

# ReCell Project 3: Supervised Learning Foundations

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# Executive Summary

- We can explain 84% of the variance in the resale price of a device based on the linear regression model built using the available dataset
- We can predict the resale price of a device within \$19.25 if we know its features
- It was found that: screen size, main camera resolution, selfie camera resolution, RAM, battery, weight, release year, price when new, brand: Lenovo, brand: Nokia, brand: Xiaomi, Non-Android nor IOs operating systems and 4G capabilities are statistically significant features we can use to predict used price.
- 93% of devices studied in this dataset run Android as operating system
- 75% of devices in this data set had a resale price below \$116
- We should avoid devices with an OS that is not Android or IOS
  - We should prefer devices that have just been released or that were released a year or two ago

# Business Problem Overview and Solution Approach

The used and refurbished device market has grown considerably over the past decade, forecasts predict that the market would be worth \$52.7bn by 2023 with a compound annual growth rate (CAGR) of 13.6% from 2018 to 2023.

ReCell , a start-up aiming to capture the potential in this market, has gathered data with different attributes of used/refurbished phones and tablets, they want to explore how it affects their resale price.

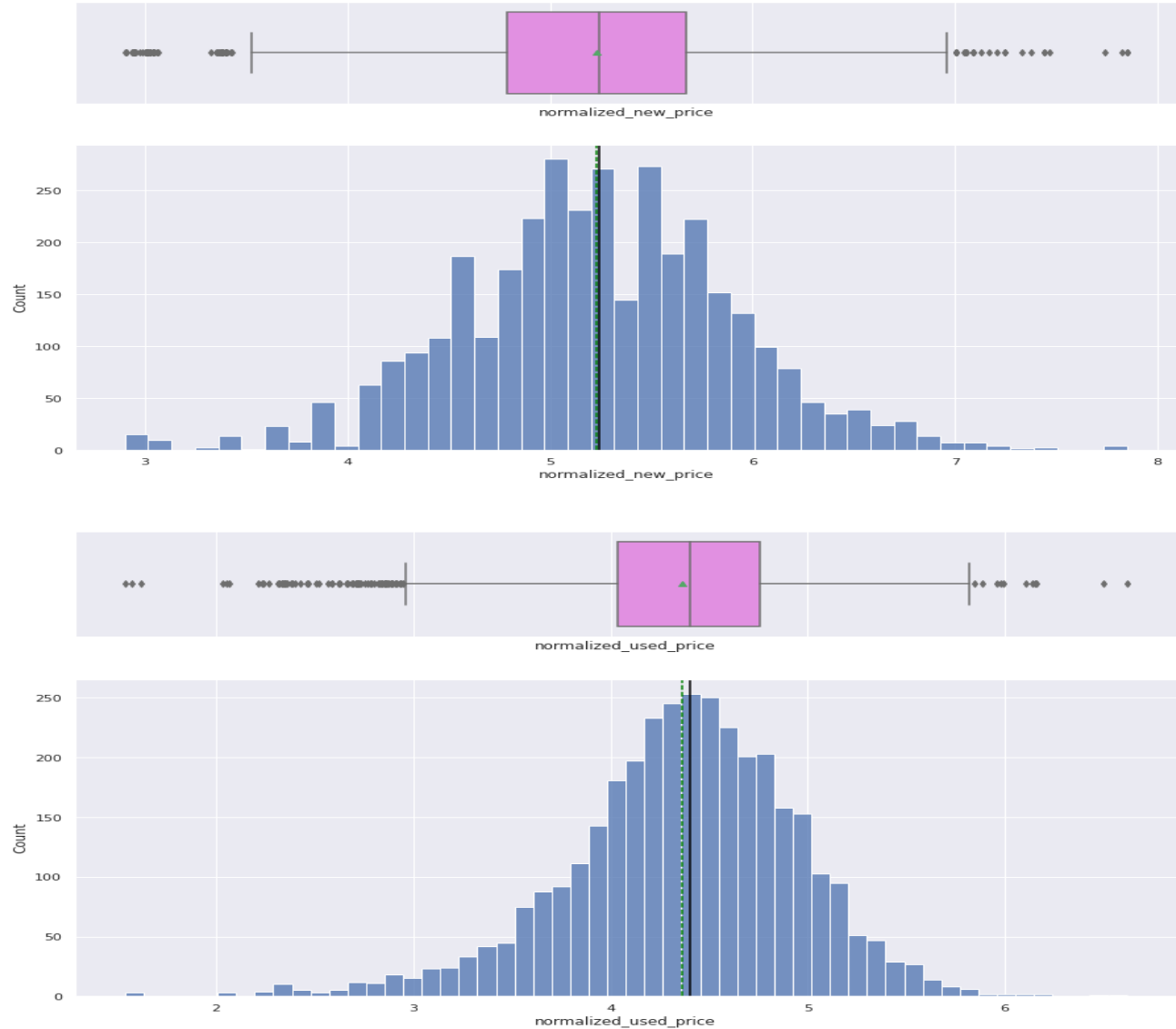
- There is a need for an ML-based solution to develop a dynamic pricing strategy for used and refurbished devices.
  - We will process the data in order to develop a linear regression model that can predict the price of a used device and understand the factors that significantly influence it.

# Data Overview

- 50% of screens are 12-15 inches
  - Average main camera resolution is 9 Mpx, 75% of cameras are below 13 Mpx
  - Average selfie camera resolution is 6Mpx, 75% of cameras are below 8Mpx
  - Average ROM is 54Gb, 75% of phones have less than 64Gb
- Only 25% of phones have more than 4Gb RAM
- 75% of phones have less than 4000mAh of battery
- Average weight is 182 grams, 75% of devices weigh less than 185 grams
- Average device was released in 2015, 75% of devices were released before 2018
- Average device is 674 days old, 75% of devices are less than 868 days old
  - Average price when device was new was \$237, with 75% of devices being less than \$291 when new
- Average used price is \$92, with 75% of devices having a resale price below \$116

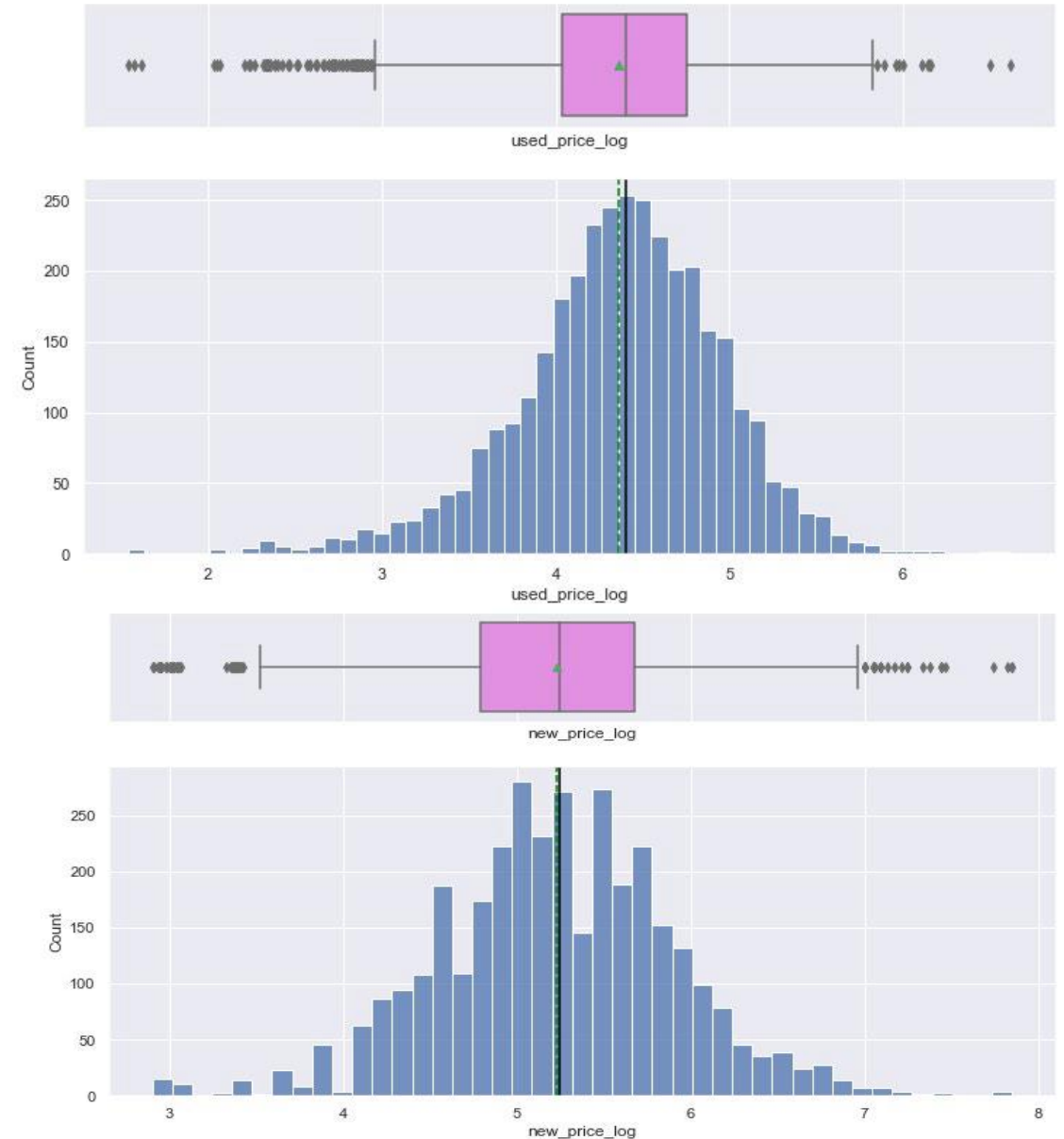
# EDA:Distributions

- We observe right skewness in the distributions for “Used\_price” and “New\_price”
- Long tails to the right displace the mean, as it is sensitive to outliers
- The linear correlation between the transformed columns (used\_price) and (new\_price) is same as before transformation; strongly positively correlated with correlation factor of 0.93



