Phase 6 Report: Data Analysis

1. Data Cleaning & Preparation:

We needed to do additional modifications to the data to make it even more suitable for the analytical methods we planned to use.

- We dropped 2 things from the table, careless-ness responses and the columns we wouldn't use or don't have a use for in the analysis itself

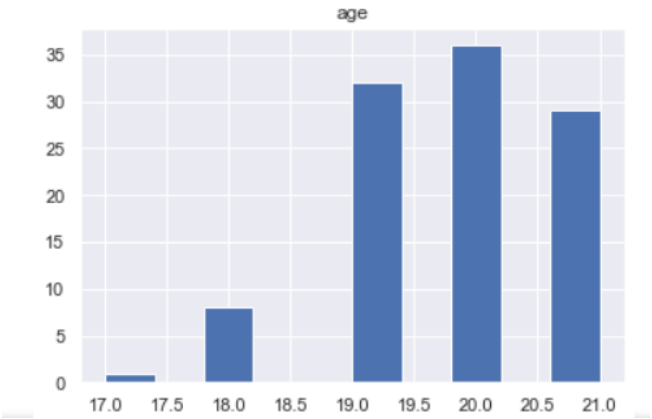
  Such as: ['ID', 'point of view','graphics card model','how powerful from 1_to_5.1', 'main device', 'is it intel ', 'sum of the time spent', 'own DeskTop', 'own Laptop', 'Data scientist?', 'would he chage his device']

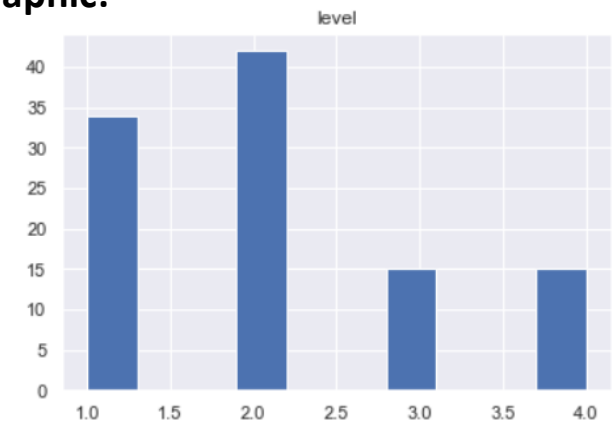
- Cleaned text strings
- Created 2 columns that measure the percentage or the ratio of laptop/pc usage
- Replaced null values in the price column with the average price of all devices
- Replaced null values in the "how powerful is your device" column with average scale of power
- Anyone having +5 devices will be considered as only having 5, for easier scalability.
- Anyone above the age of 21 will be considered as 21, for easier scalability.
- Created 2 columns for visualization's sake, the 2 columns being a ratio for which device you want to rebuy/replace.

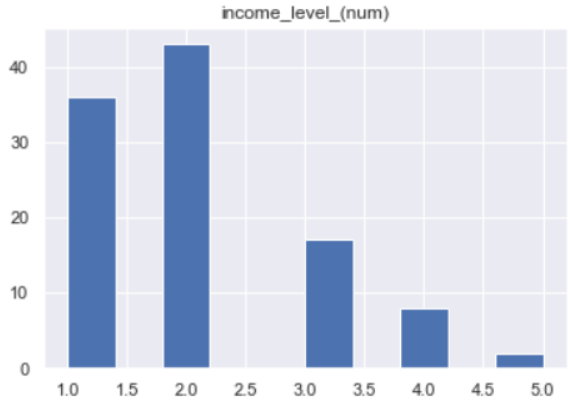
2. Descriptive Statistics:

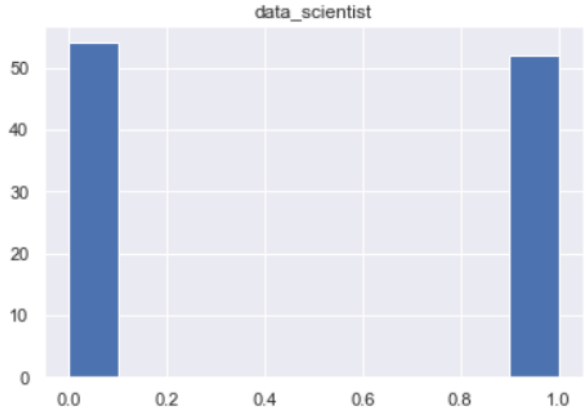
We first took a descriptive look at the data. Visualizing the data that we have using charts and histograms we were able to obtain some insights and knowledge about the data we have. First we made histograms of all important columns that we have:

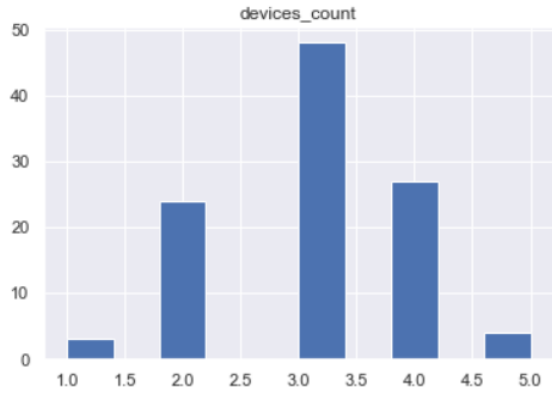
General Information about demographic:

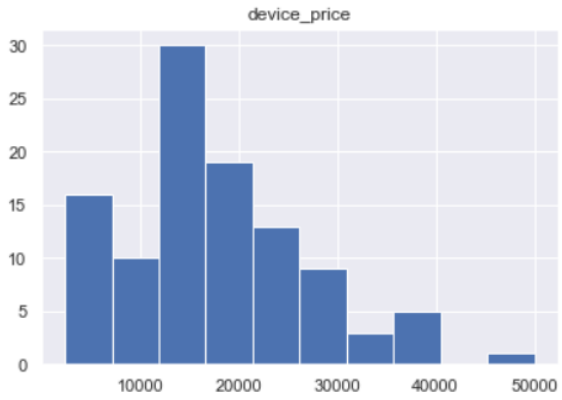




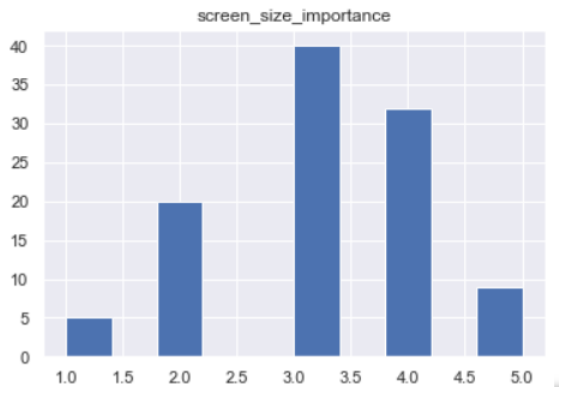


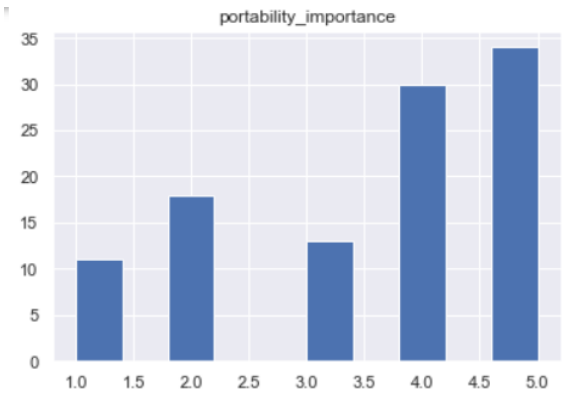




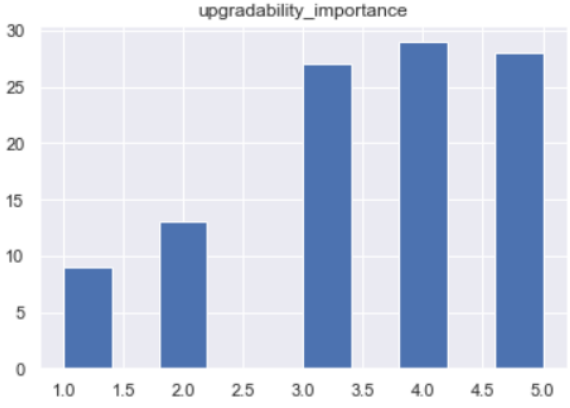


Importance :

