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Laptop Specs and Market Prices

Data Analysis and Statistical Modelling

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Executive Summary

- *Global revenue in the laptop market is projected to reach US$147.4bn by 2028.*
- *There is potential for huge revenues, but new companies face steep barriers to entry:*
    - *High input costs*
    - *Supply chain risk*
    - *Dominance of the Big 10 large firms*
- *Statistical modelling can give new companies a better idea of a laptop's market price given its specs.*
- *Our project:*
    - *Analyzes relationships between laptop specs and price, revealing significant correlations.*
    - *Builds a statistical model to predict a likely market price-point for a laptop based on its specs.*
- *Our model:*
    - *Predicts price at €268 mean error.*
    - *Performs well for low-mid market products.*
    - *Should remain robust into the future, given a regular annual retraining schedule to account for new technological advances and market conditions.*

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1. Introduction

Global revenue in the laptop-computer market is projected to reach US$147.4bn by 2028 (Statista, 2024); huge profits can be realized in this sector. However, would-be market entrants face steep barriers: high input costs, supply chain risk (Sweeney, 2021) and a market dominated by a handful of large firms (see *Figure 1*).

This project aims to assist new market entrants by designing regression models to predict an average price-point for a laptop based on its specifications. This will allow new producers to assess the expected profitability of their products by predicting a price that can be assessed against the input costs of some given specifications. Our hope is that such a model can remain robust into the future, since computational advances and their relationship with price can be captured by the specification data we use as modelling features.

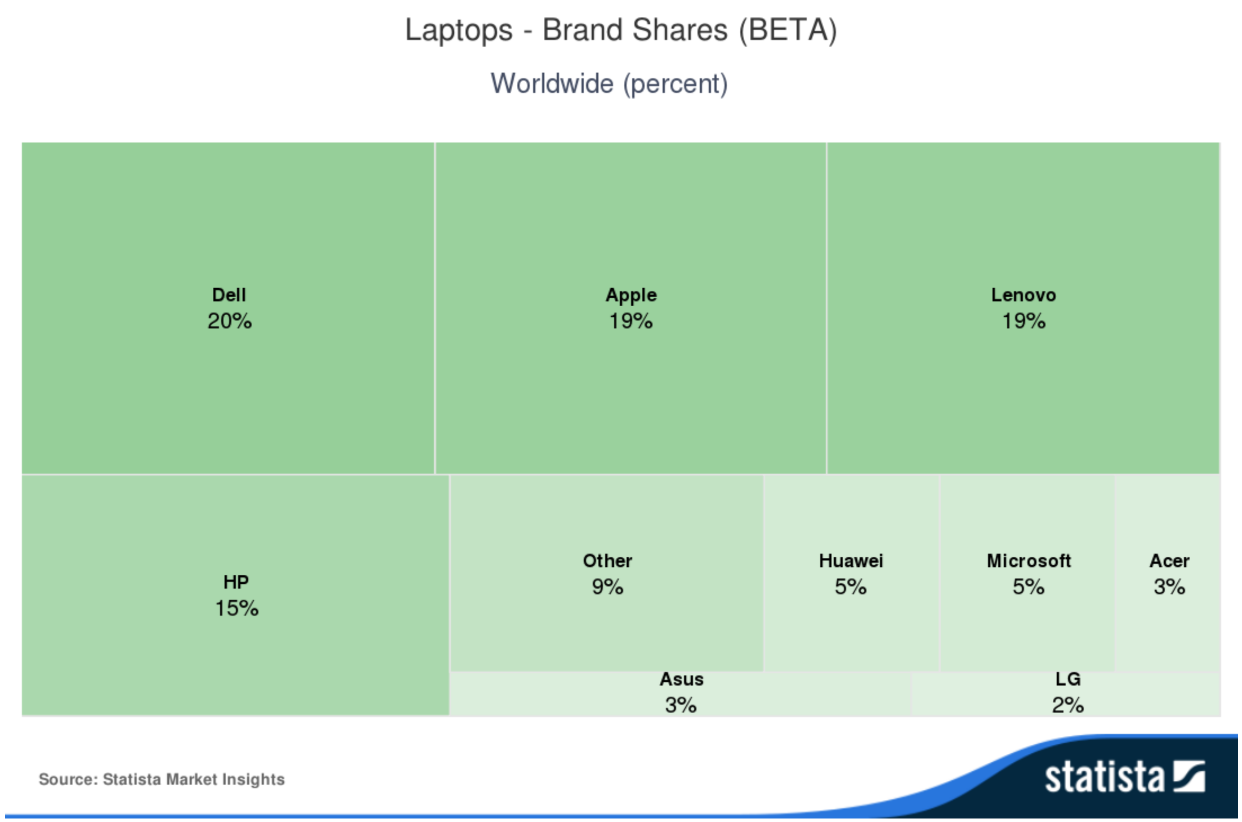


Figure 1

2. Methods

2.1 Sourcing Data and Dataset Description

Our dataset is sourced by Kaggle and comprises 1,303 observations across 12 variables. Our response variable is 'Price_euros' and the remaining 11 are potential predictors. There were no missing values or duplicate entries. *Table 1* summarizes these variables.

After preparing the dataset for analysis, our focused exploration aims to determine how key laptop specifications might influence price.

Table 1

Variable Description

Columns	Description	Mode (median) value	No. unique values	Data-Type
Company	Producer	Dell	19	object
Product	Name of laptop	XPS 13	618	object
TypeName	Laptop Type	Notebook	6	object
Inches	Screen size	15.6	18	float64
ScreenResolution	Screen resolution description	Full HD 1920x1080	40	object
Cpu	Model of Central Processing Unit	Intel Core i5 7200U 2.5GHz	118	object
Ram	GigaBytes available for Random Access Memory	8GB	9	object
Memory	Drive(s) storage description and amount	256GB SSD	39	object
Gpu	Model of Graphics Processing Unit	Intel HD Graphics 620	110	object
OpSys	Operating System	Windows 10	9	object
Weight	Weight of laptop in kilograms	2.2kg	179	object
Price_euros	Recommended Retail Price in Euros	(977.0)	791	float64

