Mobile Price Clustering

This project has been built as a part of a learning process of IBM's Unsupervised Learning course. The dataset choosen here is the `Mobile Price Classification` dataset. Several clsutering algorithms have been implemented like K-Means, Agglomerative, DBScan and Mean Shift and their results are thoroughly analyzed.

In [30]:
```
# Importing the required libraries for visualization
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
import os
# os.chdir('data')

# Visualization Prefrences.
%matplotlib inline
sns.set_style("whitegrid")
plt.style.use("fivethirtyeight")
```

In [19]:
```
%pip install xlrd==1.2.0
```

```
Requirement already satisfied: xlrd==1.2.0 in ./.venv/lib/python3.11/site-packag
es (1.2.0)
Note: you may need to restart the kernel to use updated packages.
```

01- Data Description Section

In [31]:
```
# Data Retrieving
# excel_file_path = "DryBeanDataset\Dry_Bean_Dataset.xlsx"

# df = pd.read_excel(excel_file_path,  sheet_name="sheet1", )
df=pd.read_csv("train.csv")
df.head()
```

Out[31]:

	battery_power	blue	clock_speed	dual_sim	fc	four_g	int_memory	m_dep	mobile_
0	842	0	2.20	0	1	0	7	0.60	
1	1021	1	0.50	1	0	1	53	0.70	
2	563	1	0.50	1	2	1	41	0.90	
3	615	1	2.50	0	0	0	10	0.80	
4	1821	1	1.20	0	13	1	44	0.60	

5 rows × 21 columns

In [32]:
```
df.shape
```

Out[32]: (2000, 21)

In [33]:
```
# Extract Descriptive Data.
pd.set_option("display.float", "{:.2f}".format)
df.describe()
```

Out[33]:

	battery_power	blue	clock_speed	dual_sim	fc	four_g	int_memory	
count	2000.00	2000.00	2000.00	2000.00	2000.00	2000.00	2000.00	2
mean	1238.52	0.49	1.52	0.51	4.31	0.52	32.05	
std	439.42	0.50	0.82	0.50	4.34	0.50	18.15	
min	501.00	0.00	0.50	0.00	0.00	0.00	2.00	
25%	851.75	0.00	0.70	0.00	1.00	0.00	16.00	
50%	1226.00	0.00	1.50	1.00	3.00	1.00	32.00	
75%	1615.25	1.00	2.20	1.00	7.00	1.00	48.00	
max	1998.00	1.00	3.00	1.00	19.00	1.00	64.00	

8 rows × 21 columns

02- Exploratory Data Analysis (EDA) & Feature Engineering Section

In [34]:
```
# Check for Null Values
df.isna().sum()
```

Out[34]:
```
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 [35]:
```
df.dtypes
```

Out[35]:
```
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
```

In [37]:
```
df_class_counts = df.price_range.value_counts().to_frame()
print(df_class_counts)
df.price_range.value_counts().plot(kind="bar", color='#006C31', figsize=(10,5)
```

