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Students and teacher academic evaluation perceptions: Methodology to construct a representation based on actionable knowledge discovery framework

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Abstract This research introduces a method to construct a unified representation of teachers and students perspectives based on the actionable knowledge discovery (AKD) and delivery framework. The representation is constructed using two models: one obtained from student evaluations and the other obtained from teachers' reflections about their teaching practice. We integrate both models into one that incorporates students' opinions and teachers' knowledge and meta-knowledge. This method provides a representation of a teacher's best teaching practices where student perceptions are presented as patterns in the form of association rules. The representation adds actionability to association rules by demonstrating how students' association rules are related between themselves and how they are related to teacher's meta-knowledge.

Keywords Teacher's evaluation · Students perspectives · Teacher perspective · Objective measures · Subjective measures · Knowledge and meta-knowledge

1 Introduction

Teaching skills are commonly assessed in universities using evaluation questionnaires. Most of the time, the results obtained from these questionnaires identify solely the student's perspective of the highs and lows in specific teaching areas. As we can guess,

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the students' point of view frequently differs from the teacher's view of their own work and consequently, the evaluation results may come as a surprise. Teachers may have a very poor understanding of the shortcomings perceived by students. Due to lack of precise information, they may end up applying considerable effort to improve non-problematic aspects of their teaching style without correcting the real source of the teaching problem.

The interpretation is therefore not straightforward and cannot be based solely on data obtained from surveys filled out by students; the analysis should rely on various levels of knowledge that encompass a broader perspective. For such complex problems that cannot be solved using data alone, the AKD framework proposes combining technical and business measurements, domain knowledge and meta-knowledge as part of the solution (Longbing 2010).

AKD is part of the new generation of Domain Driven Data mining (D3M) frameworks. The main objective of AKD frameworks is to discover actionable patterns that bring immediate application focusing on domain knowledge (increase in profits, better efficiency, etc.) (Longbing 2008). A pattern actionable capacity (Yang 2009; Longbing 2007) must be the result of a good balance between technical and business interests. AKD uses technical and business interestingness measures that help identify the interest of a pattern from the objective and subjective point of view. In other words each pattern is analysed both objectively, using data, and subjectively, taking into considerations the opinions of the expert who work with the data.

In this work, we evaluate and analyze both students' and teachers' perspectives using the AKD framework. The students' perspective is evaluated using association rules and objective measures, while the teacher's perspective is evaluated using subjective measures, domain knowledge and meta-knowledge. We then analyze these results to integrate them into a single representation model.

The end result is a global model representing the best teaching practices in the form of an interesting set of association rules. This representation adds actionability to association rules by including the real actions taken by teachers when they applied these rules. The model helps one understand how patterns and actions are related as well as showing what meta-knowledge is related to each rule.

This paper is organized as follows: the next section presents DK, MK, measurement concepts and some frameworks that have been proposed for AKD; section 3 presents the dataset and the questionnaire structure used; the methodology is presented in section 4 and its application to a particular case is detailed in section 5; sections 6 and 7 present conclusions and future work.

2 Literature review

One of the characteristics of AKD is to combine DK and MK. In the first section of our literature review, we will circumscribe the definition of these concepts and relate them to our specific context. The second section defines the various measures that can be found under the objective and subjective labels. Finally, we present the mainstream AKD frameworks and delimit the one that we are using.

2.1 Knowledge, domain knowledge and meta-knowledge

"*Knowledge* is a mix of constructed experiences, values, information or contextual data and expert insight that belongs to any enterprise in an implicit way and that transforms itself in assets for the organization over time" (Davenport and Prusak 1999). These assets belong on the one hand, to people who manage the knowledge and learn in everyday experiences, and on the other hand, to the organization, which saves it in different forms such as documents, processes and practices. People and organizations struggle to recognize and organize knowledge because of the large number and variety of business situations and solutions.

Domain knowledge (DK) is related to the experiences, values, and user insights implicit in user knowledge (Davenport and Prusak 1999). A simple definition about domain knowledge was given as "the knowledge of the subject area (domain), what you know about a subject or topic" (Paquette et al. 2011). DK is therefore related to the user experiences in a specific domain. For example, domain knowledge for a teacher might include academic problems that students face during the discussion of a specific topic (including insecurities and fears), feedback about the difficulties with a topic and specific abilities that the teacher has to apply to reduce fears in order to reach academic objectives.

In any industry, *domain knowledge experts* are individuals who have reached high levels of expertise in a particular domain. They specialize in specific problem resolution. They gain expertise doing similar tasks or resolving the same problem in different contexts, and store and apply these rules of thumb depending on the situation they need to solve.

To elicit domain knowledge from an expert, it is necessary to use techniques to retrieve the tacit knowledge and transform it into explicit knowledge in the form of rules (Flavell 1979; Yi-Dong et al. 2002). This knowledge can then be standardized and applied in future similar situations.

Meta-knowledge is knowledge about knowledge. It can have different levels. One example of meta-knowledge is meta-cognition–what we know about our cognitive abilities or how we learn. Some authors mention that meta-knowledge and meta-cognition are related (Herrmann et al. 2003), while others say that they form a part of each other (Valot and Amalberti 1992). In this paper, meta-knowledge will refer to both meta-knowledge and meta-cognition; we will focus on a teacher's knowledge, cognitive tools, abilities, limitations and the use of strategies (Valot and Amalberti 1992).

Meta-knowledge (MK) is knowledge about the knowledge, i.e. the range of what has been learned, and mostly concerns the context of an activity(Valot and Amalberti 1992). It identifies persons and variables that intervene in the activity as well as strategies, steps and actions needed to accomplish the activity. If we consider the academic context, MK might include how students learn, how a specific topic is taught, what is easiest and what is hardest for students, etc.

To identify meta-knowledge, three questions have to be answered (Flavell 1979; Yang et al. 2009): *why*, *what* and *how*. The *why* identifies the reasons associated with performing a specific activity; the *what* defines the objective to be reached in the performing an activity; finally, the *how* refers to the strategy or steps required to accomplish the activity. Let us look at an example to show how to apply these questions in relation to the academic evaluation. If the activity is "*to make a student evaluate a teacher fairly by filing out a questionnaire*" to obtain the relevant meta-knowledge, we will ask the following questions: *why* is this evaluation done?; *what* concept do people interested in the results of this questionnaire learn?; *how* are learned concepts going to be used. In this process of identifying meta-knowledge, teachers have to talk about why they make students do specific activities, what activities and concepts they do in class and how the teacher tries to have those activities done in the best way. These activities are related to each of the survey questions. In this paper, we will call the survey questions *attributes* to help standardize the terminology.

We add the questions *when* and *where* to this traditional approach because they are necessary in the context of our research. The *when* question will focus on the time a specific teaching technique is applied; for example, in the case of students having to summarize key ideas, we need to ask if they must do that at the beginning or at the end of the class. The *where* question will be used if the class takes place in different locations such as labs, classrooms, outdoors, etc.

