) conference, where initial results of this thesis have been presented.

The aim of this thesis is to gain insights into this learning behaviour of individuals participating in participatory modelling processes and social learning. Based on these insights the overarching goal is to improve development of actual participatory modelling processes and help develop quantifiable measurement measures of such processes for future in vivo experiments. The first goal is useful for people applying and developing participatory modelling processes, while the latter is useful for scientists interesting in social learning and/or participatory processes. It is not the aim to further develop the used theories for the model, but rather use these theories to develop a plausible narrative, discussing participatory modelling.

To do this a theoretical basis will be made, where the process is conceptualised. This conceptualisation has been formalized in an agent based model (ABM)[1] of social learning within a participatory modelling process using netlogo. An agent based model is a model that consists of agents who have states and interactions with either themselves or other agents. States are characteristics of an agent. They can take the shape of numbers or more abstract terms (E.G. age group: child, adult, elderly). These states change based on interactions and/or change interactions and other states. This means that every state has a relation with something else in the model. By changing states and have states influence behaviours one can model people or entities like companies. This ABM will be used as a proof of concept and tool of exploration on the conceptualisation. Using the ABM one can explore and experiment with theoretical social learning settings. This can be used for reflection and hypotheses building for future research.

If a researcher, for example, finds weird model behaviour. They can try to explain the behaviour based on their understanding of the model, personal experience and theories. Doing so they build a hypotheses that can be tested in vivo. This exploratory use of models can be useful as it gives hypotheses that one would be less likely to come up with without such tools.

Additionally simulation models can be used to replicate settings from vivo. This way one can compare model results with observed ones, allowing for deeper reflection on what caused certain results/behaviour.

The reason for using ABM rather than other simulation approaches are suitability and familiarity. Firstly I am most proficient with ABM modelling compared to others. Secondly ABM focusses on the behaviour and interactions of and between agents. Each agent will have its own behaviour, making them an ideal analogy to persons and their behaviour. This would not be as easy to do with system dynamics, for example.

The decision to take a PM process as the basis is that this gives a sort of structured process that has been proven to be useful. Next to this the requirement of modelling processes that information is made as explicit as possible, as on can not implement information that is not shared or vague into a model. This would potentially make information easier to track/measure than in more 'soft' SL processes like discussions or role-playing games.

To explain and understand behaviour within SL processes knowledge from other disciplines are needed. These will be used to explain behaviour of individuals in groups on the one hand and actual learning and information processing on the other. The mechanics and variables of the model are derived from social psychology and communication science to give a plausible reasons for behaviour of individuals. Social psychology in this context is seen as psychology focussing on group dynamics. Communication science is seen as theories focussing on interpretation, processing and sending of messages. Both are useful as it tells us how behaviour is shaped and when it may be positive or harmful for the process. Additionally it helps us understand when and how information shared by this behaviour is shared and processed. Giving insights into possible behaviour and results of this behaviour. Based on the model and its conceptualisation the aim is to:

1 Gitpagefor the final model, R scripts can be made public upon request, but those will not be cleaned

1. gain insights into the mechanics shaping and steering SL-, PM processes and actual learning rather than on broad process results of SL
2. gain insights into how to measure SL and PM processes on what is learnt and successfulness, enabling measuring future in vivo experiments
3. gain insight into design principles for PM processes and SL processes in general, improving development of such processes

With relation to my masters the first part focussing on the creation of a theoretical basis, explaining the mechanics and individual behaviour in a SL process, is an explicit expansion on SL theory. While it is based on a PM perspective, it can still be read as a normal SL process, be it highly structured. The theory will allow practitioners to reflect on their own SL processes. This reflection can be used for developing SL theory further and helps with designing these processes. Parts of the theory can be used to measure SL processes as well

With relation to CoSEM the theory is useful as a means to reflect on participatory modelling processes, which can be used for exploring socio-technical systems and problems. It also helps with coming up with means to measure the successfulness of these process. In a way the theory and its recommendations can be seen as a process management theory, something seen as important for policy management and part of the curriculum. The ABM development can also be seen as being specifically related to CoSEM in its way of working. This simulation modelling of social processes in this way is something uniquely to the TPM faculty in delft.

In the next chapter ,chapter 2, SL is be discussed to give additional context to the thesis and it will be related to PM. It discusses what SL is and what its issues are. Additionally a link will be made between SL and PM. Based on this context research questions are presented. Chapter 3 discusses the research methodology and approach. In Chapter 4 basic modelling concepts and a context are discussed, creating a frame of reference for the subsequent chapters. This chapter expands on this context with theories from social psychology and communication science as possible means for explaining behaviour of PM participants. Chapter 5 expands on the previous chapter by conceptualising broad behaviour that the model aims to represent. This conceptualisation is relatively broad and inclusive, including processes that have been simplified or left out in the eventual ABM model. Chapter 6 iterates on the previous chapter, focussing on the core behaviour that is perceived as important for SL. It specifically discusses how and when information is shared or internalized (learnt), what shapes it can take and how this information leads to a model (made by participants). Then chapter 7 explains how algorithms work, based on which the algorithms in the ABM will be discussed by means of visualisations or pseudo code. An explanation on how to use the model is given after this. Following this a sensitivity analysis and case based experiments are discussed in chapters 8 and 9 .Finally a discussion and conclusions are discussed regarding possible future work, a theoretical reflection and possible difficulties when expanding on the model in chapter 10.

2 THEORETICAL CONTEXT

In this chapter social learning theory will be discussed, followed by its applications and issues. The aim is to sketch a basic understanding of what SL learning is, what issues there are that this thesis aims to address; and how PM fits into the idea of social learning, These ideas will be used to present research questions.

2.1 SOCIAL LEARNING FOUNDATIONS AND ISSUES

Social learning has no fixed definition and definitions that are given are often quite broad (Pahl-Wostl, 2009; Reed et al., 2010; Muro & Jeffrey, 2008; Ison, Blackmore, & Iaquinto, 2013). It's inner workings are also not discussed, rather it seems to be discussed in a broad way and the focus is often on changing behaviour and actions rather than the acquirement of knowledge (Ison et al., 2013; Webler, Kastenholz, & Renn, 1995; Steyaert & Jiggins, 2007; Blackmore, 2007; Skule, 2004). This can be seen as good or bad. While it makes measuring SL difficult and leads to a lack of cohesion, Ison (2013) argues that the broadness of definitions is good for reflexiveness and allows for depth. Bandura, who is seen one of the most comprehensive and earliest theorists (1977) saw social learning as learnt behaviour based on imitating role models or responding to the environment . Bandura stated, for example, that someone being a bully would lead to his environment reciprocating by acting badly towards the bully in response to the bullying, which in turn would lead to the bully not fixing his bad behaviour. While one could argue that learning knowledge and imitating or changing behaviour are different Bandura does highlight that these processes take place in the social sphere. This means that 1) learning does not take place in a closed off environment and 2) environments are not static and can respond or learn as well.

Building on this idea Wenger (2014; 2000) has expanded on the idea of social learning by introducing the concepts of experience, identity, landscapes of practice and communities of practice. Wenger defines social learning as learning that happens within communities and between different communities based on personal experience and social interactions. A person by living life will become part of several communities of practice and these experiences shape someone's individuality. These communities have certain norms and skills that a participant is supposed to learn, but participants may also change or add knowledge that they learn by interacting with other communities or by acting on their own. These communities are seldom mutually exclusive and by interacting new knowledge may be created. To this end it is required that someone is able to bridge the boundaries between said communities. For example:

In my youth I went to a high school where I learnt biology and chemistry. During my minor I did a project on whole genome sequencing which required my team to read biology papers regarding the topic. While I could follow the processes within the papers my group could not as they did not chose the biology and chemistry courses during their high school careers. On the other hand a team-mate doing a bachelor on ethics was way more competent then I when reading and discussing ethical pieces regarding these topics. By being part of the same group we could explain the things we found difficult to each other and synthesise it into a good report.

This example aims to highlight how personal experience on the one hand shapes what one knows, but also with whom one is able to communicate. While I can follow basic processes, I would likely not be able to follow a high level discussion regarding genetic modification, for example. This requires a certain degree of expertise with the subject. Similarly it shows what a landscape of practices could look like. If you assume the landscape in the example is the Dutch education system, you can see separate high schools and universities as smaller communities, which in turn may be divided in, for example, bachelor or master courses. What someone knows and understands is, thus dependant on the total of communities they are part of. What one knows also determines if one is able to cross boundaries with other communities as this is unable to happen if communities do not understand each other. In the case that communities are too similar, however, crossing boundaries will not be as fruitful as there is a smaller chance of there being learnt something innovative from the other party (Wenger, 2000).

To make this crossing of boundaries easier Wenger (2000) proposes the use of boundary brokers, processes and objects. These are things that allows for coordination between different groups without requiring consensus. It does this by being fluid enough to garner group activities and several interpretations by each group, while being standardized enough to make local use relatively clear (Star & Griesemer, 1989). In the example the group project can be seen as a boundary process between students from different backgrounds. By participating in the group we gained insights into each others meanings by using the project as common ground. This enabled us to not only work together, but also organise workloads by assigning topics in a way that led to a coherent report.

2.1.1 Social learning in practice and complications

When looking at conscious application of social learning in practice in scientific literature. Most cases concern natural resource management (often focussing on water). Henly-Shepard (2015), for example made use of mental modelling to foster social learning for Tsunami prevention in Hawaii. Steyaert (2007) discussed a project group applying social learning in multiple cases with methods ranging from using GIS (graphical information system like digital maps) and modelling and diagramming to performance art.

While most cases are supposedly successful in improving either participation, public capital or relations between participants, this is not always the case. Muro & Jeffrey (Muro & Jeffrey, 2008) discuss multiple cases where social learning is used to reach agreements between stakeholders concerning matters like groundwater or river management. They state that depending on the participants the plurality of viewpoints may make successful behavioural change impossible and they claim that learning does not always lead to behavioural change. (Collins et al., 2007) Furthermore power imbalances (arguably issue of group processes in general and not particularly SL) or knowledge imbalance (Voinov et al., 2018; Shirk et al., 2012; Steyaert & Jiggins, 2007), may halt or hamper processes.

Finally one can say that measurements mainly seem to focus on participation, changing behaviour and other, group related matters like consensus or concerted action (Reed et al., 2010; Pahl-Wostl, 2009; Bouwen & Taillieu, 2004; Ison et al., 2013). While these are not bad means to measure success of group processes, they do not tell us much about the actual process of social learning. Measurements regarding actual learning has not really been done and one often confuses the requirements and supposed benefits of social learning with being social learning (Reed et al., 2010; Pahl-Wostl, 2009). These benefits may also take place without any social learning happening or none of them may take place while it is happening. Thus actual means of measuring are needed to on the one hand measure if social learning is actually taking place, and on the other if social learning is successful if it takes place.

How SL should be measured is not yet clear, however. Reed (2010) proposes measuring double or tripple loop learning, while Voinov (Voinov et al., 2018), for example discusses the comparison of before and after certain diagramming methods. Ison discusses the use of Q-methodology for measuring social learning (2013). This lack of cohesive measurement measures can be claimed to be partly to blame because of the lack of a unified definition of social learning (Reed et al., 2010; Pahl-Wostl, 2009)

When looking at social learning from the lens of learning literature another reason why measurements are difficult come to light. Whereas a lot learning that happens in classrooms or a workplace lead to a familiarity with several knowledge bases, which are testable by means of replication (think exams or graded essays with rubrics) (Bjornavold, 2000; Colardyn & Bjornavold, 2004; Skule, 2004; Clark, 2012). Social learning is a highly unpredictable form of learning. What is learnt is dependent on who participates and how and new knowledge may come into being that did not exist before. Thus where one would ideally create standardizes ways to measure social learning, this may be quite difficult to do.

Furthermore measuring matters like double loop learning will only tell that certain behaviour has been learnt and that values have changed they can be seen as valueless (neutral values) (Tosey, Visser, & Saunders, 2012). They are informative, but do not go in depth on what is actually learnt, why and if this is good. As learning is personal it makes sense to investigate the aspects regarding social learning processes that concern individual learning and behaviour in response to the group, giving insights on what leads to social learning and how to foster this.

> Claim 1. Insights into the social processes en individuals in a SL process are needed for designing SL processes and to create means for measuring SL happening (well)

2.2 SOCIAL LEARNING AND PARTICIPATORY MODELLING

As stated earlier, social learning may require the use of boundary objects to make it easier to cross boundaries between communities allowing for coordination and insights into each other's meanings (Wenger, 2000; Star & Griesemer, 1989). There are multiple successful cases of modelling and participatory (simulation) modelling being used as a boundary object/process for social learning (Bollen, Hoppe, Milrad, & Pinkwart, 2002; Henly-Shepard et al., 2015; Pahl-Wostl, 2002; Shirk et al., 2012; Pahl-Wostl & Hare, 2004; Voinov et al., 2018). They are useful in multiple ways. Firstly a certain degree of involvement can be expected as PM is a time intensive process.

Secondly it forces individuals to be specific, concise and explicit as matters that are not discussed (well) are unlikely to end up in the model. Thirdly modelling enforces a certain structure (see for example, Van Dam e.a. (Van Dam, Nikolic, & Lukszo, 2012)) As models are often diagrams pertaining to interacting systems and causality they help elucidate relations between discussed topics and support understanding in the landscape of systems shared by its participants. This understanding of systems and their interactions would allow enable systems thinking for decision making, which has been highlighted as particularly useful for sustainability problems (Arnold & Wade, 2015; Ryan, 2008). Furthermore, this structure makes a PM process easier to observe and design than several other boundary processes for social learning, like performance art, workshops or discussions.

Finally several kinds of PM can be used to make simulation models rather than conceptual ones. This enables not only understanding of problems; but also allows for the investigation of possible policy pathways or futures (van Bruggen et al., 2019).

Claim 2. PM is useful for sustainability problems as it enables systems thinking and exploration of futures and interventions
Claim 3. PM is useful as it implies consensus on an eventual model
Claim 4. PM is useful for investigating SL as it gives structure and requires for explicit concrete communication

2.3 RESEARCH QUESTIONS

In the previous sections I have discussed what social learning is, how it is used in practice and why participatory modelling is a good boundary object for both garnering and analysing social learning. It has been stated that measuring social learning is often troublesome and that there are a broad array of differing definitions and the focus of social learning in practice seems to be on broader things like cohesion and group relations. I have claimed that investigation into social processes and individuals would help measure and design social learning processes. Furthermore I have claimed that PM is useful for this as it helps structure the learning process in a way that makes the information that is shared explicit and concrete.

To this end I propose to investigate social mechanics and behaviour of individuals within SL processes. I specifically propose that this is done from a PM context as this structures this behaviour in a more predictable format. To elucidate on this behaviour a look should be taken at theories that focus on group behaviour and individual behaviour and information processing. To this end one can think about theories focussing on education, culture, anthropology, actor and process management, communication science and different fields of psychology.

To investigate SL in a broad way one could assume that a single one of these fields would not give comprehensive insights as what goes on in an individual is different than how they communicate. Thus I aim to investigate how people communicate within such processes and why they learn or not learn and when they share information or don't. As I'm familiar with communication science and can comprehend social psychology with my background I aim to build a basis for these insights. Note that an investigation using other theories may still be useful as they highlight different things or perspectives.

If one has a conceptual theory or model, based on several theories one can devise an initial idea of interactions and means of measuring SL. One can gain additional additional insights by first exploring and experimenting with the conceptual model. This can be done using in vivo experimentation, costing a lot of time and money. Additionally one can do exploration via other means like exploratory modelling. Here a simulation model is built, which can be used to derive hypotheses on possible real life behaviour. Additionally experiments in a simulation model can be used for reflection on theory and earlier cases of SL and PM. By doing so one can see the simulation model as some kind of proof of concept of the theories. This proof of concept can be used do to in vivo experimentation with clearer expectations and goals.

Thus the goals of this thesis can be divided into two research questions:

1. How would a theory look like that explains social mechanics and behaviour of SL processes from a PM perspective?

2. How would an ABM of such a theory look like?

In the next chapter these questions will be expanded upon when discussing the research methodology and approach. Question 1 is discussed, specifically in chapters 4, 5 and 6. The second question is handled in chapters 7, 8 and 9

3 RESEARCH METHODOLOGY

In this chapter the research methodology, methods and tools will be discussed, which are the basis for the following chapters.

This research takes the approach of the so called super synthesis (Cairney, 2013), combined with an exploratory modelling approach.

Super synthesis is the development of a hybrid theory, to create a broader or more complete perspective on a topic. This is done by trying to integrate different theories together. An often mentioned problem that can appear is that theories are may have different perceptions on the same term or word, making them incompatible to some. Others, however, claim that this is not fatal as all all theories need to trade comprehensiveness for the sake of simplicity or parsimony (Cairney, 2013). I am inclined to agree with the latter statement.

Reason for choosing super synthesis is that it is a means to combine the field of science communication and psychology, allowing for social learning to be defined in a more comprehensive way that focusses both on people and on the message. To do the synthesis several books and papers are analysed using coding in atlas TI or other tools according methods discussed by Babbie (2010) to define mechanics that would be useful for conceptualisation. Selection for coding is based on perceived usefulness and ease of implementation. While coding is supposedly a tool for super-synthesis, the coded sentences still required interpretations. It turned out that notes taken during the reading of the books and literature (during coding) superseded the coding in usefulness as these already include the translation into mechanics if possible.

The literature is investigated to build a theory on behaviour shaping the model narrative and its conceptualisation. The aim is to find and use theories that would be usable without straying from the source too much as this would be quicker on the one hand and would keep the theories somewhat intact. Note that the aim is not to supersede the theories, but to give insights into another matter, namely, social learning.

A second part of the approach focusses on exploratory agent based modelling, using netlogo. Within this context one can see the agent as an hypothesis, which, through emergent behaviour builds a new theory. This behaviour can be experimented with and observed without requiring time intensive group processes. The experiments, in turn can be observed and interpreted, based on which one can derive insights.

Where the first part of this thesis focusses on building the synthesised theory as a basis for an agent based model the second part aims to go further with this theory to investigate what behaviour would look like. Based on this model the aim is to come up with design criteria for both participatory modelling and social learning, while also giving insights in measuring the actual individual learning during a social learning process.

4 THEORETICAL FRAMEWORK

In this chapter an introduction will be given relating the context and problem definition for the eventual simulation model. This context frames the examples given in the following chapters when explaining the conceptualisation. An introduction to simulation modelling is discussed after this to delineate highlight the basic actions of investigations. Based on these actions theories are selected and discussed that elucidate on mechanics and behaviours around these basic actions. In the final section application of these theories in the following chapter will be shown in a table. This theoretical basis lays the foundation for the conceptualisation of the synthesised theory, answering the first research question, which will be developed in chapters 5 and 6.

4.1 CONTEXT AND PROBLEM DEFINITION

The context used in this paper is heavily inspired by the wind-masters project, which I've had the pleasure joining. Here several grid operators, energy producers and companies came together to explore possible investment strategies for the Botlek area with relation to handling a large energy influx from new offshore wind-farms. Together these parties created a multi-model (a simulation model consisting of several connected models) through participatory modelling. This simulation model used back-casting to find investment paths towards desirable futures.

The actual hypothetical context can be seen as a small group of invested parties wanting to create a simulation model together regarding sustainability options around their town. Involved parties contain several people from a grid operator, energy producers (fossil and otherwise), producers of sustainable power sources, like wind or Photovoltaics, oil companies, an NGO, pair of scientists who took the initiative with a grid operator to start the project and finally a meteorologists/climate scientist. While the wind-master case had a different set of actors, additions have been made to allow for a more varied range of perceptions and interests.

The model is supposed to include climate prediction scenario's and how these influence or are influenced by used technologies for energy production. The pair of scientists have worked on projects with the oil company and grid-operators before with positive experiences. This highlights that they are part of the same 'landscape of practice'. This term comes from social learning theory and defines a large ecosystem of communities focussing around the same topic, indicating that people in SL processes may know each other or have similar competences. In this case one can take the energy field as a landscape(Wenger-Trayner et al., 2014).

Specific departments in organisation can have their own sub-communities. These communities have their own norms, goals and competences which shape and are shaped by individuals and their experiences. Individuals aim to be seen or feel competent within the communities that they feel involved in as this is a large part of their identity. Note that this has a large social aspect as well as one based on actual competences(Wenger-Trayner et al., 2014). This means that a grid maintenance specialist form the grid operator has different skills and aims, for example. The capacity manager may want to expand the grid for the future, where the maintenance

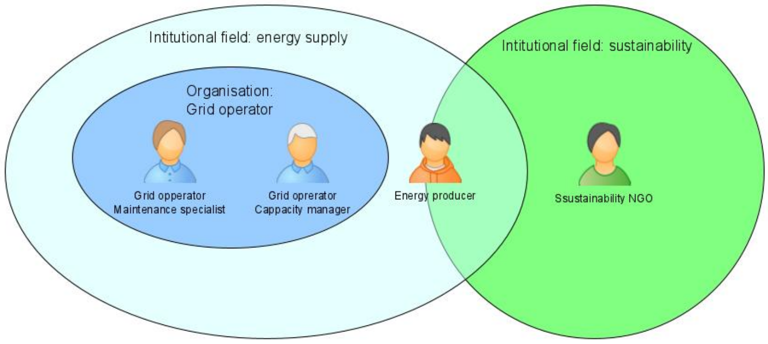


Figure 2: Different social worlds. One can see an organisation as a community of practice, where members have similar aims and knowledge. An institutional field can bee seen as a (abstract) place of working where communities operate together as part of the same social world. One can be part of multiple institutional fields/social worlds.

specialist would not want this as this increases his workload. They also have slightly differing expertise, but also share knowledge, being part of the same organisation.

This nestedness of communities within a landscape has been visualised in figure 2. From a practical perspective this informs us how people may have prior interactions with each other in a different context shaping attitudes. Additionally it tells us that people (even from the same group or organisation) may have differing competences/knowledge and aims. Competences and aims shape what someone is willing to learn or share and if they are capable of learning specific information in the first place. Where th NGO may have issues understanding technical details from an energy producer, for example, the grid operator does not. This allows the grid operator to actually learn as a certain degree of understanding is required for boundary crossing (Wenger, 2000). Furthermore one would be less likely share information or pay attention to a party that one dislikes.

Furthermore one could possibly see coalitions according to these divisions. One can assume that any overlap will lead to a certain degree of understanding of each other, required for crossing boundaries as a similar institutional field means that they work on related things.

4.2 BASIC ACTIONS IN PARTICIPATORY MODELLING PROCESSES

Now that the context has been described a discussion is held on general modelling steps and its differences and similarities with PM. Based on this the most crucial social actions in these processes will be defined. Then theories from communication science

When looking at general (agent-based) simulation modelling (Van Dam et al., 2012) one can identify several steps towards the development of a simulation model:

1. **Step 1: Problem Formulation and Actor Identification** Regards the definition of a problem. This is a question regarding a lack of insights which a model aims to provide. It consists of a definition of emergent patterns of interests (what system behaviour you we want to observe), the relevant actors and the roles of the problem owners and whose and which problems you are addressing.

2. **Step 2: System identification and decomposition** Concerns the system demarcation and structure. This is done by making an inventory of physical and social components and actors and their relations, relevant time frames, states, interactions and concepts. This inventory is then structured and an environment of the system, consisting of exogenous variables is made.

3. **Step 3: Concept formalisation** The concepts of step 2 are formalised in this step by making everything as explicit as possible. This is required for actual programming. An example would be to formalise the grid as the low voltage energy grid in the city area rather than the complete energy grid in the Netherlands.

4. **Step 4: Model formalisation** Regards the formalisation of concepts into a narrative and pseudo code. An example based on the previous step would be:

   The grid operator (agent) wakes up and gains new market information on upcoming energy production. He shares this information as he deems it important with industrial users of energy (other agent). Other agents find it important as well. The agent sends agenda tasks based on this new information, regarding the implementation of new factories. If the new information is not deemed important the agent has a 50 percent chance to not share it. If he does share it it is decided upon if new agenda tasks need to be sent to a third agent, the grid contractor, to increase grid capacity. Otherwise the grid operator does nothing and the grid will keep the same capacity.

   This narrative will then be changed in something like: If new information has goal achievement value $\geq$ (higher or equal) than threshold then sent information to others

   The aim os pseudo code is to be readable while having a similar structure to actual programming. This whole process of formalisation is ideally supported by visualisation when done with stakeholders.

5. **Step 5: Software implementation** Regards the implementation of the pseudo code into actual programming in a chosen modelling environment(E.G. netlogo for agent based modelling or Vensim for system dynamics or programming languages like Python or C#)

6. **Step 6: Model verification** Concerns thoroughly analysing model behaviour te verify that the model does what it is supposed to do according to the conceptual model (Ergo is it programmed correctly, not is the model simulation valid).

7. **Step 7: Experimentation** This step is about defining and running experiments by changing inputs or specific model behaviour.

8. **Step 8: Data analysis** This step concerns the analysis of data collected in the experiments. This regards not just the analysis of statistical data and patterns, but also interpretation, visualisation and explanation of the results.

9. **Step 9: Model validation** This step is about checking if a simulation model is valid. This is done by fitting it with historical sources (E.G. climate models are compared with actual climate data) or by comparing behaviour with external sources like literature or experts

10. **Step 10: Model use** The final step regards the presentation and follow up of the model and its results. This concerns follow up steps like policy making or the definition of new knowledge gaps or communication towards external parties.

When developing an model in a participatory setting these steps stay more or less the same, but are mostly done with other actors. Step 1, however, may be pre-defined outside of a participatory modelling group or by a part of the group. Additionally all steps after step two can have varying degrees of individual participation, meaning that a certain individual may solely define or model things based on competences. Collaboration in all other cases means that participants share information with each other.

The parts that are done in the group can be generalised as a group process where both decision making as elaboration on a problem is done through sending and receiving information through verbal and written means. Information is seen as any content that is sent. It can cover things from knowledge to compliments about someone's cat. By doing so the group as a whole negotiates the precise shape and aim of the created model. By conceptualising the model this way the model itself frames and anchors further discussion. This will steer the conversation towards an eventual model. This sending and receiving of information can be supported by means like drawings, presentations, ontologies or conceptual models.

When receiving information this gets processed into new knowledge, by means of combining and comparing competences of participants. This new knowledge would ideally be used when defining and interpreting the model.

4.3 THEORIES OF INTEREST

The general premise is that participatory modelling consists of individuals from different communities/ organisations sharing and receiving information/knowledge from each other. The aim and scope of the model are fixed (I.E. the model is made to explore future scenario's). Within this scope individuals share information they deem relevant based on their own background and competences. They process this information and if the information is comprehensible and new(different enough), social learning may take place when there is a drive to do so(Wenger-Trayner et al., 2014; Wenger, 2000). This new knowledge and existing knowledge is bundled in an eventual model definition and simulation model. Actual tasks are defined within the group, by associated organisations of individuals or by the individuals themselves. Parts of the model definition may be done by either the group as a whole or by individuals.

By focussing on this premise the actions of individuals can be simplified as sending information or tasks, receiving and processing information and tasks; and as deciding upon simulation model. By processing informations individuals may learn.

Based on these simplified actions the literature search is focused on theories that either help explain how these three actions happen or theories that explain mechanics that can either hamper or encourage these actions. For example, conflict theory gives reason why one would stop sharing information or disregards sent information if they are in conflict with one or more other participants.

From these a further selection is made on perceived programmability and theories with a lot of overlap have been omitted. From the remaining theories a conceptualisation on what the three main actions mean is made in chapter 5.

To shorten time searching for theories the main sources that have been used are two books, discussing abroad array of theories. For social psychology theories the main book was Hogg and Tindale (2008). For communication science this was Littlejohn and Foss (2010). Combined these are more than a thousand pages of theories for their respective fields. This ia assumed as comprehensive enough. In addition to the books additional literature has been used for either expansion on selected theories or based on discussion with supervisors. The selected theories are shown in table 1. The abbreviations in this table are used to signify their specific use in the models in the next chapter.

Table 1: Theories used for synthesis

Theory	Description and usage	Source
Social Psychology		
Group diversity and conflict theories (GD&C)	These cluster of theories propose three types of conflict that influence group performance, namely, relational conflict, task conflict and process conflict. Relational conflicts concerns personal attacks or perceived sleights. Task conflict regards conflict regarding the content of a task, which may lead to positive results. Process conflict regards planning and logistics. It is assumed that conflict begets other conflict, sometimes leading to certain messages being perceived, wrongfully as personal attacks. This theory highlights the need of good interpersonal relationships and how communications may break down in the face of earlier conflict. **Usage**: The idea of conflict types has been extended to encompass all types of information sharing. Thus one can share relational information, task information and content information. The idea of conflict itself, has been simplified into relational information worsening or improving attitudes towards each other. These attitudes influence behaviour regarding information sent by others. Task information has been left out as relevant in the final theory and ABM	(Jehn, Northcraft, & Neale, 1999; Jehn, Greer, Levine, & Szulanski, 2008; De Wit & Greer, 2008; L. L. Greer, Jehn, & Mannix, 2008; L. Greer, Caruso, & Jehn, 2011)
Social categorisation theory (SCaT)	This theory discusses how people will categorize themselves and others. By doing so one is able to decrease perceived uncertainty and predict someone's supposed behaviour and capabilities. This shapes interaction with others. Additionally one can categorize into groups. If one feels part of a group they may heavily conform to group behaviour. This conformity can potentially lead to self censorship to avoid conflict. One can also categorize others as being in a different group, leading to the heightening of conflicts. **Usage**: In addition to attitudes towards others it is assumed that people are part of a single affiliated organisation. To conform with this group they are more prone to accept information that this group shares or deems important. It is currently assumed that people are only affiliated with a single group as a simplification and other behaviour based on categorization is left out. In the ABM affiliation solely influences relevance of certain topics	(Hogg & Reid, 2006; Hogg & Tindale, 2008)

Table 1: Theories used for synthesis

Theory	Description and usage	Source
Common knowledge effects (KE)	Common knowledge effects (Hogg & Tindale, 2008) and the biased sampling model (Stasser & Titus, 1985) claim that information that is shared is discussed more. Shared is meant her as known by multiple people, not the sharing of information as an action. Part of this has to be with the likelihood of information being discussed being higher as more people know it. Depending on how knowledge is distributed over people, polarisation may take place if certain information is not widely known (shared) by everyone. It is also stated how knowledge of individuals shapes biases on what to share and how to act and that earlier shared information tends to be discussed more often than newly shared information. This information is seen as more important in addition to taking awat the time of not yet shared information. **Usage**: Distribution to known knowledge items and links is deemed as randomised with a bias towards topics someone deems important. Furthermore the relevance of information is perceived as higher if it is shared more often during a process.	(Hogg & Tindale, 2008; Stasser & Titus, 1985)
Communication science		
Input-process-Output model (IPO)	This is a group of theories that have been applied in several fields. With relation to communication science, theories state that group processes consists of inputs like attitudes an information. This inputs shape the process which often has an task obstacle to tackle. This task is tackled by collaboratively exploring and analyzing the task to define solutions. The task specifically relates to a certain problem or goal that the group as a whole has. This analyzing and exploration requires effective energy. During this process interpersonal obstacles may arise. This can be actual conflict or matters like clarification of ideas. The total energy someone has decreases if on of the two types of energy is required. This can lead to a lack of energy to actually solve a task if interpersonal issues take up to much energy. **Usage**: The crux of this theory is that group processes require intrinsic or effective energy. This idea has been extended upon in the conceptualisation to denote that people have a limited amount of energy for both sharing and processing information.	(Littlejohn & Foss, 2010)

Table 1: Theories used for synthesis

Theory	**Description and usage**	**Source**
Elaboration likelihood model ELM	Elaboration likelihood theory discusses when you will critically evaluate information. It states that there are two ways to process information. The first, called peripheral processing, relates to a less critical and active way of evaluation. The lasting change is smaller based on this route of thinking, but one is more prone to accept something (at least temporarily). The other way of processing is called central processing, where information is evaluated critically, leading to more scrutiny. Central processing requires a more of familiarity with information, where peripheral processing requires less **Usage**: This theory has been used as the basis for the conceptualisation of expertise and the knowledge graph (figure 10).	(Littlejohn & Foss, 2010)
Social judgement theory SJT	Social judgement theory focusses on how we make judgements about information and statements. It states that the main factor for judgement is ego involvement, perceived personal relevance to a topic. The amount of involvement determines the so called latitudes of acceptance, non-commitment and rejection. These are a range of statements regarding a topic that you will accept, reject or stay neutral about. If a massage has a degree of involvement and fits someone's own anchors (personal statements seen as true) they are prone to judge something favourably. **Usage**: Relevance has been used as a factor influencing sharing and processing of information, determining the energy that can be spent.	(Littlejohn & Foss, 2010)

Table 1: Theories used for synthesis

Theory	Description and usage	Source
Information integration theory IIT	Information integration theory discusses how information is accumulated and organised in the form of attitudes regarding an object or information, leading towards positive or negative acts regarding this object or information. This depends on the degree and with which information supports beliefs and the credibility you think the information has. You assign these variables to new information you receive from people, depending on, who says it and what is said. Someone you like is seen as more credible. The direction of the valance determines of information is received positively or negatively **Usage**: Direction of valence has been simplified in either the processing/sharing of information or not doing so. The influence of credibility, based on attitudes has been used as basis for attitudes determining how much energy on is willing to to process information from certain people	(Littlejohn & Foss, 2010)

In the next chapter these theories are used to explain the actions and underlying mechanics of a PM in a general conceptual model narrative. This initial conceptualisation is still relatively broad, including too many details. While the general conceptualisation contains interesting details it contains to many actions to be workable. This is why the subsequent chapter after this focusses on several core concepts from this conceptualisation, creating a conceptualisation that is workable for developing an ABM while still having enough depth.

