Predicting Students' Academic Performance: A Comparison between Traditional MLR and Machine
Learning Methods with PISA 2015

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Abstract

Predicting students' academic performance has long been an important area of research in education. Most existing literature have made use of traditional statistical methods that run into the problems of overfitted models, inability to effectively handle large numbers of participants and predictors, and inability to pick out non-linearities that may be present. Regression-based ML methods that can produce highly interpretable yet accurate models for new predictions, are able to provide some solutions to the aforementioned problems. The present study is the first study that develops and compares between traditional MLR methods and regression-based ML methods (i.e. ridge regression, LASSO regression, elastic net, and regression trees) to predict students' science performance in the PISA 2015. A total of 198,712 students from 60 countries, and 66 student- and school-related predictors were used to develop the predictive models. Predictive accuracy of the various models built were not that different, however, there were significant differences in the predictors identified as most important by the different methods. Although regression-based ML techniques did not outperform traditional MLR, significant advantages for using ML methods were noted and discussed. Moving forward, we strongly believe that there is merit for using such regression-based ML methods in educational research. Educational research can benefit from adopting ML practices and methods to produce models that can not only be used for explaining factors that influence academic performance prediction, but also for making more accurate predictions on unseen data.

Keywords: multiple linear regression, regression trees, penalised regression, academic performance prediction, PISA

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Chapter 1

Introduction

Within educational research, the ability to predict students' academic performance has consistently been an important research topic in many academic disciplines and across school levels. Being able to predict students' academic performance has both practical and theoretical significance; it allows for early identification of students who require additional support, helps educators design and implement in-time intervention, and increases theoretical understanding of factors that can influence academic outcomes. However, previous literature that have tried to predict and explain students' academic performance have overwhelmingly employed conventional statistical techniques (e.g. multiple linear regression and simple correlations). More complex statistical methods, namely hierarchical multilevel modelling and structural equation modelling, are sometimes used when researchers tap on large-scale educational data, such as from the Programme for International Student Assessment (PISA), or in longitudinal studies.

However, these conventional statistical methods [i.e. ordinary least squares (OLS) regression], face several problems, such as the inability to capture non-linear relations, inability to handle large amounts of predictors and data points, inability to detect all possible interaction effects, and overfitting, a phenomenon whereby a statistical model incorrectly fits sample-specific variance as if it were 'signal', which results in low accuracy and poor generalisability of your model to new data, which can result in inaccurate predictions and inconclusive outcomes (Hindman, 2015). Machine learning (ML) methods, this study specifically investigates regression-based ML approaches, namely penalised regression techniques and decision trees, offer better alternatives; they can produce interpretable, yet accurate models that predict well out of sample (Hindman, 2015). The present study employs both conventional statistical methods and regression-based ML methods, and compares their prediction accuracy on students' academic performance with data from PISA 2015, a large-scale international scholastic assessment of 15-year-old students' performance on mathematics, science, and reading.

The rest of this paper is organized as follows. First, we start by presenting the current state of literature in academic performance prediction from the educational psychology research field, then highlight the need and benefits of having a valid predictive model of academic performance. Following that, we describe the problems faced by traditional statistical methods, and explain how ML methods solve some of these problems. Next, we expand on recent work on predictive models of academic performance from ML, before describing the methods for analysing the PISA data in greater detail. We then compare between six models from five modelling methods using various accuracy and error metrics, and identify the predictor variables that are more predictive of academic performance in each model. We conclude by addressing the likely benefits and challenges of realising ML methods in academic performance prediction.

Current State of Literature

Educational research into determining the factors relevant to, and predictive of academic achievement, has been on the rise since decades ago. Since then, a number of meta-analyses and numerous empirical studies have put forth various correlates and predictors, in an attempt to account for their significance in predicting academic performance. Richardson et al. (2012) reviewed a decade of research on predicting academic performance; they identified the strongest correlates of academic performance of university students amongst 50 variables, both cognitive (e.g. standardised intelligence tests, prior grades) and non-cognitive (e.g. motivational factors, approaches to learning). The authors found performance self-efficacy ($r = .59$) having the highest correlation with university grade point average (GPA) amongst the 50 measures, followed by high school grades ($r = .40$), students' grades goal or expectation ($r = .35$), and effort regulation ($r = .32$). In contrast, they found neither the Big Five personality factors nor motivational factors (e.g. intrinsic motivation, extrinsic motivation) strong correlates of GPA ($-.04 < r_s < .17$).

In a more recent meta-analysis, Kriegbaum et al. (2018) found both intelligence and motivation ($r = .44$, $r = .27$, respectively) having a moderately positive correlation with academic achievement of primary to pre-university students. Upon separating motivation into expectancies (e.g.

self-efficacy, self-concept) and values (e.g. intrinsic motivation, achievement goals), Kriegbaum et al. (2018) found a stronger correlation between expectancies and school achievement ($r = .40$) than between values and school achievement ($r = .22$) across different school levels and gender. This is in line with findings from Richardson et al. (2012) that reported a weak relationship between motivational values constructs and academic achievement. Similarly, Huang (2011) synthesised longitudinal samples of primary to pre-university students and found a moderately positive association between self-concept and academic achievement ($.20 < rs < .27$).

Students' socioeconomic status (SES), often measured by a combination of family income, physical, and social resources one has access to, has also been identified as a predictor of academic performance. There is extensive evidence in the literature demonstrating a pervasive influence of SES on academic achievement (e.g. Gustafsson et al., 2018; Koza Çiftçi & Melis Cin, 2017). However, others have argued that the SES-achievement association may be smaller than reported (e.g. Sirin, 2005). Recently, Harwell et al. (2016) reviewed three decades of research and reported a surprisingly modest correlation between SES and academic achievement in kindergarten to pre-university students ($r = .22$). School level was found to be a potential moderator; the association between SES and achievement was strongest for kindergarten children ($r = .33$) and weakest for middle and high-school students ($r = .16$).

In addition to meta-analyses, research into determining the factors relevant to, and predictive of academic achievement, has also been conducted with a number of hierarchical linear modelling analyses and longitudinal studies. Alatlı (2020) used hierarchical linear modelling to investigate the similarities and differences in science achievement and the factors influencing students' achievement in two countries, Turkey and Singapore. Using a two-level hierarchical model (schools at level-1 and countries at level-2), Alatlı (2020) reported that school-related variables play a significant role for why students from the respective countries differed; students from Turkey differed more from one another due to school-related variables, while the opposite was observed in students from Singapore. Alatlı (2020) found some similarities in student-related predictors of science achievement in both

countries (e.g. science self-efficacy, interest in science, and research-based science applications), and some differences in student-related predictors (e.g. enjoyment of science was predictive of science achievement in Turkish students, not Singaporean students). At the school level, the proportion of science teachers in each school was found to be a significant predictor of science literacy for both Turkey and Singapore samples.

To inspect more closely the gaps in performance across countries due to differences in specific predictors, Chen and Cui (2019) investigated the association between one student-related predictor, perceived unfairness of teachers, across 52 countries with hierarchical linear modelling analyses. Their results showed that perceived teacher unfairness was negatively related with science achievement; basically, students who perceived that their teacher was highly unfair were more likely to have poorer performance in science, after a number of demographic factors and non-cognitive outcomes are controlled for. However, this was met with a small effect size across 52 countries, which was reasoned to be due to the use of only one dimension of factors influencing class climate.

Similarly, Hu et al. (2018) examined the relationship between use of information and communications technology (ICT) and students' academic performance for 44 countries in PISA 2015 using a three-level hierarchical linear model (students at level-1, schools at level-2, and countries at level-3). All ICT-related predictors that were included in the study accounted for 67% of the variance among countries, 31% of the variance among schools, and 6% of the variance among students for scientific literacy. At the student-level, the authors found one's interest in ICT, self-perceived competence in ICT, and ICT autonomy positively related with science performance. At the school- and country- levels, predictors of science performance varied widely.

Many studies have also studied predictors of students' academic performance with longitudinal data. For example, Mercader et al. (2017) found that children's mastery motivation (persistence) in kindergarten significantly predicted mathematics achievement at the end of primary two. Brock et al. (2008) examined how a set of responsive teaching approaches, when applied in the classroom, may impact students' perceptions of their classroom, students' academic and social

performance over a span of three years. The authors found that a positive classroom climate which places a strong emphasis on social skills, such as cooperation, assertion, responsibility, empathy and self-control led to improved academic and behavioural outcomes. Learning is optimised when students engage in social discourse with peers or more knowledgeable others in the classroom.

Although we are unable to review the plethora of research available in the field, these studies provide a glimpse into the current state of literature on academic performance prediction from the field of educational psychology. Put together, there is no conclusive evidence for any one or two factors that completely accounts for academic performance, but clearly a combination of several different factors that influences academic performance. As such, it is of merit to study a wide variety of factors simultaneously in order to sieve out more influential factors of academic performance.

However, most of these studies make use of traditional OLS regression methods, which estimates the relationship between predictors and the outcome by minimising the residual sum of the squares between them. This produces an unbiased estimate for the relationship between predictors and outcome, however, compensates with high between-sample variance, resulting in a typically overfitted model. Furthermore, the conditions under which much of psychological research typically occurs—e.g. having small sample sizes, or the inherent presence of noise in the data—facilitates or encourages overfitting (Yarkoni & Westfall, 2017). Thus, to be able to make more accurate predictions of unseen data, ML methods and practices (e.g. cross-validation of regression models) have been suggested, in addition to the use of traditional statistical approaches (Kenekeyaro, 2018; Yarkoni & Westfall, 2017). The progress of psychology towards a more predictive science could benefit research in these fields (e.g. education), and result in a better understanding of human behaviour. After all, to be able to understand human behaviour involves both explaining and prediction (Yarkoni & Westfall, 2017).

Benefits of Predicting Academic Performance

With a valid predictive model of academic performance, students at risk of poor performance may be identified and schools can provide timely and proactive assistance to improve learning and

performance (Huang & Fang, 2013). If a model can make a reasonably accurate prediction of a student's potential poor performance in an upcoming examination, educators can then design and implement in-time interventions, tweak instructional approaches, and personalise support. Thus, academic performance prediction is an essential stepping stone to facilitating any form of early intervention and guidance.

Along with being able to predict how well students may score in an upcoming examination, having a valid predictive model tells us which variables are significant for predicting academic performance, which in turn, allows for making informed decisions regarding intervention and curriculum, and an overall increased understanding of learning. For instance, previous research has consistently identified self-efficacy and home SES as predictors of students' academic performance. This implies that more resources could be channeled towards fostering greater self-efficacy in students, and whilst the difficulties brought about by lower home SES is more challenging to mitigate, at the school level, more can be done to induce a literacy-rich environment that is lacking from the home environment, for example.

Having such knowledge enables better planning of curriculum and could also inform policy-making to a certain extent. One-size-fits-all educational policies aimed at ensuring all students achieve a minimum standard have proven to be unsuccessful, resulting in under-achieving students falling behind others. These one-size-fits-all policies overlook the important influence of students' SES and family background on performance. It assumes that as long as each student in every school is given the standard curriculum and instruction, all students will equally succeed academically. However, students that enrol into high-poverty and racially diverse schools are at a disadvantage and at risk of continuously underachieving (Kim & Sunderman, 2005). Hence, in order to support these students to achieve their fullest potential, educational policies may need to be tailored towards individual students' needs and background.

Problems with Conventional Statistical Methods

Previous research in the educational field that attempted to predict students' academic performance, have almost always used traditional statistical methods. Such methods have several problems which may result in inaccurate predictions and conclusions (Hindman, 2015).

Firstly, these conventional methods are prone to overfitting, which occurs when the established model is unable to generalise out of the data used to build the model. Since modelling relationship between variables in any given sample inherently possess some sampling or measurement error that is sample-specific (i.e. not shared with any other samples drawn from the same population), an established model will almost always produce optimistically biased results (Yarkoni & Westfall, 2017). Thus, the more overfitting that occurs in building a model, the more unlikely that model is able to accurately generalise to new observations. The ML framework provides several solutions for controlling and preventing overfitting, for example, altering the flexibility with which the model fits to the data (Krstajic et al., 2014).

Secondly, traditional statistical methods are not able to study data that comprise a large number of participants coupled with a large number of predictors (i.e. big data) well. Typically, empirical studies pick out a few theoretical-based or evidence-based factors and study their ability for academic performance prediction using correlations or (multiple) linear regression. Even with more complex methods applied to big data sets, such as using hierarchical linear models to study the PISA data, researchers usually still pick out several factors and study them with students from one or two countries. This is most likely due to the failure to converge in the presence of a large number of parameters needing to be estimated. Bates et al. (2015) showed that the following:

Failure of convergence of model estimation is typically not a consequence of a suboptimal estimation algorithm, but rather an indicator of a model specification that is too complex to be properly supported by the data. In the absence of convergence, parameter estimates of overparameterized Linear Mixed Models (LMMs) are not interpretable. (p. 3)

Thus, ML methods are more suitable when we want to explore and study from a wide range of predictors simultaneously, while also having a large number of participants.

Lastly, although linear models are highly simplistic and interpretable, imposing the assumption of linearity on the relationships between variables lead to failure to acknowledge the non-linearities possibly present in many aspects of students' academic achievement (e.g. Strobl et al., 2009). The combination of diverse and varied factors that influence academic performance, such as students' demographics, personality, psychological, and environmental variables, may interact in complex non-linear ways (Guo et al., 2015). Forcing these relationships to fit a linear function may downplay or hide certain meaningful associations from being found, which in turn, result in poorer prediction accuracy compared to fitting a non-linear function that is able to capture the complexity of academic performance.

Therefore, we may need different approaches; fortunately, developments in ML are beginning to gain prominence in psychology and the social sciences. ML methods might offer better alternatives; they produce more parsimonious, sometimes interpretable, and accurate models that predict well out of sample, especially when sample size is small (Hindman, 2015). Hence, ML techniques may solve some of the problems faced by OLS regression.

Overview and Advantages of Machine Learning (ML) Methods

ML methods are a group of varied modelling techniques intended to help a system learn the patterns of the data, either with some or no theoretical assumptions about the population of study (Vijayakumar & Cheung, 2018). These methods can be loosely categorised into *regression-based methods* which produce more interpretable models (e.g. penalised regression methods, or decision trees) or *black-box methods* which lead to less interpretable models (e.g. support vector machine, or neural network models). Although methods in these two categories vary considerably, all ML algorithms, in general, prioritise predictive accuracy, which entails some similarities in characteristics that set them apart from traditional statistical methods (Vijayakumar & Cheung, 2018).

Firstly, there are two critical sources of error that are considered in statistics: bias and variance. Bias refers to the difference between the true population parameter and the expected or average estimate produced by one's established model; variance refers to the variability (or spread) in estimates of the established model. Both sources of error, bias and variance, are desired to be low, as larger values are associated with poorer predictions from the model. However, reducing both the bias and variance in the model is not as straightforward as it sounds; hence, there is usually a trade-off that happens between minimising the bias and minimising the variance (Hastie, Tibshirani, & Friedman, 2009). In traditional OLS models, there is a focus on producing an unbiased population estimate, which results in having a fairly large variance, and compromises predictive accuracy. However, ML methods "choose their parameters to minimise total predictive error and so can trade off an increase in bias for a decrease in variance" (Vijayakumar & Cheung, 2018), increasing predictive accuracy.

Next, another advantage all ML methods possess, is the capability to capture both the linearities and non-linearities present in the relationships between variables. Gabriel et al. (2018) analysed Australian students' mathematics literacy performance in the PISA 2012 using boosted regression trees with seven mathematical dispositions variables and five demographics variables, to predict mathematical literacy scores. They found the strongest linear relationship between mathematics self-efficacy and mathematical literacy, and the second strongest relationship between students' SES and mathematical literacy that was non-linear and fairly complex. To this end, ML techniques may provide evidence for a different underlying pattern of associations between variables that were not previously explored with traditional linear methods. Also, this implies that hidden patterns of associations and interactions between variables that are not linearly separable, may be picked up from a ML model that would have otherwise gone unspecified in a linear model (Masci et al., 2018).

Thirdly, a very common practice in ML, to prevent capitalising on chance by overfitting the data, is performing cross-validation (CV). This is most commonly carried out by first splitting the data set into two (i.e. training data set, and testing data set), or sometimes three (i.e. training data set,

testing data set, and validation data set), smaller data sets. The model is first optimised using the training data set, then validated on the testing data set. This ensures that predictive accuracy of the model is evaluated on a data set that has not learned the noise in the data, resulting in lower bias and variance, and less overfitting. To ensure that even less overfitting occurs when using the model to estimate out-of-sample performance, a validation set is used. There also exist different methods of CV, such as k -fold CV. In a typical k -fold CV process, the data set is randomly split into k approximately equally sized groups. Occasionally, a validation data set is first separated from the full data set before the split into k groups occurs. Each time, one such fold is used as the testing data set while all other folds are used as training data sets in order to estimate the model parameters. Finally, out-of-sample performance is estimated using the validation data set that was first separated from the full data set.

Lastly, some researchers posit that ML algorithms are more robust and may possibly have better replicability than conventional methods (Hindman, 2015). Several years ago, Maxwell et al. (2015) reported that much of the existing psychological and educational research have poor replicability; ML methods could provide rescue from such concerns of replicability in these fields. However, others have argued that despite higher predictive accuracy of ML methods, these methods do not always produce replicable models. Therefore, with these advantages, the field of ML can help psychology move towards becoming a more predictive science.

Regression-based ML Methods

For the purpose of this study, we focus on regression-based ML methods which produce models and model parameters that are more transparent, and easily interpreted. In a field such as education, being able to understand what goes on in the model is as important as deriving a prediction for one's performance. To allow researchers to pinpoint exactly what and how to provide timely intervention and support to students at risk of poor performance, achieving a balance between predictive accuracy and interpretability is essential. A comparison between regression-based ML approaches and traditional statistical methods could reveal possible non-linear associations between

variables not picked up by traditional methods. This comparison between regression-based ML approaches and traditional statistical methods also sheds light on the suitability of using ML methods for predicting academic performance with large data sets.

