imtiaz-mall-eda

March 12, 2024

[33]:
```
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
import  pandas as pd
from sklearn.cluster import KMeans, DBSCAN, kmeans_plusplus
```

[34]:
```
#open the data file
df = pd.read_json('electronics.json')
df.head()
```

[34]:
```
                            Customer_ID Age  Gender Income_Level  \
0  b81ee6c9-2ae4-48a7-b283-220eaa244f43  40  Female       Medium
1                                        25    Male         High
2  fdf79bcd-5908-4c90-8501-570ffb5b7648  57   Other          Low
3  878dccba-893a-48f9-8d34-6ed394fa3c9c  38  Female       Medium
4  0af0bd81-73cc-494e-aa5e-75c6d0b6d743  68   Other       Medium

                                            Address  \
0  43548 Murray Islands Suite 974\nAmyberg, CT 13457
1
2     79683 Kevin Hill Apt. 555\nJohnshire, AR 39961
3  02998 Hall Meadows Suite 809\nNorth Robertvill…
4  21411 Timothy Ford Apt. 320\nDavisborough, AR …

                         Transaction_ID Purchase_Date  \
0  c6a6c712-e36b-406a-bfde-f53bdcf4744f    2022-04-26
1  0b587838-1e4f-4231-b488-42bcd47c052a    2021-08-10
2  462925b1-a5bf-4996-bda2-59749de64eea    2021-12-09
3  3cfafa02-6b34-4d77-9e05-d223dfab64e8    2022-12-03
4  0d8dc27a-0c8f-4a82-b57e-8bf54cee9759    2020-06-08

                             Product_ID Product_Category    Brand  \
0  d2f767d6-b01a-41a2-87f7-ec1d1186f50e         Clothing  Brand_C
1  79eadc55-2de1-41cf-b1b6-40118c0bf8ec            Books  Brand_A
2  9ab75a68-4329-4bd9-a259-2233c0f34c93      Electronics  Brand_A
3  d518569b-ff79-494b-b2b6-7e2af39db86a         Clothing  Brand_C
4  b6deac9d-2b7e-4a51-8273-a6534910b3bc            Books  Brand_B
```

```
   Purchase_Amount  Average_Spending_Per_Purchase  Purchase_Frequency_Per_Month  \
0              193                             59                             2
1              318                             77                             2
2              197                            100                             9
3              262                             97                             3
4              429                             85                             7

   Brand_Affinity_Score Product_Category_Preferences Month  Year  Season
0                     2                          Low    01  2010  Winter
1                     1                          Low    08  1989    Fall
2                     1                          Low        1995  Winter
3                     4                          Low    09  2012    Fall
4                     2                         High    01  2010  Summer
```

[35]:
```
df.replace('', np.nan).isna().sum()
```

[35]:
```
Customer_ID                     32
Age                             33
Gender                          33
Income_Level                    41
Address                         32
Transaction_ID                  39
Purchase_Date                   35
Product_ID                      40
Product_Category                44
Brand                           46
Purchase_Amount                 33
Average_Spending_Per_Purchase   26
Purchase_Frequency_Per_Month    37
Brand_Affinity_Score            47
Product_Category_Preferences    31
Month                           40
Year                            39
Season                          36
dtype: int64
```

[36]:
```
df.replace('Hidden', np.nan).isna().sum()
```

[36]:
```
Customer_ID                     12
Age                              7
Gender                          15
Income_Level                     9
Address                         15
Transaction_ID                  11
Purchase_Date                   13
Product_ID                       9
```

```
Product_Category                16
Brand                           12
Purchase_Amount                 16
Average_Spending_Per_Purchase   14
Purchase_Frequency_Per_Month    18
Brand_Affinity_Score            14
Product_Category_Preferences    12
Month                           13
Year                            13
Season                          12
dtype: int64
```

