DETECTING AND IMPROVING STUDENT EMOTIONS USING ACTIONABLE PATTERN DISCOVERY IN STUDENT SURVEY DATA

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ABSTRACT

Each year number of students enrolling in higher education is increasing significantly. Students from diverse backgrounds can be found in a class. These changing circumstances are making it necessary to develop Innovative teaching and Learning methodologies. Active Learning methodology is an innovative strategy and Lightweight Team comes under this Active Learning methodology. Lightweight Team approach is one such low-stake activity and it has very little or no direct impact on a student's grade whereas it makes the learning process fun and interesting. A student's Emotion towards a class plays a major role in their class performance. In this work we use the feedback from the Student Survey Data which aims to evaluate student emotions and overall satisfaction with Course Teaching methods and Group Work experience. We use Actionable Pattern Discovery methodology to provide suggestions in the form of Action Rules to enhance student Emotions thereby achieving a Positive Learning and Teaching experience.

KEYWORDS

Actionable pattern discovery, education, emotion detection, data mining, active learning.

1. INTRODUCTION

Education plays a major role in a person's life. Importance of quality education is stressed in almost every country and educational institutions are closely monitored to ensure that they meet high quality standards. Therefore school teachers, college professors, administrators, researchers, and policy makers are expected to innovate the theory and practice of teaching and learning, as well as all other aspects of this complex organization to ensure quality preparation of all students to life and work [1]. Merriam Webster Dictionary defines Innovation as a new idea, method or device and as introduction of something new. The US Office of Education defines Educational Innovations as follows, "There are innovations in the way education systems are organized and managed, exemplified by charter schools or school accountability systems. There are innovations in instructional techniques or delivery systems, such as the use of new technologies in the classroom. There are innovations in the way teachers are recruited, and prepared, and compensated. The list goes on and on" [2].

Active Learning methodology is one such innovative approach and Lightweight Teams come under this. Lightweight Teams are a cooperative learning approach in which teams of students are assigned to work together throughout a course, but the activities performed by the team are lightweight and have little or no direct impact on each individual student's grade. This approach capitalizes the benefits of peer learning while removing the stress typically associated with team-based learning [3].

Emotion is an instinctive or intuitive feeling. There are 6 different types of emotions such as happy, sad, anger, fear, disgust and surprise [4]. A student's emotion towards a class plays a very important role in their academic performance. A positive learning experience makes it easier for students to learn and perform better in the class whereas a negative experience has adverse effect on the student's attitude towards the class. Universities all over the world collect student feedback at the end of the semester to understand their feelings towards the course material, the instructor and overall class experience.

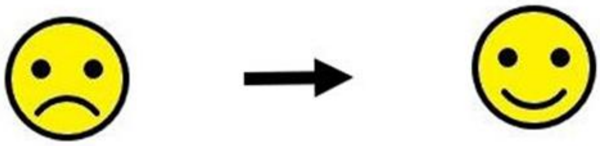

Figure 1. Improve student emotion

In this paper, we aim to provide suggestions on how to enhance student emotions from the student feedback for courses that are labeled with emotion. This is a novel approach, and it improves the teaching and learning outcomes of a course. To achieve this, we use Actionable Pattern Discovery method. Actionable patterns help the user to achieve better results and Action Rules Mining is one such approach. Action Rules are rules that suggest possible transition of data from one state to another [5]. The definition of Action Rule [5] is given in below equation (1)

$$[(\omega) \wedge (\alpha \rightarrow \beta)] \Rightarrow (\varphi \rightarrow \psi) \tag{1}$$

Here, ω represents the conjunction of fixed condition features shared by both groups, $(\alpha \rightarrow \beta)$ represents changes in flexible attributes, and $(\varphi \rightarrow \psi)$ shows the desired change in the decision attribute. There are a lot of research activities related to actionable pattern discovery with medical and social media data. But there is very little work done on actionable pattern discovery in education data like student feedback. The reminder of the paper is arranged as follows: section II - related works, section III - methodology, section IV - experiments and results followed by conclusions and future works.

2. RELATED WORK

Little work is done in the field of Education Data Mining and Emotion Detection. We review existing methods and applications. In this section we have a brief discussion on Sentiment Analysis literature with Student Evaluations.

Authors Aung and Myo [6] analyze students text feedback using Lexicon based approach to predict the level of teaching performance automatically. To achieve this, they create a database of English Sentiment words as a lexical source to get polarity of the words. They then analyze the sentiment using intensifier words which are extracted from the feedback to get opinion result of teachers that can be strongly positive, moderately positive, weakly positive, strongly negative, moderately negative, weakly negative or neutral.

