جامعة الإسكندرية

ALEXANDRIA
UNIVERSITY

كليـة الحاسبات وعلـوم البيـانات

Data Mining final project

Dr/ Magda Madboly

Name	ID	work
Abdelrahman Ahmed Elmotawakel	22010456	k-medoids clustering algorithm.
Kareem Ashraf Ahmed	22030171	Fuzzy logic clustering.
Fares Mohamed Salah	22011614	exploratory data analysis, cleaning, and preprocessing.
Ereny Wagih Massoud	2022513146	Hierarchical clustering.

Introduction:

We chose our data set for the purpose of applying an effective customer segmentation pipeline. Our data set contains transaction records for multiple customers. Our goal in this project is to clean our data, preprocess, and uncover meaningful insights, that we can later use to apply various clustering techniques to divide the customers into several groups.

Exploratory Data Analysis (EDA):

We started by printing a statistical summary of our features. We used various graphs and charts to effectively visualize important features. Some features needed to be transformed to different datatypes in order to extract information like 'ORDERDATE' column.

We then proceed to clean our data by first, checking for missing values in columns and calculating its' percentage in each column. We choose to drop columns over 30% missing values. Then we deleted any remaining rows with missing values, as we preferred not to add any bias to our data.

Next, we moved on to feature engineering. Since our data consisted of transaction records. We needed to engineer new features that were more oriented around customers. We chose to apply "RFM Analysis" technique.

RFM Analysis:

RFM stands for Recency, Frequency, and Monetary value. Those are three metrics that can be used to summarize customer behavior and divide them into segments to later apply a targeted marketing strategy for each segment.

The 'recency' metric measures how long it's been since the customer's last purchase. The 'frequency' metric measures how often the customer makes purchases in a specific time frame. The 'monetary value' metric measures the total amount of money spent by the customer on purchases in a given time frame.

After calculating these three metrics, the customers are sorted in descending order according to each metric separately. Then they are divided into groups, usually quantiles. Each group is given a rating for each metric. So, the top 20% of customers in monetary value are given a score of 5, while the last 20% of customers are given a score of 1. This process is repeated for each of the three metrics. After calculating the scores of each metric, a total RFM score is calculated by combining the three scores. This total score acts as a single indicator of the customer's engagement level or value. There are various ways to calculate that total score. The easiest way is to calculate the sum. Another way is to weight each score before summing them up.

Customer Segmentation:

After applying RFM analysis, we proceed to check the customer data for outliers and remove them. We then scaled our data using Min-Max scaling.

K-medoids clustering:

First, we needed to identify the number of medoids 'K'. So, we used the elbow method to plot the relation between 'K' and the total cost of the clustering. Then, we used the optimal 'K' obtained from the elbow point to initialize our algorithm. We plotted a 3D scatter plot to visualize the cluster shapes along the three RFM metrics. We printed the RFM data frame along with a new column representing the cluster number assigned to each customer.

Hierarchical Clustering:

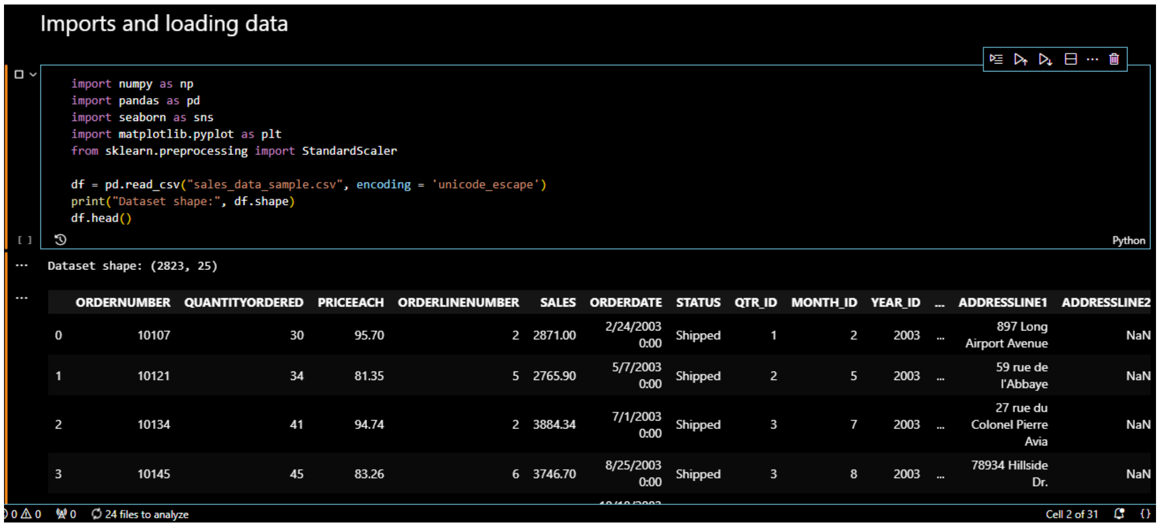
We used agglomerative clustering for our data. We used the same number of clusters for all algorithms. We plotted the dendrogram for the customer data and used Euclidean distance to measure the degree of closeness between clusters. Finally, we plotted the clusters formed using a 3D scatter plot.

Fuzzy logic clustering:

We utilized fuzzy C-means clustering algorithm for soft partitioning where data points can belong to multiple clusters with varying degrees of membership, providing flexibility in cluster assignment. We added a new column to the data frame showing which cluster each customer belongs to. We plotted the results using a 3D scatter plot.

Finally, we used different metrics (e.g. silhouette score and Calinski Harabasz score) to evaluate and compare the performance of all three algorithms. We then printed the average score for each algorithm.

Screen shoots of the code:



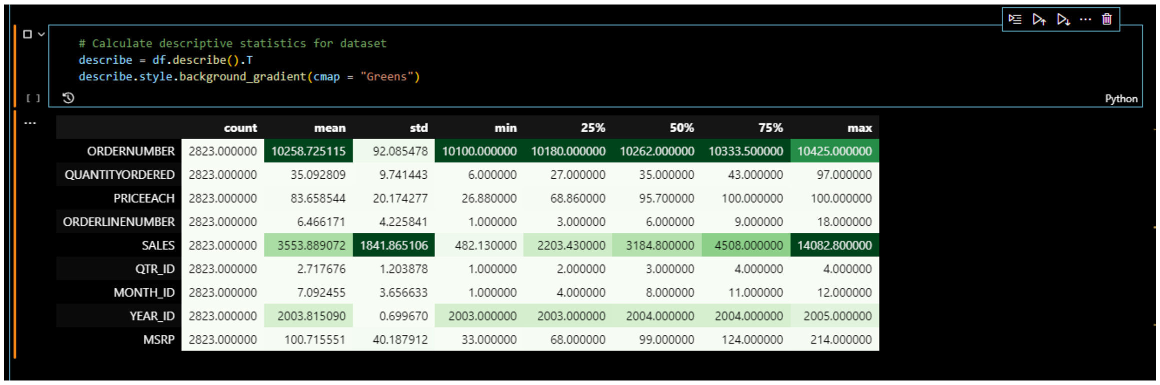
Imports and loading data

```python
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.preprocessing import StandardScaler

df = pd.read_csv("sales_data_sample.csv", encoding = 'unicode_escape')
print("Dataset shape:", df.shape)
df.head()
```

```
Dataset shape: (2823, 25)
```

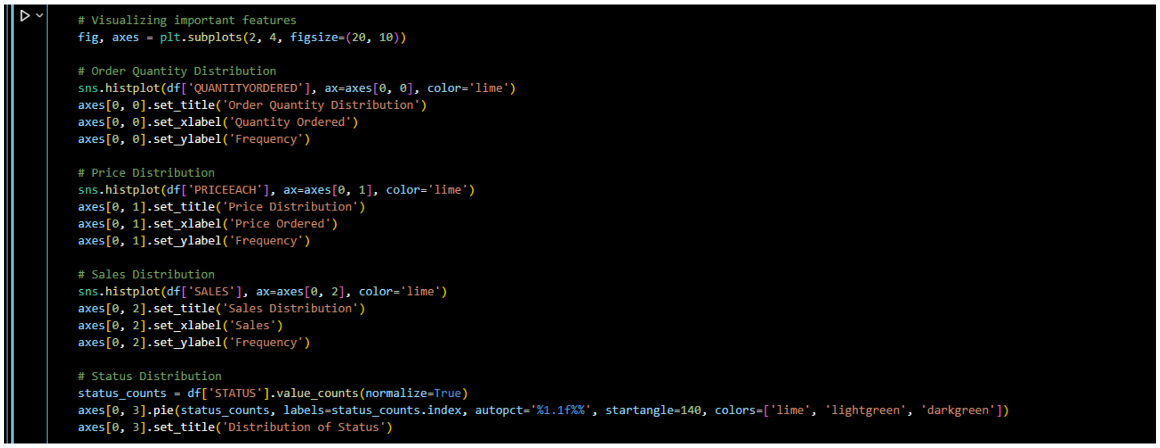
	ORDERNUMBER	QUANTITYORDERED	PRICEEACH	ORDERLINENUMBER	SALES	ORDERDATE	STATUS	QTR_ID	MONTH_ID	YEAR_ID	...	ADDRESSLINE1	ADDRESSLINE2
0	10107	30	95.70	2	2871.00	2/24/2003 0:00	Shipped	1	2	2003	...	897 Long Airport Avenue	NaN
1	10121	34	81.35	5	2765.90	5/7/2003 0:00	Shipped	2	5	2003	...	59 rue de l'Abbaye	NaN
2	10134	41	94.74	2	3884.34	7/1/2003 0:00	Shipped	3	7	2003	...	27 rue du Colonel Pierre Avia	NaN
3	10145	45	83.26	6	3746.70	8/25/2003 0:00	Shipped	3	8	2003	...	78934 Hillside Dr.	NaN