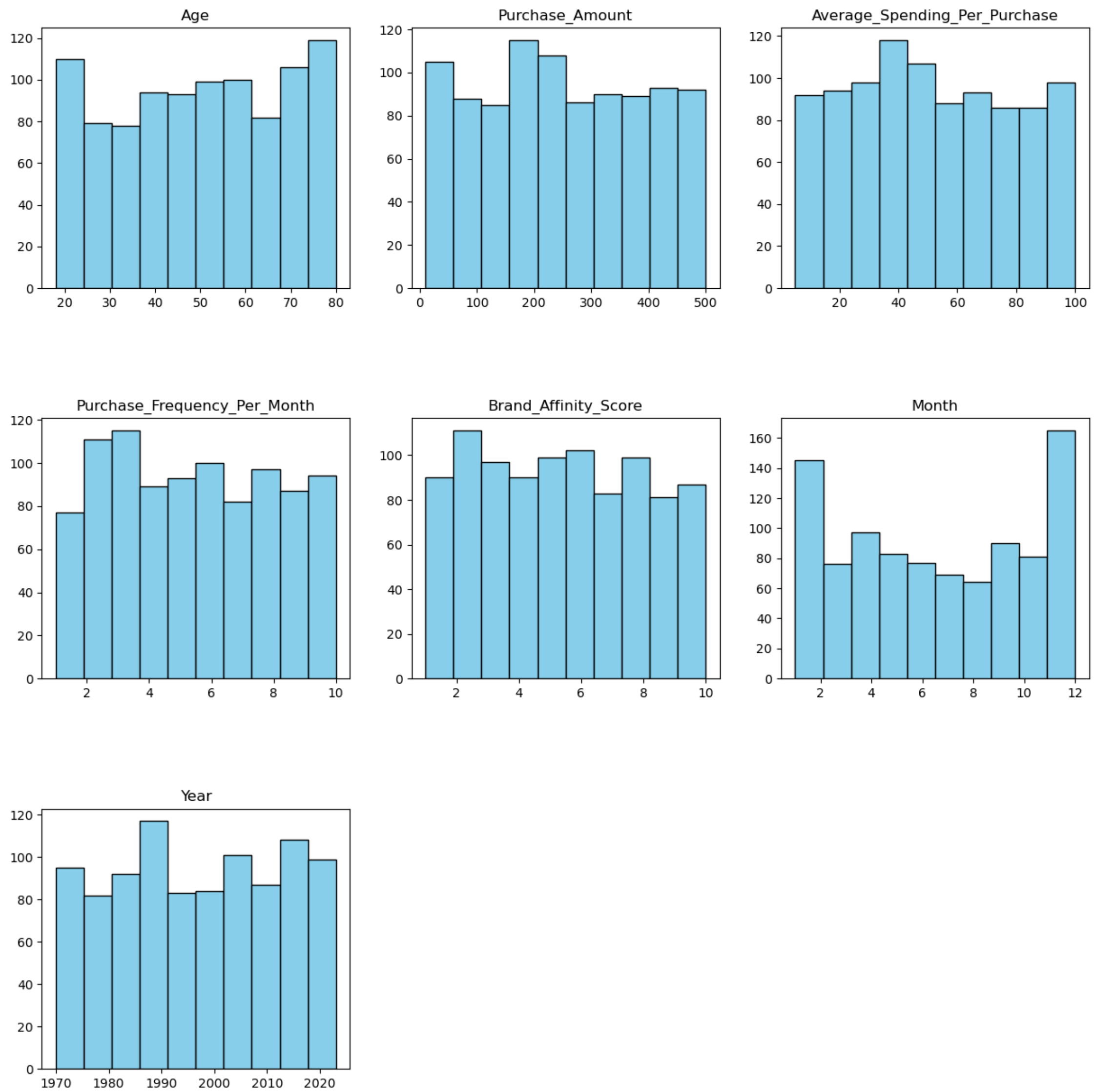
[37]:
```
df.replace('', np.nan, inplace=True)
df.replace('Hidden', np.nan, inplace=True)

df.isna().sum()
```

[37]:
```
Customer_ID                     44
Age                             40
Gender                          48
Income_Level                    50
Address                         47
Transaction_ID                  50
Purchase_Date                   48
Product_ID                      49
Product_Category                60
Brand                           58
Purchase_Amount                 49
Average_Spending_Per_Purchase   40
Purchase_Frequency_Per_Month    55
Brand_Affinity_Score            61
Product_Category_Preferences    43
Month                           53
Year                            52
Season                          48
dtype: int64
```

[38]:
```
#Convert column to numeric
df['Age'] = pd.to_numeric(df['Age'], errors='coerce')
df['Purchase_Amount'] = pd.to_numeric(df['Purchase_Amount'], errors='coerce')
df['Average_Spending_Per_Purchase'] = pd.
  ↪to_numeric(df['Average_Spending_Per_Purchase'], errors='coerce')
df['Purchase_Frequency_Per_Month'] = pd.
  ↪to_numeric(df['Purchase_Frequency_Per_Month'], errors='coerce')
df['Brand_Affinity_Score'] = pd.to_numeric(df['Brand_Affinity_Score'],␣
  ↪errors='coerce')
df['Month'] = pd.to_numeric(df['Month'], errors='coerce')
```

```
df['Year'] = pd.to_numeric(df['Year'], errors='coerce')
```

[8]:
```
# Select only numeric columns
numeric_columns = ['Age', 'Purchase_Amount', 'Average_Spending_Per_Purchase',
                   'Purchase_Frequency_Per_Month', 'Brand_Affinity_Score',
                   'Month', 'Year']

# Create subplots with 3 columns in each row
fig, axes = plt.subplots(nrows=3, ncols=3, figsize=(15, 15))
fig.subplots_adjust(hspace=0.5)  # Adjust vertical spacing between subplots

# Flatten the 2D array of subplots to make it easier to iterate
axes = axes.flatten()

# Iterate through numeric columns and plot histograms
for i, column in enumerate(numeric_columns):
    df[column].plot(kind='hist', ax=axes[i], edgecolor='black', color='skyblue')
    axes[i].set_title(column)
    axes[i].set_xlabel('')
    axes[i].set_ylabel('')

# Hide empty subplots
for j in range(len(numeric_columns), len(axes)):
    axes[j].axis('off')

plt.show()
```



[39]:
```
# df.dropna(subset=['Customer_ID'], inplace=True)

df['Customer_ID'].fillna('Unknown', inplace=True)

df['Age'].fillna(df['Age'].median(), inplace=True)

df['Gender'].fillna(df['Gender'].mode()[0], inplace=True)

df['Income_Level'].fillna(df['Income_Level'].mode()[0], inplace=True)

df['Address'].fillna('Unknown', inplace=True)

df['Transaction_ID'].fillna('Unknown', inplace=True)
```

```
df['Purchase_Date'].fillna(method='ffill', inplace=True)

df['Product_ID'].fillna('Unknown', inplace=True)

df['Product_Category'].fillna(df['Product_Category'].mode()[0], inplace=True)

df['Brand'].fillna(df['Brand'].mode()[0], inplace=True)

df['Purchase_Amount'].fillna(df['Purchase_Amount'].median(), inplace=True)

df['Average_Spending_Per_Purchase'].fillna(df['Average_Spending_Per_Purchase'].
↪median(), inplace=True)

df['Purchase_Frequency_Per_Month'].fillna(df['Purchase_Frequency_Per_Month'].
↪median(), inplace=True)

df['Brand_Affinity_Score'].fillna(df['Brand_Affinity_Score'].median(),␣
↪inplace=True)

df['Product_Category_Preferences'].fillna(df['Product_Category_Preferences'].
↪mode()[0], inplace=True)

df['Month'].fillna(df['Month'].mode()[0], inplace=True)

df['Year'].fillna(df['Year'].mode()[0], inplace=True)

df['Season'].fillna(df['Season'].mode()[0], inplace=True)

df
```