Penalised Regression Methods

Regularisation (or shrinkage) methods have been proposed as one way to overcome the issue of overfitting faced by the OLS approach; these techniques operate by imposing a penalty term on the regression coefficients to control these coefficients from exponentially increasing. The penalty term can take on any value from zero to infinity; depending on the value of this penalty parameter, different amounts of penalisation will be imposed on the regression coefficients (Acharjee et al., 2013). Since λ is the weight given to the penalty term, the closer λ is to zero, the more similar the penalised regression solution is to the OLS solution, and that also applies to all the coefficients in the model. Conversely, the further away λ is from zero, the greater the penalty on the model, resulting in fewer variables left in your model as more coefficients will be of zero weight.

Such penalised regression techniques are particularly useful in data sets where there is a much larger number of predictors compared to the number of observations. Large-scale educational assessment data such as the PISA, where there are hundreds of variables and hundred thousands of participants, can also benefit from penalised regression methods. This is as conventional statistical methods will face problems and much difficulty managing variables and participants of that amount, leading to convergence and overfitting.

Widely known regularisation methods used to optimise OLS estimates in regression models are Ridge Regression (RR; Hoerl & Kennard, 1970), Least Absolute Shrinkage and Selection Operator (LASSO; Tibshirani, 1996) and Elastic Net (EN; Zou & Hastie, 2005). RR improves OLS estimates by continuous shrinkage of regression coefficients, through applying a λ_2 -penalty on the sum of squares, resulting in increased predictive accuracy through bias variance trade-off (Hoerl & Kennard, 1970). The RR method is defined as follows:

$$\min_{\beta} \sum_{i=1}^{\eta} \left(y_i - \sum_{j=1}^p x_{ij} \beta_j \right)^2 + \lambda_2 \sum_{j=1}^p \beta_j^2$$

On the left, the usual least squares criterion still applies. On the right, the highlighted portion of the formula shows the λ_2 penalty term applied to the sum of the squared magnitude of the coefficients. The larger the λ_2 -penalty, the more severe the penalty imposed on the regression coefficients, and the more they will be shrunk towards zero. However, none of the coefficients will become exactly zero, producing a regression model that is less parsimonious, since all variables are always kept in the model. This is similar to the OLS regression approach, wherein all predictors added into the model will end up explaining some variance in the outcome variable and remain part of the model. This lack of parsimony is more so a problem for large data sets, where the number of predictors are often greater than the number of observations. Typically having a smaller number of predictors to observations in psychological and educational research also face a less severe version of the same problem. Merely having some 10 or 20 moderately correlated variables can become difficult to interpret, particularly when coupled with a large number of interactions (Hindman, 2015). Using traditional least squares procedures with large international assessment data sets, to identify significant student-related and school-related variables that fall in the hundreds, may prove to be ineffective. Despite not being able to produce coefficients of zero weight after shrinkage, RR still shrinks all added predictors as close to zero as possible. RR is also able to handle multicollinearity effectively; it manages to keep all the variables in the model but gives “equal weight to absolutely correlated variables in the data set” (Acharjee et al., 2013, p. 3).

The LASSO method can be defined as follows:

$$\min_{\beta} \sum_{i=1}^{\eta} \left(y_i - \sum_{j=1}^p x_{ij} \beta_j \right)^2 + \lambda_1 \sum_{j=1}^p \|\beta_j\|$$

As can be seen from the highlighted portion, LASSO applies a λ_1 -penalty on the sum of the absolute values of the regression coefficients, which penalises the coefficients until some of them become exactly zero, and are then dropped from the model. Due to the nature of the λ_1 -penalty, the LASSO accomplishes both continuous shrinkage and variable selection concurrently, such that only the most relevant and significant variables are chosen. In other words, fitting a LASSO model will result in a model that typically contains fewer variables than the original number of variables inputted. Any predictor variable that fails to improve prediction performance will be zeroed out. In cases of absolutely correlated regressors, LASSO tends to randomly select only one of these variables, while disregarding the rest (Acharjee et al., 2013).

The EN method is defined as follows:

$$\min_{\beta} \sum_{i=1}^{\eta} \left(y_i - \sum_{j=1}^p x_{ij} \beta_j \right)^2 + \lambda_1 \sum_{j=1}^p \|\beta_j\| + \lambda_2 \sum_{j=1}^p \beta_j^2$$

Drawing on the combination of LASSO and RR, EN was introduced to optimise both λ_1 (i.e. penalty on the sum of the absolute values of the coefficients) and λ_2 (i.e. penalty on the sum of the squares of the coefficients) penalties to do continuous shrinkage and variable selection simultaneously, while also handling multicollinearity, such that highly correlated variables are given similar regression coefficients (Zou & Hastie, 2005). In addition to selecting the optimal λ value, using the EN method allows one to tune the alpha parameter (α); an α of zero corresponds to RR, and an α of one corresponds to LASSO. In other words, using an α of zero reduces the penalty term to a λ_1 -penalty (RR) term and using an α of one reduces the penalty term to a λ_2 -penalty (LASSO) term. Thus, to optimise the EN method, an alpha value between zero and one is typically chosen. This will effectively shrink some of the model coefficients to zero.

Regression Trees (RTs)

Another branch of regression-based ML methods that produce easy-to-interpret models are tree-based methods, such as decision trees. Different methodologies for building decision trees have

been proposed, perhaps the most widely known one being the classification and regression tree (CART) algorithm proposed by Breiman and colleagues (1984). The main objectives of CART is to model an outcome variable from a set of decision rules imposed on the predictor variables (Breiman et al., 1984). CART uses binary recursive partitioning such that these decision rules are determined by repeatedly partitioning the data into successively smaller groups (i.e. subgroups) with binary splits based on one single predictor variable (Prasad et al., 2006). For CART, the best split for each predictor variable is determined by the one that yields maximum homogeneity (i.e. lowest residual sum of squares) at each partition. After partitioning the data consecutively until the stopping criteria has been met (e.g. the maximum depth of the tree), CART then predicts the outcome based on, either the mean of the response values for all observed data that fall in that subgroup (regression problem), or the class that has majority representation within each subgroup (classification problem).

Figure 1. Terminology of a decision tree.

The final decision tree can be represented as a tree diagram (see Figure 1); at the top of the tree, the root node contains all of the training data. At the bottom, the leaves represent a series of terminal nodes that contain the mean responses or majority class, and tree branches represent information flow between adjacent decision nodes determined by splitting rules (Blanch & Aluja, 2013; Prasad et al., 2006). The algorithm for building decision trees allow for trees to be grown to any depth and height; deeper trees tend to have high variance and low bias, while shallower trees tend to

have high bias and low variance (Boehmke & Greenwell, 2019). One danger of having an overly developed tree is overfitting. Hence, CV is required after a tree is grown, to prune the overfitted tree to an optimal size. The application of CV is aimed at obtaining an optimum number of tree levels (or depth) and height, while avoiding drawing any spurious conclusions about the relationships between variables due to overfitting, which leads to problematic use of the trees for out-of-sample prediction and poorer predictive power (Blanch & Aluja, 2013).

Since no *a priori* assumptions about the nature of the associations between predictor and outcome variables need to be specified or met, decision trees allow for the possibility of uncovering interactions and non-linearities between variables. The splitting rules allow for the best mapping of predictors with the largest influence on the tree, providing more insights into the predictors' spatial influence (Iverson & Prasad, 1998; Prasad et al., 2006).

Other closely related tree-based methods, such as bagged, boosted, or ensemble regression trees and random forests, often perform better than CART, but fall under black-box methods due to their lack of an open model structure and thus, are less interpretable. Individual trees in these methods cannot be assessed, which implies that one is unable to know what exactly happens during the growing and pruning of each tree. Some argue that these methods still provide means for interpretation by ranking variables in terms of their relative importance, and are much easier to interpret than say, neural networks models (Prasad et al., 2006).

Use of ML Methods for Predicting Academic Performance

Previous studies have used various techniques to build ML models to make predictions on students' academic performance. This application of ML methods to educational data has been coined, Educational Data Mining (EDM; Romero & Ventura, 2007). Surprisingly, the use of EDM in the prediction of academic performance has predominantly taken place in higher education settings (e.g. Huang & Fang, 2013; Kenekayaro, 2018; Vandamme et al., 2007). From a qualitative review of 64 papers investigating the use of ML techniques applied to the prediction of students' performance, Rastrollo-Guerrero et al. (2020) found that 90% of these papers were published between 2013 and

2019, suggesting that the use of ML in this educational area is fairly new. Most of these studies were conducted at the university level, and only a small proportion at high school levels and below.

Supervised learning techniques, namely support vector machine and artificial neural network, are the most commonly used techniques in these papers. More specifically, support vector machine was identified as the technique used by most authors, and provided the highest accuracy in predictions. In addition, decision trees, naïves bayes and random forests have also been well-studied algorithms that produce good precision in predicting students' performance.

Huang and Fang (2013) compared between four modelling methods, namely multiple linear regression (MLR), multilayer perceptron network, radial basis function network, and support vector machine, to predict undergraduate students' academic performance in an engineering dynamics course. To predict students' final examination grade for the course, the authors used various combinations of eight cognitive predictor variables (i.e. cumulative GPA, grades from four prerequisite courses (statics, calculus I, calculus II, and physics), and grades on three dynamics mid-term examinations) to build several models for each method. Upon comparing the total of 24 models built, the authors found that the models developed with the support vector machine method had the highest percentage of accurate predictions (PAP). The combination of cumulative GPA, grades from the four prerequisite courses, and grades on the first dynamics mid-term examination, as predictors produced the highest PAP (59.1%) for predicting the final examination performance of each student. However, with a sample size of 323 students and only eight predictor variables, all of which are cognitive factors, these models may not depict an accurate representation of the factors that influence academic achievement; thus, resulting in the highest PAP produced by the support vector machine method being relatively low, at 59.1%.

Masci et al. (2018) used multilevel tree-based methods to understand the determinants of students' PISA 2015 performance at the student level and school level. The use of decision trees made it possible to capture complex non-linear relationships between the predictor variables and the outcome. The authors found SES, motivation, and anxiety to be most influential at the student level; at

the school level, the determinants of academic performance largely vary between countries. In most of the countries the authors analysed, the proportion of disadvantaged students is one the most important variables. In general, schools with a higher proportion of disadvantaged students are more likely to produce lower academic performance scores. Based on the partial dependence plot, this relationship does not appear to be exactly linear in most countries. For instance, the authors found that schools in the US with a proportion of disadvantaged students between 0%-20% tend to have similar performance outcomes, but when this proportion increases above 20%, there is a monotonic negative association between the variable and performance outcomes. Indeed, the learning process and outcomes of students is not only influenced by their own and their families' characteristics, but is also largely influenced by their schooling experience and environment.

Though not discussed in any more detail in this paper, classification methods have been used in several studies to predict academic performance. Aluko et al. (2016) collected information regarding prior academic performance in mathematics, physics, chemistry, and local language, from 101 undergraduate students enrolled in an architecture degree course to be used to predict their academic success (i.e. classified as "pass" or "fail") in the course. The authors used two modelling methods, namely K-nearest neighbour (k-NN) and linear discriminant analysis. They found that the k-NN model was more accurate in correctly classifying the academic success of undergraduate architecture students than the linear discriminant analysis model. Similarly, the sole use of prior academic performance as predictors of future academic success ignores the plausible influence of other important non-cognitive factors (e.g. motivational factors, personality, and family background).

Han et al. (2017) employed an ensemble algorithm, AdaBoost, in an attempt to improve the prediction accuracy of students' classification of grades. The authors calculated undergraduates' GPA and took that as an indication of their final grades of several major courses. Their grades were separated into A ($\text{Grade} \geq 90$), B ($75 \leq \text{Grade} < 90$), and C ($\text{Grade} < 75$) levels accordingly. By comparing AdaBoost with several other algorithms, the authors were able to verify the predictive accuracy of the AdaBoost classifier. They found that the decision tree classifier had the worst accuracy

in classification (66.7%), followed by the neural classifier (80.56%), then the random forest (86.11%) and support vector machine (88.89%), and finally, the model built by Adaboost had the highest classification accuracy (91.67%).

Many studies that have been done typically employ less interpretable ML methods (e.g. support vector machine) and focus on getting a high prediction accuracy instead. Almost none of the academic performance prediction studies have been performed with more interpretable regression-based ML methods. One exception was a study by Yoo (2018); the author used the EN method with a large-scale educational data, TIMSS (Trends in International Mathematics and Science Study), to predict primary school students' mathematics achievement scores. By using the EN method, the predictive model shrunk the initial 162 TIMSS variables down to 12 student-related (e.g. math self-efficacy, and home SES) and five teacher-related variables (e.g. collaboration with other teachers) with a prediction accuracy of 76.06%. Yoo (2018) provides preliminary evidence that penalised regression methods, such as EN, can be successfully used with large-scale educational data, by pre-selecting a number of variables, and still give reasonable predictive accuracy. They also demonstrated that new variables that can potentially influence academic achievement may be unveiled when using newer methods.

Interestingly, there are times when such ML methods do not outperform conventional linear regression (e.g. Cornell-Farrow, & Garrard, 2020; Kotsiantis et al., 2004). Several reasons have been put forth; some authors argue that when ML methods are used with sample sizes that are too small, any non-linearities present may go undetected (Huang & Fang, 2013; Kotsiantis et al., 2004). However, using a substantially large data set ($N = 1.2$ million) of primary and secondary school students' performance on a standardised test, Cornell-Farrow and Garrard (2020) still found that ML methods (i.e. EN and classification trees) did not perform better than logistic regression when predicting students at risk of underperforming on the next test. This could be partly due to the limited number of predictors used in this study; the authors only used several indicators of students' demographics (e.g. SES, gender, and age) and prior grades.

Using a large data set from the German GESIS Panel, Vijayakumar and Cheung (2018) compared prediction performance of several ML methods and multiple regression for predicting individuals' well-being, and found that ML methods only performed better than MLR when the underlying structures were complex with non-linear patterns. Thus, evidence points to sample size and number of predictors used as important considerations when comparing between ML methods and conventional methods.

Goals of the Present Study

The present study aims to establish predictive models of academic performance that achieves a balance between prediction accuracy and interpretability; in educational research, it is as important to understand how and what goes into predicting one's performance as it is to arrive at a prediction value of one's performance. This will be accomplished through a comparison between ML models, specifically, regression-based ML models (i.e RR, LASSO, EN, and RTs), and traditional MLR models. We test the viability of using regression-based ML methods to analyse large-scale educational data, for the purpose of understanding the factors involved in academic performance prediction and for predicting out-of-sample academic performance on the PISA.

Therefore, the goal of the present study is to investigate and explore if regression-based ML methods improve predictive accuracy as opposed to traditional MLR approaches when used in predicting students' academic performance (RQ1), and which student-related and school-related factors influence students' achievement (RQ2).

This current study will add on to the existing literature in several ways: (a) instead of focusing on a few pre-selected predictors, we will instead utilise a wide range of predictors available on the PISA; (b) instead of only taking a subset of participants (i.e. based on country) from the PISA, we aim to have large enough sample size by including a representative sample of students from around the world; and (c) with the wide variety of predictors present, instead of only taking student-related variables, we will also include school-related variables and their interactions.

Chapter 2

Methods

We develop and compare between MLR, RR, LASSO, EN, and RT models in their fit to the PISA 2015 data set.

PISA 2015 Data

The Programme for International Student Assessment (PISA), one of several international standardised assessments, is a collaborative effort to assess how well 15-year-old students around the world are prepared for the challenges of today's knowledge society (Organisation for Economic Co-operation and Development [OECD], 2016). To succeed on this test, students not only have to be equipped with curriculum-based knowledge, but will also need to demonstrate their ability to apply adequate skills and knowledge to real-life problems (OECD, 2017).

PISA has taken place every three years since 2000, and in 2015, a total of 35 OECD countries and 37 other partner countries participated in the PISA, and more than 500,000 students were assessed. PISA is widely regarded as a means for connecting students' performance outcomes with their backgrounds, the characteristics of students, their environment, and their educational system (OECD, 2017). The outcomes on PISA are thought to offer insights for educational policies across countries, as PISA results may reveal the practices and characteristics of high performing students and education systems. The availability of such a large data set in the educational research field may allow for extraction of useful information for successful prediction of academic performance.

There is no minimum or maximum score in PISA; instead, results are scaled to approximate a normal distribution with a mean of around 500 and standard deviation of around 100. In statistical terms, a one-point score difference is equivalent to a Cohen's d effect size of 1% (OECD, 2016). For PISA 2015, the mean scientific literacy score for OECD countries, against which each country's science performance is compared to, is 493 and the standard deviation is 96 (OECD, 2016). OECD (2016) reported that the national average across 70 countries ranged from 332 to 556 in PISA 2015.

In each cycle, PISA focuses on a specific subject domain (i.e. reading literacy, mathematics literacy, or scientific literacy). Scientific literacy was the main assessment domain in PISA 2015. Scientific literacy refers to one's knowledge and skills in science and science-based technology, and matters in today's knowledge society as students are being confronted with vast amounts of scientific knowledge on a regular basis. Thus, there is an increased demand on one's ability to make sense of the scientific knowledge available, carry out scientific enquiry, and discern and evaluate scientific data and claims on its quality and accuracy. Tapping on the vast amount of data available from the PISA 2015 assessment, we use the data of these 15-year-olds to predict scientific literacy by using various student-related and school-related variables.

