lab04

June 27, 2025

1 Lab 04: Clustering and Association Rule Learning

1.0.1 E20280

1 Clustering

1.1 Importing Required Modules

[ ]:
```
from sklearn.cluster import KMeans
from sklearn.datasets import make_blobs # to generate sample datasets
```

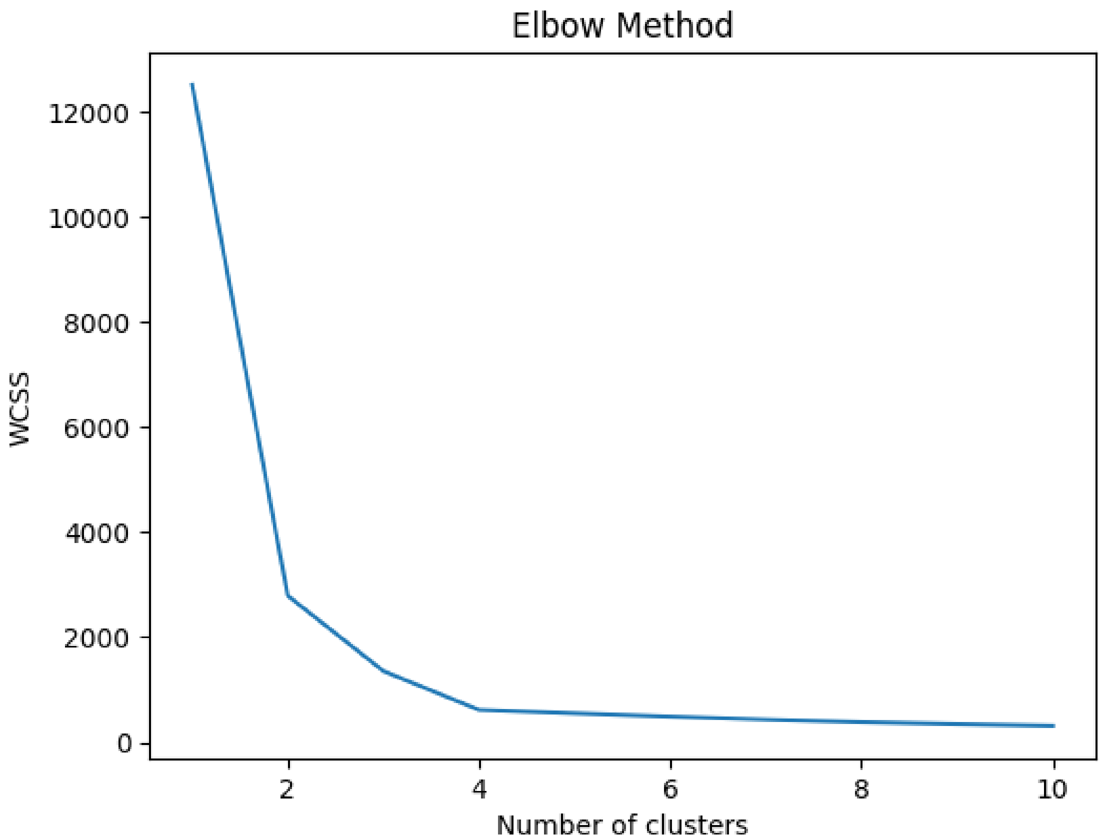
1.2 Creating a Sample Dataset with 4 Clusters

[ ]:
```
X, y = make_blobs (
    n_samples =400 ,
    centers =4 ,
    cluster_std =0.90 ,
    random_state =1
)
```

1.3 Determining the Optimum Value of k Using the Elbow Method

[ ]:
```
import matplotlib.pyplot as plt
wcss = [] # within cluster sum of squares
for i in range(1, 11):
    kmeans = KMeans(
    n_clusters=i,
    init="k-means++",
    max_iter=300,
    n_init=10,
    random_state=0
    )

    kmeans.fit(X)
    wcss.append(kmeans.inertia_)

plt.plot(range(1, 11), wcss)
plt.title("Elbow Method")
plt.xlabel("Number of clusters")
```

```
plt.ylabel("WCSS")
plt.show()
```

