Centric Model Assessment for Collaborative Data Mining

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***Abstract*— Data mining is the task of discovering interesting patterns from large amounts of data. There are many data mining tasks, such as classification, clustering, association rule mining and sequential pattern mining. Sequential pattern mining finds sets of data items that occur together frequently in some sequences. Collaborative data mining refers to a data mining setting where different groups are geographically dispersed but work together on the same problem in a collaborative way. Such a setting requires adequate software support. Group work is widespread in education. The goal is to enable the groups and their facilitators to see relevant aspects of the group's operation and provide feedbacks if these are more likely to be associated with positive or negative outcomes and where the problems are. We explore how useful mirror information can be extracted via a theory-driven approach and a range of clustering and sequential pattern mining. In this paper we describe an experiment with a simple implementation of such a collaborative data mining environment. The experiment brings to light several problems, one of which is related to model assessment. We discuss several possible solutions. This discussion can contribute to a better understanding of how collaborative data mining is best organized.**

Keywords: Data Mining, Sequential Pattern Mining, Collaborative data mining, Data Preparation.

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I. INTRODUCTION

Group work is commonplace in many aspects of life, particularly in the workplace where there are many situations which require small groups of people to work together to achieve a goal. For example, a task that requires a complex combination of skills may only be possible if a group of people, each offering different skills, can work together. To take just one other example, it may be necessary to draw on the combined efforts of a group to achieve a task in the time available [1]. Many different approaches to data mining exist. They have arisen from different communities (databases, statistics, machine learning. Thus, data mining nowadays is performed by people with highly different backgrounds, each of whom have their preferred techniques. Very few people are experts in all these domains, so to get the most out of a data mining process; ideally multiple experts should work together on the same data mining task. These observations provide motivation for the development of a methodology for collaborative data mining. Our

point of departure is that groups with different expertise who are geographically distributed should be able to collaborate on a certain problem, thus jointly achieving better results than any of them could individually. In the context of the European SolEuNet project, ideas have evolved about what functionality such an environment should offer, resulting in a proposal for a collaborative data mining methodology and supporting system called RAMSYS [3] and an implementation using the groupware system Zeno [2]. The paper is structured as follows. In Section 2 we discuss RAMSYS and Zeno. In Section 3 we describe our collaborative data mining experiment and the problems encountered, and in Section 4 we propose and compare possible solution. Section 5 concludes.

II. DATA MINING IN COLLABORATIVE MANNER WITH PROPOSED TECHNOLOGIES

We set our primary goal for the data mining as providing mirroring tools that would be useful for helping improve the learning about group work. This goal is realistic in the context of the highly complex and variable nature of long term, small group activity, especially where the learners undertake a diverse range of tasks, such as creating a software system for an authentic client. Data mining is about solving problems by analyzing data already present in databases [4]. Problem solving can be codified and a procedure or methodology can be developed. There are one methodology in data mining that is used for

industrial process we called Cross Industrial Standard Process for Data Mining, CRISP-DM [5]. This technique is used to reduce the data mining problems into six-related phases of (i) Data Understanding (ii) Data Preparation (iii) Business Understanding (iv) Modeling (v) Assessment and (vi) Deployment. These phases, although presented in a linear manner, have many cycles and feedback loops connecting the phases. Often, effort expended in one phase highlights the need for further work in a prior, previously considered complete, phase.

The Cross Industrial Standard Process for data mining method is extended by RAMSYS technology in the methodology for distributed teams who collaborate in a data mining project. The aim is to combine the great range of expertise available in the data miners to affect more valuable solutions to the data mining problem. The RAMSYS methodology attempts to achieve the combination of a problem solving methodology, knowledge sharing, and ease of communication. It is guided by the following principles [3]: it should enable light management, it should allow collaborators to start and stop any time and leave them problem solving freedom, it should provide efficient knowledge sharing and security. The RAMSYS efforts have focused on supporting the Data Preparation and Modeling phase in a remote collaborative setting; here we focus on the Assessment phase. There is the main requirement of the RAMSYS scheme is the emphasizing and availability of the current preeminent understanding [6] of the data mining problem. This has been implemented using the academic groupware platform Zeno [2], by providing coordination, collaboration, communication and awareness. The provisions of these features are achieved by utilizing (new) features in Zeno including task management, resource management, and discussion sections. The RAMSYS methodology has been trialed (in part or in full) on several data mining projects, one of which is the SPA project described in the subsequently section.