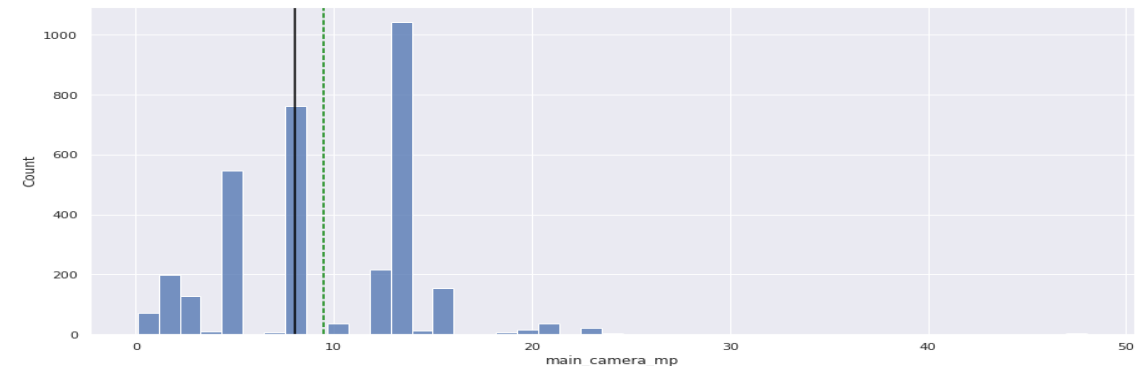
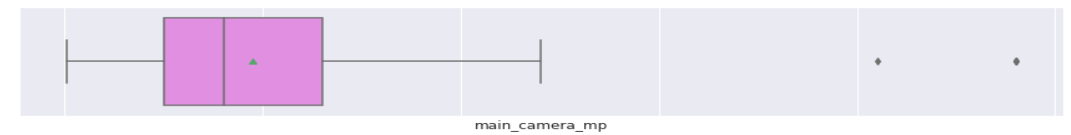
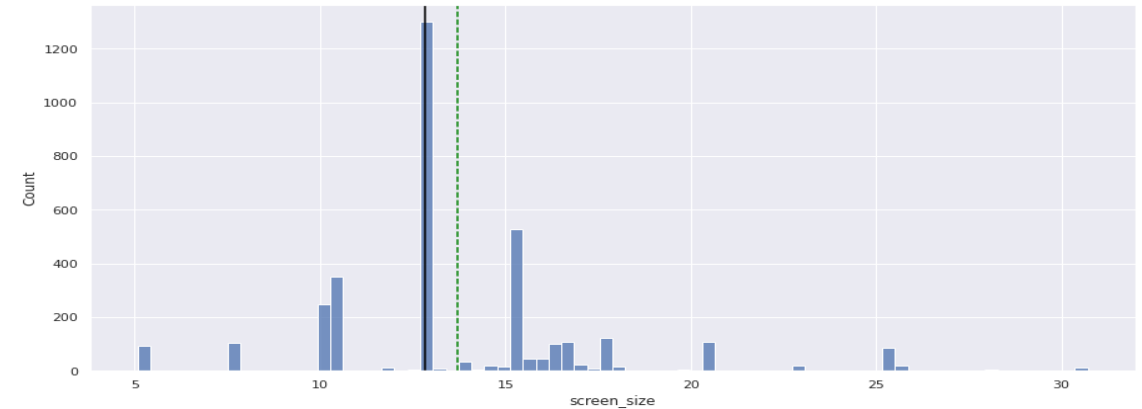
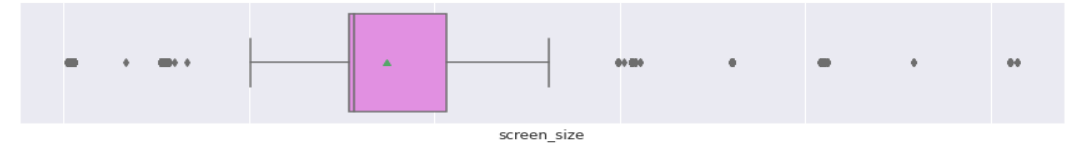
# EDA: Distributions

- After the log transformation, we observe a reduction in the skewness of both distributions
- The shapes of the distributions are now closer to being normally distributed
- We observe that the mean is much closer to the median after transformation and the tails are shorter .



# EDA: Distributions

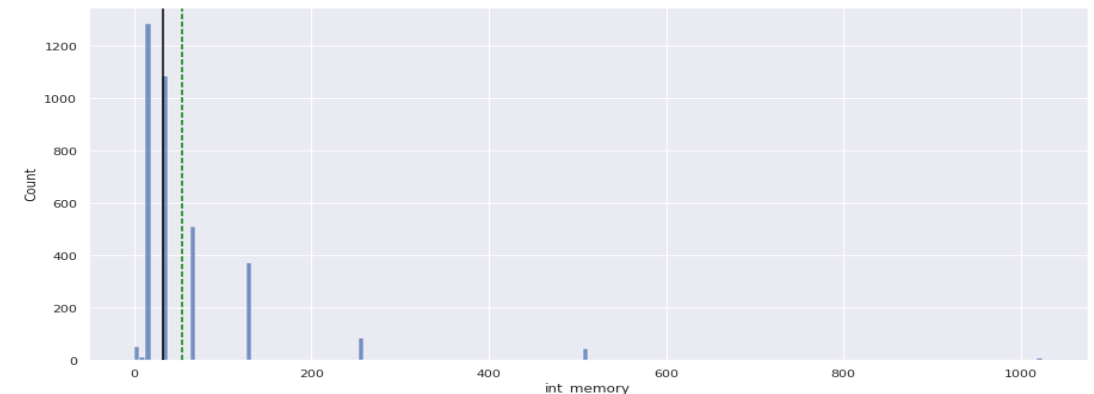
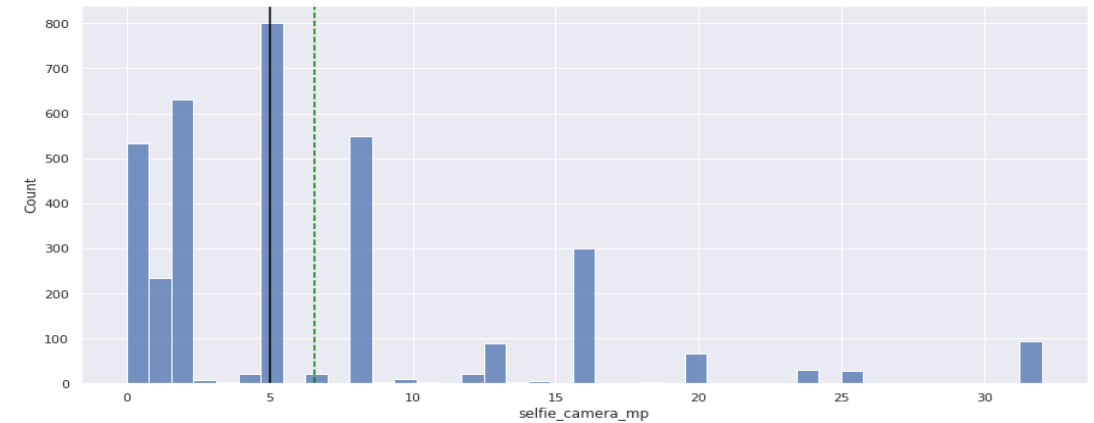
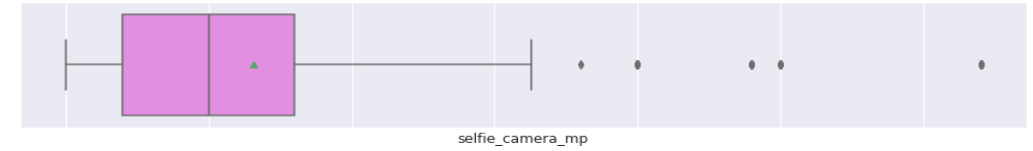
- We observe that most devices have a screen size between 10-15 inches, this makes devices with larger screens appear as outliers, however this data set includes phones and tablets, so we can not drop this values.
- We observe that most devices have main cameras between 5-18Mpx, but larger values are still valid as they might be from premium, photography-oriented Devices.





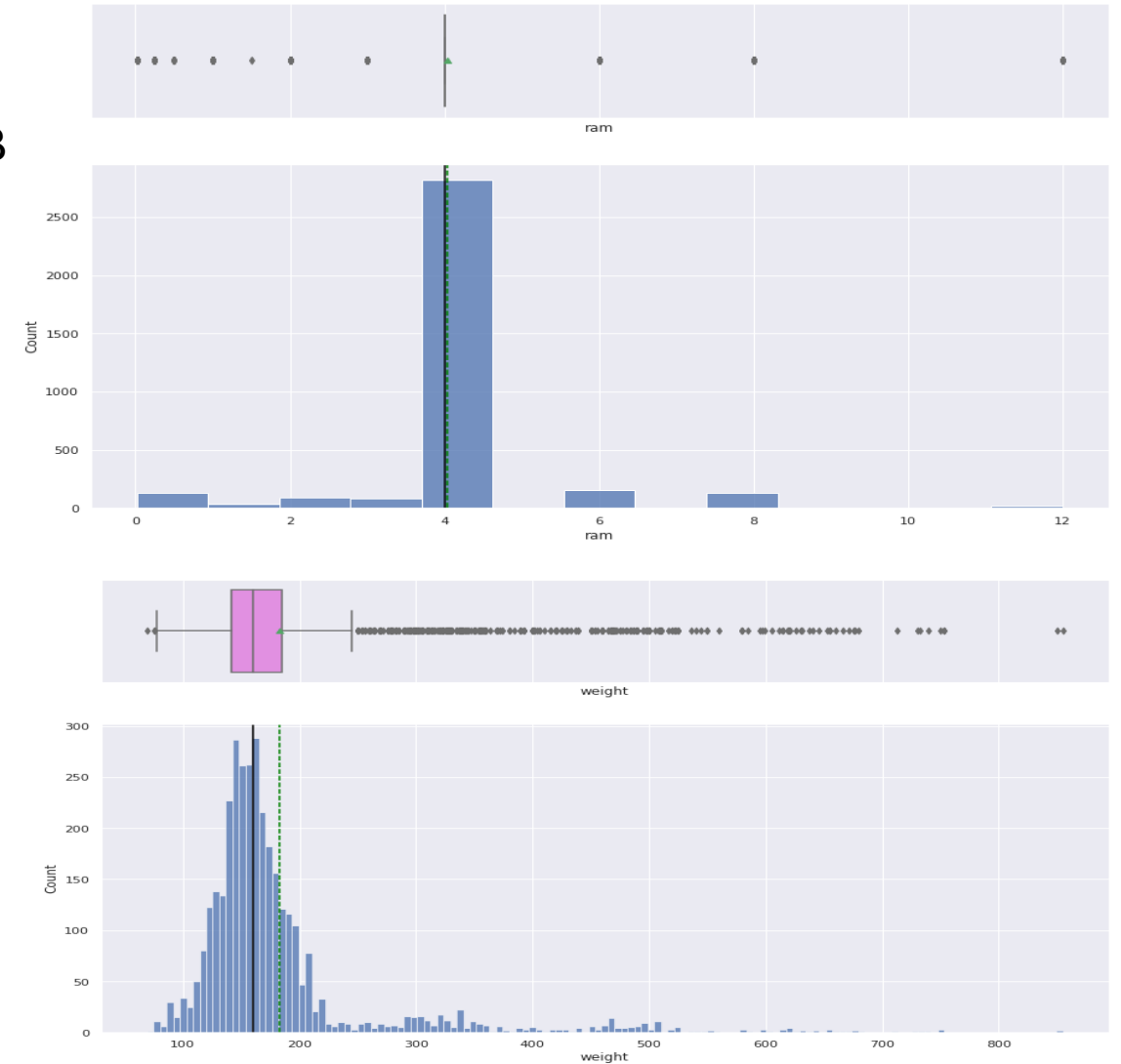
# EDA: Distributions

- We observe that most devices have a selfie camera of 5Mpx and below 17Mpx, but larger values are Valid.
- We observe the internal memory of most devices is below 100Gb, however we can accept larger values as they might be from premium devices which focuses on storage.



