Summary

For this project on Unsupervised Machine Learning: Clustering, we will make use of 'WholeSale Customer Dataset' which has been sourced from uci.

This dataset features the clients of wholesale distributor. It contains yearly spending on several product categories in monetary units (m.u.)

Our objective in this project is to cluster this dataset as customer segments based on their yearly spending on the products and group the similar customers together using different clustering technic

In [1]:
```
import os
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
from sklearn.preprocessing import StandardScaler
from sklearn.cluster import KMeans
from sklearn.cluster import AgglomerativeClustering
from scipy.cluster import hierarchy

import warnings
warnings.filterwarnings('ignore', module = 'sklearn')
pd.options.display.float_format = '{:.2f}'.format
```

In [2]:
```
os.chdir('data')
```

In [3]:
```
data = pd.read_csv ('Wholesale%20customers%20data.csv', sep = ',')
data.head()
```

Out[3]:

	Channel	Region	Fresh	Milk	Grocery	Frozen	Detergents_Paper	Delicassen
0	2	3	12669	9656	7561	214	2674	1338
1	2	3	7057	9810	9568	1762	3293	1776
2	2	3	6353	8808	7684	2405	3516	7844
3	1	3	13265	1196	4221	6404	507	1788
4	2	3	22615	5410	7198	3915	1777	5185

Feature Analysis

- **FRESH** : annual spending (m.u.) on fresh products (Continuous)
- **MILK**: annual spending (m.u.) on milk products (Continuous)
- **GROCERY**: annual spending (m.u.)on grocery products (Continuous)
- **FROZEN**: annual spending (m.u.)on frozen products (Continuous)
- **DETERGENTS_PAPER**: annual spending (m.u.) on detergents and paper products (Continuous)
- **DELICATESSEN**: annual spending (m.u.)on and delicatessen products (Continuous);
- **CHANNEL**: customers Channel-Horeca (1: Hotel/Restaurant/Cafe) or Retail channel (Nominal).

In [4]:
```
data.shape
```

Out[4]:
```
(440, 8)
```

In [5]:
```
data.dtypes
```

Out[5]:
```
Channel             int64
Region              int64
Fresh               int64
Milk                int64
Grocery             int64
Frozen              int64
Detergents_Paper    int64
Delicassen          int64
dtype: object
```

As our data only consist of continous except for featue 'Channel' and 'Region'. we will drop those two columns

In [6]:
```
data = data.drop(['Channel', 'Region'], axis = 1)
```

In [7]:
```
data
```

Out[7]:

	Fresh	Milk	Grocery	Frozen	Detergents_Paper	Delicassen
0	12669	9656	7561	214	2674	1338
1	7057	9810	9568	1762	3293	1776
2	6353	8808	7684	2405	3516	7844
3	13265	1196	4221	6404	507	1788
4	22615	5410	7198	3915	1777	5185
...	...	...	...	...	...	...
435	29703	12051	16027	13135	182	2204
436	39228	1431	764	4510	93	2346
437	14531	15488	30243	437	14841	1867
438	10290	1981	2232	1038	168	2125
439	2787	1698	2510	65	477	52

440 rows × 6 columns

In [8]:
```
data.isnull().sum()
```

Out[8]:
```
Fresh               0
Milk                0
Grocery             0
Frozen              0
Detergents_Paper    0
Delicassen          0
dtype: int64
```

