OPINION MINING AND EMOTION DETECTION IN SOCIAL NETWORK DATA AND STUDENT SURVEY DATA IN CLOUD ENVIRONMENT

by

Akshaya Easwaran

A thesis submitted to the faculty of
The University of North Carolina at Charlotte
in partial fulfillment of the requirements
for the degree of Master of Science in
Information Technology

Charlotte

2021

Approved by:

____

Dr. Angelina A. Tzacheva

____

Dr. Zbigniew Ras

____

Dr. Albert Park

____

Dr. Mohsen Dorodchi

©2021
Akshaya Easwaran
ALL RIGHTS RESERVED

ABSTRACT

AKSHAYA EASWARAN. Opinion Mining and Emotion Detection in Social Network Data and Student Survey Data in Cloud Environment. (Under the direction of DR. ANGELINA A. TZACHEVA)

Recent growth and development of big social media platforms like Twitter, Facebook, Instagram etc. and personal blog sites generate huge amount of unstructured data. Analysis of this data may provide insights into the opinion of people as well as their feelings towards certain subjects, products or services. The process of extracting valuable data from opinions of people to assess their feelings and thoughts is known as opinion mining. Mining the opinions of people has applications in several areas: understanding what people like or dislike is critical for making informed business and political decisions. In this work, we focus on Opinion Mining from Text to suggest Actionable Recommendations. The Actionable Patterns may suggest ways to alter the user's sentiment or emotion to a more positive or desirable state. We apply our method to Twitter Social Network Data, as well as Student Survey Education data. We aim to suggest ways to improve the Social Network Experience and to improve Teaching Methods and Student Learning. We implement and test our system in Scalable Environment with BigData using the Apache Spark platform.

ACKNOWLEDGEMENTS

I would like to express my deep gratitude to my advisor Dr. Angelina A. Tzacheva for her valuable and constructive suggestions through out my research development process, patient guidance and enthusiastic encouragement.

I would also like to thank Dr. Zbigniew W. Ras for his support, suggestions and guidance. I would like to extend my thanks to Dr. Albert Park for his valuable feedback and fruitful comments and Dr. Mohsen Dorodchi for his support and guidance.

I thank my collaborators Jaishree Ranganathan and Arunkumar Bagavathi for their contributions and sharing their resources for my research.

TABLE OF CONTENTS

LIST OF TABLES viii

LIST OF FIGURES x

LIST OF ABBREVIATIONS 1

CHAPTER 1: INTRODUCTION 1

1.1. Opinion Mining and Human Emotions 1

1.2. Applications of Human Emotions 2

1.3. Social Media Data - Emotion Mining and Actionable Pattern Discovery 2

1.4. Educational Data Mining - Emotion Mining and Actionable Pattern Discovery 4

CHAPTER 2: RELATED WORK 6

2.1. Opinion Mining and Sentimental Analysis 6

2.2. Sentimental Analysis - Twitter Data 6

2.3. Action Rules 7

2.4. Classification - Neural Networks 7

2.5. Educational Data Mining and Sentimental Analysis 8

CHAPTER 3: METHOD 11

3.1. Labeling Emotions in Twitter and Student Survey Data 11

3.2. Learning from Rough Sets 12

3.3. Action Rules 14

3.3.1. Information System and Decision System 14

3.3.2. Action Term 15

3.3.3. Action Rule 15

3.3.4. Support and Confidence 15

3.4. Rule Based Action Rule Mining 16

3.5. Apriori Based Association Action Rule Mining(AAR) 16

3.6. Vertical Split - Data Distribution for Scalable Association Action Rules 18

3.7. Hybrid Action Rule Mining Algorithm 19

CHAPTER 4: EXPERIMENTS AND RESULTS 24

4.1. EXPERIMENT 1 - Education Data - Student Survey Data 24

4.1.1. Data Description - Student Survey Data 24

4.1.2. Vertical Data Split Method Implementation in Spark AWS Cluster 25

4.1.3. Hybrid Method Implementation in Spark AWS Cluster 27

4.1.4. Hybrid Method with Threshold Implementation in Spark AWS Cluster 30

4.1.5. Runtime Comparison of the above 3 implementations with respect to Student Survey Data in Spark AWS Cluster 33

4.2. EXPERIMENT 2 - Student Evaluation Data 33

4.2.1. Basic Emotion 33

4.2.2. Emotion and Polarity 34

4.3. EXPERIMENT 3 - Social Media Data - Twitter Data 35

4.3.1. Data Description - Social Media Data - Twitter data 35

4.3.2. Vertical Data Split Method Implementation in Spark AWS Cluster 36

4.3.3. Hybrid Method Implementation in Spark AWS Cluster 37

4.3.4. Hybrid Method with Threshold Implementation in Spark AWS Cluster 39

4.3.5. Runtime Comparison of the above 3 implementations with respect to Social Media Data - Twitter Data in Spark AWS Cluster 40

CHAPTER 5: CONCLUSIONS 41

5.1. Student Survey Data - Emotion Mining and Action Rules Discovery 41

5.2. Student Evaluation Data - Emotion Mining from Student Comments for Pedagogical Innovation Assessment 42

5.3. Social Media Data - Twitter Data - Emotion Mining and Action Rules Discovery 42

CHAPTER 6: FUTURE WORK 43

REFERENCES 44

LIST OF TABLES

TABLE 3.1: Information System Z. 12

TABLE 3.2: Primary Action Sets. 17

TABLE 3.3: Frequent Action Sets. 18

TABLE 3.4: Sub-table for Action Rule Schema 21

TABLE 4.1: Example Survey Questions. 24

TABLE 4.2: Survey Data Properties. 25

TABLE 4.3: Sample Action Rules - ::: Sadness to Joy ::: - Student Survey Data - Vertical Data Split Method. 26

TABLE 4.4: Sample Action Rules ::: Sadness to Joy ::: - Student Survey Data - Hybrid Method. 28

TABLE 4.5: Sample Action Rules ::: Anticipation to Trust ::: - Student Survey Data - Hybrid Method. 29

TABLE 4.6: Threshold values - θ Run Time comparison. 30

TABLE 4.7: Sample Action Rules ::: Sadness to Joy ::: - Student Survey Data - Hybrid Method with Threshold. 31

TABLE 4.8: Sample Action Rules ::: Anticipation to Trust ::: - Student Survey Data - Hybrid Method with Threshold. 32

TABLE 4.9: Runtime Comparison of the above 3 implementations with respect to Student Survey Data. 33

TABLE 4.10: Properties of the Twitter Dataset 36

TABLE 4.11: Sample Action Rules ::: Sadness to Joy ::: - Twitter Data - Vertical Data Split Method. 37

TABLE 4.12: Sample Action Rules ::: Sadness to Joy ::: - Twitter Data - Hybrid Method. 38

TABLE 4.13: Sample Action Rules ::: Sadness to Joy ::: - Twitter Data - Hybrid Method with Threshold. 39

TABLE 4.14: Runtime Comparison of the above 3 implementations with respect to Student Survey Data. 40

LIST OF FIGURES

FIGURE 1.1: Enhance Student Emotion From Negative or Neutral to Positive 5

FIGURE 3.1: Emotion Labeling of Twitter and Student Survey Data 11

FIGURE 3.2: Example Data Distribution using Vertical Data Distribution. 19

FIGURE 3.3: Hybrid Action Rule Mining Algorithm. 21

FIGURE 3.4: Hybrid Action Rule Mining Algorithm - Flowchart. 22

FIGURE 3.5: Hybrid Action Rule Mining Algorithm with Table size threshold θ- Flowchart. 23

FIGURE 3.6: Hybrid Action Rule Mining Algorithm. 23

FIGURE 4.1: AWS Cluster Configuration 30

FIGURE 4.2: Basic Emotion graph. 34

FIGURE 4.3: Basic Emotion and Polarity graph. 35

CHAPTER 1: INTRODUCTION

1.1 Opinion Mining and Human Emotions

Recent growth and development of big social media platforms like Twitter, Facebook, Instagram etc. and personal blog sites generate huge amount of unstructured data. Companies providing products and services collect customer satisfaction data through surveys. Educational institutions collect data from students on their opinion for their learning experience in the courses. Analysis of this data may provide insights into the opinion of people as well as their feelings towards certain subjects, products or services. The process of extracting valuable data from opinions of people to assess their feelings and thoughts is known as opinion mining. Mining the opinions of people has applications in several areas: understanding what people like or dislike is critical for making informed business and political decisions.

Emotion is an instinctive or intuitive feeling. There are 6 different types of emotions such as happy, sad, anger, fear, disgust and surprise [1]. These emotions can be manual arousal or automatic (body's reaction) arousal. The automatic emotions are called as Fight-Flight-Freeze response from the brain. This kind of emotions are controlled by the 'amygdala' region of the brain and is hard for the humans to control. Manual emotions like happy, surprise, sad, etc. are reflected by the current mood and situation. In psychology, emotion is often defined as a complex state of feeling that results in physical and psychological changes that influence thought and behavior. It is associated with a range of psychological phenomena, including temperament, personality, mood, and motivation.

1.2 Applications of Human Emotions

Emotion is one of the aspects of our lives that influences day-to-day activities including social behavior, friendship, family, work, and many others. Emotion mining has its root in many disciplines apart from computer science as follows: human science, psychiatry, nursing, psychology, neuro-science, linguistics, social science, anthropology, communication science, economics, criminology, political-science, philosophy etc. Emotion mining techniques are used by many leading technology companies like Google, Microsoft, IBM, SAP, etc. [2] to build their own in-house industry activities like product improvement, and competitor analysis. For example, in Amazon, the customer reviews are scaled 1 to 5 with positive, neutral and negative comments. This is used to improve product analysis and overall customer satisfaction.

1.3 Social Media Data - Emotion Mining and Actionable Pattern Discovery

Twitter is one of the popular social networking site with more than 320 million monthly active users and 500 million tweets per day. Tweets are short text messages with 140 characters, but are powerful source of expressing emotional state and feelings with the society of friends. We use the dataset formed of messages collected from the popular microblogging platform Twitter. Users of this platform tend to share their opinion or feelings about political events, natural disaster, products and companies, environment, community and much more on a day-to-day basis. This kind of user information is of interest to different communities. For instance, tweets about environment, community from a particular county and state will help the government officials understand the standard of living of people. This helps them make better amendments to the policies for the well being of the people.

The process of analyzing the customer's opinion or feeling is done through determining the type of emotion in the words of their responses and this is an important task in Natural Language Processing (NLP). We focus on 8 different types of emotions such as Joy, Fear, Sadness, Anticipation, Surprise, Anger, Disgust and Trust. Neural Networks (NN) which mimic the human brain, is utilized for better understanding of human emotions. Among other Neural Networks, Recurrent Neural Network (RNN) is one network which has internal memory, for processing the input. This feature of RNN is used for processing sequential information. The issue with the standard RNN is that, it is limited to look back only few steps in the internal memory, since it will have vanishing gradient or exploding gradient problem [3]. To overcome this, techniques like Long Short Term Memory (LSTM), Gated Recurrent Unit (GRU) were introduced [4]. LSTM consists of input gate, output gate and forget gate. In addition to this, it contains a memory cell. LSTM is applied in Google Gmail Smart Compose [5], hand writing recognition, etc. GRU is also similar to LSTM [6] except that, it combines the input and the forget gate into a single gate called Update gate. In this work, we use Recurrent Neural Network - Gated Recurrent Unit for automatic classification of emotion from Twitter data.

