Capstone Project Report

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University of Canberra

Course Number: 4483 Software Technology 1

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25/10/2024

Capstone Project Report

Part 1 – Reading the Dataset

Sample data

	Brand	Processor_Speed	Ram_Size	Storage_Capacity	Screen_Size	Weight	Price
110	Dell	3.5436	32	512	14.382	4.8915	18,702.4786
889	Asus	3.655	32	1,000	16.5686	3.5111	33,239.4123
30	Lenovo	2.3659	32	1,000	13.8936	3.8794	32,817.5166
817	Dell	2.3108	8	256	11.6351	2.2059	9,303.6034
526	Acer	3.6795	8	512	15.4434	2.2075	17,397.549
851	Acer	3.5652	32	256	11.1635	2.417	10,560.3635
639	Acer	1.5749	4	256	16.5939	3.1948	9,026.5086
951	Lenovo	2.1495	32	512	16.3061	3.3313	18,385.2038
675	Acer	3.3461	32	1,000	12.197	2.0154	32,925.4034
544	Dell	2.1442	32	1,000	12.2033	2.9571	32,868.8774

Initially, the dataset was cleaned by using drop_duplicates(), then random sample of 10 rows was pulled from the CSV file using Pandas. This sample detailed that there were 7 columns, including: Processor_Speed, RAM_Size, Storage_Capacity, Screen_Size, Weight, and Price. Note that the CSV file column names were edited for Processor_Speed by removing an unnecessary space, and RAM_Size by relabeling it to Ram_Size due to issues of case sensitivity. Overall, this presented a solid initial sample snapshot of the dataset we would be working with.

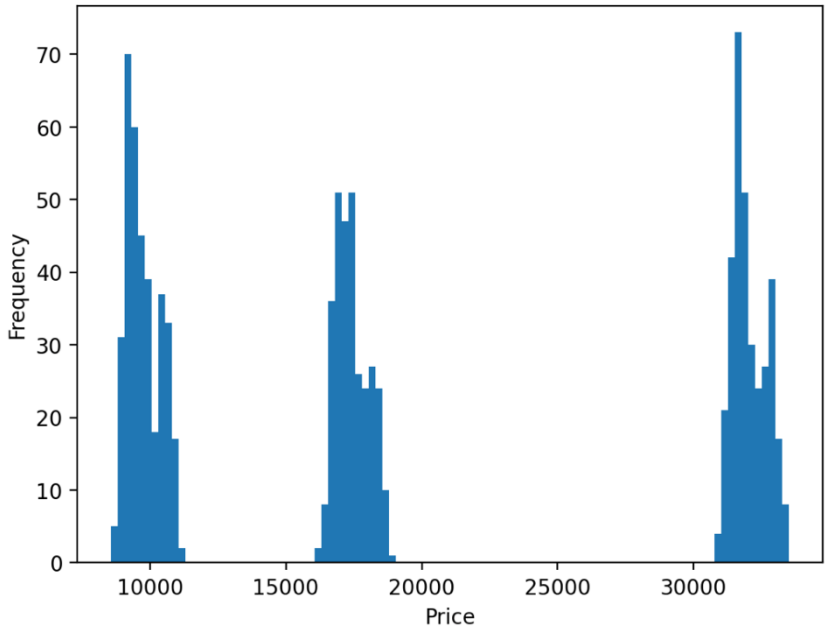
Data Shape and Size

This dataset was further explored with .shape, outputting (1000, 7). This correlates to the rows and columns. It is evident no duplicate rows were detected as the shape remained consistent. Additionally, .size was used to confirm this, resulting in 7000 (cells) of data.

Part 2 – Problem Statement Definition

The problem statement was derived from this data by investigating a target variable. This was deemed to be price as that is what one will predict with the data given. Therefore, a statement was formulated: “This analysis aims to investigate the relationship between laptop specifications and their price, identifying the features that have most correlation to the target variable of price in order to build a predictive model”.

Part 3 – Visualising the distribution of the target variable



Investigating the distribution of Price through .hist provided an interesting result. The distribution was heavily grouped around three prices: ~10000, ~17000, and ~34000, with most prices at the latter mark.

