Admissions test scores and high school grade point average predictive power on students' grade point average during first year university: A research with Correlation, Regression Analysis and Neural Network

by

DANG Ha Thu

52117632

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Certification Page

I, DANG Thu Ha (Student ID 52117632) hereby declare that the contents of this Master's Thesis are original and true, and have not been submitted at any other university or educational institution for the award of degree or diploma.
All the information derived from other published or unpublished sources has been cited and acknowledged appropriately.

DANG, Ha Thu
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Summary

The research covered the topic of artificial intelligence usage in college through answering the research question of can neural network predict students' grade point average in their first year at university based on their admission scores, which is SAT Score in the context of this research, their high school grade point average, and lastly, a combination of both of these scores.

The research answered these questions through means of correlation analysis, regression analysis in Excel and IBM SPSS as well as through construction of a neural network in Python using the programming library ScikitLearn.

As a result, the research confirmed a significant correlation between the prediction of first year university grade point average with admission score and high school grade point average. The research also suggest that further research should continue with an additional independent variable of emotional intelligence after identifying limitations with the methods and result stated in the main text.

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List of Abbreviations

ACT	American College Testing
A.I.	Artificial Intelligence
CAT	Critical Thinking Assessment Test
CTAS	Cognitive Test Anxiety Scale
DERS	Difficulties in Emotion Regulation Scale
E.I.	Emotional Intelligence
FU_GPA	First year university grade point average
GII	Global Innovative Index
GMAT	Graduate Management Admission Test
HS_GPA	High school grade point average
IBM SPSS	International Business Machine Statistical Package for Social Science
ICT	Information and Communications Technology
I.Q.	Intelligence Quotient
KNN_C	K Nearest Neighbor Classifier
KNN_R	K Nearest Neighbor Regressor
NTT	Nippon Telegraph and Telephone
MAE	Mean Absolute Error
MSE	Mean Squared Error
SAT Score	Scholastic Aptitude Test Score
UNESCO	United Nations Education, Science and Cultural Organiation

List of Footnotes

1. See Higher Education System Strengths Rankings 2018
2. See Global Innovation Index Database, Cornell, INSEAD, and WIPO as cited in THE GLOBAL INNOVATION INDEX 2018: ENERGIZING THE WORLD WITH INNOVATION
3. See Neilsen et al. book Deep Learning published in MIT Press for detailed definitions of neural network. The explanation given in this research is a less complex explanation of a neural network's structure.
4. See https://www.spss-tutorials.com/measurement-levels/#ordinal-variable for full explanation.
5. See https://towardsdatascience.com/how-to-build-your-own-neural-network-from-scratch-in-python-68998a08e4f6 for full entry
6. See https://stackoverflow.com/questions/29888233/how-to-visualize-a-neural-network for full programming code and explanation
7. Data set can be found at https://www.statcrunch.com/app/index.php?dataid=468543

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ABSTRACT

The fourth industrial revolution has deepened the involvement of technology such as automation and artificial intelligence in every industry from financial to pharmaceutical to human resource (Shanmuganathan, 2016). The next industry to experience penetration of technology is the education industry (Trivella, 2016). This research aims to present possible utilization of artificial intelligence such as neural network to predict student's academic performance during their first year in university, represented by grade point average using records from the past, represented by a combination of admission test score (SAT Score) and high school grade point average. By creating a Python model of neural network using ScikitLearn using limited time allowance, the research touches on the possibility of increased productivity for admission officer once these officers apply artificial intelligence to the admission procedures.

The research also made use of different analysis methods such as Excel Correlation, Excel Regression, and IBM SPSS Analysis. Both additional analysis methods confirm the analytical and predictive power of the neural network model created in the research. The research observed some inconsistencies which it theorized could be a part of the different robustness of the model versus that of other analytical tools. The large size of the data sets also created discord between this research and that done prior suggesting that further additional researches investigate this discord.

The research discussed several limitations, additional studies, and arguments as well as legal consideration when examining the application of artificial intelligence and

made suggestions for general managers and management board of universities in Japan as to cultural push back should implementation of artificial intelligence is necessary for the country.

INTRODUCTION

1.1 Study context

From the Meiji Era of the 1900s to our current system during Reiwa, Japan has experienced many reforms in many facets of the country. One of those facets is the education system (Beauchamp & Vardaman, 1994; Yoshikawa, Deleyer-Tiarks, Kehle & Bray, 2019). Education has long been an essential topic in Japanese conversation. Once revered by other developed countries to be the country with advance and rigorous education, Japan now ranks as the tenth worldwide and number two in Asia, fallen behind when Korea became number one in 2015[1]. With the recent and accelerating presence of new technology such as virtual classroom, online universities, artificial intelligence, universities in Japan appear to struggle with facing the issues created by these technologies. Despite the rapid application and adoption of technology worldwide, Japan's effort to innovate has slowed down, scoring 54.95 in Global Innovation Index[2].

The closure of private universities in Japan appears to be the first sign of a shrinking market which grows increasingly obligated to attract better, smarter human assets which

[1] See Higher Education System Strengths Rankings 2018

[2] See Global Innovation Index Database, Cornell, INSEAD, and WIPO as cited in THE GLOBAL INNOVATION INDEX 2018: ENERGIZING THE WORLD WITH INNOVATION

can combat the technological trend and acquire employment after graduation in a country with declining birthrate (Ito & Kawazoe, 2015; Deguchi, 2018). From the 1980s, Japan has been promoting ICT in education as an attempt to adjust to social changes that follow technology diffusion (Oshima & Muramatsu, n.d.).

This research aims to define artificial intelligence and its benefits and how those benefits could help these universities and any relevant stakeholders to identify potential students better, keep track of their progress and increase productivity for admission officers who take charge of admission procedures.

1.2 Study contribution

While there have been researches done on the predictive power of different factors in forecasting academic performance for first-year university students, there has not been little which touched on the subject of neural network application for admission procedure. Li, Zhang, Liu (2017) noted that usage of neural network and artificial intelligence, in general, had been shown to increase during the decade. This research hopes to integrate the technology into the context of education, or in a more specific context, the admission process. Foreseeable results that could come out of using neural network include heightening level of production and technology diffusion which is scarce in Japan. The neural network for this research completed construction in less than one month, without a vast amount of technical knowledge from the researcher's side which could be a good indication of the low level of technological understanding to create a similar model. Beginners to advanced technology such as artificial intelligence can thus be at ease that replication of similar models in the context of a university is plausible for institutions with employees in possession of higher technological knowledge. From this understanding, a circumstantial conclusion can also be made for individuals and institutions with a high level of technological understanding, indicating that such individuals and institutions possess more than enough resources to improve and expand the model. This research also adds to the pool of researches done on education in Japan. As Japan is unique in many facets (education, admission criteria, speed of technological adaptation) relating to the topic concerning this research, the presented result and discussion aim to contribute to the general knowledge and acting as a piece of advice to the group of stakeholders seeking to penetrate Japan with artificial intelligence.

Consideration of possible benefit from neural network model presented in this research includes the potential increase of productivity for admission officers of various universities and lower level of education. In their Harvard Business Review entry, Davenport and Ronanki (2018) discussed a comprehensive survey done by Deloitte of 250 executives who are familiar with the cognitive usage in their companies A.I.

initiatives. The survey found that the main functions of artificial intelligence in bettering existing products as the most stated reason for implementation. Optimization of internal operation and time allowance for a worker to work creatively both come in second as reasons for implementation.

Through the addition of artificial intelligence, we can decrease the need for human employees to focus their energy for an extended duration into a repetitive task that artificial intelligence could complete with decreased resources and enhance the strength of human intelligence (Daugherty, 2019).

In the case of this research, the model was created after two weeks of intensive effort by one single researcher and ran through one thousand sets of data in less than five minutes. In terms of productivity, this could have a significant impact on admission procedure moving forward should other researchers decided to conduct further researches and revisions of the model.

Despite the potential of the neural network, some precautions require dissertations. Two of those precautions listed in this research are the legal and ethical liability and quality control. The research will discuss concerns in details in later part of the research.

1.3 Artificial intelligence application in universities worldwide

Worldwide application of artificial intelligence though remains fewer than traditional means still shows signs of growth and improvement. Frequent use of artificial intelligence is in researches. One of such examples is the usage to predict degree completion done by Oztekin (2016). Other applications include student training as found in an article published in Inside Higher Ed on the application of artificial intelligence in academics. The article mentioned the collaborative mandarin project tested by IBM in 2017 and is still in use at the moment. Artificial intelligence also plays a part in student recruitment and retention. Universities such as Arizona State University, California State University utilize artificial intelligence to act as chatbots which help answers students' inquiry and propose alternatives to different issues they encounter. Other usages of artificial intelligence include academic encouragement (Carnegie Mellon University's cloud computing class) and a future project which emphasizes on behavior monitoring as suggested by Jake Whitehill at Worcester Polytechnic Institute. The University of St. Thomas in Minnesota is testing this technology to determine if students cheated in their lecture hall (McKenzie, 2018).

While engagement with artificial intelligence, in general, remains low, worldwide application of A.I. and A.I. based methods exist and have shown promising results as shown in the research done by Wang and Srinivasan (2016) on the prediction of energy use. These examples can be a promising sign for the application of artificial intelligence in other industries. In the next section, the research will discuss the progress of artificial intelligence application in Japan both in companies and in universities.

1.4 Artificial intelligence application in Japanese companies and universities

Told in the prologue of The Best of A.I. in Japan by Nishida (2012), the history of artificial intelligence in Japan started in the 1960s when a research group began at Kyoto University. This research group's main focus was on media information processing which consists of computer vision, speech processing, and natural language processing. The research group would remain in relative size before the popularization of artificial intelligence research groups in the 1970s. Artificial intelligence would see rapid expansion during 1985, and in 1986, the Japanese Society for Artificial Intelligence was established to connect Japanese A.I. communities and with the international community (Nishida, 2012).

Despite Japan's effort to push researches related to artificial intelligence, the national diffusion of the technology appears scarce, focusing on large companies like IBM Japan and NTT rather than smaller and different discipline. Usage of artificial intelligence also remains in the domain of business and has yet to reach out and penetrate other industry (Nishida, 2012).

From the beginning of the fourth industrial revolution which starts in the 18th century, Japan has been late to adjust itself to the changing face of the technological trend. As shown by the lower Global Innovative Index, Japan is slower to innovate compared to other developed countries such as the United States with Global Innovative Index of 59.81, Switzerland with Global Innovative Index of 68.40 and Singapore with Global Innovative Index of 59.83 [2]. As the world's position lands at the center of evolution brought about by artificial intelligence, the question remains of whether or not there would be any improvement in Japan. Improvements which allow it to catch up with or surpass other nations such as United States which no longer lead the world on numbers of publications related to deep learning or China where plans to seize strategic first-mover advantage to develop A.I. were announced (Cave & ÓhÉigeartaigh, 2018).

