UNIVERSITY OF CAPE TOWN

MSc Advanced Analytics

STA5004W

Prototype Learning Analytics Dashboard (LAD) for an Introductory Statistics Course at UCT

Author: ***Suvir Gajadhur***

Supervisor: ***Associate Professor Leanne Scott***

A project submitted in partial fulfilment of the requirements for the degree of Master of Science

in the

Faculty of Science
Department of Statistical Sciences

12 March 2021

University of Cape Town

The copyright of this thesis vests in the author. No quotation from it or information derived from it is to be published without full acknowledgement of the source. The thesis is to be used for private study or non-commercial research purposes only.

Published by the University of Cape Town (UCT) in terms of the non-exclusive license granted to UCT by the author.

University of Cape Town

Declaration of Authorship

I, Suvir Gajadhur, declare that "Prototype Learning Analytics Dashboard (LAD) for an Introductory Statistics Course at UCT and the work presented in it is my own.

I confirm that:

- This project was completed as a requirement for Statistics Masters at the University of Cape Town.
- Other published work has been consulted; this is always clearly attributed.
- When quoting work from others, the source is always given. This thesis is entirely my own work.
- I have acknowledged all main sources of help.

Signed: Signed by candidate

Date: 12 March 2021

UNIVERSITY OF CAPE TOWN

Abstract

Faculty of Science
Department of Statistical Sciences

Master of Science
MSc Advanced Analytics

Prototype Learning Analytics Dashboard (LAD) for an Introductory Statistics Course at UCT

by Suvir Gajadhur

A learning analytics dashboard (LAD) is an application that illustrates the activity and progress of a user in a self-regulated, online learning environment. This tool mines source data to provide meaningful information that supports decision making and positively impacts learning behaviour. Research on this topic explores how learning activities and pedagogical goals are impacted by integrating LADs into learning and/or teaching environments. Currently, the majority of the research is centred around predicting student academic performance and identifying students that are at risk of failing. The popularity of integrating technology into educational practices has led to the adoption of LADs into learning management systems (LMS) or massive open online courses (MOOCs). The objective of this paper is to develop a concept for a standalone prototype LAD, for an Introductory Statistics course (STA 1000), to be potentially integrated into the University of Cape Town's (UCT) LMS, Vula. The dashboard aims to create and incorporate meaningful visualisations, that have the potential to primarily assist students as well as educators. Visualised information in the LAD aims to positively impact students to enhance and drive effective learning, which could consequentially aid educators. Additionally, the dashboard will aim to provide actionable feedback, derived from predictive modelling and course analytics, that positively impacts learning behaviour and identifies factors that the student could most effectively use to leverage their chances of passing and improve academic performance. Predictive analytics aim to identify academic factors, that a student has control over, such as course assessments and engagement variables, at certain time points in the academic semester and provide a useful course of action at those time points. Other than variables measured throughout the course, the predictive modelling takes certain prior academic information into consideration.

Key Words: Learning Analytics Dashboards (LAD), Information Visualisation, Actionable Feedback, Academic Performance, Learning Management System (LMS)

Acknowledgments

I have received a great deal of support and assistance throughout the writing of this dissertation.

I would first like to thank my supervisor, Associate Professor Leanne Scott, whose expertise was invaluable in the fulfilment of this dissertation. Thank you for your patience and constant guidance, your insightful feedback pushed me to sharpen my thinking and brought my work to a higher level. I am truly grateful for your willingness to steer me in the right direction

Acknowledgement to UCT Learning Designer, Thomas King, and former STA 1000 Head Tutor, Michaela Takawira. Thank you for taking the time to meet with me. Your constructive feedback has greatly contributed to this dissertation.

To my family, I am honoured and blessed to have such a wonderful family. To my parents, Rikkie and Varsha, thank you for your words of encouragement and constant support throughout this journey. Without you, I would not be the person I am today. To my brother, Nimal, thank you for playing video games with me and helping me calm my nerves and destress. To my girlfriend, Alka, who has tirelessly edited my numerous draft versions of this dissertation – thank you for all your help. Your guidance, wisdom, and support are truly appreciated. Thank you for bringing out the best in me and always encouraging me to strive for greatness.

Contents

List of Figures

List of Tables

List of Abbreviations

General

CILT	Centre for Innovation in Learning and Teaching
EDA	Exploratory Data Analysis
EDM	Educational Data Mining
ICT	Information and Communication Technology
KPI	Key Performance Indicator
LA	Learning Analytics
LAD	Learning Analytics Dashboard
LAK	Learning Analytics and Knowledge
LMS	Learning Management System
MAR	Missing at Random
MCAR	Missing Completely at Random
MOOC	Massive Open Online Course
NBT	National Benchmark Test
SoLAR	Society for Learning Analytics
SRL	Self-Regulated Learning
STA 1000	Introductory Statistics course at UCT
UCT	University of Cape Town
VLE	Virtual Learning Environment
Vula	UCT's LMS

Modelling

A1 – A12	Assignment 1 – Assignment 12
AUC	Area Under the Curve
Average 1, 2, 3, 4	Cumulative average of each Assignment at a certain time point
B1 – B4	Bonus Mark 1 – Bonus Mark 4
Bonus TP1 – TP4	Cumulative number of Bonus marks obtained at each TP
OR	Odds Ratio
ROC	Receiver Operating Characteristic
T2 – T12	Tutorial 1 – Tutorial 12
TAverage 1, 2, 3, 4	Cumulative average of each Tutorial at a certain time point
TP	Time Point
TP1 – TP4	Time Point 1 – Time Point 4

1 Introduction

1.1 Overview

Traditional teaching and learning practices have transformed with the development of Information and Communication Technology (ICT) in higher education. A burgeoning amount of information is being delivered and accessed through blended and online learning courses. Online systems like Learning Management Systems (LMS), Virtual Learning Environments (VLE) and Massive Open Online Courses (MOOCs) have become key instruments in technology enhanced learning over the last few years. These platforms combine resources and tools to enhance and support learning, including specific content and multi-media resources, assessment tools, communication tools, course administration tools and learning management tools that allow students to monitor and review progress.

In order to enhance the online learning experience, there has been a growing interest in the automatic analysis of educational data. The complexity and volume of data that is collected through educational technologies is increasing rapidly. The progressively important need to understand technology-mediated learning environments has led to the development of Learning Analytics (LA). Learning Analytics is defined as "the measurement, collection, analysis, and reporting of data about learners and their contexts, for purposes of understanding and optimising learning and the environments in which it occurs" (**Siemens & Gasevic, 2012**).

The combination of explicit pedagogical goals and the need for enhanced flexibility surrounding content delivery and course engagement, defines the current state of educational practices. Given the robust integration of technology, monitoring students has become increasingly difficult, and educators are therefore placed under pressure to implement and demonstrate effective pedagogical practice. New tools and strategies are critically required to identify struggling students, so that supporting mechanisms can be effectively developed.

The appropriate integration of analytical tools into online learning platforms has the potential to enhance teaching and learning approaches. **Hadhrami (2017)** argues that "it can enable every learner to achieve his or her potential and help to build an educational environment granted to change." Research into the field of LA and EDM utilises data from online learning platforms in predictive modelling, with the aim of predicting whether a student is at risk of failing a course. Learning analytical tools integrated with a Learning Analytics Dashboard (LAD) could potentially accomplish this notion, as large amounts of complex information is often more meaningful and easily interpretable if it is visually represented.

This project aims to develop a concept for a prototype LAD that captures information pertaining to student participation throughout the semester and provide visual illustrations that enhances the learning experience. The prototype attempts to increase student awareness and influence the users' psychologies, which positively impacts self-reflection, thereby driving and supporting effective action. Additionally, the dashboard is intended to identify at risk students for an introductory statistics course at the University of Cape Town (UCT), STA1000; and mitigate the risk by providing appropriate recommendations and interventions based on predictive modelling. The LAD intends to provide actionable intelligence that positively impacts student learning behaviour and aims to improve learning and teaching practices.

1.2 Study Rationale

The step between setting a goal and achieving a goal is the crucial process of goal monitoring, which ensures that ideas are turned into actions. Promoting progress through goal monitoring has the potential to improve behavioural performance and the likelihood of attaining one's goals (**Harkin et al., 2016**). Additionally, the same study conducted by **Harkin et al. (2016)** revealed that monitoring the progress of achieving goals had a greater effect if the progression information was physically recorded or publicly reported. Similarly, pertinent, and relevant information that is graphically illustrated with appropriate visualisations in the LAD could possibly influence users' psychologies and actions to drive effective learning and teaching.

1.2.1 Goals and Target Users

The premise behind an effective LAD is that the design, structure, and content is meaningful enough to positively impact behaviour. Aesthetically appealing visualisations that illustrate appropriate information, but fails to facilitate action, is simply ineffective. **Duval (2011)** explains that, "visualisation of eating habits can help to lead a healthier life … a visualization of mobility patterns can help to explore alternative modes of transport." Similarly, the prototype dashboard presented in this project aims to include visuals pertaining to academic activity that can help students improve their performance and adopt a constructive learning behaviour.

The objective of the dashboard is to capture, monitor and visualise progress through the academic semester which will allow students to reflect on their activity. The dashboard aims to stimulate psychological aspects by improving self-knowledge and self-awareness, in order to encourage action and impact learning behaviour. Predictive modelling will identify at risk students and provide an appropriate course of action to mitigate the risk. Consequently, students will be presented with their current progress, allowing them to modify their learning strategy and increase their enthusiasm to achieve their academic goals. Although the primary users of the dashboard are students, educators could potentially use the dashboard to enhance and improve teaching practices.

Visuals that summarise progress throughout the semester will be graphically illustrated on a weekly basis, as well as on a cumulative basis. Recommendations for students will be available every second week of the semester, allowing the predictive algorithms to process more data. Recommendations are tailored to all types of students. At risk students will be provided with an appropriate course of action in order to mitigate risk and other students will be provided with recommendations that acknowledge and reinforce positive constructive learning. These recommendations aim to provide actionable intelligence that can positively impact learning behaviour and stimulate engagement throughout the duration of the course.

1.2.2 Research Objectives

- Develop a concept for standalone prototype LAD, and a conceptual framework, that has the potential to be integrated into UCT's Learning Management System (LMS), Vula, for STA 1000.
- Use course analytics to visually depict and track progression to identify important and useful information for a student.
- Identify at risk students (at risk of failing STA 1000) using predictive analytics and determine whether the output from the predictive analytics can be leveraged and used to provide an appropriate course of action (recommendations) for at risk and not at risk students.
- Develop a foundational basis or conceptual framework for recommendations in order to promote and encourage positive constructive learning and stimulate course engagement for all students, which has the potential to mitigate the risk of failure for at risk students.
- Determine whether reccomendations might differ depending on the student's prior learning experience.
- Integrate visuals from the course analytics and recommendations from the predictive and course analytics into the LAD.

1.2.3 Research Questions

- Are the variables that are recorded during STA 1000 significant/useful for predicting academic performance (identifying students at risk of failing)?
- Is it possible to develop an appropriate course of action (recommendations) from the developed predictive models?
- Does the mathematical background of a student impact performance in STA 1000? If so, is it important to know the mathematical background of a student when providing recommendations?

2 Literature Review

2.1 Education Dashboards

2.1.1 Background

Charleer et al. (2016) proposed that LADs "have the potential to be used as powerful metacognitive tools for learners, triggering them to reflect and examine their learning behaviour and learning outcomes." This notion implies that a LAD, that could visually depict pertinent information, could build on research in the fields of Learning Analytics (LA), Educational Data Mining (EDM) and visualisation. Simply, a LAD is a tool that aims to improve decision making by amplifying or directing cognition and capitalizing on human perceptual capabilities. **Romero and Ventura (2007)** indicate that there has been research regarding the interpretation of education data since 1995. In recent years, work surrounding the online educational industry has progressively developed, with the introduction of the first conference on EDM, the Journal of Educational Data Mining, and the establishment of the EDM Society in 2008. The field of LA held the first conference on Learning Analytics and Knowledge (LAK) in 2011, followed one year later by the foundation of the Society for Learning Analytics (SoLAR) (**Schwendimann et al., 2016**).

The first exhaustive systematic review of LADs was conducted by **Schwendimann et al. (2016)**.The authors examined 55 dashboards and performed an analysis of the context in which dashboards had been deployed. The purpose of LADs, the key performance indicators (KPIs) used, technologies used to develop a LAD and maturity of the evaluation of the LAD itself were examined. In their review they found that in a higher educational context, the systems are instructor-dependant and the research that is being done does not focus on the impact of these tools on teaching and learning.

2.1.2 Learning Context

Four types of users were identified: teachers, students, researchers, and administrators. Teachers and students obtained a dominant focus amongst the research papers, whilst researchers and administrators were vaguely mentioned - but still obtained a noteworthy appearance.

Three types of learning scenarios were illustrated in the research: formal learning (education that is delivered by trained personnel in a systematic intentional manner within an institution), non-formal learning (similar to formal learning but lacking a level of curriculum, syllabus, accreditation or certification associated with formal learning) and informal learning (non-intention and non-structured form of learning). The majority of the papers discussed the use of dashboards in a formal learning environment, whilst the remainder discussed non-formal learning or did not specify the learning context.

The majority of the papers examined discussed a dashboard in a tertiary educational context. Other papers either did not specify a learning context or specified the use or potential use of a dashboard at the primary or secondary educational level. Most researchers only have access to specific learning contexts explaining the lack of LAD in other learning contexts (**Schwendimann et al., 2016**). **Jivet et al. (2018)** and **Schwendimann et al. (2016)** come to similar conclusions, stating that they expect an increase in experimentation to introduce dashboards in other learning contexts and environments.

A variety of different platforms were identified amongst the literature where VLEs and/or LMSs were a dominant focus. Cognitive Tutors, computer-based and web-based environments, as well as mobile settings, are other notable platforms. Recently, MOOCs and social learning platforms have been gaining popularity. Despite the lack of specific learning activities throughout the papers, there is a popularity of using dashboards for monitoring and visualising outcomes for individual or multiple learning sessions, or for an entire course.

2.1.3 Purpose and Development

Several studies discuss the benefits of using dashboards to provide feedback that may improve learning and/or pedagogy **(Bodily & Verbert, 2017; Duval, 2011; Dyckhoff et al., 2012; Hu, Lo & Shih, 2014; Mottus, Graf & Chen, 2015; Verbert et al., 2013)**. Most of the published case studies are either exploratory or experimental. Empirical studies or surveys are common, whilst a few are evaluation studies. The context differs across studies, but focuses mostly on science, technology, engineering, and mathematics (STEM).

Most of the LADs focus on learner performance indicators: where a learner is doing well/poor, how much content has been completed, how much time was spent, how learners' progress compares to a predetermined score /or peer scores). Essentially, these tools target performance visualisation that takes the form of outcome feedback (e.g., “How do I perform?). These types of LADs do not actively support learners’ motivation and engagement.

Each study contains a different focus, as this aspect is dependent on the context to which it is applied. The key areas outlining the purpose for a LAD are: (1) Student behaviour modelling, (2) Performance prediction, (3) Increase self-reflection & self-awareness, (4) Dropout & retention prediction, (5) Improvement of assessment and feedback services, (6) Resource recommendation. The ajority of the papers focus on student behaviour, followed by performance prediction.

Six different types of data sources were identified that were used to obtain data for a particular dashboard: (1) Computer logs, (2) Analysed data from user activity, (3) Physical user activity, (4) Information asked directly from users (questionnaires, surveys etc.), (5) Database records from the institution, (6) Data collection from external sources of platforms. A noteworthy observation was that many papers relied on one or two data sources. A handful of papers made use of four or five data sources combined. Computer logs seemed to be the most frequently sought source, with analysed data from user activity following behind. Following these two data sources were information obtained directly from users, institutional databases, and physical activity.

A large the majority of the papers did not specify the medium used to construct and present the dashboard. In general, it was possible to identify that the dashboard was a web application. A handful of studies did mention specific tools used to construct the dashboard, including the frameworks and libraries (**Schwendimann et al., 2016)**. The following list includes certain software that was mentioned throughout the literature: Google App Engine, Google Maps, Google Charts, iGoogle widgets, QlikView, Tableau, D3.js, Learning Log Dashboard (L2D), GLASS tool, Navi Badgeboard, Navi Surface, LARAe, JsCharts, Highcharts, HTML, R, and Java (**Schwendimann et al., 2016**).

2.1.4 Context and Visualisation

A variety of structural content, in addition to visualisation techniques, was noted amongst the literature. Different circumstances and end users of a LAD require different structural content, as specific environments require customised content to achieve certain goals. There is a lack of knowledge regarding the topology of feedback that is relevant to a specific learning context, and what works best for different learning and pedagogical goals to provide actionable insights. **Sawyer (2014)** asserts that research on LADs lacks theoretical support from the recent advancements in the field of LA. More empirical studies are needed to build an evidence-informed foundation for selecting and communicating information, that supports in identifying useful feedback needs for learners and/or educators. As a rule, **Sedrakyan, Mannens and Verbert (2019)** assert that customised environments that facilitate representations for regulatory processes of learning are beneficial when mapping the structural content. The content with the LAD differs depending on the perspective of the user. The environment contains visual aspects that aim to simulate a metacognitive monitoring behaviour. Essentially, the LAD environment should aim to guide learners and inform educators about the coherence and alignment between earners' and teacher's specified goals and action plans. This technique will allow learners to adjust or change their goals, plans, or strategies for learning and inform learners about their level of effort.

Monitoring behaviour has been observed to enable learners to adjust or change their goals, plans or strategies for learning (**Sedrakyan et al., 2020**). The structural foundation of a LAD should contain informative comparative overviews that alert users regarding progress, with respect to defined goals that could enhance the effectiveness and efficiency of learning. The technique of quantifying achievement and promoting progress awareness has proven to be an effective tool in different learning contexts **(Sedrakyan, Mannens & Verbert, 2019)**.

The majority of the studies pertaining to the design principles for LADs amongst the literature do not follow a theoretical framework for the underlying mechanisms of learning processes. There are several arguments that highlight the importance of integrating theoretical concepts that inform a LAD framework. In other words, it is recommendend that theoretical frameworks are considered, adapted and integrated into design process; using a design or data-driven approach will probably be ineffective and have deteriorating effects on learning behaviour **(Matcha, Gašević & Pardo, 2019; Sedrakyan, Mannens & Verbert, 2019)**. **Kia et al. (2020)** also states that feedback to students needs to be dialogical and not unidirectional which can only be achieved if the design principles for a LAD are developed using theoretical standards, foundations, and strategies. The authors also suggest that the LAD will be ineffective and not provide potent and actionable feedback if the design principles do not consider or incorporate theoretical elements.

Few (2013) explains that effective communication and accurate decision making are the key aspects for a well-designed dashboard. The key design principles are as follows: firstly, the pertinent information should stand out from the rest of the dashboard; second, the information should support one's situated awareness and help rapid perception using diverse visualisation technology; lastly, information should be portrayed in a manner that is easily understandable and interpretable and supports end-goal decision making.

Additionally, **Charleer et al. (2016)** have proposed several guidelines that could lead to the development of effective LADs:

- Manual exploration of elements to empower and promote the student to reach a certain outcome.
- Abstracted and augmented approaches need to be considered to improve judgement, quality, and exploration of the data.
- Teacher and peer feedback made accessible if possible and incorporate assessment data to raise awareness and support reaction and retention.
- The design should provide insight and guidelines toward a reasonable learning path that supports reaction, peer interaction and self-regulated learning.
- Tailor the dashboard structure and content to the learning context, pedagogical goals, and technological capacity in order to obtain the most impact and effectiveness and acceptance.
- If possible, incorporate collaborative exploration that promotes discussion and peer involvement and healthy competition, that will enhance learning, reaction, and awareness.

In terms of pure visual representations, **Stoltzman (2018)** recommends focussing on the aim of visual representation to aid the selection of charting options. As a rule of thumb, the author classifies the following minimal set of mappings in terms of intended goals and possible relevant visualizations:

- Trend: Column or Line
- Comparison: Area, Bar, Bullet, Column, Line, or Scatter
- Relationship: Line or Scatter
- Distribution: Bar, Boxplot, or Column
- Composition: Donut, Pie, Stacked Bar, or Stacked Column

Various dashboards have been developed and documented across the literature. Table 2.2.1 presents the most notable mentions across published papers including the content and visualisation techniques. All the studies reported successful results in aiding performance and/or decision making.

Table 2.2.1: Tracked data and visual techniques from previous LADs

Name of Dashboard	Information Displayed	Visuals/Graphics
LOCO-Analyst	Login Trends, Performance, Content Usage, Message Analysis	Bar Graph, Pie Chart, Table Matrix, Tag Cloud
Student Success System	Performance, Social Network, Predictions	Risk Quadrant, Scatterplot, Win-Lose Chart, Sociogram
SNAPP	Content Usage, Social Network, Message Analysis	Sociogram
Student Inspector	Performance, Content Usage	Bar Graph, Pie Chart
GLASS	Login Trends, Performance, Content Usage, Message Analysis	Timeline, Bar Graph
SAM	Login Trends, Performance, Content Usage, Message Analysis	Line Chart, Bar Graph, Tag Cloud
Course Signals	Login Trends, Performance, Content Usage, Message Analysis	Signal Lights

There are a few studies that address the impact of peer-orientated dashboards. Despite the lack of research, studies still suggest that social influence could potentially affect student motivation. **Sedrakyan, Mannens and Verbert (2019)** explain that a dashboard could contain a level of peer-oriented feedback (e.g., “You seem to be efficient at completing this task. Can you give advice to your peer who seems to have difficulty with concept X?”). This technique could allow a student track performance against peers. Research suggests that these techniques could either be harmful or helpful, depending on the student, and more research is required to draw definitive conclusions.

de Freitas et al. (2017) conducted a study regarding integrating gamification into a learning dashboard. They argue that there has been a positive impact on learning abilities and reported “increases in student motivation, engagement, satisfaction, retention and performance enhancements.” The field is quite under matured and no definitive conclusions can be drawn to the actual impact of introducing games into learning dashboard environments. Further studies and developments are essential to validate the effectiveness of integrating gaming dashboards into educational practices.

2.1.5 Evaluation of LADs

The theoretical foundations that are used to supplement the design and evaluation of dashboards could be a stand-alone research topic. Although dashboard evaluation is not a major part of this review, it still plays an important role in illustrating the current state of the dashboard as an educational tool. Upon analysis of the literature, it was noted that most of the papers contained a form of evaluation criteria, whilst the remainder contained none.

Many of the dashboard evaluations used, aimed to address general concepts, with the intention of gathering feedback to improve or enhance the dashboard. A handful of studies went into specific details with mapped evaluation criteria. More complex criteria involve cognitive, metacognitive, behavioural, emotional, and self-regulatory aspects.(**Jivet et al., 2018**) The most common evaluation criteria revolved around usability, usefulness, and satisfaction. Many of the studies reviewed did not cite the mechanism used to conduct the evaluation, which indicates a lack of consistency regarding the evaluation process.

2.2 Variables Affecting Performance

2.2.1 Prior Learning

Several published studies establish that prior learning proficiency affects student performance across certain academic disciplines. While several studies are conducted internationally, **Kizito, Munyakazi and Basuayi (2016)** and **Tewari (2014)** mention the significant relationship between prior mathematical learning proficiency and performance, in a South African Context. **Van Eeden, De Beer and Coetzee (2001)** found that school achievement was the best predictor for student achievement in engineering and other science and technology disciplines for higher education in South Africa.

On a more general level, **Kennedy et al. (2015)** found that prior knowledge is the most significant predictor of success in MOOCs. These results coincide with previous educational studies that have established that prior knowledge and skills – both in terms of content knowledge and generic learning skills (such as problem solving) – can greatly influence students' learning success.

2.2.2 Pre-Entry Attributes

The predictive ability of pre-admission attributes differs according to context and setting. Within a South African context, **Van Zyl, Gravett and De Bruin (2012)** found that most significant pre-admission predictors were concentrated in a predefined academic cluster of variables. Additionally, the authors state that their findings are consistent with historic literature and confirm the importance of previous academic performance, as the strongest predictor of future academic performance.

The relationship between the National Benchmark Test (NBT) and academic performance in higher education is not well researched. **Jacobs (2018)** reported statistical significance of Grade 12 and NBT marks as predictors of academic performance in Science and Engineering programs. However, **Le Roux and Sebolai (2017)** found that the two NBT assessments are related by a curvilinear relationship and argue that the complementarity could question the value of using the performance information generated. The contrasting conclusions suggest that more research is required to determine the effectiveness of NBT results.

2.2.3 Course Achievement

There are a few empirical studies addressing the personal factors that influence students' achievement in different learning environments. **Artino Jr (2010)** conducted a study that bridged the gap in literature and established a relationship between personal factors and student achievement in online or face-to-face learning environments.

The extent to which online participation affects performance is unclear. **de Barba, Kennedy and Ainley (2016)** found that participation was the strongest predictor of performance in a MOOC environment. **Davies and Graff (2005)** found that meaningful participation did not lead to significantly higher performance for students achieving passing grades; however, students that failed contained less frequent interaction.

Several published papers indicate significant correlations between different online activities from tracked LMS data and performance. Studies indicate that different environments and contexts suggest that different variables are significant in varied circumstances. As a reference, **You (2016)** explains the "importance of self-regulated learning and reveals the advantages of using measures related to meaningful learning behaviours rather than simple frequency measures."

Conversely, the relationship between participation and performance in a non-e-learning environment is robust and clear among the literature. Although, contributions of significant variables to performance in face-to-face settings appear to generalise to online environments, weaker effects are apparent and suggest that they may be less effective, or that other, currently unexplored factors may be more important in online contexts (**Broadbent & Poon, 2015**).

2.3 Prediction Models

Empirical research structured around learning analytics are focussed towards predicting student performance, measured by unique grading systems – a final grade or whether a student has passed or not. Predictive models across the literature use data from a variety of sources that can be classified as time variant and time invariant data. Time invariant predictors relate the demographic or socioeconomic characteristics, as well as any prior academic performance of the student. Time variant predictors relate to any variables that can be measured throughout the duration of the course. Different studies across the literature either use one of the variables or a combination of the two, depending on the research objectives.

The majority of empirical studies across the literature use regression techniques, with the most popular being logistic and multiple linear regression (MLR) or analysis of variance (ANOVA) (Hailikari, Nevgi & Lindblom-Ylänne, 2007; Hicks & Richardson, 1984; Thatcher, Fridjhon & Cockcroft, 2007). Alternatively, **Lykourentzou et al. (2009)** assert that machine learning techniques are preferable to regression because model structure and parameters drive the data, whereas regression requires an explicit relationship amongst the data. The varying differences between predictive analytical tools amongst different studies may be explained by the fact that different courses vary in structure and learning design in addition to unique goals and objectives, resulting in different techniques and predictors used (**Gašević et al., 2016**).

Within the domain of machine learning, naïve Bayes, neural networks, and decision trees are the most popular used algorithms amongst the literature (Huang & Fang, 2013; Jishan et al., 2015; Lykourentzou et al., 2009). Although neural networks offer high predictive accuracy, model interpretability is sacrificed, such that specific predictor variables displaying importance may be disregarded. Different studies yield different results regarding superiority of one model compared to another. Prediction results obtained from machine learning techniques are dependent on context used and how it is used. The main thing to consider when using machine learning algorithms is the trade-off between accuracy, interpretability, and computational time. Furthermore,

Jayaprakash et al. (2014) explains that “different learning designs associated with different available activities in an LMS have been found to result in a difference in LMS usage.”

Different research and empirical studies across the literature focus on a variety of different contexts related to LMS or MOOCs. Environments are either fully online or make use of a blended learning approach. Similarly, different predictive analytical techniques are used depending on the research goal and context (**Conijn et al., 2016**). The use of different predictor variables and predictive analytics amongst the research makes it difficult to draw comparisons between studies and draw general conclusions about the most suitable predictors of student performance. **Lykourentzou et al. (2009)** suggests that different research contexts and goals will define a unique set of predictor variables and predicative analytical techniques. Researchers cannot obtain or have access to all variables within the LMS or MOOC, as different courses and institutions use different tools and variables, resulting in the disparity and differences amongst the research. **Clow (2013)** suggests that the “incomplete availability and access to data may also explain why these studies are largely data driven.”

Although similar predictor variables and predictive tools are used amongst the research, the results are not always robust. Comparison studies conducted by **Lykourentzou et al. (2009)** and **Sedrakyan, Mannens and Verbert (2019)** suggest that a reasonable amount of variance can be explained by the dependent variable (final grade or pass/fail prediction) despite the variety amongst predictor variables across the literature.

Varying results relating to different predictor variables and predictive analytics bring up the question of whether there is a set of general variables for performance prediction. **Lykourentzou et al. (2009)** poses the following question: “Can the same models be used in multiple courses and institutions, or are online courses (and perhaps also students and institutions) so diverse that they each need their own prediction model?” This issue is referred to as the portability of the prediction models (Gašević et al., 2016; Jayaprakash et al., 2014). Subsequently, the probability of prediction models needs to be addressed by conducting further empirical studies and research.

Campbell, DeBlois and Oblinger (2007) argue that certain studies report positive conclusions related to academic performance within an LMS during an entire course, however, the inference comes at a point in time where interventions are no longer meaningful. Additionally, some studies record and measure certain predictor variables and attributes infrequently during the course. Consequently, these predictions are made at inconvenient stages during the course which reduces the opportunity to promptly intervene and assist students accordingly. The issue of sparse data availability is only concerned as far as classical education; e-learning courses within an LMS or MOOC can take advantage of the online interactivity and presence of students that could generate on demand source data (Gašević et al., 2016; Jayaprakash et al., 2014).

Research regarding LA and EDM mainly aim to further the understanding of the process by developing predictive models pertaining to student behaviour and performance. The models aim to identify relationships between various predictor variables (academic, demographic, and socioeconomic etc) and performance-based outcomes to improve the quality of the teaching and learning environment. There are many drawbacks by implementing these methods, particularly at a course specific level, as educators and students would benefit from meaningful insights drawn from the use of predictive analytics. Across the literature, predictive models have been well developed and utilised in order to describe the abovementioned relationship, yet there has been minimal investigation on how this information can be used to promote reflection, action and healthy learning behaviour amongst students and educators. A knowledge gap exists between the collection, processing and use of data and how it is implemented and interpreted to support pedagogical actions and interventions. Furthermore, the output from certain predictive modelling techniques requires non-trivial interpretation which further increases the difficulty to provide and obtain valuable insight into these models, beyond the prediction capabilities. Predictive models in the field of learning analytics need to offer intuitive and actionable insight to have a widespread impact and uptake as a discipline. **Pardo et al. (2016)** have observed that the deployment of interventions and development of actionable insight has been relatively unexplored across the literature.

Additionally, Pardo et al. (2016) claims that there is potential for predictive modelling in the learning analytical context for advancing pedagogical practices, however, these techniques need to be further explored.

2.4 Discussion & Summary

The review of the literature examined LADs in the field of LA and EDM. There are many definitions that describe a LAD across the literature which suggests that there is no consensus as to what constitutes a LAD. Creating a shared definition and proper terminology for a LAD would create a foundation for further systemic research to be conducted. Schwendimann et al. (2016) propose the following definition for a learning analytics dashboard, “A learning dashboard is single display that aggregates different indicators about learner(s), learning process(es) and/or learning context(s) into one or multiple visualizations.” This definition will arguably provide distinguishable characteristics for a LAD compared to other visualisation indicators.

The most common use for a learning dashboard is in a formal tertiary educational context, with research depicting the potential to expand into other levels and types of education. Learning dashboards are used for a variety of different learning activities, which indicates that there is no standardised model or blueprint for specific situations. Consequently, there is a lack of comparative studies between different types of dashboards that are used different situations. Currently, it is difficult for LADs to become generally acceptable due to the ecological validity of LAD development and the lack of longitudinal evaluations. There is a need to conduct more long-term studies relating the impact and acceptance of LADs.

Most of the dashboards that were analysed in this review obtained source data from a single platform, using logs of user activities. Technological advancements in educational practices creates a need to obtain source data across multiple platforms. The popularity of blended and online learning expresses the need to track learning across physical and digital boundaries. Capturing a variety of source data, within a physical and technological environment, will become crucial in future analyses.

There are several different indicators and visualisation tools that are used in certain LADs. However, there is a lack of research addressing which indicators and visuals are most suitable for different contexts. Additionally, different circumstances, end users and stakeholders of a LAD require different structural content and design principles, as specific environments require customised content to achieve certain goals. This substantiates the difficulty that studies have when defining a set of criteria for the information that is displayed and how it is presented. Generic templates for dashboards risk being visually unappealing and lack the ability to provide truly useful information. The design and development of dashboards needs to be unique for certain conditions to be generally acceptable and impactful. On the other hand, in most cases, the design and visual content of dashboards are like those in other areas of dashboard applications (e.g., web analytics). This provides a rough guideline for design principles but further substantiates the lack of available visualisation to address specific learning activities and pedagogical goals.

This project will aim to identify the most suitable content and structural design for a LAD that is useful as a decision-making and learning support tool, given the current context and access to relevant source data. The guidelines that are followed will consider the design principles from similar dashboards that are developed across the literature. This will be used to display information in a timely, accurate and meaningful manner. Additionally, these guidelines will aid in identifying what and how information is used and displayed.

The predictive models used in dashboards aim to identify relationships between various predictor variables and performance-based outcomes to improve the quality of the teaching and learning environment. There has been minimal investigation on how this information can be leveraged to support learning activities and pedagogical goals. Additionally, a knowledge gap exists between the collection, processing and use of data and how it is implemented and interpreted to support pedagogical actions and interventions. Although, different modelling techniques are used throughout the literature, the output sometimes requires non-trivial interpretation which further increases the difficulty to provide and obtain valuable insight into these models. The results obtained from complex and more sophisticated modelling techniques are sometimes difficult to interpret, therefore, translating modelling outputs into meaningful information becomes problematic and sometimes impossible. This project will use easily interpretable predicative modelling techniques and integrate the output into the LAD to provide intuitive and actionable insight in order to have a widespread impact for each student.