Part 4 – Data exploration at a basic level

Head

	Brand	Processor_Speed	Ram_Size	Storage_Capacity	Screen_Size	Weight	Price
0	Asus	3.8303	16	512	11.1851	2.6411	17,395.0931
1	Acer	2.9128	4	1,000	11.3114	3.26	31,607.6059
2	Lenovo	3.2416	4	256	11.853	2.0291	9,291.0235
3	Acer	3.8062	16	512	12.2804	4.5739	17,436.7283
4	Acer	3.2681	32	1,000	14.9909	4.1935	32,917.9907

Data was initially explored with .head(), providing the first 5 rows. This did not provide any information that was not already discovered with .sample().

Info

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 7 columns):
 #   Column            Non-Null Count  Dtype  
---  ------            --------------  -----  
 0   Brand             1000 non-null   object 
 1   Processor_Speed   1000 non-null   float64
 2   Ram_Size          1000 non-null   int64  
 3   Storage_Capacity  1000 non-null   int64  
 4   Screen_Size       1000 non-null   float64
 5   Weight            1000 non-null   float64
 6   Price             1000 non-null   float64
dtypes: float64(4), int64(2), object(1)
memory usage: 54.8+ KB
```

.info() was used to identify the columns, their non-null count, and type. Each column had 1000 non-nulls, meaning every cell had a value. The datatypes displayed that there was one object type (Brand), two integer columns (Ram and Storage), and the rest float values. This aligns with what is inherently expected of these categories.

Describe

	Brand	Processor_Speed	Ram_Size	Storage_Capacity	Screen_Size	Weight	Price
count	1000	1,000	1,000	1,000	1,000	1,000	1,000
unique	5	None	None	None	None	None	None
top	Dell	None	None	None	None	None	None
freq	210	None	None	None	None	None	None
mean	None	2.7506	15.5	584.576	14.0568	3.4669	19,604.188
std	None	0.7318	10.9887	313.4385	1.7059	0.8665	9,406.0649