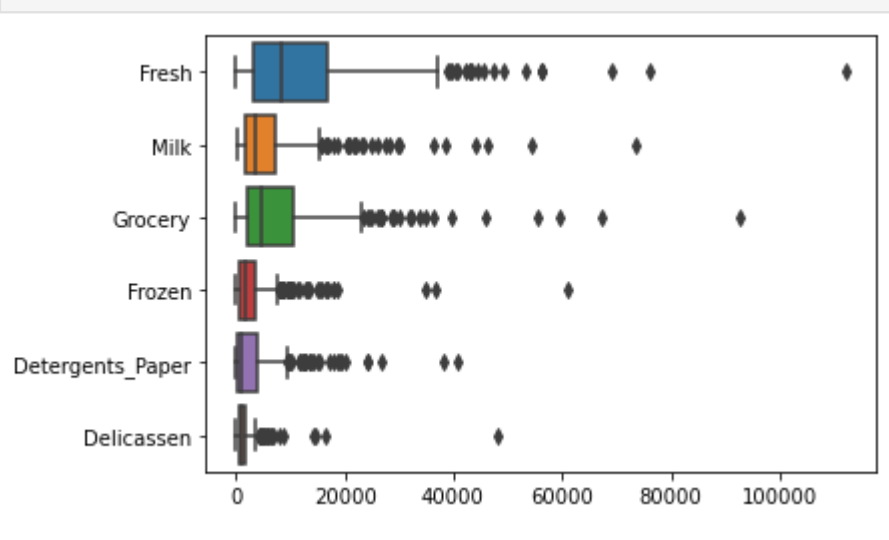
Quick Comments:

As all the attributes above are non-null and have equal nog rows , there seems to be no missing values. All the attributes are of numerical type

EDA

lets check for the distribution of our features variables and examine the amount of skewness

In [9]:
```
ax = sns.boxplot(data=data, orient="h")
```



As one can notice we have skew in almost all our features. Now, we will log transform our skew variables for skew above 0.75

In [10]:
```
log_columns = data.skew().sort_values(ascending = False)
log_columns = log_columns.loc[log_columns > 0.75]
log_columns
```

Out[10]:
```
Delicassen          11.15
Frozen               5.91
Milk                 4.05
Detergents_Paper     3.63
Grocery              3.59
Fresh                2.56
dtype: float64
```

In [11]:
```
for col in log_columns.index:
    data[col] = np.log1p(data[col])
```

In [12]:
```
data
```

Out[12]:

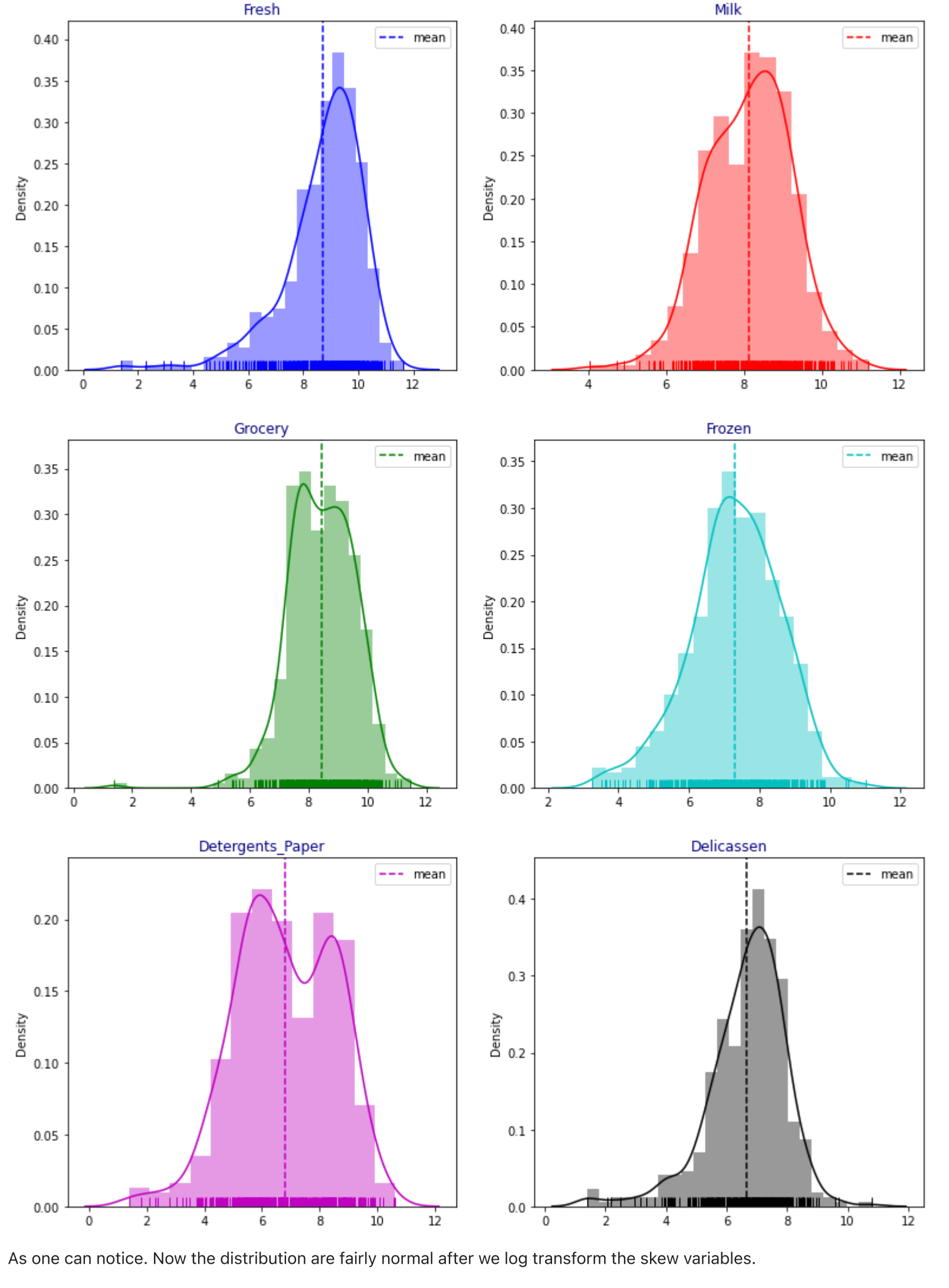
	Fresh	Milk	Grocery	Frozen	Detergents_Paper	Delicassen
0	9.45	9.18	8.93	5.37	7.89	7.20
1	8.86	9.19	9.17	7.47	8.10	7.48
2	8.76	9.08	8.95	7.79	8.17	8.97
3	9.49	7.09	8.35	8.76	6.23	7.49
4	10.03	8.60	8.88	8.27	7.48	8.55
...	...	...	...	...	...	...
435	10.30	9.40	9.68	9.48	5.21	7.70
436	10.58	7.27	6.64	8.41	4.54	7.76
437	9.58	9.65	10.32	6.08	9.61	7.53
438	9.24	7.59	7.71	6.95	5.13	7.66
439	7.93	7.44	7.83	4.19	6.17	3.97

440 rows × 6 columns

Now lets Univariate data visualization of the features and their distribution

In [14]:
```
import itertools
warnings.filterwarnings("ignore")
feature_cols = [x for x in data.columns]
length = len(feature_cols)
color = ["b","r","g","c","m","k"]
fig = plt.figure(figsize=(13,25))

for i,j,k in itertools.zip_longest(feature_cols,range(length),color):
    plt.subplot(4,2, j+1)
    ax = sns.distplot(data[i],color=k,rug=True)
    ax.set_facecolor("w")
    plt.axvline(data[i].mean(),linestyle="dashed",label="mean",color=k)
    plt.legend(loc="best")
    plt.title(i,color="navy")
    plt.xlabel("")
```



As one can notice. Now the distribution are fairly normal after we log transform the skew variables.