Knowledge Discovery is the process of extracting interesting patterns and applying such patterns to specific areas of interest. To find such interesting patterns from data there are wide range of techniques. Actionable Pattern Discovery is one of the knowledge discovery approach. Action Rule mining helps find actionable suggestions for recommendations. It helps identify appropriate interesting measure from the data. Emotion mining from the data provide the current state or feeling of the user. In order for the applications to provide valuable insights on the mined data for applications such as public policy making - by analyzing the social platform of a particular community or area, it is required to further process the data to discover interesting measures. In this work we propose the use of Action Rule mining for discovering valuable suggestions or recommendation on how to enhance user emotion.

1.4 Educational Data Mining - Emotion Mining and Actionable Pattern Discovery

Education is considered to be an indispensable need in today's world. It is continuously evolving to meet the challenges of the fast-changing and unpredictable globalized world. There is a lot of importance and attention paid to improve students educational outcomes throughout the world [7]. Therefore the educational institutions and the Instructors are expected to innovate the theory and practice of teaching and learning, and other aspects of the organization to ensure quality preparation of all students to life and work [8].In 1964 the book "Innovation in Education" [9], states that changes and revolution are in progress in Education. It is almost 55 years since then, even now it is of high demand that Education at all level needs renewal [8]. According to Merriam Webster Dictionary Innovation is the introduction of a new idea, or change made to existing idea. When we think of innovation in terms of education, it can be applied as a teaching technique, pedagogical approach, learning style or process, and institutional structure.

Active Learning is one such pedagogy or approach that is gaining attention and popular in Higher education. Lightweight teams is an Active Learning approach where students work together in a group, but they have very little or no direct impact on their final grades [10]. There are lot of works on this area, but none of them use the psychological perspective of identifying student emotions and identifying patterns to suggest how to enhance student emotions.

Emotion is a primary concern in younger generation students that have major impact on the productivity in school. The emotional influence does not stop at high school or university but may have lifelong consequences in future career outcomes. In psychology, emotion is often defined as a complex state of feeling that results in physical and psychological changes that influence thought and behavior. It is associated with a range of psychological phenomena, including temperament, personality, mood, and motivation. How students feel or their emotion towards a classroom, teaching style, and learning approach helps motivate them to achieve better outcomes. There is an increasing effort by Universities all over the world to collect student feedback. Besides various limitations, the student survey of teaching and learning provides valuable insights [11],[12], [13], [14].

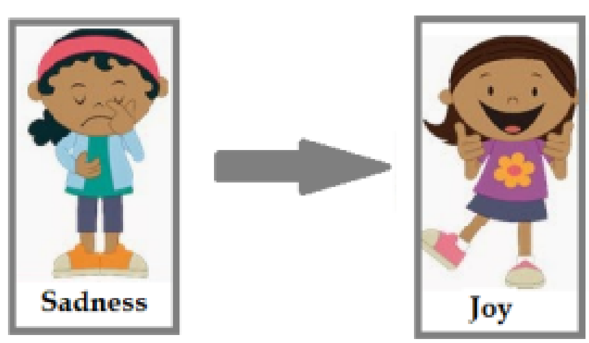


Figure 1.1: Enhance Student Emotion From Negative or Neutral to Positive

In this work we focus on mining student feedback collected from Student Survey data to identify student's emotion to understand whether incorporation of Light Weight teams [10], [15], and Flipped Classroom techniques [16] helped students during the course for the time period 2019 to 2020. In this work, we use a new method to analyze student feedback for courses labeled with emotion and provide suggestions on how to enhance emotions. This in turn leads to better teaching style, learning outcomes and a comprehensive environment. For this purpose we use actionable pattern discovery method. Actionable patterns are patterns that help benefit the user to achieve better outcomes. Action rule mining is one of the actionable pattern mining approaches. Action Rule mining is a rule based data mining method that helps extract Action Rules. Action Rules are extracted from a decision system that suggest possible transition of data from one state to another [17]. Such rules can be used to benefit the user.

CHAPTER 2: RELATED WORK

2.1 Opinion Mining and Sentimental Analysis

Opinion Mining can be accomplished through detecting the sentiment in a given text. Sentiment analysis is based on three approaches such as Document level, Sentence level and aspect-based sentiment analysis [18]. Document level analysis is based on classifying the opinionated document either positive or negative. Sentence level analysis is based on classifying each individual sentence in the document by either positive, negative or neutral. Aspect-based analysis focuses on aspect extraction, entity extraction and aspect sentiment classification.

Common approach to analyze emotions are through bag-of-words or bag-of-n-grams, where a document will be analyzed by certain combinations of terms and ignores grammar. The limitation is complexity in the elaborate vocabulary design, sparsity, discarding word/contextual meanings [19](‘this is fake’ vs ‘is this fake’).

2.2 Sentimental Analysis - Twitter Data

Authors Srivastava et. al. [20] analyze a Twitter Data with size of 500 tweets, they achieve an accuracy of 94.19 % with the application of supervised learning algorithms such as Naive Bayes (NB) and Random Forest (RF). In another similar work on Sentiment analysis of Twitter data especially McDonalds and KFC tweets data authors El Rahman et.al. [21] use several supervised learning algorithms. They compared results of: NB, RF, SVM, Decision Tree, Bagging and Maximum entropy (ME), and show that ME is the best model for both KFC and McDonalds data with 78 % and 74 % accuracy after 4-fold cross validation respectively.

2.3 Action Rules

Action Rules Mining is a method to discover Actionable Patterns from large datasets. Action Rules are rules that describe a possible transition of data from one state to another. In Data Mining literature, we see two pre-dominant frameworks for Action Rule generation: Rule based (loosely coupled) and Object based (tightly coupled) methods.

Author Dardzinska [22], summarize the frameworks for generating Action Rules from [23] as follows: loosely coupled and tightly coupled. The loosely coupled framework is often called rule-based. It is based on pairing certain classification rules which have to be discovered first by using for instance algorithms such as LERS [24] or ERID [25], [26]. The tightly coupled framework is often called object-based and it assumes that Action Rules are discovered directly from a database [27], [28], and [29]. Classical methods for discovering them follow algorithms either based on frequent sets (called Action Sets) and Association Rules Mining [30] or they use algorithms such as LERS or ERID with atomic Action Sets used as their starting step. Action Rules are one way to mine Actionable knowledge from large dataset.

2.4 Classification - Neural Networks

In Machine Learning, there are several algorithms used for sentiment analysis classification : Support Vector Machine (SVM) [31], Random Forest, Naive Bayes, K-Nearest neighbor [32], Convolutional Neural Network (CNN), Recurrent Neural Network (RNN). Neural Networks (NN) is especially used to analyze large datasets of emotions. CNN has been used for the sentiment analysis [18], where human emotions are discovered from image filtering and also for short sentence sentiment classification [33].

RNN is a network which has internal memory, for processing the input. This feature of RNN is used for processing sequential information. The issue with the standard

RNN is that, it is limited to look back only few steps in the internal memory, since it has vanishing gradient or exploding gradient problem [3].

Hierarchical Bi-directional Recurrent Neural Network (HBRNN) is used for providing output at the end of the sentence, instead of output for each word [34]. To overcome the vanishing gradient problem, algorithms like Long Short-term memory (LSTM), Gated Recurrent Unit (GRU) are used. Both these recurrent units have gated structure and GRU is the simplified version of LSTM without output gate [35]. Like LSTM, GRU doesn't make use of memory unit [36] for the information storage, instead, it uses Update and Reset gates. GRU overperforms LSTM [34] on banks and telecommunication domains.

GRU model outperforms other models like tf-idf, word2vec and LSTM in sentiment analysis on IMDB dataset [37] with 97 % AUC score. Also in [38], GRU model have been used to analyze airline sentiment in twitter data where they acquired 83% accuracy in 2-layers GRU and 88% accuracy in 3-layers GRU. Author Santur [39] uses GRU algorithm on Hepsiburada Turkish e-commercial dataset and obtained 95% accuracy using sigmoid function where the output is classified as positive and negative reviews.

2.5 Educational Data Mining and Sentimental Analysis

There is a wide range of research in the field of Education and Data Mining with methods and applications. The applications are categorized as (1) applications that focus on the objective of the task and (2) applications that focus on the end user.

Authors Bakhshinategh et al. [40] classify the Education Data Mining tasks into subcategories based on their applications. One of them is representing the cognitive aspects of students. Some of the works in this area include predicting student performance [41], identifying their motivational level [42], use of clustering and classification methods to predict undesirable student performance [43].

Sentiment Analysis has gained popularity in the recent years in the field of Education. Several researchers focus on the task of identifying sentiments (positive, negative, or neutral) from students comments. The main objective of their work is to understand the effect of teaching by using student ratings and feedback.

Authors Jagtap et al. [44], perform Sentiment Analysis on student feedback data classifying into 'positive' and 'negative' categories. They combine Hidden Markov Model (HMM) and Support Vector Machine (SVM) and use a hybrid approach for sentiment classification.

Authors Rajput et al. [44] apply text analytics methods on student's feedback data and obtain insights about teacher's performance with the help of tag clouds, and sentiment score. In this work the authors use sentiment dictionary Multi-Perspective Question Answering (MPQA) [45] to find words with positive and negative polarity. They compare the sentiment score with Likert-scale based teacher evaluation and conclude that Sentiment score with word cloud provides better insights than Likert-scale results.

Qualitative student feedback is used to identify fine grained emotion. Authors Tzacheva and Ranganathan [46] , [47] collect end of semester student feedback and process the qualitative text comments. They propose approach of automatic labeling of text comments with fine grained emotions such as 'joy', 'anticipation', 'trust', 'anger', 'fear', 'disgust', 'sadness', 'surprise'. The main objective of their study is to assess the effectiveness of the Light-weight team teaching model, through automatic detection of emotions in student feedback in computer science. They use visualization of the emotion labeled data for the purpose of analyzing the effectiveness of Active Learning pedagogies. These applications provide information to educators on how certain strategies or teaching methodology helps in the learning process and student outcomes.

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 in order to improve teaching and the learning experience.

CHAPTER 3: METHOD

3.1 Labeling Emotions in Twitter and Student Survey Data

In this work, we use the National Research Council Canada - NRC Emotion Lexicon to identify the class to which an emotion belongs to [48], [49]. The Emotion Annotation in this Lexicon are on word-sense level.