3 Data Analysis

3.1 Data Description and Overview

The data used in this study consists of students that enrolled for STA 1000 at UCT. Data from 1870 STA 1000 students over a three-year period, 2015, 2016 and 2017, has been used. Specific variables within the dataset belong to different departments at UCT. **Figure 3.1** illustrates the owners of specific variables and shows the source of each variable. In order to ensure anonymity and integrity, student numbers were not provided.

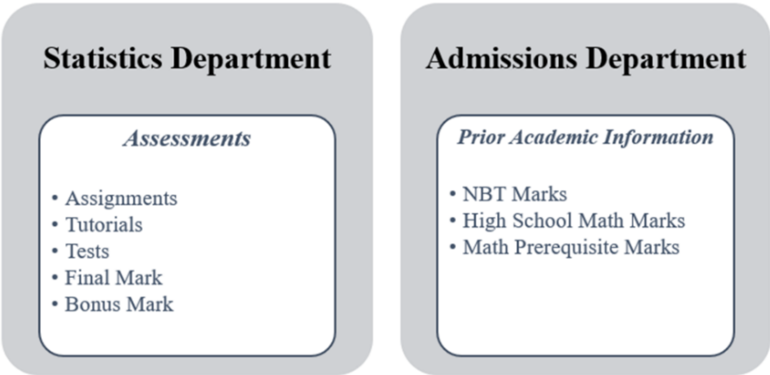


Figure 3.1: Sources and owners of data at UCT

The dataset consists of the marks obtained for assessments during STA 1000 and prior mathematical academic information. Each department collects, stores, and maintains data at different levels of granularity. *Admissions* maintain high-level data, whilst the *Statistics Department* works with data on a more granular level. A summary of each variable is presented in **Table 3.1** showing the numeric and categorical variables.

Table 3.1: Summary of the variables obtained

Variable Name	Data Type	Valid Range	Predictor Type
Final Mark	Binary	0; 1 (Fail; Pass)	Dependent
Assignment Mark	Continuous	0-100	Independent
Tutorial Mark	Continuous	0-100	Independent
Test Mark	Continuous	0-100	Independent
Bonus Mark	Binary	0; 1 (Unattained; Attained)	Independent
NBT Math	Continuous	0-100	Independent
Math Prerequisite	Continuous	0-100	Independent
Math High School	Continuous	0-100	Independent

The underlying structure and chronological order of academic assessments for STA 1000 are similar on a yearly basis. The course is 12 weeks long and each week contains various forms of academic assessments. *Tutorial Tests* and *Assignments* are given each week, except for the first week where no *Tutorial Test* is given. *Bonus Marks* are obtained by the timely completion of online quizzes throughout the duration of the course. **Table 3.2** illustrates the chronological order of assessments throughout the duration of the course. Each year, the occurrence of *Test 1* could differ to accommodate for the academic calendar; therefore, *Test 1* was placed in week 6 for the sake of simplicity when model building and illustrating the prototype dashboard in subsequent chapters. In the table below the letters: "*A*", "*T*" and "*B*", represent *Assignments*, *Tutorial Tests* and *Bonus Marks*, respectively.

Table 3.2: Chronological order of assessments for STA 1000

Week	Assessment
1	A1
2	A2; T2; B1
3	A3; T3
4	A4; T4; B2
5	A5; T5
6	A6; T6; B3; Test 1
7	A7; T7
8	A8; T8; B4
9	A9; T9
10	A10; T10; B5
11	A11; T11
12	A12; T12; B6

Predictive models will be developed at different time points (TPs) throughout the duration of the course. The results obtained from the modelling process will be interpreted and converted into useful information that will form the basis for developing recommendations. In order to reduce the level of granularity and complexity, and ease interpretation, *Assignment* and *Tutorial* marks will be aggregated at each TP instead of using each individual mark. Determining the influence of *Assignments* and *Tutorials* in general would add more value rather than focussing on one assessment over the other. Similarly, the prior mathematical assessments will be aggregated to reduce the level of granularity and complexity which will ease interpretation. Prior mathematical proficiency is an aspect that this investigation is concerned with and not the explicit strength of each prior mathematical assessment. Therefore, *NBT Math*, *Math Prerequisite* and *Math High School* will be aggregated to form a new variable: *Prior Math*.

Table 3.3 provides an overview of the variables used at each TP. *Average1, 2, 3, 4* represents the cumulative of average of all the *Assignments* at that TP, for example *Average1 = A1+A2*, *Average2 = A1+A2+A3+A4* etc. Similarly, *TAverage 1, 2, 3, 4* follows the same reasoning. Data after week 8 in the semester was disregarded and is discussed below in section **3.2.1**

Table 3.3: Variables used at each TP

Time Point	Weeks	Variables
TP1	1 - 2	*Average1; TAverage1; B1*
TP2	1 - 4	*Average2; TAverage2; B1; B2*
TP3	1 - 6	*Average3; TAverage3; B2; B3; Test 1*
TP4	1 - 8	*Average4; TAverage4; B1; B2; B3; B4; Test 1*

3.2 Exploratory Data Analysis

3.2.1 Missing Data

Significant proportions of data were missing for variables that tended to be recorded towards the end of the semester. The *Fees Must Fall* student protests led to disruptions in campus activity in the last quarter of 2016, accounting for the significant amount of missing data in that year. In 2017, tutorial tests 11 and 12 were cancelled. **Figure 3.2** illustrates the percentage of missing values for each variable. Variables that did not contain missing values were omitted from the illustration

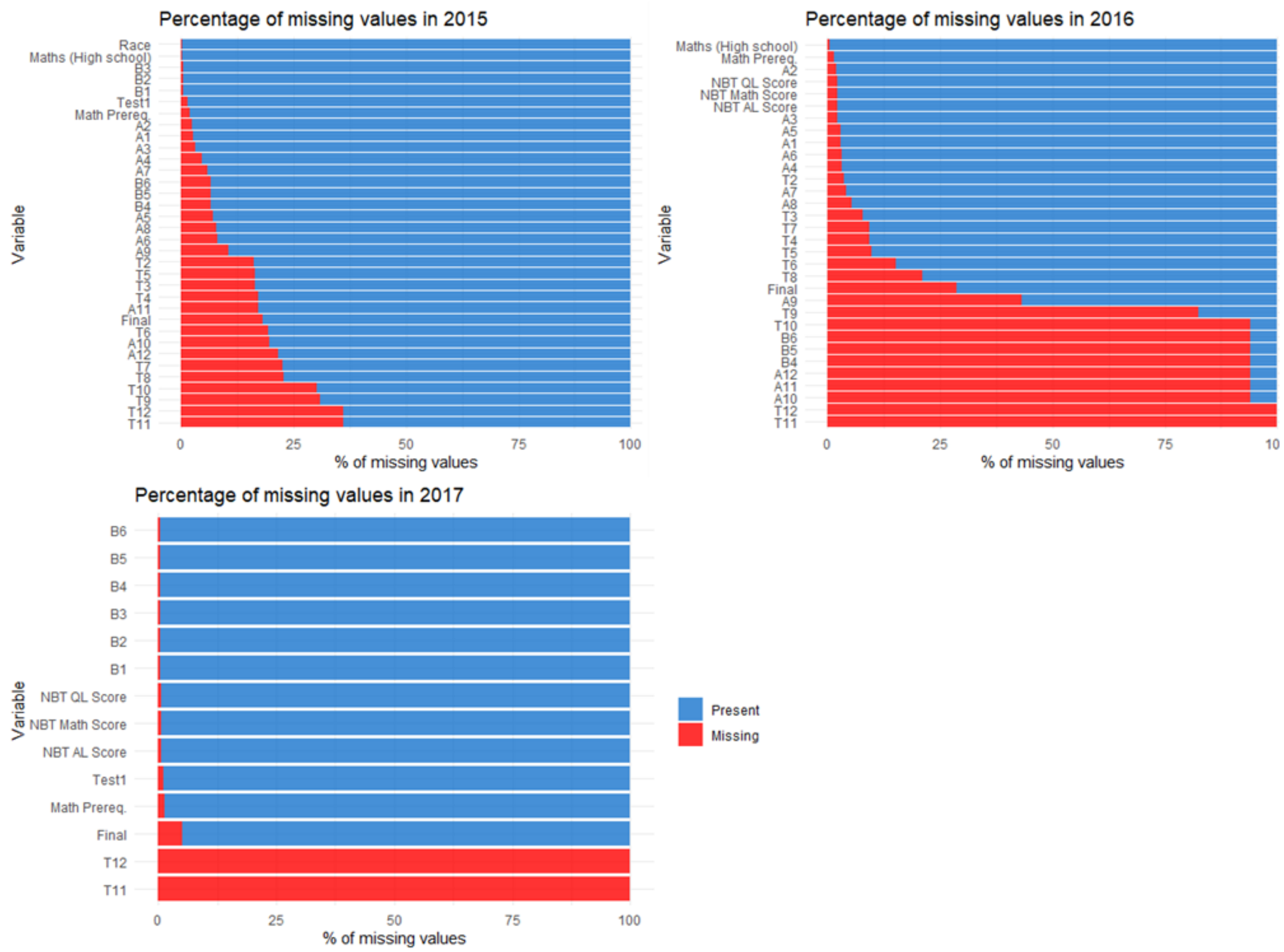


Figure 3.2: Percentage of missing values for each variable for each year respectively

Variables recorded after week 8 in the course are disregarded entirely due to the large proportion of missing values. Including missing values after week 8 would incorporate noise into the data and produce biased estimates in predictive modelling, given the large volume of values that would have to be imputed. Although these variables are removed, the objective of the predictive modelling aspect for this analysis is not severely impacted and is not rendered obsolete. The objective of the predicative modelling is to identify at risk students at certain time points throughout the duration of the course. Consequently, omitting the abovementioned variables results in the absence of a single recommendation towards the end of the course, which is not considered to have a severe impact.

It can be argued that recommendations provided towards the end of the course may be insufficient for an effective course of action to be taken in order to change the academic outcome for certain students (Campbell, DeBlois & Oblinger, 2007). The inference comes at a point in time where interventions are no longer meaningful. These predictions are made at inconvenient stages during the course which reduces the opportunity to promptly intervene and assist students accordingly. For example, a recommendation towards the end of the course for a student who consistently performs poorly throughout the semester will be ineffective. In contrast, certain students may require the final recommendation in order to change their outcome. Nevertheless, using the final recommendation to drastically change learning/studying techniques, such as rote learning, towards the end of the of the course, due to consistent underperformance throughout the duration of the course, undermines the point of recommendations. The aim of the recommendations is to aid at risk students and promote and encourage healthy, positive and effective learning. Nonetheless, the other recommendations will still be able to provide a guide into the effectiveness of predicting at risk students and providing appropriate recommendations and courses of action going forward.

Certain variables, those that are recorded throughout the duration of the course and changed over time, such as: *Tutorial*, *Assignment* and *Bonus Marks*, are generally missing due to a lack of submission for the assessment or an omitted zero. These fields within the dataset were replaced with a zero score. A small proportion of predictor variables (5%) and the dependent/outcome variable (16%) was still missing after the abovementioned adjustments had been made to the dataset. The predictor variables that are missing within the dataset are: *NBT Marks*, *Prior Mathematics* marks. Some of these variables are expected to be missing due to the presence of foreign students; these students do not contain scores for local South African assessments.

Missing data pertaining to predictor variables can be classified as structurally missing or missing completely at random (MCAR), within the context of this study. Structurally missing data is missing for a logical reason because it should not exist – for example: foreign students not containing NBT scores. MCAR data is missing data that is completely unrelated to the other information in the data – for example: the data point is missing due to being incorrectly captured or not being recorded at all. The dependant variable can be classified as MCAR or m*issing at random* (MAR). MAR occurs when the absences do not depend on the missing values, but the observed characteristics instead and assumes that we can predict the value that is missing based on the other data.

When structural or MCAR data is observed, an acceptable technique for handling the data is to use a complete case analysis or listwise deletion, which is excluding all units for which the outcome or any of the inputs are missing. This technique does reduce the sample size and predictive power but does not provide any biased results (**Van Ginkel et al., 2020**). **Little (1992)** asserts that the imputation of values pertaining to the dependent variable would add noise to the data and provide biased estimates in predictive modelling. Furthermore, **Mukaka et al. (2016)** found that the complete case approach to missing data remained unbiased and obtained similar or better precision compared to multiple imputation techniques when the outcome variable is binary. Therefore, a direct approach was taken with regards to handling the missing data and a complete case analysis was adopted.

3.2.2 Variables Measured During STA 1000

3.2.2.1 Final Mark – Dependent Variable

The histogram and box and whisker plot for *Final* marks illustrated in **Figure 4.3** shows that the data is reasonably symmetrical. The peak of the histogram occurs roughly between 60 and 70 which means that a lot of students are scoring between this range for STA 1000. The box and whisker plot illustrates that 50% of marks fall roughly between 50 and 75. The tails indicate that the marks are spread over the valid range and means that some students obtain quite low *Final* marks whereas some students obtain quite high marks or even a perfect score, which is expected. Additionally, more than 75% of the marks are above 50 which means that there is a high pass rate for STA 1000, which is further illustrated by the pie chart. The imbalance between the classes within the dependent variable needs to be addressed when modelling. The presence of minority and majority classes means that conventional machine learning algorithms will have insufficient minority classes to learn from and produce misleading or inaccurate results.

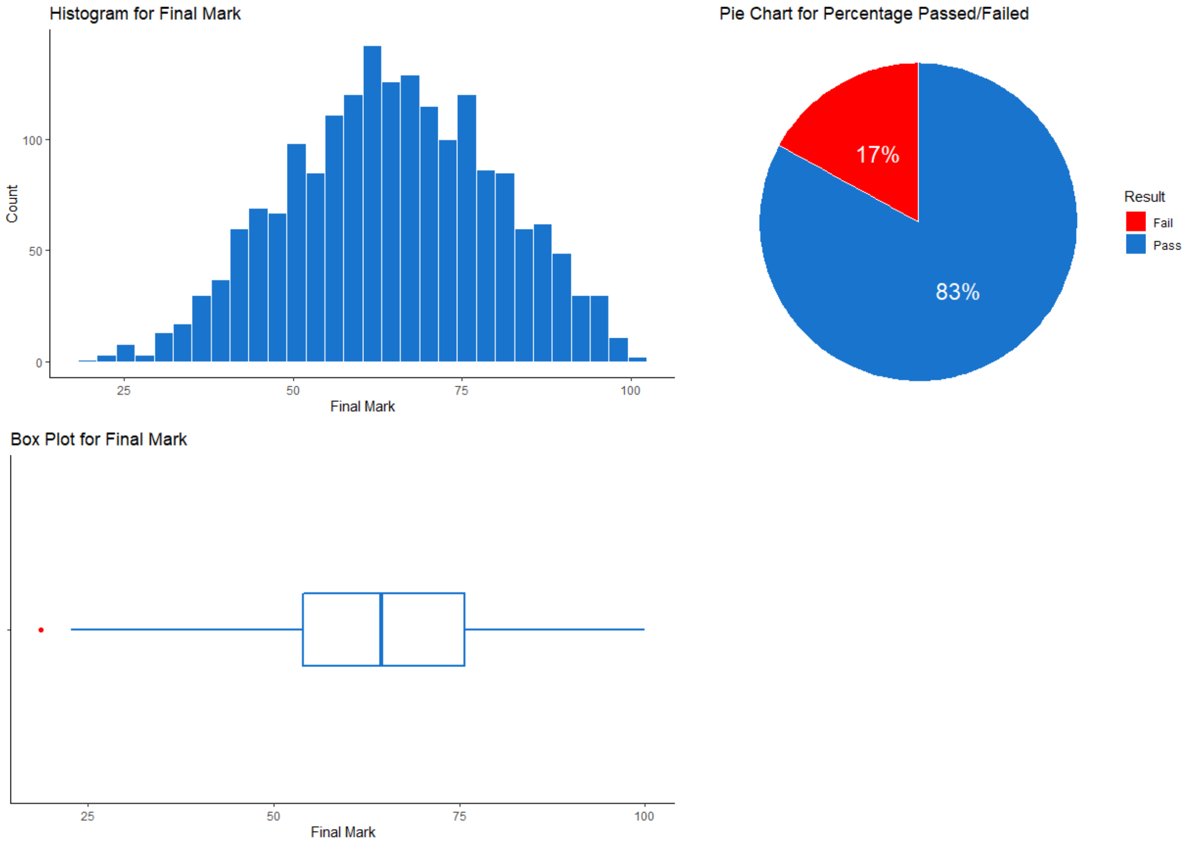


Figure 3.3: Various graphics describing the Final mark for STA 1000

3.2.2.2 Assignments

The box plots illustrated in **Figure 3.4** shows the distribution for cumulative average *Assignment* mark at each time point. Separate distributions are shown for students who passed or failed to gain insight into the relationship between *Assignment* marks and the *Final* mark at each TP.

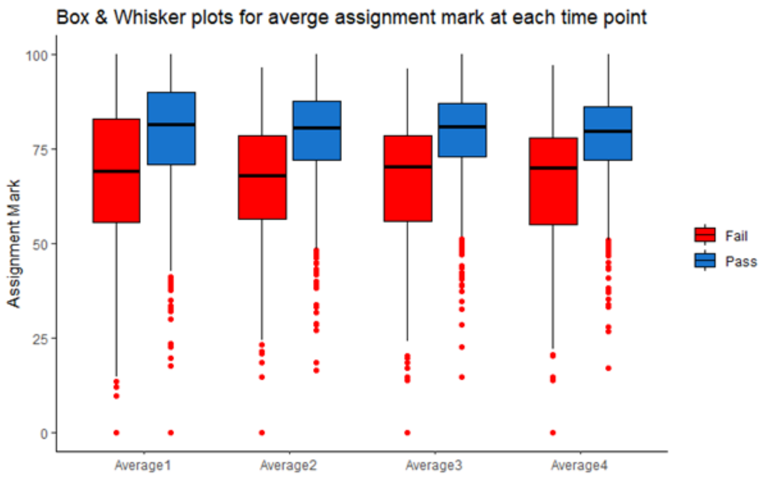


Figure 3.4: Box and whisker plot for cumulative average Assignment mark at each TP

The box and whisker plot shows that students who pass perform better in *Assignments* compared to students who fail; the median score is noticeably higher for those students who passed compared to those that failed. The distribution of the marks remains relatively similar for each group of students at each TP. This suggests that within each group, students are able to maintain their performance for each *Assignment* throughout the semester. These observations suggest that there could be a relationship between *Assignment* performance and overall performance. However, students obtain more time for *Assignments* and can refer to class material/notes and obtain help from third parties that could help them in completing the *Assignment.* Furthermore, the presence of outliers, especially within the group of students that pass, suggests that some students are unconcerned about their *Assignment* marks, which is a possible indicator of an unfavourable learning behaviour.

The mosaic plots in **Figure 3.5** further illustrate the potential relationship between *Assignment* performance and overall performance. The mosaic plot shows the proportion of students who passed or failed respectively, given the performance in *Assignments* at each time point. *Assignment* marks were arranged into two groups (*High* or *Low*) depending on whether a mark fell above or below the class average at that TP. Roughly 10% of students who obtained a "*High" Assignment* mark at each time point, failed the course. On the other hand, roughly 30% of students who obtained a "*Low" Assignment* mark at each TP failed the course.

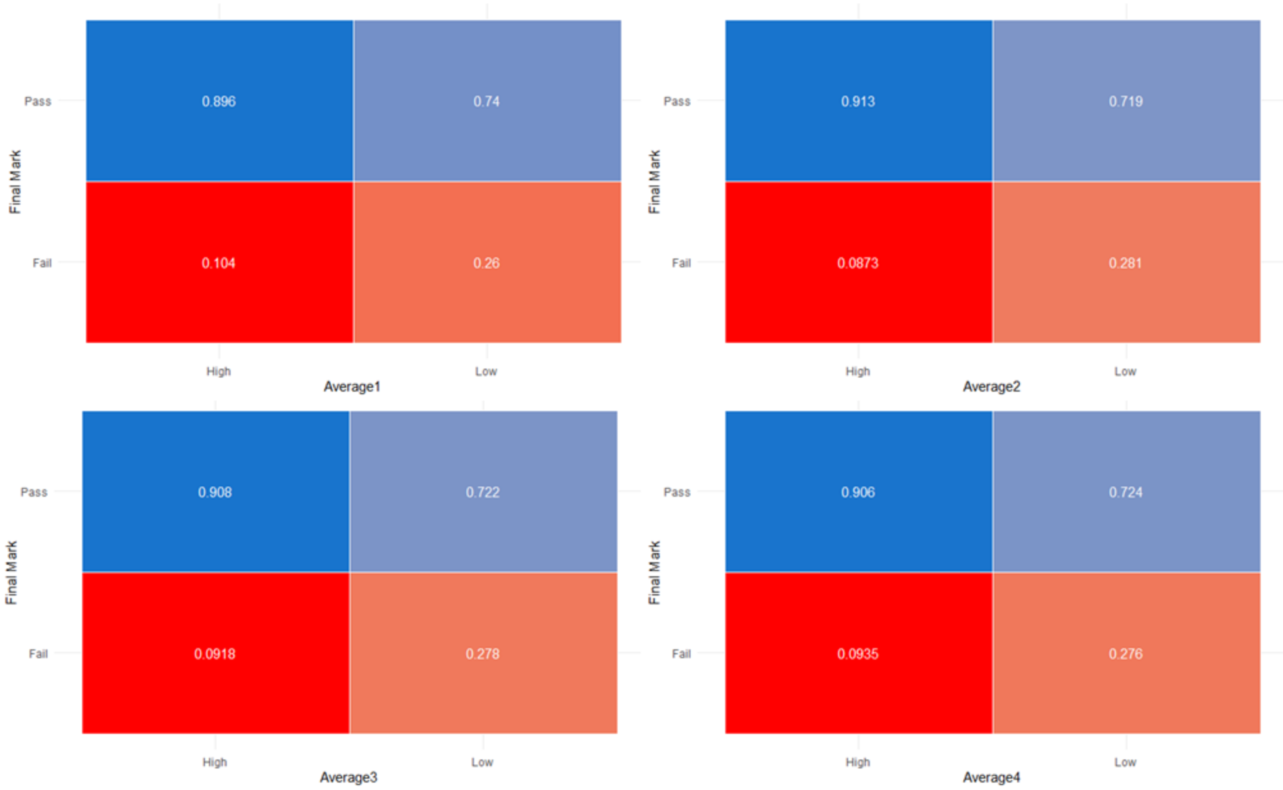


Figure 3.5: Mosaic plots for the proportion of students who passed/ failed given the Assignments

3.2.2.3 Tutorials

The box plots illustrated in **Figure 3.6** shows the distribution for cumulative average *Tutorial* mark at each TP. Separate distributions are shown for students who passed or failed, in order to gain insight into the relationship between *Tutorial* marks and the *Final* mark at each TP.

The box and whisker plots for *Tutorial Test* marks are noticeably taller compared to the box and whisker plots for *Assignment* marks. This suggests that the marks for *Tutorials* are more dispersed across the range of observable values compared to *Assignments*. Additionally, the mark for both groups of students progressively declines at each time point. A possible explanation for these discrepancies could be that *Tutorials* are completed in a simulated test or exam environment and some students are either unprepared or unconcerned about the *Tutorial*. The increasing difficulty as the course progresses, coupled with the attitude and preparedness of a student could explain the decline and dispersion of *Tutorial* marks. Furthermore, the presence of outliers, especially within the group of students that pass, suggests that some students are apathetic about their *Tutorial* marks which is a possible indicator of an unfavourable learning behaviour.

The box and whisker plot shows that students who pass perform better in *Tutorials* compared to students who fail; the median score is noticeably higher for those students who passed compared to those that failed. The distribution of the marks remains relatively similar for each group of students at each time point. These observations suggest that there could be a relationship between *Tutorial* performance and overall performance, despite the decline in performance over time.

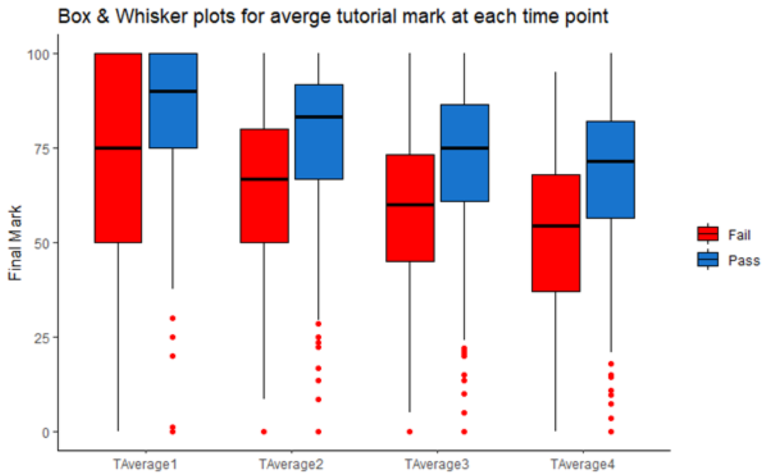


Figure 3.6: Box and whisker plot for cumulative average Tutorial mark at each TP

The mosaic plots in **Figure 3.7** further illustrate the potential relationship between *Tutorial* performance and overall performance. The mosaic plot shows the proportion of students who passed or failed respectively, given the performance in *Tutorials* at each TP. *Tutorial* marks were arranged into two groups (*High* or *Low*) depending on whether a mark fell above or below the class average at that particular TP. Roughly 12% of students at TP1 and 10% of students at all other TPs that obtained a "*High" Tutorial* mark, failed the course. On the other hand, 22% of students at TP1 and 28% of students at all other TPs that obtained a "*Low" Assignment* mark failed the course.

3.2.2.4 Test

The box plots illustrated in **Figure 3.8** shows the distribution for *Test* mark at each time point. Separate distributions are shown for students who passed or failed, in order to gain insight into the relationship between *Test* marks and the *Final* mark at each TP. The plot shows that students who pass perform better in the *Test* compared to students who fail; the median score is noticeably higher for those students who passed compared to those that failed. This observation suggests that there could be a relationship between *Test* performance and overall performance.

The mosaic plots in **Figure 3.8** further illustrate the potential relationship between *Test* performance and overall performance. The mosaic plot shows the proportion of students who passed or failed respectively, given their *Test* performance. *Test* marks were arranged into two groups (*Pass* or *Fail*) depending on whether a mark fell above or below the pass mark. Roughly 10% of students who passed the *Test* failed the course. On the other hand, roughly 38% of students who failed the *Test* failed the course

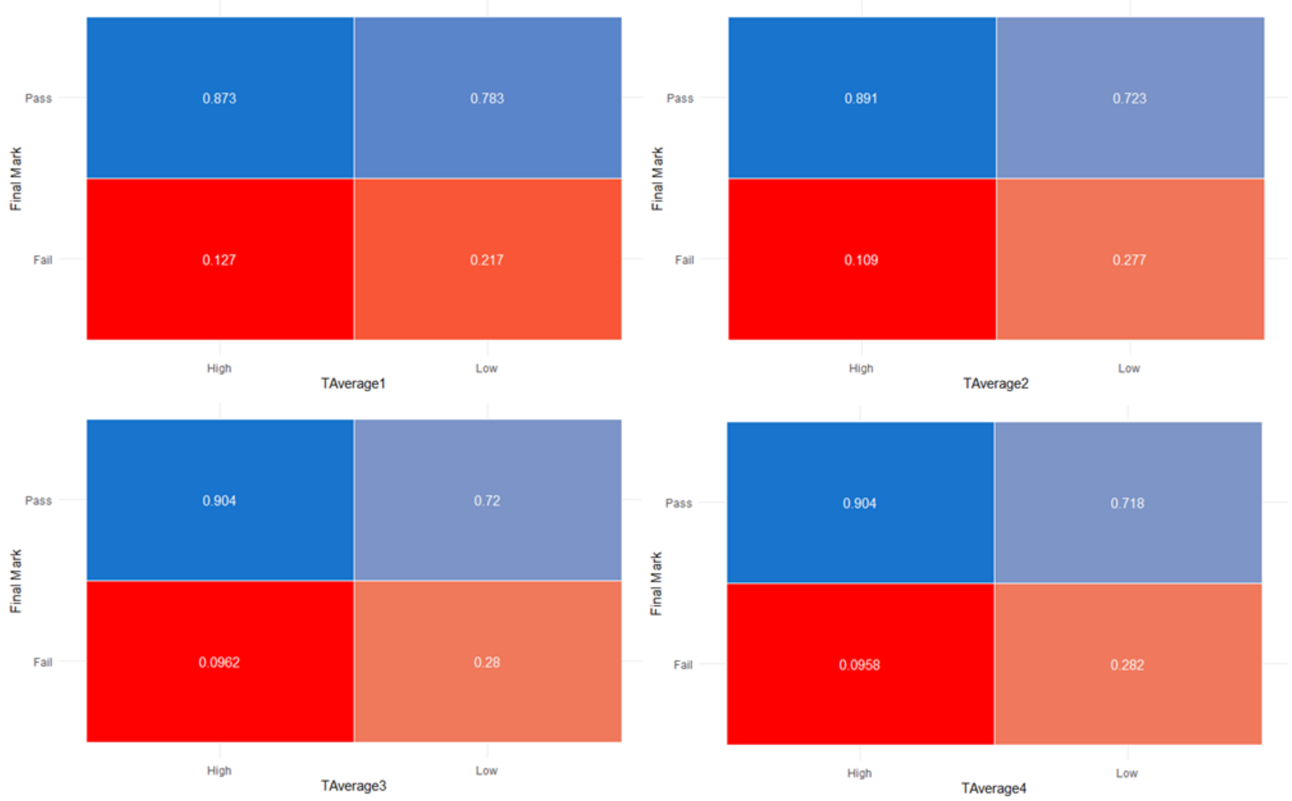


Figure 3.7: Mosaic plots for the proportion of students who passed/ failed given the Tutorials

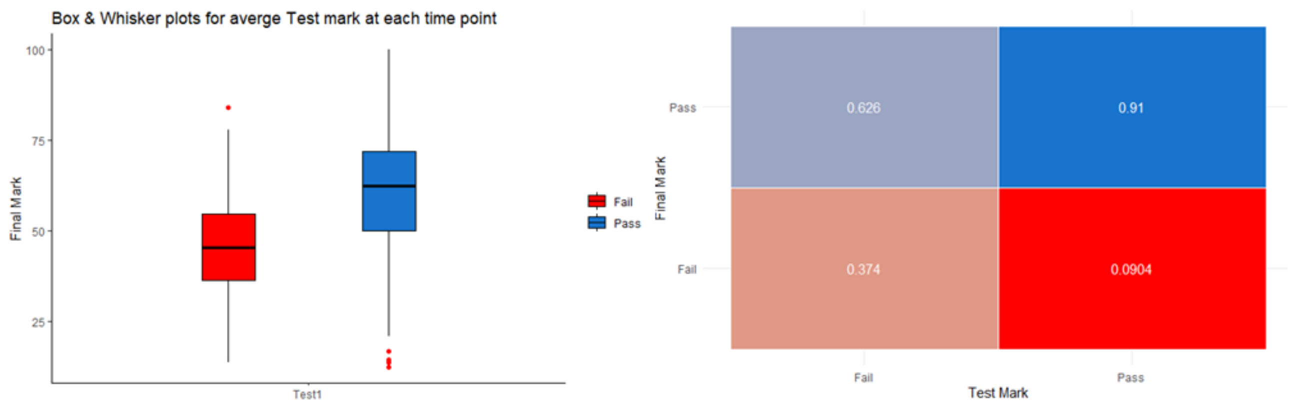


Figure 3.8: Box and whisker plot (left) and mosaic plot (right) for Test mark

3.2.2.5 Each Assessment vs Final mark

There is a noteworthy difference between the average marks for each assessment between students who failed the course compared to those who passed, as portrayed in **Figure 3.9**. This discrepancy further reinforces the observations discussed above and suggest that optimal performance in these assessments could be a guideline for the overall performance. Another prominent observation is the difference in average marks for *Assignments* compared to the *Test* and *Tutorial* marks. As discussed above, *Tutorial Tests* roughly simulate the environment and content expected during the *Test* hence the slight difference in average marks is expected. Other than the possible explanation discussed above, another reason could be that students possibly obtain too much help from their peers, or in some instances copy their peers' work. These characteristics need to be considered when modelling and providing recommendations to students. A noticeable difference between *Assignments*, *Tutorials* and *Test* marks, whereby *Assignment* marks are significantly higher than the other assessments, needs to be noted and communicated to the student.

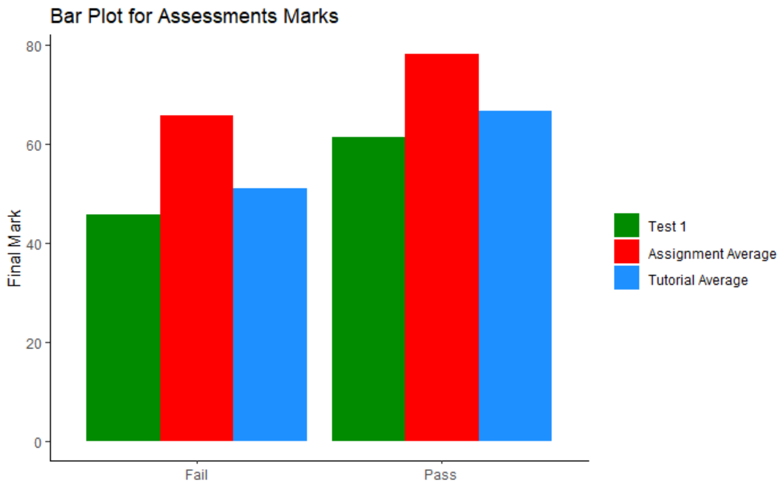


Figure 3.9: Bar plot for average assessment marks

3.2.2.6 Bonus Marks

Bonus marks play a vital role in monitoring progress and course engagement, as they are awarded based on timely completion of online quizzes.

