Mobile Price Prediction Unveiling Patterns in the Smartphone Market

In [108]:
```
# Import necessary libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import accuracy_score, confusion_matrix
from sklearn.neighbors import KNeighborsClassifier
from sklearn.naive_bayes import GaussianNB

print("All Libraries imported successfully!")
```

```
All Libraries imported successfully!
```

In [109]:
```
# Load the dataset
dataset_path = "C:\\Users\\n\\Downloads\\mobile prices.csv"
mobile_data = pd.read_csv(dataset_path)
print("Mobile price data Loaded successfully!")
```

```
Mobile price data Loaded successfully!
```

In [110]:
```
# Display the first few rows of the dataset
print(mobile_data.head())
```

```
   battery_power  blue  clock_speed  dual_sim  fc  four_g  int_memory  m_dep  \
0            842     0          2.2         0   1       0           7    0.6
1           1021     1          0.5         1   0       1          53    0.7
2            563     1          0.5         1   2       1          41    0.9
3            615     1          2.5         0   0       0          10    0.8
4           1821     1          1.2         0  13       1          44    0.6

   mobile_wt  n_cores  ...  px_height  px_width   ram  sc_h  sc_w  talk_time  \
0        188        2  ...         20       756  2549     9     7         19
1        136        3  ...        905      1988  2631    17     3          7
2        145        5  ...       1263      1716  2603    11     2          9
3        131        6  ...       1216      1786  2769    16     8         11
4        141        2  ...       1208      1212  1411     8     2         15

   three_g  touch_screen  wifi  price_range
0        0             0     1            1
1        1             1     0            2
2        1             1     0            2
3        1             0     0            2
4        1             1     0            1

[5 rows x 21 columns]
```

In [111]:
```
# Display the last few rows of the dataset
print(mobile_data.tail())
```

```
      battery_power  blue  clock_speed  dual_sim  fc  four_g  int_memory  \
```

In [111]:
```
# Display the last few rows of the dataset
print(mobile_data.tail())
```

```
      battery_power  blue  clock_speed  dual_sim  fc  four_g  int_memory  \
1995            794     1          0.5         1   0       1           2
1996           1965     1          2.6         1   0       0          39
1997           1911     0          0.9         1   1       1          36
1998           1512     0          0.9         0   4       1          46
1999            510     1          2.0         1   5       1          45

      m_dep  mobile_wt  n_cores  ...  px_height  px_width   ram  sc_h  sc_w  \
1995    0.8        106        6  ...       1222      1890   668    13     4
1996    0.2        187        4  ...        915      1965  2032    11    10
1997    0.7        108        8  ...        868      1632  3057     9     1
1998    0.1        145        5  ...        336       670   869    18    10
1999    0.9        168        6  ...        483       754  3919    19     4

      talk_time  three_g  touch_screen  wifi  price_range
1995         19        1             1     0            0
1996         16        1             1     1            2
1997          5        1             1     0            3
1998         19        1             1     1            0
1999          2        1             1     1            3

[5 rows x 21 columns]
```

1. Introduction to Data Mining and Big Data

In [112]:
```
# 1. Introduction to Data Mining and Big Data
print("1. Introduction to Data Mining and Big Data:")
print("   - Data mining and big data play a crucial role in predicting mobile pri
print("   - Mobile company can benefit from data-driven insights to compete with
print("\n")
```

```
1. Introduction to Data Mining and Big Data:
   - Data mining and big data play a crucial role in predicting mobile prices.
   - Mobile company can benefit from data-driven insights to compete with indus
try giants.
```

2. Data Types and Data Preprocessing

In [113]:
```
# 2. Data Types and Data Preprocessing
print("2. Data Types and Data Preprocessing:")
# Display data types of each column
print(mobile_data.dtypes)
```

In [113]:
```
# 2. Data Types and Data Preprocessing
print("2. Data Types and Data Preprocessing:")
# Display data types of each column
print(mobile_data.dtypes)
# Check for missing values
print("Missing Values:")
print(mobile_data.isnull().sum())
```

```
2. Data Types and Data Preprocessing:
battery_power      int64
blue               int64
clock_speed      float64
dual_sim           int64
fc                 int64
four_g             int64
int_memory         int64
m_dep            float64
mobile_wt          int64
n_cores            int64
pc                 int64
px_height          int64
px_width           int64
ram                int64
sc_h               int64
sc_w               int64
talk_time          int64
three_g            int64
touch_screen       int64
wifi               int64
price_range        int64
dtype: object
Missing Values:
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
```

In [114]:
```
#Statistical Summary
mobile_data.describe()
```

Out[114]:

In [114]:
```
#Statistical Summary
mobile_data.describe()
```

Out[114]:

	battery_power	blue	clock_speed	dual_sim	fc	four_g	int_memory
count	2000.000000	2000.0000	2000.000000	2000.000000	2000.000000	2000.000000	2000.000000
mean	1238.518500	0.4950	1.522250	0.509500	4.309500	0.521500	32.046500
std	439.418206	0.5001	0.816004	0.500035	4.341444	0.499662	18.145715
min	501.000000	0.0000	0.500000	0.000000	0.000000	0.000000	2.000000
25%	851.750000	0.0000	0.700000	0.000000	1.000000	0.000000	16.000000
50%	1226.000000	0.0000	1.500000	1.000000	3.000000	1.000000	32.000000
75%	1615.250000	1.0000	2.200000	1.000000	7.000000	1.000000	48.000000
max	1998.000000	1.0000	3.000000	1.000000	19.000000	1.000000	64.000000

8 rows × 21 columns

In [115]:
```
#Print the number of unique values for each column
mobile_data.nunique()
```

Out[115]:
```
battery_power    1094
blue                2
clock_speed        26
dual_sim            2
fc                 20
four_g              2
int_memory         63
m_dep              10
mobile_wt         121
n_cores             8
pc                 21
px_height        1137
px_width         1109
ram              1562
sc_h               15
sc_w               19
talk_time          19
three_g             2
touch_screen        2
wifi                2
price_range         4
dtype: int64
```