Authors Hynninen, Knutas and Hujala [7] use statistical computing to categorize the feedback texts by sentiment values (positive and negative). They calculate NRC emotion values which categorizes the feedback into eight basic emotions. (anger, fear, anticipation, trust, surprise, sadness, joy, and disgust) They present the analysis of the trends of how feedback are evolved through the years. Authors Newman and Joyner [8] use VADER(Valence Aware Dictionary and sEntiment Reasoner), a sentiment analysis tool, to analyze student evaluations of teaching of a course from three different sources like official evaluations, forum comments from another course, and an unofficial "reviews" site maintained by students. They compare the positive and negative valances of these sites to identify frequently used keywords and determine the positive and negative values of the comments.

In [9], [10] authors use end of semester student feedback and process the qualitative text comments. They automatically label the text comments with fine grained emotions such as 'joy', 'anticipation', 'trust', 'anger', 'fear', 'disgust', 'sadness', 'surprise'. In their work, they assess the impact of the Light-weight team teaching model, through automatic detection of emotions in student feedback.

All of the above applications focus only on identifying if certain tasks work well or not in the Education setting. In this work we propose a novel approach for analyzing student feedback data for opinion mining through fine grained emotion to identify patterns and suggest teaching improvements. This helps Teachers and Administrators to identify certain factors that need attention or change to improve teaching and the learning experience.

3. BACKGROUND

The following section includes some background information related to Actionable Pattern Mining.

3.1. Information System and Decision System

Information system in Table 1 is perceived as a system Z = (X, M, V), where X is set of objects {x1, x2, x3, x4, x5, x6, x7, x8} in the system; M is non-empty finite set of attributes {A, B, C, E, F, G, D}; V is the domain of attributes in M, for instance the domain of attribute B in the system Z is {B1, B2, B3}.

The information system in Table 1 is denoted as Decision system if the attributes M are classified into flexible M_{fl}, stable M_{st} and decision d, M = (M_{st}, M_{fl}, {d}). From Table 1, M_{st} = {A, B, C}, M_{fl} = {E, F, G}, and d = D.

Table 1. Information system Z

X	A	B	C	E	F	G	D
x1	A1	B1	C1	E1	F2	G1	D1
x2	A2	B1	C2	E2	F2	G2	D3
x3	A3	B1	C1	E2	F2	G3	D2
x4	A1	B1	C2	E2	F2	G1	D2
x5	A1	B2	C1	E3	F2	G1	D2
x6	A2	B1	C1	E2	F3	G1	D2
x7	A2	B3	C2	E2	F2	G2	D2
x8	A2	B1	C1	E3	F2	G3	D2

3.2. Action Rule

The expression $r = [t1 \rightarrow t2]$ is an Action Rule where, t1 is an action term and t2 is an atomic action term. The following is an example Action Rule from Table 1.

$$[B1 \wedge C1 \wedge (F, F3 \rightarrow F1) \wedge (G, \rightarrow G1) \rightarrow (D, D2 \rightarrow D1).$$

3.3. Support and Confidence

Support and confidence of rule r is given as below:

$sup(r) = \min\{card(Y1 \cap Z1), card(Y2 \cap Z2)\}.$
$conf(r) = (card(Y1 \cap Z1))/(card(Y1)) \cdot (card(Y2 \cap Z2))/(card(Y2))$
$card(Y1)$ 6= 0, $card(Y2)$ 6= 0, $card(Y1 \cap Z1)$ 6= 0, $card(Y2 \cap Z2)$ 6= 0.
$conf(r) = 0$ otherwise.

4. METHODOLOGY

This section contains data collection steps, and our proposed Actionable Pattern mining method.

4.1. Data Collection Steps

The Student Survey Data is collected online during the years 2019 to 2020 from courses which implement the Active Learning methods and teaching style. The Student Survey Data aims to evaluate student emotions and overall satisfaction with course teaching methods and group work experience. The data collection process is depicted in Figure 2.

