Meta-learning for predicting the best vote aggregation method: Case study in collaborative searching of LOs

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ABSTRACT

The problem of recommending learning objects to a group of users or instructors is much more difficult than the traditional problem of recommending to only one individual. To resolve this problem, this paper proposes to use meta-learning for predicting the best voting aggregation strategy in order to automatically obtain the final ratings without having to reach a consensus between all the instructors. We have carried out an experiment using data from 50 groups of instructors doing a collaborative search of LOs in AGORA repository.

Keywords

Meta-learning, Classification, LOs Collaborative Search

1. INTRODUCTION

Nowadays, there is a wide variety of e-learning repositories that provide digital resources for education in the form of Learning Objetcs (LOs). The search for and recommendation of LOs are traditionally viewed as a solitary and individual task but this is changing. On the one hand, collaborative search can be more effective than an individual search, for example in our case, a group of instructors may be interested in searching and selecting together the educational resources most appropriate to develop a new digital course. On the other hand, the goal of group recommendation is to compute a recommendation score for each item (in our case, each LO) that reflects the interests and preferences of all group members. The problem is that all group members may not always have the same tastes, and a consensus score for each item needs to be carefully designed. So, to recommend to user groups is more complicated than recommending to individuals [2]. The main problem that group recommendation needs to solve is how to adapt to the group as a whole, based on information about individual users' likes and dislikes. A solution is to use group decision strategies or aggregation methods that are inspired by social choice theory, and establish different automatic ways of how a group of people can reach a consensus. However, groups are very diverse, and no single group decision strategy works best for all groups. A way to address this issue is to identify the inherent characteristics of different groups and to determine their impacts on the group decision process [1]. Following this idea, in this paper we propose to use meta-learning for predicting the best aggregation method recommended for a group based on its characteristics. In this way, the traditional time-consuming consensus-taking among users can be avoided by using an automatic method based on meta-learning.

2. PROPOSED METHODOLOGY

In order to resolve the problem of determining which aggregation method is the most appropriate for each type of collaborative search group, we propose to use a meta-learning process (Fig. 1). The idea is to obtain automatically the aggregation method which provided/gave the best performance for a group of instructors based on its characteristics and previous rating of other similar groups. As seen in Fig. 1, the meta-learning process starts from a dataset which contains descriptive information about groups, the individual ratings of each member to all the LO's selected by the group during the collaborative search, and the consensus about the final rating assigned to all selected LO's. Next, the groups' characteristics are defined and the performance of the rating aggregation methods is evaluated in order to form a new metadata set. Then we select a classification algorithm that it used each time we have a new group of users/instructors in order to can recommend an aggregation method of their LO's rating.

Firstly, in order to create metadata, we use the following previously proposed descriptors or characteristics [1]: group size, social contact level, experience level and dissimilarity level. Additionally, we also propose a new descriptor based on the activity level of the group members in using LO repositories. Then, an evaluation phase is necessary in order to determine which aggregation method obtains the lowest error with respect to the actual consensual final rating of group members for all LOs. This actual or real rating is the final score of the group, obtained after consensus between all the members. So, it is necessary that the group have an in-person reunion or online communication in order to achieve the final score, starting with each individual rating/score and opinion. Various aggregation methods can be used to automatically obtain the final group rating for each LO [2]. We propose to use eight traditional aggregation methods

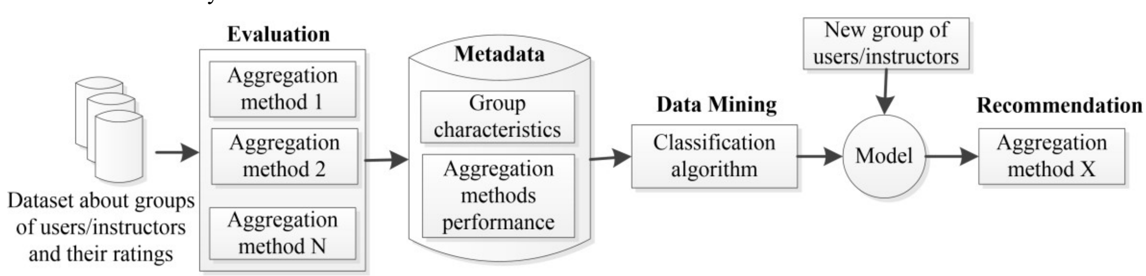

Figure 1. Meta-learning process for recommending a voting aggregation method.

