

Output –

```
weather.numeric_missing

@relation weather

@attribute outlook {sunny, overcast, rainy}
@attribute temperature numeric
@attribute humidity numeric
@attribute windy {TRUE, FALSE}
@attribute play {yes, no}

@data
sunny,?,85,FALSE,no
sunny,80,90,TRUE,no
overcast,?,86,FALSE,yes
rainy,70,96,FALSE,yes
rainy,68,80,FALSE,yes
rainy,65,70,TRUE,no
overcast,64,65,TRUE,yes
sunny,72,?,FALSE,no
sunny,69,70,FALSE,yes
rainy,75,80,FALSE,yes
sunny,?,70,TRUE,yes
overcast,72,90,TRUE,yes
overcast,81,75,FALSE,yes
rainy,71,91,TRUE,no
```

```
weather.numeric_replaced

@relation weather-weka.filters.unsupervised.attribute.ReplaceMissingValues

@attribute outlook {sunny,overcast,rainy}
@attribute temperature numeric
@attribute humidity numeric
@attribute windy {TRUE,FALSE}
@attribute play {yes,no}

@data
sunny,71.545455,85,FALSE,no
sunny,80,90,TRUE,no
overcast,71.545455,86,FALSE,yes
rainy,70,96,FALSE,yes
rainy,68,80,FALSE,yes
rainy,65,70,TRUE,no
overcast,64,65,TRUE,yes
sunny,72,80.615385,FALSE,no
sunny,69,70,FALSE,yes
rainy,75,80,FALSE,yes
sunny,71.545455,70,TRUE,yes
overcast,72,90,TRUE,yes
overcast,81,75,FALSE,yes
rainy,71,91,TRUE,no
```

Open file... Open URL... Open DB... Generate... Undo Edit... Save...

Filter: Choose **Discretize** -F -B 10 -M -1.0 -R first-last -precision 6 Apply Stop

Current relation: Relation: weather-weka.filters.unsupervised.attribute.ReplaceMissingValues-weka.filters.u... Instances: 14 Attributes: 5 Sum of weights: 14

Attributes:

No.	Name
1	outlook
2	temperature
3	humidity
4	windy
5	play

Selected attribute: Name: humidity Missing: 0 (0%) Distinct: 10 Type: Nominal Unique: 7 (50%)

No.	Label	Count	Weight
1	'[-inf-67.5]'	1	1
2	'(67.5-72.5]'	3	3
3	'(72.5-77.5]'	1	1
4	'(77.5-80.307692]'	2	2
5	'(80.307692-82.807692]'	1	1
6	'(82.807692-85.5]'	1	1
7	'(85.5-88]'	1	1
8	'(88-90.5]'	2	2

Class: play (Nom) Visualize All

Bin	Label	Count
1	'[-inf-67.5]'	1
2	'(67.5-72.5]'	3
3	'(72.5-77.5]'	1
4	'(77.5-80.307692]'	2
5	'(80.307692-82.807692]'	1
6	'(82.807692-85.5]'	1
7	'(85.5-88]'	1
8	'(88-90.5]'	2

Select attributes: weka.filters.unsupervised.attribute.Discretize

About: An instance filter that discretizes a range of numeric attributes in the dataset into nominal attributes. More Capabilities

attributeIndices: first-last

binRangePrecision: 6

bins: 10

debug: False

desiredWeightOfInstancesPerInterval: -1.0

doNotCheckCapabilities: False

findNumBins: False

ignoreClass: False

invertSelection: False

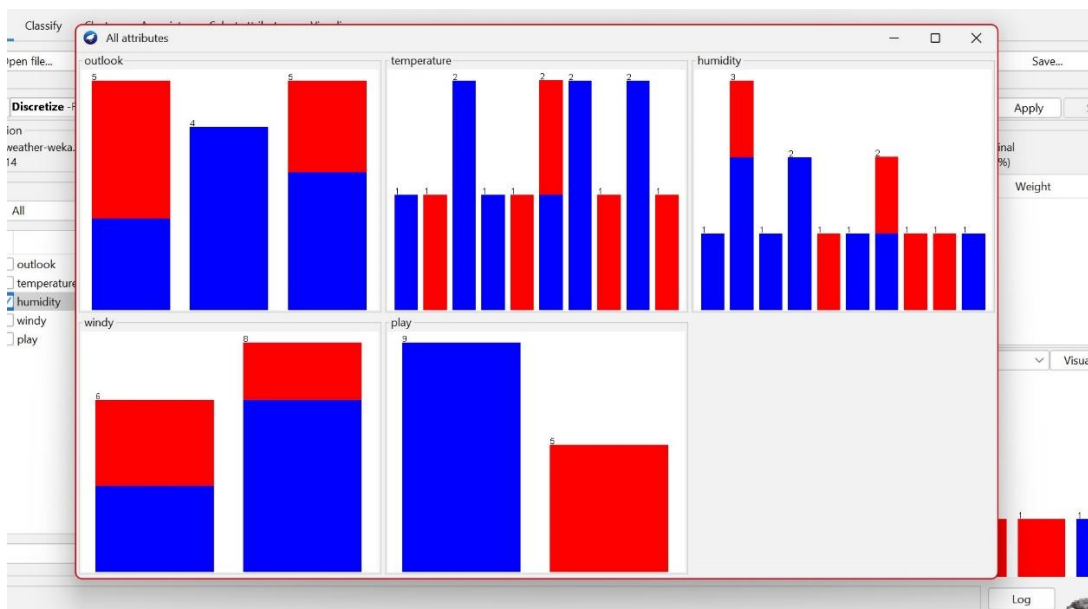
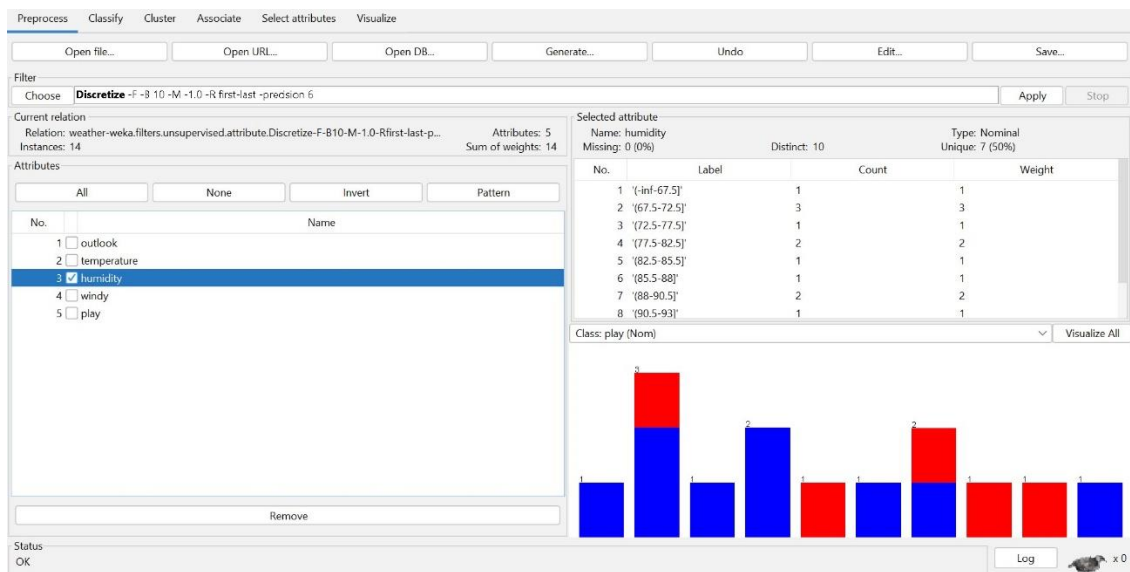
makeBinary: False

