Import all required libraries

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings("ignore")
```

Read CSV file

In [2]:
```
df = pd.read_csv("mprice.csv")
df
```

Out[2]:

	battery_power	blue	clock_speed	dual_sim	fc	four_g	int_memory	m_dep	mobile_wt
0	842	0	2.2	0	1	0	7	0.6	188
1	1021	1	0.5	1	0	1	53	0.7	136
2	563	1	0.5	1	2	1	41	0.9	145
3	615	1	2.5	0	0	0	10	0.8	131
4	1821	1	1.2	0	13	1	44	0.6	141
...	...	...	...	...	...	...	...	...	...
1995	794	1	0.5	1	0	1	2	0.8	106
1996	1965	1	2.6	1	0	0	39	0.2	187
1997	1911	0	0.9	1	1	1	36	0.7	108
1998	1512	0	0.9	0	4	1	46	0.1	145
1999	510	1	2.0	1	5	1	45	0.9	168

2000 rows × 21 columns

Features names of df

- Variable Features:

1.battery_power : Total energy a battery can store in one time measured in (mAh)

2.blue : Has bluetooth or not

3.clock_speed : Speed at which microprocessor executes instructions

4.dual_sim : Has dual sim support or not

5.fc : Front camera (Megapixels)

6.four_g : Has 4G or not

7.int_memory :Internal memory in (Gigabytes)

8.m_dep : Mobile depth in (Cm)

9.mobile_wt : Weight of mobile phone

10.pc : Primary camera (Megapixels)

11.px_height : Pixel resolution height

12.px_width : Pixel resolution width

12.ram : Random access memory in (Megabytes)

13.sc_h : Screen height of mobile in (Cm)

14.sc_w : Screen width of mobile in (Cm)

15.talk_time : Longest time that a single battery charge will last when you are constantly talking on the phone

16.three_g : Has 3G or not

17.touch_screen : Has touch screen or not

18.wifi : Has wifi or not

19.n_cores : Number of cores of processor

20.price_range : This is the Target variable with value of 0: (Low Cost), 1: (Medium Cost), 2: (High Cost), and 3: (Very High Cost)

Drop unnecessary features

In [3]:
```
df = df.drop(['blue', 'clock_speed','px_height','px_width','three_g','talk
df.head()

```

Out[3]:

	battery_power	dual_sim	fc	four_g	int_memory	mobile_wt	n_cores	ram	sc_h	touch_scr
0	842	0	1	0	7	188	2	2549	9	
1	1021	1	0	1	53	136	3	2631	17	
2	563	1	2	1	41	145	5	2603	11	
3	615	0	0	0	10	131	6	2769	16	
4	1821	0	13	1	44	141	2	1411	8	

New Features of new df

- Our Variable Features:

1.battery_power : Total energy a battery can store in one time measured in (mAh)

2.dual_sim : Has dual sim support or not

3.fc : Front camera (Megapixels)

4.four_g : Has 4G or not

5.int_memory :Internal memory in (Gigabytes)

6.mobile_wt : Weight of mobile phone

7.ram : Random access memory in (Megabytes)

8.sc_h : Screen height of mobile in (Cm)

9.sc_w : Screen width of mobile in (Cm)

10.touch_screen : Has touch screen or not

11.wifi : Has wifi or not

12.n_cores : Number of cores of processor

13.price_range : This is the Target variable with value of 0: (Low Cost), 1: (Medium Cost), 2: (High Cost), and 3: (Very High Cost)

Goal:- Given The Feature We need to Predict a price range indicating how high the price is.

In [4]:
```
1 df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2000 entries, 0 to 1999
Data columns (total 12 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   battery_power  2000 non-null   int64
 1   dual_sim       2000 non-null   int64
 2   fc             2000 non-null   int64
 3   four_g         2000 non-null   int64
 4   int_memory     2000 non-null   int64
 5   mobile_wt      2000 non-null   int64
