Fast recognition and application of Web users’ behavioral patterns\*

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ABSTRACT

Understanding of website user behavior is a crucial assumption for improving the website and user experience with it. Typical and repeating features of behavior during user’s visit of website can be represented through behavioral patterns. In this work we represent behavioral patterns as frequent itemsets of actions frequently performed by user's in their browsing sessions. Behavioral patterns have wide usage. They can be used to create recommendations, predict user’s intentions (which can be subsequently used to cache predicted pages), improve website design, structure to complex understanding of users’ behavior. This work responds to actual trend of Web personalization, focusing on needs of individual users and also to trend of data streams usage enabling processing of high number of data incoming in large volumes. In this paper we propose a method for behavioral patterns recognition combining global patterns with patterns specific to groups of similar users. Proposed method was evaluated indirectly through recommendation task. We performed several experiments over data from e-learning and news domains. Our results clearly show that combination of common global patterns and specific group patterns reaches higher prediction precision than its components used individually. Inclusion of group patterns also brings only constant computational load, which supports its maintenance in production usage.

CCS CONCEPTS

• **Information systems** ➝ **World Wide Web** ➝ **Web mining** • **Computing methodologies** ➝ **Machine learning** ➝ **Learning paradigms** ➝ **Supervised learning**

KEYWORDS

Behavioral Patterns, Frequent Itemsets, Clustering, Data Stream; Recommendation, Data mining

1 INTRODUCTION

Understanding of behavior of website users is crucial for the site personalization and adaptation of its content and structure. Every user is unique and his actions subject to his actual aim, context etc. But when we look at behavior of multiple users together, we would be able to observe some regularities and actions typical for specific situations. These regularities are in general known as the behavioral patterns. The behavioral patterns may be modelled in various ways as frequent itemsets [1], frequent sequences [2] of actions or association rules [1]. These patterns can be applied to user groups of various sizes. For example in e-learning domain users will be probably segmented according to their different learning paths or learning speed. Another example could be from news domain where users probably will be segmented according to their common preferences for different content categories (global news, local news, entertainment, sports etc.). The best segmentation of users however may be hidden and not so clear as we outlined. Smart detecting of groups of users with similar behavior and their typical patterns may lead to better understanding of users’ intentions.

Knowledge of the behavior (which may be represented by behavioral patterns) of web users have broad utilization in different applications as outlined in [3]. It may be used for supporting website personalization, predicting users’ behavior, caching web pages or making business decisions such market segmentation.

Users’ actions within the website are implicit and therefore objective source of information directly describing his behavior. Mining data from the actions results into objective information or even knowledge about users’ behavior.

Nowadays a huge amount of web usage data is generated especially in large websites with many users (i.e. big news portals, social networks). As this data come as a massive and potentially infinite stream, there become important to be able to process them as a fast in-memory process. If we want to effectively gain knowledge about recent users’ behavior and immediately use it, it is suitable to use methods able to single pass process the data as a stream. Data stream algorithms are built upon models that are updated incrementally in an online time. Traditional data mining algorithms however usually require more than one pass over all instances in database, which decrease their usability.

Goal of this work is to respond to current trends of Web personalization and to focus on needs of individual users by discovering behavioral patterns not only on the level of global site community, but also smaller communities of similarly behaving users. We believe that user behavior in small communities is strongly characteristic and differs from their behavior in global perspective. Using knowledge about both types of behavioral patterns and even their combination will enhance their quality and usability in different applications. For this reason, we propose an innovative method for identification of global and also group behavioral patterns and their combination specialized for recommendation of user’s future visited pages. We represent user session as set of actions taken by user and behavioral patterns as frequent itemsets of actions. At first, our method uses data stream clustering algorithm for segmenting active users to several groups according their actual behavior. Next, it uses algorithm for mining global and group behavioral patterns (represented as frequent closed itemsets) from data stream. As a method application, we use identified patterns for recommending interesting pages for users to visit. Proposed method is able to detect recent behavior of global community and also smaller communities, identify behavioral patterns, combine them and recommend interesting pages to the users.

The rest of this paper is organized as follows. In section 2, we review three different research areas related to method we propose: recommendation, frequent patterns mining over data stream, clustering over data stream. In section 3, we describe details of proposed method and its input variable tuning. In section 4, we describe evaluation of our method by the recommendation task and the methodology of performed experiments. We conclude the paper in section 5.

2  Related Work

Our method deals with three main tasks: segmenting users to groups, mining frequent patterns, recommendation of user’s future visited pages. We review works dealing with those tasks in this section.

2.1 Predicting users’ behavior and recommendation

Possible application of behavioral patterns is predicting next steps of user or recommending user’s future actions ..

In [4] WebPUM method was proposed, which represents behavioral patterns as partitions resulting from graph algorithm applied on user navigation graph, where nodes represent web pages and edges their mutual weighted connections. The weights are calculated based on intensity and frequency of pages pairs being visited in same sessions. Based on the graph, the patterns are identified and pages recommended to users according their actual behavior.