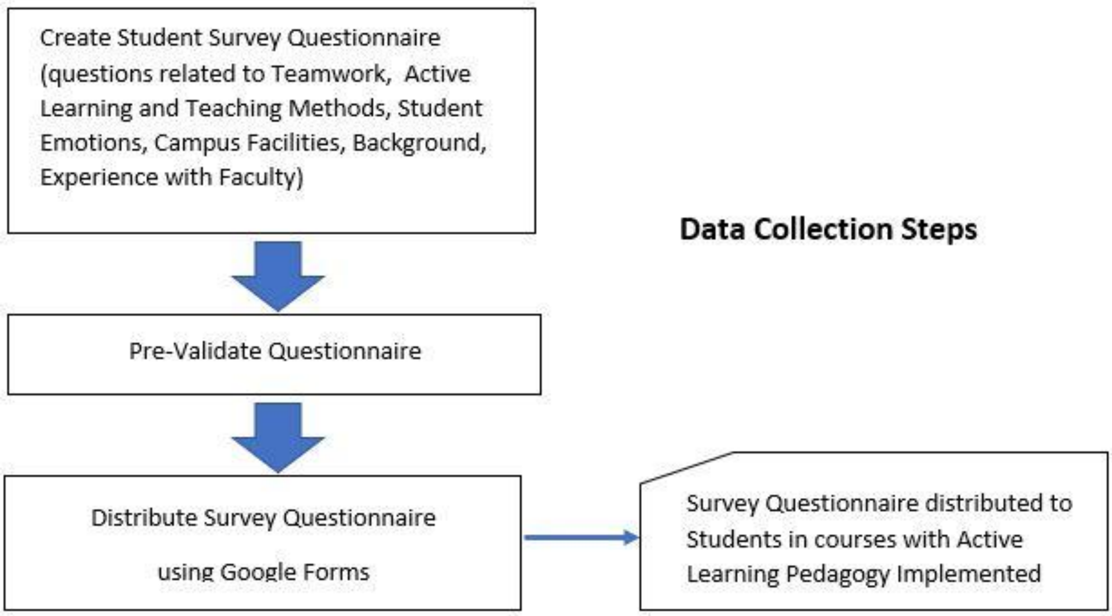

Figure 2. Data collection steps

The survey questionnaire includes some basic demographic information like gender, ethnicity, school year, relationship status etc. Table 3 shows the demographic statistics for the Student Survey Data.

Table 2. Sample student survey questions.

Survey Questions
Do you feel you belong well with the Team or Group you work with?
Other students help me to increase my understanding of the material during Team-Based GroupActivities.
The class discussions are with the subject matter

Figure 3 shows the gender distribution in the collected data and contains the options 'Male', 'Female', 'Other', and 'Prefer Not to Answer'. Figure 4 shows the student population distribution based on School Year.

Table 3. Student survey data – demographic statistics.

Demographic Category	**Count**
Participants	549
Gender	
_*Male:	210
_*Female:	324
_*Prefer Not to Answer:	6
_*Other:	3
Ethnicity	
_* Caucasian or White:	90
_* I would prefer not to identify my race/ethnicity:	37
_* Asian or Asian-American:	288
_* Caucasian or White, Asian or Asian-American:	5
_* Southeast Asian:	39
_* Southeast Asian, Asian or Asian-American:	8
_* Hispanic or Latino, Asian or Asian-American:	2
_* American Indian or Native American or Alaskan:	1
_* Middle Eastern or North African or Arab or Arab American:	10
_* African American or Black:	27
_* Pacific Islander or Native Hawaiian:	1
School Year	
_* Undergraduate:	199
_* Graduate: Master's degree:	324
_* Graduate: PhD	5
_* Non-degree seeking:	2

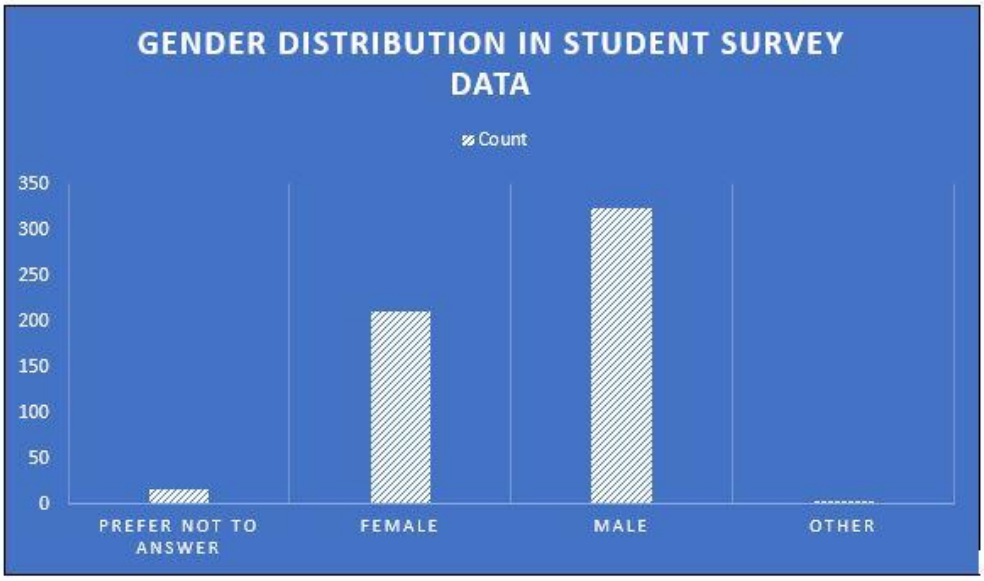

Figure 3. Gender distribution in student survey data.