spreadAttributeWeight: False

useBinNumbers: False

useQualFrequency: True

Open... Save... OK Cancel



```
@relation weather-weka.filters.unsupervised.attribute.Discretize-F-B10-M-1.0-Rfirst-last-precision6

@attribute outlook {sunny,overcast,rainy}
@attribute temperature {'(-inf-64.5]','(64.5-66.5]','(66.5-69.5]','(69.5-70.5]','(70.5-71.5]','(71.5-73.5]','(73.5-77.5]','(77.5-80.5]','(80.5-84]','(84-inf)'}
@attribute humidity {'(-inf-67.5]','(67.5-72.5]','(72.5-77.5]','(77.5-82.5]','(82.5-85.5]','(85.5-88]','(88-90.5]','(90.5-93]','(93-95.5]','(95.5-inf)'}
@attribute windy {TRUE,FALSE}
@attribute play {yes,no}

@data
sunny,'(84-inf)', '(82.5-85.5]',FALSE,no
sunny,'(77.5-80.5]', '(88-90.5]',TRUE,no
overcast,'(80.5-84]', '(85.5-88]',FALSE,yes
rainy,'(69.5-70.5]', '(95.5-inf)',FALSE,yes
rainy,'(66.5-69.5]', '(77.5-82.5]',FALSE,yes
rainy,'(64.5-66.5]', '(67.5-72.5]',TRUE,no
overcast,'(-inf-64.5]', '(-inf-67.5]',TRUE,yes
sunny,'(71.5-73.5]', '(93-95.5]',FALSE,no
sunny,'(66.5-69.5]', '(67.5-72.5]',FALSE,yes
rainy,'(73.5-77.5]', '(77.5-82.5]',FALSE,yes
sunny,'(73.5-77.5]', '(67.5-72.5]',TRUE,yes
overcast,'(71.5-73.5]', '(88-90.5]',TRUE,yes
overcast,'(80.5-84]', '(72.5-77.5]',FALSE,yes
rainy,'(70.5-71.5]', '(90.5-93]',TRUE,no
```

Preprocess Classify Cluster Associate Select attributes Visualize

Open file... Open URL... Open DB... Generate... Undo Edit... Save...

Filter

weka

- filters
 - AllFilter
 - MultiFilter
 - RenameRelation
 - supervised
 - unsupervised
 - attribute
 - Add
 - AddCluster
 - AddExpression
 - AddID
 - AddNoise
 - AddUserFields
 - AddValues
 - CartesianProduct
 - Center
 - ChangeDateFormat
 - ClassAssigner
 - ClusterMembership
 - Copy
 - DateToNumeric
 - Discretize
 - FirstOrder
 - FixedDictionaryStringToWordVector
 - InterquartileRange
 - KernelFilter
 - MakeIndicator

Attributes: 5
Sum of weights: 14

Invert Pattern

Selected attribute

Name: outlook
Missing: 0 (0%)
Distinct: 3
Type: Nominal
Unique: 0 (0%)

No.	Label	Count	Weight
1	sunny	5	5
2	overcast	4	4
3	rainy	5	5

Class: play (Nom)

Visualize All

Log

Preprocess Classify Cluster Associate Select attributes Visualize

Open file... Open URL... Open DB... Generate... Undo Edit... Save...

Filter

Choose: Add -N unnamed -C last -W 1.0

Current relation

Relation: weather-weka.filters.unsupervised.attribute.Add-Unnamed-Clas-W1.0
Instances: 14
Attributes: 6
Sum of weights: 14

Attributes

All None Invert Pattern

No.	Name
1	outlook
2	temperature
3	humidity
4	windy
5	play
6	unnamed

Remove

Selected attribute

Name: outlook
Missing: 0 (0%)
Distinct: 3
Type: Nominal
Unique: 0 (0%)

No.	Label	Count	Weight
1	sunny	5	5
2	overcast	4	4
3	rainy	5	5

Class: unnamed (Num)

Visualize All

Status OK

Log

weka.gui.GenericObjectEditor

weka.filters.unsupervised.attribute.Add

About

An instance filter that adds a new attribute to the dataset.

