TEXTUAL EMOTION RECOGNITION FOR ENHANCING SOCIAL PRESENCE IN ONLINE COMMUNICATIONS

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Abstract
This paper presents an emotion recognition model that assesses the affective content from textual messages. The focus is on emotion recognition from online non verbal textual symbols of vocalics (e.g., the use of capitals and use of punctuation "!" and "!!s!" or "?" and "???", length of response, etc), and those of chronemics (e.g. time to respond to an email or to a discussion posting, the length of the response, etc) that are used in text. The model employs a supervised machine learning approach to recognize six basic emotions (anger, disgust, fear, happiness, sadness and surprise) using an emotion-annotated training set composed of online chat messages exchanged by university students. Naive Bayes algorithm is used to classify messages to the mentioned emotional classes based on a variety of features. The model also takes into consideration the evolving language particularly the language used in online chat where people tend to use an informal style of writing. Observations from informal experiments comparing a chat system integrated with the emotion estimation model with a conventional chat system suggest that an online interface that conveys emotional information helps online users to interact with each other more efficiently thus providing an enhanced social presence.

Key words: Affect recognition from text, emotions, text symbols, social presence, and computer mediated communication

1.0 Introduction

Social interaction among people is an essential part of every society. In face to face communication, people often rely on nonverbal cues such as body language, facial expressions, gestures, physical proximity, and dress to convey meaning and establish relationships.

Today many people interact via online means and in text form (e.g., email, twitter, blogs, and online chats). However computer mediated communication lacks such signals of face to face communication. Successful deployment of computer-supported communication systems requires the consideration of social factors, such as getting to know other people's feelings, emotions, etc. In this regard, social presence has emerged as a major design principle and a core construct in studying computer-mediated communication (CMC) (Biocca *et al.,* 2003). Bovee and Thill (2000) explain that, while we communicate verbally by using words in a face-to-face conversational mode, nonverbal cues provide 93% of the meaning exchanged in the interaction, 35% from tone and 58% from gestures, expressions and other physical cues. These observations demonstrate the importance of non-verbal information, such as emotions, which are essential for human cognition and influence different aspects of peoples' lives.

Natural Language Processing (NLP) techniques have long been applied to automatically recognize information content in text including sentiments conveyed through text. Research inspired by Artificial Intelligence (AI) is increasingly focusing on developing systems that incorporate emotion. Such interfaces can greatly enhance user experience in online communications and Human-Computer Interaction (HCI) (Ma, Prendinger, & Ishizuka, 2005; Neviarouskaya, Prendinger, & Ishizuka, 2007) Emotion recognition can be applied to several area such as personality analysis and modeling (Liu and Maes, 2004), assessment of emotional responses to consumer products and e-learning applications (Zhang *et al*., 2006).

Scientific research in emotion has been pursued along several dimensions and has drawn upon research from various fields. A wide range of modalities have been considered, including affect in speech, facial display, posture, and physiological activity (Picard, R., 1997).Recently, textual information is gaining increased attention as an important modality for identifying emotions since in this global age most human knowledge is transmitted via text especially over the Internet.

2.0 Affect Recognition Model

The model employs a supervised machine learning approach to recognize six basic emotions (anger, disgust, fear, happiness, sadness and surprise) as described by Ekman (1993). Naive Bayes algorithm is used to classify messages to the mentioned emotional classes based on a variety of features discussed in the following sections.

2.1 Data Selection

For training machine learning systems and for the evaluation of any automatic learning system, it is pre-requisite to have an annotated data. The primary consideration in the selection of data for this study was that the data should be rich in emotion expressions of online non verbal vocalics and chronemics with respective textual symbols so as to permit numerous learning instances, this was based on a study carried out to determine the use of textual symbols/patterns by students to provide nonverbal communication and to express emotions in a text based online environments. The data selection took into consideration the evolving nature of language in online conversations where people use an informal style of writing. Such data can be found in chat messages exchanged in applications such as Facebook, WhatsApp, twitter social networking applications etc as they are likely to be rich in emotion content.

Messages exchanged in the mentioned environments by university students were chosen as a data source for this research as they offer real-world examples of emotion expression in text– often containing noise, such as misspellings, slang languages, onomatopoeic elements which were the focus of this study. Below are sample messages from the training set annotated with emotions.

Table 1: Sample training annotated sentences

Messages	**Happy**	**Sadness**	**Fear**	**Surprise**	**Anger**
I GET MY TRANSCRIPT TODAY!!!	0.33	0.03	0.37	0.20	0.07
I am going home!!!	0.80	0.10	0	0.03	0.07
I AM GOING HOME!!!					
AND IM NOT SINGING HAPPILY TODAY	0.33	0.30	0.03	0.07	0.33
S/he is like WOW	0.53	0.03	0	0.43	0
I do not want to go to school………….	0.20	0.57	0.10	0.03	0.07
Why does this have to be so hard?!	0.07	0.40	0.07	0.07	0.40
Why must this be so painful??	0.03	0.43	0.20	0	0.20
I bought her four pairs of socks coz all the others have holes LOL	0.70	0.03	0	0.20	0.03

2.2 Training Module: Dictionary/Training Set

The first part of this process involved creating a dictionary, a set of keywords were identified for each of the six emotion categories. The words that are commonly used in the context of a particular emotion were used. The words fall into categories indicated in Table 1, the second part of this data selection process involves entering training examples into the model.

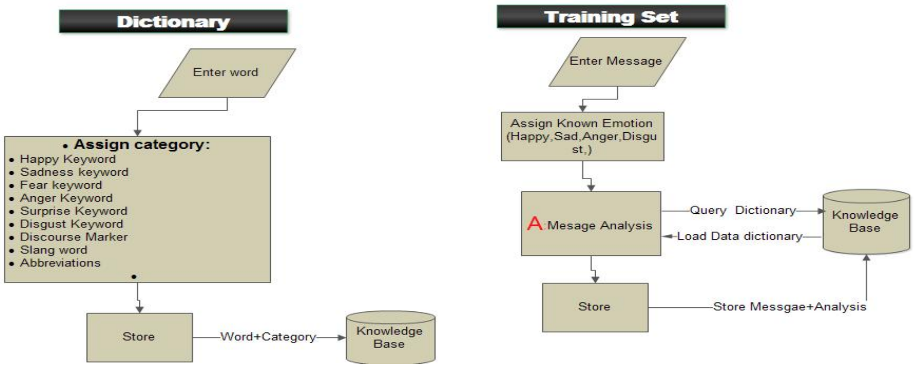

Figure: Training module

2.3 Message Analysis Process

As shown in Figure 1, each training example is analyzed as shown in Figure for a variety of training features as shown in Figure 2.

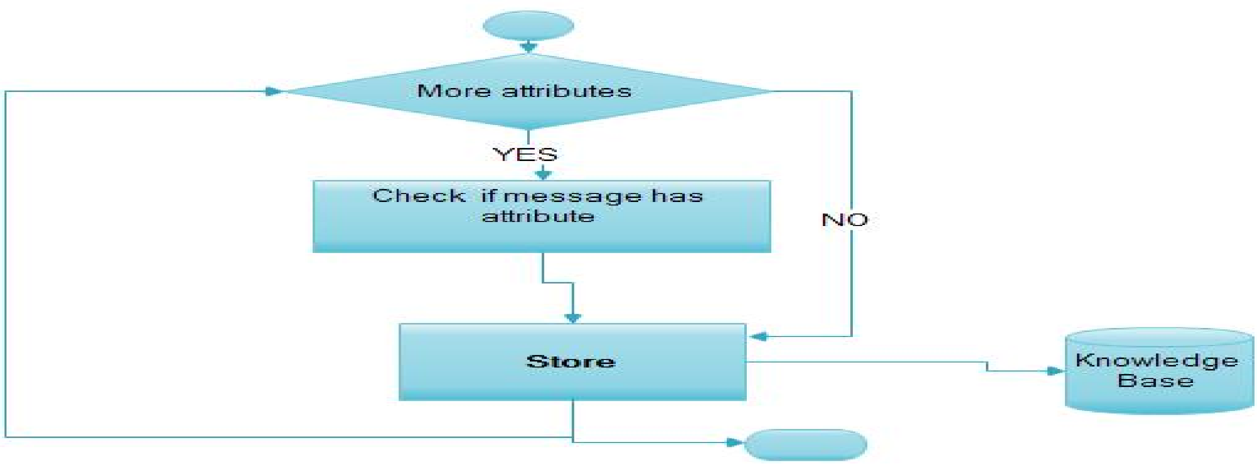

Figure 2: Message analysis process(loop)

The message analysis process results in a message map shown in Figure 3.

Message	Has Capitalizations	Has Abbreviations	has Discourse Markers	has Anger Keyword	Has Exclamation Marks	Has Fear Key word	Has FullStop Repetition	Has Happy Keyword	Has Question Marks	Has Sad Keyword	Has Slang word	Has Surprise Keyword	Is Long Response	Is short Response	is Very long Response	is Very short Response
Msg (Values)	True	False	True	False	False	True	True	False	False	True	True	True	True	True	True	False

Figure 3: Message map

2.4 Emotion Estimation Process

The initial step of analyzing an emotional scenario is to define the emotions relevant to the application scenario. This research focuses on the six (basic) emotions from Ekman (1993) research: happiness, sadness, anger, fear, surprise and disgust. The input message is analyzed to derive features described above. The attributes are used as the features in the training set.

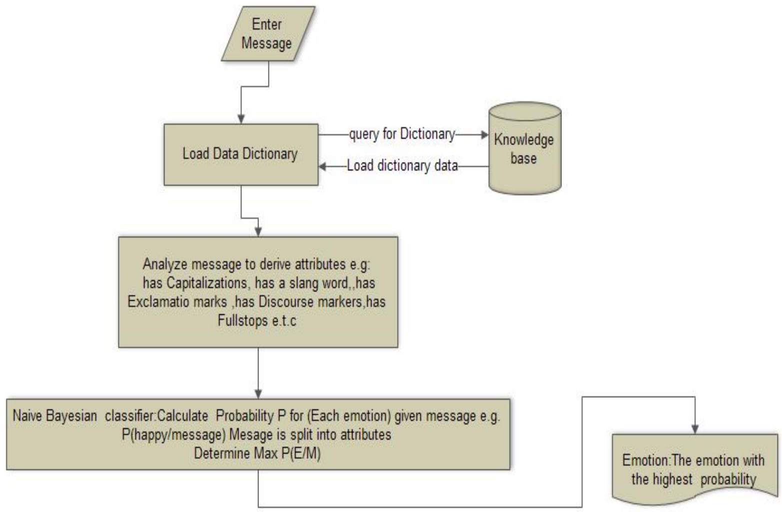

Figure 4: Emotion estimation process

2.4.1 Emotion Recognition Algorithm

- *Input:* a document *d*
- A fixed set of classes *C={c1,c2,…,cJ}*
- *Output: a* predicted class *c∈C*

  Naïve bayes Algorithm: based on Bayes rule

  Bayes Theorem: P (A/B) = P (B/A).P (A)/ P(B)
- Applied to the emotion estimation Process

  General: P (Emotion/Msg) = P (Msg/Emotion).P (Emotion)/ P (Msg)
- Applying the naïve Bayes: Dropping the denominator

  P (Happy/Msg) = P (Msg/Happy).P (Happy)
- Message is split into attributes: In this case the Message analyzed for the following features:
  - hasCapitalization hasFearKeyword
  - hasExclamationMarks hasSurpriseKeyword
  - hasFullstopRepetition hasDisgustKeyword
  - isLongResponse : AngerKeyword
  - isVeryLongResponse isShortResponse
  - isVeryShortResponse hasQuestionMarks
  - hasDiscourseMarkers hasSlangWords
  - hasAbbreviations hasHappyKeyword
  - hasSadKeyword

  = P(Msg/Emotion).P(Emotion)

  P(x1,…, xn | c) = P(x1 | c)•P(x2 | c)•P(x3 | c)•…•P(xn | c):

P (Happy/A, B, C, D) =P (Happy)*p (a/happy)* p(b/Happy)*…Other attributes…………….)
cMAX = argmaxc P(x1, x2,…, xn | c)P(c)
= argmax(P(x1, x2,…, xn | c)P(Emotion))

2.4.2 Algorithm implementation:

To compute the probability of a certain emotion (P (Emotion))

- count-all : "SELECT count(*) AS count FROM training_data"
- count-emotion : "SELECT count(*) AS count FROM training_data WHERE emotion = ?" emotion
- P(emotion) = count-emotion)/ (count-all
- Emotion property value= "SELECT count (*) AS count FROM training_data WHERE emotion =? AND "property "=?
- p-property-emotion = (property value)/ (count-emotion)
- Property stands for the features mentioned in section 2.3.1
- Emotion-value= (p-emotion * property-emotion/*…..*
- get-max-emotion: Compare Emotion-value: The process is repeated for all classes of emotions, the algorithm returns the emotion with the highest probability (P (Max))

3.0 Chat Application

Based on the affect recognition model described in section 2, the chat system was developed as a web based application running through the internet browser, the developed chat system is endowed with emotional intelligence. The system extracts the emotion from the user's input sentence. The web based application is written in JavaScript using node.js platform. The chat system database was created using My SQL 5.0. In the following sections, the chat system is described.

3.1 System Architecture and User Interfaces

The architecture of the chat system is depicted in Figure 5. On the server side, the Chat Engine module is used to listen to incoming messages. The module evaluates the emotion of the incoming messages and returns the result back to the Chat Application module. Once the emotion of a message is estimated, an avatar appears with affective expression i.e. Sad, Happy e.tc. As shown in Figure 5 .The analysis of emotion is based on an emotion database and the algorithm mentioned in section 2.

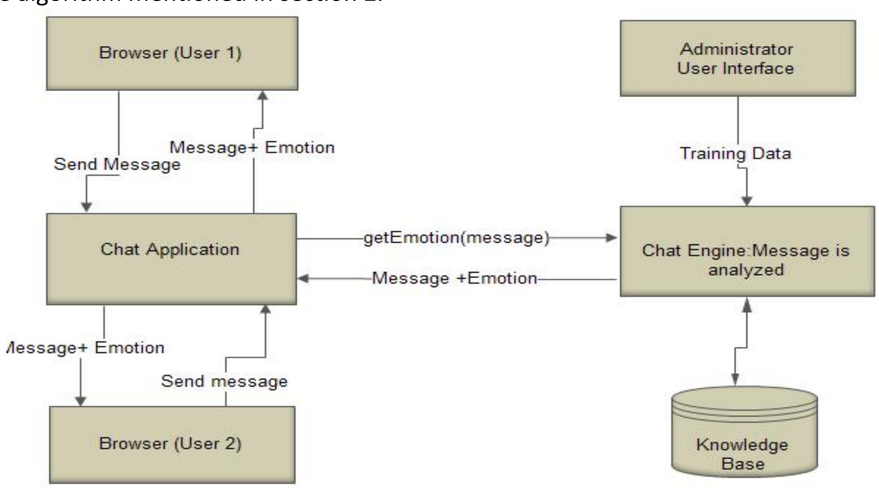

Figure 5: Architecture of the chat system

3.2 Chat Engine Module

The chat engine has two interfaces as described in Figure 6.

3.2.1 Dictionary: Word Categories

The interface allows the administrator to enter words and their categories; as described in section.

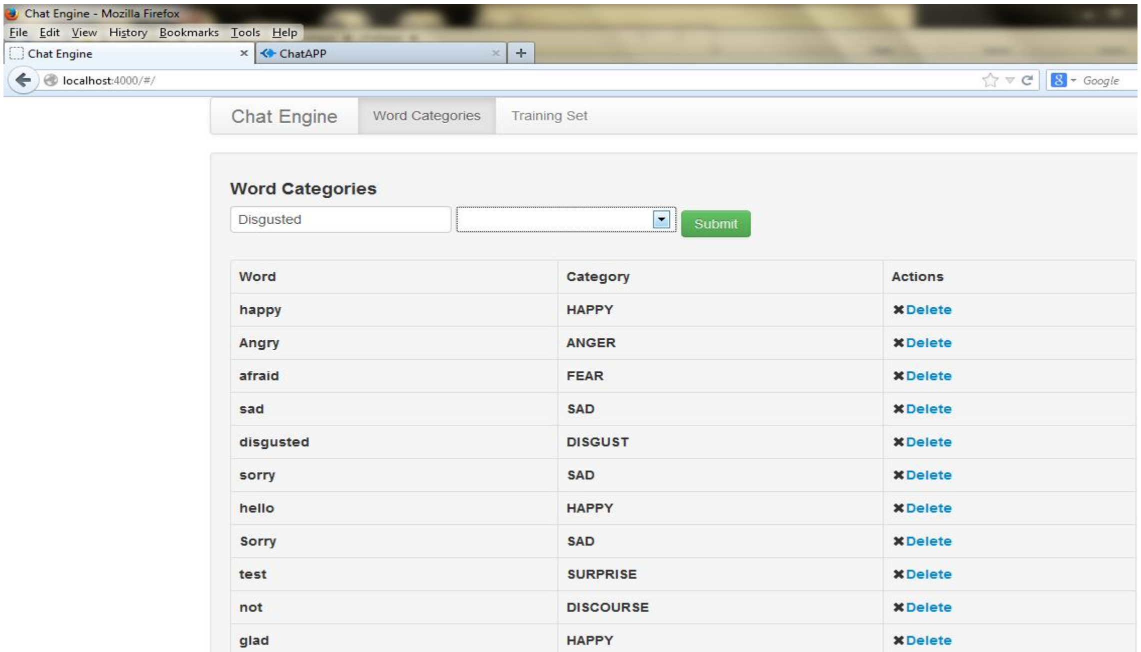

Figure 6: Dictionary interface

3.2.2 Chat Engine: The Training Set

This interface allows the training messages to be submitted to the training data table with the associated emotions. The messages are then analyzed for training features as shown below, this is then saved to the training data table in the chat App database.

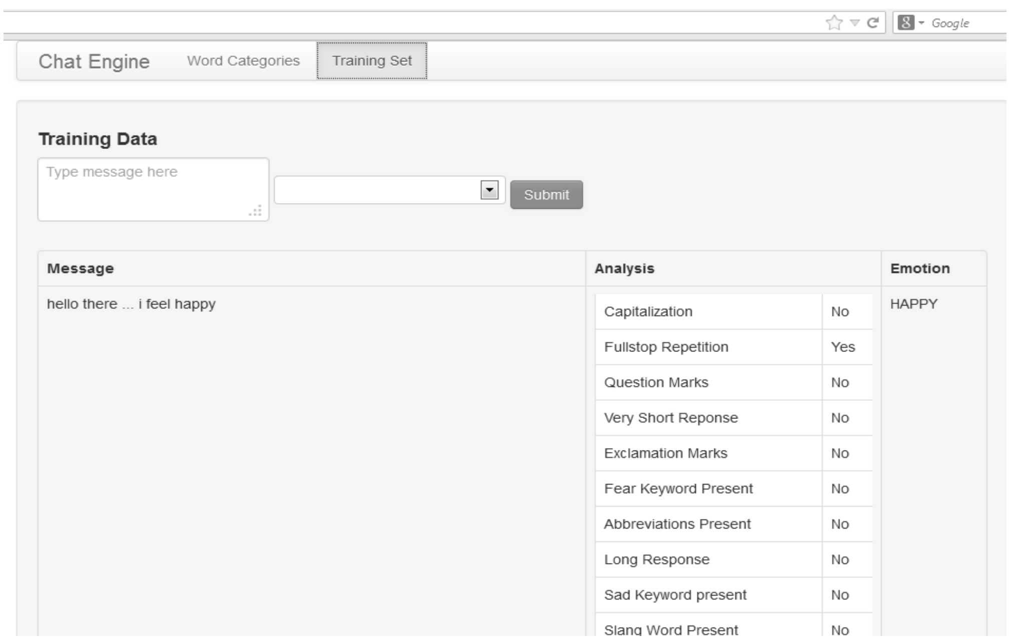

Figure 7: Training interface

3.3 Chat Application

The chat application is designed as a broadcast, and the messages sent can be seen by everyone that is logged to the chat, the text input at the bottom allows users to type and send the messages by clicking the send button. Once the user is logged to the system, they are able to see the other users that have joined the chat .The main window of the chat system while in online conversation is shown in the Figure 8.

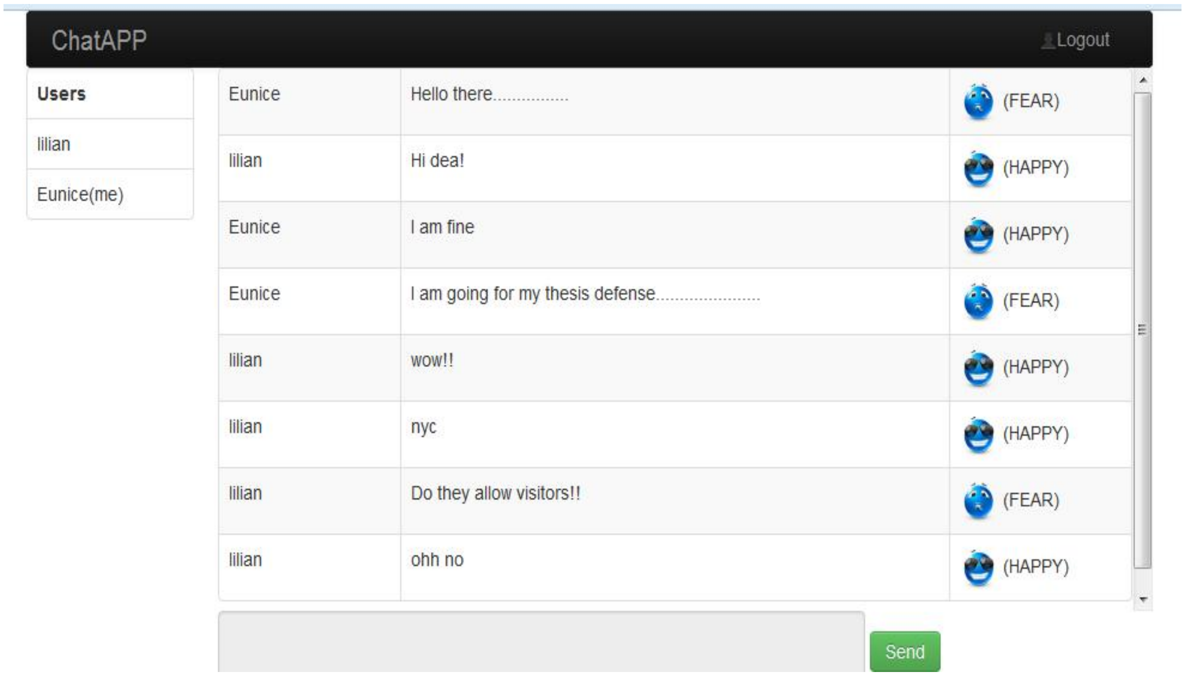

Figure 8: Chat interface demonstration

4.0 Conclusion and Future Work

This paper presents a supervised learning approach toward automatic emotion recognition from text. The proposed algorithm is capable of handling correct text messages as well as messages written in informal style, the affect recognition model is designed to take into consideration of the peculiarities of online language. Future work would involve incorporating more emotions and intensities, e.g., levels of happiness etc. as well as improve the level to which the system is able to interpret informal messages since messages are open to a variety of interpretations, or possibly misinterpretations.

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