In [116]:
```
#Print information about the DataFrame
mobile_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
```

In [116]:
```
#Print information about the DataFrame
mobile_data.info()
```

```
<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
```

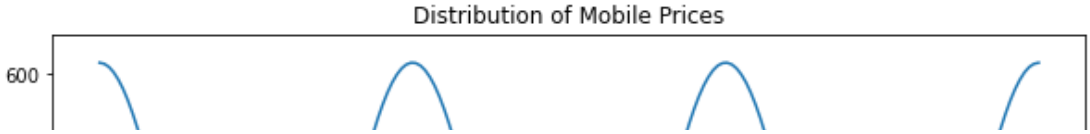
3. Data Exploration + Visualization

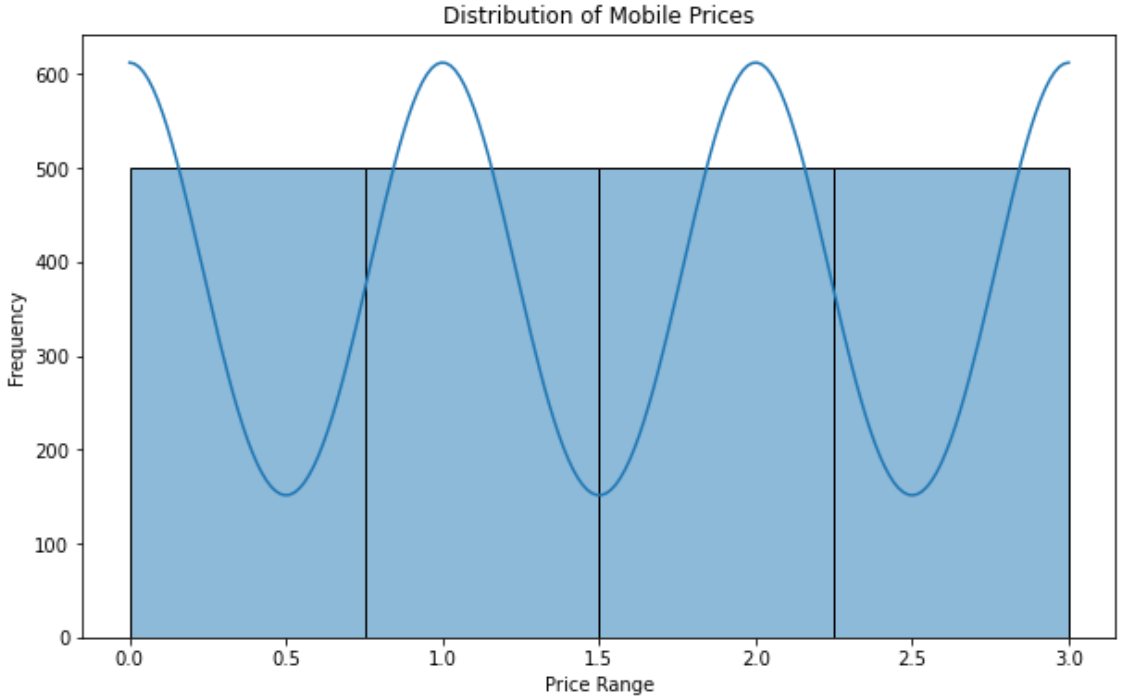
In [117]:
```
# 3. Data Exploration + Visualization
print("3. Data Exploration + Visualization:")
# Explore dataset characteristics
print("Dataset Statistics:")
```