More Capabilities

attributeIndex: last

attributeName: Color

attributeType: Numeric attribute

dateFormat: yyyy-MM-dd'T'HH:mm:ss

debug: False

doNotCheckCapabilities: False

nominalLabels:

weight: 1.0

Open... Save... OK Cancel

Filter

Choose
Add -N Color -C last -W 1.0

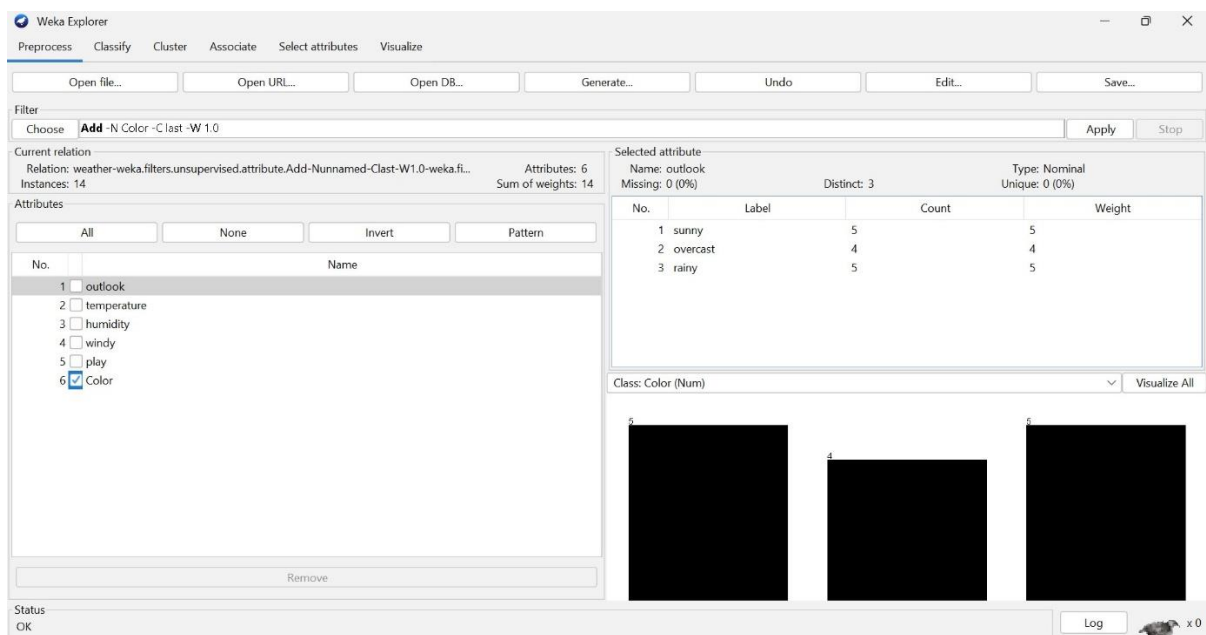
Current relation
Relation: weather-weka.filters.unsupervised.attribute.Add-Nunnamed-Clast-W1.0-weka.fi...
Instances: 14
Attributes: 7
Sum of weights: 14

Attributes

All
None
Invert
Pattern

No.	Name
1	<input type="checkbox"/> outlook
2	<input type="checkbox"/> temperature
3	<input type="checkbox"/> humidity
4	<input type="checkbox"/> windy
5	<input type="checkbox"/> play
6	<input checked="" type="checkbox"/> unnamed
7	<input type="checkbox"/> Color

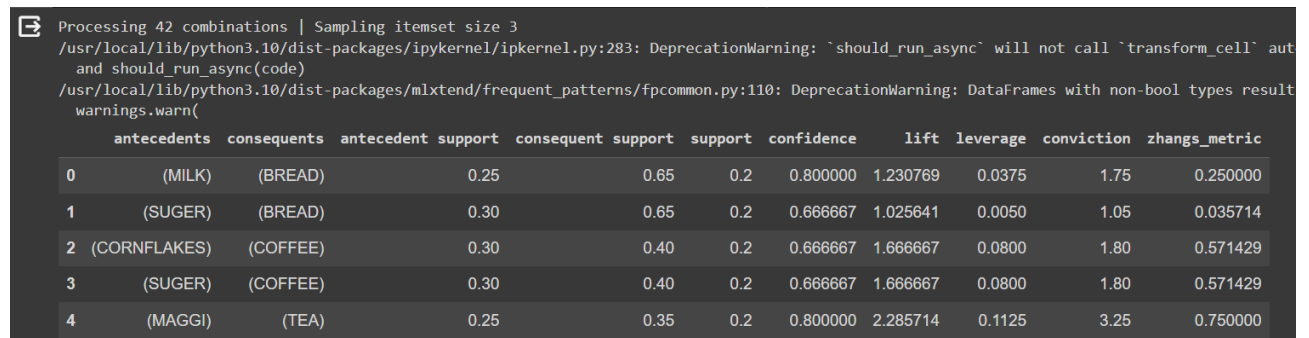
Remove



Program –

```
import pandas as pd
import numpy as np
from mlxtend.frequent_patterns import apriori, association_rules
df = pd.read_csv('GroceryStoreDataSet.csv', names = ['products'], sep = ',')
df.head()
df.shape
data = list(df["products"].apply(lambda x:x.split(",") ))
data
from mlxtend.preprocessing import TransactionEncoder
a = TransactionEncoder()
a_data = a.fit(data).transform(data)
df = pd.DataFrame(a_data,columns=a.columns_)
df = df.replace(False,0)
df
df = apriori(df, min_support = 0.2, use_colnames = True, verbose = 1)
df
df_ar = association_rules(df, metric = "confidence", min_threshold = 0.6)
df_ar
```

