# Machine Learning - Clustering and Dimensionality Reduction

## Assignment 3

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Flatten the data in 4070 columns (each corresponding to a stock-code), and 4373 rows (each corresponding to a customer id). Your numbers may differ depending on the way you do flattening.

```
In [38]: import pandas as pd
    from sklearn.cluster import KMeans, DBSCAN
    from sklearn.preprocessing import StandardScaler, MinMaxScaler
    import matplotlib.pyplot as plt
    from scipy.cluster.hierarchy import dendrogram, linkage, fcluster
    from sklearn.decomposition import PCA
In [2]: df = pd.read_excel('Online Retail.xlsx')
In [3]: df
```

Out[3]:		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
	•••							<b></b>	
	541904	581587	22613	PACK OF 20 SPACEBOY NAPKINS	12	2011-12-09 12:50:00	0.85	12680.0	France
	541905	581587	22899	CHILDREN'S APRON DOLLY GIRL	6	2011-12-09 12:50:00	2.10	12680.0	France
	541906	581587	23254	CHILDRENS CUTLERY DOLLY GIRL	4	2011-12-09 12:50:00	4.15	12680.0	France
	541907	581587	23255	CHILDRENS CUTLERY CIRCUS PARADE	4	2011-12-09 12:50:00	4.15	12680.0	France
	541908	581587	22138	BAKING SET 9 PIECE RETROSPOT	3	2011-12-09 12:50:00	4.95	12680.0	France

541909 rows × 8 columns

```
In [4]: # Checking Unique Items
    len(df["StockCode"].unique())
Out[4]:

In [5]: # Pivoting the CustomerID and StockCode with the calues as the Quantity
    pivot_df = df.pivot_table(index='CustomerID', columns='StockCode', values='Quantity', aggfunc='sum', fill_value=0)
    pivot_df
```

Out[5]

]:	StockCode	10002	10080	10120	10125	10133	10135	11001	15030	15034	15036	•••	90214Y	90214Z	BANK CHARGES	C2	CRUK	D	DO1
	CustomerID																		
	12346.0	0	0	0	0	0	0	0	0	0	0		0	0	0	0	0	0	C
	12347.0	0	0	0	0	0	0	0	0	0	0		0	0	0	0	0	0	C
	12348.0	0	0	0	0	0	0	0	0	0	0		0	0	0	0	0	0	C
	12349.0	0	0	0	0	0	0	0	0	0	0		0	0	0	0	0	0	C
	12350.0	0	0	0	0	0	0	0	0	0	0		0	0	0	0	0	0	C
	•••																		
	18280.0	0	0	0	0	0	0	0	0	0	0		0	0	0	0	0	0	C
	18281.0	0	0	0	0	0	0	0	0	0	0		0	0	0	0	0	0	C
	18282.0	0	0	0	0	0	0	0	0	0	0		0	0	0	0	0	0	C
	18283.0	0	0	0	0	0	0	0	0	0	0		0	0	0	0	0	0	C
	18287.0	0	0	0	0	0	0	0	0	0	0		0	0	0	0	0	0	C

4372 rows × 3684 columns

```
In [6]: # Checking which item is bought the most.
         pivot_df.max().sort_values()
        StockCode
Out[6]:
         21412
                       0
         79320
                       0
         85023C
         35832
         85098B
                       0
         21915
                    8120
         17003
                  10077
                  10080
         84077
         22197
                  11692
         84826
                   12540
         Length: 3684, dtype: int64
```

```
In [7]: # Converting the columns to be all string.
          pivot df.columns = pivot df.columns.astype(str)
In [8]: # Checking if the conversion happened.
         pivot df.columns[1]
          '10080'
Out[8]:
 In [9]: # Scaling the Quantity Values.
         scaler = StandardScaler()
         scaled = scaler.fit transform(pivot df)
In [10]: scaled
         array([[-0.04089274, -0.04348365, -0.04752299, ..., -0.00995053,
Out[10]:
                  -0.03026138, -0.15831688],
                 [-0.04089274, -0.04348365, -0.04752299, ..., -0.00995053,
                 -0.03026138, -0.15831688],
                 [-0.04089274, -0.04348365, -0.04752299, \ldots, -0.00995053,
                  -0.03026138, 1.91678387],
                 . . . ,
                 [-0.04089274, -0.04348365, -0.04752299, \ldots, -0.00995053,
                 -0.03026138, -0.15831688],
                 [-0.04089274, -0.04348365, -0.04752299, \ldots, 0.01737593,
                 -0.03026138, -0.15831688],
                 [-0.04089274, -0.04348365, -0.04752299, ..., -0.00995053,
                  -0.03026138, -0.15831688]])
```