0 ⚠ 0 0 24 files to analyze Cell 2 of 31



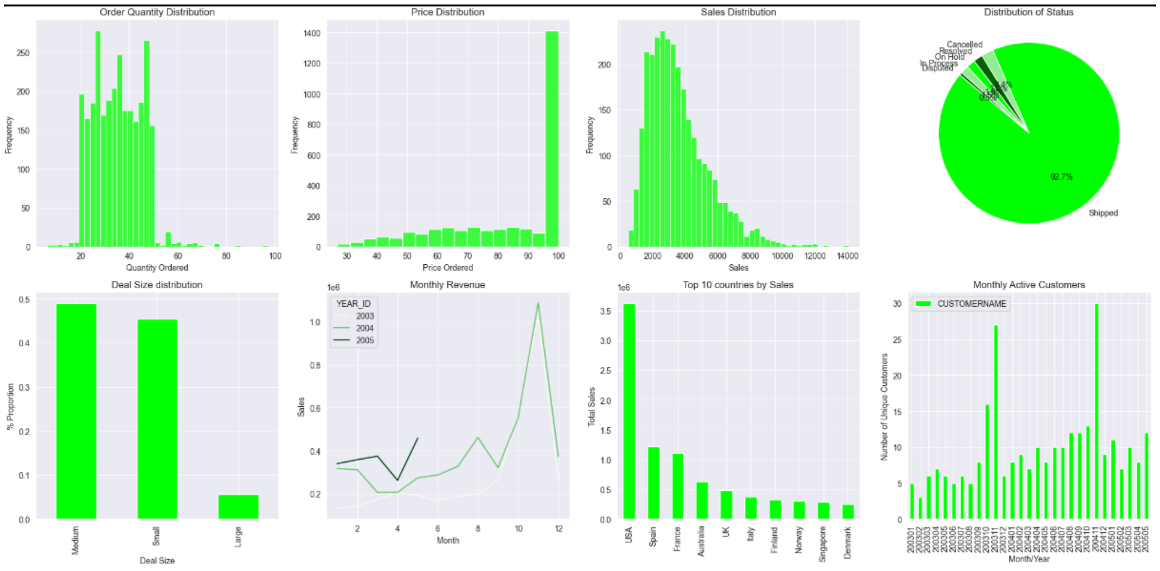
```python
# Calculate descriptive statistics for dataset
describe = df.describe().T
describe.style.background_gradient(cmap = "Greens")
```

	count	mean	std	min	25%	50%	75%	max
ORDERNUMBER	2823.000000	10258.725115	92.085478	10100.000000	10180.000000	10262.000000	10333.500000	10425.000000
QUANTITYORDERED	2823.000000	35.092809	9.741443	6.000000	27.000000	35.000000	43.000000	97.000000
PRICEEACH	2823.000000	83.658544	20.174277	26.880000	68.860000	95.700000	100.000000	100.000000
ORDERLINENUMBER	2823.000000	6.466171	4.225841	1.000000	3.000000	6.000000	9.000000	18.000000
SALES	2823.000000	3553.889072	1841.865106	482.130000	2203.430000	3184.800000	4508.000000	14082.800000
QTR_ID	2823.000000	2.717676	1.203878	1.000000	2.000000	3.000000	4.000000	4.000000
MONTH_ID	2823.000000	7.092455	3.656633	1.000000	4.000000	8.000000	11.000000	12.000000
YEAR_ID	2823.000000	2003.815090	0.699670	2003.000000	2003.000000	2004.000000	2004.000000	2005.000000
MSRP	2823.000000	100.715551	40.187912	33.000000	68.000000	99.000000	124.000000	214.000000



```python
# Visualizing important features
fig, axes = plt.subplots(2, 4, figsize=(20, 10))

# Order Quantity Distribution
sns.histplot(df['QUANTITYORDERED'], ax=axes[0, 0], color='lime')
axes[0, 0].set_title('Order Quantity Distribution')
axes[0, 0].set_xlabel('Quantity Ordered')
axes[0, 0].set_ylabel('Frequency')

# Price Distribution
sns.histplot(df['PRICEEACH'], ax=axes[0, 1], color='lime')
axes[0, 1].set_title('Price Distribution')
axes[0, 1].set_xlabel('Price Ordered')
axes[0, 1].set_ylabel('Frequency')

# Sales Distribution
sns.histplot(df['SALES'], ax=axes[0, 2], color='lime')
axes[0, 2].set_title('Sales Distribution')
axes[0, 2].set_xlabel('Sales')
axes[0, 2].set_ylabel('Frequency')

# Status Distribution
status_counts = df['STATUS'].value_counts(normalize=True)
axes[0, 3].pie(status_counts, labels=status_counts.index, autopct='%1.1f%%', startangle=140, colors=['lime', 'lightgreen', 'darkgreen'])
axes[0, 3].set_title('Distribution of Status')
```

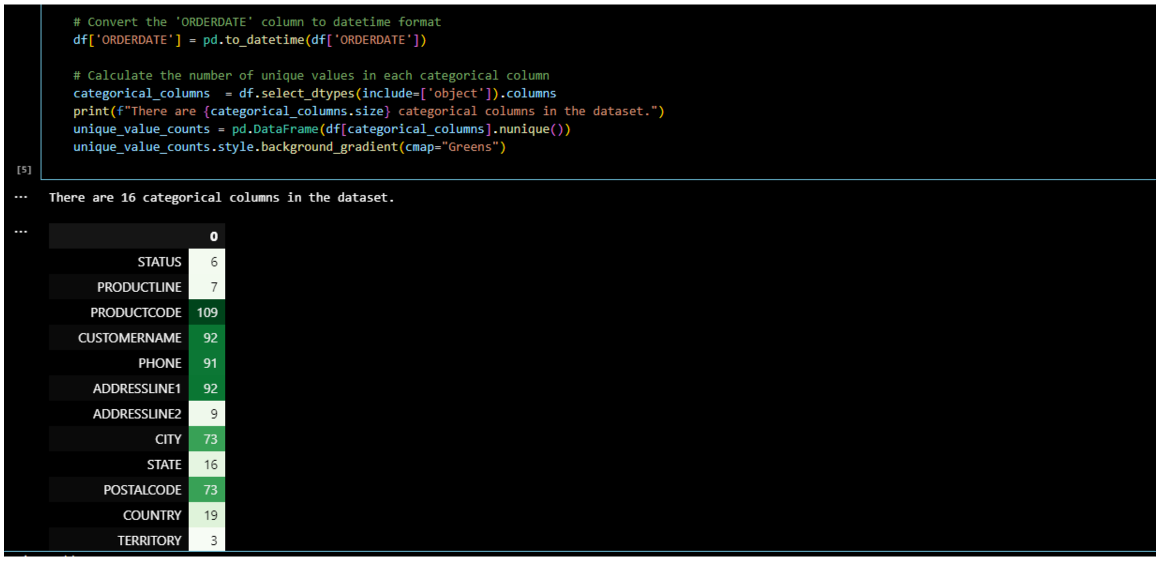
```python
    # Deal size Distribution
    df['DEALSIZE'].value_counts(normalize=True).plot(kind='bar', ax=axes[1, 0], color='lime')
    axes[1, 0].set_title('Deal Size distribution')
    axes[1, 0].set_xlabel('Deal Size')
    axes[1, 0].set_ylabel('% Proportion')

    # Monthly Revenue
    monthly_revenue = df.groupby(['YEAR_ID', 'MONTH_ID'])['SALES'].sum().reset_index()
    sns.lineplot(x="MONTH_ID", y="SALES", hue="YEAR_ID", data=monthly_revenue, ax=axes[1, 1], palette='Greens')
    axes[1, 1].set_xlabel('Month')
    axes[1, 1].set_ylabel('Sales')
    axes[1, 1].set_title('Monthly Revenue')

    # Top 10 countries by Sales
    top_cities = df.groupby(['COUNTRY'])['SALES'].sum().sort_values(ascending=False)[:10]
    top_cities.plot(kind='bar', ax=axes[1, 2], color='lime')
    axes[1, 2].set_title('Top 10 countries by Sales')
    axes[1, 2].set_xlabel('Country')
    axes[1, 2].set_ylabel('Total Sales')

    # Monthly Active Customers
    df['YEAR_MONTH'] = df['YEAR_ID'].astype(str) + df['MONTH_ID'].apply(lambda x: str(x).zfill(2))
    monthly_active = df.groupby(['YEAR_MONTH'])['CUSTOMERNAME'].nunique().reset_index()
    monthly_active.plot(kind='bar', x='YEAR_MONTH', y='CUSTOMERNAME', ax=axes[1, 3], color='lime')
    axes[1, 3].set_title('Monthly Active Customers')
    axes[1, 3].set_xlabel('Month/Year')
    axes[1, 3].set_ylabel('Number of Unique Customers')
    axes[1, 3].tick_params(axis='x', rotation=90)
```



```python
    # View top customers
    customer_totals = df.groupby('CUSTOMERNAME')['SALES'].sum().reset_index()
    top_customers = customer_totals.sort_values(by='SALES', ascending=False)
    print("Top Customers:")
    top_customers.head().style.background_gradient(cmap = "Greens")
```
[4] Python

```
Top Customers:
```

