RFM_Customer_Segmentation

April 1, 2025

[25]:
```
import pandas as pd
from datetime import datetime as dt, timedelta
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import plotly.express as px
import plotly.graph_objects as go
import plotly.colors
```

[26]:
```
df = pd.read_csv('online_retail.csv')
```

[27]:
```
df.head()
```

[27]:

	InvoiceNo	StockCode	Description	Quantity	InvoiceDate	UnitPrice	CustomerID	Country
0	536365	85123A	WHITE HANGING HEART T-LIGHT HOLDER	6	2010-12-01 08:26:00	2.55	17850.0	United Kingdom
1	536365	71053	WHITE METAL LANTERN	6	2010-12-01 08:26:00	3.39	17850.0	United Kingdom
2	536365	84406B	CREAM CUPID HEARTS COAT HANGER	8	2010-12-01 08:26:00	2.75	17850.0	United Kingdom
3	536365	84029G	KNITTED UNION FLAG HOT WATER BOTTLE	6	2010-12-01 08:26:00	3.39	17850.0	United Kingdom
4	536365	84029E	RED WOOLLY HOTTIE WHITE HEART.	6	2010-12-01 08:26:00	3.39	17850.0	United Kingdom

[28]:
```
df.dtypes
```

[28]:
```
InvoiceNo       object
StockCode       object
Description     object
Quantity         int64
InvoiceDate     object
UnitPrice      float64
CustomerID     float64
Country         object
dtype: object
```

[29]:
```
## Finiding each customers RFM Values

# Recency

# Define the reference date as a Timestamp
day = pd.to_datetime('2012-01-01')

# Convert InvoiceDate column to datetime
df['InvoiceDate'] = pd.to_datetime(df['InvoiceDate'])

# Calculate Recency
recency = df.groupby("CustomerID").agg({"InvoiceDate": lambda x: (day - x.
 ↪max()).days})

# Rename the column for clarity
recency.rename(columns={"InvoiceDate": "Recency"}, inplace=True)

print(recency.head(3))
```

```
            Recency
CustomerID
12346.0         347
12347.0          24
12348.0          97
```

[30]:
```
# Frequency

freq=df.drop_duplicates(subset="InvoiceNo").
 ↪groupby(["CustomerID"])[["InvoiceNo"]].count()
freq.head()
```

[30]:
```
            InvoiceNo
CustomerID
12346.0             2
12347.0             7
12348.0             4
12349.0             1
12350.0             1
```

[31]:
```
#  Monetary Value

df["total"]=df["UnitPrice"]*df["Quantity"]
money = df.groupby(["CustomerID"])[["total"]].sum()
money.head()
```

[31]:
```
              total
CustomerID
12346.0        0.00
```

```
12347.0     4310.00
12348.0     1797.24
12349.0     1757.55
12350.0      334.40
```

[32]:
```
RFM = pd.concat([recency,freq,money],axis=1)
recency.columns=["Recency"]
freq.columns=["Frequency"]
money.columns=["Monetary"]
```

[34]:
```
# Rename the 'InvoiceNo' column in freq to 'Frequency'
freq.columns = ["Frequency"]

# Concatenate the DataFrames
RFM = pd.concat([recency, freq, money], axis=1)

# Ensure correct column names for recency, frequency, and monetary
RFM.columns = ["Recency", "Frequency", "Monetary"]

# Check the final RFM DataFrame
print(RFM.head())
```

