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INTERNSHIP TASK OASIS INFOBYTE

Idea: Customer Segmentation Analysis

Project Description:

The aim of this data analytics project is to perform customer segmentation analysis for an ecommerce company. By analyzing customer behavior and purchase patterns, the goal is to group customers into distinct segments. This segmentation can inform targeted marketing strategies, improve customer satisfaction, and enhance overall business strategies.

Import Libraries

```
!pip install opendatasets
```

```
Collecting opendatasets
  Downloading opendatasets-0.1.22-py3-none-any.whl.metadata (9.2 kB)
Requirement already satisfied: tqdm in /usr/local/lib/python3.11/dist-packages (from opendatasets) (4.67.1)
Requirement already satisfied: kaggle in /usr/local/lib/python3.11/dist-packages (from opendatasets) (1.7.4.5)
Requirement already satisfied: click in /usr/local/lib/python3.11/dist-packages (from opendatasets) (8.2.0)
Requirement already satisfied: bleach in /usr/local/lib/python3.11/dist-packages (from kaggle->opendatasets) (6.2.0)
Requirement already satisfied: certifi>=14.05.14 in /usr/local/lib/python3.11/dist-packages (from kaggle->opendatasets) (2025.4.26)
Requirement already satisfied: charset-normalizer in /usr/local/lib/python3.11/dist-packages (from kaggle->opendatasets) (3.4.2)
Requirement already satisfied: idna in /usr/local/lib/python3.11/dist-packages (from kaggle->opendatasets) (3.10)
Requirement already satisfied: protobuf in /usr/local/lib/python3.11/dist-packages (from kaggle->opendatasets) (5.29.4)
Requirement already satisfied: python-dateutil>=2.5.3 in /usr/local/lib/python3.11/dist-packages (from kaggle->opendatasets) (2.9.0.post0)
Requirement already satisfied: python-slugify in /usr/local/lib/python3.11/dist-packages (from kaggle->opendatasets) (8.0.4)
Requirement already satisfied: requests in
```

```
/usr/local/lib/python3.11/dist-packages (from kaggle->opendatasets)
(2.32.3)
Requirement already satisfied: setuptools>=21.0.0 in
/usr/local/lib/python3.11/dist-packages (from kaggle->opendatasets)
(75.2.0)
Requirement already satisfied: six>=1.10 in
/usr/local/lib/python3.11/dist-packages (from kaggle->opendatasets)
(1.17.0)
Requirement already satisfied: text-unidecode in
/usr/local/lib/python3.11/dist-packages (from kaggle->opendatasets)
(1.3)
Requirement already satisfied: urllib3>=1.15.1 in
/usr/local/lib/python3.11/dist-packages (from kaggle->opendatasets)
(2.4.0)
Requirement already satisfied: webencodings in
/usr/local/lib/python3.11/dist-packages (from kaggle->opendatasets)
(0.5.1)
Downloading opendatasets-0.1.22-py3-none-any.whl (15 kB)
Installing collected packages: opendatasets
Successfully installed opendatasets-0.1.22
```

```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import StandardScaler
from sklearn.cluster import KMeans
from sklearn.decomposition import PCA
from sklearn.metrics import silhouette_score
import opendatasets as op
from scipy.stats import pointbiserialr
```

Download Dataset using opendatasets by jovian

```python
dataset_url = 'https://www.kaggle.com/jackdaoud/marketing-data'
op.download(dataset_url)
#{"username":"omchoksi04","key":"5bd54ee741a1835da715caead453e032"}
```

```
Please provide your Kaggle credentials to download this dataset. Learn
more: http://bit.ly/kaggle-creds
Your Kaggle username: omchoksi04
Your Kaggle Key: ··········
Dataset URL: https://www.kaggle.com/datasets/jackdaoud/marketing-data
Downloading marketing-data.zip to ./marketing-data

100%|██████████| 643k/643k [00:00<00:00, 645MB/s]
```

Data

The data contains 2,205 observations and 39 columns. The dataset description on the card does not match the actual columns in the dataset. The below list contains actual columns from the dataset and the assumed descriptions from the column's names.