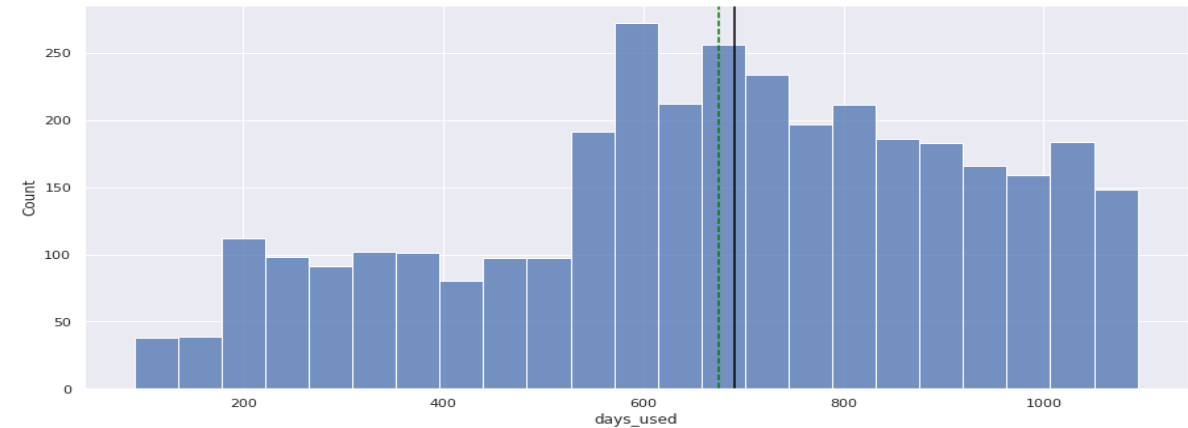
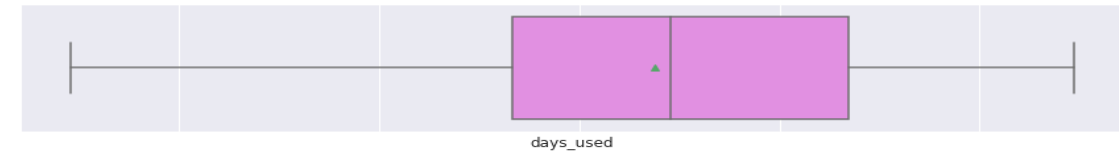
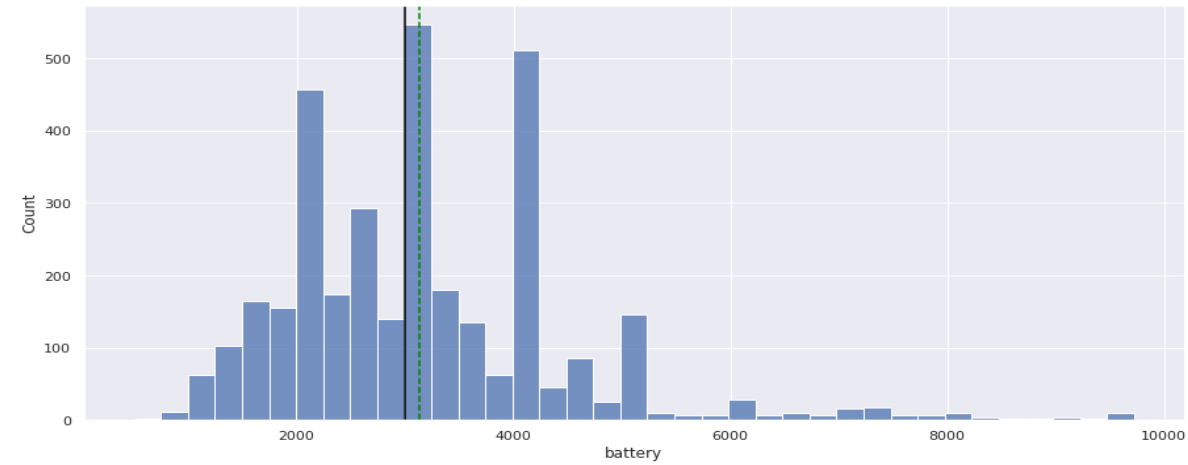
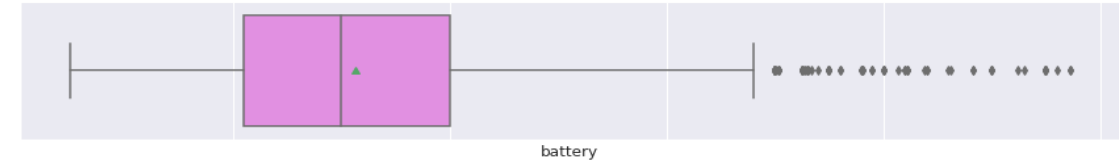
# EDA: Distributions

- We observe that a vast majority of devices have 4GB of Ram memory, this makes all other values appear as outliers, however we will not drop this values because they are valid values.
- We observe that most devices are lightweight, below 200 grams, however weight might increase with screen size, battery capacity and other features so, we can not drop the heavy devices .

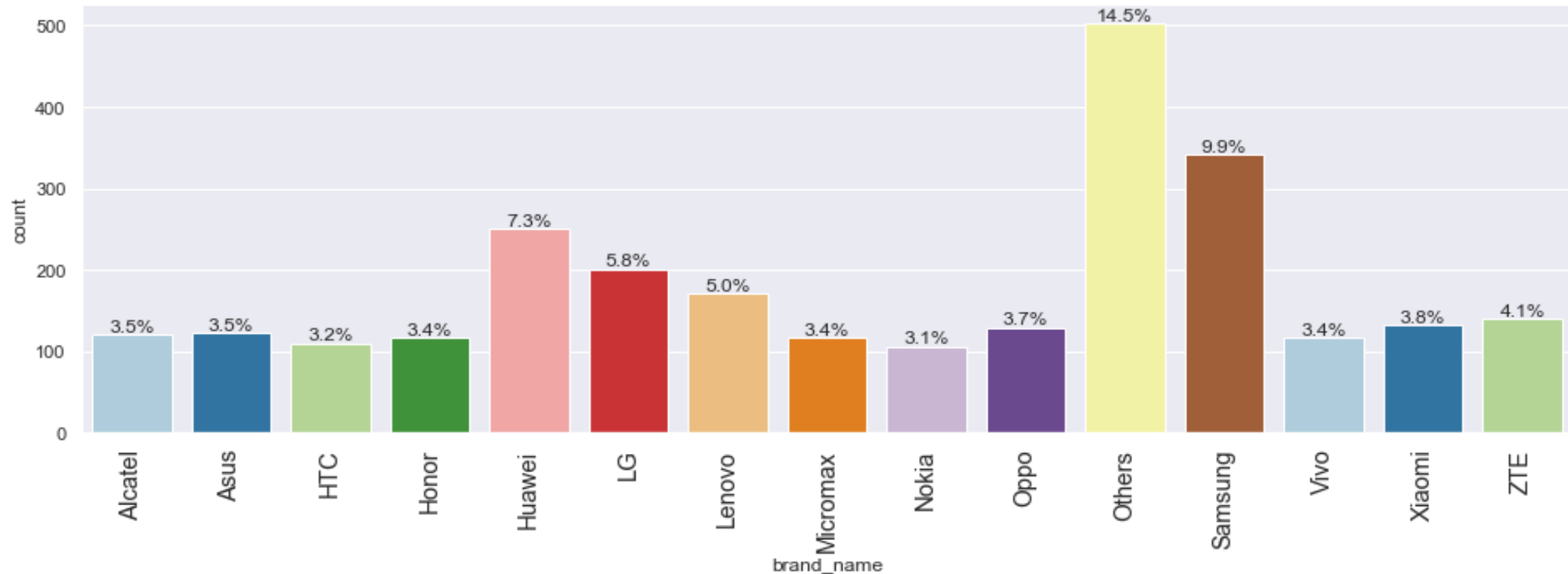


# EDA: Distributions

- We observe that most devices have a battery between 2000-4000mAh, this makes devices with higher battery capacities appear as outliers, but we can not exclude this information
- “Days\_used” distribution has no outlying values as per 1.5IQR definition, majority of phones have more than 600 days of use.



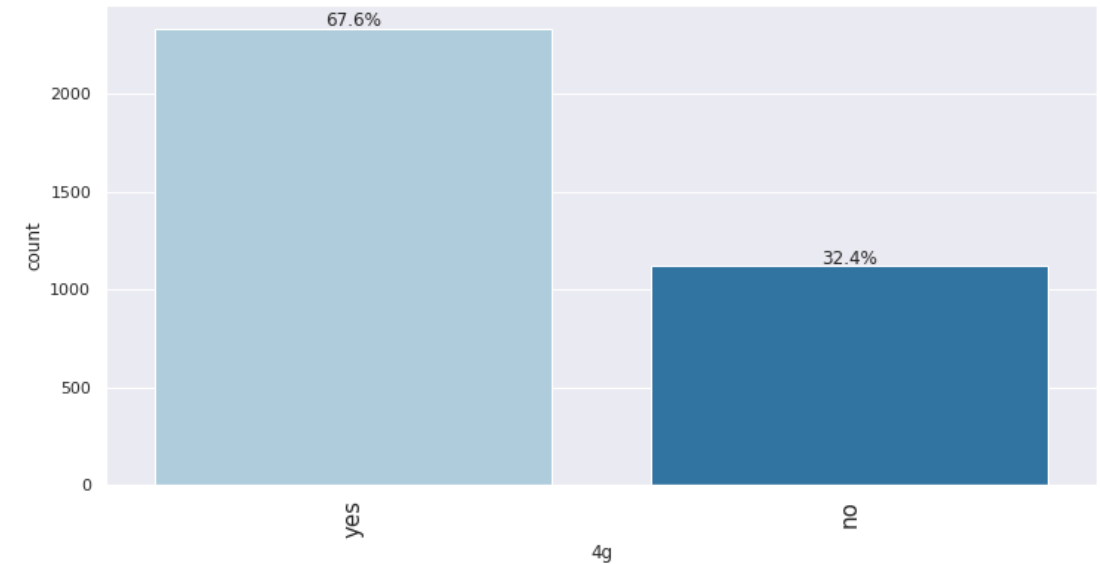
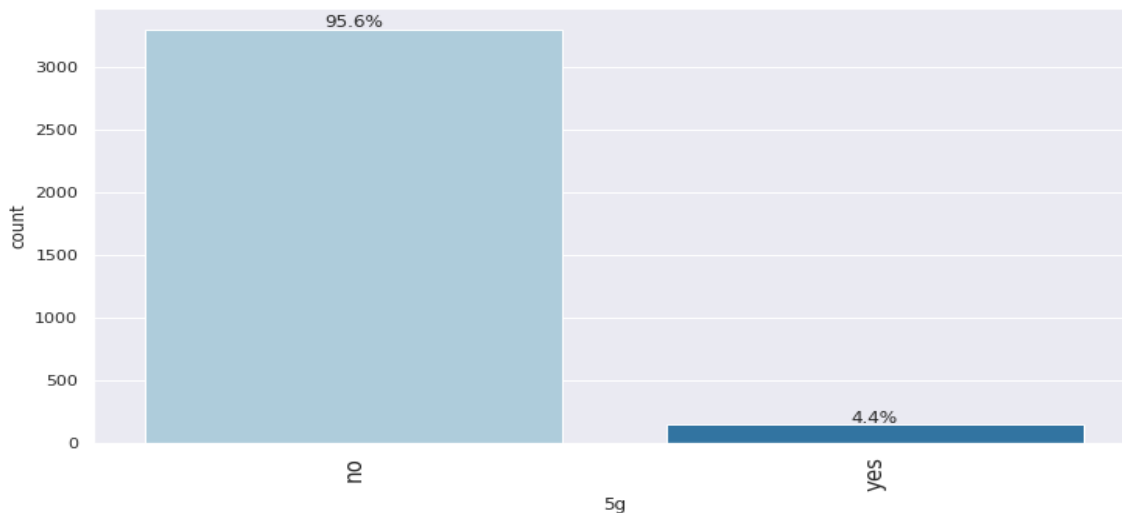
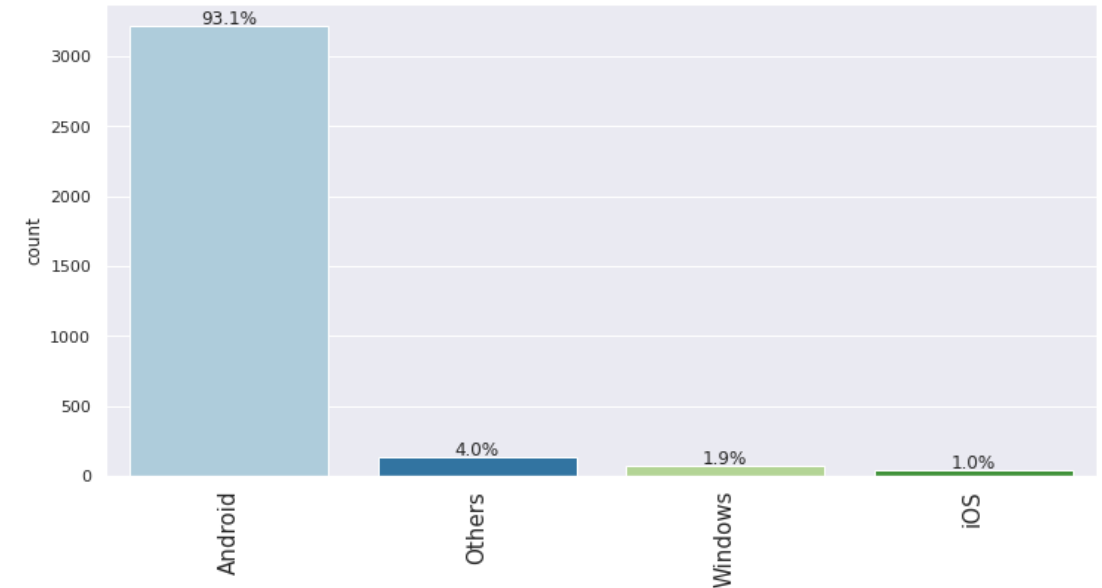
# EDA: Manufacturers