[39]:

```
                                Customer_ID   Age  Gender Income_Level  \
0    b81ee6c9-2ae4-48a7-b283-220eaa244f43  40.0  Female       Medium
1                                 Unknown  25.0    Male         High
2    fdf79bcd-5908-4c90-8501-570ffb5b7648  57.0   Other          Low
3    878dccba-893a-48f9-8d34-6ed394fa3c9c  38.0  Female       Medium
4    0af0bd81-73cc-494e-aa5e-75c6d0b6d743  68.0   Other       Medium
..                                    …     …     …            …
995                               Unknown  70.0    Male       Medium
996  2116266d-8d1c-48cc-ac28-e4e675cb2a4d  78.0  Female          Low
997  562cee08-f909-4e1c-a811-5711f967bea5  63.0    Male         High
998  84da2eea-6e9e-46d4-8d94-1e9b0c377d78  43.0    Male         High
999  87629baf-a138-4374-be37-8bab776379b8  19.0   Other         High

                                         Address  \
0    43548 Murray Islands Suite 974\nAmyberg, CT 13457
1                                          Unknown
```

```
2       79683 Kevin Hill Apt. 555\nJohnshire, AR 39961
3    02998 Hall Meadows Suite 809\nNorth Robertvill…
4    21411 Timothy Ford Apt. 320\nDavisborough, AR …
..                                                 …
995          566 Butler Turnpike\nPort Holly, OK 22329
996  45710 Wilson Circles Apt. 411\nWalterton, NC 8…
997         243 Emily Creek\nSouth Lindaport, CO 81594
998    1129 Kirby Ferry Suite 743\nBillyfurt, UT 41587
999                 896 Troy Branch\nAmytown, NJ 62321

                           Transaction_ID Purchase_Date  \
0    c6a6c712-e36b-406a-bfde-f53bdcf4744f    2022-04-26
1    0b587838-1e4f-4231-b488-42bcd47c052a    2021-08-10
2    462925b1-a5bf-4996-bda2-59749de64eea    2021-12-09
3    3cfafa02-6b34-4d77-9e05-d223dfab64e8    2022-12-03
4    0d8dc27a-0c8f-4a82-b57e-8bf54cee9759    2020-06-08
..                                    …           …
995  776be313-5308-468e-a0ed-7409a4303364    2023-03-17
996  51f771bf-2562-46c1-a25d-2f46f4bb1525    2023-08-30
997  74eba598-ee91-4396-a137-6b869702ef29    2023-08-30
998  4d2e213e-bcc0-4a8a-9501-6ca8361381c4    2021-05-13
999  69afa592-2658-48ac-9b37-33a3a473d0be    2022-09-13

                               Product_ID Product_Category    Brand  \
0    d2f767d6-b01a-41a2-87f7-ec1d1186f50e         Clothing  Brand_C
1    79eadc55-2de1-41cf-b1b6-40118c0bf8ec            Books  Brand_A
2    9ab75a68-4329-4bd9-a259-2233c0f34c93      Electronics  Brand_A
3    d518569b-ff79-494b-b2b6-7e2af39db86a         Clothing  Brand_C
4    b6deac9d-2b7e-4a51-8273-a6534910b3bc            Books  Brand_B
..                                    …                …        …
995  1802f115-80d8-48fd-ad97-94038fe31b82      Electronics  Brand_C
996  546d8d8f-1498-4aa9-8123-29550d911a17            Books  Brand_B
997  8b6ffec8-de54-445c-90d0-1399858b2e16      Electronics  Brand_C
998  51ed2d86-c9ab-4922-a8ff-469acf6ac91e         Clothing  Brand_C
999  91ba2109-15aa-40a0-aa9c-732a1e2e1e27         Clothing  Brand_B

     Purchase_Amount  Average_Spending_Per_Purchase  \
0              193.0                           59.0
1              318.0                           77.0
2              197.0                          100.0
3              262.0                           97.0
4              429.0                           85.0
..               …                            …
995            180.0                           92.0
996            176.0                           53.0
997            212.0                           99.0
998            246.0                           98.0
```

```
999           208.0                           12.0

     Purchase_Frequency_Per_Month  Brand_Affinity_Score  \
0                             2.0                   2.0
1                             2.0                   1.0
2                             9.0                   1.0
3                             3.0                   4.0
4                             7.0                   2.0
..                            …                   …
995                           2.0                   5.0
996                           3.0                   3.0
997                           2.0                   9.0
998                           8.0                   7.0
999                          10.0                   1.0

    Product_Category_Preferences  Month    Year  Season
0                            Low    1.0  2010.0  Winter
1                            Low    8.0  1989.0    Fall
2                            Low    4.0  1995.0  Winter
3                            Low    9.0  2012.0    Fall
4                           High    1.0  2010.0  Summer
..                           …    …     …     …
995                       Medium    5.0  1987.0    Fall
996                       Medium    9.0  1977.0  Winter
997                          Low   12.0  1995.0  Summer
998                          Low    3.0  2000.0    Fall
999                       Medium   12.0  1970.0  Summer

[1000 rows x 18 columns]
```

