ST3189 Assessed Coursework Project

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Introduction

This report will be focused on using the different types of machine learning models on real world datasets. In this project, I will be using unsupervised learning models to find clusters of customers spending habits based on their demographics from the mall datasets. Regression models will be used to find factors affecting world happiness score on the 2018 world happiness dataset and classification models will be used to find out if a person will get diabetes based on their health factors. This project is done in python and will display graphs and models to support as evidence for our research question.

Classification Dataset – Diabetes Outcome

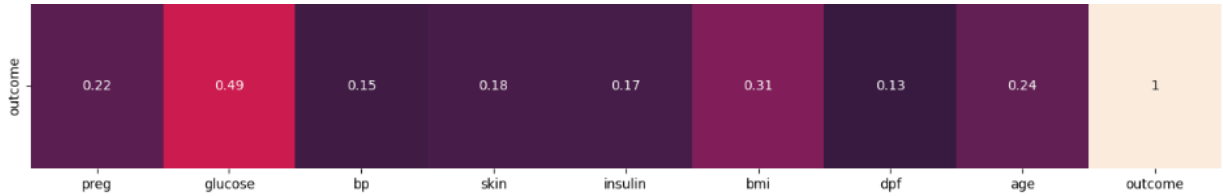
Diabetes is a rampant problem that is projected to only increase in the near future, therefore it is important to understand its causes and trends to find a prevention for future generations. Our research focuses solely on females with diabetes as it is shown that females are more prone to serious complications and at a higher risk of death. The dataset is obtained from National Institute of Diabetes and Digestive Kidney Diseases, and it consist of medical predictor variables and one dependent variable (outcome) from females aged 21 and above.

I start by identifying key research questions to focus on when building the machine learning models.

- What are the health factors that result in diabetes? Build a model to predict if a female patient will get diabetes with the given health factors.
- What are the top 3 highest correlated factors that result in diabetes?
- Does an older age patient affect the chance of diabetes?
- Does food and lifestyle choices play a part in the chances of getting diabetes?

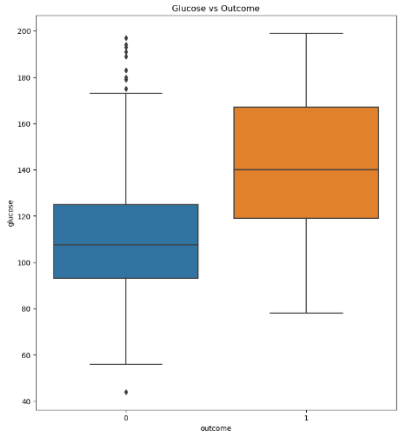
After importing the dataset and doing preprocessing of the data such as handling missing values and standardization, I proceed to check for multi-collinearity using VIF among the independent variables and It can be noted that variables such as glucose and bp had a higher VIF which could indicate a possibility of multi-collinearity existing, which I will use standard scaler to reduce the multi collinearity before splitting the data into training and testing sets. I also plotted a boxplot to note the outliers and replaced the outliers with the median of the variable, this method is also known as Median Absolute Deviation.

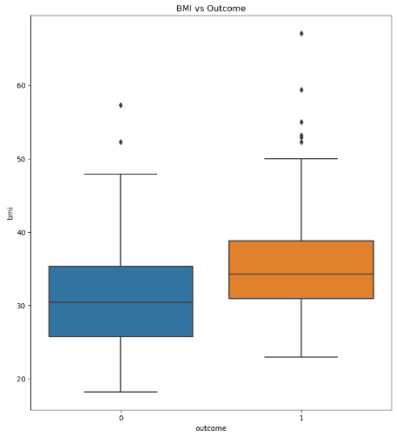
Lastly, I plot a heat map to understand the correlation of all the variables together. It can be noted that glucose, BMI and age of the patient are the top 3 variables that correlate with the outcome of getting diabetes.