5 CONCEPTUAL MODEL NARRATIVE

5.1 CONCEPTUAL MODEL

Based on the theories discussed in the previous chapter, several models are made, discussing the behaviour of participants within a participatory modelling process. Note that this chapter and chapter 6 are conceptualisations of ideas and reasoning behind model behaviour. The actual ABM model is not a direct translation and disregards some ideas that are stated here as part of participatory modelling or social learning processes.

Aim of this chapter is to get a comprehensive view of every action that one can conceivably take in a PM SL process, that influences the outcomes. For each of these actions variables and mechanics are integrated. From this general model a more specific one is made, focussing on the behaviour that is assumed to be most important for the process. By doing so a broad demarcation is made on what actions and details are important. The initial width of the conceptualisation in this chapter aims to show all actions that could potentially influence SL. From these actions and mechanics the parts that are deemed most important for SL are selected and expanded upon in the following chapter, shaping a theory on SL from a PM process, that can be used for an ABM.

First an inventory of concepts and agent behaviour is discussed, including several assumptions. This inventory is the basis for the subsequent sections, discussing behaviour and related variables via visualisation.

5.1.1 System identification and decomposition

In this section the model behaviour is explained by creating an inventory of concepts and agent behaviour. This has been visualised in a general model and two additional models have been made, focussing on specific behaviour. For each model a description is giving discussing behaviour.

Agents/actors

Individuals - In a this model participants of the participatory modelling process are seen as individuals. They regard other individuals as others and the conglomerate of all individuals as the group
They have:

1. **Norms** Behavioural tendencies based on prior affiliations, personality and group behaviour. Determines the likelihood to share information and interpret information critically.
2. **Attitudes** A general term to describe if someone likes or dislikes other members, changes depending on the process and prior attitudes may exist based on earlier meetings or bias with regards to other individuals. Determines the credibility they assign to information given by others and the likelihood of interpreting information in a distorted way or as an attack.

3. **Knowledge** Competences, Data and knowledge regarding certain topics
4. **Goals** The aim an individual has. Partly determined by organisational goals, which together with personal goals shape behaviour. Takes shape as a preference/push towards certain topics and model behaviour and makes them involved with certain topics.
5. **Identity/role** Someone's background and affiliation. Influences attitudes of others based on biasses and prior interactions. Additionally determines core knowledge and aims.

They do:

1. Send information towards others
2. Receive, interpret and processes information received from others
3. May learn by internalizing processed information into their own knowledge
4. May create new knowledge by combining and changing different kinds of information and knowledge
5. Conceptualise an implement the boundary object (simulation model)

Assumptions:

1. Their goals are not to stop or sabotage the process
2. They only sent interpersonal information and information directly related to the project aim
3. They will not leave the project
4. They are affiliated with an organisation
5. Have no internal coalitions with others
6. Have a limited amount of energy for actions and processing information
7. Will not learn based of sources outside of the process

Boundary object - In this model the boundary object (BO) is both the definition as implementation of the simulation model. It has a shape and content which is defined before and during the process. The shape defines the environment of the model (exogenous), what is measured (metrics) and what can be used to influence model behaviour (levers). The relationships an behaviour defined in the simulation is the content. The BO frames the process, but is also defined during the process. A model supposed to explore fish populations, for example, will not lead to individuals discussing cows

Concepts

Information, data and knowledge Information is seen as any content that is communicated between actors. It may consist of data and knowledge. Data are values or small details relating to a specific topic (E.G. solar panels cost Y). Knowledge are relations or mechanics based on data (Solar panels cost Y or X leading to yields of Yn and Xn). A Topic is a collection of data and knowledge regarding a thing or system. See chapter 6 section 6.1 for a more detailed discussion on knowledge and figure 6 for examples of relevant knowledge.
Information has:

1. **A type** Information can either be interpersonal (intrinsic) information relating to emotions and relations with others, process information, relating to task assignments, planning and logistics ans task information, relating to all knowledge and data related to the task (the content).

2. **Is conflict?** If the information is aimed at instigating conflict or stating a disagreement it is a conflict. A question on task information has a task type regarding specific information that an individual does not know. A question regarding the process has a process type. Statements are either beliefs, task delegations or knowledge that one possesses.

3. **Sharedness** The degree (percentage of group members) to which the information is known. Not relevant for interpersonal information

4. **Relevance** Relevance with regards to certain topics. Can be loosely, strongly or not related at all. Determines involvement of individuals with regards to the information based on goals and interests. The relevance is attributed on a personal basis by each individual.

5. **Topic** A topic consists of multiple pieces of knowledge taking the shape of data and knowledge. Depending on the demarcation it may be impossible to know everything in a topic. E.G. to have complete knowledge on physics would mean a complete understanding of gravity and forces, nuclear physics, light refraction and more. By combining information items (data and knowledge) within and between topics, new knowledge is created. New topics can also be created. The concept of a topic can also be sent, which may be useful if it is elaborated upon with information (E.G. physics is important rather than these mechanics from Newtonian physics are important).

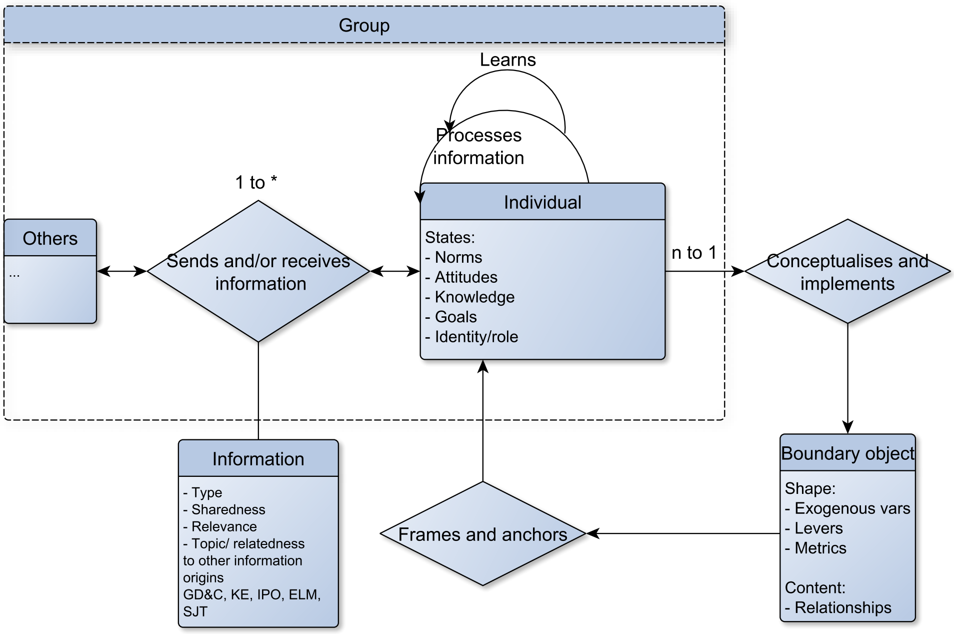


Figure 3: General conceptual model

5.1.2 General model

The general model shown in Figure 1. aims to visualise the broad actions that take place within a participatory modelling process. Here individuals receive and sent information to and from others. Received information is processed and learning may take place. Based on the shared information individuals learn new knowledge, change their norms or change their attitudes. How they process information is also based on these things in addition with group norms, their attitude towards others and their personal goals. These things also determine what they sent and if they sent information in the first place. The information has types, meaning interpersonal, task or process information. These types influence how information is processed by others. Furthermore, information has a certain degree of sharedness, relating to common knowledge effects. These common knowledge affects in combination with attitudes towards others, personal goals and perceived relevance, determine the amount of effort that is put into processing, potentially leading to learning. After multiple rounds the conglomerate of all shared information allows the group to build collective knowledge with which they decide how the simulation model will look.

Together with the group and partly individually these individuals shape and determine how the model will look. The model, in turn, influences how the task is framed and what information gets anchored. The model has a shape, determined by exogenous variables, levers (things that you can influence) and metrics and content, determining behaviour via relationships between the shape concepts. Individuals build the models that the group decides upon. Additionally a part of the model is likely pre-defined as a project has a certain aim or goal. This pre-defined part and the evolved model frame and anchor discussions towards certain topics and discussion.

The group has been visualised as an encapsulating box around individuals. This has been done to make the influence of the group more obvious. The group can be seen as all emergent behaviour that comes into existence during the process. This can relate to group norms and actions that are taken by the group as a whole as things like conflict an co-creation of knowledge are impossible alone. It is also visualised to highlight that people are nested in groups, meaning that they are not only participants in the participatory modelling process, but also of an organisation that they work for.

5.1.3 The information sharing model

To determine when and what information is shared a model has been made, discussing possible impetus for sharing information.

As can be seen there are different reasons for sharing information. If someone has a lack of knowledge he lacks either process or task information. If he feels respected, cares about the lack of information and has no personal inhibitions (personal and group norms and attitudes towards other) he will ask for clarification. Based on queries like this other individuals may decide to answer the questions.

If someone sees that the group lacks certain information regarding a topic he will share this information if it is relevant to his goals and he has no inhibitions.

If the group has an intrinsic obstacle (lack of moral, for example) or if someone's esteem is in danger someone can finally decide to share (most likely interpersonal) information with the group. With a bad attitude towards others this can take the shape of an interpersonal conflict

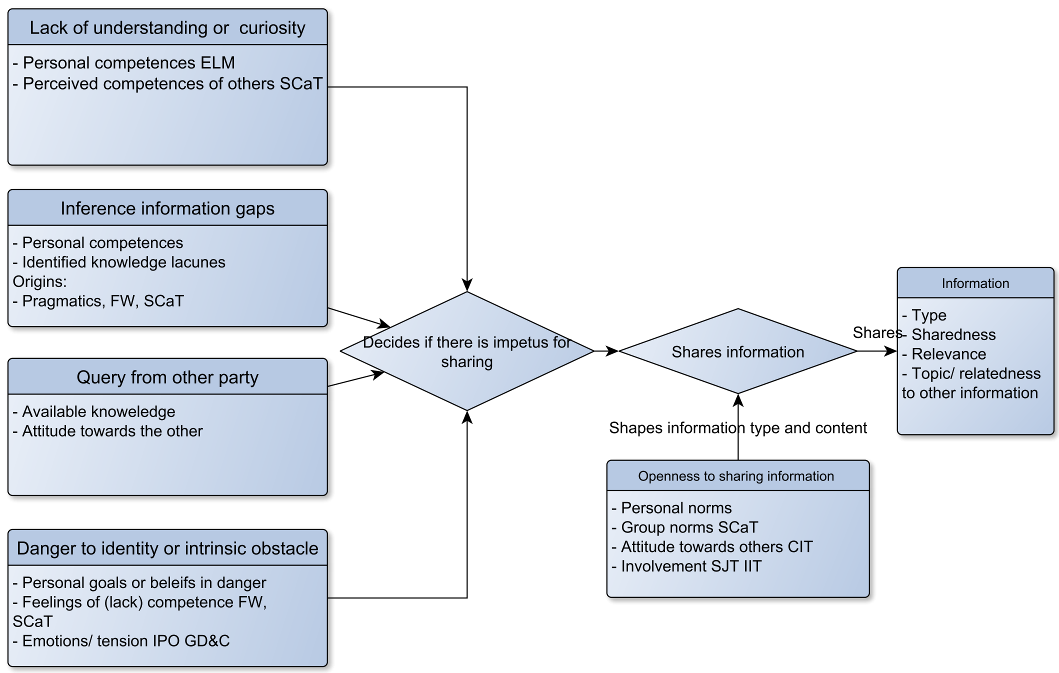


Figure 4: Information sharing model

5.1.4 Information processing model

This model discusses how information is processed. Depending on someone's attitudes, beliefs and knowledge someone may interpret incoming information in different ways.

Firstly someone can interpret information as interpersonal, meaning information about another person rather than the project. This can be seen as an attack on his self esteem/person. This means that he interprets something as interpersonal conflict. This can be a correct interpretation, but earlier conflict and bad attitudes may lead to faulty interpretations. Interpretations of conflict and other interpersonal information only shift attitudes as someone's knowledge stays the same.

Secondly someone can interpret information wrongly or in a distorted way (leading to the boomerang effect, immunization or the assimilation effect), leading to an internalization of information that is wrong. And, thirdly, someone can interpret information correctly. If information is internalized depends on perceived value of the information based on their own knowledge (valance with own perceptions), attitudes towards others and involvement with the topic. A low assumed value will lead to a rejection of the shared information or a neutral stance regarding shared information. A high value leads to more critical thinking, increasing the likelihood of actual learning going further than a simple internalization of a fact.

Finally someone can lack the required knowledge to understand the information, leading to either a neutral reaction or an impetus for asking a query.

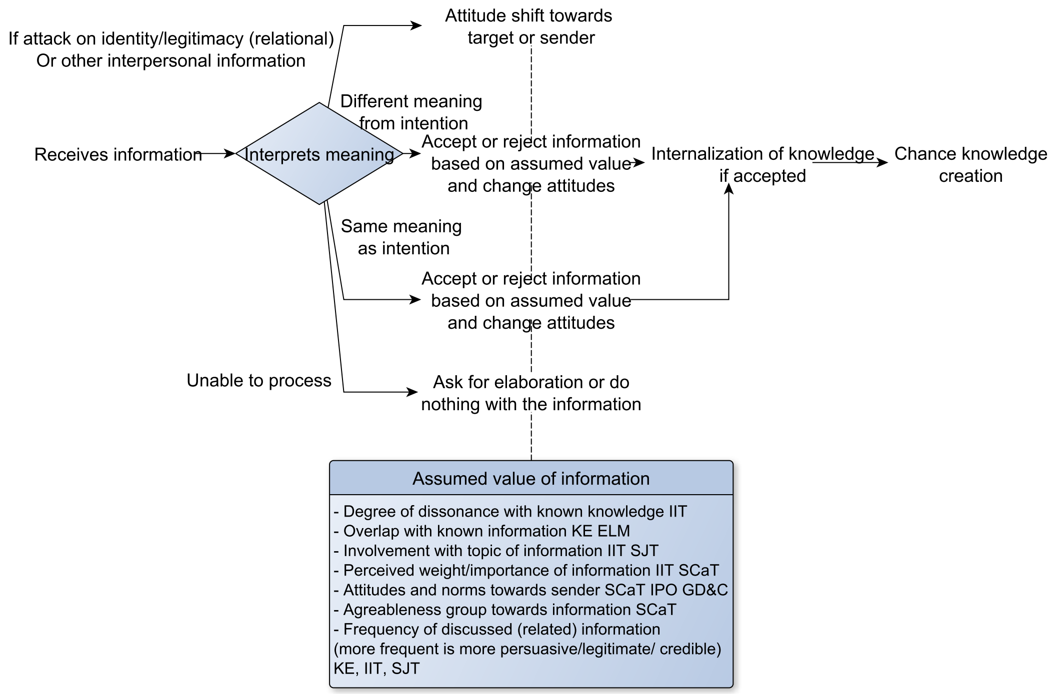


Figure 5: Information processing diagram

6 LEARNING AND KNOWLEDGE CONCEPTUALISATION

In the previous chapter the broad model behaviour of a PM has been discussed. This chapter focusses on elaborating on several of these actions further.

They extend on specific items from the models in the previous chapter. For example, the shape of sent information, discussed in section 6.2.1, correlates to the result of figure 4, the information sharing model, which is the input of figure 5, the information processing diagram. Section 6.2.2 discussing energy and learning, goes in depth on how information is internalized into knowledge expanding on figure 5.

In this extension the main actions of importance are assumed to be sharing of relational (interpersonal) information and the sharing of content information, meaning information about the problem. Task information is not deemed as important as things like planning meetings or logistics does not lead to learning directly. It only ensures that and when the process happens and may cause conflicts. It is also assumed that people only share this information based on their own volition, meaning that they will not receive (or ask) questions or other interactions which will lead to sharing. Other interactions would simply add a lot of complexity, making the theory hard to construct or explain.

In addition to sharing of information the processing of shared information is elaborated; and a simple conceptualisation is made on decision making regarding the boundary object (the simulation model). To support these conceptualisations section 6.1 starts with a conceptualisation of knowledge. This is needed to differentiate information that is shared, processed and known. Additionally it influences how easily people share known information, based on perceptions on specific pieces of information and on matters like expertise in the related topic of this information.

These extended conceptualisation are the basis for agent (individuals) behaviour and their states of the simulation model. The visualisation of knowledge subsets,for example, are highly similar to how knowledge is visualised and used in the model. This chapter can also be seen as the theory explaining the social mechanics and behaviour of SL processes from a PM. To this end a short synthesis is given at the end of the chapter, discussing how the conceptualisations interact.

The idea of knowledge topics and information items is loosely based on the Data, information, knowledge, wisdom (DIKW) pyramid. Where Data represent information items, Information represents the links between the items and knowledge can be seen as the collective of these items and links in a topic. The idea that learning takes energy is taken from theories relating to information processing (elaboration likelihood and social judgement theory). It is assumed that critical thinking or a high involvement is required for learning. The idea of network distance for learning is related to the general idea that a certain degree of understanding is required for social learning and topics closer to what you already know are seen as easier to understand.

6.1 CONCEPTUALISING KNOWLEDGE

It is assumed that knowledge consists of clusters of bundled information. These bundles of related knowledge are called topics. Here a topic can be weather, photovoltaics (PV), the energy grid or any other grouping that suits the context.

These topics consist of information pieces related to the topic. With relation to the weather these information items can be things like climate statistics, climate predictions or general weather mechanics (how are clouds formed, what does ozone do for the weather). These information items are linked with one or more other information items. Climate predictions are made combining climate statistics and weather mechanics, for example.

These information items may also have an overlap with an item from another topic. Cloudiness, for example, is a different perception of sun hours, an information item from the topic of photovoltaics; and Energy production on the grid has a direct relationships with PV yields.

Regarding the topics and links it is assumed that they are finite and there is a complete knowledge set with all topics, information items and links and information items ar immutable. An example has been show in figure 6. In this figure an example of a complete set of knowledge is shown regarding three topics relating to the energy grid, photovoltaics and the weather. As can be seen there are indirect links, combining all topics through specific information items. If one would have this complete knowledge they could state how the climate impacts the energy grid by influencing sun hours and yields of photovoltaics, for example. With regards to a model result this complete set would allow for the implementation of climate predictions and weather models as factors influencing grid load and required capacity. Note that this complete model is still a subset of immediate information that may be relevant with regards to each other. Adding things like wind energy or nuclear energy as a topic is possible, but would lead to bloating of the figure, making it less legible.

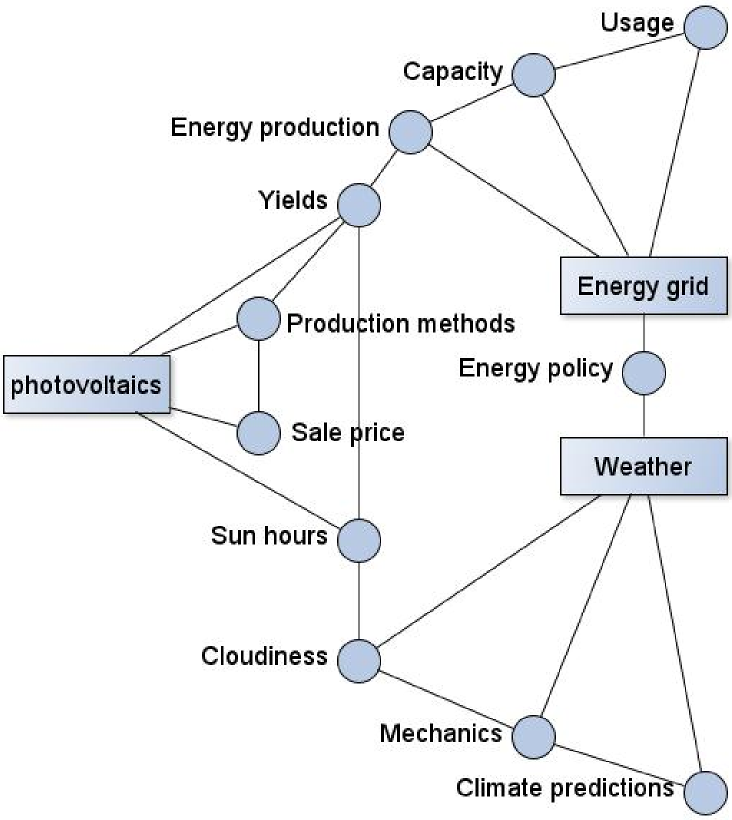


Figure 6: Theoretical 'complete' knowledge set

6.1.1 Personal knowledge and group knowledge

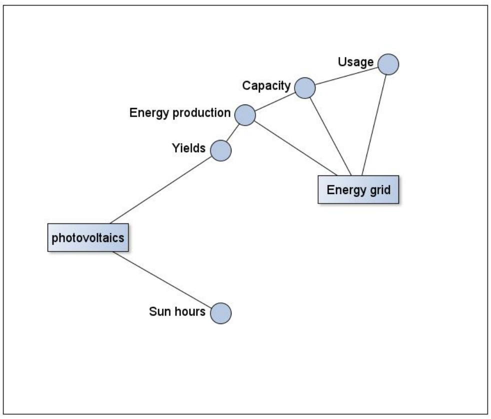
It is assumed that no individual knows the complete knowledge set. Each individual has a subset of the complete knowledge set relating to their personal competences and interests. This means that they may have a limited amount of information items and relations. What they know is dependent on the organisation they have been a part of and, to a certain degree, the fields in which they have operated in. Even if they know all information items they may still not know about relationships between them. Examples have been given in figure 7. These examples have been discussed in the following paragraphs.

A grid operator may know everything regarding grid capacity, usage and energy production. Next to (not visualised) knowing about several production methods like gas and nuclear he also knows about photovoltaic (PV) yields and its relation to sun hours. He does not know different types of photovoltaics and how these types relate to different production methods and yields. Knowing this, he would be able to better anticipate future scenario's as he would know possible ranges of production of different kinds PVs and their associated costs. If this gets extended with climate trends he can explore possible future yields of PVs (and wind energy that is not visualised). This subset can be seen in sub-figure 7a.

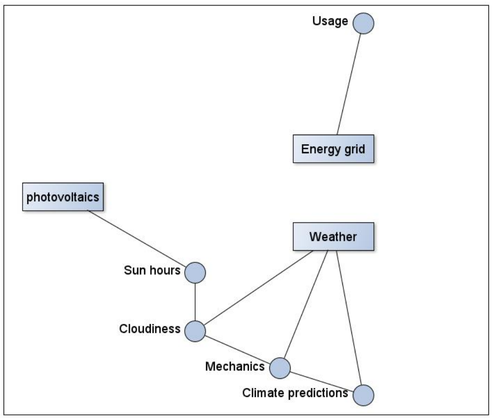
A meteorologist may know how the weather leads to clouds, how the climate is changing and what this does with the amount of sun hours. He may also know that photovoltaics require sun hours. All these things are related to his personal field of competence. He may also have an interests in sustainability. Through this interest he may know things like general energy usage that should become green. By knowing more about energy usage and the grid he may learn to improve weather climate predictions as he may know emission ranges that are possible in different scenario's. This subset can be seen in sub-figure 7b.

A producer of photovoltaics may know all about yields and production costs and methods regarding photovoltaics, but not much from the weather and the grid. He may know that the usage of energy, requires a stable production, hindering his business. By knowing more about the weather, he may better tailor PVs to certain region and by knowing more about the grid he may come up with implementation strategies. This subset can be seen in sub-figure 7c.

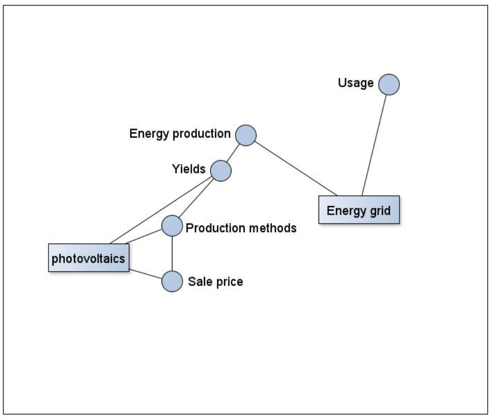
It is assumed that the learning that can happen within the process can only concern information topics that are known by members. If an information item is not known it can not be shared. If information is only part of the subset of a single individual the likelihood of it being shared or seen as relevant may be smaller. The degree of sharedness has been visualised in sub-figure 7d.



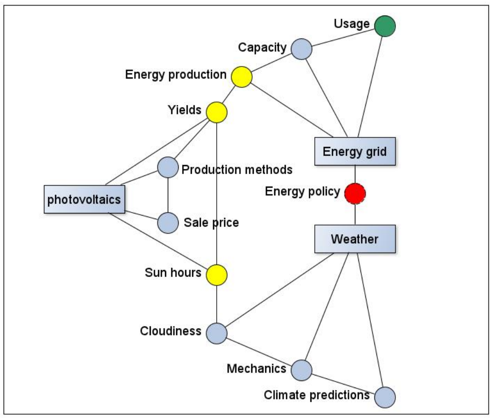
(a) Personal knowledge subset grid operator



(b) Personal knowledge subset meteorologist



(c) Personal knowledge subset Photovoltaic producer



(d) Knowledge distribution. Yellow nodes are shared between two people, red is unshared and green is known by everyone

Figure 7: Individual knowledge subsets

6.1.2 Knowledge basis, social worlds and communities of practice

To what extent information is shared and known is dependent on the nestedness of of a persons affiliations(see figure 2 in section 4.1 for a visualisation).

For this thesis the general division will be into organisations and institutional fields. The first relates to the organisation that someone is part of. It is assumed that there are no sub-divisions or organisations. In reality this is, of course, possible. This affiliation with an organisation determines the core information items and topics which an individual is knowledgeable about. It also determines general interests. Furthermore it is assumed that individuals from the same organisation will agree on things more quickly, regardless if they like each other. They will conform via means of social catagorisation (same group, so identify with group members)

The institutional fields relates to a broad field of rules, interactions and organisation in which individuals act as part of their respective organisations. They interact with each other in certain situations if they are part of these fields. By doing this one can assume that they know of others in the fields they are part of and gain knowledge on topics related to this institutional field. A sustainability NGO, for example, could learn about energy production means and their advantages and disadvantages by participating in the institutional field of sustainability with energy producers. One can say that institutional fields determine prior social learning.

6.2 CONCEPTUALISATION LEARNING

Now that knowledge and information has been conceptualised, a conceptualisation of the social learning processes can be made. This in combination with the knowledge conceptualisation is seen as the workable theory. Apart from several assumptions and simplifications this theory is translated into an ABM.

Assuming that an individual has a subset of all knowledge, it is assumed that one learns by making this subset larger and more complete, it is also assumed that the complete knowledge subset is complete and unchanging. To learn things, information needs to be shared and an individual needs to internalize shared information by means of processing it. What is shared can be either one or more information items or items and some of their respective links or a general topic and its relations. If an individual is interested in the shared information he will internalize it into his own subset of knowledge (copy), assuming he has the knowledge and energy to do so and accepts the information as true. *Energy* in this sense is seen as the required effort for internalization and understanding. There is a limit to this energy based on interest in the topic, but also expertise on the topic. Most people, for example, would require a significant investment to understand nuclear physics and most of us lack the required knowledge to do so in the first place. This knowledge needs to be gained through sharing via classes, lectures and literature.

6.2.1 Sharing of information

Sharing of information within a participatory modelling process happen gradually. By sharing information over multiple rounds a subset of information is created that contains everything that is shared. What is shared depends on the process. If the project leader wants information regarding a topic, any information item may get shared, without including links between them. Making these links requires the sharing of said links or creation of these links by means of learning.

The shape of what is shared is variable. For example, one can share a topic if a project leader asks for important discussion points. One can share information items with or without their relations and one can even share a relation between information items without elaborating on what these items are or mean (E.G. stating that solar yields are part of the total energy production without stating that it is a variable yield, what part of the energy production they consist of etc.). Additionally one can state that certain topics are related without stating how or why they are related. Depending on what is shared one may require to invest more or less energy. If one is highly motivated and interested less energy will be required to share something. The possibilities and order of required energy have been visualised in figure 8.

Visualisation	Description	Information weight	Required relative energy
photovoltaics	Topic	No real information requires elaboration	0
photovoltaics — Energy grid	Relation between topics	Useful if many information items are known requires elaboration otherwise	1
Energy production — Yields	Relation without information item(s)	Relation without information item(s)	2
Production methods Sale price	Information item(s)	Building blocks of knowledge. Required for knowledge creation	3
Energy production — Yields	Relation and information item(s)	Relation and information item(s)	4

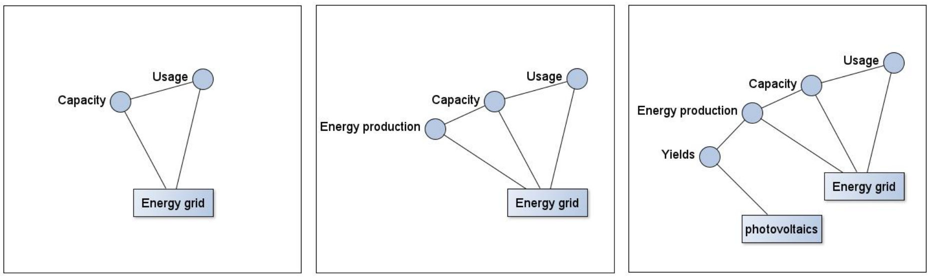
Figure 8: List of kinds of information that can be shared. Note that a topic in this case is the concept of a topic. E.G. physics is important instead of physics, the science of...