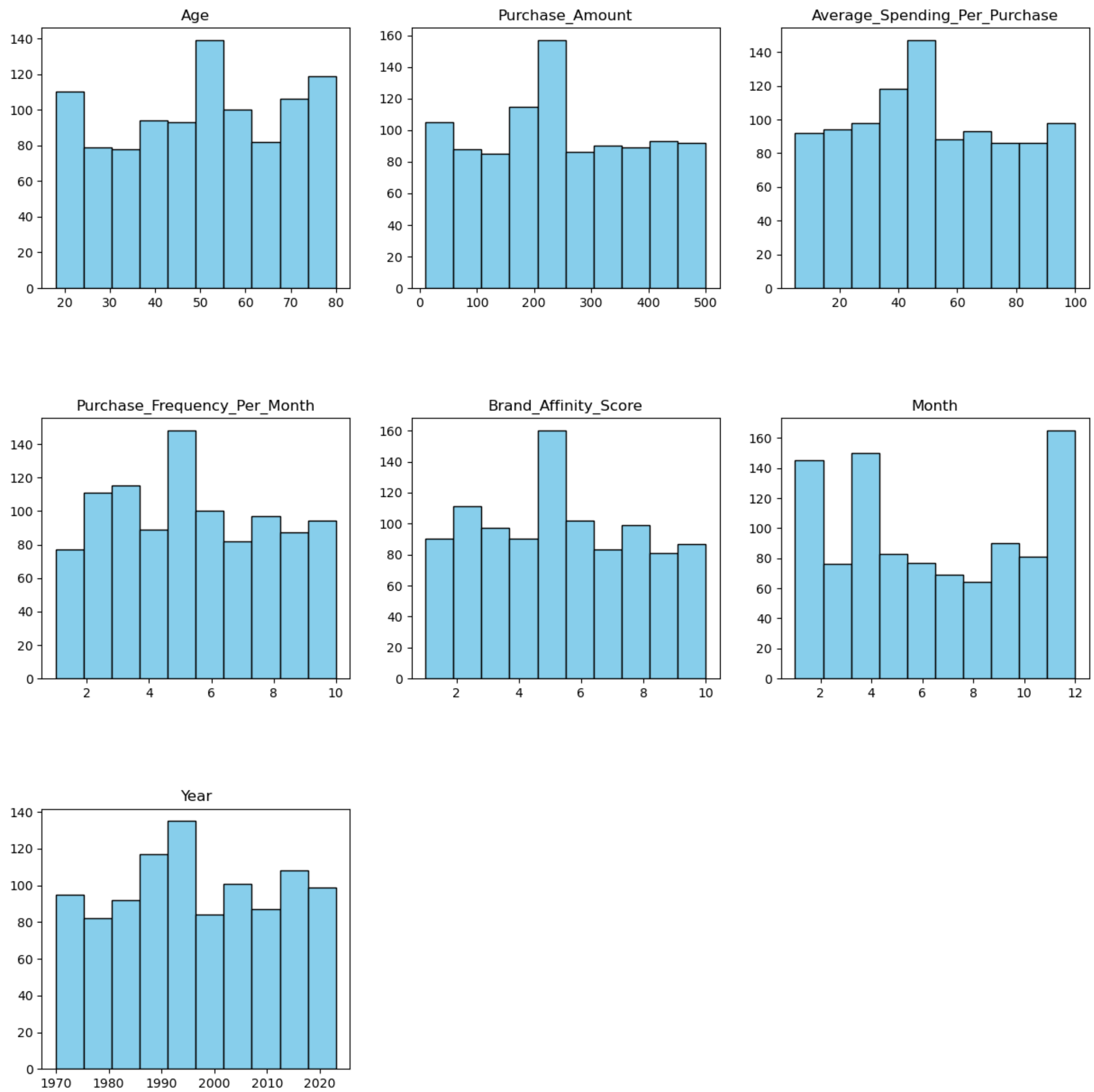
[40]:
```
df.isna().sum()
```

[40]:
```
Customer_ID                     0
Age                             0
Gender                          0
Income_Level                    0
Address                         0
Transaction_ID                  0
Purchase_Date                   0
Product_ID                      0
Product_Category                0
Brand                           0
Purchase_Amount                 0
Average_Spending_Per_Purchase   0
Purchase_Frequency_Per_Month    0
Brand_Affinity_Score            0
Product_Category_Preferences    0
```

```
Month                             0
Year                              0
Season                            0
dtype: int64
```

[ ]:

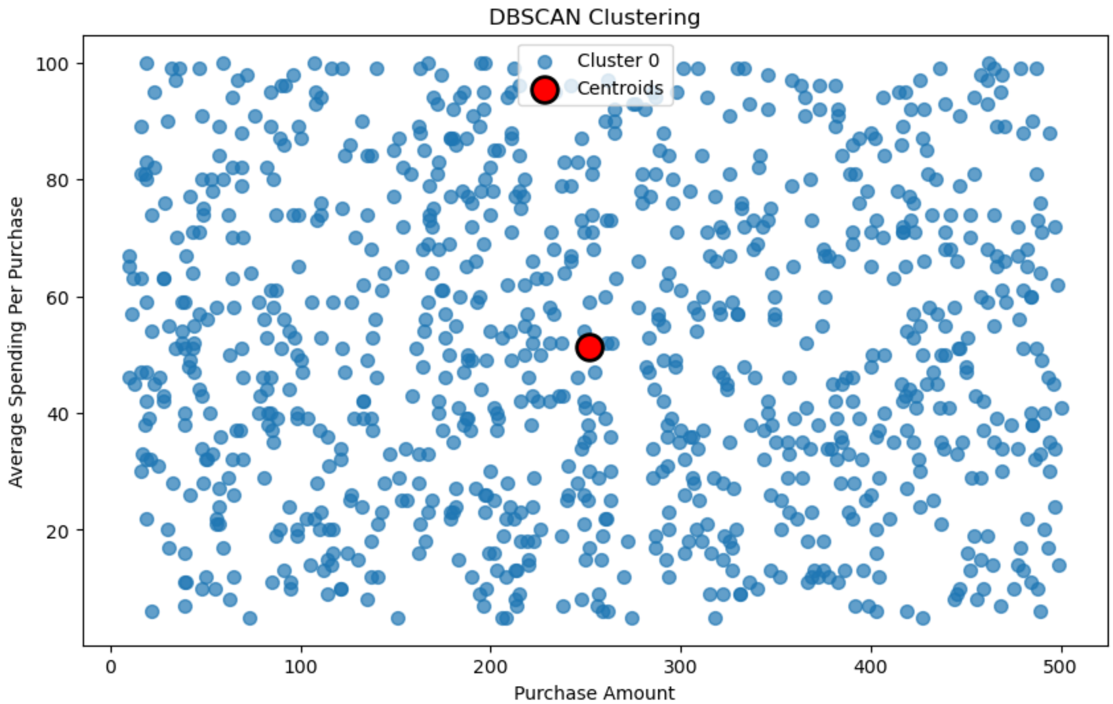
[11]:
```python
# Select only numeric columns
numeric_columns = ['Age', 'Purchase_Amount', 'Average_Spending_Per_Purchase',
                   'Purchase_Frequency_Per_Month', 'Brand_Affinity_Score',
                   'Month', 'Year']

# Create subplots with 3 columns in each row
fig, axes = plt.subplots(nrows=3, ncols=3, figsize=(15, 15))
fig.subplots_adjust(hspace=0.5)  # Adjust vertical spacing between subplots

# Flatten the 2D array of subplots to make it easier to iterate
axes = axes.flatten()

# Iterate through numeric columns and plot histograms
for i, column in enumerate(numeric_columns):
    df[column].plot(kind='hist', ax=axes[i], edgecolor='black', color='skyblue')
    axes[i].set_title(column)
    axes[i].set_xlabel('')
    axes[i].set_ylabel('')

# Hide empty subplots
for j in range(len(numeric_columns), len(axes)):
    axes[j].axis('off')

plt.show()
```



[31]:

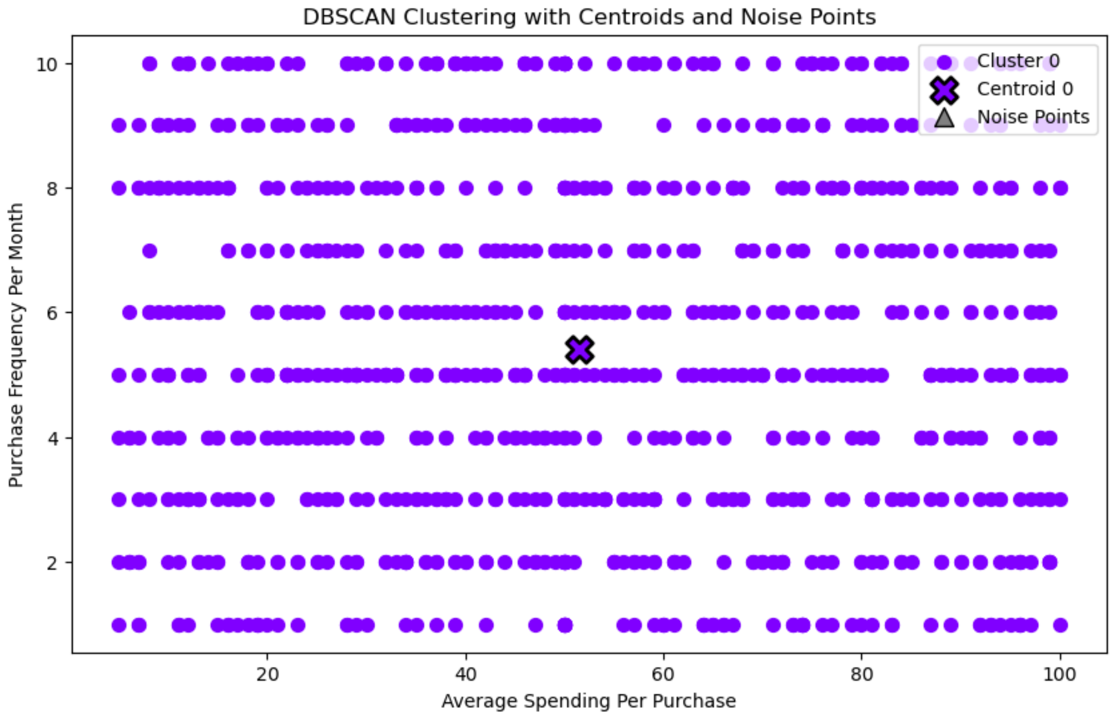
```python
import pandas as pd
from sklearn.cluster import DBSCAN
from sklearn.preprocessing import StandardScaler
import matplotlib.pyplot as plt

# Select relevant columns for clustering
columns_for_clustering = ['Purchase_Amount', 'Average_Spending_Per_Purchase']

# Convert selected columns to float, handling missing values
df[columns_for_clustering] = df[columns_for_clustering].apply(pd.to_numeric, errors='coerce')

# Drop rows with missing values
```

```
df.dropna(subset=columns_for_clustering, inplace=True)

# Standardize the data
scaler = StandardScaler()
data_for_clustering = scaler.fit_transform(df[columns_for_clustering])

# Apply DBSCAN
dbscan = DBSCAN(eps=0.5, min_samples=5)
df['Cluster'] = dbscan.fit_predict(data_for_clustering)

# Get cluster labels
labels = df['Cluster'].unique()

# Plotting
plt.figure(figsize=(10, 6))

# Plot each cluster separately
for label in labels:
    cluster_points = df[df['Cluster'] == label]

    if label == -1:
        # Border points (outliers)
        plt.scatter(cluster_points['Purchase_Amount'],␣
 ↪cluster_points['Average_Spending_Per_Purchase'],
                    c='black', label='Border Points', marker='x', s=100)
    else:
        # Core points
        plt.scatter(cluster_points['Purchase_Amount'],␣
 ↪cluster_points['Average_Spending_Per_Purchase'],
                    label=f'Cluster {label}', s=50, alpha=0.7)

# Centroids of each cluster
centroids = df.groupby('Cluster')[columns_for_clustering].mean()
plt.scatter(centroids['Purchase_Amount'],␣
 ↪centroids['Average_Spending_Per_Purchase'],
            marker='o', color='red', s=200, edgecolors='black', linewidths=2,␣
 ↪label='Centroids')

plt.title('DBSCAN Clustering')
plt.xlabel('Purchase Amount')
plt.ylabel('Average Spending Per Purchase')
plt.legend()
plt.show()
```