Measures

Outcome Variable

Instead of a single estimate of each student's scientific literacy abilities, PISA provides 10 plausible values (PVs) generated from an estimated distribution of outcomes that could be reasonably assigned to each student (see [OECD, 2017] for more details). Since students have to complete the PISA test in two hours across all subject domains, each student only answers a subset of test items from the item pool. Thus, to generate population-level performance estimates from this arrangement where students only take a number of test items, PV scores are imputed (OECD, 2017). From these 10 PVs in scientific literacy, we used the first PV of each student (*PV1SCIE*) as the measure of that student's scientific literacy performance. OECD (2009) cautioned against the use of the average of the 10 PVs as that may lead to biased results. Instead, the use of one or all 10 PVs is recommended to ensure an unbiased estimate of population parameters; in a large sample, the use of a single PV or 10 PVs does not make a significant difference.

Independent Variables

Instead of only selecting literature-based predictors for the current study, which could mask new interesting patterns or relationships, we took an exploratory route and aimed to use most of the available variables from the PISA data. In general, these variables map onto broad categories of

demographics, family and home SES, psychological factors, sociocultural influences, and school-related factors (see Appendix A for details of these predictor variables).

Variables used in the present study were chosen on the basis of availability of data; variables with more than 15% of missing values were dropped. This was a way to ensure greater informative potential and higher quality and validity of statistical inferences. Hence, omitting variables with a 15% or greater missing rate was acceptable, while still managing to retain most variables for our analyses. We arrived at a final input predictor size of 66.

PISA develops a series of numerical scales to collect information on various student and school variables. Student-related variables such as enjoyment of science (*JOYSCIE*), instrumental motivation for science (*INSTSCIE*), epistemological beliefs of science (*EPIST*), perceived sense of belonging to school (*BELONG*), and awareness of environmental matters (*ENVAWARE*), are measured on a four-point Likert scale with several statements (OECD, 2017). Students then indicate the extent to which they agree or disagree with the respective statements. School-related variables such as educational leadership (*LEAD*), teacher-related factors affecting school climate (*TEACHBEHA*), and shortage of educational material (*EDUSHORT*), are measured on a four- or six-point Likert scale. Principals will respond by indicating the extent to which they agree or disagree to the respective statements. Answers from these statements are then used to represent one underlying construct (or variable), and scaling methods were applied to construct meaningful indices (OECD, 2017). The constructs, as opposed to individual statements, will be used to build the various predictive models. As opposed to the aforementioned variables that are scaled indices, there are some other student-related and school-related variables that are simple questionnaire items; hence, these are unstandardised and not scaled (e.g. *SC034Q03TA* - How often are students assessed with teacher-developed tests?)

The index of SES (i.e. *ESCS* in the PISA data) was computed slightly differently. Principal component analysis (PCA) was used to obtain the *ESCS* values from the constructs of highest parental

education (*hisei*), parental occupation (*PARED*), and home possessions (*HOMEPOS*). Missing data on one of the three constructs was imputed by running a regression on the two other available data.

Data Preprocessing

As mentioned above, the raw data available for PISA 2015 were initially a mixture of standardised and unstandardised scales of measurement. Variables such as *EPIST*, *SCIEEFF*, or *TEACHBEHA* are scaled indices, while data for variables such as *TOTAT*, *TOTST*, or *AGE* are retained in their original unstandardised units. Data preprocessing, a crucial step prior to conducting MLR and penalised regression analyses, was performed on the raw data to avoid having any one variable receiving either a higher or lower weight for its coefficient resulting from the initial high or low measurement scale, and to allow for easier interpretation and comparison of coefficients.

Data preprocessing was conducted as such: First, all predictor variables which were not standardised were first standardised. Second, variables that were coded as ‘1’ or ‘2’ were dummy coded such that they now took on the values of ‘0’ or ‘1’ respectively. Third, variables that had numerical values albeit being a categorical variable were converted to factors.

Data Analyses

All statistical analyses were performed using the statistical software R 3.6.0 (R Core Team, 2019). For this study, we made use of *caret* (v6.0-86; Kuhn, 2020), *corrplot* (v0.84; Wei & Simko, 2017), *data.table* (v1.12.8; Dowle & Srinivasan, 2019), *doParallel* (v1.0.15; Microsoft Corporation & Weston, 2019), *ggeffects* (v0.15.1; Lüdtke, 2018), *ggplot2* (v3.3.2; Wickham, 2016), *parallel* (R Core Team, 2019), *pdp* (v0.7.0; Greenwell, 2017), *psych* (v1.9.12; Revelle, 2019), *stats* (R Core Team, 2019), and *tidyverse* (v1.3.0; Wickham et al., 2019) helper packages. Specific modelling packages are mentioned below. Reproducible R-scripts, and data files for our analyses can be found here (<https://osf.io/ngdz8/>), while the complete PISA data files can be found here (<https://www.oecd.org/pisa/data/2015database/>).

Missing Data

The reasons for missing data in the PISA study typically occurred due to *missing by design* or item non-response; when some items did not apply to certain subsamples of respondents, or are intentionally skipped or left unanswered, the data is therefore missing (OECD, 2016). Rubin (1976) described three mechanisms of missing data, namely missing-completely-at-random (MCAR), missing-at-random (MAR), and missing-not-at-random (MNAR). The former two missing data mechanisms are ignorable because the probability of missingness is deemed as random (Little & Rubin, 2002). However, MNAR is not ignorable since the probability of missingness is not random, but depends on the missing value itself.

Dong and Peng (2013) highlighted that both large proportions of missing data and missing data deriving from a missing-not-at-random (MNAR) mechanism would introduce bias into our models, compromise the predictive models, and have a detrimental effect on the results or any interpretations made of the results. Although there is yet an established cut-off for the acceptable proportion of missing data in a data set, previous studies have reported that a missing rate smaller than 5% in a large sample has little consequences on the analyses (Tabachnick & Fidell, 2007), while having a missing rate of more than 10% is more likely to result in biased analyses (Bennett, 2001).

Although a much bigger problem than the proportion of missing data is the possibility of missing-not-at-random (MNAR) data, which might be an explanation for some of the missing data in the PISA study, we found a small percentage of missing responses at an individual level (7.43%), and not an extremely large correlation between missing and observed data ($r = .37$). Hence, it could be reasonably assumed that the missing data in our data set are deriving from at least a missing-at-random (MAR) mechanism. In general, most missing data analysis approaches would assume that one's data is at least MAR, although from a practical stance, it is almost impossible to prove that the data is MAR or MCAR.

For the purpose of this study, complete cases analysis (CCA) was performed (i.e. we only used observations with complete data), and no additional missing data imputations were carried out.

CCA is sometimes discouraged because removing rows of observations results in information loss. However, we still managed to retain a sample size of 198,712 after CCA which meant that there was still sufficient statistical power to prevent estimation bias for the model parameters and standard errors (De Jong et al., 2010).

K-fold Cross-Validation (CV) for data with hierarchical structures

In the current study, we used k-fold CV to estimate the prediction errors of the models built. All CV performed in this paper were unrepeated 5-fold CV; using an unrepeated process with five is a commonly used number of folds in large samples as it provides a good compromise between computational speed and bias (Hastie et al., 2009).

We attempted to account for the nested or hierarchical structure of the PISA data by ensuring that students from the same schools were placed in the same CV fold. Students from the same schools are inherently similar to a certain extent, and treating them as independent observations when performing CV will seriously underestimate predictive errors and increase the chances of constructing an overfitted model that does not predict unseen data well (Roberts et al., 2017). To account for the similarity between students of the same school (i.e. dependency in observations), we performed k-fold CV with the *groupdata2* (v1.3.0; Olsen, 2020) and *rsample* (v0.0.7; Kuhn et al., 2020) packages that were suitable for data with hierarchical structures.

The data set was first split into a 70% cross-validation set and 30% validation set. Of the 70% data in the cross-validation set, the data is strategically split into five approximately equally sized folds, using country-school-id (*CNTSCHID*) as an identifier to ensure that students of the same schools are placed in the same fold. Each time, one fold is used as the testing set while all other four folds are used as training data sets in order to tune the model hyperparameters and fit the model. To evaluate the performance of the established cross-validated model, the most optimal set of hyperparameters were identified and applied to the validation data set.

Prediction Accuracy

All established models were evaluated for their ability to make accurate predictions on the validation data set; a comparison of prediction accuracy of the various models was done. Since our outcome variable is measured as a continuous variable, prediction accuracy and performance of the predictive models were assessed with several continuous error metrics, namely root mean square error (RMSE), mean absolute error (MAE), and R^2 (Sandoval et al., 2018). The RMSE refers to the square root of the average squared difference between the predicted and actual values. A rather similar error metric, the MAE refers to the average absolute difference between the predicted and actual values. These two standard error metrics signify how well, on average, a model fits unseen test data in units of the outcome variable (lower is better). However, the RMSE and MAE differ in the weight given to larger errors; since errors are squared before being averaged, larger errors are weighted more highly in the RMSE metric (Li & Shi, 2010). This is more beneficial when larger errors are not as desirable. The R^2 metric, commonly used in psychology and social science research, is interpreted as the proportion of the variance in the outcome variable that is explained by the model (higher is better).

Predictive Models of Academic Performance

All models built used a single PV, more specifically the first PV (*PVISCIE*), for scientific literacy as the outcome variable. All models had 24 student-related variables and 42 school-related variables as input variables. To assess for possible interactions, interaction terms between all variables were specified, except in the RT model. Since tree-based models consider predictors sequentially, the RT algorithm automatically considers possible interactions without the need to explicitly specify them. A total of six models were trained and tested for their ability to predict students' scientific literacy performance.

Multiple Linear Regression (MLR) Models

MLR attempts to account for the effect of multiple predictor variables on an outcome variable and determines a linear quantitative relationship between them (Field, 2005). Two MLR models were developed for the present study; both models were identical with the exception of CV being carried

out for only one of the models. The absence of any form of CV would mimic how the vast majority of psychological and educational research currently operates. In the present study, the MLR model with CV was developed with the *cvms* package (v1.0.2; Olsen & Zachariae, 2020).

Penalised Regression Models

Three models were developed, one for each of three penalised regression methods (i.e. RR, LASSO, and EN). Each model used a fixed alpha parameter (α) of 0 for RR, 1 for LASSO, and 0.5 for EN, while an extensive grid search with 5-fold CV was executed to determine the optimal penalty hyperparameter, λ , in each model. All penalised regression models were developed with the *glmnet* package (v4.0; Friedman et al., 2010).

Regression Tree (RT) Model

Since the outcome variable is measured on a continuous scale, a regression tree (RT) was developed using the CART algorithm. We developed the RT model using the *tidymodels* package (v0.1.0; Kuhn & Wickham, 2020). Hyperparameters namely, maximum tree depth, minimum terminal node size, and complexity parameter (cp), were estimated with a grid search and 5-fold CV. All three hyperparameters determined the stopping rules for how large the tree could become. The maximum tree depth value refers to the maximum distance between the root node and terminal node; a deeper tree increases the chance of the model overfitting. The minimum terminal node size refers to the minimum number of observations for each terminal node; a smaller node size makes the model prone to overfitting. The cp serves as an indication of balance between tree size and predictive accuracy, and is used for both growing and pruning the tree (Prasad et al., 2006). When the cp gets too small, there is an increased chance of overfitting; on the other hand, a cp value that is too large results in an extremely small tree. In both cases, the predictive performance of the model will be affected.

Chapter 3

Results

The present study compared between five different modelling methods (i.e. MLR, RR, LASSO, EN, and RT) in terms of their accuracy in predicting students' academic performance on the PISA.

Descriptive Analysis

After removing predictors with more than 15% of missing data, and using CCA, our final sample consists of 101,815 females and 96,897 males (51.23% females; $N_{\text{total}} = 198,712$) from 60 countries¹. Although this sample size is just slightly more than one third of the original full sample of PISA 2015 ($N_{\text{PISA 2015}} = 519,334$), on average, students from the sample we analysed scored 492 ($SD = 96.87$), which is no different from the reported OECD countries' average of 493 ($SD = 96$). Amongst the 60 countries, Singapore had the highest academic performance average of 563 ($SD = 97.51$) while Dominican Republic had the lowest average of 371 ($SD = 73.55$). Descriptive statistics for the sample analysed can be found in Table 1. Figure 2 includes a correlation matrix between most highly correlated variables; to prevent overplotting, only correlated variables with a correlational value above .5 were presented with a coloured circle (Williams, 2020).

Table 1
Descriptive statistics of PISA sample

	Scientific Literacy Mean (<i>SD</i>)
<i>Gender</i>	
Female ($N = 101,815$)	488 (93.52)
Male ($N = 96,897$)	495 (100.13)
<i>Country</i>	

¹ Country, as a variable, was used only for reporting descriptive statistics of our sample. It has not been included in any other analyses. This was done as it has been established, from previous studies, that originating from different countries would be a significant explaining factor for differing performance in students. However, we wanted to capture the deeper and underlying nuances at the school and student level; hence, lest it overwhelms our results, 'country' was excluded as a predictor of students' academic performance.

ARE - United Arab Emirates ($N = 5472$)	458 (96.54)
BEL - Belgium ($N = 1197$)	528 (81.23)
BGR - Bulgaria ($N = 2912$)	476 (90.67)
BRA - Brazil ($N = 3619$)	432 (82.14)
CAN - Canada ($N = 9059$)	533 (86.01)
CHE - Switzerland ($N = 1802$)	515 (93.72)
CHL - Chile ($N = 2917$)	482 (83.99)
CRI - Costa Rica ($N = 2883$)	429 (68.32)
CZE - Czech Republic ($N = 4505$)	525 (92.37)
DEU - Germany ($N = 1404$)	540 (90.13)
DNK - Denmark ($N = 2404$)	510 (86.41)
DOM - Dominican Republic ($N = 1603$)	371 (73.55)
DZA - Algeria ($N = 1554$)	392 (71.08)
ESP - Spain ($N = 3287$)	513 (84.65)
EST - Estonia ($N = 3849$)	545 (85.33)
FIN - Finland ($N = 3527$)	544 (90.91)
FRA - France ($N = 2095$)	533 (88.19)
GBR - United Kingdom ($N = 5105$)	529 (88.51)
GEO - Georgia ($N = 1927$)	430 (87.31)
GRC - Greece ($N = 2803$)	480 (85.73)
HKG - Hong Kong ($N = 2474$)	545 (76.75)
HRV - Croatia ($N = 3760$)	494 (84.20)
HUN - Hungary ($N = 2624$)	503 (86.58)
IDN - Indonesia ($N = 3013$)	416 (69.53)
IRL - Ireland ($N = 2775$)	517 (84.24)
ISL - Iceland ($N = 1615$)	490 (88.45)
ITA - Italy ($N = 4961$)	510 (84.1)
JOR - Jordan ($N = 3401$)	431 (77.21)

KOR - Korea (<i>N</i> = 4164)	526 (91.85)
KSV - Kosovo (<i>N</i> = 2432)	386 (70.74)
LBN - Lebanon (<i>N</i> = 952)	418 (88.66)
LTU - Lithuania (<i>N</i> = 4502)	485 (86.96)
LUX - Luxembourg (<i>N</i> = 2065)	507 (98.65)
LVA - Latvia (<i>N</i> = 3104)	501 (77.96)
MAC - Macao (<i>N</i> = 3023)	532 (82.03)
MDA - Moldova (<i>N</i> = 2836)	444 (82.57)
MEX - Mexico (<i>N</i> = 3929)	427 (70.55)
MKD - FYROM (<i>N</i> = 1584)	392 (83.18)
MLT - Malta (<i>N</i> = 1110)	486 (103.60)
MNE - Montenegro (<i>N</i> = 3080)	436 (81.43)
NLD - Netherlands (<i>N</i> = 1382)	522 (95.28)
PER - Peru (<i>N</i> = 3293)	413 (71.73)
POL - Poland (<i>N</i> = 3221)	509 (87.43)
PRT - Portugal (<i>N</i> = 2370)	528 (91.88)
QAR - Argentina (Ciudad Autónoma de Buenos) (<i>N</i> = 878)	495 (79.59)
QAT - Qatar (<i>N</i> = 4615)	445 (95.69)
QCH - B-S-J-G (China) (<i>N</i> = 6898)	547 (91.99)
QES - Spain (Regions) (<i>N</i> = 16013)	512 (84.69)
ROU - Romania (<i>N</i> = 3605)	443 (76.92)
RUS - Russian Federation (<i>N</i> = 4156)	499 (80.32)
SGP - Singapore (<i>N</i> = 3808)	563 (97.51)
SVK - Slovak Republic (<i>N</i> = 3603)	484 (89.76)
SVN - Slovenia (<i>N</i> = 1434)	511 (92.13)
TAP - Chinese Taipei (<i>N</i> = 4873)	546 (96.00)
TTO - Trinidad and Tobago (<i>N</i> = 1870)	449 (86.75)
TUN - Tunisia (<i>N</i> = 1046)	396 (68.65)

TUR - Turkey ($N = 3785$)	433 (75.96)
URY - Uruguay ($N = 3123$)	469 (83.37)
USA - United States ($N = 2797$)	513 (93.42)
VNM - Vietnam ($N = 4614$)	530 (75.24)

Figure 2. Correlation matrix for the most highly correlated variables ($.51 < r_s < .97$). Note that absolute correlations were also not plotted.

Model Accuracy

In general, all six models had quite similar performance in predicting students' science performance on the PISA with R^2 ranging from .38–.49, RMSE ranging from 69.79–76.40, and MAE ranging from 55.54–60.68. Despite the model using the RT method being an exception and performing slightly worse ($R^2 = .38$, RMSE = 76.15, MAE = 60.68), none of the models appear to

significantly outperform the rest. Of the five methods, the model developed with the LASSO ($R^2 = .48$, $RMSE = 69.91$, $MAE = 55.64$) and EN ($R^2 = .48$, $RMSE = 69.88$, $MAE = 55.61$) methods performed the best, albeit a very minor improvement from the other models. The results for each method are reported in Table 2.

