Laboratory Module 8

Mining Frequent Itemsets – Apriori Algorithm

Purpose:

- key concepts in mining frequent itemsets
- understand the Apriori algorithm
- run Apriori in Weka GUI and in programatic way

1 Theoretical aspects

In data mining, association rule learning is a popular and well researched method for discovering interesting relations between variables in large databases. Piatetsky-Shapiro describes analyzing and presenting strong rules discovered in databases using different measures of interestingness. Based on the concept of strong rules, Agrawal introduced association rules for discovering regularities between products in large scale transaction data recorded by point-of-sale (POS) systems in supermarkets. For example, the rule {onion,potatoes}=>{burger} found in the sales data of a supermarket would indicate that if a customer buys onions and potatoes together, he or she is likely to also buy burger. Such information can be used as the basis for decisions about marketing activities such as, e.g., promotional pricing or product placements. In addition to the above example from market basket analysis association rules are employed today in many application areas including Web usage mining, intrusion detection and bioinformatics.

In computer science and data mining, Apriori is a classic algorithm for learning association rules. Apriori is designed to operate on databases containing transactions (for example, collections of items bought by customers, or details of a website frequentation). Other algorithms are designed for finding association rules in data having no transactions (Winepi and Minepi), or having no timestamps (DNA sequencing).

Definition:

Following the original definition by Agrawal the problem of association rule mining is defined as:

Let $\mathbf{I} = \{\mathbf{i_1}, \mathbf{i_2}, ..., \mathbf{i_n}\}$ be a set of n binary attributes called *items*. Let $\mathbf{D} = \{\mathbf{t_1}, \mathbf{t_2}, ..., \mathbf{t_n}\}$ be a set of transactions called the *database*. Each transaction in **D** has a unique transaction ID and contains a subset of the items in **I**. A *rule* is defined as an implication of the form $\mathbf{X} \rightarrow \mathbf{Y}$ where $\mathbf{X}, \mathbf{Y} \subseteq \mathbf{I}$ and $X \cap Y = \emptyset$. The sets of items (for short *itemsets*) **X** and **Y** are called *antecedent* (left-hand-side or LHS) and *consequent* (right-hand-side or RHS) of the rule respectively.

To illustrate the concepts, we use a small example from the supermarket domain. The set of items is ***I* = {milk,bread,butter,beer}** and a small database containing the items (1 codes presence and 0 absence of an item in a transaction) is shown in the table below. An example rule for the supermarket could be {milk,bread}=>{butter} meaning that if milk and bread is bought, customers also buy butter.

Note: this example is extremely small. In practical applications, a rule needs a support of several hundred transactions before it can be considered statistically significant, and datasets often contain thousands or millions of transactions.

Transaction ID	milk	Bread	butter	beer
1	1	1	0	0
2	0	1	1	0
3	0	0	0	1
4	1	1	1	0
5	0	1	0	0

6	1	0	0	0
7	0	1	1	1
8	1	1	1	1
9	0	1	0	1
10	1	1	0	0
11	1	0	0	0
12	0	0	0	1
13	1	1	1	0
14	1	0	1	0
15	1	1	1	1

Useful Concepts

To select interesting rules from the set of all possible rules, constraints on various measures of significance and interest can be used. The best-known constraints are minimum thresholds on support and confidence.

Support

The support **supp(*X*)** of an itemset *X* is defined as the proportion of transactions in the data set which contain the itemset.

supp(X)= no. of transactions which contain the itemset X / total no. of transactions

In the example database, the itemset {milk,bread,butter} has a support of 4 /15 = 0.26 since it occurs in 26% of all transactions. To be even more explicit we can point out that 4 is the number of transactions from the database which contain the itemset {milk,bread,butter} while 15 represents the total number of transactions.

Confidence

The ***confidence*** of a rule is defined:

$$\boldsymbol{conf(X \rightarrow Y) = supp(X \cup Y)/supp(X)}$$

For the rule {milk,bread}=>{butter} we have the following confidence:

supp({milk,bread,butter}) / supp({milk,bread}) = 0.26 / 0.4 = 0.65

This means that for 65% of the transactions containing milk and bread the rule is correct. Confidence can be interpreted as an estimate of the probability $\boldsymbol{P(Y \mid X)}$, the probability of finding the RHS of the rule in transactions under the condition that these transactions also contain the LHS.