This research explores a possibility for artificial intelligence in predicting student's performance in universities and thus hopefully would lead to consideration of development and implementation of neural network models in Japan as an application of artificial intelligence in educational institutions.

LITERATURE

2.1 Neural Network

Researches have often seen applications of a variety of data mining methods like the algorithm to predict students' performance in university courses (Badr, Algobail, Almutairi & Almutery, 2016), to select and appoint human resource (Mehrabad & Brojeny, 2007). This research discusses the involvement of neural network in the prediction of a student's first-year university grade point average.

As of the current non-research-oriented usage, the neural network has been a substantial contribution to the predicting power throughout multiple sectors such as health care (Jiang, Jiang, Dong, Li, Ma & Wang, 2017), finance (Dunis, 2016; Hongjiu, Rieg, Yanrong, 2012), and engineering (Salehi & Burgueño, 2018). While there have been applications of neural network in the recruitment sector similar to that of which this research aims to address, those applications have been mainly in the area of human resource management. In order to better comprehend the predictive power of this system and how it could benefit the prediction process in this research, we first need to understand the nature of a neural network, how it operates and its capability.

2.1.1 The nature of neural network and its operations

Sun-Chong Wang (2003) defined a neural network in the fifth chapter of Interdisciplinary Computing in Java Programming as a system which took inspiration by biological networks in the human's brain where billions of interconnected neurons work to serve multiple sophisticated functionalities. Its primary structure includes one input layer, one output layer and one or more hidden layer(s) between the input and output layers. This structure is described by Nielsen, Bengio, Goodfellow & Courville (2016)3 on their website as Figure 2.1 below.

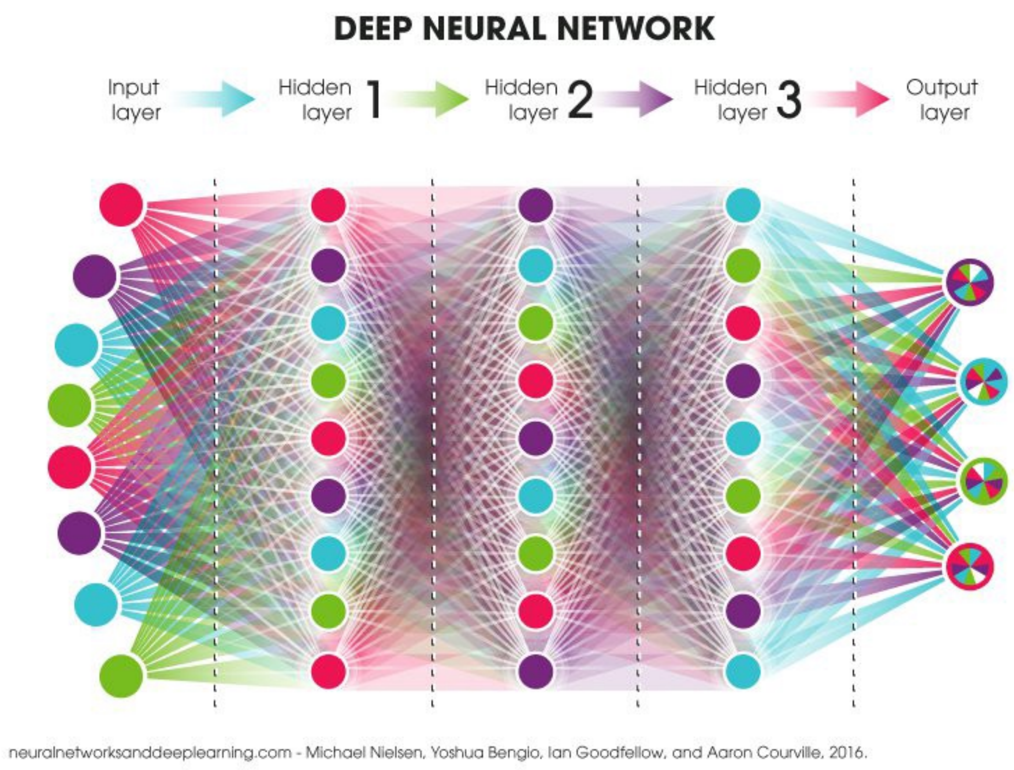

Figure 2.1 Neural network structure

[3] See Neilsen et al. book Deep Learning published in MIT Press for detailed definitions of neural network. The explanation given in this research is a less complex explanation of a neural network's structure.

Each circle in the figure above represents one node. Each node represents one neuron in the network. Each line in the system connecting each node in one layer to another in the next layer is assigned a weight (w) that could change according to each input and output provided for system training. Each weight would be assigned a value that indicates how predictive one input is with the output whether the output is the hidden layer(s) or the final yielding of the model. These various weights would adjust their value constantly throughout the training stage when it processes the training data set(s). The hidden layer or layers create an algorithm fitting of the training data provided and is responsible for the failure or success of the model. Summary of the output or result of this model shortened into the following formula.

$$a(n) = \sigma\ (W\times\ a(n-1) + b)$$

a(n) in this equation is the output of the data after it ran through the input layer or hidden layer. a(n-1) is the input layer or hidden layer right before a(1). Depend on the number of layers n, and n-1 value varies. W is the total value of each weight assigned to the nodes and b is the total value of biases from each run. While the equation seems simple and the logic behind the operation of the neural network is simple, mathematically, the neural network requires a multitude of complex and intricated functions.

In the context of this research, the neural network allows for an increase in prediction's efficiency as it can process the amount of data increasingly faster than one human would while performing a constant update of its algorithm to determine the result of the prediction better.

2.1.2 A neural network's capability

Yano (2017) discusses the potential of artificial intelligence in human resource management. Yano addresses the five misconceptions of artificial intelligence which could be found with the neural network as well since the neural network is a type of artificial intelligence. These five misconceptions include complexity (cannot be understood by those lacking a technological background), novelty (new technology or machine), availability of data (requires a large amount of data to be useful), fear (the scenario of 'Big Brother'), and futuristic usage (relevant only for the future and not applicable now).

While a neural network could look complicated to the inexperienced eyes, it can be put to great use even by those without experience as the purpose and operation of a neural network alters and depends on the specific goal its programmer(s) set (Pagel & Kirshtein, 2017). Sommer, Olbrich & Arendasy (2004) researched using a neural network to improve personnel selection in the field of aviation psychology. The research tested eighty-two participants to compare the classic analysis method of SPSS 10.0 to the application of a neural network. The result shows an improvement in the classification rate and the separability of correct and incorrect classifications. Despite the small sample in Sommer's study, the result showed still that the neural network avoided a local minimum or a point in which whose value is smaller than the ones around it but not all points as a whole during the learning process. This finding further solidifies the necessity to examine a neural network's capability in predicting the grade point average in the first year of the university known below as FU_GPA. Consequentially, to help to bring the predictive power that the discipline of human resource management has used to university admission through analyzing admission tests score and a student's high school cumulative grade point average known below as HS_GPA.

2.2 Admission tests and high school grade point average

Researches on admission put forth a presentation of different types of admission tests as the superior version of predictive attributes. Some of these tests include the Scholastic Aptitude Test (SAT), American College Testing (ACT), Critical Thinking Assessment Test (CAT). Examination of works of literature on the topic of admission criteria concluded that SAT and ACT appear the most mentioned in literature. Due to data restraint, this research will focus solely on the predictive power of the SAT and high school grade point average and not all the listed admission tests. However, alternative literature could be reference as evidence of conclusion made in regards to ACT's validity in predicting first-year university grade point averages. One of this literature is the report done by Noble and Sawyer (2002) which concluded a link between ACT score and university first-year grade point average. More researches also focused on the different sections or types of these tests (SAT-M, SAT-CR, ACT-M, ACT-R, and more) as an indication of a better forecast of grade point average compare to the other (Geiser & Studley, 2002). This research, however, will focus on the general totaled score of the SAT to ensure a more generalized result when comparing with that given by high school grade point average.

Ragan, Li & Matos-Díaz (2011) concluded that HS_GPA is a better predictor of FU_GPA than a test score. The researcher also includes in the conclusion that HS_GPA is generally higher for the female population while test scores are better for that of male. Instances of this phenomena are also available for public high school students and that from private high schools where the former has better HS_GPA, and the latter has better test scores. Atkinson & Geiser (2009) and Camara & Echternacht (2000) concurs with Ragan on this point as well, stating that high school grade point averages better indicate a student's readiness for university. Burton & Ramist (2001) and Morgan (1989) offered confirmation on the same findings in a majority of predictive-validity studies since 1976 on the matter.

This research agrees with the abovementioned researcher's discoveries as to the superior predictive power of HS_GPA over admission test scores. Previous studies focused on the predictive power of admission test scores, in this research's context SAT score, as they believe that such is the indication of a student's I.Q. However, the factors that contribute to one's SAT scores are socioeconomic. One's parents' income, education, and social standing affect the correlation to a great extent. HS_GPA, in contrast, has less of a close relationship with a student's socioeconomic background (Patterson & Mattern, 2013).

Gelser & Santelices (2007) researched the validity of HS_GPA on the outcome of FU_GPA and found similar results while emphasizing that the accuracy of HS_GPA predictive power increases as the university year progresses. Their study while providing insight into the topic of this research need to consider the basis that its method made use of the linear model. This model could result in a less adaptive model. A neural network would provide a non-linear model and thus is more flexible, unbiased and produce smaller residual in a regression model.

2.3 Academic success versus academic performance

It is important to discern between the definition of academic success against that of academic performance. Academic success is often complicated and broad as a definition and frequently misused to ensure desired outcomes accordingly to different goals of academic researches. The component of academic success according to the suggested theory from York, Gibson and Rankin (2015) include six components as follow: academic achievement, satisfaction, acquisition of skills and competencies, persistence, attainment of learning objectives, and career success.

This research henceforth should be contemplated and examined as an attempt to tackle the predictability of academic performance which tightly relates to the academic results definable through university students' first-year grade point average.

As academic success is not measured simply with one component, readers of this research is advised to consider it as one of the previously mentioned components than a definitive measure of academic success.

The next section of this research will discuss further the short-comings of literature found on this subject and explain the direction the researcher wished to take to contribute to the general knowledge in this topic. It will discuss admission test score concerning student's background and similarly high school grade point average to student's academic persistence.

METHODS

Research done by Naik and Ragothaman (2004) has explored neural network's predictive ability on the performance of MBA students based on their undergraduate GPA, GMAT score, discipline, junior or senior GPA and more. While this research has less data than that done by Naik and Ragothaman, it attempts similar concept with undergraduate level as criteria for admission into universities.

