Sardar Patel Institute of Technology, Mumbai
Department of Electronics and Telecommunication Engineering
B.E. Sem-VII

Experiment 7: Apriori Algorithm and Association rule mining with WEKA

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Objective:
Apply Apriori Algorithm to the given dataset

Platform:
WeKa

Given problem statements, code and output:

Consider the dataset “Groceries” and apply apriori algorithm on it. What are the first 5 rules

generated when the min support is 0.001 (0.1%) and min confidence is 0.9 (90%) .

Exercise 1:
The 'database' below has four transactions. What association rules can be found in this set, if the minimum support (i.e coverage) is 60% and the minimum confidence (i.e. accuracy) is 80% ?
Trans_id Itemlist
T1 {K, A, D, B}
T2 {D, A C, E, B}
T3 {C, A, B, E}
T4 {B, A, D}
Hint:
Make a tabular and binary representation of the data in order to better see the relationship

between Items. First generate all item sets with minimum support of 60%. Then form rules

and

calculate their confidence base on the conditional probability P(B|A) = |B∩A| / |A|. Remember to only take the item sets from the previous phase whose support is 60% or more.

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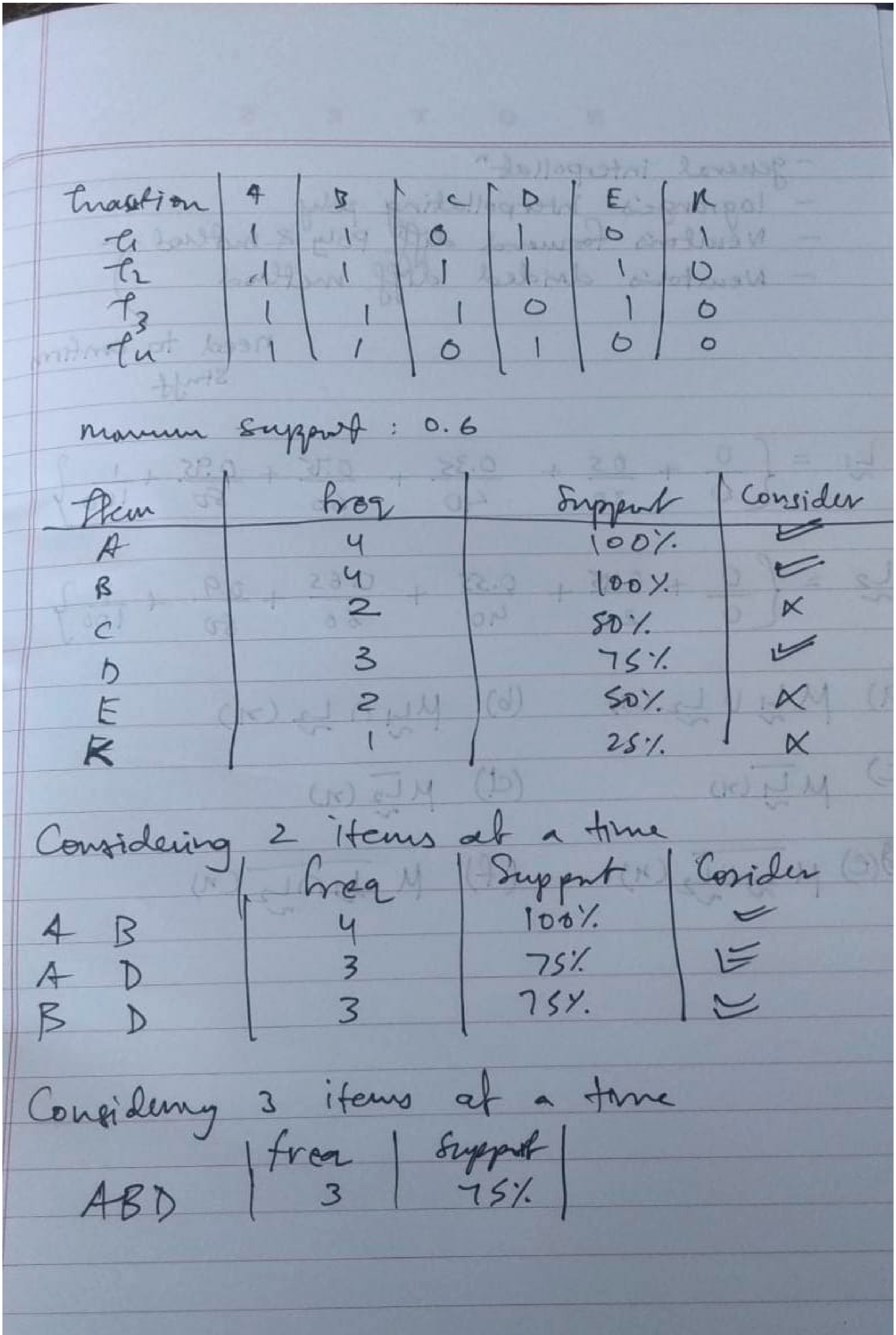
Hand-calculated solution



Trasation	A	B	C	D	E	K
T_1	1	1	0	1	0	1
T_2	1	1	1	1	1	0
T_3	1	1	1	0	1	0
T_4	1	1	0	1	0	0

minimum support : 0.6

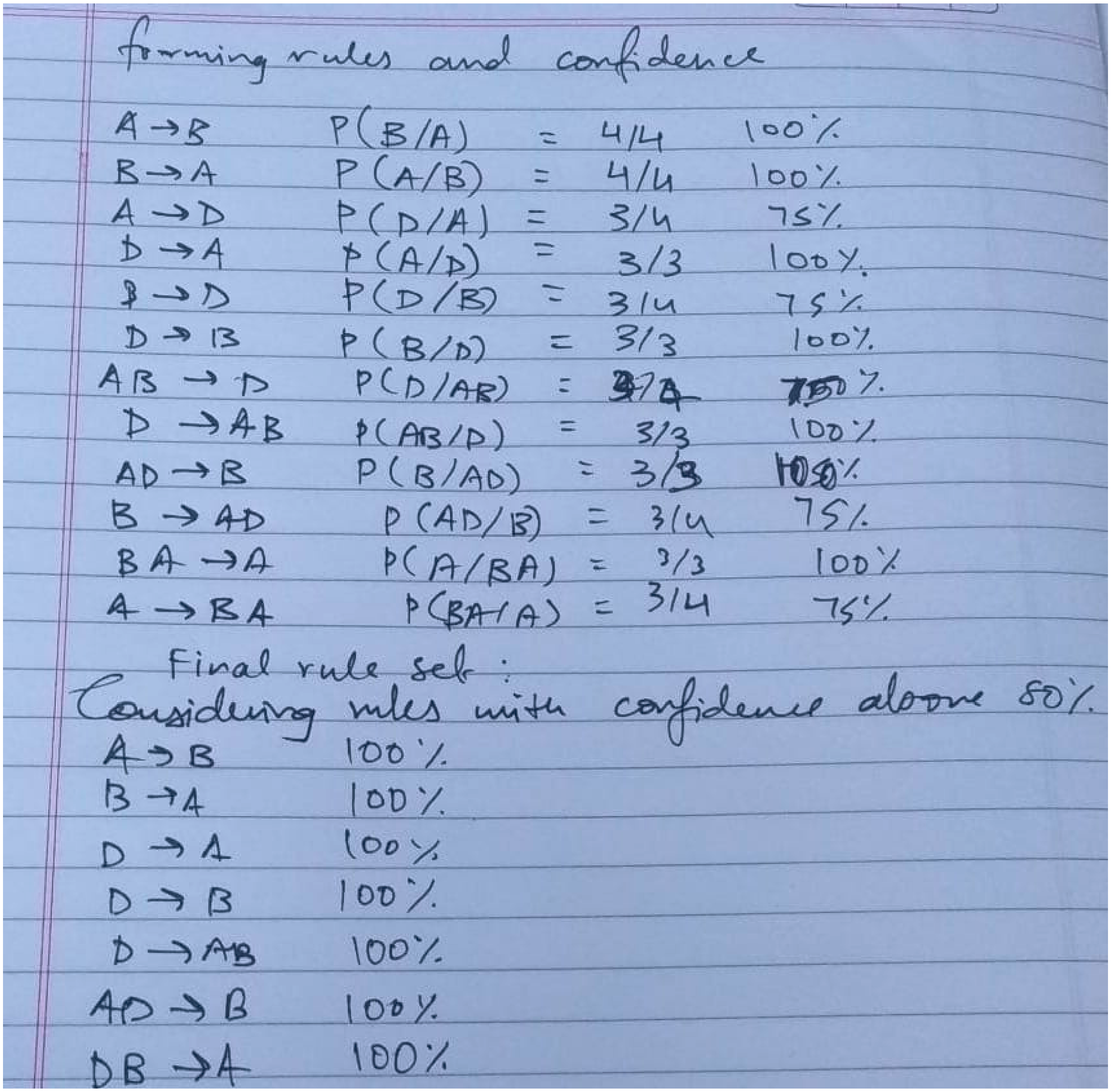
Item	freq	Support	Consider
A	4	100%	✓
B	4	100%	✓
C	2	50%	✗
D	3	75%	✓
E	2	50%	✗
K	1	25%	✗

