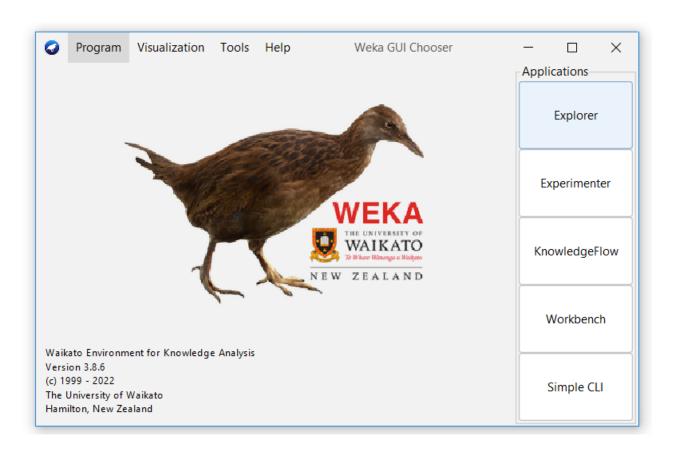
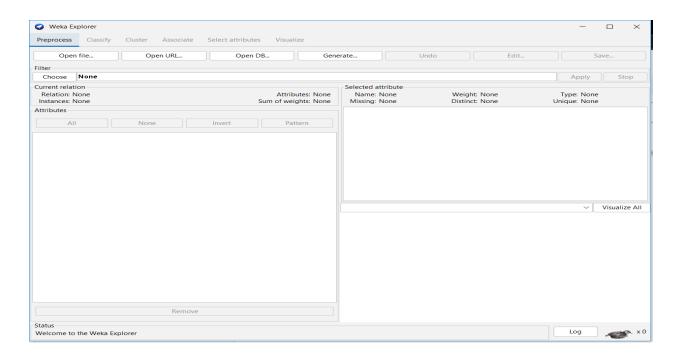
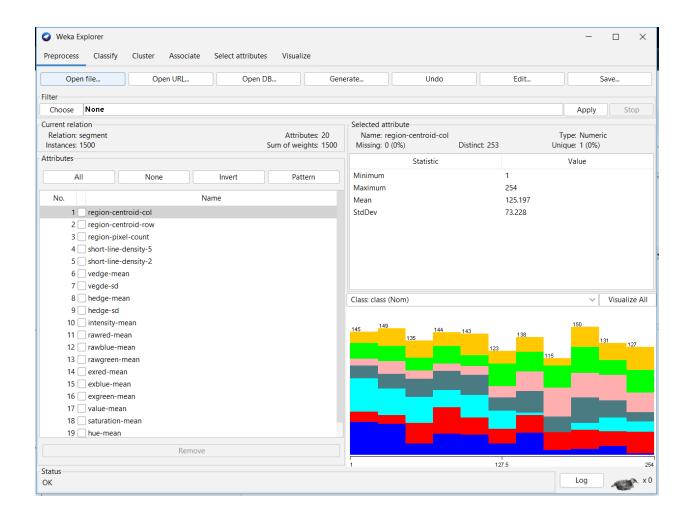
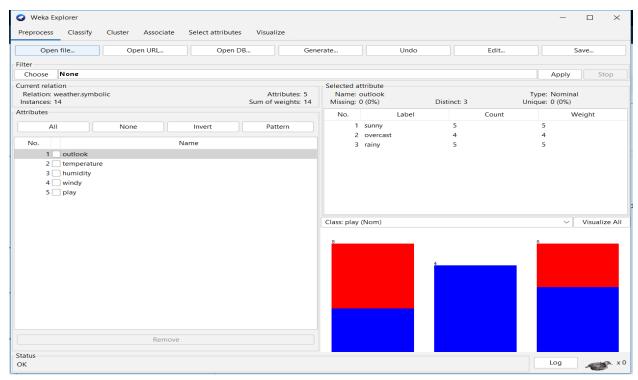
BUILD DATA WAREHOUSE AND EXPLORE WEKA







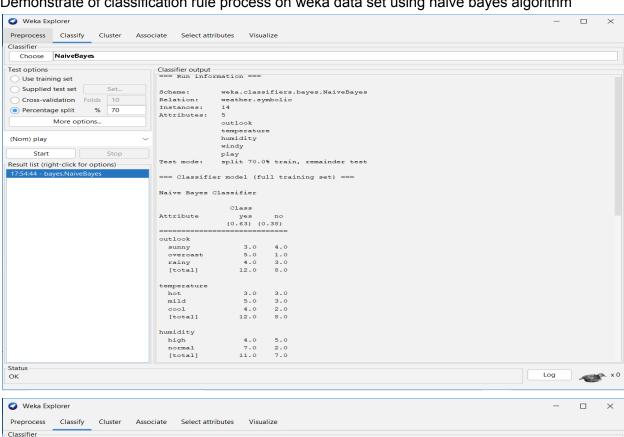
Perform data preprocessing task and demonstrate performing association rule mining on data sets