The traditional MLR model which included all predictors and all two-way interactions between variables without CV was found to be statistically significant, $F(2344, 196367) = 77.57$, $p < .001$, and accounted for 47% variance in scientific literacy scores. Considering the sheer number of predictors that have been added into the model, it is not surprising to obtain a model that provides a better fit to the data than one that contains no predictor variables (i.e. the null model). The MLR model with 5-fold CV was also found to be statistically significant, $F(2344, 136551) = 54.99$, $p < .001$, and accounted for 49% variance in scientific literacy scores. The model was able to be replicated in our validation data set fairly well.

Three separate grid searches performed with 5-fold CV found and applied the shrinkage parameter lambda (λ) of 5.04 on the RR model, a λ of 0.05 on the LASSO model, and a λ of 0.09 on the EN model. All three penalised regression models replicated well in the validation data set. Figure 3 shows the 5-fold CV results of the mean squared error (MSE) measure. The values above the plot indicate the number of non-zero coefficients with increasing $\log(\lambda)$ values on the X-axis. The dotted lines in each plot represent the λ value which produces the smallest cross-validated MSE (left line), and the λ value which produces the cross-validated MSE that is within one-standard error of the smallest cross-validated MSE (right line). To decrease the probability of overfitting, the latter λ value was used to build the models. The number of non-zero coefficients that remain in the model based on the λ value which produces the smallest cross-validated MSE is lowest for the LASSO model ($k = 1720$), followed by the EN model ($k = 1758$), then the RR model ($k = 2344^2$). Figure 4 shows coefficients' paths with increasing values of the shrinkage tuning parameter lambda (λ) for each model. Every curved line represents one predictor. The decreasing values above each plot also

² Since RR shrinks model coefficients towards zero, but is unable to shrink them to exactly zero, the number of coefficients that remain in the model after the L1 penalty is imposed does not change or decrease.

indicate the number of non-zero coefficients that remain in the model with increasing $\log(\lambda)$ values on the X-axis.

One RT model was built, however that model performed most poorly in terms of being able to predict students' performance. Generally, it is widely known that individual decision trees do not typically achieve exceptional predictive accuracy. This is a result of decision trees being composed of simple binary yes-or-no splitting rules that create rigid non-smooth decision boundaries (Boehmke & Greenwell, 2019). Thus, practitioners commonly combine multiple trees together (i.e. ensemble tree methods) to achieve better prediction accuracy, while compromising on interpretability. The grid search found and selected the best hyperparameters (i.e. maximum tree depth, minimum terminal node size, and cp) through 5-fold CV. The RT was built to a maximum depth of 13, had at least 31 observations for each terminal node, and used a cp of 0.00016. Although this single RT was fairly large with a very small cp, the RT model replicated fairly well in the validation data set, indicating that there was not much overfitting in the model.

Table 2

Prediction accuracy from five modelling methods for all six models

Method	CV (<i>N</i> = 138896)			Validation (<i>N</i> = 59816)			Without CV (<i>N</i> = 198712)		
	R ²	RMSE	MAE	R ²	RMSE	MAE	R ²	RMSE	MAE
MLR							.47	70.21	55.55
MLR	.49	76.40	60.40	.48	74.40	59.0			
RR	.47	70.29	55.97	.43	73.83	58.79			
LASSO	.48	69.91	55.64	.43	73.46	58.43			
EN	.48	69.88	55.61	.43	73.50	58.47			
RT	.38	76.15	60.68	.33	79.61	63.52			

Note. CV = cross-validation; RMSE = root mean square error; MAE = mean absolute error.

Models in bold indicate the methods that produced the best predictive accuracy.

Figure 3. 5-fold CV results of the relation between MSE and $\log(\lambda)$. From left to right: RR, LASSO, EN.

Figure 4. Model coefficients vs. shrinkage parameter λ (λ). From left to right: RR, LASSO, EN.

Variable Importance

Of particular interest to the current study was finding the variables most important for predicting students' performance in each method, and understanding the nature of the relationship between scientific literacy performance and various predictor variables. Table 3 lists the 10 most important and influential variables in each model. 18 of these variables were overlapping and shared between the different methods, while 11 predictor variables were single occurring variables.

Figure 5 and 6 shows the partial effects of one or two predictor variable(s) on the predicted outcome measure while simultaneously accounting for all other variables in the MLR models. Figures 7–10 includes partial dependence plots to aid our understanding of the nature of the relationship between scientific literacy performance and the 10 most important predictor variables for each regression-based ML model. A partial dependence plot examines the marginal effect one or two predictor variable(s) have on the predicted outcome measure while simultaneously accounting for all other variables in the model (Friedman, 2001). Through such partial dependence plots, one is able to visualise whether the relationship between a predictor and the outcome is linear, non-linear, or even more complex (Molnar, 2018). Hence, when applied to a linear model such as MLR, or penalised regression, the partial dependence plots always show a linear relationship.

In general, home possessions (*HOMEPPOS*) emerged constantly as one of the most important variables in each model. All models report *HOMEPPOS* as being positively related with scientific literacy scores. Although *HOMEPPOS* was one of the constructs used to obtain the *ESCS* values through PCA, *ESCS* was only one of the top most influential variables for the traditional MLR without CV and RT models. Surprisingly, *ESCS* was found to be negatively related to scientific literacy performance in the MLR model; students from families with higher SES are associated with poorer science performance. Additionally, although family wealth (*WEALTH*) is a subset of *HOMEPPOS*, the LASSO and EN models found *WEALTH* to be negatively related with science performance. This will be discussed at length in our discussion.

Table 3

Model	Variable									
	1	2	3	4	5	6	7	8	9	10
MLR	TOTST ($\beta = 7474.7$)	TOTAT ($\beta = -4775.23$)	PROSTAT ($\beta = -3994.3$)	TOTAT*PROSTAT ($\beta = -3409$)	HOMEPOS ($\beta = 72.68$)	GRADE*ESCS ($\beta = -59.57$)	<i>SCHSIZE</i> ($\beta = 53.94$)	ESCS ($\beta = -52.10$)	ESCS*LEAD ($\beta = 48.36$)	<i>ESCS*PARE D</i> ($\beta = -46.08$)
MLR (with CV)	TOTST ($\beta = 9616.65$)	TOTAT ($\beta = -6109.32$)	PROSTAT ($\beta = -5142.89$)	TOTAT*PROSTAT ($\beta = -4397.29$)	ESCS*LEAD ($\beta = 84.67$)	ESCS*SCHLTYPE3 ($\beta = -78.53$)	<i>ESCS*TOTAL</i> ($\beta = 67.82$)	GRADE*ESCS ($\beta = -61.13$)	<i>ESCS*SCHSIZ E</i> ($\beta = -56.71$)	HOMEPOS ($\beta = 52.89$)
RR	REPEAT ($\beta = -21.51$)	<i>REPEAT*SCHLTYPE3</i> ($\beta = -12.02$)	HOMEPOS ($\beta = 11.79$)	IMMIG3*REPEAT ($\beta = 11.24$)	EPIST ($\beta = 10.95$)	<i>TOTST*SCHLTYPE2</i> ($\beta = 10.62$)	ST022Q01TA ($\beta = -9.89$)	SCHLTYPE2 ($\beta = 9.75$)	HOMEPOS*SCHLTYPE3 ($\beta = 9.33$)	<i>WEALTH*SCHLTYPE3</i> ($\beta = -9.04$)
LASSO	HOMEPOS ($\beta = 47.74$)	WEALTH ($\beta = -34.26$)	REPEAT ($\beta = -32.32$)	EPIST ($\beta = 15.62$)	HOMEPOS*SCHLTYPE3 ($\beta = 13.90$)	ST022Q01TA ($\beta = -13.69$)	ESCS*SCHLTYPE3 ($\beta = -13.15$)	GRADE ($\beta = 12.91$)	TOTST ($\beta = 12.85$)	SCHLTYPE2 ($\beta = 12.49$)
EN	HOMEPOS ($\beta = 43.02$)	REPEAT ($\beta = -32.19$)	WEALTH ($\beta = -30.65$)	HOMEPOS*SCHLTYPE3 ($\beta = 16.79$)	EPIST ($\beta = 15.63$)	ST022Q01TA ($\beta = -13.67$)	GRADE ($\beta = 12.88$)	SCHLTYPE2 ($\beta = 12.46$)	TOTST ($\beta = 12.16$)	IMMIG3*REPEAT ($\beta = 12.00$)
RT ⁺	HOMEPOS	EPIST	WEALTH	<i>ENVAWARE</i>	<i>ICTRES</i>	ESCS	<i>HEDRES</i>	TOTST	REPEAT	<i>SCIEEFF</i>

Note. ⁺Variable importance based on the total reduction in MSE for the RT. * denotes an interaction effect between two variables. Overlapping variables are colour coded, while single occurring variables are italicised.

In the two models trained using the conventional MLR method, the four most important predictors of students' performance namely, total number of science teachers (*TOTST*), total number of teachers (*TOTAT*), proportion of science teachers (*PROSTAT*), and the interaction between *TOTAT* and *PROSTAT* were highly correlated variables. In contrast, none of these variables, with the exception of *TOTST* in the LASSO, EN and RT models, emerged as most important predictors with the other methods. This points to a stark difference in the way different methods manage with highly correlated variables.

The MLR models produced several regression estimates that were somewhat baffling. First, it was clear that the regression coefficients obtained for the first four variables in both MLR models ($-3409 > \beta_s > 7474.7$) are much larger than what we would expect with an average science score of 492. Second, while the total number of science teachers (*TOTST*) was positively associated with better science performance, the proportion of science teachers (*PROSTAT*) produced a negative association with science performance. A possible explanation for these baffling results is the presence of excessive multicollinearity between predictor variables, which resulted in extremely unstable regression estimates.

Of the top most important variables, *HOMEPOS* and *SCHSIZE* was found to be positively related to science performance in the traditional MLR model that was not cross-validated; students with more household possessions and who are in a larger school are more likely to achieve better science scores. *ESCS*, surprisingly, was negatively related to science performance. However, this was qualified by interactions between *ESCS* and one's grade compared to modal grade in country (*GRADE*), *ESCS* and *LEAD*, and between *ESCS* and *PARED*. In other words, the size of the effect of *ESCS* depends on the levels of *GRADE*, *LEAD*, and *PARED*, respectively. The MLR model that was cross-validated identified similar important variables, with the addition of two other interactions between *ESCS* and *TOTAT*, and between *ESCS* and *SCHLTYPE*.

Figure 5. Partial effect plots of the MLR model without CV. Each plot shows the relationship between each of the 10 most important predictors and predicted scientific literacy scores.

Figure 6. Partial effect plots of the MLR model with 5-fold CV. Each plot shows the relationship between each of the 10 most important predictors and predicted scientific literacy scores.

In all models built with regression-based ML methods, the presence of grade repetition (*REPEAT*), and epistemological beliefs about science (*EPIST*) were found to be important predictors of students' performance. These were, however, not found for conventional MLR models.

Consistent across the RR, LASSO, and EN models were the variables *HOMEPPOS*, *REPEAT*, *EPIST*, language spoken at home (*ST022Q01TA*), the second school type (*SCHLTYPE2*; private government-dependent schools), and the interaction between *HOMEPPOS* and public schools (*HOMEPPOS*SCHLTYPE3*). *REPEAT* and *ST022Q01TA* were found to be negatively related to science performance; having repeated a grade or speaking a language at home that is different from the language of the test is associated with lower scores on scientific literacy. Conversely, *HOMEPPOS*, *SCHLTYPE2*, and *HOMEPPOS*SCHLTYPE3* were found to be positively related to science performance; possessing more or better household items (however, this is also dependent on whether one is schooling at public school or not), or schooling at private government-dependent schools is associated with higher scores on scientific literacy.

There were several variables picked out by individual penalised regression models that were not found in the other models. In the model built by the RR method, three two-way interactions were identified as important variables. One of which is the relationship between *REPEAT* and science performance that was moderated by *SCHLTYPE3*. The likelihood of students who have had to repeat a grade scoring lower on scientific literacy depends on the school they attend; attending a public school is associated with poorer performance. *GRADE* was found to be an important predictor of science performance in the LASSO and EN models. Students with better grades compared to modal grades in their country (*GRADE*) were more likely to score better.

Figure 7. Partial dependence plots of the RR model. Each plot shows the relationship between each of the 10 most important predictors and predicted scientific literacy scores.

Figure 8. Partial dependence plots of the LASSO model. Each plot shows the relationship between each of the 10 most important predictors and predicted scientific literacy scores.

Figure 9. Partial dependence plots of the EN model. Each plot shows the relationship between each of the 10 most important predictors and predicted scientific literacy scores.

The RT model picked out several student-related variables, namely one's awareness of environmental matters (*ENVAWARE*), presence of technological resources at home (*ICTRES*), presence of educational resources at home (*HEDRES*), and science self-efficacy (*SCIEEFF*), that were not present in the top most important predictors of the other models. These three predictors were found to have non-linear relationships with science performance. For example, students with very poor awareness of environmental issues (< -2 *SD* below average) typically have similar performance outcomes, but when their environmental awareness increases above -1 *SD*, there is a monotonic positive association between *ENVAWARE* and science performance outcomes. In terms of students' science self-efficacy (*SCIEEFF*), as self-efficacy increases from -4 *SD* below the average to an average level, there are short bursts of monotonic increases in science performance. However, at high

levels of self-efficacy (i.e. above the mean of 0), there is no longer an increase in performance and students have similar performance outcomes, regardless of whether they have a mean self-efficacy level or self-efficacy 2 *SD* above average.

From the best fitted RT model, the tree output provides various information about the different splits. For instance, starting with 138,896 observations at the root node, the first variable that produces the initial split (i.e. the first variable producing the largest reduction in MSE) is *HOMEPOS*. At this first node, all observations ($N = 46,668$) with *HOMEPOS* values less than -0.64 follow through to the second branch. The average scientific literacy scores for this group of observations is 451. Observations ($N = 92,228$) with *HOMEPOS* values more than or equal to -0.64 follow through to the third branch instead. The average scientific literacy scores for this group of observations is then 512. In other words, this demonstrates that *HOMEPOS* is an important predictor for science performance on the PISA with those having better quality or more household possessions scoring slightly more than half a standard deviation better.

The second variable producing the largest reduction in MSE is *EPIST*. All observations ($N = 48,447$) with *EPIST* values less than -0.13 follow through to the next branch and have an average scientific literacy score of 487, while observations with *EPIST* values more than or equal to -0.13 follow through to the another branch instead and this group has an average scientific literacy score of 541. Basically, this shows that those who endorse less sophisticated (i.e. lower than average) *EPIST*, also score less than average science performance, while students who hold more sophisticated *EPIST*, generally score above average in scientific literacy. See Appendix B for the full RT output.

Figure 10. Partial dependence plots of the RT model. Each plot shows the relationship between each of the 10 most important predictors and predicted scientific literacy scores.

Although the RT algorithm is able to consider possible interactions without them having to be explicitly specified, we were limited by the functions available in the *tidymodels* package³ for CART and computational memory of the author's device. Instead, we visualised some of these interactions between the most important predictors variables and predicted science performance with partial dependence plots. Figure 11 shows the six most notable interactions between the top most important variables.

The relationship between *HOMEPOS* and science performance was moderated by *EPIST*. With more household possessions (*HOMEPOS*), the probability that a student would perform better than average depends on the sophistication of one's epistemological beliefs (*EPIST*), wherein endorsing more sophisticated epistemological beliefs produces better science performance. An

³ We used *tidymodels* to build our RT as other packages available for CART analyses (e.g. *rpart*) are unable to accommodate k-fold CV for hierarchically structured data. Using *tidymodels*, we are able to develop the model with hyperparameters tuned with strategically grouped k-fold CV, but are then unable to test all possible two-way interactions due to exhaustion in computational memory.

interaction between *ICTRES* and *WEALTH* on science performance was also found. When one possesses a great deal of technological resources at home, the probability that a student would perform better in scientific literacy depends on one's familial wealth, with an average wealth status proving to be associated with better performance. Additionally, the relationship between *EPIST* and science performance was found to be moderated by *ENVAWARE*. With more sophisticated epistemological beliefs (*EPIST*), the likelihood that a student would perform better than average depends on the one's awareness of various environmental issues (*ENVAWARE*), wherein a greater level of environmental awareness is associated with better science performance. Furthermore, the relationship between *EPIST* and science performance, *ENVAWARE* and performance, and *HOMEPOS* and performance, was moderated by *SCIEEFF*. In all three interactions, when students endorse more sophisticated epistemological beliefs (*EPIST*), or have a greater awareness of various environmental issues (*ENVAWARE*), or possess more household possessions (*HOMEPOS*), the probability that a student would perform better than average depends on one's perceived science self-efficacy (*SCIEEFF*), with students who are higher on self-efficacy achieving better science performance.

Figure 11. Partial dependence plots of notable interactions between some of the most important predictors in the RT model.

Chapter 4

Discussion

With the developments in ML beginning to gain prominence in psychology and the social sciences, we explored between various predictive models of academic performance that are able to achieve a balance between prediction accuracy and interpretability. The purpose of this study was to compare between models built with regression-based ML methods (i.e RR, LASSO, EN, and RT), and traditional MLR. We tested the viability of using such regression-based ML methods to analyse data from PISA, a large-scale educational assessment, for the purpose of understanding the factors involved in academic performance prediction and for developing a predictive model that can predict accurately out-of-sample.

By taking an exploratory route, we investigated if regression-based ML methods improved predictive accuracy as opposed to traditional MLR approaches when used in predicting students' academic performance (RQ1), and identified student-related and school-related factors that are highly predictive of students' performance (RQ2).

