An Approach To Understand Human Behaviour Pattern

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***Abstract*— Mining Human Interaction in Meetings helps to identify how a person reacts in different situations. Nature of the person is represented through behaviour and mining technique helps to analyze the opinion a person exhibits. Discovering semantic knowledge is significant for understanding and interpreting how people interact in a meeting discussion. Patterns of human interaction is extracted from the minutes of the meetings. Different Human interactions, such as proposing an idea, giving comments, and acknowledgements, indicate user intention toward a topic or role in a discussion. To further understand and interpret human interactions in meetings, we need to discover higher level semantic knowledge about them, such as which interaction often occur in a discussion, what interaction flow a discussion usually follow, and what relationship exist among interactions. This knowledge describe important patterns of interaction. Based on the human interaction the behavior of the members are identified and people of similar nature are grouped together.**

***Keywords*—Human interaction, interaction pattern, meeting**

I. Introduction

Opinion mining refers to the use of natural language processing, text analysis and computational linguistics to identify and extract subjective information in source materials. Generally speaking, sentiment analysis aims to determine the attitude of a speaker or a writer with respect to some topic or the overall contextual polarity of a document. The attitude may be his or her judgment or evaluation, affective state (that is to say, the emotional state of the author when writing), or the intended emotional communication.

Opinion mining (sentiment mining, opinion/sentiment extraction) attempts to make the automatic systems to determine the human opinion from text written in natural language. It seeks to identify the view point (s) underlying a text span. Opinion mining draws on computational linguistic, information retrieval, text mining, natural language processing, machine learning, statistics and predictive analysis. In real life, facts are important, but opinion also plays a crucial role. Search engines do not search for opinions. Opinions are hard to express with a few keywords.

The main characteristics of opinion mining are:

1. Sentiment is expressed in a more subtle manner, making it difficult to be identified by term information alone.
2. Sentiment orientation is quite context-sensitive and domain-dependent. This means that the same sentiment word may have different sentiment orientations in different sentences or domains.
3. The granularity of sentiment varies according to different applications.

An opinion can be defined as a quintuple (o_j, f_{jk}, so_{ijkl}, h_i, t_l), where

o_j is a target object.

f_{jk} is a feature of the object o_j.

so_{ijkl} is the sentiment value of the opinion of the opinion holder h_i on feature f_{jk} of object o_j at time t_l. so_{ijkl} is positive, negative, neutral or a more granular rating.

h_i is an opinion holder.

t_l is the time when the opinion is expressed.

A. Basic Components of Opinion

The basic components of an opinion are opinion holder which defines the person or organization holding a specific opinion on a particular object; object is the one on which the opinion is expressed and finally opinion provides the view, attitude or appraisal on an object from an opinion holder.

B. Overview

Human interaction is one of the most important characteristic of group social dynamics in meetings. A smart meeting system is developed for capturing the human interactions and recognizing their types, such as proposing an idea, giving comments, expressing a positive opinion, and requesting information. To further understand and interpret human interactions in meetings, higher level semantic knowledge has to be discovered. Interactions that often occur in a discussion, the interaction flow a discussion usually follow, and relationships exist among interactions. This knowledge likely describes important patterns of interaction. We also can regard it as a grammar of the meeting discussion. Based on the human interactions the behaviour of the members of the meeting is identified and people of similar interactions are grouped together. Human interactions are mined in meetings which help to understand how people react in different situations and help to determine the relationships between the different types of interactions.

C. Problem Statement

From the meetings which are given as the data set we are trying to identify human behaviour based on grouping of activities. Some of the common activities or types of interactions include proposing an idea, giving suggestions or commenting, acknowledging or accepting or giving positive or negative opinions. Based on cluster analysis and pattern mining behaviour of persons can be analyzed.

In the social dynamic network, human interaction is one of the important features required for understanding the human reaction or human activities which take place in the meetings. Thus it helps to determine whether the meeting was well organized or not. Some of the issues which need to be overcome are these meeting interactions do not help to identify human behaviours. There are no comparisons among the meetings. The paper is mainly focusing on the task-oriented interactions which address task-related aspect.

D. Objectives

The objective of the paper is to analyse the behaviour of each individual in a meeting and thus helps in identifying and group people based on the interactions. Similarly features of various categories of meetings are being analysed.