Output –

The image shows a Jupyter Notebook interface. At the top, there is a terminal window with three lines of text: 'Processing 42 combinations | Sampling itemset size 3', a DeprecationWarning from ipykernel about 'should_run_async', and another DeprecationWarning from mlxtend about DataFrames with non-bool types. Below the terminal is a table with 11 columns: antecedents, consequents, antecedent support, consequent support, support, confidence, lift, leverage, conviction, and zhangs_metric. The table contains 5 rows of data, indexed 0 to 4. Row 0 shows (MILK) as antecedent and (BREAD) as consequent. Row 1 shows (SUGER) as antecedent and (BREAD) as consequent. Row 2 shows (CORNFLAKES) as antecedent and (COFFEE) as consequent. Row 3 shows (SUGER) as antecedent and (COFFEE) as consequent. Row 4 shows (MAGGI) as antecedent and (TEA) as consequent.

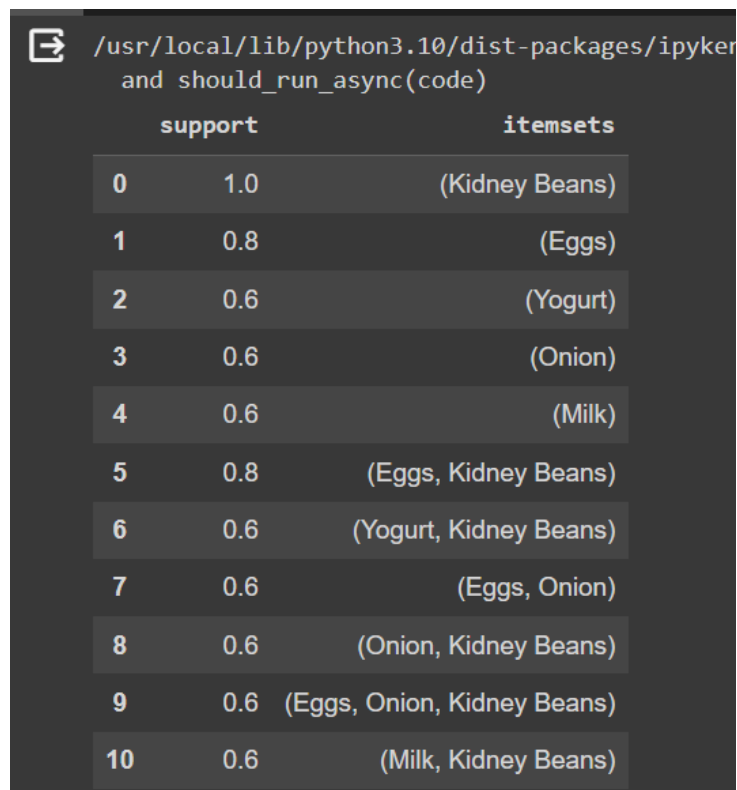
	antecedents	consequents	antecedent support	consequent support	support	confidence	lift	leverage	conviction	zhangs_metric
0	(MILK)	(BREAD)	0.25	0.65	0.2	0.800000	1.230769	0.0375	1.75	0.250000
1	(SUGER)	(BREAD)	0.30	0.65	0.2	0.666667	1.025641	0.0050	1.05	0.035714
2	(CORNFLAKES)	(COFFEE)	0.30	0.40	0.2	0.666667	1.666667	0.0800	1.80	0.571429
3	(SUGER)	(COFFEE)	0.30	0.40	0.2	0.666667	1.666667	0.0800	1.80	0.571429
4	(MAGGI)	(TEA)	0.25	0.35	0.2	0.800000	2.285714	0.1125	3.25	0.750000

Program –

```
import pandas as pd
from mlxtend.preprocessing import TransactionEncoder
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']]
te = TransactionEncoder()
te_ary = te.fit(dataset).transform(dataset)
df = pd.DataFrame(te_ary, columns=te.columns_)
df
from mlxtend.frequent_patterns import fpgrowth

fpgrowth(df, min_support=0.6)
fpgrowth(df, min_support=0.6, use_colnames=True)
```

Output –



```
/usr/local/lib/python3.10/dist-packages/ipykernel
and should_run_async(code)
```

	support	itemsets
0	1.0	(Kidney Beans)
1	0.8	(Eggs)
2	0.6	(Yogurt)
3	0.6	(Onion)
4	0.6	(Milk)
5	0.8	(Eggs, Kidney Beans)
6	0.6	(Yogurt, Kidney Beans)
7	0.6	(Eggs, Onion)
8	0.6	(Onion, Kidney Beans)
9	0.6	(Eggs, Onion, Kidney Beans)
10	0.6	(Milk, Kidney Beans)