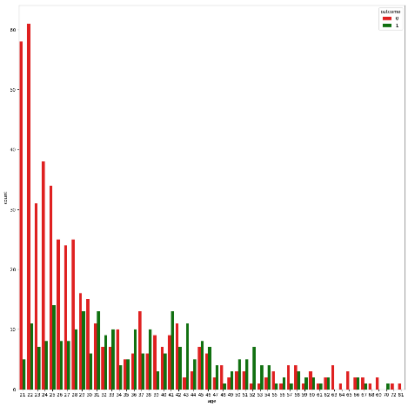


Our statement can be further supported by visualizing the data using charts. As seen below in the boxplots, it can be noted that a higher glucose level and BMI would lead to diabetes. Research done by European Society of Cardiology proves similar findings, therefore preventive measure such as selecting healthier food options and partaking in exercise regularly can reduce the chance of diabetes. Age is also a factor that plays a part, but not as severe as the previous two factors. In the barchart below, it is noted that the diabetes (green bar) is more common among female patients after age 30 – 54, which is also known as middle age diabetes due to the fact that these group of patients are not taking care of their health by eating healthy and keeping an active lifestyle because of factors such as too copped up with work or pregnancies. When looking further into whether the number of pregnancies can risk the patient getting diabetes, it is observed from the boxplot that this is infact a possibility. This is also further supported by the medical reason that women is associated with a higher risk of developing gestational diabetes and type 2 diabetes due to factors such as weight gain, changes in hormones and an increased

in insulin resistance. Research done by National Medical Birth Register also suggest similar findings that can be use to support this argument.





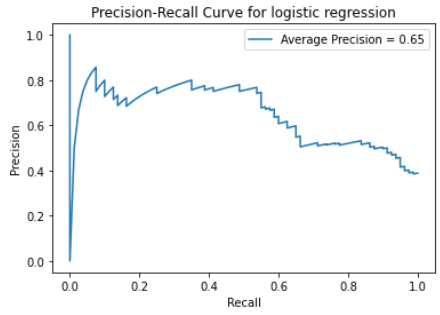


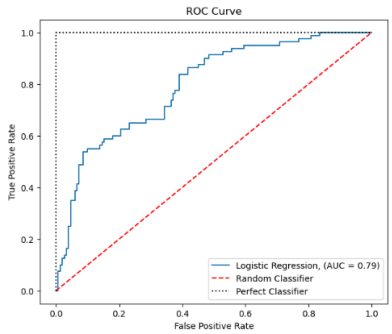
Moving on to create the machine learning models, I proceed to split the dataset into training and test dataset with proportions of 70% and 30% respectively. The dataset is noted to have a slight imbalance where 65% of patients has no diabetes but a slight imbalance should not be a major concern for the models. The model will be evaluated using F1 Score, AUC score and Accuracy (since the model is close to being balanced, accuracy is a useful scoring metric). The F1 score combines precision and recall using their harmonic mean and is used to compare performance of a binary classifier. The AUC score represents the area under the ROC curve, which tells us how efficient our model is at distinguishing between the positive and negative classes. Lastly, accuracy score measures the number of correct predictions made by a model over the total predictions made.

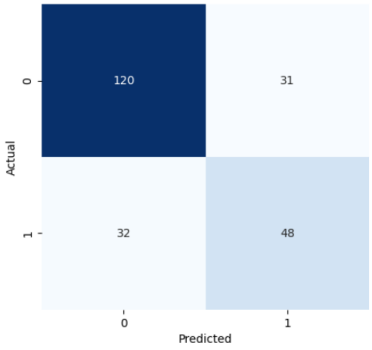
Logistic Regression

The first model I will be using is logistic regression as this model is a popular algorithm used for binary classification. It is based on a sigmoid function that transforms linear regression into a logistic regression that predicts the probability of patients that does not have diabetes. The formular for precision is tp/(tp+fp) which result in us getting 0.61, that means if the model predicts a patient has diabetes, it is correct 61% of the time.

The formular for recall = tp/(tp+fn) which result in us getting 0.60, which means the model correctly identifies 60% of all patients who has diabetes. The AUROC score of 0.79 suggest this model has good discriminatory ability such that a randomly selected patient with diabetes has a higher probability of having diabetes. The model also has an accuracy score of 0.72, which is ideal and realistic. Therefore, this model is a suitable model to be used but it could still be improved upon to increase its f1 score, such as hyperparameter tuning or adjusting the decision threshold.

