1. Aim of the project

Aim of the project is to prepare, implement and verify experimentally SPAM algorithm, regarding mining sequential patterns. The project should be implemented in Python language without using any of the datamining libraries available.

2. Description of the algorithm

The pseudo-code of the algorithm is presented below:

SPAM(*SDB*, *minsup*)
1. Scan *SDB* to create *V*(*SDB*) and identify F_1, the list of frequent items.
2. **FOR** each item s $\in F_1$,
3. **SEARCH**($\langle s \rangle$, F_1, $\{e \in F_1 \mid e \succ_{lex} s\}$, *minsup*).

SEARCH(*pat*, S_n, I_n, *minsup*)
1. Output pattern *pat*.
2. $S_{temp} := I_{temp} := \emptyset$
3. **FOR** each item $j \in S_n$,
4. **IF** the s-extension of *pat* is frequent **THEN** $S_{temp} := S_{temp} \cup \{i\}$.
5. **FOR** each item $j \in S_{temp}$,
6. **SEARCH**(the s-extension of *pat* with *j*, S_{temp}, $\{e \in S_{temp} \mid e \succ_{lex} j\}$, *minsup*).
7. **FOR** each item $j \in I_n$,
8. **IF** the i-extension of *pat* is frequent **THEN** $I_{temp} := I_{temp} \cup \{i\}$.
9. **FOR** each item $j \in I_{temp}$,
10. **SEARCH**(i-extension of *pat* with *j*, S_{temp}, $\{e \in I_{temp} \mid e \succ_{lex} j\}$, *minsup*).

3. Datasets used for testing

During the project two datasets have been used:

- small, generated by hand dataset with 4 sequences and 2 different items to verify proper implementation of the algorithm, as follows:
    - 1: {a}, {a,b}, {a}, {a,b}
    - 2: {a,b}, {b}
    - 3: {a,b}, {a}, {b}
    - 4. {a}, {b}

- Sign dataset, containing 731 sequences and 310 different items;

4. Results

Algorithm has been used to find sequential patterns in both datasets above:

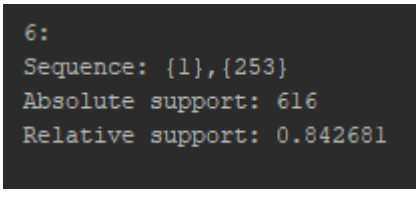
4.1. Custom dataset

Algorithm with *minSup* set to 3 returned following frequent patterns: {a}; {b}; {a,b}; {a}, {b}; {b}, {b}; {a,b}, {b};

Verifying results by hand yields the same results (Searching for frequent patterns with *sup*>=3 implies that it has to be supported from at least one of transaction sets 2,4, which means that the only possible frequent patterns are those sequences which are subsequences of either of those two) .

4.2. Sign dataset

The SPAM algorithm launched on our main dataset has found 100 frequent sequential patterns using a support threshold equal to 400 which corresponds to the relative support of around 0.547.
Instead, considering a higher threshold (i.e. 600), we can notice how the set of results is significantly reduced to just 7 frequent sequential patterns discovered. Example mined pattern is presented below:



5. Conclusions

5.1. Results analysis

Tests show that although the algorithm works for the given dataset, this specific dataset contains only itemsets with one item each, therefore the i-extension part of the algorithm remains unused and one of the strengths of it is neutralized.
Despite this, SPAM performs well and is one of the fastest sequential pattern mining algorithm

5.2. Potential uses

One of the fields that the algorithm really shines is finding a comprehensive list of all sequential patterns, which later can be processed via means of rule induction to generate sequential rules about the dataset. One can obtain vital information from a dataset this way, assuming the dataset is appropriate for finding such rules. One of the examples would be the laboratory task where one had to find out what occurrences may cause hypoglycemic symptoms to appear. One of the methods to achieve this will be described and implemented as an additional project task.

6. Sequential rule generation

6.1. Methodology

Given a list of all frequent sequences in a dataset firstly we gather all the sequences with length of at least 2. From those sequences we can generate possible *length-1* rules, e.g.:

- sequence {a},{b} generate rule {a} → {b};
- sequence {a},{b},{c} generate rules {a},{b}→{c} and {a}→{b},{c};

Of course, longer sequences can generate more rules than suggested but since all of the subsequences of a frequent sequence are also frequent, those will be included while processing the subsequences.

In the next step the potential rules will be evaluated. Since all of the subsequences of frequent sequence are also frequent, the data regarding support for them is also available - therefore we can calculate support, confidence and lift of a rule.

6.2. Results

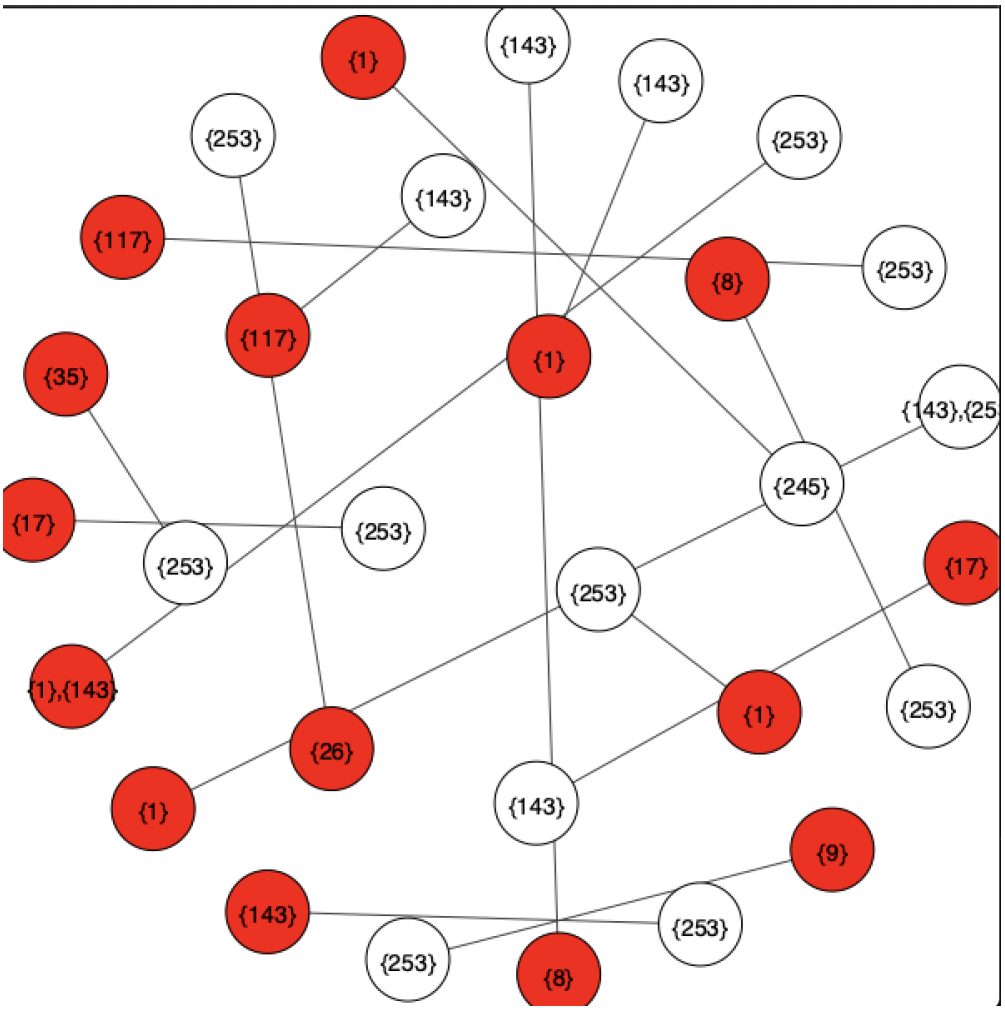
Example set of rules discovered for the Sign dataset with *minsup* = 500 is presented below:

```
Found 15 sequential rules:

Rule 1:
lh: {1}
rh: {143}
Support: 0.785226
Confidence: 0.844118
Lift: 0.907426

Rule 2:
lh: {1}
rh: {143},{253}
Support: 0.711354
Confidence: 0.764706
Lift: 0.822059
```

Those rules have been visualised using *igraph* library (red nodes represent left-hand side of the rule and white nodes represent right-hand side of the rule):



7. CM-SPAM

To improve the performance of the SPAM algorithm, an extended version of it was implemented called CM-SPAM which involves pruning the candidate searching process by using CMAP structures. To qualitatively compare approaches several tests have been performed and the execution time was measured. Each test was performed on the same sign dataset with minimal support equal to 500:

- standard SPAM algorithm approach: 5,43s
- CM-SPAM algorithm approach counting constructing CMAP structures: 43,23s
- CM-SPAM algorithm approach not counting constructing CMAP structures: 5,42s

The experiments were repeated, this time for value of minimal support of 300:

- standard SPAM algorithm approach: 9,35s
- CM-SPAM algorithm approach counting constructing CMAP structures: 48,11s
- CM-SPAM algorithm approach not counting constructing CMAP structures: 9,34s

It is clearly visible that the introduction of pruning does not improve the performance of the algorithm in a significant way. Moreover it introduces costly implementation of CMAP, even when using hashing algorithms. Perhaps the dataset experimented on does not benefit in pruning in a major way.

8. Sources

- http://www.philippe-fournier-viger.com/spmf/PAKDD2014_sequential_pattern_mining_CM-SPADE_CM-SPAM.pdf
- http://www.philippe-fournier-viger.com/spmf/index.php?link=datasets.php
- http://www.philippe-fournier-viger.com/spmf/datasets/SIGN.txt