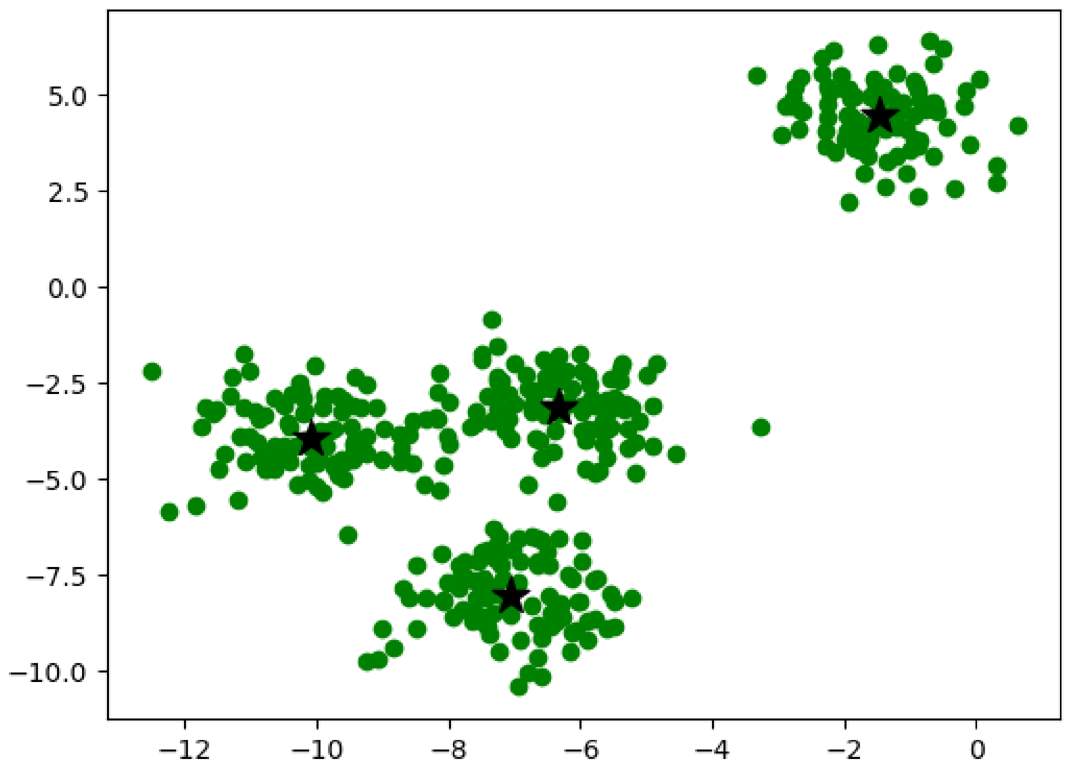


1.4 ApplyingtheK-MeansAlgorithm

[ ]:
```
kmeans = KMeans(n_clusters=4, random_state=0) # from Elbow method
closest_cluster_index = kmeans.fit_predict(X)
cluster_centers = kmeans.cluster_centers_
```

1.5 VisualizingClusters

[ ]:
```
plt.scatter(X[:, 0], X[:, 1], c="green")
plt.scatter(
    cluster_centers[:, 0],
    cluster_centers[:, 1],
    s=200,
    c="black",
    marker="*"
    )
plt.show()
```