	CUSTOMERNAME	SALES
33	Euro Shopping Channel	912294.110000
55	Mini Gifts Distributors Ltd.	654858.060000
6	Australian Collectors, Co.	200995.410000
58	Muscle Machine Inc	197736.940000
44	La Rochelle Gifts	180124.900000

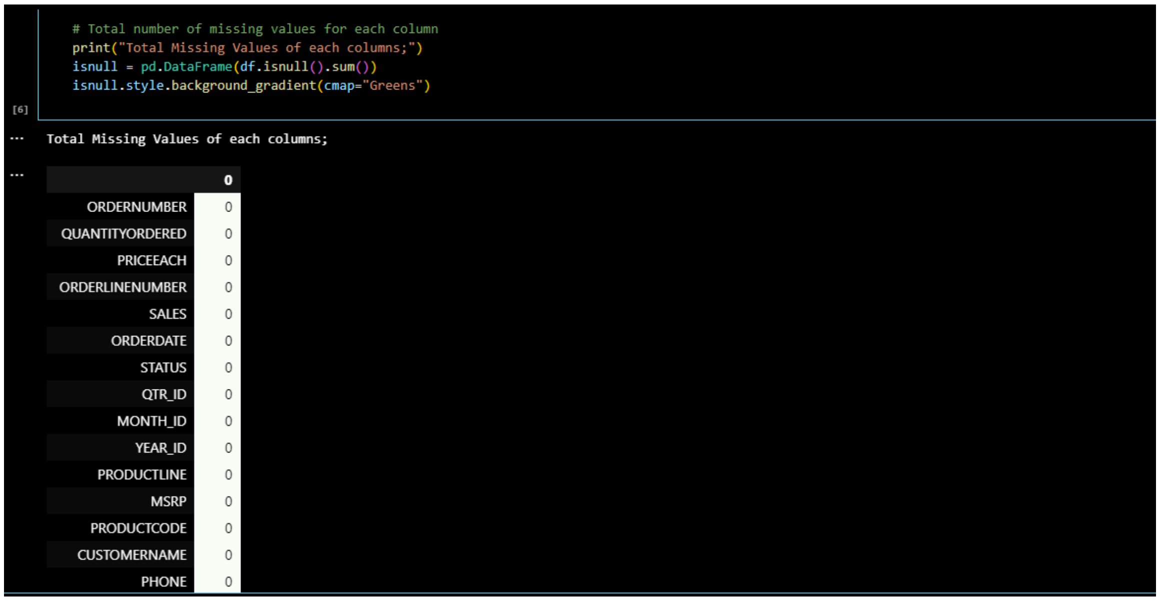


```python
# Convert the 'ORDERDATE' column to datetime format
df['ORDERDATE'] = pd.to_datetime(df['ORDERDATE'])

# Calculate the number of unique values in each categorical column
categorical_columns  = df.select_dtypes(include=['object']).columns
print(f"There are {categorical_columns.size} categorical columns in the dataset.")
unique_value_counts = pd.DataFrame(df[categorical_columns].nunique())
unique_value_counts.style.background_gradient(cmap="Greens")
```

[5]

```
There are 16 categorical columns in the dataset.
```

	0
STATUS	6
PRODUCTLINE	7
PRODUCTCODE	109
CUSTOMERNAME	92
PHONE	91
ADDRESSLINE1	92
ADDRESSLINE2	9
CITY	73
STATE	16
POSTALCODE	73
COUNTRY	19
TERRITORY	3

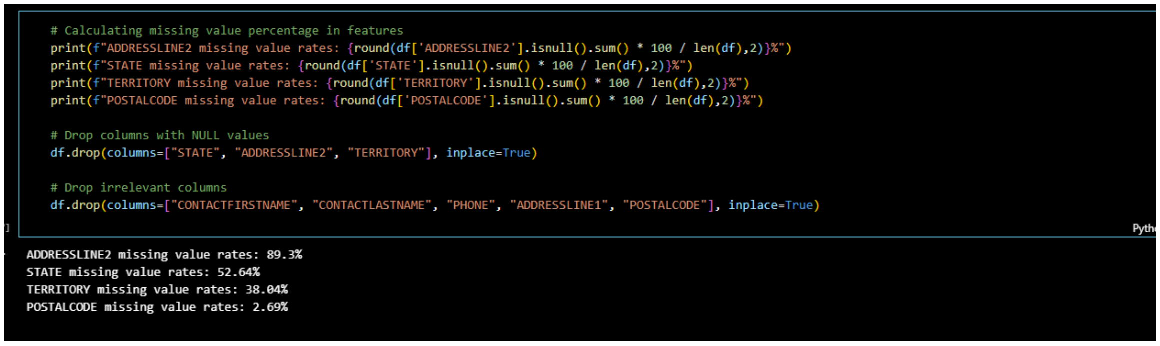


```python
# Total number of missing values for each column
print("Total Missing Values of each columns;")
isnull = pd.DataFrame(df.isnull().sum())
isnull.style.background_gradient(cmap="Greens")
```

[6]

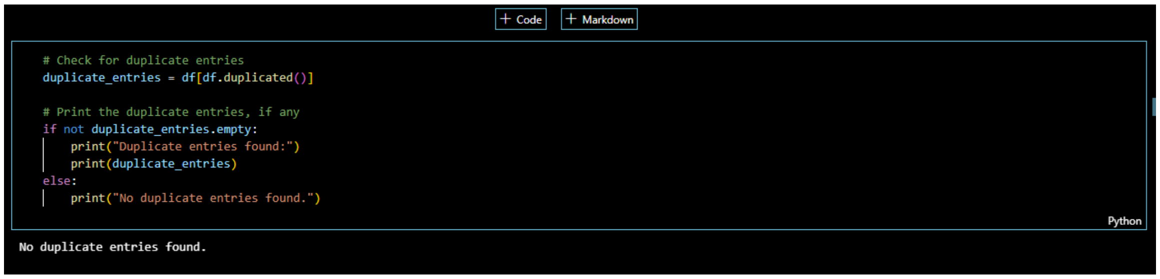
```
Total Missing Values of each columns;
```

	0
ORDERNUMBER	0
QUANTITYORDERED	0
PRICEEACH	0
ORDERLINENUMBER	0
SALES	0
ORDERDATE	0
STATUS	0
QTR_ID	0
MONTH_ID	0
YEAR_ID	0
PRODUCTLINE	0
MSRP	0
PRODUCTCODE	0
CUSTOMERNAME	0
PHONE	0



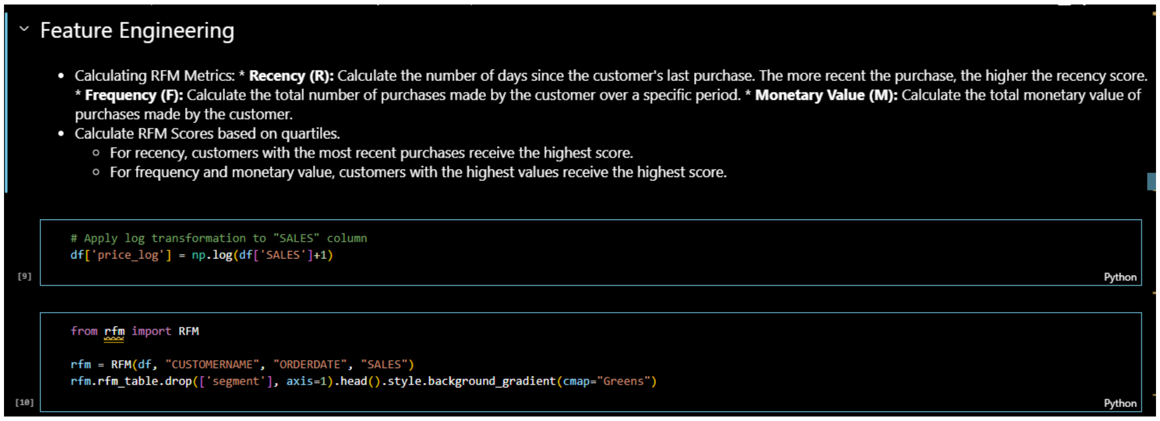
```python
# Calculating missing value percentage in features
print(f"ADDRESSLINE2 missing value rates: {round(df['ADDRESSLINE2'].isnull().sum() * 100 / len(df),2)}%")
print(f"STATE missing value rates: {round(df['STATE'].isnull().sum() * 100 / len(df),2)}%")
print(f"TERRITORY missing value rates: {round(df['TERRITORY'].isnull().sum() * 100 / len(df),2)}%")
print(f"POSTALCODE missing value rates: {round(df['POSTALCODE'].isnull().sum() * 100 / len(df),2)}%")

# Drop columns with NULL values
df.drop(columns=["STATE", "ADDRESSLINE2", "TERRITORY"], inplace=True)

# Drop irrelevant columns
df.drop(columns=["CONTACTFIRSTNAME", "CONTACTLASTNAME", "PHONE", "ADDRESSLINE1", "POSTALCODE"], inplace=True)
```

```
ADDRESSLINE2 missing value rates: 89.3%
STATE missing value rates: 52.64%
TERRITORY missing value rates: 38.04%
POSTALCODE missing value rates: 2.69%
```



```python
# Check for duplicate entries
duplicate_entries = df[df.duplicated()]

# Print the duplicate entries, if any
if not duplicate_entries.empty:
    print("Duplicate entries found:")
    print(duplicate_entries)
else:
    print("No duplicate entries found.")
```

```
No duplicate entries found.
```