Considering 2 items at a time

	freq	Support	Consider
A B	4	100%	✓
A D	3	75%	✓
B D	3	75%	✓

Considering 3 items at a time

	freq	Support
ABD	3	75%



forming rules and confidence

A → B	P(B/A)	=	4/4	100%
B → A	P(A/B)	=	4/4	100%
A → D	P(D/A)	=	3/4	75%
D → A	P(A/D)	=	3/3	100%
B → D	P(D/B)	=	3/4	75%
D → B	P(B/D)	=	3/3	100%
AB → D	P(D/AB)	=	3/4	75%
D → AB	P(AB/D)	=	3/3	100%
AD → B	P(B/AD)	=	3/3	100%
B → AD	P(AD/B)	=	3/4	75%
BA → A	P(A/BA)	=	3/3	100%
A → BA	P(BA/A)	=	3/4	75%

Final rule set :

Considering rules with confidence above 80%.

A → B	100%
B → A	100%
D → A	100%
D → B	100%
D → AB	100%
AD → B	100%
DB → A	100%

Exercise:2

Input file generation and Initial experiments with Weka's association rule discovery.

1. Launch Weka and try to do the calculations you performed manually in the previous exercise.
Use
the apriori algorithm for generating the association rules.

The file may be given to Weka in e.g. two different formats. They are called ARFF
(attribute-relation
file format) and CSV (comma separated values). Both are given below:

ARFF:

```
@relation exercise
 @attribute exista {TRUE, FALSE}
 ...
@data
```

TRUE,TRUE,FALSE,TRUE,FALSE,TRUE

...

...

CSV:

exista,existb,existc,existd,existe,existk

TRUE,TRUE,FALSE,TRUE,FALSE,TRUE

...

...

3

2. Once Data is loaded Click Associate Tab on top of the window.

3. Left click the field of Associator, choose Show Property from the drop down list. The property window of Apriori opens.

4. Weka runs an Apriori-type algorithm to find association rules, but this algorithm is not exact the same one as we discussed in class.

a. The min. support is not fixed. This algorithm starts with min. support as upperBoundMinSupport (default 1.0 = 100%), iteratively decrease it by delta (default 0.05 = 5%). Note that upperBoundMinSupport is decreased by delta before the basic Apriori algorithm is run for the first time.

b. The algorithm stops when lowerBoundMinSupport (default 0.1 = 10%) is reached, or required number of rules – numRules (default value 10) have been generated.

c. c. Rules generated are ranked by metricType (default Confidence). Only rules with score higher than minMetric (default 0.9 for Confidence) are considered and delivered as the output.

d. If you choose to show the all frequent itemsets found, outputItemSets should be set as True.

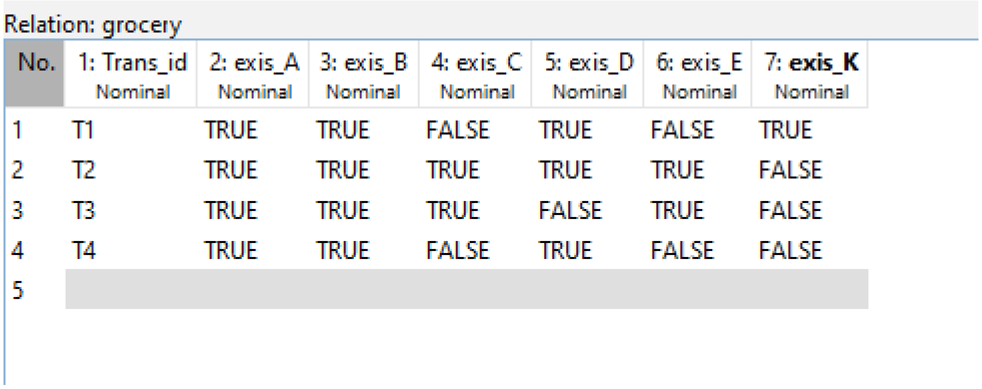
5. Click Start button on the left of the window, the algorithm begins to run. The output is showing in the right window.

Did you succeed? Are the results the same as in your calculations? What kind of file did you use as input?

Yes the results are same as my calculations.

The file used as an input is a CSV file as the dataset.

Dataset:

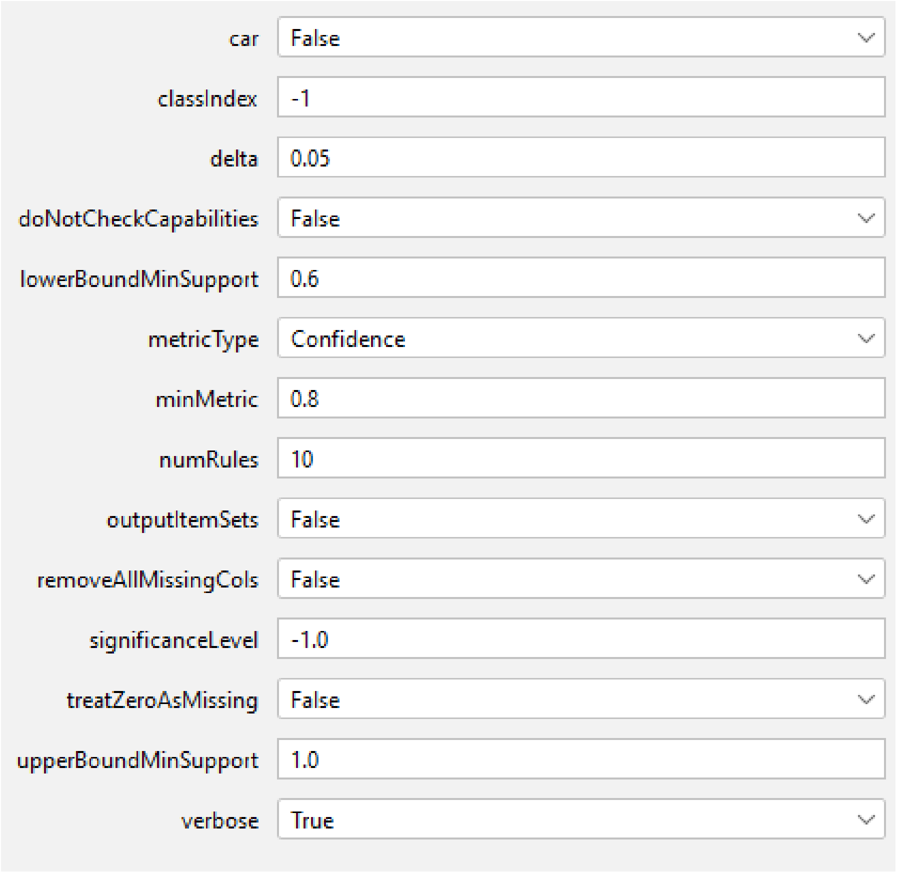


Relation: grocery

No.	1: Trans_id Nominal	2: exis_A Nominal	3: exis_B Nominal	4: exis_C Nominal	5: exis_D Nominal	6: exis_E Nominal	7: **exis_K** Nominal
1	T1	TRUE	TRUE	FALSE	TRUE	FALSE	TRUE
2	T2	TRUE	TRUE	TRUE	TRUE	TRUE	FALSE
3	T3	TRUE	TRUE	TRUE	FALSE	TRUE	FALSE
4	T4	TRUE	TRUE	FALSE	TRUE	FALSE	FALSE
5							

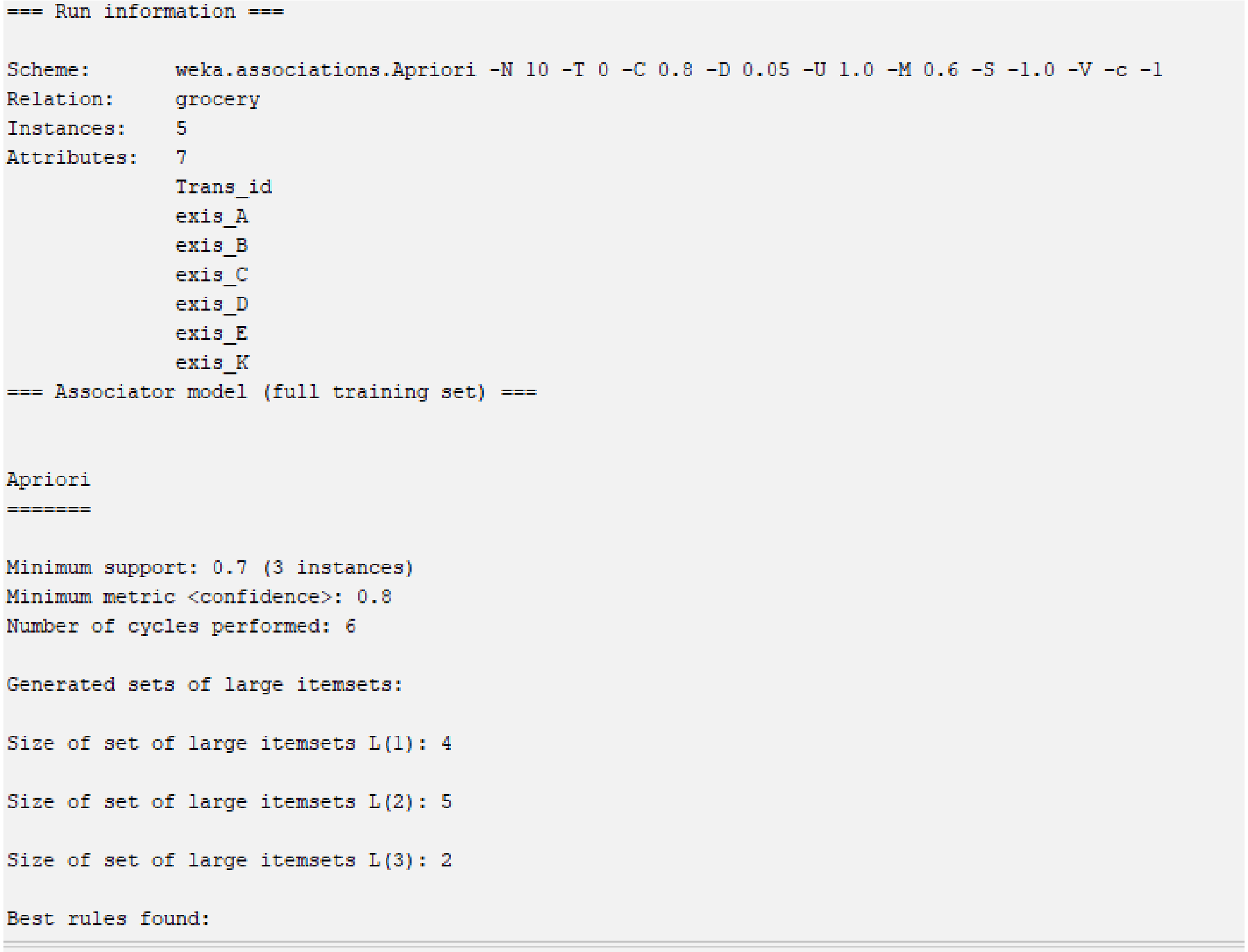
Output:

Properties

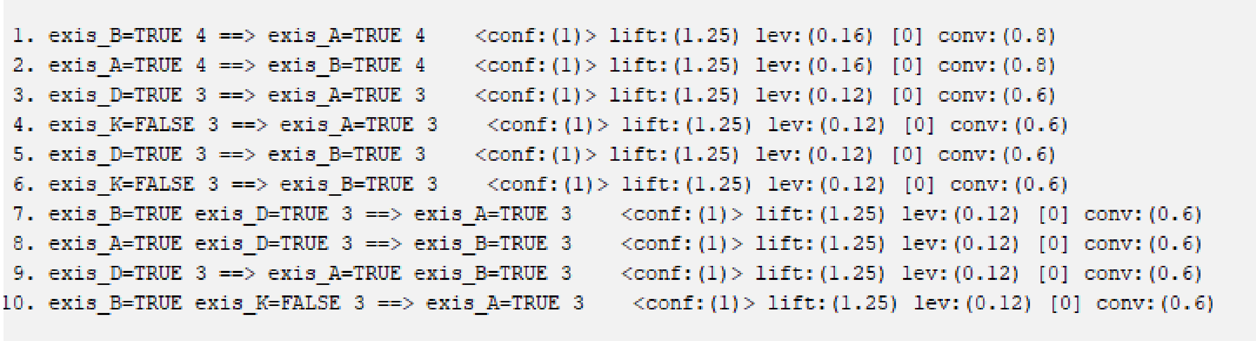


car	False
classIndex	-1
delta	0.05
doNotCheckCapabilities	False
lowerBoundMinSupport	0.6
metricType	Confidence
minMetric	0.8
numRules	10
outputItemSets	False
removeAllMissingCols	False
significanceLevel	-1.0
treatZeroAsMissing	False
upperBoundMinSupport	1.0
verbose	True