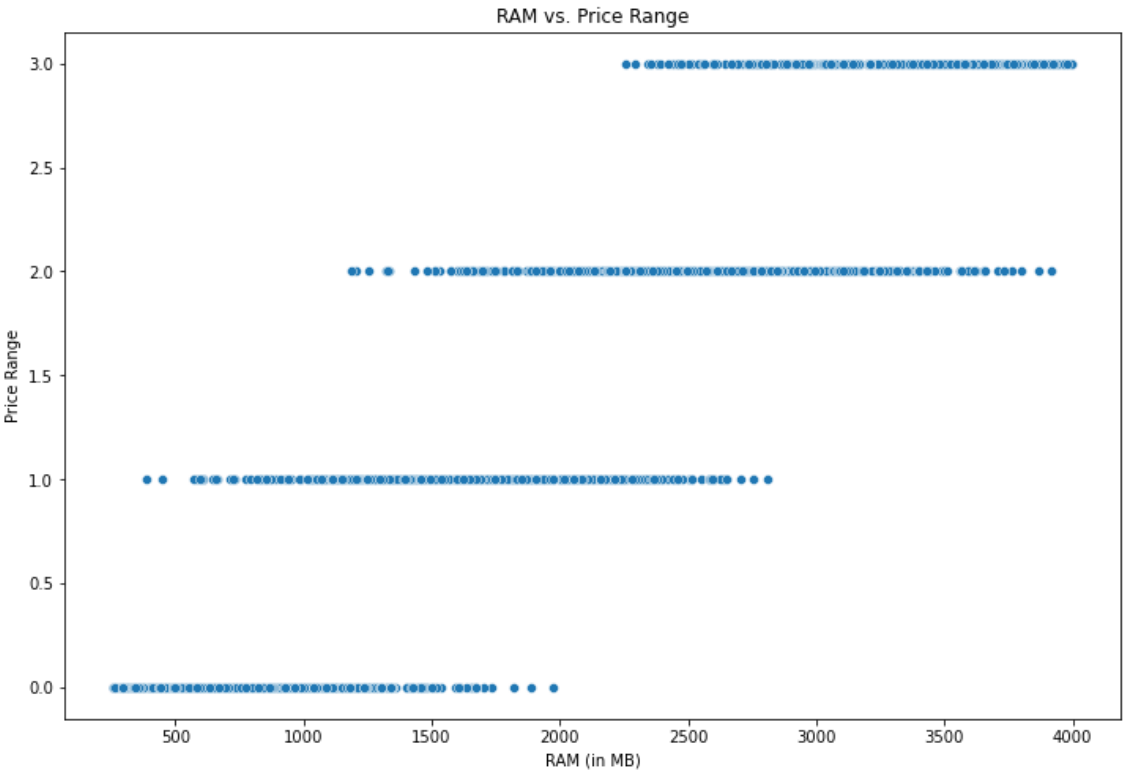
In [117]:
```
# 3. Data Exploration + Visualization
print("3. Data Exploration + Visualization:")
# Explore dataset characteristics
print("Dataset Statistics:")
print(mobile_data.describe())

# Visualize distribution of mobile prices
plt.figure(figsize=(10, 6))
sns.histplot(mobile_data['price_range'], bins=4, kde=True)
plt.title('Distribution of Mobile Prices')
plt.xlabel('Price Range')
plt.ylabel('Frequency')
plt.show()
# Visualize relationships between features (e.g., RAM vs. Price)
plt.figure(figsize=(12, 8))
sns.scatterplot(x='ram', y='price_range', data=mobile_data)
plt.title('RAM vs. Price Range')
plt.xlabel('RAM (in MB)')
plt.ylabel('Price Range')
plt.show()
```

```
3. Data Exploration + Visualization:
Dataset Statistics:
       battery_power       blue  clock_speed     dual_sim           fc  \
count    2000.000000  2000.0000  2000.000000  2000.000000  2000.000000
```

```
3. Data Exploration + Visualization:
Dataset Statistics:
       battery_power       blue  clock_speed     dual_sim           fc  \
count    2000.000000  2000.0000  2000.000000  2000.000000  2000.000000
mean     1238.518500     0.4950     1.522250     0.509500     4.309500
std       439.418206     0.5001     0.816004     0.500035     4.341444
min       501.000000     0.0000     0.500000     0.000000     0.000000
25%       851.750000     0.0000     0.700000     0.000000     1.000000
50%      1226.000000     0.0000     1.500000     1.000000     3.000000
75%      1615.250000     1.0000     2.200000     1.000000     7.000000
max      1998.000000     1.0000     3.000000     1.000000    19.000000

            four_g   int_memory        m_dep    mobile_wt      n_cores  ...  \
count  2000.000000  2000.000000  2000.000000  2000.000000  2000.000000  ...
mean      0.521500    32.046500     0.501750   140.249000     4.520500  ...
std       0.499662    18.145715     0.288416    35.399655     2.287837  ...
min       0.000000     2.000000     0.100000    80.000000     1.000000  ...
25%       0.000000    16.000000     0.200000   109.000000     3.000000  ...
50%       1.000000    32.000000     0.500000   141.000000     4.000000  ...
75%       1.000000    48.000000     0.800000   170.000000     7.000000  ...
max       1.000000    64.000000     1.000000   200.000000     8.000000  ...

         px_height     px_width          ram         sc_h         sc_w  \
count  2000.000000  2000.000000  2000.000000  2000.000000  2000.000000
mean    645.108000  1251.515500  2124.213000    12.306500     5.767000
std     443.780811   432.199447  1084.732044     4.213245     4.356398
min       0.000000   500.000000   256.000000     5.000000     0.000000
25%     282.750000   874.750000  1207.500000     9.000000     2.000000
50%     564.000000  1247.000000  2146.500000    12.000000     5.000000
75%     947.250000  1633.000000  3064.500000    16.000000     9.000000
max    1960.000000  1998.000000  3998.000000    19.000000    18.000000

         talk_time      three_g  touch_screen         wifi  price_range
count  2000.000000  2000.000000   2000.000000  2000.000000  2000.000000
mean     11.011000     0.761500      0.503000     0.507000     1.500000
std       5.463955     0.426273      0.500116     0.500076     1.118314
min       2.000000     0.000000      0.000000     0.000000     0.000000
25%       6.000000     1.000000      0.000000     0.000000     0.750000
50%      11.000000     1.000000      1.000000     1.000000     1.500000
75%      16.000000     1.000000      1.000000     1.000000     2.250000
max      20.000000     1.000000      1.000000     1.000000     3.000000

[8 rows x 21 columns]
```



