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Evolutionary Learner Profile Optimization Using Rare and Negative Association Rules for Micro Open Learning

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Abstract

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Keywords

rare, micro, optimization, open, profile, learning, rules, association, learner, negative, evolutionary

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Abstract. The actual data availability, readiness and publicity has slowed down the research of making use of computational intelligence to improve the knowledge delivery in an emerging learning mode, namely adaptive micro open learning, which naturally has high demand in quality and quantity of data to be fed. In this study, we contribute a novel approach to tackle the current scarcity of both data and rules in micro open learning, by adopting evolutionary algorithm to produce association rules with both rare and negative associations taken into account. These rules further drive the generation and optimization of learner profiles through refinement and augmentation, in order to maintain them in a low-dimensional, descriptive and interpretable form.

Keywords: Micro Learning, Open Educational Resources, Evolutionary Algorithm, Data Refinement and Augmentation, Association Rule Mining.

1 Introduction

The fast-paced lifestyle and wide use of mobile devices have given rise to the phenomenal trend of micro learning, which becomes increasingly popular in the most recent quadrennium [1]. It usually sees that the learning activities are carried out on-the-move within fragmented time pieces. Many previous works believe that the adoption of micro learning has advantages on knowledge retention and reproduction [2], and its benefit can be maximized by delivering OERs in micro interactions to help learners acquire knowledge without information overload [1][2]. The overall temporal distribution of accessing an open educational resource (OER) is often reflected in an intermittent manner, while each segment of time is notably shorter than fifteen minutes.

Owing to the booming of computational intelligence and data analytic techniques, the interests of researchers and practitioners in educational area obviously evolve, from merely supporting its routine operation and provision over virtual learning environment (VLE), to running it smartly over personalized learning environment (PLE).

Being frequently discussed with the development and delivery of online educational resources, the computational or artificial intelligence works best with massive data sources. Nevertheless, the readiness, availability and quality of data sources in educational area remain significantly unsatisfactory [3][4]. Hence, the learner profiling fails to properly represent a learner with valuable information for computational purpose.

In this paper we introduce a new approach to tackle the learner profiling problem in the present adaptive micro open learning research. Accordingly, a path to engage educational computation into the micro learning scenario can be created, by reducing the barriers of source to be consumed in data-hungry artificial or computational intelligence. This approach involves mining rare association (RARs) and negative association rules (NARs) from both frequent and infrequent itemsets, followed by the rules' self-growing and survival of the fittest. Subsequently, the discovered meaningful RARs and NARs will be made use in the optimization of learner profile, which improves the scarcity and sparsity of raw materials for educational computation through data refinement and augmentation.

2 Background

2.1 Association Rule Mining in Educational Data Mining and Learning Analytics

The Micro Learning as a Service (MLaaS) described in [5] draws a blueprint to organize a PLE over cloud to support micro learning through OERs. Looking into its entire architecture, a core component, namely the adaptive engine, functions behind the user interface as a think tank to make decision of OER delivery, by taking advantages of a knowledge base. The educational data mining (EDM) and learning analytics (LA) are organized in the knowledge base, running continuously to inspect learners' daily learning activities circularly. It converts raw data derived from MOOC platforms and LMSs operated by OER providers into useful informational, which is generally concluded in the form of aggregation of association rules that describes the correlation between OERs and the reflection mapped from learner behaviours to OER usages.

As one of the most researched data mining techniques, association rule mining (ARM) has been widely adopted in the extraction of frequent patterns, including in educational domains [6]. It is effective in: discovery of interesting relationships from student's usage information in order to provide feedback to the course author [9]; discovery of students' common mistakes [7]; enquiry of relationships between each pattern of a learner's behaviour [8]; guidance of the search for the best fitting transfer model of student learning [9]; and extraction of patterns to help educators and web masters evaluate and interpret on-line course activities [10].

This effort is naturally anticipated to be inherited into the micro open learning research. Most of recent literature merely focus on mining the frequent patterns. Inevitably, educational datasets in the real world naturally comprise a large portion of infrequent data, which can also be very useful for instructors and intelligent systems to identify students that may need extra guidance in their learning process.

In the education field, association rules that exist in online learning commonly refer to the co-occurrence regularities between the itemset *A* and *B*. From the standpoint of educational ARM, an item can be either defined as: 1) a micro open learning activity which contains a set of learning resources accessed within a given timespan 2) a set of learning resources, together with their educational settings and attributes with values.