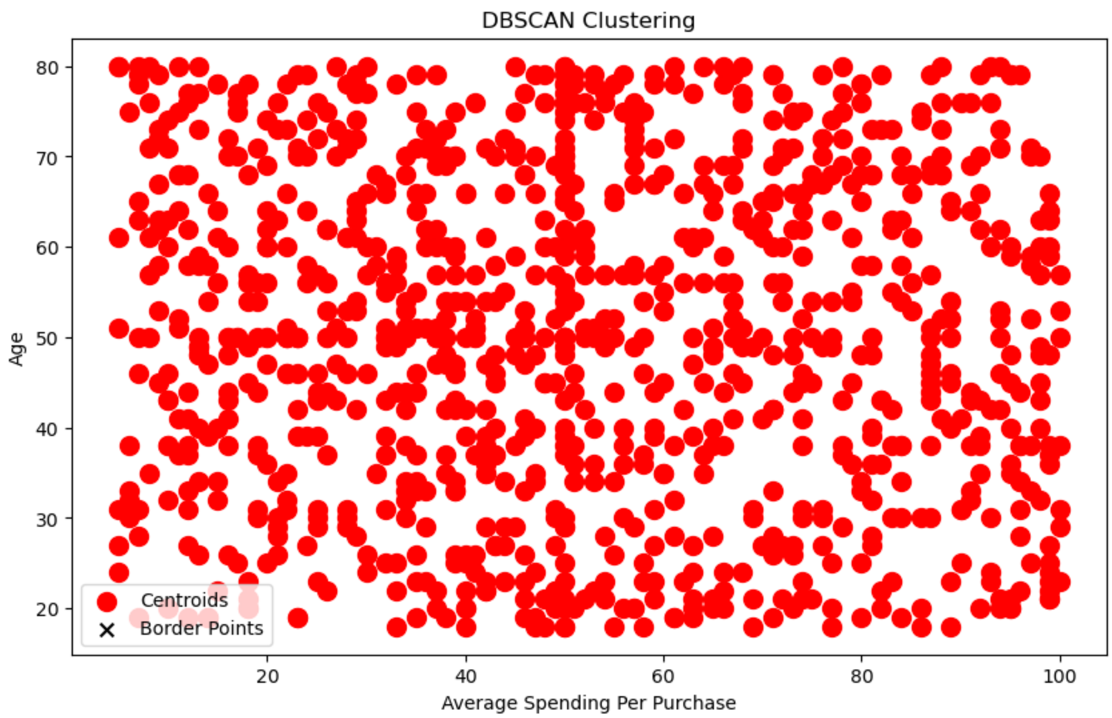

```
[44]: import pandas as pd
from sklearn.cluster import DBSCAN
from sklearn.preprocessing import StandardScaler
import matplotlib.pyplot as plt
import numpy as np

# Extract the numerical columns for clustering
numerical_columns = ['Average_Spending_Per_Purchase',␣
 ↪'Purchase_Frequency_Per_Month']
X = df[numerical_columns]

# Standardize the numerical data
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

# Apply DBSCAN
dbscan = DBSCAN(eps=0.5, min_samples=5)
labels = dbscan.fit_predict(X_scaled)

# Add the cluster labels to the original DataFrame
df['Cluster_Labels'] = labels

# Visualize the results (scatter plot for two numerical columns)
plt.figure(figsize=(10, 6))
```

```python
# Define colors for each cluster (including noise points)
unique_labels = np.unique(labels)
colors = plt.cm.rainbow(np.linspace(0, 1, len(unique_labels)))

# Plot each cluster with different markers
for cluster_label, color in zip(unique_labels, colors):
    cluster_mask = (labels == cluster_label)

    # Plot cluster points
    plt.scatter(X[cluster_mask]['Average_Spending_Per_Purchase'],
                X[cluster_mask]['Purchase_Frequency_Per_Month'],
                c=[color], label=f'Cluster {cluster_label}', marker='o', s=50)

    # Highlight cluster centroid (mean of cluster points)
    if cluster_label != -1:  # Avoid calculating centroid for noise points
        centroid = X[cluster_mask].mean()
        plt.scatter(centroid['Average_Spending_Per_Purchase'],
                    centroid['Purchase_Frequency_Per_Month'],
                    c=[color], marker='X', s=200, edgecolors='k', linewidth=2,␣
 ↪label=f'Centroid {cluster_label}')

# Identify noise points (points not belonging to any cluster)
noise_points_mask = (labels == -1)
plt.scatter(X[noise_points_mask]['Average_Spending_Per_Purchase'],
            X[noise_points_mask]['Purchase_Frequency_Per_Month'],
            c='gray', marker='^', s=100, edgecolors='k', linewidth=1,␣
 ↪label='Noise Points')

plt.title('DBSCAN Clustering with Centroids and Noise Points')
plt.xlabel('Average Spending Per Purchase')
plt.ylabel('Purchase Frequency Per Month')
plt.legend()
plt.show()
```