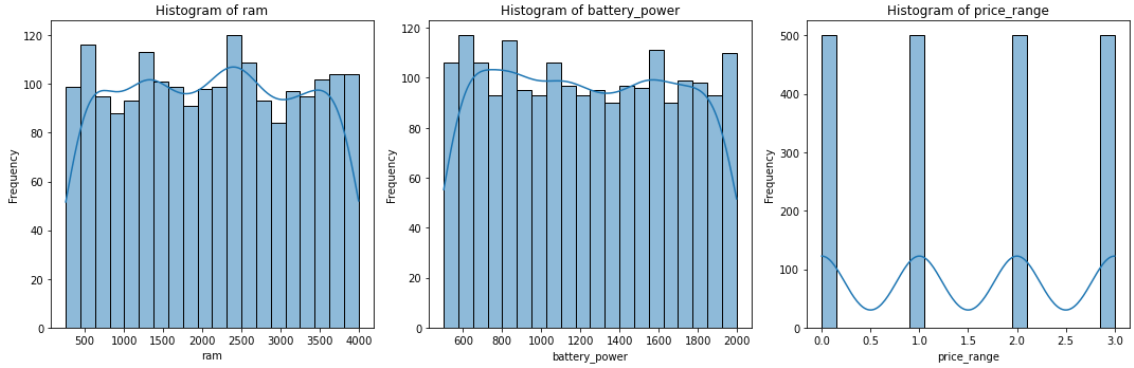




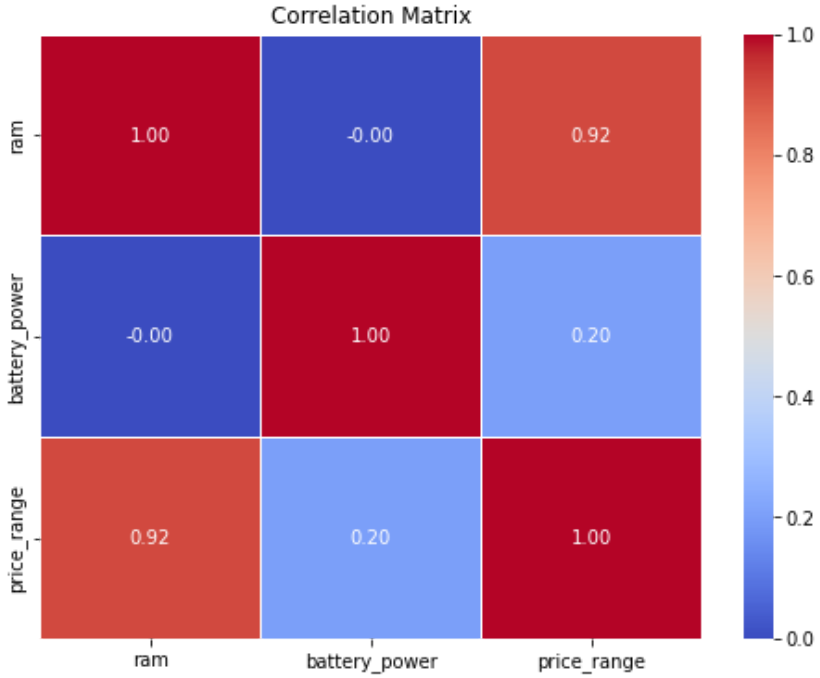

```
# Sampled columns for exploration
```

In [118]:
```
# Sampled columns for exploration
sampled_columns = ['ram', 'battery_power', 'price_range']

# 1. Histogram
```

In [118]:
```
# Sampled columns for exploration
sampled_columns = ['ram', 'battery_power', 'price_range']

# 1. Histogram
plt.figure(figsize=(15, 5))
for i, column in enumerate(sampled_columns, 1):
    plt.subplot(1, 3, i)
    sns.histplot(mobile_data[column], bins=20, kde=True)
    plt.title(f'Histogram of {column}')
    plt.xlabel(column)
    plt.ylabel('Frequency')
plt.tight_layout()
plt.show()
```

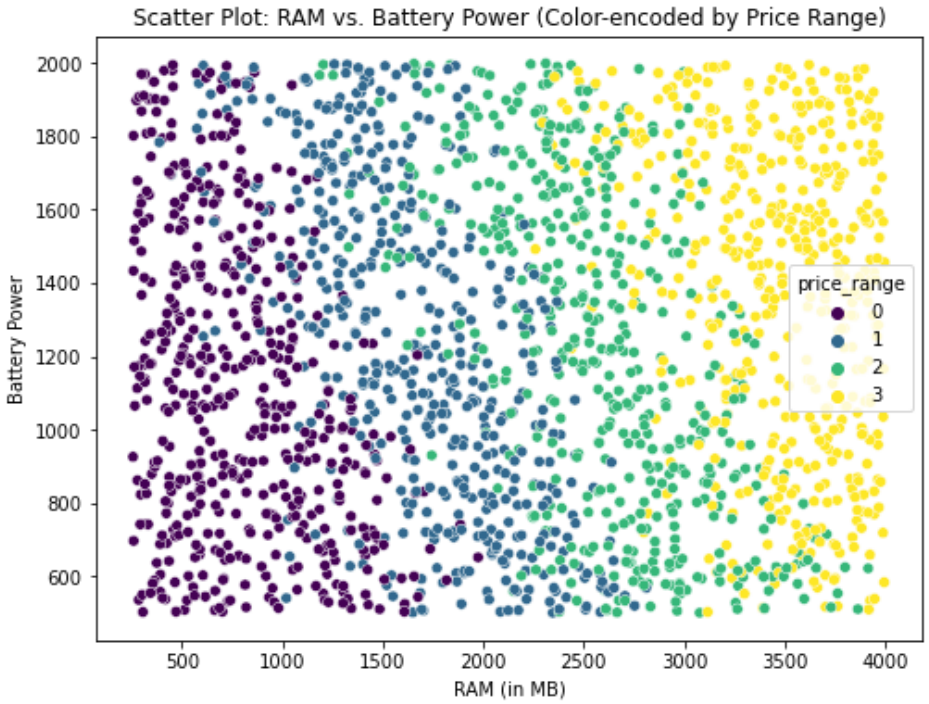


In [119]:
```
# 2. Correlation Matrix
correlation_matrix = mobile_data[sampled_columns].corr()
plt.figure(figsize=(8, 6))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt='.2f', linewidth
plt.title('Correlation Matrix')
plt.show()
```