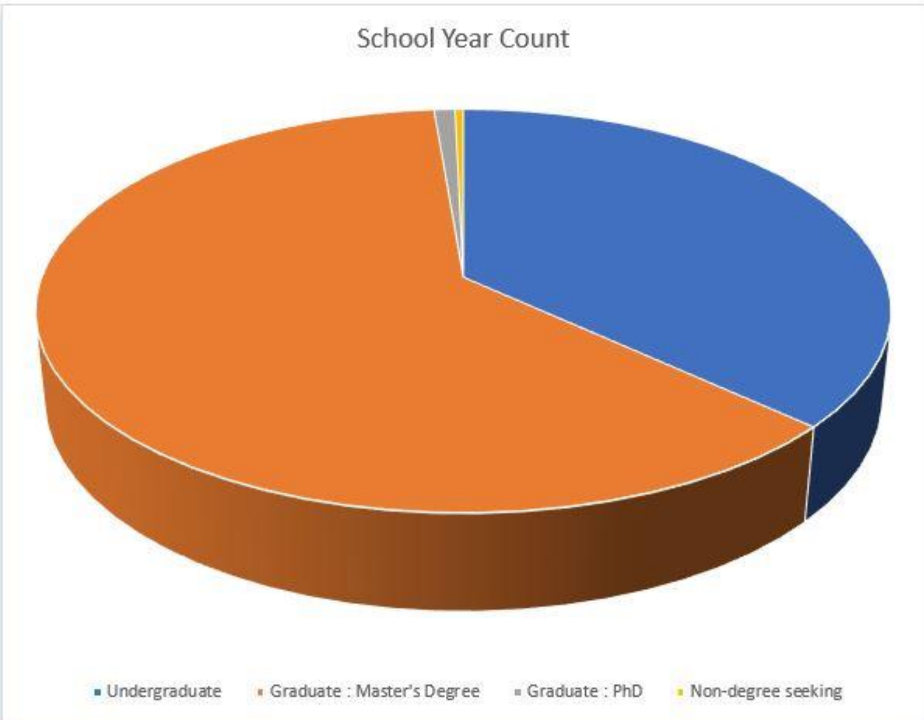

Figure 4. Student population distribution based on school year.

4.2. Learning from Example using Rough Sets

In our work, we apply the Learning from Example using Rough Sets (LERS) [11] strategy that finds the certain rules and possible rules describing the decision attribute in terms of other attributes in the system. The Table 1 has the following attributes $P = (P_{st}, P_{fl}, \{d\})$, where P_{fl} $P_{st} = \{A, B, C\}$, $P_{fl} = \{E, F, G\}$, and $d = D$.

The list of certain and possible rules that LERS strategy finds from the Table 1 is as follows:
Certain Rules

E1 → D1
G3 → D2
F3 → D2
E3 → D2
B2 → D2
B3 → D2
A3 → D2
A2 ∧ G1 → D2
A1 ∧ E2 → D2
A2 ∧ C1 → D2
A1 ∧ C2 → D2
E2 ∧ C1 → D2
G2 ∧ B1 → D3
G1 ∧ E2 → D2
G1 ∧ C2 → D2
A1 ∧ C1 ∧ B1 → D1
A2 ∧ B1 ∧ C2 → D3
A2 ∧ E2 ∧ B1 ∧ C2 → D3
A2 ∧ F2 ∧ E2 ∧ B1 → D3
A1 ∧ G1 ∧ C1 ∧ B1 → D1
A2 ∧ F2 ∧ B1 ∧ C2 → D3
A1 ∧ F2 ∧ C1 ∧ B1 → D1
G1 ∧ F2 ∧ C1 ∧ B1 → D1

Possible Rules

A2 ∧ G2 ∧ F2 ∧ E2 ∧ C2 → D1
A2 ∧ G2 ∧ F2 ∧ E2 ∧ C2 → D2
A2 ∧ G2 ∧ F2 ∧ E2 ∧ C2 → D1

4.3. Apriori Based Association Action Rule Mining (AAR)

The Association Action Rules described by Ras et al. [5] generates Action Rules using frequent action sets in Apriori like fashion. The frequent action set generation is divided in two steps: merging step and pruning step.

4.3.1. Merging step: In this step the algorithm merges the previous two frequent action sets to a new action set.
4.3.2. Pruning step: In this step the algorithm ignores the newly formed action set if it does not contain the decision action (e.g., the user desired value of decision attribute).

For our example, using the data from Table 1, the primary action sets generated by Association Action Rules are shown in Table 4. The frequent action sets generated by Association Action Rules are shown in Table 5. In our example, the action set is discarded if (D, 2 → 1) is not present in it. From each frequent action set, the association Action Rules are formed. Therefore, the algorithm generates frequent action sets and forms the association Action Rules from these action sets. For our example, using the data from the Information system in Table 1 the algorithm generates Association Action Rules, an example is shown below:

$$(B, B1 \rightarrow B1) \wedge (C, C1 \rightarrow C1) \wedge (E, E3 \rightarrow E1) \rightarrow (D, D2 \rightarrow D1)$$

Table 4. Primary action sets.