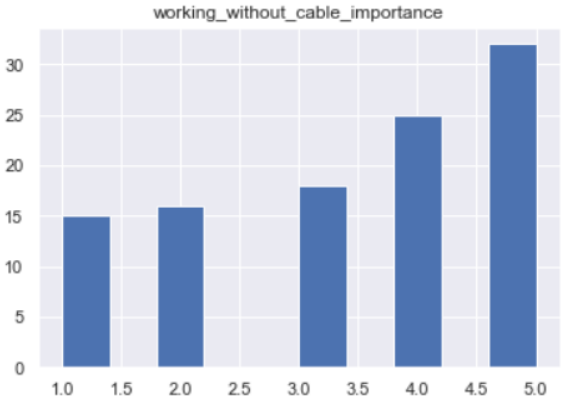




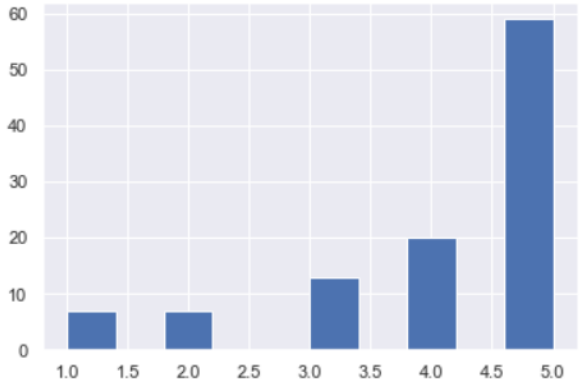
upgradability_importance



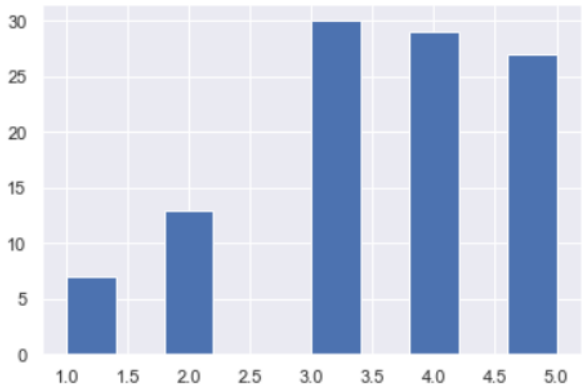
working_without_cable_importance



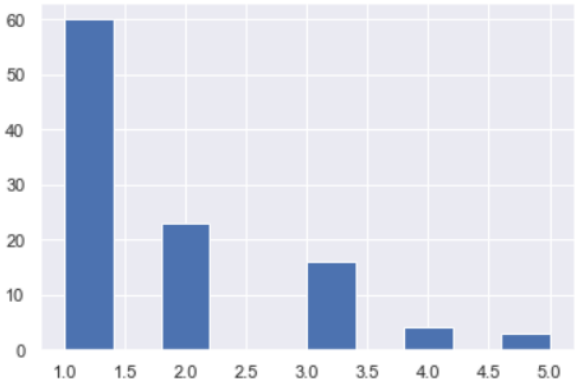
performance_importance



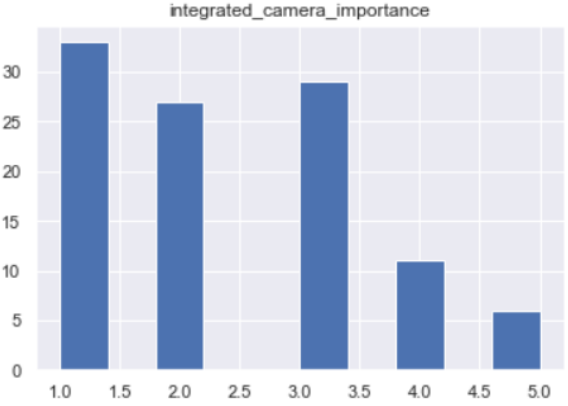
affordability_importance



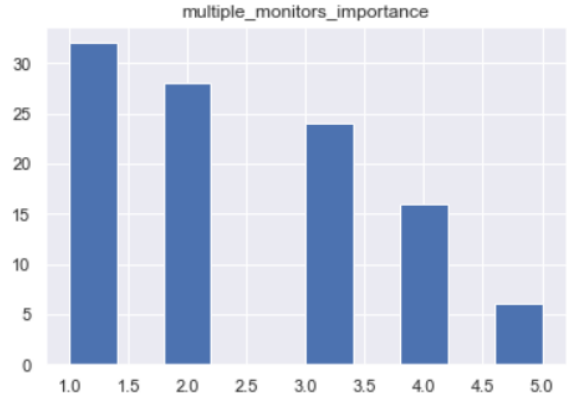
cd_existence_importance