From the collection of literature in section II, this research chose to focus on the hypothetical scenario of a combination between admission test score and high school GPA as the better indication for student's grade point average during their first-year of university. This assumption is tested using two methods and through three hypotheses which follows:

H1: Test score (SAT score) predicts student's GPA during the first year of university.

H2: High school GPA predicts student's GPA during the first year of university.

H3: A combination of test score and high school GPA give a better prediction of student's GPA during the first year of university.

Literature, as mentioned above though engaged in a deep understanding of the subject matter, failed to consider the possibility of a combination of contributing factor. As concluded, test scores such as SAT score represent the portion of the population that has obtained specific standards of life and skill set for one four-hour test. Patterson and Mattern (2013) presented their research on the validity of SAT for predicting first-year grades which the Educational Policy Institute graphed on January of 2015 to show the relation between household income versus the SAT and GPA. Their graph is presented below as figure 3.1.

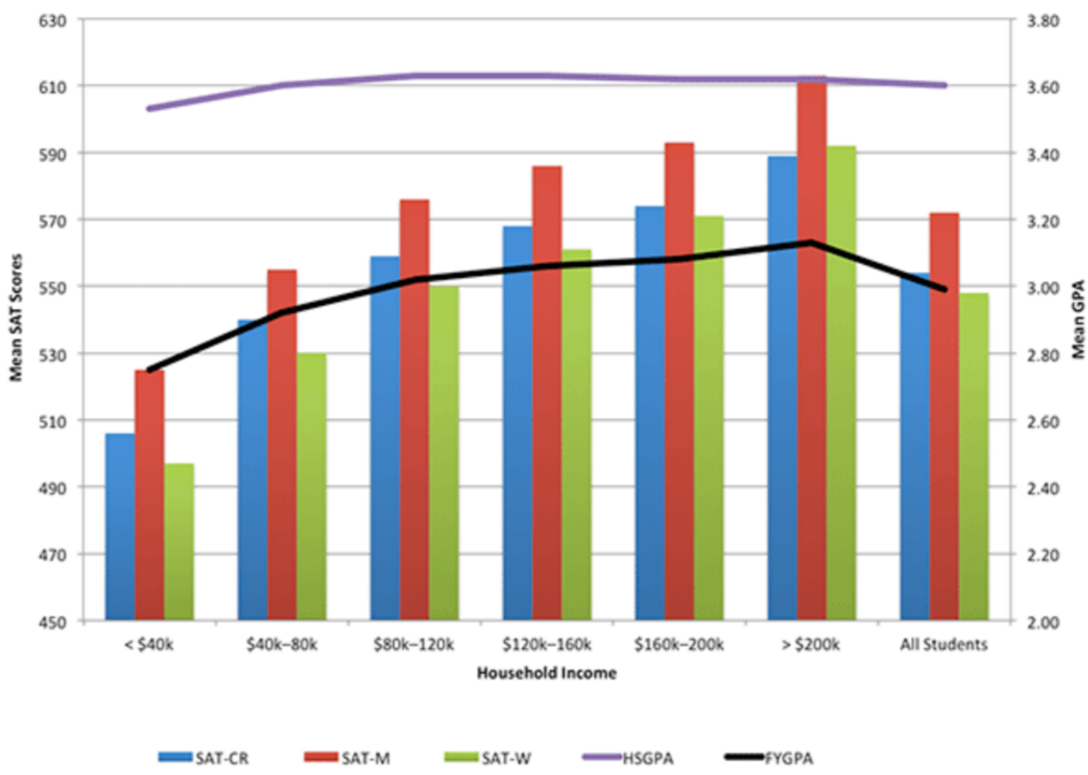

Figure 3.1 Household income versus the SAT and GPA

As observed in Figure 3.1, while the level of income change affected the sectional scores and the final score of SAT scores, it has little effect on the overall high school grade point average. This sentiment is also resonated by many as researchers found high school GPA to be more closely related to one's ability to perform well in a long-term as it better predicts the result of student in university (Gelser & Santelices, 2007). While these works of literature can confirm high school GPA's superiority over test scores when the subject of predictability is concerned, they missed the consideration of both these inputs as part of the predictive equation.

Increasing household income also displays an apparent correlation with the grade point average of students in the first-year university according to Figure 3.1. In future researches, it is crucial to understand that in order to judge fairly and equally a student's ability, the significant effects that follow household income need to be leveled out for the sake of a more unbiased assessment of students' academic performance.

Admission tests such as SAT claims to measure knowledge, application of knowledge and in different cases, also critical thinking (Atkinson & Geiser, 2009).However, these tests measure mainly the cognitive domain which includes knowledge, comprehension, application, analysis, synthesis, and evaluation and while these six categories are essential in one's academic career, it is also vital to remember that a higher level of education is where student most likely build their knowledge upon what they have learned from secondary education. Thus, following this logic, it could be reasoned that high school GPA would be more compatible when measuring GPA in the first year of university since such measurement requires a lower level of the cognitive domain which high school GPA represents. (Steenman, Bakker & Tartwijk, 2014; Hassan & Al-Razgan, 2016).

One's standard of life and one's ability to perform well in a long-term might be related but not mutually exclusive. This research used that as foundation and suggested that two inputs should be considered to work together in predicting one's first-year GPA in university rather than against each other to decide which is the best indication since one's performance in university is often time a combination of long-term effort and quick intensive strive rather than a single approach.

The methods used in this research consist of Excel analysis accompanied by IBM SPSS Analysis and Model Construction using ScikitLearn library of the programming language Python. A majority of papers in the literature section presented mixed result when analyzing the correlation between test score and high school GPA with first-year student GPA in university hence prompts this research to seek definitive confirmation on the subject matter through correlation analysis.

Correlation analysis is done using Excel and Regression analysis done using IBM SPSS which would give a precise number that indicates the level of correlation. SPSS Correlation makes use of Pearson Correlation algorithm, applicable to metric variables which according to the definition by SPSS Tutorial page[4] mean variable on which calculation are meaningful. Nominal variables, for example, the country's name; and ordinal variables, for example ethical, wrong, neutral values, does not fit the criteria for Pearson Correlation.

However, this research also recognizes the importance of the array of methods for analysis which might explain the differentiation in conclusions of previous papers. Therefore, the analysis and predictive power of Python model is used to confirm or deny the result of the Excel Correlation equation and SPSS Analysis.

The Python model based on Figure 2.1 is built using ScikitLearn which is a machine learning library in the Python programming language and of which structure Figure 3.2 describes. Nine-hundreds of which are used to train the model and the remaining one hundred are used to test the validity of the model. It features regression and classification. For this research, the choice for the prediction algorithm for the development of the model if K Nearest Neighbor.

[4] See https://www.spss-tutorials.com/measurement-levels/#ordinal-variable for full explanation.

K Nearest Neighbor algorithm, explained in a practical sense by Aishwarya Singh in the 2018 August entry of article in Analytics Vidhya, is a classification and regression algorithm that makes use of ‘feature similarity’ to predict values of new data points. In other words, when the algorithm encounters a new data point, it judges how close the assigned value of that new data point is to the points in the training set and performs prediction. The optimization of the model and validity of the predicted result depends on the number of k or number of neighbors requested of the model. A k of 1 might overfit the data, defined by Jason Brownlee (2018) at Machine Learning Master.com as the model perform negatively on new data or test data due to it learning the noise or irrelevant details of the training data. A k too large might drive the model to perform poorly both in training and testing. The decision of k value, or the number of neighbors, can be made after observation of the elbow curve, named because of its elbow shape, of error validation.

This research selected K Nearest Neighbor for the method of the neural network construction because of its simplicity. The algorithm is built into the ScikitLearn library, allowing users more accessibility to a complex concept like artificial intelligence. The proof of this simplicity can be found below in Figure 4. Another reason for using the K Nearest Neighbor instead of other regression and classification models is because it can perform both regression and classification. This basic design of the model creates more flexibility for the research to consider the best model for the prediction.

In James Loy's entry on May, 2018 at Towardsdatascience.com[5], the amount of coding necessary to build a neural network from nothing is more than twenty line of complex codes (Loy, 2018). However, with the ScikitLearn library, these twenty steps of coding are reduced to less than five step and the code became simpler than if building from scratch. Thus, the ScikitLearn Library has been chosen to create the model for this research due to its simplicity and user-friendliness for stakeholders interested in this research who have little knowledge of programming. The decision to use K Nearest Neighbor Regressor over K Nearest Neighbor Classifier was due to K Nearest Neighbor Regressor's ability to process continuous data. K Nearest Neighbor Classifier is a classifying algorithm, and while both algorithms can perform regression on the data set, K Nearest Neighbor can perform regression on data that take specific values. In other words, discrete data. K Nearest Neighbor Regressor, however, process data that takes value from a range of value. For example, K Nearest Neighbor Regressor can process data in any value between 1 to 4, but K Nearest Neighbor Classifier can process only the value 1, 2, 3 and 4. The data value of high school grade point average falls in the range between 0 to 4, similar to that of admission tests from 0 to 1600. From the reasons mentioned, the regressor is determined to be a more appropriate choice for the model than

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[5] See https://towardsdatascience.com/how-to-build-your-own-neural-network-from-scratch-in-python-68998a08e4f6 for full entry

the classifier. Result of both models will be presented in the next section to prove this point further.

The model created will process the training data set to settle a specific algorithm that predict the result of the testing set as a standard in building a neural network. Using Figure 2.1 of the artificial neural network, the framework for this research model is as follow, and reference to actual programming codes is in the Appendix.

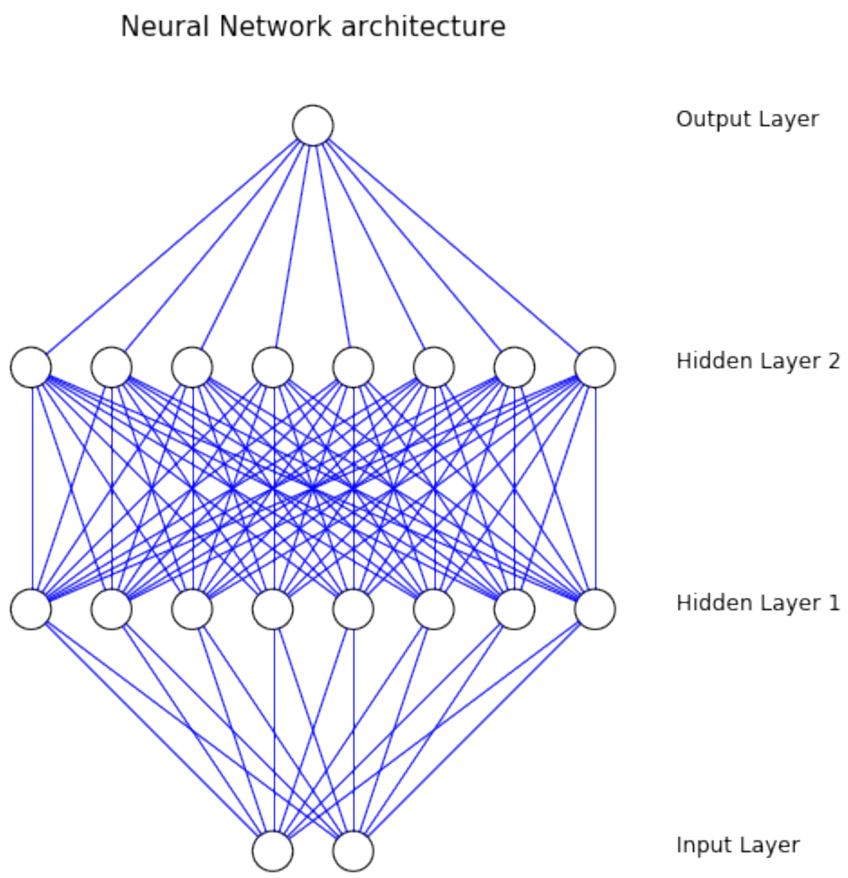

Figure 3.2 Neural network structure by Oli Blum on Stackoverflow.com

Alongside with Excel and SPSS analysis, this research proceeded with the application of two models created using Python's library ScikitLearn. Figure 3.2[6] presents the structure of the neural network used for this research. Two nodes representing SAT Score and HS_GPA are in the input layer. There are currently two hidden layers set for the model, however, the number of layers can change according to the need of the programmer. One single node in the output represent the FU_GPA which the model is predicting.

The first model is created using the algorithm K Nearest Neighbor Regressor with a k value of 9 as the most optimal while the second model is created using the algorithm K Nearest Neighbor Classifier. After importing the necessary libraries and data, the construction of the model starts. The split of data set created two new sets of data: training and test. The training set includes 900 random datasets of three variables which are admission score (coded as SAT Score), high school grade point average (coded as HS_GPA) and GPA in the first year of university (coded as FU_GPA) using built-in random splitting. The test set includes the remaining 100 datasets. An extensive training set of data serves to better the accuracy of the model because neural networks which

[6] See https://stackoverflow.com/questions/29888233/how-to-visualize-a-neural-network for full programming code and explanation

mimic human brain activity operates better with more information.

The threshold set for the accuracy of predictions made by the model is set at 40% or 0.4 after consideration the volatile nature of factors that influence FU_GPA such as test anxiety tied to admission score.

The usage of a neural network is superior to that of simple linear regression in the sense that a neural network will allow for more addition of input should the requirement for such event arise. A majority of observations and data are not directly linear in their relationship which could create faults in prediction when applying linear regression. For this reason, this research suggested that a neural network which is non-linear and evolving is a better replacement as a predictor.

DATA

The data used in this research is that of one thousand students and is founded online through a data bank called StatCrunch[7] for the availability of data and anonymity. The data comes as one thousand sets consist of SAT scores to represent test scores, high school GPA and first-year GPA. The data has no name or gender attached to it to ensure no discrimination against the participant and applies the same logic for the participant's nationality and background. The data has a mean of 1033.29 and standard deviation of 143 for SAT Scores, a mean of 3.2 and a standard deviation of 0.543 for grade point average in high school. SAT Score data set is closer to a normal distribution than high school grade point average.

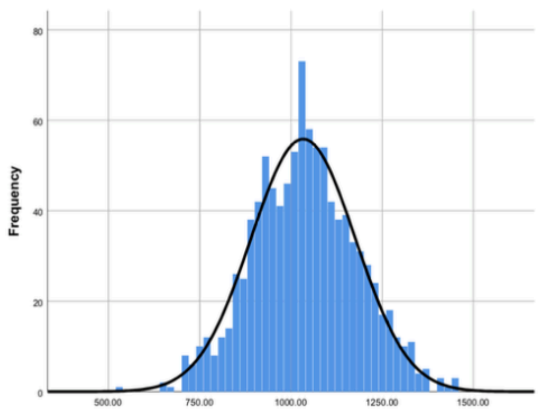

Figure 4.1 SAT Scores histogram

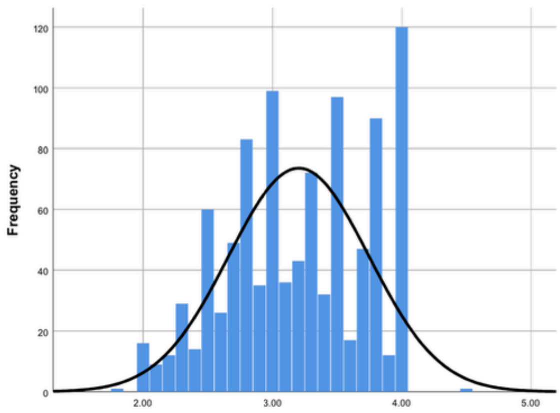

Figure 4.2 High school GPA histogram

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[7] Data set can be found at https://www.statcrunch.com/app/index.php?dataid=468543

The data is run through the Correlation algorithm in Excel and Regression in IBM SPSS to test the three hypotheses first, then break down into two random sets called training set and testing set for processing through the neural network created in Python. Despite the observation of data that shows a non-normally distributed data, the regression and correlation analysis done in this research should be valid as the data set is large.

Python training set and testing set are randomly chosen to ensure the non-biased predictive result from the Python model.

The following section will present findings from both the excel correlation equation and compare them to the result from the Python model of neural network.

RESULTS AND DISCUSSION

This section presents and explains the results found through both Excel built-in algorithms and construction of the Python model of a neural network.

5.1 Excel Analysis

As research in the literature section, the central claim made by on-going literature is that high school GPA is more largely responsible for predicting one's GPA in their first year in university than is test score. After correlation analysis in Excel, the result is as follow.

	Test Score	HS GPA
Test Score	1	
HS_GPA	0.42964857	1
FU_GPA	0.46028102	0.54296471

Table 5.1 Excel Correlation analysis of HS_GPA and FU_GPA in comparison to test score

Observations from Table 1 show that high school GPA is indeed more correlated to GPA in the first-year university than is test score which confirms the claim in the literature.

In an attempt to determine all three hypotheses, the research makes use of Excel Regression Analysis done on the same data set for the Python model and achieves the following results. The most important value of these results are the values of significant F. Significant F represents the probability of null hypothesis H0 that denies H1, H2, H3 are correct. In other words, a smaller value of significant F is the indication of a better regression model.

ANOVA	df	SS	MS	F	Significance F
Regression	1	116.150109	116.150109	268.270266	1.39029E-53
Residual	998	432.093389	0.43295931		
Total	999	548.243498			

Table 5.2 Excel Regression Analysis of Admission Test Scores to FU_GPA

Observations from Table 2 include that test score such as SAT does contribute to the predictability of GPA in the first year of university, confirming H1 which dictates that test score predicts student's GPA during the first year of university.

ANOVA	df	SS	MS	F	Significance F
Regression	1	161.628034	161.628034	417.222777	9.35453E-78
Residual	998	386.615464	0.38739024		
Total	999	548.243498			

Table 5.3 Excel Regression Analysis of HS_GPA to FU_GPA

Table 3 also shows a significant correlation between high school GPA and student's first-year GPA in university and confirms H2 which dictates that high school GPA predicts student's GPA during the first year in university. Furthermore, from consideration of the significance value between high school GPA and test score, table 2 and 3 shows concurrence with prior correlation analysis and literature's claim of stronger relationship for high school GPA than that for test score when predicting the first-year GPA in university.

ANOVA	df	SS	MS	F	Significance F
Regression	2	196.273143	98.1365715	277.984099	1.135E-96
Residual	997	351.970354	0.35302944		
Total	999	548.243498			

Table 5.4 Excel Regression Analysis of test score, HS_GPA combination to FU_GPA

Table 4 is the result of the regression analysis of the test score-HS_GPA combination in comparison to the results in table 2 and 3. Conclusions from the observation of the value of significance from Table 4 are that a combination of test score and HS_GPA has a stronger connection to the predictability of the first-year GPA in the university which confirms the third hypothesis.

5.2 IBM SPSS Analysis

Further analysis was done with IBM's SPSS also confirm Excel regression's result and presented below.

Regression function of SPSS yields the coefficient of multiple determination of 0.358 which led to the interpretation of the model's prediction close to 36% of the value variation is explainable by the model. While the coefficient of multiple determination is lower than 50%, this does not inherently decide that the model was unsatisfactory. Since the model was created to predict human's behavior and performance, the expectation for a high coefficient of multiple determination is often absent. The additional independent variable could potentially increase the level of the coefficient of multiple determination in the future. However, with both independent variables, the model has a higher value variation explained than analysis done with either of the two of which coefficient of determination is respectively 21.2% for SAT Scores and 29.5% for high school grade point average.

Following Regression analysis by SPSS, this research also conducted Correlation analysis of which result is below. The confidence level of correlation is at 99%, and the regression is done using 2-tailed significance statistic. Thus, if the score of significant is lower than 0.01 then the null hypothesis H0 which denies all H1, H2, or H3 is rejected, confirming H1, H2, and H3.

Table 5 expresses the correlation between admission test score (SAT) with predicting GPA of students during their first year in university and table 6 is accordingly that of high school grade point average.

		SAT Score	FU_GPA
SAT Score	Pearson Correlation	1	0.460**
	Sig. (2-tailed)		.000
	N	1000	1000
FU_GPA	Pearson Correlation	0.460**	1
	Sig. (2-tailed)	.000	
	N	1000	1000

**. Correlation is significant at the 0.01 level (2-tailed)

Table 5.5 Correlation between SAT score and GPA of first-year university

		HS_GPA	FU_GPA
HS_GPA	Pearson Correlation	1	0.543**
	Sig. (2-tailed)		.000
	N	1000	1000
FU_GPA	Pearson Correlation	0.543**	1
	Sig. (2-tailed)	.000	
	N	1000	1000

**. Correlation is significant at the 0.01 level (2-tailed)

Table 5.6 Correlation between SAT score and GPA of first-year university

Comparison between table 5 and table 6 with table 1 shows that there is a significant correlation between both admission score and high school grade point average with grade point average during university first year confirmed by SPSS Correlations. SPSS result also shows that high school grade point average possesses a stronger correlation than does admission test score when predicting GPA of first-year in university.

This result is understandable as high school GPA generally display the student's quality to maintain result during their education consistently. This trait is more likely to be desirable as the university's learning process mirrors that of high school where students are consistently required to maintain their performance throughout four years.

While test scores are shown to have less correlation alone, when combined with high school GPA emphasizes a different aspect of education in the university which is the ability to perform well under shortage of time or duress. Often admission tests are conducted for a shorter period, four hours approximately, and require a significant level of stamina and focus. Similar situations are that during one's university's life where deadlines and multiple exams are required.

The conclusion which sprout from examined literature, such as Patterson & Mattern (2013) and Ragan et al. (2011), is that one's ability to perform well consistently and in a short period applies to two different sides of a majority of courses in the university. Corresponding to how one student would be less likely to follow a single approach to proceed with their studies, predictions for first-year GPA is hence proven to be more accurate when combining such student's ability to perform under different circumstances. In other words, to combine student's high school GPA and their test score when predicting their result in the first year of university.

5.3 Python Neural Network

5.3.1 Accuracy score algorithm

Due to their different nature, the regressor and classifier algorithms require different programming syntax to determine the accuracy of their predictions. In the regressor algorithm, this syntax yield error score such as MSE and r2 scores. In the classifier algorithm, the syntax yield accuracy score of the model. For this reason, the understanding for values presented in table 7 and table 8 should be lower error scores in table 7 means a better model whereas higher accuracy scores in table 8 mean a better model.

Walker Rowe explained in his blog entry at bmcblog.com that MSE or Means Squared Error is the average of the squared error and the lower it is, the better the model (Rowe, 2018). Gaurav Bansal explained in his entry in the Green Bay University of Wisconsin that r2 score determines the percentage of dependent variable explained by the independent variable or the percentage of output value explained by input value.

5.3.2 K Nearest Neighbor Regressor

Results from the Python model of K Nearest Neighbor Regressor algorithm with data sets consist of both HS_GPA and SAT Score, only HS_GPA, and only SAT Score. The set error threshold is 0.6, and the model has the accuracy scores presented as follow.

Data set	**HS_GPA**	**SAT Score**	**Both**
Optimized k	9	9	6
MAE	0.53	0.60	0.52
r2score	0.23	0.11	0.05

Table 5.7 Accuracy of K Nearest Neighbor Regression in Python

Observation of table 7 suggests that the value of error resulted from omitting one set of value, either HS_GPA or SAT Score, from the full data set result in a higher value of error made to the prediction. The omission of HS_GPA created more considerable error value than that of SAT Score which means that prediction made using only SAT Score is worse than that made using only HS_GPA. Prediction made with both values results in the lowest value of error.

Observation of r2 score yields notable results as r2 represents the percentage of dependent variable y explained by independent variable x, or in this case, the percentage of FU_GPA explained by either HS_GPA, SAT Score, or both. R2 score yielded by HS_GPA is the highest among the three data set and that yield by a combination of HS_GPA, and SAT Score is the lowest.

HS_GPA explained the most of FU_GPA but the model made using HS_GPA is second in accuracy. SAT Score explains 11% of FU_GPA with an r2 score of 0.11 but has the lowest accuracy. Prediction made using both independent variables explained only 5% of FU_GPA but has the highest accuracy out of the three models. Further research could be done to explore the reasoning behind this occurrence. However, at the moment, little can be said for what created these conflicting results.

5.3.3 K Nearest Neighbor Classifier

Results from the Python model of K Nearest Neighbor Regressor algorithm with data sets consist of both HS_GPA and SAT Score, only HS_GPA, and only SAT Score. The set accuracy threshold is 0.4, and the model has the accuracy scores presented as follow.

Data set	**HS_GPA**	**SAT Score**	**Both**
Optimized k	5	2	2
Accuracy score	0.01	< 0.01	0.01

Table 5.8 Accuracy of K Nearest Neighbor Classifier in Python

The accuracy score yielded after changing K Nearest Neighbor Regressor out for K Nearest Neighbor Classifier with an optimized k value of 2 is 0.01 or 1% for a combination of both HS_GPA and SAT Score. Optimized k of 5 for HS_GPA only classification yielded similar score to that for both HS_GPA and SAT Score. Optimized k of 2 for SAT Score yielded less than 0.01 accuracy.

An accuracy score of 0.01 means that the model correctly predicted only 1% of the test data set which is understandable as explained in chapter IV about the effectiveness of K Nearest Neighbor Regressor comparing with that of K Nearest Neighbor Classifier.

The result of the accuracy score when using the classifier algorithm supports the superiority of regressor algorithm in this specific case of prediction analysis.

LIMITATIONS AND SUGGESTIONS

While the result of this research contributes to the topic of artificial intelligence and college admission, it is not without limitations. The following discusses some of the flaws in this research.

6.1 Artificial intelligence

The first limitation is artificial intelligence. The design of a neural network while mimic human's brain rationalization lacks many considerations are necessary to any fully developed homo sapiens. Despite its added benefits such as efficiency, analytics, meaningful data and ability to open up new opportunities for at-home workers and in-office workers to view the same type of data and documents (Hey, 2016), it is not the perfect model.

First, the system lacks an ethical and moral order. The effect of this was made part of the discussion between experts in Japan though it could be applied worldwide as well. In recognition of powerful benefits from technologies such as artificial intelligence, governments have attempted to implement policies to encourage innovation. The most prominent effort is in Germany's Industry. There have been concerns raised in regards to

AI-induced unemployment, security risk, and the loss of control over threats posed by super-intelligent machines. (Sugiyama, Deguchi, Ema, Kishimoto, Mori, Shiroyama & Scholz, 2017; Barrat, 2015).

While these concerns are valid, a correction is vital in regards to the loss of control by technology. Artificial intelligence has yet to dominate completely human's existence in societies and industries at current rate, and time will be necessary for realizing any significant ramification. A scenario as grave as loss of control is doubtful with the growth rate of current technology, but it neither should be ignored. In his book named Our Final Invention, author James Barrat (2015) interviewed ethicists, artificial intelligence experts and scientists of related area to answer the question of whether or not something as impactful as artificial superintelligence is yet to exist and if it is, then what are the ramifications facing humanity. He received mixed responses between a positive scenario of Singularity coined by Ray Kurzweil as a period during which changes to technology is so deep it irreversibly changes human life, and a negative one proposed by Venor Vinge and Eliezer Yudowsky. The negative scenario proposed, however, was not due to catastrophic human mistake but rather due to the lack of a vital human element in an A.I.'s operation – ethics (Barrat, 2015). George L. Head (2006) stated on his entry to the website of International Risk Management Institute, Inc. that human's ethics are taught and practiced over a long course of time and through various means. These include anecdotes, texts and personal experience, which can be found in prestigious titles such as Republic by Plato, After Virtue by Alasdair MacIntyre, and Justice by Michael J. Sandel. Human ethics and morality evolve over decades of studying and most importantly, mistakes. However, this is not the case for an A.I. system.

An A.I. system is a goal-oriented human-made creation, yet it remains in a grey territory on moral ground. Many share concerns of the legal and ethical binding of an autonomous system. Computer ethics become a debate of to what extent should computers program such as artificial intelligence be held responsible, of the responsibility gap between a human and an autonomous artificial agent and of if there exist legal groundings available to accommodate these newer additions to the society (Johnson, 2015; Frohman, 2008; Vladeck, 2014).

The security risk is the most evident consequence from misusage of an A.I. system similar to the one created in this research. Powerful A.I.'s ability to crunch data in considerable amount across multiple online platforms raise the potential for the system to have access to personal information (Cunningham, 2016). Privacy in which case become less of a human right and more currency of trade for the highest bidder since an A.I. system is a creation and held neither legal liabilities nor moral obligations.

Discrimination arises too as a result of the exposure any persons might endure due to the use of an A.I. system. The argument, as mentioned above, stated that A.I. is a human-made system which is goal-oriented, which means that it could be customizable to the wants and needs of its creator. An A.I. system is open for training and flexible through the data to which it has access. Should the data be biased or untrue, so will the result the system produces.

A recent case reported on ProPublica of researches done on the formula COMPAS which is used by courts and parole boards to predict future criminal behaviors indicates that the formula favor predictions of black defendant increased the likelihood to carry out criminal acts. (Angwin & Larson, 2019). While this research's range does not cover the racial issue in any country, it uses this example as a possible scenario which could happen to any discriminative conflicts that result from system usage.

A.I. is not human and thus will not share the same experience in the way that a human would. It thinks and acts rationally and is different from conventional computer algorithms. Its ability to learn from experience and work independently creates preconditions for damage, and since it is not considered a legal person according to national and international law, it is questionable who would stand to be accountable for those potential damages (Čerka, Grigienė & Sirbikytė, 2015). Article 12 of the United

Nations Convention on the Use of Electronic Communications in International Contracts states that a person on whose behalf a computer was programmed should ultimately be responsible for any message generated by the machine. However, this applies solely when A.I. concept insists that an A.I. system is a tool. Any changes to this concept could further create a legal loophole in the process, hinting at the danger that artificial intelligence poses to inattentive users and creators.

This research recognizes the power that A.I. has in assisting human's decision-making progress, especially those in college admission. However, it also acknowledges the underlying threat that the system might pose to its very user. It is essential that all researchers in the area of A.I. application who might find use in this research consider the research's primary goal. This goal was to argue that a combination of two selection criteria through a neural network could aid a lengthy and rigorous process better than a separate consideration for each approach, with concerns of the legal, ethical and interpersonal limitations such a system would pose; but not using one to dismiss the other.

6.2 Admission criteria

The next limitation of the research is the admission criteria. It is vital that we make clear what universities exist to do, what admission test predict or measure before we enter this discussion. Research by Steven E. Stemler from the Department of Psychology at Wesleyan University studied these exact questions. Stemler mentioned a range of answers as to what a university's existence is, quoting Labaree (1997) saying universities 'serve as a mechanism for professional credentialing' and Martin, Smith, & Phillips (2005) defining universities as 'a hub for social and intellectual activity in the local community.' He argues that universities aim to develop two types of expertise in students: domain-specific expertise (majors) and domain-general expertise (reasoning, cultural understanding).

Stemler continued his research by studying what admission tests should predict. He concluded that universities should not focus on achievement-based criteria but rather a cognitive process as a criterion for what the tests should predict. In other words, admission tests need to predict a student's ability to adapt and develop personally within the university and not what they can achieve after admission. He concluded that whichever the selection criteria might be, admission tests need to serve the institution through aligning its purposes with the stated objectives of the institution.

In Bloom's Taxonomy (1984), there state three classifications of educational objectives: affective, cognitive, and psychomotor domain. Academic skills, which consists of critical evaluation, ethics, and communicational presentation of acquired knowledge, falls into the affective area of Bloom's traditional taxonomy (Steenman et al., 2014). The renewed taxonomy of cognitive domain (Anderson & Krathwohl, 2001) acknowledges the skills that affective domain plays alongside the elements of cognitive domain while noting the importance psychomotor has as well in academic program belonging to fields such as medical and technical. The conclusion, therefore, is that different institutions or programs will require various combining or singular consideration of admission criteria matching the expectations projected at potential students.

