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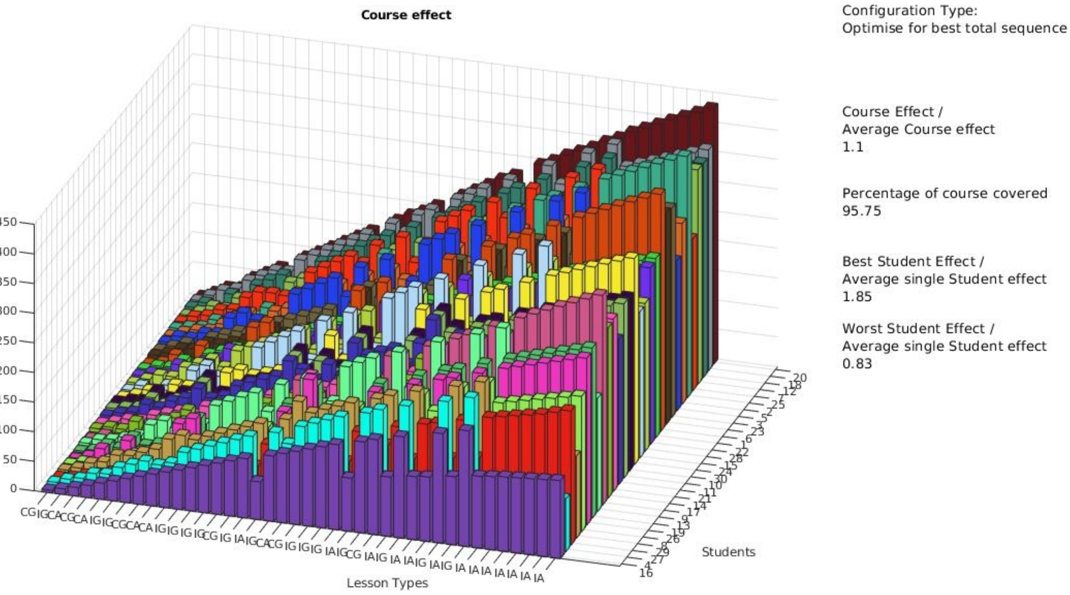

Lesson Sequence Optimisation for a Group of Students with Different Learning Styles

Master's thesis in Complex Adaptive Systems, and Learning and Leadership

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Department of Communication and Learning in Science
Chalmers University of Technology
Gothenburg, Sweden 2020

Master's thesis 2020:CLSX35

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Cover: Student engagement for a class of 30 different students and a course of 40 lessons in Matlab showing the optimal sequence of lessons for that particular set of students.

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During this long journey of sacrifices, victories and failures, many people have been part of this dream. Friends and family who have been there to support, but the person who I owe everything and who has been there at every step I take, is you Mom, thanks for all the support, I will never have enough time to thank you, te amo. Dante.

Andreas Standár & Dante Landa Vega, Gothenburg, June 2020

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Sammandrag

När lärare planerar upplägg för kurser så ligger det svårigheter i att veta om det kommer att väcka engagemang bland studenterna. Denna rapport ämnar att undersöka möjligheten att använda matematik, datavetenskap och pedagogiska modeller för att skapa en lektionssekvensmodell som kan simulera och maximera engagemanget för en klass med elever med olika lektionspreferenser. Modellen som utvecklades i detta arbete löses med hjälp av evolutionära algoritmer, en biologiskt inspirerad optimeringsmetod som ofta används för att optimera problem med komplicerad lösningsrymd. I den utvecklade modellen så användes data insamlad från gymnasieelever på teknikprogram i Göteborg med omnejd (N=104) angående deras preferenser kring lärstilspreferenser från Kolbs erfarenhetsinlärning samt lektionstypspreferenser enligt en model för lektionsklassificering utvecklad för detta arbete. Den insamlade datan analyserades med Kendalls rankkorrelationskoefficient för att undersöka korrelationen mellan preferens av lärstil och lektionstyp, vilken inte var statistiskt signifikant. Datan indikerar att den undersökta populationen har högst preferens för lektioner där eleverna får jobba individuellt enligt direkta instruktioner. Vidare så gjordes simuleringar enligt åtta olika optimeringsnormer. Från dessa simuleringar så gick det att hitta en unik sekvens av lektioner som genererar högsta möjliga ebgagemang i klassen. Från andra optimeringsnormer så drogs även slutsatsen att en bra strategi för lärare är at fokusera på engagemanget hos de minst engagerade studenterna i klassrummet då dessa elever verkar fluktuera mest i deras engagemang mellan de olika optimeringsnormerna.

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Summary

When teachers are planning courses there is difficulty in knowing whether or not the course will evoke engagement among the students. This work aims to investigate the possibility of using mathematics, computer science, and pedagogical models to create a lesson sequence optimisation model that can simulate the engagement of a class of students with different preferences when it comes to the lessons they prefer. The model that was developed is solved using evolutionary algorithms, a biologically inspired optimisation method often used to optimise problems with complicated solution spaces. To facilitate this, data was collected from students in upper secondary school, studying the technology programme in the city of Gothenburg with vicinity (N=104) regarding their learning style preferences from Kolb's Experiential learning theory as well as their lesson type preferences according to a lesson classification model developed for this purpose. Investigations were made to see if there was a correlation between learning style and lesson type preferences in the students, which analysis using Kendall's rank correlation coefficient disproved. However, the data collected indicates that the population prefers lessons where they receive direct instructions and are working alone. Moreover, simulations were made using the data from the students for eight different optimisation norms. From the simulations an optimal and unique lesson sequence was found to maximise the students' engagement in the course. From the other optimisation norms the conclusion was drawn that the least engaged student in the class fluctuates the most with different optimisation norms. Thus from the different optimisation norms the conclusion was drawn that a good strategy for a teacher is to focus on the least engaged students.

Keywords: course planning, optimisation, genetic algorithms, Kolb's learning styles, lesson classification.

Contents

1 Introduction

Imagine being in the shoes of a teacher; sitting down by their desk, about to start planning a course. This course will be the sequence of lessons that will convey the knowledge the students require to complete their education. But then a thought emerges worth pondering over, "How do I make sure that this course will keep my students engaged?". Is there a method one could use where a small amount of information regarding the students could be used to generate the sequence of lessons that guarantees that the students are as engaged as possible while the course takes the curriculum that has to be covered into account? What about the sequence of lessons that would be optimal if the curriculum is not a thing? Maybe the sequence could be tailored to produce the best possible student? Or maybe, if maliciousness is the goal, the worst possible sequence could be found for the course?

However, such a method does not exist, but an attempt could be made to make it real. It would be difficult to solve with pen and paper, but a mathematical model can be constructed and then solved using methods from computer science. Similar tools for simulation of live classrooms already exist for teacher training purposes. But a method of simulating outcomes of courses could become a tool that might eventually interest teachers.

In this report the idea of such a course planning tool will be explored by developing a mathematical model for representing certain aspects of the classroom environment as well as finding the optimal solutions for several different norms by using "Evolutionary algorithms" from computer science as optimisation method, using data on lesson type preferences from students in upper secondary school. Here follows the background of this project, its purpose, the delimitations, as well as the research questions to answer.

1.1 Background

A potential problem for a teacher when planning a course is that the students in the class may lose interest in the course over time. This may be due to the fact that the lesson type does not benefit the students' preferences both when it comes to the learning style of the student, or when it comes to the type of lesson. Thus the lessons may become tedious and confusing for the student, leading to a loss of motivation and interest. That is why having a tool that works as a guide to find a sequence of lesson types that takes the different preferences of the students into consideration might be helpful to maintain the interest and motivation for a long period. Besides that, the students as a group might manage to understand more of the knowledge that the teacher tries to transmit. However, such a daunting optimisation problem is impossible to solve by hand. The classroom as a system, with all of the dynamics that go into it, is very complex which means that the better alternative is to create a model of the engagement of the students and optimise it using methods found in computer science.

1.2 Purpose

The purpose of the project is to:

"Investigate the possibility of, as well as to create a symbolic model that can help teachers with the sequencing of lesson types in a course, such that their students' engagement in the course does not decrease."

1.3 Ethical Aspects

As the purpose of the project was to develop a model there were no real environmental or economical aspects that were controllable within the project. However, as a part of the research was to gather data for the implementation of the model there are some social aspects to consider regarding the data collection. The data was collected from upper secondary school students and therefore the data was collected with consent from the schools at which they attend as well as the students themselves, and participating in the data collection was completely voluntary. The data was collected anonymously and the identities of the participants has not been disclosed. Finally, the participants were also made aware why the data was collected, as well as what the data would be used for as well as how it was going to be used.

1.4 Delimitations

As the purpose is to create a model, there has to be delimitations set around how it will be constructed as everything that happens inside of a classroom can't be taken into consideration. The model is only supposed to be a representation and an estimate of reality. Many of the aspects that will not be taken into consideration is the socialisation that happens within a classroom, both between peers and the teacher.

However, the influence that the students have on each others' engagements will be considered to some extent, which can affect the interest in the lessons either positively or negatively. This does not resemble the reality, where other more complex factors play a very important role, such as social intelligence, personality, maturity and personal desires of each person. Moreover, the teacher-student relationship will not be taken into account, nor will emerging behaviours that may occur due to personal problems on both sides. Assuming that those issues do not change the quality of the lesson, it is expected of the student to have the same performance as if the classroom is a closed system. Similarly, the personal interest of the teacher will be omitted, focusing only on the engagement of the students in the class instead of grades or performance.

Furthermore, the way in which students learn can be a mixture of different styles, so it becomes even more complex than what is intended to be included in this model. However, there is an assumption in that there will always be a dominant learning style that dominates and determines the students preferences when it comes to lesson types, thus only the main learning style will be taken into account.

Another important delimitation of the model is that of the dynamics of the class. Work done at home and the interactions that could occur after lesson time will not be taken into consideration, as mentioned above one assumption will be that the classroom is a closed system. In the same way, it will be taken for granted that the school's facilities does not matter, and that all teacher's skills are uniform when it comes to giving lessons. So the teachers will not be considered as a variable that could affect the personal engagement of the student, only the lesson types. Finally, the student's prior knowledge will not be a factor that affects the engagement in the course.

There will also be delimitations regarding the data collection. Since the data collection will be relatively small, at least when compared to other scientific data collections, the investigation will be limited to one subject or programme in order to have a more even distribution of students when it comes to their learning styles. The hope of this delimitation is to increase the accuracy when the model is applied to the chosen subject or programme, and thus increase its relevance.

The data collection will also be restricted geographically to the city of Gothenburg with vicinity. This is mainly due to convenience with regards to both travelling, as well as establishing contact with teachers. The geographical restriction is also economical since the data collection is not funded.

1.5 Research Questions

Here follows the research questions aimed to be answered in this report:

1. Is there a unique sequence of different lesson types, with which a maximum amount of engagement is obtained?

2. How much do different optimisation norms affect the amount of engagement in the class?

3. Does the learning style preference in a student correlate to preference in lesson types?

4. Which lesson type from the lesson classification model do students most prefer?

2 Theory

In order to answer the research questions, there is some amount of relevant theory that should be covered that this report mainly is built upon. Covered in this section are the following: Kolb's experiential learning theory, and more specifically the learning styles of individuals according to the theory; theories and models about how to classify education in a way that makes it simpler to analyse, as well as the difficulties that goes into classifying education; Kendall's rank coefficient, a measure used to analyse rankings of objects, which will be utilised in the data analysis; and some theory about genetic algorithms which is used in the implementation of the eventual model.

2.1 Experiential Learning and Kolb's Learning Styles

Experiential Learning Theory (ELT), developed by David A. Kolb (D. A. Kolb, 2014), is a theory built on the cognitive learning theories of psychologists John Dewey, Kurt Lewin and Jean Piaget (D. A. Kolb, Boyatzis, Mainemelis, & ..., 2001). The term "experiential" is used in order to both differentiate the theory from other learning theories as well as emphasise the role experience plays in learning. The theory defines learning as "The process whereby knowledge is created through the transformation of experience. Knowledge results from the combination of grasping and transforming experience" (D. A. Kolb et al., 2001).

To describe this combination, D. A. Kolb et al. (2001) portrays grasping and transforming experience with two dialectically related modes respectively. The two modes for grasping experience are Concrete Experience (CE) and Abstract Conceptualisation (AC), while the two modes for transforming experience are Reflective Observation (RO) and Active Experimentation (AE). When grasping experience, some people like to perceive the new information through tangible means, feeling the world around them and rely on their senses to *experience the concrete*. On the other hand, others perceive or grasp information by thinking, analysing or systematically planning, taking hold of it through symbolical representations or *abstract conceptualisation*. Likewise, when it comes to processing experience, some like to carefully watch others being involved in an experience, *reflecting and observing* the process taking place. On the contrary, some like to jump into the process in order to be able to do things by *actively experimenting*. (D. A. Kolb et al., 2001)

In order to motivate the dialectical relativity of the modes D. A. Kolb et al. (2001) claim that "each dimension of the learning process provides us with a choice. Since it is virtually impossible, for example, to simultaneously drive a car (Concrete Experience) and analyse a driver's manual about the car's functioning (Abstract Conceptualisation), we resolve the conflict by choosing. Because of our hereditary equipment, our particular past life experiences, and the demands of our present environment, we develop a preferred way of choosing to do one of the two. We resolve the conflict between concrete or abstract and between active or reflective in some patterned, characteristic ways. We call these patterned ways 'learning styles'.", suggesting that Concrete Experience and Abstract Conceptualisation can't occur simultaneously.

When assessing these learning styles D. A. Kolb et al. (2001) found four statistically prevalent learning styles which were named Diverging, Assimilating, Converging, and Accommodating. These learning styles and their respective combinations of modes are visualised in figure 1. Here each learning style is a combination of one mode of grasping, and one mode of transforming experience. These styles can in short be described as follows:

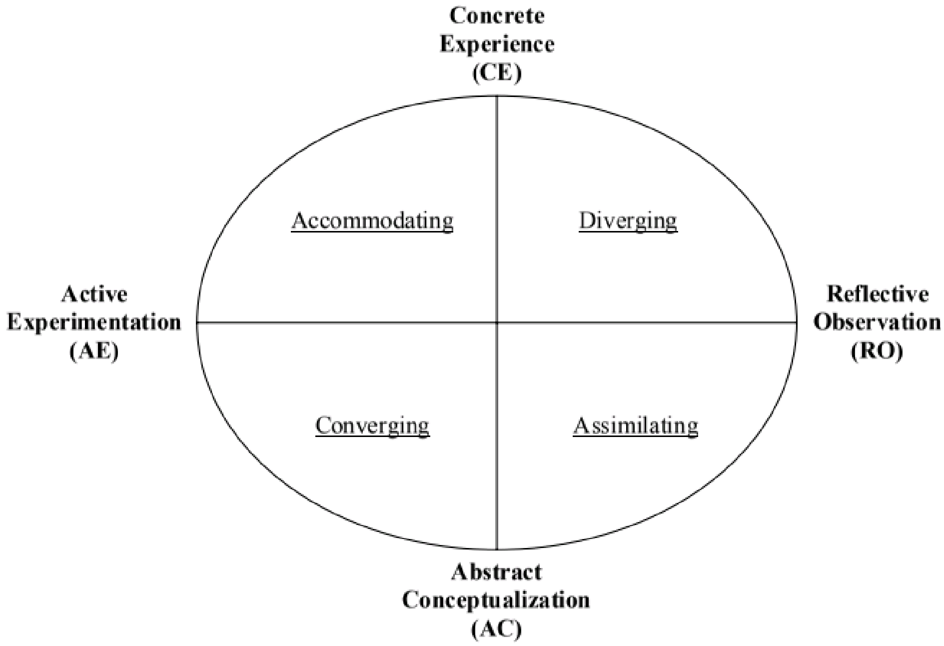

Figure 1: Visualisation of the different modes of grasping and transforming experience and the resulting learning styles. (D. A. Kolb et al., 2001)

- The *Diverging* learning style is dominated by the modes Concrete Experience (CE) and Reflective Observation (RO). The most important characteristics of the divergers are their thinking ability and being aware of value and concept. They prefer working in groups and like to look at concrete situations from many different points of view and to organise relations in a meaningful way. They tend to be patient and objective, not seeking out action in their learning. While forming thoughts, the divergers take their own thoughts and feelings into account.

- The *Accommodating* learning style is dominated by the modes Concrete Experience (CE) and Active Experimentation (AE). The main characteristics of the accommodators are to make plans, carry out plans and to experiment. They are intuitive and like to act on gut feeling. Accommodators adapt easily to change and are broad minded while aquiring new knowledge.

- The *Converging* learning style include the modes of Abstract Conceptualisation (AC) and Active Experimentation (AE). The convergers are characterised by their problem solving, decision making, and their analytical abilities, thinking logically and systematically. They like to learn by being active and analysing results, preferring working with technical problems rather than with social and interpersonal issues.

- The modes of the *Assimilating* learning style are Abstract Conceptualisation (AC) and Reflective Observation (RO). These persons have the main characteristic of creating conceptual models. They like to work with abstract concepts and thoughts while obtaining new knowledge, finding it more important that a theory has logical soundness rather than practical value. (D. A. Kolb et al., 2001; Kaya, Özabaci, & Tezel, 2009)

While Kolb's theory on Experiential Learning introduces one way of modelling learning styles, there are plenty of other models that one might consider. Coffield, Mosely, Hall and Ecclestone (2004) had identified 71 learning style models at the time of writing their article, but according to Kayes (2005) Kolb's model is the most influential one. The appeal of Kolb's Experiential learning theory is that the focus of the model is on the learning process rather than the learning traits (Turesky & Gallhager, 2011) while also lending itself into multiple other theoretical perspectives on learning such as cognitivism, phenomenology, and adult learning (Holman, Pavlica & Thorpe, 1997). The theory also receives empirical support from several studies (e.g., Abdulwahed & Nagy, 2009; JilardiDamvandi, Mahyuddin, Elias, Daud & Shabani, 2011; Massey, Kim & Mitchel, 2011; as cited by Manolis, Burns, Assudani, & Chinta, 2013, p. 44).

The amount of consistent empirical support for the ELT is enabled by Kolb's Learning Style Inventory (LSI) which was developed by David Kolb in 1971 in order to assess the learning styles of individuals. The LSI has been used in various fields, e.g. education, management, computer science, psychology, medicine, nursing, accounting and law (D. A. Kolb et al., 2001). The LSI is constructed as a questionnaire where the respondent ranks four different statements according to how they believe the statements relate to themselves. Four points are given to the statement that conforms the most with the respondent, three points to the second most, and so on all the way down to one point. The respondent also has to assign the different points to every set of statements (Manolis et al., 2013). The LSI has had multiple iterations and is continually being worked on by Kolb (D. A. Kolb et al., 2001) as well as others who are either trying to improve the questionnaire (e.g, Manolis et al., 2013), or translate it to other languages (e.g., Marke & Cesarec, 2007, to Swedish).

Although the ELT seemingly has a lot of empirical support as well as being cited by numerous sources, well over 4000 according to A. Kolb and Kolb (n.d.), it has not gone without criticism. Here the support for the LSI is not in accordance, where research about the LSI has been less affirming (e.g., Fox, 1985; Fredman & Stumpf, 1978; Geller, 1979; Lamb & Certo. 1978; West, 1982; as cited by Manolis et al., 2013). According to Manolis et al. (2013), most of the criticism towards the ELT should be directed towards the LSI. They are of the impression that as the theory has such widespread support it is the meassuring tool, the LSI, that needs improvements in order to improve consistency in test-retest measurements and suggest a new scale with an altered set of statements.

In the report containing the Swedish translation of the LSI, Marke and Cesarec (2007) mention that factor analysis does not confirm Kolb's original four modes being orthogonal. They, like Manolis et al. (2013), suggest an altered set of statements as well as a change in the four modes in order to avoid "loaded" items in the questionnaire that might affect the choices of the respondents. The change in modes mainly being aesthetic and not altering the core concept of the ELT. The changes they make when it comes to the four modes is to alter the scales from Concrete Experience and Abstract Conceptualisation as well as Active Experimentation and Reflective Observation to Emotive, Intuitive (EI) and Rational, Logical (RL), and Pragmatic, Acting (PA) and Reflective, Questioning (RQ) respectively (Marke & Cesarec, 2007). Work has also been made by Manolis et al. (2013); Marke and Cesarec (2007) to make the scale more continuous, rather than just indicating one definite learning style of the respondent since the original ELT only indicates the main learning style preference of the respondent and not how well they resonate with that learning style. It might be the case that a person is considered to be Diverging by the LSI but in reality the person is virtually equally Diverging and Assimilating, barely leaning more towards the Diverging learning style.

While there are several studies indicating that the test-retest measurements are inconsistent (Manolis et al., 2013), there are also studies that claim that the inconsistencies are statistically insignificant as well as being natural due to individuals' learning style preferences being subject to change over time (e.g, Geiger & Pinto, 1991). In their investigation, Geiger and Pinto (1991, $N = 40$) find that while learning style preferences in individuals change from a statistical point of view, the impact is marginal in practice. They suggest that over a time period of three years, preferences in learning styles are highly unlikely to change when using the LSI, indicating that the learning styles of students remain somewhat the same over a short amount of time like the span of a course.

2.2 On Classifying Education

Classifying education, and more specifically lessons in this work, is a difficult task (Davis, 2017). There are many different factors that go into what education actually is, such as age, personality, class size or mix, classroom environment, race, genders of both students and professors, and discipline as well as if the teaching methods are preformed in a traditional or non-traditional way, or by utilising emerging techniques such as interactive lectures, games, simulations etcetera (Faust & Paulson, 1998; Emerson & Taylor, 2007; Tanner, 2013; Pawlowska, Westerman, Bergman & Heulsman, 2014; Ziegert, 2000, as cited in Murphy, Eduljee, Corteau, & Parkman, 2020, pp. 100), with most of the research being performed on university or college level.

One of the earlier theories on how to classify education comes from Muska Mosston and is called "The Spectrum of Teaching Styles" which in modern time has been inherited by Sara Ashworth (Mosston & Ashworth, 2008). The theory is built on the axiom stating that "teaching behaviour is a chain of decision making. Every deliberate act of teaching is a result of a previous decision", focusing mainly on the decision making between the students and teacher. Thus, the different kinds of teaching styles are deducted by establishing which decision is being made, about what, and when (Mosston & Ashworth, 2008). In total the theory introduces 10 different *teaching styles*.

While Mosston and Ashworth (2008) focus on teaching styles, i.e. the style that the teacher uses to transfer knowledge to the students, there are other classifications that can be made from the list of factors above. One factor that is related to the style that the teacher uses is the *teaching method*. Crombag (1978) proposes a classification of university level teaching methods in order to determine which are the most efficient with regards to different objectives. The overlying classification of Crombag (1978) is (1) *Lecture*, (2) *Reading*, (3) *Exercises*, (4) *Practical experiences*, (5) *Independent work*, and (6) *Tests*. All of these categories of teaching methods have a number of underlying, more distinct teaching methods, such as *Systematic lecture* or *Commentarial lecture* under Category (1) *Lecture*, all with a short descriptor.

While on the topic of teaching methods, Westwood (2008) writes in his book "What teachers need to know about teaching methods" about two main classes of teaching styles: *teacher-directed methods* which relate to instructivism (Terhart, 2003), and *student-centred methods* which relate to constructivism (Terhart, 2003). The teacher-directed methods were dominant in the first half of the twentieth century, heavily utilising textbooks, drill, and practice. With these methods, the focus lies more on mastery of the subject matter rather than facilitating learning in the students. Moreover, in the second half of the twentieth century it became more common for teachers to engage in methods with a focus on projects and group work. With the introduction of project based learning followed other innovative methods such as activity based learning and the introductions of non-tradition mediums such as television and film. These methods are called student-centred methods. (Westwood, 2008)

While student-centred methods are more resent additions to the teacher's repertoire as recognised teaching styles, it does not mean that they necessarily are the best to use in every teaching situation. According to Ormrod (2000) the teacher-directed methods, and more specifically the use of direct instructions, has a good place in education when it comes to basic information and skills that have to be learned in a step-by-step sequence (as cited in Westwood, 2008, pp. 12). Westwood (2008) also writes that research has shown that direct teaching methods can be highly effective for those purposes and that it can lead to substantial boosts in students achievements and self-efficacies. However, the critique directed towards these teacher-directed methods come from the constructivists who react negatively towards them, claiming they are too prescriptive, too highly structured, too rapidly paced, and with too much emphasis on basic skills, leaving little room for creativity (Westwood, 2008). But there is also a subclass of direct teaching methods that focus more on the constructivistic perspective which are dubbed “interactive whole-class teaching”. These methods strive to generate high levels of attention as well as active participation of the students by presenting parts of the information to the students and then have them discuss and fill in the gap with their own thoughts and ideas (Westwood, 2008).

Just as there are advantages and disadvantages with the teacher-directed methods, the same can be said about the student-centred methods. However, the two classes of methods complement each other fairly well. Westwood (2008) writes that “In some areas of the curriculum these approaches are highly appropriate, particularly for involving students more actively in acquiring knowledge, skills, and strategies” about student-centred methods. Moreover, he writes that these methods are deemed to be the best practice when the objectives are to acquire independent study skills, improve student autonomy, work collaboratively with others, construct knowledge from firsthand experience, and apply basic academic skills for authentic purposes.

The weaknesses of the student-centred, or constructivistic, methods lies in what their strengths are when also considering the temporal aspects of education. While these methods are good at constructing knowledge, they require more time in order to have a higher and long-lasting quality (Airasian & Walsh, 1997). The planning of lessons that are built with a student-centred method in mind requires not only knowledge about the normal sequence in which the students will learn, it also requires knowledge about the current construction of the individual students' knowledge (Clements & Battista, 1990) leading to the teacher investing more time in such a lesson outside of the lesson time. There is also the aspect of time efficiency when it comes to the curriculum to keep in mind. Terhart (2003) writes that “the subject matter is the matter of the school” claiming that if the subject matter is dissolved or “virtualised” for all content and areas in the education it would mean learning in the school will lose its substance. With this in mind, Airasian and Walsh (1997) writes “Implicit in the need for increased time are other important time-related issues, such as tradeoff between coverage and depth. It is likely that the quality of students' knowledge constructions will depend in part on the time they are given to construct. More time will mean richer and deeper constructions. Teachers and schools will have to face the question of whether it is better to cover a large amount of content at a rather shallow level or to cover a smaller amount of content in great depth" regarding the temporal consequences of constructivistic and student-centred methods. Thus, since it is a common claim that mixing different teaching methods generate better results (e.g Westwood, 2008; Airasian & Walsh, 1997; Terhart, 2003), considering the tradeoff between the different methods employed by the teacher is of importance.

2.3 Kendall's Rank Correlation Coefficient

When simulating the effect that a course will have on a class of students, one of the more important aspects is to consider what the students' opinions are about the types of lessons in the course. These opinions will be collected from real students using a data collection (see section 3.3). But what is that data going to look like? And how will that data be implemented into the model? In this case the opinions of the students will be implemented as preferences, where the most preferred lesson type will have the highest amount of points, and the least preferred lesson type will have the smallest amount of points. When considering four different lesson types (LT), a student preference could for example look like in table 1.

Table 1: Example of a student preference. The student prefers lesson type one the most and lesson type 3 the least

LT1	LT2	LT3	LT4
4	2	1	3

In addition to the lesson type preferences, the data collection will also measure learning style preferences according to Kolb's four learning styles "Divergent", "Accomodating", "Convergent", and "Assimilating" (D. A. Kolb et al., 2001), see 2.1. As one of the research questions is to investigate the dependency between learning style preference and lesson type preference, it is of interest to investigate how concordant students who have the same main learning style are in their ranks of lesson types. And in order to measure this concordance, or rank correlation, Kendall's rank correlation coefficient, τ (Kendall, 1938), can be calculated and analysed to find if there is a statistically significant dependency between the two preferences.

Kendall's rank correlation coefficient τ is a statistic used to measure the ordinal association between two or more measured quantities, or in other words the degree of similarity between two rankings or between one and several other where $\tau \in [-1, 1]$. When τ takes on a value of -1 it represents perfect discordance or complete negative association, and when τ takes on a value of 1 it represents perfect concordance or complete positive association. A value of 0 would indicate the absence of association. As an example, consider the following natural sequence as a ranking of five elements (e_1, e_2, e_3, e_4, e_5):

e_1	e_2	e_3	e_4	e_5
1	2	3	4	5

as well as an arbitrary ranking of those elements:

$$\begin{array}{ccccc} e_1 & e_2 & e_3 & e_4 & e_5 \\ 1 & 3 & 4 & 5 & 2 \end{array}$$

In order to compare the second ranking with the first, consider how well the order of the numbers in the second sequence corresponds to the first and add a score of $+1$ for each pair of numbers in succeeding order that are in the same order as the first sequence, and similarly add a score of -1 when the pairs are not in the same order. Looking at the first number in the second sequence, 1, and pairing it with the first succeeding number, 3, the first pair is obtained as 1 3. In the first sequence the first pair is obtained as 1 2. The pair 1 3 is in the same order as 1 2 since both $1 < 3$ and $1 < 2$, thus a score of $+1$ is added. Now compare the next pairs in succeeding order, 1 4 from the second sequence and 1 3 from the first. Once again the pairs are in the same order, adding a score of $+1$ once again. Continuing the same process for the rest of the pairs with the first number in the respective sequences, a sequence of four scores will be generated:

$$+1 \quad +1 \quad +1 \quad +1, \text{ totalling in } +4.$$

Obviously this score was to be expected since both sequences start with 1. Now let us consider the three respective succeeding pairs starting with the second numbers:

$$\begin{array}{lll} 3\,4 & 3\,5 & 3\,2 \text{ and} \\ 2\,3 & 2\,4 & 2\,5 \end{array}$$

for the second and the first ranking respectively. These pairs result in the following sequence of scores:

$$+1 \quad +1 \quad -1, \text{ totalling in } +1.$$

Continuing the same process for the third and fourth number, the following sequences of scores are obtained:

$$\begin{array}{rl} +1 \quad -1, & \text{totalling in } 0; \\ -1, & \text{totalling in } -1. \end{array}$$

The total score now becomes the sum of the totals above: $4+1+0-1 = 4$. But what does this mean? In order to compute the value of τ one must consider the maximum possible score, which would be obtained if the rankings were identical. In this case the maximum score is 10 since that is the number of pairs that could be concordant. Thus, the rank correlation coefficient becomes (Kendall, 1938):

$$\tau = \frac{\text{actual total score}}{\text{maximum possible total score}} = \frac{4}{10} = 0.4. \tag{2.1}$$

In the general case, let $\mathbb{S}$ be the sample space of an arbitrary ordinal scale for n numbered elements. Let X and Y be two random variables defined on $\mathbb{S}$. Consider an element i in

$\mathbb{S}$ and let (x_i, y_i) be the positions of element i on the ordinal scale according to X and Y. (X, Y) can then be defined as:

$$(X,Y) = \{(x_i, y_i);\ i = 1, \ldots, n \in \mathbb{S} \text{ and } X(i) = x_i, Y(i) = y_i\}. \tag{2.2}$$

Here, x_i and y_i would represent two different rankings of the same object i out of n objects. Then, according to (2.2) (x_1, y_1), (x_2, y_2), ..., (x_n, y_n) becomes the *observations* of (X, Y). Any pair of observations can either be concordant or discordant depending on if they agree or disagree according to:

$$\begin{cases} (x_i, y_i) \text{ concordant pair} & \text{if } x_i > x_j \text{ and } y_i > y_j; \text{ or if } x_i < x_j \text{ and } y_i < y_j, \text{ where } i < j \\ (x_i, y_i) \text{ discordant pair} & \text{if } x_i > x_j \text{ and } y_i < y_j; \text{ or if } x_i < x_j \text{ and } y_i > y_j, \text{ where } i < j \end{cases} \tag{2.3}$$

Ties between x_i and x_j as well as y_i and y_j can also be considered; in that case the Kendall's rank correlation coefficient is denoted τ_B which will not be considered in this report. In the case where ties are not considered, the Kendall's rank coefficient is denoted τ_A and can be calculated as follows: Let the actual total score between the rankings from X and Y be the difference of the number of concordant and discordant pairs, denoted Σ. As the maximum possible score that can be obtained when there are n elements in $\mathbb{S}$ is the same as the number of ways to pick two elements from n elements, the Kendall's rank correlation coefficient τ_A becomes:

$$\tau_A = \frac{\text{actual total score}}{\text{maximum possible total score}} = \frac{\Sigma}{\binom{n}{2}} = \frac{\Sigma}{\frac{n(n-1)}{2}} = \frac{2\Sigma}{n(n-1)}. \tag{2.4}$$

Once τ_A has been calculated, it may not be immediate how significant or insignificant the result is. However, one can find a z-score from τ_A using the following formula:

$$z = \frac{3\tau_A \sqrt{n(n-1)}}{\sqrt{2(2n+5)}} \tag{2.5}$$

from which a p-value (probability value) can be obtained by using a z-table, which in turn is compared to the significance level α which in the case of this study will be the standard value $\alpha = 0.05$.

