Customized and Autonomous Learning in Computer Science: A conceptualized Learning Activity Recommendation System

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I am grateful to the University of Bergen for offering me the opportunity to teach other students programming in the role as group leader for the course “Introduction to programming”. This experience has allowed me to grow in the role as an educator and has been a large inspiration for my thesis.

Though being a master thesis amongst countless others, the ideas I wish to emphasize are products of my genuine passion for teaching, and I hope my work can contribute to the vast collection of didactical literature and inspire future growth within the Norwegian education system.

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Contents

Chapter 1. Introduction

1.1 The relevancy of computer science

Computer science knowledge has become increasingly relevant for numerous disciplines. Modern technology dependant on information systems is soon to be integrated into every aspect of society, and the demand for competence to apprehend these tremendous amounts of data and digital tools is as high as ever. As a result, programming courses are becoming part of more majors than just computer science. However, computer science courses in higher education remains known for having relatively high failure and dropout rates[1] where 25-33% of students fail.[2,3,4,5]

1.2 Challenges of teaching programming

Due to the many aspects of programming which students must learn in parallel, such as syntax, problem solving, semantics, abstract thinking, etc., students are frequently driven into a cognitive overload. One reason for this could be that many students might not be prepared to think algorithmically when entering their first programming course. In most aspects of education, students are only exposed to numeric computation, and might lack the ability to solve problems by producing a formal stepwise algorithm. This process can be broken down to stating the problem clearly, breaking down the problem to well defined, smaller problems, then eventually solve the sub tasks by a step-by-step solution.[6]

Additionally, students enrolled in programming courses are dependent on correlating their programming knowledge with a programming strategy, where programming knowledge can be defined as the syntax and semantics of a specific programming language while a programming strategy describes how the knowledge should be applied to solve a given problem.[7] Robins[8] suggests that programming courses should contain a significant focus on teaching programming strategies in addition to programming knowledge.

1.3 Programming in Norwegian schools today

In response to high failure rates and technological advancement, many countries are renewing their curriculum to better prepare students in secondary school for this development.[9] The Norwegian curriculum was renewed in 2020 (known as "LK20"). Following the renewal, programming is specifically mentioned to students as early as 5th grade, and where algorithmic thinking is already introduced from 2nd grade to enhance problem solving skills.[10]

When a drastic academical shift like this occur, the competence of the educators does not necessarily keep up with the change. Teachers have expressed deficient programming knowledge when the curricular change took place.[11] While being mostly supportive of the new curriculum, many teachers are unhappy with the lack of support, courses, and subject didactics. They also feel the time to prepare themselves for teaching algorithmic thinking have been too short.[12]

1.4 Potential improvements of the educational sector

As a society, education is one of the most important sectors to ensure our future economically, politically and socially. This emphasizes the importance of making learning in academical institutions as efficient as possible. The learning process is a complex mental development. The teacher's role is to facilitate learning for students by designing curricular activities which addresses the students' academical level and learning preferences.

This quickly becomes a challenge with large cohorts of students. Teachers can only lecture at a single academic level and strategy simultaneously while students' understanding of the content is vastly dispersed, meaning classroom activities are either hampering the most capable students' learning potential by teaching at a lower level or leaving the least capable students behind by teaching at a higher level. Teachers can only stimulate certain learning modalities simultaneously regardless of what student preferences are, squandering individual potential of understanding the content better.

There is no simple answer to how to design ideal classroom activities due to the various preferences and capabilities students possess, where the teacher is additionally often limited in their role by external conditions. There exist various strategies which can be utilized to facilitate learning, ranging from utilizing natural traits such as memorization and motivation to didactic principles such as active- and visual learning.

The field of didactics is looking for ways of employing theoretical concepts to establish more effective and appealing learning. I believe the biggest problems in educational institutions today are the large workload teachers are faced with which limits their teacher role, and the lack of addressing students' individual learning potential and preferences in classrooms. Teachers are given barely enough time to design classroom activities and pre- and post-processing of assessments all while they are burdened with a large social responsibility in lower education. The classrooms of today have been "upgraded" with electronical equipment, both for individual and collective use, however, the learning form is still traditionally teacher centred. I believe technology, which have proved useful for automating numerous processes in society, has untapped potential in the educational sector where information systems could be utilized to help automate and improve educational activities for both students and teachers.

Learning activity design and learning content modality is crucial in order for students to maintain both motivation and understanding throughout a course. Finding classroom activities which facilitates this is an important job for teachers. Research has been conducted on alternative learning activities and modalities, where game based learning is frequently mentioned as a promising learning activity. I believe game based learning can be an ideal learning modality for youth today, however, there has not been conducted enough empirical research regarding game based learning to prove its effectiveness.

I wish to address the problems of student motivation by suggesting game based learning as a valid mediation of educational content, and the problems of large teacher workloads and lack of individual adjustment of learning material by designing a conceptualized information system which automatically recommends appropriate learning material for students. Though technological educational aid does exist with case by case examples with minor impact on the learning process, I wish to discuss what advantages can be derived from a potential thorough implementation of an automated recommendation system of learning material in the educational sector.

Chapter 2. Didactic Preliminaries

2.1 Didactics

Didactics can be defined as a design based on theory intended to teach.[13] Hernández[14] differentiates pedagogy from didactics by explaining how pedagogy is the science which studies the learning process at a social level, while didactics analyses the learning process on an institutional and theoretical level. The content of pedagogical knowledge is based upon the experience and practice each individual teacher have separately, not a collective knowledge forming a thorough discipline.[15] Marius-Costel[16] differentiates didactics from pedagogy in depth by a division of didactical concepts into respective principles:

Didactical principles summarized:

- The principle of *conscious and active participation of students* in the educational process emphasizes the active participation of the ones being educated, urging them to meet the subject with a conscious attitude and actively participate in the didactic activity. This helps bringing the subject down to a comprehensive dimension by making the students correlate previously built information with the newly acquired one.
- The principle of *thorough acquisition of knowledge, skills and abilities* emphasizes the gradual increment of knowledge and complexity throughout a course. Different information should avoid being presented simultaneously, and the revision of the information should not become a rigid routine to maintain student motivation.
- The principle of *accessibility and individuality* states that the design of a learning activity should consider a series of properties in the students: Age, sex, level of anterior training, physical and intellectual potential, motivation and social factors. By mapping previous knowledge in students and customize the learning activity with respect to individual interests can increase student dedication to the learning activity.
- The principle of *connecting theory with practice* emphasizes that to simultaneously reinforce the understanding of course content as well as the intrinsic motivation for the subject, the information obtained by the student needs to be transferred into practical value. This is obtained by connecting the newly obtained information to previous experience of the student or demonstrating a new concept which relevancy is acknowledged.
- The principle of *systematization and continuity* ensures a systematic acquisition of information. It is beneficial for a subject to be educational-logically structured. The

information should be presented in logical sequences with a certain coherence, which stepwise build an understanding of the subject. The teaching-learning activity should form a perspective of the educational paradigms and allow students to make cognoscible connections.

- The principle of *intuition* suggests that learning should rely on an intuitive basis. Making the learning sensorial by giving students a direct perception or intermediated substitutional perception of reality brings the subject down to a more comprehensible dimension.
- The principle of *reverse connection* reinforces obtained knowledge. Certain concepts or behaviour should be possible to be confirmed using the taught material. This is obtained by establishing an objective at the very start of the learning activity which reflects the course of actions, and by applying the theory to practical instances to prove its applications.

While these didactical principles are a generalization intended to be applicable to any field of education, they can be interpreted as highly relevant for programming courses. Solving a programming problem requires an active participation of the student, where the answer to programming problems is rarely obtainable solely by memorization but requires a set of problem-solving skills. This is well depicted by the principle of conscious and active participation. Like mathematics, given a problem statement, the learner needs to actively perform operations to advance towards a correct solution. Theoretically, the solution could be known to the learner by memorizing the problem statement and answer from previous experience, but this approach misses the intended learning goal of education. The memorization of formulas and algorithms, which can be obtained by rote learning, might suffice to produce the same results in an imitative approach. But the goal for courses in higher education is usually for the learner to develop a creative set of problem-solving skills based on a deeper understanding.[17,18]

Developers of the educational tools "Hedy" and "ProfessorJ" emphasizes the principle of thorough acquisition of knowledge, where programming concepts need to be gradually introduced to the students beginning as the simplest "Hello world!" programs, eventually progressing into more complex data structures and algorithms.[19,20] Given a 73% rate of compilation errors in student submissions due to syntax errors, which is recorded as high as 50% even for the most competent students, Hermans[19] argue that syntactic details should be gradually introduced to novice programmers to maintain focus on programming concepts instead of spending precious classroom time and resources on interpreting error messages.

At the same time, it is reported that teachers express that introductory programming courses are becoming harder to teach instead of easier.[21] In contrast to most other disciplines which have been taught for centuries, computer science is still in its early stages and lacks educational experience. At the same time, the content of the subject is drastically changing and increasing on a short-term scale: group work, implementation of GUI, debugging tools, refactoring and other topics are common modules of introductory courses which were much less present just a decade ago. As an answer to this, gradually introducing concepts one by one is one solution to avoid work- and cognitive overload.[21]

Programming courses being integrated into other majors raises the problem that lack of motivation can be an issue for many non-computer science (CS) major students. The principle of accessibility and individuality emphasizes basing the pace and content of the course on the different backgrounds student may have. At the same time, given the fact that computer science is already integrated into most scientific professions, relating the activities of a programming course to the respective majors of students should be possible in most cases to increase motivation, which is fulfilling the principle of connecting theory with practice. Forte[22] concluded that tailoring an introductory programming course for nonmajor CS students instead of having them participate in the traditional course resulted in higher success rates and the respective students expressed fewer negative reactions towards the course. Students enrolled in the tailored courses had many reported students interested in taking additional CS courses with content related to their majors.

The remaining principles describe how the content should be organized and presented to maximize the educational outcome for students. To make programming and related concepts intuitive for students to grasp, which are abstract concepts in many cases, is a big responsibility of the educator. These concepts have high potential of being better understood through metaphorical, visualized and interactive teaching strategies. For example, graph algorithms have a high visualization potential, concepts such as functions can be mapped to anterior mathematical knowledge, and data structures can be presented metaphorically for students to faster grasp the core ideas. Chibaya[23] conducted research resulting in a group of students enrolled in a programming course heavily reliant on metaphorical representation of programming concepts outperforming the control group of the experiment. Having a metaphorical approach to teaching can manifest deep learning for students more intuitively.[24]

While this division into principles is a general description of didactics, more specific models of how these and similar principles can be interpreted and integrated into education have been developed.

2.2 Didactic models

A didactic model is a representation of the educational process, containing selected elements to facilitate understanding and uncovering intermediate relationships between said concepts. Multiple models have been developed to better understand different aspects of didactics. Some are custom made for certain fields, while others are more generally applicable. These models are intentionally constructed to aid educators' analysis and educational choices of the courses they teach.[25] An experiment was conducted where teachers were asked what kind of didactic model they followed when designing their courses, where the teachers responded they did not have a certain model in mind. When a set of different didactic models for teaching programming were introduced to the same teachers, a discussion was sparked about which model reflects their strategy the most.[26] This indicates the usefulness of didactic models to classify different teaching strategies, though this might be rarely actively utilized by teachers.

2.3 The didactic triangle

One of the most frequently mentioned models is the didactic triangle. The didactic triangle's motivation is to be used as a pattern to better understand the correlation between the three aspects of education: teacher, student, and subject.[27] The three aspects of the triangle are each playing a role in the learning process, and implies relationships between student-subject, teacher-subject and teacher-student.[28]

The didactic triangle is a simple and generalized model, containing little detail beyond the obvious. It can prove helpful when developing other models and reflections about classroom scenarios. The model represents concepts of essence when analysing a learning environment. Role assignments, material approach for both teachers and learners, what kind of social setting the learning activity is taking place in and how the teacher should approach the learners most appropriately based on their previous experience and background can be deduced from the triangle.

While grasping the root of didactics, this model has also been criticized for not covering enough aspects to properly represent an ideal learning situation, where Schoenfield[29] emphasises the role which social/cultural factors plays within a classroom, which is not represented in this model. Schoenfield[29] discusses the existence of factors resulting in healthy learning environments which are non-analysable using the didactic triangle, encouraging farther research in identifying these factors.

In the case for teaching modern classrooms, the didactic triangle is also being challenged by another aspect, namely the role of the computer and how it affects the relationships within the triangle. It is argued that the use of artifacts within a learning environment is institutionally, culturally, and historically situated, and therefore defines a focal point of the education system.[30] For being one of the earliest models of education, the didactic triangle might not have considered the factor of modern tools and artifacts when analysing the educational process. With the computer partially taking over the role as an educator and being part of the learning material itself in programming courses, it seems almost impossible to properly teach the material without such artifacts being present in the learning process. With computers being absent from the field of informatics, the theoretical applications become unobtainable by human processing power and could be considered irrelevant or too theoretical by students.

A computerless CS course could be possible by having the educator going through all the necessary course material vocally, but the learning outcome would not include any practical training in programming strategies. With the absence of computers in the learning environment, there would not be given enough attention to volume training for programming strategies which as previously mentioned might be of equal importance as programming theory.[8] It could be argued that students could manage to pass programming courses without relying on artifacts like computers. However, by certainly proving useful for students' learning experience, including artifacts like computers into the didactic models of STEM fields (science, technology, engineering and mathematics) is appropriate.

A working group from the Conference of European Research in Mathematics Education (CERME3) presents another version of the didactic triangle: The triangle of themes, consisting of "the teacher's teaching", "the student's learning" and "the tool's mediation".[31] Their article emphasizes the importance of the role the computer plays in the learning environment for mathematics. The article concludes that students' understanding of geometry can be enhanced using technological mediations of the academical content, and certain theorems were shown to have practical properties which the students had not considered before the visualization by technological aid. Rephrasing the traditional didactic triangle's edge "subject" with "the tool's mediation" results in a more flexible definition, creating space for technological tools in the educational process.

To conclude the didactic triangle, it is frequently criticized by certain STEM fields for being too narrow to properly represent the learning process of modern disciplines. There are many opinions on how the model should be modified to be a better fit for certain courses, with many indications of the need for technological tools being introduced to the model.

2.4 Blooms taxonomy

In the year 1956 Bloom[32] released his book "Taxonomy of Educational Objectives: The Classification of Educational Goals". Its motivation was to create a classification to better understand the goals of our educational system. Familiar to most readers, the field of biology is consistently dependent on taxonomies to have a reliant method of communication and to build a common understanding of the field.[33] Bloom acknowledged the value of such a way to systemize a discipline to promote farther development. While researching what gives students a deep understanding of a subject; "… Such interchanges are frequently disappointing now because all too frequently what appears to be common ground between schools disappears on closer examination of the descriptive terms being used."[32 (p.1)] While lacking the vocabulary to properly discuss defined terms within didactics, it is close to impossible to create common ground to build a science upon. Bloom identified this problem, and together with a group of measurement specialists, they frequently met over the course of the 7 years prior to the taxonomy's release to discuss and produce said taxonomy for education.[34]

One of the first problems discussed by Bloom's group was the question of whether it would be possible to develop a taxonomy for phenomena which are unobservable and not possible to manipulate, unlike other physical and biological sciences. However, the group concluded that the individual- and group behaviour within a situation where educational objectives have been stated can be observed and described - and is therefore classifiable.[32] In the making of the taxonomy, they agreed upon protecting the objectives of any discipline, the possible loss of fragmentation, as well as the teacher's creative role in the planning of curriculum and in the classroom by creating the taxonomy with a level of generality with respect to said criterium.

The major purpose of having these well-defined terms to describe concepts and strategies within an educational framework is the facilitation of communication. Having an effective exchange of ideas and materials between institutions allows for better evaluating the effectiveness of different learning programs. Going forth from here, Bloom also emphasized the importance of the taxonomy being put together of appropriate terms, or “symbols” as he labelled them. They were required to be concise to promote communication between teachers, curriculum workers, administrative organs and any other who might find use of the taxonomy. The symbols representing different classes of aspects sharing common traits of the educational process needs to be objectively intuitive and usable, creating a consensus among users that this is a reasonable way to classify the field.[32]

The taxonomy does not aim to classify the methodology of teachers, the teacher-student relation or what kind of instructional material is being used. The goal of the taxonomy is to identify the “… intended behaviour of students – the ways in which individuals are to act, think, or feel as the result of participating in some unit of instruction.”[32] (p. 12) As a purely descriptive scheme, any kind of educational goal should be possible to be represented in a relatively neutral fashion. The taxonomy treads carefully to avoid making any value- or quality-based judgements, and is intended to be as inclusive as possible, where any given goal in the form of intended behaviour should be possible to be classified by the taxonomy. The taxonomy is divided into six major classes with respective subclasses (Figure 1), where the items are ordered from simple to complex and concrete to abstract. This ordering is intended to illustrate the cognitive progression the students undergo during an educational process.

Structure of the Original Taxonomy

1.0 Knowledge
- *1.10 Knowledge of specifics*
  - *1.11 Knowledge of terminology*
  - *1.12 Knowledge of specific facts*
- *1.20 Knowledge of ways and means of dealing with specifics*
  - *1.21 Knowledge of conventions*
  - *1.22 Knowledge of trends and sequences*
  - *1.23 Knowledge of classifications and categories*
  - *1.24 Knowledge of criteria*
  - *1.25 Knowledge of methodology*
- *1.30 Knowledge of universals and abstractions in a field*
  - *1.31 Knowledge of principles and generalizations*
  - *1.32 Knowledge of theories and structures*

2.0 Comprehension
- *2.1 Translation*
- *2.2 Interpretation*
- *2.3 Extrapolation*

3.0 Application

4.0 Analysis
- *4.1 Analysis of elements*
- *4.2 Analysis of relationships*
- *4.3 Analysis of organizational principles*

5.0 Synthesis
- *5.1 Production of a unique communication*
- *5.2 Production of a plan, or proposed set of operations*
- *5.3 Derivation of a set of abstract relations*

6.0 Evaluation
- *6.1 Evaluation in terms of internal evidence*
- *6.2 Judgments in terms of external criteria*

Figure 1, Blooms original taxonomy

From “A revision of Bloom’s Taxonomy: An overview”

Krathwohl (2002)[34]

The term “taxonomy” was not known to the educational sector prior to the release of Bloom’s book, however, many in the field quickly came to acknowledge the value it possessed. During many evaluations of test content across different disciplines, the model measured a heavy emphasis on the knowledge aspect of the taxonomy. Students did well by only revising the material and learning it by heart, all while the institutions in general wish for their students to develop skills within the comprehension, application and analysis section.[34] With repeatedly getting this result in different subjects, the objectives of the curriculums were pushed in the direction of the more complex categories to reinforce students’ understanding of their courses. Testing students’ skills by including questions from all six categories grants better measurements of where students tend to fall off during the course.[35] Students with poor understanding are usually able to answer questions related to the first couple of categories from the taxonomy, while struggling to answer questions based on the latter. Therefore, having an examination solely consisting of questions from a singular taxonomic level would not be a good measurement of students' complete understanding of the subject.

Another main function of the taxonomy is to help educators design their courses by identifying what level of understanding is required at every topic. Given this information, the distribution of time for each topic within a course can be more efficient.[36] Also, the taxonomy proves to be a valuable tool for designing course assignments, in-class activities, projects etc. to complement the current level the students should have advanced to at the given point in the course.

In a faculty involving many educators or organs, the model can be used as a tool of communication, where advanced courses can be founded upon the expected mastery of previous courses that students have already passed. Having a linguistic foundation to build a course upon, giving structure and clear goals to a subject, has proven to be effective for numerous disciplines.[37]

2.5 Bloom and Computer Science

Johnson et al.[38] raises the question whether Bloom's taxonomy is applicable for analysing the field of CS. The taxonomy has various interpretations, where some educators consider each cognitive level of the model to be applied to individual topics, while others consider it to represent the process of learning a whole study programme, where the final levels cannot be reached until later in the degree. When evaluating an assessment of a CS course in their study, Johnson et al.[38] noted a significant disagreement between the assessors over which cognitive processes were targeted by different assessment tasks. The academics who participated in the teaching of a CS course had a different view than those who did not participate in the teaching of the course. It was argued that this was due to two factors, one being the lack of general agreement on how to apply the taxonomy to CS courses, and secondly that to properly evaluate the cognitive process of the assessments, one need to have prior knowledge of how the course have been taught.

Other documented difficulties with the taxonomy include complications with classifying learning goals for each level of the taxonomy, precisely specifying what knowledge is relevant for each learning goal, and the difficulty of measuring the progress of students' understanding and problem solving.[39] Lahtinen[40] also criticises the linearity of the model, whereas some students could produce results identified by the latter steps in the taxonomy without the mastery of the first steps. This contradicts the hierarchical structure of the model, where the achievement of one cognitive level assumes the mastery of the previous ones.[41] All while Bloom envisioned the Taxonomy to be universally applicable to any subject, it proves difficult to utilize within CS. It deems valuable to establish a shared understanding of the taxonomy within computer science to properly make use of the model.[42] The taxonomy might be too generalized in its descriptions to establish a collective comprehension of the discipline.

Anderson and Krathwohl[43] concluded that in the original taxonomy, the knowledge section was inconveniently trying to describe a duality of concepts. When describing the objective of learning, the process is divided into the subject matter content and the cognitive processing of the same content. Anderson and Krathwohl[43] labels this section as an anomaly which needed to be eliminated, which motivated the revision of the taxonomy, which we refer to today as "the revised Bloom's taxonomy". In this model, many of the concepts were preserved from the original taxonomy but rephrased to be a better representation of its contents as well as being more convenient to refer to in practice. Especially with respect to the knowledge category, the taxonomy was divided into two dimensions instead of just one, having the first dimension consisting of the revised elements from the first taxonomy: Remember, Understand, Apply, Analyse, Evaluate and Create. The second dimension consists of four categories: factual, conceptual, procedural, and metacognitive.

Improved results have been presented when the revised taxonomy have been applied in place of the original.[44,45] However, the results were better for the educators who had undergone a certain amount of training than those who did not, suggesting a proper training for non-expert educators for increased performance. The most standard form for teaching programming is to cover the lower levels of the taxonomy during lecture-time (remember, understand), while the higher levels of the taxonomies (create, evaluate) are usually taught in isolation through homework projects.

A reverse classroom experiment was conducted by Sarawagi[46], where this division of course content was reversed. The content required to be memorized was presented through videos as homework, while the problem solving and implementation was being taught during lecture time. In this instance, the taxonomy was utilized to acknowledge what parts of the course are the most difficult to master, and the lecturer designed their course in such a way that the students are exposed to the lower-level knowledge aspects of the course at home, granting the lecturer as much time as possible to guide the students through the application, creation and evaluation levels of the taxonomy. Like Kiesler[44] concluded, this form of irregular educational design based on the revised taxonomy requires more experienced teachers to execute.

A paper of Olina and Sullivan[47] concluded that students receiving evaluation from their teacher and/or conducting a self-evaluation performed better than the students receiving no evaluation. The students in the self-evaluation group also showed a bigger confidence in conducting future experiments. Exploiting the revised taxonomy for self-evaluation has proved to give a good general picture of the students' current knowledge level.[44,48] The revised taxonomy also provides the teacher with a precise scale of what cognitive levels have been achieved by the student, lending a hand with planning the next steps of their course.

Following the ITiCSE 2007 conference, a working group formed to compose an alternative taxonomy which is specific to CS. By studying existing taxonomies and courses based on these, the work resulted in a two-dimensional matrix taxonomy, divided into two axes: interpreting and producing.[49] The interpreting axis is farther divided into 4 subcategories: remember, understand, analyse and evaluate, while producing is divided into applying and creating. There is also a blank row preceding the production levels, which allows the learner to categorically enter the interpreting phase independently before embarking on the producing aspect of the model. The levels of this taxonomy are designed similar to Blooms', where the elements of the model are ordered by the increment of understanding of the subject. The goal is for the learner to reach the level where they are capable of both creating and evaluating, however, the "learning path" for each student may vary depending on the student's own preference. Some student wish to first reach a certain understanding of the concepts before trying to implement their programs, while others form their understanding based on a trial-and-error strategy where they start creating from the first minute.[40] This flexibility in matrix traversal could prove helpful for teachers to map at what level – or what path the individual students are on at any given point, which highlights what farther steps should be the most helpful for the respective student to reach the depth of the taxonomy.

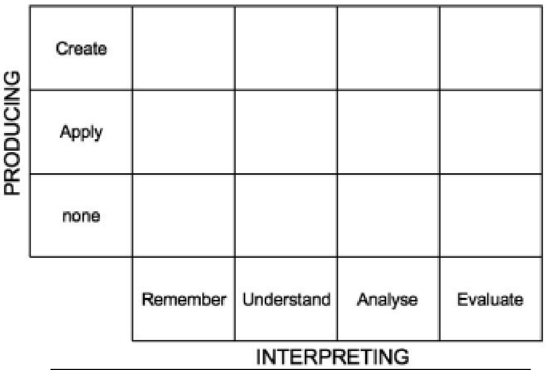

Figure 2: The two dimensional CS specific rework of Bloom's taxonomy

Fuller et al. (2007)[49]

Having a didactic model can be helpful to design the instructional material as well as a tool for measuring the evaluation of the students, but it is also of essence to discuss what criteria should be set for the teachers to be able to deliver an ideal learning situation for its' students.

2.6 Pedagogical Content Knowledge for Computer Science

Hattie[50] describes how the knowledge, competencies and beliefs of the teacher are the biggest factors for students' success in the educational process. However, teachers are accepted to have their "professional independence" with individual teaching styles, which results in a discipline where the quality of the teachers' work varies and often goes unquestioned. Having success with one cohort of students with a given teaching strategy does not imply the same results the following year for different students.

Some teachers might evaluate their students' performance before evaluating their own work's quality due to a mentality of "this have worked before". The vast difference between students of different backgrounds and experiences with previous teachers and learning environments pose a challenge for teachers to design their teaching and organize their classrooms. There is little use of discussing all the details and different aspects of a classroom environment when there exist limitless variations. However, we can discuss what should be expected competence of a teacher to lay a foundation for handling these scenarios and standardize the quality of CS education.[50]

Bender[51] claims that teachers having an adequate development during their own education is important to address the didactical challenges within the field of computer science. Teachers must build their courses upon their own sound understanding of the subject. Regarding the situation of programming education in Norway, many teachers are currently lacking this understanding as well as practical experience due to the sudden implementation of programming into the curriculum, where the teachers are lacking time, material and possibly individual motivation to welcome such a change.[12]

Shulman[52] emphasizes how the teachers' knowledge of the subject is crucial for the quality of their teaching. He differentiates between content knowledge and pedagogical knowledge, which can be equally important for teaching. Pedagogical knowledge can be defined as the different methods of teaching, consisting of general principles such as curriculum design, assessment design, pre-instructional strategies and formative testing.[53] The personalized experiences teachers might possess also falls under the pedagogical knowledge category. Content knowledge on the other hand consists of specified elements, definable to possibly create a common ground for the discipline across the board. Subject content knowledge includes the amount of knowledge a teacher has obtained, how it is mentally organized and the ability to be able to identify which ideas are considered truthful within a domain. Teachers must be able to explain why a proposition is worth knowing and how they relate to other propositions inside and outside of the discipline theoretically and practically.[52] This requires a deep understanding of the subject, which many Norwegian teachers have not got time to acquire in the CS learning objectives they are supposed to teach due to the sudden curricular shift.[12] There are many ways to represent content knowledge, where Bloom's taxonomy is a well-known model for this purpose. Like Bloom tries to emphasize with his taxonomy, content knowledge stretches beyond the pure factual knowledge of the subject to the dimensions of being capable of synthesising and evaluating the content and the intra-subject deductible relationships.

Knowledge regarding subject matter and pedagogical knowledge have been the primary focus when developing teachers in the past.[53] As previously mentioned, the methods of teaching are ideally flexible strategies to facilitate the subject in a personally fitting way for students, which is hard to define due to the disparateness of individual classrooms. The effort of obtaining content knowledge comes to no avail without teachers having developed what is called "pedagogical content knowledge" (PCK). PCK describes how teachers synthesizes their pedagogical knowledge in respect to their subject content knowledge. PCK aims to bring the subject down to an understandable dimension for their students through various fitting representations of the information. PCK includes ways of formulating and representing content to make it comprehensible for the students given the students' conceptions, preconceptions and potential misconceptions. PCK can also be redefined as "subject matter knowledge *for teaching*".[54] In the case for computer science, practical experience with implementation of theoretical concepts helps teachers foresee and prevent potential misconceptions for their students, as well as helping the students reach a complete understanding of the subject faster.

To have CS as an academic discipline reach the level of other traditional subjects like mathematics, physics or history, which all are built upon decades of teaching experience, there remains a lot of didactical research to be conducted.[55] Research should aim to develop appropriate competency models for the field given the fact that CS is rapidly evolving academically, as well as finding common ground for what should be considered subject content knowledge and PCK for the teaching of CS.

The PCK in CS education wish to uncover solutions to certain questions: why CS is being taught, how CS should be taught, what concepts should be taught and what misconceptions occur most commonly.[56] To achieve a deep understanding of computational thinking, algorithmic thinking and problem solving, which is the primary goals of introductory CS courses, we need to discuss different strategies to best facilitate these skills for the students.

2.7 Shallow and deep understanding

The field of psychology is yet to uncover what specific mechanisms the brain carries out to acquire information through learning and store information through memorization.[57] While a lot of research remains to define the technicalities of how the brain processes information, there have been developed many plausible models for how the different parts of the brain operates. Though this thesis will not dive into the field of psychology, it is convenient to briefly define what is meant by deep understanding before venturing into how to aid students develop this.

When a student reads a text, the first step is to understand what is being read. A mental representation of the content is being made, where words are memorized, such that the content is accessible.[58] This mental activity is enough to obtain a shallow level of understanding, consisting of the ability to recall information, identify properties and generally describing concepts. Shallow understanding can be just as useful as deep understanding, for example, most people know how to drive a car without understanding how every aspect of the vehicle works. It is enough to have a shallow understanding of how the gas, break, wheel and gears affect the speed and direction of the driving. There is no need for every chauffeur to know how every pipe, valve and chamber is involved during engine combustion. However, for a car producer it would be crucial to know every tiny aspect of how a car works to be able to put one together safely and effectively.

All while there exists numerous metaphorical representations of what understanding is, a definition should not depend on practical examples. Many articles vary their definitions of what deep understanding consist of. In Biggs[59] attempt to describe what a deep approach to learning consists of, he mentions how a well-structured knowledge base is crucial for the student to be able to focus on the underlying meaning of what is being learnt. In addition to a sound foundation of prior knowledge, Biggs also brings forth the ability to focus on a high conceptual level. This means given a student having all necessary background information to understand a concept, the deep understanding will not be a direct consequence of these passive factors. The student must also be actively participating in the learning process, where the ability to think at a high enough conceptual level and having a focus strong enough to grasp the ideas is required.

Since there is no standardized definition of what is meant by deep understanding, I wish to deduct a customized one for this thesis inspired by Biggs[59]. In the learning process it is clear that new, more complex knowledge is being built upon previous, more fundamental knowledge. In a way, knowledge can be categorized into a layered mental structure, where each layer consists of information and experience from a certain academic level categorizable by Bloom's taxonomy, and where each new layer builds upon the previous. For a given layer of knowledge, the layer's informational content can at any given point be learnt by rote learning. Formulas, facts and applications of the layer can be memorized and recalled, sufficing for a shallow understanding of the layer. However, this process becomes increasingly harder and less applicable the deeper into the layers the information belongs.

For a student to properly understand each layer, it is important to have connected each layer to the preceding ones by understanding how the information is consequently deducted from the information in the previous layers. Given a new layer where the preceding layers have not been properly reinforced in the fashion of this mental structure, it is impossible to forge the necessary connections from previous knowledge to the new one. Attempting to farther build a firm understanding from such an incompletely understood layer will become impossible. It should neither be possible to create new informational advancements within a discipline without a deep understanding of the layers required to deduct such a discovery.

A reinforced mental structure of information will catalyse the process of obtaining new understanding of more complex concepts. How deep an understanding is can be considered as at what depth of these mental layers is the knowledge still deductively connected to the preceding layers.

Much like Biggs[59] explains, to approach a deep understanding of a subject, there are two requirements: the necessary background information must be properly understood, and an active mental participation to connect newly obtained information to previous knowledge. The focus required by this active mental participation of forging these connections often requires the individual to have a curiosity and a motivation to do well due to being an exhausting mental process. If a student is struggling to understand an academical course, they might be lacking either the motivation to spend their energy on actively participating mentally in the learning process or they might lack the ability to think at a high enough level of conceptuality.

Teachers also plays an important role to facilitate this understanding. Their teaching should explicitly bring out the content structure and pinpoint the underlying meanings of the content, build the lectures based off what the students already understand, and confronting misconceptions students may have.[59] Instead of presenting individual facts, teachers should help build a connected mental structure of the content, emphasizing depth instead of breadth of coverage. To teach a large, diverse cohort of students, it is important to make the mental participation required to understand the course as relaxed as possible. This can be done by finding the teaching strategies which motivates and engages the students, and also eases the mental processing by presenting the information in a more intuitive fashion. Examples of such strategies can be visualisation techniques, active learning, cooperative learning or game based learning.

Though being a rough explanation of what is meant by deep understanding, it applies well for the understanding of computer science - and proves helpful for farther discussion of ways of achieving it. For a novice programming course, a shallow understanding would consist of elements such as syntactic features, raw information about datatypes and factual knowledge about loops and functions. To master the latter levels of Bloom's taxonomy within computer science, students aim to develop problem solving skills which relies on a deep understanding of the subject. Per this definition of deep understanding, we aim for students to obtain the knowledge of all necessary programming features in such a way that they can develop an understanding of their applications when solving problems. Such problem-solving skills require an understanding of how the features correlates through the layers of information to produce solutions which are only achievable by combining multiple lines of code in an algorithmic fashion.

2.8 Active learning

CS by its nature is an active learning discipline, which means that the deep understanding of the subject is unlikely to be obtained solely by passive learning-forms such as listening to lectures and reading textbooks.[60] Developing problem solving skills within CS requires active learning strategies such as discussing, answering questions and solving problems.

As previously mentioned, a deep understanding requires an active mental participation of the students to connect the different layers of information. Without this reinforced understanding of computer science, students are unlikely to be able to solve challenging problems. CS, like certain other STEM fields, have very little information which needs to be memorized at each layer of understanding. To teach how to program, all syntactic features and information about programming concepts could be presented over the course of a much shorter term compared to the subject content of many other disciplines. What makes STEM sciences like CS challenging is the effort required to make all the connections between layers of information, such that they combine to a thorough understanding capable of solving various problems. This is why having an active learning environment can help facilitate the active mental activities required to form this kind of understanding. We will farther investigate what strategies have been utilised to actively engage students in CS education.

Caceffo[61] studied how two classrooms, one which consisted purely of lecturing while the other consisted of mostly problem solving, would compare based off their results. The lecture-based classroom was in a traditional fashion instructor-centred, where the students solely learnt by passively absorbing the information the lecturer presented. The instructor-centred teaching style can be considered to belong to an older teaching paradigm.[62] Caceffo's study[61] concluded that the paradigm shift from the traditional instructor-centred classroom to a student-centred classroom has positive effects on both learning outcomes and motivation for students.

Norris[63] examined how regular quizzing of students throughout a course would affect their final grades. Students underwent pre-quizzes before classroom activities, preparing them mentally to learn about certain topics, and post-quizzes during lecture time after engaging in discussions, consisting of questions covering the same material they were faced with in the pre-quizzes. With large amounts of data, the study could safely conclude that this instant feedback, active classroom activity proved more effective than a traditional lecturing approach, with an eight- and ten-point increase in pass rate of two different CS courses.

Though being a seemingly effective learning strategy, an active classroom relevantly also brings more overhead work upon the instructor. In many cases, lecturers are aware of the downsides of student passivity in the classroom, but they keep lecturing anyway due to various reasons.[61,64,65] Some might find it impossible due to the orientation of the classroom where chairs are bolted to the floor in rows, making student interaction impractical. Others report they are having too large cohorts of students to teach simultaneously, they have got too much material to cover or do not have enough time to prepare student activities preceding the lectures. A responsibility lies with the educational organizations to plan and fund better solutions for their classrooms and organization of courses such that they are easier to teach. This is obtained by customization of material coverage, access to fitting classrooms, adjusting cohort sizes and paid preparation time for lecturers. Having an increased focus on active teaching strategies during teacher education could result in teachers being better prepared to enact this kind of teaching. Although efforts and expenses increase with such an implementation, the learning outcomes are arguably worth the extra overhead.

2.9 Visualisation

There are various ways of presenting information, but they all boil down to two main perceptual channels: visual and verbal. The *Visualizer-Verbalizer theory* suggests that people can be divided into two groups, one having a better perception and understanding of visually presented information, and the other of verbal or written information.[66] It is commonly argued that students have the best learning outcome when learning through their preferred modality.[67,68]

Derived from this theory, a set of teaching strategies have emerged.[69] The first, most commonly discussed approach is simply to match student modular preference with modality-specific lessons and activities. A second strategy is self-direction, where students can choose from a pool of activities to match their own preference. Special scheduling is the strategy where students initially learn through their modular strength but is later rotated to a review lesson exploiting a different modularity. Lastly, a holistic lecture approach is when the teacher presents the same information through multiple modalities.[69]

Although being an intuitively appealing model of subject content perception, a student's preferred modal form does not necessarily correspond with their strongest modal form.[67] Preferred modal form is also inconsistent with different problems. The visualizer-verbalizer theory might be an explanation too simplified to describe cognitive processing, becoming a too restrictive division of students. With a lack of consistent empirical support, certain studies suggest designing customized education for individuals through models based off the visualizer-verbalizer theory should be discontinued.[69,70] However, this does not imply the discontinuing of exploiting multimodal ways of presenting information during lectures.

Gates[71] claims that students will not acquire a full understanding of a subject by purely being presented the content verbally. Supported by Mayer[72] who found a 75% increase in creative answers to problem solving for students who received multi-media lectures compared to those who did not, claim that meaningful deep learning occurs when students coordinate and combine information of the same content through different modalities. By visualizing the content, it becomes easier for students to connect information and discover underlying relationships, which are key concepts for fostering deep understanding per our definition.

Some studies claims that most students actually prefer to learn in a format combining both visual and verbal information to different extents[73,74,75] - also known as the dual-channel assumption.[76,77] In a learning situation, a visual model might be difficult to interpret on its own, but combined with a verbal explanation, the model might become clarified. Similarly, a text based explanation of a concept might be hard for a student to understand, but it might become clear much faster with a simple visual representation next to it. Different modalities should not be considered to be opposites, where performance in one implies a lower performance in the other, instead they reinforce each other, where the combination of different modalities holistically facilitates understanding. Many studies find a better result in learning outcome for students when visual learning is combined with verbal, arguably because no individual is a pure visual or verbal learner, and exploiting both of these modalities simultaneously stimulates more of the students' learning capabilities.[71,78,79] It is also theorized that both pictorial and verbal learning has a limited "capacity" of how much information can be processed simultaneously (limited-capacity assumption) [77,80], where the total "capacity" is increased when making connections between these cognitive channels.

2.10 Motivation

One of the main challenges for educational organizations is to motivate their students to become more mentally committed and engaged to their schoolwork.[81,82] As previously described, the students need to be mentally engaged and actively focused to obtain a deep understanding of presented information. This active participation is highly affected by motivation.

Motivation can be defined as the reason- or reasons for behaving or acting a certain way. How to make a person *motivated* is more complicated to answer concisely. Herzberg[83] raises the question whether the goal of motivating is simply to make others perform a certain task. There are various strategies to make people adopt a certain behaviour, however, many of these strategies are simple rewarding systems which arguably does not foster proper motivation.

An example of a positive rewarding system is when a pet-owner offers a treat to their pet if they shake hands. But in this scenario, Herzberg[83] points out how it is the owner who is motivated to shake hands while the pet remains only motivated to obtain the treat, meaning utilizing this strategy fails to motivate the subject for the right objective. True motivation would be for the target individual to not rely solely on external stimulation, but truly *wanting* to accomplish the objective themselves, an internal state where the goal itself is what drives the individual to accomplish or obtain it.

I would argue that student motivation in modern education systems is to some degree reliant on a rewarding system, where many students are partially extrinsically motivated to learn the material to obtain a certain grade or degree, shifting the focus away from knowledge to achievement. While intrinsic motivation would ideally be present in every learning situation for a student, this is unlikely to happen due to the disparateness and breadth of different courses they take simultaneously. The aim for educational institutions should be to foster as much intrinsic motivation as possible within their students, but realistically an average student will also have to be extrinsically motivated to be able to cover the workload associated with the courses and specific concepts which does not fall within their interests.

Intrinsic motivation achieves well in terms of cognition, generalized expectancy of success and self-reinforcement during learning, while extrinsic motivation positively relates only to generalized expectancy of success out of the three factors.[84] It is important for students' self-esteem and personal academical responsibility that the teaching they receive is supporting autonomous learning-motivation instead of being controlling or reward-driven.[85]

Students who are extrinsically motivated to outperform other students tend to pick simpler tasks they already know they can perform, while those being motivated to master a subject tend to pick more difficult tasks, having a larger focus on self-development.[86] This indicates that students which are intrinsically motivated instead of extrinsically and competitively motivated tend to improve their skills more efficiently.

To develop intrinsic motivation within students, we are mainly looking to improve personal enjoyment, competence, autonomy and relatedness associated with the material.[87] Motivation can be considered as a temporary mental state, where commitment and effort constantly change in a fluctuating manner.[88] Though intrinsic motivation is usually high for students enrolling new courses, this motivation is usually slowly declining over time. This decline can be fought by presenting students with collaborative tasks, academical variation, cooperative learning and choices in their education.[89] Although schools should have a focus on motivating their students, individual motivation is not solely the educators' responsibility. A crucial role for maintaining motivation lies just as much upon the individual students.[90]

We learn from Ito[91] that the most resilient and effective learning comes from what he describes as "connected learning". Connected learning is an approach to education visioned to broaden access to learning by making it interest-driven and socially embedded, realized when a person's passion or interest is linked to the material, facilitating academical achievement. This is an answer to the problem statement that today's education is too disconnected from other meaningful aspects of students' lives. Reconnecting these fields through peer culture, subjects and personal interest can make education feel meaningful and promote better academic results through intrinsic motivation.

The field of motivational psychology is vast and complex, with no cut and dried answers to explain exactly how motivation is formed and preserved.[88] We will not dive any deeper into specific mechanisms of motivation than we already have.

Chapter 3. Game based learning

3.1 Game based learning

One definition of game based learning (GBL) is “a system in which players engage in an artificial conflict, defined by rules, that results in a quantifiable outcome”.[92,93]

3.2 Digital Game Based Learning

Digital game based learning (DGBL) is the utilization of digital games during a learning process. Being an innovative and modern approach to presenting information, there is limited literature available on how effective games are for learning.[94,95,96] Some literature reports no difference in increased learning outcome for DGBL[97], while others report an increase in both motivation and assessment scores.[98,99,100,101] Though digital games are yet to be acknowledged as a reliable method of teaching, video games in general have been recognized to be a valuable tool for developing planning, strategic thinking, communication, number application, negotiation, cooperation, and data-handling skills.[102] Research agrees more qualitative studies are required to form a sound foundation to justify DGBL as a reliable method of teaching.

3.2.1 DGBL: Implementation

There are many reported issues with the implementation of DGBL.[103] Having fixed classroom time can be constraining for planning and executing game-based activities. Though games are likely to be a motivating factor, the potential motivation is dependent on whether the game experience is familiar to the student’s personal interest. For DGBL to be motivating also depends on whether the students are able to work autonomously in the games, whereas this is limiting the teacher from student follow-up. Before the academical potential digital games possess can be realised, there are many challenges which both the teachers and game developers need to be aware of under development.

While teachers decide the learning activities for their students, there is a certain level of production quality required for academical games to be accepted by students. The educational games must somewhat satisfy the expectations students may have from the gaming industry, or else the games might not catch student interest. The modern market of video games has grown rapidly the past decades in terms of technological capabilities and human resources[104], and some qualitative studies regarding certain educational games finds that both educational outcomes and student motivation have little to no increase due to poor game quality.[105] Many studies attempting to measure learning outcomes from DGBL are not necessarily ensuring that the quality of the game is high enough to obtain representative results for the potential of DGBL.[106]

The cost of assessment data regarding educational games is expensive, often close to the production cost itself.[107] Due to this expense, most funders are discouraged from investing in educational games. It is simply not profitable to produce high quality educational games when the production cost becomes higher than if it was a regular game. The gaming market is driven by the money spent by consumers. However, students are unlikely to spend private funds on educational games, especially considering the high competition educational games face in the gaming market. For educational games to become a reliable industry, it would take investors who are willing to put money into such non-profitable projects to cover the production costs.

Various factors including learning outcome, expenses, teachers' time consumption, social impact and student satisfaction needs to be addressed compared to traditional learning methods before DGBL can be justifiably implemented into the educational sector. There remain tons of research regarding whether such an investment of educational budget into DGBL is profitable in terms of learning outcome, and if this is the case, action needs to be taken by the government who manage the educational budget.

Teachers are faced with certain challenges if DGBL is implemented into curricula where teachers must adapt to various new roles and responsibilities. Teachers will have to troubleshoot technical issues regarding the game activities, tracking student progress in an untraditional manner - making sure students are on track in their autonomous learning, and being expected to not only have knowledge about the discipline they teach, but also the games being utilized in their classrooms.[108] The role of the teacher can be as decisive for the success of the game activity as the game itself for certain students.[109] Teachers and educational organs will also have a responsibility to identify which games can be useful in a learning scenario and are also playing a big role in the qualitative studies of DGBL development.[108]

Another issue with the implementation of DGBL is a cultural stigma regarding digital games being utilized as a learning activity in schools, which is dependent on a wider public perception instead of solely the academic sector. The current school equipment is not necessarily compatible with the required technology either, which might demand costly upgrades in hardware and procurement of accessories if required.

There will be economical and legal challenges to licence games for schools to utilize, which will require funding.[108] Without acknowledged studies verifying the effectiveness of DGBL, the funding of DGBL becomes unappealing for the government, and if there is no interest in investing in the production of DGBL, there are no games to verify its effectiveness, creating a vicious cycle which impedes the DGBL development.

3.2.2 DGBL and Academical Goals

Games intend to make themselves appropriately challenging for their audience, much like teachers intend with their lectures.[110] Games are at risk of becoming boring due to the player not being challenged enough by the game's learning curve, and a game being too difficult might see the player quit gameplay due to the lack of mastery. An ideal game will try to be challenging but doable, such that the player is on their peak of interest and learn as much as possible.

Schools aims to challenge their students in the same way, but due to cohort sizes, it becomes challenging to address all the different levels of students in a classroom simultaneously. While having to design lectures at one specific level, the material either becomes too difficult for some students, or too dull for the sharpest students. Games, however, designed with a skill measure with respect to the player's individual learning curve, can adapt themselves to their level of competence and pacing, giving the player enough time to process information before progressing farther into more complicated material.

Teachers and teacher assistants might be able to track their students in a similar fashion, customizing the material each student receives manually. Humans are arguably better at understanding their students and their needs than a computer game would be – per now. However, with time and expenses considered, partially exploiting games to track this process and automatically customize the material each student receives might be a more efficient way of organizing a classroom, buying time for teachers to better prepare other classroom activities and putting extra effort in helping the students with academical struggles.

3.2.3 DGBL: Transferability

What is meant by academical transfer is that learning in one context either enhances (positive transfer) or undermines (negative transfer) performances in similar contexts. Said transfer can be a near transfer (learning is appliable to closely related contexts) or far (learning is widely appliable to dissimilar contexts).[111] For DBGL to be proven as an effective learning strategy, it is important for the capabilities acquired during game play to be transferrable to real life situations.[112] Though some studies implies a transfer of learning outcomes taking place in DGBL, qualitative evidence is still weak, and this needs to be farther examined. To facilitate this transfer, it is crucial to design cognitive overlap between the academical games and the real life applications of the information. Developing intelligent assessment for academical games to facilitate knowledge transfer is likely to become a main challenge for DGBL to become effective.[113]

DGBL is known for increasing knowledge through experimental learning, but this knowledge is usually implicit, meaning the learning was not necessarily intentional, but a byproduct of an activity.[114] Explicit knowledge, knowledge which is consciously understood and conceptualized, is generally more desirable in a learning situation than implicit knowledge and improves knowledge transfer from the game environment. ter Vrugte et al.[114] suggests that explicit knowledge is not automatically derived from implicit knowledge, and activities such as self-explanation is required to ensure formation of explicit knowledge. Learning activities can be integrated into game environments to elicit self-explanation such as collaboration among students, question prompts and partially worked examples.

However, Brom et al. [115] argues that the transfer problem is not as significant as others might argue, where Brom et al.[115] propose that humans are psychologically capable of converting implicit to explicit knowledge in most cases. We are not limited to applying information solely in the environment it was obtained due to our natural capability of converting information into useful tools. Yet, if the problem of transferability still hinders learning outcome for DGBL, Brom et al.[115] have proposed five points of how to facilitate this process:

- Designing game content around everyday contexts.
- Designing game content closely related to lecture content, such that the information learnt in game can be directly connected to other classroom activities.
- Exploiting the information seeking behaviour of students, assisting contextualization of game material with real world context and vice versa.
- Designing supplementary material and training for teachers.
- Describing what the learning environment visibly offers students in terms of learning opportunity.

3.2.4 DGBL: Memorization

Games have the potential to perfectly time the access to information, where information can be presented in just the right moments or requested on demand by the player.[110] This is beneficial due to the fact that people are more likely to remember information which they can apply shortly after being obtained, while information given out of context or long before it can be applied is more likely to be forgotten.[116] In a way, it is an attempt to climb Blooms taxonomy ladder as quickly as possible while the information is freshly stored in working memory, rapidly reaching the application level to reinforce the previous taxonomical steps.

Glenberg and Robertson[117] draws the conclusion that memorization of information becomes more effective when information is connected to physical or abstract objects. According to their "indexing" theory, it is required to refer words and concepts to objects to be able to comprehend their meaning. They performed an experiment where two groups were asked to identify landmarks using map and compass, where one group utilized an indexing learning strategy, and outperformed the control group. In a virtual game, information is naturally connected to the game objects, events, characters and storylines, promoting better memorization according to the indexing theory.

Games also have an adaptability potential for individual learners; "… the capability of the game to engage each learning in a way that reflects his or her specific situation".[93] This refers to a range of abilities such as the learner's cognitive abilities, background knowledge, and even emotions. Given that the game is implemented with a measure of the users' capabilities, the content can be adapted to better fit their current academical level. When teachers and teacher assistants help students correct misconceptions, they spend a lot of time mapping the students' current understanding to find out where it ruptures, then customizing their explanation such that the student have a better chance of understanding based on their current knowledge. If educational games are designed to estimate the players' current knowledge by providing in game tasks which carefully assess different parts of the subject content - and based on these designs customized material to address student misconceptions, DGBL can save teachers a lot of time by making the student autonomously correct misconceptions through game instruction.

3.2.5 DGBL: Applying information

While games are an entertaining source of information, they also require the player to synthesize, analyse and evaluate the multimodal information available to form strategies and solutions through critical thinking to overcome various obstacles.[118] In a learning environment, this means games as a singular method of teaching can guide their players through all the levels of blooms taxonomy. In traditional classrooms, teachers are usually required to design various learning activities for students to obtain and apply information, which can be partially or completely replaced by educational games. It is not always clear to teachers when all of their students have reached a certain level of understanding. Game completion gives a strong indication of when the students have progressed through the cognitive steps of understanding the content, where level progression should require the player to apply obtained knowledge correctly. It is crucial that level progression by design cannot be obtained by chance and that the obstacles are carefully designed to only be possible to overcome by correctly applying obtained information.

3.2.6 DGBL: Motivation

The key to increase motivation for a subject is to facilitate satisfaction, interest and enjoyment connected to the subject. A survey made by Medietilsynet[119] found that for a group of 3'400 Norwegian teens between 9-18 of age, 96% of boys and 76% of girls have played video games in their spare time. Combining academic subjects with video games can increase student motivation if done correctly, as described by Ito[91]. Despite boys having a greater involvement and interest in computer games, gender have no significant influence in learning outcome in DGBL environments.[101] A paper by Ariffin et al.[120] finds a connection between student background and motivation affecting their performance and suggests connecting student background and culture to course material through DGBL.

There are few instructional methods which motivates students as much as DGBL and keeps them engaged with subject content as persistently.[112] A research found that students doubled the amount of time spent on homework when the homework was substituted by an educational game.[107] Designing content modality based on student interest is a great way of increasing motivation, making education more entertaining simply by presenting information through modalities and activities which students already have interest in.

For students enrolled in an academic program, lack of mastery or failure can be a demotivating factor. Video games allows the user to fail "gracefully", where failure is considered expected or even necessary for game progression instead of being experienced as an undesirable outcome.[93] When the consequences of failure are lowered, students are more willing to explore new strategies and take more risks. While failing to produce correct results in most disciplines are related with negative emotions, neutral and even positive attitudes were recorded when students made errors in digital game environments.[121] Removing negative associations with a course increase the overall satisfaction students have. Students are additionally naturally exposed to a self-regulated way of approaching subject content, where they need to form their own goals, track goal progression and assess the effectiveness of their strategies, making the learning more autonomous.[122]

Another way of fostering motivation is through collaborative learning, where students solve a problem by combining individual knowledge to produce a collective solution. This learning is based upon the idea that humans are social learners, where learning comes naturally when a problem is being discussed among learners of different levels.[123] The participating students in a cooperative learning environment needs to be made aware of a social interdependence, where all participating students should take responsibility for their share of the workload. However, in many learning situations with varying levels of motivation within a group, workload is partially or completely transferred from the lesser motivated to the more capable students. Motivated and capable students tend to personally ensure project progression if their group does not share the same ambitions, even if it means an unevenly distribution of workload, which leads to the group having varying levels of learning outcome.

Cooperative learning can easily be embedded within educational games by adding multiplayer features. Game design is crucial to ensure correct learning outcome. Collaborative games can require plenary participation from all players to progress through the levels such that the workload cannot be interchanged unevenly between them. Game design requiring all players to complete their assignments facilitates a motivation to collectively master each level, promoting students helping each other understand the content and disallowing anyone to individually drop out when discouraged.

For students being more individualistic in their approach to schoolwork, cooperative educational games could be replaced with competitive educational games instead, putting students up against each other in game based assessment. Competition has for a long time been a key aspect of games, driving different players to outperform one another. A meta study by Chen et al.[124] finds that competitive games have positive effect on math, science, and language disciplines, where puzzle, strategy, role playing, and simulation games were effective genres to enhance learning. However, social science and action games had little effect of this approach. Chen concludes that research regarding how different aspects and genres of games affect learning outcomes is required to fill a large gap within DGBL research.

Students expressed an increased motivation and satisfaction level when facing school material in a digital competitive game environment instead of a cooperative one.[125] Students falling behind academically is a big concern for the educational sector, but implementing cooperative and competitive DGBL environments can contribute to lowering the achievement gap between students of different levels in a classroom.[126]

3.2.7 DGBL: Learning styles

People have different preferences when it comes to receiving information, where most have a combination of visual- and verbal preference.[73,74,75] Digital games have a unique potential of combining visual representation of information with visual game play elements. An ideal combination of game dialogue and the visualization of the same information creates a highly sensorial experience of the subject material, having the potential to satisfy both visual- and verbal aspects of learning-preferences.

Mayer and Moreno[127] describes a learning problem where the learner is presented with visual and verbal information but does not have the time to process these segments of information into mental models. This processing of information is a necessity to obtain a deep understanding of the concepts. Reasons for this problem can be timing, where traditional lectures do not necessarily respect individual pacing by continuously progressing through the next segment of information before some students have completed the mental processing of preceding information. Doolittle et al.[128] concluded that a segmented video lecture, where each segment contains a "continue" button allowing students to pace the lecture progression manually, had a positive effect on their learning outcome. Video games have the same potential of segmenting information and adapting pacing to individual student need. In video games, dialogue is often paced by the player. Many games have dialogue where the player is often presented with a combination of written and verbal interactions, where the player can themselves click "continue" when they have finished processing the presented dialogue. In games where players need to understand presented information to progress through a puzzle or some other cognitive tasks, the player will be naturally paced by the game progression where they are not allowed to progress farther before the required information have been understood.

DGBL differs in effectiveness depending on the user's preference, not only based on the visual/verbal learning theory, but also on "intuitive" and "senser" learners. Senser learners are individuals who enjoy absorbing information sensorially through practical experience, while intuitive learners are more interested in exploring the deeper meaning behind given material conceptually. Game based learning is found to be more attractive and effective for the sensorial learners more than intuitive learners.[129]

Apart from preferences in learning styles, there exists other conditions which can benefit from alternative learning strategies. Between 2-7% of children worldwide, averaging about 5%, suffer from attention-deficit hyperactivity disorder (ADHD).[130] Due to difficulties with reading and concentration in general, students with ADHD tend to have a worse academical performance than those who does not suffer from this disorder. Introducing a game based learning environment for students who struggles with concentration have proved efficient for both academical achievement, but also for increasing their attention-span.[131,132] By giving the player instant feedback on their actions and visual/auditory stimulation, the students remain engaged with the learning activity for longer periods of time.

3.2.8 DGBL: Social aspects

To create an ideal learning scenario, teachers are trying to engage their students by having them respond in class. Student response is a clear indication of when the students are engaged with- and understanding the content. However, big classrooms tend to have very little response in students when prompted with questions from the lecturer. Karp and Yoels[133] observed how student interaction typically occurred in classrooms. Regardless of classroom size, most student interactions were performed by a small portion of the present students, where less than 10 percent of these interactions included student response to other students.

Reported concerns for why the majority of students usually do not participate vocally in class includes lack of preparation by reading the assigned material, not knowing enough about the subject matter, concerns about appearing unintelligent by classmates and a fear of their grade being affected by wrong answers.[133,134] Other social factors are also affecting student participation, where male and female participation appears dependant on the gender of the lecturer. Some researchers discuss student participation as a function of personalities instead of academical achievement.[135]

While some students might be completely disengaged from course content, a large group are avoiding vocal participation due to a large scale of social factors. Some of the social concerns regarding student participation in the classroom can be addressed by digital classroom aids. Various studies find positive relations with student participation and the utilization of digital response systems such as “clickers”, where it becomes easier for students to participate in lecture activities and academical achievement has reportedly been improved.[136,137,138]

Game based learning has a high potential of creating anonymity among students, allowing students to respond to course material without being personally associated with the interaction by the lecturer or peer students. Mediating the communication into alternative forms than solely vocal interactions can positively impact students who are less vocal or suffering from social anxiety and the teacher obtain more representative feedback from a bigger proportion of the student cohort.

3.2.9 DGBL: Evaluation

As the discipline of didactics conclude, there remains a lot of research for DGBL to be implemented as a standardized medium for teaching. The research that has been conducted is lacking a proper quality measure of the games they are studying.[139,140] Results from various studies are usually based on individual games which greatly vary in terms of production- and educational quality. The role of the game producer for DGBL development cannot be overstated, where game quality is likely to be a deciding factor for any qualitative study of educational games.[100,113,141] The empirical evidence from studies regarding DGBL is also doubtful due to the variety in activity design of different subject groups, assessment efficiency scales and data collection.[142] These factors make comparison of results across studies problematic.

To have a fair didactical evaluation of DGBL, the studies regarding the learning efficiency of DGBL should be conducted with respect to an acknowledged game quality measure, such that results are more representative given the production level of the games. There exist models of how to improve game quality and how to ensure proper assessment of games[140,143], but there is no standardized model to measure the overall quality of educational games. The amount of research in serious games – games with purposes other than entertainment – has increased in recent years, but farther research regarding playability factors remains.[144] Though qualitative studies research whether games increase player understanding of an academical concept, they often also lack measure of player enjoyment.[145] Without player enjoyment and motivation within the game based activity, the learning method is more of a traditional learning activity than a game, losing the potential and purpose of game based learning. I wish to first look at what frameworks exists to evaluate educational games, then prepare a framework which I believe describes ideal content and information mediation for educational games based off previously mentioned literature.

3.3 DGBL: Game quality framework

One of the key issues reported when developing serious games is the need of interdisciplinary cooperation to implement all the necessary aspects of these games in terms of educational- and entertainment features.[146] A multifaceted process like this, which stretches across various disciplines, needs a unifying methodology to aid planning and management. This is where acknowledged models for developing educational games is lacking, where many have attempted on making games without having these meet with DGBL expectations for learning outcome and motivation arguably due to a lack of development guidelines.

Very little effort has been made to analyse what game design choices promotes a balanced combination of entertainment and meaningful learning.[147] A possible reason for this is because of the competition between different developers in the game market, where companies are unlikely interested in sharing development guidelines with the public. It is important to identify what aspects of traditional games makes them entertaining and which of these features are transferrable to educational games. The same goes for didactical strategies, which need to be carefully selected and implemented, avoiding interference with student motivation and engagement with game-based learning. It might be a deciding factor for the success of future educational games to develop a framework which helps preserve every aspect of ideal DGBL, and to obtain such a framework, the relevant disciplines need to come together in this process to preserve the aspects they can contribute with.

Another reported issue with implementation of successful educational games is task design, where problem solving and gameplay obstacles fail to meet expectations. Kirriemuir et al.[108] points at where educational entertainment, or edutainment, tends to fail:

- Games are too simplistic in comparison to the modern gaming industry.
- Tasks become repetitive, and is experienced as "work", losing its entertainment value.
- Tasks are poorly designed, not supporting progressive understanding.
- Homogenous content, which limits the player to learning only a limited set of skills.
- Game experience can be patronizing if students feel forced into a "fun" learning environment.

In response to these issues, Kirriemuir et al.[108] argues that when implemented correctly, game based learning can help create a learning environment where students are learning in a flow state, referring to Malone's[148] model of how to achieve such a learning activity.

Malone[148] have put forth 5 points to what grants a learning activity its entertainment value, inspired by Csikszentmihalyi's[149] theory about flow. The flow state can be described as being fully immersed, full of involvement, enjoyment, gratification, and energized focus. The flow state can be considered tightly connected with intrinsic motivation, creating an environment where the activity at hand is genuinely pursued. Though being over 40 years old, this model is still relevant and can be applied to DGBL. This model consists of 5 elements describing how to create an intrinsically motivating learning activity, and adapted to a DGBL scenario, the elements can be defined as:

- The player can adjust the level of challenge to fit their own level of skills.
- The activity should be isolatable, such that superfluous stimulations does not interfere with the player's involvement with the learning activity.
- There should be a clear goal of the activity such that the player can visualize the overall intended progression, and how far they have progressed towards the goal.
- Concrete feedback, which is ideally instant for video games, giving the player an indication of how well they are meeting with the criteria of performance.
- The game should contain a broad range of challenges of different qualitative range, such that the player gradually obtains information with increasing complexity.

Kirriemuir et al.[108] farther concretize these principles into more specific requirements of a learning task which helps the learner achieve flow state:

- Tasks that can be completed.
- Ability to concentrate on the task.
- Tasks which have clear goals.
- Immediate feedback on player interaction.
- Effortless and deep involvement.
- Player has a feeling of autonomy, where they have a sense of control over their actions.
- Concern of self disappears when in flow state, but is increased after flow activity.
- Sense of time and activity duration is altered.

The extended amount of time people can be engaged with video games is a clear identifier that game based environments are good at facilitating flow state for their players. Cowley et al.[150] hypothesized that video games provide an activity which forces their players into a cognitive state which fosters flow state. Achieving a flow state when in a learning situation is highly beneficial in terms of learning outcome and student satisfaction. Flow state learning also enables exploratory behaviour in students, encouraging autonomous and deeper learning. Yet, a significant share of educational organs is not actively designing their learning activities to drive students into flow states.[151]

Malone[152] have also developed a theory of why video games are such a popular activity for children and young adults. He states that people are often finding an activity entertaining when it is stimulative in three aspects: Fantasy, challenge, and curiosity. Studies have later confirmed that these principles are highly relevant for video games, where games often have the addressing of players' curiosity as a common motive, where players are regularly intrigued by "what happens if I do this?" in successful games.[153] These studies also show that the right degree of challenge is decisive for a person's commitment to the activity they are engaged in.[102]

Laamarti et al.[154] have also recognized the growth in serious games over the last decades - and given the expected growth in the future they decided to develop a taxonomy to concretize the different characteristics of such applications. The taxonomy contains elements which they consider important for the success of serious games, which are derived from various articles and other serious game related applications. Note that "serious games" is a category including educational games, but also includes other types of games which are not academically focused, but still intent to teach the player its informational content.

Their taxonomy is divided into five taxa, describing the core features of serious games:

- Activity. What type of activity is performed by the player as input or response to the game, and to what degree does the game activities require mental or physical exertion.
- Modality. This part of the taxonomy categorizes what sensory modalities are utilized by the game to transmit information, most commonly visual, auditive, or haptic.
- Interaction style. Defines how the player interacts with the game. Examples of traditional ways of interacting with games can be keyboard and mouse, joystick, mobile phone, and movement tracking. Laamarti et al.[154] argues that picking a fitting modality which allows the player more freedom and realism can positively impact game experience.
- Environment. Determines what environment – or combination of different environments the game takes place in. Examples are 2D and 3D environments, virtual/mixed reality, offline/online, single/multiplayer and other environments such as utilizing real time positioning and mobility.
- Application area. This describes the application of the game, whether it is for educational purposes, advertising, healthcare, well-being, interpersonal communication etc.

As this is a taxonomy for categorizing different types of serious games, it does not provide any farther information of implementation details. Though being a useful tool to gain an overview of different serious games and their applications, it does not give any instructions of *how* these games should be implemented. As Roungas et al.[155] explains, many different frameworks for developing serious academical games have been made, where many of these are too abstract or general to provide enough information of what key features should be implemented for them to be successful tools of learning.

Aleven et al.[147] argues that to uncover the properties defining good gameplay, which lies the foundation of good educational values, game design needs to be analysed from various perspectives by cause of a successful game consists of many factors. Aleven et al.[147] therefore developed a framework for educational games to ensure their value as a motivational learning tool. They divided the framework into three main components: Learning objectives, MDA (mechanics, dynamics, and aesthetics) and instructional principles.

The first component, learning objectives, describes how the design of educational games should ensure that the learning activity satisfies the learning goal. This means that the intended learning that takes place does not only cover certain instances of the targeted cognitive skill but is transferrable information which is generically appliable to similar problems. Game design is also important to ensure that students participate in all intended learning and does not avoid difficult tasks.

Learning objectives is farther divided into three sub-principles. The first being "prior knowledge" which addresses what knowledge students should ideally have before venturing into the game, which lies the foundation of what academical content should be implemented for students to master the early stages of the game. The second principle of learning objectives is "learning and retention", which describes what is the intended learning outcome of the game activity, how is the information presented to the player and to what extent can the player process this information in terms of repetition and application. This principle emphasizes the importance of the game developers having the required pedagogical content knowledge to ensure correct and efficient learning in game. The third and final principle of learning objectives is "potential transfer". Students might acquire information or skill to solve a learning activity without understanding how the information can be applied outside of these specific scenarios. An educational game would be pointless if the student only knows how to complete the game-tasks without having any valuable learning applicable outside of the game environment.

The second component of Aleven et al.'s framework[147], MDA, is a framework itself, categorizing game elements into mechanics, dynamics, and aesthetics. Mechanics consist of fundamental aspects of the game, such as basic movement, controls, game rules, game objectives etc. Dynamics are the opportunities and personalized gameplay the player has with the game when interacting with the game mechanics. Lastly, the aesthetics are the elements which intrigues the player and creates enjoyment. While dynamics and mechanics are not clearly defined by any taxonomy and are left for the game producer to evaluate, aesthetics does have such a categorization. There are eight principles which the aesthetics of a game can be considered to be built upon[156]:

- Sensation
- Fantasy
- Narration
- Challenge
- Fellowship
- Discovery
- Expression
- Submission

A single game does not need to include all of the elements mentioned above to create an aesthetic experience for their users, however, game features which fall under this categorization can be considered to contribute to the game aesthetics. These aesthetic features can be challenging for game developers to implement into games since these are partially and indirectly derived from game mechanics and dynamics. It requires game developing experience to plan every aspect of game MDA to produce an aesthetic experience for players playing their game.

These three MDA components of game development are all contributing to the player's experience and perception of the game, determining student dedication and satisfaction of a game based learning activity.

The last component of this framework is "instructional principles". Educational games should like other instructional methods be built upon research based instructional principles to become educationally effective. Instructional principles mentioned by Aleven et al.[147] are the Multi-Media principles by Mayer and Moreno[66], the advanced tutoring computer tutoring theory by Anderson et al.[157], and Gee's[158] 36 GBL principles. Aleven et al.[147] points out that it is not necessary for games to include every didactical principle which have been listed up in the development of educational games, since games differs widely in design where not every principle is of relevance. What they do want to emphasize is that the game implementation still needs to be based on certain relevant principles from didactical research, such that game features are justified scientifically instead of arbitrarily designed by the developers.

3.3.2 Game quality measure

Due to the lack of a standardized framework for development and quality assurance of educational games, I wish to develop my own, containing elements which I believe are essential with respect to the different models we have already examined. For my model, I wish to divide the elements between game quality descriptive features, and elements regarding didactic strategies and learning outcome.

3.3.3 Game quality measure: Gameplay quality

Apart from how academical features are implemented, an entertaining game must have high production quality, where characters, dialogue, and feedback on player interaction are thoroughly designed to satisfy player expectations. Other game elements such as attractive graphics, music and quality sounds effects are also considered fundamental building blocks of a satisfying game.[159] Poorly written text in academical textbooks is proven to affect student learning outcome and perception of the quality of the material.[160] In the same sense, if a game is not of convincing quality, the player will be less engaged with the game play, resulting in a less conscious and active mental participation in the learning activity, with respect to the first didactic principle of Marius-Costel[16]. Ensuring the game is captivating due to its production quality is important for students to reach a flow state when working with the material, which is increasing learning outcome, as Kirriemuir et al.[108] emphasized in their studies. As Aleven et al.[147] described when mentioning the MDA framework, a game is based on a complex collection of small elements building up to a complete experience for the player. I agree that this design is crucial for games' success, but I will not include the MDA framework in my description since I believe aesthetics should be analysed separately because of the impact of personalized and emotional aspects games have on their players.

- The game should be of high production quality to engage students with real entertainment value.

What game aesthetics which are appealing to the player is a strongly subjective matter, where it is not possible to define a clear description of how the aesthetics should be implemented. Due to subjectivity, by giving the player an opportunity to create their own game content besides the predefined game content contributes to a personalized experience for the player.[161]

This can be achieved by allowing players to autonomously decide their course of actions, cosmeticize their avatars and impacting dialogue options in game helps bringing the game to life and increase believability for the player.[162] When presented with such adaptable game mechanics, players become more engaged during gameplay, creating room for more autonomous learning. If possible, having an adaptable game plot or game environment which tweaks itself based off individual preferences can make the game relatable and more interesting for a bigger audience. It is shown that game pleasure is clearly derived from game preference, which relies on social and cultural background as well as previous experience with games.[163] This principle in our model is made with respect to the didactic principle of accessibility and individuality[16]:

- Game theme and playable characters are designed to likely relate to player interest and preference.

Cookie clicker is a game released in 2013 and became a big trend as an "incremental game", inspiring the genre of "idle games" which became a popular game-genre later on.[164] The whole game play consists of a cookie in the middle of the screen, which generates one cookie when clicked. These accumulated cookies can be spent to purchase upgrades and "buildings" which boost cookie generation. The game goes on, where the generation of cookies increase, and upgrades are gradually being unlocked. These incremental games start out with an initial income rate, where earnings are spent to farther increase this rate of income. Some producers of such idle games have not developed these games for serious purposes initially, creating them mostly to mock certain game genres where the core game mechanic is simply to continuously level up gear and power by completing certain tasks.[165] Cookie clicker is a very simplistic implementation of this concept, ridiculing how people are entertained by such a simple concept in other games which are heavily focused on progression-mechanics.

However, Cookie clicker became a successful game either way, and gained instant popularity shortly after its release. It makes us raise the question: What makes such a simple game appealing for such a large audience? As simple as Cookie clicker is as a game, we do not have to dive deep into analysis to uncover what game features it consists of. The reason why people find such a game amusing is the feeling of progression: When experiencing the number of cookies increasing for every click, for every upgrade, some part of us is stimulated when such a progression is made by our own interactions. Much like getting good grades in school, completing a university course, or getting a promotion at work, we experience a productive step toward a goal which motivates us. Experiencing this progress towards a desirable goal gives satisfying stimulation and increase motivation, and the examples of this from different scenarios are numerous. It is important for a game to reward the player with noticeable progression and feedback throughout the gameplay to keep the player motivated and satisfied when interacting with it. This is also described in Malone's[148] work,

- The game includes a rewarding system, giving the player a sense of progression.

As previously described, good games have found the balance between challenging and giving the player a feeling of mastery to maintain player interest. For our quality framework, we will try to identify if the game has a reasonable learning curve, and ideally adapts the pacing to the player's need. Insignificant potential challenging aspects, such as learning the controls or understanding assignments, should not be a frustrating factor for the player, unless the understanding of these mechanics is a learning outcome itself, for example simulations teaching how to control a vehicle. This is connected to the principle of thorough acquisition of knowledge, which states that the pacing of information and progression needs to be efficiently balanced to create an ideal learning situation and the principle of systematization and continuity by Marius-Costel[16], as well as Malone's[148] first principle.

- The game has a reasonable challenge-pacing, ideally adapting to player capabilities.

3.3.4 Game quality framework: Information mediation

DGBL is an attractive learning platform for students, given that the game satisfies student expectations. The game must contain certain elements to remain interesting for the user. Let us make an example of a simplistic math game, where each level is text based and user interaction is simply typing in the correct answer, with a set of levels to be cleared. Such a game is unlikely to become more engaging than traditional math assessment if the experience of the game is essentially the same as the experience of a paper questionnaire.

For a game to have better effect on student motivation and engagement than traditional methods, it is required that the game keeps the game objective from simply being to answer questions correctly. The educational assessment of the student should not be the goal of the game itself, like traditional assessment, but a mediation towards some other objective fostering motivation. Given that the learning happens when approaching the objective, is it unimportant what the objective is. The objective should be of interest to the student, which differs subjectively between individuals. Intelligent game design would either create a commonly desirable goal, as in unveiling an appealing plot conclusion or resolving an engaging conflict.

- Academical features are not directly implemented as game objectives.

Gee[158] makes some important observations when describing what didactical principles successful academical games are built upon. It is important for student motivation to receive feedback when performing a learning activity, to see that they have mastered different techniques such as getting a division problem right by obtaining a correct answer. Aside from motivational factors, Gee[158] points out the importance of instant feedback in a learning activity to avoid student misconceptions. If a student performs multiple mathematical operations without being informed whether the results they achieve are correct or not, they might develop a false understanding of the concepts which needs to be addressed later on, making the learning process less effective. It is therefore important for multiple reasons that the game lets their player know quickly whether they are off track or are producing incorrect results. This helps satisfy Marius-Costel's[16] principle of reverse connection.

- The game gives instant feedback to the player after applying intended learning.

An educational game should not only satisfy student expectations regarding video games in general, but also teacher expectations to ensure learning outcome. If the game can be completed without acquiring the intended information, the learning activity cannot be considered effective. Poorly designed game progression can be game obstacles being solvable by chance or by inadvertent methods such that the player completes a level of the game without having learnt and applied the intended information or techniques. Examples of poor game design allowing such behaviour can be questionnaires where wrong answers go unpunished such that the player can keep guessing until they get it right, solutions to game puzzles can be randomly discovered, or game glitches can be exploited to clear levels. This requires the game producers to have experience with game development and pedagogical content knowledge about the material such that the information must be properly applied by the player in game to solve obstacles.

- Intelligent obstacle design, ensuring intended learning takes place before level completion.

To ensure that the intended learning takes place during gameplay, we need to analyse whether the amount of informational content fulfils the desirable learning outcome for such an activity. Information should be integrated into the game with respect to both quantity and quality. Game designers need to make sure enough material is covered during gameplay – with a prioritization of what concepts should receive more attention. There must be a balance between densely packing information in the game to maximize learning efficiency and respecting the entertainment aspects of a game based learning environment, where these two aspects have the potential of cancelling each other out.

- Informational content needs to be balanced to ensure an appropriate degree of learning and entertainment.

Based on the limited-capacity assumption[77,80], we theorize that the human brain is only capable of processing a certain workload simultaneously. Meaningful learning is dependent on the learner performing essential mental processing of the intended learning material.[127] We therefore wish to avoid student cognitive overload when being presented with information in the games. To avoid this, educational games should also reduce any unnecessary information processing which is neither of use for the learning process or gameplay which might help drive students to overload. Educational games should also divide the information into different modules or levels, such that only one or a couple of concepts are processed simultaneously. This is also in respect to Marius-Costel's[16] principle of systematization and continuity, where there should be a natural increment and logical ordering of presented information.

- Different information is logically distributed into separate levels or modules.

Lastly, as previously discussed, forcibly integrating information into a game environment does not suffice to create an ideal learning situation for students. The importance of pedagogical content knowledge – how information should be presented to facilitate understanding – remains as important in a DGBL-environment. There is a need for teachers' experience on how to present information to make it easier to process for the students. Picking correct metaphors, applications and ordering of information will help with learning efficiency and quality. With teachers possessing academical knowledge and game developers' strategies of making quality games, these disciplines need to cooperate on the production of educational games to preserve both aspects of learning outcome and entertainment in DGBL.

- The game is designed around pedagogical content knowledge, easing the process of understanding the presented content for the students.

3.3.5 Game quality framework summarized

Gameplay quality (GP):

- GP1: The game should be of good production quality to engage students with real entertainment value.
- GP2: Game theme and playable characters are designed to likely relate to player interest and preference.
- GP3: The game includes a rewarding system, giving the player a sense of progression.
- GP4: The game has a reasonable challenge-pacing, ideally adapting to player’s learning curve.

Information mediation (IM):

- IM1: Academical features are not directly implemented as game objectives.
- IM2: Intelligent obstacle design, ensuring intended learning takes place before level completion.
- IM3: The game gives (instant) feedback to the player after applying intended learning.
- IM4: Informational content needs to be balanced to ensure an appropriate degree of learning and entertainment.
- IM6: Different information is logically distributed into separate levels or modules.
- IM5: The game is designed around pedagogical content knowledge, easing the process of understanding the presented content for the students.

Chapter 4. Learning Activity Recommendation System (LARS)

4.1 LARS: introduction

LARS is my idea of a system in which students each have their own user profile and with access to a large library of educational modules, designed to teach introductory programming. Though CS is being specifically addressed in this paper, LARS can also be employed in some other disciplines which have academical objectives similar to programming, like mathematics. Student competence will automatically be modelled individually for specific learning objectives by the system, where learning objectives can for example be collected from the national curriculum.

I believe this system has the potential of developing the educational sector with respect to the didactic principles previously discussed in this thesis. This is a system which intelligently collects, stores and recommends modules to individual students in order to foster more autonomous learning with respect to student individual capabilities and preferences. The system will recommend learning modules with respect to the student's competencies, such that the academical activities feel rewarding and motivating, and the student is guided to have a reasonable progression through the course. Having more autonomous, customized and motivational learning helps obtain the individual potential students possess. This is arguably the most desirable development modern classrooms can undergo in the near future.

For LARS to be realized, the system is heavily dependent on a large enough collection of learning modules. If this system was to be implemented and tested, an idea of ensuring a sufficient number of modules for LARS is to allow teachers to chargeless utilize the application in return of contributing with 1-3 modules to the system. Alternatively, LARS could be an open market, where anyone can contribute with learning modules where learning modules generate revenue for the developers based on popularity. These modules can be anything from informational text to videos, quizzes, and educational games.

4.2 LARS: Recommending learning modules

The main functionality of LARS is to recommend ideal learning modules to students. The problem statement needs to clearly define what properties an ideal learning module contain to make such a judgement.

4.2.1 Learning outcome (LO)

The system will need to store data to represent both students and modules in the system. The system will have one simple goal, calculate some property between a given student and a module which is comparable such that the best evaluated module can be recommended to the student. This value will be the calculated learning outcome of recommending module m to student *s*:

$$LO(s, m)$$

Problem statement:

$$Find\ a\ module\ m\ s.t.\ LO(s, m)\ is\ maximized$$

The naïve approach to solving this problem is to calculate the LO value for every module *m* in the system:

$$arg\ max\ \{score(m) |\ for\ \forall m \in M: score(m) = LO(s, m)\ \}$$

If the complexity of the LO function is expressed as F_{LO}, the complexity of the naïve solution is:

$$|M| * F_{LO}$$

It can be challenging to find a reasonable implementation of *LO* such that the produced value is a fitting representation of the actual learning outcome.

4.2.2 Expected learning outcome (ELO)

For this specific implementation of LARS, I wish to specify what the produced value of a possible LO implementation can look like.

When a student has completed a learning module, their representation of academical competency will increase. This increase can be calculated by some function D:

$$D(s, m)$$

If this was the only criterium, the system would naturally recommend the hardest learning modules to the students, where completing these would increase the students' competencies the most. However, there is little use of recommending a learning module which the student does not have the prerequisite knowledge to complete. Therefore, we also need a function P which calculates the probability of student *s* completing a learning module *m*:

$$P(s, m)$$

These two functions can be combined to a variation of the LO function, which I name "expected learning outcome" (ELO), calculating the expected learning outcome if a student s is recommended module m:

$$ELO(s, m) = P(s, m) * D(s, m)$$

$ELO(s, m) > 0$ means that the student had some learning outcome of completing module m, while if $ELO(s, m) \leq 0$ means the student is estimated to not have any learning outcome. Potential implementations of *P* and *D* are presented in section *4.10*.

4.3 LARS preliminaries

4.3.1 The "curse of dimensionality"

A frequently faced problem in vector space algorithms is the "curse of dimensionality". Many algorithms are effectively dealing with two- and three-dimensional vector spaces, however, when the dimensionality is increasing drastically, many of these algorithms lose their effectiveness. This is because the number of unique points in the system grows exponentially in terms of dimensionality, which is a parameter many algorithms depend on. Also, datasets of high dimensionality often suffer from distances between points being increased, which makes the vector space sparse.

4.3.2 Pythagoras theorem

Given a right rectangle with sides *a*, *b* and *c,* where sides *a* and *b* have one endpoint each in the right angle, the length of the hypotenuse *c* can be calculated as follows:

$$c = \sqrt{a^2 + b^2}$$

4.3.3 Euclidean distance

Derived from the formula of calculating the hypotenuse, Euclidean distance is popularly used to calculate distances in vector spaces. Given two points: $p_1 = (x_1, y_1), p_2 = (x_2, y_2)$, the Euclidean distance can be calculated as follows:

$$Distance(p_1, p_2) = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2}$$

Given points with *d* number of dimensions: $p_1 = (x_1, x_2, \ldots, x_d), p_2 = (y_1, y_2, \ldots, y_d)$ Euclidean distance is calculated as follows:

$$eucDist(p_1, p_2) = \sqrt{(y_1 - x_1)^2 + (y_2 - x_2)^2 + \cdots + (y_d - x_d)^2} = \sqrt{\sum_{i=1}^{d} (y_i - x_i)^2}$$

4.3.4 Modified Euclidean distance

For certain minimization problems, the Euclidean distance formula can be modified to calculate distances between two points with respect only to dimensions in which $y_i > x_i$.[166] This can be done as follows:

$$modDist(p_1, p_2) = \sqrt{\sum_{i=1}^{d} \max(0, y_i - x_i)^2}$$

4.3.5 Manhattan distance

Manhattan distance is another way of calculating the distance between two points, which is done by summarizing the absolute difference of every dimension:

$$manDist(p_1, p_2) = \sum_{i=1}^{d} |y_i - x_i|$$

4.3.6 Modified Manhattan distance

Similar to modified Euclidean distance, we can calculate a modified Manhattan distance by a similar formula:

$$modManDist(p_1, p_2) = \sum_{i=1}^{d} \max\,(0, y_i - x_i)$$

4.3.7 Vector L1 Norm

Similarly, the L1 Norm of a vector can be calculated as the sum of every dimension's absolute value:

$$norm(v) = \sum_{i=1}^{d} |v_i|$$

4.3.8 KD-trees

The KD-tree is a popular data structure used to partition space into a tree structure to efficiently query sets of datapoints.[167] The data structure contains a tree where each node is a value in a certain dimension, which splits the dataset based on the dimension for the given value in each step. The traditional strategy is to cycle through every dimension and split the data based on the given dimension for each generation in the tree, where every non-leaf node acts as a hyperplane, and where each leaf node are the datapoints. To ensure a balanced KD-tree, which admits the most efficient queries, the splitting points for every non-leaf node is popularly decided by finding the median of the given dimension of the datapoints in the parent node.[168]

4.4 LARS: Design choices

4.4.1 Competency vectors

It is difficult to accurately estimate and represent how much knowledge a student possesses in an information system. For LARS to be able to measure student progression, I wish to create a system which utilizes the taxonomy Bloom developed, such that the representation of different mastery levels is represented in a familiar way to most teachers, where different values have proper definitions. The numbers which I use to represent knowledge therefore lies on the scale between zero and six, which reflects the ladder steps in Bloom's taxonomy, where zero represents no knowledge about the respective learning objective and six the mastery of all levels of blooms taxonomy for given learning objective. A "competency vector" (CV) is a vector of *d* dimensions with entries between zero and six for every dimension:

$$CV \in \left[[0 \dots 6]\right]^d$$

Where entry CV_i represents the mastery score of learning objective i.

4.4.2 Representing students as CVS

Every student is mapped by a mapping *g* to a personalized CV which represents their mastery of every learning objective:

$Given$

$\boldsymbol{d}$: $the\ number\ of\ learning\ objectives$

$\boldsymbol{S}$: $the\ set\ of\ studentIDs$

$\boldsymbol{g}$: $a\ mapping\ of\ students\ s\ to\ their\ corresponding\ competency\ vectors\ v$:

$\forall s \in S, g(s) = v, v \in \left[[0 \dots 6]\right]^d$

The number of learning objectives *d* can take on any number depending on how many learning objectives are covered and how nuanced the learning objectives are defined in the system.

Examples of the first learning objectives in a CS course can be variables, memory, integer type, string type, run-time errors and if statements, while latter objectives can be more advanced, such as nested for-loops, CSV-file management and run time complexity analysis.

4.4.3 Representing learning modules as CVs

The other main component of LARS is a large collection of learning modules. These modules will vary in terms of modality and difficulty. Some modules will be plain textual descriptions of concepts, others can be videos, quizzes, problems and educational video games. Each module will be represented as CVs of equal dimensions as the ones for the students, where entries in these vectors describes at what level of Blooms taxonomy does the module address given learning objectives. A zero means the module does not provide or require any information from a given learning objective, and where a number l means an understanding of the learning objective at level l in Bloom's taxonomy is required to complete the module.

$$\begin{aligned}
&Given \\
&\boldsymbol{d}: the\ number\ of\ learning\ objectives \\
&\boldsymbol{M}: a\ set\ of\ moduleIDs \\
&\boldsymbol{g}: a\ mapping\ of\ modules\ to\ their\ corresponding\ competency\ vectors: \\
&\forall m \in M\ , g(m) = v, v \in \left[[0 \ldots 6]\right]^d
\end{aligned}$$

For example, the first lecture given in the course, which might address the first two learning objectives in the remember and understand levels of Bloom's taxonomy, will have a vector v_m which might look similar to:

$$v_m = [1,1,0, \ldots ,0]$$

An appropriate learning module for a given student will address certain learning objectives at a higher level than what is stored in the student's corresponding competency score, while the rest of the competency scores will be equal or lower to the student. If a student is facing a module with lower competency expectancy in certain learning objectives, it will not provide any progress, but this does not necessarily make the learning module unfit. As long as the learning objectives which are aimed to be developed in the student are higher in the module CV such that if the student completes the module, their own vector entries will advance with respect to the difficulty of the module, and the other, lower, competency scores remain unchanged.

For example, as a student might not learn anything new about variables, declaring variables when solving challenging algorithmic problems is necessary and good volume practice, and does not negatively impact the experience/effectiveness of the learning module. The learning module should aim to develop one or more learning objectives within the student, and there exist various strategies to recommend appropriate learning modules to students.

4.4.4 Expected learning curve

Before addressing the specific algorithmic problems in the LARS system, we need to discuss how the curse of dimensionality affects our system. Let us assume a system of learning modules where the system consists only of two learning objectives, which means two dimensions for the vector space. Each dimension is delimited on a range between 0-6, as previously described, if we measure learning objective assessment on a scale inspired by Blooms taxonomy. The vector space will in X and Y axis consist of $6 * 6$ unique points in the system. Now, let us assume the system is increased to d dimensions. Then the system consists of 6^d dimensions, and as a realistic number for d might be as large as 40, unique points in the system will be 6^{40}. With a tremendous number of unique points in the system, it will become practically impossible to cover the whole system with vector points. Other brute-force algorithms which evaluates every possible point in the system becomes useless due to the exponential number of points in the system.

Therefore, I wish to introduce an “expected learning curve” (ELC) to the system, which represents the most generalized “path” a student is expected to progress through the vector space in the duration of a course. The ELC have various implementation designs. For my initial implementation, with the aim to simplify the algorithms regarding ELC, I wish to represent the ELC as an ordered list of CVs in the vector space, such that comparisons of ELC vectors and module/student vectors are conveniently streamlined into simple calculations.

When designing the number of points in the ELC, I wish to recall one of the first design choices in LARS, where every entry in CVs are always an integer between zero and six to represent the levels of Blooms taxonomy for each learning objective. This means that the final ideal CV in the ELC should be *[6,6,…,6]* and the first, lowest CV is *[0,0,…,0]*. We wish for students to progress through the ELC from some individual start point towards the final vector, which has a maximum score for every learning objective.

For my initial design, from the first point in the ELC, every step is an increase of 1 in a singular competency entry in the vector. Alternative design choices for the ELC can be empirically experimented. We can quickly deduce that to reach the top of the ELC will take $6 * d$ steps using this design, which will correspond to the number of vector points in the ELC. This number is linear in terms of dimensionality, and is unproblematic in regards to memory consumption and is therefore a simple and feasible design.

$$ELC = \{v_1, v_2, \dots, v_{6*d}\}$$
$$where\ ELC_i = v_i$$

$$\forall i\ where\ 2 \leq i \leq 6 * d:$$
$$norm(ELC_i) = 1 + norm(ELC_{i-1})$$
$$where\ norm(ELC_1) = 0$$

And equivalently:

$$\forall (i, j) \in \{1,2, \dots, 6 * d\}, where\ i < j$$
$$norm(ELC_i) < norm(ELC_j)$$

And:

$$\forall n \in \{1,2, \dots, d\}: ELC_{i_n} \leq ELC_{j_n}$$

Although the system is designed such that the points in the ELC suggests that students are expected to increase their CV for each step, this is not the case, as it is possible for student vectors to decrease in values given some calculated negative learning outcome for failed learning modules.

4.4.5 Mapping of CVs to the ELC

Having mappings from CVs to ELC steps in the system helps us utilize certain vector properties. There are two mapping strategies: to map a CV to the highest step in the ELC such that every entry in the CV is as high or higher than the corresponding values in the ELC step:

$mapDown(CV)$:
$map\ CV\ to\ ELC_p\ s.t. p = \arg max_p \{p\ |\forall i \in \{1,2, \dots, d\}: CV_i \geq ELC_{p_i}\}$
$output: ELC_p$

And likewise, a CV can also be mapped to the lowest step in the ELC such that every entry in the CV is as low or lower than the corresponding values in the ELC step:

$mapUp(CV)$:

$map\ CV\ to\ ELC_p\ s.t.p = \arg\ min_p\ \{p\ |\forall i \in \{1,2,\dots,d\}: CV_i \leq ELC_{p_i}\}$

$output: ELC_p$

4.5 Introducing students to LARS

As students might have been exposed to programming in previous experiences, it is important for LARS to recommend them appropriate learning modules from the beginning to make positive first impressions. Therefore, LARS should avoid automatically assigning new students to the system the $[0,0,\dots,0]$ vector. Instead, it is appropriate for students to undergo a pre-knowledge test which briefly and effectively classifies the student to a fitting CV such that they receive appropriate challenge from the very first recommendation in LARS. One example of a test like this have been developed by Bolland[169], which have been implemented in seven universities and colleges across Norway with promising results.

4.6 Mapping learning modules to the ELC

Although the points in the ELC represents the expected learning progression of a generalized student, this does not mean that every learning module will perfectly overlap with these points. Learning modules can theoretically address any learning objective at any level. Therefore, we need to develop a systematic categorization of these modules such that they can be recommended to students.

The strategy will be to map every learning module to a singular step in the ELC. The step to which the modules should be mapped to is determined by what step has the smallest sum of numbers where every learning objective is as high or higher than the ones in the learning module:

$$\forall m \in M:$$
$$mapUp(m)$$

4.7 Mapping student competencies to the ELC

To determine at what step in the ELC a student belongs to, I wish to consider their CVs the other way around, where instead of categorizing a module based on the hardest competency requirement with respect to ELC steps, we wish to categorize students based on the lowest competency skill with respect to the ELC steps. A student vector is mapped to a step on the ELC only when they have mastered every learning objective at an equal or greater level to the ELC step:

$$\forall s \in S:$$

$$mapDown(s)$$

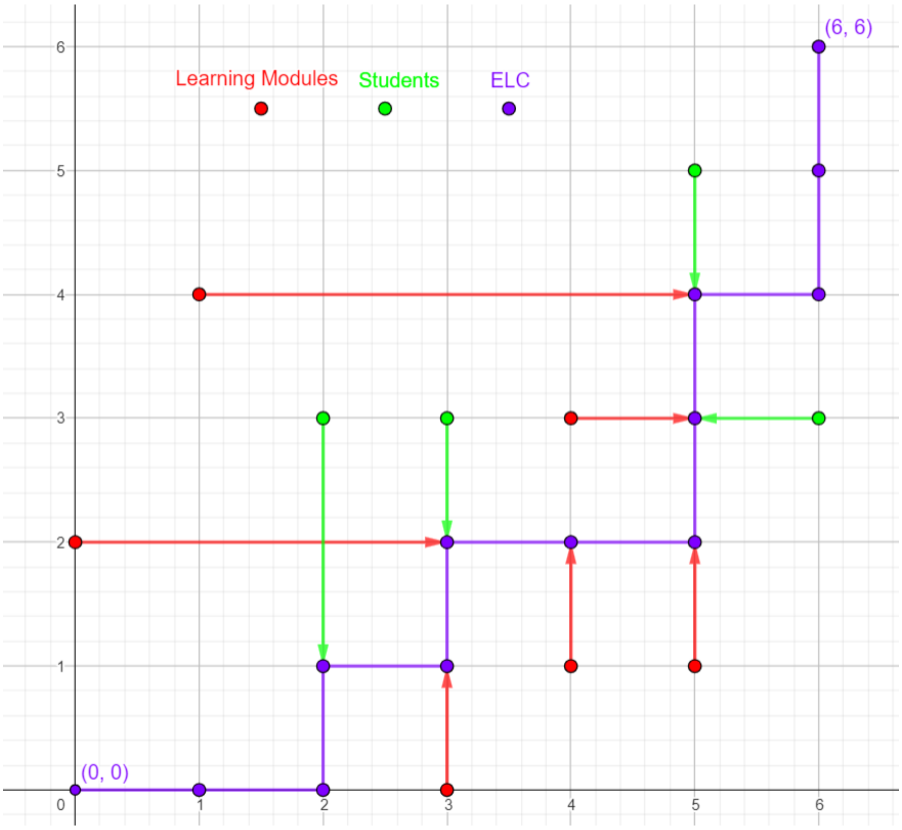

Figure 3: A two dimensional ELC system with module- and student vectors visualized. (Geogebra version 6.0.841.0)

4.8 Distances in LARS

There are various strategy choices when implementing a distance metric in LARS. Questions like whether increasing two learning objectives one step should be considered as hard as increasing one learning objective two steps is debatable. I would argue that any increment of any learning objective can be considered of equal value, and that the learning objectives can be designed thereafter. As learning modules with learning objectives with lower scores than the respective learning objectives for a given student CV should not negatively affect learning outcome, negative differences should not count towards the distance metric. I therefore wish to utilize modified Manhattan distances when calculating distances between CVs within LARS.

$$dist_{s,m} = modManDist(g(s), g(m))$$

4.9 Students academical reach in LARS

There is one last concept I wish to introduce to the system. How fast/efficiently different students acquire information is what I like to call their "learning rate". We can safely assume that no student can progress an unlimited number of steps in the ELC by completing a single learning module. Still, some students learn quicklier than others and the system should take this into account when determining how challenging recommended modules should be for a given student.

Therefore, LARS should contain a mapping LR of students s from the set of students S, where each student can be mapped to a certain learning rate R_s. R_s will be an integer which represents how much "learning capacity" a student has, which I defined the max total sum of increased learning objective values a student can obtain per completed module:

$$\forall s \in S, LR(s) = R_s, R_s \in \mathrm{N}$$

Where a student's CV before and after (v_1, v_2) completing a learning module can increase with a number between 1 and R_s:

$$norm(v_2) - norm(v_1) \leq R_s$$

In practice, this number will function as an upper bound distance when searching for learning modules in LARS. Though a student can increase their total CV by R_s, they can still make more than R_s steps in the ELC. A student might increase their competency by one point in a certain dimension and climb more than one step in the ELC given that the student vector already had higher values in the dimensions required to progress the next ELC steps.

Note that a learning rate value can be over- or underestimated and should be continuously adjusted based on some calculated performance score for the student such that the system can recommend harder/easier modules. I consider reaching $R_s \geq 5$ highly unlikely, where most students will probably have value either one or two, where the most capable have value three, but this also depends on how nuanced the learning objectives are defined.

4.10 Recommending learning module: Algorithmic approach

The goal of having an algorithmic approach to the recommendation problem is to make a solution as efficient as possible. As the naïve complexity is expressed as the product of the number of learning modules and the complexity of ELO, the goal is to decrease either one of these factors to improve efficiency.

The ELC system helps us practically categorize student competencies and module difficulties. Utilizing certain properties in the ELC system, we are able to reduce the number of learning modules which need to be considered when searching for an ideal recommendation.

4.10.1 Defining D, P and ELO

This is one example of how the functions D, P and ELO, which are defined in chapter 4.2, can be implemented for LARS. Note that if $mapDown(s) = ELC_c$, $norm(mapDown(s)) = c$

$\boldsymbol{define\ function}\ D(s, m)$:

$newVs \leftarrow list$

$\boldsymbol{for}\ i \in \{1,2, \dots, d\}\ \boldsymbol{do}$:

$\quad \boldsymbol{add}\ \max(g(s)_i, g(m)_i)\ \boldsymbol{to}\ newVs_i$

$c \leftarrow norm(mapDown(s))$

$\boldsymbol{for}\ step \in \{c, c+1, \dots, 6 * d\}\ \boldsymbol{do}$:

$\quad \boldsymbol{for}\ i \in \{1,2, \dots, d\}\ \boldsymbol{do}$:

$\qquad \boldsymbol{if}\ not\ newVs_i \geq ELC_{step_i}\ \boldsymbol{do}$:

$\qquad\quad \boldsymbol{output}: step - 1 - c$

$\qquad\quad \boldsymbol{end}$

$\boldsymbol{output}: 6 * d - c$

$\boldsymbol{end}$

$\boldsymbol{define\ function}\ P(s, m)$:

$\boldsymbol{output}: 1 - \dfrac{modManDist(g(s), g(m))}{LR(s)}$

$\boldsymbol{end}$

$\boldsymbol{define\ function}\ ELO(s, m)$:

$\boldsymbol{output}: P(s, m) * D(s, m)$

$\boldsymbol{end}$

4.10.2 Observations

Observation 1:

If a student is “mapped down” to step c in the ELC, all modules *m* which are “mapped up” to a step p where $p \leq c$ will always produce $ELO(v, s) = 0$, and should therefore be excluded from the search space for the ideal recommendation module.

$$norm\big(mapUp(m)\big) \leq norm\big(mapDown(s)\big) \Rightarrow ELO(s, m) = 0$$
$$where\ norm(ELC_i) = i$$

Proof for observation 1:

Given student *s* where $mapDown(s) = ELC_c$ and $norm(mapDown(s)) = c$ means that for every entry in *g(s)* - the CV representing the competencies of *s* - the corresponding entry in ELC_c will be smaller or equal:

$$\forall i \in \{1,2, \dots, d\}: g(s)_i \geq ELC_{c_i}$$

Similarly, given module *m* where $norm(mapUp(m)) = p$ means that for every entry in *g(m)*, the corresponding entry in ELC_p will be greater or equal:

$$\forall i \in \{0,1, \dots d\}: g(m)_i \leq ELC_{p_i}$$

Recall that:

$$\forall (i, j) \in \{1,2, \dots ,6 * d\}, where\ i < j:$$
$$norm(ELC_i) < norm\big(ELC_j\big),$$

And:

$$\forall n \in \{1,2, \dots, d\}: ELC_{i_n} \leq ELC_{j_n}$$

Which means:

$$\forall (p, c) \in \{1,2, \dots ,6 * d\}, where\ p \leq c:$$
$$\forall i \in \{1,2, \dots, d\}: ELC_{p_i} \leq ELC_{c_i}$$

Transitively,

$$\forall i \in \{1,2, \dots, d\}: g(m)_i \leq g(s)_i \mid norm\big(mapUp(m)\big) \leq norm(mapDown(s))$$

And hence:

$$modManDist\big(g(s), g(m)\big) = 0$$
$$\Rightarrow D(s, m) = 0$$
$$\Rightarrow ELO(s, m) = 0$$

Observation 2:

If a learning module vector *g(m)* has a modified Manhattan distance greater than R_s from student vector *g(s)*, m is not a possible candidate for an ideal module.

$$modManDist\big(g(s), g(m)\big) > R_S$$
$$\Rightarrow ELO(s, m) = 0$$

Proof for observation 2:

Recall our definition of P. Note that:

$$if: modManDist(g(s), g(m)) > R_s$$
$$\Rightarrow 1 - \frac{modManDist(g(s), g(m))}{R_s} < 0$$
$$\Rightarrow ELO(s, v) < 0$$

Observation 3:

For a student which is mapped to a given ELC step *c*, the next step *c+1* must have one value increased by one in some dimension *p*. There will be no learning outcome unless the recommended module contains a higher score in *p* than in ELC_c :

$$if: ELO_{(c+1)_p} = ELO_{c_p} + 1$$
$$then\ if: ELO_{c_p} \geq m_p \Rightarrow ELO(s, m) \leq 0$$

Proof for observation 3:

The calculated value for ELO is based on the number of steps in the ELC a student *s* will progress by completing a module *m.* All students are "mapped down" to a specific step in the ELC, recall the definition:

$mapDown(CV)$:

$map\ CV\ to\ ELC_c\ s.t.c = \arg\ max_c \{c\ |\forall i \in \{1,2,\dots,d\}: CV_i \geq ELC_{c_i}\}$

$output: ELC_c$

The fact that a student is mapped down to a certain step ELC_c gives us valuable information about the student's CV in a specific dimension, p, while for the other dimensions, a student can theoretically have any value greater than the ones in ELC_c.

For students to reach any step in the ELC, $c_{new} > c$, the student must also reach step $c + 1$.

We know that the student has competency scores equal to or higher than every corresponding competency score in ELC_c, and since the only difference from ELC_c to ELC_{c+1} is one value in dimension p:

$$ELC_{(c+1)_p} - ELC_{c_p} = 1$$

$$norm(ELC_{c+1}) = norm(ELC_c) + 1$$

means that the student will advance to ELC_{c+1} if and only if they increase their score $g(s)_p$ by at least one. Also, following observation 2, we can set R_s as an upper bound for the difference between the values $g(s)_p$ and $g(m)_p$.

Hence, for any $m, we\ have: ELC(s,m) > 0 \iff g(s)_p < g(m)_p \leq g(s)_p + R_s$

4.11 Preprocessing algorithm

4.11.1 ELC step specific KD trees

The strategy to improve the naïve time complexity of this problem will be to do a preprocessing of the module CVs in the system. We will build a KD tree which allows us to effectively query for sets of modules which are potentially ideal recommendations to the query student. The different choices for partitioning the set of modules needs to be examined to obtain good results from this strategy.

The first properties affecting our design choice is observation 1 and observation 3. They tell us that for each step in the ELC, the ELC will have certain learning modules which are irrelevant to the search for ideal modules for students mapping down to the step if the modules map up to a lower or equal step in the ELC. Naturally, this filtering of modules is less effective the lower the ELC step we consider is, and will therefore vary in effectiveness for every step in the ELC.

There will be presented other splitting strategies, and these strategies also varies in terms of effectiveness for each step in the ELC. This means that splitting criteria should not necessarily be the same for each step in the ELC. Therefore, it is reasonable to design a unique KD tree with a mapping *DT* from steps along the ELC to their corresponding decision tree KD_c:

$$\forall c \in \{1,2,\ldots,6*d\}: KD(c) = KD_c$$

4.11.2 Strategy 1: Initialize trees by observation 1

According to observation 1, we already know for each step *c* in the ELC that for every m: if $norm\big(mapUp(m)\big) \leq norm(ELC_c)$, m is excluded from the set of possible solutions for ELC_c.

If *c* is a low number, this splitting strategy will not prune away any meaningful number of learning modules, but if *c* is large, this will become very effective.

This property will not function as a splitting criterion in any trees, but we will utilize the observation to reduce the starting number of potential modules in the root of each three. Therefore, each tree can have a different number of potential modules from the beginning. The set of initial modules is large in the KD tree, close to $|M|$, for the earlier steps in the ELC, where the set of modules becomes smaller for KD trees representing higher steps in the ELC.

4.11.3 Strategy 2: Make splits based on observation 2 & 3

Observation 2 and 3 gives us a good foundation for making splits for every tree. If *c* is the step in the ELC and *p* is the dimension which is in increased by one between ELC_c and ELC_{c+1}, we can split based on different values of *p* (observation 3) in respect to the value of *R* (observation 2). If M_{node} is the set of modules considered in the current node in KD_c, we can categorize and split modules m into a maximum number of 6 branches, as $m_p \leq 6$:

$$Branch\ 1: \forall m \in M_{node}\ s.t: m_p = ELC_{c_p} + 1,$$

$$Branch\ 2: \forall m \in M_{node}\ s.t: m_p = ELC_{c_p} + 2,$$

$$\ldots$$

$$Branch\ R_{max}: \forall m \in M_{node}\ s.t: m_p = 6$$

For a query, we will follow the KD tree down R_s number of branches, such that modules with values $m_p - ELC_{c_p} > R_s$ are filtered out. For higher values for R_s, this step prunes less modules, however for expected values of R_s (1-3), we can expect some meaningful reduction in possible solutions.

4.11.4 Strategy 3: Split upon L1 norm values

Observation 2 tells us that if a module CV lies more than R_s distance away in modified Manhattan distance from the student's CV, we already know that this module vector cannot be a solution due to exceeding the student's learning capacity. However, when designing the tree KD_c, we do not know how the student vector looks like, and we cannot design the splitting strategy solely based on this.

However, if we expect $g(s)$ to lie somewhat close to ELC_c, we can make an estimation of how much larger L1 norm values a student CV can have than corresponding step $mapDown(s)$.

We know that $norm(g(s)) \geq norm(mapDown(s))$ based on the definition of $mapDown(s)$. We can empirically or statistically create some function ED which calculates the estimated distance between ELC_c and an arbitrary s where $mapDown(s) = c$:

$$ED(ELC_c) \in N$$

Now, we can calculate some value n_{split}:

$$n_{split} = norm(ELC_c) + ED(ELC_c)$$

Which we can utilize to split as follows:

$$Branch\ 1: \forall m \in M_{node}\ s.t: norm(m) \leq n_{split},$$

$$Branch\ 2:: \forall m \in M_{node}\ (no\ pruning)$$

We will only obtain a better solution if a large percentage of student CVs fulfil the requirement of Branch 1 and where Branch 1 prunes a feasible number of modules from the search space. If student vector $g(s)$ have larger norm value than n_{split}, the split will have no effect. Therefore, finding an appropriate value for n_{split} which can be estimated to be larger than $80 - 90\%$ of student queries can help efficiently prune the tree.

However, this split criterium is most effective for small values of c for ELC_c, as fewer and fewer modules will fall under the threshold n_{split} the farther up in the system we come. Therefore, this split operation might not be present in the KD trees representing later steps in the ELC.

4.11.5 Strategy 4: Split upon dimensions higher than p

Let us assume that dimension *p* represents an essential learning objective, for example variables in an introductory programming course. Let us assume we have value $ELC_{c_p} = 1$, meaning the student have recently been introduced to the learning objective of variables if they belong to this ELC step. The next step ELC_{c+1} is to increase the competency value about variables from one to two.

Later in the system, there will be numerous modules regarding much more difficult topics than variables, but where variables will be part of the module. There is no need for us to consider modules which have competency values for much more difficult topics for ELC_c if the goal is to increase the student from one to two in specifically variables. It is possible that a student, for some reason, have a high competency in topics such as CSV handling or BFS algorithms while still remaining on competency one in variables, however, this is highly unlikely for most students, and we can therefore make an efficient pruning strategy based on this.

To define the splitting criteria based on a specific learning objective, we need to find some learning objective q which is commonly combined with learning objective p where $p < q$ and a corresponding competency score Q which we expect most students with score 1 in variables to have a lower score than Q in q such that:

$$\forall s \in S \; if \; g(s)_p = 1 \Rightarrow g(s)_q < Q$$

Holds for as many students as possible while as many modules are pruned away as possible. Finding a fitting Q value should be empirically determined when we know roughly how the distribution of student CVs look like.

Then, split as follows:

$$Branch\ 1: \forall m \in M_{node}\ s.t: m_q < Q$$
$$Branch\ 2: \forall m \in M_{node}\ (no\ pruning)$$

For a more generalized splitting criteria where we do not find a specific correlation between criterium p and some other criteria q, we can replace q with a range of learning objectives which the student is expected to have a low total score in:

$$Branch\ 1: \forall m \in M_{node}\ s.t: norm\left(m_{[q_1:q_2]}\right) < Q$$
$$Branch\ 2: \forall m \in M_{node}\ (no\ pruning)$$

4.11.6 Concluding the preprocessing algorithm

When the query of search trees reaches leaf nodes, the search space stores in the leaves are combined, which will be a subset of the set of all learning modules, and LARS performs the ELO function on every module found in the leaves.

How each KD tree will look like will vary between the steps in the ELC. We have defined different strategies which varies in efficiency based on which step in the ELC is being queried. We can combine these strategies up to multiple times to create a search tree at a depth which is as effective as possible. Poor decision nodes will only increase run time, so the number of nodes in the KD tree and what the values in these partitioning operations should be needs to be empirically determined. It is hard to propose exactly how these trees might look like without having information about CV distributions for both students and learning modules, and this will be left for potential future works.

4.12 Discussion

4.12.1 ELO: Alternative approaches

Though we have various strategies of pruning the search space of modules when querying for a module recommendation, I cannot formulate some guaranteed improvement in worst case time complexities, but the average run time for these queries will surpass the naïve algorithms. This means, for some unfit query to our model, we can always switch back to the brute force method which is still a feasible running time.

As the algorithmic approach does not drastically improve the complexity of this system, looking into other strategies such as collaborative filtering and artificial intelligence approaches are good ideas. However, these approaches require some training data, where their approaches will also be dependant either on the naïve approach or this algorithmic approach until they have enough information to base their recommendation decisions upon.

4.12.2 Learning progression

As this system is a recommendation system, it is important to not override student ambitions when they work in the system. Should a student suddenly find intrinsic motivation to look deeper into some learning objective which does not correspond with the steps in the ELC, they should be allowed to do so. Letting students freely browse any learning modules is therefore respecting the individuality of students, such that they do not feel a sense of being controlled in the learning process.

However, it is still important for academical institutions to ensure academical progression through every learning objective for students, so perhaps designing a course such that students are “forced” to follow LARS recommendations either if they fall behind the expected competencies at a given point in the course or generally during some specified classroom time is appropriate. LARS can therefore balance individual academical interests at the same time as academical institutions expectations.

4.12.3 Loss of teacher control

If LARS were to be thoroughly implemented throughout the educational sector on a national level, LARS is partially taking over the role as a teacher for good and bad. One of the main motivational factors for implementing LARS is to reduce teacher workload, however, if the planning of classroom activities is overrun by an automated system, the teacher role will drastically change.

Some teachers might welcome such a change, while others might feel more detached from their students, as technology partially takes over the role as an educational guidance. While some teachers are happy with having more time for the other responsibilities of a teacher, others might lose some of the tasks which they found meaningful. As LARS has the potential of bringing both benefits and subjectively unwanted aspects to academical institutions, having a steady and step by step implementation of it deems appropriate. Teachers should have a big say to what degree LARS should be implemented in their classrooms in respect to the teacher profession.

4.12.4 Increased screen time

The amount of screen time youth is exposed to during a day is correlated with negative effects, such as worse sleeping patterns[170], physical[171] and psychological[172] health, and is widely discussed whether youth should be exposed to even more screen time during school. The LARS system is probable to increase the screen time in education and must therefore be implemented with respect to the guidelines proposed by professionals.

This problem can be addressed by LARS also containing exercises which are done physically without the utilization of screens or computers. The activities could still be logged in LARS, where perhaps the teacher logs the attendance of students such that LARS can take such activities into account when farther recommending new activities.

4.12.5 Academically sparse classrooms

As stated earlier, having a teacher teach on a singular academical level simultaneously either hampers capable students' progression, or leaves less capable students behind. With students autonomously progressing through learning objectives, some students are likely to progress farther than their classmates in courses, and classrooms might face an increase in academical sparsity.

However, I would argue that if students of any level can have a better learning outcome by utilizing such a system, that value will be greater than minor inconveniences like academical sparsity.

4.12.6 Instant feedback

As mentioned in the didactic preliminaries, having instant feedback during learning activities is an effective way of minimizing misconceptions and increasing the satisfaction of success for students. The feedback can be more elaborative than just pass/fail, where machine learning algorithms can be employed to analyse the performance of students and grant instant constructive feedback of what students did well and why potential mistakes were made. This is usually a teacher responsibility and can become very time preserving.

For students to be able to individually ask specific questions to the system and have some answer automatically generated, much like how AI applications are used today, can facilitate students asking more questions without social constraints and consuming collective classroom time. However, in contrast to the AI applications which are used today for academical questions, given that a LARS system has stored user profiles for students, such a system could do a better job at giving customized explanations to better fit students' personal learning style.

4.12.7 Higher quality teaching

Norwegian teachers have completed the required degree and practical pedagogical examinations in order to be allowed to teach in their institutions. As long as teachers have completed a minimum assessment of their teaching capabilities, they are allowed to teach mostly unquestioned in their own teaching style.

However, if LARS is implemented as an open platform where educators post learning modules and earn revenue based on popularity, the quality of the teaching is faced with, what I would consider, a healthy competition. Teachers would have to continuously work towards improving their pedagogical competencies in order to compete against other educators. This will bring the quality of teaching to a higher level than it is today, as teachers are currently not faced with any external competitive pressure to create better learning experiences for their students. Though most Norwegians teachers are passionately doing their best to teach their students in the best possible manner, sadly there exist exceptions where teachers who are less motivated creates low quality learning scenarios to the students' frustration.

4.12.8 Recommending the creation of new learning modules

Another interesting aspect of LARS which could be implemented is to find some solution to how LARS can determine what learning module should be created next to optimally fill the vector space with an evenly distribution of points. This is a much more difficult task, as recommending modules to students is based on information about what modules exist, this problem needs to base its solution on what modules doesn’t exist. In this problem, the curse of dimensionality plays a much bigger role than in the student recommendation algorithm.

Chapter 5. Concluding remarks

Teachers are faced with various challenges in the modern classroom. Their job is most importantly to facilitate learning among their students. However, problems like large cohorts of students and loss of individual potential needs to be addressed, where alternatives to traditional teaching strategies might be effective solutions.

Game based learning is one way of fostering intrinsic motivation among students. Utilizing video games for educational purposes addresses student interest better than many traditional modalities, however, more studies and a universal quality scale of video games are required to make any conclusions regarding the effectiveness of game based learning.

An information system which promotes autonomous and motivational learning and automatically adjusts the pace of challenge for individual students can be an answer to reducing teacher workload and bringing out individual potential among students. Such a system is demanding in terms of having a large enough collection of learning modules to make reasonable recommendations and requires some external marketing and academical approvement in order to be implemented.

Chapter 6. Future work

LARS is only one suggestion to promote more autonomous and motivational learning. I encourage the continuation of searching for alternative ways to organize classrooms in order to establish more effective learning activities and improving individual academical results.

LARS has many different design approaches, where machine learning is one appealing strategy of creating an efficient recommender system for academical purposes. Machine learning approaches can also farther replace the role of a tutor, farther reducing teacher workload.

Whether the drastic changes an automated learning module recommendation system brings to the educational sector is welcome by both teachers and students could be investigated by social experiments before venturing into implementing one.

The idea of LARS could be presented to the academic corporations which have vast experience and influence within the educational sector. As an automated academic recommender system is supposedly to be of interest by academical institutions, the teachers should be closely involved in such a development, as they are the most familiar with the challenges of modern classrooms.

To better understand whether digital game based learning is an effective mediation of educational content, the government could budget some investment in serious games of high quality and conduct research on these games. Only when the serious games are developed on a certain quality level can the study results give truthful values to the question of whether games based learning belongs to fantasy or future.

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