Program –

```
!pip install mmh3
```

```
!pip install bitarray
```

```
!pip install bloomfilter
```

```
import math
```

```
import mmh3
```

```
from bitarray import bitarray
```

```
class BloomFilter(object):
```

```
    def __init__(self, items_count, fp_prob):
```

```
        self.fp_prob = fp_prob
```

```
        self.size = self.get_size(items_count, fp_prob)
```

```
        self.hash_count = self.get_hash_count(self.size, items_count)
```

```
        self.bit_array = bitarray(self.size)
```

```
        self.bit_array.setall(0)
```

```
    def add(self, item):
```

```
        digests = []
```

```
        for i in range(self.hash_count):
```

```
            digest = mmh3.hash(item, i) % self.size
```

```
            digests.append(digest)
```

```
            self.bit_array[digest] = True
```

```
    def check(self, item):
```

```
        for i in range(self.hash_count):
```

```
            digest = mmh3.hash(item, i) % self.size
```

```
            if self.bit_array[digest] == False:
```

```
                return False
```

```
        return True
```

```
    @classmethod
```

```
    def get_size(self, n, p):
```

```
        m = -(n * math.log(p))/(math.log(2)**2)
```

```
        return int(m)
```

```
    @classmethod
```

```
    def get_hash_count(self, m, n):
```

```
k = (m/n) * math.log(2)
return int(k)
```

```
from random import shuffle
```

```
n = 20
p = 0.05
```

```
bloomf = BloomFilter(n,p)
print("Size of bit array:{}".format(bloomf.size))
print("False positive Probability:{}".format(bloomf.fp_prob))
print("Number of hash functions:{}".format(bloomf.hash_count))
```

```
word_present = ['abound','abounds','abundance','abundant','accessible',
'bloom','blossom','bolster','bonny','bonus','bonuses',
'coherent','cohesive','colorful','comely','comfort',
'gems','generosity','generous','generously','genial']
```

```
word_absent = ['bluff','cheater','hate','war','humanity',
'racism','hurt','nuke','gloomy','facebook', 'geeksforgeeks','twitter']
```

```
for item in word_present:
    bloomf.add(item)
```

```
shuffle(word_present)
shuffle(word_absent)
```

```
test_words = word_present[:10] + word_absent
shuffle(test_words)
for word in test_words:
    if bloomf.check(word):
        if word in word_absent:
            print("{} is a false positive!".format(word))
        else:
            print("{} is probably present!".format(word))
    else:
        print("{} is definitely not present!".format(word))
```


Output –



```
Size of bit array:124
False positive Probability:0.05
Number of hash functions:4
'hate' is definitely not present!
'facebook' is definitely not present!
'bloom' is probably present!
'abounds' is probably present!
'cheater' is definitely not present!
'nuke' is definitely not present!
'war' is definitely not present!
'comely' is probably present!
'generously' is probably present!
'geeksforgeeks' is definitely not present!
'bluff' is definitely not present!
'gloomy' is definitely not present!
'racism' is definitely not present!
'generosity' is probably present!
'bonuses' is probably present!
'blossom' is probably present!
'humanity' is a false positive!
'twitter' is a false positive!
'hurt' is definitely not present!
'bonny' is probably present!
'colorful' is probably present!
'abundant' is probably present!
```

Program –

```
import numpy
def PageRank(A, d = 0.85, eps = 0.0005, maxIterations = 1000,
            verbose = False):
    # find the size of the "Internet"
    N = A.shape[0]

    # initialize the old and new PageRank vectors
    vOld = numpy.ones([N])
    vNew = numpy.ones([N])/N

    # initialize a counter
    i = 0

    # compute the update matrix
    U = d * A.T + (1 - d) / N

    while numpy.linalg.norm(vOld - vNew) >= eps:
        # if the verbose flag is true, print the progress at each iteration
        if verbose:
            print('At iteration', i, 'the error is',
                  numpy.round(numpy.linalg.norm(vOld - vNew), 3),
                  'with PageRank', numpy.round(vNew, 3))

        # save the current PageRank as the old PageRank
        vOld = vNew

        # update the PageRank vector
        vNew = numpy.dot(U, vOld)

        # increment the counter
        i += 1

    # if it runs too long before converging, stop and notify the user
    if i == maxIterations:
        print('The PageRank algorithm ran for',
              maxIterations, 'with error',
              numpy.round(numpy.linalg.norm(vOld - vNew), 3))

    # return the PageRank vector and the
    return vNew, i
```

```

# return the steady state PageRank vector and iteration number
return vNew, i

# transition probability matrix
A = numpy.array([[0, 1/4, 1/4, 1/4, 1/4],
                 [1/2, 0, 0, 1/2, 0],
                 [1/3, 0, 0, 1/3, 1/3],
                 [1, 0, 0, 0, 0],
                 [0, 0, 0, 1, 0]])

# Run the PageRank algorithm with default settings
PageRank(A, verbose = True)

```

Output –

```

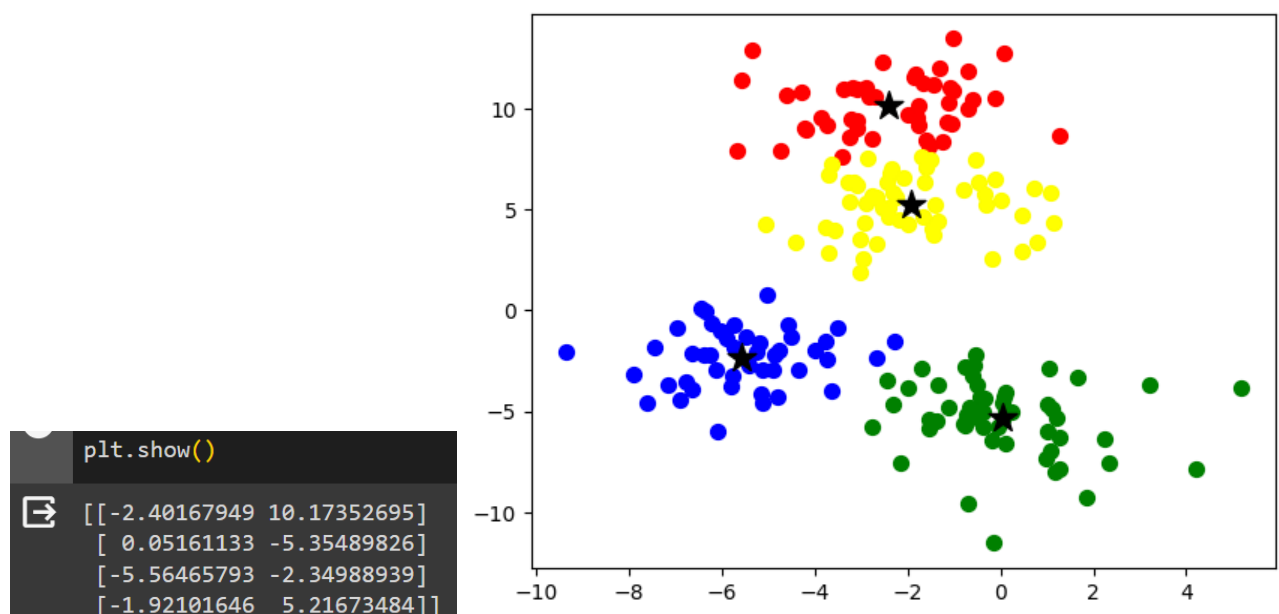
PageRank(A, verbose = True)
➡ At iteration 0 the error is 1.789 with PageRank [0.2 0.2 0.2 0.2 0.2]
At iteration 1 the error is 0.303 with PageRank [0.342 0.073 0.073 0.384 0.129]
At iteration 2 the error is 0.144 with PageRank [0.408 0.103 0.103 0.264 0.123]
At iteration 3 the error is 0.092 with PageRank [0.327 0.117 0.117 0.294 0.146]
At iteration 4 the error is 0.047 with PageRank [0.363 0.099 0.099 0.306 0.133]
At iteration 5 the error is 0.019 with PageRank [0.361 0.107 0.107 0.29 0.135]
At iteration 6 the error is 0.011 with PageRank [0.352 0.107 0.107 0.297 0.137]
At iteration 7 the error is 0.007 with PageRank [0.358 0.105 0.105 0.297 0.135]
At iteration 8 the error is 0.003 with PageRank [0.357 0.106 0.106 0.295 0.136]
At iteration 9 the error is 0.001 with PageRank [0.356 0.106 0.106 0.296 0.136]
At iteration 10 the error is 0.001 with PageRank [0.357 0.106 0.106 0.296 0.136]
(array([0.3565286 , 0.10584025, 0.10584025, 0.29600666, 0.13578424]), 11)