II. LITERATURE SURVEY

Human interaction in meetings has attracted much research in the fields of image/speech processing, computer vision, and human-computer interaction (see [2] for a full review). Stiefelhagen et al. [3] used microphones to detect the current speaker and combined acoustic cues with visual information for tracking the focus of attention in meeting situations. McCowan et al. [5] recognized group actions in meetings by modelling the joint behaviour of participants based on a two-layer Hidden Markov Model (HMM) framework. The AMI project [6] was proposed for studying human interaction issues in meetings, such as turn-taking, gaze behavior, influence, and talkativeness. Otsuka et al. [7] used gaze, head gestures, and utterances in determining interactions regarding who responds to whom in multiparty face-to-face conversations. DiMicco et al. [8] presented visualization systems for reviewing a group's interaction dynamics,e.g., speaking time, gaze behaviour, turn-taking patterns, and overlapping speech in meetings. In general, the above-mentioned systems aim at detecting and visualizing human interactions in meetings, while our work focuses on discovering higher level knowledge about human interaction.

Mining human interactions is important for accessing and understanding meeting content [1]. First, the mining results can be used for indexing meeting semantics, also existing meeting capture systems could use this technique as a smarter indexing tool to search and access particular semantics of the meetings [9], [10]. Second, the extracted patterns are useful for interpreting human interaction in meetings. Cognitive science researchers could use them as domain knowledge for further analysis of human interaction. Moreover, the discovered patterns can be utilized to evaluate whether a meeting discussion is efficient and to compare two meeting discussions using interaction flow as a key feature.

Unlike mining patterns of actions occurring together [11], patterns of trajectories [12], and patterns of activities [13], our study aims at discovering interaction flow patterns in meeting discussions, such as relationships between different types of interactions. We are aiming at identifying human behaviour patterns from the interactions. With the identification of the pattern with the human we can find out the nature of the person during meetings.

Several works done in discovering human behaviour patterns by using stochastic techniques. Bakeman and Gottman [14] applied sequential analysis to observe and analyze human interactions. Magnusson [15] proposed a pattern detection method, called T-pattern to discover hidden time patterns in human behaviour. T-pattern has been adopted in several applications such as interaction analysis and sports research .Although the purpose of these techniques is similar to our work, we conduct analysis on human interaction in meetings and address the problem of discovering interaction patterns from the perspective of data mining.

Casas-Garriga [16] proposed algorithms to mine unbounded episodes (those with unfixed window width or interval) from a sequence of events on a time line. The work is generally used to extract frequent episodes, i.e., collections of events occurring frequently together. Morita et al. [17] proposed a pattern mining method for the interpretation of human interactions in a poster exhibition. It extracts simultaneously occurring patterns of primitive actions such as gaze and speech. Sawamoto et al. [17] presented a method for extracting important interaction patterns in medical interviews (i.e., doctor-patient communication) using non-verbal information

Human interactions in a meeting discussion are defined as social behaviours or communicative actions taken by meeting participants corresponding to the current topic. Various interactions imply different user roles, attitudes, and intentions about a topic during a discussion. The definition of interaction types naturally varies according to usage [1].

Our study aims at discovering interaction flow patterns in meeting discussions, such as relationships between different types of interactions. We are aiming at identifying human behaviour patterns from the interactions. With the identification of the pattern with the human we can find out the nature of the person during meetings.

Human Interaction is a vital event to understand communicative information. Understanding human behaviour is essential in applications including automated surveillance, video archival/retrieval, medical diagnosis, and human-computer interaction.

Group social dynamics can be useful for determining whether meeting was well organized and whether the conclusion was rational. Human interaction plays an important role in understanding this communicative information and different from physical interactions (e.g. turn-taking and addressing), the human interactions here are defined as behaviours among meeting participants with respect to the current topic, such as proposing an idea, giving some comments, expressing positive opinion, and requesting information.

III. SYSTEM DESIGN

A. System Architecture

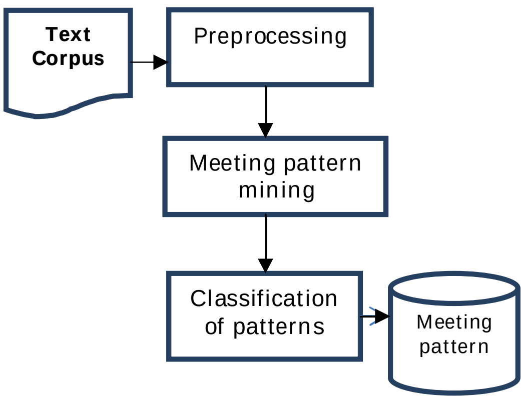


Figure 1. Architecture for identifying and grouping meeting patterns

Minutes of meeting are read from the text corpus and preprocessed as given in figure 1. These are then matched with patterns of interactions and are grouped together .They are then classified and form patterns of individual members of the meeting.

IV. MODULES DESCRIPTION

A. Pre-Processing

This module consists of three steps. They are stopword removal, stemming and POS Tagging

1. Stopword Removal

Common techniques for removing words that occur frequently but has no meaning (conjunctions, articles and so on) are considered as stopword removal.

2. Stemming

Stemming or lemmatization is a technique for the reduction of words into their root. Many words in the English language can be reduced to their base form or stem e.g. agreed, agreeing, disagree, agreement and disagreement belong to agree.

The following are the steps of Porter Stemming Algorithm:

Step 1: Get rid of plurals and ed or ing
Step 2: Turns terminal to i
Step 3: Maps double suffices into single ones
Step 4: Deals with -ic, -full, -ness etc.,
Step 5: Takes off -ant, -ence etc.,
Step 6: Removes a final -e

3. Pseudo code for Pre-processing

Input: Reviewer comments
Output: Words
Step 1: Remove the stop words.
Step 2: Perform stemming.
Step 3: Display keywords in the document.

Pre-processing reviewer comments consists of the following steps by trying to remove the stop words from the input given and perform stemming by extracting the root words. Once keywords have been identified from the document it can be used for processing.

4. POS Tagging

It is the process of marking up a word in a text (corpus) as corresponding to a particular part of speech, based on both its definition, as well as its context—i.e. relationship with adjacent and related words in a phrase, sentence, or paragraph

B. Pattern Matching

The words are defined for the features of Proposal, Comment and Acknowledgment.

1. Pseudo code for Pattern matching

Input: Keywords present in the document
Output: Patterns are formed
Step 1: The keywords are checked with the features defined
Step 2: The matched words are extracted and identified
Step 3: Using Apriori algorithm these words are mined to get a pattern

The keywords identified are matched with the lexicon table that has been created for the interactions of Proposal (PRO), Comment (COM) and Acknowledgement (ACK).Using Apriori algorithm similar patterns are mined out. Some examples of patterns can be PRO, COM, ACK, PRO-COM, PRO-ACK, PRO-COM-ACK

C. Classification of Patterns

The features and corresponding persons are identified and placed in a table.

1. Pseudo code for Grouping

Input: Matched words from the pattern
Output: A table which contain the patterns of each individual present in the meeting

Step 1: The matched words are counted for the corresponding person

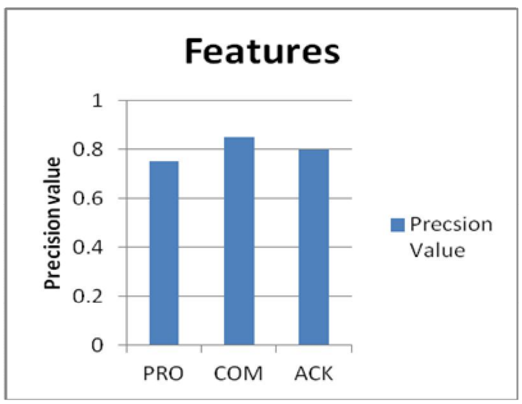
Step 2: They are grouped based on similarity of words
Step 3: Pattern generated for each person based on the data in the table

V. EVALUATION PARAMETERS

Precision (also called positive predictive value) is the fraction of retrieved instances that are relevant, while recall (also known as sensitivity) is the fraction of relevant instances that are retrieved. Both precision and recall are therefore based on an understanding and measure of relevance. High precision means that an algorithm returned comparatively more relevant results than irrelevant.
Precision = true positives/total elements in the positive class i.e. Precision = true positives/ (true positive+ false positives)

The three features extracted are PRO, COM, and ACK
For the case of PRO – proposal
Assert, recommend, inform are identified as Comment and are False Positive.
For the case of COM- comment
Announce, observe are identified as Acknowledgement and are False Positive.
For the case of ACK-acknowledgement
Defend, admit are identified as Comment and are False Positive

A. Performance Analysis



2. Feature extraction

The graph (Figure 2) indicates the values obtained when the features Proposal (PRO), Comment (COM), Acknowledgment (ACK) are calculated based on the factors of true positives and false positives. The Precision values when reaches 1 shows maximum accuracy.

VI. CONCLUSION

Based on the interactions among the people present in the meeting we are able to retrieve a pattern for each meeting. Mining results can be used for interpreting human interactions in the meetings. As future work, plan to perform clustering based on the interaction patterns to identify the behaviour of each individual in the meeting, thus exploring the involvement of each person in the meeting.

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