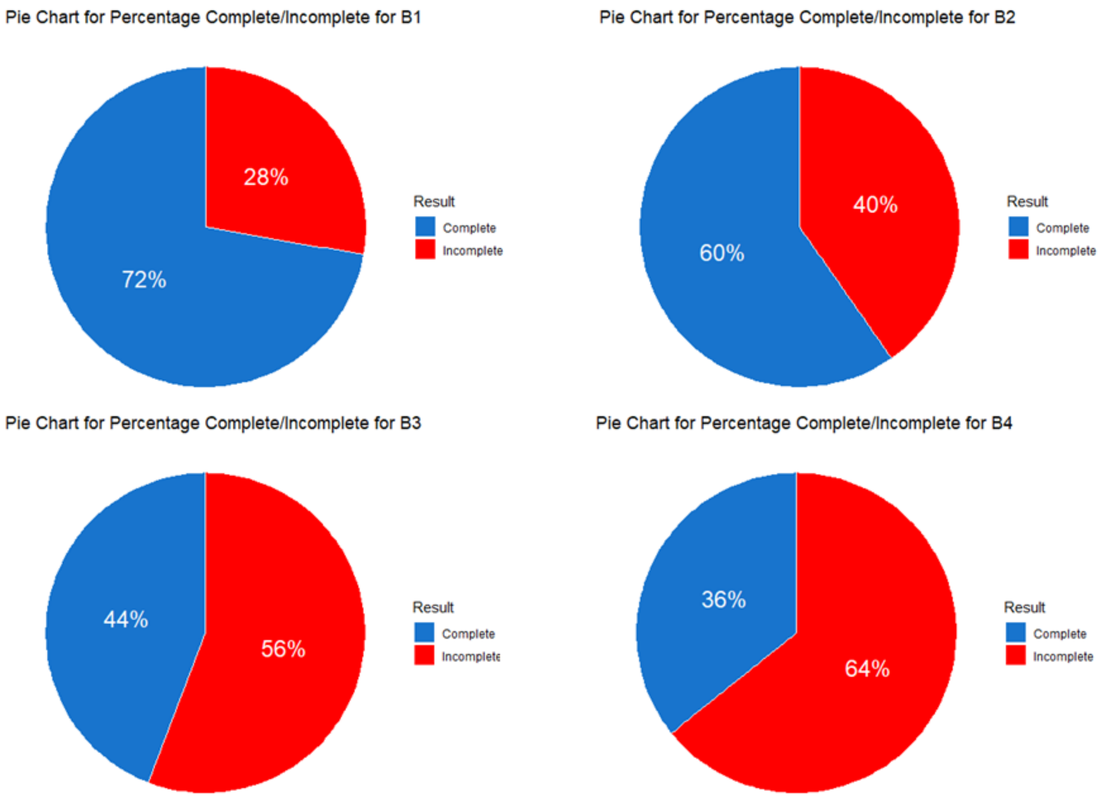
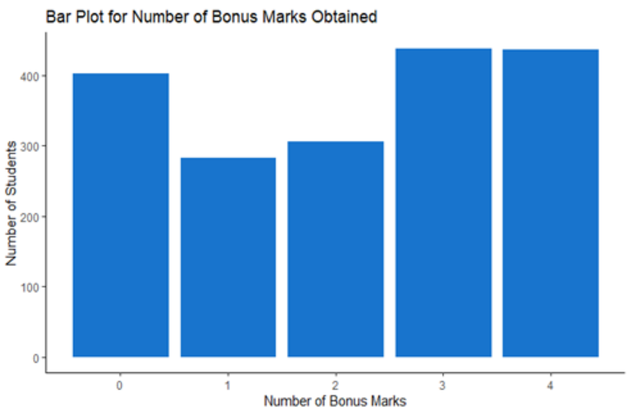


Figure 3.10: Pie chart for proportion of students that obtained a certain Bonus Mark:

The pie charts depicted in **Figure 3.10** illustrate the proportion of students that obtained or did not obtain the *Bonus* mark. “Complete” signifies that the student obtained the *Bonus* mark, whereas “Incomplete” signifies that the student did not obtain the *Bonus* mark. Noticeably, as the course progresses, the proportion of students that obtain the *Bonus* mark declines. This trend could indicate that some students develop destructive learning habits and engage less with the course material as time progresses; and refer to the material only when needed or right before formal assessments.

The bar plot illustrated in **Figure 3.11** shows that most students either obtain no *Bonus* marks or obtain four or five *Bonus* marks. A slightly smaller number of students obtain two or three *Bonus Marks*. Consequently, the total number of *Bonus Marks* obtained remains similar across each cumulative value. The bar plot indicates that the number of students that are actively engaging with the course, by obtaining a higher amount of *Bonus* marks, are relatively equal compared to the other students.

This observation supports the need to provide constructive recommendations to all students regardless of the risk factor of passing or failing the course. The recommendations need to be individually tailored to each student to encourage and promote healthy and active learning as well as provide appropriate measures for all students alike.



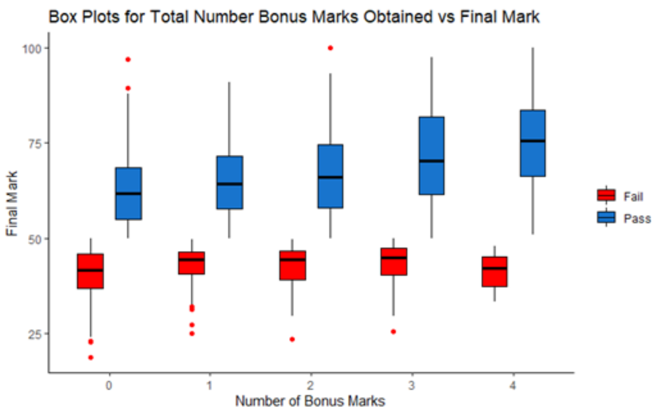


Figure 3.11: Bar plot (left) and Box and whisker plot (right) showing the cumulative number of Bonus Marks obtained

The box plot illustrated in **Figure 3.11** illustrates that students who complete *Bonus Marks* obtain higher scores for their final mark compared to students who do not obtain *Bonus Marks*. Obtaining *Bonus Marks* indicates that a student regularly engages with the course material which could form part of a healthy and constructive learning behaviour that enables a student to achieve higher marks. Additionally, students who obtain more *Bonus Marks* achieve higher *Final* marks compared to students who obtain less *Bonus Marks*.

Although different students utilise different learning techniques, the data suggests that regular engagement with the course material can boost overall academic performance. Furthermore, the mosaic charts illustrated in **Figure 3.12** show that the proportion of students who fail is lower as additional *Bonus Marks* are obtained at each time point. This trend suggests that the likelihood of passing the course is noticeably higher as more *Bonus Marks* are obtained and support the notion that obtaining *Bonus Marks* can boost academic performance in STA 1000.

3.2.2.7 Correlation Analysis

Figure 3.13 depicts the Pearson Correlation Coefficient Matrix for each predictor variable within the dataset, as well as the *Prior Math* marks. The noticeably taller shape of the box and whisker plots for *Tutorial* marks as well as the presence of outliers, indicate that the marks are dispersed or scattered over the observable range of values (see **Figure 3.6**). Furthermore, the box and whisker plots indicate that the *Assignment* marks are also slightly spread over the observable range of values and contain outliers (see **Figure 3.4**). Therefore, a high correlation between *Assignments* and *Tutorials* with the *Final* mark is not expected.

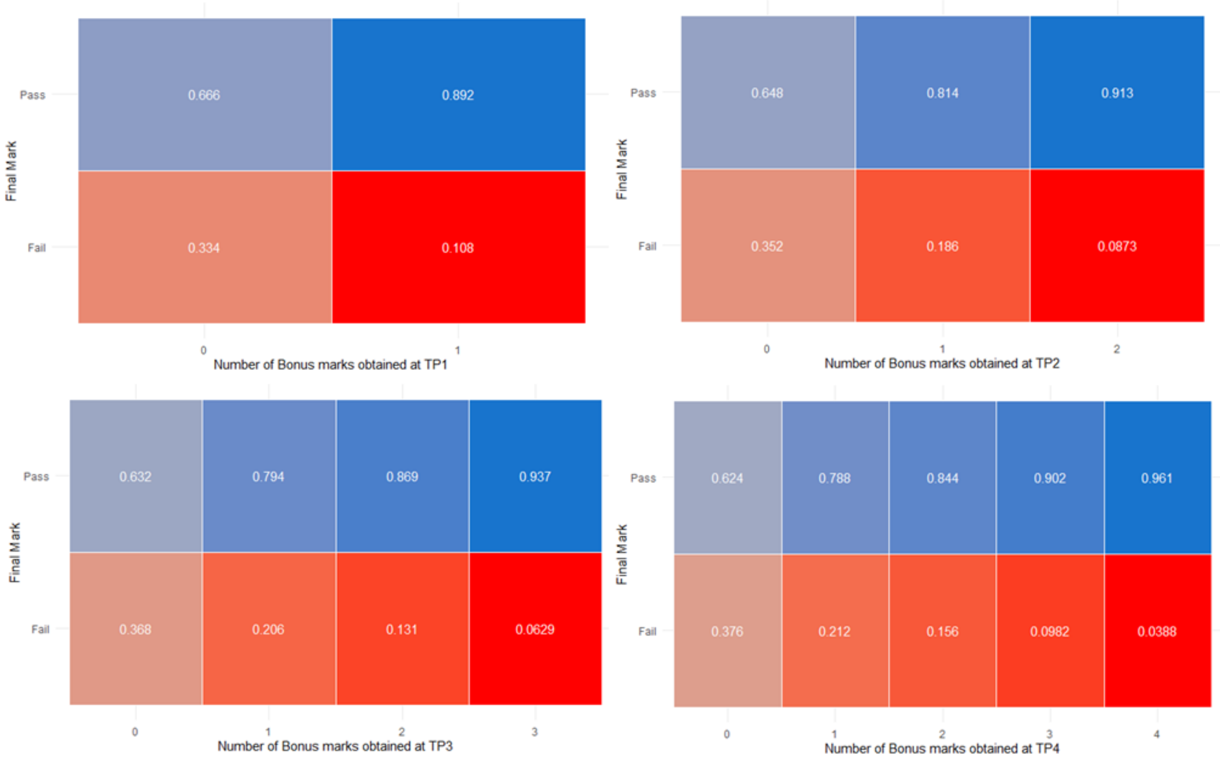


Figure 3.12: Mosaic chart for students who pass given the number of Bonus Marks obtained at each TP

Although the correlation between the *Assignment* and *Tutorial* marks is not strong, the correlation matrix illustrates that a moderately positive linear relationship exists. The correlation coefficient lies between 0.21 and 0.37 for *Tutorials* and 0.36 and 0.45 for *Assignments*. Generally, such low values would indicate a weak or moderate linear relationship between these variables and the outcome variable. Since the marks obtained for these assessments include students who achieve optimal results in addition to students who obtain low or zero scores for the assessments, a low correlation is expected. The low correlation between these variables does not necessarily suggest that there is no relationship between the predictor and outcome variable, as meaningful observations have been made in the sections above.

In contrast, the box and whisker plot in **Figure 3.13** illustrates that the *Test* marks are not highly dispersed over the range of observable values relative to the box and whisker plots for *Assignments* and *Tutorial Tests*. Furthermore, most of the marks are gathered around a common point and there are only a few outliers present. The correlation of 0.6 exists between the *Test* marks and the *Final* mark, which indicates that a moderate or strong linear relationship exists. The correlation for the total number of *Bonus Marks* obtained over the duration of the semester is 0.45, which indicates that a moderate linear relationship exists. Additionally, the correlation for *Prior Math* is 0.66 which indicates that a strong linear relationship exists.

3.2.3 Prior Academic Information

3.2.3.1 Assignments and Tutorials

The box plots illustrated in **Figure 3.14** shows the distribution for cumulative average *Tutorial* mark and cumulative average *Assignment* mark at each time point. Separate distributions are shown for students who have strong or weak prior mathematical proficiency, to gain insight into the relationship between *Tutorial* and *Assignment* marks and *Prior Math* at each time point. The categories for *Prior Math* are determined by the average score for obtained. If a student obtained the average score or higher, they would be classified into the *strong* category; if a student obtained below the average score they would be classified into the *weak* category.

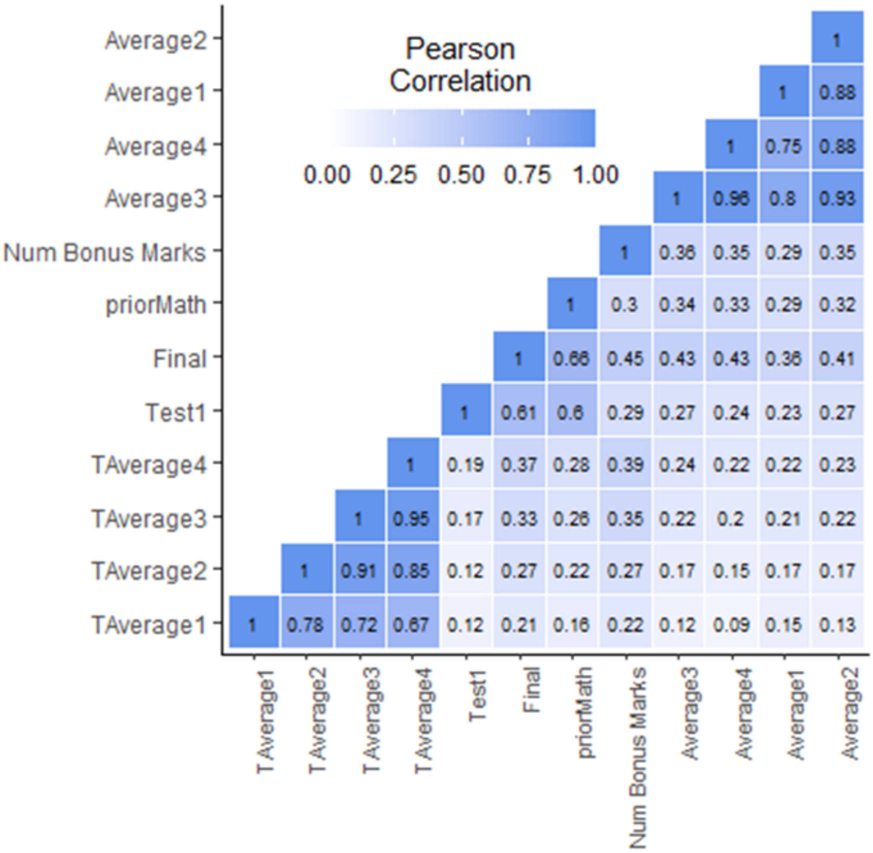


Figure 3.13:Pearson Correlation Matrix

The distribution of the marks for each assessment at each TP for *strong* and *weak* students is similar to that observed for students that pass of fail the course, as discussed in the above sections. The distribution of the *Assignment* remains relatively similar for each group of students at each TP. This suggests that students within each group are able to maintain their performance for each *Assignment* throughout the semester

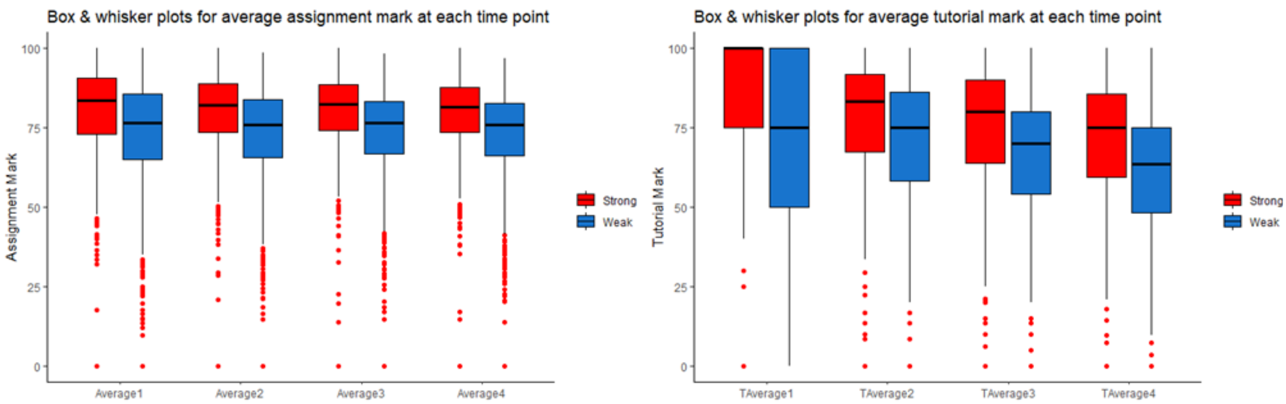


Figure 3.14: Box and whisker plot for cumulative average Assignment mark (left) and Tutorial mark (right) for strong/weak Prior Math backgrounds

The *Tutorial* marks are noticeably taller compared to the box and whisker plots for *Assignment* marks. This suggests that the marks for *Tutorial Tests* are more scattered across the range of observable values compared to *Assignments*. Additionally, the mark for both groups of students progressively declines at each time point. The box and whisker plot shows that students with a strong prior mathematical proficiency perform better in *Assignments* and *Tutorials* compared to students with a weak proficiency - the median score is noticeably higher for those students with a strong proficiency compared to those that have a weaker proficiency.

The box and whisker plot for *Assignment* and *Tutorial* marks, in **Figure 3.14,** suggests that a strong mathematical background is beneficial towards performance in these assessments. However, roughly 50% of students that have a weak prior mathematical proficiency obtain a high *Assignment/Tutorial* mark. On the contrary, roughly 33% of students that have a strong prior mathematical proficiency obtain a low *Assignment* mark, and roughly 30% (in all TPs expect TP1) and 42% (in TP1) of students that have a strong prior mathematical proficiency obtain a low *Tutorial* mark. This suggests that students who have weak prior mathematical proficiency do not necessarily perform worse in assessments compared to students with a strong proficiency. In general, optimal performance in these assessments are not necessarily hindered by a weaker mathematical background and that performance is not completely dependent on prior mathematical proficiency, however a strong maths background is beneficial. The mosaic and scatter plots in **Appendix Figure A.1**and **Appendix Figure A.2** provide an illustration for these abovementioned observations

Figure 3.15 illustrates the cumulative average *Assignment* and *Tutorial* mark, at each time point, for students who have passed or failed STA 1000, according to their prior mathematical proficiency. The line graphs reinforce that a strong mathematical proficiency is beneficial for performance towards each assessment; there is a notable difference between assessment marks between students who passed that have a weak (orange line) or strong (light-blue line) prior mathematical proficiency. Except for students that failed the course with a strong maths background, the line graphs support the observation that the assessment marks stay consistent at each time point regardless of the prior mathematical proficiency. The *Assignment* mark stays relatively consistent for each group whereas the *Tutorial* mark progressively declines. There is a slight decrease in the *Assignment* average from TP1 and TP2 for students with a strong maths background that failed the course; additionally, a decline in the *Tutorial* average is only experienced after TP2. A possible explanation for this is that these students are more familiar with the initial concepts that are taught in the introductory phase of the course due to their stronger mathematical foundation. These students then find it more difficult as the course progresses, and new concepts are being introduced.

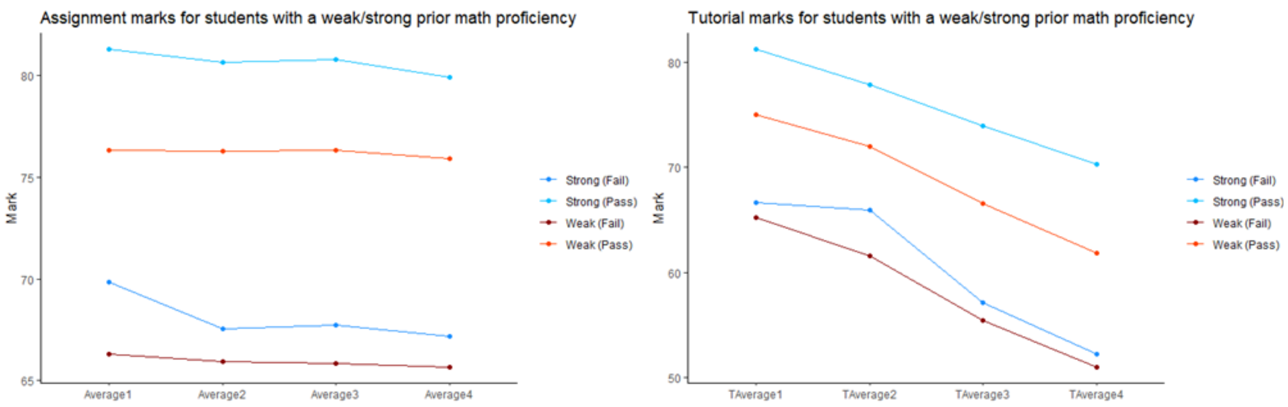


Figure 3.15: Line graphs for Assignments (Right) and Tutorials (Left) for weak/strong maths backgrounds

Additionally, the observations from the line graphs do not suggest that students with a weak maths background that failed the course are obtaining unusually high marks for each assessment. This could indicate that students with a weak maths background are receiving help from their peers or third parties or simply copying their peers' work. On the other hand, for students with a strong maths background, the observations from the line graph do not suggest that the majority of these students are apathetic towards each assessment. In each case, both subsets of students essentially develop a destructive learning behaviour and only refer to course material before formal assessments (*Test* and *Final Exam*).

Overall, the most important observation from the line graphs is the discrepancy between the marks for students with a weak or strong prior mathematical proficiency. There is a noteworthy difference between marks between students that passed or failed the course from each maths background. This could indicate that students with a weaker maths background, that ultimately passed the course, work harder towards assessments, and therefore achieve superior performance compared to students that fail. On the other hand, this could also indicate that students with a strong maths background, that ultimately fail the course, neglect assessments and achieve inferior performance compared to students who passed. In general, students with a weaker prior mathematical may find it more difficult to understand the course material as most of the coursework, especially the foundational elements taught at the beginning of the course, are based on mathematical concepts.

This observation supports the remarks discussed above regarding the proportion of students that obtain a low or high assessment mark given their maths background and the relationship between performance and prior mathematical proficiency. Simply, if roughly one half of students with a weak maths background obtain a high assessment mark, this could imply that some students work harder to obtain superior performance. On the other hand, if roughly one third of students with a strong maths background obtain a low assessment mark, this could imply that these students simply underestimate the importance of the assessments and are unconcerned about performance. In general, these observations support the remark that optimal performance is not necessarily hindered by a weaker maths background and that performance is not completely dependent on prior mathematical proficiency; however, a strong prior mathematical proficiency is beneficial.

3.2.3.2 Test and Final Mark

The scatter plot, box and whisker plots and mosaic plots for the relationship between the *Test* and *Final* mark and *Prior Math* is illustrated in **Figure 3.16**. The box and whisker plot shows that students with a strong prior mathematical proficiency perform better in the *Test* compared to students with a weak proficiency - the median score is noticeably higher for those students with a strong proficiency compared to those that have a weaker proficiency. However, there is a noteworthy number of students that passed the *Test* whilst having a weak prior mathematical proficiency. The mosaic plots show that roughly 56% of students with a weak maths background passed the *Test*. This suggests that the prior mathematical proficiency of a student does not necessarily impact the performance on the *Test*, which is further demonstrated by the scatter plot. This observation is similar to those made for the relationship between performance in *Assignments*/*Tutorials* and prior mathematical proficiency.

Similarly, the graphs in **Figure 3.16** show that students with a strong prior mathematical proficiency perform better in overall performance (*Final* mark) compared to students with a weak proficiency; the median score is noticeably higher for those students with a strong maths background compared to students with a weak maths background.

The most notable observation, which strengthens the remarks discussed for all the other assessments within the course, is that there is a noteworthy number of students that passed STA 1000 whilst containing a weak prior mathematical proficiency. However, the majority of the students with a strong maths background pass STA 1000. This suggests that a weak prior mathematical proficiency does not necessarily relate to poor performance, however, a strong prior mathematical proficiency is advantageous. In general, performance in assessments and overall performance in STA 1000 is not necessarily dependant on prior mathematical proficiency.

Table 3.4 illustrates the average *Test* and *Final* mark for each subgroup of student. The table reinforces the insights mentioned above regarding difference between marks for students with different maths backgrounds. There is a noteworthy difference between marks between students that passed or failed the course from each maths background. In general, students with a weaker maths background that pass the course work harder towards assessments, and therefore achieve superior performance compared to students that fail; students with a strong maths background, that ultimately fail the course, neglect assessments, and achieve inferior performance compared to students who passed.

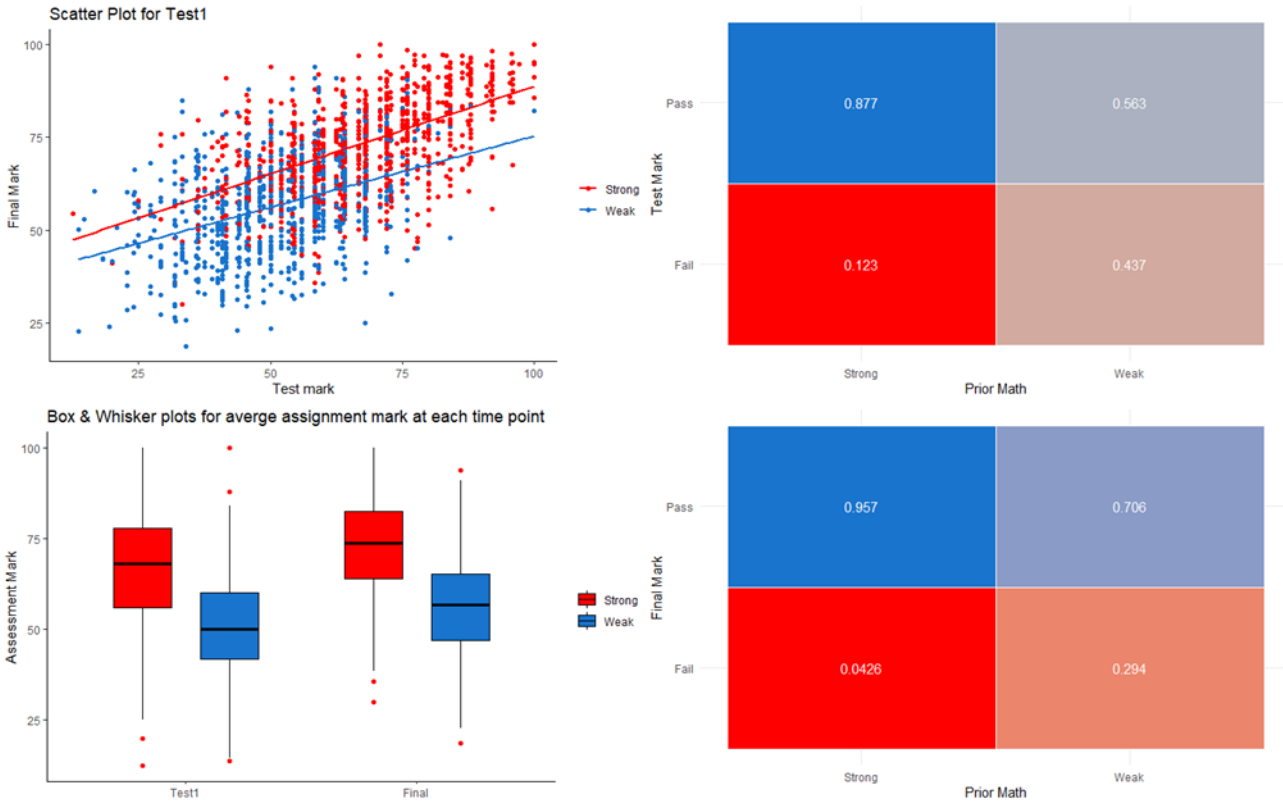


Figure 3.16: Scatter plot, box and whisker and mosaic plot for Test and Final and the relationship with Prior Maths background

Table 3.4: Average Test and Final marks for different subgroups of students

	Test	Final
Strong Maths – Pass	67.46	74.33
Strong Maths – Fail	51.39	44.88
Weak Maths – Pass	53.74	62.99
Weak Maths – Fail	44.91	41.10

3.2.3.3 Bonus Marks

The box and whisker plot in Figure 3.17 shows the relationship between the total number of *Bonus Marks* obtained at the end of the course and the *Final* mark. As previously observed, students who obtain more *Bonus Marks* achieve higher *Final* marks compared to students who obtain less *Bonus Marks*. This observation supports the remark that regular engagement with the course material can boost overall academic performance. Most notably, students with a stronger prior mathematical proficiency perform better than students with weaker proficiency, regardless of the amount of *Bonus Marks* obtained.

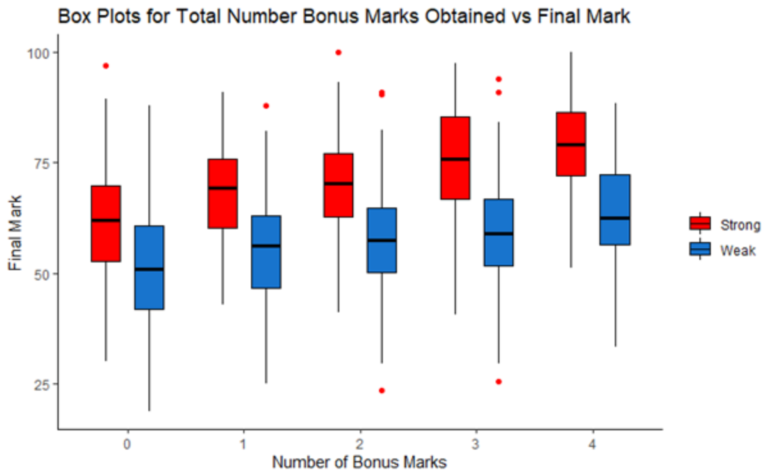


Figure 3.17: Box and whisker plot for total number of Bonus Marks obtained for Prior Math background

The bar plots in **Figure 4.18** illustrate the number of *Bonus Marks* obtained at each TP for students with different prior mathematical proficiencies. Overall, the most notable observation from the bar graphs is that students with a stronger prior mathematical proficiency obtain more *Bonus Marks* at each TP compared to students with a weak prior mathematical proficiency. Students with a weak maths background could struggle to understand the concepts being taught as most of the course material is mathematically based. This could explain why students with a stronger maths background generally obtain more *Bonus Marks*.

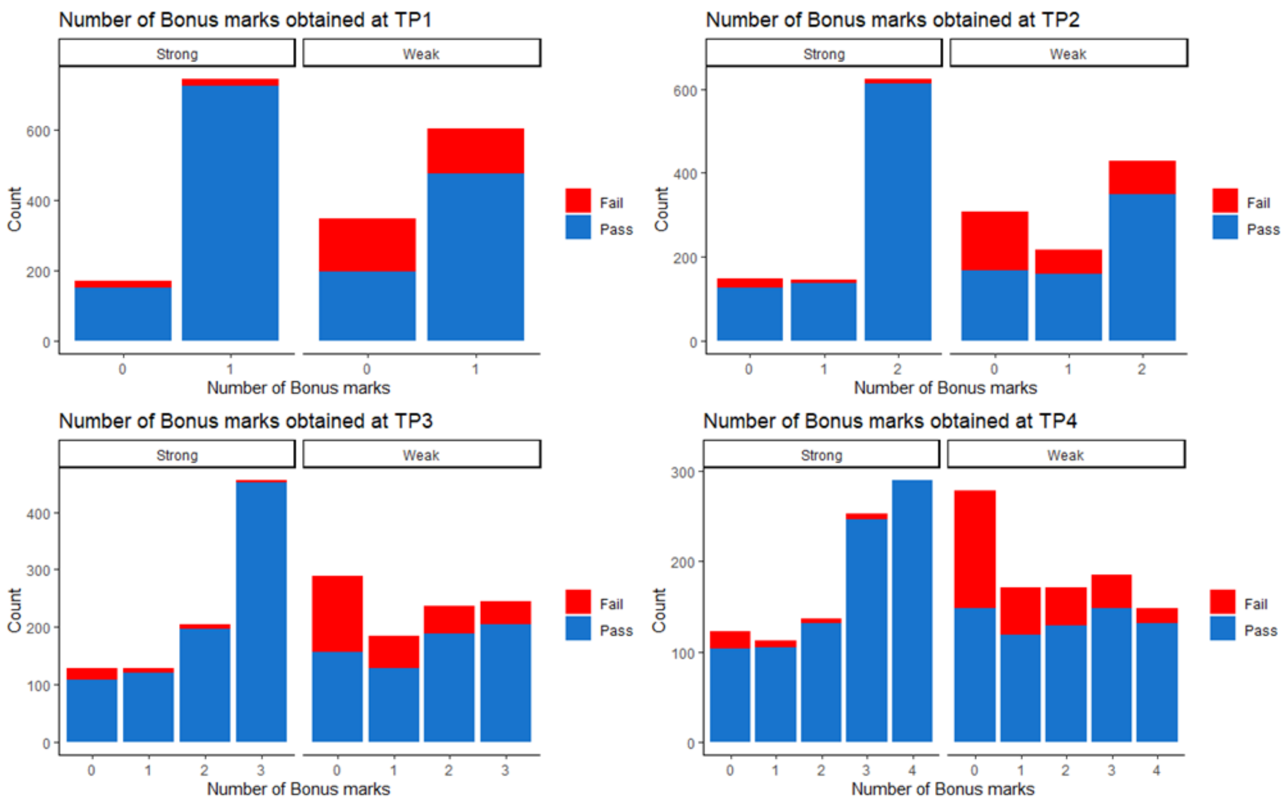


Figure 3.18: Bar plot for the total number of Bonus Marks obtain at each TP for weak/strong maths backgrounds

Simply, students with a stronger maths background may complete the quizzes in a timely manner (hence obtaining the *Bonus Marks*) because they better understand the course material. On the other hand, students with a weaker maths background may struggle to understand the course material, therefore they could possibly ignore the quizzes (as noted by the large number of students who obtain no *Bonus Marks*); or they do not complete quizzes in a timely manner, because it takes them much longer to understand certain concepts.