Let $A \cup B \subseteq T$ and $A \cap B = \emptyset$. $T \subseteq I$. T depicts the set of transactions (i.e., learning activities in the micro open learning scenario). I represents the entire data source. The association rules are literally explained in the form of IF-THEN. Therefore, the association rule represented in the form $A \rightarrow B$ can be understood as how likely the two learning activities or resources can appear together. Its strength is typically measured by the *Support-Confidence* framework

In addition, the interestingness and comprehensiveness are also taken into account. The work in [11] argues the value of *Lift* is better suited to measure the interestingness of a discovered association rule for educational data sets, which provides the theoretical basis. Subsequently, an association rule's *Comprehensibility* can be quantified by the number of items presented in its both antecedent and consequent domains.

Provided with the three major conditions (i.e., over open education resources, in mobile spaces and fragmented time pieces), the regular micro open learning behaviors differ from traditional learning in blocks of time significantly. The specification of micro open learning motivates the definition of learning behaviours and discovery for interesting patterns that could be, however, usual or abnormal in traditional online learning. In other words, a new mechanism is needed in order to discover rare and negative association rules out of the usage of massive OERs, which has been paid little attention in current EDM and LA works. In addition, previous ARM works in other related fields (e.g., non-open online learning and non-micro online learning) can be hardly migrated into the new micro open learning scenario.

2.2 Rare Association Rules and Negative Association Rules

In the overall research design of MLaaS, the purpose of engaging ARM is to generate machine-understandable knowledge that can drive the segmentation of non-micro learning OERs, and establish mechanisms for learning resources delivery which can meet personalized demands, dynamic context and different learning styles.

The comprehensive learner model discussed in [1] raises the thoughts on what learning behaviors could be specific to micro open learning, and what new patterns could be derived in the brand-new learning scenarios. The extent of such patterns is to be revealed by discovered association rules. For example, during micro open learning quite often learners are studying on-the-move. How the learning intense is affected the noise level of the surrounding is a concern. The ARM is anticipated to distinguish if the learner is situated in a public or private setting, in an instructor-led or self-paced learning mode, feels stressful or comfortable during learning progress and so on. The aggregation of association rules performs as evidence for forecasting if the learner perform additional activities during learning, is under unexpected situation, and the likely sequence of learning tasks in the to-do list.

2.3 Research Challenges

To adapt learners with personalized learning resources, it is insufficient to merely investigate the learners' pre-knowledge and preference without understanding their behavioural patterns. All items in a same dataset are of the same nature and/or have similar frequencies by giving a single threshold for the whole data set. As such, when there are user-defined minimum *Supports*, it is not possible to use Apriori straightforward without proper modification to the algorithm [12].

Researchers have investigated the feasibility to apply multiple minimum *Supports*, which conforms with a layer-by-layer searching process [13]. Enormous candidate itemsets are generated, among which numerous scanning are managed to discover the ARMs. Notably, it is very time consuming and needs considerable computational resources for each search, whilst it drops some uninteresting rules sporadically.

3 Evolutionary Learner Profile Generation

The optimized learner profile is constructed from an evolutionary approach, joining a refined domain and an augmented domain. In particular, the former one is refined from the high-dimensional raw behavioural data, and the latter is predicted by complementary features with values. This is enabled from a two-phase workflow: 1)The EA empowers a rule generator to commence the computation. A comparatively small amount of behavioral data collected from open learning usage is examined to explore association rules, which are further represented as itemset pairs with IF-THEN conditions. These rules are taken as seeds to grow and produce much larger volume of crafted rules. 2) Original and produced rules are combinedly taken to treat available data through refinement and augmentation in order to infer quality learner profiles from a scratch.

3.1 Encoding of Candidate Solutions

To initiate the EA, association rules are encoded into individuals in a computer-understandable mode to form populations. The candidate solutions come from two origins. Firstly, typical ARM algorithms, such as the Apriori algorithm, are borrowed to produce association rules from frequent items [8][14]. Because of the unsatisfactory volume of readily available data in education field [3][4], the outcome from this mining process is evidently insufficient. As a major innovation, the second step makes up the insufficient rules, from which human-crafted rules from domain experts are employed in the production of new rules. This is capable of refining generated rules complying with their original forms while resembling the well-established human-crafted rules, so as to retain the interpretability of generated rules.