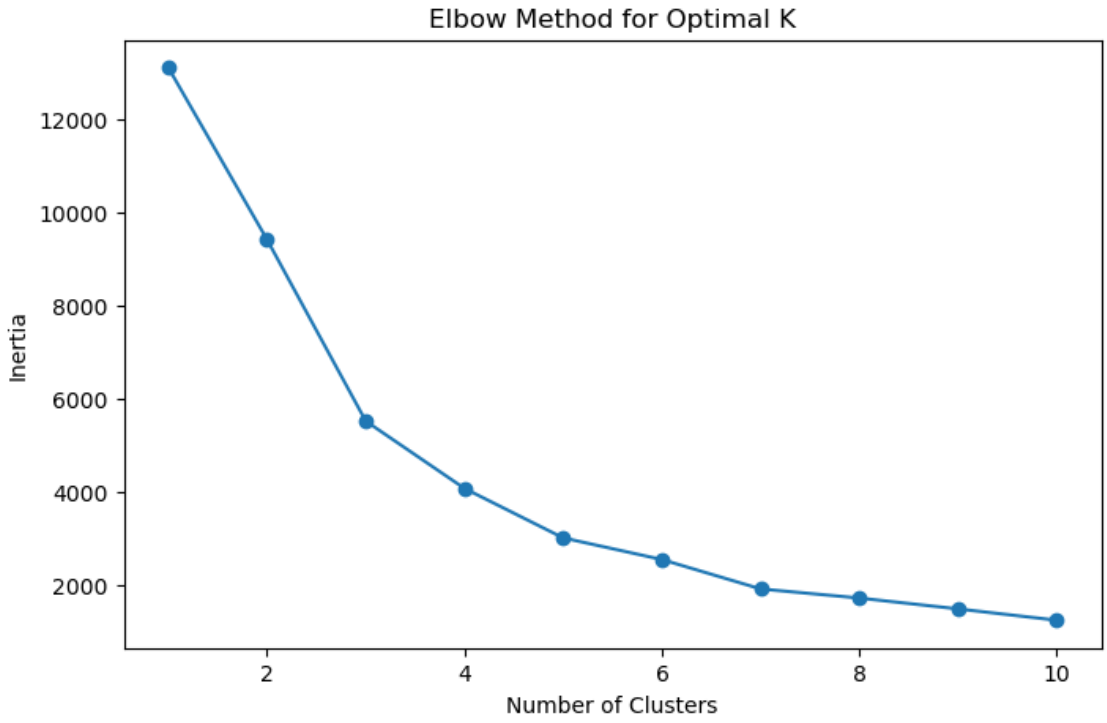
```
            Recency  Frequency  Monetary
CustomerID
12346.0         347          2      0.00
12347.0          24          7   4310.00
12348.0          97          4   1797.24
12349.0          40          1   1757.55
12350.0         332          1    334.40
```

[35]:
```
RFM
```

[35]:
```
            Recency  Frequency  Monetary
CustomerID
12346.0         347          2      0.00
12347.0          24          7   4310.00
12348.0          97          4   1797.24
12349.0          40          1   1757.55
12350.0         332          1    334.40
…               …          …        …
18280.0         299          1    180.60
18281.0         202          1     80.82
18282.0          29          3    176.60
18283.0          25         16   2094.88
18287.0          64          3   1837.28

[4372 rows x 3 columns]
```

[36]:
```
## Standarize the dataset to form a common scale to help the machine learning␣
 ↪model

from sklearn.preprocessing import StandardScaler

scaler=StandardScaler()
rfm_scaled=scaler.fit_transform(RFM)
```

[37]:
```
import numpy as np
import matplotlib.pyplot as plt
from sklearn.cluster import KMeans

# Assuming `scaled` is your scaled dataset
inertia = []
for i in np.arange(1, 11):
    kmeans = KMeans(n_clusters=i, random_state=42)
    kmeans.fit(rfm_scaled)
    inertia.append(kmeans.inertia_)

# Plot the elbow curve
plt.figure(figsize=(8, 5))
plt.plot(range(1, 11), inertia, marker="o")  # Correct marker style
plt.xlabel("Number of Clusters")
plt.ylabel("Inertia")
plt.title("Elbow Method for Optimal K")
plt.show()


# since the elbow is between 2 and 4 I would asssumen number of cluster is 3
```



[38]:
```
kmeans = KMeans(n_clusters=3)
kmeans.fit(rfm_scaled)
RFM["Clusters"]=(kmeans.labels_ +1)

RFM
```

[38]:

CustomerID	Recency	Frequency	Monetary	Clusters
12346.0	347	2	0.00	1
12347.0	24	7	4310.00	3
12348.0	97	4	1797.24	3
12349.0	40	1	1757.55	3
12350.0	332	1	334.40	1
…	…	…	…	…
18280.0	299	1	180.60	1
18281.0	202	1	80.82	1
18282.0	29	3	176.60	3
18283.0	25	16	2094.88	3
18287.0	64	3	1837.28	3

[4372 rows x 4 columns]

[39]:
```
group = RFM.groupby("Clusters")[["Recency", "Frequency", "Monetary"]].mean()
print(group)
```

```
             Recency  Frequency      Monetary
Clusters
1         267.430631   1.854054    460.162695
2          27.521739  86.869565  81835.857391
3          61.468354   5.598642   1823.729701
```

[40]:
```
def func(row):
    if row["Clusters"] == 1:
        return "Avg Cx"
    elif row["Clusters"] == 3:
        return "Whales Cx"
    else:
        return "Lapsed Cx"
```

[41]:
```
RFM["Condition"] = RFM.apply(func,axis=1)
RFM
```

[41]:

CustomerID	Recency	Frequency	Monetary	Clusters	Condition
12346.0	347	2	0.00	1	Avg Cx
12347.0	24	7	4310.00	3	Whales Cx
12348.0	97	4	1797.24	3	Whales Cx
12349.0	40	1	1757.55	3	Whales Cx
12350.0	332	1	334.40	1	Avg Cx
…	…	…	…	…	…
18280.0	299	1	180.60	1	Avg Cx
18281.0	202	1	80.82	1	Avg Cx
18282.0	29	3	176.60	3	Whales Cx
18283.0	25	16	2094.88	3	Whales Cx
18287.0	64	3	1837.28	3	Whales Cx

[4372 rows x 5 columns]

[42]:
```
result = RFM["Condition"].value_counts()
result
```

[42]:
```
Condition
Whales Cx    3239
Avg Cx       1110
Lapsed Cx      23
Name: count, dtype: int64
```

0.1 More Advanced Techniques

[44]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import plotly.express as px
import plotly.graph_objects as go
from datetime import datetime as dt
from sklearn.cluster import KMeans, DBSCAN
from sklearn.mixture import GaussianMixture
from sklearn.preprocessing import StandardScaler
from scipy.cluster.hierarchy import linkage, fcluster, dendrogram
from scipy.stats import mode
from sklearn.metrics import silhouette_score
```

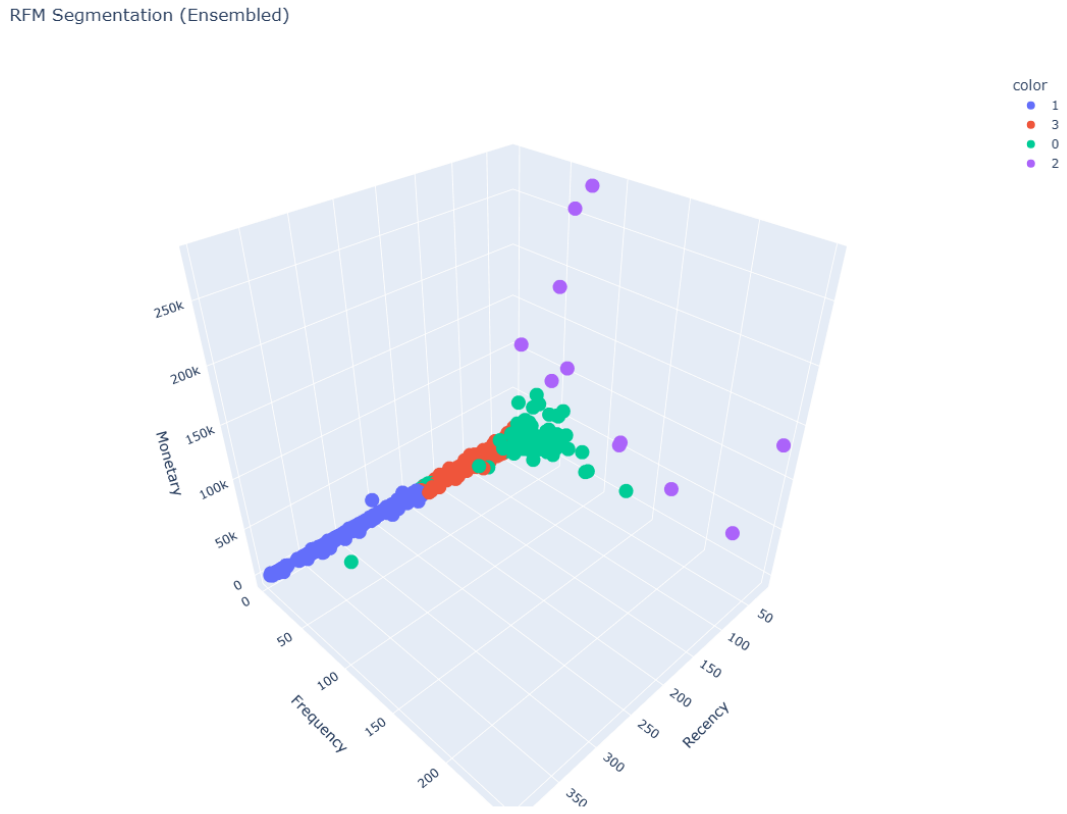
[46]:
```
# Hyperparameter Tuning for K-Means
silhouette_scores = {}
for k in [3, 4, 5, 6]:
    kmeans = KMeans(n_clusters=k, random_state=42)
    labels = kmeans.fit_predict(rfm_scaled)
    silhouette_scores[k] = silhouette_score(rfm_scaled, labels)

