Classifying Mobile Phones

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The Problem Statement

In this report we will try to use the Mobile Price Classification dataset to create a model which can predict the price range of a mobile phone.

We will test different algorithms like ID3, Naive Bayesian, and K-Means and compare their performance.

The Dataset

Dataset has 2000 rows and 21 columns.

Columns

Column Name	Description
battery_power	Total energy a battery can store in one charge measured in mAh.
blue	Has Bluetooth or not
clock_speed	speed at which microprocessor executes instructions
dual_sim	Has dual sim support or not
fc	Front Camera megapixels
pc	Primary Camera megapixels
four_g	Has 4G or not
int_memory	Internal Memory in Gigabytes
m_dep	Mobile Depth in cm
mobile_wt	Weight of mobile phone
n_cores	Number of cores of processor
px_height	Pixel Resolution Height
px_width	Pixel Resolution Width
ram	Random Access Memory in Megabytes
sc_h	Screen Height of mobile in cm

sc_w	Screen Width of mobile in cm
talk_time	longest time that a single battery charge will last when you are
three_g	Has 3G or not
touch_screen	Has touch screen or not
wifi	Has wifi or not

There are no categorical values in the dataset. Every column is numeric.

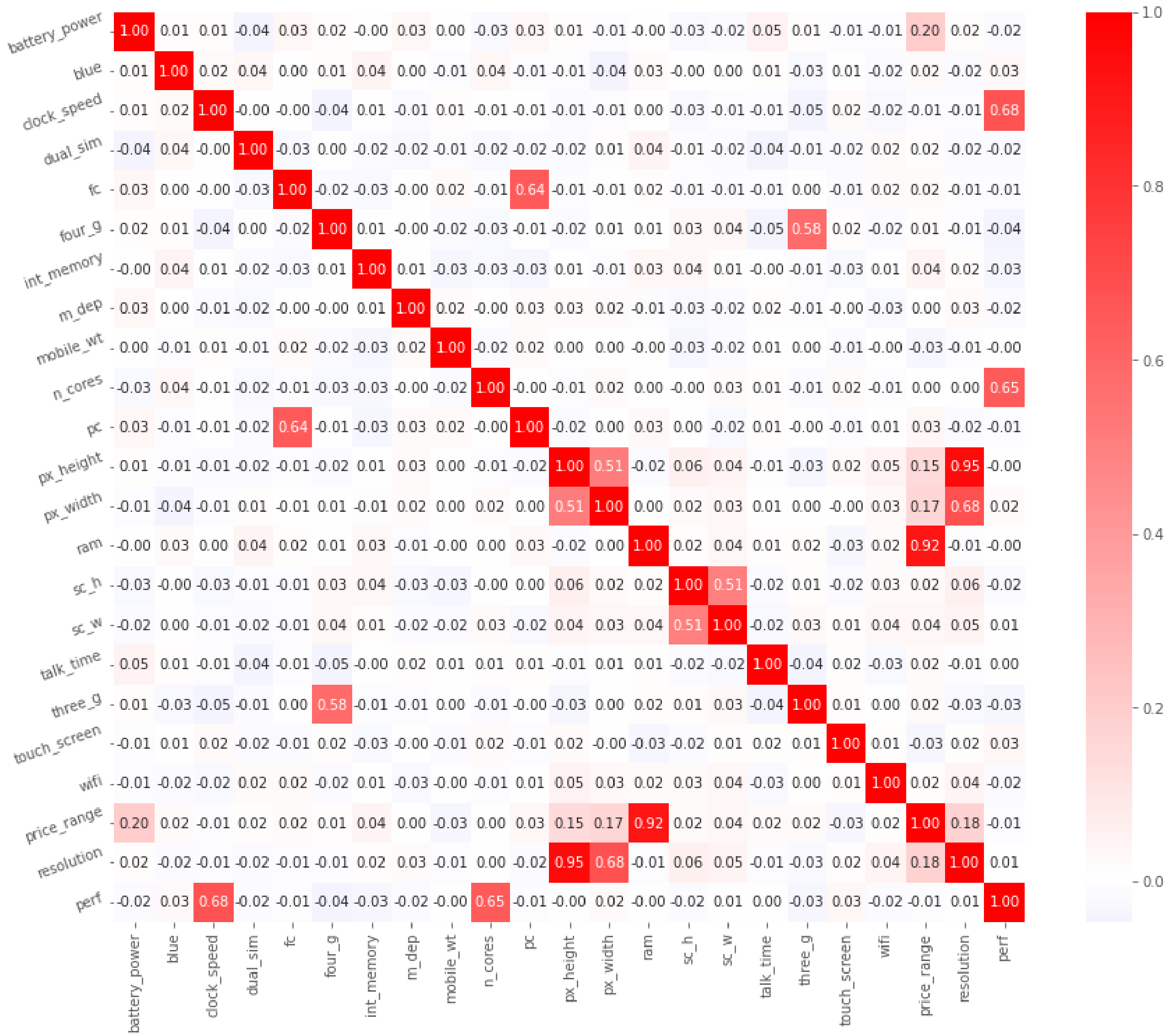
	battery_power	blue	clock_speed	dual_sim	fc	four_g	int_memory	m_dep	mobile_wt	n_cores	pc
1	842	0	2.2	0	1	0	7	0.6	188	2	2
2	1021	1	0.5	1	0	1	53	0.7	136	3	6
3	563	1	0.5	1	2	1	41	0.9	145	5	6
4	615	1	2.5	0	0	0	10	0.8	131	6	9
5	1821	1	1.2	0	13	1	44	0.6	141	2	14
6	1859	0	0.5	1	3	0	22	0.7	164	1	7

px_height	px_width	ram	sc_h	sc_w	talk_time	three_g	touch_screen	wifi	price_range
20	756	2549	9	7	19	0	0	1	1
905	1988	2631	17	3	7	1	1	0	2
1263	1716	2603	11	2	9	1	1	0	2
1216	1786	2769	16	8	11	1	0	0	2
1208	1212	1411	8	2	15	1	1	0	1
1004	1654	1067	17	1	10	1	0	0	1