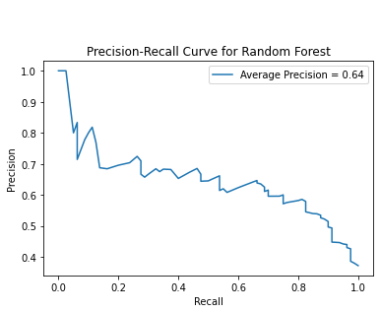


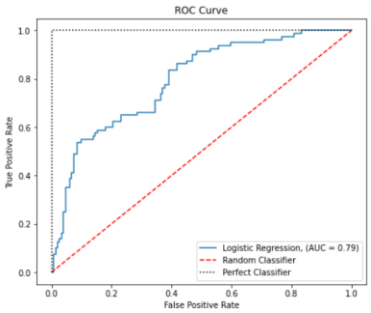


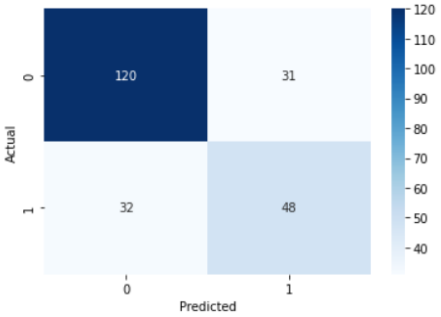


Random Forest Classifier

The second model is random forest classifier. it is an ensemble learning method that contains multiple decision trees. Random forest overcomes the problem of overfitting that stems from a single decision tree by averaging the predictions of multiple decision trees which reduces the variance. The f1 score for random forest is 0.65 which is still considerably acceptable, along with a decent AUROC score of 0.79 and accuracy score of 0.75. This is by far the best model.

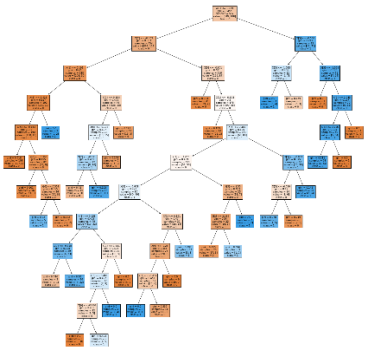


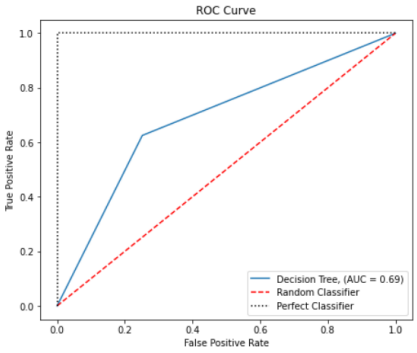




Decision Tree Classifier

The next model is decision trees model, which works by splitting the dataset based on splitting criteria until a stopping condition is met. New data would be filtered through the root nodes and follow the branches based on its feature values and stops at the leaf note which provides the final output. It is an easy model to understand and interpret at a cost of being prone to overfitting. The model has a f1 score of 0.59 and AUROC score of 0.68667 and a decent accuracy score of 0.7, which makes it the poorest model in the bunch. Before visualizing the decision tree, I have to use the pruning technique to remove branches that use features of low importance, which reduces the chances of overfitting. Once that is done, the decision tree is shown below.





Conclusion

Upon revisiting the research questions, I used as a guideline in the beginning, I can determine that the most significant factors correlated with diabetes are BMI, glucose level, and the number of pregnancies. This is further supported by evidence from external research studies from other medical research. The classification models used are also able to predict the outcome of diabetes with a decent accuracy and reliability using the variables above. However, there is room for improvement by applying methods such as hyper-parameter tuning and cross validation which will be able to create a better model with better performance. The models can be used by healthcare workers to better understand and curb the increasing issue of diabetes by recommending patients healthier diets to reduce their BMI and glucose level.

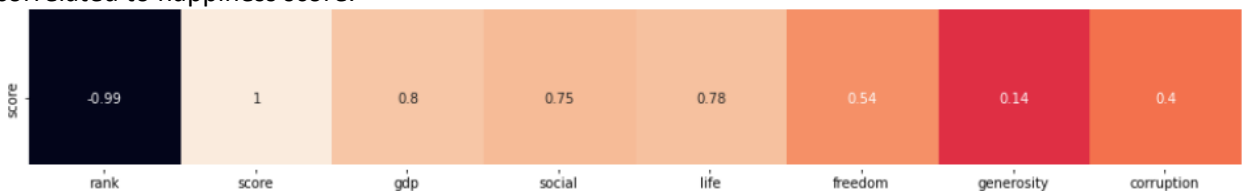
Regression Dataset – 2018 World Happiness Report

We as humans have always been interested in the pursuit of happiness. In recent years, data has been gathered about the world happiness report that scores countries on its happiness score based on social and economic factors of the country. This report aims to use machine learning and data analysis to find relationships and insights on how these variables can affect a nation's happiness, which can benefit by allowing government bodies to adjust and set policies to keep the country happy.