In this paper, teachers are considered "domain knowledge experts". The domain knowledge will be related to what teachers specifically know about the activities they perform during the class. For the meta–knowledge component, we will focus on the five questions mentioned above to extract the teacher's personal variables, the activities needed to be performed to reach an objective in class, and the strategies they apply to reach these objectives. The result will be a model aimed at expressing a teacher's best teaching practices in the form of an improved set of association rules. The resulting representation adds actionability to association rules and helps understand how the association rules are inter-related.

2.2 Technical and business interestingness measures

Technical experts in data mining (DM), are in charge of improving methods, algorithms and creating new measures to find and evaluate interestingness patterns. Business experts are interested in these technical expert improvement methods because these patterns should reveal new knowledge from within the business data. However, the patterns discovered by technical experts do not always fulfill the expectations of business experts mainly because they are not immediately applicable, they are not interesting to business experts or they do not matters to the business.

Table 1 shows a comparison between technical patterns and business patterns. Each of them shows a specific focus and none of them show relation between them. One focuses in the objective side and the other focus completely to the subjective side. That is why authors mentioned that a gap exists between the technical and the business interestingness patterns (Longbing 2007, 2008).

Both patterns are considered relevant and complementary but they do not mix. Therefore, it is necessary to find a middle point; AKD suggest to integrate technical and business interestingness measures in its framework in the way that a pattern could be evaluated objectively with the technical considerations and evaluated subjectively with the expert considerations.

Table 1 Differences between technical interestingness and business interestingness patterns

	Technical Interestingness Patterns	Business Interestingness Patterns
Measures used to evaluate patterns	Objective or statistical measures	Subjective, semantics, business measures
Understood by	Technical people	Business people
Based on	Data	Business domain knowledge, user experience
Focused on	Efficient data mining techniques	Business concerns as profit, client satisfaction and improve business
Performed by	Academic world	Business world
Discover	Interesting patterns from data	Interesting and actionable patterns from the mix of data and the knowledge of the user
Driven by	Data driven	Domain driven
Satisfy	Satisfying expected technical significance	Satisfying business expectations
Aimed towards	Academic objectives	Business goals
Concerned with	Academia outputs	Business expectations

In AKD, two groups of measures are used for evaluating the interestingness of a pattern: *objective* and *subjective measures*.

Objective measures concern technical interestingness (Bing et al. 2000)–rule structure, predictive performance, and statistical significance–of the data. Many objective measures have been proposed and some authors have studied their characteristics, properties (Tan et al. 2002),(Geng and Hamilton 2007) and the suitability of a measure with respect to a certain domain(Xuan-Hiep et al. 2006). Among these metrics we find: *support*, *confidence*, *lift* (or interest factor), *correlation*, *entropy*, *conviction*, *specificity*, *added value*, *Piatetsky–Shapiro*, *certainty factor* and others. Several authors (Geng and Hamilton 2006; Sandhu et al. 2010; Tan et al. 2004; Yi-Dong et al. 2002) present a complete list of these measures and discuss their significance.

In this study, we will be using association rules with *support*, *confidence* and *lift* measures. *Support* is the measurement resulting when we divide the number of occurrences of a specific itemset by the number of transactions. *Confidence* measures the probability of the appearance of item “b” in the consequent after item “a” appears in the antecedent. Depending on the context of the problem, *support* and *confidence* are commonly used in association rules to distinguish between strong and weak rules. The *lift* measure compares whether the proportion of transactions containing item “b” and item “a” is greater than the proportion of transactions that only contain item “b” among all transactions (Merceron and Yacef 2008). The *lift* measures the strength between two items.

Subjective measures are therefore related to the needs and interests of the user and the domain (Bing et al. 2000; Oliviera et al. 2009). Many authors have proposed subjective measures (Bing et al. 2000; Geng and Hamilton 2006), (Silberschatz and Tuzhilin 1996); in particular, Geng and Hamilton (Geng and Hamilton 2006) propose nine criteria to determine whether a pattern is interesting: *conciseness*, *coverage*, *reliability*, *peculiarity*, *diversity*, *novelty*, *unexpectedness* (also called *surprisingness*), *utility* and *actionability* (also called *applicability*). We retained three of these nine criteria to apply to teacher's dataset: *novelty*, *unexpectedness* and *actionability.* They were selected because we are interested in patterns that correspond to accepted beliefs, patterns that contradict beliefs, and patterns that lead to the actions that can be taken to obtain an advantage.

Novelty (Geng and Hamilton 2006) can be recognized directly by the user as something new that does not contradict his own beliefs. A novelty pattern is an unknown pattern that cannot be inferred from other patterns (Geng and Hamilton 2007) (Xin Chen 2006). A related measure to the novelty criteria is usefulness. Usefulness conveys the sense of action, immediate application, does not contradict any belief, conveying a sense of action. For these reasons, our research will focus on the *usefulness* as part of the *novelty* criteria.

Unexpectedness is a pattern that contradicts a user's beliefs. Three different approaches have been proposed to cover this measure (Geng and Hamilton 2006). The first one consists of choosing unexpected patterns based on the user knowledge specifications. In the second approach, uninteresting patterns are eliminated using the feedback from the user. For the third approach, the user gives specific constraints to narrow the search space (Geng and Hamilton 2007). Our research focuses on the first approach because it provides an entry point for user's knowledge.

With respect to the *actionability* measure, if the pattern is immediately applicable then it is actionable. The use of *actionability* to measure the applicability of a pattern presents a difficulty because the actions taken after knowing a pattern is actionable could vary depending on the background of the decision makers, their personality and their decision making style (Bing et al. 2000). To avoid this it is necessary to reinforce the use of *unexpectedness* as a way to reach the *actionability.*

In summary, we retained three subjective criteria to help us find interesting patterns: *usefulness*, *unexpectedness*, and *actionability.*

2.2.1 Subjective criteria evaluation form

A subjective criteria based on the knowledge was proposed (Oliviera et al. 2009). Knowledge can be divided into five categories: *unexpected*, *useful*, *obvious*, *previous* and *irrelevant*. *Unexpected* knowledge is a pattern completely new to the user; he or she is surprised when it happens. *Useful* knowledge is a pattern that is not outstanding but could help the user in decision making. *Obvious* knowledge is a pattern that is already known and users are aware of it. *Previous* knowledge is a pattern that represents some old knowledge. Finally, *irrelevant* knowledge is a pattern without any importance. We extended this list (Oliviera et al. 2009) by adding the *interesting* classification. This *interesting* classification allows the teacher to evaluate his own rules and include two of the subjective measures mentioned before, usefulness and unexpectedness. Teacher completes the evaluation within a group of patterns pertaining to him and chooses the *interesting* one within a group. We propose both an individual and a group evaluation of rules in this step. In this way, the teacher suggests which unexpected patterns or useful patterns are more interesting to them. This will be explained in detail in section 4.2.2.

2.3 D3M and PA-AKD framework

The fusion of DM results with DK is the fundamental trait of the domain driven data mining methodology (D3M). D3M focuses not only on the data but also on the peripheral domain knowledge. D3M presents four layers (Longbing 2010): the domain layer, the knowledge management and ubiquitous intelligence layer, the theoretical foundations layer, and the specialized techniques layer. Cao et al. (Longbing 2010) describe these four layers in detail, while suggesting to complement them with new tools, methodologies and frameworks that will contribute to both D3M and AKD.