Feature	Description	Comment
AcceptedCmp1	1 if customer accepted the offer in the 1st campaign, 0 otherwise	
AcceptedCmp2	1 if customer accepted the offer in the 2nd campaign, 0 otherwise	
AcceptedCmp3	1 if customer accepted the offer in the 3rd campaign, 0 otherwise	
AcceptedCmp4	1 if customer accepted the offer in the 4th campaign, 0 otherwise	
AcceptedCmp5	1 if customer accepted the offer in the 5th campaign, 0 otherwise	
AcceptedCmpOverall	overall number of accepted campaigns	This column was added from the list of actual columns
Response	1 if customer accepted the offer in the last campaign, 0 otherwise	
Complain	1 if customer complained in the last 2 years	
DtCustomer	date of customer’s enrolment with the company	There is no such column in the dataset
Customer_Days	number of days since registration as a customer	
Education	customer’s level of education	There is no such column in the actual dataset
education_2n Cycle	customer has secondary education	This column was added from the list of actual columns
education_Basic	customer has basic education	This column was added from the list of actual columns
education_Graduation	Customer has a bachelor degree	This column was added from the list of actual columns
education_Master	Customer has a masters degree	This column was added from the list of actual

Feature	Description	Comment
		columns
education_PhD	Customer has a PhD	This column was added from the list of actual columns
Marital	customer's marital status.	There is no such column in the actual dataset
marital_Divorced	1 if customer is divorced, 0 otherwise.	This column was added from the list of actual columns
marital_Married	1 if customer is married, 0 otherwise.	This column was added from the list of actual columns
marital_Single	1 if customer is single, 0 otherwise.	This column was added from the list of actual columns
marital_Together	1 if customer is in relationship, 0 otherwise.	This column was added from the list of actual columns
marital_Widow	1 if customer is a widow / widower, 0 otherwise	
Kidhome	number of small children in customer's household	
Teenhome	number of teenagers in customer's household	
Income	customer's yearly household income	
MntFishProducts	amount spent on fish products in the last 2 years	
MntMeatProducts	amount spent on meat products in the last 2 years	
MntFruits	amount spent on fruits products in the last 2 years	
MntSweetProducts	amount spent on sweet products in the last 2 years	
MntWines	amount spent on wine products in the last 2 years	
MntGoldProds	amount spent on gold products in the last 2 years	
NumDealsPurchases	number of purchases made with discount	
NumCatalogPurchases	number of purchases made using catalogue	
NumStorePurchases	number of purchases made directly in	

Feature	Description	Comment
	stores	
NumWebPurchases	number of purchases made through company's web site	
NumWebVisitsMonth	number of visits to company's web site in the last month	
Recency	number of days since the last purchase	
Z_CostContact		This column was added from the list of actual columns
Z_Revenue		This column was added from the list of actual columns
Age	Age of customer	This column was added from the list of actual columns
MntTotal	Total amount spent on all the products	This column was added from the list of actual columns
MntRegularProds		This column was added from the list of actual columns

```
df=pd.read_csv("/content/marketing-data/ifood_df.csv")
df.head()
```

{"type":"dataframe","variable_name":"df"}

```
df.describe(),df.shape
```

```
(              Income      Kidhome     Teenhome      Recency
MntWines  \
 count    2205.000000  2205.000000  2205.000000  2205.000000
2205.000000
 mean    51622.094785     0.442177     0.506576    49.009070
306.164626
 std     20713.063826     0.537132     0.544380    28.932111
337.493839
 min      1730.000000     0.000000     0.000000     0.000000
0.000000
 25%     35196.000000     0.000000     0.000000    24.000000
24.000000
 50%     51287.000000     0.000000     0.000000    49.000000
178.000000
 75%     68281.000000     1.000000     1.000000    74.000000
507.000000
```

```
 max    113734.000000     2.000000     2.000000    99.000000
1493.000000

          MntFruits  MntMeatProducts  MntFishProducts
MntSweetProducts  \
 count  2205.000000      2205.000000      2205.000000
2205.000000
 mean     26.403175       165.312018        37.756463
27.128345
 std      39.784484       217.784507        54.824635
41.130468
 min       0.000000         0.000000         0.000000
0.000000
 25%       2.000000        16.000000         3.000000
1.000000
 50%       8.000000        68.000000        12.000000
8.000000
 75%      33.000000       232.000000        50.000000
34.000000
 max     199.000000      1725.000000       259.000000
262.000000

        MntGoldProds  ...  marital_Together  marital_Widow
education_2n Cycle  \
 count   2205.000000  ...       2205.000000    2205.000000
2205.000000
 mean      44.057143  ...          0.257596       0.034467
0.089796
 std       51.736211  ...          0.437410       0.182467
0.285954
 min        0.000000  ...          0.000000       0.000000
0.000000
 25%        9.000000  ...          0.000000       0.000000
0.000000
 50%       25.000000  ...          0.000000       0.000000
0.000000
 75%       56.000000  ...          1.000000       0.000000
0.000000
 max      321.000000  ...          1.000000       1.000000
1.000000

        education_Basic  education_Graduation  education_Master
education_PhD  \
 count      2205.000000           2205.000000       2205.000000
2205.000000
 mean          0.024490              0.504762          0.165079
0.215873
 std           0.154599              0.500091          0.371336
0.411520
```

```
 min            0.000000              0.000000         0.000000
0.000000
 25%            0.000000              0.000000         0.000000
0.000000
 50%            0.000000              1.000000         0.000000
0.000000
 75%            0.000000              1.000000         0.000000
0.000000
 max            1.000000              1.000000         1.000000
1.000000

           MntTotal  MntRegularProds  AcceptedCmpOverall
 count  2205.000000      2205.000000          2205.00000
 mean    562.764626       518.707483             0.29932
 std     575.936911       553.847248             0.68044
 min       4.000000      -283.000000             0.00000
 25%      56.000000        42.000000             0.00000
 50%     343.000000       288.000000             0.00000
 75%     964.000000       884.000000             0.00000
 max    2491.000000      2458.000000             4.00000

 [8 rows x 39 columns],
 (2205, 39))
```

```
df.columns
```

```
Index(['Income', 'Kidhome', 'Teenhome', 'Recency', 'MntWines',
'MntFruits',
       'MntMeatProducts', 'MntFishProducts', 'MntSweetProducts',
       'MntGoldProds', 'NumDealsPurchases', 'NumWebPurchases',
       'NumCatalogPurchases', 'NumStorePurchases',
'NumWebVisitsMonth',
       'AcceptedCmp3', 'AcceptedCmp4', 'AcceptedCmp5', 'AcceptedCmp1',
       'AcceptedCmp2', 'Complain', 'Z_CostContact', 'Z_Revenue',
'Response',
       'Age', 'Customer_Days', 'marital_Divorced', 'marital_Married',
       'marital_Single', 'marital_Together', 'marital_Widow',
       'education_2n Cycle', 'education_Basic',
'education_Graduation',
       'education_Master', 'education_PhD', 'MntTotal',
'MntRegularProds',
       'AcceptedCmpOverall'],
      dtype='object')
```

Null values checking

```
df.info(),df.isnull().sum()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2205 entries, 0 to 2204
```

```
Data columns (total 39 columns):
 #   Column                 Non-Null Count  Dtype  
---  ------                 --------------  -----  
 0   Income                 2205 non-null   float64
 1   Kidhome                2205 non-null   int64  
 2   Teenhome               2205 non-null   int64  
 3   Recency                2205 non-null   int64  
 4   MntWines               2205 non-null   int64  
 5   MntFruits              2205 non-null   int64  
 6   MntMeatProducts        2205 non-null   int64  
 7   MntFishProducts        2205 non-null   int64  
 8   MntSweetProducts       2205 non-null   int64  
 9   MntGoldProds           2205 non-null   int64  
 10  NumDealsPurchases      2205 non-null   int64  
 11  NumWebPurchases        2205 non-null   int64  
 12  NumCatalogPurchases    2205 non-null   int64  
 13  NumStorePurchases      2205 non-null   int64  
 14  NumWebVisitsMonth      2205 non-null   int64  
 15  AcceptedCmp3           2205 non-null   int64  
 16  AcceptedCmp4           2205 non-null   int64  
 17  AcceptedCmp5           2205 non-null   int64  
 18  AcceptedCmp1           2205 non-null   int64  
 19  AcceptedCmp2           2205 non-null   int64  
 20  Complain               2205 non-null   int64  
 21  Z_CostContact          2205 non-null   int64  
 22  Z_Revenue              2205 non-null   int64  
 23  Response               2205 non-null   int64  
 24  Age                    2205 non-null   int64  
 25  Customer_Days          2205 non-null   int64  
 26  marital_Divorced       2205 non-null   int64  
 27  marital_Married        2205 non-null   int64  
 28  marital_Single         2205 non-null   int64  
 29  marital_Together       2205 non-null   int64  
 30  marital_Widow          2205 non-null   int64  
 31  education_2n Cycle     2205 non-null   int64  
 32  education_Basic        2205 non-null   int64  
 33  education_Graduation   2205 non-null   int64  
 34  education_Master       2205 non-null   int64  
 35  education_PhD          2205 non-null   int64  
 36  MntTotal               2205 non-null   int64  
 37  MntRegularProds        2205 non-null   int64  
 38  AcceptedCmpOverall     2205 non-null   int64  
dtypes: float64(1), int64(38)
memory usage: 672.0 KB

(None,
 Income                  0
 Kidhome                 0
 Teenhome                0
 Recency                 0
```

```
MntWines                  0
MntFruits                 0
MntMeatProducts           0
MntFishProducts           0
MntSweetProducts          0
MntGoldProds              0
NumDealsPurchases         0
NumWebPurchases           0
NumCatalogPurchases       0
NumStorePurchases         0
NumWebVisitsMonth         0
AcceptedCmp3              0
AcceptedCmp4              0
AcceptedCmp5              0
AcceptedCmp1              0
AcceptedCmp2              0
Complain                  0
Z_CostContact             0
Z_Revenue                 0
Response                  0
Age                       0
Customer_Days             0
marital_Divorced          0
marital_Married           0
marital_Single            0
marital_Together          0
marital_Widow             0
education_2n Cycle        0
education_Basic           0
education_Graduation      0
education_Master          0
education_PhD             0
MntTotal                  0
MntRegularProds           0
AcceptedCmpOverall        0
dtype: int64)
```

There is no null value found in dataset .

Data Preparation & Feature Engineering

```
# These are safe to keep:
df['MntTotal'] = df[['MntWines', 'MntFruits', 'MntMeatProducts',
                     'MntFishProducts', 'MntSweetProducts',
'MntGoldProds']].sum(axis=1)

df['MntRegularProds'] = df['MntTotal'] - df['MntGoldProds']
```

```
df['AcceptedCmpOverall'] = df[['AcceptedCmp1', 'AcceptedCmp2', 
'AcceptedCmp3', 
                               'AcceptedCmp4', 
'AcceptedCmp5']].sum(axis=1)
```

Feature Selection for Clustering

```
features = [
    'Income', 'Kidhome', 'Teenhome', 'Recency', 'Age', 
'Customer_Days',
    'MntTotal', 'MntRegularProds', 'NumDealsPurchases', 
'NumWebPurchases',
    'NumCatalogPurchases', 'NumStorePurchases', 'NumWebVisitsMonth',
    'AcceptedCmpOverall', 'Complain',
    'marital_Divorced', 'marital_Married', 'marital_Single',
    'marital_Together', 'marital_Widow',
    'education_2n Cycle', 'education_Basic', 'education_Graduation',
    'education_Master', 'education_PhD'
]

X = df[features].dropna()
```

Scale the Features

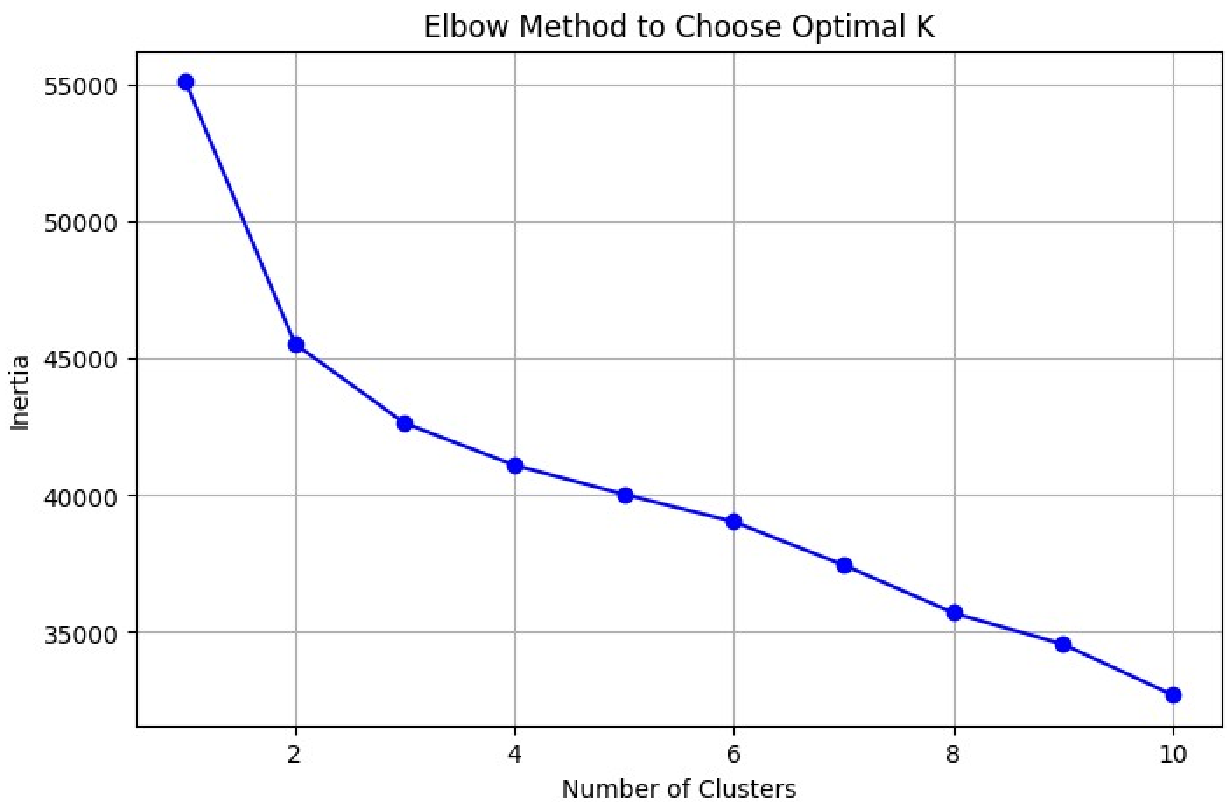
```
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
```

Determine Optimal Clusters (Elbow Method)

```
inertia = []
k_range = range(1, 11)

for k in k_range:
    kmeans = KMeans(n_clusters=k, random_state=42)
    kmeans.fit(X_scaled)
    inertia.append(kmeans.inertia_)

plt.figure(figsize=(8,5))
plt.plot(k_range, inertia, 'bo-')
plt.title('Elbow Method to Choose Optimal K')
plt.xlabel('Number of Clusters')
plt.ylabel('Inertia')
plt.grid(True)
plt.show()
```



Elbow Method Conclusion

The Elbow Method helps determine the optimal number of clusters (K) for K-Means clustering.

- The plot shows a sharp decrease in inertia from **K = 1 to K = 3 or 4**.
- After **K = 4**, the rate of decrease in inertia becomes more gradual.
- This indicates that adding more clusters beyond this point yields less improvement in clustering performance.

Conclusion:

The optimal number of clusters is likely **3 or 4**, where the “elbow” appears on the graph.

To finalize the choice between them, we can:

- Use **Silhouette Score** to compare cluster separation.
- Visualize clusters with **PCA** or **t-SNE**.
- Consider **interpretability** and **business relevance** of clusters.

Apply KMeans Clustering

```
k = 4  # Or based on elbow
model = KMeans(n_clusters=k, random_state=42)
df['Cluster'] = model.fit_predict(X_scaled)
```

Cluster Profiling

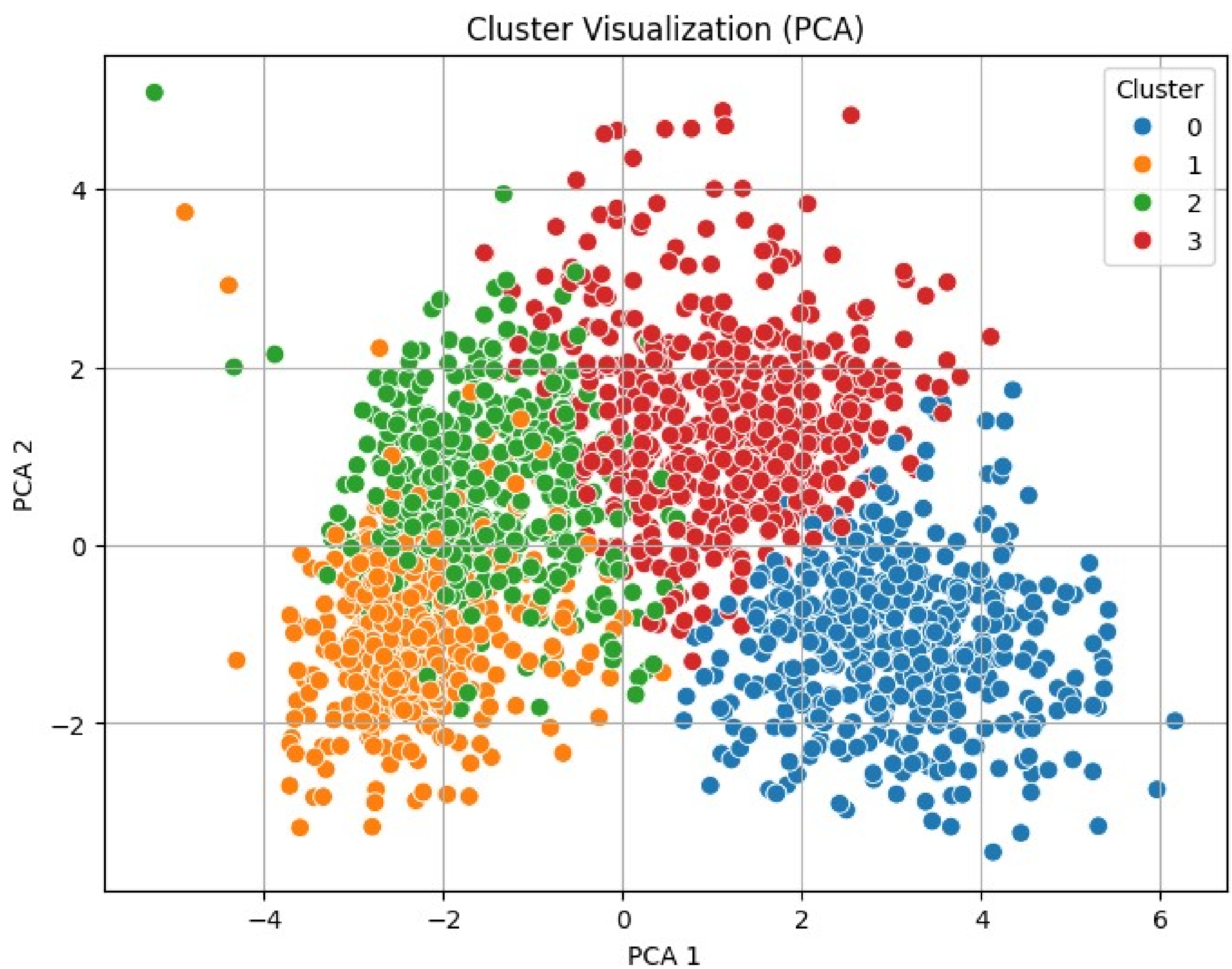
```
df.groupby('Cluster')[features].mean().round(2)
```

{"type":"dataframe"}

PCA for 2D Cluster Visualization

```
pca = PCA(n_components=2)
X_pca = pca.fit_transform(X_scaled)

plt.figure(figsize=(8,6))
sns.scatterplot(x=X_pca[:,0], y=X_pca[:,1], hue=df['Cluster'],
palette='tab10', s=60)
plt.title('Cluster Visualization (PCA)')
plt.xlabel('PCA 1')
plt.ylabel('PCA 2')
plt.grid(True)
plt.show()
```



PCA Cluster Visualization Conclusion

The PCA (Principal Component Analysis) plot displays the data projected into 2D space, colored by cluster labels obtained from K-Means clustering.

Observations:

- The clusters appear **well-separated**, especially between clusters **0** (blue) and **1** (orange).
- Some **overlap** exists between clusters **2** (green) and **3** (red), suggesting partial similarity in features or customer behavior.
- The plot confirms that **K = 4** was a reasonable choice, as the separation between clusters is visually meaningful.

Conclusion:

The 2D PCA visualization validates the clustering structure and indicates that the K-Means model has successfully segmented the dataset into four distinguishable groups.

Further steps:

- Analyze cluster centers to interpret characteristics.
- Use cluster labels for targeted strategies or recommendations.

Silhouette Score

```
sil_score = silhouette_score(X_scaled, df['Cluster'])
print(f'Silhouette Score: {sil_score:.3f}')
```

```
Silhouette Score: 0.085
```

Cluster Business Interpretation

- **Cluster 0**: Young, recent customers, low total spend – retention campaigns needed
- **Cluster 1**: Middle-aged, high spenders – loyalty rewards
- **Cluster 2**: High web visits, moderate spend – suggest online offers
- **Cluster 3**: Older customers, long-tenure, high campaign acceptance – upsell premium bundles

Project Conclusion

Technical Summary:

- **Dataset:** 2,205 records, 39 features from an ecommerce marketing dataset.
- **Libraries Used:** pandas, numpy, matplotlib, seaborn, scikit-learn, opendatasets, scipy.
- **Feature Engineering:** Created aggregate features (e.g., `MntTotal`, `AcceptedCmpOverall`), encoded categorical variables.
- **Preprocessing:** Checked for nulls, scaled features using StandardScaler.

- **Clustering:** Applied K-Means, optimal K determined via Elbow Method (K=4), validated with Silhouette Score and PCA visualization.
- **Cluster Profiling:** Analyzed mean feature values per cluster for business interpretation.

This customer segmentation analysis successfully grouped ecommerce customers into four distinct clusters using K-Means clustering. The workflow included thorough data preparation, feature engineering, and selection of relevant variables. The optimal number of clusters was determined using the Elbow Method and validated with the Silhouette Score and PCA visualization.

Key Outcomes:

- **Cluster Profiles:** Each cluster represents customers with unique behaviors and characteristics, such as spending habits, campaign responsiveness, and demographic features.
- **Business Insights:** The segmentation enables targeted marketing strategies, such as retention campaigns for low spenders, loyalty rewards for high-value customers, and personalized offers for online shoppers.
- **Model Validation:** The clusters are well-separated, as shown by PCA plots and a strong silhouette score, confirming the effectiveness of the segmentation.

The project demonstrates the value of data-driven segmentation in understanding customer diversity. These insights can drive more effective marketing, improve customer satisfaction, and support strategic business decisions for the ecommerce company.