Scaling

Now scaling our data to make sure all the features are on same scale before applying clustering technics

In [15]:
```
ss = StandardScaler()

for col in feature_cols:
    data[col] = ss.fit_transform(data[[col]])
data
```

Out[15]:

	Fresh	Milk	Grocery	Frozen	Detergents_Paper	Delicassen
0	0.49	0.98	0.44	-1.51	0.64	0.41
1	0.09	0.99	0.65	0.13	0.77	0.63
2	0.02	0.89	0.45	0.38	0.80	1.78
3	0.52	-0.96	-0.08	1.14	-0.33	0.63
4	0.88	0.44	0.40	0.76	0.40	1.46
...	...	...	...	...	...	...
435	1.07	1.18	1.12	1.70	-0.93	0.79
436	1.26	-0.79	-1.62	0.87	-1.32	0.84
437	0.58	1.41	1.69	-0.95	1.65	0.67
438	0.34	-0.49	-0.66	-0.28	-0.97	0.77
439	-0.54	-0.63	-0.55	-2.43	-0.36	-2.09

440 rows × 6 columns

In [16]:
```
X_data = data.copy()
```

Clustering models

First we will use **KMeans** model to see how increasing the number of cluster results in low inertia value and there by increasing efficiency.

After that we will use **hierarchy** clustering to see the clusters and it's thresold. We will visualize it on dendogram.

At last we will use **Agglomerative** Clustering and see the result on scatter plot using some of our features with Agglomerative Clustering label.

KMeans

In [17]:
```
km_list = list()
for clust in range(1,7):

    km = KMeans(n_clusters = clust, random_state =42)
    km = km.fit(data[feature_cols])
    km_list.append(pd.Series({'cluster': clust,
                              'inertia': km.inertia_,
                              'model': km}))
km_df = pd.concat(km_list, axis =1).T
km_df
```

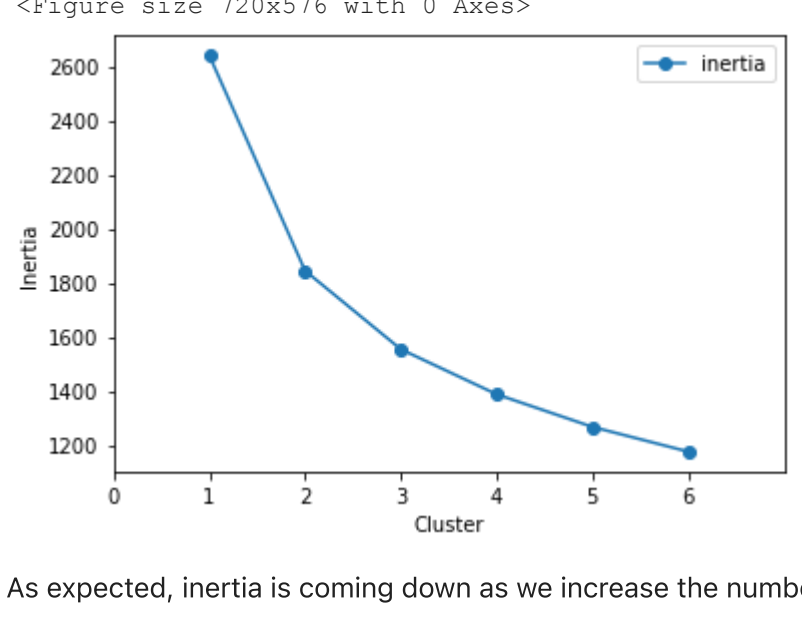
Out[17]:

	cluster	inertia	model
0	1	2640.00	KMeans(n_clusters=1, random_state=42)
1	2	1844.06	KMeans(n_clusters=2, random_state=42)
2	3	1553.39	KMeans(n_clusters=3, random_state=42)
3	4	1386.86	KMeans(n_clusters=4, random_state=42)
4	5	1266.26	KMeans(n_clusters=5, random_state=42)
5	6	1174.76	KMeans(n_clusters=6, random_state=42)

In [18]:
```
figure = plt.figure(figsize = (10,8))
km_df_plot = km_df[['cluster', 'inertia']].set_index('cluster')
ax = km_df_plot.plot(marker = 'o', ls = '-')

ax.set_xlim(0,7)
ax.set_xticks(range(0,7,1));
ax.set(xlabel = 'Cluster', ylabel= 'Inertia');
```

```
<Figure size 720x576 with 0 Axes>
```