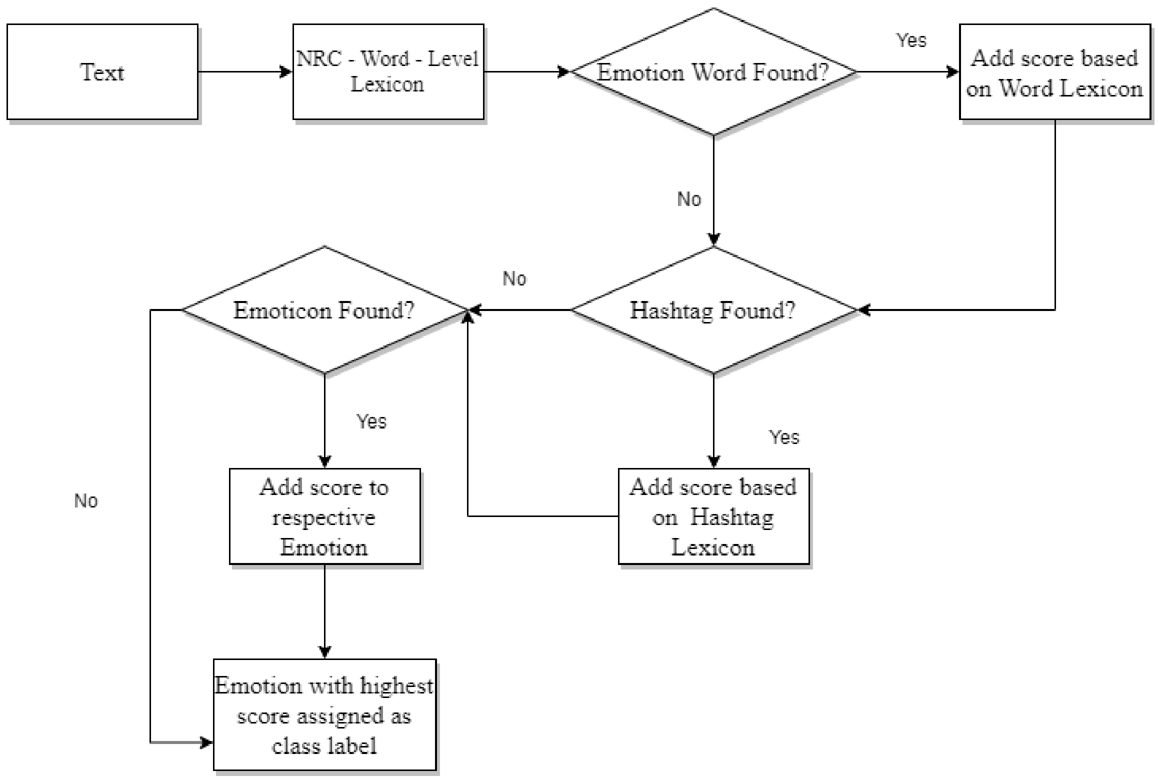


Figure 3.1: Emotion Labeling of Twitter and Student Survey Data.

We obtained the NRC Lexicon from National Research Council Canada - NRC Hashtag Emotion Lexicon [50],[51]. These Researchers spent several years designing this lexicon , which is trusted that the Words correspond to the Correct Emotion , as given in the Lexicon . The authors shared their work with us for research purpose .

3.2 Learning from Rough Sets

In our work, we use LERS [24] strategy that finds the certain rules and possible rules describing the decision attribute in terms of other attributes in the system. The table 3.1 has the following attributes $P = (P_{st}, P_{fl}, \{d\})$, where $P_{st} = \{A, B, C\}$, $P_{fl} = \{E, F, G\}$, and $d = D$.

The list of certain and possible rules that LERS strategy finds from the below table is as follows.

Table 3.1: Information System Z.

X	A	B	C	E	F	G	D
x_1	a_1	b_1	c_1	e_1	f_2	g_1	d_1
x_2	a_2	b_1	c_2	e_2	f_2	g_2	d_3
x_3	a_3	b_1	c_1	e_2	f_2	g_3	d_2
x_4	a_1	b_1	c_2	e_2	f_2	g_1	d_2
x_5	a_1	b_2	c_1	e_3	f_2	g_1	d_2
x_6	a_2	b_1	c_1	e_2	f_3	g_1	d_2
x_7	a_2	b_3	c_2	e_2	f_2	g_2	d_2
x_8	a_2	b_1	c_1	e_3	f_2	g_3	d_2

- Certain Rules
- $b_2 \rightarrow d_2$
- $b_3 \rightarrow d_2$
- $a_3 \rightarrow d_2$
- $e_1 \rightarrow d_1$
- $g_3 \rightarrow d_2$

- $f_3 \to d_2$
- $e_3 \to d_2$
- $a_2 \wedge g_1 \to d_2$
- $a_1 \wedge e_2 \to d_2$
- $a_2 \wedge c_1 \to d_2$
- $a_1 \wedge c_2 \to d_2$
- $g_1 \wedge e_2 \to d_2$
- $g_1 \wedge c_2 \to d_2$
- $e_2 \wedge c_1 \to d_2$
- $g_2 \wedge b_1 \to d_3$
- $a_1 \wedge c_1 \wedge b_1 \to d_1$
- $a_2 \wedge b_1 \wedge c_2 \to d_3$
- $a_2 \wedge e_2 \wedge b_1 \wedge c_2 \to d_3$
- $a_2 \wedge f_2 \wedge e_2 \wedge b_1 \to d_3$
- $a_1 \wedge g_1 \wedge c_1 \wedge b_1 \to d_1$
- $a_2 \wedge f_2 \wedge b_1 \wedge c_2 \to d_3$
- $g_1 \wedge f_2 \wedge c_1 \wedge b_1 \to d_1$
- $a_1 \wedge f_2 \wedge c_1 \wedge b_1 \to d_1$
- Possible Rules
- $a_2 \wedge g_2 \wedge f_2 \wedge e_2 \wedge c_2 \to d_2$

- $a_2 \wedge g_2 \wedge f_2 \wedge e_2 \wedge c_2 \rightarrow d_1$
- $a_2 \wedge g_2 \wedge f_2 \wedge e_2 \wedge c_2 \rightarrow d_1$

3.3 Action Rules

Action Rules Mining is a method to discover Actionable Patterns from large datasets. Action Rules are rules that describe a possible transition of data from one state to another, or in other words, Action Rules reclassify data from one category to another [52]. In Data Mining literature, we see two pre-dominant frameworks for Action Rule generation: Rule based (loosely coupled) and Object based (tightly coupled) methods.

Author dardzinska [22], summarize the frameworks for generating Action Rules from [23] as follows: loosely coupled and tightly coupled. The loosely coupled framework is often called rule-based. It is based on pairing certain classification rules which have to be discovered first by using for instance algorithms such as LERS [24] or ERID [25], [26]. The tightly coupled framework is often called object-based and it assumes that Action Rules are discovered directly from a database [27], [28], and [29]. Classical methods for discovering them follow algorithms either based on frequent sets (called action sets) and association rules mining [30] or they use algorithms such as LERS or ERID with atomic action sets used as their starting step. Action Rules are one way to mine Actionable knowledge from large dataset.

3.3.1 Information System and Decision System

Information system Table. 3.1 is percieved as a system $Z = (X, M, V)$, where X is set of objects $\{x_1, x_2, x_3, x_4, x_5, x_6, x_7, x_8\}$ 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 $\{B_1, B_2, B_3\}$.

The information system in Table. 3.1 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. 3.1 $M_{st} = \{A, B, C\}$, $M_{fl} = \{E, F, G\}$, and $d = D$.

3.3.2 Action Term

The expression $(y, y_1 \rightarrow y_2)$ is an atomic action term, where y is an attribute and $y_1, y_2 \in V_y$. If $y_1 = y_2$), then y is stable on y_1. In this case action term is denoted as (y, y_1) for simplicity.

- If t is an atomic action term, then t is an action term.
- If t_1 , t_2 are action terms, then $t_1 * t_2$ is an action term.
- If t is an action term containing $(y, y_1 \rightarrow y_2)$, $(z, z_1 \rightarrow z_2)$ as its sub-terms, then $y \neq z$.
- Domain of action term is denoted by Dom(t), which includes all attributes listed in t.

3.3.3 Action Rule

The expression $r = [t_1 \rightarrow t_2]$ is an Action Rule where, t_1 is an action term and t_2 is an atomic action term. The following is an example Action Rule from Table.3.1. $[B_1 \wedge C_1 \wedge (F, F_3 \rightarrow F_1) \wedge (G, \rightarrow G_1) \rightarrow (D, D_2 \rightarrow D_1)$.

3.3.4 Support and Confidence

Support and confidence of rule r is given as below:

- $sup(r) = min\{card(Y_1 \cap Z_1), card(Y_2 \cap Z_2)\}$.
- $conf(r) = \frac{card(Y_1 \cap Z_1)}{card(Y_1)} \cdot \frac{card(Y_2 \cap Z_2)}{card(Y_2)}$.
- $card(Y_1) \neq 0$, $card(Y_2) \neq 0$, $card(Y_1 \cap Z_1) \neq 0$, $card(Y_2 \cap Z_2) \neq 0$.
- $conf(r) = 0$ otherwise.

3.4 Rule Based Action Rule Mining

In Rule based method, extraction of Action Rules or actionable knowledge is dependent on the pre-processing step of classification rule discovery. These methods use pre-existing classification rules or generate rules using algorithms like Learning Based on Rough Sets (LERS) [24] and Extracting Rules from Incomplete Decision (ERID) [25] Systems. Rule based methods are further sub-divided into methods generating Action Rules from certain pairs of classification rules like Discovering Extended Action Rules (DEAR) [53],[54], and methods that generate Action Rules from single classification rule Action Rules Based on Agglomerative Strategy (ARoGs) [55].

3.5 Apriori Based Association Action Rule Mining(AAR)

The Association Action Rules described by Ras et al. [17] generates association type 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.

- **Merging step**: The algorithm merges the previous two frequent action sets into a new action set.

- **Pruning step**: The algorithm discards 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. 3.1, the primary action sets generated by AAR are shown in Table. 3.2. The frequent action sets generated by AAR are shown in Table.3.3.

Table 3.2: Primary Action Sets.

Attribute	Primary Action Set
B	(B, B_1), (B, B_2), (B, B_3)
C	(C, C_1), (C, C_2)
E	(E, E_1), (E, E_2), (E, E_3), (E, $E_1 \rightarrow E_2$), (E, $E_1 \rightarrow E_3$), (E, $E_2 \rightarrow E_1$), (E, $E_2 \rightarrow E_3$), (E, $E_3 \rightarrow E_1$), (E, $E_3 \rightarrow E_2$)
F	(F, F_2), (F, F_3), (F, $F_2 \rightarrow F_1$), (F, $F_2 \rightarrow F_3$), (F, $F_3 \rightarrow F_1$), (F, $F_3 \rightarrow F_2$)
G	(G, G_1), (G, G_2), (G, G_3), (G, $G_1 \rightarrow G_2$), (G, $G_1 \rightarrow G_3$), (G, $G_2 \rightarrow G_1$), (G, $G_2 \rightarrow G_3$), (G, $G_3 \rightarrow G_1$), (G, $G_3 \rightarrow G_2$)
D	(D, D_1), (D, D_2), (D, D_3), (D, $D_1 \rightarrow D_2$), (D, $D_1 \rightarrow D_3$), (D, $D_2 \rightarrow D_1$), (D, $D_2 \rightarrow D_3$), (D, $D_3 \rightarrow D_1$), (D, $D_3 \rightarrow D_2$)

Table 3.3: Frequent Action Sets.