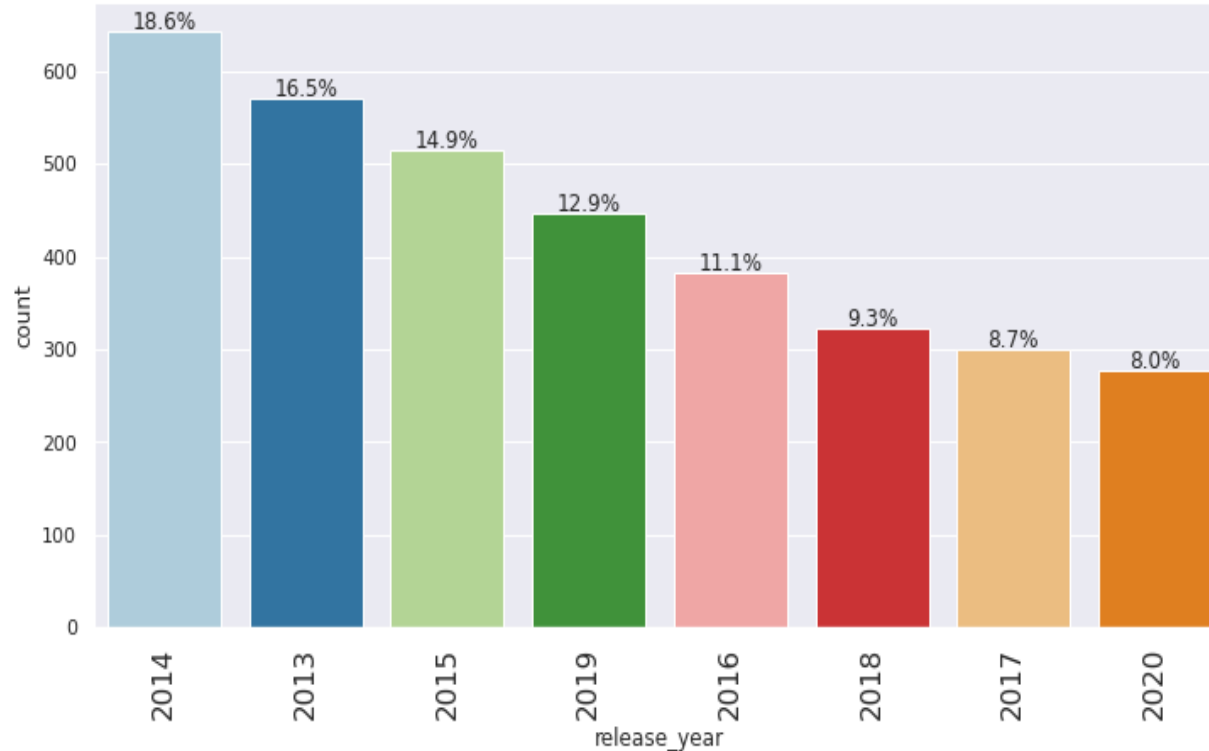
- This are the top 15 manufactures in our data set, together they account for 77% of all devices
- The top 5: Others, Samsung, Huawei, LG and Lenovo have a share of 42.5% of all devices
- Apple does not appear as a brand in the data set, is it dominant in the “Others” category?

# EDA: Operating System and Mobile Technology

- We can see that only 1% of the devices are Apple, In contrast with Android's 93%. This means that the "Others" category must include majority of other Android manufacturers .
- 67% of devices have 4G technology while only 4.4% have 5G technology, the number of devices with pre 4G technology is important at around 32%



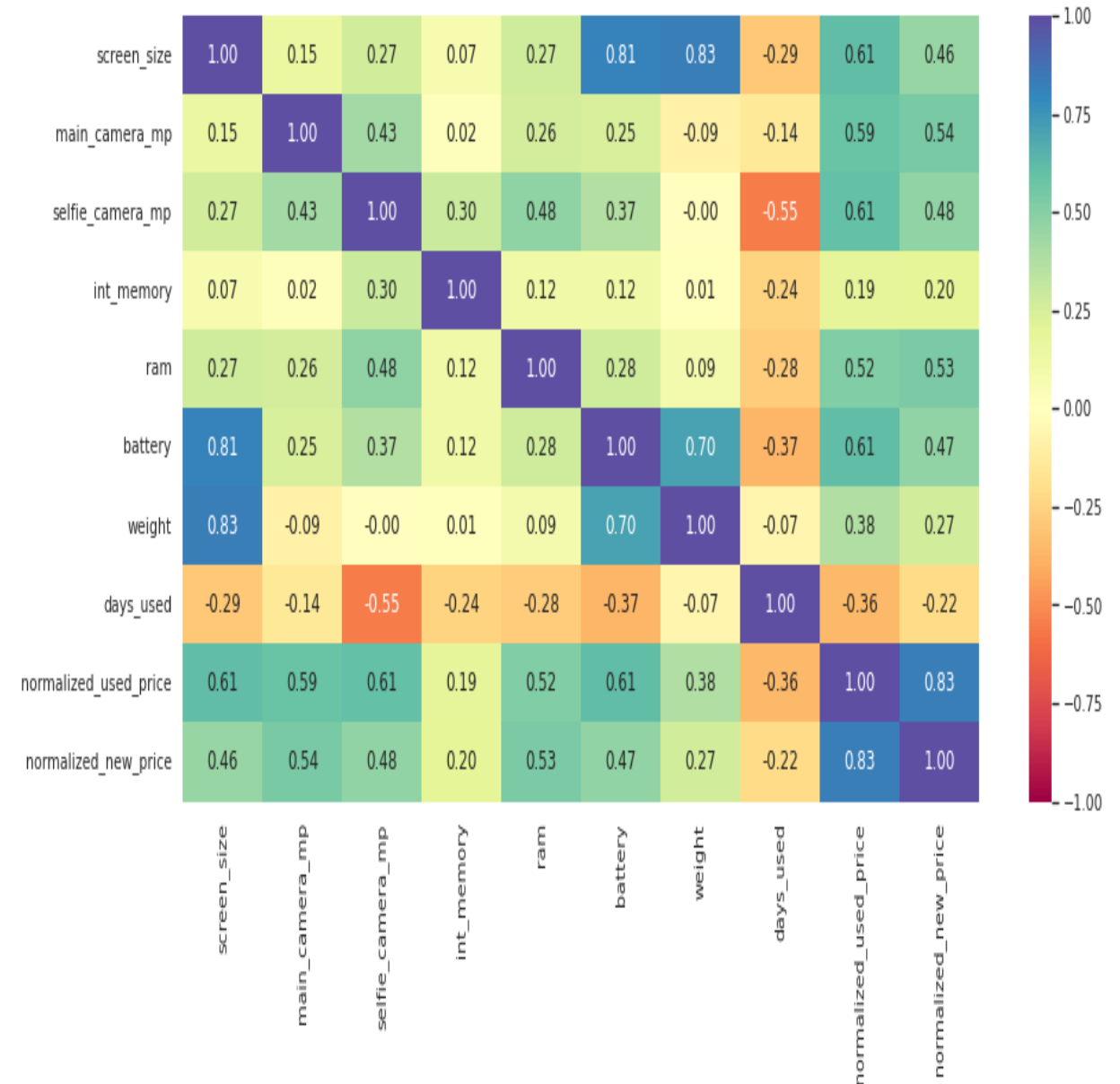
# EDA: Release Year



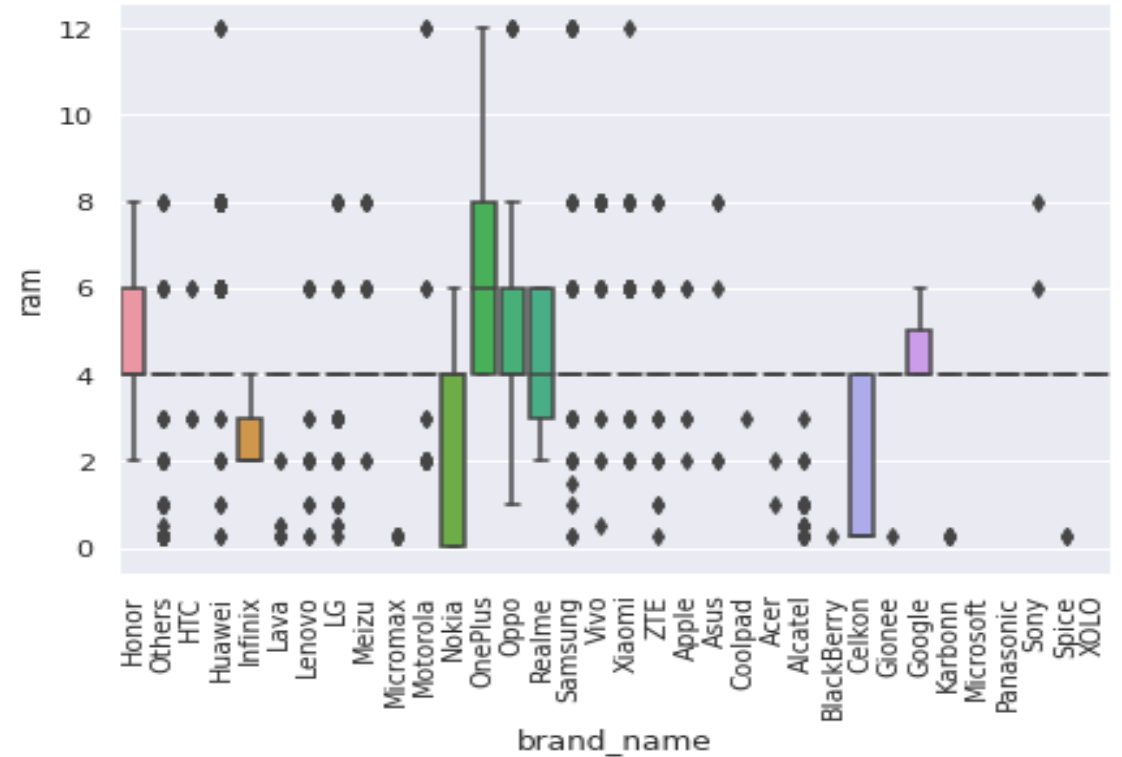
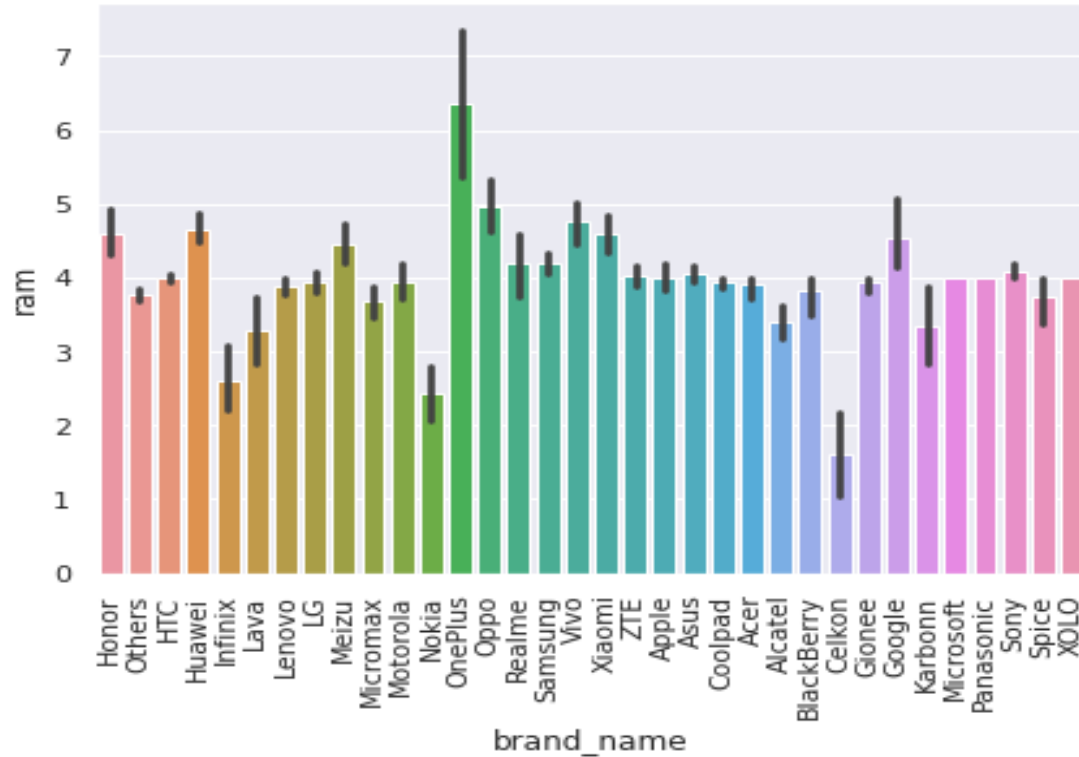
- 70% of devices were released before 2017, the remaining 30% was released between 2017-2020
- The bar plot of “used\_price” vs “release\_year” uncovers a linear relationship between this two features, with newer devices having a higher resale price as used devices.
- The same linear relationship is true for “new\_price” vs “release\_year”

