A New Modified Framework For Mining Frequent Interaction Patterns Discovery From Human Meeting Databases

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Abstract- *A meeting is a most important communication coordinate activity of teams: status is firstly discussed, new decisions is made, alternatives methods are considered, details should be presented, information is explained, and new ideas are created. As a, meetings contains a large amounts of rich project information's that is often but not formally documented. Capturing techniques all of this familiar congregation information's has been a topics of study in several commune over the past decided. In this works, data mining technique is used to detects and analyze of the frequent interactions pattern to discover a various types of knowledge on human interactions. An interaction tree based pattern mining algorithm is proposed to analyze the tree structures and extracts interactions flow pattern for the meetings. In this works tree based mining algorithms proposed to a human interaction flows, where the human interaction flows in a new discussion session is represented as a tree. Proposed systems extend an interactive tree based pattern mining algorithms in two ways. First, it is mainly proposed to mining methods to extract the frequent patterns of human interactions to support several category of meeting. Second, it is explored modified to embed tree mining for a hidden interactions pattern discovery. Modified embedded sub tree is the generalization methods of induced sub trees, which not allows direct parent child branches, also consider ancestor descendant branches. The experimental result shows the discovered patterns can be utilized to an evaluates the meeting discussions is efficient to compare the results of different algorithms of interaction flow.*

Keywords- Tree based mining, sub tree mining, frequent interaction mining

I. INTRODUCTION

In the social human interactions is the one of the important method for how a human's behaviours and human activities under the meeting and determining. Whether the meeting was well organized or not is the one of the main issues in the meeting. Several methods have used to find the interactions of the flowing in the meeting in each human. A further understanding the human and interference of the human interactions in meeting, and here it needs to discovers a higher level semantic knowledge such as which interactions often occurs in a discussion ,what interactions flow a discussion usually follow, and relationships between the exist among interactions. This knowledge will help to describes important pattern of interaction. Meetings constitute of the natural and important causes in the people interactions, becomes a challenging problem for several conditions and relatively a well defined dictionary of relevant events.

The previous works of the paper investigate to discover pattern can be utilized to evaluates the whether a meeting discussion is efficient and to compares two meeting discussions using an interaction flow as a key features. Capturing all of this informal meeting information's has been to topic of research in several communities over the past decades. Data mining is a powerful method of discovering new knowledge. A mining way to supply recurrent pattern of individual communications based on the captured substance of face-to-face congregation. Human interactions flow in the meeting is defined as the proposing of new idea expressing positive opinions, negative opinions and giving comment. The mining marks can been worn for a indexing gathering semantics; also existing assembly confine systems could using this techniques as a smarter indexing tools to search and access particular semantic of the meetings. Interaction tree patterns mining algorithm to analyze the tree structures and extract interactions flow pattern.

The Previous works of the tree based mining methods discover the human interactional only one data set or various categories of the data set not considered. An interaction flows that appears frequently reveals relationships between different types of interaction. It is valuable to capturing various categories of meeting and planned to develop several applications based on the discovered patterns in human meetings. So i propose my work with the meetings (debates). It is extract from previous work with the two ways in first method it is proposed the mining method that extract frequents pattern of human interactions and in second, it is proposed to a work with the embedded sub tree mining.

II. DATAMINING

A. Data mining

Data mining, which is a powerful methods of discovering a new knowledge, has been widely adopts in many field, such as Bioinformatics, marketing, and securities. Knowledge discovery in a databases process is relatively young and inter disciplinary fields of computer science is the process of discovers a new patterns from large data set involving method at the connection of synthetic intellect, machine education, data and file system. The goal of data mining is extract knowledge from a data set in human understandable structures. Data mining is the whole process of Applying computer based methodology, includes new techniques for a knowledge discovery, from data. Databases, Text Documents, Computer Simulation, and Social Networks are the Sources of the Data for Mining.