RQ1: Comparison Between Traditional MLR and Regression-based ML Methods

To answer RQ1 from the research findings described above, we can conclude that the type of modelling method only has a small effect on prediction accuracy. All six models were found to have quite similar performance in predicting students' science performance on the PISA. Although differences between the models were minute, the models developed with the LASSO ($R^2 = .48$, RMSE = 69.91, MAE = 55.64) and EN ($R^2 = .48$, RMSE = 69.88, MAE = 55.61) methods have the best prediction accuracy, while the model developed with the RT method performed the worst ($R^2 = .38$, RMSE = 76.15, MAE = 60.68). Additionally, we can also conclude that all the models developed were rather poor in accounting for variance in science performance, with R^2 hovering around 50%. This implies that a large proportion of variance in the outcome is not accounted for by the variables and the combination of variables in the model. A possible explanation is that the nesting of students within schools, and schools within countries, were not accounted for. Additionally, since cognitive

predictor variables (i.e. measures of fluid intelligence or IQ, previous academic grades) were not measured in the PISA and thus, not included in these models, our suggested models were incomplete; this may have resulted in model parameters being biased to an unknown extent.

However, based on our best fitting models, LASSO and EN, we achieved a RMSE value of approximately 70, suggesting that the standard deviation of the error for a typical single observation in our data is about 70 score-points. Considering that the mean and standard deviation on the scientific literacy test is 492 ($SD = 96.87$) for our sample, a RMSE of 70 is relatively small. In general, all our models replicated well in the validation data set, suggesting that there is low occurrence of overfitting and high generalisability of our models to new data.

Although the use of regression-based ML approaches with the PISA 2015 data set did not significantly improve prediction accuracy as compared to the conventional MLR approach, there were significant advantages for using these regression-based ML methods.

Firstly, we were able to make use of a large number of predictors, schools, and students. This would be almost impossible with conventional statistical methods such as hierarchical linear modelling or structural equation modelling, as these methods would likely fail to converge due to the sheer number of parameters to be estimated (Yoo, 2018). Using penalised regression methods that accomplish both continuous shrinkage and variable selection simultaneously (i.e. LASSO and EN), produced more parsimonious models that are extremely beneficial for large data sets. Using the LASSO and EN methods, we were able to reduce the number of variables by at least 30% and 25% respectively, from the original 2344 variables. Steering away from a selected few variables that were identified consistently in previous literature, and drawing on a larger set of predictors meant that new variables that might have otherwise gone undetected in the literature, new important predictors could be potentially identified and further studied.

Secondly, most ML approaches, including regression-based ML methods, tend to be rather useful in cases of highly correlated predictors. In the present study, it was observed that the models trained using the conventional MLR method were evidently poorer at managing highly correlated

variables. Producing regression coefficients that are in the thousands, despite the mean and standard deviation of science scores being 492 and 96.87 respectively, for the first four most important variables (i.e. *TOTST*, *TOTAT*, *PROSTAT*, and *TOTAT*PROSTAT*), is evidence for the presence of excessive multicollinearity in the model (Deegan, 1978). Excessive multicollinearity between various predictor variables in a linear model can potentially make the regression estimates unstable, resulting in highly inflated or deflated coefficients. Thus, in the presence of correlated predictors, MLR tends to underperform and should not be one's choice of statistical method.

Lastly, most ML approaches are able to manage with some or no theoretical assumptions about the population of study (Vijayakumar & Cheung, 2018). Researchers are also able to take an exploratory route to uncover new patterns in the data without specifying hypotheses based on existing theories or findings beforehand. With that being said, ML algorithms are able to handle imperfect (or messy) data which typically occurs with large data sets. However, it is important to note that imperfect data could still affect the results of penalised regression methods in the case of heteroscedasticity, correlated residuals, high number of outliers, or severe skewness in the data. As the least squares criterion is still applied in penalised regression methods, the presence of these problems will affect the results the same way it would affect results when using a typical OLS estimator. Decision trees and other black-box ML methods are still better suited for dealing with unclean and messy data that may have these characteristics.

Despite the aforementioned advantages of ML methods, this is not to say that researchers using conventional statistical methods should entirely discard these conventional methods and switch to ML methods. Instead, being aware of the suitability and advantages of different ML methods and practices, may help researchers make a more informed decision when choosing a modelling method. Starting to adopt the practice of CV that is extremely common in the field of ML may be a first step; simply performing a hold-out CV will reduce the chances of overfitting and allow for better generalisability of results.

RQ2: Predictors of Academic Performance

After extracting 30 of the most important and influential variables in each model, we observed that 18 of these variables (e.g. *HOMEPOS*, *EPIST*, *HOMEPOS*SCHLTYPE3*, and *TOTST*) were overlapping and shared between the different methods, while 11 predictor variables (e.g. *SCHSIZE*, *ENVAWARE*, and *SCIEEFF*) were single occurring variables.

From the present study, we were able to identify prominent student-related and school-related factors that highly influence students' science performance from a global perspective. As previously mentioned, social sciences and psychological research typically prioritise easily interpretable models. In these areas, especially in education, research findings should be translatable to actionable goals and behaviours for these findings to be useful and beneficial. To allow researchers and practitioners to pinpoint exactly what and how to provide timely intervention and support to students at risk of poor performance, achieving a balance between predictive accuracy and interpretability is essential. Since all six models from the five modelling methods performed similarly, and none of the models appear to significantly outperform the rest, it will be of merit to discuss the most important variables from all models. Doing so can shed light on the differences in variables picked out by different methods and also shed light on the ease of interpretability of various regression-based ML methods.

In line with previous findings, components of SES, *HOMEPOS* and *WEALTH*, were two variables that were identified as important predictors of students' academic performance in the present study. *WEALTH*, measured by the existence of household items (e.g. televisions, cars, computers, e-book readers), is a subset of *HOMEPOS*, where the latter has additional measures of cultural resources (e.g. poetry books, classic literature, works of art, books on music or design, musical instruments) and home educational resources (e.g. dictionary, study desk, quiet study area, books and computer for school work) (see Table 4). However, what stood out as peculiar was that *WEALTH* was found having a negative relationship with science performance from the LASSO and EN models, while *HOMEPOS* was found having a positive relationship with science performance in all other models. In other words, the wealthier one's family, the worse one would perform on the PISA test.

However, possessing more household items tends to result in better science performance. One would expect that both components of SES would be associated with academic performance in the same direction.

One possible explanation could be, although wealthier families have the capabilities to provide the home with more material possessions, the availability of cultural and home educational resources in the home environment, which makes up part of the *HOMEPOS* index, is what determines students' performance. Spiezia (2011) found that the variation between *HOMEPOS* and *WEALTH* can be explained by the effect of cultural and educational possessions. Specifically, he reported that the effect of cultural and educational possessions was always significant and positive, while the effect of familial wealth is always negative when significant. Spiezia (2011) reasoned that high levels of family wealth (*WEALTH*), indicated by possession of many wealth items, negatively impacts students' incentives to learn by discounting the cost of leisure relative to education, resulting in poorer performance. On the other hand, high levels of household possessions (*HOMEPOS*) captures the strong positive effect of possessing educational and cultural resources on academic performance.

In fact, the presence of educational resources at home (*HEDRES*), which makes up part of the *HOMEPOS* index, was one unique variable only identified as the top 10 most important variables in the RT model developed. Furthermore, from the RT model, this effect of *WEALTH* on science performance was found to be not monotonic. Students from less wealthy and very wealthy families tend to perform worse than the average. This drop in performance is more apparent for very wealthy families.

Spiezia (2011) also found that students who responded to having a large book collection in the home (i.e. more than 100 books) are more likely to score better in science. Since the number of books one has at home makes up part of the *HOMEPOS* index, this could also be one explanation for why *HOMEPOS*, but not *WEALTH*, is positively associated with students' performance.

Table 4

Items included in the PISA indices of *HOMEPOS* and *WEALTH*

		Item is used in the measure of the index (X)	
		<i>HOMEPOS</i>	<i>WEALTH</i>
ST011Q01TA	A desk to study at	X	
ST011Q02TA	A room of your own	X	X
ST011Q03TA	A quiet place to study	X	
ST011Q04TA	A computer you can use for school work	X	
ST011Q05TA	Educational software	X	
ST011Q06TA	A link to the Internet	X	X
ST011Q07TA	Classic literature (e.g. <Shakespeare>)	X	
ST011Q08TA	Books of poetry	X	
ST011Q09TA	Works of art (e.g. paintings)	X	
ST011Q10TA	Books to help with your school work	X	
ST011Q11TA	<Technical reference books>	X	
ST011Q12TA	A dictionary	X	
ST011Q16NA	Books on art, music, or design	X	
ST011Q17TA	<Country-specific wealth item 1>	X	X
ST011Q18TA	<Country-specific wealth item 2>	X	X
ST011Q19TA	<Country-specific wealth item 3>	X	X
ST012Q01TA	Televisions	X	X
ST012Q02TA	Cars	X	X
ST012Q03TA	Rooms with a bath or shower	X	X
ST012Q05NA	<Cell phones> with Internet access (e.g. smartphones)	X	X
ST012Q06NA	Computers (desktop computer, portable laptop, or notebook)	X	X
ST012Q07NA	<Tablet computers> (e.g. <iPad®>, <BlackBerry® PlayBook™>)	X	X
ST012Q08NA	E-book readers (e.g. <Kindle™>, <Kobo>, <Bookeen>)	X	X

ST012Q09NA	Musical instruments (e.g. guitar, piano)	X
ST013Q01TA	How many books are there in your home?	X

Note. Adapted from *PISA 2015 Technical Report* (p. 300) by OECD, 2017. Copyright 2017 by OECD Publishing.

Interestingly, the overarching measure of SES (*ESCS* in PISA), which is a composite index of parental education (*PARED*), highest parental occupation (*hisei*), and home possessions (*HOMEPOS*), was less identified as one of the top 10 variables across the different methods. This may allude to certain components or dimensions of SES playing a bigger role in predicting academic performance than others. In fact, there have been calls for analysing and studying the various components of SES independently, rather than combining them into a single index (Ensminger & Fothergill, 2003). Unfortunately, research so far on the impact of SES on students' performance is most commonly studied as a composite construct of various measures of the home environment and parental background (Harwell, 2018; Lee et al., 2019).

Grade retention (*REPEAT*) was consistently shown to have a negative association with academic performance in the present study. Students who have had to repeat a grade were more likely to score lower than others who have not had to repeat a grade. There is a long standing debate of whether having students repeat a grade is beneficial, detrimental, or simply unnecessary (e.g. Shepard & Smith, 1990). On one hand, arguments for grade repetition posit that doing so gives students an additional year to improve or remediate their performance, grasp the material better, rectify their misconceptions, and be afforded an equal learning opportunity (e.g. Tomchin & Impara, 1992).

On the other hand, many researchers have found adverse effects of grade retention on socioemotional development, social adjustment, and academic performance. Numerous studies have reported that grade retention not only does not improve students' performance, but has a negative impact on one's self-esteem, academic self-concept, social and emotional adjustment, attitudes towards school, and increases school dropout rates (Alexander et al., 2001; Holmes & Matthews, 1984; Hughes et al., 2017; Jimerson, 2001). In other words, there is no guarantee that having students

repeat a grade will have academic performance advantages, and might even produce adverse effects on students. Results from the current study also support the notion that grade retention has adverse effects on academic performance. Furthermore, this result was replicated across all modelling methods, and found to be a strong predictor of academic performance in all regression-based ML methods. Unfortunately, despite the abundance of research advocating against grade retention, it is still widespread and practised in many countries.

Students' epistemological beliefs (*EPIST*), like *REPEAT*, was one predictor of academic performance picked out only in the models developed with the regression-based ML methods. Epistemological (or epistemic) beliefs, defined as individuals' beliefs of or relating to knowledge and knowing (Hofer, 2000; Schommer, 1990), "are a critical part of epistemic cognition because individuals bring these beliefs, either tacitly or explicitly, to their reasoning about knowledge and knowing" (Sinatra et al., 2014, p. 124). *EPIST* become particularly salient when individuals are confronted with complex scientific issues, necessitating critical evaluation of various knowledge sources, assessment of validity of scientific claims, consideration of multiple perspectives, and making decisions amidst uncertainty (Kammerer 2013; Sinatra & Chinn, 2012; Sinatra et al., 2014). The scientific literacy questions from the PISA 2015 was targeted at invoking such a scientific inquiry process in students. Hence, it seems natural that *EPIST* plays a significant role in predicting students' scientific literacy performance.

Many studies have consistently reported a positive association between epistemic beliefs and academic performance; that is, the more sophisticated or mature one's beliefs are, the better scores one would have on the PISA science test (e.g. Hofer 2000; Schommer-Aikins et al., 2005). A recent meta-analysis by Greene et al. (2018) reported a small positive correlation between epistemic beliefs and academic achievement ($r = .162$). Another study analysed the data from the PISA 2015 for Taiwanese students using a stepwise regression method and found that out of 12 non-cognitive factors they preselected, *EPIST* was the most robust predictor of students' science performance (She et al., 2019). Besides reporting that epistemic beliefs are directly related to overall academic performance in

undergraduates, Hofer (2000) also documented that epistemic beliefs are a multifaceted construct; epistemic beliefs involve both domain-general components and domain-specific components. Students' endorsed different beliefs about knowledge and knowing depending on the discipline or subject, which then influenced their final course grades differently. Hence, this highlights an important consideration when interpreting results of the present study; EPIST may be a strong predictor of students' scientific literacy performance, but one should caution against using this as support for other subjects.

The language spoken at home (*ST022Q01TA*) was found as an important predictor of students' science performance. Students who spoke a different language at home than the test language were more likely to perform poorly on scientific literacy. These students may be thought of as having a different mother tongue or native language. Typically, these students have either immigrated from another country (e.g. first-generation immigrants), or have parents who immigrated from another country (e.g. second-generation immigrants). This is an important predictor to investigate as it is becoming increasingly common in the last decades for families to move from old to new destinations. As a result of such migration patterns, an increasing number of first- or second-generation immigrant children have entered the educational systems of various countries (Azzolini et al., 2012). Thus, understanding how to support these students better is becoming an increasingly important task at this point in time.

Studies have reported that the language spoken at home is more strongly predictive of performance in some countries compared to others. Azzolini et al. (2012) investigated academic achievement gaps between native and immigrant students in Italy and Spain using data from PISA 2009, and found that, in general, immigrant students underperform natives in both countries. However, the language spoken at home is more strongly related to academic achievement in Italy; basically, students who speak a different home language perform worse in Italy than in Spain. The reason cited for this was the stronger emphasis placed on academic tracking in Italy (Azzolini et al., 2012). Hence, certain characteristics of a country's educational system, such as academic tracking,

may contribute to the underperformance of students with immigrant backgrounds. Bol and Van de Werfhorst (2013) demonstrated that a highly tracked school system contributes to an increase in unequal educational opportunities, as the influence of family and social backgrounds on tracking outcomes in such systems is greater. Thus, it seems that speaking a different home language than the native language of one's residing country is strongly predictive of poorer academic performance, and this could be made worse by certain characteristics of the educational system.

The inclusion of school-related factors proved that the school environment does play an important role in how well a student performs. We found that the total number of science teachers (*TOTST*) at a school is a strong predictor of science performance across various modelling methods. Although investigating such a predictor specifically, is rather obscure and limited in the literature, as most of the research investigating teacher-related factors have placed a greater focus on teaching quality and effectiveness. One such study was conducted in Nigerian secondary schools; the authors investigated the relationship between the number of qualified teachers and students' academic performance (Akinsolu, 2010). They found that teachers' qualifications and experience in their field were significantly related to how well students performed. Alath (2020) analysed the PISA data, and also found that the proportion of science teachers in each school was found to be a significant predictor of science literacy for both Turkey and Singapore samples. Future research should look into why and what about (e.g. educational qualifications or years of experience) ensuring that schools are staffed with an adequate number of teachers qualified in their teaching subject is an important predictor.

The type of school students attend (*SCHLTYPE*) was found to be strongly predictive of science performance in all three penalised regression models. In particular, attending a private government-dependent school (*SCHLTYPE2*) was associated with better science performance. This was similarly reported by several other studies. Dronkers and Robert (2003) examined the differences in effectiveness between private and public schools in 19 countries using the PISA 2000 data. They found that private government-dependent schools were more effective and produced better

mathematics and science results than public schools, after students, parents, and school composition have been controlled. Additionally, they found that private independent schools were the least effective of the three school types, after controlling for the school composition. The authors hypothesised that a more positive school climate in private government-dependent schools explains the differences in effectiveness between the school types. Various student- and teacher-related factors contribute to the school climate. These include teachers' expectations of the students, teacher and student absenteeism, turnover rate of teaching staff, teachers' encouragement towards students, students' respect towards teachers, use of alcohol or drugs, and disruption of class. Additionally, better educational resources provided by private government-dependent schools also makes these schools more effective than the rest (Dronkers & Avram, 2009).

Contributions and Implications

To our knowledge, this is the first study that attempted a comparison between a conventional statistical method (i.e. MLR) and several regression-based ML methods (i.e. RR, LASSO, EN, and RT) using a large-scale assessment data like PISA, with the aims of establishing the method that gives the highest prediction accuracy and identifying the strongest predictors of academic performance. Moreover, instead of using a few pre-selected predictors based on theory or previous literature, which is commonly done by studies investigating the predictors of academic performance, we made use of a large number of predictors ($k = 66$) in a data-driven manner in an attempt to uncover new interesting relationships between predictors and the outcome. Furthermore, we were able to take into account many non-cognitive psychological factors such as motivation, interest, school learning and teaching environment, family background, to increase the chances of accurate predictions.

At the same time, using regression-based ML methods ensured that the models and results were highly interpretable. Also, this is the first study that employed the use of different penalised regression methods for the prediction of students' performance (Rastrollo-Guerrero et al., 2020). Since the literature investigating academic performance prediction using ML methods is still very new, there is plenty of room for future research to improve on the current study. In general, more

studies should look into developing an accurate, yet interpretable model for the prediction of students' performance.