1.0.2 Exercise01

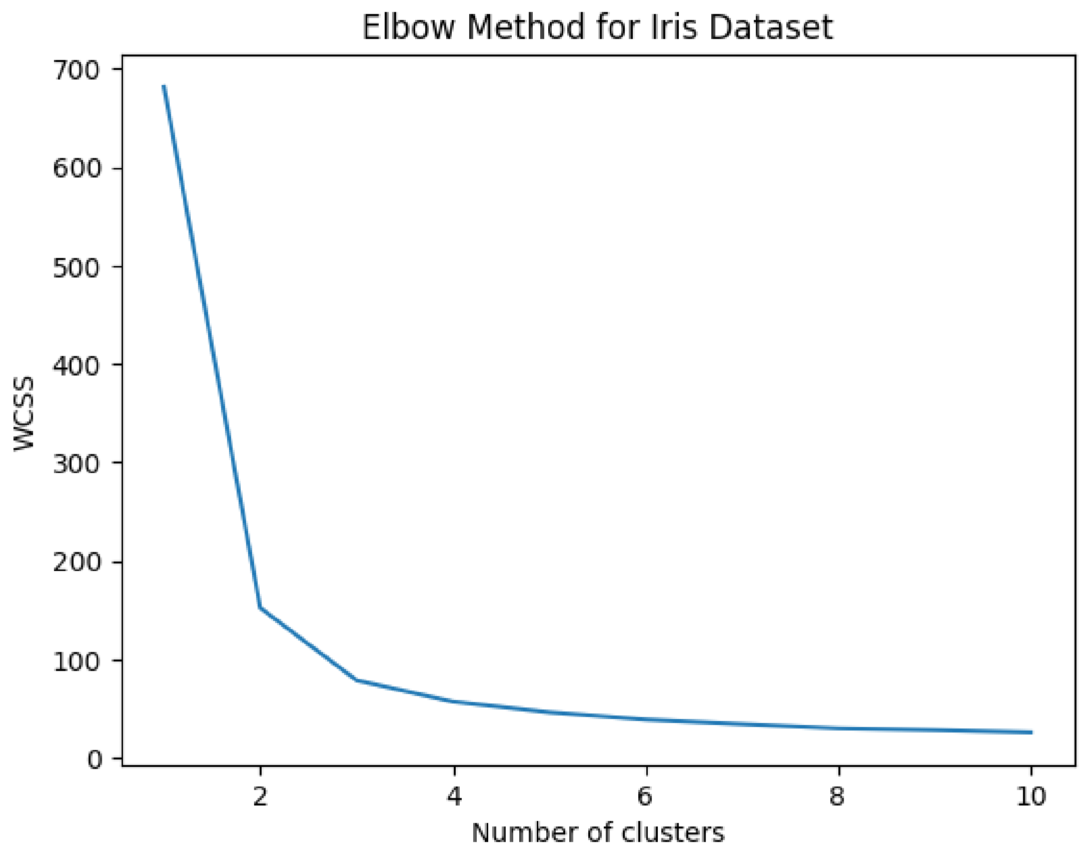
1. Import the iris dataset from scikit-learn. Convert it into an unlabeled dataset by removing the class attribute.

[ ]:
```python
from sklearn.datasets import load_iris

iris = load_iris()
iris_X = iris.data  # features only, unlabeled dataset
```

2. Use the Elbow method to identify the best value for k (minimizing WCSS).

[ ]:
```python
wcss_iris = [] # Within Cluster Sum of Squares for iris dataset
# Using the Elbow Method to find the optimal number of clusters for the Iris dataset
for k in range(1, 11):
    # kmeans with k clusters
    kmeans_iris = KMeans(n_clusters=k, init="k-means++", max_iter=300, n_init=10, random_state=0)
    # fit the model (train the model)
    kmeans_iris.fit(iris_X)
```

```
    # append the inertia (WCSS) to the list (Inertia is the sum of squared
 ↪distances of samples to their closest cluster center)
    wcss_iris.append(kmeans_iris.inertia_)

plt.plot(range(1, 11), wcss_iris)
plt.title("Elbow Method for Iris Dataset")
plt.xlabel("Number of clusters")
plt.ylabel("WCSS")
plt.show()
```