```
             count
price_range
1              500
2              500
3              500
0              500
```

Out[37]: <Axes: title={'center': 'Price Counts'}, xlabel='price_range'>

In [39]:
```
# Check the percentage of each class
df_class_perc = df.price_range.value_counts(normalize=True).to_frame()
print(df_class_perc)
df_class_perc["proportion"] = df_class_perc["proportion"] * 100
df_class_perc.rename(columns = {"proportion": "proportion%"}, inplace=True)
df_class_perc
```

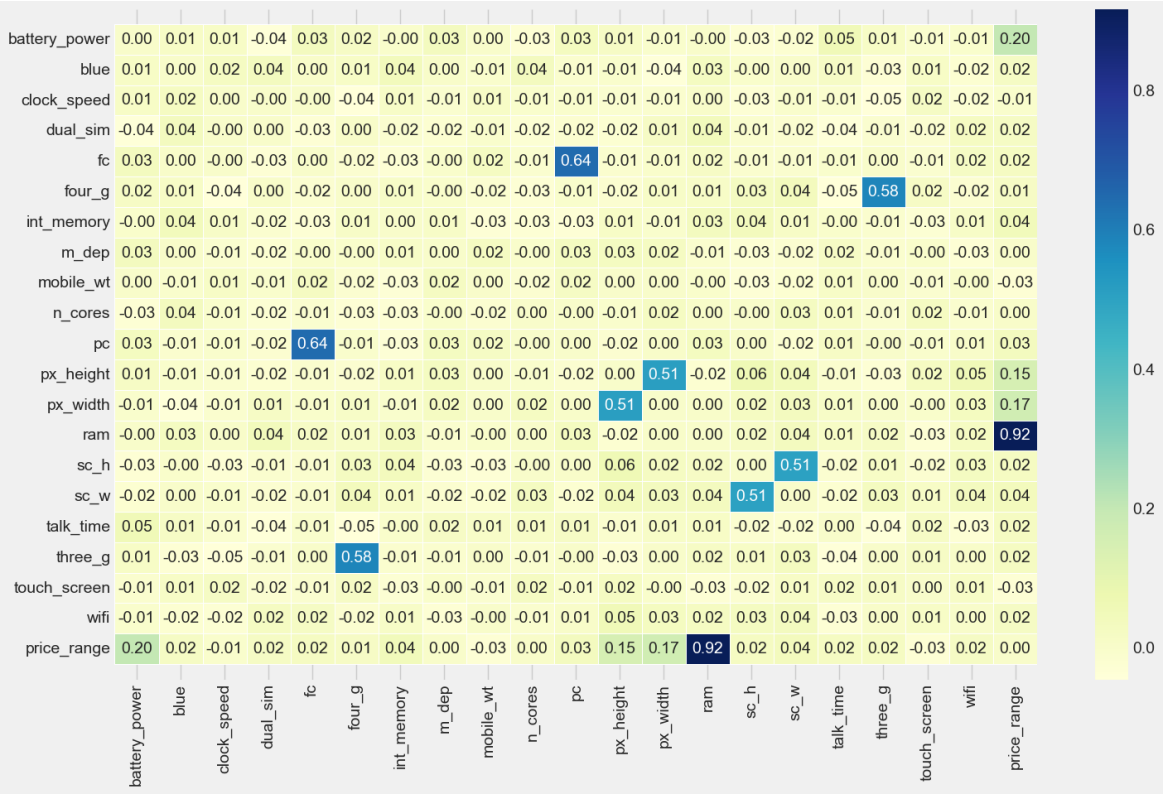
```
             proportion
price_range
1                  0.25
2                  0.25
3                  0.25
0                  0.25
```

Out[39]:

price_range	proportion%
1	25.00
2	25.00
3	25.00
0	25.00

In [40]:
```
# Studying the correlations between features using Heat Map!
corr_matrix = df.corr()
for x in range(corr_matrix.shape[0]):
    corr_matrix.iloc[x,x] = 0.0

fig, ax = plt.subplots(figsize=(16, 10))
ax = sns.heatmap(corr_matrix,
                 annot=True,
                 linewidths=0.5,
                 fmt=".2f",
                 cmap="YlGnBu");
bottom, top = ax.get_ylim()
ax.set_ylim(bottom + 0.5, top - 0.5)
```

Out[40]: (21.5, -0.5)



In [41]:
```
# The correlation matrix
corr_mat = df.corr()

