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.

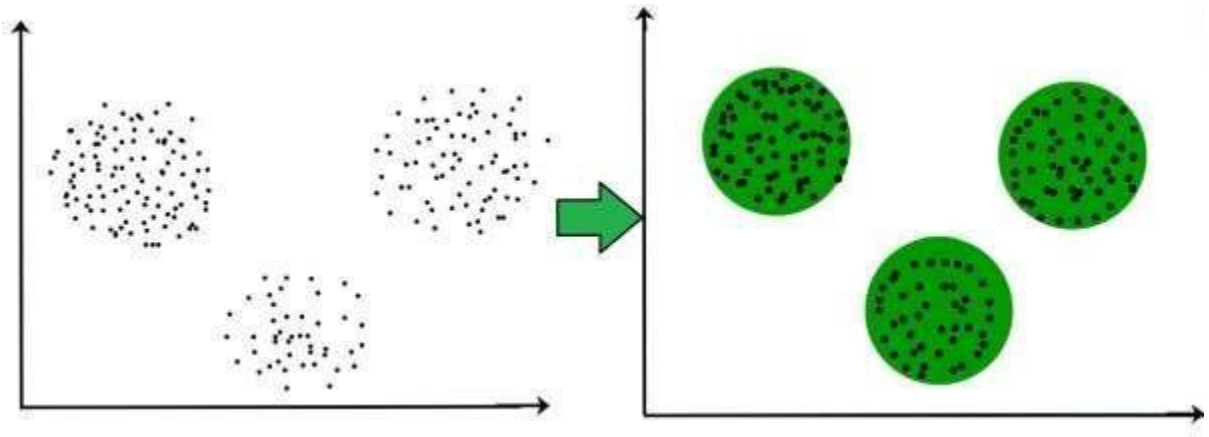
Objective: Able to perform various feature engineering tasks, apply Clustering Algorithm on the given dataset.

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
```

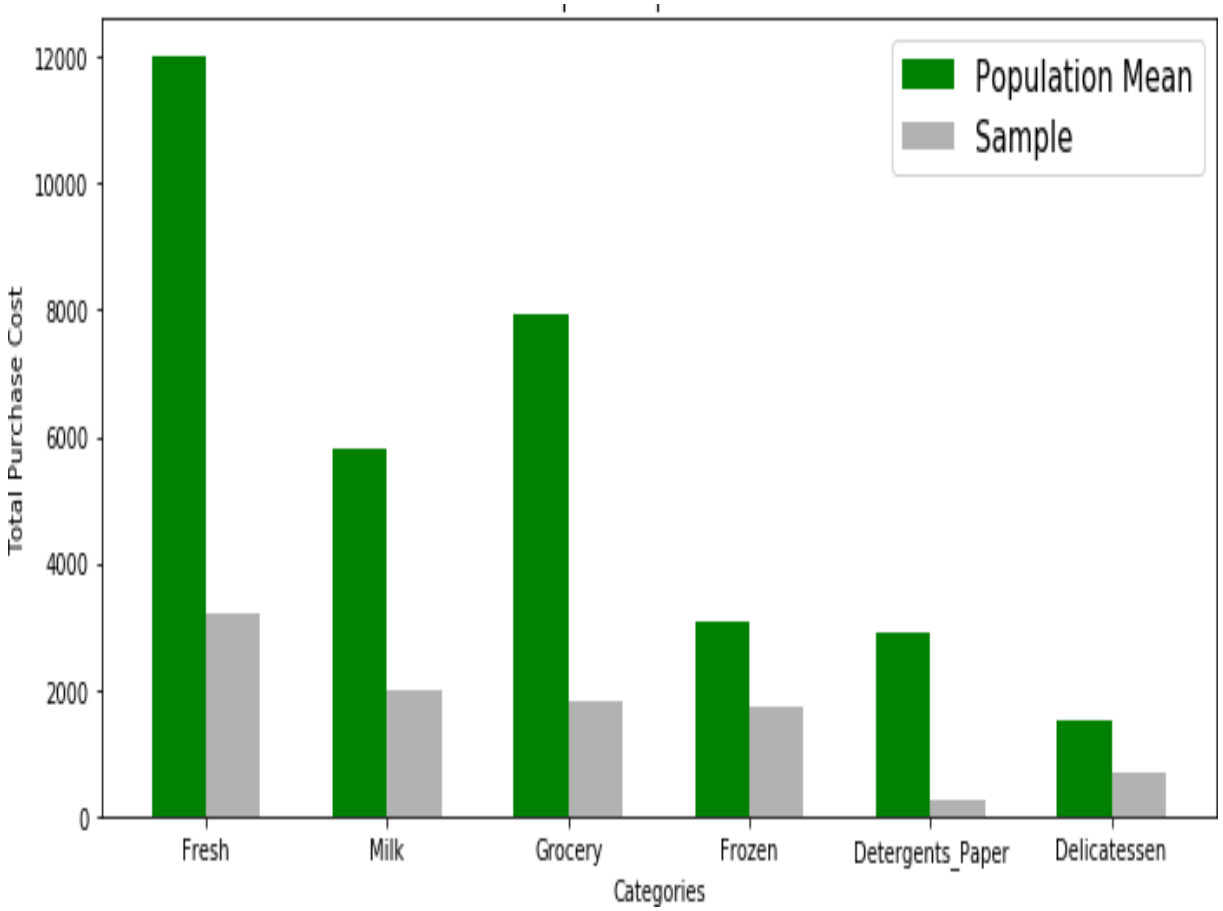
```
get_ipython().run_line_magic('matplotlib', 'inline')
import matplotlib.pyplot as plt
import matplotlib.cm as cm import pandas as pd
import numpy as np