2.2 Exploratory Data Analysis

Figure 2

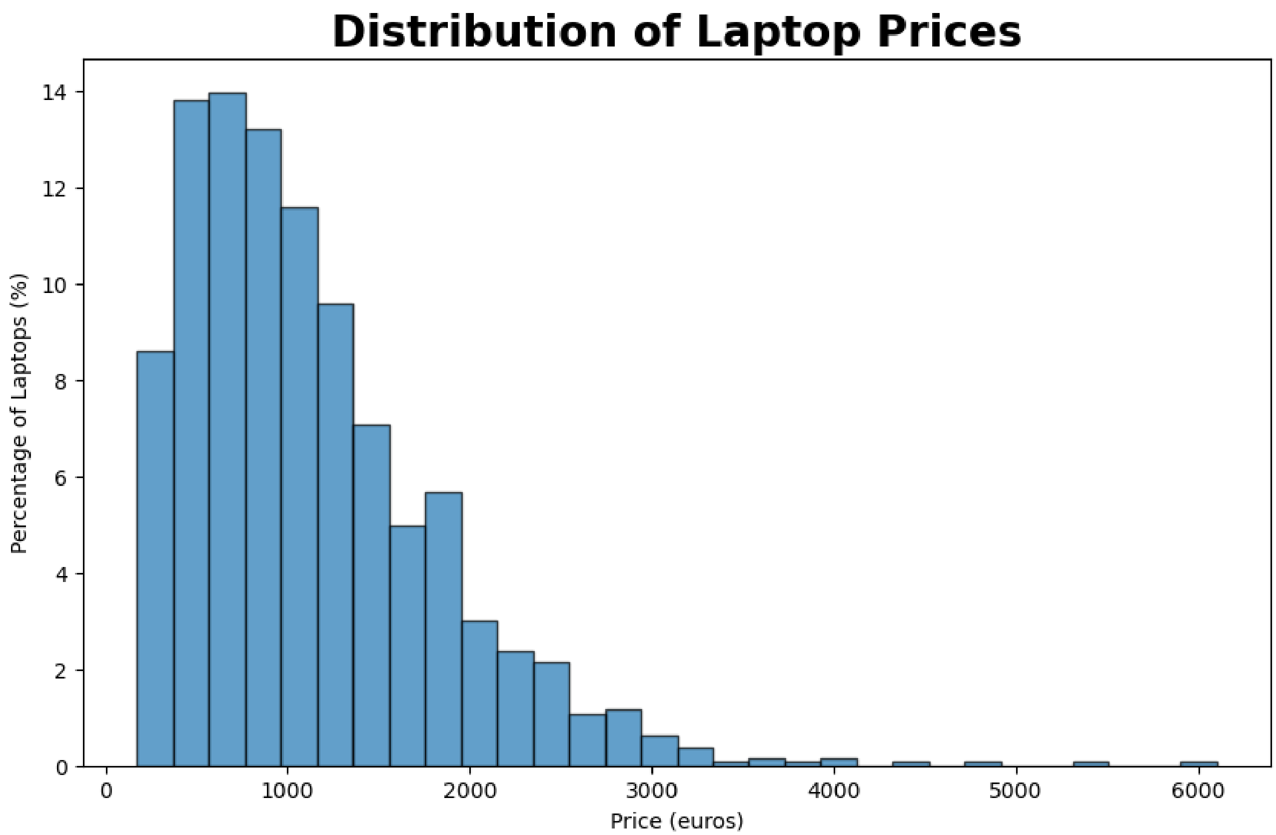
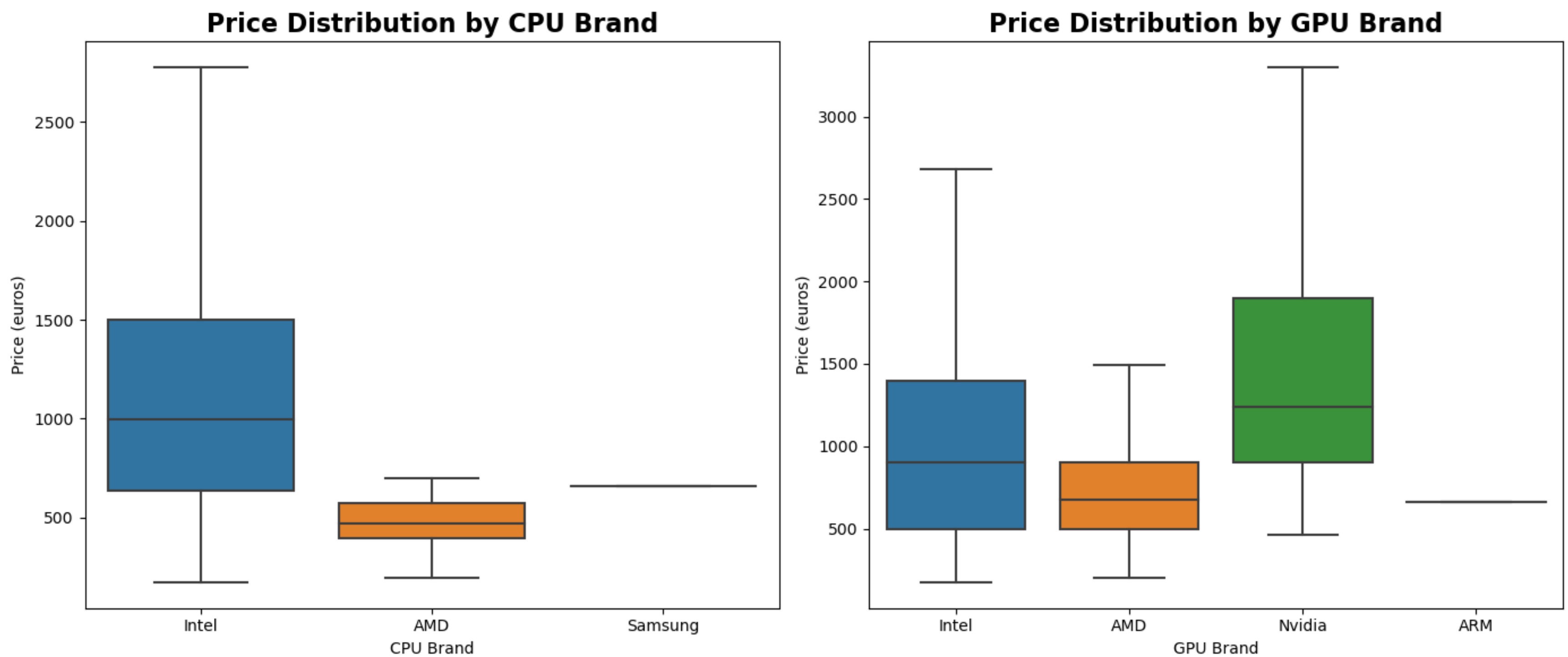


Figure 1 shows that the distribution of laptop prices is right-skewed, with a higher concentration in the lower to mid-range segments. This indicates that most consumers prefer more affordable laptops, while premium, higher-priced models are less common, suggesting a niche market for these segments. The distribution is abnormal.

Figure 3



Intel Central Processing Units (CPUs) span a broad price range, particularly in mid-range to premium segments, with the highest median price. AMD targets more affordable options with lower median prices and a tighter price distribution, focusing on budget to mid-range consumers. The dataset contains only one CPU produced by Samsung.

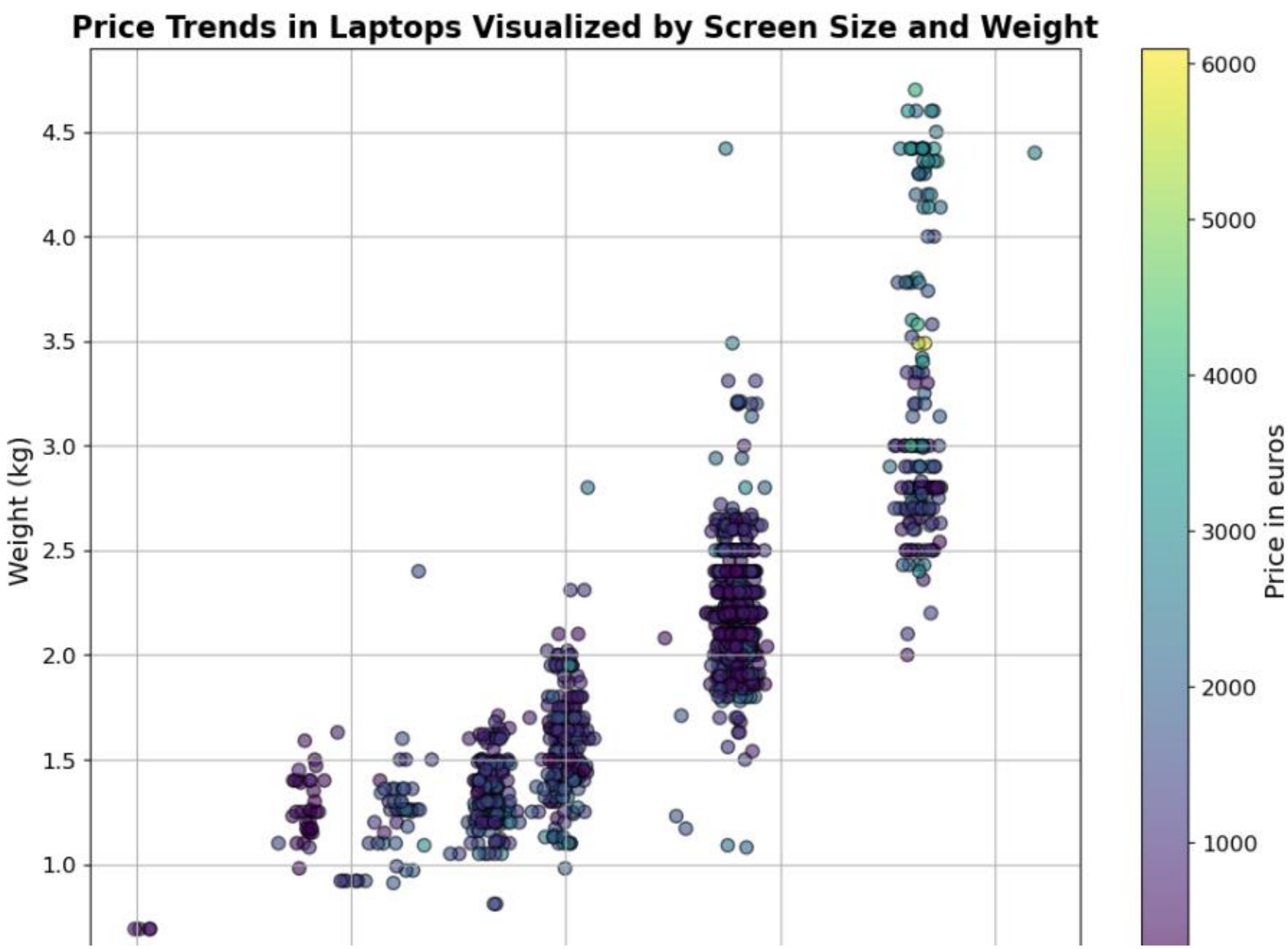
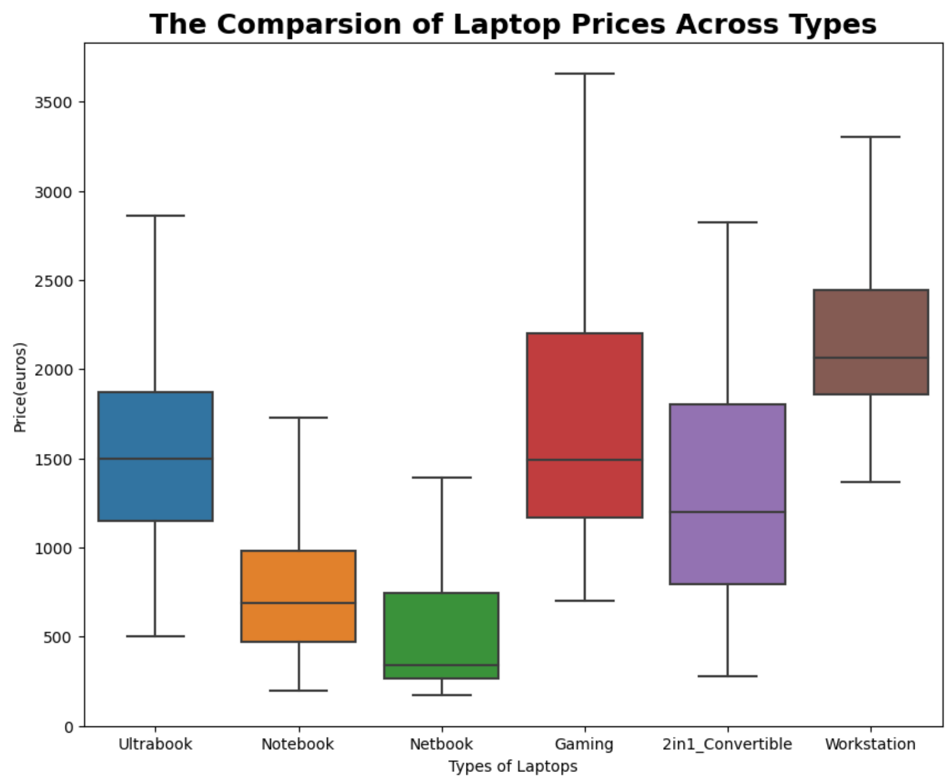


Figure 4

Figure 3 shows most laptops weigh between 1.5 to 2.5 kg with screen sizes of 14 to 16 inches. Notably, the most expensive laptops typically weigh around 2 kg and have 15-inch screens, suggesting consumers value a balance of portability and screen size.

Workstations, designed for professional use with powerful specifications, have the highest mean price. Gaming laptops also command high prices due to advanced graphics and performance features. Ultrabooks occupy the mid-range, balancing performance and portability, while notebooks and netbooks are the most affordable, targeting budget-conscious buyers. Convertibles show a broad price range, emphasising their versatility.

Figure 4



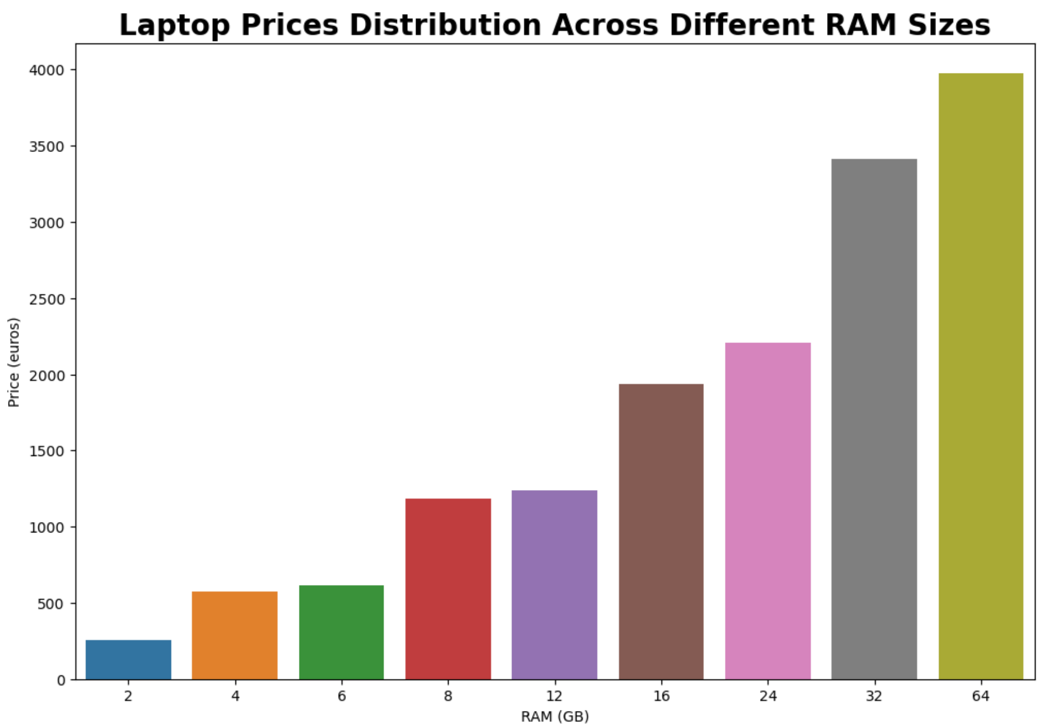


Figure 5

Figure 5 shows a highly linear relationship between RAM and price, suggesting the utility of this variable as a feature in predictive modelling.