Four different frameworks have been proposed for D3M (Cao et al. 2010a): *post-analysis based AKD* (PA-AKD), *unified interestingness metrics based AKD* (UI-AKD), *combined mining based AKD* (CM AKD) and *multisource + combined mining based AKD* (MSCM-AKD). Each framework has relevant characteristics. For this work, we choose to apply the PA-AKD framework because it treats technical and subjective aspects of the problem, and also because it focuses on only one dataset. The framework works in two steps as is described in Fig. 1.

The DM step consists in finding patterns and evaluating them using technical interestingness measures. Figure 2 shows the complete data mining step. General patterns are obtained using DM tools. This output is used as the input in the D3M-AKD step.

The D3M-AKD step takes the results from DM and with the help of business interestingness measures as well as domain knowledge and meta-knowledge, identifies the most applicable interesting patterns in the form of *deliverables* or applicable patterns. Figure 3 shows the D3M-AKD process.

3 Dataset

Our study uses a survey database from a Latin-American university. The database holds 64,138 survey questionnaires answered anonymously for the year 2009 (43 Mbytes in CSV format). It contains information about 798 teachers who, as a whole, have given courses to 13,000 students. The university is composed of twelve schools (faculties or schools) and institutes. Each of them provides services to between 218 and 2300 students per year.

We chose to work with the questionnaires for the faculty of electricity and computing (FIEC) because it has a high percentage of surveys as seen in Fig. 4. Moreover, this faculty has a mean evaluation of over 8/10; we therefore have a better chance of finding teachers with well established, well defined and well evaluated teaching abilities.

Students usually take four to six courses each semester, resulting in eight to twelve courses per academic year. At the end of each course, each student has to fill out a

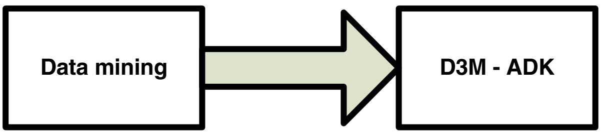

Fig. 1 Post Analysis Based AKD process

survey. The data collected in these questionnaires includes information about the year, the semester, the teacher's name and answers to the 24 questions that evaluate his teaching practices.

Table 2 describes the questions that help evaluate each area.

These 24 questions evaluate four areas of the class development: *design* (D), *learning promotion* (LP), *production of learning materials* (PM) and *education management* (EM).

The Research Center and Education Services (CISE) has been using this survey every semester for now, 20 years. The center uses the data from the survey and then constructs and delivers the results to the teachers. Each area has specific questions that capture students' satisfaction. Up till now, each question is presented with a Likert scale (Marshall 2005) between 1 (strong disagreement) and 10 (strong agreement). For the moment, the university do not intend to change the type of scale used. Future work will show if it might be possible to use a wider scale in order to capture shadows of opinion.

For ease of exposition, we use the short form "$X_{N\text{-}DA}$" to refer to each question; the prefix "X" to identify it as a variable, "N″ to specify the question number, and "DA" to supply a short description.

At the end of the semester, students evaluate the course using a general score for attribute X24. This attribute is not part of those that we are going to evaluate. We use the X24 attribute as the dependent variable in the teacher's regression process.

We are interested in the antecedents and consequents of the association rules. We will look for 3-itemsets with 2 attributes in the antecedent side and identify 1 attribute in the consequent side.

4 Methodology

Our methodology consists of three steps: first, we apply DM to obtain general patterns from students' dataset; second, we construct two questionnaires and one interview to elicit DK and MK from the teacher; finally, we construct a model with the rules, the knowledge and meta-knowledge retrieved. Figure 5 presents a synthetic view of the three processes of the methodology: DM, DK and MK. In the following subsections, we explain each step in detail.

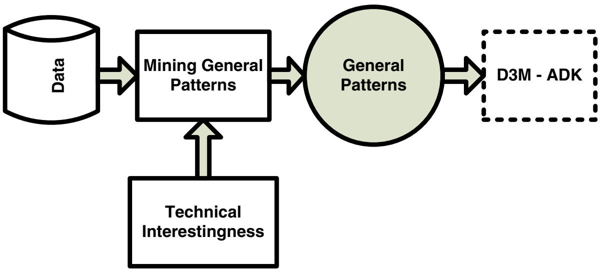

Fig. 2 Data mining steps

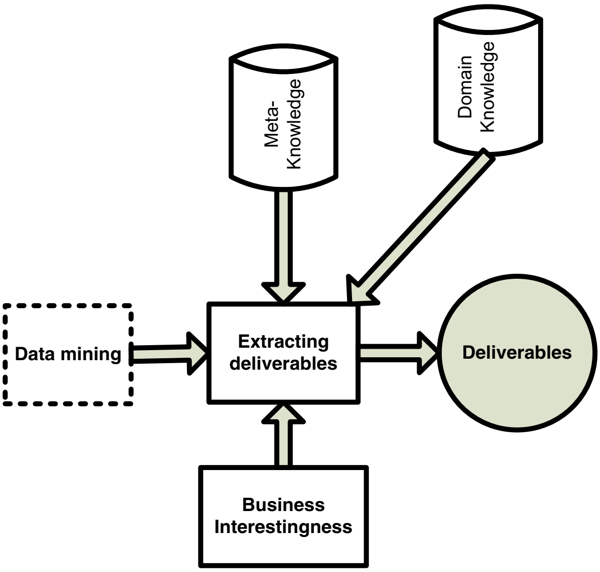

Fig. 3 Post Analysis -AKD's approach (Cao et al. 2010b)

4.1 Objective evaluation

We will refer to the student evaluations at the end of each course as the *objective questionnaire* (or *obj-Q*). The *obj-Q* is the dataset containing the teacher evaluation surveys filled out by students. The attributes are listed in Table 2. The *obj-Q* questionnaire