Next interesting method predicting users’ next steps was proposed in [5]. It is a sophisticated system using fuzzy c-means clustering to find behavioral patterns represented as association rules.

In [6] authors propose new heuristic used to identify users’ sessions. They use DBscan algorithm to cluster users’ sessions into clusters representing behavioral patterns. DBScan is able to reveal otherwise ignored patterns because of their low support but high confidence when represented as association rules. Finally, they propose usage of inverted index to effectively predict users’ behavior online.

2.2 Mining frequent closed itemsets over data stream

Several algorithms were proposed for mining frequent closed itemsets task. Frequent itemset can be considered as simple, but effective representation of behavioral pattern which is less complex than e.g. frequent sequences. Frequent itemsets can be further used to compute association rules, which may be considered as more complex behavioral patterns representation and may lead to new knowledge about users’ behavior. We focus on algorithms mining only frequent closed itemsets, which are complete and not redundant representations of all frequent itemsets [7].

Existing algorithms can be classified according to window model they use [8]. There exist several representations as landmark window containing all items from start of the stream or sliding window containing only most recent elements. Algorithms could be mining exact set of frequent itemsets or approximate set of frequent itemsets. Approximate mining is much more effective because it doesn't have to track all itemsets (frequent and not frequent) in history (compared to exact frequent itemset mining) and is able to well respond to conceptual drift.

First algorithm for incremental mining of closed frequent itemsets over a data stream is MOMENT [9]. It mines exact frequent itemsets using sliding window approach. It has become a reference for solutions proposed later. It uses in-memory prefix-tree-based data structure called closed enumeration tree, which effectively stores information about infrequent itemsets, nodes that are likely to become frequent, and closed itemsets.

A successor of MOMENT algorithm called NEWMOMENT represents itemsets and window as bitsets [10]. It allows usage of efficient bitwise operations as for example to count support of itemsets or perform shift of sliding window. .

CLOSTREAM uses different data structures and approach to mine exact closed frequent itemsets over sliding window than MOMENT [11] It uses Cid List and the SET function to find the closed itemsets which have the common items with incoming transaction. Different from previous approaches it doesn’t take a lot of time to search from a tree structure and only needs to intersect transaction on the certain closed itemsets. Experimental results show it outperforms MOMENT and NEWMOMENT.

Abandoning requirement to mine exact frequent itemsets helps to design fast algorithms for mining approximation of frequent closed itemsets like IncMine proposed in [12]. They use relaxed minimal support threshold to keep infrequent itemsets that are promising to become frequent later. They use update per batch policy that is different to all other algorithms we described here. It results in better time-per-transaction at risk of temporarily loosing accuracy of the maintained set while each batch is being collected [13]. In [13] authors use inverted index to efficiently address stored itemsets with IncMine algorithm.

Next algorithm named CLAIM for approximate frequent closed itemsets mining was proposed in [14]. This algorithm solves problem when conceptual drifts appear frequently and they slow down algorithm, by redefining frequent itemset definition and proposing usage of support value intervals considered as same value.

2.3 Clustering over data stream

Several algorithms were proposed for task of data stream clustering. In [15] CluStream algorithm was introduced. It is based on two (online and offline) components. Online microclustering component performs fast transformation of incoming data instances into compact approximate statistical representation. Offline macroclustering component uses this representation to get final results of clustering on demand. This approach is adapted in other works using different macroclustering algorithms and altering microclustering phase slightly, like density based algorithm Denstream proposed in [16] that uses DBScan as macroclustering algorithm and defines new concepts of core-microclusters and outlier-microclusters. Denstream is able to detect clusters of arbitrary shapes, while it requires no assumption on the number of clusters. CluStream approach is adapted also in HPStream – projected clustering for high-dimensional data streams proposed in [17]. It outperforms basic CluStream with high-dimensional streaming data.

There are also other algorithms not based on CluStream. For example another density based clustering algorithm D-Stream proposed in [18]. It maps input data into a density grid. Offline component clusters the grid. It adopts decaying technique to capture dynamic changes of a data stream. ClusTree [19] is parameter free algorithm that automatically adapts to the speed of the data stream with usage of compact and self-adaptive index structure for maintaining stream summaries. It incorporates the age of the objects to reflect the greater importance of more recent data.

3  Method for mining personalized behavioral patterns over a data stream

In this section, we describe method for online mining of behavioral patterns from the user activity within the website. The method combines global patterns, identified from behavior of all website users, with the group patterns determined for dynamically identified groups of similar users. Based on identified behavioral patterns, proposed method is able to recommend to individual users the pages they are probably going to visit in current session, cache these pages etc.

User sessions represented as set of user actions are input to the method. Actions could be diverse from webpage visits to product purchases, shopping basket manages (adding or removing items), etc.

Our method comprises of three logical components. First component ensures clustering of users into groups based on similarity of their behavior. Second component is used for searching for global and group behavioral patterns represented as closed frequent itemsets over data stream. Third component ensures application of found patterns.. In this paper we focus to recommendation task, because of wide usage possibilities of process results (e.g., recommendation of interesting pages, caching probable future visits in advance). The third component of our method in addition ensures evaluation of the used application task. All these components are joined into process described in section 3.2 and illustrated in Figure 1.