III. A PRACTICAL APPROACH WITH COLLABORATIVE DATA MINING

There are numerous health farms, provide a number of facilities that can be used by its visitors. More specifically, upon their arrival visitors are prescribed certain procedures to follow during their stay at the spa, as well as a schedule for them. The number of people that can simultaneously make use of certain facilities is limited. Thus the spa is faced with a scheduling task: given the procedures that newly arrived visitors need to follow and the limited capacity of certain facilities, create a suitable schedule. The “SPA problem” was offered to the SolEuNet conglomerate by a health farm.

In practice there is insufficient information to solve this scheduling task for the following reason. Visitors stay for several weeks and a schedule for their whole period of stay is made, but during their stay new visitors will arrive. While some information about these new visitors is available in advance (such as time of arrival, age, sex …) the procedures they need to follow will be known only at the time of their arrival. The best one can do is to estimate the demand for the facilities for the near future, and use these estimates for producing schedules for the current patients. It is here that data mining comes in: by mining a database of previous visitors and trying to link properties of these visitors to the procedures they followed, predictive models could be built that estimate the demand for certain facilities based on known properties of future visitors.

Thus the data mining task can concisely be described as follows: given a set of visitor descriptions that will arrive during a certain week, estimate how many of these visitors will need to follow each of some available procedures.

3.1 DATA MINING METHOD IN COLLABORATIVE APPROACH

Group work is used in this scenario, so we make 4 groups in college students. Those are described as: CSE (Computer Science Engineering), ECE (Electronics Communication Engineering), and EE (Electrical Engineering), ME (Mechanical Engineering). CSE served as contact with the end user (the health farm). Following the RAMSYS methodology implies following the CRISP-DM methodology, hence we here briefly describe the efforts according to the different phases Phase 1 (business understanding) involved becoming familiar with the data mining problem, which was done by all groups separately. During Phase 2 (data understanding) several groups explored the data using visualization techniques, association rule discovery, etc. and published their results on Zeno. In Phase 3 (data preparation) the main effort consisted of data transformations. As the original database consisted of multiple tables, this involved to some extent computation of aggregate functions. Data transformations were performed mainly using CSE’s Sumatra TT tool [7].

Mainly we focus on Phases 4 and 5: modeling and assessment. Concerning modeling, a wide variety of approaches was taken by the different groups: support vector machines (ECE), neural nets (ECE, EE), linear regression (EE, ME), instance based learning (EE, CSE),

decision trees (EE, CSE, ME), etc. Besides the different algorithms, approaches also differed in the version of the data set that was used (these versions resulting from different data transformations). There is an intense feedback from 5 to 4: based on model assessment, data miners wish to change their model building approach and go through Phases 4 and 5 once more. In the collaborative setting, the feedback should not remain within one group but flow to all groups for which it is relevant.

3.2 ASSESSMENT OF THE COLLABORATIVE DATA MINING PROCESS

In this Collaborative data mining, assessment is ambiguous. The end-user found the results interesting and useful [8]. An awful thing is that the added value of collaboration of different groups on this task was much smaller than hoped. The most notable collaboration was that the results of data transformations performed by one group were used for modeling by another group. This is in line with the kind of collaboration that RAMSYS promotes, but it is only a minimal version of it. To achieve more intensive collaboration, several processes must be made more efficient. The CRISP-DM process is iterative, consisting of many steps and cycles. If collaboration is to happen at the level of a single step, it needs to happen very efficiently. To make this possible, information exchange should be made more efficient and synchronization should be improved. The information flow between groups was often hampered because documentation of results was too concise, too extensive, or even both (groups being flooded with information from colleagues without being able to find the most relevant information in there). As groups do not always have the right resources available at the right time, it may take a while before a group reacts to results from other groups. The solutions to these problems are to be found both at the technical and management level (e.g. defining strict formats for exchanged documents so that relevant information is easier to identify).

Second, process that needs to be made more efficient is comparative assessment of models. In order to compare different models, they must be evaluated according to the same criteria. The original RAMSYS methodology proposed to determine an assessment criterion in advance so that each group can assess their models according to this criterion. The SPA experiment revealed several problems with this proposal. Firstly, it may be difficult to propose a good assessment criterion in advance, and the preferred assessment criteria may change over time, because insight in what are good and bad criteria typically develops during the knowledge discovery process. E.g., in the SPA experiment, visual data analysis revealed strong outliers. These turned out (after discussion with the end user) to be related t unavailability of certain procedures due to maintenance and were therefore irrelevant, but they strongly influenced certain error criteria and needed to be left out.

In other approach, one criterion may not be sufficient. Different criteria measure different properties, all of which may be relevant, see e.g. [9]. It is more realistic to talk of a set of criteria, instead of a single one. And finally, subtle differences in the computation of certain criteria, the data set from which they are computed, the partitioning used for cross-validation can make the comparison unreliable.

Due to the rate at which criteria may change, the number of criteria, and the care that must be taken when implementing them, it is unrealistic to expect that the different groups will continuously use the right criteria. An assessment scheme is needed in which criteria can flexibly be changed or added and it is guaranteed that every group uses exactly the same version of a criterion, without too much overhead.

We suggest centralized model assessment. Instead of having all different groups assess their own models, one should have a kind of model assessment server to which groups send the models they have produced, or the predictions produced by their models. When a group decides they are interested in some specific criterion, they should be able to add the criterion to the central assessment server and immediately see the scores of all earlier submitted models on these criteria. In the next section we explore this direction further.

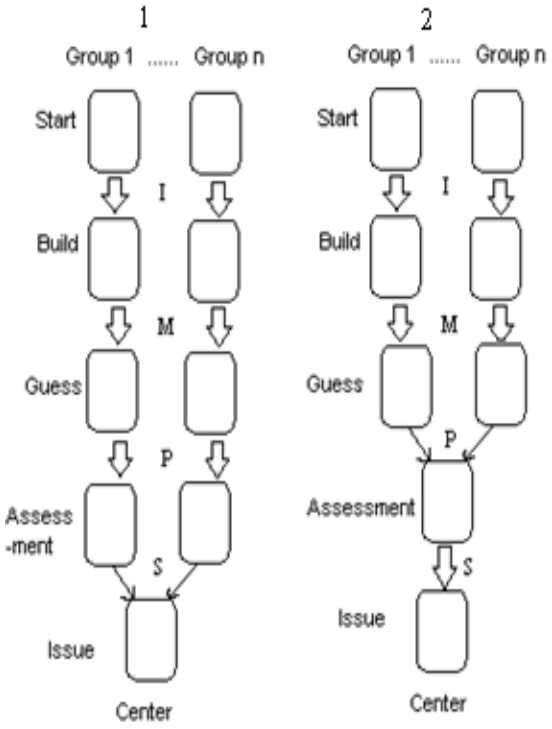
IV. CENTRIC ASSESSMENT APPROACH

In our idea, data mining groups (“clients”) should send forecasts or even the models themselves to a “model assessment server”, which is responsible for the assessment of the prognostic model and automatically publishes the results.

There are several levels of communication are possible. An inductive system typically has a number of parameters; for a given set of parameters values the system implements a function I: 2 $X \times C \rightarrow (X \rightarrow C)$ that maps a dataset (a subset of the universe of labeled instances $X \times C$ with X the instance universe and C the set of target values) onto a function M (a predictive model) that in turn maps single instances onto some target value. One has the option to submit the inductive function I; the model M learnt from

a given data set T; or a set of predictions for some data set S, P = {(e, M(e))|e ∈ S}. In all cases the server should be able to derive from the submission a score on one or more evaluation criteria, which we assume to be a function c(M,P). The original RAMSYS procedure corresponds to a fourth option, communicating s = c(M,P).

A schematic overview of these options (in reverse order compared to above) is given in Figure 1. It is assumed that I consist of a combination of a machine learning tool and parameter settings, so I is the result of tuning the tool with the parameters. Using I a model M is built from a training set, this M is used to predicted labels for a test set S, from these predictions a score s is computed using the evaluation criterion c. In the case of a cross-validation the process is more complicated but the same basic scheme is valid: different models M are then built from different training sets to produce one set of predictions P.