3. Fit the K-Means algorithm with the k found in part (b)

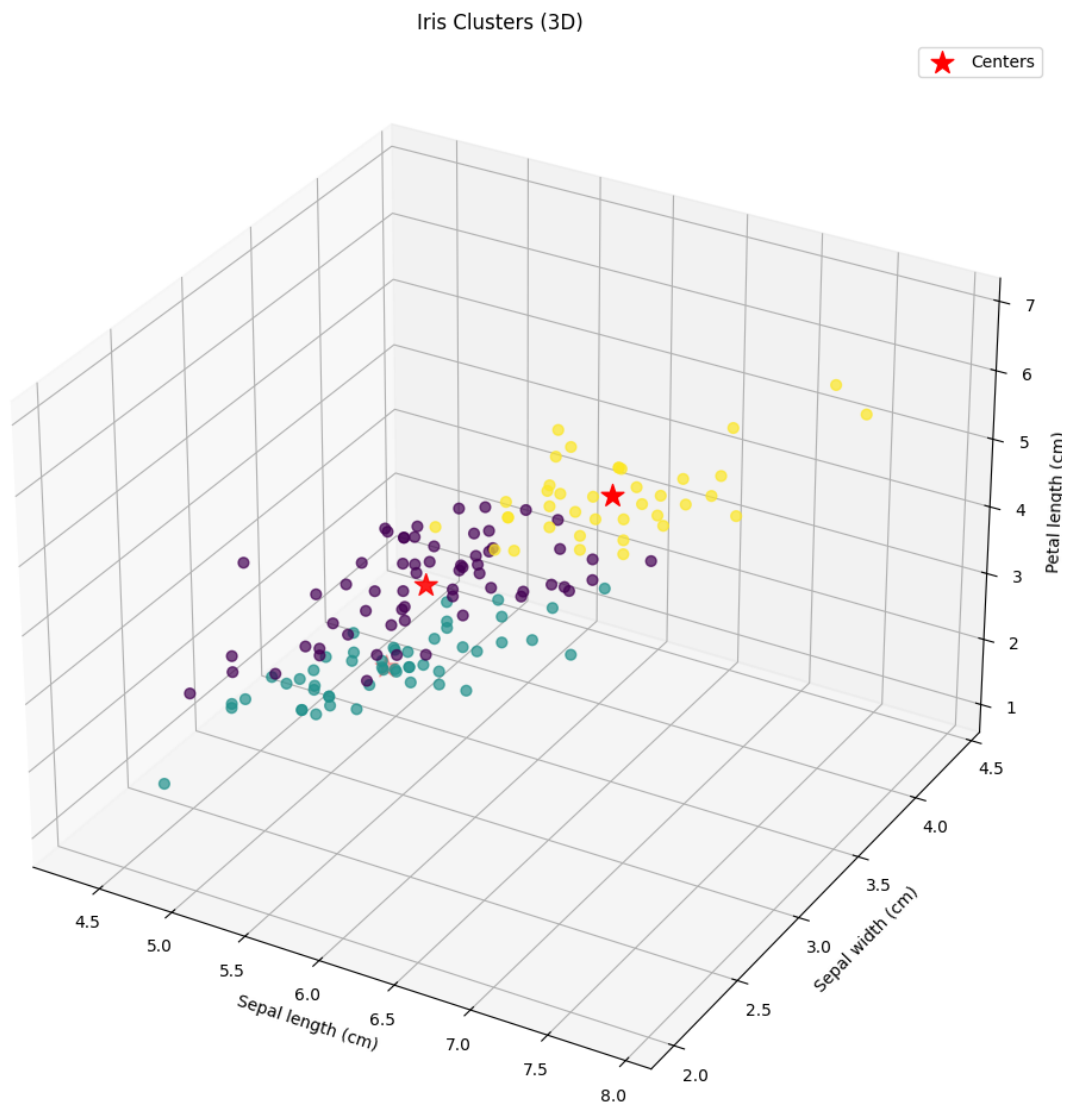
[ ]:
```
# Fit KMeans with the optimal k (3) found from the Elbow method for the iris
 ↪dataset
kmeans_iris = KMeans(n_clusters=3, init="k-means++", max_iter=300, n_init=10,
 ↪random_state=0)
iris_clusters = kmeans_iris.fit_predict(iris_X)
```

4. Explain the output of: ‘kmeans . cluster_centers_’

The output of `kmeans.cluster_centers_` is a NumPy array containing the coordinates of the centroids (centers) of each cluster found by the K-Means algorithm. Each row in this array represents the center of a cluster in the feature space, and each column corresponds to a feature. These centroids are the mean positions of all the points assigned to each cluster and are used to define the clusters in the data.