B. In The Human Interaction

In this learning, it is necessary to examine the data mining methods to identify and analyze frequent interaction pattern; I hope to discover various types of new knowledge on interactions. Human interaction flow in a congregation debate gathering is represented as a Embedded tree mining for hidden interactions pattern discovery and proposed a modified embedded sub tree based mining methods to extract frequent patterns item of human interactions based mine on the captured content of face to face meetings. Human interaction flows in a discussion sessions is represented as a tree. Embedded sub tree mining algorithms is designed to analyze the structures of the trees and to extract interactions flow patterns.

III. PROBLEM DEFINITION

Discovering semantic knowledge is a significant for an understanding and interpreting people interact in meeting discussions. As such, meetings contain a large amount of rich project information that is often not formally documented. Capturing this entire familiar summit in sequence has been an area to explore in numerous communities over the past decade. The most common way to capture meeting information is through note-taking. However, fully writing down the content of a meeting is a difficult task, and can result in an inability to both take notes and participate in the meeting. The existing tree based mining method for discovering frequent patterns of human interaction in meeting discussions at the same meeting.

IV. RELATED WORK

Human interactions are one of the most important characteristics of group social dynamics in the meetings. In this paper, proposed an approach to captures the human reaction, recognition of human interactions and visualization of human interaction. Unlike physical interactions such as, turn-taking and addressing the human interactions are incorporated with semantics. Before it is adopts to a collaborative approaches for capturing interactions by employing a multiple sensors, such as microphones, motion sensors and video cameras. The collaborative based systems mainly focused on detecting a physical interaction between participants without any relations with topics. Hence they cannot clearly to determine participant's attitude or role in topic discussions. Every increasing tree. Motivated by tree-based mining algorithms are used to analyze tree structures and extract interaction flow patterns in human. An interface surge that appears regularly reveals relations between different types of interactions.

Tree Based Mining

Association based rule data mining is the fundamental methods to find a frequent item sets in databases. The problems of mining association rule over transactional database in the larger database. Mining frequent tree patterns have a many useful applications in the XML mining, Bioinformatics, network routing. A tree is used to represent an communication flow in a session. It is an acyclic connected graph. Trees are also rooted, directed, and labelled. There would be some difference in the frequent interactions pattern for different congregation styles.volume of recorded meeting data is driving the need for the implementation of tools to efficiently access and quickly retrieves important pieces.

TREEMINER is a novel algorithm to discover all frequent sub trees in a tree-plant, using a new data structure called scope-list. In this system TREEMINER with a pattern matching tree mining algorithm (PATTERN MATCHER) were contrasted by the author. After performing these steps, several experiments were conducted test the performance of system and scalability of these methods and find that pattern matching approach performs better than another system; it also has good scale up properties. It also present an function of tree mining to examine real web logs for usage pattern. In earlier work Chopper [3] and XSpanner systematically develop the two algorithm pattern growth methods for mining frequent tree patterns. Experimental results shows that the newly developed algorithms outperforms TreeMinerV. Moreover XSpanner is considerably earlier than Chopper in numerous cases. The system for recurrent tree model mining is well-organized and scalable when the patterns are not too complex. Even though there are many complex patterns in the data set. Modeling and tracking a person’s focal point of interest is useful for many applications. For multimodal person computer interaction, the user’s focal point of concentration can be used to decide his/her message objective. [4] Of interactive meetings is the present speaker, who is, by definition, changing frequently. Thus, conventional meeting viewing interfaces for such meetings encompass an automatic speaker's view, which all the time shows the current speaker.

Previous work has also identified that the speaker's view should be coupled with a fixed context view, which shows an overview of all of the attendees. Research indicates that for viewing recorded meetings, the combination of an automatic speaker and fixed context views does not provide sufficient information. It also found that they desire control of the context views.

Requirement 1: The interface should correctly convey to the user who an attendee is looking at. Requirement 2: The context view should allow the user to focus on any attendee or any part of the meeting room.