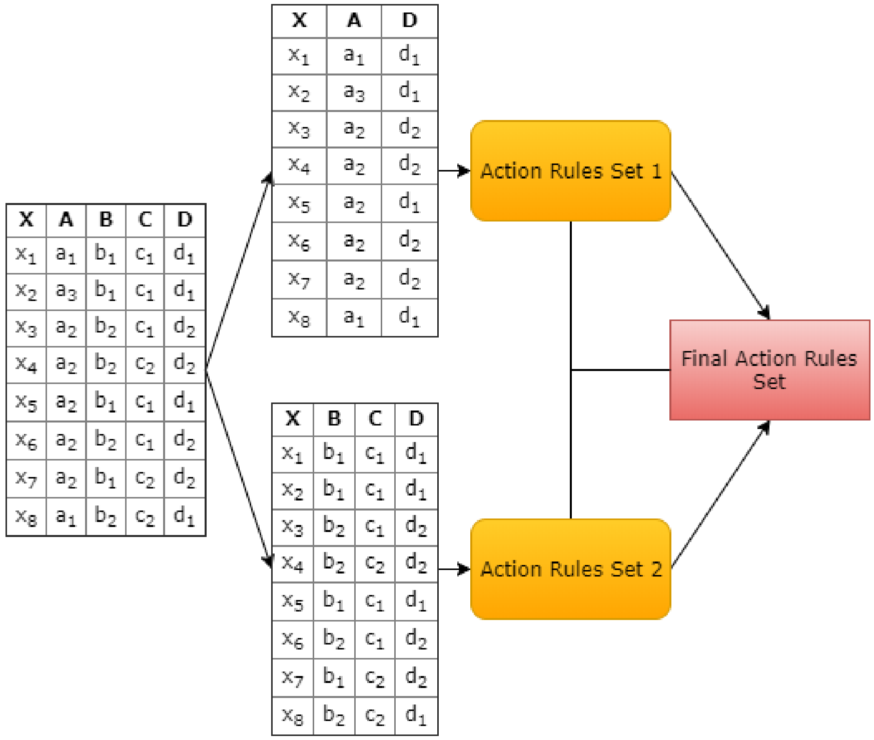
Iteration	Frequent Action Set
Iteration 1	(A, A_1) $\wedge$ (D, $D_2 \rightarrow D_1$) (A, A_2) $\wedge$ (D, $D_2 \rightarrow D_1$) (A, A_3) $\wedge$ (D, $D_2 \rightarrow D_1$) (B, B_1) $\wedge$ (D, $D_2 \rightarrow D_1$) (B, B_2) $\wedge$ (D, $D_2 \rightarrow D_1$) (B, B_3) $\wedge$ (D, $D_2 \rightarrow D_1$) ....
Iteration 2	(A, A_1) $\wedge$ (B, B_1) $\wedge$ (D, $D_2 \rightarrow D_1$) (A, A_1) $\wedge$ (B, B_2) $\wedge$ (D, $D_2 \rightarrow D_1$) (A, A_1) $\wedge$ (B, B_3) $\wedge$ (D, $D_2 \rightarrow D_1$) ....
Iteration n	....

In our example, the action set is discarded if $(\mathrm{D}, 2 \rightarrow 1)$ 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. 3.1, the algorithm generates Association Action Rules, an example is shown below:

$$(\mathrm{B}, \mathrm{B}_1 \rightarrow \mathrm{B}_1) \wedge (\mathrm{C}, \mathrm{C}_1 \rightarrow \mathrm{C}_1) \wedge (\mathrm{E}, \mathrm{E}_3 \rightarrow \mathrm{E}_1) \rightarrow (\mathrm{D}, \mathrm{D}_2 \rightarrow \mathrm{D}_1)$$

3.6 Vertical Split - Data Distribution for Scalable Association Action Rules

Authors Bagavathi et al. [56] in method 2 propose extracting Action Rules by splitting the data vertically, in contrast to the classical horizontal split, which is performed by parallel processing systems. This method utilizes Association Action Rules



X	A	B	C	D
x_1	a_1	b_1	c_1	d_1
x_2	a_3	b_1	c_1	d_1
x_3	a_2	b_2	c_1	d_2
x_4	a_2	b_2	c_2	d_2
x_5	a_2	b_1	c_1	d_1
x_6	a_2	b_2	c_1	d_2
x_7	a_2	b_1	c_2	d_2
x_8	a_1	b_2	c_2	d_1

X	A	D
x_1	a_1	d_1
x_2	a_3	d_1
x_3	a_2	d_2
x_4	a_2	d_2
x_5	a_2	d_1
x_6	a_2	d_2
x_7	a_2	d_2
x_8	a_1	d_1

X	B	C	D
x_1	b_1	c_1	d_1
x_2	b_1	c_1	d_1
x_3	b_2	c_1	d_2
x_4	b_2	c_2	d_2
x_5	b_1	c_1	d_1
x_6	b_2	c_1	d_2
x_7	b_1	c_2	d_2
x_8	b_2	c_2	d_1

Figure 3.2: Example Data Distribution using Vertical Data Distribution.

[17] which follows iterative method to extract all possible action rules. In order to overcome the computational complexity and expense, authors in [56] propose vertical data split method for faster computation and parallel processing. In this method, the data is split vertically into 2 or more partitions, with each partition having only a small subset of attributes. The example Data Distribution using Vertical Data Distribution is shown in the Fig. 3.2 The algorithm runs separately on each partition, does transformations like map(), flatmap() functions and combine results with join() and groupBy() operations.

3.7 Hybrid Action Rule Mining Algorithm

Action Rule mining involves two major frameworks:

- **Rule-Based Method:** where extraction of Action Rules is dependent on the pre-processing step of classification rule discovery such as LERS and
- **Object-Based Method:** extracts Action Rule directly from the database

without the use of classification rules, such as Association Action Rules [17], an apriori like method using frequent action sets.

The Rule-Based method using LERS [24] 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 [56] , 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 [57] 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 Iterative Association Action Rule approach. The pseudocode of the algorithm is given in Fig.3.3.

The Hybrid Action Rule Mining Algorithm works with the Information System as follows. The information system in Table. 3.1 has the following attributes: flexible P_{fl} , stable P_{st} and decision d, $P = (P_{st}, P_{fl}, \{d\})$. From Table. 3.1 $P_{st} = \{A, B, C\}$, $P_{fl} = \{E, F, G\}$, and $d = D$.

The following example re-classifies the decision attribute D from $d_2 \rightarrow d_1$. The algorithm Fig. 3.3. initially uses the LERS method explained in section " 3.2" to extract the classification rules that are certain and then generates Action Rule schema as given in the following equations " 3.1" , " 3.2".

$$[\mathrm{b}_1 \wedge \mathrm{c}_1 \wedge (\mathrm{f}, \rightarrow \mathrm{f}_1) \wedge (\mathrm{g}, \rightarrow \mathrm{g}_1)] \rightarrow (\mathrm{D}, \mathrm{d}_2 \rightarrow \mathrm{d}_1). \quad (3.1)$$

```
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 3.3: Hybrid Action Rule Mining Algorithm.

$$[(\mathrm{e}, \rightarrow \mathrm{e}_1)] \rightarrow (\mathrm{D}, \mathrm{d}_2 \rightarrow \mathrm{d}_1). \tag{3.2}$$

The algorithm then creates sub-table for each Action Schema. For example " 3.1", generates the following sub-table Table. 3.4.

Table 3.4: Sub-table for Action Rule Schema

X	**B**	**C**	**F**	**G**	**D**
x_1	b_1	c_1	f_2	g_1	d_1
x_3	b_1	c_1	f_2	g_3	d_2
x_6	b_1	c_1	f_3	g_1	d_2
x_8	b_1	c_1	f_2	g_3	d_2

The Hybrid Action Rule Mining Algorithm applies the Association Action Rule

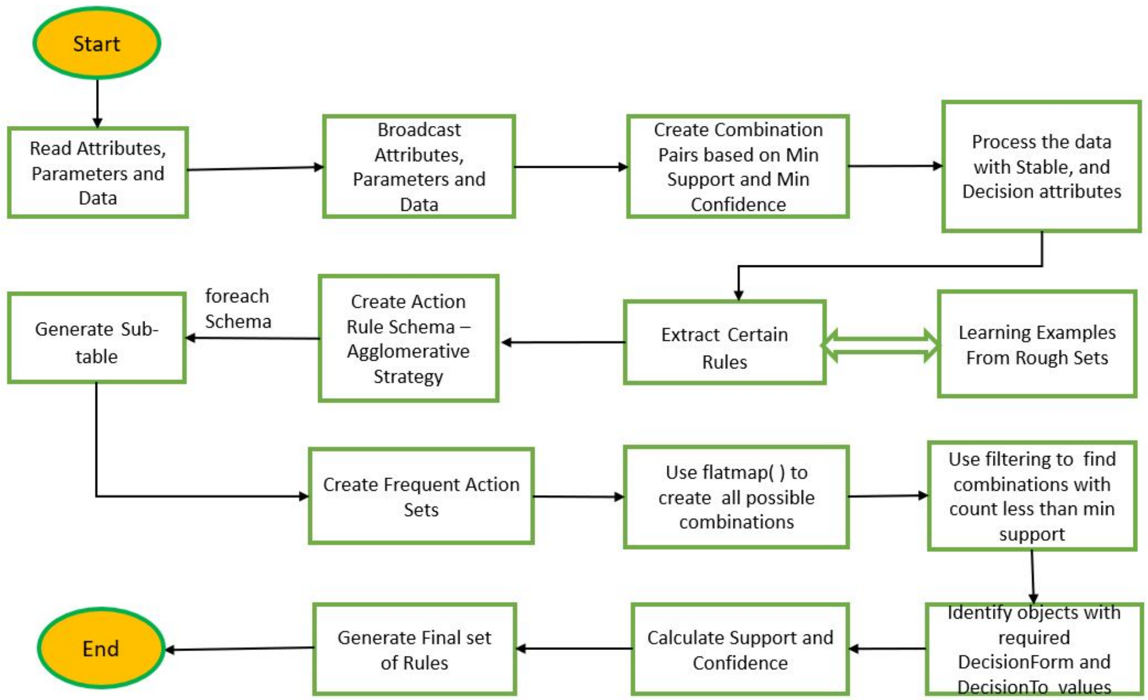


Figure 3.4: Hybrid Action Rule Algorithm Mining - Flowchart.

extraction algorithm in parallel on each of the sub-tables. The algorithm generates the following Action Rules " 3.3" based on the sub-table Table. 3.4.

$$[b_1 \wedge c_1 \wedge (f, \rightarrow f_1) \wedge (g, g_3 \rightarrow g_1)] \rightarrow (D, d_2 \rightarrow d_1). \tag{3.3}$$

This hybrid Action Rule algorithm is implemented in Spark [58] and runs separately on each sub-table and performs transformations like map(), flatmap(), join(). The methodology of this algorithm is shown in Fig. 3.4.

But the above method has a major disadvantage. If the Size of the Intermediate Table becomes very large it affects the performance and the scalability of this method. To solve this problem , we propose a Threshold θ to control the size of the table and increase the computational speed.

Our proposed modified version of the Hybrid Action Rule Mining algorithm is presented in the figure 3.5 and 3.6.

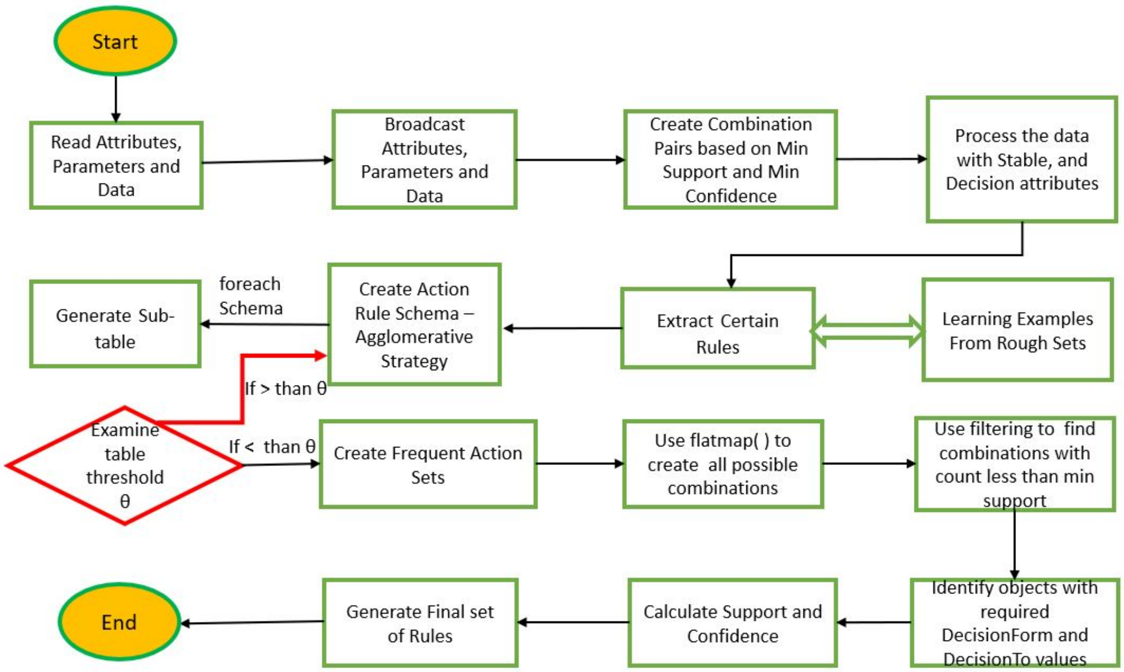


Figure 3.5: Hybrid Action Rule Algorithm Mining with Table size threshold θ - Flowchart.