# Strip out the diagonal values for the next step
for x in range(corr_mat.shape[0]):
    corr_mat.iloc[x,x] = 0.0

corr_mat
```

Out[41]:

	battery_power	blue	clock_speed	dual_sim	fc	four_g	int_memory
battery_power	0.00	0.01	0.01	-0.04	0.03	0.02	-0.00
blue	0.01	0.00	0.02	0.04	0.00	0.01	0.04
clock_speed	0.01	0.02	0.00	-0.00	-0.00	-0.04	0.01
dual_sim	-0.04	0.04	-0.00	0.00	-0.03	0.00	-0.02
fc	0.03	0.00	-0.00	-0.03	0.00	-0.02	-0.03
four_g	0.02	0.01	-0.04	0.00	-0.02	0.00	0.01
int_memory	-0.00	0.04	0.01	-0.02	-0.03	0.01	0.00
m_dep	0.03	0.00	0.01	0.02	0.00	0.00	0.01

m_dep	0.03	0.00	-0.01	-0.02	-0.00	-0.00	0.01
mobile_wt	0.00	-0.01	0.01	-0.01	0.02	-0.02	-0.03
n_cores	-0.03	0.04	-0.01	-0.02	-0.01	-0.03	-0.03
pc	0.03	-0.01	-0.01	-0.02	0.64	-0.01	-0.03
px_height	0.01	-0.01	-0.01	-0.02	-0.01	-0.02	0.01
px_width	-0.01	-0.04	-0.01	0.01	-0.01	0.01	-0.01
ram	-0.00	0.03	0.00	0.04	0.02	0.01	0.03
sc_h	-0.03	-0.00	-0.03	-0.01	-0.01	0.03	0.04
sc_w	-0.02	0.00	-0.01	-0.02	-0.01	0.04	0.01
talk_time	0.05	0.01	-0.01	-0.04	-0.01	-0.05	-0.00
three_g	0.01	-0.03	-0.05	-0.01	0.00	0.58	-0.01
touch_screen	-0.01	0.01	0.02	-0.02	-0.01	0.02	-0.03
wifi	-0.01	-0.02	-0.02	0.02	0.02	-0.02	0.01
price_range	0.20	0.02	-0.01	0.02	0.02	0.01	0.04

21 rows × 21 columns

In [42]:
```
# Pairwise maximal correlations
corr_max  = corr_mat.abs().max().to_frame()
corr_id_max = corr_mat.abs().idxmax().to_frame()

# dataframe aggrigation and processing
pair_features_corr = pd.merge(corr_id_max, corr_max, on = corr_max.index)
pair_features_corr = pair_features_corr.rename(columns = {'key_0':'Feature_one
                                                          .sort_values('correlation', as
                                                          .reset_index().drop('index', a

pair_features_corr
```

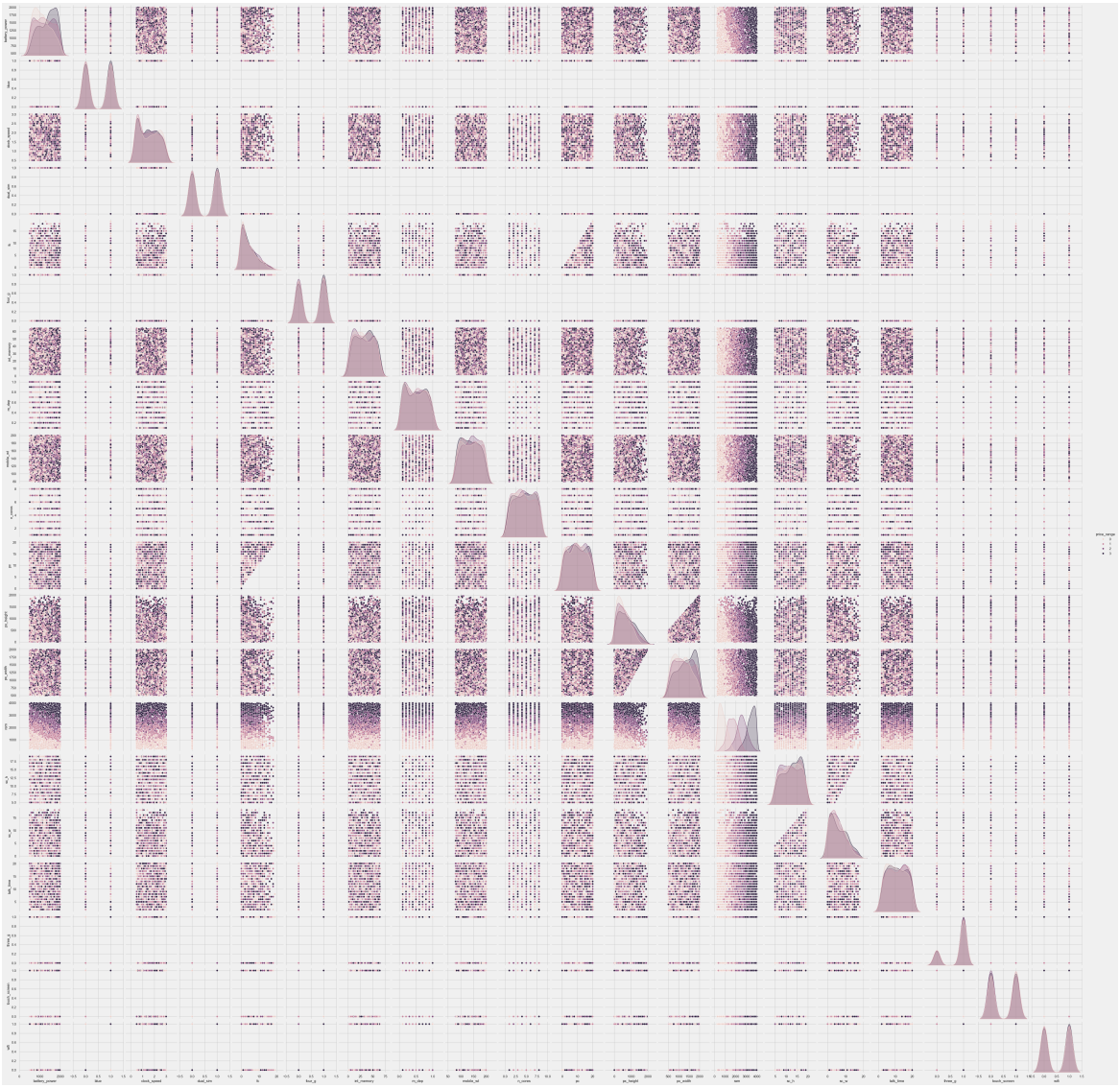
Out[42]:

	Feature_one	Feature_two	correlation
0	price_range	ram	0.92
1	ram	price_range	0.92
2	fc	pc	0.64
3	pc	fc	0.64
4	three_g	four_g	0.58
5	four_g	three_g	0.58
6	px_width	px_height	0.51
7	px_height	px_width	0.51
8	sc_w	sc_h	0.51
9	sc_h	sc_w	0.51
10	battery_power	price_range	0.20
11	talk_time	battery_power	0.05
12	wifi	px_height	0.05
13	clock_speed	three_g	0.05
14	int_memory	price_range	0.04

15	dual_sim	battery_power	0.04
16	blue	px_width	0.04
17	n_cores	blue	0.04
18	mobile_wt	int_memory	0.03
19	m_dep	battery_power	0.03
20	touch_screen	ram	0.03

In [44]:

```
float_columns = [col for col in df.columns if col != 'price_range']

sns.set_context('notebook')
sns.pairplot(df[float_columns + ['price_range']],
             hue='price_range'
             );
### END SOLUTION
```



And an examination of the skew values in anticipation of transformations.

- 0 : no skew
- pos : right skew
- neg : left skew

In [45]:

```
skew_columns = (df
                .skew()
                .sort_values(ascending=False).to_frame("skewness value")
```

```
.sort_values(ascending=False)).to_frame('skewness_value')
skew_columns
```

Out[45]:

	skewness_value
fc	1.02
px_height	0.67
sc_w	0.63
clock_speed	0.18
m_dep	0.09
int_memory	0.06
battery_power	0.03
blue	0.02
pc	0.02
px_width	0.01
talk_time	0.01
ram	0.01
mobile_wt	0.01
n_cores	0.00
price_range	0.00
touch_screen	-0.01
wifi	-0.03
dual_sim	-0.04
four_g	-0.09
sc_h	-0.10
three_g	-1.23

In [46]:

```
skew_columns = (df
                .skew()
                .sort_values(ascending=False)).to_frame("skewness_value")
skew_columns = skew_columns.query('skewness_value > 0.75')
skew_columns
```

Out[46]:

	skewness_value
fc	1.02

In [47]:

```
# Perform log transform on skewed columns
for col in skew_columns['skewness_value'].index.tolist():
    df[col] = np.log1p(df[col])
```

In [48]:

```
skew_trans_columns = (df
                .skew()
                .sort_values(ascending=False)).to_frame("skewness_value")
skew_trans_columns
```

Out[48]:

	skewness_value
px_height	0.67

sc_w	0.63
clock_speed	0.18
m_dep	0.09
int_memory	0.06
battery_power	0.03
blue	0.02
pc	0.02
px_width	0.01
talk_time	0.01
ram	0.01
mobile_wt	0.01
n_cores	0.00
price_range	0.00
touch_screen	-0.01
wifi	-0.03
dual_sim	-0.04
four_g	-0.09
sc_h	-0.10
fc	-0.12
three_g	-1.23

In [49]:
```
df.dtypes
```

Out[49]:
```
battery_power      int64
blue               int64
clock_speed      float64
dual_sim           int64
fc               float64
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
```

In [50]:
```
df.head(7)
```

Out[50]:

	battery_power	blue	clock_speed	dual_sim	fc	four_g	int_memory	m_dep	mobil
0	842	0	2.20	0	0.69	0	7	0.60	

1	1021	1	0.50	1	0.00	1	53	0.70
2	563	1	0.50	1	1.10	1	41	0.90
3	615	1	2.50	0	0.00	0	10	0.80
4	1821	1	1.20	0	2.64	1	44	0.60
5	1859	0	0.50	1	1.39	0	22	0.70
6	1821	0	1.70	0	1.61	1	10	0.80

7 rows × 21 columns

In [51]:
```
from sklearn.preprocessing import StandardScaler
float_columns = [col for col in df.columns if col != 'price_range']
sc = StandardScaler()
df[float_columns] = sc.fit_transform(df[float_columns])
df.head(7)
```

Out[51]:

	battery_power	blue	clock_speed	dual_sim	fc	four_g	int_memory	m_dep	mol
0	-0.90	-0.99	0.83	-1.02	-0.65	-1.04	-1.38	0.34	
1	-0.50	1.01	-1.25	0.98	-1.41	0.96	1.16	0.69	
2	-1.54	1.01	-1.25	0.98	-0.21	0.96	0.49	1.38	
3	-1.42	1.01	1.20	-1.02	-1.41	-1.04	-1.22	1.03	
4	1.33	1.01	-0.40	-1.02	1.47	0.96	0.66	0.34	
5	1.41	-0.99	-1.25	0.98	0.10	-1.04	-0.55	0.69	
6	1.33	-0.99	0.22	-1.02	0.35	0.96	-1.22	1.03	

7 rows × 21 columns

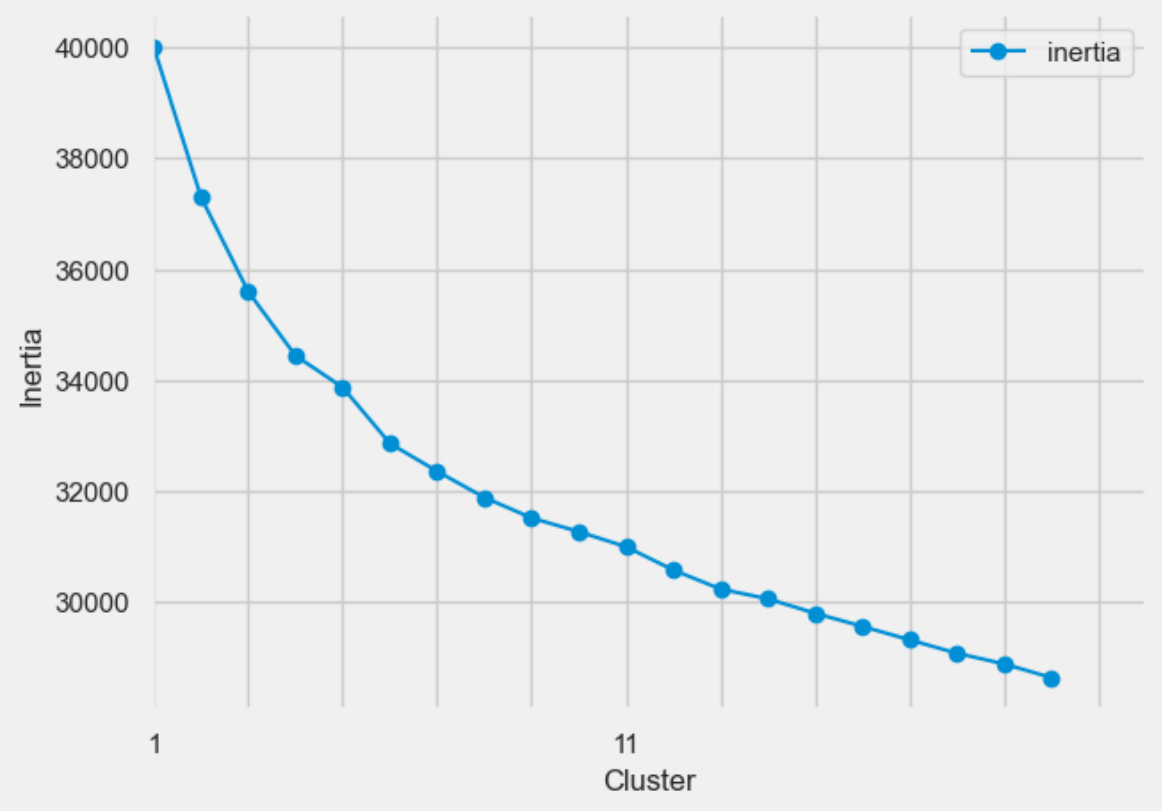
03- Machine Learning Section : clusterning methods

1- K-means Algorithm

In [52]:
```
### BEGIN SOLUTION
from sklearn.cluster import KMeans