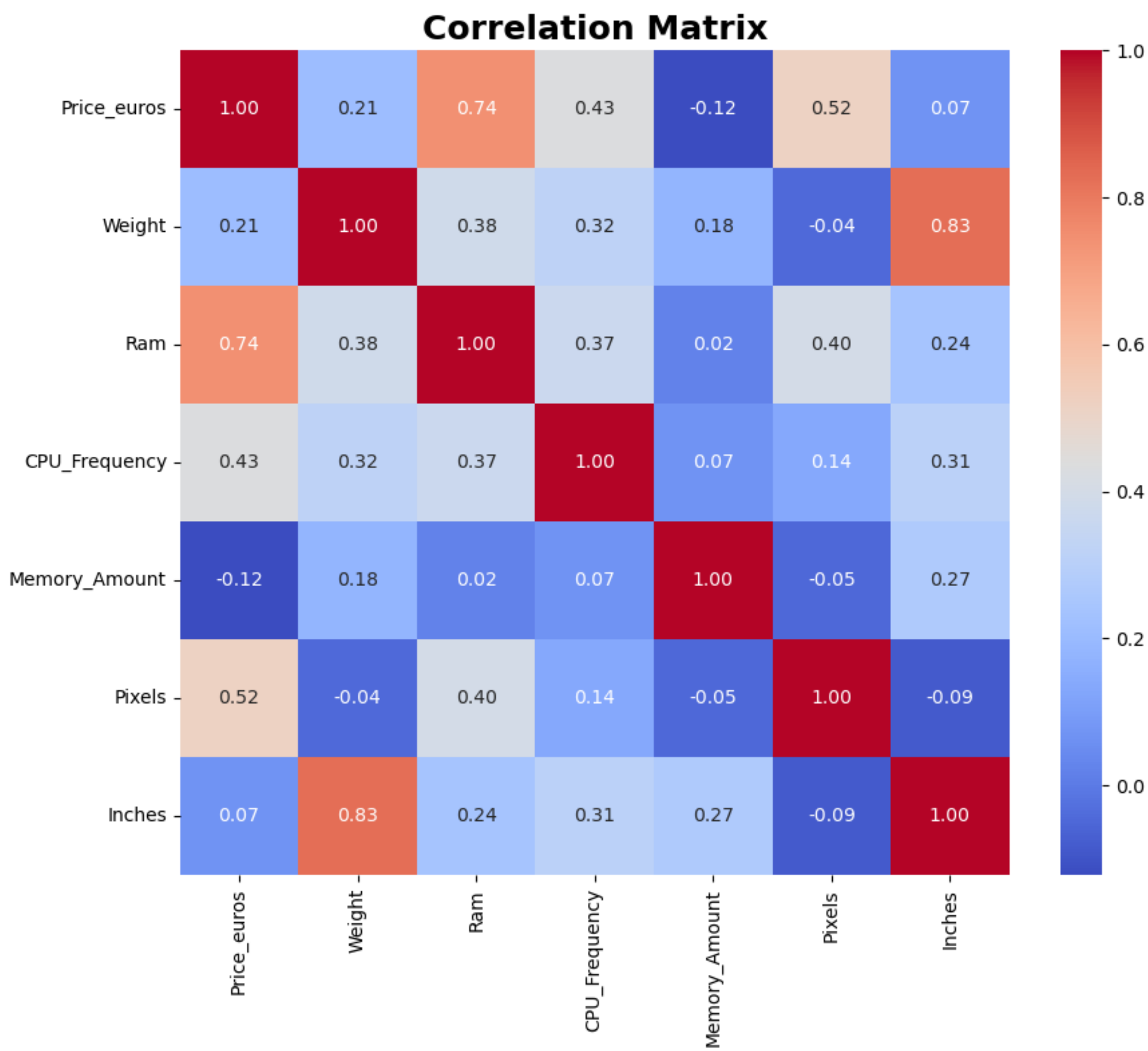


Figure 6

Figure 6 shows that RAM and CPU frequency positively correlate with price. Memory storage anti-correlates slightly, suggesting more storage doesn't necessarily mean higher prices. Screen resolution (Pixels) has a moderate positive correlation, while screen size shows a very weak correlation with price.

2.3 Preprocessing and further analysis

Ten of the eleven potential predictor variables consisted of text-data which had to be processed into numbers interpretable by regression models; *Appendix A* summarizes this processing.

The complexity in processing the 'Cpu' column resulted in a large number of new covariant variables (see *Figure 7*). We dealt with this by using Principal Components Analysis (PCA) on these new variables (see *Table 3)*.

Table 3

Results of Principal Components Analysis of CPU specifications

Principal Component	**Explained Variance (%)**	**Cumulative Explained Variance (%)**
PC1	41.55	41.55
PC2	33.95	75.5
PC3	9.95	85.45
PC4	6.48	91.93
PC5	4.17	96.10
PC6	3.25	99.35
PC7	0.52	99.87
PC8	0.13	100.0

Analyzing these Prinicpal Components (PCs) led us to drop PCs 6-8, which appeared less distinctive and explained less than 4% of the total variance together. By analyzing these Principal Components we also made an informed guess as to what they might represent, and renamed the columns accordingly (see *Table 4*).