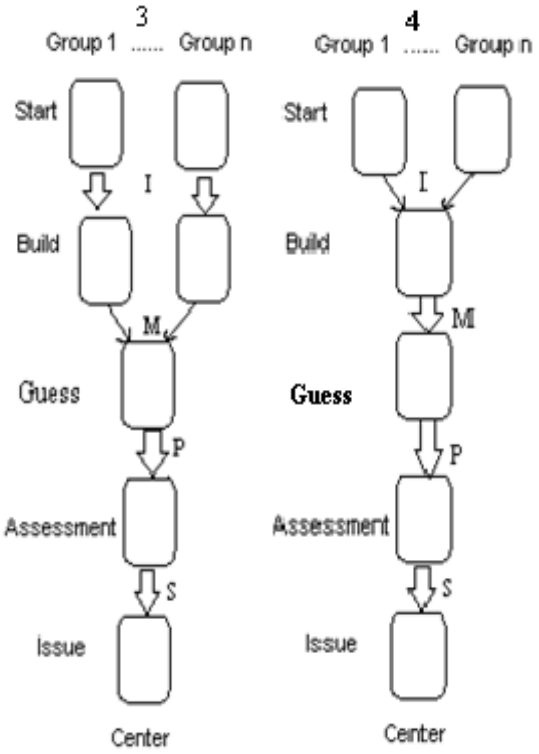


Figure 1: Overview of Centric Model Assessment For Collaborative data mining

In data mining, we describe a data set in a table, in which various states are identified as following shown table.

States	1	2	3	4
Question difficulty	L	L	M	H
Efforts cost	L	H	M	M
Result availability	L	H	H	H
Comparability	M	H	H	H
Student transparency	H	M	M	L
Flexibility of assessment	H	M	H	H

Table 1: Characteristics of Different Options

Table 1 precise some characteristics of the four options. In the table H, M and L refer to High, Medium and Low respectively. Question difficulty refers to the questions that are needed for examination. Options 3 and 4 impose the challenge of developing relatively complex languages and interpreters for them (e.g., when submitting a

model M the server needs to be able to compute the predictions M makes on some test set).

Efforts cost is low when result just a score, high when communicating a (possibly large) set of predictions, and medium when communicating functions. Result availability refers to how fast the scores of different models for a new criterion are made available to everyone. It is low for Option 1 (groups need to implement the new criterion themselves); for other options new scores are automatically computed as soon as a single implementation of the new criterion is available. Comparability reflects the trust in the comparability of the results, which is higher when a single implementation is used. Student transparency refers to the overhead for the data mining groups when some option is adopted. In Option 1 it is highest, in Option 4 lowest because the user need only submit I (induction system + parameters) and all testing is then done automatically. In Options 2 and 3 the user needs to implement e.g. cross validation according to given folds. Finally flexibility of assessment is lowest for Option 2 because here the criterion cannot involve the model itself (complexity, interpretability but only its predictions.

Option 1 is the current mode of operation within SolEuNet. Option 2 provides significant advantages over Option 1 and is still easy to implement. Option 3 imposes the challenge that a good model description language and an interpreter for it need to be available. A reasonable choice for such a language would be PMML [10], which is already being proposed as a common language for representing models; it handles a reasonable variety of types of models and there exist visualizes for them. If PMML is going to be used anyway in a collaborative data mining system, an interpreter for PMML models would be sufficient to cater for a wide range of different model assessment criteria.

Option 4 is the most powerful one but seems least feasible. There are different sub options: (4a) all model building systems are translated into a single common language; (4b) the central model assessment server has the necessary interpreters for the different languages in which inductive systems, data preprocessing systems, etc. are programmed; (4c) the server has its own versions of the inductive systems, and all that is actually submitted is an identifier of the system to be used and a list of parameters. Option 4c is quite feasible but has the disadvantage that only the systems and versions available at the server can be used.

In the short term, we believe the most realistic improvement to RAMSYS corresponds to Option 2, which is easy to implement and presents a significant improvement over the current mode of operation. In the longer run, assuming that PMML is general enough to describe any kind of model that could be submitted and that interpreters are available, it seems desirable to shift to Option 3.

Summarizing, centralized model evaluation reduces workload; increases confidence in comparisons between systems; guarantees availability of all criteria for all models; reduces the time needed to obtain scores on new criteria; and adds flexibility w.r.t. defining new criteria. All of these contribute to the added value that collaborative data mining can have over the non-collaborative approach.

V. CONCLUSIONS

We performed mining of data collected from students working in teams and using a collaboration tool in a one-semester. Our goal was to support learning group skills in the context of a standard state-of-the art tool.

Collaborative data mining, as promoted by and used within the SolEuNet project, is not a trivial enterprise. In order for it to work well, a highly tuned supporting environment is needed. An experiment with collaborative data mining, following the RAMSYS methodology as much as possible, indicated the need for more efficient and flexible model evaluation. Our answer to this is centric assessment model, of which we have presented and compared several versions. The conclusion is that significant improvements over the approach used for SPA can easily be obtained, while implementing an ideal system will need some more work.

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