```
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
                  while subtable size > Theta θ
                        Divide subtable until subtable < Theta θ
                  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 3.6: Hybrid Action Rule Mining with Threshold Algorithm.

CHAPTER 4: EXPERIMENTS AND RESULTS

4.1 EXPERIMENT 1 - Education Data - Student Survey Data

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. This survey dataset contains close to 50 attributes. Example Survey Questions are shown in 4.1.

4.1.1 Data Description - Student Survey Data

The original data contains 549 instances and 59 attributes. Example attributes are shown in figure 4.2. 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 4.1: Example Survey Questions.

Survey Questions
Did you gain any Benefits from Group Assignments?
Course group helped me get acquainted with students from different background
The class discussions are with the subject matter

Table 4.2: Survey Data Properties.

Property	Student Survey Data
	59 attributes including - Team-Sense of Belonging - Team Member Responsibility - Team Work Helped Diversity - Group Assignment Benefits - Video Case Assignments - Helpfulness - Active Learning Method - Rating - Flipped Class Helped Better Learning - Helpfulness - Peer Teaching Helped Better Learning - Student Emotion

For scalability purpose to test the performance of our proposed method with Big-Data 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.

4.1.2 Vertical Data Split Method Implementation in Spark AWS Cluster

We perform this experiment on the Student Survey Data - using Amazon Web Services (AWS) cluster with two nodes, 4 vCore and 16GiB memory and EBS Storage 64GiB. The Cluster configuration is shown in Fig.4.1. For very large data this method requires additional resources. We find we must provide extra 32 Gigabytes of memory to complete computation on the replicated data in 2400 seconds. Otherwise, the method receives OutOfMemory Exception with our replicated Student Survey Data. This occurs because of iterative nature of the algorithm with large data that causes computational overhead and requires extra hardware memory resources to work successfully. This method only works for Association Action Rules because it considers only subset of the attributes.

Selected Action Rules generated by this experiment are shown in 4.3.

Table 4.3: Sample Action Rules ::: Sadness to Joy ::: - Student Survey Data - Vertical Data Split Method.

Enhance Student Emotion - Sadness → Joy
1. $AR1SadnesstoJoy : (GroupAssignmentBenefit, SharedKnowledge \rightarrow SocialLearning) \wedge (LikeTeamWork, 1Dont \rightarrow 5VeryMuch) \wedge (TeamMemberResponsibility, HelpfulMembers \rightarrow ResponsibleMembers) \implies (StudentEmotion, Sadness \rightarrow Joy)[Support : 100.0, Confidence : 75.0\%]$ 2. $AR2SadnesstoJoy : (GroupAssignmentBenefit, None \rightarrow None) \wedge (LikeTeamWork, 3Somewhat \rightarrow 5VeryMuch) \wedge (TeamMemberResponsibility, TechnicallyIneffectiveMembers \rightarrow FriendlyMembers) \implies (StudentEmotion, Sadness \rightarrow Joy)[Support : 100.0, Confidence : 50.0\%]$ 3. $AR3SadnesstoJoy : (NumberofTeamMembers, 8to10 \rightarrow 10orMore) \wedge (LikeTeamWork, 3Somewhat \rightarrow 5VeryMuch) \wedge (GroupAssignmentBenefit, None \rightarrow SocialLearning) \implies (StudentEmotion, Sadness \rightarrow Joy)[Support : 100.0, Confidence : 16.6\%]$

The Action Rule 1 says that when GroupAssignmentBenefit changes from SharedKnowledge to SocialLearning and LikeTeamWork changes from 1Donât to 5VeryMuch and TeamMemberResponsibility changes from HelpfulMembers to ResponsibleMembers then the StudentEmotion changes from Sadness to Joy. This shows that when the Student likes TeamWork and the group contains Responsible TeamMembers and benefits from GroupAssignment then it enhances the Student's Emotion from Sadness to Joy.

4.1.3 Hybrid Method Implementation in Spark AWS Cluster

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. The Cluster configuration is shown in figure 4.1. This method takes 5088 seconds to complete computation on our replicated Student Survey Data.

Selected Action Rules generated by this experiment are shown in 4.4 and 4.5.

Table 4.4: Sample Action Rules ::: Sadness to Joy ::: - Student Survey Data - Hybrid Method.

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

The Action Rule 1 in table 4.4 says when TeamSenseOfBelonging changes from 2BelowAverageSenseofBelongingtotheTeam to 3AverageSenseofBelongingtotheTeam and the NumberofTeamMembers changes from 5to7 to 10orMore then the StudentEmotion 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.

Table 4.5: Sample Action Rules ::: Anticipation to Trust ::: - Student Survey Data - Hybrid Method.

Enhance Student Emotion - Anticipation → Trust
1. $AR1AnticipationtoTrust : (LikeTeamWork, 1Dont \rightarrow 3Somewhat) \wedge (GroupAssignmentBenefit, None \rightarrow EliminateStress) \Longrightarrow (StudentEmotion, Anticipation \rightarrow Trust)[Support : 500.0, Confidence : 83.0\%]$
2. $AR2AnticipationtoTrust : (TeamSenseofBelonging, 2BelowAverageSenseofBelongingtotheTeam \rightarrow 4CompleteSenseofBelongingtotheTeam) \wedge (TeamWorkHelpedDiversity, 2Occasionally \rightarrow 4VeryOften) \Longrightarrow (StudentEmotion, Anticipation \rightarrow Trust)[Support : 500.0, Confidence : 100\%]$
3. $AR3AnticipationtoTrust : (TeamFormation, 2BelowAverage \rightarrow 3Average) \wedge (GroupAssignmentBenefit, None \rightarrow EliminateStress) \Longrightarrow (StudentEmotion, Anticipation \rightarrow Trust)[Support : 600.0, Confidence : 86.0\%]$

The Action Rule 1 in table 4.5 says when LikeTeamWork changes from 1Don't to 3Somewhat and the GroupAssignmentBenefit changes from None to EliminateStress then the StudentEmotion changes from Anticipation to Trust. This rule has support of 500 and confidence of 83%. This shows that if the Student likes TeamWork and the GroupAssignment benefits the student by eliminating stress then it enhances the StudentEmotion from Anticipation to Trust.

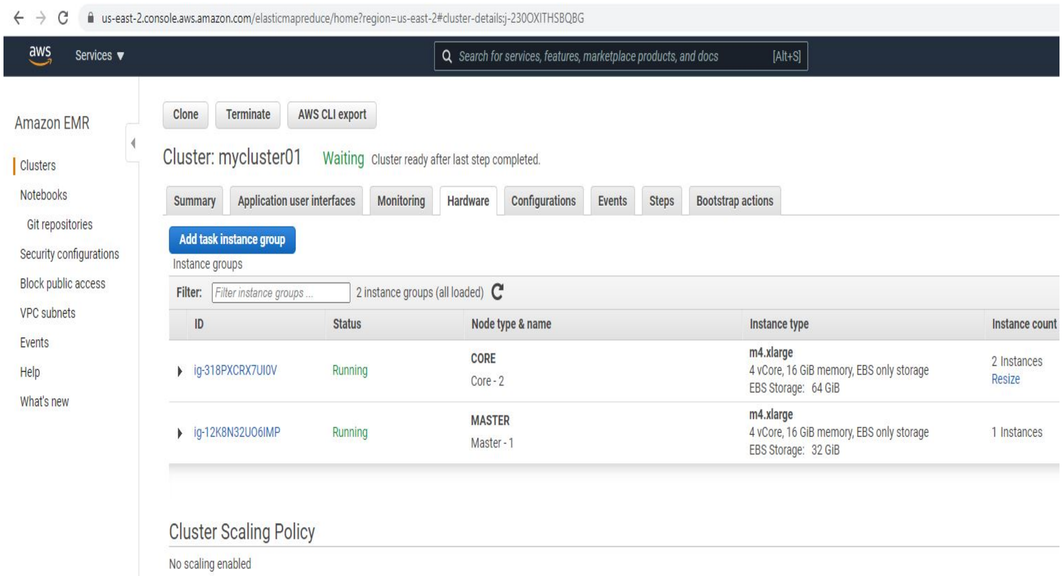


Figure 4.1: AWS Cluster Configuration.

4.1.4 Hybrid Method with Threshold Implementation in Spark AWS Cluster

We perform this experiment on the Student Survey Data with our proposed Hybrid Action Rule Mining with Threshold Method - using Amazon Web Services (AWS) cluster with two nodes, 4 vCore and 16GiB memory and EBS Storage 64GiB. The Cluster configuration is shown in figure 4.1. Our proposed method takes 4002 seconds to complete computation on the replicated Student Survey Data. We experiment with 3 different Threshold values of θ ::: 10, 15 and 20.