We implemented the method into MOA framework [20], which contains implementations of data stream frequent patterns mining algorithm *IncMine* and data stream clustering algorithm *Clustream*. We use them to quickly prove concepts proposed in this paper. Later on we plan to experiment with other algorithms and compare with existing results.

3.1  Clustering and user model representation

Important part of designed process is user clustering according to their similar behavior in recent past. Proposed method uses Clustream algorithm. Clustream algorithm consists of fast update of microclusters phase and macroclustering phase where k-means or other traditional clustering algorithms can be applied in microclusters to find the final clusters. As our method needs to perform macroclustering regularly as part of data streaming processing, this phase should be fast enough. Therefore, we use k-means, which is fast and easy to adjust algorithm. The defined process, however, should be considered as a framework and macroclustering algorithm as well as frequent patterns mining algorithm should be matter of choice depending on usage domain requirements.

As a data stream could be potentially infinite we need to prevent possible memory leak caused by adding new user models to memory and not maintaining the unused ones. We represent users’ behavior simply as different frequency spectrums of their recent actions. The actions are stored to queue with limited capacity.

User model *u* consists of following attributes:

* *uid* : user identifier.
* *aq*: actions queue. Queue with limited capacity to store actions user took in recent history.
* *gid*: group identifier. Id of group where user was classified to in last macroclustering.
* *nsc*: new sessions count. Number of new sessions of this user since last macroclustering.
* *lmid*: last macroclustering id. Identifier of last macroclustering performed when this user model was active.

Macroclustering phase is performed on regular basis (always after defined number of updates in microclusters). Let *lmid* (last macroclustering id) be global macroclusterings counter. It is incremented always when new macroclustering phase is performed. User *u* is assigned new group identifier on his first session after new macroclustering was performed. So only if his *u.lmid* < *lmid*. Always after new macroclustering is performed, every user model *u* where *lmid* - *u.lmid* > *tcdiff*, where *tcdiff* (threshold of clustering identifiers difference) is input parameter, is deleted to prevent memory leak.

3.2  User session processing

In this section we describe user session processing. The process is designed as a framework, where individual components are independent and can be replaced by another implementation (e.g., different clustering or frequent patterns mining algorithm) (Figure 1). Every user session, represented as set of actions, is continuously loaded from the data stream. Method uses evaluation approach interleaved test-then-train [20] where each individual example can be used to test the model before it is used for training. When intentionally performed in this order, the model is always being tested on examples it has not seen. Therefore, at first, user session is used in recommendation task as we proposed in previous section and other evaluation purposes as we describe them later. Next, the user model *u* is updated. Actions from current session are added to queue in user model and *u.nsc* (new sessions count) counter is incremented. If *u.nsc* is greater than input parameter *tcu* (threshold number of changes in user model) then *u.nsc* is nulled and microclusters are updated with instance generated from *u.aq* (user model’s actions queue) and *u.muc* (microclusters updates counter) is incremented by 1. If number of updates in microclusters (*muc*) is greater than given threshold *tcm* (threshold number of changes in microclusters) then *muc* is nulled and macroclustering is performed. With macroclustering *lmid* (last macroclustering id) is incremented. And every old user model *u*, meeting condition that , (where *tcdiff* parameter is threshold of clustering identifiers difference) is deleted from memory. Next if user model *u* has *u.lmid* attribute value other than current global *lmid* then *u.gid* is assigned identifier of group he belongs to according to last macroclustering performed. Lastly, user session becomes an input for algorithm mining frequent patterns (both global and group).