```

Program –

```
!pip install -U scikit-learn
import numpy as np
import matplotlib.pyplot as plt
from sklearn.datasets import make_blobs
dataset = make_blobs(n_samples=200, centers=4, n_features=2, cluster_std=1.6,
random_state=50)
points = dataset[0]
from sklearn.cluster import KMeans
kmeans = KMeans(n_clusters=4)
kmeans.fit(points)
plt.scatter(dataset[0][:,0], dataset[0][:,1])
clusters = kmeans.cluster_centers_
print(clusters)
y_km = kmeans.fit_predict(points)
y_km
plt.scatter(points[y_km== 1,0], points[y_km == 1,1], s=50, color= 'blue')
plt.scatter(points[y_km== 0,0], points[y_km == 0,1], s=50, color= 'red')
plt.scatter(points[y_km== 2,0], points[y_km == 2,1], s=50, color= 'green')
plt.scatter(points[y_km== 3,0], points[y_km == 3,1], s=50, color= 'yellow')
plt.scatter(clusters[0][0], clusters[0][1], marker='*', s=200, color= 'black')
plt.scatter(clusters[1][0], clusters[1][1], marker='*', s=200, color= 'black')
plt.scatter(clusters[2][0], clusters[2][1], marker='*', s=200, color= 'black')
plt.scatter(clusters[3][0], clusters[3][1], marker='*', s=200, color= 'black')
plt.show()
```

Output –



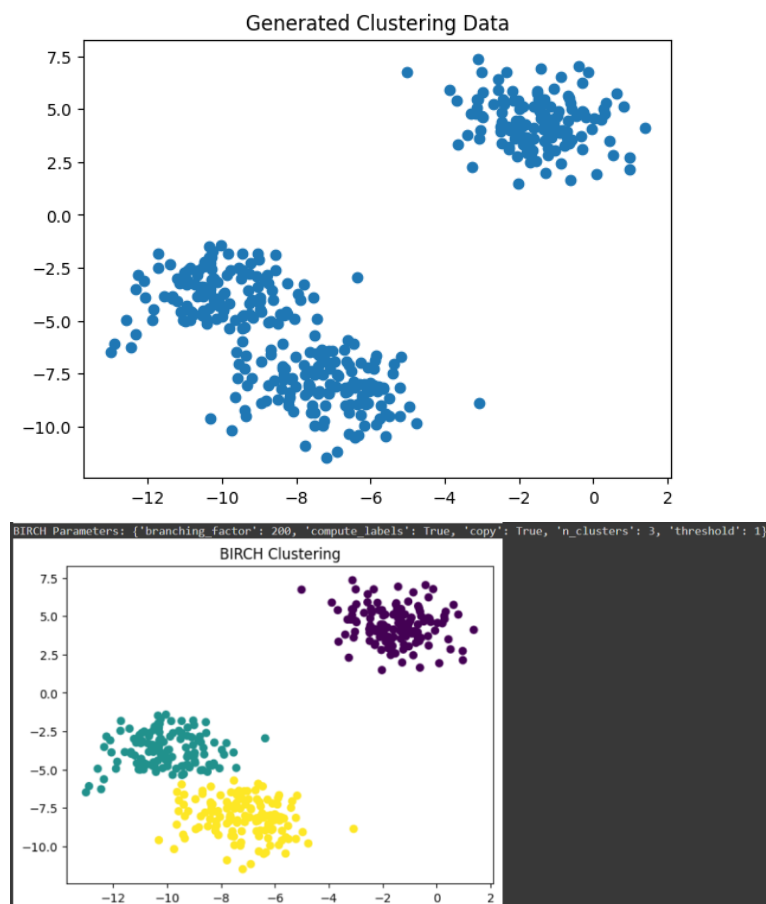
Program –

```
from sklearn.cluster import Birch
from sklearn.datasets import make_blobs
import matplotlib.pyplot as plt
from numpy import random

random.seed(1)
x, _ = make_blobs(n_samples=400, centers=3, cluster_std=1.2)
plt.scatter(x[:,0], x[:,1])
plt.title("Generated Clustering Data")
plt.show()

bclust = Birch(branching_factor=200, threshold=1).fit(x)
print("BIRCH Parameters:", bclust.get_params())
labels = bclust.predict(x)
plt.scatter(x[:,0], x[:,1], c=labels)
plt.title("BIRCH Clustering")
plt.show()
```

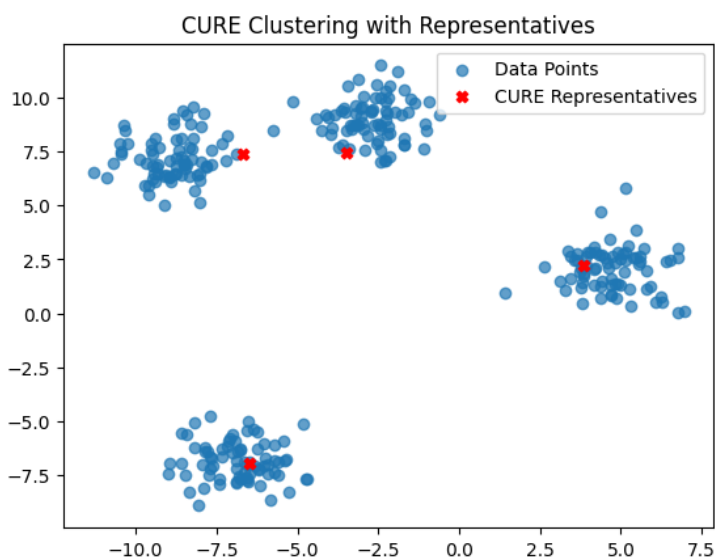
Output –



Program –

```
import numpy as np
import matplotlib.pyplot as plt
from sklearn.datasets import make_blobs
from sklearn.cluster import AgglomerativeClustering
from scipy.spatial.distance import euclidean
X, _ = make_blobs(n_samples=300, centers=4, random_state=42)
def cure_algorithm(X, num_clusters, reduction_factor=0.1):
    clustering = AgglomerativeClustering(n_clusters=num_clusters).fit(X)
    reduced_representatives = []
    for cluster_label in range(num_clusters):
        cluster_points = X[clustering.labels_ == cluster_label]
        representative_index = np.random.choice(len(cluster_points))
        representative_point = cluster_points[representative_index]
        reduced_point = representative_point - reduction_factor * np.mean(cluster_points -
        representative_point, axis=0)
        reduced_representatives.append(reduced_point)
    return np.array(reduced_representatives)
num_clusters = 4
cure_representatives = cure_algorithm(X, num_clusters)
plt.scatter(X[:, 0], X[:, 1], alpha=0.7, label='Data Points')
plt.scatter(cure_representatives[:, 0], cure_representatives[:, 1], c='red', marker='X',
label='CURE Representatives')
plt.title('CURE Clustering with Representatives')
plt.legend()
plt.show()
```

Output –



Program –

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

X = pd.read_csv('CC GENERAL.csv')

X = X.drop('CUST_ID', axis = 1)
X.fillna(method = 'ffill', inplace = True)

print(X.head())

scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
X_normalized = normalize(X_scaled)
X_normalized = pd.DataFrame(X_normalized)

pca = PCA(n_components = 2)
X_principal = pca.fit_transform(X_normalized)
X_principal = pd.DataFrame(X_principal)
X_principal.columns = ['P1', 'P2']
print(X_principal.head())

db_default = DBSCAN(eps = 0.0375, min_samples = 3).fit(X_principal)
labels = db_default.labels_

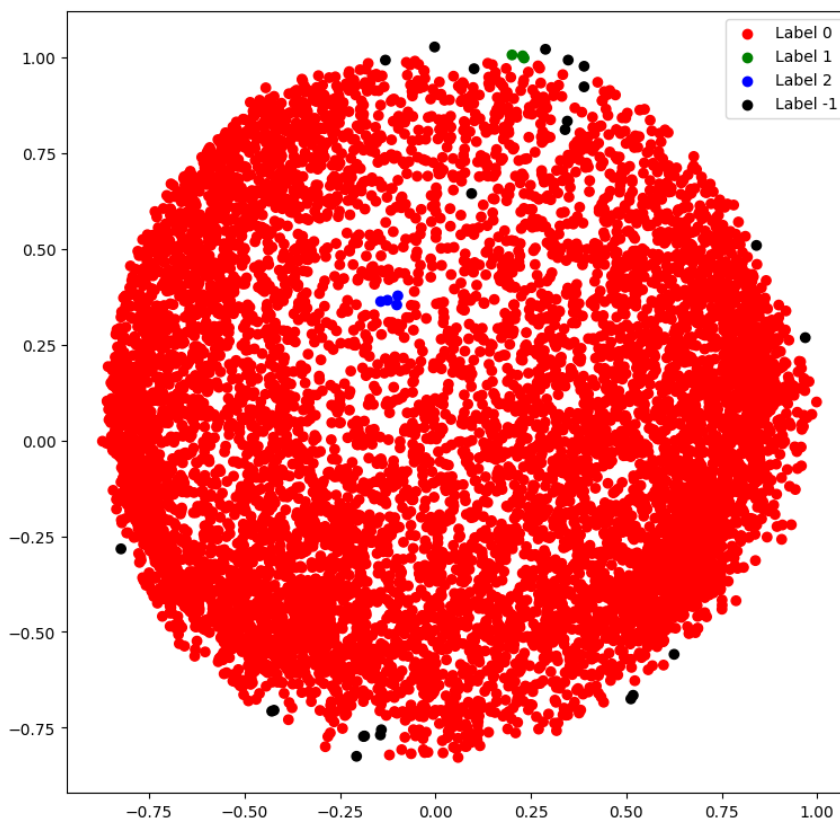
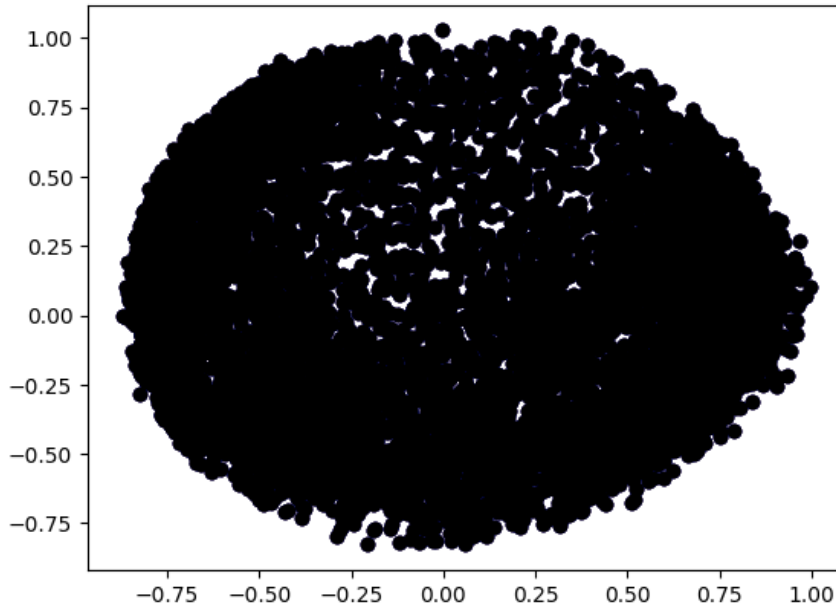
colours = {}
colours[0] = 'r'
colours[1] = 'g'
colours[2] = 'b'
colours[-1] = 'k'