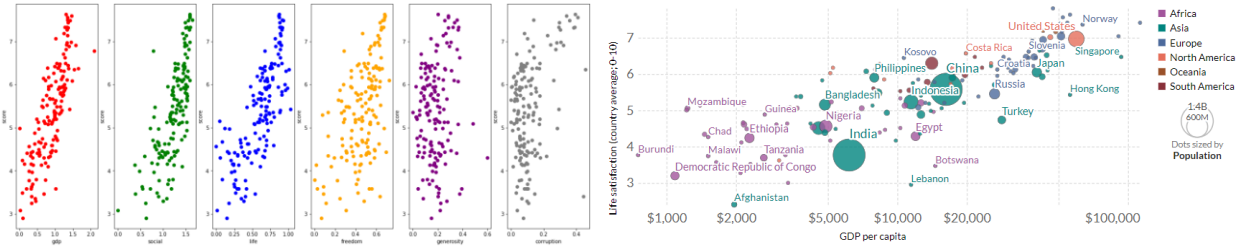
These are the research questions that I have proposed to have an idea for the development of the model.

- What are the variables that have a high correlation to happiness score?
- Why are some countries happier than others? How can we improve the country's happiness?

I begin by importing the dataset and proceed to perform data preprocessing, cleaning up the data, checking and fixing outliers using the median absolute deviation method and checking for multi-collinearity. There are some missing values in the corruption column which are fixed by replacing the missing values with the mean of the column. A heatmap is plotted to identify which variables are highly correlated to happiness score.



It is seen that all these factors except generosity and corruption are highly correlated, this is further supported by analyzing each independent variable against score using a scatterplot, which all shows a linear trend. With the support of external research, it is seen that GDP has with national happiness, as a higher GDP tend to lead to citizens being wealthier, however social factors such as social support, healthy life expectancy and freedom of choice are also important factors that play a part besides wealth of a country.



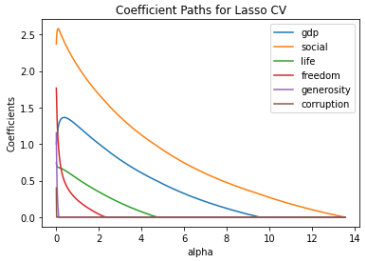
I proceed to standardize the data using standard scaler before splitting the data into training and test groups with a test size of 30%. The scoring metric that will be used for this regression dataset will be Mean Square Error (MSE) is the mean squared differences between the predicted and actual values. A loser MSE results in better performance, however it is sensitive to outliers. Root MSE (RMSE) is used by rooting square root of MSE, which is a better interpretation of MSE. Similar to MSE, a lower MSE indicates a better performance, but it is also sensitive to outliers and emphasizes large errors. R^2 Score is a scoring metric that explains how well the data fit with the regression model.

Lasso Regression

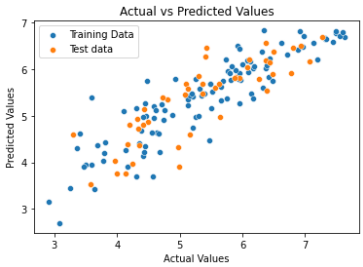
Lasso regression is a linear model with regularization techniques which uses a shrinkage method, The model uses the L1 regularization technique with parameter 'alpha' as the penalty term which is the amount of shrinkage implemented. Lasso regression shrinks the coefficients and helps to reduce model complexity and multi-collinearity.

The original model is decently scored, but after performing a 10-fold cross validation using GridsearchCV, there is a slight improvement in all scores except accuracy. It is also found that hyperparameter alpha is the best for the model when alpha = 0.01. A coefficient plot is to see the coefficient shrinking as alpha

changes, which indicates which features are important by observing which coefficients become zero first indicating less importance compared to features that remain non-zero for higher alpha values. We can observe that social and gdp are important features. Another plot used is actual vs predicted values, to visualize the model's performance by observing how much the predicted values differ from the training values. Despite having a few inaccurate points, generally predicted values are very similar to training values.