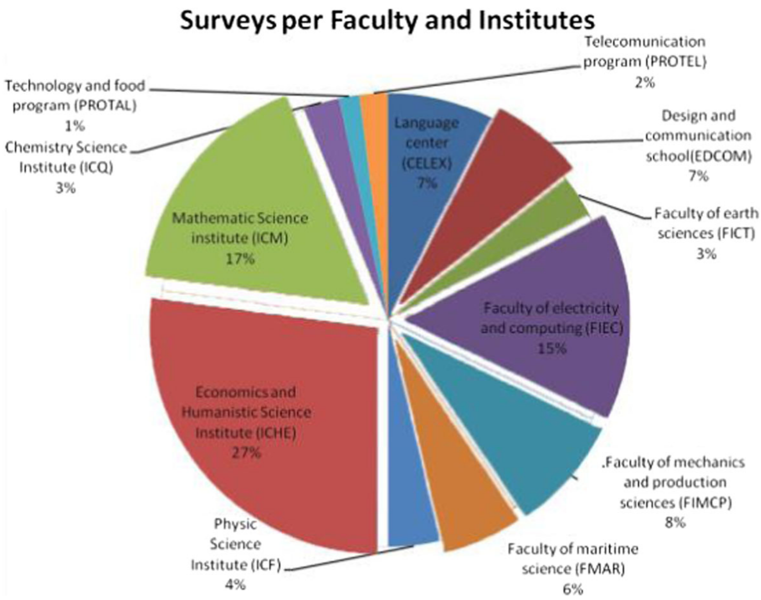

Fig. 4 Surveys per University Faculty and Institute

Table 2 Areas and questions/items per area

Area	Attributes
Design (D)	X_1 Uses audiovisual help to support the content of the class
	X_2 Fulfills the program proposed at the beginning of course
	X_3 Evaluates student participation periodically in class
	X_4 Evaluations fit the themes developed in class
	X_5 Provides clear instructions for learning assessment (tests, quizzes, presentations, simulations, dramatic representation, role playing, etc.)
	X_6 Motivates students to do additional research
Learning promotion (LP)	X_7 Explains the course schedule at the beginning of the course
	X_8 Explains class policies at the beginning of the course
	X_9 Encourages active student participation in class
	X_{10} Summarizes key ideas discussed before moving to a new unit or topic
	X_{11} Establishes relationships between new concepts and those already known whenever possible
	X_{12} Motivates learning of the course material
	X_{13} The teacher is willing to answer questions and offer advice within and outside of the classroom
	X_{14} Promotes reflection on topics covered
	X_{15} Maintains fluid communication with students
	X_{16} He/she is respectful towards students
	X_{17} Responds to questions in class about subjects related to the field
	X_{18} Delivers class content in an organized way
	X_{19} Develops class content in an understandable way
Production and teaching materials (PM)	X_{20} Prepares instructional, bibliographic or other resources to facilitate learning
	X_{21} Frequently uses schemes and graphics to support his/her explanations
Education management (EM)	X_{22} Provides the results of the assessments on time
	X_{23} Attends classes on time
General evaluation	X_{24} Considering all the features, choose a score between 1 and 10 to evaluate teacher's overall performance

conveys the students' perspective about the teacher. In section 5, we illustrate our proposed methodology by analyzing *obj-Q* for a specific teacher and course.

The dataset *obj-Q* is cleaned and converted to a csv format file. Evaluations with values of 0 or 1 in all questions as well as evaluations with text in the fields instead of numbers are eliminated. Using SPSS (Foundation 2000), we apply linear regression to control the dimensionality of the data and obtain a set of variables that have a strong correlation between them. We refer to this regression result as $obj\text{-}Q_{reg}$.

We construct another dataset based on the teacher's preferred attributes–where they choose their own attributes from the same questionnaire *obj-Q*. This second dataset is called *sub-Q1-Tatt*, and is part of the *sub-Q1* questionnaire. The *sub-Q1* is a

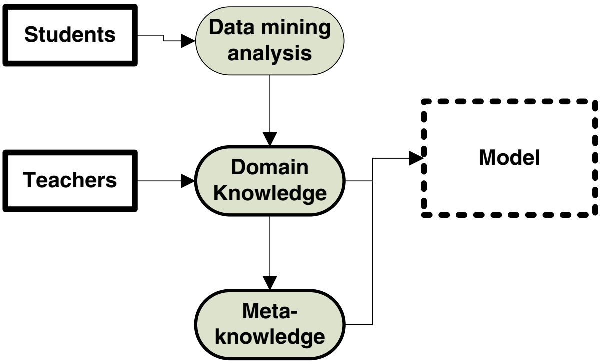

Fig. 5 General view of the methodology

questionnaire that retrieves the domain knowledge from the teacher. We now provide a brief explanation of this dataset with more detail in section 4.2.

We apply regression to the *sub-Q1-Tatt* dataset, where the teacher selected the attributes of the *obj-Q* that were most representative for him. We obtain a reduced model based on the attributes selected by each teacher. We call this result *sub-Q1*$_{reg}$.

We compare the two regressions: *obj-Q*$_{reg}$ and *sub-Q1*$_{reg}$. If the attributes are the same in the student's model (resulting from the *obj-Q*$_{reg}$) and in the teacher's model (resulting from the *sub-Q1*$_{reg}$), then no further treatment is necessary because students perspective variables are the same as teachers perspective variables. If they are not the same, we apply the data mining procedure to *obj-Q*$_{reg}$ variables as explained in the next sub-section. Figure 6 shows the comparison between these two datasets.

4.1.1 Data mining analysis

Starting with *obj-Q*$_{reg}$ variables, we first apply the *Apriori* Algorithm of the Arules package in R to generate the rules and we use the item frequency plot from the same

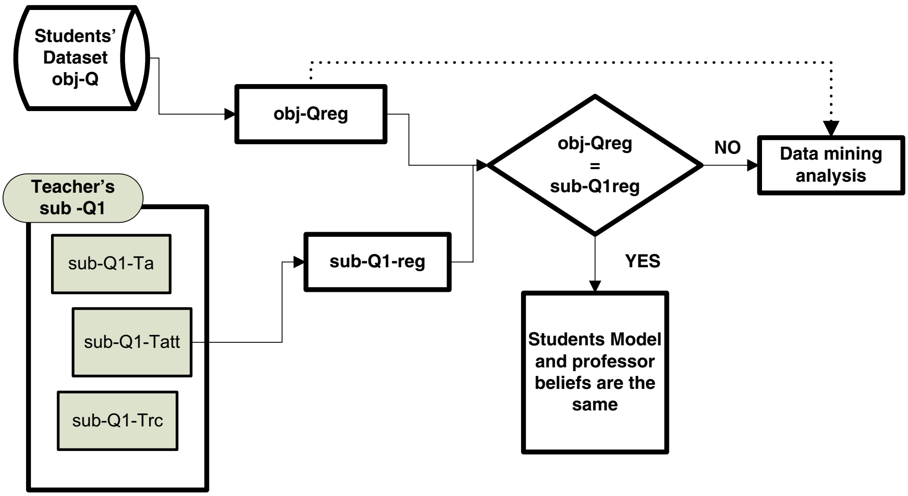

Fig. 6 Comparison between obj-Q$_{reg}$ and sub-Q1$_{reg}$

package to identify the frequencies of the variables. We search for association rules with specific *support*, *confidence*, and *lift* boundaries. Rules with *lift* values higher than 1 are selected. A high lift value tends to express stronger relationships between attributes. These rules are called *general rules*. We obtain association rules in the form of X, Y- > Z. The association rule is formed by antecedents and consequent. X and Y are in the antecedent side and Z is the consequent side. The teacher is then asked to evaluate *general rules* in *sub-Q2*; this is explained in section 4.2.2.

4.2 Subjective evaluation

For the subjective evaluation, we construct two questionnaires (*sub-Q1*, *sub-Q2*) plus an interview (*meta-I*). The *sub-Q1* is a questionnaire that retrieves the domain knowledge from the teacher. The *sub-Q2* is the second questionnaire that identifies the interesting rules and rules that are part of the domain knowledge. The *meta-I* will help to obtain the meta-knowledge from teachers that is not available in *obj-Q*.

4.2.1 Domain knowledge: sub-Q1

We start the subjective evaluation with *sub-Q1*. Figure 7 summarizes the process of this questionnaire and what it achieves.

The *sub-Q1* gives the teacher the opportunity to evaluate the same *obj-Q* filled out by the students, but in this case with the teacher's preferences. The *sub-Q1* is composed of three components that capture the domain knowledge from the teacher. First, teachers select the most important areas from the *obj-Q* (we call this the *teacher area selection* or *sub-Q1-Ta*). These areas were mentioned previously in Table 2: D, LP, PM and EM.

Second, the teachers choose the most important attributes per area that help them attain high evaluations (we call this *teacher attribute selection* or *sub-Q1-Tatt*). Each area has a group of attributes. Each attribute focuses on an aspect of teaching in that area. The attributes that can be chosen are those presented in Table 2. We construct a new dataset with the selected attributes. As was mentioned in section 4.1, *sub-Q1-Tatt* was the teachers' dataset to which we applied regression and obtained *sub-Q1*$_{reg}$.

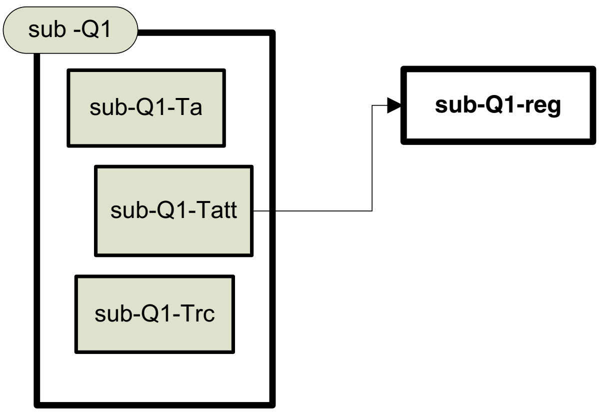

Fig. 7 Subjective endorsement sub-Q1

In the third part of *sub-Q1*, teachers are invited to construct rules based on what they believe has worked in their classes (we call this *teacher rule construction* or *sub-Q1-Trc*). Teachers construct their own rules, suggest attributes and place them in the antecedent or consequent areas from an association rule, as they deem relevant. These manually constructed rules are the rules of thumb that they perceive work in their class. Teachers suggest which attributes placed in the antecedent could produce a specific attribute placed in the consequent. This process is repeated for each important area identified for the teacher. *The sub-Q1-Trc* is part of the domain knowledge. The rules suggested by the teacher are incorporated into the domain knowledge.

4.2.2 Interesting rules and domain knowledge: sub-Q2

General rules are the input for the s*ub-Q2* questionnaire. The task is to identify those rules that, according to a teacher's experience, help them improve their teaching abilities. To accomplish this task, the questionnaire *sub-Q2* proposes one set of *interestingness* criteria along with five knowledge categories: *unexpected*, *useful*, *obvious*, *previous*, and *irrelevant* (as indicated in section 2.2.1).

Each rule is evaluated individually and within a group of rules with the same consequent but with different antecedents. For the individual analysis, each rule has to be evaluated using the five knowledge categories. The teachers select only one of the knowledge categories per rule. In the case that a teacher finds a rule classified as *irrelevant*, he/she explains why this association rule is irrelevant.

During the group evaluation, teachers select the most *interesting* rule from the group (interestingness classification). Each group has one interesting rule, because only one rule associated with a specific consequent should attract their attention the most; we encourage teachers to select those that really suggest something different from what they were doing in class. An example of the individual and global evaluation is presented in Table 3**.**

In Table 3, there are three rules that evaluate the same consequent X5. Each rule is evaluated using the five categories, *unexpected*, *useful*, *obvious*, *previous*, and *irrelevant* and only one rule from the group is evaluated in the interesting classification.

All the rules evaluated as *interesting*, *unexpected* and *useful* constitute the *interesting* rules. These rules show aspects that are noticed by students and not by the teacher; we use them to generate the "new and improved rules model". This model should provide suggestions to improve a teacher's performance (what students think the teacher is doing but the teacher is not aware of).

All the rules classified as *obvious*, *previous* and *irrelevant* constitute the common rules and show aspects already known by the teacher and by students. We called this

Table 3 Sub-Q2 Questionnaire

	Interesting	Unexpected	Useful	Obvious	Previous	Irrelevant
X1-X3- > X5	x	x				
X1, X4- > X5			x			
X2, X4- > X5					x	

the "real and actual rules model". This model represents the domain knowledge in class and is referred to by students through the questionnaire *obj-Q* and confirmed by teachers through the s*ub-Q2*. Figure 8 summarizes this process.

This analysis helps gather domain knowledge in the form of common rules from the teacher. It identifies the interesting and new rules as well. Next, teachers are interviewed using a questionnaire called meta interview or *meta-I* to examine the selected interesting rules and understand the meta-knowledge associated with their course activities as explained in the next section.

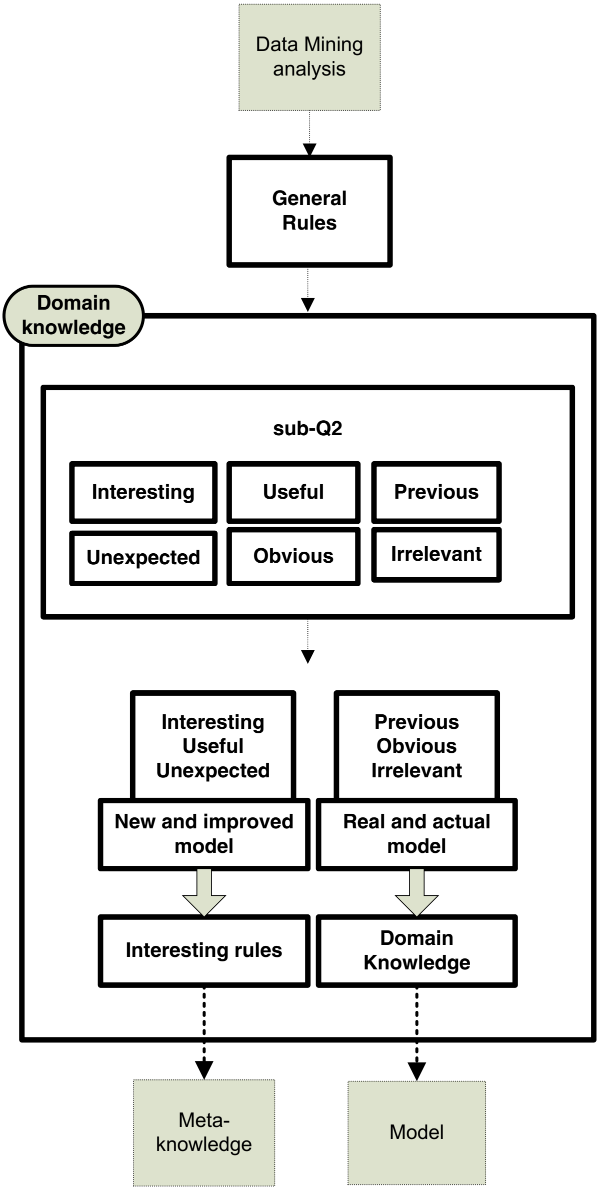

Fig. 8 Domain knowledge retrieving process

4.2.3 Meta-knowledge: meta-I interview

The interview (*meta-I*) is based on the interesting rules classified in the last step. The interview covers a teacher's practices, activities, organization of the course, and the hidden knowledge about how they teach in class. The purpose of the *meta-I* is to extract meta-knowledge about each interesting rule. The final model can then be constructed. Figure 9 summarizes the process.

We asked questions about each interesting rule evaluated. The questions explore the three traditional questions we need to ask to identify meta-knowledge: *why*, *what* and

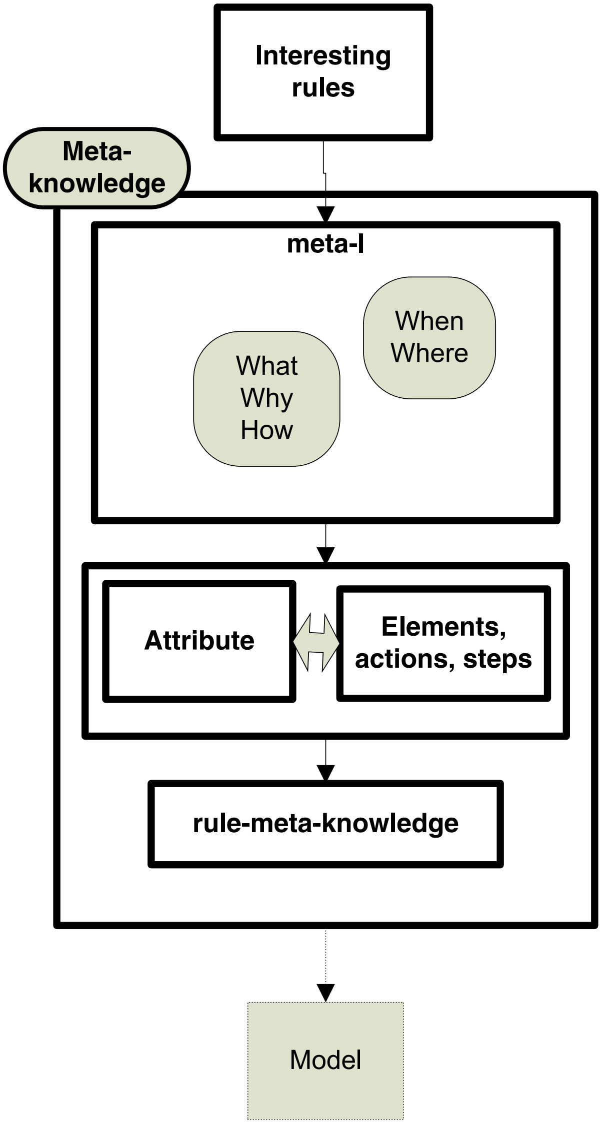

Fig. 9 Meta-knowledge retrieving process

how, and in addition we considered *where* and *when* questions to be pertinent. Each rule is composed of one or two antecedents and only one consequent. During the interview, we asked teachers questions such as: *Why* is attribute X10, in the antecedent of this rule, interesting?; *How* do you reach the objective of the attribute X10?; *What* activities do you perform to reach a well developed X10 attribute?; *When* do you apply this rule with the attribute X10 in the timeline of the class, at the starting point of the course (first class) or at the beginning of each class?; *Where* do you make students work in regards to attribute X10–in the lab or in class?

Answers to these questions provide descriptions of teaching processes that include different elements not explicit in the objective questionnaire and that are related to each rule. These elements include: the actions needed to complete the activity, the elements taken into account during the activity and the steps students need to perform to accomplish the activity. We call this new knowledge *rule-meta-knowledge*. This knowledge is going to fuse the rule attribute descriptions with the acquired meta-knowledge. As mentioned earlier, the attribute description is the *DA* component of the "$X_{N\text{-}\boldsymbol{DA}}$" attribute short form, used to refer to each question in the questionnaire *obj-Q1* and *sub-Q1-Tatt*.

In the following example, X9 is the attribute and "Encourages active student participation in class" is the description of the attribute, or *DA*:

(*DA1*): *X9* Encourages active student participation in class

When we adapt the attribute description to the *rule-meta-knowledge*, it will describe more elements associated with the *DA*. This includes all the different elements teachers use to express an attribute during the interview. (DA1) is an example of an attribute description,(DA2), (DA3), and (DA4) are attribute descriptions where the meta-knowledge has been incorporated.

Let us say that the teacher used the following expression during the interview: "I encourage students to ask questions–not to agree with me–it is better this way, students then need to find stronger arguments to defend their points". This information will then be incorporated into the model as follows (DA2, DA3, DA4):

(*DA2*) *X9***:** The teacher encourages students to ask questions
(*DA3*) *X9***:** The teacher encourages students not to agree with his/her ideas

And

(*DA4*) *X9***:** The teacher reinforces student's self-confidence to make judgments conducting a questions session, eliciting an opinion and contrasting it with other student opinions

Each attribute is enriched with more details obtained from the meta-knowledge. It is improved in an explicit way and made more comprehensible to the teacher. The *rule-meta-knowledge* per attribute is not the same for every teacher; it changes from teacher to teacher.

Figure 10 presents the complete methodology with DM, KD, MK and the participants (teachers and students).

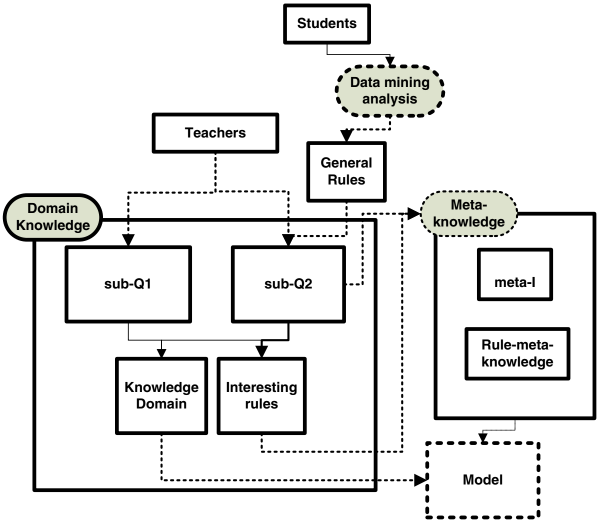

Fig. 10 Complete methodology

Then, the final model includes the *sub-Q1-Trc* rules that are part of our domain knowledge (see Fig. 7), as well as the *interesting rules* and the domain knowledge in the form of rules classified as the "new and improved rules model" and the "real and actual rules model", respectively (see Fig. 8) which are obtained from *sub-Q2*. Lastly the *rule-meta-knowledge* from meta-I (see Fig. 9) is incorporated.

5 Results for the entrepreneurship course example

In this section, we present the results of applying our methodology to an entrepreneurship course.

Section 5.1 refers to the objective evaluation phase. Section 5.2 presents the results of the subjective evaluation with *sub-Q1* questionnaire. Section 5.3 focuses on the results of the questionnaire *sub-Q2* and the rules from the improved and actual rules model. Section 5.4 focuses on the interview *meta I* and the meta-knowledge obtained from the teacher himself. Finally, section 5.5 presents the complete model for this course.

5.1 Objective evaluation phase

The *obj-Q* is the dataset for the entrepreneurship course. At the beginning, we had 23 attributes. We applied regression to this dataset using SPSS (Foundation 2000). After the regression, we obtained five significant attributes. The attributes are: LP(X7, X9, X12, X16) and EM(X22) with high correlation. $Obj\text{-}Q_{reg}$ is represented with these five attributes. The significant attributes belong to the LP and EM questionnaire areas.

5.2 Results from sub-Q1

The teacher completed the s*ub-Q1* questionnaire. In the first part, he began by selecting all the areas of interest and then the attributes for each area that he thought allowed him to achieve high evaluations. The selected areas represented by s*ub-Q1-Ta* are: *design*, *learning promotion*, *production of materials* and *education management*. The selected group of attributes per area represented by *sub-Q1-Tatt* are: D(X1, X3, X5, X6); LP(X9, X10, X11, X12, X13, X14, X16); PM(X20, X21); and EM(X23).

We then applied regression to *sub-Q1-Tatt* on the attributes selected by the teacher. We obtained a group of attributes that form the *sub-Q1*$_{reg}$: X12, X13, X16, and X23. We compared o*bj-Q*$_{reg}$ with s*ub-Q1*$_{reg}$. Two variables were similar (X12, X16), and the remaining ones were different. Next we used the R script and applied *Apriori* on the results from o*bj-Q*$_{reg}$. We obtained a set of association rules with support of 0.2, confidence of 0.9, and a lift greater than 1. The rules obtained in this step are called *general rules* and are the input to the s*ub-Q2*.

Finally, the teacher generated his own rules. Some of the rules included in his domain knowledge are represented by s*ub-Q1-Trc* as:

X3, X14 -> X6	X5, X13 ->X12
X21, X1 -> X9	X21, X16 -> X23
X11, X20 -> X6	

5.3 Results from sub-Q2, actual model and improved model

We constructed s*ub-Q2* with the *general rules* obtained from the previous step. The teacher evaluated them using the five knowledge categories and the "interesting classification" mentioned earlier. From s*ub-Q2*, two rules were classified as part of the "new and improved model" (interesting rules). The rest of the rules were classified as "real and actual model" (knowledge domain). We added to these rules the ones created by the teacher in s*ub-Q1-Trc* as part of the actual model. The new model is built using the two interesting rules:

X9, X22- > X7
X12, X22- > X16

In Fig. 11, all white nodes represent association rules that are part of the DK. All black nodes represent interesting association rules and all nodes with black and white circles represent association rules that connect domain knowledge with the interesting rule. Antecedents and consequents in each association rule are connected with a connector (small black circle in Fig. 11).

In **part (a)** of Fig. 11**,** association rule attributes X3 and X14 are in the antecedent and attribute X6 is in the consequent. In **part (b)** of Fig. 11**,** association rule attributes X9 and X22 are in the antecedent side of the rule X9, X22 - > X7, but X9 is also in the consequent for association rule X21, X1 - > X9. Nodes X9 and X12 have double circles (white and black) representing the fact that attribute X9 and X12 are part of both DK and interesting rules and help connect them. We have two interesting rules represented by black circles, X9, X22 - > X7 and X22, X12- > X16 where attribute X9, X22 and X12 are in the antecedent of the interesting rules and X7 and X16 are in the consequent in the same interesting rules. These two rules complement the DK.

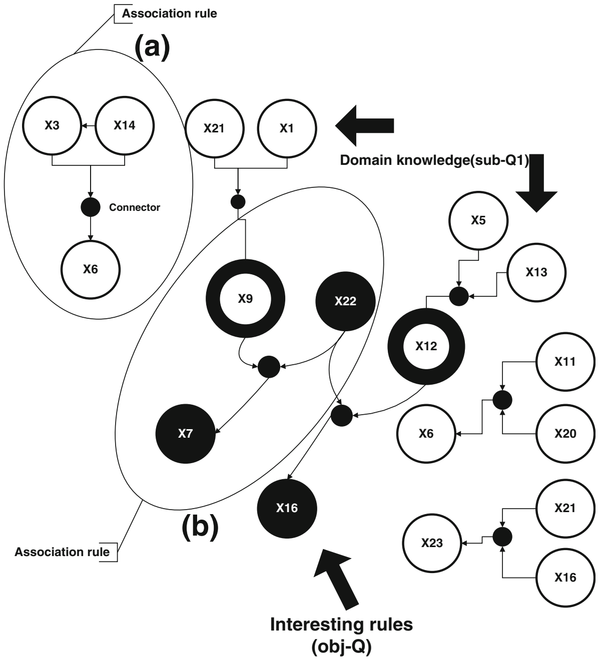

Fig. 11 Domain knowledge and Interesting rules graphic

5.4 The interview and the meta-knowledge

With this diagram in hand, we interviewed the teacher. We applied the questions to obtain the meta-knowledge for each association rule and each attribute in the rule:

> *Why* is attribute X12 important for your class? *What* objectives do you have to reach to ensure attribute X12 is well evaluated? *How* do you reach this attribute (strategies)? *Where* do you apply the actions to realize attribute X12? *When* do you try to develop this attribute X12?

We applied the same questions to the association rules presented in the domain knowledge. We asked how he reaches each association rule. In this case, rules X9, X22 and X7, and each of the attributes associated with these rules. In this step, the teacher applies the *why*, *what*, *how*, *when and where* question to each of the attributes and then makes an analysis of the attributes together. It is possible that during the interview a few more questions are asked to clarify the teacher's response. For example:

- When did you develop this rule in class, at the beginning of the course or at the end?
- What does this rule mean to you?
- Do you have specific examples of where this rule has been applied?
- Is this a frequent rule? Do you use it in every class, or every semester?

The teacher gave information related to each of the rules in the domain. He explained them in detail, and he provided different interpretations of the same rule. This constitutes the *rule-meta-knowledge* about this specific course and this particular teacher. For example:

> Attribute X22: Provides the results of the assessments on time and is expressed in the attribute's rule-meta-knowledge as follows:
> X22a: Provides the results of the assessments on time using all the communication tools he has on hand; email, web publications and paper.
> X22b: Provides the results of the assessments and informs students how these results are connected to the theory and the failed or erroneous parts of the exam.
> X22c: Provides the results of the assessments on time; and thus shows that the teacher is very organized with his own time.

In this way, we obtained different interpretations of the same attribute.

5.5 Construction of the graphical model

After the interview with the teacher, we are ready to develop a model with the meta-knowledge, domain knowledge, and the interesting rules. Because of space limitations, Fig. 12 only shows one of the two best rules with the *rule-meta-knowledge* retrieved from the teacher's interview. It shows a rule with two antecedents and one consequent. The nodes X9 and X22 are the antecedents of the rule and its consequent is X7. X9 comes from domain knowledge; X22 and X7 come from the interesting rules. We represented the meta-knowledge with letters A, B, C, D, E, F, G and H and attached them to their corresponding attribute. The smallest black circle in the middle is a connector used to attach attributes in association rules.

