

# A model development Analysis

ReCell and Supervised Learning – Foundations

04/03/2022

### **Contents / Agenda**



- Business Problem Overview and Solution Approach
- Executive Summary
- EDA Results
- Data Preprocessing
- Model Performance Summary
- Conclusions and Recomendations
- Appendix



### **Business Problem Overview and Solution Approach**

- The used and refurbished device market has grown considerably over the past decade, and a new IDC (International Data Corporation) forecast predicts that the used phone market would be worth \$52.7bn by 2023 with a compound annual growth rate (CAGR) of 13.6% from 2018 to 2023. This growth can be attributed to an uptick in demand for used phones and tablets that offer considerable savings compared with new models. The rising potential of this comparatively underthe-radar market fuels the need for an ML-based solution to develop a dynamic pricing strategy for used and refurbished devices.
- Based on the data provided an ML Solution based on a linear regression model was built to predict the price of a used phone/tablet and identify factors that significantly influence it.

### **Executive Summary**



- A linear regression model was developed in order to predict the prices of the used price market of the different cellphones. As a result of the model developed, one of the variables with the most impact is the released price of the cellphone. This is understandable as this gives a perspective of the quality and features of the cellphone.
- The model highlights two brands with a negative impact on the model which are Samsung and Sony. The brands Nokia and Xiaomi are shown on the model as the ones preferred by the consumers of the used market.
- The model currently considers 4g as a variable of interest for the model. This variable is expected to decline in the future as more cellphones will use a 5g network as this type of connection becomes more popular around the world.
- Due to the changes and disruptions that occur on the market of cellphones it is recommended to update the database constantly and run the model at least every semester in order to update the parameters of the model to obtain the maximum benefit of the market.

#### **EDA Results**



- The provided data set contains 3454 rows and 15 variables.
- The following table shows a statistical summary of the data:

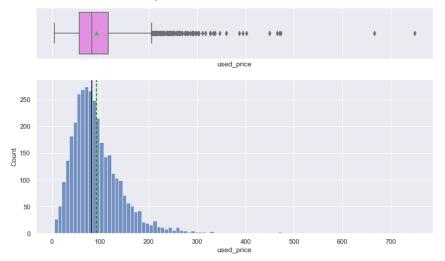
Variables	count	mean	std	min	25%	50%	75%	max
screen_size	3454.0	13.713115	3.805280	5.08	12.7000	12.830	15.340	30.71
main_camera_mp	3275.0	9.460208	4.815461	0.08	5.0000	8.000	13.000	48.00
selfie_camera_mp	3452.0	6.554229	6.970372	0.00	2.0000	5.000	8.000	32.00
int_memory	3450.0	54.573099	84.972371	0.01	16.0000	32.000	64.000	1024.00
ram	3450.0	4.036122	1.365105	0.02	4.0000	4.000	4.000	12.00
battery	3448.0	3133.402697	1299.682844	500.00	2100.0000	3000.000	4000.000	9720.00
weight	3447.0	182.751871	88.413228	69.00	142.0000	160.000	185.000	855.00
release_year	3454.0	2015.965258	2.298455	2013.00	2014.0000	2015.500	2018.000	2020.00
days_used	3454.0	674.869716	248.580166	91.00	533.5000	690.500	868.750	1094.00
new_price	3454.0	237.038848	194.302782	18.20	120.3425	189.785	291.115	2560.20
used_price	3454.0	92.302936	54.701648	4.65	56.4825	81.870	116.245	749.52

Link to Appendix slide on data background check



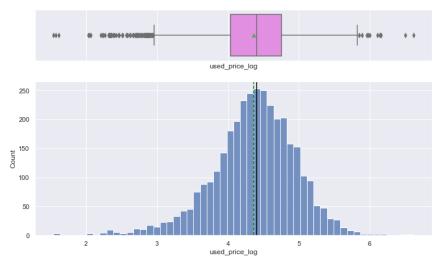
#### Used\_price

The used price variables show how this variable is skewed to the right. Therefore, there are many outliers for this variable.