The runtime comparison for different Threshold values is shown in the below table 4.6

Table 4.6: Threshold values - θ Run Time comparison.

Threshold θ	Time Taken
10	4628 seconds
15	4002 seconds
20	8670 seconds

Threshold value $\theta = 15$ provides optimum performance.

Selected Action Rules generated by this method are shown in 4.7 and 4.8.

Table 4.7: Sample Action Rules ::: Sadness to Joy ::: - Student Survey Data - Hybrid Method with Threshold.

Enhance Student Emotion - Sadness → Joy
1. $AR1SadnesstoJoy : (TeamFormation, 2BelowAverage \rightarrow 4Perfect) \wedge (NumberofTeamMembers, 5to7 \rightarrow 8to10) \implies (StudentEmotion, Sadness \rightarrow Joy)[Support : 21.0, Confidence : 62.0\%]$ 2. $AR2SadnesstoJoy : (LikeTeamWork, 1Dont \rightarrow 3Somewhat) \implies (StudentEmotion, Sadness \rightarrow Joy)[Support : 21.0, Confidence : 91.0\%]$ 3. $AR3SadnesstoJoy : (NumberofTeamMembers, 5to7 \rightarrow 8to10) \wedge (GroupAssignmentBenefit, None \rightarrow SocialLearning) \implies (StudentEmotion, Sadness \rightarrow Joy)[Support : 34.0, Confidence : 85.0\%]$

The Action Rule 1 in table 4.7 says when TeamFormation changes from 2BelowAverage to 4Perfect and the NumberofTeamMembers changes from 5to7 to 8to10 then the StudentEmotion changes from Sadness to Joy. This rule has support of 21 and confidence of 62%. This shows how having a good team and increased number of Team Members enhances a Student's Emotion from Sadness to Joy.

Table 4.8: Sample Action Rules ::: Anticipation to Trust ::: - Student Survey Data - Hybrid Method with Threshold.

Enhance Student Emotion - Anticipation → Trust
1. $AR1AnticipationtoTrust : (LikeTeamWork, 3Somewhat \rightarrow 5VeryMuch) \wedge (TeamFormation, 3Average \rightarrow 4Perfect) \Longrightarrow (StudentEmotion, Anticipation \rightarrow Trust)[Support : 3.0, Confidence : 100.0\%]$
2. $AR2AnticipationtoTrust : (TeamSenseofBelonging, AverageSenseofBelongingtotheTeam \rightarrow 4CompleteSenseofBelongingtotheTeam) \Longrightarrow (StudentEmotion, Anticipation \rightarrow Trust)[Support : 5.0, Confidence : 56.0\%]$
3. $AR3AnticipationtoTrust : (NumberofTeamMembers, 5to7 \rightarrow 8to10) \wedge (GroupAssignmentBenefit, None \rightarrow SocialLearning) \Longrightarrow (StudentEmotion, Anticipation \rightarrow Trust)[Support : 3.0, Confidence : 100.0\%]$

The Action Rule 1 in table 4.8 says when LikeTeamWork changes from 3Somewhat to 5VeryMuch and the TeamFormation changes from 3Average to 4Perfect then the StudentEmotion changes from Anticipation to Trust. This rule has support of 3 and confidence of 100%. This shows that if the Student likes TeamWork very much and has a good Team then the Student Emotion enhances from Anticipation to Trust.

4.1.5 Runtime Comparison of the above 3 implementations with respect to Student Survey Data in Spark AWS Cluster

We compare the execution runtime of the above described implementations:Vertical Data Split Method in Spark AWS Cluster, Hybrid Method Implementation in Spark AWS Cluster and Hybrid Method with Threshold Implementation in Spark AWS Cluster. The runtimes are given in below table4.9

Table 4.9: Runtime Comparison of the above 3 implementations with respect to Student Survey Data.

Method	Time Taken
Vertical Data Split Method in Spark AWS Cluster _* with additional resources: 32 GB cluster memory _* with standard memory	 2400 seconds OutOfMemoryException
Hybrid Method in Spark AWS Cluster	5088 seconds
Hybrid Method with Threshold in Spark AWS Cluster	4002 seconds

Our proposed Hybrid Method with Threshold shows improved performance over the previous Hybrid Method, and shows the best performance with standard memory.

4.2 EXPERIMENT 2 - Student Evaluation Data

In this experiment we use, Student Evaluation Data. This experiment shows Temporal Information, and Changes over time with regards to the Student Evaluations and Emotions.

4.2.1 Basic Emotion

To find the Basic Emotion, the pre-processed data is passed to the system and it finds the word associated with 8 basic emotions for each of the student evaluation feedback response. The sentiment scores are then calculated based on the frequency of each of the emotion related words. The sentiment with highest score is assigned as overall emotion of the student response. The results are shown on a temporal basis from 2013 until 2020 on the X-axis and the count of each emotion on the Y-axis in Fig.4.2. It is observed that emotion 'trust' has a growing trend through the time. We also see that 'anticipation' was high during the year 2014 which has gradually decreased in the year 2020.

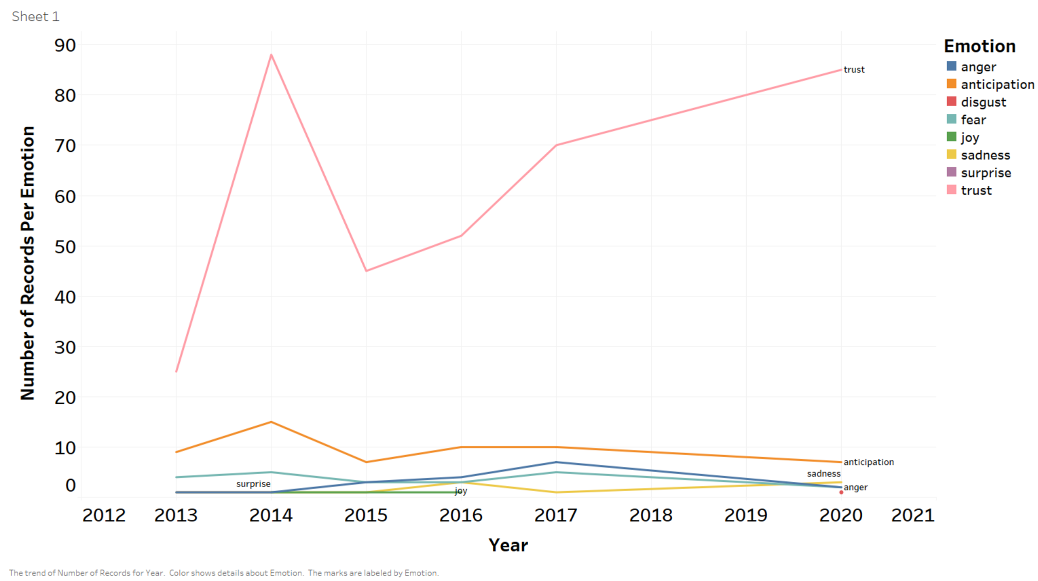


Figure 4.2: Basic Emotion graph.

4.2.2 Emotion and Polarity

In addition to finding the Emotion we also show the Polarity :: positive, neutral, negative. To find the Emotion and Polarity the pre-processed data is passed to the system and it finds the word associated with 8 basic emotions and the polarity associated for each of the student feedback response. The sentiment scores are calculated based on the frequency of each emotion and polarity related words. The sentiment that has highest score is assigned as the overall emotion or polarity of the student response. The results are shown on a temporal basis from 2013 until 2020 on the X-axis and the count of each emotion on the Y-axis in Fig.4.3. It is observed that emotion 'trust' and polarity 'positive' has a growing trend through the time. We also observe that 'anticipation' was high during the year 2014 which has gradually decreased in the year 2020. We observe positive change in Emotion since year 2015 when active learning methodologies were introduced and implemented.

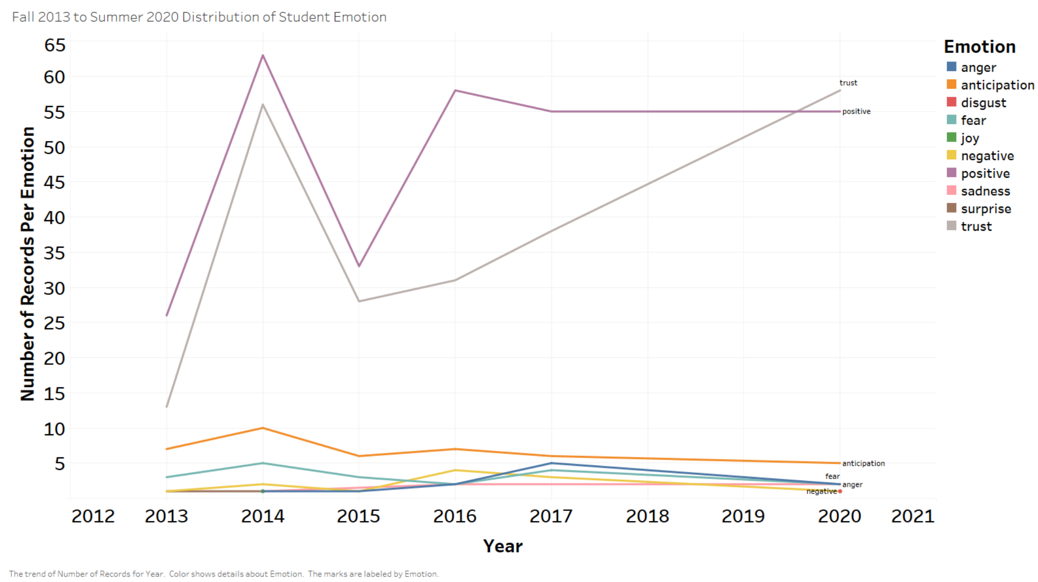


Figure 4.3: Basic Emotion and Polarity graph.

4.3 EXPERIMENT 3 - Social Media Data - Twitter Data

In this work we use the densely populated Twitter dataset which is obtained using Twitter API. The dataset contains tweets with emotion related data and other tweet attributes. For this experiment we choose Emotion as the decision attribute. The Action Rules generated in this experiment help identify changes that are required for the emotion to be more positive.

4.3.1 Data Description - Social Media Data - Twitter data

The dataset contains 25 attributes and 174890 instances in total. To test the performance we use 25000 twitter records. The data size on disk is 1866 Kilobytes.

Table 4.10 gives an overview of the Twitter dataset used for the experiment.

Table 4.10: Properties of the Twitter Dataset

Property	**Values**
Attributes	25 attributes
Decision Attribute Values	Emotions: Joy, Sadness, Anger, Anticipation, Trust, Disgust, Surprise, Fear
Number of Instances	174890

4.3.2 Vertical Data Split Method Implementation in Spark AWS Cluster

We perform this experiment on the Twitter Data using Amazon Web Services (AWS) cluster with two nodes, 4 vCore and 16GiB memory and EBS Storage 64GiB. The Cluster configuration is shown in Fig.4.1. For very large data this method requires additional resources. We find we must provide extra 32 Gigabytes of memory to complete computation on the twitter data in 4620 seconds. Otherwise, the method receives OutOfMemory Exception with the Twitter Data.