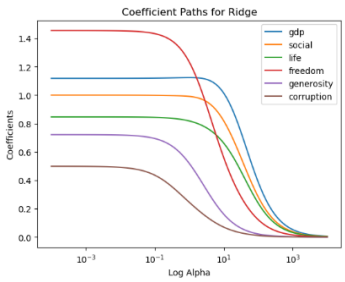


Model	R^2 Score	MSE	RMSE	Accuracy
Lasso	0.776	0.278	0.527	0.713
Lasso CV	0.781	0.272	0.522	0.712

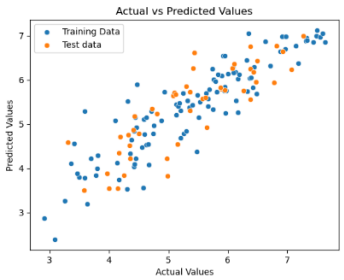


Ridge Regression

Ridge regression is a linear model that employs L2 regularization to reduce overfitting and multi-collinearity. L2 regularization functions by introducing a penalty term to the ordinary least squares, controlled by parameter alpha, which dictates the degree of shrinkage applied to the model. In this case, the model R^2 score is 0.785, indicating that it can explain 78.5% of the variation in the target variable.
Looking at the coefficient path plot, it is observed with similar effect that GDP and Social are the 2 most important feature, remaining non-zero for higher values of alpha. Similar to lasso regression, ridge regression actual vs predicted values are similar to each other, which indicates good performance.
When cross-validation is performed, the model's results slightly worsen, potentially due to instability, such as noise present in the dataset. Examining the coefficient path plot reveals that GDP and Social factors are the two most important features, as they remain non-zero for higher alpha values. The actual vs. predicted values in ridge regression are similar to those in lasso regression, suggesting good model performance



Model	R^2 Score	MSE	RMSE	Accuracy
Ridge	0.785	0.267	0.517	0.702
Ridge CV	0.782	0.270	0.519	0.712



Multiple Linear Regression

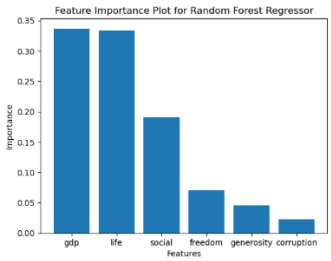
Multiple Linear Regression is a linear model that explain the relationship between the independent variables and the dependent variable. This is a basic linear model that uses the ordinary least squares method, which minimizes the sum of squared differences of the actual and predicted values on dependent variable to obtain the best fit line. As seen, all the coefficients are positive, which indicates all of them are positively correlated to the happiness Score, with Social , Life and freedom being the most impact on happiness score.

Model	R^2 Score	MSE	RMSE	Accuracy
MLR	0.785	0.267	0.517	0.702

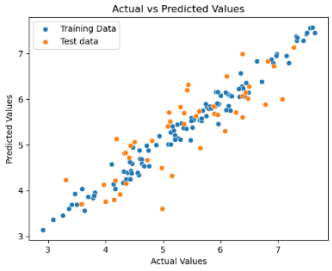
	Coefficient
gdp	0.986259
social	1.057343
life	1.119536
freedom	1.468661
generosity	0.892868
corruption	0.145474

Random Forest Regressor

A random forest regressor is an ensemble of multiple decision trees constructed together and averaging their predictions to create a more accurate model. This reduces the overfitting problem that occurs in single decision tree models. In comparison, this model has the best performance with a R^2 Score of 0.908 and lowest MSE and RMSE score of 0.114 and 0.338 respectively. Upon performing 10-fold cross validation with parameters 'n_estimator', we get an increase in accuracy and a lower MSE and RMSE, therefore. The feature importance plot allows us to visualize which features are important based on their impact on the model performance. As seen GDP and life are the most important features based on this model.

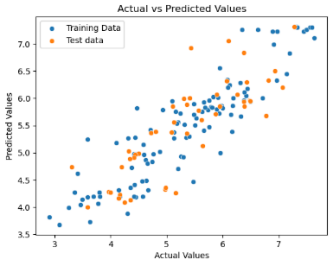


Model	R^2 Score	MSE	RMSE	Accuracy
RFR	0.908	0.114	0.338	0.703
RFR CV	0.908	0.113	0.337	0.711



K Neighbors Regressor

K neighbors regressor is based on the k nearest neighbors' algorithm. This model uses feature similarity to predict values of new data points. The model decides the class using K-nearest data points using the Euclidean distance, the center point for class is determined by the class with the highest number of datapoints in K-nearest data point. The model has a decent score and performing a 10-fold cross validation improves the R^2 and accuracy score significantly by 0.052 and 0.11 respectively. The actual vs predicted plot shows that some of the test data are not similar and there are outlying data points.



Model	R^2 Score	MSE	RMSE	Accuracy
KNN	0.777	0.276	0.525	0.658
KNN CV	0.829	0.211	0.460	0.768

Conclusion

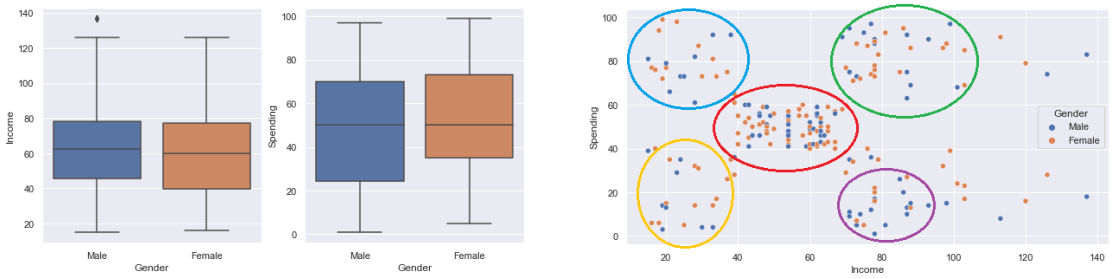
After analyzing the data set and examining the important features using different models, it is seen that GDP, social support and a healthy life expectancy are the top 3 variables that contributes to a country's happiness. Happy citizens are key to a prosperous and successful country, as happy citizens would tend to stay in the country and contribute to the economy in the long run, which also increases GDP naturally. Countries that are trying to make their citizens happier can follow in the footsteps the top 10 happiest countries, implementing certain policies and rights for their citizens. This research gives us an insight on the variables that has the most impact. The most accurate model is the random forest regressor and it shows that GDP and healthy life expectancy are the most important features.

Unsupervised Learning – Mall customer segmentation dataset

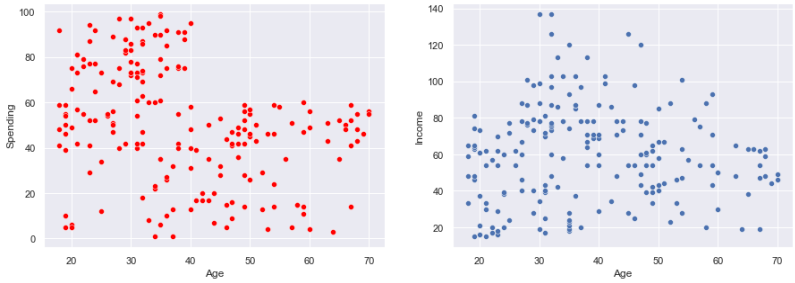
Understanding customers demographic and shopping patterns is an important process for retailers and business owners to stay ahead of competition. By doing so, retailers are able to create targeted marketing campaigns tailored for their customers and also improve overall customer shopping experience. This dataset contains the basic demographics of 200 customers such as gender, age, annual income and the spending score. In this report, I will be using various unsupervised learning models to group customers and understand their shopping habits and examine its relationship to their demographics. The clustering algorithms used are k means clustering and hierarchical clustering. Before moving on, certain research questions are drafted to find relationship between the variables and to build a model around it.

- Which gender has a higher income? Does a higher income correlate with a higher spending?
- Do older shoppers tend to have a higher spending score?
- Find groupings of customers by clustering

We first begin by doing some data preprocessing, renaming columns and ensuring there is no missing values before doing some data analysis. To understand the distribution of income and spending against gender, a boxplot is plotted. It is seen that males earn slightly more but has a lower spending compared to females. With this knowledge, a scatterplot is made to plot annual income against spending score categorized by gender. A few clusters can be seen in the scatterplot, showing different groupings of customer spending score by their income. The most common group are the medium earners and medium spenders, followed by the 4 other groups that are low and higher earners with low and higher spenders. We will further analyze these groups with k-means cluster and DB scan later on.