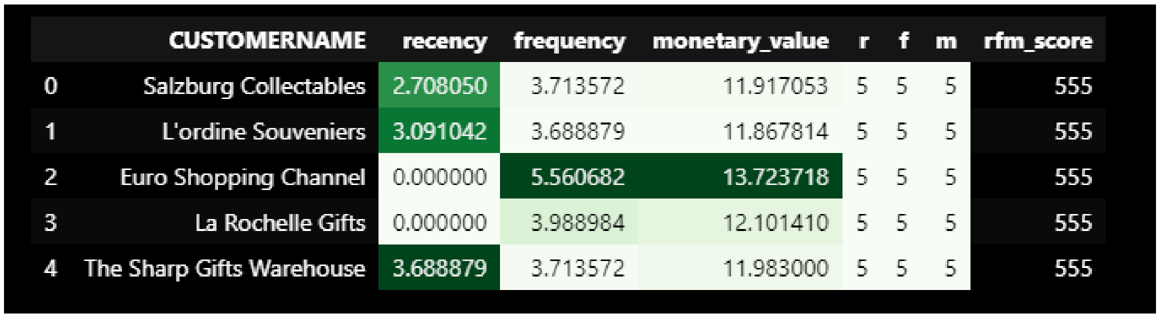


Feature Engineering

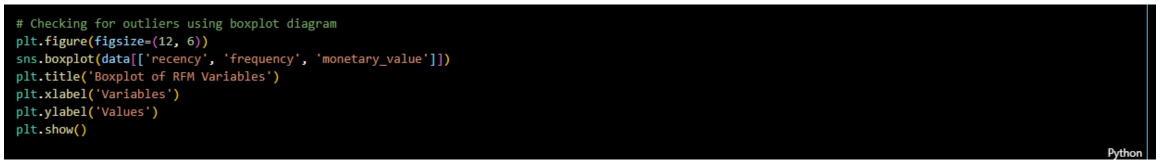
- Calculating RFM Metrics: * **Recency (R):** Calculate the number of days since the customer's last purchase. The more recent the purchase, the higher the recency score. * **Frequency (F):** Calculate the total number of purchases made by the customer over a specific period. * **Monetary Value (M):** Calculate the total monetary value of purchases made by the customer.
- Calculate RFM Scores based on quartiles.
  - For recency, customers with the most recent purchases receive the highest score.
  - For frequency and monetary value, customers with the highest values receive the highest score.

```
# Apply log transformation to "SALES" column
df['price_log'] = np.log(df['SALES']+1)
```
[9] Python

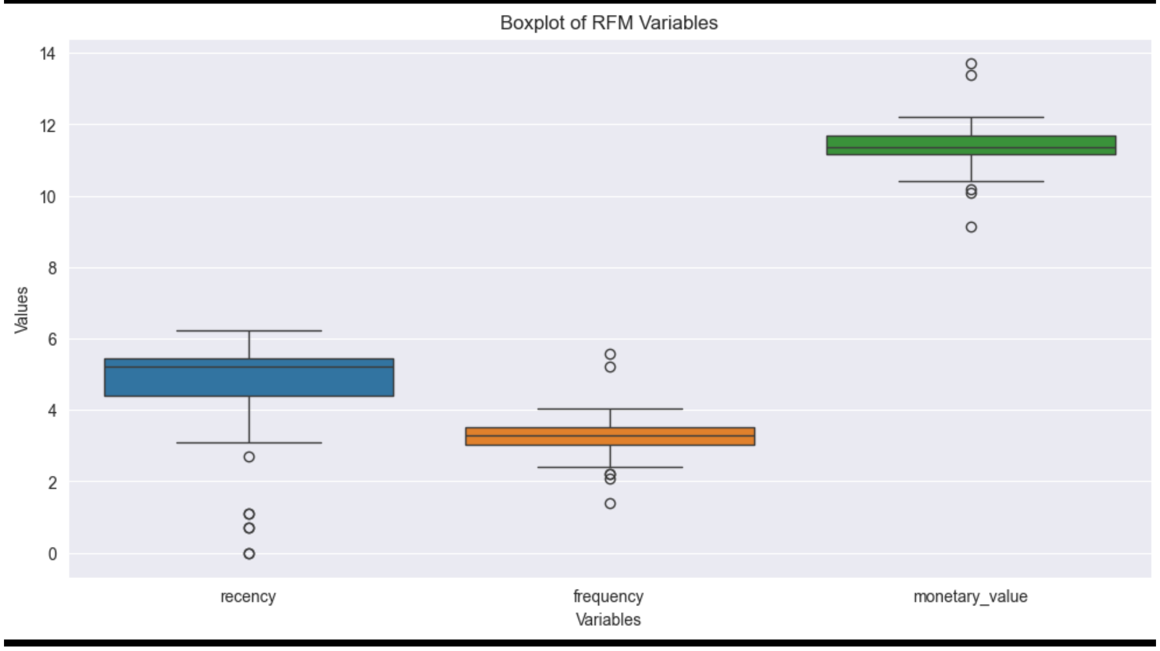
```
from rfm import RFM

rfm = RFM(df, "CUSTOMERNAME", "ORDERDATE", "SALES")
rfm.rfm_table.drop(['segment'], axis=1).head().style.background_gradient(cmap="Greens")
```
[10] Python



	CUSTOMERNAME	recency	frequency	monetary_value	r	f	m	rfm_score
0	Salzburg Collectables	2.708050	3.713572	11.917053	5	5	5	555
1	L'ordine Souveniers	3.091042	3.688879	11.867814	5	5	5	555
2	Euro Shopping Channel	0.000000	5.560682	13.723718	5	5	5	555
3	La Rochelle Gifts	0.000000	3.988984	12.101410	5	5	5	555
4	The Sharp Gifts Warehouse	3.688879	3.713572	11.983000	5	5	5	555



```
# Checking for outliers using boxplot diagram
plt.figure(figsize=(12, 6))
sns.boxplot(data[['recency', 'frequency', 'monetary_value']])
plt.title('Boxplot of RFM Variables')
plt.xlabel('Variables')
plt.ylabel('Values')
plt.show()
```
Python



```python
# Removing outliers for each feature separately
for col in ['recency', 'frequency', 'monetary_value']:
    Q1 = data[col].quantile(0.25)
    Q3 = data[col].quantile(0.75)
    IQR = Q3 - Q1
    lower_bound = Q1 - 1.5 * IQR
    upper_bound = Q3 + 1.5 * IQR
    length_before = len(data)
    data = data[(data[col] >= lower_bound) & (data[col] <= upper_bound)]
    length_after = len(data)

print("Number of outliers removed:", length_before - length_after)

data.head().style.background_gradient(cmap="Greens")
```

Python

```
Number of outliers removed: 1
```

	CUSTOMERNAME	recency	frequency	monetary_value	r	f	m	rfm_score
1	L'ordine Souveniers	3.091042	3.688879	11.867814	5	5	5	555
4	The Sharp Gifts Warehouse	3.688879	3.713572	11.983000	5	5	5	555
7	Handji Gifts& Co	3.663562	3.610918	11.657022	5	5	4	554
8	Danish Wholesale Imports	3.850148	3.610918	11.884782	5	4	5	545
9	UK Collectables, Ltd.	3.988984	3.401197	11.678518	5	4	4	544

```python
# Data scaling
sc = StandardScaler()
scaled_data =sc.fit_transform(data[['recency', 'frequency', 'monetary_value']])
data[['recency', 'frequency', 'monetary_value']] = scaled_data

# Data description
data.describe().T.style.background_gradient(cmap="Greens")
```

[14] Python

	count	mean	std	min	25%	50%	75%	max
recency	80.000000	0.000000	1.006309	-2.450956	-0.666749	0.293099	0.572636	1.504373
frequency	80.000000	0.000000	1.006309	-2.226568	-0.634635	0.080276	0.651121	2.155518
monetary_value	80.000000	-0.000000	1.006309	-2.441493	-0.509501	-0.078674	0.706477	2.121736
r	80.000000	2.812500	1.397047	1.000000	2.000000	3.000000	4.000000	5.000000
f	80.000000	2.987500	1.364039	1.000000	2.000000	3.000000	4.000000	5.000000
m	80.000000	3.000000	1.359449	1.000000	2.000000	3.000000	4.000000	5.000000

```python
data.head().style.background_gradient(cmap="Greens")
```