:



```
=== Run information ===

Scheme:       weka.associations.Apriori -N 10 -T 0 -C 0.8 -D 0.05 -U 1.0 -M 0.6 -S -1.0 -V -c -1
Relation:     grocery
Instances:    5
Attributes:   7
              Trans_id
              exis_A
              exis_B
              exis_C
              exis_D
              exis_E
              exis_K
=== Associator model (full training set) ===


Apriori
=======

Minimum support: 0.7 (3 instances)
Minimum metric <confidence>: 0.8
Number of cycles performed: 6

Generated sets of large itemsets:

Size of set of large itemsets L(1): 4

Size of set of large itemsets L(2): 5

Size of set of large itemsets L(3): 2

Best rules found:
```



```
 1. exis_B=TRUE 4 ==> exis_A=TRUE 4    <conf:(1)> lift:(1.25) lev:(0.16) [0] conv:(0.8)
 2. exis_A=TRUE 4 ==> exis_B=TRUE 4    <conf:(1)> lift:(1.25) lev:(0.16) [0] conv:(0.8)
 3. exis_D=TRUE 3 ==> exis_A=TRUE 3    <conf:(1)> lift:(1.25) lev:(0.12) [0] conv:(0.6)
 4. exis_K=FALSE 3 ==> exis_A=TRUE 3    <conf:(1)> lift:(1.25) lev:(0.12) [0] conv:(0.6)
 5. exis_D=TRUE 3 ==> exis_B=TRUE 3    <conf:(1)> lift:(1.25) lev:(0.12) [0] conv:(0.6)
 6. exis_K=FALSE 3 ==> exis_B=TRUE 3    <conf:(1)> lift:(1.25) lev:(0.12) [0] conv:(0.6)
 7. exis_B=TRUE exis_D=TRUE 3 ==> exis_A=TRUE 3    <conf:(1)> lift:(1.25) lev:(0.12) [0] conv:(0.6)
 8. exis_A=TRUE exis_D=TRUE 3 ==> exis_B=TRUE 3    <conf:(1)> lift:(1.25) lev:(0.12) [0] conv:(0.6)
 9. exis_D=TRUE 3 ==> exis_A=TRUE exis_B=TRUE 3    <conf:(1)> lift:(1.25) lev:(0.12) [0] conv:(0.6)
10. exis_B=TRUE exis_K=FALSE 3 ==> exis_A=TRUE 3    <conf:(1)> lift:(1.25) lev:(0.12) [0] conv:(0.6)
```

Exercise 3:

Mining Association Rule with WEKA Explorer – Weather dataset

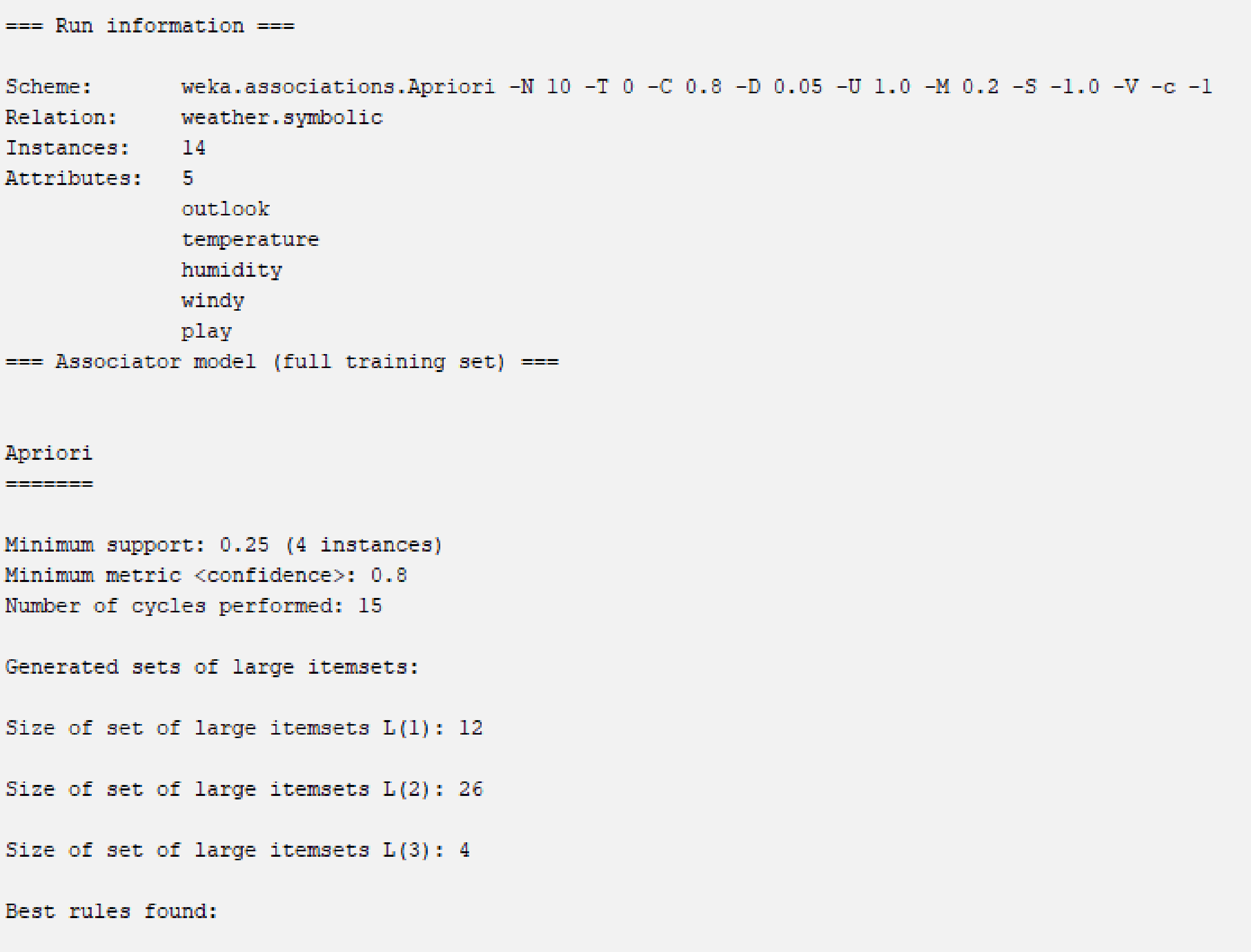
1. To get a feel for how to apply Apriori to prepared data set, start by mining association rules from the weather.nominal.arff data set of Lab One. Note that Apriori algorithm expects data that is purely nominal: If present, numeric attributes must be discretized first.

2. Like in the previous example choose Associate and Click Start button on the left of the window, the algorithm begins to run. The output is showing in the right window.