The recording equipment [4] has a large impact on the rest of the system. For example, if a single, regular camera captures the meeting, the video presented in the interface is simply the one captured by the camera. Similarly at the other way if a high-resolution, wide-angle camera is used, then the video can be processed to extract separate video streams of all of the attendees, which can be presented as thumbnails in the interface.

A smart meeting system which record and analyze the generated audio for future viewing, the above mentioned topic becomes a great challenge in recent years. A successful smart meeting system relies on various technologies, ranging from devices and algorithms. This system [5] presents a survey of existing research and technologies, including smart meeting system, meeting capture, semantic processing, , meeting recognition, and evaluation methods. This article also describes various issues of all possible ways to extend the capabilities of current smart meeting systems. Improves the productivity of a team by automating Capture of the meeting. Displaying of that information accurately and effectively to the end user through a client application. An omni directional camera [6] is used to capture the scene around a meeting table. Here real time face tracker is used to detect and track participants in the panoramic image .Moreover, neural networks (NN) are used to compute head pose of each person concurrently from the panoramic image.

Then use a Bayesian approach to estimate a person’s focus of attention from the computed head pose. Because Hand recorded notes have many drawbacks. Taking notes is time consuming; it requires additional focus and thus reduces one’s attention .For this reason and remarks tend to be incomplete and moderately summarized. In our framework, the layer models [7] typical actions of individuals in meetings using supervised HMM learning and low-level audio-visual features. Numeral option explicitly models certain aspect of the data. In this HMM model second layer the group actions using unsupervised learning. These two layers are linked by a set of probability based features produced by the individual action. The methodology was assessed on a set of multimodal turn-takinggroup actions, using a public -hour meeting corpus. From the results says that layered framework are compared to various baseline methods.

The head gestures [8] including shaking and tilt, nodding are recognized with a Wavelet-based technique from magnetic sensor signals. The simple utterance of a few platitudes is detected using data captured by lapel microphones.

Experiments were conducted on four-person conversations, it validates the effectiveness of the framework in discovering interactions such as question-and-answer and addressing behavior followed by back-channel responses. Face-to-face conversation is one of the most basic forms of communication in our life and is used for conveying/sharing information, understanding others’ intention/emotion, and making decisions. To enhance our communication capability beyond conversations on the spot, the automatic analysis of discussion scenes is a basic technical to realize communication via social agents and robots. The discussion scene analysis targets various aspects of conversation, from individuals. In these systems [15] and[16] provides a way of storing the data in cloud and retrieve.

V. HUMAN INTERACTION AND PROPOSED SYSTEM

A. Human Interaction

The definition of human interaction types naturally varies according to the usage of the meetings or the types of the meetings. In this research, I mainly focus on the task-oriented interactions.

Fig. 2. Examples of tree representation human interaction flow the other communicative actions that concern the meeting and the group itself (e.g., when someone invited another participant to take the floor) are not included. For a statistical framework for conceptualizing, investigating, and designing

Communication gush creates a set of communication types based on a pattern utterance-unit tagging scheme: propose, comment, acknowledgement, request Info, ask Opinion, pos Opinion, and neg Opinion.

B. Human Interaction Flow

Human interaction flow is designed as the tree .An interaction flow is a list of all interactions in a discussion with the relationship between them. An communication flow is a catalogue of all connections in a conversation session with trigger association between them. L = {PRO; COM; ACK; REQ; ASK; POS; NEG} Labels are abbreviated names of interactions, i.e., PRO—Propose, COM—comment, ACK—acknowledgement, REQ— request Info, ASK—ask Opinion, POS—pos Opinion, and NEG-negative Opinion .Three examples of interaction trees shown in the figure 2.