Figure 7

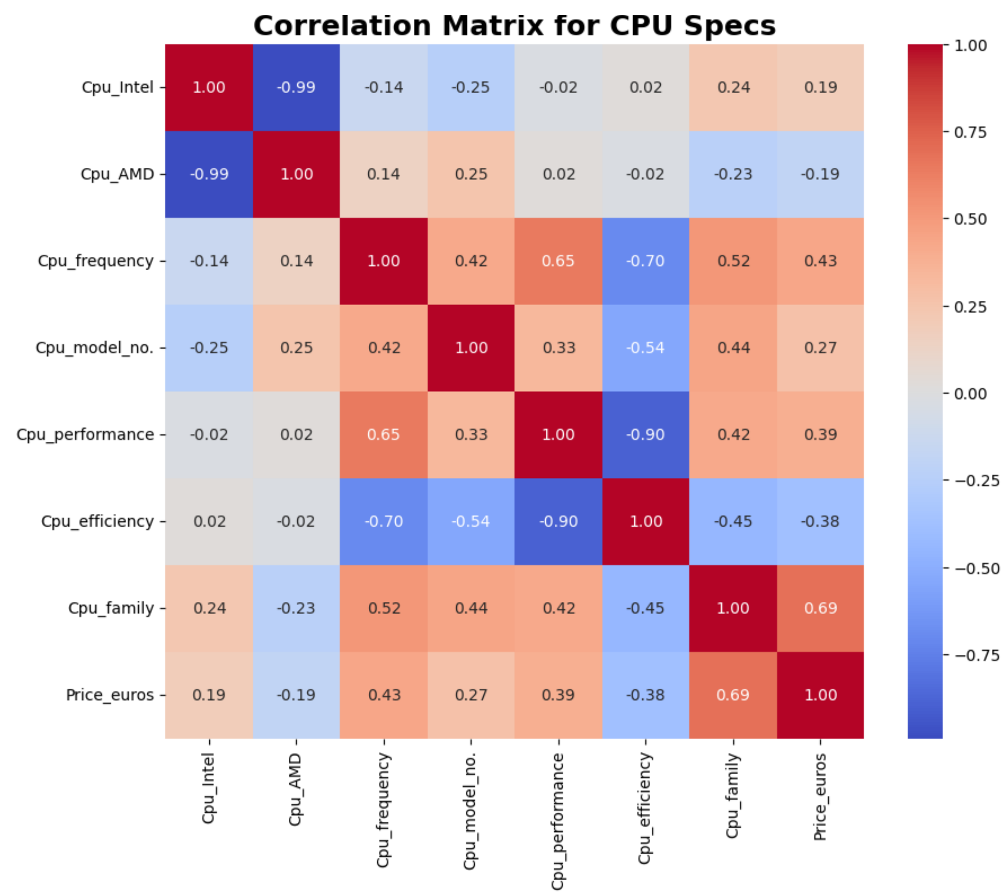


Table 4

Feature Variance Captured by Principal Components

Features	**PC1**	**PC2**	**PC3**	**PC4**	**PC5**
Cpu_Intel	-0.1754	-0.6472	-0.1659	-0.117	0.0203
Cpu_AMD	0.1729	0.6427	0.1654	0.1172	-0.0143
Cpu_frequency	-0.3905	0.2433	-0.3232	0.3032	0.5177
Cpu_model_no.	-0.2594	0.2559	0.0945	-0.8252	-0.1593
Cpu_performance	-0.2743	0.1217	-0.4327	0.1188	-0.2183
Cpu_efficiency	0.3455	-0.1649	0.5045	0.1212	0.2366
Cpu_family	-0.6178	-0.031	0.5298	-0.0172	0.3753
Price_euros	-0.3785	-0.021	0.3305	0.4131	-0.6793
***Renamed as* Cpu_**	**efficient_low_end**	**AMD_mid_range**	**efficient_high_end**	**fast_high_end**	**fast_low_end**

Logarithmic transformation of the target variable *Price_euros*, along with dropping extreme outliers, failed to yield a normal distribution, as demonstrated in *Figure 8;* the p-value for the normality test was 8×10^{-10} (Appendix B [3.1]).

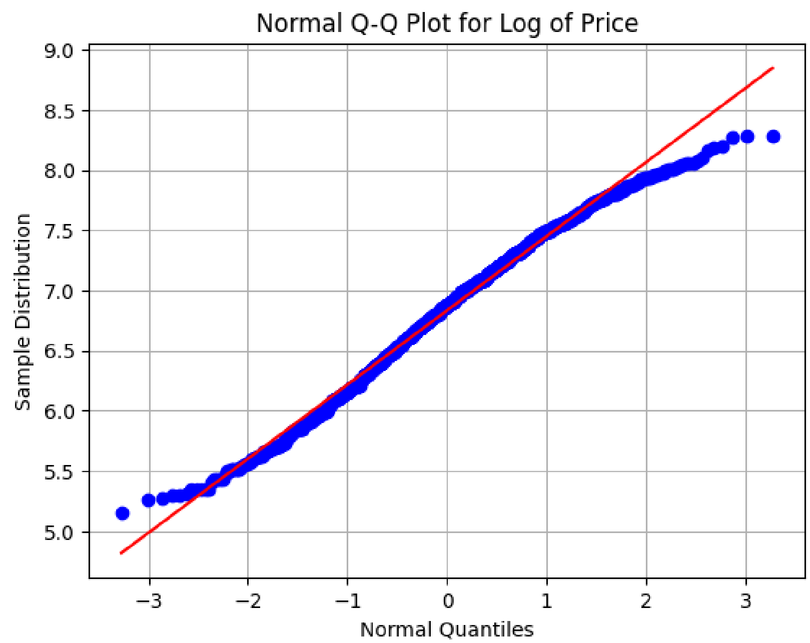


Figure 8

2.4 Modelling

Our modelling approaches can be grouped into:

1. Non-parametric tree-based models, including:
    a. Simple Decision Trees
    b. Random Forest ensembles

2. Parametric Linear models, including:
    a. Ordinary Least Squares (OLS)
    b. Lasso
    c. Ridge
    d. ElasticNet

2.5 Data Splitting and Feature Engineering

We split our dataset between training, validation and test data by an 80:20:20 ratio.

We took two complementary approaches to feature selection.

2.5.1 The "levelling up" approach

Based on our EDA (cf. §2), we selected a narrow range of features (labelled *X_basic)* to fit to OLS models, then analyzed coefficient weights and t-statistics for those features. Our first OLS model was fitted with 'Inches', 'Ram' and 'Weight'. *Table 5* displays some summary statistics for those features, along with a 'Constant' column which predicts the intercept term. We can see for instance that 'Ram' and 'Inches' are almost certainly predictive of price given their t-statistics, while the predictive power of 'Weight' is less certain.

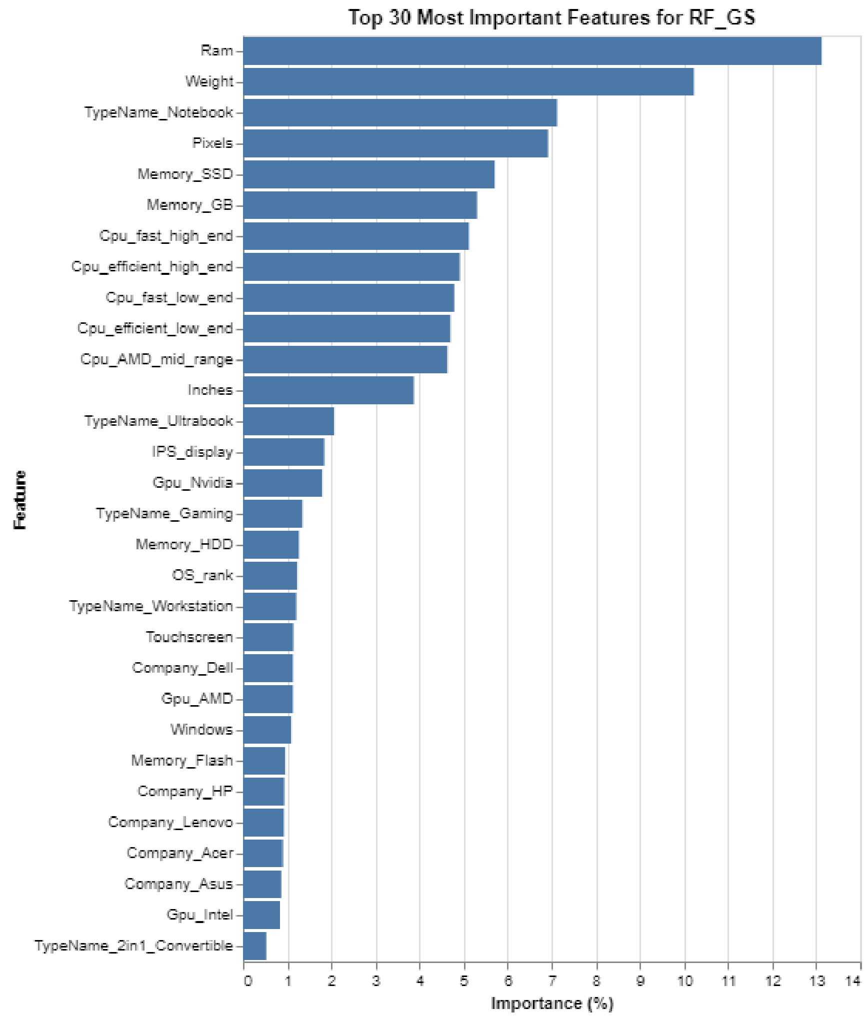
Table 5

Feature Statistics for OLS

Feature	**coef**	**std err**	**t**	**P>|t|**	**0.025**	**0.975**
Constant	803.8037	61.757	13.016	0.000	682.584	925.024
Inches	-615.0228	160.404	-3.834	0.000	-929.871	-300.175
Ram	6064.6834	212.610	28.525	0.000	5647.362	6482.005
Weight	160.6220	174.585	0.920	0.358	-182.062	503.306

2.6.2 The "bulk and shred" approach

Figure 9



The opposite approach is to start with many features and progressively winnow them down. Our RandomForest (RF) models were useful in this approach for two reasons:

1. Each tree in the forest can be limited to observing only a specified number of features. For example, our best performing RF limited each tree to observing only five features.