Regardless of the number of *Bonus Marks* obtained for students with a strong prior mathematical proficiency, the proportion of students that pass STA 1000 is notably higher compared to students that fail. This implies that the number of *Bonus Marks* obtained, for students with a strong maths background, does not necessarily affect overall performance (i.e. in terms of passing and failing). On the other hand, the amount of *Bonus Marks* obtained at each TP does seem to have an impact on the overall performance for students with a weak prior mathematical proficiency. The proportion of students who pass STA 1000 increases as more *Bonus Marks* are obtained for students with a weaker maths background.

This observation supports the remark that students with a weaker maths background, that pass STA 1000, work harder towards assessments, and regularly engage with the course material thereby obtaining superior performance compared to students that fail. However, the discrepancy between obtaining a certain number of *Bonus Marks* at each TP is not as large as compared to students with a stronger prior mathematical proficiency. There is roughly a similar number of students obtaining a specific number of *Bonus Marks* at each TP except for those students that obtain zero *Bonus Marks*. It is possible that students who have a weak mathematical foundation may initially struggle with understanding and interacting with the course material, but as the course progresses, they work harder and are able to cope with the new learning environment. Simply, students with a stronger maths background generally obtain more *Bonus Marks*.

3.3 Chapter Summary

The exploratory analysis presented in this chapter highlights the relationship between the predictor variables and the outcome variable. The observations made in this chapter provide some insights into the research questions posed in section Error! Reference source not found. and builds a foundation for further investigation and exploration through predictive modelling.

The class imbalance within the outcome variable has the potential to affect model performance and needs to be considered. Suboptimal model performance impacts the appropriateness and credibility of the recommendations that will be developed. Simply, the recommendations may not necessarily be trustworthy if the underlying models from which they are developed, perform poorly. Various methods in order to address the imbalance need to be considered, if the predictive modelling involves classification techniques.

Overall, the exploratory analysis suggests that there is an apparent relationship between performance in assessments and the final outcome. Although *Assignments* and *Tutorials* may not necessarily be strong predictors of performance, better-quality performance in *Assignments* and/or *Tutorials* noticeably impact overall performance. A similar relationship is observed between *Test* performance and the final outcome. In general, students who passed the course obtained noticeably higher scores for *Assignments*, *Tutorials*, and the class *Test*, compared to students who failed.

The exploratory analysis highlights that regular engagement with the course material impacts overall performance. Although course engagement declines as the course progresses, which strengthens the need to provide custom recommendations to all students regardless of their risk factor, students who obtain more *Bonus Marks* perform better than students who obtain fewer *Bonus Marks*. This indicates that regular engagement with the course material could form part of a healthy and constructive learning behaviour that enables a student to achieve higher marks. The recommendations need to be individually tailored to each student and provide appropriate measures for all students alike.

The observations discussed above do not necessarily validate that overall/assessment performance is dependent on prior mathematical proficiency. Optimal performance in course assessments is not necessarily hindered by a weaker mathematical background; performance is not completely dependent on prior mathematical proficiency; however, a strong maths background is beneficial. The quantitative value of overall/assessment performance and obtaining *Bonus Marks* is somewhat affected by prior mathematical proficiency. Additionally, obtaining more *Bonus Marks* does not largely affect the final outcome for students with a strong maths background. Conversely, there is an impact on the final outcome for students with a weaker maths background that obtain more *Bonus Marks*. In general, the broad impact on performance is similar for each group of students; there is only a quantitative impact on overall/assessment performance that differs depending on the prior mathematical proficiency of the student. This suggests that the recommendations provided to each group of students do not necessarily need to be different, since recommendations are personalised. However, it may be useful for the course convenor to be aware of a students' prior mathematical proficiency in order to develop interventions of another kind. For example, the course convenor can provide extra classes at the beginning of the course for students with a weaker background to strengthen their mathematical proficiency. In general, the observations do not strongly suggest that the relationship between overall performance based on certain predictor variables is dependent on prior mathematical proficiency.

The observations and insights that are discovered in the exploratory analysis discuss whether the variables that are measured throughout the duration of STA 1000 are appropriate for determining overall performance and developing recommendations for students. Additionally, the analysis examines the relationship between prior mathematical proficiency and overall performance. The analysis proposes that the predictor variables have the potential to determine overall performance as a relationship is observed between assessment performance and overall performance. Furthermore, the analysis does not strongly suggest that there is an interaction between prior mathematical proficiency and other predictor variables. However, there are noticeable effects on assessment performance based on prior mathematical proficiency. Therefore, interaction effects need to be taken into consideration.

The EDA demonstrates that there is a potential to leverage predictive model outputs (due to the observed relationships between predictor variables and the dependent variable) in order to develop suitable personalised recommendations. Overall, constructive recommendations need to be provided to all students regardless of the risk factor of passing or failing the course. The recommendations need to be individually tailored to each student to encourage and promote healthy and active learning as well as provide appropriate measures for all students alike.

4 Modelling Methodology

4.1 Modelling Objective

Predictive modelling will be used to determine the risk status of a student. The models categorise students as being at risk or not by predicting whether the student will pass (positive case; 1) or fail (negative case; 0) STA 1000. The aim is to determine the factors which a student could most effectively use to alter their learning behaviour. The predictive analytics is used to extract and leverage as much information from model outputs to provide meaningful insights to students. This allows students to direct their energies in the most efficient way to mitigate the risk and/or encourage a good learning behaviour. The modelling aims to use variables that the student has control over (*Assignments*, *Tutorials*, *Test* & *Bonus Marks*) compared to variables that are fixed and cannot be altered. In other words, the idea is to help students work smartly to leverage their chances of success and not explicitly predict failure or success based on factors which the student cannot control.

The focus of the predictive modelling is to draw inference from the output and leverage the results to develop recommendations and not on the actual model itself. An easily interpretable and simple predictive modelling technique needs to be used to make the desired inference. The intention is to gain insight into the educational process and underlying student learning behaviour. Easily interpretable outputs are required to develop meaningful insights and actionable intelligence for students. Therefore, the trade-off between interpretability and complexity needs to be taken into consideration when selecting a suitable modelling technique. Model flexibility allows for a variety of shapes to be considered for the outcome variable, leading to increased predictive power. An increase in model flexibility subsequently increases model complexity, leading to higher accuracy at the cost of interpretability. Highly flexible and complex models are also prone to overfitting, which leads to overall poor performance on unseen data. However, a model that is easily interpretable will allow for clear insights to be drawn from the relationship between predictor and outcome variables.

For the purposes of this investigation, model interpretability is more desirable compared to model complexity. A suitable and reasonable model needs to be chosen that allows for simple yet effective interpretation. There is a wide range of predictive models available which are used throughout the literature focussing on predicting student performance, as discussed in section **2.3**. Essentially, the output from the predictive models need to offer intuitive and actionable insight and provide output that requires simple interpretations.

4.2 Developing Recommendations from Predictive Model Outputs

A possible starting point in developing recommendations from model outputs would be to determine the marginal effect of the predictor variable on the outcome variable; how does a unit change in the predictor variable change the response variable? This relationship has the potential to describe the most important predictor variables and provide insight into how predictor variables can be changed to change the outcome variable. In other words, how can the predictor variables be changed to change the outcome (passing STA 1000)? The relationship between predictor variables and the outcome variable can provide quantitative estimates, which can be used as a foundation for developing recommendations.

Another approach would be to use recursive partitioning. Recursive partitioning is essentially a nonparametric technique for prediction and classification. This technique creates prediction rules by repeatedly dividing the feature space into subgroups, with each subdivision being formed by separating the sample on the value of one of the predictor variables. The result is a branching set of questions that forms a treelike structure in which each final branch provides a yes/no prediction of the outcome. The tree like structure has the potential to identify appropriate subpopulations within the data set that lead to different prediction outcomes. Therefore, inferential techniques can then be applied to a new data sample to make statements about its parameters. For the purposes of this investigation, certain subpopulations can be identified using the predictor variables that lead to a specific outcome (pass or fail). Given the criteria that lead to these subpopulations, certain recommendations can be formed using the criteria for obtaining the subpopulations. Recommendations can be tailored to specific groups to address a specific aspect relating to a predictor variable.

4.3 Modelling Techniques

4.3.1 Logistic Regression

Regression techniques allow for relatively clear interpretation and inference to be made while possessing strong prediction capabilities. Although many techniques are available and used throughout the literature, regression seems to be used frequently in predicting academic performance. Regression techniques describes a relationship between the outcome variable and the predictor variables. This relationship describes how a marginal change in a predictor variable changes the outcome variable. Given the context of this investigation, in combination with the predictive capabilities and ease of interpretation regarding the model outputs, logistic regression was chosen as one of the preferable modelling techniques.

The outcome variable, Y, is binary and the aim is to model the conditional probability $Pr(Y = interested\ outcome | X = x, a\ specific\ value)$ as a function of x. The model allows one to establish a linear relationship between a binary outcome variable and a group of predictor variables. More formally, let Y be the binary outcome variable indicating fail/pass with $(0,1)$ and p be the probability of Y to be 1, $p = P(Y = 1)$.

In the context of this investigation, the aim is to model the probability that a student will pass STA 1000; therefore, the p $(probability)$ represents the probability that a student will pass. The logistic regression model aims to model the log odds of passing. An exponential relationship exists between the probability and the odds, while a monotonic relationship exists between the probability and the log odds. The outputs from the regression model, the β coefficients, indicate the marginal effect of a specific predictor variable on the log odds, whilst holding all other variables constant. Simply, an increase/decrease in the predictor variable by 1 unit increases/decreases the log odds by 1 unit respectively, whilst holding all other predictor variables constant. Intuitively, an increase in the log odds, increases the odds and in turn increases the probability.

The comparative measure of two odds relative to different events is referred to as the odds ratio (OR). The odds of a particular event refers to the probability that the event occurs divided by the probability that the event does not occur. The OR is a measure that describes the association between an exposure and an outcome. The OR represents the odds that an outcome will occur given a particular exposure, compared to the odds of the outcome occurring in the absence of that exposure. In other words, the OR is used to compare the relative odds of the occurrence of the outcome of interest, given exposure to the variable of interest. Given the context of this investigation, the OR can be used to compare the relative odds of passing given a change in assessment marks or obtaining a *Bonus Mark*.

For two events A and B, the corresponding odds of A occurring relative to B occurring is, where P_A and P_B refer to the probability that A or B will occur:

$$OR\ \{A\ vs\ B\} = \frac{odds\{A\}}{odds\{B\}} = \frac{{}^{P_A}\!/_{1 - P_A}}{{}^{P_B}\!/_{1 - P_B}}$$

The logistic regression coefficients, β, denotes the change in the log odds of the outcome per unit change of the predictor variable. Subsequently, the exponentiated coefficients, e^{β}, denotes the OR associated with a one unit change in the predictor variable. Essentially, the OR can be used to assess how exposure to a predictor variable can impact the odds of passing.

An $OR = 1$ indicates that exposure does not affect the odds of an outcome; practically, an OR = 1 indicates that changing a predictor variable does not affect the odds of passing. An $OR > 1$ indicates that exposure is associated with a higher odds of the outcome occurring. On the other hand, an $OR < 1$ indicates that exposure is associated with a lower odds of the outcome occurring.

Practically, for numeric predictor variables, ORs that are greater than 1 indicate that the outcome (passing STA 1000) is more likely to occur as the predictor increases, whereas ORs that are less than 1 indicate that the outcome is less likely to occur as the predictor increases. For categorical or binary variables (*Bonus Marks*), ORs that are greater than 1 indicate that the outcome is more likely to occur when *Bonus Marks* are obtained, whereas ORs that are less than 1 indicate that the outcome is less likely to occur when *Bonus Marks* are obtained

4.3.2 Decision Trees

Decision trees is a predictive technique that involves segmenting a feature space into several regions. In general, decision trees mimic the human decision-making process and allows for intuitive and clear interpretation, while possessing strong prediction capabilities. Apart from regression techniques, decision tree classification techniques are also widely used throughout the literature for predicting academic performance. This technique can manage complex problems by providing easily interpretable outputs. Essentially, the entire feature space is recursively partitioned into smaller manageable subspaces based on values of certain predictor variables. This means that certain predictor variables are grouped together to provide logical rules, to determine the criteria for obtaining subspaces, which can be leveraged to gain meaningful interpretation. Given the context of this investigation, in combination with the predictive capabilities and ease of interpretation, decision trees were chosen as the other preferable modelling technique for this investigation.

Tree-based techniques are similar for regression and classification problems. Regression problems aim to model a continuous predictor variable, whilst classification problems aim to model a binary/categorical variable. The two steps for building a decision tree are as follows:

- Partition the feature space into J distinct non-overlapping regions $R_1, \ldots, R_J$
- For every observation that falls into R_J, the predicted value of Y is simply the mean response for all the training observations in R_J.

More formally, to perform recursive binary partitioning, a predictor X_p is selected and a cut point s that partitions the predictor feature space into regions $\{X|X_p < s\}$ and $\{X|X_p > s\}$. **Figure 5.1** below illustrates a five-region example of the above process.

Within the context of this investigation, the outcome for each region within the feature space either represents a quantitative value for the final mark or a pass/fail outcome depending on whether a regression or classification tree is used. Each region contains a specific set of criteria that is developed using the predictor variables. Each region defines a unique and manageable subpopulation of all the students. For example, in **Figure 4.1**, *Region 1 (R1)* is obtained by the following set of criteria: $X_1 < t_1 \ AND \ X_2 < t_2$. Given this set of criteria for $R1$ and the outcome of the entire region, inference can be drawn about the region based on the values for specific predictors. The inference obtained from the above analysis can act as a foundation for developing personalised recommendations to each subpopulation within the feature space.

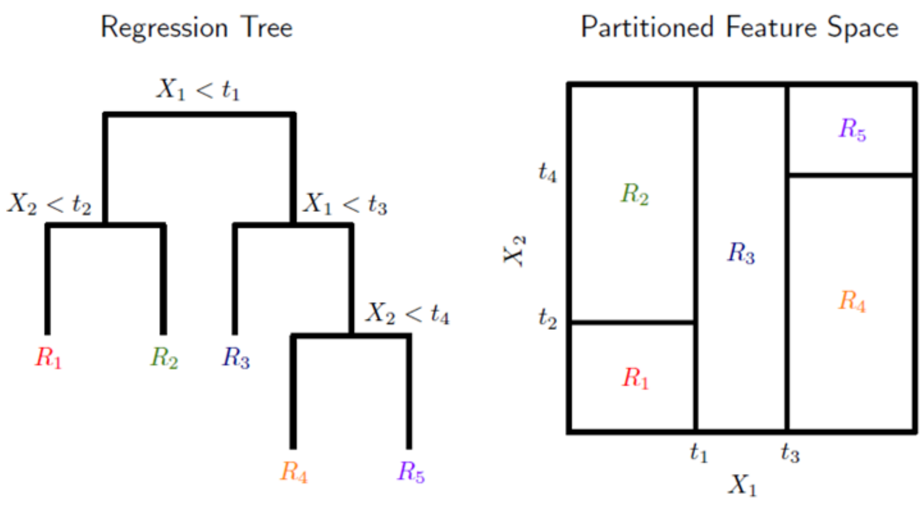


Figure 4.1: Regression tree and partitioned feature space using recursive binary partitioning

4.4 Data Imbalances

Conventional machine learning algorithms tend to be biased towards majority predictor classes which can potentially lead to inaccurate or misleading results. The models aim to minimise overall error and are accuracy driven. The majority class tends to dominate the prediction process and the minority class is treated as white noise and is often ignored. Consequently, a high misclassification rate occurs for the minority class and a misleadingly high classification rate for the majority class. The EDA highlights the non-equal representation of the classes within the outcome variable, which demonstrates an existence of data imbalances. The experimental setup regarding the predictive modelling considers the imbalances and employs different techniques to address the imbalance, namely resampling and thresholding techniques.

There are various sampling methods available to address data imbalances. The most popular sampling methods are under sampling, over sampling, Random Over-Sampling Examples (ROSE) and Synthetic Minority Oversampling Technique (SMOTE). These techniques use different random sampling principles in order to balance the predictor classes. The ROSE and SMOTE algorithms use synthetic data generation in order to balance the data set. The SMOTE algorithm generates synthetic data points using k nearest neighbours. The ROSE algorithm generates synthetic data points within the feature space using a smoothed-bootstrap approach. New data points are generated from specific data points, belonging to a particular class, which is a certain width from the original data point. Given the low proportion of the minority class in the data, a 50/50 split (minority/majority), after resampling, could severely alter the structure of the data from the original data set. This could potentially lead to inaccurate modelling and misleading model performance. Therefore, the dataset was split into different proportions (minority/majority) and analysed independently.

These techniques are used in conjunction with varying thresholding in order to address imbalanced data. The output from the logistic model is the probability for a particular outcome. In practice, the most common approach is to classify observations as a positive outcome (the outcome has occurred; the student has passed STA 1000) when the probability exceeds 0.5 and classify observations as a negative outcome (the outcome has not occurred; the student has failed STA 1000) otherwise; where the positive case relates to a binary indicator of 1 and the negative case relates to a value of 0. In general:

$$outcome = \begin{cases} 1 & p \geq 0.5 \\ 0 & p < 0.5 \end{cases}$$

Altering the threshold value of 0.5 can address the data imbalances by aiming to maximise certain performance metrics. This approach is discussed in more detail below.

4.5 Performance Metrics

Different performance metrics are used to assess model performance individually and comparatively. The objective is to develop accurate, high performance models that are easily interpretable that provide significant predictor variables at each point in time. Suitable model performance is required to support the credibility of the recommendations. Unsatisfactory model performance could undermine the appropriateness of the recommendations and provide advice that is not meaningful. Given the context of this investigation, a balance between correctly classified passes and failures is required; a high misclassification rate would mean that students could receive inappropriate recommendations that could have unintentional and undesirable consequences.

4.5.1 Classification Based Metrics

A confusion matrix is commonly used in predictive analytics to measure the performance of classification algorithms, as depicted in **Table 5.3**. The confusion matrix presents a summary of the prediction results that illustrates the number of correct and incorrect predictions with count values and is broken down by class. True Positive (TP) and True Negative (TN) represents students who were correctly classified as passing or failing STA 1000, respectively. False Negative (FN) and False Positive (FP) represents a misclassification whereby the student passed or failed respectively, but the classifier predicted otherwise.

Table 4.1: Confusion matrix with certain performance metrics

Predicted Class

Actual Class		Positive	Negative	
	Positive	True Positive (TP)	False Negative (FN) *Type II Error*	**Sensitivity** $\frac{TP}{TP+FN}$
	Negative	False Positive (FP) *Type I Error*	True Negative (TN)	**Specificity** $\frac{TN}{TN+FP}$
		Precision $\frac{TP}{TP+FP}$	**Negative Predicative Value** $\frac{TN}{TN+FN}$	**Accuracy** $\frac{TP+TN}{TP+TN+FP+FN}$

These measurements can be used to compute several performance metrics commonly used in binary classification problems, as illustrated in **Table 4.1**. Accuracy, sensitivity, and specificity are the performance metrics of choice for this investigation. Accuracy measures the proportion of accurately classified observations. Sensitivity and specificity measure the proportion of accurately classified true passes and true fails, respectively. The precision and NPV measure the proportion of pass or fail predictions that were correct.

Due to the presence of data imbalances, the accuracy can become misleading when assessing model performance. Although accuracy is still taken into consideration, preference is given to sensitivity and specificity.

4.5.2 ROC Analysis

The Receiving Operating Characteristic (ROC) curve is a plot of Sensitivity vs False Positive Rate (1 – Specificity) as the thresholding value is varied. Increases in the thresholding value subsequently increases the sensitivity and FPR (decreases specificity), which quantifies the trade-off between sensitivity and specificity. The least costly trade-off occurs when the area under the ROC curve (AUC) is maximised and increases in sensitivity results in marginal increases in FPR.

The closest to (0,1) criteria (ER) is used in order to determine the optimal threshold value. Essentially, the ER criteria is defined as the closest point from the ROC curve to (0,1); the Euclidean distance from the ROC curve to point (0,1):

$$ER(c) = \left(\sqrt{\left(1 - sensitivity(c)\right)^2 + \left(1 - specificity(c)\right)^2}\right)$$

Mathematically, the point $\widehat{c_{ER}}$ minimising the $ER(c)$ function is called the optimal cut-point value. This point would provide the best possible values for sensitivity and specificity while ensuring that a suitable AUC is obtained, therefore, this technique was chosen to determine the most suitable threshold value.

4.6 Experimental Design

Stratified sampling will be used to ensure that the proportion of minority and majority classes (passes and fails) within the outcome variable (*Final* mark) is maintained in the training and testing data set. This ensures that the predictive models can effectively classify passes and fails. The data set is split into training and testing sets using the conventional 75/25 split. Predictive models are developed at different TPs in the semester as outlined in section **3.1**. The variables that are used as predictor variables are summarised in **Table 3.1**

It is not necessary to develop different predictive models for students that have different prior mathematical proficiencies due to the insights discussed in Chapter **3**. Developing separate models to determine whether recommendations are needed for different groups of students will depend on the modelling technique. Overall, the broad impact on academic performance is similar for each group of students; there is only a quantitative impact on overall/assessment performance that differs depending on the prior mathematical proficiency of the student. This suggests that the recommendations provided to each group of students do not necessarily need to be different, since recommendations are personalised.

Interaction effects can be introduced into the modelling when using logistic regression; this would omit the need to develop separate models based on prior mathematical proficiency. However, separate models need to be developed when using decision trees.

The training data set is divided into 2 sub-groups, each group contains students with a weak or strong prior mathematical proficiency, respectively, when decision trees is used. Different predictive models will be developed for each of the 3 data sets: the full training set, the set containing only students with a weak maths background and the set containing students with a strong maths background. On the contrary, the full training set will be used for logistic regression.

4.6.1 Logistic Regression

The first step is to address the data imbalances. Logistic regression models will be developed at each TP for the data set using a default and optimal threshold for classification. The performance metrics will be observed and analysed for each model that is developed, to determine which threshold should be used for classification and whether balancing the data is required.

If the performance metrics are reasonable and suitable for predictive purposes, in terms of classification of passes and failures and AUC, the prior mathematical proficiency variable will be introduced into the models to determine whether overall performance related to a specific predictor variable is dependent on prior mathematical proficiency. Although the EDA discusses that there is not a strong possibility that interaction effects may exist, the predictive models will still take the interaction effects into account. This will determine whether there are any significant interaction effects and if there is a quantitative difference between recommendations for students with different prior mathematical proficiencies.

The performance and interaction effects will be analysed to determine whether developing recommendations from model outputs would be appropriate. Models with poor predictive capabilities may produce recommendations that are unreliable and misleading. Lastly, the model outputs will be computed and analyzed to determine whether suitable recommendations can be developed; essentially, the aim is to determine whether converting the model outputs into recommendations would be beneficial to students.

4.6.2 Decision Trees

The experimental design will follow a similar method as logistic regression, as discussed above, with some modifications. The first step is to address the data imbalances. Unlike logistic regression, decision tree methods only use balancing techniques to address the class imbalance within the data. Decision tree models will be developed at each TP for each data set. The performance metrics will be observed and analysed for each model that is developed, to determine whether balancing the data is required.

Intuitively, the effectiveness of the recursive partitioning algorithm is dependent on the strength of association between the predictor variables and the outcome variable. Consequently, the algorithm could potentially obtain suboptimal performance if the predictor variables exhibit too much dispersion, which is the case as observed in the Chapter **3.** For this investigation, the aim is to obtain a set of criteria that describes subpopulations of the entire feature space. Thereafter, these set of criteria can act as a foundation for developing personalised recommendations for each subpopulation. Explicit numerical values for predictor variables are not needed. For example, if *Region 1 (R1)* in **Table 4.1** represents a subpopulation of students who are predicted to fail STA 1000 and $X_1 = Tutorial\ Average$ and $X_2 = Assignment\ Average$, the recommendations that will be developed does not depend on the characteristic of t_1 and t_2. The characteristic for t_1 and t_2 can be numeric or categorical and the recommendation would still follow the same structure, which would be to focus on obtaining better performance in the relevant assessments. All that is required is whether a specific assessment (*Assignment*, *Tutorial* or *Test*) is below or above a certain value. Therefore, *Assignment*, *Tutorial* and *Test* marks will be recategorised into "*High*" or "*Low*" for *Assignment* and *Tutorials* and "*Pass*" or "*Fail*" for *Test* marks. The criteria for recategorising these assessments are discussed in the EDA.

The performance will be analysed to determine whether developing recommendations from model outputs would be appropriate. Models with poor predictive capabilities may produce recommendations that are unreliable and misleading. Lastly, the model outputs will be computed and analyzed to determine whether suitable recommendations can be developed; essentially, the aim is to determine whether converting the model outputs into recommendations would be beneficial to students.

5 Modelling Results

5.1 Logistic Regression

5.1.1 Data Imbalance Correct Techniques

5.1.1.1 Default Threshold

The models that are developed using the unaltered data set (not balanced using balancing techniques) are inadequate for developing recommendations due to the unsatisfactory modelling performance and predictive capabilities. There is an imbalance between the classes within the dependent variable, therefore, there is a discrepancy between sensitivity and specificity. The predictive models do not have sufficient minority classes to learn from, therefore, the models are unable to correctly classify students that fail. In each circumstance, the sensitivity and specificity are high and low respectively; essentially, the predictive models simply classify all observations as passing STA 1000 with a few or no observations being classified as fail.

The data balancing techniques addresses the imbalance within the dependent variable and the discrepancy between sensitivity and specificity. As the proportion of minority classes increases within the dependent variable, the predictive models gain more minority classes to learn from, which subsequently increases the specificity. However, the specificity increases, and sensitivity decreases as the proportion of minority classes increases. As the proportion of minority classes are increased, the ability to correctly classify fails is strengthened at the cost of correctly classifying passes. The predictive models obtain arguably satisfactory performance when the minority to majority class ratio is rebalanced to 45/55 from the original ratio of 17/83. Overall, the AUC, sensitivity and specify, as well as the balance between sensitivity and specificity, is reasonable therefore, the models are suitable for developing recommendations.

5.1.1.2 Optimal Threshold

The models that are developed using the unaltered data sets (not balanced using balancing techniques) are adequate for developing recommendations due to the satisfactory modelling performance and predictive capabilities. The optimal thresholding technique directly addresses the imbalances within the data set. This technique strengthens the ability to correctly classify passes and fails and allows for a suitable balance to be obtained between sensitivity and specificity.

Additionally, using data sampling techniques in conjunction with an optimal threshold does not largely impact the overall performance and balance between sensitivity and specificity. There are slight differences between the sensitivity and specificity for each rebalancing technique as the proportion of minority classes increases. Overall, the performance between each data sampling technique, for different proportions of the minority class, are similar to the unaltered data set.

Overall, the performance and balance between sensitivity and specificity is better when an optimal thresholding technique is used for classification. Additionally, the unaltered data set obtains similar performance compared to data sets that have been rebalanced when an optimal threshold is used. Therefore, the original unaltered data set in conjunction with an optimal thresholding technique for classification will be used for further analysis.

The scores for the performance metrics using a default or optimal threshold for different proportions of minority classes can be found in **Appendix Table A.1** and **Appendix Table A.2.** The scores represented in tables are averages over each TP.

5.1.2 Models at Different Time Points

5.1.2.1 Performance Metrics Original Data with Optimal Threshold

The next step of the modelling process is to determine whether the performance across each TP is reasonable for predictive purposes. Suitable model performance is required to support the credibility of the recommendations that will be developed. **Table 5.1** below summarises the performance metrics at each TP for the original unaltered data sets using an optimal thresholding value for classification.

Table 5.1: Performance metrics at each TP

	Accuracy	Sensitivity	Specificity	AUC
TP1	0.72	0.73	0.68	0.71
TP2	0.72	0.72	0.72	0.72
TP3	0.83	0.84	0.78	0.81
TP4	0.79	0.77	0.86	0.81

As time progresses throughout the semester, more data becomes available which strengthens the ability of the predictor variables to represent student learning behaviour. In general, model performance strengthens over time in terms of AUC, sensitivity, and specificity.

The AUC and specificity steadily improve as time progresses. However, a cyclical pattern is observed with regards to the sensitivity. Sensitivity initially declines, then rises, then declines again as time progresses. The difference between each TP for the changes in sensitivity is not substantial or concerning. At TP3, the *Test* mark is introduced as a predictor variable which could explain the sharp rise in sensitivity. A possible explanation for the cyclical movement in sensitivity relates to the size of the testing data set. The testing data set consists of 466 observations; therefore, a misclassification of a few students could slightly affect the sensitivity and explain the small changes occurring over time.

In general, the AUC indicates that the model is acceptable for prediction purposes. The sensitivity and specificity stabilise over time and a suitable balance is achieved. Given the amount of predictor variables within the model, the performance metrics achieved is reasonably suitable to develop appropriate and credible recommendations for students.

5.1.2.2 Introducing Prior Mathematical Proficiency into the Model Building

The interaction effect between prior mathematical proficiency and each predictor variable is examined below. An interaction effect determines whether the effect of a predictor variable on the outcome variable is different, depending on another predictor variable. In the context of this investigation, the interaction effect determines whether there is a different impact for each predictor variable on the outcome variable (pass or fail STA 1000) depending on prior mathematical proficiency.

The only significant interaction effect is at TP3 between prior mathematical proficiency and obtaining *B3*. However, the interaction between *B3* and prior mathematical proficiency is not significant at TP4. The interaction between prior mathematical proficiency is expected as outlined in the EDA. As the course progresses, the course material for Introductory Statistics becomes heavily dependent on mathematical concepts. Therefore, students with a weaker maths background may struggle to understand the course material, which makes it difficult to obtain *B3* or *Bonus Marks* in general. Nevertheless, some students with a weaker background still manage to obtain *Bonus Marks* throughout the duration of the course, which could explain why the interaction effect is not significant at TP4.

Apart from TP3, at each time point there was no significant interaction effects between prior mathematical proficiency and any predictor variable. This suggests that the impact for each predictor variable on the outcome variable does not necessarily depend on prior mathematical proficiency. In general, the broad impact on performance is similar for students belonging to different maths backgrounds. This suggests that the recommendations provided to each group of students do not necessarily need to be different, since recommendations are personalised. However, given the significant interaction between prior maths and *B3*, it may be useful for the course convenor to be aware of a students' prior mathematical proficiency to develop interventions of another kind, as discussed in the EDA.

Including the interaction effect in further analyses would be appropriate if more than one predictor variable consistently exhibited an interaction effect at each TP, which is not the case in this instance. Including the interaction effect could add bias or noise into the model and provide misleading results. Consequently, the rest of the investigation will not include the interaction effect. The p-values for the interaction effects for each variable at each TP is provided in **Appendix Table A.3**.

5.1.3 Model Output & Interpretation

Table 5.2 below summarises the output obtained from the models developed at each TP. The *estimate* refers to the β coefficients obtained; the *odds ratio (OR)* is the exponentiated *estimate*. The *p-value* measures the statistical significance of including the variable in the model. *Bonus Marks* are depicted as Bi, the "i" represents the TP at which a *Bonus Mark* is obtainable, for example *B1* represents the first *Bonus Mark* and so on.

The *p-value* for *Assignments*, *Tutorials*, *Tests* and *Bonus Mark* at each TP (for example: *B1* at TP1, *B2* at TP2 etc) are all statistically significant at the 5% significance level ($p < 0.05$). The only exception is *B1* at TP2, *B1* and *B2* at TP3 and *B1*, *B2* and *B3* at TP4. Although the *Bonus Marks* are insignificant at these TPs, in terms of developing recommendations, they do not add any value. Practically, at these TPs, the recommendations will be focussed towards the current and upcoming *Bonus Marks* that are obtainable and not previous *Bonus Marks* that are unobtainable. Preceding *Bonus Marks* at certain TPs are simply used for prediction purposes, therefore, the significance of *Bonus Marks* 1, 2 and 3 at TP3 and TP4 are not concerning.

The OR at each TP relating to the *Intercept* of the model, refers to the odds of passing for a student who does not obtain any *Bonus Marks* and obtained a theoretical value of zero for all the assessments at a specific TP. Intuitively, this should be a very small value, as demonstrated by the diminishing value for each *Intercept* as time progresses.

The OR for *Assignments*, *Tutorials*, *Test* and *Bonus Mark* at each TP (for example: *B1* at TP1, *B2* at TP2 etc) are greater than 1. This indicates that the outcome (passing STA 1000) is more likely to occur as the predictor increases (increase in *Assignments*, *Tutorials* and *Test*). Additionally, for *Bonus Marks*, this indicates that the outcome is more likely to occur when *Bonus Marks* are obtained. For example, at TP2, increasing the *Assignment* by 1 unit increases the odds of passing by 4.9%, while keeping all other variables constant. Increasing the *Tutorial* by 1 unit increases the odds of passing by 1.1%, while keeping all other variables constant. Similarly, obtaining *B2* increases the odds of passing by 77.8%, while keeping all other variables constant. The interpretations for the other variables at other TPs follow the same reasoning.

Figure 5.1 illustrates the percentage increase in odds of passing for a specific unit change in *Assignments*, *Tutorial* and *Test* Marks for each TP, while keeping all other variables constant. The x-axis measures the increased change in value for each assessment and y-axis measures the percentage change in the odds of passing. The percentage change in the odds of passing does not depend on the current value of the assessment. If two students have a mark of 50 and 60 respectively, the increase in odds of passing will be the same if either student increases their assessment mark by 10 marks. For example, if either student increases their *Assignment Average* by 10 marks, the odds of passing will increase by roughly 60% (red line in top left line graph in **Figure 5.1.**

Table 5.2: Coefficient estimates, odds ratios (OR) and p-values for logistic regression models developed at each TP

		Estimate	Odds Ratio	P value
TP1	**(Intercept)**	-2.067	0.127	0.000
	Assignment Average	0.035	1.035	0.000
	T2	0.007	1.007	0.001
	B1	0.828	2.289	0.000
TP2	**(Intercept)**	-3.204	0.041	0.000
	Assignment Average	0.048	1.049	0.000
	Tutorial Average	0.011	1.011	0.000
	B1	0.330	1.392	0.087
	B2	0.576	1.778	0.003
TP3	**(Intercept)**	-6.730	0.001	0.000
	Assignment Average	0.044	1.045	0.000
	Tutorial Average	0.016	1.016	0.000
	Test1	0.069	1.072	0.000
	B1	0.087	1.091	0.681
	B2	0.283	1.327	0.199
	B3	0.483	1.620	0.026
TP4	**(Intercept)**	-7.2540	0.0010	0.0000
	Assignment Average	0.0500	1.0510	0.0000
	Tutorial Average	0.0190	1.0190	0.0000
	Test1	0.0700	1.0730	0.0000
	B1	-0.0010	0.9990	0.9970
	B2	0.1970	1.2180	0.3810
	B3	0.1740	1.1900	0.4500
	B4	0.7620	2.1430	0.0020

The line graphs in **Figure 5.1** below stops at a value of 25 marks for illustrative purposes, but the upward trend reinforces that a larger increase will have a larger impact on the odds of passing, as demonstrated by each OR being greater than 1.

