# Review & Analyze Chat Messages of the Chatting Partner

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*Abstract*—Instant Messaging (IM) is a service for users to communicate with each other. There are many Instant Messaging (IM) systems in the world such as MSN Messenger [1] and Yahoo Messenger [2], which are used by millions of people. IM monitoring systems have been developed for monitoring chat messages. Although most of these systems can provide good monitoring functions, most of them provide simple message analysis features such as browsing and simple keyword based searching of the recorded messages. In this paper, we propose a system, called Chat Reviews that supports intelligent chat message analysis using machine learning techniques and this system provides four IM monitoring modules to analyze IM. Final statistics generated by those four modules in this IM system are used to analyze chat session of a particular user.

***Keywords—Chat Message Analysis; instant messages; Social Network Analysis; Topic Analysis; Machine Learning; IM monitoring systems; feature vectors;***

## I. Introduction

Nowadays people frequently use *Instant Messaging* (IM) system for communication all the time in their day to day life. It provides us convenience to interact with others, IM monitoring systems can help people to understand their chat log along with their chatting partner in an analytical way.

In this paper, we introduce chat monitoring system which analyzes Instant Messages using four chat monitoring modules. **Topic Detection**, **Emotion Extraction**, **Evaluate Healthy** and **Personal Information Sharing Analysis** are the four chat monitoring modules introduced by this paper. Details of those modules will be presented in later sections. (In this work, we only focus on text messages in English.)

Instant messaging (IM) has become increasingly popular. It is estimated that there are several millions of instant messaging users all over the world. The Use of IM has been become widely adopted in personal and business society. Therefore the system (IM monitoring system) we introduce can be implemented for deferent purposes by adopting different chat monitoring modules rather than modules introduced in this paper such as Topic Detection, Emotion Extraction etc.

## II. Research Background

In chat message analysis of most IM monitoring systems, only simple message analysis and visualization functions for displaying the recorded chat messages are provided. However, these functions are insufficient for the processing of a large quantity of chat messages. Human inspection of chat contents could be very tedious. Still those chat monitoring systems provides basic GUI output for the users to be interacted with.

## III. Instant Message Monitoring Modules

### A. Topic Detection

Topic detection module detects the topic associated with messages. There are defined topic classes along with the training data associated with each topic class. With topic analysis, we aim to analyze chat sessions limited to a number of important topics. Therefore, we have adopted supervised topic detection approaches based on Naïve **Bayes Theorem** [3], and **Bernoulli document model** [4] which have been demonstrated with good performance for text classification.

Topic detection module use training dataset collected from social networks based on related topics and classification algorithm (supervised learning) [5] to classify message. Text classifiers often don't use any kind of deep representation about language: often a message is represented as **a bag of words** [6]. Consider a Message M, whose class is given by C. In the case of topic detection there are set of classes C = S (Sport) and C = P (Politics) etc... We classify M as the class which has the highest posterior probability P(C|M), which can be re-expressed using **Bayes' Theorem** [3]:

$$P(C|M) = \frac{P(M|C)P(C)}{P(M)} \propto P(M|C)P(C) \qquad (1)$$

Topic Detection module uses **Bernoulli document model**. This model represents messages using feature vectors [7] whose components correspond to word types. If we have a vocabulary

V, containing |V| word types, then the feature vector dimension d=|V|.

If we make the naive Bayes assumption, that the probability of each word occurring in the message is independent of the occurrences of the other words, then we can write the message likelihood P($M_i$ | C) in terms of the individual word likelihoods P($w_t$ |C):

$$P(M_i|C) \sim P(b_i|C) = \prod_{t=1}^{|v|}[b_{it}P(w_t|C) + (1-b_{it})(1-P(w_t|C))] \tag{2}$$

This product goes over all words in the vocabulary. We can use this as a model for generating message feature vectors of class C. The parameters of the likelihoods are the probabilities of each word given the message class P($w_t$ |C); this model is also parameterized by the prior probabilities, P(C). Then we can estimate the parameters of the word likelihoods as,

$$\hat{P}(w_t \mid C=k) = \frac{n_k(w_t)}{N_k}, \tag{3}$$

$$\hat{P}(C=k) = \frac{N_k}{N}. \tag{4}$$

Thus given a training set of messages (each labelled with a class), and a set of K classes, we can estimate a Bernoulli text classification model as follows:

1. Define the vocabulary V; the number of words in the vocabulary defines the dimension of the feature vectors.

2. Count the following in the training set:

- N the total number of messages
- $N_k$ the number of messages labelled with class C=k, for k=1,… K,
- $n_k(w_t)$ the number of messages of class C=k containing word $w_t$ for every class and for each word in the vocabulary.

3. Estimate the likelihoods using equation (3)

4. Estimate the priors using equation (4)

To classify an unlabeled message $M_j$, we estimate the posterior probability for each topic class combining equations (1) and (2):

$$\begin{aligned} P(C|M_j) &= P(C|b_j) \\ &\propto P(b_j|C)P(C) \\ &\propto P(C)\ \prod_{t=1}^{|v|}[b_{jt}P(w_t|C) + (1-b_{jt})(1-P(w_t|C))] \end{aligned} \tag{5}$$

Then message will be labeled into specific topic class based on the highest posterior probability computed by above equation.

### B. *Emotion Extraction*

Affective computing is human-computer interaction in which a device has the ability to detect and appropriately respond to its user's emotions and other stimuli. A computing device with this capacity could gather cues to user emotion from a variety of sources. Human beings expose their emotions in every single step of life by reading, writing, speaking or listening. Everything they do or make is followed by or follows an emotional expression. For example, some people are afraid of being among many people. So they act accordingly by avoiding congestion. If they cannot, they are feeling anxious and nervous. Another example of the role of the emotions in our life is that people find themselves to be more productive when they are happy than when being depressed or unhappy. Thus emotions play a significant role in our daily life.

With the usage of the internet in everyday life mounting high, human-machine communication places greater emphasis on recognition of non-verbal information, especially of emotional reactions. Any kind of written communication along with sentimental expression makes remarkable effect on the brain.

As a consequence, there is a need for exploring new features such as sentiment and emotion which may pave the way to differentiate the data in an effective and efficient manner, thereby improving the information retrieval effectiveness.

Over the last decades, many researchers established numerous methodologies to extract emotion from text however, surprisingly enough, a little effort is initiated in real time messenger which will have the ability to analyze one's emotional state. Here, we address a rule based approach to dig up emotional state from chat box with seven basic emotional categories namely anger, disgust, fear, guilt, joy, sadness and shame.

The greatest challenge in this component is to find a data set. Over a period of many years during the 1990s, a large group of psychologists all over the world collected data in the ISEAR project directed by Klaus R. Scherer and Harald Wallbott. Student respondents, both psychologists and non-psychologists, were asked to report situations in which they had experienced all of 7 major emotions (anger, disgust, fear, guilt, joy, sadness, and shame).
This section describes the proposed method for emotion extraction from sentences. The features are extracted from the

ISEAR dataset. The proposed system (refer Figure 1) selects features and perform classification using Multinomial Naïve Bayes classifier.

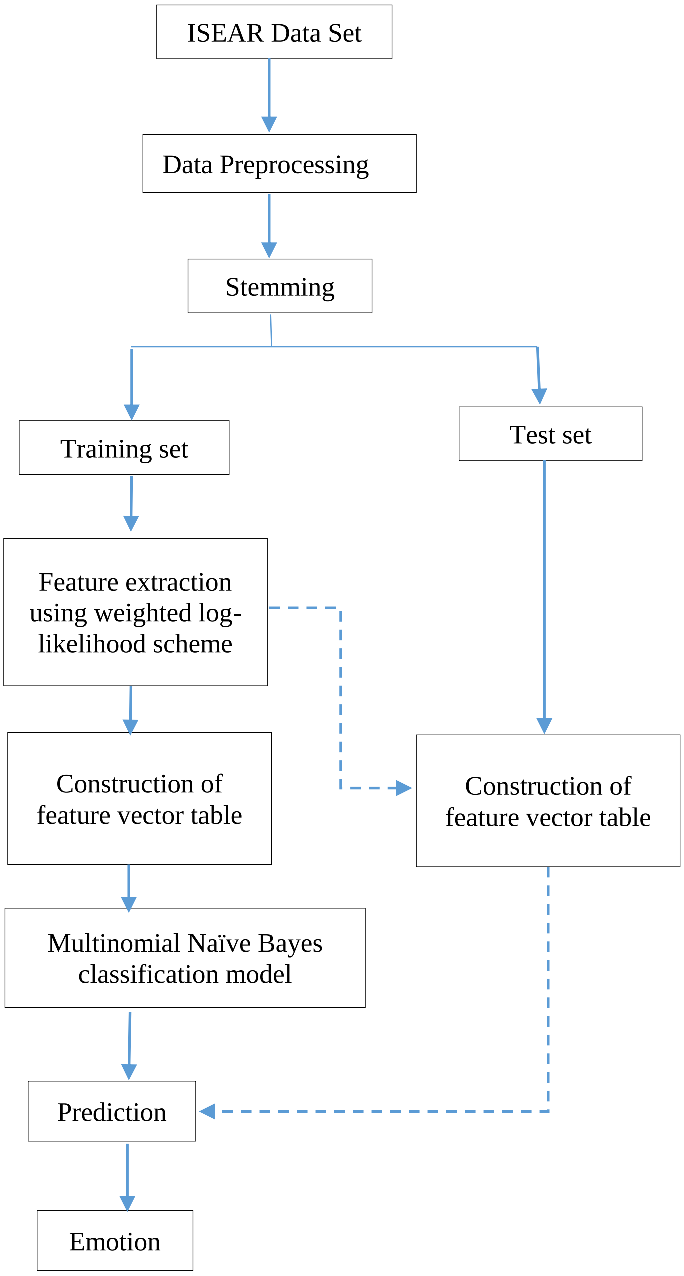


Figure 1

**Data Preprocessing**,

The ISEAR dataset is in the form of sentences which are tagged with the emotion experienced by the user, who are writing the sentence. There are seven emotions in the dataset: anger, disgust, fear, guilt, joy, sadness, and shame. The sentences in the dataset need to be pre-processed before performing any type of operations in it.

**Stemming**,

Stemming is the process of replacing words (inflected words) to their root form or stems. For example, the words listener, listening, listened etc. are all reduced to their root word 'listen'. But the stemmed word may not be same as the morphological root of the word. For example, cookery is reduced to cookery, which is not the actual word. In stemming, the ending characters of a word is just stripped to produce a stemmed form of the word rather than doing a dictionary look up to identify the actual root form of the word, which makes this technique computationally less expensive.

**Feature extraction**,

Ngram features are found to be useful for text classification tasks. Here unigrams, bigrams and trigrams are used as features for emotion identification. The unigrams are found to be very useful features. These include adjectives, adverbs, verbs, and nouns.

**Emotion Classification**,

For emotion identification from text, the multinomial implementation of Naïve Bayes classifier is used here. A Naive Bayes classifier is a simple probabilistic classifier based on applying Bayes theorem with strong (naive) independence assumptions. NB classifiers are used because it is fast, easy to implement and relatively effective. Multinomial Naive Bayes (MNB) classifier is a specific instance of a Naive Bayes classifier which uses a multinomial distribution for each of the features. Feature vector tables are constructed with the selected features for the seven emotion datasets: anger, disgust, fear, guilt, joy, sadness, and shame. These feature vector tables are used to build the classification model.

*C. Evaluate healthy*

Nowadays we meet strangers all the time in our day to day life. So, we attempt to have partnership with them without any fear at all. Also, some time they are more and smarter than we think, then it's very difficult to find the characteristics by only looking at their messages. So, we can Analysis chat sessions and Extract fewer first-person pronouns, fewer exclusionary words, unusual detail from collected messages. Identify those tics with message counts using write algorithms and visualize using diagrams and graphs format. After analysis we can get a better idea of particular chat. Compare and analyze the identified module based on analytical data of topic. We used machine learning technique to analysis process. It's a web application that analyzes messages in the chat box in short time of period. It simply gives us clear idea about the message by analyzing it in various ways. In that case we can be very much aware about our chatting partner. So, this application let you deal with that strange people in understandable way.

Used **Weka Data Analysis algorithm,**

**F-measure,**

A measure that combines precision and recall is the harmonic mean of precision and recall, the traditional or balance f -score

**Weka Confusion Matrix**

| | a | b | <-- classified as |
|---|---|---|---|
| actual a=0 | TP | FN | |
| actual b=1 | FN | TP | |

Recall is the TP rate (also referred to as sensitivity)
What fraction of those that are positive were predicted positive?
TP / actual positives

**Precision TP / predicted positive,**
What fraction of those predicted positive are positive?
Precision is also referred to as positive predictive value (PPV); Other related measures used in classification include true negative
Rate and accuracy:

$$F = 2 \cdot \frac{\mathrm{precision} \cdot \mathrm{recall}}{\mathrm{precision} + \mathrm{recall}}$$

This is also known as the F1 measure, because recall and precision are evenly weighted.

TP = true positives: number of examples predicted positive that are actually positive

FP = false positives: number of examples predicted positive that are actually negative

$$\mathrm{Recall} = \frac{tp}{tp + fn}$$

$$\mathrm{Precision} = \frac{tp}{tp + fp}$$

- True negative rate is also called specificity. (TN/actual negatives)
- 1-specificity is x-axis of ROC curve: this is the same as the FP rate ( FP / actual negatives)
- What fraction of those that are actually negative were found to be positive? (hopefully very low)

### *D. Personal Information Sharing analysis*

Personal Information Analysis gives the social interactions between the target users and their contacts from the lists. It extracts sender-receiver information of chat messages according to the specified criteria on the target user and chat history. The social interactions between the sender-receiver pair are described in terms of quantity and message direction. If there are many chat messages exchanged between the sender and receiver, it implies a close relationship or strong tie between the sender and receiver. This criteria use open NLP techniques to extract data and put that data to extract important data between the users share. The inbound or outbound message direction indicates the respective receiving or sending of messages of the target user. After the user has selected the target user it display to analysis options. The target user has exchanged chat messages with two contacts. Chat users (both the target user and his contacts) are represented as nodes and the sender-receiver relationships are represented as links. We use to indicate the amount of messages exchanged between the target user and the contact. When the system user wants to know the statistical information of a social relationship between the target users, he can either click on a link. When a link is selected, the information for a social relationship between the target user and is displayed. This information includes the trust worthiness of personal information sharing and information that they share. When a node is selected, the information on the target user is then displayed. This information includes the number of connections, the number of inbound messages, and the number of outbound messages of the target user. Chat message retrieval supports the browsing and retrieval particular chat session data archived in the chat log database.

## IV. Training Data Collection

This research target is to analyze trustworthiness of chatting partners using social media network on the internet. Training data have been collected in different ways for the IM monitoring modules from social networks. For Topic Detection module training data have been collected and grouped according to topic classes such as Politics, Food etc.

## V. Analyzing Thrustworthiness

Statistics computed by modules will be used to generate trustworthiness of chatting partner, therefore topics changing rate from **Topic Detection Module**, negative/positive emotions from **Emotion Extraction** Module, analysis of healthy from **Evaluate Healthy Module** and analysis of personal information from **Personal Information Sharing Analysis Module** are considered to be more critical analytical data in this system.

This system will graphically review statistics computed from IM monitoring modules. System will show **higher trustworthiness, if**

- Topic Changing Rate is Low
- Positive emotions is high
- Healthy(positive)
- Personal information sharing is high

System will show **less trustworthiness, if**

- Topic Changing Rate is high
- Negative emotions is high
- Not healthy(Negative)
- Personal information sharing is low

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