As stated in the literature section, the argument of whether or not to favor admission tests such as SAT over GPA when implementing a forecasting system has been the most popular. However, while GPA shows a stronger correlation to accurately predicting a student's first year GPA in college or university, it is affected by factors such as students' neighborhood income, financial need and the nature of their high school (Cyrenne & Chan, 2012). Admission test scores grow inferior to GPA due to its small sample and dependence on the students' family background (Clark, Rothstein & Schanzenbach, 2009).

This research concludes that despite a combination of GPA and SAT score can provide a more accurate prediction of a student's GPA in their first year at a university, it remains that this combination is not enough to accurately predict a student's ability to obtain and retain knowledge as well as future performance.

6.3 Additional studies and arguments

There exist countering studies within the same topic of interest with findings that indicate a lesser connection between high school grade point average and admission scores to grade point average in the first year of university. One of such studies is by Credé and Kuncel (2008) that found inconsistency with previous theories. Their study stated that despite claims of correlation between test scores and high school and academic performance, personality construct has a stronger relationship with academic performance. This personality construct includes study skills, study habits, study attitudes, and study motivation.

Further additional researches are needed to determine this claim. However, it is essential to note that there is a counter-argument to the selected attributes being appropriate for the prediction of academic performance.

A different study was done by Tekin (2014) on the early prediction of student's grade point average at graduation using three different data mining algorithms to process the first, second and third-year grade point averages from 127 computer education and instructional technology students of Firat University in Turkey shows notable findings.

The three algorithms are that of neural networks, support vector machines (SVM), and extreme learning machine (ELM). The results state that despite their ability to predict accurately above 90% of the observation, support vector machines algorithm has the highest accuracy at 97.98% followed by extreme learning machine algorithm at 94.92% and neural networks at 93.76% (Tekin, 2014). This finding is significant to suggest future researches could be done on different algorithms using the same data set in this research to determine the best models for prediction of university grade point average. However, it is notable that with the small size of the data in Tekin's study, raising the question of the validity of the result were more substantial, more dynamic sets of data are processed through the algorithms.

While support vector machines algorithm has been the favored method for data mining in the early 2000s, from 2011 to 2017, neural networks algorithm has seen increased usage in research over SVM for the following reasons according to data scientist Manikandan Jeeva at Analytics Vidhya[8].

(0) Backpropagation: the mechanism that allow a model to change the weight of each connection between the nodes to allow for adjustments to future predictions.

(1) Number of hidden layers and neurons (nodes): more layers and nodes create

[8] See https://medium.com/analytics-vidhya/the-scuffle-between-two-algorithms-neural-network-vs-support-vector-machine-16abe0eb4181 for detailed article

more possibilities for the learning capability of the model. However, the numbers of layers and neurons must go under scrutiny for an increase in number of hidden layers and nodes means a higher chance for overfitting a model.

(2) Activation functions: A function that decides when to activate a node and the magnitude of the output based on prior results.

(3) Batch normalization: allow the model to learn the optimal scale and mean of each value in the data set through each layer.

(4) Transfer learning or the reusing of pre-trained layers: pre-trained layers can be used instead of training another model from scratch hence saving time and effort.

(5) Faster optimizers: calculate the backpropagation signals and adjust the weights in each connection.

(6) Learning rate scheduling: Optimizer will decide this for user. Higher learning rate is common in the beginning for deciding a general range of learning boundaries before narrowing down to a smaller learning rate for the optimized solution.

(7) Early stopping and L1, L2 regularization: allow the model to stop training the network when the performance drops compare to previous instances.

(8) Drop out: help train the model to avoid overfitting while improving model's

accuracy.

(9) Data augmentation: allow addition of labels to already labeled data. For example, from the image of a dog, new labels of cropped image, rotated image can be added.

Yang, Baraldi, and Zio (2017)'s study on extreme learning machine and neural network finds contradicting result with that done by Tekin (2014). Yang, Baraldi, and Zio found that extreme learning machine performs worse that did neural network; however, advantageously took less time to train. This discrepancy could indicate that a difference like the data sets might result in the different performance level of given models.

Musso, Kyndt, Cascallar & Dochy (2013) concluded in research for Frontline Learning Research to predict general academic performance using artificial neural networks that neural networks can bypass problems created by the lack of linear relationship between independent variables. In comparison with traditional discriminant analysis, neural networks appear to be superior in performance according to the authors.

With the results of this research and collection of additional contradicting findings from other researchers, further study must be done to determine which model of data mining might be most appropriate to process students' data for prediction of university grade point average.

6.4 Data Bias

Data in this research is directly downloaded from a secondary source of the data bank and represent one thousand sets of result including high school grade point average, SAT scores, and grade point average of students during their first year in university from one university in America. While the names, genders, and socioeconomic background of the students were omitted to ensure an unbiased judgment and sensitive conclusion in regards to the current political climate, this omission poses the following problem.

(1) Questionable conclusiveness between SAT scores and students' backgrounds: Due to a lack of background information, it is possible that an important link between social context and academic performance is missed.

(2) Gender-related difference in academic achievement.

(3) Program-result match where the criteria for each student's particular skill in the three domains of Bloom's taxonomy could be specified.

(4) A small pool of data which could result in a conclusion, be determined solely based on the given sets.

In “The dangers of faulty, biased, or malicious algorithms requires independent oversight” by Shneiderman (2016), Nissenbaum (1994) and Friedman & Nissenbaum (1996) are quoted referring to the “systematic erosion of accountability” in computerized item and discussing biases in the system through three categories: pre-existing bias from social practice and attitudes, technical bias from design constraint, and emergent bias from a change in use context. Silva & Kenney (2018) and Gillis & Spiess (2019) argued similar point in their research regarding racial bias and discrimination resulting from big data analysis.

This research is not free from such bias. While the omission of gender and background might have cleared inherent bias coming from social practice and attitudes, Williams, Brooks and Shmargad (2018) presented in their research that a lack of social category data can lead to or sustain biases in some contexts. The addition of social category data such as gender or ethnicity might lead to the discovery of discriminatory structure within automatic system and thus create the opportunity to tackle them for the improvement of the system.

From these mentioned possible biases in data, and with the independent oversight method suggested in Shneiderman (2016) there calls for additional research in the future to confirm suspicions on genders, background and amount of data needed for a more conclusive statement.

6.5 Recommended additional independent variable

From the discussion above, the necessity of a different and additive criterion became evident. This additional criterion must increase the accuracy of the system when deciding the results of a student's GPA after their first year of college. Researches exist to prove a correlation between high school grade point average and admissions test scores with academic performance in university, and one suggests additional association to the students', campus socioeconomic environment, and resources. Betts and Morell (1999) indicated a more complex model is necessary to explain a student's performance through analyzing the background of their upbringings rather than insisting on a simple analysis of one or two scores. This research agrees with Betts and Morell's logic and suggests the additional criterion for a future revision of the predictive model be emotional intelligence, known below as E.I., because it would explain how well-regulated students' emotional and mental state might be in the environment of the university.

Early researches show a positive correlation between students' E.I. with academic performance in secondary school (Akhar, Shah, Khan, Akhter & Riaz, 2011) and high school (Ratnaprabha, Shanbhag, Goud, Anupa, Fernandez & Adrian, 2013), and prediction of academic achievement in universities (Bukhari & Khanam, 2016). In the research done by Hartman, Wasieleski & Whatley (2016) from Valdosta State University on emotional dysregulation done through correlation and regression analysis of Difficulties in Emotion Regulation Scale (DERS) and Cognitive Test Anxiety Scale (CTAS), there claims a link between emotional dysregulation with grade point average. The claim, in details, describes students who lack access to effective psychological regulation strategies suffer from lower grade point average.

To first understand how E.I. is vital as an additional variable to the model, one must first understand the definition of the term. Emotional intelligence is the ability to make sense of one's own emotions and make use of those emotions for thought-enhancement (Miners, Côté & Lievens, 2017). In the context of this research, as reasoned above, the ability to achieve scholastic results in universities is not strictly defined by the student's ability to do well on the academic aspect. Instead, it is by their ability to navigate through the, at times, an isolated, harsh and closer-to-post-education environment of the university where expectations for them mirrors that for a more mature individual of the society.

While there are criticisms on which stream of E.I. testing is most fit for the prediction of academic performance and which gender is triumphant in regards to the level of intelligence. A majority of the researches on the topic claims that E.I. has a positive link to the students' ability to perform well in university and even after it regardless of genders and streams (O'Boyle, Humphrey, Pollack, Hawver & Story, 2010;

Lanciano & Curci, 2014). This is due to E.I.'s relationship to the characteristics of an individual. A research on personality predictive ability on college performance and retention show that conscientiousness or an individual's tendency to complete their task accurately is highly correlated to their ability to achieve an excellent scholastic result and increase college retention (Tross, Harper, Osher & Kneidinger, 2000). It is evident that one's ability to understand and control their emotional intelligence is a contributing factor to their performance in school no matter the level of education; however, especially in universities.

Emotional intelligence receives criticisms in regards to the validity and appropriateness of one test compared to the others. However, it is observed to be proportionally related to academic performance, measures of relatedness, the ability to communicate motivating messages such as vision statements. When E.I. declines in an individual, the observation shows an increase in problem behaviors, deviance, and drug use (Mayer, Salovey & Caruso, 2004). Usage of E.I. as a criterion could thus, enhance the predictive ability of the model to identify individuals who can not only absorb and process academic information but also regulate their emotional capacity to optimize that effort.

6.6 Suggestion for managers

In the context of Japan, managers who wish to attempt technology integration should consider the currently inadequate and ambiguous technological level in the country. UNESCO recorded a low technology uptake in Japan and ICT being behind in the priority ranking of the country (Towndrow, 2012). The resistance in the adoption of technology in Japan described by Whittaker (2001) suggests that attempts to introduce or integrate new technology such as artificial intelligence in the country might prove to be arduous if not implausible. Example of this push back could be found in the instance of Kyoto University’s statement (Towndrow, 2012) for a revision of the evaluation metrics of worldwide universities showing how the existence of barrier in Japanese university to external scrutinization.

As a direction moving forward, it is crucial for the management of educational institutions to increase ICT integration before the adoption of a neural network for the sake of a smooth internal transition.

Field leaders not only need to educate others in the same field to reach a singularity in the adaptation of technology but also need to contribute to the collaborative effort to increase ICT comprehension nation-wide. Furthermore, it is necessary for managers to understand the role of human users in automated working system. As Shein (2018) stated

“Humans are better than computers at exploring those grey areas around the edges of problems. Computers are better at the black-and-white decisions in the middle.”, managers who misunderstand the role of human’s role in the system could allow for the processing of inherently biased data which leads to biased decisions.