By employing the famous Michigan approach to encode a single rule in an individual rather than a batch of rules, both the antecedent and consequent section of each individual contains n predictive values.

3.2 Discovery of RAR

To avoid predefining to many minimum *Support* and *Confidence* in a single ARM framework, in this study we start from a new line to discover RARs, where the association rules are firstly classified into four types. Herein, an itemset is defined as a minimal rare item set (MRI) if it is rare but all its proper subsets are frequent.

A single *Support* threshold is predefined before the entire data set is scanned to cluster itemsets into non-present, frequent and rare itemsets according to their values of *Support*. If one subset R_j of a screened rare itemset, R, meets the condition of MRI, its closure is built as $\overline{R_j}$, and a rare association rule is generated as: $R_j \rightarrow (\overline{R_j} - R_j)$

3.3 Discovery of NAR

A negative item, which is also known as non-present item [15], is a learning activity absent from the present activity set T. The inverse association between two itemset A and B are denoted as $\neg A \rightarrow B$, $A \rightarrow \neg B$ and $\neg A \rightarrow \neg B$, where the antecedent A and/or consequent B contain(s) at least one negative item, where $A \subseteq I$, $B \subseteq I$, and $A \cap B = \emptyset$.

All frequent and rare itemsets generated in Section 3.2 are reused for producing NARs. For all frequent itemsets, all inverse associations between two itemsets are selected; while for all rare itemsets, all inverse associations between two MRIs are selected. The *Confidence* values and *Lift* values for all selections are evaluated to compare with the minimum Confidence and 1, respectively, and recorded as NAR if both metrics are greater than or equal to the benchmarks.

3.4 Class Association Rules on Learning Style

The class association rule (CAR) [16] is a special type of association rule which describes an implicative co-occurring relationship between a set of items and a predefined class in its consequent. By the means in [17], learners' hints in learning activities can be numericized against learning styles. Therefore, the CAR is effective in identifying learning styles at different levels.

3.5 Association Rules Generation by EA

The principle of rule generation is shown as in the Fig. 1. Herein, the EA consists of two loops, the outer loop is realized by a genetic algorithm (GA), whose mutation process is polished by an additional inner loop to contribute candidate solutions (i.e., mutated individuals) by taking into account RARs and NARs. The inner loop is realized by an artificial bee colony algorithm (ABC), which blends in the data augmentation in the reproduction of rules towards better fitness, on top of the refinement empowered by the outer GA. For the data augmentation in the inner loop of ABC, existing itemsets with non-present learning activities are made up with their inverse items.

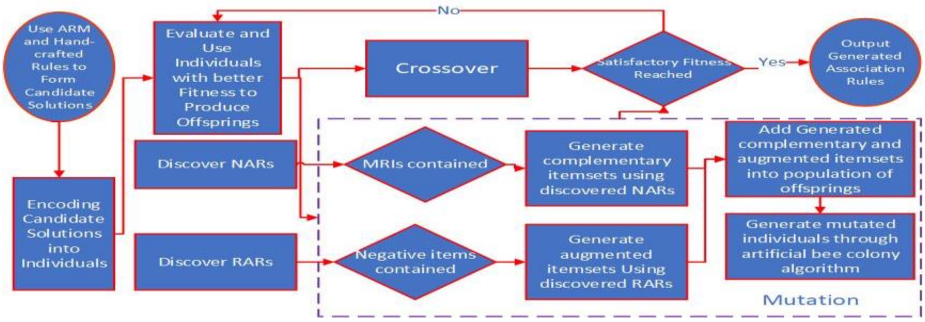

Fig. 1. Evolutionary Algorithm for Association Rule Generation (Outer Loop and Inner Loop)

3.6 Rule-based Optimization for Learner Profile

As the available association rules are booming after the evolutionary production, raw data can be further refined and augmented to generate the optimized learner profile.

A learner's profile is denoted as a vector, in which the feature generation is activated by a CAR-based learning style identification. Association rules fall in the domain of the particular learner's learning style are selected out, which are consequently applied to produce a set of refined behavioral features with values, or predict complementary features with values for each learner [18].