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,
```

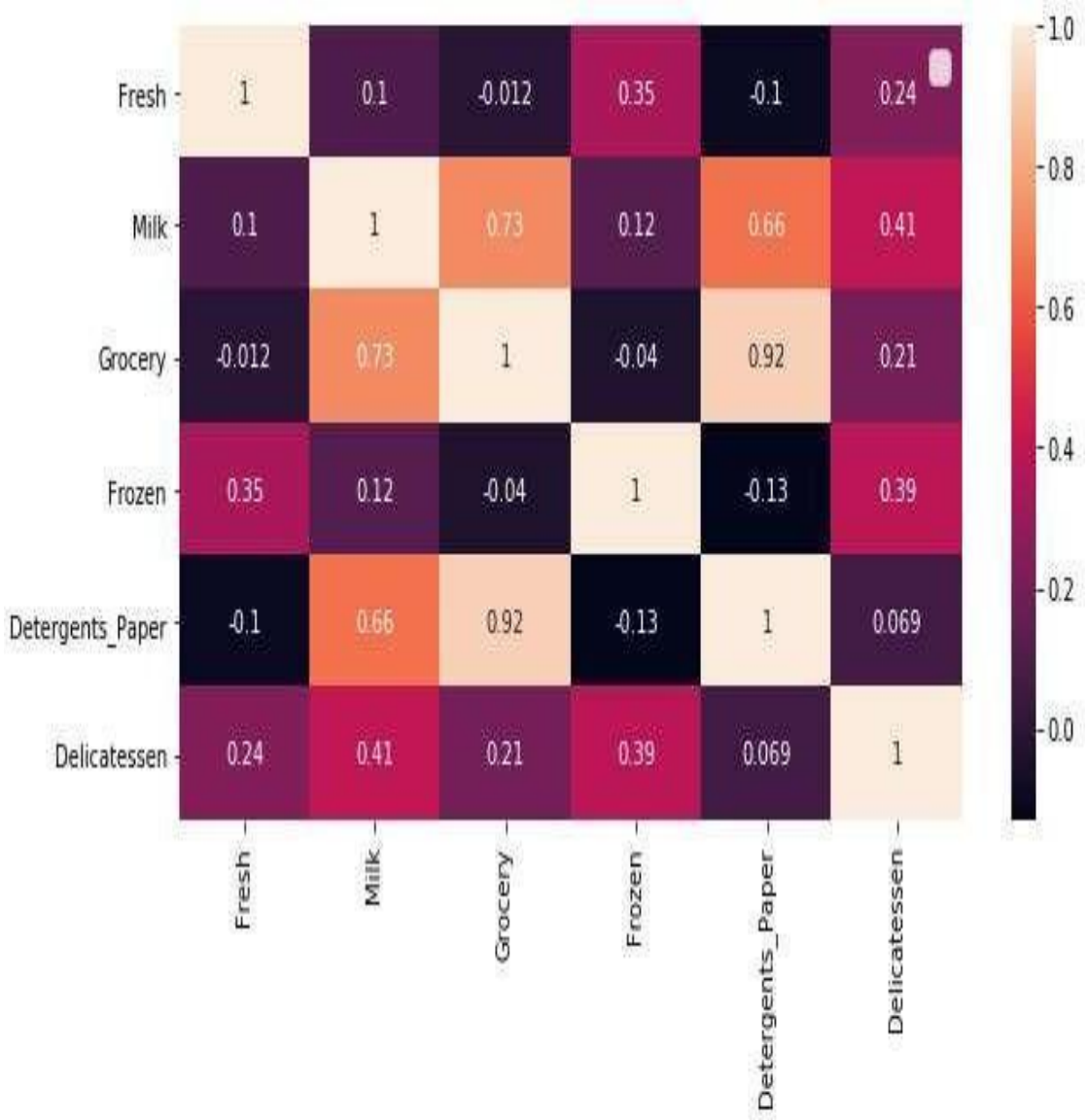
```
    for i, v in enumerate(feature_vectors):

        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')
```

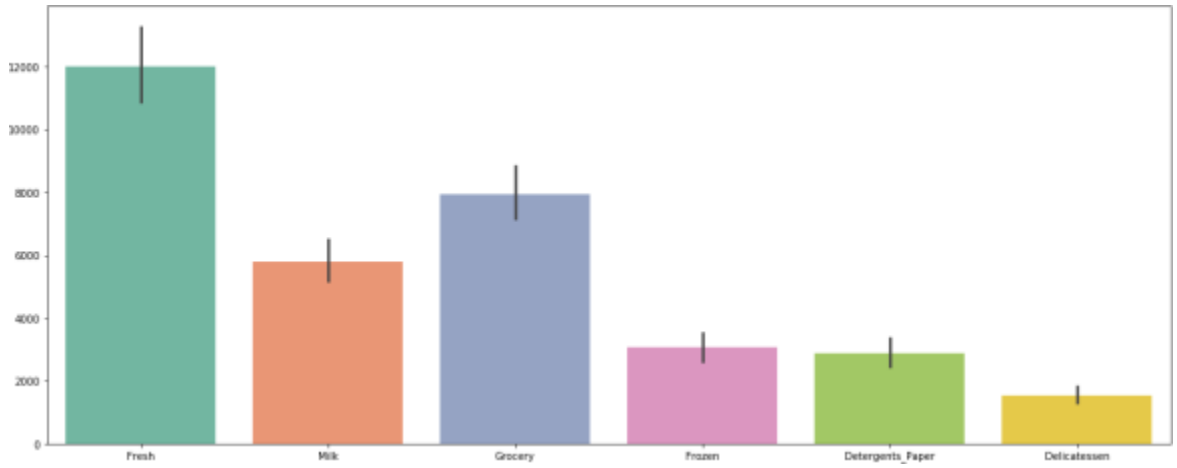
```
ax.set_title('Sample vs Population Mean')
ax.set_xticks(index + bar_width / 2)
ax.set_xticklabels(samples.columns)
ax.legend(loc=0, prop={'size': 15})
fig.tight_layout()
plt.show()
```



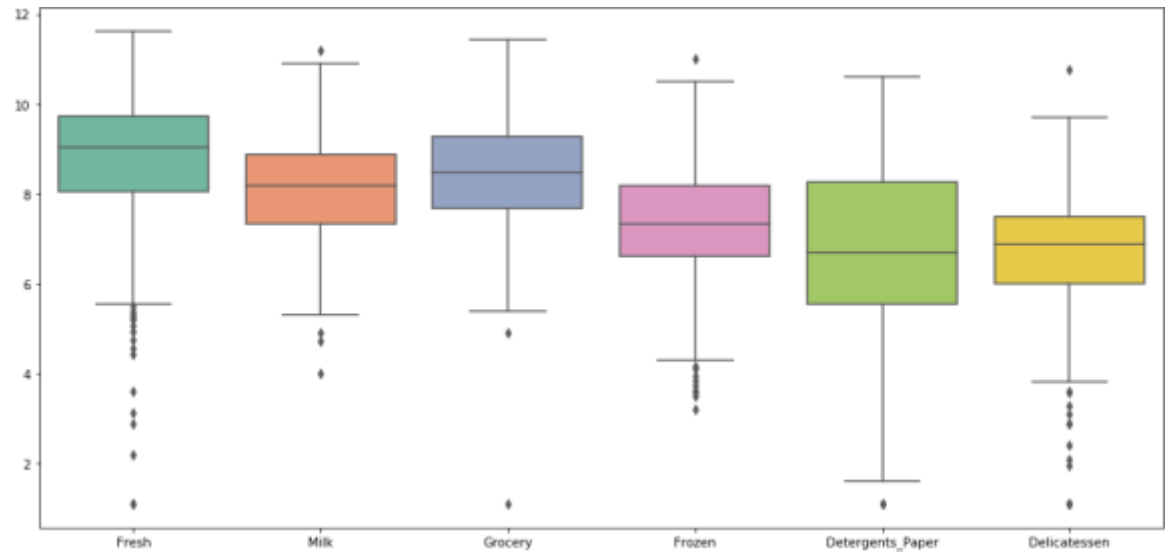
```
percentiles_data = 100*data.rank(pct=True)
percentiles_samples = percentiles_data.iloc[indices]
plt.subplots(figsize=(10,5))
_ = sns.heatmap(percentiles_samples, annot=True)
```



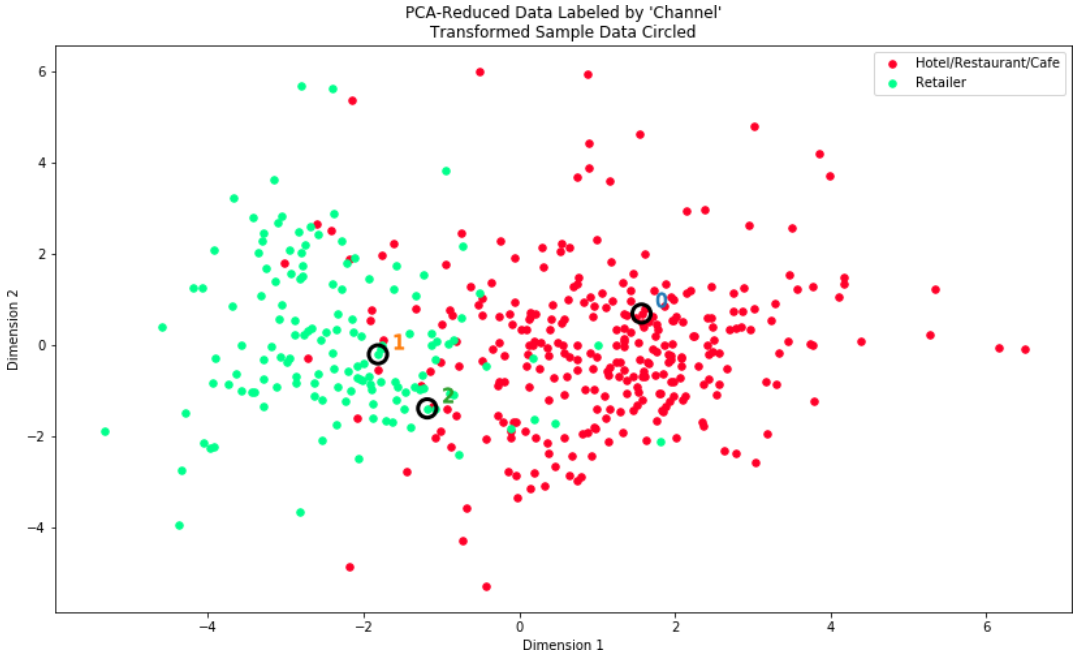
```
plt.figure(figsize = (20,8))

_ = 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:

Using clustered data can provide valuable insights into customer behavior and preferences, helping you tailor your business strategies, including delivery schemes, to better meet the needs of different customer segments.

Clustered Data Utilization: Clustered data allows you to understand distinct customer segments based on spending patterns, enabling you to customize marketing, product offerings, and service approaches for each segment. It guides decision-making and resource allocation to optimize overall business performance.

Effect of Delivery Schemes on Customer Segments: Different customer segments may respond differently to specific delivery schemes. By conducting experiments, gathering feedback, and analyzing data, you can fine-tune delivery strategies to maximize customer satisfaction and loyalty, recognizing that one-size-fits-all approaches may not be the most effective solution.