Noticeably, certain predictor variables have a larger impact on the odds of passing over other predictor variables; the marginal effect of certain predictor variables on the outcome is higher, compared to other predictor variables. This phenomenon is expected to occur due to the method used by Maximum Likelihood Estimation (MLE) to determine the coefficient estimates (β). For the purposes of this investigation, in terms of developing recommendations from the above-mentioned model outputs, the difference in the marginal effects between predictor variables on the outcome is not concerning. The direction (and broad magnitude) of the change in mark and whether there is a positive impact on the odds of passing is what matters.

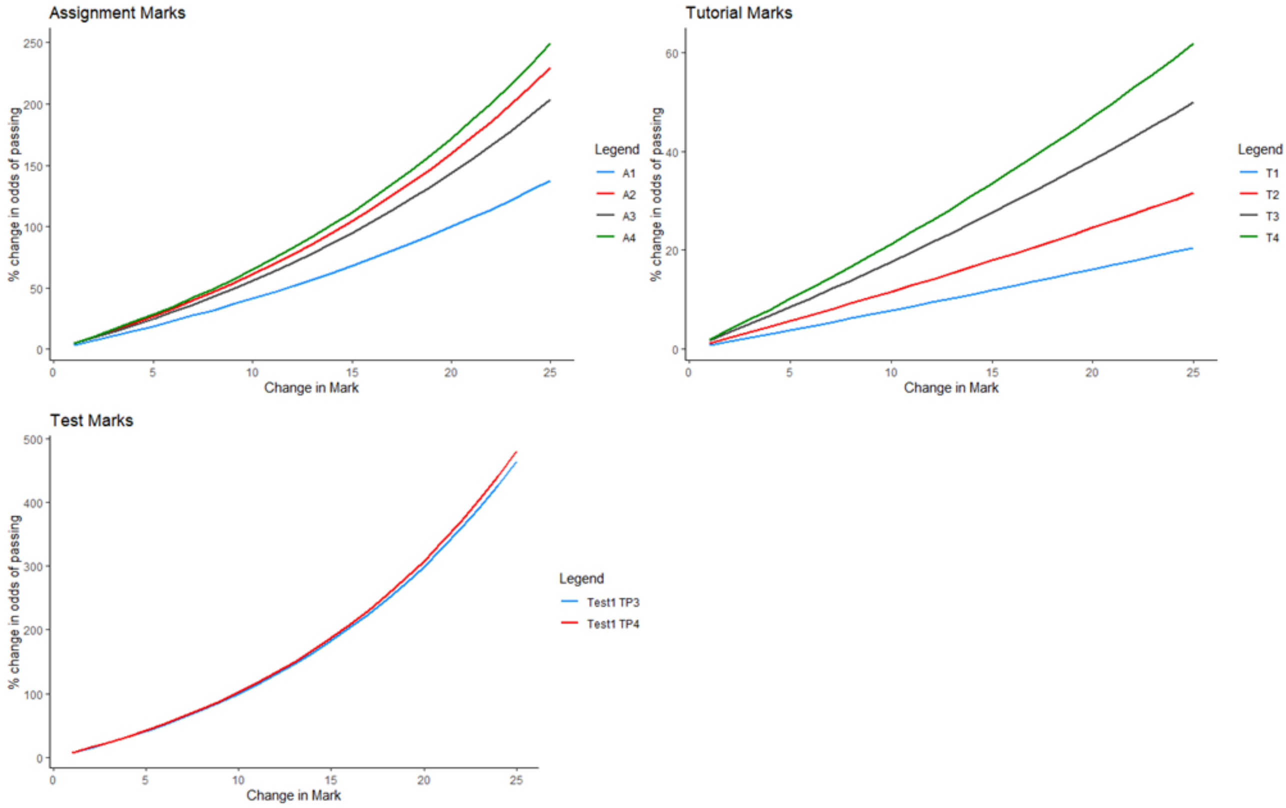


Figure 5.1: Line graph illustrating the % change in the odds of passing for a change in Assignments (top left), Tutorials (top right) and Test (bottom left).

Overall, the recommendations will incorporate all the predictor variables to provide a holistic course of action for students. Essentially, the recommendations will provide actionable insights pertaining to each assessment that will provide information to the student that stimulates them to work harder or smarter. For example, if a particular student can alter their mark for either *Assignments* or *Tutorials* by a reasonable amount, there could be a noteworthy impact on the odds of passing. Consequently, a combination of altering each assessment mark by a reasonable amount and obtaining upcoming *Bonus Marks* can have a significant impact on the odds of passing.

5.1.4 Discussion

In summary, developing recommendations from interpreting the model results appears to be plausible. This is driven by the significant predictor variables (indicated by low p-values in **Table 5.2**) and reasonable performance metrics obtained for each model (illustrated in **Table 5.1**).

The marginal effects of numeric variables (*Assignments*, *Tutorials* and *Test* marks) have a noteworthy impact on the odds of passing STA 1000. Similarly, there is a noteworthy impact on the odds of passing STA 1000 by obtaining each respective *Bonus* mark at each TP. Subsequently, there is a potential to derive suitable recommendations for students to leverage their chances of success and encourage a positive learning behaviour.

The recommendations could be tailored to aim to achieve better performance in certain assessments by increasing student engagement with the course and the course material. For example, TP2, the recommendations can guide a student to try and engage more with the formal assessments and increase their mark by 5% or 10%.

Additionally, the recommendations can communicate the potential to increase their chances of success if they alter their mark by the given guidelines. Furthermore, the recommendations will communicate the potential to increase their chances of success if the next *Bonus* mark is obtained and will encourage them to obtain all upcoming *Bonus Marks*. This example recommendation has the potential to incorporate a focus on the weak aspects of each student and indirectly encourage students to engage with the course material and form a healthy learning behaviour.

5.2 Decision Trees

5.2.1 Data Imbalance Correction Techniques

The models that are developed using the unaltered data set (not balanced using balancing techniques) are inadequate for developing recommendations due to the unsatisfactory modelling performance and predictive capabilities. There is an imbalance between the classes within the dependent variable (the full training set, the subset containing only students with a weak maths background and the subset containing students with a strong maths background), therefore, there is a discrepancy between sensitivity and specificity. The predictive models do not have sufficient minority classes to learn from, therefore, the models are unable to correctly classify students that fail. In each circumstance, the sensitivity and specificity are high and low respectively; essentially, the predictive models simply classify all observations as passing STA 1000 with a few or no observations being classified as fail.

The data balancing techniques addresses the imbalance within the dependent variable and address the discrepancy between sensitivity and specificity. As the proportion of minority classes increases within the dependent variable, the predictive models gain more minority classes to learn from, which subsequently increases the specificity. However, the specificity increases, and sensitivity decreases as the proportion of minority classes increases. As the proportion of minority classes are increased, the ability to correctly classify fails is strengthened at the cost of correctly classifying passes. The predictive models obtain arguably satisfactory performance when the minority to majority class ratio is rebalanced to between 35/65 and 45/55 from the original ratio of 17/83. Overall, the AUC, sensitivity, and specificity, as well as the balance between sensitivity and specificity, is reasonable therefore, the models are suitable for developing recommendations.

The performance using ROSE rebalancing, with a 45/55 rebalance, obtained reasonable results compared to the other sampled data sets for the full training set and the subset containing only students with a weak maths background. On the other hand, the under sampled rebalancing technique, with a 35/65 rebalance, obtained reasonable results compared to the other sampled datasets for the subset containing students with a strong maths background. Consequently, these techniques were chosen for further investigation. The scores for the performance metrics for different proportions of minority classes can be found in **Appendix Table A.4**. The scores represented the table are averages over each TP.

5.2.2 Models At Different Time Points

The next step of the modelling process is to determine whether the performance across each TP is reasonable for predictive purposes. Suitable model performance is required to support the credibility of the recommendations that will be developed. **Table 5.3** below summarises the performance metrics at each TP for each data set.

As time progresses throughout the semester, more data becomes available which strengthens the ability of the predictor variables to represent student learning behaviour. In general, model performance either strengthens or remains relatively constant over time in terms of AUC, sensitivity, and specificity.

For each data set the AUC steadily improves over time. The sensitivity improves slightly for the full training set and subset containing students with a strong maths background; specificity remains relatively constant for each data set, respectively. The sensitivity slightly increases then decreases over time for the subset containing students with a weak maths background; on the other hand, specificity slightly decreases then sharply increases at TP3. Overall, the small changes in performance metrics over time is not concerning; the difference between each TP for the changes in performance metrics is not substantial or concerning.

Table 5.3: Performance metrics for each data set at each TP

		Accuracy	Sensitivity	Specificity	AUC
Full	**TP1**	0.73	0.77	0.75	0.71
	TP2	0.79	0.82	0.76	0.73
	TP3	0.79	0.81	0.71	0.76
	TP4	0.80	0.83	0.75	0.77
Strong	**TP1**	0.78	0.82	0.67	0.73
	TP2	0.83	0.90	0.66	0.73
	TP3	0.80	0.85	0.70	0.75
	TP4	0.86	0.95	0.71	0.77
Weak	**TP1**	0.76	0.78	0.67	0.73
	TP2	0.79	0.82	0.61	0.71
	TP3	0.76	0.75	0.79	0.77
	TP4	0.75	0.73	0.82	0.77

At TP3, the *Test* mark is introduced as a predictor variable which could explain the variability in specificity. Another possible explanation for the movements in performance relates to the size of the testing data set. The testing data set consists of 466 observations; therefore, a misclassification of a few students could slightly affect the performance and explain the small changes occurring over time. Additionally, dividing the full training set into subsets containing students with a weak or strong prior mathematical proficiency, further increases the imbalance within the outcome variable. Although rebalancing techniques are used, a few unique minority observations are resampled, which makes it difficult for the models to learn what characteristics constitutes as a failure. Therefore, the slight changes in performance are expected.

In general, the AUC indicates that the model is acceptable for prediction purposes. The sensitivity and specificity stabilise over time and a suitable balance is achieved. Given the amount of predictor variables within the model, the performance metrics achieved is reasonably suitable to develop appropriate and credible recommendations for students.

5.2.3 Model Output and Interpretation

5.2.3.1 Different Models for Weak/Strong Students

The next step of the modelling process is to determine whether different models need to be developed for students that contain different maths backgrounds. As discussed above, there is a further increase in the imbalance within the outcome variable for each subset. Although rebalancing techniques are used, a few unique minority observations are resampled, which makes it difficult for the models to learn what characteristics constitutes as a failure. Additionally, the predictor variables do not provide enough information to grow a particular tree; the decision tree may not contain enough branches resulting in inadequate output. Therefore, it is not possible to develop meaningful recommendations. The decision trees for the first two TPs for the subset containing students with a strong maths background, exhibits this phenomenon. Given, that it is not possible to develop meaningful recommendations for the subset containing students with a strong maths background, the full training set was used for further analysis. Different recommendations will not be given to the different subsets of students. The decision trees for the first two TPs for students with a strong prior mathematical proficiency is illustrated in **Appendix Figure A.3** and **Appendix Figure A.4**; and in **Appendix Figure A.5** and **Appendix Figure A.6** for students with a weak prior mathematical proficiency.

5.2.3.2 Final Decision Tree Model

Each tree has a different number of nodes and rules for classification. The structure of the tree represents how the entire population of students is recursively partitioned into subsets. The top node represents the entire feature space and shows the condition used to divide it into two subsets, represented by the sub-trees. Subsequently, child nodes follow the same notion as the parent node, until the leaf node is reached, with each node containing the rule for the partition. The final partition of the feature space is represented by the leaf nodes at the bottom of the trees. The model at each TP has partitioned the entire feature space into n subpopulations, where n is the number of leaf nodes.

An equivalent interpretation of the model is that every path from the top node to a leaf node provides the set of conditions satisfied by that subset of students. Simply, the conditions provide a rule to identify subpopulations of students. The advantage of this technique is that inputs for the algorithm are indicators derived directly from the learning design and the result divides the feature space into manageable subpopulations.

The set of rules that determine a path from the root node to a leaf node does not need to contain all the predictor variables, which implies that the outcome for a certain subpopulation is not affected by certain variables. Consequently, the recommendations derived would be focussed on certain predictor variables over others. However, there is no value associated to the impact each predictor variable has on the outcomes as observed in regression techniques. Therefore, recommendations can be tailored to provide some focus on certain predictor variables whilst incorporating all other predictor variables. Additionally, incorporating all the variables could reclassify the student into a subpopulation that exhibits success. In general, the results can divide the entire cohort into manageable subpopulations which allows for personalised recommendations to be developed.

Figure 5.2 illustrates the decision tree at TP2. The root node represents the entire feature space whilst the child nodes represent the percentage of the feature space that falls within that partition. Consequently, the percentage of observations that belong to a child node is related to the number of observations within the respective parent node and not the entire feature space. For example, node 1 represents the root node and contains the entire cohort. Note 3 contains 68% of the entire cohort whilst node 5 contains 29% of the subpopulation found in node 3. The probability of failure/success is represented by the middle decimal values on the left and right respectively; in node 3 the probability of failure and success is 0.32 and 0.68, respectively.

In the decision tree at TP2 in **Figure 5.2** there are 5 partitions of the feature space represented by the 4 leaf nodes. The model predicts that 3 of these subpopulations (green in colour) of students will fail and the other 2 will pass (blue in colour) according to specific partitioning rules. For example, the subpopulation of students represented in node 12 are predicted to fail and are identified by the property that *Average2=Low* AND *TAverage* = low. In other words, if a student obtains a low *Assignment* and *Tutorial Average* (below the class average) they will fail STA 1000. A possible recommendation that could be developed for the subpopulation in node 12 could guide and encourage the student to achieve for higher marks in the *Tutorial* and *Assignment*. Increasing engagement with the course and the course material could ensure that the upcoming *Bonus Marks* will be obtained. The interpretation and possible recommendations for the other leaf nodes (subpopulations) and other trees at different TPs follow the same reasoning and procedure as discussed above. The decision trees for TP1, TP3 and TP4 can be found in **Appendix Figure A.7**, **Appendix Figure A.8** and **Appendix Figure A.9**.

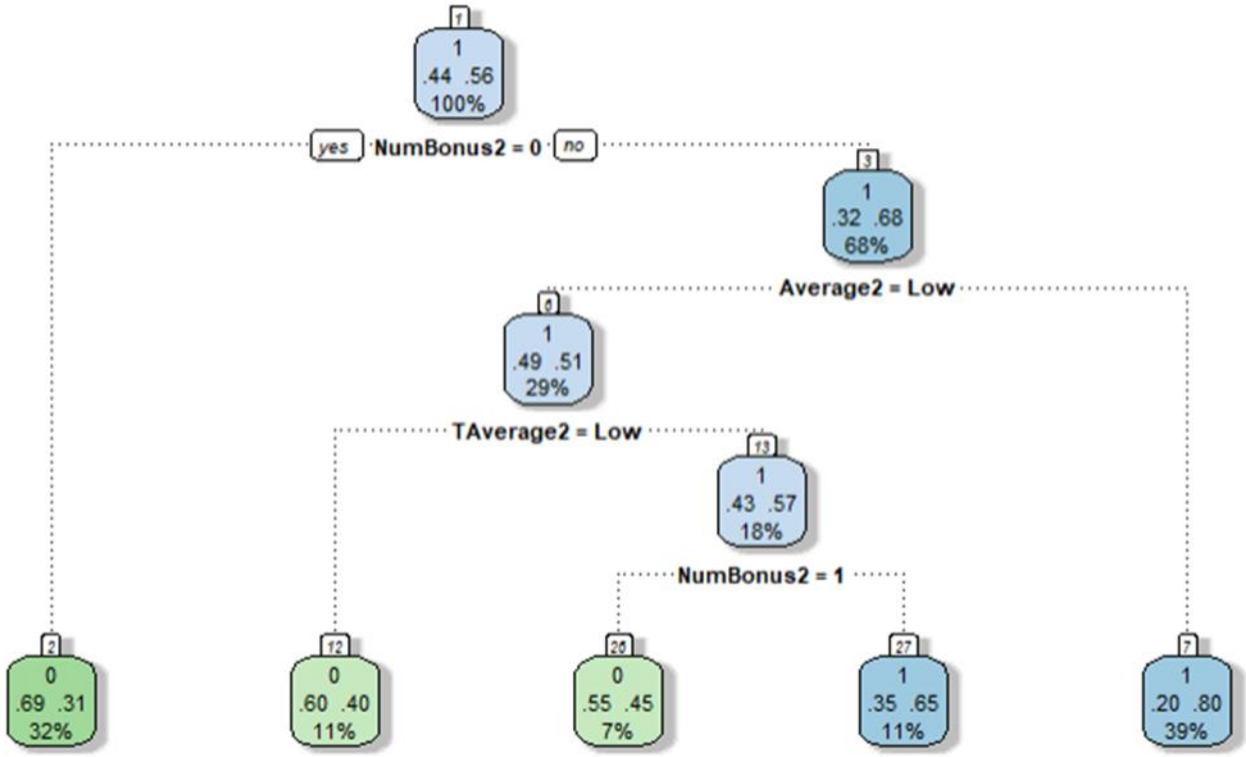


Figure 5.2: Decision Tree at TP2

5.2.4 Discussion

In summary, developing recommendations from interpreting the model results appears to be plausible. This is driven by the intuitive set of partitioning criteria derived from obtaining each subpopulation of students and reasonable performance metrics obtained for each model (illustrated in **Table 5.3**).

Practically, the partitions provide a useful understanding of how the entire cohort of students are performing and can effectively identify specific aspects that certain subpopulations are struggling with. The recommendations can achieve a high level of personalisation for each subset and address possible issues each subset is experiencing whilst incorporating other aspects that do not necessarily need focus but are included to promote a healthy learning behaviour. Consequently, there is a potential to derive suitable recommendations to students in order to leverage their chances of success and encourage a positive learning behaviour. Furthermore, if a student is categorised into a subpopulation that exhibits success, recommendations can provide constructive and meaningful information to promote and encourage a healthy learning behaviour and further boost performance.

5.3 Chapter Summary

The focus of the predictive analytics is to draw inference from the model output and leverage the results to develop recommendations. The intention is to gain insight into the educational process and underlying student learning behaviour. Simply, the modelling techniques provide support in identifying how different factors (course assessments) can be altered to increase the chances of success and positively impact learning behaviour.

Two different approaches for developing recommendations from predictive models were examined. The first approach, marginal effect technique, uses logistic regression to determine the marginal effect of a predictor variable on the outcome variable. The second approach, recursive partitioning technique, uses decision trees to repeatedly divide the feature space into subgroups, with each subdivision being formed by separating the feature space on the value of one of the predictor variables.

Suitable model performance is required to support the credibility of the recommendations that will be developed. In general, the AUC obtained from both techniques indicates that the models are acceptable for prediction purposes. The sensitivity and specificity stabilise over time and a suitable balance is achieved; given the context of this investigation a balance between correctly classified passes (sensitivity) and failures (specificity) is required.

Each modelling technique incorporated and examined the effect of prior mathematical proficiency on performance. In summary, the investigation, for both modelling techniques, concluded that it is not necessary to develop separate models for students with different prior mathematical proficiencies. Subsequently, it is not necessary or possible to develop meaningful recommendations if different models are developed for students with different maths backgrounds.

The marginal effects obtained using logistic regression, of the predictor variables have a noteworthy impact on the odds of passing STA 1000. On the other hand, partitions obtained using decision trees, provide a useful understanding of how the entire cohort of students are performing and can effectively identify specific aspects pertaining to each subpopulation. The marginal effect technique has the potential to provide granular and individualised recommendations; whilst the recursive partitioning technique can achieve a high level of personalisation for each subpopulation and address possible issues accordingly. Overall, there is a potential to practically derive suitable recommendations for students to leverage their chances of success and encourage a positive learning behaviour.

Depending on pedagogical goals, any technique can be used to develop recommendations and be incorporated into the LAD as actionable intelligence for students. For the purposes of this project, it would be more suitable to use logistic regression to develop individualised recommendations for each student, however, using decision trees to develop personalised recommendations to certain subsets of students could be another potential option

6 LAD and Recommendation Design Overview

6.1 General Concepts for Designing Feedback

Learning is primarily driven by two approaches: cognitive theories and behavioural theories. Cognitive theories, cognitivism, views the learning process as a step-by-step knowledge construction process. On the other hand, behavioural theories, behaviourism, asserts that a student will reinforce an aspect of their learning habit to change their overall learning behaviour (**Sedrakyan, Mannens & Verbert, 2019**) Practically, these principles include forms of explanations that aim to improve a cognitive dimension of knowledge and/or providing guidance to positively impact learning behaviour.

In general, verbal, or visual cognitive feedback encourages a student to reflect on the problem solving process (e.g., thinking, understanding, reasoning) and aims to improve students' understanding and facilitate engagement. Verbal, or visual behavioural feedback aims to improve learning behaviour, and promote awareness regarding learning progress and any necessary changes that need to be made to the current learning behaviour. Practically, in the context of LADs, these forms of feedback inform a student whether they are on a successful learning path and provides guidance if that is not the case. **Sedrakyan et al. (2020)** defines feedback as "an interactive process in which the output or effect of an action is returned (fed back) to modify the next action toward reaching a goal." The feedback aims to create a link between past and future work (performance) and help a student create a progressive developmental trajectory.

Cognitive advice (feedback) provides information pertaining to the success or failure of a specific task. There are three types of cognitive feedback: epistemic, requests and/or stimulates explanations and/or clarifications in a critical way; suggestive, advising a student to proceed in a certain manner and prompts the student to explore, expand or improve their current activity; and corrective feedback, providing comments on the adequacy and quality of performance.

Effective feedback needs to include regulatory mechanisms of the underlying learning process and awareness of the level of knowledge, competence, and expertise that the student targets. Feedback is often intertwined with the concept of self-regulated learning (SRL), which is defined as a students' ability to evaluate and monitor progress that promotes self-improvement and facilitates goal achievement. In other words, effective feedback, should support a student in avoiding failure or perform equal to peers, obtain skills and competence, and set preference for specific topics. Consequently, this mechanism aims to raise self-reflection/awareness and prompts action which strengthens the ability to monitor and evaluate progress to achieve self-improvement.

SRL is a goal-directed, intentional, and metacognitive activity in which learners take strategic control of their actions (behaviour), thinking (cognitive), and beliefs (motivation, emotions) toward the completion of a task. Successful students use a repertoire of these strategies to guide and enhance their learning process and motivation toward obtaining academic goals (**Zimmerman & Schunk, 2011**). SRL, in practice, involves experimenting and learning about different and effective strategies for regulating learning behaviour and involves planning, setting goals, organizing, monitoring, and adapting.

Sadler (1989) asserts that it may be possible for learners to benefit from feedback, referred to as the general principles of feedback construction, if the following conditions are satisfied:

- Clarify what good performance is
- Facilitate self-assessment (allow assessment of how current performance relates to good performance), and

- Provide opportunities to close the identified gap between current and good performance (allowing reflection on how to act).

6.2 Relevant LAD Concepts

LADs are a potentially powerful tool that could allow learners to overcome difficulties in controlling and monitoring their progress. On the other hand, LADs allow educators to improve their pedagogical goals and strategies to improve learning activities and promote regular engagement with the course material. This tool aims to create a shaped and supporting learning environment that encourages growth and helps a student to achieve optimal academic performance. Furthermore, LADs have the potential to use perceptual capabilities and cognition to improve decision making.

Visualisations that monitor performance can show students how to align their learning goals with their actions. This type of external feedback aims to drive cognitive evaluation and promote self-reflection, which will help students optimise their learning strategies, adjust, or select different actions to reach their learning goals. Simply, the aim of the LAD is to promote a healthy learning behaviour that encourages action and engagement.

The design principles of a LAD drive the characteristics of the visual feedback that is communicated to a student. **Sedrakyan, Mannens and Verbert (2019)** asserts that the type of feedback that is given to students with unsatisfactory performance, depends on whether performance is affected by a misunderstanding of a problem, task, or concept or rather a procedural aspect of learning (e.g., not sufficient effort put in verifying a solution).

Goal orientation impacts learning behaviour within a self-regulated online learning environment. The type of academic goals that a student aspires to achieve will determine how learning outcomes are focussed on different levels of knowledge, skills, competences, or task completion. Subsequently, these goals influence the engagement within a self-regulated learning environment **(Matcha, Gašević & Pardo, 2019; Sedrakyan, Mannens & Verbert, 2019**).This suggests that goal orientations need to be carefully considered in the design of any intervention, as the resulting approach and tools can affect students' interpretations of the data and subsequent academic success. Students orientated around performance will be influenced by the desire to avoid underperforming compared to peers (performance goal orientation) whilst mastery orientated students avoid underperformance in relation to personal aspirations or goals (mastery goal orientation).

Visual aspects should be illustrated through a sequential representation to portray a trajectory of learning sequences towards a predefined learning goal. Different colouring schemes can differentiate performance or mastery orientation and could facilitate interactive decision making. **Charleer et al. (2016)** highlight the effectiveness, within different learning contexts, of visual techniques (such as bar, line, area charts etc.) in quantifying achievement and monitoring progress towards goals. The intention of these visualisations is to stimulate a monitoring behaviour within the LAD, enabling students to adjust or change their goals, plans or strategies.

6.3 Interview with UCT Learning Designer

A personal interview was conducted on the 28th of January 2021 with Thomas King, to gain insight into the practical elements and design principles for a LAD within Vula. Thomas King is a Learning Designer, part of the Course and Curriculum Design[1] (CCD) Team, based in the Centre for Innovation in Learning and Teaching[2] (CILT). Thomas King's work focusses on the Formal Online Education Project, which seeks to assist UCT lecturers interested in taking parts of their teaching online. His primary research interests revolve around Open

1 CCD team enhances teaching and learning at UCT by providing support to academic staff and departments on a range of curriculum and course design projects

2 CILT is an organisation that responds to teaching and learning challenges at UCT and the broader higher education environment through learner-centred pedagogic practices

Educational Resources, and Open Data, particularly in the fields of qualitative de-identification and management.

Vula currently lacks a mechanism to provide meaningful and actionable intelligence to students, therefore, integrating a LAD into Vula could be potentially valuable (**King, personal interview, 2021**). Integrating a LAD that provides holistic feedback on student performance and course engagement could build a foundation for courses across UCT to implement a blended online learning approach. In general, once the LAD is implemented across Vula for all courses, King states that it is up to the course convenor to reinforce the existence and encourage the use of this tool. More precisely, **King (2021)** suggests that this LAD would work for STA 1000 given that the course is partially online and there is a blended learning pedagogical approach.

The prototype LAD designed in this project has the potential to be used at UCT as a whole and could be used for multiple courses (**King, personal interview, 2021**). The core design and basic fundamental principles of designing this prototype LAD has been taken into consideration, and implemented effectively, according to King. King explained that the prototype LAD has “the correct ratio of colour, direction and “physical movement…”, which creates a multi-language dashboard, in terms of the content and visual aspects. Overall, King indicates that the prototype LAD designed in this project has the potential to impact student behaviour and has noted that the LAD is being conscious of how the student perceives information.

6.4 Interview with STA 1000 Head Tutor

A personal interview was conducted on the 3rd of February 2021 with Michaela Takawira, to gain insight into the practical elements and design principles for recommendations for students. Michaela Takawira was the Head Tutor for STA 1000 in 2018-2020. The Head Tutor plays an integral role offering leadership and guidance on matters relating to student welfare, providing support to students, and acting as a point of communication between academic units and central support services. As Head Tutor, one would be experienced in providing supporting advice and constructive criticism to students that are aspiring to achieve improved performance.

In general, students taking STA 1000 are dedicated to their studies and actively seek advice to identify any shortfalls and obtain guidance to improve academic performance (**Takawira, personal interview, 2021**). The transition from high school to university can be difficult for some students, therefore, (**Takawira, personal interview, 2021**) suggests that this LAD would be beneficial for students and has the potential to make a student want do better.

Careful consideration needs to be taken when developing recommendations. Students generally prefer positive feedback; negative feedback has the potential to harmfully impact a student’s well-being and mental health. Takwira has suggested that “the terminology is neutral or positive and leaning towards motherly.” Overall, the recommendations cannot negatively impact the student and needs to be clear, simple, and understandable.

Takawira states that the most common question received is: “what do I need to do to pass?” The best sort of advice would be to notify the student to willingly complete quizzes, assignments, and tutorial/workshop questions. Additionally, the student needs to understand the underlying principle and not study using memorisation techniques (rote learning). On the other hand, Takawira, advises students who are on track but want to further improve their performance to research the relevant principles to gain a deeper understanding. A student who is willing to go the extra mile should not just stick to the textbook. Overall, Takawira, would advise that practice makes perfect and that students should aim to improve the rate at which they can answer questions in formal assessments (tests and exams).

6.5 Chapter Summary

Cognitive and behavioural theories aim improve a dimension of knowledge and/or provide guidance to positively impact learning behaviour. These principles are intended to improve students’ understanding and facilitate engagement in order to promote awareness regarding learning progress and any necessary changes that need to be made to the current learning behaviour. Practically, these principles are portrayed verbally and/or visually and informs a student whether they are on a successful learning path and provides guidance if that is not the case.

In order for visual and/or verbal feedback to be effective, the mechanism should support a student in avoiding failure or perform equal to peers, obtain skills and competence, and set preference for specific topics. Consequently, this technique aims to raise self-reflection/awareness and prompts action which strengthens the ability to monitor and evaluate progress to achieve self-improvement. Ultimately, the effective feedback supports self-regulated learning (SRL) whereby learners take strategic control of their actions (behaviour), thinking (cognitive), and beliefs (motivation, emotions) toward the completion of a task and enhance their learning process and motivation toward obtaining academic goals.

The purpose of a LAD is to create a shaped and supporting learning environment that encourages growth and helps a student to achieve optimal academic performance. The LAD should primarily drive cognitive evaluation and promote self-reflection, which will help optimise their strategies, and allow students to adjust or select different actions to reach their learning goals. Simply, the aim of the LAD is to promote a healthy learning behaviour that encourages action and engagement and enables a student to align their learning goals with their actions. Additionally, this tool helps educators to improve their pedagogical goals and strategies to improve learning activities and promote regular engagement with the course material.

Careful consideration needs to be taken when designing any interventions pertaining to goal orientations (performance or mastery), as certain verbal and/or visual feedback may affect students' interpretations and subsequent academic success. Furthermore, the type of feedback that is given to students with unsatisfactory performance, depends on whether performance is affected by a misunderstanding of a problem, task, or concept or rather a procedural aspect of learning.

Visual aspects should be illustrated through a sequential representation to portray a trajectory of learning sequences towards a predefined learning goal and contain different colouring schemes that differentiate performance or mastery orientation that could facilitate interactive decision making. The intention of these visualisations is to stimulate a monitoring behaviour within the LAD, enabling students to adjust or change their goals, plans or strategies.

Learning Designer, Thomas King, has stated that UCT's LMS currently lacks a mechanism to provide meaningful and actionable intelligence to students. Integrating a LAD into Vula that provides holistic feedback on student performance and course engagement could build a foundation for courses across UCT to implement. Ultimately, King suggests that the LAD design concepts and principles has the potential to impact student behaviour and could be potentially valuable.

Former STA 1000 Head Tutor, Michaela Takawira, suggests that this LAD would be beneficial for students and has the potential to make a student want to do better. Takawira has stated that students generally prefer positive feedback, and that negative feedback has the potential to harmfully impact a student’s well-being and mental health. Overall, the recommendations cannot negatively impact the student and needs to be clear, simple, and understandable. In general, Takawira has advised that the recommendations should focus on the principle of practice makes perfect and that students should aim to improve the rate at which they can answer questions in formal assessments.

7 Developing Recommendations

7.1 Design Approach

The design strategy used for developing recommendations is driven by SRL theory, which is combined with elements of cognitivism and behaviourism, as discussed in section **6.1**. The recommendations consider the regulatory mechanisms of the underlying learning process and awareness of the level of knowledge, competence, and expertise of a student. The design principles aim to focus on accessible and actionable information that will potentially support self-regulated learning constructs, such as planning, setting goals, organizing, monitoring, and adapting. These mechanisms will be used to develop actionable intelligence that encourages a student to engage in activities believed to be related to a successful learning path. The recommendations aim to drive cognitive evaluation and promote self-reflection, which will help students optimize their learning strategies, adjust, or select different actions to reach their learning goals. Simply, the recommendations aim to promote a healthy learning behaviour that encourages action and engagement.

The design of the recommendations followed a two-step process and considers the context of this project, the target users, intended use and available tools and information. First, the theoretical aspects were evaluated and assessed to determine how the recommendations will provide actionable information that supports self-regulated learning. The recommendations aim to follow the general principles of feedback construction discussed in section **6.1**. Second, the language used aims to follow the advice from a previous STA 1000 Head Tutor and a UCT Learning Designer, discussed in sections **6.3** and **6.4**.

Careful consideration and a tactful approach need to be adopted when developing recommendations. The advice given to students needs to be appropriate and realistic. Providing impossible or unrealistic objectives could potentially have a negative impact on performance and motivation (**Brusso & Orvis, 2013**). The recommendations will aim to be encouraging and have positive psychological effects on a student when providing positive or negative feedback. Negative feedback does not highlight bad learning behaviour; negative feedback simply highlights how far a student is away from reaching a particular goal and attempts to reduce the deviation from the goal. Overall, negative feedback discusses what is missing or what needs to be done and provides suggestions to achieve to desired objective. On the other hand, positive feedback recognises and commends the current learning behaviour and can lead a student away from the original goal onto future outcomes. Simply, positive feedback attempts to strengthen the current learning behaviour by looking beyond the original objective once it has been achieved.

In general, the recommendations attempt to follow theoretical design principles based on empirical evidence from research that examined and/or tested these techniques in various learning contexts, and practical principles based on advice from relevant professionals, UCT Learning Designer and STA 1000 Head Tutor. The purpose of the recommendations is to support the students' awareness and provide actionable intelligence to mitigate the risk of failing STA 1000 and improve overall academic performance.

7.2 General Concepts

This section provides a general overview of the content included in the recommendations. Additionally, this section explores and provides a strategy for developing suitable and actionable advice from predictive modelling output. In general, if a student is at risk of failing, the recommendations will inform them of the necessary adjustments that are needed to get back on track within reasonable limits. On the other hand, if a student is not at risk of failing, the recommendations will acknowledge the good performance and encourage the student to maintain their current performance and aim for reasonably higher scores.

The content included in the recommendations consists of three aspects. The first aspect includes general commentary on the performance of a student thus far. The second aspect provides actionable insight based on the commentary. The last part provides a reminder of the upcoming *Test* and provides possible areas of focus or weak points.

7.2.1 Guidelines

The following list provides an overview of all the aspects that are considered when recommendations are developed, “at risk” refers to at risk of failing STA 1000:

1. If a student is at risk, the recommendations will acknowledge the inadequate performance in a supporting and comforting manner. Positive and emotive language will be used to provide encouragement, inspiration, and boost morale.
2. If a student is not at risk, the recommendations will acknowledge and commend the student on their current performance. Similarly, positive, and emotive language will be used to provide encouragement and boost morale.
3. If a student is at risk, the recommendations will inform the student of the necessary adjustments needed to get back on track within reasonable limits.
4. If a student is not at risk, the recommendations will encourage the student to aim for reasonably higher scores (first class (75%+), second class division one (70-74%) etc. The student will be encouraged to aim for the next academic tier (for example, from second class division two to second class division 1)
5. The recommendations will recognise whether students are completing tutorial and workshop questions, reading the course notes, and watching the lectures videos. The recommendations will recognise whether the student is consistently engaging with the course material and provide an appropriate commendation. On the other hand, the recommendations will provide awareness if the student is not regularly engaging with the course material.
6. The recommendations will always encourage the student to try and obtain the upcoming *Bonus* mark, regardless of whether they have obtained any previous *Bonus* marks or not. The importance of obtaining *Bonus* marks will be communicated to the student.
7. The recommendations will recognise whether there is an improvement in assessment scores and provide an appropriate commendation. On the other hand, the recommendations will provide awareness if there is a decline in assessment scores.
8. If a student obtains low marks for both *Assignments* and *Tutorials*, the recommendations will encourage the student to place emphasis on both assessments to improve. Conversely, if a student obtains high marks for both *Assignments* and *Tutorials*, the recommendations will encourage the student to maintain or aim for reasonably higher scores.
9. If a student obtains a low for one assessment and high mark for the other, the recommendations will suggest that the student maintain or improve their performance on the assessment with the higher score and place emphasis on the assessment with the lower mark without neglecting the other assessments.
10. The recommendations will recognise whether there is a high discrepancy between assessment marks. The value of the difference between assessment marks, that determines whether a recommendation will be provided, will be assessed by the course convenor based on professional judgment. For example, excessively high *Assignment* marks and excessively low *Tutorial*/*Test* marks needs to be acknowledged.

11. The recommendations will provide reminders of the upcoming class *Test/s* and provide guidelines on possible areas of improvement, weak points, and gaps in their current learning behaviour.

7.2.2 Actual Recommendations

Krahenbuhl (2016) asserts that the contemporary higher education paradigm for teaching and learning should be driven by a student centred constructivist pedagogy. This approach describes the educator as a mentor that encourages and nurtures the student whilst providing positive and constructive feedback. This notion further substantiates that verbal feedback, within a LAD, needs to be positively driven in terms of the tone that is used.

The pervasive use of communication within digital environments has made it increasingly difficult to interpret or gauge the emotional sentiment of virtual interactions. Digital communication lacks the subtle non-verbal aspects that are associated with face-to-face interactions. Subsequently, virtual communication (more specifically, feedback within a LAD) could be misinterpreted and could possibly impact a student's emotional and social affordances, perceptions, and appraisals.

Apart from the explicit graphical visualisations within a LAD, there are other forms of visualisation techniques that can be included into verbal feedback. Current research suggests that the use of emojis, within an educational context, could potentially bridge the gap between digital and traditional communication by lightening the mood and improving what might be perceived as criticism (Kaye, Malone & Wall, 2017). **Alshenqeeti (2016)** states that emojis can expand the linguistic ability of feedback and opens "new possibilities for innovative communication channels and expansion of traditional writing, making language more visual and playful."

Feedback provided to students, within a higher educational context, should consider the use of introducing emojis to reduce social barriers and develop more personal student-teacher relationships. The use of emojis has the potential to make writing, teaching, and commenting more vivid and memorable (**Doiron, 2018**).

Given the context of this project, the target audience, and findings across the literature, the explicit verbal feedback will include emojis. The use of emojis aim to create verbal feedback that is light-hearted, vivid, and memorable. The emojis will potentially aid the recommendations to hold a positive and playful tone and avoid being mistaken for criticism or contain any negative connotation

Table 7.1 and **Table 7.2** illustrates a semi-structured composition of the recommendations that will be provided to students who are predicted to be at risk or not. The recommendations are provided for each guideline and demonstrates an overview of the terminology, language and phrasing used. Overall, the recommendations aim to contain an informal and playful tone. These are the recommendations that will be communicated to the student and what the student would see in the LAD. The goal is to produce actionable intelligence and meaningful feedback —in this case, the recommendations comments on the current learning behaviour which promotes awareness and provides an appropriate course of action. The verbal recommendations and graphical illustrations in the LAD are used together to provide actionable intelligence and meaningful feedback.

Table 7.1: Semi-structured composition of the actual recommendations for students not at risk

*: *LAD will keep a track of the lowest marks for each assessment and suggest those in order of lowest mark*
†: *Similar composition for recommendations if marginal effect technique is used (see Recursive Partition Technique)*

Recommendation Guideline	Proposed Recommendation
2	Well done on the great work so far! 😊 At the moment your learning behaviour mimics those that generally succeed. Keep it up, CHAMP! 🙌 **AND** Quotes (*one of the following*): "Be like a postage stamp, stick to one thing until you get there." "Learning is not a spectator sport." "You don't have to be extreme, just be consistent' "Keep practising like a champion. True champions are not born, they are trained!"
4	You cannot put a limit to anything. The more you strive for, the more you achieve. 💯 If you are looking to improve, go deeper within the material and do not just stick to the textbook. Do a bit a bit of research and take your level of understanding to the next level. Shoot for the stars! 🌟 You miss 100% of the shots you do not take. 👀 Try aim for a (*first class, second class division one etc.*) Practice makes perfect. Speed up the motion of completing assessment questions. Speed is an essential skill for advanced learners that becomes very helpful when taking the Test/Exam.
5	It seems you are on the right track and keeping up to date with the course material. You are awesome! 😊 Keep up the good work! 💪 **OR** Oops! 😟 It seems like you aren't keeping up to date with the course material. Completing these activities will help you succeed. You can do it. Don't be shy! 😋
6	You rock! 😊Completing the quizzes and obtaining the Bonus Marks is a recipe for success. Keep up the pace and knock it out of the park! **OR** Completing the quizzes and obtaining the Bonus Marks is a recipe for success. You can do this! 💪

7	The hard work and the sacrifices paid off. Excellent job on improving your marks! **OR** Uh oh. Your assessment marks slipping; you can do better. Don't worry, the comeback is always stronger than the setback! Keep your head in the game!
8,9,10[†]	*Include only if high discrepancy is observed:* Its best to focus on the broader picture. Rather be a Jack of all trades over a master of one. Focus your energy equally across course. Balance is the key to success. Chat to the tutors or lectures if you are struggling with the pace/pressure of taking Tutorial Tests. They will advise you on study routines and time management skills etc. **AND** Lovin' the consistent performance between Assignments and Tutorials! Let's try to take it up a notch. You got this! Some areas you may want to focus on are: (eg: random variables, probability distributions I) * **OR** You're crushing Assignments/Tutorials! Let's work on bringing the Assignments/Tutorials to the party! The assessments that you struggled with are: (e.g., A3, A4) which covers: (e.g., probability theory, random variables) *
11	Hey you. Yes you. Just your friendly neighbourhood dashboard reminding you on the upcoming class Test (or Exam) . Just remember being prepared is half the victory! Go get em'! Be sure to review the relevant course material and make sure you understand.

Table 7.2: Semi-structured composition of the actual recommendations for students at risk

*: *LAD will keep a track of the lowest marks for each assessment and suggest those in order of lowest mark*
†: *Similar composition for recommendations if marginal effect technique is used (see Recursive Partition Technique)*

Recommendation Guideline	Proposed Recommendation
1	STA 1000 can be challenging, but you can get through it! 💪 Put on your thinking cap, it is time to get your GAME ON! 😈 **AND** Quotes (*one of the following*): "Success is not built on success, its built on failure, its built on frustration. Sometimes it's built on catastrophe" "Be like a postage stamp, stick to one thing until you get there" "Learning is not a spectator sport" "Successful and unsuccessful people do not vary greatly in their abilities. They vary in their desires to reach their potential"
3	The comeback is always better than the setback! 💯 The only thing that matters is that you try your best. 🙌 You need to make sure that you are understand the principles. Seek advice from tutors or lectures. Frequently visit the hotseat and workshops. Do not be afraid to ask questions! Practice makes perfect. Go through the course material again and seek help if you are unsure about anything. There is always help available. 😊 Always remember that education is the one thing that cannot be taken away from you. 🤓
5	It seems you are on the right track and keeping up to date with the course material. You are awesome! 😊 Keep up the good work! 💪 **OR** Oops! 😟 It seems like you aren't keeping up to date with the course material. Completing these activities will help you succeed. You can do it. Don't be shy! 😋
6	Great work on completing the quizzes and obtaining the Bonus Mark. 😊 Lets keep this up so we can knock it out of the park! 💪

	OR Completing the quizzes and obtaining the Bonus Marks is a recipe for success. You can do this! 💪
7	Excellent job on improving your marks! 😎 Your hard work is slowly paying off. 😅 Don't stop. Push harder. Keep going. You can do this champ! 😇 OR Uh oh. 🤐 Your assessment marks are slipping; you can do better. Don't worry, the comeback is always stronger than the setback! 😈 Keep your head in the game!
8,9,10†	*Include only if high discrepancy is observed:* Its best to focus on the broader picture. Rather be a Jack of all trades over a master of one. 👌 Focus your energy equally across the course. Balance is the key to success. 🙏 Chat to the tutors or lectures if you are struggling with the pace/pressure of taking Tutorial Tests. They will advise you on study routines and time management skills etc. 😊 **AND** Let's try to take it up a notch. You got this! Falling is an accident, staying down is a choice. 😉 Some areas you may want to focus on are: (eg: random variables, probability distributions I) *
11	Hey you. Yes you. 😋 Just your friendly neighbourhood dashboard reminding you on the upcoming class test (or exam) 😊. Just remember being prepared is half the victory! Go get em'! 💪 Be sure to review the relevant course material and make sure you understand.

7.3 Strategy for Using Predictive Models

The strategy for developing recommendations using the modelling techniques is straightforward. At each TP, the risk status of a student will be determined by the logistic regression/decision tree model that was developed at that specific TP. The recommendations need to inform the student how they can modify their current learning behaviour to change their risk status and/or improve their performance by the next TP.

For the purposes of this investigation, recommendations can only be provided at TP2, TP4 and TP6 due to the lack of data beyond week 8 (see section 3.2.1). The recommendations are then constructed using the follow reasoning:

- The scores for assessments at the current TP, will be fed into the predictive model at the next TP. The recommendations will depend on the risk status and the model output at the next TP in order provide advice at the current TP.

- For example, at TP2, the scores for the assessments will be fed into the predictive model at TP3. Intuitively, certain assessment marks can be altered to change the risk status that is predicted for TP3 given that the model at TP3 is using the assessment scores for TP2. A simple example only using a single predictor variable will be as follows: If a student obtains 50% for *Assignments* at TP2, the model at TP3 will use this score. If the model at TP3 predicts that the student will fail, the student can still alter their *Assignment* mark over week 3 and 4 to change their risk status. Subsequently, this methodology applies to all the other predictor variables.

The characteristics of the recommendations will be different depending on the predictive modelling technique that is used. For the purposes of this investigation, recommendations developed using both techniques will be discussed and elaborated on. At this stage of the dashboard development process, it is unclear and difficult to determine which technique for developing recommendations should be used. Selecting a suitable modelling technique would depend on a variety of factors such as, but not limited to user preference, pedagogical goals and learning and teaching strategies of students and course instructors.

7.3.1 Marginal Effect Technique

When the marginal effect technique is being used, each assessment needs to be given equal priority when developing recommendations. The recommendations will provide the same guidelines for adjusting each assessment score. This approach aims to avoid the tendency to neglect certain assessments in favour of more attractive assessments that have a larger impact on the odds of passing. The change in the odds of success will be determined, and communicated to the student, using all the predictor variables collectively and not on an induvial basis.

For example, the recommendations will disclose that a student will have an x% increase in the odds of passing by increasing their *Assignment* AND *Tutorial* mark by y% AND obtaining the next *Bonus* mark. These values will be determined by the regression estimates (coefficients) in **Table 6.2**. A good guideline that would be reasonable for all types of students would be to increase their mark by 5%-20%, anything above this guideline is arguably unrealistic and could potentially demotivate the student; however, this guideline can be changed at the discretion of the course convenor. Although the other forms of assessments are not included in the modelling process (watching *Lecture Videos*, reading C*ourse Notes* and completing *Tutorial*/*Workshop* questions), the student will be notified that regular engagement with these materials will help in obtaining the *Bonus Mark*, which is an essential aspect of success.

The recommendation would have the following structure and composition:

> $(1.00)^{365} = 1$
>
> $(1.01)^{365} = 37.7$
>
> All you need is small consistent effort 😊. Increasing your assessment marks by 5-25% and regular engaging with the material and obtaining *Bonus Marks* will increase your chances of success by x-y%.

7.3.2 Recursive Partition Technique

When the recursive partitioning technique is being used, similarly to the marginal effect technique, each assessment needs to be given equal priority when developing recommendations, and each assessment needs to be included in the recommendation.

Each subpopulation that a student is categorized into is determined by a non-numeric partitioning criterion. Therefore, deriving recommendations using this technique does not allow for a quantitative value to be attached to achieving success. Although each subpopulation of students (represented by the root nodes of each decision tree) contains a probability for failing/passing, it is arguable whether the probability for success (in each subpopulation that exhibits success) is reasonably high enough to motivate the student to take action. Therefore, providing quantitative values for the probability of success will be omitted. The decision tree models at each TP are illustrated in **Figure 5.2**, **Appendix Figure A.7**, **Appendix Figure A.8** and **Appendix Figure A.9**.

In general, the course convenor can use the decision tree to provide personalised feedback to each subpopulation of students. Each subpopulation contains unique set of partitioning criteria; therefore, a more in-depth analysis of the decision tree will allow the recommendations to focus on specific aspects (predictor variables). For example, in **Figure 5.2**, the subpopulation in *node 2* needs to focus on *Bonus Marks* and assessments whilst the subpopulation in *node 12* needs to focus on assessments.

In extreme cases where the student scores are significantly lower compared to the class average, the recommendations will encourage the student to improve their mark by a reasonable amount. Similarly, to the marginal effective technique, a good guideline that would be reasonable for all types of students would be to increase their mark by 5%-20%, anything above this guideline is arguably unrealistic and could potentially demotivate the student; however, this guideline can be changed at the discretion of the course convenor. The recommendations will constantly encourage the student to slowly improve their marks over time until they are able to achieve optimal performance.

The recommendations will encourage the student to keep consistent over each TP. In cases whereby the student scores are relatively close to the class average, the student will be encouraged to improve their marks so that they are able to perform on par with their peers, without making an explicit comparison to peers. The recommendations will not force peer comparison; the class average is simply used a benchmark. In cases whereby the student scores are above the class average, the recommendations will inform the student to maintain their current level of performance and try to improve their marks by a reasonable amount. The actual composition and structure of the recommendations will be similar to guidelines 8, 9 and 10 (see **7.2.1**) and is illustrated in **Table 7.1** and **Table 7.2**. Recommendation guidelines 8, 9 and 10 effectively provide comments regarding assessment performance and then give insights into certain areas a student may need to improve in. The areas of focus that will be communicated to the student will depend on the current node that the student is classified into and the partition criteria used for that particular node within the decision tree. In general, all the recommendation guidelines address information that needs to be communicated to the student.

There are two challenges to using this technique in practice. Firstly, a student may be categorised into a subpopulation this exhibits failure whilst still obtaining relatively high scores for each assessment. In most circumstances, a student who is categorised into a sub population that exhibits failure but obtains high scores for the assessments, did not obtain any *Bonus Marks*. There needs to be an emphasis on the fact obtaining *Bonus Marks* and keeping up to date with the course content is a major factor for success. Secondly, if a student is categorised into a subpopulation that exhibits failure, it is possible to be reclassified into another subpopulation that exhibits success, by only altering a single predictor variable. This phenomenon makes it difficult to provide holistic recommendations. In hindsight, using the recursive partitioning technique is arguably more suitable for course instructors and teachers. Educators are able identify areas of improvement for subpopulations of students in order to devise customised interventions.

8 Prototype LAD

8.1 Overview

The prototype LAD essentially provides meaningful feedback to a student based on their current performance and on predictive modelling. The premise behind the dashboard is straightforward: monitor, capture and visualise progress through the academic semester (every two weeks) The goal is to provide actionable intelligence, in this case, providing at risk students with an appropriate course of action to mitigate risk and provide recommendations that acknowledge and reinforce positive constructive learning.

The dashboard functionality is not complex and resembles a prototype that could be built upon and implemented into UCT's LMS, Vula. In order to integrate the dashboard into an LMS, the dashboard would need to be in the form of a web application. This requirement is usually addressed using the IMS LTI[3] standard which enables an LMS to call another web application and pass through authentication and context information (the user accessing it and the context, e.g., course or site, in which it was accessed). Developing a solution to integrate the dashboard into Vula falls outside the scope of this project. Therefore, this project focussed on developing a standalone prototype in a suitable language and environment, rather than solving the LTI integration challenges.

The general approach to building real-time dashboards for Learning Analytics data is to use a Learning Records Warehouse/Store (LRW/LRS) that ingests events in real-time from xAPI or Caliper[4] feeds (competing standards for providing event information from learning environments), and then provides searchable views and/or dashboard visualisations. UCT does not have this infrastructure in place. Event data is exported from Vula and *Opencast* (Lecture Recording) into Business Objects (SAP Data Warehouse product), from where it can run reports that extract the data in various ways.

Given that the dashboard is not able to be integrated with Vula certain data is not automatically obtainable. Once integrated and linked with the relevant database/s within UCT, the dashboard will be able to extract the data that is required, and the user will need to input minimal information. At this stage, the user is required to manually input specific data. Additionally, once integrated into Vula, the dashboard will have access to activity log data (amount of time spent on an assessment, resource downloads, chatroom activity, completion/progress of assessment etc.) which can be used in the modelling process. Log data can also be used to notify the course instructor whether the progress or completion of course material depending on the sophistication of the log data.

Shiny is an R package that makes it easy to build interactive web apps straight from R. This application allows hosting of standalone apps on a webpage by embedding them in R Markdown documents to build dashboards. Given that a prototype dashboard is needed, R and R *Shiny* was used due to the robust capabilities and simplicity and structure of the coding language.

8.2 Design Approach

The design strategy used for the prototype LAD is driven by SRL theory, which is combined with goal orientation theory, as discussed in sections **6.1** and **6.2**. The design principles aim to focus on accessible and actionable information that will potentially support self-regulated learning constructs, such as planning, setting goals, organising, monitoring, and adapting. These mechanisms will be used to develop a process-oriented

3. The IMS Learning Tools Interoperability (LTI) standard prescribes a way to connect learning applications and tools easily and securely with platforms like learning management systems (LMS), portals and learning object repositories on your premise or in the cloud, in a secure and standard manner and without the need for expensive custom programming.

4. xAPI and Caliper are specifications for learning technology that makes it possible to collect data about the wide range of experiences a person has (online and offline).

feedback model in the context of the dashboard. A process-oriented approach refers to the procedure of presenting students with early feedback opportunities before a formal assessment commences.

The design of the dashboard followed a two-step process and considers the context of this project, the target users, intended use and available tools and information. First, the theoretical aspects were evaluated and assessed to determine how the dashboard will provide actionable information that supports self-regulated learning, which has been shown to be critically related to academic performance (Matcha, Gašević & Pardo, 2019). Second, the visualisation aspects aimed to follow the good design principles and practices within the context of a LAD, as summarised in section **2.1.4.**

Consistent visual encodings and graphical schemas are used to reduce cognitive load so that students can use the interpretation from a single construct across all visual aspects within the LAD. The content and visual display of the dashboard aims to support metacognitive progress monitoring by allowing students to keep track of their upcoming assessments and to monitor their progress. Additionally, the dashboard aims to aid students with their planning skills by providing information about their upcoming assessments and their prior performance. This intends to encourage students to be motivated and develop a positive healthy learning behaviour which will potentially ensure academic success.

In general, the LAD attempts to follow the design principles and visualisation techniques based on empirical evidence from research that examined and/or tested these techniques in various learning contexts (Bodily & Verbert, 2017; Charleer et al., 2016; Jivet et al., 2018; Matcha, Gašević & Pardo, 2019; Sedrakyan et al., 2020; Yoo et al., 2015)The design layout intends to mimic the recommendations from **Few (2013)**, as discussed in Chapter **2**. The pertinent information stands out from the rest of the dashboard as various tasks are dominantly displayed on the main page. The layout attempts to follow a logical and sequential style to maintain user friendliness and facilitates easy readability and navigation. The purpose of the information is to support the students' awareness and help rapid perception; the visuals depict information pertaining to progress, completion and results thereby facilitating goal and progress monitoring and awareness. Overall, the content and visualisation principles attempt to follow all the above mentioned insights and theoretical aspects discussed in sections **2.1.4**, **6.1** and **6.2**.

8.3 Description of The Dashboard Interface

8.3.1 Navigation Panel

Figure 8.1 illustrates the navigation panel of the dashboard. Intuitively, the panel allows the user to navigate between different aspects of the dashboard. The *Overall View* displays the relevant visuals for each week in the semester, which is determined by the *Week Selector* slider. The *Weekly View* displays graphics for a specific week, which is determined by the *Week Selector* slider. The *Weekly View* is included to allow certain users who have a preference of viewing their progress on a week by week basis, compared to an overall cumulative overview. This design principle aims to address both performance and mastery goal orientation, the *Overall View* appeals to performance oriented users while the *Weekly View* appeals to mastery oriented users.

In general, both views are provided to accommodate both types of users, and users who exhibit an interest in a combination of both goal orientations. In essence, the *Overall View* provides a sequential display of a student's progress and aims to portray a trajectory of learning sequences towards a predefined learning goal; the *Weekly View* simply acts as a tool for monitoring progress while quantifying and visualising performance.

The *Week Selector* is used to support the backend modelling process and allows the *Overall View* to depict information up until that particular week. *Diagnostics* provide relevant recommendations regarding performance that is measured from the information that the user enters. The *Enter Completed Tasks* and subsequent *Weeks* allows the user to enter information pertaining to specific assessments for that week.

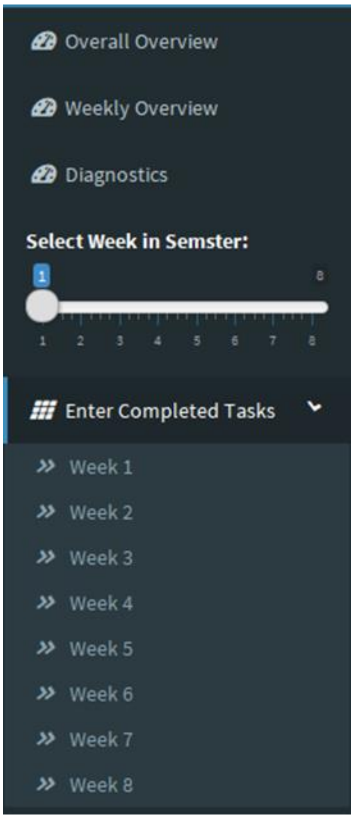


Figure 8.1: LAD navigation panel

8.3.2 Inputting Information Into the LAD

Figure 8.2 illustrates the information that a student must input into the dashboard in order to display certain graphics and allow predictions and diagnostics to be performed.

This view can be accessed by selecting a specific *week* in the *Enter Completed Tasks* tab in the navigation panel (Figure 8.1). Given the integration limitations discussed in 8.1 above, this information must be manually entered into the dashboard. Once integrated into *Vula*, the LMS will provide the dashboard with the necessary information automatically. The information required in this aspect of the dashboard relates to the assessments and tasks outlined in STA 1000. The *Quizzes* and *Lecture Videos* are individual tasks therefore the user is presented with checkboxes. In contrast, *Course Notes* and *Questions* (*Workshop* and *Tutorial*) are tasks that are either completed or not, therefore, the user is presented with radio buttons, with the option of selecting "Yes" or "No." Numerical value inputs such as *Tutorials*, *Assignments* and *Test* marks are made convenient by providing a slider input.

8.3.3 Overall Dashboard View

Figure 8.3 displays the view of the dashboard when the "*Overall View*" tab is selected. *Section A* represents the status box visuals for *Tutorial*, *Course Notes* and *Workshop Question* assessments. *Section B* represents the gauge charts for *Quizzes* and *Lecture Video* assessments. *Section C* represents status boxes that act an achievement badge for obtaining certain *Bonus Marks*. In this example, the course is in the 6th week (TP6) and the student has obtained *Bonus Mark* 1 and 3. The graphics at the bottom of the dashboard illustrate the marks for *Assignments*, *Tutorials* and the *Test*. The *Weekly Overview* only displays visualisations that pertain to that specific week and does not go into detail as the main "*Overall View*". A *Weekly Overview* is provided in **Appendix Figure A.10.**

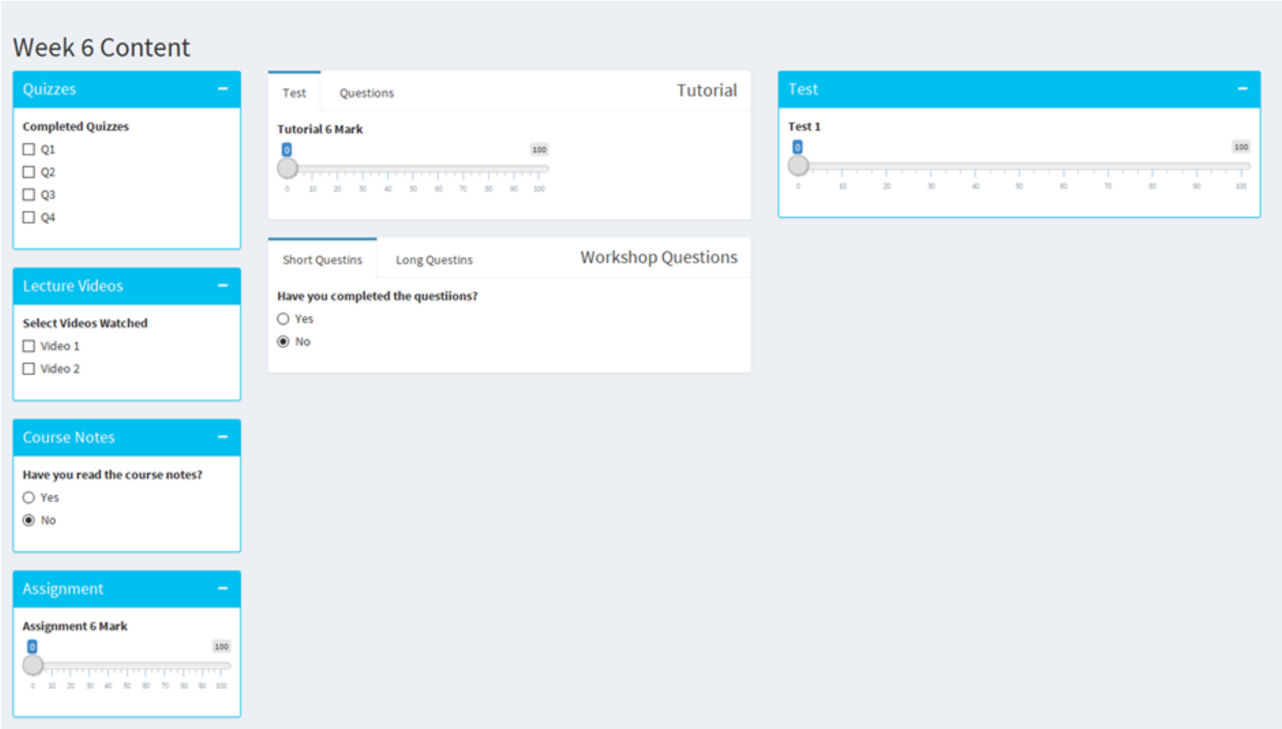


Figure 8.2: Content for Week 6 that needs to be inputted into the LAD

Visualisation techniques are limited regarding components that contain a binary outcome. In the case of *Course Notes*, *Workshop* and *Tutorial* questions, the outcome is either complete or incomplete. Status box visuals were chosen to represent the completion of these tasks due to simplicity and vivid characteristics of the visual encodings, as illustrated in *Section C* in **Figure 8.3**. Different colour schemes were added (green for complete and red for incomplete) which aims to appeal to a sense of fulfilment if completed and initiate action and provide motivation if not completed.

The rationale for selecting for the gauge chart is the same for that of the status boxes. The gauge charts, in *Section B* in **Figure 7.3**, represent the status of completion for *Quizzes* and *Lecture Videos*. The completion of *Quizzes* and *Lecture Videos* is numerically quantifiable, allowing for numerical feedback to be reported. The colour scheme and content of the progression chart dynamically changes as the user completes each task. Depending on the value in the *Week Selector*, the *Overall View* will output information for each week up until the week selected in a cumulative manner, whilst the *Weekly View* will display the progress for that particular week.

Components such as experience points (XP), badges and virtual currency have the potential to provide effective feedback and appeal to a sense of accomplishment as well as goal orientation (Dicheva, Irwin & Dichev, 2019; Hakulinen, Auvinen & Korhonen, 2015). *Section C* in **Figure 8.3** represents the achievement badges that are awarded and displayed as students complete *Quizzes* and obtain *Bonus Marks*. This concept aims to appeal to a sense of fulfilment and attempts to capture any individual goal orientation a student may contain.

Tutorial, *Assignment* and *Test Marks* are the core numeric predictors that are used in the modelling process to provide appropriate recommendations. Therefore, it is important for the student to visualise the data to quantify achievement and monitor progress.

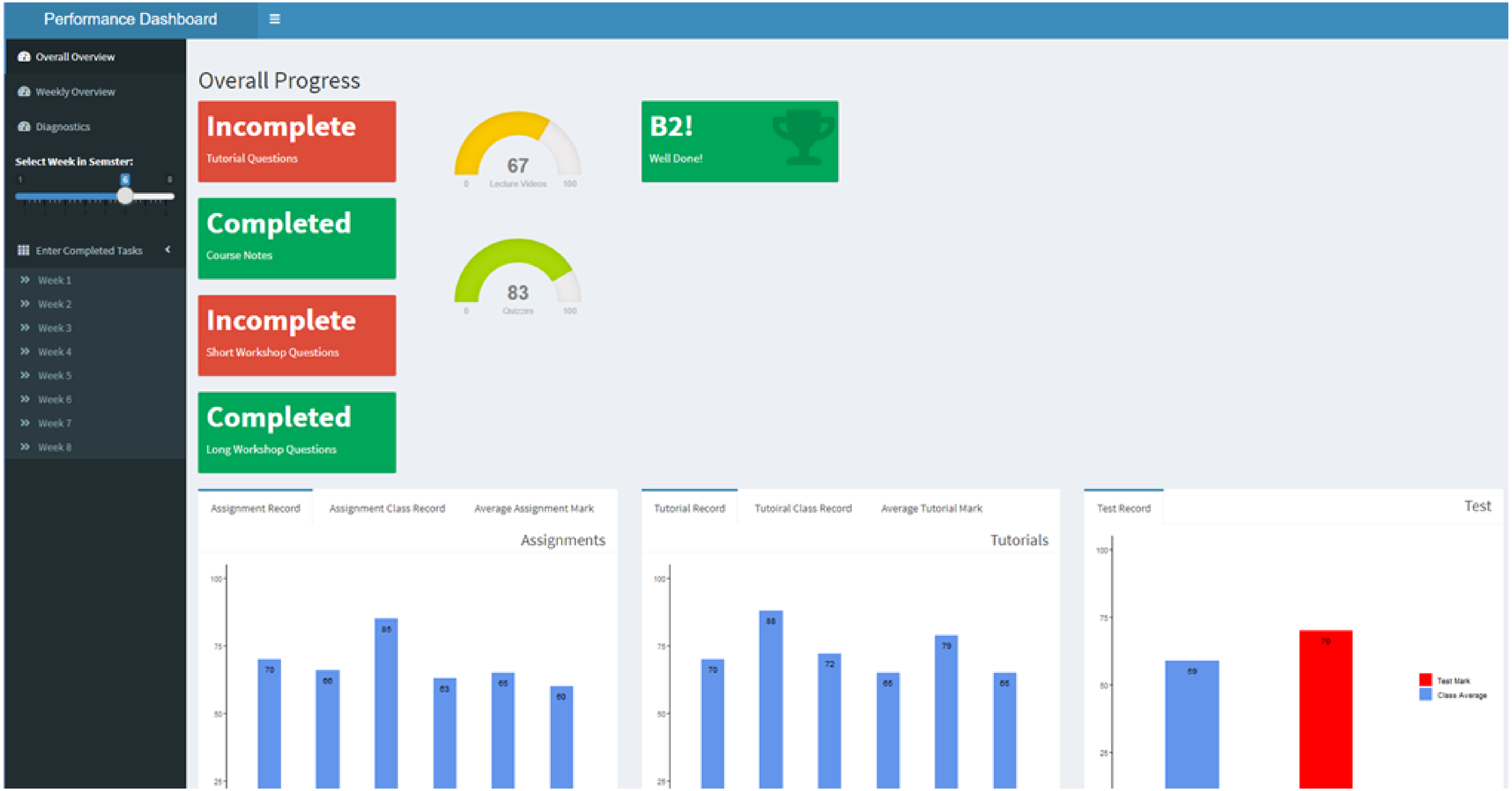


Figure 8.3: View of the dashboard, when the 'Overall View" tab is selected.
Note: the dashboard is cut off at the bottom in this screenshot; scrolling is required to see the graphs

Figure 8.4 illustrates the graphics for each assessment that is displayed at the bottom of the *Overall View* illustrated in **Figure 8.3.** Each assessment is displayed in a tab box with different graphs in each tab. *Assignments* and *Tutorials* contain three tabs: the first tab (*Assignment Record*/*Tutorial Record*) contains a bar graph displaying all the marks at each TP up until the current TP; the second tab (*Assignment Class Record/Tutorial Class Record*) contains two line graphs that displays the all the marks at each TP up until the current TP, in comparison to the class average at a specific time point; the third tab (*Average Assignment Mark*/*Average Tutorial Mark*) displays a bar graph that shows the average mark for that particular assessment. The *Test* visualisations has a single tab (*Test Record*) that contains two bar graphs that displays the *Test* mark in comparison to the class average.

Visualising, monitoring and quantifying marks for specific assessments plays an important role in the dashboard. **Lonn, Aguilar and Teasley (2015)** propose that analyses pertaining to peer performance can be used as an appropriate approach to exploit the concept of social influence. Visualisations can illustrate the relative performance between the user and peers at given TP for similar goal-specific tasks or objectives. These techniques have been observed to play an important role in student's motivation. The graphics illustrated in **Figure 8.4** provide the student with the option to view their marks relative to the class average mark. King (2021) has stated that the information box illustrating graphics for each assessment (**Figure 8.4**) is a clever technique for introducing peer comparison as it does not explicitly force a student to compare themselves to their peers.

The graphical visualisations portray the marks for each assessment in a sequential representation to show a trajectory of learning sequences towards a predefined learning goal. This technique appeals to the goal/performance orientation of the student. The student is visually presented with their marks for each week for each task, therefore, they will be able to compare performance amongst different weeks which will allow the student to identify weak points and pinpoint areas relating to course content that require focus. This aims to be a form of effective feedback by supporting a student in avoiding failure or perform equal to peers, obtain skills and competence, and set preference for specific topics. The content in the dashboard aims to allow a student to align their learning goals with their actions. This could potentially drive cognitive evaluation and promote self-reflection, which will help students optimize their learning strategies, adjust, or select different actions to reach their learning goals. Simply, the content in the dashboard is a form of cognitive and behaviour feedback that facilitates self-assessment and provides opportunities to close the identified gap between current and desired performance.

Figure 8.4: Various graphics displayed in the "Overall View" of the LAD

Top screenshot shows the bar graphs illustrated for each assessment at each week. Middle screenshot shows the student marks vs the class average for each assessment.
Bottom screenshot shows the cumulative average for each assessment.
The graph for test marks is only shown after week 6

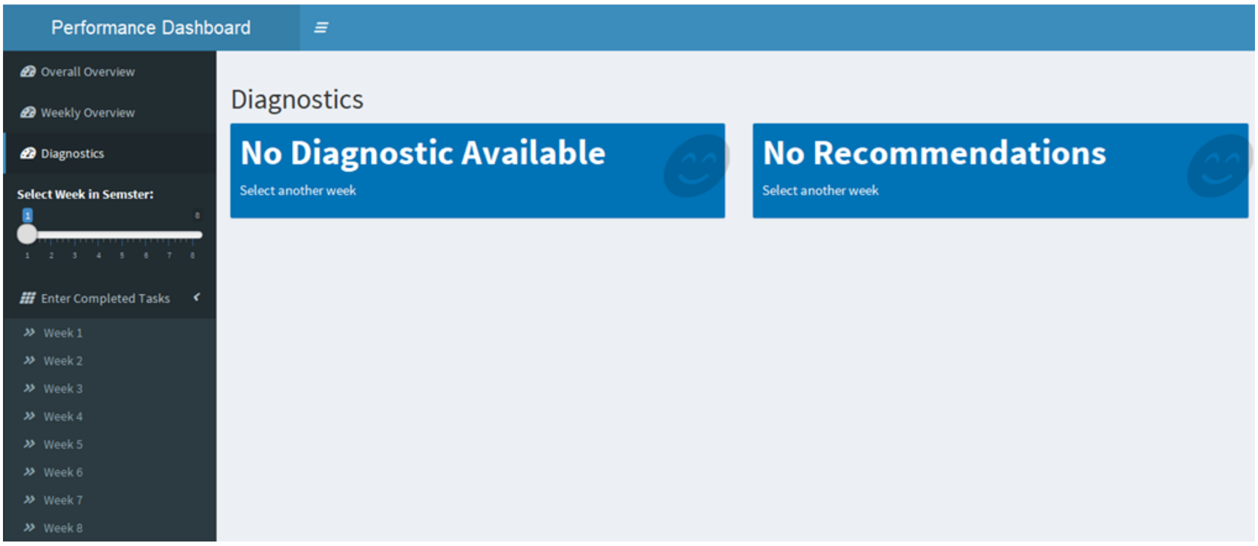
8.4 Recommendations and Appropriate Courses of Action

8.4.1 Dashboard Diagnostic Tab

Figure 8.5 displays the view of the dashboard when the *Diagnostics* tab is selected. Different visual aspects will appear in this view depending on the week that is selected using the *Week Selector*. The status boxes illustrate whether diagnostics and recommendations are available. Predictive models are only developed every two weeks therefore certain weeks will not contain any diagnostic results. The diagnostics status box (on the left hand side) will indicate whether a student is at risk of failing the course or not at specific TPs in the semester, whereas the recommendation status box (on the right side) will provide appropriate recommendations.

Course Signals (Arnold & Pistilli, 2012) is LAD that uses a traffic signal indicator to communicate risk statuses. A red light indicates a high likelihood of being unsuccessful; yellow indicates a potential problem of succeeding; and a green signal demonstrates a high likelihood of succeeding in the course. Empirical evidence suggests that there is a positive impact on academic performance; instructors and students have benefitted from using Course Signals. Instructors and teaching assistants have noted that students have become more proactive and regularly engage with the course material because of using Course Signals (Arnold & Pistilli, 2012). Given the positive effect that Course Signals has on student behaviour, the prototype LAD developed in this project will employ a similar traffic signal indicator to communicate risk statuses.

Figure 8.5 illustrates the indicator signals that are used in the LAD. Two colour schemes were added to the status boxes pertaining to the risk status: green for a student not at risk (green signal demonstrates a high likelihood of succeeding in the course) (top right) and yellow/amber for students who are at risk (yellow indicates a potential problem of succeeding) (bottom left). A blue indicator will be shown when no diagnostic information is available (top left). Each visualisation in is merely an illustration of the different states of the status that can occur.



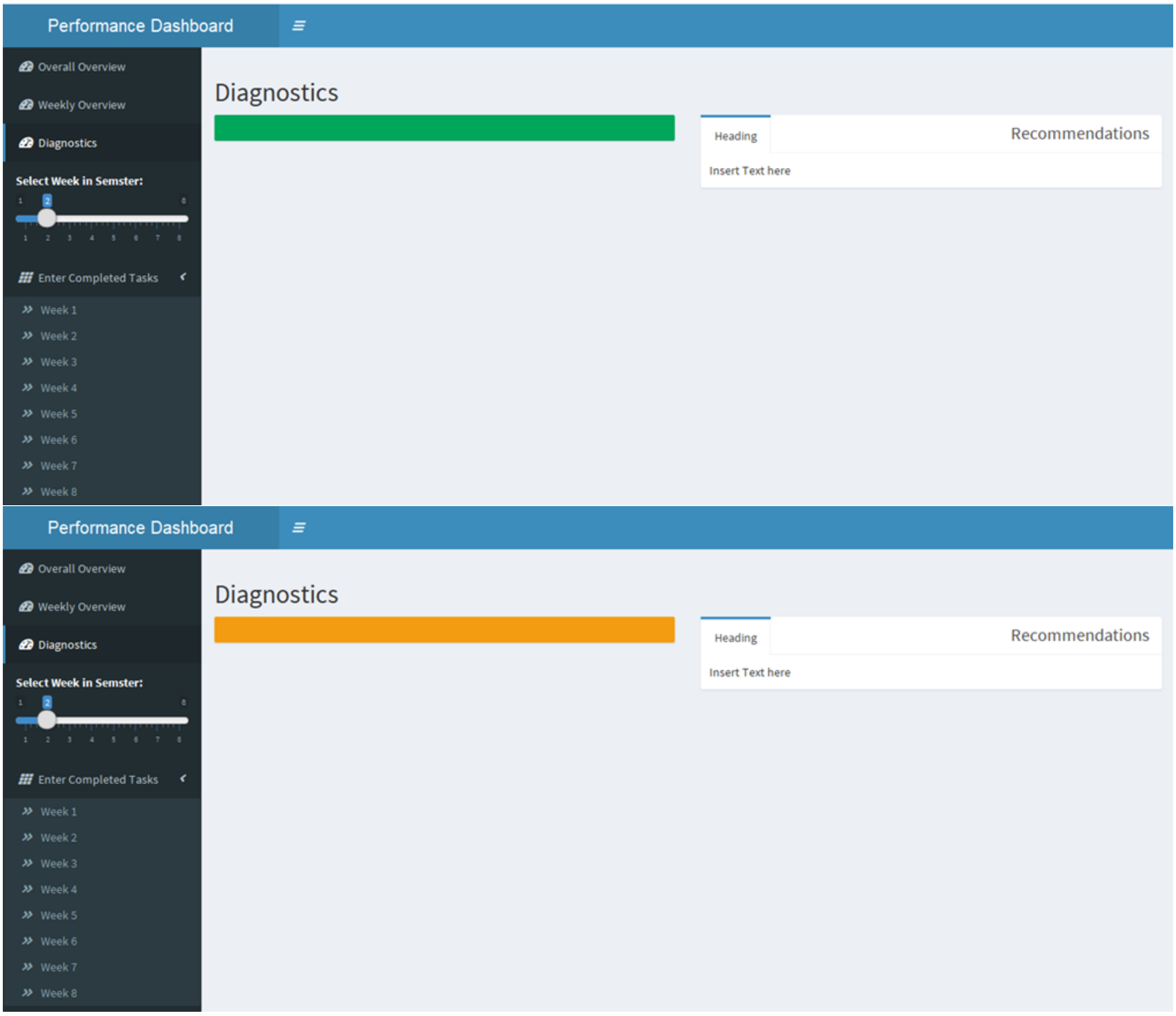


Figure 8.5: Visualisations for the diagnostic tabs for different circumstances.
The visuals above are simplified and do not include the recommendations the student would see Top screen shot is displayed when no recommendations are available. Middle screenshot is displayed when the student is not at risk. Bottom screenshot is displayed when the student is at risk

8.4.2 Example

The following section will provide a brief overview of how the *Diagnostic* tab will work and communicate recommendations to the student. Table 8.1 below illustrates the marks for a dummy student taking STA1000. For the purposes of this example, the marginal effect technique will be used to provide feedback to the student. The example aims to provide the reader with a more structured format of the recommendations discussed in table x and y and give a more holistic view of how the recommendations are constructed for a particular student.

At TP1 and TP2, the logistic regression model (see section 4.3.1) predicts that the student is at risk of failing the course. The student would see bottom screenshot in Figure 8.5. The recommendations at TP1 and TP2 are displayed in Table 8.2 and Table 8.3

At TP3, logistic regression model (see section 4.3.1) predicts that the student is not at risk of failing the course. The student would see middle screenshot in Figure 8.5. The recommendations at TP3 are displayed in Table 8.4.

Table 8.1: Marks for fictional student

	TP1	TP2	TP3
Test 1			65
B1	0		
B2		0	
B3			1
A1	80		
A2	70		
A3		100	
A4		90	
A5			83
A6			87
T2	50		
T3		30	
T4		30	
T5			70
T6			70
Completed Tutorial Questions	No	No	Yes
Completed Course Notes	No	Yes	Yes
Completed Short Workshop Questions	No	No	Yes
Completed Long Workshop Questions	No	No	Yes

Table 8.2: Recommendations for examples student at TP1

STA 1000 can be challenging, but you can get through it! 💪 Put on your thinking cap, it is time to get your GAME ON! 😈 “Success is not built on success, its built on failure, its built on frustration. Sometimes it’s built on catastrophe”
The comeback is always better than the setback! 💯 The only thing that matters is that you try your best. 🙌 You need to make sure that you are understand the principles. Seek advice from tutors or lectures. Frequently visit the hotseat and workshops. Do not be afraid to ask questions! Practice makes perfect. Go through the course material again and seek help if you are unsure about anything. There is always help available. 😊 Always remember that education is the one thing that cannot be taken away from you. 😳
Oops! 😕 It seems like you aren’t keeping up to date with the course material. Completing these activities will help you succeed. You can do it. Don’t be shy! 😋
Completing the quizzes and obtaining the Bonus Marks is a recipe for success. You can do this! 💪
Uh oh. 😬 Your assessment marks are slipping; you can do better. Don’t worry, the comeback is always stronger than the setback! 😈 Keep your head in the game!
Let’s try to take it up a notch. You got this! Falling is an accident, staying down is a choice. 😉 Some areas you may want to focus on are: Set Theory (Chp2); Exploring Data (Chp1)
Hey you. Yes you. 😋 Just your friendly neighbourhood dashboard reminding you on the upcoming class test (or exam) 😊. Just remember being prepared is half the victory! Go get em’! 💪 Be sure to review the relevant course material and make sure you understand.

Table 8.3: Recommendations for example student at TP2

STA 1000 can be challenging, but you can get through it! 💪 Put on your thinking cap, it is time to get your GAME ON! 😈 “Learning is not a spectator sport”
The comeback is always better than the setback! 💯 The only thing that matters is that you try your best. 🙌 You need to make sure that you are understand the principles. Seek advice from tutors or lectures. Frequently visit the hotseat and workshops. Do not be afraid to ask questions! Practice makes perfect. Go through the course material again and seek help if you are unsure about anything. There is always help available. 😊 Always remember that education is the one thing that cannot be taken away from you. 🤓
Oops! 😟 It seems like you aren’t keeping up to date with the course material. Completing these activities will help you succeed. You can do it. Don’t be shy! 😋
Completing the quizzes and obtaining the Bonus Marks is a recipe for success. You can do this! 💪
Excellent job on improving your marks! 😎 Your hard work is slowly paying off. 😅 Don’t stop. Push harder. Keep going. You can do this champ! 😇
Its best to focus on the broader picture. Rather be a Jack of all trades over a master of one. 👌 Focus your energy equally across the course. Balance is the key to success. 🙏 Chat to the tutors or lectures if you are struggling with the pace/pressure of taking Tutorial Tests. They will advise you on study routines and time management skills etc. 😊 Let’s try to take it up a notch. You got this! Falling is an accident, staying down is a choice. 😉 Some areas you may want to focus on are: Set Theory (Chp2), Exploring Data (Chp1), Random Variables (Chp4)
Hey you. Yes you. 😋 Just your friendly neighbourhood dashboard reminding you on the upcoming class test (or exam) 😊. Just remember being prepared is half the victory! Go get em’! 💪 Be sure to review the relevant course material and make sure you understand.

Table 8.4: Recommendations for example student at TP3

Well done on the great work so far! 😊 At the moment your learning behaviour mimics those that generally succeed. Keep it up, CHAMP! 🙌 “Be like a postage stamp, stick to one thing until you get there.”
You cannot put a limit to anything. The more you strive for, the more you achieve. 💯 If you are looking to improve, go deeper within the material and do not just stick to the textbook. Do a bit a bit of research and take your level of understanding to the next level. Shoot for the stars! 💫 You miss 100% of the shots you do not take. 👀 Try aim for a second-class division one or higher! Practice makes perfect. Speed up the motion of completing assessment questions. Speed is a an essential skill for advanced learners that becomes very helpful when taking the Test/Exam.
It seems you are on the right track and keeping up to date with the course material. You are awesome! 😊 Keep up the good work! 💪
You rock! 😊Completing the quizzes and obtaining the Bonus Marks is a recipe for success. Keep up the pace and knock it out of the park!
Excellent job on improving your Tutorial marks! 😎 Your hard work is slowly paying off. 😅 Don’t stop. Push harder. Keep going. You can do this champ! 😇 Uh oh. 🤦 Your Assignment marks slipping; you can do better. Don’t worry, the comeback is always stronger than the setback! 😈 Keep your head in the game!
You’re crushing Assignments! 😎 Let’s work on bringing the Tutorials to the party! 🥳 The assessments that you struggled with are: T2-T4 which covers: Set Theory (Chp2), Probability Theory (Chp3), Random Variables (Chp4)
Hey you. Yes you. 😋 Just your friendly neighbourhood dashboard reminding you on the upcoming class test (or exam) 😊. Just remember being prepared is half the victory! Go get em’! 💪 Be sure to review the relevant course material and make sure you understand.

9 Final Remarks

9.1 Overview

Analysing student behaviour within an online, self-regulated context that supports multimodality, mobility, and motivation has the potential to provide a holistic view of learning characteristics. This project was able to develop a conceptual framework and prototype LAD within a uniquely customised educational context, given certain limitations. A review of the different techniques for designing and developing LADs across the literature contributed to the design of this work; however, a challenge was to address the gap in the literature and develop and integrate meaningful and actionable feedback into the LAD. Within this learning context, this project determined simple factors as predictors of performance and explored the predictive value and capabilities thereof, by capturing data changes on academic performance data. The goal was to identify the most significant factors to develop a system that supports learning behaviour and provides actionable intelligence. The LAD aimed to provide the student with the ability to easily monitor, track and visualise their performance and progress, which may allow them to adjust their learning strategy. Additionally, the LAD aimed to promote motivation and encourage self-reflection, thereby strengthening academic performance. On a conceptual level, this investigation has the potential to be meaningful in terms of suggesting implications for the development of more refined and effective dashboard treatments, as well as, integrating the dashboard into UCT's LMS, and providing specific directions for future research.

Research across the literature frequently discusses the importance of theory-informed designs for online, user centred and self-regulated LADs. Although the design principles should be derived from theoretical frameworks, different techniques are required to satisfy the unique learning contexts and the needs of different target audiences. In other words, as suggested by **Matcha, Gašević and Pardo (2019)**, designing LADs should be informed by theories that consider motivation dimensions and improved performance that play a significant role in adopting new learning tactics, strategies, and tools. Furthermore, **Gašević et al. (2016)** argue that LADs that design principles, conceptual frameworks and visualisation are circumstantial and differ to each unique context; there is no "one-size-fits-all" approach. Overall, insights from the interviews with Thomas King and Michaela Takawira and theoretical design principles were used to develop a suitable LAD framework for STA 1000.

The first and second research question discussed whether the current engagement variables are adequate for predictive modelling purposes and whether deriving meaningful interpretations that will be translated into actionable intelligence is reasonable. The investigation and discussion in Chapter **5** suggests that the predictive techniques explored in this project demonstrated reasonable predictive capabilities. Furthermore, developing recommendations from interpreting the model results appears to be plausible; there is a potential to derive suitable recommendations to students.

The third research question addressed whether the educational background of the student needs to be considered when providing recommendations to students. The size and imbalance of the entire data set had an impact on the predictive capabilities of the modelling techniques. Overall, the investigation concluded that dividing the entire cohort of students and providing separate recommendations to different subsets of students based on their educational background is infeasible and could potentially be unreliable.

9.2 Limitations

One of the main limitations of this project is that it was incapable of integrating the dashboard into the LMS infrastructure. Therefore, data is not sourced and processed automatically, which means that the student needs to manually enter information to use the dashboard. Another notable limitation of this project is that it was unable to demonstrate the dashboard to a particular target audience. Consequentially, the project was unable to incorporate any forms of feedback received into the design and development process. Furthermore, this project was unable to explore the relationship between activity log data (time spent on assessments, resource downloads, completion/progress of assessments, login trends, general activity within the LMS etc.) within the dashboard and other activities occurring within the LMS. Several studies suggest that adding LMS log data into the LAD will allow for additional SRL behavioural indicators to be developed (**Matcha, Gašević & Pardo, 2019**; **Schwendimann et al., 2016**; **Sedrakyan et al., 2020)**. These new indicators can be used in predictive models to improve predictive capabilities, thus enhancing the reliability and accuracy of the recommendations that are developed. Another consequence of the integration challenges is that the framework and supporting mechanisms of the dashboard ignores a key aspect of learning, namely social learning or learning network analysis. Social and peer interaction has the potential to stimulate and accelerate learning. Studies are beginning to propose that social/learning network analysis can be used to provide insight into student learning and used to improve learning behaviour, motivation, and overall academic performance (**Matcha, Gašević & Pardo, 2019**). Although the concept of exploiting social influence to promote positive motivation is used in the dashboard, there is a potential for a greater impact.

The size and imbalance of the entire data set, and subpopulations affects the generalizability of this project. Generally, larger sample sizes increase the validity and reliability of the results obtained from predictive modelling techniques, as larger sample sizes increase the model's ability to generalize. Expanding the sample size has the potential to reduce the imbalances within the outcome variable. Furthermore, introducing/obtaining extra predictor variables, that the student has control over, has the potential to strengthen modelling predictive power. Nevertheless, the findings in this project are arguably reasonable enough to lay a foundation for future initiatives that seek to use predictive analytics and develop recommendations to improve learning behaviour and promote success.

9.3 Suggestions for Future Work

The main recommendation for future work related to this project would be to address, facilitate and implement the integration of the dashboard into UCT's LMS, Vula, which has the potential to address the two main limitations of the project. Furthermore, this would greatly expand the opportunity to strengthen the effectiveness of the dashboard. Further investigation in this regard, should develop empirically sound answers to how the dashboard can fulfil the ability of supporting and improving learning and pedagogical goals. Furthermore, integrating the dashboard into Vula**,** allows for several new aspects to be examined: understanding the behavioural and habitual characteristics that students bring into a tertiary education context and how these aspects affect academic performance, goals, and determination; building on the current recommendations and developing new ones to ensure a productive and healthy learning behaviour is adopted by students, and how these students react to the suggested courses of action. Learning practices and assessing academic performance is not limited to a self-regulated online learning environment. Courses such as STA 1000 have frequented online assessments that measure academic performance; however, other courses rely on traditional face-to-face interactions to measure academic performance. A possible direction for future research, in terms of LAD feedback, would be to explore approaches to integrate non-traditional learning practices and assessment into the LAD.

Generally, there is a difficulty in understanding the results from predictive analytics; and there is a difficulty in deriving meaningful interpretations from predictive model outputs, especially for complex and sophisticated modelling techniques. It becomes problematic to derive meaningful feedback that facilitates decision making and encourages action, whenever the underlying mechanism of a prediction is black box or obscure. This investigation used two simple, yet effective modelling techniques. However, if the integration of the dashboard into Vula is implemented and more data is collected, new predictor variables will become available. Therefore, more sophisticated modelling techniques or ensemble methods can be explored to improve the predictive capabilities and the validity of the derived recommendations.

The framework and design principles for the dashboard are merely conceptual; the objective of this investigation was to develop a prototype dashboard. This investigation represents the first phase or initial/conceptual stage for developing a fully functioning LAD for STA 1000. One of the key goals in future stages of the development process is to incorporate an evaluation aspect for the dashboard itself. The evaluation, based on empirical research, needs to primarily focus on whether the goals are fulfilled, the impact on learning behaviour and motivation, and the usability. The usability should include whether the dashboard is able to promote confidence and academic success and not just usability and usefulness. The evaluation should include some form of feedback mechanism (e.g., an assessment or survey) for the LAD design framework. Furthermore, visualisations and the recommendations need to be assessed to examine the influence on the student and how a student responds to it, thereby demonstrating the student's perception/acceptance of the tool. The evaluations will allow for the dashboard design principles and framework to be altered in favour of the educational context, intended use and target users. Consequently, this will improve overall effectiveness and empower students by promoting a healthy learning behaviour and helping them achieve their academic goals.

9.4 Conclusion

The field of Learning Analytics has become predominant in contemporary educational research. Learning Analytics can capture and process pertinent data, which has the potential to enhance learning mechanisms and pedagogical goals. Advancements in technology has led to an increased interest in previously non-feasible feedback in the form of LADs. Essentially, these tools are intended to improve decision making and positively influence learning behaviour by directing or strengthening human cognition and perceptual capabilities. Additionally, LADs aim to boost academic performance for the learner and support institutions in achieving acceptable levels of student performance whilst improving teaching practices and effectiveness.

This project presents the design and development process for a conceptual prototype LAD that primarily supports student activities. The work aims to contribute to the learning sciences with respect to the lack of methodologies for designing and building LADs that contain meaningful and actionable feedback. Additionally, this project discusses the potential of the LAD to act as a supporting tool that facilitates constructive learning and promotes active participation in STA 1000. Despite the contextual and circumstantial limitations, the concept of the prototype dashboard has the potential to support student learning activities. The dashboard contains visuals that allow progress tracking and monitoring, and diagnostic tools that provide recommendations based on current performance.

The recommendations aim to support the students' awareness and provide actionable intelligence to mitigate the risk of failing STA 1000 and improve overall academic performance. The recommendation content is derived from the progress towards course assessments and interpreting the results of predictive models. This project explored two predictive modelling techniques to process features within the learning environment. The results can provide a distinct characterisation of the entire cohort of students, based on the features extracted from the learning environment, therefore, facilitating its interpretation into action.

Overall, the design model enables meaningful visual and textual explanations in the form of cognitive and behavioural feedback that is easily interpretable by the student. The design and development process of the dashboard, as well as the modelling techniques and subsequent interpretations, act as a basis to support learning methodology, pedagogical practices, and provide frequent and effective formative and personalised feedback.

References

Abu-Mostafa, Y.S., Magdon-Ismail, M. & Lin, H.-T. 2012. *Learning from data.* AMLBook New York, NY, USA:.

Ahlin, Å. 2003. *Does school competition matter? Effects of a large-scale school choice reform on student performance*.

Allen, I.E. & Seaman, J. 2014. Grade Change: Tracking Online Education in the United States. *Babson Survey Research Group.*

Alshenqeeti, H. 2016. Are emojis creating a new or old visual language for new generations? A socio-semiotic study. *Advances in Language and Literary Studies.* 7(6).

Arnold, K.E. & Pistilli, M.D. Eds. 2012. Course signals at Purdue: Using learning analytics to increase student success. 267-270.

Artino Jr, A.R. 2010. Online or face-to-face learning? Exploring the personal factors that predict students' choice of instructional format. *The Internet and Higher Education.* 13(4):272-276.

Avella, J.T., Kebritchi, M., Nunn, S.G. & Kanai, T. 2016. Learning analytics methods, benefits, and challenges in higher education: A systematic literature review. *Online Learning.* 20(2):13-29.

Bakharia, A. & Dawson, S. Eds. 2011. SNAPP: a bird's-eye view of temporal participant interaction. 168-173.

Bodily, R. & Verbert, K. 2017. Review of research on student-facing learning analytics dashboards and educational recommender systems. *IEEE Transactions on Learning Technologies.* 10(4):405-418.

Bokana, K. & Tewari, D. 2014. Determinants of student success at a South African university: An econometric analysis. *The Anthropologist.* 17(1):259-277.

Broadbent, J. & Poon, W.L. 2015. Self-regulated learning strategies & academic achievement in online higher education learning environments: A systematic review. *The Internet and Higher Education.* 27:1-13.

Brusso, R.C. & Orvis, K.A. 2013. The impeding role of initial unrealistic goal-setting on videogame-based training performance: Identifying underpinning processes and a solution. *Computers in Human Behavior.* 29(4):1686-1694.

Campbell, J.P., DeBlois, P.B. & Oblinger, D.G. 2007. Academic analytics: A new tool for a new era. *EDUCAUSE review.* 42(4):40.

Charleer, S., Klerkx, J., Duval, E., De Laet, T. & Verbert, K. Eds. 2016. Creating effective learning analytics dashboards: Lessons learnt. Springer. 42-56.

Clow, D. 2013. An overview of learning analytics. *Teaching in Higher Education.* 18(6):683-695.

Conijn, R., Snijders, C., Kleingeld, A. & Matzat, U. 2016. Predicting student performance from LMS data: A comparison of 17 blended courses using Moodle LMS. *IEEE Transactions on Learning Technologies.* 10(1):17-29.

Davies, J. & Graff, M. 2005. Performance in e-learning: online participation and student grades. *British Journal of Educational Technology.* 36(4):657-663.

de Barba, P.G., Kennedy, G.E. & Ainley, M. 2016. The role of students' motivation and participation in predicting performance in a MOOC. *Journal of Computer Assisted Learning.* 32(3):218-231.

de Freitas, S., Gibson, D., Alvarez, V., Irving, L., Star, K., Charleer, S. & Verbert, K. Eds. 2017. How to use gamified dashboards and learning analytics for providing immediate student feedback and performance tracking in higher education. 429-434.

Dicheva, D., Irwin, K. & Dichev, C. Eds. 2019. OneUp: Engaging students in a gamified data structures course. 386-392.

Doiron, J. 2018. Emojis: Visual communication in higher education. *PUPIL: International Journal of Teaching, Education and Learning.* 2(2):1-11.

Dollár, A. & Steif, P.S. 2012. Web-based statics course with learning dashboard for instructors. *Proceedings of computers and advanced technology in education (CATE 2012).*

Duval, E. Ed. 2011. Attention please! Learning analytics for visualization and recommendation. 9-17.

Duval, E., Klerkx, J., Verbert, K., Nagel, T., Govaerts, S., Parra Chico, G.A., Santos Odriozola, J.L. & Vandeputte, B. 2012. Learning dashboards & learnscapes. *Educational interfaces, software, and technology.*1-5.

Dyckhoff, A.L., Zielke, D., Bültmann, M., Chatti, M.A. & Schroeder, U. 2012. Design and implementation of a learning analytics toolkit for teachers. *Educational Technology & Society.* 15(3):58-76.

Ferguson, R. 2012. Learning analytics: drivers, developments and challenges. *International Journal of Technology Enhanced Learning.* 4(5-6):304-317.

Ferguson, R., Sharkey, M. & Mirriahi, N. 2016. Practitioner Track Proceedings of the 6th International Learning Analytics & Knowledge Conference (LAK16).

Few, S. 2013. *Information Dashboard Design: Displaying data for at-a-glance monitoring.* Analytics Press Burlingame, CA.

Foster, E. & Siddle, R. 2020. The effectiveness of learning analytics for identifying at-risk students in higher education. *Assessment & Evaluation in Higher Education.* 45(6):842-854.

Gašević, D., Dawson, S., Rogers, T. & Gasevic, D. 2016. Learning analytics should not promote one size fits all: The effects of instructional conditions in predicting academic success. *The Internet and Higher Education.* 28:68-84.

Guruler, H., Istanbullu, A. & Karahasan, M. 2010. A new student performance analysing system using knowledge discovery in higher educational databases. *Computers & Education.* 55(1):247-254.

Hadhrami, G. 2017. Learning analytics dashboard to improve students’ performance and success. *IOSR J Res Method Educ (IOSRJRME).* 7(1):39-45.

Hailikari, T., Nevgi, A. & Lindblom-Ylänne, S. 2007. Exploring alternative ways of assessing prior knowledge, its components and their relation to student achievement: A mathematics based case study. *Studies in Educational Evaluation.* 33(3-4):320-337.

Hakulinen, L., Auvinen, T. & Korhonen, A. 2015. The Effect of Achievement Badges on Students' Behavior: An Empirical Study in a University-Level Computer Science Course. *International Journal of Emerging Technologies in Learning.* 10(1).

Harkin, B., Webb, T.L., Chang, B.P., Prestwich, A., Conner, M., Kellar, I., Benn, Y. & Sheeran, P. 2016. Does monitoring goal progress promote goal attainment? A meta-analysis of the experimental evidence. *Psychological bulletin.* 142(2):198.

Hastie, T., Tibshirani, R. & Friedman, J. 2009. *The elements of statistical learning: data mining, inference, and prediction.* Springer Science & Business Media.

Hicks, D.W. & Richardson, F.M. 1984. Predicting early success in intermediate accounting: The influence of entry examination and GPA. *Issues in Accounting Education.* 2(1):61-67.

Hu, Y.-H., Lo, C.-L. & Shih, S.-P. 2014. Developing early warning systems to predict students’ online learning performance. *Computers in Human Behavior.* 36:469-478.

Huang, S. & Fang, N. 2013. Predicting student academic performance in an engineering dynamics course: A comparison of four types of predictive mathematical models. *Computers & Education.* 61:133-145.

Jacobs, M. 2018. An investigation of the use of NBTs in placement of first year students in sciences.

Janssen, R., Van Herwijnen, M., Stewart, T.J. & Aerts, J.C. 2008. Multiobjective decision support for land-use planning. *Environment and planning B: Planning and design.* 35(4):740-756.

Jayaprakash, S.M., Moody, E.W., Lauría, E.J., Regan, J.R. & Baron, J.D. 2014. Early alert of academically at-risk students: An open source analytics initiative. *Journal of Learning Analytics.* 1(1):6-47.

Ji, M., Michel, C., Lavoué, E. & George, S. Eds. 2014. DDART, a dynamic dashboard for collection, analysis and visualization of activity and reporting traces. Springer. 440-445.

Jishan, S.T., Rashu, R.I., Haque, N. & Rahman, R.M. 2015. Improving accuracy of students’ final grade prediction model using optimal equal width binning and synthetic minority over-sampling technique. *Decision Analytics.* 2(1):1-25.

Jivet, I., Scheffel, M., Drachsler, H. & Specht, M. Eds. 2017. Awareness is not enough: Pitfalls of learning analytics dashboards in the educational practice. September 2017. Springer. 82-96.

Jivet, I., Scheffel, M., Specht, M. & Drachsler, H. Eds. 2018. License to evaluate: Preparing learning analytics dashboards for educational practice. 31-40.

Kaye, L.K., Wall, H.J. & Malone, S.A. 2016. “Turn that frown upside-down”: A contextual account of emoticon usage on different virtual platforms. *Computers in Human Behavior.* 60:463-467.

Kaye, L.K., Malone, S.A. & Wall, H.J. 2017. Emojis: Insights, affordances, and possibilities for psychological science. *Trends in cognitive sciences.* 21(2):66-68.

Kennedy, G., Coffrin, C., De Barba, P. & Corrin, L. Eds. 2015. Predicting success: how learners' prior knowledge, skills and activities predict MOOC performance. 136-140.

Kia, F.S., Teasley, S.D., Hatala, M., Karabenick, S.A. & Kay, M. Eds. 2020. How patterns of students dashboard use are related to their achievement and self-regulatory engagement. 340-349.

King, G. & Zeng, L. 2001. Logistic regression in rare events data. *Political analysis.* 9(2):137-163.

Kitchenham, B. 2004. Procedures for performing systematic reviews. *Keele, UK, Keele University.* 33(2004):1-26.

Kitto, K., Cross, S., Waters, Z. & Lupton, M. Eds. 2015. Learning analytics beyond the LMS: the connected learning analytics toolkit. 11-15.

Kizito, R., Munyakazi, J. & Basuayi, C. 2016. Factors affecting student success in a first-year mathematics course: a South African experience. *International Journal of Mathematical Education in Science and Technology.* 47(1):100-119.

Krahenbuhl, K.S. 2016. Student-centered education and constructivism: Challenges, concerns, and clarity for teachers. *The Clearing House: A Journal of Educational Strategies, Issues and Ideas.* 89(3):97-105.

Le Roux, N. & Sebolai, K. 2017. The National Benchmark Test of quantitative literacy: does it complement the Grade 12 Mathematical Literacy examination? *South African Journal of Education.* 37(1).

Little, R.J. 1992. Regression with missing X's: a review. *Journal of the American statistical association.* 87(420):1227-1237.

Lonn, S., Aguilar, S.J. & Teasley, S.D. 2015. Investigating student motivation in the context of a learning analytics intervention during a summer bridge program. *Computers in Human Behavior.* 47:90-97.

Lykourentzou, I., Giannoukos, I., Nikolopoulos, V., Mpardis, G. & Loumos, V. 2009. Dropout prediction in e-learning courses through the combination of machine learning techniques. *Computers & Education.* 53(3):950-965.

Malefo, V. 2000. Psycho-social factors and academic performance among African women students at a predominantly white university in South Africa. *South African Journal of Psychology.* 30(4):40-45.

Martinez-Maldonado, R., Pardo, A., Mirriahi, N., Yacef, K., Kay, J. & Clayphan, A. 2015. LATUX: An Iterative Workflow for Designing, Validating, and Deploying Learning Analytics Visualizations. *Journal of Learning Analytics.* 2(3):9-39.

Matcha, W., Gašević, D. & Pardo, A. 2019. A systematic review of empirical studies on learning analytics dashboards: A self-regulated learning perspective. *IEEE Transactions on Learning Technologies.* 13(2):226-245.

Mottus, A., Graf, S. & Chen, N.-S. 2015. Use of dashboards and visualization techniques to support teacher decision making. In *Ubiquitous Learning Environments and Technologies.* Springer. 181-199.

Mukaka, M., White, S.A., Terlouw, D.J., Mwapasa, V., Kalilani-Phiri, L. & Faragher, E.B. 2016. Is using multiple imputation better than complete case analysis for estimating a prevalence (risk) difference in randomized controlled trials when binary outcome observations are missing? *Trials.* 17(1):1-12.

Pardo, A., Mirriahi, N., Martinez-Maldonado, R., Jovanovic, J., Dawson, S. & Gašević, D. Eds. 2016. Generating actionable predictive models of academic performance. 474-478.

Park, Y. & Jo, I.-H. 2015. Development of the learning analytics dashboard to support students' learning performance. *Journal of Universal Computer Science.* 21(1):110.

Petersen, I.h., Louw, J. & Dumont, K. 2009. Adjustment to university and academic performance among disadvantaged students in South Africa. *Educational psychology.* 29(1):99-115.

Richards, G. 2011. Measuring engagement: Learning analytics in online learning. *electronic Kazan.* 2011.

Riordan, M.A. 2017. The communicative role of non-face emojis: Affect and disambiguation. *Computers in Human Behavior.* 76:75-86.

Romero-Zaldivar, V.-A., Pardo, A., Burgos, D. & Kloos, C.D. 2012. Monitoring student progress using virtual appliances: A case study. *Computers & Education.* 58(4):1058-1067.

Romero, C. & Ventura, S. 2007. Educational data mining: A survey from 1995 to 2005. *Expert systems with applications.* 33(1):135-146.

Sadler, D.R. 1989. Formative assessment and the design of instructional systems. *Instructional science.* 18(2):119-144.

Santos, J.L., Govaerts, S., Verbert, K. & Duval, E. Eds. 2012. Goal-oriented visualizations of activity tracking: a case study with engineering students. 143-152.

Santos, J.L., Verbert, K., Govaerts, S. & Duval, E. Eds. 2013. Addressing learner issues with StepUp! an evaluation. 14-22.

Santos, J.L., Verbert, K., Klerkx, J., Charleer, S., Duval, E. & Ternier, S. 2015. Tracking data in open learning environments. *Journal of Universal Computer Science.* 21(7):976-996.

Sartorius, K. & Sartorius, B. 2013. The comparative performance of chartered accountancy students in South Africa: The impact of historical legacies. *Development Southern Africa.* 30(3):401-416.

Sawyer, R.K. 2014. The future of learning: Grounding educational innovation in the learning sciences. *The Cambridge handbook of the learning sciences.*726-746.

Schwendimann, B.A., Rodriguez-Triana, M.J., Vozniuk, A., Prieto, L.P., Boroujeni, M.S., Holzer, A., Gillet, D. & Dillenbourg, P. 2016. Perceiving learning at a glance: A systematic literature review of learning dashboard research. *IEEE Transactions on Learning Technologies.* 10(1):30-41.

Sedrakyan, G., Mannens, E. & Verbert, K. 2019. Guiding the choice of learning dashboard visualizations: Linking dashboard design and data visualization concepts. *Journal of Computer Languages.* 50:19-38.

Sedrakyan, G., Malmberg, J., Verbert, K., Järvelä, S. & Kirschner, P.A. 2020. Linking learning behavior analytics and learning science concepts: Designing a learning analytics dashboard for feedback to support learning regulation. *Computers in Human Behavior.* 107:105512.

Siemens, G. & Gasevic, D. 2012. Guest editorial-learning and knowledge analytics. *Journal of Educational Technology & Society.* 15(3):1-2.

Soller, A., Martínez, A., Jermann, P. & Muehlenbrock, M. 2005. From mirroring to guiding: A review of state of the art technology for supporting collaborative learning. *International Journal of Artificial Intelligence in Education.* 15(4):261-290.

Stewart, T.J., Janssen, R. & Van Herwijnen, M. 2004. A genetic algorithm approach to multiobjective land use planning. *Computers & Operations Research.* 31(14):2293-2313.

Stoltzman, S. 2018. *What Type of Data Visualization Do You Choose (if any)?* [Blog, Available: https://opendatascience.com/data-visualization-part-3/. Available: https://opendatascience.com/data-visualization-part-3/ [2021, January 25].

Team, R. 2015. *RStudio: integrated development for R. Boston, MA: RStudio.* Inc.

Tewari, D. 2014. Is Matric math a good predictor of student's performance in the first year of university degree? A case study of Faculty of Management Studies, University of KwaZulu-Natal, South Africa. *International Journal of Educational Sciences.* 6(2):233-237.

Thatcher, A., Fridjhon, P. & Cockcroft, K. 2007. The relationship between lecture attendance and academic performance in an undergraduate psychology class. *South African Journal of Psychology.* 37(3):656-660.

Van Eeden, R., De Beer, M. & Coetzee, C. 2001. Cognitive ability, learning potential, and personality traits as predictors of academic achievement by engineering and other science and technology students. *South African Journal of Higher Education.* 15(1):171-179.

Van Ginkel, J.R., Linting, M., Rippe, R.C. & van der Voort, A. 2020. Rebutting existing misconceptions about multiple imputation as a method for handling missing data. *Journal of Personality Assessment.* 102(3):297-308.

Van Zyl, A., Gravett, S. & De Bruin, G. 2012. To what extent do pre-entry attributes predict first year student academic performance in the South African context? *South African Journal of Higher Education.* 26(5).

Verbert, K., Duval, E., Klerkx, J., Govaerts, S. & Santos, J.L. 2013. Learning analytics dashboard applications. *American Behavioral Scientist.* 57(10):1500-1509.

Vozniuk, A., Govaerts, S. & Gillet, D. Eds. 2013. Towards portable learning analytics dashboards. IEEE. 412-416.

Wilson, K., Boyd, C., Chen, L. & Jamal, S. 2011. Improving student performance in a first-year geography course: Examining the importance of computer-assisted formative assessment. *Computers & Education.* 57(2):1493-1500.

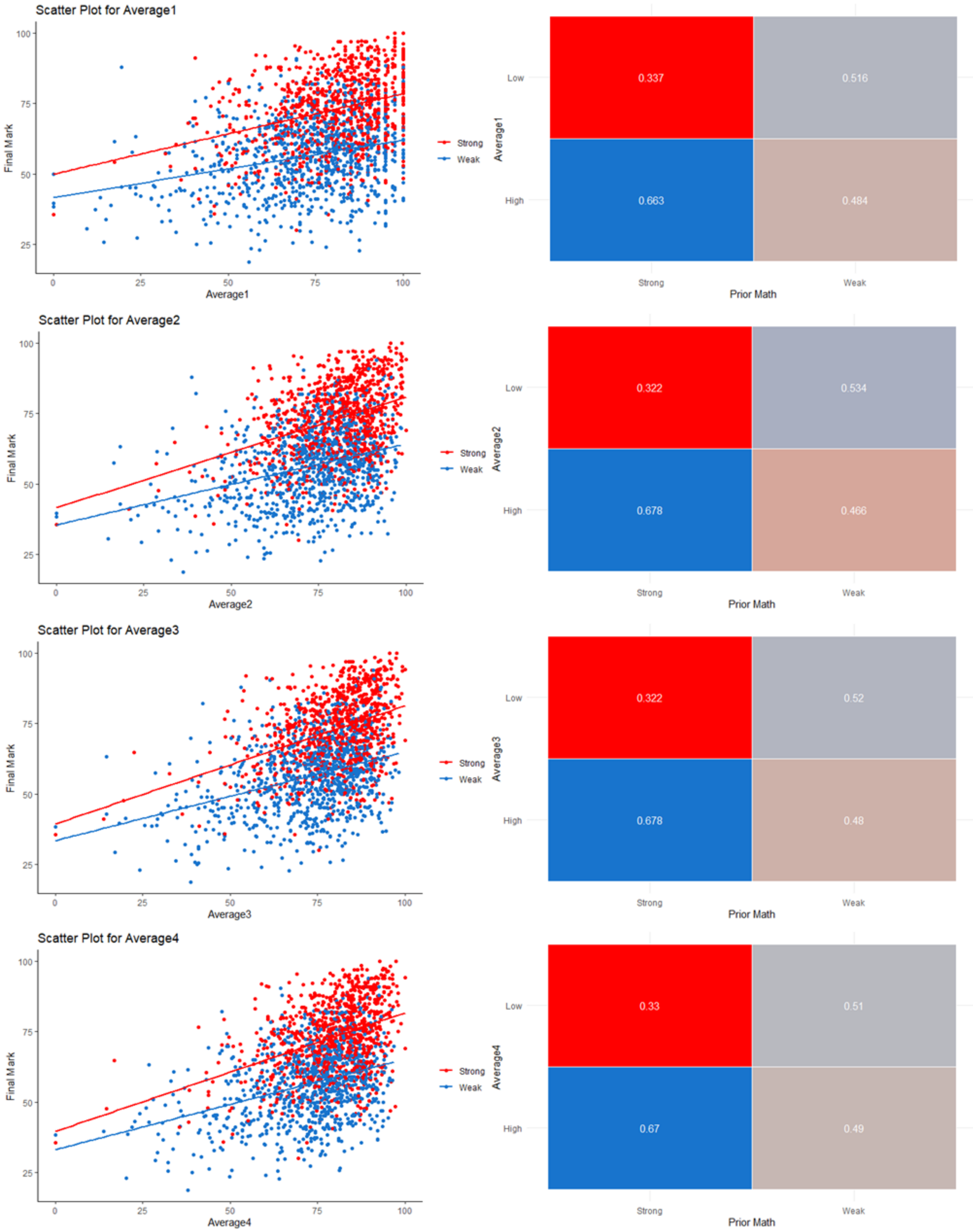
Wood, S.N. 2017. *Generalized additive models: an introduction with R.* CRC press.

Yoo, Y., Lee, H., Jo, I.-H. & Park, Y. 2015. Educational dashboards for smart learning: Review of case studies. *Emerging issues in smart learning.*145-155.

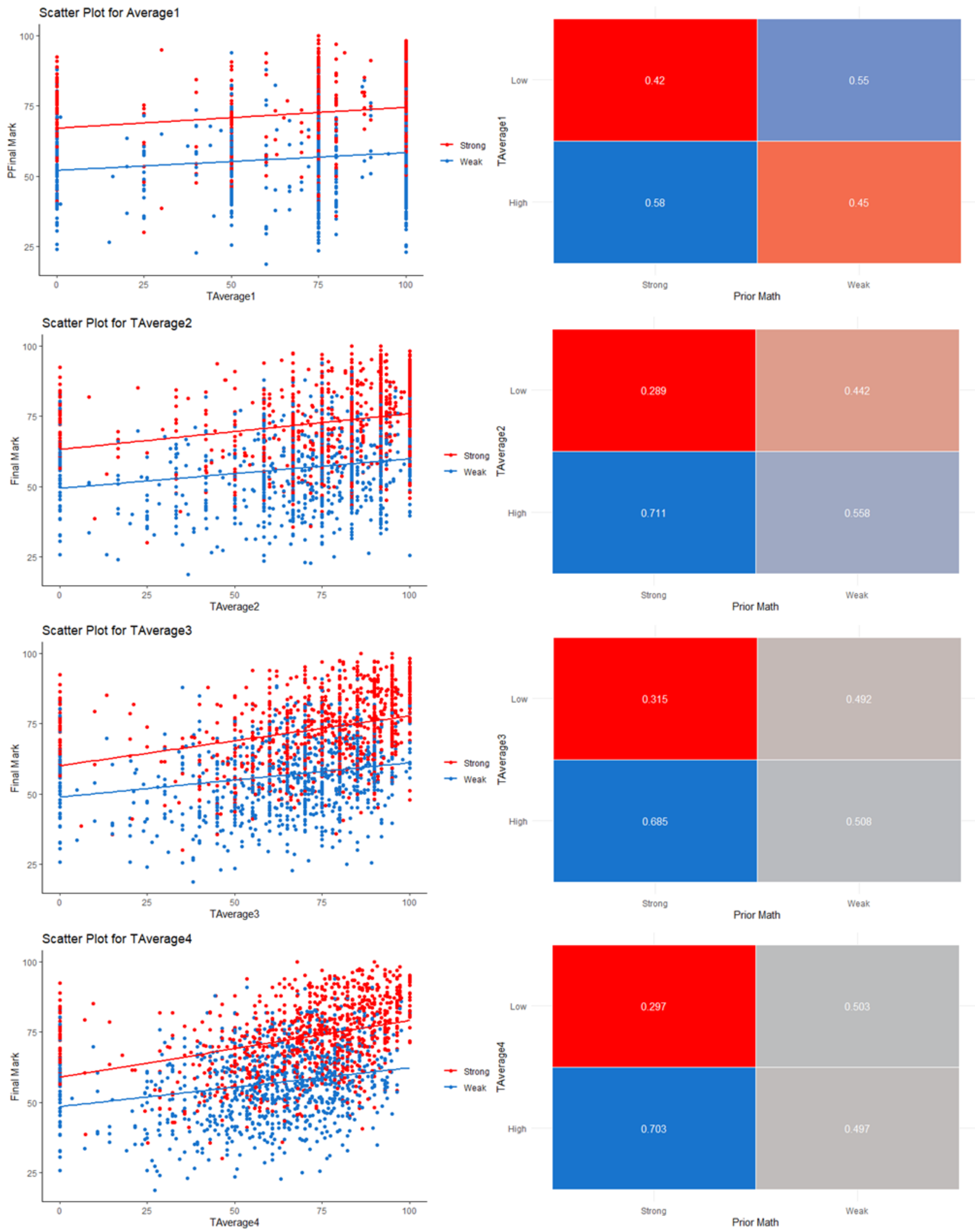
You, J.W. 2016. Identifying significant indicators using LMS data to predict course achievement in online learning. *The Internet and Higher Education.* 29:23-30.

Zimmerman, B.J. & Schunk, D.H. 2011. *Handbook of self-regulation of learning and performance.* Routledge/Taylor & Francis Group.

Appendix



Appendix Figure A.1:Scatter and mosaic plot for Assignment Average vs Prior Math



Appendix Figure A.2: Scatter and mosaic plot for Tutorial Average vs Prior Math

Appendix Table A.1: Performance metrics for logistic regression using a default threshold (0.5)
Rows show different proportions of the minor class within the predictor variable

		Accuracy	Sensitivity	Specificity	AUC
		0.86	0.98	0.26	0.62
Over Sampling	**0.2**	0.86	0.97	0.28	0.62
	0.25	0.86	0.95	0.35	0.65
	0.3	0.84	0.92	0.46	0.69
	0.35	0.83	0.88	0.59	0.74
	0.4	0.81	0.84	0.65	0.75
	0.45	0.78	0.80	0.70	0.75
Under Sampling	**0.2**	0.86	0.97	0.28	0.63
	0.25	0.86	0.96	0.35	0.65
	0.3	0.85	0.93	0.46	0.69
	0.35	0.83	0.88	0.59	0.73
	0.4	0.80	0.83	0.65	0.74
	0.45	0.78	0.79	0.72	0.75
ROSE	**0.2**	0.86	0.99	0.19	0.59
	0.25	0.86	0.97	0.30	0.64
	0.3	0.86	0.94	0.42	0.68
	0.35	0.84	0.90	0.54	0.72
	0.4	0.82	0.86	0.62	0.74
	0.45	0.79	0.81	0.69	0.75
SMOTE	**0.2**	0.86	0.96	0.33	0.64
	0.25	0.84	0.93	0.38	0.66
	0.3	0.83	0.91	0.46	0.68
	0.35	0.82	0.87	0.57	0.72
	0.4	0.80	0.83	0.63	0.73
	0.45	0.78	0.80	0.69	0.74

Appendix Table A.2: Performance metrics for logistic regression using an optimal threshold
Rows show different proportions of the minor class within the predictor variable

		Accuracy	Sensitivity	Specificity	AUC
Original		0.77	0.77	0.76	0.76
Over Sampling	**0.2**	0.77	0.77	0.75	0.76
	0.25	0.76	0.76	0.76	0.76
	0.3	0.78	0.78	0.74	0.76
	0.35	0.76	0.75	0.77	0.76
	0.4	0.76	0.77	0.76	0.76
	0.45	0.75	0.74	0.78	0.76
Under Sampling	**0.2**	0.77	0.77	0.75	0.76
	0.25	0.75	0.75	0.77	0.76
	0.3	0.77	0.78	0.76	0.77
	0.35	0.75	0.75	0.78	0.76
	0.4	0.78	0.79	0.74	0.76
	0.45	0.77	0.77	0.77	0.77
ROSE	**0.2**	0.76	0.76	0.76	0.76
	0.25	0.75	0.74	0.78	0.76
	0.3	0.77	0.77	0.75	0.76
	0.35	0.75	0.75	0.77	0.76
	0.4	0.77	0.77	0.76	0.77
	0.45	0.76	0.76	0.76	0.76
SMOTE	**0.2**	0.76	0.76	0.74	0.75
	0.25	0.78	0.79	0.73	0.76
	0.3	0.76	0.76	0.76	0.76
	0.35	0.76	0.76	0.75	0.75
	0.4	0.76	0.76	0.74	0.75
	0.45	0.75	0.75	0.76	0.75

Appendix Table A.3: P values for the interaction terms

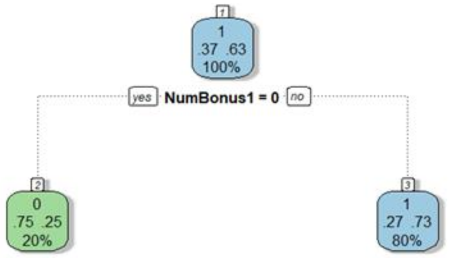
Cells highlighted in green represent significant interaction terms

	Interaction Terms	P Value
TP1	**Assignment Average:priorMath**	0.241
	Tutorial Average:priorMath	0.075
	B1:priorMath	0.782
TP2	**Assignment Average:priorMath**	0.494
	Tutorial Average:priorMath	0.860
	B1:priorMath	0.995
	B2:priorMath	0.868
TP3	**Assignment Average:priorMath**	0.952
	Tutorial Average:priorMath	0.761
	Test1:priorMath	0.410
	B1:priorMath	0.803
	B2:priorMath	0.471
	B3:priorMath	0.038
TP4	**Assignment Average:priorMath**	0.623
	Tutorial Average:priorMath	0.887
	Test1:priorMath	0.376
	B1:priorMath	0.557
	B2:priorMath	0.271
	B3:priorMath	0.108
	B4:priorMath	0.126

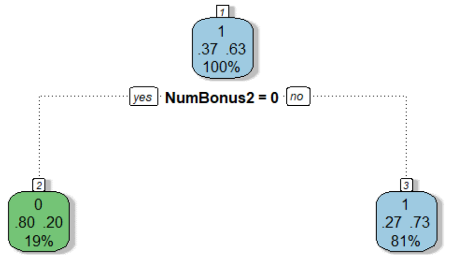
Appendix Table A.4: Performance metrics for decision trees

Rows show different proportions of the minor class within the predictor variable. Performance shown for the full training set, strong and weak students.

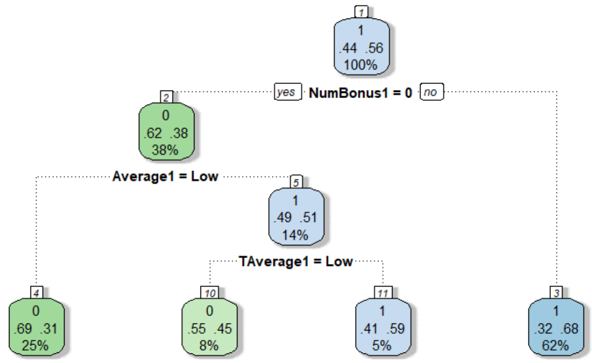
		Full Set				Strong				Weak			
		Accuracy	**Sensitivity**	**Specificity**	**AUC**	**Accuracy**	**Sensitivity**	**Specificity**	**AUC**	**Accuracy**	**Sensitivity**	**Specificity**	**AUC**
Unbalanced		0.84	0.98	0.16	0.57	0.84	1.00	0.00	0.50	0.85	0.94	0.35	0.65
Oversampling	*0.2*	0.86	0.97	0.27	0.62	0.85	0.95	0.34	0.64				
	0.25	0.85	0.96	0.28	0.62	0.84	0.93	0.37	0.65				
	0.3	0.84	0.94	0.37	0.65	0.80	0.86	0.48	0.67	0.85	0.95	0.32	0.63
	0.35	0.83	0.91	0.43	0.67	0.79	0.84	0.53	0.68	0.84	0.94	0.36	0.65
	0.4	0.81	0.85	0.58	0.72	0.75	0.79	0.55	0.67	0.83	0.91	0.45	0.68
	0.45	0.76	0.78	0.68	0.73	0.72	0.74	0.61	0.68	0.73	0.75	0.64	0.69
Undersampling	*0.2*	0.85	0.97	0.25	0.61	0.83	0.93	0.32	0.63				
	0.25	0.84	0.94	0.37	0.65	0.84	0.94	0.31	0.62				
	0.3	0.84	0.92	0.39	0.66	0.82	0.91	0.36	0.64	0.85	0.94	0.35	0.65
	0.35	0.83	0.90	0.48	0.69	0.76	0.77	0.72	0.75	0.84	0.93	0.38	0.66
	0.4	0.78	0.80	0.68	0.74	0.77	0.78	0.70	0.74	0.83	0.92	0.40	0.66
	0.45	0.73	0.73	0.74	0.74	0.72	0.72	0.73	0.73	0.79	0.82	0.62	0.72
ROSE	*0.2*	0.85	0.96	0.28	0.62	0.84	0.95	0.30	0.62				
	0.25	0.85	0.95	0.35	0.65	0.84	0.94	0.32	0.63				
	0.3	0.84	0.93	0.39	0.66	0.80	0.87	0.46	0.66	0.84	0.95	0.28	0.61
	0.35	0.84	0.93	0.39	0.66	0.77	0.83	0.50	0.67	0.84	0.94	0.37	0.65
	0.4	0.81	0.86	0.56	0.71	0.74	0.76	0.63	0.69	0.83	0.89	0.47	0.68
	0.45	0.73	0.73	0.74	0.73	0.69	0.69	0.70	0.70	0.78	0.80	0.64	0.72
SMOTE	*0.2*	0.84	0.95	0.29	0.62	0.83	0.94	0.26	0.60				
	0.25	0.84	0.93	0.39	0.66	0.82	0.93	0.26	0.60				
	0.3	0.84	0.93	0.38	0.66	0.81	0.91	0.30	0.61	0.84	0.94	0.36	0.65
	0.35	0.82	0.90	0.40	0.65	0.78	0.83	0.53	0.68	0.84	0.93	0.38	0.66
	0.4	0.79	0.85	0.52	0.68	0.77	0.82	0.54	0.68	0.82	0.89	0.44	0.67
	0.45	0.77	0.78	0.67	0.73	0.70	0.71	0.66	0.69	0.79	0.84	0.51	0.67



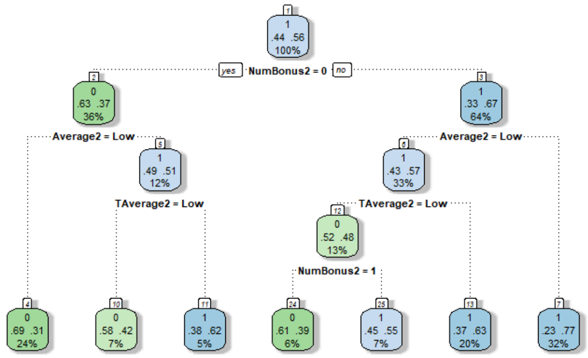
Appendix Figure A.3: Decision Tree at TP1 for strong students



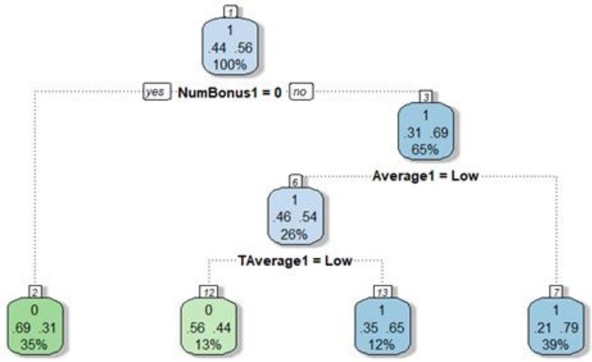
Appendix Figure A.4: Decision Tree at TP2 for strong students



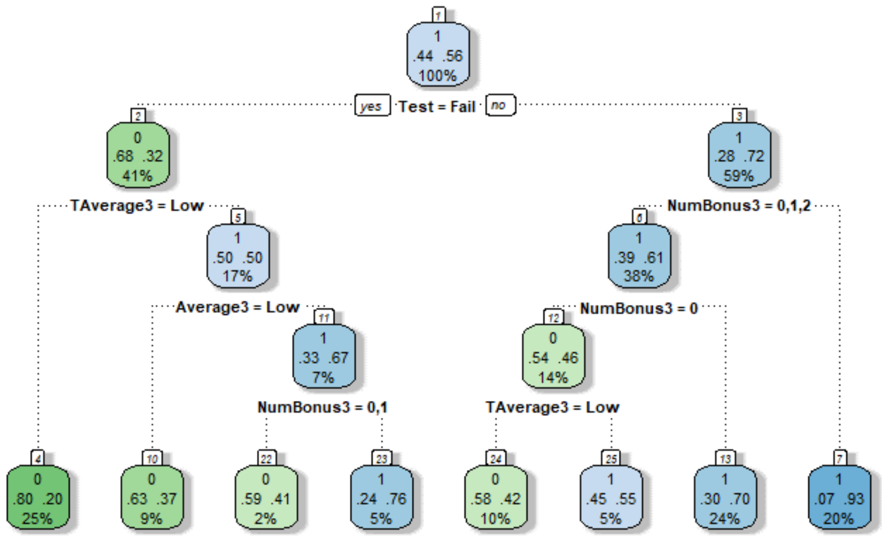
Appendix Figure A.5: Decision Tree at TP1 for weak students



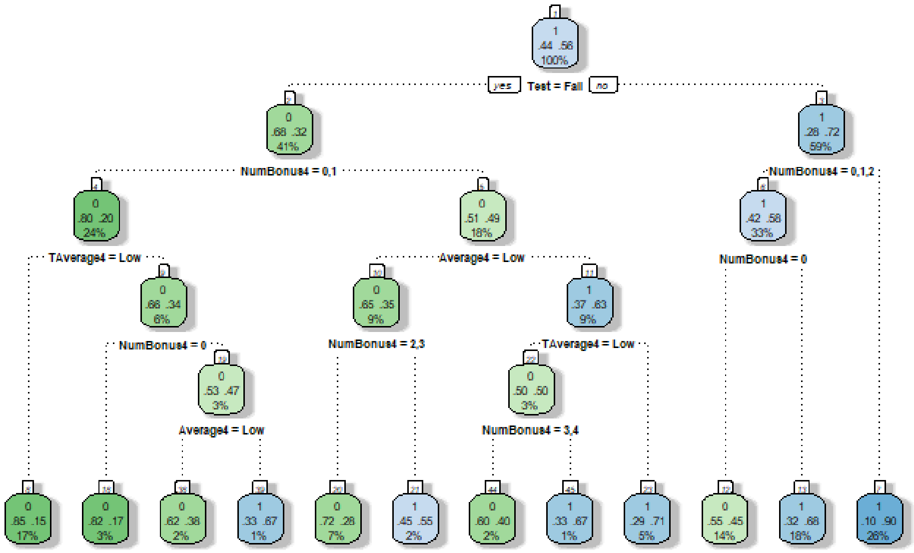
Appendix Figure A.6: Decision Tree at TP2 for weak students



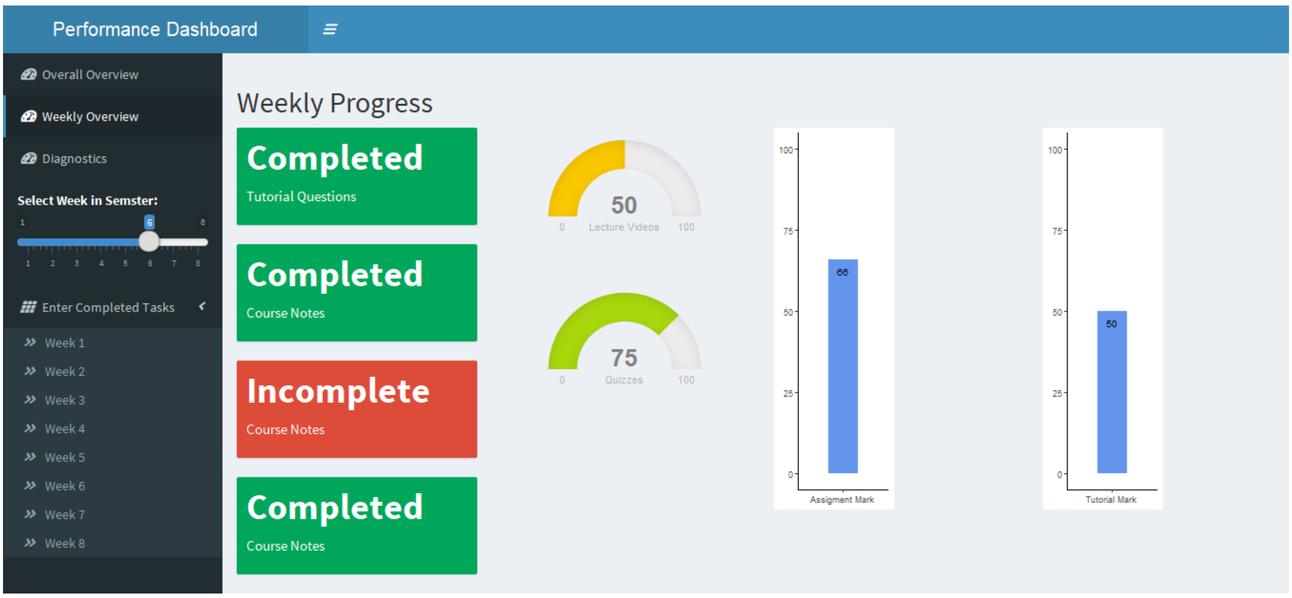
Appendix Figure A.7: Decision Tree at TP1



Appendix Figure A.8: Decision Tree at TP3



Appendix Figure A.9: Decision Tree at TP4



Appendix Figure A.10: A view of the dashboard when the “Weekly Overview” is selected