The second step starts with an empty set of features in each vector. In the commencement of iteration, the rules with the best fitness for the premier learning style are examined and adopted to add the first feature. The selected rules connect a candidate feature to be accepted or rejected into the construction of the vector; if the feature is accepted, by referencing rules again, the existing value will be kept or a new value will be predicted to join each accepted feature as a full pair.

The second and subsequent feature-value pair are added into the vector in the same fashion until the termination condition is met. Instead of keeping only the best set feature-value pairs, the procedure is improved a little by keeping *k* best sets of pairs (k>1) in each iteration. The refined and complementary features in the vector are jointly taken to profile the learner's behavior in a low-dimensional, descriptive and interpretable form meanwhile retaining high fidelity compared to the high-dimensional raw data.

The refined and augmented learner profiles, data, and association rules are iteratively fed into the AI-based LA and decision-making applications to (re)construct and polish the establishment of intelligent delivery mechanism of adaptive micro OERs.

4 Empirical Evaluation

In this section we demonstrate the empirical study to examine the quality of learner profile generated through evolutionary rule-based optimization. The seed association rules rooted from 1) structured datasets Harvard DataVerse[1]and a MITx dataset from Kaggle[2] 2) Human-crafted rules borrowed from [19]. The feature appeared in the 'explored' field of the HarvardX dataset[1] was selected as the index to evaluate the prediction accuracy [20]. It had a binary value of either 0 or 1, where the value equals to 1 if the learner interacted with or viewed more than 50 percent of the course modules. Learner vectors constructed by only original data (shown as V1 in Fig. 2), refined data (shown as V2), augmented data (V3) and both refined and augmented data(V4) were send through the basic logic regression (LR) and linear discriminant analysis (LDA) to predict the target exploration rate.

The comparison results obtained from these approaches are shown in the left and right domain of the Fig. 2, respectively. The X-axis shows the gradually incremental size of the learner set while the accuracies of prediction are represented by the Y-axis. Please note the scale of the X-axis is 1000 learners.

[1] https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/1XORAL
[2] https://www.kaggle.com/chellaindu/mooc-dataset/data

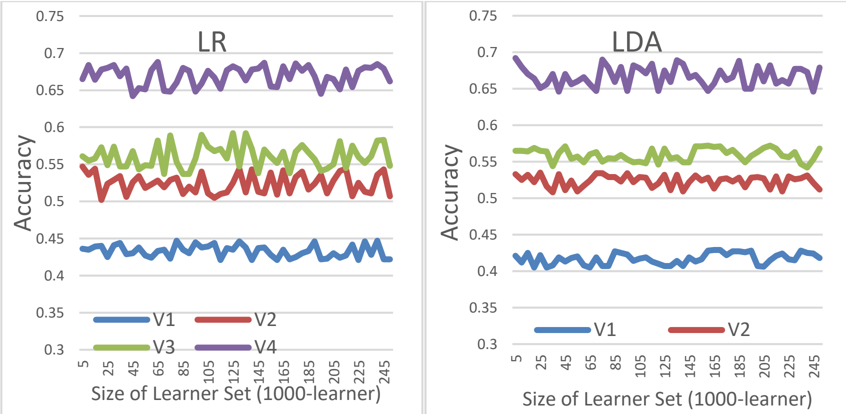

Fig. 2. Accuracy of Exploration Prediction: by Logic Regression (Left)and Linear Discriminant Analysis (Right)

The results from the evolutionary rule generator reveal that the refined data using eleven features to summarize the redundant information from the high-dimensional data. Given all curves shock in a narrow range, the size of learner sets, ranging from 5,000 to 250,000, does not affect the performance of prediction considerably.

Adopting the refined or augmented data can enhance the performance of original data to a remarkable extent, while the sole adoption of augmented data generally surpasses the refined data. For both approaches, the prediction generated using the combination of refined and augmented data outperform the other three trials in accuracy. This can prove the EA-based approach is conductive to enhance the quality of data that are eagerly demanded in AI-empowered computation in education.

5 Conclusion

In this paper we have introduced a novel approach to generate and optimize learner profiles for micro open learning, in terms of association rules from an evolutionary generator, The generated rules are evaluated and those with optimal fitness are selected as benchmark for data refinement and augmentation, which can better ensure the trade-off between accuracy and interpretability. This work covers the current gap of learner profiling which suffers from the deficiencies of readiness and availability of public data sources in educational area, and contributes to the present practices of computational intelligence in educational research and application.

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