#### Used\_price\_log

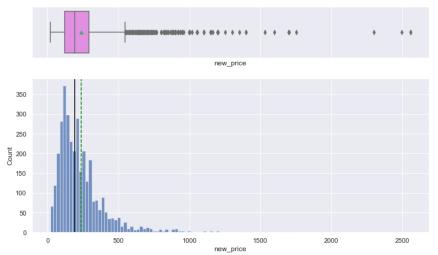
A log transformation was used. This shows a normal distribution for the used price variable, a little bit skewed to the left.





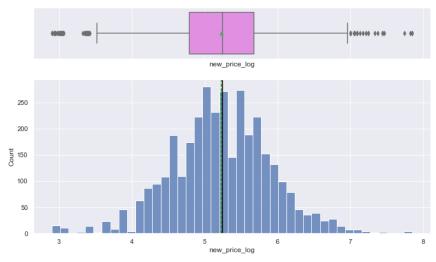
#### New\_price

The new price variables show how this variable is skewed to the right. Therefore, there are many outliers for this variable.



#### New\_price\_log

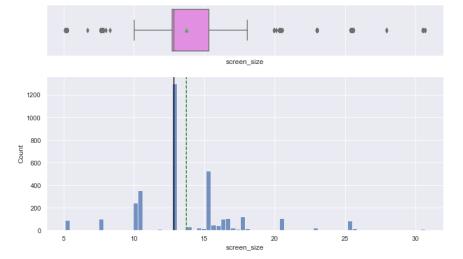
A log transformation was used. This shows a normal distribution for the new price variable, this would be useful for the model.





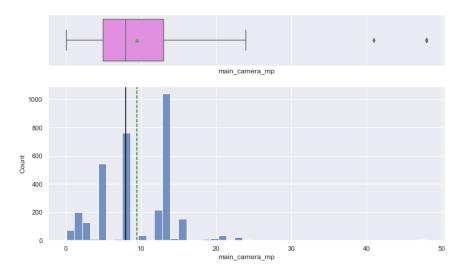
#### Screen size

This variable shows that the median and the mean are relatively close, but the 15 cm phones are the ones moving the mean.



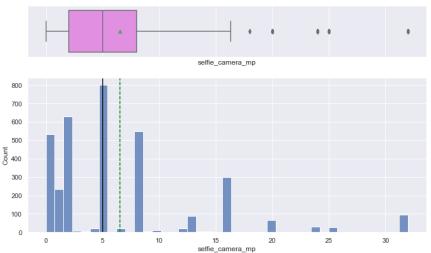
#### Main\_camera\_mp

This variable shows how more phones are getting more mp in the main camera. As result, the median is to the left, but the mode is to the right.



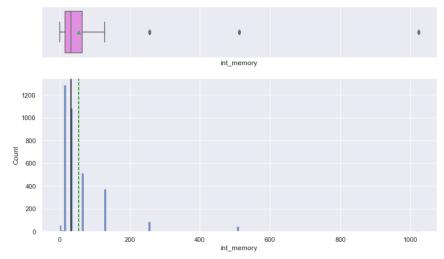


Selfie\_camera\_mp
 Most of the selfie cameras stay under 17 mp,
 the 20 mp and over cameras shown to be for more premium phones.



#### Int\_memory

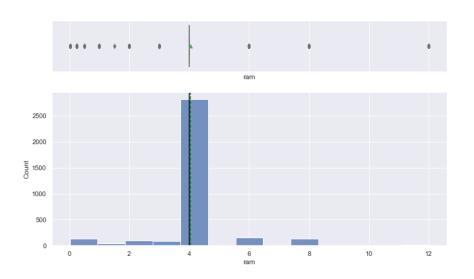
The must common internal memory is under the 150 GB. The premium cellphones must have over 200 GB of memory.





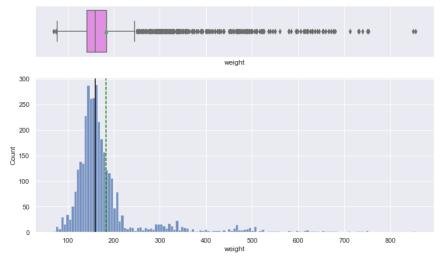
#### Ram

The most common size of memory if 4 gb, leaving any other number as an outlier.