Attribute	**Primary Action Set**
A	(A, A1), (A, A2), (A, A3)
B	(B, B1), (B, B2), (B, B3)
C	(C, C1), (C, C2)
E	(E, E1), (E, E2), (E, E3), (E, E1 → E2), (E, E1 → E3), (E, E2 → E1), (E, E2 → E3), (E, E3 → E1), (E, E3 → E2)
F	(F, F2), (F, F3), (F, F2 → F1), (F, F2 → F3), (F, F3 → F1), (F, F3 → F2)
G	(G, G1), (G, G2), (G, G3), (G, G1 → G2), (G, G1 → G3), (G, G2 → G1), (G, G2 → G3), (G, G3 → G1), (G, G3 → G2)
D	(D, D1), (D, D2), (D, D3), (D, D1 → D2), (D, D1 → D3), (D, D2 → D1), (D, D2 → D3), (D, D3 → D1), (D, D3 → D2)

Table 5. Frequent action sets.

Iteration	**Frequent Action Set**
Iteration 1	(A, A1) ^ (D, D2 → D1) (A, A2) ^ (D, D2 → D1) (A, A3) ^ (D, D2 → D1) (B, B1) ^ (D, D2 → D1) (B, B2) ^ (D, D2 → D1) (B, B3) ^ (D, D2 → D1)
Iteration 2	(A, A1) ^ (B, B1) ^ (D, D2 → D1) (A, A1) ^ (B, B2) ^ (D, D2 → D1) (A, A1) ^ (B, B3) ^ (D, D2 → D1)
Iteration n	………………………

4.4. Hybrid Action Rule Mining Algorithm

Action Rule mining involves two major frameworks:

Rule-Based Method: In this method the extraction of Action Rules is dependent on the pre-processing step of classification rule discovery such as LERS and

Object-Based Method: This method extracts Action Rule directly from the database without the use of classification rules, such as Association Action Rules [5], an apriori like method using frequent action sets.

The Rule-Based method using LERS [11] has the disadvantage of computing pre-existing decision rules in order to generate the Action Rule. For that it requires complete set of attributes which makes it difficult to implement it in a distributed cloud environment. The Object-Based method can be implemented in distributed cloud environment by using vertical data split [12], where only subsets of the attributes are taken for scalability purpose. However, since this method is iterative it takes longer time to process huge datasets. In this work we propose using a hybrid approach [13] to generate complete set of Action Rules by combining the Rule-Based and Object-Based methods. The hybrid method provides scalability for big datasets and allows for improved performance compared to the Association Action Rule Mining method which is an iterative approach. The pseudocode of the algorithm is given in Figure 5.

```
Algorithm(certainRules, decisionFrom, decisionTo, support, confidence)
    (where certainRules are provided by algorithm LERS)
    for each rule r in certainRules
        if consequent(r) equals decisionTo
            Form ActionRuleSchema(r)
            ARS ← ActionRuleSchema(r)
        end if
    end for
    for each schema in ARS
        Identify objects satisfying schema
        Form subtable
        Generate frequent action sets using Apriori
        Combine frequent action set to form Action Rules
        (Such that the frequent action sets satisfy the decisionFrom → decisionTo)
        Output ← Action Rules
    end for
```

Figure 5. Hybrid action rule mining algorithm.

The Hybrid Action Rule Mining Algorithm works with the Information System as follows. The information system in Table 1 has the following attributes: flexible P_{fl}, stable P_{st} and decision d, P = (P_{fl}, P_{st}, {d}). From Table 1 = P_{st} {A, B, C}, P_{fl} = {E, F, G}, and d = D. The following example re-classifies the decision attribute D from d2 → d1. The algorithm in Figure 5 initially uses the LERS method to extract the classification rules that are certain and then generates Action Rule schema as given in the following equations (2), (3).

$$[B1 \wedge C1 \wedge (F, \rightarrow F1) \wedge (G, \rightarrow G1)] \rightarrow (D, D2 \rightarrow D1). \quad (2)$$

$$[(E, \rightarrow E1)] \rightarrow (D, D2 \rightarrow D1). \quad (3)$$

The algorithm then creates sub-table for each Action Schema. For example, equation (2) generates the following sub-table Table 6.

Table 6. Subtable for action rule schema.