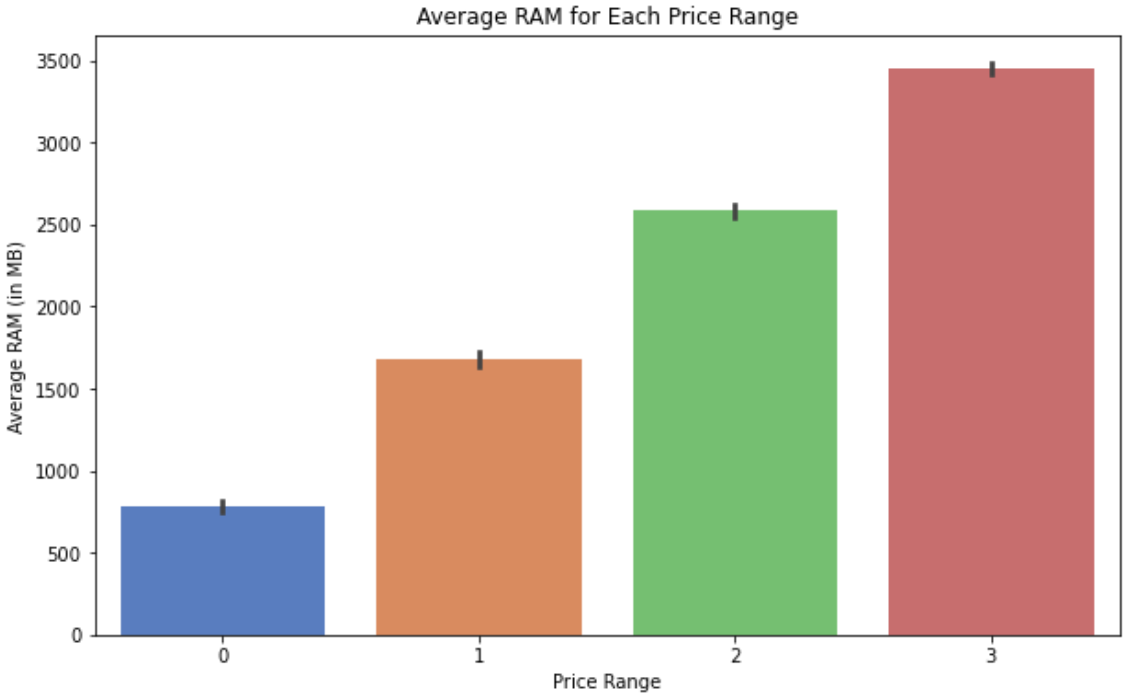
In [120]:
```
# 3. Scatter Plot
plt.figure(figsize=(8, 6))
sns.scatterplot(x='ram', y='battery_power', hue='price_range', data=mobile_data,
plt.title('Scatter Plot: RAM vs. Battery Power (Color-encoded by Price Range)')
```

In [120]:
```
# 3. Scatter Plot
plt.figure(figsize=(8, 6))
sns.scatterplot(x='ram', y='battery_power', hue='price_range', data=mobile_data,
plt.title('Scatter Plot: RAM vs. Battery Power (Color-encoded by Price Range)')
plt.xlabel('RAM (in MB)')
plt.ylabel('Battery Power')
plt.show()
```



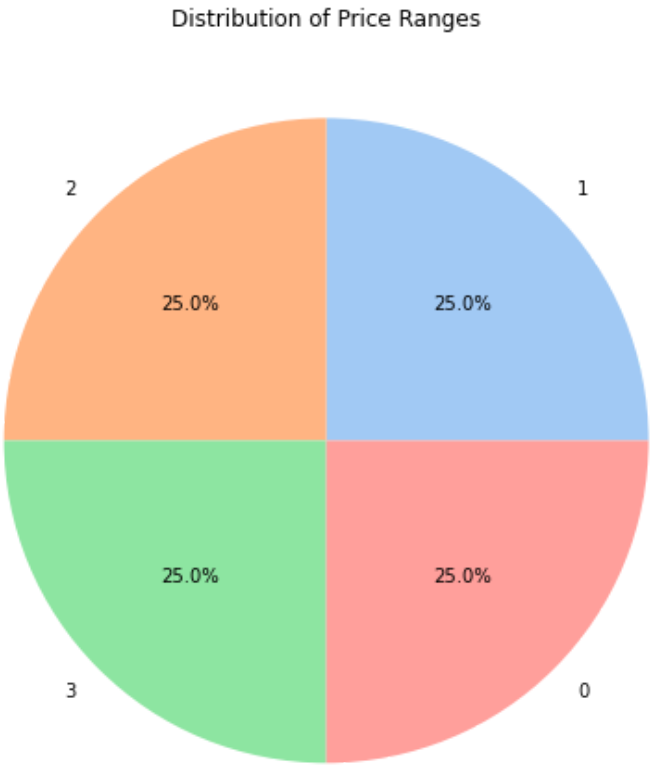
In [121]:
```
# 4. Bar Graph
plt.figure(figsize=(10, 6))
sns.barplot(x='price_range', y='ram', data=mobile_data, palette='muted')
plt.title('Average RAM for Each Price Range')
```

In [121]:
```
# 4. Bar Graph
plt.figure(figsize=(10, 6))
sns.barplot(x='price_range', y='ram', data=mobile_data, palette='muted')
plt.title('Average RAM for Each Price Range')
plt.xlabel('Price Range')
plt.ylabel('Average RAM (in MB)')
plt.show()
```



In [122]:
```
# 5. Pie Chart
price_range_counts = mobile_data['price_range'].value_counts()
plt.figure(figsize=(8, 8))
```

In [122]:
```
# 5. Pie Chart
price_range_counts = mobile_data['price_range'].value_counts()
plt.figure(figsize=(8, 8))
plt.pie(price_range_counts, labels=price_range_counts.index, autopct='%1.1f%%', 
plt.title('Distribution of Price Ranges')
plt.show()
```



4. Decision Trees + Overfitting

In [123]:
```
# 4. Decision Trees + Overfitting
print("4. Decision Trees + Overfitting:")
# Select features and target variable
```

In [123]:
```
# 4. Decision Trees + Overfitting
print("4. Decision Trees + Overfitting:")
# Select features and target variable
X = mobile_data.drop('price_range', axis=1)
y = mobile_data['price_range']

# Split the dataset into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_s

# Initialize and train the decision tree model
dt_model = DecisionTreeClassifier(random_state=42)
dt_model.fit(X_train, y_train)

# Evaluate the model
y_pred = dt_model.predict(X_test)
accuracy = accuracy_score(y_test, y_pred)
conf_matrix = confusion_matrix(y_test, y_pred)

print("Decision Tree Accuracy:", accuracy)
print("Confusion Matrix:")
print(conf_matrix)
print("\n")
```

```
4. Decision Trees + Overfitting:
Decision Tree Accuracy: 0.8325
Confusion Matrix:
[[ 92  13   0   0]
 [ 10  76   5   0]
 [  0  12  64  16]
 [  0   0  11 101]]
```

5. Classification: Rule-based + kNN + Naïve Bayes

The below code defines a simple rule-based classifier based on RAM and internal memory conditions. It then applies this rule to the test set and evaluates its accuracy.Also it covers the implementation of a decision tree classifier, addressing overfitting, and evaluating its accuracy. It also includes the implementation and evaluation of k-nearest neighbors (kNN) and Naïve Bayes classifiers.

In [132]:
```
# 5. Classification: Rule-based + kNN + Naïve Bayes
print("5. Classification: Rule-based + kNN + Naïve Bayes")
```

In [132]:
```
# 5. Classification: Rule-based + kNN + Naïve Bayes
print("5. Classification: Rule-based + kNN + Naïve Bayes")

# Rule-based classification function
def rule_based_classifier(row):
    if row['ram'] >= 2000 and row['int_memory'] >= 16:
        return 3
    elif row['ram'] >= 1000:
        return 2
    else:
        return 1

# Apply the rule-based classifier to the test set
rule_based_predictions = X_test.apply(rule_based_classifier, axis=1)

# Evaluate the rule-based classifier
rule_based_accuracy = accuracy_score(y_test, rule_based_predictions)
rule_based_conf_matrix = confusion_matrix(y_test, rule_based_predictions)


# Initialize and train the kNN model
knn_model = KNeighborsClassifier()
knn_model.fit(X_train, y_train)

# Initialize and train the Naïve Bayes model
nb_model = GaussianNB()
nb_model.fit(X_train, y_train)

# Evaluate the models
knn_accuracy = knn_model.score(X_test, y_test)
nb_accuracy = nb_model.score(X_test, y_test)

print("Rule-based Classifier Accuracy:", rule_based_accuracy)
print("Confusion Matrix:")
print(rule_based_conf_matrix)
print("\n")
print("kNN Accuracy:", knn_accuracy)
print("Naïve Bayes Accuracy:", nb_accuracy)
```

```
5. Classification: Rule-based + kNN + Naïve Bayes
Rule-based Classifier Accuracy: 0.2975
Confusion Matrix:
[[ 0 74 31  0]
 [ 0  6 63 22]
 [ 0  0 27 65]
 [ 0  0 26 86]]


kNN Accuracy: 0.9425
Naïve Bayes Accuracy: 0.7975
```

6. Classification: SVM + Ensemble

```
This code includes the implementation of Support Vector Machine (SVM) and
Random Forest Ensemble classifiers. Additionally, it demonstrates clustering
using KMeans on selected features (RAM and Internal Memory) and visualizes the
clusters.
```

This code includes the implementation of Support Vector Machine (SVM) and Random Forest Ensemble classifiers. Additionally, it demonstrates clustering using KMeans on selected features (RAM and Internal Memory) and visualizes the clusters.

In [133]:
```
# Import necessary libraries for SVM and Ensemble
from sklearn.svm import SVC
from sklearn.ensemble import RandomForestClassifier

# 6. Classification: SVM + Ensemble
print("6. Classification: SVM + Ensemble:")
# Initialize and train the Support Vector Machine (SVM) model
svm_model = SVC(kernel='linear', C=1)
svm_model.fit(X_train, y_train)

# Initialize and train a Random Forest Ensemble model
rf_model = RandomForestClassifier(n_estimators=100, random_state=42)
rf_model.fit(X_train, y_train)

# Evaluate the models
svm_accuracy = svm_model.score(X_test, y_test)
rf_accuracy = rf_model.score(X_test, y_test)

print("SVM Accuracy:", svm_accuracy)
print("Random Forest Accuracy:", rf_accuracy)
print("\n")
```

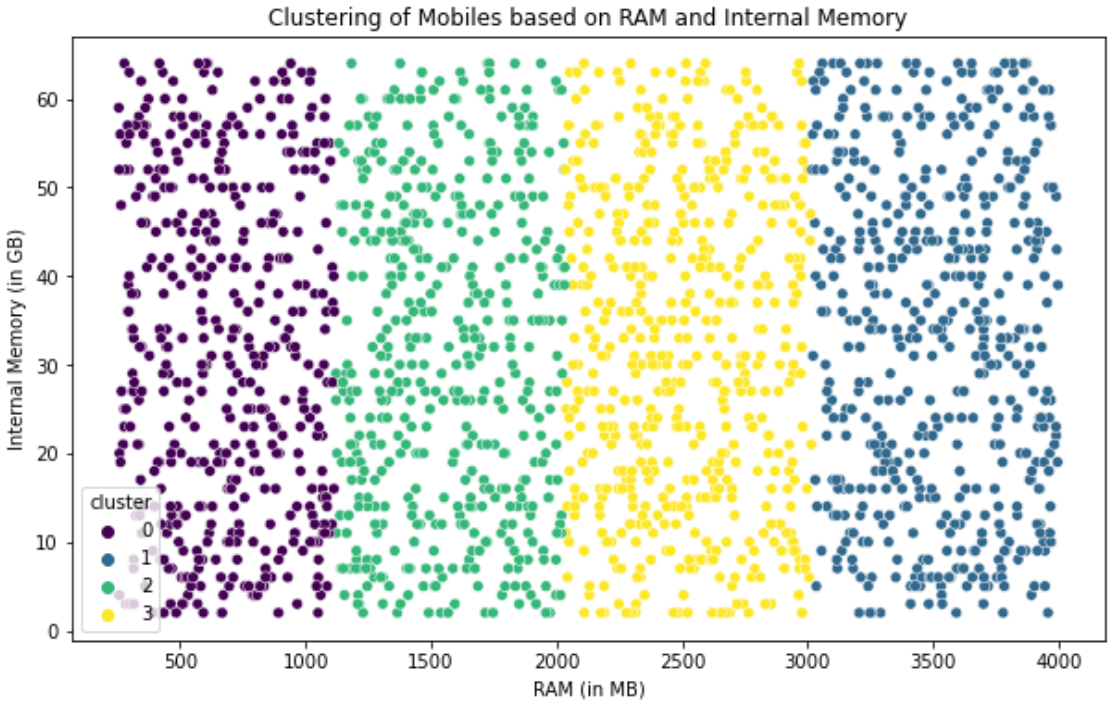
```
6. Classification: SVM + Ensemble:
SVM Accuracy: 0.97
Random Forest Accuracy: 0.8925
```