cvec = [colours[label] for label in labels]

r = plt.scatter(X_principal['P1'], X_principal['P2'], color = 'r');
g = plt.scatter(X_principal['P1'], X_principal['P2'], color = 'g');
b = plt.scatter(X_principal['P1'], X_principal['P2'], color = 'b');
```

```
k = plt.scatter(X_principal['P1'], X_principal['P2'], color='k');  
plt.figure(figsize=(9, 9))  
plt.scatter(X_principal['P1'], X_principal['P2'], c=cvec)  
plt.legend((r, g, b, k), ('Label 0', 'Label 1', 'Label 2', 'Label -1'))  
plt.show()
```

Output –



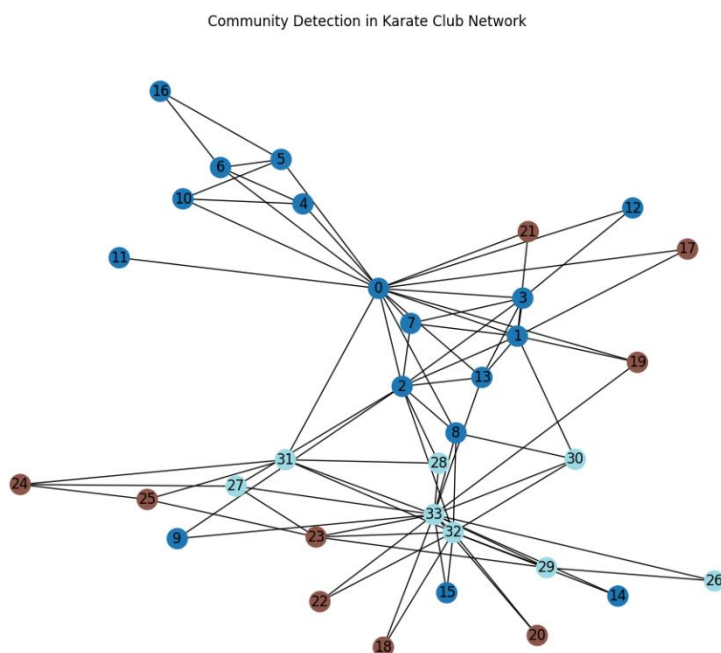
Program –

```
import networkx as nx
import matplotlib.pyplot as plt
from networkx.algorithms import community

G = nx.karate_club_graph()
communities = community.greedy_modularity_communities(G)
pos = nx.spring_layout(G)
plt.figure(figsize=(10, 8))
nx.draw(G, pos, node_color=[i for i, c in enumerate(communities) for _ in c],
        cmap=plt.cm.tab20, with_labels=True)
plt.title("Community Detection in Karate Club Network")
plt.show()

print("Communities identified:")
for i, community in enumerate(communities):
    print(f"Community {i + 1}: {community}")
```

Output –



```
Communities identified:
Community 1: frozenset({8, 14, 15, 18, 20, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33})
Community 2: frozenset({1, 2, 3, 7, 9, 12, 13, 17, 21})
Community 3: frozenset({0, 16, 19, 4, 5, 6, 10, 11})
```

Program –

```
import pandas as pd
import matplotlib.pyplot as plt

ad_data = pd.read_csv('Advertising.csv')
print(ad_data.head())
plt.figure(figsize=(10, 6))
# plt.hist(ad_data['Sales'], bins=20, color='blue', alpha=0.7, label='Sales')
plt.hist(ad_data['TV'], bins=20, color='green', alpha=0.7, label='TV')
plt.hist(ad_data['Radio'], bins=20, color='yellow', alpha=0.7, label='Radio')
plt.hist(ad_data['Newspaper'], bins=20, color='pink', alpha=0.7, label='Newspaper')
plt.xlabel('Engagement Metrics')
plt.ylabel('Frequency')
plt.title('Distribution of Ad Engagement Metrics')
plt.legend()
plt.show()
```

Output –

	TV	Radio	Newspaper	Sales
0	230.1	37.8	69.2	22.1
1	44.5	39.3	45.1	10.4
2	17.2	45.9	69.3	9.3
3	151.5	41.3	58.5	18.5
4	180.8	10.8	58.4	12.9