# EDA: Heat Map

- The used device price is highly correlated with the price of a new device model. This makes sense as the price of a new model is likely to affect the used device price.
- Weight, screen size, and battery capacity of a device show a good amount of correlation. This makes sense as larger battery capacity requires bigger space, thereby increasing screen size and weight.
- The number of days a device is used is negatively correlated with the resolution of its front camera. This makes sense as older devices did not offer as powerful front cameras as the recent ones.



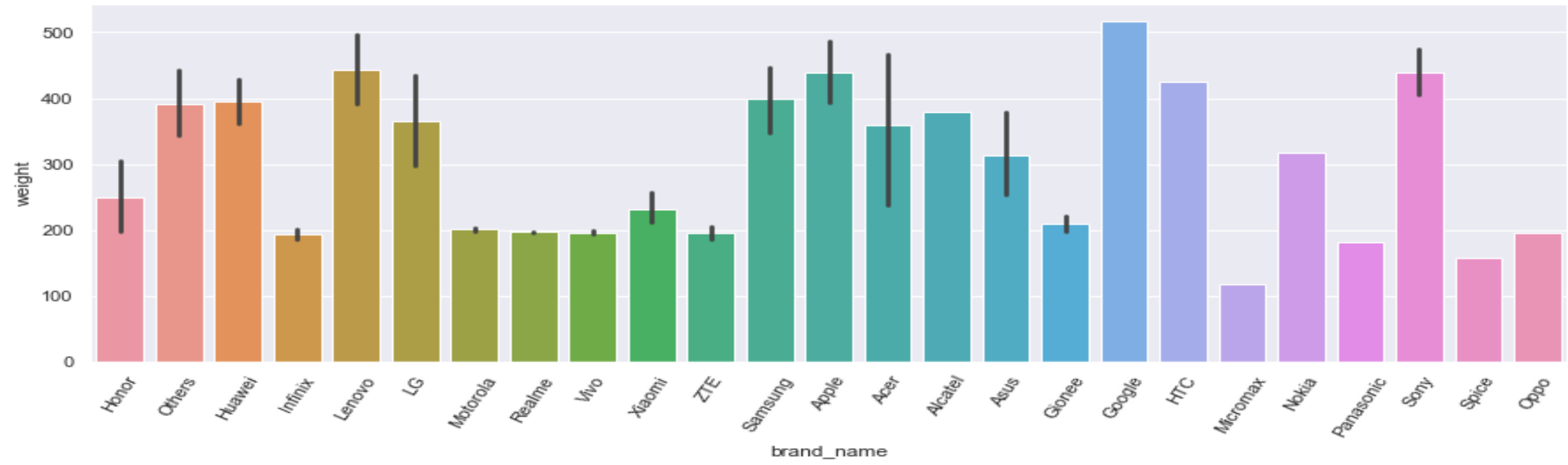
# EDA :Ram



- 81% of devices have 4GB of RAM on average. One Plus offers the highest amount of RAM in general, while Celkon offers the least.
- Customers specifically look for good front cameras to click cool selfies can consider Huawei as go-to brand as they offer many phones across different price ranges with powerful front cameras.

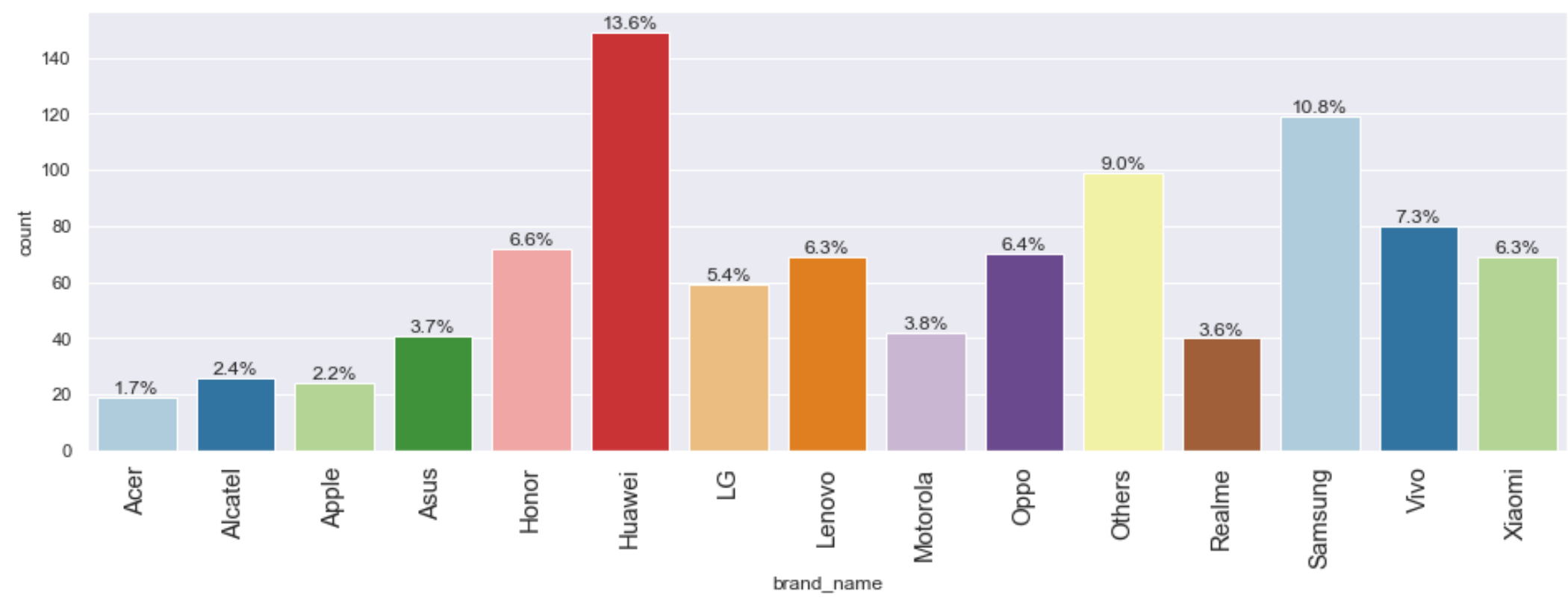


# EDA: Large Battery



- Weight of devices with battery capacities higher than 4500mAh are concentrated around 200grams and 400grams.

# EDA: Large Screen



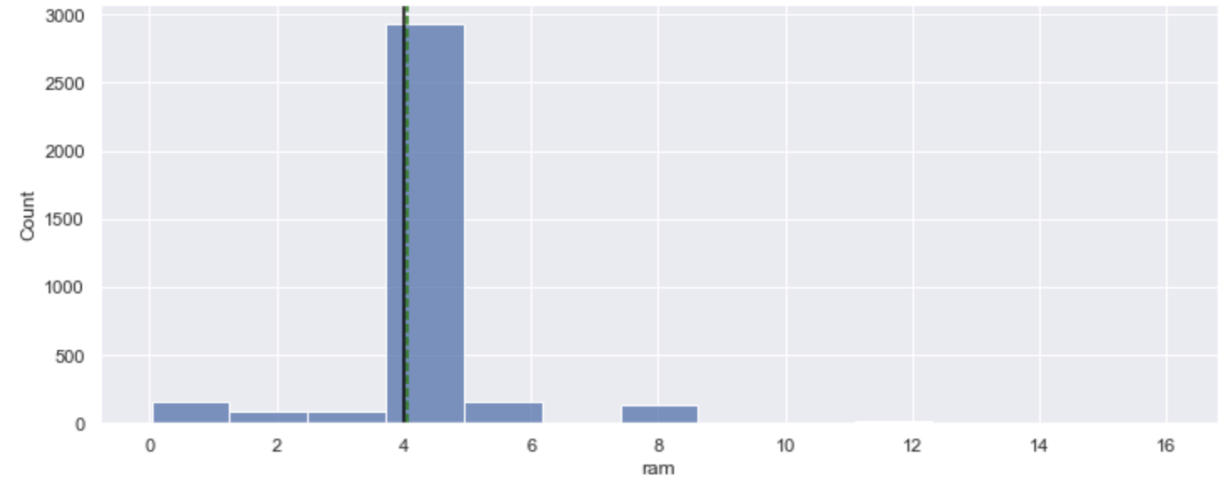
- Huawei and Samsung offer a lot of devices suitable for customers buying phones and tablets with bigger screens for entertainment purposes

# Data Pre-Processing

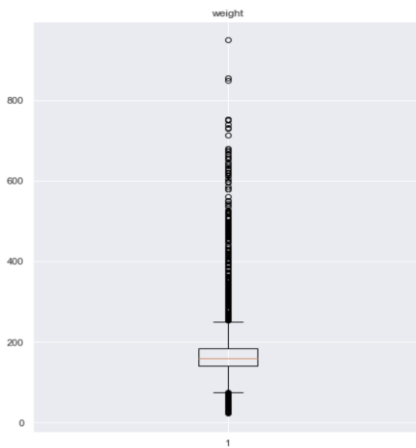
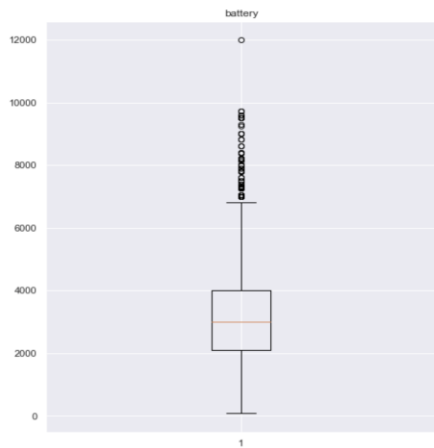
- Duplicate value check
- Missing value treatment
- Outlier check (treatment if needed)
- Feature engineering
- Data preparation for modeling