2.4 Evolutionary Algorithms

Evolutionary algorithms are optimisation methods based on a simplified version of biological processes, for this reason, the terminology used in these algorithms is similar to the terminology used in biology. For example, terms such as "genes", "chromosomes", "mutation" are used in *genetic algorithms*, which are a classification of evolutionary algorithms. This section will focus precisely on these types of algorithms. The theory here regarding genetic algorithms will be related to the purposes of the eventual symbolic model.

2.4.1 Genetic Algorithms

In genetic algorithms, a population has to be defined which will evolve and find the optimal solution to a problem. This population consists of different individuals composed of binary strings called chromosomes. Each bit of these strings, called genes, encodes the information of the variables in the optimisation problem into the individuals. In this case, the individuals would be the sequences of lesson types in the course that will be optimised. Once the individuals are defined, they will be part of the first generation of the population. The new generations will be obtained when the individuals go through the process of selection, reproduction and mutation. Essentially, the individuals with the highest fitness value, which in the upcoming model is the lesson effect in the students from the lesson sequence, have a higher probability to be selected to spread their genes. Thus, individuals with lower fitness value have a higher probability to be discarded. In this way, each new generation will have individuals with better characteristics until the best possible individual is obtained (Wahde, 2008).

First, to be able to talk in detail about how these algorithms work, one must first understand more about the biological background of them. The main idea in genetic algorithms is the evolution of a population that advance generation after generation. Once the population is settled in its advancement, an evaluation criterion needs to be defined and applied among the individuals. This will help to classify the value of each individual what is known as fitness value. The fitness value indicates how far or how close an individual is to meet the evaluation criteria. A simple example can be seen in the biological part when an individual defines the criteria to be to look for a partner. According to this criteria, a classification is generated, which helps the individual to know who best fits their search criteria. In reality, this process is much more complex than just a search criterion and a classification, but it helps to understand the main operation of these types of algorithms.

Proceeding with the same example of seeking a partner, some important aspects of the use of these types of algorithms can be explained. When defining the search criteria, the person does not know what type of individuals can be found out there or where they will find them, so it is not easy to visualise the search space. In the same way, these types of algorithms address problems in which the search space is complex and the possible solutions or individuals, in this case, are very broad. This means that there may be solutions that fit the search criteria to some extent, but they may not actually be the optimal solution.

After obtaining the fitness values of each individual a selection process is carried out where the best individual is picked to spread its genes into the population. Thus a few exact copies are placed into the new population for the next generation. This procedure is known as “Elitism”. Then, a certain number of individuals are chosen randomly from the population and among them, with some probability, the best individual is selected. The best individual is not always chosen to avoid the algorithm getting stuck in local solutions instead of finding the global one.

This procedure is repeated to obtain two individuals that will combine genes to create two new individuals that will be introduced into the population for the next generation, replacing the original ones. This part of the algorithm is called “Crossover”. This step consists of taking the two individuals from the Selection process and randomly determining a point, called crossover point, to divide the two chromosomes as can be seen in figure 2.

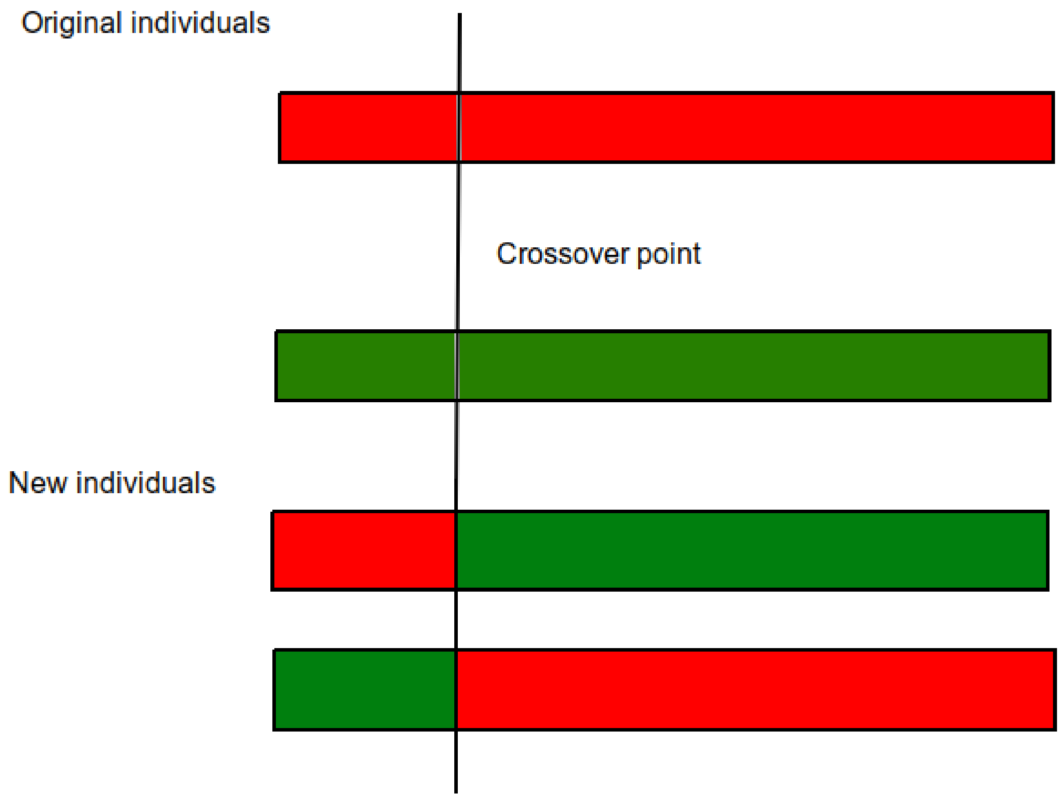

Figure 2: The two individuals in the top of the picture, whose chromosomes are represented by the bars, are selected with one crossover point. The genes on either side of the crossover point are recombined to create two new individuals to replace them in the next generation. There could be cases with more than one crossover point.

Right after finishing the Crossover step, a "Mutation" takes place for all the individuals in the population. This procedure consists in flipping, with a certain probability, each of the binary genes, that is, if the gene was 0 before it will change to 1 and vice versa. The purpose of this step is to bring new material to the evolution process. Even though mutations are not a good thing in practice, they can be helpful in the long run in order to find the best individual, that is, the optimal solution. However, this probability should be very low, with approximately one mutation per chromosome. It is computed as c/m where c is a constant, typically set to 1, and m is equal to the length of the chromosome (Wahde, 2008).

Finally, after all the individuals from the population have gone through the Mutation, the old individuals are replaced with the newly modified ones to form the new population for the next generation. This procedure iterates until the desired number of generations is reached.

3 Method

In the following sections the methods used to obtain the results are presented. What follows are the descriptions for how the lesson classification model was developed, How the mathematical model or the set of equations for the model implementation were developed, how the data of students was collected, and how all these were implemented into the lesson sequence optimisation model.

3.1 Lesson Classification

In order to investigate the correlation between students' preferences in Kolb's learning styles and preferences in lesson types, a model for classifying lessons was established since no suitable model for that purpose was already established. In order to investigate the existence of such a correlation, a simple model was developed that drew from the theories in section 2.2 regarding classification of lesson types, such as considering the roles of students and teachers inspired by (Mosston & Ashworth, 2008) as well as the difficulties of classifying education inspired by (Davis, 2017).

The model was developed ad hoc, and during development considerations were made with Kolb's experiential learning theory in mind such that the existence of a correlation between learning style and lesson type preferences easily could be determined. This did not necessarily mean that the intention was that the classification of lessons would be determined by Kolb's learning styles in order to make it more likely to find a correlation, but rather that the developed model also would be two-dimensional, with a main preference that dictates the succeeding preferences as pointed out by Manolis et al. (2013). In this way the lesson classification model and Kolb's experiential learning theory had a similar functionality.

The simplicity of the lesson classification model would hopefully overestimate the correlation (if it exists) between the preferences, as the smaller decision space might reduce eventual variance. The disadvantage of having a less holistic model is that in the case of a strong correlation between learning style and lesson type preferences, it would be less conclusive as the lesson types would have too broad descriptors.

3.2 The Mathematical Model

The mathematical model would be the set of equations that drives the simulation of the students' perception of a course over time. The equations were developed in an ad hoc fashion where the equations were developed to fit the phenomenons and interactions they were supposed to represent. An example of this could be the effort a student has to put into a lesson. If the student is in a lesson they enjoy, they should not have to put as much effort into completing the tasks of that lesson. Thus, a function that tries to describes effort should depend on the lesson preference as well being a decreasing function with respect to preference. In this case the positive aspects of effort, such as the theory on desirable difficulties (Bjork & Bjork, 2011), are not considered in order to keep the model simpler. Equations that contained parameters and constants had them adjusted to generate outputs that "made sense" both in how they varied depending on input as well as in their magnitude relative to other equations.

When developing this mathematical model the first step was to identify the elements of classroom interactions and phenomenons that were of interest. The second step was to determine the dependencies between the chosen elements as variables and functions. The third step was to develop the equations ad hoc to symbolically describe the dependencies.

3.3 Data Collection

In order to analyse how the learning style preference of students affect their preferences of different types of lessons a quantitative descriptive data collection was performed on students studying technology on upper secondary level ($N = 104$) in the form of a questionnaire which can be seen in Appendix A. The data was then analysed in order to find the means and standard deviations in the lesson type preferences depending on the learning style preferences of the students. The data was also analysed with Kendall's rank coefficient by using the τ_A-statistic. Here follows the methods related to the data collection in more depth.

3.3.1 Variables and Definitions

As mentioned, the goal of the data collection is to describe the preferences in types of lessons depending on the main preference of learning style in the students. These will be the two variables in the investigation. Note that the students are considered to only have one main preference when it comes to learning style as in (D. A. Kolb et al., 2001), and not multiple as suggested by Manolis et al. (2013) in order to not make the analysis too complicated. In this case, the main learning style preference of the student is defined by the learning style indicated by the LSI (D. A. Kolb et al., 2001) (see section 2.1).

As classification of education, and more specifically "lesson types" for this purpose, is subject to a plethora of different variables which possibly explains the lack of prior research (as motivated by Crombag, 1978, see 2.2), the types of lessons will be defined by the four quadrants in the model mentioned in section 3.1 and is written about in detail in section 4.1. For reference, the model can be seen here in figure 3. In short, the idea of the model is that a lesson can be described by the two dimensions "Teacher instruction" and "Student constellation" which represent if the teacher is taking an instructive or coaching role towards the students, and if the students are working individually or in groups. The "grey zone" in the middle represent lessons where these dimensions are not obvious. The grey zone is there in order to account for the difficulties of classifying education, abstracting away the lessons that are difficult to describe by only using these two dimensions. These two dimensions form four quadrants: "Instructions-Alone", "Coaching-Alone", "Coaching-Group" and "Instructions-Group" (IA, CA, CG and IG). Only lesson descriptions firmly related to the quadrants will be considered valid to include in the questionnaire, excluding as much as possible lesson descriptions closer to, or inside of, the grey zone. A student's preference of the lesson types is then defined as the ranking that the student gives each lesson type from best (4 points) to worst (1 point).

In order to describe the relationship of the two variables, the learning style preference is considered to be an independent variable and the lesson type preference is considered to be a dependent variable. The relation between these variables will be the mean and the standard deviations of the individual students' lesson type preferences depending on their learning style preferences. The concordance of the rankings within each learning style group will be measured using Kendall's rank correlation coefficient, see section 2.3.

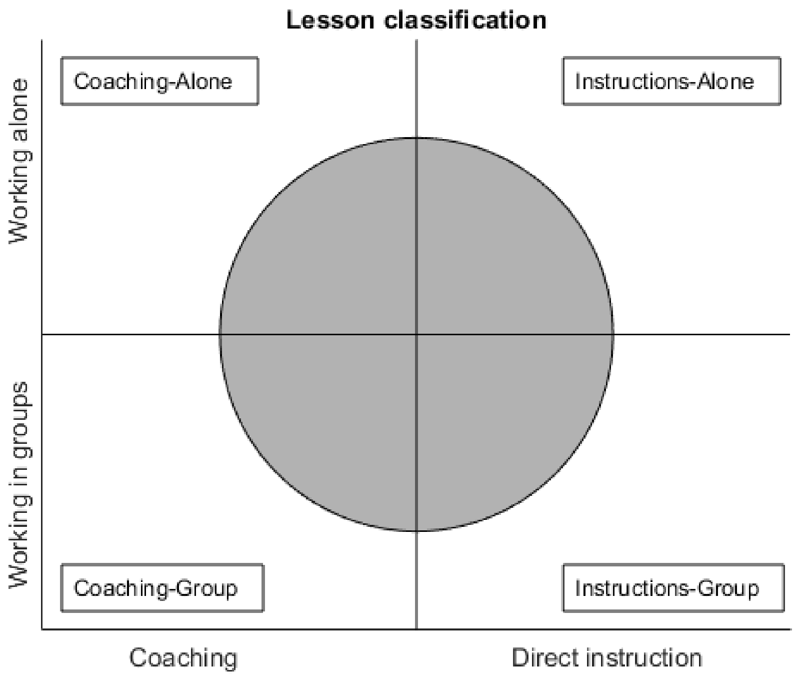

Figure 3: The simple model developed for classifying lessons into four types. The model consists of the two dimensions Teacher engagement ranging from Coaching to Direct instructions, and Student constellations ranging from Working in groups to Working alone. These dimensions form the quadrants that represents the four lesson types Instructions-Alone, Coaching-Alone, Coaching-Group, and Instructions-Group. The filled area in the middle has been dubbed the "Grey zone", and represents the uncertainty with the model in that there are many types of lessons that are not distinct in this model. This is to take into account the difficulties of classifying education that are brought up by Davis (2017)
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3.3.2 Population, Analytical Units, and Selection

The population for the data collection was chosen to be classes from the technology programme in upper secondary school (grades 10-12) in the city of Gothenburg with vicinity. Thus the analytical units of the investigation becomes the students in the classes. The total size of the population was estimated to have the lower bound of 5130 individuals from knowing that there are 57 technology programmes in the city of Gothenburg with vicinity (gymnasium.se, 2020), assuming that every programme has at minimum three classes - one for each year - and that one class has around 30 students: $57 \cdot 3 \cdot 30 = 5130$.

To make a selection from this population the strategy of "first-best" selection was employed (Esaiasson, Gilljam, Oscarsson, Towns, & Wängnerud, 2017) where the selection is made by choosing the analytical units that are the most available. For this purpose, three familiar teachers were contacted who offered one to two classes each, resulting in a total of four classes and 104 students in total which corresponds to around 2% of the total population. While first-best selection may be insufficient when it comes to represent the population as a whole it could still be considered a viable method in smaller pilot studies (Esaiasson et al., 2017) which this data collection could be considered to be as time and resources are not sufficient to make a data collection based on large scale random selection.

3.3.3 Questionnaire

The questionnaire was split in two parts: the first for investigating the learning style preferences of the students, and the second for investigating their lesson type preferences. As indicated above, the first part was inspired by LSI-1985 (D. A. Kolb et al., 2001), which is the tool developed by Kolb for analysing learning styles. As the the LSI was originally made in English, the questionnaire was instead based on a translation to Swedish by Marke and Cesarec (2007), slightly modified to fit the students' vocabulary in order to reduce inconsistencies in the responses due to language barrier and vocabulary. These modifications were made after receiving feedback from a test of the translated version on a student in the population (but outside of the selection). The changes made to the translated LSI were to either use a synonym of a word, considered by the student to be difficult, or by adding information to the statements in order to make them more understandable. The questionnaire by Marke and Cesarec (2007) as well as a list of the modifications can be seen in Appendix B.

The first part consists of 13 incomplete sentences about how one enjoys learning in different contexts which the respondents complete by assigning points to four potential completions of each sentence. Four points are assigned to the most preferred completion, three points to the second most preferred completion and so on in decreasing order. Each of the sentence completions has correspondence to one of Kolb's four learning styles (see section 2.1). Thus the number of items in the first part ends up at 52. Moreover, the second part of the questionnaire consists of ten descriptions of lessons which the respondent rate on a four item Likert scale, from "I do not prefer this type of lesson at all" (1) to "I prefer this type of lesson completely" (4). The descriptions of lessons, two from each above described lesson type, as well as two statements regarding how students like lessons to be structured, related to the dimensions that describe the lesson types. The second part then consists of 36 items, so 88 items in total for the whole questionnaire. And the whole questionnaire was estimated to take 20-30 minutes to complete.

4 Results

This section is the first part of two that cover the results. This first section will focus on the minor parts of the project, Lesson classification model, Data collection, and Mathematical model, while section 5 will focus on the major result: the implementation and simulations.

In this section the Lesson classification model will be presented first (4), followed by the results and analysis of the data from the Data collection (3.3), and the final part of the section will be the equations that attempt to describe the dynamics of the students' engagement in a course.

4.1 Lesson Classification Model

Before properly walking through the lesson classification model, there will be a "glossary" for the terms introduced in the model that may be confusing in their context due to the similarity of many of the terms used as well as the lack of finesse in the names chosen for the terms. This glossary can be used in combination with figure 4 for better understanding of the model.

Term	Explanation
Teacher engagement	One of the two dimensions of the lesson classification model. In the figure it is the "horizontal" dimension consisting of the two parts "Coaching" and "Direct instructions". This dimension is inspired by how the teacher conveys information to the students.
Student constellation	The second ("vertical" in the figure) dimension that consists of the two parts "Working in groups" and "Working alone". This dimension is inspired by the seating and interaction between the students that is dictated by the constellations in which they are seated.
Polar opposite pairs	Refers to the two different parts of one of the dimensions which are assumed to be "opposite" each other.
Direct instructions	One part of the "Teacher engagement" dimension. This part refers to when teachers engage with students in a more instructivistic way.
Coaching	The other part of the "Teacher engagement" dimension. This part refers to when teachers engage with students in a more constructivistic way.
Working alone	One part of the "Student constellation" dimension. This part refers to when the students are participating in the lesson alone, or in special cases in pairs.
Working in groups	The other part of the "Student constellation" dimension. This part refers to when the students are participating in the lesson in groups.
Grey zone	This is represented in the figure as the grey circle and in the model it is supposed to represent the difficulties of classifying lessons with only two dimensions, making many distinct types of lessons disappear in the hazy dimensions.

Instructions-Alone	The first out of four lesson types. In the figure, Instructions-Alone is represented by the first quadrant, and is the type of lesson one would receive if "Direct instructions" is combined with "Working alone".
Coaching-Alone	The second out of four lesson types. In the figure, Coaching-Alone is represented by the second quadrant, and is the type of lesson one would receive if "Coaching" is combined with "Working alone".
Coaching-Group	The third out of four lesson types. In the figure, Coaching-Group is represented by the third quadrant, and is the type of lesson one would receive if "Coaching" is combined with "Working in groups".
Instruction-Group	The fourth out of four lesson types. In the figure, Instructions-Group is represented by the fourth quadrant, and is the type of lesson one would receive if "Direct instructions" is combined with "Working in groups".

As mentioned in section 3.1, a simple model for classifying lesson types was developed in order to both investigate the relation between students learning style preferences and preferences in lesson types. But the data regarding the respondents' lesson type preferences will also be implemented in the actual lesson sequence optimisation model to represent the different students in the class. See section 4.3 for the mathematical model, and 5 for the implemented model. The lesson classification model drew inspiration from the construction of the experiential learning theory (ELT) as well as the Learning style inventory (LSI) of Kolb (D. A. Kolb et al., 2001) for how to both construct and investigate the model. The lesson type classification model can be seen in figure 4. As seen in the figure, the model consists of two dimensions assumed to be orthogonal and to be general, fundamental parts of what makes a lesson: *Teacher engagement* and *Student constellation*. Obviously, as motivated by (Davis, 2017), there is great difficulty in classifying education due to the large amount of variables that go into any given lesson which means that classifying lessons according to two dimensions arguably is either too general where information about the lessons are lost in the definitions of the dimensions, or is too narrow where information about the lessons is left out of the definitions. What is of importance is to consider the purpose of the model that has been developed. The main purposes of the lesson classification model is to function as a simple preference system to gather data of opinions of real students on lesson types; being indicative of whether or not there is a dependency between those opinions and the main learning style of the students; as well as also describing the roles of the teacher and the students. For that purpose the two dimensions each consist of what is considered to be a polar opposite pair, *Direct instruction* and *Coaching* for the Teacher engagement dimension, as well as *Working alone* and *Working in groups* for the Student constellation dimension. Furthermore, in order to account for the difficulties of classifications mentioned above, a grey zone is introduced in between the polar opposite pairs where lessons that cannot be clearly described using the model are positioned.

But that is only the construction of that model, what do these dimensions and polar opposite pairs actually mean? As mentioned above, one of the purposes of this model is to

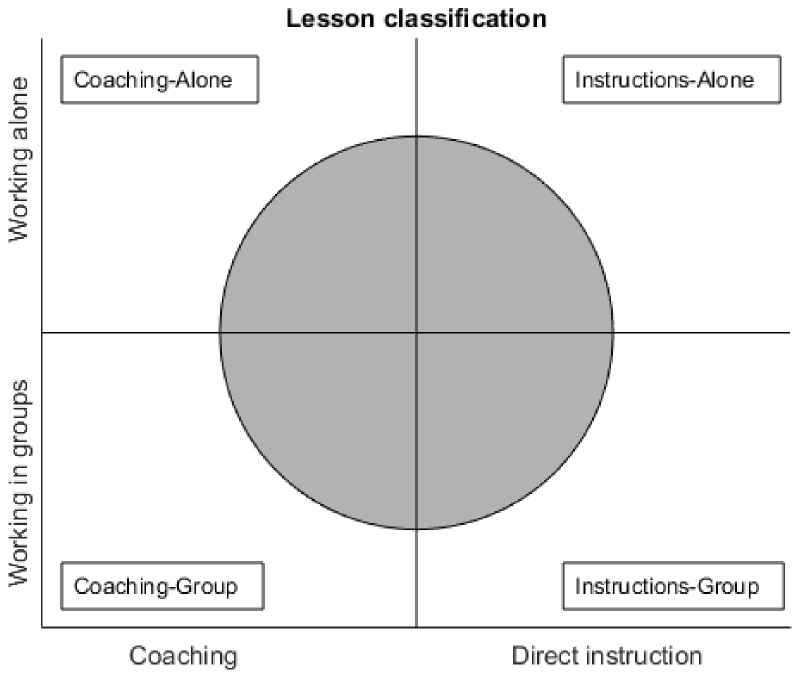

Figure 4: The simple model developed for classifying lessons into four types. The model consists of the two dimensions Teacher engagement ranging from Coaching to Direct instructions, and Student constellations ranging from Working in groups to Working alone. These dimensions form the quadrants that represents the four lesson types Instructions-Alone, Coaching-Alone, Coaching-Group, and Instructions-Group. The filled area in the middle has been dubbed the "Grey zone", and represents the uncertainty with the model in that there are many types of lessons that are not distinct in this model. This is to take into account the difficulties of classifying education that are brought up by Davis (2017)

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describe the teacher's and students' roles during a given lesson. Westwood (2008) writes about two main categories of lessons: Direct teaching, and Student-centred methods, which are the inspiration for the Teacher engagement dimension. As the name suggests, the Direct teaching lessons focuses on the instructive role of the teacher, where the teacher gives students information in a systematic and controlled way such that the students are aware of what is going on and where the lesson is heading. Here the teacher has a more hands-on role when it comes to the constructions of knowledge which the students build up during the lessons. The Direct teaching methods ensures that the individual constructions of the students knowledge are more uniform, which can be useful when the subject taught follows fundamental rules, or if it is built on pure facts. When moving forward with a course, the uniformity of knowledge constructions makes sure that all students have the same base knowledge. On the other hand there are the Student-centred methods where the role of the teacher is less instructive and more constructive where the focus lies on the students building their own knowledge constructions. A diversity of knowledge constructions can help to manifest more nuanced discussions around the subject taught. What is common for most of the student-centred methods is that the teacher's focus lies more on coaching the students. Thus these two main teaching methods from Westwood (2008) are the foundation to the Teacher engagement dimension and the descriptors for the polar opposite pairs Direct instructions, and Coaching.

The other dimension, Student constellation, describes one way that the students engage in the lesson: alone or in groups. One important aspect of lessons is the interaction between students and the teacher which is affected by the constellation that the students are in (Mosston & Ashworth, 2008). Depending on if the students are working alone, in pairs, or in groups the lesson will most likely be different as these different constellations support the building of knowledge constructions in different ways as with the different teacher engagements. Mosston and Ashworth (2008) write that interaction is one of the key components of the model for teaching styles, which in this case became the foundation for the Student constellation dimension. This dimension is simple in that it is very binary; either students work alone or in groups. In reality, however, this dimension would be much more nuanced as there are differences with regards to student performances and engagement depending on the size of the groups that the students are working in.

The dimensions Teacher engagement, and Student constellation, or more specifically their respective polar opposite pairs, form four different types of lessons outside of the grey zone that can be described by each quadrant: *Instructions-Alone* (IA) as a combination of the pairs Direct instructions, and Working alone; *Coaching-Alone* (CA) as a combination of Coaching and Working alone; *Coaching-Group* (CG) as a combination of Coaching and Working in groups; and *Instructions-Group* as a combination of Direct instructions and Working in groups.

How the lessons are constructed depending on type might be fairly self explanatory, but there is still merit in going over a couple of examples of how these lesson types are reflected in a real classroom.

In Instructions-Alone (IA) lessons students are taking direct instructions from the teacher on what they are going to do, and carry out that work alone. But working alone does not mean that the students can't interact with the teacher from whom they are receiving the instructions. Lessons that are structured in the form of lectures or where the students are working with assignments in the book are both examples of IA-lessons. Those lessons follow the conditions of the students working individually by either doing the exercises, or listening and writing, but in both of those cases the students can still ask the teacher for help or clarification.

Coaching-Alone (CA) lessons are constructed in a way where students are working alone and are being coached by the teacher during their work. One example of lessons that would be of this type could be problem solving lessons where the solutions to the assignments may be both difficult and without a clear solution, or where there are multiple correct answers and solutions to one assignment. Another example of a CA-lesson would be where the students are writing individual reports; working alone to gather information about a certain concept while having an ongoing discussion with the teacher while they are writing.

In Coaching-Group (CG) lessons, students work in groups while being coached by the teacher. Similarly to the CA-lessons, one example would be a group project where the students are working together to create something as a group, such as a report and/or presentation. In such a lesson, the students would be able to toss ideas back and forth with the teacher who also can help the group with teamwork related issues as well as subject related issues. A second example of a CG-lesson is one where students are given problem to discuss in groups, for example about something they have not yet learned about where they can exchange ideas and construct knowledge together while getting guidance from the teacher.

Finally, Instructions-Group (IG) lessons has one fairly distinct lesson associated which is lab sessions. During lab sessions it is of importance that the students follow a set of instructions for multiple reasons, such as getting consistent results between the groups as well as for their own safety in some cases. Another example of an IG-lesson could be where students work in groups with more difficult assignments, similar to IA-lessons, where the teacher then gives a walk-through of the solutions for the whole class.

4.2 Data Collection

In this section the data collected will be analysed in order to accept or reject the hypothesis that Kolb's learning styles are correlated with the lesson types presented in section 4.1.

The first step of this analysis will be to look at the distribution of the participants' main learning styles from Kolb's Experiential learning theory (D. A. Kolb et al., 2001, see 2.1). When only looking at the main learning style of the students, the distribution can be seen in figure 5 as a histogram and in figure 6 as a pie chart.

From these figures it is easy to see that the most common learning style in the population is the Converging, $N = 50$ which represents 48% of the respondents. In succeeding order they are: Assimilating, $N = 27$ or 26% of the respondents; Diverging, $N = 16$ or 15% of the respondents; and Accommodating, $N = 11$ or 11% of the respondents. This does not correspond with the results of Marke and Cesarec (2007, p. 31) where the most common learning style among students in upper secondary school is Assimilating, and in succeeding order: Accommodating, Diverging, and Converging. However, this comparison might not be valid as the data of Marke and Cesarec (2007) is collected from "students in upper secondary school" while the data in this report comes from "student of the *technology*

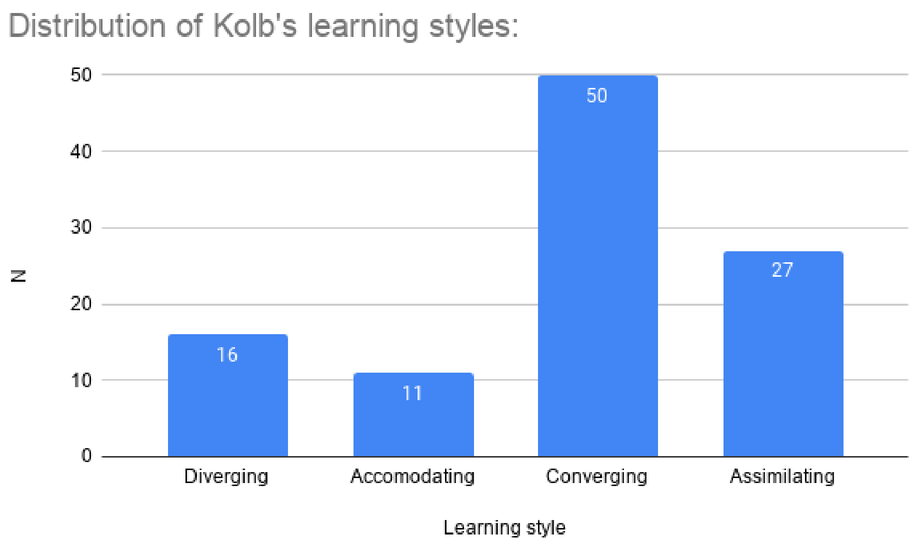


Figure 5: Distribution of the main learning style of the participants in this syudy of Kolb's Experiential learning theory in the form of a histogram. The most common learning style is Converging ($N = 50$); the second most common is Assimilating ($N = 27$); the third most common is Diverging; and the least common is Accommodating ($N = 11$).

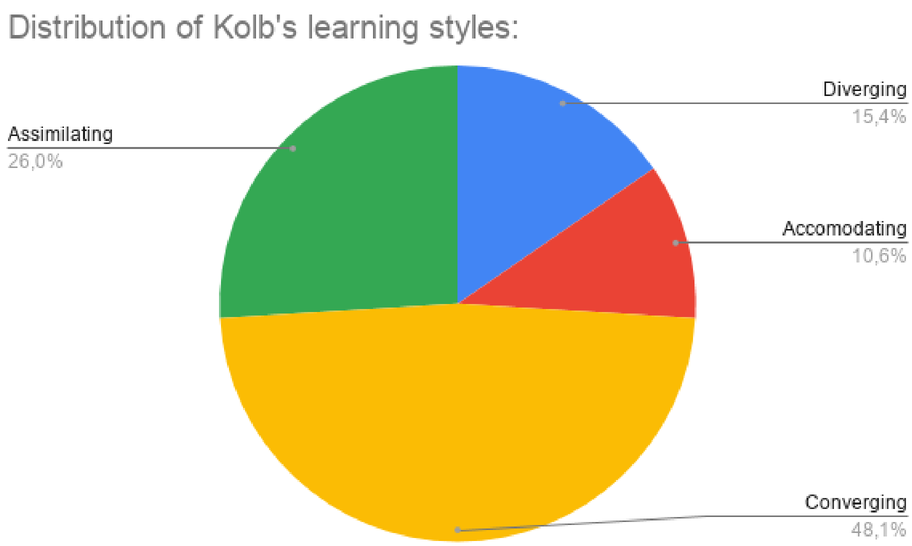


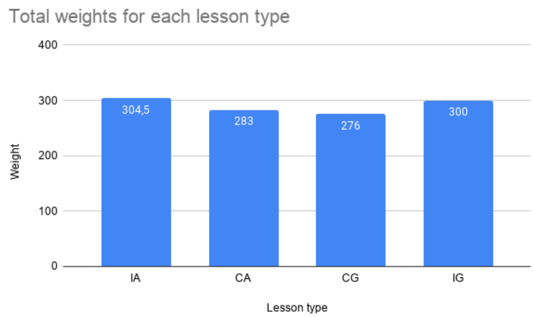
Figure 6: Distribution of the main learning styles in the form of a pie chart. Here it is clear what the distribution is in percentages rather than raw numbers. The Converging learning style makes up 48.1% of the respondents; the Assimilating learning style, 26.0%; the Diverging learning style, 15.4%; and the Accommodating learning style, 10.6%.

programme in upper secondary school", so there may be different types of students from which the data is collected. As the technology programme is a university preparatory programme with, as the name suggests, a focus on technology, it might be better to compare with "technologists" instead of "upper secondary students". For technologists ($N_{tot} = 81$), the learning styles are in the following succeeding order: Assimilating (40), Convergent (26), Accommodating (20), and Diverging (15) (Marke & Cesarec, 2007, p. 40). From that data, the difference is that the two most common learning styles, Assimilating and Converging, are in reverse order, as are the two least common learning styles, Accommodating and Diverging. One thing to consider when investigating the learning styles in upper secondary students is that it is one of the groups with the most heterogeneous distribution of learning styles as there is a greater mix of interests among students. (Marke & Cesarec, 2007).

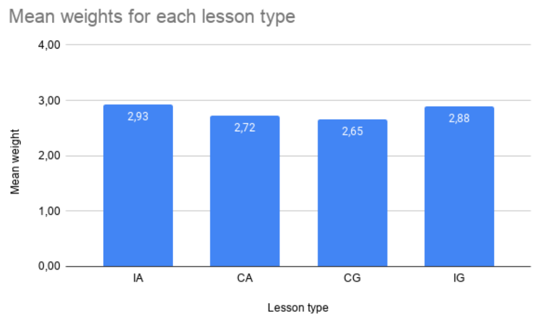
Moving on to the second part of the data collection regarding the lesson type preferences in the students. In the questionnaire there are two ways to investigate the preferences. As mentioned in section 3.3, there are eight statements focusing on describing the four lesson types from section 4.1: Instructions-Alone (IA), Coaching-Alone (CA), Coaching-Group (CG), and Instructions-Group (IG). When ranking these statements on the four item Likert scale they will be assigned a weight of 1-4 depending on the selected item. After all eight lesson descriptions have been ranked, the average weight of each lesson type can be calculated for each individual. The second way to investigate the preferences is by looking at the two final questions that refer to the dimensions that define the lesson types, Teacher Engagement and Student Constellation. These questions are considered to be "control" questions that can be used to check if the rankings of the descriptions relate to the types of lessons that are described. These two questions are direct in that they are asking the respondent if they prefer lessons where they receive direct instructions and have a clearly defined goal or where they are coached and can influence the goal themselves, as well as asking the respondent if they prefer lessons where they work alone or in groups. Thus it is possible to check the reliability of the lesson classification model compared to the dimensions.

In figure 7a the total weights given to each of the lesson types from the data can be seen as well as the average weights, or preferences, of the lesson types in figure 7b. Considering the dimensions that define the lesson types, Teacher engagement (Coaching - Direct instructions) and Student constellation (Working alone - Working in groups), see figure 4, and where the lesson types are positioned in relation to these dimensions one can see that the most preferred teacher engagement should be Direct instructions as there is a bias towards the lesson types Instructions Alone and Instructions Group, and the most preferred student constellation is working alone as there is a bias towards Instructions Alone and Coaching Alone. This can be compared to the data from the control questions related to the dimensions which can be seen as histograms in figures 8a, and 8b. From those diagrams it becomes clear that the most preferred teacher engagement is Direct instructions, and that the most preferred student constellation is Working alone. This should mean that the most preferred lesson type is Instructions Alone which is the case from the data in figure 7b where it is depicted as the most popular among the respondents. If one looks at the preferences from the control questions, one can also see that the same preferences are shown in figure 7b for all the lesson types (or quadrants), albeit the biases are more distinct from the control questions.

Furthermore, with the information gathered on both the learning style preferences and

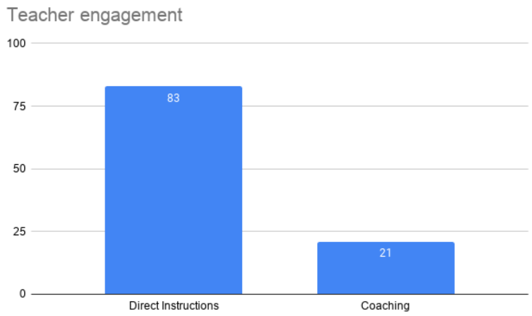


(a) Total weights of the lesson types.

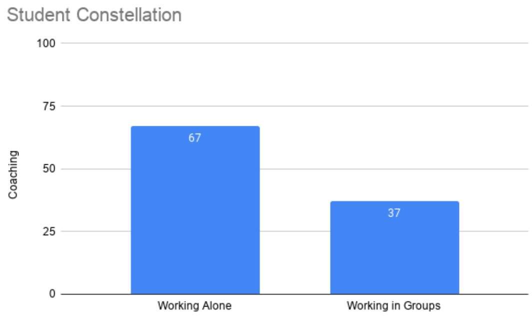


(b) Mean weights of the lesson types.

Figure 7: The sum of the average weights of each lesson type by each respondent (7a) as well as the mean of the total weights (7b) as histograms. This diagram shows the popularity of each lesson type as these weights corresponds to some preference according to the Likert scale on which the lesson types are ranked. As seen in the histograms, the weights are fairly equal with the most preferred lesson type being Instructions Alone (total weight 304.5, average weight 2.93) followed by Instructions Group (total weight 300, average weight 2.88), Coaching Alone (total weight 283, average weight 2.72), and Coaching Group (total weight 276, average weight 2.65). One can also see that all lesson types are ranked higher than the average of the Likert scale (2.5).



(a) Preferences in teacher engagement from control questions.



(b) Preferences in student constellation from control questions

Figure 8: Data from the control questions regarding the dimensions in the lesson classification model. Here one can see a clear bias towards Direct instructions and Working alone for the respective dimensions.

the lesson type preferences, one can investigate if there exists a correlation between the two preferences. In order to analyse this, the data from the respondents regarding the lesson types will be converted from the preferences given by the Likert scale into a point rank where the least preferred lesson type will have rank 1, and the most preferred lesson type rank 4. This conversion will be made by imagining every respondent as a point in the lesson classification model according to their most preferred lesson type (see figure 4). The quadrant in which the respondent is positioned will determine the lesson type of rank 4 and the succeeding ranks will be the same order as the euclidian distance to the other quadrants. As an example, consider a person with Instructions Alone, the first quadrant, as the most preferred lesson type with a stronger bias towards Direct instructions than Working alone. This means that Instructions Alone will be the lesson type of rank 4, and since the closest quadrant is the fourth, which represents the Instructions Group lesson type, that will be the lesson type of rank 3. Continuing the same procedure, the lesson type of rank 2 is the second quadrant, Coaching Alone, and thus the least preferred lesson type of rank 1 is the third quadrant, Coaching Group.

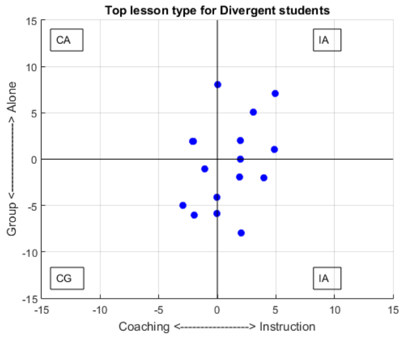
After all of the preferences have been converted to rankings using the above procedure, the rankings can be compared to the learning style preferences among the respondents to see if there exists a correlation. First this will be done by looking at the means and standard deviations of the rank of every lesson type depending on the learning style preference assuming normality in the data. All of the means (μ) and variances (σ^2) depending on learning style preference can be seen in table 3. An indication of concordance among the learning styles would be if the mean values are distinct with little variance.

Table 3: Mean scores and variances of each lesson type (LT) depending on learning style preference. Here one can see that the scores on average are more even for the learning styles Diverging and Accomodating. One can also see that the variances among the Assimilating respondents is the lowest. As with figure 7b one can see the same pattern here where the lessons based on Direct instruction (IA and IG) seemingly are the most popular.

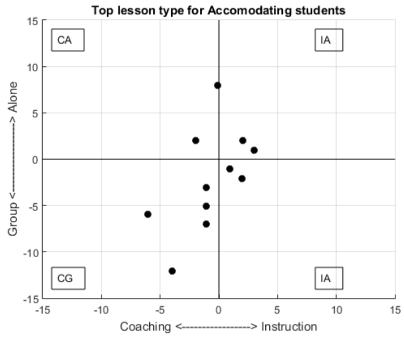
	Diverging				Accommodating				Converging				Assimilating			
LT	IA	CA	CG	IG	IA	CA	CG	IG	IA	CA	CG	IG	IA	CA	CG	IG
μ	2.81	2.13	2.19	2.88	2.27	2.18	2.73	2.82	3.12	2.12	1.88	2.88	3.63	2.37	1.37	2.62
σ^2	1.17	1.02	1.17	1.02	1.35	0.87	1.35	0.87	0.92	1.08	0.92	1.08	0.69	0.88	0.69	0.88

From these tables one can see that the learning style with the most consistent rankings is the Assimilating learning style as the respondents of that learning style shows the lowest variances among the learning styles. One can also see that on average, the rankings are more distinct for the Converging and Assimilating respondents as the mean ranks of the lesson types are further apart while the rankings for the Diverging and Accommodating respondents are more even as the mean ranks are closer together.

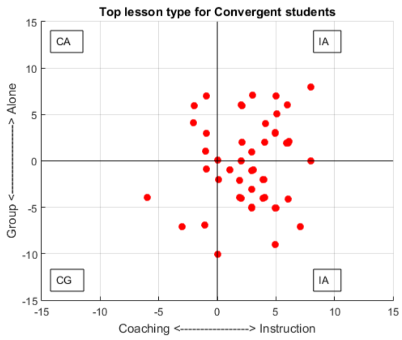
However, it is difficult to imagine seeing a correlation from just the numbers in table 3 even though one might imagine there being a correlation for the Assimilating, and maybe Converging respondents. Therefore it might be of interest to plot the data points of where in the lesson classification model the students are located depending or their learning style preference. The position is determined by weighting the respondent's rankings of each lesson type on the Likert scale positively or negatively. For example, a respondent ranking lesson type Coaching-Alone as "I prefer this type of lesson" (three out of four on the Likert scale), one unit step is taken in the direction associated with that lesson type,



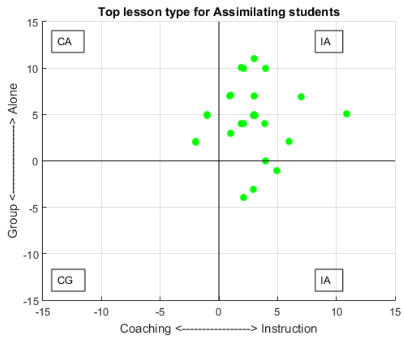
(a) Position of Diverging respondents in the lesson classification model.



(b) Position of Accommodating respondents in the lesson classification model.



(c) Position of Converging respondents in the lesson classification model.



(d) Position of Assimilating respondents in the lesson classification model.

Figure 9: Positions and top ranked lesson type depending on learning style preference as scatter plots. These plots better visualises the variance in the data listed in table 3. In order to visualise coinciding data points, a small random value has been added. While there seems to be trends in some of the plots, the only learning style with a clear visual correlation is Assimilating weighting towards the Instructions-Alone lesson type.

in this case Coaching and Working alone (or up and left). If the ranking would be “I don't prefer this type of lesson at all” (one out of four), then two units steps would be taken in the opposite direction associated with that lesson type, in this case Direct instruction, and Working in groups. The position of the respondent also represents their most preferred lesson type.

In figures 9a-9d one can see the positions of the respondents in the lesson classification model depending on their learning styles as scatter plots where the points have been added small random values in order to make them distinguishable in case they overlap with one another. From these plots one can see that there seems to be no clear visual concordance among the learning styles except for maybe Assimilating that seems to weight towards Instructions Alone. More plots where the data instead is viewed as what is the top learning style for the different lesson types, as well as plots with all data for both cases can be seen in Appendix C. However, in order to reject the null hypothesis that lesson type preference does not depend on learning style, a more formal method has to be implemented, not only due to the assumption of normality in the data which may not be correct, but also because the rankings of the lesson types from least preferred to most preferred is discrete, not continuous, so analysing the data as real values muddles the interpretation.

The method that will be implemented to analyse the rankings further is the Kendall's rank correlation coefficient, τ_A, which measures the level of concordance between rankings, see section 2.3. The correlation of the rankings within each learning style will be measured by finding the ranking for each learning style that generates the highest τ_A-value. This will be done by simply calculating the τ_A-value for each possible permutation of the numbers 1, 2, 3, and 4 which corresponds to all $4! = 24$ possible rankings, and then pick the ranking with the highest value of τ_A. The results from the procedure can be seen in table 4.

Table 4: The most concordant rankings of the lesson types from the lesson classification model for each learning style according to Kendall's rank correlation coefficient, τ_A. Here one can see that the most concordant learning style is Assimilating, and in succeeding order: Converging, Diverging, and Accommodating. Interestingly, the learning styles Divergent, Converging, and Assimilating are most concordant with the same ranking of Instructions-Alone as the most preferred lesson type, and in succeeding order: Instructions-Group, Coaching-Alone, and Coaching-Group. This differs from the rankings one would receive from looking at the mean values in table 3.

	Diverging				Accomodating				Converging				Assimilating			
Lesson type	IA	CA	CG	IG	IA	CA	CG	IG	IA	CA	CG	IG	IA	CA	CG	IG
Ranking	4	2	1	3	1	2	4	3	4	2	1	3	4	2	1	3
τ_A	0.23				0.21				0.33				0.68			

As a reminder, the closer the value of τ_A is to 1, the more concordant the ranking is to the ones it is compared with, and the closer the value is to -1, the more discordant the ranking is. Thus the Assimilating learning style is the most concordant with $\tau_A = 0.68$, and in succeeding order: Converging with $\tau_A = 0.33$, Diverging with $\tau_A = 0.23$, and Accommodating with $\tau_A = 0.21$. But what do these numbers mean? Are any of these values statistically significant? Fortunately, one can find the z-score, or standard score, from τ_A using formula 2.5 from section 2.3:

$$z = \frac{3\tau_A\sqrt{n(n-1)}}{\sqrt{2(2n+5)}}$$

where n is the number of items that are ranked, in this case $n = 4$ for the four types of lessons. Calculating the z-score for the learning style with the highest concordance, Assimilating, one finds that $z_{Assimilating} = 1.38$. From the z-score one can find a corresponding p-value, which for $z_{Assimilating} = 1.38$ is $p_{Assimilating} = 0.083$. This is not statistically significant when compared to the significance level $\alpha = 0.05$ as $p_{Assimilating} > \alpha$. From this follows that none of the other learning styles' rankings are statistically significant since τ_A is largest for Assimilating, and $n = 4$ for all learning styles. Thus, the null hypothesis that lesson type preference does not depend on learning style preference cannot be rejected.

4.3 Mathematical Model

In this section follows the set of equations used to describe the dynamics of the classroom. The main goal of the mathematical model is to describe the so called "course effect" which will be the total engagement of all students in the class over the whole course. However, in order to calculate the course effect, there are many assumptions and equations that have to be presented. First, there will be a list of all symbols with short descriptions for reference after which the equations and assumptions are presented.

4.3.1 List of Symbols

Symbol	Description
χ	Course effect. The sum of all lesson effects over the whole course. Also the fitness value of a chromosome;
$\boldsymbol{\upsilon}$	Course, or lesson sequence vector that contains the lesson types in temporal order;
κ	Total lesson effect of one lesson;
τ	Individual lesson effect of a student;
γ	Individual lesson engagement of a student;
$\boldsymbol{\lambda}$	Individual preference vector listing the lesson type preferences of a student;
$\boldsymbol{\Psi}$	Student influence matrix. Describes the influence that one student has on another;
h	The Heaviside step function;
β	Individual stress value of a student;
φ	Cognitive component, or individual self efficacy of a student;
ℓ	The logistic function;
k	Sensitivity coefficient;
ω	Workload value of one lesson;
$\boldsymbol{\epsilon}$	Individual effort vector listing the lesson type efforts of a student;
L	Total number of lessons;
N	Total number of students;
$\overline{\kappa_c}$	Average total lesson effect of lesson c;
$\overline{\tau_{j,c}}$	Average lesson effect of student j up to lesson c;
i,j	Index for students;
c	Index for lesson number.

4.3.2 Equations

As mentioned above, the goal of the mathematical model is to symbolically describe the fitness of the population, or chromosomes, in the final model implemented with evolutionary algorithms. The fitness value is going to be the sum of all students' engagements over all lessons in the whole course, or the "course effect", and it will be denoted by χ. The considered course will consist of a set amount of lessons, L, and the class will consist of a set number of students, N. Let the course be defined as a sequence of lessons denoted by the vector $\boldsymbol{\upsilon}$, and let υ_1, υ_2, υ_3 and υ_4 be the numbers representing the types of lessons from the lesson classification model in section 4.1: Instructions-Alone, Coaching-Alone, Coaching-Group, and Instructions-Group respectively. The course vector will have L positions, one for each lesson, and the lesson type in every position will be represented by one of $\upsilon_1, \ldots, \upsilon_4$. As mentioned earlier, χ will be the sum of all students' engagements over the whole course, so to simplify let κ_c, called the "lesson effect" denote the sum of all students' engagements after *one* lesson, c. Then the course effect becomes:

$$\chi = \sum_{c=1}^{L} \kappa_c. \tag{4.1}$$

There also has to be a way of representing the individual students' engagements in the lessons, and not only on a collective level, so let $\tau_{j,c}$ be the lesson effect of student j after class c. Then the lesson effect can be expressed as:

$$\kappa_c = \sum_{j=1}^{N} \tau_{j,c}. \tag{4.2}$$

As every student in the class realistically should have their own preferences when it comes to the types of lessons that the course consists of, and that set of preferences should affect the student's individual lesson effect. The lesson types will as above be numbered as 1, 2, 3 and 4 respectively. The simplest way to represent a student's preference would then be a vector with a value representing how "preferred" that every lesson type is for that student. Let this "preference vector" be denoted by $\boldsymbol{\lambda} = [\lambda(\upsilon_1)\ \lambda(\upsilon_2)\ \lambda(\upsilon_3)\ \lambda(\upsilon_4)]$, or for the sake of notation: $\boldsymbol{\lambda} = [\lambda_1\ \lambda_2\ \lambda_3\ \lambda_4]$, where $\lambda_1, \ldots, \lambda_4 \in [1,4]$, constant, are the preference values of the lesson types above. Then let $\boldsymbol{\lambda}_j = [\lambda_{j,1}\ \lambda_{j,2}\ \lambda_{j,3}\ \lambda_{j,4}]$ be the preference vector of student j. It is assumed that the preferences of the students are constant during the course.

In addition to the lesson type preferences, the lesson effect should also depend on the students engagement in the course, which should change after every lesson according to some dynamic since the students' preference vectors will be constant. This "student engagement" will be denoted by $\gamma_{j,c}$ for student j and lesson c. The assumption here will be that the lesson effect for one student and lesson will be higher if the student had a high engagement in the course during that lesson, and the lesson effect will also be higher if the student preferred the type of the lesson. Thus the individual lesson effect for student j and lesson c, $\tau_{j,c}$, will be expressed as:

$$\tau_{j,c} = \gamma_{j,c}\lambda_{j,c}, \tag{4.3}$$

where $\lambda_{j,c}$ represents student j's preference of the lesson type in lesson c, and the notation has been simplified here to make it more intuitive.

Next step will be to further describe what sort of dynamics that will affect the individual student engagement, $\gamma_{j,c}$. One dynamic that should affect the engagement is the opinion that the peers have on the course, or in other words the personal interest of the peers. In order to represent these opinions a "student influence matrix", $\boldsymbol{\Psi} \in N{\times}N$, will be introduced. The elements in $\boldsymbol{\Psi}$, $\boldsymbol{\Psi}_{ij} \in [0,1]$ will represent the influence that student i has on student j where a value of 0 means that student i has no influence on student j and a value of 1 means that student i has maximum influence on student j. $\boldsymbol{\Psi}$ will be non-symmetrical, meaning that $\boldsymbol{\Psi}_{ij} \neq \boldsymbol{\Psi}_{ij}$. Also, the diagonal elements of $\boldsymbol{\Psi}$ will have the value 0, meaning that the student only influences itself in relation to its peers. For convenience, since an investigation has not been made on student influence, the influence will be represented by a uniformly distributed random value on [0,1]: $\boldsymbol{\Psi}_{ij} \sim \mathcal{U}(0,1)$.

As the desire is to have the engagement change iteratively between lessons it will start on a base value of $\gamma_{j,1}$ for the first lesson and then update from lesson c to $c+1$ according to the following expression:

$$\gamma_{j,c+1} = \frac{1}{N-1}\sum_{i\neq j}(1-\boldsymbol{\Psi}_{ij})\cdot\gamma^{'}_{j,c} + \boldsymbol{\Psi}_{ij}\cdot\gamma_{i,c}\ , \tag{4.4}$$

where $\gamma^{'}_{j,c}$ for the moment going to denote the expressions that go into iterating the engagement and will be formally explained further down. The idea of (4.4) is that the engagement that student j has for the next lesson will be the average of all the influence from the peers, as well as the self influence relative to the peers. Here one part is how student j is affected by the engagement of student i, where a higher engagement in student i makes the engagement of student j increase, weighted by the influence: $\boldsymbol{\Psi}_{ij} \cdot \gamma_{i,c}$. The other part of the influence $(1 - \boldsymbol{\Psi}_{ij})$ is how much the student influences itself which will consist of the expressions hidden inside of $\gamma_{j,c}^{'}$, which can be seen as some sort of "internal coefficient" that will influence the engagement of the next lesson: $(1 - \boldsymbol{\Psi}_{ij}) \cdot \gamma_{j,c}^{'}$. This expresses that a student that is not influenced as much by other students will be more influenced by its own internal process.

One alteration will be made to (4.4) in order to make sure that the value of the student engagement, γ, does not go below 0 as having negative engagement does not make sense in practise. The Heaviside step function will be utilised here, which is defined as:

$$h(x) = \begin{cases} 0, \, x \leq 0 \\ 1, \, x > 0 \end{cases} . \tag{4.5}$$

Let $*$ be the right hand side of (4.4). After applying the Heaviside function (4.4) becomes:

$$\gamma_{j,c+1} = h(*) \cdot \underbrace{\frac{1}{N-1} \sum_{i \neq j} (1 - \boldsymbol{\Psi}_{ij}) \cdot \gamma_{j,c}^{'} + \boldsymbol{\Psi}_{ij} \cdot \gamma_{i,c} \geq 0}_{*} \, . \tag{4.6}$$

The next step will be to go into more details about the expressions that hide inside of $\gamma_{j,c}^{'}$. The two dynamics that go inside of $\gamma_{j,c}^{'}$ are self efficacy, and stress. Self efficacy is similar to confidence in that it is one's belief in one's ability to succeed, where in this case a higher self efficacy will make a student be less affected by the stress caused by a lesson as well as being less affected by the lesson effect caused by peers and weights its own lesson effect higher. The stress caused by a lesson is in this case going to be depend on the workload of the lesson as well as the effort that the student has to put into the lesson which is dependent on the lesson type of the lesson. A higher value of the stress will have a negative effect on the student's engagement.

First the stress will be defined. Let $\beta_{j,c}$ denote the stress caused to student j by lesson c. Then let ω denote the workload of the lesson. The workload will represent how much of the curriculum of the course that is covered in a given lesson and will depend on the lesson type of lesson c, $\boldsymbol{v}_c$, in the following way:

$$\omega_c = \omega(\boldsymbol{v}_c) = \begin{cases} 1.5, & \boldsymbol{v}_c = v_1 \text{ (Instructions-Alone)} \\ 0.8, & \boldsymbol{v}_c = v_2 \text{ (Coaching-Alone)} \\ 0.6, & \boldsymbol{v}_c = v_3 \text{ (Coaching-Group)} \\ 0.7, & \boldsymbol{v}_c = v_4 \text{ (Instructions-Group)} \end{cases} . \tag{4.7}$$

The idea of these numbers is how "effectively" the different lesson types cover the curriculum. The nature of the Instructions-Alone lesson type allows the teacher to cover a lot more of the curriculum than they would be able to with the Coaching-Group lesson type. And while the choice of values that ω can assume may seem arbitrary, those values were a set of values that seemed to influence the equations in a more "realistic" way. But these values can be seen as parameters that can be tweaked for different scenarios.

Now the effort for student j from lesson c, denoted by $\epsilon_{j,c}$ will be defined as follows:

$$\epsilon_{j,c}(\boldsymbol{\lambda}_{j,c}) = 2.5 - \frac{\boldsymbol{\lambda}_{j,c}}{2}\,, \tag{4.8}$$

where $\boldsymbol{\lambda}_{j,c}$ is the preference of lesson c for student j. By defining the effort as (4.8), the most preferred lesson type has an effort value of 0.5 meaning that participating in a lesson type they prefer highly is half the effort, and twice the effort if it is a lesson type they prefer lowly.

Thus with the workload and effort defined, the expression for the stress can be constructed:

$$\beta_{j,c} = \omega_c \cdot \epsilon_{j,c}\,, \tag{4.9}$$

where the value of the stress increases or decreases if the workload or effort increases or decreases.

Moving on to the self efficacy, which will be denoted by $\varphi_{j,c}$, another function will be utilised in order to make sure that the value of the self efficacy stays between 0 and 1. This can be interpreted as a percentage of how much trust the student has in their own ability. The function that will be used here is a version of a sigmoid function called the logistic function:

$$\ell(x) = \frac{1}{1+e^{-kx}}\,, \tag{4.10}$$

where $\ell(x) \in (0,1)$, $\forall x \in \mathbb{R}$, and k is the "growth rate" of the function, or how quickly it tends towards the lower and upper bounds. In this case, the value of k can be interpreted as how sensitive the students' self efficacy is, and how susceptible it is to change between lessons and will therefore be denoted as the "sensitivity coefficient". For the purposes of this model, the value of the sensitivity coefficient is set to $k = \frac{1}{100}$.

As for the dynamics that affect the self efficacy, the assumption is that any individual student "updates" it according to how engaged they were this lesson compared to other lessons as well as how engaged they were compared to their peers this lesson. Here a lower self efficacy value will make it so that a student weights their peers engagement higher than their own, and vice versa for high values. This, like the individual engagement, updates iteratively according to the following expression:

$$\varphi_{j,c+1} = \ell\big((1-\varphi_{j,c})(\tau_{j,c} - \overline{\kappa_{j,c}}) + \varphi_{j,c}(\tau_{j,c} - \overline{\tau_{j,c}})\big) \tag{4.11}$$

where $\overline{\kappa_{j,c}}$ is the average engagement of the whole class excluding student j for lesson c, and $\overline{\tau_{j,c}}$ is the average engagement of student j over the lessons up to c, calculated according to:

$$\overline{\kappa_c} = \frac{1}{N-1}\sum_{i\neq j}\tau_{i,c} \tag{4.12}$$

$$\overline{\tau_{j,c}} = \frac{1}{c}\sum_{k=1}^{c}\tau_{j,c}\,. \tag{4.13}$$

Here it becomes more clear why the logistic function is utilised, as the value of the expression inside of ℓ in (4.11) can take on values that are below 0 or above 1. As mentioned, the self efficacy value is a measure of how well the students trust their own abilities compared to both themselves and the other students, and the inspiration for this term comes from the social and cognitive components in particle swarm optimisation (Wahde, 2008).