[58]:
```
import pandas as pd
import numpy as np
from sklearn.cluster import DBSCAN
from sklearn.preprocessing import StandardScaler, LabelEncoder
import matplotlib.pyplot as plt

# Load the data

# Select numerical columns for clustering
numerical_cols = ['Average_Spending_Per_Purchase', 'Age']
X = df[numerical_cols]

# Standardize the data
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

# Apply DBSCAN
dbscan = DBSCAN(eps=0.5, min_samples=5)
labels = dbscan.fit_predict(X_scaled)

# Visualize the results
plt.figure(figsize=(10, 6))

# Scatter plot for clusters
```

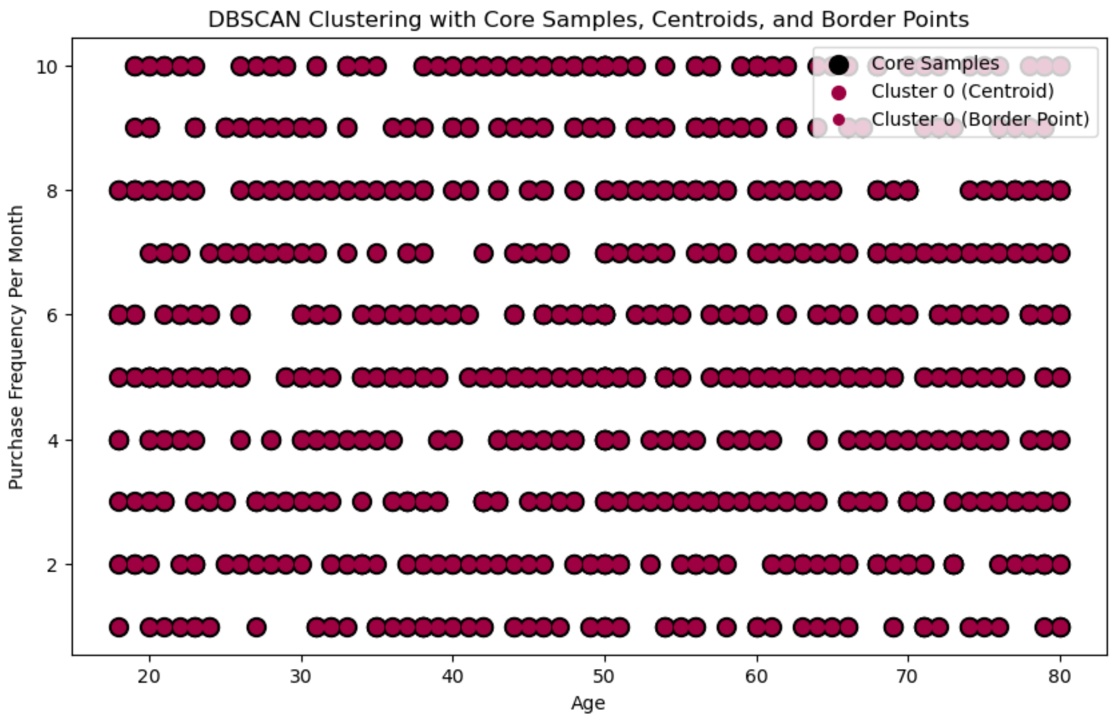
```
scatter = plt.scatter(X['Average_Spending_Per_Purchase'], X['Age'], c=labels,␣
↪cmap='viridis', s=50, alpha=0.8)

# Plot centroids (core samples)
core_samples_mask = np.zeros_like(labels, dtype=bool)
core_samples_mask[dbscan.core_sample_indices_] = True
core_samples = X[core_samples_mask]
plt.scatter(core_samples['Average_Spending_Per_Purchase'], core_samples['Age'],␣
↪c='red', marker='o', s=100, label='Centroids')

# Plot border points
border_points = X[labels == -1]
plt.scatter(border_points['Average_Spending_Per_Purchase'],␣
↪border_points['Age'], c='black', marker='x', s=50, label='Border Points')

plt.title('DBSCAN Clustering')
plt.xlabel('Average Spending Per Purchase')
plt.ylabel('Age')
plt.legend()
plt.show()
```




```
[61]: import pandas as pd
import numpy as np
```

```python
from sklearn.cluster import DBSCAN
from sklearn.preprocessing import StandardScaler
import matplotlib.pyplot as plt

# Extract the relevant numerical columns
numerical_columns = ['Age', 'Purchase_Frequency_Per_Month']
X = df[numerical_columns]

# Standardize the data
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

# Apply DBSCAN
dbscan = DBSCAN(eps=0.5, min_samples=5)
labels = dbscan.fit_predict(X_scaled)

# Add cluster labels to the DataFrame
df['Cluster'] = labels

# Plot the data points, centroids, and border points
core_samples_mask = np.zeros_like(dbscan.labels_, dtype=bool)
core_samples_mask[dbscan.core_sample_indices_] = True

unique_labels = set(labels)
colors = [plt.cm.Spectral(each) for each in np.linspace(0, 1,␣
↪len(unique_labels))]

plt.figure(figsize=(10, 6))

# Plot core samples in black
plt.scatter(X.iloc[core_samples_mask, 0], X.iloc[core_samples_mask, 1], c='k',␣
↪marker='o', s=100, label='Core Samples')

for k, col in zip(unique_labels, colors):
    if k == -1:
        col = [0, 0, 0, 1]

    class_member_mask = (labels == k)

    xy = X[class_member_mask & core_samples_mask]
    plt.scatter(xy.iloc[:, 0], xy.iloc[:, 1], c=[col], marker='o', s=50,␣
↪label=f'Cluster {k} (Centroid)')

    xy = X[class_member_mask & ~core_samples_mask]
    plt.scatter(xy.iloc[:, 0], xy.iloc[:, 1], c=[col], marker='o', s=30,␣
↪label=f'Cluster {k} (Border Point)')
```

