AMERICAN INTERNATIONAL UNIVERSITY–BANGLADESH (AIUB)

Faculty of Science and Technology (FST)

Course Title: DATA WAREHOUSING AND DATA MINING

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Section: (B)

Project Title: To Predict Supermarket Marketing Using K-Means Clustering Algorithm.

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Dataset Description:

This is a supermarket predictive marketing dataset consisting of 1048575 samples. There are twelves variables consisting of order_id, user_id, order_number, order_dow, order_hour_of_day, days_since¬_prior_order, product_id, add_to_card-order, reordered, department_id, department, product_name .In the dataset the department and product_name variable consist of categorical except those all are numerical.

Attributes:

ORDER_ID: This gives us an idea about the order.

USER_ID: This gives us an idea about the user.

ORDER_NUMBER: It is us idea about the number of the product.

ORDER_DOW: Number of orders appear from the customer.

ORDER_HOUR_OF_DAY: It gives us an idea the hour of order that was placed in.

DAYS_SINCE_PRIOR_ORDER: The specified number of calendar days before the occurrence of the event specified.

PRODUCT_ID: It gives us an idea about the number of products.

ADD_ TO _CARD_ORDER: That allows customers to choose items to purchase without actually completing the payment.

REORDERED: To ask someone to make deliver the same goods again.

DEPARTMENT_ID: It gives us an idea about the number of departments.

DEPARTMENT: It gives us an idea about the existence of which product belongs to which categories.

PRODUCT_NAME: It gives us an idea about the name of the product.

PURPOSE: The dataset is used to predict the suitable combination about the product, that need to be place one after another in a supermarket. It is based on order_id, user_id, order_number, order_dow, order_hour_of_day, days_since_prior_order, product_id, add_to_card-order, reordered, department_id, department, product_name.

Project Overview:

The project involves leveraging a dataset with order details, user behaviour, and product information to optimize supermarket product placement. Through analysis of order patterns and user behaviour, the aim is to create a predictive model for recommending strategic product combinations that enhance the overall shopping experience and potentially increase sales.

It is noticeable that the data set is not well formatted. The dataset must be cleaned and pre-processed before using it.

Importing required packages

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from mpl_toolkits.mplot3d import Axes3D
import plotly.express as px
import plotly.graph_objects as go
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.cluster import KMeans
from sklearn.metrics import mean_squared_error, r2_score
from sklearn.metrics import mean_absolute_error
from sklearn.decomposition import PCA
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis
import warnings
warnings.filterwarnings("ignore")
```

Documentation for Importing Required Packages

The following Python code snippet imports various libraries and modules for data analysis, visualization, and machine learning. Additionally, it suppresses warning messages using the `warnings` module.

- **NumPy (`np`):** A library for numerical operations in Python.
- **Pandas (`pd`):** A data manipulation library that provides data structures like DataFrame.
- **Matplotlib (`plt`):** A plotting library for creating static, animated, and interactive visualizations.
- **Axes3D from mpl_toolkits.mplot3d:** A module for 3D plotting in Matplotlib.
- **Plotly Express (`px`):** A high-level interface for creating interactive plots using Plotly.
- **Plotly Graph Objects (`go`):** A module for creating interactive plots using Plotly.
- **Seaborn (`sns`):** A statistical data visualization library based on Matplotlib.
- **train_test_split from sklearn.model_selection:** A function for splitting datasets into training and testing sets.
- **KMeans from sklearn.cluster:** A clustering algorithm for partitioning data into clusters.
- **mean_squared_error, r2_score, mean_absolute_error from sklearn.metrics:** Evaluation metrics for regression models.
- **PCA from sklearn.decomposition:** Principal Component Analysis for dimensionality reduction.
- **LinearDiscriminantAnalysis from sklearn.discriminant_analysis:** Linear Discriminant Analysis for feature extraction.
- **warnings:** A module for handling warning messages; warnings are suppressed using `filterwarnings` .

```
from google.colab import files
uploaded=files.upload()
```

Choose Files ECommerc…ehaviour.csv

- **ECommerce_consumer behaviour.csv**(text/csv) - 121560786 bytes, last modified: 12/5/2023 - 100% done

```
Saving ECommerce_consumer behaviour.csv to ECommerce_consumer behaviour.csv
```

from google.colab import files: Imports the files module from the Google Colab library. **uploaded=files.upload():** Executes the command to upload files.

```
Dataset = pd.read_csv('ECommerce_consumer behaviour.csv')
Dataset
```

	order_id	user_id	order_number	order_dow	order_hour_of_day	days_since_prior
0	2425083	49125	1	2	18	
1	2425083	49125	1	2	18	
2	2425083	49125	1	2	18	
3	2425083	49125	1	2	18	
4	2425083	49125	1	2	18	
...	...	...	...	...	...	
2019496	3390742	199430	16	3	18	

```
Dataset.shape
```

```
(2019501, 12)
```

Dataset.shape is used to check the dimensions of a DataFrame in Python using the Pandas library

```
Dataset.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2019501 entries, 0 to 2019500
Data columns (total 12 columns):
 #   Column                  Dtype
---  ------                  -----
 0   order_id                int64
 1   user_id                 int64
 2   order_number            int64
 3   order_dow               int64
 4   order_hour_of_day       int64
 5   days_since_prior_order  float64
 6   product_id              int64
 7   add_to_cart_order       int64
 8   reordered               int64
 9   department_id           int64
 10  department              object
 11  product_name            object
dtypes: float64(1), int64(9), object(2)
memory usage: 184.9+ MB
```

The **Dataset.info()** method in Pandas is used to print a concise summary of a DataFrame, including information about the data types, non-null values, and memory usage.

```
Dataset.isnull().sum()
```

```
order_id                       0
user_id                        0
order_number                   0
order_dow                      0
order_hour_of_day              0
days_since_prior_order    124342
product_id                     0
add_to_cart_order              0
reordered                      0
department_id                  0
department                     0
product_name                   0
dtype: int64
```

The code **Dataset.isnull().sum()** is used to count the number of missing (NaN) values in each column of the Pandas DataFrame df. The **isnull()** method creates a boolean mask indicating whether each element in the DataFrame is null, and then **sum()** is applied to count the number of True values (missing values) in each column.

```
Dataset['days_since_prior_order'].unique()
```

```
array([nan,  3.,  6.,  7., 30., 20.,  4.,  8., 15., 10., 28.,  9., 12.,
       11.,  2., 25., 13., 29., 14., 21.,  5.,  1., 18.,  0., 19., 17.,
       22., 26., 24., 16., 23., 27.])
```

unique(): This method is applied to the extracted column and returns an array of unique values in that column.

```
# replace null value into zero beacause this is the first buy for the customer
Dataset['days_since_prior_order'].fillna(0, inplace=True)
```

The code **Dataset['days_since_prior_order'].fillna(0, inplace=True)** is used to fill missing (NaN) values in the 'days_since_prior_order' column of the Pandas DataFrame df with the value 0. The inplace=True parameter modifies the DataFrame in place, meaning the changes are applied directly to the original DataFrame rather than creating a new one.

```
# Converting Data Types
Dataset['days_since_prior_order']= Dataset['days_since_prior_order'].astype(np.int64)
```

The code **Dataset['days_since_prior_order'] = Dataset['days_since_prior_order'].astype(np.int64)** is used to convert the 'days_since_prior_order' column in the Pandas DataFrame Dataset to the integer data type (np.int64).

```
Dataset['days_since_prior_order'].isnull().sum()
```

```
0
```

The code **Dataset['days_since_prior_order'].isnull().sum()** is used to count the number of missing (NaN) values in the 'days_since_prior_order' column of the Pandas DataFrame Dataset. It utilizes the isnull() method to create a boolean mask indicating whether each element in the column is null, and then sum() is applied to count the number of True values, which represent missing values.

```
Dataset.drop(['product_name', 'department'], axis=1, inplace=True)
```

The code **Dataset.drop(['product_name', 'department'], axis=1, inplace=True)** is used to remove the specified columns ('product_name' and 'department') from the Pandas DataFrame Dataset. The axis=1 parameter indicates that columns should be dropped, and inplace=True means that the changes should be applied directly to the original DataFrame.

Data Visualization

```
plt.hist(Dataset['order_dow'],bins=13, edgecolor='black')
plt.title('Distribution of Orders Across Days of the Week')
plt.xlabel('Day of the Week')
plt.ylabel('Number of Orders')
```

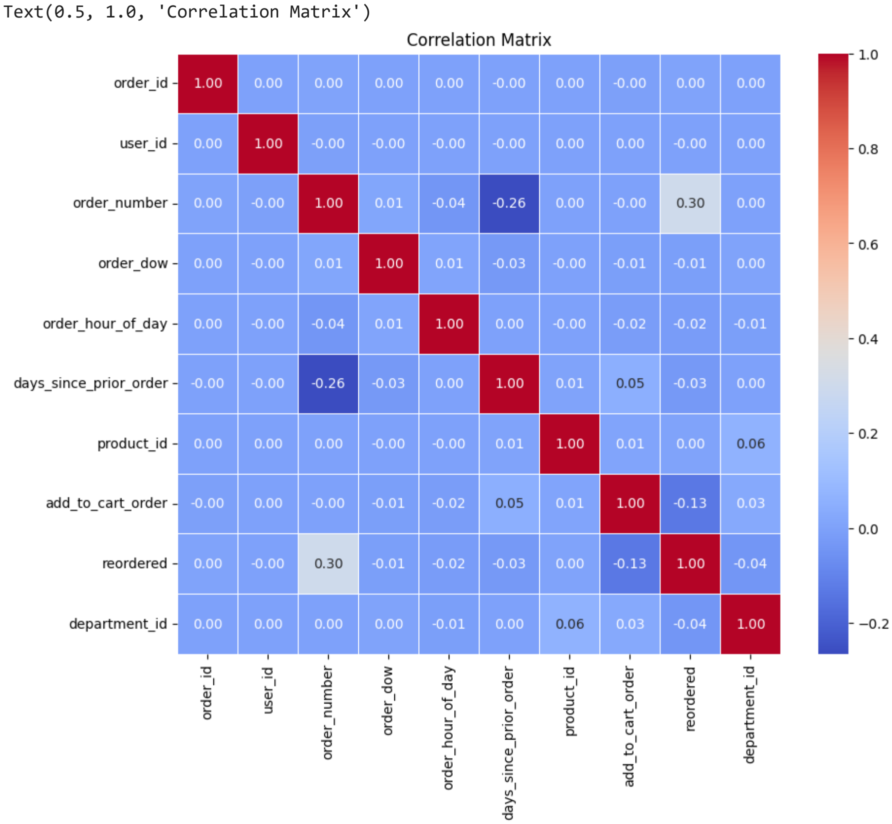
```
Text(0, 0.5, 'Number of Orders')
```

1. **Creating a Histogram using Matplotlib:**
   - `plt.hist(Dataset['order_dow'], bins=13, edgecolor='black')` : This line creates a histogram of the 'order_dow' column from the DataFrame `Dataset` . The data is divided into 13 bins (representing each day of the week), and the edges of the bins are colored black for better visibility.
2. **Adding a Title to the Plot:**
   - `plt.title('Distribution of Orders Across Days of the Week')` : This line adds a title to the plot, indicating that it represents the distribution of orders across different days of the week.
3. **Labeling the X-axis:**
   - `plt.xlabel('Day of the Week')` : This line labels the x-axis as 'Day of the Week'.
4. **Labeling the Y-axis:**
   - `plt.ylabel('Number of Orders')` : This line labels the y-axis as 'Number of Orders'.

Correlation between variable

```
corr_matrix = Dataset.corr()
plt.figure(figsize=(10, 8))
sns.heatmap(corr_matrix, annot=True, cmap='coolwarm', fmt='.2f', linewidths=.5)
plt.title('Correlation Matrix')
```

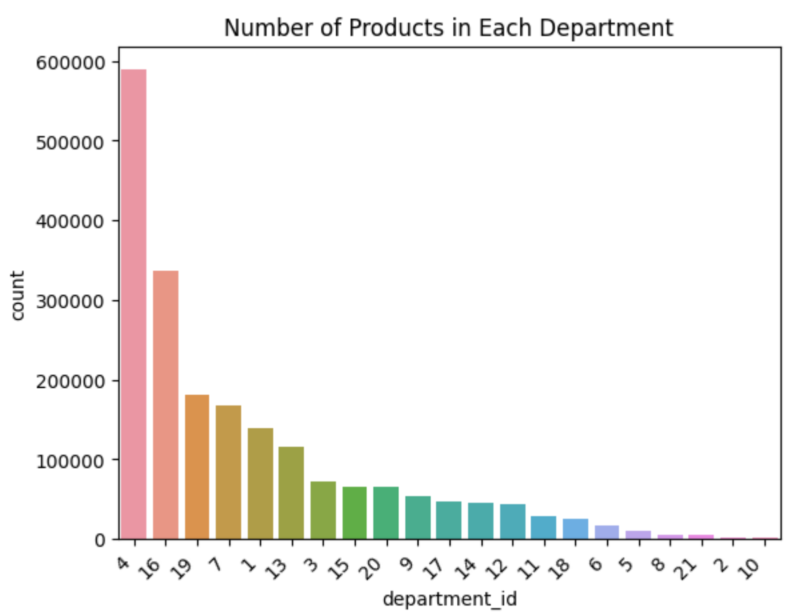
```
Text(0.5, 1.0, 'Correlation Matrix')
```



1. **Creating a Correlation Matrix:**
   - `corr_matrix = Dataset.corr()` : This line computes the correlation coefficients between different numerical variables in the DataFrame `Dataset` and stores the result in the `corr_matrix` variable.
2. **Setting up the Figure Size:**
   - `plt.figure(figsize=(10, 8))` : This line sets up the figure size for the plot to be 10 units in width and 8 units in height using Matplotlib.
3. **Generating a Heatmap using Seaborn:**
   - `sns.heatmap(corr_matrix, annot=True, cmap='coolwarm', fmt='.2f', linewidths=.5)` : This line uses Seaborn to create a heatmap of the correlation matrix. The `annot=True` parameter adds the correlation values to the cells, `cmap='coolwarm'` sets the color map, `fmt='.2f'` formats the annotations to display two decimal places, and `linewidths=.5` adds lines between the cells for better visibility.
4. **Adding a Title to the Plot:**
   - `plt.title('Correlation Matrix')` : This line adds a title to the plot, indicating that it represents a correlation matrix.

Countplot of the number of products in each department

```
sns.countplot(x='department_id', data=Dataset, order=Dataset['department_id'].value_counts().index)
plt.title('Number of Products in Each Department')
plt.xticks(rotation=45, ha='right')
plt.show()
```

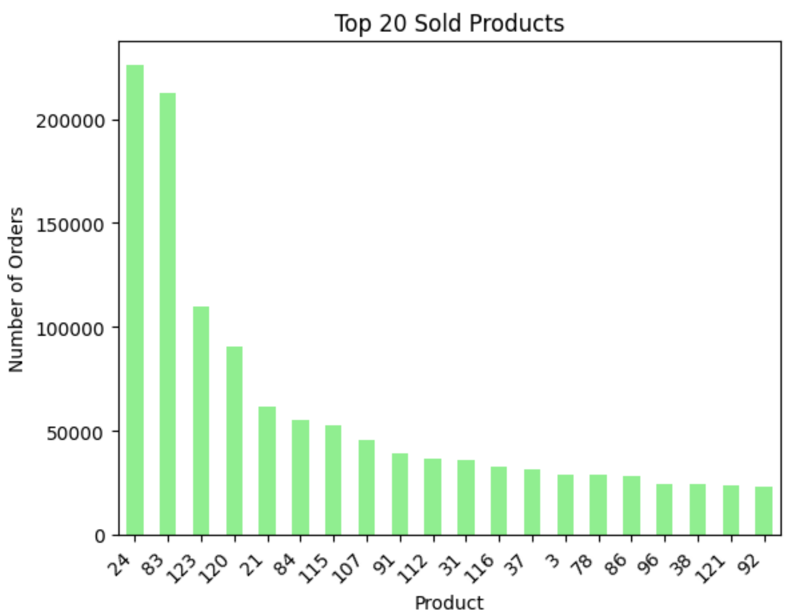


1. **Creating a Count Plot using Seaborn:**
   - `sns.countplot(x='department_id', data=Dataset, order=Dataset['department_id'].value_counts().index)` : This line uses Seaborn to create a count plot. It counts the occurrences of each unique value in the 'department_id' column of the DataFrame `Dataset` and orders the bars based on the count.
2. **Adding a Title to the Plot:**
   - `plt.title('Number of Products in Each Department')` : This line adds a title to the plot, indicating that it represents the number of products in each department.
3. **Rotating and Aligning X-axis Labels for Better Visibility:**
   - `plt.xticks(rotation=45, ha='right')` : This line rotates the x-axis labels by 45 degrees and aligns them to the right for better visibility.
4. **Displaying the Plot:**

- `plt.show()` : This line displays the generated count plot.

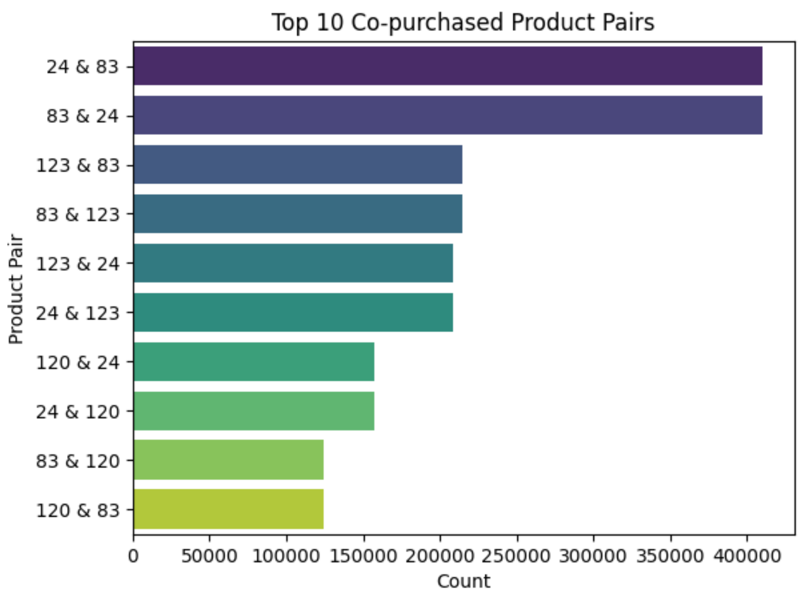
Top 20 Sold Products

```
product_counts = Dataset['product_id'].value_counts()

top_products = product_counts.head(20)

top_products.plot(kind='bar', color='lightgreen')
plt.title('Top 20 Sold Products')
plt.xlabel('Product')
plt.ylabel('Number of Orders')
plt.xticks(rotation=45, ha='right')
plt.show()
```



1. **Counting the Occurrences of Each Product:**
   - `product_counts = Dataset['product_id'].value_counts()` : This line counts the occurrences of each unique product in the 'product_id' column of the DataFrame `Dataset` .
2. **Selecting the Top 20 Sold Products:**
   - `top_products = product_counts.head(20)` : This line selects the top 20 sold products based on the previously computed counts.
3. **Creating a Bar Plot for the Top 20 Sold Products:**
   - `top_products.plot(kind='bar', color='lightgreen')` : This line creates a bar plot to visualize the top 20 sold products, with bars colored in lightgreen.
4. **Adding a Title and Labels:**
   - `plt.title('Top 20 Sold Products')` : This line adds a title to the plot.
   - `plt.xlabel('Product')` and `plt.ylabel('Number of Orders')` : These lines label the x-axis and y-axis, respectively.
5. **Rotating and Aligning X-axis Labels:**
   - `plt.xticks(rotation=45, ha='right')` : This line rotates the x-axis labels by 45 degrees and aligns them to the right for better visibility.
6. **Displaying the Plot:**
   - `plt.show()` : This line displays the generated bar plot.

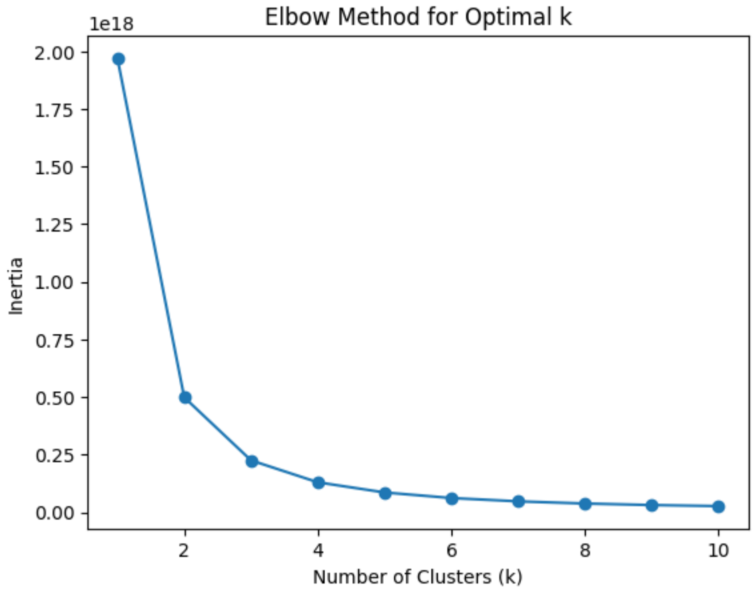
```
order_products = Dataset[['order_id', 'product_id']]
merged_products = pd.merge(order_products, order_products, on='order_id')
co_purchased_products = merged_products[merged_products['product_id_x'] != merged_products['product_id_y']][['product_id_x', 'product_id_y']]
common_pairs = co_purchased_products.value_counts().reset_index(name='count')
top_pairs = common_pairs.head(10)

sns.barplot(x='count', y=top_pairs['product_id_x'].astype(str) + ' & ' + top_pairs['product_id_y'].astype(str), data=top_pairs, palette='vir
plt.title('Top 10 Co-purchased Product Pairs')
plt.xlabel('Count')
plt.ylabel('Product Pair')
plt.show()
```



1. **Extracting Relevant Columns:**
    - `order_products = Dataset[['order_id', 'product_id']]` : This line extracts the 'order_id' and 'product_id' columns from the DataFrame `Dataset`.
2. **Creating Pairs of Co-purchased Products:**
    - `merged_products = pd.merge(order_products, order_products, on='order_id')` : This line creates pairs of co-purchased products by merging the `order_products` DataFrame with itself based on the 'order_id'.
    - `co_purchased_products = merged_products[merged_products['product_id_x'] != merged_products['product_id_y']][['product_id_x', 'product_id_y']]` : This line filters out pairs where the product IDs are the same.
3. **Counting the Occurrences of Each Co-purchased Product Pair:**
    - `common_pairs = co_purchased_products.value_counts().reset_index(name='count')` : This line counts the occurrences of each co-purchased product pair and resets the index to create a DataFrame.
4. **Selecting the Top 10 Co-purchased Product Pairs:**
    - `top_pairs = common_pairs.head(10)` : This line selects the top 10 co-purchased product pairs based on

Model Building And Clustring

```
X = Dataset[['order_id', 'user_id', 'order_number', 'order_dow', 'order_hour_of_day', 'days_since_prior_order', 'product_id', 'add_to_cart_c

inertia_values = []

for n_clusters in range(1, 11):
    kmeans = KMeans(n_clusters=n_clusters, random_state=42)
    kmeans.fit(X)
    inertia_values.append(kmeans.inertia_)

plt.plot(range(1, 11), inertia_values, marker='o')
plt.title('Elbow Method for Optimal k')
plt.xlabel('Number of Clusters (k)')
plt.ylabel('Inertia')
plt.show()
```

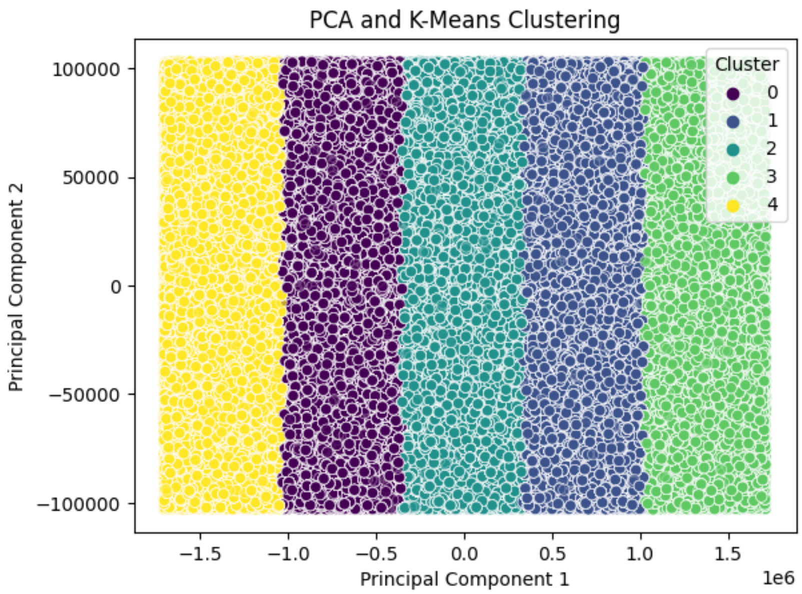


Code Explanation:

1. **Selecting Relevant Columns:**
    - `X = Dataset[['order_id', 'user_id', 'order_number', 'order_dow', 'order_hour_of_day', 'days_since_prior_order', 'product_id', 'add_to_cart_order', 'reordered', 'department_id']]` : This line selects a subset of columns from the DataFrame `Dataset` to be used as features for the KMeans clustering algorithm.
2. **Initializing an Empty List for Inertia Values:**
    - `inertia_values = []` : This line creates an empty list to store the inertia values for different values of k.
3. **Looping Over Different Values of k:**
    - `for n_clusters in range(1, 11):` : This loop iterates over values of k from 1 to 10.
4. **Creating and Fitting KMeans Models:**
    - `kmeans = KMeans(n_clusters=n_clusters, random_state=42)` : This line creates a KMeans model with the current value of k.
    - `kmeans.fit(X)` : This line fits the KMeans model to the data.
5. **Appending Inertia Values:**
    - `inertia_values.append(kmeans.inertia_)` : This line appends the inertia (within-cluster sum of squares) of the current model to the list.
6. **Plotting the Elbow Method Curve:**
    - `plt.plot(range(1, 11), inertia_values, marker='o')` : This line plots the Elbow Method curve. The x-axis represents the number of clusters (k), and the y-axis represents the inertia values.
    - `plt.title('Elbow Method for Optimal k')` : This line adds a title to the plot.
    - `plt.xlabel('Number of Clusters (k)')` and `plt.ylabel('Inertia')` : These lines label the x-axis and y-axis, respectively.
7. **Displaying the Plot:**
    - `plt.show()` : This line displays the generated Elbow Method curve.

Elbow Method for optimal K

```
n_clusters = 5

# K-Means clustering
kmeans = KMeans(n_clusters=n_clusters, random_state=100)
labels = kmeans.fit_predict(X)

# Apply PCA
pca = PCA(n_components=2)
principal_components = pca.fit_transform(X)

# Create DataFrame
Dataset = pd.DataFrame(principal_components, columns=['PC1', 'PC2'])
Dataset['Cluster'] = labels

# Visualize clusters
sns.scatterplot(x='PC1', y='PC2', hue='Cluster', data=Dataset, palette='viridis', alpha=0.7)
plt.title('PCA and K-Means Clustering')
plt.xlabel('Principal Component 1')
plt.ylabel('Principal Component 2')
plt.legend(title='Cluster')
plt.show()
```



Code Explanation:

1. **Number of Clusters:**
   - `n_clusters = 5` : This line specifies the number of clusters for the K-Means algorithm.
2. **K-Means Clustering:**
   - `kmeans = KMeans(n_clusters=n_clusters, random_state=100)` : This line creates a KMeans model with the specified number of clusters.
   - `labels = kmeans.fit_predict(X)` : This line fits the KMeans model to the data (`X`) and assigns cluster labels to each data point.
3. **Applying PCA (Principal Component Analysis):**
   - `pca = PCA(n_components=2)` : This line creates a PCA model with two components.
   - `principal_components = pca.fit_transform(X)` : This line applies PCA to the data (`X`) and reduces it to two principal components.
4. **Creating DataFrame:**
   - `Dataset = pd.DataFrame(principal_components, columns=['PC1', 'PC2'])` : This line creates a DataFrame with the two principal components.
   - `Dataset['Cluster'] = labels` : This line adds a column 'Cluster' to the DataFrame, containing the cluster labels assigned by K-Means.

5. **Visualizing Clusters:**
    - `sns.scatterplot(x='PC1', y='PC2', hue='Cluster', data=Dataset, palette='viridis', alpha=0.7)` : This line creates a scatter plot of the principal components, color-coded by cluster.
    - `plt.title('PCA and K-Means Clustering')` : This line adds a title to the plot.
    - `plt.xlabel('Principal Component 1')` and `plt.ylabel('Principal Component 2')` : These lines label the x-axis and y-axis, respectively.
    - `plt.legend(title='Cluster')` : This line adds a legend indicating the cluster labels.
    - `plt.show()` : This line displays the scatter plot.

Conclusion:

In conclusion, utilizing the dataset for supermarket product placement optimization has the potential to enhance user experience and boost sales. Through a focus on order patterns and user behavior, the project aims to provide actionable recommendations for strategically placing products in the supermarket.