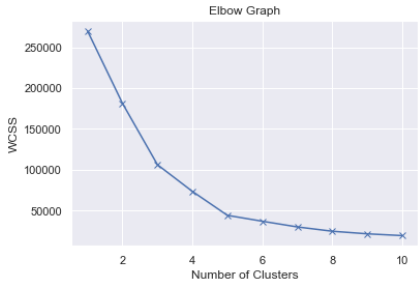
Moving on, we try to understand if the age of a shoppers has a relationship to the spending score by plotting a 2 scatterplots side by side. There is no clear obvious clusters but the general trend noticeable is that older age customers have a lower spending while income is on the lower side, and middle aged customers (30-40 years old) have a highest spending due to earning the highest income. Therefore, it can be generalized that a higher income generally leads to a higher spending.

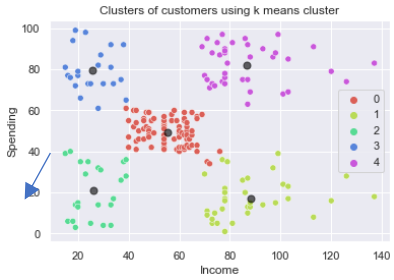


Clustering based on Income and Spending

I will be using K-means cluster, Hierarchical cluster and DB scan to find distinct groups of customers based on their income and spending. K means cluster is an algorithm that splits a dataset into k number of clusters. Data points are repeatedly assigned to each cluster based on the nearest centroid. By using this we can have insights on the groups of customers. Before implementing the K-means cluster, it is important to determine the optimal K number of clusters. That can be done by using the elbow method or silhouette score, however in this project, I opted to use the elbow method. The elbow method calculates WCSS

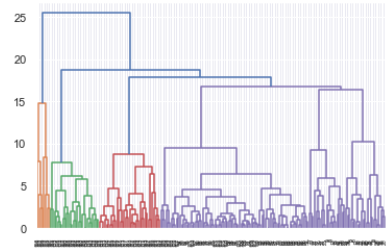
(Within cluster sum of square) for different number of clusters. The WCSS value decreases as the number of clusters increases, the point where the graph rapidly curves making the graph look like an elbow will be the optimal number of k clusters. In this elbow plot, it is noted that the elbow is formed when number of clusters is 5. I proceed to plot the k means cluster with parameter 'n_cluster' set to 5. The centroid is also created by finding the mean for each cluster. Each cluster is assigned with a unique color for easier viewing. From the plot, we can see there are 5 distinct groups of customers. This was similar to the earlier scatterplot but k-means clustering defines each cluster more clearly.



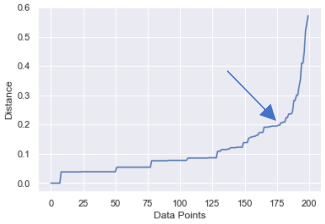


Blue	Low income but high spending (Reckless shoppers)
Green	Low income and low spending (Poorer shoppers)
Red	Average income and Average spending (Common shoppers)
Purple	High income and high spending (Rich shoppers)
Yellow	High Income but low spending (Thrifty shoppers)

Moving on to hierarchical clustering, we first scale the variables because the algorithm is sensitive to the scale of input data it is an algorithm that groups clusters based on their similarity. It begins by treating each datapoint as an individual cluster and continuously merges the closest clusters into one big cluster. The linkage criterion determines the how the distance between each cluster is calculated and the linkage used here is average linkage, which is the average distance between all pairs of points in the clusters. This hierarchical cluster slightly differs from the k-means cluster as low and medium income spenders are classified together, while there are very few high income and high spenders. This can also be displayed in a dendrogram, which is a tree like diagram that displays the order where the clusters are merged.