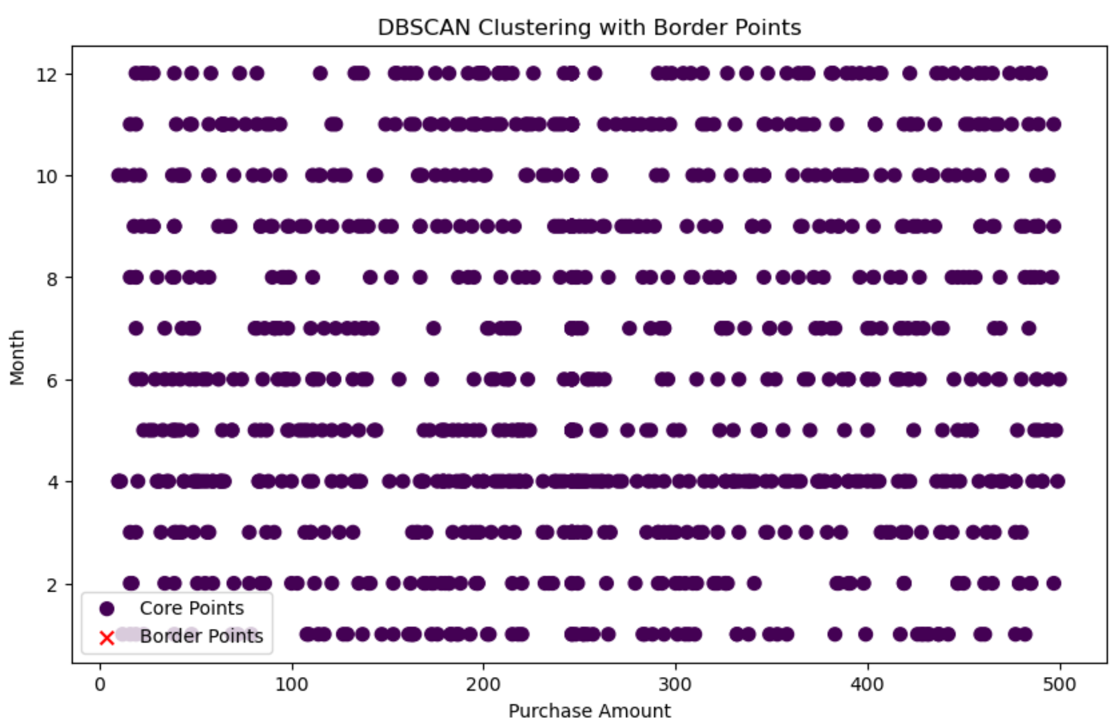
```python
plt.title('DBSCAN Clustering with Core Samples, Centroids, and Border Points')
plt.xlabel('Age')
plt.ylabel('Purchase Frequency Per Month')
plt.legend()
plt.show()
```



[66]:

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

# Open the data file

# Extract relevant columns
data = df[['Purchase_Amount', 'Month']]

# Standardize the data
scaler = StandardScaler()
data_scaled = scaler.fit_transform(data)

# Apply DBSCAN
dbscan = DBSCAN(eps=0.5, min_samples=5)
labels = dbscan.fit_predict(data_scaled)
```

```python
# Visualize the results
plt.figure(figsize=(10, 6))

# Core points
core_samples_mask = np.zeros_like(labels, dtype=bool)
core_samples_mask[dbscan.core_sample_indices_] = True
plt.scatter(data['Purchase_Amount'][core_samples_mask],␣
 ↪data['Month'][core_samples_mask],
            c=labels[core_samples_mask], cmap='viridis', marker='o', s=50,␣
 ↪label='Core Points')

# Border points
border_points_mask = (labels == -1) & ~core_samples_mask
plt.scatter(data['Purchase_Amount'][border_points_mask],␣
 ↪data['Month'][border_points_mask],
            c='red', marker='x', s=50, label='Border Points')

plt.title('DBSCAN Clustering with Border Points')
plt.xlabel('Purchase Amount')
plt.ylabel('Month')
plt.legend()
plt.show()
```



```
[ ]:
```