 6   n_cores        2000 non-null   int64
 7   ram            2000 non-null   int64
 8   sc_h           2000 non-null   int64
 9   touch_screen   2000 non-null   int64
 10  wifi           2000 non-null   int64
 11  price_range    2000 non-null   int64
dtypes: int64(12)
memory usage: 187.6 KB
```

In [5]:
```
1 df.isna().sum()
```

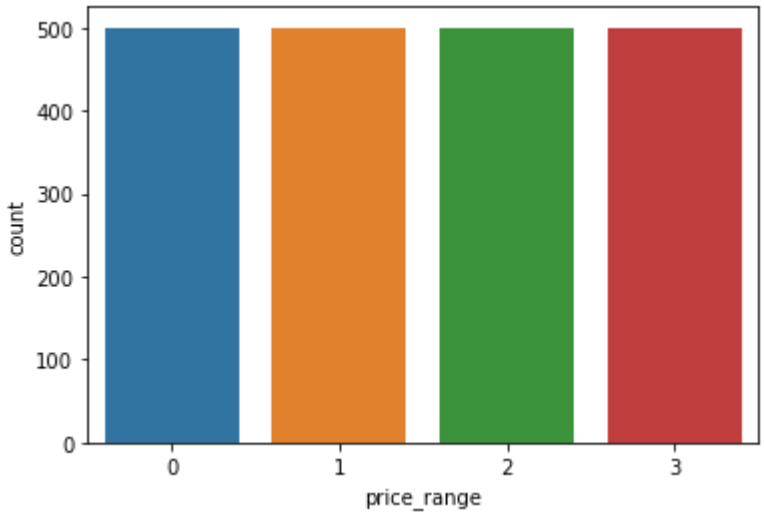
Out[5]:
```
battery_power    0
dual_sim         0
fc               0
four_g           0
int_memory       0
mobile_wt        0
n_cores          0
ram              0
sc_h             0
touch_screen     0
wifi             0
price_range      0
dtype: int64
```

Visualization

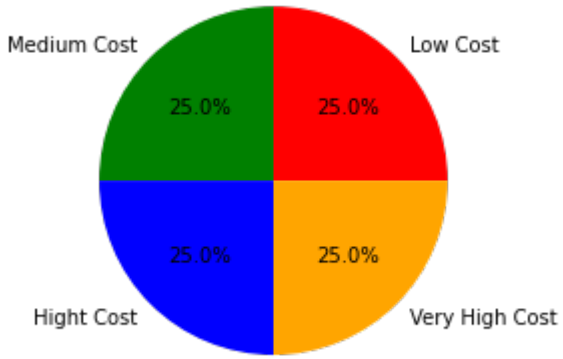
In [6]:
```
1 df["price_range"].value_counts()
```

Out[6]:
```
1    500
2    500
3    500
0    500
Name: price_range, dtype: int64
```

In [7]:
```
1 sns.countplot(data=df, x="price_range")
2 plt.show()
```



In [8]:
```
1 plt.pie(df["price_range"].value_counts(),labels=["Low Cost","Medium Cost",
2 plt.show()
```



Conclusion:

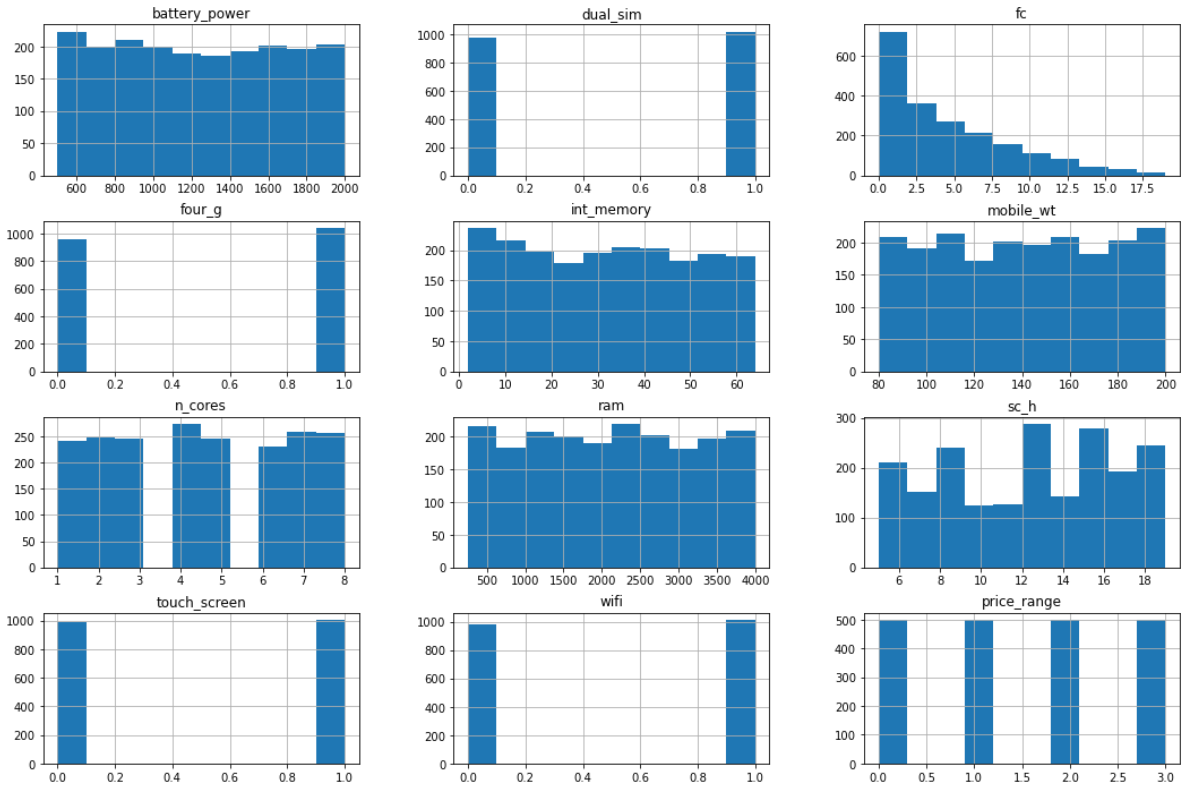
Mobile phones are divided with the same frequency across the 4 price_ range classes. Therefore, the dataset is completely balanced.

In [9]:
```
1 df.describe()
```

Out[9]:

	battery_power	dual_sim	fc	four_g	int_memory	mobile_wt	n_c
count	2000.000000	2000.000000	2000.000000	2000.000000	2000.000000	2000.000000	2000.00(
mean	1238.518500	0.509500	4.309500	0.521500	32.046500	140.249000	4.52(
std	439.418206	0.500035	4.341444	0.499662	18.145715	35.399655	2.28
min	501.000000	0.000000	0.000000	0.000000	2.000000	80.000000	1.00(
25%	851.750000	0.000000	1.000000	0.000000	16.000000	109.000000	3.00(
50%	1226.000000	1.000000	3.000000	1.000000	32.000000	141.000000	4.00(
75%	1615.250000	1.000000	7.000000	1.000000	48.000000	170.000000	7.00(
max	1998.000000	1.000000	19.000000	1.000000	64.000000	200.000000	8.00(

In [10]:
```
1 df.hist(figsize=(18,12))
2 plt.show()
```



In [11]:
```
1 df.corr()
```

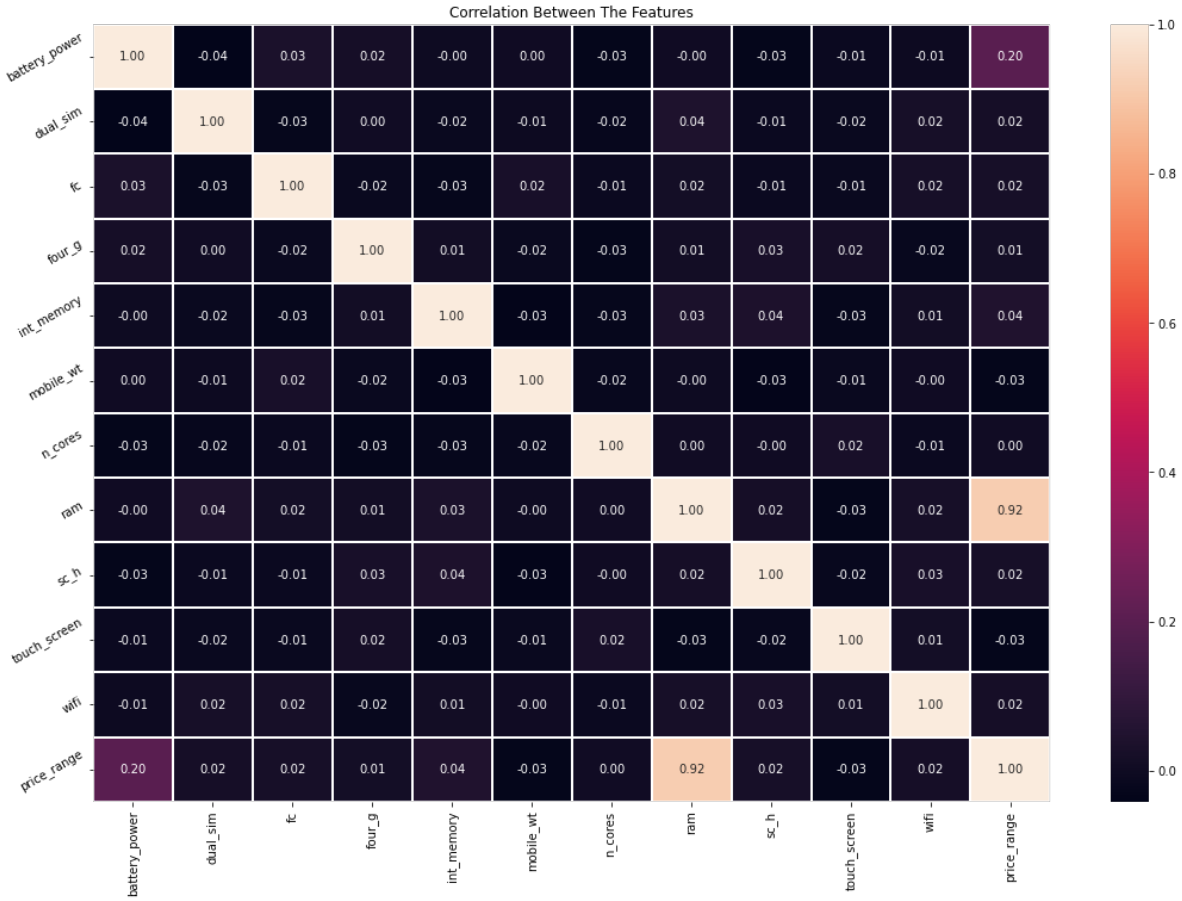
Out[11]:

	battery_power	dual_sim	fc	four_g	int_memory	mobile_wt	n_cores
battery_power	1.000000	-0.041847	0.033334	0.015665	-0.004004	0.001844	-0.029727
dual_sim	-0.041847	1.000000	-0.029123	0.003187	-0.015679	-0.008979	-0.024658
fc	0.033334	-0.029123	1.000000	-0.016560	-0.029133	0.023618	-0.013356
four_g	0.015665	0.003187	-0.016560	1.000000	0.008690	-0.016537	-0.029706
int_memory	-0.004004	-0.015679	-0.029133	0.008690	1.000000	-0.034214	-0.028310
mobile_wt	0.001844	-0.008979	0.023618	-0.016537	-0.034214	1.000000	-0.018989
n_cores	-0.029727	-0.024658	-0.013356	-0.029706	-0.028310	-0.018989	1.000000
ram	-0.000653	0.041072	0.015099	0.007313	0.032813	-0.002581	0.004868
sc_h	-0.029959	-0.011949	-0.011014	0.027166	0.037771	-0.033855	-0.000315
touch_screen	-0.010516	-0.017117	-0.014828	0.016758	-0.026999	-0.014368	0.023774
wifi	-0.008343	0.022740	0.020085	-0.017620	0.006993	-0.000409	-0.009964
price_range	0.200723	0.017444	0.021998	0.014772	0.044435	-0.030302	0.004399

Conclusion: The correlation measures the strength of the linear relationship between two variables. It has a value between -1 to 1, with a value of -1 meaning a total negative linear correlation, 0 being no correlation, and + 1 meaning a total positive correlation.

In [12]:

```
fig=plt.gcf()
fig.set_size_inches(18, 12)
plt.title('Correlation Between The Features')
a = sns.heatmap(df.corr(), annot = True, fmt='.2f', linewidths=0.2)
a.set_xticklabels(a.get_xticklabels(), rotation=90)
a.set_yticklabels(a.get_yticklabels(), rotation=30)
plt.show()
```

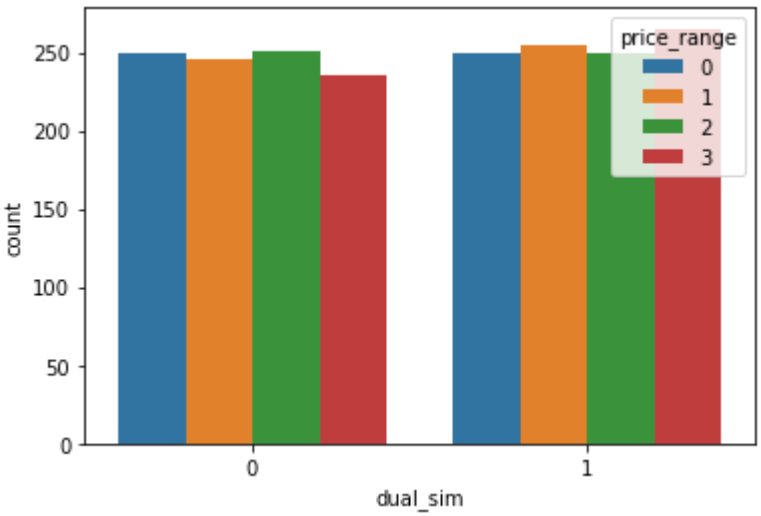


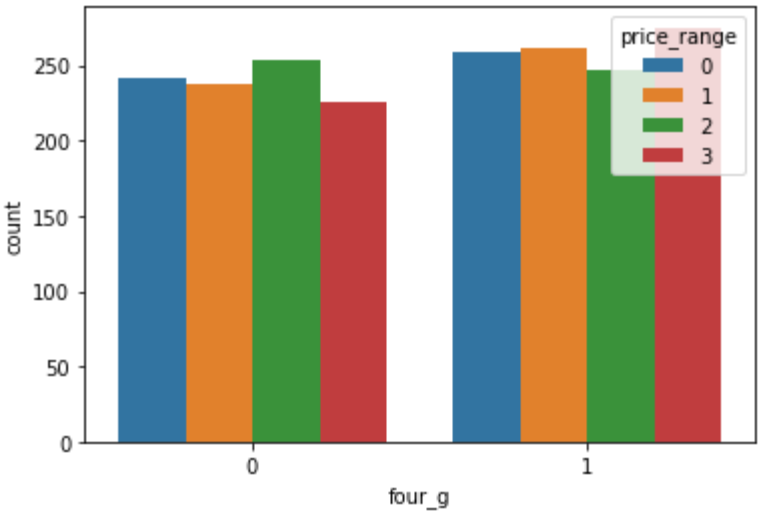
In [13]:
```
1 plt.figure (figsize = (12, 7), dpi = 100)
2 heatmap = sns.heatmap (df.corr()[['price_range']].sort_values (by = 'price
3 heatmap.set_title ('Features Correlating with Price Range', fontdict = {'f
```

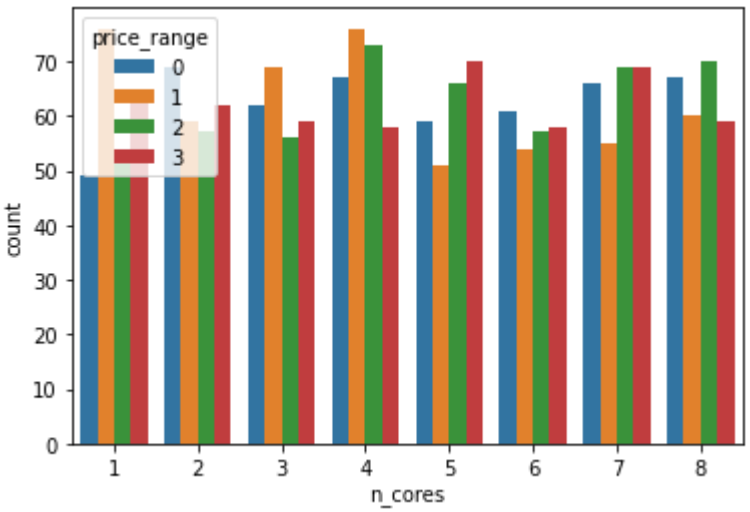
Conclusion:

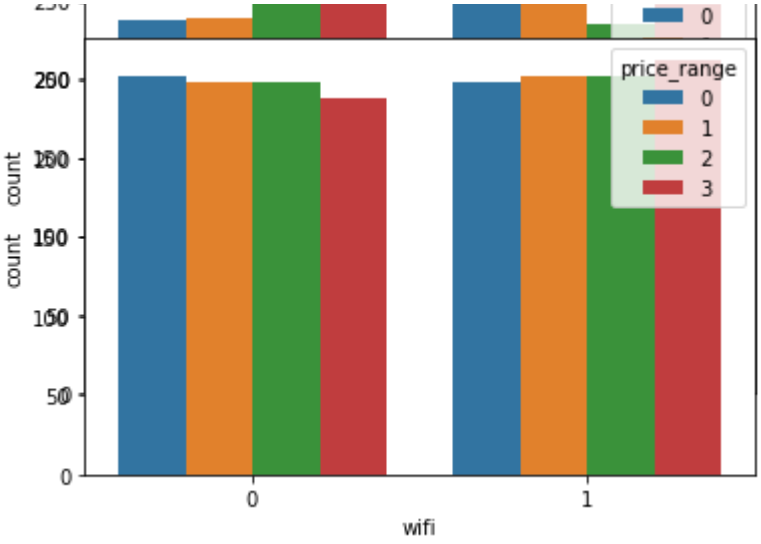
There is a strong correlation between ram and price_range.
price_range has a low correlation value with the rest of the feature