2. RFs have a *feature_importances_* attribute which allows us to learn how important the given features were for the model in making predictions. By way of illustration, see *Figure 9*, which shows feature importances for our best performing RF model. We can see for example that the analysis corroborates both the strong coefficient weight assigned to 'Ram' by the OLS model, and the correlation discovered by EDA. On the other hand, the high degree of importance assigned to 'Weight' contradicts the OLS' relative skepticism about this feature.

Our regularizing models – Lasso, Ridge and ElasticNet – also accommodate this approach, since they automatically increase model sparsity by applying penalties to coefficients.

3. Results

3.1 Parametric Models

For the OLS model mentioned above, the p-values for Omnibus and Jarque-Bera tests were 0 or near 0, indicating a non-normal distribution of residuals, and thereby a violation of the parametric assumption of linear regression models. We tested the same model on a logarithmically transformed sample of the target data and got the same results (see *Table 6* below), suggesting that even log-transformation was insufficient to normalize the distribution of the target variable. Possibly a larger dataset would conform to a more normal distribution. As a consequence, we achieved lowest overall error and best fit using non-parametric models which don't assume normality.

Table 6

OLS Regression Results (with log-transformation)

Dep. Variable:	Log_Price_euros	R-squared:	0.458
Model:	OLS	Adj. R-squared:	0.457
Method:	Least Squares	F-statistic:	232.6
Date:	Fri, 10 May 2024	Prob (F-statistic):	2.72e-109
Time:	10:08:12	Log-Likelihood:	-521.95
No. Observations:	828	AIC:	1052.
Df Residuals:	824	BIC:	1071.
Df Model:	3		
Covariance Type:	nonrobust		
Omnibus:	98.857	Durbin-Watson:	2.059
Prob(Omnibus):	**0.000**	Jarque-Bera (JB):	290.833
Skew:	-0.592	**Prob(JB):**	**7.02e-64**
Kurtosis:	5.651	Cond. No.	20.1

Our best performing linear model was a Lasso regressor (L1 Regularization) with α=2.0. L1 Regularization seemed best suited to offsetting the violation of parametric assumptions. The best models used a large feature-set and mitigated overfitting through regularization. *Table 7* below shows results for linear models on the test data.

Table 7

Test Metrics for Linear Models

Model Name	**Model Type**	**RMSE**	**MAE**	**R2**	**RMSE Generalization**	**MAE Generalization**	**R2 Generalization**
LC2	<u>Lasso</u>	367.78	268.25	72.17	34.81	19.09	1.9
EN_opt	ElasticNet	369.09	269.58	71.97	45.45	26.89	3.5
RC2	Ridge	372.77	276.85	71.40	40.01	25.79	2.7
OLS3	Ordinary Least Squares	382.68	279.51	69.86	37.66	21.21	2.3

The Lasso model's residual plot (*Figure 11* overleaf) reveals a fairly regular pattern of errors. Most large errors occur when predicting over €1500; there are more large undervaluations than overvaluations. 97% of predictions fall within the prediction interval represesented by the dotted green line, defined as ± 2 x Standard Error.

Figure 10

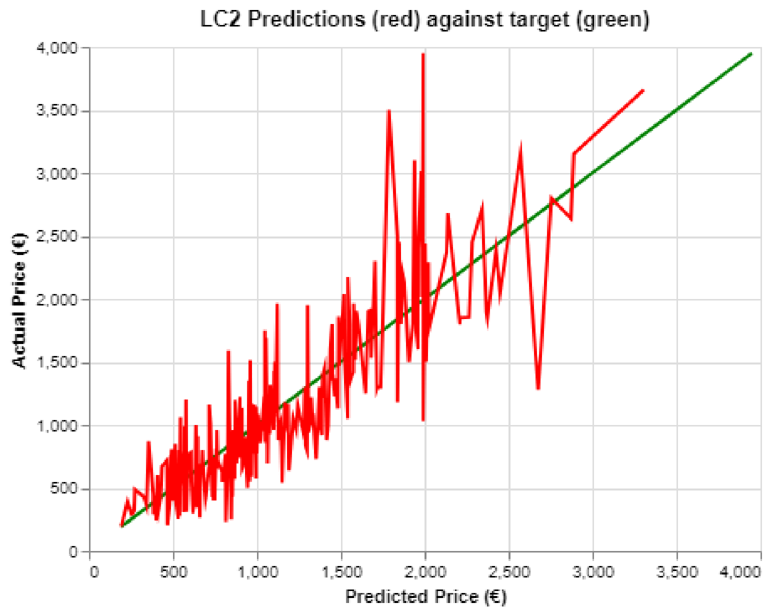
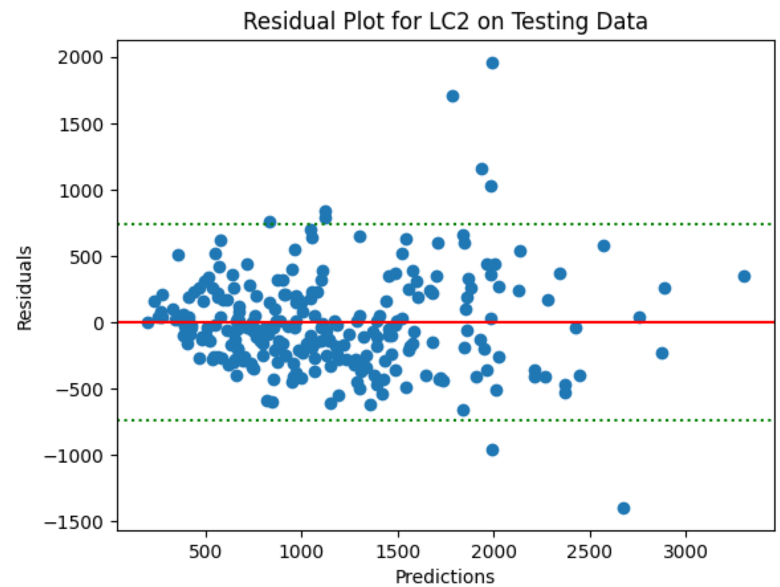


Figure 11



3.2 Non-Parametric Models

Decision Tree and Random Forest models had lower error and better fit (R^2 Score) on the test data, despite a bigger gulf between training and test error than we achieved with linear models. Our **Random Forest** model had the lowest Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE) and highest R^2-score even while overfitting much more than the linear models, as shown by the higher error generalization, which subtracts test from training error.