min	None	1.5116	4	256	11.0121	2.0006	8,570.013
25%	None	2.0892	8	256	12.6355	2.7172	10,114.0129
50%	None	2.7609	16	512	14.0996	3.4646	17,287.2419
75%	None	3.3626	32	1,000	15.5286	4.2126	31,566.2148
max	None	3.9985	32	1,000	16.9857	4.9907	33,503.935

.describe() displayed valuable information about each category. Notably, the five unique brands, the minimum values, and the maximum values of the numerical columns.

Nunique

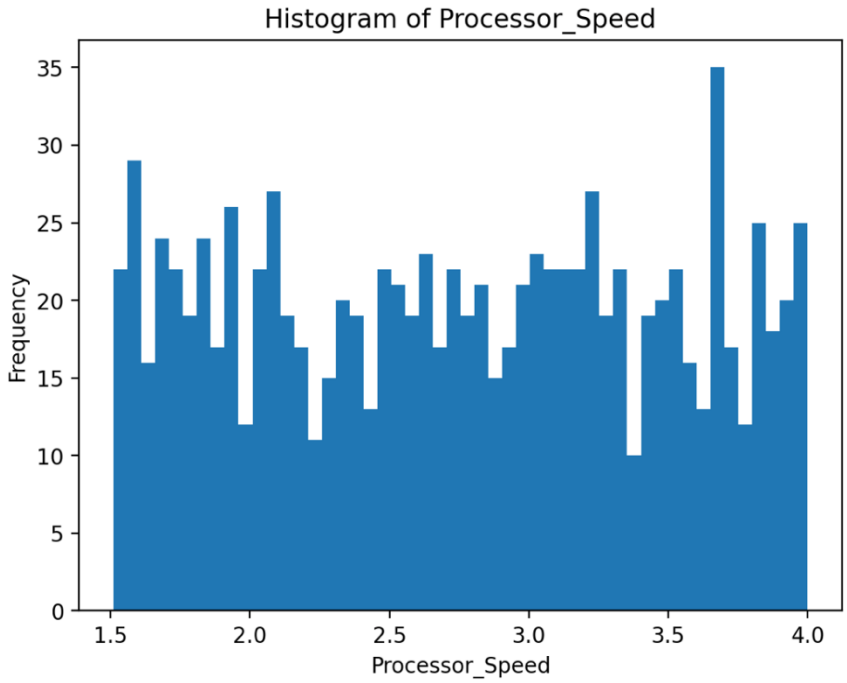
	0
Brand	5
Processor_Speed	1,000
Ram_Size	4
Storage_Capacity	3
Screen_Size	1,000
Weight	1,000
Price	1,000

.nunique() provided the number of unique values in each column. All float values had unique values due to their precision factor. The integer value of RAM size had four discrete values, whilst storage capacity had three. Additionally, the aforementioned Brand category had five unique values.

Part 5 – Visual Exploratory Data Analysis (EDA) of data

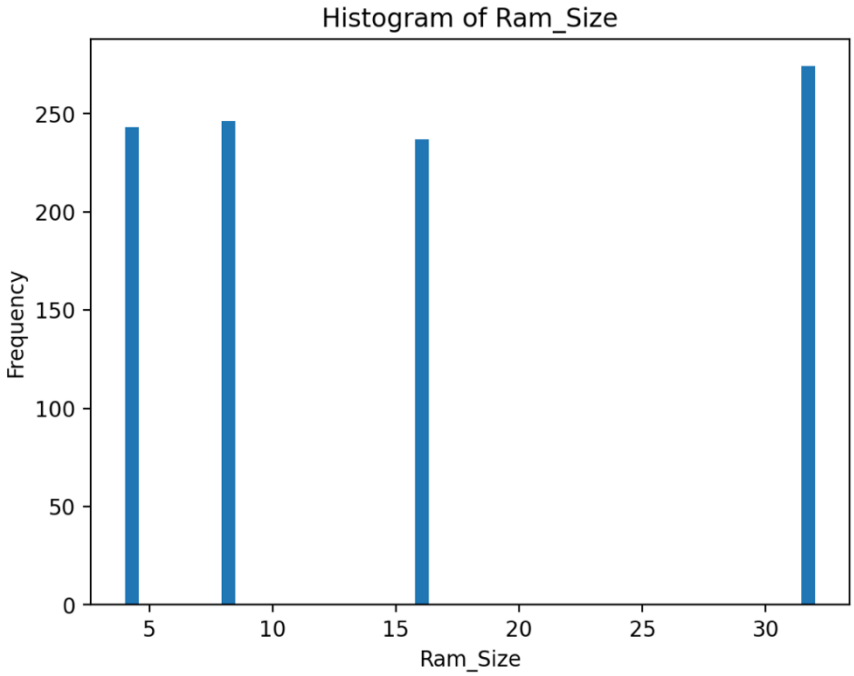
The visual exploratory data analysis (EDA) gave insight into the distribution of each variable by looping through each and producing a histogram.

Processor Speed



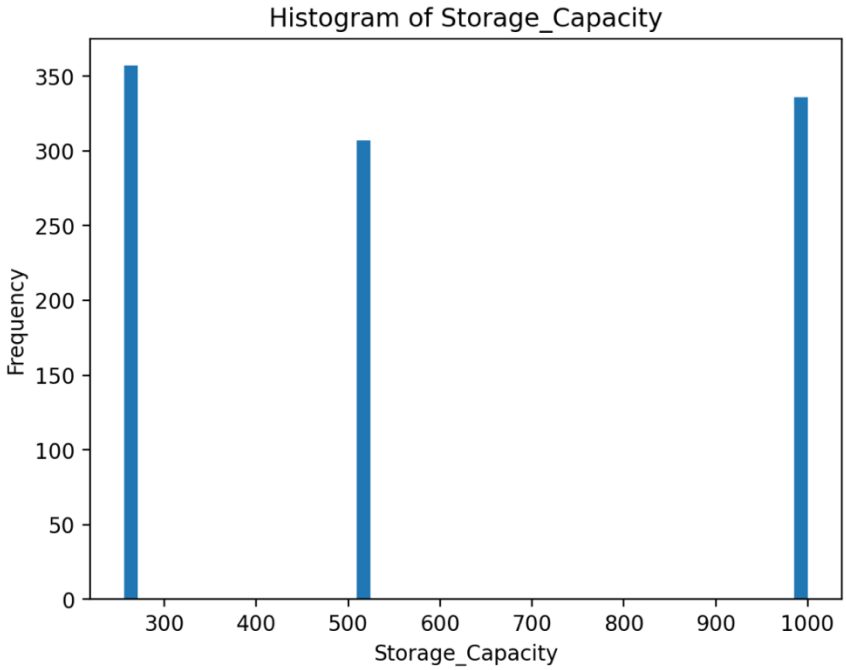
Processor speed appeared to have no correlation of the speed to how often they occur, therefore it is unlikely this would be a good predictor of price as there is no trend.

RAM Size



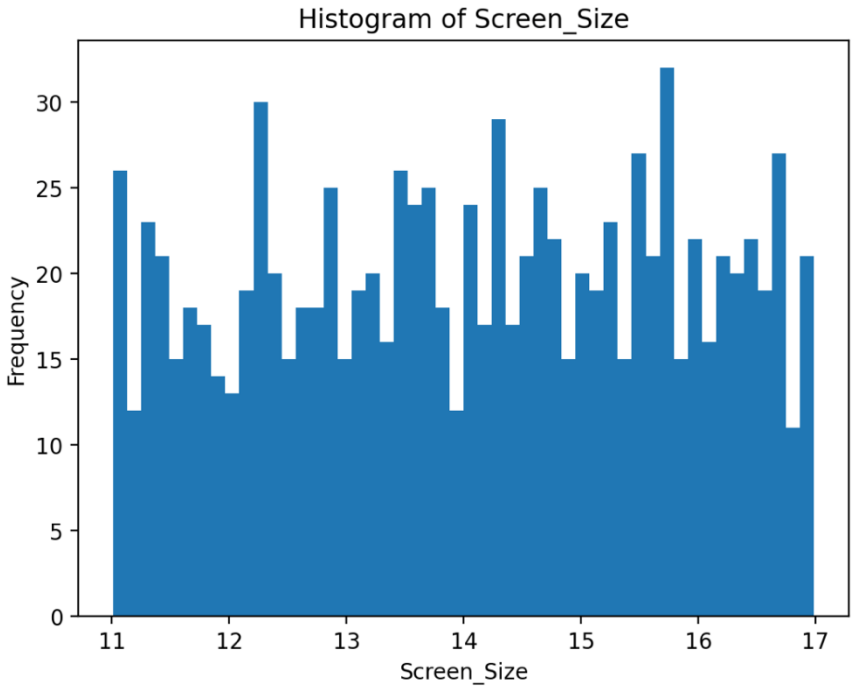
RAM Size is a discrete variable, featuring capacities of 4, 8, 16, and 32 gigabytes. This may prove to be a possible indicator of price, however, may not be accurate due to price having three primary groupings instead of four.

Storage Capacity



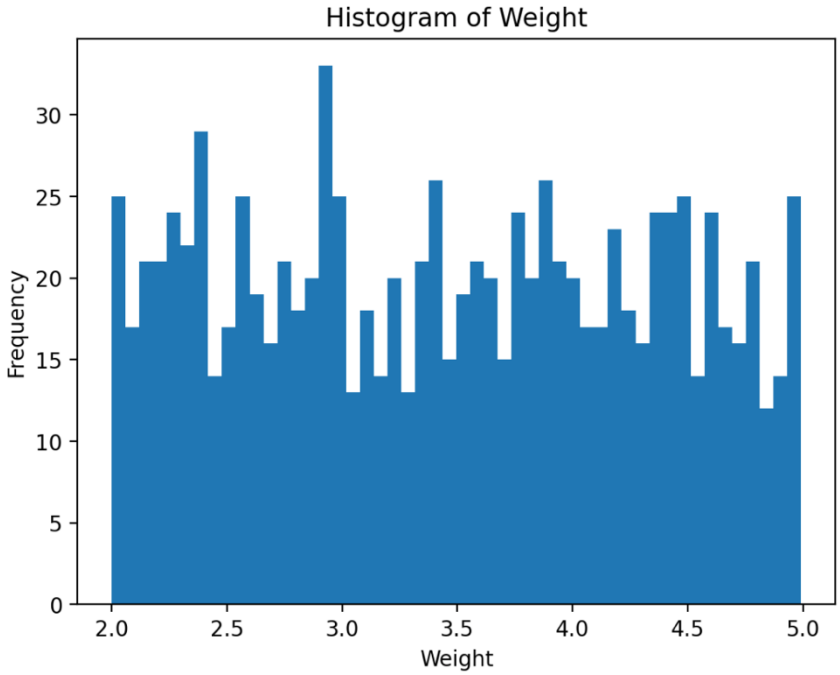