<u>6.7 Indication for the adoption of technology in Japanese universities</u>

From the Japanese Ministry of Finance’s Highlight of the Draft Financial Year 2000-2019, the trend of expenditure on education has been shown to have slightly decreased. This could be the result of a reduced number of students in Japanese educational institutions – a direct result of the declining birthrate in Japan. As the expenditure on education decrease, so does the support for university to attract students and improve in-school technological structure. Diffusion of new technologies such as artificial intelligence could, therefore, slows down, cost to hire professionals, and installing such a system would thus increase further Japan moves towards the future.

Management of Japanese universities must hence understand the threat facing their institution coming from different directions both directly and indirectly. While declining birthrate might affect admission quota at first glance, the long-term consequence of this phenomena is the difficulty to implement a new, innovative system, difficulty in attracting students when compared to other global universities and most fatally, closure of universities.

Management of Japanese universities, especially those that are private needs to comprehend the competitiveness of their market, the demand for more advanced educational system and methods so that their universities could flourish during the incoming time of hardship. One suggestion for this situation could be to call upon sponsors from different countries or companies to facilitate technological installment in the schools, outsourcing talents from overseas and most importantly, creating an environment that accepts and advance technological innovation.

CONCLUSION

Advancement in technology has rippled a change in how global businesses and institution must operate in the future. As part of the movement, artificial intelligence is gradual but certain incorporation into operational systems across industries. In Japan, the history of A.I. starts in the 1960s and sees rapid growth in 1985 (Nishida, 2012). The majority of discussion on artificial intelligence in Japan focuses on researches and conferences rather than real-world application. The trend has been shifting, however, not enough to diffuse the technology in the country widely.

This research examined the validity predictions made on students' performance in their first year in university by inputting a combination of high school grade point average and admissions test scores through a Python neural network. Through confirming three hypotheses, the research concludes that both high school grade point average and admissions tests significantly correlate with the grade point average in the first-year university. However, high school grade point average shows a stronger correlation than admissions test scores, and a combination of both has the most active association with university grade point average.

To confirm the validity of the neural network in predicting university grade point average, analysis of other traditional tools such as Excel and IBM SPSS have also been implemented. The report from traditional tools validated results from the Python neural network, which yields better results when a combination of grades was used. However, the model's performance proves to require improvements. For future examination, the research suggested an investigation into emotional intelligence as an additional independent variable to input into the model.

Researchers and managers interested in the topic must take into consideration Japan's attitude towards innovation and application of new, non-robotics technology in the nation. Evidence has shown that there is a certain level of resistance coming from the country that slowed down Japan's progress towards the national diffusion of artificial intelligence. As universities in Japan are disappearing due to the declining birthrate and a small workforce, technological implementation could act as one solution to halt the decreasing economic growth. Application of artificial neural network in universities could assist these educational institutions to combat the need to employ more human workers as well as increase productivity for admissions officers.

APPENDIX 1: K Nearest Neighbor Regressor Code

HS_GPA:

I imported the necessary library so I could import data, do the train-test split funtion, and measure accuracy of the model later.

In [1]:

```
import numpy as np
import pandas as pd
import scipy
import sklearn
from sklearn import neighbors
from sklearn.cross_validation import train_test_split
from sklearn import metrics
```

```
/anaconda3/lib/python3.6/site-packages/sklearn/cross_validation.py:41:
DeprecationWarning: This module was deprecated in version 0.18 in favor
of the model_selection module into which all the refactored classes and
functions are moved. Also note that the interface of the new CV iterators
are different from that of this module. This module will be removed in 0.
20.
  "This module will be removed in 0.20.", DeprecationWarning)
```

Here I import the data and indicate the columns of the dataset.

In [2]:

```
grade = pd.read_csv("/Users/noriko/AnacondaProjects/HSGPA.csv")
grade.columns = ['HS_GPA', 'FU_GPA']
```

Here I'm just checking a few beginning value of the data to make sure it's loaded properly.

In [3]:

```
grade.head()
```

Out[3]:

	HS_GPA	FU_GPA
0	3.4	3.18
1	4.0	3.33
2	3.8	3.25
3	3.8	2.42
4	4.0	2.63

Checking the shape of my dataset.

In [4]:

```
grade.shape
```

Out[4]:

```
(1000, 2)
```

Creating numpy array for features and target

In [5]:

```
X=grade.drop('FU_GPA',axis=1).values
y=grade['FU_GPA'].values
```

Spliting my data into training and test set

In [6]:

```
X_train, X_test, y_train, y_test = train_test_split(X,y,test_size = 0.1)
```

Importing the regressor and building the regressor model

In [7]:

```
from sklearn.neighbors import KNeighborsRegressor
```

Start training the model

In [19]:

```
KNR=KNeighborsRegressor(9)
KNR.fit(X_train, y_train)
```

Out[19]:

```
KNeighborsRegressor(algorithm='auto', leaf_size=30, metric='minkowski',
        metric_params=None, n_jobs=1, n_neighbors=9, p=2,
        weights='uniform')
```

Testing the model

In [20]:

```
y_test_predict=KNR.predict(X_test)
```

In [21]:

```
from sklearn.metrics import mean_absolute_error
from sklearn.metrics import mean_squared_error
from sklearn.metrics import mean_squared_log_error
from sklearn.metrics import median_absolute_error
from sklearn.metrics import r2_score
```

In [22]:

```
mean_absolute_error(y_test,y_test_predict)
```

Out[22]:

0.5333999999999987

In [23]:

```
mean_squared_error(y_test,y_test_predict)
```

Out[23]:

0.46733839506172842

In [24]:

```
mean_squared_log_error(y_test,y_test_predict)
```

Out[24]:

0.057204567129843877

In [25]:

```
median_absolute_error(y_test,y_test_predict)
```

Out[25]:

0.40444444444444461

In [26]:

```
r2_score(y_test,y_test_predict)
```

Out[26]:

0.22510448074214784

Testing for the best k

In [27]:

```
from sklearn.model_selection import GridSearchCV
params = {'n_neighbors':[2,3,4,5,6,7,8,9]}
```

In [28]:

```
model = GridSearchCV(KNR, params, cv=5)
```

In [29]:

```
model.fit(X_train,y_train)
model.best_params_
```

Out[29]:

{'n_neighbors': 9}

SAT Score:

I imported the necessary library so I could import data, do the train-test split funtion, and measure accuracy of the model later.

In [4]:

```
import numpy as np
import pandas as pd
import scipy
import sklearn
from sklearn import neighbors
from sklearn.cross_validation import train_test_split
from sklearn import metrics
```

Here I import the data and indicate the columns of the dataset.

In [35]:

```
grade = pd.read_csv("/Users/noriko/AnacondaProjects/SAT.csv")
grade.columns = ['SAT Score', 'FU_GPA']
```

Here I'm just checking a few beginning value of the data to make sure it's loaded properly.

In [36]:

```
grade.head()
```

Out[36]:

	SAT Score	FU_GPA
0	1270	3.18
1	1220	3.33
2	1160	3.25
3	950	2.42
4	1070	2.63

Checking the shape of my dataset.

In [37]:

```
grade.shape
```

Out[37]:

```
(1000, 2)
```

Creating numpy array for features and target

In [38]:

```
X=grade.drop('FU_GPA',axis=1).values
y=grade['FU_GPA'].values
```

Spliting my data into training and test set

In [39]:

```
X_train, X_test, y_train, y_test = train_test_split(X,y,test_size = 0.1)
```

Importing the regressor and building the regressor model

In [40]:

```
from sklearn.neighbors import KNeighborsRegressor
```

Start training the model

In [52]:

```
KNR=KNeighborsRegressor(9)
KNR.fit(X_train, y_train)
```

Out[52]:

```
KNeighborsRegressor(algorithm='auto', leaf_size=30, metric='minkowski',
        metric_params=None, n_jobs=1, n_neighbors=9, p=2,
        weights='uniform')
```

Testing the model

In [53]:

```
y_test_predict=KNR.predict(X_test)
```

In [54]:

```
from sklearn.metrics import mean_absolute_error
from sklearn.metrics import mean_squared_error
from sklearn.metrics import mean_squared_log_error
from sklearn.metrics import median_absolute_error
from sklearn.metrics import r2_score
```

In [55]:

```
mean_absolute_error(y_test,y_test_predict)
```

Out[55]:

```
0.6022111111111103
```

In [56]:

```
mean_squared_error(y_test,y_test_predict)
```

Out[56]:

0.52364186419753078

In [57]:

```
mean_squared_log_error(y_test,y_test_predict)
```

Out[57]:

0.049911237533179352

In [58]:

```
median_absolute_error(y_test,y_test_predict)
```

Out[58]:

0.5477777777777777

In [59]:

```
r2_score(y_test,y_test_predict)
```

Out[59]:

0.10708827885905037

Testing for the best k

In [60]:

```
from sklearn.model_selection import GridSearchCV
params = {'n_neighbors':[2,3,4,5,6,7,8,9]}
```

In [61]:

```
model = GridSearchCV(KNR, params, cv=5)
```

In [62]:

```
model.fit(X_train,y_train)
model.best_params_
```

Out[62]:

{'n_neighbors': 9}

Combined SAT Score and HS_GPA

I imported the necessary library so I could import data, do the train-test split funtion, and measure accuracy of the model later.

In [4]:

```
import numpy as np
import pandas as pd
import scipy
import sklearn
from sklearn import neighbors
from sklearn.cross_validation import train_test_split
from sklearn import metrics
```

Here I import the data and indicate the columns of the dataset.

In [6]:

```
grade = pd.read_csv("/Users/noriko/AnacondaProjects/Data Final.csv")
grade.columns = ['SAT Score','HS_GPA', 'FU_GPA']
```

Here I'm just checking a few beginning value of the data to make sure it's loaded properly.

In [7]:

```
grade.head()
```

Out[7]:

	SAT Score	HS_GPA	FU_GPA
0	1270	3.4	3.18
1	1220	4.0	3.33
2	1160	3.8	3.25
3	950	3.8	2.42
4	1070	4.0	2.63

Checking the shape of my dataset.