s, but this cannot be used as a criterion to remove these features si
nce the pearson correlation only expresses the linear relationship be
tween two variables.

In [14]:
```
def create_countplothue(x,data):
    sns.countplot(x=x, data=data, hue="price_range")
    plt.show()
for feature in ["dual_sim","four_g","n_cores","touch_screen","wifi"]:
    create_countplothue(x = feature, data = df)
```



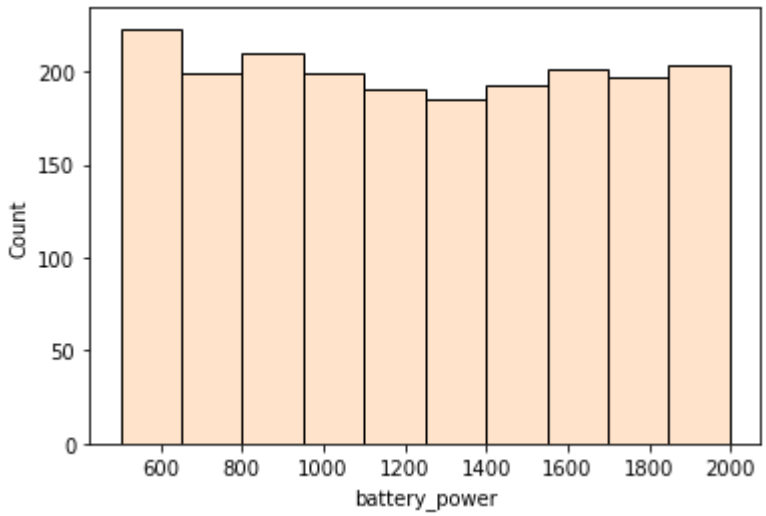


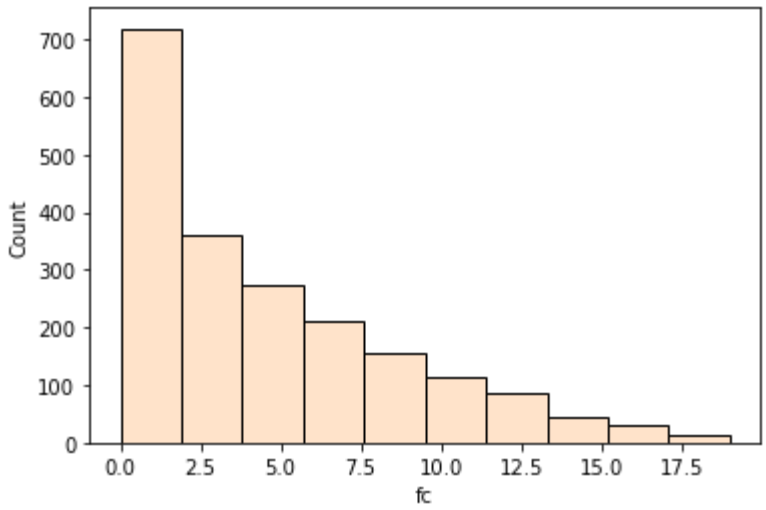


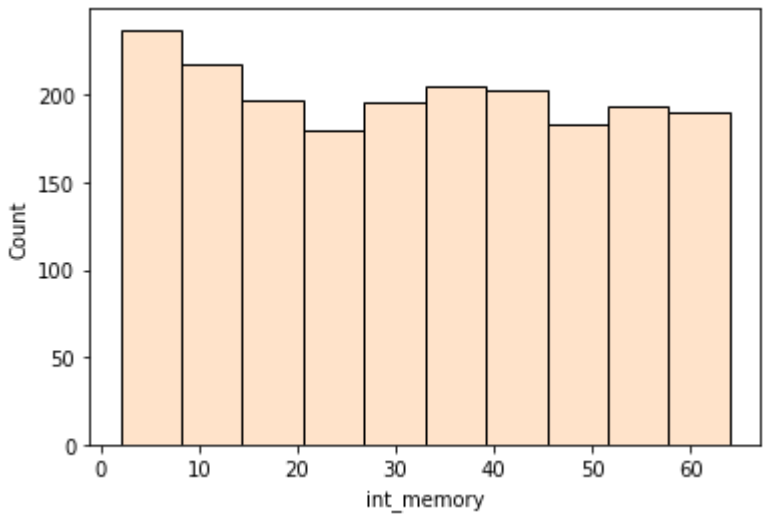


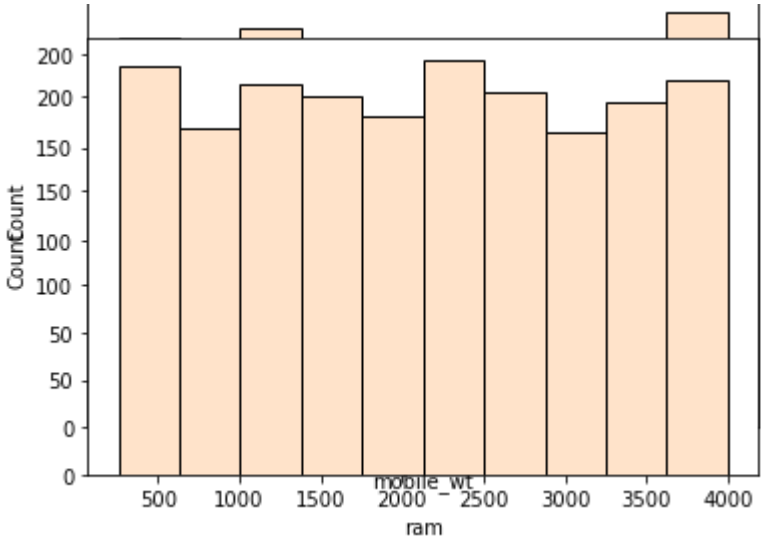
We see almost the same frequency in terms of having or not having 4G, two SIM cards, touch screen and the number of processing cores used.

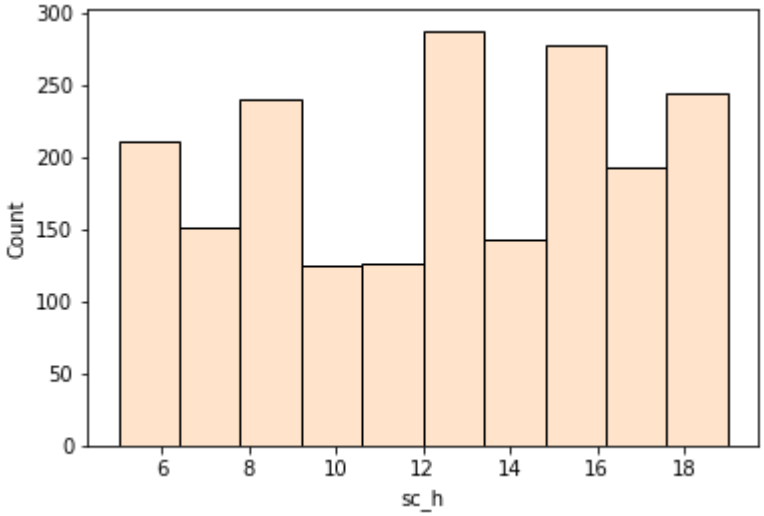
In [15]:
```
def create_histplot(x,data):
    sns.histplot(x=x, data=data,color="peachpuff",bins=10)
    plt.show()

