Mobile Price Classification

Background of The Company and The Problem:

Bob has started his own mobile company. He wants to give tough fights to big companies like Apple,Samsung etc.
He does not know how to estimate the price of mobiles his company creates. In this competitive mobile phone market you cannot simply assume things. To solve this problem he collects sales data of mobile phones of various companies.
Bob wants to find out some relation between features of a mobile phone(eg:- RAM,Internal Memory etc) and its selling price.

Dataset Website: https://www.kaggle.com/datasets/iabhishekofficial/mobile-price-classification/data

Data Wrangling

By displaying the data information, we can see that there are too many individual units and too many features in the data. We have done some data cleaning to make the features in our data look clearer, thus clarifying our judgment.

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2000 entries, 0 to 1999
Data columns (total 21 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   battery_power  2000 non-null   int64  
 1   blue           2000 non-null   int64  
 2   clock_speed    2000 non-null   float64
 3   dual_sim       2000 non-null   int64  
 4   fc             2000 non-null   int64  
 5   four_g         2000 non-null   int64  
 6   int_memory     2000 non-null   int64  
 7   m_dep          2000 non-null   float64
 8   mobile_wt      2000 non-null   int64  
 9   n_cores        2000 non-null   int64  
 10  pc             2000 non-null   int64  
 11  px_height      2000 non-null   int64  
 12  px_width       2000 non-null   int64  
 13  ram            2000 non-null   int64  
 14  sc_h           2000 non-null   int64  
 15  sc_w           2000 non-null   int64  
 16  talk_time      2000 non-null   int64  
 17  three_g        2000 non-null   int64  
 18  touch_screen   2000 non-null   int64  
 19  wifi           2000 non-null   int64  
 20  price_range    2000 non-null   int64  
dtypes: float64(2), int64(19)
memory usage: 328.2 KB
```

Data Cleaning

After we did the data cleaning we found 0 NaN values in the dataframe. Very good, the data looks much clearer, which is very helpful for the EDA process.

```
battery_power    0
blue             0
clock_speed      0
dual_sim         0
fc               0
four_g           0
int_memory       0
m_dep            0
mobile_wt        0
n_cores          0
pc               0
px_height        0
px_width         0
ram              0
sc_h             0
sc_w             0
talk_time        0
three_g          0
touch_screen     0
wifi             0
price_range      0
dtype: int64
```

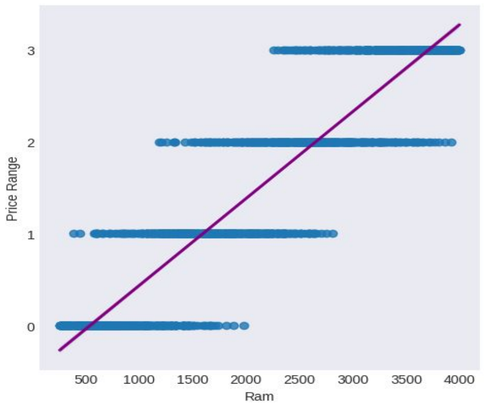
EDA

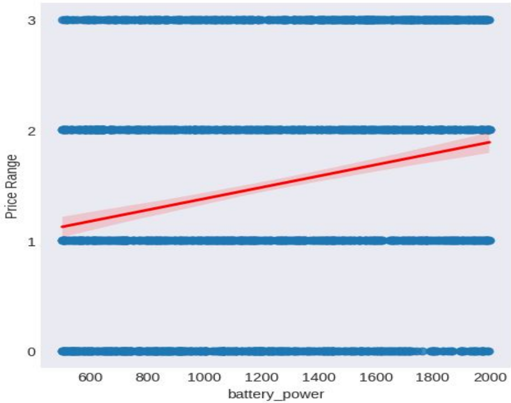

```
ram              0.917046
battery_power    0.200723
px_width         0.165818
px_height        0.148858
int_memory       0.044435
sc_w             0.038711
pc               0.033599
touch_screen     0.030411
mobile_wt        0.030302
three_g          0.023611
sc_h             0.022986
fc               0.021998
talk_time        0.021859
blue             0.020573
wifi             0.018785
dual_sim         0.017444
four_g           0.014772
clock_speed      0.006606
n_cores          0.004399
m_dep            0.000853
price_range           NaN
Name: price_range, dtype: float64
```

EDA

Used a heat map to show the highest correlation between Price_range and other features in the dataset. We found that the correlation between "price_range" and "ram" is very high, which means that in future modeling we may need to use the important feature of "ram" to predict the price range of mobile phones.Moreover, battery power also has a high correlation with our target variable.

EDA and Some Data Visualization

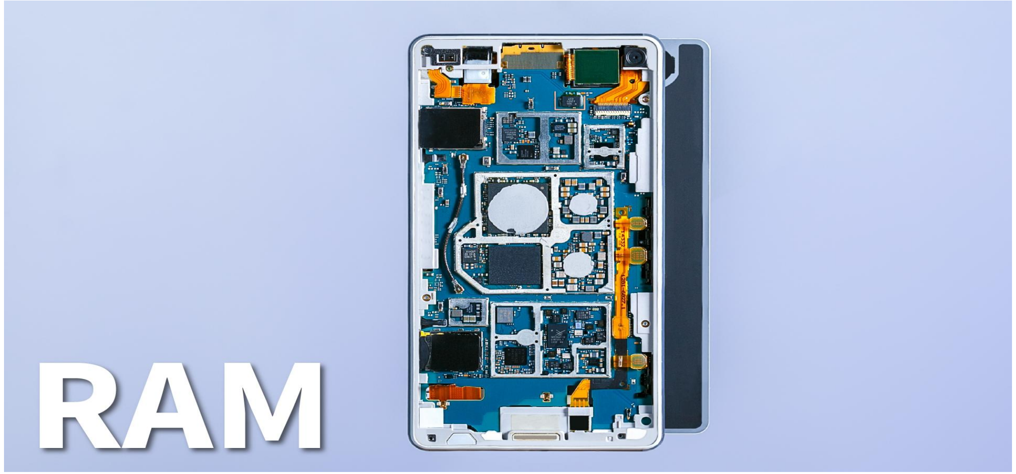




After we identified the two features that most affect the price range (battery power and ram), we made some comparisons using bar charts and found that the increasing trend of ram is stronger than that of battery power.

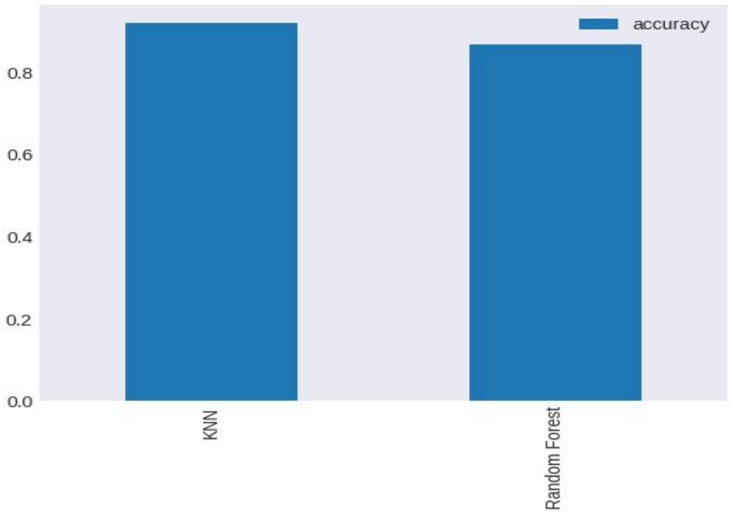
EDA

There is an increasing relationship between RAM and mobile phone prices. Let's also see some relations between price range and battery power.We can see that although there is an increasing relationship between battery power and price range, it does not have as big an impact as ram on the price range. This strengthens our reason for choosing the ram feature for modeling.



Pre-Processing and Training Data

Two modeling methods, KNN and random forest regression, are established and compared. After comparing the data, we found that the KNN modeling method has more accuracy, so KNN is a more suitable modeling method.



Modeling and Hyperparameter Method

Model accuracy comparison cannot produce a model with a final high score. We used the Hyperparameter Method to ensure that KNN is the final model we want to choose.

1. Hyperparemeter tuning for Random Forest:

```
In [38]: rf_grid = {"n_estimators": np.arange(10, 1000, 50),
                    "max_depth": [None, 3, 5, 10],
                    "min_samples_split": np.arange(2, 20, 2),
                    "min_samples_leaf": np.arange(1, 20, 2)}
```