Overview of the Dataset

Data Visualization

Let’s start by plotting the correlation matrix for our dataset (or the heat map)

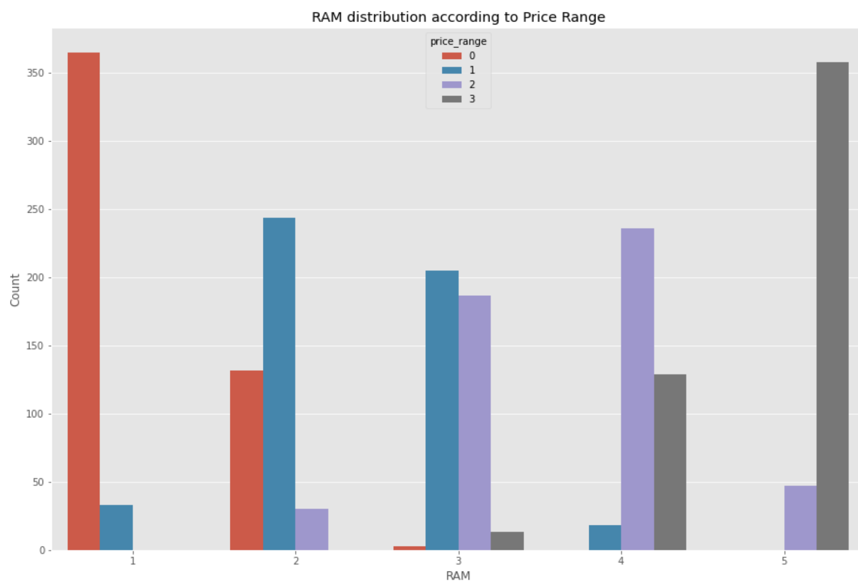


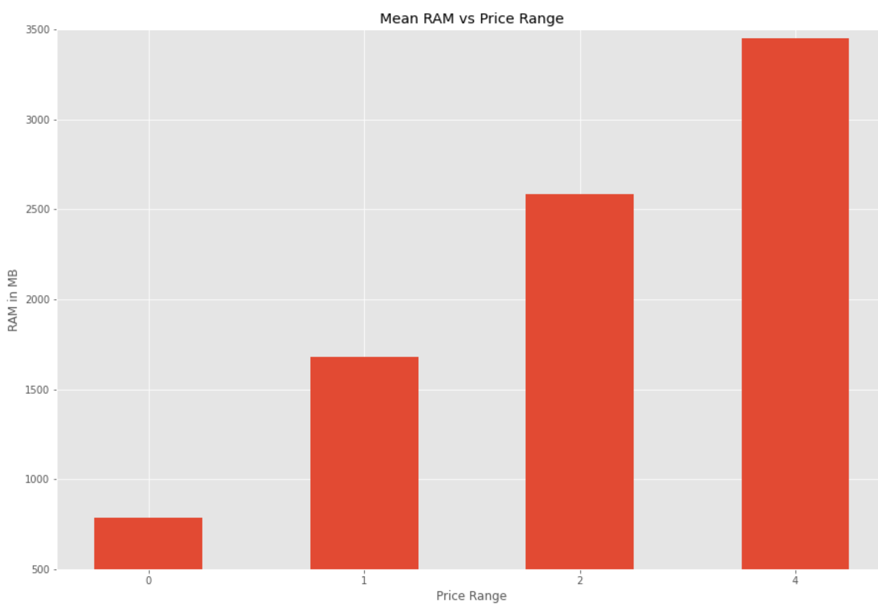
Note : I have added `perf` and `resolution` columns which are `(n_cores * clock_speed)` and `(px_height * px_width)` respectively

Strong correlations exist between the following variables :

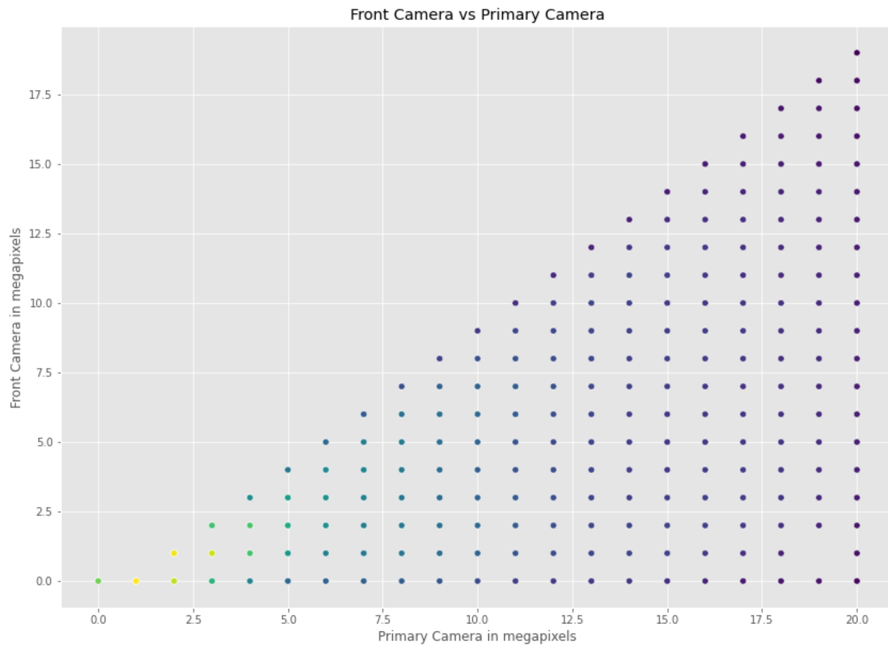
- `price_range` and `ram` have strong positive correlation of 0.92
- `fc` and `pc` have strong positive correlation of 0.64

