Global Journal of Computer Science and Technology
Software & Data Engineering
Volume 13 Issue 6 Version 1.0 Year 2013
Type: Double Blind Peer Reviewed International Research Journal
Publisher: Global Journals Inc. (USA)
Online ISSN: 0975-4172 & Print ISSN: 0975-4350

Deriving Association between Student's Comprehension and Facial Expressions using Class Association Rule Mining

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GJCST-C Classification : H.2.8

DERIVING ASSOCIATION BETWEEN STUDENTS COMPREHENSION AND FACIAL EXPRESSIONS USING CLASS ASSOCIATION RULE MINING

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Deriving Association between Student's Comprehension and Facial Expressions using Class Association Rule Mining

Dr. M. Mohamed Sathik [α] & G. Sofia [σ]

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I. Introduction

Today's learning community focus on the vision of faculty and students working collaboratively towards deep, meaningful, high quality learning. The achievements of digital communication lead learning communities into a new dimension. There is an increase in virtual schools worldwide as education mediated by computer is considered very important for the future [12]. Nowadays, Learning Management Systems (LMS) are being installed more and more by universities, community colleges, schools, businesses, and even individual instructors in order to add web technology to their courses and to supplement traditional face-to-face courses [10]. LMS systems accumulate a vast amount of information which is valuable for analyzing the students' behavior and could create a gold mine of educational data [7].

Teacher student Interaction plays a vital role in the classroom environment. [5] In the classroom, lecturers and students both consciously and students

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Students' behavior and could create a gold mine of educational data [7].

Teacher student Interaction plays a vital role in the classroom environment. [5] In the classroom, lecturers and students--both consciously and unconsciously--send and receive nonverbal cue several hundred times a day. Lecturers should be aware of nonverbal communication in the classroom for two basic reasons: to become better receivers of student's messages and to gain the ability to send positive signals that reinforces students' learning. Lecturers should be skilled at avoiding negative signals that stifle their learning.

Studies have evaluated that student emotional states are expressed with specific behaviors that can be automatically detected [17]. A preliminary study, carried out as the first part of this research, proved that the communicative impact of the face is so powerful in interaction. The most expressive way students display emotions is through facial expressions. Facial expressions are the primary source of information, next to words, in determining the student's emotional feelings to express their comprehension. It also strongly recommends that there is a direct connection between the facial expressiveness of the students and their level of comprehension. Momentary expressions that signal emotions include muscle movements such as raising the eyebrows, wrinkling the forehead, shrinking or enlarging the eyes or curling the lip [9].

This research specifically focused on studying the relationship between facial expressions of the students in an academic lecture and the level of comprehension shown by their expressions. The aim was to identify physical behaviors that are linked to emotional states, and to identify how these emotional states are linked to student's comprehension. The significance of the study was statistically interpreted. Hence it derives the Association rules which show the relationship between facial expressions of students in an academic lecture and the level of comprehension shown by their expressions.

The remainder of this paper is organized as follows. The Concepts implemented in this paper are explained in section II .Methods adopted in this paper are presented in section III. The experimental results are discussed in section IV. Finally, a conclusion and directions for future work are briefly covered in the last section.

II. Concepts

a) Association Rule Mining

Data mining is the analysis of observational data sets to find the relationships among the data and to summaries it in novel ways that are both understandable and useful to the data owner [4]. The mining of association rules is a typical data mining task that works in an unsupervised manner. A major advantage of association rules is that they are theoretically capable of revealing all interesting relationships, called associations. It discovers relationships among attributes, producing if-then statements concerning attribute-values [1]. An association rule X ⇒ Y expresses that in those transactions where X occurs; there is a high probability of having Y as well. X and Y are called respectively the antecedent and consequent of the rule. The strength of such a rule is measured by its support and confidence. The confidence of the rule is the percentage of transactions with X in the dataset that contain the consequent Y also. The support of the rule is the percentage of transactions in the dataset that contain both the antecedent and the consequent.

Definition of Association Rule: Let I = {i1, i2… im} be set of items, D be task relevant data of transactions, T be each transaction, a set of items, such that $T \subset I$ where $\subset$ denotes proper subset and TID be the Transaction Identifier. An Association Rule is defined as an implication of type A => B, where $A \subset I$, $B \subset I$ and $A \cap B = \Phi$. The Rule hold in D with confidence C and support S, where C: Confidence (A=>B) = P (A U B), S: Support (A=>B) = P (B | A) where P is probability. [20]If B be a dataset with n items, then the support of an item set X is the number of instances which satisfy X given by the formula:

$$\sup(X) = \frac{|\{t \in B \mid X \subseteq t\}|}{|B|} \qquad (1)$$

The confidence of an association rule is a percentage value that shows how frequently the consequent part occurs among all the groups containing the rule antecedent part:

$$\text{conf}\left(X \rightarrow Y\right) = \frac{|\{t \in B \mid X \cup Y \subseteq t\}|}{|\{t \in B \mid X \subseteq t\}|} \qquad (2)$$

Association rule mining has been applied to e-learning systems for traditional association analysis (finding correlations between items), such as discovering interesting relationships from student's usage information in order to provide feedback to course author [11], finding out the relationships between each pattern of learner's behaviour [18] etc. Association rule mining also has been applied to the learning of sequential patterns mining, which is a restrictive form of association rule mining in the sense that not only the occurrences themselves, but also the order between the occurrences of the items is taken into account. The extraction of sequential patterns has been mainly used in e-learning for evaluating the learners' activities and can be used in adapting and customizing resource delivery [19]; discovering and comparison with expected behavioural patterns specified by the instructor that describes an ideal learning path [8]; classification [2].

Classification using association rules combines association rule mining and classification, and is therefore concerned with finding rules that accurately predict a single target (class) variable. The key strength of association rule mining is that all interesting rules are found. The number of associations present in even moderate sized databases can be, however, very large – usually too large to be applied directly for classification purposes. Therefore, any classification learner using association rules has to perform three major steps: Mining a set of potentially accurate rules, evaluating and pruning rules, and classifying future instances using the found rule set.

b) Class Association Rules

Normal association rule mining does not have any target. It finds all possible rules that exist in data, i.e., any item can appear as a consequent or a condition of a rule. However, in some applications, the user is interested in some targets. Let T be a transaction data set consisting of n transactions. Each transaction is also labeled with a class y. Let I be the set of all items in T, Y be the set of all class labels and $I \cap Y = \varnothing$. A class association rule (CAR) is an implication of the form $X \rightarrow y$, where $X \subseteq I$, and $y \in Y$. The definitions of support and confidence are the same as those for normal association rules.

A class Association rule is defined to be an implication with a pre-specified target (a value of target attribute) as its consequence and its support and confidence are above given thresholds from a dataset respectively. Given a target attribute, minimum support σ and minimum confidenceψ, a complete class association rule set is a set of all class association rules, denoted by Rc(σ,ψ).

Conceptually, class association rules differ from standard association rules in their consequence. The objective is to generate the complete set of class association rules that satisfy the minimum support as well as the minimum confidence constraints and to build a classifier from the class association rule set. To this aim, one combines the prediction of all rules which satisfy the example: if there is only one rule, the consequent of this rule is taken to be the predicted class for the example; if there is no rule satisfying the example, then a default class is taken to be the predicted class; and if there are multiple rules satisfying the example, then their predictions must be combined. Our goal is to find the minimum subset of the complete class association rule set that has the same prediction power as the complete association rule set [6].

C) Pruning

Association rule mining algorithms normally discover a huge quantity of rules and do not guarantee that all the rules found are relevant [3]. Support and confidence factors can be used for obtaining interesting rules which have values for these factors greater than a threshold value. Although these two parameters allow the pruning of many associations, another common constraint is to indicate the attributes that must or cannot be present in the antecedent or consequent of the discovered rules. Hence the solution is to evaluate, and post-prune the obtained rules in order to find the most interesting rules for a specific problem. A pruning technique is used for removing redundant or insignificant rules.

For practical applications the number of mined rules is usually too large to be exploited entirely. This is why the pruning phase is more essential in order to build accurate and compact classifiers. The smaller the number of rules a classifier needs to approximate the target concept satisfactorily and the human can interpret the result easily. Pruning strategies try to close the gap between the mining of a large number of class association rules and a small and powerful set of classification rules. Hence Pruning is an imperative step in mining association rules which helps in accurate classification.

III. Methods

In this research a study was conducted for observing the facial expressions of the students in academic lecture-environments. The scope of this study was to establish whether there is a relationship between the student's facial expressions and the comprehension of the students. Also to examine whether facial expression of the students is a tool for the lecturer to interpret comprehension level of students in virtual classroom.

In order to perform the experiment for the study, survey was taken using stratified sampling technique with a questionnaire. Questionnaire was given to 100 Lecturers from 10 academic institutions, and their responses were collected. It focuses on the role of facial expressions in non-verbal communication. It ranks the order in which the lecturer interprets the level of comprehension in the classroom through various nonverbal communication modes. It also measures the frequency of the expressions exhibited by the action units of face for the purpose of communication. Finally, how the expressions are correlated with the emotions of the students was analyzed. Experimental data in the domain is integrated into a dataset after statistical interpretation to serve as the basis for analysis.

The goal of association rule mining is to find all rules satisfying some basic requirement such as minimum support and the minimum confidence. A set of association rules for the purpose of classification is called predictive association rule set. Predictive association rules are based on attribute values where the consequences of rules are pre-specified categories. A class association rule set is a subset of Predictive association rules with the specified targets (classes) as their consequences [6]. Hence mining predictive association rules undergoes the following two steps.
Find all class association rules.

Prune and organize the found class association rules and return a sequence of predictive association rules. Here in this paper all the class association rules are derived by Predictive Apriori Algorithm and the derived rules are pruned by objective and subjective measures.

a) Mining Class Association Rules

The mining of association rules is a typical data mining task that works in an unsupervised manner. A major advantage of association rules is that they are theoretically capable of revealing all interesting relationships in a set of data.

The improved version of the Apriori algorithm is the Predictive Apriori algorithm [13], which automatically resolves the problem of balance between two parameters, maximizing the probability of making an accurate prediction for the dataset. In order to achieve this, a parameter called the exact expected predictive accuracy is defined and calculated using the Bayesian method [15], which provides information about the accuracy of the rule found. In this way the user only has to specify the maximal number or rules to discover.

Apriori mines considerably more rules than predictive Apriori but most of them are pruned in the final set of classification rules. The advantage of predictive Apriori is that it generates fewer rules right from the start [14].

b) Predictive Apriori Algorithm

The Predictive Apriori algorithm [13] generates frequent item sets, but it uses a dynamically increasing minimum support threshold. It searches with an increasing support threshold for the best rules concerning a support-based corrected confidence value. A rule is added if: the expected predictive accuracy of this rule is among the "n" best and it is not subsumed by a rule with atleast the same expected predictive accuracy.

This scheme is an adapted version from Scheffer [13]

1. Predictive Apriori Algorithm:

2. Input the number of desired association rules and a dataset D with class attribute C.
3. Set optimal class association Rule set R= {∅}.
4. Set the support threshold as 1.
5. Determine all frequent item sets whose support value is greater than the support threshold.
6. With such frequent item sets generate rules with high predictive accuracy.
7. Select the strong rules and include them in R.
8. Repeat the generation of rules till you get the desired number of association rules.
9. Output the optimal class association rule set R.
10. An important improvement in the Predictive Apriori (PA) is that there is no need to specify any of the parameters. Its objective is to find the best N association rules, being N a fixed number. An optimum set of class association rules are the output of this algorithm.

c) Predictive Accuracy

The Predictive Apriori algorithm differs from standard apriori in such a way that it employs a different measure of interesting of an association rule[14]. Predictive apriori evaluates the confidence of rules depending on their support. Its measure of interestingness is to maximize the expected accuracy an association rule will have on unseen data. This suits the requirements of the classification task we want to perform afterwards.

Scheffer [13] uses a Bayesian framework to calculate the predictive accuracy out of the support and confidence of a rule. In doing so the support is a rough guideline of how much we should mistrust the confidence. The higher the support, the more the confidence converges to the expected accuracy on future data.

This algorithm uses the Bayesian method to propose a solution that quantifies the expected predictive accuracy of an association rule with a given confidence and the support of the rule's body (left side of the rule). Scheffer [13] defines predictive accuracy as: Let $X \Rightarrow Y$ is an association rule. The predictive accuracy, $C(X \Rightarrow Y) = \Pr(r \text{ satisfies } Y \mid r \text{ satisfies } X)$ is the conditional probability of $Y \subseteq r$ given that $X \subseteq r$ when the distribution of r (records) is governed by P(Process). The confidence $conf(X \Rightarrow Y)$ of the association rule $X \Rightarrow Y$ is the relative frequency of the predictive accuracy in the data. Hence the confidence value is optimistically biased if one wants to use it for a predictive task.

The predictive accuracy describes whether the predicted values match the actual values of the target field due to statistical fluctuations and noise in the input data values. Hence it refers the ability of the model to correctly predict the class label of new or previously unseen data.

Using Bayesian formula the expected accuracy E of a rule r, $X \Rightarrow Y$ given its confidence conf and the support of the rule body s(X) is calculated as

$$E(c(r)|conf(r), s(X)) = \frac{\int cB[c, s(X)](conf(r))P(c)dc}{\int B[c, s(X)](conf(r))P(c)dc} \quad (3)$$

This equation calculates the expected accuracy over unseen instances given the support of the rule body and the confidence of the rule, given that the instances are independent and identically distributed. This expectation value is called predictive accuracy.

d) Pruning

Traditionally for Pruning, [16] the use of objective interesting measures such as Predictive accuracy, support and confidence, Laplace, chi-square statistic, correlation coefficient, Entropy gain, Gini index, conviction, etc can be used for ranking the obtained rules in order. Subjective measures can also be used based on subjective factors controlled by the user. The subjective approaches involve user participation in order to express, in accordance with his or her previous knowledge, which rules are of interest so that the user can select the rules with highest values in the measures that he/she is more interested. The number of rules can be decreased by only applying these objective and subjective measures.

In this paper the class association rules derived by Predictive Apriori are pruned by applying the objective measure, Accuracy Rule Ranking followed by the subjective measure Expert Domain Knowledge.

e) Pruning using Objective Measure

For Pruning using objective measure, the obtained class association rules are to be ranked first. The ranking of class association rules can be done using the objective measure of interestingness. Predictive apriori considers predictive accuracy for ranking and so it sorts rules according to their predictive accuracy. Threshold accuracy is considered and the rules with predictive accuracies below the threshold accuracy will be pruned.

f) Pruning using Subjective Measure

However, the rules discovered by Predictive Apriori Algorithm and pruned by Accuracy Rule Ranking method may not all be useful with respect to the domain. Hence it is essential to prune the rules guided by Expert domain knowledge. Also, some interesting rules may not be found from experimental data. Thus it is advisable to extend the Association Analysis to other sources such as the related literature in the domain, to enhance the Knowledgebase.

Prior experience and domain knowledge [3] of the persons play an important role in ranking the rules. Experts use linguistic values to indicate their knowledge about the matter in response through relationships

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among the attributes in the dataset. To improve the comprehension of the rules, incorporate Expert domain knowledge and semantics.

Steps to Prune using Basic Domain Knowledge

1. Consider rules derived using the Predictive Apriori Algorithm which is ranked by objective measure.
2. Use domain expert opinion to determine obvious and uninteresting rules.
3. If a derived rule matches an obvious rule or identified as uninteresting, then prune the derived rule.
4. Store obvious rules in a rule base for future use. These represent interesting information.
5. Repeat this process until all rules discovered are considered interesting in the domain.

Before running the class association rule mining algorithm, the relevant knowledgebase on the dataset in accordance with statistical interpretation associated with expert's response have to be prepared. In the context of Virtual educational environments, we can identify some common attributes that is observed from the students as seen in table1. Attributes are evaluated and ranked using Gain Ranking Filter in Weka. Ranking exhibits the extent of the attribute in expressing the comprehension level.

Table 1 : Attributes common for student's facial expressions

Rank	Attribute	Instance
1	Eye	Neutral/Enlarge/Shrink
2	Eyebrow	Neutral /Raised/Lowered
3	Forehead	Wrinkles/No Wrinkles
4	Mouth	Neutral /Curl/Stretch

Finally, we use the knowledgebase as a basis of rule repository in which subjective analysis is performed and associations are identified to discover the rules. In this context the use of standard metadata about the action units represent the facial expressions of students and allows the creation and maintenance of a common knowledge base with a common vocabulary as shown in Table1.

IV. Experimental Results

Experimental data in the domain is integrated into a dataset to serve as the basis for analysis. On analyzing the experimental data, association between facial expressions of students in an academic lecture and the level of comprehension shown by their expressions could be observed and the rules that were sufficient to answer any question with respect to the problem domain could be derived.

Table 2 : Student's Facial Expression Dataset

Row id	Attributes				Class Label
	Eye	Mouth	Forehead	Eyebrow	
1	Neutral	Neutral	NoWrinkles	Neutral	UD
2	Neutral	Smile	NoWrinkles	Neutral	UD
3	Neutral	Curled	NoWrinkles	Neutral	IC
4	Shrink	Neutral	Wrinkles	Lowered	IC
5	Shrink	Curled	Wrinkles	Lowered	IC
6	Neutral	Neutral	Wrinkles	Raised	IC
7	Enlarge	Neutral	NoWrinkles	Raised	C
8	Enlarge	Smile	NoWrinkles	Raised	C

C-Comprehensible, IC-Incomprehensible, UD-Undecided.

Using the statistical measure of interestingness such as correlation and mean on the attributes, data is cleaned, grouped and categorized to form a dataset as shown in Table2 as good data preparation is the key to produce valid and reliable model.

Prior Experiments and statistical analysis on this research strongly suggested that facial expression is the most frequently used nonverbal communication mode used by the students in the classroom and student's expressions are significantly correlated to their emotions which can help to recognize their comprehension in the lecture. In particular, the more expressive the student is, more the lecturer recognizes the comprehension of the students. Facial Expressions that signal emotions include muscle movements such as raising eyebrows, wrinkling the forehead, rolling the eyes or curling the lip. So the action units of face such as eyes, mouth, eyebrow and forehead are the emotion indicators. Here we analyzed whether the emotional feelings of the students with respect to comprehension are indicated through expressions of facial action units. Experiments were made with survey and analysis was done through SPSS.

In order to find the association between the facial expressions of students in an academic lecture and the level of comprehension shown by their expressions, Predictive apriori algorithm is applied on the above dataset and the class association rules are being derived using Weka tool.

The discovered rules are sorted and ranked according to their Predictive accuracy. Irrespective of the number of rules to be predicted set as 100, Objective pruning got the optimal number of rules by applying the threshold accuracy 0.46584 as shown in Table4. Hence the number of class association rules generated was 14 as shown in Table3.

Table 3 : Generated Class Association Rules

Rule No.	Rule
1	Forehead=Wrinkles ==> Class=IC
2	Eye=Shrink ==> Class=IC
3	Eye=Enlarge ==> Class=C
4	Mouth=Curled ==> Class=IC
5	Eyebrow=Lowered ==> Class=IC
6	Forehead=NoWrinkles Eyebrow=Raised ==> Class=C
7	Eyebrow=Neutral ==> Class=UD
8	Eyebrow=Raised ==> Class=C
9	Eye=Neutral Forehead=NoWrinkles ==> Class=UD
10	Eye=Neutral ==> Class=UD
11	Eye=Neutral ==> Class=IC
12	Mouth=Neutral ==> Class=IC
13	Forehead=NoWrinkles ==> Class=UD
14	Forehead=NoWrinkles ==> Class=C

Table 4 : Calculated Predictive accuracy

Rule No.	Predictive Accuracy
1	0.98292
2	0.9729
3	0.9729
4	0.9729
5	0.9729
6	0.9729
7	0.61331
8	0.61331
9	0.61331
10	0.49952
11	0.49952
12	0.49952
13	0.46584
14	0.46584

For further simplification of rules subjective pruning was done on the pruned rules to get the best optimal set of rules. The obtained results or rules are interpreted and evaluated by the domain expert's knowledge for further actions. Rules with similar Predictive accuracies are grouped and some interesting rules that may not be found from experimental data are identified and included. The final objective is to put the results into use in form of if-then rules as shown below.

1. If Forehead=Wrinkles then
   Class =Incomprehensible
2. If Eye=Shrink or Mouth=Curled or
   Eyebrow= Lowered then
   Class =Incomprehensible
3. If Eye=Enlarge then
   Class=Comprehensible
4. If Forehead=No Wrinkles and Eyebrow=Raised and Eye=Enlarge then
   Class= Comprehensible
5. If Eyebrow=Neutral and Eye =Neutral and Mouth = Neutral and Forehead=Nowrinkles then
   Class=Undecided
6. If Eyebrow=Raised and Eye=Enlarge then
   Class=Comprehensible
7. If Forehead=No Wrinkles and Eye=Neutral and Eyebrow=Neutral then
   Class= Undecided
8. If Forehead=Wrinkles and Eyebrow=Raised and Eye=Neutral and Mouth Neutral then
   Class= Incomprehensible

Lecturers use the above discovered rules for making decisions about the comprehension of the student in the virtual classrooms in order to improve the student's learning.

These interesting Class Association Rules are useful for predictive analysis and are used to populate a knowledgebase. They represent the knowledge that a domain expert discovers on learning from experimental data and literature surveys which can be used for decision support and classification.

V. Conclusion

Recent research tells teachers and students use facial expressions to form impressions of another. Facial Expression plays a vital role in identification of Emotions and Comprehension of the students in the virtual classrooms. This study derived the association between the specific elements of learner's behaviour for the different emotional states and the relevant expression that could be observed from individual students.This paper derived association rules that represent the relationship between the physical behaviors that are linked to emotional state with the student's comprehension and it was being formulated in the form of rules. The effectiveness of this method will be improved by correlating more features from different action units of the face which would improve the classification process.

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