Storage capacity is another integer value that may provide a strong correlation and predictor for price. This is as it has three discrete values at 256, 512, and 1000 gigabytes which may align with the three groupings of price.

Screen Size



Screen Size, similarly to Processor Speed, does not appear to form any distinct distribution whether bell curve or otherwise. There is little trend in this data, foreshadowing a low correlation to price.

Weight



Finally, Weight also appears to have another distribution without trend, another indicator of a poor predictor.

Part 6 – Outlier analysis

In order to remove any outliers from the data set, a dataframe of numerical-only columns was created by dropping brand. A z-score function was applied to the dataset (taking the absolute value to make all positive) and assigning it to a variable which was then used to create a dataframe where the z score was less than 3 standard deviations. Printed below is a summary of this new dataframe:

	Processor_Speed	Ram_Size	Storage_Capacity	Screen_Size	Weight	Price
count	1,000	1,000	1,000	1,000	1,000	1,000
mean	2.7506	15.5	584.576	14.0568	3.4669	19,604.188
std	0.7318	10.9887	313.4385	1.7059	0.8665	9,406.0649
min	1.5116	4	256	11.0121	2.0006	8,570.013
25%	2.0892	8	256	12.6355	2.7172	10,114.0129
50%	2.7609	16	512	14.0996	3.4646	17,287.2419
75%	3.3626	32	1,000	15.5286	4.2126	31,566.2148
max	3.9985	32	1,000	16.9857	4.9907	33,503.935

As is shown, there are still 1000 rows. This evidences that there were no outliers in the dataset, allowing the analysis to proceed.

Part 7 – Missing values analysis

In order to determine any missing values, the dataframe was checked for .isnull() and summed each instance where there were no values. Below is the result:

	0
empty	

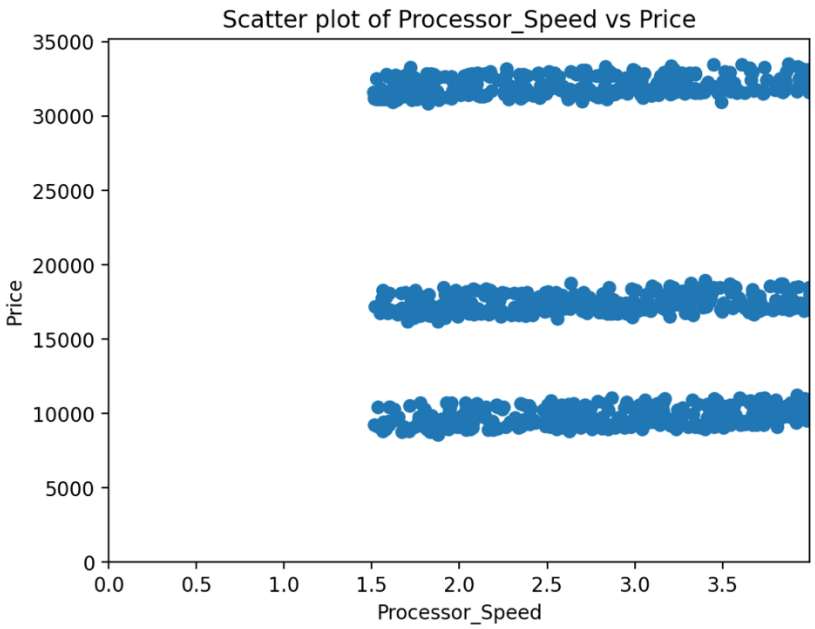
This dataframe sum is empty, once again confirming that there are no null values in the dataframe.