Lift

The ***lift*** of a rule is defined as:

$$\boldsymbol{lift(X \rightarrow Y) = \frac{supp(X \cup Y)}{supp(Y) * supp(X)}}$$

The rule {milk,bread}=>{butter} has the following lift:

supp({milk,bread,butter}) / supp({butter}) x supp({milk,bread})= 0.26/0.46 x 0.4= 1.4

Conviction

The ***conviction*** of a rule is defined as:

$$\boldsymbol{conv(X \rightarrow Y) = \frac{1 - supp(Y)}{1 - conf(X \rightarrow Y)}}$$

The rule {milk,bread}=>{butter} has the following conviction:

1 – supp({butter})/ 1- conf({milk,bread}=>{butter}) = 1-0.46/1-0.65 = 1.54

The conviction of the rule **X=>Y** can be interpreted as the ratio of the expected frequency that **X** occurs without **Y** (that is to say, the frequency that the rule makes an incorrect prediction) if **X** and **Y** were independent divided by the observed frequency of incorrect predictions.

In this example, the conviction value of 1.54 shows that the rule {milk,bread}=>{butter} would be incorrect 54% more often (1.54 times as often) if the association between X and Y was purely random chance.

2. Apriori algorithm

General Process

Association rule generation is usually split up into two separate steps:

1. First, minimum support is applied to find all *frequent itemsets* in a database.
2. Second, these frequent itemsets and the minimum confidence constraint are used to form rules.

While the second step is straight forward, the first step needs more attention.

Finding all frequent itemsets in a database is difficult since it involves searching all possible itemsets (item combinations). The set of possible itemsets is the power set over *I* and has size $2^n - 1$ (excluding the empty set which is not a valid itemset). Although the size of the powerset grows exponentially in the number of items *n* in *I*, efficient search is possible using the ***downward-closure property*** of support (also called *anti-monotonicity*) which guarantees that for a frequent itemset, all its subsets are also frequent and thus for an infrequent itemset, all its supersets must also be infrequent. Exploiting this property, efficient algorithms (e.g., Apriori and Eclat) can find all frequent itemsets.

Apriori Algorithm Pseudocode

```
procedure Apriori (T, minSupport) { //T is the database and minSupport is the minimum support
    L1= {frequent items};
    for (k= 2; $L_{k-1}$ !=∅; k++) {
        $C_k$= candidates generated from $L_{k-1}$
        //that iscartesian product $L_{k-1}$ x $L_{k-1}$ and eliminating any k-1 size itemset that is not
        //frequent
        for each transaction t in database do{
            #increment the count of all candidates in $C_k$ that are contained in t
            $L_k$ = candidates in $C_k$ with minSupport
        }//end for each
    }//end for
    return $\bigcup_k L_k$;
}
```

As is common in association rule mining, given a set of *itemsets* (for instance, sets of retail transactions, each listing individual items purchased), the algorithm attempts to find subsets which are common to at least a minimum number C of the itemsets. Apriori uses a "bottom up" approach, where frequent subsets are extended one item at a time (a step known as *candidate generation*), and groups of candidates are tested against the data. The algorithm terminates when no further successful extensions are found.

Apriori uses breadth-first search and a tree structure to count candidate item sets efficiently. It generates candidate item sets of length *k* from item sets of length $k - 1$. Then it prunes the candidates which have an infrequent sub pattern. According to the downward closure lemma, the candidate set contains all frequent *k*-length item sets. After that, it scans the transaction database to determine frequent item sets among the candidates.

Apriori, while historically significant, suffers from a number of inefficiencies or trade-offs, which have spawned other algorithms. Candidate generation generates large numbers of subsets (the algorithm attempts to load up the candidate set with as many as possible before each scan). Bottom-up subset exploration (essentially a breadth-first traversal of the subset lattice) finds any maximal subset S only after all $2^{|S|} - 1$ of its proper subsets.

3. Sample usage of Apriori algorithm

A large supermarket tracks sales data by Stock-keeping unit (SKU) for each item, and thus is able to know what items are typically purchased together. Apriori is a moderately efficient way to build a list of frequent purchased item pairs from this data. Let the database of transactions consist of the sets {1,2,3,4}, {1,2,3,4,5}, {2,3,4}, {2,3,5}, {1,2,4}, {1,3,4}, {2,3,4,5}, {1,3,4,5}, {3,4,5}, {1,2,3,5}. Each number corresponds to a product such as "butter" or "water". The first step of Apriori is to count up the frequencies, called the supports, of each member item separately:

Item	Support
1	**6**
2	**7**
3	**9**
4	**8**
5	**6**

We can define a minimum support level to qualify as "frequent," which depends on the context. For this case, let min support = 4. Therefore, all are frequent. The next step is to generate a list of all 2-pairs of the frequent items. Had any of the above items not been frequent, they wouldn't have been included as a possible member of possible 2-item pairs. In this way, Apriori *prunes* the tree of all possible sets. In next step we again select only these items (now 2-pairs are items) which are frequent (the pairs written in bold text):

Item	Support
{1,2}	**4**
{1,3}	**5**
{1,4}	**5**
{1,5}	3
{2,3}	**6**
{2,4}	**5**
{2,5}	**4**
{3,4}	**7**
{3,5}	**6**
{4,5}	**4**

We generate the list of all 3-triples of the frequent items (by connecting frequent pair with frequent single item).

Item	Support
{1,3,4}	**4**
{2,3,4}	**4**
{2,3,5}	**4**
{3,4,5}	**4**

The algorithm will end here because the pair {2,3,4,5} generated at the next step does not have the desired support.

We will now apply the same algorithm on the same set of data considering that the min support is 5. We get the following results:

Step 1:

Item	Support
1	**6**
2	**7**
3	**9**
4	**8**
5	**6**

Step 2:

Item	Support
{1,2}	4
{1,3}	**5**
{1,4}	**5**
{1,5}	3
{2,3}	**6**
{2,4}	**5**
{2,5}	4
{3,4}	**7**
{3,5}	**6**
{4,5}	4

The algorithm ends here because none of the 3-triples generated at Step 3 have de desired support.

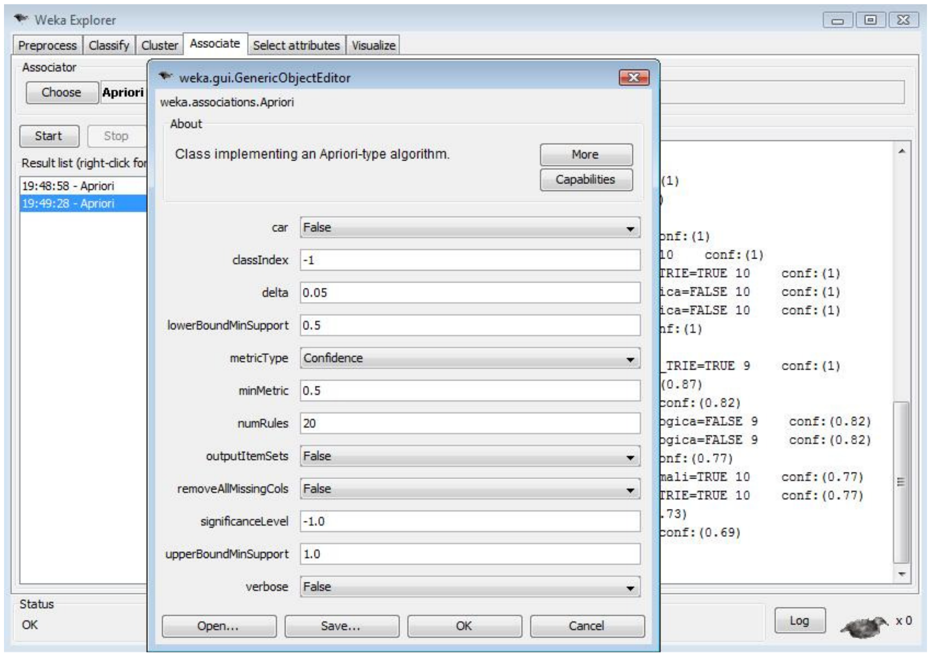
4. Sample usage of Apriori in Weka

For our test we shall consider 15 students that have attended lectures of the Algorithms and Data Structures course. Each student has attended specific lectures. The ARFF file presented bellow contains information regarding each student's attendance.

```
@relation test_studenti

@attribute Arbori_binari_de_cautare {TRUE, FALSE}
@attribute Arbori_optimali {TRUE, FALSE}
@attribute Arbori_echilibrati_in_inaltime {TRUE, FALSE}
@attribute Arbori_Splay {TRUE, FALSE}
@attribute Arbori_rosu_negru {TRUE, FALSE}
@attribute Arbori_2_3 {TRUE, FALSE}
@attribute Arbori_B {TRUE, FALSE}
@attribute Arbori_TRIE {TRUE, FALSE}
@attribute Sortare_topologica {TRUE, FALSE}
@attribute Algoritmul_Dijkstra {TRUE, FALSE}



@data
TRUE,TRUE,TRUE,TRUE,FALSE,FALSE,TRUE,TRUE,FALSE,FALSE
TRUE,TRUE,TRUE,TRUE,TRUE,TRUE,FALSE,TRUE,FALSE,FALSE
FALSE,TRUE,TRUE,TRUE,FALSE,FALSE,FALSE,TRUE,FALSE,TRUE
FALSE,TRUE,FALSE,FALSE,TRUE,FALSE,TRUE,TRUE,FALSE,TRUE
TRUE,TRUE,FALSE,TRUE,TRUE,FALSE,TRUE,TRUE,FALSE,TRUE
TRUE,FALSE,TRUE,FALSE,FALSE,TRUE,TRUE,TRUE,FALSE,FALSE
FALSE,TRUE,FALSE,TRUE,TRUE,FALSE,TRUE,TRUE,FALSE,TRUE
TRUE,FALSE,TRUE,TRUE,TRUE,FALSE,TRUE,TRUE,TRUE,FALSE
FALSE,TRUE,TRUE,TRUE,TRUE,FALSE,FALSE,TRUE,FALSE,FALSE
TRUE,FALSE,TRUE,FALSE,TRUE,TRUE,FALSE,TRUE,FALSE,TRUE
FALSE,FALSE,TRUE,FALSE,TRUE,FALSE,FALSE,TRUE,TRUE,TRUE
TRUE,FALSE,FALSE,TRUE,TRUE,TRUE,FALSE,TRUE,FALSE,TRUE
FALSE,TRUE,TRUE,FALSE,TRUE,TRUE,FALSE,TRUE,FALSE,TRUE
TRUE,TRUE,TRUE,FALSE,FALSE,TRUE,FALSE,TRUE,FALSE,FALSE
TRUE,TRUE,FALSE,FALSE,TRUE,TRUE,FALSE,TRUE,FALSE,FALSE
```

Using the Apriori Algorithm we want to find the association rules that have **minSupport=50%** and minimum confidence=50%. We will do this using WEKA GUI.

After we launch the WEKA application and open the ***TestStudenti.arff*** file, we move to the **Associate** tab and we set up the following configuration:



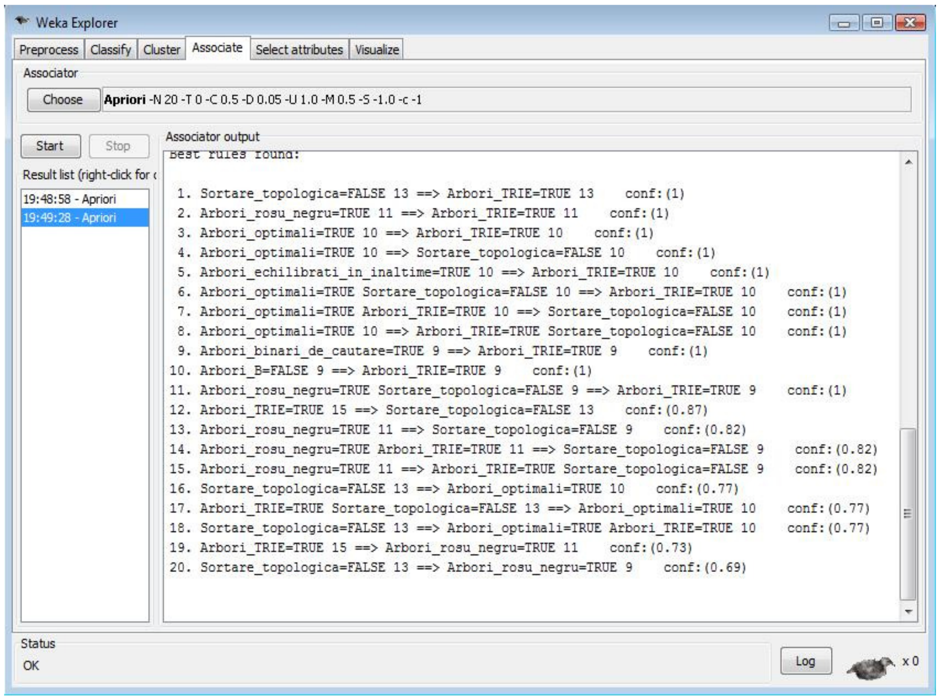
weka.associations.Apriori

Class implementing an Apriori-type algorithm.

car	False
classIndex	-1
delta	0.05
lowerBoundMinSupport	0.5
metricType	Confidence
minMetric	0.5
numRules	20
outputItemSets	False
removeAllMissingCols	False
significanceLevel	-1.0
upperBoundMinSupport	1.0
verbose	False

```
(1)
)
onf:(1)
10    conf:(1)
TRIE=TRUE 10    conf:(1)
ica=FALSE 10    conf:(1)
ica=FALSE 10    conf:(1)
nf:(1)

_TRIE=TRUE 9    conf:(1)
(0.87)
conf:(0.82)
ogica=FALSE 9    conf:(0.82)
ogica=FALSE 9    conf:(0.82)
onf:(0.77)
mali=TRUE 10    conf:(0.77)
TRIE=TRUE 10    conf:(0.77)
.73)
conf:(0.69)
```

After the algorithm is finished, we get the following results:



Apriori -N 20 -T 0 -C 0.5 -D 0.05 -U 1.0 -M 0.5 -S -1.0 -c -1

```
Best rules found:

 1. Sortare_topologica=FALSE 13 ==> Arbori_TRIE=TRUE 13    conf:(1)
 2. Arbori_rosu_negru=TRUE 11 ==> Arbori_TRIE=TRUE 11    conf:(1)
 3. Arbori_optimali=TRUE 10 ==> Arbori_TRIE=TRUE 10    conf:(1)
 4. Arbori_optimali=TRUE 10 ==> Sortare_topologica=FALSE 10    conf:(1)
 5. Arbori_echilibrati_in_inaltime=TRUE 10 ==> Arbori_TRIE=TRUE 10    conf:(1)
 6. Arbori_optimali=TRUE Sortare_topologica=FALSE 10 ==> Arbori_TRIE=TRUE 10    conf:(1)
 7. Arbori_optimali=TRUE Arbori_TRIE=TRUE 10 ==> Sortare_topologica=FALSE 10    conf:(1)
 8. Arbori_optimali=TRUE 10 ==> Arbori_TRIE=TRUE Sortare_topologica=FALSE 10    conf:(1)
 9. Arbori_binari_de_cautare=TRUE 9 ==> Arbori_TRIE=TRUE 9    conf:(1)
10. Arbori_B=FALSE 9 ==> Arbori_TRIE=TRUE 9    conf:(1)
11. Arbori_rosu_negru=TRUE Sortare_topologica=FALSE 9 ==> Arbori_TRIE=TRUE 9    conf:(1)
12. Arbori_TRIE=TRUE 15 ==> Sortare_topologica=FALSE 13    conf:(0.87)
13. Arbori_rosu_negru=TRUE 11 ==> Sortare_topologica=FALSE 9    conf:(0.82)
14. Arbori_rosu_negru=TRUE Arbori_TRIE=TRUE 11 ==> Sortare_topologica=FALSE 9    conf:(0.82)
15. Arbori_rosu_negru=TRUE 11 ==> Arbori_TRIE=TRUE Sortare_topologica=FALSE 9    conf:(0.82)
16. Sortare_topologica=FALSE 13 ==> Arbori_optimali=TRUE 10    conf:(0.77)
17. Arbori_TRIE=TRUE Sortare_topologica=FALSE 13 ==> Arbori_optimali=TRUE 10    conf:(0.77)
18. Sortare_topologica=FALSE 13 ==> Arbori_optimali=TRUE Arbori_TRIE=TRUE 10    conf:(0.77)
19. Arbori_TRIE=TRUE 15 ==> Arbori_rosu_negru=TRUE 11    conf:(0.73)
20. Sortare_topologica=FALSE 13 ==> Arbori_rosu_negru=TRUE 9    conf:(0.69)
```