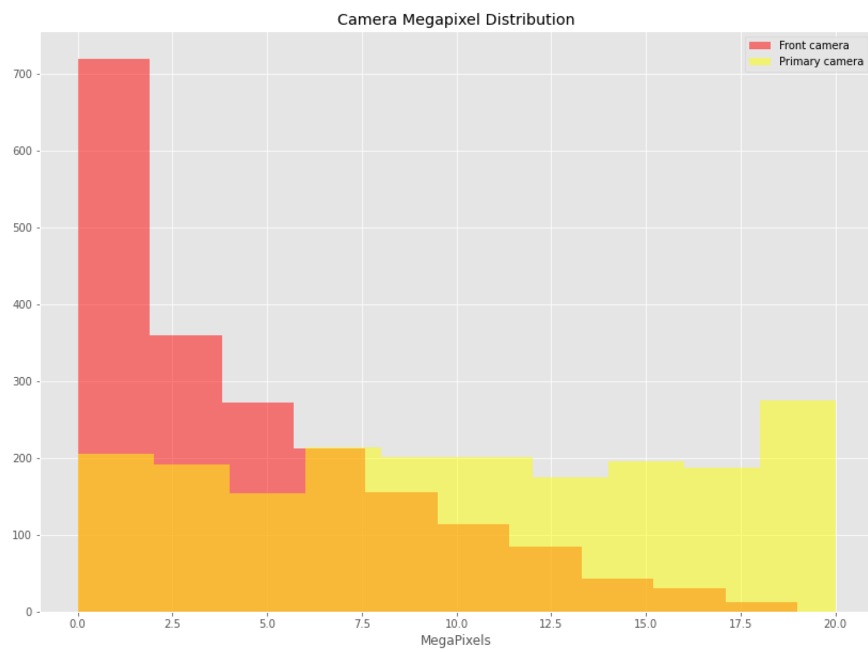
Let's observe the relationship between `ram` and `price_range`