We used two different datasets with two different perspectives to construct this model. Both perspectives have a representation in the final model. The student

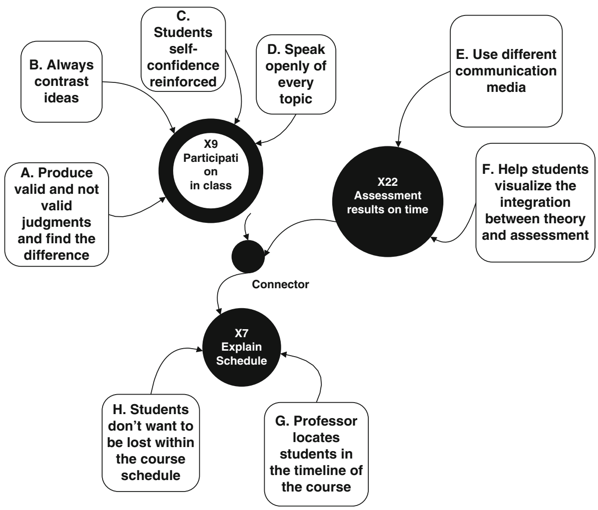

Fig. 12 Improved model with the meta-knowledge included

perspective is shown with the white nodes and a teacher's domain knowledge is shown with the black nodes. The double circle node X9 shows that its attributes are part of both, the old and the new knowledge, and that they are connected. The teacher of the entrepreneurship course found different elements interesting in this rule. For example, A, B, C and D rule-meta-knowledge show the different strategies he uses to stimulate student participation in class: freedom to express themselves; confidence expressing ideas; contrasting concepts; and generating judgments and decision making.

Antecedent X22 has the rule-meta-knowledge E and F. E expresses that the teacher uses all types of communication media (internet, SMS, content system management) to deliver their grades to students and to be available to them at all times. The F expresses that providing the assessment results on time helps students visualize the integration between theory and tests (see Fig. 12). In the same rule, the consequent X7 has the rule-meta-knowledge H and G. H expresses the fact that students do not want to be confused in regards to the course schedule. G expresses how the teacher establishes the point students have reached within the timeline of the course.

The student dataset creates the teacher's domain knowledge; the teacher can select and analyze the association rules and select those that show something interesting. These interesting characteristics, combined with the usefulness and unexpected knowledge categories, produce actionable patterns. The teacher classifies the patterns as useful or unexpected. He recognizes specific patterns applied and defines them as part of his signature during class. This is more frequent with patterns classified as useful.

We said these patterns are actionable for different reasons: first, rules can be tested during the following semester using the different actions and strategies the teacher mentioned in the graphical model. The graphical representation shows different strategies and actions related to specific attributes; therefore he can increase, improve or reduce the amount of activities he performs for each attribute. Finally, new relations between attributes, actions and strategies can also lead to discovering new relations or patterns between attributes.

For example, in this rule X9, X22 - > X7, these antecedents and consequent in and of themselves do not describe anything understandable for the teacher at first sight. When the rule-meta-knowledge is added, a relationship is found between antecedent X22 and the consequent X7 and the relation with attribute X9 gives more meaning to the relationship. The communication factor exists when the teacher returns the assessment to the students (attribute X22). Students and teacher work with this communication. Feedback develops between them based on the homework or course timeline (attribute X7). Finally, being informed about their grades and having homework feedback helps students reinforce their self-confidence in class.

The representation helps teachers further improve their effectiveness at work. A database of different descriptions about each attribute helps provide clarification to express and understand the questions of the survey. The same attribute could mean different things to different teachers. This methodology shares some common understandings for an attribute.

5.6 Discussion

These final models visually express teachers' experience or, what can be called, their "rules of thumb". In so doing, the university authorities are in a better position to advise new teachers in the field. For teachers, the graphical resulting models offer a comprehensive access to good practices giving them an integrated view of students' perception and teachers' reflections.

6 Conclusions

The methodology presented in this paper provides a bridge between association rules, knowledge domain and meta-knowledge. We start with association rules that once evaluated and filtered, form the basis for the construction of a model from the point of view of the student. We complement this student model with the teacher's model. The teacher's model is constructed with the interestingness rules, the knowledge domain and the meta-knowledge. An interview with the teacher creates the rule-meta-knowledge that further adapts and enriches attributes in the models.

6.1 Results

The proposed methodology provides the following results:

- The methodology complements the AKD framework because it proposes a new graphical representation of the meta-knowledge and the domain knowledge.
- The model provides a useful tool to integrate different perspectives that complement each other.
- Association rules about old knowledge and association rules about new knowledge are presented in a unified representation.
- The methodology allows for the creation of meta-knowledge and domain knowledge. The AKD framework assumes the pre-existence of a meta-knowledge base and a domain knowledge base and treats them as independent elements. In our methodology, we start by creating domain knowledge and rules of thumb which are then used, along with the user knowledge, to construct the meta-knowledge.
- We show how to effectively use *interestingness*, *unexpectedness* and *usefulness* as subjective measures to obtain actionable patterns.
- We use the usefulness measure to identify interesting rules. Rules that are classified as useful can be more easily explained by the user than those evaluated as unexpected. Users express more meta-knowledge from useful rules than from the unexpected rules. This provides much more actionability to the rules. It is clearer and more action-oriented for stakeholders.
- The evaluation of the rules through subjective measurements helps select specific rules and prevents us from testing rules of no interest to the user.
- We suggest the addition of *where* and *when* questions to any well-planned interview for the retrieving of meta-knowledge. These questions retrieve meta-knowledge about time and space where the knowledge process is generated.
- The meta-knowledge obtained from the interviews can be used to create a database of common understandings to different users of what an attribute expresses. The construction of the rule-meta-knowledge database helps reduce confusion with respect to the descriptions of attributes.

- The final representation with association rules, domain knowledge and meta-knowledge provides valuable insights of the models for the stakeholders, managers as well as authorities from the institution and shows how association rules are related.
- In case we applied a different scale than Likert scale, it is necessary to understand the new one first and then adapt it to the methodology. The methodology might work with a different one.

7 Future work

Actually, there exist some platforms that deal with interviews and feedback from clients such as “Customer Insight and Action” platforms or “Enterprise Feedback Management” (surveys, contact centers conversations, customer feedback comments, phone interviews and behavioural interviews)(Hirschowitz 2001; Bailey et al. 2009).

These platforms are used in Human Resources, IT, or Marketing and Sales groups, where questionnaires and the indirect interaction with clients or with workers clarify different expressions related to what the client senses as good service or in the case of an employee, what he senses as a good work environment.

Our future work will be focused on the application of the same methodology to the customer relationship or the client service department to identify the meta-knowledge associated with an enterprise and demonstrate how this representation model can be applied to provide actionable patterns that lead to better customer service.

This kind of work, in conjunction with client service, represents a new way to analyse patterns within a business. The identification of meta-knowledge that is part of “day to day” activities and the effort to relate this meta-knowledge to known activities can transform the way people see simple patterns in data mining and applicable patterns in any business area.

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