C. Tree Based Pattern Mining Algorithm

Designed a tree based pattern mining's algorithm interactions flow mining. It formulates the frequent tree pattern mining algorithm for each node in the tree .For each tree in TD the algorithm foremost interchanges the spaces of siblings (i.e., performs commutation processing) to produce the entire set of isomorphic trees (ITD). The aim of producing isomorphic trees is to alleviate string correspondence. After generating the isomorphic trees then calculates support values of each tree at Steps 2-3. In Step 4, it selects the trees whose supports are larger than □ and detects isomorphic trees within them. If m trees are isomorphic, it selects one of them and discards the others. It finally outputs all frequent tree patterns with respect to Where,

TD – A dataset of interaction tree.
ITD - The full set of isomorphic trees to TD
T – A Tree
Tk – A sub tree with k nodes, i.e K-sub tree ,
Ck – A set of candidates with k-nodes.
Fk – A set of frequent k-sub trees
□–A support threshold min sup
Algorithm 1. FITM (TD) (Frequent interaction tree pattern mining)
Input: Tree database (TD) and a support threshold □
Output: Frequent tree patterns with respect to □
Procedure:
(1) Scan database TD, generate its full set of isomorphic trees, ITD
(2) Scan database ITD, count the number of occurrences for Each tree t
(3) Calculate the support of each tree
(4) Select the trees whose supports are larger than □ and Detect isomorphic trees; if m trees are isomorphic, select one of them and discard the others
(5) Output the frequent trees

D. Frequent Interaction Sub tree Pattern Mining

It first calculates the support of each node and selects the Nodes whose supports are larger than □ to form the set of Frequent nodes, F1 (Steps 2-3). It then adds a frequent node to Existing frequent i-sub trees to generate the set of candidates With i + 1 node (Steps 4-8).
Algorithm 2. FISTM (TD;) (Frequent interaction sub tree Pattern mining)
Input: Tree database (TD) and a support threshold □
Output: Frequent sub tree patterns with respect to □
Procedure:
(1) i ← 0
(2) Scan database TD, calculate the support of each node
(3) Select the nodes whose supports are larger than □ to form F1
(4) I ← i +1
(5) For each tree ti in Fi, do
(6) For each node t1 in F1, do
(7) Join ti and t1 to generate C
(8) Sub tree Support Calculating (TD; ti+1)
//calculate the support of each tree in Ci+1
(9) if there are any trees whose supports are larger than ,then Select them to form Fi+1 and return to Step (4)
(10) Else output the frequent sub trees whose supports are Larger than □
If there are any trees whose supports are larger than, it selects them to form F i+1 and repeats the procedure from Step
4; otherwise, it stops to output of frequent sub trees. In Step 7, it is joined ti and t1 to generate the candidate sub tree set of Size.
Sub procedure: Sub tree_Support_Calculating (TD , st)
Count ← 0
Supp (st) ← 0
(1) For each tree t ϵTD do
(2) Create sub tree S of t with any item s ϵ S,|s| = |st|
(3) Flag ← false
(4) For each item s ϵ S do
(5) Generate isomorphic trees IS of s
(6) For each item is ϵ IS do
(7) if tsc (st) = tsc (is) then
(8) count ← count + 1

(9) Flag ← true
(10) Break
(11) if flag = true then
(12) Break
(13) supp (st) ← count/|TD|
(14) return supp(st)

E. Various Categories of Datasets

In proposed system the tree mining algorithm is applied for extracting interaction pattern from debates. The common pattern from all types meetings and unique patterns of different types of meetings are analyzed. They are, panel, debate and general meetings ect., I investigate data mining techniques to detect and analyze frequent interaction patterns .It also develops several applications based on the discovered patterns from data. In this step develops various categories of the datasets in frequent common interaction mining.