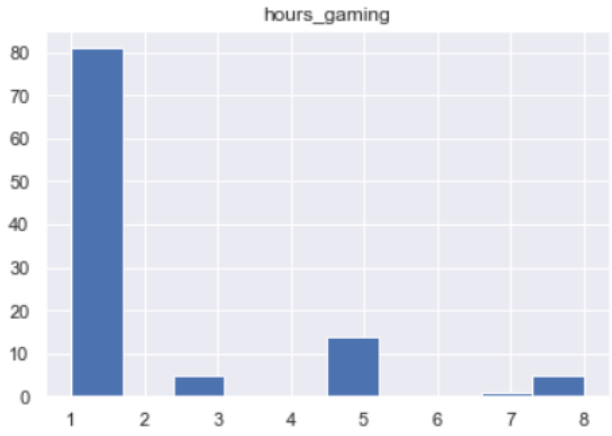
integrated_camera_importance



multiple_monitors_importance



Usage hours:


hours_gaming
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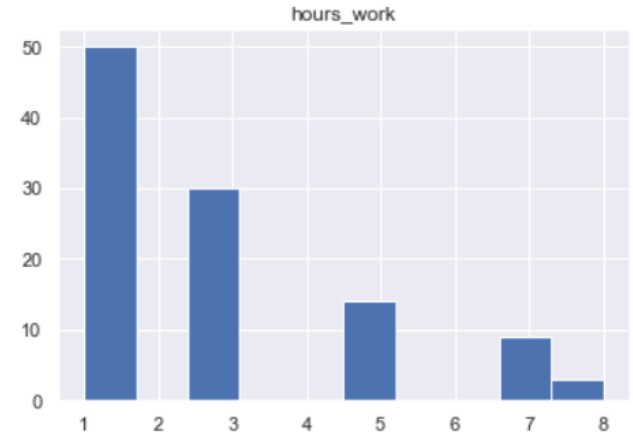
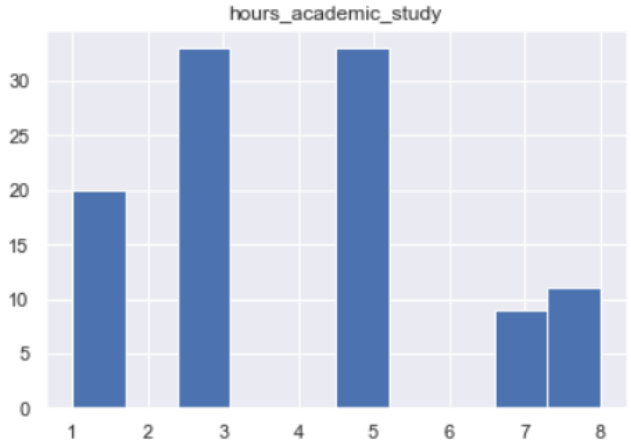
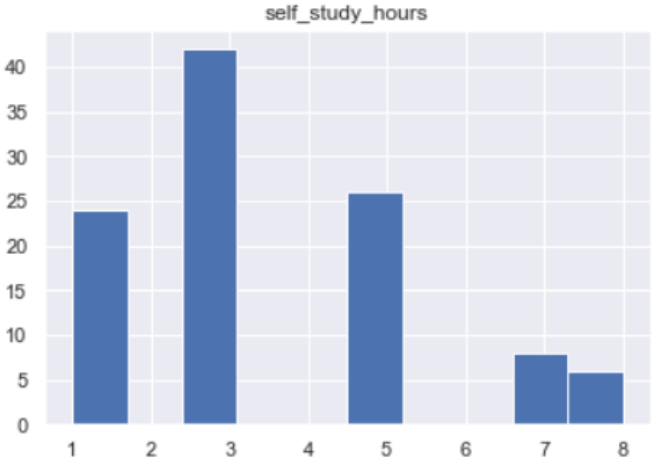
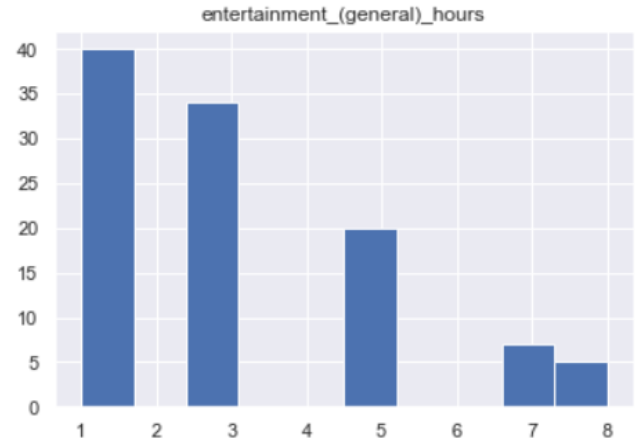
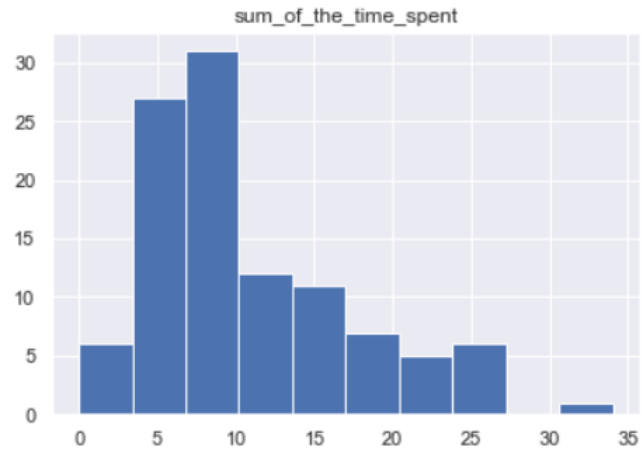
70
60
50
40
30
20
10
0
1
2
3
4
5
6
7
8