Table 8

Test Metrics for All Models

Model Name	Model Type	RMSE	MAE	R^2	RMSE Generalization	MAE Generalization	R^2 Generalization
RF_gs	Random Forest	343.68	226.42	75.7	210.04	133.02	20.1
tree3a	Decision Tree	393.99	263.37	68.1	163.33	129.32	19.5
tree_gs_X4	Decision Tree	388.83	265.61	68.9	82.75	64.74	9.2
LC2	Lasso	367.78	268.25	72.2	34.81	19.09	1.9
EN_opt	ElasticNet	369.09	269.58	72.0	45.45	26.89	3.5
RC2	Ridge	372.77	276.85	71.4	40.01	25.79	2.7
OLS3	Ordinary Least Squares	386.80	279.51	69.9	37.66	21.21	2.2

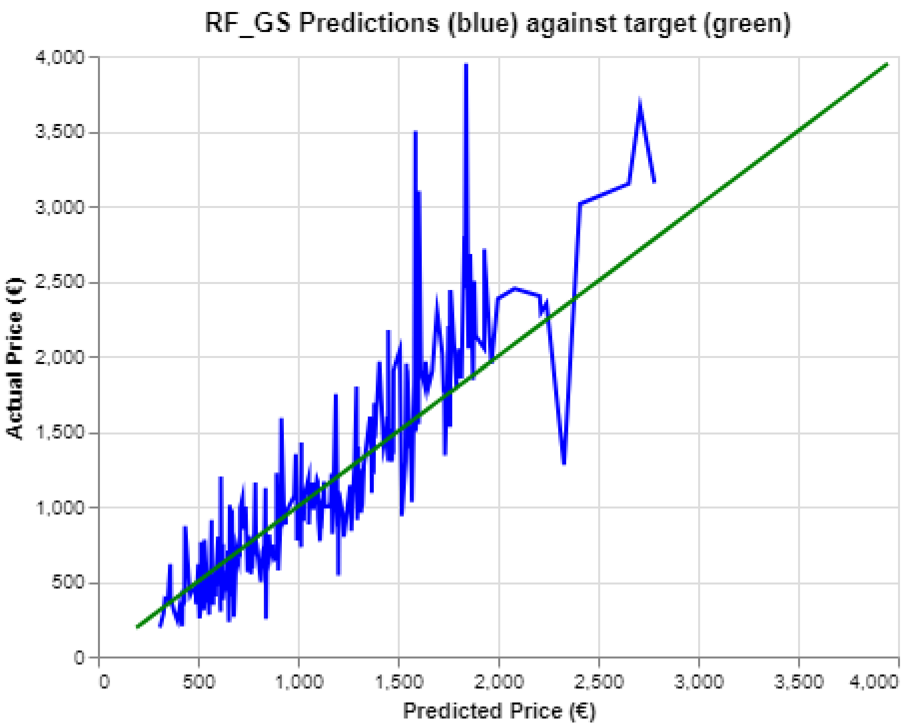


Figure 12

Figure 12 shows the RandomForest's predictions in blue against the target in green. We can see that the model keeps track of the price-trend fairly well up to around Quartile 3 (Q3=€1487.87), after which much larger errors occur. These larger errors in predicting pricier laptops explain the difference between RMSE and MAE, since the former magnifies larger errors through squaring. 96% of predictions fall within the prediction interval.

Figure 13 plots the model's residuals, revealing:

1. A highly abnormal distribution of residuals.
2. The model undervalues more often than it overvalues: there is only one overvaluation large enough to exceed the prediction interval represented by the dotted green line.

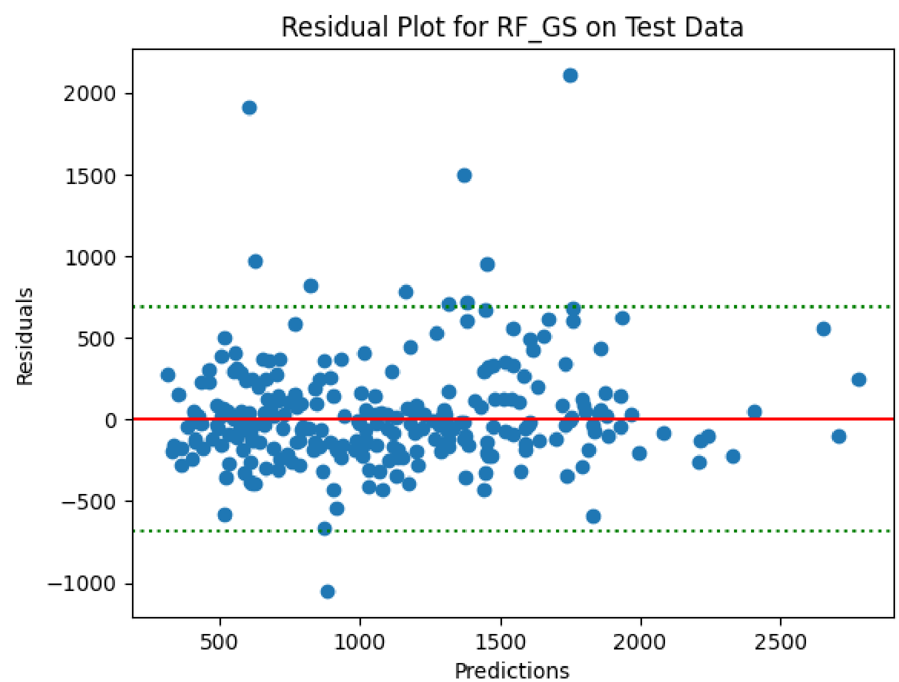


Figure 13

4. Discussion

The popular understanding of Moore's Law is the claim that "computing power at fixed cost is doubling every 18 months" (Tuomi, 2002). Although the validity of the "Law" is a matter of controversy, the relevant point is that the relationship between computing power and price does not remain constant over time.

There are two main implications to this. The first is that we should prefer a linear model over a tree-based regressor like RandomForest, even if the latter scores better on test data. This is because tree models are not capable of extrapolating trends forward in time in the way linear models are. For example, if we look at an example Decision-Tree structure (*Figure 14* overleaf), we'll see that price predictions ("value=y") are conditioned on fixed values for x, like Ram <= 14 for example. In other words, the model wouldn't be concerned if every laptop it predicted on met that condition, nor update its valuation if a future laptop had 1400GB RAM.

On the other hand, a linear model like the Lasso will predict by applying coefficient weights to the overall magnitude of the specification. For example, as *Table 9* shows, every additional GB RAM increases price prediction by ~€33.83 *ceteris paribus* (units of the target variable are denominated to the cent).

The essential caveat to be borne in mind is the non-constant relationship between computing power and price. On deployment, a linear model must be updated on a minimum 18-month schedule to halve coefficient weights related to computing power described by Moore's Law, like 'Ram' and 'Pixels'. Better yet, it should be retrained on new data, ideally every year, or on every major release of new products. More data is also likely to normalize the distribution of our target variable given the Central Limit Theorem, and thereby better meet the parametric assumptions of linear models.