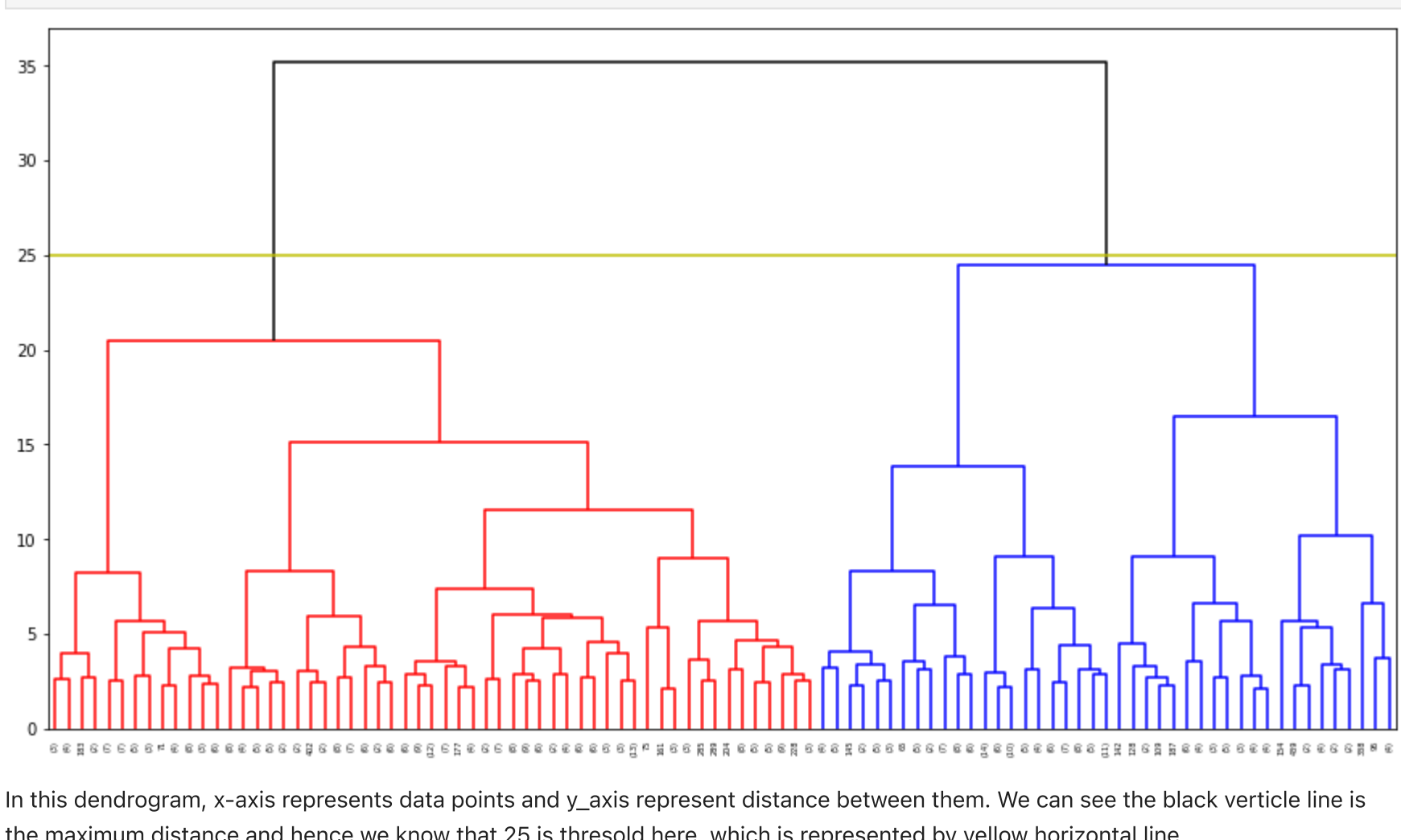


As expected, inertia is coming down as we increase the number of cluster for our model.