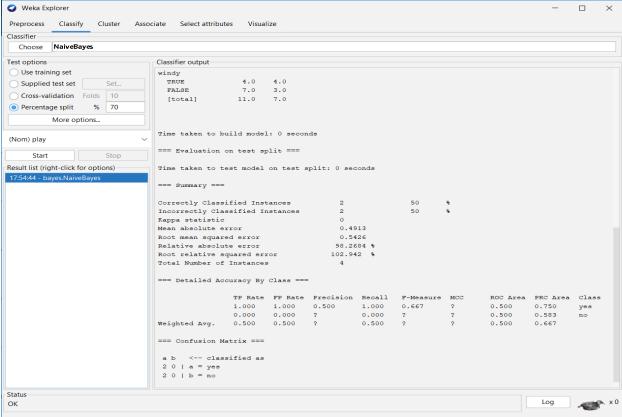


Association rule

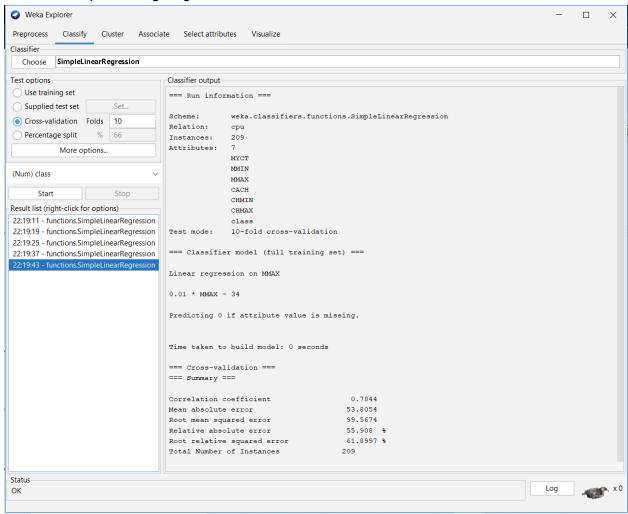


Demonstrate of classification rule process on weka data set using naive bayes algorithm

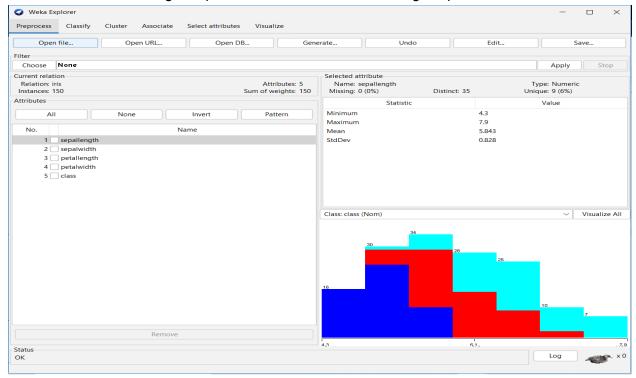




Demonstrate performing Regression on datasets



Demonstrate of clustering rule process on data set iris.arff using simple k-mean



=== Run information ===

Scheme: weka.clusterers.SimpleKMeans -init 0 -max-candidates 100 -periodic-pruning 10000 -min-density 2.0 -t1 -1.25 -t2 -1.0 -N 3 -A "weka.core.EuclideanDistance -R first-last" -I 500 -num-slots 1 -S 10

Relation: iris Instances: 150 Attributes: 5

> sepallength sepalwidth petallength petalwidth class

Test mode: split 66% train, remainder test

=== Clustering model (full training set) ===

kMeans

=====

Number of iterations: 3

Within cluster sum of squared errors: 7.817456892309574

Initial starting points (random):

Cluster 0: 6.1,2.9,4.7,1.4, Iris-versicolor Cluster 1: 6.2,2.9,4.3,1.3, Iris-versicolor Cluster 2: 6.9,3.1,5.1,2.3, Iris-virginica

Missing values globally replaced with mean/mode

Final cluster centroids:

Cluster#

Attribute	Full Data (150.0)	0 (50.0)	1 (50.0)	2 (50.0)	
========	========	=======	=======	=======	=======================================
sepallength	5.8433	5.936	5.006	6.588	
sepalwidth	3.054	2.77	3.418	2.974	
petallength	3.7587	4.26	1.464	5.552	
petalwidth	1.1987	1.326	0.244	2.026	
class	Iris-setosa Iri	s-versicolor	Iris-setosa	Iris-virginica	

Time taken to build model (full training data): 0 seconds

=== Model and evaluation on test split ===

kMeans

=====

Number of iterations: 3

Within cluster sum of squared errors: 5.344375826509504

Initial starting points (random):

Cluster 0: 4.8,3,1.4,0.3, Iris-setosa

Cluster 1: 6.7,3.1,4.7,1.5, Iris-versicolor Cluster 2: 5.6,3,4.1,1.3, Iris-versicolor

Missing values globally replaced with mean/mode

Final cluster centroids:

Cluster#

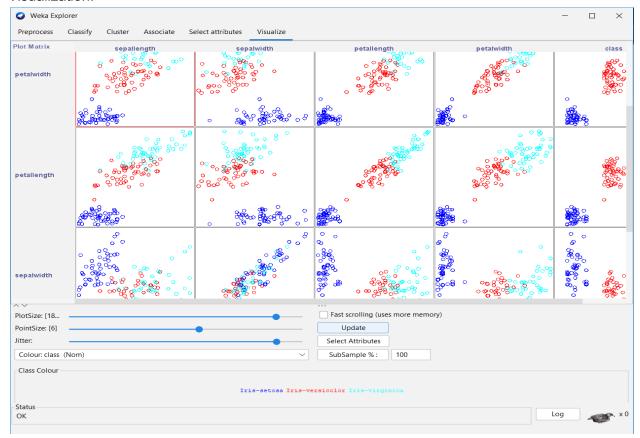
Attribute	Full Data	0	1	2			
	(99.0)	(35.0)	(33.0)	(31.0)			
========		======	======	=====	======	======	======
=======							
sepallength	5.8313	5.051	4 6.6	061	5.8871		
sepalwidth	3.0586	3.454	3 2.9	576	2.7194		
petallength	3.6848	1.477	1 5.50	697	4.171		
petalwidth	1.1657	0.257	1 1.98	379	1.3161		
class	Iris-setosa	Iris-setosa	Iris-viraini	ca Iris-ve	rsicolor		

Time taken to build model (percentage split): 0 seconds

Clustered Instances

- 0 15 (29%)
- 1 17 (33%)
- 2 19 (37%)

Visualization:



```
Write a program of Apriori algorithm using any programming language (implemented in Python)
#import required library
import pandas as pd
import numpy as np
from mlxtend.frequent patterns import association rules, apriori
#read the data from csv
df = pd.read csv('bread basket.csv')
# cleaning the item column
df['Item'] = df['Item'].str.strip()
df['Item'] = df['Item'].str.lower()
#reset index and group together
transactions str = df.groupby(['Transaction',
'Item'])['Item'].count().reset index(name = 'Count')
# making a mxn matrice where m=transaction and n=items and each row
represents whether the item was in the transaction or not
my basket = transactions str.pivot table(index='Transaction',
columns='Item', values='Count', aggfunc='sum').fillna(0)
# making a function which returns 0 or 1
# 0 means item was not in that transaction, 1 means item present in that
transaction
def encode(x):
   if x \le 0:
        return 0
    if x>=1:
        return 1
# applying the function to the dataset
my basket sets = my basket.applymap(encode)
# using the 'apriori algorithm' with min support=0.01 (1% of 9465)
# It means the item should be present in atleast 94 transaction out of
9465 transactions only when we considered that item in frequent itemset
frequent items = apriori(my basket sets, min support = 0.01, use colnames
```

= True)

```
# now making the rules from frequent itemset generated above
rules = association_rules(frequent_items, metric = "lift", min_threshold =
1)
rules.sort_values('confidence', ascending = False, inplace = True)
# arranging the data from highest to lowest with respect to 'confidence'
rules.sort_values('confidence', ascending=False)
```

Output:

index	antecedents	consequents	support	confidence	lift
30	frozenset({'toast'})	frozenset({'coffee'})			1.472431495
28	frozenset({'spanish brunch'})	frozenset({'coffee'})	0.010882198	0.598837209	1.2517655
19	frozenset({'medialuna'})	frozenset({'coffee'})	0.03518225	0.569230769	1.189878364
23	frozenset({'pastry'})	frozenset({'coffee'})	0.047543582	0.552147239	1.154168202
1	frozenset({'alfajores'})	frozenset({'coffee'})	0.019651347	0.540697674	1.130234869