7. Clustering

In [134]:
```
# 7. Clustering
print("7. Clustering:")
# Import necessary libraries for clustering
```

In [134]:
```
# 7. Clustering
print("7. Clustering:")
# Import necessary libraries for clustering
from sklearn.cluster import KMeans

# Select features for clustering (e.g., RAM and Internal Memory)
clustering_features = ['ram', 'int_memory']
X_cluster = mobile_data[clustering_features]

# Initialize and fit the KMeans clustering model
kmeans = KMeans(n_clusters=4, random_state=42)
mobile_data['cluster'] = kmeans.fit_predict(X_cluster)

# Visualize clusters
plt.figure(figsize=(10, 6))
sns.scatterplot(x='ram', y='int_memory', hue='cluster', data=mobile_data, palette
plt.title('Clustering of Mobiles based on RAM and Internal Memory')
plt.xlabel('RAM (in MB)')
plt.ylabel('Internal Memory (in GB)')
plt.show()
```

```
7. Clustering:
```



8. Association Rule Mining

In [135]:
```
# !pip install mlxtend #Uncomment to install if not available
```

In [136]:
```
print("Unique values in 'price_range' column:", association_data['price_range'].u
```

```
Unique values in 'price_range' column: [1 0]
```

In [137]:
```
# 8. Association Rule Mining (Updated)
print("8. Association Rule Mining (Updated):")
# Select relevant features for association rule mining
association_features = ['wifi', 'four_g', 'price_range']
```

In [137]:
```
# 8. Association Rule Mining (Updated)
print("8. Association Rule Mining (Updated):")
# Select relevant features for association rule mining
association_features = ['wifi', 'four_g', 'price_range']
association_data = mobile_data[association_features]

# Convert categorical variables to boolean for association rule mining
association_data['price_range'] = (association_data['price_range'] > 0).astype(in
association_data = pd.get_dummies(association_data, columns=['wifi', 'four_g'], c

# Find frequent itemsets using Apriori algorithm
frequent_itemsets = apriori(association_data, min_support=0.1, use_colnames=True)

# Generate association rules
rules = association_rules(frequent_itemsets, metric='confidence', min_threshold=0
print("Association Rules:")
print(rules)
print("\n")
```

```
8. Association Rule Mining (Updated):
Association Rules:
          antecedents    consequents  antecedent support  consequent support  \
0           (wifi_1)  (price_range)              0.5070                0.75
1          (four_g_1)  (price_range)              0.5215                0.75
2  (wifi_1, four_g_1)  (price_range)              0.2600                0.75

   support  confidence      lift  leverage  conviction  zhangs_metric
0   0.3830    0.755424  1.007232  0.002750    1.022177       0.014564
1   0.3920    0.751678  1.002237  0.000875    1.006757       0.004665
2   0.2015    0.775000  1.033333  0.006500    1.111111       0.043592


C:\Users\n\AppData\Local\Temp\ipykernel_2676\3860843413.py:8: SettingWithCopyWa
rning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/sta
ble/user_guide/indexing.html#returning-a-view-versus-a-copy (https://pandas.pyd
ata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-c
opy)
  association_data['price_range'] = (association_data['price_range'] > 0).astyp
e(int)
C:\Users\n\anaconda3\lib\site-packages\mlxtend\frequent_patterns\fpcommon.py:11
0: DeprecationWarning: DataFrames with non-bool types result in worse computati
onalperformance and their support might be discontinued in the future.Please us
e a DataFrame with bool type
  warnings.warn(
```

9. Big Data: Hadoop + MapReduce

In [138]:
```
# !pip install mrjob #Uncomment to install if not available
```

In [139]:
```
# 9. Big Data: Hadoop + MapReduce
print("9. Big Data: Hadoop + MapReduce:")
# Save this code in a file, e.g., mobile_count_mapper.py
```

In [139]:
```
# 9. Big Data: Hadoop + MapReduce
print("9. Big Data: Hadoop + MapReduce:")
# Save this code in a file, e.g., mobile_count_mapper.py

from mrjob.job import MRJob
from mrjob.step import MRStep

class MobileCountJob(MRJob):

    def mapper(self, _, line):
        # Split the CSV line
        values = line.strip().split(',')

        # Emit each value in the 'ram' column with count 1
        yield values[13], 1

    def combiner(self, key, counts):
        # Sum the counts for each value
        yield key, sum(counts)

    def reducer(self, key, counts):
        # Output the total count for each value
        yield key, sum(counts)

if __name__ == '__main__':
    MobileCountJob().run()

#  To run this job locally, use the following command in your terminal: python mo
```

```
9. Big Data: Hadoop + MapReduce:

usage: ipykernel_launcher.py [options] [input files]
ipykernel_launcher.py: error: unrecognized arguments: -f

An exception has occurred, use %tb to see the full traceback.

SystemExit: 2



C:\Users\n\anaconda3\lib\site-packages\IPython\core\interactiveshell.py:3377: U
serWarning: To exit: use 'exit', 'quit', or Ctrl-D.
  warn("To exit: use 'exit', 'quit', or Ctrl-D.", stacklevel=1)
```