In [8]:

```
grade.shape
```

Out[8]:

```
(1000, 3)
```

Creating numpy array for features and target

In [9]:

```
X=grade.drop('FU_GPA',axis=1).values
y=grade['FU_GPA'].values
```

Spliting my data into training and test set

In [10]:

```
X_train, X_test, y_train, y_test = train_test_split(X,y,test_size = 0.1)
```

Importing the regressor and building the regressor model

In [11]:

```
from sklearn.neighbors import KNeighborsRegressor
```

Start training the model

In [24]:

```
KNR=KNeighborsRegressor(6)
KNR.fit(X_train, y_train)
```

Out[24]:

```
KNeighborsRegressor(algorithm='auto', leaf_size=30, metric='minkowski',
         metric_params=None, n_jobs=1, n_neighbors=6, p=2,
         weights='uniform')
```

Testing the model

In [25]:

```
y_test_predict=KNR.predict(X_test)
```

In [26]:

```
from sklearn.metrics import mean_absolute_error
from sklearn.metrics import mean_squared_error
from sklearn.metrics import mean_squared_log_error
from sklearn.metrics import median_absolute_error
from sklearn.metrics import r2_score
```

In [27]:

```
mean_absolute_error(y_test,y_test_predict)
```

Out[27]:

```
0.51719999999999999
```

In [28]:

```
mean_squared_error(y_test,y_test_predict)
```

Out[28]:

0.39881872222222225

In [29]:

```
mean_squared_log_error(y_test,y_test_predict)
```

Out[29]:

0.035967468006127538

In [30]:

```
median_absolute_error(y_test,y_test_predict)
```

Out[30]:

0.4375

In [31]:

```
r2_score(y_test,y_test_predict)
```

Out[31]:

0.052351819726470739

Testing for the best k

In [32]:

```
from sklearn.model_selection import GridSearchCV
params = {'n_neighbors':[2,3,4,5,6,7,8,9]}
```

In [33]:

```
model = GridSearchCV(KNR, params, cv=5)
```

In [34]:

```
model.fit(X_train,y_train)
model.best_params_
```

Out[34]:

{'n_neighbors': 6}

APPENDIX 2: K Nearest Neighbor Classifier Code

HS_GPA

I imported the necessary library so I could import data, do the train-test split funtion, and measure accuracy of the model later.

In [1]:

```
import numpy as np
import pandas as pd
import scipy
import sklearn
from sklearn import preprocessing
from sklearn import neighbors
from sklearn.cross_validation import train_test_split
from sklearn import metrics
```

```
/anaconda3/lib/python3.6/site-packages/sklearn/cross_validation.py:41:
DeprecationWarning: This module was deprecated in version 0.18 in favor
of the model_selection module into which all the refactored classes and
functions are moved. Also note that the interface of the new CV iterators
are different from that of this module. This module will be removed in 0.
20.
  "This module will be removed in 0.20.", DeprecationWarning)
```

Here I import the data and indicate the columns of the dataset.

In [14]:

```
grade = pd.read_csv("HSGPA.csv")
grade.columns = ['HS_GPA','FU_GPA']
```

Creating numpy array for features and target

In [15]:

```
X=grade.drop('FU_GPA',axis=1).values
y=grade['FU_GPA'].values
```

Spliting my data into training and test set

In [16]:

```
X_train, X_test, y_train, y_test = train_test_split(X,y,test_size = 0.1)
```

Import preprocessort to convert Float to Int

In [17]:

```
lab_enc = preprocessing.LabelEncoder()
y_train_encoded = lab_enc.fit_transform(y_train)
```

Importing the classifier and building the classifier model

In [18]:

```
from sklearn.neighbors import KNeighborsClassifier
```

Start training the model

In [26]:

```
knn = KNeighborsClassifier(n_neighbors=5)
```

In [27]:

```
knn.fit(X_train, y_train_encoded)
```

Out[27]:

```
KNeighborsClassifier(algorithm='auto', leaf_size=30, metric='minkowsk
i',
           metric_params=None, n_jobs=1, n_neighbors=5, p=2,
           weights='uniform')
```

In [28]:

```
y_pred = knn.predict(X_test)
```

In [29]:

```
lab_enc = preprocessing.LabelEncoder()
y_test_encoded = lab_enc.fit_transform(y_test)
lab_enc = preprocessing.LabelEncoder()
y_pred_encoded = lab_enc.fit_transform(y_pred)
```

In [30]:

```
from sklearn.metrics import accuracy_score
```

In [31]:

```
accuracy_score(y_test_encoded,y_pred_encoded,normalize=True, sample_weight=None)
```

Out[31]:

```
0.01
```

In [32]:

```
from sklearn.model_selection import GridSearchCV
params = {'n_neighbors':[2,3,4,5,6,7,8,9]}
model = GridSearchCV(knn, params, cv=5)
model.fit(X_train,y_train_encoded)
model.best_params_
```

```
/anaconda3/lib/python3.6/site-packages/sklearn/model_selection/_split.p
y:605: Warning: The least populated class in y has only 1 members, which
is too few. The minimum number of members in any class cannot be less tha
n n_splits=5.
  % (min_groups, self.n_splits)), Warning)
```

Out[32]:

```
{'n_neighbors': 5}
```

SAT Score

I imported the necessary library so I could import data, do the train-test split funtion, and measure accuracy of the model later.

In [1]:

```
import numpy as np
import pandas as pd
import scipy
import sklearn
from sklearn import preprocessing
from sklearn import neighbors
from sklearn.cross_validation import train_test_split
from sklearn import metrics
```

```
/anaconda3/lib/python3.6/site-packages/sklearn/cross_validation.py:41:
DeprecationWarning: This module was deprecated in version 0.18 in favor
of the model_selection module into which all the refactored classes and
functions are moved. Also note that the interface of the new CV iterators
are different from that of this module. This module will be removed in 0.
20.
  "This module will be removed in 0.20.", DeprecationWarning)
```

Here I import the data and indicate the columns of the dataset.

In [2]:

```
grade = pd.read_csv("SAT.csv")
grade.columns = ['SAT Score','FU_GPA']
```

Creating numpy array for features and target

In [3]:

```
X=grade.drop('FU_GPA',axis=1).values
y=grade['FU_GPA'].values
```

Spliting my data into training and test set

In [4]:

```
X_train, X_test, y_train, y_test = train_test_split(X,y,test_size = 0.1)
```

Import preprocessort to convert Float to Int

In [5]:

```
lab_enc = preprocessing.LabelEncoder()
y_train_encoded = lab_enc.fit_transform(y_train)
```

Importing the classifier and building the classifier model

In [6]:

```
from sklearn.neighbors import KNeighborsClassifier
```

Start training the model

In [7]:

```
knn = KNeighborsClassifier(n_neighbors=2)
```

In [8]:

```
knn.fit(X_train, y_train_encoded)
```

Out[8]:

```
KNeighborsClassifier(algorithm='auto', leaf_size=30, metric='minkowsk
i',
           metric_params=None, n_jobs=1, n_neighbors=2, p=2,
           weights='uniform')
```

In [9]:

```
y_pred = knn.predict(X_test)
```

In [10]:

```
lab_enc = preprocessing.LabelEncoder()
y_test_encoded = lab_enc.fit_transform(y_test)
lab_enc = preprocessing.LabelEncoder()
y_pred_encoded = lab_enc.fit_transform(y_pred)
```

In [11]:

```
from sklearn.metrics import accuracy_score
```

In [12]:

```
accuracy_score(y_test_encoded,y_pred_encoded,normalize=True, sample_weight=None)
```

Out[12]:

```
0.0
```

In [13]:

```
from sklearn.model_selection import GridSearchCV
params = {'n_neighbors':[2,3,4,5,6,7,8,9]}
model = GridSearchCV(knn, params, cv=5)
model.fit(X_train,y_train_encoded)
model.best_params_
```

```
/anaconda3/lib/python3.6/site-packages/sklearn/model_selection/_split.p
y:605: Warning: The least populated class in y has only 1 members, which
is too few. The minimum number of members in any class cannot be less tha
n n_splits=5.
  % (min_groups, self.n_splits)), Warning)
```

Out[13]:

```
{'n_neighbors': 2}
```

Combined SAT Score and HS_GPA

I imported the necessary library so I could import data, do the train-test split funtion, and measure accuracy of the model later.

In [1]:

```
import numpy as np
import pandas as pd
import scipy
import sklearn
from sklearn import preprocessing
from sklearn import neighbors
from sklearn.cross_validation import train_test_split
from sklearn import metrics
```

```
/anaconda3/lib/python3.6/site-packages/sklearn/cross_validation.py:41:
DeprecationWarning: This module was deprecated in version 0.18 in favor
of the model_selection module into which all the refactored classes and
functions are moved. Also note that the interface of the new CV iterators
are different from that of this module. This module will be removed in 0.
20.
  "This module will be removed in 0.20.", DeprecationWarning)
```

Here I import the data and indicate the columns of the dataset.

In [2]:

```
grade = pd.read_csv("Data Final.csv")
grade.columns = ['SAT Score','HS_GPA','FU_GPA']
```

Creating numpy array for features and target

In [3]:

```
X=grade.drop('FU_GPA',axis=1).values
y=grade['FU_GPA'].values
```

Spliting my data into training and test set

In [4]:

```
X_train, X_test, y_train, y_test = train_test_split(X,y,test_size = 0.1)
```

Import preprocessort to convert Float to Int

In [15]:

```
lab_enc = preprocessing.LabelEncoder()
y_train_encoded = lab_enc.fit_transform(y_train)
```

Importing the classifier and building the classifier model

In [16]:

```
from sklearn.neighbors import KNeighborsClassifier
```

Start training the model

In [23]:

```
knn = KNeighborsClassifier(n_neighbors=2)
```

In [24]:

```
knn.fit(X_train, y_train_encoded)
```

Out[24]:

```
KNeighborsClassifier(algorithm='auto', leaf_size=30, metric='minkowsk
i',
           metric_params=None, n_jobs=1, n_neighbors=2, p=2,
           weights='uniform')
```

In [25]:

```
y_pred = knn.predict(X_test)
```

In [26]:

```
lab_enc = preprocessing.LabelEncoder()
y_test_encoded = lab_enc.fit_transform(y_test)
lab_enc = preprocessing.LabelEncoder()
y_pred_encoded = lab_enc.fit_transform(y_pred)
```

In [27]:

```
from sklearn.metrics import accuracy_score
```

In [28]:

```
accuracy_score(y_test_encoded,y_pred_encoded,normalize=True, sample_weight=None)
```

Out[28]:

```
0.01
```

In [29]:

```
from sklearn.model_selection import GridSearchCV
params = {'n_neighbors':[2,3,4,5,6,7,8,9]}
model = GridSearchCV(knn, params, cv=5)
model.fit(X_train,y_train_encoded)
model.best_params_
```

```
/anaconda3/lib/python3.6/site-packages/sklearn/model_selection/_split.p
y:605: Warning: The least populated class in y has only 1 members, which
is too few. The minimum number of members in any class cannot be less tha
n n_splits=5.
  % (min_groups, self.n_splits)), Warning)
```

Out[29]:

```
{'n_neighbors': 2}
```

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