Selected Action Rules generated by this method are shown in the below Table 4.11

Table 4.11: Sample Action Rules ::: Sadness to Joy ::: - Twitter Data - Vertical Data Split Method.

Enhance User Emotion - Sadness → Joy
1. $AR1SadnesstoJoy : (FearScore, High \rightarrow Medium) \wedge (JoyScore, VeryLow \rightarrow High) \wedge (SadnessScore, High \rightarrow Medium) \wedge (UserFriendsCount, VeryLow \rightarrow VeryLow) \implies (FinalEmotion, Sadness \rightarrow Joy)[Support : 88.0, Confidence : 43.1\%]$ 2. $AR2SadnesstoJoy : (DisgustScore, Medium \rightarrow VeryLow) \wedge (JoyScore, Medium \rightarrow High) \wedge (SurpriseScore, VeryLow \rightarrow VeryLow) \wedge (UserFriendsCount, High \rightarrow High) \implies (FinalEmotion, Sadness \rightarrow Joy)[Support : 55.0, Confidence : 29.8\%]$ 3. $AR3SadnesstoJoy : (DisgustScore, VeryLow \rightarrow VeryLow) \wedge (JoyScore, VeryLow \rightarrow High) \wedge (SadnessScore, Medium \rightarrow VeryLow) \wedge (UserFriendsCount, Medium \rightarrow High) \implies (FinalEmotion, Sadness \rightarrow Joy)[Support : 156.0, Confidence : 52.6\%]$

The Action Rule 1 in table 4.11 says when FearScore changes from High to Medium and the JoyScore changes from VeryLow to High and the SadnessScore changes from High to Medium and the UserFriendsCount remains the same then the User Emotion changes from Sadness to Joy. This rule has support of 88 and confidence of 43.1%.

4.3.3 Hybrid Method Implementation in Spark AWS Cluster

We perform this experiment on the Twitter Data using Amazon Web Services (AWS) cluster with two nodes, 4 vCore and 16GiB memory and EBS Storage 64GiB. The Cluster configuration is shown in Fig.4.1. This method takes 7592 seconds to complete computation on the twitter data.

Some of the Action Rules generated are shown in the below table4.12

Table 4.12: Sample Action Rules ::: Sadness to Joy ::: - Twitter Data - Hybrid Method.

Enhance User Emotion - Sadness → Joy
1. $AR1SadnesstoJoy : (FearScore, Medium \rightarrow VeryLow) \wedge (SadnessScore, Medium \rightarrow VeryLow) \wedge (SurpriseScore, VeryLow \rightarrow VeryLow) \implies (FinalEmotion, Sadness \rightarrow Joy)[Support : 142.0, Confidence : 97.0\%]$ 2. $AR2SadnesstoJoy : (SadnessScore, Medium \rightarrow VeryLow) \wedge (AnticipationScore, Medium \rightarrow VeryLow) \wedge (DisgustScore, VeryLow \rightarrow VeryLow) \implies (FinalEmotion, Sadness \rightarrow Joy)[Support : 56.0, Confidence : 90.0\%]$ 3. $AR3SadnesstoJoy : (TrustScore, VeryLow \rightarrow Medium) \wedge (DisgustScore, Medium \rightarrow VeryLow) \wedge (JoyScore, VeryLow \rightarrow Medium) \implies (FinalEmotion, Sadness \rightarrow Joy)[Support : 76.0, Confidence : 75.2\%]$

The Action Rule 1 in table 4.12 says when FearScore changes from Medium to VeryLow and the SadnessScore changes from Medium to VeryLow then the User Emotion changes from Sadness to Joy. This rule has support of 142 and confidence of 97%.

4.3.4 Hybrid Method with Threshold Implementation in Spark AWS Cluster

We perform this experiment on the Twitter Data using Amazon Web Services (AWS) cluster with two nodes, 4 vCore and 16GiB memory and EBS Storage 64GiB. The Cluster configuration is shown in Fig.4.1. Our proposed method takes 6467 seconds.

Selected Action Rules generated by Hybrid Method with Threshold are shown in the below table4.13

Table 4.13: Sample Action Rules ::: Sadness to Joy ::: - Twitter Data - Hybrid Method with Threshold.

Enhance User Emotion - Sadness → Joy
1. $AR1SadnesstoJoy : (TrustScore, VeryLow \rightarrow Medium) \wedge (SadnessScore, Medium \rightarrow VeryLow) \wedge (JoyScore, VeryLow \rightarrow Medium) \implies (FinalEmotion, Sadness \rightarrow Joy)[Support : 76.0, Confidence : 100.0\%]$ 2. $AR2SadnesstoJoy : (SadnessScore, Medium \rightarrow VeryLow) \wedge (UserFriendsCount, Low \rightarrow Medium) \implies (FinalEmotion, Sadness \rightarrow Joy)[Support : 51.0, Confidence : 95.0\%]$ 3. $AR3SadnesstoJoy : (FearScore, Medium \rightarrow VeryLow) \wedge (JoyScore, VeryLow \rightarrow Medium) \implies (FinalEmotion, Sadness \rightarrow Joy)[Support : 123.0, Confidence : 79.4\%]$

The Action Rule 1 in table 4.13 says when TrustScore changes from VeryLow to Medium and the SadnessScore changes from Medium to VeryLow and the JoyScore changes from VeryLow to Medium then the User Emotion changes from Sadness to

Joy. This rule has support of 76 and confidence of 100%.

4.3.5 Runtime Comparison of the above 3 implementations with respect to Social Media Data - Twitter Data in Spark AWS Cluster

We compare the execution runtime of the above described implementations:Vertical Data Split Method in Spark AWS Cluster, Hybrid Method Implementation in Spark AWS Cluster and Hybrid Method with Threshold Implementation in Spark AWS Cluster. The runtimes are given in below table4.14

Table 4.14: Runtime Comparison of the above 3 implementations with respect to Twitter Data.

Method	Time Taken
Vertical Data Split Method in Spark AWS Cluster _* with additional resources: 32 GB cluster memory _* with standard memory	 4620 seconds OutOfMemoryException
Hybrid Method in Spark AWS Cluster	7592 seconds
Hybrid Method with Threshold in Spark AWS Cluster	6467 seconds

Our proposed Hybrid Method with Threshold shows improved performance over the previous Hybrid Method, and shows the best performance with standard memory.

CHAPTER 5: CONCLUSIONS

Emotions play a very important role in the lives of people all over the world. Today we have multiple platforms available for electronic communication. The expansion of social media, online surveys, customer surveys, blogs, industrial and educational data generates large amounts of data. Hidden in the data are valuable insights on people's opinions and their emotions. Recognizing emotions from the text data through Natural Language Processing (NLP) can benefit a lot of industries [59], including social media and education. In this work we mine Student Survey Dataset and Social Media Twitter Data.

We perform opinion mining in text by detecting Emotions automatically. We achieve faster computation through our proposed method.

5.1 Student Survey Data - Emotion Mining and Action Rules Discovery

We experiment with Student Survey Data to test our proposed Hybrid Action Rule Mining Algorithm with Threshold to suggest ways for improving student emotions. The data contains student opinions regarding the use of Active Learning methods, Teamwork and other class experiences. The discovered Action Rules help to enhance the student learning experience from negative to positive and from neutral to positive. The Emotion class includes 8 basic emotions: Anger, Disgust, Sadness, Fear, Surprise, Anticipation, Trust, Joy.

5.2 Student Evaluation Data - Emotion Mining from Student Comments for Pedagogical Innovation Assessment

In this work we perform sentiment analysis, and emotion detection on the qualitative feedback provided by the students in course evaluations. We identify eight basic human emotions: 'anger', 'fear', 'joy', 'surprise', 'anticipation', 'disgust', 'sadness', and 'trust' along with the two sentiment polarities 'positive' and 'negative'. We use these emotions to analyze and assess the impact and effectiveness of Active Learning methods incorporated in the classroom during the years 2015 to 2020, compared to previous years.Results show evidence that words associated with positive emotions, and trust have increased in the recent years compared to 2014. At the same time, occurrences of negative emotion words have decreased. This shows that the implementation of Light Weight Teams and Flipped Classroom Active Learning methods increase positive emotions among students and improve their learning experience.

5.3 Social Media Data - Twitter Data - Emotion Mining and Action Rules Discovery

We experiment with Social Media Data - Twitter Data to test our proposed Hybrid Action Rule Mining Algorithm with Threshold. The discovered Action Rules suggest ways for improving Twitter User Emotions. The data contains tweets with emotion related data and other tweet attributes. The discovered Action Rules help to enhance the Twitter User Emotion from negative or neutral to positive. The Emotion class includes 8 basic emotions: Anger, Disgust, Sadness, Fear, Surprise, Anticipation, Trust, Joy.

CHAPTER 6: FUTURE WORK

Our proposed method improves the processing time. However, the quality of rules may decrease. In the future, we plan to use Correlation of Attributes and run classical Clustering Algorithm. This obtains optimal Vertical Partitioning which is flexible. We plan to apply Agglomerative strategy to change levels of vertical partitions. We also plan to examine the Quality of the Action Rules using F-Score.

In the future, we plan to experiment with detecting Sarcastic Responses in Text. For example in Student Evaluations dataset, the following statements are classified as Positive Sentiment: "Oh, this class was so easy." "I guess she is good at reading PowerPoints" when in fact, the student meant these negatively in sarcastic way.

REFERENCES

[1] P. Ekman, "An argument for basic emotions," *Cognition & emotion*, vol. 6, no. 3-4, pp. 169–200, 1992.

[2] F. A. Pozzi, E. Fersini, E. Messina, and B. Liu, *Sentiment analysis in social networks.* Morgan Kaufmann, 2016.

[3] S. Minaee, E. Azimi, and A. Abdolrashidi, "Deep-sentiment: Sentiment analysis using ensemble of cnn and bi-lstm models," *arXiv preprint arXiv:1904.04206*, 2019.

[4] S. Hochreiter and J. Schmidhuber, "Long short-term memory," *Neural computation*, vol. 9, no. 8, pp. 1735–1780, 1997.

[5] M. X. Chen, B. N. Lee, G. Bansal, Y. Cao, S. Zhang, J. Lu, J. Tsay, Y. Wang, A. M. Dai, Z. Chen, *et al.*, "Gmail smart compose: Real-time assisted writing," in *Proceedings of the 25th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining*, pp. 2287–2295, 2019.

[6] L. Wu, C. Kong, X. Hao, and W. Chen, "A short-term load forecasting method based on gru-cnn hybrid neural network model," *Mathematical Problems in Engineering*, vol. 2020, 2020.

[7] V. Svenja, K. David, K. Eckhard, and B. Sonja, *TALIS teaching practices and pedagogical Innovations evidence from TALIS: Evidence from TALIS.* OECD Publishing, 2012.

[8] P. Serdyukov, "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, 2017.

[9] M. B. Miles, *Innovation in education.* Bureau of Publication, Teachers College, Columbia University, 1964.

