Agent-Assisted Collaborative Learning

Mario Mallia-Milanes

Supervisor: Professor Matthew Montebello

February, 2023

Submitted in partial fulfilment of the requirements for the degree of PhD in Intelligent Computing.

L-Università ta' Malta
Faculty of Information & Communication Technology

www.um.edu.mt

First edition, Friday 10th February, 2023

This work was made possible through the Endeavour Group B Scholarship Scheme

To My Father, Joseph

The driving force behind this work.

Acknowledgements

I appreciate the patience and kindness of all those who contributed, or had to suffer through this work of mine. There are too many to list, but I cannot go without mentioning my wife Pauline, and my supervisor, Professor Matthew Montebello. Last but not least, I would like to include a good friend who preferred anonymity. His incessant prodding and diligence never faded. Thank you all.

Abstract

This work started off as an inquisitive question in our minds relating to whether students enrolling in large e-Learning courses can be helped to remain committed in the course that they enrolled in. This theses has been a journey of discovery and learning which started in 2016. Right from the very start a number of processes were investigated in order to better understand the problem at hand and offer a possible solution to the matter. To achieve this aim, the study had to move out of the fringes of a purely technical solution and delve into other disciplines. Although the proposal being offered through this work is purely a technical one, it is based on different disciplines such as psychology of learning, philosophy. The historical and economic importance of learning was also explored, but the research was placed in appendices at the end of the document in order not to detract from the main line of the work: that of finding a way forward to assist students in completing their on-line commitments.

In the Literature Overview chapter the creation of an e-learning ecosystem was discussed. Then the research moved into the way people learn and what makes them hold focus better. These phenomena were initially examined so as to lay a foundation on which the rest of the document would rest. Namely that people need to be involved in learning by giving them the means to follow up on the whole process, to scaffold through their learning and by making connections between facts that have been added to their repertoire. In essence this makes learning a holistic experience. It was argued that many of the main-stay e-learning platforms do not offer such an experience. Material production is excellent, but largely the student is left on his own. Collaboration between the different actors or agents in the learning process is necessary. So once the missing link was identified the research focused onto how one could fill in the gap and assume agent collaboration in learning. The focus then moved to examine various technologies that exist in different contexts but found to be lacking in education. An approach very similar to that of a recommendation system has been introduced. Just as buyers on a retail site are profiled and offered suggestions, students can be profiled in the same manner using their their progress and behaviour as input. The outcome of which would be that of suggesting areas that are of concern to the stu-

dent. Another step in the learning process has also been put forward to complement recommendation. That of explanation. Many a time artificial intelligence algorithms work well, but leave little clues as to how they arrived to their conclusions. Consequently excluding the human from the loop. The solution proposed in this thesis was not that of creating new algorithms that keep tabs on their internal workings. But that of annotating data to facilitate understanding, for the human actor, as he goes through the learning path.

To achieve a better automated explanation the research departed from the rigid regimen of relational databases and moved to a more novel approach of representing data as a network or graph. In this way data could be linked, added and modified at will, adding flexibility and freedom to the underlying structures. Students, and even teachers, could then follow on the ever growing database as their own personal knowledge base. The traversal through the knowledge graph would then explain the "why" certain facts are linked together or else possibly highlight missing relationships in the knowledge. Also leaving open the possibility of exploration through the knowledge base.

An artificial student performance data-set was used, closely reflecting that of a real class. This was used as a basis for profiling students. The data was labelled, and classified using a KNN algorithm. Students performance was then input back into the algorithm to profile the unknown performance metric with known groups in the data-set. After proper classification the student was then directed onto a pre-built knowledge graph containing the answers needed to improve knowledge.

Through this study it has been shown that one can, with effort, set up a system that is able to follow users through their learning journey. This has been achieved by closely imitating the way humans expect knowledge to be presented. Rather than taking the human out of his context, technology was moved into the realm of the human.

Contents

List of Figures

List of Tables

List of Abbreviations

1 Introduction

1.1 Motivation

The idea and direction for this journey spawned off from lengthy discussions with my supervisor (Montebello, 2014). We discussed the impact technology has on education and questioned why such an impact was was hardly visible. Technology has slowly started to be available in the Maltese educational system. No one has the audacity to deny that it will not remain in use. But the way it is being used is on the sidelines or fringes of our teaching where the impact can hardly be felt. My personal experience in educating youngsters at a tertiary level is that technology is many-a-time seen as a novelty. Lecturers or teachers that are not into the use of technology shy away from it. Moreover many are not even aware that technology can extend our reach on many fronts, education is not an exception to this. Taking a closer look at what is being done world wide, the use of technology in education is taking prominence. A lot of questions emerged. What if technology was trusted further and moved into the forefront, we asked? What would be the real impact? Would it be yet another fad, or will it extend the reach of teaching? Naturally this idea is not a novel one. But certainly its outcome would be interesting (Montebello, 2015).

Distance learning is not novel. It has been around since the late 19^{th} century and has kept up with the times by riding along technology of dissemination. The speed of dissemination and spread was only limited by the distribution capability of technology. Starting off with a postal service distribution, to computer-based training packages it has now reached a zenith with the availability of rich content transmission through the second iteration of the Internet. Rich content has opened up many possibilities to course content creators. In recent times Massive Open On-Line Courses (MOOCs), have made their way to the headlines. Massive Open On-Line Courses (MOOCs) are available to all through the Internet. Many courses are offered either for free or at an affordable price. Access to MOOCs is virtually unrestricted and there is no direct face-to-face contact with lecturers or peers. Courses try to mimic the traditional delivery of lectures as closely as possible

(Driscoll, 2016). Since the advent of massive open on-line courses, discussions about their effectiveness has never ceased. But little has been said about their history. MOOCs evolved considerably, but the evolution has been largely permitted by that of technology. The idea of having courses open to many more people a class can reach appealed long before computers found their way into mainstream life.

Sadly, despite good intentions, results show otherwise. Mainly that education is not really reaching everyone around the globe. Moreover a curious factor that is coming to light is that of student retention on a course. Many factors are at play. Notably that many educational institutions decided to get on the bandwagon too quickly too soon. Courses being delivered in video format, with very little interaction between student and teacher. Moreover most of the course work follows a one-size-fits-all regime.

But despite being seen as a disruptive bit of technology, more needs to be done in order to elevate MOOCs to offer classroom level performance on demand. MOOCs, like any other novelty caught the public eye back in the last decade of the previous century (Marques, 2013). But despite that they have been in the public eye for a long time, they have not really gained momentum as one should have expected after a 25 year run (Driscoll, 2016). At this point one has to start thinking why has this happened. The question asked at this point is whether one can improve on existing designs and whether they are a true contender against traditional teaching. So as a first approach we shall examine the history of MOOCs and why they are relevant to today's education systems. A tour of their humble beginnings and current status will be made and finally we shall open up the discussion to the starting point of the ultimate goal of this research (Marques, 2013).

These factors led us to think about whether there is a solution to this problem. Could student cohorts can be kept motivated enough to complete a course? There has been much work published on the subject, but very little has been done in the way of student retention. It has been shown that the design of new pedagogical approaches is unnecessary (Marques, 2013). Learning and the distribution medium are largely independent. Novel teaching techniques appeal only for a short while. In the next paragraph we will follow a short overview of MOOCs to properly understand our departure point in this study.

1.2 Proposal

When one sees MOOCs implementations is is evident that many are done with care. The graphics are right, the material is well-paced and the overall package is attractive. Many though lack the collaborative aspect. In addition to this, the lecturers developing course material seldom have experience as on-line educators. The approach one takes in a classroom cannot be the same as that on-line.

People like the group aspect of life, where one can share experiences as part of the learning activity. Learning is also a social experience and need. It can be safely asserted that people mostly like interacting with peers or in groups. This is a very important aspect of the whole package. When disconnected, people tend not to be driven. This can be attested by the low completion rates of 5% to 10% are often cited in relation to MOOCs. Adults tend to be more self motivated than youngsters, and supposedly can discipline themselves better. Many-a-time adults go into life-long learning either to update their skills or to regain skills that they should have had when younger. The merits of life-long learning are evident and amply discussed and do not need further analysis. Through MOOCs adults are able to catch up on lost years in their own time, at their own pace.

In this work we are mainly concerned with the issue of de-motivation and what causes it. With this in mind the next part of the voyage will be to suggest a plausible solution. MOOCs are not a lost cause after all. I think that they are not exploited better. A closer look at the technology one notices that the software governing MOOCs generates data that can be studied. There are aspects of human behaviour that cannot really be tended to, let alone captured, in a class. So up to a certain extent we can say that MOOCs bring advantages to teaching and learning that can be exploited. The study of data generated from MOOCs could then be reduced to a Big-Data problem.

1.3 Research Question and Main Hypothesis

1.3.1 Aims and Objectives

This work focuses on assisting students to keep their motivation to attend on-line courses by making them feel assisted and part of a cohort. This is done by:

- Introducing human-line explanations to conclusions derived from algorithms;
- Re-arranging information in such a way as to facilitate explanation;
- Removing rigid constraints on knowledge databases;
- Automatically identifying student weakness and prompting assistance.

The environment selected for the study shall be an e-learning environment which will entail close cooperation between a system of agents and a human actor. Naturally we have to ensure that there is a binding factor between human and artificial agents which will lead to teamwork. The loop in this study will close when team work will eventually facilitate commitment on e-learning courses.

1.3.2 Research Questions

From the aims and objectives for this work, as described above, the following research question is derived:

What technological assistance can be given to adult students in an e-learning environment to help them maintain motivation?

Many a time a sizeable cohort enlists for on-line learning sessions. Sadly it is common for students to drop out because they feel uncommitted or isolated. Furthermore this makes it hard for a single teacher to give personalised attention to all in the class. So through this work we explore technological solutions to bridge the gap. The research question will guide us through the technological methods that are available, and applying them in a correct manner to assist in improving student commitment.

1.4 Ethical Issues

Although all the necessary permission to involve students was sought for, no human participation was necessary for this project.

1.5 Summary of Contributions

Through this work it has been shown that giving context to data and storing it in an appropriate manner, i.e. graph form, will assist human understanding. Systems store relationships along side data are capable of explaining why certain results are being suggested, rather than just presenting a plausible answer. This can be done without sacrificing the performance of algorithms.

1.6 Summary of Results

Due to the lack of proper data it was decided that data be generated. Samples of school results present on the site www.kaggle.com were used to study the behavioural patterns of student performance. Synthetic data was then modelled on the behaviour so that it would approximate as best as possible real live data. Many classification algorithms were then compared for suitability. Students could then supply their results and the algorithm comes up with a classification code describing the areas that need to be revised better. Then a small subject area, namely that of forces in Physics, was set up in graph form in a data base. This set up allowed the linkage of data entities to each other in a way that the reason for the relationship was also part of the data. So when extracting results from the database it would be identical to the traversal of a path in a graph. The graph provides the nodes and relations between them so the user can also understand why to nodes on a graph are linked.

1.7 Thesis Outline

1.7.1 Background & Literature Overview

The literature review chapter discussed the various aspects necessary for understanding and explaining. An ecosystem was proposed as it has been envisaged that such a system should work in the end. The discussion included the aspects of human perception and understanding, Bruno Latour's Actor Network Theory on how people exchange information based on perception. Moreover the concepts of learning and collaboration was was also entertained. The latter part of the chapter proceeded to discuss the tools that would be necessary to build our solution to the problem at hand. Namely that of Recommendation systems and the explanation of results that are brought forward by the system.

1.7.2 Methods

In the Methods chapter we describe what technology has been used to approach the problem of inducing commitment from students who enrol in e-learning courses. The chapter starts off by describing the problem scenario and proposes an architectural diagram describing the system. The chapter then comprised a detailed description of software that was used for the experimentation setup. A description of a theoretical framework for the experiment was also put forward comprising variables that can be measured through the experiment being set up. The concluding part of the Methodology chapter discussed the data, how it was generated and what properties it exhibited. The process of classifying and extracting information in such a way as to make it more intelligible to human agents was described.

1.7.3 Results & Discussion

In this chapter the outcome of the experiment was described. An Overview of the proposed system was given, together with a detailed description of the data dimensionality. Scripts used to generated the data and the ensuing approach to the generation was also discussed. A number of candidate algorithms were used and described comparing the outcome of each. The classification candidate, K Nearest Neighbours, was selected as the algorithm to use. This was used as part a recommendation system for students. After data was classified, the students could input their performance graded and the algorithm would suggest areas of concern. The chapter then moved onto describing how sample data from a particular subject could be transformed into graph format. Once in this form it was easier to manipulate data and give meaning to the connections between nodes, thus enhancing explanation.

1.7.4 Conclusion

In the concluding chapter of this work a roundup of all the findings was made. A section offering a critique of the work together with its limitations was put forward. In addition to this ideas and directions for future research.

2 Background & Literature Overview

2.1 Chapter Introduction

In this literature review the important steps necessary to automate collaborative learning are going to be discussed. Naturally an understanding of the human psyche needs to be mentioned. And in order not to distract from the main point a better treatise of the subject is added in the appendices of this work for the reader to follow.

By creating a crowd-sourced recommender system that could adapt to the needs of students individually would put the learner at the centre of learning. This would help students gain experience as they progress along with their studies and in turn collaborate with others in their learning experience (Montebello, 2018). An intelligent environment will certainly help with student retention rate and additionally improve skill acquisition. A recommender system is only a small, but important, part of the e-learning ecosystem (Aoun, 2017). Information must be media neutral and different elements have to be combined to display the same results by different means that appeal to the user. In this article arguments have been put forward in favour of the use of artificially intelligent techniques to overcome specific shortcomings within e-learning systems. It is strongly believed that the lack of personalization brings about a unfavourable sense of isolation that hinders rather than facilitates the learning process (Mallia-Milanes and Montebello, 2018).

The use of a recommender systems based on latest technologies to deliver personalised education material is opportune and suits all requirements and objectives. Such a methodology further assists to alleviate the issue of information overload as specifically targeted educational material will be put forward to the individual learners. The recent developments in technology has enabled recommender systems to move to their next phase whereby networked technologies unleashed resourceful affordances that before were not possible, and that potentially they can take e-Learning to its next generation (Montebello, 2016).

2.2 Defining an e-Learning Eco System

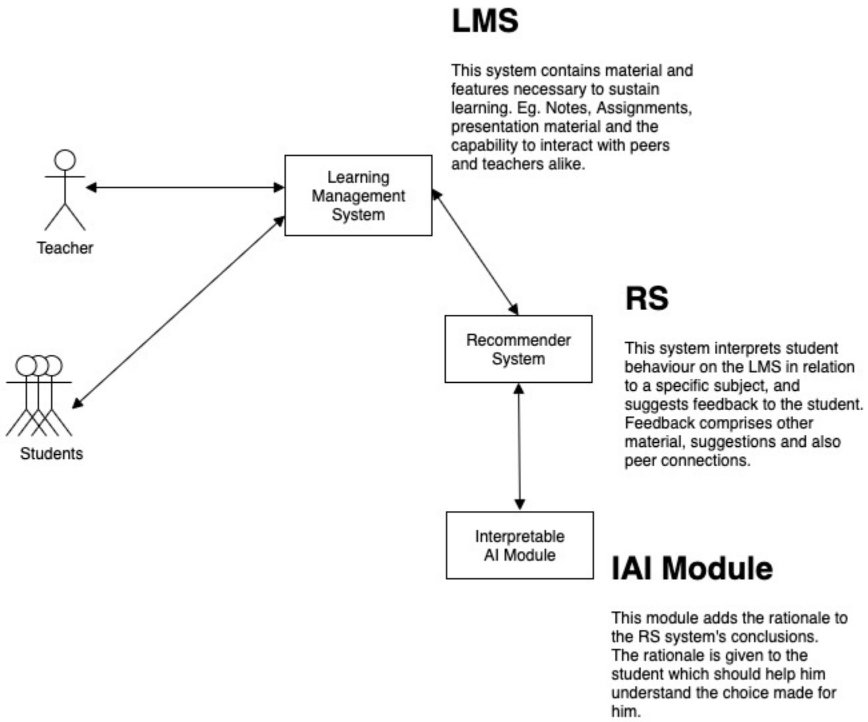


Figure 2.1: Proposed Learning Eco System

2.2.1 Human Perception and the Nature of Explanation

It is felt that an argument would be largely incomplete without considering the human aspect of a mixed team. Curiously enough, people ascribe agency to their robotic partners (Bradshaw et al., 2012). It is common to have people ascribe ethnicity, gender, knowledge and character to machines. Within a team a certain level of bonding is expected to happen, even if one of the team is an artificial agent (Wissen et al., 2012).

Human perception is linked to emotions and cognition (Papa, 2014). It distinguishes how people think about happiness or sadness. Perception also regulates thinking by transforming input (preceptory) into reasoning. As expected, perceptions are formed by past an individual's experiences and skill level. Competence in performing tasks helps humans to rise to complete tasks and challenges(Petronzi and Hadi, 2016). The successful completion of tasks in turn reinforces internal gratification. Cognitive investment, training, then improves the perception of competence. This gives one the willingness to engage, learn and establish goals (Deschênes, 2020). So, decisions are ultimately based on perceptions of the world an agent would face.

This links to the next path in the argument that perceptions do not always offer accuracy. As discussed earlier, perceptions are based on experience and consequently suffer from bias (Cambo and Gergle, 2018). This permits an agent to err, despite taking decisions based on experience. Learning is no exception to this statement. The element of subjectivity would be evident in students who dislike certain subjects and subconsciously resist learning due to lack of confidence they have in carrying out the task (Wang et al., 2019). Bad experiences reinforce the belief that the agent lacks the necessary skill to perform a task.

When learning, perception is also engaged. People evaluate their learning understanding through the experience-perception bias they possess (Rodrigues et al., 2018). In a normal class setting a student frequently relies on his own perception but also on that of the educator. This forms an exchange or better still a conversation. In an eLearning environment this is exchange cannot take place as the student is frequently interacting with text and videos (Gauci, 2014; Sin and Muthu, 2015).

Miller (Miller, 2019) asserts that perception implies social attribution. The motives and intention of a person are strongly linked to intention of action and also explanation. The argument, as proposed by Hilton and Miller has a two-step process(Hilton, 1990). At first the explainer determines why an event occurred. Then is explained or conveyed to someone else, an explainee. The explanation of such an event is seen as a social process by which an event information is transferred. This be viewed as "resolving a puzzle in the explainee's mind about why the event happened". This transfer process closes knowledge-gap in the explainee's mind (Lim et al., 2019).

Miller also (Miller, 2019) adds that transfer of information alone is not sufficient to constitute explanation. The transfer of information must follow certain prescribed norms. In their separate contributions both Hilton and Miller's put forward a conversational model that ascribes exchange must be relevant to be good. The exchange of information between parties should not merely offer known facts . The exchange must add to knowledge to become relevant.

The most important part of the explanation process occurs at the second stage of conversation. During the explanation-presentation process both parties within the discourse must be engaged in conversation following a certain protocol. The explainer must limit himself to saying only what he believes, saying only what is relevant and saying only what is necessary (Gilpin et al., 2019a)

Putting all the above in context and extending it to mixed teammates it can be said that a proper relationship between agents, human and artificial, must be established to ensure trust(Polajnar et al., 2012). This would be conducive to the facilitation of learning.

Empathy between team members improves teamwork, irrespective of the nature of the team. Now we can build upon what Hilton and Miller described by viewing the act of teaching and learning as a flow of communication between parties (Gilpin et al., 2019b). If trust fails, all the process suffers. Perception thus must be supported and made available throughout a team (Halonen and Hintikka, 2005). This will enable team members who reject common beliefs to leave a team as they would not ascribe to common values. Polajnar described these as emotional states. In his work Polajnar et al puts (Hoffman et al., 2018) forward a Perception Action Model to facilitate artificial agents exchanging their emotional state with peers in a team of artificial agents (Hilton, 1990).

Groom (Groom and Nass, 2007) separately follows on Polanger's work stating that agents must have common beliefs, desires, and intentions to foster some sort of bond. That the same happens in human teams. A group with common goals is better poised to succeed than one who does not. Explanation therefore is not a mere act or action that one does or expects. It must have a context (Barrett et al., 2012; Dunin-Keplicz and Verbrugge, 2010). So, in order to be relevant algorithms must also offer perception. They must be able to explain by putting forward their "perceptions" to the user. This enables decisions to be properly understood and accepted or rejected with greater confidence (Gunning and Aha, 2019).

2.2.2 Actor Network Theory

The Actor Network Theory (ANT) is a theoretical framework to social theory describing how everything in the social and natural world co-exists (Latour, 2005a). Relationships, as in real life are depicted as constantly shifting. ANT takes a constructivist view of the world and explains everything as relationships and interactions between "actors" in the system (Latour, 2005a). In ANT, humanity does not define agency. Each actor is given equal value irrespective of the fact if he is a human or an object. ANT also introduces the concept of intermediaries and mediators. Both exist within the social group or network, but even though mediators have an influence on the existing network, intermediaries do not (Latour, 2005a). Groups, or teams negotiate for power and influence, just as in a real context. The framework, or proposed theory, does not influence how such relations or struggles develop (Latour, 2005b).

2.2.3 Learning Collaboratively

Theories of teaching and learning are plentiful and offer a good insight into teaching and learning. These theories, amply described in Appendix C on page 100, need to be applied directly to MOOCs as a new disruptive environment. But the new medium of teaching and learning should not encourage unnecessary development of new theories (Young, 2013). Being disseminated through a distributed environment across the Internet one needs to keep different socio-cultural influences in mind. Yet another framework of connetivism describing learning is gaining ground. What sets it apart from the others is that it describes knowledge as external rather than internal (Young, 2013).

2.2.4 The E-learning Concept

As a concept e-learning means different things to different people. In this work it is taken to mean the use of technology to facilitate learning. In other words, the act of transcribing manual notes into a digital format is not accepted as e-learning. Commonly e-Learning is delivered over the Internet and provides interactivity with the student, having materials focused on the student (Nicholson, 2007).

Early in the 20th century John Dewey, and later on Carl Rogers, insisted that education should focus on the experience of the learner. Many criticize modern e-learning tools with their incapacity to do this. Despite the benefit of having material shared globally at one go the issue of having personalized material still remains. No two learners are alike, and hence the task of assimilating material to each individual still needs to be handled properly. The environment students are placed in when taking an on-line course is that of autonomy and self-direction. And the user, the student, is not at the centre of the equation (Garrison, 2017).

2.2.5 Tools for e-Learning

There are a plethora of tools that are available for the content designer today. E-mail, presentation packages, video material, content management systems, social media and blogs practically cover the whole spectrum. But in taking a closer look at these tools it can be noticed that they cannot scale well to a user's needs. Collaboration is limited and may not be in real-time either. Thus, one of the most important elements, that of peer collaboration, would be conspicuous by its absence (Mallia-Milanes and Montebello, 2017). Collaboration uniquely helps the development of the identity of the learner by allowing him to interact with an environment that projects roles and values on that person. Conversely by limiting the ability to share and interact with others would induce demotivation and make a student leave a course. This is reflected in the low completion rates experienced on e-learning courses (Rivard, 2013).

2.2.6 Adaptation to e-Learning

As discussed earlier on, one of the main issues of current e-learning systems are that they suffer from the lack of personalisation. One way to jump over this hurdle is to "cocoon" the student within an automated learning environment that recommends and coaches learners with adequate resources and personalised suggestions Montebello (2018). This would be made up of a teacher, peers, and material to draw on. Material can be crowd-sourced, by having many input points feeding the student with his necessities (Montebello, 2015). The point of the recommender system in this setup would be to prevent a cognitive overload by supplying too much in too little time to the user. Moreover, the system would have to deal with information relevance apart from its timeliness (Jannach and Zanker, 2011).

2.3 Current Trends and Directions in Research

Most of the current research is focused on aiding students learn rather than assisting them in their difficulties. This is approached by providing adaptive learning technologies which can attune themselves to the learning style of the student. Providing suitable material that the student can understand and go through and last but not least by giving the student a personalised experience. Some tools such as Carnegie Learning's Platforms also add features that mimic human teachers.

Another area of focus is that of increasing student engagement by reducing the chunks of information that is given to the student to learn at any one time. Moreover many solutions are also offering the assistance of a chat-bot which can verbally guide a student through material. This is assisted with proper speech recognition software to enable information exchange to be done verbally, rather than using a keyboard [1].

2.4 Recommender Systems

2.4.1 Introduction

Recommender systems have come into play for a number of applications. Their main stay has been in sales websites where a client is offered items that he may also like. Netflix, Amazon and also YouTube are typical examples of such websites. So, in essence the aim of a recommender system is twofold; to induce sales, and to reduce information over-

[1] Refer to www.unite.ai and https://onlinedegrees.sandiego.edu/artificial-intelligence-education/

load (Nunes and Jannach, 2017). The techniques are rooted in information retrieval and filtering.

There are two basic approaches to recommender systems, namely, Collaborative filtering (Dietmar et al., 2010), and Similarity indexing (Jannach and Zanker, 2011). In collaborative filtering, the algorithm has to match a closest neighbour. This is basically done by comparing the buying patterns of the current user, with that to others who have purchased similar items in the past. Recommendations are then put forward on the basis of the likelihood that the current user would probably have the same taste as other users with similar patterns (Mallia-Milanes and Montebello, 2018). The similarity indexing approach rates and marks each product on offer. When a user chooses a particular product then others similar to it are put forward as a recommendation. Both approaches have issues. Typically, the collaborative filtering approach suffers from cold start. How shall we compare if we have very little or no data to go on? On the other hand, a similarity indexing solution is computationally intensive. Imagine a situation with thousands of users on-line at the same time each going through many items available for sale (Pos, 2020).

2.4.2 Techniques

2.4.2.1 Collaborative Filtering

The method of collaborative filtering is based on the users or item choice (Benhamdi et al., 2017; Wan and Niu, 2018). Typically the problem is approached using Spearman Ranking Coefficient or for better performance Pearson's Ranking Coefficient. To select the most popular items a technique called Cosine coefficient is used (Moharm, 2019). Collaborative filtering is known to suffer from sparsity problems where similarity ratings are based on user ranking (Wan and Niu, 2018). Moreover if there is insufficient data rating may suffer from the cold-start problem. Insufficient rating can be due to new users or items being introduced into a system. In addition to this lack of motivation by current users to score their choices may also contribute to the lack of data (Tarus et al., 2018). A matrix is constructed consisting of a user rating U_i and product popularity rating P_j.

$$Rank = U_i P_j$$

Recommendation will be based on the best U_i, P_j product ranking (Batmaz et al., 2019b).

2.4.2.2 Knowledge-based Filtering

As the name suggests a knowledge-base is built with particulars of items available for selection . This approach is rule-based in nature, implying that it depends on a preprogrammed set of rules for its behaviour (Aggarwal, 2016). In addition to this similarity functions are used for retrieval. This ensures that items similar to those selected are also displayed along side the original user's choice(Kane, 2018).

Commonly there are two types of Knowledge-based filters employed. Constraint-based or case-based filtering (Odilinye, 2019). In the former the user specifies the domain of selection, commonly by inputting a lower and upper bound to act as a constraint for the filtering process. The limitation may be price range for instance (Lu et al., 2018). For case-based solutions the user specifies targets or anchor points for the algorithm to use as its constraint (Tarus et al., 2018).

2.4.2.3 Content-based Filtering

Content-based filtering selects items based on a number of factors such as the item rank (Batmaz et al., 2019a). The rank is derived from the features of the chosen item and the similarity, or closeness, these features are to those of other items. A learning environment comprising matching rules based on learner choices also boost selection (Dascalu et al., 2015). The Content-filtering algorithm is very good at recommending new items to a user (Baidada et al., 2019). In addition to this it is immune to the effects of sparse data as similarity rankings are feature-based. This way the cold-start problem is avoided. On the other hand the algorithm introduces new problems (Gomez-Uribe and Hunt, 2015). Mainly it does not leverage on the knowledge of the community. In addition to this at times the obvious choices are recommended to the user as the proximity is based on feature comparison (Benhamdi et al., 2017). The selection process, as indicated earlier, heavily depends on item features discounting user preference or behaviour (Bogers and Bosch, 2009; Wan and Niu, 2018).

2.4.2.4 Hybrid Filtering

The hybrid filtering approach tries to leverage on the positives of previous techniques discussed. Compensating for each method's shortfall (Batmaz et al., 2019a).

2.4.3 Privacy

Care must be taken no to expose private data. Many recommendation systems only give suggestions based on user and item profiles that fit the current user profile. No mention is made of the people or the items behind the computation (Drachsler et al., 2010). Naturally the data for profiling has to be built, so it is not easy to obtain. Commercialisation of data should not be done without a user's consent. Such data would help initialise databases and recommendation engines. It would be expected that this is discouraged given that awareness has reached unprecedented levels and breaches may seriously impact client confidence on brand repute (Drachsler et al., 2015).

2.4.4 Common Issues

As data on user behaviour is being built over time proper profiling takes time and may lag. the consequence of this is giving suggestions based on previous behavioural patterns. During the COVID-19 pandemic many changed their purchasing patterns. People possibly bought less items, or changed their purchasing habits. Needs and wants were affected. Algorithms would need retraining to adapt to the new reality taking into consideration the changes in behaviour hat a customer exhibits. The tolerance for this may vary by application area. Health recommendations are treated quite differently to purchase recommendations (Pos, 2020).

2.4.5 Focused Recommendation

Recommendations can take various forms but the more relevant they are to the inquiry at hand the better. In the case of learning recommendations have to be very focused so as not to lose the learner (Ye et al., 2013). Nowadays one can rely on ontologies that break down subjects into various levels of components, meta data to enrich an already existing corpus of data and knowledge databases (Covington et al., 2016). Knowledge databases can be categorised in two. Closed, whereby access is restricted and require periodical updates to include new information. On the other hand, open knowledge bases are maintained by and informal learning network (Odilinye, 2019). Strictly speaking no maintenance is required. In the latter case it would be more difficult to ascertain the correctness of the information within the database.

In education recommender systems can deliver information in a variety of ways to suit the student. Information can be better tuned to a student's way of learning. It would seem like a win for adaptive and personalised learning. But this is still a challenge to generate automatically for each and every learning style (Dascalu et al., 2015). Nonetheless it has been shown that when recommender system output matches a student's learning style improvements are registered (Moharm, 2019). Traditional methods of teaching still work well, but in the context of large-scale on-line teaching additional help is necessary (Tarus et al., 2018).

2.4.6 Goals of a Recommender System

2.4.6.1 Conceptual Goals

The table 2.1 below highlights conceptual goals of a recommender system. The end goal is largely dependent on the approach used for recommendation (Aggarwal, 2016).