F. Modified Embedded Sub-Tree Mining

In this modified embedded sub tree mining is also plan to explore embedded tree mining for hidden interaction pattern discovery. Modified Embedded sub trees (MEST) are a generalization of induced sub trees, which allow not only straight parent and child branches, also considering the ancestor-descendant branches. For example, when there is an interaction of propose, there always follows a comment, directly or indirectly. It focuses on mining frequent embedded sub trees from databases of rooted labelled ordered sub trees.
Algorithm 3. MESTM (TD;) (Modified embedded sub tree pattern mining)

Input: Tree database TD and a support threshold
Output: Embedded sub tree patterns with respect to
Procedure:
(1) i ← 0
(2) Scan database TD, calculate the support of each node
(3) Select the nodes whose supports are larger than to form F1
(4) I ← i +1
(5) For each tree ti in Fi, do
(6) For each parent node P in the tree t1 in F1, and each child Node C, ancestor (their child) -descendant branches in the tree Tree t1 in F1 do
(7) Join ti and t1 to generate C
(8) Subtree Support Calculating (TD; ti +1)
//calculate the support of each tree in Ci+1
(9) if there are any trees whose supports are larger than , then Select them to form Fi+1 and return to Step (4)
(10) Else output the embedded sub trees whose supports are Larger than

G. Association Rule

The association rule learning is a popular and well researched method for discovering interesting relations between variables in large databases. It explains about examining and presenting tough rules exposed in database using altered measures of interestingness. In our approach the association rules mining are used to discovering the confidence and support value.

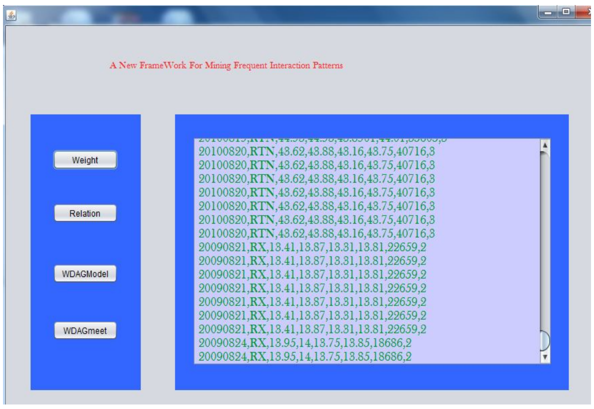
H. Confidence and Support Value

Confidence value is calculated to find or how much time the event occurs at the during the frequent pattern mining .Support value is calculated between the number of occurrences of tree or sub-tree and the total number of the trees in the dataset of interaction trees. The support value is calculated using the following formula; Support =number of occurrences of T/ total number of trees in TD

Finally it discovers the maximum support value is displayed after the embedded sub tree mining is performed.

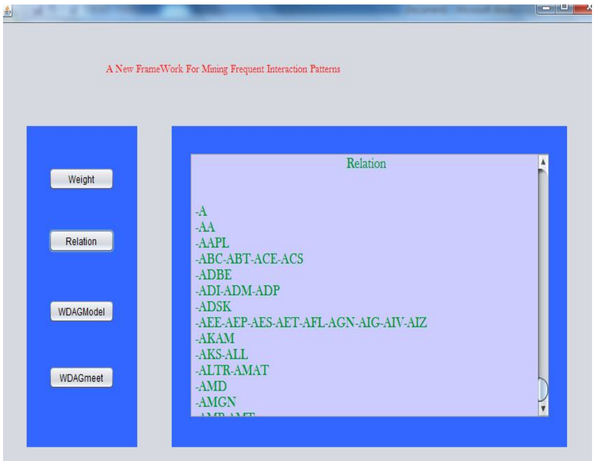
VI. RESULTS AND DISCUSSION

In the fig. 3 (graph) result shows that the performance level of the four models: Frequent interaction tree mining (FITM), Frequent interaction subtree mining (FISTM), Modified Embedded subtree mining (MESTM).