We identified predictors of science performance that influence all students globally, transcending differences between schools and countries. Since our analyses were not limited to specified few countries, our results are relevant on a global level and contribute to forming a “big picture” of academic performance prediction. From the results found in the present study, we identified many important predictors of science performance that are worth further investigation. Noteworthy findings include, (1) the importance of having cultural and educational resources in the home environment, (2) the adverse effect of simply possessing too much familial material wealth on academic achievement, (3) the adverse effects of grade retention practices, and (4) the importance of having teachers that are qualified in their teaching subject.

A study such as the present one is crucial for introducing new directions of research, instead of basing research on the same few predictors that have been heavily studied previously. Although replication studies that aim to solidify and give support for previous findings of predictors of academic achievement are important, we should not neglect finding new and important predictors. Predictors that may have been important in the past decades, may or may not be as relevant tomorrow, and placing too much emphasis on replicating previous studies could cause us to lose sight of new or hidden important predictors.

Limitations

Firstly, we were unable to account for the nested data structure of our sample as (1) the sheer amount of parameters used in the study would cause a failure to converge in a hierarchical linear model, and (2) the regression-based ML methods chosen are not able to accommodate mixed or random effects at the time the study was conducted. However, this definitely posed as a huge limitation for our study. In situations where data are nested (e.g. students nested within schools, or schools nested within countries) and the effect of predictor variables on the outcome may be dependent on that nesting, it is important that the nested structure be accounted for in the model to

avoid misrepresentation of effects, aggregation bias, poor estimation of standard errors, and heterogeneity of regression (Anderson, 2012; Raudenbush & Bryk, 2002).

Secondly, making use of data from a cross-sectional study, as in the case of PISA, makes apparent the issue of how much into the future a prediction is valid. Although the models developed in the present study may be used to predict future batches of students' performance on the PISA, it is unforeseeable how long such a prediction will be useful for. Hence, further longitudinal studies are required to test the validity of any predictive model.

Thirdly, using data that was not collected firsthand, our results reflect only the available predictor variables measured from the PISA. This implies that many other variables, that could very well be important, were not considered. For example, most predictor variables measured in PISA are non-cognitive variables, with the exception of students' grades compared to modal grades in one's country (*GRADE*). Existing literature have consistently pointed out that students' prior achievement is one of the best predictors of future achievement (Ayán, 2008; Huang & Fang, 2013). *GRADE* was found to be one of the top 10 predictors in the LASSO and EN models, but not in the other models. It could be hypothesised that perhaps including students' prior science achievement may produce slightly different results.

Fourthly, in ensuring that we use the exact same data set for all the different comparisons between modelling methods, we sacrificed being able to make full use of the advantages of decision trees. Decision trees actually require very little preprocessing; trees can easily manage categorical features, are able to handle missing data and do not require imputation, and do not require for variables to be standardised beforehand (Hastie et al., 2009).

Next, although we attempted to predict students' *academic* performance, we only made use of students' scores on the scientific literacy component of the PISA test. Future research should look into developing prediction models for different subjects.

Lastly, we took an inclusive approach in order to make full use of the wide range of student, school, and country data available from PISA. This gave us a global perspective and a magnified view

of the average predictive accuracy as a whole and enabled us to identify predictors of science performance globally, but is unable to communicate specific country-wise or school-wise information, making it difficult to give individualised recommendations at those levels.

Conclusions

Predicting students' academic performance has long been an important area of research in education. Most existing literature have made use of traditional statistical methods that run into the problems of overfitted models, inability to effectively handle large numbers of participants and predictors, and inability to pick out non-linearities that may be present. Regression-based ML methods that can produce highly interpretable yet accurate models for new predictions, are able to provide some solutions to the aforementioned problems. ML practices, namely CV, greatly reduces the chances of overfitting, and ML algorithms are able to model non-linear relationships and manage big data effortlessly.

Using several regression-based ML methods (i.e. RR, LASSO, EN, and RT), we compared these with models developed with traditional MLR methods to explore if these different methods differed in prediction accuracy and the variables that were identified as important predictors of academic performance. We analysed a total of 198,712 students from 60 countries, and used 66 student-related and school-related predictors to build the models with these different modelling methods. We found that although predictive accuracy did not differ much between ML methods and traditional MLR, there were significant advantages for using the former (e.g. handling excessive multicollinearity). There were prominent variables found by several different methods, proving that these were strongly predictive of academic performance (e.g. household possessions) regardless of modelling method used.

Moving forward, we strongly believe that there is merit for using such regression-based ML methods in educational research. In addition to being able to handle big data, ML methods are also particularly useful with small sample sizes (Yarkoni & Westfall, 2017). Thus, even without using a large-scale assessment data such as the PISA, psychology and social science research can benefit from

adopting ML practices and methods to produce models that can not only be used for explaining factors that influence academic performance prediction, but also for making accurate predictions on unseen data. It appears necessary to investigate academic performance prediction through ML techniques and explore new variables that predict students' performance. New variables found from ML methods can shed light on existing theories of learning and teaching from a new and different perspective, which in turn may lead to creation of new theories or complement existing theories.

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Appendix A

Predictor Variables (OECD, 2017)

Category	Variable Name	Description	Raw Response	Predictor Type
Student-related	ST004D01T	Student's sex/gender	{Female, Male}	0-1
	AGE	Student's age	Open-ended numeric format	numeric
	DISCLSCI	Perceived disciplinary climate of science lessons	Four-point Likert scale	numeric
	ENVAWARE	Awareness of environmental matters	Four-point Likert scale	numeric
	JOYSCIE	Enjoyment of science	Four-point Likert scale	numeric
	INSTSCIE	Instrumental motivation for science	Four-point Likert scale	numeric
	SCIEEFF	Science self-efficacy	Four-point Likert scale	numeric
	EPIST	Epistemological beliefs about science	Four-point Likert scale	numeric
	GRADE	Grade (or score) compared to modal grade in country	Open-ended numeric format	numeric
	IMMIG	Immigration status	{Native, Second-Generation, First-Generation}	1-3
	MISCED	Mother's highest education level	{None, ISCED 1, ISCED 2, ISCED 3B/C, ISCED 3A, ISCED 4, ISCED 5B, ISCED 5A/6}	numeric
	FISCED	Father's highest education level	{None, ISCED 1, ISCED 2, ISCED 3B/C, ISCED 3A, ISCED 4, ISCED 5B, ISCED 5A/6}	numeric

	HISCED	Highest education of either parent	{None, ISCED 1, ISCED 2, ISCED 3B/C, ISCED 3A, ISCED 4, ISCED 5B, ISCED 5A/6}	numeric
	hisei	Highest occupational status of parents	Open-ended numeric format	numeric
	REPEAT	Grade repetition, if any	{Did not repeat a grade, Repeated a grade}	0-1
	BELONG	Sense of belonging to their school	Four-point Likert scale	numeric
	ESCS	Composite score built by several derived indicators to form an index of economic, social, and cultural status (SES)	Open-ended numeric format	numeric
	ST022Q01TA	Language spoken at home	{Language of test, Other language}	0-1
	PARED	Highest educational level of parents in terms of years of schooling	Open-ended numeric format	numeric
	CULTPOSS	Amount of cultural possession at home	{Yes, No}	numeric
	HEDRES	Educational resources at home	{Yes, No}	numeric
	HOMEPOS	Home possessions	{Yes, No}	numeric
	ICTRES	Technological resources at home	{Yes, No}	numeric
	WEALTH	Family wealth possessions	{Yes, No}	numeric
School-related	SCHSIZE	School size	Open-ended numeric format	numeric
	CLSIZE	Class size	Open-ended numeric format	numeric

LEAD	School/educational leadership	Six-point Likert scale	numeric
LEADCOM	School's goals and curricular development	Six-point Likert scale	numeric
LEADINST	Instructional leadership	Six-point Likert scale	numeric
LEADPD	Professional development	Six-point Likert scale	numeric
LEADTCH	Teacher participation in leadership	Six-point Likert scale	numeric
RESPCUR	Level of responsibility of school staff in issues relating to curriculum and assessment	Open-ended numeric format	numeric
RESPRES	Level of responsibility of school staff in allocating resources	Open-ended numeric format	numeric
SCHAUT	School autonomy	Open-ended numeric format	numeric
TEACHPART	Teacher participation	Open-ended numeric format	numeric
EDUSHORT	Shortage of educational material	Four-point Likert scale	numeric
STAFFSHORT	Shortage of teaching staff	Four-point Likert scale	numeric
TOTAT	Total number of teachers	Open-ended numeric format	numeric
PROSTAT	Proportion of science teachers	Open-ended numeric format	numeric
PROSTMAS	Proportion of science teachers with an ISCED 5A qualification and a major in science	Open-ended numeric format	numeric
TOTST	Total number of science teachers	Open-ended numeric format	numeric
CREACTIV	Number of creative extra-curricular activities at school	Open-ended numeric format	numeric

SCIRES	Science-specific resources	{Yes, No}	numeric
STUBEHA	Student-related factors influencing school climate	Four-point Likert scale	numeric
TEACHBEHA	Teacher-related factors influencing school climate	Four-point Likert scale	numeric
STRATIO	Student-teacher ratio	Open-ended numeric format	numeric
SCHLTYPE	School type	{Private Independent, Private Government-dependent, Public}	1-3
SC001Q01TA	Location of school	{A village, hamlet or rural area (fewer than 3 000 people), A small town (3 000 to about 15 000 people), A town (15 000 to about 100 000 people), A city (100 000 to about 1 000 000 people), A large city (with over 1 000 000 people)}	numeric
STU.HELP	Support/help that is provided by the school for students	{Yes, No}	numeric
SC012Q01TA	Student admission to school: Student's record of academic performance (including placement tests)	{Never, Sometimes, Always}	numeric
SC012Q02TA	Student admission to school: Recommendation of feeder schools	{Never, Sometimes, Always}	numeric
SC012Q03TA	Student admission to school: Parents' endorsement of the instructional or religious philosophy of the school	{Never, Sometimes, Always}	numeric

SC012Q04TA	Student admission to school: Whether the student requires or is interested in a special programme	{Never, Sometimes, Always}	numeric
SC012Q05TA	Student admission to school: Preference given to family members of current or former students	{Never, Sometimes, Always}	numeric
SC012Q06TA	Student admission to school: Residence in a particular area	{Never, Sometimes, Always}	numeric
SC025Q01NA	Percentage of teaching staff in your school that has attended a programme of professional development	{0 - 100}	numeric
INHOUSEPD	Availability of in-house professional development	{Yes, No}	numeric
ASSESSMENT	Assessment/evaluation of teachers' practice/methods	{Yes, No}	numeric
SC034Q03TA	How often students are assessed with teacher-developed tests	{Never, 1-2 times a year, 3-5 times a year, Monthly, More than once a month}	numeric
SC034Q04TA	How often students are assessed with teachers judgmental ratings	{Never, 1-2 times a year, 3-5 times a year, Monthly, More than once a month}	numeric
ACCDATA	Availability of achievement data for accountability	{Yes, No}	numeric
SC042Q01TA	Students are grouped by ability into different classes	{For all subjects, For some subjects, Not for any subjects}	numeric
SC042Q02TA	Students are grouped by ability within their classes	{For all subjects, For some subjects, Not for any subjects}	numeric

SC064Q01TA	Percentage of students' parents that discussed their child's progress with a teacher on their own initiative	{0 - 100}	numeric
SC064Q02TA	Percentage of students' parents that discussed their child's progress on the initiative of one of their child's teachers	{0 - 100}	numeric
SC064Q03TA	Percentage of students' parents that participated in local school government (e.g. parent council or school management committee)	{0 - 100}	numeric

Note. Adapted from *PISA 2015 Technical Report* (p. 300) by OECD, 2017. Copyright 2017 by OECD Publishing. All variables of type n_1 - n_2 assume integer values ranging from n_1 to n_2 , with the maximum value corresponding to n_2 .

Appendix B

Regression Tree (RT) Output

rt_object

n= 138896

##

node), split, n, deviance, yval

* denotes terminal node

##

1) root 138896 1.297533e+09 491.8023

2) HOMEPOS< -0.64015 46668 3.936220e+08 451.3837

4) ENVAWARE< -0.7079 10662 6.815461e+07 403.1274

8) REPEAT>=0.5 2545 1.196561e+07 372.0539

16) ICTRES< -1.4923 1112 4.359844e+06 357.3013 *

17) ICTRES>=-1.4923 1433 7.175954e+06 383.5018

34) TEACHPART< 0.05789018 823 3.986972e+06 372.3909 *

35) TEACHPART>=0.05789018 610 2.950303e+06 398.4924 *

9) REPEAT< 0.5 8117 5.296116e+07 412.8702

18) TOTST< -0.4313536 3222 1.733052e+07 392.1159

36) HOMEPOS< -1.5114 1568 6.488117e+06 373.5080 *

37) HOMEPOS>=-1.5114 1654 9.784784e+06 409.7563

74) RESPCUR< -0.72845 788 4.161307e+06 395.0148 *

75) RESPCUR>=-0.72845 866 5.296418e+06 423.1700 *

19) TOTST>=-0.4313536 4895 3.332928e+07 426.5311

38) EPIST< -0.9573 1222 6.968619e+06 394.2515

76) INSTSCIE>=-0.36805 892 4.888129e+06 385.3373 *

77) INSTSCIE< -0.36805 330 1.818012e+06 418.3470 *

```

##      39) EPIST>=-0.9573 3673 2.466375e+07 437.2705
##
##      78) ENVAWARE< -1.2331 1687 1.032350e+07 421.8545
##
##      156) SCHLTYPE=1,3 1570 9.298724e+06 418.3510
##
##      312) SCIEEFF>=0.52985 185 8.787072e+05 386.2605 *
##
##      313) SCIEEFF< 0.52985 1385 8.204054e+06 422.6375 *
##
##      157) SCHLTYPE=2 117 7.469187e+05 468.8666 *
##
##      79) ENVAWARE>=-1.2331 1986 1.359878e+07 450.3655
##
##      158) TOTAT< -0.2456169 720 4.333082e+06 431.3893 *
##
##      159) TOTAT>=-0.2456169 1266 8.858971e+06 461.1577
##
##      318) EPIST< 0.5965 1109 7.669185e+06 455.8050
##
##      636) SCIERES< -0.6288442 294 1.737012e+06 431.6107 *
##
##      637) SCIERES>=-0.6288442 815 5.697995e+06 464.5328 *
##
##      319) EPIST>=0.5965 157 9.335708e+05 498.9673 *
##
##      5) ENVAWARE>=-0.7079 36006 2.932871e+08 465.6732
##
##      10) TOTST< -0.20554 21124 1.488331e+08 445.5689
##
##      20) HOMEPOS< -1.60415 6873 3.715785e+07 412.8408
##
##      40) REPEAT>=0.5 1446 6.909560e+06 384.7567
##
##      80) ICTRES< -1.68245 1073 4.627014e+06 376.7219 *
##
##      81) ICTRES>=-1.68245 373 2.014006e+06 407.8702
##
##      162) SCHLTYPE=1,3 332 1.484221e+06 399.2975 *
##
##      163) SCHLTYPE=2 41 3.078093e+05 477.2887 *
##
##      41) REPEAT< 0.5 5427 2.880393e+07 420.3237
##
##      82) EPIST< -0.1746 3320 1.588120e+07 409.2246
##
##      164) WEALTH< -2.6094 984 4.053152e+06 393.3690 *
##
##      165) WEALTH>=-2.6094 2336 1.147647e+07 415.9035
##
##      330) TOTST< -0.3668354 1806 8.719887e+06 410.5010 *

```

```

##      331) TOTST>=-0.3668354 530 2.524251e+06 434.3127 *
##
##      83) EPIST>=-0.1746 2107 1.186928e+07 437.8127
##
##      166) ICTRES< -2.0861 773 3.816975e+06 417.0506 *
##
##      167) ICTRES>=-2.0861 1334 7.526006e+06 449.8435 *
##
##      21) HOMEPOS>=-1.60415 14251 1.007629e+08 461.3531
##
##      42) EPIST< 0.1475 9052 5.942177e+07 447.9501
##
##      84) RESPCUR< -0.5622 5166 3.108215e+07 434.9935
##
##      168) REPEAT>=0.5 678 3.535656e+06 394.2270 *
##
##      169) REPEAT< 0.5 4488 2.624950e+07 441.1520
##
##      338) EPIST< -0.80645 1117 6.154472e+06 421.0489 *
##
##      339) EPIST>=-0.80645 3371 1.949403e+07 447.8133
##
##      678) SCIERES< -0.6288442 1376 7.438089e+06 435.7330 *
##
##      679) SCIERES>=-0.6288442 1995 1.171664e+07 456.1453 *
##
##      85) RESPCUR>=-0.5622 3886 2.631947e+07 465.1746
##
##      170) EPIST< -0.80895 865 5.304408e+06 437.0845 *
##
##      171) EPIST>=-0.80895 3021 2.013710e+07 473.2176
##
##      342) TOTAT< -0.6001134 1076 6.536414e+06 453.4440
##
##      684) REPEAT>=0.5 119 5.499574e+05 413.5479 *
##
##      685) REPEAT< 0.5 957 5.773491e+06 458.4049 *
##
##      343) TOTAT>=-0.6001134 1945 1.294722e+07 484.1567
##
##      686) SC001Q01TA< 1.11714 1506 9.941238e+06 476.9531
##
##      1372) hisei< -0.5592604 785 4.754317e+06 465.5956 *
##
##      1373) hisei>=-0.5592604 721 4.975412e+06 489.3188 *
##
##      687) SC001Q01TA>=1.11714 439 2.659751e+06 508.8686
##
##      1374) CLSIZE>=2.312091 25 1.437201e+05 420.1484 *
##
##      1375) CLSIZE< 2.312091 414 2.307366e+06 514.2261 *