X	B	C	F	G	D
x1	B1	C1	F2	G1	D1
x3	B1	C1	F2	G3	D2
x6	B1	C1	F3	G1	D2
x8	B1	C1	F2	G3	D2

The Hybrid Action Rule Mining Algorithm applies the Association Action Rule extraction algorithm in parallel on each of the sub-tables. The algorithm generates the following Action Rules "(4)" based on the sub-table Table 6.

$$[B1 \wedge C1 \wedge (F, \rightarrow F1) \wedge (G, G3 \rightarrow G1)] \rightarrow (D, D2 \rightarrow D1). \quad (4)$$

This hybrid Action Rule algorithm is implemented in Spark [14] and runs separately on each sub-table and performs transformations like map(), flatmap(), join(). The methodology of this algorithm is shown in Figure 6.

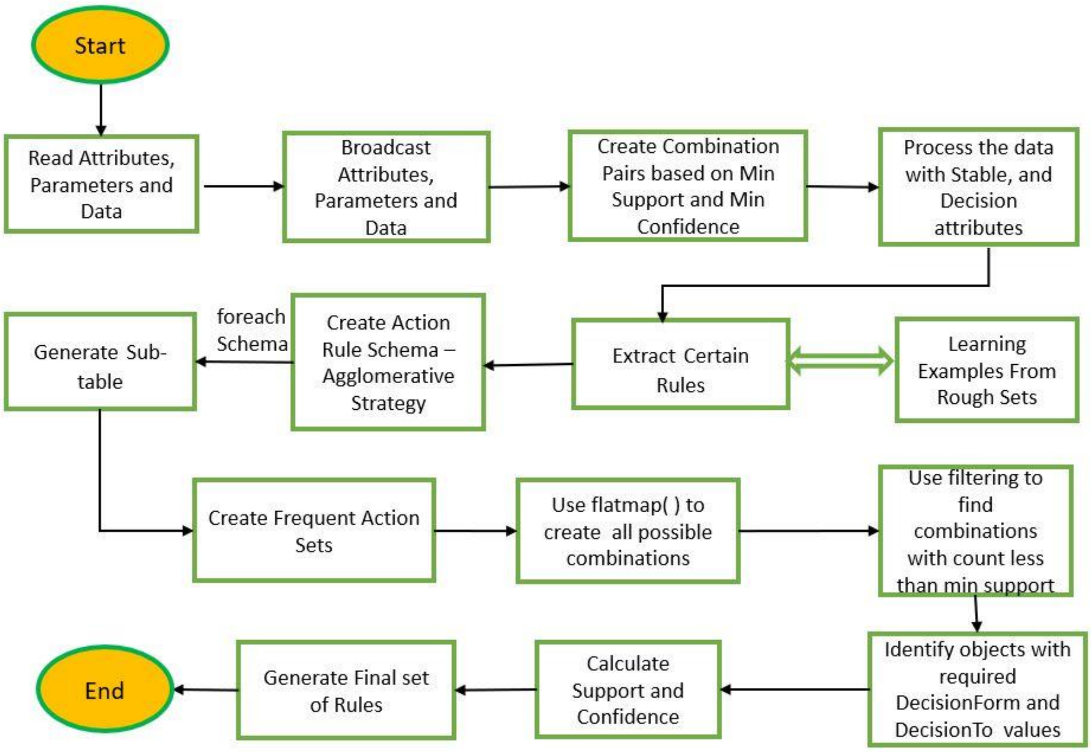

Figure 6. Hybrid action rule mining algorithm - Flowchart.

5. EXPERIMENTS AND RESULTS

In this work we use, student survey data which aims to evaluate student emotions and overall satisfaction with course teaching methods and group work experience. The survey is designed to get meaningful insights on students' feelings towards the Active Learning methods and other factors that can help students in their learning process. The data is collected in the courses which implement the Active Learning methods and teaching style.

The original data contains 549 instances and 59 attributes. The properties of the dataset are shown in Table 7. Data is collected in classes employing Active Learning methods to assess student opinions about their learning experience in the years 2019, 2020. The data size on disk is 59 Kilobytes.

Table 7. Properties of student survey dataset used for experiments.

Property	**Values**
Attributes	59 attributes
Decision Attribute Values	StudentEmotion: Joy, Sadness, Anger, Anticipation, Trust, Disgust, Surprise, Fear
# of Instances	54900

For scalability purpose to test the performance of our proposed method with BigData set, we replicate the original Student Survey Data 100 times. The replicated dataset has a total of 54900 instances. Size on disk is 5.815 Megabytes.

Hybrid Action Rule Mining Implementation in Spark AWS Cluster on Student Survey Data to enhance Student Emotion from Sadness to Joy

We perform this experiment on the Student Survey Data with Hybrid Action Rule Mining Method - using Amazon Web Services (AWS) cluster with two nodes, 4 vCore and 16GiB memory and EBS Storage 64GiB. It takes 5088 seconds to complete computation on the replicated Student Survey Data.

In this experiment we provide the Decision Attribute StudentEmotion to be changed from "Sadness" to "Joy". Selected Action Rules generated by this experiment are shown in Figure 7 and Figure 8.