# Data Pre-processing

- Majority of phones provide a RAM of 4GB with negligible upper and lower outliers. Hence, this was dropped out of consideration while building the model

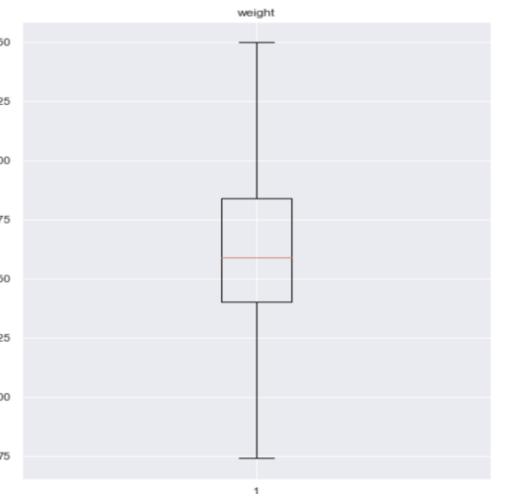
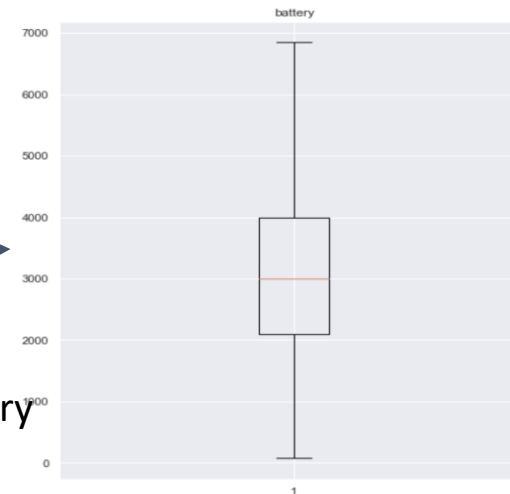


- All numeric columns were further treated for missing values (filled with median value of the column of respective manufacturing brands) as well as for outliers (flooring and capping –  $Q1 - 1.5 \times IQR$  to  $Q3 + 1.5 \times IQR$ )



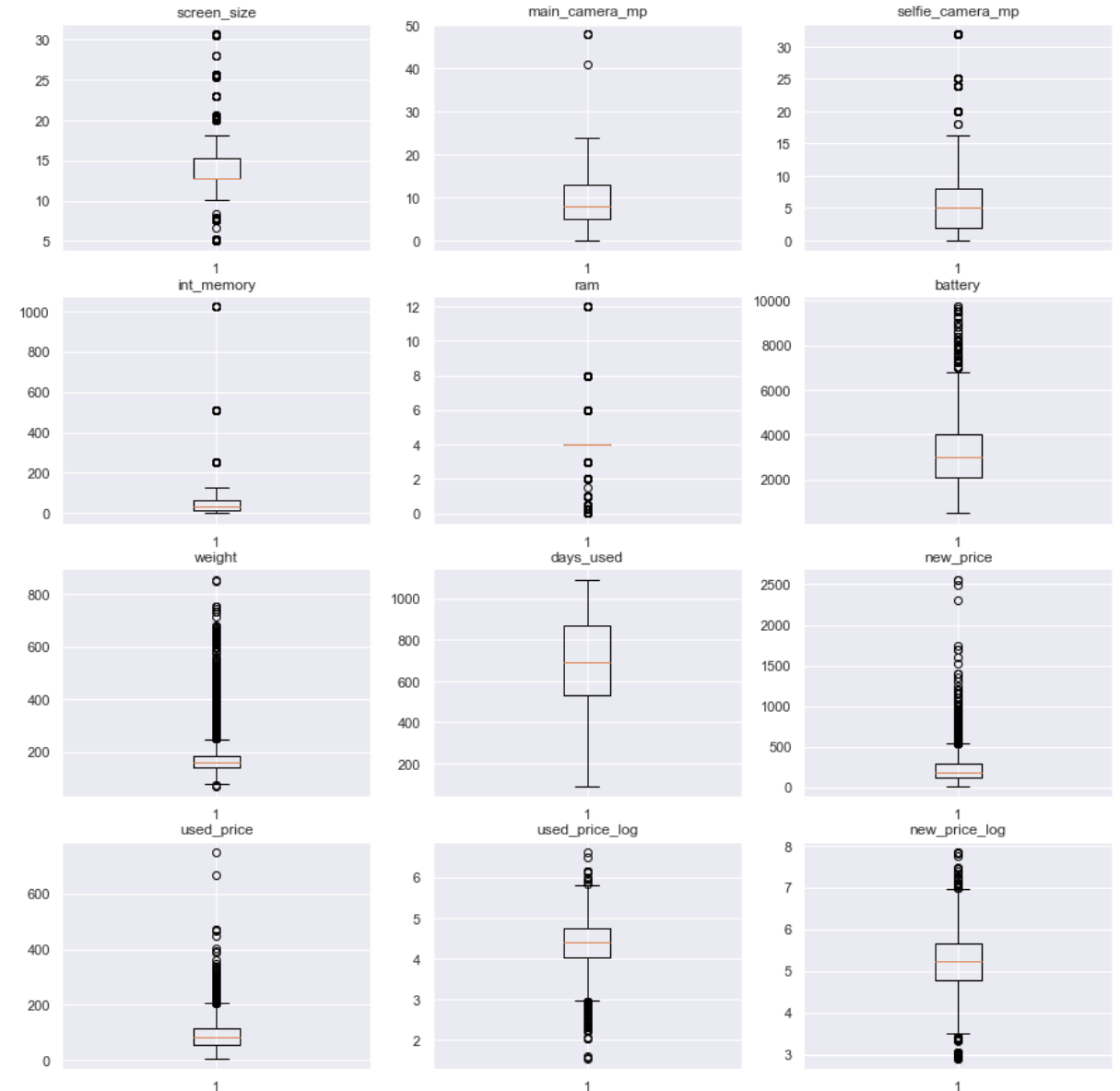
transformation

(missing value & outlier treatment)  
on weight and battery



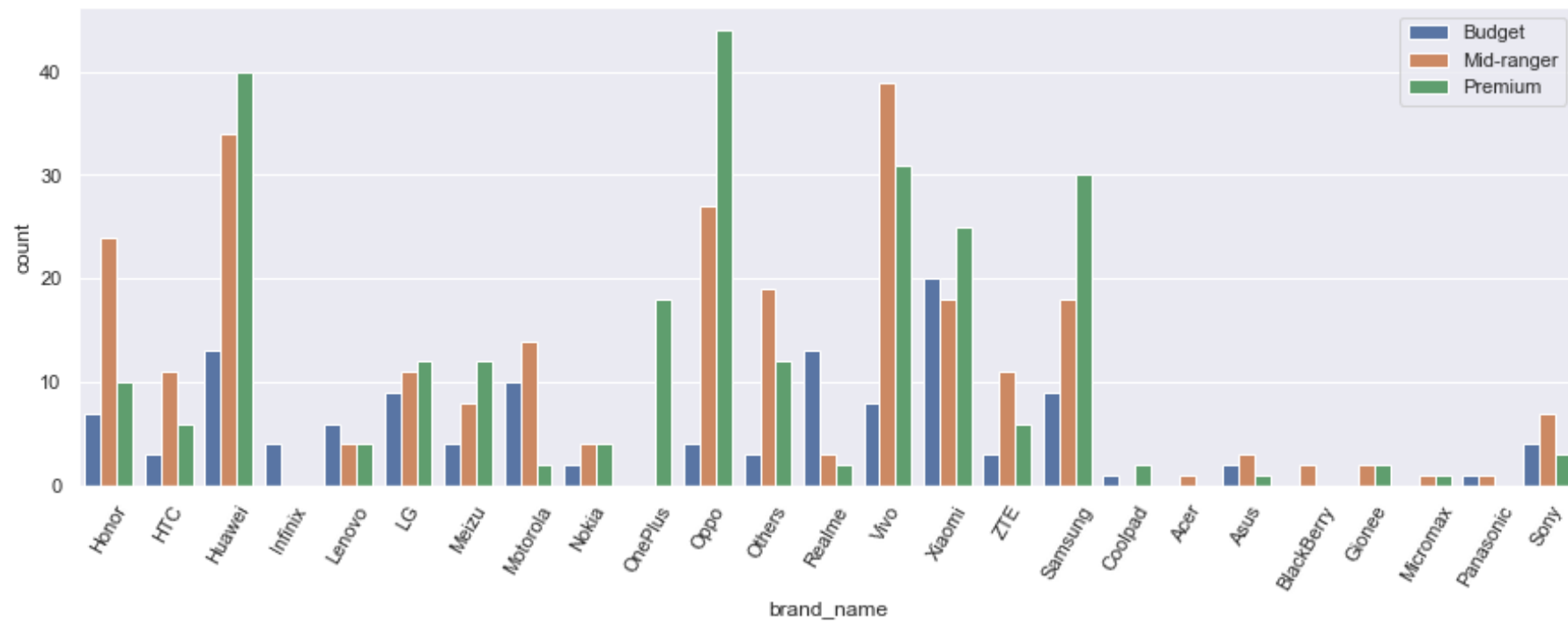
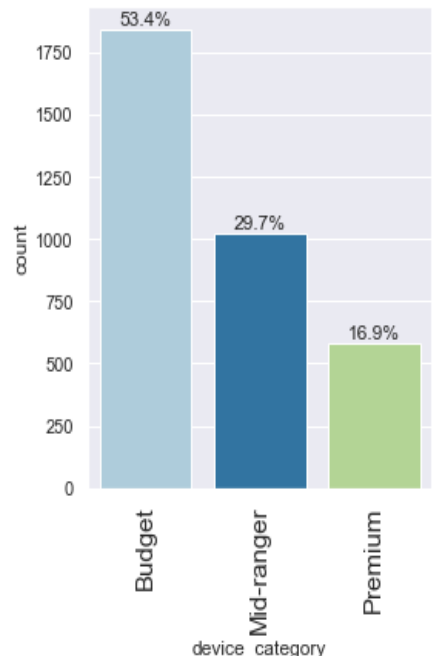
# Data Pre-Processing-Outlier treatment

- We can see that there are outliers in all Distributions as per the 1.5IQR rule, however, we have no reason to believe that these values are invalid.
- Values that appear as outliers might contain valid information about screen sizes, main camera, Ram, Rom, Battery, Weight & Prices.
- One of the reasons might be outlying is the most devices share the same traits, while premium devices have high values for specific features.
- No Outlier treatment was performed in the dataset.