# Create and fit a range of models
km_list = list()

for clust in range(1,21):
    km = KMeans(n_clusters=clust, random_state=42)
    km = km.fit(df[float_columns])

    km_list.append(pd.Series({'clusters': clust,
                              'inertia': km.inertia_,
                              'model': km}))
```

In [53]:
```
plot_data = (pd.concat(km_list, axis=1)
             .T
             [['clusters','inertia']]
             .set_index('clusters'))

ax = plot_data.plot(marker='o',ls='-')
```

```
ax = plot_data.plot(marker='o',ls='-')
ax.set_xticks(range(0,21,2))
ax.set_xlim(0,21)
ax.set(xlabel='Cluster', ylabel='Inertia');
### END SOLUTION
```



In [54]:

```
Bean_classes = pd.merge(df_class_counts, df_class_perc, on = df_class_counts.i
Bean_classes.rename(columns={'key_0':'class_name'}, inplace=True)
Bean_classes
```

Out[54]:

	class_name	count	proportion%
0	1	500	25.00
1	2	500	25.00
2	3	500	25.00
3	0	500	25.00

In [56]:

```
### BEGIN SOLUTION
km = KMeans(n_clusters=5, random_state=42)
km = km.fit(df[float_columns])
df['k-means'] = km.predict(df[float_columns])
df.sample(7)
```

Out[56]:

	battery_power	blue	clock_speed	dual_sim	fc	four_g	int_memory	m_dep	
363	-0.82	-0.99	-0.03	0.98	-1.41	0.96	-0.61	1.03	
521	-0.25	1.01	-0.52	-1.02	1.10	0.96	0.77	1.38	
1484	1.03	1.01	-1.25	-1.02	1.30	-1.04	-1.27	-0.01	
640	-1.45	-0.99	-1.25	-1.02	-1.41	-1.04	-0.99	1.03	
1225	-1.18	-0.99	-1.25	0.98	0.71	0.96	-1.44	-0.35	
1245	0.98	1.01	0.10	0.98	-1.41	-1.04	0.82	1.03	

644	1.08	-0.99	0.46	-1.02	0.35	0.96	-1.60	-1.39	

7 rows × 22 columns

In [57]:
```
# Group by Class and K-means for comparsion between clustered classes and actu
(df[['price_range','k-means']]
 .groupby(['price_range','k-means'])
 .size()
 .to_frame()
 .rename(columns={0:'number'}))
### END SOLUTION
```

Out[57]:

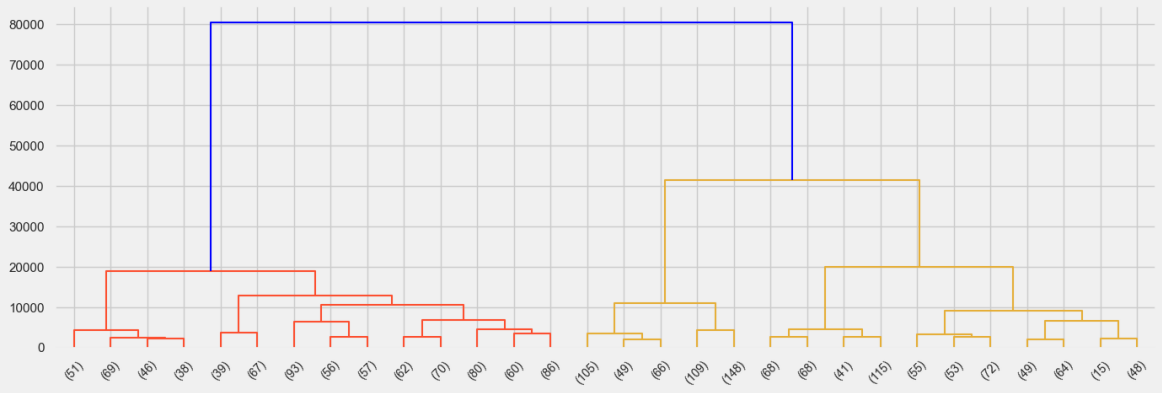
		number
price_range	**k-means**	
	0	62
	1	144
0	**2**	90
	3	135
	4	69
	0	71
	1	142
1	**2**	71
	3	111
	4	105
	0	62
	1	165
2	**2**	74
	3	102
	4	97
	0	68
	1	130
3	**2**	68
	3	91
	4	143

2- Agglomerative Algorithm

In [63]:
```
from sklearn.cluster import AgglomerativeClustering
### BEGIN SOLUTION
ag = AgglomerativeClustering(n_clusters=5, linkage='ward', compute_full_tree=T
ag = ag.fit(df[float_columns])
df['agglom'] = ag.fit_predict(df[float_columns])
```

In [64]:
```
# First, we import the cluster hierarchy module from SciPy (described above) t
from scipy.cluster import hierarchy
```