```

```

##      43) EPIST>=0.1475 5199 3.688382e+07 484.6891
##      86) RESPCUR< 1.19555 4182 2.815101e+07 476.7955
##     172) GRADE< -0.5 689 4.237285e+06 439.8993 *
##     173) GRADE>=-0.5 3493 2.279076e+07 484.0733
##     346) SCIEEFF< -0.6294 606 3.439889e+06 455.8318 *
##     347) SCIEEFF>=-0.6294 2887 1.876608e+07 490.0014
##     694) STRATIO>=0.4347906 804 4.704243e+06 467.1121
##    1388) RESPRES< -0.4609 559 2.970893e+06 455.2028 *
##    1389) RESPRES>=-0.4609 245 1.473173e+06 494.2845 *
##     695) STRATIO< 0.4347906 2083 1.347802e+07 498.8363
##    1390) ASSESSMENT< 0.4225337 1572 9.734648e+06 491.6443 *
##    1391) ASSESSMENT>=0.4225337 511 3.411917e+06 520.9611 *
##     87) RESPCUR>=1.19555 1017 7.400718e+06 517.1482
##    174) LEADPD>=-0.4797 686 5.024913e+06 505.7497 *
##    175) LEADPD< -0.4797 331 2.101953e+06 540.7718 *
##    11) TOTST>=-0.20554 14882 1.237971e+08 494.2098
##    22) CLSIZE< 0.1783008 6069 4.901113e+07 471.0657
##    44) HOMEPOS< -1.6157 1100 7.396719e+06 428.2535
##    88) STUBEHA>=-0.6749 876 5.127366e+06 418.2036
##    176) RESPRES< -0.2234 788 4.209370e+06 412.2667
##    352) PROSTAT>=2.40977 139 4.352106e+05 376.4192 *
##    353) PROSTAT< 2.40977 649 3.557282e+06 419.9444 *
##    177) RESPRES>=-0.2234 88 6.415116e+05 471.3661 *
##    89) STUBEHA< -0.6749 224 1.834871e+06 467.5558 *
##    45) HOMEPOS>=-1.6157 4969 3.915192e+07 480.5432
##    90) EPIST< -0.5851 1062 7.256639e+06 444.4285

```

```

##      180) LEADPD>=-0.1921 676 4.281040e+06 432.7689 *
##      181) LEADPD< -0.1921 386 2.722755e+06 464.8479 *
##      91) EPIST>=-0.5851 3907 3.013364e+07 490.3598
##      182) REPEAT>=0.5 537 2.803080e+06 450.9289 *
##      183) REPEAT< 0.5 3370 2.636259e+07 496.6430
##      366) SCHLTYPE=1,3 3084 2.388863e+07 491.4719
##      732) SC064Q03TA>=0.3933863 919 6.692240e+06 467.0576
##      1464) RESPCUR< -1.0562 262 1.768152e+06 430.3548 *
##      1465) RESPCUR>=-1.0562 657 4.430401e+06 481.6941
##      2930) ASSESSMENT< -0.4901222 359 2.394664e+06 463.7217 *
##      2931) ASSESSMENT>=-0.4901222 298 1.780081e+06 503.3454 *
##      733) SC064Q03TA< 0.3933863 2165 1.641609e+07 501.8353
##      1466) PROSTAT>=2.797187 108 7.166987e+05 431.3117 *
##      1467) PROSTAT< 2.797187 2057 1.513404e+07 505.5381
##      2934) EPIST< 0.5572 1439 9.945509e+06 495.2848
##      5868) LEAD>=0.7032 374 2.573519e+06 472.5956 *
##      5869) LEAD< 0.7032 1065 7.111841e+06 503.2526
##      11738) SC042Q01TA< -1.43426 135 6.389792e+05 465.3424 *
##      11739) SC042Q01TA>=-1.43426 930 6.250678e+06 508.7557 *
##      2935) EPIST>=0.5572 618 4.684992e+06 529.4127
##      5870) SCIEEFF< -0.22845 193 1.461387e+06 500.4307 *
##      5871) SCIEEFF>=-0.22845 425 2.987875e+06 542.5740 *
##      367) SCHLTYPE=2 286 1.502238e+06 552.4041
##      734) STRATIO< -0.597192 32 1.791536e+05 475.9819 *
##      735) STRATIO>=-0.597192 254 1.112647e+06 562.0321 *
##      23) CLSIZE>=0.1783008 8813 6.929641e+07 510.1478

```

```

##      46) TOTST< 0.2783463 3853 2.910790e+07 484.5086
##
##      92) PROSTMAS< 0.1213244 1047 6.944079e+06 448.1019
##
##      184) EPIST< -0.57355 271 1.558562e+06 416.7692 *
##
##      185) EPIST>=-0.57355 776 5.026553e+06 459.0442
##
##      370) REPEAT>=0.5 123 7.247860e+05 416.3221 *
##
##      371) REPEAT< 0.5 653 4.034984e+06 467.0914
##
##      742) SCIERES< -0.6288442 223 1.184521e+06 440.5507 *
##
##      743) SCIERES>=-0.6288442 430 2.611916e+06 480.8555
##
##      1486) STRATIO>=0.8755895 115 5.682743e+05 439.6823 *
##
##      1487) STRATIO< 0.8755895 315 1.777516e+06 495.8870 *
##
##      93) PROSTMAS>=0.1213244 2806 2.025827e+07 498.0930
##
##      186) SCHAUT< -0.5222901 1195 8.380751e+06 475.6504
##
##      372) PROSTAT< 0.2799701 728 4.815301e+06 453.0588
##
##      744) PROSTMAS>=0.4012851 671 4.191039e+06 446.3973
##
##      1488) SCIERES< -1.090537 247 1.126330e+06 421.4434 *
##
##      1489) SCIERES>=-1.090537 424 2.821302e+06 460.9341
##
##      2978) STAFFSHORT>=0.7623 140 6.992702e+05 420.3895 *
##
##      2979) STAFFSHORT< 0.7623 284 1.778441e+06 480.9209
##
##      5958) STAFFSHORT< -1.06855 100 3.430888e+05 437.0426 *
##
##      5959) STAFFSHORT>=-1.06855 184 1.138184e+06 504.7679 *
##
##      745) PROSTMAS< 0.4012851 57 2.439608e+05 531.4780 *
##
##      373) PROSTAT>=0.2799701 467 2.614680e+06 510.8681
##
##      746) CLSIZE< 0.7117484 139 7.734145e+05 466.6278 *
##
##      747) CLSIZE>=0.7117484 328 1.453924e+06 529.6163 *
##
##      187) SCHAUT>=-0.5222901 1611 1.082917e+07 514.7404
##
##      374) HOMEPOS< -1.32265 578 3.435004e+06 492.2010 *