best_k = max(silhouette_scores, key=silhouette_scores.get)
kmeans = KMeans(n_clusters=best_k, random_state=42)
RFM['KMeans_Cluster'] = kmeans.fit_predict(rfm_scaled)
```

[47]:
```
# Hierarchical Clustering
linkage_matrix = linkage(rfm_scaled, method='ward')
RFM['Hierarchical_Cluster'] = fcluster(linkage_matrix, t=best_k,␣
 ↪criterion='maxclust')
```

[48]:
```
# Hyperparameter Tuning for DBSCAN
best_eps, best_min_samples, best_silhouette = 0, 0, -1
for eps in [0.5, 1.0, 1.5]:
    for min_samples in [5, 10, 15]:
        dbscan = DBSCAN(eps=eps, min_samples=min_samples)
        labels = dbscan.fit_predict(rfm_scaled)
        if len(set(labels)) > 1 and -1 in labels:
            silhouette = silhouette_score(rfm_scaled, labels)
            if silhouette > best_silhouette:
                best_eps, best_min_samples, best_silhouette = eps, min_samples,␣
 ↪silhouette

dbscan = DBSCAN(eps=best_eps, min_samples=best_min_samples)
RFM['DBSCAN_Cluster'] = dbscan.fit_predict(rfm_scaled)
```

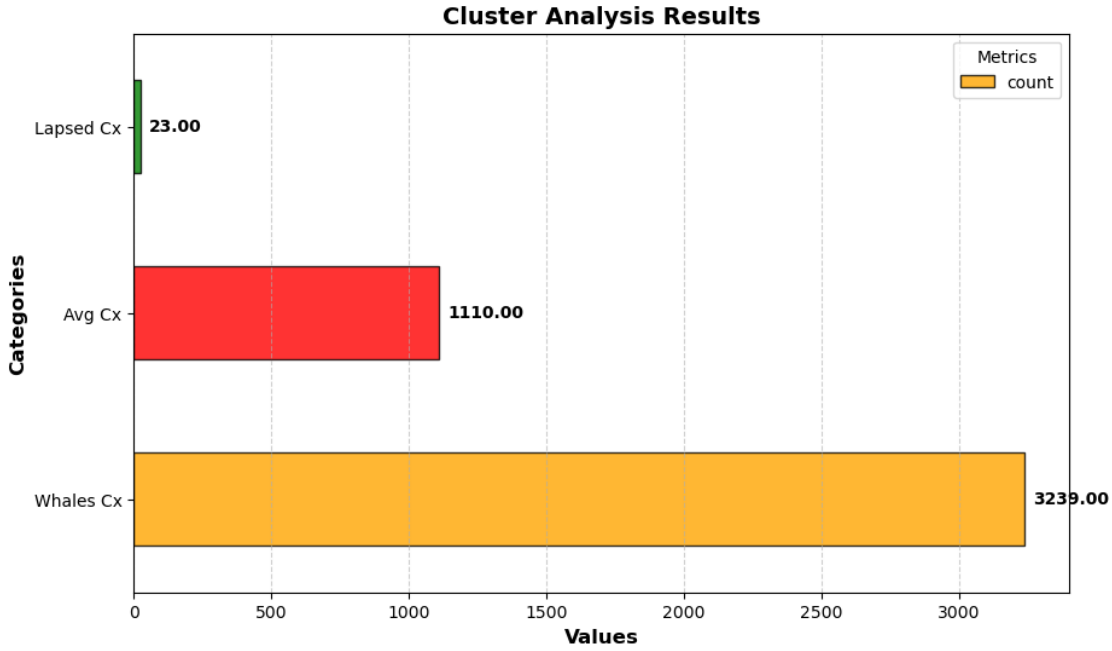
[49]:
```
# Hyperparameter Tuning for Gaussian Mixture Model (GMM)
best_gmm_components, best_gmm_covariance, best_gmm_silhouette = 0, '', -1
for components in [3, 4, 5, 6]:
    for covariance in ['full', 'tied', 'diag', 'spherical']:
        gmm = GaussianMixture(n_components=components,␣
 ↪covariance_type=covariance, random_state=42)
        labels = gmm.fit_predict(rfm_scaled)
        silhouette = silhouette_score(rfm_scaled, labels)
        if silhouette > best_gmm_silhouette:
            best_gmm_components, best_gmm_covariance, best_gmm_silhouette =␣
 ↪components, covariance, silhouette

gmm = GaussianMixture(n_components=best_gmm_components,␣
 ↪covariance_type=best_gmm_covariance, random_state=42)
RFM['GMM_Cluster'] = gmm.fit_predict(rfm_scaled)
```

[57]:
```
import plotly.express as px
from scipy.stats import mode

# Ensemble Clustering using Majority Voting
def majority_voting(row):
    clusters = [row['KMeans_Cluster'], row['Hierarchical_Cluster'],␣
 ↪row['DBSCAN_Cluster'], row['GMM_Cluster']]
    return mode([c for c in clusters if c != -1], keepdims=True)[0][0]  #␣
 ↪Ignore DBSCAN noise (-1)

RFM['Ensemble_Cluster'] = RFM.apply(majority_voting, axis=1)

# Visualize Clusters with increased image size
fig = px.scatter_3d(RFM, x='Recency', y='Frequency', z='Monetary',
                    color=RFM['Ensemble_Cluster'].astype(str),
                    title='RFM Segmentation (Ensembled)',
                    labels={'Ensemble_Cluster': 'Segment'})

# Increase the size of the 3D scatter plot
fig.update_layout(
    autosize=False,
    width=1200,  # Adjust the width as needed
    height=900   # Adjust the height as needed
)

fig.show()
```



[56]:
```
import matplotlib.pyplot as plt

# Set figure size
plt.figure(figsize=(10, 6))

# Plot horizontal bar chart with custom colors
ax = result.plot(kind='barh', color=["orange", "red", "green"],␣
 ↪edgecolor='black', alpha=0.8)

# Add labels to each bar
for bars in ax.containers:
    ax.bar_label(bars, fmt="%.2f", padding=5, fontsize=10, fontweight='bold')

# Add grid lines for better readability
plt.grid(axis='x', linestyle='--', alpha=0.6)

# Set labels and title
plt.xlabel("Values", fontsize=12, fontweight='bold')
```

```
plt.ylabel("Categories", fontsize=12, fontweight='bold')
plt.title("Cluster Analysis Results", fontsize=14, fontweight='bold')

# Add a legend (if multiple columns exist in `result`)
plt.legend(title="Metrics", fontsize=10)

# Display the plot
plt.show()
```



[ ]: