Adaptive Machine Learning Approach for Emotional Email Classification

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Abstract. Emotional e-mail classification is one of the important issues in the service oriented organizations. E-mails are served in a first come first serve basis. Few e-mails express the unfair treatment or dissatisfaction of service. It is essential to serve such e-mails with a high priority. In this paper an attempt is made to identify such mails which express the strong emotions of the customers / stakeholders. This system classifies the e-mails in to three categories via positive, negative and other mails. An adaptive machine learning algorithm that uses combined SVD and KNN methods is developed to solve the problem of emotional e-mail classification. Also an emotional dictionary is used as a central component of this system that serves various emotional words and phrases for classification. The system also adaptive in nature and adapts various new words and phrases that explicates the emotion.

Keywords: E-mail Classification, Emotion, Machine Learning Algorithm, Emotional Dictionary.

1 Introduction

Electronic mail is a method of exchanging digital messages from an author to one or more recipients. Modern email operates across the Internet or other computer networks. Today's email systems are based on a store-and-forward model. Email servers accept, forward, deliver and store messages. It is a most preferred communication channel for any service. Educational Institutions are not exception to this. Take for instance, an educational institution which houses around 5000 students and receives the complaints, grievances etc. through email from students as well as parents. Such educational institutions receive on average of 1000 – 1500 emails per month. All emails are served on a first come first serve basis. But, a few e-mails often contain complaints about unfair treatment due to negligence and incompetence. Similarly, a few emails express their high service satisfaction and in such cases it is essential to record messages to measure the value of the service to provide high-quality service.

The emotion fundamentally involves "physiological arousal, expressive behaviors, and conscious experience". Emotion is associated with mood, temperament, personality and disposition, and motivation. These emotions are described by different hierarchy

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such as primary, secondary and tertiary emotions [1]. Emotions involve complex processes produced by interactions between motives, beliefs, percepts, situations etc. In general the emotions are primarily classified as positive and negative emotions.

In psychology, emotional expression is observable verbal and nonverbal behaviour that communicates emotion. Emotional expression can occur with or without self-awareness. An individual can control such expression, to some extent, and may have deliberate intent in displaying it. A method of expression of emotion is through the verbal communication. Verbal communication is usually understood as the process of communication through sending and receiving word messages. i.e., language is the only source of communication, there are other means also. Written texts have verbal elements to recognize the emoticons.

In this paper an attempt is made to classify the e-mail student and parent messages and emails based on the emotional status. The e-mails are classified into different hierarchical levels as given by Parrott, W. 2001[1]. It contains two levels; at the first level it classifies the messages in to three levels, viz. positive emails, negative emails and other mails. In the case of second levels, it classifies the emails as per the hierarchy.

In this approach we have used adaptive machine learning algorithm that uses the combination of K-NN and SVD algorithms for the classification of emails. Certain words and phrases are already included in the levels of emotional responses, which is helpful in identifying the emotional content of the email. The algorithm introduced is based on adaptive learning, in which the positive/negative emotion n-gram list is learned from the systems previous classification records. An adaptive method can be more efficient, as the emotion n-gram list is modified by the new classification records.

In this paper in Section 2 reviews the previous works in emotional email and message classification. Section 3 explains the components and functions of emotional e-mail classifier in details. Section 4 presents the machine learned classification algorithm in detail. Section 5 gives the implementation as well as experiment results. Section 6 concludes this paper.

2 Previous Works

In 2004, Soo-Min Kim [2] made at attempt to identify sentiments (the affective parts of opinions) from the opinions. This system is able to automatically find the people who hold opinions about that topic and the sentiment of each opinion. Further, Cecilia Ovesdotter Alm, et. al, 2005 [3] explores the text-based emotion prediction problem empirically, using supervised machine learning. The goal is to classify the emotional affinity of sentences in the narrative domain of children's fairy tales, for subsequent usage in appropriate expressive rendering of text-to-speech synthesis. Narendra Gupta[4] and his team, in 2010 made an attempt to present knowledgeable responses to customers' emails are critical in maximizing customer satisfaction. This work reflects customer frustration, dissatisfaction with the business, and threats to either leave, take legal action and/or report to authorities.

Extensive work has been done on emotion detection. In 2003, Liu Hugo [5] and his team had made an attempt to predict basic emotions within text. The authors adopt the

notion of basic emotions of Paul Ekman, 1993 [6], and use six emotion categories: ANGER, DISGUST, FEAR, HAPPINESS, SADNESS and SURPRISE.

The work on emotion classification from the point of view of natural speech and human computer dialogues is fairly extensive, e.g. Klaus Scherer's work on vocal communication of emotion [7], Litman and Forbes-Riley's work on text-to-speech synthesis (TTS) [8]. A short study by Sugimoto [9] to addresses sentence-level emotion recognition for Japanese TTS. Their model uses a composition assumption: the emotion of a sentence is a function of the emotional affinity of the words in the sentence. They obtain emotional judgments of 73 adjectives and a set of sentences from 15 human subjects and compute words' emotional strength based on the ratio of times a word or a sentence was judged to fall into a particular emotion bucket, given the number of human subjects. Additionally, they conducted an interactive experiment concerning the acoustic rendering of emotion, using manual tuning of prosodic parameters for Japanese sentences. While the authors actually address the two fundamental problems of emotional text-to-speech synthesis, their approach is impractical and most likely cannot scale up for a real corpus. Again, while lexical items with clear emotional meaning, such as happy or sad, matter, emotion classification probably needs to consider additional inference mechanisms. Moreover, a naive compositional approach to emotion recognition is risky due to simple linguistic facts, such as context-dependent semantics, domination of words with multiple meanings, and emotional negation.

3 Emotional E-Mail Classifier

This system is designed to take the stored e-mails from the server and classify the e-mail in the respective category. The system is designed with the following components, 1. Emotional Dictionary, 2. Classifier and 3. Phrase Extraction Component. These components are explained in detail.

3.1 Emotional Dictionary

It provides a list of emotional words and phrases required to run the system. At the initial stages a list of independent emotional words and phrases are taken from web. The user through the user interface agent to provide systems ontology enters these phrases and words. Later additions of words and phrases will automatically take-place after the identification of new technical phrases. Usually it considers the occurrences of the emotional words and phrase for the new phrase addition.

3.2 Classifier

The classifier initially computes the relationship between the emotional words/phrases as well as the e-mails using the K-NN approach. If it is able to find a match then those e-mails contain the phrases are taken for the analysis. Later, the system arranges the list of words/phrases in the third level sub-category versus list of documents taken for emotional classification. After forming this matrix, the system performs the Singular

Value Decomposing of the given matrix. Then, it computes the correlation between the document and list of words/subcategory. If it finds -1 or +1 then the same document is considered to fall under the emotional category, otherwise it will move to the next category. If it is not able to find the match with any of the given category then the e-mail considered to be the non-emotional e-mail.

3.3 Phrase Extraction Component

This emotional phrase-extraction component performs a list of preprocessing steps. These preprocessing steps involve stop-word elimination, phrase comparison and phrase matching. The phrase comparison through the emotional dictionary is provided with the system. It also does the phrase matching to eliminate slight differences and it will record the new phrases in the emotional dictionary. After extracting the phrase, the system will frame the emotion-matrix.

4 Machine Learning Algorithm

The classifier learns from the set of rules that are passed onto it and based on the level of similarity in the email content and the emotional phrases, further the classifier decides the appropriate Parrot category to which the e-mail should belong. The classifier uses a combined SVD [10] and K-NN Algorithm which is presented below. This choice of machine learning algorithm is not strategic and there is no reason to believe that SVMs or maximum entropy–based classifiers will not perform equally well. The SVD is able to exactly identify the phrase/word relation ship with the words. Also, the number of emotional words and phrases are less and so there would not be any dimensional reduction problem.

The classifier also adds the new emotional words and phrases in the respective categories. In SVD, a rectangular matrix is decomposed into the product of three other matrices. One component matrix describes the original column entries in the same way, and the third is a diagonal matrix containing scaling values such that when the three components are matrix-multiplied, the original matrix is reconstructed. The reconstructed two-dimensional matrix that approximates the original matrix and a few highest values are selected to reconstruct the original matrix.

Each document in the particular sub-hierarchy represents the rows and each phrase with respect to the document is represented as the column. Learning human like knowledge consists in formulating a bi-variate frequency table with row i representing the ith phrase and column j representing the jth document (or between any two entities) and f_{ij} evaluated by the Shannon's measure of information $\sum p \log p$. This together with the dimension reduction will constitute the constraint satisfaction for prediction between the observed and the expected values to make classification. Actual data pertaining to any two measurable entities (phrases and sentences, text classification in digital libraries, etc.) will have to be collected. Sets of examples pertaining to each of the two entities can be exhibited in a bi-variate frequency table for determining the relationships between any two examples.

Machine Learning Classification Algorithm

Input: M - Set of E-mails $\{m_1, m_2, \ldots\ldots m_i\}$, N – Set of emotional words and phrases $\{ n1, n2, n2 \ldots n_j \}$, X – Set of emotional E-mails $\{ x_1, x_2, \ldots\ldots x_r \}$

Output: O- $\{o_1, o2 \ldots o_r\}$ a set $o_1 = \{x1, u\}$ List of emotional mail x_1 with category u.

Step 1: Begin
Let $R = \{r_1, r_2, r_3 \ldots\ldots\ldots r_i\}$
Let r_1 = List of all words and phrases in message m1, r_2 = List of all words and phrases in message $m_2 \ldots r_i$ list of all words and phrases in message m_i.
Let $S = \{s_1, s_2, s_3 \ldots\ldots\ldots s_M\}$
Let s_1 = List of all emotional words and phrases in message x_1, s_2 = list of all emotional words and phrases in message $x_2 \ldots s_r$ list of all emotional words and phrases in message x_r.

Step 2: Do for k = 1 to i
If $((N \times r_i) >= 1)$ then
Add r_i in to X;
End if
End do

Step 3: Do X Not (empty)
For k= 1 to i
A = SVD (N, S)
If $(Corr(n1, s_k)) >= 0.8)$
Add s_k to respective N (Change the Emotional Phrase List)
Add (x_k to O)
End If
End For
End Do

Step 4: Procedure End.

5 Simulation Experiment and Evaluation

The system under consideration is simulated using apache e-mail server. In this present experiment the server is hosted with IBM Tehiti server to run the Aglets [11]. The Aglet is a Java based autonomous agent. The Aglets Workbench, developed at IBM's research labs in Japan, is aimed at producing stand-alone agents. The specific emotion agent, phrase-extraction agent and user interfaces agent are developed using these aglets. The standard emotion dictionary developed in this system stores the required emotional words and phrases of each category.

We performed several experiments to compare the emotional e-mail classifier using machine learning algorithm with the combination of K-NN and SVD approach. In these experiments, the Parrot classification system at the three-level hierarchy there

exists nearly 135 categories and the present system is trained with few e-mails under each category. To evaluate this approach the server is hosted with sum of 300 e-mails collected form Aarupadai Veedu Institute of Technology e-mails received from parents, students and other suppliers. To evaluate this approach the data sets collected for experimentation are given to designed system and results are compared with Narendra Gupta's work. In order to evaluate the effectiveness of classification system two metrics are measured. The well known metrics Precision, Recall (George Forman 2003) are measured and are shown by

$$\text{Precision} = \frac{\text{Number of E-mails Classified under particular category}}{\text{Total number of E-mails taken for classification}}$$

$$\text{Recall} = \frac{\text{Total Number of E-mails Classified by Machine}}{\text{Total Number of E-mails Classified by Human Expert Judgment}}$$

Table 1. Precision - Recall Comparison

Approach	Precision	Recall
N-Gram Features – Narendra Gupta	0.45	0.61
Combined KNN-SVD Method	0.61	0.72

6 Conclusion

An attempt is made in this paper to design and develop an adaptive emotional e-mail classification using Parrot hierarchy. This work has revealed that the machine learning algorithm using a combined K-NN and Latent Semantic Analysis approach enables one to identify the related emotional e-mails effectively. The initial system is setup with a few set of predefined words and phrases and later on it acquires all the set of phrases. It also yields good results in terms of emotional text identification. This classification system is able to achieve the defined objective of deep level of classification compared to the previous work (Narendra Gupta's) which just identifies the emotion.

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