for feature in ['battery_power', 'fc', 'int_memory', 'mobile_wt', 'ram', '
    create_histplot(x=feature, data=df)
```





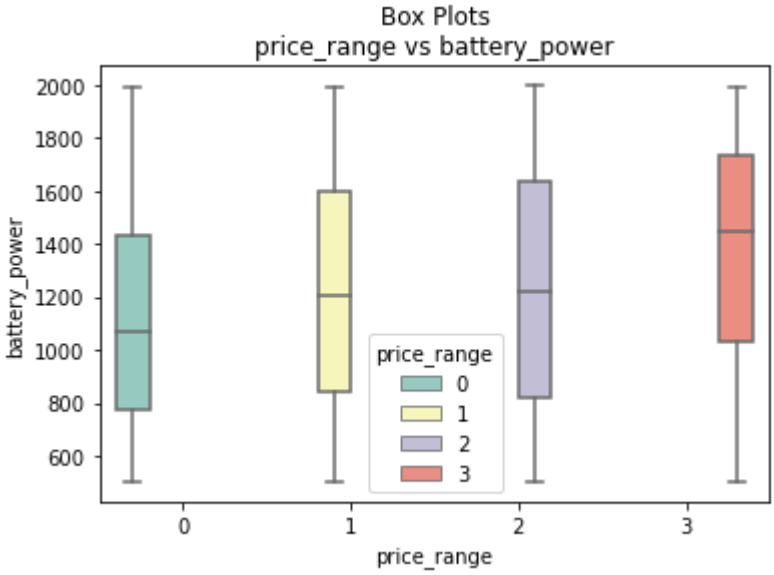



Count
200
200
150
150
100
100
50
50
0
0
500
1000
1500
2000
2500
3000
3500
4000
mobile_wt
ram


Count
300
250
200
150
100
50
0
6
8
10
12
14
16
18
sc_h

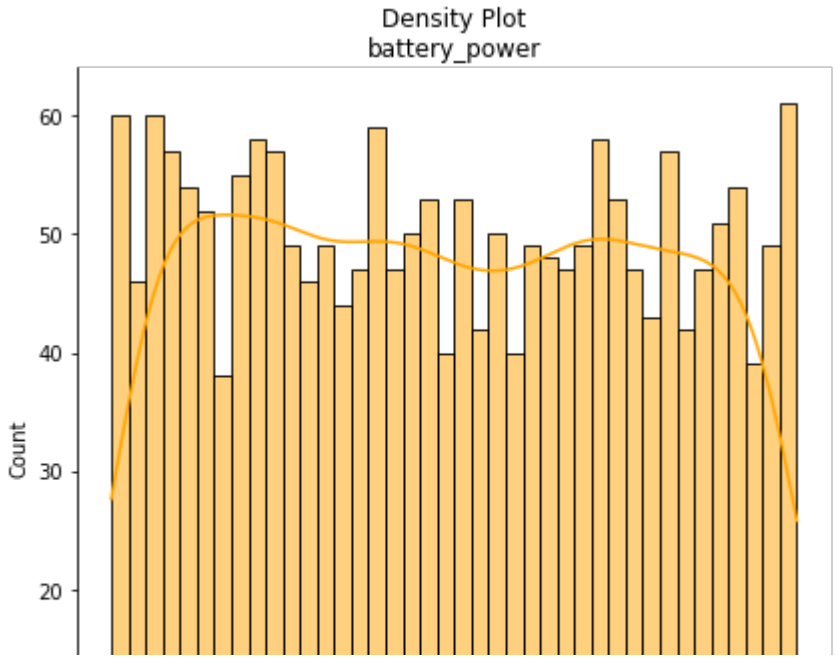
In [16]:

```
def create_boxplot(data, x, y):
    fig = sns.boxplot(data=data, x=x, y=y, hue='price_range', palette='Set
    fig.set(title=f"Box Plots\n{x} vs {y}")
    plt.show()

for feature in ['battery_power', 'fc', 'int_memory', 'mobile_wt', 'ram', '
    create_boxplot(data=df, x='price_range', y=feature)


```



Box Plots

In [17]:
```
def displot(data,x):
    sns.displot(data=data,x=x,kde=True,bins=40, color="orange", height=6).
    fig.show()

for feature in ['battery_power', 'fc', 'int_memory', 'mobile_wt', 'ram', '
    displot(data=df, x = feature)
```



Separating of X and Y

In [18]:
```
x = df.iloc[:,:-1]
y = df.iloc[:,-1]
```

In [19]:
```
1 x
```

Out[19]:

	battery_power	dual_sim	fc	four_g	int_memory	mobile_wt	n_cores	ram	sc_h	touch_
0	842	0	1	0	7	188	2	2549	9	
1	1021	1	0	1	53	136	3	2631	17	
2	563	1	2	1	41	145	5	2603	11	
3	615	0	0	0	10	131	6	2769	16	
4	1821	0	13	1	44	141	2	1411	8	
...	...	...	...	...	...	...	...	...	...	
1995	794	1	0	1	2	106	6	668	13	
1996	1965	1	0	0	39	187	4	2032	11	
1997	1911	1	1	1	36	108	8	3057	9	
1998	1512	0	4	1	46	145	5	869	18	
1999	510	1	5	1	45	168	6	3919	19	

2000 rows × 11 columns

In [20]:
```
1 y
```

Out[20]:
```
0       1
1       2
2       2
3       2
4       1
       ..
1995    0
1996    2
1997    3
1998    0
1999    3
Name: price_range, Length: 2000, dtype: int64
```

Train Test Split

In [21]:
```
1 from sklearn.model_selection import train_test_split
2 xtrain,xtest,ytrain,ytest = train_test_split(x,y,test_size=0.3,random_stat
```

Model Building

In [22]:
```
1 from sklearn.metrics import classification_report, accuracy_score
```

In [23]:
```
def mymodel(model):
    model.fit(xtrain,ytrain)
    ypred = model.predict(xtest)

    train = model.score(xtrain,ytrain)
    test = model.score(xtest,ytest)

    print(f"Training Accuracy :- {train}\n Testing Accuracy:- {test}")

    print(classification_report(ytest,ypred))
    return model
```

In [24]:
```
from sklearn.neighbors import KNeighborsClassifier
from  sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC
from sklearn.tree import DecisionTreeClassifier
```

In [25]:
```
knn = mymodel(KNeighborsClassifier()) #low bias and high varience ==> over
```

```
Training Accuracy :- 0.8485714285714285
 Testing Accuracy:- 0.7783333333333333
              precision    recall  f1-score   support

           0       0.88      0.91      0.90       135
           1       0.72      0.77      0.74       149
           2       0.70      0.68      0.69       168
           3       0.84      0.78      0.81       148

    accuracy                           0.78       600
   macro avg       0.78      0.78      0.78       600
weighted avg       0.78      0.78      0.78       600
```

In [26]:
```
logreg = mymodel(LogisticRegression())
```

```
Training Accuracy :- 0.645
 Testing Accuracy:- 0.6233333333333333
              precision    recall  f1-score   support

           0       0.79      0.81      0.80       135
           1       0.57      0.54      0.55       149
           2       0.51      0.43      0.47       168
           3       0.63      0.76      0.69       148

    accuracy                           0.62       600
   macro avg       0.62      0.63      0.63       600
weighted avg       0.62      0.62      0.62       600
```

In [27]:
```
1 svm = mymodel(SVC())
```

```
Training Accuracy :- 0.8328571428571429
 Testing Accuracy:- 0.8066666666666666
              precision    recall  f1-score   support

           0       0.90      0.91      0.91       135
           1       0.76      0.81      0.78       149
           2       0.74      0.71      0.73       168
           3       0.85      0.81      0.83       148

    accuracy                           0.81       600
   macro avg       0.81      0.81      0.81       600
weighted avg       0.81      0.81      0.81       600
```

In [28]:
```
1 dt = mymodel(DecisionTreeClassifier()) #low bias and high varience ==> ove
```

```
Training Accuracy :- 1.0
 Testing Accuracy:- 0.7383333333333333
              precision    recall  f1-score   support