10. Big Data: Spark

In [140]:
```
# Import necessary libraries for Spark and PySpark
from pyspark.sql import SparkSession
from pyspark.ml.feature import PCA
from pyspark.ml.classification import RandomForestClassifier
```

In [140]:
```
# Import necessary libraries for Spark and PySpark
from pyspark.sql import SparkSession
from pyspark.ml.feature import PCA
from pyspark.ml.classification import RandomForestClassifier
from pyspark.ml.evaluation import MulticlassClassificationEvaluator

# 10. Big Data: Spark
print("10. Big Data: Spark:")
# Initialize Spark session
spark = SparkSession.builder.appName("MobilePrices").getOrCreate()

# Load the dataset into a Spark DataFrame
spark_mobile_data = spark.read.csv("C:\\Users\\n\\Downloads\\mobile prices.csv",

# Perform basic operations using Spark DataFrame (e.g., show the first few rows)
spark_mobile_data.show(5)
```

```
10. Big Data: Spark:
+-------------+----+-----------+--------+---+------+----------+-----+---------+
-------+---+---------+--------+----+----+----+---------+-------+------------+--
--+-----------+
|battery_power|blue|clock_speed|dual_sim| fc|four_g|int_memory|m_dep|mobile_wt|
n_cores| pc|px_height|px_width| ram|sc_h|sc_w|talk_time|three_g|touch_screen|wi
fi|price_range|
+-------------+----+-----------+--------+---+------+----------+-----+---------+
-------+---+---------+--------+----+----+----+---------+-------+------------+--
--+-----------+
|          842|   0|        2.2|       0|  1|     0|         7|  0.6|      188|
2|  2|       20|     756|2549|   9|   7|       19|      0|           0|   1|
1|
|         1021|   1|        0.5|       1|  0|     1|        53|  0.7|      136|
3|  6|      905|    1988|2631|  17|   3|        7|      1|           1|   0|
2|
|          563|   1|        0.5|       1|  2|     1|        41|  0.9|      145|
5|  6|     1263|    1716|2603|  11|   2|        9|      1|           1|   0|
2|
|          615|   1|        2.5|       0|  0|     0|        10|  0.8|      131|
6|  9|     1216|    1786|2769|  16|   8|       11|      1|           0|   0|
2|
|         1821|   1|        1.2|       0| 13|     1|        44|  0.6|      141|
2| 14|     1208|    1212|1411|   8|   2|       15|      1|           1|   0|
1|
+-------------+----+-----------+--------+---+------+----------+-----+---------+
-------+---+---------+--------+----+----+----+---------+-------+------------+--
--+-----------+
only showing top 5 rows
```

11. Big Data: Curse of Dimensionality + Principal Component Analysis

In [141]:
```
# 11. Big Data: Curse of Dimensionality + Principal Component Analysis
print("11. Big Data: Curse of Dimensionality + Principal Component Analysis:")
# Apply Principal Component Analysis (PCA) using Spark MLlib
```

In [141]:
```
# 11. Big Data: Curse of Dimensionality + Principal Component Analysis
print("11. Big Data: Curse of Dimensionality + Principal Component Analysis:")
# Apply Principal Component Analysis (PCA) using Spark MLlib

# Convert features to vector
from pyspark.ml.feature import VectorAssembler
feature_cols = spark_mobile_data.columns[:-1]
assembler = VectorAssembler(inputCols=feature_cols, outputCol='features')
spark_mobile_data = assembler.transform(spark_mobile_data)

# Apply PCA
pca = PCA(k=5, inputCol='features', outputCol='pca_features')
pca_model = pca.fit(spark_mobile_data)
transformed_data = pca_model.transform(spark_mobile_data)

# Show the transformed data
transformed_data.select('pca_features').show(5, truncate=False)
```

```
11. Big Data: Curse of Dimensionality + Principal Component Analysis:
+------------------------------------------------------------------------------
--------------------+
|pca_features
|
+------------------------------------------------------------------------------
--------------------+
|[-2549.103138015877,560.4619954589616,-820.3819006564911,-541.5099305237064,-1
87.8721200291185]   |
|[-2623.4907790173547,2052.872594075998,-974.8231505737197,-829.7997675566984,-
134.71542505250451] |
|[-2591.83587154947,2120.192362814396,-530.392765635983,-371.9569102470679,-14
4.07372841169865]    |
|[-2758.32836764516,2135.9414065855594,-579.668585211679,-455.4715439053401,-13
0.79528957764606]   |
|[-1399.520859883131,1738.5547517982027,-1801.4925941603829,-93.51655537575225,
-139.76901449853113]|
+------------------------------------------------------------------------------
--------------------+
only showing top 5 rows
```

12. Big Data: Applications with PySpark

In [142]:
```
# 12. Big Data: Applications with PySpark
print("12. Big Data: Applications with PySpark:")
# Apply PySpark for machine learning tasks (e.g., RandomForestClassifier)
```

In [142]:
```
# 12. Big Data: Applications with PySpark
print("12. Big Data: Applications with PySpark:")
# Apply PySpark for machine learning tasks (e.g., RandomForestClassifier)
# Train-test split
spark_train_data, spark_test_data = spark_mobile_data.randomSplit([0.8, 0.2], see

# Initialize and train a RandomForestClassifier model
rf_model_spark = RandomForestClassifier(labelCol='price_range', featuresCol='feat
rf_model_spark = rf_model_spark.fit(spark_train_data)

# Make predictions on the test set
predictions_spark = rf_model_spark.transform(spark_test_data)

# Evaluate the model
evaluator = MulticlassClassificationEvaluator(labelCol='price_range', predictionC
accuracy_spark = evaluator.evaluate(predictions_spark)
print("Random Forest Classifier Accuracy (PySpark):", accuracy_spark)

# Stop the Spark session
spark.stop()
```

```
12. Big Data: Applications with PySpark:
Random Forest Classifier Accuracy (PySpark): 0.8212290502793296
```

In [ ]:
```
#THE END!
```