[15] Python

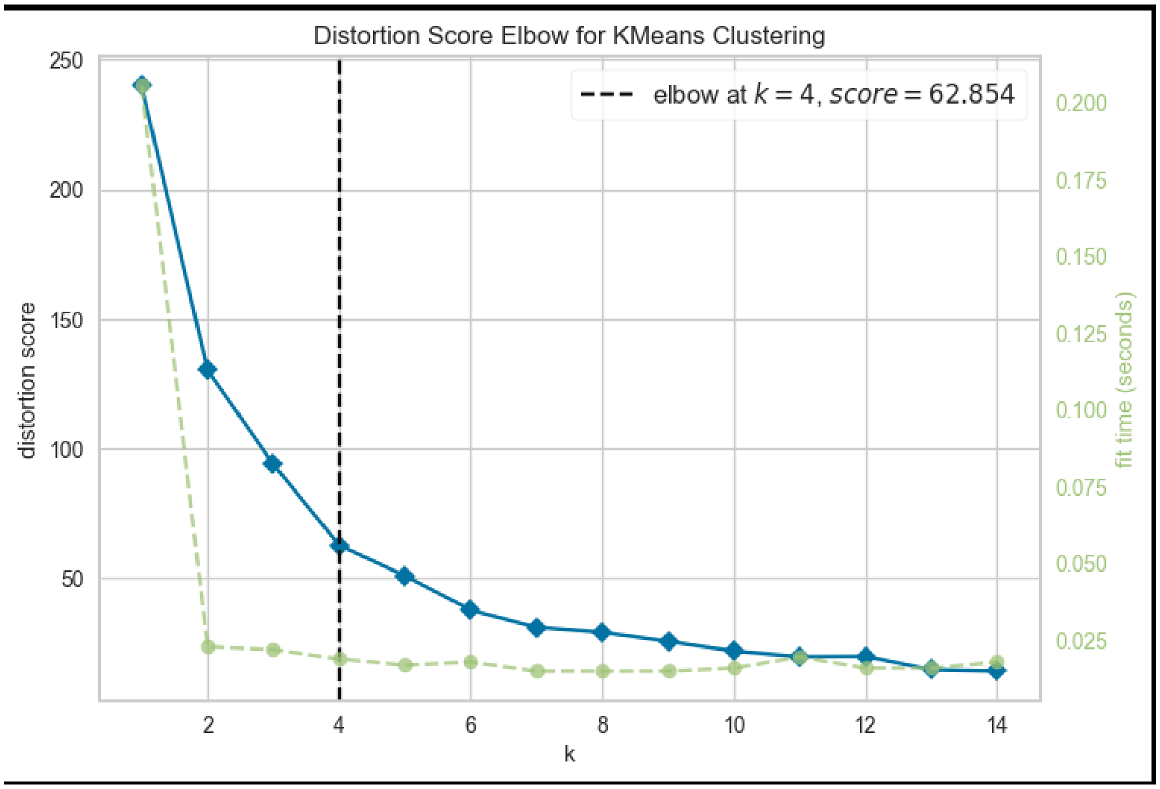
	CUSTOMERNAME	recency	frequency	monetary_value	r	f	m	rfm_score
1	L'ordine Souveniers	-2.450956	1.198359	1.225767	5	5	5	555
4	The Sharp Gifts Warehouse	-1.698222	1.268602	1.526450	5	5	5	555
7	Handji Gifts& Co	-1.730100	0.976583	0.675513	5	5	4	554
8	Danish Wholesale Imports	-1.495170	0.976583	1.270062	5	4	5	545
9	UK Collectables, Ltd.	-1.320362	0.379994	0.731626	5	4	4	544

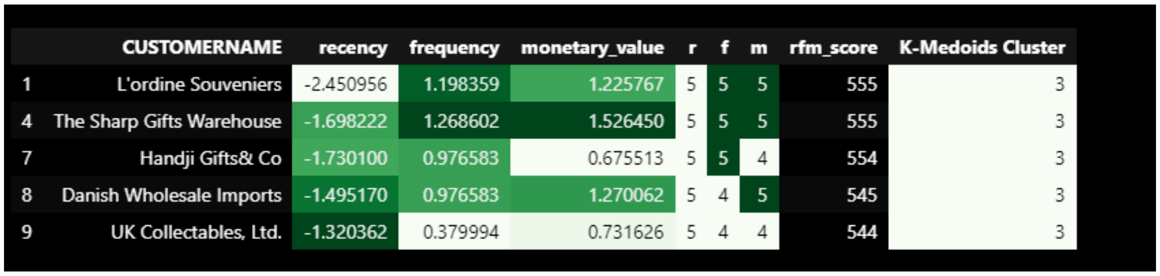
Applying K-Medoids clustering Algorithm

- Choosing a range of values for K.
- Using Elbow method to visualize the error rate as a function of K.
- Setting the number of clusters to the value of the "elbow" point (the point of maximum curvature).
- Applying K-Medoids algorithm.
- Adding the labels as a column in the dataframe.
- Using a scatter plot to visualize the clusters.

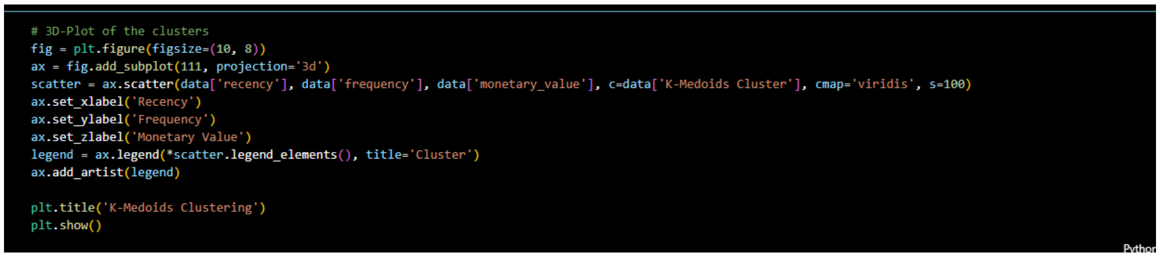
```python
from sklearn_extra.cluster import KMedoids
from sklearn.cluster import KMeans
from yellowbrick.cluster import KElbowVisualizer

# Implement k-Medoids Algorithm
def k_medoids_clustering(dataset, n_clusters):
    kmedoids = KMedoids(n_clusters=n_clusters, random_state=0).fit(dataset)
    return kmedoids.labels_, kmedoids.cluster_centers_

# Determine the optimal number of clusters using KElbowVisualizer
visualizer = KElbowVisualizer(KMeans(), k=(1, 15))
visualizer.fit(scaled_data)
visualizer.show()
```

```python
# Assign Data Points to Clusters
optimal_k = visualizer.elbow_value_
labels, medoids = k_medoids_clustering(scaled_data, optimal_k)
labels += 1
data['K-Medoids Cluster'] = labels
data.head().style.background_gradient(cmap="Greens")
```

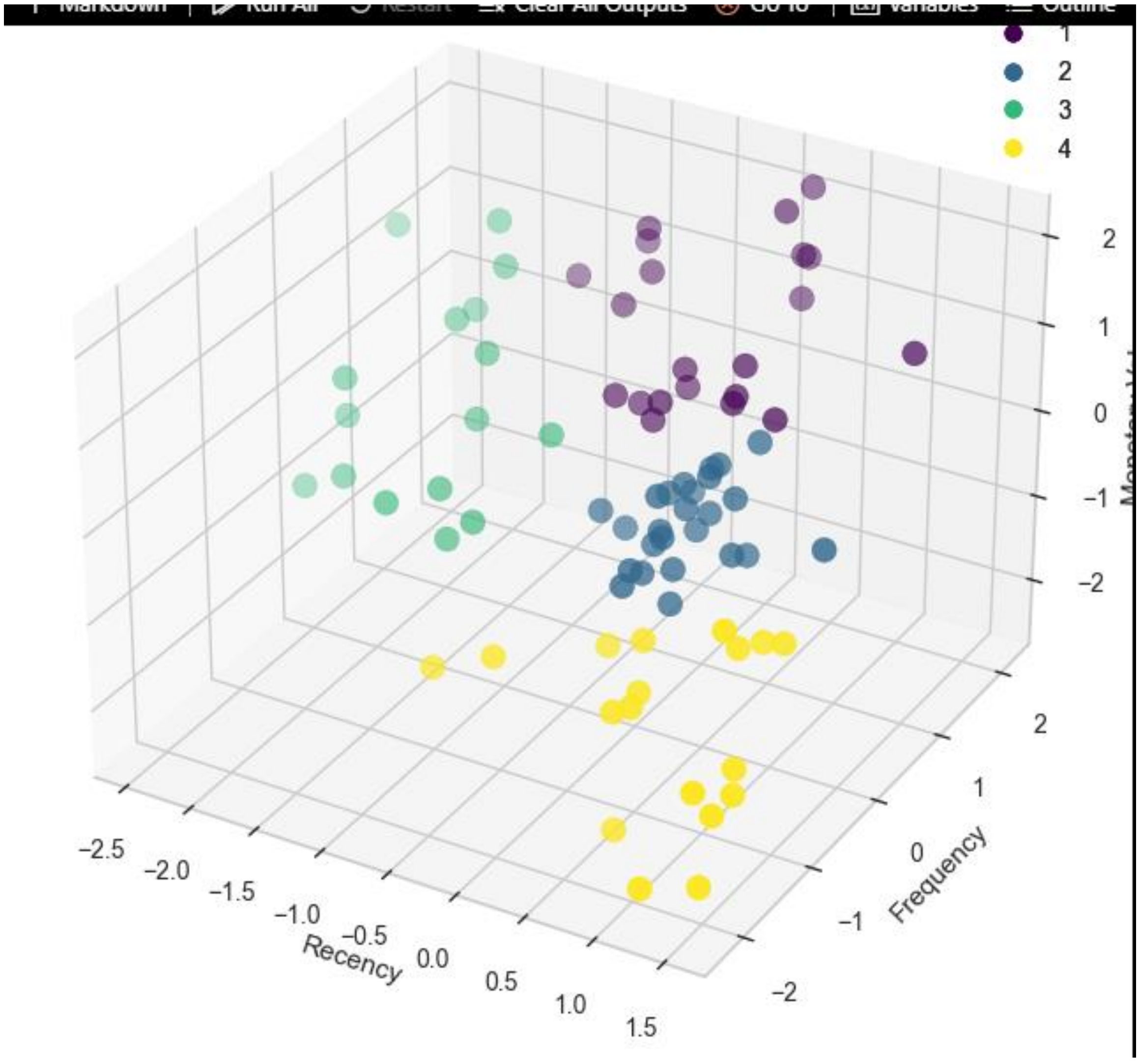




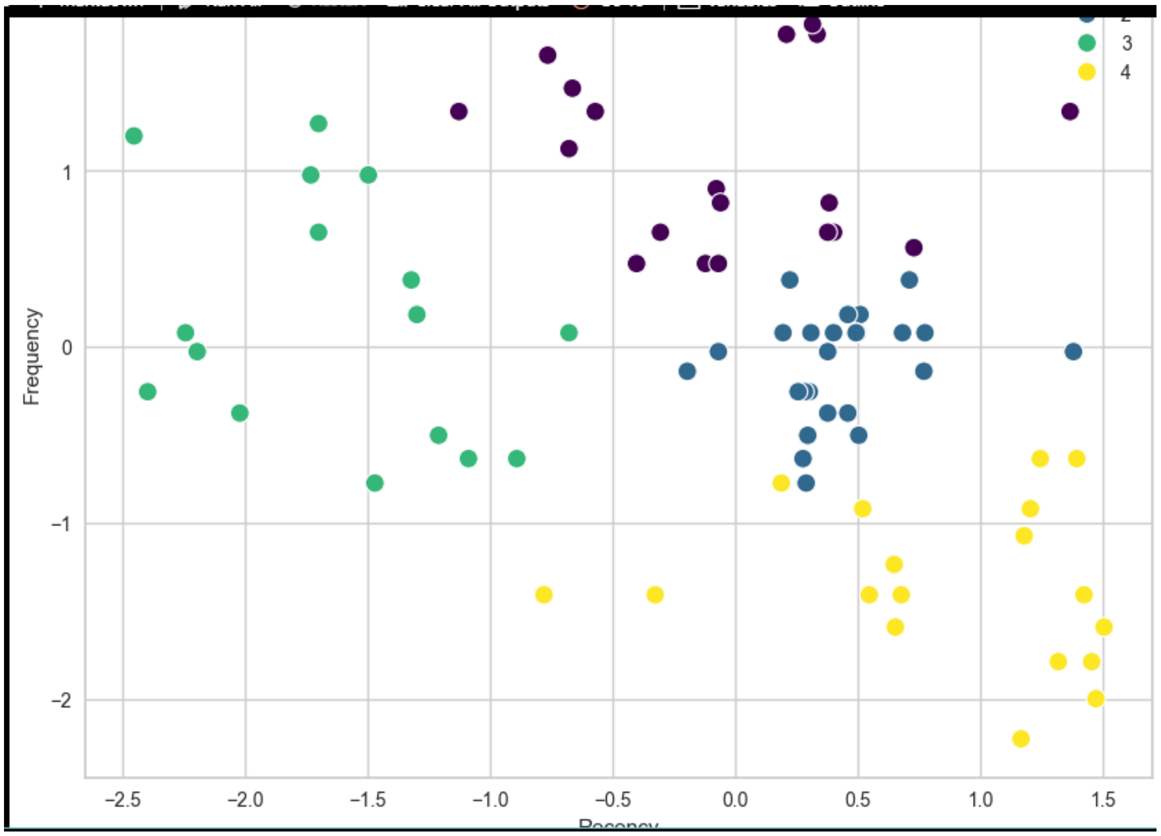
	CUSTOMERNAME	recency	frequency	monetary_value	r	f	m	rfm_score	K-Medoids Cluster
1	L'ordine Souveniers	-2.450956	1.198359	1.225767	5	5	5	555	3
4	The Sharp Gifts Warehouse	-1.698222	1.268602	1.526450	5	5	5	555	3
7	Handji Gifts& Co	-1.730100	0.976583	0.675513	5	5	4	554	3
8	Danish Wholesale Imports	-1.495170	0.976583	1.270062	5	4	5	545	3
9	UK Collectables, Ltd.	-1.320362	0.379994	0.731626	5	4	4	544	3



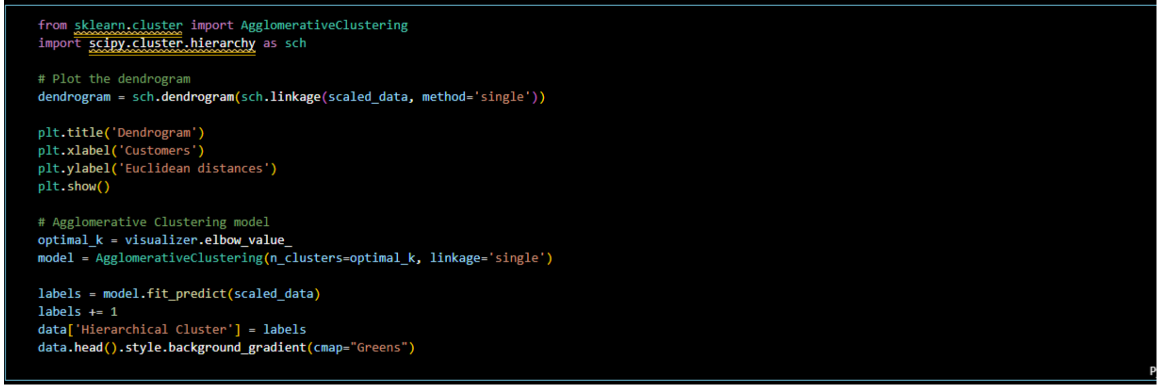
```
# 3D-Plot of the clusters
fig = plt.figure(figsize=(10, 8))
ax = fig.add_subplot(111, projection='3d')
scatter = ax.scatter(data['recency'], data['frequency'], data['monetary_value'], c=data['K-Medoids Cluster'], cmap='viridis', s=100)
ax.set_xlabel('Recency')
ax.set_ylabel('Frequency')
ax.set_zlabel('Monetary Value')
legend = ax.legend(*scatter.legend_elements(), title='Cluster')
ax.add_artist(legend)

plt.title('K-Medoids Clustering')
plt.show()
```



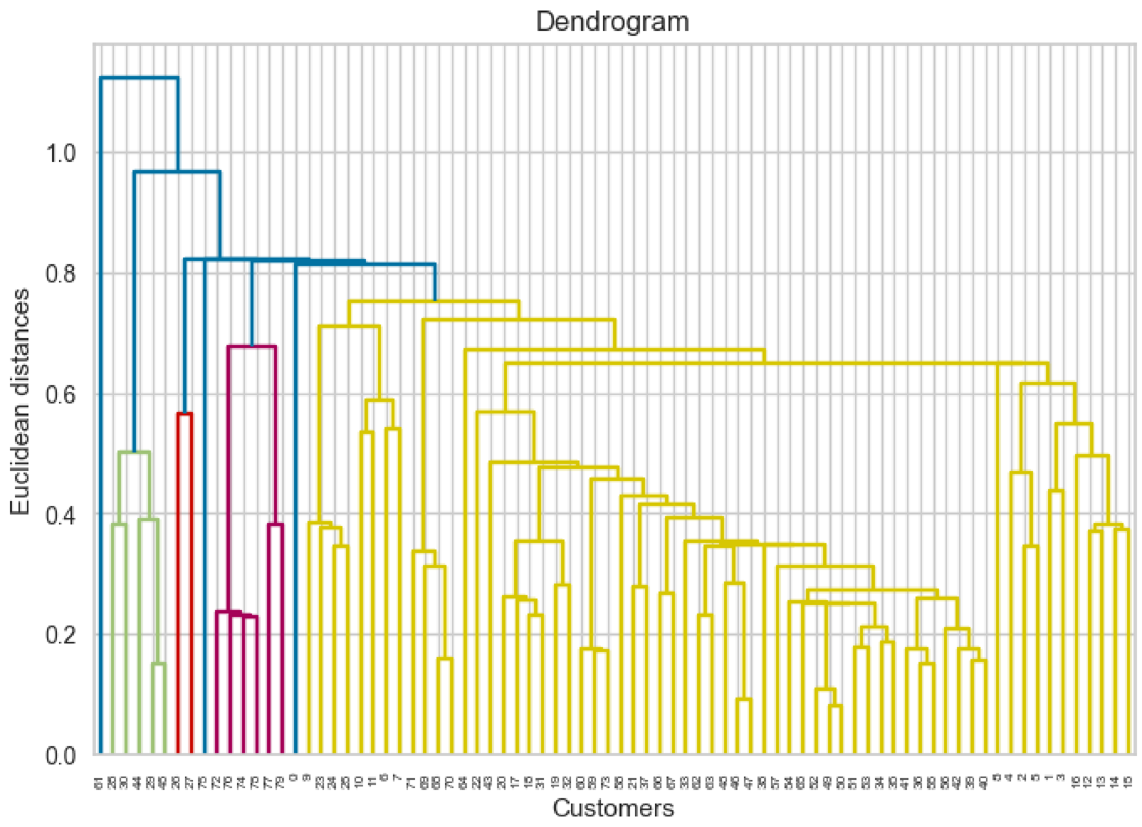
```
# 2D-Plot of the clusters
plt.figure(figsize=(10, 8))
sns.scatterplot(x='recency', y='frequency', hue='K-Medoids Cluster', data=data, palette='viridis', s=100)
plt.title('K-Medoids Clustering')
plt.xlabel('Recency')
plt.ylabel('Frequency')
plt.legend(title='Cluster')
plt.grid(True)
plt.show()
```