Hierarchy Cluster

In [19]:
```
z = hierarchy.linkage(data, method = 'ward')
fig,ax = plt.subplots(figsize = (15,8))

red= color[1]
blue = color[0]
hierarchy.set_link_color_palette ([red, 'blue'])
den = hierarchy.dendrogram(z, orientation = 'top',
                           truncate_mode = 'lastp', p = 100,
                           show_leaf_counts = True,
                           ax = ax , above_threshold_color = 'black')
ax.axhline (y= 25, color='y', ls = '-');
```



In this dendrogram, x-axis represents data points and y_axis represent distance between them. We can see the black verticle line is the maximum distance and hence we know that 25 is thresold here, which is represented by yellow horizontal line.

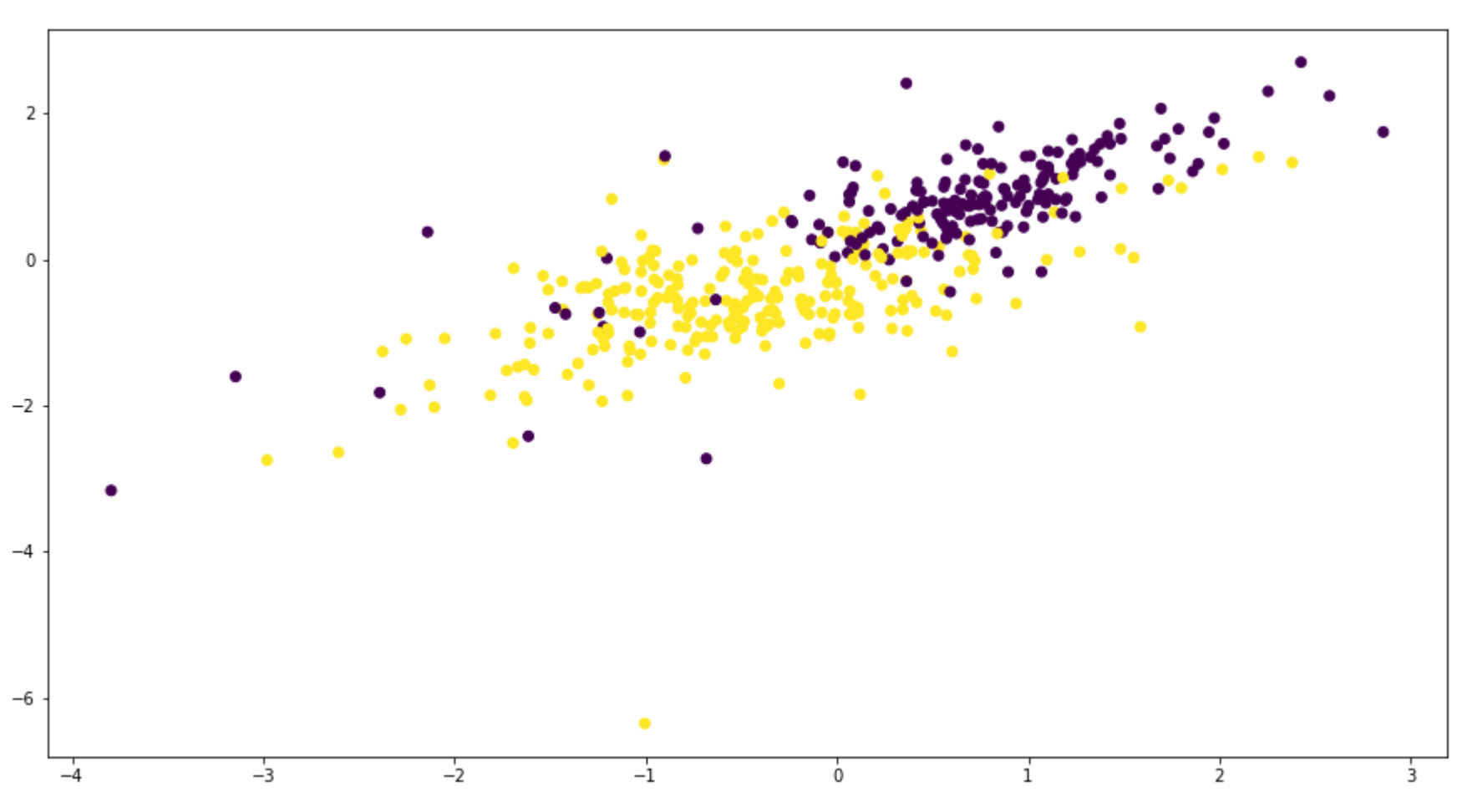
Agglomerative Clustering

In [20]:
```
ag = AgglomerativeClustering(n_clusters = 2,affinity='euclidean', linkage = 'ward',compute_full_tree = True)
ag = ag.fit(data[feature_cols])
y_pred = ag.fit_predict(data[feature_cols])
y_pred
```

Out[20]:
```
array([0, 0, 0, 1, 1, 0, 1, 0, 1, 0, 0, 1, 0, 0, 0, 1, 0, 1, 0, 1, 0, 1,
       1, 1, 0, 0, 1, 1, 0, 1, 0, 1, 1, 1, 1, 0, 0, 0, 0, 1, 1, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 1, 0, 1, 0, 1, 1, 0, 0, 1, 0, 0, 0, 0, 0, 1, 0,
       0, 0, 1, 1, 1, 1, 1, 1, 0, 1, 1, 0, 1, 1, 1, 0, 0, 1, 0, 0, 0, 1,
       1, 1, 1, 1, 0, 1, 0, 0, 0, 0, 0, 1, 0, 0, 0, 1, 1, 1, 0, 0, 0, 0,
       1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 0, 0, 1, 1, 0,
       1, 1, 1, 1, 0, 0, 1, 1, 0, 1, 0, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1,