Now that both the stress, β, and the self efficacy, φ, have been defined it is possible to go back and describe the mysterious term $\gamma_{j,c}^{'}$ in (4.4). This term will be different according to if the self efficacy of the student is "high" or "low", or mathematically, if it is over or under a certain value which in this case will be 0.5. If a student's self efficacy is high it should be less susceptible to stress, and vice versa if the self efficacy is low. Thus $\gamma_{j,c}^{'}$ will be defined as:

$$\gamma_{j,c}^{'} = \begin{cases} \gamma_{j,c} + (3 + \varphi_{j,c+1} - \beta_{j,c}), & \text{for } \varphi_{j,c+1} \geq 0.5 \\ \gamma_{j,c} + (3 - \varphi_{j,c+1} - \beta_{j,c}), & \text{for } \varphi_{j,c+1} < 0.5 \end{cases}. \tag{4.14}$$

Again, the value of 3 in the equation may seem like an arbitrary choice, but it is the maximum value of the stress value times the maximum value of the workload: $\max\{\beta\} \cdot \max\{\omega\}$ which turned out to be a good value in practice. And with that, the mathematical model of the course effect is concluded. The set of equations can be seen in their entirety in Appendix D.

To summarise the ideas of the structure of the functions and equations presented above, consider the diagram in figure 10 that visualises the dependencies of the equations.

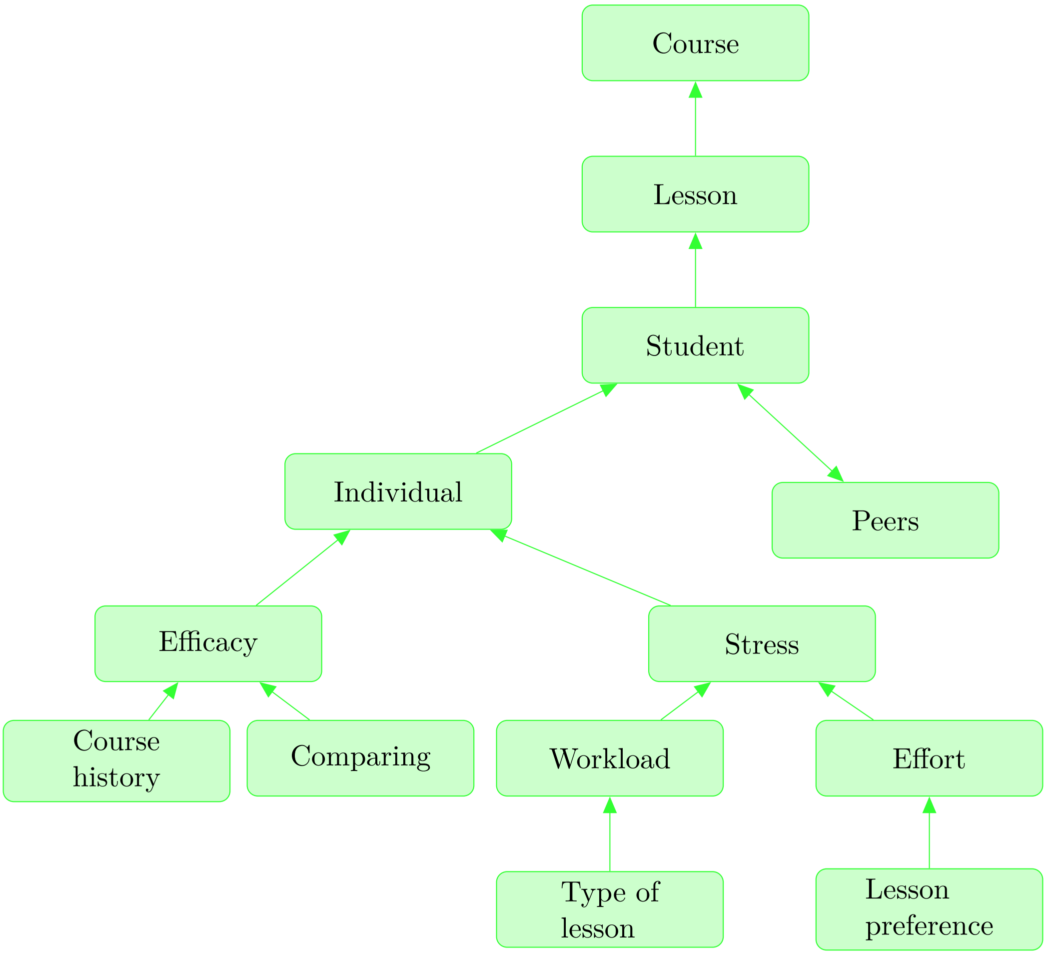


Figure 10: Conceptual structure of the functions and equations presented in this section. Note the double sided arrow between "Student" and "Peers" that indicate the interactions between the students in the class. Also note that the "Individual" category contains all of the internal processes that go into the mathematical model.

5 Lesson Sequence Optimisation Model

In order to capture the functioning of the mathematical model and data collection together, it was decided to use Matlab for the implementation of the genetic algorithm. This section will focus on describing each of the important steps that are part of the algorithm. In the same way, a GitHub link will be provided with access to the code to get a better idea of how the implementation works.

5.1 Algorithm

As previously described in section 2.4, genetic algorithms need to start with a population, which will be modified generation after generation. This population will be made up of individuals, also called chromosomes, which in turn are binary strings. For the implementation of the model was decided to form individuals of 40 lessons. Each of these lessons consists of 2 genes, which results in chromosomes with a length of 80 genes. To differentiate between lesson types within the chromosome, every lesson type should have a unique binary pair. The values can be assigned in any desired order, this will not modify the performance of the algorithm, but it should be consistent during the whole process. The lesson types were assigned a lesson type in the following way:

00	Instructions Alone
01	Coaching Alone
10	Coaching Group
11	Instructions Group

Right after the population is defined, the evaluation of the individuals will be carried out to determine their fitness values and choose the best individual among them. During this step, the values of the efficacy, as well as the students' engagement, will be obtained to observe the evolution of the students' performance through the whole sequence. Once the whole population is evaluated and the best individual is selected, its sequence will be stored to make an exact copy of the individual's genes to introduce it within the population without making any modifications. This process is known as Elitism, which consists in introducing a certain number of copies of the best individual, so that there is a lower probability of losing it during the evolution process.

The next step will be to start forming the new population for the next generation. For this, the selection process will begin, which consists of taking a certain number of individuals (depending on the context of the optimisation) randomly and then selecting the best individual among them with a certain probability. This process is repeated twice to obtain two individuals that will be used in the next stage, called Crossover.

Crossover, as described in section 2.4, consists of mixing the genes from the previously selected individuals with a certain probability to create two new individuals that will be introduced into the population. Thereafter the next stage will be the Mutation part, which consists of changing each of the genes with a probability of c/m, where c is a constant value of order 1 and m is the length of the chromosome. In such a way, one mutation occurs per chromosome on average. These three stages, Selection, Crossover and Mutation, will be repeated until every individual has been modified. As new individuals are obtained, the Elitism section will take place. To finally replace the old individuals with the new ones, reaching a new population for the next generation.

Hence, this process will take place generation after generation until a certain number of generations is reached. Every step of the algorithm can be seen in figure 11. In addition, Figure 12 shows a flowchart of the algorithm to facilitate the visualisation of each step.

---

1. Initialise population, (binary strings(lesson sequences))
2. Evaluate sequences (Obtain fitness value(lesson effect))
   (a) Pick best individual
3. Form Next generation
   (a) Select a certain number of individuals randomly and choose the best individual among them with a certain probability. Repeat this step until two individuals are selected.
   (b) Generate two new individuals with a certain probability by defining a crossover point and crossing the selected ones. Otherwise leave the individuals as they are.
   (c) Mutate with a certain probability every individual generated.
   (d) Repeat a-c until the entire population has been modified
   (e) Replace old individuals with the new ones
   (f) Allocate a certain number of copies of the best individual at the beginning of the population by replacing those individuals (elitism)
4. Return to step 2, unless the termination criterion is reached
5. Plot Results

Figure 11: Genetic algorithm implemented for optimising lesson sequences in step-by-step form. The theory behind the proper choice of probabilities for each of the steps can be found in Wahde (2008). However, the conventional probabilities for Selection of the best individual $P_{best} = 0.8$, Crossover $P_{cross} = 0.8$, Mutation $P_{mut} = c/m = 0.0125$ were chosen respectively

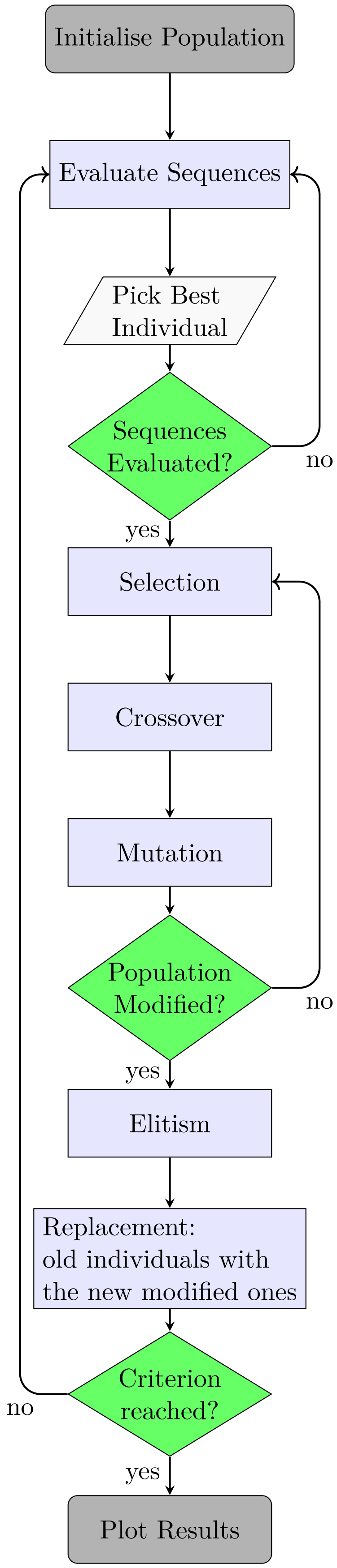


Figure 12: Algorithm's Flowchart showing the main steps of the implementation.

5.2 Toy Model

In order to better understand the complete model, a simpler "Toy model" will be considered first, where the dynamics of the complete model will be introduced step by step.

The toy model starts in the simplest possible way, which is with two students with no interactions between them and a course of four lessons. That is, the influence matrix $\mathbf{\Psi}$ form the mathematical model is not used. The sequences only have two different lesson types, Instructions-Alone and Coaching-Group from the lesson classification model in section 4.1. The students in this step were chosen from the data collection in such a way that they have opposite lesson preferences. At the end of the simulation, the best sequence obtained can be seen in figure 13.

In order to better quantify the course effect that is obtained from the simulations, the value "Course Effect / Average Course effect" can be seen to the right in the figures. The value of the "Course effect" is simply the value of χ from section 4.3. The value called "Average Course effect" needs more clarification. In order to determine the average value of the course effect it was estimated by randomly generating 10,000 lesson sequences and averaging their course effects. This value will be denoted $\overline{\chi}$ in text.

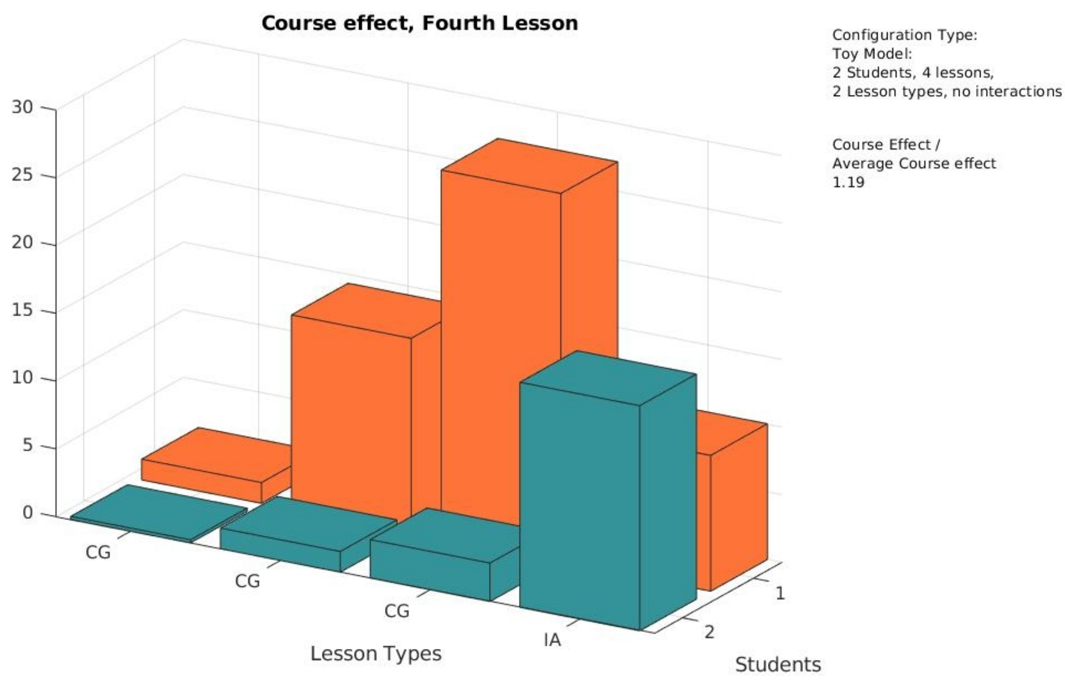


Figure 13: It can be seen in the plot, that Student 1 had better average performance through the lessons. However, Student 2 performs better in the last lesson, when it changes from Coaching Group to Instructions Alone. This shows that student preferences influence their engagement depending on the lesson type. Z-axis represents the individual lesson effect.

After observing the behaviour of the students, the level of complexity was increased by adding interactions between the same students as in the previous case, which means introducing the influence matrix $\mathbf{\Psi}$. However, it can be observed in Figure 14, that this introduction did not change the optimal lesson sequence, but it influenced the effect of the class positively, generating a higher value of $\chi/\overline{\chi}$. One can see in that figure that Student 2 has higher values at each lesson compared to figure 13, suggesting that student 1 has a positive influence on student 2.

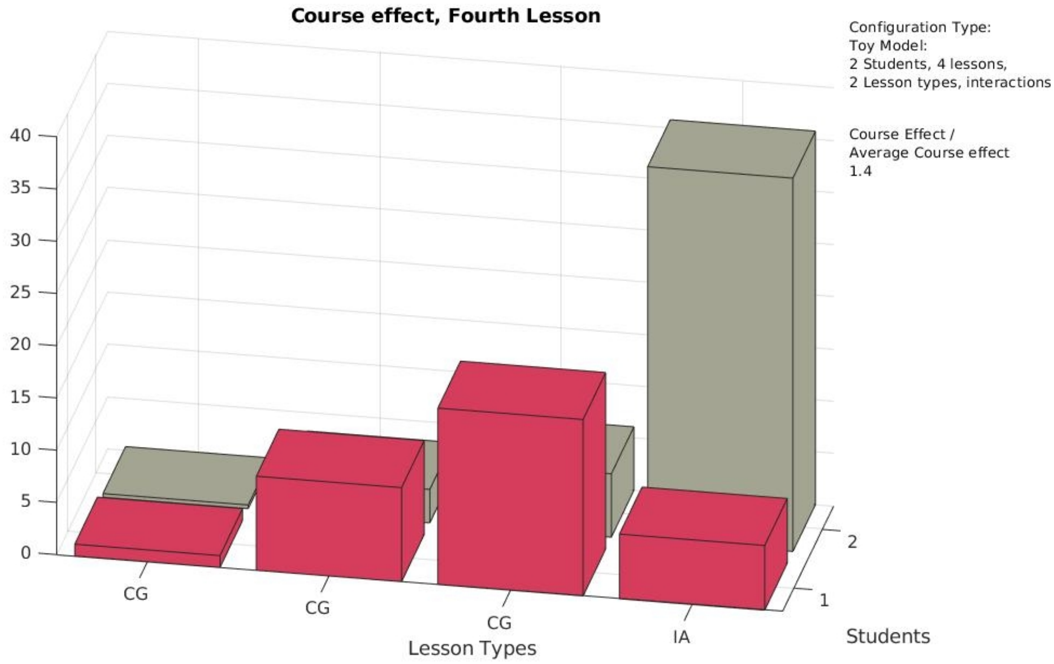


Figure 14: It can be seen that the sequence of lessons is the same as in Figure 13, and Student 1 performs better than Student 2 during the first three lessons as before. However, in the last lesson, the effect on Student 2 is greater than in the previous case, even though is the same lesson type. This means that the interactions between the students have a big impact on the lesson effect. Z-axis represents the individual lesson effect.

Once again, the complexity of the Toy model was increased by adding two more students. The preferences of the students chosen from the data collection can be seen in figure 15. For this configuration, in addition to having four students instead of two, the sequence of lessons will be ten instead of four with all four different lesson types available. Also, the students will have interactions between them. The results obtained for this configuration can be seen in figure 16.

Student	Lesson type preferences			
	IA	CA	CG	IG
1	1	1.5	4	3.5
2	4	2.5	1	2.5
3	3	4	1	2
4	2.5	1.5	2.5	4

Figure 15: Students chosen for the toy model. The first two students were chosen for the first level of complexity. Since this level only has two different types of lesson IA and CG, those two students are opposite, which it helps to see the conflict when choosing the lesson sequence. The two following students were added for the last level of complexity. In the same way, it was sought that they were opposed to the other two students to create conflict when choosing the sequence of lessons.

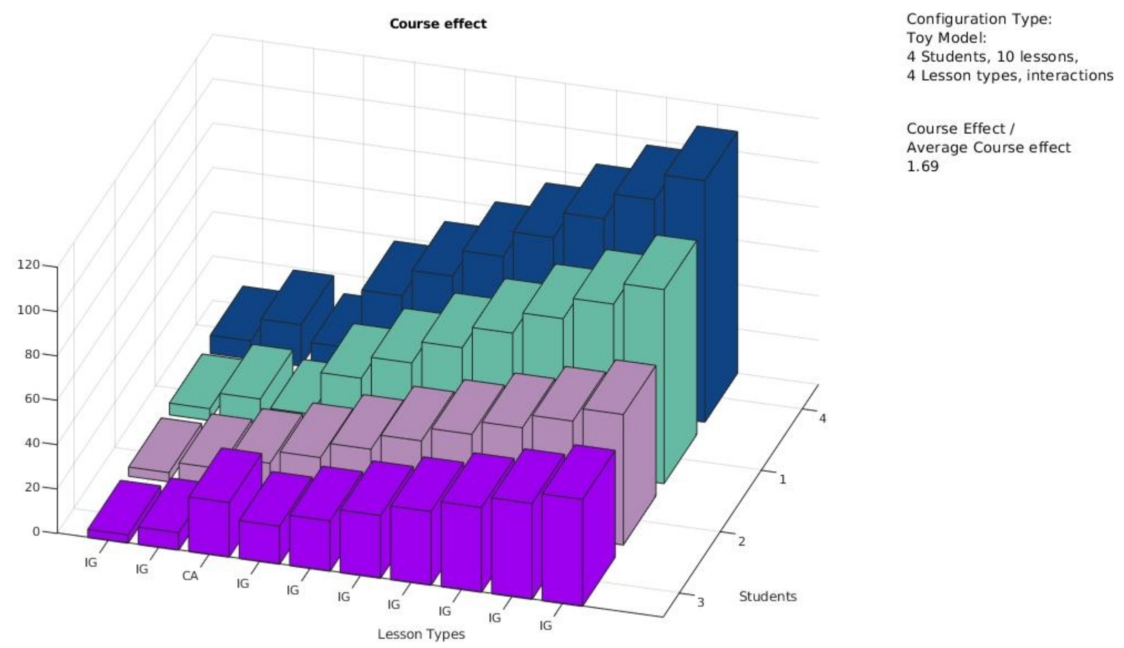


Figure 16: With this configuration it can be observed that the increments in complexity of the problem is making it more and more difficult to obtain a optimal sequence of lessons. One has to take into consideration that this is an extreme case where the students have opposite preferences, which makes it even harder to establish the optimal sequence of lessons. However, in reality, it could be the case that the majority of the students has similar preferences or at least not preferences that are so scattered. Z-axis represents the individual lesson effect.

For the final configuration of the toy model, the requirement to meet at least 95% of the curriculum will be added. The way this will be implemented is by introducing the "workload" from the mathematical model and adding a condition where the sum of the workload over the whole course has to be at least 95. This will yet again increase the complexity since the ability of selecting the most suiting lesson type to fulfil the students' preferences is going to be restricted. This affects the course effect as can be seen in figure

17, reducing $\chi/\overline{\chi}$ from 1.69 to 1.53 from the previous example. All these configurations of the toy model provide an idea of the complexity and nature of the problem involved in designing a sequence of 40 lessons for 30 students with different preferences, which is a more suitable scale for a course with a real class.

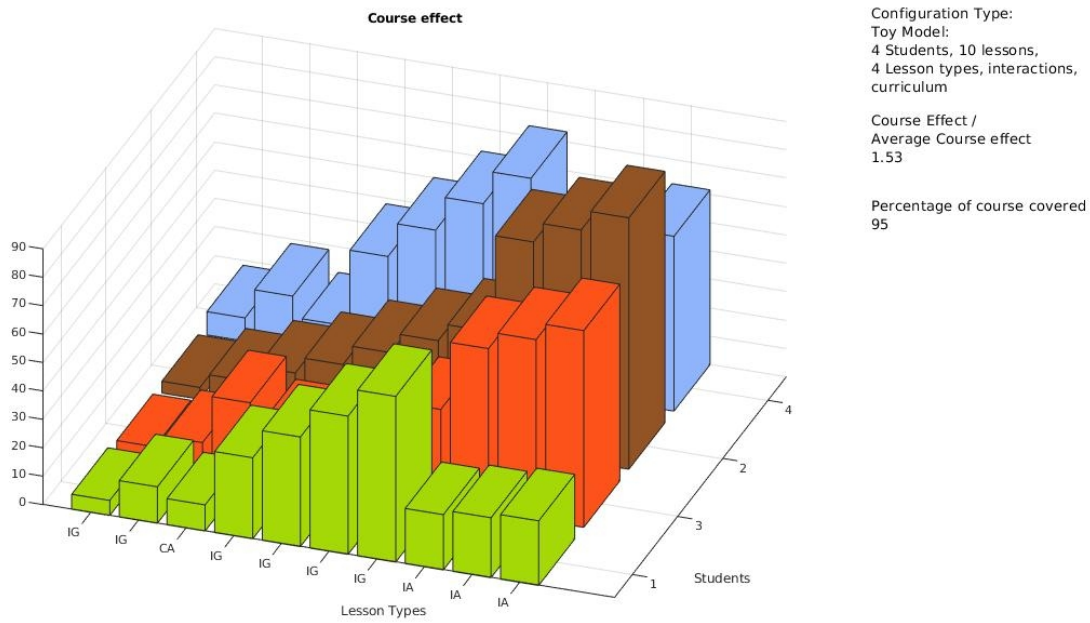


Figure 17: As can be seen in the plot in figure 16, the sequence of lessons starts the same way, but the last three lessons provoke that the effect on some of the students decreases considerably in favor of the condition of fulfilling the curriculum. For example, Student 1 was one of the best students in the previous configuration, but this time was the worst Student due to the last lessons. All this was caused by simply adding the condition of fulfilling the curriculum. Z-axis represents the individual lesson effect.

5.3 Simulations

The toy model above as well as the complete lesson sequence optimisation model that will follow below were implemented in Matlab[1].

In the next section, all the various configurations made to the model will be presented. Although the main goal is to obtain the sequence that will cause the greatest possible effect on the students as a class, different configurations were implemented, which can be seen as different norms to optimise for. This to test the efficiency of the model and to pose different possible scenarios that teachers may face in the design of their courses. There are also a number of unrealistic but interesting scenarios that are investigated as well. The configurations that the model is tested with are the following:

- "Best total sequence": the standard configuration where the lesson sequence is optimised to generate the maximum value of the course effect for the whole class while fulfilling the condition of the curriculum.

[1]Code can be found at: `https://github.com/DanteLV/Lesson-sequence-optimisation-model.git`

- "Worst total sequence": the opposite of the "best total sequence" where the goal is to find the sequence of lessons that generates the lowest possible course effect among the students while fulfilling the condition of the curriculum.

- "Random sequences": mainly used in order to define the value of "Course Effect / Average Course effect". When using this configuration, 10,000 sequences are generated in order to calculate an estimate of the "average" course effect. However, it could also be interesting to consider a random sample to compare with the other configurations.

- "Maximal course evaluation": this is the lesson sequence where the teacher doesn't care about fulfilling the curriculum, but only cares about maximising the student engagement. Other than that it is the same as "best total sequence".

- "Best single student": the goal with this configuration is to produce the singe most engaged student by the end o the course instead of optimising for the whole class.

- "Worst single student": the opposite of "best single student" where the goal is to produce the single least engaged student.

- "Best of worst single student": in this configuration the goal is to find the lesson sequence that that gives the highest individual effect possible for the student with the lowest effect in the class. In other words it is maximising the minimum individual effect.

- "Worst of best single student": similar to "Best of worst single student", but the other way around. This time the goal is the find the lesson sequence that generates the lowest individual effect for the student in the class with the highest effect. Or in other words, minimising the maximum individual effect.

In every plot can be seen, on the right side, the course effect obtained compared with the effect on average by generating random sequences. For this, an average of 10,000 random sequences was calculated to have a better idea of how good or bad the optimisation is doing in each configuration. At the same time, the average effect generated in one single student was computed to compare it with the best and worst student generated in every configuration. It is worth mentioning that for all the settings the same class was used with exactly the same order in the students, that is, that student number 20 will be the same in every configuration.

5.3.1 Best Total Sequence

The main configuration is the one that aims to obtain the greatest possible effect on the students, that is, the one that will seek to maximise the fitness value of the lesson sequences. However, it must be taken into account that the requirement to complete at least 95% of the curriculum should be satisfied too. This setup can be seen as the primary goal of any teacher, which is already a huge challenge to accomplish. The results obtained for this configuration can be seen in figure 18.

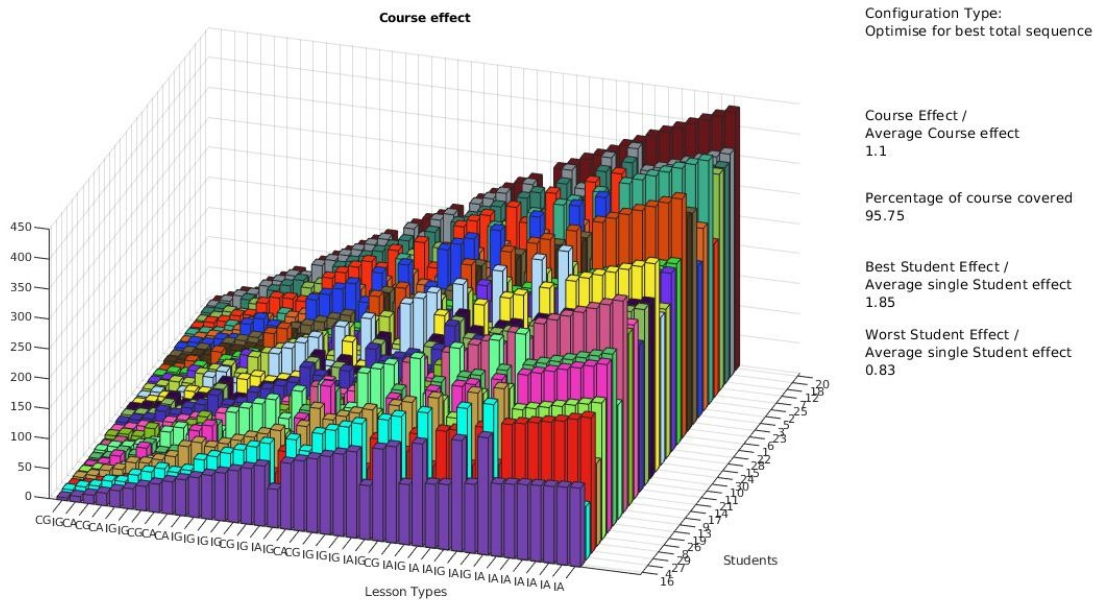


Figure 18: In the y-axis are the lesson types used in every session, starting from left to right. On the other hand, the x-axis shows the students sorted by average effect, being the first student, the number 8 in this case, the one with the lowest course effect in average. Moreover, The plot shows that the effect obtained is 10% better than the one generated with random sequences. At the same time it can be seen that the best student in this configuration is more than 80% better than the effect of one single student with random sequences. Likewise, the worst student with 83% almost approaches the same effect generated on average. Finally it can be seen that more than 95% of the curriculum was covered. Z-axis represents the individual lesson effect.

5.3.2 Worst Total Sequence

For the second configuration, what will be sought is to obtain the sequence that generates the lowest possible course effect while still fulfilling the condition of the curriculum, that is, aiming to minimise the fitness value. In a first glance, it is something that the teacher would never try to obtain, but it is interesting to know what lesson types the worst sequence would be composed of. The results of this configuration can be seen in figure 19.

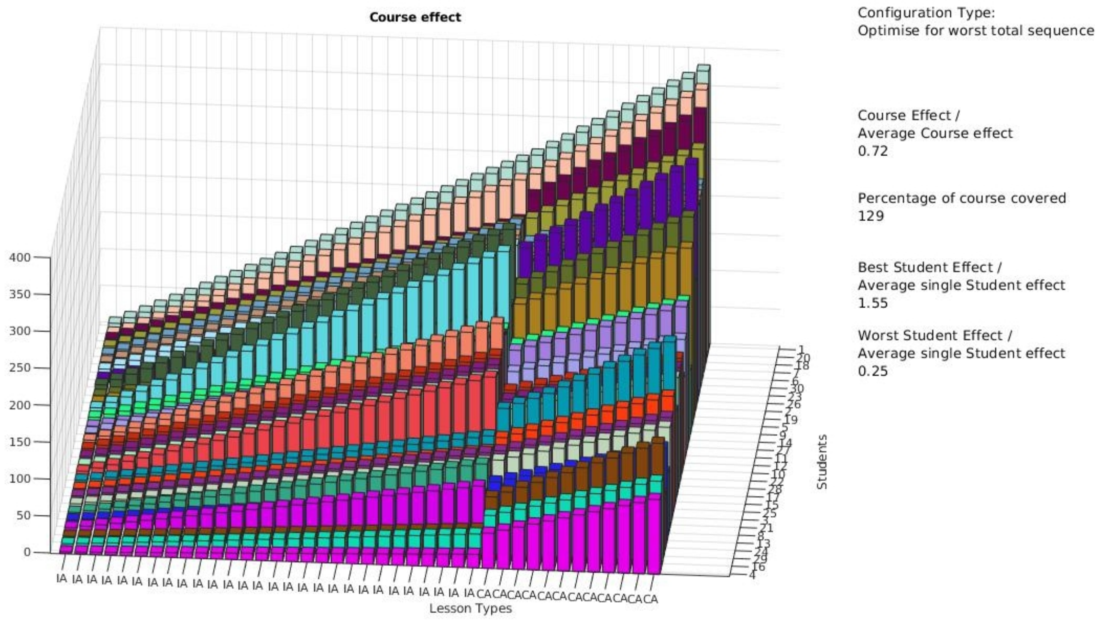


Figure 19: As can be seen in the sequence obtained, the lessons that generate the lowest course effect are those that are based on the traditionalist teaching method, in which the teacher speaks and the students listen, without any real active participation by the students. In addition, a part of this sequence is made up of sessions where the student works alone and there is no active interaction with their peers. Despite this, this configuration is the one that generates greater coverage of the curriculum. However, students may not have a significant learning. Z-axis represents the individual lesson effect.

