Experiment 5

Ojas Patil

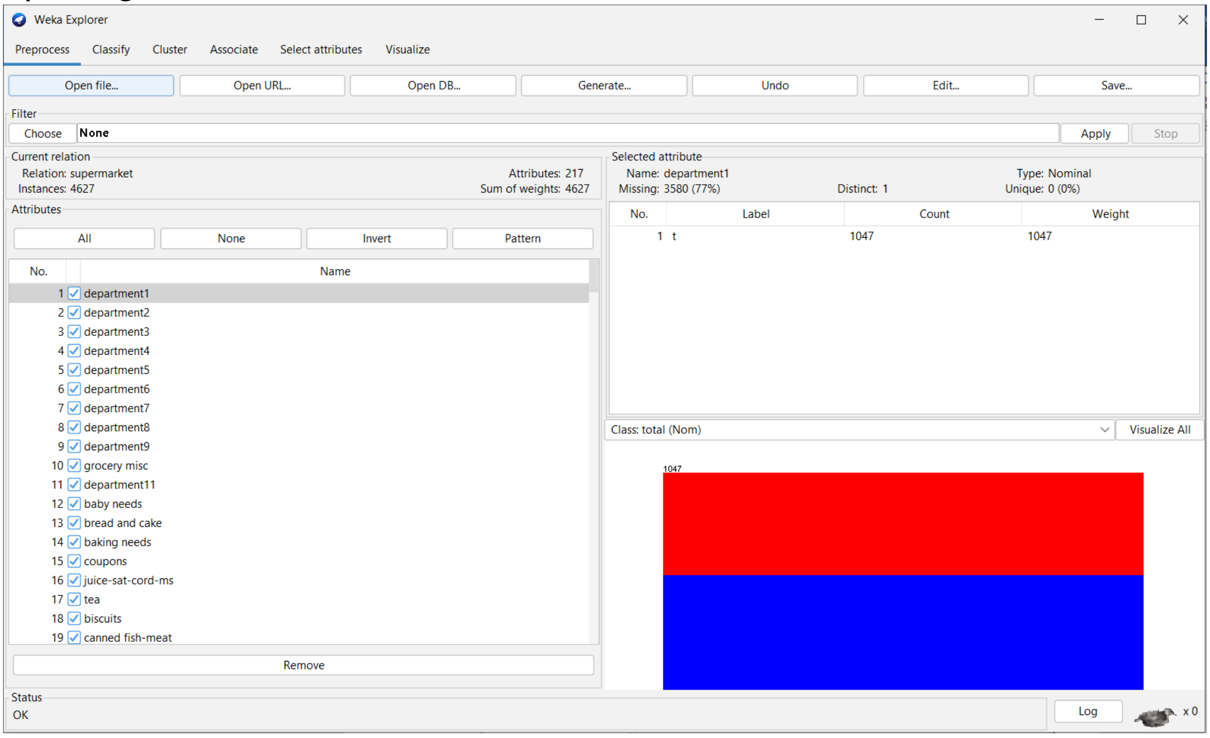
2019130048

TE COMPS

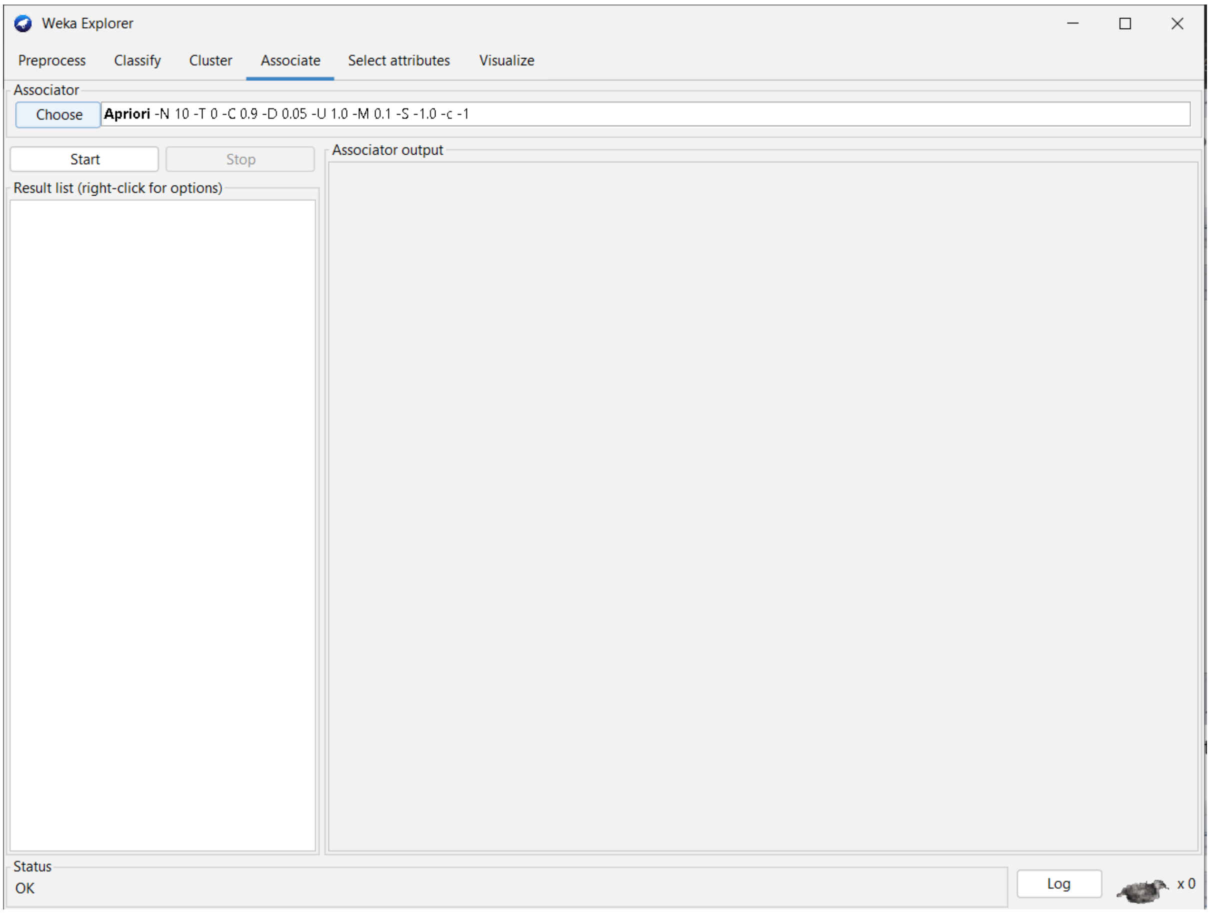
Aim: To apply Apriori algorithm to given dataset Association Rule mining with WEKA

Procedure:

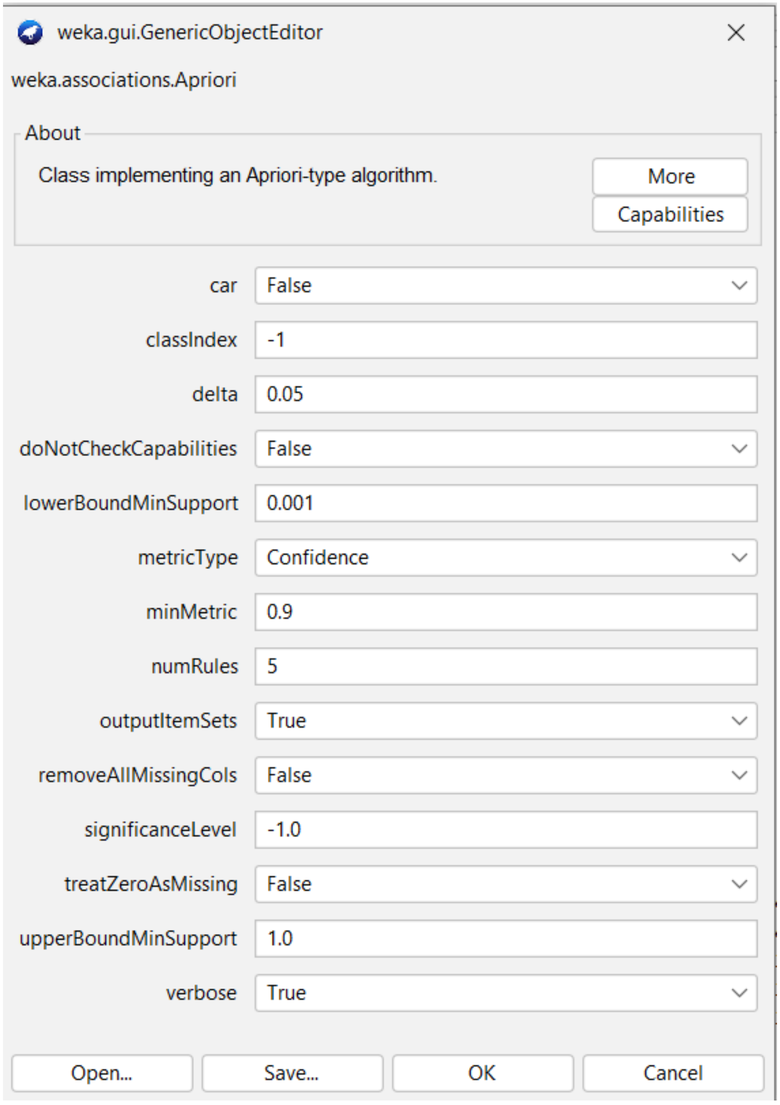
1. Open the concerned CSV file in WEKA. It will look like this after opening



2. Click on Associate tab and select 'Apriori' from drop down appeared after clicking 'Choose' button



3. Click on Choose and select Apriori algorithm
4. Now double click apriori algorithm to open option menu pop up where you have to set up appropriate values.



5. Now click start and WEKA will automatically process the data and return us the required output

```
Best rules found:

1. biscuits=t frozen foods=t fruit=t total=high 788 ==> bread and cake=t 723    <conf:(0.92)> lift:(1.27) lev:(0.03) [155] conv:(3.35)
2. baking needs=t biscuits=t fruit=t total=high 760 ==> bread and cake=t 696    <conf:(0.92)> lift:(1.27) lev:(0.03) [149] conv:(3.28)
3. baking needs=t frozen foods=t fruit=t total=high 770 ==> bread and cake=t 705    <conf:(0.92)> lift:(1.27) lev:(0.03) [150] conv:(3.27)
4. biscuits=t fruit=t vegetables=t total=high 815 ==> bread and cake=t 746    <conf:(0.92)> lift:(1.27) lev:(0.03) [159] conv:(3.26)
5. party snack foods=t fruit=t total=high 854 ==> bread and cake=t 779    <conf:(0.91)> lift:(1.27) lev:(0.04) [164] conv:(3.15)
```

Here, the output of WEKA shows the 5 association rules. These, indicates that bread and cake are always bought by buyers when total is generally high. Rules state that if a buyer buys biscuits, frozen foods, fruits and total is high then it is very likely that buyer will buy bread and cake. If a buyer buys baking needs, biscuits, fruits and total is high then it is very likely that buyer will buy bread and cake. If a buyer buys baking needs, frozen foods, fruits and total is high then it is very likely that buyer will buy bread and cake. These are all frequently bought items.

Exercise 1: (Refer the .ipynb file [here])

Exercise 2:

1. Create a .arff file for given dataset.

supermarket.arff - Notepad

File Edit Format View Help

```
@relation supermarket

@attribute A {1, 0}
@attribute B {1, 0}
@attribute C {1, 0}
@attribute D {1, 0}
@attribute E {1, 0}
@attribute K {1, 0}

@data
1, 1, 0, 1, 0, 1
1, 1, 1, 1, 1, 0
1, 1, 1, 0, 1, 0
1, 1, 0, 1, 0, 0
```

