Population-based metaheuristics for Association Rule Text Mining

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Introduction

- Stochastic population-based nature-inspired metaheuristics offer a very effective way for Association Rule Mining (ARM)
- Most of the existing methods are intended for mining categorical features that are stored in transaction databases
- In contrast, there is a lack of works for discovering the association rules in text (ARTM)
- No methods exist for ARTM that are based fully on stochastic population-based nature-inspired metaheuristics
- In this paper, we tackle the problem of ARTM using Particle Swarm Optimization

Research questions

- Are stochastic population-based nature-inspired metaheuristic algorithms suitable for ARTM?
- Can we find a viable interpretation of discovered association rules in text?
- Is there a bright way of developing these algorithms in the future?

Particle swarm optimization

```
ParticleSwarmOptimiza-
 1: procedure
     TION
         t \leftarrow 0;
          P^{(t)} \leftarrow \text{INITIALIZE};
                                           ▷ initialization of
     population
          while not TerminationCondition-
     Meet do
             for all \mathbf{x}_i^{(t)} \in P^{(t)} do
               f_i^{(t)} = \text{EVALUATE}(\mathbf{x}_i^{(t)});
     evaluation of candidate
                   if f_i^{(t)} \leq f_{best_i}^{(t)} then
                        \mathbf{p}_{i}^{(t)} = \mathbf{x}_{i}^{(t)}; f_{best_{i}}^{(t)} = f_{i}^{(t)};
                    end if > preserve the local best
 9:
     solution
                   if f_i^{(t)} \leq f_{best}^{(t)} then
10:
                        \mathbf{g}^{(t)} = \mathbf{x}_{i}^{(t)}; f_{best}^{(t)} = f_{i}^{(t)};
                    end if ▷ preserve the global best
12:
     solution
                   \mathbf{x}_{i}^{(t)} = \text{Move}(\mathbf{x}_{i}^{(t)});
13:
                                                           > move
     candidate
```

Proposed method

Text preprocessing

$$TF_{i,j} = \frac{n(d_i, w_j)}{|d_i|},\tag{1}$$

$$ITF_j = \left| \log \frac{n(d|w_j)}{N} \right|, \tag{2}$$

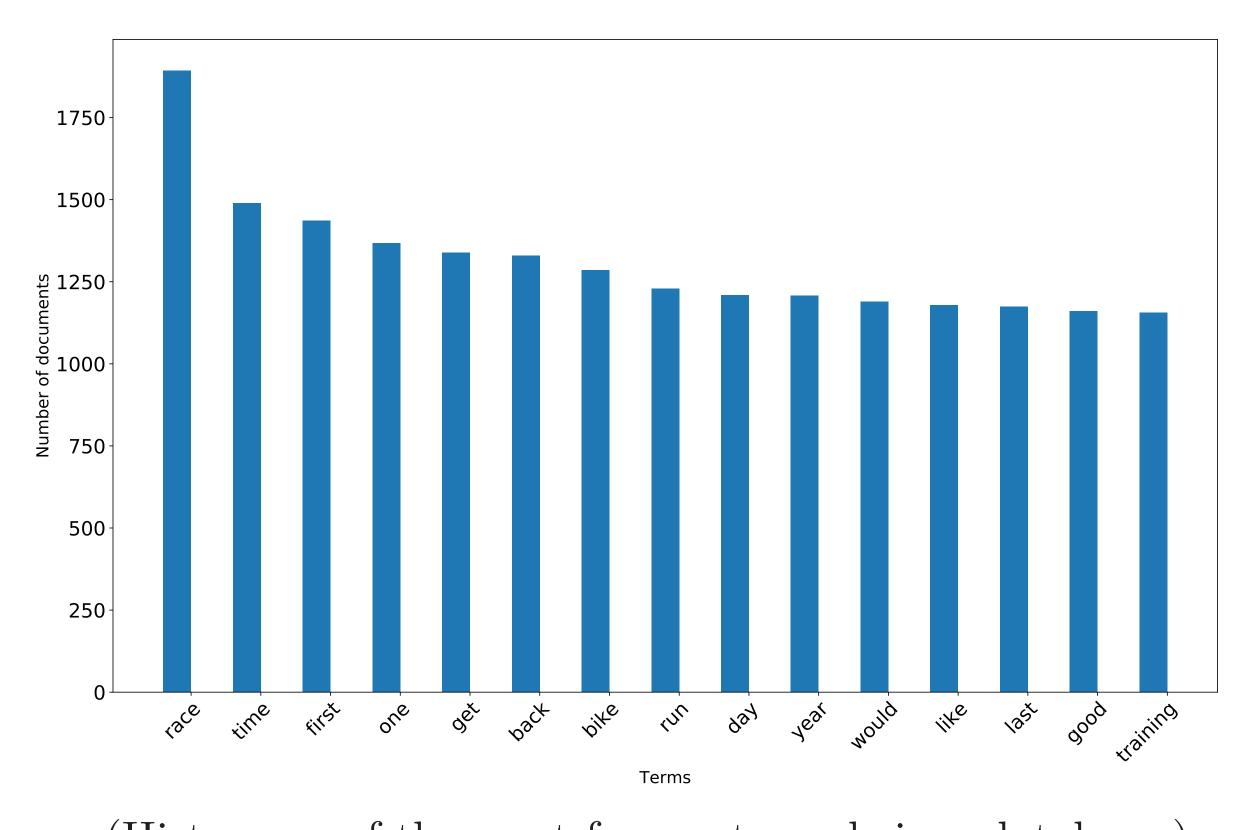
Optimization

$$AWS = \sum_{j=1}^{M} \sum_{i=1}^{N} w_{i,j} \cdot y_j \tag{3}$$

$$f(X \Rightarrow Y) = \frac{\alpha \cdot supp(X \Rightarrow Y) + \beta \cdot conf(X \Rightarrow Y) + \gamma \cdot AWS}{\alpha + \beta + \gamma},$$
(4)

Test data

Dataset that represents the blog/website posts of various world triathletes.



(Histogram of the most frequent words in a database.)

Results

K	5	6	7	8
No. Rules	4594	1947	282	273
Avg Ant.	1.693	2.776	2.148	2.520
Avg Cons.	2.306	2.223	3.851	4.479

end for

t = t + 1;

end while

17: end procedure

14:

Rule	Antecedent	Consequence
1	amazing \land ride \land next	running \land hurt \land hopefully \land fine
2	championship \land skills	$race \wedge technical$
3	great	year \land news \land mph \land course \land start \land always
4	one \wedge race	$hard \land bike \land finish \land week \land amount$
5	$triathlete \land people$	$right \wedge family \wedge sprint$

Conclusions and Future Work

- The stochastic population-based nature-inspired metaheuristics are suitable tools for solving ARTM
- The interpretation of the discovered associated rules is not trivial, especially for rules with either one antecedent or one consequence
- There is a bright way for the future development of these algorithms.