Part 8 – Feature selection (Visual and statistic correlation analysis for selection of best features)

Continuous

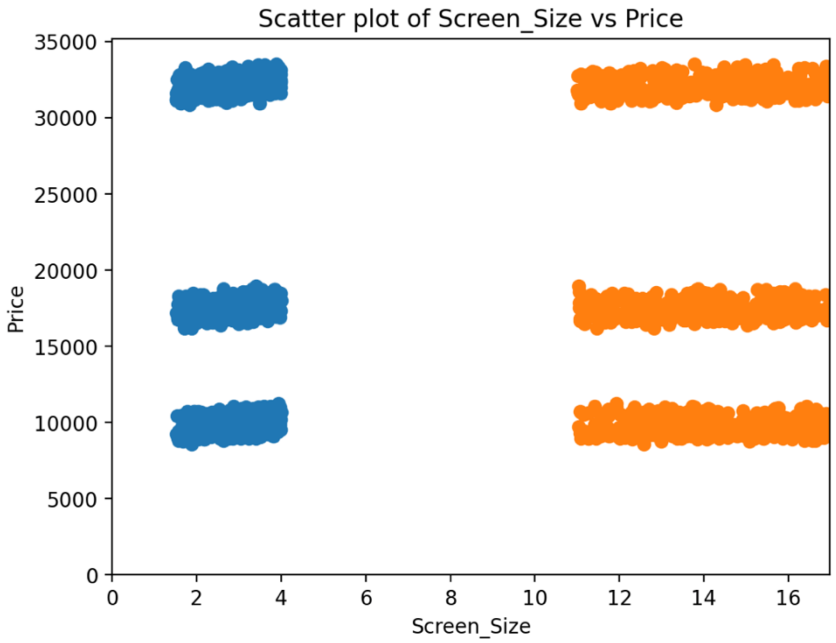
Correlations for the continuous variables against price were plotted through scatterplots, limiting the x values to the maximum of the variable.

Processor Speed



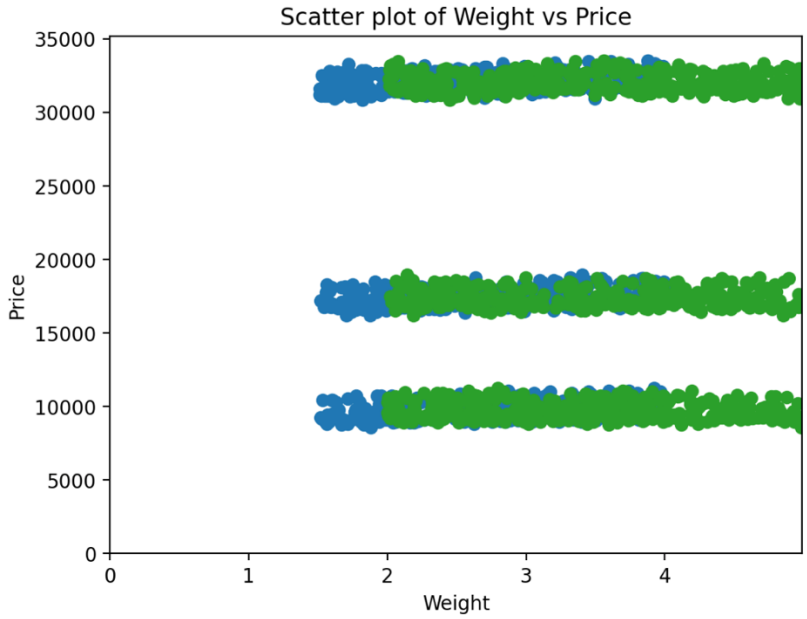
Processor speed, as predicted, had a weak correlation of -0.05 (using .corr). This is evident in the graph, as a $10000 laptop may have a 1.5GHz or 4GHz processor. This is likewise with a $32000 laptop, having processor speeds ranging from 1.5GHz to 4GHz.

Screen Size



Screen size had peculiar data, as screen sizes were split in a 2-4in range as well as an 11-17in range. However, just as with the Processor Speed, there is no correlation – as would be evident with a scatterplot that may follow a general line. The correlation coefficient was even smaller at -0.03.

Weight

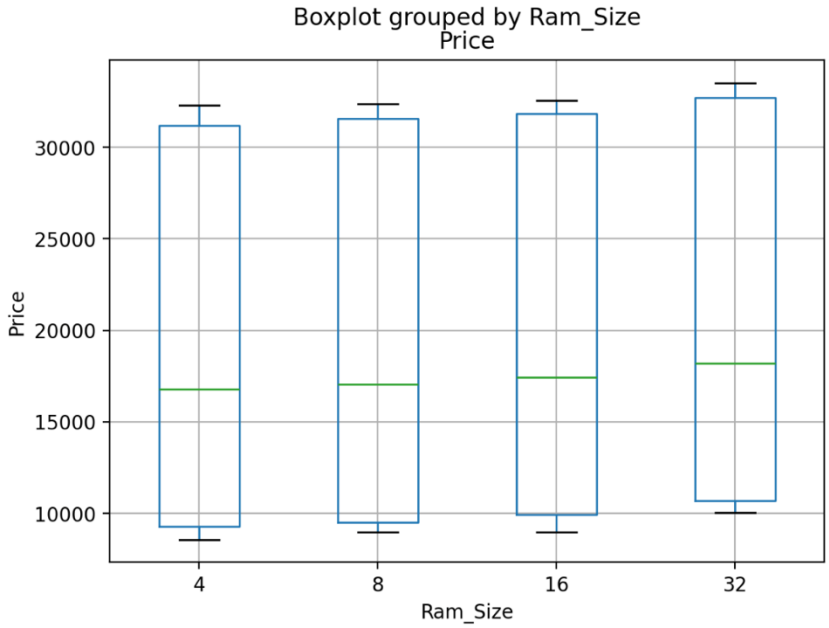


The weight correlations also provided no correlation, featuring a coefficient of 0.04.

Integer

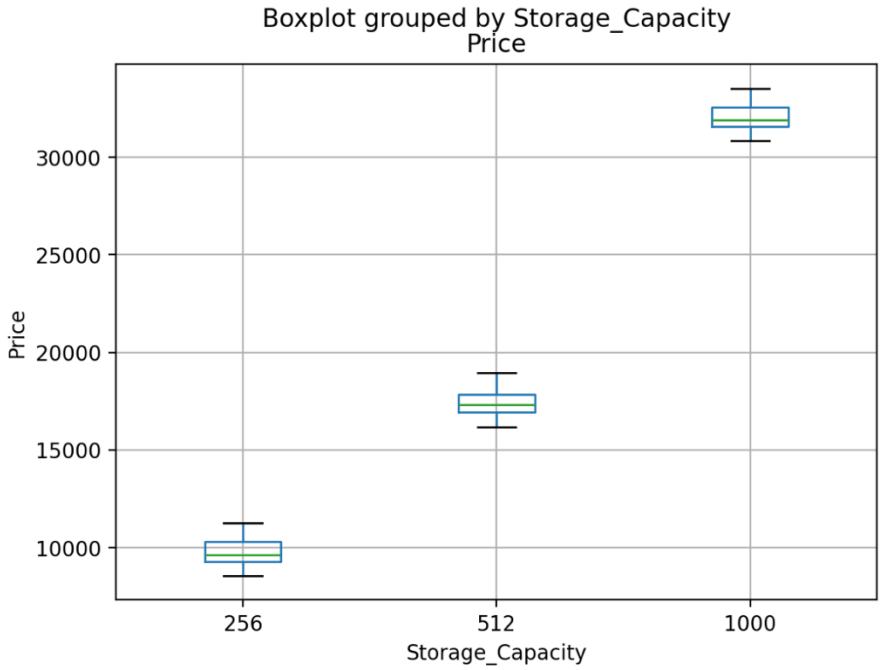
Integer value correlations to price were displayed using box plots. These are useful for the discrete values possessed by RAM and Storage capacities.

RAM Size



Unlike what was anticipated, RAM Size had a very large range of values for each capacity. For the most part, each capacity correlated to almost the entire range of price points, where a laptop with 4GB or 32GB of RAM could both be priced at the ~$10000 mark. The correlation value was 0.06, whilst being the most correlated so far, unfortunately is still a very weak correlation.

Storage Capacity