2. Load into WEKA and perform association rule mining.

```
1. B=1 4 ==> A=1 4    <conf:(1)> lift:(1) lev:(0) [0] conv:(0)
2. A=1 4 ==> B=1 4    <conf:(1)> lift:(1) lev:(0) [0] conv:(0)
3. D=1 3 ==> A=1 3    <conf:(1)> lift:(1) lev:(0) [0] conv:(0)
4. K=0 3 ==> A=1 3    <conf:(1)> lift:(1) lev:(0) [0] conv:(0)
5. D=1 3 ==> B=1 3    <conf:(1)> lift:(1) lev:(0) [0] conv:(0)
6. K=0 3 ==> B=1 3    <conf:(1)> lift:(1) lev:(0) [0] conv:(0)
7. B=1 D=1 3 ==> A=1 3    <conf:(1)> lift:(1) lev:(0) [0] conv:(0)
8. A=1 D=1 3 ==> B=1 3    <conf:(1)> lift:(1) lev:(0) [0] conv:(0)
9. D=1 3 ==> A=1 B=1 3    <conf:(1)> lift:(1) lev:(0) [0] conv:(0)
```

We observe that association rules that we determined using manual method, are exactly same as that of given by WEKA. I created and used a .arff file (See point 1)

Exercise 3:

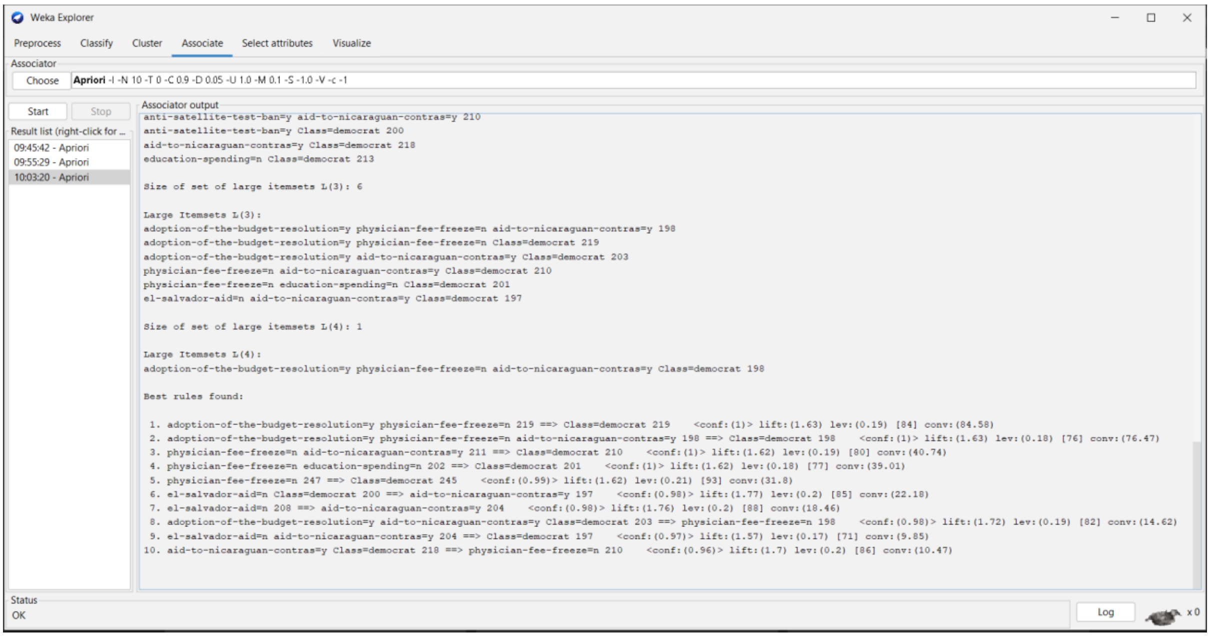
```
Best rules found:

 1. outlook=overcast 4 ==> play=yes 4    <conf:(1)> lift:(1.56) lev:(0.1) [1] conv:(1.43)
 2. temperature=cool 4 ==> humidity=normal 4    <conf:(1)> lift:(2) lev:(0.14) [2] conv:(2)
 3. humidity=normal windy=FALSE 4 ==> play=yes 4    <conf:(1)> lift:(1.56) lev:(0.1) [1] conv:(1.43)
 4. outlook=sunny play=no 3 ==> humidity=high 3    <conf:(1)> lift:(2) lev:(0.11) [1] conv:(1.5)
 5. outlook=sunny humidity=high 3 ==> play=no 3    <conf:(1)> lift:(2.8) lev:(0.14) [1] conv:(1.93)
 6. outlook=rainy play=yes 3 ==> windy=FALSE 3    <conf:(1)> lift:(1.75) lev:(0.09) [1] conv:(1.29)
 7. outlook=rainy windy=FALSE 3 ==> play=yes 3    <conf:(1)> lift:(1.56) lev:(0.08) [1] conv:(1.07)
 8. temperature=cool play=yes 3 ==> humidity=normal 3    <conf:(1)> lift:(2) lev:(0.11) [1] conv:(1.5)
 9. outlook=sunny temperature=hot 2 ==> humidity=high 2    <conf:(1)> lift:(2) lev:(0.07) [1] conv:(1)
10. temperature=hot play=no 2 ==> outlook=sunny 2    <conf:(1)> lift:(2.8) lev:(0.09) [1] conv:(1.29)
```