What is shared depends on several factors. Firstly it can be reaction based and interest based. If an individual asks for elaboration on a topic or information item, others may share related information items. If one asks a broad question regarding what is important one may simply share topics. Additionally one may share items that one finds interesting or relevant.

Secondly what is shared depends on the known knowledge. If a group has repeatedly discussed certain information items one is more prone to discuss related items and topics rather than other information following common knowledge effects (Hogg & Tindale, 2008). Thus frequency of an item being discussed increases the chance of related items and the item itself being discussed more

Any sharing of information requires an energy investment. If one is willing to invest this energy depends on his identification with the group and his attitude with certain peers. Here it is assumed that one is willing to invest less energy if someone who he/she dislikes asks for certain information, fore example. A moderating effect appears if one is part of the same institutional field or organisation. One would be more willing to help someone from his own organisation by sharing knowledge than someone outside of the organisation, even if he likes the outsider a bit more on a personal level.

Next to information regarding topics and information items (task information) one can share relational or process information. These have not been visualised. It is assumed that relational information influences attitudes regarding others, whereas process information is required to actually actuate the shared information into a plan of action to develop and use the model. Important is that the total of all information sharing is limited (total available energy). At the same time all types of sharing are required according to the input-output-model (Littlejohn & Foss, 2010). Relational information is required to tackle interpersonal obstacles (using intrinsic energy) and



(a) Shared process knowledge after one possible round

(b) Shared process knowledge after two possible rounds

(c) Shared process knowledge after the third possible round

Figure 9: Shared information subset growth over multiplbe rounds

a combination of task (the topics and information items) and process information are required to solve task obstacles (effective energy).

Regarding the task information, the same information can be shared multiple times by different people and. It is assumed that people can only learn and internalize knowledge based on shared knowledge. The likelihood of certain types being shared is dependent on the shape of the round. It is assumed that you have task rounds and downtime/break rounds. The former will mostly consist of sharing process and task information. The latter consists of mostly personal information during a break from the main task. A break can be used finish discussing tasks or process information discussions that have been cut of due to time constraints outside of the break or to finish deiscussions that have happened just before the break. Multiple rounds have been visualised in figure 9.

6.2.2 Energy & learning

To process and internalize information, a certain amount of effort is required that individual must be willing to use. This effort and willingness have been conceptualised as energy. The effort to learn something becomes smaller as one knows more about a topic, to a certain extent.

It is assumed that if one does not process something via the central processing route, a concept relating to critical thinking from the elaboration likelihood theory (Littlejohn & Foss, 2010), people are less critical and thus require less energy to internalize new information. In this case one can assume, however that only part of the information is internalized as this internalization is not based on actual understanding.

If one does think via the central route, however, internalization requires a declining amount of energy as one will find it easier to internalize information that are close to ideas and concepts that are already known. Internalization with a small amount of knowledge will require more energy, however, as critical thinking requires more effort. In general the required amount of effort becomes larger if the new information has a large distance from what you know (based on the complete knowledge set). The required energy compared to knowledge has been visualised in figure 10.

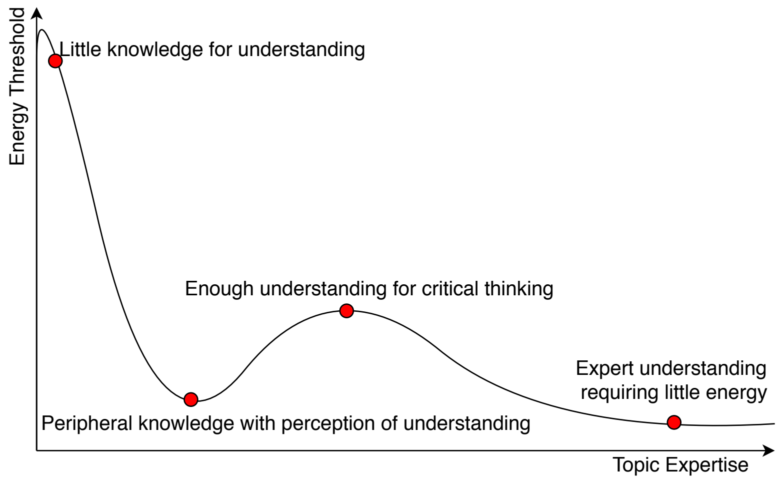


Figure 10: Energy threshold for internalisation vs expertise - expertise is the total percentage of links and items known form a related

6.2.3 Learning energy and attitude

Regardless of the processing route, someone needs enough energy to internalize knowledge. On the one hand this is based on interests in the topic (close to own information of interest, E.G. a pv producer will be interested in how weather will influence his PV performance, but not necessarily how weather is shaped or measured) and on the other hand it is based on the sender of said knowledge. One will be more prone to internalize information from someone he has a high opinion off than someone he has a dislike for. One may even actively reject information given out by certain people. These relationships are not symmetrical and may be based on an initial bias. Attitudes can be moderated by being part of the same organisation or field One is more willing to accept information from a colleague than an outsider. These attitudes change based on shared information regardless of its type. If one perceives task and process information as wrong or as a personal attack attitudes will decline. Similarly personal remarks can make relationships better or worse. An example has been given in figure 11.

Here the scientist and an environmental organisation representative do not know each other. The scientist has a neutral stance towards the other because of this. The representative has a positive preconception towards the scientist because he perceives scientist as a natural ally. The representative is likely willing to spent more information to internalize information shared by the scientist.

The scientist and the oil company employee already know each other and have a positive relationship from prior work. The employee perceived the scientist as highly authoritative person, leading to quite a positive opinion. Just like the replresentative the oil company will be willing to spent more effort to internalize information shared by the scientist. The scientist sees the employee as a person that is nice to work with, but still lacking knowledge on broader issues, leading to a less positive opinion. The scientists will likely spent a bit more energy into internalizing information from the oil company.

The employee and representative have clashed before and have extremely low attitudes of each other. This leads to an open conflict between both parties making them actively reject each other's information and, possibly, even overt lobbying to reject this information. They will not spent any energy internalizing each others information.

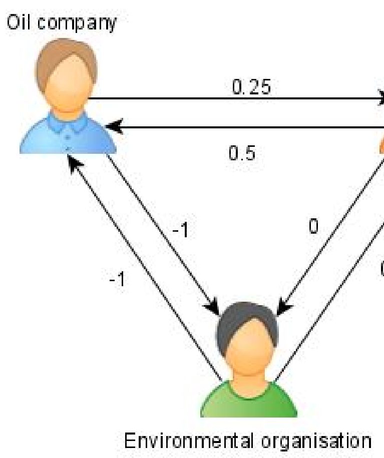


Figure 11: Relational attitudes example. 0 is a neutral attitude with everything between -1 and 1 being varying amounts of dislike (negative) or like (positive). Attitude is not just like and dislike, but also concerns matters like trustworthiness and perceived authoritativeness. Reciprocated negative attitudes are seen as an open conflict

These attitudes are not only regulated by prior history with people, but also by means of sharing personal information. The more personal information one shares the more someone learns about the other. If the shared information is similar to oneself or interesting one will gain a more positive attitude of that person. This private information can be seen as a unique topic with information items that are initially only shared by the owner.

If one does not agree with personal opinions or beliefs or clashes with someone on a personal level attitudes may worsen. The personal information may additionally be linked to certain 'work topics' relating to information items that are related to the task. These may not yet be shared, but may be brought up as a result of discussing personal information. If one cycles near a certain factory when cycling his weekend route as a hobby, it may be brought up when discussing this hobby. The factory may come up which opens up that topic for discussion if it is important or if, for example, another party works there. An example of personal information has been given in figure 12.

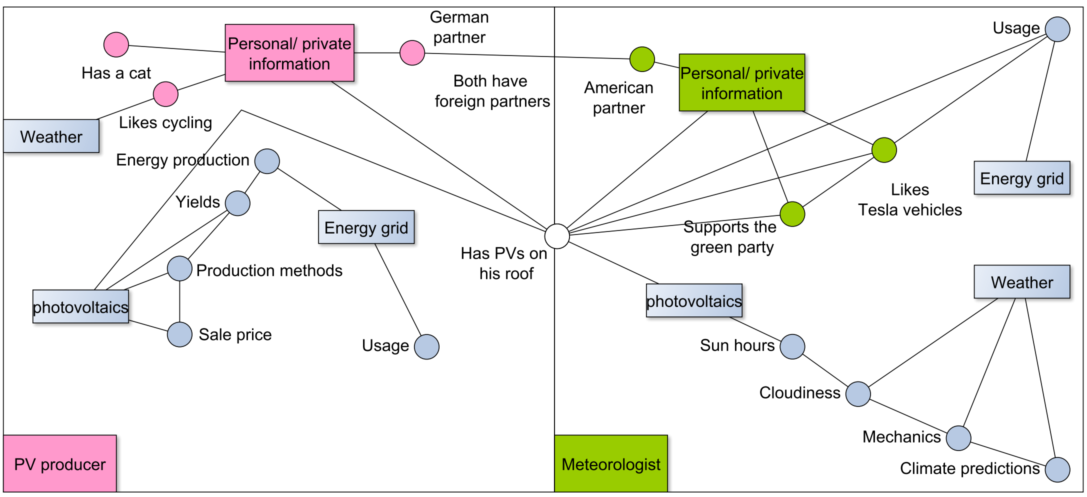


Figure 12: Differences and similarities private information between a Meteorologist and PV producer

Learning

If one has internalizes information one can learn in different ways, namely, by means of copying or by means of knowledge creation. What is learnt is highly dependent on what has been shared over the whole process (see figure 9).

It is assumed that during the process one has break/downtimes and actual working times. From experience I have seen that during the modelling process one will likely only process and internalize information when it is shared as the process goes too quickly to focus on earlier shared information. Here one can assume that available energy for knowledge creation will be limited. Internalization via means of copying is more likely to happen.

When one takes a break one is able to reflect more deeply on the total amount of information that is shared. Thus it is assumed that breaks and downtime are required for certain kinds of learning. One is able to spent energy creating new knowledge during this time as the shared information is likely to be of a personal nature, requiring less energy to internalize.

For example, if one asks what influences PV yields someone may state that sun hours influence these yields in addition to the type of PV. If one then asks more information regarding PV types, one may state that these have different production methods and costs. All these types of sharing show that items with new links are shared. If individuals implement shared information into their own knowledge subset, learning takes place by means of copying and comparing. This can be done at all times at it requires relatively little energy.

After someone shares that sun hours relate to PV yields a meteorologist may see that sun hours are influenced by cloudiness. This is a link that is new for the actor subsets, meaning that knowledge creation took place, by inferring new information links (between topics in this case). This requires more effort than simple copying in most cases. As one may compare all shared information with his own one may not have time to do this when the information itself is shared. Without time pressure this creation of new links is more likely.

It is also possible that someone is really invested in a project, but lacks knowledge. In this situation one can assume that he will copy all shared information without understanding and in the best case ask questions regarding the shared information. Eventually he will know enough to understand it and, possibly, even create new knowledge. As relations between information are less necessary this processing can happen directly when information is shared.

Thus learning happens by looking at shared information, comparing it with your own and implementing new information and making new information links. Based rounds of sharing that have been visualised in figure 9. Of course, one needs to remember that this sharing is subject to the whims of the individuals sharing said information. If they are not invested they may not learn. If they only care about their own field, they may share every minute (but often unnecessary) detail regarding their topics of interest. If someone thinks it hampers their organisational goals they may even decide to not share certain information. But what is shared by everyone can, potentially, be learnt by everyone.

6.3 DECISION MAKING ON THE BOUNDARY OBJECT

Based on the social field one is part of and on someone's affiliation with an organisation, individuals have certain goals and interests. Depending on their topics of interests it is assumed that they want a certain amount of information items and their relations implemented in the model. They do this by sharing information. Shared information that is internalized by every member is supposed to be accepted in the model.

The model itself is the basis for which topics are discussed. A participatory modelling process starts with the aim to explore a certain thing. The topics that will be discussed are related to that thing. E.G. for a population model people will not discuss thermal physics, they will discuss birthrates or food supply.

6.4 THEORY SYNTHESIS

In this chapter a theory has been defined describing the most important actions that a participant of a SL process is assumed to take with regards to actual learning. Summarized the theory is as follows:

1. Information and knowledge take the shape of a knowledge graph. This is a graph consisting out of topics. these topics have a selection of information items, which are linked to one or more other information items. All items within a topic are at least indirectly connected. For example, there is a connection between clouds and rainfall from the topic climate. Clouds are also conected to sun hours from the topic Photovoltaics. It is assumed that there exist something like a complete knowledge graph.

2. Each participant has knowledge about certain topic. This is a subset of the complete knowledge graph. Expertise in a topic is determined by the number of information items and links between these items that someone knows. what one knows and finds important is dependent on someones affiliation (job) and personal interests. A climate scientist, for example, is likely interested in climate and has a high expertise in this topic.

3. In a social learning process participants share knowledge if they are able. What is shared can take the shape of information items, information links or a combination of (multiples) these. Additionally one can generally discuss a topic. The later does not lead to much learning.

   How much and what is shared depends on how much energy someone is able or willing to spend on sharing knowledge. One is able to spend less energy when they share information from topics where they have a lot of expertise and they are willing to spend more energy if it is about a topic they relevant. Relevance is a combination between interests, affiliation and times something has been discussed. Items and links with a higher frequency are more important because of common knowledge effects.

4. If information is shared other participants receive it and start to process it. Integration/ learning of information follows similar energy rules as sharing. However, attitudes regarding the sender are assumed to influence perceived relevance what is shared. E.G. the NGO dislikes the oil company and disregards all shared information from this company on principle. The same information when shared by the grid operator is deemed as important.

   Processing also happens during downtime. Individuals may reflect on what has been said and integrate anything that has been shared. Here processing energy ia more plentiful than during the actual session and attitudes are assumed to not matter any more. The exact amount of processing energy required is based on a expertise curve. Here it harder to process information if expertise is low. There is a small exception, where required energy becomes a bit higher as on starts to have enough knowledge to think critically about the information.

5. In addition to sharing actual knowledge participants may share and integrate interpersonal information. These concern things like hobbies, having kids or disliking a president. This influences attitudes regarding in both positive and negative ways. Note that participants may have interacted earlier or have a bias against someone. These starting attitudes do not need to mirrored between participants. Newly shared personal information is assumed to have more impact on attitudes than already known things.

6. Information that has been integrated by everyone is assumed to be part of the model. Note that this part of the theory is arguably still way to simple as this is likely to be the results of coalition forming and negotiation. This is, however less important for the actual learn and, thus, has not received a lot of attention.

7 MODEL FORMALISATION

In the last few chapters a theory has been conceptualised, explaining actions and underlying mechanics of participants in a SL process. In this chapter this conceptualisation is changed into model behaviour, that has been modelled into an ABM in netlogo. By doing so

In this chapter the previously discussed diagrams and conceptualisation are formalised in a sort of pseudo code. Here visualisations have been made to make it more legible by people without programming experience. Before this a short introduction on the workings of agent based models be given to explain the structure and possibilities of modelling. After the formalisation an explanation will be given on the actual model interface.

7.1 PROGRAMMING ABM INTRODUCTION

As stated in the introduction an ABM is a model concerning agents, their behaviour and interactions with each other.

When modelling these agents can be seen as objects that have states and behaviour. They can represent things like animals, people, actual objects like factories or abstract concepts. Different kinds of agents may exist in a single model. These are called agent breeds (E.G. an information item vs a individual). A special kind of agent is a link. A link is something that connects two other agents in a unidirectional or directional way. It is an edge in a graph (E.G. lines in figure 13), with its own states and behaviour. A link can do most things any normal agent is able to do.

States are details and variables pertaining to a single agent. These can represent discrete things like gender, values like net-worth or representations of abstract things like attitude. In a model all of them are often codified using numbers which are either discrete or continuous.

These states are set during the model set-up. During this step an initial set of agents gets 'created' with states that may be set in a predefined manner or through means like randomisation. The set-up creates a new world in a sense. The set-up state may be changed when running experiment. One could, for example, create a world with only one gender in one experiment and another one with multiples. After a model has been set-up it can be run, leading to time ticking up. Time passes in discrete steps most of the time. These steps are called ticks. Depending on the model the ticks can be conceptualised in different ways. It can relate to time passing in the sense of days or hours, for example, but it can also represent process steps, like a negotiation round. During these ticks agents follow their coded behaviour.

Behaviour influences states of the acting agent or other agents. If someone acts by insulting someone else, for example, the attitude of the insulted person will drop, influencing resulting behaviour. Thus behaviour influences states and are often influenced by states. Each tick a subset or all agents are asked to act out certain things. These can be simple things like walking a certain amount of distance or complex behaviour influenced by conditionals.

Conditionals often form the basis of most models (and software). They take the shape of ifs, whiles, elses and ands. Several simplified examples: If my workplace is shell I love oil, else I hate oil; while I am angry enough (likely a numerical threshold) then I will curse. If I have PVs on my roof and work at an NGO I feel good about my job.

These conditionals may also lead to application of new conditionals. Behaviour and conditionals can be changed during certain experimental set-ups. Certain behaviour may also be turned off.

Experiments are run influencing behaviour and set-up states. They are repeated numerous times (depending on model complexity this can be up to thousands ot times per experiment) and have a set number of ticks. They measure metrics during model runs, based on which emergent behaviour can be inferred. Some models have a warm-up phase where a model is running without measurements to get in a state that represents reality better. Each experiment has a set amount of ticks (E.G. 12 ticks (months) for a year).

7.2 SIMPLIFICATIONS REGARDING THE CONCEPTUALISATIONS

Im addition to the assumption in chapter 5 some additional simplifications/assumptions have been made to make the model simpler and less prone to chance:

1. Individuals do not send information with the aim to start conflict and interpersonal information only regards the sharing of someone's own private details. This makes model behaviour significantly easier to interpret and program as determining when someone would instigate or offend someone would add a layer of behaviour that could be basis for another thesis.
2. Individuals only share a single topic if they share topics. Sharing a topic modifies perceived relevance of related information. By sharing multiple topics the result would be less pronounced. They do not learn from shared topics
3. Individuals either share a single link or information item or a (partially) complete set consisting of one to two information items and one link maximum. this makes model behaviour more deterministic, easier to program and easier to interpret. Doing otherwise would add unnecessarily complex behaviour
4. Only private information is shared during a break and outside of a break only other information is shared. While possible that people discuss both of them outside of these times, the depths of what is discussed are likely different. While both could happen during to other by adding some random functions this would lead to a break being superior to a normal round if someone shares information as the other processes both what is shared and what has been said earlier. This does not seem particularly realistic as it is unlikely that someone will go in depth on personal information (E.G. go in depth on their dog) outside of breaks and they are unlikely to discuss information as deeply as during the regular process during a break.
5. Links between regular information and private information are currently not utilised. This would add an additional layer of complexity as they should act differently than regular information links, whereas I'm not sure how that different behaviour would or should look like

7.3 SET-UP

At the model set-up several things need to be created. Firstly the complete knowledge graph needs to be created to calculate distances between shared information items and personal knowledge and to define individual subsets with similar features. Secondly individuals need to be created and their states need to be set. Thirdly individual subsets need to be created for each individual. Fourthly graphs need to be created pertaining to private information of individuals. Finally individuals get linked to each other via two-way links and attitudes get assigned.

1. The creation of the complete graph follows the following logic:

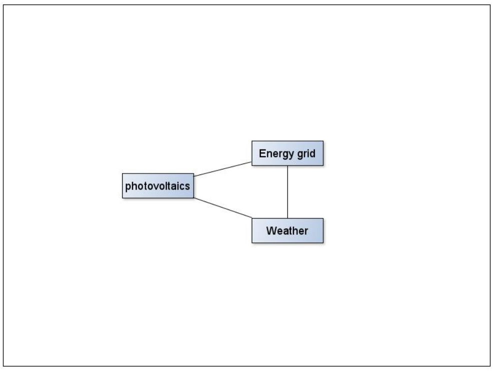
   1. Create n topic nodes that are connected. N is a settable variable
   2. Have each topic node create x information items that are linked to the topic node. The number of x is determined by model settings, but has a minimum of 1
   3. Make all information items connect to one or more other information items from the same topic. Make y number of information items make a link to items from any other topic. Y is a settable variable determining connectivity between topics
   4. Create private information items

2. An settable n number of individuals gets created and gets assigned values for:

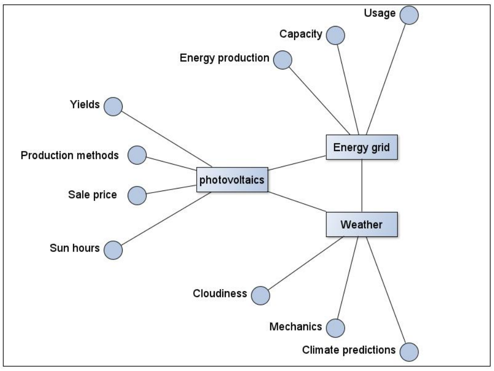
   1. processing energy, numerical value symbolizing tendency for critical thinking and effort someone is willing to spent to internalize information. The range of this values is settable.
   2. sharing energy, numerical value symbolizing effort someone is willing to spent sharing information. The range of this values is settable.
   3. affiliation, a value symbolizing the organisation of origin. Influences assignment of relevance and known information items and links. The number of affiliations is settable and influences how many unique affiliations are in the model. A value lower than the amount of individuals in the model will lead to people sharing affiliations
   4. ID, used to keep track of who does what, who knows information and how relevance does an individual fins items or topics

3. Individual knowledge subsets get created and relevance values get assigned. To create individual knowledge sets each knowledge item has an array, a 1-dimensional matrix ([0,1,2]) with the placement referring to the ID value of individuals (1st number is a 0 not a 1). These arrays have a value of 0 if an individual does not know the information and a 1 if an individual does know it. These values get a assigned based off of settable percentage ceilings with settable distributions. These percentages differ depending per topic depending on someone assigned affiliation. The assignment goes as follows for each id value:

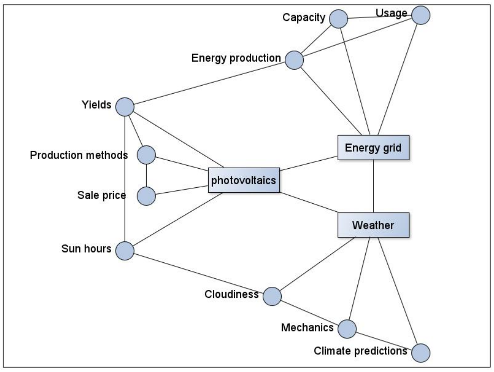
   1. Set an X percentage of all information items and links as known. X is based on a settable distribution for non-relevant items and links. Non-relevant means items, links and topics not related to your affiliation
   2. Set the relevance of all items and links to distribution Y. Y is a settable distribution for non relevant items and links
   3. Ask all relevant items and links to be set as unknown
   4. Ask Z percentage of relevant items and links as known. Z is a settable distribution for relevant items and links



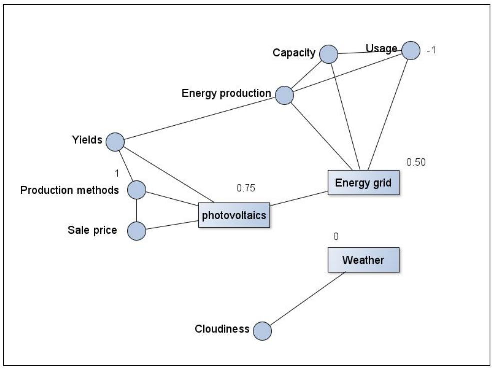
(a) Creation of topic nodes



(b) Creation of information items



(c) Creation of links between information item



(d) Subset with several assigned relevance values from a PV developer, this is a visual representation if one would hide the information with 0 vallues for a specific person

Figure 13: Graph creation steps and subset creation

5. Ask relevant items to set relevance as A. A is a settable distribution for relevant items and links

4. Assign ownership and liking to personal information. Liking is an array, determining how well someone likes or dislikes certain personal information.

5. Connects each individual with each other via a two-way path. These paths get assigned a value between X and Y. Both the minimum X and maximum Y are settable. A -1 value relates to an extremely bad attitude towards the person while a 1 can be seen as adoration. See figure 11 for an example. The attitude values never get larger than 1 or smaller than -1

7.4 BEHAVIOUR

In this section the agent actions and their results will be formalised. The behaviour consists of two main actions, sharing information and processing shared information. Depending on the settings a break may take place where only personal information is shared. During these breaks people may process earlier shared information by means of synchronous processing.

7.4.1 information sharing

The way information is shared is dependent on a settable sharing mechanic. These are based on two two ways for sharing that seem the most likely to happen . The first is agenda based, where people share information related to agenda topics. The second is a brainstorm where people share whatever they fancy. Agenda based sharing is something I have personally observed in participatory modelling processes. Brain storms seem likely for either badly organized processes or processes focussing on context exploration or product design. In the ABM these settable ptions do the following:

- Random brainstorm. Individuals can share a link-set or part of a link-set from every topic each round. A link-set are two information items connected by an information link.
- Agenda based. Individuals may only share as link-set or components from a link-set with at least one component being part of an obligatory agenda topic. The topic changes every X rounds, with X being a settable value.

The general behaviour has been visualised in figure 14. First an individual selects an item topic or link that is known by that individual and follows the agenda topics if there is an agenda. predisposition for sharing certain information types can be set using weights.

For the chosen information type an individual determines if it has enough sharing energy to share said item, link or topic. This is determined by the following calculation:

$$Requiredsharingenergy = 1 - relevanceofsharedthing * sharingcostsharedthing \quad (1)$$

The relevance and sharing costs are both settable in the model set-up. If a topic has been selected, the sharing stops there.

If an information link or item has been selected the remaining sharing energy for the round will be lowered. An individual will see if there are any known connected information links or items and select one of them.

If the individual has sharing energy left the item or link will be shared And the individual lowers the remaining sharing energy for the round.

The individual will look if the final item of the link-set is known and try to share it with the remaining sharing energy. If there is enough energy the item will also be shared

When sharing an item, link or topic its frequency increases.

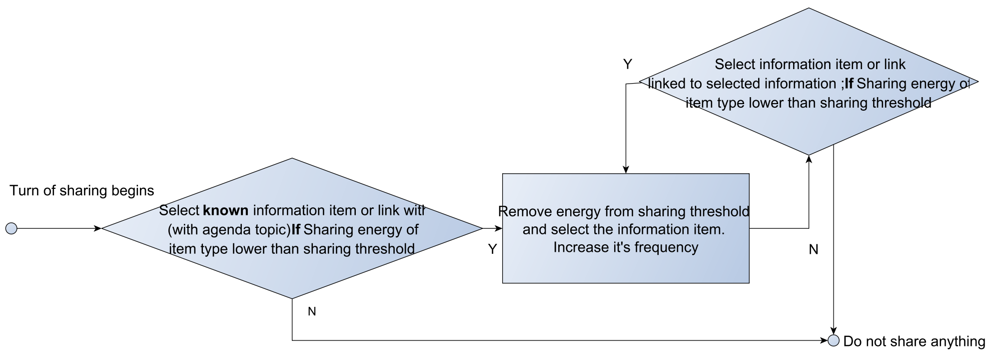


Figure 14: Sharing process during a round

7.4.2 Information processing

Whenever an individual is done with sharing information items and links, others will aim to process what is shared to internalize information and learn it. Figure 15 shows the conditionals on how an individual processes said information.

First individuals determine the so called attitude modifier with regards to the sender of information This follows the following equation:

$$attitudemodifier = 1 + attitudeofsender * Attitude_multiplier \tag{2}$$

The attitude multiplier is settable in the model settings

Then one will select one of the shared, not yet known, things at random and determine the required amount of processing energy

$$Requiredprocessingenergy = expertisecurve(expertise) * processingcostofitemtype \tag{3}$$

The the expertise curve is a sinusoid (figure 10) with expertise as its input. Expertise is the percentage of information items and links known from the related topic.

After calculating the required processing energy. One determines the frequency modifier. This is calculated as:

$$\begin{aligned} frequencymodifier = 1 + frequencyofthesharedthing * learningfrequencymodifier \\ + topicfrequencymodifier * frequencyofrelatedtopics \end{aligned} \tag{4}$$

The topic and learning modifiers are settable in the model settings

After calculating the required processing energy and the frequency modifier, the available energy will be calculated as follows

$$\begin{aligned} Availableenergy = Remainingprocessingenergy * (1 + relevanceofsharedthing) \\ * attitudemodifier * frequencymodifiermodifier \end{aligned} \tag{5}$$

Here remaining processing energy starts as the processing energy assigned by the model at the set-up minus the decay if one has not yet processed a shared thing by from the same sharer.

Then one will process and learn the shared thing if the available energy is higher then the required processing energy. After this the remaining processing energy gets lowered by the required processing energy and one selects and tries to process another shared thing. If that is successful and there are still any shared things this repeats itself again.

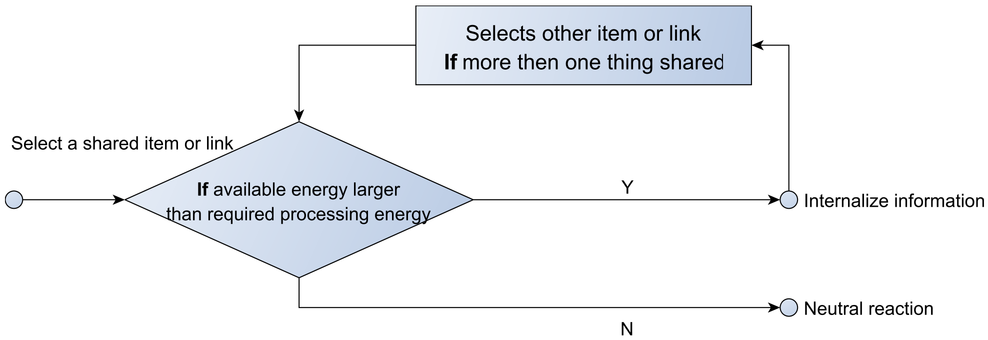
In the case of a break (figure 15b) each individual can select any thing that has a frequency higher than one that is not known by that individual. It then aims to process that information in a similar manner as during a normal round. The available processing energy will be higher, based on a settable multiplier, however, and attitude modifiers are not taken into account. This is synchronous processing.