```



```

##      375) HOMEPOS>=-1.32265 1033 6.936221e+06 527.3520
##      750) EPIST< -0.0358 626 3.968816e+06 512.6869 *
##      751) EPIST>=-0.0358 407 2.625702e+06 549.9081 *
## 47) TOTST>=0.2783463 4960 3.568812e+07 530.0647
##      94) PROSTMAS< 0.4501029 1237 8.658311e+06 492.3006
##      188) GRADE< -0.5 221 1.405645e+06 445.4110 *
##      189) GRADE>=-0.5 1016 6.661076e+06 502.5000
##      378) SC064Q01TA< 1.292374 764 4.877930e+06 490.2248
##      756) ICTRES< -1.3298 310 1.765750e+06 466.1893
##      1512) SC034Q04TA>=-0.9812677 150 8.545165e+05 439.4434 *
##      1513) SC034Q04TA< -0.9812677 160 7.033364e+05 491.2637 *
##      757) ICTRES>=-1.3298 454 2.810807e+06 506.6367 *
##      379) SC064Q01TA>=1.292374 252 1.319013e+06 539.7152 *
## 95) PROSTMAS>=0.4501029 3723 2.467953e+07 542.6122
##      190) EPIST< -0.14095 2138 1.289324e+07 526.7196
##      380) TOTAT< 1.398361 1537 8.514542e+06 516.4302
##      760) SCHSIZE>=1.46403 106 4.405751e+05 440.4872 *
##      761) SCHSIZE< 1.46403 1431 7.417344e+06 522.0556
##      1522) STUBEHA>=-1.6467 1339 6.738847e+06 518.5772 *
##      1523) STUBEHA< -1.6467 92 4.265109e+05 572.6805 *
##      381) TOTAT>=1.398361 601 3.799823e+06 553.0337
##      762) STRATIO>=-0.2129229 388 2.609102e+06 538.2092 *
##      763) STRATIO< -0.2129229 213 9.501255e+05 580.0380 *
## 191) EPIST>=-0.14095 1585 1.051786e+07 564.0498
##      382) SCIERES< -0.1671518 452 3.132996e+06 528.4936
##      764) LEADPD>=1.1121 52 2.859714e+05 428.4050 *

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##      765) LEADPD< 1.1121 400 2.258383e+06 541.5051
##      1530) ACCDATA< 0.6503952 329 1.730424e+06 530.6077 *
##      1531) ACCDATA>=0.6503952 71 3.078484e+05 592.0014 *
##      383) SCIERES>=-0.1671518 1133 6.585460e+06 578.2346
##      766) STUBEHA>=-1.0754 864 4.606830e+06 568.9185
##      1532) PROSTAT>=1.949089 54 1.929296e+05 500.3514 *
##      1533) PROSTAT< 1.949089 810 4.143097e+06 573.4896
##      3066) TOTST< 1.90743 688 3.470295e+06 566.3092 *
##      3067) TOTST>=1.90743 122 4.372917e+05 613.9823 *
##      767) STUBEHA< -1.0754 269 1.662792e+06 608.1571 *
##      3) HOMEPOS>=-0.64015 92228 7.890929e+08 512.2544
##      6) EPIST< -0.1347 48447 3.852384e+08 486.6346
##      12) ENVAWARE< -0.53135 12281 9.095701e+07 445.9932
##      24) EPIST< -0.80795 4274 2.788683e+07 416.9382
##      48) RESPCUR< -1.0087 980 5.725174e+06 380.7432
##      96) ASSESSMENT< -0.4901222 604 2.899480e+06 367.0899 *
##      97) ASSESSMENT>=-0.4901222 376 2.532235e+06 402.6756 *
##      49) RESPCUR>=-1.0087 3294 2.049582e+07 427.7066
##      98) ENVAWARE< -1.22785 1455 7.714482e+06 410.7194 *
##      99) ENVAWARE>=-1.22785 1839 1.202928e+07 441.1467
##      198) REPEAT>=0.5 300 1.632369e+06 403.7478 *
##      199) REPEAT< 0.5 1539 9.895514e+06 448.4370
##      398) INSTSCIE>=-0.70805 1150 7.422807e+06 440.8472
##      796) hisei< -0.739145 366 2.077695e+06 420.3408 *
##      797) hisei>=-0.739145 784 5.119355e+06 450.4203 *
##      399) INSTSCIE< -0.70805 389 2.210618e+06 470.8747 *

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##      25) EPIST>=-0.80795 8007 5.753618e+07 461.5022
##
##      50) ENVAWARE< -1.26975 2565 1.612910e+07 433.3227
##
##      100) REPEAT>=0.5 423 2.163314e+06 394.4116 *
##
##      101) REPEAT< 0.5 2142 1.319885e+07 441.0068
##
##      202) RESPCUR< -1.0087 476 2.739341e+06 408.3420 *
##
##      203) RESPCUR>=-1.0087 1666 9.806509e+06 450.3397
##
##      406) hisei< 0.0703359 816 4.331932e+06 434.4535 *
##
##      407) hisei>=0.0703359 850 5.070948e+06 465.5903 *
##
##      51) ENVAWARE>=-1.26975 5442 3.841023e+07 474.7842
##
##      102) REPEAT>=0.5 612 3.599941e+06 426.7202 *
##
##      103) REPEAT< 0.5 4830 3.321734e+07 480.8743
##
##      206) hisei< -0.739145 1246 8.053604e+06 456.2679
##
##      412) RESPCUR< -1.20345 65 3.482418e+05 392.3375 *
##
##      413) RESPCUR>=-1.20345 1181 7.425079e+06 459.7866 *
##
##      207) hisei>=-0.739145 3584 2.414704e+07 489.4288
##
##      414) RESPCUR< -1.1132 371 2.432029e+06 446.7006
##
##      828) PARED< 0.858813 305 1.735512e+06 434.2618 *
##
##      829) PARED>=0.858813 66 4.312453e+05 504.1832 *
##
##      415) RESPCUR>=-1.1132 3213 2.095947e+07 494.3626
##
##      830) LEADCOM>=0.29645 1391 9.281727e+06 483.1763 *
##
##      831) LEADCOM< 0.29645 1822 1.137080e+07 502.9026
##
##      1662) TOTST< -0.3668354 668 4.040867e+06 487.9976 *
##
##      1663) TOTST>=-0.3668354 1154 7.095628e+06 511.5305 *
##
##      13) ENVAWARE>=-0.53135 36166 2.671084e+08 500.4353
##
##      26) REPEAT>=0.5 3138 1.982388e+07 446.2300
##
##      52) EPIST< -0.81075 831 4.969364e+06 422.1183

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##      104) GRADE< -1.5 116 5.512187e+05 383.1805 *
##      105) GRADE>=-1.5 715 4.213739e+06 428.4355
##      210) RESPCUR< -1.1132 79 4.367616e+05 377.0932 *
##      211) RESPCUR>=-1.1132 636 3.542864e+06 434.8129 *
##      53) EPIST>=-0.81075 2307 1.419737e+07 454.9153
##      106) SCHAUT< 0.1497588 1401 8.165421e+06 443.7765
##      212) GRADE< -1.5 207 8.171345e+05 411.4229 *
##      213) GRADE>=-1.5 1194 7.094043e+06 449.3856
##      426) WEALTH>=1.26315 133 8.664618e+05 406.6091 *
##      427) WEALTH< 1.26315 1061 5.953708e+06 454.7477 *
##      107) SCHAUT>=0.1497588 906 5.589331e+06 472.1397
##      214) TOTST< -0.3668354 296 1.453761e+06 447.8401 *
##      215) TOTST>=-0.3668354 610 3.875979e+06 483.9310
##      430) CREATIV< -0.3510227 111 6.690854e+05 442.4804 *
##      431) CREATIV>=-0.3510227 499 2.973755e+06 493.1515 *
##      27) REPEAT< 0.5 33028 2.371884e+08 505.5854
##      54) RESPCUR< -1.0087 5815 4.513015e+07 474.5687
##      108) TOTAT< 0.3570272 4795 3.290011e+07 463.2992
##      216) PARED< 0.858813 3538 2.208695e+07 450.3380
##      432) WEALTH>=1.50855 492 2.722670e+06 415.1902 *
##      433) WEALTH< 1.50855 3046 1.865831e+07 456.0152
##      866) EPIST< -0.95255 597 3.601349e+06 430.2783 *
##      867) EPIST>=-0.95255 2449 1.456511e+07 462.2892
##      1734) SC064Q01TA< 0.666013 1581 9.437375e+06 453.2017
##      3468) RESPCUR< -1.1132 928 5.097743e+06 441.8361 *
##      3469) RESPCUR>=-1.1132 653 4.049394e+06 469.3538 *

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1735) SC064Q01TA>=0.666013 868 4.759368e+06 478.8413 *

217) PARED>=0.858813 1257 8.545892e+06 499.7803

434) PARED>=1.326928 74 3.963177e+05 411.3447 *

435) PARED< 1.326928 1183 7.534628e+06 505.3122

870) hisei< 0.4750764 425 2.452209e+06 481.1850 *

871) hisei>=0.4750764 758 4.696301e+06 518.8401

1742) SC001Q01TA< 0.2848347 408 2.563056e+06 502.8781 *

1743) SC001Q01TA>=0.2848347 350 1.908117e+06 537.4471 *

109) TOTAT>=0.3570272 1020 8.758326e+06 527.5461

218) INHOUSEPD>=-0.2575208 308 2.216121e+06 477.8772

436) SCIERES< -1.090537 51 1.917698e+05 399.7534 *

437) SCIERES>=-1.090537 257 1.651312e+06 493.3803 *

219) INHOUSEPD< -0.2575208 712 5.453674e+06 549.0321

438) CLSIZE< 0.1783008 238 1.843751e+06 507.7261

876) RESPRES>=-0.17065 56 3.072502e+05 422.3572 *

877) RESPRES< -0.17065 182 1.002807e+06 533.9935 *

439) CLSIZE>=0.1783008 474 2.999957e+06 569.7723

878) SC064Q01TA< 0.1440455 157 1.069730e+06 535.0190 *

879) SC064Q01TA>=0.1440455 317 1.646688e+06 586.9845 *

55) RESPCUR>=-1.0087 27213 1.852686e+08 512.2132

110) hisei< 0.1602782 11409 7.455222e+07 494.8400

220) EPIST< -0.80305 2290 1.501526e+07 470.8800

440) JOYSCIE< 1.09935 2014 1.244485e+07 465.8497

880) hisei< -0.8290873 1099 6.347341e+06 456.1333 *

881) hisei>=-0.8290873 915 5.869137e+06 477.5199 *

441) JOYSCIE>=1.09935 276 2.147574e+06 507.5864

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##      882) SCIERES< -0.6288442 59 4.637532e+05 453.2983 *
##      883) SCIERES>=-0.6288442 217 1.462659e+06 522.3467 *
##      221) EPIST>=-0.80305 9119 5.789217e+07 500.8570
##      442) TOTST< -0.2700582 4741 2.915180e+07 490.9819
##      884) SCIEEFF< 0.3597 3451 1.981225e+07 485.3468
##      1768) STUBEHA>=-0.2443 2014 1.137857e+07 477.9469 *
##      1769) STUBEHA< -0.2443 1437 8.168834e+06 495.7179 *
##      885) SCIEEFF>=0.3597 1290 8.936798e+06 506.0571 *
##      443) TOTST>=-0.2700582 4378 2.777739e+07 511.5508
##      886) SC001Q01TA< 0.2848347 2463 1.502974e+07 500.9268
##      1772) LEAD>=0.87805 443 2.709722e+06 476.0993 *
##      1773) LEAD< 0.87805 2020 1.198707e+07 506.3716
##      3546) hisei< -0.6492027 1180 7.155207e+06 497.2569 *
##      3547) hisei>=-0.6492027 840 4.596116e+06 519.1756 *
##      887) SC001Q01TA>=0.2848347 1915 1.211210e+07 525.2149
##      1774) STUBEHA>=-1.73725 1648 1.020520e+07 520.4927
##      3548) SCIEEFF< -0.5468 408 2.231329e+06 500.2937 *
##      3549) SCIEEFF>=-0.5468 1240 7.752637e+06 527.1389 *
##      1775) STUBEHA< -1.73725 267 1.643322e+06 554.3618 *
##      111) hisei>=0.1602782 15804 1.047869e+08 524.7550
##      222) SCIEEFF< -0.57035 3002 1.759334e+07 500.6827
##      444) SCIEEFF< -0.92265 1481 8.536607e+06 489.7147 *
##      445) SCIEEFF>=-0.92265 1521 8.705100e+06 511.3623 *
##      223) SCIEEFF>=-0.57035 12802 8.504606e+07 530.3998
##      446) EPIST< -0.80895 2229 1.509646e+07 505.5179
##      892) JOYSCIE< 0.07775 1048 6.155711e+06 488.9681

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##      1784) INSTSCIE>=-0.30345 667 3.929360e+06 478.0673 *
##      1785) INSTSCIE< -0.30345 381 2.008342e+06 508.0516 *
##      893) JOYSCIE>=0.07775 1181 8.398991e+06 520.2039
##      1786) LEADPD>=0.72855 303 2.125903e+06 493.8392 *
##      1787) LEADPD< 0.72855 878 5.989790e+06 529.3025 *
##      447) EPIST>=-0.80895 10573 6.827868e+07 535.6454
##      894) TOTST< -0.20554 5208 3.270022e+07 525.1035
##      1788) HOMEPOS< 0.3204 2699 1.671870e+07 516.1894
##      3576) LEADCOM>=-0.159 1816 1.123154e+07 508.6925
##      7152) RESPCUR< -0.72845 484 2.934866e+06 489.6968 *
##      7153) RESPCUR>=-0.72845 1332 8.058567e+06 515.5948 *
##      3577) LEADCOM< -0.159 883 5.175185e+06 531.6077 *
##      1789) HOMEPOS>=0.3204 2509 1.553634e+07 534.6927
##      3578) JOYSCIE< 0.63925 2023 1.238458e+07 529.9410 *
##      3579) JOYSCIE>=0.63925 486 2.915946e+06 554.4721 *
##      895) TOTST>=-0.20554 5365 3.443786e+07 545.8788
##      1790) ST022Q01TA>=0.5 838 6.056944e+06 514.1177
##      3580) LEAD>=0.30825 472 3.381485e+06 495.2294
##      7160) PROSTMAS< 0.3547598 247 1.462390e+06 470.5124 *
##      7161) PROSTMAS>=0.3547598 225 1.602541e+06 522.3632 *
##      3581) LEAD< 0.30825 366 2.289901e+06 538.4764 *
##      1791) ST022Q01TA< 0.5 4527 2.737908e+07 551.7581
##      3582) STUBEHA>=0.51465 863 5.525694e+06 529.8165
##      7164) SC064Q03TA>=-0.562183 448 2.763935e+06 514.8623 *
##      7165) SC064Q03TA< -0.562183 415 2.553421e+06 545.9599 *
##      3583) STUBEHA< 0.51465 3664 2.134006e+07 556.9261

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##          7166) SCIERES< -1.090537 253 1.695304e+06 519.9238 *
##          7167) SCIERES>=-1.090537 3411 1.927266e+07 559.6706
##          14334) TOTST< 0.6977145 2789 1.498941e+07 555.0600 *
##          14335) TOTST>=0.6977145 622 3.958111e+06 580.3444 *
## 7) EPIST>=-0.1347 43781 3.368665e+08 540.6047
## 14) REPEAT>=0.5 2725 1.927715e+07 470.8616
## 28) ENVAWARE< -0.55695 507 3.256230e+06 432.5733
## 56) RESPCUR< -1.1132 43 2.364421e+05 358.3354 *
## 57) RESPCUR>=-1.1132 464 2.760842e+06 439.4531 *
## 29) ENVAWARE>=-0.55695 2218 1.510776e+07 479.6137
## 58) SCIEEFF< -0.67825 407 2.282447e+06 447.5326 *
## 59) SCIEEFF>=-0.67825 1811 1.231229e+07 486.8235
## 118) CREATIV< 0.6311152 1333 8.466182e+06 477.6436
## 236) GRADE< -1.5 173 7.759007e+05 435.8178 *
## 237) GRADE>=-1.5 1160 7.342500e+06 483.8814
## 474) RESPCUR< -1.1132 109 6.857121e+05 431.1099 *
## 475) RESPCUR>=-1.1132 1051 6.321759e+06 489.3544 *
## 119) CREATIV>=0.6311152 478 3.420513e+06 512.4236
## 238) TOTAT< -0.2810665 129 9.331434e+05 477.1547 *
## 239) TOTAT>=-0.2810665 349 2.267596e+06 525.4599 *
## 15) REPEAT< 0.5 41056 3.034549e+08 545.2338
## 30) SCIEEFF< -0.11275 11906 7.847467e+07 518.7596
## 60) SCIEEFF< -0.99295 2952 1.835064e+07 494.4428
## 120) SCIEEFF< -2.8398 287 1.668961e+06 450.1236 *
## 121) SCIEEFF>=-2.8398 2665 1.605724e+07 499.2157
## 242) RESPCUR< -1.0087 444 3.093108e+06 468.5034

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##      484) PARED< 0.858813 309 1.854584e+06 452.9736 *
##      485) PARED>=0.858813 135 9.934274e+05 504.0493
##      970) PARED>=1.326928 18 5.096698e+04 396.0014 *
##      971) PARED< 1.326928 117 6.999934e+05 520.6720 *
##      243) RESPCUR>=-1.0087 2221 1.246161e+07 505.3554
##      486) hisei< 0.0703359 925 5.037263e+06 489.2856 *
##      487) hisei>=0.0703359 1296 7.014986e+06 516.8249 *
##      61) SCIEEFF>=-0.99295 8954 5.780303e+07 526.7764
##      122) hisei< 0.0703359 3502 2.165291e+07 510.9197
##      244) TOTAT< -0.1304055 2069 1.227131e+07 500.3633
##      488) ASSESSMENT< -0.4901222 608 3.909799e+06 482.2158 *
##      489) ASSESSMENT>=-0.4901222 1461 8.077947e+06 507.9155 *
##      245) TOTAT>=-0.1304055 1433 8.818148e+06 526.1613
##      490) SCIERES< -0.6288442 249 1.557159e+06 497.9168 *
##      491) SCIERES>=-0.6288442 1184 7.020575e+06 532.1012
##      982) ENVAWARE< -0.5697 239 1.585696e+06 505.2465 *
##      983) ENVAWARE>=-0.5697 945 5.218928e+06 538.8930 *
##      123) hisei>=0.0703359 5452 3.470400e+07 536.9617
##      246) RESPCUR< -0.92795 1099 7.541922e+06 509.5966
##      492) PARED< 0.858813 633 4.507896e+06 492.1414
##      984) SCHSIZE< 0.05537909 454 2.827193e+06 477.5678 *
##      985) SCHSIZE>=0.05537909 179 1.339717e+06 529.1044 *
##      493) PARED>=0.858813 466 2.579175e+06 533.3073
##      986) TOTST< 0.8267508 412 2.135318e+06 525.4267 *
##      987) TOTST>=0.8267508 54 2.230500e+05 593.4338 *
##      247) RESPCUR>=-0.92795 4353 2.613132e+07 543.8706

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```

##      494) TOTST< -0.07650365 2724 1.618407e+07 535.1531
##      988) JOYSCIE< 0.8329 2112 1.189045e+07 530.2953 *
##      989) JOYSCIE>=0.8329 612 4.071787e+06 551.9172 *
##      495) TOTST>=-0.07650365 1629 9.394081e+06 558.4478
##      990) SC001Q01TA< 1.11714 1165 6.431158e+06 550.9335
##      1980) ESCS< 0.8165 574 3.175373e+06 536.7117 *
##      1981) ESCS>=0.8165 591 3.026932e+06 564.7461 *
##      991) SC001Q01TA>=1.11714 464 2.731978e+06 577.3146 *
##      31) SCIEEFF>=-0.11275 29150 2.132272e+08 556.0469
##      62) RESPCUR< -1.1132 2558 1.996953e+07 503.6937
##      124) PARED< 0.858813 1976 1.416175e+07 489.0741
##      248) TOTAT< 0.3924768 1671 1.053090e+07 478.0964
##      496) ENVAWARE< -0.46725 158 1.025307e+06 423.9462 *
##      497) ENVAWARE>=-0.46725 1513 8.993922e+06 483.7513
##      994) ASSESSMENT< -0.4901222 949 5.306675e+06 472.5971
##      1988) SC064Q01TA< 0.3876303 625 3.151485e+06 459.7228 *
##      1989) SC064Q01TA>=0.3876303 324 1.851770e+06 497.4317
##      3978) WEALTH>=-0.14465 221 1.184954e+06 479.2382 *
##      3979) WEALTH< -0.14465 103 4.367081e+05 536.4681 *
##      995) ASSESSMENT>=-0.4901222 564 3.370510e+06 502.5195 *
##      249) TOTAT>=0.3924768 305 2.326234e+06 549.2171
##      498) PROSTAT< -0.4594275 86 5.765739e+05 492.4378 *
##      499) PROSTAT>=-0.4594275 219 1.363529e+06 571.5140
##      998) SC064Q01TA< -1.143474 42 2.534791e+05 505.7813 *
##      999) SC064Q01TA>=-1.143474 177 8.855156e+05 587.1116 *
##      125) PARED>=0.858813 582 3.951517e+06 553.3303

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##      250) CREATIV< 0.6311152 334 1.983577e+06 532.7101 *
##      251) CREATIV>=0.6311152 248 1.634665e+06 581.1010
##      502) TOTST< 1.068694 197 1.262612e+06 565.8396 *
##      503) TOTST>=1.068694 51 1.489358e+05 640.0517 *
##      63) RESPCUR>=-1.1132 26592 1.855721e+08 561.0830
##      126) hisei< 0.1602782 8747 5.970367e+07 540.5223
##      252) ENVAWARE< -0.80425 325 2.320540e+06 470.0253 *
##      253) ENVAWARE>=-0.80425 8422 5.570561e+07 543.2428
##      506) TOTST< -0.3023173 3662 2.460372e+07 529.7565
##      1012) STRATIO>=1.195696 166 9.983636e+05 476.6403 *
##      1013) STRATIO< 1.195696 3496 2.311478e+07 532.2786
##      2026) HOMEPOS< -0.03995 1415 9.488028e+06 519.1417
##      4052) SCHSIZE< -0.5537673 649 4.638443e+06 503.9877
##      8104) ASSESSMENT< 0.4225337 401 2.812747e+06 489.0204 *
##      8105) ASSESSMENT>=0.4225337 248 1.590614e+06 528.1888 *
##      4053) SCHSIZE>=-0.5537673 766 4.574270e+06 531.9812 *
##      2027) HOMEPOS>=-0.03995 2081 1.321651e+07 541.2111 *
##      507) TOTST>=-0.3023173 4760 2.992343e+07 553.6181
##      1014) ST004D01T< 0.5 2510 1.523714e+07 544.5314
##      2028) SCIEEFF< 0.58765 1241 6.792545e+06 534.2148 *
##      2029) SCIEEFF>=0.58765 1269 8.183338e+06 554.6205 *
##      1015) ST004D01T>=0.5 2250 1.424786e+07 563.7548
##      2030) JOYSCIE< 0.1354 472 2.898876e+06 541.1831 *
##      2031) JOYSCIE>=0.1354 1778 1.104467e+07 569.7469 *
##      127) hisei>=0.1602782 17845 1.203583e+08 571.1611
##      254) TOTST< -0.2700582 7243 4.739528e+07 556.2939

```

```

##      508) JOYSCIE< 1.10155 4305 2.621683e+07 547.0267
##
##      1016) STRATIO>=0.960185 232 1.494703e+06 503.0337 *
##
##      1017) STRATIO< 0.960185 4073 2.424754e+07 549.5325
##
##      2034) ENVAWARE< -0.8477 158 1.021517e+06 497.9739 *
##
##      2035) ENVAWARE>=-0.8477 3915 2.278906e+07 551.6133
##
##      4070) hisei< 0.9697591 1834 1.046920e+07 542.1509 *
##
##      4071) hisei>=0.9697591 2081 1.201093e+07 559.9526
##
##      8142) BELONG>=-0.05015 1110 6.178465e+06 550.5491 *
##
##      8143) BELONG< -0.05015 971 5.622111e+06 570.7022 *
##
##      509) JOYSCIE>=1.10155 2938 2.026699e+07 569.8730
##
##      1018) RESPCUR< -0.72845 873 6.684184e+06 547.7140
##
##      2036) PARED< 0.858813 432 3.062594e+06 524.9020
##
##      4072) STAFFSHORT>=1.2128 67 3.421576e+05 473.2987 *
##
##      4073) STAFFSHORT< 1.2128 365 2.509272e+06 534.3744 *
##
##      2037) PARED>=0.858813 441 3.176565e+06 570.0604 *
##
##      1019) RESPCUR>=-0.72845 2065 1.297293e+07 579.2409
##
##      2038) HOMEPOS< -0.09635 378 2.620101e+06 555.5637 *
##
##      2039) HOMEPOS>=-0.09635 1687 1.009343e+07 584.5462 *
##
##      255) TOTST>=-0.2700582 10602 7.026833e+07 581.3179
##
##      510) ST022Q01TA>=0.5 1627 1.240169e+07 555.1615
##
##      1020) ASSESSMENT< -0.4901222 887 6.652075e+06 536.3264
##
##      2040) SC064Q03TA>=-0.05144769 390 2.680364e+06 509.9015
##
##      4080) SC064Q02TA< 1.123605 236 1.479865e+06 489.9674 *
##
##      4081) SC064Q02TA>=1.123605 154 9.630072e+05 540.4499 *
##
##      2041) SC064Q03TA< -0.05144769 497 3.485688e+06 557.0621
##
##      4082) TOTST< 2.230021 481 3.161892e+06 552.6588 *

```

```

##          4083) TOTST>=2.230021 16 3.409224e+04 689.4389 *
##          1021) ASSESSMENT>=-0.4901222 740 5.057758e+06 577.7382 *
##          511) ST022Q01TA< 0.5 8975 5.655172e+07 586.0596
##          1022) EPIST< 0.5582 2673 1.705257e+07 571.0772
##          2044) STRATIO>=0.05257458 1065 7.150426e+06 554.6515
##          4088) SC025Q01NA< -1.429469 21 2.201801e+05 449.7104 *
##          4089) SC025Q01NA>=-1.429469 1044 6.694328e+06 556.7623 *
##          2045) STRATIO< 0.05257458 1608 9.424491e+06 581.9562
##          4090) CLSIZE< 0.1783008 1174 7.159142e+06 574.6694
##          8180) RESPCUR< -0.0871 671 4.029995e+06 562.7334 *
##          8181) RESPCUR>=-0.0871 503 2.906027e+06 590.5919 *
##          4091) CLSIZE>=0.1783008 434 2.034386e+06 601.6676 *
##          1023) EPIST>=0.5582 6302 3.864464e+07 592.4144
##          2046) SCIERES< -1.090537 383 2.849316e+06 555.1202
##          4092) STU.HELP>=0.8504734 124 1.008021e+06 516.8358
##          8184) SC034Q03TA< -0.5036566 44 4.162780e+05 457.2862 *
##          8185) SC034Q03TA>=-0.5036566 80 3.498959e+05 549.5881 *
##          4093) STU.HELP< 0.8504734 259 1.572535e+06 573.4494 *
##          2047) SCIERES>=-1.090537 5919 3.522816e+07 594.8276
##          4094) CREATIV< -0.3510227 1199 6.879747e+06 576.9877
##          8188) JOYSCIE< -0.77205 71 4.015016e+05 522.3755 *
##          8189) JOYSCIE>=-0.77205 1128 6.253160e+06 580.4251 *
##          4095) CREATIV>=-0.3510227 4720 2.786988e+07 599.3594
##          8190) TOTST< 0.2783463 3030 1.709952e+07 592.1927
##          16380) SCIEEFF< 0.6936 1137 6.448545e+06 579.3522 *
##          16381) SCIEEFF>=0.6936 1893 1.035091e+07 599.9052 *

```

8191) TOTST $\geq$ 0.2783463 1690 1.033571e+07 612.2085

16382) SCHSIZE $\geq$ 3.879023 48 3.092986e+05 515.9810 *

16383) SCHSIZE $<$ 3.879023 1642 9.568955e+06 615.0214 *

Academic Integrity Statement

I, **Shermain Puah**, hereby confirm that I completed this master's thesis with the title: "**Predicting Students' Academic Performance: A Comparison between Traditional MLR and Machine Learning Methods with PISA 2015**" independently, that I have not heretofore presented this paper to another department or university, and I have listed all references used, and have given credit to all additional sources of assistance

Munich, **21.08.2020**

Shermain Puah

Name (signature above)