5. Visualize the data points and cluster centers in a 3D plot using the first three features as axes.

[ ]:
```
from mpl_toolkits.mplot3d import Axes3D

fig = plt.figure(figsize=(12, 12))
ax = fig.add_subplot(111, projection='3d')

# Plot data points, colored by cluster assignment
ax.scatter(
    iris_X[:, 0], iris_X[:, 1], iris_X[:, 2],
    c=iris_clusters, cmap='viridis', s=40, alpha=0.7
)

# Plot cluster centers
centers = kmeans_iris.cluster_centers_
ax.scatter(
    centers[:, 0], centers[:, 1], centers[:, 2],
    c='red', s=200, marker='*', label='Centers'
)

ax.set_xlabel('Sepal length (cm)')
ax.set_ylabel('Sepal width (cm)')
ax.set_zlabel('Petal length (cm)')
ax.set_title('Iris Clusters (3D)')
ax.legend()
plt.show()
```



2 AssociationRuleLearning

2.1 InstallingApriori

[ ]:
```
!pip install mlxtend
```

```
Requirement already satisfied: mlxtend in e:\my projects\python\co544 machine
learnning\venv\lib\site-packages (0.23.4)
Requirement already satisfied: pandas>=0.24.2 in e:\my projects\python\co544
machine learnning\venv\lib\site-packages (from mlxtend) (2.2.3)
Requirement already satisfied: joblib>=0.13.2 in e:\my projects\python\co544
machine learnning\venv\lib\site-packages (from mlxtend) (1.4.2)
Requirement already satisfied: numpy>=1.16.2 in e:\my projects\python\co544
```

```
machine learnning\venv\lib\site-packages (from mlxtend) (2.0.2)
Requirement already satisfied: matplotlib>=3.0.0 in e:\my projects\python\co544
machine learnning\venv\lib\site-packages (from mlxtend) (3.9.4)
Requirement already satisfied: scikit-learn>=1.3.1 in e:\my
projects\python\co544 machine learnning\venv\lib\site-packages (from mlxtend)
(1.6.1)
Requirement already satisfied: scipy>=1.2.1 in e:\my projects\python\co544
machine learnning\venv\lib\site-packages (from mlxtend) (1.13.1)
Requirement already satisfied: fonttools>=4.22.0 in e:\my projects\python\co544
machine learnning\venv\lib\site-packages (from matplotlib>=3.0.0->mlxtend)
(4.57.0)
Requirement already satisfied: cycler>=0.10 in e:\my projects\python\co544
machine learnning\venv\lib\site-packages (from matplotlib>=3.0.0->mlxtend)
(0.12.1)
Requirement already satisfied: importlib-resources>=3.2.0 in e:\my
projects\python\co544 machine learnning\venv\lib\site-packages (from
matplotlib>=3.0.0->mlxtend) (6.5.2)
Requirement already satisfied: pyparsing>=2.3.1 in e:\my projects\python\co544
machine learnning\venv\lib\site-packages (from matplotlib>=3.0.0->mlxtend)
(3.2.3)
Requirement already satisfied: kiwisolver>=1.3.1 in e:\my projects\python\co544
machine learnning\venv\lib\site-packages (from matplotlib>=3.0.0->mlxtend)
(1.4.7)
Requirement already satisfied: packaging>=20.0 in e:\my projects\python\co544
machine learnning\venv\lib\site-packages (from matplotlib>=3.0.0->mlxtend)
(25.0)
Requirement already satisfied: python-dateutil>=2.7 in e:\my
projects\python\co544 machine learnning\venv\lib\site-packages (from
matplotlib>=3.0.0->mlxtend) (2.9.0.post0)
Requirement already satisfied: pillow>=8 in e:\my projects\python\co544 machine
learnning\venv\lib\site-packages (from matplotlib>=3.0.0->mlxtend) (11.2.1)
Requirement already satisfied: contourpy>=1.0.1 in e:\my projects\python\co544
machine learnning\venv\lib\site-packages (from matplotlib>=3.0.0->mlxtend)
(1.3.0)
Requirement already satisfied: pytz>=2020.1 in e:\my projects\python\co544
machine learnning\venv\lib\site-packages (from pandas>=0.24.2->mlxtend) (2025.2)
Requirement already satisfied: tzdata>=2022.7 in e:\my projects\python\co544
machine learnning\venv\lib\site-packages (from pandas>=0.24.2->mlxtend) (2025.2)
Requirement already satisfied: threadpoolctl>=3.1.0 in e:\my
projects\python\co544 machine learnning\venv\lib\site-packages (from scikit-
learn>=1.3.1->mlxtend) (3.6.0)
Requirement already satisfied: zipp>=3.1.0 in e:\my projects\python\co544
machine learnning\venv\lib\site-packages (from importlib-
resources>=3.2.0->matplotlib>=3.0.0->mlxtend) (3.21.0)
Requirement already satisfied: six>=1.5 in e:\my projects\python\co544 machine
learnning\venv\lib\site-packages (from python-
dateutil>=2.7->matplotlib>=3.0.0->mlxtend) (1.17.0)
```

```
WARNING: You are using pip version 22.0.4; however, version 25.1.1 is available.
You should consider upgrading via the 'E:\My Projects\python\CO544 Machine
Learnning\venv\Scripts\python.exe -m pip install --upgrade pip' command.
```