Enhance Student Emotion - Sadness $\rightarrow$ Joy

1) $AR1SadnesstoJoy : (TeamSenseofBelonging, 2BelowAverageSenseofBelongingtotheTeam \rightarrow 3AverageSenseofBelongingtotheTeam) \wedge (NumberofTeamMembers, 5to7 \rightarrow 10orMore) \Longrightarrow (StudentEmotion, Sadness \rightarrow Joy)[Support : 20.0, Confidence : 59.0\%]$
2) $AR2SadnesstoJoy : (NumberofTeamMembers, 5to7 \rightarrow 8to10) \wedge (TeamWorkHelpedDiversity, 2Occasionally \rightarrow 3Often) \wedge (GroupAssignmentBenefit, None \rightarrow AllofThem) \Longrightarrow (StudentEmotion, Sadness \rightarrow Joy)[Support : 20.0, Confidence : 100\%]$
3) $AR3SadnesstoJoy : (NumberofTeamMembers, 5to7 \rightarrow 8to10) \wedge (GroupAssignmentBenefit, None \rightarrow SharedKnowledge) \Longrightarrow (StudentEmotion, Sadness \rightarrow Joy)[Support : 34.0, Confidence : 85.0\%]$

Figure 7. Sample action rules ::: sadness to joy ::: - student survey data – hybrid method .

The Action Rule 1 in Figure 7 says when Team Sense Of Belonging changes from 2 Below Average Sense of Belonging to the Team to 3 Average Sense of Belonging to the Team and the

Number of Team Members changes from 5to7 to 10orMore then the Student Emotion changes from Sadness to Joy. This rule has support of 20 and confidence of 59%. This shows that when the Student has an average sense of belonging to the Team and the team contains 10orMore members then it enhances the Student's Emotion from Sadness to Joy. This shows the impact of team and team members in enhancing a Student's Emotion from "Sadness" to "Joy". Course instructors must ensure that students like the team they are in, and this can be done by asking for anonymous responses from students after a couple of classes at the start of the semester.

Hybrid Action Rule Mining Implementation in Spark AWS Cluster on Student Survey Data to enhance Student Emotion from Anticipation to Trust

In this experiment we provide the Decision Attribute Student Emotion to be changed from "Anticipation" to "Trust".

Enhance Student Emotion - Anticipation → Trust

1) $AR1AnticipationtoTrust : (LikeTeamWork, 1Don't \rightarrow 3Somewhat) \wedge (GroupAssignmentBenefit, None \rightarrow EliminateStress) \Longrightarrow (StudentEmotion, Anticipation \rightarrow Trust)[Support : 500.0, Confidence : 83.0\%]$
2) $AR2AnticipationtoTrust : (TeamSenseofBelonging, 2BelowAverageSenseofBelongingtotheTeam \rightarrow 4CompleteSenseofBelongingtotheTeam) \wedge (TeamWorkHelpedDiversity, 2Occasionally \rightarrow 4VeryOften) \Longrightarrow (StudentEmotion, Anticipation \rightarrow Trust)[Support : 500.0, Confidence : 100\%]$
3) $AR3AnticipationtoTrust : (TeamFormation, 2BelowAverage \rightarrow 3Average) \wedge (GroupAssignmentBenefit, None \rightarrow EliminateStress) \Longrightarrow (StudentEmotion, Anticipation \rightarrow Trust)[Support : 600.0, Confidence : 86.0\%]$

Figure 8. Sample action rules ::: anticipation to trust ::: - 2020 student survey data – hybrid method .

The Action Rule 1 in Figure 8 says when Like Team Work changes from 1Don't to 3Somewhat and the Group Assignment Benefit changes from None to Eliminate Stress then the Student Emotion changes from Anticipation to Trust. This rule has support of 500 and confidence of 83%. This shows that if the Student likes Team Work and the Group Assignment benefits the student by eliminating stress then it enhances the Student Emotion from Anticipation to Trust. This rule shows that when a student likes to do teamwork and when group assignments are given to students such that they eliminate their stress then it enhances the Student's Emotion from "Anticipation" to "Trust". This shows that course instructors should prepare group assignments for students in a way that they are interesting and fun to do such that they eliminate their stress.

Selected Action Rules generated using the 2019 Student Survey Data is shown in Figure 9.

The Action Rule 1 in Figure 9 says when Team Member Responsibility changes from Friendly Members to Responsible Members then the Student Emotion changes from Anticipation to Trust. This rule has support of 3 and confidence of 83%. This shows that if friendly members of a team can be more responsible towards project, student Anticipation can be transformed into Trust. This shows that course instructors should take care when creating Groups and make sure that the students are as equally Responsible as they are Friendly.