During a break individuals can also share any one personal information items at random. Others process this and internalize it if they do not know it yet. They adjust their attitude as follows

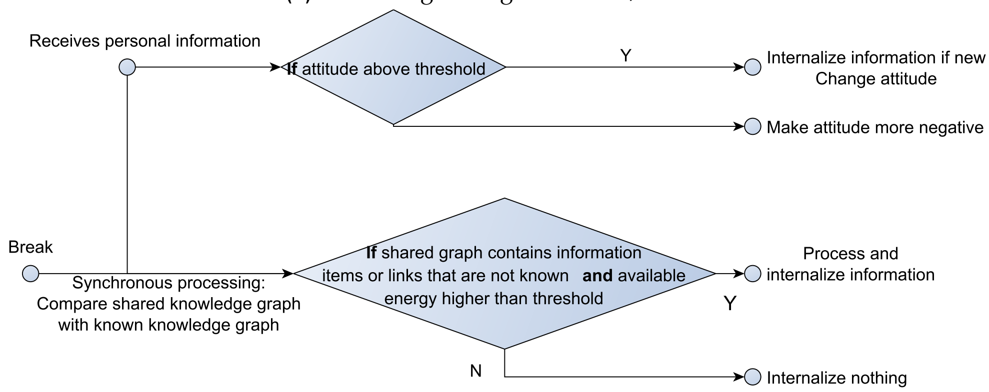
$$attitudechangeis 0.1 * (attitude + likingvalue) if shareditemisnew \tag{6}$$

$$attitudechangeis0.0.5 * (attitude + likingvalue) if shareditemisknown \tag{7}$$

After a normal round or break has been concluded the base energy for sharing and processing that each individual has gets lowered by its relevant decay. These decays are settable in the model



(a) Processing during a task tick/round



(b) Synchronous processing during downtime and breaks

Figure 15: Information processing conditionals

7.5 INTERFACE

In this final formalisation section the interface of the actual netlogo model will be explained, elaborating on how to use the model. This has been done by assigning numbers to sections of the interface in figure 16. These section will be discussed in order

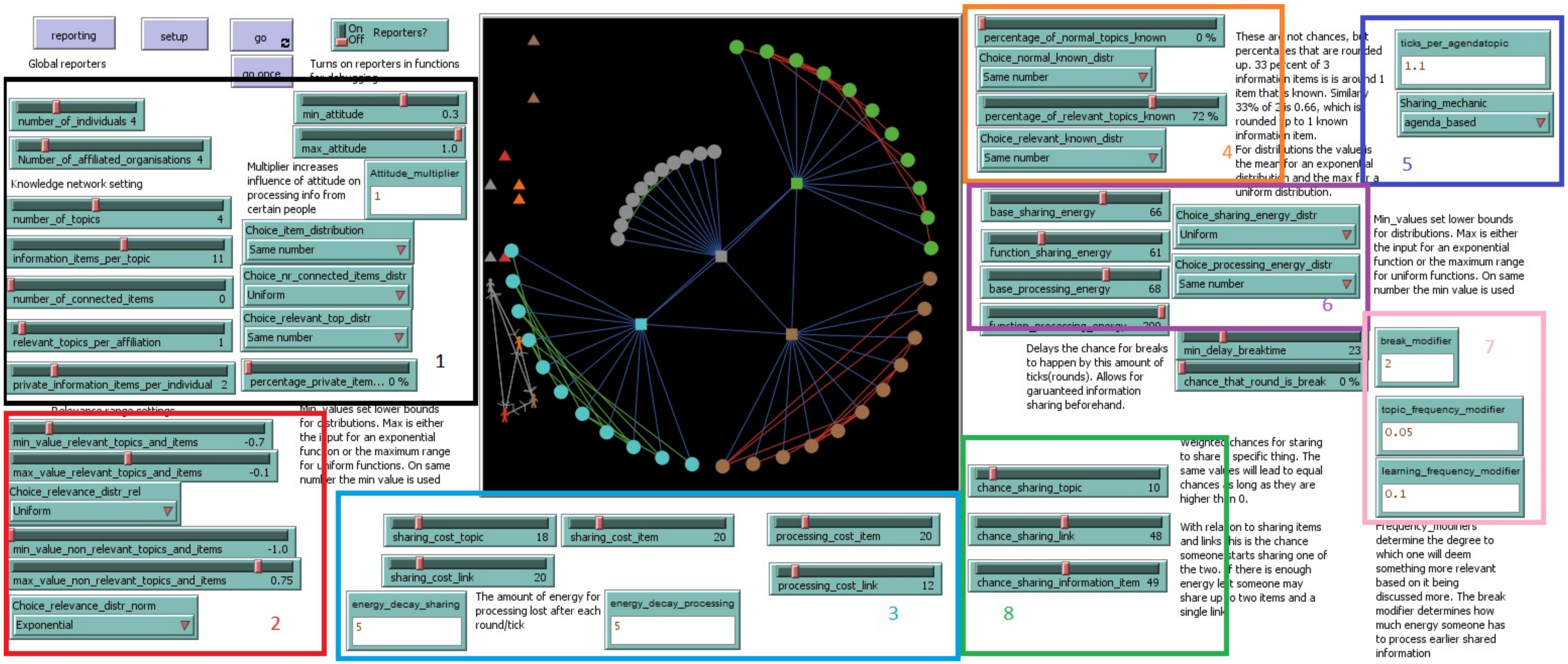


Figure 16: Netlogo interface

1. The first block relates to population settings. Here one can set:

- How many individuals are in the model
- How many affiliations are in the model (higher affiliation than individuals will give each individual a unique one as if the value was equal to the number of individual. A lower number will give individual the same affiliation)
- How many topics there are, how many items each of these topics can have and how well connected items from different topics are. These values can be set to use different distribution or the same value.
- How many relevant topics each affiliation has. This can also be set as a distribution
- The number of private information items per individual and the percentage of these with links towards normal information items. The links do not do anything in the model for this.
- Attitude ranges and the importance of attitudes when determining available processing energy

2. In the second block one can set the relevance values for both relevant and non relevant topics. Relevant topics are those that are decided as important for certain affiliations. These can be set according to different distributions or as a fixed value.

3. The third block relates to the settable base costs for sharing and processing information items, links and topics. Additionally one can set the decay for both sharing and process energy that happens at the end of each round.

4. The fourth block contains settings with relation to starting expertise for relevant and non relevant items and links. This is a percentage value that differs per person if one uses the settings uniform or exponential distribution.

5. The fifth block allows one to change the sharing method to random brainstorm or agenda based. One can also set the duration of an agenda topic. Note that decimal values will be rounded to the nearest integer. After this integer has passed in ticks a new agenda topic will be selected at random.

6. The sixth block allows one to set the starting processing and sharing energy. If distributions are set here as uniform or exponential the base values give a minimum value. The function value determines the height of the uniform function on top of this if uniform is used; and the mean of an exponential function if an exponential function is used.

7. The seventh block allows one to set how much extra energy one has during a break, how much ticks need to happen before a break can happen and what the chance is for a break to happen. Additionally it allows for the setting of the frequency multipliers.

8. The eight block allows one to change the weights for information sharing. These determine the likelihood that an individual shares a topic, information item or information link. Note that information items and links are the starting point of what is shared. With enough sharing energy and expertise one is able to share a complete link-set of which the starting point is part off.

7.6 SUMMARY

In this section a model formalisation has been made used for programming and explaining the netlogo model. Additionally the model interface has been explained, giving insights into the possible model settings. These settings and model working help to understand the following chapters.

8 MODEL EXPLORATION

In this chapter a is will be held on the model exploration. This together with the following chapter help answer the second research question, namely how an ABM would look like based on my conceptualised theory. First an explanation of the methods will be held, followed by the set-up of these experiments. Finally the experiments will be analysed and discussed. By doing these analyses strange behaviour may be identified and trends can be interpreted.

8.1 LHS AND RANDOM FORESTS INTRODUCTION

To determine the importance of variables in a model one would ideally run each possible combination of settings. However, the amount of combinations increases exponentially for each additional variable. Two binary variables lead to four options, three to eight and so on. This increasing amount of options is even larger for non-binary values as one can imagine. These combinations need te be run multiple repetitions, repeating a whole model run. Ergo the more options that one aims to try the more computational resources are needed.

To tackle this dimensionality one can use specific sampling methods LHS, running a model on samples rather then the whole possible space of variables. Latin Hypercube Sampling is a statistical method that does this. Based on given distributions LHS will create samples closely following said distribution. For each variable it creates such a sample and combinations of these samples are used to run the model. The samples are made independently. The sample size determines how many samples are taken for each variable.

By taking samples that follow an assumed distribution (either observed or self determined) a model is ran with a high degree of accuracy for less resources and time. A larger amount of variables requires a larger sample size to follow these distributions for all variables.

8.1.1 Random forests and extremely randomized forests

Having made an exploratory model run with LHS, investigation in it's workings can start. To gain insights into the effect of certain features one would want to know which features to look at first. To this end one could do multiple things. For example, one could make regression models between an output parameter and all variables, with linear and non-linear regressions or one could make decision trees. Descriptive statistics can also be used. However these methods are both work- and time-intensive when the amount of parameters increases.

To handle this one can use machine learning methods. These are methods that find structural patterns in data that are not predefined by humans. In the case of this thesis extremely randomized forests have been used. To explain what this entails a discussion on decision trees will be held first, which is the basis for random forests and extremely randomized forests.

A decision tree can be seen as a string of events leading to certain outcomes. For example, if a doctor sees three out of the four symptoms of a flu he will decide that you have the flu. In the case of a specific set of two symptoms, like sneezing and a sore throat he will classify you as having a cold. In most cases the classification will be correct. This idea of having certain facets that determine a classification or prediction is the essence of a decision tree. Note that you can also have regression trees, where classifiers aim to predict the value of outcomes based on a reduction of variance with regards to the outcome. This is done by splitting data recursively (E.G. if above a certain value or if positive). When making decision trees in machine learning the algorithm aims to create such decision trees automatically (Witten, Frank, & Hall, 2011).

However, as the example stated, the doctor can be wrong sometimes. If one wants to improve accuracy of a classification one would check with several doctors. This is the basic premise behind assembly machine learning. Rather then one tree, multiple trees are made. This leads to improved accuracy of the trees. The use of multiple trees leads to the idea of a forest. Normal random forests build and evaluate trees based by 'bagging' a certain amount of data, this can be seen as setting a part of the dataset aside. The method creates the forest based on the remaining training set by finding the optimal splits. This forest is then evaluated with regards to predictability of the target variable, by comparing predicted outcomes of the forest with the actual outcomes of the earlier bagged data.

Extremely randomized forests, are random forests where the split is random rather than optimized. Furthermore it does not use bagging. It is supposed to deliver greater accuracy then normal random forests as they are less prone to over-fitting and capture more variance (Geurts, Ernst, & Wehenkel, 2006). Over-fitting happens when a statistical follows the data too closely to predict things other than the data set.

By analysing the results of random forests and extremely randomized forests one can investigate to what extent certain variables capture outcomes on their own and how well the whole forest is able to correctly predict outcomes. The first is done by comparing the extent to which a variable leads to less classification errors.

8.2 experimental set-up

To make the model for the initial sensitivity analysis the nlrx package for R has been used. This package allows for the interfacing between netlogo and R allowing for more advanced experimental set-ups. It is a relatively fast way to run elaborate experimental set-ups with relation to processing power and less prone to errors than earlier integrations or R with netlogo (Salecker, Sciaini, Meyer, & Wiegand, 2019). In the case of this thesis it was used to run a latin hypercube.

The work-flow consists of the setting up of a model object. This model object then allows for the development of an experiment where one can set intended metrics, constant values and variables. The variables can be set as a distribution, which is the basis for the latin hypercube. After setting the variables one can define the intended settings for the hypercube, relating to sample size, number of cores and precision. One is also able to rune methods like monte carlo approximation using this package.

The model was ran with distributions of 31 variables, with a sample size of 120. This was decided based on advice from a researcher on research gate, who stated that 30 variables require around 4 times as many samples. Several variables that were deemed less influential or that were deemed realistic have been assumed as constants. Most distributions for values in the model have been set as uniform, with several ones being chosen as exponential in case a higher variance of numbers was deemed important. Note that these are the distribution options in the model. All values, including the means, maximum or minimum of these internal distribution were assigned uniformly by LHS. While the hypercube sampling as a whole worked well, several metrics that work in the netlogo model do not work in the hypercube, where they did in netlogo. These metrics have been omitted.

The omitted metrics are: the mean frequencies that information items and links have been sent; the mean expertise that someone has (items and topics known compared to the whole); and Items and links that are known by everyone and shared (the reason that this last one is zero could be that it really is rare for this to happen).

The outcomes of the LHS model have been used as input for analysis by means of an extremely randomized forest, using the ranger package in R. Features have been scored using the extremely randomized forest, which has been the basis for the descriptive analysis. These are discussed in the next section.

8.3 EXPERIMENTAL OUTPUT

The random forest model had as metric to predict the mean of things learnt, meaning the amount of things that a person has integrated in its own knowledge set. The other metrics are used to explain pattens with relation to this metric, which is why they were not used for the extremely random forest analysis (ERF).

The ERF has made 500 trees leading to an RMSE of more then 15.11, which is quite high. One is able to learn up to three information items per person in an optimal setting, which most cases in the LHS model are not. This is not that strange all things considering, as random forests are based on linear regression. Variables in the model are unlikely to act linearly and some of them actively act as ceilings and floors for what can be learnt or shared. For example, if there are only 15 information items and information links in total, the maximum things that can learnt can be at most 15 (disregarding expertise as not knowing anything would make you unable to process information). Likewise, having more individuals will lead to 0 to 3 extra shared things in a round, which is dependent on individual variables like relevance or available sharing energy. Ergo it is not recommended to try to predict outcomes based on the ERF.

When looking at how the variables are scored on importance (figure 17), one can see that several variables are deemed less important then time(ticks). This is quite surprising as especially the energy decay for sharing information was anticipated as one of the main variables of importance. If the energy sharing decay is high people would quickly run out of energy to share information, stopping learning all together. The variable could be under-represented with regards to prediction if the range is too large. If a decay of, say, 20 and 40 is the same and most variability is between 0 and 20 then the correlation would seem weaker then it actually is.

Two of the most important variables are the amount of individuals and the amount of information items. Both can be explained as important as one 1) needs information items to share if one needs to learn them and 2) a larger amount of individuals leads to a larger part of the dataset being known and a larger amount of shared things. Furthermore, following expectations the amount of agenda ticks (I.E. ticks that one can only share items relating to a single topic or connected to an item from that topic) was one of the most important variables according to the ERF. This was expected as it creates a ceiling on sharing new information items after a topic has been exhausted. An agenda tick value of 25, for example would mean that people only share information on a single topic for 25 ticks, half the model run. Eventually people would have learnt everything they can, while continuing to talk about the same topic. The behaviour of agenda ticks has been investigated in depth in the next chapter.

The other most important variables are all related to processing and sharing energy, the main things needed to share information and process information to learn it. Interesting is how the sharing and processing costs of information links are important as well when compared with the costs of information items. It is likely that this happens because in most cases there are a few more information links than items per topic (includes outgoing links to items from other topics). Because there are often more links there is a higher likelihood that the shared link has not been shared before, increasing the chances that people can learn from it.

In the next section the most important variables discussed here, have been analysed using descriptive statistical analysis.

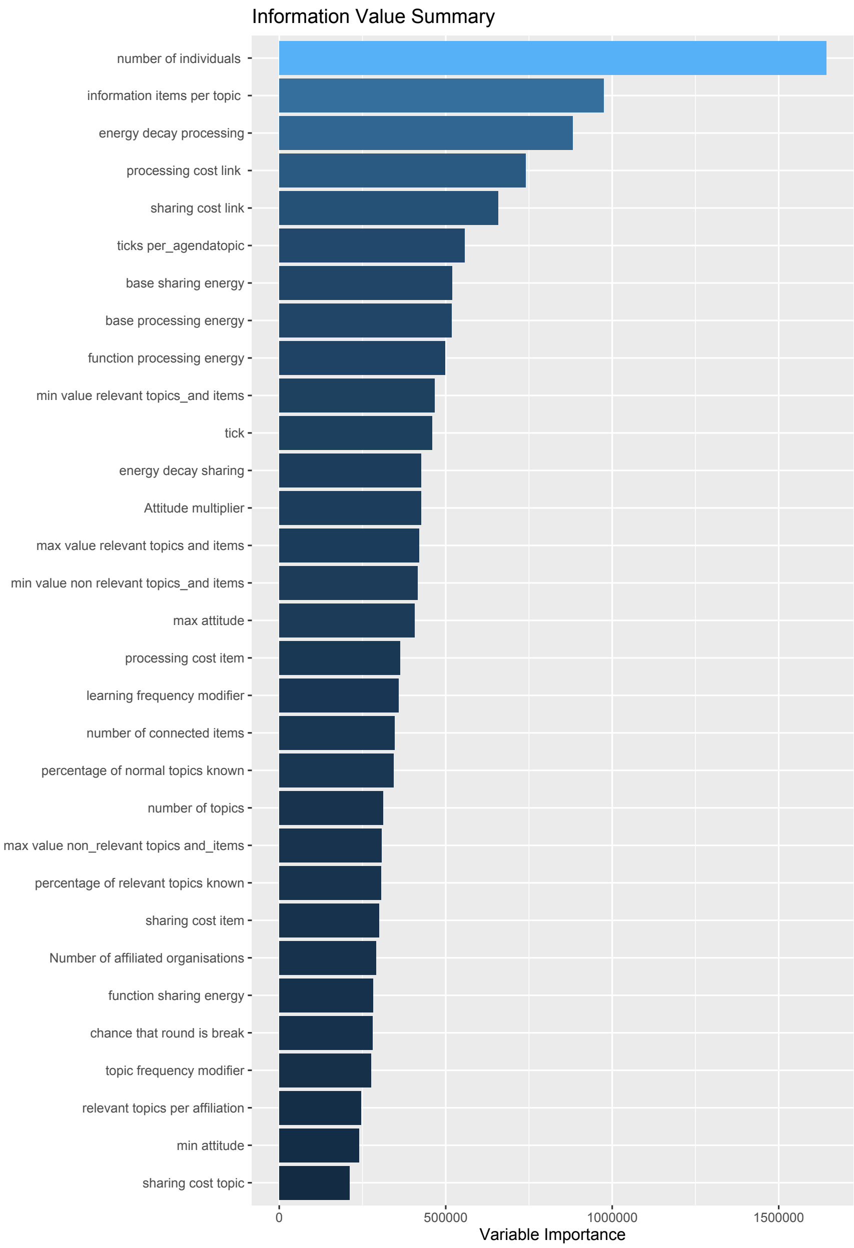


Figure 17: Scoring of variables based on GINI impurity values. These scores give insights into which variables reduce prediction error the most. Note that they do not tell anything relating to the actual regression a variable has with the predictor

8.3.1 Exploratory descriptive analysis

To further investigate model behaviour descriptive plots have been made to investigate important variables and their interactions. Preliminary analysis has been done making scatter-plots using facet grids on supposed important variables according to the gini values. Facet grids are an R functionality that allows one to dissect large data set based on specific variables. These variables (or a single one) are plotted for differing values on a grid of graphs. While they are really interesting in analysing relations between specific variables they may not be the most legible for people who are not used to them or the model. This is why the preliminary analyses have been moved to the appendices. Note that the dataset has more than 600 thousand observations, leading to a loss of detail with regards to the gradient (colours may overlap), making interpretation of the appendices for the exploratory modelling especially hard. Furthermore the LHS may have not created samples for certain variable ranges created for sub-setting data for facet grids. The more simple facet grids in this chapter do not have this issue

Based on these preliminary plots more specific ones have been made that are easier to interpret. These are discussed in this section. Al y-axes show the mean things learnt, meaning the average number of items and links processed/integrated by al agents in the model (average of a single run).

Sharing and processing energy

When looking at available sharing and processing energy, their decays and their costs in the preliminary analysis, the most influential variables seemed to be decays

The most impactful variable that seems important from the preliminary analysis is energy sharing decay, meaning the amount of energy someone loses each discussion round. Above a certain values sharing of information stops quickly. This happens quicker the higher the value. This has been visualised in figure 18 as a boxplot over time . Here the facets show different values for sharing energy decays. As can be seen the higher values lead to a stabilisation of learning. Interestingly enough the median and both quartiles also seem to rise for values between 10 to 20. This could mean that values under twenty ar not that influential for the used base values or it could mean that the LHS drew less optimal values between 0 to 10. One can also see that low decays have relatively extreme outliers. These are likely runs with optimal circumstances like a low process energy decay. This seems likely as the shape of the outliers between low values of processing energy decay look highly similar (figure 19). One can claim that the outliers show the optimum boundaries that a value can achieve.

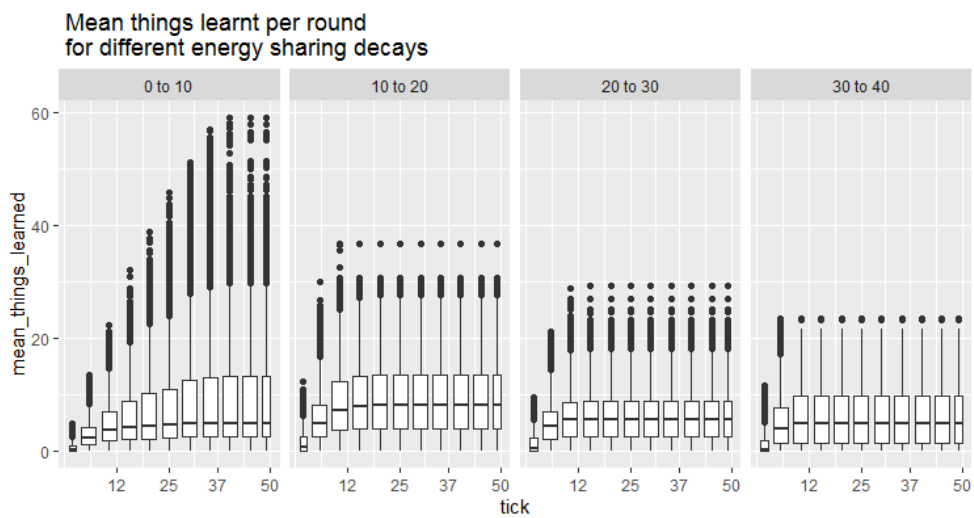


Figure 18: Boxplot of mean things learnt over time for different sharing energy decays

When looking at processing energy decays on se that these have the most influence between values between 0 and 5. Apart from that it is shown that on values higher than this trends seem to stop, meaning that learning reaches a plateau, but the median and quartiles do not follow a straight trend downwards. This has likely to do with at least half of the runs having a high sharing decay. If less information is shared chances of learning something decline. If the shared information also requires more energy than someone has for processing the chances decline even more. When looking at the maxima on can clearly see the limiting factor of the decay in what assumed are optimum conditions.

From this combination of decays it can be concluded that sharing energy decays may be overtuned in the model, pushing away real influence of several other values. During the preliminary analysis, the decays did seem to dominate the model to the extend that attitudes and base energy values nearly seem irrelevant

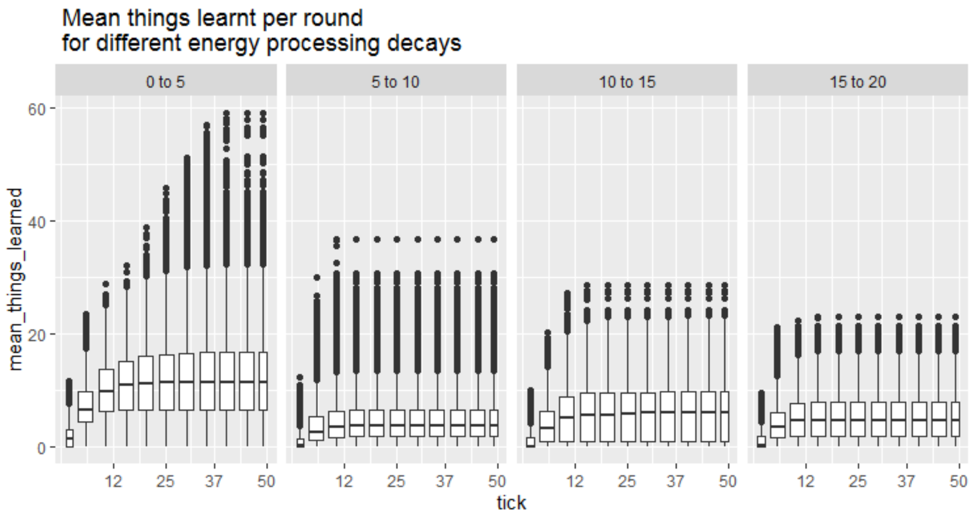


Figure 19: Boxplot of mean things learnt over time for different processing energy decays

To tackle over-tuning one would ideally get numbers on decays versus work capacity from real life data to find out what are realistic values. As I doubt these are available one could try laboratory experimentation, measuring effectiveness of the sharing of a pre-defined list of information. During a break one could measure what was retained of the shared information and one can do the same in the end. Note that this is likely influenced by measures like having a good memory. Matters like expertise in a topic are also hard to include.

The decay mechanics themselves may be overly simplistic as well as they are a flat value each round. Furthermore, they are seen as separate which is unlikely to actually be the case. An argument can be made to make them more complex, although one can wonder how useful this will be if one does not know realistic values in the first place.

Finally one can extend the idea of sharing energy with means of lowering sharing costs. This will happen, fer example, if someone who shares information uses drawing or diagrams to get his point across. This would come at the cost of a higher energy usage for sharing information.

Population of knowledge and participants

Two other important variables are number of participants and number of information items per topic (more nodes in the knowledge graph). From these one sees a clear increase in mean things learnt for both.

With relation to number of individuals (20). This can be explained when looking at model behaviour. Meaning, if there are more people, more information is shared each round. In other words if more people speak up and share information, more information can be learned. In reality, there is off course a limit to which this works. It is doubtful that a 100 people trying to form a model together would lead to all of them learning much, additionally rounds would take longer with more people, which would likely lead to more fatigue and less energy for sharing and processing.

The amount of information items per topic also seems to increase what is learnt (figure 21). This can be explained as a larger amount of information items leading to more variety. More variety means that more items are shared, which all have a chance of being processed. A smaller amount of items would lead to more information being repeated. If one has successfully processed and integrated it they will not learn it again and they may even share that information later down the line

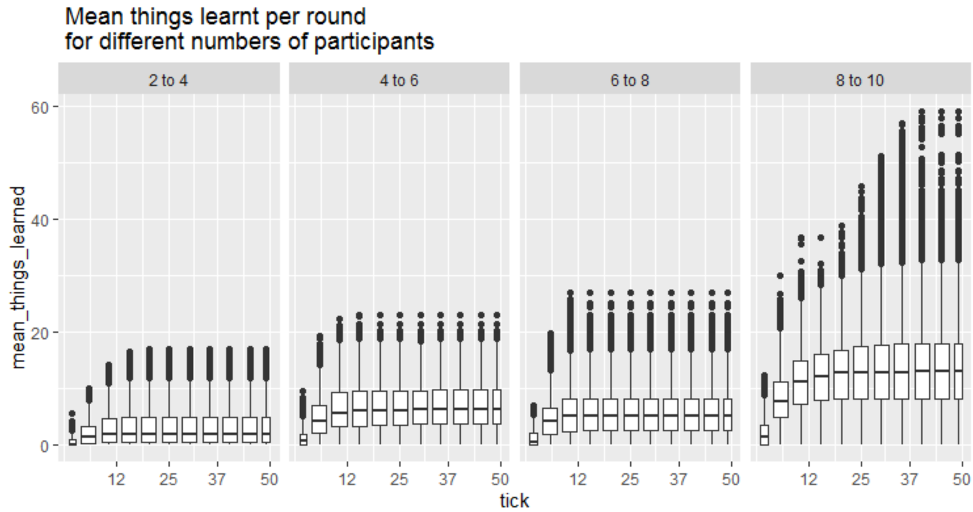


Figure 20: Boxplot of mean things learnt over time for differing numbers of individual decays

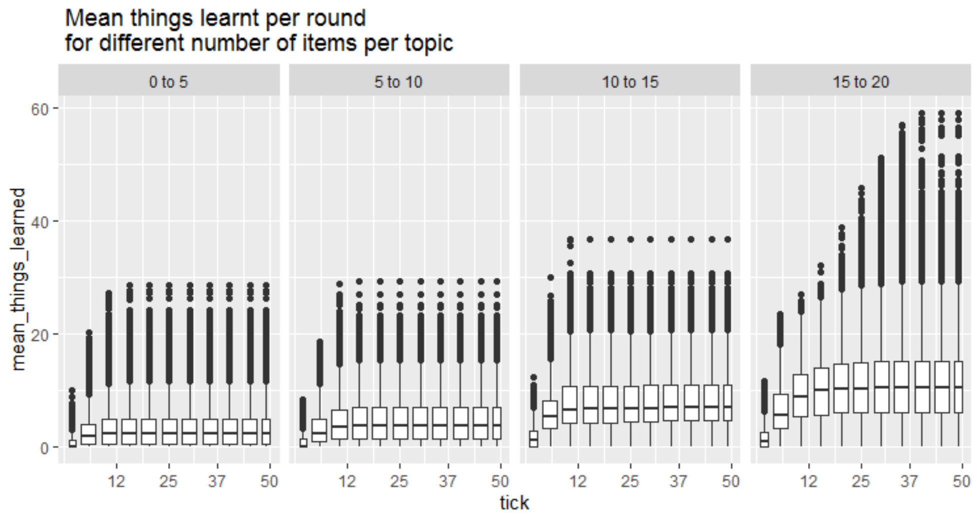


Figure 21: Boxplot of mean things learnt over time for different durations of agenda items

The amount of knowledge someone has on their own relevant topics or those of others does not seem to influence learning overly much (22 and figure 23). Note relevant topics of their own are the topics someone deems more important based on affiliation. All other topics are deemed topics from others It may increase the maxima, but the medians do not change for both. This may point towards the expertise curve being highly undertuned. As the expertise curve is based on assumptions with no real data it could be useful to investigate ease of learning for topics where someone has a certain degree of prior knowledge (E.G. a employee of an NGO with a sociology background learning the physics behind photovoltaics, versus a grid operator with a electrical engineering background). Future work may need to include a retuning or expansion focussing solely on expertise.

