2020

Lab 8: Association Rules

Assoc. Prof. Dr. Mohammed Al-Sarem

Taibah University, Information System Department

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Lab Objectives:

The goal of this lab is to explain the role of association rules in mining hidden relationships in data. After completion of this lab, you will be able to:

- Generate association rules using Apriori algorithm
- Evaluate the goodness of the findings rules

Methodology

First you have to install the required library that allow you to run Apriori algorithm. Then, as usual, you have to load and read dataset. After executing the algorithm, a set of generated rules are found. Your task is to analyze these rules and reports only the most interesting.

In class task:

At the end of this lab, the student will be able to:

- Explain how the Apriori algorithm works.
- Extract rules from the generated set.
- Evaluate the findings using Support and Confidence.

home task:

Complete your **Course Project** (See Home task in lab 5).

References:

- Agrawal, Rakesh, and Ramakrishnan Srikant. "Fast algorithms for mining association rules." Proc. 20th int. conf. very large data bases, VLDB. Vol. 1215. 1994.
- https://en.wikipedia.org/wiki/Apriori_algorithm

1. Frequent Itemsets via Apriori Algorithm

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Now

```
In [4]: dataset

Out[4]: [['drink', 'nuts', 'diaper'],
         ['drink', 'coffee', 'diaper'],
         ['drink', 'diaper', 'eggs'],
         ['nuts', 'eggs', 'milk'],
         ['nuts', 'coffee', 'diaper', 'eggs', 'milk']]
```

Generating Frequent Itemsets

Suppose we have the following transaction data as depicted in the Table below.

Table 1: Transaction Data

Tid	Items bought
1	Drink, Nuts, Diaper
2	Drink, Coffee, Diaper
3	Drink, Diaper, Eggs
4	Nuts, Eggs, Milk
5	Nuts, Coffee, Diaper, Eggs, Milk

Exercise 1.1: The apriori function expects data in a one-hot encoded pandas DataFrame. Use the transaction data that is presented in the Table 1 and convert the them into 2 dimensional array. Display the output here!

```
In [4]: dataset

Out[4]: [['drink', 'nuts', 'diaper'],
         ['drink', 'coffee', 'diaper'],
         ['drink', 'diaper', 'eggs'],
         ['nuts', 'eggs', 'milk'],
         ['nuts', 'coffee', 'diaper', 'eggs', 'milk']]
```

```
TranEncod = TransactionEncoder()
te_ary = TranEncod.fit(dataset).transform(dataset)
df = pd.DataFrame(te_ary, columns=TranEncod.columns_)
```

Exercise 1.2: Display the dataset below! What do you see?

```
In [18]:  import pandas as pd
          from mlxtend.preprocessing import TransactionEncoder
          TranEncod=TransactionEncoder()
          te_ary=TranEncod.fit(dataset).transform(dataset)
          df=pd.DataFrame(te_ary,columns=TranEncod.columns_)

          df
```

Out[18]:

	coffee	diaper	drink	eggs	milk	nuts
0	False	True	True	False	False	True
1	True	True	True	False	False	False
2	False	True	True	True	False	False
3	False	False	False	True	True	True
4	True	True	False	True	True	True

it shows the item exist or not exist

Remember that to work with association rules, the algorithm required as input beside the dataset, the minimum support value ε:

Apriori(T, ϵ)
  $L_1 \leftarrow \{\text{large } 1-\text{itemsets}\}$
  $k \leftarrow 2$
  while $L_{k-1} \neq \emptyset$
    $C_k \leftarrow \{c = a \cup \{b\} \mid a \in L_{k-1} \wedge b \notin a, \{s \subseteq c \mid |s| = k-1\} \subseteq L_{k-1}\}$
    for transactions $t \in T$
      $D_t \leftarrow \{c \in C_k \mid c \subseteq t\}$
      for candidates $c \in D_t$
        $count[c] \leftarrow count[c] + 1$
    $L_k \leftarrow \{c \in C_k \mid count[c] \geq \epsilon\}$
    $k \leftarrow k + 1$
  return $\bigcup_k L_k$

So, let us return the items and itemsets with at least 60% support.

```
apriori(df, min_support=0.6)
```

By default, `apriori` returns the column indices of the items, which may be useful in downstream operations such as association rule mining. For better readability, we can set `use_colnames=True` to convert these integer values into the respective item names:

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

	support	itemsets
0	0.8	(Diaper)
1	0.6	(Drink)
2	0.6	(Eggs)
3	0.6	(Nuts)
4	0.6	(Diaper, Drink)

Exercise 1.3: Find the possible rules and calculate the confidence of each rule you find?

```
In [23]: from mlxtend.frequent_patterns import association_rules
         association_rules(frequent_itemsets, metric="confidence", min_threshold=0.7)
```

Out[23]:

	antecedents	consequents	antecedent support	consequent support	support	confidence	lift	leverage	conviction
0	(coffee)	(diaper)	0.4	0.8	0.4	1.00	1.250000	0.08	inf
1	(drink)	(diaper)	0.6	0.8	0.6	1.00	1.250000	0.12	inf
2	(diaper)	(drink)	0.8	0.6	0.6	0.75	1.250000	0.12	1.6
3	(milk)	(eggs)	0.4	0.6	0.4	1.00	1.666667	0.16	inf
4	(milk)	(nuts)	0.4	0.6	0.4	1.00	1.666667	0.16	inf
...	...	...	...	...	...	...	...	...	...
67	(eggs, coffee, milk)	(nuts, diaper)	0.2	0.4	0.2	1.00	2.500000	0.12	inf
68	(diaper, milk)	(nuts, coffee, eggs)	0.2	0.2	0.2	1.00	5.000000	0.16	inf
69	(nuts, coffee)	(eggs, diaper, milk)	0.2	0.2	0.2	1.00	5.000000	0.16	inf
70	(coffee, milk)	(nuts, eggs, diaper)	0.2	0.2	0.2	1.00	5.000000	0.16	inf
71	(eggs, coffee)	(nuts, diaper, milk)	0.2	0.2	0.2	1.00	5.000000	0.16	inf

72 rows × 9 columns

2. Selecting and Filtering Results

Before moving ahead, let us decrease the minimum support to 30%. This leads to increase the number of returned items and itemsets. Let us now filter out these rules.The advantage of working with pandas `DataFrames` is that we can use its convenient features to filter the results. For instance, let's assume we are only interested in `itemsets` of length 2 that have a support of at least 50% percent. First, we create the frequent itemsets via `apriori` and add a new column that stores the length of each itemset:

```
frequent_itemsets = apriori(df, min_support=0.5, use_colnames=True)
frequent_itemsets['length'] = frequent_itemsets['itemsets'].apply(lambda x: len(x))
frequent_itemsets
```

	support	itemsets	length
0	0.8	(Diaper)	1
1	0.6	(Drink)	1
2	0.6	(Eggs)	1
3	0.6	(Nuts)	1
4	0.6	(Diaper, Drink)	2

Then, you can select the results that satisfy our desired criteria as follows:

```
frequent_itemsets[ (frequent_itemsets['length'] == 2) &
                   (frequent_itemsets['support'] >= 0.5) ]
```

	support	itemsets	length
4	0.6	(Diaper, Drink)	2

Similarly, using the Pandas API, we can select entries based on the "itemsets" column:

```
frequent_itemsets[ frequent_itemsets['itemsets'] == {'Diaper', 'Drink'} ]
```

Good luck