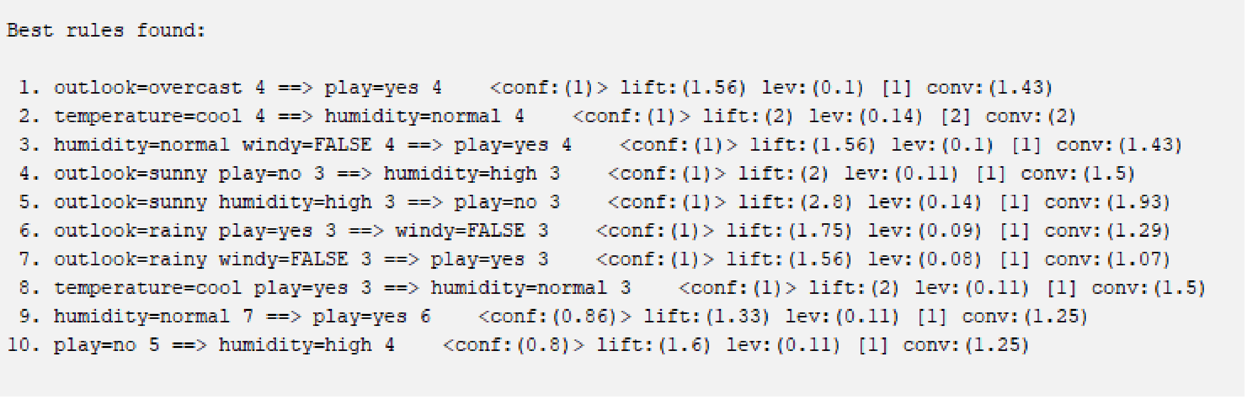
3. You could re-run Apriori algorithm by selecting different parameters, such as

lowerBoundMinSupport, minMetric (min. confidence level), and different evaluation metric confidence vs.lift),and so on.

Below rules have been formed with min Support: 0.2 and confidence:0.8

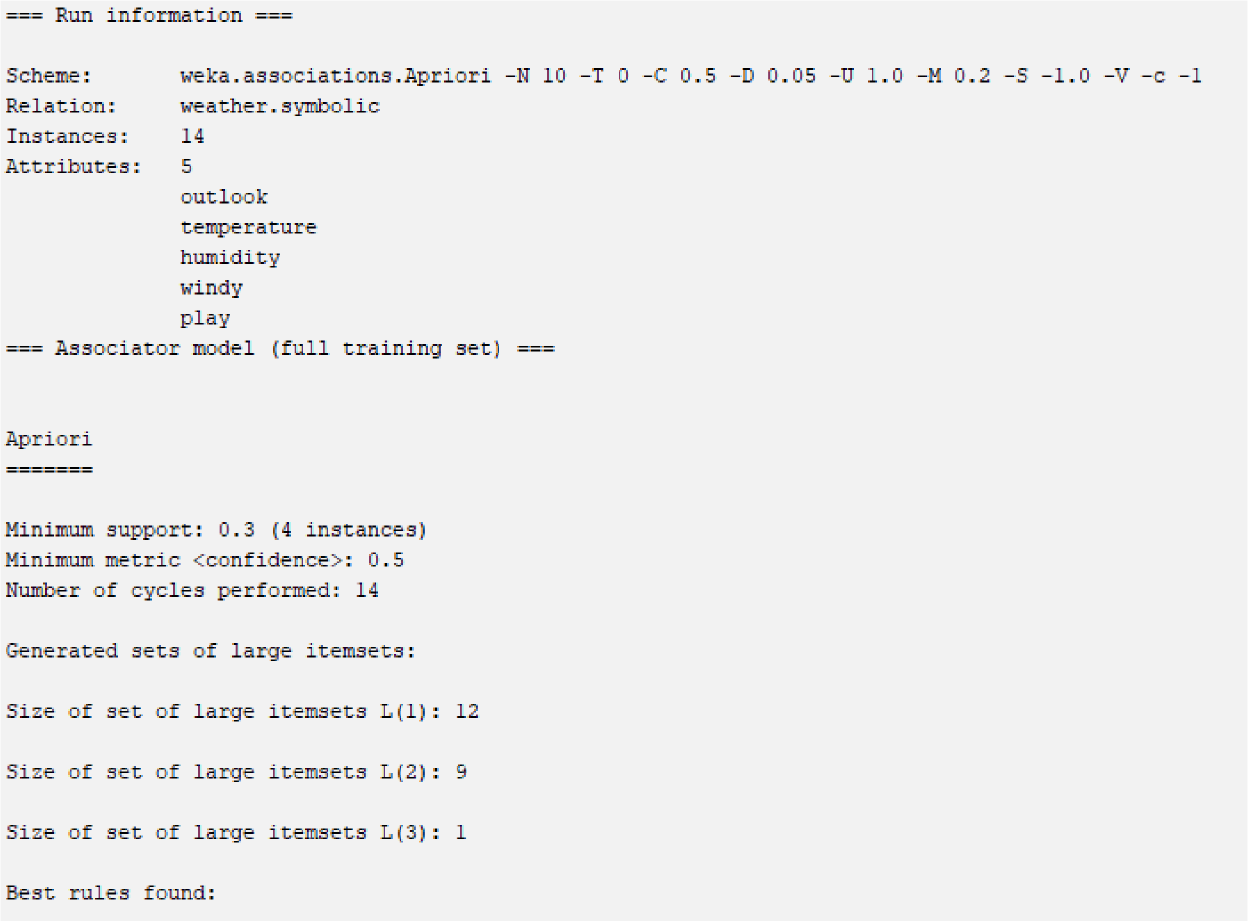


```
=== Run information ===

Scheme:       weka.associations.Apriori -N 10 -T 0 -C 0.8 -D 0.05 -U 1.0 -M 0.2 -S -1.0 -V -c -1
Relation:     weather.symbolic
Instances:    14
Attributes:   5
              outlook
              temperature
              humidity
              windy
              play
=== Associator model (full training set) ===


Apriori
=======

Minimum support: 0.25 (4 instances)
Minimum metric <confidence>: 0.8
Number of cycles performed: 15

Generated sets of large itemsets:

Size of set of large itemsets L(1): 12

Size of set of large itemsets L(2): 26

Size of set of large itemsets L(3): 4

Best rules found:
```

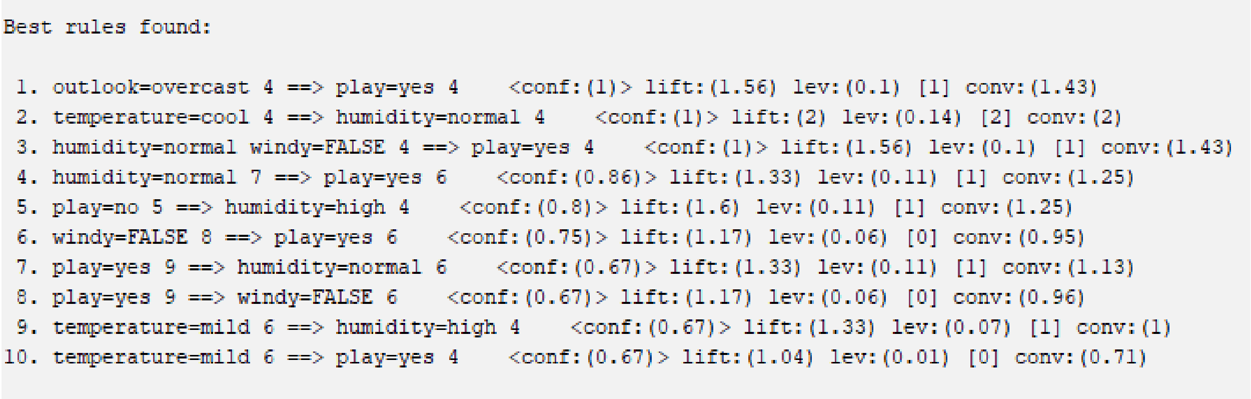


```
Best rules found:

 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. humidity=normal 7 ==> play=yes 6    <conf:(0.86)> lift:(1.33) lev:(0.11) [1] conv:(1.25)
10. play=no 5 ==> humidity=high 4    <conf:(0.8)> lift:(1.6) lev:(0.11) [1] conv:(1.25)
```

Changing the parameters:
With minSupport:0.2 and confidence:0.5



```
=== Run information ===

Scheme:       weka.associations.Apriori -N 10 -T 0 -C 0.5 -D 0.05 -U 1.0 -M 0.2 -S -1.0 -V -c -1
Relation:     weather.symbolic
Instances:    14
Attributes:   5
              outlook
              temperature
              humidity
              windy
              play
=== Associator model (full training set) ===


Apriori
=======

Minimum support: 0.3 (4 instances)
Minimum metric <confidence>: 0.5
Number of cycles performed: 14

Generated sets of large itemsets:

Size of set of large itemsets L(1): 12

Size of set of large itemsets L(2): 9

Size of set of large itemsets L(3): 1

Best rules found:
```



```
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. humidity=normal 7 ==> play=yes 6    <conf:(0.86)> lift:(1.33) lev:(0.11) [1] conv:(1.25)
 5. play=no 5 ==> humidity=high 4    <conf:(0.8)> lift:(1.6) lev:(0.11) [1] conv:(1.25)
 6. windy=FALSE 8 ==> play=yes 6    <conf:(0.75)> lift:(1.17) lev:(0.06) [0] conv:(0.95)
 7. play=yes 9 ==> humidity=normal 6    <conf:(0.67)> lift:(1.33) lev:(0.11) [1] conv:(1.13)
 8. play=yes 9 ==> windy=FALSE 6    <conf:(0.67)> lift:(1.17) lev:(0.06) [0] conv:(0.96)
 9. temperature=mild 6 ==> humidity=high 4    <conf:(0.67)> lift:(1.33) lev:(0.07) [1] conv:(1)
10. temperature=mild 6 ==> play=yes 4    <conf:(0.67)> lift:(1.04) lev:(0.01) [0] conv:(0.71)
```

The aforementioned outcomes demonstrate that the best rules also include the rules with a confidence level of 0.67.A person can play when the temperature is comfortable and cool. When the humidity is excessive in the first scenario, the person does not play. In contrast, the individual plays when the humidity is high and the temperature is moderate with a 0.67 confidence level.

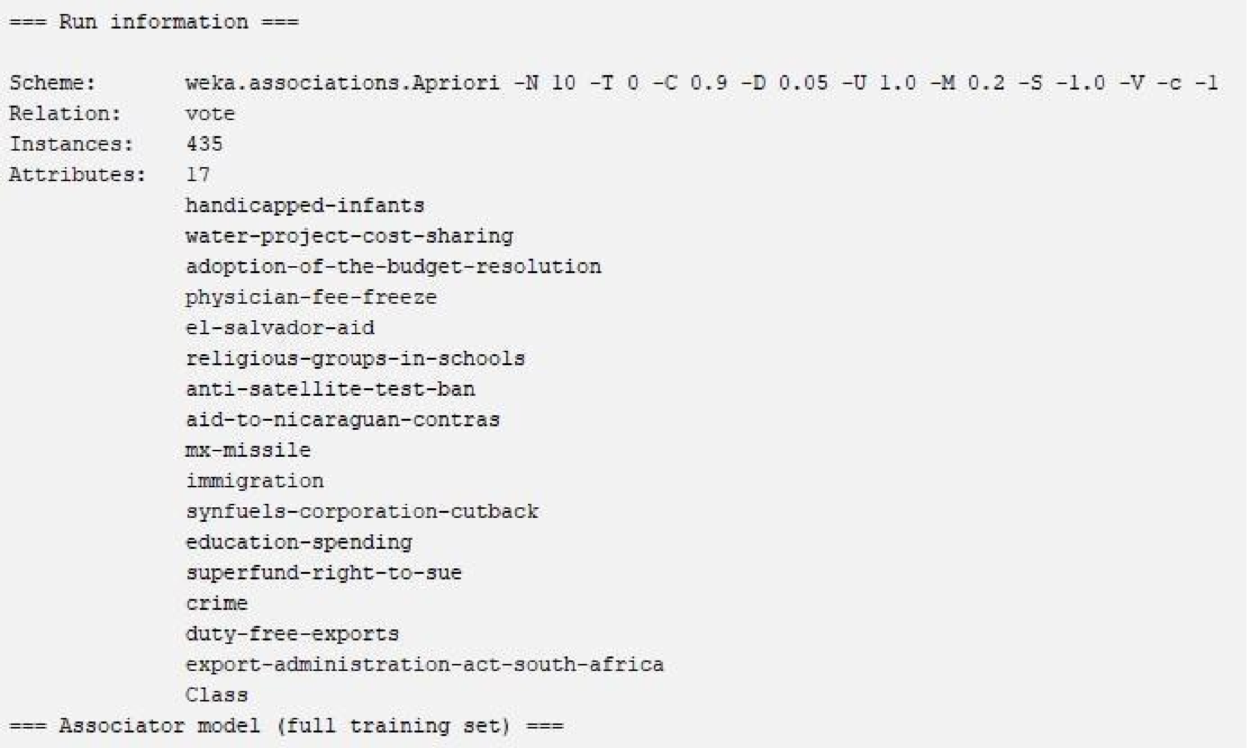
Exercise 4:

Mining Association Rule with WEKA Explorer – Vote

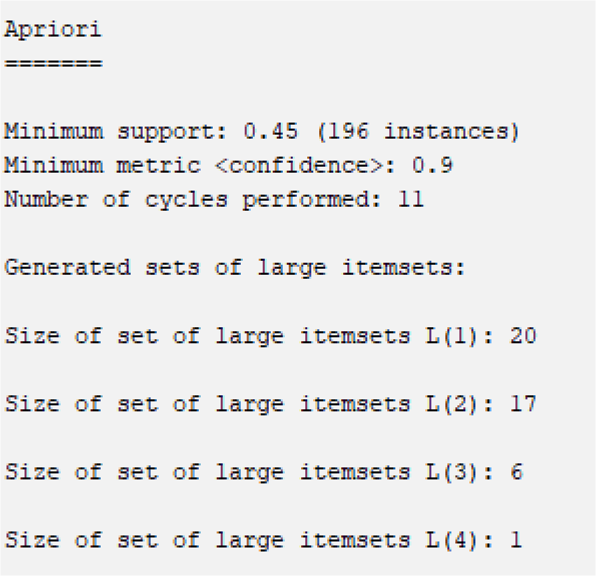
Now consider a real-world dataset, vote.arff, which gives the votes of 435 U.S. congressmen on 16

key issues gathered in the mid-1980s, and also includes their party affiliation as a binary attribute.
Association-rule mining can also be applied to this data to seek interesting associations.