```
Z = hierarchy.linkage(ag.children_, method='ward')

fig, ax = plt.subplots(figsize=(15,5))

den = hierarchy.dendrogram(Z, orientation='top',
                           p=30, truncate_mode='lastp',
                           show_leaf_counts=True, ax=ax,
                           above_threshold_color='blue')
### END SOLUTION
```



In [65]:

```
# First, for Agglomerative Clustering:
(df[['price_range','agglom']]
 .groupby(['price_range','agglom'])
 .size()
 .to_frame()
 .rename(columns={0:'number'}))
```

Out[65]:

		number
price_range	agglom	
	0	152
	1	140
0	2	84
	3	71
	4	53
	0	144
	1	141
1	2	100
	3	78
	4	37
	0	154
	1	128
2	2	91
	3	82
	4	45
	0	117
	1	133
3	2	111
	3	107

	4	32

3- MeanShift Algorithm

In [61]:
```
from sklearn.cluster import MeanShift
ms  = MeanShift(bandwidth=2.8, n_jobs=-1)
ms = ms.fit(df[float_columns])
```

In [62]:
```
np.unique(ms.labels_)
```

Out[62]:
```
array([   0,    1,    2, ..., 1769, 1770, 1771])
```

In [66]:
```
df['MeanShift'] = ms.fit_predict(df[float_columns])
```

In [67]:
```
(df[['price_range','MeanShift']]
 .groupby(['price_range','MeanShift'])
 .size()
 .to_frame()
 .rename(columns={0:'number'}))
```

Out[67]:

		number
price_range	**MeanShift**	
	0	1
	2	1
0	**3**	1
	4	3
	5	1
...	**...**	...
	1728	1
	1739	1
3	**1745**	1
	1753	1
	1767	1

1870 rows × 1 columns

4- DBSCAN Algorithm

In [72]:
```
from sklearn.cluster import DBSCAN
dbs = DBSCAN(eps=0.5, min_samples=5, metric='euclidean')
dbs = dbs.fit(df[float_columns])
```

In [73]:
```
np.unique(dbs.labels_)
```

Out[73]:
```
array([-1])
```

In [74]:
```
df['dbscan'] = dbs.fit_predict(df[float_columns])
```

In [75]:
```
# First, for Agglomerative Clustering:
(df[['price_range','dbscan']]
 .groupby(['price_range','dbscan'])
 .size()
 .to_frame()
 .rename(columns={0:'number'}))
```

Out[75]:

		number
price_range	**dbscan**	
0	**-1**	500
1	**-1**	500
2	**-1**	500
3	**-1**	500

In [ ]:

In [ ]: