Experiment No. 5
Apply appropriate Unsupervised Learning Technique on the Wholesale Customers Dataset
Date of Performance:
Date of Submission:

Aim: Apply appropriate Unsupervised Learning Technique on the Wholesale Customers Dataset.

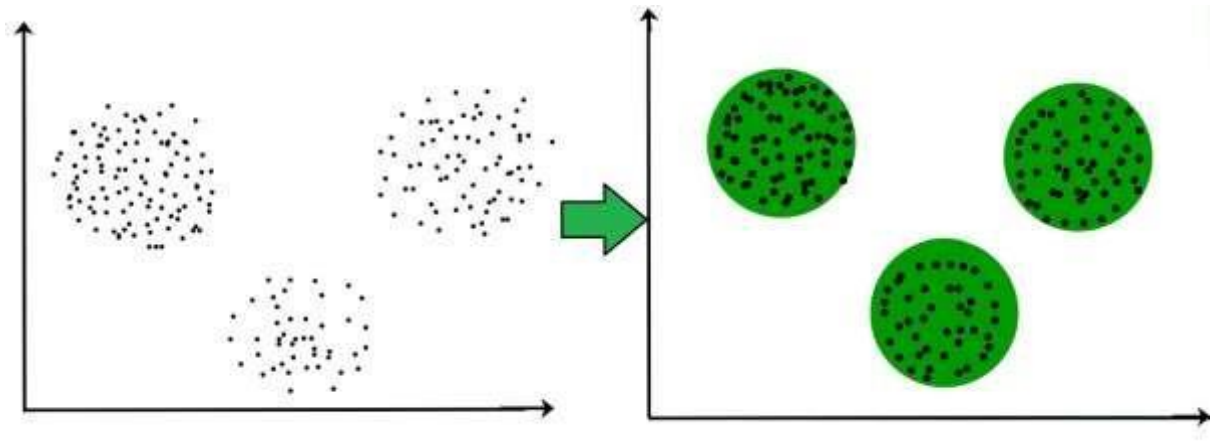
Objective: Able to perform various feature engineering tasks, apply Clustering Algorithm on the given dataset.

Theory:

It is basically a type of unsupervised learning method. An unsupervised learning method is a method in which we draw references from datasets consisting of input data without labeled responses. Generally, it is used as a process to find meaningful structure, explanatory underlying processes, generative features, and groupings inherent in a set of examples.

Clustering is the task of dividing the population or data points into a number of groups such that data points in the same groups are more similar to other data points in the same group and dissimilar to the data points in other groups. It is basically a collection of objects on the basis of similarity and dissimilarity between them.

For example: The data points in the graph below clustered together can be classified into one single group. We can distinguish the clusters, and we can identify that there are 3 clusters in the below picture.



Dataset:

This data set refers to clients of a wholesale distributor. It includes the annual spending in monetary units (m.u.) on diverse product categories. The wholesale distributor operating in different regions of Portugal has information on annual spending of several items in their stores across different regions and channels. The dataset consist of 440 large retailers annual spending on 6 different varieties of product in 3 different regions (lisbon , oporto, other) and across different sales channel (Hotel, channel). Detailed overview of dataset

Records in the dataset = 440 ROWS

Columns in the dataset = 8 COLUMNS

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: - sales channel Hotel and Retailer

REGION:- three regions (Lisbon, Oporto, Other)

Code:

```
import numpy as np import pandas as pd from
IPython.display import display from
sklearn.model_selection import train_test_split from
sklearn.tree import DecisionTreeRegressor from
sklearn.decomposition import PCA from
sklearn.cluster import KMeans from sklearn.metrics
import silhouette_score import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
try:
    data = pd.read_csv("../input/customers.csv")
data.drop(['Region', 'Channel'], axis = 1, inplace = True)
    print("Wholesale customers dataset has {} samples with {}
features each.".format(*data.shape)) except:
    print("Dataset could not be loaded. Is the dataset missing?") import warnings
warnings.filterwarnings("ignore", category = UserWarning, module = "matplotlib")
from IPython import get_ipython

get_ipython().run_line_magic('matplotlib', 'inline')
import matplotlib.pyplot as plt import
matplotlib.cm as cm import pandas as pd import
numpy as np def pca_results(good_data, pca):
```

```
dimensions = dimensions = ['Dimension {}'.format(i) for i in range(1,len(pca.components_)+1)]

components = pd.DataFrame(np.round(pca.components_, 4), columns = list(good_data.keys()))

components.index = dimensions ratios = pca.explained_variance_ratio_.reshape(len(pca.components_), 1) variance_ratios = pd.DataFrame(np.round(ratios, 4), columns = ['Explained Variance'])

variance_ratios.index = dimensions fig, ax = plt.subplots(figsize = (14,8))

components.plot(ax = ax, kind = 'bar'); ax.set_ylabel("Feature Weights")

ax.set_xticklabels(dimensions, rotation=0) for i, ev in enumerate(pca.explained_variance_ratio_): ax.text(i-0.40, ax.get_ylim()[1] + 0.05, "Explained Variance\n %.4f"%(ev)) return pd.concat([variance_ratios, components], axis = 1)

def cluster_results(reduced_data, preds, centers, pca_samples):

predictions = pd.DataFrame(preds, columns = ['Cluster'])

plot_data = pd.concat([predictions, reduced_data], axis = 1)

fig, ax = plt.subplots(figsize = (14,8)) cmap = cm.get_cmap('gist_rainbow') for i, cluster in plot_data.groupby('Cluster'):
```

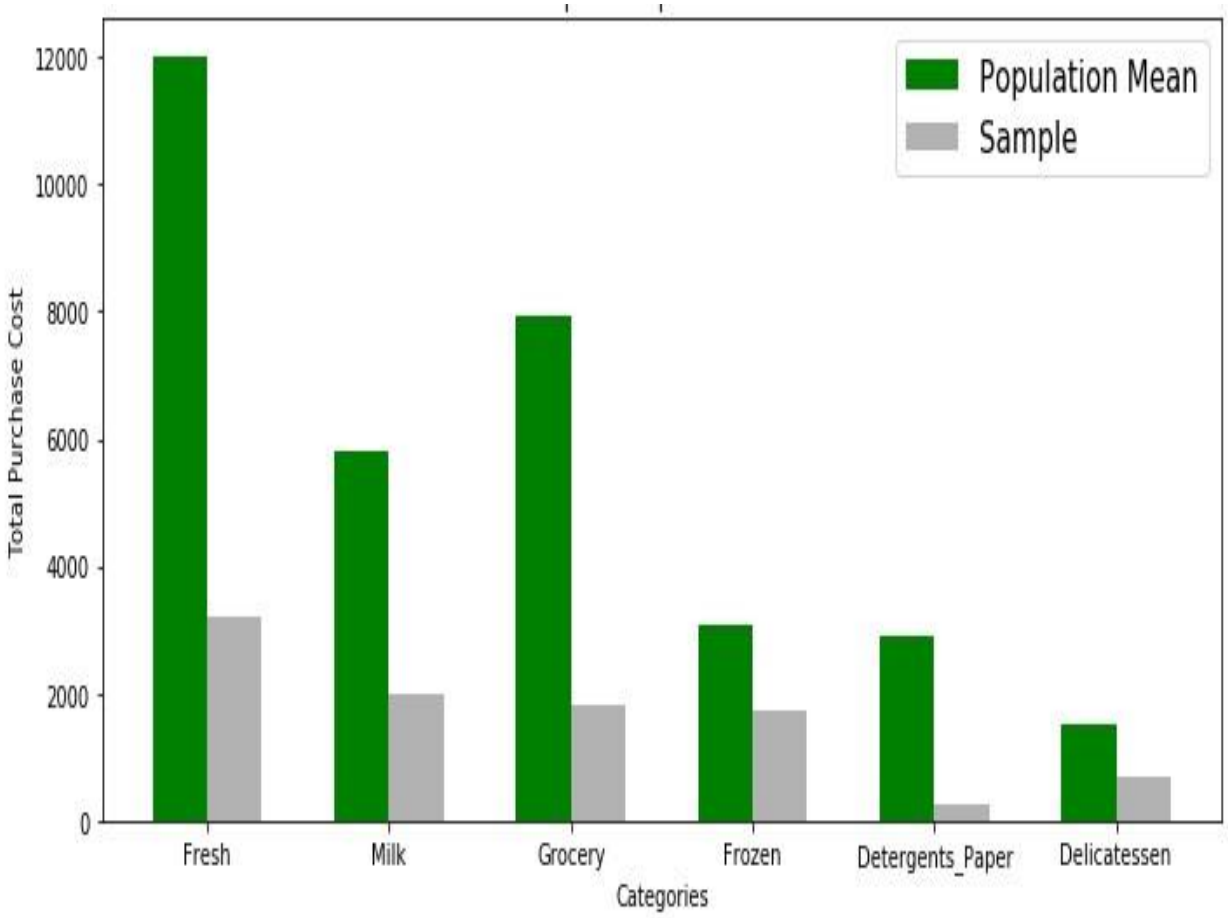
```
cluster.plot(ax = ax, kind = 'scatter', x = 'Dimension 1', y = 'Dimension 2', \
color = cmap((i)*1.0/(len(centers)-1)), label = 'Cluster %i'%(i), s=30);  for i, c in
enumerate(centers):
ax.scatter(x = c[0], y = c[1], color = 'white', edgecolors = 'black', \
alpha = 1, linewidth = 2, marker = 'o', s=200);  ax.scatter(x =
c[0], y = c[1], marker='$%d$'%(i), alpha = 1, s=100);  ax.scatter(x =
pca_samples[:,0], y = pca_samples[:,1], \  s = 150, linewidth = 4,
color = 'black', marker = 'x');
ax.set_title("Cluster Learning on PCA-Reduced Data - Centroids Marked by
Number\nTransformed Sample Data Marked by Black Cross"); def biplot(good_data,
reduced_data, pca):  fig, ax = plt.subplots(figsize = (14,8))  ax.scatter(x=reduced_data.loc[:,
'Dimension 1'], y=reduced_data.loc[:, 'Dimension 2'],  facecolors='b', edgecolors='b', s=70,
alpha=0.5)  feature_vectors = pca.components_.T  arrow_size, text_pos = 7.0, 8.0,
  for i, v in enumerate(feature_vectors):
    ax.arrow(0, 0, arrow_size*v[0], arrow_size*v[1],
head_width=0.2, head_length=0.2, linewidth=2, color='red')
ax.text(v[0]*text_pos, v[1]*text_pos, good_data.columns[i], color='black',
ha='center', va='center', fontsize=18)  ax.set_xlabel("Dimension 1",
fontsize=14)  ax.set_ylabel("Dimension 2", fontsize=14)  ax.set_title("PC
plane with original feature projections.", fontsize=16);  return ax def
channel_results(reduced_data, outliers, pca_samples):
```

```
        try:
            full_data = pd.read_csv("../input/customers.csv")
        except:
            print("Dataset could not be loaded. Is the file missing?")
return False     channel = pd.DataFrame(full_data['Channel'], columns =
['Channel'])     channel = channel.drop(channel.index[outliers]).reset_index(drop
= True)          labeled = pd.concat([reduced_data, channel], axis = 1)        fig, ax
= plt.subplots(figsize = (14,8))          cmap = cm.get_cmap('gist_rainbow')
labels = ['Hotel/Restaurant/Cafe', 'Retailer']   grouped =
labeled.groupby('Channel')

        for i, channel in grouped:
            channel.plot(ax = ax, kind = 'scatter', x = 'Dimension 1', y = 'Dimension 2', \
             color = cmap((i-1)*1.0/2), label = labels[i-1], s=30);       for i, sample in
enumerate(pca_samples):
                ax.scatter(x = sample[0], y = sample[1], \
               s = 200, linewidth = 3, color = 'black', marker = 'o', facecolors = 'none');
ax.scatter(x = sample[0]+0.25, y = sample[1]+0.3, marker='$%d$'%(i), alpha = 1, s=125);
ax.set_title("PCA-Reduced Data Labeled by 'Channel'\nTransformed Sample Data Circled");
def sampl_pop_plotting(sample):
```

```
fig, ax = plt.subplots(figsize=(10,5))     index =
np.arange(sample.count())     bar_width = 0.3
opacity_pop = 1     opacity_sample = 0.3     rect1 =
ax.bar(index, data.mean(), bar_width,
alpha=opacity_pop, color='g',
label='Population Mean')         rect2 = ax.bar(index +
bar_width, sample, bar_width,
alpha=opacity_sample, color='k',
label='Sample')     ax.set_xlabel('Categories')
ax.set_ylabel('Total Purchase Cost')

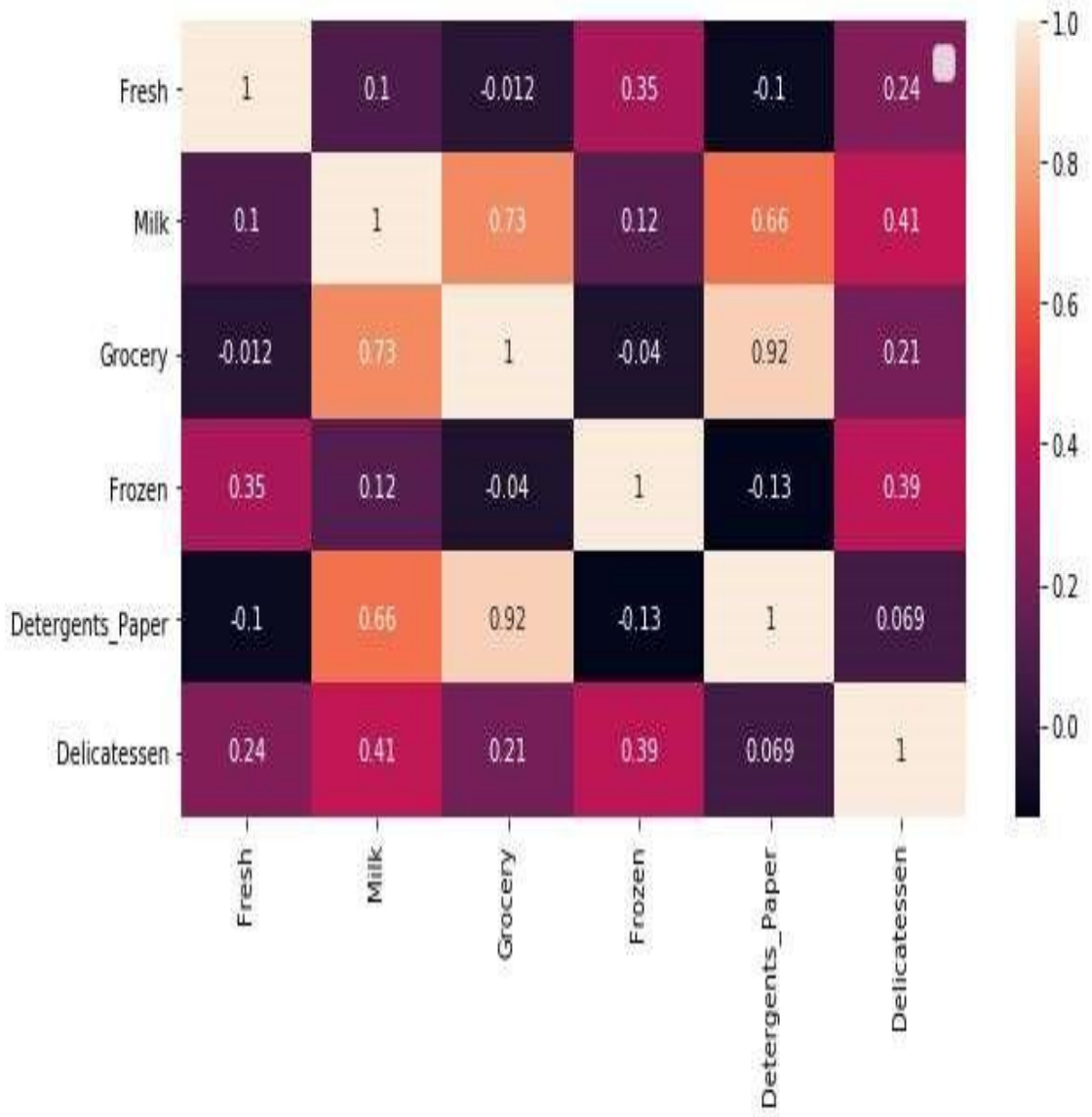
   ax.set_title('Sample vs Population Mean')
ax.set_xticks(index + bar_width / 2)
ax.set_xticklabels(samples.columns)
ax.legend(loc=0, prop={'size': 15})
fig.tight_layout()     plt.show()
```



percentiles_data = 100*data.rank(pct=True) percentiles_samples

= percentiles_data.iloc[indices] plt.subplots(figsize=(10,5))

_ = sns.heatmap(percentiles_samples, annot=True)

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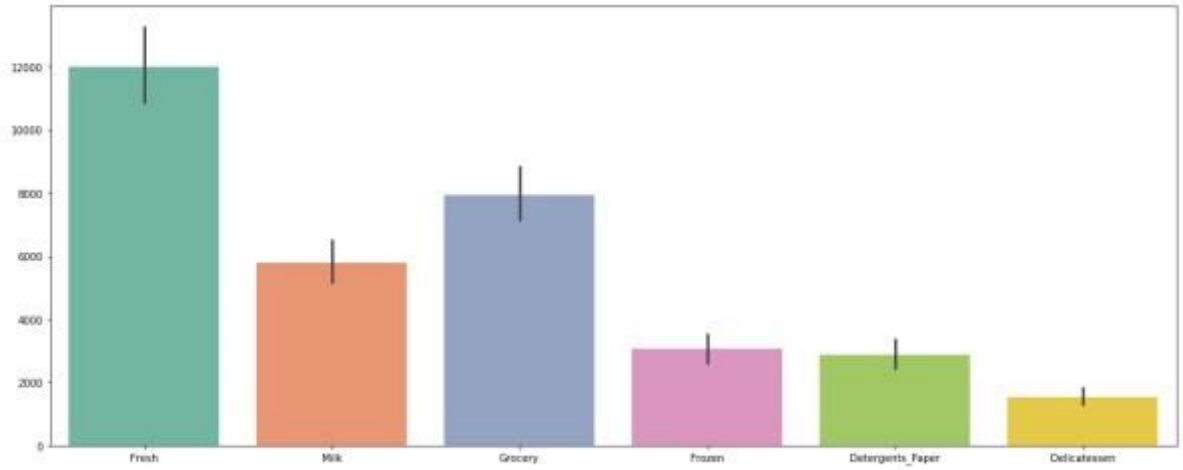
plt.figure(figsize = (20,8))

_ = sns.barplot(data=data, palette="Set2")
```



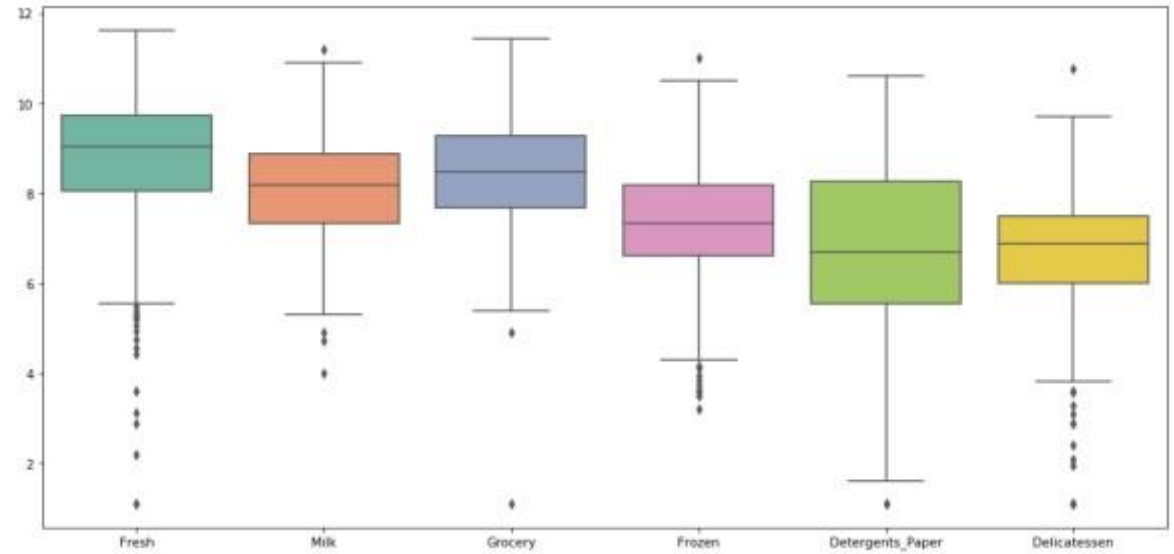
pca = PCA(n_components = 2, random_state=0) pca.fit(good_data) reduced_data =

pca.transform(good_data) pca_samples = pca.transform(log_samples) reduced_data =

pd.DataFrame(reduced_data, columns = ['Dimension 1', 'Dimension 2'])

plt.figure(figsize = (16,8))

_ = sns.boxplot(data=log_data, palette="Set2")



clusterer = KMeans(n_clusters = 2)

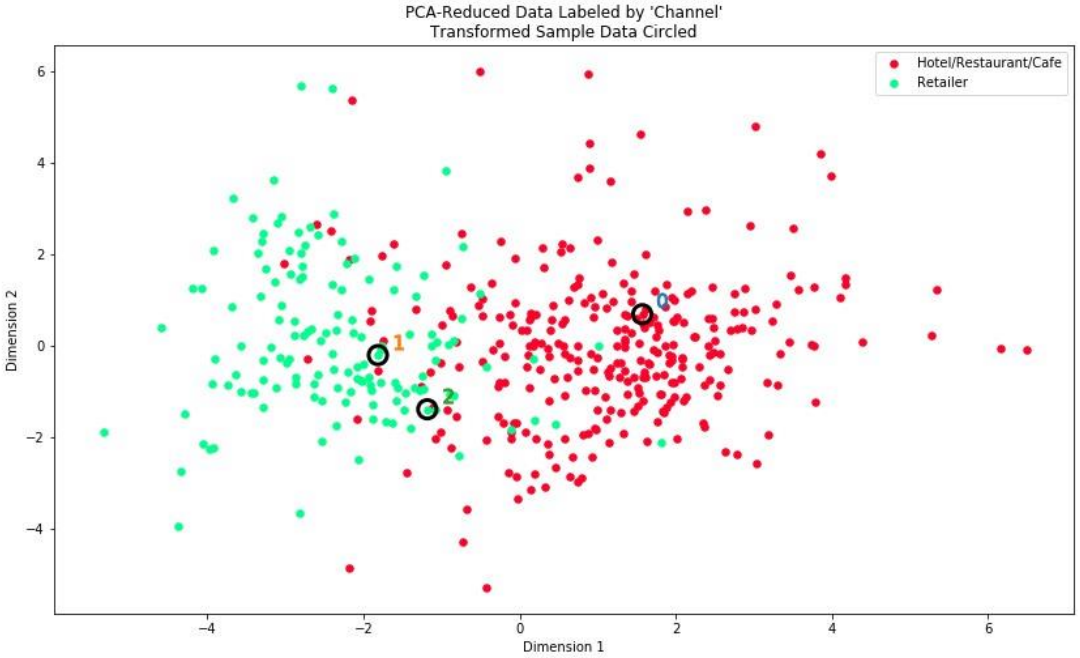
clusterer.fit(reduced_data) preds =

clusterer.predict(reduced_data) centers =

clusterer.cluster_centers_ sample_preds =

clusterer.predict(pca_samples)

cluster_results(reduced_data, preds, centers, pca_samples)



Conclusion:

1. How can you can make use of the clustered data?

- The clustered data can be utilised to identify specific patterns as well as to extract other dataset properties. Customer datasets can be utilised to provide insights into customer purchases, allowing for effective inventory management

2. How the different groups of customers, the ***customer segments***, may be affected differently by a specific delivery scheme?

- Because each group's needs are different, being able to cater to them allows firms to set up their delivery schemes successfully and increase customer satisfaction.