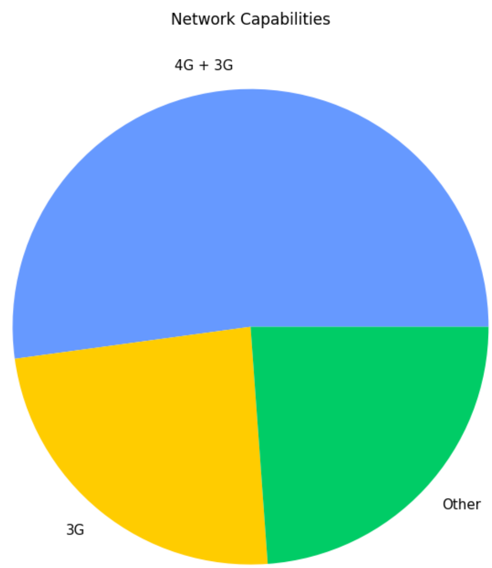


Relationship between `front camera` and `primary camera`

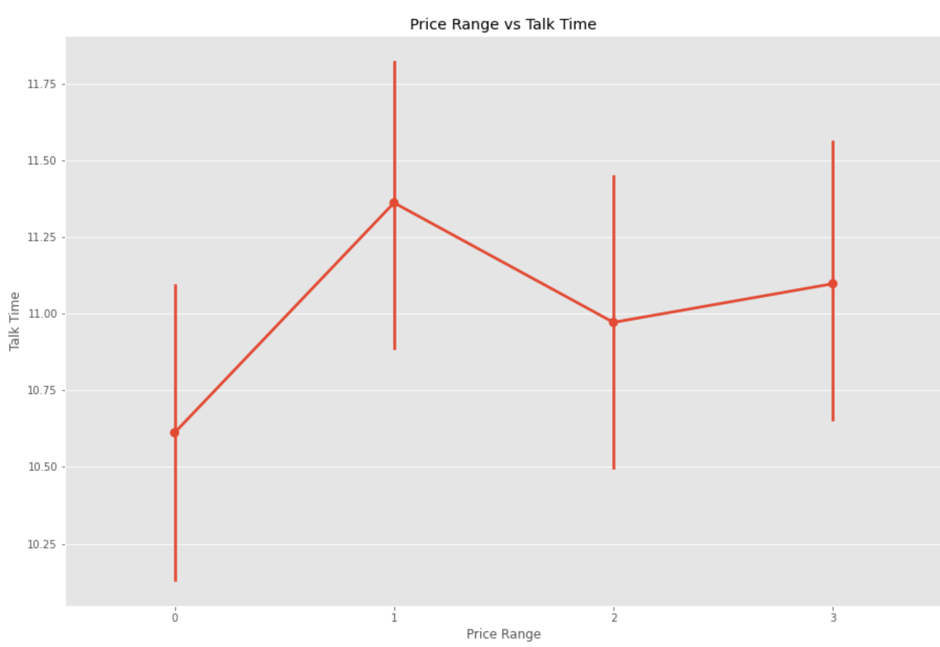




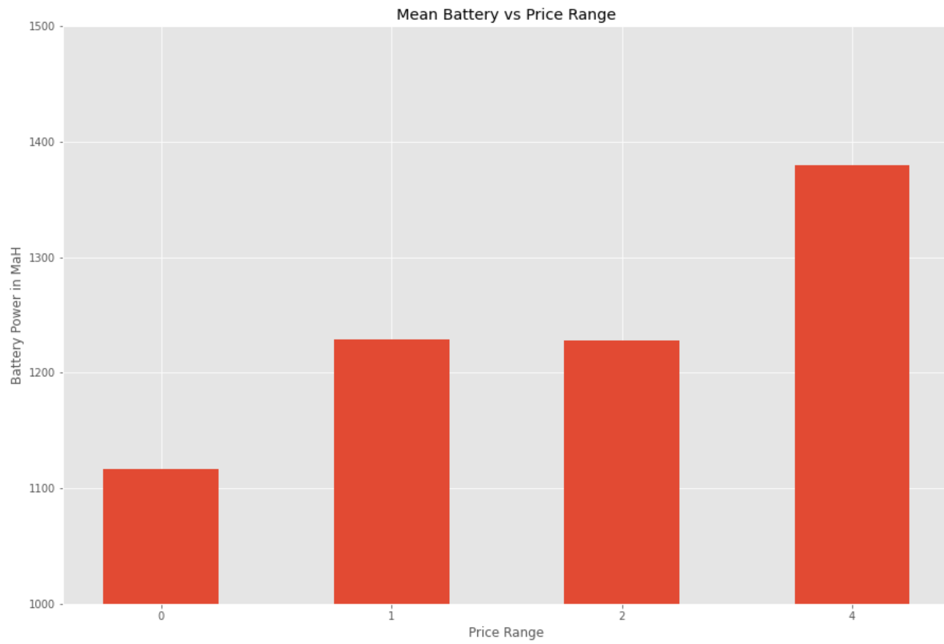
Network capabilities of smartphones



Let’s see how `talk time` changes with `price range`



Let's see how `battery power` changes with `price range`

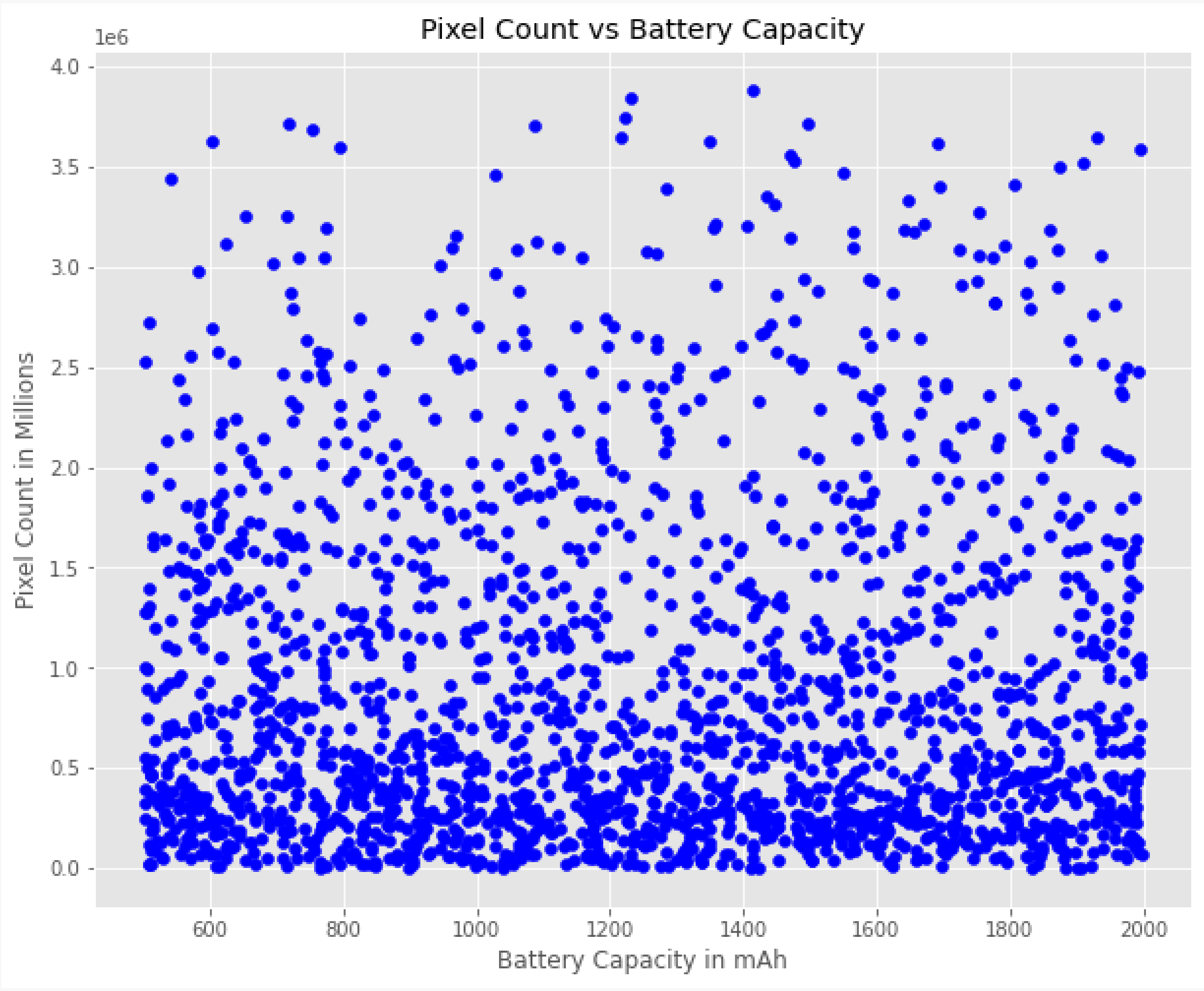


Let's see how `screen resolution` changes with the `price range`.

Case Study

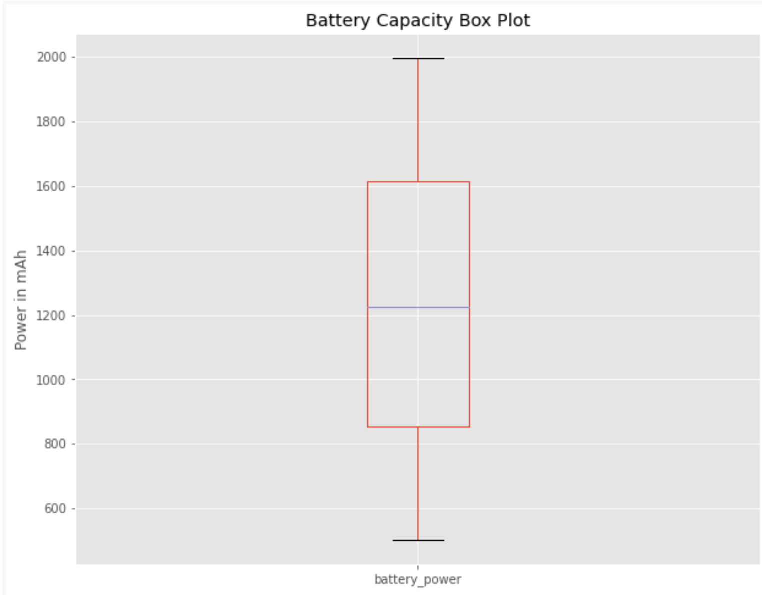
Hypothesis : Battery capacity should show a positive correlation with screen resolution. In modern smartphones, the screen is the