5.3.3 Random Sequences

For this configuration, a population is generated and one of the sequences is chosen randomly, that is, there is no optimisation. Nevertheless, it helps to compare its results with the other configurations as a way of measuring the effectiveness of the algorithm.

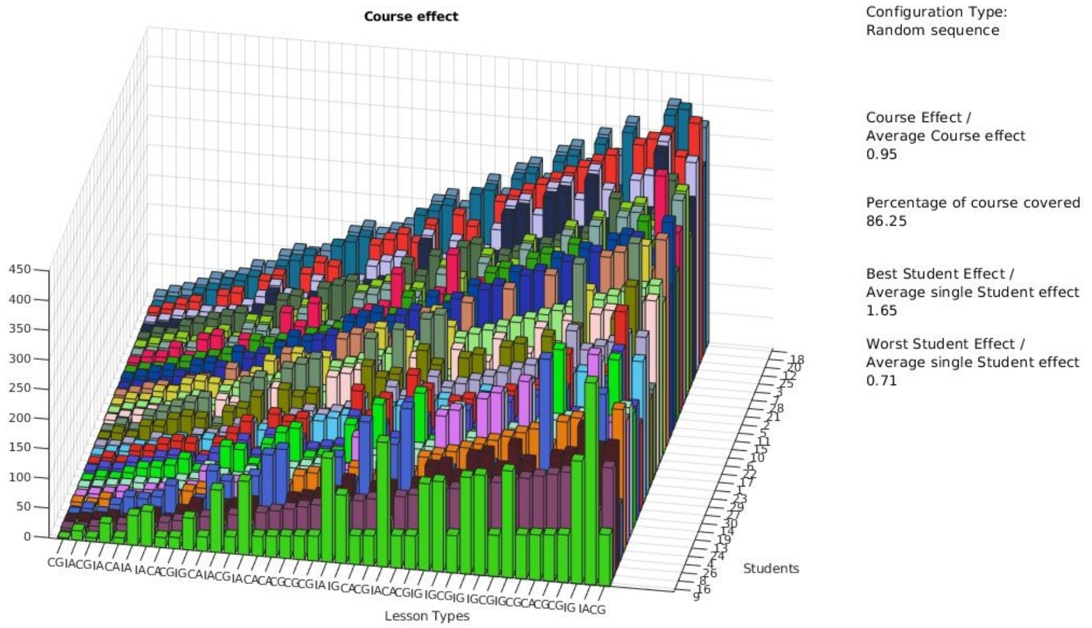


Figure 20: In this configuration there is nothing relevant to highlight, it is simply a randomly generated sequence. However, it can be seen that if it is compared with figure 18, both the individual effect of the students and in general of the entire sequence are much lower. In addition to that the percentage of the curriculum is not met. Z-axis represents the individual lesson effect.

5.3.4 Maximal Course Evaluation

For the configuration of Maximal course evaluation, the goal is basically the same as in the configuration of Best total sequence except that the constraint of the curriculum is not considered. This would then be considered to be the optimum of the model as a whole for any given class of students. While this configuration may not be the most realistic to use for all classes it is interesting to see the behaviour of the unrestricted model. In figure 21 one can see that the lesson sequence is fairly similar to the one in figure 18, but with fewer Instruction-Alone lessons meaning that the percentage of the course covered is dropped from 95.75% to 91.75%

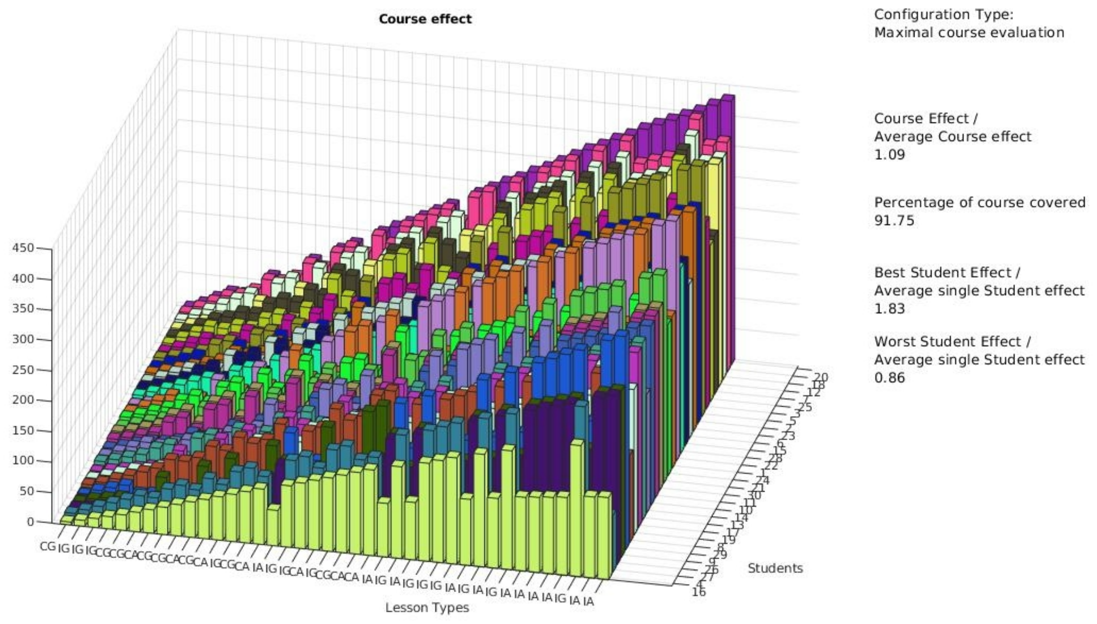


Figure 21: For the maximal course evaluation it can be seen that the results obtained are very similar to those seen in figure 18. However, unlike the Best Total Sequence, this sequence does not meet the curriculum requirement. Z-axis represents the individual lesson effect.

5.3.5 Best Single Student

For the Best Single Student, what is sought instead of maximising the fitness value for the whole sequence, is trying to maximise the value of the best student generated by the lesson sequence. In other words, it seeks to obtain the max(Best student) value. In this way, the teacher would focus only on their best student and design the course from there. Nevertheless, this in practice could be detrimental to other students. The results can be seen in figure 22.

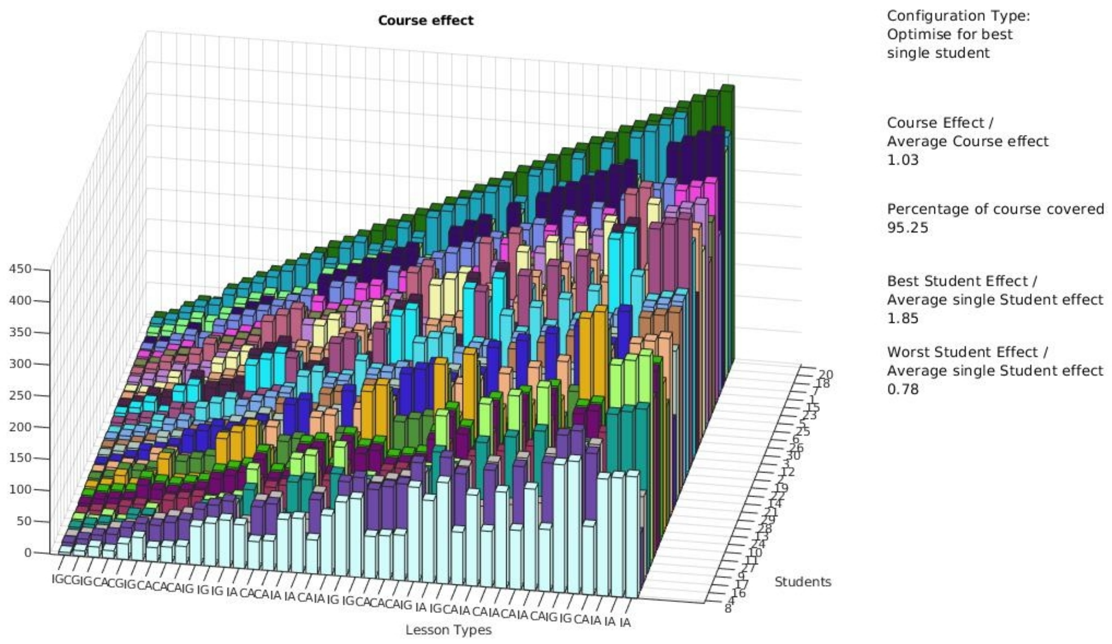


Figure 22: In this plot can be seen that the effect in the best student is quite high, but it is the same as the one obtained in figure 18 for the Best Total Sequence. Furthermore, the effect of the worst student is lower than the one obtained for the Best Total Sequence. Z-axis represents the individual lesson effect.

5.3.6 Worst Single Student

Similarly to the configuration of Best single student, the focus only lies on optimising for one single individual. However, in this case, as the name suggests, the goal is to find the student with the lowest possible engagement in the course, while fulfilling the curriculum. As can be seen in figure 23 this solution is trivial since the existence of a student with a low preference for Instructions-Alone lessons means that the condition of the curriculum will be fulfilled even if all the lesson types are the same.

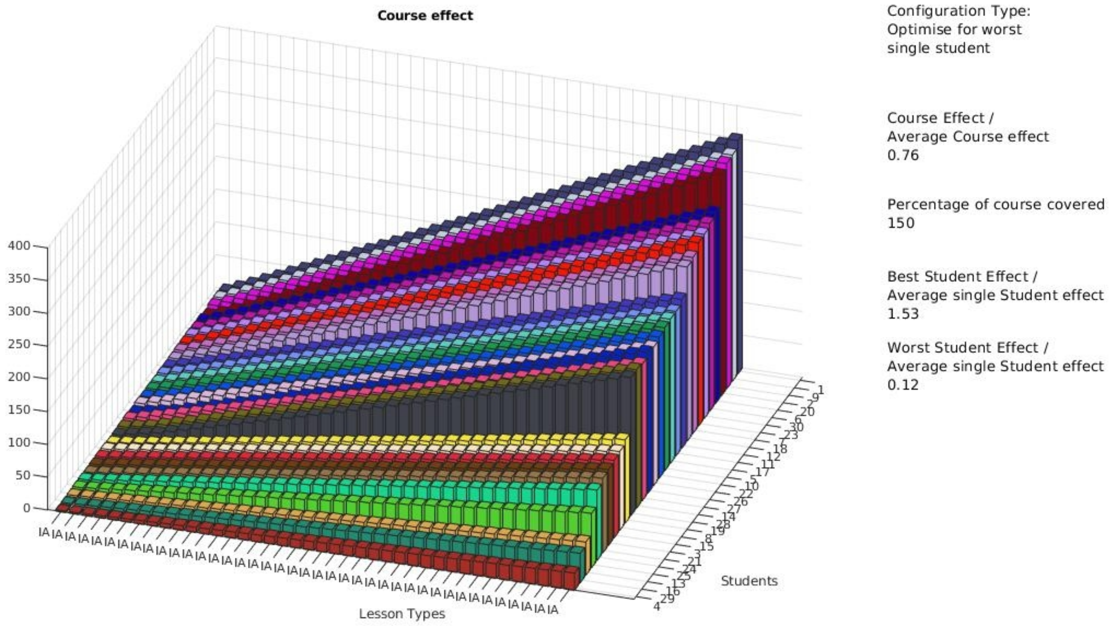


Figure 23: Plot of the course effect for the configuration of Worst single student. As can be seen from the lesson sequence for this configuration it can be trivial to cause a student to have the lowest possible engagement. Trying to minimise the value of the worst student, resulted in a sequence in which there is only one type of lesson, Instructions Alone. This produced the worst student, which makes it clear that the worst selection of lessons is the one where the teacher speaks and the student listens without having active participation. However, it has to be considered that it is also the sequence that causes the highest percentage of the curriculum covered. Z-axis represents the individual lesson effect.

5.3.7 Best of Worst Single Student

For the Best of Worst Single Student, what is sought to optimise is to obtain the sequence of lessons that generate the greatest possible effect among the worst students. In other words, it is looking for the max(Worst Student) value. From the teacher's point of view this would be a good approach to their course design, as it would leave no one behind. Although possibly the effect on the best students would be affected by focusing only on the worst ones, as can be seen in figure 24.

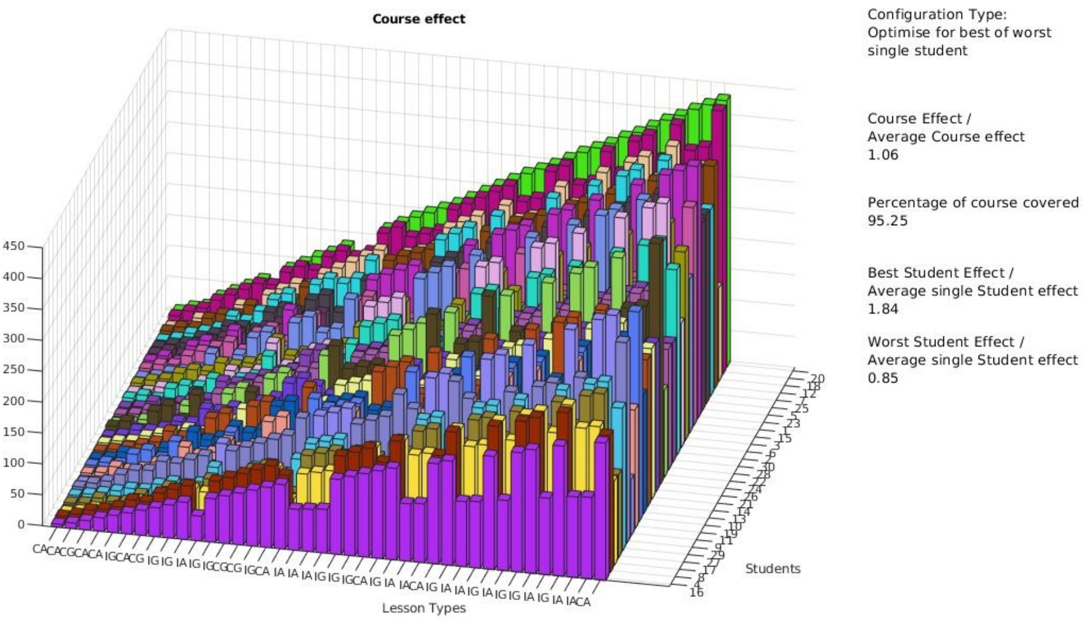


Figure 24: As can be seen, the values obtained for the worst student are quite high, even higher than those obtained for the Best Total Sequence in figure 18. However, the effect on the best student was slightly reduced, compared to the value obtained in the Best Total Sequence. In addition to that, the total effect of the course is also reduced compared to the one obtained by maximising the fitness value of the entire sequence. Z-axis represents the individual lesson effect.

5.3.8 Worst of Best Single Student

Once more this is a setting that will probably not be an option for the teacher when designing their course, as it involves reducing the effect on their best students. In other words, what you are looking for is min(Best Student). However, for research purposes, the results could be interesting as can be seen in figure 25.

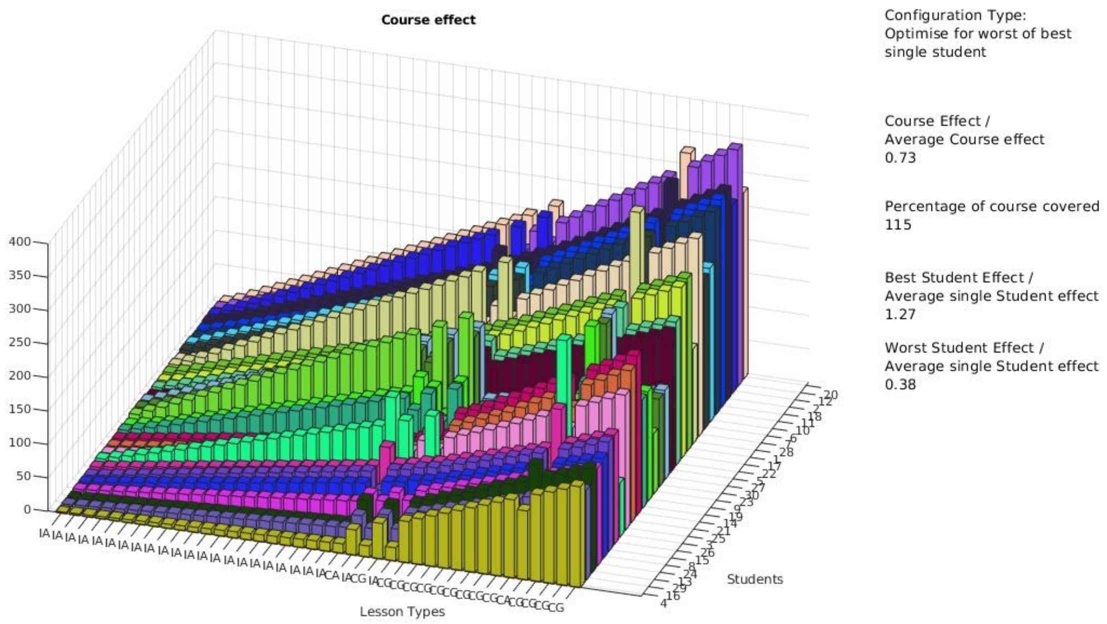


Figure 25: As can be seen, all the values obtained for this configuration are low, but the percentage covered in the curriculum is quite high. Which could indicate that there is a certain relationship between the percentage of curricula covered and the effect of the course obtained. Apparently as soon as the percentage of the curriculum begins to grow beyond 100%, the effect on students begins to decrease. Z-axis represents the individual lesson effect.

6 Discussion

In this section it is time to discuss the results from the previous sections and relate them to the available theory. The format of the result parts will be followed where the "minor" results of section 4 will be discussed first, followed by the "major" results of section 5.

6.1 Lesson Classification Model and Data Collection

As the Lesson classification model from section 4.1 and the data collection from section 3.3 go hand in hand, it is reasonable to discuss them together. As mentioned in section 4.1, one of the purposes was to investigate if there was a correlation between the learning style preferences of the students and their preferences of the lessons that the lesson classification model describes. For reference, the four lesson types that are described by the lesson classification model are: Instructions-Alone (IA), Coaching-Alone (CA), Coaching-Group (CG), and Instructions-Group (IG). From the data collection, the analysis indicated that there was no correlation of statistical significance. Interestingly, however, is the fact that the respondents of the Assimilating learning style from Kolb's Experiential learning theory (D. A. Kolb et al., 2001) is close to have a statistically significant concordance in how they rank the lesson types. The Assimilating learning style with the rank correlation coefficient value $\tau_A = 0.68$ generated a p-value of 0.083. Why is it that one of the learning styles was significantly more concordant than the others?

Consider the lesson classification model in relation to the Experiential learning theory, the data collected, the methods used as well as the difficulties of classifying education that are brought up by Davis (2017). Looking at the rankings that were most concordant with the learning styles from table 4 one can see that the lesson type Instructions-Alone is the highest ranked lesson for the Assimilating learning style. That lesson type is defined in section 4.1 as lessons where "students are taking direct instructions from the teacher on what they are going to do, and carry out that work alone", and examples of lessons of that type were "lessons structured as lectures" and "lessons where the students are working with assignments". Taking a look at the descriptions of Assimilating students from section 2.1 one finds the following: "They like to work with abstract concepts and thoughts while obtaining new knowledge...", and by D. A. Kolb et al. (2001) the learning style the learning style is described to prefer lectures in formal learning situations. Usually assignments are handed to students in order to let them process, understand, and analyse new knowledge by themselves. Thus it seems likely that Assimilating students would enjoy the Instructions-Alone lesson type as there is some overlap in what defines both. The other definitions of the learning styles do not have as much overlap with the definitions of the lesson types.

Looking at table 4 and figure 7b, one can also see that the Instructions-Alone lesson type is the most popular in the whole population. So the combination of Instructions-Alone being the most popular lesson type with it also having a good connection with the Assimilating students makes it likely that it is picked as the highest ranked lesson type by an arbitrary Assimilating student. Now, consider the way that Kendall's rank correlation coefficient is calculated when comparing two ranks of N elements. The method starts by looking at how the first element is ranked, and if that element happens to have the same rank for the ranks that are being compared it means that the score added for the first pair will be $N-1$ which by itself would give a value of $\tau_A = \frac{2(N-1)}{N(N-1)} = \frac{2}{N}$. If the situation is to rank four elements ($N = 4$) as in the data collection, then $\tau_A = \frac{2}{4} = 0.5$. The score can still be reduced if there is discordance between the ranking of other elements, but ranking the first element the same has a big impact, especially if there is a small number of elements to begin with.

There is also the fact that education is difficult to classify (Davis, 2017), so finding a lesson classification system that would be balanced towards all the four learning styles is unlikely, and in this case it seems likely that there was a heavy bias towards the Assimilating students assuming that the questionnaire correctly classified the respondents' learning style preferences.

But even with a possible bias towards one of the investigated learning styles, a simple and broad lesson classification system, and a method of analysis that may favour the same bias, the hypothesis of there being a correlation between learning style preference and lesson type preference was rejected. And unless a much more sophisticated model for classifying lessons emerges, such a correlation may not exist at all.

6.2 Most Popular Lesson Type

As mentioned above, the most popular lesson type among the respondents is Instructions-Alone, as seen in table 4 and figure 7b which also was in concordance with the "control questions" seen in figures 8a and 8b. This result is not that surprising given the population that is being investigated, namely technology students in upper secondary school. The technology programme is a university preparatory programme with a lot of emphasis on technology, natural science, and mathematics (Skolverket, 2020). It would be expected that mostly Converging and Assimilating individuals would attend that program as those are the learning styles with the biggest attraction to technology and science (D. A. Kolb et al., 2001). This may be the reasons as to why the results are the way they are, but more importantly all of the analysis in section 3.3 points towards Instructions-Alone being the most popular lesson type among the population: technology students in upper secondary school in the city of Gothenburg with vicinity.

6.3 The Mathematical Model

The mathematical model was as mentioned in section 3 developed ad hoc and can either be seen in section 4.3 or in Appendix D. When using the model to simulate the engagement of students in section 5 some results were received with a lot of additional plots in Appendix E that can be used to evaluate the mathematical model and control if the equations behave in an expected way. Looking at figure 18, which is the result received when trying to optimise for the whole class, with the goal being that the class will collectively have as high engagement as possible during the course. At first glance, the plots generate a interesting result that where the optimal course, or sequence of lessons that is fairly varied with a mix of lesson types in accordance with the claim brought up in section 2.2 from Westwood (2008); Airasian and Walsh (1997); Terhart (2003) regarding the positive impact a mixture of different lessons can have on a class.

From figure 18 one can also see that the "lesson effects" represented by the bars tends to increase during the course for every student, albeit differently for every student. There seems to be decrements in the lesson effects for the students at some points. However if one considers the cases where there is a decrement due to a change of lesson type, followed by one or more of the same lesson that the sequence changed to, one sees that the lesson effects is still increasing. This is most clear in the figure for student number 16, in the front, when looking at the eighth lesson from the left where the sequence goes from an Instructions-Group (IG) lesson to a sub sequence of seven Instructions-Alone (IA) lessons in a row. And even though the lesson effect of student 16 drops at the shift of lesson type, the effect still increases, and the lesson effect generated for any specific lesson type will not be lower than the first time that lesson type occurred in the sequence, for any student.

So while the result of the lesson sequence may seem reasonable, why is the graph and values for the lesson effects behaving the way they do? Consider the plots in Appendix E depicting the students' engagements over the course, figures 30, 33, 36, 39, etcetera. In those figures one can see that the engagement is always growing fairly uniformly. This seems to be the dynamic that behaves anomalously as one could expect the engagement of a student to decrease if they were put in a lesson of a type they do not prefer, but instead of decreasing it is only "growing less". Here follows a potential explanation of this behaviour.

Consider the other simulated dynamic, namely the "self efficacy" of the students which can be seen in figures 29, 32, 35, 38, etcetera. This dynamic seems to be following the desirable pattern of decreasing when students participate in lessons they do not prefer. Thus the suspicion is that the anomalous behaviour of the student engagement stems from how it is calculated. Consider the expression describing the student engagement (4.6):

$$\gamma_{j,c+1} = h(*) \cdot \frac{1}{N-1} \sum_{i \neq j} (1 - \mathbf{\Psi}_{ij}) \cdot \gamma'_{j,c} + \mathbf{\Psi}_{ij} \cdot \gamma_{i,c} \geq 0 \,.$$

More specifically, consider what was called the "internal coefficient" that dictates the impact the student has on itself. This coefficient was calculated using (4.14):

$$\gamma'_{j,c} = \begin{cases} \gamma_{j,c} + \underbrace{(3 + \varphi_{j,c+1} - \beta_{j,c})}_{(1)}, & \text{for } \varphi_{j,c+1} \geq 0.5 \\ \gamma_{j,c} + \underbrace{(3 - \varphi_{j,c+1} - \beta_{j,c})}_{(2)}, & \text{for } \varphi_{j,c+1} < 0.5 \end{cases} .$$

When dissecting this expression one finds what may be the reason to the behaviour of the student engagement. In order for the engagement to decrease over time instead of increasing less, $\gamma'_{j,c}$ has decrease, which would only happen if (1) or (2) takes on negative values. This cannot be the case for (1) as:

$$\min((1)) = 3 + \min(\varphi_{j,c+1}) - \max(\beta_{j,c}) = 3 + 0.5 - 3 = 0.5 \,, \tag{6.1}$$

so the remaining alternative is (2) < 0:

$$(2) < 0 \;\Leftrightarrow\; \varphi_{j,c+1} + \beta_{j,c} > 3 \tag{6.2}$$

which can only happen if the lesson type is Instructions-Alone because if $\varphi_{j,c+1}$ is taking on the limit value of the upper bound (0.5):

$$\beta_{j,c} > 3 - \max(\varphi_{j,c+1}) = 2.5, \tag{6.3}$$

and due to the definition of the stress from (4.9) using (4.7) and (4.8) one can see that the maximal value of the stress for a lesson type that is not Instructions-Alone takes on the maximal value of 1.6. Thus the only cases where the internal coefficient decreases is where the efficacy of the considered student is "low" ($\varphi_{j,c+1} < 0.5$), and the lesson is Instructions-Alone, which the student has to have given a preference value of 1 or 1.5 which are the two lowest values in our model.

Now that the behaviour has been figured out, the question is what effect this has on the model. The main implication is that the lesson effects are always on average increasing. However, to find the optimal sequences according to the configurations set in section 5 the algorithm still has to find the sequence that generate the largest growths according to those norms. So while a different result would be expected if the expression for the student engagement was altered to better fit the expectations while also keeping the property that the preference dictates the rate of change, we conjecture that the optimal lesson sequence to a large extent will be the same.

Overall, the mathematical model could use some more work as the ad hoc development method has resulted in it being fairly crude. It does however serve its purpose for the intentions if this project, but a model with more finesse and intuition would be desirable.

6.4 Implementation and Simulations

From section 5 the figures can be seen for the different configurations for which the model was optimised. Those figures together with the plethora of plots in Appendix E there is plenty of material to discuss. First, the histograms in the mentioned appendix will be introduced and discussed in short. The reason as to why the plots have been developed is to be a measure of how close the algorithm got to the optimal solution. As the optimal solutions for all these configurations are unknown it is of course difficult to know if the optimal solution has been obtained. As it is the case that calculating the course effect for a given lesson sequence is simple computationally, and since the order the lessons are in matters for the value of the course effect, randomness is being used to see if it is possible to find a better sequence than the given optimal sequence from the algorithm in section 5. So once the algorithm hands over the optimal sequence, a process is started where the order of that sequence is randomised 1000 times and the course effect of the scrambled sequences are added to the bins of the histograms. Assuming that the algorithm has found a solution near the optimal solution, then it shouldn't be likely that a better sequence is found by just scrambling the optimal one. And as can be seen from the histograms in most configurations the optimal sequence, marked by the red dot. The obvious exception to this is the scrambling of the random sequence, which doesn't really add anything other than completion for all the configurations. Due to an unknown error, it looks like there is a more optimal sequence than the one marked in figure 48, however when looking at the data that is being put into the plot, there is no better sequence for that configuration either. Also, the histogram for the worst single student has been left out as that sequence only consists of one type of lesson, Instructions-Alone, so the scrambled sequences would all be the same

Something interesting that is depicted by these histograms is the sensitivity to order in the model. When considering the histogram for the Best total sequence configuration in figure 31, and compare the value for the optimal solution with the lowest value from scrambling that sequence, one can see that there is a difference of nearly 20%. There also seems to be a trend among the configurations aiming at maximising to put many of the Instructions-Alone (IA) lessons at the end of the sequence, as if the algorithm is using the less “stressful” or “workload heavy” lesson types in the beginning to build up as high of an engagement as possible so that the engagement is not lowered as much when the IA-lessons are more prominent at the end of the course. It might be the case that negative impacts early in the lesson sequence may prevent the course from reaching near optimal values. Should that assumption be true, the interpretation would be that it is better to put IA-lessons, lessons with direct instructions and where the students are working alone, at the end of the course in order to maintain a high engagement.

Now, consider some of the more realistic configurations that were simulated, namely “Best total sequence”, “Best course evaluation sequence”, “Best single student”, and “Best of worst single students”. In order to more easily reason about these configurations a table of the relevant values have been constructed:

Table 5: Data gathered from simulations according to the different configurations. The values presented for each configuration are: course effect / average, best student effect / average, worst student effect / average, and course percentage. From the first four, “realistic”, configuration types it can be seen that the course effect gain is not very large (at most 10% compared to the average course) which most likely is due to the fact that the different preferences makes it difficult to optimise as some students almost always will dislike the course and have a decreasing efficacy (see Appendix E). From the best student effect and worst student effect one can see that the most significant impact is made on the least engaged student in the class, as the most engaged student in the class always has an increasing efficacy (see Appendix E). In general it seems like the courses that generate the lowest course effects have a higher course percentage, or in other words a higher workload, than the ones that generate higher course effects.

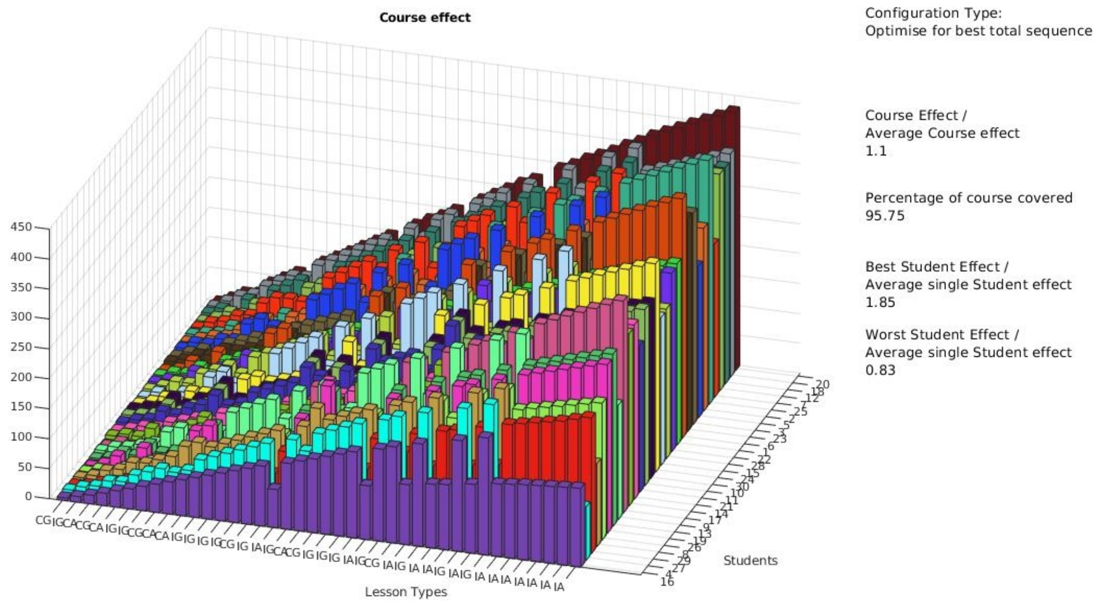
Configuration type	Course Effect/ average	Best Student Effect/ average	Worst Student Effect/ average	Course Percentage
Best Total Sequence	1.1	1.85	0.83	95.75%
Maximal Course Evaluation	1.09	1.83	0.86	91.75%
Best of Worst Single Student	1.06	1.84	0.85	95.25%
Best Single Student	1.03	1.85	0.78	95.25%
Random Sequences	0.95	1.65	0.71	86.25%
Worst Single Student	0.76	1.53	0.12	150%
Worst Of Best Single Student	0.73	1.27	0.38	115%
Worst Total Sequence	0.72	1.55	0.25	129%

Just to clarify again what the purpose is of the Best of worst single student configuration is and what the real life interpretation is, it is the sequence that finds the highest individual effect for the least engaged student in the class (maximising the minimum), within the restriction of the curriculum. This strategy can be seen as common among teachers where a goal can become to engage the least engaged student or students. But how effective is the strategy of focusing on the least engaged student in that way? As seen in the table, there is not a very big difference between the effects of the most engaged students and least engaged students between either of the configurations, except between the configurations “Best single student” and “Best of worst single student” for the worst student effect. The difference between those configurations seem to indicate that focusing on producing the single most engaged student in the class can affect the less engaged students negatively. Moreover, when considering the values for the course effects (Course effect / Average course effect), one can see that the configurations that focus on single students do miss out on course effect compared to the the configuration “Best total sequence”. That result in combination with the numbers being fairly close for the Best and Worst student effects may indicate that the better choice overall is to optimise for the class as a whole, while not losing a lot when it comes to the engagement of the most and least engaged students compared to when focusing on them.

7 Conclusions

In this section, the research questions will be answered as their own paragraphs.

Is there a unique sequence of different lesson types, with which a maximum amount of engagement is obtained? With the mathematical model being implemented as it is in section 4.3, it is possible to find a unique sequence using all four different lesson types from the lesson classification model in section 4.1 by using the genetic algorithm from section 5. The resulting sequence and course effect can be seen in the following figure (z-axis represents the individual lesson effect):



How much do different optimisation norms affect the amount of engagement in the class? There are several norms, or configurations, that have been optimised which can be seen listed in section 5 and their results in table 5. However, the most realistic norms can be seen in table 6. From that table, there does not seem to be a significant difference in the the type of optimisation norm that is being used as long as the purpose is to maximise either the engagement of the class or a particular part of the class, with the exception being the best lesson sequence that does not take the curriculum into consideration where the percentage of the course covered is lowered.

Table 6: Realistic configurations from table 5.

Configuration type	Course Effect/ average	Best Student Effect/ average	Worst Student Effect/ average	Course Percentage
Best Total Sequence	1.1	1.85	0.83	95.75%
Maximal Course Evaluation	1.09	1.83	0.86	91.75%
Best of Worst Single Student	1.06	1.84	0.85	95.25%
Best Single Student	1.03	1.85	0.78	95.25%

Does the learning style preference in a student correlate to preference in lesson types? According to the analysis of the data from section 4.2 there exists no statistically significant correlation between the learning style from Kolb's Experiential learning theory (D. A. Kolb et al., 2001) and the lesson classification model in section 4.1.

Which lesson type from the lesson classification model do students most prefer? When considering lessons of the types defined by the lesson classification model in section 4.1, students of the investigated population (students of the technology programme in upper secondary school in the city of Gothenburg with vicinity) prefer lessons of the type Instructions-Alone according to the analysis from section 4.2, where the students are given direct instructions by the teacher and work alone during the lesson.

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A Questionnaire

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Undersökning - lärstilar och lektionstyper

Tack för att du deltar i den här undersökningen!

Detta projekt har som mål att utveckla en modell för hur elever engagerar sig i kurser för att finna en "optimal" sekvens av lektioner. Detta kommer att ske genom att se på vad du som elev har för preferenser när det kommer till hur du föredrar att lära dig och vilka sorters lektioner du föredrar. För att detta projekt ska fungera så betyder det att ditt deltagande är av stor vikt. Dina svar är och förblir anonyma och kommer att bli implementerade i vår modell.

*Obligatorisk

Del 1

I denna del skall du poängsätta hur väl du anser att följande påståenden stämmer överens med hur du föredrar att lära dig. På varje påstående så måste varje alternativ poängsättas med 1-4 poäng. Du får endast använda en poängmängd per alternativ. Till exempel så kan du inte för ett påstående ge 4 poäng till två olika alternativ.

1. 1. När jag ska lära mig något vill jag... *

Markera endast en oval per rad.

	4	3	2	1
a) ... engagera mig känslomässigt.	⬭	⬭	⬭	⬭
b) ... observera och lyssna.	⬭	⬭	⬭	⬭
c) ... tänka över begreppen och idéerna	⬭	⬭	⬭	⬭
d) ... pröva det i praktiken	⬭	⬭	⬭	⬭

2. 2. Då jag lär mig så... *

Markera endast en oval per rad.

	4	3	2	1
a) ... analyserar jag problemet och bryter ner det i dess delar.				
b) ... är jag inriktad på den praktiska användbarheten.				
c) ... ser jag problemet ur många infallsvinklar.				
d) ... är jag öppen för nya erfarenheter och intryck.				

3. 3. Jag lär bäst då jag... *

Markera endast en oval per rad.

	4	3	2	1
a) ... neutralt lyssnar och betraktar.				
b) ... utgår från mina konkreta upplevelser.				
c) ... ser att det är genomförbart.				
d) ... stöder mig på logiskt tänkande.				

4. 4. Medan jag lär... *

Markera endast en oval per rad.

	4	3	2	1
a) ... känner jag ansvar för att det skall leda till något användbart.				
b) ... resonerar jag mig fram.				
c) ... väcks starkt responser och känslor hos mig.				
d) ... är jag tyst, tillbakadragen och reserverad.				

5. 5. Under inlärning är jag... *

Markera endast en oval per rad.

	4	3	2	1
a) ... aktiv och handlingsinriktad.				
b) ... instinktiv.				
c) ... lyhörd och uppmärksam.				
d) ... logisk och konsekvent.				

6. 6. Jag lär bäst... *

Markera endast en oval per rad.

	4	3	2	1
a) ... i samverkan och dialog med andra.				
b) ... då jag kan göra praktiska tillämpningar.				
c) ... utifrån teorier och modeller.				
d) ... genom reflektion över egna iakttagelser				

7. 7. När jag lär... *

Markera endast en oval per rad.

	4	3	2	1
a) ... tar jag tid på mig innan jag handlar.				
b) ... gillar jag idéer, begrepp och tankar.				
c) ... känner jag mig personligt involverad i ämnet.				
d) ... vill jag se resultat av mitt arbete.				

8. 8. Jag lär bäst då jag litar på... *

Markera endast en oval per rad.

	4	3	2	1
a) ... mina tankar och teorier.				
b) ... nyttan och funktionsdugligheten.				
c) ... mina egna erfarenheter och iakttagelser.				
d) ... mina infall och plötsliga tankar.				

9. 9. Jag lär genom att... *

Markera endast en oval per rad.

	4	3	2	1
a) ... känna känslor.				
b) ... observera.				
c) ... handla.				
d) ... tänka.				

10. 10. Vid inlärande är jag... *

Markera endast en oval per rad.

	4	3	2	1
a) ... rationell och klarsynt.				
b) ... försiktig och avvaktande.				
c) ... accepterande och oförbehållsam.				
d) ... ansvarstagande och resultatinriktad				

11. 11. När jag lär... *

Markera endast en oval per rad.

	4	3	2	1
a) ... är jag aktiv och experimenterande.				
b) ... blir jag engagerad och indragen.				
c) ... bedömer och utvärderar jag.				
d) ... föredrar jag att vara observatör.				

12. 12. Jag lär bäst då jag... *

Markera endast en oval per rad.

	4	3	2	1
a) ... är eftertänksam och begrundande.				
b) ... argumenterar och drar slutledningar.				
c) ... är mottaglig, öppen och bekräftande.				
d) ... arbetar praktiskt och konkret.				

13. 13. För att lära mig något behöver jag... *

Markera endast en oval per rad.

	4	3	2	1
a) ... systematisera det.				
b) ... hålla distans till det.				
c) ... se handlingsmöjligheterna i det.				
d) ... känna starkt för det.				

Del 2

Här skall du poängsätta åtta olika beskrivningar av lektioner efter hur mycket du hade föredragit dem. 1 poöng = föredrar inte alls, och 4 poäng = föredrar helt och hållet. Efter det följer även två frågor om hur du föredrar att lektioner är utformade.

14. 14) Ni har jobbat lite med ett nytt avsnitt i kursen. Nu ska ni i grupper om 3-4 tillsammans komma på ett eget litet praktiskt projekt (relaterat till avsnittet) som ni ska jobba med under lektionstid (tre lektioner totalt). Detta projekt skall ni sedan presentera för läraren och klassen. Under projektets gång så får ni diskutera projektet med läraren. *

Markera endast en oval.

	1	2	3	4	
Föredrar inte alls					Föredrar helt och hållet

15. 15) Ni har börjat på ett nytt avsnitt i kursen och läraren ber er att göra en inlämningsuppgift där ni individuellt skall läsa om ett nytt begrepp i avsnittet, både i boken och genom att leta information på nätet. Efter det skall ni skriva om och förklara det nya begreppet med egna ord. *

Markera endast en oval.

	1	2	3	4	
Föredrar inte alls					Föredrar helt och hållet

16. 16) Ni har börjat gå igenom ett nytt begrepp. För att bättre förstå begreppet så vill läraren att ni i grupper om 3-4 (som läraren valt åt er) skall utföra en laboration (eller ett experiment) efter givna instruktioner. *

Markera endast en oval.

	1	2	3	4	
Föredrar inte alls	◯	◯	◯	◯	Föredrar helt och hållet

17. 17) Läraren har precis visat, eller berättat om, ett nytt begrepp/fenomen. Ni skall i grupper om 3-4 försöka diskutera er fram till en förklaring om hur det fungerar och sedan berätta vad ni tänkt för resten av klassen. Under tiden som ni diskuterar i grupperna så kan ni även diskutera med läraren. *

Markera endast en oval.

	1	2	3	4	
Föredrar inte alls	◯	◯	◯	◯	Föredrar helt och hållet

18. 18) Ni ska jobba individuellt med problem som inte nödvändigtvis har ett rätt eller fel svar. Frågorna och dina lösningar får du diskutera med läraren, som coachar dig mot en bra lösning med tips eller följdfrågor. *

Markera endast en oval.

	1	2	3	4	
Föredrar inte alls	◯	◯	◯	◯	Föredrar helt och hållet

19. 19) Ni ska individuellt göra uppgifter som handlar om ett begrepp ni nyligen har gått igenom. Uppgifterna är i kursboken eller på stenciler. Om du ber om det så får du hjälp av läraren att lösa uppgiften. *

Markera endast en oval.

	1	2	3	4	
Föredrar inte alls	( )	( )	( )	( )	Föredrar helt och hållet

20. 20) Ni skall lära er ett nytt begrepp. Läraren går igenom begreppet och exempel i helklass med PowerPoint och/eller på tavlan. Ni får sitta och lyssna, anteckna samt ställa frågor. *

Markera endast en oval.

	1	2	3	4	
Föredrar inte alls	( )	( )	( )	( )	Föredrar helt och hållet

21. 21) Ni skall i grupper om 3-4 diskutera och lösa svårare uppgifter. Efter att ni har jobbat i grupp går läraren igenom, och diskuterar, uppgifterna i helklass efter gruppernas lösningsförslag. *

Markera endast en oval.

	1	2	3	4	
Föredrar inte alls	( )	( )	( )	( )	Föredrar helt och hållet

22. 22) Jag föredrar lektioner där... *

Markera endast en oval.

( ) ... instruktionerna är direkta så att jag vet vad som förväntas av mig och vad jag ska göra.

( ) ... instruktionerna är öppna så att jag har inflytande och kan bestämma lite själv över hur jag ska göra.

23. 22) Jag föredrar lektioner där... *

Markera endast en oval.

- ... jag kan jobba för det mesta enskilt, eventuellt i par.
- ... jag för det mesta får jobba tillsammans med andra.

B Changes made to the translated version of LSI

Statement 2 “Då jag lär” was changed to “Då jag lär *mig så*”.

Statement 4, alternative 1 “känner jag ansvar för att det ska leda till något” was changed to “känner jag ansvar för att det ska leda till något *användbart*”

Statement 8, alternative 4 “mina infall och *ingivelser*” was changed to “mina infall och *plötsliga tankar*”

Statement 9, alternative 1 “känna” was changed to “känna *känslor*”

See next page for the translated version of the LSI by Marke and Cesarec (2007)

LSI II (Learning-Style Inventory, D.A. Kolb/S. Marke)

Här nedan ombeds du fullborda 13 meningar. Varje mening har fyra olika, alternativa, slut.

Poängsätt, för varje mening, de fyra alternativen utifrån hur pass bra vart och ett av dom passar in på **hur du är eller går tillväga när du lär dig något**.

Utgå gärna från någon närliggande situation då du hade att lära dig något nytt, t ex i arbete eller studier.

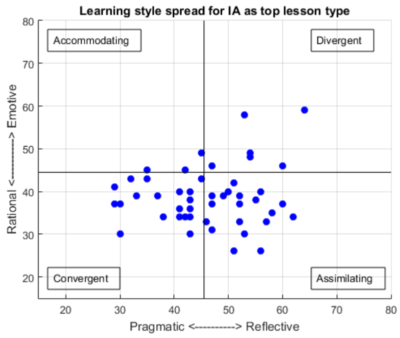
Sätt för varje mening siffran
4 för det alternativ som **bäst** passar in på dig
3 för det **näst bästa** alternativet
2 för det **näst sämsta** alternativet
1 för det alternativ som **sämst** passar in på dig

Var noga med att poängsätta **alla** alternativen för var och en av de 13 meningarna. Arbeta spontant, fundera inte för länge!

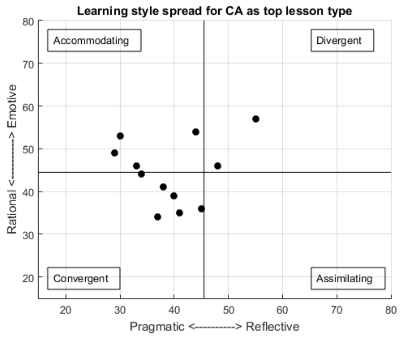
Kod: ________
Kön:
☐ Kvinna
☐ Man
Ålder: ________

1. När jag skall lära mig något vill jag	☐ engagera mig känslomässigt	☐ observera och lyssna	☐ tänka över begreppen och idéerna	☐ omsätta och pröva det i praktiken
2. Då jag lär	☐ analyserar jag problemet och bryter ner det i dess delar	☐ är jag inriktad på den praktiska användbarheten	☐ ser jag problemet ur många infallsvinklar	☐ är jag öppen för nya erfarenheter och intryck
3. Jag lär bäst då jag	☐ opartiskt lyssnar och betraktar	☐ utgår från mina egna konkretra upplevelser	☐ ser att det är genomförbart	☐ stöder mig på logiskt tänkande
4. Medan jag lär	☐ känner jag ansvar för att det skall leda till något	☐ resonerar jag mig fram	☐ väcks starkt gensvar och känslor hos mig	☐ är jag tyst, tillbakadragen och reserverad
5. Under inlärning är jag	☐ aktiv och handlingsinriktad	☐ intuitiv	☐ lyhörd och uppmärksam	☐ logisk och konsekvent
6. Jag lär bäst	☐ i samverkan och dialog med andra	☐ då jag kan göra praktiska tillämpningar	☐ utifrån teorier och modeller	☐ genom reflektion över egna iakttagelser
7. När jag lär	☐ tar jag tid på mig innan jag handlar	☐ gillar jag idéer, begrepp och tankar	☐ känner jag mig personligt involverad i ämnet	☐ vill jag se resultat av mitt arbete
8. Jag lär bäst då jag litar på	☐ mina tankar och teorier	☐ nyttan och funktions-dugligheten	☐ mina egna rön och iakttagelser	☐ mina infall och ingivelser
9. Jag lär genom att	☐ känna	☐ observera	☐ handla	☐ tänka
10. Vid inlärande är jag	☐ rationell och klarsynt	☐ försiktig och avvaktande	☐ accepterande och oförbehållsam	☐ ansvarstagande och resultatinriktad
11. När jag lär	☐ är jag aktiv och experimenterande	☐ blir jag engagerad och indragen	☐ bedömer och utvärderar jag	☐ föredrar jag att vara observatör
12. Jag lär bäst då jag	☐ är eftertänksam och begrundande	☐ argumenterar och drar slutledningar	☐ är mottaglig, öppen och bejakande	☐ arbetar praktiskt och konkret
13. För att lära mig något behöver jag	☐ systematisera det	☐ hålla distans till det	☐ se handlingsmöjligheterna i det	☐ känna starkt för det

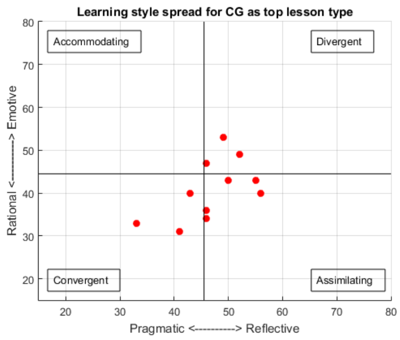
C More data plots



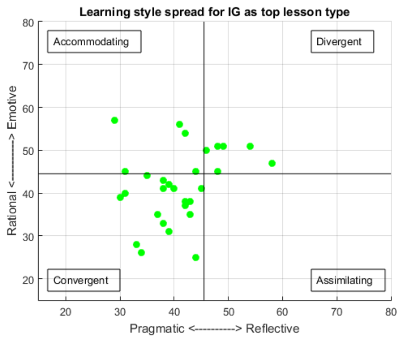
(a) Main learning styles of the respondents with Instructions-Alone as most preferred lesson type.



(b) Main learning styles of the respondents with Coaching-Alone as most preferred lesson type.



(c) Main learning styles of the respondents with Coaching-Group as most preferred lesson type.



(d) Main learning styles of the respondents with Instructions-Group as most preferred lesson type.

Figure 26: In these plots one can see the main learning styles of the respondents with one specific lesson type as the highest ranked. While the data shows strong tendencies towards the Converging and Assimilating learning styles it is important to remember that there is a big bias towards those learning styles in the population (around 75% of the population is either Converging or Assimilating). Thus it is difficult to draw conclusions from these plots alone.

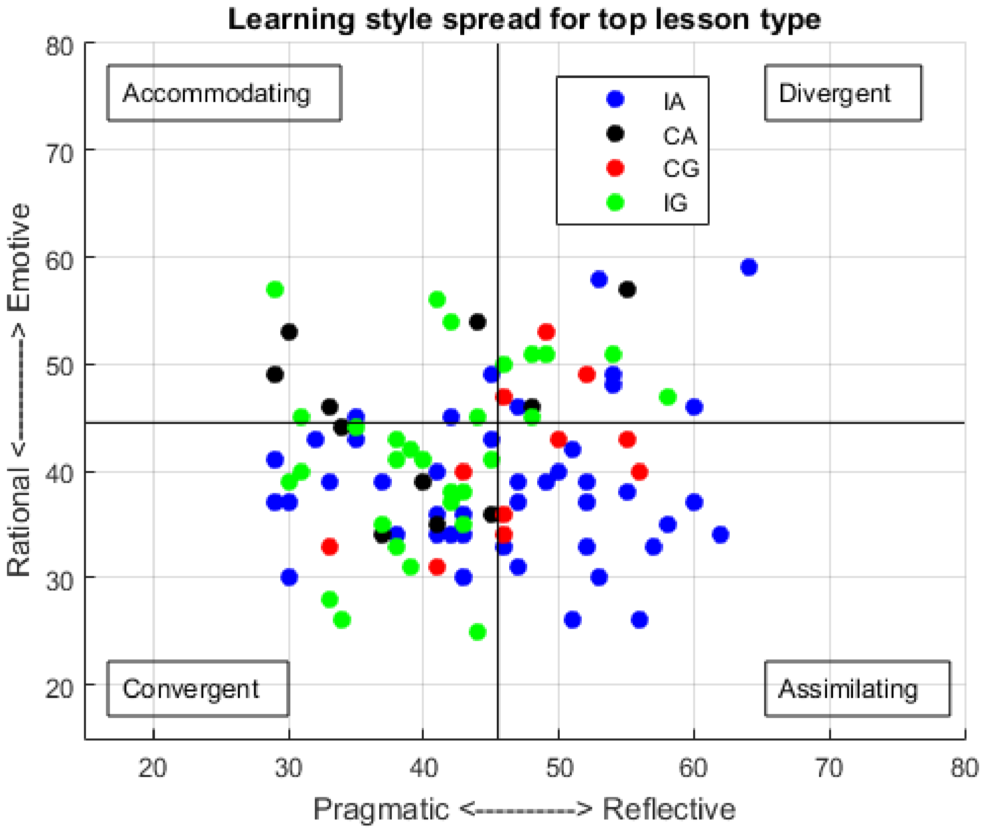


Figure 27: Preferred learning styles of all respondents colour coded according to highest ranked lesson type.

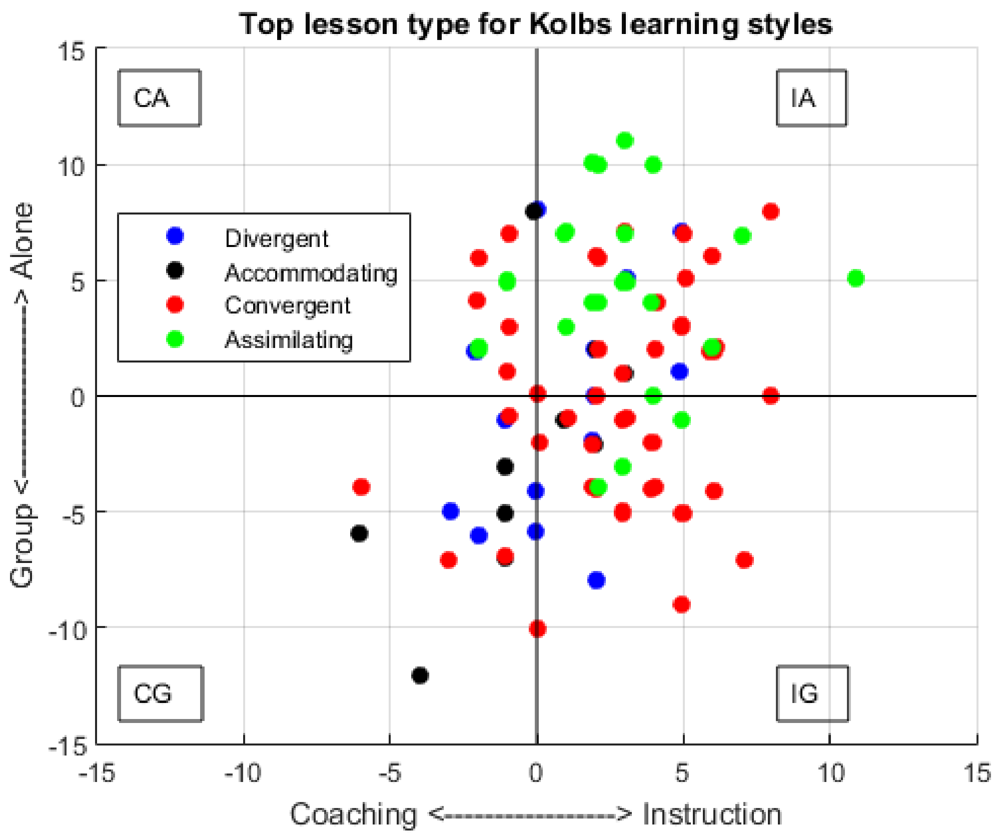


Figure 28: Preferred lesson types among the respondents colour coded according to main learning style.

D Mathematical model

List of symbols as well as all the equations of the mathematical model gathered in one place.

D.1 List of symbols

Symbol	Description
χ	Course effect. The sum of all lesson effects over the whole course. Also the fitness value of a chromosome;
$\boldsymbol{\upsilon}$	Course, or lesson sequence vector that contains the lesson types in temporal order;
κ	Total lesson effect of one lesson;
τ	Individual lesson effect of a student;
γ	Individual lesson engagement of a student;
$\boldsymbol{\lambda}$	Individual preference vector listing the lesson type preferences of a student;
$\boldsymbol{\Psi}$	Student influence matrix. Describes the influence that one student has on another;
h	The Heaviside step function;
β	Individual stress value of a student;
φ	Cognitive component, or individual self efficacy of a student;
ℓ	The logistic function;
k	Sensitivity coefficient;
ω	Workload value of one lesson;
$\boldsymbol{\epsilon}$	Individual effort vector listing the lesson type efforts of a student;
L	Total number of lessons;
N	Total number of students;
$\overline{\kappa_c}$	Average total lesson effect of lesson c;
$\overline{\tau_{j,c}}$	Average lesson effect of student j up to lesson c;
i,j	Index for students;
c	Index for lesson number.

D.2 Equations

$$\chi = \sum_{c=1}^{L} \kappa_c. \tag{D.1}$$

$$\boldsymbol{\upsilon} = \begin{bmatrix} \upsilon_1 & \upsilon_2 & \dots & \upsilon_L \end{bmatrix} \tag{D.2}$$

$$\kappa_c = \sum_{j=1}^{N} \tau_{j,c}. \tag{D.3}$$

$$\boldsymbol{\lambda}_j = \lambda_j(\boldsymbol{\upsilon}) = \begin{bmatrix} \lambda_j(\upsilon_1) & \lambda_j(\upsilon_2) & \dots & \lambda_j(\upsilon_L) \end{bmatrix} = \begin{bmatrix} \lambda_{j,1} & \lambda_{j,2} & \dots & \lambda_{j,L} \end{bmatrix} \tag{D.4}$$

$$\tau_{j,c} = \gamma_{j,c}\lambda_{j,c} \tag{D.5}$$

$$\gamma_{j,c+1} = h(*) \cdot \underbrace{\frac{1}{N-1} \sum_{i \neq j} (1 - \boldsymbol{\Psi}_{ij}) \cdot \gamma_{j,c}^{'} + \boldsymbol{\Psi}_{ij} \cdot \gamma_{i,c} \geq 0}_{=*} \tag{D.6}$$

$$h(x) = \begin{cases} 0, \; x \leq 0 \\ 1, \; x > 0 \end{cases} \tag{D.7}$$

$$\boldsymbol{\Psi} \in N \times N \,, \; \boldsymbol{\Psi}_{ij} \sim \mathcal{U}(0{,}1) \,, \; \boldsymbol{\Psi}_{i,i} = 0 \tag{D.8}$$

$$\gamma_{j,c}^{'} = \begin{cases} \gamma_{j,c} + (3 + \varphi_{j,c+1} - \beta_{j,c}), & \text{for } \varphi_{j,c+1} \geq 0.5 \\ \gamma_{j,c} + (3 - \varphi_{j,c+1} - \beta_{j,c}), & \text{for } \varphi_{j,c+1} < 0.5 \end{cases} \tag{D.9}$$

$$\varphi_{j,c+1} = \ell\big((1 - \varphi_{j,c})(\tau_{j,c} - \overline{\kappa_{j,c}}) + \varphi_{j,c}(\tau_{j,c} - \overline{\tau_{j,c}})\big) \tag{D.10}$$

$$\ell(x) = \frac{1}{1 + e^{-kx}} \tag{D.11}$$

$$\overline{\kappa_c} = \frac{1}{N-1} \sum_{i \neq j} \tau_{i,c} \tag{D.12}$$

$$\overline{\tau_{j,c}} = \frac{1}{c} \sum_{k=1}^{c} \tau_{j,c} \tag{D.13}$$

$$\beta_{j,c} = \omega_c \cdot \epsilon_{j,c} \tag{D.14}$$

$$\omega_c = \omega(\boldsymbol{\upsilon}_c) = \begin{cases} 1.5, & \boldsymbol{\upsilon}_c = \upsilon_1 \text{ (Instructions-Alone)} \\ 0.8, & \boldsymbol{\upsilon}_c = \upsilon_2 \text{ (Coaching-Alone)} \\ 0.6, & \boldsymbol{\upsilon}_c = \upsilon_3 \text{ (Coaching-Group)} \\ 0.7, & \boldsymbol{\upsilon}_c = \upsilon_4 \text{ (Instructions-Group)} \end{cases} \tag{D.15}$$

$$\epsilon_{j,c} = \epsilon(\boldsymbol{\lambda}_{j,c}) = 2.5 - \frac{\boldsymbol{\lambda}_{j,c}}{2} \tag{D.16}$$

E Simulation results

Various results obtained from the different implementation configurations.

E.1 Best Total Sequence

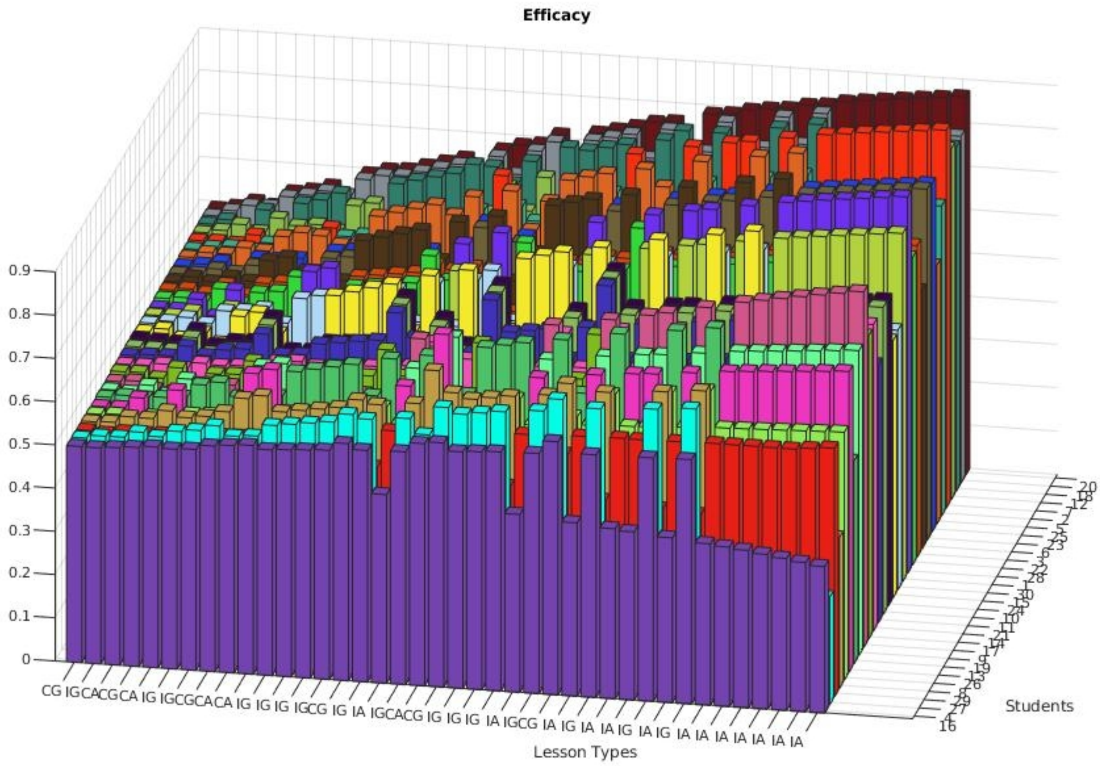


Figure 29: Best Total Sequence Efficacy.

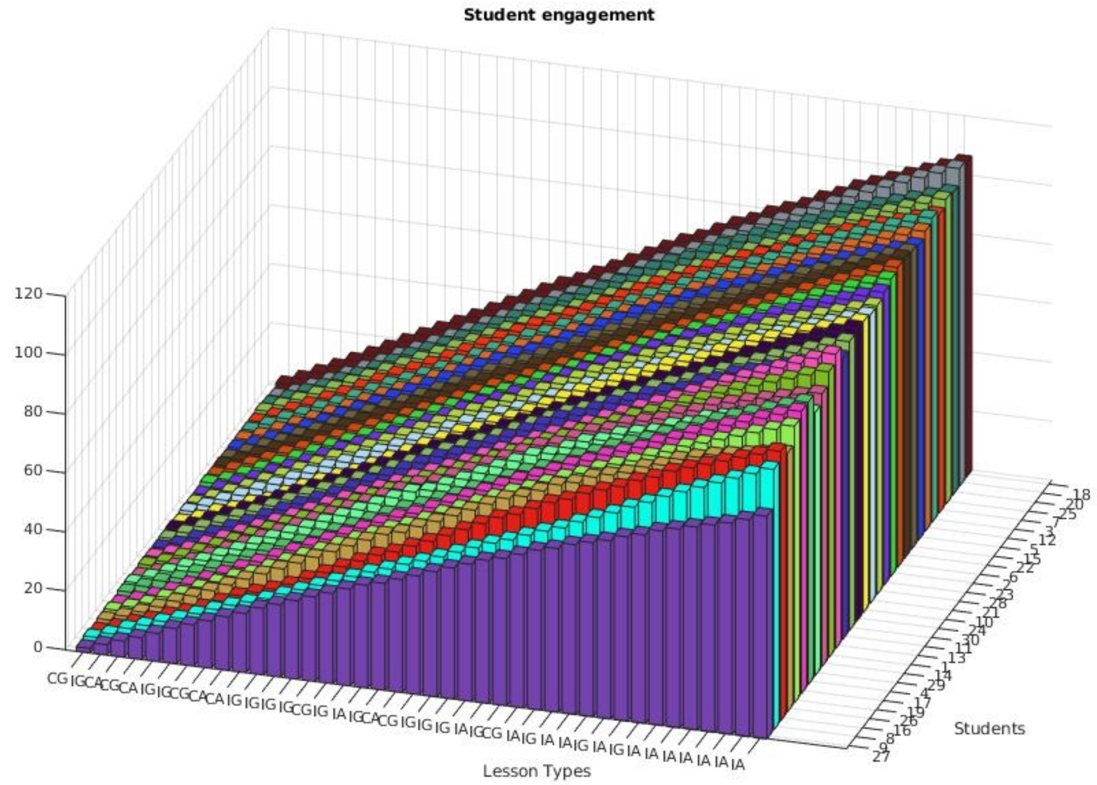


Figure 30: Best Total Sequence Student Engagement.

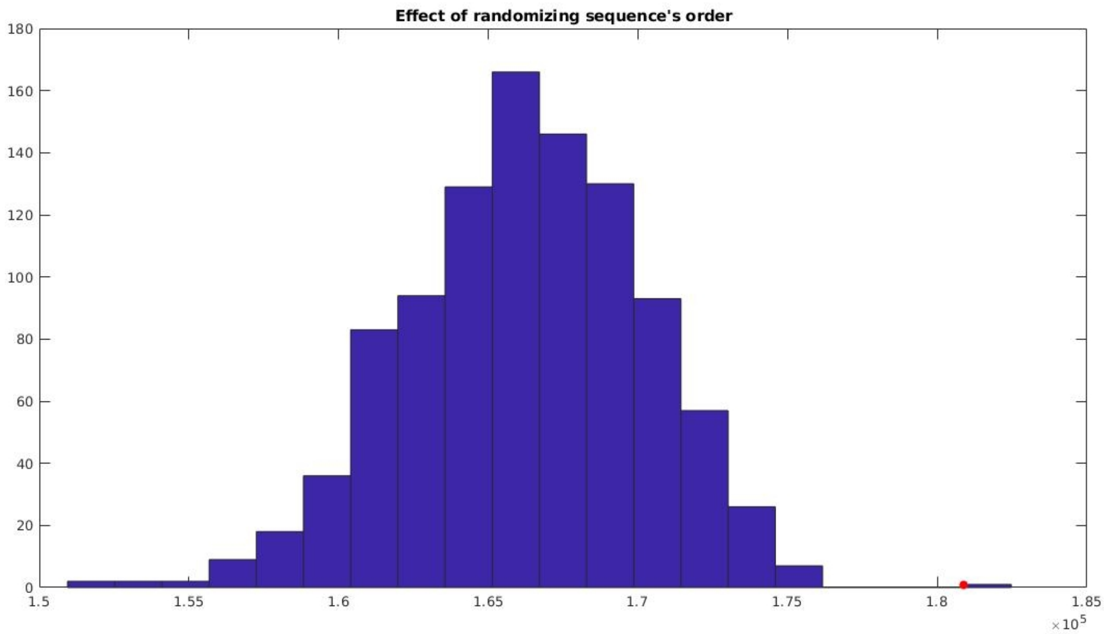


Figure 31: Course effect randomising the sequence order for the Best total sequence configuration.

E.2 Worst Total Sequence

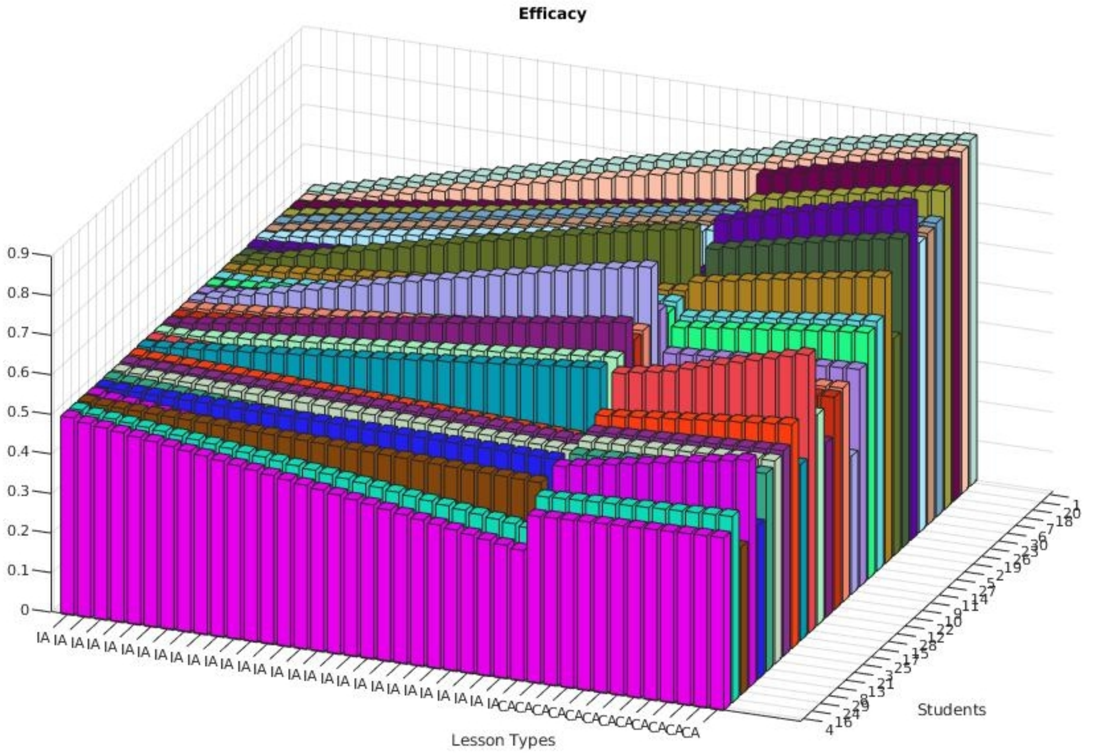


Figure 32: Worst Total Sequence Efficacy.

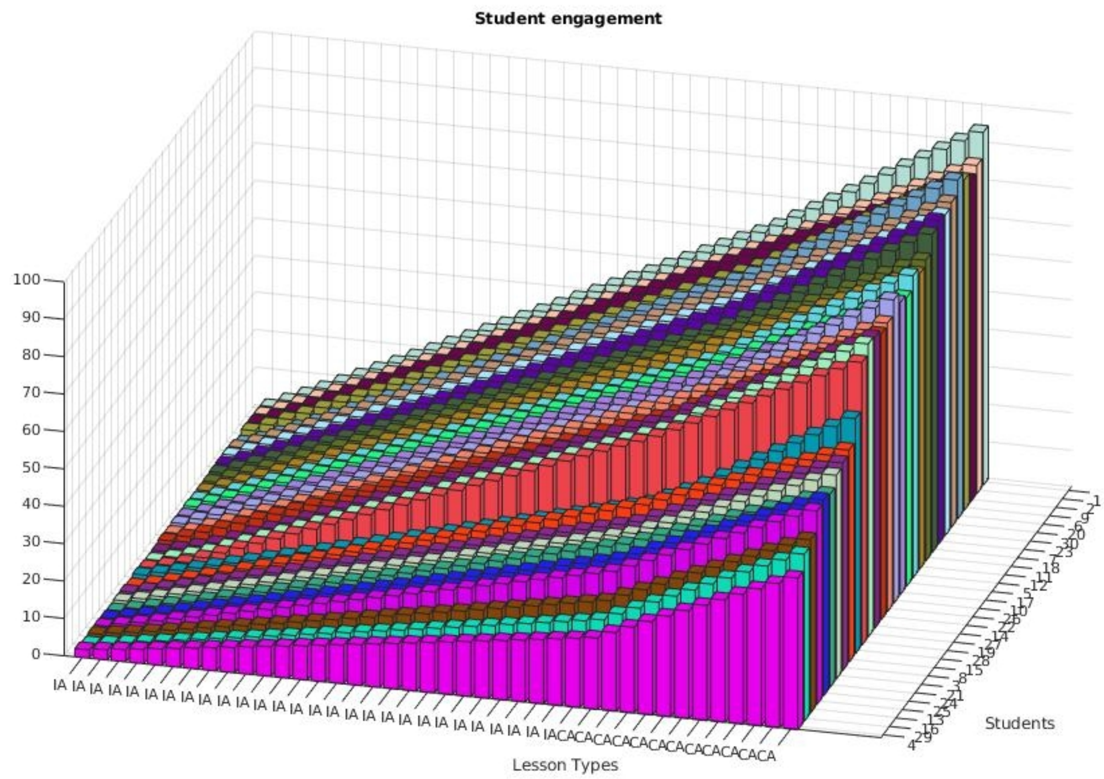


Figure 33: Worst Total Sequence Student Engagement.

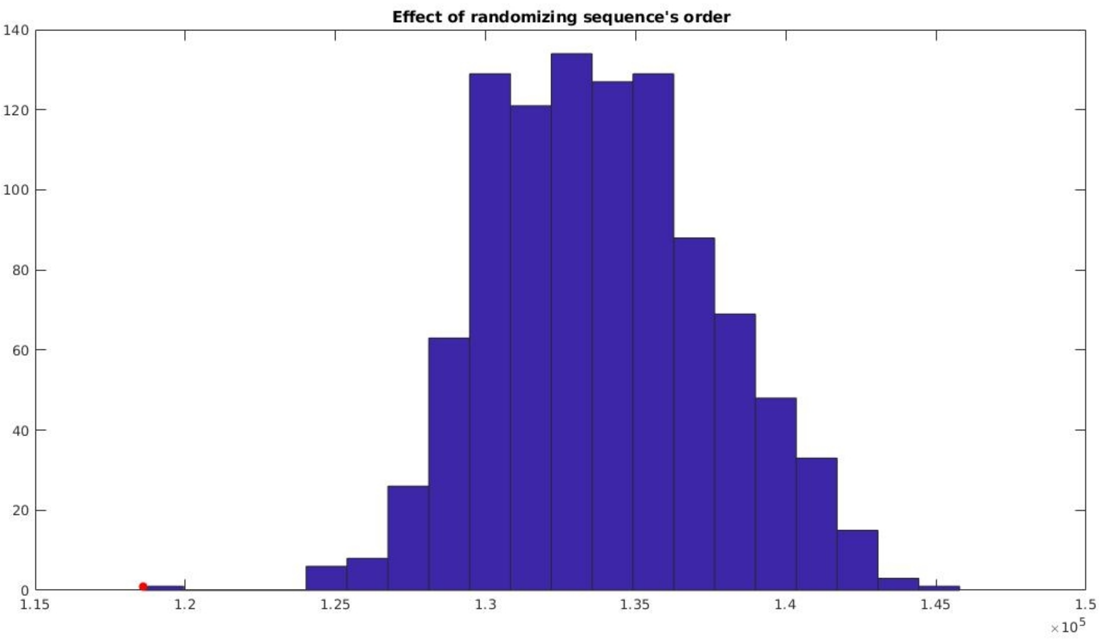


Figure 34: Course effect randomising the sequence order for the Worst total sequence configuration.

E.3 Random Sequences

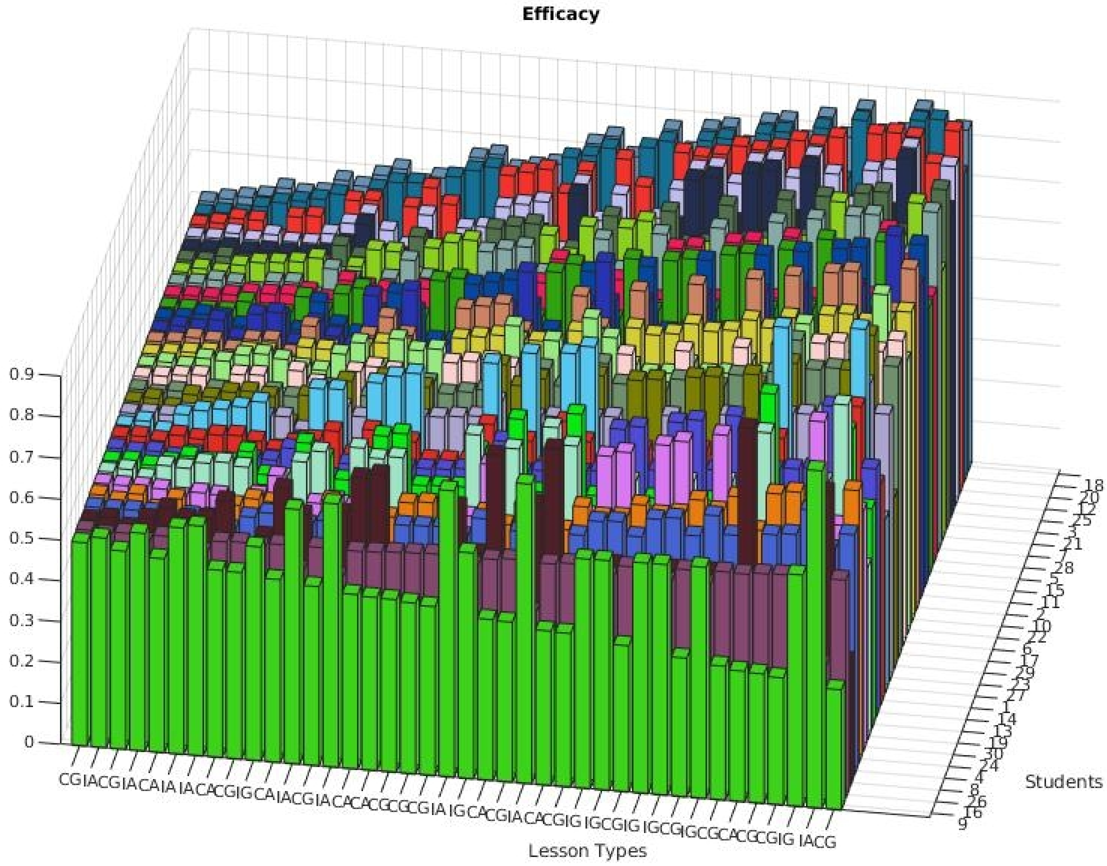


Figure 35: Random Sequence Efficacy.

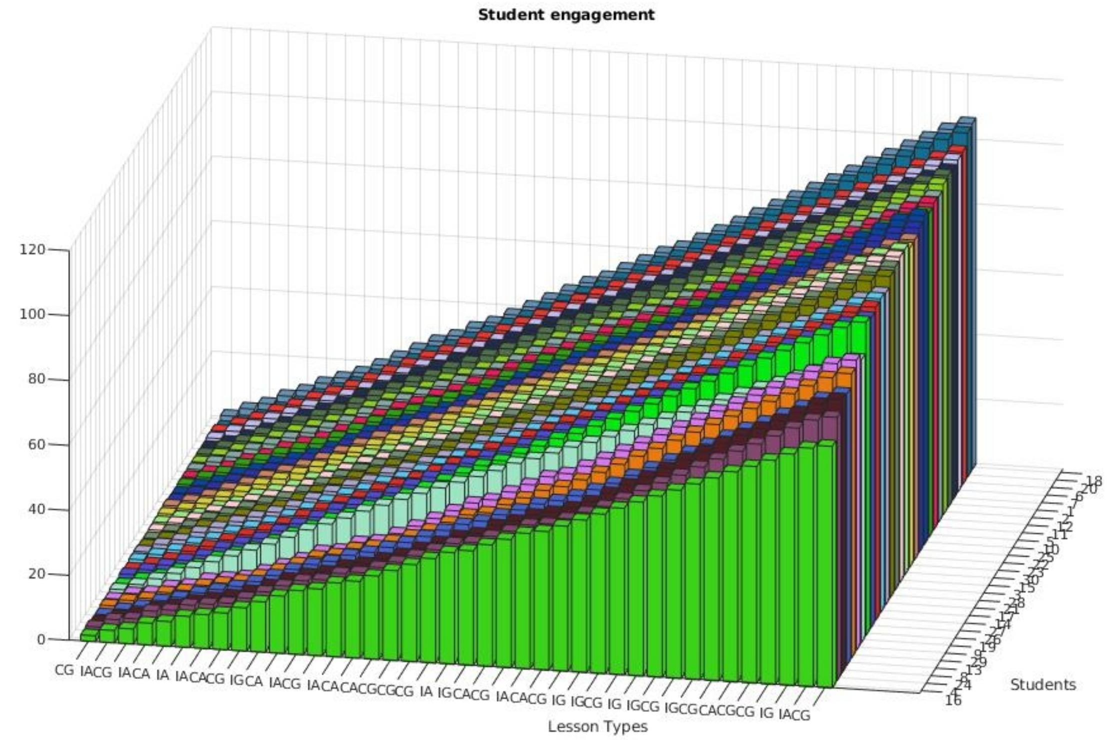


Figure 36: Random Sequence Student Engagement.

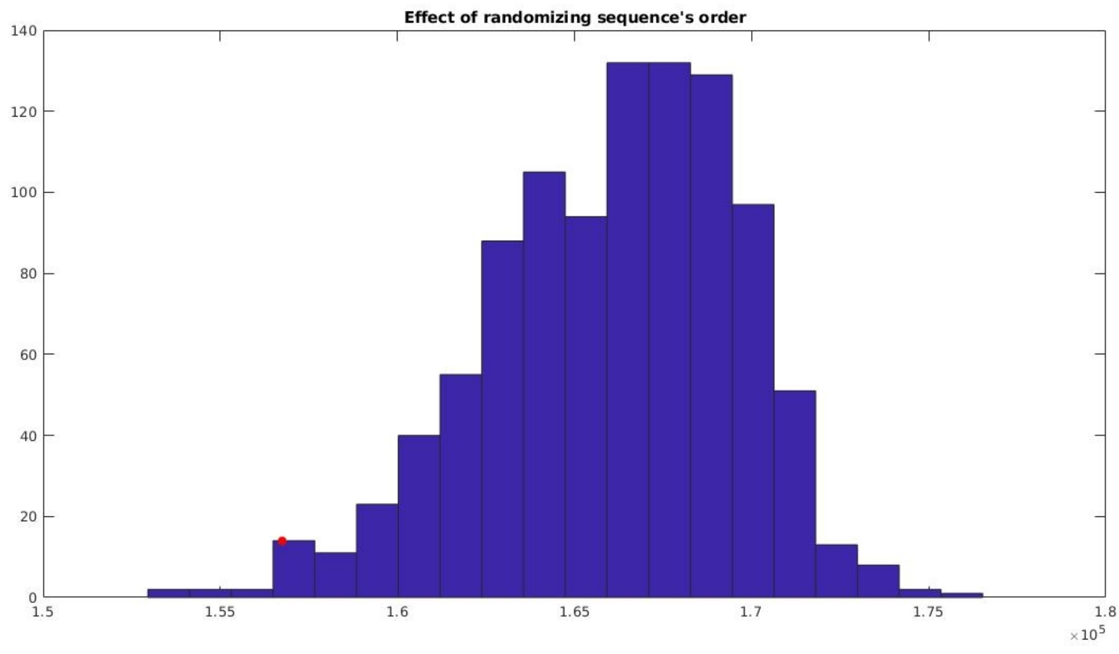


Figure 37: Course effect randomising the sequence order for the random sequence.

E.4 Maximal course evaluation

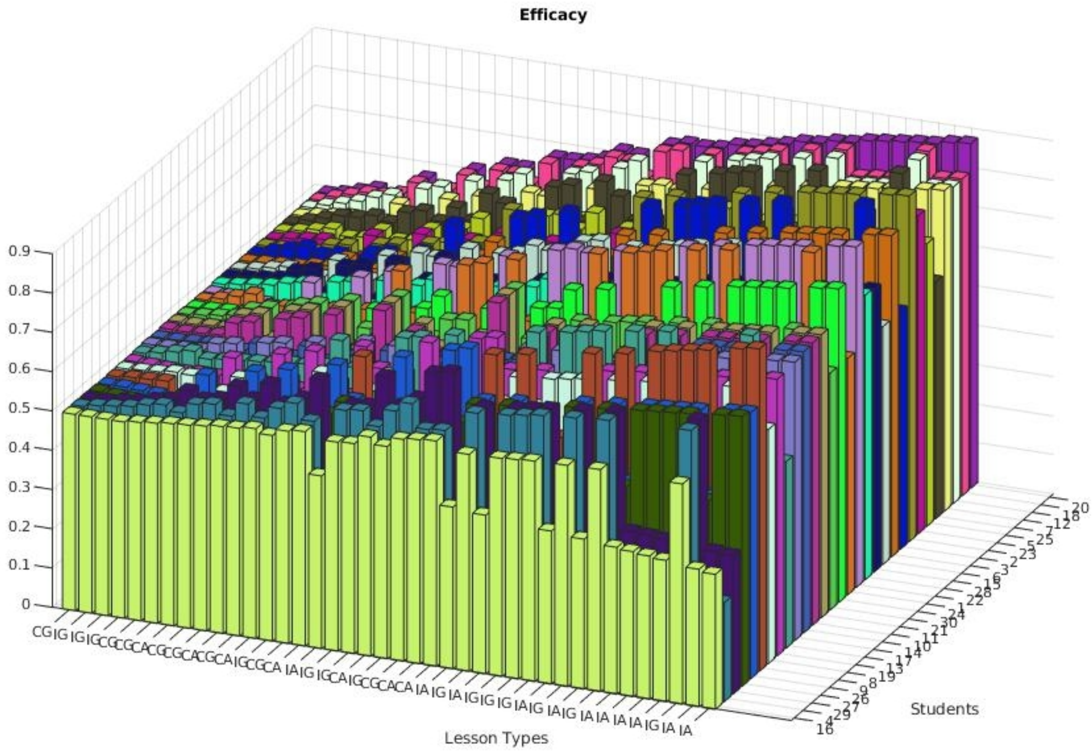


Figure 38: Maximal course evaluation Efficacy.

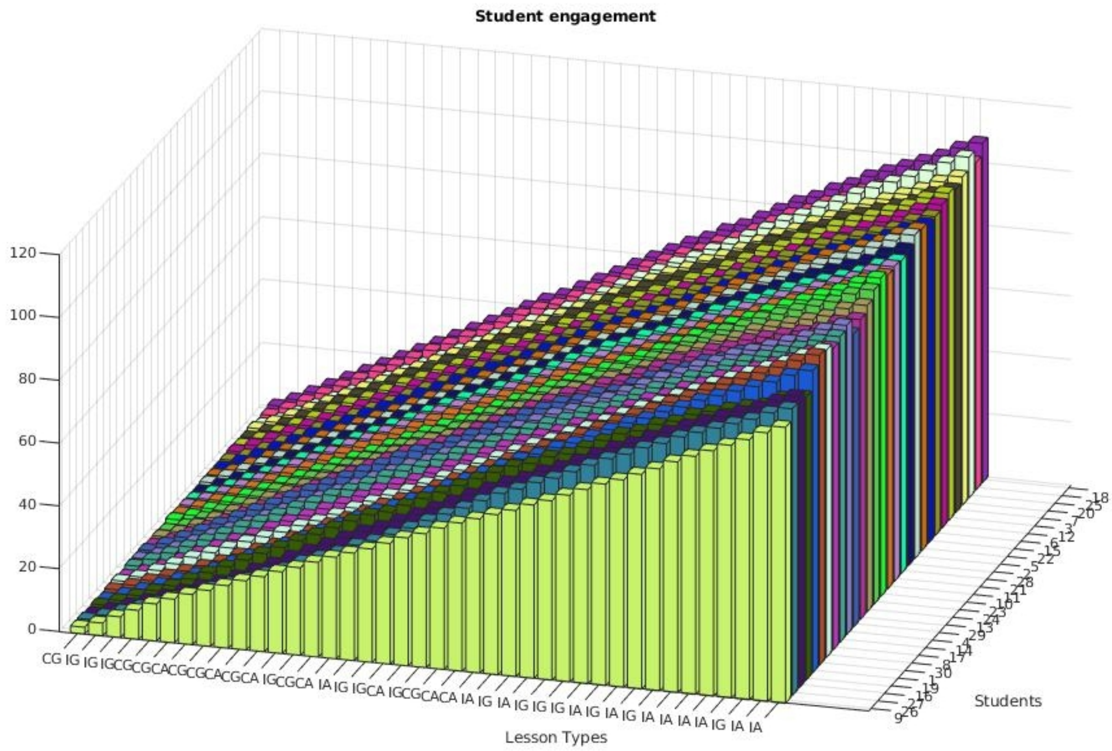


Figure 39: Maximal course evaluation Student Engagement.

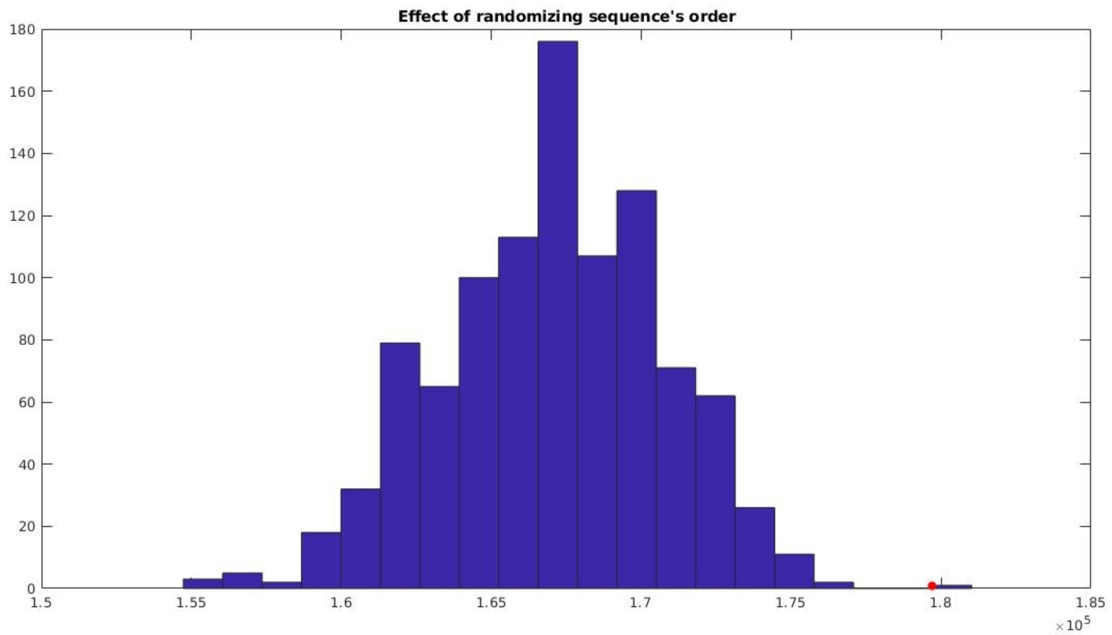


Figure 40: Course effect randomising the sequence order for the Maximal course evaluation configuration.