# Data Preprocessing: Feature Engineering

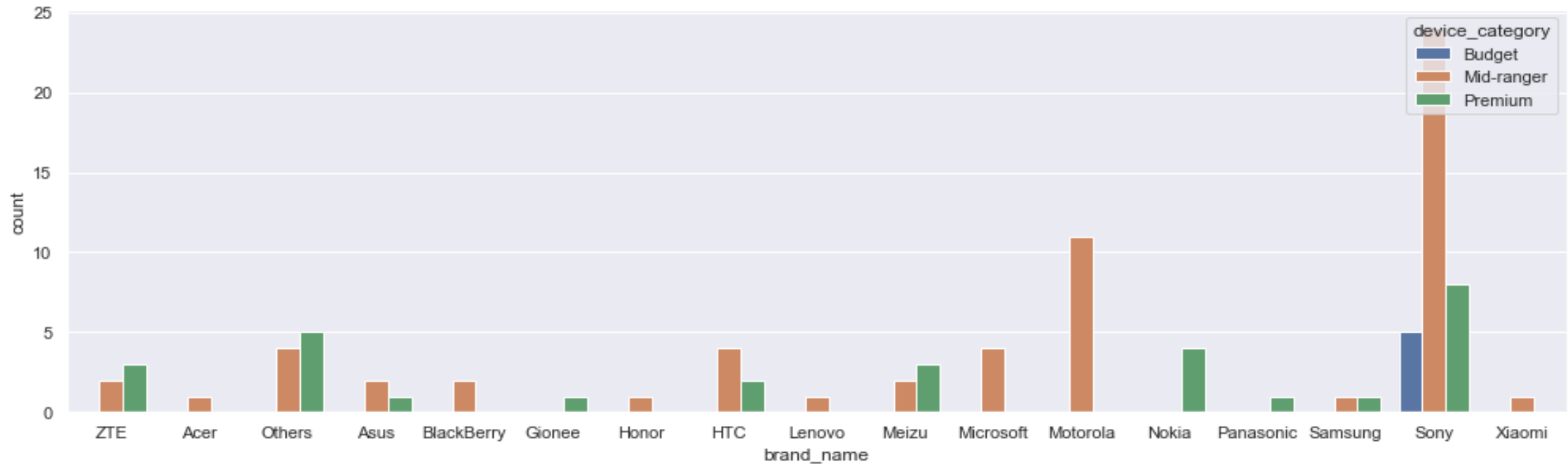
## Camera Resolution above 8MP



- Most devices with selfie camera resolution higher than 8Mpx are in the Mid-Ranger to Premium category, although Budget alternatives can be found across in most of the brands
- Xiaomi stands out as the brand with more Budget devices with selfie camera resolution above 8Mpx in this dataset

# Data Preprocessing: Feature Engineering

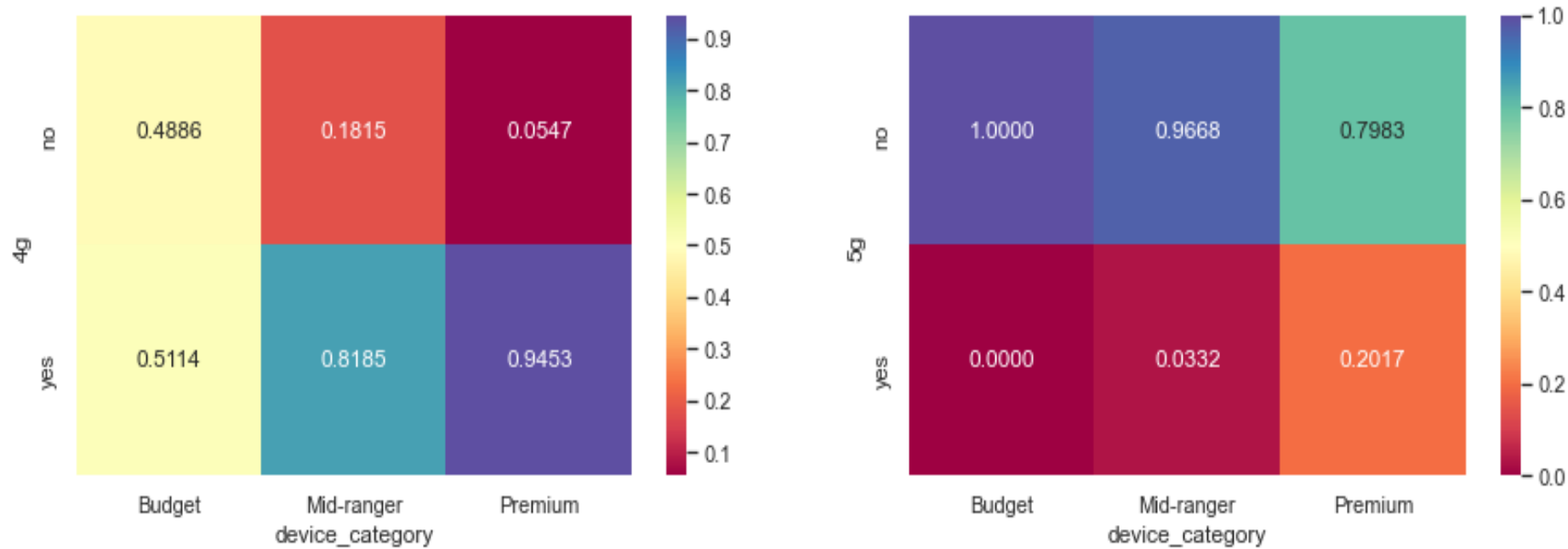
## Camera Resolution above 16MP



- Sony stands out as the only brand with a Budget device with main camera resolution above 16Mpx in this dataset
- Devices with main camera resolutions above 16Mpx are Midrange and Premium devices, Motorola and Sony stand out as the brands with most devices in this category that is focused on clients interested in photography

# Data Preprocessing: Feature Engineering

## Mobile Technology



- 94% of premium devices in this dataset have 4G capabilities, in contrast only 20% of premium devices have 5G
- 48% of Budgets devices have pre 4G technology, while only 18% and 5% of Midrange and Premium devices are not 4G
- Very few mid-rangers (~3%) and around 20% of the premium devices offer 5G network



# Data Preprocessing: Data Preparation for Modeling

$$y = a + b_1x_1 + \cdots + b_kx_k$$

- We will build the model for the transformed independent variable  $\ln(\text{used\_price})$  so we drop the not transformed
- We will use the transformed predictor  $\ln(\text{new\_price})$  so we drop the not transformed
- Encoded categorical variables and dropped the first encoded variable as it is redundant
- Split data in to train and test sets with a 70:30 ratio
- Added the intercept for train and test independent variables
- Data is now ready to fit a Linear Regression model!

# Model Performance Summary

- Overview of ML model and its parameters
- Summary of most important factors used by the ML model for prediction
- Summary of key performance metrics for training and test data:
  - Root Mean Squared Error
  - Mean Absolute Error
  - Mean Absolute Percentage Error

# Model Performance Summary

- Model explains 84.2% of the variance in the training set.
- Initial model had 48 predictors, after programmatically dropping predictors with p-values > 0.05 we have 13 predictors
- We can conclude that the model is good for prediction!

## OLS Regression Results

Dep. Variable:	used_price_log	R-squared:	0.842
Model:	OLS	Adj. R-squared:	0.842
Method:	Least Squares	F-statistic:	988.1
Date:	Thu, 03 Feb 2022	Prob (F-statistic):	0.00
Time:	21:29:55	Log-Likelihood:	104.71
No. Observations:	2417	AIC:	-181.4
Df Residuals:	2403	BIC:	-100.4
Df Model:	13		
Covariance Type:	nonrobust		

# Model Performance Summary

- Mean Absolute Error indicates that our current model can predict used phone prices within a mean error of 16.4 euros on the test data.
- MAPE is around 19 on the test data, which means that we can predict within 19% of the price value.

	RMSE	MAE	MAPE
Performance Train Set:	25.586129	16.733439	19.040517
Performance Test Set:	24.088241	16.47575	19.256199

# Model Performance Summary: Coefficients

After removing all coefficients with p-val

- A unit increase in screen size will result in a 2.59% increase in used price
- A unit increase in main camera resolution will result in a 2.14% increase in used price
- A unit increase in selfie camera resolution will result in a 1.40% increase in used price
- A unit increase in RAM will result in a 1.76% increase in used price
- A unit increase in battery will result in a 0.001% decrease in used price
- A unit increase in weight will result in a 0.09% increase in used price
- A unit increase in release year will result in a 2.0% increase in used price
- A 1% increase in new price will result in a 0.42% increase in used price
- A device from Lenovo will result in a 5.04% increase in used price
- A device from Nokia will result in a 7% increase in used price
- A device from Xiaomi will result in a 9% increase in used price
- A device that is not Android nor IOS will decrease used price by 6.8%
- A device having 4G will increase used price by 5.11%

	coef	std err	t	P> t
const	-38.9410	7.287	-5.344	0.000
screen_size	0.0256	0.003	7.764	0.000
main_camera_mp	0.0212	0.001	15.313	0.000
selfie_camera_mp	0.0140	0.001	13.203	0.000
ram	0.0175	0.004	3.950	0.000
battery	-1.507e-05	7.1e-06	-2.122	0.034
weight	0.0009	0.000	7.177	0.000
release_year	0.0199	0.004	5.516	0.000
new_price_log	0.4222	0.011	39.125	0.000
brand_name_Lenovo	0.0492	0.021	2.288	0.022
brand_name_Nokia	0.0675	0.031	2.203	0.028
brand_name_Xiaomi	0.0893	0.026	3.498	0.000
os_Others	-0.0704	0.030	-2.356	0.019
4g_yes	0.0499	0.015	3.357	0.001

# Appendix: Data Background

## 5-point summary of Raw dataset

	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

# Appendix: Model Performance

## Model Assumptions: Multicollinearity

OLS Regression Results

Dep. Variable:	used_price_log	R-squared:	0.845
Model:	OLS	Adj. R-squared:	0.842
Method:	Least Squares	F-statistic:	268.7
Date:	Thu, 03 Feb 2022	Prob (F-statistic):	0.00
Time:	21:28:04	Log-Likelihood:	123.85
No. Observations:	2417	AIC:	-149.7
Df Residuals:	2368	BIC:	134.0
Df Model:	48		
Covariance Type:	nonrobust		

	coef	std err	t	P> t	[0.025	0.975]
const	-46.5094	9.199	-5.056	0.000	-64.548	-28.471
screen_size	0.0244	0.003	7.163	0.000	0.018	0.031
main_camera_mp	0.0208	0.002	13.848	0.000	0.018	0.024
selfie_camera_mp	0.0135	0.001	11.997	0.000	0.011	0.016
int_memory	0.0001	6.97e-05	1.651	0.099	-2.16e-05	0.000
ram	0.0230	0.005	4.451	0.000	0.013	0.033
battery	-1.689e-05	7.27e-06	-2.321	0.020	-3.12e-05	-2.62e-06
weight	0.0010	0.000	7.480	0.000	0.001	0.001
release_year	0.0237	0.005	5.193	0.000	0.015	0.033
days_used	4.216e-05	3.09e-05	1.366	0.172	-1.84e-05	0.000
new_price_log	0.4311	0.012	35.147	0.000	0.407	0.455
brand_name_Alcatel	0.0154	0.048	0.323	0.747	-0.078	0.109
brand_name_Apple	-0.0038	0.147	-0.026	0.980	-0.292	0.285
brand_name_Asus	0.0151	0.048	0.314	0.753	-0.079	0.109
brand_name_BlackBerry	-0.0300	0.070	-0.427	0.669	-0.168	0.108
brand_name_Celkon	-0.0468	0.066	-0.707	0.480	-0.177	0.083
brand_name_Coolpad	0.0209	0.073	0.287	0.774	-0.122	0.164
brand_name_Gionee	0.0448	0.058	0.775	0.438	-0.068	0.158
brand_name_Google	-0.0326	0.085	-0.385	0.700	-0.199	0.133
brand_name_HTC	-0.0130	0.048	-0.270	0.787	-0.108	0.081
brand_name_Honor	0.0317	0.049	0.644	0.520	-0.065	0.128
brand_name_Huawei	-0.0020	0.044	-0.046	0.964	-0.089	0.085
brand_name_Infinix	0.1633	0.093	1.752	0.080	-0.019	0.346
brand_name_Karbonn	0.0943	0.067	1.405	0.160	-0.037	0.226
brand_name_LG	-0.0132	0.045	-0.291	0.771	-0.102	0.076
brand_name_Lava	0.0332	0.062	0.533	0.594	-0.089	0.155
brand_name_Lenovo	0.0454	0.045	1.004	0.316	-0.043	0.134
brand_name_Meizu	-0.0129	0.056	-0.230	0.818	-0.123	0.097
brand_name_Micromax	-0.0337	0.048	-0.704	0.481	-0.128	0.060
brand_name_Microsoft	0.0952	0.088	1.078	0.281	-0.078	0.268
brand_name_Motorola	-0.0112	0.050	-0.226	0.821	-0.109	0.086
brand_name_Nokia	0.0719	0.052	1.387	0.166	-0.030	0.174
brand_name_OnePlus	0.0709	0.077	0.916	0.360	-0.081	0.223
brand_name_Oppo	0.0124	0.048	0.261	0.794	-0.081	0.106

After encoding categorical variables, the first model that was fitted had 48 predictors, with an Adj. R-squared of 0.842

## Appendix: Model Performance

### Model Assumptions: Multicollinearity

## OLS Regression Results

Dep. Variable:	used_price_log	R-squared:	0.845
Model:	OLS	Adj. R-squared:	0.842
Method:	Least Squares	F-statistic:	268.7
Date:	Thu, 03 Feb 2022	Prob (F-statistic):	0.00
Time:	21:28:04	Log-Likelihood:	123.85
No. Observations:	2417	AIC:	-149.7
Df Residuals:	2368	BIC:	134.0
Df Model:	48		
Covariance Type:	nonrobust		

After checking this model for multicollinearity most predictors in this model have high variance inflation factor confirming that the model have strong multicollinearity issues.