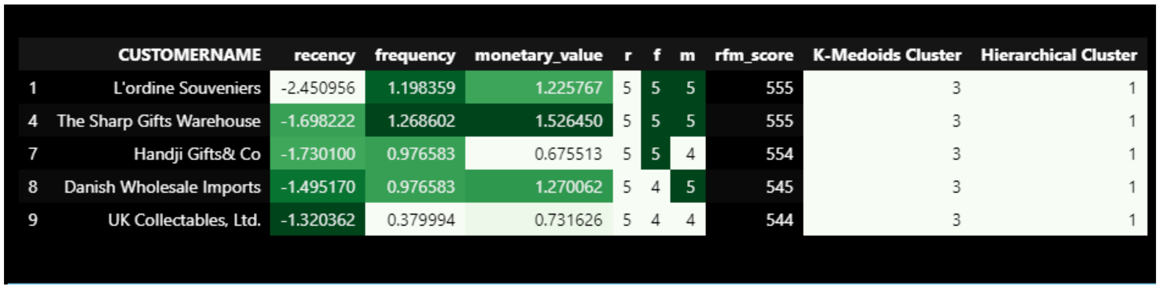


Agglomerative Clustering

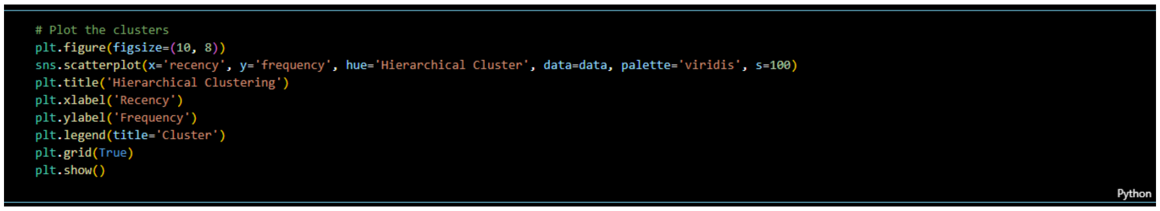


```
from sklearn.cluster import AgglomerativeClustering
import scipy.cluster.hierarchy as sch

# Plot the dendrogram
dendrogram = sch.dendrogram(sch.linkage(scaled_data, method='single'))

plt.title('Dendrogram')
plt.xlabel('Customers')
plt.ylabel('Euclidean distances')
plt.show()

# Agglomerative Clustering model
optimal_k = visualizer.elbow_value_
model = AgglomerativeClustering(n_clusters=optimal_k, linkage='single')

labels = model.fit_predict(scaled_data)
labels += 1
data['Hierarchical Cluster'] = labels
data.head().style.background_gradient(cmap="Greens")
```

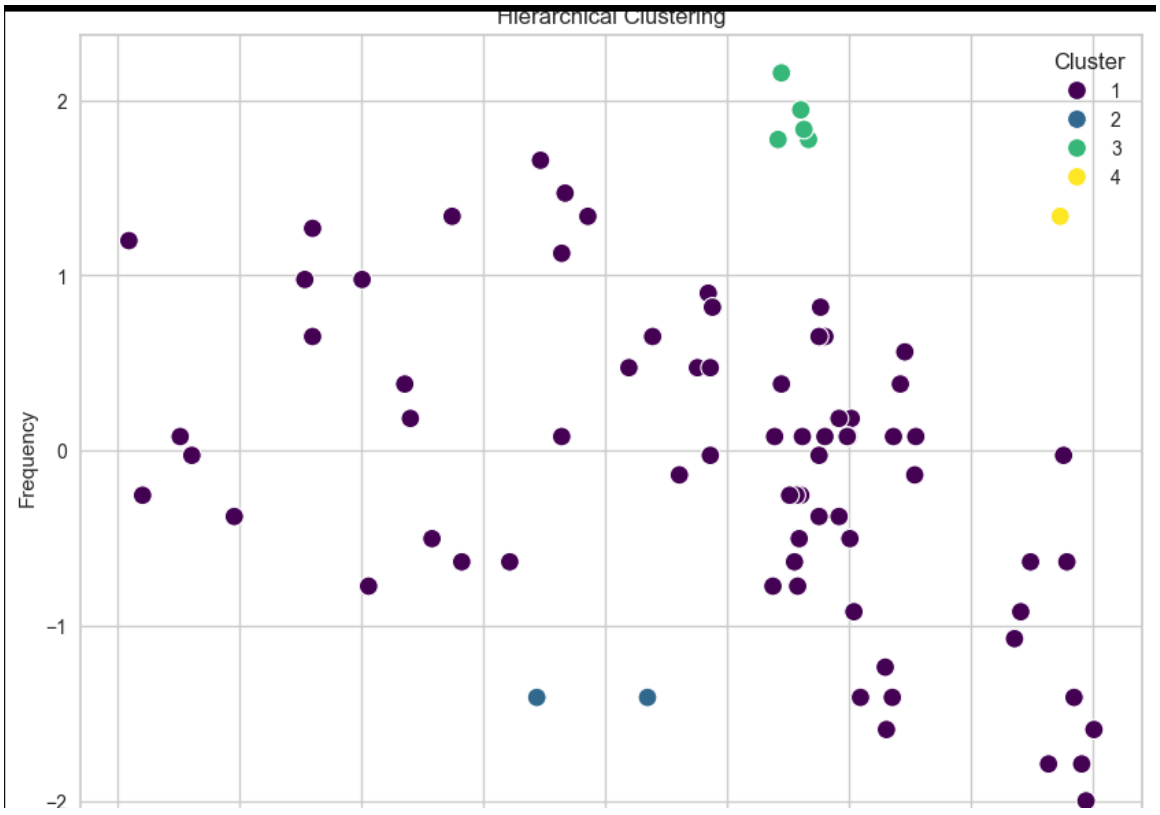


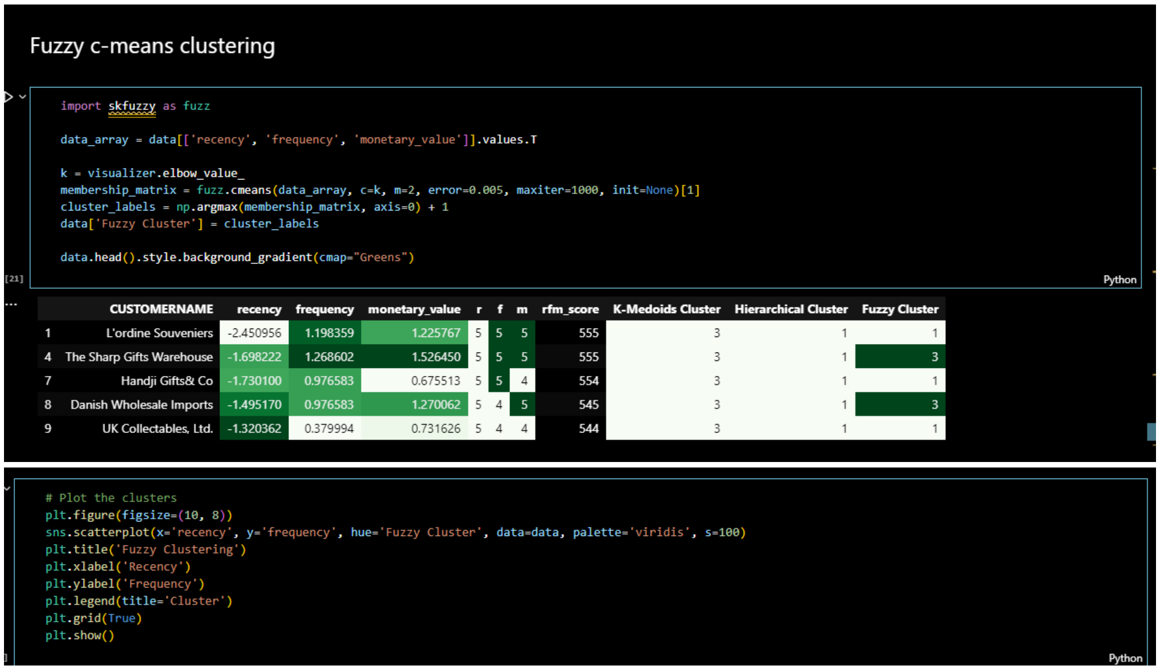


	CUSTOMERNAME	recency	frequency	monetary_value	r	f	m	rfm_score	K-Medoids Cluster	Hierarchical Cluster
1	L'ordine Souveniers	-2.450956	1.198359	1.225767	5	5	5	555	3	1
4	The Sharp Gifts Warehouse	-1.698222	1.268602	1.526450	5	5	5	555	3	1
7	Handji Gifts& Co	-1.730100	0.976583	0.675513	5	5	4	554	3	1
8	Danish Wholesale Imports	-1.495170	0.976583	1.270062	5	4	5	545	3	1
9	UK Collectables, Ltd.	-1.320362	0.379994	0.731626	5	4	4	544	3	1



```
# Plot the clusters
plt.figure(figsize=(10, 8))
sns.scatterplot(x='recency', y='frequency', hue='Hierarchical Cluster', data=data, palette='viridis', s=100)
plt.title('Hierarchical Clustering')
plt.xlabel('Recency')
plt.ylabel('Frequency')
plt.legend(title='Cluster')
plt.grid(True)
plt.show()
```





