Analyzing Emotion on Twitter for User Modeling

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Analyzing Emotion on Twitter for User Modeling

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Analyzing Emotion on Twitter for User Modeling

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Abstract

With the development of networks, social platforms play an indispensable role in people's daily lives. As the most popular microblogging platform, Twitter has a vast amount of information available in the form of tweets shared by millions of users. Since this data stream is constantly growing, it is difficult to extract relevant information for users. More and more people want to benefit from these data and get a personalized service from Twitter. Extracting the semantic meaning of Twitter and modeling the interests of users allows people to enjoy a personalized service on Twitter. Meanwhile, research shows that people tend to express their emotions on Twitter. These emotional tweets usually clearly express the users' preferences compared with other normal tweets. Therefore, our goal is to design some emotion-based user modeling strategies which exploit these emotional data.

In this thesis, we introduce and analyze the approaches for detecting emotion on Twitter. First we evaluate and compare the performance of our approaches of emotion detection. Then we use these approaches of emotion detection to analyze our Twitter sample dataset for the purpose of user modeling. We also propose a set of emotion-based user modeling strategies on the Twitter platform based on these detected emotional data. Furthermore, we evaluate our emotion-based user modeling strategies and investigate their impacts on normal user profiles in the context of recommendation systems. Our results show that our emotion-based user profiles enhance the quality of user profiles and have a better performance in terms of recommendation accuracy.

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Preface

This master thesis is my last task for my master study in Delft. My study in Delft started in August 2011 when I decided to follow the track in web information systems group. I am interested in this area since web information has been a hot spot in computer science area for a long time. With the development of social networks, it will stay popular in the future as well. I finished most courses in the first year and started doing my thesis in October 2012. I did a literature survey and chose this topic at the beginning of November. Instead of doing my thesis in a company, I did the whole thesis in the web information systems group. The main reason is that I also wanted to experience real research study and see whether I have the potential to be a PHD student.

At first, things were not so clear to me. It took me some time to find the right direction to start. When finishing the literature survey, I had some vague ideas. After some group discussions and meetings with my professor and daily supervisor, my thesis topic became to clear. And now I feel confident enough to present my thesis work and say that I made a good decision to do this project in the WIS group.

I really want to take this chance to thank my supervisor Prof. Geert-Jan Houben. I would like to thank him for allowing me to do my thesis in the web information group. During my thesis work, he was always kind and he had the patience to help me at group meetings and with mails. With his skillful and helpful guidance, I overcame some difficulties and found the right direction for my thesis in a short period of time. He did not only give me detailed advice, but also taught me a way of thinking. His efficient way of working also impressed me. During my thesis work, I received useful feedback.

Secondly, I want to express my thanks to my daily supervisor QiGao. As a PHD student, he is experienced in his research area. He gave me many detailed suggestions from the direction of my thesis to skills to use for presentations. When I had any problems, he would try to help me as best as he could. At the weekly meetings, I was always inspired by his suggestions and guidance. I also would like to thank Bozzon and Claudia. During the group meetings, they always helped me by offering the researchers' perspectives.

Finally, I would like to thank all of my friends and family. Without their support, I could not have done my degree course in Delft. I hope you enjoy reading my thesis.

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1 Introduction

The development of social network platforms has given people a new way to generate and consume a great deal of information on the web. In the past, people used to get information from portal websites. A large number of websites provide a long list of topics varying from politics to entertainment. These traditional online information sources are useful but less efficient because they often contain redundant information. However, since the arrival of online social network platforms, people tend to get information from these platforms because of their fast and efficient features. These platforms are available for users to choose the information source they are interested in. And also a large number of social network platforms such as Twitter, Google+, and Facebook provide information for users.

Twitter is the most popular microblogging platform in the world. It is also the fastest growing social network platform and has a dominant position in the area of mircroblogging. More than 500 million registered users post 340 million twitter messages every day, sharing their opinions and daily activities. Compared with regular microblogging platforms, Twitter messages are much shorter. You are only allowed to post 140 characters or less in one Twitter message. This feature makes Twitter easier for people to get the main point from the massive amount of information available online. Depending on the need of the users, Twitter users can follow whichever people and information source they prefer. With all of the advantages mentioned above, Twitter thus has become a powerful platform with many kinds of information from worldwide breaking news to purchasing products at home.

In the last few years, the information streams on Twitter have experienced an unbelievable increase in the popularity of this social network. The users dispose a massive amount of information about different aspects. However, not all of the information is useful for users and each user has their own interests and preferences. There is urgency for users to have personalized services. Nowadays, more and more personalized services are provided to benefit the users. People need this personalized service to make their fast-paced lives more efficient. Every day, a large amount of information is published by users on the Twitter platform. These data relate to users' behavior and many research studies therefore focus on Twitter and this data collection. One of the research studies in the field of Twitter is user modeling. In order to provide a personalized service, researchers started to explore ranking and recommendations of web resources referenced from Twitter. A large amount of research focus on modeling users' interests based on users' published tweets data. And these studies will be presented in this thesis.

Regardless of the tweets' content and Twitter's potential use, researchers also noticed that tweets often convey pertinent information about the users' emotional states [1]. Emotion analysis on Twitter has thus become an important research issue in the microblogging area. Most research related to emotion focuses on the sentiment classification on Twitter [2] [3].

A number of features and methods for training classifier for sentiment on Twitter platform have been researched in the past few years with varying results. There are also some other research studies related to emotion analysis on Twitter. One of the studies in this area is about getting feedback about products by extracting the customers' emotion on the Twitter platform. Also, investigating public attitudes by extraction of emotions from Twitter messages has been the focus of previous studies [1].

Our idea for this thesis was generated by combining the emotion and the user modeling parts on Twitter platform. The intuition is straightforward. Since emotion plays an indispensable role in Twitter, we may expect a better strategy for constructing the user profile when we take users' emotions into consideration. Combining emotion and user modeling is not a totally new idea. Some previous studies already focused on this combination and they proved that the combination of emotion and user modeling could improve the quality of user profile and recommendations accuracy [4]. However, most of these studies have a user-interaction part to collect the emotive response from users and no one has combined emotion and user modeling on the Twitter platform. The research study of this thesis is to analyze the emotion features in Twitter and add these users' emotion features in user modeling strategies. All of these details will be presented in the rest of this thesis.

1.1 Research objective

To combine emotions and user modeling on Twitter, we designed several research questions to go through our whole design of this thesis work step by step. Within this thesis, we will answer the following research questions:

1. How can we detect emotion from Twitter data?

This question is the basis of our whole research project. To make this research question much clear and concrete, we define this basic research question in the following way.

Given a tweet T from a specific user U, design an approach of emotion detection, trying to detect user's emotion E for user U in tweet T.

Emotion detection in tweets is always a main issue in Twitter research areas. Different approaches were proposed in previous works. Most of these emotion works are related to train the classifier for emotion classification. Rather than finding a new approach for emotion detection on twitter, we focus on analyzing the emotion for user modeling. We noticed that Twitter's features are short and informal. To detect users' emotive response from Twitter messages for user modeling, our approaches of emotions detection should be carried out with the aim of high accuracy to identify the emotional states.

Most previous studies designed an interactive part to acquire emotive responses from users [4] [5]. And then these emotive responses were quantified and used as affective parameters in their user modeling studies. We do not have any interaction parts like previous work. In the emotion part, we will investigate what approaches we can use to detect users emotions in Twitter messages. Are there any differences between different approaches of emotion detection in terms of accuracy? To answer these questions, we analyzed twitter users' emotion on our user sample and all of these will be presented in chapter 3 emotion part.

2. How can we construct user profiles from micro-blogging activities on Twitter? How can we construct the emotion-based user profiles by different strategies? How do different emotion-based user modeling strategies impact the characteristics of user profiles?

The user modeling is the main part of thesis. In this part, there are two steps to go. Firstly, we have to investigate how we can construct the user profiles from Twitter messages. There are some related studies [6] [7] regarding this topic. And our thesis is based on their research. The second step is to put emotion features in our user modeling strategies. As we described in the introduction part, combining emotions and user modeling is not a completely new area. There are some related studies that have investigated this topic, but no one has combined them on the Twitter platform before. In our thesis, the most important issue is how we can combine these two parts, emotion and user modeling, in our emotion-based user modeling strategies. Except these two steps, we will also analyze impacts of emotion-based user profiles on our user profiles. How can we model users' emotions in our strategies? What are the differences between these strategies? And these questions will be answered in chapter 4 emotion-based user modeling part.

3. How can different user modeling strategies impact the recommendation performance? To which degree are the emotion-based user profiles constructed by the different user modeling strategies appropriate for recommending tweets compared with normal user profiles?

This set of questions was designed for our evaluation part. To evaluate the quality of our emotion-based user profile, the recommendation systems will be used. Exploiting recommendation systems to evaluate the user profiles is not a new task. Many related studies were done before [4] [5] [7]. The underlying assumption is, if our emotion-based user profiles have a better quality than the normal user profiles, the recommendation accuracy of emotion-based user profiles will be higher than the normal user profiles. In the evaluation part, we will try to find out whether our emotion-based user modeling strategies are better than the normal user modeling strategies. All of the evaluation of our emotion-based user modeling strategies will be presented in chapter 5.

1.2 Research methodology

As has been mentioned, the main track of this thesis is to design a set of user-modeling strategies based on the user's emotions on Twitter platform. In order to gain some background information about this issue, we did a literature survey to acquire the basic knowledge about this topic including the emotions and the user modeling two parts. From previous studies [4] [5], we were aware of the fact that using emotion features in user modeling could improve the quality of user profiles. After we realized this, the issue was transformed to two parts. The first part is how we can detect the users' emotion to get the emotion features from users' Twitter data. And the second part is how we can put these features into our user modeling strategies. To achieve these, we used related approaches to get the emotion features from tweets and put these features in normal user profiles to construct the emotion-based user profiles. Evaluation is performed on recommendation systems to check the performance of our emotion-based user profiles followed by analysis to explain the reasons behind current results.

1.3 Thesis outline

Chapter 2 states the background by describing the relevant concepts and existing studies about our thesis topic. In chapter 3, we present our approach to detect the emotion in Twitter messages and the sample dataset is analyzed by our approach. Next, in chapter 4, we present our main design for emotion-based user modeling strategies at both high level and detailed level together and followed by the analysis part. The evaluation is performed in chapter 5. The conclusion and future works are discussed in chapter 6.

2 Background

Chapter 2 contains some background which is helpful in designing our work. We will first introduce some basic concepts in section 2.1 and then give the related work part in section 2.2. Our main objective of this thesis is to combine emotion and user modeling. Basic concepts of these two parts will be presented in subsection 2.1.1 and subsection 2.1.2 respectively. Also, the basic concept of the recommendation system will be discussed in subsection 2.1.3 since we use recommendation systems as our evaluation platform.

2.1 Basic concepts

Before we dive into the thesis, some basic concepts we use in this work will be explained. In this section, we will explain our concepts from three perspectives: emotion, user modeling and recommendation systems.

2.1.1 Emotion

Emotion definition

"In psychology and philosophy, emotion is a subjective, conscious experience that is characterized primarily by psychophysiological expressions, biological reactions, and metal states." [8]. Particularly, in computer science area, researchers focus on affective computing, which is the branch of the artificial that deals with the design of the systems and devices that can recognize, interpret, and process human emotions [9]. In this thesis, we focus on the emotions in Twitter messages posted by Twitter users. And in the following parts, the concepts related to emotion will also be introduced.

Emotional labels

Emotional labels [10] are defined by the symbols represented users' emotion in Twitter messages. There are different emotional labels which are used for identification of emotion in Twitter. In this thesis work, we specify two types of emotional labels: affective words and emoticons, which will be explained in the following.

Affective words

Affective words [11] are the words influenced by or resulting from the emotions. In computer science area, researchers also focus on proposing the different affective words lists for emotion detection in text with the purpose to classify the users' emotions. Different affective word lists were proposed by different researchers. In chapter 3, we will discuss these affective word lists and explain our design of affective word list.

Emoticons

Emoticons are defined as constructed by combining punctuation marks (sometimes along with characters or numerals) on the computer keyboard to represent emotions or semantic nuances such as happiness, sadness, or qualification [12]. To be more concrete, we will give a set of emoticon examples [13] as follows.

Emoticons	Emotions
: -)	happiness, humor
: -o	shocked, amazed
: -(	sadness, displeasure
: .(	crying
; -)	winking
: -]	sarcastic

Table 1 Examples of a set of emoticons

There are a large number of emoticons representing different facial expressions. Different people may have different preferences for using emoticons. For instance, according to the research results, people from Asian countries use the different emoticons to express their emotions in microblogging or text messages compared with European people [14]. In this thesis, we will use a set of emoticons which were used in previous studies [2].The details will be discussed in chapter 3.

2.1.2 User modeling

User modeling definition

User modeling describes the process of building up and modifying a user model with the aim to provide the personalized service according to the user's specific needs [15]. In this thesis, we exploit tweets data to construct the user profiles in order to give the recommendation based on users' preference.

User profile

User profiles can be used to store a description of the characteristics of a person. This information can be exploited by systems taking into account the persons' characteristics and preferences [16]. On the Twitter platform, we extract the users' interests of topics from published tweets to construct the user profiles and then use vector space model to represent the user profile. Vector space model (term vector model) is an algebraic model for representing text document as vectors of identifiers [17]. It is used in information filtering, information retrieval, indexing and relevancy rankings. We will take a content-based recommendation system as an example to explain the vector space model. In content-based recommendation systems, both user profiles and candidate profiles are represented as these two vectors.

$$d_j = (\omega_{1,j}, \omega_{2,j}, \omega_{3,j}, \omega_{4,j}, \dots, \omega_{t-1,j}, \omega_{t,j})$$

$$q = (\omega_{1,q}, \omega_{2,q,}\omega_{3,q}, \omega_{4,q}, \dots, \omega_{t-1,q}, \omega_{t,q})$$

These two vectors have the same dimensions and each dimension corresponds to a separate term and an assigned weight in vector d_j and vector q respectively. And content-based recommendation systems will give the recommendation results based on the cosine similarity between the vector of candidate profiles and the user profiles.

<u>Data sparsity</u>

Data sparsity is one of the main problems for user modeling, which means a lack of user related information when modeling a user [18]. When we try to recommend some items, this problem will lead to the missing links between user profiles and recommendation items. This problem is quite common in user modeling. For instance, research studies try to address cold start problem, which is one of the data sparsity problems, in the context of recommendation systems [19]. Cold start problem means systems do not have any information related to the new users. Researchers proposed some approaches to overcome or minimize data sparsity aiming to provide accurate recommendation items to users. Different ways of enrichment for user profile are explored in these studies [6] [20].

2.1.3 Recommendation systems

<u>Recommendation systems definition</u>

Recommendation systems can be defined as "any system that produces individualized recommendation as output or has the effect of guiding the user in a personalized way to interesting or useful objects in a large space of possible options " [21]. Nowadays, massive amount of information rushes into people's life and recommendation systems could help people to find their own preference. In general, there are two different recommendation systems: collaborative recommendation systems and content-based recommendation systems. The details related to these two systems will be discussed in the following paragraphs.

<u>Collaborative recommendation system</u>

This is the most mature and widespread type of recommendation system. Instead of focusing on recommendation items, the idea behind of collaborative recommendation system is to measure the similarity between users. The systems will use rated items to construct profiles from interests of users. And the system will find similar users by matching the constructed user profiles. The rated recommendation items from those similar users will be recommended. The underlying assumption for collaborative recommendation system is straightforward. If you can find a user who has similar taste to you, it has high probability that you will also have the same preference as this user.

<u>Content-based recommendation system</u>

This type of recommendation system is a different story. The content-based recommendation system rates items by comparing the similarity of the items to other items that user has already preferred. Usually, the user profiles and candidate profiles are represented by a set of key words. However, some words may characterize the recommendation items better than other words. According to the importance of different words, the content-based recommendation system will assign different weights to different words to enhance the recommendation accuracy. These weights could indicate the importance of each keyword. In this thesis, our evaluation will be performed on content-based recommendation systems.

2.2 Related work

In this section, the related work part will be discussed. We will also present our related work from three main components of our thesis: emotion, user modeling and recommendation systems.

2.2.1 Emotion research in microblogging

Long before computer researchers focused on emotion, research into emotion was explored in the field of psychology. The most important issue in psychology area regarding emotion is definition and description of emotion. Ekman defined seven universal emotions, which are classified by observable facial expressions (neutral, anger, disgust, fear, happiness, sadness and surprise) [22]. Likewise, Plutchik proposed the wheel of eight emotions (joy, acceptance, fear, surprise, sadness, disgust, anger and anticipation) [23]. These two definitions of emotion are widespread in the field of psychology. Also, several other definitions have been used as well [24] [25].

With the development of social network platforms, microblogging platforms, such as Twitter, have become a very popular communication tool among internet users. People share their experience or opinions on a variety of topics and discuss current issues on the Twitter platform, which provides a continuous data stream generated by users.

Recently, many research studies have focused on emotion analysis on Twitter. Some of these studies are involved with sentiment classifier on Twitter. Alec et al. proposed a machine learning algorithm for classifying emotions of tweets using distant supervision [2]. Their training data consists of emoticons, which are used as noisy labels. And the results showed their accuracy could achieve 80% when trained with emoticon data. In previous studies [26], Pak et al. showed how to automatically collect corpus for sentiment analysis and opinion mining purpose. By using their corpus, a document could be determined into positive, negative and neutral sentiment. Their evaluation showed that their approach has better performance than previous studies. Some research studies have been focused on users' sentiments toward a specific topic or product. These sentiments on Twitter could be regarded as the feedback of people's attitudes. For instance, Tumasjan et al. conducted a content analysis of over 100,000 Twitter messages with the purpose of finding the relationship between tweets and election results [27]. Their analysis of the tweets' political sentiment showed the close correspondence to the parties' and politicians' political positions indicating that the content of Twitter messages could reflect the political landscape.

Some other emotion analysis research studies on Twitter are with broader issues of detecting emotion on Twitter platform, with the aim of predicting the emotional trend for users. Bollen et al. performed an analysis for all public tweets by using an extended version of the Profile of Mood States (POMS) in their research [1], which is a well-established psychometric instrument. By analyzing their Twitter dataset, they reached the conclusion that "events in the social, political, cultural and economic sphere do have significant, immediate and highly specific effect on the various dimensions of public mood".

In this section, we introduced the background related to the emotions. Several previous studies relating to sentiment analysis on Twitter were introduced. And in the next section, the studies related to the combination of emotion and user modeling will be discussed.

2.2.2 Exploiting emotions for user modeling

User modeling combined with emotions is always an important task for researchers. A large number of research studies have been done in the bio-informatics area. For instance, in Fatma's research [28], they developed a framework for modeling users' emotions from sensory input and interpretations of their multi-modal system. They also proposed an algorithm, which is used in physiological signals associated with emotions in order to recognize the affective states of users via noninvasive technologies.

In the computer science area, modeling the emotion has been researched for a long time as well. Conati et al. presented a model of user effect to recognize multiple users' emotion during interaction with a computer game [29]. Their model deals with high levels of uncertainty involved with recognizing a variety of user emotions by combining information on both the causes and effects of emotional reactions. Researchers are also aware that using affective parameters in user modeling could improve the quality of user profiles as well. In Marko's work [4], they investigated the influence of affective metadata in context of a content-based recommendation system for images. The underlying assumption is that affective data are more close to the user's experience and they are more suitable for separating relevant items and non-relevant items. They proposed an affective modeling approach based on users' emotive response and the results showed that proposed affective parameters could improve the performance of recommendation system significantly. Arapakis et al. presented a novel video search interface that predicts the topic relevance of a video by analyzing emotive response from users. They proposed the method to incorporate the emotions features into user profiles, to improve the recommendation accuracy for unseen videos [5]. Their experiments showed that their approach improved the performance of the recommendations.

2.2.3 Recommendation systems for evaluation of user modeling strategies

As mentioned in the previous chapter, users are overwhelmed by the massive flux of information with the development of networks. In order to benefit the users, researchers focus on user modeling to provide the personalized service to decrease the amount of redundant information. To achieve this purpose, recommendation systems play an important role in matching the needs of the user with product offering available over the web. Different methods like collaborative filtering, content-based filtering and others are available to perform the underlying tasks required to produce useful recommendations to users. There is a need for recommendation system to have users' information (user profile) in order to recommend the right items based on users preference. Since the recommendation results depend on the user profile, recommendation systems are also considered to be one of the important evaluation platforms for quality of user profiles.

Abel et al. developed a framework for user modeling on Twitter which enriches the semantic of tweets with identified topics and entities in their research studies [7]. They measured their user modeling strategies in context of a personalized news recommendation system and results show that their strategies with semantic enrichment could improve the quality of the user profiles. Instead of using Twitter data, Jia et al. built profiles of users' news interests based on their past click behavior in their work [30]. And then they evaluated their user profiles in the context of content-based recommendation systems. The results showed that their approach improved the quality of news recommendation. There are also some recommendation systems based on users' emotions. For instance, Kuo et al. proposed a novel model for emotion-based music recommendations, which is based on the association discovery from film music. And their experiment showed their proposed approach achieved 85% accuracy on average [31].

In this chapter, we presented the background of our thesis from three aspects: emotions, user modeling combined with emotions and recommendation systems. In the first section, we introduced the basic concepts we use in our thesis, and then the related work parts were discussed in the second section. In the next chapter, the emotion analysis chapter of our thesis will be explained.

3 Emotion Analysis on Twitter

In chapter 3, emotion analysis in this thesis will be presented. We will first introduce some emotion research work regarding Twitter, including some of Twitter's sentiments analysis and its web applications. And then the following section explains our approaches of emotion detection. In the next section, we evaluate our approach of emotion detection, and we also analyze users' emotions on the dataset in order to better understand our users' emotion features and the nature of datasets. The summary is given in the last section.

3.1 Introduction

As we discussed in chapter 2, emotion is not a new issue in the area of computer science. With the development of microblogging on social networks, people began to express their opinions and emotions on Twitter platform. There is a large amount of work analyzing user's tweets and detecting user's emotions on Twitter. Emotion analysis on Twitter thus has become a hotspot for researchers to focus on.

The users' emotional states are subjective, which can reflect people's attitudes towards different activities. In book [32], Castellanos developed a system that is able to analyze the evolution of sentiment in microblogging activities for any given topic or event. And some web applications have been developed for sentiment analysis of Twitter as well [33] [34] [35]. For instance, Sentiment140 [33] can discover the user's sentiments regarding a product or brand by typing the name of the brand or the product. As a result, Twitter users' sentiment towards this brand or product will be shown on the screen as the percentage.

Generally speaking, there are two main approaches to detect the emotional states in tweets. The first one is called the text classification approach, which is involved with building classifiers from labeled texts samples, for instance supervised classification task [2]. In most of these research studies, the support vector machine classifiers are built, which are trained on a collected dataset using different features, such as unigrams or bigrams. In research study [2], Go et al. proposed an idea to use Tweets with emoticons for distant supervised learning, and results showed that their machine learning algorithm achieved 80% accuracy when trained with emoticon data. The second approach detecting the emotional states in tweets is lexicon-based approach. In research work [26], Pak et al. showed how to automatically collect the corpus for sentiment analysis and opinion mining purposes. Usually, the emotion lexicon is created for this approach. Thus some studies were carried out to validate the lexicon of emotions. For instance, Kouloumpis et al. evaluated the usefulness of existing lexical resource and features for detecting informal and creative languages in their research [36].

In most of these works mentioned above, authors or developers use positive, negative and neutral to describe the emotional states in Twitter. Our approach is lexicon based and we also use positive, negative and neutral to describe emotions in tweets. The reasons are as follows. Firstly, in this thesis study, we focus on analyzing emotions for user modeling instead of emotional states themselves. There is no need to use too many emotional states to specify the different emotional states in details. Our main point is to investigate whether our emotion-based user modeling strategies could improve the quality of user profiles. Secondly, using only one specific emotional state for user modeling may lead to the data sparsity problem [18] on the Twitter platform. For instance, if we use specific emotional state "disgust" in our emotion-based user modeling strategies, we may need enough tweets containing "disgust" emotion for constructing the emotion-based user profiles. However, the user might not post enough "disgust" Twitter messages to construct their profiles. So these are the reasons why we use these positive, negative and neutral to describe emotional states for our emotion-based user modeling strategies on Twitter.

3.2 Emotion detection

In this section, we will introduce our approach to emotion detection. Emotion detection is one of the main tasks in this thesis study. We will investigate our sample dataset in respect to emotions by our approaches. Our purpose of detection is to identify whether a tweet has a user's emotions and what polarity of the user's emotion is in this tweet by approach of emotion detection.

Emoticons and affective words are two emotional labels we use in our approach of emotion detection. Based on these two emotional labels, there are mainly two different approaches we use in our emotion detection.

- Emoticon based approach
- Affective word based approach

In this section, first of all, we will explain above two approaches in details, and then we will introduce our emotion lexicon.

3.2.1 Emoticon based approach

As has been mentioned, we use emoticons to detect the users' emotions in Twitter messages. Here are some definitions we will use in our approach to emoticon based approach. In the following, the definition of emotional label frequency and emoticon frequency are given.

Definition

Emotional Label Frequency. Emotional label frequency ELF(t) refers to the number of emotional labels presented in a tweet t. Emotional labels have two types: emoticons and affective words. The polarities of emotional label frequency are positive and negative.

Definition

Emoticon Frequency. Emoticon frequency EF(t) refers to the number of emoticon presented in a tweet t. The polarities of emoticon frequency are positive and negative.

Definition

Emoticon Based Approach. Emoticon based approach calculates the positive emoticon frequency $EF_p(t)$ and negative emoticon frequency $EF_n(t)$ and then derives the polarity E(t) for the given tweet t (when tweet's emotional label is only emoticon). The equation is given as below.

$$\mathrm{E(t)} = \begin{cases} Positive & EF_p(\mathrm{t}) > EF_n(t) \\ Neutral & EF_p(\mathrm{t}) = EF_n(t) \\ Negative & EF_p(\mathrm{t}) < EF_n(t) \end{cases}$$

Example

	Only positive or negative emoticon	Both positive and negative emoticons
Tweet	Watching NBA now :)	got a Birthday party from my friends :)…but still have to work tomorrow :-<
Emoticon	:)	:), :-<
Emoticon frequency	$EF_p(t) = 1$ $EF_n(t) = 0$	$EF_p(t) = 1$ $EF_n(t) = 1$
Polarity of emotion	Positive	Neutral

Table 2 Detection of emotions by emoticon based approach

3.2.2 Affective word based approach

Likewise, the second emotional label we use is affective word. As previous with the emoticon based approach, we will present some definitions related to affective word based approach first.

Definition

Affective Word Frequency. Affective word frequency AF(t) refers to the number of affective words presented in a tweet t. The polarities of affective word frequency are positive and negative.

Definition

Affective Word Based Approach. Affective word based approach calculates the positive affective word frequency $AF_p(t)$ and negative affective word frequency $AF_n(t)$ and then derives the polarity E(t) for the given tweet t (when tweet's emotional label is only affective word). The equation is given as below.

$$E(t) = \begin{cases} Positive & AF_p(t) > AF_n(t) \\ Neutral & AF_p(t) = AF_n(t) \\ Negative & AF_p(t) < AF_n(t) \end{cases}$$

Example

	Only positive or negative affective word	Both positive and negative affective words
Tweet	Today is a sunny day. I really like it	This is my room in Rotterdam…It looks nice but a little bit noisy
Affective word	Like	Nice, noisy
Affective word labels	$AF_p(t) = 1$ $AF_n(t) = 0$	$AF_p(t) = 1$ $AF_n(t) = 1$
Polarity of emotion	Positive	Neutral

Table 3 Detection of emotions by affective word based approach

However, sometimes users will use both emoticons and affective words to express their emotions in a tweet. In this situation, we just add both of them to the count of the emotional label frequency.

Example

Tweet: "All of us enjoy ourselves at party :). But it is stupid for me to drink too much…"

This tweet has two different emotional labels, both emoticons and affective words. And we will take all of them into consideration. The higher count should be the polarity of emotion. In this tweet, two positive emotional labels are ":)" and "enjoy", while one negative emotional label is affective word "stupid". This tweet is considered to be positive by our approach.

Compared to the emoticon based approach, affective word based approach is a little bit complex. The reason is that we have to solve some semantic problems in this approach. And the steps are as follows. First of all, we separate sentences of tweets word by word without punctuation marks. And then we transfer all the words to lower cases. If any word in the tweets is the same as the word on our affective word list, we will add affective words count of this tweet according to the detected affective word polarity. If there are some negation words ("no" and "not") before our affective words, the emotion polarity of the word will be changed to the opposite one.

3.2.3 Emotion lexicon

As we mentioned in the previous subsection, we will use the lexicon based approach to detect the emotions in tweets. Therefore, a good emotion lexicon is an indispensable part for our emotion detection. A large number of emotion lexicons were built in different languages [37] [38] [39] and different emotional labels [14]. Our emotion lexicon focuses on English and comprises two different emotional labels: emoticons and affective words. These are the symbols we use to identify the users' emotional states in Twitter. The assumption behind is that the use of these symbols could reflect the user's emotional states of the tweet.

<u>Lexicon of Emoticons</u>

Emoticons are considered to be one of the most important identifications to detect emotions in others' research [2] [12] [13]. A lot of studies discussed this issue before and they are widely used in sentiment analysis area. Liu et al. proposed an emoticons smoothed language model to train a language model based on the manually labeled data, and then use the noisy emoticon data for smoothing [40]. Ptaszynski et al. designed a fully automatic emoticon analysis system, which extracts emoticons from input and determines specific emotion they express [41]. In this thesis work, we also use emoticons as our emotional labels. Our lexicon of emoticons is based on the Ansari's taxonomy and used in the previous research study [2]. Regardless of other definitions of emotion, we divided the emoticons into two groups: positive and negative, according to their valence dimension [4]. The valence means accounts for the pleasantness of the emotions [4]. The positive emotion (happy) is represented by high valence emoticons and the negative emotion (sad, anger, fear, and disgust) is represented by low valence emoticons. And table 4 shows the emoticons we use in this thesis work.

<table>
<tr><th>Emotion definition</th><th>Emotional states</th><th>Emoticons</th></tr>
<tr><td>Positive</td><td>Happy</td><td>:-) :) ;-) :D :P 8) 8-| <@o</td></tr>
<tr><td rowspan="4">Negative</td><td>Sad</td><td>:-(:(;-(:-< :'(</td></tr>
<tr><td>Anger</td><td>:-@ :@</td></tr>
<tr><td>Fear</td><td>:| :-o :-O</td></tr>
<tr><td>Disgust</td><td>:$ +o(</td></tr>
</table>

Table 4 Conventional markers used for emotion classes

<u>Lexicon of affective words</u>

With the development of Twitter, the lexical resources of affective words for sentiment analysis on Twitter have become highly popular. Many affective word lists already exist in research areas. Wilson et al. labeled a list of English words in positive and negative categories, releasing the Opinion Finder lexicon. Bradley et al. proposed an English word list named Affective Norms for English Words (ANEW). On this list, 1034 words are rated for valence dimension, arousal dimension and dominance dimension. Another affective word list Balance Affective Word List was proposed by Greg Siegle. The word list consists of two parts. One part is collected by Greg Siegle and Mark Shibley, while the other part is collected by Carolyn H. John. On this list, they specified the valence code by 1=positive 2=negative 3=anxious 4=neutral. Based on the Wordnet [42] lexical database, Baccianella et al. developed sentiWordnet by using sentiment ratings to a large number of synsets. There are also some other affective word lists without the valence code, for instance, Compass DeRose Guide to Emotion Words proposed by Steven J. DeRose. However, these affective word lists are not our choice for the approach to emotion detection. As we discussed in chapter 2, the length of Twitter messages is limited to 140 characters and people may express their ideas in informal ways. These affective word lists do not take these characters of tweets into consideration.

In this thesis study, our affective word list is based on AFINN, which was proposed by Finn Årup Nielsen. Nielsen et al. extended ANEW affective word list and created AFINN affective word list using in Twitter sentiment area. Compared to other affective word lists, the advantages of AFINN are as follows. First of all, this word list is designed for sentiment analysis in microblogging. For instance, the affective word list has some informal words like "WOW, haha, WTF", which are quite popular in tweets. Secondly, it has more affective words compared to other affective word lists. There are 878 positive affective words and 1598 negative affective words included. Thirdly, all words are rated for valence between minus 5 and plus 5, which matches our description of emotions (positive, negative and neutral) well. The authors also evaluated this affective word list in research [43], and the results showed this list performed better than other affective word lists in Twitter sentiment analysis area.

However, sometimes AFINN word list may have some semantic problems. Because AFINN word list contains a larger number of affective words, different meaning of words in different situations may lead to the deviation. For instance, affective word "crazy" is on negative affective word list. But in tweets "I am crazy for you, Justin Bieber!!!!", word "crazy" indicates the positive emotion. To solve this problem, we selected the AFINN words according to their valence and part of speech. We thus obtained our own affective words list to detect emotion in twitter messages. The reason we select the words is that our emotion-based user modeling strategies require a high accuracy instead of a wide range for detecting emotion.

3.3 Analysis

In this section, we will analyze our dataset by our approach to emotion detection. Firstly, the dataset we use will be described. And then we will evaluate our approaches of emotion detection. Finally, our results of emotion analysis on the dataset will be presented.

3.3.1 Dataset description

Twitter dataset used in this thesis is from previous work [7].The period of data collection is from 15-11-2010 to 4-1-2011. During this period, some big events were repeated by tweets, for instance Christmas Day. Different types of tweets are in the dataset including re-tweets and replies. The whole dataset contains 1675 user accounts and 2342425 tweets. And each user posted at least 20 tweets and each month of the period contains at least one tweet. The OpenCalais [44] has been used for extracting the entities in the dataset. And all these entities mentioned in these tweets are identified by semantic enrichment of user modeling framework. The relations between tweets and news are acquired by different linking strategies. In previous research study, authors evaluated their method for correlating the news and tweets and the results showed that the accuracy of their approach could be higher than 70% [6].

3.3.2 Evaluation of emotion detection

In this subsection, we will evaluate our approach of emotion detection. Our approach of emotion detection relies on the assumption that the Twitter user's emotions could be indicated by a set of emoticons and affective words if these emotional labels show up in the tweets. To validate this assumption, our method is as follows. We selected tweets which indicate the user's emotions by our approach, and then we divided these tweets into four groups.

- Positive tweets detected by affective word based approach
- Negative tweets detected by affective word based approach
- Positive tweets detected by emoticon based approach
- Negative tweets detected by emoticon based approach

Each group has 50 tweets. If a tweet contains both emoticon and affective word, it will be selected by both approaches. In order to validate our approaches, we check the semantic meaning of each tweet to establish the ground truth for our approaches. And then we compare the ground truth with the results of our approach to get the results of our approaches accuracy. Here, we present an example to show how we evaluate our approach.

Example

Tweet: The NBA final is so amazing. Finally, the Heats win the championship. lol,go James!!

Ground truth: positive

Result of emotion detection by affective words: positive

In this example, it shows out that our approach is correct. We have 50 tweets for each group and calculate the accuracy of our approaches for each group. The evaluation outcomes are given in tables 5.

	Affective word	Emoticon
Positive	78%	96%
Negative	76%	90%

Table 5 Accuracy of emoticon based approach

From the table above, we can see that our positive and negative affective word based approaches could achieve 78% and 76% accuracy respectively. While both positive and negative emoticon based approaches achieve high accuracy around 90%, which are higher than the affective word based approach.

We also compare the difference from these two approaches regarding accuracy and semantic meaning. The table 6 shows the comparison of two different approaches

	Semantic meaning	Accuracy
Affective word based approach	More	Low
Emoticon based approach	Less	High

Table 6 Comparison of two different approaches

The following example shows the existing problems for these two different approaches of emotion detection with the purpose of constructing the emotion-based user profiles.

Example

Tweet 1: Finally it comes.:)

Tweet 2: @JustDiii Friday afternoon my friend - having a lazy weekend

In the first tweet detected by emoticon, we could see :) indicating the positive emotion of the tweet. However, the problem is that we cannot know the interest of the user from this tweet to construct the user profiles because it is lacking of semantic meaning.

In the second tweet detected by an affective word, the affective word “lazy” shows the negative emotion from user, but this tweet’s real meaning is to enjoy a “nice” weekend. This may affect our accuracy for modeling emotions.

3.3.3 Analysis of emotional tweets

The evaluation of our emotion detection approach proved that our approach is effective with high accuracy. In this subsection, we apply our approach to the dataset to analyze our dataset in respect to emotions. And the results are presented as follows.

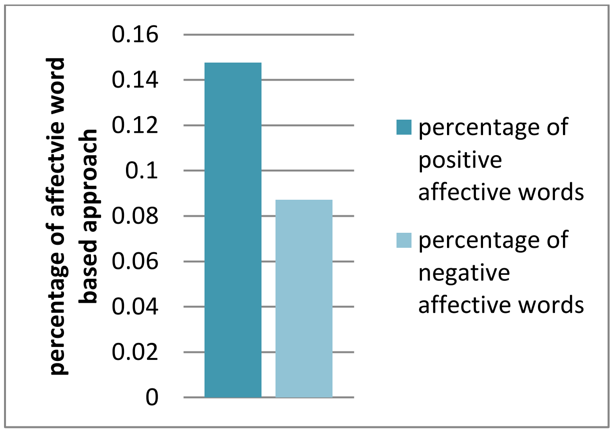


Figure 1 Percentage of emotional tweets detected by affective words

Figure 1 describes our results of emotion detection by affective word based approach. From figure 1, we can see that our affective word based approach for detecting emotion is effective. The percentage of positive tweets detected by affective words is 14.8%. While the percentage of negative tweets detected by affective words is 8.7%, which is lower than the positive tweets.

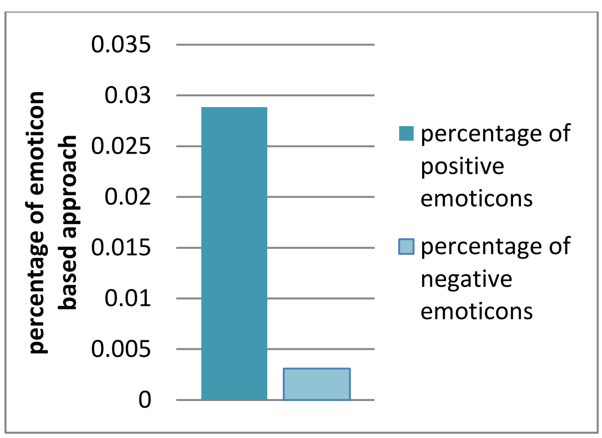


Figure 2 Percentage of emotional tweets detected by emoticons

Figure 2 shows the percentages of emotion detection by emoticon based approach. The figure 2 reveals the fact that the number of emoticons is lower than the affective words in our dataset. The percentage of negative emoticons only accounts for 0.3%. Compared to the percentage of negative emoticons, the percentage of positive emoticons reaches 2.9%, which is much higher than the negative one.

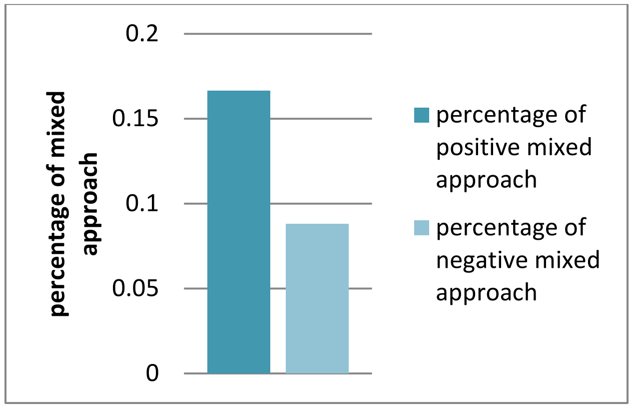


Figure 3 Percentage of emotional tweets detected by mixed approach

Figure 3 presents the percentages of emotion detection by mixed affective words and emoticons approach. We can see that the percentage of detected emotional tweets by mixed approach is higher than both the emoticon and affective word approach. Both number of positive emotional tweets and negative emotional tweets increased compared to the emoticon based approach and affective word based approach, which are 16.6% and 8.8% respectively.

3.4 Summary

From the evaluation of our approaches and results of detection on our sample dataset, we have come to the following observations through our analysis.

- Emoticon based approach has higher accuracy for emotion detection than the affective word based approach.
- Emotional tweets containing emoticons usually have less semantic meaning (users' interests of topic) than the emotional tweets detected by affective words.
- Emotional tweets containing affective words usually have more semantic problems than tweets with emoticons.
- People tend to show more positive emotion on Twitter than the negative emotion.
- Affective word based approach could detect more emotional tweets than the emoticon based approach.
- Using both emoticon and affective word approach could improve the quantity of detected emotional tweets.

By comparing two different approaches for detecting emotion, we find that they have different features. It seems that emotional tweets detected by affective word based approach are more suitable for constructing the emotion-based user profiles because of their rich semantic meaning. Compared to the affective word based approach, there are fewer tweets containing emoticons, which indicate they may have data sparsity problems [18] to construct the emotion-based user profiles. However, the emoticon based approach has a better accuracy for detecting emotion, which meets our requirements well. In this thesis, our main task is to investigate the use of emotion in user modeling strategies. Since emoticon based approach has a higher accuracy, one of the challenges we face is how we can exploit emotional tweets detected by emoticons in our emotion-based user modeling strategy even though it lacks of semantic meaning. This challenge will be discussed in chapter 4.

From our analysis on sample dataset, we could also notice that people tend to publish the tweets containing positive emotion on Twitter. There are many more tweets containing positive affective words and emoticons than negative ones. All of these observations have inspired us to model users' emotions. And in the next chapter, we will present how we exploit these emotional tweets in our emotion-based user modeling strategies.

4 Emotion-based User Modeling

In chapter 4, we go through the design phase of our work. The aim is to design the emotion-based user modeling strategies. As we discussed in chapter 2, exploiting Twitter messages for user modeling and sentiment analysis these two fields have been the hotspots already. However, no previous research combined them. In this chapter, we focus on designing the user modeling strategies based on users' emotions on the Twitter platform. We select and combine different design dimensions and alternatives to obtain a set of emotion-based user modeling strategies, which will be evaluated in next chapter of this thesis. In the end of this chapter, the analysis of our emotion-based user modeling will be given. All these details of emotion-based user modeling strategies will be discussed in the following sections.

4.1 Introduction

The use of microblogging has exploded in recent years, and there also has been an increasing interest in effective personalization techniques. Learning and modeling the semantic of individual microblogging activities has become more and more important because users want to benefit from personalized service on microblogging. Therefore, researchers focus on developing these personalized techniques with the aim to provide such service to their users. These personalization techniques rely on information or knowledge about users contained in user profiles. A user profile should have the user's information of interests to provide the personalization agents.

As mentioned in chapter 3, Twitter is one of the biggest social platforms in the world. The numbers of users and tweets published have experienced an exponential growth in last few years. Millions of tweets are published every day, which provides a large amount of users' personal data. Researchers thus focus on exploiting Twitter messages for different research activities. In research study [45], by conducting temporal analysis authors proposed that hashtags in tweets are good indicators for representing events and trending topics. Since one of the Twitter's important features is called "real time nature", the algorithms of event detection on Twitter are explored based on this feature. Takeshi et al. proposed a real-time event detection algorithm to detect earthquakes [46]. Mario et al. also proposed a novel topic detection technique for emerging topic detection on Twitter in their research [47]. Recently, researchers have focused on exploiting Twitter data to understand users' preferences and behavior patterns. For instance, authors investigated the dynamics of user influence across time and topics, by using three measures: indegree, re-tweets and mentions [48]. Exploiting Twitter messages for user modeling is also one main issue in Twitter research work. Abel et al. introduced a framework for user modeling on Twitter which enriches the semantics of Twitter messages by identifying topics or entities from outsource. They also analyzed how the different strategies for constructing the users' profile can benefit from semantic enrichment in their study [7]. All of these studies inspired us to develop our thesis work.

In this chapter, we will focus on three design dimensions of user modeling on Twitter platform and investigate how we can construct our emotion-based user profiles. In general, our three design dimensions are as follows.

- Modeling users' interests
- Modeling users' emotions
- Semantic enrichment

In the rest of this chapter, we will give the general idea of our design dimensions first, and then we will discuss these three design dimensions in details.

4.2 General design

In this section, we will give the general design of our emotion-based user modeling strategies. As has been mentioned above, three dimensions are taken into consideration in our design. By combining these design dimensions, our emotion-based user modeling strategies are constructed. Compared with previous work, our improvement is to take the users emotion into consideration.

On the Twitter platform, millions of tweets are published every day, and it is very common for users to post tweets which contain the user's topics of interest. These topics of interests are distinguished for each user. With the purpose of providing personalized service, these important concepts play an indispensable role in constructing user profiles on the Twitter platform. Abel et al. defined a generic model for user profiles in a previous research study [7] . In this thesis, their definition for generic model of a user profile [7] is used and given as follows.

Definition

Generic Model of a User Profile. The profile of a user $\mathrm{u} \in \mathbf{U}$ is a set of weighted concepts where with respect to the given user u for a concept $\mathrm{c} \in \mathbf{C}$ its weight $\omega(\mathrm{u},\mathrm{c})$ is computed by a certain function ω

$$\mathrm{P(u)} = \{(\mathrm{c}, \omega(\mathrm{u},\mathrm{c})) | \mathrm{c} \in \mathbf{C}, \mathrm{u} \in \mathbf{U}\}$$

Here, C and U denote the set of concepts and users respectively.

Example

Tweet: "What a wonderful match!!! I will support Ajax forever. Go Ajax!"

In this tweet, the user is a football fan and his favorite team is Ajax apparently. In this case, "Ajax" is one of the user's topics of interest. We exploit Twitter messages like this example for user modeling by extracting the interests of users from these tweets to construct their user profiles.

The weighting scheme $\omega(\mathrm{u}, \mathrm{c})$ relies on the frequency of occurrence of concepts. There are different methods for the weighting scheme. The most straightforward one is used in our work. We counted the number of each concept in users' tweets as their frequency of occurrence. Our weighting scheme is defined as follows.

Definition

Weighting Scheme of User Modeling. $\omega(\mathrm{u}, \mathrm{c})$ is the weighting scheme that is associated with a concept $\mathrm{c} \in \mathbf{C}$ for a given user $\mathrm{u} \in \mathbf{U}$. U and C denote the set of users and concepts respectively. Lower case n represents the number of a specific concept occurrence, while N represents the number of all concepts occurrence. Our assumption lied behind is that the more concepts of interests mentioned by users' tweets, the more important these concepts are for this user. The equation is given as below.

$$\omega(\mathrm{u}, \mathrm{c}) = \frac{\mathbf{n}}{\mathbf{N}}$$

After assigning the weight, as we discussed in the chapter 2, the user profiles will be represented by vector space model with the purpose to calculate the cosine similarity between the user profiles and candidate profiles. As generic user profile definition described, we have to decide what kind of concepts $\mathrm{c} \in \mathbf{C}$ we should use in our user profiles. These concepts should be able to describe the users' interests accurately in order to have a good performance for our user modeling strategies.

The following table describes the design space for emotion-based user modeling strategies.

Design dimension	Design choice
Modeling users' interests	1)Hashtag -based 2)Entity-based
Modeling users' emotions	1)Only positive emotion 2)Positive and negative emotions 3)Emotion correlation
Semantic enrichment	1)With enrichment 2)Without enrichment

Table 7 Design space for the emotion-based user modeling strategies

Modeling users' interests

This dimension describes what concepts we will use to model user's topics of interests. There are many different types to construct the user profiles. In a previous study [7], researchers used hashtag, entity and topic etc. to construct the user profiles. Whatever the type of user profile is, it should correspond well to users' interests. In this thesis, we will use two different types of concepts to model users' interests: hashtag-based user profile and entity-based user profile. The details related to this dimension will be discussed in section 4.3.

Modeling users' emotions

The dimension of modeling users' emotions is the most important issue in this thesis. We want to find some user modeling strategies which take users' emotion features into consideration. Users' emotion feature is extracted by our approach to emotion detection described in chapter 3.

Compared with other dimensions, "modeling users' emotions" has three choices.

- Only positive emotion
- Positive and negative emotions
- Emotion correlation

The first and second choices are to choose emotional polarity of concepts, and the third choice "emotion correlation" is to choose whether the emotion correlation will be used. The combination of these three choices thus constructs the second design dimension "modeling users' emotions". All these details will be given in section 4.4.

Semantic enrichment

Given the content of the tweet, one of the challenges to construct the user profiles is how we can extract useful semantics from Twitter short text. Data sparsity problem [18] is common since a tweet is limited to 140 characters. There are different ways to alleviate this data sparsity problem [18]. Abel et al. introduced a user modeling framework with news semantic enrichment in their study [6]. In my thesis, we will use their semantic enrichment approach to construct our emotion-based user profile in order to see what the impact of semantic enrichment is on our emotion-based user profiles. All of these details will be presented in section 4.5.

Up till now, we gave a short introduction for our design dimensions. From table 8, we can choose variables to construct our emotion-based user modeling strategy from each design dimension. For instance, we can choose "entity-based" in design dimension "type of user profile", "only positive emotion and without emotion correlation" in design dimension "modeling users' emotions", and "with semantic enrichment" in design dimension "semantic enrichment" to construct the emotion-based user profiles.

However, not all of the combinations are available in our design of emotion-based user modeling strategies. Some of the design dimensions are only designed for some certain strategies. For instance, the hashtag-based user profiles do not have the design dimension of semantic enrichment. The reason is that hashtags are unique for users and we can only extract the entities from outsource to enrich our entity-based user profiles. The hashtags cannot be obtained from outsource. Emotion correlation is used only for the emoticon-based approach. It is not necessary for affective word to use emotion correlation since there are enough concepts detected by affective words based approach to construct the emotion-based user profiles. Furthermore, as described in chapter 3, the affective word based approach is not as accurate as the emoticon based approach because of the semantic problems. Using emotion correlation will bring more wrong concepts which will lead to the deviation of our results. The details related to this will be discussed in subsection 4.4.3. And from the next section, we will begin to go through our design dimensions one by one in details.

4.3 Modeling users' interests on Twitter

In this section, we begin by introducing our first design dimension: modeling interests of users. To construct the user profiles, one of the important design dimensions is the type of user profiles. We will discuss different types of user profiles created in our emotion-based user modeling strategies:

- Hashtag-based user profile
- Entity-based user profile

Hashtag-based user profile

A hashtag-based user profile models user's interests by exploring a set of hashtags which are present in the user's Twitter messages. The reasons for using hashtags to construct the user profiles are as follows. Firstly, using hashtags is a popular way for users to express their ideas about specific topic. Nearly every user has published some tweets with hashtags as the identities of their interests. Secondly, Twitter specifies the hashtag by "#", which are easily and conveniently extracted from Twitter messages. Furthermore, some hashtags are listed in the Twitter trends topics, which also prove that the hashtags could represent the interests of users. We thus use the definition of hashtag-based user profile in research study [7] and the definition is given as follows.

Definition

Hashtag-based User Profile. The hashtag-based profile of a user $u \in \mathbf{U}$ is a set of weighted hashtags where the weight of a hashtag $h \in \mathbf{H}$ is computed by a certain strategy ω with respect to the given user u. U and H denote a set of users and hashtags respectively.

$$P(u) = \{(h, \omega(u, c)) | h \in \mathbf{H}, u \in \mathbf{U}\}$$

Except the hashtags in tweets, we also noticed that more entities are present in users' tweets than hashtags, such as locations, activities and breaking news etc. In this case, using entities for constructing user profiles is a straightforward and effective way, which will be explained in the next part.

<u>Entity-based user profile</u>

As we explained before, another type of user profile is entity-based user profile. An entity-based user profile models user's interests by a set of entities which are present in the user's Twitter messages. From our analysis of our sample dataset, we observed that entities are a more efficient way to construct the user profiles than the hashtags since it is accurate and usually mentioned by users themselves. The entity could be news, locations and events etc. The definition of entity-based user profile is under below [7].

Definition

Entity-based User Profile. The entity-based profile of a user $u \in \mathbf{U}$ is a set of weighted entities where the weight of an entity $e \in \mathbf{E}$ is computed by a certain strategy ω with respect to the given user u. U and E denote a set of users and entities respectively.

$$\mathrm{P(u)} = \{(\mathrm{e}, \omega(\mathrm{u}, \mathrm{c}))|\mathrm{e} \in \mathbf{E}, \mathrm{u} \in \mathbf{U}\}$$

Here, we would like to present an example to show how to construct the entity-based user profile from published tweets.

Example

Tweet: We will go to New York next Tuesday

In this tweet, the city "New York" will be extracted as one of the entities to construct the user entity-based profile. And after we extract all of the entities in this user's published tweets, the weight will be assigned to the entity "New York". For instance, different entities are present 500 times in all tweets and "New York" is present two times, and then the weight of dimension representing New York in users profile's vector space model will be assigned to 2/500.

In this section, we explained our first design dimension: modeling users' interests. And in the next section 4.4, we will explain our main idea of how we can model users' emotions on Twitter platform.

4.4 Modeling users' emotions on Twitter

In this section, we will explain our second design dimension: modeling user's emotions. This is our most important design for this thesis. The introduction of our general idea for modeling emotions will be explained first, and then our different strategies for modeling emotions will be presented.

Combining emotions and user modeling is not a new task. Some related studies have carried out before. Marko et al. proposed an approach for user modeling based on user's affective metadata (users' emotive response) [4]. And according to their assumption, affective metadata extracted by emotive response are closer to the user's experience than the normal data. They used these data in their user modeling strategy and performed the experiments on recommendation systems. Their results showed that using affective parameters had positive influence on the recommendation accuracy. In research study [5], Arapakis et al. proposed a novel video search interface that predicts the topic relevance of a video by analyzing affective aspects of user behavior. In this thesis work, we will follow their tracks to investigate how to model users based on emotion data.

To design the emotion-based user modeling strategies, the main challenge we face is how we can use emotion features extracted by our detection of emotion approach in constructing the user profiles. Before diving into designing strategies details, firstly we will give our underlying assumption in constructing the emotion-based user profiles.

Assumption

The concepts presented in emotional tweets should have more impact on user profiles than those concepts in normal tweets.

In the following part, example is presented to show why we make this assumption.

Example

Emotional tweet: "really like PizzaHut!! They offer the best pizza!!! Cannot stop eating… "

Normal tweet: "hey guys, shall we meet at PizzaHut 12 o'clock? "

From the examples above, we can figure out that the concept "PizzaHut" is present in both tweets. In the emotional tweet, "PizzaHut" is used to describe the user's preference with affective words such as "like" and "best". While in the normal tweet, "PizzaHut" just refers to a place for the user to meet friends. Apparently, the concepts in emotional tweets are closer to the user's interests than in the normal tweets. The intuition is straightforward. The tweets containing users' emotions are closer to the users' experience. According to this observation, we make our assumption for constructing emotion-based user profiles. Based on this assumption, our challenge to construct the emotion-based user profile will transfer to this question.

Question

How can we increase the impact on our emotion-based user modeling strategies for those concepts in emotional tweets?

Aware of the weighting strategies we described before, answering this question is not so difficult. Normally, we would assign the weight for each concept according to its occurrence frequency. However, in order to construct the emotion-based user profiles, we will increase the concepts' weights in their vector space models for those concepts in emotional tweets. By analyzing the emotional tweets detected by our approaches, we have designed the following three strategies to model users' emotions on Twitter.

- Only positive emotion
- Positive and negative emotions
- Emotion correlation

And the details will be discussed in the following subsections.

4.4.1 Only positive emotion

From the observation of our dataset in chapter 3, we observed that more positive tweets are published than negative tweets. It shows the fact that people tend to publish tweets containing positive emotion since we detected more positive emotional labels than the negative emotional labels.

Based on this observation, our first approach to model emotion is to increase the concepts' weights in positive emotional tweets. For each concept in these tweets, the weight is doubled compared with the normal user profile. The weighting scheme for emotion-based user profile will be described in subsection 4.4.4.

4.4.2 Positive and negative emotions

Instead of focusing on negative emotion only, we focus on both positive and negative emotions. We do not use only negative emotion to construct the emotion-based user profiles. The reasons are as follows. Firstly, the negative emotional labels are not closely related to the user's experience. People naturally usually tries to avoid the negative experience and do not want to have them again and again. Secondly, from our observation in chapter 3, we could see that there are fewer negative emotional labels than positive ones. Especially for emoticons, the number of negative emoticons is only ten percent compared to positive emoticons. These negative emotional labels are not enough to construct the emotion-based user profiles for most users, which will lead to the data sparsity problem [18].

Because of these reasons, our second way of modeling users' emotions will take both positive and negative emotions into consideration. With the positive emotional concepts, the data sparsity problem [18] of negative emotional concepts will be alleviated. Furthermore, if we take both negative and positive concepts, we can see how users' complete "emotions" could impact on our quality of user profiles.

For each concept in positive and negative emotional tweets, the weight is doubled compared with the normal user profiles. The details of our weighting scheme for emotion-based user modeling strategy will be discussed in subsection 4.4.4.

4.4.3 Emotion correlation

From our observations in chapter 3, we also noticed that some users may not publish enough emotional tweets for us to construct their emotion-based user profiles. As chapter 3 described, only about 3% of all tweets have emoticons. Even if the user writes some emotional tweets containing emoticons, it is not necessary for those tweets to have concepts which can be extracted as emotional concepts. In this case, if we want to use emoticons to construct our emotion-based user profiles, we need to find out some solutions to enrich the emotion-based user profiles.

In this thesis, we use the consistency theory [49] to solve this data sparsity problem [18]. The psychological literature has confirmed consistency is important in human nature. According to this theory [49], people expect consistency and prefer it to inconsistency. Our approach to emotion correlation is based on consistency theory [49] in order to alleviate the data sparsity problem [18] of emotional tweets. There are also some related studies regarding consistency theory [49] in the field of computer science. For instance, Hu et al. presented a mathematical optimization formulation that incorporates the sentiment consistency and emotional contagion in microblogging field [50]. Based on these related studies, our emotion correlation is defined as follows

Definition

Emotion Correlation. Emotion correlation refers to the same emotion reflecting the correlation between tweet and tweet.

Based on this definition, if a user publishes a tweet containing emoticons, we assume that the tweets correlated to this tweet have the same emotion. From chapter 3 observations, we noticed that emoticon based approach has higher accuracy for detecting emotions. This observation also provides the accurate identifier for using emotion correlation theory to enrich the concepts of emoticon-based user profiles.

We will give another example to show how to use emotion correlation for emoticon-based user profiles.

Example

Tweet: prepare for holiday to Australia. Sun and beach!!!   Timestamp: 10-10-2010 09:23:53

Tweet: Let's go!!!! :) Timestamp: 11-10-2010 12:23:12

Tweet: A lot of people are waiting for sunrise! Timestamp: 13-10:2010 15:02:22

In the example above, we can see that the middle tweet contains the positive emoticon, but it lacks of semantic meaning for us to know what makes the user happy. By our emotion correlation approach, all these three tweets are considered to be emotional tweets. We find out that the first and the last tweet also showed the same emotion. What is more, the first tweet also has the emotional concepts: "Australia", which could be extracted for our emotion-based user profiles. We thus enrich our emotion-based user profiles by emotion correlation approach.

4.4.4 Weighting scheme of emotion-based user profiles

As explained at the beginning of this section, our solution to the previously stated question is to increase the weight for those concepts presented in emotional tweets. In this subsection, the definition of the weighting scheme will be described.

In the previous subsections, we specified the different concepts which are presented in the emotional tweets by our different strategies of modeling users' emotions. In order to increase the impact of these concepts on our emotion-based user profiles, the weight is doubled in our emotion-based user profile for each concept in these emotional tweets. The definition of the weighting scheme is given as follows.

Definition

Weighting Scheme of Emotion-based User Profiles. ω (u, c) is the weighting scheme of emotion-based user profile that is associated with a concept c $\in \mathbf{C}$ for a given user u $\in \mathbf{U}$. Lowe case c denotes the specific concept in the emotional tweets (collected by different strategies) and u denotes the specific user u. C denotes the set of concepts in the emotional tweets (collected by different strategies) and U denotes the set of users. Lower case n represents the number of a specific concept occurrence, while N represents the number of all concepts occurrence. For those concepts presented in the normal tweets, they remain the same weight as the normal user profiles. The equation is given as below.

$$\omega(\mathrm{u,c}) = 2 \times \frac{\mathbf{n}}{\mathbf{N}}$$

4.5 Semantic enrichment

In this section, the dimension of our semantic enrichment for constructing emotion-based user profile will be presented.

As we introduced in previous chapters, Twitter messages are limited in 140 characters. Some important semantic meanings thus may be missing from Twitter messages. To solve this problem, a large number of studies have focused on semantic enrichment. One of the semantic enrichment strategies is based on the URL. Anlei et al. proposed a method to use microblogging streams to detect the fresh URLs mentioned in Twitter messages and compute rankings of these URLs [51]. Chen et al also focused on recommending URLs posted in Twitter messages and proposed to structure the problem of content recommendations into three different dimensions: discovering the source of content, modeling the interests of the users to rank content and exploiting the social network structure to adjust the ranking according to the general popularity of the items. Their assumptions lied behind is the URL should be related to the semantic meaning of the tweets if users mentioned the URL in their tweets messages [52].

The URL-based strategy is straightforward to understand. There are also some other external sources to enrich the semantic of tweets. Kwak et al. claimed that over 85% of the tweets on the Twitter are related to news from their observation in their research [45]. Based on this observation, news-enrichment is developed for semantic enrichment on Twitter. Abel et al. introduced the method to link tweets with related news articles in order to contextualize Twitter activities. Their evaluation showed that their approach has higher precision and coverage [6]. To better understand this strategy, an example is presented as below.

Example

Tweet: Yes!!! I am so happy to see this. You did it!! Neymar!!!!

This tweet contains positive emotion. However, the problem is that we cannot get any semantic meaning from a name "Neymar". If we related this tweet to the CNN breaking news on that day "Brazil Top Confederations Cup grow after 4-2 win over Italy", the semantic meaning of this tweet would be much clearer to understand. Furthermore, the concepts in this news report could be extracted to enrich the user profiles.

In this work, we will also use the news semantic enrichment strategy for constructing our emotion-based user profiles. Apart from URL-based strategy, we acquired the relations between news and the tweet by comparing the similarity between the news and the tweets as well. The reasons we use semantic enrichment are as follows. Firstly, we want to investigate what the impacts are on emotion-based user profiles with semantic enrichment. It is reported that strategies for constructing the user profiles with the semantic enrichment of news have better performance than the normal strategies [6]. This is interesting for us to see what will happen if our emotion-based user modelling strategies have semantic enrichment. Furthermore, after the semantic enrichment of external resource, both emotion-based user profiles and normal user profiles are enriched with same concepts, which will alleviate the data sparsity problems [18] as well.

4.6 Analysis

After introducing our design space of emotion-based user modeling strategies, the analysis of our emotion-based user profiles will be given in this section with the purpose of better understanding our strategies. In the following subsections, we will first give the dataset preprocessing in subsection 4.6.1, and then followed with the analysis of our emotion-based user profiles.

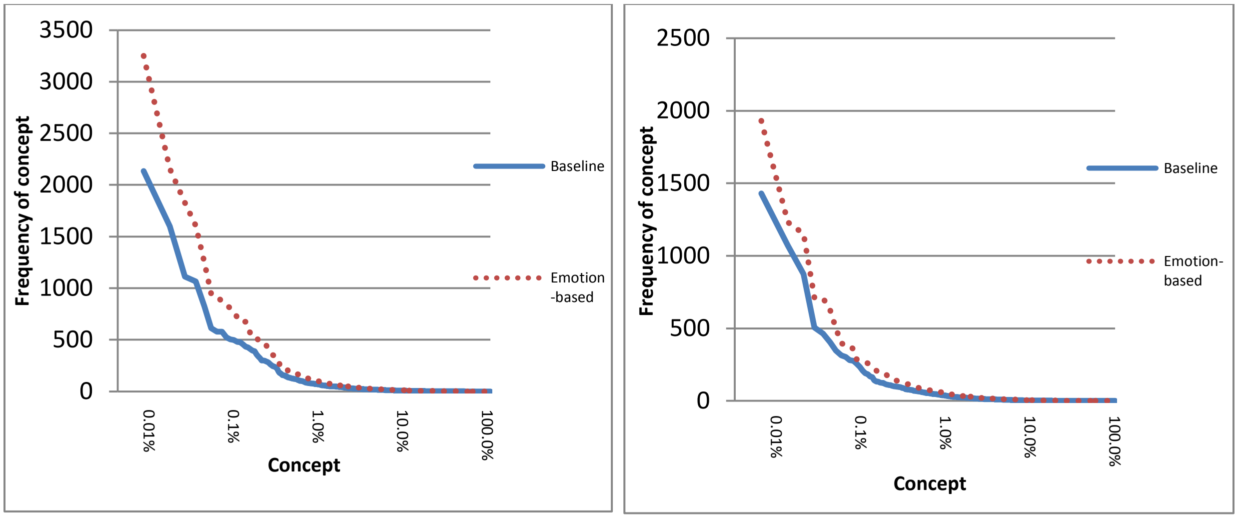
4.6.1 Dataset preprocessing

The dataset we use is described in chapter 3. However, we do not use all of the dataset in our analysis work. We will select some users who have published the most emotional tweets. In order to do so, we check the users' published tweets and emotional tweets, then select the top ranking users by their percentages.

As we described in chapter 2, there are two different emotional tweets. One is identified by emoticons, and the other is identified by affective words. We thus select our users by emoticon based approach and affective word based approach respectively. The reason we do not select them by mixed approach is follows. These two approaches of emotion detection have different features. Affective word based approach has rich semantic meaning, which is helpful for us to extract the user's interests of topics. However the problem is that the affective word based approach is not as accurate as the emoticon based approach. For emoticon based approach, even if it has a higher accuracy, the problem is that it does not have rich semantic meaning. If we select users by mixed approach, we cannot distinguish these differences in our experiments. We thus select 150 users from dataset described in chapter 3 for both affective word based approach and emoticon based approach respectively. And the user sample selected by affective word is named U_A , while the user sample selected by emoticon is U_E . These users published more tweets containing emotions than other users. We extract the entities and the hashtags from the dataset and rank them based on their frequencies. And then we select top 10000 hashtags and top 10000 entities to construct the dimensions of our user profiles based on their frequencies number. The semantic meaning of these hashtags and entities include the locations, activities and news, etc.

4.6.2 Analysis of emotion-based user profiles

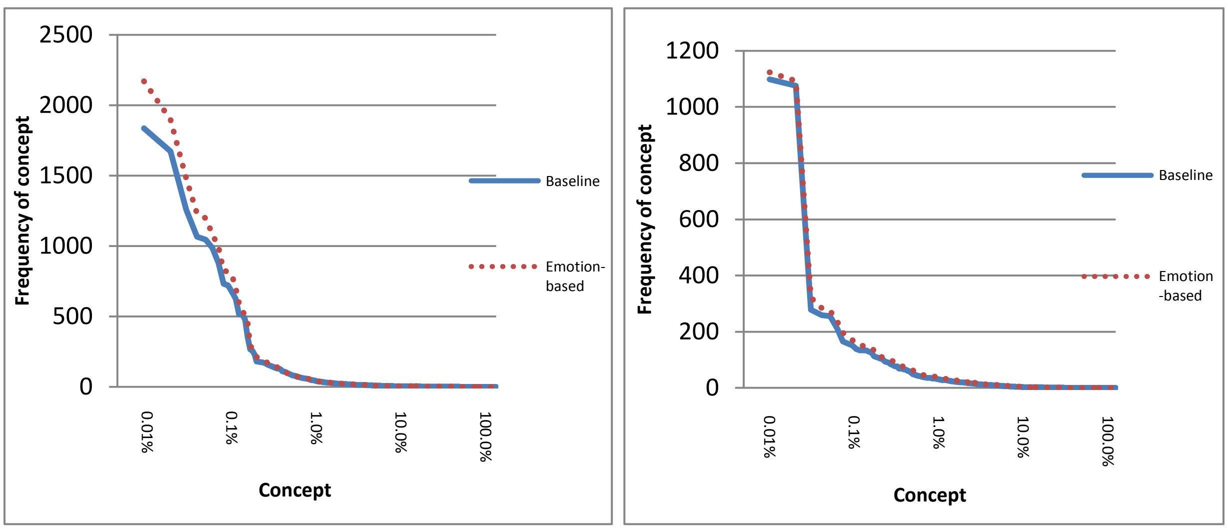
In this subsection, we will give our analysis of our emotion-based user profiles. The frequency of each concept presented in emotion-based user profiles are shown first. And the results are as follows



a)The frequency of entity in all user profiles

b) The frequency of hashtag in all user profiles

Figure 4 Frequency of concept for user sample U_A



a)The frequency of entity in all user profiles

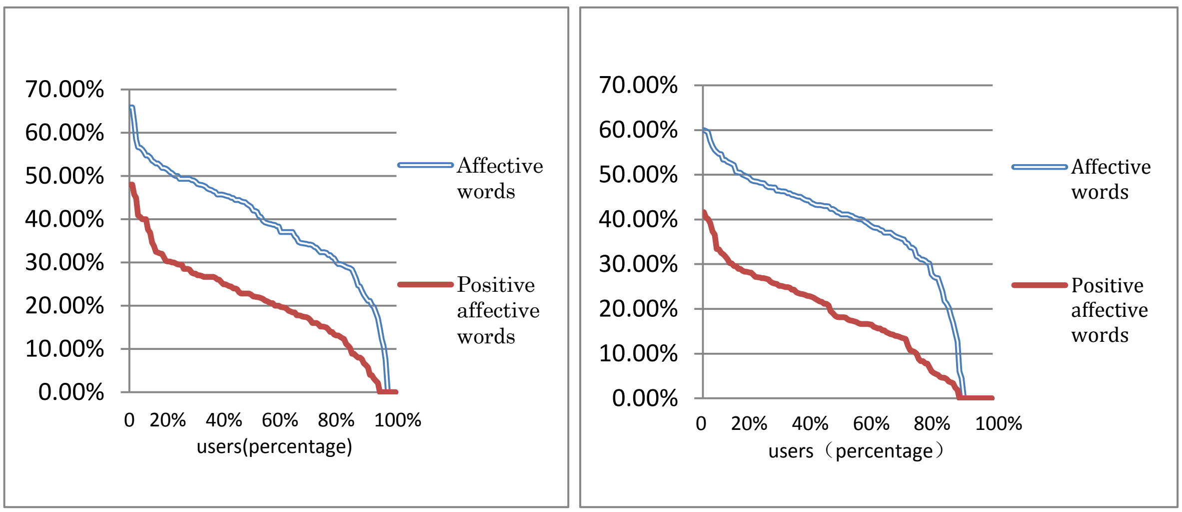
b) The frequency of hashtag in all user profiles

Figure 5 Frequency of concept for user sample U_E

The above four figures show the frequency of concept in user profiles. It can be seen that the frequency of entity-based user profiles is higher than the hashtag-based user profiles in general. Also, we noticed that the concepts with a high frequency increased more compared with the concepts with a low frequency. In the dataset selected by affective words, there are about 80 entities which have a distinguished difference of frequency compared with the baseline. While in the dataset selected by emoticons, this number decreases to 40. This observation shows that users turned to publish emoticons in some specific concepts and affective words are used more separately in many other concepts.

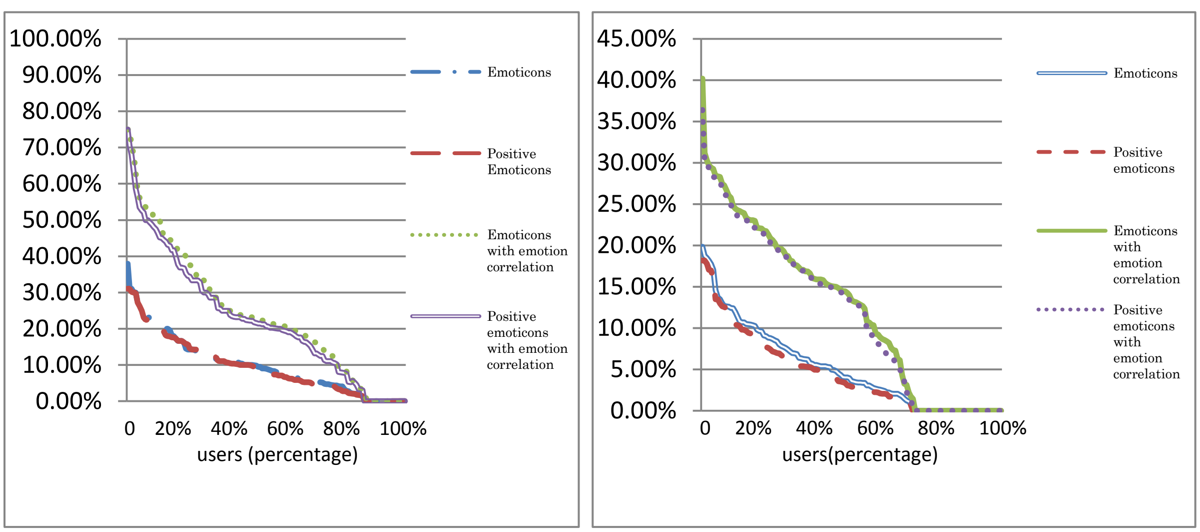
Furthermore, we could see that the frequency of concepts detected by emoticon cannot distinguish the emotion-based and baseline strategies well since these two lines almost overlap. It reveals the fact that emotional tweets detected by emoticons are much less frequent than the affective words we described in chapter 3. Especially in hashtag-based user profiles, two lines are almost the same, which indicates there may be a data sparsity problem [18]

Next, we investigated the percentage of emotional concepts in emotion-based user profiles and the results are given in figures 6 and 7.



a)The percentage of emotional entity in emotion-based user profiles b) The percentage of emotional hashtag in emotion-based user profiles

Figure 6 Percentages of emotional concepts for user sample U_A



a)The percentage of emotional entity in emotion-based user profiles b) The percentage of emotional hashtag in emotion-based user profiles

Figure 7 Percentages of emotional concepts for user sample U_E

From the analysis of the emotion-based user profiles, we can see that the percentages of concepts selected by affective words are higher than the profiles selected by emoticons. Figure 7 (b), reveals that the hashtag-based user profiles selected by emoticon have data sparsity problems [18] since more than 20% users do not have the emotional hashtags in their user profiles. Even though we selected the users who publish mostly emoticons, it is not necessary for them to publish the tweets with both emoticons and hashtags. That is the reason for this problem. Apart from these observations from the figures, we furthermore investigated the size of the entity-based and hashtag-based user profiles. We found out that the size of hashtag-based user profiles is much smaller than the size of entity-based user profiles. A small size of the user profiles may also lead to the data sparsity problem [18] .

In this chapter, we introduced our design for the emotion-based user modeling strategies from three design dimensions followed by the analysis. In the next chapter, the evaluation of these strategies will be presented.

5 Evaluation of User Modeling

In this chapter, the experiments of evaluation will be performed with the purpose to evaluate our emotion-based user modeling strategies. We will find out whether our emotion-based user modeling strategies could improve the performance of recommendation accuracy or not. First of all, we will introduce the overview of our evaluation, and then the evaluation methodology will be presented. Finally, results of the evaluation will be described in details.

5.1 Introduction

To solve problems of information overload, personalized recommendation systems are presented. Providing personalized recommendation is one of the most important issues in information retrieval area. A large number of studies related to recommendation systems have been done to investigate this issue. The recommendation systems used to solve this problem can be classified into roughly two types. As mentioned in chapter 2, they are content-based recommendation systems and collaborative recommendation systems. The content-based recommendation systems recommend items based on the description of recommendations items and user profiles. Learning from user profiles, content-based recommendation systems could provide the personalized information to each user without typing queries.

In this thesis work, the content-based recommendation systems will be our platform to analyze and evaluate our emotion-based user modeling strategies. As mentioned in the chapter 2, firstly, both user profiles and candidate profiles will be represented by weighted vectors. And we will calculate the cosine similarity between the candidate profiles and user profiles then rank the recommendation results based on their cosine similarity. Those candidate profiles which have higher results of cosine similarity with user profiles will be recommended. Finally, we compared these results with our ground truth to evaluate our quality of user profiles.

5.2 Evaluation methodology

This section is divided into two subsections. We will first explain our experiment set up, and then the evaluation measures will be given.

5.2.1 Experiments set up

In this subsection, we will describe our experiments set up. Firstly, the dataset we use will be described. Secondly, we will introduce the recommendation parameters of our experiments. Finally, the recommendation algorithm will be explained.

Dataset description

In this experiment, we will still use the same users sample described in previous subsection 4.6.1. We select two user samples ($U_A and\ U_E$) who publish most emotional tweets detected by affective word based approach and emoticon based approach. Each user sample has 150 users.

Recommendation parameters

Our recommendation items are the re-tweets. The assumption lied behind is that the users' re-tweets reflect the users' interests. Since the period of whole dataset is 51 days from 15-11-2010 to 04-01-2011, we separate the dataset into two parts. For the period from 15-11-2010 to 22-12-2010, we construct the user profile by these data. For the rest of the days from 23-12-2010 to 04-01-2011, we use it as the recommendation period. The data in this period are considered to be the ground truth. The recommendation is based on content-based approach. Our recommendation algorithm will be explained as follows.