Approach	Conceptual Goal	Input
Collaborative	Recommendation based on a collaborative approach that leverage the ratings and actions.	User Ratings + Community ratings
Content-based	Recommendation based on content favoured in past ratings.	User ratings + Item attributes
Knowledge-based	Recommendation based on explicit specification of the kind of content requested.	User ratings + Item attributes + Domain knowledge

Table 2.1: Conceptual Goals for a Recommender System.

2.4.6.2 Recommendation Goals

The main goal of a recommender system is that of supplying the user with correct recommendations. This can be also described as prediction. As described earlier to predict correctly one must have a rating value, preference data and an MxN matrix of observations (Mertens, 1997). Rather than predicting what a user might need we can resort to ranking. This makes prediction unnecessary and depends on user ratings for specific products or subjects (Lü et al., 2012).

2.4.6.3 Operational and Technical Goals

Apart from generic recommendations, a recommender system has to achieve goals which are operations or technical related. The table 2.2 below describes the main objectives.

Goal	Comment
Relevance	This is important to excite interest. Although users take only items that interest them most
Novelty	Repeated recommendations reduce interest. so it is important that the algorithm suggests new items.
Serendipity	Recommend unexpected items. This surprises the user and may lead to new and interesting threads.
Recommendation Diversity	Strike a balance in recommendation output. Just enough to excite user interest.

Table 2.2: Operational and Technical Goals for a Recommender System. (Aggarwal, 2016)

2.4.7 Conclusion

Recommendation systems were selected as an approach to assist explanation in learning because of properties they have. Firstly, the technology is reliable and in use in a lot of domains. Secondly because it offers an opportunity for reinforcement learning which scales up well with a student's progress. Lastly recommendations are model agnostic (Wang et al., 2018).

2.5 Explainable Artificial Intelligence

2.5.1 Introduction

During the last decade AI has moved to the forefront of computer science and has gained prominence. Algorithms and Big Data also contributed to its proliferation (Arrieta et al., 2020) . But in the process, we have come to be familiar with software that simulates human cognitive reasoning. Hence the demand for more is being requested (Murdoch et al., 2019). But when one takes stock of the current arsenal of algorithms many, if not all, are closed-box systems offering little to no justification on their outcome (Gilpin et al., 2019a,b). If artificial intelligence is to be used properly, especially in a support role, humans must be kept in the loop and given the facility to follow on conclusions reached. This facility would help people, experts and non-experts alike, to gain trust in the systems assisting them. One of the main inhibitors of progress to explanability is the lack of consistency and measurement metrics (Preece, 2018). Much of the literature reviewed seeks a unified approach to the research, but as the topic is in its infancy this will take time (Páez, 2019). Hopefully a time will come when a common structure for Explainable Artificial Intelligence (xAI) models is designed and accepted. This will facilitate interoperability between different models.

2.5.1.1 The Current Situation

As computing machinery is pervasive nowadays one hardly notices it more. This subtilness has many a time led to misuse of our data, quite often data landing up in places where we never intended it to. In addition to this we also face countless instances where we are served by machines or software algorithms (Hind, 2019). Unfair refusal of credit, automated exam paper markings without supporting explanation, unjust profiling are only a few of the frustrations one may face. This leads to lack of trust in automation by people (Monroe, 2018). Despite all this research in user satisfaction is still somewhat lacking (Galitsky et al., 2019).

2.5.1.2 Demand

The above has moved countries to legislate in favour of people's rights. Legislation puts pressure on algorithm creators and adopters to be more ethical in their development and operation of such algorithms. As part of its General Data Protection Regulation (GDPR) the European Union at Recital 71 of this law gives people the right to an explanation (Ciatto et al., 2020). This spurs research further. One of the key impediments to explanation being the nature of many algorithms. Many are black boxes and lack transparency (Adadi and Berrada, 2018). As it stands this makes understanding them very hard, if not impossible. So better solutions to explanation have to be found (Rudin and Radin, 2019). Otherwise automatic processing would be legally limited in order to safeguard human rights (Hoffman et al., 2018)

Apart from legal pressures, there are also goal oriented pressures put of algorithm designers. Many a time research environments demand the ability to audit and validate third party algorithms they use. Moreover, discovery, part of a scientific project, imposes the need that one may follow through and replicate experimentation. Black box algorithms do not facilitate this (Watson and Floridi, 2020). Designing models that lend themselves to being interpreted and explained usually comes at the expense of performance. This expressed as a function of time and accuracy. Putting further pressure on researchers to come up with solutions that are better designed (Spreeuwenberg, 2020).

2.5.2 The Problems and Challenges Being Faced

In an ordinary sense explanation implies that one examines the inputs and outputs of a system and would be able to come to a possible understanding of the mechanism by which a decision was taken (Murdoch et al., 2019). To date many algorithms, offer some sort of surface-level explanation but we are still far from answering 'why?' a certain course of action was taken (Bromberger, 1994). Many models lack the transparency necessary to make them understandable. Let us give an example to clarify (Goodman and Flaxman, 2017). How could a proper assessment of an accident be made in the case of a driverless car that took certain evasive action? Or else why was a certain diagnosis put forward in favour of another one? Transparency by itself is also offers subjectivity (Mueller et al., 2019). Are models which can be exclusively interpreted by experts or programmers deemed to be transparent? What about the user that faces technology each day? Shouldn't one have the right to understand or even opt out from such decisions (Watson and Floridi, 2020).

Recapping our argument, we are left with more questions than answers namely in the direction of (Gilpin et al., 2019a,b):

- How should we produce models that are more explainable?
- How are the interfaces to these models to be designed?
- We need to properly understand the psychological requirements necessary for an effective explanation;
- How can we effectively measure explanation or explanability.

Finally, we face another possible fork along the road. Do we create new AI algorithms that are inherently explainable, or do we adapt what we have at hand? (Díez et al., 2013)

2.5.3 Goals We Have to Reach

As stressed earlier, explanability is complex. The direction this work is trying to address is that explanability enhances trust which in turn facilitates the interaction between man and machine (Lee and See, 2004). We have identified nine characteristics necessary to enable explanation in algorithms (Arrieta et al., 2019; Gilpin et al., 2019a; Murdoch et al., 2019):

- Trustworthiness: This implies the confidence humans have in a given model or system;
- Causality: Finding relationships within data sets. The ability to explain properly requires knowledge of such relationships. Elements within a data-set need to be correlated apriori;
- Transferability: Can we use one common explainable framework to all algorithms with the hope of obtaining a consistent output that is understandable.
- Informativeness: This is one of the targets of any AI algorithm. It is the capability to solve problems, assist in taking decisions. Machines are capable of recursively going through data but rarely leave a trace of their trajectory;
- Confidence: This characteristic is necessary if trust must take place. Algorithms must be robust and stable;
- Fairness: Decisions taken by an algorithm must be just and open to scrutiny. The user must be able to have clear visibility to any relationships within the data that can possibly affect impartiality and proper ethical analysis;
- Accessibility: Humans should be part of the system. People working with intelligent algorithms should be allowed to interact with the decision making process. This must also be made available even to non-experts;
- Interactivity: Human operators or co-decision makers are to have the capability to follow the decision process;
- Privacy: This is one of the very important aspects of explanability that much of the literature reviewed shies away from. In practical terms algorithms may have access to data that has been restricted by the user. The issue here is that such data, if included or not in the decision process, may affect the resultant outcome. For the work of this theses privacy within algorithms shall not be entertained.

As it can be seen from this short introduction to the subject, explanation poses many challenges and questions in many domains. I am of the conviction that effort must be made in all spheres to make explanability work for us (Chia, 2019).

2.5.4 Classification Terminology

As discussed previously one of the issues that frequently bars the way to progress is the lack of common parlance within the confines of explainable Artificial Intelligence. In this paragraph we shall try to give some commonly used terms a proper definition as follows (Arrieta et al., 2019; Páez, 2019):

- Understandability: Humans can understand how a model works with no need of knowing the internal structure of the algorithm;
- Comprehensibility: This can be expressed as a factor of algorithm complexity. This term defines the changes needed to a model to make it understandable;
- Interpretability: To provide meaning;
- Transparency: This term can have several meanings, the one I really prefer is that quality which makes an algorithm understandable by itself. Transparency can have several characteristics that go with it. These are as follows:
  - Simutable: the algorithm can be simulated;
  - Decomposable: the algorithm can be deconstructed for better understanding;
  - Algorithmic transparency: The inner workings of the algorithm are open to scrutiny.

2.5.5 Areas of Application

Machine Learning can help us extend our reach as educators. This by facilitating communication between all stakeholders. Everyone in the loop, teacher, parent and student would be aware of what is going on. Naturally this must not be a student-humiliation exercise (Rodrigues et al., 2018). But one which builds the person up. Better information and analytics drawn from databases will also contribute to the improvement of courses. Analysis will highlight weak areas that can be addressed by updating curricula to keep them current, interesting and useful (Samek et al., 2019). Another interesting application area that builds on the previous mentioned is that of generating recommendations. Analysing student on-line behaviour or even following their on-line activity will permit algorithms to suggest possible alternatives to information or better scaffolds to assist in the learning process(Google, 2019). Analysis can go as far as predicting student performance. Although student profiling is not new, but automated profiling may identify the weakest people in a cohort. Last, but not least, apart from profiling a student study domains can be examined too. The examination of study domains assist educators in improving material and syllabus.

2.5.6 Approaches to Explanability

Currently two methods are used to add explanability to algorithms. These namely are post-hoc and embedded approaches(Akula et al., 2019).

2.5.6.1 Embedded Approach to Explanability

In this scenario explanability will form part of the algorithm itself. New algorithms will have to be devised whereby explanability forms an integral part of the recommendation model (Tjoa and Guan, 2019). Opaque algorithms would not be allowed under this scenario (Murdoch et al., 2019). Users should be able to analyse the internal working of an algorithm plus also understand the rationale behind the output. Output should be padded with human-readable instructions which facilitate understanding (Wang et al., 2019).

2.5.6.2 Post-Hoc Approach to Explanability

Post-Hoc models are those to which explanablitiy is applied retroactively. The advantage in this case is that we can still use current models and benefit for the explanation. One of the common occurrences is this type of model can be found in recommender systems (Tjoa and Guan, 2019). Users are informed that their choices are usually accompanied by other options (Bohlender and Köhl, 2019). Explanations are usually very dry, and they are frequently ignored (Zhang, 2017). Algorithms that are usually customised are opaque algorithms which typically comprise Deep Neural Networks(Preece, 2018). Post-Hoc explanability can be specifically designed for each type of artificially intelligent algorithm. The disadvantage coupled with such an approach is that each different algorithm would have a customised explainable algorithm to it. Thus, dispensing with the need of common methodologies to explanability (Dosilovic et al., 2018).

Another Post-Hoc approach to explanability is by using model-agnostic models which are designed give a common look and feel to the resulting output or level of explanation (Shaban-Nejad et al., 2020). In this case the explanation is made to seamlessly hook up to existing algorithms and be able to extract information from them (Deeks, 2019). Currently the favoured approach is that of using a second taxonomy that complements the first. In this case both models run in tandem, and the second model collects information from the first. The information would be used as feedback to the user (Paudyal et al., 2019).

2.5.7 What is the Main Take?

As artificial intelligence has become more pervasive the need of more transparency in algorithms has become evident. If one takes a look at Deep Neural networking algorithms it becomes apparent that the workings of these algorithms are very opaque. Leaving little evidence of why or how conclusions were reached (Adadi and Berrada, 2018).

In order to counteract opacity, algorithms have to be developed with new goals in mind namely those of fairness, explanability and accountability. In other words Artificial Intelligence (AI) algorithms must be developed within an ethical and responsible framework(Roscher et al., 2020).

Expalanability is a hard term to pin down. And a concise definition of the term is not readily available. But this can lead to a number of benefits, namely collaboration between teams which are mixed. In other words natural agents and artificial ones. Artificial agents may comprise also a mixture of computer and robots working in tandem to achieve a goal. Each system, human or otherwise, must be able to understand and communicate properly with each other in order to be effective (Lawless et al., 2019). Understandably this greatly improves team autonomy which will also increase trust and cohesion in the team (Oh et al., 2017). Each agent has to be aware of the context and the environment that they are working is so as to communicate effectively with each member in the team.

2.5.8 Envisaged Issues

As with any technology one has to weigh the benefits against the disadvantages. Algorithms tend to perform poorly when not enough data is given to them and result in over-fitting. They tend to perform better on test data than on live, so a lot of testing and experimentation is necessary until the best model is found to suit the job well (Watson and Floridi, 2020).

One of the main issues many research papers were found to remark about is the lack of a proper definition of the terms explanability or interpretation. While this is true one can look at how other domains of study to circumvent the issue. Typically philosophy distinguishes between casual explanation and personal reasons. The former being ascribed to natural events and the latter to personal reasons or more precisely human decisions (Liang et al., 2019). Another useful domain that ascribes interpretation or explanability is that of the legal profession. Argument and interpretation of law is clearly prescribed in the legal domain. In Malta, the legal professionals refer to the Interpretation Act in Chapter 249 of the Laws of Malta. This Act defines how one should interpret specific legal jargon. In the real world such a luxury does not exist.

2.5.9 The Need

Legal and natural pressures have amply settled the argument of rights. But there is one side of the equation that still remains unbalanced. In order to properly address the demands better explainable models are needed which ideally retain the same performance are needed (Ciatto et al., 2020). But as stated previously because of the lack of a proper definition of explanability as a term we are not in a position to say that we have achieved our goal (Nunes and Jannach, 2017). Definitions have been put forward by many but they are very inconsistent along different research papers (Ribera and Lapedriza, 2019).

2.5.10 Controversial Usage

The value of Artificial Intelligence (AI) does not need to be discussed. Many-a-time its use leads to controversy about the ethics or the morality about letting an unconscious algorithm decide. The proliferation of Artificial Intelligence (AI) can be seen in many aspects of life such as loan applications, student admissions, criminal recidivism and military applications. All of which affect human lives directly (Watson and Floridi, 2020). So if data is not screened and applications properly audited injustice, which is part of society, will be carried forward to the digital world (Watson and Floridi, 2020).

2.5.11 Extracting a Definition

One of the earliest papers to address Explainable Artificial Intelligence (xAI) was published through Defence Advanced Research Projects Agency (DARPA). This US agency, although having a military interest, gave the community many good initiatives through its research(DARPA, 2016). This paper sparked the search to define what is meant and expected of an algorithm producing intelligible and comprehensible feedback. While the definitions of explanation or interpretation abounds in its succinct sense an explanation entails information about a topic moving from A to B. Where A provides enough justification to B for actions performed. Sufficient justification leads to trust between A and B (Hind, 2019).

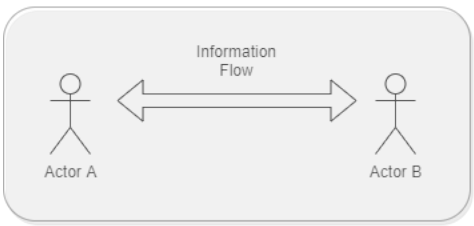


Figure 2.2: Communicating Within a System

And the process must be grounded in logic and formalism. Despite my best efforts to come up with such a definition the loop has not been closed completely. As what really constitutes "sufficient" and "enough" is hardly grounded (Hind, 2019). No wonder there is no consensus in the field of what explainable really is (Dosilovic et al., 2018; Hacker et al., 2020; Hoff and Bashir, 2015).

As one might expect, the topic is hotly debated (Fandinno and Schulz, 2019) as the necessity for consensus is pressing. Different fields of study see the term under different perspectives (Watson and Floridi, 2020). Loose interpretation can also present legal challenges if anyone dares to argue in a court of law (Hacker et al., 2020). Very little consensus makes evaluation of algorithms hard to benchmark or evaluate (Kindermans et al., 2017). Many have settled for a less philosophical, albeit incomplete, definition of the term by deciding whether the output of an algorithm is simple and useful then the explanation works (Goodman and Flaxman, 2017). Many of the existing Machine Learning (ML) models in current use are not transparent, leaving little elbow-room for adaptation. They are mainly tuned of speed and accuracy. It has to be added that much of the modes in use today were developed long before the formalisation of a need to explain came into being. Having said this there are algorithms which are easier to adapt than others. Typically sparse linear models, rule lists and gradient-boosted trees are more suitable to adaptation than Deep Neural Networks for instance (Mueller et al., 2019).

The different perspectives on the definition are expected as many a time it is the researcher's perspective that is exclusively taken into account. Researchers tend to have a very narrow focus which leads to definitions fitting very specific domains (Ciatto et al., 2020).

A lexical definition must be offered at this point. What does explanation mean in lexical terms? The Cambridge on-line dictionary defines explanation as follows: "the details or reasons that someone gives to make something clear or easy to understand". Interestingly enough Doshi-Valez, and Kim stretched the definition to "in understandable ways to a human" (Doshi-Velez and Kim, 2017). Firmly relating the interaction between any system and people.

A proper definition will assist researchers in creating a better suite of Machine Learning (ML) techniques that produce truly explainable models and enables consumers to understand, trust and manage technology (Galitsky et al., 2019). We cannot leave this argument by putting a number of questions, namely what does Explainable Artificial Intelligence (xAI) really mean? What are the expectations when it comes to assisting humans perform their jobs better (Díez et al., 2013)?

The lack of consensus has been given serious thought by many. But it should not be used as a stumbling block. While it is true that a commonly accepted formalised definition is not available other domains such as that of Philosophy, Psychology, Logic and Linguistics. Approaching a workable solution would entail coming up with a definition ourselves. We will start by understanding what an explanation is. What really makes an explanation? An explanation is an interaction between at least two entities, a giver and a receiver. This also depends on the needs, the knows and goals of each (**?**). Let us start by taking a closer look at explanations. And explanation session can be separated into three distinct phases. Namely:

- Explanation Generation;
- Explanation Communication;
- Explanation Reception

When a situation arises that necessitates explanation the first phase comprises the understanding of the situation that needs to be communicated. Once understanding is complete an explanation is generated and communicated to the recipient (Anjomshoae et al., 2019). The recipient then receives the information and uses it as an augmentation to the situation at hand. The extra information helps the recipient understand the situation it is facing. Explanation can then be subdivided into the following attributes:

- Understandable;
- Feeling of Satisfaction;
- Sufficiency of Detail;
- Completeness;
- Usefulness;
- Accuracy;
- Trustworthiness.

(Hoffman et al., 2018)

These attributes offer a granular decomposition of the act of explaining. Trustworthiness being a necessary component. The information being communicated has to be dependable in such a way as to be useful and worthwhile learning. Otherwise the whole process would be rather futile. Extending the process even further we can say that explanation depends on reasoning. To understand the behaviour of a concept necessitates that it makes sense. Or that it can be logically followed; reasoned. We can also reduce reasoning to a number of concepts:

- Casual Reasoning;
- Abductive Reasoning;
- Comprehension of Complex System;
- Counterfactual Reasoning;
- Contrastive Reasoning.

(Hoffman et al., 2018)
Each concept helps the agent disseminating the explanation to understand an outcome and relay it in such a way as to assist the recipient agent. Thus completing the transaction. So we have seen that although many papers correctly assert that the lack of a proper definition may hinder progress. Other fields of study have for quite some time tried to dissect the anatomy of an explanation. Although the result is not an immutable mathematical formula but it still serves a purpose.

2.5.12 Evaluating an Explanation

In an artificial setting one would have to measure the effectiveness of an explanation (Carvalho et al., 2019; Hoffman et al., 2018). This can only be measured from the recipient agent's viewpoint. We would need to know how well was the explanation generated, and if the receiving agent is satisfied with the explanation given (Samek et al., 2019). In the case of a human agent as a recipient there necessitates more skill on the part of the recipient (M et al., 2020). Such as how well would the agent understand an AI system. If there is any curiosity induced by the explanation to make the agent search for more information. Much of this also depends on the recipient's perspective and will vary in the case of humans. As no two humans are identical (Rudin and Radin, 2019).

2.5.13 Approach

Despite that many papers describe the lack of a common definition that underpins explanability all offer some resolution to the problem. The first way that this is attained is by describing models which facilitate explanation. Many start off by describing the inner workings of a particular model. This way a person may understand how the model works and consequently there can be a human interpretation of the outcome presented to the user (Demajo et al., 2021; Guo, 2020). Another way to approach interpretation is to probe models with similar data and then try to understand the factors that influenced an outcome. The last approach is by creating a second model which is simpler by design and more open to being followed by human operators (Yongfeng, 2018). The second model works in tandem with the first and exists to facilitate interpretation. A second model is not about efficiency but facilitation. The internal workings of a model vary and consequently offer better opportunity to understand. A Support Vector Machine and using the logic behind the model to extract an explanation (Holzinger, 2018).

In essence there is no right or wrong way to approach explanability. Each approach has its own merits. One has to bear in mind that research into Artificial Intelligence (AI) has outstripped that on explanability and it would be a a pity to restart research to accommodate explanability (Hind, 2019).

So how should we approach this study? By developing new algorithms or by adjusting older ones? Could we add explainable features to existing data? Which in turn would facilitate classification and understanding (Hagras, 2018). Another direction could be to simplify existing models. Further still we can bolt-on algorithms to existing models. Model transparency is a desirable facet for bringing explanability closer into the realm of machine learning. The tendency of researchers is to get more information out of the process and leave the conclusions to the human in the loop (Krötzsch et al., 2019). This gives rise to post-hoc explanation where one looks at what information can be extracted from a model (Abdollahi and Nasraoui, 2016).

2.5.14 Trust - A Consequence of Explanability

If anything is to be taken on by human endeavour trust must be a factor to consider. Trust involves the opportunity to vulnerability or abuse of intentions, capability and actions. We cannot underestimate a person's bias on trust too. This is dependent on the user's experience and disposition (Liang et al., 2019). Trust, in a logical sense should be grounded in a way decisions are taken in the human realm of reasoning. This not necessarily logical. Proper communication is also necessary to ensure correct flow of information between giver and receiver (Monroe, 2018). Systems can be trained to contain bias, just as any human, although it is ethically unacceptable to do so.

Trust must be effective and this is done if people can understand how data is processed. Many black-box models need to be more open to interpretation, ideally without losing their accuracy (Branley-Bell et al., 2020; Galitsky et al., 2019)

Computational reasoning offers a framework to follow on decisions properly, which may ultimately help to understand underlying reasoning. But are people bound by formal reasoning? What about impulsive and emotional reasoning (Cocarascu et al., 2020)? The challenge here is to balance the collaboration between humans and artificial agents in a decision-making process. The interpretation process must not be over-relied on as it may be abused. And when things go wrong trust is lost.

2.5.15 Local Interpretable Model-Agnostic Explanations - LIME

LIME is one of the ready-made libraries one can find for Python which facilitates explanation. The approach to explanation by LIME designers is a simple, yet robust one (Ribeiro et al., 2016a,b). The designers chose to approximate black-box algorithms (Adadiand and Berrada, 2018; Google, 2019). Output is simulated and approximated without really affecting the original algorithm (Du et al., 2020). So a user can still run black-box deep neural networks without losing out on the efficiency and gain explanablity along side his results (Adadi and Berrada, 2018; Rai, 2020). The algorithm designers for LIME banked heavily on the trust factor for their work (Weblog and Jun, 2020) . The consumers of LIME will gather trust the more they use it. And this is done by giving the user a consistent and clear output explaning how the black-box algorithm came to its conclusions (Hara and Hayashi, 2016). One important point worth noting is that even though an algorithm may not be accurate trust may still be gained if the approximation and error are consistent (Samek et al., 2019). Humans adjust as long as they become aware of the environment they are dealing with (Preece, 2018). The approach to explaining a prediction would be that of understanding the relationship between words in text or any patches in an image (Hagenbuchner, 2020). This relationship helps an algorithm infer a relationship and add meaning between the different entities being studied (Escalante et al., 2018).

2.5.16 The Performance Aspect

When one approaches the problem of which algorithm to use for getting an explanable outcome there are many. Support Vector Machines, Neural Networks and Deep Forests are very efficient algorithms, but their internals are hard to understand (Galitsky et al., 2019). On the other hand inductive inference, linear regression and single decision trees offer more transparency but are very inflexible and cumbersome as algorithms (Preece, 2018).

2.6 Approach to The Proposed Solution

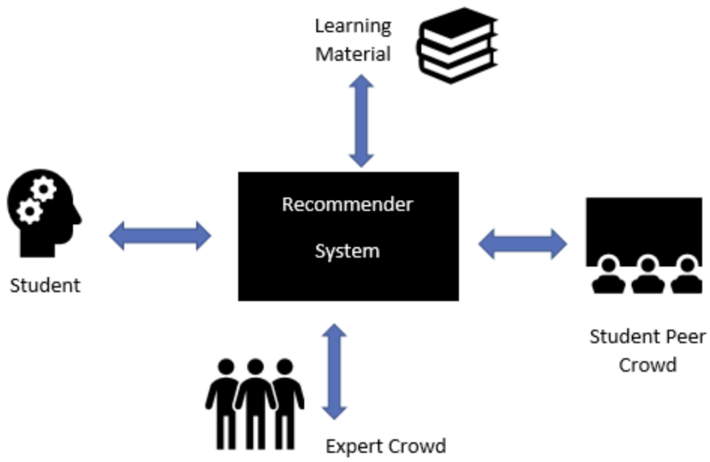


Figure 2.3: A Learning Recommender system Model

So, we are proposing a system as shown in figure 2.3 whereby data is brought up to the student which is relevant to his learning needs. This can be done in a straightforward way as if one is buying items of the Internet (Mallia-Milanes and Montebello, 2018). In addition to the material, the recommender system will have to match the current user with others who have similar needs or experiences, and also a teacher who has a declared expertise in the subject matter. Crowd-sourced material, experts and peers can be pulled together on the fly to create an environment similar to a class, but without the boundaries imposed by space and time. This would give the student the opportunity to share, experience and scaffold though material till the level of skill is acquired (Shaban-Nejad et al., 2020). Teams of agents can be employed to make up the learning system. A recommender system can also comprise a sub team of agents which cooperate to deliver timely information to the student.

2.7 Chapter Conclusion

By creating a crowd-sourced recommender system that could adapt to the needs of students individually would put the learner at the centre of learning. This would help students gain experience as they progress along with their studies and in turn collaborate with others in their learning experience. An intelligent environment will certainly help with student retention rate and additionally improve skill acquisition. A recommender system is only a small, but important, part of the e-learning ecosystem (Mallia-Milanes and Montebello, 2018). Information has to be media neutral and different elements have to be combined to display the same results by different means that appeal to the user. In this paper we have put forward our arguments in favour of the use of artificially intelligent techniques to overcome specific shortcomings within e-learning systems. We strongly believe that the lack of personalization brings about a unfavourable sense of isolation that hinders rather than facilitates the learning process (Mu, 2018). The use of a recommender systems based on latest technologies to deliver personalised education material is opportune and suits all our requirements and objectives. Such a methodology further assists alleviate the issue of information overload as specifically targeted educational material will be put forward to the individual learners. In our opinion the recent developments in technology has enabled recommender systems to move to their next phase whereby networked technologies unleashed resourceful affordances that before were not possible, and that potentially they can take e-learning to its next generation (Batmaz et al., 2019b).

Current algorithms do not offer a reasoning capacity and lack the awareness to make judgement. Machine Learning lead to the deployment of a decision making process but one cannot trace conclusions through the algorithms. To properly satisfy explanability one has to have a very large corpus of data that is properly labelled to lead to a properly justified output which humans can follow and understand (Burrell). But expressing oneself at a human level is hard. Mathematics, Philosophy and Psychology offer insight and decision theory has been devised to support conclusions. But this hardly approaches daily reasoning semantics. In retrospect the best domain that lends itself closest to human reasoning is the legal domain, in which argumentation has become a properly honed craft (DARPA, 2016).

3 Materials & Methods

3.1 Chapter Introduction

This section of our work gives perspective on how our research was conducted and the rationale behind it. We shall discuss what tools have been used and why. This together with the approach that unifies this work.

3.2 Performance Metrics

Performance metrics can be gatherer in a variety of ways. The easiest being exam or test performance. On the other hand, one can make the model more sophisticated by introducing other variables such as the time spent by a student referring to material and performing revision exercises before moving onto the next level. The length of time spent, together with the frequency of visits imply that the student is not ready to move to the next level yet and may need attention.

For this work it was neither possible nor feasible to set up a scenario where students would use a MOOC to simulate study. This because the artificiality of the set up would not be conducive to the outcome of the study and moreover the main purpose of this work is to find a computer-based solution rather than look at humanities. Moreover, the output of such a system would be grades and time which could be simulated without the need of going through the setup plus experimenting with people. It is to be added that despite consent was sought and given by the Malta College for Arts Science and Technology the data is unfortunately not retained in their MOOC implementation. So student performance will be judged in a very traditional way, by a marking scheme. The marking scheme adopted was a simple Likert scale where 0 represents the least performance and 10 the best performance of a student on any given subject. Follow up then can be made by linking the classification of the student's performance to the subject area where the student needs more attention.

3.3 Data and Environment Creation

3.3.1 Moodle

Moodle is a powerful, secure Open-Source free Learning Management system which enables teachers and educators set their own website or stand-alone system which can be filled with dynamic course material made available to the student to extend learning time. Moodle offers an attractive easy-to-use interface designed to be responsive and facilitate navigation both on a desktop or mobile device. In addition to the interface a personalised dashboard could display past and future courses along-side material and keeps track of any tasks that are due by the student. Collaborative tools are also available in Moodle and are made to enable students to learn in groups through the setting up of fora, wikis, glossaries, or database activities.

Moodle also offers useful tools for students such as a calendar, a file management system that can sync to common cloud drives such as One Drive, Google Drive and Dropbox. Finally, Moodle offers facilities to prompt users with alerts on assignments, deadlines, forum posts plus a messaging system that enables communications with people in a group or cohort. Progress can be tracked via a Progress Tracking feature which keeps track of task completion, and any individual activities, or resources and course performance.

In addition to the features described above the Moodle is equipped with numerous administration features that enable:

- Layout customisation;
- Secure authentication and mass enrolment;
- Multilingual support;
- Bulk Course creation and backup features;
- Management of user roles and permissions;
- Support for open standards;
- Offers high interoperability with external applications;
- Has a very simple plugin management approach;
- Receives regular updates;
- Detailed reporting and logging facilities;

3.3.1.1 Course Development and Management Features

Apart from a rich administrative set of features Moodle offers the ability to design and manage courses that meet different needs. Classes can be instructor-led, self-paced blended or completely on-line. Another good feature present in Moodle is its built-in collaborative features. These as explained earlier foster engagement at various levels and encourage content-driven collaboration between students and teachers. External Resources can be used to include material from other sources, such as external websites, and can be connected to Moodle's grade book

3.3.2 Python 3.9

Python is an open-source language that was created by Guido Van Rossum in 1981 and released for use in 1991. Its name is derived from the popular TV show "Monty Python's Flying Circus" Python reached its popularity in the decade of the 2010's. Van Rossum still retains a central role in the subsequent development of Python. Today there are two main branches of Python namely version 2, and 3. Although the gap from version 2 to 3 is not difficult to bridge, both languages are not compatible. Version 2.7 gathered a lot of popularity, and despite being unsupported it is still widely used. Python 3.0 is a multi-paradigm language that allows programmers to follow object oriented, structured or functional models. It has been designed to help programmers develop code with only one option at hand. Removing unnecessary redundant commands and functions.

Python being a script-like language quickly found favour in scenarios that did not necessitate fully developed code. This enabled data scientists and researchers to use it as a gateway to analyse data without getting dragged into lengthy coding assignments. One of the main features of Python is its easy extensibility with the use of libraries The version of Python used for this project is 3.9.9, a recent version. The choice to use Python was chiefly based on the following details about it:

- It is an interpreted language that is extremely easy to learn;
- Very easy to set up an environment;
- Documentation is readily available on the Internet;
- Many robust open-source libraries that extend Python are available;
- It does not require specialised hardware to run;
- It is a very popular language and is extensively used in AI and data analysis scenarios;

- Python depends on a run-time environment thus is practically platform independent.

3.3.3 Scikit-Learn

Scikit-Learn is an open-source machine learning library of tools to facilitate data analytics. The tools within are made to be easily accessible and could be reused in various contexts. The library depends on other libraries, namely NumPy, SciPy and matplotlib. Scikit offers various interfaces to enable programmers achieve the following:

- Classification – Identifying in which category an object within a data-set belongs to;
- Regression – Used to predict a continuous-valued attribute associated with data;
- Clustering – Used for grouping similar objects into sets;
- Dimensionality Reduction – Useful for lessening the number of random variables to consider when analysing data;
- Model selection – Gives the ability for comparing, validating, and choosing proper parameters and models for data;
- Pre-processing - Used for feature extraction and normalisation in data.

The Scikit-Learn project started way back in 2007 as a Google summer of code project and has since developed into a fully-fledged library that supports machine learning. Scikit-Learn has since then gone through several iterations and become a go-to library for machine learning coding in Python 3.x. J.P. Morgan, Evernote, Spotify, Booking.com are just a few of the notable testimonials to Sci-Kit. Scikit-Learn does not lack support either. Its website gives the uninitiated a good overview of the API that enables the programmer to use the functions within the library. The documentation supported is updated regularly. Furthermore, this is also covered by a quarterly release cycle of bug-fixes and improvements. (Learn, 2022)

3.3.4 Neo4J

Neo4J is a native graph data base that stores data in a more natural way. This is done by having relationships between data elements maintained within the database itself. Resulting in extremely responsive queries, deeper context for analysis and an easier to follow data model. But the main reason why this type of database was chosen was for its ability to support connections between elements just like nodes within a graph. Hence mathematical graph theory can also be used as support. Relationships are stores as part of data thus permitting a high level of performance. The database can be deployed both as on premise and on cloud. The Neo4j Graph Data Science Library uses relationships and the structure of a graph network to help researchers address otherwise complex questions about data. These insights can be used to make predictions that can identify the most common elements in behaviour depicted by the data itself. Network structures can be easily added on to infer meaning, increase accuracy of machine learning models and drive contextual AI. This improves prediction rates. Neo4J uses proprietary algorithms supporting machine learning workflows.

Apart from the useful technical features Neo4j has and easy-to-use graph exploration application which facilitate the interaction with graphs themselves. This affords researchers the opportunity to visualise data and relationships which enriches the outlook on the data. As the connections, otherwise referred to as relationships, are stored in the database directly this leads to fast query times. This because the relationship, as in a normal SQL database, is not computed at the time of execution. Typical interaction with Neo4J is done through a purpose-built query language called Cypher. This language natively uses the underlying graph structure of the database. Its creators claim that it was inspired by SQL and by SPARQL.

Neo4J is platform independent and supports several connectors that enable it to be installed within various types of architecture. In addition to this the database comes with a very good toolbox that makes life easier for the developer. Neo4j is used for a variety of complex scenarios by large industries such as NASA, eBay, and Caterpillar.

3.4 Theoretical Framework

The interaction between man and machine has been studied at length and many conclusions drawn. Rather than repeating what others have established, this study aims to propose a framework by which human learning can be enhanced and aided when learning takes place exclusively over the Internet and through electronic means. We have already established that explanation, in the Literature Review, helps motivation which in motivates students. Thus, the remainder of this text will be dedicated to the setting up of a framework to facilitate the implementation of the suggested approach (Yang et al., 2021).

Characteristically, humans interact with Information Technology on several levels which can be described as follows:

- Social;
- Cultural;
- Personal Communication;
- Negotiation.

To support such needs information systems, must be properly implemented to be as seamless and as pervasive as possible. This to the point that the users hardly notice its presence. Consequently, aiding users to trust in system. This is the first step in instilling interest. Without trust, which also comes from system reliability, all the ideas put forward in this study would fall apart. Just as in a workplace where technology takes over the drudgery of repeated, low cognitive work, when learning people lean on technology to assist them. This will also serve the purpose of sharing. Hinging on intra-group communication. Where a group can consist of many human and artificial actors. This synergy between man and machine makes an implementation more successful and fruitful. Sadly, this area of behaviour, although widely researched, has been overlooked or not fully understood.

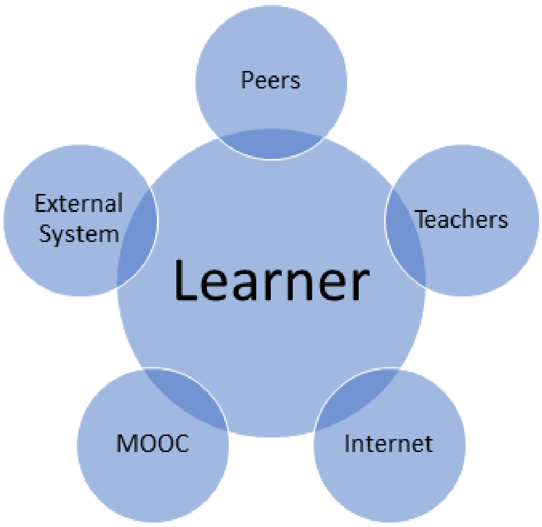


Figure 3.1: Learning Environment

3.4.0.1 Variables

In this proposal we shall extract several variables that will help describe the co-dependence of the system on such variables. The relationship between variables will be proposed in a simple framework that links user perception to the success of the setup being proposed. When tracing the route from the learner to the MOOC the following can be observed (Yang et al., 2021):

- Learner makes judgement by means of past experience (moderator variables);
- Experience can possibly be quantified as a measure (independent variables);
- Measures will explicitly relate to the success of the framework (outcome).

The classes of identified variables can be explained as below:

- Moderators: These types of variables are also known as “First Order Variables”. This class of variables consists of all those factors that were deemed to be very important and are not impacted by any other action within the proposed system. For example the skill of the teacher in designing the material required for a lesson. These variables can be very complex to assess.
- Independent Variables: These shall be described as “Second Order Variables”. These variables do not depend on the MOOC implementation but are a visible factor of the effects of success or otherwise. An example would be the time it takes a teacher to give assistance to the student.
- Dependent Variables: These are the “Outcomes”. These variables depend on the Moderator and Independent variables. They comprise measurable factors such as cohort retention and student pass rates.

(Mohamad and Tasir, 2013)

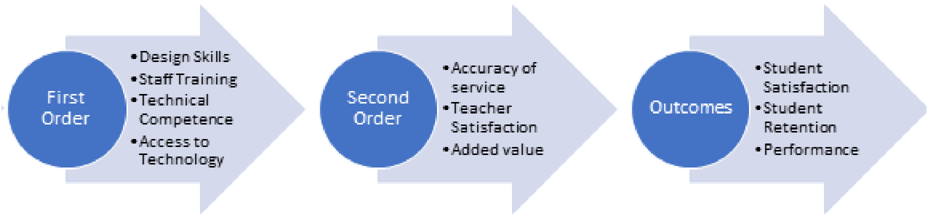


Figure 3.2: Relationship Between Variable Classes

3.4.1 First Order Variables

These are moderator type variables because they affect the second order variables or outcome variables directly.

Variable	Measurable	Comment
Involvement of operational staff at design and implementation.	Yes	This variable can be seen along with the associated levels of involvement because it is deemed to be an important factor relating to the study.
Teacher Training	Yes	Training and the degree to which it was given effects the attitude of the teacher.
Skills of the person designing the coursework. (Technical and Communication skills)	No	This variable is hard to gauge for implementations of MOOCS and the courses within.
Changes sustained to the school structure because of new way of working.	No	This may not be measured properly as documentation would be incomplete.
Process re-engineering.	No	No formal BPR would have been carried out.
Access to new technology.	Yes	The availability of technology would certainly limit or improve potential.

Table 3.1: First Order Variables (Alonso-Mencía et al., 2019).

3.4.2 Second Order Variables

This class of variables are also referred to as independent variables. This because they do not directly depend on the MOOC implementation or eLearning setup that one may be experimenting with. But these variables heavily influence the Outcome variables. Examples of such variables are as below:

Variable	Measurable	Comment
Student Retention Ratio	Yes	This is an indicator of success and can be easily assessed.
Payback or ROI	Yes	The return on investment made by the learning establishment.
School "Brand" reputation	No	Cannot be measured effectively. Especially in Maltese environment where price or repute is not a barrier to entry to students.

Table 3.2: Second Order Variables (Sclater et al., 2016).

3.4.3 The Outcomes

The Outcomes are the dependent variables within the system. These variables are impacted directly by first and second order variables.

Variable	Measurable	Comment
The accuracy of the service implementation	No	It is difficult to assess the accuracy of the system implementation. User satisfaction can be better depended on.
Value added features	Yes	This is a very important aspect that affects people using the system. If a learning environment is perceived as not giving added value to the student, then the likelihood that a course is abandoned is increased.
Teacher and Student satisfaction.	Yes	This variable can be measured by student / teacher retention on courses.

Table 3.3: Outcomes (Sin and Muthu, 2015).

3.4.3.1 Other Factors

There are other factors that tie in strictly to a technical environment of an e-Learning environment. As such factors are largely related to the technical infrastructure of a project. Some variables that fall into this category can be as follows (Montebello, 2016):

- Proper requirements analysis
- Proper implementation review
- Implementation team skills
- Vision and communication by school administration

3.5 Empirical Study

3.5.1 Working with Data

The data used for this study has been synthetically generated to simulate data collected from student tests. The aim is to have a reliable metric that gives us a clear picture of a student's performance. Shedding light on a student's weak and strong points in his learning. This in turn will assist the automation to focus on what needs reinforcing. There are two ways to gather such data:

- From a Learning Management System;
- Directly from the outcome of tests designed to assess student abilities.

Learning management systems offer a better insight into a student's abilities as not only marks directly related to performance is recorded. Student access to a Learning Management System, how long he spent in areas pertaining to a particular subject and what subject was being visited provide additional information. This can be used to fine-tune research outcomes rather than relying exclusively on grades.

3.5.2 Issues Encountered Collecting the Test Data Set

We have experienced issues collecting data as much of the institutions queried were not prepared to hand over the data, despite accepting to do so in the first place. Moreover, none keep Learning Management System data necessary to follow up students during a course. The Learning Management System used in our case was the open-source package Moodle. Moodle offers a very good array of functions that can help teachers assist students. A more detailed account of Moodle is described above.

3.5.3 Data Analysis

One of the fist challenges faced when generating synthetic data was to simulate the real-life behaviour of a class. So, a data set from Kaggle.com showing performance of a particular American high school students was downloaded and used as a benchmark[1]. It was lightly analysed, and its distribution plot is as shown below.

[1] www.kaggle.com

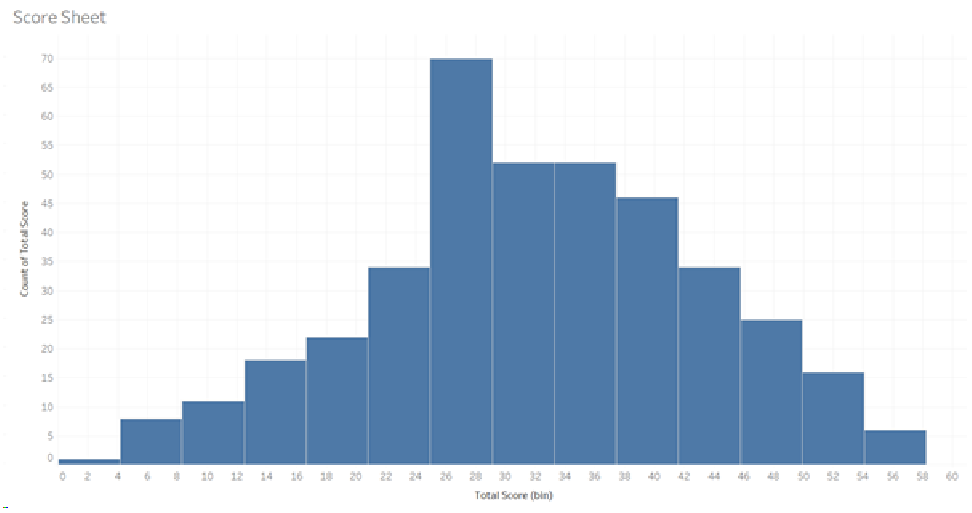


Figure 3.3: Actual Data for a Class (Source Kaggle.com)

3.5.4 Data Generation

As stated earlier, to make our data more credible it must follow the above plot as closely as possible. A Python program was written to generate and label the data in such a way as to simulate a normally distributed population of numbers. The whole script can be seen at Appendix G of this work. Two libraries were used to generate marks between 0 and 10 which are normally distributed over a sample. These were as follows:

- NumPy – is a comprehensive library of mathematical functions;
- Scipy stats – is another set of tools that provides algorithms for statistics.

The sample size was arbitrarily chosen to be 3,000. To the study the sample size does not really matter. But in principle on-line classes tend to be larger than face to face classes. A small number would have defeated the scope of the whole theory as a single class of say 30 would not have made the process being proposed justifiable. The main challenge of the code written was to generate a discrete distribution that approaches a normal distribution. This because we are simulating the data rather than collecting it from a naturally occurring sample. So, a multinomial distribution with probability calculation based on a normal distribution function was used. This produced a normally distributed set of integers. In the code the function *np.random.choice* calculates an integer over the range -5 till 5. The probability for selecting any element, for example 0, is calculated by p $(-0.5 < x < 0.5)$ where x is a normal random variable with mean zero and standard deviation 1. The standard deviation of 1 was chosen as it was found to approximate the ideal distribution from the Kaggle sample.

As marks awarded for tests are not normally negative the output sample was then normalised to map -5 as 0 and 5 as 10 of over the data space. After the data the generated it was checked for appropriateness. From the figures below it can be noted that the data generated forms a normal distribution with mean approximating 5 and Standard Deviation of approximately 1.

Stat.	Physics	Chemistry	Biology	Math.
Mean	4.97	4.99	4.99	5.02
Standard Dev.	1.06	1.04	1.02	1.06

Table 3.4: Class Data Analysis

The synthetic data generated was very close to a normal distribution behaviour. The plots below show the distribution for four hypothetical subjects.

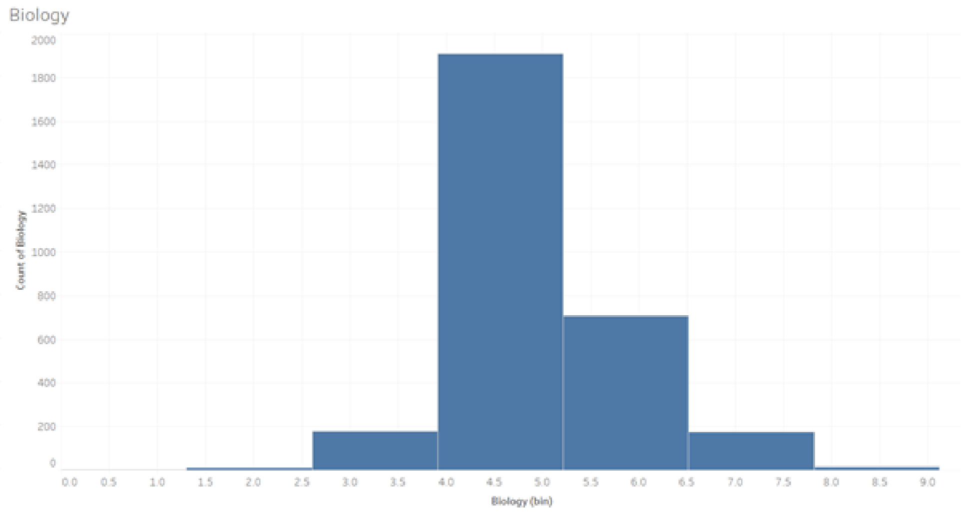


Figure 3.4: Synthetic Data for Biology n=3000

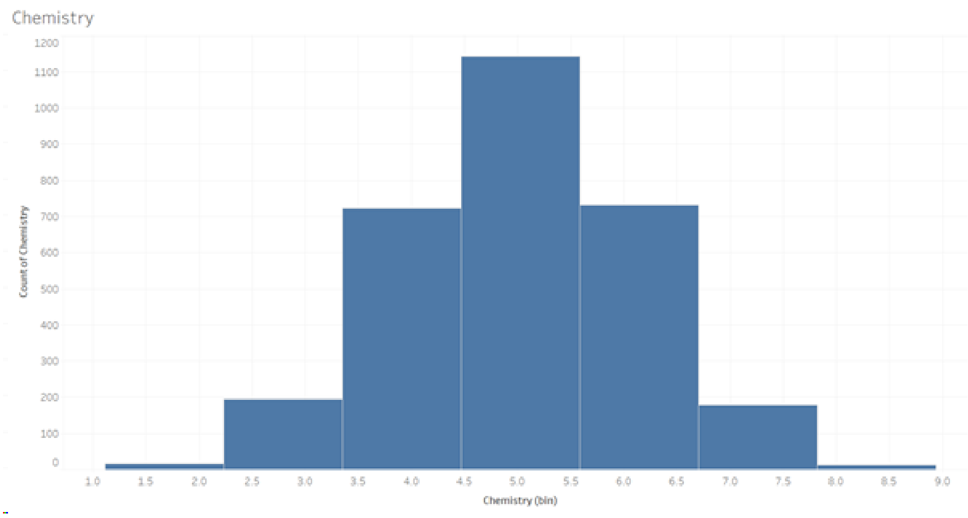


Figure 3.5: Synthetic Data for Chemistry n=3000

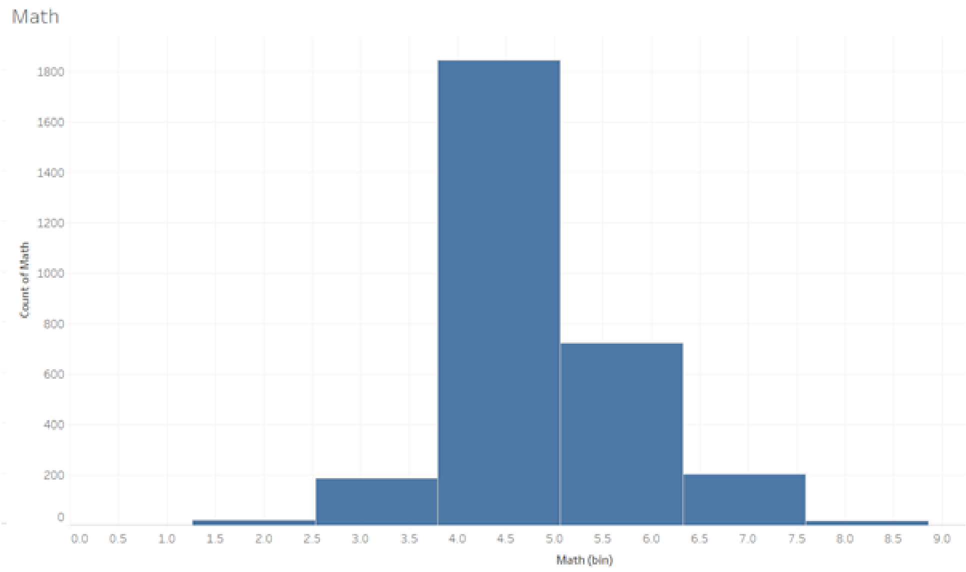


Figure 3.6: Synthetic Data for Mathematics n=3000

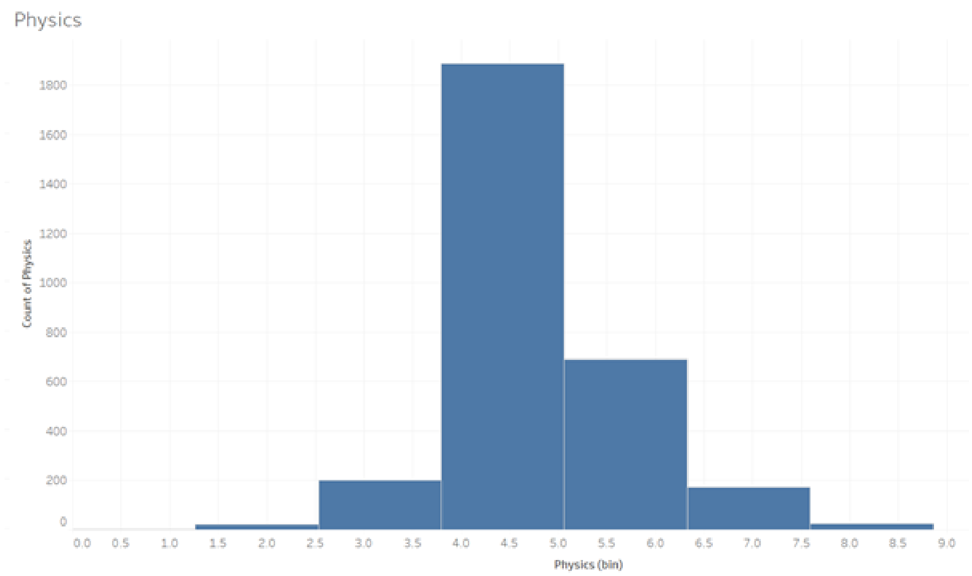


Figure 3.7: Synthetic Data for Physics n=3000

Data was automatically labelled during the generation process. The labelling process facilitates suggestion and a more reasonable grouping by bin-like properties rather than marks themselves. A failure grade in a subject was considered the same irrespective of the measure of failure. If a student was marked as 3, he was grouped with others who scored more poorly. This reduces the dimensionality of data and improves the clustering abilities of the algorithms. The labelling was designed as shown below.

Subject Failed	Label
Physics	A
Chemistry	B
Biology	C
Mathematics	D
All Passed	P

Table 3.5: Data Labels

A label of AB would mean that the student did not make the required pass grade of 45% in both Physics and Chemistry. An overall pass is labelled as P irrespective of the grade awarded above 45%. The distribution is not normal as each grade is independent of each other. The graph below shows the distribution of performance across the 3,000 sized sample for four subjects. It can be noted that most students failed in a subject or group of subjects.

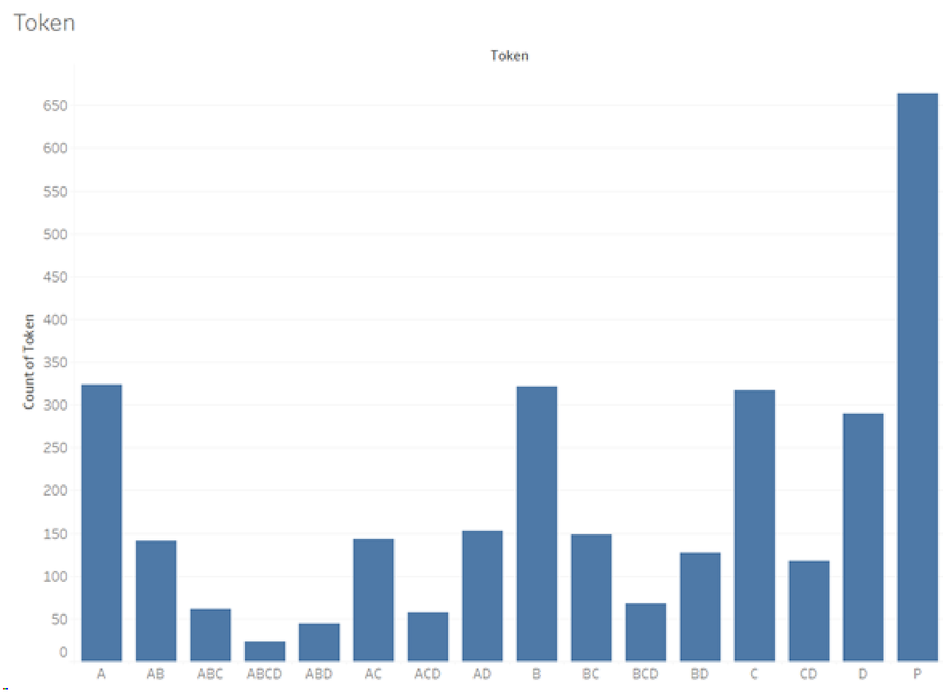


Figure 3.8: Student Performance n=3000

3.6 Process

The experiment comprises the following parts:

- Automatic student assessment;
- Automatic student classification;
- Automatic allocation of student to subject areas that need more attention.

When a student is lead onto the area that needs attention, material enriches the output of the feedback. Thus, making the circumstance of failure more explainable or evident by the lack of preparation. In the first part, Python script (refer to Appendix E) was used to automatically generate student marks. As described earlier on the data closely simulated a natural class marking by making the data follow a normally distributed pattern of grades.

Then two algorithms, namely K Nearest Neighbours and Multinomial Naïve Bayes were used for classification purposes. Both generated a high percentage of accuracy, 98.7% and 98% respectively. Curiously enough when initially data was generated as a stream of random numbers the performance of both algorithms was quite poor averaging

56% accuracy. It can be deduced that as the distribution of data affected performance visibly the algorithms are more tuned to perform on naturally occurring data Wimott (2020). The final part of the experiment comprised most elaborate of the whole system. This comprised the setting up of a graph database, namely Neo4j, to contain the necessary data to support students. Graph databases differ significantly from the normal SQL databases. Graph databases give the use the option of loading unstructured data into the database and store relationships as part of the data schema. This helps relate different items within the database to other items. As the link is a data item stored in the database the performance is largely constant irrespective of the database size O(n). Moreover, one can store and link as in a natural way forming a web of information that can be viewed from different perspectives.

Any search, or classification mapping can thus be enriched with as much info as the maintainers of the system would give enhanced feedback to the user in a way one can understand.

3.6.1 Classification methods

Classification methods used were two, namely K-Nearest Neighbours and Naïve Bayes algorithms. The outcomes from the algorithms was similar, both generating an accuracy score of approximately 98%. One comment that seems pertinent to add at this point is that both algorithms scored poorly when the data was a flat generation of random numbers each returning an accuracy rate of about 56%. This was not acceptable as there would be a very large probability (0.44) of misclassification. After changing the nature of the data dispersion to be more normally distributed around a mean the algorithms' accuracy doubled.

3.6.1.1 K-Nearest Neighbour

The KNN is a supervised algorithm whereby labelled data is considered and represented by a vector of features. In our case whether a student passed or not his tests in a subject area. Each data point is clustered in the data space and if we want to classify a new data point, student performance in our case, we plot the new data point in the given space and by proximity to other performance values we can figure put the performance of the new data point. Distances are measured between the new data point and the already classified K neighbours and we can conclude that the new label, or performance attribute, is by majority voting of closest proximity to the already classified data. This method does away with classes and can associate each data point in space with neighbours by regression (Wimott, 2020). KNN is useful for classifying samples according to numerical features, in our case marks indicating performance on a test. In strict terms KNN does not involve any learning but can do one of two things, group an existing point to an already classified set of data points or predict the data point based on the label of the existing sample. Hence KNN is labelled as a lazy algorithm. The algorithm starts off by classifying already existing data called N. In our case N was arbitrarily chosen to be 3,000. This makes KNN a supervised learning technique. Each data point n, for $n \epsilon N$, has a set of features M. In our case M = 4: Mathematics, Physics, Chemistry, Biology. To classify then we must look at the closest points to the position of the new data point we have plotted in our data space. Choosing the value of K is tricky. A small value of K will result in a low bias but high variance, and on the other hand a large value will result in a high bias and a low variance. One of the main issues using a KNN may be skewing of the outcome. This may happen if there is a dominant group within the data set which happens to attract proximity. In this case the data point distance is biased by a decaying weight.

3.6.1.2 Naïve Bayes Classifier

The NB Classifier is also a supervised learning technique whereby samples that represent different classes within the data are given to the algorithm to be analysed. The probability that a new data point belongs to a predefined class is then calculated by the algorithm consequently determining the class of the data point. This type of classifier is often used in Natural Language Processing scenarios and email spam identification. It works well with text and can classify even the sentiment behind text. The algorithm learns which words are good and which are bad, classifying an unknown text based on the words it contains relative to the training set. A relatively large data set of labelled data is needed. Patterns pertaining to labelled data are noted by the algorithm. Then a probability of each pattern appearing within a certain class, denoted by its label, is calculated, and maintained for reference. This would be known as the learning phase. As the relationship between classes is rather insignificant the algorithm then can associate a pattern with a given class.

3.7 Evaluating the Set Up

The algorithms selected for classification were initially chosen because of their theoretical suitability for the exercise (Wimott, 2020). The final selection of the candidate algorithm was carried out empirically by testing each algorithm in turn using the Weka[2] software package to rate accuracy of recall for each algorithm. Extreme values were discarded discarded. This was done by splitting the data set into two components, a train set and a

[2] https://sourceforge.net/projects/weka/

test set, and gauging the precision of the algorithm through its recall accuracy rate. As for data accuracy was not considered to be an issue as this has been synthetically generated, a distribution plot of the data will map its behaviour to that of a normal class as sought through open data.

The recommender system has been tested against a pre-classified data set which was given tot he algorithm as input an validated for the output. In addition to this accuracy of the model is also retrieved from the learning/testing phases of the classification execution. Finally the graph data base setup was tested by following on the feedback given after query input. A detailed description of the evaluation process is described in section 4.3.2 at page 54.

3.8 Ethical Considerations

Working with data is sensitive. Hence care has been taken not to use data from real world persons but simulate it in the closest possible way. This way there would be no problem with the utilisation of sensitive data irresponsibly. In addition to the utilisation of data care was also taken not to subject any person to experimentation without his express consent and freedom to stop participation at any point in time. So wherever possible no people were involved in the project.

3.9 Chapter Conclusion

In this chapter we have seen all the tools and techniques that were used in this work. The software tools that are commonly used as MOOC or centralised databases for content were described. In addition to that the way the data was generated and why was amply described. The algorithms used for classifying data together with their merits and disadvantages. In this way one can replicate the work that has been done and proposed. In the next chapter we shall describe the experimental setup, who it works and the contribution to the outcome of this work.

4 Results & Discussion

4.1 Chapter Introduction

In this chapter we shall follow on to the experimentation and setup of our proposal. The experimentation output shall be analysed and explained. Firstly we shall deal with the setting up of the environment that supports the software necessary for our experiment then we will discuss the outcomes from each of the software we have set up. The software mainly consists of two parts, first a Python environment and then a Neo4j database which takes care of the data handing and the output of the results that we will find.

The main idea behind this approach to encode data with relationships and make outcomes smarter will help us achieve our goal. That of aiding understanding in a way accessible to all and retaining student cohort in online courses. Graphs help achieve this aim by making the data smarter or richer, rather than modifying algorithms to achieve the same aim. Information is organised in such a way as layers can be added as needed, without being constrained by structure or performance. Agents, human or otherwise, would be able to traverse graphs in a mechanical way making discoveries within knowledge available to all and without being tied down to particular methodologies.

4.2 The Need

As iterated in the Literature Overview chapter of this work, on-line learning has come a long way. But it still does not manage to hold most students in place to complete the course that they initially signed up for. This may be due to many factors but one that this thesis outlines is the personal care and attention that is generally prevalent in a physical class setup is not possible to follow on-line, especially when thousands have signed up for the course. The lack of meeting up, together with the size of the cohort plus the automated setup invites anonymity. Anonymity also leads to a lack of commitment thus facilitating dropout. It has been contended that if AI is used and helps the student, and teacher, by enhancing explanation and facilitating burdens of follow up, the student will be encouraged to stay on. It is important to highlight at this point that in this work the focus is to propose a technical solution to the problem, and not to delve into the psychological aspect of cohort retention. This has been amply discussed in the literature review chapter and does not need further amplification.

4.3 Overview of Proposed System

In principle the proposed solution shall comprise two stages. The first stage is where the student data is prepared, and the model created to be used as a template for comparison. With this model a student's weak points are highlighted, and each student is given a report of what topics need to be revised for better future performance. In the second instance a graph database, namely Neo4j is set up with material that enable the student to follow and flow through.

Apart from serving as a retrieval tool, Neo4j can be used to analyse relations between students and problematic areas. This may add different aspects to the thesis by highlighting areas where teaching may have been lacking. A teacher can view these relationships to see which part of his class has not grasped a particular topic, and possibly revise the approach to the teaching method if there is a high incidence of failure in a particular area. Moreover, if this is not the case, then attention can be given to the students who are finding it difficult to grasp specific concepts.

A flexible and automated way to quickly highlight issues and leave no student behind, independent of the cohort size is the main outcome of this work.

4.3.1 Candidate Data Generation

The data used for this study is based on synthetic data. This approach was taken for several reasons, namely the unavailability of data, despite permission to access was granted. Secondly that data in large quantities that simulate an on-line course was not available. The next best approach was to generate the data. This proved to be a challenge as we had to closely map the behaviour of a class to generate relevant results.

Initially a flat random data set was generated and evaluated for recall and classification. This proved to be a weak arrangement and the classification algorithm only yielded a 56% precision in accuracy on recall, which was deemed to be exceptionally low.

In order to correct this issue real-live data had to be obtained studied and simulated. Anonymous data was obtained from the site www.Kaggle.com and was used as a basis to build a model from. The downloaded data was observed to follow a normal distribution pattern. This was essential to use as a prototype and base my synthetic model model off. The data set used described student performance in US high schools in Mathematics, or Portuguese. The details of the data set are as shown in Appendix G on page 124.

The data set was cleaned off unwanted dimensions as what interested the research mostly is was student performance values experienced. The data set had high dimensionality and was subsequently reduced to the G1, G2, G3 component grades in Mathematics. Following a distribution plot, marks exhibited a skewed normally distributed behaviour as shown in the figure 4.1 below.

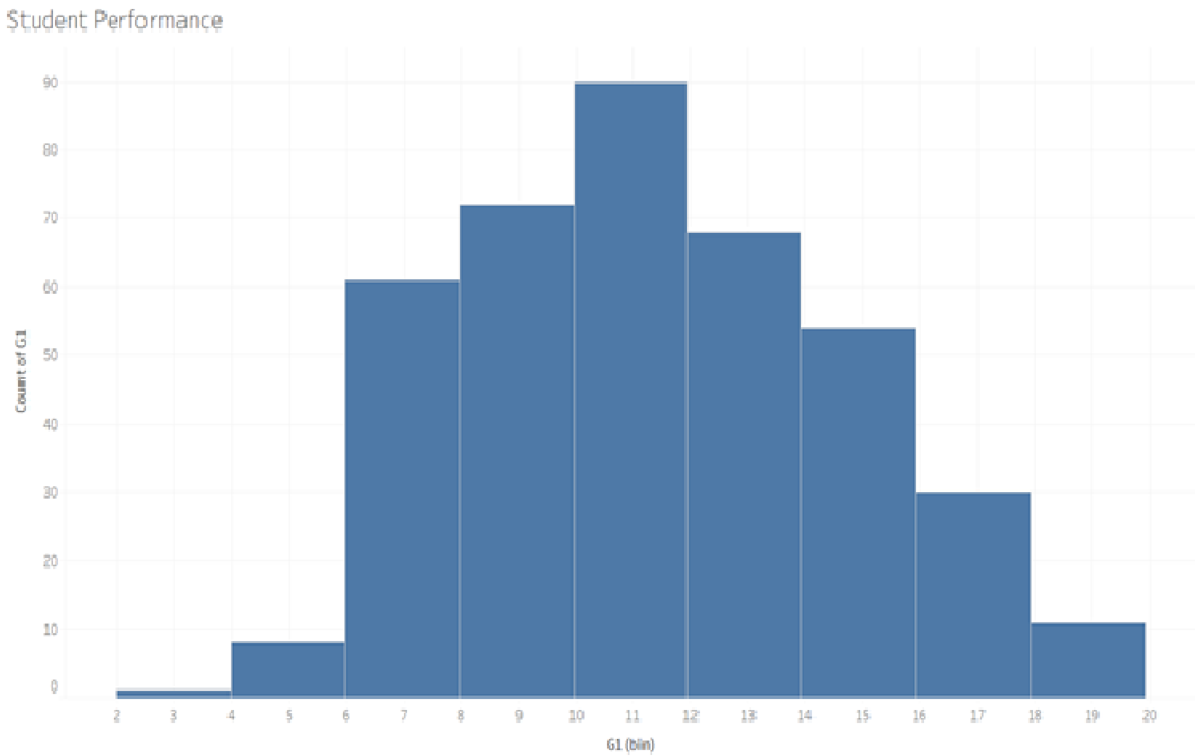


Figure 4.1: Student Performance

After extracting a pattern from the sample data it was then decided to model the synthetic data set over this behaviour so as to imitate a real class as closely as possible. This would make the synthetic data set more true to life. The data was generated using a purpose built Python script shown in Appendix E on page 120.

The script was set up to generate a sample of 3,000 grades across four subjects, namely Physics, Chemistry, Biology and Mathematics. Generating 12,000 normally distributed grades in total. Then Python libraries called, SciPy.Stats, NumPy and Pandas were used to assist statistical computation. The SciPy.Stats library supported the generation of the distribution probabilities, NumPy the mathematical computation and pandas for the formatting of the data set as a table.

In order to generate a random normal distribution we had to draw from a multinomial distribution where probabilities are calculated very closely to a normal distribution. In addition to this the required grades had to be generated as integers, and not as numbers between 0 and 1. So further manipulation of the data was needed. A number range from -5 to 6 was asserted. This bound the range of numbers between -6 and 6. These numbers were then normalised and mapped over the desired range of positive integers. The value of -5 being 0 and 5 being mapped onto the value of 10. Thus, the set was scaled over a positive range. The grades were generated using the function np.random.choice. The probability of selecting an element is calculated by p(-0.5 < x <0.5). Where x is an normal random variable with mean zero and standard deviation 3. This was selected because this way p(-5 < x < 5) would then be approximately 1. Then in order to generate a continuous probability distribution then the range interval was selected to be between -0.5 and 0.5 which has been defined by the values in xU (Upper) and xL (Lower) (Overflow, 2016).

During the generation process the data was also automatically labelled. This facilitated the identification of data and helped the algorithm training process. After the generation process was completed the data set was then analysed for groups using the K Nearest Neighbours technique. This was done to build a behavioural model of the data.

4.3.2 Algorithm Selection & Comparison

4.3.2.1 K Nearest Neighbours

KNN works on the principle of classification. It is allows for the fast computation of neighbours in a data set. Placing an unknown vector point next to others closely associated to it will imply closeness in feature representation too. KNN uses distances from a central vector to calculate closeness and consequently classify. There are four different ways for calculating distances between neighbours. These are Euclidian Distance, Manhattan Distance, Chebyshev Distance and Cosine Similarity. The latter three are used for data with high dimensionality.

For this work we used the implementation provided through the SciKit-Learn library. The algorithm implemented in the script for this work,Appendix E on page 120, was that supplied through the Scikit-learn library. The Scikit library is a widely used library. It's KNN implementation provides four modes of operation to calculate distances. Namely Auto, BallTree, KDTree and Brute (Learn, 2022).

Brute Force Algorithm The most unsophisticated neighbour search of the available options is the brute-force algorithm. This computes of distances between all pairs of points in the data set. Efficient brute-force neighbours searches can be very competitive for small data samples. However, as the data set's size grows the more inefficient the algorithm becomes.

KDTree Algorithm To address the inherent inefficiencies of a brute-force approach, the KDTree was designed in an attempt to reduce the required number of distance calculations by efficiently encoding aggregate distance information for the sample. This makes the algorithm very fast, but it can only handle low dimensions in data.

BallTree Algorithm The BallTree algorithm was designed to overcome issues with KD Trees when operating with higher dimensionality in data in higher dimensions. Ball trees partition data in a series of nesting hyper-spheres which makes the maintenance of the overall data structure more costly than that of the KD tree. But can be very efficient on highly structured data, even in very high dimensions.

For this work the Auto Option was used so that the algorithm could automatically select the best approach for classification. The outcome should not be affected by the choice though as dimensionality was purposefully reduced. The simplicity of the KNN algorithm make it an efficient and good algorithm to use. Although Paul Wilmot (Wimott, 2020) in his book suggests that re-classification of a vector, when a new and unknown is presented to the algorithm, is rather slow. We did not experience this in our experiment. But it may have been to the hardware being used namely a 10th generation i5 processor with 64 gigabytes of memory.

Possible Bias With KNN KNN is a supervised learning technique where classified data is represented by several features. Based on these features a vector is calculated and placed in a given arbitrary space. Any objects with with similar characteristics would have close vector values and thus considered be considered as classes of similar objects. A central measure is calculated for all vectors close to each other. Proximity to this centre would place new vectors into the formed groups thus classifying objects. Proximity is calculated in several ways which shall be described further on in the text. These techniques are called majority voting schemes.

Majority voting can also cause issues though. As Wilmot aptly comments that one short coming of a KNN is that of bias being introduced by an overly large group within the data set (Wimott, 2020). As the algorithm works by consensus voting a larger group will "attract" new vectors to it and possibly mis-classify them. Outliers, for instance may be placed into the larger group because of their remote proximity to that group. This can be considered as one of the main failing points of KNN.

4.3.2.2 Decision Trees

Decision Trees are also known as Classification Regression Trees. They are a supervised learning technique where features describe each data point. Initially data is labelled for multiple features. Then by using a hierarchy, just like in an inverted graph or tree, information is organised along nodes and edges according to the attributes of each data point. The main use of the trees are classification, they tend to be very accurate and fast.

J48 is one such Decision tree algorithm. It works by using, just as all trees, a top-down approach together with a divide and conquer strategy to achieve classification. An attribute is selected for the root node, which uncharacteristic to trees is at the top of the tree. Branches and nodes consist of other possible attribute value. Instances are further split into subsets. One for each branch extending to the root note.

Random Forests are another supervised learning technique that build on Decision Trees. This algorithm is widely used for regression and classification problems. And classifies vectors based on consensus majority voting. Many Decision Trees are built to represent different samples and then a majority vote for proper classification of taken. The algorithm can handle both continuous and categorical data. It has been found to perform better for classification problems. During our tests we reached 100% accuracy with Random Forests. See section 4.3.3 below for further details.

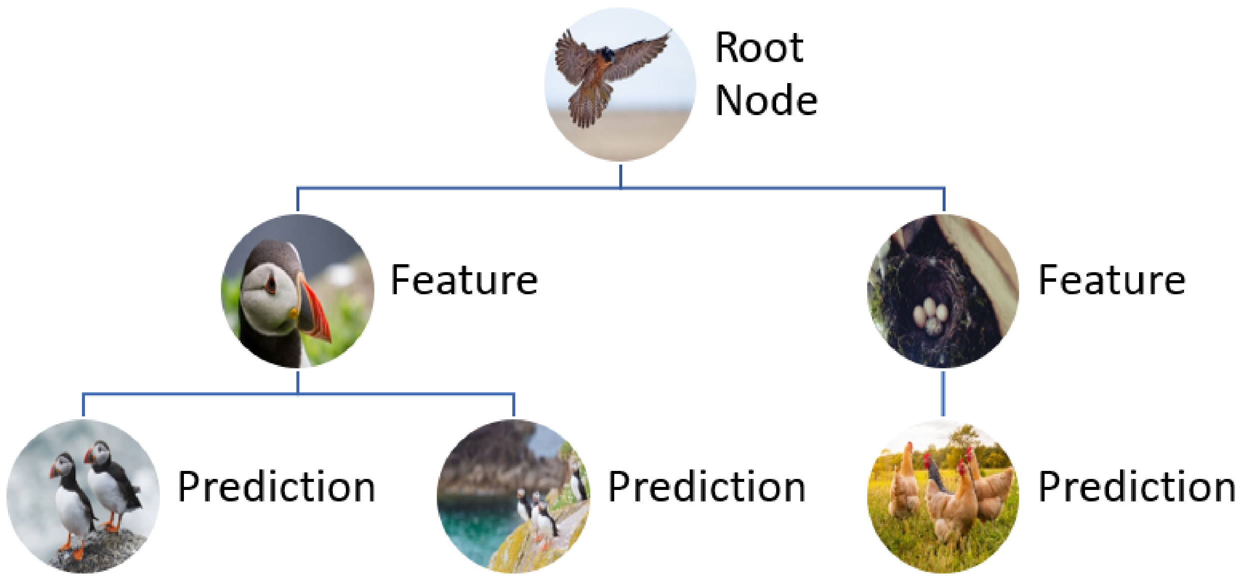


Figure 4.2: Decision Tree

4.3.2.3 Naïve Bayes

Just as in the previous cases the Naïve Bayes Algorithm is a supervised learning technique. Initially labelled data is presented to the algorithm. The probability that an unknown belong to a class can be then calculated. The main uses of this method are that of spam detection, sentiment analysis and classification of news content. The Naïve Bayes algorithm depends on a large corpus of data, n = 3,000 in our case, to be able to pre-classify the training set.

4.3.3 Choosing the Algorithm

Prior to using an algorithm for our script, it was decided that a short test would be run on the precision of each the algorithm. This was done using the same data generated and another open source package called Weka [1], the data generated was subjected to the different algorithms which helped us understand the difference between each algorithm and the accuracy for recall each provided. The following was noted:

[1] Downloaded from https://sourceforge.net/projects/weka/

Algorithm	Precision
J48	100.00%
Random Forest	100.00%
KNN	99.20%
Naïve Bayes	98.80%
Decision Tree	71.00%
Naïve Bayes Multinomial	25.67%

Table 4.1: Algorithm Performance

It can be noted that most of the algorithms scored highly in their recall capability. Save for Multinomial Naïve Bayes and the generic Decision Tree. All algorithms were subjected to the same test data. A train/test split of 80/20 was adopted. This gives each algorithm a training set of 2,400 students and a test set of 600. Both the testing and training set were representative samples from the whole corpus. The KNN was selected as the algorithm of choice due to a number of reasons, namely that it was felt that algorithms which displayed 100% precision was not very reliable, as an amount of error is always expected. From the rest of the algorithms the KNN exhibited the best value in terms of accuracy and implementation cost.

4.4 Data Classification

In our experiment the algorithm was first made to learn to classify data pertaining to 3,000 students. Each data row was previously automatically labelled to highlight the performance of a student on a particular subject. This creates discrete classes of data and facilitates grouping. The distribution can be seen in the table 4.2 below.

A	329
AB	128
ABC	66
ABCD	30
ABD	60
AC	151
ACD	79
AD	137
B	305
BC	129
BCD	86
BD	124
C	277
CD	129
D	289
P	681

Table 4.2: Data Distribution

4.5 Learning Enhancement

Once the various classification models were experimented with the K-Nearest Neighbours was selected because if its ease of implementation in Python and relative efficiency. The training data served as a basis for our classification and consequential recommendation to students and teacher alike. Students inputting their grade profile could easily, and visibly, have a classification returned to them. This classification can then be fed into another part of the architecture – the Knowledge Base system. This part of the architecture will support many facets of learning. Namely scaffolding, information retrieval, information relationship and explanation of choices. Moreover the flexibility of a graph offers a medium that does not restrict users in any way.

4.6 Initialising the Database

Using a concept map for Physics, similar to that shown in figure 4.8 below, the subject and dependencies are added to the graph. Once this is completed, traversal along the tree, or graph can help the user infer meaning or add new information. In addition students who have performed badly in certain areas could be pointed towards the right area that needs attention. Teachers assigned to the subject can also follow if the majority of students are doing badly at a specific subject then the issue may lie be with the teaching rather than the learning. This offers adjustments from both ends. The main advantage of this approach is as follows. It is easy to link to MOODLE, a student-teacher database. Assisting both teacher and student alike.

4.7 Classification as a Recommendation Method

There are various methods of recommendation systems available which are used to propose options to users of different systems. Most common applications are that where consumption of goods or services are required, and an algorithm tries to entice buyers into purchasing or experiencing new products. There are three types of recommendation systems available today which we have apply described in the literature review. Our proposal is a simplified model of voting consensus which enables both teacher and student to understand academic performance by classification. The use of KNN or Decision trees to find proximity of a given vector to others.

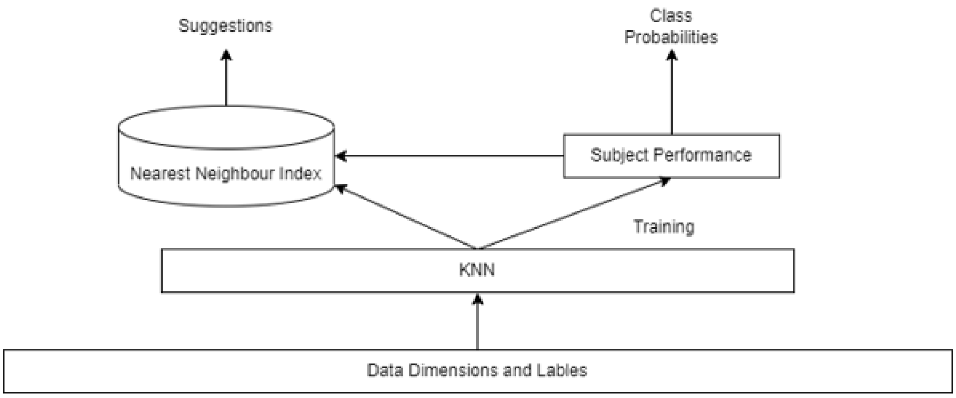


Figure 4.3: Architectural Model

4.7.1 Neighbourhood-Based Collaborative Filtering

This technique was selected form the many observed because of its directness, ability to scale and accuracy rating. K-Nearest Neighbour based recommendation system was set up to aid users rate students focus on their area of issue. KNN avoids the need of having users to rate choices, but bases itself on user behaviour. This is called collaborative filtering whereby a new vector is placed in proximity of others based on its characteristics. Proximity being the main aspect of association.

4.8 Evaluation of the Recommendation Model

One of the main ideas used for this work is to evaluate the recommendation system to be used. This is done by calculating the recall accuracy. The data set was spit up into an 80/20 proportion. 80% was used as a training set, while the remaining 20% was used as the test set. The recommender system was then trained on pre-labelled data and then tested against unseen, but labelled data. Different algorithms were used for comparison and effectiveness.

Bias in sample selection was reduced by selecting members of the 80/20 split to be representative of the whole rather than slicing the data set at a convenient point. This way we would have a better learning and recall rate.

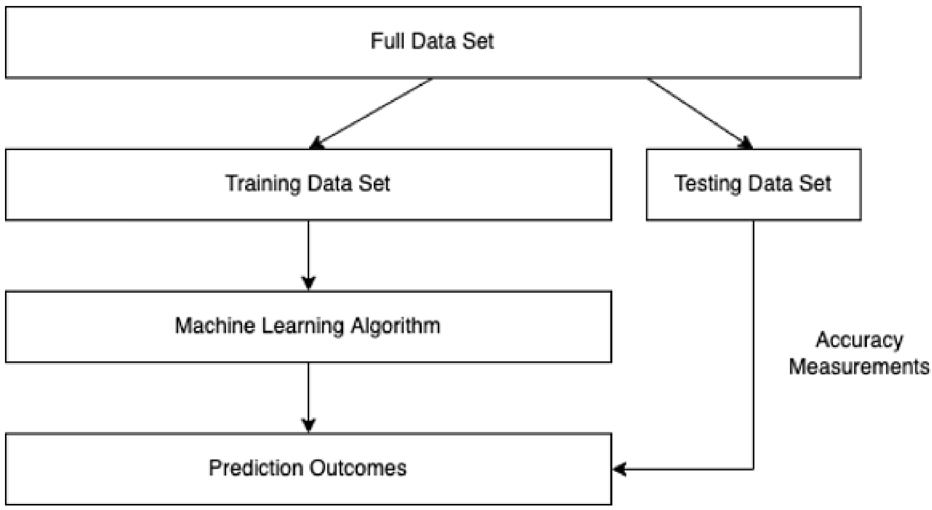


Figure 4.4: Classification Process

When training the data and establishing a baseline for accuracy it was noted that algorithms worked better when data was normally distributed rather than having a flat distribution. The random normal distribution was done to emulate naturally occurring data as best s possible.

Moreover in certain instances such as Random Forests a k-fold validation was carried out while training. This approach split the training set into further folds, X in our case, each fold representing a tree data-structure. Accuracy measures are then made using the test set against each fold, and an average value over all folds represents the overall accuracy score for the algorithm. Although there are many methods of calculating an accuracy score of an algorithm the recall rate is one of the best because it can be performed on all algorithms. Most of the literature reviews suggests the Root Mean Squared Error as a measure of accuracy, but this was found not to be suitable across all algorithms. The reason behind the popularity of RMSE emerged because of the Netflix Prize. Where Netflix asked competitors to come up with and algorithm that can scale down their RSME rate by at least 10%. After awarding the prize the algorithm was not used as a benchmark and nether did RSME matter, but the fame lingered on. Netflix realised that in case of viewing selection the dependence on the top 10 is enough to make a prediction. In our case, as we are working for an education environment this cannot be considered suitable. Hence the use of accuracy prediction was adopted.

4.8.1 Empirical Evaluation of KNN Algorithm

To assess whether our recommendation system reached its goals unknown data was supplied to the algorithm used for classification, in our case KNN, and the outcome of retrieval was measured. Most of the data has already been shown in section 4.3.3 on page 57. Further analysis was carried out using the KNN algorithm on our data set Using the script shown in Appendix I on page 127 and Weka to understand the algorithm's performance better. The following can be observed in line to the initial assessment. From the figure 4.5 below that the algorithm has a high precision rate and relatively low error rates. This makes it suitable for our implementation because of its reliability, precision and recall rates seen also in the output shown in figure 4.6 below.

```
Relation:     StudentData2
Instances:    3000
Attributes:   5
              physics
              chemistry
              biology
              math
              Token
Test mode:    10-fold cross-validation

=== Classifier model (full training set) ===

IB1 instance-based classifier
using 1 nearest neighbour(s) for classification


Time taken to build model: 0 seconds

=== Stratified cross-validation ===
=== Summary ===

Correctly Classified Instances        2984               99.4667 %
Incorrectly Classified Instances        16                0.5333 %
Kappa statistic                          0.994
Mean absolute error                      0.0015
Root mean squared error                  0.0263
Relative absolute error                  1.3006 %
Root relative squared error             11.1438 %
Total Number of Instances             3000
```

Figure 4.5: Generic KNN Run Information

=== Detailed Accuracy By Class ===

	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class
	1.000	0.001	0.993	1.000	0.996	0.996	1.000	1.000	C
	0.999	0.001	0.996	0.999	0.997	0.996	1.000	1.000	P
	0.987	0.000	0.987	0.987	0.987	0.987	1.000	0.990	ACD
	0.997	0.000	1.000	0.997	0.998	0.998	1.000	1.000	D
	1.000	0.001	0.988	1.000	0.994	0.993	1.000	0.999	A
	1.000	0.001	0.977	1.000	0.989	0.988	1.000	0.999	BCD
	0.984	0.000	0.992	0.984	0.988	0.987	1.000	0.999	BD
	1.000	0.000	0.985	1.000	0.992	0.992	1.000	0.995	ABC
	0.985	0.000	0.993	0.985	0.989	0.988	1.000	0.994	AD
	1.000	0.000	0.992	1.000	0.996	0.996	1.000	0.999	CD
	0.967	0.000	1.000	0.967	0.983	0.983	0.999	0.974	ABD
	0.980	0.000	1.000	0.980	0.990	0.989	0.999	0.987	AC
	0.992	0.000	1.000	0.992	0.996	0.996	1.000	0.995	AB
	0.992	0.000	1.000	0.992	0.996	0.996	1.000	1.000	BC
	1.000	0.000	1.000	1.000	1.000	1.000	1.000	1.000	ABCD
	0.993	0.000	1.000	0.993	0.997	0.996	1.000	1.000	B
Weighted Avg.	0.995	0.001	0.995	0.995	0.995	0.994	1.000	0.998	

Figure 4.6: KNN Precision By Data Class

A confusion matrix, as seen in figure 4.7 below, was also plotted to attest the error rates for each data attribute in the test which was also found to be very low. Only 16 instances out of a total of 3,000 were incorrectly classified.

```
=== Confusion Matrix ===

   a   b   c   d   e   f   g   h   i   j   k   l   m   n   o   p   <-- classified as
 277   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0 |   a = C
   1 680   0   0   0   0   0   0   0   0   0   0   0   0   0   0 |   b = P
   0   0  78   0   0   0   0   0   1   0   0   0   0   0   0   0 |   c = ACD
   0   1   0 288   0   0   0   0   0   0   0   0   0   0   0   0 |   d = D
   0   0   0   0 329   0   0   0   0   0   0   0   0   0   0   0 |   e = A
   0   0   0   0   0  86   0   0   0   0   0   0   0   0   0   0 |   f = BCD
   0   0   0   0   0   2 122   0   0   0   0   0   0   0   0   0 |   g = BD
   0   0   0   0   0   0   0  66   0   0   0   0   0   0   0   0 |   h = ABC
   0   0   1   0   1   0   0   0 135   0   0   0   0   0   0   0 |   i = AD
   0   0   0   0   0   0   0   0   0 129   0   0   0   0   0   0 |   j = CD
   0   0   0   0   0   0   1   0   0   1  58   0   0   0   0   0 |   k = ABD
   0   0   0   0   2   0   0   1   0   0   0 148   0   0   0   0 |   l = AC
   0   0   0   0   1   0   0   0   0   0   0   0 127   0   0   0 |   m = AB
   1   0   0   0   0   0   0   0   0   0   0   0   0 128   0   0 |   n = BC
   0   0   0   0   0   0   0   0   0   0   0   0   0   0  30   0 |   o = ABCD
   0   2   0   0   0   0   0   0   0   0   0   0   0   0   0 303 |   p = B
```

Figure 4.7: KNN Confusion Matrix

From the above it can be concluded that the KNN algorithm scales well, is reliable and simple to implement in Python code.

4.9 Moving from Relational to Graph Think

4.9.1 Graph Properties

There are differences between Relational versus Graph ways of expressing data. While both systems can represent entities and relationships both systems are built differently. Relational databases optimise entities over the relationships between them, while Graph databases focus on the relationships that tie entities together. We will see how the latter feature becomes important in our case (Gosnell and Broecheler, 2020).

A graph represents data using two distinct elements: vertices and edges. A vertex stands for the entity or concept we want to represent, while an edge is the relationship linking entities together. The first term that shall be discussed is adjacency. Two nodes, or entities, are deemed to be adjacent to each other if they are connected through an edge. Edge connections also have directional properties. Directions may either not exist, or be unidirectional, or bidirectional. The direction property dictates the way one should traverse a graph. A graph that has its vertices connected via directional edges is called a directed graph (Gosnell and Broecheler, 2020).

These types of properties were noted to be useful when one starts to interpret data along a graph. Extending this property further, we can say connected entities form what are described as neighbourhoods. A neighbourhood a close relationship between entities, hence the data contained within somehow relates. The relationship being explained by the edge.

The further one traverses along a graph it would become apparent that a concept of distance will be experienced. That is entities may not be directly related, by the property of adjacency, but there would still be a connection, also known as a path, which enables one to understand the flow between entities.

The last concept that will be mentioned is the degree of a vertex. This describes how well connected a node in the graph is. This implies that the node would be an important topic or a basic concept necessary for other topics which are unrelated to themselves. An element with an extremely high value of connectivity is referred to as a super node (Gosnell and Broecheler, 2020).

4.9.2 Giving Meaning to Data

Vertices and edges should be named in meaningful ways, otherwise the whole concept of explanability will not hold well. Generally, data is described using a subject-predicate approach. Where facts, for instance, would be contained in entities and the edges contain the relationship. The latter being described by a verb preferably indicating direction. An example would be “owned by” or “owns” implying the way a relationship holds.

4.9.3 The Graph Database

Graphs are a very natural way of expressing relationships between entities. Moreover the theory behind graphs is very stable as they have been studied fro more than a century. With the recent introduction of NOSQL (Not Only SQL) databases, graphs are gaining even more prominence in the computer science world. As described in our methodology section we shall use Neo4j for our graph database environment. This will help in setting up a recommendation system with in-line explanation to the results. This way users are supplied with a justification to the conclusions of the algorithm. As described earlier on in this chapter, we shall use the input of the KNN as a primer towards the area of revision that a student needs. This may also be used by teachers to follow on students. For the purpose and scope of this experiment an arbitrary subject, namely:

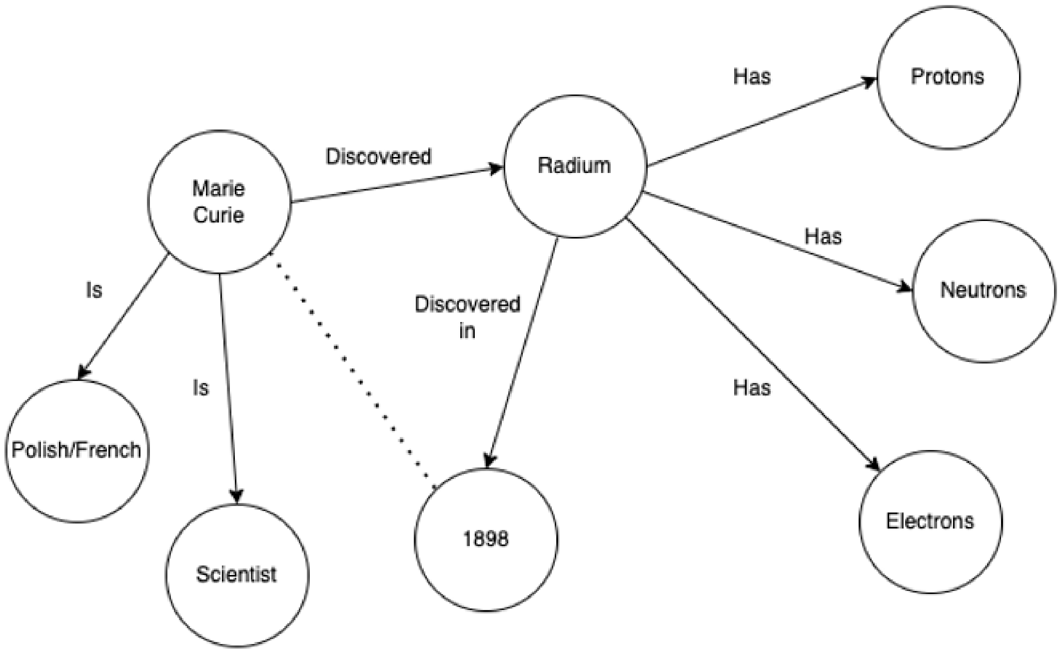


Figure 4.8: Data in Graph Form

Physics, was chosen to be our proof of concept case. This was purely an arbitrary choice as in reality graph databases do not discriminate the their content. During the first part of the exercise we shall describe the data upload and the relationship between each element in the database. Each element or subject is represented by a node in the database. Relationships are represented by edges that connect each nodes to each other. Relationships between nodes are directional so the resultant graph represented in Neo4j will be a directed graph. The data-structure could then be treated as a normal graph structure.

The graph above shows a simple schematic in Neo4j and how relationships are represented between each node. Also not the direction of the relationship between each node. Following the a path along a graph one can arrive at a conclusion plus the reason behind the conclusion. For example although there is no direct relationship between Marie Curie and the date 1898 we can infer that Radium was discovered by her in 1898. The above structure also allows for growth and new additions to the data-structure producing a highly-knit interrelated graph.

4.9.4 Scalability

Contrary to expectations reaction or retrieval time for a graph database remains quite constant. This because of two main properties of the database. First relations are part of the structure and do not need to be computed, just like in an SQL database, and second is that a query only acts on part of the graph rather than the whole. These two properties make data retrieval efficient and scaleable. The performance of a graph database is one of the reasons that a NOSQL database was chosen for this research. Relational databases are very join intensive and performance consequently decreases with the size if the database. As joins have to be computed. For our proof of concept experiment a desktop version of Neo4j was used. But for larger databases this can be replaced by could-based versions of Neo4j supported through Hadoop. The same functionality and properties are offered throughout, with the added benefit of Big Data support.

Database flexibility can be derived from the fact that NOSQL databases do not have a rigid pre-planned schema. This changes with the need of the database at time of use. New nodes, edges and sub-graphs can be added to the existing structure without disrupting the rest of the graph. In addition to this schema-free databases also do away with maintenance costs. In an education scenario, where teachers tend not to be too technical this could be of an advantage.

4.10 Setting Up the Data-Structure

For the first part of out experiment we converted a concept map into a graph. The environment was prepared for a Physics map. The data comprised a set of facts based on Newton's Laws of Motion and forces. Each entity was created manually using Neo4j's Cypher language with a script similar to the following:

CREATE (n name: 'Newton's Laws of Motion')

Each node n was given a label name to identify it from other nodes. Each node, then was given a relationship to other nodes whereby many of the nodes were linked. This produced a graph of facts linked together by various relationships. Thus the data structure now has meaning to it stored as part of the database, which is something that cannot be easily done using traditional SQL. Creating a relationship between nodes was also a tedious process. The following script was repeatedly used for such a purpose:

MATCH (f1:Fact), (f2:Fact)
WHERE f1.name = 'Forces' AND f2.name = 'Vectors'
CREATE (f1)-[r:ARE]->(f2)

This set up all nodes and relationships between nodes to form a graph. From the script above it can be seen that the graph is directional. It implies that that Forces are Vectors, but not all Vectors may be Forces. It is possible to program the bijection by adding a new CREATE statement to depict the reflexive relationship if needed. A full database schema can be observed in Appendix H on page 126. Once the map has been set up the patterns then start to emerge which can be analysed and followed through the database software. Thus making revision, and explanation easier to follow and maintain.

4.10.1 Predictive Analytics

Graphs tend to be very useful when it comes to prediction. The first principle we shall discuss to aid our predictions is the Triadic Closure Principle. This principle states that if two nodes are connected via a path passing through a third node the two nodes could become directly connected. Using this principle on the above graph we came to the conclusion that Marie Curie discovered Radium in 1898. Indirectly linking 1898 with the scientist. This principle is often seen in social media networks. This principle is a powerful principle when it comes to assisting users through their knowledge. This because data can be viewed in which ever way one wants, and moreover relationships are easily inferred. Learning graphs are more fluid than social graphs and predicting opportunities may be more challenging. Balancing trees or looking for closing biases would help discover more knowledge. To facilitate this relationships are not made equal. So one has to decide beforehand which relationships are weak and which are strong. Taking the previous graph as our example we note that Radium has Protons and Neutrons will not lead to closure directly relating Protons and Neutrons. Graph traversal can facilitate prediction and also assist in enhancing the results by retrieving rich information from a particular node.

4.10.2 Graph Traversal Algorithms

There are two reasons why one would need to traverse a path on a graph. One is an explicit search, the other is for knowledge discovery. Although these search algorithms have many uses such as reducing travel time or optimising route paths we shall use them in a novel way. Namely by interpreting the shortest path between A and B as closely related clusters of information. Two such algorithms to achieve this are the A* and Yen's algorithms to find the shortest connection between two nodes. One can also add the Minimum Spanning Tree algorithm which helps discover the least cost to travel between two nodes. There are other algorithms which can also be employed such as the breadth first or depth first search but they shall not be considered for two reasons, mainly because Neo4j does not support them, and secondly because they do not give significant advantage over other methods.

One idiosyncrasy that we have to deal with in knowledge graphs is that all single hops between nodes carry the same weight. So the calculation of optimal distance is based on the number of hops it takes to arrive from source to destination. Conversely we may deduce that the lower the degree of separation of nodes implies the closer the relationship between two nodes on the graph. One example that comes into mind is when using graph technology to describe social networks. The degree of separation is considered important in this case as one may infer that two people can know a third just because there is an indirect connection. In Neo4j the shortest path algorithm is used to compute both weighted and unweighted shortest paths. This is expressed as the follows:

MATCH (Source:factid:"Force")
(Destination: factid:"Newtons Laws of Motion")
CALL algorithm.shortestPath.Stream (Source, Destination, null)
YIELD nodeID, Cost
Return algorithm.getNodeById(nodeID).id as fact, cost

Fact	Cost
Force	0
Motion	1
Newton's Laws of Motion	2
Free Body Diagrams	1
Real world Applications	2

Table 4.3: Shortest Path Cost

In this case we are using the standard shortest path stream algorithm. This can be replaced, by changing the third line of code, using A* or Yen's algorithms. These algorithms are variations on the first. Yen's notably calculates the K shortest loop-less path in a network.

4.10.3 Centrality Theory

Shortest path algorithms help understand which nodes are close to each other, thus reinforcing or negating possible relationship. In addition to this centrality can tell us which nodes are more readily converted into sub-graphs. In other words centrality algorithms are used to understand roles of particular nodes in a graph and their importance on the network.

The degree of centrality is also an important concept necessary in explaining. This describes the most popular node in the network. This factor together with the reach of a node highlights the main points in networks. The reach of a node is the number of other nodes that can be influenced by particular nodes. This would mean the importance of a topic within a subject as many paths would be through the particular node. Another centrality measure that helps one understand the underlying information is called the closeness centrality. This describes which nodes are most likely to spread information, or in our case the nodes that are likely to have further attachments to them when designing a knowledge graph. These are the nodes best positioned or centralised in a graph.

Another variation to the problem may be seen through detached communities that develop within graphs as they organically grow. Communities bring up also relationships that would have otherwise gone unnoticed within networks and are essential to the identification of possible related topics. Such communities despite being detached can give insight into how knowledge is best acquired for better understanding.

4.10.3.1 Centrality in Context

This technique is useful to address proximity of isolated items or sub graphs and the way through which information could flow within the data structure. As time progresses on the database it is inevitable that sub structures start to form organically. So a method is needed to assess the relevance of whole or isolated topic areas, to areas of interest. To do this in Neo4J one has to call on one of several centrality algorithms, in our case the beta algorithm as shown below:

```
CALL gds.beta.closeness.stats(graphName: String,configuration: Map)
YIELD centralityDistribution: Map,
computeMillis: Integer,
postProcessingMillis: Integer,
preProcessingMillis: Integer,
configuration: Map
```

The beta algorithm was chosen because it is capable of identifying nodes that may easily spread information throughout a graph[2].

[2]https://neo4j.com/docs/graph-data-science/current/algorithms/closeness-centrality/

4.11 Formalising the Solution

After discussing the constituent parts of the proposed solution it would be fitting that each component be seen and described as part of a whole system. One of the objectives in our research is to gain insight into student performance so that we will be able to help students progress in their studies. And consequently reinforcing their interest in the subjects reducing the need to abandon their studies. In the case of an e-Learning course, the student cohort is expected to be quite large and dispersed without any possibility of uniting a whole class. This makes teacher follow-up quite hard and generally not entertained at all. Figure 4.9 describes the architecture proposed.

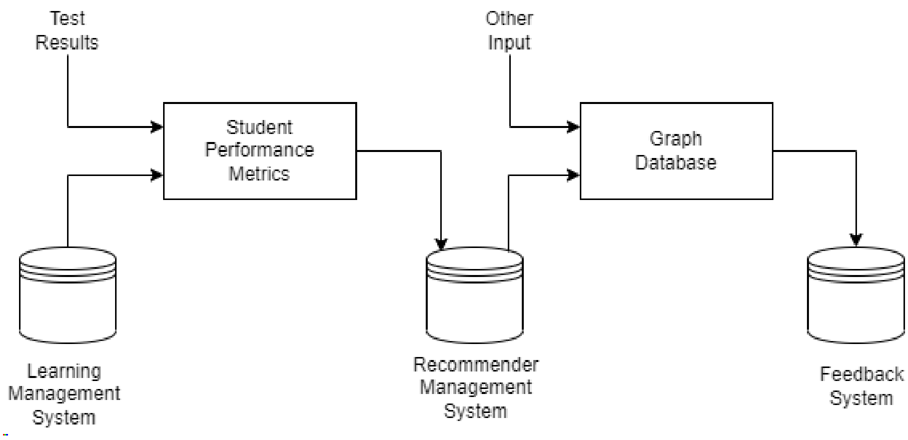


Figure 4.9: System Architecture

The model being proposed in this work does not to disturb the normal operations of daily work. With the use of MOOC, in our case Moodle, performance can be assessed, gathered and classified automatically. Naturally this would only be feasible where the student cohort is excessively large to manage. In the case for this study the cohort was arbitrarily placed at 3,000 members. We may divide the process into three distinct stages.

The best way to approach the addition to an already functioning system is to use software robots that would be able to extract data automatically with little to no human intervention. Robots can be of two types, assisted or non-assisted. In the first case a robot process could be triggered off by a user to extract and process data repeatedly on command. In the second case the robot could intervene autonomously at a prearranged time interval. The existing systems are not disturbed or modified in any way leaving the existing interface unmodified. Robots are gaining traction in today's world and are taking over many processes which would otherwise take up people's time. Moreover robots can be augmented with AI skills in order to add cognitive features to the robot such as taking decisions based on outcomes. The only downside to this is that Robot Software Automation carries a hefty price to purchase and implement.

The after data is extracted and cleaned the next process is to classify test results, this would cluster similarly performing students together. The pertinent data is picked off Moodle automatically, labelled and then classified.

A student's performance can then be compared with the overall class performance for proper categorisation. In the following stage will use the output of the previous stage by transforming categorisations into suggestions for the user highlighting the problem areas. At the third stage the user is directed onto a database which will extend the reach of the recommender system by supplying rich data to the user. The database is a graph-type database whereby all information is related in a similar way humans relate through experience. This will make the output of the data more easy to query and relatable. Concepts are stored as elements and are linked to one another. Each link offers an explanation as to why concepts are related together. This enriches the feedback given as concepts are supported by explanations.

Both students and teachers are allowed to add new information, but a moderator to the data must exist so as to ensure correctness and follow students up. This also addresses the need of the self-assistance of students which ultimately helps keep them engaged.

4.12 Comparison to Existing Systems

Existing systems that can be commercially available are on the increase. The most notable of them are IBM Watson and Explainable AI Google Cloud but both Google and IBM do not produce education specific produces. Generally What APIs are supplied to expose the internal working of their systems making them available to programmers wishing to leverage on ready made generic technology. The employment of explanation techniques to induce commitment within educational programmes is a novel idea.

4.12.1 IBM Watson Open Scale

Through their explainable AI initiative IBM offer a generic package which enables users to leverage the power of their software to enhance conclusions derived from algorithms. The power of the Watson platform has been amply demonstrated by IBM many a time. IBM take the approach of AI models understanding the inherent relationships between data elements residing in databases. This is undoubtedly useful, as most of the spadework is done automatically. Humans on the other hand are left with the task of interpreting the output. Essentially IBM Watson is aimed at facilitating model interpretation when it comes to the analysis of big data. Insights into the underlying relationships are can be gained by tuning Watson to explore different possibilities or outcomes withing a given data set.

Although quite a powerful tool, Watson's core competence seems to be aimed at the non-trivial problem of data mining. This does not sustain the argument of this theses as what is needed in our case is a human-like explanation to human knowledge and conclusions.

4.12.2 Explainable AI Google Cloud

In November 2019, Google added an explainable AI service to their already rich portfolio. This service is designed to analyse models put into production by developers. It helps developers understand what factors in the training sets are biasing the outcomes. As discussed earlier in this work, few seem to agree on a common definition of what explainability is. Regardless of which approach one takes, all have value. The most common approach is that of enhancing model transparency though rather than direct, non technical human assistance.

4.12.2.1 Microsoft Azure

Microsoft's on-line platform has grown to be a world leading cloud computing service. It offers around 600 options to users ranging from a wide variety of development tools to frameworks. One of these services is called model interpretation. It offers nine techniques, through the library azureml.interpret, based on SHAP model variations. Just like its competitors Microsoft looks at interpretation as AI model transparency.

4.12.3 Others

Other companies like Data Robot and H20 Driverless AI also offer similar software as services, SaaS. The common focus being that of assisting data analysts tune their models to a high degree [3].

4.13 Chapter Conclusion

We have seen in this chapter how to convert data models into graphs which attenuate relationships in such a way as to make them part of the information itself. These relation-

[3] https://www.getapp.com/resources/5-toolkits-to-build-explainable-AI/

ships benefit machine learning greatly as now we have an option to codify understanding into the data itself. Thus graph-enhanced machine learning can greatly contribute towards contextual information aiding better decisions. Moreover the necessity of more powerful algorithms that keep track of logic to induce explanation is unnecessary at best. Relationships between data elements are strong predictors of behaviour which contribute to exerting influence on one another. Adding layers to a graph will boost machine learning in the explanation world because of the access to connected data will make outcomes richer.

When one takes a glimpse at what the leading technology companies are doing it is evident that the direction is towards algorithm transparency which in turn assists the analyst in properly tuning models for use in industry. This can be seen from a list of leading AI manufacturing companies, none of which exploit the possibility of using AI in fostering learning commitment[4].

[4] https://www.ventureradar.com/keyword/Explainable%20AI

5 Conclusions

5.1 Chapter Introduction

This work has finally arrived to its closure where the lessons learnt, conclusions and future directions shall be resented. Starting by a discussion on the hypothesis put forward at the start of this work and the necessary evaluation put forward to support it.

During the course of this work new ways of assisting students to maintain their commitment to e-learning have been proposed and studied. Without doubt this is not the final word, but this work took on a unique direction and suggested a novel way as to instil interest in people. The main approach to the thesis was based on the premise that people normally scaffold instruction and information. Learning is based in mentally linked facts in people's mind and perspectives. This ability to link naturally was not observed in the way many material is presented in e-learning environments that have been seen during the course of this work. Conversely we have decided to try to come up with a novel approach enabling to link information in such a way as to help people maintain their interest in the courses they are doing on-line.

The recent years, especially due to COVID-19, have shown that although on-line teaching is technically possible, but the remote human contact and the teaching methodology did not engage students enough. This work focused more on the technological aspect rather than the sociological one. So given that if sufficiently helped people can remain motivated, the work focused on finding a way to address the lack. Focusing on whether technology can bridge the gap.

5.2 Achieved Aims and Objectives

Let us commence by revisiting the research question and objectives. As stated in our introductory chapter the research question is as follows:

What technological assistance can be given to adult students in an e-learning environment to help them maintain motivation?

In addition to the research question, a number of objectives were also put forward, namely:

- Introducing human-line explanations to conclusions derived from algorithms;
- Re-arranging information in such a way as to facilitate explanation;
- Removing rigid constraints on knowledge databases;
- Automatically identifying student weakness and prompting assistance.

From the Results and Discussion chapter a number of proposals were put forward addressing the aims of this work. By using of Artificial Intelligence, Graph Theory and software a proof of concept was set up giving flexibility and explainability to the answers that many a student need on their learning journey. Student's performance measures are grouped with those of other students with similar capabilities. The outcomes of which are then used to retrieve the relative information from a Graph Database. The graph database provides human explanation by containing all the necessary information at nodes and edges that lead to other nodes. Thus delivering the necessary relational information across data. This addresses most of the objectives as information needs to be accessible, flexible and useful. This setup also allows educators to follow on students even if the cohort is too large to handle. And they are able to focus where the issues are.

It was also shown that, students could also be directed to further material to assist them in the learning journey. As the resultant information has been organised in such a way to facilitate understanding and explanation. At this point in time it is unwise to suggest the removal of human interaction from the loop. The proposition put forward is intended to do only the heavy lifting. Highlighting the pain points and assisting the human teacher in collaboration with the student to fill in the gaps.

Whilst going through this work it was also noted that one can look at the problem from a different perspective (Mallia-Milanes and Montebello, 2021). The lack of understanding, connection or motivation can also be due to issues in teaching methods or materials. If most of the students in the class are found to be failing to understand specific concepts then it should be the teacher who changes tack to suit or adapt the material in a better way as to reach the student. This point of view was not apparent to me until I managed to see the potential through outcomes from software that has been developed for the purpose of this contribution (Mallia-Milanes and Montebello, 2021). This point of view is both compelling and interesting. Whilst in a normal classroom setting the educator can adjust and revise material to make sure that the learning outcomes have been reached. In a complete virtual setting this is not readily possible as the lack of direct communication between teacher and student. This is compounded by the size and variety of the class. Although the physical realm of learning will not be abandoned any time soon, COVID-19 has forced us to become aware of the potential reach, even financial gains, of an on-line course. Courses devoted to the masses are more than a service. It hardly needs showing that on-line courses are accessible, relatively cheaper to run and need less intervention on the educator's part once set up. But as any educator knows that the act of teaching does not exclusively comprise the imparting of knowledge. Following up with the student in a constructive way is part of the process too. And this is precisely what this thesis has tried to approach.

All the software used in this work were open source versions of popular software such as Python and Neo4j. Apart from assisting me in keeping costs down it should also act as an encouragement to cash-strapped, but willing, institutions to try to assist their students in any way possible.

5.3 Critique and Limitations

The outcome of this work has been supported by software tools in common usage. Building a complete prototype would have been an overkill in order to support the premise of this thesis. It can be added that educational institutions are reluctant to move in the direction of electronic assistance to students. This lack of inertia to embrace technology, especially in Malta, has still to be overcome. Various studied have shown (Montebello, 2016) that students still prefer face-to-face learning. And that is mainly because a healthy discourse that can be conducted in class.

But as it is very common that adults try to learn new skills while working full time jobs. The role e-Learning plays cannot be ignored principally because of its reach, accessibility and price. As Montebello aptly states e-Learning should not be considered as a replacement to physical act of teaching and learning (Montebello, 2016). This work moved in the direction of proposing augmentation rather than replacement. From the research done for this work, it is felt that the temptation to overlook human involvement seemed interesting but was not entertained. Especially in the light that electronic media were trust hastily into the foreground because of the COVID-19 pandemic. It must be emphasised that the effectiveness of media is not a panacea. Preparation and proper delivery must still prevail despite the media. Just as one expects that that badly prepared physical lesson can still harm the learning process. Now that e-Learning has proved itself and the demand for remote learning has far-exceeded the supply, we cannot ignore it as a tool. e-Learning sessions backed up by proper pedagogy and sound planning could be just as effective as a physical lesson.

The methods proposed in this text do not address proper preparation, this is still the job of the educator. The proposal attempts to suggest that if used properly technology can be used to address the falling attention span and commitment of students. This has been shown to be possible by creating a system where students can be directed to their weaknesses and helped on by reinforcing their needs in a way they can understand. Finding an institution that is prepared to invest and develop such an approach is difficult at best. Primarily because a lot of time and money are required to go beyond the proof of concept we are proposing. Although e-learning can be a profitable proposal to many an institution the hassle of setting up shop still needs to be overcome.

A fact that may have affected this study is the lack of physical data collected. There were many reasons behind this, namely that behaviour and markings were not made available in the large quantities that was required. It would have been interesting to see if people really reacted better to the fact that they were given systems that followed them in a more personal way rather than a one size fits all situation found on many e-learning sites.

5.4 Future Work

This research shows that technology can assist people learning and becoming more committed when material is presented in such a way that is natural to the student. This would possibly spawn more parallel studies that may actually build a complete system used to assist students in their learning journey. Giving people the necessary “crutch” to support their learning. Moreover as we grow more accustomed to get support from computer systems it would be interesting to see the psychological effects on students being mentored remotely or automatically by machines. A further step which is attracting attention is the use of chat bots. The idea of assistance being supported by natural language interaction would surely humanise help and increase commitment. Language technologies have matured enough to hold conversation with people and satisfy their needs. Application to education would be both beneficial and interesting.

5.5 Evaluating the System

Another avenue of study that would certainly proves useful would be that of evaluating the effectiveness of the proposed solution on willing human participants. Evaluating such a setup is not an easy task. Apart from the necessity of getting people on board, both the student and school administration, one has to allow time to accumulate data and follow on students to measure the benefits reaped. Nevertheless it would be a good opportunity to be able to follow on the effectiveness of the proposal set forward in this thesis.

The necessary software and hardware are already present in most educational institutions, the addition of a knowledge base would be the only hurdle as this would take time to develop to a useful state. This could possibly be substituted with ready-made open knowledge bases such as Google's knowledge graph or the Open Knowledge Graph from the Open University.

The setup should be prepared to take care of the following:

- Material Preparation
- Follow up and regular classification of student performance and behaviour
- Pushing back enhanced explanation
- Comparing the outcome against courses that are equally prepared but do not offer support

Such studies take time to setup and evaluate properly. Moreover participation from students is essential together with the by-in from school administration and proper preparation. Such a system could be implemented, with the student's consent, on on-line courses as a self help mechanism, comparing the outcome to other courses which do not offer the same level of help.

5.6 Revisiting Agency & Collaboration

Going back to the title of this work Agent-Assisted Collaborative Learning it is worth spending some reflection on this too. A complete system would work collaboratively with a student. Collaboration with peers is certainly essential to learning, once this cannot be achieved in a virtual environment but can be simulated through the feedback such a system gives. Agency on the other hand is given through the whole system that takes on the role of the human teacher by guiding the student through.

5.7 Final Remarks

This work has been but a minute contribution towards suggesting the viability of assisting large cohorts automatically. The availability of software that manages course curricula by supporting material is amply available. Interactivity is the next step that should be entertained. And it can be done. Pedagogy in combination with various tried and tested theories of learning and teaching would be pretty useless without the support to the student. Naturally, support is medium independent. If not there, learning will be surely hindered. The new-found dependence on technological media necessitates the inclusion of individualised support too. The initial hypothesis of this work as shown can be summed up by saying that support for students is crucial to learning, and can be supported by:

- Designing material in such a way as to allow for scaffolded learning
- Allowing the student to move along the learning experience at his own pace
- Supporting the pace by including methods that offer a natural way to understanding
- Removing all linear relationships between concepts and replacing them by a fluid, in-built, relations that also enrich data or material concepts being produced.

.

In going through this six year journey many obstacles have been experienced which only served as a personal learning experience. My appetite has been whetted to further understand the complex relationship between man and machine. And how to facilitate this unnatural union. It cannot claimed that this work would be the final chapter in research, but only one that may open new doors to further research enhancing ways we can leverage technology to reach and support students.

References

Data science driven recommender systems in the post-covid era, 2020. URL https://www.dasca.org/world-of-big-data/article/data-science-driven-recommender-systems-in-the-post-covid-era.

Abdollahi, B. and Nasraoui, O. Explainable restricted boltzmann machines for collaborative filtering. 2016.

Adadi, A. and Berrada, M. Peeking inside the black-box: A survey on explainable artificial intelligence (xai). *IEEE Access*, 6: 52138–52160, 2018. ISSN 21693536. doi: 10.1109/ACCESS.2018.2870052.

Adadiand, A. and Berrada, M. Ieee xplore full-text pdf:. *IEEE Xplore*, 6:52138 – 52160, 2018.

Aggarwal, C. C. *Recommender Systems: The Text Book*. Springer International Publishing, 2016.

Akula, A., Liu, C., Todorovic, S., Chai, J., and Zhu, S.-C. Explainable ai as collaborative task solving. *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops*, pages 91–94, 2019.

AlDahdouh, A. A., Osorio, A. J., and Caires, S. Understanding knowledge network, learning and connectivism. *International Journal of Instructional Technology and Distance Learning*, 12:3–22, 2015.

Alonso-Mencía, M. E., Alario-Hoyos, C., and Maldonado-Mahauad, J. Educational review self-regulated learning in moocs: lessons learned from a literature review. 2019. ISSN 1465-3397. doi: 10.1080/00131911.2019.1566208.

Amiotte, S. *The Turkish online journal of distance education : TOJDE*, volume 6. Anadolu University, 2000. URL http://journaldatabase.info/articles/designing_instruction_for_traditional.htmlhttp://dergipark.ulakbim.gov.tr/tojde/article/view/5000102864/5000095959.

Anderson, A., Huttenlocher, D., Kleinberg, J., and Leskovec, J. Engaging with massive online courses. *WWW '14 Proceedings of the 23rd international conference on World wide web*, pages 687–698, 2014. ISSN 14923831. doi: 10.1145/2566486.2568042.

Anjomshoae, S., Calvaresi, D., Najjar, A., and Främling, K. Explainable agents and robots: Results from a systematic literature review. *Proceedings of the International Joint Conference on Autonomous Agents and Multiagent Systems, AAMAS*, 2:1078–1088, 2019. ISSN 15582914.

Aoun, J. E. *Robot-proof: Higher education in the age of artificial intelligence*. MIT Press, 2017. ISBN 9780262344319. doi: 10.1080/02607476.2018.1500792.

Arrieta, A. B., Díaz-Rodríguez, N., Ser, J. D., Bennetot, A., Tabik, S., Barbado, A., García, S., Gil-López, S., Molina, D., Benjamins, R., Chatila, R., and Herrera, F. Explainable artificial intelligence (xai): Concepts, taxonomies, opportunities and challenges toward responsible ai. 10 2019.

Arrieta, A. B., Díaz-Rodríguez, N., Ser, J. D., Bennetot, A., Tabik, S., Barbado, A., Garcia, S., Gil-Lopez, S., Molina, D., Benjamins, R., Chatila, R., and Herrera, F. Explainable explainable artificial intelligence (xai): Concepts, taxonomies, opportunities and challenges toward responsible ai. *Information Fusion*, 58:82–115, 2020. ISSN 15662535. doi: 10.1016/j.inffus.2019.12.012.

Baidada, M., Mansouri, K., and Poirier, F. Personalized e-learning recommender system to adjust learners' level. *EdMedia+*

Innovate Learning, pages 1353–1357, 2019.

Barrett, S., Stone, P., Kraus, S., and Rosenfeld, A. Learning teammate models for ad hoc teamwork. *AAMAS Adaptive Learning Agents (ALA) Workshop*, pages 57–63, 2012.

Bates, B. *Learning Theories Simplified*. Sage Publications, 2nd edition, 2015. ISBN 1473925320. doi: 978-1-47392-533-5.

Batmaz, Z., Yurekli, A., Bilge, A., and Kaleli, C. A review on deep learning for recommender systems: challenges and remedies. *Artificial Intelligence Review*, 52:1–37, 2019a. ISSN 15737462. doi: 10.1007/s10462-018-9654-y.

Batmaz, Z., Yurekli, A., Bilge, A., and Kaleli, C. A review on deep learning for recommender systems: challenges and remedies. *Artificial Intelligence Review*, 52:1–37, 2019b. ISSN 15737462. doi: 10.1007/s10462-018-9654-y.

Baturay, M. H. Sciencedirect an overview of the world of moocs. *Procedia - Social and Behavioral Sciences*, 174:427–433, 2015. ISSN 18770428. doi: 10.1016/j.sbspro.2015.01.685.

Benhamdi, S., Babouri, A., and Chiky, R. Personalized recommender system for e-learning environment. *Education and Information Technologies*, 22:1455–1477, 2017. ISSN 15737608. doi: 10.1007/s10639-016-9504-y.

Bogers, T. and Bosch, A. V. D. *Collaborative and content-based filtering for item recommendation on social bookmarking websites*, volume 532. 2009. ISBN 978-0-387-85819-7. doi: 10.1007/978-0-387-85820-3.

Bohlender, D. and Köhl, M. A. Towards a characterization of explainable systems. pages 2–3, 2019.

Bradshaw, J. M., Dignum, V., Jonker, C., and Sierhuis, M. Human-agent-robot teamwork. *IEEE Intelligent Systems*, 27:8–13, 2012. doi: 10.1109/MIS.2012.37.

Branley-Bell, D., Whitworth, R., and Coventry, L. User trust and understanding of explainable ai: Exploring algorithm visualisations and user biases. volume 12183 LNCS, pages 382–399. Springer, 7 2020. ISBN 9783030490645. doi: 10.1007/978-3-030-49065-2_27. URL https://doi.org/10.1007/978-3-030-49065-2_27.

Bromberger, S. On what we know we don't know: Explanation, theory, linguistics, and how questions shape them. *Anthropological Linguistics*, 36:260–262, 1994.

Burge, J. Insights into teaching and learning : Reflections on mooc experiences. *SIGCSE '15 Proceedings of the 46th ACM Technical Symposium on Computer Science Education. ACM*, pages 600–603, 2015. doi: 10.1145/2676723.2677243. A very good paper, worth citing and using as a primer.

Burrell, J. How the machine 'thinks': Understanding opacity in machine learning algorithms. doi: 10.1177/2053951715622512.

Calleja, J. The evolution of education in malta. a philosophy in the making. *Revue du monde musulman et de la Mediteranee*, pages 185–197, 1994.

Cambo, S. A. and Gergle, D. *User-Centred Evaluation for Machine Learning*. 2018. ISBN 9783319904023. doi: 10.1007/978-3-319-90403-0_16.

Carvalho, D., Pereira, E., and Cardoso, J. Machine learning interpretability: A survey on methods and metrics. *Electronics (Switzerland)*, 8, 2019. ISSN 20799292. doi: 10.3390/electronics8080832.

Chia, H. X. In machines we trust: Are robo-advisers more trustworthy than human financial advisers? *Law, Technology and Humans*, pages 129–141, 2019. doi: 10.5204/lthj.v1i0.1261.

Ciatto, G., Schumacher, M. I., Omicini, A., and Calvaresi, D. Agent-based explanations in ai: Towards an abstract framework. volume 12175 LNAI, pages 3–20. Springer, 5 2020. ISBN 9783030519230. doi: 10.1007/978-3-030-51924-7_1. URL https://doi.org/10.1007/978-3-030-51924-7_1.

Cocarascu, O., Rago, A., and Toni, F. Explanation via machine arguing. volume 12258 LNCS, pages 53–84. Springer Science and Business Media Deutschland GmbH, 6 2020. ISBN 9783030600662. doi: 10.1007/978-3-030-60067-9_3. URL https://doi.org/10.1007/978-3-030-60067-9_3.

Cooper, S. and Sahami, M. Reflections on stanford's moocs. *Communications of the ACM*, 56:3–5, 2013. ISSN 00010782. doi: 10.1145/2408776.2408787. This paper does not discuss the failing retention rate of students. It optimistically focusses on their potential as teaching methods. But hints that there are many challenges faced and need research to hopefully surmount the issues faced. The thing that I liked most is that MOOCS are here to stay, a sort of works-in-progress, and that they will not replace the teacher, but augment him.

Covington, P., Adams, J., and Sargin, E. Deep neural networks for youtube recommendations. pages 191–198. Association for Computing Machinery, Inc, 9 2016. ISBN 9781450340359. doi: 10.1145/2959100.2959190.

Daniel, J. Making sense of moocs: Musings in a maze of myth, paradox and possibility. *Journal of Interactive Media in Education*, 2012:18, 2012. ISSN 1365-893X. doi: 10.5334/2012-18.

DARPA. Broad agency announcement: Explainable artificial intelligence (xai). pages 1–52, 2016. ISSN 15580644. doi: 10.1109/36.210458.

Dascalu, M. I., Bodea, C. N., Moldoveanu, A., Mohora, A., Lytras, M., and Pablos, P. O. D. A recommender agent based on learning styles for better virtual collaborative learning experiences. *Computers in Human Behavior*, 45:243–253, 2015. ISSN 07475632. doi: 10.1016/j.chb.2014.12.027.

Deeks, A. The judicial demand for explainable artificial intelligence. *Columbia Law Review*, 119:1829–1850, 2019. ISSN 00101958.

Demajo, L. M., Vella, V., and Dingli, A. An explanation framework for interpretable credit scoring. *International Journal of Artificial Intelligence and Applications (IJAIA)*, 12:19–38, 2021. doi: 10.5121/ijaia.2021.12102.

Deschênes, M. Recommender systems to support learners' agency in a learning context: a systematic review. *International Journal of Educational Technology in Higher Education*, 17, 2020. ISSN 23659440. doi: 10.1186/s41239-020-00219-w.

Dietmar, J., Zanker, M., Felfernig, A., and Friedrich, G. *Recommendation system -An Introduction*, volume 91. 2010. ISBN 978-0-521-49336-9. URL http://scholar.google.com/scholar?hl=en&btnG=Search&q=intitle:No+Title#0.

Doshi-Velez, F. and Kim, B. Towards a rigorous science of interpretable machine learning. 2017.

Dosilovic, F. K., Brcic, M., and Hlupic, N. Explainable artificial intelligence: A survey. pages 210–215. Institute of Electrical and Electronics Engineers Inc., 6 2018. ISBN 9789532330977. doi: 10.23919/MIPRO.2018.8400040.

Drachsler, H., Verbert, K., Santos, O. C., and Manouselis, N. Panorama of recommender systems to support learning. *Recommender Systems Handbook, Second Edition*, pages 421–451, 2015. doi: 10.1007/978-1-4899-7637-12.

Drachsler, H., Bogers, T., Vuorikari, R., Verbert, K., Duval, E., Manouselis, N., Beham, G., Lindstaedt, S., Stern, H., Friedrich, M., and Wolpers, M. Issues and considerations regarding sharable data sets for recommender systems in technology enhanced learning. *Procedia Computer Science*, 1:2849–2858, 2010. ISSN 18770509. doi: 10.1016/j.procs.2010.08.010.

Driscoll, A. *To MOOC or not to MOOC: How can online learning help to build the future of higher education? by Sarah Porter*, volume 28. 2016. ISBN 0081000618. doi: 10.1080/00049670.2016.1183469. URL http://www.against-the-grain.com.

Du, M., Liu, N., and Hu, X. Techniques for interpretable machine learning. *Communications of the ACM*, 63:68–77, 2020. ISSN 15577317. doi: 10.1145/3359786.

Dunin-Keplicz, B. and Verbrugge, R. *Teamwor in Multi-Agent Systems: A Formal Approach*. John Wiley Sons Ltd, 1st edition, 2010. ISBN 978-0-470-69988-1.

Díez, J., Khalifa, K., Leuridan, B., Díez, J., Khalifa, K., and Leuridan, B. General theories of explanation: buyer beware. *Synthese*, 190:379–396, 2013. doi: 10.1007/s11229-011-0020-8.

Erkens, M. and Bodemer, D. Improving collaborative learning: Guiding knowledge exchange through the provision of information about learning partners and learning contents. 2018. doi: 10.1016/j.compedu.2018.10.009.

Escalante, H. J., Escalera, S., Guyon, I., Baró, X., Güçlütürk, Y., Güçlü, U., and van Gerven, M. *Explainable and Interpretable Models in Computer Vision and Machine Learning (The Springer Series on Challenges in Machine Learning)*. 2018. ISBN 978-33-1998-130-7. URL http://www.springer.com/series/15602.

Evans, S. and Myrick, J. G. How mooc instructors view the pedagogy and purposes of massive open online courses. *Distance Education*, 36, 2015. ISSN 14750198. doi: 10.1080/01587919.2015.1081736.

Fan, X., chun Chun Chen, P., and Yen, J. Learning hmm-based cognitive load models for supporting human-agent teamwork. *Cognitive Systems Research*, 11:108–119, 2010. ISSN 13890417. doi: 10.1016/j.cogsys.2008.08.004.

Fandinno, J. and Schulz, C. Answering the "why" in answer set programming - a survey of explanation approaches. *Theory and Practice of Logic Programming*, 19:114–203, 2019. ISSN 14753081. doi: 10.1017/S1471068418000534.

Farrow, R., de los Arcos, B., Pitt, R., and Weller, M. Who are the open learners? a comparative study profiling non-formal users of open educational resources. *European Journal of Open, Distance and E-Learning*, 18:50–74, 2015. ISSN 1027-5207. doi: 10.1515/eurodl-2015-0013.

Freitas, S. D. Review of e-learning theories , frameworks and models jisc e-learning models desk study. pages 0–43, 2013.

Frey, B. B. Zone of proximal development, 2018. URL http://www.innovativelearning.com/educational_psychology/development/zone-of-proximal-development.html.

Fu, Q. K. and Hwang, G. J. Trends in mobile technology-supported collaborative learning: A systematic review of journal publications from 2007 to 2016. *Computers and Education*, 119:129–143, 2018. ISSN 03601315. doi: 10.1016/j.compedu.2018.01.004.

Galitsky, B., Galitsky, B., and Goldberg, S. Explainable machine learning for chatbots, 2019. URL https://doi.org/10.1007/978-3-030-04299-8_3.

Garrison, R. D. *IE-learning in the 21st century: A framework for research and practice*. 3rd edition, 2017. ISBN 0415263468. doi: 10.4324/9780203838761.

Gauci, A. Machine learning for mega-dimensional data. 2014.

Gilpin, L. H., Bau, D., Yuan, B. Z., Bajwa, A., Specter, M., and Kagal, L. Explaining explanations: An overview of interpretability of machine learning. pages 80–89, 2019a. ISBN 9781538650905. doi: 10.1109/DSAA.2018.00018. URL http://www.aiindex.org/2017-report.pdfhttp://arxiv.org/abs/1901.06560.

Gilpin, L. H., Testart, C., Fruchter, N., and Adebayo, J. Explaining explanations to society. 2019b.

Gomez-Uribe, C. A. and Hunt, N. The netflix recommender system. *ACM Transactions on Management Information Systems*, 6:1–19, 2015. ISSN 2158656X. doi: 10.1145/2843948.

Goodman, B. and Flaxman, S. European union regulations on algorithmic decision making and a "right to explanation". *AI Magazine*, 38:50–57, 2017. ISSN 07384602. doi: 10.1609/aimag.v38i3.2741.

Google. Ai explainability whitepaper about this whitepaper. pages 1–27, 2019.

Gosnell, D. K. and Broecheler, M. The practitioner's guide to graph data applying graph thinking and graph technologies to solve complex problems, 2020.

Groom, V. and Nass, C. Can robots be teammates?: Benchmarks in human–robot teams. *Interaction Studies*, 8:483–500, 2007. ISSN 1572-0373. doi: 10.1075/is.8.3.10gro.

Gunning, D. and Aha, D. W. Darpa's explainable artificial intelligence program deep learning and security. *AI Magazine*, pages 44–59, 2019. ISSN 0738-4602.

Guo, W. Explainable artificial intelligence for 6g: Improving trust between human and machine. *IEEE Communications Magazine*, 58:39–45, 2020. ISSN 15581896. doi: 10.1109/MCOM.001.2000050.

Guy, T. V., Kárný, M., and Wolpert, D. H. *SCI 474 - Decision Making and Imperfection*. Springer Berlin Heidelberg, 2013.

ISBN 9783642364051.

Hacker, P., Krestel, R., Grundmann, S., and Naumann, F. Explainable ai under contract and tort law: legal incentives and technical challenges. *Artificial Intelligence and Law*, 28:415–439, 12 2020. ISSN 15728382. doi: 10.1007/s10506-020-09260-6.

Hagenbuchner, M. The black box problem of ai in oncology. *Journal of Physics: Conference Series*, 1662:12012, 2020. doi: 10.1088/1742-6596/1662/1/012012.

Hagras, H. Toward human-understandable, explainable ai. *Computer*, 51:28–36, 2018. ISSN 15580814. doi: 10.1109/MC.2018.3620965.

Halonen, I. and Hintikka, J. Toward a theory of the process of explanation. *Synthese*, 143:5–61, 2005. ISSN 00397857. doi: 10.1007/s11229-005-3113-4.

Hara, S. and Hayashi, K. Making tree ensembles interpretable. 6 2016.

Hilton, D. J. Conversational processes and causal explanation. *Psychological Bulletin*, 107:65–81, 1990. ISSN 00332909. doi: 10.1037/0033-2909.107.1.65.

Hind, M. Explaining explainable ai. *XRDS: Crossroads, The ACM Magazine for Students*, 25:16–19, 2019. ISSN 1528-4972. doi: 10.1145/3313096.

Hoff, K. A. and Bashir, M. Trust in automation: Integrating empirical evidence on factors that influence trust. *Human Factors*, 57:407–434, 5 2015. ISSN 15478181. doi: 10.1177/0018720814547570.

Hoffman, R. R., Mueller, S. T., Klein, G., and Litman, J. Metrics for explainable ai: Challenges and prospects. pages 1–50, 2018.

Holzinger, A. From machine learning to explainable ai. *DISA 2018 - IEEE World Symposium on Digital Intelligence for Systems and Machines, Proceedings*, 2018. doi: 10.1109/DISA.2018.8490530.

Jaldemark, J., Hrastinski, S., Olofsson, A. D., and Öberg, L. M. Editorial introduction: Collaborative learning enhanced by mobile technologies. *British Journal of Educational Technology*, 49:201–206, 2018. ISSN 14678535. doi: 10.1111/bjet.12596.

Jannach, D. and Zanker, M. *Recommender Systems: An Introduction*. Oxford University Press, 2011.

Jung, E., Kim, D., Yoon, M., Park, S., and Oakley, B. Computers education the influence of instructional design on learner control , sense of achievement , and perceived effectiveness in a supersize mooc course. *Computers Education*, 128: 377–388, 2019. ISSN 0360-1315. doi: 10.1016/j.compedu.2018.10.001.

Kane, F. *Building Recommender Systems*. Sundog Education, 2018. ISBN 9781718120129.

Kelly, J. Collaborative learning: Higher education, interdependence, and collaborative learning: Higher education, interdependence, and the authority of knowledge the authority of knowledge by kenneth bruffee: A critical study by kenneth bruffee: A critical study. URL https://digitalcommons.unl.edu/nchcjournal.

Kindermans, P.-J., Schütt, K. T., Alber, M., Müller, K.-R., Erhan, D., Kim, B., and Dähne, S. Learning how to explain neural networks: Patternnet and patternattribution. 5 2017.

Krötzsch, M., Stepanova, D., and Goos, G. *Reasoning Web. Explainable Artificial Intelligence*, volume 1. 2019. ISBN 9783030314224. doi: 10.1007/978-3-030-31423-1. URL http://dx.doi.org/10.1007/978-3-030-31423-1_4.

Kuusisaari, H. Teachers at the zone of proximal development e collaboration promoting or hindering the development process. 2014. doi: 10.1016/j.tate.2014.06.001.

Latour, B. Reassembling the social: an introduction to actor-network-theory - proquest, 2005a. URL https://search-proquest-com.ejournals.um.edu.mt/docview/839134206?rfr_id=info%3Axri%

2Fsid%3Aprimo.

Latour, B. *Reassembling the Social - An Introduction to ANT*, volume 53. 2005b. ISBN 9788578110796. doi: 10.1017/CBO9781107415324.004.

Lawless, W. F., Mittu, R., Sofge, D., and Hiatt, L. Artificial intelligence, autonomy, and human-machine teams: Interdependence, context, and explainable ai, 2019. ISSN 07384602.

Learn, S. Scikit learn library reference, 2 2022. URL https://scikit-learn.org/stable/getting_started.html.

Lee, J. D. . and See, K. A. Trust in automation: Designing for appropriate reliance, 2004.

Liang, C., Proft, J., Andersen, E., and Knepper, R. A. Implicit communication of actionable information in human-ai teams. 2019. ISBN 9781450359702. doi: 10.1145/3290605.3300325. URL https://doi.org/10.1145/3290605.3300325.

Lim, B. Y., Yang, Q., Abdul, A., and Wang, D. Why these explanations? selecting intelligibility types for explanation goals. *CEUR Workshop Proceedings*, 2019. ISSN 16130073.

Lu, Y., Dong, R., and Smyth, B. Why i like it: multi-task learning for recommendation and explanation. *Proceedings of the 12th ACM Conference on Recommender Systems - RecSys '18*, pages 4–12, 2018. doi: 10.1145/3240323.3240365.

Lü, L., Medo, M., Ho, C., cheng Zhang, Y., and ke Zhang, Z. Recommender systems. *Physics Reports*, 519:1–49, 2012. ISSN 0370-1573. doi: 10.1016/j.physrep.2012.02.006.

M, G., V, A., and S, M.-M. Nc-nd license concept attribution: Explaining cnn decisions to physicians . *Computers in Biology and Medicine*, 123:103865, 2020. doi: 10.1016/j.compbiomed.2020.103865.

Mallia-Milanes, M. and Montebello, M. Agent-assisted collaborative learning using agent teamwork as a collaborative method to facilitate e-learning. *Icaart*, 2017.

Mallia-Milanes, M. and Montebello, M. Crowdsourced recommender system. *4th International Conference on Higher Education Advances (HEAd'18) Universitat Politecnica de Valencia, Valencia, 2018*, pages 497–503, 2018. doi: 10.4995/head18.2018.8020.

Mallia-Milanes, M. and Montebello, M. Enhancing educators' credibility in intelligent learning environments. volume 53, pages 625–629. inScience Press, 2021. ISBN 978-989-54815-8-3. URL http://end-educationconference.org/proceedings/.

Marcuse, H. Herbert marcuse's "review of john dewey's logic: The theory of inquiry". *Transactions of the Charles S. Peirce Society*, 46:258–265, 2010. ISSN 00091774, 15589587.

Marques, J. A short history of moocs and distance learning - moocnewsandreviews.com, 2013. URL http://moocnewsandreviews.com/a-short-history-of-moocs-and-distance-learning/.

Mertens, P. *Recommender Systems*, volume 39. 1997. ISBN 9783319296579.

Miller, T. Explanation in artificial intelligence: Insights from the social sciences. *Artificial Intelligence*, 267:1–38, 2019. ISSN 00043702. doi: 10.1016/j.artint.2018.07.007.

Mohamad, S. K. and Tasir, Z. Educational data mining: A review. *Procedia - Social and Behavioral Sciences*, 97:320–324, 11 2013. ISSN 1877-0428. doi: 10.1016/J.SBSPRO.2013.10.240.

Moharm, K. A framework for adaptive personalized e-learning recommender systems. *International Journal of Intelligent Information Systems*, 8:12, 2019. ISSN 2328-7675. doi: 10.11648/j.ijiis.20190801.13.

Monroe, D. Ai, explain yourself. *Communications of the ACM*, 61:11–13, 2018. ISSN 0001-0782. doi: 10.1145/3276742.

Montebello, M. *Jien Manwel Dimech*. Sensiela Kotba Socjalisti, 2nd edition, 2017. ISBN 978-99932-17-47-3.

Montebello, M. Artificial intelligence to the rescue of elearning. *EDULEARN14 Proceedings*, pages 7029–7038, 2014. ISSN 2340-1117.

Montebello, M. *Investigating crowd sourcing in higher education*. 2015. URL https://www.um.edu.mt/library/oar/handle/123456789/25334.

Montebello, M. Perslonalised e-learning: Using social networks and personal learning environments with secondary schools teachers, 2016.

Montebello, M. *AI Injected e-Learning*, volume 745. Springer International Publishing, 1st edition, 2018. ISBN 978-3-319-67927-3. doi: 10.1007/978-3-319-67928-0. URL http://link.springer.com/10.1007/978-3-319-67928-0.

Moreno, R. and Mayer, R. E. Cognitive principles of multimedia learning: The role of modality and contiguity. *Journal of Educational Psychology*, 91:358–368, 1999. ISSN 0022-0663. doi: 10.1037/0022-0663.91.2.358.

Mu, R. A survey of recommender systems based on deep learning. *IEEE Access*, 6:69009–69022, 2018. ISSN 21693536. doi: 10.1109/ACCESS.2018.2880197.

Mueller, S. T., Hoffman, R. R., Clancey, W., Emrey, A., and Klein, G. Explanation in human-ai systems: A literature meta-review, synopsis of key ideas and publications, and bibliography for explainable ai. 2019.

Murdoch, W. J., Singh, C., Kumbier, K., Abbasi-Asl, R., and Yu, B. Definitions, methods, and applications in interpretable machine learning. *Proceedings of the National Academy of Sciences of the United States of America*, 116:22071–22080, 2019. ISSN 10916490. doi: 10.1073/pnas.1900654116. This is a very good paper for keeping and using.

Nicholson, P. *Computers and Education: E-Learning from Theory to Practice. In a Hybrid Intelligence-Aided Approach to Affect-Sensitive e-Learning*. Springer, 2007.

Nunes, I. and Jannach, D. A systematic review and taxonomy of explanations in decision support and recommender systems. *User Modeling and User-Adapted Interaction*, 2017. ISSN 15731391. doi: 10.1007/s11257-017-9195-0.

Odilinye, L. Personalized recommender system for technology enhanced learning using learners ' metacognitive activities by. 2019.

Oh, J., Howard, T. M., Walter, M. R., Barber, D., Zhu, M., Park, S., Suppe, A., Navarro-Serment, L., Duvallet, F., Boularias, A., Romero, O., Vinokurov, J., Keegan, T., Dean, R., Lennon, C., Bodt, B., Childers, M., Shi, J., Daniilidis, K., Roy, N., Lebiere, C., Hebert, M., and Stentz, A. Integrated intelligence for human-robot teams. pages 309–322, 2017. doi: 10.1007/978-3-319-50115-4_28.

Overflow, S. How to generate a random normal distribution of integers, 2016. URL https://stackoverflow.com/questions/37411633/how-to-generate-a-random-normal-distribution-of-integers.

Papa, R. *Media rich instruction: Connecting curriculum to all learners*. 2014. ISBN 9783319001524. doi: 10.1007/978-3-319-00152-4.

Paudyal, P., Lee, J., Kamzin, A., Soudki, M., Banerjee, A., and Gupta, S. K. Learn2sign: Explainable ai for sign language learning. *CEUR Workshop Proceedings*, 2019. ISSN 16130073.

Petronzi, D. and Hadi, M. Exploring the factors associated with mooc engagement, retention and the wider benefits for learners. *European Journal of Open, Distance and E-Learning*, 19:129–146, 2016. ISSN 1027-5207. doi: 10.1515/eurodl-2016-0011.

Polajnar, J., Nalbandyan, N., Alemi, O., and Polajnar, D. An interaction protocol for mutual assistance in agent teamwork. pages 6–11, 2012. ISBN 9780769546872. doi: 10.1109/CISIS.2012.169.

Preece, A. Asking 'why' in ai: Explainability of intelligent systems – perspectives and challenges. *Intelligent Systems in Accounting, Finance and Management*, 25:63–72, 2018. ISSN 21600074. doi: 10.1002/isaf.1422.

Páez, A. The pragmatic turn in explainable artificial intelligence (xai). *Minds and Machines*, 29:441–459, 2019. ISSN 15728641. doi: 10.1007/s11023-019-09502-w.

Rai, A. Explainable ai: from black box to glass box, 1 2020. ISSN 15527824.

Retnowati, E., Ayres, P., and Sweller, J. Collaborative learning effects when students have complete or incomplete knowledge. *Applied Cognitive Psychology*, 32:681–692, 11 2018. ISSN 10990720. doi: 10.1002/acp.3444.

Ribeiro, M. T., Singh, S., and Guestrin, C. Model-agnostic interpretability of machine learning. 6 2016a.

Ribeiro, M. T., Singh, S., and Guestrin, C. "why should i trust you?" explaining the predictions of any classifier. volume 13-17-Augu, pages 1135–1144, 2016b. ISBN 9781450342322. doi: 10.1145/2939672.2939778. URL http://dx.doi.org/10.1145/2939672.2939778.

Ribera, M. and Lapedriza, A. Can we do better explanations? a proposal of user-centered explainable ai. volume 2327, 2019.

Rivard, R. Measuring the mooc dropout rate. *Inside Higher Ed*, 2013.

Rodrigues, M. W., Isotani, S., and Zárate, L. E. Educational data mining: A review of evaluation process in the e-learning, 2018. ISSN 07365853. URL https://doi.org/10.1016/j.tele.2018.04.015.

Roscher, R., Bohn, B., Duarte, M. F., and Garcke, J. Explainable machine learning for scientific insights and discoveries. *IEEE Access*, 8:42200–42216, 2020. ISSN 21693536. doi: 10.1109/ACCESS.2020.2976199.

Rudin, C. and Radin, J. Why are we using black box models in ai when we don't need to? a lesson from an explainable ai competition. *Harvard Data Science Review*, 1:1–9, 2019. doi: 10.1162/99608f92.5a8a3a3d.

Samek, W., Montavon, G., Vedaldi, A., Hansen, L. K., and Muller, K.-R. *Explainable AI: Interpreting, Explaining and Visualizing Deep Learning*, volume 11700. 2019. ISBN 9783030289539. doi: 10.1007/978-3-030-28954-6. URL http://arxiv.org/abs/1606.06565.

Sclater, N., Peasgood, A., and Mullan, J. Learning analytics in higher education a review of uk and international practice full report, 2016.

Selingooct, J. Demystifying the mooc, 2014. ISSN 0930-5157. URL http://www.slideshare.net/zaid/demystifying-moocs.

Shaban-Nejad, A., Michalowski, M., Buckeridge, D. L., and (Editors). *Explainable AI in Healthcare and Medicine*. 2020. ISBN 9783030533519.

Sin, K. and Muthu, L. Application of big data in education data mining and learning analytics-a literature review. *ICTACT JOURNAL ON SOFT COMPUTING: SPECIAL ISSUE ON SOFT COMPUTING MODELS FOR BIG DATA*, page 4, 2015. ISSN 2229-6956. doi: 10.21917/ijsc.2015.0145.

Spreeuwenberg, S. Choose for ai and for explainability. volume 11878 LNCS, pages 3–8. Springer, 10 2020. ISBN 9783030409067. doi: 10.1007/978-3-030-40907-4_1. URL https://doi.org/10.1007/978-3-030-40907-4_1.

Tarus, J. K., Niu, Z., and Kalui, D. A hybrid recommender system for e-learning based on context awareness and sequential pattern mining. *Soft Computing*, 22:2449–2461, 2018. ISSN 14337479. doi: 10.1007/s00500-017-2720-6.

Tjoa, E. and Guan, C. A survey on explainable artificial intelligence (xai): Towards medical xai. 7 2019.

Turkmen, H. An effect of technology based inquiry approach on the learning of "earth, sun, moon" subject. *Asia-Pacific Forum on Science Learning and Teaching*, 10:1–20, 2009. ISSN 16094913.

Ubell, R. *Virtual Teamwork: Mastering the Art and Practice of Online Learning and Corporate Collaboration*. 2010. ISBN 9780470449943. doi: 10.1002/9780470615782.

Wan, S. and Niu, Z. An e-learning recommendation approach based on the self-organization of learning resource. *Knowledge-Based Systems*, 160:71–87, 2018. ISSN 09507051. doi: 10.1016/j.knosys.2018.06.014.

Wang, D., Yang, Q., Abdul, A., and Lim, B. Y. Designing theory-driven user-centric explainable ai. 2019. ISBN

9781450359702. doi: 10.1145/3290605.3300831. URL https://doi.org/10.1145/3290605.3300831.

Wang, X., Chen, Y., Yang, J., Wu, L., Wu, Z., and Xie, X. A reinforcement learning framework for explainable recommendation. volume 2018-Novem, pages 587–596, 2018. ISBN 9781538691588. doi: 10.1109/ICDM.2018.00074.

Watson, D. S. and Floridi, L. The explanation game: a formal framework for interpretable machine learning. *Synthese*, 2020. ISSN 15730964. doi: 10.1007/s11229-020-02629-9.

Weblog, B. and Jun, A. N. The advantages of self-explainable ai over interpretable ai. pages 1–4, 2020.

Wimott, P. *Machine Learning: An Applied Mathematics Introduction*. Panda Ohana Publishing, first edition, 2020. ISBN 978-1-9160816-0-4. URL www.wilmott.compandaohana.com.

Wissen, A. V., Gal, Y., Kamphorst, B. A., and Dignum, M. V. Human-agent teamwork in dynamic environments. *Computers in Human Behavior*, 28:23–33, 2012. ISSN 07475632. doi: 10.1016/j.chb.2011.08.006.

Xerri, J. A. *L-Zvilupp tal-Edukazzjoni F"Malta 1430 - 1924*. Sensiela Kotba Socjalisti, 1st edition, 2016. ISBN 978-99932-17-44-2.

Yang, C. C. Y., Chen, I. Y. L., and Ogata, H. Toward precision education: Educational data mining and learning analytics for identifying students' learning patterns with ebook systems, 2021.

Ye, T., Bickson, D., and Yuan, Q. First workshop on large-scale recommender systems: Research and best practice(lsrs 2013). *Proceedings of the 7th ACM Conference on Recommender Systems*, pages 487–488, 2013. doi: 10.1145/2507157.2508007. NULL.

Yongfeng, Z. Explainable recommendation: A survey and new perspectives. *Foundations and Trends in Information Retrieval*, 20:1–87, 2018.

Young, R. J. *Beyond the MOOC Hype | EDUCAUSE.edu*. The Chronicle of Higher Education, 2013. URL http://www.educause.edu/library/resources/beyond-mooc-hype.

Zhang, Y. Explainable recommendation: Theory and applications. pages 1417–1418, 2017.

A History of Education in Malta

A.1 Introduction

It would be incomplete if I had to leave out the political, historical and social developments which led to the status quo in education in Malta. Its importance for our small island-state can only be explained through a short historical overview. This will only strengthen the argument for a better, long-lasting system of education which in turn should sustain the economy and well-being of both country and individual.

A.2 Tracing the Path

The geographic position of Malta together with its size and lack of natural resources contributed to the islands being occupied by many an invader for most of its history. The ethos throughout the ages largely comprised an assimilation to the policy of the ruler at the time (Calleja, 1994). From very early recorded history, particularly through the Arab rule in Malta (870 – 1090 AD) education was noted to have been a practice on the islands. This should not be mistaken as a jest towards the inhabitant's welfare. But more as an oppressive, divisive imposition from ruler towards subjects. None the less it existed. During the periods that followed nothing of note really happened right until the latter part of the middle ages where the islands were given by King Charles I of Spain as king of Sicily in 1530 to the Order of Knights of the Hospital of Saint John of Jerusalem after their defeat and eventual expulsion from Rhodes by the Ottomans seven years earlier (Calleja, 1994).

A.3 The Middle Ages

The Order made Malta their home until 1798. Their influence and political connections granted Malta autonomy from Spain, although this was never formalised. During their 268-year rule, education in Malta flourished principally due to the influx of religious orders setting up convents in Malta and taking over some educational duties (James Calleja – The evolution of education in Malta). The Knights set up a college for education in 1592 which covered subjects such as medicine, theology, law, navigation, naval architecture and cartography. The Jesuit order further transformed this college into a university. Towards the end of the order's stay in Malta, in 1769, Grand Master Manoel Pinto de Fonseca reconstituted the university. Alas, although available to all, education was only within the reach of the wealthy. The large majority of the populace lived in poverty, and survival was more of a concern to them than education. So, one cannot say that the educational institutions available at the time impacted much on the islands and their prosperity(Calleja, 1994; Xerri, 2016).

A.4 Liberté, Egalité, Fraternité: A Premature Promise

By the end of the rule of the Order of St. John a Maltese educator, writer and thinker, Mikiel Anton Vassalli, was promoting the idea of free schooling to all. He has been attributed of being the first to refer to Malta as a nation, and Maltese as a national language. After being granted permission in 1795 he opened a public school for the teaching of Maltese to children. He was actively, and vociferously, in favour of schooling being available to all (see Xerri, 2016, pages 209 - 213). He proposed an idea for setting up schools in every town and village in Malta. These schools had to be free, available to all, and most notably their upkeep crowd-sourced by the community that hosted the school in its midst. The schools had to be independent from the Università or the Seminary. Sadly the idea was ignored. Subsequent to this the Knights of St John had Vassalli imprisoned for plotting against the government(Xerri, 2016). In later years his further clashes with state and Church earned him frequent exile. But the tides of change were being felt, and Vassalli garnished fresh hope for the execution of his ideas.

In 1798 the winds of the French revolution reached Malta's shores, and subsequently the Knights were displaced as rulers of Malta. During their two-year stay the French, governed by Napoleon, imposed their own ways of working in Malta. Their republican ideals abolished distinction between social classes. Reform was set in motion; primary education was set up. The university changed into l' Ecolé Central with more broader terms of teaching (Calleja, 1994). Private schools were closed. Malta was not ready for this "quantum leap" though. Despite being retrained, the clergy and nobility still wielded plenty of power. And the former managed to rouse the general populace against Napoleon notwithstanding that these changes actually benefited the people. After a short but intense struggle

Napoleon's army was expelled from Malta in 1800 through a popular uprising and with the help of a British Navy blockade.

A.5 Education Under the British Rule

British rule in Malta lasted 164 years. Their eagerness to help the Maltese was only motivated by colonial ambitions. The occupation of the archipelago served Britain's colonial interests well throughout numerous wars and conflicts. The British learnt not to upset the clergy if they wanted to control the islands. In fact, the Colonial Government artfully managed a symbiotic relationship with the Catholic clergy. Both the Government and the clergy were very much aware about the power that unfettered knowledge may wield. Consequently, nothing substantial was ever done to improve the state of education for a further 46 years into British rule. During 1847 a new constitution was drafted and granted to Malta. This subtly unlocked the impasse. Various commissions were set up to address needs to start organising the islands. One of the needs was education. Canon Paolo Pullicino was invited by the Colonial Government to develop, set up and manage primary education for the Maltese. Primary schools soon started opening up in many towns and villages on the islands. In 1878 the Julyan and Keenan reports brought profound changes to the educational system (Xerri, 2016). But by now political sentiments were let loose from the proverbial Pandora's box, never to return. The question of language started to be put forward by the Government. Malta was bi-lingual, by convenience, at the time. Italian was used for official business, Maltese for the common day-to-day communication. The British naturally wanted to push English as an official language. It should also be thought at schools instead of Italian(Calleja, 1994; Xerri, 2016).

An ensuing ideological war was triggered between the local intelligentsia and the Government. This battle was bitterly contested and fought. Sadly, this confrontation left its casualties too, notably that of the philosopher, journalist and educator, Emanuele Dimech (1860 – 1921) who became inconvenient for both Church and state and subsequently ended his life in permanent exile (1914 – 1921) in Alexandria Egypt (Montebello, 2017). The resolution of the language problem though was brought about through an unlikely source, the rise of Italian Fascism. This gave the Colonial Government the opportunity to exploit the situation and consequently facilitated the forceful removal of Italian as a national language by a legal act in 1934 and replaced by English.

A.6 The Road to Independence

The pressure of both world wars affected the islands deeply and caused much unrest. This unrest paved the way for the development of independence sentiments. In the latter part of the twentieth century, precisely on the 21st of September 1964, Malta gained the much-coveted independence. Now Malta was an independent nation. The newly achieved independence came along with an Independence Act which outlined principles for the new small island-state. Education was included within the guiding principles (17th September 1964 Independence Act, Laws of Malta). The Independence Act outlined that:

- Education is a right to all citizens irrespective of religious belief, ethnicity, social standing and financial sustenance;
- Primary education was made compulsory;
- Deserving students who hand no means of financial support were to be assisted by the state. This after they passed a competitive exam and achieving good grades.

A.7 The Republic of Malta: Napoleon Revisited

In 1974, Malta became a republic with executive authority now vested in a President. This act displaced the British Monarch as the head of state, represented by a Governor-General who exercise administrative power on the British throne's behalf. Despite this the guiding principles laid out ten years earlier remained the corner stone of education. This holds still till today despite the principles hailing from a previous century. The education act underwent several refinements over the years such as the addition of compulsory secondary education in 1970, the extension of school age to 16 and state-funded tertiary education (Xerri, 2016). The guiding principles laid down in 1964 were never betrayed but used as a foundation. This despite different political ideologies that formed over the years since. The recent Education Act of 2018 (Laws of Malta) outlines the duties of the state, and parents towards children. Education is to be given to all as outlined in the 1964 act, the state had the duty to provide, fund and govern education as a service to its citizens. The parents on the other hand have to ensure that their children attend school, are respectful to authorities and their peers. The existence of such a service caters for the well being of each citizen and grants him / her the opportunity to work. Education is now also seen as a lever or an enabler. While it is no longer necessary to remind politicians and people that it is a civil right, Governments still struggle to ensure that people are involving themselves and keeping abreast with skills needed for the workforce (Xerri, 2016).

A.8 Conclusion

As seen though the brief trace through history, education has to be supported by political will. People who are forward thinking put ideas into the hands of the populace and try to garner as much support they can for eventual implementation. Political ideas through the ages also held effect on education. Lately the need for education served as no contest in politics or daily life, save for the wish to improve its availability and delivery.

B Socio-Economic Significance of Education

B.1 Introduction

The socio-economic significance of education is obvious. But despite this many countries still fail to deliver a sufficient infrastructure that sustains their children and workforce. The ramifications are wide. Higher education relates to a better GDP, better standard of living and lower crime rates. The ideal also has its difficulty as it seems that in the better countries people prefer to stay away from education where possible. Moreover the uptake into higher education also struggles.

Taking Malta as an example, only 10.7% of young people aged 18–24 (12.2% of men and 9.2% of women) who had completed secondary education but were yet no longer in education and training in 2016. A headline target is set by the European Union (EU) to decrease this rate to less than 10% by 2020 within the Europe 2020 strategy. This rate is commonly called 'early leavers from education and training.

The main worry for government is the lack of interest most youths show in updating their skills after leaving secondary, obligatory education. In Malta, the education sector receives a sizeable proportion of the national annual budget, second only to health. This investment, seems to be working but figures show that the uptake is not commensurate to the investment. Employers still argue that there are not enough skilled employees. It is a continuous battle to keep the workforce engine trimmed. The challenge becomes greater when people leave obligatory education, generally but the time they are 16 years of age. This because motivating people to upgrade themselves, in a life long learning environment, is not easy.

B.2 Government Commitment

B.2.1 National Budget

Curiously enough one entry in the 2017 budget estimates shows that Government is gearing up to e-learning. National institutions such as the University of Malta, and the Malta College for Arts Science and Technology have jumped onto the bandwagon to provide such services as e-learning. But what is really expected out of e-learning courses? Personally I think that the allure promised by the new technology has captivated the powers that be to introduce e-learning as a means of providing training tailored to the person's needs. The many benefits are obvious and over-studied. But the actual success of the outcome has not yet been measured properly. Is it a panacea for other shortcomings in education? Certainly not. Should we discontinue research just because the approach failed to deliver on the goods as promised? Certainly not.

B.2.2 Administrative Adjustments

Another interesting fact is that with a new legislature the Government has decided that Malta should have a secretariat for Digital Economy. The hints are clear. Government is actively looking at the digital world as yet another vent for boosting our chances of survival in this age of bits and bytes. Former Governments focused on connectivity and the facilitation of entry to digital-based companies. Naturally the tax climate made it easy for betting companies to move to the island. Again this created an unsatisfied need. The need for the development of human capital, locally. Subsequent governments developed infrastructure, but also focused on enabling people address the new untapped resource. This by focusing on education of the workforce. So we can see a natural progression here, from infrastructure to the opening up of new opportunities. Naturally new opportunities need to be taken up and picked.

B.2.3 Necessary Legislation

Governments now see Information Technology as a medium that unlocks a lot of potential. E-Learning has also one good aspect to its credit, that of availability and easy access. So this medium is being used as a way to help people enhance their skills. Another interesting fact is that with a new legislature the Government has decided that Malta should have a secretariat for Digital Economy[1] The hints are clear. Government is actively looking at the

[1]The legislature of 2017 established a Secretariat for Digital Economy under the auspices of the Prime Minister's Office.

digital world as yet another vent for boosting our chances of survival in this age of bits and bytes. Former Governments focused on connectivity and the facilitation of entry to digital-based companies. Naturally the tax climate made it easy for betting companies to move to the island. Again this created an unsatisfied need. The need for the development of human capital, locally. Subsequent governments developed infrastructure, but also focused on enabling people address the new untapped resource. This by focusing on education of the workforce. So we can see a natural progression here, from infrastructure to the opening up of new opportunities. Naturally new opportunities need to be taken up and picked.

B.3 The e-Learning Lever

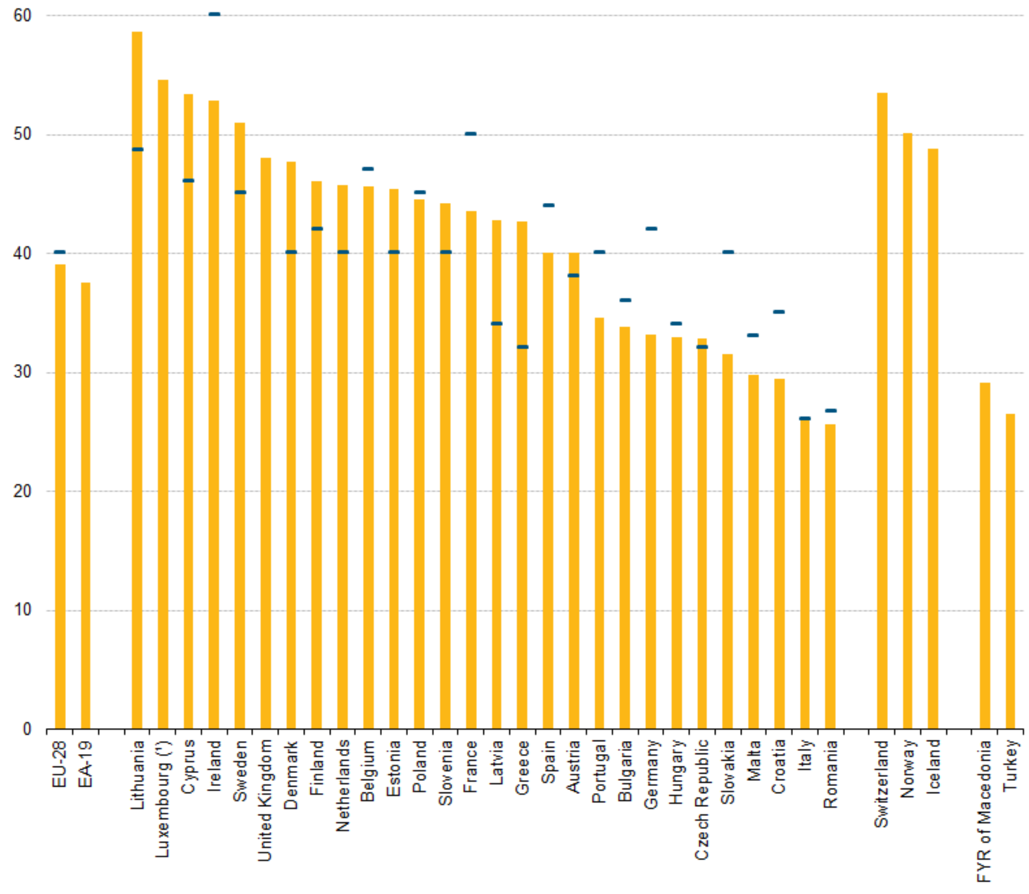
The implementation of e-learning as a nation-wide initiative is a tricky business. This because the proper foundations of e-literacy must be laid first. Students must be familiar with computer technology and supplement themselves with the skills necessary to help them augment their careers or knowledge. The first generation of students who never knew a world without computers or the Internet is slowly emerging to form part of the workforce. With these people it may not be as difficult to persuade or encourage. But what about those who are 10 years there senior, and are already in the workforce?

e-learning really offers a double edged sword to the economy. One can view it in the light of facilitating life long learning and improvement. Moreover there is another opportunity, that of providing training to global clients. Whichever way a lot of study has to be done before really putting all the eggs in one basket. The population is not homogeneous. So learning abilities and styles really differ, just as in a classroom setting.

B.4 Education Attainment in the EU 2016

Data relating educational attainment shows that, in 2016, more than 83 percent of the EU-28 population aged 20–24 had completed at least an upper secondary level of education (i.e. International Standard Classification of Education (ISCED) level 3 and above), a figure that reached 85 percent for women (see table B.2). On the other hand, almost 11 percent of young people aged between 18–24 (12.2% of men and 9.2% of women) had at most completed lower secondary education but were yet no longer in education and training in 2016. A headline target is set by the EU to decrease this rate to less than 10% by 2020 within the Europe 2020 strategy.

When one considers tertiary education in the EU 40% students completed tertiary education in 2016; this was also the case in Norway, Iceland and Switzerland. In contrast, the lowest shares of those having completed tertiary education were observed in Romania, Italy, Croatia and Malta, as well as in the Former Yugoslav Republic of Macedonia and Turkey, where the proportion of persons with tertiary educational attainment was below 30%. National targets vary from 66% in Luxembourg to 26% in Italy; 13 countries have already achieved their national target[2].



Note: In the cases where the national target has been set within a range between two possible values, the lower level has been taken.
The United Kingdom did not set a specific Europe 2020 target.
(¹) Low reliability. The national target for Luxembourg is 66%.

Figure B.1: EU Education Attainment Statistics.

Data on educational attainment also shows that, in 2016, more than four fifths (83.2%) of the EU-28 population aged 20–24 had completed at least an upper secondary level of

[2]Source: $http : //ec.europa.eu/eurostat/statistics - explained/index.php/Educational_{a}ttainment_{s}tatistics$

education (i.e. ISCED level 3 and above), a figure that reached 85.6% for women. Please refer to Figure B.2 below.

	Total	Men	Women
EU-28	83.2	80.8	85.6
EA-19	81.6	78.8	84.4
Belgium	85.3	82.8	87.8
Bulgaria	85.0	84.8	85.2
Czech Republic	89.6	89.7	89.6
Denmark	75.4	71.1	79.8
Germany	77.9	76.1	79.9
Estonia	83.8	79.3	88.3
Ireland	93.6	92.3	95.1
Greece	91.2	90.1	92.4
Spain	70.9	65.3	76.6
France	87.7	86.1	89.3
Croatia	96.3	95.5	97.1
Italy	81.0	77.6	84.6
Cyprus	91.2	86.7	95.4
Latvia	84.8	80.4	89.4
Lithuania	91.7	89.3	94.2
Luxembourg	77.0	72.2	81.7
Hungary	83.5	82.9	84.1
Malta	77.5	73.0	82.4
Netherlands	80.5	77.1	83.9
Austria	89.5	88.0	91.1
Poland	90.8	89.0	92.7
Portugal	77.5	72.8	82.3
Romania	79.9	80.5	79.3
Slovenia	90.9	87.6	94.1
Slovakia	90.4	90.5	90.3
Finland	87.7	86.2	89.3
Sweden	86.9	85.7	88.2
United Kingdom	85.1	82.8	87.6
Iceland	65.2	58.0	73.3
Norway	78.1	75.1	81.2
Switzerland	88.2	87.0	89.4
FYR of Macedonia	88.0	89.1	86.9
Turkey	56.1	55.9	56.3

Figure B.2: Secondary Education Completion - by Gender.

B.5 Conclusion

e-learning really offers a double edged sword to the economy. One can view it in the light of facilitating life long learning and improvement. Moreover there is another opportunity, that of providing training to global clients. Whichever way a lot of study has to be done before really putting all the eggs in one basket. The population is not homogeneous. So learning abilities and styles really differ, just as in a classroom setting. In the next chapter we shall discuss the utility of pedagogical form to learning.

C Learning - Theory, Pedagogy and Mechanics

C.1 Introduction

This chapter dives into the marvelous and yet alien world of the human psychology of learning. Pedagogy, learning, teaching methods and distance learning are discussed to help the reader better understand the argument.

C.2 What is the way people learn?

According to John Dewey, students have to be engaged. They have to experience learning. What does experience mean? It is a sensory engagement (Marcuse, 2010)? So you have to use all your senses to actively learn something? This theory was put forward in 1910, by John Dewey. so despite the fact that the digital world was not yet conceived, thinkers of the early 20thcentury already started discussing the effect of teacher-centered learning against experiential learning. The argument placed is that taking a lot of notes and trying to absorb is not tantamount to learning. Student retention and commitment will also suffer too (Marcuse, 2010). So in essence we have two things that make learning:

- Experience learning holistically;
- Communication with peers.

In his Theory of Practical Inquiry, John Dewey asserts that learning is made by the student experiencing through all his senses (Marcuse, 2010). This theory places the student at the centre of learning. The challenge for our work is to create a situation that centres on the student to give him a richer learning experience. He insists that there is an immediate reference to the environment which is needed to sustain learning. Typically a physical world and communication with peers (Marcuse, 2010). Testing our thoughts through action, learning then occurs when all our senses are engaged (Marcuse, 2010). In our case student engagement is a priority, so our proposal shall engage this line of thinking.

Sadly in today's world there is too much emphasis on fact and too little on the science of thinking and attitude of mind. Dewey proposed that students be thought what they want to know (Marcuse, 2010). To accomplish this students must address problems on what they want to know. Even learning to surmount obstacles in the way of learning. to properly engage students subject material must really relate to student experience and also must also be within his intellectual capacity. Then we would have transformed students into active learners and make them actively search for their answers (Marcuse, 2010).

C.3 Distance Learning

Distance learning has traditionally been used to reach large amounts of people. It is a great idea, but in order to be profitable study material is produced on a one-size-fits-all (Farrow et al., 2015). This addresses the economies of scale but short-changes learning and deep thinking. But when one examines the outcome from a campus-style learning it becomes evident that distance learning follows on the same lines (Farrow et al., 2015). Normally students are left to their own devices to gather and understand the context of the lesson to assimilate knowledge through notes. In essence we are repeating the same mistake but with different media. Distance learning delivers the following:

- Mass produced independent study package is given as material to the student;
- A very important factor called "critical discourse";
- Content flexibility;
- Supportive climate;
- Opportunity to critically and collaboratively explore ideas and consistent knowledge;
- This will allow the student to set goals, select content, method of assessment and collaboratively confirm understanding.

In order to properly sustain learning an E-learning environment should be able to create and sustain communities of inquiry that will facilitate developing deep and meaningful approaches to learning (Amiotte, 2000). Information technology has brought a new meaning to learning which can be characterised by the following:

- Information is distributed and available;
- Collaboration on a wider scale is possible;
- New ways of learning and teaching have to be devised;
- IT has to sustain discourse and precipitate learning in a purposeful community of learners.

When looking at the distance learning model it can be noticed that great gains have been achieved and as such the economies of scale for producing and for reaching larger amounts of people was encouraging. But the one-size-fits-all regime lacks in the learning and deep thinking.

Interestingly enough Garrison (Garrison, 2017) makes immediate reference to the environment necessary to sustain proper learning. The physical need of communication with peers is mandatory. In addition to this, John Dewey, in his Theory Practical of Inquiry, proposed that the testing thoughts through action, learning then occurs we engage all senses. Thus supporting learning. Giving students a holistic experience(Garrison, 2017; Marcuse, 2010). Dewey proposed that the students be thought to add to their personal knowledge. To accomplish this the students must address problems they want to know about and apply the knowledge to observable phenomena. So in order to keep students engaged better the approach to learning must actively address a student's experience and be in reach within his intellectual capacity (Marcuse, 2010). So students must become active learners in the search for answers. So in essence we have to see (Marcuse, 2010):

- What engages the student and makes him truly want to study;
- Why is this so?;
- Can an artificial system be designed in order to help the student achieve this aim?

As the main focus of this study is squarely placed at remote learning. We shall primarily focus on technology as the prime disseminating medium. Technology has amply facilitated this way of learning. Computers have forced educators to rethink the way knowledge to be transferred. E-learning has the potential to support communities (Freitas, 2013). In a certain sense we have to issue to sustain communities of inquiry that will facilitate developing deep and meaningful approaches to e-learning. Learning technologies have been a catalyst to explore different methods and ways of learning like critical thinking, creative thinking and learning itself. Despite all these challenges there is also yet another hurdle. Human beings are social. Isolation really has negative effects on students wanting to learn with no one to refer to or compare with. According to Garrison (Garrison, 2017), the downside of isolation experience requires students to become *"autonomous and self regulated, with regards to goals, methods and media"*. Isolation in itself offers a restricted opportunity for meaningful feedback. This in turn contributes to an extremely high drop-out rate (see Garrison, 2017, pages 209 - 213). The design of learning material and on-line environments should be mindful of the following:

- Critical discourse;
- Content flexibility;
- Supportive climate;
- Opportunity to critically and collaboratively explore ideas and construct knowledge.
- This will allow the student to set goals, select content, and method of assessment, and confirm understanding.

C.3.1 A Brief Look Into Inquiry

Inquiry is the study into a worthy question, issue, problem, or idea and understanding to be able to typically ask questions such as (Páez, 2019):

- Evidence - How do we know what we know?;
- Viewpoint - who is speaking?;
- Pattern and connection - What causes what?;
- Supposition - How might have things have been different?;
- Why does it matter? - Who cares?

The traditional model of students sitting in neat rows all filling out work sheets is not completely conducive to the needs of all students now. Dewey contested this model early in the 20th century and said that this promoted shallow thinking, and a dislike for learning. Dewey believed that learning is heavily social(Marcuse, 2010). The information transfer method has been also rejected by Ralph Tyler, and also contested by Paolo Freire. Vigotsky added that social interaction or better co-operative learning has a significant impact on how students internalise what they learnt. Dewey argued that education must be experience based. An experiment held by Turkmen Hakan in 2009 (Turkmen, 2009) the above is shown to be significant.

C.3.2 Learning Through Social Media

Leaning through social media is highly subjective. Group members are subject to mindless group think and tend to follow an echo-chamber effect. Participants blindly follow the thought process of the rest of the group without thinking twice. But despite this social media create a virtual peer group necessary to learning (Papa, 2014). Sharing and discussing is facilitated. Naturally the most vociferous or forceful in the group can take over with other members either quitting or following sheepishly. John Dewey concluded that there is a transaction process to learning. This takes place through exchange(Garrison, 2017). Within a classroom environment the teacher has the following complex roles to balance and maintain:

- Creating;
- Shaping;
- Evolving the learning environment.

Technologies make it possible to sustain the necessary social and cognitive conditions. Students are able to stay connected to a learning community. As learning must be designed with vast knowledge extraction in mind getting this knowledge from the Internet poses two issues. Firstly content is freely and easily accessible possibly leading to cognitive overload. And secondly the quality of the content is unregulated.

C.4 Some Reflections on MOOC Experiences

In his paper called *Insights into Teaching and Learning*, Burge negatively describes Massive Open On-Line Course (MOOC) as disruptive technology which is simply over hyped (Burge, 2015). Some MOOC, he continues, are a replacement of direct college courses, while others are new. Studies show that the majority of those enrolled are already reasonably well educated (see Burge, 2015, pages 600).The completion rates of Massive Open On-Line Courses (MOOCs) have been shown to be as low as 6.8% (see Burge, 2015, pages 600). I like the idea proposed in this paper discussing success for completion but it is felt that this is only personal reflection of the author(see Burge, 2015, pages 601). The author puts forward some reasons that would have possibly been the cause of the negative outcome in a MOOCs design (Burge, 2015).

- The author had an immediate need for material;
- Engaging material and low time commitment of course;
- Novelty of the presentation medium and interest in the subject.

In all fairness the author said that she could have felt disengaged on courses due to personal attitudes as outlined (Burge, 2015):

- Overcommitment by signing up to too many courses
- Lack of time;
- Fear of failure;
- Boredom in watching videos;
- Motivation is a combination of value and expectancy - learning something that you think will be useful to you.

Student attitude cannot be underestimated although there is hardly any technology which alters attitude and responsibility. One thing I can concur with the author of this paper is when I enrolled to an on-line learning course through Malta College for Arts Science and Technology (MCAST). The material provided was old, and not updated. The e-Learning portal, at time of viewing, was unattended and I was left to do whatever I pleased. This naturally resulted in me quitting after a while[1] .

[1] https://www.mcast.edu.mt/e-learning/

C.5 Learning Theory and Pedagogy

In this section we shall explore the necessity of having a plan for knowledge transfer preparation, what are the different approaches to building this plan, and the outcomes of having such a plan. Such plans can be termed as pedagogy. Pedagogy can be defined as the art, science or the profession of teaching (Evans and Myrick, 2015). It can be defined as a system or a method by which one teaches. Otherwise the approach to pedagogy would be a haphazard and would reap little benefit. The term pedagogy normally refers to the teaching of infants or youth. Andragogy would be its counterpart describing the teaching of adults. Many a time both terms are collapsed under the single term of pedagogy.

C.5.1 Common Pedagogical Approaches

One can broadly classify pedagogy in three clusters. These are broadly defined as:

- Associationist;
- Cognitive;
- Situational.

The associationist approach to teaching implies that one must be allowed to associate, link, knowledge items together. This results from reinforced practice of a certain skill (Ubell, 2010). Ideas and experience fuse together to extend the knowledge of an organism. this approach is a very natural approach to learning by which the student is subjected to new concepts and then linked with the learner's past experience. The hope is that the learner can fit in new concepts within his already formed dimension (Ubell, 2010). Information in this case is grouped naturally, by the learner and this makes it easier to recall. The acquisition of new skills or information would subsequently give rise to perceptions. Perceptions form thought such as If A is associated with B then A' is also associated with B' (Ubell, 2010). This could be beautifully shown through Pavlov's experimentation with dogs. An action implied a conditioned response. Later on Thorndike and Skinner also asserted that it was not only consequences that could be condition, but also learning (Ubell, 2010). In this approach, learning is seen as an association between a set of stimuli to specific responses. This makes learning an operant conditioned response.

The cognitive approach to learning really focuses on the learner per se. It operates on the belief that the learner is affected by a number of variables that may assist or inhibit him to learn. These are (Moreno and Mayer, 1999):

- Behavioural;
- Environmental;
- Personal;
- Interplay.

These four factors affect the person directly and one can say that whey weigh down on him. For instance the environmental variable, much like nurture, consists of events outside a person's remit of influence, but condition him directly. typically one can include culture, upbringing, social norms, climate and parents. This values have a direct effect on the way a person perceives the world around him and up to a certain extent condition his perceptive abilities too (Fan et al., 2010). Much of cognitive learning is based on following what others do and repeating the action until it is reinforced and acquired as a skill. The student needs to be kept continuously motivated to follow instructions and methods needed to acquire the new skill. At one point in time, when the skill has been acquired the student then can experiment with ways of extending his knowledge or even to pass it on to others in some form of apprenticeship (Fan et al., 2010).

Situational learning is in my opinion the maverick of the lot (Kuusisaari, 2014). According to Vigotsky[2], situational learning is accidental. It does not depend on classrooms but depends on situations which arise and from which the learner may benefit (Kuusisaari, 2014). As one can expect, learning differs from traditional means because there is no transfer of abstract materials. Situational learning is grounded in concrete examples that happen within activities and have a context. The settings necessary for the transfer of knowledge are very important as the learner needs to assimilate the skill he is learning with the situation or problem that needs a solution (Kuusisaari, 2014). Furthermore one can describe situational learning as a community experience. People learn as a group, and many-a-time learn by sharing values and opinions. As the learner improves he is drawn closer to the centre of the community consequently gaining in experience until he assumes the role of an expert.