#### Weight

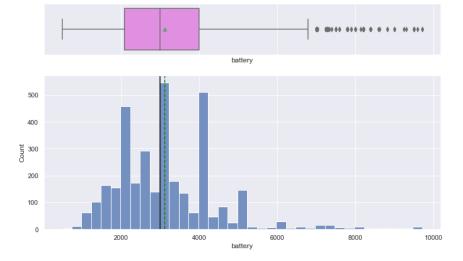
Most of the data concentrates under 250 grams of weight, with this the variables shows it is skewed to the right.





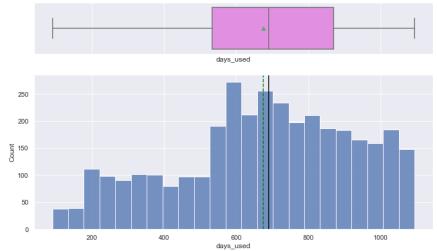
#### Battery

The battery capacity of the cellphones shows a tendency of being grow with of the bigger phones on the market.



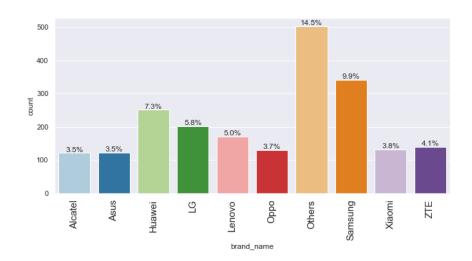
#### Days\_used

Most of the users spend almost two years with their current cellphone before looking to sell it.



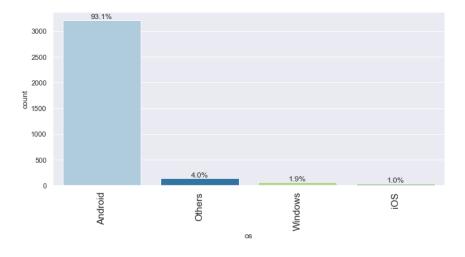


Brand\_name
 The prinicpals brands of the used markets are
 Samsung, Huawei and LG.



#### Os

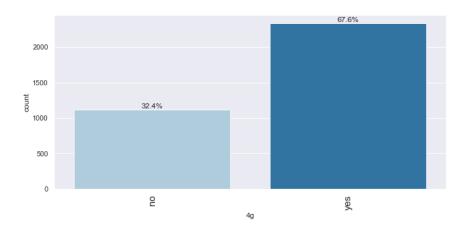
Over 90% of the phones used the OS Android. Even thought iOS, is well regarded by their users it has the smallest share of the market.



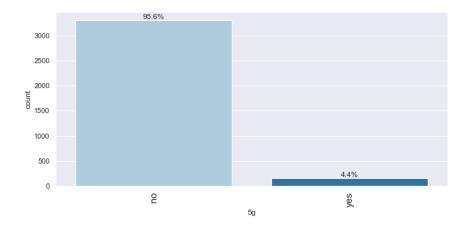




4g
 The 67.6% of the used phone market have a
 4g connection.



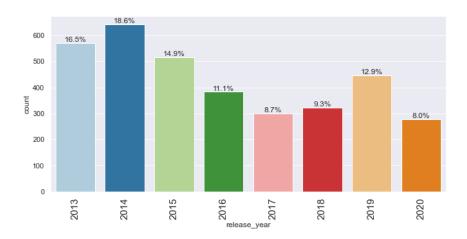
5g
 Only a 4.4% of the used phones has a 4g connection.





#### Release\_year

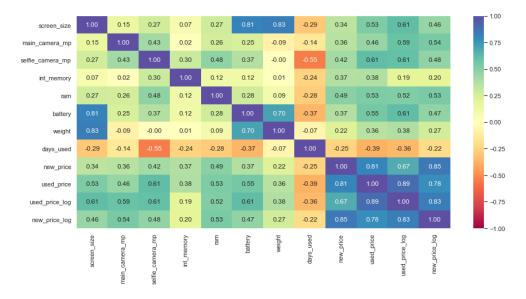
The used market shows that the phones of between 2013 – 2015 have the 50% of the market. But a change on this distributions is expected with the pass of time.







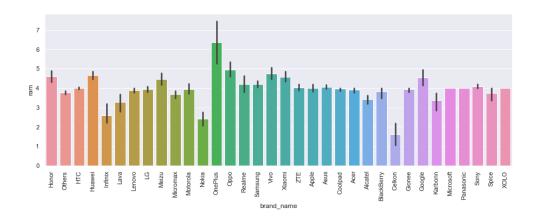
• The results between correlation between the variables shows some expected relationships such as the screen\_size with weight and battery. One relation ship that shows the interest in the used market is the relation ship between used\_price with the selfie\_camara\_mp. Also, the relationship between price and battery shows a that a bigger phones has a bigger price. The must interesting negative relationships are the selfie\_camara\_mp and days\_used and used\_price and days\_used the last one is the expected with the used market.





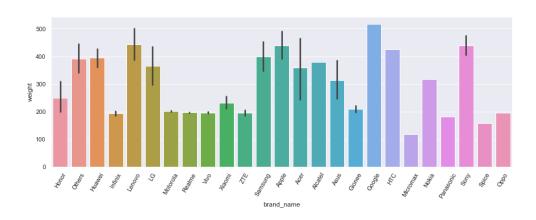


 The relationship between ram memory and brand\_name is to see if a brand has as a differentiate characteristic the amount of memory. In this case OnePlus is the one with the must ram. The rest of the brands are bellow the 6gb and almost all stay near 4 gb. The exceptional cases are Nokia and Celkon.



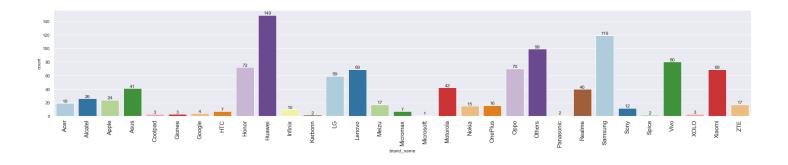


• The weigh between different brands shows that the brands with known premium phones have the must features and therefore the phones are heavier. For example, Samsung with their top-of-the-line phones that have an included stylus.





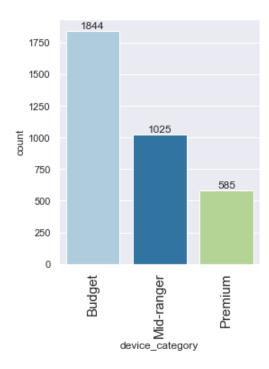
The relationship between the used market brands and the number of cellphones on the data base.
 This show us that Huawei has the higher count for cellphones available in the market with 149. The following brands includes Samsung with 119, Honor with 72and Vivo with 80.



### **Data Preprocessing – Feature engineering**



 For the preprocessing it's necessary to understand for which category the cellphone is designed. Therefore, three categories were designated: Budget, Mid-ranger and Premium. The First category consists of phones under € 200, the Mid-ranger between € 200 and € 350, and premium over € 350.







- A duplicate analysis was realized, and it found 0 duplicated values in the data set.
- For the missing value treatment an analysis of the variables was realized, and it was found that the following variables had some missing values:

Variables	Total Missing Values
Main_camera_mp	179
Selfie_camera_mp	2
Int_memory	4
Ram	4
Battery	6
Weight	7

### Data Preprocessing – Missing values

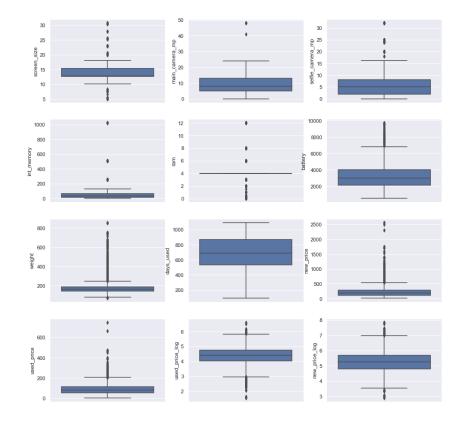


- For the first treatment of the missing values the cellphones were grouped by their release\_year and brand\_name to fill the missing values with their respective medians. This approach solve the issue for int\_memory and ram.
- Then the same procedure was used for the previous variables but, only grouping them by brand\_name. This solved the issue for the following variables: selfie\_camera\_mp, battery and weight. main\_camera\_mp had still 10 missing values after this point.
- Finally, the missing values of main\_camera\_mp were filled with the median of the variable.

### **Data Preprocessing – Outlier Check**



• For the outlier check of all the variables the one that was highlighted the most for our analysis was the used price. As it is our target variable, we need to be normalized in order to achieve a better result for our analysis. The rest of the variables even though, some can some signs of outliers such as weight, or ram are in the normal range for these kinds of products.





# Data Preprocessing – Data Preparation for modeling

- For the preparation of the model the independent variable used\_price\_log is dropped. These variables were also dropped new\_price, used\_price, and device\_category. The variable new\_price\_log will remain as is a normalized version of the new\_price variable.
- The target values will be used\_price\_log as it's the normalized version of the used\_price.
- With the previous treatment dummy variable was added to the model.
- As the last step taken the data was split into a 70:30 ratio for training and testing.

### **Model Performance Summary**



- The result obtained through linear regression is a model with an R-Squared of 0.997 and an Adj. R-Squared of 0.997 which is considered very precise as it explains 99.7% of the variation in the sets.
- The principal variables includes screen\_size, main\_camera\_mp, selfie\_camera\_mp, ram, weight, release\_year, new\_price\_log, brand\_name\_Nokia, brand\_name\_Samsung, brand\_name\_Sony, brand\_name\_Xiaomi, and 4G.
- The overall performance of the model brings the following results for the train and test set:

Data	RMSE	MAE	MAPE
Train	25.772441	16.828725	19.15624
Test	24.489763	16.616165	19.43771

- With the results of the RMSE it can be observed that the model fits well as the results are similar.
- Our model can predict used\_price with a mean error of € 16.62.
- With the MAPE the model can predict within the 19.44% of the value of the used price of the cellphone.

Link to Appendix slide on model assumptions

### **Model Performance Summary**



 Based on the coefficients the most important variable is new\_price\_log. The connection to a 4g network as one of the relevant components to be considered in the model. The brands Samsung and Sony have a negative perspective on the expected price of the used price.

		,	gression Resu	ults		
5						
•	used_price_log					0.997
Model:				red (uncenter	ea):	0.997
Method:	Least 9		F-statistic:	•		7.159e+04
Date:			Prob (F-stat			0.00
Time:	0		Log-Likeliho	ood:		93.022
No. Observations:		2417				-162.0
Df Residuals:			BIC:			-92.56
Df Model:		12				
Covariance Type:	noi	nrobust				
	coef	std er	r t	P> t	[0.025	0.975]
_				0.000		
main_camera_mp				0.000		0.024
selfie_camera_mp	0.0160	0.00	17.594	0.000	0.014	0.018
ram	0.0207	0.00	4.723	0.000	0.012	0.029
weight	0.0007	0.00	5.826	0.000	0.000	0.001
release_year	0.0006	2.14e-0	28.302	0.000	0.001	0.001
new_price_log	0.4102	0.01	1 38.980	0.000	0.390	0.431
brand_name_Nokia	0.0723	0.02	2.458	0.014	0.015	0.130
brand_name_Samsung	-0.0364	0.01	5 -2.238	0.025	-0.068	-0.005
brand_name_Sony	-0.0727	0.03	-2.398	0.017	-0.132	-0.013
brand name Xiaomi	0.0793	0.02	3.104	0.002	0.029	0.129
4g_yes	0.0780	0.01	5.812		0.052	0.104
Omnibus:		214 920	 Durbin-Watso		1.9	
Prob(Omnibus):					385.5	
Skew:			Jarque-Bera	(36):	1.95e-	
5110111			Prob(JB):			
Kurtosis:		4.520	Cond. No.		1.30e+	

#### **Conclusions and Recomendations**



- The generated model can explain the 99.7% of the variance that occurred in the dataset. With this, we can obtain a price value of the phones in the used market.
- The results of the model show that the current model values the original price greatly to calculate a future used price. Usually, this correlates to a higher-quality cellphone. Right now, 4g is considered the standard and 5g capability is in less than 5% of the cellphones. But this is expected to be changing in the future as this type of network becomes more popular around the world.
- Due to the changes in technology, an update of the model should be done consistently. This update should help to understand what consumers of the used market value the most. For example, in the used market place a Xiaomi cellphone is more valued than a Samsung cellphone. But his can be canning in the future as the brands develop their name and quality over time.

Link to Appendix slide on model assumptions



# **APPENDIX**

# **Data Background and Contents - Ductionary**



•	The v	ariables '	of the	data set	are the	following:

- 1. brand\_name: Name of manufacturing brand
- 2. os: OS on which the device runs
- 3. screen\_size: Size of the screen in cm
- 4. 4g: Whether 4G is available or not
- 5. 5g: Whether 5G is available or not
- 6. main\_camera\_mp: Resolution of the rear camera in megapixels
- 7. selfie\_camera\_mp: Resolution of the front camera in megapixels

- 8. int\_memory: Amount of internal memory (ROM) in GB
- 9. ram: Amount of RAM in GB
- 10. battery: Energy capacity of the device battery in mAh
- 11. weight: Weight of the device in grams
- 12. release\_year: Year when the device model was released
- days\_used: Number of days the used/refurbished device has been used
- 14. new\_price: Price of a new device of the same model in euros
- 15. used\_price: Price of the used/refurbished device in euros





The variables used are dived as follows

Object	Float64	int64
<ul><li>Brand Name</li><li>Os</li><li>4g</li><li>5g</li></ul>	<ul> <li>Scree_size</li> <li>Main_camera_mp</li> <li>Selfie_camera_mp</li> <li>Int_memory</li> <li>Ram</li> <li>Battery</li> <li>Weight</li> <li>New_price</li> <li>Used_price</li> </ul>	Realease_year Days_used

#### **Model Assumptions**



- The variables used\_price and new\_price were transformed into a log variable in order to seek better treatment through normalization of the values obtained.
- The variable device\_category was created using the new\_price to determine the type of segment of the market that the cellphone is intended to be placed.
- The independent variables of the dataset are new\_price, used\_price, used\_price\_log, and device\_category. The new\_price is considered independent as it is defined by the manufacturer, and it can't be explained with the information provided in the data set.
- The dummy variables were created for the object and category type of variables. This resulted in a total of 48 variables for the model.



### Model Assumptions – No Multicollinearity

- A test for Multicollinearity was released on the data set after the first drop of variables was done. The results of this test show that none of the variables obtained a value higher than 10 in the variance of inflation factor (VIF).
- Following this a test was realized to drop the variables that had a p-value over 0.05. this reduces the 48 variables of the model to 12 variables (final model).
- These changes brought the following results for the model:

Data	RMSE	MAE	MAPE
Train	25.772441	16.828725	19.15624
Test	24.489763	16.616165	19.43771



### **Model Assumptions – Linearity and Independence Test**

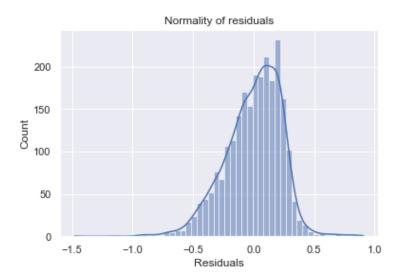
- For this test the difference between the fitted values and actual values was obtained and the residuals were plotted.
- The values of the residuals don't show any pattern and are distributed between negative and positive values.



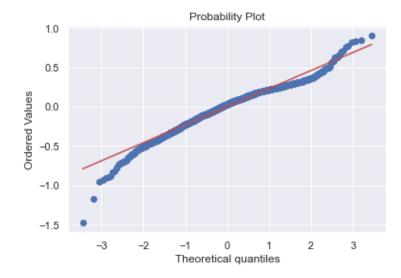
### Model Assumptions – Normality of error terms



 The residuals show a normal distribution with a skew to the right.



 The probability plot shows that the values are around the diagonal line.
 Showing the normality of the error.



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### Model Assumptions – No Heteroscedasticity

• In order to check the homoscedasticity, the Goldfeld-Quandt test was realized. This test indicated with a p-value of **0.1924** that there is no statistical evidence of heteroscedasticity in the variables for the model.



# **OLS Model – Original vs Final**

·						
Den Variable:	used price	log P-sai	ared (uncent	ered).		0.997
Model:	Least Squa Wed, 02 Mar 2 07:53	DLS Adj.	ared (uncent R-squared (u	incentered	):	0.997
Method:	Least Squa	res F-sta	tistic:			1.792e+04
Date:	Wed, 02 Mar 2	822 Prob	(F-statistic	):		0.00
Time:			ikelihood:			112.56
No. Observations: Df Residuals:		417 AIC: 369 BIC:				-129.1
DC Hadali	_	40				148.8
Covariance Type:	nonnoh	48				
covariance Type.	HOTH OD	usc				
			t			0.975]
screen_size	0.0275	0.003	8.161	0.000	0.021	0.034
main_camera_mp	0.0216	0.002	14.288	0.000	0.019	0.025
selfie_camera_mp	0.0154	0.001	14.473	0.000	0.013	0.018
int_memory	0.0002	6.96e-05	2.175	0.030	1.49e-05	0.000
hattan.	1 0000 05	7 100 00	4.525	0.000	2 470 05	2 400 00
weight	0 0000	0.150-00	6 600	0.140	0.001	0.400-00
release year	0.0005	3.51e-05	17.886	0.000	0.001	0.001
screen_size main_camera_mp selfie_camera_mp int_memory ram battery weight release_year days_used	-4.078e-05	2.62e-05	-1.554	0.120	-9.22e-05	1.07e-05
release_year days_used new_price_log	0.4132	0.012	34.660	0.000	0.390	0.437
new_Drice_log brand_name_Alcatel brand_name_Alcatel brand_name_Asus brand_name_Calkon brand_name_Celkon brand_name_Celkon brand_name_Colopad brand_name_Gionee brand_name_Horn brand_name_Horn brand_name_Horn brand_name_Horn brand_name_Horn brand_name_Lorninx brand_name_Lorninx brand_name_Lorninx brand_name_Lorninx	0.0166	0.048	0.347	0.729	-0.077	0.110
brand_name_Apple	0.0262	0.148	0.178	0.859	-0.263	0.316
brand_name_Asus	0.0174	0.048	0.361	0.718		
brand_name_BlackBerry	-0.0508	0.071	-0.720	0.472		
brand_name_Celkon	-0.0702	0.066	-1.057	0.291	-0.200	
brand_name_Coolpad	0.0346	0.073	0.472	0.637		
brand_name_Glonee	0.0429	0.058	0.740	0.460	-0.071	
brand_name_Google	-0.0035	0.085	-0.041 -0.316	0.967 0.752		
brand name Honon	-0.0155	0.040	0.674	0.752		
brand name Huawei	-0.0333	0.045	-0.015	0.988		
brand name Infinix	0.1704	0.094	1.821	0.069		
brand name Karbonn	0.0757	0.067	1.124	0.261	-0.056	0.208
brand name LG	-0.0113	0.046	-0.249	0.803		
brand_name_Lava	0.0335	0.063	0.535	0.593	-0.089	
brand_name_Lenovo	0.0422	0.045	0.930	0.352	-0.047	
brand_name_Lava brand_name_Lenovo brand_name_Meizu brand_name_Micromax	-0.0098	0.056	0.930 -0.174 -0.736	0.862	-0.120	
brand_name_Micromax	-0.0354	0.048	-0.736	0.462		
brand_name_Microsoft	0.1183	0.089		0.182		
brand_name_Motorola	-0.0074	0.050	-0.149	0.882	-0.105	
brand_name_Nokia	0.0530	0.052 0.078 0.048	1.822 0.681	0.496		
brand name Onno	0.0171	0.0/0	0.356	0.722		
brand_name_Microsoft brand_name_Motorola brand_name_Nokia brand_name_OnePlus brand_name_Oppo brand_name_Others brand_name_Panasonic	-0.0048	0.042 0.056	-0.115	0.722		
brand name Panasonic	0.0592	0.056	1.055	0.292	-0.051	
brand_name_Realme	0.0427	0.062	0.690	0.490	-0.079	0.164
based sens Communication	-0.0310	0.062 0.043	-0.714	0.476	-0.116	
brand_name_Sony	-0.0704	0.051	-1.388	0.165	-0.170	
brand_name_sony brand_name_spice brand_name_yivo brand_name_vivo brand_name_Xiaomi brand_name_ZIE	-0.0264	0.063	-0.417	0.677	-0.151	
brand_name_Vivo	-0.0155	0.049	-0.319	0.750	-0.111	
brand_name_XOLO	0.0049	0.049 0.055 0.048	0.088	0.930	-0.103	
brand_name_Xiaomi	0.0882 -0.0075	0.048		0.068		
prand_name_ZTE	-0.0075 -0.0492	0.048	-0.157	0.875		
os_Others os_Windows	-0.0492 -0.0363	0.033	-1.491	0.136 0.423		
os_ios	-0.0303	0.147	-0.524	0.423		
4g ves	0.0822	0.015		0.000		
5g ves		0.032		0.152		
28_703						
	215	114 Dumbi	n Matconi		1 011	
Omnibus: Prob(Omnibus): Skew:	0.0	000 Jarqu	ie-Bera (JB): JB):		397.246	•
Skew:	-0.	607 Prob(	JB):		5.50e-87	7
Kurtosis:	4.	S/I Cond.	NO.		2.010+05	•

		OLS Reg	gression Resu	ults		
Dep. Variable:	used_pri		R-squared (uncentered):			0.997
Model:			-	red (uncenter	ed):	0.997
Method:			F-statistic			7.159e+04
	•		Prob (F-stat	,		0.00
Time:	97		Log-Likelih	ood:		93.022
No. Observations:		2417				-162.0
Df Residuals:		2405	BIC:			-92.56
Df Model:		12				
Covariance Type:		robust				
		std er	t t	P> t	[0.025	0.975]
screen_size	0.0310	0.00	10.911	0.000	0.025	0.037
main_camera_mp	0.0216	0.001	15.410	0.000	0.019	0.024
selfie_camera_mp	0.0160	0.001	17.594	0.000	0.014	0.018
ram	0.0207	0.004	4.723	0.000	0.012	0.029
weight	0.0007	0.000	5.826	0.000	0.000	0.001
release year	0.0006	2.14e-09	28.302	0.000	0.001	0.001
new price log	0.4102	0.011	1 38.980	0.000	0.390	0.431
brand name Nokia	0.0723	0.029	2.458	0.014	0.015	0.130
brand name Samsung	-0.0364	0.016	-2.238	0.025	-0.068	-0.005
brand name Sony	-0.0727	0.036	-2.398	0.017	-0.132	-0.013
brand name Xiaomi		0.026	3.104	0.002	0.029	0.129
4g_yes	0.0780	0.01	5.812	0.000	0.052	0.104
						==
Omnibus:	_		Durbin-Watso		1.9	
Prob(Omnibus):			Jarque-Bera	(JB):	385.5	
Skew:		-0.616	Prob(JB):		1.95e-	84
Kurtosis:		4.520	Cond. No.		1.30e+	04
						==



**Happy Learning!** 