Recommendation Algorithm

We use content-based recommendation systems so that we can compare the cosine similarity between items. Given a user profile p(u) and a set of candidates, both represented in the vector space model using the same vector representations, the recommendation algorithm ranks the candidate item based on their cosine similarity $\mathrm{sim_{cosine}}(\vec{p}(u), \vec{p}(r_i))$ to p(u). In the following equation, $\vec{p}(u)$ and $\vec{p}(r_i)$ are the vector representations for user profiles and a set of candidate profiles respectively.

$$\mathrm{sim_{cosine}}(\vec{p}(u), \vec{p}(r_i)) = \frac{\vec{p}(u) \cdot \vec{p}(r_i)}{||\vec{p}(u)|| \cdot ||\vec{p}(r_i)||}$$

5.2.2 Evaluation measures

In the evaluation part, our main purpose is to check whether our emotion-based user modeling strategies can improve the recommendation accuracy. Usually, recommendation systems are evaluated and ranked by their accuracy of prediction, which means their ability to predict users' preference. In information retrieval area, performance measures have been developed and focus more on the top of the ranking [53]. Examples of such measures are the Mean Reciprocal Rank (MRR) and Success at Rank k (S@k). Therefore, we use S@k(Success at Rank k) and MRR(Mean Reciprocal Rank) to evaluate our accuracy of recommendation systems.

- S@k
- MRR

S@k

Success at rank k is the ratio of times where there was at least one relevant recommendation item in the first k returned. Success at rank k is regarded as the probability of finding a good descriptive item among the top k recommendation items. In particular, we use the success at 5(S@5) to measure our performance of recommendation systems.

MRR

Mean reciprocal rank measures at which rank the first item relevant to the user occurs on average. This measure provides the ability of recommendation systems for providing the relevant item at the top of the ranking. If the first correct recommendation result is ranked as the 3^{rd}, then the reciprocal rank (RR) is 1/3. Mean reciprocal rank is defined as the average of the reciprocal rank of results for a sample of queries Q. The equation is given as below.

$$MRR = \frac{\mathbf{1}}{|\mathbf{Q}|}\sum_{i=1}^{|\mathbf{Q}|}\frac{1}{rank_i}$$

5.3 Results

In this section, the results of the evaluation of our approaches will be described. Before diving into results of our emotion-based user profiles, we will present some observation of normal user profiles in the first subsection. And then our results of emotion-based user profiles will be performed in the next subsection. As described before, we compare the performance of emotion and non-emotion user profiles in two user samples: selected by affective words U_A and selected by emoticons U_E respectively. Each user sample has 150 users who publish the most emotional tweets detected by affective word and emoticon respectively. Results of our emotion-based user modeling strategies will be explained in hashtag-based user profiles first and then followed entity-based user profiles. All of these details will be discussed in the following subsections.

5.3.1 Results of normal user profiles

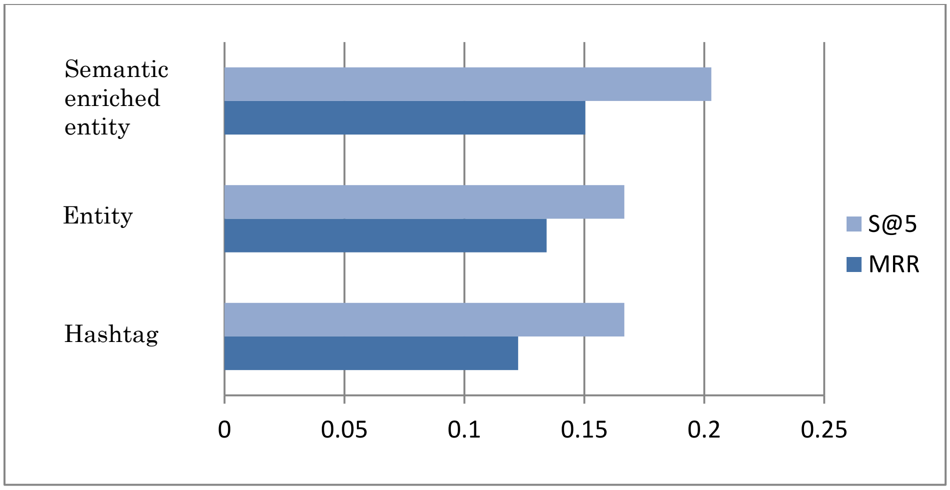


Figure 8 Results of baseline for user sample U_A

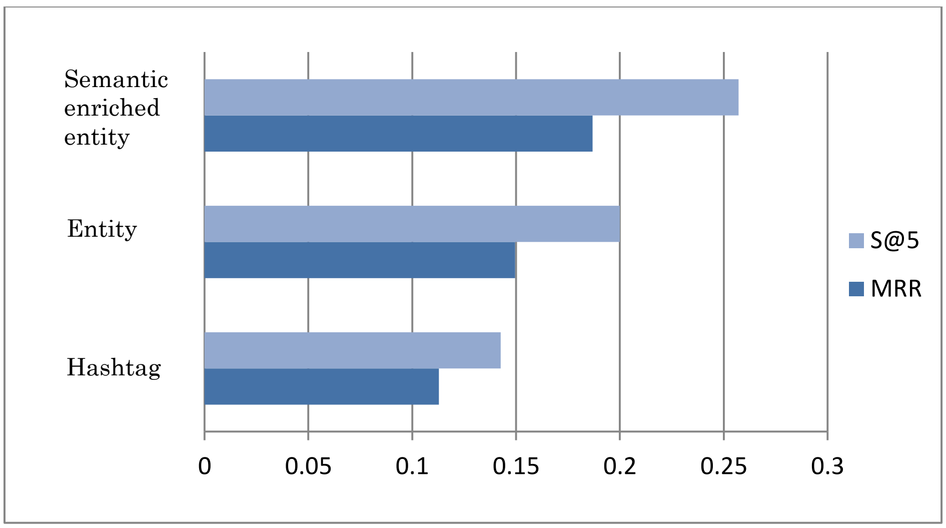


Figure 9 Results of baseline for user sample U_E

Figure 8 and figure 9 illustrate results of normal user profiles. It reveals that the entity-based user profiles are better than the hashtag-based user profiles in terms of recommendation accuracy. And also, we noticed that semantic enrichment could enhance the quality of entity-based user profiles as previous study [6] and the results of recommendation show that entity-based user profiles with semantic enrichment have best quality among these three strategies.

5.3.2 Results of emotion-based user profiles

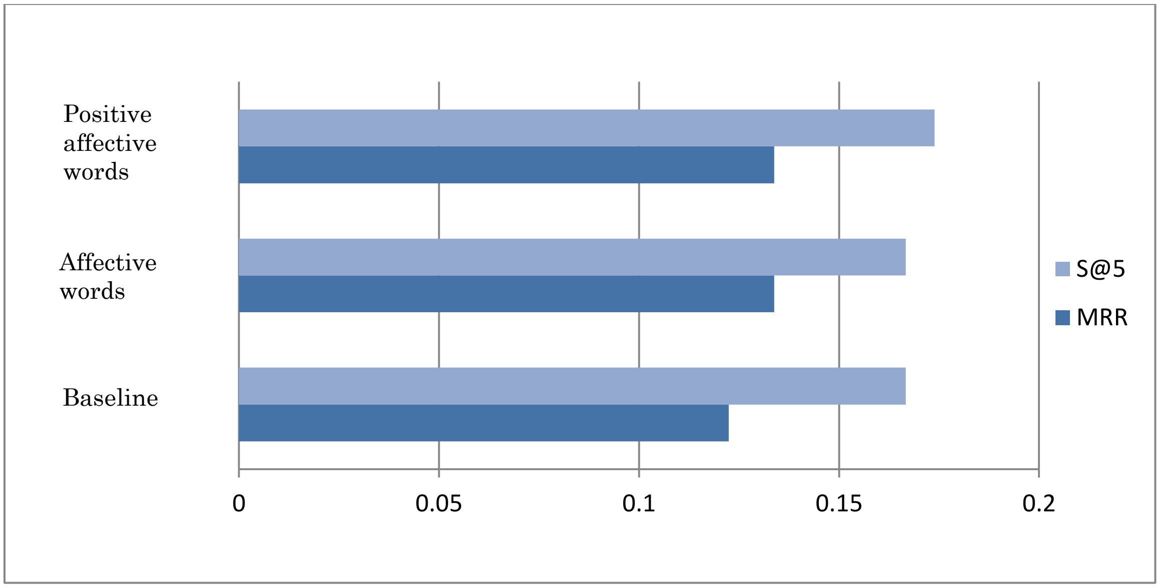


Figure 10 Results of hashtag-based profile for user sample U_A

The result of hashtag-based user profiles for user sample U_A is presented in figure 10. In this figure, we could see that emotion-based user profiles have better performance than the normal user profiles in terms of recommendation accuracy. For our best emotion-based user modeling strategies, MRR increased by more than 9% and S@5 experienced a slight increase of about 4%.

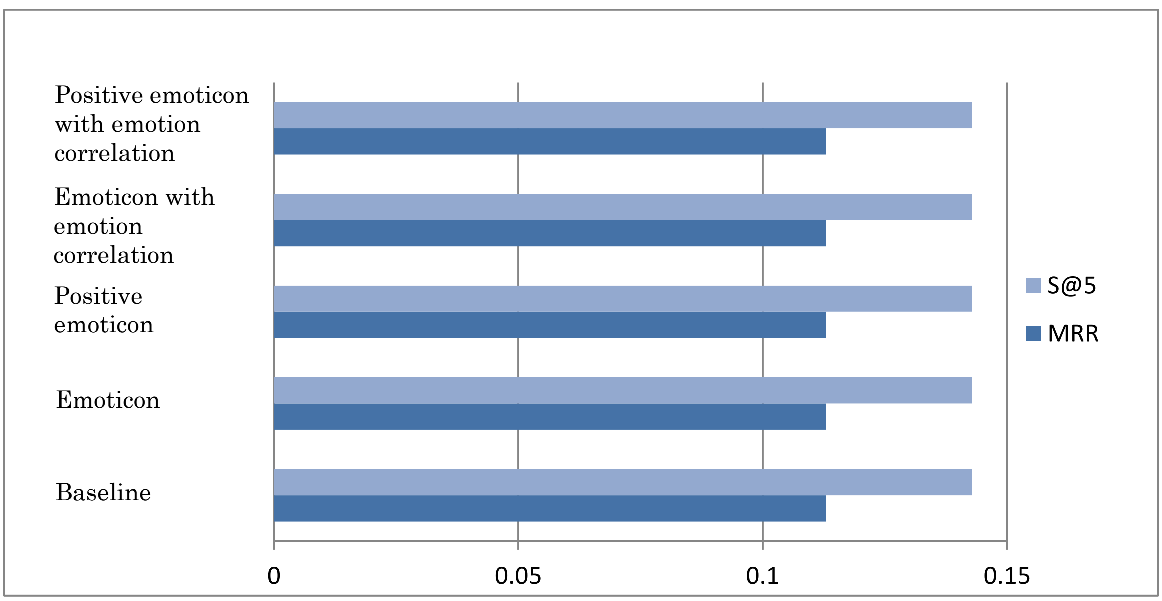


Figure 11 Results of hashtag-based profile for user sample U_E

Figure 11 shows the results of hashtag-based user profiles for user sample U_E. Compared with other results, we cannot see the advantages of our emotion-based user profiles. The results of five different strategies are close to each other. However, it does not mean that our emotion-based user profile does not work. The real reason is data sparsity[15] to construct the emotion-based user profiles. We analyzed the user profiles and noticed that few tweets have both emoticons and hashtags. This data sparsity problem [15] thus leads to such results.