2.2 Importing Required Modules

```
[ ]: from mlxtend . frequent_patterns import apriori
     from mlxtend . frequent_patterns import association_rules
     from mlxtend . preprocessing import TransactionEncoder
     import pandas as pd
```

2.3 Input Data

```
[ ]: dataset = [
         ["Milk", "Onion", "Nutmeg", "Kidney Beans", "Eggs", "Yogurt"],
         ["Dill", "Onion", "Nutmeg", "Kidney Beans", "Eggs", "Yogurt"],
         ["Milk", "Apple", "Kidney Beans", "Eggs"],
         ["Milk", "Unicorn", "Corn", "Kidney Beans", "Yogurt"],
         ["Corn", "Onion", "Onion", "Kidney Beans", "Ice cream", "Eggs"]
     ]
```

2.4 Creating the DataFrame of Frequent Itemsets

```
[ ]: te = TransactionEncoder()
     te_ary = te.fit( dataset ).transform( dataset )
     df = pd.DataFrame( te_ary , columns = te . columns_ )
```

2.5 Applying Apriori Algorithm and Finding Association Rules

```
[ ]: freq = apriori( df , min_support =0.002 , use_colnames = True )
     rules = association_rules( freq , metric ="lift" , min_threshold =1)
```

```
e:\My Projects\python\CO544 Machine Learnning\venv\lib\site-
packages\mlxtend\frequent_patterns\association_rules.py:186: RuntimeWarning:
invalid value encountered in divide
  cert_metric = np.where(certainty_denom == 0, 0, certainty_num /
certainty_denom)
```

1.0.3 Exercise02

1. Import the provided groceries.csv dataset.

```
[ ]: groceries_df = pd.read_csv('groceries.csv')
     groceries_df.head()
```

```
[ ]:        citrus fruit semi-finished bread       margarine  \
     0    tropical fruit              yogurt          coffee
     1        whole milk                 NaN             NaN
     2         pip fruit              yogurt    cream cheese
     3  other vegetables          whole milk  condensed milk
```

```
4        whole milk              butter          yogurt

                   ready soups        Unnamed: 4 Unnamed: 5 Unnamed: 6  \
0                          NaN               NaN        NaN        NaN
1                          NaN               NaN        NaN        NaN
2                 meat spreads               NaN        NaN        NaN
3  long life bakery product                  NaN        NaN        NaN
4                         rice  abrasive cleaner        NaN        NaN

  Unnamed: 7 Unnamed: 8 Unnamed: 9  … Unnamed: 22 Unnamed: 23 Unnamed: 24  \
0        NaN        NaN        NaN  …         NaN         NaN         NaN
1        NaN        NaN        NaN  …         NaN         NaN         NaN
2        NaN        NaN        NaN  …         NaN         NaN         NaN
3        NaN        NaN        NaN  …         NaN         NaN         NaN
4        NaN        NaN        NaN  …         NaN         NaN         NaN

  Unnamed: 25 Unnamed: 26 Unnamed: 27 Unnamed: 28 Unnamed: 29 Unnamed: 30  \
0         NaN         NaN         NaN         NaN         NaN         NaN
1         NaN         NaN         NaN         NaN         NaN         NaN
2         NaN         NaN         NaN         NaN         NaN         NaN
3         NaN         NaN         NaN         NaN         NaN         NaN
4         NaN         NaN         NaN         NaN         NaN         NaN

  Unnamed: 31
0         NaN
1         NaN
2         NaN
3         NaN
4         NaN

[5 rows x 32 columns]
```

2. Explore the dataset and build the frequent-item DataFrame.

[ ]:
```python
# Explore the groceries_df dataset
print("Number of transactions:", len(groceries_df))
print("Sample transactions:")
print(groceries_df.head())

# Convert the DataFrame into a list of transactions (dropping NaNs)
transactions = groceries_df.apply(lambda row: [item for item in row if pd.
 ↪notnull(item)], axis=1).tolist()

# Use TransactionEncoder to encode the transactions
te_groceries = TransactionEncoder()
te_groceries_ary = te_groceries.fit(transactions).transform(transactions)
groceries_onehot = pd.DataFrame(te_groceries_ary, columns=te_groceries.columns_)
```

```
# Build the frequent-item DataFrame using apriori
freq_groceries = apriori(groceries_onehot, min_support=0.01, use_colnames=True)
freq_groceries.head()
```

```
Number of transactions: 9834
Sample transactions:
       citrus fruit semi-finished bread       margarine  \
0    tropical fruit              yogurt          coffee
1        whole milk                 NaN             NaN
2         pip fruit              yogurt    cream cheese
3  other vegetables          whole milk  condensed milk
4        whole milk              butter          yogurt

                ready soups       Unnamed: 4 Unnamed: 5 Unnamed: 6  \
0                       NaN              NaN        NaN        NaN
1                       NaN              NaN        NaN        NaN
2              meat spreads              NaN        NaN        NaN
3  long life bakery product              NaN        NaN        NaN
4                      rice  abrasive cleaner        NaN        NaN

  Unnamed: 7 Unnamed: 8 Unnamed: 9  … Unnamed: 22 Unnamed: 23 Unnamed: 24  \
0        NaN        NaN        NaN  …         NaN         NaN         NaN
1        NaN        NaN        NaN  …         NaN         NaN         NaN
2        NaN        NaN        NaN  …         NaN         NaN         NaN
3        NaN        NaN        NaN  …         NaN         NaN         NaN
4        NaN        NaN        NaN  …         NaN         NaN         NaN

  Unnamed: 25 Unnamed: 26 Unnamed: 27 Unnamed: 28 Unnamed: 29 Unnamed: 30  \
0         NaN         NaN         NaN         NaN         NaN         NaN
1         NaN         NaN         NaN         NaN         NaN         NaN
2         NaN         NaN         NaN         NaN         NaN         NaN
3         NaN         NaN         NaN         NaN         NaN         NaN
4         NaN         NaN         NaN         NaN         NaN         NaN

  Unnamed: 31
0         NaN
1         NaN
2         NaN
3         NaN
4         NaN

[5 rows x 32 columns]
```

[ ]:

	support	itemsets
0	0.033455	(UHT-milk)
1	0.017694	(baking powder)

```
2  0.052471           (beef)
3  0.033252        (berries)
4  0.026032      (beverages)
```

3. Apply the Apriori algorithm to find itemsets with support > 8%.

[ ]:
```
# Find frequent itemsets in groceries_onehot with support greater than 8%
freq_groceries_08 = apriori(groceries_onehot, min_support=0.08,␣
 ↪use_colnames=True)
freq_groceries_08
```

[ ]:
```
     support             itemsets
0   0.080537        (bottled beer)
1   0.110535       (bottled water)
2   0.082672        (citrus fruit)
3   0.193512    (other vegetables)
4   0.088977              (pastry)
5   0.183954          (rolls/buns)
6   0.109010     (root vegetables)
7   0.093960             (sausage)
8   0.098536       (shopping bags)
9   0.174395                (soda)
10  0.104942      (tropical fruit)
11  0.255542          (whole milk)
12  0.139516              (yogurt)
```

4. Generate association rules using the lift metric.

[ ]:
```
# Generate association rules for the groceries dataset using the lift metric
rules_groceries = association_rules(freq_groceries, metric="lift",␣
 ↪min_threshold=1)
rules_groceries.head()
```

[ ]:
```
          antecedents         consequents  antecedent support  \
0              (beef)  (other vegetables)            0.052471
1  (other vegetables)              (beef)            0.193512
2              (beef)        (rolls/buns)            0.052471
3        (rolls/buns)              (beef)            0.183954
4              (beef)   (root vegetables)            0.052471

   consequent support   support  confidence      lift  representativity  \
0            0.193512  0.019727    0.375969  1.942869               1.0
1            0.052471  0.019727    0.101944  1.942869               1.0
2            0.183954  0.013626    0.259690  1.411714               1.0
3            0.052471  0.013626    0.074074  1.411714               1.0
4            0.109010  0.017389    0.331395  3.040058               1.0
```

```
   leverage  conviction  zhangs_metric   jaccard  certainty  kulczynski
0  0.009574    1.292384       0.512171  0.087191   0.226236    0.238957
1  0.009574    1.055089       0.601742  0.087191   0.052213    0.238957
2  0.003974    1.102303       0.307791  0.061159   0.092809    0.166882
3  0.003974    1.023331       0.357383  0.061159   0.022799    0.166882
4  0.011669    1.332612       0.708220  0.120677   0.249594    0.245455
```

5. Select one rule and interpret it in your own words.

```
[ ]: # Select the first rule from rules_groceries and display it
selected_rule = rules_groceries.iloc[0]
print("Selected Rule:")
print(selected_rule)

# Interpretation
print("\nInterpretation:")
print(f"If a customer buys {list(selected_rule['antecedents'])}, they are␣
↪likely to also buy {list(selected_rule['consequents'])}.")
print(f"This rule has a confidence of {selected_rule['confidence']:.2f} and a␣
↪lift of {selected_rule['lift']:.2f}, meaning the likelihood of buying␣
↪{list(selected_rule['consequents'])} increases by a factor of␣
↪{selected_rule['lift']:.2f} when {list(selected_rule['antecedents'])} is␣
↪purchased.")
```

```
Selected Rule:
antecedents                          (beef)
consequents              (other vegetables)
antecedent support                 0.052471
consequent support                 0.193512
support                            0.019727
confidence                         0.375969
lift                               1.942869
representativity                        1.0
leverage                           0.009574
conviction                         1.292384
zhangs_metric                      0.512171
jaccard                            0.087191
certainty                          0.226236
kulczynski                         0.238957
Name: 0, dtype: object

Interpretation:
If a customer buys ['beef'], they are likely to also buy ['other vegetables'].
This rule has a confidence of 0.38 and a lift of 1.94, meaning the likelihood of
buying ['other vegetables'] increases by a factor of 1.94 when ['beef'] is
purchased.
```

6. How many rules satisfy both lift $>$ 4 and confidence $>$ 0.8?

[ ]:
```python
# Count the number of rules with lift > 4 and confidence > 0.8 in the 'rules'␣
↪DataFrame
num_rules = rules[(rules['lift'] > 4) & (rules['confidence'] > 0.8)].shape[0]
print("Number of rules with lift > 4 and confidence > 0.8:", num_rules)
```

```
Number of rules with lift > 4 and confidence > 0.8: 60
```