If we look at the first rule we can see that the students who don't attend the *Sortare topologica* lecture have a tendency to attend the *Arbori TRIE* lecture. The confidence of this rule is 100% so it is very believable. Using the same logic we can interpret all the the other rules that the algorithm has revealed.

The same results presented above can be obtained by implementing the WEKA Apriori Algorithm in your own Java code. A simple Java program that takes the ***TestStudenti.arff*** file as input, configures the Apriori class and displays the results of the Apriori algorithm is presented bellow:

```
import java.io.BufferedReader;
import java.io.FileReader;
import java.io.IOException;

import weka.associations.Apriori;
import weka.core.Instances;

public class Main
{

        public static void main(String[] args)
        {
                Instances data = null;

                try {
                        BufferedReader reader = new BufferedReader( new
        FileReader( "...\\TestStudenti.arff" ) );
                        data = new Instances(reader);
                        reader.close();
                        data.setClassIndex(data.numAttributes() - 1);

                }
                catch ( IOException e )    {
                        e.printStackTrace();
                }

          double deltaValue              = 0.05;
          double lowerBoundMinSupportValue = 0.1;
          double minMetricValue          = 0.5;
          int numRulesValue              = 20;
          double upperBoundMinSupportValue = 1.0;
          String resultapriori;
          Apriori apriori = new Apriori();
          apriori.setDelta(deltaValue);
      apriori.setLowerBoundMinSupport(lowerBoundMinSupportValue);
      apriori.setNumRules(numRulesValue);
      apriori.setUpperBoundMinSupport(upperBoundMinSupportValue);
      apriori.setMinMetric(minMetricValue);
          try
                {
                        apriori.buildAssociations( data );

                }
                catch ( Exception e ) {
                        e.printStackTrace();
                }
                  resultapriori = apriori.toString();

          System.out.println(resultapriori);
        }
}
```

5. Domains where Apriori is used

Application of the Apriori algorithm for adverse drug reaction detection

The objective is to use the Apriori association analysis algorithm for the detection of adverse drug reactions (ADR) in health care data. The Apriori algorithm is used to perform association analysis on the characteristics of patients, the drugs they are taking, their primary diagnosis, co-morbid conditions, and the ADRs or adverse events (AE) they experience. This analysis produces association rules that indicate what combinations of medications and patient characteristics lead to ADRs.

Application of Apriori Algorithm in Oracle Bone Inscription Explication

Oracle Bone Inscription (OBI) is one of the oldest writing in the world, but of all 6000 words found till now there are only about 1500 words that can be explicated explicitly. So explication for OBI is a key and open problem in this field. Exploring the correlation between the OBI words by Association Rules algorithm can aid in the research of explication for OBI. Firstly the OBI data extracted from the OBI corpus are preprocessed; with these processed data as input for Apriori algorithm we get the frequent itemset. And combined by the interestingness measurement the strong association rules between OBI words are produced. Experimental results on the OBI corpus demonstrate that this proposed method is feasible and effective in finding semantic correlation for OBI.