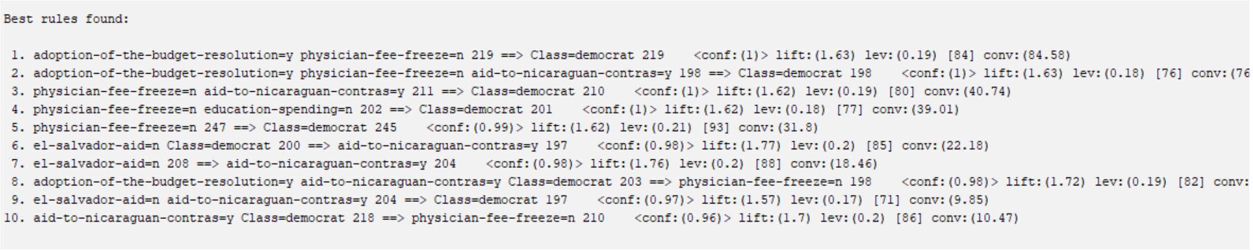
Load data at the Preprocess tab. Click the Open file button to bring up a standard dialog through which
you can select a file. Choose the vote.arff file. To see the original dataset, click the Edit button, a viewer window opens with dataset loaded. This is a purely nominal dataset with some missing values
(corresponding to abstentions).
Task 1. Run Apriori on this data with default settings. Comment on the rules that are generated. Several of them are quite similar. How are their support and confidence values related?



```
=== Run information ===

Scheme:       weka.associations.Apriori -N 10 -T 0 -C 0.9 -D 0.05 -U 1.0 -M 0.2 -S -1.0 -V -c -1
Relation:     vote
Instances:    435
Attributes:   17
              handicapped-infants
              water-project-cost-sharing
              adoption-of-the-budget-resolution
              physician-fee-freeze
              el-salvador-aid
              religious-groups-in-schools
              anti-satellite-test-ban
              aid-to-nicaraguan-contras
              mx-missile
              immigration
              synfuels-corporation-cutback
              education-spending
              superfund-right-to-sue
              crime
              duty-free-exports
              export-administration-act-south-africa
              Class
=== Associator model (full training set) ===
```



```
Apriori
=======

Minimum support: 0.45 (196 instances)
Minimum metric <confidence>: 0.9
Number of cycles performed: 11

Generated sets of large itemsets:

Size of set of large itemsets L(1): 20

Size of set of large itemsets L(2): 17

Size of set of large itemsets L(3): 6

Size of set of large itemsets L(4): 1
```



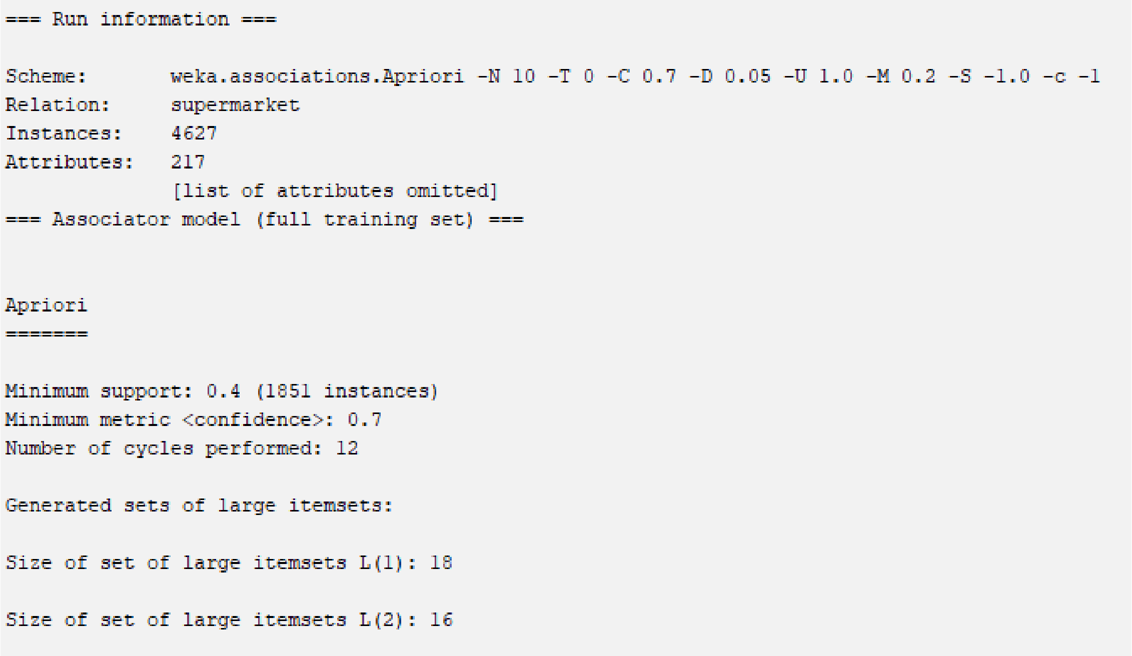
```
Best rules found:

 1. adoption-of-the-budget-resolution=y physician-fee-freeze=n 219 ==> Class=democrat 219    <conf:(1)> lift:(1.63) lev:(0.19) [84] conv:(84.58)
 2. adoption-of-the-budget-resolution=y physician-fee-freeze=n aid-to-nicaraguan-contras=y 198 ==> Class=democrat 198    <conf:(1)> lift:(1.63) lev:(0.18) [76] conv:(76
 3. physician-fee-freeze=n aid-to-nicaraguan-contras=y 211 ==> Class=democrat 210    <conf:(1)> lift:(1.62) lev:(0.19) [80] conv:(40.74)
 4. physician-fee-freeze=n education-spending=n 202 ==> Class=democrat 201    <conf:(1)> lift:(1.62) lev:(0.18) [77] conv:(39.01)
 5. physician-fee-freeze=n 247 ==> Class=democrat 245    <conf:(0.99)> lift:(1.62) lev:(0.21) [93] conv:(31.8)
 6. el-salvador-aid=n Class=democrat 200 ==> aid-to-nicaraguan-contras=y 197    <conf:(0.98)> lift:(1.77) lev:(0.2) [85] conv:(22.18)
 7. el-salvador-aid=n 208 ==> aid-to-nicaraguan-contras=y 204    <conf:(0.98)> lift:(1.76) lev:(0.2) [88] conv:(18.46)
 8. adoption-of-the-budget-resolution=y aid-to-nicaraguan-contras=y Class=democrat 203 ==> physician-fee-freeze=n 198    <conf:(0.98)> lift:(1.72) lev:(0.19) [82] conv:
 9. el-salvador-aid=n aid-to-nicaraguan-contras=y 204 ==> Class=democrat 197    <conf:(0.97)> lift:(1.57) lev:(0.17) [71] conv:(9.85)
10. aid-to-nicaraguan-contras=y Class=democrat 218 ==> physician-fee-freeze=n 210    <conf:(0.96)> lift:(1.7) lev:(0.2) [86] conv:(10.47)
```