Enhance Student Emotion - Anticipation → Trust

1) $AR1AnticipationtoTrust : (TeamMemberResponsibility, FriendlyMembers \rightarrow ResponsibleMembers) \Longrightarrow (StudentEmotion, Anticipation \rightarrow Trust)[Support : 3.0, Confidence : 83.0\%]$
2) $AR2AnticipationtoTrust : (TeamWorkHelpedDiversity, 2Occasionally \rightarrow 3Often) \Longrightarrow (StudentEmotion, Anticipation \rightarrow Trust)[Support : 3.0, Confidence : 75\%]$
3) $AR3AnticipationtoTrust : (TeamFormation, 3Average \rightarrow 4Perfect) \wedge (NumberofTeamMembers, 5to7 \rightarrow 5to7) \Longrightarrow (StudentEmotion, Anticipation \rightarrow Trust)[Support : 3.0, Confidence : 60.1\%]$

Figure 9. Sample action rules ::: anticipation to trust ::: - 2019 student survey data – hybrid method .

6. CONCLUSIONS

In this work, we experiment with Student Survey Data using Hybrid Action Rule Mining Algorithm to suggest ways for improving student Emotions. Improved Emotions suggest a better student Learning experience. There is very little work done in this regard. We collect original data from classes implementing Active Teaching Innovations and Active Learning Methodologies. Our data contains student opinions regarding the use of Active Learning methods, Teamwork and other class experiences. The Emotion class includes 8 basic emotions: Anger, Disgust, Sadness, Fear, Surprise, Anticipation, Trust, Joy. The discovered Action Rules help to enhance the student Emotion from Negative to Positive and from Neutral to Positive. Finally, the Action Rules suggest specific ways for Instructors to improve their Teaching methodology and the Student Learning experience.

REFERENCES

[1] Serdyukov, P. (2017). Innovation in education: what works, what doesn’t, and what to do about it?. Journal of Research in Innovative Teaching & Learning, vol. 10, no. 1, pp. 4–33.
[2] What do we mean by ‘innovation’?.(2004), US Department of Education. [Online]. Available: www2.ed.gov/about/offices/list/oii/about/definition.html
[3] Latulipe, C., Long N. B., MacNeil ,S., & Yadav A. (2016). Exploring lightweight teams in a distributed learning environment. Proceedings of the 47th ACM Technical Symposium on Computer Science Education. ACM. pp. 193–198.
[4] Ekman P. (1992). An argument for basic emotions. Cognition & emotion, vol. 6, no. 3-4, pp. 169–200, 1992.
[5] Ras, Z. W., Dardzinska, A., Tsay L. S., & Wasyluk, H. (2008). Association action rules. “IEEE/ICDM Workshop on Mining Complex Data (MCD 2008)”. Pisa, Italy, ICDM Workshops Proceedings, IEEE Computer Society, pp. 283–290.
[6] Aung K. & Myo N. (2017 May). Sentiment analysis of open-ended student feedback. Proceedings of the 16th International Conference on Computer and Information Science (ICIS). pp. 149–154.

[7] Hynninen, T., Knutas ,A., & Hujala M. (2020). Sentiment analysis of students' comment using lexicon based approach. 43rd International Convention on Information, Communication and Electronic Technology (MIPRO). pp. 755–759.

[8] Joyner D. & Newman H. (2018). Sentiment analysis of open-ended student feedback. Penstein Rose C. et al. (eds) Artificial Intelligence in ´Education. AIED 2018. Lecture Notes in Computer Science, vol. 10948, 2018, pp. 246–250.

[9] Tzacheva, A., Ranganathan, J., & Jadi, R. (2019). Multi-label emotion mining from student comments. Proceedings of the 2019 4th International Conference on Information and Education Innovations, ser. ICIEI 2019. New York, NY, USA: ACM. pp. 120–124. [Online]. Available: http://doi.acm.org/10.1145/3345094.3345112 .

[10] Tzacheva , A. & Ranganathan, J. (2018). Emotion mining from student comments a lexicon based approach for pedagogical innovation assessment. The European Journal of Education and Applied Psychology. pp. 3–13.

[11] Grzymala-Busse, J. W. (1997). A new version of the rule induction system lers. Fundamenta Informaticae, vol. 31, no. 1, pp. 27–39.

[12] Bagavathi, A., Rao, V., & Tzacheva, A. A. (2018). Data distribution method for scalable actionable pattern mining. Proceedings of the First International Conference on Data Science, E-learning and Information Systems. ACM, p. 3.

[13] Tzacheva, A. & Ranganathan, J. (2021, Jan). Pattern discovery from student feedback - identifying factors to improve student emotions in learning. IOP Publishing.

[14] Zaharia, M., Chowdhury, M., Franklin, M. J., Shenker, S., & Stoica, I. (2010). Spark: Cluster computing with working sets. HotCloud, vol. 10, no. 10-10, p. 95.