[10] C. Latulipe, N. B. Long, and C. E. Seminario, "Structuring flipped classes with lightweight teams and gamification," in *Proceedings of the 46th ACM Technical Symposium on Computer Science Education*, pp. 392–397, ACM, 2015.

[11] E. Santhanam, B. Lynch, and J. Jones, "Making sense of student feedback using text analysis–adapting and expanding a common lexicon," *Quality Assurance in Education*, vol. 26, no. 1, pp. 60–69, 2018.

[12] L. Alderman, S. Towers, and S. Bannah, "Student feedback systems in higher education: A focused literature review and environmental scan," *Quality in Higher Education*, vol. 18, no. 3, pp. 261–280, 2012.

[13] L. Harvey, "The nexus of feedback and improvement," in *Student Feedback*, pp. 3–26, Elsevier, 2011.

[14] S. Palmer, "Student evaluation of teaching: keeping in touch with reality," *Quality in higher education*, vol. 18, no. 3, pp. 297–311, 2012.

[15] S. MacNeil, C. Latulipe, B. Long, and A. Yadav, "Exploring lightweight teams in a distributed learning environment," in *Proceedings of the 47th ACM Technical Symposium on Computing Science Education*, pp. 193–198, ACM, 2016.

[16] M. L. Maher, C. Latulipe, H. Lipford, and A. Rorrer, "Flipped classroom strategies for cs education," in *Proceedings of the 46th ACM Technical Symposium on Computer Science Education*, pp. 218–223, ACM, 2015.

[17] Z. W. Ras, A. Dardzinska, L.-S. Tsay, and H. Wasyluk, "Association action rules," in *IEEE/ICDM Workshop on Mining Complex Data (MCD 2008), Pisa, Italy, ICDM Workshops Proceedings,*, pp. 283–290, IEEE Computer Society, 2008.

[18] F. Siraj, N. Yusoff, and L. C. Kee, "Emotion classification using neural network," in *2006 International Conference on Computing & Informatics*, pp. 1–7, IEEE, 2006.

[19] L. Guo, Y. Han, H. Jiang, X. Yang, X. Wang, and X. Liu, "Learning to make document context-aware recommendation with joint convolutional matrix factorization," *Complexity*, vol. 2020, 2020.

[20] A. Srivastava, V. Singh, and G. S. Drall, "Sentiment analysis of twitter data: A hybrid approach," *International Journal of Healthcare Information Systems and Informatics (IJHISI)*, vol. 14, no. 2, pp. 1–16, 2019.

[21] S. A. El Rahman, F. A. AlOtaibi, and W. A. AlShehri, "Sentiment analysis of twitter data," in *2019 International Conference on Computer and Information Sciences (ICCIS)*, pp. 1–4, IEEE, 2019.

[22] A. Dardzinska, *Action rules mining*, vol. 468. Springer, 2012.

[23] H. Kaur, "Actionable rules: Issues and new directions.," in *in Transactions on Engineering, Computing and Technology, World Informatica Society*, pp. 61–64, Citeseer, 2005.

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

[25] A. Dardzinska and Z. W. Ras, "Extracting rules from incomplete decision systems: System erid," in *Foundations and Novel Approaches in Data Mining, (Eds. T.Y. Lin, S. Ohsuga, C.J. Liau, X. Hu), Studies in Computational Intelligence*, vol. 9, pp. 143–154, Springer, 2005.

[26] A. Dardzinska and Z. W. Ras, "On rules discovery from incomplete information systems," in *the Proceedings of ICDM'03 Workshop on Foundations and New Directions of Data Mining, (Eds: T.Y. Lin, X. Hu, S. Ohsuga, C. Liau), Melbourne, Florida, IEEE Computer Society*, pp. 31–35, 2003.

[27] A. Dardzinska and Z. W. Ras, "Cooperative discovery of interesting action rules," in *the Proceedings of FQAS 2006 Conference, Milano, Italy, (Eds. H.L. Larsen et al.), LNAI*, vol. 4027, pp. 489–497, Springer, 2006.

[28] Z. He, X. Xu, S. Deng, and R. Ma, "Mining action rules from scratch," *Expert Systems with Applications*, vol. 29, no. 3, pp. 691–699, 2005.

[29] S. Im and Z. W. Ras, "Action rule extraction from a decision table: Ared," in *Foundations of Intelligent Systems, Proceedings of ISMIS'08, A. An et al. (Eds.), Toronto, Canada, LNAI*, vol. 4994, pp. 160–168, Springer, 2008.

[30] R. Agrawal, R. Srikant, *et al.*, "Fast algorithms for mining association rules," in *Proc. 20th int. conf. very large data bases, VLDB*, vol. 1215, pp. 487–499, 1994.

[31] R. P. Mehta, M. A. Sanghvi, D. K. Shah, and A. Singh, "Sentiment analysis of tweets using supervised learning algorithms," in *First International Conference on Sustainable Technologies for Computational Intelligence*, pp. 323–338, Springer, 2020.

[32] J. Ranganathan and A. Tzacheva, "Emotion mining in social media data," *Procedia Computer Science*, vol. 159, pp. 58–66, 2019.

[33] F. Krebs, B. Lubascher, T. Moers, P. Schaap, and G. Spanakis, "Social emotion mining techniques for facebook posts reaction prediction," *arXiv preprint arXiv:1712.03249*, 2017.

[34] J. Trofimovich, "Comparison of neural network architectures for sentiment analysis of russian tweets," in *Computational Linguistics and Intellectual Technologies: Proceedings of the International Conference Dialogue*, pp. 50–59, 2016.

[35] J. Nowak, A. Taspinar, and R. Scherer, "Lstm recurrent neural networks for short text and sentiment classification," in *International Conference on Artificial Intelligence and Soft Computing*, pp. 553–562, Springer, 2017.

[36] S. Sachin, A. Tripathi, N. Mahajan, S. Aggarwal, and P. Nagrath, "Sentiment analysis using gated recurrent neural networks," *SN Computer Science*, vol. 1, no. 2, pp. 1–13, 2020.

[37] S. Biswas, E. Chadda, and F. Ahmad, "Sentiment analysis with gated recurrent units," *Department of Computer Engineering. Annual Report Jamia Millia Islamia New Delhi, India*, 2015.

[38] Y. Tang and J. Liu, "Gated recurrent units for airline sentiment analysis of twitter data,"

[39] Y. Santur, "Sentiment analysis based on gated recurrent unit," in *2019 International Artificial Intelligence and Data Processing Symposium (IDAP)*, pp. 1–5, IEEE, 2019.

[40] B. Bakhshinategh, O. R. Zaiane, S. ElAtia, and D. Ipperciel, “Educational data mining applications and tasks: A survey of the last 10 years,” *Education and Information Technologies*, vol. 23, no. 1, pp. 537–553, 2018.

[41] L. D. Miller, L.-K. Soh, A. Samal, K. Kupzyk, and G. Nugent, “A comparison of educational statistics and data mining approaches to identify characteristics that impact online learning.,” *Journal of Educational Data Mining*, vol. 7, no. 3, pp. 117–150, 2015.

[42] M. Cocea and S. Weibelzahl, “Can log files analysis estimate learners' level of motivation?,” in *LWA*, pp. 32–35, University of Hildesheim, Institute of Computer Science, 2006.

[43] J. Bravo and A. Ortigosa, “Detecting symptoms of low performance using production rules.,” *International working group on educational data mining*, 2009.

[44] B. Jagtap and V. Dhotre, “Svm and hmm based hybrid approach of sentiment analysis for teacher feedback assessment,” *International Journal of Emerging Trends & Technology in Computer Science (IJETTCS)*, vol. 3, no. 3, pp. 229–232, 2014.

[45] J. Wiebe, T. Wilson, and C. Cardie, “Annotating expressions of opinions and emotions in language,” *Language resources and evaluation*, vol. 39, no. 2-3, pp. 165–210, 2005.

[46] A. Tzacheva, J. Ranganathan, and R. Jadi, “Multi-label emotion mining from student comments,” in *Proceedings of the 2019 4th International Conference on Information and Education Innovations*, ICIEI 2019, (New York, NY, USA), pp. 120–124, ACM, 2019.

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

[48] S. M. Mohammad and P. D. Turney, “Crowdsourcing a word–emotion association lexicon,” *Computational Intelligence*, vol. 29, no. 3, pp. 436–465, 2013.

[49] S. M. Mohammad and P. D. Turney, “Emotions evoked by common words and phrases: Using mechanical turk to create an emotion lexicon,” in *Proceedings of the NAACL HLT 2010 workshop on computational approaches to analysis and generation of emotion in text*, pp. 26–34, Association for Computational Linguistics, 2010.

[50] S. M. Mohammad and S. Kiritchenko, “Using hashtags to capture fine emotion categories from tweets,” *Computational Intelligence*, vol. 31, pp. 301–326, May 2015.

[51] S. M. Mohammad, "# emotional tweets," in *Proceedings of the First Joint Conference on Lexical and Computational Semantics-Volume 1: Proceedings of the main conference and the shared task, and Volume 2: Proceedings of the Sixth International Workshop on Semantic Evaluation*, pp. 246–255, Association for Computational Linguistics, 2012.

[52] A. Bagavathi and A. A. Tzacheva, "Rule based systems in distributed environment: Survey," in *Proceedings of International Conference on Cloud Computing and Applications (CCA17), 3rd World Congress on Electrical Engineering and Computer Systems and Science (EECSS'17)*, pp. 1–17, 2017.

[53] Z. W. Ras and L.-S. Tsay, "Discovering extended action-rules (system dear)," in *Intelligent Information Systems 2003, Advances in Soft Computing, Proceedings of the IIS'2003 Symposium, Zakopane, Poland*, pp. 293–300, Springer, 2003.

[54] L.-S. Tsay and Z. W. Ras, "Action rules discovery: system dear2, method and experiments," *in the Special Issue on Knowledge Discovery, Journal of Experimental & Theoretical Artificial Intelligence*, vol. 17, no. 1-2, pp. 119–128, 2005.

[55] Z. W. Ras and E. Wyrzykowska, "Arogs: Action rules discovery based on grabbing strategy and lers," in *Proceedings of 2007 ECML/PKDD Third International Workshop on Mining Complex Data (MCD 2007), Univ. of Warsaw, Poland*, pp. 95–105, 2007.

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

[57] A. Tzacheva and J. Ranganathan, "Pattern discovery from student feedback - identifying factors to improve student emotions in learning," IOP Publishing, jan 2021.

[58] M. Zaharia, M. Chowdhury, M. J. Franklin, S. Shenker, and I. Stoica, "Spark: Cluster computing with working sets," in *Proceedings of the 2Nd USENIX Conference on Hot Topics in Cloud Computing*, HotCloud'10, (Berkeley, CA, USA), pp. 10–10, USENIX Association, 2010.

[59] A. F. A. Nasir, E. S. Nee, C. S. Choong, A. S. A. Ghani, A. P. P. A. Majeed, A. Adam, and M. Furqan, "Text-based emotion prediction system using machine learning approach," *IOP Conference Series: Materials Science and Engineering*, vol. 769, p. 012022, jun 2020.