E.5 Best single student

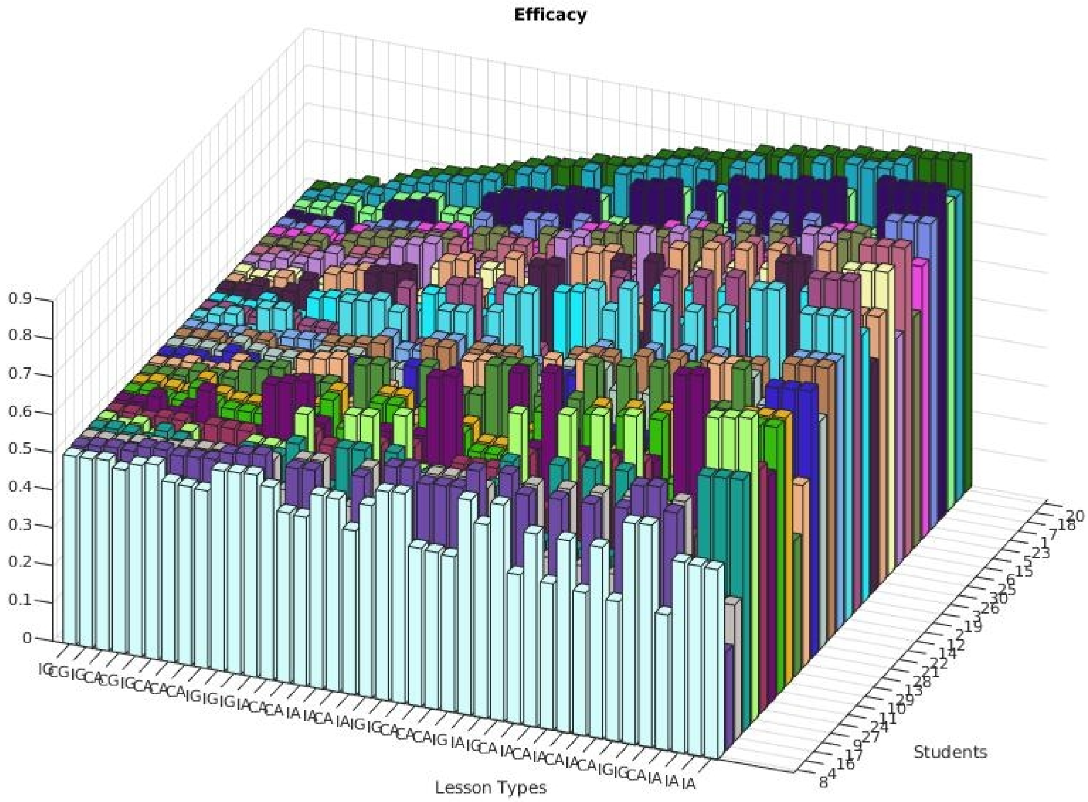


Figure 41: Best Single Student Efficacy.

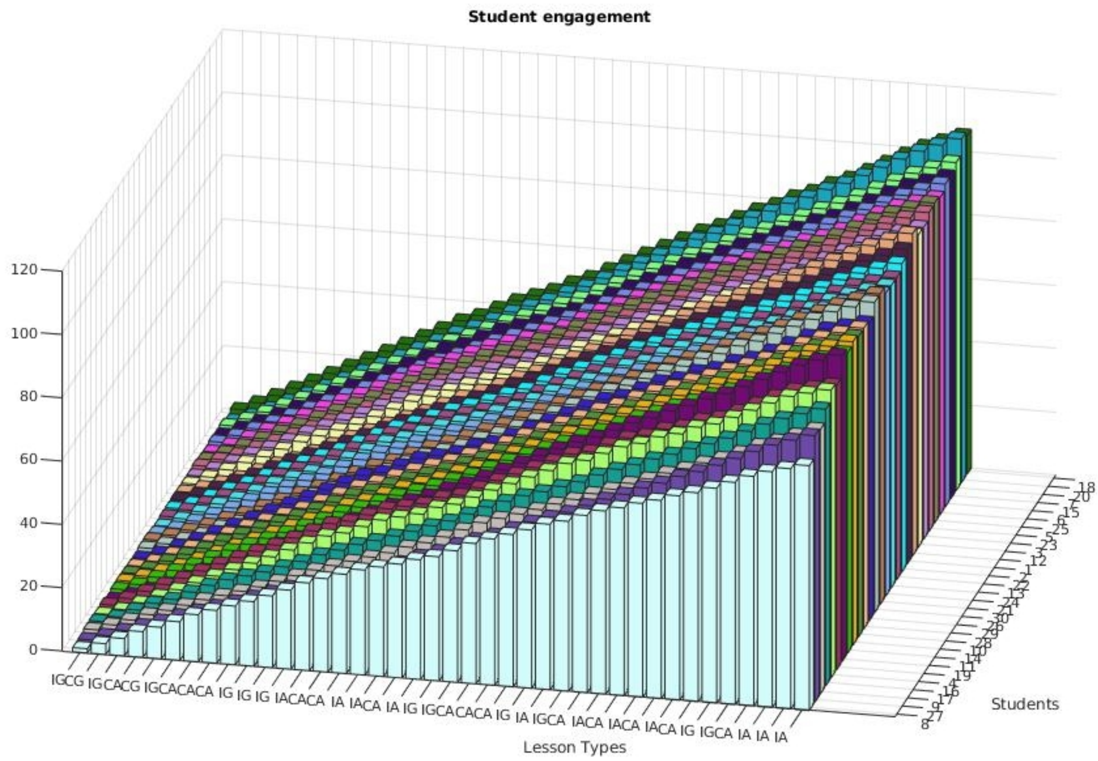


Figure 42: Best Single Student Engagement.

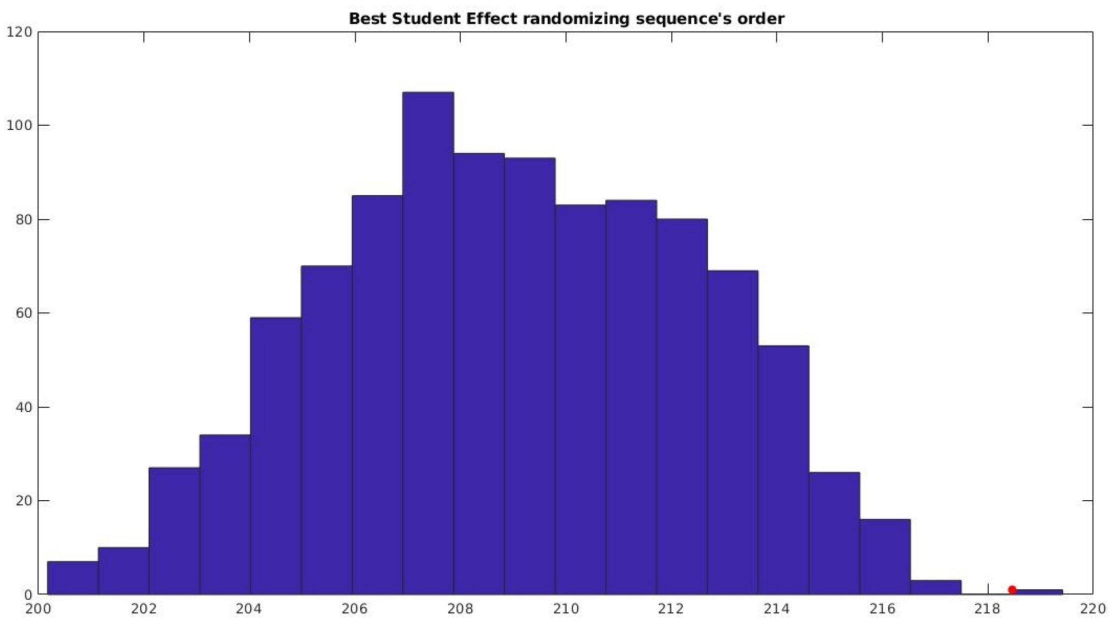


Figure 43: Best single student configuration effect. Randomisation of the sequence order.

E.6 Worst single student

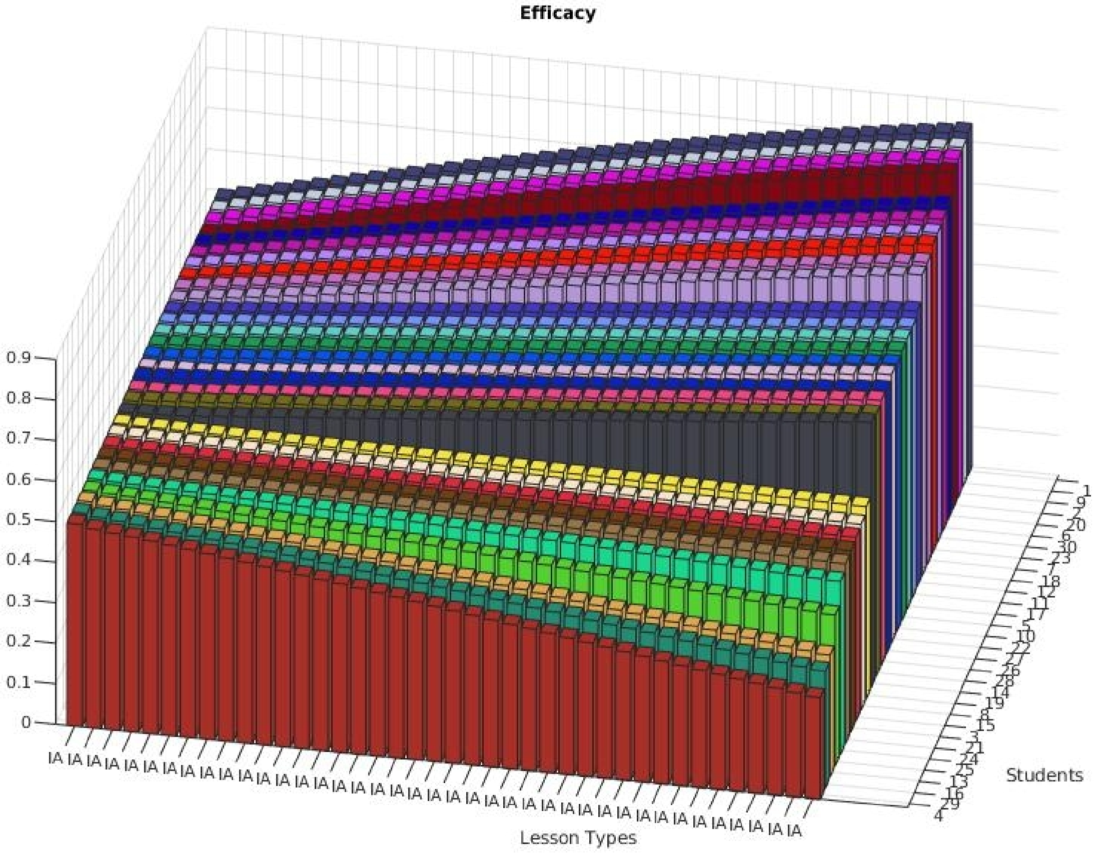


Figure 44: Worst Single Student Efficacy.

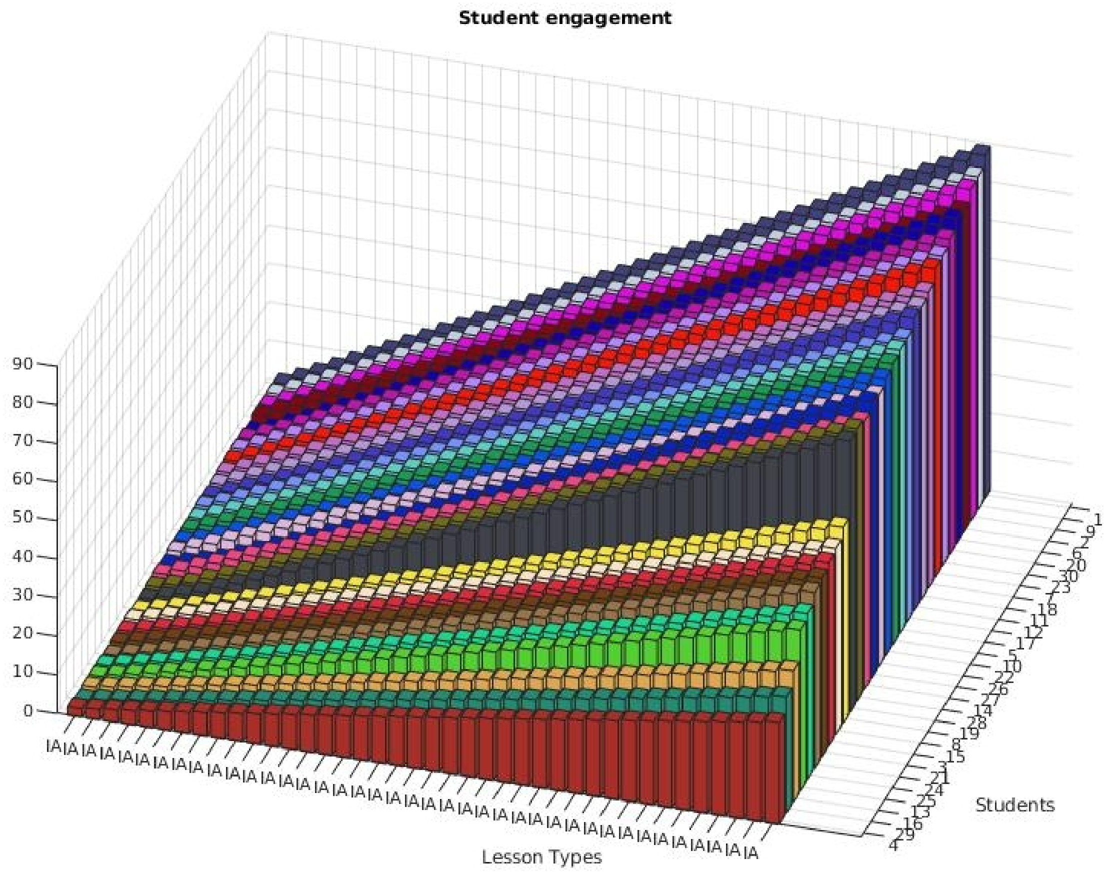


Figure 45: Worst Single Student Engagement.

E.7 Best of worst single student

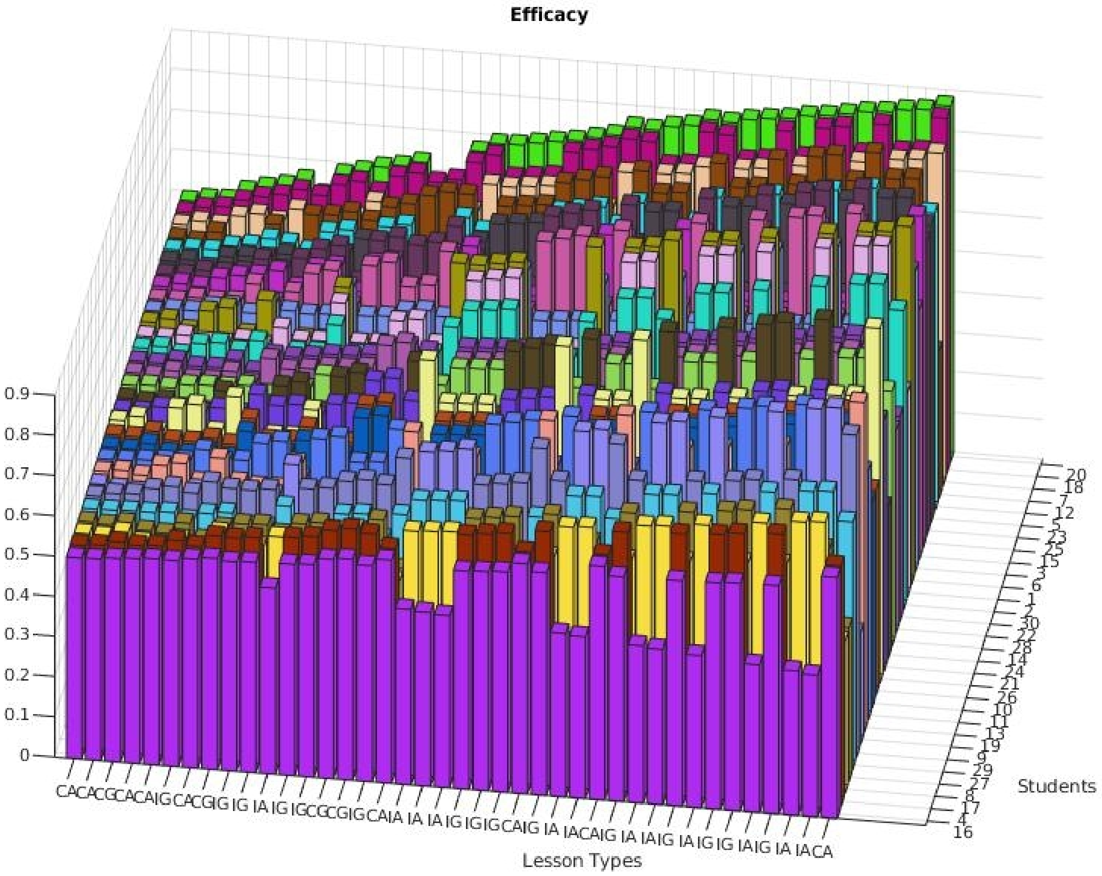


Figure 46: Best of Worst Single Student Efficacy.

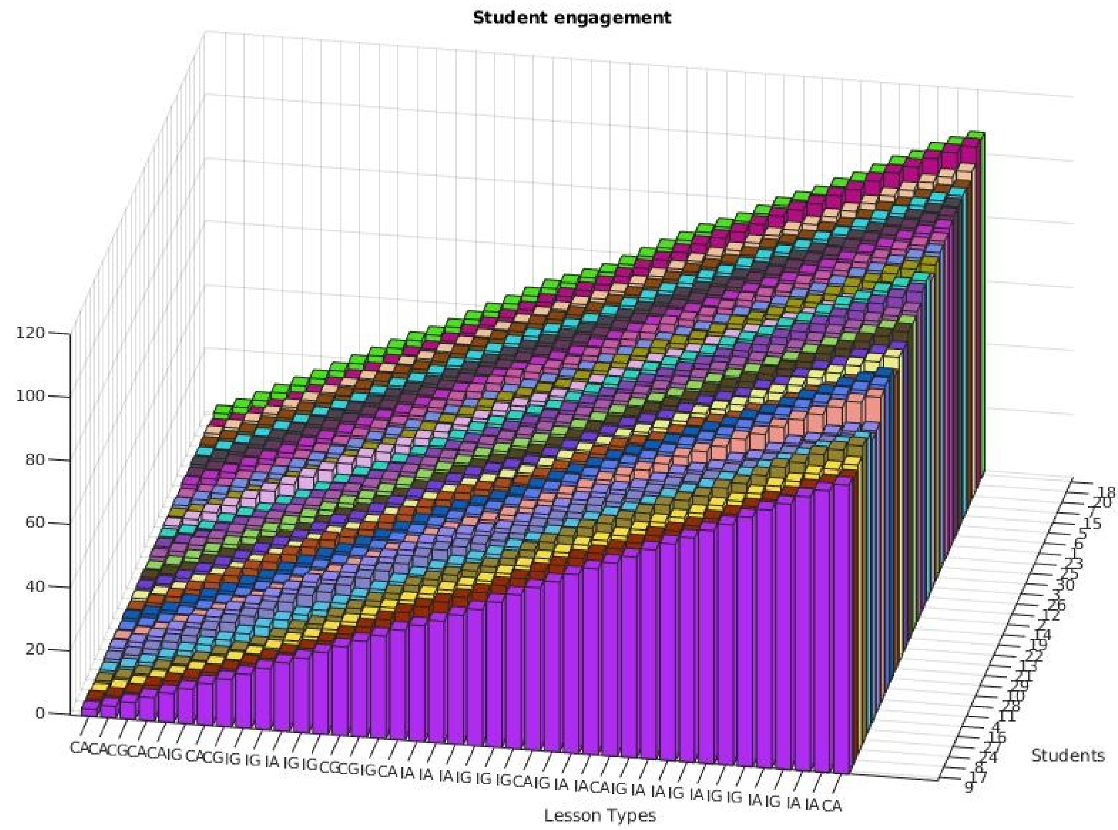


Figure 47: Best of Worst Single Student Engagement.

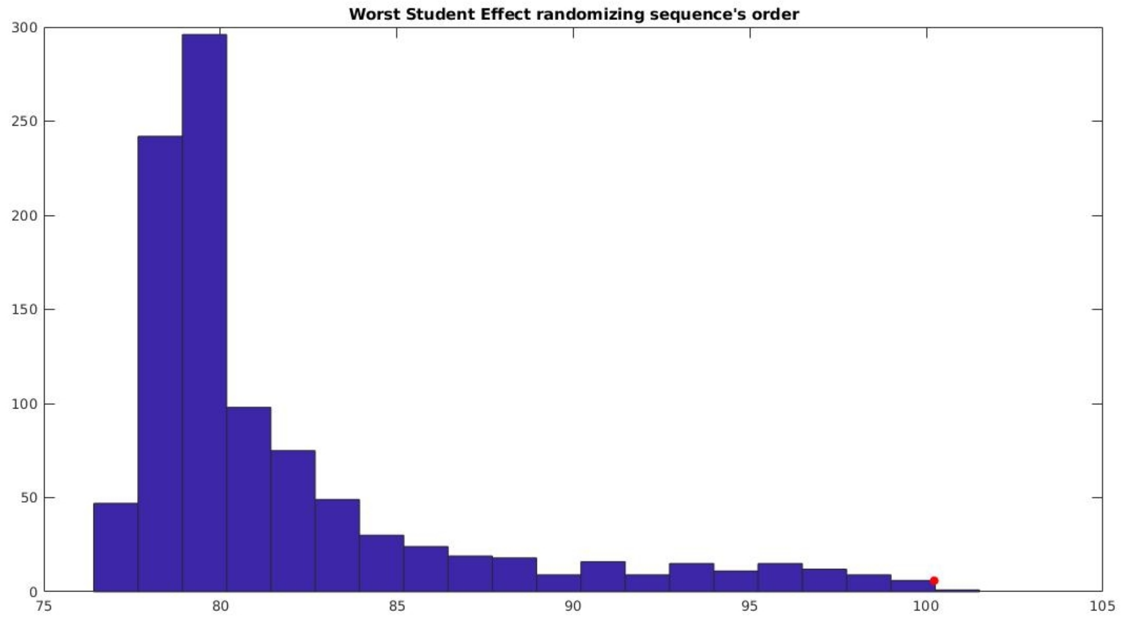


Figure 48: Best of Worst Student configuration effect. Randomisation of the sequence order.

E.8 Worst of best single student

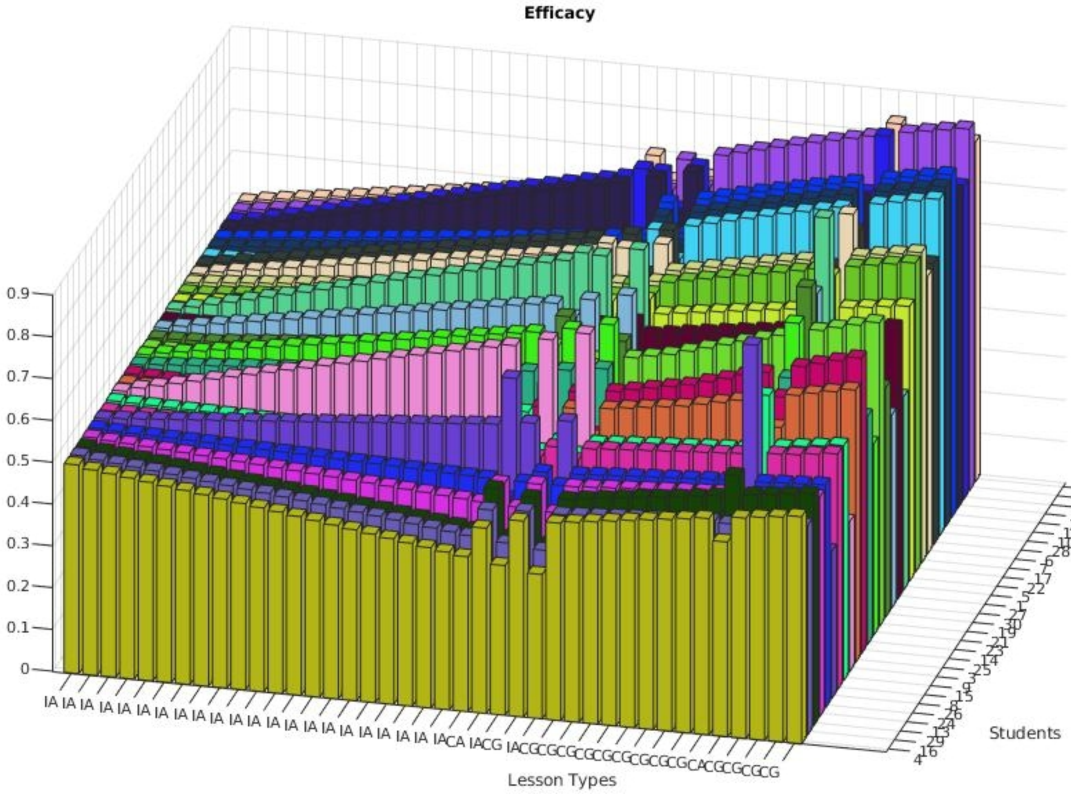


Figure 49: Worst of Best Single Student Efficacy.

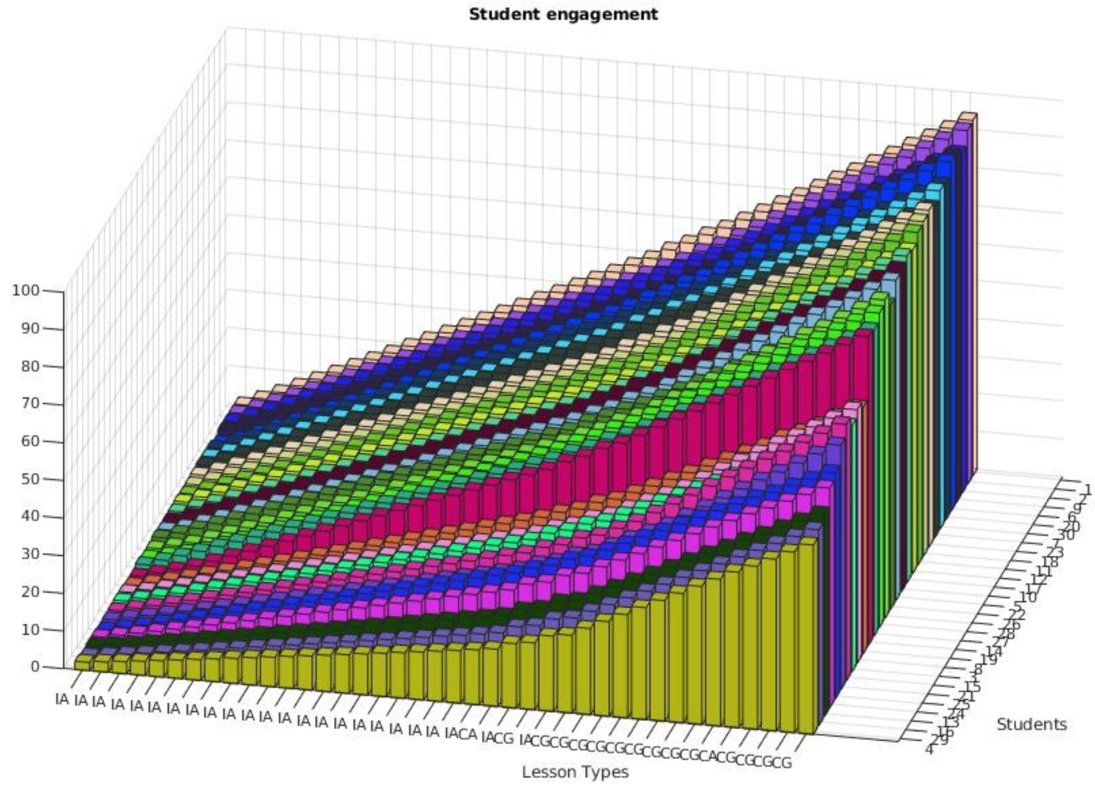


Figure 50: Worst of Best Single Student Engagement.

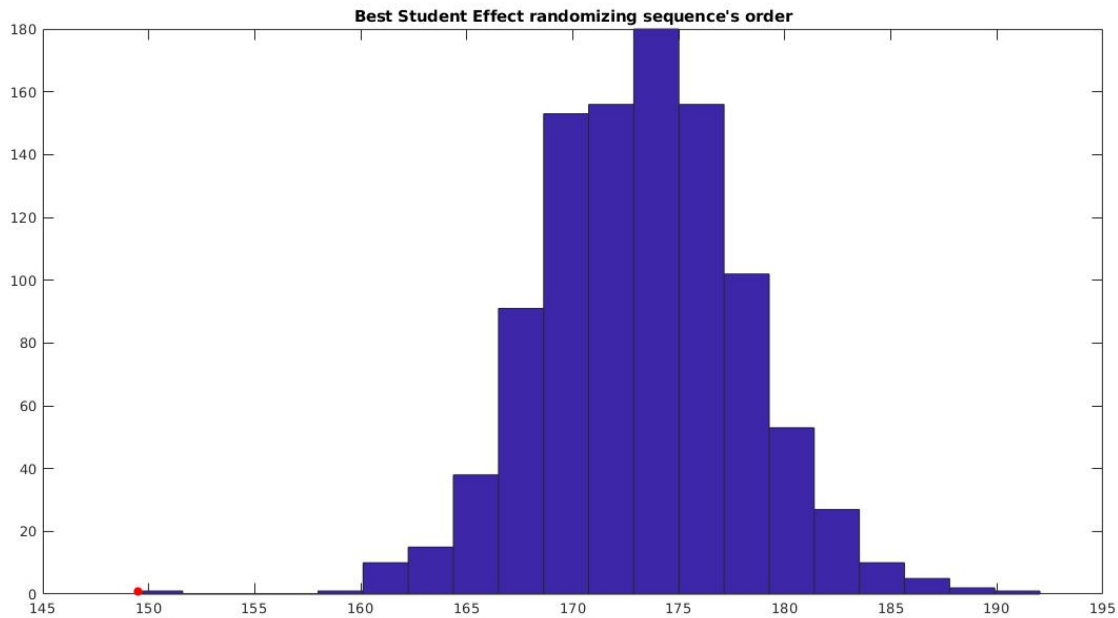


Figure 51: Worst of Best Student configuration effect. Randomisation of the sequence order.