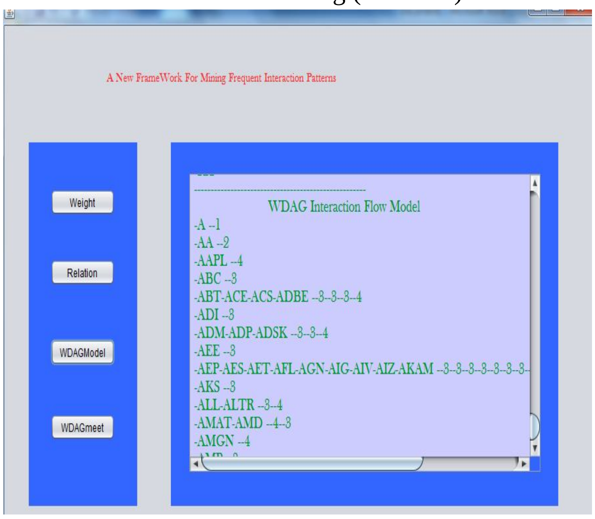
Module 1: weight assignment

consider the number of frequent patterns and minimum support value is the most considerable parameter to evaluate the performance of the system. So the results show that the Xaxis defines the minimum support value and the Y-axis defines the Number of the Frequent Pattern. Finally the performance of the MESTM is high other then two models. Because the human

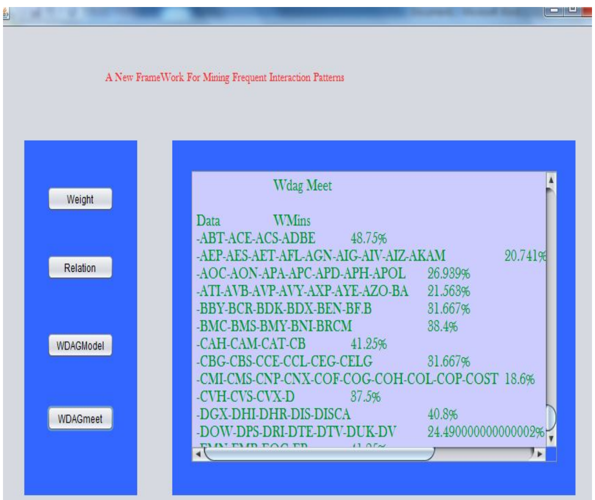


Module 2

In this graph the result shows that the performance level of the four models: Frequent interaction tree mining (FITM), Frequent interaction subtree mining (FISTM), Modified Embedded subtree mining (MESTM).



Module 3



Module 4

I consider the number of frequent patterns and minimum support value is the most considerable parameter toevaluate the performance of the system. So the results show that the X-axis defines the minimum support value and the Y-axis defines the accuracy percentage of the system. The performance of the MESTM is high because it covers the number of the frequent pattern in the less time of the system. Finally the performance of the MESTM is high other than two models. Because the human interaction activities varied based on the time to find the frequent patterns.

VII. CONCLUSION AND FUTURE WORK

A. Conclusion

Discovering frequent patterns for human interaction in meeting Tree-based mining method was proposed. The tree based mining results would be useful for indexing, summarization, and comparison of meeting records. The proposed system is valuable to analysis the various categories of meetings such as panel, debate, and interview. The proposed work is to discover frequent interaction trees and analyzes the behaviour of the algorithms with different categories of meetings. The proposed Works develop modified embedded sub tree mining based on the discovered patterns of human interaction and final plan to incorporate more meeting content in both amount and category. From the results i can say that modified embedded sub tree mining is more efficient than frequent interaction mining and frequent interaction sub tree mining.

Experimental results improve the accuracy by increasing the overall mining results also it is more effective.

B. Future Enhancement

Many data mining problems can be represented by non- linear data structures like trees. In future introduce a new scalable algorithm to mine partially-ordered trees. The algorithm, POT Miner, is able to identify both induced and embedded sub trees; also it can handle both completely ordered and completely unordered trees .I also extend my work to apply TMap more real datasets and evaluate its performance.

Furthermore, the consideration works by constructing of T Map with temporal interval.

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