major source of power draw accounting for almost [50% of total power use](). To counter this smartphone makers should equip larger screens with bigger batteries.

Let's first draw a scatterplot between `battery_power` and `px_count`

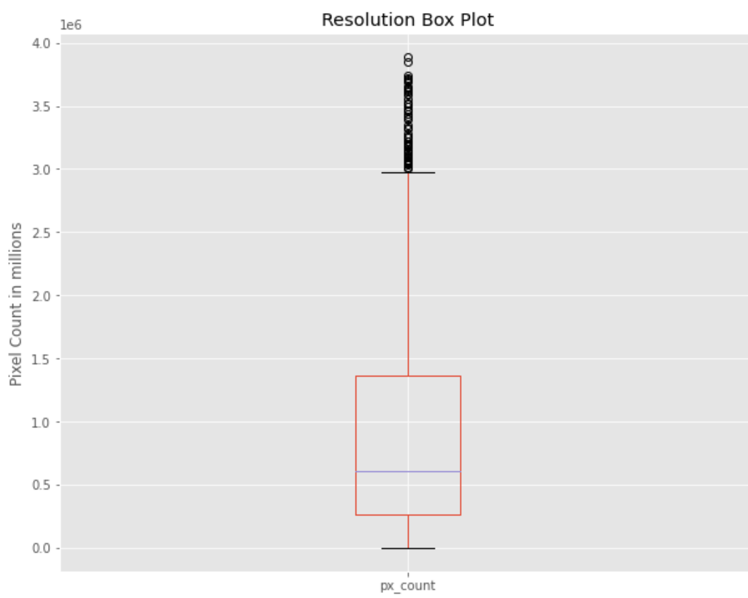


No relation can be seen.

This can be due to outliers in data. Let's check for outliers in `px_count` and `battery_power`



Battery Power variable is distributed normally, and has no outliers. Let's check `px_count`



Large Number of outliers present in `px_count`

Let's remove outliers, by eliminating rows which are not in the interquartile range (IQR).