           0       0.84      0.86      0.85       135
           1       0.68      0.64      0.66       149
           2       0.65      0.69      0.67       168
           3       0.82      0.78      0.80       148

    accuracy                           0.74       600
   macro avg       0.75      0.74      0.74       600
weighted avg       0.74      0.74      0.74       600
```

Cross Validation

In [29]:
```
models = []
accuracy = []


models.append(("logreg",LogisticRegression()))
models.append(("DT",DecisionTreeClassifier()))
models.append(("DT-e",DecisionTreeClassifier(criterion="entropy")))
models.append(("KNN",KNeighborsClassifier()))
models.append(("svm",SVC()))



for name,model in models:
    model.fit(xtrain,ytrain)
    ypred = model.predict(xtest)

    ac = accuracy_score(ytest,ypred)
    accuracy.append(ac)

arr = np.array(accuracy)
print(f"Avg Accuracy:- {arr.mean()}")
```

```
Avg Accuracy:- 0.7386666666666667
```

In [30]:
```
models
```

Out[30]:
```
[('logreg', LogisticRegression()),
 ('DT', DecisionTreeClassifier()),
 ('DT-e', DecisionTreeClassifier(criterion='entropy')),
 ('KNN', KNeighborsClassifier()),
 ('svm', SVC())]
```

In [31]:
```
accuracy
```

Out[31]:
```
[0.6233333333333333,
 0.7266666666666667,
 0.7583333333333333,
 0.7783333333333333,
 0.8066666666666666]
```

Hyperparameter Tuning For KNN :-

In [32]:
```
for i in range(1,31):
    knn = KNeighborsClassifier(n_neighbors=i)
    knn.fit(xtrain,ytrain)

    train = knn.score(xtrain,ytrain)
    test = knn.score(xtest,ytest)

    print(f"{i}  {train}  {test} {train-test}")
```

```
1  1.0  0.735 0.265
2  0.8721428571428571  0.7633333333333333 0.1088095238095238
3  0.8892857142857142  0.7716666666666666 0.11761904761904762
4  0.8614285714285714  0.78 0.0814285714285714
5  0.8485714285714285  0.7783333333333333 0.07023809523809521
6  0.8478571428571429  0.78 0.06785714285714284
7  0.8428571428571429  0.7833333333333333 0.059523809523809534
8  0.8435714285714285  0.7816666666666666 0.06190476190476191
9  0.8471428571428572  0.78 0.06714285714285717
10  0.8428571428571429  0.78 0.06285714285714283
11  0.84  0.785 0.05499999999999994
12  0.8414285714285714  0.78 0.06142857142857139
13  0.8407142857142857  0.7916666666666666 0.04904761904761912
14  0.8457142857142858  0.79 0.055714285714285716
15  0.8378571428571429  0.7916666666666666 0.046190476190476226
16  0.8392857142857143  0.7916666666666666 0.04761904761904767
17  0.8435714285714285  0.79 0.05357142857142849
18  0.8428571428571429  0.7966666666666666 0.046190476190476226
19  0.8435714285714285  0.7933333333333333 0.05023809523809519
20  0.8464285714285714  0.7933333333333333 0.053095238095238084
21  0.8435714285714285  0.7933333333333333 0.05023809523809519
22  0.8428571428571429  0.785 0.05785714285714283
23  0.8371428571428572  0.7866666666666666 0.05047619047619056
24  0.8407142857142857  0.79 0.05071428571428571
25  0.8378571428571429  0.7933333333333333 0.04452380952380952
26  0.8414285714285714  0.7983333333333333 0.043095238095238075
27  0.8364285714285714  0.8033333333333333 0.033095238095238066
28  0.8392857142857143  0.7966666666666666 0.04261904761904767
29  0.835  0.795 0.039999999999999925
30  0.84  0.7966666666666666 0.043333333333333335
```

In [33]:
```
from sklearn.neighbors import KNeighborsClassifier
knn = KNeighborsClassifier(n_neighbors=27)
knn.fit(xtrain,ytrain)
ypred = knn.predict(xtest)

from sklearn.metrics import classification_report,confusion_matrix
print(f"Training Accuracy :- {train}\n Testing Accuracy:- {test}")  #low b

print(classification_report(ytest,ypred))
```

```
Training Accuracy :- 0.84
 Testing Accuracy:- 0.7966666666666666
              precision    recall  f1-score   support

           0       0.91      0.94      0.93       135
           1       0.75      0.79      0.77       149
           2       0.71      0.70      0.71       168
           3       0.87      0.80      0.84       148

    accuracy                           0.80       600
   macro avg       0.81      0.81      0.81       600
weighted avg       0.80      0.80      0.80       600
```

Grid Search CV For Decision Tree

In [34]:
```
parameter = {
            "criterion":["gini","entropy"],
            "max_depth":list(range(1,20)),
            "min_samples_leaf":list(range(1,20))
}
```

In [35]:
```
1 from sklearn.model_selection import GridSearchCV
2 grid = GridSearchCV(DecisionTreeClassifier(), parameter, verbose=2)
3 grid.fit(xtrain,ytrain)
```

```
Fitting 5 folds for each of 722 candidates, totalling 3610 fits
[CV] END ....criterion=gini, max_depth=1, min_samples_leaf=1; total time=
0.0s
[CV] END ....criterion=gini, max_depth=1, min_samples_leaf=1; total time=
0.0s
[CV] END ....criterion=gini, max_depth=1, min_samples_leaf=1; total time=
0.0s
[CV] END ....criterion=gini, max_depth=1, min_samples_leaf=1; total time=
0.0s
[CV] END ....criterion=gini, max_depth=1, min_samples_leaf=1; total time=
0.0s
[CV] END ....criterion=gini, max_depth=1, min_samples_leaf=2; total time=
0.0s
[CV] END ....criterion=gini, max_depth=1, min_samples_leaf=2; total time=
0.0s
[CV] END ....criterion=gini, max_depth=1, min_samples_leaf=2; total time=
0.0s
[CV] END ....criterion=gini, max_depth=1, min_samples_leaf=2; total time=
0.0s
```

In [36]:
```
1 grid.best_estimator_
```

Out[36]:
```
DecisionTreeClassifier(criterion='entropy', max_depth=6, min_samples_leaf=17)
```

In [37]:
```
1 grid.best_score_
```

Out[37]:
```
0.8114285714285714
```

In [38]:
```
1 dt = mymodel(grid.best_estimator_) #low bias and high varience ==> overfit
```