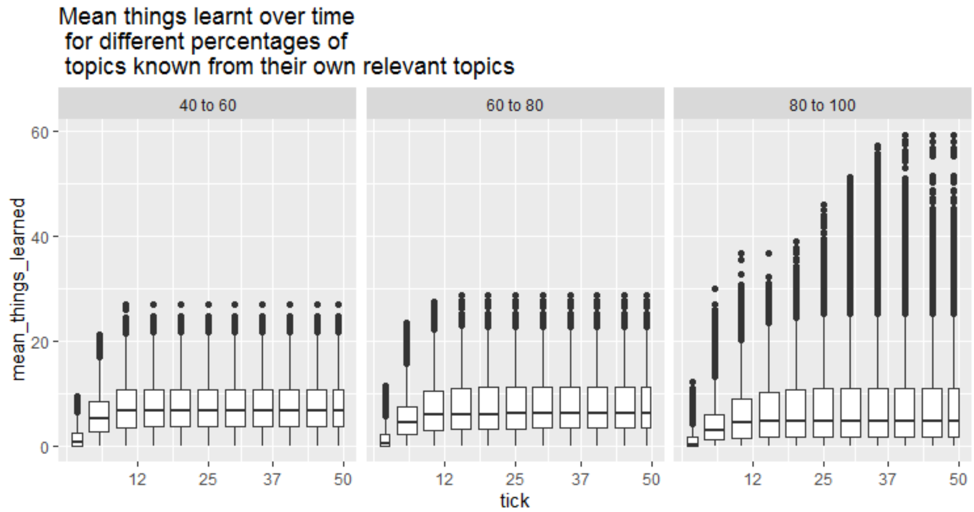


Figure 22: Boxplot of mean things learnt over time for different percentages of topics known from their own relevant topics

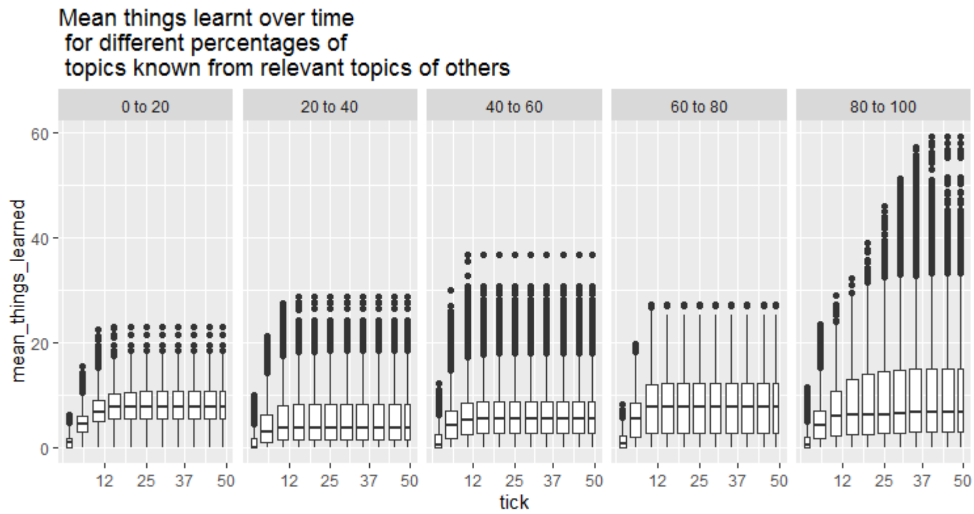


Figure 23: Boxplot of mean things learnt over time for different durations of agenda items

Agenda duration

The final variable that is deemed interesting is the duration of agenda topics. As these agenda round enforce that only information regarding as specific topics is shared, it is assumed that they limit the sharing of new information. Reason is that eventually all information items and their connections will have been shared already if there is enough energy to do so. The graph seems to follow the expected trend. This is not all that surprising considering that an agenda can be seen as a stringent constraining of the number of information items that can be shared and, thus, integrated

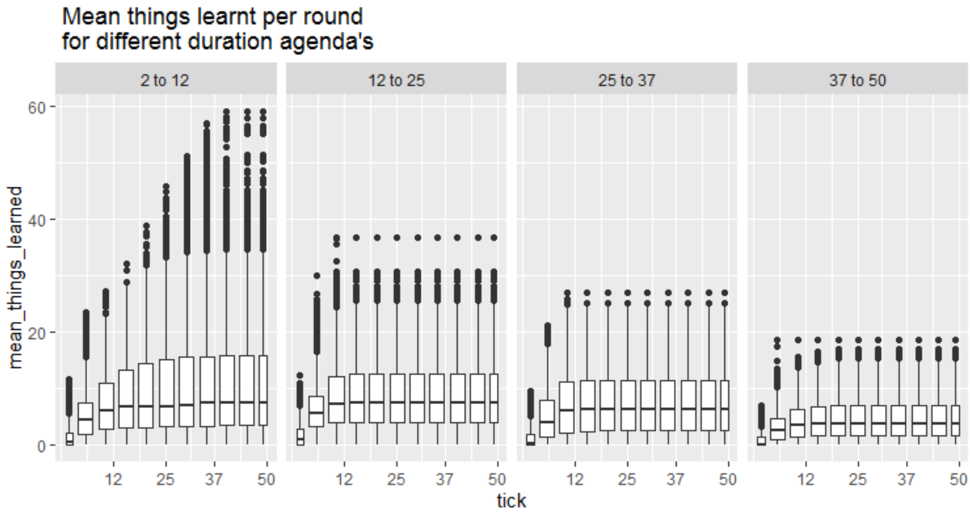


Figure 24: Boxplot of mean things learnt over time for durations of agenda rounds

8.4 DISCUSSION

In this chapter a sensitivity analysis and model exploration has been done using LHS methods in combination with extremely randomized forests. Via the extremely randomized forests the most important predictors have been found, which have been analysed in the exploratory descriptive analysis. Selection of variables of interest for this analysis has been based on a preliminary analysis of all variable that were deemed relevant according to the LHS methods, which can be read in the appendix.

Based on these analyses it can be concluded that energy decay for information sharing is the main factor that can hinder learning in the model if the decay is set too high. A high decay of sharing energy makes it so that less information is shared. Without information being shared nothing can be learned. A higher processing energy decay will eventually make it so that no individuals have any energy left to learn new information regarding of the base cost for processing information. It needs to be further investigated what kinds of decays are realistic, not only with relation to the model, but also in reality. One can also think about making decays influence available energy during a round rather than after a round, however this would make parametrization harder. For example a decay of 5 each round is easily compared with energy costs and supply as 1/4th of its processing costs is lost and people start with enough energy to process 5 items whenever something is shared (E.G. figure 40). This is not as easy if decay happens during a round.

Additionally a link may need to be made that makes individuals able to invest more energy into sharing something to make it easier to interpret, lowering processing costs. This investment, will likely lead to ones energy depleting quicker as one is sharing in a more extensive matter. This balance between spending energy to make things easier to process for others and the fatigue this gives someone is a particularly interesting topic of investigation

Furthermore one can state that a higher number of individuals will lead to a higher degree of learning if there is enough information sharing (low sharing energy decay) and there are enough items to share that are new. This is an interesting finding as it may mean that more people, all with topics with plenty of important details (items and links) will only learn from each other if everyone is sharing information. This may be an important metric for measuring learning of a group. Note that in reality there is likely to be a ceiling for the number of people that stay workable for both sharing and having time to process information.

The mechanics related to amount of prior knowledge on topics seem undertuned in the current model. Tuning this to something reasonable would require a lot of work and testing as the expertise curve, which determines the effect of known information on sharing and processing is purely theoretical with nor real life data to base it on.

Finally one can see that an agenda for what is discussed in a SL process may potentially harm learning if the topics are discussed for too long. An agenda item that takes a lot of time will lead to more repeats of the same information which may already be processed successfully by others or it may keep not being processed if it is not deemed relevant, for example.

There is also some unanticipated, but explainable, behaviour that would require more stringent testing. Namely, the other sharing and processing variables did not seem to influence learning overly much. This could be explained by energy decays being overtuned or by themselves being undertuned. Additionally it could simply be the case that the ranges for other variables that were not as influential being too small. In the next chapter a small example will be given on how to investigate model behaviour more deeply based case inspired experiments. More stringent testing, investigating behaviour like this, could be inspired by that. Note that interpretability and explaining behaviour is quite hard with a high variability of variables in a high dimensional space, thus investigating specific behaviour mar require many different parametrizations.

9 EXPERIMENTATION

In this section an experiments with smaller ranges and more fixed variables are discussed inspired by two real cases. First the cases are introduced, followed by a discussion on the implementation. Following this a descriptive analysis is done and discussed. This is more of a in depth analysis of behaviour as lower variance of input values makes plots easier to interpret and more stable. Note that with the second case several liberties have been taken to make it more different from the first case.

These analyses can be use to explore behaviour in a more specific way and shows how it could be used to reflect on real or hypothetical cases. It informs how th ABM could be used and show that the ABM works as a proof of concept of the theory

9.1 CASE LAYOUT

To come up with reasonable variables for experimentation, two cases are used as inspiration, supported by either discussion information from the case owner or by personal experience a hypothetical list of variables is defined. Here the values are based on what is assumed to be a high or low input variable. Around these input variables a numerical range has been applied that has been used as the ranges for use in Latin hypercube sampling. By doing so a certain degree of noise is introduced in the results. These are used to investigate sensitivity of certain input variables. If the spread because of this is high one can conclude that the variable is heavily influenced by others.

The experiments have been run making use of latin hypercube sampling using the nlrx packet in R. Both experiments were separate. For the experiments the variables are brought down from 31 to 21 compared to the sensitivity analysis and the ranges the variables can take have been made more precise. The most important constants for both experiments are:

1. there are 8 individuals
2. processing and sharing costs of items and links have been set to 20
3. the influence of frequency and topic frequency on information items and links have been set to 0.1 and 0.05 respectively
4. there is only a 5 percent chance that a round is a break

9.1.1 Windmasters

Windmasters was a participatory modelling project which I had the pleasure of attending a few session. The aim was to develop a model regarding futures and scenario's for the Botlek area with relation to a possible upcoming offshore wind farm. The model and discussions focused on grid management and all kinds of energy demands and supplies. This is the main inspiration for the context of this thesis as has been noted before.

In this project it was observed how participants are genuinely interested in what others have to share and discussions, questions and remarks were done often and in a friendly manner. Participant came from several different organisations in the field of energy, meaning that their specific fields of expertise were from the same landscape, but still different. However, they were quite informed on expertises of the others as well. They were willing to not only share information, but also discuss and accept information from others. Additionally they seemed amicable with each others. During the process quite a bit of planning was done on what to discuss and when, with multiple modelling and discussion sessions spanning whole days. There was a clear goal with the process and people are convinced the agenda helps reach this goal (building of a simulation model). Based on this the hypothetical case interpretation the following input variables for the latin hypercube sampling have been defined:

The experiment based on this has the fallowing layout:

1. High attitudes towards each other: minimum attitudes between 0.2 and 0.8 and maximum attitudes between 0.6 and 1. The attitude value van have values between -1 (heavily negative) and 1 (extremely positive) in the model.
2. High relevance for topics in their own organisation: minimum values between 0.4 and 1 and maxima between 0.8 and 1. This is also on a scale from -1 to 1 normally.
3. low amount relevance for topics from others: minimum values between 0.4 and 1. Maxima between 0.6 and 1. Can have a scale between -1 and 1
4. High processing energy: between 40 and 200. The base cost of sharing and processing a link or item is 20, meaning that someone could theoretically process 10 items if there was no delay and if the model allowed for that kind of sharing.
5. Low processing and sharing energy decay: values between 0 and 20. Note that 20 may still be quite high in retrospect
6. Relatively long agenda items: between 5 to 25 ticks. A round is a total of 50 ticks
7. high knowledge on their own information topics, meaning uniform values up to 65 to a 100 percent of items and links known from these topics
8. high knowledge on other's information topics, meaning uniform values up to 30 to 60 of items and links known from these topics

9.2 DUTCH BLOCKHAIN

The second case is based on a group of stakeholder discussing block-chain technology. The Dutch block-chain coalition to build alliances between business, state and knowledge institutions (both public and private), with the aim to nurture start-ups, technological advancement and economic intelligence (Lagendijk, Hillebrand, Kalmar, van Marion, & van der Sanden, 2019).

Based on communication with one of the case owners, the following hypothetical case has been defined. Participants were highly, educated. Many of them are from different organisations, focused mainly on their own topics, being disinterested in others. Because a lot of topics that are discussed that they are not interested in the enthusiasm for the process drops relatively quickly, sharing and processing energy decays at a high speed. Information regarding certain topics were quickly discussed with no clear order, with everyone focussing on whatever they felt like, meaning there was no strict agenda or the agenda was simply ignored. The latter can be attributed to a lack of a shared vision.

When one would take this to a participatory modelling context. One would get a group of people with one or 2 topics that they know a lot about and find highly interesting. The other topics they deem irrelevant. Furthermore it is assumed that attitudes towards other in the group are lukewarm as one would likely find irrelevant topics interesting if someone they like discusses it. Decays for both sharing energy and processing energy are quite high as a lack enthusiasm after a short while can be interpreted as them not being interested any more, meaning they are less willing to spend much energy on the process. This all culminates to both a high energy decay for information processing and information sharing.

The experiment based on this has the fallowing layout:

1. Middling to low attitudes towards each other: meaning minimum values between -0.5 and 0.1 and maxima betwen 0 and 0.6
2. Low relevance in topics falling outside their own organisation: relevance values between -1 and 0.5 and maximum values between 0 to 0.6
3. Middling amount of knowledge in general
4. High amount of knowledge on personal topics
5. Middling to low processing energy
6. High processing and sharing energy decay
7. No fixed agenda
8. High amount relevance for topics from others: minimum values between 0.4 and 1. Maxima between 0.6 and 1. Can have a scale between -1 and 1
9. High processing energy: between 40 and 200. The base cost of sharing and processing a link or item is 20, meaning that someone could theoretically process 10 items if there was no delay and if the model allowed for that kind of sharing.
10. Low processing and sharing energy decay: values between 0 and 20. Note that 20 may still be quite high in retrospect
11. Relatively long agenda items: between 5 to 25 ticks. A round is a total of 50 ticks
12. high knowledge on their own information topics, meaning uniform values up to 65 to a 100 percent of items and links known from these topics
13. high knowledge on other's information topics, meaning uniform values up to 30 to 60 of items and links known from these topics

9.3 EXPERIMENTATION

In this section the experiments that have been ran will be discussed and compared. As the input variables are different between experiments, facets grid including both at the same time will not work as the facets have completely different values. In the appendix an investigation on trends can be found showing at least two dimensional facet grids. As these are not easily interpretable these have been used only for initial exploration and to discern potential weird behaviour

9.3.1 Learning mean differences between experiments

When looking at the means of both experiments it can be seen that although behavioural trends on average seem similar, the windmasters case has significantly more learning. This is to be expected as the values that are supposed to influence learning in a positive way are better in every aspect.

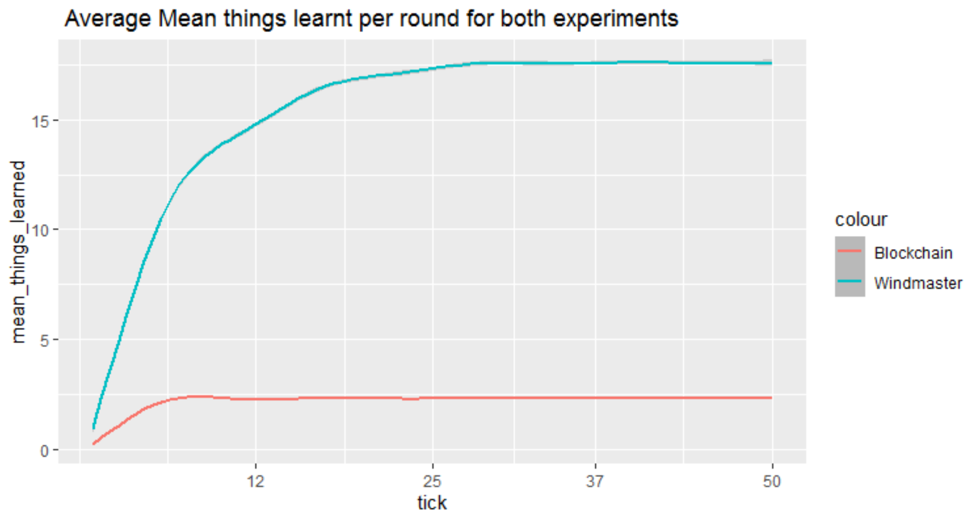


Figure 25: Lineplot average of mean things learnt over time of both cases

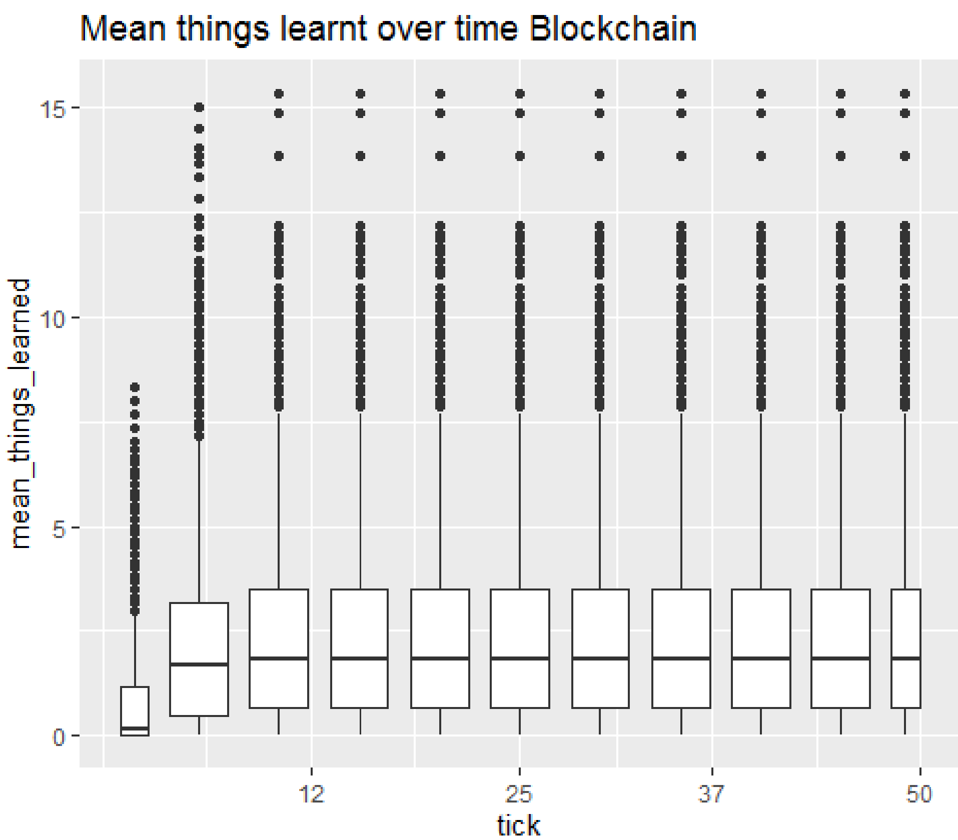


Figure 26: Boxplot of average of mean things learnt over time blockchain experiment

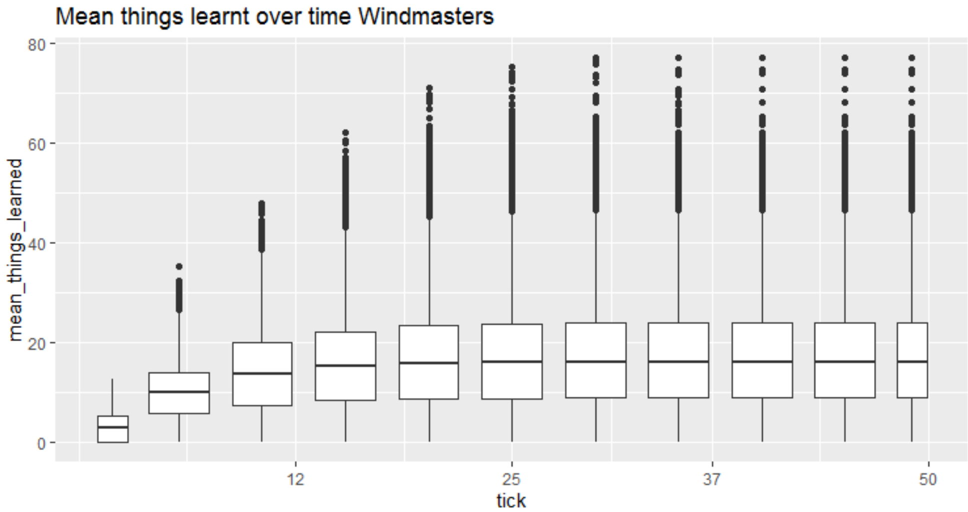


Figure 27: Boxplot of average of mean things learnt over time windmasters experiment

When looking at the boxplots of both experiments this disparity in learning becomes even more extreme as the median in the blockchain case has a value between 1 or 2 items learnt. While I assume that the real case median would be higher, it does show how a accumulation of bad starting conditions can basically ruin a process. More surprising is how the most optimal set of starting conditions from the LHS method, the outliers, of the blockchain case do not even reach the median of the windmasters case. The base sharing and processing energy settings are similar over both experiments, thus the combination of decays, relevance and attitudes together are enough to stop most learning in a few rounds if they are set high enough.

Energy decays

When looking at sharing energy decays for the blockchain case only small differences can be found for the median with somewhat larger maxima. in the windmasters case the differences seem larger as the width of the quartiles is larger and the maxima have larger disparities. Interesting is how the overlapping decays still have highly different values of learning, be it with similar patterns. Furthermore the last two settings from the windmaster case have similar values. This is quite tricky to explain. It could be based on the randomness of the LHS or that the value differences are too small to decrease sharing at a differing rate.

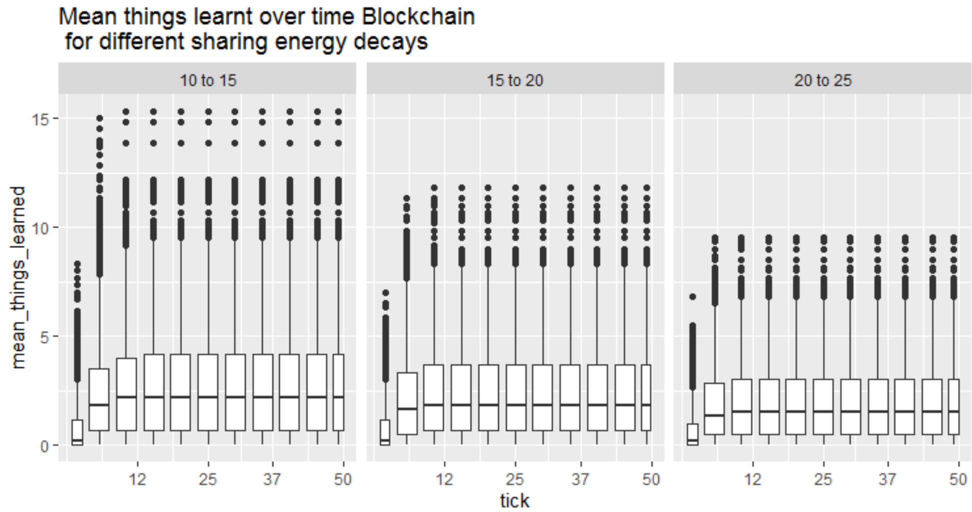


Figure 28: Boxplot of average of mean things learnt over time for different sharing energy decays for the blockchain case

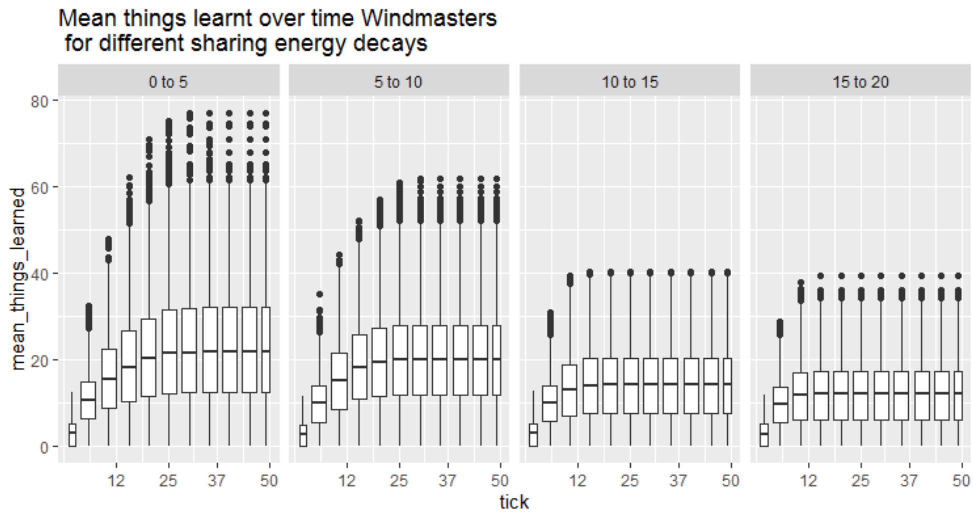


Figure 29: Boxplot of average of mean things learnt over time for different sharing energy decays for the windmasters case

When looking at processing energy decays on can see some differences. For the windmaster case processing decays, do decrease what is learnt. In the Blockchain case these decreases are not as straightforward. This likely indicates that processing energy is less relevant if nothing is shared as one is unable to process new information if there is no new information to begin with.

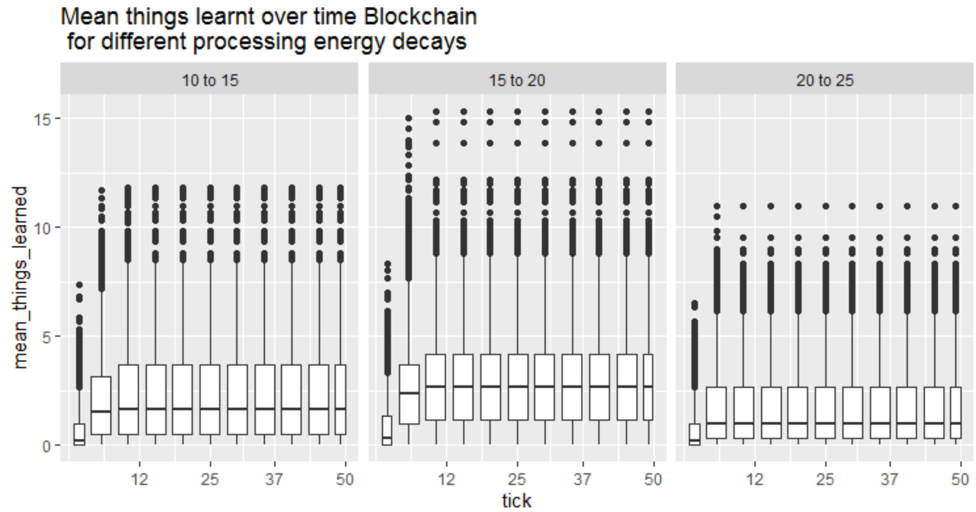


Figure 30: Boxplot of average of mean things learnt over time for different processing energy decays for the blockchain case

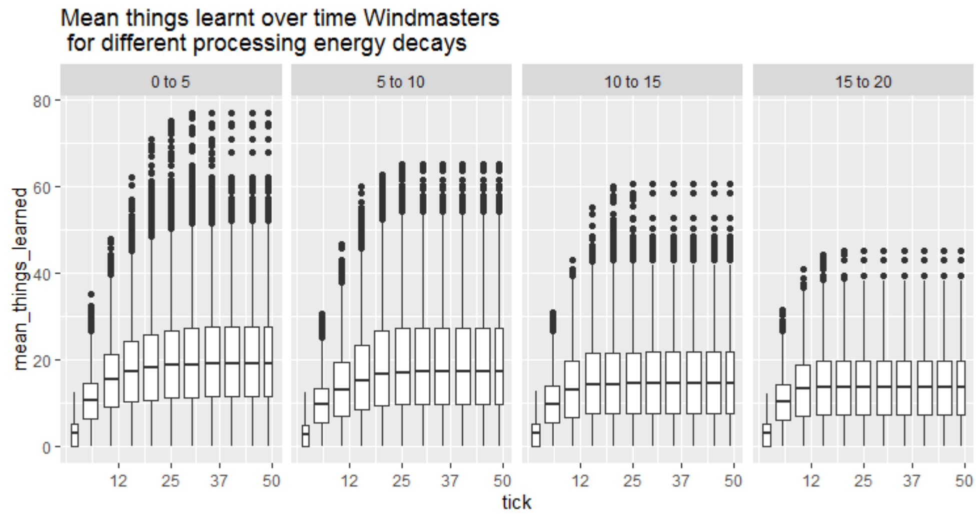


Figure 31: Boxplot of average of mean things learnt over time for different processing energy decays for the windmaster scase

Attitudes

Attitudes in the model are set by setting minimum value and a maximum value. The values that participants get is uniformly distributed between these (if the maximum is smaller than the minimum it will be reversed automatically in the model). Because these ranges on their own are not that informative because of this (I.E. a minimum of -1 and a maximum of 0.5 is lower on average than -0.5 and 0.5). To tackle this the rounded average attitudes have been used.

When looking at the blockchain a slight increase in learning can be found for better attitudes. In the windmasters case attitudes seem to matter less. The only case where changes seem pronounced is for an average value of 0.9. Here the learning stabilises later, meaning processing of information continues longer. This could mean that attitudes matter less when there is enough relevance and energy to process information from people, unless the attitude are positive to the extend that they actually make energy decays relevant later.

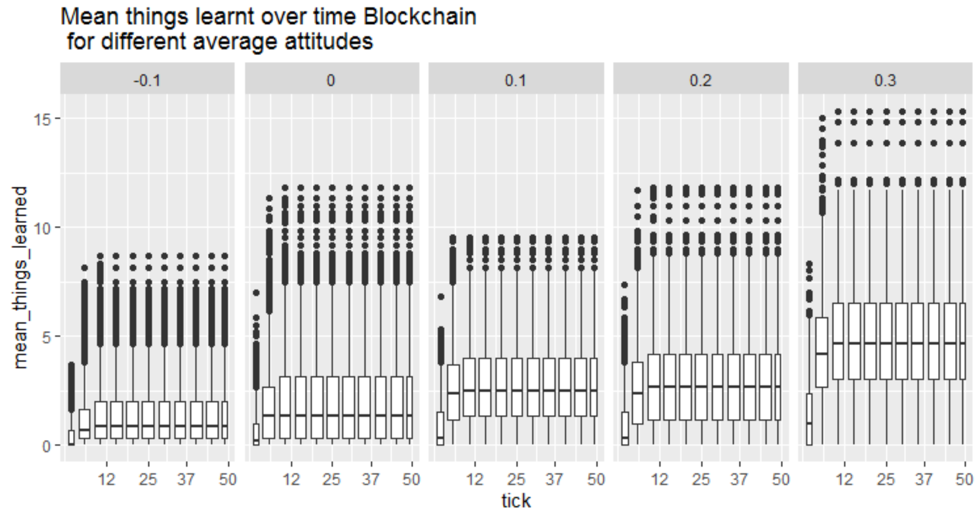


Figure 32: Boxplot of average of mean things learnt over time for attitudes for the blockchain case

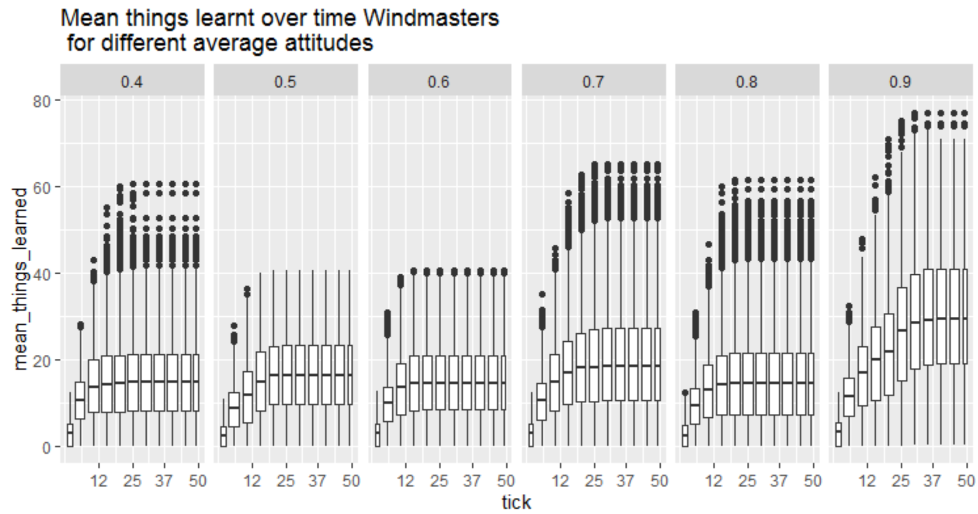


Figure 33: Boxplot of average of mean things learnt over time for different attitudess for the windmasterscase

Relevance

When looking at average relevance of information topics from other parties. This relevance does not seem to matter much in both cases. This variable may be severely under-tuned compared to variables.