C.5.2 Learning Styles

As expected there are different learning styles, much depending on the person (Guy et al., 2013). A learning style is the way a person learns. We can also extend this simple definition further by adding which part of the brain is activated during learning. Obviously

[2]Vigotsky describes this as learning through social development.

this really depends on the style which the person prefers (Guy et al., 2013). Let us discuss each lightly (Guy et al., 2013):

- Visual: In this style people prefer pictorial information through images and spatial understanding. In this case the most active parts of the brain are the occipital and parietal lobes;
- Aural: People who prefer this style of learning gain most through sound such as music. The most active parts of the brain are the temporal lobe and the right lobe[3].
- Physical: This style of learning requires people to touch or handle things to experience learning. In this style the most active parts of the brain are the cerebellum and the motor cortex;
- Social: People who love grouping up with others like to share experience as a way of learning. In this situation people team up to solve problems and share solutions. Here the most active part of the brain would be the frontal temporal and limbic system;
- Solitary: This type of learning is for those who need to understand it by them selves. They prefer self study. The active parts of the brain during this process are the frontal parietal and limbic system;
- Verbal: This style of learning requires people to absorb information writing and verbal communication. The active parts of the brain are the temporal and frontal lobes;
- Logical: This style of learning entails the use of reasoning, logic and systems to absorb information. In this case brain activity can be found at the parietal system.

C.5.3 Modern Theorists

In addition to the above, there are also various theories that have been developed over the past decades with the aim of better understanding learners and offering them material in a form they can assimilate to. We shall only go over the main ones briefly below (Bates, 2015):

- Herrmann - The brain dominance instrument;
- Fleming - The Visual, Aural, Read/Write, and Kinesthetic model (VARK);

[3] Responsible for musicality in people.

- Kolb - Learning style inventory;
- Honey and Mumford - Learning style preferences;
- Gregorc - Mind styles;
- Meyers and Briggs - Type indicator;
- Sternberg - The mental self-government model.

Ned Hermann developed the concept first identified by Robert Sperry suggesting difference between left and right brain thinkers. Left brain people see things as a sequence of parts, while right brain thinkers see things as a whole. Next we see Neil Fleming's Visual Auditory, Reading and Kinaesthetic learning style model. This is a widely used model and principally used in learning style assessment. David Kohb devised his model as a continuum with two aspects to it. Namely by analysing how people take in information and how people internalise information (Guy et al., 2013). Peter Honey and Alan Mumford suggest that learning styles are more fluid and depend on the task at hand. They co-developed a questionnaire which helps identify specific styles for tasks(Bates, 2015). Anthony Gregoric defined learning styles as a mixture of hoe a person learns and his adaptation to the environment where the learning takes place. One of the oldest system in this compendium is the one defined by Isabel Briggs-Myers and Katherine Cook-Briggs. This was developed in the latter half of the last century and based on the work of Carl Jung as a way to describe personality types which ultimately fit into a definite learning style. Last but not least, Robert Sternberg proposed a Mental Self-Government model which uses the terms thinking and learning interchangeably. The model describes 13 different thinking and learning styles. Here learners minds are described as systems that need to be organised and governed mirroring society (Bates, 2015).

C.5.4 The Social Constructivist Theory of Learning

E-Learning requires a lot of discipline and responsibility on the part of the learner. This type of responsibility is normally attributed to adults. Adults normally have a level of knowledge and are deemed to be motivated. The style used most frequently in e-learning scenarios is called the constructivist approach to learning which we shall discuss and focus on.

The Constructivist approach to learning places the responsibility of learning with the learner. As the learner is involved in the learning process himself. So here we actually depart from there notion of instruction lead training. Learners construct their own understanding of the subject matter they are studying and are not really forced into relaying what they have actually studied. Learners look for meaning and they try to find it regularly. They assimilate the material being learnt with their own experiences. So this type of approach greatly depends on the experience of the learner. Apart from having each student focus on the task at hand, teams of students can be allowed to collaborate with each other and contribute their viewpoints. The collaboration experience greatly enhances learning and the learning experience (Marcuse, 2010).

Much of this approach to learning basis itself on the motivation of the student to learn. His intrinsic confidence to move forward. The first-hand experience the learner has to solve problems he can relate too will come in very handy with this approach, and consequently is a very powerful driver. It can be said that this approach is a better motivator than reward. But in order to apply this type of teaching style a number of preconditions must be observed. These namely are (Marcuse, 2010):

- The student must have some level of experience in learning;
- The student must also have some experience with the subject being learnt;
- The teacher must take the role of facilitator, rather than teacher.

Learning is a active process where the students are encouraged to discover facts form themselves. As added earlier on, collaboration among peers greatly facilitate this approach to learning. As whenever this happens, people grow and share. Lev Vigotsky claimed that instruction is goon only when it proceeds ahead of development (Guy et al., 2013). It has to arouse a set of functions within the individual that awaken maturity. This can be referred to as the zone of proximal development. To fully engage a learner the task presented to him must reside within the complexity of the environment of the learner (Freitas, 2013). The learner should be capable of understanding the task even after the learning phase has ended. Learners must have ownership of the learning process and the tasks set before them to learn.

Instructors must first be asked to give the student an overview of the basic ideas that give life to the topic. Then revisit them and build upon them regularly. The emotions and ;one contexts of those involved in the learning process must be considered as part of the learning process. There are several critics against this idea. The *"Neo-Piagetan"* theories of cognitive development says that learning at any age really depends on the processing and resources available at the particular age (Freitas, 2013). Naturally not all subscriube to this point of view. Learners with no proof knowledge should be given structured learning. This is an *"objectivist"* view to learning. The *"objectivist"* theory of learning is contrary to *"constructivism"*. It is a view of the nature of knowledge and what is means to know something. Basically it is founded on the idea of symbolic manipulation and minor states. This describes the learner as an *“empty vessel”* that the instructor has to *“fill in”*.

C.5.5 Connectivism

Connectivism is a theory of learning in a digital age that emphasises the role of social and cultural context in how and where learning occurs (AlDahdouh et al., 2015). Too much information is being given in notes, and in associated websites. See the theory of connectives by Vigotsky. Connectivism is a theory of learning in a digital age that emphasises the role of social and cultural context in how and where learning occurs. Principles of connectivism can be summarised as follows (AlDahdouh et al., 2015):

- Learning and knowledge rests in diversity of opinions;
- Learning is a process of connecting specialised nodes or information sources;
- Learning may reside in non-human appliances;
- Learning is more critical than knowing;
- Maintaining and nurturing connections is needed to facilitate continual learning;
- Perceiving connections between fields, ideas and concepts is a core skill;
- Currency (accurate, up-to-date knowledge) is the intent of learning activities;
- Decision-making is itself a learning process. Choosing what to learn and the meaning of incoming information is seen through the lens of a shifting reality. While there is a right answer now, it may be wrong tomorrow due to alterations in the information climate affecting the decision.

As is evident even theory is not completely clear. The fact that different styles of learning exist, we all agree. But what exactly are these styles and to what extent can they be addressed, is still not completely clear. This because each theorist has his own particular approach to the problem at hand and expresses it in a way he can understand it. By this it seems that we are back at the starting block.

Can one teach anything without pedagogical preparation? The answer to this is in the affirmative. But pedagogy helps us to understand the most effective ways people learn. Moreover the teacher can focus on the best methods of how to transfer skill or knowledge. In addition to the short discussion above another question could also be posed. Are we to stick to time proven pedagogical methods or should we seek new ways to fit the digital medium. Personally I believe that there is no need for new methods. The digital offers new ways of expression, but the human will remain the same. New ways of pedagogy should be exclusively built around people not the medium.

C.6 Collaborative Learning

Once we have discussed the effectiveness and necessity of education together with the best ways of preparing teaching material it would be correct to conclude this rather lengthy treatise by considering collaboration as a learning tool. Why collaboration? Collaborative learning has for long been eyed as an efficient way to get students to learn by teaming up and forming part of the learning process (Jaldemark et al., 2018). Learning is the ability to acquire new skills or knowledge by stretching oneself beyond his comfort zone of capabilities. The theories of Collaborative Learning are largely based on the work done by Lev Vygotsky referred to as the Zone of Proximal Development(Frey, 2018).

C.6.1 Zone of Proximal Development

Lev Vygotsky showed that there is a difference between what a learner can achieve without help and what can be achieved with help. Children tend to follow adults directing them until they develop the necessary skills to be able to carry out the task unaided. Vygotsky was of the belief that education should provide children with experiences within their Zone of Proximal Development (ZPD) consequently enabling them to advance their learning(Frey, 2018). ZPD has been defined by Vygotsky as the distance between the potential to solve problems unaided to that of solving problems under supervision of a domain expert (Fu and Hwang, 2018). For this to be successful there must be (Fu and Hwang, 2018):

- Collaboration between capable peers;
- A meaningful interconnection of theoretical and practical everyday experience;
- Meet the goal of change in a collaborative process.

As with all things, this idea was adapted and used in a concept known as scaffolding whereby learners extend themselves across a knowledge domain with the scaffold supporting their journey (Frey, 2018). Under this regime the teacher or more experienced peer will support the learner as necessary till the scaffold is removed.

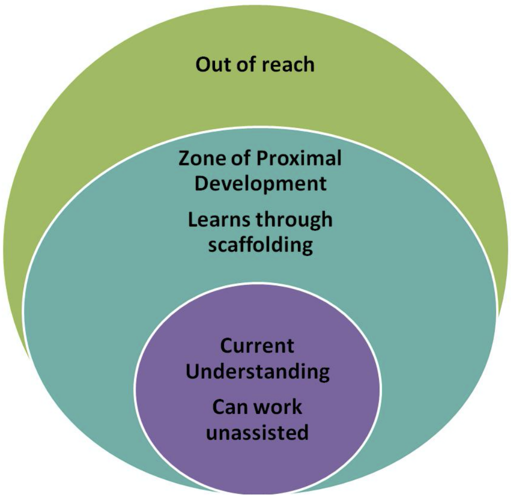


Figure C.1: Zone of Proximal Development (Frey, 2018)

C.6.2 Learning in Collaboration

Many studies have shown that learning in small groups is more effective than learning individually (Retnowati et al., 2018) . The main identifying thread of such a learning situation is the social context formed during the learning process. It is shown that when members of a group have gaps in their knowledge the group fills in (Retnowati et al., 2018). The impact on the learner who is lacking is great as his confidence is gradually extended to the point of proficiency. On human terms teams is formed along the basis of society. Exchange of information flows within the group. Just as in society there may be cooperation and antagonism within a group which ultimately hinders or aids the flow of information. This flows naturally, even within classroom settings. Social or group support, helps members learn from each other, develop distributed expertise and gives members a wider access to ideas (Fu and Hwang, 2018). New knowledge is acquired independently by people talking together in a social setting (Kelly).

C.6.3 Disadvantages of Learning Collaboratively

As with everything in life Collaborative Learning has its disadvantages too. Particularly there may be instances that learners within a group that slack and rely on the group to get the work done. There may also be instances where the tasks at hand are not well suited for group-work (Retnowati et al., 2018). Collaboration many a times was also found to be dependent on prior familiarity of other group members, rather than the knowledge other peers within the group possess (Erkens and Bodemer, 2018). This is interesting as the societal effect largely impacts the formation of groups. Additionally, even the availability of information was found to be a significant factor affecting a group (Erkens and Bodemer, 2018). Cognitive group awareness is the perception of the level of expertise co-members have. These attributes become known through social interactions (Erkens and Bodemer, 2018). They serve as a means of “sizing-up” group members, whether they are expert or beginners (Erkens and Bodemer, 2018).

C.6.4 Technology Assisted Collaborative Learning

As expected, technology, if correctly applied, can have a very positive effect on Collaborative Learning (Jaldemark et al., 2018). This is frequently termed as Computer Supported Collaborative Learning (CSCL) (Erkens and Bodemer, 2018). One of the benefits technologies brings to the table is that learning can take place anywhere. Collaborative Learning is also assisted by the fact that content is easily distributed among groups or peers. This even to the extent that dialogue and togetherness within a group is enhanced Editorial introduction. Mobile technologies have been found to be the most suited due to their pervasive nature (Jaldemark et al., 2018). Computer assisted support may also be expected to supply a group member with knowledge about the rest of the team’s capabilities (Erkens and Bodemer, 2018).

C.7 Teaching Adults

C.7.1 Common Approach to Teaching

Previously in this text we have looked at learning from the viewpoint of the student. A teacher's approach is also necessary, mainly because the imparting of knowledge has to be done with a systematic preparation. The *objectivist* approach is a teacher-centric model, highly structured and requires convergent answers from the student when challenged to assess knowledge. Content is generally a good mix between abstract and concrete concepts. More often than not the student is left with the task of acquiring the information "fed" to him (Jung et al., 2019). Thus making such systems very individualistic, and reliant on feedback given by the student. In this case the student's role can range from being passive to active. When it comes to assessing learning, assignments are generally multiple choice (Jung et al., 2019). This is really forced onto the system as firstly there are too many students to be handled by a single lecturer, and secondly assignments are automatically graded. Offering very little feedback to the student (Jung et al., 2019).

C.7.2 Personal Experiences

People have unique experiences that must be respected and also must be reflected into lesson planning and design. This has lead to a fork in MOOCs development. So now MOOCs are evolving into what we can describe as cMOOCs, connectivist MOOCs. A typical expression of this is called the "Salesman Khan" Model where short videos are presented and notes are sparingly used. This approach seems to have gained popularity recently (Petronzi and Hadi, 2016). This approach offers a way of getting learning material through to the student, without being forceful. Each chapter is covered by a set of auto-graded questions that help the user along his knowledge acquisition experience. The system keeps throwing questions at students until they get all questions right in a row (Petronzi and Hadi, 2016).

C.8 Conclusion

In this short synthesis we have seen how teaching and learning has been studied in different ways. It can be also noted that education theory is largely media indifferent. We can safely add that new media will reach out better towards its consumers, the students, by making education more available, easier to reach and more interesting. A point has to be stressed here in these concluding words. Social collaboration is a necessity in learning.

But despite this it does not imply that Collaborative Learning can be achieved exclusively through social interaction. It also requires collective learning and socializing whereby the whole group strives in unison towards reaching a common shared goal (Fu and Hwang, 2018). This approach is very lacking in many modern MOOC offerings today. The natural collaborative setting in which even classrooms tend to assimilate to often, is absent from most MOOC contributions. Thus, contributing to the lack of commitment (Fu and Hwang, 2018).

D Massive Open Online Courses

D.1 A Bit About MOOCs

D.1.1 Background

MOOCs started life in 2008, when Stephen Downes and George Siemens created their first course open for masses. Since then many jumped onto the bandwagon (Driscoll, 2016). Notably in 2011, the University of Stanford decided to investigate the possibility of making courses massively available backed up by its prestige. The model used was that of having university professors create material, typically video taped lessons, and made available to students for free. The idea, at least in principle, was to make education universally available to all. People anywhere, irrespective of age and situation, would be able to follow a course. Most courses would be provided for free, or at a reasonable price. So at this point one can safely say that price and availability are not a barrier to entry for courses (Driscoll, 2016).

In 2012, more decided to join the fray and Coursera, Udacity and Udemy were born. The UK's Open University responded with its own called Future Learn. Since then the playing field became more crowded. Udacity, founded by Sebastian Thrum, can be considered one of the earliest MOOC successes (Cooper and Sahami, 2013; Driscoll, 2016). In 2011, an Artificial Intelligence (AI) course was launched through Udacity and 160,000 students from 190 different countries enrolled. After careful analysis it was noted that the course was really designed for bright, motivated Stanford University students. Hardly the villager in a remote place (Baturay, 2015). This course was suitable for the top 5% of the curve. If one examines the major players in the MOOCs industry, it becomes evident that they originate from top American universities. Thus the people designing the courses, typically university professors, are used to face students coming from the best of the crop (Marques, 2013).

In order to be effective a MOOCs course should address a wider range of audience with wider abilities. Research done in 2013 only exposed a further weakness. Many of the MOOCs lecturers, although competent in their domain of influence, never taught or designed on-line courses. They were pressured into doing so by their employers so that the institution would be able to get in on the trend (Daniel, 2012). In addition to this , the competitive attitude of US universities is focused on getting the best students and lecturers on board. Money is devoted to getting top staff and good research prospects abound too. This bias does not lend itself well to the intentions behind MOOCs. As is obvious MOOCs are not selective to a cohort (Daniel, 2012). MOOCs found favour from many institutions as they seem to adapt well for *"Just In Time Education"*. Or even for quickly propping up of existing facilities or the lack thereof. MOOCs are by nature very flexible and adaptable but also focused in scope and purpose (Selingooct, 2014).

D.1.2 Various Models

The MOOC phenomenon can be generally considered a disruptive one. This in the sense that it destabilises current or conventional teaching approaches. Many institutions jump on the band wagon simply not to fall behind other competitors (Petronzi and Hadi, 2016). MOOCs can be generally seen to ride on technology by using communication media as their backbone. This enables better distribution of course material and possibly more participation options become available. There are two main models to MOOCs these are Connectivist Massive Open On-Line Courses (cMOOCs) and Content-Based Massive Open On-Line Courses (xMOOCs) as shown below (Burge, 2015):

- cMOOCs: Take a *connectivist* learning approach. These packages generally appeal to academics. They can be typically found on university platforms and are often based upon open source software which enable delivery and dissemination.;

- xMOOCs: More content based system. They comprise the majority of platforms available. Software used in these cases are closed or proprietary.

D.1.3 Criticism

As always no idea is really without flaws and critics. MOOCs are no exception to the rule and many criticise this approach to learning as leaning heavily towards an *objectivist* based learning model. The *objectivist* model relies on knowledge through reason (Burge, 2015). And many dislike this view by stating that if a learner has not matured enough in a specific subject area, he cannot really apply proper reasoning to extend his knowledge.

The *connectivist* approach takes a different stance though. Knowledge in the latter case is built from the experience of the student and then put the test for validity (Burge, 2015).

D.2 Conclusion

Theories of teaching and learning are largely independent of media [1]. Despite the copious work done along the past century or so, media never plays the leading role in transmitting teaching and learning. If this is so why can we see that e-Learning is on the resurgence, but it is hardly making a dent in statistics. It is as if a novelty that has exceeded its lifetime. Or else the coursework has not yet developed as much to keep people engaged. In his paper Engaging with Massive On-line Courses, Anderson describes how difficult it is to retain students in courses as they stand (Anderson et al., 2014). Despite giving a lot of information the paper no way forward. It states that despite the high interactivity we still do not understand what really motivates students to keep on working on courses. So we need to understand how students interact with MOOCs (Anderson et al., 2014).

[1] Appendix C refers.

E Data Classification Script

```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from pandas.plotting import parallel_coordinates
from sklearn.tree import DecisionTreeClassifier, plot_tree
from sklearn import metrics
from sklearn.naive_bayes import GaussianNB
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis,
    QuadraticDiscriminantAnalysis
from sklearn.neighbors import KNeighborsClassifier
from sklearn.svm import SVC
from sklearn.linear_model import LogisticRegression

# Read the file
data = pd.read_csv('C:/Users/HP-User/Dropbox/Data Files/StudentData.csv')

# Some Stats on the Data
print(data.head())
print(data.describe())
# Analyse contents of the dataframe
print(data.groupby('Token').size())

# Stratified hold-out approach to estimate model accuracy
train, test = train_test_split(data, test_size = 0.4, stratify = data['Token'
    ], random_state = 42)

# Plot and analyse
n_bins = 10
fig, axs = plt.subplots(2, 2)
axs[0,0].hist(train['physics'], bins = n_bins);
axs[0,0].set_title('Physics');
axs[0,1].hist(train['chemistry'], bins = n_bins);
```

```python
axs[0,1].set_title('Chemistry');
axs[1,0].hist(train['biology'], bins = n_bins);
axs[1,0].set_title('Biology');
axs[1,1].hist(train['math'], bins = n_bins);
axs[1,1].set_title('Math');
# add some spacing between subplots
fig.tight_layout(pad=1.0);

sns.pairplot(train, hue="Token", height = 2, palette = 'colorblind');
plt.show()

#Pearson Method Correlation
print(train.corr(method='pearson'))

#Let's Start Classifying
X_train = train[['physics','chemistry','biology','math']]
y_train = train.Token
X_test = test[['physics','chemistry','biology','math']]
y_test = test.Token

mod_dt = DecisionTreeClassifier(max_depth = 3, random_state = 1)
mod_dt.fit(X_train,y_train)
prediction=mod_dt.predict(X_test)
print('The accuracy of the Decision Tree is',metrics.accuracy_score(
    prediction,y_test))
print(X_test)
```

Listing E.1: Data Classification Script

F Data Generation Script

```
import scipy.stats as ss
import numpy as np
import pandas as pd


SampleSize = 3000

def studentGrade(SampleSize):
    phy = genNums(SampleSize)
    chm = genNums(SampleSize)
    bio = genNums(SampleSize)
    mth = genNums(SampleSize)

    return phy, chm, bio, mth

def genNums(SampleSize):
    x = np.arange(-5, 6)
    xU, xL = x + 0.5, x - 0.5
    prob = ss.norm.cdf(xU, scale = 1) - ss.norm.cdf(xL, scale = 1)
    prob = prob / prob.sum() # normalize the probabilities so their sum is 1
    nums = np.random.choice(x, size = SampleSize, p = prob)

    return nums

myDataFrame = pd.DataFrame()
gradLable = "ABCD"
gr = []
e = ""

print("Generating Grades.  Please wait ...")
phy, chm, bio, mth = studentGrade(SampleSize)

for i in range (0,SampleSize):
    gr.insert(0,phy[i]+5)
```

```
    gr.insert(1,chm[i]+5)
    gr.insert(2,bio[i]+5)
    gr.insert(3,mth[i]+5)

    for x in range (0,4):
        if gr[x] < 4.5:
            e = e + gradLable[x]
    if e == "":
        e = "P"

    res = {"physics": gr[0], "chemistry": gr[1],"biology": gr[2],"math": gr
    [3],"Token": e}
    myDataFrame = myDataFrame.append(res,ignore_index=True)
    e = ""

# Save dataframe into a CSV file
myDataFrame.to_csv(r'C:\Users\HP-User\Dropbox\Data Files\StudentData.csv')

# Analyse contents of the dataframe
print(myDataFrame.groupby('Token').size())

print("Data export ready")
```

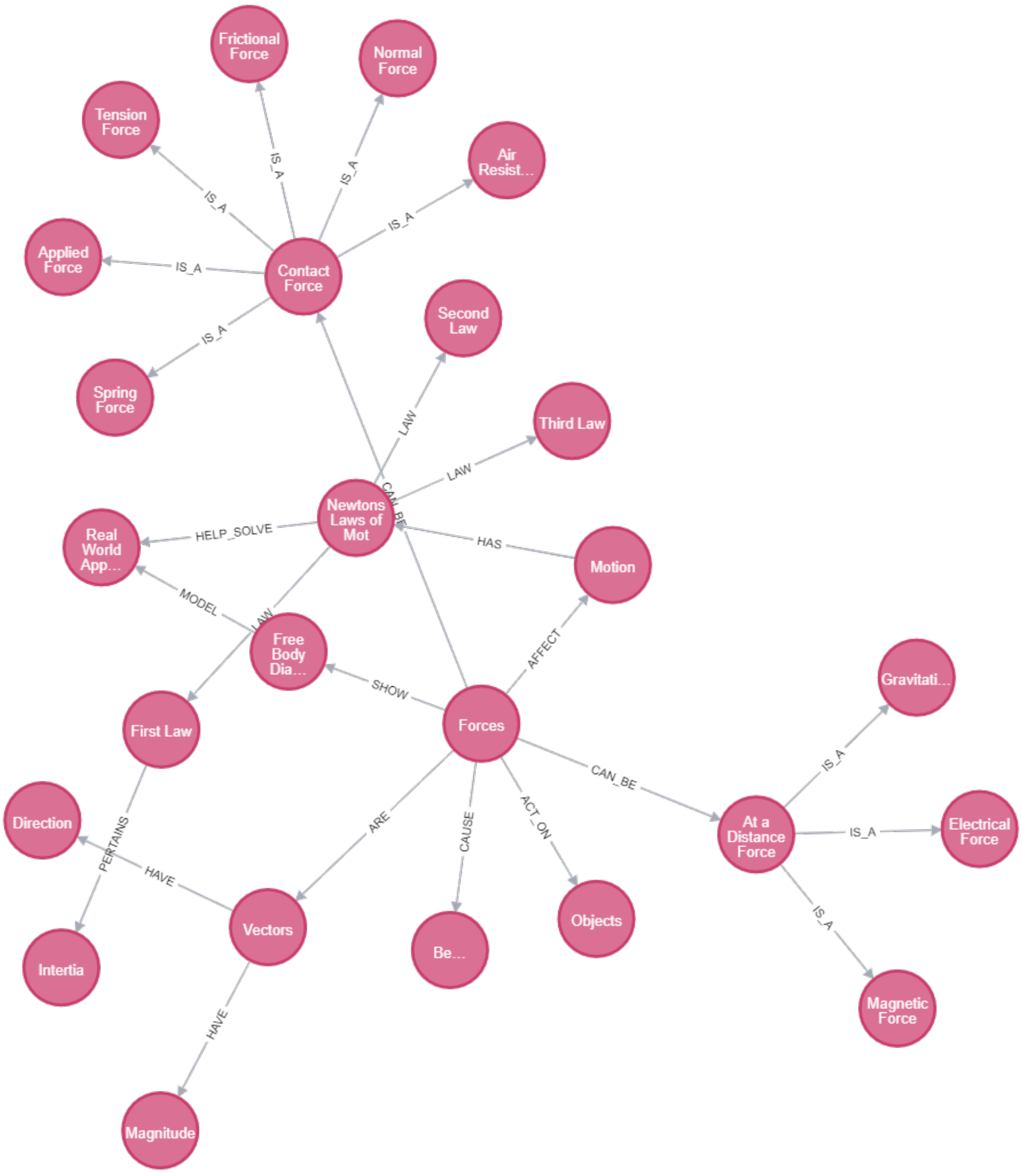
Listing F.1: Data Generation Script

G Sample Data Set Features

- school - student's school (binary: "GP" - Gabriel Pereira or "MS" - Mousinho da Silveira)
- sex - student's sex (binary: "F" - female or "M" - male)
- age - student's age (numeric: from 15 to 22)
- address - student's home address type (binary: "U" - urban or "R" - rural)
- famsize - family size (binary: "LE3" - less or equal to 3 or "GT3" - greater than 3)
- Pstatus - parent's cohabitation status (binary: "T" - living together or "A" - apart)
- Medu - mother's education (numeric: 0 - none, 1 - primary education (4th grade), 2 – 5th to 9th grade, 3 – secondary education or 4 – higher education)
- Fedu - father's education (numeric: 0 - none, 1 - primary education (4th grade), 2 – 5th to 9th grade, 3 – secondary education or 4 – higher education)
- Mjob - mother's job (nominal: "teacher", "health" care related, civil "services" (e.g. administrative or police), "at-home" or "other")
- Fjob - father's job (nominal: "teacher", "health" care related, civil "services" (e.g. administrative or police), "at-home" or "other")
- reason - reason to choose this school (nominal: close to "home", school "reputation", "course" preference or "other")
- guardian - student's guardian (nominal: "mother", "father" or "other")
- traveltime - home to school travel time (numeric: 1 - <15 min., 2 - 15 to 30 min., 3 - 30 min. to 1 hour, or 4 - >1 hour)
- studytime - weekly study time (numeric: 1 - <2 hours, 2 - 2 to 5 hours, 3 - 5 to 10 hours, or 4 - >10 hours)

- failures - number of past class failures (numeric: n if 1<=n<3, else 4)
- schoolsup - extra educational support (binary: yes or no)
- famsup - family educational support (binary: yes or no)
- paid - extra paid classes within the course subject (Math or Portuguese) (binary: yes or no)
- activities - extra-curricular activities (binary: yes or no)
- nursery - attended nursery school (binary: yes or no)
- higher - wants to take higher education (binary: yes or no)
- internet - Internet access at home (binary: yes or no)
- romantic - with a romantic relationship (binary: yes or no)
- famrel - quality of family relationships (numeric: from 1 - very bad to 5 - excellent)
- freetime - free time after school (numeric: from 1 - very low to 5 - very high)
- goout - going out with friends (numeric: from 1 - very low to 5 - very high)
- Dalc - workday alcohol consumption (numeric: from 1 - very low to 5 - very high)
- Walc - weekend alcohol consumption (numeric: from 1 - very low to 5 - very high)
- health - current health status (numeric: from 1 - very bad to 5 - very good)
- absences - number of school absences (numeric: from 0 to 93)
- G1 - first period grade (numeric: from 0 to 20)
- G2 - second period grade (numeric: from 0 to 20)
- G3 - final grade (numeric: from 0 to 20, output target)

H Neo4J Schema



I Algorithm Analysis Script

```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from pandas.plotting import parallel_coordinates
from sklearn.tree import DecisionTreeClassifier, plot_tree
from sklearn import metrics
from sklearn.naive_bayes import GaussianNB
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis, QuadraticDiscriminantAnalysis
from sklearn.neighbors import KNeighborsClassifier
from sklearn.svm import SVC
from sklearn.linear_model import LogisticRegression

# Read the file
data = pd.read_csv('C:/Users/HP-User/Dropbox/Data Files/StudentData.csv')

# Some Stats on the Data
print(data.head())
print(data.describe())
# Analyse contents of the dataframe
print(data.groupby('Token').size())

# Stratified hold-out approach to estimate model accuracy
train, test = train_test_split(data, test_size = 0.4, stratify = data['Token'], random_state = 42)

# Plot and analyse
n_bins = 10
fig, axs = plt.subplots(2, 2)
axs[0,0].hist(train['physics'], bins = n_bins);
axs[0,0].set_title('Physics');
axs[0,1].hist(train['chemistry'], bins = n_bins);
```

```
axs[0,1].set_title('Chemistry');
axs[1,0].hist(train['biology'], bins = n_bins);
axs[1,0].set_title('Biology');
axs[1,1].hist(train['math'], bins = n_bins);
axs[1,1].set_title('Math');
# add some spacing between subplots
fig.tight_layout(pad=1.0);

sns.pairplot(train, hue="Token", height = 2, palette = 'colorblind');
plt.show()

#Pearson Method Correlation
print(train.corr(method='pearson'))

#Let's Start Classifying
X_train = train[['physics','chemistry','biology','math']]
y_train = train.Token
X_test = test[['physics','chemistry','biology','math']]
y_test = test.Token

mod_dt = DecisionTreeClassifier(max_depth = 3, random_state = 1)

mod_dt.fit(X_train,y_train)
prediction=mod_dt.predict(X_test)
print('The accuracy of the Decision Tree is',metrics.accuracy_score(
    prediction,y_test))
print(X_test)
```

Listing I.1: Algorithm Analysis Script