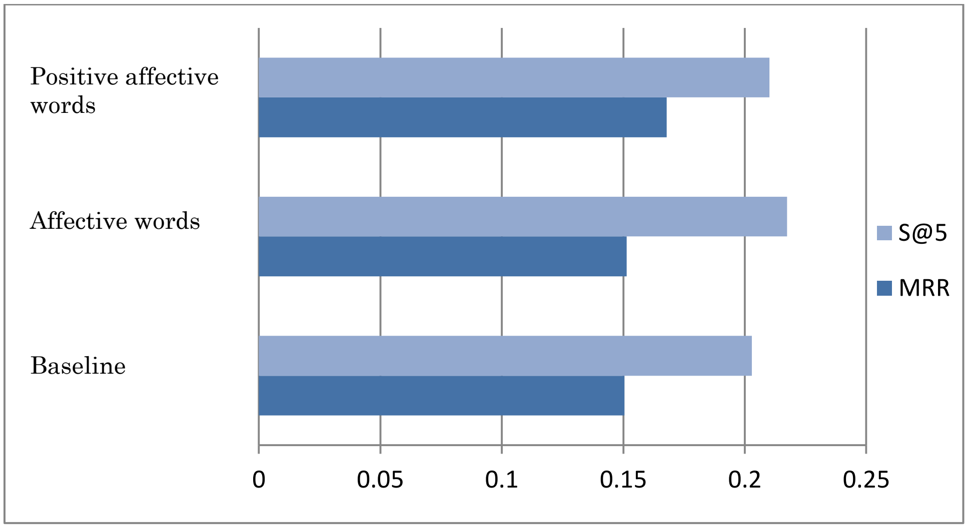


Figure 12 Results of entity-based profile with semantic enrichment for user sample U_A

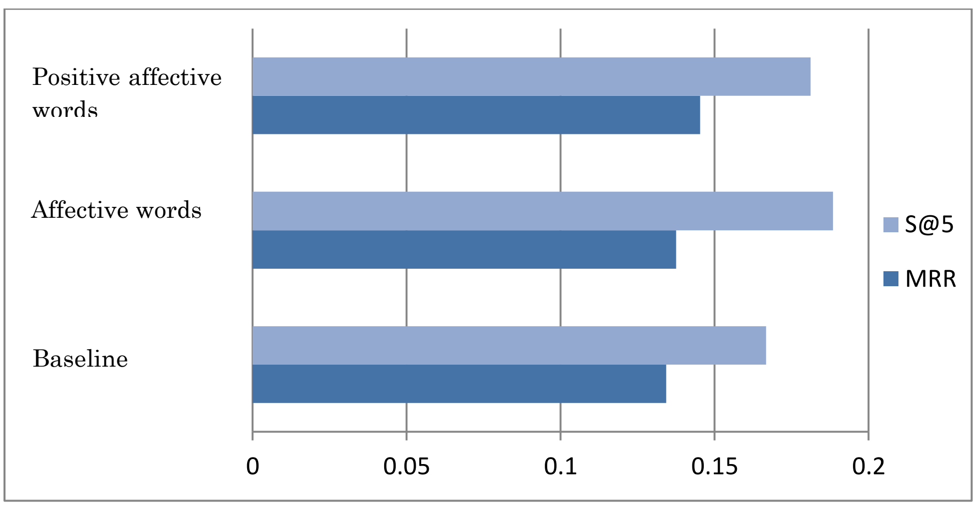


Figure 13 Results of entity-based profile for user sample U_A

These two figures summarize the results of entity-based profiles for user sample U_A. Figure 12 is the result of a semantic enriched emotion-based user profile. In figure 12, it shows out that our emotion-based user profiles performed better than the normal user profiles. Our best strategy of enriched emotion-based user profile regarding MRR improved 11.6%, while another measure S@5 increased more than 7.4%. From figure 13, it can be seen that our emotion-based user profile also performed better than the normal user profiles. The S@5 for our best emotion-based user modeling strategies improved by more than 13% compared with the baseline, while the MRR increased 8.1%.

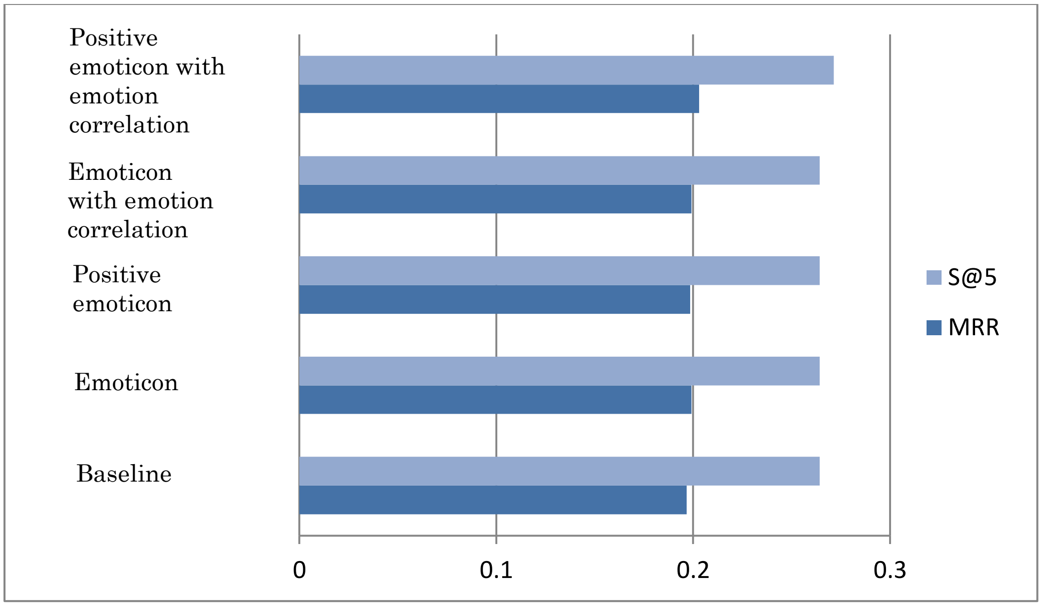


Figure 14 Results of entity-based profile with semantic enrichment for user sample U_E

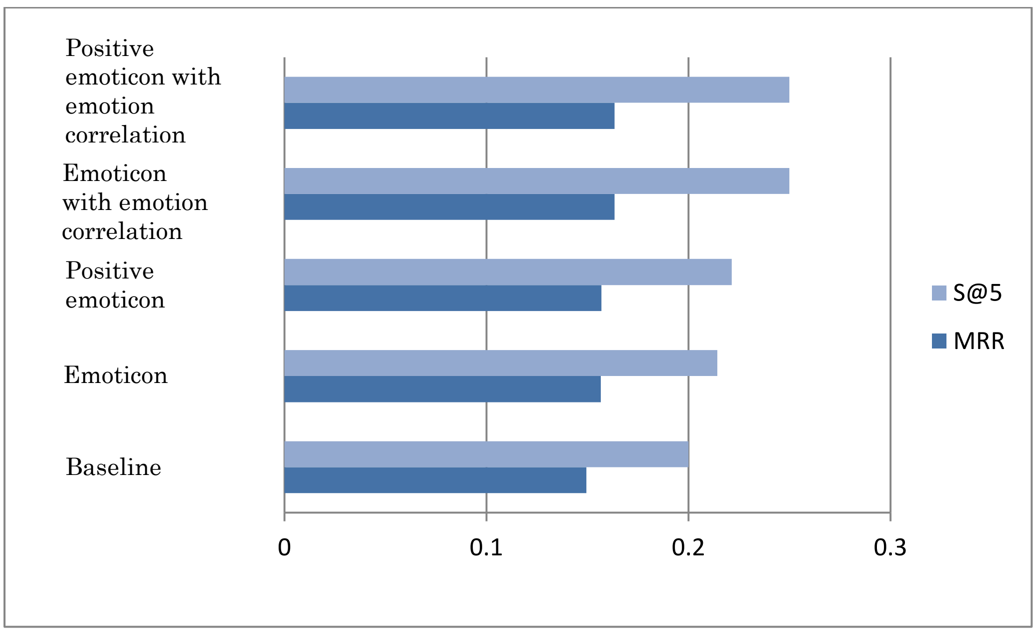


Figure 15 Results of entity-based profile for user sample U_E

The results of entity-based profiles for user sample U_E are summarized above. We analyzed three types of emotion-based user modeling strategies: positive emoticon, emoticon and emotion correlation. From our observation, we find that the recommendation quality was positively influenced by the emotion-based user profiles. We first analyzed the impact of our proposed emotion-based user modeling strategies with semantic enrichment in terms of recommendation accuracy, which is shown in figure 14. Our best strategies of enriched emotion-based user profiles performed slightly better than the baseline. However, the results are not as clear as previous results. Both MRR and S@5 in our best strategy only increased about 3%, which is lower than the previous improvement. The results show that semantic enrichment strategy has a negative impact on our improvement of emotion-based user profiles for user sample U_E.

The results of normal entity-based user profiles are present in figure 15. Without emotion correlation, performance of emotion-based user profiles regarding S@5 improved by more than 10% compared to the normal user profiles, while MRR increased slightly (5%). For the emotion-based user profile with emotion correlation, emotion-based user profiles improved the recommendation quality over the baseline significantly, which are 9.4% and 25% regarding MRR and S@5 respectively. This evidence clearly shows that our hypothesis of emotion-based user profiles performing better than the baseline entity-based user profiles.

6 Conclusions and Future Work

In this chapter, we will first give an overview of contribution for this study in the first section. And then we will present the answers to our research questions proposed at the beginning of our thesis work. Finally, we will give some possible directions of future work.

6.1 Contributions

We believe our work is beneficial for the user modeling on the Twitter platform and seeks to combine two hotspots, the emotion and user modeling, in the field of microblogging area. Through whole thesis work, our main contributions are as follows.

First of all, we investigated approaches for detection of emotion on Twitter platforms by using two emotional labels: emoticons and affective words, which are reported in previous studies [1] [2] [26] to detect emotion efficiently on the Twitter platform. In general, our approach for detection of emotion achieved a high accuracy, i.e., emoticon based approach achieved a 96% accuracy for the detection of users' emotion.

Secondly, we analyzed the sample users of our detection of emotion approaches and observed the difference from different emotional labels to detect emotions on the Twitter platform. From our analysis, we established the foundation that the approach of emoticon has a better accuracy to detect emotion than the approach of affective word. However, the number of emoticons is lower than the number of affective words, which shows that affective words are still the main way for people to express emotions on Twitter. What is more, emotional tweets detected by affective words usually have richer semantic meaning than the approach of emoticon, which is convenient when constructing the user profiles.

Thirdly, we gave a set of approaches for emotion-based user modeling strategies on the Twitter platform. By increasing the weights in the vector space models, we achieved the purpose of increasing the impact for those users' interests presented in emotional tweets. Different emotion-based user modeling strategies have been designed, and we also investigated their different impacts on normal user modeling strategies in the context of recommendation systems. Our design space includes modeling users' interests, different ways of modeling users' emotions, and semantic enrichment. By analyzing the results of our evaluation, we get the following results:

- Our emotion-based user profiles have a positive influence on recommendation accuracy.
- Semantic enrichment can increase the recommendation accuracy in both normal user profiles and emotion-based user profiles.

- Performances of entity profiles are better than the hashtag-based user profile in terms of recommendation accuracy.

Finally, we also explored the emotion correlation theory [49] and implemented it in our emoticon-based user profile to alleviate the emoticon data sparsity problem [15]. We tested this theory on our emoticon dataset, and found that our entity-based user profile had a positive influence in terms of recommendation accuracy about 16.8% compared with the normal emotion entity-based user profiles.

6.2 Answers to the research questions

1. How can we detect emotion from Twitter messages?

This question is answered in chapter 3. In this thesis, we use two classical approaches to detect emotion in Twitter messages. The first approach is based on the emoticons and the second approach is based on affective words. And we also evaluated our approach of emotion detection. We analyzed and compared these two approaches regarding user modeling. All of these details are presented in chapter 3.

2. How can we construct user profiles from micro-blogging activities on Twitter? How can we construct the emotion-based user profiles by different strategies? How do different emotion-based user modeling strategies impact the characteristics of user profiles?

To construct the user profiles from Twitter data, we extract the users' topics of interests from their published tweets, and then these "topics of interests" are weighted by their term frequency. Constructing the emotion-based user profiles is the main issue in this thesis. We noticed that concepts presented in emotional tweets are closer related to the users' experience. Based on this observation, we tried to increase the impact on our normal user profiles for those concepts which were present in emotional tweets. To achieve this purpose, we increase the weights in their vector space models for those concepts which are present in emotional tweets. Our design space includes modeling users' interests, modeling users' emotions and semantic enrichment. From our analysis of emotion-based user profiles, we could see different impacts of our emotion-based user modeling strategies on normal user profiles represented by figures. All of these details are given in chapter 4.

3. How could different user modeling strategies impact the recommendation performance? To which degree are the emotion based user profiles constructed by the different user modeling strategies appropriate for recommending tweets compared with normal user profiles?

In chapter 5, we investigated these research questions in context of recommendation system. We used two measures to evaluate the performance of our user profiles (S@k and

MRR) and results show that nearly every emotion-based user profile has positive influence than the normal user profile in terms of the recommendation accuracy. All of these works are discussed in chapter 5.

6.3 Future work

We already presented our conclusion and answered our research questions for this thesis. In this part, we will present some other possible future directions related to this work.

For the emotion part, we used two emotional labels for detecting emotion in Twitter: affective words and emoticons. Some other emotional labels could be tried. For instance, one new emotional label emoji was used as a new identification of emotions [14]. We also noticed that punctuation marks could be the identification of emotions when it is accompanied with some other emotional labels. In future work, different combinations of emotional labels (affective words, emoticons, emoji, and punctuation marks etc.) could be a possible direction for emotion detection. Furthermore, as has been mentioned in chapter 3, there are some semantic problems which may lead to the deviation of our detection. For instance, the affective word based approach relies on the semantic meaning of the words. In the following, we list some semantic problems from our observations in chapter 3.

- Different semantic meaning of words
- Negation problem

For future studies, some other strategies may be developed to solve these problems. In this thesis, detection of emotion from Twitter message is just one step of our work. We mainly focus on constructing emotion-based user modeling strategies instead of detection. These future works could be carried out in order to improve accuracy of emotion detection.

In user modeling area, some other strategies may be explored to construct the emotion-based user modeling strategies. For instance, in this thesis, we only focused on hashtag-based and entity-based these two types of user profiles. As discussed in chapter 4, these two types have their own advantages and disadvantages for emotion-based user modeling strategies. Some other types of emotion-based profiles may be explored for future work, for instance, using topics [7] to construct the emotion-based user profiles. And we also noticed that the data sparsity problem [15] in emoticon and hashtag-based user modeling strategies. Few tweets contain hashtags, emotional labels at same time, which makes it difficult to construct the distinguished emotion-based user profiles. Strategies for enriching this type of emotion-based user profiles could be the focus of future studies as well.

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