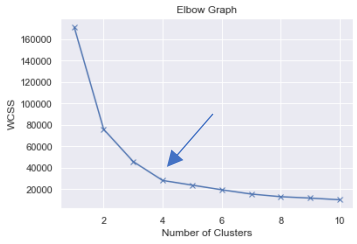


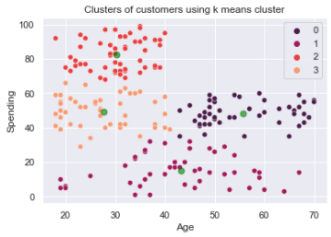
Density Based Spatial Clustering of Application with noise (DB Scan) is an unsupervised learning algorithm. It identifies clusters by looking at the local density of the data points. It also does not require the number of k clusters to be defined before the model, unlike k-means or hierarchical clusters. However, DB Scan requires the parameters epsilon and min points. The optimal value of epsilon can be found using the k-distance plot. To optimal eps is found at the sharp change in the graph where distances is 6. We train the model using eps = 6 and min samples 2* number of features and every individual cluster is mapped to a color. The dark blue dots are noise in the dataset.



Clustering based on Age and Spending

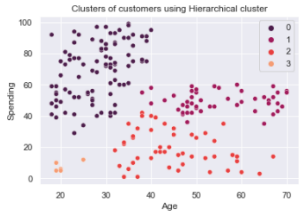
Using the same process as above, the elbow plot shows that the optimal k clusters is 4. Creating the k-means algorithm with parameters 'n_clusters' set to 4, we can observe that there are 4 distinct age groups of customers with different spendings. The green dots are the clusters centroid.

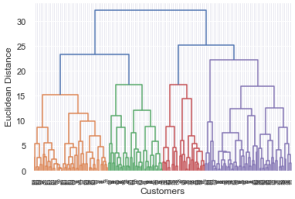




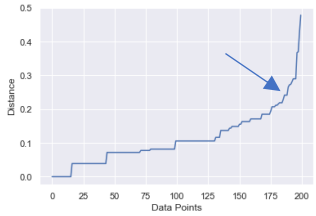
Red	Age 20-40, high spendings (Rich young adults)
Beige	Age 20-40, average spendings (Average young adults)
Dark purple	Age 45-70, average spendings (Average Seniors)
Violet	Age 30-60, low spendings (Poor/thrifty adults in general)

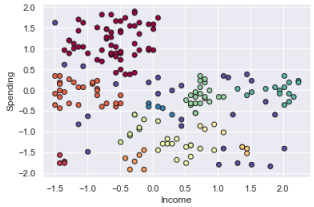
Moving on to hierarchical clustering, we make sure the variables are scaled to prevent any feature dominating the distance calculation before using the same parameters and average linkage, it is observed there are 3 distinct clusters with a small cluster for beige.





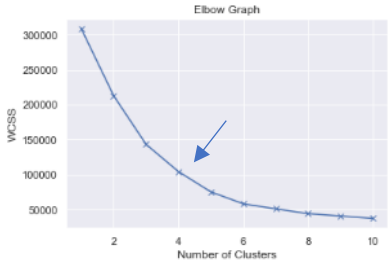
Moving on to DB scan, we find that the optimal epsilon is 0.25, and min samples would be 2* number of features. We can see 7 distinct clusters while the dark blue dots are noise in the data.

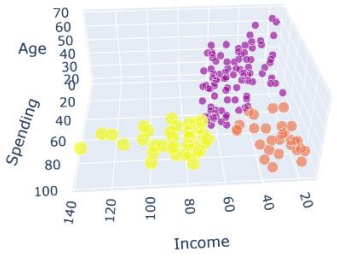




Clustering using Age, Income and Spending

Moving on to cluster the 3 variables together using k-means algorithm, we find that k-cluster is 4 by plotting the elbow plot. From the k-means plot, we can identify 3 distinct groups of customers. Therefore, it seems the most common type of customer would be purple, followed by yellow and orange. Malls could follow the same ratio to sell targeted goods and marketing strategies to target their audience such as lesser luxury stores and more of necessity shops.





Yellow	Young Adults and high spenders w high income (Wealthy Customers)
Purple	All ages, low to average spenders and income (Average Customers)
Orange	Young Adults with high spending, low income (Rich/Reckless young shoppers)

Conclusion

By using these models, malls can use these results to understand the customer market and can create targeted advertisement. There are mainly 3 main groups of customers that is observed, rich shoppers that spends a lot , therefore malls could have luxury shops to cater to their needs. Average shoppers which has the highest ratio, shops could target these groups by having special promotions to attract and

build a customer base and lastly poor/thrifty shoppers that spends the least , therefore malls could have certain value stores that sells very cheap necessities as these would attract the customer group.

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