# Apply PCA and pick top 3 PCs to transform your 4070x4373 matrix into 3x4373 one.

```
In [11]: # Applying PCA so we are only left with 3 columns.
    pca = PCA(n_components=3)
    scaled_pca = pca.fit_transform(scaled)
In [12]: scaled_pca
```

```
array([[-2.40439108, -1.35824465, -1.12467836],
Out[12]:
                  [ 4.53401998, 4.77331158, 5.52102463],
                  [0.43233602, -0.89957571, -0.58101546],
                  [-2.09091299, -0.80098264, -0.41156032],
                  [0.59991994, -1.23800721, -0.47412906],
                  [ 1.99955835, 7.31157919, -1.31877326]])
          # Converting the scaled data into a dataframe for easier use.
          scaled_df = pd.DataFrame(data=scaled, columns=pivot_df.columns, index=pivot_df.index)
          scaled df
Out[13]:
           StockCode
                         10002
                                   10080
                                             10120
                                                       10125
                                                                10133
                                                                                              15030
                                                                                                        15034
                                                                                                                  15036 ...
                                                                                                                              90214Y
                                                                                                                                        90214
                                                                           10135
                                                                                    11001
          CustomerID
                      -0.040893 -0.043484
                                          -0.047523 -0.038833 -0.102894 -0.076524 -0.051014 -0.032103 -0.047351 -0.077025 ... -0.018645 -0.0151
              12346.0
              12347.0 -0.040893 -0.043484
                                         -0.047523 -0.038833
                                                            -0.102894 -0.076524 -0.051014 -0.032103 -0.047351 -0.077025 ... -0.018645 -0.0151
             12348.0
                      -0.040893
                                -0.043484
                                          -0.047523
                                                   -0.038833
                                                             -0.102894
                                                                       -0.076524 -0.051014 -0.032103 -0.047351 -0.077025 ... -0.018645
                                                                                                                                      -0.0151
                               -0.043484
              12349.0 -0.040893
                                          -0.047523
                                                   -0.038833
                                                             -0.102894 -0.076524 -0.051014 -0.032103 -0.047351 -0.077025 ... -0.018645
                                                                                                                                     -0.0151
                      -0.040893 -0.043484
                                          -0.047523
                                                   -0.038833 -0.102894
                                                                       -0.076524 -0.051014 -0.032103 -0.047351 -0.077025 ... -0.018645
                      -0.040893
                                -0.043484
                                          -0.047523
                                                   -0.038833
                                                             -0.102894 -0.076524 -0.051014 -0.032103 -0.047351 -0.077025 ... -0.018645 -0.0151
              18281.0 -0.040893 -0.043484
                                         -0.047523 -0.038833
                                                             -0.102894 -0.076524 -0.051014 -0.032103 -0.047351 -0.077025 ... -0.018645 -0.0151
                      -0.040893
                               -0.043484
                                          -0.047523
                                                   -0.038833
                                                             -0.102894
                                                                       -0.076524 -0.051014 -0.032103 -0.047351 -0.077025 ... -0.018645
                                                                                                                                      -0.0151
              18283.0
                      -0.040893
                               -0.043484
                                          -0.047523
                                                   -0.038833
                                                             -0.102894 -0.076524 -0.051014 -0.032103 -0.047351 -0.077025 ... -0.018645
                                                                                                                                      -0.0151
              18287.0 -0.040893 -0.043484 -0.047523 -0.038833 -0.102894 -0.076524 -0.051014 -0.032103 -0.047351 -0.077025 ... -0.018645 -0.0151
         4372 rows × 3684 columns
          # Converting the scaled and PCA transformed data into a dataframe for easier use.
          scaled pca df = pd.DataFrame(data=scaled pca, columns=['Principal Component 1', 'Principal Component 2', 'Principal Com
```

scaled pca df

Out[14]:

#### Principal Component 1 Principal Component 2 Principal Component 3

CustomerID			
12346.0	-2.404391	-1.358245	-1.124678
12347.0	4.534020	4.773312	5.521025
12348.0	0.432336	-0.899576	-0.581015
12349.0	-0.266184	-0.597366	0.383031
12350.0	-1.918710	-0.589165	-0.547577
•••			
18280.0	-2.315659	-1.261694	-0.943462
18281.0	-2.089671	-1.432836	-1.041452
18282.0	-2.090913	-0.800983	-0.411560
18283.0	0.599920	-1.238007	-0.474129
18287.0	1.999558	7.311579	-1.318773

4372 rows × 3 columns

```
In [46]: # Viewing a 3D visual of the scaled and PCA transformed data.
import plotly.express as px
fig = px.scatter_3d(scaled_pca_df, x='Principal Component 1', y='Principal Component 2', z='Principal Component 3', tit
fig.show()
```

# Get cluster labels from each algorithm.

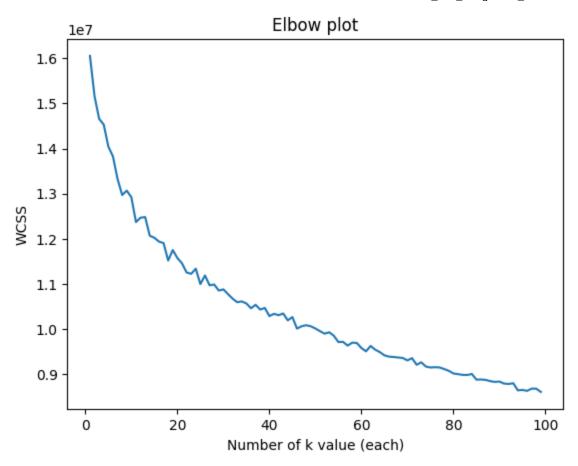
## K-Means

```
In [16]: # Finding the optimal number of clusters for K-Means.
wcss = []

for each in range(1, 100):
    kmeans = KMeans(n_clusters=each)
```

```
kmeans.fit(scaled_df)
    wcss.append(kmeans.inertia_)

plt.plot(range(1, 100), wcss)
plt.title('Elbow plot')
plt.xlabel("Number of k value (each)")
plt.ylabel("WCSS")
plt.show()
```



```
In [17]: # Initializing the cluster size to be 4 for K-Means.
kmeans1 = KMeans(n_clusters=4)
cluster_k = kmeans1.fit_predict(scaled_pca_df)

/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning:
```

The default value of `n\_init` will change from 10 to 'auto' in 1.4. Set the value of `n\_init` explicitly to suppress the warning

```
In [18]: # Creating a DataFrame for the prediction of K-Means.
with_km_df = pd.DataFrame(scaled_pca_df, columns=scaled_pca_df.columns, index=scaled_pca_df.index)
with_km_df['cluster'] = cluster_k
with_km_df.head()
```

#### Out[18]: Principal Component 1 Principal Component 2 Principal Component 3 cluster

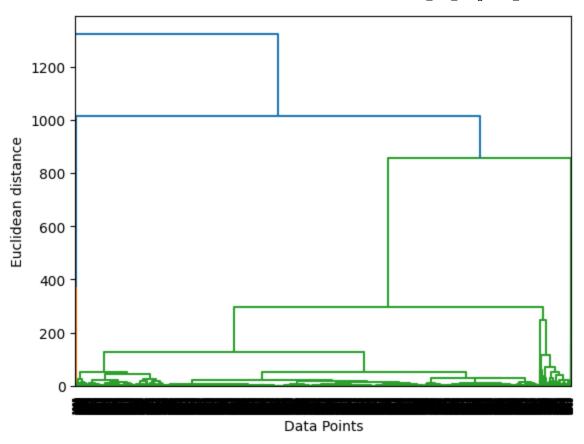
CustomerID				
12346.0	-2.404391	-1.358245	-1.124678	0
12347.0	4.534020	4.773312	5.521025	0
12348.0	0.432336	-0.899576	-0.581015	0
12349.0	-0.266184	-0.597366	0.383031	0
12350.0	-1.918710	-0.589165	-0.547577	0

3 4 0 4365

Name: cluster, dtype: int64

### **Hierarchical Clustering**

```
In [28]: # Initializing hierarchical clustering and plotting a dendrogram.
merging = linkage(scaled_pca_df.drop(columns=['cluster']), method='ward')
dendrogram(merging, leaf_rotation=90)
plt.xlabel('Data Points')
plt.ylabel('Euclidean distance')
plt.show()
```



```
In [40]: # Perform hierarchical clustering
Z = linkage(scaled_pca_df.drop(columns=['cluster']), method='ward')

# Cut the dendrogram to have exactly 4 clusters
clusters_hierarchical = fcluster(Z, 4, criterion='maxclust')

# clusters will contain the cluster labels (from 1 to 4) for each point in the dataset
print(clusters_hierarchical)

[2 2 2 ... 2 2 2]

In [41]: # Creating a DataFrame for the prediction of hierarchical clustering.
with_hierarchical_df = pd.DataFrame(scaled_pca_df, columns=scaled_pca_df.columns, index=scaled_pca_df.index)
with_hierarchical_df['cluster'] = clusters_hierarchical
with_hierarchical_df.head()
```

Out[41]:

CustomerID				
12346.0	-2.404391	-1.358245	-1.124678	2
12347.0	4.534020	4.773312	5.521025	2
12348.0	0.432336	-0.899576	-0.581015	2
12349.0	-0.266184	-0.597366	0.383031	2
12350.0	-1.918710	-0.589165	-0.547577	2

Principal Component 1 Principal Component 2 Principal Component 3 cluster

#### **DB** Scan

```
In [83]: # Initializing DB Scan.
    dbscan = DBSCAN(eps=100, min_samples=10)

In [84]: # Predicting the clusters with DB Scan.
    cluster_dbscan = dbscan.fit_predict(scaled_pca)

In [85]: # Viewing the predicted clusters.
    cluster_dbscan

Out[85]: array([0, 0, 0, ..., 0, 0, 0])

In [86]: # Creating a DataFrame for the prediction of DB Scan.
    with_dbscan_df = pd.DataFrame(scaled_pca_df, columns=scaled_pca_df.columns, index=scaled_pca_df.index)
    with_dbscan_df['cluster'] = cluster_dbscan
    with_dbscan_df.head()
```

Out[86]:

CustomerID				
12346.0	-2.404391	-1.358245	-1.124678	0
12347.0	4.534020	4.773312	5.521025	0
12348.0	0.432336	-0.899576	-0.581015	0
12349.0	-0.266184	-0.597366	0.383031	0
12350.0	-1.918710	-0.589165	-0.547577	0

Principal Component 1 Principal Component 2 Principal Component 3 cluster

0 4365

Name: cluster, dtype: int64

## Visualize the transformed data-points in 3D.

- Use cluster-labels to color the data-points.
- There will be 3 plots each for a given algorithm.

```
In [45]: fig = px.scatter_3d(with_km_df, x='Principal Component 1', y='Principal Component 2', z='Principal Component 3', color=
fig.show()
```

In [44]: fig = px.scatter\_3d(with\_hierarchical\_df, x='Principal Component 1', y='Principal Component 2', z='Principal Component
fig.show()

```
In [88]: fig = px.scatter_3d(with_dbscan_df, x='Principal Component 1', y='Principal Component 2', z='Principal Component 3', co
fig.show()
```

For this experiment I believe K-Means performed the best as it has identified the most accurate clusters. Hierarchical comes second as it also performed pretty well, However, it got confused with the clusters close to each other in the middle of the plot. Whereas DB Scan performed the worst because it was only able to identify the clusters which were close in proximity.