hours_work
50
40
30
20
10
0
1
2
3
4
5
6
7
8

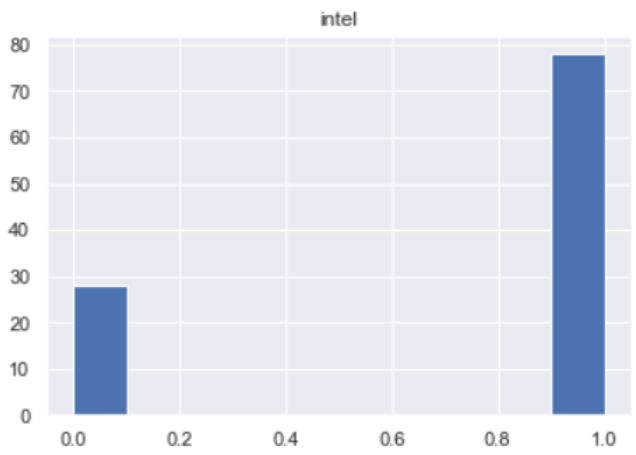

hours_academic_study
30
25
20
15
10
5
0
1
2
3
4
5
6
7
8

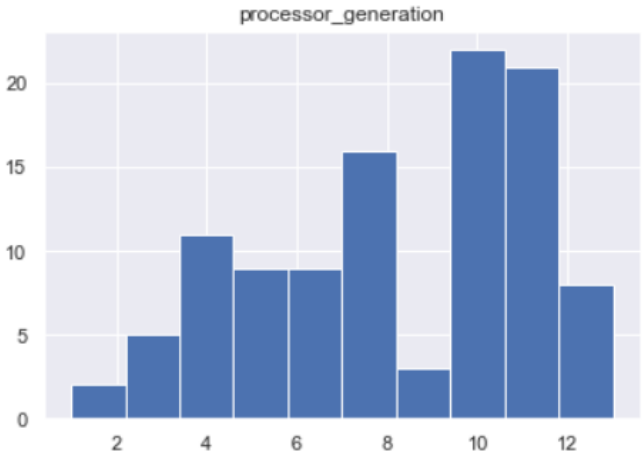

self_study_hours
40
35
30
25
20
15
10
5
0
1
2
3
4
5
6
7
8

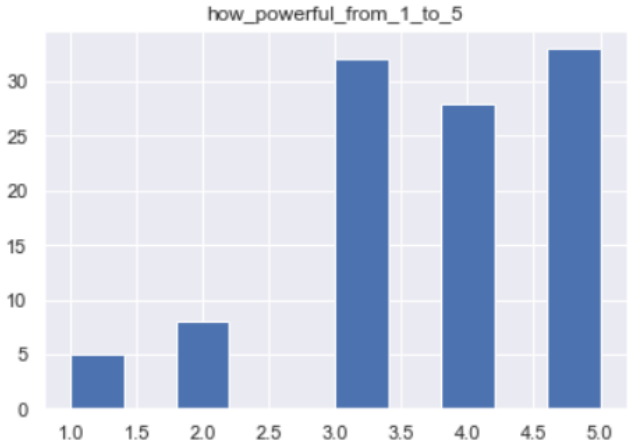

entertainment_(general)_hours
40
35
30
25
20
15
10
5
0
1
2
3
4
5
6
7
8

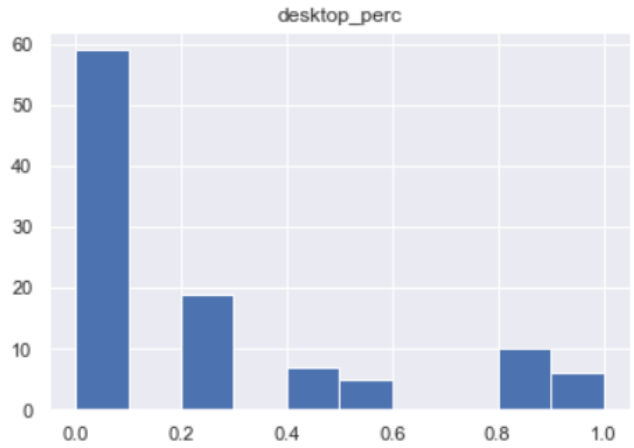

sum_of_the_time_spent
30
25
20
15
10
5
0
0
5
10
15
20
25
30
35

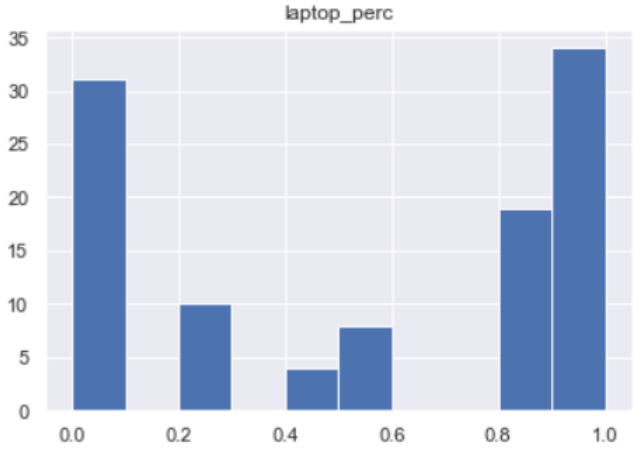
Device related information:

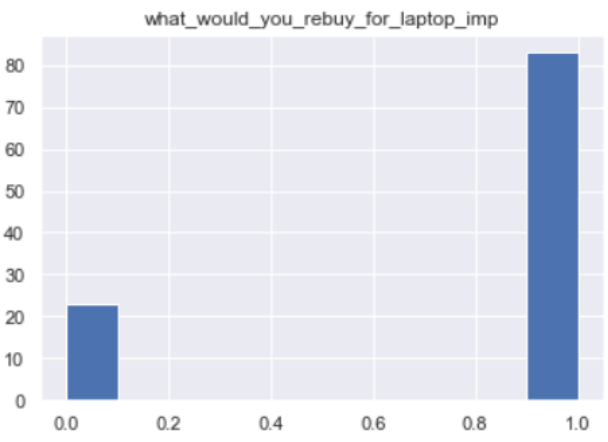


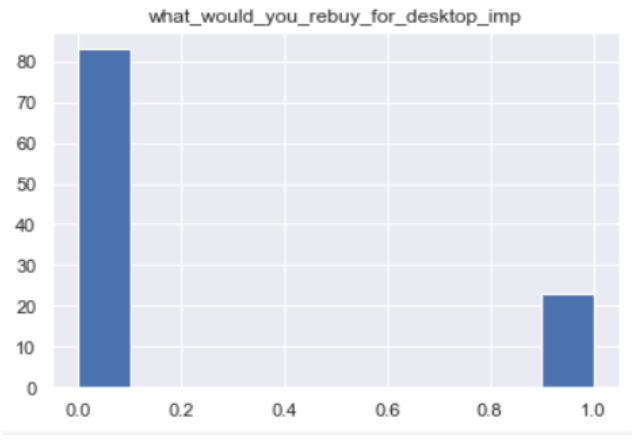






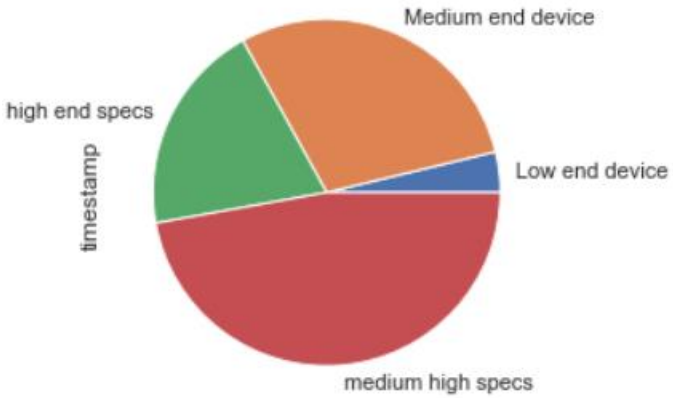




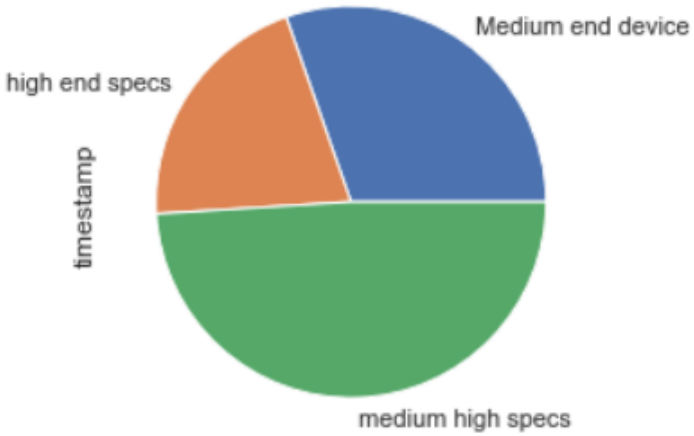


We tried to test the correlation between a few attributes and these are examples of what we found:

- Correlation coefficient between people who would rebuy a laptop and hours spent gaming was -0.4129, which means the more hours people spend on gaming, the more they are likely to get a PC instead.
- We found a very high correlation value between the portability of the device and the need to work without a cable, the value was 0.7188
- Looking for more information about device performance:



We see that the sampling is not representative enough for low end devices, which is expected given that the sample is drawn from Computer science majors and professionals, we focus on analyzing the differences between the other 3 segments:



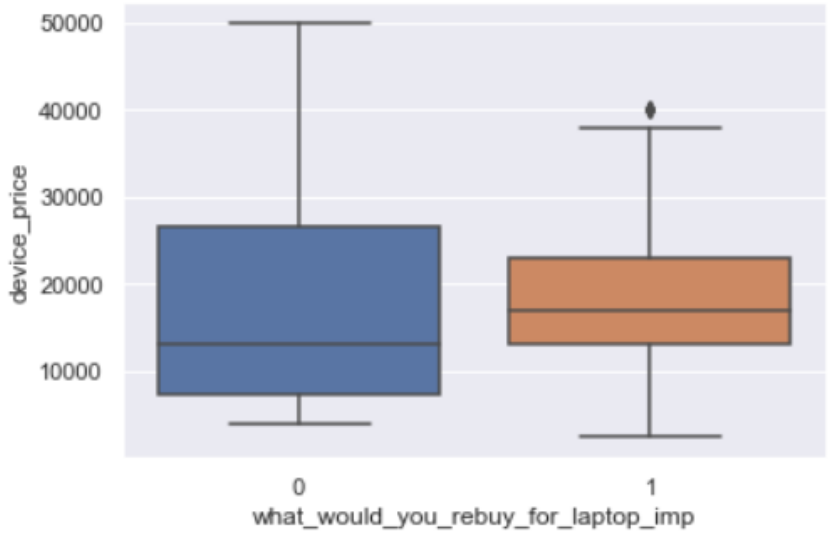
The target audience seems to be in favor of medium high devices.

And when we look at the average prices of each device specs :

```
device_performance
Medium end device    13345.161290
high end specs       26180.952381
medium high specs    16997.000000
```

We see that device price is consistent with device performance.

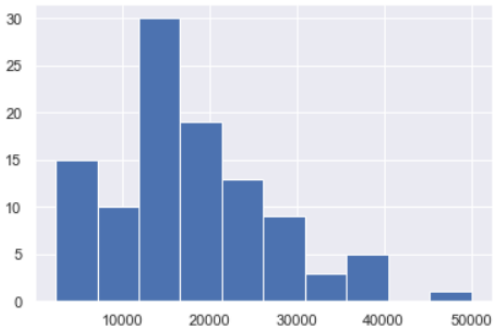
Also:



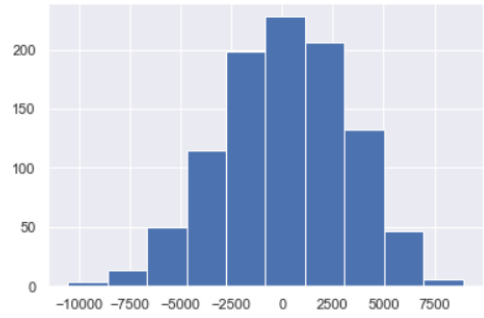
The people who would prefer keeping or rebuying laptops have a higher average income than those who would prefer to buy PCs, yet the price range is shorter which stands out well with general laptop prices.

3.Inferential statistics:

- We tried to find out whether people spend more on laptops or on PCs. We would use the alternative hypothesis, but because the sample size is very small and the distributions are hard to identify, we had to resort to empirical statistical methods. The most suitable here would be **Bootstrap Algorithm**.



These are the results from running the algorithm:



- Bootstrap mean = 110.28260869565234
- Bootstrap confidence interval is constructed by taking the value at
  - (alpha*iterations) and(iteration-alpha*iteration)
- 95% confidence interval for mu1 - mu2:
  [-5252.17391304348 , 5250.0]
- The bootstrap hypothesis test is performed by checking whether the value for the variable lies within the acceptance region or not, since the null hypothesis states that $\bar{X}=0$ where $\bar{X}=\mu 1-\mu 2$, and 0 lies inside the acceptance region, therefore we do not have enough evidence to reject the null hypothesis, that people tend to spend more on one device than another.

- We also tried to find out if the two variables, gender and purchase choice, are dependent. So we used **Chi-Square Test (95% confidence level)**.
  $H0$: The gender has no relationship with one's purchase choice.
  $H1$: The two variables, gender and purchase choice, are dependent.

  - The p-value we extracted was 0.12639457846098398
  - Since p-value = 0.12639 > α, we cannot reliably reject the null hypothesis. **There is not enough evidence to say that the two variables, gender and purchase decision are dependent.**

- We conducted a similar test for age and purchase decision. **(95% conf)**

  - P-value = 0.4463577738771113
  - Since p-value = 0.44635 >α, we cannot reliably reject the null hypothesis. **There is not enough evidence to say that the two variables, age and purchase decision are dependent.**

- When we did the same thing with the factors matrix, this is what we gathered. Since all the variables are ordinal, we use the chi-square test to test all of them for dependency.
    - With alpha = 0.05, the only two factors that show dependency is how much a user cares about portability and working without cable, which are highly correlated because the latter is part of the first.
    - Using alpha = 0.1, we can be at least 90% confident that the screen size also shows dependency.
    - For other tests, there is not enough evidence for dependency.
    - Other factors will be checked through logistic regression analysis.

4.Model building and interpretation:

- Dropped ['working_without_cable_importance', 'affordability_importance', 'processor_generation'] columns due to multicollinearity
- The main statistical algorithm used is **Logistic Regression**, to obtain odds ratio in the presence of more than one explanatory variable based on prior observation of a dataset.
- Used **One-hot encoding** from the **sklearn** library, which can be used to transform one or more categorical features into numerical dummy features useful for training machine learning model.
- We split data for training and testing.
- Upon testing the model we found:
    - The accuracy is better than the baseline.
    - We evaluated the model, and we can see that it's valuable. Now we can use the whole data for training.
- Using the model for the entire dataset the results when it comes to importance for Laptops were:
    - The 'portability importance' is the most effective feature for increasing the odds of buying a laptop as the next device. An increase of the 'portability importance' feature by one unit increases the odds of buying a laptop by a factor of 3.5 when all other features remain the same.

- An increase of the 'income level' feature by one unit increases the odds of buying a laptop by a factor of 2.42 when all other features remain the same.
- An increase of the 'laptop usage percentage' feature by one unit increases the odds of buying a laptop by a factor of 2.21 when all other features remain the same.
- An increase of the 'CD existence importance ' feature by one unit increases the odds of buying a laptop by a factor of 1.87 when all other features remain the same.
- Using the device for studying mainly increases the odds of buying a laptop by a factor of 1.74 when all other features remain the same.

- Using the model for the entire dataset the results when it comes to importance for PCs were:
  - The 'desktop usage percentage' is the most effective feature for increasing the odds of buying a desktop as the next device. An increase of the 'desktop usage percentage' feature by one unit increases the odds of buying a desktop by a factor of 2.48 when all other features remain the same.
  - Having a Core i5 processor increases the odds of buying a desktop by a factor of 1.98 when all other features remain the same.
  - An increase of the 'performance importance' feature by one unit increases the odds of buying a desktop as the next by a factor of 1.84 when all other features remain the same.
  - An increase of the 'screen size importance' feature by one unit increases the odds of buying a desktop by a factor of 1.83 when all other features remain the same.
  - Being a Data scientist increases the odds of buying a desktop by a factor of 1.6 when all other features remain the same.