```
Training Accuracy :- 0.8578571428571429
 Testing Accuracy:- 0.7866666666666666
              precision    recall  f1-score   support

           0       0.92      0.92      0.92       135
           1       0.75      0.77      0.76       149
           2       0.67      0.71      0.69       168
           3       0.84      0.77      0.80       148

    accuracy                           0.79       600
   macro avg       0.80      0.79      0.79       600
weighted avg       0.79      0.79      0.79       600
```

Ensemble With Voting Classifier

In [39]:
```
from sklearn.ensemble import VotingClassifier

vc = VotingClassifier(estimators=models,voting="hard")
vc.fit(xtrain,ytrain)
ypred = vc.predict(xtest)

train = vc.score(xtrain,ytrain)
test = vc.score(xtest,ytest)

print(f"Training Accuracy:- {train}\n Testing Accuracy:-{test}") #low bias
print(classification_report(ytest,ypred))
```

```
Training Accuracy:- 0.9357142857142857
 Testing Accuracy:-0.8
              precision    recall  f1-score   support

           0       0.88      0.90      0.89       135
           1       0.74      0.81      0.77       149
           2       0.75      0.69      0.72       168
           3       0.84      0.82      0.83       148

    accuracy                           0.80       600
   macro avg       0.80      0.81      0.80       600
weighted avg       0.80      0.80      0.80       600
```

Bagging Classifier

In [40]:
```
from sklearn.ensemble import BaggingClassifier
bg = BaggingClassifier(LogisticRegression())

bg.fit(xtrain,ytrain)
ypred = bg.predict(xtest)


train = bg.score(xtrain,ytrain)
test = bg.score(xtest,ytest)

print(f"Training Accuracy:- {train}\n Testing Accuracy:-{test}")
print(classification_report(ytest,ypred))
```

```
Training Accuracy:- 0.64
 Testing Accuracy:-0.6333333333333333
              precision    recall  f1-score   support

           0       0.79      0.82      0.81       135
           1       0.58      0.58      0.58       149
           2       0.52      0.42      0.46       168
           3       0.64      0.76      0.69       148

    accuracy                           0.63       600
   macro avg       0.63      0.64      0.64       600
weighted avg       0.63      0.63      0.63       600
```

In [41]:
```
from sklearn.ensemble import BaggingClassifier
bg = BaggingClassifier(DecisionTreeClassifier())

bg.fit(xtrain,ytrain)
ypred = bg.predict(xtest)


train = bg.score(xtrain,ytrain)
test = bg.score(xtest,ytest)

print(f"Training Accuracy:- {train}\n Testing Accuracy:-{test}") #low bias
print(classification_report(ytest,ypred))
```

```
Training Accuracy:- 0.9828571428571429
 Testing Accuracy:-0.765
              precision    recall  f1-score   support

           0       0.88      0.93      0.90       135
           1       0.68      0.74      0.71       149
           2       0.66      0.65      0.66       168
           3       0.88      0.76      0.82       148

    accuracy                           0.77       600
   macro avg       0.77      0.77      0.77       600
weighted avg       0.77      0.77      0.77       600
```

In [42]:
```
from sklearn.ensemble import RandomForestClassifier
rf = RandomForestClassifier()

rf.fit(xtrain,ytrain)
ypred = rf.predict(xtest)


train = rf.score(xtrain,ytrain)
test = rf.score(xtest,ytest)

print(f"Training Accuracy:- {train}\n Testing Accuracy:-{test}") #low bias
print(classification_report(ytest,ypred))
```

```
Training Accuracy:- 1.0
 Testing Accuracy:-0.795
              precision    recall  f1-score   support

           0       0.89      0.93      0.91       135
           1       0.74      0.77      0.76       149
           2       0.71      0.69      0.70       168
           3       0.85      0.81      0.83       148

    accuracy                           0.80       600
   macro avg       0.80      0.80      0.80       600
weighted avg       0.79      0.80      0.79       600
```

In [43]:
```
df.head()
```

Out[43]:

	battery_power	dual_sim	fc	four_g	int_memory	mobile_wt	n_cores	ram	sc_h	touch_scr
0	842	0	1	0	7	188	2	2549	9	
1	1021	1	0	1	53	136	3	2631	17	
2	563	1	2	1	41	145	5	2603	11	
3	615	0	0	0	10	131	6	2769	16	
4	1821	0	13	1	44	141	2	1411	8	

Forcast New Observation

In [44]:
```
def makeprediction():
    battery_power = int(input("Enter No of Battery Power:- "))
    dual_sim = int(input("Dual sim (1) or not (0):- "))
    fc = int(input("Enter No of Front Camera:- "))
    four_g = int(input("4G (1) or not (0):- "))
    int_memory = int(input("Enter No of internal memory:- "))
    mobile_wt = int(input("Enter Mobile Weight:- "))
    n_cores = int(input("Enter No of Core Processor:- "))
    ram = int(input("Enter No of Ram:- "))
    sc_h = int(input("Enter Screen Height:- "))
    touch_screen = int(input("Touch Screen (1) or not (0):- "))
    wifi = int(input("Wifi (1) or not (0):- "))

    newob = [battery_power, dual_sim , fc , four_g , int_memory, mobile_wt
    v = svm.predict([newob])[0]

    if v==0:
        print("The Price Range is Low i.e 0 ..!!!")
    elif v==1:
        print("The Price Range is Medium i.e 1 ..!!!")
    elif v==2:
        print("The Price Range is High i.e 2 ..!!!")
    elif v==3:
        print("The Price Range is Very High i.e 3 ..!!!")
    else:
        print("Can not Predict Price Range..!!!")

    return v

```

In [48]:
```
makeprediction()
```

```
Enter No of Battery Power:- 14504
Dual sim (1) or not (0):- 1
Enter No of Front Camera:- 4
4G (1) or not (0):- 1
Enter No of internal memory:- 1547852
Enter Mobile Weight:- 14
Enter No of Core Processor:- 2
Enter No of Ram:- 254781
Enter Screen Height:- 14
Touch Screen (1) or not (0):- 1
Wifi (1) or not (0):- 1
The Price Range is High i.e 2 ..!!!
```

Out[48]: 2

In [ ]:
```

```