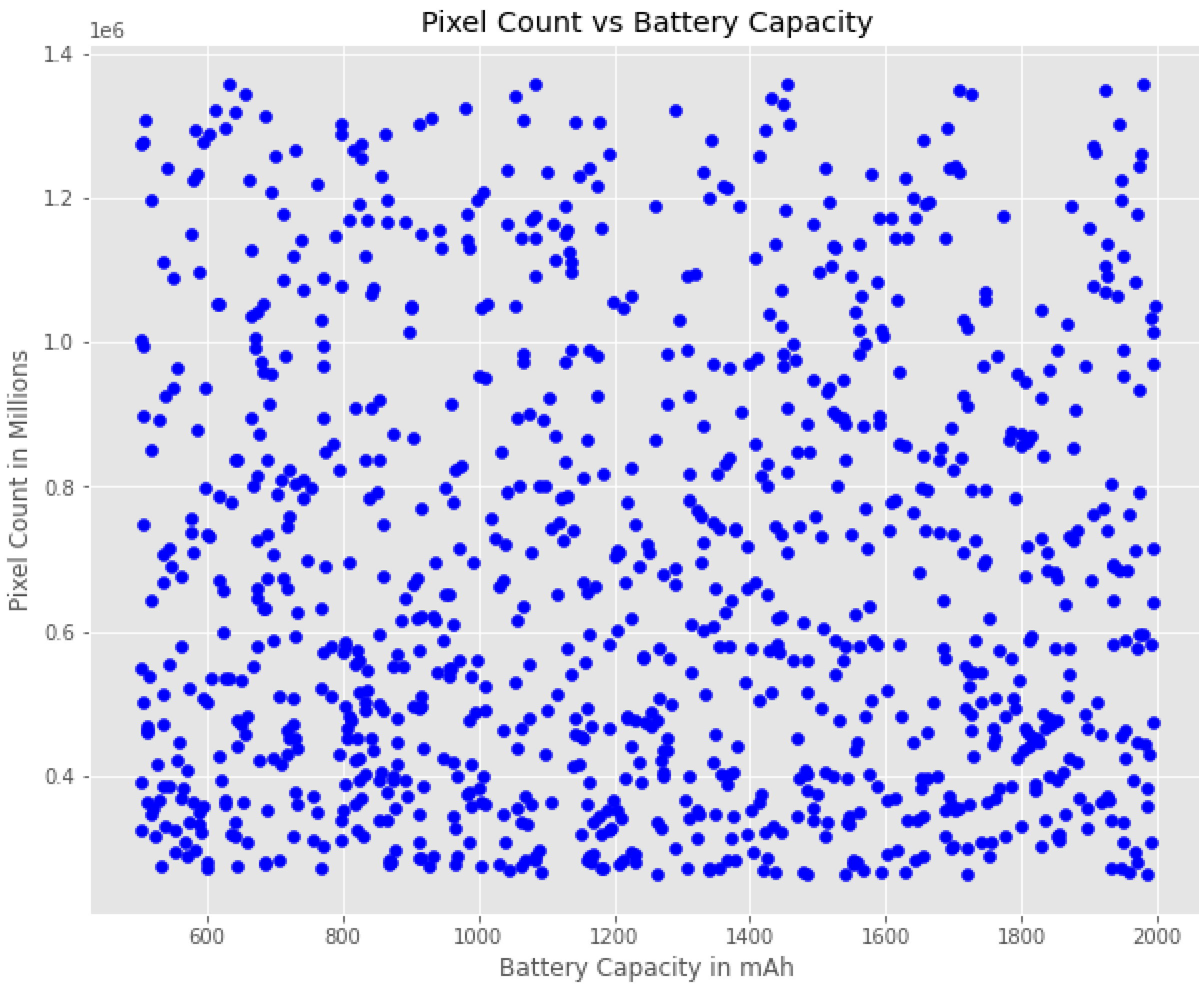
Code

```
per_25 = train["px_count"].quantile(0.25)
per_75 = train["px_count"].quantile(0.75)

iqr = per_75 - per_25
lower_fence = per_25
upper_fence = per_75

print("lower boundary {lower} and upper boundary {upper}\nIQR =
{iqr}".format(lower = lower_fence, upper = upper_fence, iqr = iqr))



pixels = []
battery_cap = []

# removing rows which are not in the interquartile range.
for i in range (len(train)):
    if (train.iloc[i]["px_count"] > lower_fence and
train.iloc[i]["px_count"] < upper_fence):
        pixels.append(train.iloc[i]["px_count"])
        battery_cap.append(train.iloc[i]["battery_power"])

# creating new dataframe with IQR values
pixels_vs_battery = pd.DataFrame()
pixels_vs_battery["px_count"] = pixels
pixels_vs_battery["battery_power"] = battery_cap
```

Output

```
lower boundary 263200.5 and upper boundary 1359027.25
IQR = 1095826.75
```

Let's draw the scatter plot again.