(plurality voting, average, median, approval voting, least misery, most pleasure, average without misery, and fairness) plus three new weighted versions (active, social and experience user) of the average method based on [3]. In our case, instead of assuming equal weights for all the members, we give more weight to some users based on their characteristics, assuming that some members are more influential and can persuade others to agree with them. Next, a new metadata set is created by using both the characteristics of each group and the obtained aggregation method that provided the best group performance. After that, a classification algorithm is used to predict which aggregation method is most appropriate for a new group, given its characteristics. However, because there are a lot of classification techniques, we must therefore select a representative number of classification algorithms in order to compare their performance when using our metadata set. Finally, the classification algorithm that provides a better general performance will be the one selected for predicting the aggregation method most appropriate for each new group. In this way, the classification model obtained by the selected algorithm will be used for selecting, in real time, the best aggregation method for a new group according to the characteristics of the group and their individual ratings.

3. EXPERIMENTAL WORK

We have carried out an experiment in order to test our proposal of predicting the most appropriate aggregation method to use with a new group, based on the characteristics of the group members and the previous rating of similar groups. We have used data from a collaborative search of LOs in DELPHOS system [5]. We sent invitations, without using any incentive, to all instructors and final-year students of the Faculty of Education of the Autonomous University of Yucatan in Mexico to participate in the experiment. Only 75 users accepted our invitation: 27 professors or university teachers at different levels (assistant, associate and full) and 48 final-year students. We defined a total of 50 different groups of instructors and students with different typologies on their characteristics. We created a metadata set that contains both the previous characteristics/descriptors of the 50 groups as well as the best aggregation methods for each group by evaluating the performance of the 11 used rating aggregation strategies (see Table 1). In order to do this, we have used RMSE (Root-Mean-Square Error) of each aggregation method in each group. Starting from this metadata set, it is possible to predict the best aggregation method to a new group by using a classification algorithm. This is a classification in which the class or attribute to predict is precisely the aggregation method that obtains the best ranking. To this end, we have used different classification algorithms provided by the WEKA software, which is one of the most popular and most used tools for data mining. We have selected a representative number of the best known classification algorithms available in WEKA: JRip (implementation of RIPPER algorithm), J48 (implementation of C4.5 algorithm), NaiveBayesSimple (implementation of Bayes classifier), SMO (implementation of support vector classifier) and IBk (implementation of KNN or Nearest Neighbours algorithm). We have executed the previous five classification algorithms using their default parameter values and 10-fold cross-validation. In order to evaluate the classification performance and to determine the best algorithm for each group, we have used two measures that have previously been used to evaluate classification algorithm recommendation methods [4]. The first is called ARE (Average Recommendation Error) and it measures the average error of the current recommendation (predicted aggregation method) regarding the best and the worst recommendation (best and worst aggregation methods from the list of methods ordered from the lowest to the highest RMSE). The second measure is the Reciprocal Average Hit Rate, also known as Mean Reciprocal Rank (MRR), which measures the median position occupied by the method currently predicted for each of the groups in the complete list of methods ordered by RMSE.

Table 1. Average Recommendation Error and Mean Reciprocal Rank obtained by the 5 classification algorithms.

Algorithm	ARE	MRR
IBk	0,9418	0,3506
J48	0,9492	0,4239
JRIP	0,9594	0,5453
NaiveBayes	0,9458	0,4113
SMO	0,9583	0,4689

As we can see in Table 1, IBk was the best classification/prediction algorithm (followed by NaiveBayes and J48) because it obtained the lowest value of Average Recommendation Error and the lowest value of Mean Reciprocal Rank. So, since the algorithm IBk achieved the best results, it is our selected classification algorithm to automatically recommend the best aggregation method of the most similar group or nearest neighbours to every new group as the best method for rating all the LOs added to the group. In this way, the moderator of the group would use the recommended aggregation method obtained by the IBk algorithm instead of having to conduct the traditional consensual decision process.

4. ACKNOWLEDGMENTS

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