Finally, the box plot of Storage Capacity produced values that were very reliable. With low variations of maximums, minimums, and small interquartile ranges, the three capacities appear to accurately predict the grouped price points. This was also confirmed by the correlation coefficient of 1.00. Note: This was rounded to 2 decimal places, so whilst not a flawlessly accurate predictor, Storage Capacity was a very high correlation.

Part 9 – Statistical feature selection (categorical vs continuous) using ANOVA test

An Analysis of Variance test was run, looping over each unique brand name and creating a subset of price for each. This produced a list of series of prices for each brand. f_oneway was used to conduct the ANOVA test, storing the output in p and stat, where p is the probability of observing the stat, and stat is the ratio between the averages of the groups to the variance thereof. If these are approximately equal, then a null hypothesis is assumed. These were the results:

Stat: 0.55, p=0.70

Therefore, a null hypothesis was assumed as the p value was more than 0.05, suggesting the brand does not affect the price.

Part 10 – Selecting final predictors/features for building machine learning/AI model

Despite their lower correlations, all integer and float values would be used despite the lower correlations. This is due to the lack of high correlating data in the dataset, and guidance given to the investigator from their tutor. These inclusions will be adequate to show the method of prediction, however the reliability of the outcome will be impacted. Also note, object types (Brand) will not be included due to the null hypothesis.

Part 11 – Data conversion to numeric values for machine learning/predictive analysis

	Processor_Speed	Ram_Size	Storage_Capacity	Screen_Size	Weight	Price	Acer	Asus	Dell	HP	Lenovo