```
In [39]: rs_rf = RandomizedSearchCV(RandomForestClassifier(),
                                    param_distributions=rf_grid,
                                    cv=5,
                                    n_iter=20,
                                    verbose=True)

         rs_rf.fit(X_train, y_train);

         rs_rf.best_params_

Fitting 5 folds for each of 20 candidates, totalling 100 fits
Out[39]: {'n_estimators': 410,
          'min_samples_split': 8,
          'min_samples_leaf': 1,
          'max_depth': None}
```

```
In [40]: rs_rf.score(X_test, y_test)

Out[40]: 0.8818181818181818
```

As we can see the test secor is around 88%, let's see how KNN goes.

2. Hyperparemeter tuning KNN:

```
In [43]: train_scores = []

         test_scores = []

         neighbors = range(1, 21)

         kNN = KNeighborsClassifier()

         for i in neighbors:
             kNN.set_params(n_neighbors = i)

             kNN.fit(X_train, y_train)

             train_scores.append(kNN.score(X_train, y_train))

             test_scores.append(kNN.score(X_test, y_test))
```

```
In [44]: kNN = KNeighborsClassifier(n_neighbors=13)
         kNN.fit(X_train, y_train)
         y_pred = kNN.predict(X_test)
         print(f'KNN Model Score: {kNN.score(X_test, y_test) * 100}%')

KNN Model Score: 92.42424242424242%
```

Modeling and Hyperparameter Method

The outlook from last silde pretty much says that the KNN model is correct to use the best model with the best hyperparameters.After we determined the best model, we did the model evaluation. We used two model evaluation methods: classification report and Cross Validation.

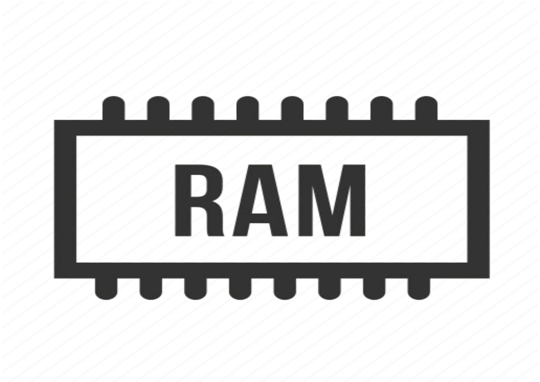
	precision	recall	f1-score	support
0	0.96	0.98	0.97	178
1	0.91	0.90	0.90	163
2	0.87	0.88	0.88	161
3	0.95	0.93	0.94	158
accuracy			0.92	660
macro avg	0.92	0.92	0.92	660
weighted avg	0.92	0.92	0.92	660

```
Cross Validation Scores: [0.94   0.935  0.9425 0.935  0.9175]

print(f'Cross Validation Score (Mean): ' + str(np.mean(cross_val_score(kNN, X, y, cv=5))))

Cross Validation Score (Mean): 0.9339999999999999
```

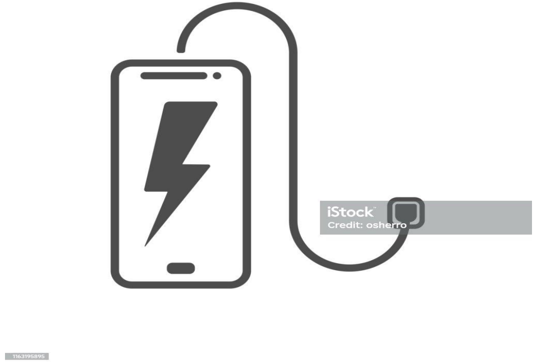
Through the cross validation method, it is not difficult to see that similar scores can be maintained by performing data segmentation in time and even increasing some accuracy.

Conclusion

The important factors that affect the price range of mobile phones are RAM and battery power. The important factors that affect the price range of mobile phones are RAM and battery power. The company can use these two pieces of information to make changes in the production of mobile phones to compete with Major mobile phone brands.



VS



Advice on business:

1. While maintaining almost the same price range and the same phone conditions, appropriately increase the phone RAM. Because in our opinion, mobile phone RAM is an important factor that affects the price range, and companies need to pay attention to it, so that they can compete with big-brand mobile phone companies.

2. If the first method does not achieve good results, we can also try to improve the battery performance while also increasing the RAM, because battery performance, as a factor second only to the mobile phone RAM, will also affect pricing.


THANK
YOU!