Fuzzy c-means clustering

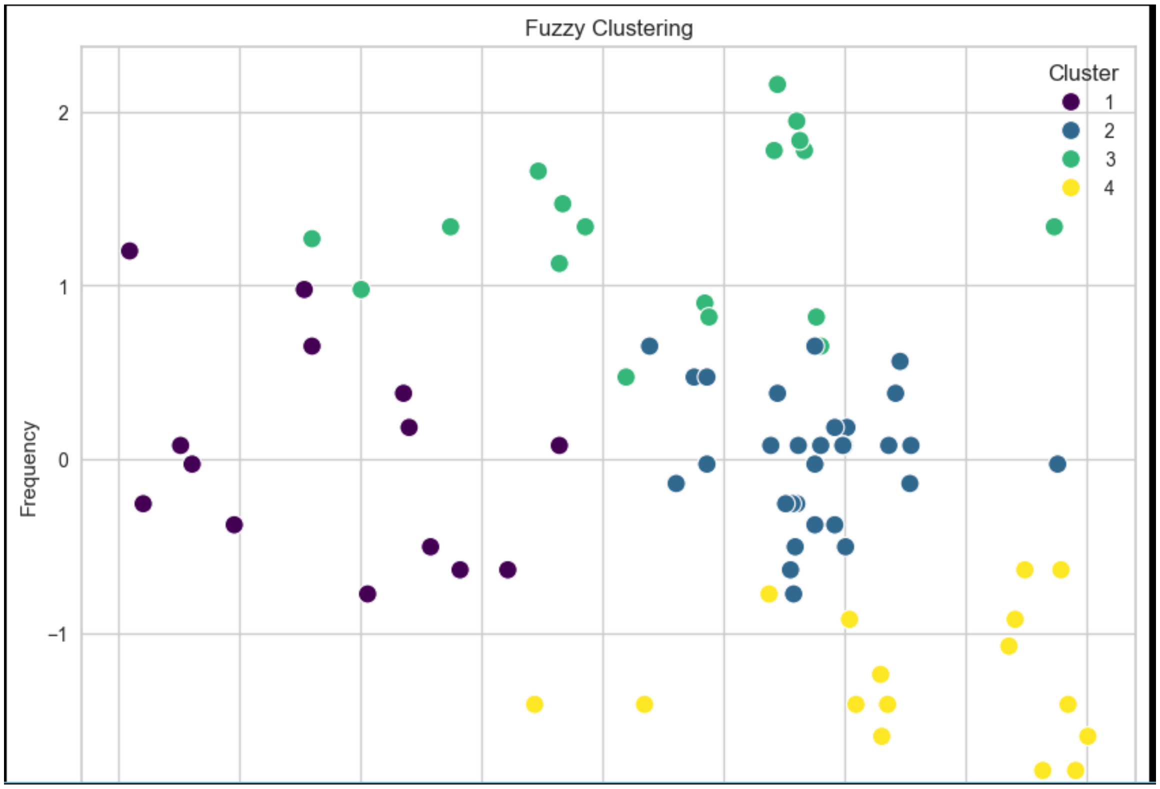
```
import skfuzzy as fuzz

data_array = data[['recency', 'frequency', 'monetary_value']].values.T

k = visualizer.elbow_value_
membership_matrix = fuzz.cmeans(data_array, c=k, m=2, error=0.005, maxiter=1000, init=None)[1]
cluster_labels = np.argmax(membership_matrix, axis=0) + 1
data['Fuzzy Cluster'] = cluster_labels

data.head().style.background_gradient(cmap="Greens")
```

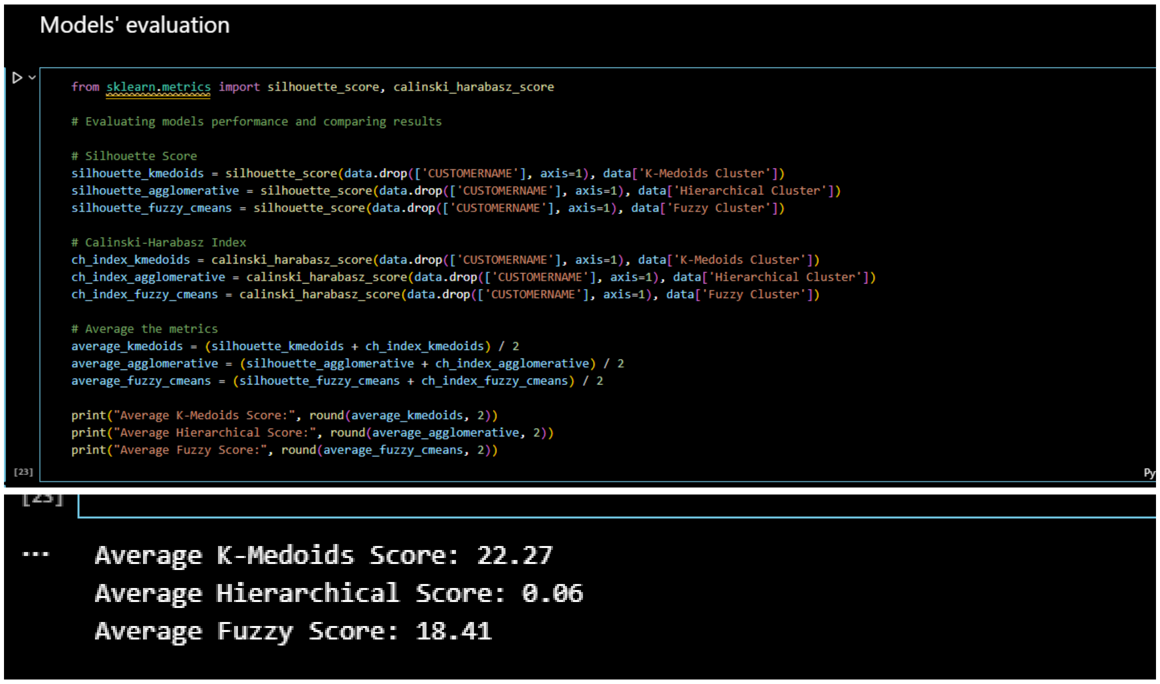
[21] Python

	CUSTOMERNAME	recency	frequency	monetary_value	r	f	m	rfm_score	K-Medoids Cluster	Hierarchical Cluster	Fuzzy Cluster
1	L'ordine Souveniers	-2.450956	1.198359	1.225767	5	5	5	555	3	1	1
4	The Sharp Gifts Warehouse	-1.698222	1.268602	1.526450	5	5	5	555	3	1	3
7	Handji Gifts& Co	-1.730100	0.976583	0.675513	5	5	4	554	3	1	1
8	Danish Wholesale Imports	-1.495170	0.976583	1.270062	5	4	5	545	3	1	3
9	UK Collectables, Ltd.	-1.320362	0.379994	0.731626	5	4	4	544	3	1	1

```
# Plot the clusters
plt.figure(figsize=(10, 8))
sns.scatterplot(x='recency', y='frequency', hue='Fuzzy Cluster', data=data, palette='viridis', s=100)
plt.title('Fuzzy Clustering')
plt.xlabel('Recency')
plt.ylabel('Frequency')
plt.legend(title='Cluster')
plt.grid(True)
plt.show()
```

Python





Models' evaluation

```
from sklearn.metrics import silhouette_score, calinski_harabasz_score

# Evaluating models performance and comparing results

# Silhouette Score
silhouette_kmedoids = silhouette_score(data.drop(['CUSTOMERNAME'], axis=1), data['K-Medoids Cluster'])
silhouette_agglomerative = silhouette_score(data.drop(['CUSTOMERNAME'], axis=1), data['Hierarchical Cluster'])
silhouette_fuzzy_cmeans = silhouette_score(data.drop(['CUSTOMERNAME'], axis=1), data['Fuzzy Cluster'])

# Calinski-Harabasz Index
ch_index_kmedoids = calinski_harabasz_score(data.drop(['CUSTOMERNAME'], axis=1), data['K-Medoids Cluster'])
ch_index_agglomerative = calinski_harabasz_score(data.drop(['CUSTOMERNAME'], axis=1), data['Hierarchical Cluster'])
ch_index_fuzzy_cmeans = calinski_harabasz_score(data.drop(['CUSTOMERNAME'], axis=1), data['Fuzzy Cluster'])

# Average the metrics
average_kmedoids = (silhouette_kmedoids + ch_index_kmedoids) / 2
average_agglomerative = (silhouette_agglomerative + ch_index_agglomerative) / 2
average_fuzzy_cmeans = (silhouette_fuzzy_cmeans + ch_index_fuzzy_cmeans) / 2

print("Average K-Medoids Score:", round(average_kmedoids, 2))
print("Average Hierarchical Score:", round(average_agglomerative, 2))
print("Average Fuzzy Score:", round(average_fuzzy_cmeans, 2))
```

[23]

```
Average K-Medoids Score: 22.27
Average Hierarchical Score: 0.06
Average Fuzzy Score: 18.41
```