LAB # 06

UNSUPERVISED LEARNING (K-MEANS CLUSTERING ALGORITHM) AND UNSUPERVISED LEARNING (APRIORI ALGORITHM)

OBJECTIVES:

Implementing unsupervised learning, K-means clustering algorithm for training, testing and classification and Implementing Apriori Algorithm for training, testing and classification.

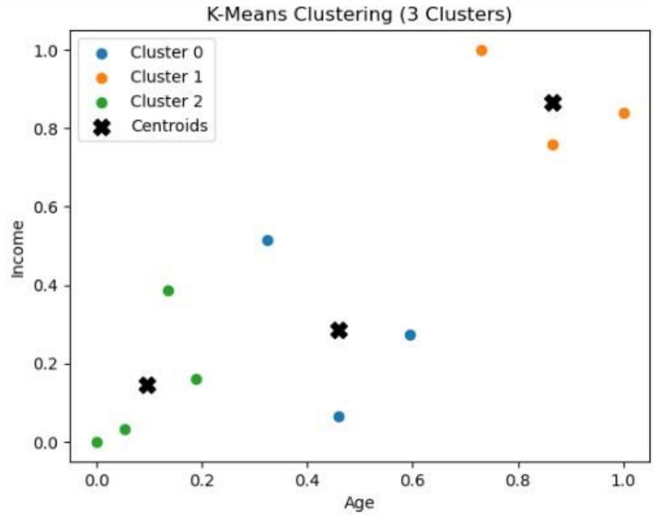
Lab Task

1. A dataset (income.csv) has been provided. Implement K-Means Clustering Algorithm on this dataset using K (number of clusters = 3). Also find out new centroid values based on the mean values of the coordinates of all the data instances from the corresponding cluster.

ID	Age	Income($)
1	25	50000
2	45	65000
3	35	80000
4	50	110000
5	23	48000
6	40	52000
7	60	100000
8	30	58000
9	28	72000
10	55	95000

```
[1]: import pandas as pd
from sklearn.cluster import KMeans
from sklearn.preprocessing import MinMaxScaler
import matplotlib.pyplot as plt
df = pd.read_csv("income.csv")
scaler = MinMaxScaler()
df[['Age', 'Income($)']] = scaler.fit_transform(df[['Age', 'Income($)']])
kmeans = KMeans(n_clusters=3, random_state=0)
df['Cluster'] = kmeans.fit_predict(df[['Age', 'Income($)']])
centroids = kmeans.cluster_centers_
print("Cluster Centers (Centroids):")
print(centroids)
for cluster in range(3):
    cluster_data = df[df['Cluster'] == cluster]
    plt.scatter(cluster_data['Age'], cluster_data['Income($)'], label=f'Cluster {cluster}')
plt.scatter(centroids[:, 0], centroids[:, 1], color='black', marker='X', s=100, label='Centroids')
plt.title('K-Means Clustering (3 Clusters)')
plt.xlabel('Age')
plt.ylabel('Income')
plt.legend()
plt.show()
```

```
C:\Users\wajiz.pk\anaconda3\Lib\site-packages\sklearn\cluster\_kmeans.py:1429: UserWarning: KMeans is known to have a memory leak on Windows with MKL, w
hen there are less chunks than available threads. You can avoid it by setting the environment variable OMP_NUM_THREADS=1.
  warnings.warn(
Cluster Centers (Centroids):
[[0.45945946 0.28494624]
 [0.86486486 0.8655914 ]
 [0.09459459 0.14516129]]
```



2. The following sample dataset contains 8 objects with their X, Y and Z coordinates. Your task is to cluster these objects into two clusters using K-Means Clustering Algorithm (here you define the value of K (of K-Means) in essence to be 2).

Objects	X	Y	Z
OB-1	1	4	1
OB-2	1	2	2
OB-3	1	4	2
OB-4	2	1	2
OB-5	1	1	1
OB-6	2	4	2
OB-7	1	1	2
OB-8	2	1	1

[2]:
```
import numpy as np
data = np.array([
    [1, 4, 1],
    [1, 2, 2],
    [1, 4, 2],
    [2, 1, 2],
    [1, 1, 1],
    [2, 4, 2],
    [1, 1, 2],
    [2, 1, 1]
])
kmeans = KMeans(n_clusters=2, random_state=0)
clusters = kmeans.fit_predict(data)
centroids = kmeans.cluster_centers_
print("Cluster Assignments:")
print(clusters)
print("Cluster Centers (Centroids):")
print(centroids)
```

```
Cluster Assignments:
[1 0 1 0 0 1 0 0]
Cluster Centers (Centroids):
[[1.4        1.2        1.6       ]
 [1.33333333 4.         1.66666667]]
```

3. Run the given code of Apriori Algorithm and show the output.

[3]:
```python
import pandas as pd
from mlxtend.frequent_patterns import apriori
from mlxtend.frequent_patterns import association_rules
df = pd.read_excel('Online_Retail.xlsx')
df.head()
```

[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

[4]:
```python
df['Description'] = df['Description'].str.strip()
df.dropna(axis=0, subset=['InvoiceNo'], inplace=True)
df['InvoiceNo'] = df['InvoiceNo'].astype('str')
df = df[~df['InvoiceNo'].str.contains('C')]
```

[5]:
```python
basket = (df[df['Country'] =="France"]
.groupby(['InvoiceNo', 'Description'])['Quantity']
.sum().unstack().reset_index().fillna(0)
.set_index('InvoiceNo'))
```

[11]:
```python
def encode_units(x):
    if x <= 0:
        return 0
    if x >= 1:
        return 1
    basket_sets = basket.applymap(encode_units)
    basket_sets.drop('POSTAGE', inplace=True, axis=1)
    basket_sets
```

[14]:
```python
frequent_itemsets = apriori(basket_sets, min_support=0.07, use_colnames=True)
rules = association_rules(frequent_itemsets, metric="lift", min_threshold=1, num_itemsets=len(frequent_itemsets))
rules.head()
```

[14]:

	antecedents	consequents	antecedent support	consequent support	support	confidence	lift	representativity	leverage	conviction	zhangs_metric	jaccard	certainty	kulczy
0	(ALARM CLOCK BAKELIKE PINK)	(ALARM CLOCK BAKELIKE GREEN)	0.102041	0.096939	0.073980	0.725000	7.478947	1.0	0.064088	3.283859	0.964734	0.591837	0.695480	0.74
1	(ALARM CLOCK BAKELIKE GREEN)	(ALARM CLOCK BAKELIKE PINK)	0.096939	0.102041	0.073980	0.763158	7.478947	1.0	0.064088	3.791383	0.959283	0.591837	0.736244	0.74
2	(ALARM CLOCK BAKELIKE GREEN)	(ALARM CLOCK BAKELIKE RED)	0.096939	0.094388	0.079082	0.815789	8.642959	1.0	0.069932	4.916181	0.979224	0.704545	0.796590	0.82
3	(ALARM CLOCK BAKELIKE RED)	(ALARM CLOCK BAKELIKE GREEN)	0.094388	0.096939	0.079082	0.837838	8.642959	1.0	0.069932	5.568878	0.976465	0.704545	0.820431	0.82
4	(ALARM CLOCK BAKELIKE PINK)	(ALARM CLOCK BAKELIKE RED)	0.102041	0.094388	0.073980	0.725000	7.681081	1.0	0.064348	3.293135	0.968652	0.604167	0.696338	0.75

[16]:
```python
rules[ (rules['lift'] >= 6) &
(rules['confidence'] >= 0.8) ]
```

[16]:

	antecedents	consequents	antecedent support	consequent support	support	confidence	lift	representativity	leverage	conviction	zhangs_metric	jaccard	certainty	kulcz
2	(ALARM CLOCK BAKELIKE GREEN)	(ALARM CLOCK BAKELIKE RED)	0.096939	0.094388	0.079082	0.815789	8.642959	1.0	0.069932	4.916181	0.979224	0.704545	0.796590	0.8
3	(ALARM CLOCK BAKELIKE RED)	(ALARM CLOCK BAKELIKE GREEN)	0.094388	0.096939	0.079082	0.837838	8.642959	1.0	0.069932	5.568878	0.976465	0.704545	0.820431	0.8
17	(SET/6 RED SPOTTY PAPER PLATES)	(SET/20 RED RETROSPOT PAPER NAPKINS)	0.127551	0.132653	0.102041	0.800000	6.030769	1.0	0.085121	4.336735	0.956140	0.645161	0.769412	0.7
18	(SET/6 RED SPOTTY PAPER PLATES)	(SET/6 RED SPOTTY PAPER CUPS)	0.127551	0.137755	0.122449	0.960000	6.968889	1.0	0.104878	21.556122	0.981725	0.857143	0.953609	0.9
19	(SET/6 RED SPOTTY PAPER CUPS)	(SET/6 RED SPOTTY PAPER PLATES)	0.137755	0.127551	0.122449	0.888889	6.968889	1.0	0.104878	7.852041	0.993343	0.857143	0.872645	0.9
20	(SET/20 RED RETROSPOT PAPER NAPKINS, SET/6 RED...	(SET/6 RED SPOTTY PAPER CUPS)	0.102041	0.137755	0.099490	0.975000	7.077778	1.0	0.085433	34.489796	0.956294	0.709091	0.971006	0.8
21	(SET/20 RED RETROSPOT PAPER NAPKINS, SET/6 RED...	(SET/6 RED SPOTTY PAPER PLATES)	0.102041	0.127551	0.099490	0.975000	7.644000	1.0	0.086474	34.897959	0.967949	0.764706	0.971345	0.8
22	(SET/6 RED SPOTTY PAPER PLATES, SET/6 RED SPOT...	(SET/20 RED RETROSPOT PAPER NAPKINS)	0.122449	0.132653	0.099490	0.812500	6.125000	1.0	0.083247	4.625850	0.953488	0.639344	0.783824	0.7

4. In given code there is a support value of at least 7%, Generate frequent item sets that have Support value of at least 5%.

[18]:
```
frequent_itemsets_5 = apriori(basket_sets, min_support=0.05, use_colnames=True)
rules_5 = association_rules(frequent_itemsets_5, metric="lift", min_threshold=1, num_itemsets=len(frequent_itemsets))
rules_5
```

[18]:

	antecedents	consequents	antecedent support	consequent support	support	confidence	lift	representativity	leverage	conviction	zhangs_metric	jaccard	certainty	kulcz
0	(ALARM CLOCK BAKELIKE PINK)	(ALARM CLOCK BAKELIKE GREEN)	0.102041	0.096939	0.073980	0.725000	7.478947	1.0	0.064088	3.283859	0.964734	0.591837	0.695480	0.7
1	(ALARM CLOCK BAKELIKE GREEN)	(ALARM CLOCK BAKELIKE PINK)	0.096939	0.102041	0.073980	0.763158	7.478947	1.0	0.064088	3.791383	0.959283	0.591837	0.736244	0.7
2	(ALARM CLOCK BAKELIKE GREEN)	(ALARM CLOCK BAKELIKE RED)	0.096939	0.094388	0.079082	0.815789	8.642959	1.0	0.069932	4.916181	0.979224	0.704545	0.796590	0.8
3	(ALARM CLOCK BAKELIKE RED)	(ALARM CLOCK BAKELIKE GREEN)	0.094388	0.096939	0.079082	0.837838	8.642959	1.0	0.069932	5.568878	0.976465	0.704545	0.820431	0.8
4	(ALARM CLOCK BAKELIKE PINK)	(ALARM CLOCK BAKELIKE RED)	0.102041	0.094388	0.073980	0.725000	7.681081	1.0	0.064348	3.293135	0.968652	0.604167	0.696338	0.7

...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
81	(SET/20 RED RETROSPOT PAPER NAPKINS, SET/6 RED...	(SET/6 RED SPOTTY PAPER PLATES)	0.102041	0.127551	0.099490	0.975000	7.644000	1.0	0.086474	34.897959	0.967949	0.764706	0.971345	0.8
82	(SET/6 RED SPOTTY PAPER PLATES, SET/6 RED SPOT...	(SET/20 RED RETROSPOT PAPER NAPKINS)	0.122449	0.132653	0.099490	0.812500	6.125000	1.0	0.083247	4.625850	0.953488	0.639344	0.783824	0.7
83	(SET/20 RED RETROSPOT PAPER NAPKINS)	(SET/6 RED SPOTTY PAPER PLATES, SET/6 RED SPOT...	0.132653	0.122449	0.099490	0.750000	6.125000	1.0	0.083247	3.510204	0.964706	0.639344	0.715116	0.7
84	(SET/6 RED SPOTTY PAPER PLATES)	(SET/20 RED RETROSPOT PAPER NAPKINS, SET/6 RED...	0.127551	0.102041	0.099490	0.780000	7.644000	1.0	0.086474	4.081633	0.996251	0.764706	0.755000	0.8
85	(SET/6 RED SPOTTY PAPER CUPS)	(SET/20 RED RETROSPOT PAPER NAPKINS, SET/6 RED...	0.137755	0.102041	0.099490	0.722222	7.077778	1.0	0.085433	3.232653	0.995904	0.709091	0.690657	0.8

86 rows × 14 columns

Home Task

1. Cluster customers based on annual income and spending score using K-Means.

jupyter Mall_Customers.csv Last Checkpoint: 9 minutes ago

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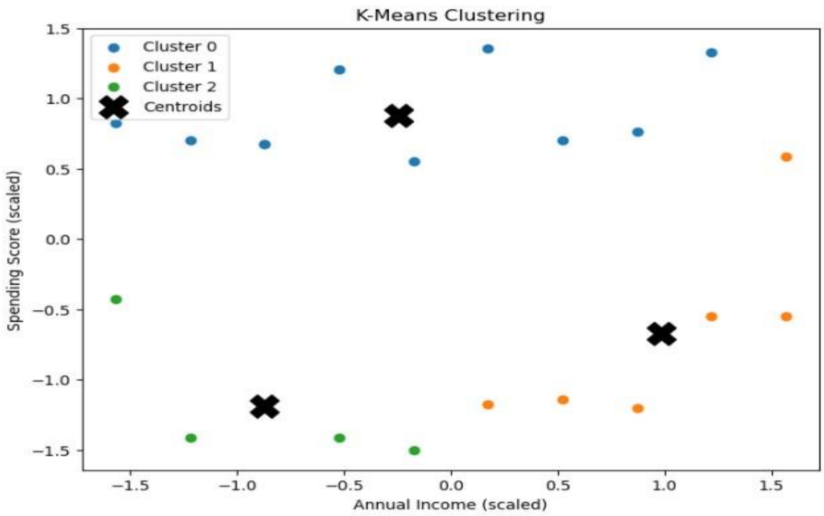
	CustomerID	Gender	Age	Annual Income (k$)	Spending Score (1-100)
1	1	Male	19	15	39
2	2	Female	21	15	81
3	3	Female	20	16	6
4	4	Female	23	16	77
5	5	Male	31	17	76
6	6	Male	22	17	76
7	7	Female	35	18	6
8	8	Female	23	18	94
9	9	Male	64	19	3
10	10	Female	30	19	72
11	11	Male	67	20	14
12	12	Female	35	20	99
13	13	Female	58	21	15
14	14	Female	24	21	77
15	15	Male	37	22	13
16	16	Female	22	22	79
17	17	Male	35	23	35
18	18	Female	20	23	98
19	19	Male	52	24	35
20	20	Female	40	24	73

[19]:
```python
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.cluster import KMeans
from sklearn.preprocessing import StandardScaler
data = pd.read_csv('Mall_Customers.csv')
X = data[['Annual Income (k$)', 'Spending Score (1-100)']]
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
kmeans = KMeans(n_clusters=3, random_state=42)
data['Cluster'] = kmeans.fit_predict(X_scaled)
plt.figure(figsize=(8, 6))
for cluster in range(3):
    plt.scatter(X_scaled[data['Cluster'] == cluster, 0],
                X_scaled[data['Cluster'] == cluster, 1],
                label=f'Cluster {cluster}')
plt.scatter(kmeans.cluster_centers_[:, 0],
            kmeans.cluster_centers_[:, 1],
            s=300, c='black', marker='X', label='Centroids')
plt.title('K-Means Clustering')
plt.xlabel('Annual Income (scaled)')
plt.ylabel('Spending Score (scaled)')
plt.legend()
plt.show()
```



2. Identify frequent itemsets and generate association rules using the Apriori algorithm.

jupyter Groceries.csv Last Checkpoint: 10 minutes ago

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	TransactionID	Item
1	1	Bread
2	1	Milk
3	1	Eggs
4	2	Bread
5	2	Butter
6	3	Milk
7	3	Eggs
8	3	Cheese
9	4	Cheese
10	4	Bread
11	5	Bread
12	5	Butter
13	5	Eggs
14	6	Milk
15	6	Cheese

```
[22]: from mlxtend.frequent_patterns import apriori, association_rules
data = pd.read_csv('Groceries.csv')
basket = (data.groupby(['TransactionID', 'Item'])['Item']
          .count().unstack().reset_index().fillna(0)
          .set_index('TransactionID'))
basket_sets = basket.applymap(lambda x: 1 if x >= 1 else 0)
basket_sets = basket_sets.astype(bool)
frequent_itemsets = apriori(basket_sets, min_support=0.05, use_colnames=True)
rules = association_rules(frequent_itemsets, metric="lift", min_threshold=1, num_itemsets=len(frequent_itemsets))
rules
```

```
C:\Users\wajiz.pk\AppData\Local\Temp\ipykernel_2728\3628561315.py:6: FutureWarning: DataFrame.applymap has been deprecated. Use DataFrame.map instead.
  basket_sets = basket.applymap(lambda x: 1 if x >= 1 else 0)
```

[22]:

	antecedents	consequents	antecedent support	consequent support	support	confidence	lift	representativity	leverage	conviction	zhangs_metric	jaccard	certainty	kulczy
0	(Butter)	(Bread)	0.35	0.55	0.30	0.857143	1.558442	1.0	0.1075	3.150000	0.551282	0.500000	0.682540	0.70
1	(Bread)	(Butter)	0.55	0.35	0.30	0.545455	1.558442	1.0	0.1075	1.430000	0.796296	0.500000	0.300699	0.70
2	(Eggs)	(Milk)	0.50	0.50	0.25	0.500000	1.000000	1.0	0.0000	1.000000	0.000000	0.333333	0.000000	0.50
3	(Milk)	(Eggs)	0.50	0.50	0.25	0.500000	1.000000	1.0	0.0000	1.000000	0.000000	0.333333	0.000000	0.50
4	(Eggs, Butter)	(Bread)	0.10	0.55	0.10	1.000000	1.818182	1.0	0.0450	inf	0.500000	0.181818	1.000000	0.59
5	(Eggs, Bread)	(Butter)	0.25	0.35	0.10	0.400000	1.142857	1.0	0.0125	1.083333	0.166667	0.200000	0.076923	0.34
6	(Butter)	(Eggs, Bread)	0.35	0.25	0.10	0.285714	1.142857	1.0	0.0125	1.050000	0.192308	0.200000	0.047619	0.34
7	(Bread)	(Eggs, Butter)	0.55	0.10	0.10	0.181818	1.818182	1.0	0.0450	1.100000	1.000000	0.181818	0.090909	0.59
8	(Butter, Milk)	(Bread)	0.10	0.55	0.10	1.000000	1.818182	1.0	0.0450	inf	0.500000	0.181818	1.000000	0.59
9	(Milk, Bread)	(Butter)	0.20	0.35	0.10	0.500000	1.428571	1.0	0.0300	1.300000	0.375000	0.222222	0.230769	0.39
10	(Butter)	(Milk, Bread)	0.35	0.20	0.10	0.285714	1.428571	1.0	0.0300	1.120000	0.461538	0.222222	0.107143	0.39
11	(Bread)	(Butter, Milk)	0.55	0.10	0.10	0.181818	1.818182	1.0	0.0450	1.100000	1.000000	0.181818	0.090909	0.59
12	(Milk, Bread)	(Eggs)	0.20	0.50	0.10	0.500000	1.000000	1.0	0.0000	1.000000	0.000000	0.166667	0.000000	0.35
13	(Eggs)	(Milk, Bread)	0.50	0.20	0.10	0.200000	1.000000	1.0	0.0000	1.000000	0.000000	0.166667	0.000000	0.35

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```
In [1]: import pandas as pd
from sklearn.cluster import KMeans
from sklearn.preprocessing import MinMaxScaler
import matplotlib.pyplot as plt
df = pd.read_csv("income.csv")
scaler = MinMaxScaler()
df[['Age', 'Income($)']] = scaler.fit_transform(df[['Age', 'Income($)']])
kmeans = KMeans(n_clusters=3, random_state=0)
df['Cluster'] = kmeans.fit_predict(df[['Age', 'Income($)']])
centroids = kmeans.cluster_centers_
print("Cluster Centers (Centroids):")
print(centroids)
for cluster in range(3):
    cluster_data = df[df['Cluster'] == cluster]
    plt.scatter(cluster_data['Age'], cluster_data['Income($)'], label=f'Cluster {cluster}')
plt.scatter(centroids[:, 0], centroids[:, 1], color='black', marker='X', s=100, label='Centroids')
plt.title('K-Means Clustering (3 Clusters)')
plt.xlabel('Age')
plt.ylabel('Income')
plt.legend()
```