0	3.8303	16	512	11.1851	2.6411	17,395.0931	☐	☑	☐	☐	☐
1	2.9128	4	1,000	11.3114	3.26	31,607.6059	☑	☐	☐	☐	☐
2	3.2416	4	256	11.853	2.0291	9,291.0235	☐	☐	☐	☐	☑
3	3.8062	16	512	12.2804	4.5739	17,436.7283	☑	☐	☐	☐	☐
4	3.2681	32	1,000	14.9909	4.1935	32,917.9907	☑	☐	☐	☐	☐

Whilst not using the categorical data, the Brands were converted to numerical values with get_dummies() and concatenating the columns to the data frame to produce the above result.

Part 12 – Train/test data split and standardisation/normalisation of data

The data was split into a training and testing set with a test_size of 0.5 using train_test_split(). This data is shown below and ready to be analysed and predicted by the models in the next step.

Test Data

	Processor_Speed	Ram_Size	Storage_Capacity	Screen_Size	Weight	Price
295	3.1241	4	512	16.5988	2.4982	17,299.4301
706	1.5641	16	1,000	16.1179	4.7975	31,727.4133
183	2.9921	32	1,000	12.2373	4.4403	32,653.1
655	3.0446	4	1,000	16.6334	4.4372	31,234.9289
420	1.706	8	512	15.642	3.4233	16,518.0798

Training Data

	Processor_Speed	Ram_Size	Storage_Capacity	Screen_Size	Weight	Price
534	2.8884	8	256	12.4777	3.2372	9,048.6091
965	3.6109	8	256	13.7264	2.1635	9,506.2436
152	3.6847	16	256	15.0241	2.0741	9,941.8501
763	3.7501	16	256	14.246	3.7123	10,001.8328
386	3.0816	4	1,000	13.4898	2.7934	31,513.2969

Part 13 – Investigating multiple regression algorithms

Five algorithms were explored including Linear Regression, Decision Tree Regressor, Random Forest Regressor, K-Nearest Neighbour Regressor, and the SVM Regressor. These models were trained using the x and y split of data, then made predictions for the x test set, and finally determined Pearson's correlation coefficient of the y test set and the prediction made. Below are the results for each:

Linear Regression

Linear Regression's r2 value: 0.99954

Linear Regression's predictions per column (Speed, RAM, Storage, Screen, Weight): [$16725.51 $9060.75 $32666.60 $9357.07 $9274.16]

Decision Tree Regressor

Decision Tree Regressor's r2 value: 0.99904

Decision Tree Regressor's predictions per column (Speed, RAM, Storage, Screen, Weight): [$16372.18 $9087.07 $32533.07 $9432.75 $9471.95]

Random Forest Regressor

Random Forest Regressor's r2 value: 0.99938

Random Forest Regressor's predictions per column (Speed, RAM, Storage, Screen, Weight): [$16647.24 $9025.63 $32619.06 $9202.99 $9379.63]

K-Nearest Neighbour Regressor

K-Nearest Neighbour Regressor's r2 value: 0.99933

K-Nearest Neighbour Regressor's predictions per column (Speed, RAM, Storage, Screen, Weight): [$16757.13 $9095.19 $32779.96 $9253.56 $9227.26]

SVM Regressor

SVM Regressor's r2 value: -0.05857

SVM Regressor's predictions per column (Speed, RAM, Storage, Screen, Weight): [$17161.52 $17077.75 $17343.76 $17077.74 $17077.75]

Part 14 – Selection of best model

The linear regression model appeared to produce the best r2 value, indicating a very strong correlation (at 0.9995) between its prediction and the actual data. This was selected to be the model that would be deployed.

Part 15 – Deployment of the best model in production

The model was deployed in a serialized file that may be run by any user. The CSV and model.py files are available from the GitHub repository https://github.com/tane-simons/assessment3. Dependencies for the model include pandas, streamlit, scikit-learn, and scipy.stats. The deployment of the model is run through streamlit in order to provide a usable and streamlined interface with native support for input validation.

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