Performed association rule mining on the weather dataset that I found online. Unlike decision tree, it has no target attribute. Instead, it tries to associate all the columns. In decision tree, depending upon values of outlook, temp, humidity and windy columns, values of play column is predicted. In association rule, values of play column is also considered and rest columns can also be predicted.

For example, in rule 1, it states that if outlook is overcast then we can play. But in rule 4, it states that, if outlook is sunny and you are playing then humidity must be high.

Exercise 4:



Here, number of members of Democratic party are more in number as compared to members of Republic party which ultimately increases the probability of their appearance in the most frequent item sets. Hence, we see no member of republic party in the rules. Probably if we increase the number of members of Republic party, we may find few entries in rules.

Exercise 5:

1. minConfidence 0.9:

```
Best rules found:
```

At minConf = 0.9 with minsupport 0.3, no rule is generated.

2. minConfidence 0.6:

```
Best rules found:

 1. biscuits=t 2605 ==> bread and cake=t 2083    <conf:(0.8)> lift:(1.11) lev:(0.04) [208] conv:(1.4)
 2. milk-cream=t 2939 ==> bread and cake=t 2337    <conf:(0.8)> lift:(1.1) lev:(0.05) [221] conv:(1.37)
 3. fruit=t 2962 ==> bread and cake=t 2325    <conf:(0.78)> lift:(1.09) lev:(0.04) [193] conv:(1.3)
 4. baking needs=t 2795 ==> bread and cake=t 2191    <conf:(0.78)> lift:(1.09) lev:(0.04) [179] conv:(1.29)
 5. frozen foods=t 2717 ==> bread and cake=t 2129    <conf:(0.78)> lift:(1.09) lev:(0.04) [173] conv:(1.29)
 6. vegetables=t 2961 ==> bread and cake=t 2298    <conf:(0.78)> lift:(1.08) lev:(0.04) [167] conv:(1.25)
 7. vegetables=t 2961 ==> fruit=t 2207    <conf:(0.75)> lift:(1.16) lev:(0.07) [311] conv:(1.41)
 8. fruit=t 2962 ==> vegetables=t 2207    <conf:(0.75)> lift:(1.16) lev:(0.07) [311] conv:(1.41)
 9. bread and cake=t 3330 ==> milk-cream=t 2337    <conf:(0.7)> lift:(1.1) lev:(0.05) [221] conv:(1.22)
10. bread and cake=t 3330 ==> fruit=t 2325    <conf:(0.7)> lift:(1.09) lev:(0.04) [193] conv:(1.19)
```

At minConf = 0.6 with minSupport 0.3, we can see generated rules

Conclusion:

Association rule mining finds interesting associations and relationships among large sets of data items. This rule shows how frequently a itemset occurs in a transaction. Given a set of transactions, we can find rules that will predict the occurrence of an item based on the occurrences of other items in the transaction.

Apriori algorithm allows us to mine the frequent itemset in order to generate association rule between them. The main limitation is time required to hold a vast number of candidate sets with much frequent item sets, low minimum support or large item sets i.e. it is not an efficient approach for large number of datasets.