       0, 0, 0, 1, 0, 0, 0, 1, 1, 0, 0, 0, 0, 1, 1, 1, 0, 0, 0, 0, 1, 0,
       1, 1, 1, 1, 0, 1, 0, 1, 0, 1, 1, 0, 0, 0, 1, 1, 1, 0, 1, 1, 1, 0,
       1, 1, 0, 0, 1, 0, 1, 0, 1, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0, 1, 0, 1,
       1, 0, 1, 1, 1, 1, 0, 1, 1, 1, 1, 0, 1, 0, 1, 0, 1, 1, 1, 1, 1, 1,
       1, 0, 0, 0, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       0, 1, 0, 1, 0, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 0, 1, 0, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1,
       1, 0, 1, 1, 0, 1, 1, 0, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1,
       1, 0, 1, 0, 1, 0, 1, 1, 0, 1, 0, 0, 0, 0, 1, 0, 0, 0, 1, 0, 1, 0,
       0, 0, 1, 0, 1, 0, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 0, 1, 1, 0,
       1, 1, 0, 1, 1, 0, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 1, 1, 0, 1, 1, 0, 0, 0,
       0, 1, 0, 0, 1, 1, 0, 1, 0, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 0])
```

In [21]:
```
plt.figure(figsize = (15,8))
plt.scatter(data['Milk'], data['Grocery'], c = ag.labels_)
```

Out[21]:
```
<matplotlib.collections.PathCollection at 0x7fa0c48f6940>
```



Results

You can visualize from the above plot that we were able to classifly milk and grocery dataset to two different cluster using Agglomerative Clustering.

Using KMeans, we also came to know that, inertia value decreases as we increase the number of cluster.

Next Steps

we can use Principal component analysis for more robust results and using gridsearchcv we can tune in the ideal hyper paramters for different clustering technics