For the Final model we dropped all predictors with  $P > 0.05$  ,This Reduced the model from 48 predictors to 13 predictors.

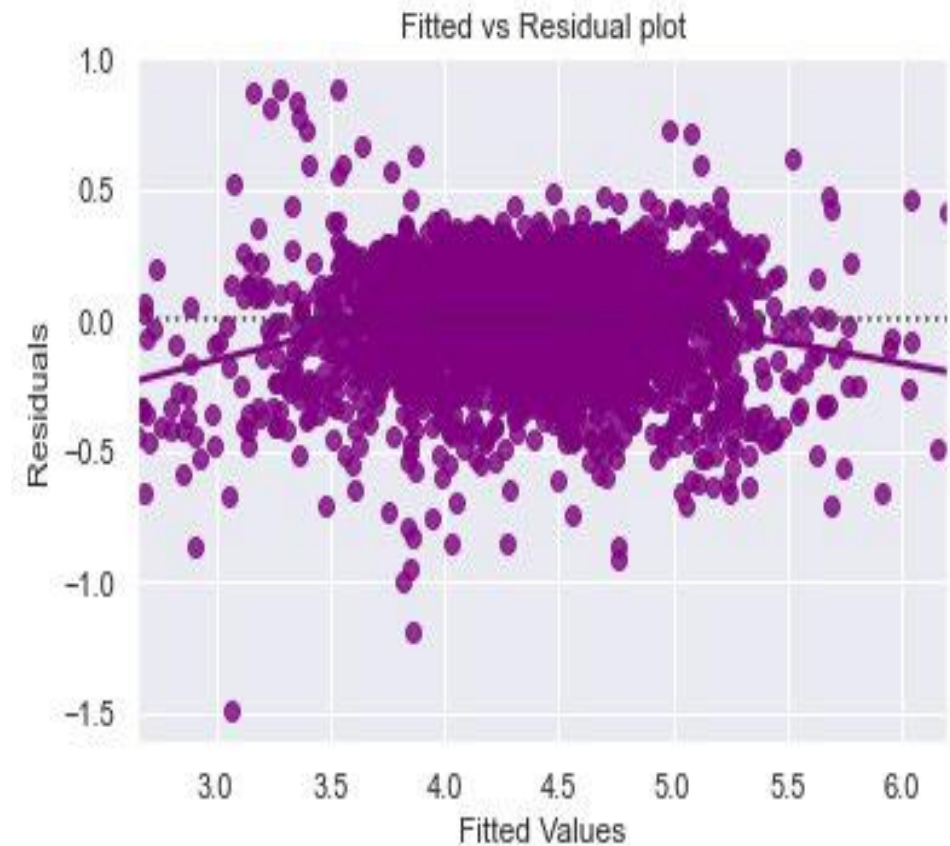
brand_name_Oppo	0.0124	0.048	0.261	0.794	-0.081	0.106
brand_name_Others	-0.0080	0.042	-0.190	0.849	-0.091	0.075
brand_name_Panasonic	0.0563	0.056	1.008	0.314	-0.053	0.166
brand_name_Realme	0.0319	0.062	0.518	0.605	-0.089	0.153
brand_name_Samsung	-0.0313	0.043	-0.725	0.469	-0.116	0.053
brand_name_Sony	-0.0616	0.050	-1.220	0.223	-0.161	0.037
brand_name_Spice	-0.0147	0.063	-0.233	0.816	-0.139	0.109
brand_name_Vivo	-0.0154	0.048	-0.318	0.750	-0.110	0.080
brand_name_XOLO	0.0152	0.055	0.277	0.782	-0.092	0.123
brand_name_Xiaomi	0.0869	0.048	1.806	0.071	-0.007	0.181
brand_name_ZTE	-0.0057	0.047	-0.121	0.904	-0.099	0.087
os_Others	-0.0510	0.033	-1.555	0.120	-0.115	0.013
os_Windows	-0.0207	0.045	-0.459	0.646	-0.109	0.068
os_iOS	-0.0663	0.146	-0.453	0.651	-0.354	0.221
4g_yes	0.0528	0.016	3.326	0.001	0.022	0.084
5g_yes	-0.0714	0.031	-2.268	0.023	-0.133	-0.010

Omnibus:	223.612	Durbin-Watson:	1.910
Prob(Omnibus):	0.000	Jarque-Bera (JB):	422.275
Skew:	-0.620	Prob(JB):	2.01e-92
Kurtosis:	4.630	Cond. No.	7.70e+06



# Model Assumptions: Test for linearity and Independence

- We know that after removing linearity from the data, the residuals should not exhibit any pattern, as they should be entirely noise.
- We also know that no point should influence any other point, as noise is random.
- Residual plot is acceptable for us to say that there is no pattern in the residual plot
- Residual plot is acceptable for us as to say that there is independence among the residuals
- This model passes the test for linearity and Independence.



# Model Assumptions: Test for Normality

We want our residuals to be normally distributed, we can Visually explore this by plotting the distribution of residuals Or using a Qqplot with normality in the 45-degree diagonal.

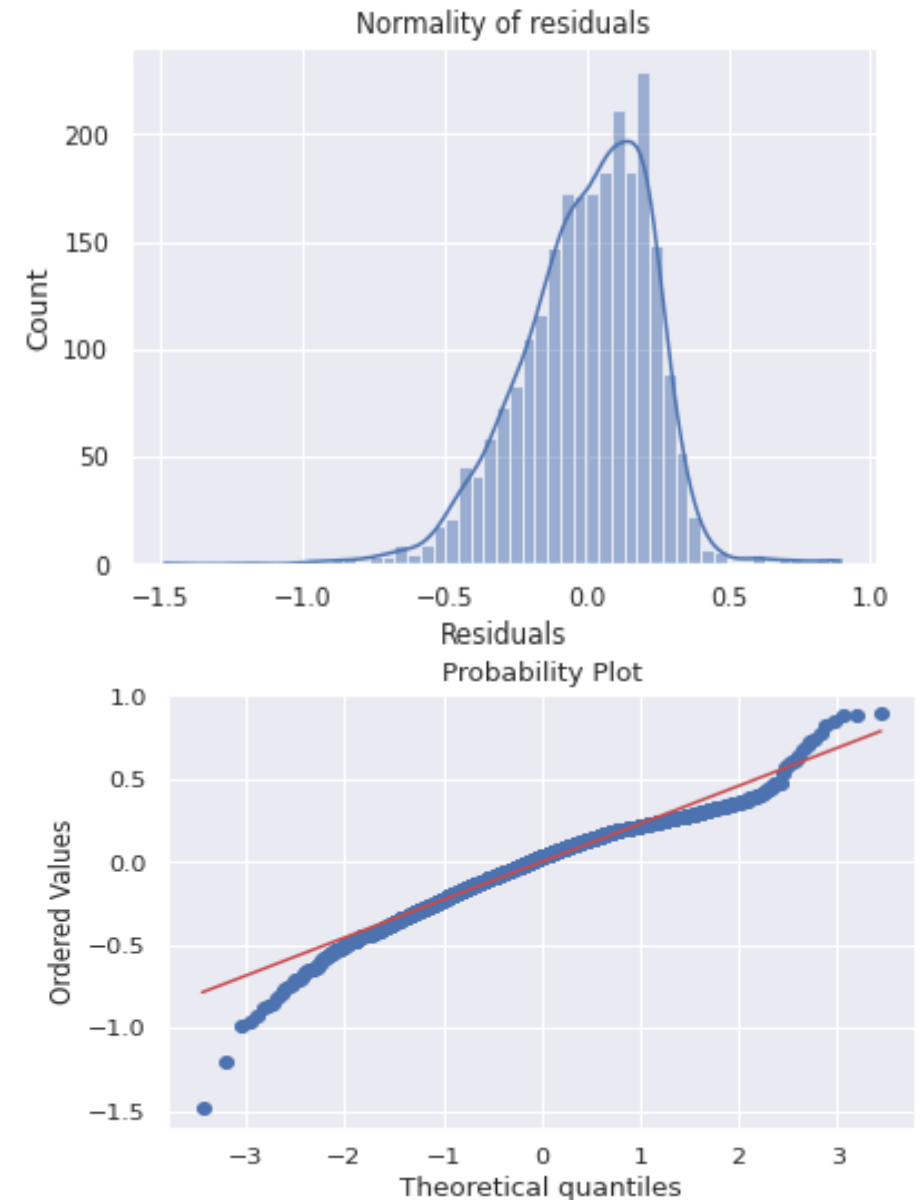
We can also use the Shapiro test; however, this is a Statistical test ,and it tends to be very strict.

- Based on the distribution plot and QQ plot we can accept this residuals as Normally distributed ,as they are close Enough coming from real world data.
- However, this residuals do not pass the Shapiro test this Is because statistical test are very strict.
- For Practical purpose, we accept normality of residuals using visual exploration and the model passes test for normality.

```
In [88]: 1 print("(Test statistic ,          p-value)")
         2 stats.shapiro(df_pred["Residuals"])
         3 ## Complete the code to check p-value
```

```
(Test statistic ,          p-value)
```

```
Out[88]: ShapiroResult(statistic=0.9690961837768555, pvalue=2.130726936518395e-22)
```



# Model Assumptions: Test for Homoscedasticity

## TEST FOR HOMOSCEDASTICITY

- We will test for homoscedasticity by using the goldfeldquandt test.

```
In [89]: 1 import statsmodels.stats.api as sms
          2 from statsmodels.compat import lzip
          3
          4 name = ["F statistic", "p-value"]
          5 test = sms.het_goldfeldquandt(
          6     df_pred["Residuals"], x_train2
          7 ) ## Complete the code to check homoscedasticity
          8 lzip(name, test)
```

```
Out[89]: [('F statistic', 1.0438035947010265), ('p-value', 0.22944475832466343)]
```

Since  $p\text{-value} > 0.05$  we can say that residuals are homoscedastic

All the assumptions of Linear regression are now satisfied.

# Business Insights & Recommendations

- ReCell should look to attract people who want to sell used phones and tablets which have not been used for many days and have good front and rear camera resolutions.
- Devices with larger screens and more RAM are also good devices for reselling to certain customer segments.
- Phones with 4g and Gionee brand phones have lower used price, they seem to not be in demand for customers and should probably be discontinued.
- They can focus on volume for the budget phones and offer discounts during festive sales on premium phones.
- Additional data regarding customer demographics (age, gender, income, etc.) can be collected and analyzed to gain better insights into the preferences of customers across different segments.
- Focus on newer phones with high selfie camera resolution and 5g. There have a favorable impact on used phone prices.

# Summary

The factors that significantly influence the price of refurbished devices in the market are as listed as below:

- Size of the screen of the devices
- Main camera mega pixels
- Selfie camera pixels
- Internal memory
- RAM of the devices
- Price of the similar new device
- Weight of the devices
- Whether the device is a 4G or not
- Operating system