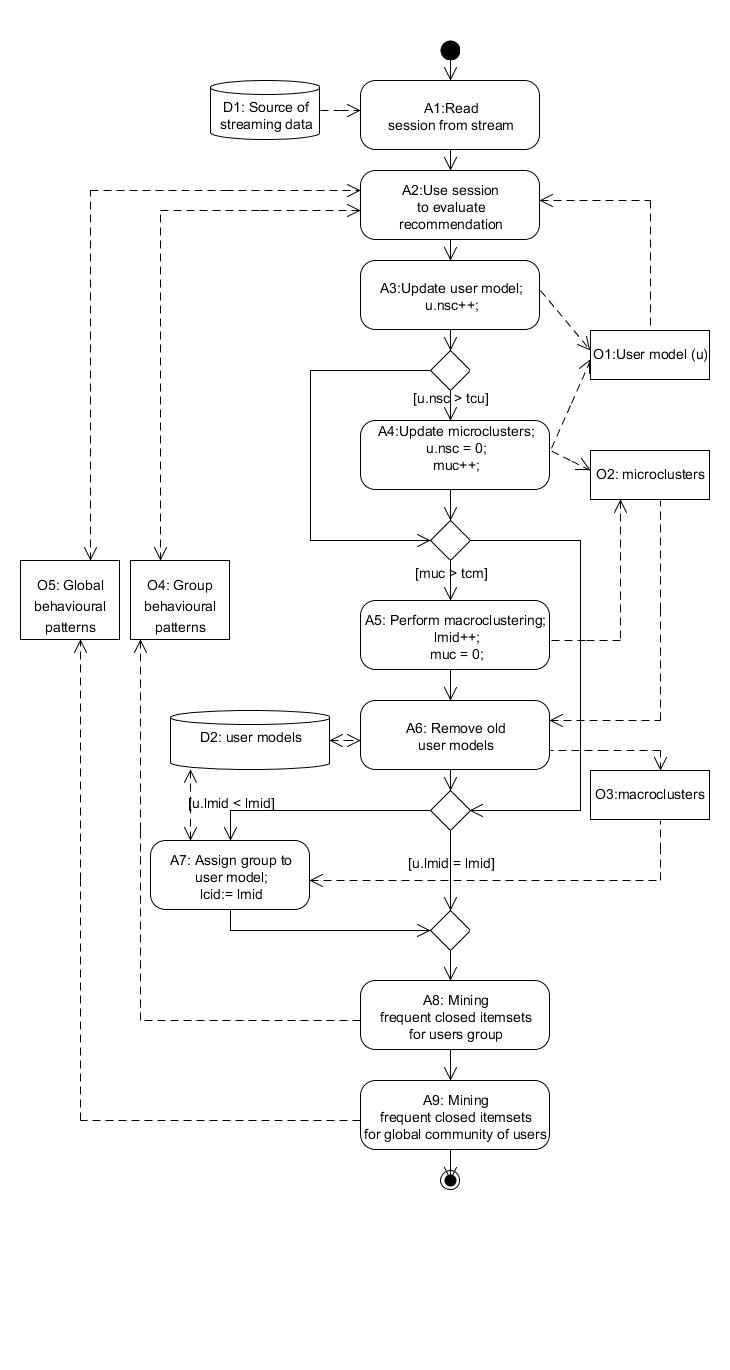


Figure 1: Activity diagram displaying processing of user sessions within proposed method. Diagram elements are tagged with prefixes describing their types: actions are tagged as A, data objects as O, data sources as D.

3.3  Application of behavioral patterns

As we mentioned before, behavioral patterns can be applied in wide scale of tasks. In this paper we used them to recommend pages to users based on their previous behavior in the actual session. Let the session be represented as vector of user actions .Found behavioral patterns are . Each pattern is represented as set of actions . Let *ews* be size of evaluation window part of session. Condition must be true to use actual session for evaluation of recommendation. Let first *k* actions of *S* be dedicated as evaluation window and all other actions from *S* as testing part . Let *r* be number of recommended items. If condition is not met, then *S* is ignored for evaluation. We use following strategy to choose behavioral patterns according to actual evaluation window:

1. For each in (containing global patterns and patterns from group user belongs to) approximate support value normalized to *<0,1>* interval is computed. Let’s mark it as . Size of intersection of with is determined with *LCS* algorithm (least common subset). It is also normalized to *<0,1>* interval. Let’s mark it as .
2. All patterns (global and group) are sorted. First by size of intersection with descending. Second by descending support value.
3. Let *M* be map of items and their *"votes"*. By iterating over all patterns votes values of items are updated. Votes value of item *i* that is contained in pattern and not in is incremented by .
4. Finally, *M* is sorted descending by votes values and best *r* items are picked to be recommended to user.

3.4  Speed regulation



As mentioned in [21], mining of frequent itemsets over the data stream requires balancing requirements for method accuracy and effectivity according to needs of specific task it will be used in. Higher speed means worse accuracy and vice versa. Our method offers option to set minimal required speed as input parameter *mts* (minimal transactions per second). As we mentioned, *IncMine* algorithm processes transactions in batches. Every update of batch (segment) is a critical part. Let *ctrans* be actual number of processed transactions from start of measuring. Let tstart be a time when measuring started and tsupdate a time when batch update started. The maximal allowed time of update tmax before each update is calculated as:

|  |  |
| --- | --- |
|  | (1) |

When frequent itemsets update in current batch takes more time than *tmax* it is simply stopped. It means that some frequent itemsets won't be discovered. On the other hand, the process guarantee the maximal processing time..An interesting solution for the problem of patterns omitting would be using of algorithm for mining frequent itemsets from transactions batch [22]. In this case, the *k* most frequent itemsets are mined, which result to no need of explicit setting of minimal support threshold. In addition, there is guarantee of discovering the best patterns first. The implementation of this kind of solution is however outside of scope.

3.5  Summary of parameters used

One of critical parts of designed process is to properly set up the input parameters of individual method parts (clustering algorithm, frequent patterns mining algorithm, etc.). As there exist high number of input values combinations, the method tuning could have exponential complexity. To optimize such a process, there should be used some optimizations as for example tuning individual method parts separately etc. For this reason we divided method input parameters into four categories according their purpose (Table 1).

We use *IncMine* algorithm [13] implemented in MOA framework for mining frequent closed itemsets over data stream. We search for best settings of its input parameters: minimal support, relaxation rate, segment length, window size.Minimal support is value corresponding to parameter in *IncMine* algorithm that is used to compute progressive function of minimal support (MST) for different segments of actual window. Relaxation rate is value corresponding to *r* parameter in *IncMine* algorithm that is used to compute relaxed MST, which prevents it from deleting potentially frequent itemsets. Segment length is number of transactions (in our case these are user sessions) in one batch update. Window size is number of segments sliding window consists of.

We use *Clustream* algorithm with k-means macroclustering algorithm as implemented in MOA framework. We search for best settings of its input parameters: number of clusters, maximal microclusters count, together with input parameters specific to our method related to clustering part: threshold number of changes in user model, threshold number of changes in microclusters (we explained their usage in process description 3.2).

Category of recommendation parameters contains: evaluation window size, recommendations count. Evaluation window size represents number of actions in user session used to identify best patterns to use with recommendation. All other actions in user session following this window are used as test set to evaluate generated recommendations. Recommendation count represents number of actions recommended to user.

Category of general method parameters contains: minimal transactions per second, threshold of clustering ids difference. Minimal transactions per second represents minimal processing speed requirement. Threshold of clustering ids difference represents maximal difference between global macroclusterings counter (lmid) and counter in user model u (u.lmid). If this threshold is crossed user model is marked as inactive and deleted.

Table 1: Summary of parameters.

|  |  |  |
| --- | --- | --- |
| **abbr.** | **full name** | **category** |
| *ms* | minimal support | IncMine |
| *rr* | relaxation rate | IncMine |
| *sl* | segment length | IncMine |
| *ws* | window size | IncMine |
| *gc* | groups count | clustering |
| *tcu* | threshold number of changes in usermodel | clustering |
| *tcm* | threshold number of changes in microclusters | clustering |
| *mmc* | maximal microclusters count | clustering |
| *ews* | evaluation window size | recommendation |
| *rc* | recommendations count | recommendation |
| *mts* | minimal transactions per second | general |
| *tcdiff* | threshold of clustering ids difference | general |

4  Evaluation

As mentioned before, we evaluate proposed method indirectly by recommendation of items for user to visit within the actual session. We compare results of 3 different methods for behavioral patterns identification. First method generates recommendations using global patterns only (*GL*), second identify patterns specific for groups of users with similar behavior (*GR*) while third, our proposed method, combines previous two into new hybrid method (*GG*).

Recommendation results are compared based on *precision* metric. The recommendation is generated and evaluated for every session *S* from used datasets. The session is divided into training window *A* (its length is equal to input parameter *ews*) and testing window *B*. Let number of recommended items be *N*, and set of recommended items *R*. We compute *precision* as

|  |  |
| --- | --- |
|  | (2) |

Processing speed results are compared based on speed metric we defined as average number of sessions processed in a second. It is computed as

|  |  |
| --- | --- |
|  | (3) |

4.1  Datasets

We evaluated proposed method on two datasets from domains with different characteristics. First used dataset come from e-learning system ALEF (Adaptive Learning Framework) [23], second dataset belongs to news portal (NP).

Preprocessing of both datasets consisted mainly of users’ sessions identification and omitting of too short sessions (1 action long).

ALEF dataset contains 24k user sessions from 870 users. The actions were performed between 26/10/2010 and 30/04/2013 (917 days but only 737 active). There is in average 33.37 sessions per active day with 15 actions in average per session. In this e-learning system, users could visit 2072 different learning objects (web pages).

In NP dataset there exist 334k sessions. Data was collected between 01/03/2015 and 01/07/2015 (122 active days). In average there exist 2739.8 sessions per day with 3 actions in average per session, which is significant difference from ALEF dataset. For simplicity of evaluation we removed all user sessions with length less than 3 as these sessions act as noise for patterns mining algorithm. In NP there is 199k users. Many of them are much less active than users in ALEF and they don’t return to the site so often if even. In news portal there exist several thousands of pages (articels) and they are active for too short time to be able to recognize behavioral patterns over their visits. For this reason we abstract the pages into 85 categories (e.g., culture, sport) and recognized patterns over them. This abstraction brings significant patterns recognition method speed (lower number of possible actions and patterns) and patterns quality (higher patterns occurrence) increase in comparison to ALEF dataset.

4.2  Searching for best configurations

Considering number of input parameters our method takes (described in section 3.5), we used grid search approach to find most promising configurations maximizing recommendation precision. To reduce space of possible parameter values combinations, we tuned method parts independently based on their category (Table 1).

In this section we describe best found configurations of individual categories of parameters. Results from ALEF dataset are affected by minimal speed requirements (*mts*), which we set to 15 transactions per second. Patterns for ALEF are discovered in high dimensional space of all possible pages, which slows down the processing. For this reason multiple parameter configurations met the minimal speed requirements and have to be skipped. In NP dataset, processing is much faster due to lower dimensionality of actions (page categories) and therefore *mts* value we set doesn’t affect the results quality. In Table 2 there are enumerated all parameters’ values we searched for.

Table 2: Parameters values used as search space in grid search.

|  |  |
| --- | --- |
| **abbr.** | **Values** |
| *ms* | 0.005, 0.01, 0.02, 0.03, 0.04, 0.05, 0.1 |
| *rr* | 0.1, 0.5, 0.9 |
| *sl* | 25, 50, 100, 150, 200, 500 |
| *ws* | 5,10,15 |
| *Gc* | 2, 4, 6, 8 |
| *Tcu* | 5,10,15 |
| *tcm* | 50, 100, 200, 400, 800 |
| *mmc* | 100,1000 |
| *ews* | 1,2,3,4,5,6,7, 8, 9, 10 |
| *rc* | 1,2,3,4,5,10,15 |
| *mts* | 15 |
| *tcdiff* | 1,2,3,4, 5,6,7,8,9,10 |

Let *h* be number of recent sessions stored in memory. It is computed as: .Evaluation of every parameter configuration always starts after certain number of transactions are processed. It is computed as: . Where *C* is set of all searched configurations of parameters. This approach is used for the reason that the configuration with smaller *h* is able to recommend sooner than configurations with higher *h* value. For first category (*IncMine* algorithm) we evaluated 270 different parameter configurations. In both domains we observed that configurations with longer window size (*ws* = 15) and shorter segment length (*sl* = 25) reach higher precision.

Next, we observed that too small value of *ms* causes generation of too many patterns, which causes slowing down the method and failing in minimal method speed requirement in ALEF domain. On the other hand, too high *ms* value causes generating of small number of patterns only, which could cause missing of some potentially important patterns.

Tuning the parameters from second category used for clustering brought 120 different configurations. We observed that clustering users to small number of groups (<4) was less successful, because some groups were incorrectly joined together. In both domains, we observed best results when using smaller value of *tuc* (threshold of user model updates) in combination with higher *tcm* (threshold of microclusters updates). It means that microclusters are updated more often for recent users’ behavior and also number of microclusters updates required, to perform macroclustering, is reasonably higher to capture enough information to be able to cluster users correctly.

Table 3: Best configurations of parameters for both domains.

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **ms** | **ews** | **rr** | **sl** | **ws** | **gc** | **Tcu** | **Tcm** | **mmc** | **tcdiff** |
| ***ALEF*** | | | | | | | | | |
| **0.05** | **2** | **0.1** | **25** | **15** | **6** | **5** | **400** | **100** | **5** |
| ***NEWSPAPERS PORTAL*** | | | | | | | | | |
| **0.05** | **1** | **0.5** | **25** | **15** | **8** | **5** | **800** | **1000** | **15** |

Table 4: Differences in precision of methods for best configuration in ALEF and NP. GG marks recommendation method using global and group patterns combination. GL marks method using global patterns only. GR marks method using only group patterns.

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  | **P@1** | **P@2** | **P@3** | **P@4** | **P@5** | **P@10** |
| **ALEF** | | | | | | |
| ***GG*** | **50.91%** | **50.97%** | **50.78%** | **50.70%** | **50.86%** | **50.38%** |
| ***GL*** | **48.94%** | **49.16%** | **49.12%** | **49.07%** | **49.04%** | **48.42%** |
| ***GR*** | **38.07%** | **37.98%** | **37.82%** | **37.67%** | **37.79%** | **37.13%** |
| ***GG – GL*** | **1.97%** | **1.81%** | **1.66%** | **1.63%** | **1.82%** | **1.96%** |
| ***GG -GR*** | **12.84%** | **12.99%** | **12.96%** | **13.02%** | **13.07%** | **13.25%** |
| **NEWSPAPERS PORTAL** | | | | | | |
| ***GG*** | **65.08%** | **53.90%** | **55.79%** | **55.73%** | **54.79%** | **51.15%** |
| ***GL*** | **63.86%** | **52.81%** | **54.66%** | **54.23%** | **52.76%** | **48.89%** |
| ***GR*** | **13.35%** | **11.09%** | **15.78%** | **20.35%** | **23.65%** | **12.18%** |
| ***GG - GL*** | **1.21%** | **1.09%** | **1.13%** | **1.50%** | **2.21%** | **2.26.%** |
| ***GG – GR*** | **50.51%** | **41.71%** | **38.88%** | **30.82%** | **31.58%** | **50.34%** |



For third category of parameters (recommendation) we tuned only a parameter *ews* (evaluation window size). Different values of other parameters from this category (*rc*) were evaluated implicitly for every configuration to be able to compare all results for different number of recommended items. Let be length of session *s*. For recommendation evaluation we could only use sessions with . That’s why changing *ews* and *rc* causes change in number of sessions valid for evaluation. We cannot directly compare parameter configurations with different values of *ews* and *rc* (it would be only possible if we omit great number of short sessions). However, we observed that for ALEF dataset, the best results were accomplished for *ews* > 2 and *ews* < 6. For NP with many short sessions, *ews=1* performed the best results for recommendation of less than 4 items. Recommendation of multiple items, however, reached better results with higher *ews* value.

For last category of parameters (general), we observed that deleting inactive user models too soon (when *tcdiff* is low), after new macroclustering is performed, cause worse results. In both domains, we observed trend of precision increase after increasing the *tcdiff* threshold. User models should be removed after certain time of inactivity to prevent possible memory leak and slowing down the method. In ALEF dataset ascending precision trend was visible until *tcdiff = 5.* Student behavior in ALEF is highly joined with actual course studied. For this reason, their user model should be removed after finishing the course. In news domain ascending precision trend (with ascending *tcdiff*) was visible for all evaluated *tcdiff* values (1-10). In news domain we represent user actions as category visits, which are stable and thus usable for longer time periods. In this case, the models should remain until users are active in the website.

4.3 Evaluating relations between group and global patterns

Finally, according to performed search, for each dataset, we chose the best configuration maximizing precision metric and processing speed (Table 3). For these best settings we compare proposed method to the baseline methods using global and group only patterns (Table 4). We performed statistical t-test to compare precisions of compared methods. For ALEF dataset proposed method reached significant increase of precision when compared to method using only global patterns (p < 0.0001, t= 9.7153, df= 7600, difference of means 0.0165) and also compared to method using only group patterns (p < 0.0001, t=103.2904, df=7600, difference of means 0.2143). For NP dataset we reached also significant increase compared to method using only global patterns (p < 0.0001, t=3.8976, df=12598, difference of means 0.0086) and also compared to method using only group patterns (p < 0.0001, t=239.6845, df=12598, difference of means 0.4137).

For each user session, we evaluate separately results of recommendation approach that is using global behavioral patterns only (*GL*), group behavioral patterns only (*GR*) and using their combination (*GG*). This results in three different sets of successful recommendations (Figure 2

To be able to compare results of combined *GG* method not only to its parts (*GL*, *GR*), we present also the best theoretical combination of both individual methods (Table 5). In this case, the better result of *GL* and *GR* is chosen for every session. Based on this information, it is possible to evaluate the quality of used approaches combination.

From the experiment results, we observe quite large intersection of successful recommendations generated based on global and group patterns (*H110*). Number of successful recommendations generated by usage of global patterns only (*H100*) is much higher than number of successful recommendations generated with usage of group patterns only (*H010*). The reason is that small number of sessions within groups results into low quality patterns (low support). We observed that precision is higher in larger groups with many active users.

In addition to overall precision, we observed recommendation precision inside each user group during the stream processing. The results were logged in regular intervals before new macroclustering (in total, 9 measurements were realised during stream processing in ALEF and 18 measurements in NP) (Figure 3).

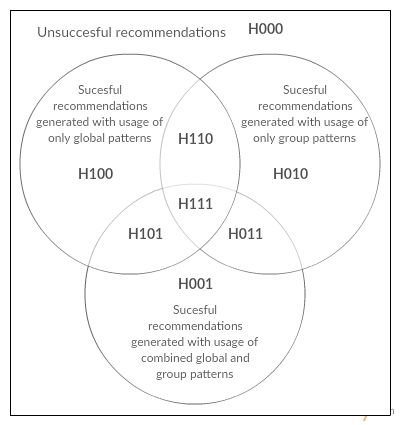


Figure 2: Venn diagram displaying sets of successful recommendations gained by different methods and marking of their intersections. (hits)

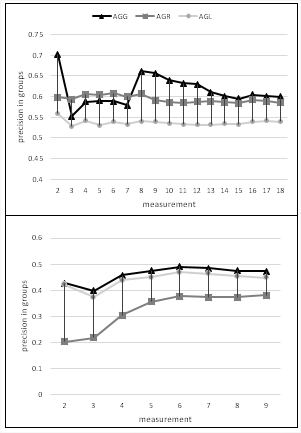


Figure 3: Average recommendation precision within groups for NP (upper) and ALEF datasets (lower). Precision is computed as average of precisions inside each group. *GG* marks method using global and group patterns combination. *GL* marks method using only global patterns. *GR* means method using only group patterns.

Table 5: Facts computed from sets of successful recommendations from different methods using only global patterns or using only group patterns or both.

|  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Description of** | **Computed as** | **ALEF** | | | | | **NEWSPAPERS PORTAL** | | | | |
| **P@1** | **P@2** | **P@3** | **P@4** | **P@5** | **P@1** | **P@2** | **P@3** | **P@4** | **P@5** |
| Hypothetic situation, where more precise result is always chosen (from *GL* and *GR*) | H111+H110+H101+H100+H011+H010 | **55.14** | **57.02** | **58.40** | **59.06** | **59.88** | **66.79** | **55.92** | **59.33** | **60.65** | **61.00** |
| *GG* | H101+H011+H001+H111 | **50.71** | **51.26** | **51.73** | **51.96** | **52.41** | **64.88** | **53.68** | **55.68** | **55.66** | **54.91** |
| *GL* | H111+H110+H101+H100 | **49.27** | **49.85** | **50.44** | **50.73** | **51.06** | **63.69** | **52.62** | **54.58** | **54.19** | **52.76** |
| GR | H111+H011+H110+H010 | **32.41** | **32.93** | **33.21** | **33.24** | **33.57** | **13.06** | **10.86** | **15.43** | **19.88** | **23.07** |
| Recommendations generated uniquely of group patterns and not global patterns. | H011 + H010 | **5.86** | **7.17** | **7.97** | **8.33** | **8.82** | **3.10** | **3.30** | **4.74** | **6.46** | **8.24** |
| Recommendations generated uniquely of global patterns and not group patterns. | H101+H100 | **22.72** | **24.09** | **25.19** | **25.82** | **26.31** | **53.72** | **45.06** | **43.90** | **40.78** | **37.93** |
| Recommendations generated uniquely by combination of global and group patterns. | H001 | **0.32** | **0.84** | **1.19** | **1.54** | **1.84** | **0.08** | **0.49** | **0.80** | **1.24** | **1.70** |

From these results is visible that *GG* for both datasets reached the highest precision, which shows that it is suitable to combine global and group patterns. The difference, however, lies in results of *GL* and *GR*. In ALEF dataset, *GL* reached better precision in comparison to *GR*, while in the case of NP dataset, the situation is opposite. It is caused by the number of users in the datasets. In NP, there exist high amount of users, so they can be clustered into highly similar and quality groups. For this reason and despite the short sessions, there can be identified quality patterns. In ALEF, there are less users, who in addition perform more specific sessions and thus it is unable to create such quality behavioral patterns. Despite this restriction, group patterns are useful, as can be seen from results of *AGG*, which outperformed the *AGL* method. Results of both methods are able to find unique patterns.

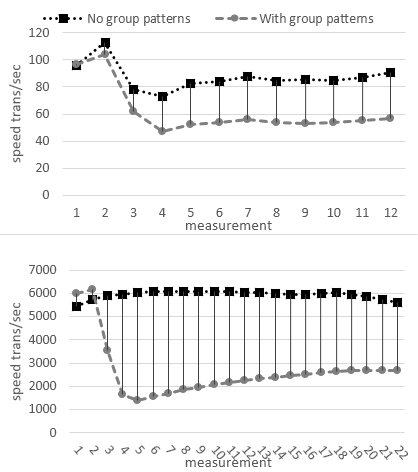


Figure 4: Average processing speed of ALEF (upper) and NP datasets (lower). The measurements are taken every 2000 transactions.

4.4 Evaluating speed

For approaches specialized in data stream processing, computation time represent one of the crucial criterions of usability. For this reason, we observed, in addition to recommendation precision, also the processing speed of proposed method. For both datasets, we ran proposed method (*AGG*) 20 times measuring the average speed logged in regular time intervals. To be able to consider computational cost of user clustering, group patterns creation and their combination with global patterns, we compared it to result of AGL method computing global patterns only (Figure 4).

From the results is visible that additional cost caused by clustering and searching for group patterns is constant and thus maintainable in production. Another finding came from comparison of results between both domains. We can see that computation is faster in order in the case of NP dataset. The reason is the number of possible items, from which are identified the behavioral patterns (tens of categories in NP, hundreds of pages in ALEF). This in addition shows up, how items abstraction help to significantly reduce computation time.

5 CONCLUSIONS

In this paper we propose a method, which is able to perform multiple tasks over data stream: segmenting users to groups dynamically, searching for group and global behavioral patterns and applying these patterns in recommendation task.

The method was evaluated on e-learning and news data, which have highly different characteristics (total size, number of users, different average length of session). We performed multiple experiments mainly with purpose to investigate how useful is combining global and group patterns. The method was evaluated indirectly through recommendation task, where we observed precision and speed (which is important because of data stream processing) of the method.

GG method reached significant increase of precision when compared to GL and GR methods with both datasets.

In addition to overall precision, we observed recommendation precision inside each user group during the stream processing. In NP dataset, *GR* method outperforms *GL* inside of groups thanks to high amount of users forming high quality groups and therefore quality patterns. In ALEF dataset, however, *GL* method outperforms *GR* because there are less users performing more specific sessions and thus it is unable to create such quality patterns. Our method (*GG*) outperformed *GR* and *GL* in both datasets inside of groups.

We showed that additional computational cost of GG compared to GL, caused by clustering and searching for group patterns, is constant and thus maintainable in production. Also that, abstraction of items from which are identified behavioral patterns results in significantly faster computation.

Next, we plan to evaluate proposed method with multiple different algorithms for mining frequent itemsets (top-k frequent itemsets mining algorithm) and clustering (D-Stream and Clustree) and compare results. We will also try to parallelize individual tasks of the method, which can help to make method even faster. Input data stream could be copied to 3 kinds of separate branches – user clustering, mining of group behavioral patterns and mining of global behavioral patterns.

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