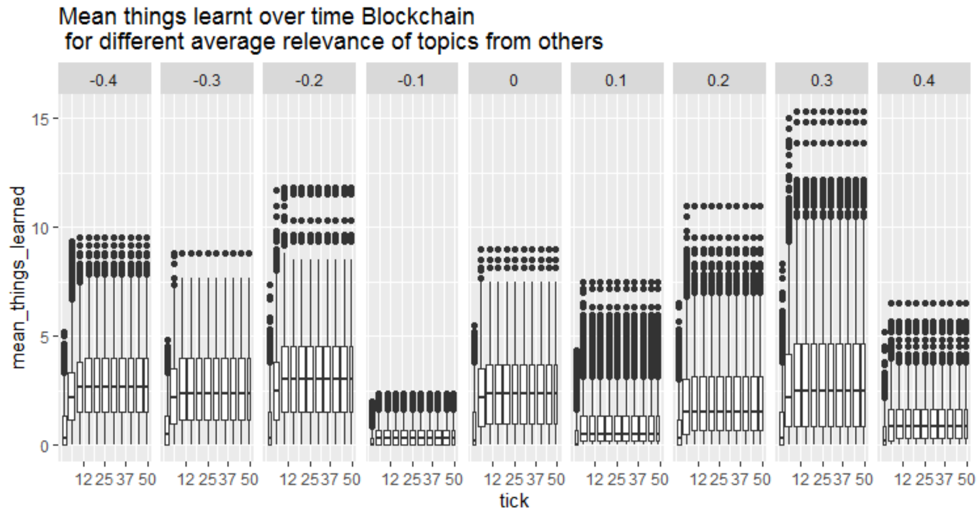


Figure 34: Boxplot of average of mean things learnt over time for different relevance ratings for topics of others for the blockchain case

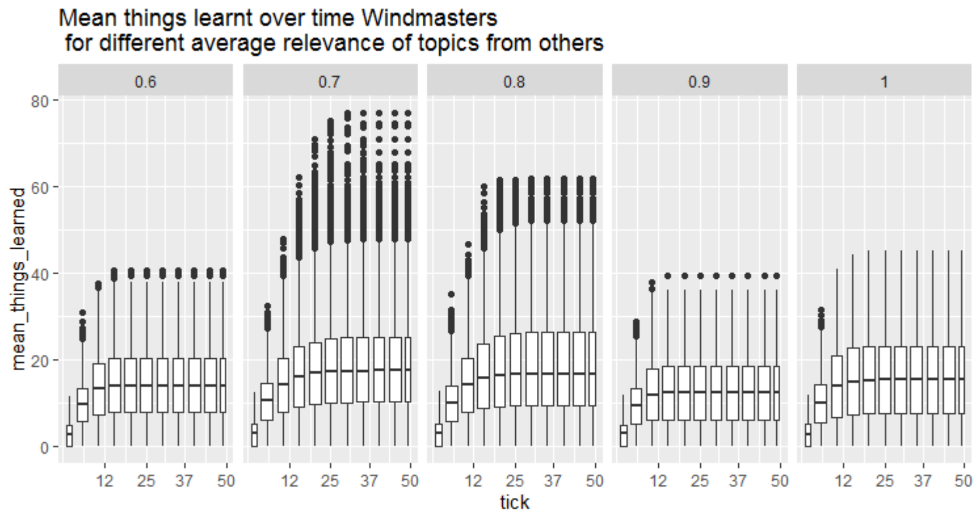


Figure 35: Boxplot of average of mean things learnt over time for different relevance ratings for topics of others for the windmasters case

Agenda duration

Both cases have severely differing durations for agenda topics. When looking at the blockchain case one can see that values from 1 to 5 do not differ much. This is not that surprising as the total duration is 50 rounds. These values may be to small to really have influence. In the windmasters case one can see that longer agenda topics decrease the amount of learning that happens. If one looks closely at the topics between 20 to 25 ticks one can see a slight increase in learning when the agenda changes. This can indicate that all information items and links have been discussed at that moment. If this happens no new information can be shared, little learning is likely to happen for repeated information. This finding is particularly interesting to me as I didn't expect this. I am curious if this is observable in practice, where if an agenda item is too long people will start to discuss the same thing without adding much new information.

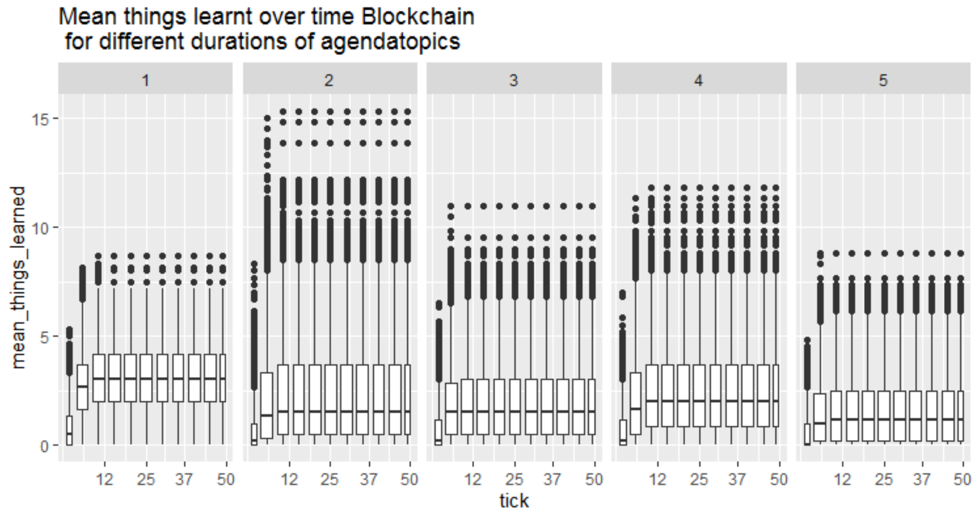


Figure 36: Boxplot of average of mean things learnt over time for different agenda topic durations for the blockchain case

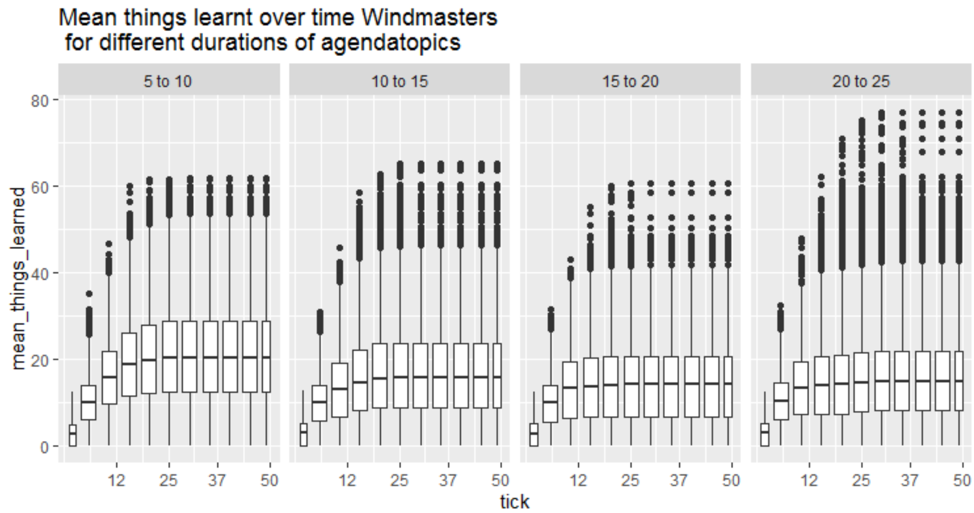


Figure 37: Boxplot of average of mean things learnt over time for different agenda topic durations for the windmasters case

9.3.2 Discussion

In this chapter theoretical cases have been implemented in the ABM. By doing so quirks from the model are found and a reflection is done on the theory and cases.

The first theoretical case is inspired on the windmasters project. Here model input is set in a way that should guarantee a good process with much learning.

In the second case, the block-chain case, inspiration has been extremized into values that are supposedly bad for learning.

Compared the windmaster case had around ten times more learning on average. One can also see how learning seemingly stabilizes and stops after a certain amount of rounds. This can mean that either the energy for sharing and processing is spent or that all information has been shared already. If information is shared a second time people who did not integrate it already are not likely to do it when it is shared again (it can happen based on knowledge effects and better attitudes if it sent by a different person). People who did integrate it successfully and learnt it can not learn it again.

Based on these cases one can see that sharing energy decays, meaning a roundly decay on the the amount of energy one has available each round for sharing information, were clear indicators for learning. Low decays increase potential learning. When compared to reality this can be translated as much sharing makes it more likely that something sticks.

For processing energy decays one can see something similar in the windmasters case, with higher decays decreasing the amount of learning that happens. This is not the case in the blockchain case. From this it is assumed that processing energy does not matter if no new information is shared with high sharing energy decays. When translated to reality this can be translated as without shared information it doesn't matter how easy one can learn as there is nothing to learn.

When looking at attitudes participants have regarding each other. The blockchain case showed the strongest differences, with positive attitudes leading to more learning. In the windmaster case one could only see a clear difference with an extremely positive attitude. In the later all attitudes are already quite positive, however. Attitudes increase the amount of energy one is willing to spend on processing and sharing information. If there is already an abundance of energy for these things. This abundance is likely in the windmasters case as decays are lower, relevance and expertise in topics is higher. Note that an attitude of 1 potentially doubles the amount of available sharing and processing energy by 2 times if other modifiers like relevance and expertise are disregarded.

The relevance values for topics from other people did not seem to influence learning overly much. This mechanic is likely undertuned.

The duration of agenda items influences learning if they are overly large. Eventually nothing new will be discussed, stifling what can be learnt. If a new agenda topic is started learning may pick up again assuming there is enough processing and sharing energy left.

While not every variable is as influential these experiments did follow the intended behaviour when designing them. It is the intention to make them completely different. The blockchain case was severely worse learning-wise than the windmaster case. Actually the differences were even more extreme than intended. Based of this I would recommend additional testing of the influence of only a handful of variables at a time to investigate the size with which each variable influences learning. Additionally these mechanics would ideally be based on real world data, which is not available as far as I know. Doing both would require a significant time investment

10 DISCUSSION AND CONCLUSIONS

In this final chapter a short run-down of the thesis will be given followed by a discussion concessions with relation to the research question. After this a discussion will be held on future work Finally, a discussion will be held on issues I ran into during the project as these are important with regards to reproducibility and future work. The final section is meant for modellers on model use and can be ignored by others.

10.1 RUN-DOWN, DISCUSSION ON THE THESIS AND RESEARH QUESTION

The aim of this thesis was to gain insights into:

1. mechanics shaping and steering social learning
2. how to measure social learning processes for in vivo experimentation
3. design mechanics for participatory modelling processes and Social learning in general to improve development of such processes

Reason for this is the perceived usefulness of social learning in participatory modelling for tackling complex socio-technical issues. This is because they enforce a certain degree of involvement of participants, requiring commitment. Secondly they require shared ideas for the model to be explicit enough to be modelled and enforce a certain structure, improving interpretability of knowledge by highlighting interactions and causalities between the knowledge of participant. This enables systems thinking which is required to foresee the results of possible scenario's and interventions. Finally participatory modelling may lead to simulation models, allowing for deeper investigation into certain problems, via means of model analysis. This model may also be assumed to have a certain amount of acceptance as it has been built by individuals participating in the process.

To gain insights into the mechanics and measurements, which are ultimately required to come up with design criteria, one would like to gain insights into how they can possibly interact. This is done by first creating a theory on the behaviour and mechanics underlying SL processes from a PM perspective. This theory is developed by investigating possible mechanics and behaviour by means of supersynthesis of theories from communication science and social psychology. This is done as integration of already existing theories is quicker than coming up with completely new ones. Furthermore a single pespective is not enough to capture both behaviour and mechanics. While social psychology tells us how group processes work and how and why people act a certain way, it does not focus on how one shares and processes information. This is why communication science has been used to this end. The first research question was:

1. How would a theory look like that explains social mechanics and behaviour of SL processes from a PM perspective?

This is answered in the first 6 chapters. The theory is as follows: Knowledge takes the shape of a knowledge graph. In this graph fields of expertise are called topics. One can think about the weather as such a topic. These topics consist out of information items, think cloudiness or temperature, and links between these items indicating their relation, think cloudiness leads to lower temperatures. These items may have links to items from other topics. For example cloudiness is related to sun hours and yields of Photovoltaics from th topic of Photovoltaics.

It is assumed that a complete knowledge graph exists. Each individual knows part of this graph, signifying knowledge or expertise in the topic. The larger part of a topic they know the more expertise they have in that topic. This includes both information items as their links (relationships). All these items, links and topics also have a perceived relevance for people. This is based on interests or affiliation. Affiliation means relationship with a group of people, for example, meteorologists. Something is also seen as more relevant if it is discussed often, attributed to common knowledge effects.

In a social learning process there are several individuals. Each round they are able to share information. Information is seen as information items and/or their links. A topic as a whole can also be discussed, but this is not seen as actual information for learning. What they share is based on the amount of energy they have and are willing to spend on sharing information. This is dependent on perceived relevance of the item they are considering to share, their expertise on the related topic and their tiredness. It is assumed that the energy one has decays over rounds.

Shared energy is received by others and they start to process it. Here something is integrated or learned if they are able or willing to invest enough energy in the processing. This is dependent on their expertise of the related topic, their perceived relevance of what is shared and their attitude with regards to the sender. If expertise, relevance and attitudes are high enough someone will process and integrate information. Processing energy is also assumed to decay each round.

In addition to information on knowledge, individuals can also share relational information. These are details like hobbies and other personal details. These are processed as either positive or negative and influence attitudes.

Processing of shared information may also happen during breaks or downtime. Here one has more energy to spend and attitudes are less relevant. Total recall of information is assumed in the whole model (I.E. people do not forget anything).

As one would ideally test a proposed theory observations and experimentation are useful. To this end in vivo experiments could be used but these are time intensive and costly. A cheaper way to get a proof of concept, allowing one to explore and experiment with a theory is through use of simulation modelling. To this end the second research question was:

2. How would an ABM of such a theory look like?

The decision for an agent based model has been made as ABMs are specifically made for simulating entities with behaviours. The model has been built by translating the theory into code and by simplifying parts of the theory to make the theory more easy to code or understand. This model has been developed and used for exploration through analysis in chapters 7 to 9. Experimentation and sensitivity analysis have been done in R using latin hypercube sampling. Analysis have been done using boxplots and extremely randomized forests. From these, reflection on the theory have been made and recommendations have been developed.

10.2 RESULTS DISCUSSION AND CONCLUSIONS ON A THEORETICAL PERSPECTIVE

Firstly with relation to the super synthesis of theories it has been stated that these are used to develop a new theory that is not meant to supersede the ones that are used. However, from these theories a lot of things have been simplified for developing the eventual theory. Matters like conflict and increasing conflict, coalitions, personal inhibitions and norms are some of the values that would make sense to include in the theory. This would make the theory less usable for simulation modelling, however and would add a lot of behaviour that is not directly related to the learning process. To implement these additional behaviour could be conceptualised and added, making the theory more complete but less comprehensive. The most important addition that could be made according to me would be an extension on the actions influencing attitudes and the actual definition of a process result (a participatory built model or a plan).

Additionally these theories are selected based on available sources within a short time-frame. This means that only several sources have been used. Other theories could be used to conceptualise behaviour and mechanics if one would spend more time on searching. Additionally completely different perspectives on behaviour could be theorised using different fields. For example, evolutionary theory could be used to conceptualise learning or process management can be used to conceptualise how one should manage these processes. These are interesting perspectives that add something new. Here social psychology and communication science are specifically useful for investigating the behaviour of individuals, making the developed theory easy to simulate as an agent based model. This individual based perspective on social learning or participatory modelling processes has not been done yet and it allows us to come up with means of measuring social learning, which is currently not sufficiently done (Reed et al., 2010).

To this end the theory can be used to reflect on social learning from the perspective of participants rather than that of the process as a whole. This makes it easier to understand why process may be successful or fail. Furthermore one can look at the mechanics and come up with ways to influence these or measure them. For example, to make the processing costs of something that is shared lower one can use drawings or other boundary objects. To improve attitudes one can do group training or events. Another way to lower sharing and processing energy would be to spend time on workshops regarding specific topics. E.G. if one would want to start a SL process with farmers regarding Nitrogen one can first do a workshop on how Nitrogen is bad for the environment, what can be done to lessen these impacts etc.

The part of the theory that has been built from scratch is the idea of the knowledge graph (figure 38). This idea is particularly valuable as it is a conceptualisation that does multiple things:

1. It takes a shape similar to how someone's memory is supposed to work when looking at personal knowledge, namely by association between things. Additionally links between topics and items from different topics can be seen as bridging knowledge boundaries from social learning as someone gets introduced to a new topic via these links. This makes crossing boundaries tangible with relation to knowledge

2. It creates an anchor for mechanics and behaviour allowing for someone to apply different theories together to form a cohesive whole. Furthermore this enables simulation modelling

3. It allows for quantification of possessed knowledge and learning in simulation models. This can be translated to potential metrics

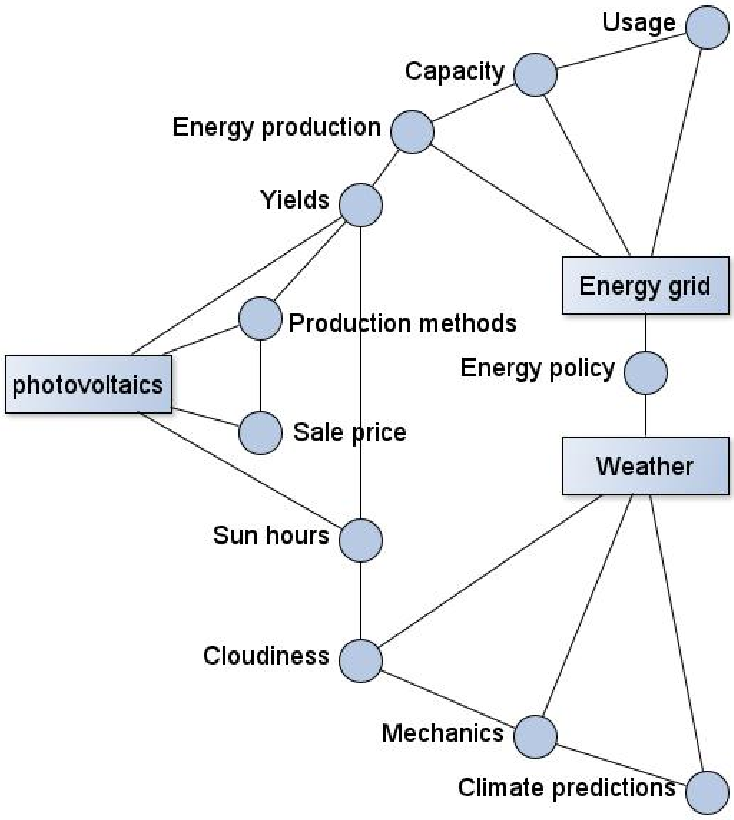


Figure 38: Theoretical 'complete' knowledge set

This knowledge graph is worthwhile as it allows us to specify what social learning means with relation to knowledge. It also allows for the conceptualisation of distance between social landscapes by means of different topics with links between them. Furthermore these graphs can be used to map knowledge before and after a SL process. Additionally the idea of a graph can be used to build new theories on the workings of social learning with a means of comparison. This makes different perspectives comparable to others and potentially allows for integration of these theories into a larger one. Additionally if one would expand on social learning without focussing on learning part one can wonder if they are really expanding on social *learning*.

With relation to social learning literature the conceptualisation of sharing and processing energy based on information processing theories is highly valuable. It tells us why boundary objects are useful in social learning as they decrease processing costs. Furthermore it helps explain why certain people may or may not learn during participatory processes in general. If someone does not have the energy to process something, be it because of a lack of capability, interest, fatigue or other reasons, they will not process it and thus not learn it.

This tells us why tiredness leads to the quality of learning declining, it tells us why an anthropologist may be unable to understand the maths behind quantum physics and it tells us about the importance of making shared knowledge digestible.

With relation to learning literature focussing on matters like double or tripple loop learning, the current theory on learning ca not be seen as either. While social learning should cause double loop learning it can not be identified by the currently developed theory or model as these contain just the idea of information rather than behavioural norms or individual beliefs.

10.2.1 Theoretical implication of the ABM

When looking at the model results and experimentation what is highlighted is the influence of energy decays, be it for processing or for sharing information. Simply stated, learning stops if nothing is being shared and a lot of processing energy is useful if there is enough shared information to actually process. A significant increase in what is learnt can be seen when sharing and processing energy decays are low. In reality these sharing and processing energy and their decays are likely not separate, however. If someone becomes tired they are tired for everything, not just a single thing.

In reality this energy is highly related (in the model only indirectly). One can assume that making something more interpretable for others (lowering their processing costs) will cost more sharing energy. By spending more energy one will run out of energy quicker, leading to less processing and worse sharing in the future. This balance seems like a highly interesting topic of investigation; and something to design means around to make processes better.

From a social learning perspective it gives an interpretation on how a boundary object or process actually helps make learning easier. It can be assumed that boundary processes make sharing and processing costs lower by improving understanding between parties.

As sharing is required for learning the amount of times that new information is shared could be used as an indirect measurement for learning. Assuming that information that is shared is of high quality. This also assumes that others find what is shared relevant enough and have the capacity to do so.

Another interesting finding is related to ticks per agenda item, meaning the rounds that a group spends on a specific topic. Here one could see that in certain cases people may finish learning during an agenda item if everything is discussed already. This made me relate to group processes I have seen where people start to repeat what has been said after a while. Assuming this is people trying to fill the silence or people trying to convince others again that their ideas are good, it may be fruitful to not follow a scheduled agenda precisely, and allow for agenda topics to take less time if people are done.

With relation to the idea of expertise/knowledge on topics. The ABM highlighted that the current conceptualisation of the knowledge graph and the relation between this graph and processing and sharing of information needs to be expanded upon. The current conceptualisation does not influence the simulation model to a high enough extent compared to other variables.

Similarly relevance of items and topics needs to be investigated further as ther influence on the model is also limited at the moment.

10.2.2 Theoretical implications CoSEM

With relation to CoSEM the theory and ABM tell us how a PM could work when looking at individuals rather than the process as a whole. This combination between Social learning and participatory modelling has not been made this explicit before. To this end it is a new perspective on the practices of the participatory modelling community. This allows for reflection on earlier work from a new perspective.

Additionally, PM and other SL processes are useful for approaching large socio-technical problems as they allow groups of people to come together to explore and formulate a complex system from multiple perspectives. Understanding these group processes can be helpful when organising or leading such processes. Here the earlier

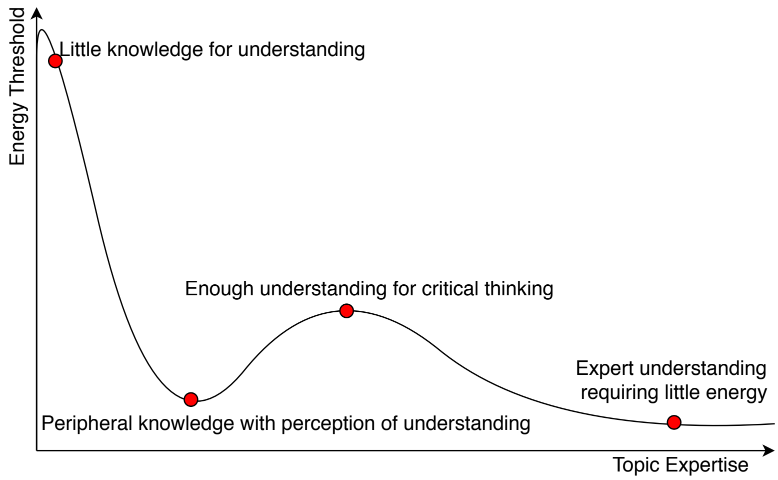


Figure 39: Energy threshold for internalisation vs expertise - expertise is the total percentage of links and items known form a related

mentioned steering of the process can be seen as possible process management tools.

10.3 CONCLUSIONS FROM A PRACTICAL PERSPECTIVE

Apart from expanding on social learning theory this thesis can help inform people in how to manage, measure and design SL processes and PM processes. Measuring SL would be useful as it can tell us something about the quality of learning, rather than the process. These things are different. Knowing that a process was democratic, perceived as fair and that people learned should be defined as a successful SL process, where it is currently measured by means like fairness only. These are not directly to learning and thus do not tell if social learning actually happened.

To measure social learning the knowledge graph could be used. At the start of a process a researcher or practitioner can graph what people know by means of a drawing session with these people. These graphs can initially be used to shape agenda's for the processes. At the end or at intervals these graphs can be expanded with these individuals or with the group as a whole. The final graph can be compared to the initial one to see how much has been learnt and if several ideas have been changed.

Number of items and links can then be observed and compared with starting values to quantify learning. Additionally on could identify information not in the initial graphs from anyone. These can indicate either not earlier shared information or newly created information. The later could be particularly interesting as it highlights the radical innovation that can happen in SL (Wenger, 2000).

The knowledge graphs can also be used to identify what people should know before starting a SL process, so they have enough information to understand topics that they are not familiar with. Here supposed pathways between topics may be identified and followed as items that are close to what someone knows are more likely to be understood. These relations can also be used to make new information more relate-able as information from others can be related to their own.

With relation to design mechanisms The concepts of processing and sharing energy and their decay is highly relevant. The balancing of these values is essential to keep sharing and learning things. For design on can look into ways to make the sharing of information both low cost and easily interpretable. To this end I propose either a set suggestion structure or a physical aid, like a paper model, structuring how information is shared. The aim is to keep the shared information short and to the point and make it clear why it is important. These things are meant to act as boundary objects lowering processing costs for others one the one hand, making learning easier, and could be used as inspiration for simulation models in PM on the other. Furthermore these structures can also be related to knowledge graphs, which could be dynamically expanded or built during a process via these means. The later is useful for measuring of the process by researchers.

The general structure could be:

- I propose that we take [the gas grid] into account for the model
- the [gas grid] is important because of (three sentences)
- the [gas grid] is influenced by [mice]
- the [gas grid] influences [the future of Tesla]
- I require this in the model because of (three sentences)

One can also keep in mind that to keep energy high one should also aim to keep processes and discussions short and give people time to gather their bearings. A too high tempo process may lead to people not being able to process what has just been said. This can be done by a process lead preparing specific spots where what has been said is summarized. This can be seen as a reminder of what has been shared, giving an extra moment for people to process. A process that is to slow or long-winded may also lead to people having less energy if they get bored. To this end a process leader can use an agenda as a means for forcing a discussion along to other topics.

Another thing to take into account is the duration of agenda topics. As one could see in the simulation runs, topics that take to long may run out off things to discuss. It may be helpful to skip to another agenda topic if people start repeating the same information.

In summary I propose the following design mechanics:

1. Usage of a knowledge graph to keep track of what is learned by researchers
2. Usage of knowledge graph to steer the process order that makes learning more likely (topics that closely relate to all participants first and expand that towards specific participants later down the line).
3. Use set structures, conceptual modelling, drawings and other tools to make information sharing and processing easier and less intensive. This would make the process spend less energy if the used tools are chosen well (I.E. a conceptual drawing of what is said or what someone wants to explain using causal diagramming is probably better to explain ideas than doing so via live programming of a simulation model).
4. Use actions like summarizing what has been said to slow down the process if it becomes to quick, leading to a processing energy deficit.
5. Use means like using an agenda to ensure the speed of the process does not become to slow, leading to boredom and potential energy decays

10.4 FUTURE WORK

With regards to future work I propose foci: 1) the model tuning and expansion and 2) in vivo experimentation.

With regards to the first point I the model could be expanded upon on the following things:

- Interpersonal relationships and coalitions. This is a thing that can be observed in many real cases, but is quite simplified in the model. Currently this is simplified into individuals having attitudes regarding others, that are only influenced by sharing personal information.

  This can be expanded by implementing interpretation of information, discussed in chapter 5. Her one can think about interpretation of information as a slight, challenge to authority. These interpretations then influence attitudes. One can also add positive influences to attitudes regarding what is shared. If someone seems really well informed and shares what someone perceives as good or interesting information they will likely be perceived in a more positive light.

  Additionally one can implement existing collaborations/coalitions. This can take the shape of people not agreeing(read processing) information on principle together with other actors based on agreements and shared goals. This kind of bad behaviour would be a really interesting addition as breaking theories and models is a great way to reflect on them and find their weaknesses.

- Tuning and complicating of expertise. The idea of expertise making processing easier may have been over-tuned and made too simple. Its influence in the ABM is negligible, while it is an important part of the theory. While this could be done by adding modifiers to the expertise curve (figure 39) in the model or by using a different curve all together, trying to find theories on learning with relation to prior knowledge should be taken a look at first (assuming these exist) to make it more realistic.

  Finally the expertise curve includes critical thinking as a small bump. While the idea of critical processing of information is one that seems reasonable it implicitly indicates how information that is integrated with expertise before the bump is of lesser quality. One could expand the actual processing with quality of learning based on the current knowledge. Partial knowledge in the model can be done by making the state of information being a scale between 0 and 1 rather than 1 (0 I do not know this, 0.5 I sort off know this or 1 I am an expert on this item). This would need changes in the model on the processing steps and set-up function specifically.

- Extension on processing energy decay during rounds. The current implementation is quite simplistic and the processing energy has a fixed starting value for each new person that shares something (At the end of a round this starting value decays. The processing energy only drops during a round when processing items and links from a single person. Then it resets to the starting value when the next person shares information). This is not realistic.

  One can make this more realistic by making decays more dynamic using time based functions and randomness that either makes decays smaller or larger. Additionally both decays should be unified in a single one or at least be influencing each other as energy in reality is not an array of energy for specific things, but more of a whole. Finally decays should happen permanently during rounds and not reset. The latter would make setting these variables conceptually quite difficult, however. Currently one can set available energy as a multitude of what it costs to process something. If on needs to come up with a supply that needs to fulfil processing and sharing energy needs over a whole model run this becomes less intuitive (it can be easily done by just removing the function that resets the values in the ABM, however).

- As energy decays are important it could be interesting to add modifiers to these that signify the using of boundary objects like like conceptual models in the model by means of giving/forcing individuals in the model to spend more sharing energy (can be less if one assumes a perfectly designed boundary object), to lower the required processing energy.

These expansions or additions would make the model more comparable to a assumed real situation. Furthermore they focus on the topic most important for future investigation of social learning processes, namely, the balancing of energy for processing and sharing and learning quality, allowing for better exploration and reflection on SL when using the ABM. By investigating these topics a large step towards better process design can be made

With regards to in vivo experimentation experimental processes should be run using the knowledge graph conceptualisation, mentioned as design mechanics. This may be a large step towards actually measuring the quality of social learning rather than the group process.

Another thing that would be interesting would be a large case study of SL processes where, cases are replicated in the ABM together with case owners. Through discussions case owners and the modeller can reflect on results and discern reasons for these results according to the simulation. In discussion these can be reflected upon end one could discuss how realistic the model results are according to the case owner or what behaviour the model is still missing. Through these means the theory can be improved and practitioners of SL may be able to improve future processes as the understand the underlying mechanics better.

10.5 ISSUES AND LOOPHOLES TO LOOK OUT FOR

This last section is meant for people who would want to expand or experiment with the ABM model that has been built

For experimentation R has been used in combination with the nlrx and ranger packages. The nlrx package is quite fast when running, but the parametrization can be quite tricky and time intensive. Metrics, variables and constant all have small differences in syntax in nlrx, making mistakes happen easily. Additionally it is quite easy to make mistakes in the parametrization if it is a list of lots of variables. If a variable was set incorrectly you need to run it again and errors, caused by the java implementation are only given after a whole experiment has been ran, possibly taking hours per run. This java implementation to link netlogo with R also seems to make metrics which can be 0 at 0 ticks using means to not work as intended. This likely has to do with java assigning the wrong data type as not setting these variables as 0 during the set-up led to errors because they were assigned as a null value in java, while the mean calculated after that was an integer or double. One needs to take this into account when using nlrx for running models

Furthermore nlrx disregards step sizes you put into distributions, making everything follow the given distribution, without regarding the given step-sizes, leading to input variables that are never integers (numbers without decimals). This requires a lot of data transformation when one wants to analyse a high dimensional model as one needs to change metrics and variables into specific classifier or ranges, which you then need to turn into factors. This is a lot of manual work, prone to easy mistakes like typos or using the wrong variable. This may also break model behaviour when using things like modulo function.

The ranger package also worked relatively well and was quite quick in running. However, getting importance values out of it in a presentable way is quite tricky. I recommend looking at other machine learning packages with extremely randomised trees or finding extensions on the ranger package that are user friendly.

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LIST OF FIGURES

Figure 1 Theoretical 'complete' knowledge set 7
Figure 2 Different social worlds. One can see an organisation as a community of practice, where members have similar aims and knowledge. An institutional field can bee seen as a (abstract) place of working where communities operate together as part of the same social world. One can be part of multiple institutional fields/social worlds. 21
Figure 3 General conceptual model 30
Figure 4 Information sharing model 32
Figure 5 Information processing diagram 33
Figure 6 Theoretical 'complete' knowledge set 36
Figure 7 Individual knowledge subsets 37
Figure 8 List of kinds of information that can be shared. Note that a topic in this case is the concept of a topic. E.G. physics is important instead of physics, the science of... 39
Figure 9 Shared information subset growth over multiplbe rounds 40
Figure 10 Energy threshold for internalisation vs expertise - expertise is the total percentage of links and items known form a related 41
Figure 11 Relational attitudes example. 0 is a neutral attitude with everything between -1 and 1 being varying amounts of dislike (negative) or like (positive). Attitude is not just like and dislike, but also concerns matters like trustworthiness and perceived authoritativeness. Reciprocated negative attitudes are seen as an open conflict 42
Figure 12 Differences and similarities private information between a Meteorologist and PV producer 42
Figure 13 Graph creation steps and subset creation 49
Figure 14 Sharing process during a round 50
Figure 15 Information processing conditionals 52
Figure 16 Netlogo interface 53
Figure 17 Scoring of variables based on GINI impurity values. These scores give insights into which variables reduce prediction error the most. Note that they do not tell anything relating to the actual regression a variable has with the predictor 60
Figure 18 Boxplot of mean things learnt over time for different sharing energy decays 61
Figure 19 Boxplot of mean things learnt over time for different processing energy decays 62
Figure 20 Boxplot of mean things learnt over time for differing numbers of individual decays 63
Figure 21 Boxplot of mean things learnt over time for different durations of agenda items 63
Figure 22 Boxplot of mean things learnt over time for different percentages of topics known from their own relevant topics 64
Figure 23 Boxplot of mean things learnt over time for different durations of agenda items 64
Figure 24 Boxplot of mean things learnt over time for durations of agenda rounds 65

Figure 25 Lineplot average of mean things learnt over time of both cases 70
Figure 26 Boxplot of average of mean things learnt over time blockchain experiment 70
Figure 27 Boxplot of average of mean things learnt over time windmasters experiment 71
Figure 28 Boxplot of average of mean things learnt over time for different sharing energy decays for the blockchain case 72
Figure 29 Boxplot of average of mean things learnt over time for different sharing energy decays for the windmasters case 72
Figure 30 Boxplot of average of mean things learnt over time for different processing energy decays for the blockchain case 73
Figure 31 Boxplot of average of mean things learnt over time for different processing energy decays for the windmaster scase 73
Figure 32 Boxplot of average of mean things learnt over time for attitudes for the blockchain case 74
Figure 33 Boxplot of average of mean things learnt over time for different attitudess for the windmasterscase 74
Figure 34 Boxplot of average of mean things learnt over time for different relevance ratings for topics of others for the blockchain case 75
Figure 35 Boxplot of average of mean things learnt over time for different relevance ratings for topics of others for the windmasters case 75
Figure 36 Boxplot of average of mean things learnt over time for different agenda topic durations for the blockchain case 76
Figure 37 Boxplot of average of mean things learnt over time for different agenda topic durations for the windmasters case 76
Figure 38 Theoretical 'complete' knowledge set 81
Figure 39 Energy threshold for internalisation vs expertise - expertise is the total percentage of links and items known form a related 83
Figure 40 Mean things learnt for different processing energy variables. On the vertical facets are different base values for energy processing(the minimum value). On the Horizontal facets are different settings for the processing energy function mean. This is the mean of an exponential function that gets added on top of the base. 96
Figure 41 Population numbers of the model. The facets signify subsets of data based on sharing energy decay heights 98
Figure 42 Number of ticks per agenda topic. Faceted subsets are heights of sharing energy decays 99
Figure 43 Energy decays vs mean things learnt. The horizontal facets are subsets relating the link costs, the vertical facets relate to item costs. The costs for the sharing decay plot relate to sharing and the ones in the processing plot to processing 100
Figure 44 Mean things learnt over time. The horizontal facets relate to the duration of agenda topics. The vertical facets relate to sharing energy decays and the gradient relates to processing energy decay 102
Figure 45 Unshared links over time. The horizontal facets relate to the duration of agenda topics. The vertical facets relate to sharing energy decays and the gradient relates to processing energy decay. A decrease unshared links means that earlier unshared links have been shared for at least once 103

Figure 46 Unshared links over time. The horizontal facets relate to the duration of agenda topics. The vertical facets relate to sharing energy decays and the gradient relates to processing energy decay. A decrease in unshared items means that earlier unshared links have been shared for at least once 104

Figure 47 Mean things learnt over time. The horizontal facets relate to the duration of agenda topics. The vertical facets relate to sharing energy decays. The colours relate to the minimum number of items each topic has that are connected to other topics 105

Figure 48 Mean things learnt over time. The horizontal facets relate to the duration of agenda topics. The vertical facets relate to sharing energy decays. The colours relate to the minimum number of items each topic has that are connected to other topics 106

Figure 49 Mean things learnt over time. The horizontal facets relate to the duration of agenda topics. The vertical facets relate to the base processing energy and the colour relates to the mean of the processing function variable. This is the mean of an exponential function that gets added to the base value 108

Figure 50 Mean things learnt over time. The horizontal facets relate to the duration of agenda topics. The vertical facets relate to the base Sharing energy and the colour relates to the mean of the sharing function variable. This is the mean of an exponential function that gets added to the base value 109

Figure 51 Mean things learnt. The horizontal facets relate to the duration of agenda topics. The vertical facets signify the maximum relevance that a non-relevant 'other' thing can have and the colours relate to the maximum relevance of these items. Other or non-relevant things are items, topics and links that are not part of someone's relevant topics. The relevant topics are based on someone's affiliation 111

Figure 52 Mean learning over time. The horizontal facets relate to the minimum starting attitude someone may have towards others, the vertical facets relate to the maximum starting attitude someone may have. The actual attitude is uniformly distributed between these values 113

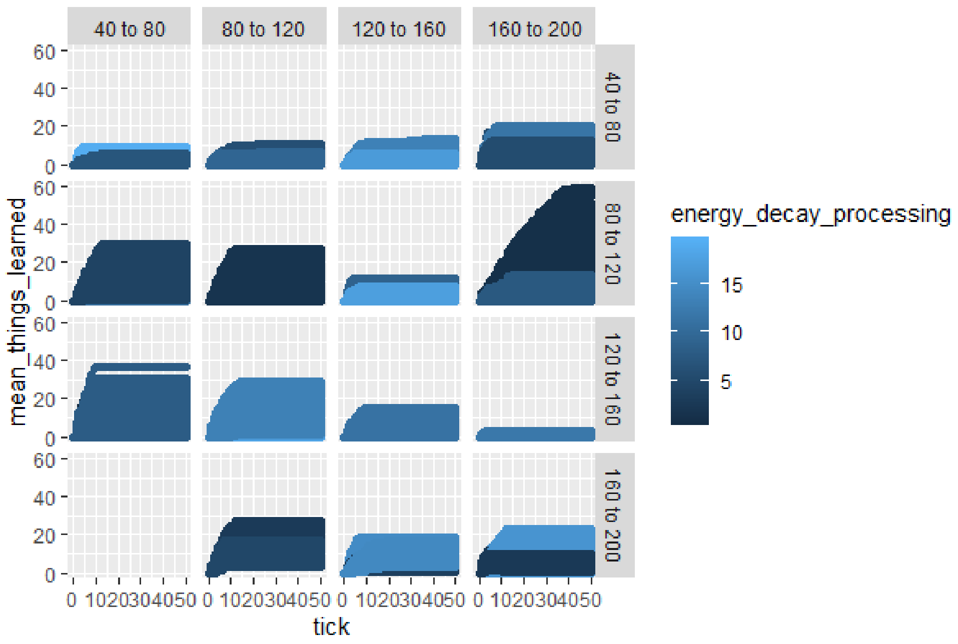
A SCATTERPLOTS EXPLORATORY ANALYSIS

In this section the preliminary data analysis of the experiment has been shown. Based on this more specific plots have been made that are more easily interpretable for others. These visualisation contain description of what can be seen. Note that interpretation can be hard if you do not know the model as well as I do or are not familiar with facet grids. Additionally less wokr has been put into the layout of the graphs compared to the main text

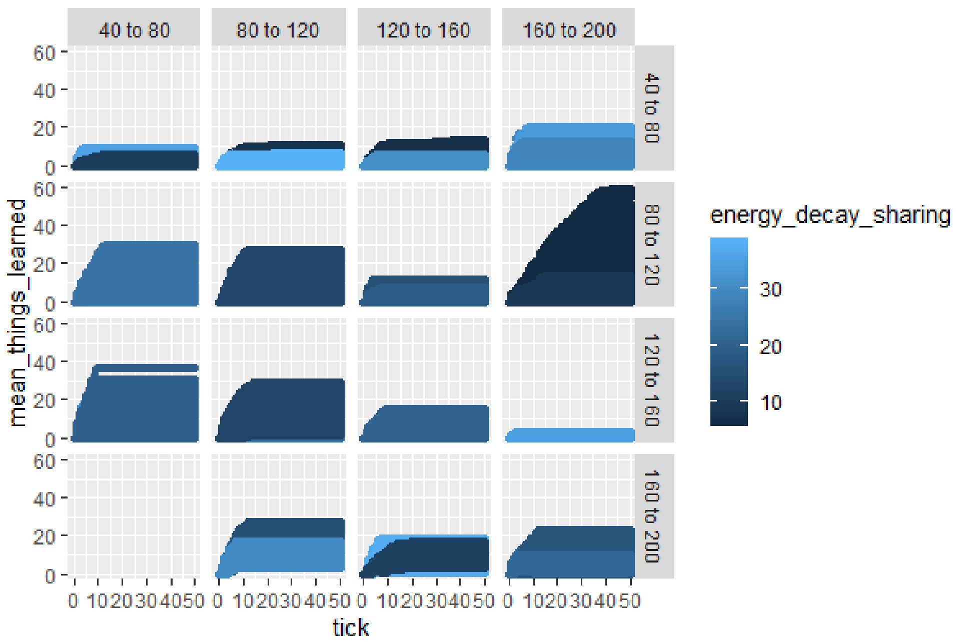
Processing energy

The first topic of investigation is the influence of processing energy, meaning the energy someone has to process and learn things actually influences the amount of learning. Additionally a look has been taken on the influence of the sharing energy decay, meaning the energy loss each round that someone has for sharing energy in the next round. A energy that is too low would lead to less or no information being shared and no learning in extension. Processing decay has also been included. This is the decay of processing energy at the end of each round

By looking at the plots (40) the largest influence seems to come from actual decays of energy. Both decay options lead to a high mean of things learnt when they are low as the highest mean come from cases where both sharing and processing decay are low. When sharing energy decay is high and and processing energy decay is low, even in cases with a high starting processing energy, one can see that the mean of things learnt evens out at low values. One can conclude that the sharing energy decay is likely the stronger predictor for what is learnt then the processing energy decay, although both are important. Because one can see heavy influence of sharing energy decay in the plot, the assumption that it results in similar behaviour past a certain value may be true.



(a) Mean things learnt vs energy processing decay in gradients



(b) Mean things learnt vs energy processing decay in gradients

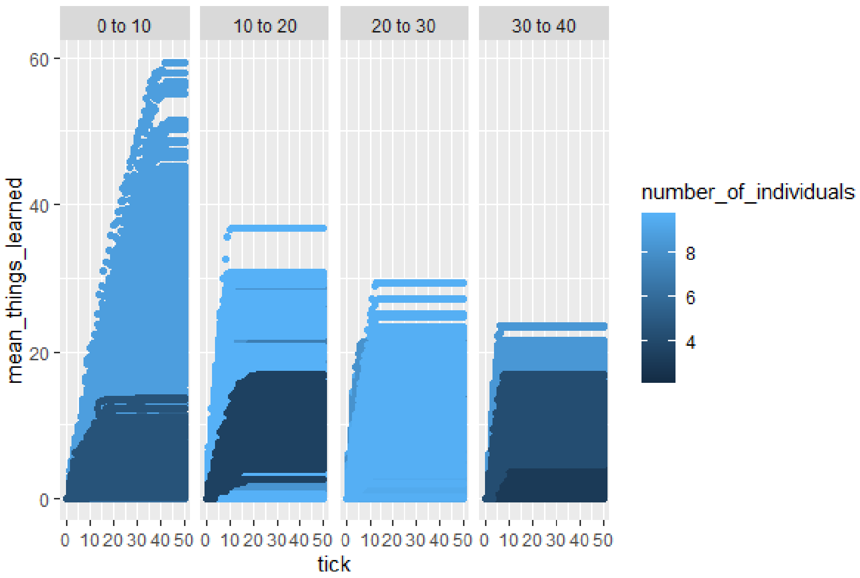
Figure 40: Mean things learnt for different processing energy variables. On the vertical facets are different base values for energy processing(the minimum value). On the Horizontal facets are different settings for the processing energy function mean. This is the mean of an exponential function that gets added on top of the base.

A.0.1 Number of individuals and information items

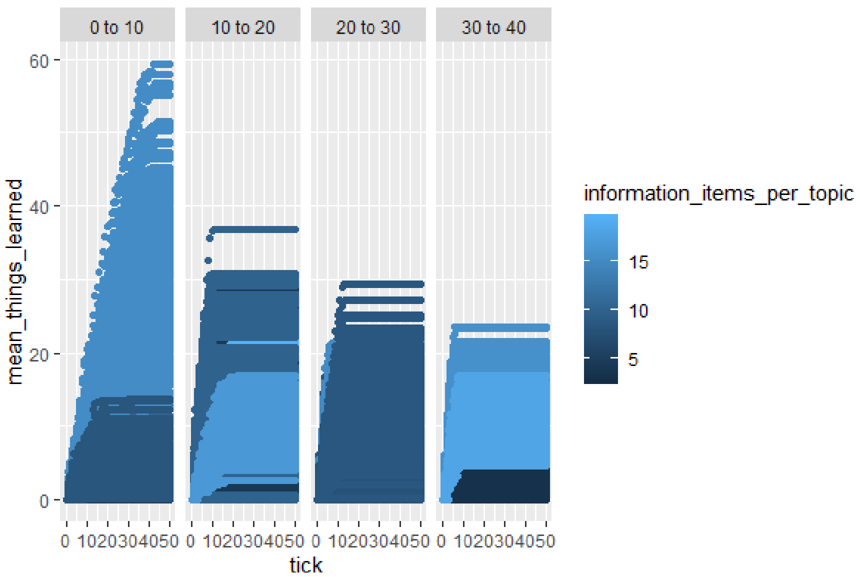
The second focus that has been investigated are the influence of number of information items per topic and the number of individuals participating. The first is the mean of an exponential function, determining how many items each topic has; whereas the second is simply the number of individuals participating.

When looking at the plots (figure 41a) one can see that many people sharing is great for learning, assuming people have the energy to share information (low sharing energy decay). This is quite an interesting observation as it seems straightforward and logical when comparing it to reality, but often overlooked. Namely, if more people are in a room, people learn more from each other if they all open their mouth and share information. If people are quiet, others will learn less. Assuming that information that is shared is of good quality, number of people sharing information could be a metric for in vivo experimentation if one wants to measure actual learning. This will be further discussed in the discussion of this chapter.

When looking at the importance of information items it also seems that topics with more items increase what is learnt (figure 41b). That a higher number of items per information topic leads to more learning is not surprising. If there are more things to discuss the chances that something new is shared are higher. This can be highlighted even further if an agenda item does not take too long as one can discuss a larger array of new topic if a topic is not yet discussed.



(a) Mean things learnt vs number of individuals in the model



(b) Mean things learnt vs number of information items per topic (mean of exponential function for each topic)

Figure 41: Population numbers of the model. The facets signify subsets of data based on sharing energy decay heights

To see if the cases with a lot more learning also had short agenda topics (ticks per agenda topic), meaning more chance to discuss new things, a plot has been made (figure 42). It indeed seems to be the case that the most extreme cases of learning had 1). a low sharing energy decay; 2) short agenda items; 3) a high number of individuals and; 4) a high number of information items per topic. One could surmise that in the case of the model, ensuring that a lot of sharing of information happens is paramount for learning. When compared with reality, these results should be taken with a grain of salt, however. In The model sharing energy and processing energy have a value that only decreases at the end of a round. In reality the energy likely fluctuates in a non-linear manner, during a round rather than at the end of a round. Having a larger number of things to process each round is also likely to be more tiring than having to process information shared by only one or two people.

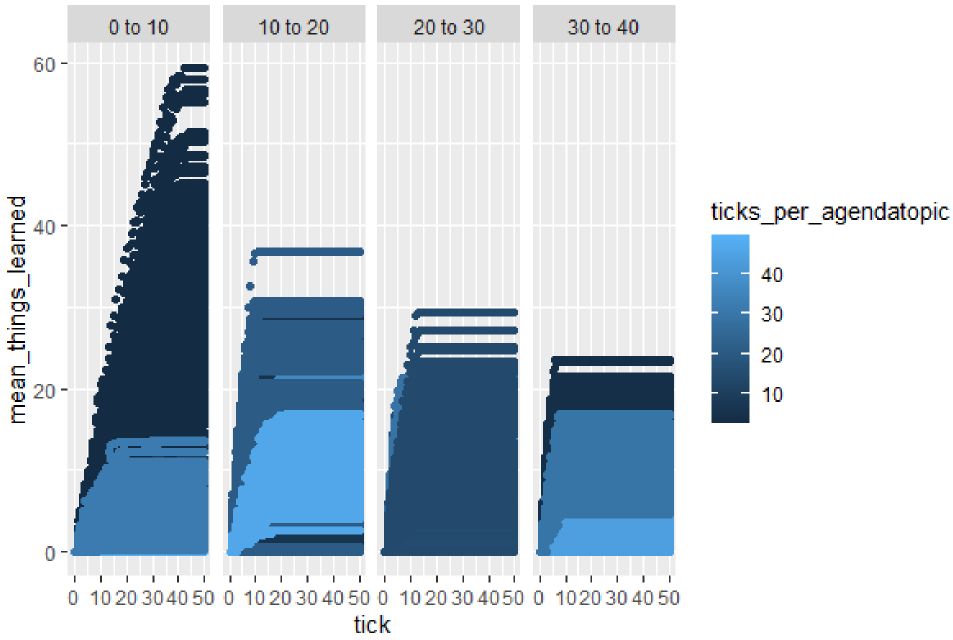


Figure 42: Number of ticks per agenda topic. Faceted subsets are heights of sharing energy decays

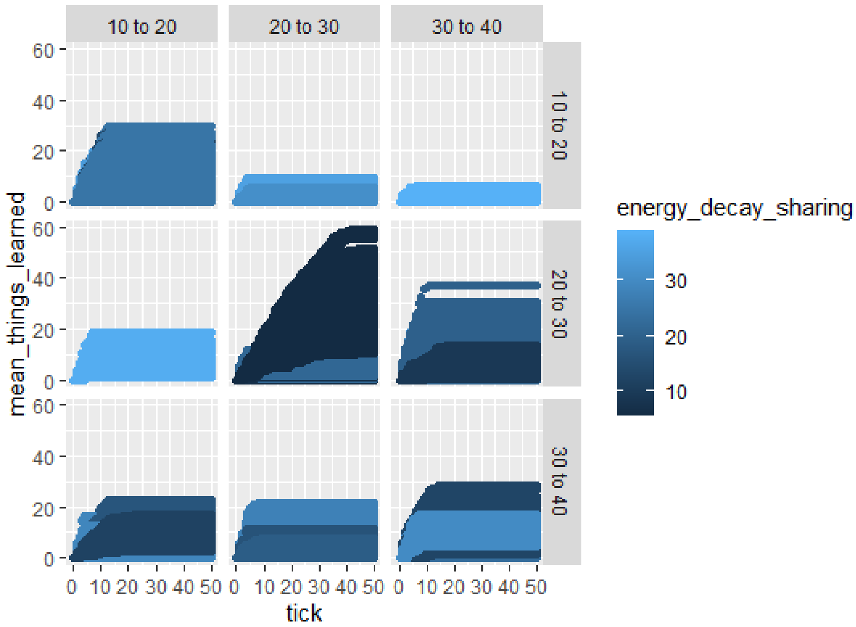
A.0.2 Processing and sharing costs

The final exploration has been focused on sharing and processing costs of links and items. These have been plotted with a gradient signifying related energy decays (figure 43). One would expect a higher decay and cost of both would lead to less learning. Note that these costs are not the actual costs per individual. It is a base value that gets influenced by matters like attitude, expertise and relevance of said items. This is the first observed behaviour that did not meet the expectation, but it is explainable by means of other model variables.

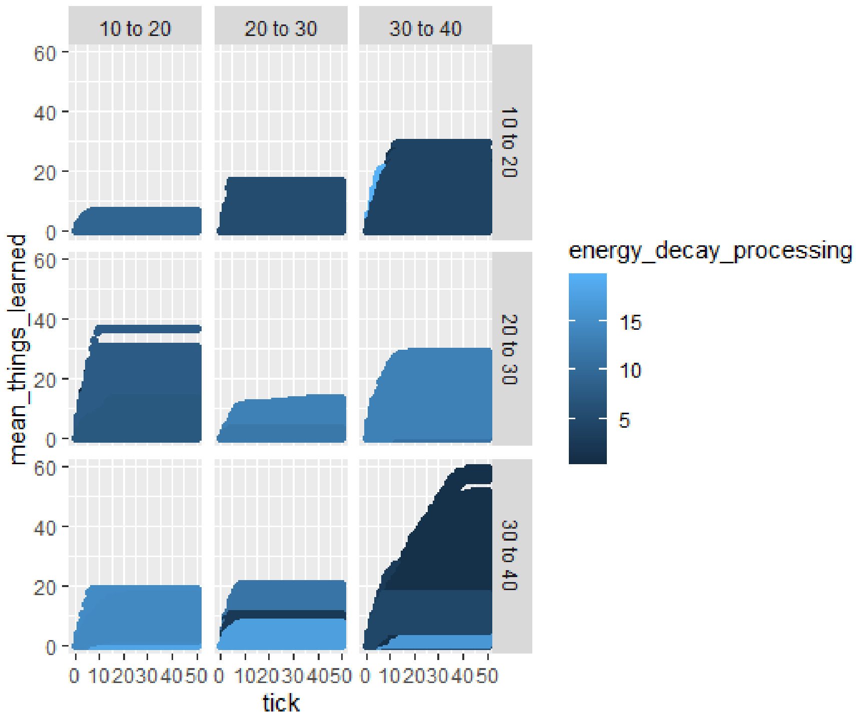
For processing energy one can see that with the average model settings processing costs do not seem to matter that much in the grand scheme of things as they get suppressed by the decay (figure **??**). This is not that strange as the decay of processing an item or link can be as high as the cost it. Furthermore it is likely that the average settings related to sharing energy decay may lead to high processing energy being irrelevant as there is less to process with lower sharing energy available (if nothing is shared nothing is processed).

With relation to sharing costs and decays one can see a somewhat larger influence of the related costs, however, these also get overshadowed by its decay (figure 43a). Based on this one can conclude that the processing and sharing decays may have been set too high on average. Assuming that the behaviour is correct, however, it may be interesting to investigate energy decay in vivo.

While in the model the decays are separate, just like the amount of processing and sharing energy someone has are separate, it is likely that they are in fact linked closely in reality in an interplay. If one not only needs more sharing energy, but spends more energy to make something clearer, the processing costs may decline. Spending more energy can then lead to having less energy in further rounds, where what is learnt is influenced heavily by this balance of sharing costs vs processing costs. This relation is not currently in the model, however.



(a) Mean things learnt vs sharing energy decay



(b) Mean things learnt vs processing energy decay

Figure 43: Energy decays vs mean things learnt. The horizontal facets are subsets relating the link costs, the vertical facets relate to item costs. The costs for the sharing decay plot relate to sharing and the ones in the processing plot to processing

B PRELIMINARY EXPERIMENT PLOTS

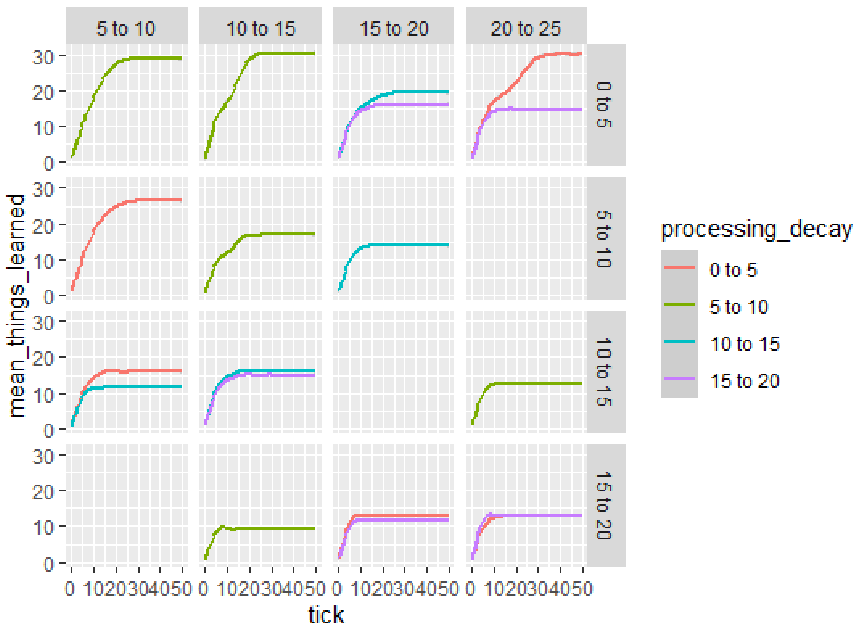
In this section the preliminary data analysis of the experiment has been shown. Based on this more specific plots have been made that are more easily interpretable for others.

B.0.1 Energy decay vs learning over different agenda topic durations

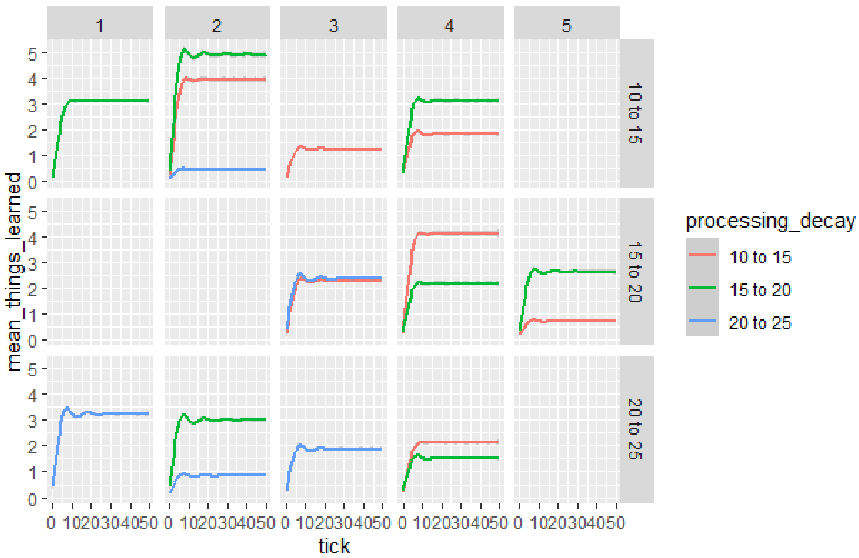
The first thing that has been investigated is the influence of an agenda on processes. This has been show in figure 44. The horizontal facets signify the amount of ticks per agenda topic. This is the amount of rounds it will take to switch to a new topic. These topics determine which items and links someone will share. Note that someone can still share information items and links if they are linked to an item from the agenda topic.

When looking at the plot from the wind-masters experiment (figure 44a) one can see that with a large amount of ticks per agenda topic learning slows down in cases where there is a large amount of processing and sharing energy (small decays). This means that eventually people will have discussed everything there is to discuss. Even if sharing of known items still happens it will be already discussed. If everyone that is capable has already learnt it nothing new will be learnt. With decays too high one sees that learning quickly flattens out.

Interestingly enough, the blockchain case (figure 44b with shorter agenda durations seems to still react to agenda topics taking longer. If agenda topics take more or equal then three ticks what is learnt is lower. This may have to do with the relevance of topics. If one switches agenda topics more often the chance is higher to discuss one that an individual deems relevant. If an item is shared that is unknown a individual will likely learn it. Note that the scales of learning are quite a bit lower then in the windmaster case and the decay values are higher as well.



(a) Windmasters

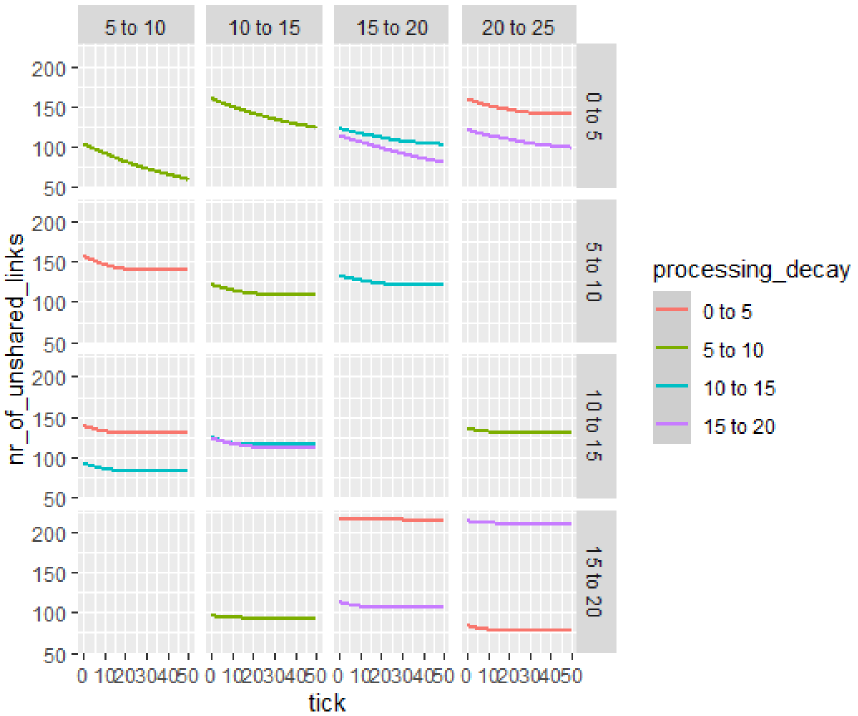


(b) Blockchain

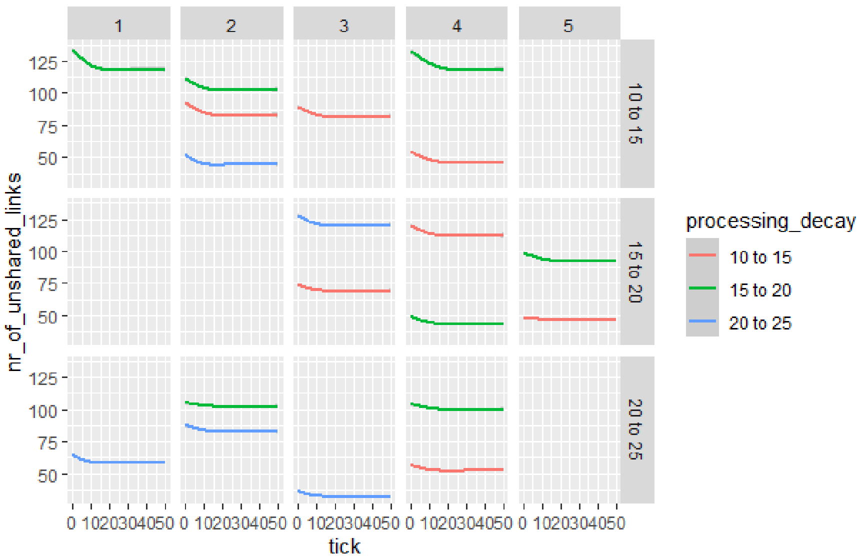
Figure 44: Mean things learnt over time. The horizontal facets relate to the duration of agenda topics. The vertical facets relate to sharing energy decays and the gradient relates to processing energy decay

When looking at the number of unshared items and links on can see that those flatten out more or less immediately with the maximum sharing decay in the windmasters case. However, the curve did not flatten out completely at the points where learning got slower. As both figure 45a and figure 46a did not flatten out completely there must either be a large pool of items and links in the topic or there is a higher degree of connectivity between items as there are still items being shared for the first time. Connectivity relates to the amount of links the items from a topic have with items from other topics.

When looking at the blockchain case one can see that sharing of links (figure 45b) and items (46b) quickly flattens out and that the amount of shared items and links is lower then the windmasters case. When looking at the minimum sharing decay in the blockchain case one can see that information sharing stops at around 20 ticks in the best of cases, whereas the windmaster case stops around 40 to 50 ticks for lower sharing energy decays. Sharing energy decay values above 10 may be too extreme for the model.

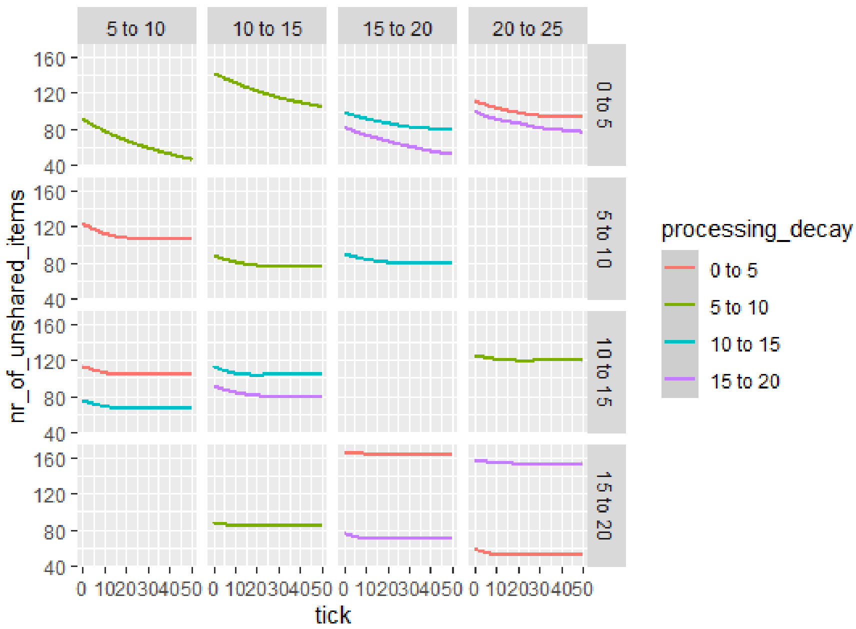


(a) Windmasters

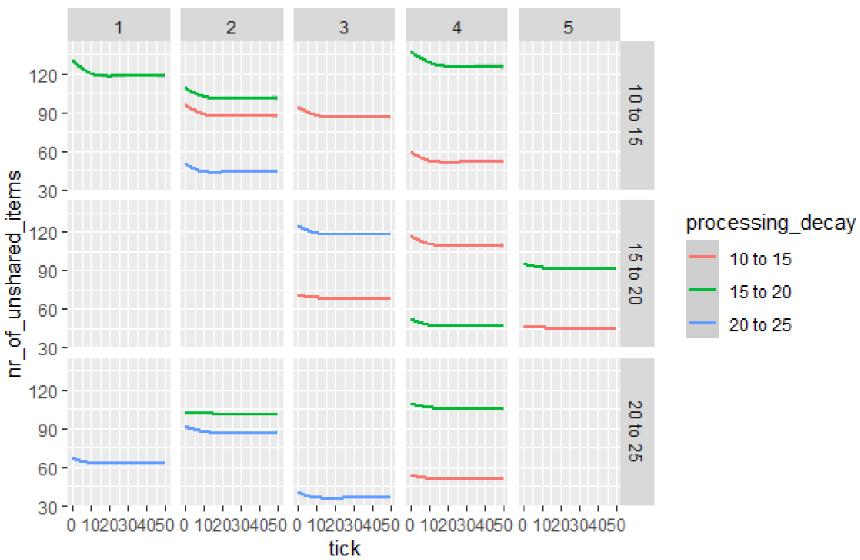


(b) Blockchain

Figure 45: Unshared links over time. The horizontal facets relate to the duration of agenda topics. The vertical facets relate to sharing energy decays and the gradient relates to processing energy decay. A decrease unshared links means that earlier unshared links have been shared for at least once



(a) Windmasters



(b) Blockchain

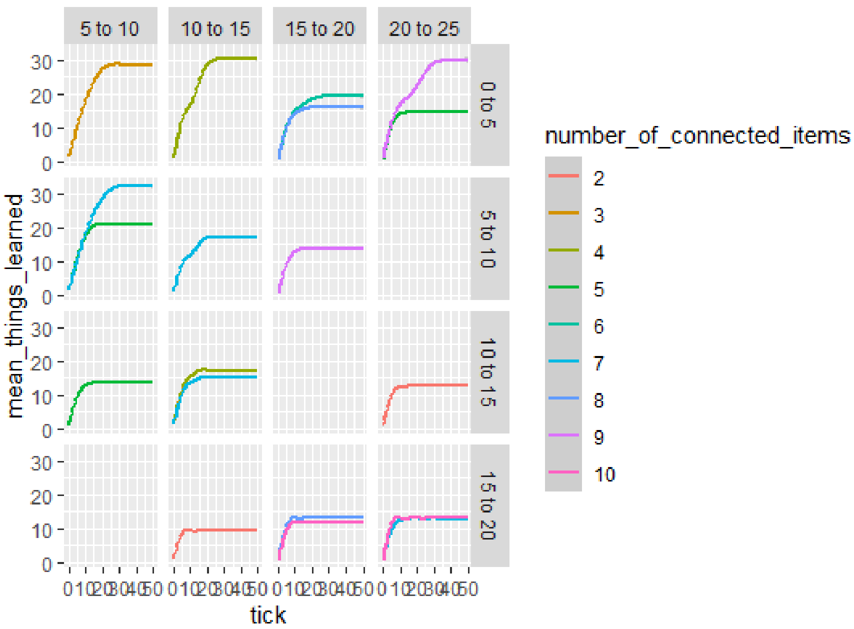
Figure 46: Unshared links over time. The horizontal facets relate to the duration of agenda topics. The vertical facets relate to sharing energy decays and the gradient relates to processing energy decay. A decrease in unshared items means that earlier unshared links have been shared for at least once

B.0.2 Number of items per topic and connectivity of topics

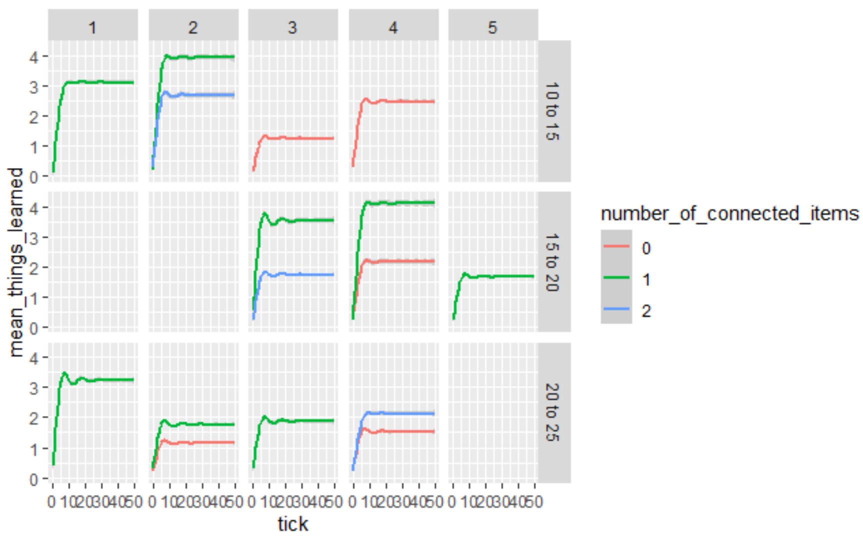
When plotting connectivity, it does seem to increase learning, assuming the energy decay for sharing is low. This is especially evident in the blockchain case where there are cases with no connectivity that always score less then the ones with any connectivity. Increasing the number of items per topic does not seem to fit the expectations. While there are cases where a larger number of items seems to increase learning this is not always the case. This is likely heavily influenced by things like processing and sharing decay as the curves seem to follow those of figure for the windmaster case (figure 44. For the blockchain case The sharing of items and links may be so low that the amount of items per topic does simply not matter.

Thus one can state that number of items per agenda topic is most influential if individuals have the capability to share them all and others find all shared things relevant enough. This was also surmised based on the exploratory analysis in the previous.

Connectivity is most important if either the amount of items in a topic is small, limiting sharing option or if others deem several topics as irrelevant.

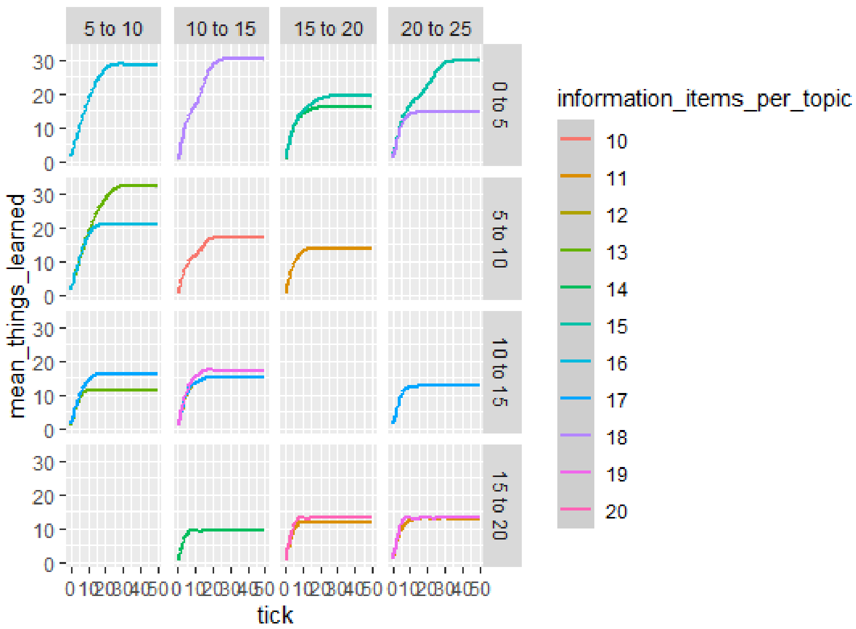


(a) Windmasters

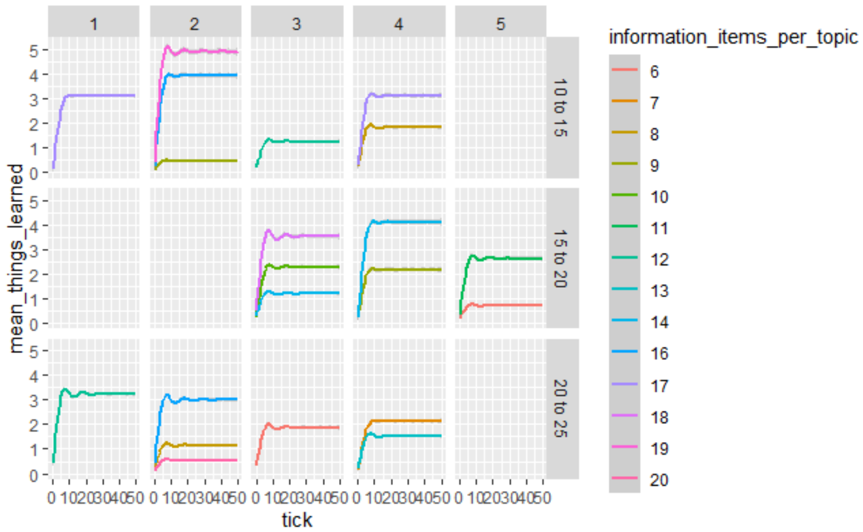


(b) Blockchain

Figure 47: Mean things learnt over time. The horizontal facets relate to the duration of agenda topics. The vertical facets relate to sharing energy decays. The colours relate to the minimum number of items each topic has that are connected to other topics



(a) Windmasters



(b) Blockchain

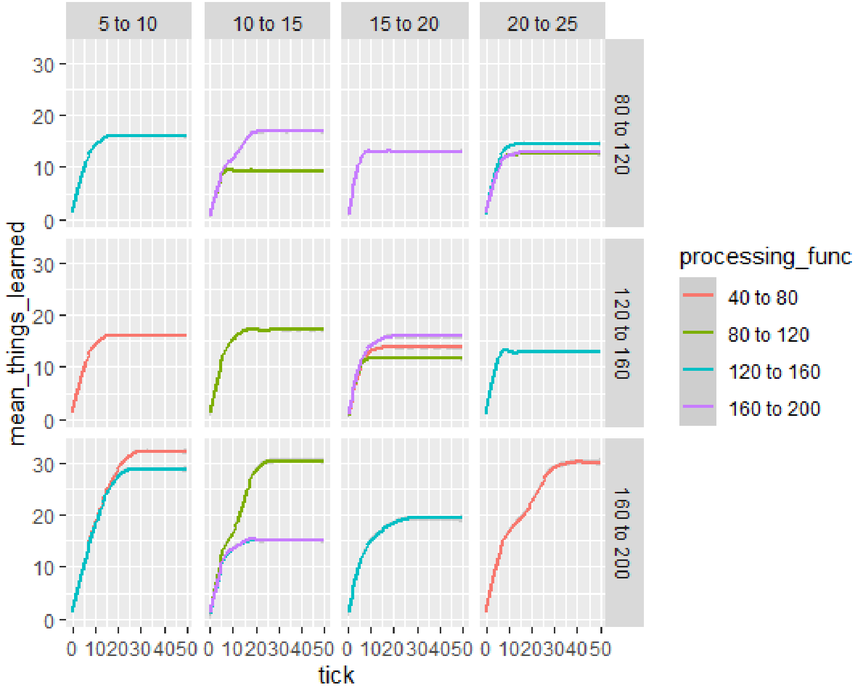
Figure 48: Mean things learnt over time. The horizontal facets relate to the duration of agenda topics. The vertical facets relate to sharing energy decays. The colours relate to the minimum number of items each topic has that are connected to other topics

B.0.3 Processing and Sharing energy vs learning over different agenda topic durations

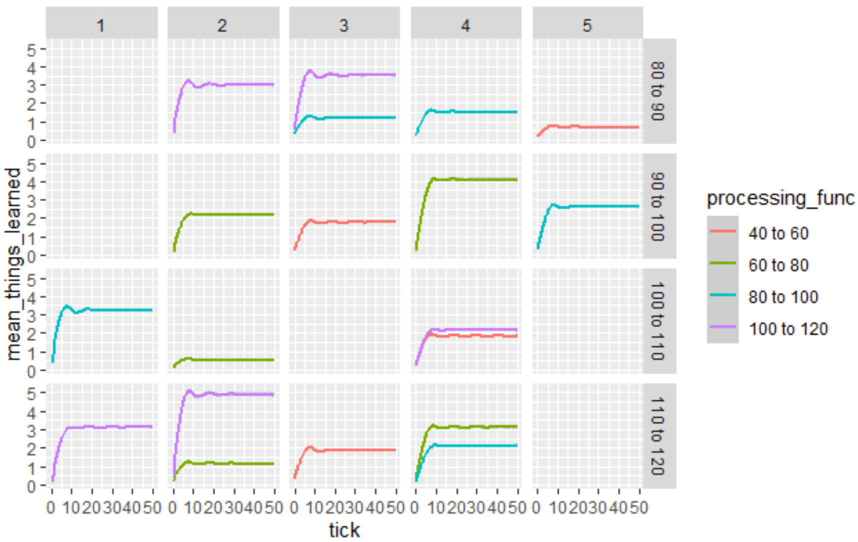
When looking at variables related to processing energy (figure 49), one can see that the base amount of processing energy is most important in the windmaster (figure 49a). This is not that strange as the function variable adds a value to that based on a uniform distribution. For example with a decay of processing energy of 20, a uniform distribution of 40 would add at most a single round of extra energy (between 0 and smaller than 40), whereas a base value of forty always add as much as two rounds of decay. In the blockchain case this is not the case (figure 49b). Here the function variable increases the amount of learnt things for the better in all cases when the value is between 100 to 120. However, the base value in the blockchain case does not seem to have the same effect. Chances are that the sharing energy decay is simply too high for the processing energy to matter much as all blockchain plots stop learning around 10 ticks. Another explanation could be the under-tuning of expertise. Expertise is a model variable determined by the amount of items and links from a topic an individual knows compared to the whole topic. A higher amount of known things leads to a lower value based on the expertise curve discussed in chapter 6 and defined in chapter 7. This value is multiplied with the base processing cost of an item or link to calculate the total processing costs. Important to note is that both the base and the function variable of processing energy for the blockchain case have lower ranges then the windmaster case

When looking at sharing energy (figure 50), one can see no clear patterns in the windmaster case (figure 50a). The S curve in to of the graphs for the winmaster case are reminiscent of earlier plots where there was a low processing energy (E.G. figure 44a), however. One could surmise that sharing energy decay has a higher influence in these cases than the starting energy, which are not low in any of the windmaster runs. In the blockchain graph one does see that a higher base sharing energy makes a difference for learning. The starting values in these runs may be more important as both the energy and processing decay are large. This would lead the the first few ticks being highly important for learning possibilities.

In general, however, one can assume that the impact of the sharing and processing energy decay is larger than the starting sharing and processing energy someone has. Here processing energy decay becomes less influential the higher the sharing energy decay is. When relating this to reality this graph further highlights the need to investigate the balance between energy decay (or fatigue if you will) and the sharing and learning of things.

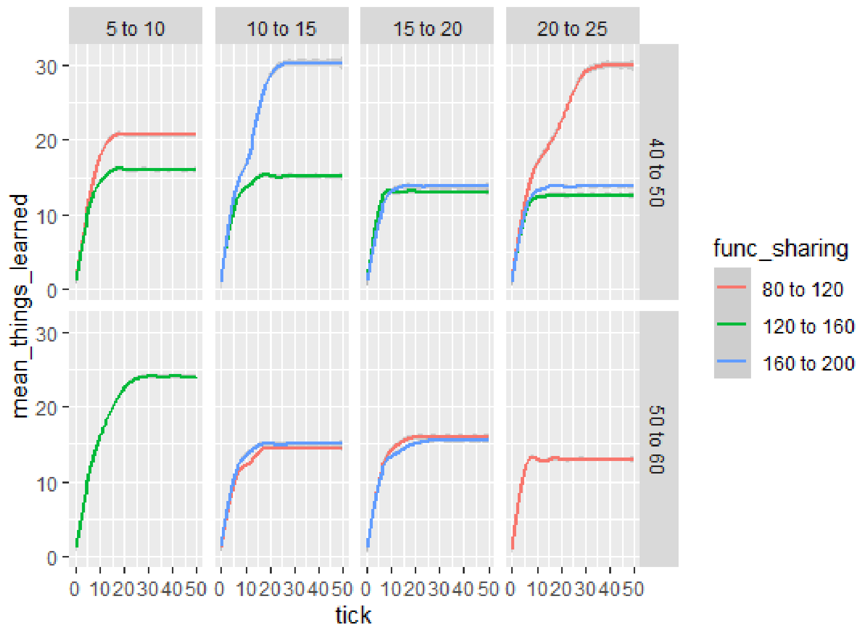


(a) Windmasters

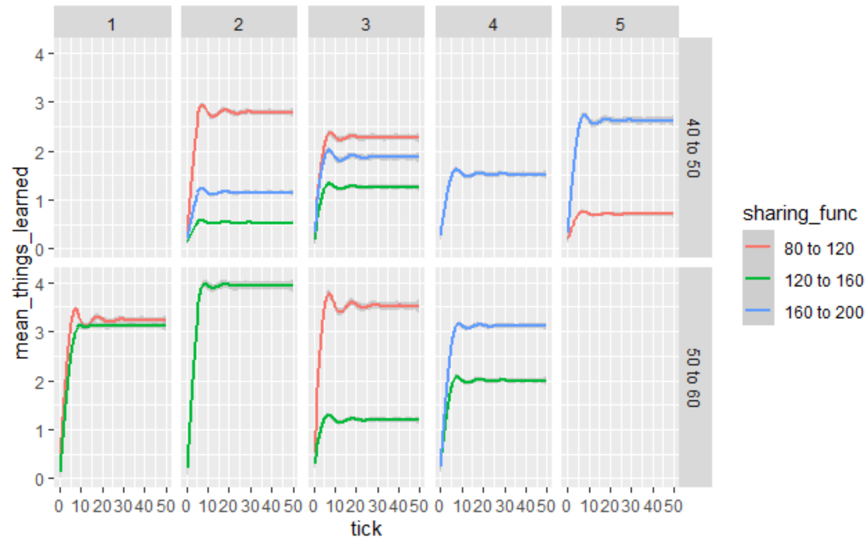


(b) Blockchain

Figure 49: Mean things learnt over time. The horizontal facets relate to the duration of agenda topics. The vertical facets relate to the base processing energy and the colour relates to the mean of the processing function variable. This is the mean of an exponential function that gets added to the base value



(a) Windmasters



(b) Blockchain

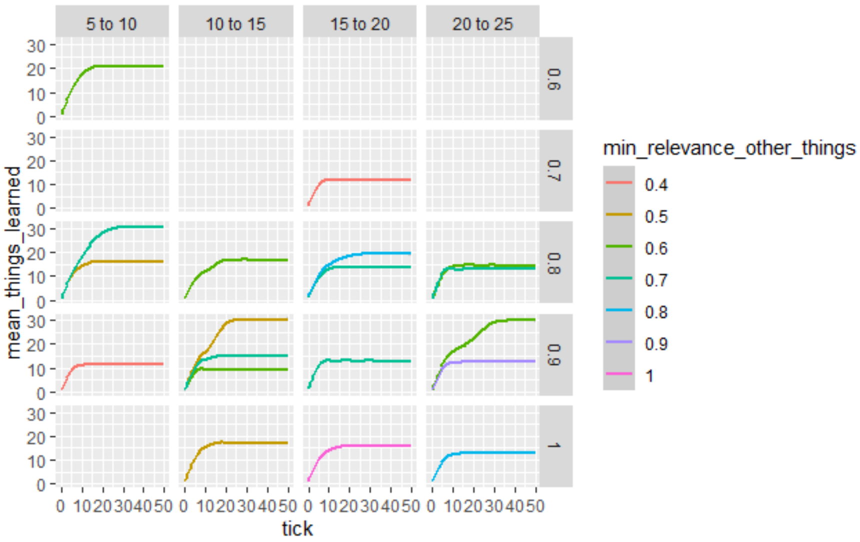
Figure 50: Mean things learnt over time. The horizontal facets relate to the duration of agenda topics. The vertical facets relate to the base Sharing energy and the colour relates to the mean of the sharing function variable. This is the mean of an exponential function that gets added to the base value

B.0.4 Relevance vs learning over different agenda topic durations

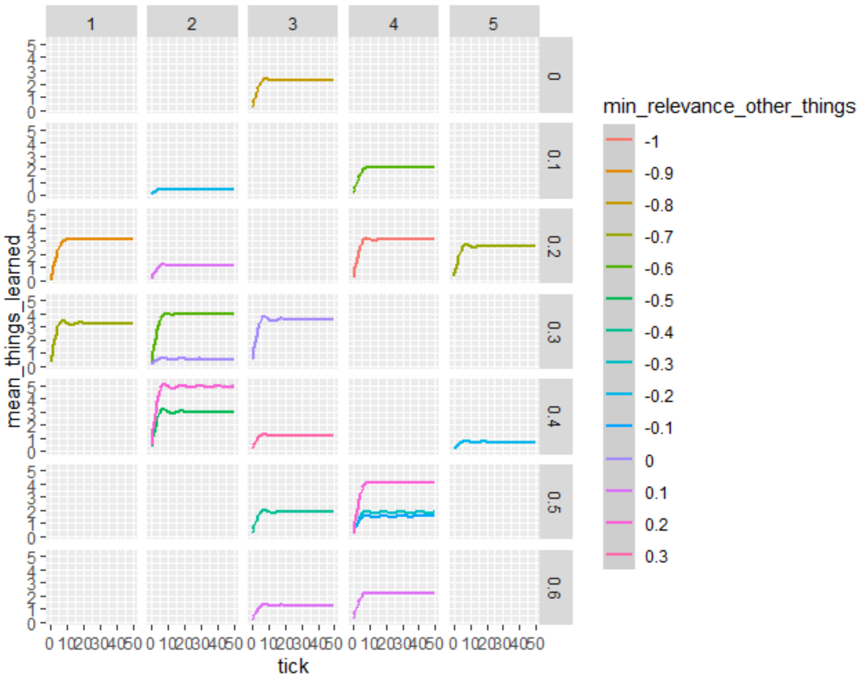
When looking at the relevance of non-relevant items and links (the topics that fall outside of someone's own work), one first needs to consider how to interpret the graph. To read these graphs correctly one needs to consider the colour signifying the minimum relevance first. A minimum relevance of 1 with a maximum of 1 would give a relevance of 1 always. With a minimum value of 0.9 this becomes a value between 0.9 and 1. (note that the values in the graph are rounded). Thus pink is a higher relevance then purple in all cases.

In the windmaster case (figure 51a) one can see no predictable differences at first glance. When looking at the curves of the graphs, one can see that the only lines with a lower minimum relevance that break the pattern are all S shaped. From earlier plots we know that these lines are coupled with a low sharing and processing energy decay. All other lines follow the pattern where the higher minimum value leads to more learning. Based on this one can assume that with an energy decays lower than 5, relevance is less important if all relevance values are positive and one has high starting values for energy sharing and processing. When one does not have an over-abundance of energy, the minimum relevance values are important.

In the blockchain case (figure 51b) one can see that minimum relevance values that are negative always perform worse than ones that are positive. Of note is that the numerical differences between the lines in the blockchain graphs are higher than those in the windmaster graphs and the larger range of values makes interpretation beyond this observation difficult. Further analysis regarding relevance may be needed. Furthermore one could change the model to increase the influence of relevance on either sharing, processing or both.



(a) Windmasters



(b) Blockchain

Figure 51: Mean things learnt. The horizontal facets relate to the duration of agenda topics. The vertical facets signify the maximum relevance that a non-relevant 'other' thing can have and the colours relate to the maximum relevance of these items. Other or non-relevant things are items, topics and links that are not part of someone's relevant topics. The relevant topics are based on someone's affiliation

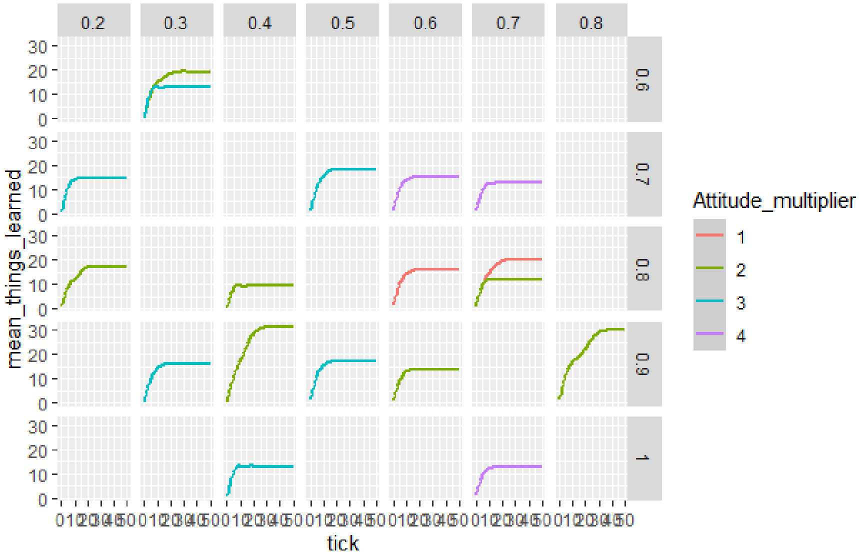
B.0.5 Attitudes vs Learning

When looking at attitudes of the windmaster case (figure 52a) one can see that the maximum attitude one can occasionally lead to more learning, but this is not always the case. Furthermore, the highest graphs in windmasters follows the S curve, meaning that it has a low sharing and processing decay. Another odd thing is how the attitude multiplier does not seem to increase learning with a substantial amount.

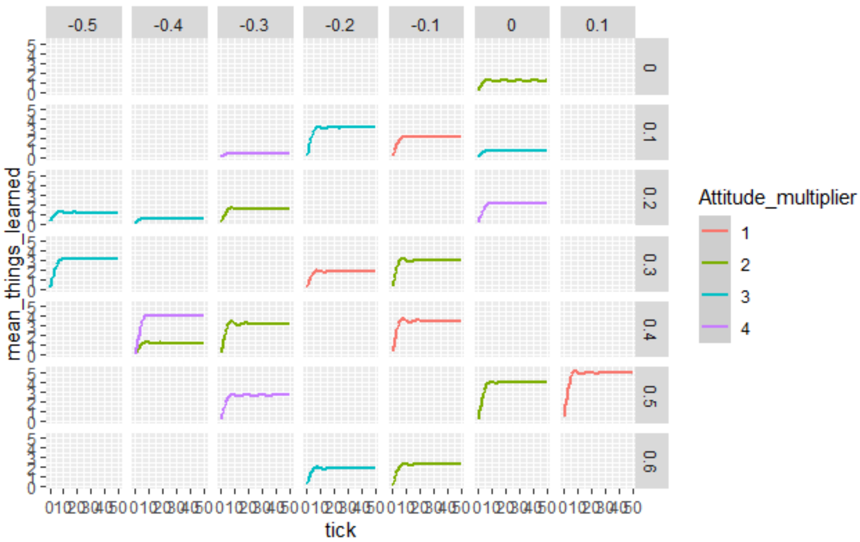
A high attitude increases the amount of processing energy available for learning. The multiplier increases this.

Considering the model settings it may be the case that a low energy sharing decay leads to items and links being discussed more often, increasing its sharing frequency. After a few rounds this frequency modifier gets bigger, making attitudes matter less. A higher relevance of items also increases processing energy.

When looking at the blockchain case (figure 52b) the attitude multiplier does seem to have a large effect in a single case, but it does so in a peculiar case. The attitude multiplier makes the effect of both positive and negative attitudes twice as strong. In the case where a difference between multipliers is clearly visible the mean of the attitude will be 0 (note it is rounded so likely not exactly 0). With such a mean learning could have also been lower with a higher multiplier as there are negative attitudes. Other than this oddity one is able to see that negative minimum values with low maximum values are bad for learning. The blockchain case is, however, likely a 'purer' indicator of how attitudes influence learning as sharing as sharing frequencies are likely to be low.



(a) Windmasters



(b) Blockchain

Figure 52: Mean learning over time. The horizontal facets relate to the minimum starting attitude someone may have towards others, the vertical facets relate to the maximum starting attitude someone may have. The actual attitude is uniformly distributed between these values