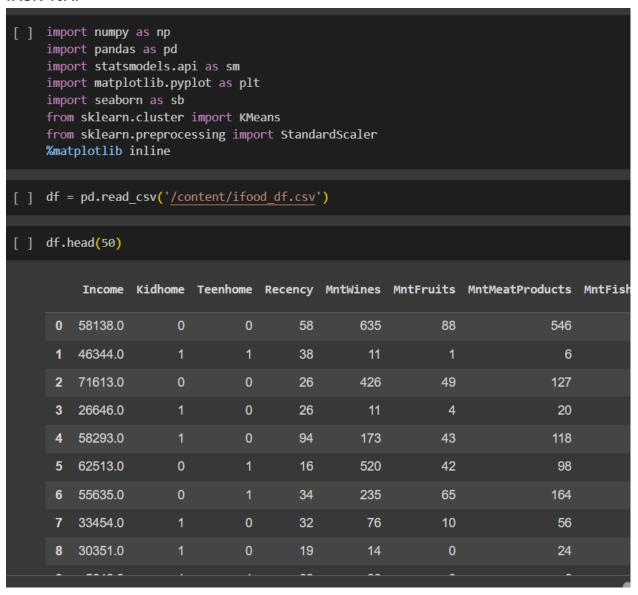
COMP450 LAB WORK WEEK-10

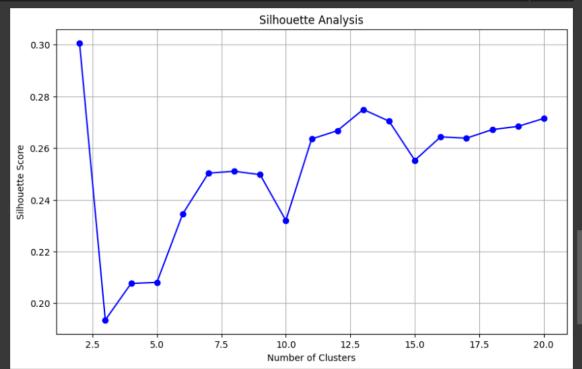
Aga Saltikalp 041901048

TASK-10A:

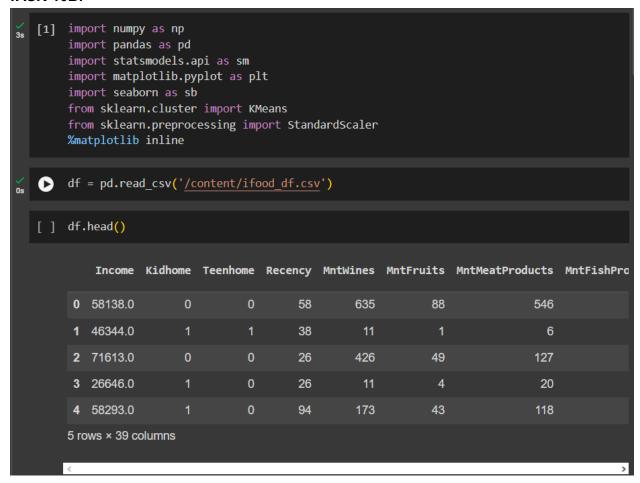


```
[ ] # standardizing features
    scaler = StandardScaler()
    scaled_features = scaler.fit_transform(df[['Income', 'Kidhome', 'Teenhome', 'Recency'
                                                              ↑ ↓ ⊖ 目 ☆  □ ⅰ ∶
    kmeans = KMeans(n_clusters=7, random_state=42)
    kmeans.fit(scaled_features)
    /usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning:
      warnings.warn(
                     KMeans
     KMeans(n_clusters=7, random_state=42)
[ ] from sklearn.metrics import silhouette score
    n_clusters = list(range(2, 21))
[ ] silhouette_scores = []
    for n in n clusters:
        kmeans = KMeans(n_clusters=n, random_state=42)
        cluster_labels = kmeans.fit_predict(scaled_features)
        silhouette_avg = silhouette_score(scaled_features, cluster_labels)
        silhouette scores.append(silhouette avg)
    /usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning:
```

```
[ ] plt.figure(figsize=(10, 6))
   plt.plot(n_clusters, silhouette_scores, marker='o', linestyle='-', color='b')
   plt.title('Silhouette Analysis')
   plt.xlabel('Number of Clusters')
   plt.ylabel('Silhouette Score')
   plt.grid(True)
   plt.show()
```

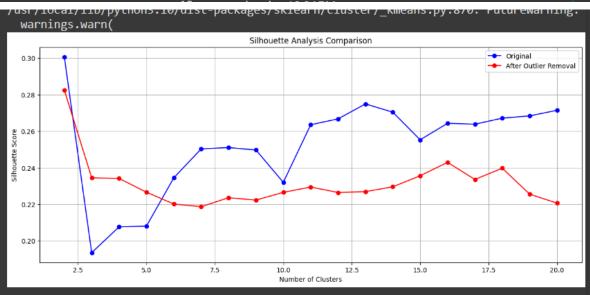


TASK-10B:



```
def remove_outliers(df, column_names):
   0
            for column in column names:
                Q1 = df[column].quantile(0.25)
                Q3 = df[column].quantile(0.75)
                IQR = Q3 - Q1
                lower bound = Q1 - 1.5 * \overline{IQR}
                upper_bound = Q3 + 1.5 * IQR
                df = df[(df[column] >= lower_bound) & (df[column] <= upper_bound)]</pre>
            return df
[7] columns = ['Income', 'Kidhome', 'Teenhome', 'Recency', 'MntFruits', 'MntMeatProducts',
                   'NumDealsPurchases', 'AcceptedCmp1', 'AcceptedCmp2', 'AcceptedCmp3',
                   'AcceptedCmp4', 'AcceptedCmp5']
v [8]
        df no outliers = remove outliers(df, columns)
   # Scaling original features
        scaler = StandardScaler()
        scaled_features = scaler.fit_transform(df[columns])
os [21] # Standardizing features after removing outliers
        scaled features no outliers = scaler.fit transform(df no outliers[columns])
```

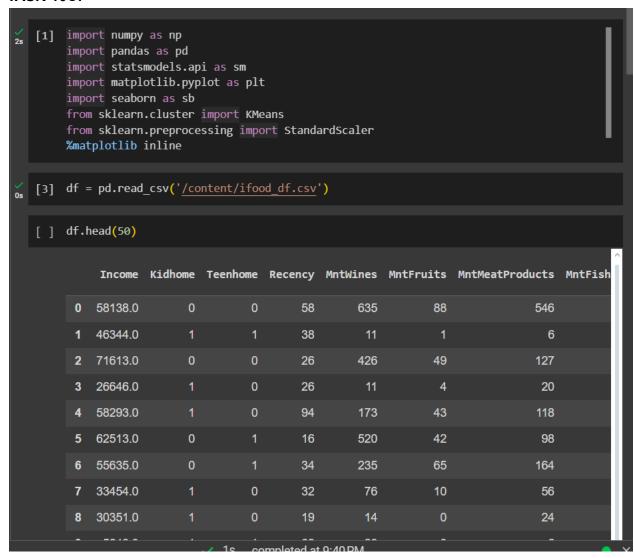
```
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# n clusters for the original dataset
n_clusters_original = range(2, 21)
silhouette scores original = []
                                                                                    ı
# silhouette scores for the original dataset
for n in n clusters original:
    kmeans_original = KMeans(n_clusters=n, random state=42)
    cluster_labels_original = kmeans_original.fit_predict(scaled_features)
    silhouette avg original = silhouette score(scaled features, cluster labels origin
    silhouette scores original.append(silhouette avg original)
# Plotting the silhouette scores for comparison
plt.figure(figsize=(15, 6))
plt.plot(n clusters original, silhouette scores original, marker='o', linestyle='-', c
plt.plot(n clusters range, silhouette scores no outliers, marker='o', linestyle='-', c
plt.title('Silhouette Analysis Comparison')
plt.xlabel('Number of Clusters')
plt.ylabel('Silhouette Score')
plt.grid(True)
plt.legend()
plt.show()
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning:
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning:
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/ kmeans.py:870: FutureWarning:
```



Differences:

Outlier elimination and feature scaling are expected to significantly enhance the quality of KMeans clustering in your dataset. By removing extreme values, outlier elimination will help create more homogeneous clusters, reducing the skewness caused by these anomalies. Feature scaling ensures all variables contribute equally, regardless of their original scale, leading to a more balanced clustering process. This will not only stabilize cluster assignments by reducing the influence of outliers, but it may also result in different optimal cluster numbers, as indicated by changes in silhouette scores. Additionally, these preprocessing steps generally lead to cleaner, more distinct clusters, facilitating easier interpretation and clearer insights into customer segments.

TASK-10C:



```
[4] def remove outliers(df, column names):
            for column in column names:
                Q1 = df[column].quantile(0.25)
                Q3 = df[column].quantile(0.75)
                IQR = Q3 - Q1
                lower bound = Q1 - 1.5 * IQR
                upper bound = Q3 + 1.5 * IQR
                df = df[(df[column] >= lower_bound) & (df[column] <= upper_bound)]</pre>
            return df
[5] columns = ['Income', 'Kidhome', 'Teenhome', 'Recency', 'MntFruits', 'MntMeatProducts',
                   'NumDealsPurchases', 'AcceptedCmp1', 'AcceptedCmp2', 'AcceptedCmp3',
                   'AcceptedCmp4', 'AcceptedCmp5']
  [6]
        df_no_outliers = remove_outliers(df, columns)
   [7] # Standardizing features
        scaler = StandardScaler()
        scaled_features_no_outliers = scaler.fit_transform(df_no_outliers[columns])
[8] from sklearn.mixture import GaussianMixture
        # Rerun KMeans clustering and silhouette analysis
        n components range = range(2, 21)
        aic scores = []
        bic_scores = []
        for n in n_components_range:
                             1s completed at 9:40 PM
```

```
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plt.figure(figsize=(15, 6))
    plt.plot(n_components_range, aic_scores, marker='o', linestyle='-', color='b', label='
    plt.plot(n_components_range, bic_scores, marker='o', linestyle='-', color='r', label='
    plt.title('GMM AIC and BIC Scores')
    plt.xlabel('Number of Components (Clusters)')
    plt.ylabel('Scores')
    plt.grid(True)
    plt.legend()
    plt.show()
                                              GMM AIC and BIC Scores
       -60000
                                                                                         AIC BIC
       -65000
       -75000
       -80000
       -85000
       -90000
       -100000
                                                                                          20.0
```