Table 9

LC2 Coefficient Weights

Feature	Coefficient Weight
Ram	3383
Pixels	693
TypeName_Workstation	471
Weight	365
Memory_SSD	247
Cpu_fast_high_end	223
TypeName_Ultrabook	172
Windows	155
Company_Apple	77
Company_Toshiba	69
IPS_display	27
Gpu_Nvidia	27
Cpu_efficient_low_end	9
Touchscreen	-17
Company_Dell	-17
Memory_Flash	-68
Company_Asus	-129
TypeName_Netbook	-132
Gpu_AMD	-141
Company_Acer	-158
TypeName_Notebook	-249

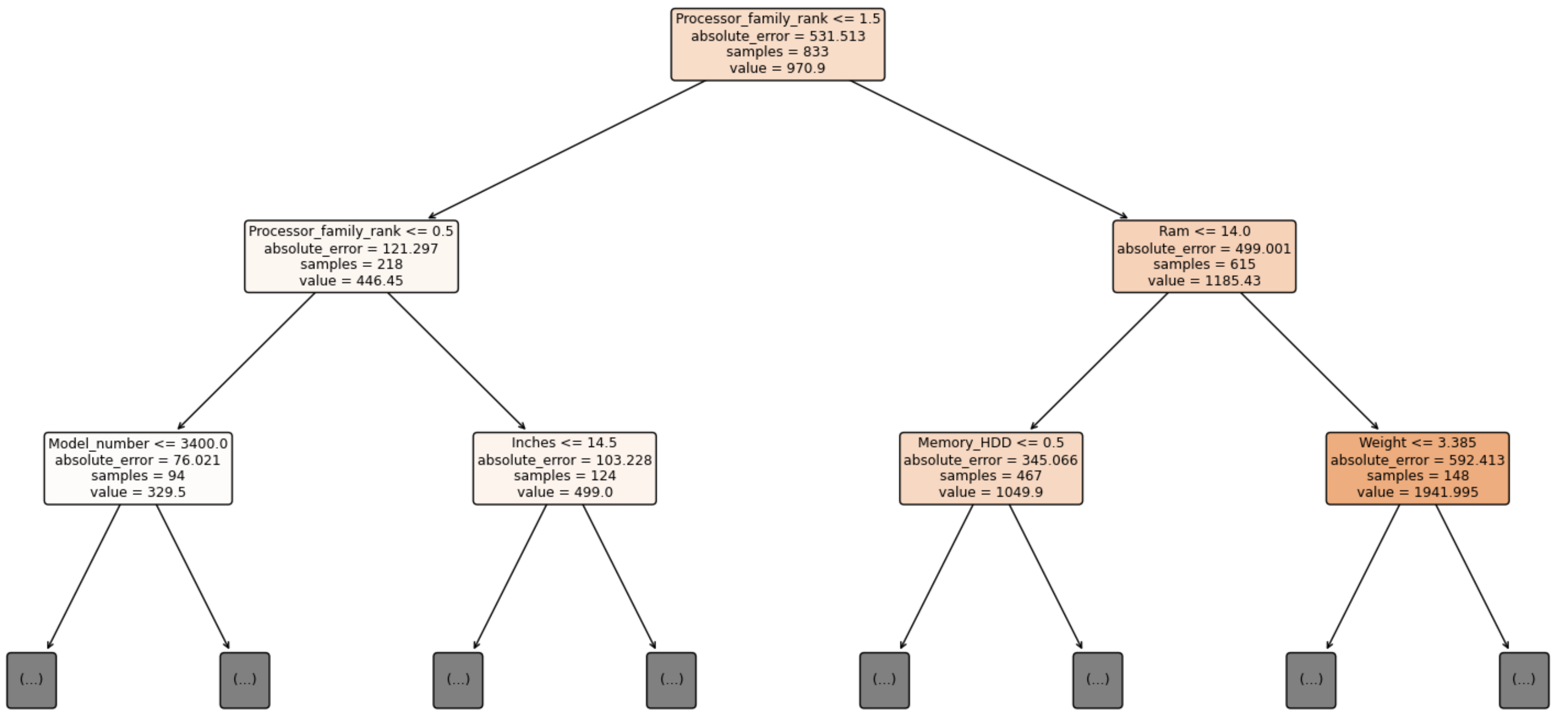


Figure 14

Example Decision Tree Structure

5. Conclusion

Our Lasso model, *LC2,* although imperfect, will provide new businesses looking to enter the laptop market with a good sense of an expected market price for a laptop based on its specifications. We found RAM, Screen Resolution, Weight and the inclusion of a Solid State Drive (SSD) to be the most price-predictive specifications. Workstations sold highest and Netbooks lowest. Acer is most represented in the market for cheaper products, and Apple for premium products. Fast, high-end CPUs sold for most.

This tool will aid new companies in assessing potential profit when balancing input costs against expected revenue. The model works best for cheap to mid-range products; companies should exercise caution when using the model to predict prices for higher-end products. Users should also bear in mind a roughly €275 average error even in these ranges.

We recommend finally that the model must be retrained with new data on a minimum 18-month schedule to keep pace with computational advances and market conditions.

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Tuomi, I. (2002). ‘The Lives and Death of Moore’s Law’. *First Monday*, 7: 11. https://firstmonday.org/ojs/index.php/fm/article/download/1000/921.

The dataset was sourced at:

https://www.kaggle.com/datasets/ultimus/laptop-prices-prediction.

Appendix A

Table A

Summary of Data Preprocessing

Original Column Names	**Original Dtype**	**Data Preparation Technique(s)**	**Appendix §**	**Rationale(s)**	**Cleaned Column Name(s)**	**Original (cleaned) Column(s) Dropped?**	**New Datatype(s)**
Company	object	One-hot encoding	3.3	Machine interpretation	19 new columns formatted as 'Company_{unique_value}' e.g. 'Company_Razer'	Yes	Binary Integers
Product	object	Dropped column	3.2	Too many unique values	NA	Yes	NA
TypeName	object	One-hot encoding	3.3	Machine interpretation	6 new columns formatted as 'TypeName_{unique_value}' e.g. 'TypeName_Notebook'	Yes	Binary Integers
ScreenResolution	object	Dummies for screen type	2.6, 3.4	Machine interpretation, retaining information	'Touchscreen', 'IPS_display'	Yes	Binary Integers
		Extracting int for overall resolution	3.4		'Pixels'		Int
Ram	object	Extracting int for GBs	2.8	Machine interpretation	'Ram'	No	Int
Memory	object	Dummies for drive type(s)	3.7.1	Machine interpretation, retaining information	4 new columns formatted as 'Memory_{drivetype}'	Yes	Binary Integers
		Extracting int for total GBs storage	3.7.2		'Memory_GB'		Int
Gpu[1]	object	Dummies for maker	3.5	Machine interpretation,	'Gpu_AMD', 'Gpu_Nvidia', 'Gpu_Intel'	Yes	Binary

[1] A more skilled preprocessing team might have been able to make more of this column, as we could with the 'Cpu' column, but we were ultimately stumped by the sheer variety of naming conventions for GPU models.

				retaining information			
Cpu	object	Dummies for maker	3.6.1	Machine interpretation, retaining information, differentiation	'Cpu_Intel', 'Cpu_AMD', 'Cpu_Samsung'	(Yes)	Binary
		Extracting float for GHz frequency	3.6.2		'Cpu_frequency'	(Yes)	Float
		Extracting Model Number	3.6.3.1		'Cpu_model_no.'	(Yes)	Int
		Mapping to performance and efficiency scales	3.6.3.2		'Cpu_efficiency', 'Cpu_performance'	(Yes)	Ordinal integers
		Ranking processor family	3.6.4		'Cpu_family'	(Yes)	Ordinal integers
		Principal Components Analysis	3.11	Dimensionality reduction	'Cpu_efficient_low_end', 'Cpu_AMD_mid_range', 'Cpu_efficient_high_end', 'Cpu_fast_high_end', 'Cpu_fast_low_end'	Yes (No)	Floats
OpSys	object	Dummies for software company	3.8.1	Machine interpretation, retaining information	'Mac', 'Windows', 'Linux', 'Google'. 'No OS' represented with 0s in all columns.	Yes	Binary
		Ranking OS for same company	3.8.2	Scaling values	'OS_rank'		Ordinal Integers 0-3
Weight	object	Extracting float for KGs	2.8	Machine interpretation	'Weight'	No	Float (2 decimal places)
Price_euros	float64	Dropping extreme outliers defined as outside 3*IQR+Q3	3.1	Normalization, anomaly cleaning	'Price_euros'	No	Float (2 decimal places)
		Log transformation			'Log_Price_euros'		Float (log notation)