1. adoption-of-the-budget-resolution=y physician-fee-freeze=n 219 ==> Class=democrat 219 <conf:(1)> lift:(1.63) lev:(0.19) [84] conv:(84.58)
2. adoption-of-the-budget-resolution=y physician-fee-freeze=n aid-to-nicaraguan-contras=y 198 ==> Class=democrat 198 <conf:(1)> lift:(1.63) lev:(0.18) [76] conv:(76.47)
3. physician-fee-freeze=n aid-to-nicaraguan-contras=y 211 ==> Class=democrat 210 <conf:(1)> lift:(1.62) lev:(0.19) [80] conv:(40.74)
4. physician-fee-freeze=n education-spending=n 202 ==> Class=democrat 201 <conf:(1)> lift:(1.62) lev:(0.18) [77] conv:(39.01)
5. physician-fee-freeze=n 247 ==> Class=democrat 245<conf:(0.99)> lift:(1.62) lev:(0.21) [93] conv:(31.8)
6. el-salvador-aid=n Class=democrat 200 ==> aid-to-nicaraguan-contras=y 197 <conf:(0.98)> lift:(1.77) lev:(0.2) [85] conv:(22.18)
7. el-salvador-aid=n 208 ==> aid-to-nicaraguan-contras=y 204 <conf:(0.98)> lift:(1.76) lev:(0.2) [88] conv:(18.46)
8. adoption-of-the-budget-resolution=y aid-to-nicaraguan-contras=y Class=democrat 203 ==> physician-fee-freeze=n 198 <conf:(0.98)> lift:(1.72) lev:(0.19) [82] conv:(14.62)
9. el-salvador-aid=n aid-to-nicaraguan-contras=y 204 ==> Class=democrat 197 <conf:(0.97)> lift:(1.57) lev:(0.17) [71] conv:(9.85)
10. aid-to-nicaraguan-contras=y Class=democrat 218 ==> physician-fee-freeze=n 210 <conf:(0.96)> lift:(1.7) lev:(0.2) [86] conv:(10.47)

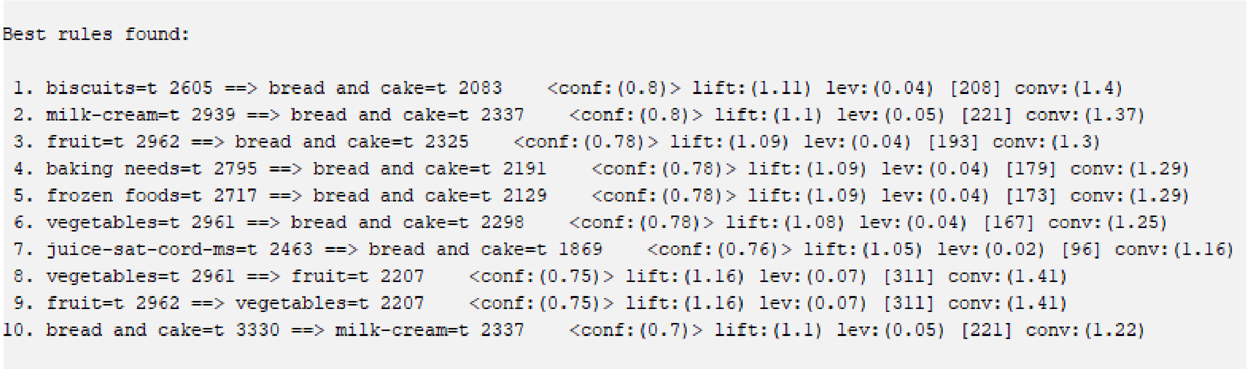
According to the rules, it is possible to identify someone as a democrat with a confidence level of at least 90%. The person is typically a democrat. The class is considered democratic if the budget resolution is adopted, physician fees are frozen, and no education funding is allocated. The class belongs to a democrat when aid is given to the Nicaraguan contras but not to El Salvador. With a minimum 98% confidence that the class will be a Democrat under the following circumstances, the data demonstrates high confidence levels with regard to the rules.

Task 2. It is interesting to see that none of the rules in the default output involve Class
= republican. Why do you think that is?
Apriori algorithm bases its rule-making on the frequency of each incident. 267 cases in the provided dataset belong to Democrats, whereas 168 instances belong to Republicans. The class is more likely to be predicted as a Democrat than a Republican due to the bias in the data and the higher frequency of Democrats.

Exercise 5:
Let’s run Apriori on another real-world dataset.
Load data at Preprocess tab. Click the Open file button to bring up a standard dialog through which
you can select a file. Choose the supermarket.arff file. To see the original dataset, click the Edit button, a viewer window opens with dataset loaded.
To do market basket analysis in Weka, each transaction is coded as an instance of which the attributes represent the items in the store. Each attribute has only one value: If a particular transaction
does not contain it (i.e., the customer did not buy that item), this is coded as a missing value.
Task 1. Experiment with Apriori and investigate the effect of the various parameters described before. Prepare a brief oral presentation on the main findings of your investigation.



```
=== Run information ===

Scheme:       weka.associations.Apriori -N 10 -T 0 -C 0.7 -D 0.05 -U 1.0 -M 0.2 -S -1.0 -c -1
Relation:     supermarket
Instances:    4627
Attributes:   217
              [list of attributes omitted]
=== Associator model (full training set) ===


Apriori
=======

Minimum support: 0.4 (1851 instances)
Minimum metric <confidence>: 0.7
Number of cycles performed: 12

Generated sets of large itemsets:

Size of set of large itemsets L(1): 18

Size of set of large itemsets L(2): 16
```



```
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. juice-sat-cord-ms=t 2463 ==> bread and cake=t 1869    <conf:(0.76)> lift:(1.05) lev:(0.02) [96] conv:(1.16)
 8. vegetables=t 2961 ==> fruit=t 2207    <conf:(0.75)> lift:(1.16) lev:(0.07) [311] conv:(1.41)
 9. fruit=t 2962 ==> vegetables=t 2207    <conf:(0.75)> lift:(1.16) lev:(0.07) [311] conv:(1.41)
10. bread and cake=t 3330 ==> milk-cream=t 2337    <conf:(0.7)> lift:(1.1) lev:(0.05) [221] conv:(1.22)
```

From the above dataset around 217 attributes have been omitted.
With a min support of 0.4 and min confidence of 0.7 the following can be be interpreted:

1. A customer who buys biscuits and milk cream is 80% likely to buy bread and cake.
2. A customer who buys fruit is78% likely to buy bread and cake.
3. The person who has baking needs, frozen foods and vegetables is 78% likely to buy bread and cake.
4. A customer buying fruits is 75% likely to buy vegetables and vice-versa.
5. A customer purchasing bread and cakes is 70% likely to buy milk cream.
6. In a supermarket, the following foods can be grouped:.
   a. Biscuits, Milk cream, baking needs, frozen foods, bread and cake
   b. Vegetables and fruits can be stacked together.
   c. Juices and bread and cake together

7. The above strategy can give a more customer friendly service and increase the sales of the supermarket

Inferences:

1. Apriori algorithm considers an element's frequency and likelihood that it will occur while anticipating the rules.
2. The rules include a confidence level that indicates how confidently they can be stated.
3. The kind of data that must be forecasted determine the values of confidence and minimum support.
4. The frequency of the class value determines how a rule will behave.
5. The algorithm may produce findings that are biassed or erroneous if the data is unbalanced.
6. Weka is an effective tool for studying the apriori algorithm in practical situations and applying it for the user's benefit.