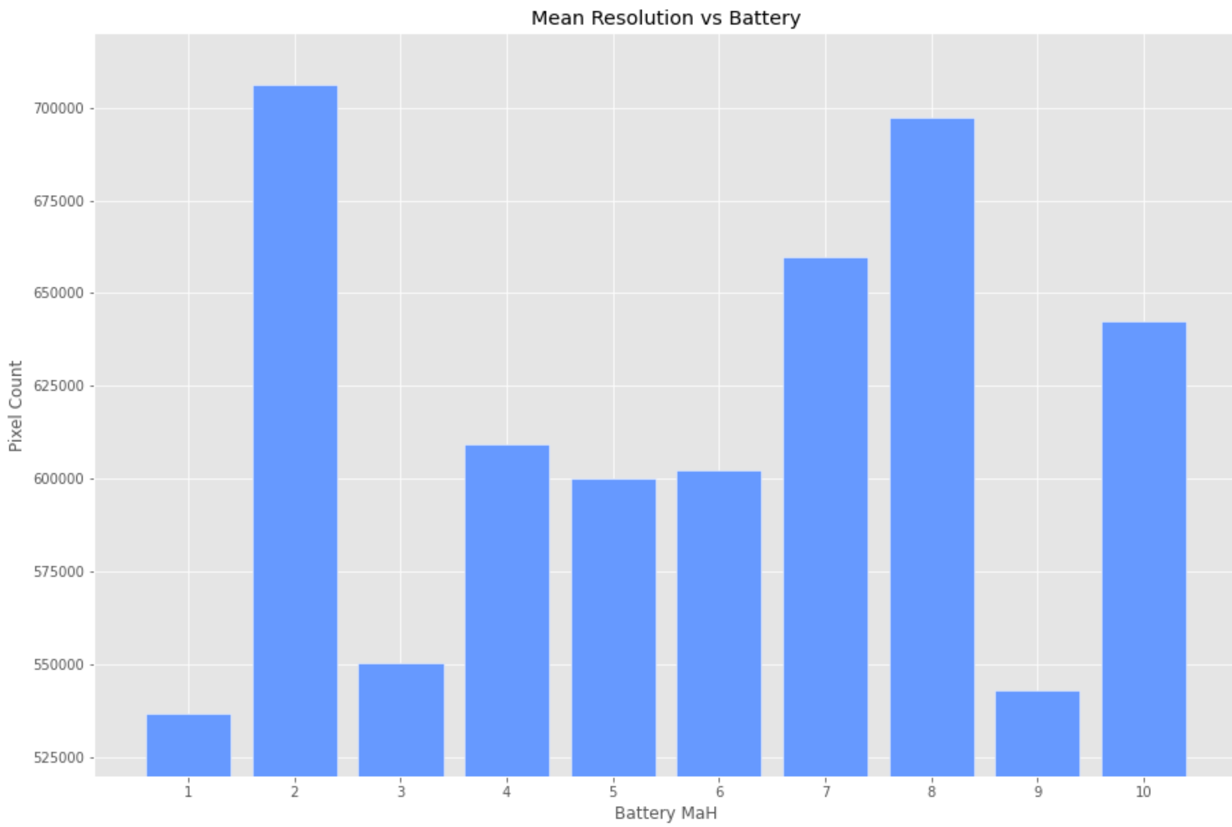
Still no pattern visible.

Finally let's try to plot the median `px_count` per `battery_power` group.

Code

```
pixels_vs_battery['battery_power_category'] =
pd.cut(pixels_vs_battery['battery_power'], bins = 10, labels = [var
for var in range (10)])
# calculating median per battery_power_category
median_res =
pixels_vs_battery.groupby("battery_power_category")["px_count"].media
n()
```

Barplot



A slight increasing pattern can be observed, but many exceptions such as battery group 2 and group 9 are present.

Data doesn't support the hypothesis.

Hypothesis rejected.

Data Preprocessing

- ***Missing Values***

  The dataset is complete. No missing values present.

```
> print(nrow(df) - sum(complete.cases(df)))
[1] 0
```

- ***Encoding Categorical Data***

  Not needed as no categorical data is present in the dataset.

- ***Splitting dataset into Train and Test***

  We have opted for a 80-20 split between train and test.

```
train_idx <- sample(1 : nrow(df), size = floor(0.8 * nrow(df)), replace = FALSE)
train <- df[train_idx, ]
test <- df[-train_idx, ]
```

  Number of rows in train : 1600

  Number of rows in test : 400

- ***Feature Scaling***

  Although feature scaling can be applied in our dataset, we are not planning to use models which require feature scaling like KNN (K-Nearest Neighbours), Neural Networks, Linear Regression, and Logistic Regression.

Model Training

K-Means Clustering

Creating Model

K-means doesn't require the dataset to be split into test and train. So we'll work with a complete dataset df.

```
km<-kmeans(df,4)
```

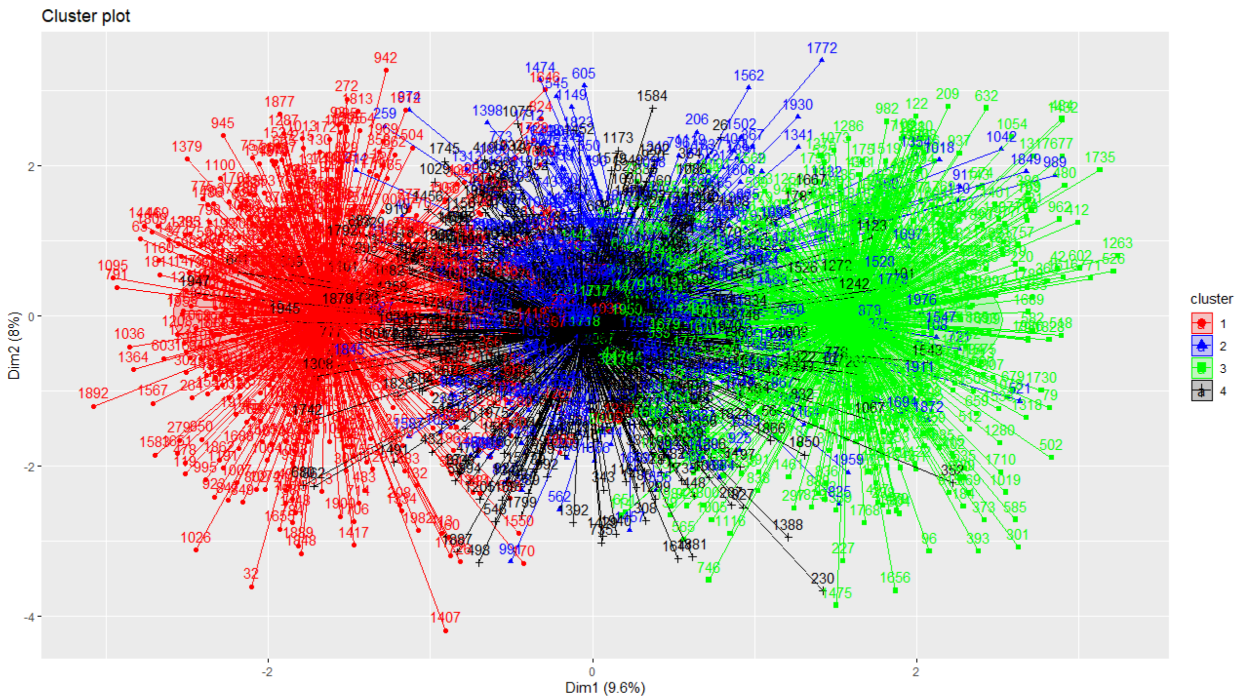
Predicting model and checking accuracy

```
df$price_range<-as.factor(km$cluster)
confusionMatrix(table(price_range,df$price_range))
```

Output

```
Confusion Matrix and Statistics


price_range   1   2   3   4
          1 478   9   0  13
          2 113 175   0 212
          3   0 116 127 257
          4   0  23 459  18

Overall Statistics

               Accuracy : 0.399
                 95% CI : (0.3775, 0.4208)
    No Information Rate : 0.2955
    P-Value [Acc > NIR] : < 2.2e-16

                  Kappa : 0.1987

 Mcnemar's Test P-Value : NA
```

Visualizing Clusters



Observation

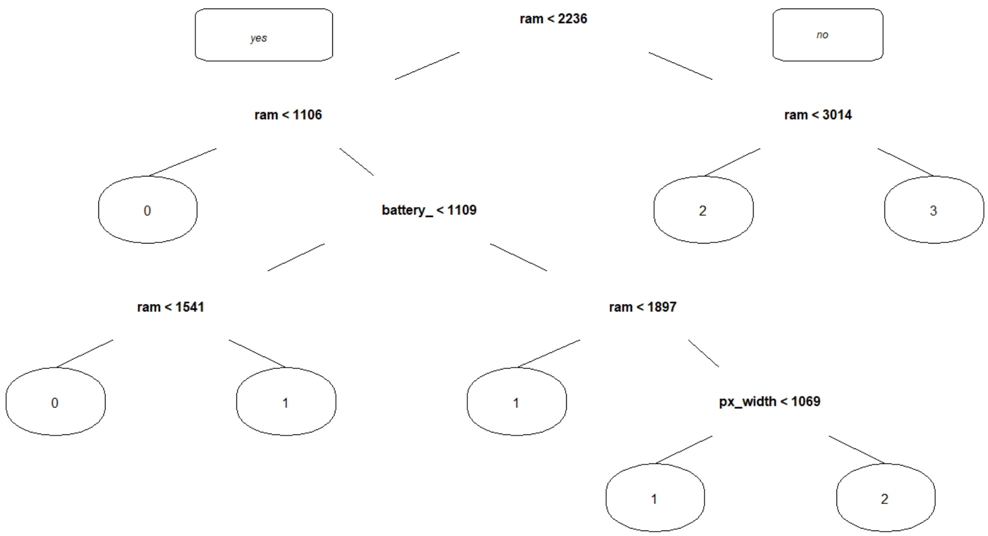
K-means Clustering has an accuracy of only ~40%. We'll try to improve this by testing out new models based on ID3 and Naive Bayesian classifier.

Decision Tree

Creating Model

Creating a decision tree through rpart function.

```
tree<-rpart(price_range~.,data=df)
summary(tree)
```



Predicting model and checking accuracy

Code

```
p<-predict(object = tree,test,type="class")

confusionMatrix(table(p,test$price_range))
```

Output

```
Confusion Matrix and Statistics


p     0   1   2   3
  0 102  13   0   0
  1   7  72  19   0
  2   0  12  64  16
  3   0   0  20  75

Overall Statistics

               Accuracy : 0.7825
                 95% CI : (0.7388, 0.822)
    No Information Rate : 0.2725
    P-Value [Acc > NIR] : < 2.2e-16

                  Kappa : 0.7096

 Mcnemar's Test P-Value : NA
```

Observation

Decision Tree gives us an accuracy of ~79%. This is a lot better than K-means clustering.

Naive Bayesian

Creating Model

```
library(e1071)
model<-naiveBayes(price_range~., train)
```

Predicting model and checking accuracy

Code

```
p<-predict(model,test)
confusionMatrix(table(p,test$price_range))
```

Output

```
Confusion Matrix and Statistics


p    0  1  2  3
  0 98  8  0  0
  1 11 74 17  0
  2  0 15 78  7
  3  0  0  8 84

Overall Statistics

               Accuracy : 0.835
                 95% CI : (0.7949, 0.87)
    No Information Rate : 0.2725
    P-Value [Acc > NIR] : < 2.2e-16

                  Kappa : 0.7798

 Mcnemar's Test P-Value : NA
```

Observation

Naive Bayesian gives us the best accuracy of 83.5%.

Conclusion

Using independent variables such as ram, camera quality, screen resolution, battery life, and network capabilities we successfully predicted the price range of a smartphone.

We also visualized trends between variables such as ram, battery capacity, network, talk time, screen resolution, and camera quality.

We used classification techniques such as Naive Bayesian and Decision Tree algorithm, and clustering techniques such as K-Means to build an accurate model.

Out of all these techniques we conclude that Naive Bayesian is the most accurate on this dataset with an accuracy of 83.5%

Acknowledgement

We would like to thank our professor **Mr. Suraj Patil** for providing this golden opportunity to showcase our skills and for his guidance and support in completing this project.