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Enhancing Emotion Elicitation using the Contextual, Multimodal Features of a Social Network

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1 Introduction

People nowadays use social networks like Facebook, twitter and Instagram on a daily basis. They tend to rely on them for a lot of functions like checking for news, keeping up with friends and most importantly as a way to express their emotions and thoughts. These networks provide a rich source of data that could be analyzed to provide information about different aspects of people's lives. These data could be used to elicit people's emotions from their social network statuses and interactions, which is the main focus of our research work.

There are numerous works in the literature that aim to detect people's emotions from various data sources like text and social network data. The current textual emotion detection techniques focus on the text analysis. Among those techniques are keyword spotting, lexical affinity and sentiment analysis. Keyword spotting detects certain affect words, such as happy, angry, sad and depressed in statements and assign an emotion category for each statement. Lexical affinity studies the relationship between words that co-occur in the same document through three models of lexical affinity, the document, functional, and distance models. Sentiment analysis handles emotion detection as a text classification problem. The current emotion detection attempts of social networks heavily depend on the textual techniques of emotion detection. They do not pay attention to other contextual information other than text, such as likes, comments and relationships between social network users who made the likes and comments and many other features of social networks. In section 2.0, we will detail the current literature. In the following sections, we will provide a detailed overview of social networks and define some terminology related to emotion and mood. We then define our research problem and present our thesis statement and our motivation to do this work and in the end present a layout of the thesis document.

1.1 Social Networks

A Social network is a social structure where individuals or groups interact. Social networks constitute a new kind of communication medium. They compete with older communication media such as phone calls, SMS messages, E-mails and chat services. There are many social networks on the Internet. Facebook, Twitter, Google Plus, and Instagram are examples of social networks. Social networks have become very popular recently, millions of people log on to social networks every day. This reflects how popular social networks are becoming and how integrated they are becoming in our daily lives Figure 1. shows the numbers of social networks users in millions until July 2013 [1].

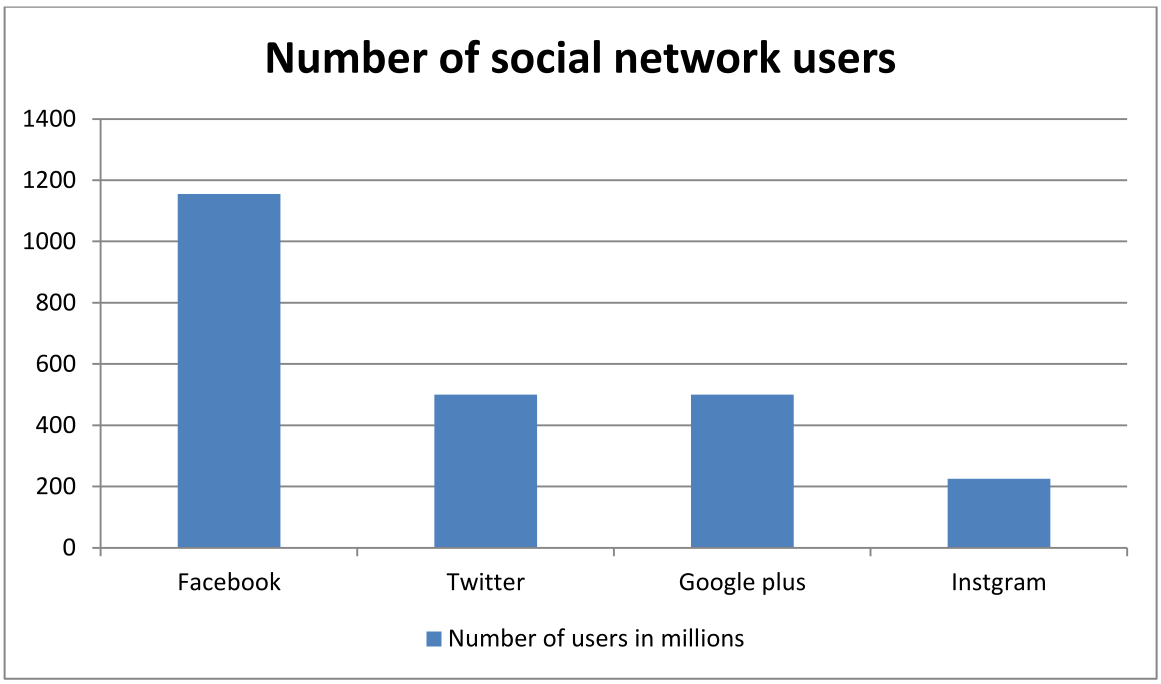

Figure 1: Statisitcs of Social Networks users [1].

In social networks each user has a profile. Users of Social networks have their personal information stored in their profiles like their name, e-mail addresses, phone numbers, religious beliefs, political views, employment information, calendar, events, photo albums, wall, current status, games, applications, groups, and much more information. Figure 2 shows an overview of a sample profile of a social network user:

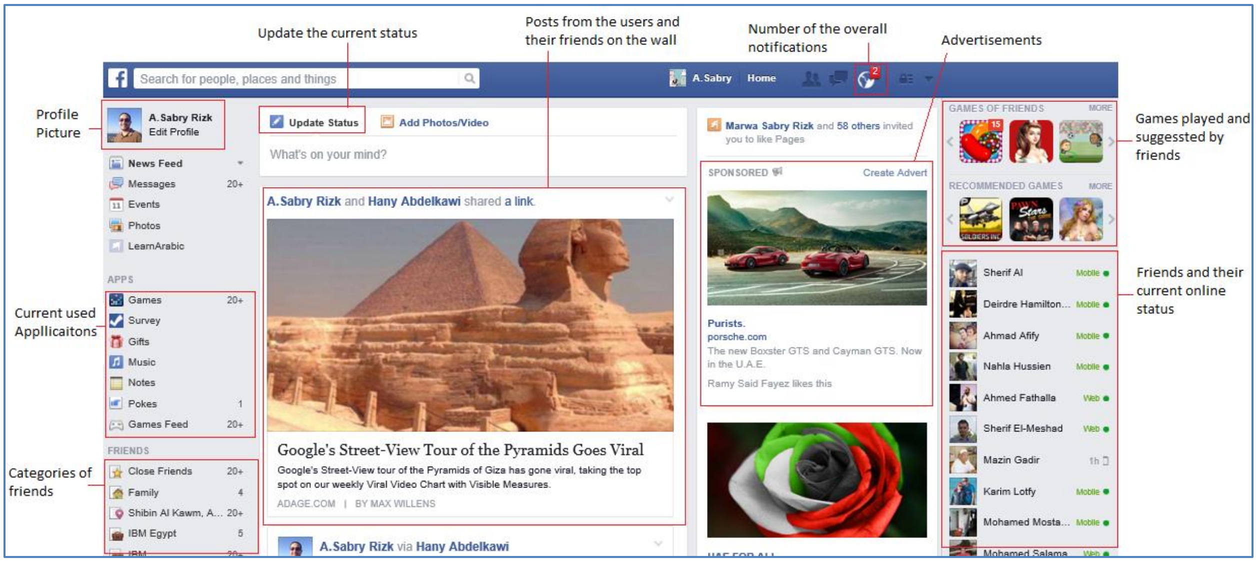

Figure 2: Sample profile of a social network user

Users of social networks invite each other to form their virtual community of friends. After forming this virtual community that consists of clusters of friends, they start to interact together. Some of the social networks provide people with the ability to write blogs about their activities and interests. They also provide users with means of exchanging data, posting text messages, music, videos, and links. Friends interact by commenting on the shared data or like. They share their ideas of what they are thinking of, their preferences, and interests. Table 1 summarizes features of social networks that represent the distinguishing factors between social networks and normal text.

Interaction	**Recipient(s)**	**Visibility/ notification**	**Intention(s)**
Profile message	Contact/own Profile	Public (all contacts)	- Introduction of a newly added user - Public display of interest/affection, or recommendation of the recipient, e.g., business - Let the recipient's contacts know what is going on between them
Bulletin/Posted item	Contact/own Profile	Public (all contacts)	- Share interesting content with contacts - Announce an important event to all contacts - Request feedback from contacts
Gift	Contact	Public (all contacts)	- Public display of interest/affection with more impact that a profile message because gifts are usually not free

Events (invitation)	Contact	Public or Private	- Invite (some) contacts to an event - Enable communication between attending People, e.g., for arranging a common gift, adding contacts) - Share content related to the event, e.g., photos, videos, links)
Groups (invitation)	Contact	Public or Private	- Gather people around a same interest or cause to enable communication about it - Opportunity to add contacts
Poke	Any person	Private	- Say "hello, check out my profile" to someone probably just met in real life (less formal than a connection request) - Temporary inclusion of the recipient in the sender's contacts, allowing visibility of his or her profile and rich communication
Private message	Any person	Private	- Have private interpersonal discussions (no particular interest for social networking)

Table 1: Typical interaction modalities on Social Networking Sites [1]

Facebook is one of the heavily used social networks, which report having around 1155 million active users[1]. It has more than 900 million objects that people interact with (pages, groups, events, and community pages). Also, it has more than 350 million active users currently access Facebook through their mobile devices. Facebook encapsulates much information about its users. In addition, each Facebook profile has the following features:

- Status message: a post by Facebook users that can be text, image, audio or video on their walls. Status message receives various interactions, such as likes, comments of the friends within Facebook and comments of Facebook users themselves as well. The below figure shows a sample of Facebook status message and the interactions between Facebook friends.

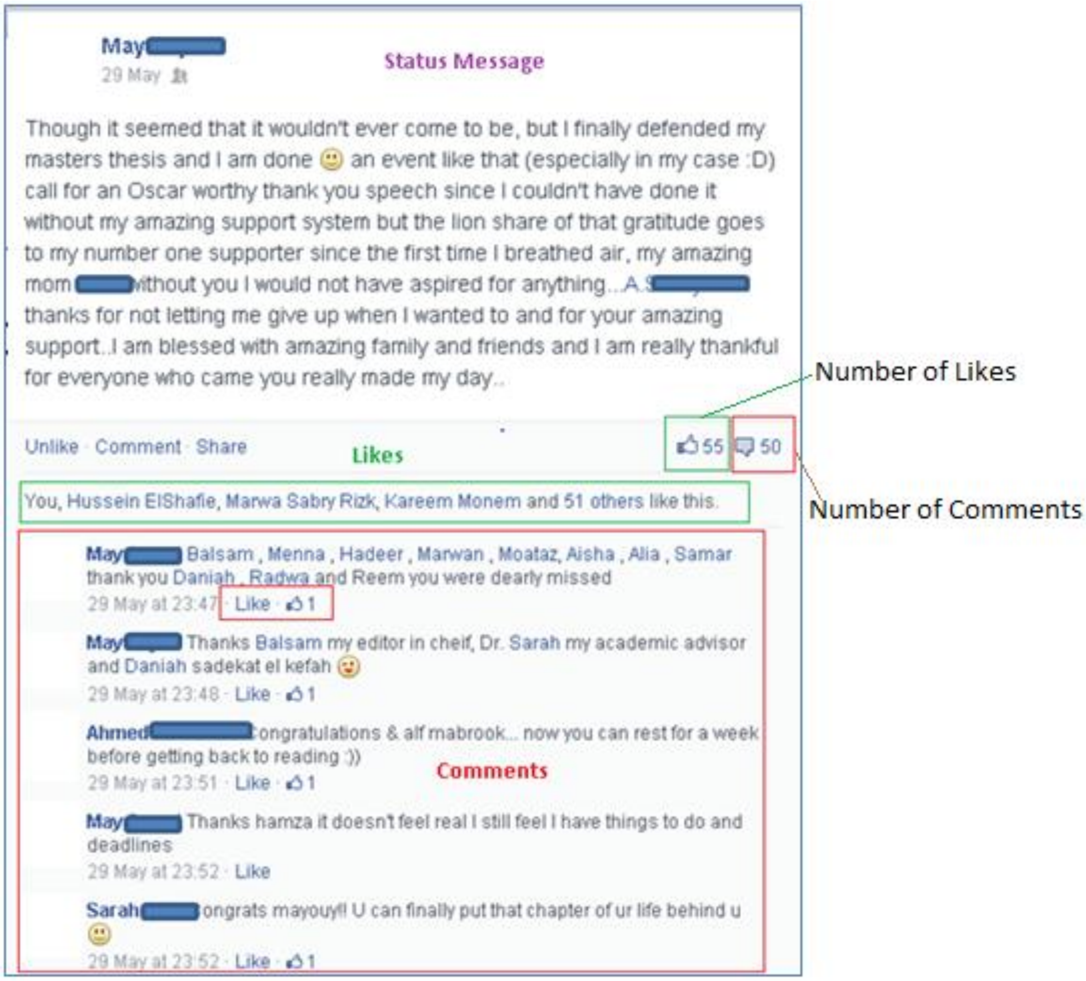

Figure 3: Facebook status message sample

- Status messages likes: Facebook allows the friends of its network to like each other's status message. They can click a like button. This feature notifies the users by the names of their friends who liked the post and their number.

- Status messages comments: friends of Facebook users communicate with Facebook users by posting comments to their posts. This feature notifies the users by the details of the comment and the total number of comments that they received. Facebook users and their friends can like the comments as well.

- Degree of connection (relationships between friends): Facebook allows its users to add their friends to categories such as family, close friends, general friends and many others. Facebook users can even create their own customized categories.
- Wall: the home page of each Facebook users, where they post their status messages photos, links, songs, videos …etc
- Events: provide the Facebook feature with the ability to held events like Birthday, Wedding, Meeting, conference…etc
- Gifts: users of Facebook can send to each other gifts in special events like birthdays
- Notes: users of Facebook use the Facebook notes as a blogging feature. They write topics they are interested in and share it with their friends. They receive comments and likes about them
- Applications: Facebook is very good framework for games, quizzes, surveys, favorite books, music, movies, and many other applications
- Albums of Photos: Facebook users share their albums and photos with their friends.
- Places: This feature allows mobile users to interact with their Facebook accounts. They can post their location instantly through it.
- Shared links: Songs and audio files, URL links, and videos
- My notification: whenever a person comments on or likes one of the Facebook users posted items, they are notified about this activity

Having all this rich information is valuable and worth analysis, Facebook social networks can be thought of as a virtual replica of our real social life. Analyzing these data extensively and determining the emotions of the users based on those data, we can build automated software services for social networks' users that are based on their current emotion like filtering what posts to appear on their newsfeed. In our research, we focused on how to automatically elicit the emotions of the users of social networks. We asked the social network users to tag their emotions after receiving social network interactions to their status messages. We automatically detected their emotions. We calculated the correctly detected emotions. Then, we evaluated our methodology by calculating the accuracy of the automatically detected emotions against the real tagged emotions of the social network users. In the following section, we will explain some of the basic definitions and concepts of emotions that will help us throughout the document.

1.2 Emotion, Mood, and Affect

Humans communicate together using languages, which are composed of a set of sentences. Sentences carry both information and emotional feelings. Following are definitions of various terminologies that will be used throughout the document in regard to the psychology behind mood concepts. It will provide us with the difference between emotion and other psychological terms like affect and mood. Emotion: is a short-term state of mind, which includes a psychological arousal [2]. An Emotion cannot be a physical state like pain or a behavioral state like aggression. For example, love, happy, anger, and fear are all considered an emotion. An Emotion can be positive or negative. Mood: is a state of mind that includes a psychological arousal. However, the duration of the state that the mind experience is the main difference between emotion and mood. Mood lasts longer than emotion [3]. Affect: Affective valence is a measure that indicates how an emotion is positive or negative [2]. It is a characteristic feature of an emotion as emotions cannot be neutral. For example happy is a positive emotion and sad is negative emotion.

Ekman classified emotions into six basic emotional categories, which are happiness, sadness, anger, fear, disgust, and surprise [4]. They are known as the six basic emotions. There have been other classification models for emotions, such as International Affective Picture System (IAPS), the International Affective Digital Sounds (IADS) and the Affective Norms for English Words (ANEW) [4]. IAPS, and IADS are collections of picture and sound stimuli, respectively. They include the affective ratings. The aim of the ANEW is to complement both of IAPS and IADS. In ANEW, they assumed that emotion can be defined in terms of different dimensional views. Affective valence, arousal and dominance or control, are the major three dimensions. We will detail the problem that we are solving in the following section.

1.3 Problem Definition

Automatic emotion elicitation of people has been an open research question for many years, and can be the foundation of a significant amount of intelligent applications. Some attempts have been made to elicit a limited set of emotions of social network users, however with significant limitations. On one hand, some approaches rely on invasively asking users a set of questions to ultimately elicit their emotions [5]: an approach that lacks automation, and is considered significantly invasive to typical application usage.

On another hand, and most importantly, other researches have purely dealt with the emotion elicitation problem of social networking from a very limited perspective, and only used the textual features of the status messages of the social networks [6][7], entirely ignoring the wealth of other sources of information that could be used to better detect emotions, such as the social graph of participants(also known as degree of connection or relationships between friends), location, comments, likes, events, images, audio and much more. They also did not address how this information impacts the emotions of the social networks.

1.4 Thesis Statement

In this research, we used social networks as a viable source of user emotions. We conducted a survey to understand the features of social networks that impact the emotions of the social network users. To distinguish ourselves from other researchers who only dealt with emotion elicitation from social networks as a pure textual problem, we capitalized the various multi-modal features of social networks to include the social graph of users, and their corresponding interaction with the posts of their social network contacts such as comments and likes. We fine-grained the emotion detection of users into a total of eighteen possible emotions as opposed to the classical six emotions used by Ekman with a comparable or even better accuracy [4].

The below table shows the list of sub-categories that we will classify social networks' emotions to:

Weak strength	**Basic Ekman emotion**	**Strong strength**
Content	Happy	Joyful
Excited	Surprised	Astonished
Discontent	Sad	Grief
Annoyed	Angry	Furious
Bored	Disgusted	Loathing
Anxious	Fearful	Terrified

Table 1: Extended labels of emotions

We collected our own dataset which consisted of 296 status message and 1278 comments that are annotated with the relevant emotions by the social network users. To achieve this proposed contribution, we started by using ConceptNet applied on status messages to identify the emotion of users into one of the six basic emotions identified by Ekman, namely: Happy, surprised, sad, angry, disgusted, and fearful. We subsequently analyzed the likes of the status message and the sentiment detected in the status message, the associated comments, and the degree of connection of the social contacts contributing to both of the comments and the likes to be able to map the detected emotions into one of eighteen different categories of emotions that include the six basic Ekman emotions, and 12 other emotions representing weak and strong variations of the six basic Ekman emotions. We compared our results to the manually annotated data, hoping to achieve better or comparable accuracy. We calculated how many emotions we managed to correctly detect. Then, we calculated our accuracy by dividing the number of correctly detected emotions with the total number of emotions. In the following section, we will explain our motivation to conduct our research.

1.5 Motivation

The popularity of social networks continues to grow; users of social networks instantly update their profiles with their daily statuses, comments, photos, and more. Social networks can be thought of as an online replica of our real lives. This encourages us to research the effect of social networks on the emotional and psychological state of their users. We will experiment how the extensive interaction between the contextual and multimodal features of social networks will affect the emotions of their users. Emotion detection from social networks aims at providing better experiences to their users. Knowing the current emotional state of the social networks users, we can build customized software services for them. Social networks may personalize their interface and features based on users' current state. For example, the current themes of the social network can change automatically to adapt with the current emotion of the user. If the system detects that the user is experiencing a bad emotion during last few days, the theme of the social network will be changed automatically, trying to make the user feel better.

Emotions are essential for recommendation systems [8]. Automatic recommendation systems can be built based on the emotions of the users. The system can automatically suggest a new set of activities to the users based on the profile information and the automatically detected emotions from their interactions. These activities help the users feel better or enhance their emotions. For example, the system may suggest watching movie, listening to music [9], reading a novel or use applications and games based on the profile of the user and the detected emotion. Online advertisement business is tremendously growing as well. Automatic recommendation systems can display customized advertisements to the users based on their emotion. Personalizing the advertisement according to social networks users' emotion and preferences will increase the number of responses directed towards the advertisements. This will positively impact both the satisfaction of the users and the revenue generated from these advertisements.

Emotion and mood of social networks users can be an indicator for stock market. Research shows that stock market prices can be predicted to some degree as they donot follow random patterns [10] [11] [12]. Recent studies suggest that very early indicator can be extracted from online social media, such as Twitter blogs and other feeds that predict changes in various economic and commercial indicators [13]. In addition to information, emotions play an important role in human decision making [11][14]. In stock market, public mood states and sentiment play an important role beside news to influence the prices. Behavioral finance showed that financial decisions are very much driven by emotion and mood [15].Therefore, understanding the public emotion and mood sentiment is important to predict stock market values as they can drive it as much as news. Bollen et al. presented a technique to predict stock market trends from the mood detected from twitter tweets [13].

In the following section, we will detail the thesis layout.

1.6 Thesis Layout

We present our literature review in the following section. Then, we explain our research methodology in section 3 which we start by our survey to understand how the social network users are affected by social network features in section 3.1. We explain our dataset and Facebook data extraction methodology in section 3.2. We detail our emotion elicitation approach which describes the various experiments which we conducted and their output in section 3.3. We finally present our conclusion and future work in section 4.

2 Literature Review

In this section, we will present a literature review of emotion and mood detection problem and what research has been done so far. We will analyze some of the more relevant related work that pertains to the study of emotion detection in social systems.

2.1 Computational Models of Emotion

There are two major computational models of emotions: the categorical emotion model and the dimensional emotion model. The two models have different methods of estimating the emotional state of the person. We will discuss these two models in details.

2.2 Categorical Emotion Models

Categorical emotion models map the emotional state of the people to a set of discrete emotions. Ekman mapped the emotional state of the people to six basic emotions: anger, disgust, fear, happiness, sadness and surprise [4]. Some of the researchers categorized emotions based on the domain. D'Mello, Picard and Graesser studied the domain of education. They noticed that learners rarely experience sadness, fear or disgust [16]. They came up with a specific set of emotions that is more suitable for the domain of education. They proposed boredom, confusion, delight, flow and frustration. Categorical emotion models offer a limited number of labels (categories) which imposes limitations on this method. For instance, there are several emotions and there are variations between those emotions that are grouped under the same category. This approach can force the users of this emotional model to select an irrelevant category. For example, if the users of the Ekman model donot find their emotional category within the six basic emotions anger, disgust, fear, happiness, sadness and surprise, they will have to select one of them. They have no other option. The categories donot adequately cover all the emotions. There are other factors that impact how the same affect state can be expressed by means of emotional categories, such as cultural, linguistic, environmental and personal differences.

2.3 Dimensional Emotion Models

Dimensional emotion models approach represents affect in a dimensional form. The relationships between emotional states are defined according to one or more dimensions. We will briefly review some of the dimensional emotion models.

2.3.1 Circumplex model

Russell et al. represented the emotional states in a valence-arousal bipolar space [17]. The valence dimension represents the horizontal axis. It has positive and negative directions. The arousal dimension represents the vertical axis and shows excited vs. calm states. The center of circumplex represents the neutral state. Figure 4 illustrates the circumplex model.

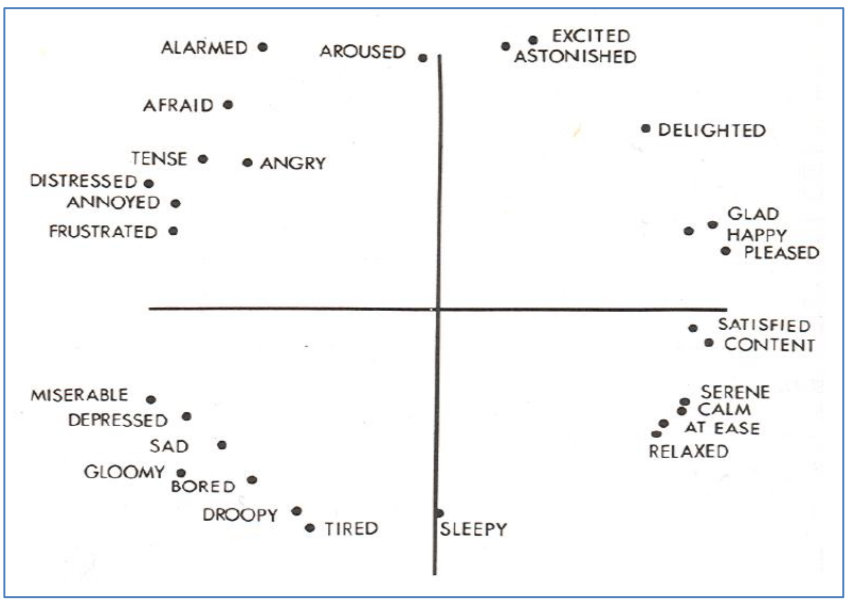

Figure 4: Multidimensional scaling of Russell's Circumplex model of emotion [17]

2.3.2 Thayer's model

Thayer represented his model as a two dimensional model of energy and stress [18]. Contentment is located in the low energy-low stress, depression is in low energy-high stress, exuberance is in the high energy-low stress and anxious-frantic high energy-high stress as illustrated in Figure 5.

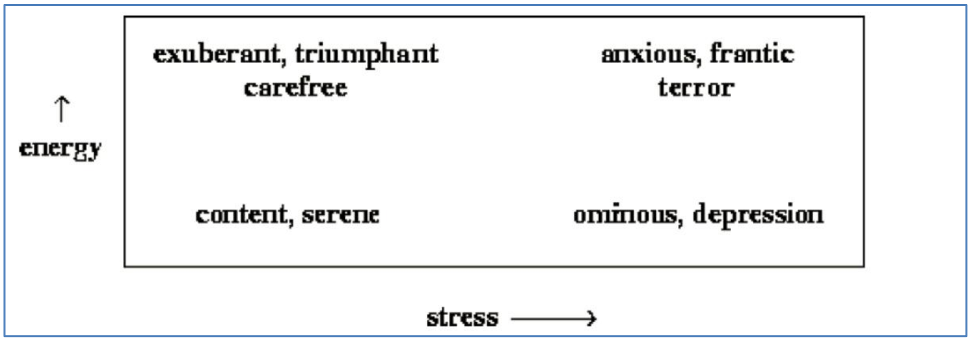

Figure 5: Thayer's dimensional emotion model [18]

2.3.3 Plutchik's emotion wheel

Plutchik classified emotions to 8 basic emotions and 8 advanced ones each one of them is composed of the 2 basic ones [19]. Plutchik's emotion model is called the emotion wheel. Figure 6 shows an overview of Plutchik model. The 8 basic emotions are joy, sadness, trust, disgust, fear, anger, surprise and anticipation. The advanced 8 are optimism, love, submission, awe, disappointment, remorse, contempt and aggressiveness. Table 2 explains how each of the advanced emotions is composed of two of the basic emotions.

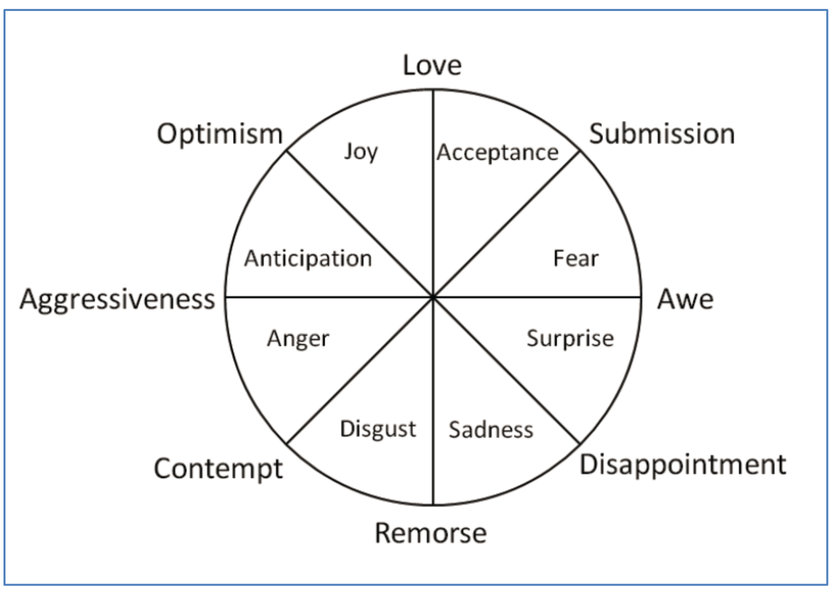

Figure 6: Plutchik's emotion wheel [19]

Human feelings (results of emotions)	Feelings	Opposite
Optimism	Anticipation + Joy	Disapproval
Love	Joy + Trust	Remorse
Submission	Trust + Fear	Contempt
Awe	Fear + Surprise	Aggression
Disapproval	Surprise + Sadness	Optimism
Remorse	Sadness + Disgust	Love
Contempt	Disgust + Anger	Submission
Aggressiveness	Anger + Anticipation	Awe

Table 2: Plutchik's emotion model [19]

2.3.4 Affective Model of Interplay between Emotions and Learning

Kort et al. created a model which correlated the phases of learning to emotions in a two dimensional space of valence and arousal [20]. Figure 7 shows the two dimensional space of valence and arousal that they used to build their computerized system to detect the emotions of the learner.

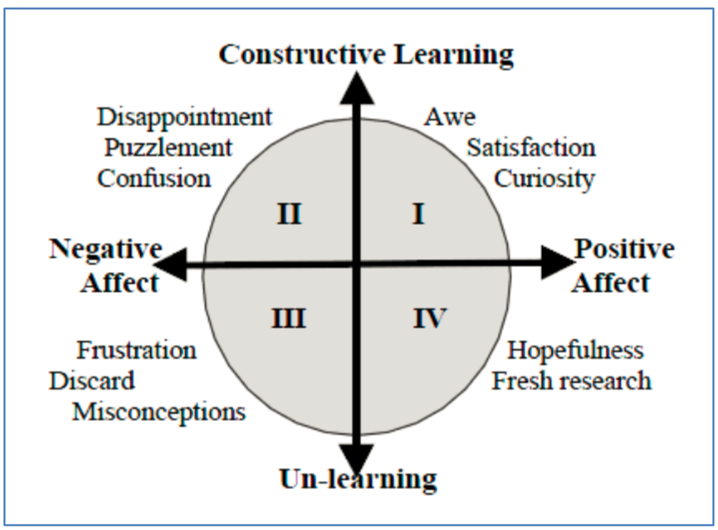

Figure 7: Affective model of interplay between emotions and learning [20][4]

2.4 Mapping categorical and dimensional emotion models

Krenn attempted to map the categorical and dimensional emotion models in the Net Environments for Embodied Emotional Conversational Agents (NECA) project [21]. Krenn developed an affective reasoning component to determine the appropriate emotion in a given dialogue situation. Figure 8 shows the outcome of the mapping.

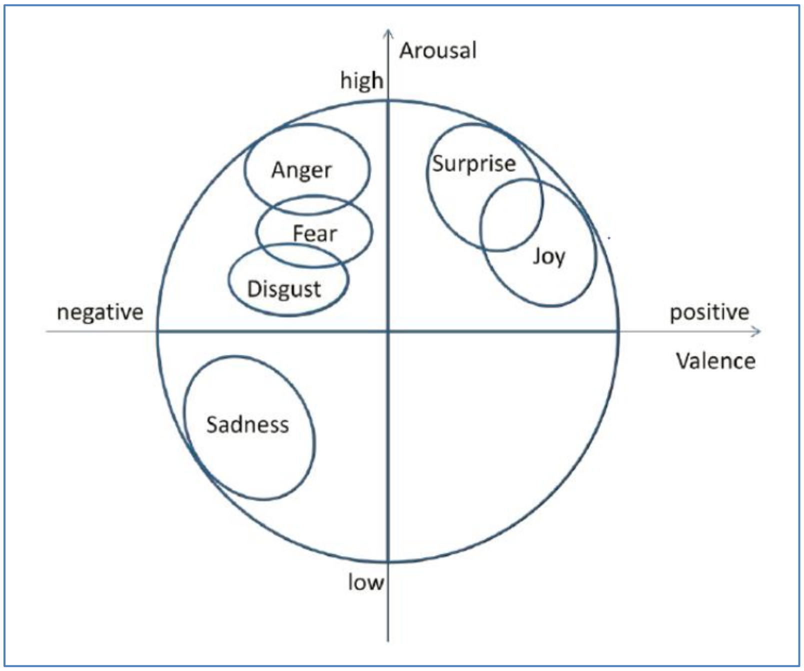

Figure 8: Mapping six basic emotions onto Russell's circumplex [21]

2.5 The impact of social networks on the emotional and psychological state of the users of social networks

With the widespread of social network in our daily lives, their effect on our emotions and mood is yet to be investigated thoroughly. Few studies have been conducted in order to study emotional affect and expression in social media using novel approaches other than simple text mining. The more their impact is understood, the more social networks can continue to provide valuable contextual information to pervasive systems.

In January 2012 for one week Facebook data scientists altered the news feeds of almost 700,000 Facebook users. Some of the users were shown feeds which contain positive content and some were shown content analyzed as negative. After the one week was over the users who were shown positive feeds tended to share positive posts and the one were shown negative feeds tended to share negative posts [22].

In [23] and [24] Kramer analyzed the status updates of 400 million Facebook users in North America over time. The author showed that status updates provides cues to the emotional state of the user and can provide insights to the state of the groups updating status. He counted the relative rates of positive and negative emotion word use to identify culturally shared positive and negative events. In another study, the author aimed to research emotion contagion in social networks. Emotional contagion is the process by which people "catch" emotions form each other [25]. Through the study of Facebook status update, they show that when users exhibit a certain emotion in their status, their friends are more likely to make a similar emotion oriented posts. They indicate that emotion contagion is possible through online communication and that emotion is expressed and flow through social networks.

In [26], a study is conducted to investigate emotional communication in computer-meditated communication. The study examined negative emotion expression and contagion and they concluded that negative emotion was expressed and sensed by the communicating parties and that emotional contagion takes place in computer-meditated communication.

Also in [27], a study of Facebook investigated the self-expression tendency of Facebook users through their status updates. A sample of four million Facebook users has been used from four different English-language speaking countries. The results reflected that there are some country-level differences regarding formality of speech while expressing the status updates. However, the more remarkable finding was that the four countries showed remarkably similar results.

Otto in [28] investigated how the daily usage of social networks can affect the life and the wellbeing of their users. He conducted his study using a sample of 84 international Facebook users. His experiments focused on how the daily usage of Facebook activities and features can affect life satisfaction, self-esteem and loneliness.

Toma studied the behavioral impact of social networks on self-affirmation [29]. Self-affirmation is the process of bringing to awareness important aspects of the self, such as values, goals, and treasured characteristics. People are more open-minded and less defensive when they have more awareness about their values, goals, and characteristics. Toma examined within his study the ability of social networks, such as Facebook to increase the self-affirming value of the users. In this experiment, the users of Facebook were asked to spend more time on their own Facebook profile or someone else's profile. Then, they were given a negative feedback on a task. The results of the experiments reflected that participants who spent more time on their own profiles were more accepting of the negative feedback. These results showed that viewing user's own profile page serves the psychological goal of self-affirmation

2.6 Current Emotion and Mood detection based on Textual Techniques

We will discuss how computational techniques have been used so far across different textual communication mediums such as text, blogs and social networks to detect emotions and moods in this section.

2.6.1 Text

Human being use languages to communicate in their daily lives. These languages describe what they have in their minds and what they feel. They use words and those words are put together to build sentences. Humans communicate their language by speaking or writing. Researchers who are interested in mining the emotional state of humans direct their research to this representation of the human language. They analyze speech and text to predict the emotional state of the person. In this section, we will show previous attempts to detect emotions and moods from text.

2.6.1.1 Keyword Spotting

People in their normal daily conversation use words that express their feelings and emotions. If we examine statements said by humans, we can guess their emotional state and categorize it. Keyword spotting is one of the most popular techniques for emotion mining. It detects certain affect words such as happy, angry, sad and depressed in statements and assign an emotion category for each statements [31]. The statement "I am happy," contains the affect word "happy." A keyword spotting technique would assign this statement to the happiness category. The statement "I am afraid" contains the affect word "afraid" this will make it a good candidate for the fear category. Xu and Anthony designed Text-to-Emotion Engine for Real-Time Internet Communication [31]. This Engine was constructed of three models, the input analysis function, tagging system and parser. Figure 9 shows those three models and how they interact with each other.

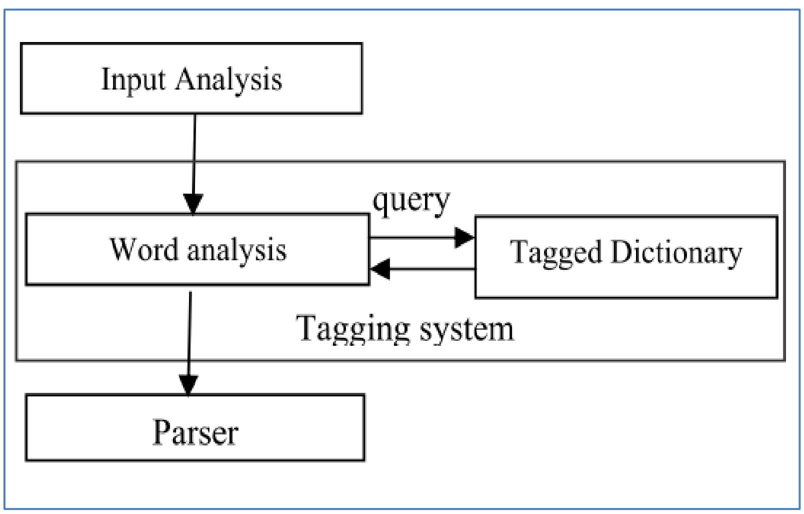

Figure 9: Text-To-Emotion Engine Real-Time Internet Communication [31]

The input analysis function analyzed the corpus sentence by sentence. The engine independently processed each sentence from the context. It replaced the punctuation with a set of predefined delimiters. The Tagging system tags split each sentence into words. It looks up the tag category of each word from a dictionary and assigns this tag to the word and also assigns an intensity level for the word.

In case the word was not found in the dictionary, the tagging system will try to guess the affect category for the word from its suffix and prefix. Figure 10 shows how the tagging system works.

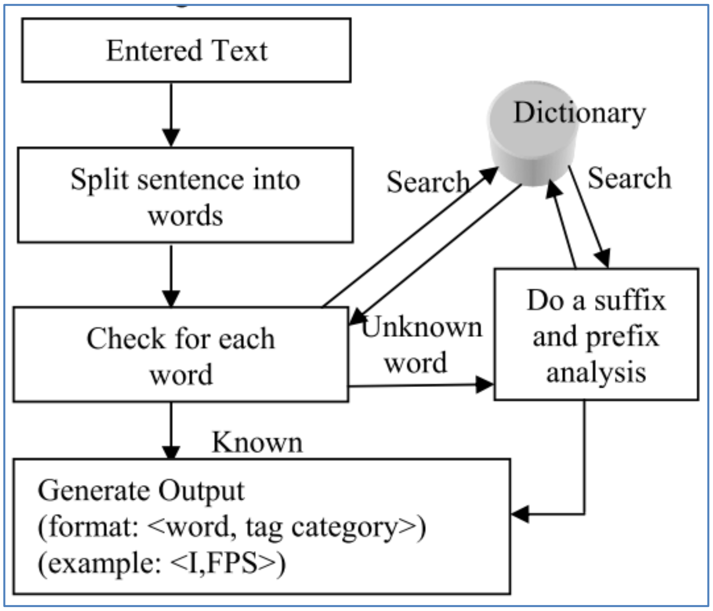

Figure 10: Tagging System [31]

The parser works according to a set of rules. The parser accepts only sentences, which have emotional words. It discards all other sentences. If the parser finds an expressive adjective in front of the affect word, it will increase the intensity of the word automatically. If no adjective found, the parser will assign the intensity passed with the word from the tagging system. The text-to-emotion engine is looking for the current emotion of the user. Thus, if the parser finds an auxiliary verb, it has to be in the present continuous form to be taken into consideration. If the parser matched a sentence, which starts with an auxiliary verb, this is considered a question so it will ignore it. The parser will ignore the words, which contain negation. The output of the parser will contain the emotional category, the expression intensity, and the tense. Figure 11 represents a flowchart of how the parser works.

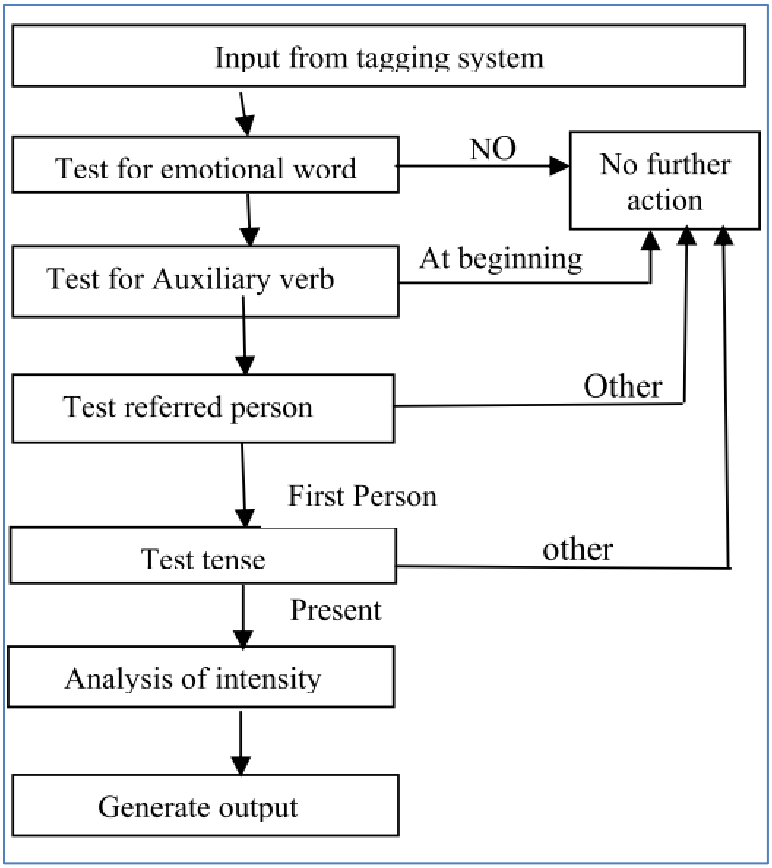

Figure 11: Parser of Text-To-Emotion Engine [31]

Keyword spotting techniques depend on the existing lexicons, such as WordNet-Affect [33] and SentiWordNet [33]. WordNet-Affect is based on WordNet. WordNet groups English nouns, verbs, adjectives, and adverbs into a set of synonyms. Those synonyms are called synsets. Synsets have conceptual-semantic and lexical relations. WordNet-Affect extends the ability of WordNet to encapsulate an annotation for the synsets that have affect content. For each synset of WordNetSentiWordNet assigns three sentiment scores: positivity, negativity, objectivity. Some of the Keyword spotting techniques combine between the existing lexicons to increase their accuracy. François-Régis combined between WordNet andSentiWordNet to get better results [34].

Keyword spotting can be extended to include pictogram and graphical symbols spotting. Pictograms are graphical symbols that represent the meaning of a word [35]. For example, the following symbol of ball like this symbol "⚽" represents succor. Emoticons use punctuations to represent facial expressions. For example, ":)" is used to represent a smile, ":@" is used to represent anger and many other of combinations used frequently by the users of the Internet. Both of Pictograms and Emoticons are used by email users in their daily lives activity of writing e-mails. Yamashita et al., implemented a system that analyze e-mails and extract both pictograms and emoticons [35]. They selected a pool of pictograms. They classified them into 6 groups: foods and drinks, sports, actions, places, transportation means, and goods. In addition, they classified emotion elements into four categories: happy, angry, sad, and optimistic.

They created a vector mood for each pictogram or emoticon. The made a rating criteria for those pictograms and emoticons. This rating starts from 0 to 5 for each emotion element. Below is an explanation for the ratings:

0: one is not conscious of that particular emotion.

1: there is a slight sign of that particular emotion, but it may be a misunderstanding.

2: one may perceive that particular emotion from time to time.

3: one clearly can perceive that particular emotion.

4: one feels like expressing the particular emotion actively.

5: the emotion is overwhelming, and one wants to show it to others.

Figure 12 illustrates how this rating system works. The final mood of the user is estimated from calculating the ratings for all pictograms and emoticons in the email of the user. This mood can be used to determine which content matches the users' mood to deliver personalized content to them.

Pictogram	Meaning	Happy	Angry	Sad	Optimistic	Tired	Affectionate
	Wow	5	0	0	3	0	2
		5	0	0	4	0	2
	Enough	0	0	3	0	3	0
		0	0	4	0	4	0
	Black heart symbol	3	0	0	2	0	5
		5	0	0	4	0	5
	Yay	5	0	0	2	0	2
		5	0	0	5	0	3

Figure 12: Emotion database for men (upper row) and that for women (lower row) [35]

Keyword spotting techniques are popular because they are easy to implement and economical too. On the other hand, their performance is very poor if the meaning of the sentence is understood from the group of words that exist in the sentence itself not from a specific word in the sentence. Negation statements are example of statements, which you have to understand the whole sentence to get the correct meaning. "I have never been happy" although it contains the affect word "happy" the overall meaning does not imply happiness. Idioms are also examples of such statements, which the meaning is implied from the words. "When does this movie end?" is a statement that implies that the speaker is bored of the movie although it does not contain any affect words.

2.6.1.2 Lexical affinity

Lexical affinity measures the relationship between words that co-occur in the same document [36]. There are three models of lexical affinity, the document, functional, and distance models. The document distance model is used mostly in information retrieval. The relationships between the words are measured based on how frequent the words appear together. The functional models use the syntactic information of the words to measure the co-occurrence frequencies. For example, "play" as verb and "ball" as noun. The distance models measure the frequency at which the two words may appear within a distance. They can be next to each other or away by x number of words, where x is an integer. For example, the n-gram models the strength of the affinity is given by P(w|h) where P(w|h) is the probability of the occurrence of w after a sequence of one or more h.

Lexical affinity techniques are more advanced than the keyword spotting techniques. They are used to assign certain probabilistic affinity for each emotion. For example, the word "birthday" will be assigned an 80% probability of indicating a positive affect. Ma et al. presented an approach that used lexical affinity to detect emotion from textual messages. Words can have many meanings although few of them can be emotional. The word "beat" has 23 senses in WordNet; only 5 of them are emotional. Ma et al. assigned a weight for of 0.22 for the word “beat” [37]. Each weight that they have assigned to emotional category has to lie between 0 and 1. They performed word level and sentence level processing. For the word level processing they used word spotting technique to evaluate the emotional indication of the words. Then, the whole phrase is assigned an emotional estimation by summing all the emotional indications of its words. To enhance the performance of the word processing level, Ma et al. used sentence splitting, part of speech tagging (POS) and negation detection techniques. They converted multiple-sentence to single sentence. Then, using the POS they derived the syntactic phrase types. They masked out non-emotional sentences, such as questions and clause phrases beginning with "when," "after," "before," or "if". The remaining sentences are processed. In addition, Ma et al. checked for the negation and derived cases to handle negative verb forms, such as "have not," "was not," and "did not". Whenever any of these negative forms were detected, they changed indication of the motion from positive to negative. Figure 13 shows the architecture of the system design and implemented by Ma et al. The ChatServer Module listened to the connections coming from the clients. The Emotion Estimation Module processed the incoming messages and tags it with an emotional tag. Once this tag was done it was sent to the Agent Behavior Control Module.

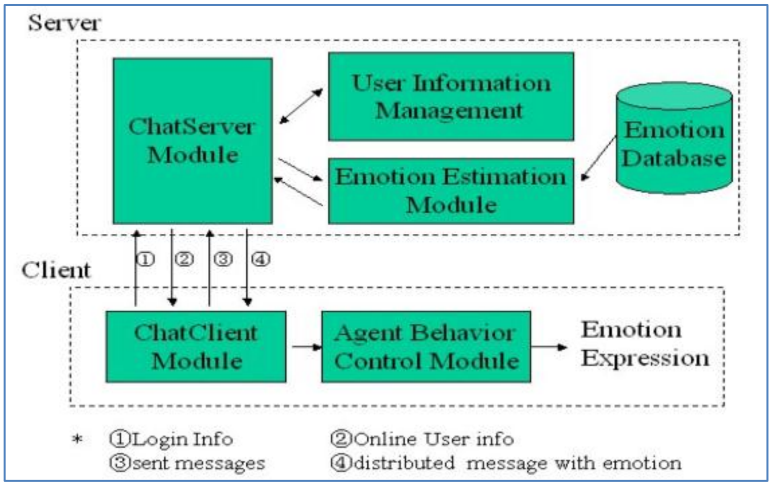

Figure 13: Architecture of the chat system [37]

The Agent Behavior Control Module displayed the message to the user and animated the avatar according to the estimated emotional expression.

Jianhua represented another example of lexical affinity [38]. Jianhua classified the emotion functional words into emotional words, modifier words, and metaphor words in his attempts to detect the emotions from text input. Emotional keywords are keywords that represent the emotional state of a person. For example, the word “unhappy” may indicate “angry” or “sad.” This indication differs according to the personality and the context in which the word was mentioned. A weight is assigned for each of them to increase the accuracy. In our previous example the word “unhappy” was assigned a weight of 0.5 for “angry” and a weight of 0.5 for “sad.” Then, the result was calculated based on a combination of the weights assigned for each emotional keyword. Modifier words are words such as “very, so, too much, not, etc.” The modifier words can increase or decrease the intensity of the mood. For example, the sentence “I am so angry” includes the modifier “so,” this modifier increases the intensity of the anger mood. Thus, "I am so angry" is considered stronger than "I am angry." This means that the anger level is strengthened with adding the modifier word "so." Metaphor words give an indication about the attitude and moral character of a person. For example, “asperity” is more related to negative emotions like “anger” or “hate.” However, “Kindness” is related to positive emotions like “joy” or “neutral.” Jianhua introduced a unified architecture based on Emotion eStimation Net (ESiN). ESIN integrates context dependent probabilistic hierarchical sub-lexical modeling. Figure 14shows the lexicon structure used in ESiN:

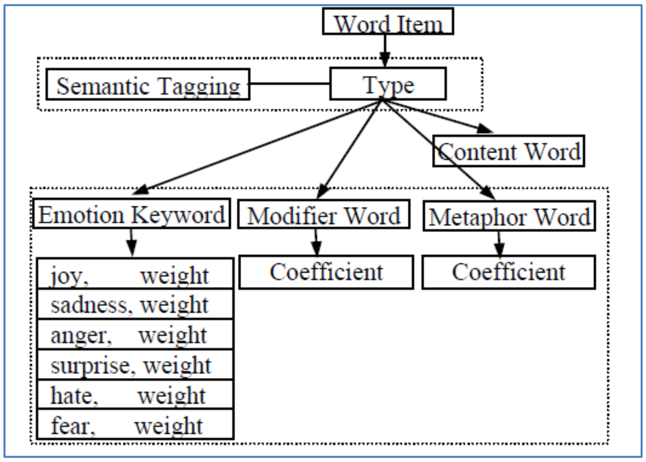

Figure 14: ESiN Lexicon Structure [38]

In ESiN a word is represented as a node that has: emotion states, the corresponding weights, and semantic tagging. There are routes between those nodes. The routes are propagation of the emotion. It has three attributes: direction, transmission probability, and propagation decreasing coefficient. The final emotion value of the node t is calculated from the following formula.

$$\vec{E}_t = D(\vec{E}_{t-1}) = \vec{\delta}(t) + \vec{E}_{t-1}\exp(-\alpha \times t^2) + \vec{C}_t \qquad (1)$$

Where, $\vec{E}_t = (e_{t,joy}, e_{t,sadness}, e_{t,anger}, e_{t,suprise}, e_{t,hate}, e_{t,fear})$

Lexical affinity techniques do not operate very well on sentence level. Concerning negation, they do not perform as expected. For example, the following two sentences “I avoided an accident,” (negation) and “I met my girlfriend by accident” has totally two different senses but there is a high probability that they will be tagged with the same emotional tag with lexical affinity techniques. Lexical affinity techniques heavily depend on the probabilities, which are calculated out of linguistic corpora. If the linguistic corpora are biased to a particular genre this will reflect on the probabilities used in the lexical affinity technique [30]. Thus, it is very hard to implement a domain-independent model.

2.6.1.3 Sentiment Analysis

Sentiment analysis field started with sentiment and subjectivity classification, which treated the problem as a text classification problem. Sentiment classification classifies whether an opinionated document (e.g., product reviews) or sentence expresses a positive or negative opinion [39].

SentiStrength is a lexicon-based classifier. To detect sentiment strength in short informal English text, it uses non-lexical linguistic information. SentiStrength outputs two integers: a positive integer from 1 to 5 for positive sentiment strength and a negative integer which ranges from -1 to -5 for negative sentiment strength. if there is no sentiment detected the text will be tagged 1 or -1 and it will be tagged 5 or -5 if the text has a strong sentiment of each type. If a text is tagged 3, -5 then it contains moderate positive sentiment and strong negative sentiment. 1, -1 signifies a neutral text [40]. SentiStrength's key features are explained in details in [40].

- It has a sentiment word list with human polarity and strength judgment.
- It has a spelling correction algorithm to correct words with repeated letters.
- It uses a booster word list to strengthen or weaken the emotion of following sentiment words.
- It uses an idiom list to indicate the sentiment of common phrases.
- It uses a negating word list is to invert following emotion words
- It boosts the strength of sentiment words with more than two repeated letters like haaappy is more positive than happy. It boosts it by 1. If a word is neutral it is given positive sentiment strength of 2.
- It uses an emoticon list with polarities to indicate additional sentiment.

- It considers sentences with exclamation marks to have a minimum positive strength of 2, unless it is negative.
- If there is a repeated punctuation with one or more exclamation marks, the strength of the immediately preceding sentiment word is boosted by 1.

2.6.1.4 Machine Learning

Machine learning is a field of computer science that develops algorithms, which operate on empirical data to provide an automatic action based on these data. Classification is one task of the machine learning tasks. It is also known as pattern recognition. Emotion detection can be thought of as a multi-class classification problem. Alm et al. [41] used Winnow update rule implemented in Sparse Network of Winnows (SNoW) learning Architecture [42] which uses linear functions over the incrementally learned feature space. They have studied two cases. The set of Emotion classes E includes Emotional (E) vs. Non-Emotional or Neutral (N) where E = {E, N} in the first case. They extended E to support the emotional distinction according to valence, E = {N, PE, NE} where PE stands for Positive Emotion and NE stands for Negative Emotion. Alm et al. used 185 children stories, including Grimms', H.C. Andersen's and B. Potter's stories. They applied annotators worked in pairs on the same stories. Each of the annotators was applied separately to avoid annotation bias. The task of each annotator was to assign an emotional mark to each sentence. Those emotional marks map the eight primary emotions, which Ekman discussed in [4]. Table 3 shows the basic emotions used in the annotation process.

Abbreviation	Emotion Class
A	ANGRY
D	DISGUSTED
F	FEARFUL
H	HAPPY

Sa	SAD
Su+	POSITIVELY SURPRISED
Su-	NEGATIVELY SURPRISED

Table 3: Basic emotions used in annotation [41]

The annotation process resulted in an annotated, tie-broken data set of 1580 sentences. Table 4 shows the percent of the annotated labels. For the first case study, from this annotation data we can see that 59.94% is Neutral and 40.06% is emotional. For the second case study, the Positive Emotions represented 9.87%, Negative Emotions represented 30.19% and Neutral represented 59.94%.

A	D	F	H
12.34%	0.89%	7.03%	6.77%
N	Sa	Su+	Su-
59.94%	7.34%	2.59%	3.10%

Table 4: Percent of annotated labels [41]

SNoW requires active features as input, thus Alm et al. implemented the following features:

1. First sentence in story
2. Conjunctions of selected features (see below)
3. Direct speech (i.e. whole quote) in sentence
4. Thematic story type (3 top and 15 sub-types)
5. Special punctuation (! and ?)
6. Complete upper-case word
7. Sentence length in words (0-1, 2-3, 4-8, 9-15, 16-25, 26-35, >35)
8. Ranges of story progress (5-100%, 15-100%, 80-100%, 90-100%)
9. Percent of JJ, N, V, RB (0%, 1-100%, 50- 100%, 80-100%)

10. V count in sentence, excluding participles (0-1, 0-3, 0-5, 0-7, 0-9, > 9).

11. Positive and negative word counts (≥ 1, ≥ 2, ≥ 3, ≥ 4, ≥ 5, ≥ 6)

12. WordNet emotion words

13. Interjections and affective words

14. Content BOW: N, V, JJ, RB words by POS

Features 1, 3, 5, 6, 7, 8, 9, 10 and 14 are obtained automatically from the sentences of the stories. They used SNoW POS-tagger to extract features 9, 10, and 14. Group 10 represents the number of active verbs in the sentence. The thematic story type represented by feature group 4 is obtained from Finish scholar Antti Aarne's classes of folk-tale. Aarne classified the tales according to their informative thematic contents [43]. Animal tales, ordinary folk-tales, and jokes and anecdotes are the top 3 story types. There are around 15 subtypes according to classes of folk-tale. This feature tries to capture a general affect of the story. Group 11 depend on the semantics of the words. Fetaure group 12 depend on lexical lists obtained from WordNet [44]. They also used Py-WordNet's SIMILAR features [45] to detect similar items, i.e., similar items of all senses of all words in the synset. Feature group 13 concentrates on interjections and affective words. Consequently, they manually compiled a list of 22 interjections by browsing educational ESL sites. They made an affective word list of 771 words consisted of a combination of the non-neutral words from [46] and [47]. Feature group 14 uses the content BOW, which assigns the most neutral category.

Alm et al. tuned Winnow parameters such as promotional α, demotional β, activation threshold θ, initial weights ω, and the regularization parameter, S, which implements a margin between positive and negative examples [48]. They created two different tuning methods, *sep-tune-eval* and *same-tune-eval*. In the *sep-tune-eval*, the authors used random 50% of the sentences. They left the remaining 50% for the parameter tuning process. They used 90% of the data for the training process and left 10% as a test set. In the *same-tune-eval*, they tuned all the data set. Table 5 shows the results of classifying the sentence either neutral or emotional.

	Same-tune-eval	Sep-tune-eval
P (Neutral)	59.94	60.05
Content BOW	61.01	58.30
All features except BOW	64.68	63.45
All features	68.99	63.31
All features + sequencing	69.37	62.94

Table 5: Mean classification accuracy: N vs. E, 2 conditions [48]

More detailed averaged results of Classifying N vs. E (*all features*, *sep-tune-eval*) are included in Table 6.

Measure	N	E
Averaged accuracy	0.63	0.63
Averaged error	0.37	0.37
Averaged precision	0.66	0.56
Averaged recall	0.75	0.42
Averaged F-score	0.70	0.47

Table 6: Classifying N vs. E (all features, sep-tune-eval) [48]

Also the results of including N, PE, and NE (*all features*, *sep-tune-eval*) are listed in Table 7.

	N	NE	PE
Averaged precision	0.64	0.45	0.13
Averaged recall	0.75	0.27	0.19
Averaged F-score	0.69	0.32	0.13

Table 7: N, PE, and NE (all features, sep-tune-eval) [48]

Applying machine learning techniques provided very promising results when given a sufficient number of input sentences within the domain of children's fairy tales. However, these types of techniques are very domain specific and not easily extensible, i.e., you cannot apply that classifier on any other domain.

2.6.1.5 Web mining

Web mining is the application of data mining techniques to extract knowledge from Web data, including Web documents, usage logs of Wed sites, etc [48]. There have been several research attempts that utilize Web mining to elicit emotions. Cheng-Yu et al. built a system for emotion detection [49]. They employed semantic role labeling tool [50] and web mining engine (Google) to predict the emotion of chat room users. The semantic labeling tools parse the input sentence and label it with subject, verb or object components. For example, the output of the semantic role labeling tool for the sentence "A girl met a tiger" is detailed as follows:

1. "A girl" is tagged with A0 (i.e. subject);
2. "met" is tagged with V:met ;
3. "a tiger" is tagged with A1 (i.e. object).

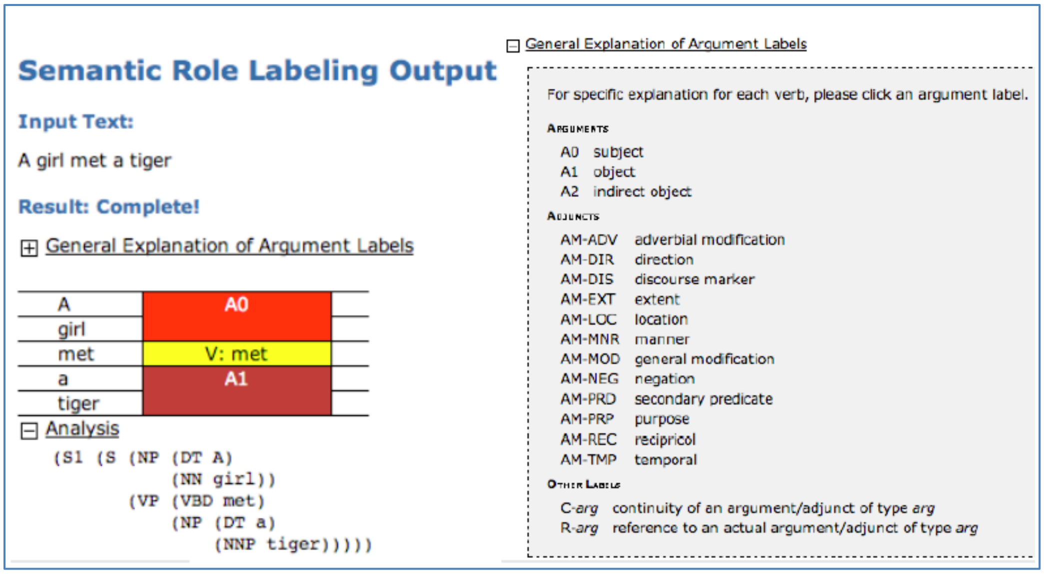

Figure 15: Semantic Role Labeling of the sentence "A girl met a tiger[49].

They used the function "define" of Google to get lexical answers for specific keywords. The define function provides a compiled set of most recent definitions, which are gathered from online sources for the keyword. Figure 15 and Figure 16 shows the results of define function when used with tiger and wolf.

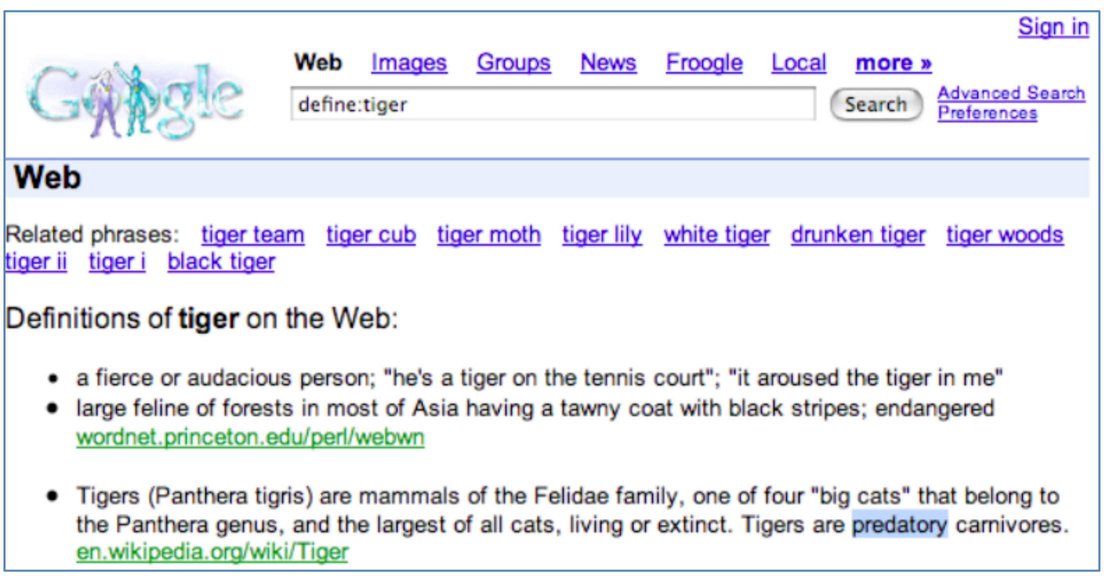

Figure 16: Google's definition of "Tiger" [49]

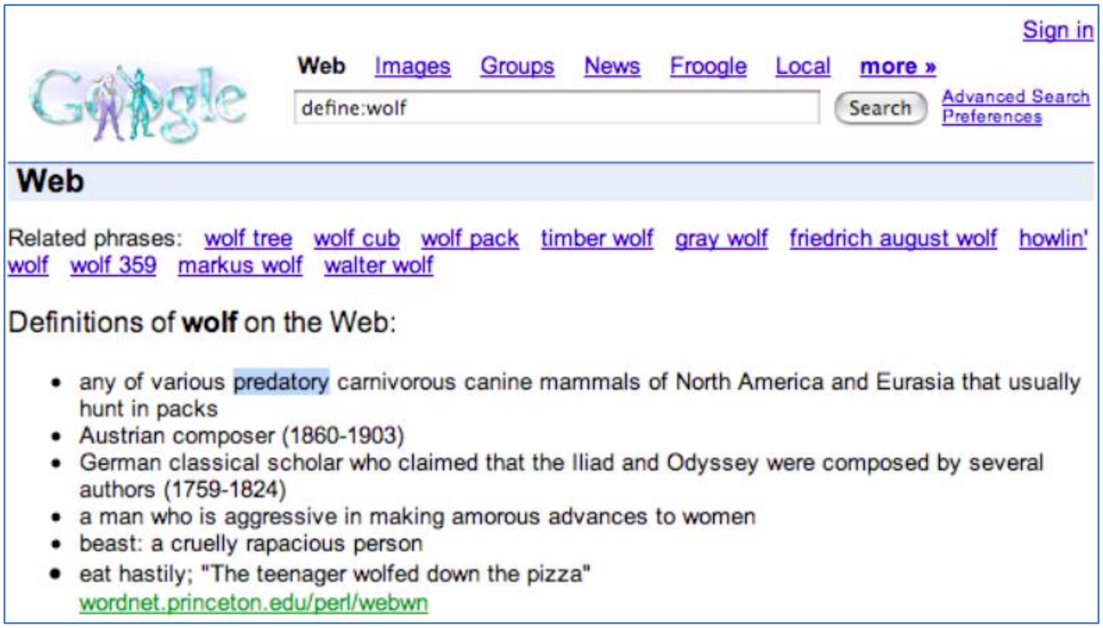

Figure 17: Google's definition of "Wolf" [49].

From both of the definitions, they noticed that the adjective predatory is common. Thus, they saved the adjective "predatory" as "adj_#" in a table. Whenever the system finds a new word, which has the same adjective in its definition, it is referenced with the same "adj_#." Processing the sentence "A girl met a tiger" results are shown in Table 8.

Id	Adjective	adj code	Id	Adjective	adj code
29	illicit	ADJ_13	6	Youthful	ADJ_3
30	illegitimate	ADJ_13	7	Carnivorous	ADJ_5
31	criminal	ADJ_13	4	Predatory	ADJ_5
32	felonious	ADJ_13	5	Rapacious	ADJ_5
25	unlawful	ADJ_13	13	Reptile	ADJ_7
37	difficult	ADJ_14	17	Hazardous	ADJ_8
38	hard	ADJ_14	8	Lacking	ADJ_9
39	rough	ADJ_14	83	Precious	ADJ_20

40	laborious	ADJ_14	33	Awful	ADJ_18

Table 8: Some adjective categories and their corresponding code numbers [49]

Cheng-Yu et al. provided combinations of different possibilities between “Adj_#,” which resulted in different emotions. Figure 18 and Table 9 show how they combine “Adj_#” to get emotions.

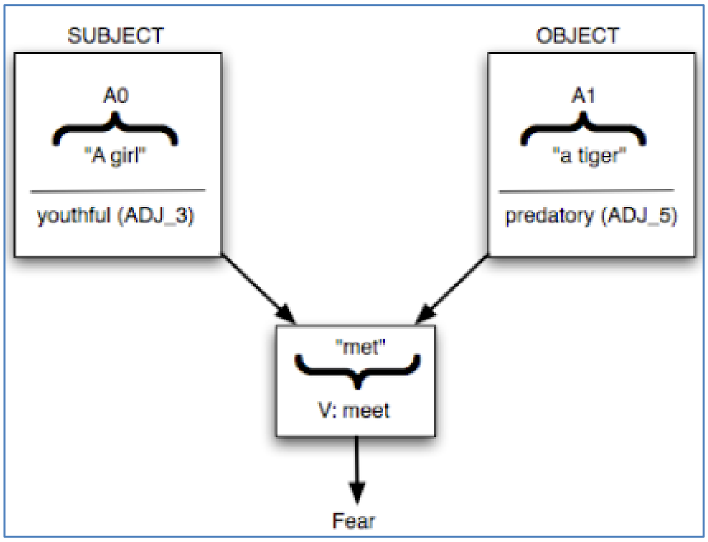

Figure 18: Combining subjects and objects with verbs for emotion detection [49]

id	Verb	combination	Emotion	Example
35	buy	ADJ_3:ADJ_20	happy	Girl buy jewel
22	abandon	ADJ_3:ADJ_8	happy	Girl abandon smoking
23	kill	ADJ_5:ADJ_3	sad	Tiger kill girl
25	kill	ADJ_3:ADJ_5	surprised	Girl kill tiger
34	compete	ADJ_3:ADJ_5	surprised	Girl compete tiger
36	ease	ADJ_3:ADJ_8	happy	Girl ease smoking
30	hate	ADJ_3:ADJ_16	angry	Girl hate tsunami
31	hate	ADJ_3:ADJ_5	angry	Girl hate tiger
4	meet	ADJ_3:ADJ_7	fear	Girl meet tiger
6	meet	ADJ_5:ADJ_3	fear	Tiger meet girl
7	meet	ADJ_9:ADJ_3	sad	Poor meet girl
8	meet	ADJ_3:ADJ_9	sad	Girl meet poor
9	meet	ADJ_3:ADJ_5	fear	Girl meet tiger
33	compete	ADJ_3:ADJ_16	surprised	Girl compete tsunami.

Table 9: Combining adjectives and verbs [49]

In our example “A girl met a tiger”, “A girl” is linked to the adjective “youthful,” which is set to ADJ_3 and “a tiger” is linked to the adjective “predatory,” which is set to ADJ_5. Combining both ADJ_3 and ADJ_5 using the verb “meet” results in Fear emotion according to Figure 18 and Table 9.

Chegn-Yu et al. used ConceptNet [51] to get additional information about the words. For example, the retrieved the location of the word “tiger,” and it resulted in “jungle”. They used this additional information to change the background of the chat room. Figure 19shows the general architecture of the system.

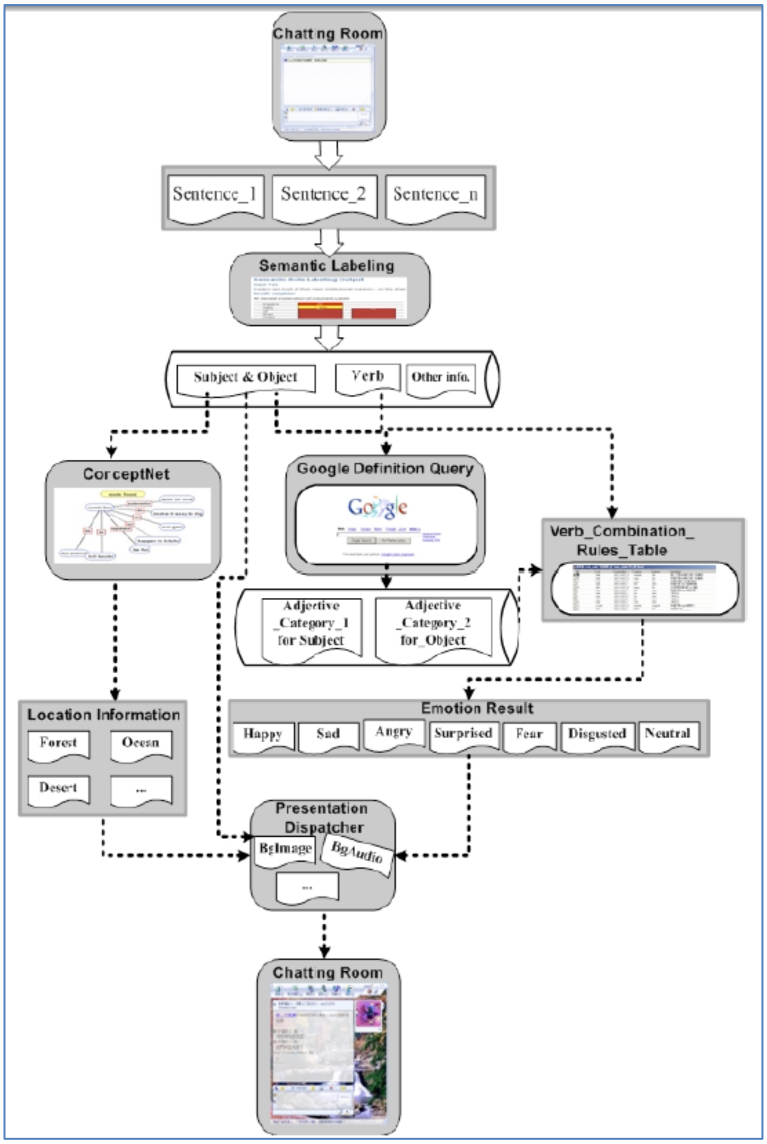

Figure 19: The general architecture of a “chatting room application" [49]

Jen-Ming et al. built a framework for affective chatting room system using web mining approach too [52]. This framework included several modules, such as affective keyword spotter, semantic role recognizer, Hybrid Emotion Recognizer, and text/emotion styling module. The hybrid Recognizer is the unique contribution of this system. Figure 20 shows the overall architecture of the proposed affective chatting room.

Figure 20: Overall framework of the proposed affective chatting room [52].

The keyword spotting module is responsible for sentences, which have clear affect words, such as "I am very depressed today." The keyword spotting module detects the affect word "depressed" and assigns a mood to the sentence based on this affect word. Jen-Ming et al. used semantic role labeling (SRL) to obtain the semantic roles of the statements like subject, verb, object …etc. For example, for the sentence "I saw Bin Laden in the market this morning. I shot him on the site," the result of the SRL can be as follows: "I" is the subject, "saw" is the verb and "Bin Laden" is the object. However, there is no indication about the person that the word "him" refers to. Thus, the need for a conference engine to resolve the co-references arises [52]. Jen-Minget al. developed an emotion detection system based on common actions between the subject and the object. When two words exist in the same sentence, in general a set of actions are predicted. For example, when the two words "robber" and "person" they usually imply a negative action like rob, beat, chase, and harass. The emotion of the object, which is "person" in our case is fear. "A person met a robber" implies that the emotion of the person is fear.

In their emotion detection system, they assumed that the person talking in the chat is a girl. Thus, in their methodology they started by building a list of common actions between a girl and real life entities. Common actions between a girl and the word "snake" can be obtained by formulating the correct query strings, i.e., "she was * by a snake", "the snake * the girl." A typical Web search engine is used to get results. The following represents a sample of a web engine response:

. . . in the morning she was bitten by the snake.

. . . they saw Cleopatra scream after she was bitten by the snake.

. . . She was blinded by the snake and got bitten instead.

. . . She was returning through her garden when she was attacked by the snake.

. . . She was so fascinated by the snake and wanting to hold it all the time.

. . . Then she was poisoned by the snake and died.

. . . Eve answer she was told by the snake to eat the fruit.

. . . She was seduced by the snake

Statistically most of the returned results have the actions “bite,” “attack,” “poison,” and other unpleasant actions and all of them can be recognized as “scary stuff.” The emotion associated to these actions is fear. Jen-Ming et al. wanted to prove that web search can provide reliable common actions between two entities. They made many tests to prove that. Table 10, Table 11, Table 12 and Table 13 list selected entities and related common actions.

Girl, Snake	bite(0.87), kill(0.09), scare(0.029), attack(0.029), eat(0.014)
Girl, Tiger	attack(0.53), eat(0.31), kill(0.085), bite(0.42), murder(0.02)
Girl, Vampire	bite(0.69), attack(0.25), kill(0.03), chase(0.01), capture(0.01)
Girl, Lion	attack(0.5), kill(0.21), eat(0.15), scare(0.078), frighten(0.05)
Girl, Robber	attack(0.44), threaten(0.18), shoot(0.17), chase(0.11), slay(0.07)
Girl, Enemy	capture(0.49), kill(0.07), hurt(0.21), wound(0.18), shoot(0.04)

Table 10: Dominant common actions and the probability distributions between a girl and several example “scary stuff” [52]

Girl, Diamond	love(0.45), buy(0.12), adore(0.09), expect (0.09), receive(0.08)
Girl, Ring	love(0.31), like(0.27), kiss(0.2), buy(0.12), keep (0.09)
Girl, Puppy	love(0.3), like(0.28), kiss(0.16), need(0.10), buy(0.14)
Girl, Gift	receive(0.25), love(0.22), buy(0.21), like(0.17), show(0.13)

Girl, New skirt	buy(0.47), need(0.32), like(0.16), love(0.02), give(0.01)
Girl, Wii	love(0.28), win(0.13), like(0.26), buy(0.16), play(0.15)

Table 11: Dominant common actions and the probability distributions between a girl and several example "pleasant stuff"[52]

Girl, Tragedy	move(0.34), affect(0.28), shock(0.25), strike(0.09), horrify(0.03)
Girl, Patient	strike(0.26), move(0.25), surprise(0.22), infect(0.14), attack(0.11)
Girl, the poor	frustrate(0.28), move(0.28), shock(0.17), concern(0.14), surprised (0.1)
Girl, Car accident	hit(0.47), strike(0.41), shock(0.08), crush(0.01), injure(0.01)
Girl, Dying man	touch(0.23), frustrated(0.21), move(0.2), surprise(0.17), infect(0.11)

Table 12: Dominant common actions and the probability distributions between a girl and several example "grievous stuff" [52]

Girl, Annoying boy	strike(0.44), bother(0.3), bite(0.1), attack(0.05), overwhelm(0.05)
Girl, Evil thing	kill(0.34), delude(0.28), threaten(0.21), frightened(0.15)
Girl, Mean girl	play(0.38), drighten(0.23), hit(0.15), bullied(0.15), bit(0.07)
Girl, Dirty thing	bother(0.28), annoy(0.24), punch(0.17), embarrass(0.23), upset(0.13)
Girl, Crazy kid	kill(0.28), murder(0.26), attack(0.21), hit(0.15), chase(0.07)

Table 13: Dominant common actions and the probability distributions between a girl and several examples "provoking stuff" [52]

The results of the tests showed that the web search of common actions and girl are reliable and coherent. Using the obtained common actions between an entity and a girl we get affective-categories using a typical classifier like SNOW [42]. They faced the problem of getting all common actions of any entity. They simply used web mining to get common actions for any entity. Referring to the web as a source of information is better than normal lexical resources like WordNet[11] because it contains up-to-date information about new words and technologies, e.g., iPad, wii, iPhone…etc. Those new terms can be found in many pages and daily conversations. They used Assert [53], which is a publicly available semantic role labeling tool to determine the subject and object of the sentence. Figure 21 shows how the emotion detection system handles the sentence "Girl bought a jewel." The SRL parses the sentence and detects buy as a verb, girl as a subject and Jewel as an object. The subject (girl) and the object (jewel) are used in the web mining phase to generate the common actions. After getting the results of the web mining phase the matching process starts between the obtained common actions and the previously built Categories for entities. In our case, pleasant objects are the best match.

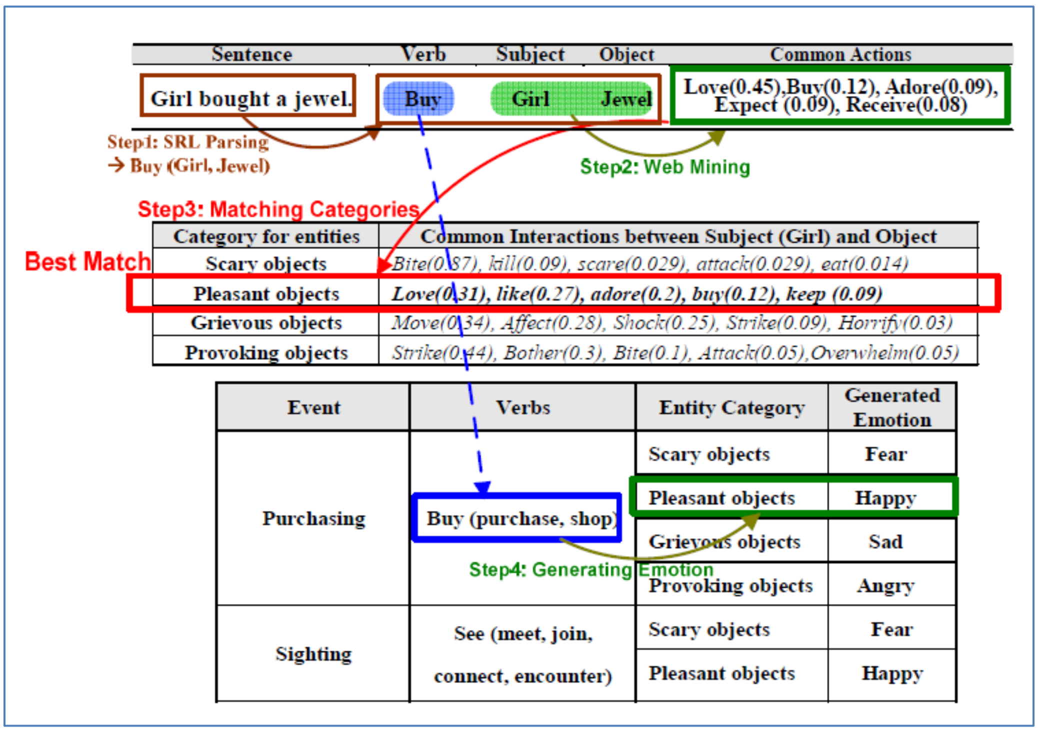

Figure 21: An illustrative scenario showing the processes of the event-level emotion sensing engine based on semantic roles and common actions [52]

2.6.1.6 Hand-crafted models

Some of the researchers used hybrid approaches to elicit emotions in text. They tend to combine one or more of the above approaches to achieve better results. Wu et al. used semantic labels (SLs) and attributes (ATTs) of entities of a sentence to detect emotions [13]. They manually extracted emotion generation rules (EGRs) from psychology. They used EGRs to represent each sentence as a sequence of semantic labels (SLs) and attributes (ATT). SLs are domain independent features and ATTs are domain dependent. SLs are manually classified into three categories Active SLs (e.g. obtain, reach, lost, and hinder), Negative SLs (e.g. no, and never), and Transitive SLs (e.g. finally, but, and fortunately). ATTs of an entity are obtained automatically from a lexical resource, WordNet [44]. They used a priori algorithm to derive automatically the emotion association rules (EARs) which is represented by SLs and ATTs for each emotion. Wu et al. used a separable mixture model (SMM) to estimate the similarity between an input sentence and the EARs of each emotion. Figure 22 illustrates the block diagram presented by Wu et al. They experimented only three emotional states, happy, unhappy, and neutral are considered for performance evaluation.

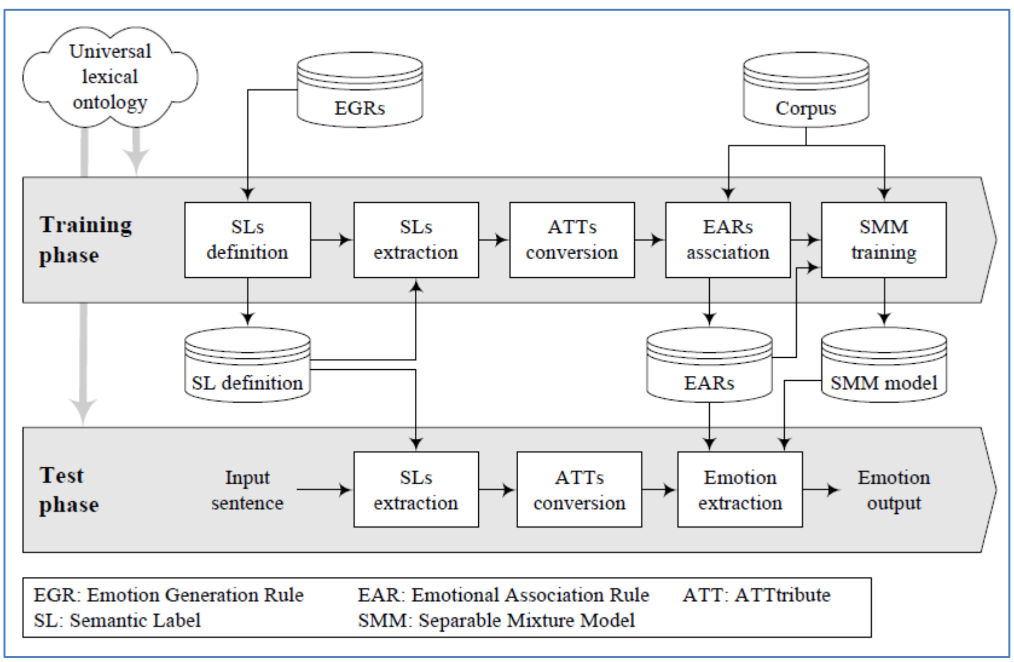

Figure 22: Emotion detection System block diagram [13]

Liu et al. derived a knowledge-based approach to detect emotions based on a large-scale common sense knowledgebase [30]. They used real-world knowledge about the inherent affective nature of everyday situations to classify sentences into basic emotion categories. They used Open Mind

Common Sense (OMCS). OMCS has a real-world corpus of 400,000 facts about our life. The affect sensing engine analyzes the affective qualities of sentences. The affect sensing engine is composed of model trainer and text analyzer. The model trainer consists of three sequential modules, which are linguistic processing suite, affective commonsense filter and Grounder, and propagation trainer. Part-of-speech tagging, phrase chunking, constituent parsing, subject-verb-object-object identification, and semantic class generalization are performed as part of the linguistic module. In the affective Commonsense Filter and Grounder module Liu et al. used the six Ekman emotions [4] to filer the whole OMCS. The propagation trainer uses the commonsense relations to propagate the affect valence from the emotion grounds to concepts. The text analyzer architecture consists of five sequential modules, which are text segmenter, linguistic processing suite, story interpreter, smoother, and expresser. The input text was segmented to paragraphs. Afterwards paragraphs were segmented to sentences and independent closes after that. In the interpreter module, sentences were evaluated against the trained models. The smoother performs pattern matches over the emotion annotations. Then, the expresser expresses the annotated emotions.

ConceptNet is a freely available commonsense knowledge base and natural-language-processing tool-kit [51]. ConceptNet provides support for many practical textual-reasoning tasks over real-world documents including topic-gisting, analogy-making, and other context oriented inferences. It is a semantic network presently consisting of over 1.6 million assertions of commonsense knowledge encompassing the spatial, physical, social, temporal, and psychological aspects of everyday life. ConceptNet is generated automatically from the 700,000 sentences of the Open Mind Common Sense Project — a World Wide Web based collaboration with over 14,000 authors [8].

ConceptNet tools provide a GuessMood function. GuessMood is a more specialized version of ConceptNet's Classification functions. GuessMood function takes a word, a statement or a paragraph and returns an inferred emotion for that input. The algorithm is a simplification of Liu et al.'s [14]. Liu et al. derived a knowledge-based approach to detect emotions based on a large-scale common sense knowledgebase. They used real-world knowledge about the inherent affective nature of everyday situations to classify sentences into basic emotion categories. They used Open Mind Common Sense (OMCS). OMCS has a real-world corpus of 400,000 facts about our life. The affect sensing engine analyzes the affective qualities of sentences. The affect sensing engine is composed of model trainer and text analyzer. The model trainer consists of three sequential modules, which are linguistic processing suite, affective commonsense filter and Grounder, and propagation trainer. Part-of-speech tagging, phrase chunking, constituent parsing, subject-verb-object-object identification, and semantic class generalization are performed as part of the linguistic module. In the affective Commonsense Filter and Grounder module Liu et al. used the six Ekman emotions [4] to filer the whole OMCS. The propagation trainer uses the commonsense relations to propagate the affect valence from the emotion grounds to concepts. The text analyzer architecture consists of five sequential modules, which are text segmenter, linguistic processing suite, story interpreter, smoother, and expresser. The input text is segmented to paragraphs. Afterwards paragraphs are segmented to sentences and independent closes after that. In the interpreter module, sentences were evaluated against the trained models. The smoother performs pattern matches over the emotion annotations. Then, the expresser expresses the annotated emotions.

The result of the GuessMood function will be a vector of the probabilities of the six Ekman basic emotion categories (happy, sad, angry, fearful, disgusted, and surprised). The effect of any unclassified concept can be assessed by finding all the paths, which led to each of these six affectively known categories, and judging the strength and frequency of each set of paths. We will utilize the ConceptNet GuessMood function to estimate the emotion of a status update, comments or any textual information that will be retrieved from the users of Facebook. Figure 23 shows a pilot for testing the GuessMood function.

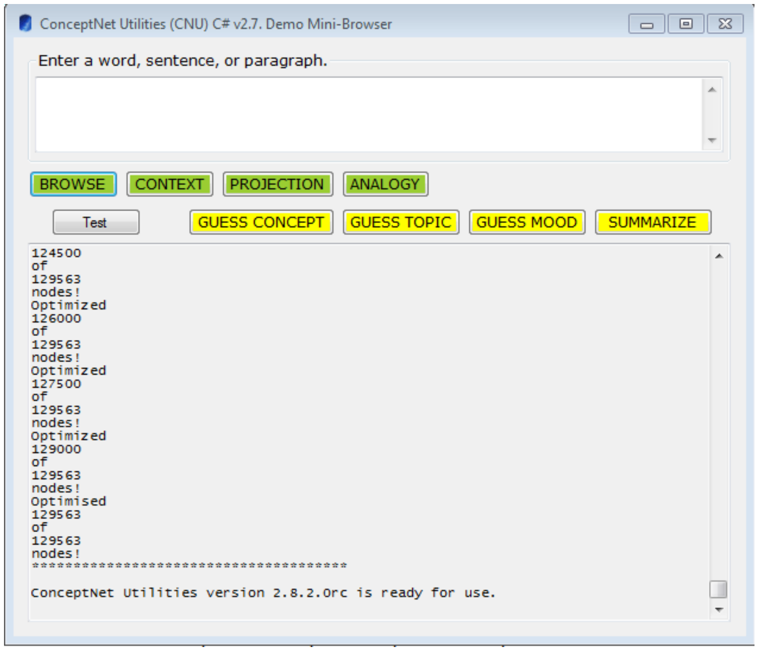

Figure 23: GuessMood function

2.6.2 Blogs

Blogs are websites that gives people the ability to share their daily activities, express their opinions, comment about certain topics, show how they feel or describe events via text, images or videos. Blogs can be thought of as personal diaries. Blog users can comment and share their opinion about the topic of the blog. For example, a blogger will create a new page in his or her blog about weather changes. He or she will write his or her opinion about these weather changes and their causes. He or she may add some photos, links or related videos. People who read this topic will add their comments. They may agree or disagree with him, show their feelings about this topic or even add more information to the topic itself.

Blog information implies the current state of mind of the bloggers and expresses their feelings at the moment of writing blog itself or commenting on another blog. Mishne and De Rijke tried to process the textual information available on blogs to get the general level of moods of blog posts [54]. At a certain time slot, such as five days of a month, they wanted to get the intensity of the bloggers' mood, e.g., happy, sad … etc. They identified the textual features for estimating the mood to achieve this goal. They detected certain words or phrases, which implied a certain mood at this phase. They used word n-gram features, which measure the frequency of word n-gram in a corpus. This corpus had to be annotated corpus; at the time of writing the users enter their mood. Then, the authors used a learning method that uses this annotated corpus to predict the mood of a blogger at certain time slot.

Gilly et al. classified the approaches of automatic emotion recognition into two main approaches [55]. Those two main approaches are Linguistic Analysis and Automated Text Categorization. In Linguistic Analysis, the word was checked in a dictionary, which contained words and word stems. Afterwards, this word was assigned to a category. The linguistic characteristics of the written words were used to understand the psychological states of the people. Hence, it gave an indication about the emotional states of the words writers.

In Automated Text Categorization, researchers tried to assign a set of possible emotions for each blog entry. Machine learning provides us with many techniques that can be used for the process of categorizing the blogs automatically [56]. The machine learning techniques usually passes with several stages. The first stage is called the learning stage, in which the learner processes a pre-classified set of documents. Those pre-classified set of documents are called the training set. The larger the training set, the more accurate the results will be. Directly after the learning process, the classifying stage of the blog documents starts. The classifier will take both the training set and the test blog entries and output the set of possible emotions, which are closely related to the blog entries. Gilly et al. used a training set of the 812,000 blog entry feature vectors. This training set was fed to SVMlight learner (svmlight.joachims.org). The result of the learning phase and the test set of blog entries were used as an input to SVMlight classifier to classify the feature vectors. To evaluate the results, they compared the SVM's decision with the mood of each entry in the test set.

There are other approaches that have been investigated by others like textual affect sensing. Common-sense knowledge bases are used in this approach to tag sentences with basic emotions. The system will use a common-sense knowledge base to assign a basic emotion category for a sentence like "getting into a car accident" [30].

2.6.3 Social networks

Researchers have done several attempts to detect the emotions and mood of social networks. This section shows an overview of state-of-the-art of detecting emotion and mood from social networks.

Matthew and Christian designed a framework (emotitude) for an emotional social network [57]. Over this network users used distributed devices and software to communicate their emotional state with a larger social group. This framework helped in studying the emotive behavior and emotional communication of social networks' users. Figure 24 provides an overview of the framework's architecture.

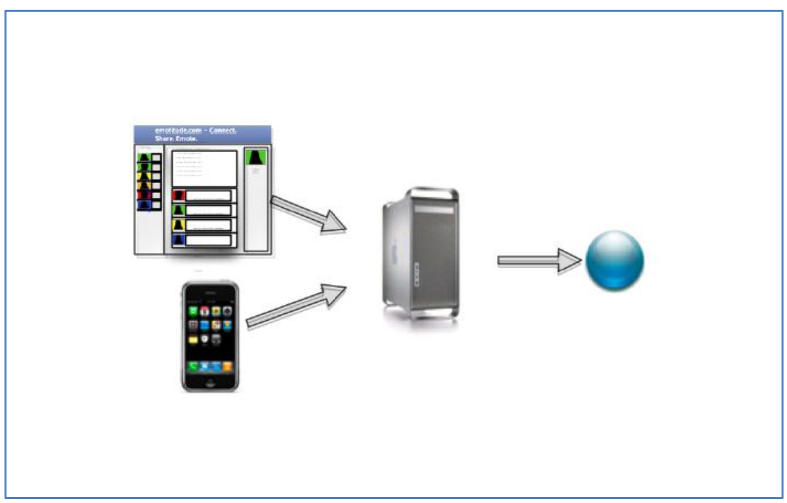

Figure 24: Emotitude's System Architecture [57]

They implemented the social network and provided the users with an interface that will allow them to enter their mood through it. Figure 25 provides an illustration of this interface.

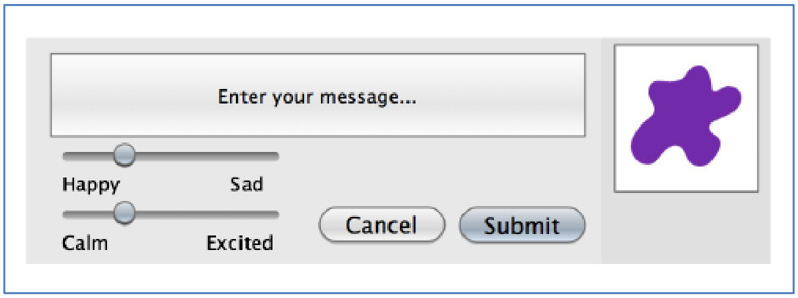

Figure 25: User interface to assign mood to users' posts [57]

They also extended the social network so it allowed automatic mood detection from the instant messages exchanged between the users. This extended the ability of the framework beyond the self-emotion reporting used. In this framework they allowed a group administrators or researchers to get an overall view of users of the emotitude system. The Framework provided statistics about the emotional states and group memberships, and investigate phenomenon, such as emotional contagion and group emotional dynamics.

Thelwall et al. built a system that mined MySpace comments to detect emotion based on gender[58]. They collected a large number sample of MySpace comments from USA. They got these data from public profiles for users who are active and long-term members. MySpace comments include pictures, videos, and URLs. All these non-textual content have been removed and only plain text remained before starting the classification process.

Thelwall et al. used a Likert classification scheme to measure which positive and negative emotions were written in the comments. Table 14 shows classification guidelines given to all classifiers to guide their decisions. They did preliminary experiments to determine issues in classifications and class descriptors. The preliminary experiments showed that some sentences are hard to classify. For instance, the sentence “I miss you” inferred sadness; however, it can indicate a positive feeling almost similar to “I love you” sometimes. The sentences “I love you” or “Love you” usually infer a very strong positive emotion but in MySpace they were used casually without having this strong inferred positive emotion.

	1	2	3	4	5
Expresses ostensibly positive emotion or general energy (ignore all negative)	Absence of anything positive.	Some weak positive elements or generic enthusiasm without a negative slant, e.g., hey!	Clear positive elements of message (includes fun, happiness, optimism, positive evaluation	Overwhelmingly positive or several positive elements or some emphasis of positive elements	Enthusiastically positive (e.g., I am very happy!!!!)
Expresses ostensibly negative emotion (ignore all positive)	Absence of anything negative.	Some negative elements, (e.g., casual "miss you")	Clear negative elements of message	Overwhelmingly negative or several negative elements or some emphasis of negative elements	Definitely negative (e.g., This is totally shit.)

Table 14: Classification guidelines given to all classifiers to guide their [58]

As a result of these preliminary experiments, they made a list of phrases that are frequently used and not easy to classify. They suggested classification for them. Table 15 shows a sample of such sentences and their corresponding custom classification. They did extensive testing during the preliminary experiments before they put the final classification scheme. There methodology processed the comments individually. The authors did not process them in relation to the context, i.e., they did not process earlier comments by the user and how may that affect identifying the emotion evaluation process of the current comment. They processed 1,000 comments with the main classifier and 500 comments with the second classifier. Some of the words were identified as spam or non-English so the sample was reduced by 18%. Cohen's kappa reliability measure [59] was used to compare the emotion classification between coders. The classifiers had a "moderate" degree of agreement: kappa=0.56 for negative and kappa=0.47 for positive emotion ratings. The settings of the classifiers were adjusted to make the positive emotions around two-thirds of the emotions.

Positive Comment Element	Rating	Negative Comment element	Rating
hey!	2	i miss you	2
Thank you	2	im sorry	2
have a great day	2	damnitt	2
Lol	3	i hate u	3
Hehe	3	shithead	3
i love u	3	Im hungry	3
im really excited	4	i'm bored	4
BIG HUG	4	emo scum	4
You ***rock	4	Loser!!	4
super excited	5	DIE	5
I LOVE YOU SO MUCH!!!!	5	*** You	5
U R DA COOLEST MOM EVER	5	was soo sad	5

Table 15: Examples of indicative emotion-related phrases and suggested classifications extracted from the pilot study and given to the classifiers (total: 154 positive; 142 negative) [58].

Table 16 shows the classification results of both the main and the second classifier on the sample data. They ran ANOVA [60] analysis on the results based on the gender of the commenter and the commentee. This analysis showed that women send and receive more positive comments than men.

Emotion Strength	Positive (main)	Negative (main)	Positive (second)	Negative (second)
1	34.0%	80.1%	27.1%	62.5%
2	27.8%	5.6%	38.2%	22.5%
3	35.0%	10.9%	29.2%	9.8%

4	3.2%	2.2%	3.6%	4.4%
5	0.0%	0.6%	1.0%	0.0%

Table 16: Percentage of 819 public comments (main coder) and 387comments (secondary coder) of normal US MySpace members that were judged to express various strengths of emotion [58].

Yassine and Hajj [61] built a framework for mining emotion from text in online social media. They built their framework according to the following steps: raw data collection, lexicons development, feature generation, data preprocessing, creating a training model for text subjectivity, text subjectivity classification and friendship classification. Figure 26 illustrates these steps.

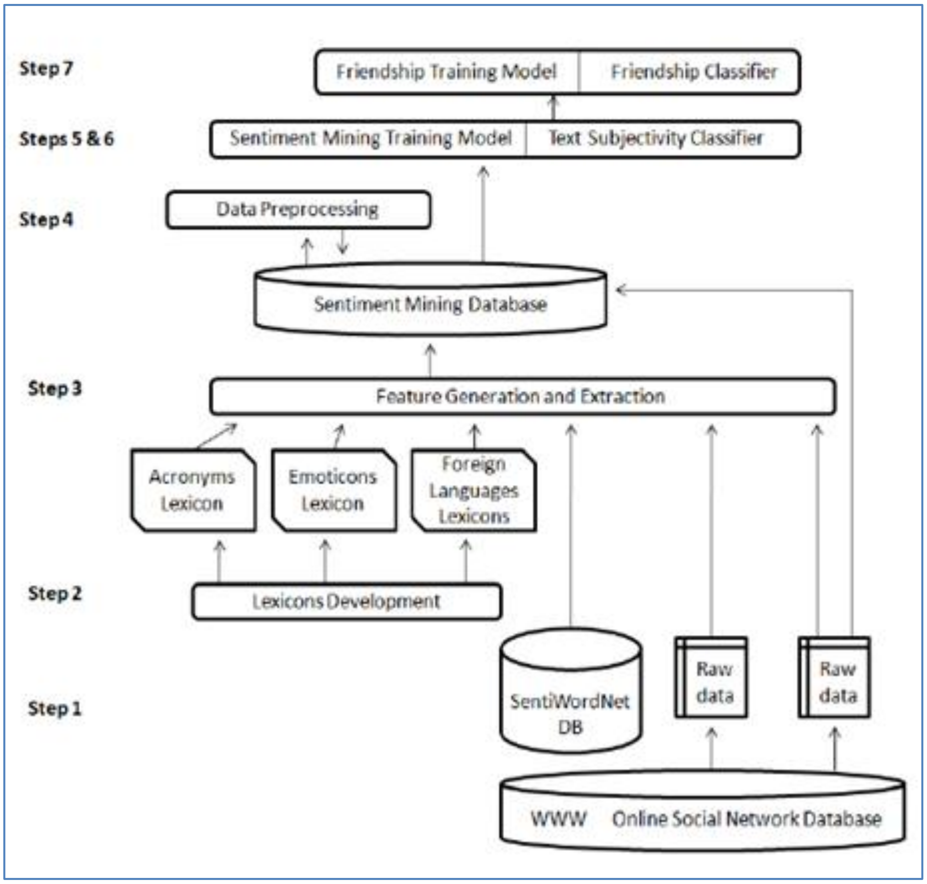

Figure 26: Architecture of the framework [61]

The authors used Facebook as a case study. They created a Facebook application that automatically retrieves the raw data after getting permission from users. These raw data was used as input for a database that they built. The database schema is shown in the below figure.

This database has tables to contain information from social network. They had User Info table that contains information contained in the user profile like name, current location, and birthday. It was linked to Friends, Post and Comments tables. Friends table had the user friends, and Posts table contain all messages posted on the user's wall. Comments table contained all responses by user for wall posts.

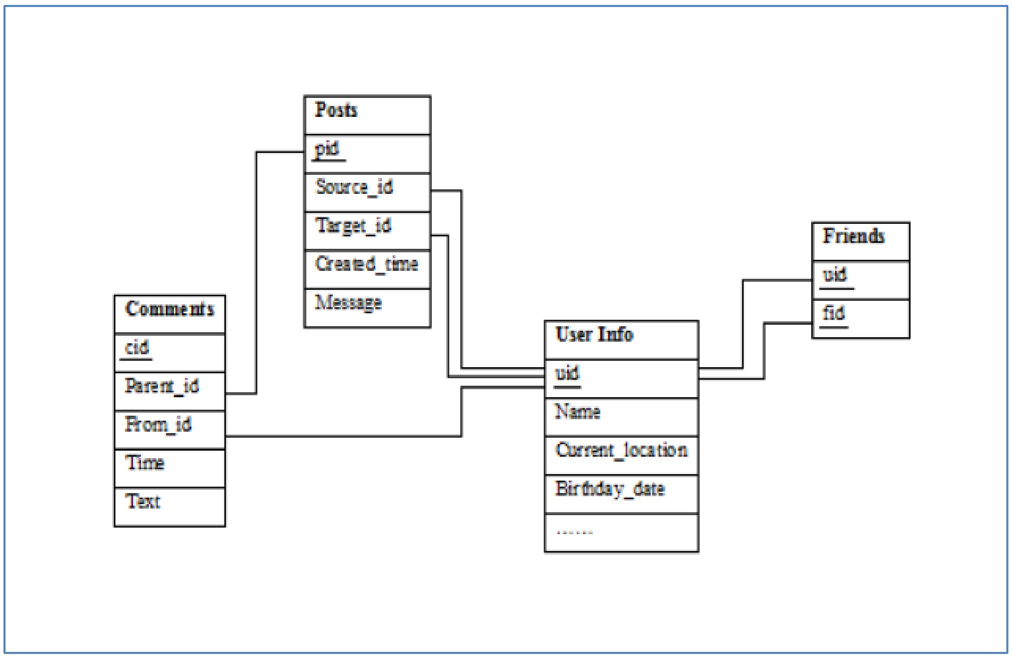

Figure 27: Tables containing raw data [61]

In social networks, users tend to use informal language more. Yassine and Hajj developed a set of lexicons to handle the informal language used in social networks [61]. It was impractical to track all words and sentences in informal language so they dedicated their lexicon to handle a defined set of the informal language. Table 17 shows some of the popular acronyms.

Acronym	significance
B4N	By for now

CU	See you
Gr8	Great
LOL	Laugh out loud
TTYL	Talk to you later

Table 17: Social Acronyms[61] [61]

In addition, they developed a lexicon to handle interjections and emoticons. They did not cover all the cases but they covered a large percentage of the interjections and emotions used over social networks. Table 18 shows sample of covered interjections. Table 19 shows sample of emoticons and their corresponding emotions.

Interjections
Haha, heheh
Waw, wow
Oh
Hey

Table 18: Interjections [61]

Emoticons	Significance
☺ ; ;) :> :]	Smiling
☹ : -(:< :[	Sad
:* :-* :-X	kissing
:P ; :-P	Joking

Table 19: Emotions [61]

The authors took care of using the Arabic language as a foreign language because their sample data were taken from Lebanese Facebook users. Moreover, they included support for some French words commonly used between Lebanese Facebook users. They made a lexicon for the commonly used Arabic words. Table 20 shows a sample of the Arabic Transliterated in English Alphabet.

Root	Different Spellings	English Translation
7eb	b7ebbak, b7ebak, b7ebbik, b7ebik, 7ebbak…	I Love you

Table 20: Arabic Transliterated in English Alphabet [61]

Yassine and Hajj grouped features into three categories to evaluate the subjectivity of the text. Features in the first category included the number of affective words, the average subjectivity measure and many other features that are based on SentiWordNet. SentiWordNet is lexical resource for opinion mining. Features in the second category include the number of punctuation marks, number of capitalized letters, average number of repeated letters when letters were repeated consecutively at least three times and many other features that were based on intentional misspelling errors and grammatical markers. Features in the third category included number of interjections, emotional weight of emoticons and other features based on social acronyms, interjections and emoticons.

In step four data preprocessing techniques were run against the data after generating several features. Yassine and hajj ran feature selection to reduce redundant features. This resulted in the below 9 attributes as shown in Table 21.

Attributes
Number of affective words
Average subjectivity measure of affective words
Number of capitalized letters
Number of punctuation marks
Number of repeated letters when letters are repeated consecutively at least three times
Number of interjections
Number of social acronyms
Number of emoticons
Average rating of emoticons

Table 21: List of Attributes [61]

The values of the attributes were continuous; however, they should be mapped to discrete values. They used K-means algorithm to do this mapping. They ran k-means with k=3 or k=4 on each attribute. They replaced the values of the attributes with the centroids of the cluster that they are in to map the continuous value to a discrete value. Then, the values were normalized using the min-max normalization to map them to [0, 1] range.

Yassine and Hajj's goal was to cluster the texts into categories. Those three categories are objective or factual texts, moderately subjective texts suggesting some kind of friendship between the users and subjective texts suggesting a close friendship between the two users. To achieve that goal, they used an unsupervised approach in step number six. They used k-means clustering algorithm with k =3. The centroids of the three clusters represented the desired output. In step seven, they applied text subjectivity mining to classify friends.

Bradley and Lang generated the Affective Norms for English Words (ANEW). ANEW is being developed to provide a set of normative emotional ratings for a large number of words in the English language. The goal is to develop a set of verbal materials that have been rated in terms of pleasure, arousal, and dominance [4]. They have developed ANEW to complement the existing International Affective Picture System (IAPS) and International Affective Digitized Sounds (IADS). IAPS, and IADS are collections of picture and sound stimuli, respectively, also include these affective ratings. Bradley and Lang have generated ANEW, IAPS, and IADS to act as standard material for researchers who are interested in studying emotion and attention. They assumed that emotion can be defined in terms of different dimensional views. Affective valence, arousal, and dominance or control, are the major three dimensions. The first two are considered the primary dimensions and the third one is considered less strongly related. Affective valence ranges from pleasant to unpleasant. Arousal ranges from calm to excited. Figure 28shows a sample of how each word is represented in ANEW. The final column lists the word "frequency", which represents the number of times the word appeared in the database that Kucera and Francis used [62]. When the frequency is high, this means that this word appear more in the corpus.

Description	Word No.	Valence Mean(SD)	Arousal Mean(SD)	Dominance Mean (SD)	Word Frequency
anguished	19	2.12 (1.56)	5.33 (2.69)	3.45 (2.37)	2
ankle	638	5.27 (1.54)	4.16 (2.03)	4.77 (1.74)	8
annoy	20	2.74 (1.81)	6.49 (2.17)	5.09 (2.04)	2
answer	639	6.63 (1.68)	5.41 (2.43)	5.85 (1.88)	152
anxious	21	4.81 (1.98)	6.92 (1.81)	5.33 (1.82)	29
applause	640	7.50 (1.50)	5.80 (2.79)	6.48 (2.11)	14
appliance	641	5.10 (1.21)	4.05 (2.06)	5.05 (1.34)	5
arm	642	5.34 (1.82)	3.59 (2.40)	5.07 (1.50)	94
army	23	4.72 (1.75)	5.03 (2.03)	5.03 (2.45)	132
aroused	24	7.97 (1.00)	6.63 (2.70)	6.14 (1.97)	20
arrogant	25	3.69 (2.40)	5.65 (2.23)	5.14 (2.71)	2
art	643	6.68 (2.10)	4.86 (2.88)	5.30 (2.33)	208
assassin	26	3.09 (2.09)	6.28 (2.53)	4.33 (2.68)	6
assault	27	2.03 (1.55)	7.51 (2.28)	3.94 (3.10)	15
astonished	28	6.56 (1.61)	6.58 (2.22)	5.16 (1.79)	6
astronaut	501	6.66 (1.60)	5.28 (2.11)	5.20 (1.95)	2
athletics	644	6.61 (2.08)	6.10 (2.29)	6.12 (2.12)	9
autumn	29	6.30 (2.14)	4.51 (2.50)	5.15 (1.85)	22
avalanche	645	3.29 (1.95)	5.54 (2.37)	3.61 (2.00)	1
avenue	646	5.50 (1.37)	4.12 (2.01)	5.40 (1.53)	46
awed	30	6.70 (1.38)	5.74 (2.31)	5.30 (2.03)	5
baby	31	8.22 (1.20)	5.53 (2.80)	5.00 (2.80)	62
bake	647	6.17 (1.71)	5.10 (2.30)	5.49 (1.88)	12
bandage	648	4.54 (1.75)	3.90 (2.07)	4.52 (1.89)	4
bankrupt	32	2.00 (1.31)	6.21 (2.79)	3.27 (2.39)	5
banner	649	5.40 (0.83)	3.83 (1.95)	4.80 (1.57)	8
bar	650	6.42 (2.05)	5.00 (2.83)	5.47 (1.94)	82
barrel	651	5.05 (1.46)	3.36 (2.28)	4.89 (1.57)	24
basket	547	5.45 (1.15)	3.63 (2.02)	5.76 (1.45)	17
bastard	33	3.36 (2.16)	6.07 (2.15)	4.17 (2.40)	12

Figure 28: Means and standard deviations for pleasure, arousal, and dominance ratings a sample of words [4]

Pulse of the nation is a scientific study, carried out by a research team at college of Computer and Information Science in Northeastern University [6]. This study analyzed more than 300 million tweets to detect the mood of twitter's users across the USA. Public Tweets posted during the period from 2006 to 2009, containing words from ANEW were processed by semantic analysis. Each tweet were given a mood score based on how many ANEW words did it contain. They calculated the overall mood of the user based on his tweets. Afterwards, the research team calculated the average score of all USA's users hour by hour. The results were displayed on map for USA that showed the mood of each state. Figure 29 shows a map of USA that shows the mood of each state based on the mood detected from the tweets of its citizens. The color rages from red to green according to the mood where the green color indicates that the citizens are happy.

Figure 29: Map of USA that shows the mood of the citizens according to their tweets [6]

They also provided a daily and weekly analysis of the users' mood. The charted the daily and weekly analysis. The first graph represented the overall daily variations. We can see that happy tweets are more likely at early morning and late evening. Figure 30shows a comparison between the east coast and west coast. The graph shows that happier tweets in West Coast are three hours behind the east coast.

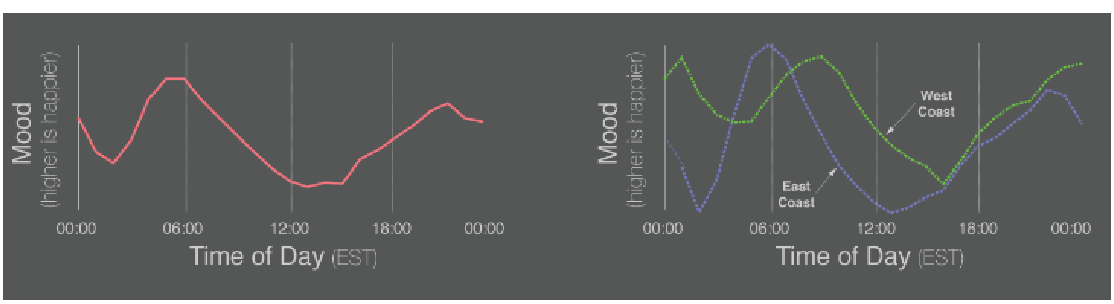

Figure 30: Daily chart for tweets [6]

Weekly variations showed that twitter users post happy tweets in weekends more than other weekdays. The peak of the happy tweets was observed on Sunday and Thursday evening represented the peak of the unhappy tweets. Figure 31 shows the weekly trends and patterns of mood.

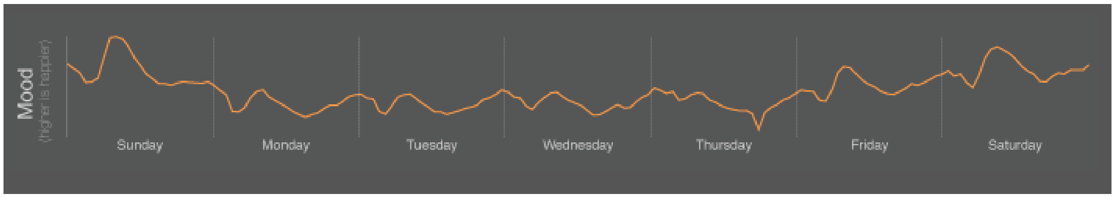

Figure 31: Weekly tweets [6]

Facebook provides a set of APIs that allow developers to create applications and surveys on top of Facebook platform. Facebook application program interfaces (APIs) provide a set of function to get friends, wall posts, events, activities, check-ins and much more. Facebook users create applications to interact and communicate together. Sébastien [5] created a Mood State application. This application asked Facebook users a set of predefined questions and users had to answer all of these questions. The mood state application analyzed the answers and predicted the users' mood. Figure 32 represents a flowchart that shows the flow of the application and how it works.

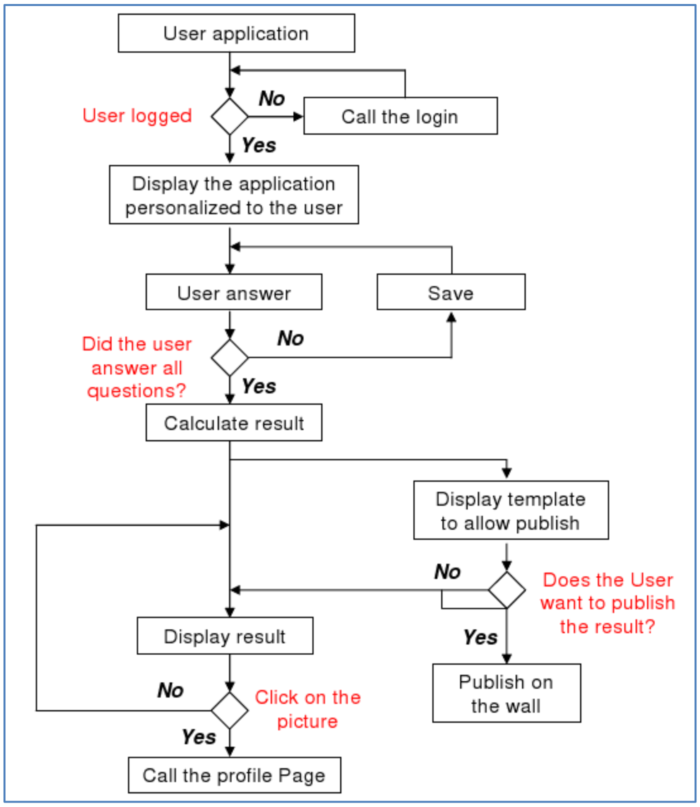

Figure 32: flowchart of mood survey application [5]

The users of the application were able to personalize the mood results by selecting an image that represents their mood. They had the option to share mood results with their friends as the application provided them with the ability to post their mood results on their walls. The application kept track of this mood on server side for statistical purposes. However, the users had to answer all the questions before the mood is calculated. This type of applications involves direct interaction of the user which is not recommended in pervasive computing.

2.7 Mood detection based on images techniques

In this section, we will demonstrate the state-of-the-art techniques of detecting mood from images. The hue wheel helps us understand the colors in pictures as shown in Figure 33. The hue values are range from 0 to 360 degrees as it constitutes a circle. The basic colors of red, orange, yellow, green, blue, purple, and pink are divided into ranges. The hue wheel does not include Black, white and grey colors since those colors are basically high or low saturations or lightness values of a certain hue.

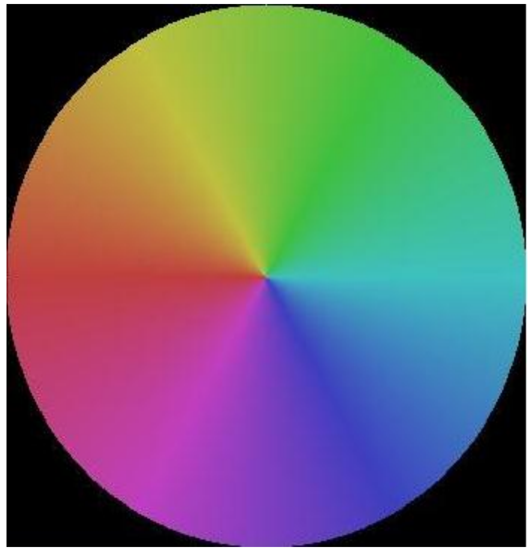

Figure 33: Hue Wheel [63]

Cho analyzed the hue of the images to extract the mood associated with the image [63]. She processed each pixel of the image and converted the RGB to HSL (Hue, Saturation, and Lightness). She saved the output of the conversion in a tab delimited file. This file is parsed then recorded in a database. Cho calculated the dominant value of the hue, and she looked up this value in the color-to-mood rules. Then, she saved the results in files which is kept as a reference in case the system needs to automatically look up the mood of the image.

2.8 Mood detection based on Audio techniques

Cho used Marsyas to detect mood from audio files [64]. Marsyas used and accepts .WAV and .AU format. All other formats can be converted to .WAV or .AU with the appropriate audio converter. Pre-processing must be completed. She created a training set of the audio files to do that the pre-processing.

She fed the training set to Marsyas. Then she extracted the following audio features Series, SoundFileSource, AudioSink, Stereo2Mono, TimbreFeatures, ShiftInput, Fanout, ZeroCrossings, Windowing, PowerSpectrum, PowerSpectrumNet1, STFT_features, Centroid, Rolloff, Flux, MFCC, Spectrum2Chroma, SCF, SFM, Filter, LPC, LSP, LPCC, TextureStats, Memory, Mean, StandardDeviation, Annotator, Classifier, ZeroRClassifier, GaussianClassifier, SVMClassifier, and Confidence. At the same time of training the set, she trained the Gaussian and SVM classifiers. She passed 100 songs passed to Marsyas then they were classified based on the training set. Marsyas analyzed each second and predicted the sector that one second belongs to. Afterwards, it assigned a confidence level. To get the dominant sector, each sector was grouped and each group's confidences values were added. The output files were then fed into the AUDIO_ANALYSIS table and the dominant sector saved into the database for future use during matching.

3 Research methodology

In this section, we will present the methodology that we will use to enhance emotion elicitation using contextual information and multimodal features of social networks. Our approach consists of three phases:

- In phase one, we closely stud the behavior of social network users and understand how the multimodal features of the social network affect them.
- In phase two, we extract Facebook data that we experiment with. We concentrate on identifying the contextual information and multimodal features from the users' profiles.
- In phase three, we use the information from the previous phases to elicit the emotions of the social network users followed by evaluation of our results. Figure 34 shows the flow diagram of the steps. Following is a detailed discussion of each phase.

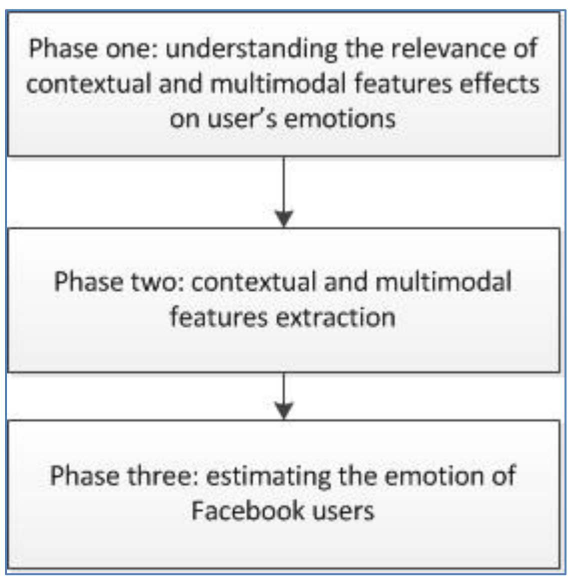

Figure 34: flow diagram of our methodology of emotion detection

3.1 Phase one: Understanding the relevance of contextual and multimodal features effects on users' emotions

In section 2.1 "The impact of social networks on the emotional and psychological state of the users of social networks" of our literature review, we provided a survey of the current studies that have been done until now to investigate the effect of social networks on the emotional and psychological state of the users of social networks. Those studies covered some of the effects of various social networks features but not all of them. To understand the effects of contextual and multimodal features of social networks on their users, we conducted a survey with the users of social networks to gather more insights about different features of social networks on the emotional state of their users. We investigated the impact of receiving likes in terms of the number and influence of the social contact generating the likes. In specific, we researched the impact of receiving comments and updates from friends according to their relationship degree to the social network's user, e.g., Family members, close friends, and others and how they affected the emotions of the social networks users. We also wanted to highlight the most used features for expressing emotions by the users of social networks. With this knowhow, we can create a more accurate emotion detection system using the multimodal features of social networks and not only rely on the text of such social networks. The aim of this survey is to study the patterns in which the emotion of social networks users is affected by some of their daily interactions within the social network. The objective is to identify the most prominent used features in the social network and how they can affect the emotions of the user. We will detail how we reached our conclusions throughout the following sections.

3.1.1 Research type

- Paradigm: Quantitative
- Purpose: Analytical Research

- Outcome: Applied
- Logic: Deductive Research
- Methodology: Cross-Sectional Surveys

3.1.2 Hypotheses

In this section, we will demonstrate our research hypotheses in details. Let a hypothesis be denoted by the letter H. The null hypothesis is that multimodal features of social networks have no effect on emotions.

H1: Users of social networks express their emotions through different features of social networks.

H2: Status messages are used more than any other feature to express emotions.

H3: When the number of likes toward one of the social networks users increases, this positively affects the user's emotions.

H4: Emotions of users of social networks are affected according to the relationship between them and the person who made the post, e.g., if a family member or a close friend made a comment or a post, this will affect him or her emotionally more than other posts.

H5: Receiving virtual gifts may positively affect the emotions of the social networks users.

H6: Being invited to a social network event, such as birthdays, weddings, etc will have a positive impact on the emotions of the users of social networks.

The survey questionnaire mapping matrix is illustrated in Table 22, we explain it in details in a later section.

3.1.3 Sample

A total of 220 users of social networks contributed to this online survey. The sample consisted of international adults of different backgrounds and nationalities. The participants were from both genders with age range of (18-35). We choose Facebook as our social networks as it is the most popular of the available social networks with the largest number of users having more than one billion users [1]. The questionnaire was published on the Internet through an online survey using the surveymonkey website and posted to the researcher's Facebook profile page; that contains more than 487 of friends and different Facebook pages and groups; to ensure high response rate.

3.1.4 Data Collection Instruments and Sources

We have used close-ended questions as the main source for this survey to investigate the effect of the social network on its users. The survey questionnaire mapping matrix is illustrated in Table 22. The table shows the purpose of the question group, the number of questions related to each group, and a short description on the purpose of that group.

Purpose of the question	Question number	Description	Hypothesis
Exclusion Question	1	Excludes respondents with limited usage of their Facebook accounts	H1
Tendency to express emotions through Facebook features	2-3	Illustrate if the users tend to express their emotions through various features of Facebook and being impacted by posts made by friends	H1
Effect of likes	4	Explains how the increase of the number of likes to a user's post may affect his or her emotions	H3
Most used features and emotion expression	5-8	Capture the most frequently used features by Facebook users and their tendency to express emotions through them	H2, H5,H6

Which posts affect the users emotions	9-10	Investigate, which posts affects the users' emotions the most, e.g., posts from close friends, family members, work colleagues, … etc	H4

Table 22: Survey Questionnaire Mapping Matrix

The online survey was launched on the 19th of June 2012 until the 29th of July 2012. The total study duration was 10 days. The following section will reveal the results and details of our survey.

3.1.5 Study results

When asked about their daily usage of Facebook, 90% of the surveyed sample answered that they use it on a daily basis. The graph in Figure 35 shows that 7% of the sample used Facebook at least once weekly, 2% of the sample used Facebook at least once monthly and only 1% does not use it [65]. This reflects how extensively people are keen on using social networks and how integrated it is in their daily lives.

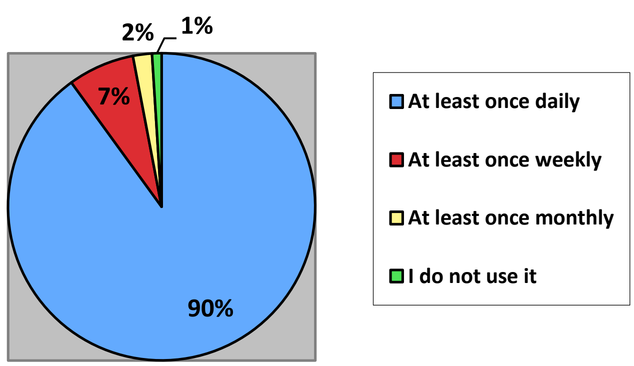

Figure 35: H1: How often do online users use Facebook? [65]

Users on Facebook post their status updates and receive comments and likes about the posts. "Like" is an action in Facebook where users can click a Like button that indicates their liking to the posts, the number of likes to the posts are aggregated and shown. Users also post photos, links, videos, and commentary conversations, and likes are received for those multimodal features as well. During these interactions within the social networks, users tend to be emotionally affected by posts, comments, and likes made by friends and other users of social networks. The graph in Figure 36 shows the high tendency of users to express their emotions through Facebook, and it also shows that friends' posts can affect the emotions of the social networks users. Users of social networks read many updates from their friends, which carry emotional implications and these updates affect their emotions.

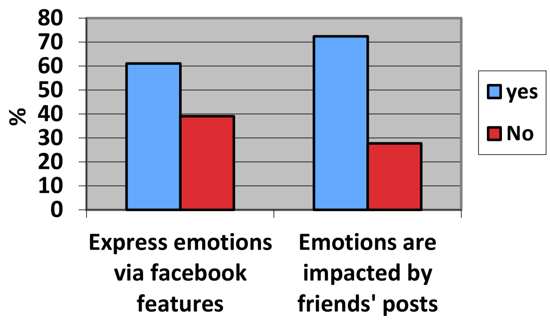

Figure 36: H1: Expressing emotions through Facebook [65]

The survey reflected that status updates, comments, and likes are the most used features by the social networks sample. After which users tend to use private messaging, photos, events, and notes prospectively. Users of social networks use status updates, comments, and by liking their friends posts the most to express their emotions. Figure 37 shows a graphical representation of the number of responses that we received. In this survey question, users were allowed to select multiple answers.

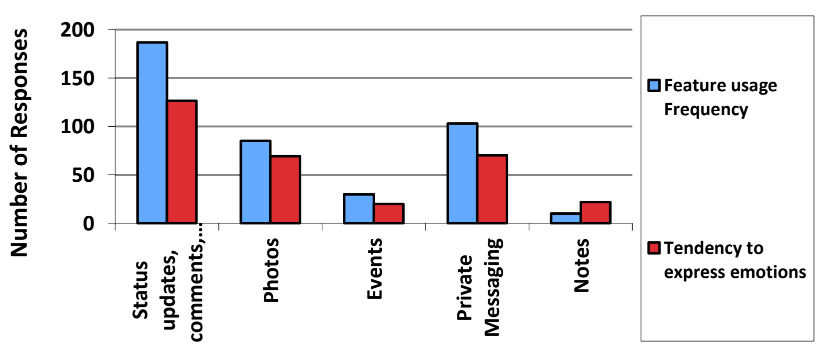

Figure 37: H2: Facebook features usage frequency Vs tendency to express emotions through them [65]

We investigated the effect of increase in the number of likes received for one of the user's posts on the emotions of the social network users. As shown in Figure 38, 81% of the sample showed that the increase of the number of likes on their posts affects their emotions positively. Only 19% reported that the increase in the number of likes on their posts does not affect their emotions [65].

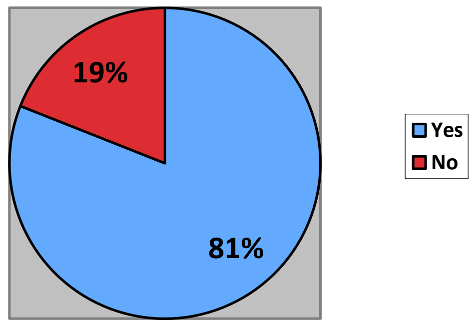

Figure 38: H3: The effect of an increase in the number of "Likes" upon the emotions of social networks users [65]

Facebook recognizes the relationships between friends within the same social network. For example, a friend can be a close friend, a family member or general friend. We aimed at identifying the category that has the most effect on the users of social networks emotionally and provides a better indicator of the emotions of the users. Users could select more than one answer for this question. Figure 39 shows that the majority of responses out of our sample tends to be affected more by posts, comments, and likes from close friends.

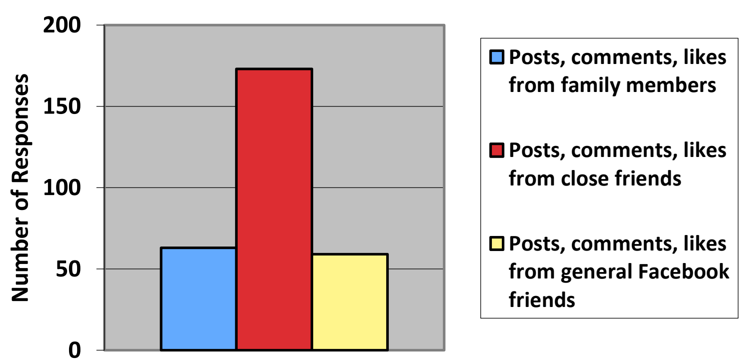

Figure 39: H4: How emotions are impacted by different types of social contacts [65]

The following figure shows how receiving a Facebook gift from a friend within a social network can affect the emotions of the user. The emotions of 41% of the sample were affected positively if they received a Facebook gift and 59% of the sample users showed that receiving a gift does not affect their emotions. It also shows that 47% of the sample's emotions are affected positively if they are invited to an event, such as birthdays or weddings and 53% of the sample will not be affected by such invitations [65].

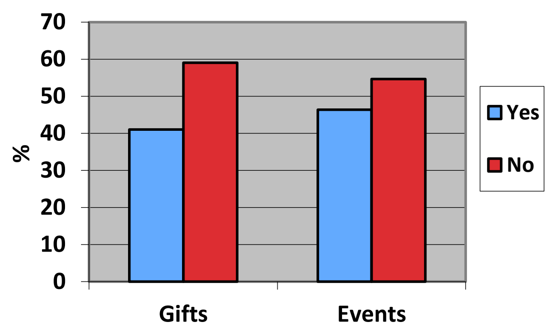

Figure 40: H5 and H6: The impact of receiving a gift or being invited to an event on emotions [65]

3.1.6 Study Conclusion

In our study, we investigated the way Facebook-users utilized Facebook multimodal features, such as comments, likes, virtual gifts, virtual events and relationships between contacts to express emotions. The results of our survey indicated that not only do users express emotions on Facebook, but their emotions were also affected by the type of interaction happening [65]. They tended to express their emotions through status updates and comments more than other features. They tended to be affected by written exchange between users in the form of status updates, comments, and the likes of their friends on their activities. The number of likes to their posts affected their emotions positively. In specific, users are affected more by emotions exhibited in their close friends' posts. These results match our hypotheses H1 through H4. However, the results invalidated hypotheses H5 and H6 as social networks users were not impacted by the virtual gifts that they receive from their friends nor the events that they were invited to [65]. From these results, we have a better understanding on how social network features and the information they encompass can be used to automatically elicit the emotions of their user. Table 23 shows a summary of the results of social networks' study.

Hypothesis	Question number	Validity
H1: Users of social networks express their emotions through different features of social networks.	1,2,3	Valid
H2: Status messages are used more than any other feature to express emotions.	5,8	Valid
H3: When the number of likes toward one of the social networks users increases, this positively affects the user's emotions.	4	Not valid
H4: Emotions of users of social networks are affected according to the relationship between them and the person who made the post, e.g., if a family member or a close friend made a comment or a post, this will affect him or her emotionally more than other posts.	9,10	Valid
H5: Receiving virtual gifts may positively affect the emotions of the social networks users	6	Not Valid
H6: Being invited to a social network event, such as birthday, weeding …etc will have a positive impact on the emotions of the users of social networks.	7	Not Valid

Table 23: Social networks study results [65]

3.1.7 Further analysis

According to the survey that we conducted, status updates, comments, and likes are the most used features by the social networks sample. The survey results reflected also that users of social networks use status updates, comments, and likes the most to express their emotions. We would like to investigate how we can use this contextual and multi-modal information to elicit the emotions of the social networks' users. For example, if the user posts a status message that implies a certain emotion and he or she gets many the comments from different friends with different degree of connection. How can we use this information to elicit the emotion of the user implied in this post?

We will experiment with a sample of social network profiles. We will collect the profiles of active social network users and analyze them according to the results of our study. We will explain in details our dataset in the following section.

3.2 Phase two: Contextual information and multimodal features extraction

In this section, we will discuss the dataset that we will use, the characteristics of Facebook data, and the data extraction method.

3.2.1 Data set that we will use

Unfortunately, due to the privacy restrictions of Facebook there is no standard Facebook dataset, which is used as a benchmark for emotion detection. We prepared a list of the current data sets that we have found and the issues with them:

- Online social research dataset : does not show the real posts, comments nor relationships between the users
- Networking group : does not include status updates, wall posts nor the friendship relationships
- Dataverse network dataset : the last update about this data set was created (10/13/10). The updates states that "the T3 dataset is still offline as we take further steps to ensure the privacy of students in the dataset. Please check back later at this site for additional updates- a notice will be posted when the distribution process has resumed." This comment is from 2010. We do not see that this is an option for us.
- Fbnames : Has all the above issues

Table 24 summarizes the differences between the existing databases and the required data of our research.

Database name/required data	Available	Profile information	Status messages	Comments	Relationships between users
Online social research dataset	x				
Networking group	x				
Dataverse network dataset					
Fbnames	x				

Table 24: The details of the current Facebook datasets

Thus, we have built our data set that consists of 20 Facebook dataset of 20 profiles of the users of social network, 296 status message and 1278 comments 7408 Likes. These profiles will contain real data of the Facebook users.

3.2.2 Facebook Data Extraction

We extracted the top used features and at the same time the users of social networks tend to use them as a way to express their mood. According to the survey that we conducted, status updates, comments, and likes are the most used features by the social networks sample. After which users tend to use private messaging, photos, events, and notes prospectively. The survey results reflected also that users of social networks use status updates, comments, and likes the most to express their emotions. Facebook recognizes the degree of connection (the relationships) between friends within the same social network. For example, a friend can be a close friend, a family member, general friend …etc. In our survey, we aimed at identifying the category that affects the emotions of the Facebook users the most. Results reflected that 79% out of our sample tend to be affected more by posts, comments, and likes from close friends. We found out that 81% of the sample agreed that the increase of the number of likes on the users' posts affects their emotions positively. Therefore, we will focus on status updates, comments, likes, and friend relationships to elicit users' emotion from them.

For Facebook, social graph is the core of Facebook. Everything about users and their connections is represented in the social graph. Facebook provides a Graph API to access the users' data. Graph API represents the objects of Facebook social graph, e.g., people, photos, events …etc. and the connections between them, e.g., friend relationships, shared content, and photo tags [66]. Objects in the social graph have unique ids. Each object can be retrieved using this unique id. As for people and pages, the also can be retrieved using their names.

Facebook provides its responses in JavaScript Object Notation (JSON) format. Parsing responses from the above requests, we can get the content of status messages, comments, likes, and friend relationships. We have created a set of classes (Status Message, comment, and user) to encapsulate the content of the JSON response:

Status Message: this object contains information about the status message such as the textual content, the comments, and likes of this status message.

Comment: this object contains information about the comment itself. It contains the textual content of the comment, likes of the comments, the user who made the content and the time when this comment was created.

User: this object encapsulates information of a Facebook user. It contains his profile information such as name, first name, second name, gender, email, birthdate…etc, friends, notifications, notes, groups, and events.

We wrote an application in asp.net that connects to the graph API and retrieves the details of the profile and wall of a Facebook user and encapsulates them in the above classes.

3.2.3 Data preparation

Since our research handles textual status messages, comments, likes and relationships. We removed all other non-relevant content i.e. posted pictures, links and videos. We focus on English status messages only so we filtered English statuses and masked out all other statuses posted in different languages. Below is a sample of a status message, which shows the structure of the final dataset.


```
<status>
    <message>
        <text>Though it seemed that it wouldn't ever come to be, but I finally defended my masters thesis and I am done  an event like that (especially in my case :D) call for an Oscar worthy thank you speech since I couldn't have done it without my amazing support system but the lion share of that gratitude goes to my number one supporter since the first time I breathed air, my amazing mom Aida without you I would not have aspired for anything...A.Sabry Rizk thanks for not letting me give up when I wanted to and for your amazing support. I am blessed with amazing family and friends and I am really thankful for everyone who came you really made my day..
        </text>
         <likes>55</likes>
        <FriendsLikes> 40</FriendsLikes>
        <FamilyLikes>6</FamilyLikes>
        <CloseFriendsLikes> 9 </CloseFriendsLikes>
    </message>
    <comment>
        <text> Congratulations ... now you can rest for a week before getting back to reading :))</text>
        <likes>1</likes>
        <FriendsLikes>1</FriendsLikes>
        <FamilyLikes>0</FamilyLikes>
        <CloseFriendsLikes>0</CloseFriendsLikes>
        <relationship>friend</relationship>
        <userLike>yes</userLike>
    </comment>
.....
</status>
```


Figure 41: Facebook data set snap shot

3.3 Phase three: Emotion elicitation approach

We will explain the steps that we followed to elicit the emotions of social network users in this section.

- In experiment one, we start by validating the accuracy of the ConceptNet GuessMood function which tags the status message with one of the six basic Ekman emotions. We ran ConceptNet GuessMood function on a copy of our dataset. We compared the results of the ConceptNet

GuessMood function against a copy of the dataset which is manually tagged by the social network users.

- Secondly, we investigate the sentiment of the text of the status message using SentiStrength to provide a hybrid approach that expands the Ekman six basic emotions [4] into 18 emotions in experiment two.
- Thirdly, we research how to incorporate the impact of the likes on the status message in order to increase the accuracy of the emotion detected in experiment three A. Then, we will research the impact of the likes of different relationships. i.e. we will study the impact of receiving likes from closefriends and family vs likes from general friends on the accuracy of the emotion detected in experiment three B. In our approach, we give more weight to the likes of closefriends and family since our survey showed that interactions from this group of friends tends to impact users emotions the most. We experiment with several weights of the likes to identify the weights that maximize the accuracy of the correctly detected emotions.
- Fourthly, we investigate the impact of receiving comments on the status to provide more accurate emotions elicitation. In this step, we propose an update to our hybrid approach that incorporate the sentiment detected within each comments in experiment four A. Then, we investigate the use of close friends and family comments as a better indicator of the user's emotions in the status update in experiment four B. We experiment with several weights of the comments to identify the weights that maximize the accuracy of the correctly detected emotions.
- Finally, we examine the overall effect of the likes and the comments all together and how they affect the emotions of the social networks' users after they receive them in experiment five. We experiment with several weights of the likes and comments to identify the weights that maximize the accuracy of the correctly detected emotions. For example, the user was in a bad

mood and he posted a status message of a negative emotion. He/she got likes from close friends, family and general friends. He/she also got various positive and negative comments from close friends, family and general friends. He/she may have made some comments and liked some others. We aim to detect his/her emotion after he/she received all those interactions of the likes and comments.

3.3.1 Experiment one - Validating the accuracy of ConceptNet GuessMood function

__Objective__: The objective of this experiment is to validate the accuracy of the ConceptNet GuessMood function since our emotion tagging is based partially on its output.

__DataSet__: We extracted the Facebook status messages of our participants. Then, we made two copies of the dataset. We asked the participants of our experiment to tag their status messages at the time of posting them with one of the six basic Ekman emotions. We kept the other copy not tagged to run our experiments on.

__Method__: The below figure shows a quick overview of the experiment.

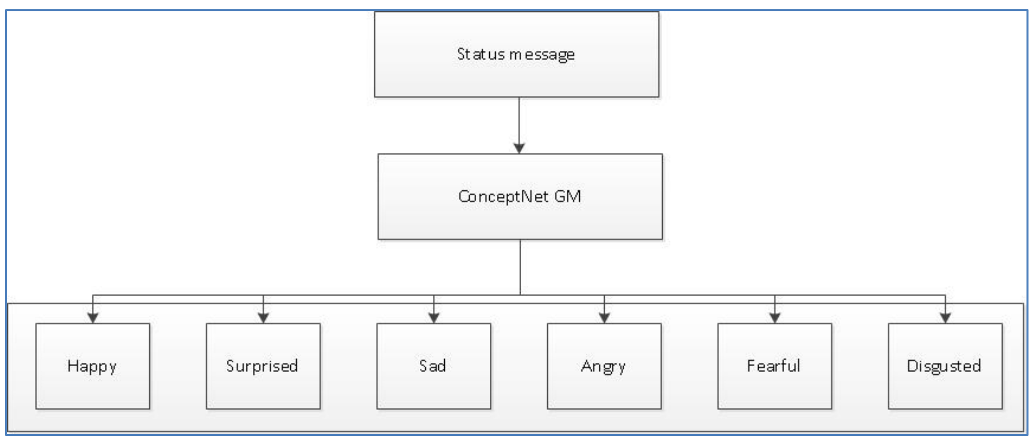

Figure 42: Validating the accuracy of ConceptNet GuessMood function

To validate the output of GuessMood, we ran the below steps:

1. We ran the GuessMood function across all the status messages of the not tagged copy of the dataset. GuessMood automatically represented each status message in a tuple of one of the six Ekman emotions and their percentages. For example, for the status message "What a sandstorm looks like in our neighborhood. My regular hour long dog walk got cut short as I could barely keep my eyes open from all the dust" the output of the GuessMood function is:

Emotion	**%**	**Emotion**	**%**
Sad	60%	Happy	49%
Angry	8%	Fearful	34%
Disgusted	0%	Surprised	0%

Table 25: Sample of ConceptNet GuessMood output

2. We tagged the status message with the emotion of the highest percentage (%). i.e. in the above example the status message was tagged by the sad emotion. If the difference between the emotions of the highest percentage is less than 5 percent we will not consider this status message in our experiment. The status message will be qualified only if the difference between the percentage of the highest two emotions is larger than 5 percent.
3. We used the tagged copy of the dataset as our ground truth. We calculated the accuracy of the GuessMood function by calculating the percentage (%) of the correctly tagged status messages divided by the number of all statuses in the dataset.

$$Accuracy\ (GuessMood) = \frac{Number\ of\ correctly\ tagged\ statuses}{Number\ of\ all\ statuses\ in\ the\ dataset}$$

Results:

They current accuracy of the ConceptNet GM function is **74.5%**

3.3.2 Experiment two - Status Message – Measuring the accuracy of method of expanding the six basic Ekman emotions to eighteen emotions

Objective: The objective of this experiment is to study the impact of the polarity of the sentiment detected in the status message on the emotion detected and expand the Ekman six basic emotions into an extended new set of emotions which are illustrated in Table 26 based on polarity of the text of the status message i.e. positive or negative.

Weak emotion	**Basic Ekman emotion**	**Strong emotion**
Content	Happy	Joyful
Excited	Surprised	Astonished
Discontent	Sad	Grief
Annoyed	Angry	Furious
Bored	Disgusted	Loathing
Anxious	Fearful	Terrified

Table 26: Extended labels of emotions

We use SentiStrength tool to provide a tag indicating whether the status is a positive or negative status. Utilizing this tag along with the emotion from the GuessMood function, we tag the status with one of the extended emotions set.

DataSet: We extracted the Facebook status messages of our participants. Then, we made two copies of the dataset. We asked the participants of our experiment to tag their status messages at the time of posting them with one of the 18 emotions in Table 26. We kept the other copy not tagged to run our experiments on.

Assumptions:

- The likes of the status message and the relationships between the Facebook user and the users who liked the status message are not taken into consideration.
- The comments of the status message and the relationship between the friends who made the likes are not taken into consideration

Method:

The below figure provides a high level overview of the experiment.

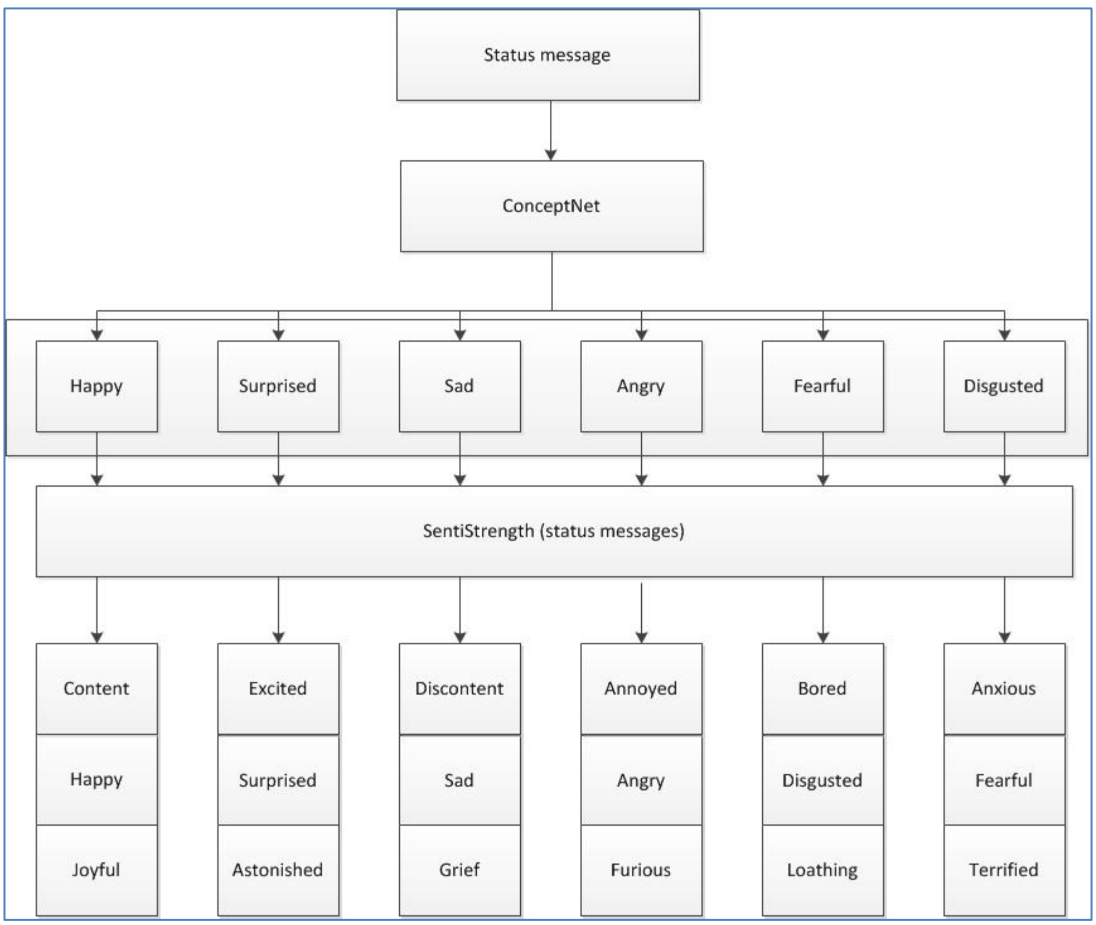

Figure 43: Expanding 6 basic Ekman emotions to 18 emotions

1. We ran the GuessMood function across all the status messages of the non-tagged copy of the dataset. GuessMood automatically represented each status message in a tuple of one of the six Ekman emotions and its percentage as explained earlier in Table 25.
2. The emotion with the highest percentage represented the basic emotion label of the status message.
3. We subsequently analyze the sentiment detected in the status message. We ran SentiStrength to detect the sentiment of the status message. SentiStrength outputs two numbers. A positive number *(pos)* from 1 to 5 which indicates the positive sentiment in the status message and a negative number from -1 to -5 *(neg)* which indicates the negative sentiment in the status message.
4. Paltoglou and Thelwall mapped the output of SentiStrength based on heuristic data to a five-point ordinal scale using an intuitive, heuristic rule that takes *pos* and *neg* numbers and outputs a single prediction. We calculated a final sentiment weight and its corresponding tag for the status message called SentiStrengthOutput (SSO) using the below formula which is adopted from [70]

$$SSO(pos, neg) = \begin{cases} Very\ negative\ (0), & if |Neg| = 5\ and\ Pos\ \in \{1,2\} \\ Negative\ (1), & if\ 3\ \leq |Neg| < 5\ and\ |Neg| > Pos \\ Neutral(2), & otherwise \\ Positive\ (3), & if\ 3 \leq\ Pos < 5\ and\ pos >\ |Neg| \\ Very\ Positive\ (4), & if\ Pos = 5\ and\ Neg \in \{-1, -2\} \end{cases}$$

5. Based on the final sentiment, we mapped the detected emotions into one of the eighteen different categories of emotions that include the six basic Ekman emotions, and 12 other emotions representing weak and strong variations of the six basic Ekman emotions.

When positive emotions such as happy and surprised receive positive sentiment, they are more likely to move to the strong state. When positive emotions receive negative sentiment, they are more likely to move to the weak state. On the other hand, when negative emotions such as sad and angry receive positive sentiment, they are more likely to move to the weak state. When negative emotions receive negative sentiment they are more likely to move to the strong state. Thus, we had to separate handling positive emotions from negative emotions. We will use the same technique for the following experiments as well.

6. To map the results of the positive emotions of happy and surprised we used the below formula

$$Porisitve\ Extended\ Emotion\ (SSO, positive\ emotion)$$
$$= \begin{cases} Strong\ positive\ emotion, if\ SSO >= 3 \\ positive\ emotion,\ \ if\ 3 > SSO > 1 \\ Weak\ positive\ emotion, \quad\ if\ \ SSO =< 1 \end{cases}$$

   For positive emotions such as happy and surprised, if the final sentiment is 0 or 1, we map the emotion to the weak emotion which is content and excited respectively. If the final sentiment is 2, we keep the emotion as happy and surprised respectively. If the final emotion is 3 or 4, we map the emotion to the strong emotion which is joyful and astonished respectively.

7. To map the results of the negative emotions of sad, angry, fearful and disgusted we used the below formula

$$Negative\ Extended\ Emotion\ (SSO, negative\ emotion) =$$
$$\begin{cases} Weak\ negative\ emotion, if\ SSO >= 3 \\ negative\ emotoin,\ \ if\ \ 3 > SSO > 1 \\ Strong\ negative\ emotion,\ \ \ if\ SSO =< 1 \end{cases}$$

   For the negative emotions such as sad, angry, disgusted and fearful, if the final sentiment is 0 or 1, we map the emotion to the strong emotion which is grief, furious, loathing and terrified respectively. If the final sentiment is 2, we keep the emotion as is; sad, angry, disgusted and fearful respectively. If the final sentiment is 3 or 4, we map the emotion to the negative emotion which is discontent, annoyed, bored and anxious. Table 26 shows the extended set of emotions.

8. To validate the tags produced by this process, we compared the automatically generated tags to the manual tags given by the users to their Facebook statues and we calculated the accuracy of

our tags. We compare our accuracy to that of the tags produced by GuessMood in our baseline.

We will calculate the $\text{Accuracy} = \frac{\#\ of\ correctly\ detected\ emotions}{\#\ of\ status\ messages}$

Example:

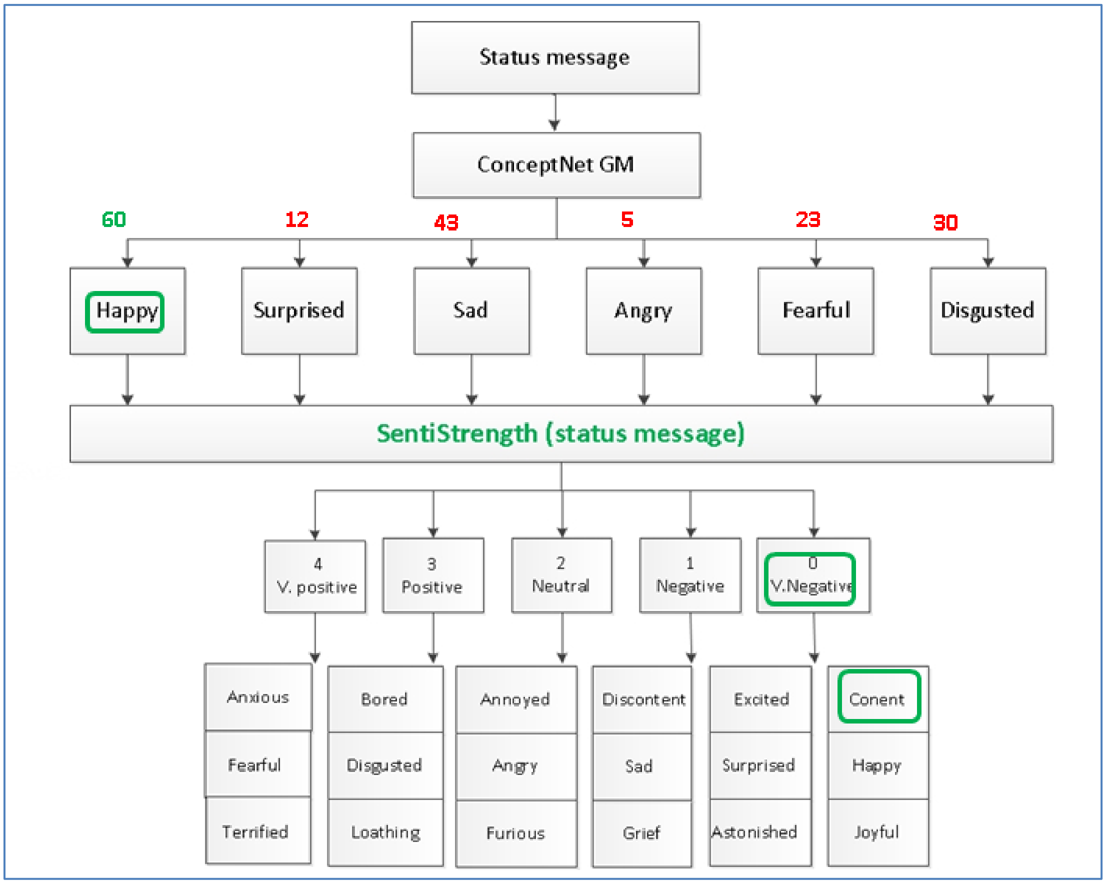

Figure 44: Expanding 6 basic Ekman emotions to 18 emotions example

In the above example the ConceptNet GuessMood output is {(happy, 60), (surprised, 12), (sad, 43), (angry, 5), (fearful, 23), (disgusted, 30)}. Since the emotion with the highest percentage was happy, this status message was tagged by the happy emotion. Afterwards, we ran the SentiStrength on the same status message. The final SSO of the status message is 0 which means that the sentiment detected of the status message is very negative. This impacted the current detected emotion (happy) and moved it to the weak emotion state. The final emotion of this status message is content.

Results:

The accuracy is **64.39**% within the correctly detected emotions by ConceptNet GuessMood

Setup of the following experiments:

We asked our users to tag their status messages with their emotions after they receive likes and comments from different friend relationships. Once the social network users see the status message, they see the status message, likes of the status message, who made the likes, comments and who made the comments at the same time. They see all those variables once they spot their status message. Hence, it is impossible to ask the users to tag their status messages with their emotions after receiving likes without them being impacted by the type of friends who made the likes. Also, it is the same for comments. Once the users spot the status message, they see the comments, the likes of the comments and who made the comments which impacts their emotions.

In experiment three and four, we continue as if we can experiment with one variable and keep the remaining constant. We understand that this is not valid in our case however we run those experiments just to observe the findings.

Having this challenge of the social network users seeing all the variables at the same time and affected by them, we no longer can study the likes as a variable and keep all the other variables constant with zero impact on the social network users. We will not be able to study the impact of the comments as a variable and keep all other variables constant.

Therefore, we design our experiment as an experiment with multiple independent variables where the variables change at the same time [67]. We will use factorial design in experiment five where we try all the permutations of the variables to determine which values maximizes the number of correctly detected emotions.

3.3.3 Experiment three A - Studying the impact of the likes of the status message on the emotions of the users of social networks

Objective: The objective of this experiment is to study the impact of the increase of number of likes to the status message of the user and how they can impact the emotions of the users. Then, identify the weight of likes that maximizes the number of correctly detected emotions of the Facebook users. This is based on our survey were users indicated that increased number of likes on their status message tend to affect them in a positive manner.

Assumptions:

- The relationship of the person who made the likes is not taken into consideration
- The sentiment detected within the comments of the status message and their relationships is not taken into consideration.

DataSet: We asked the participants of our experiment to tag their status messages with one of the 18 emotions as their final emotion that they experience after receiving the likes and comments interactions. We use those tags as our ground truth. We will compare our findings against them to calculate the accuracy

Method:

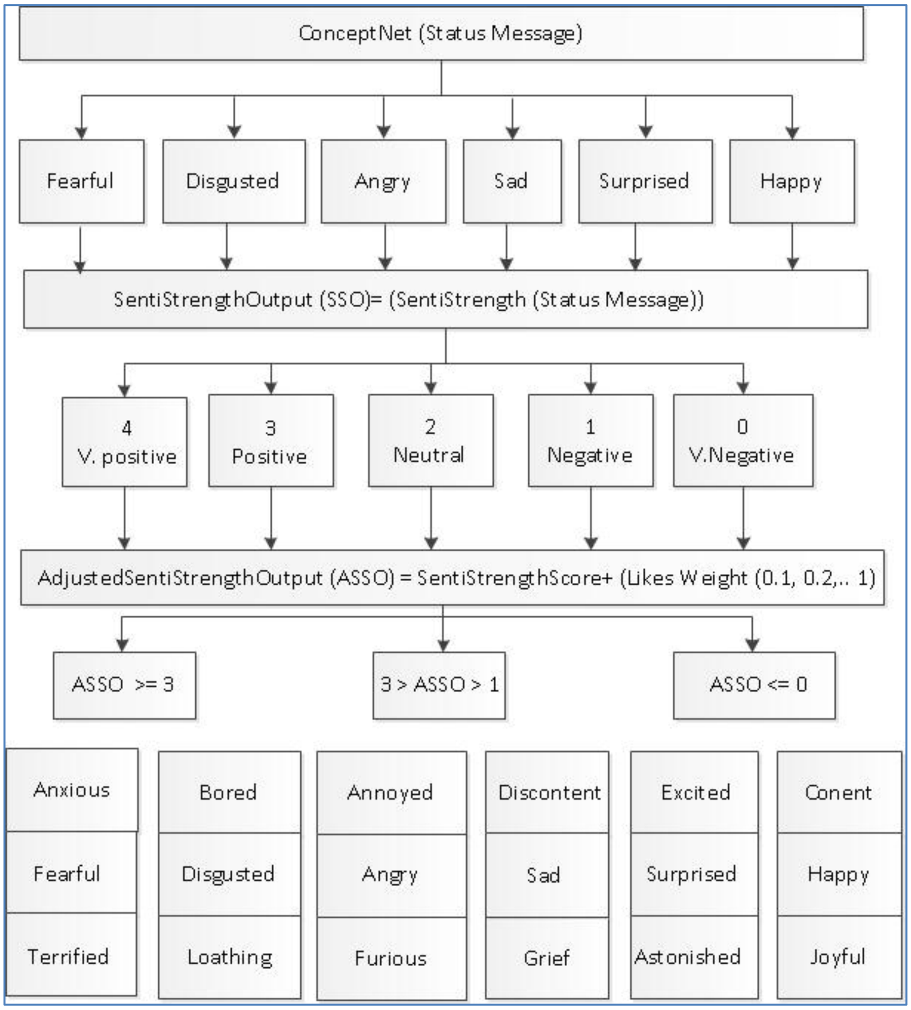

Figure 45: Experiment 3 A - Studying the impact of Status Messages Likes

1. We used GussMood function (GM) to tag each status message of the non-tagged copy of the dataset with one of the six Ekman emotions. The status is tagged with the emotion of the highest %.
2. Then, we ran SentiStrength on the status message. SentiStrength outputs two numbers pos and neg. We calculated the SentiStrengthOutput (SSO) using the below formula as explained in the previous experiment:

$$SSO(pos, neg) = \begin{cases} Very\ negative\ (0),\ if |Neg| = 5\ and\ Pos\ \in \{1,2\} \\ Negative\ (1), \quad if\ 3\ \leq |Neg| < 5\ and\ |Neg| > Pos \\ Neutral(2), \qquad\qquad\qquad\qquad otherwise \\ Positive\ (3),\ if\ 3 \leq\ Pos < 5\ and\ pos >\ |Neg| \\ Very\ Positive\ (4),\ if\ Pos = 5\ and\ Neg \in \{-1,-2\} \end{cases}$$

3. As per our survey, the increase in the number of likes on the status message affects the emotions of the users positively.
4. For each like we will add a weight to the SSO to calculate the adjustedSentiStrengthOutput (ASSO)

   $$ASSO(SSO) = SSO + \#\text{ of likes} * \alpha$$

   Where α start by 0.1 and incrementally increases by 0.1 until it reaches the value of 1; α =0.1, 0.2 …1 to identify which weight of α maximizes the percentage of the correctly detected status messages.
5. To map the results of the positive emotions of happy and surprised we used the below formula

   $$Porisitve\ Extended\ Emotion\ (ASSO, positive\ emotion)$$
   $$= \begin{cases} Strong\ positive\ emotion, if\ ASSO >= 3 \\ positive\ emotoin,\ \ if\ 3 > ASSO > 1 \\ Weak\ positive\ emotion, \qquad if\ \ ASSO =< 1 \end{cases}$$

6. To map the results of the negative emotions of sad, angry, fearful and disgusted we used the below formula

   $$Negative\ Extended\ Emotion\ (ASSO, negative\ emotion)$$
   $$= \begin{cases} Weak\ negative\ emotion, if\ ASSO >= 3 \\ negative\ emotoin, \qquad if\ \ 3 > ASSO > 1 \\ Strong\ negative\ emotion, \quad if\ ASSO =< 1 \end{cases}$$

7. To validate the tags produced by this process, we compare the automatically generated tags to the manual tags given by the users to their Facebook statues and we calculate the accuracy of our tags. We calculated the Accuracy= $\frac{\#\ of\ correctly\ detected\ emotions}{\#\ of\ status\ messages}$

__Example__:

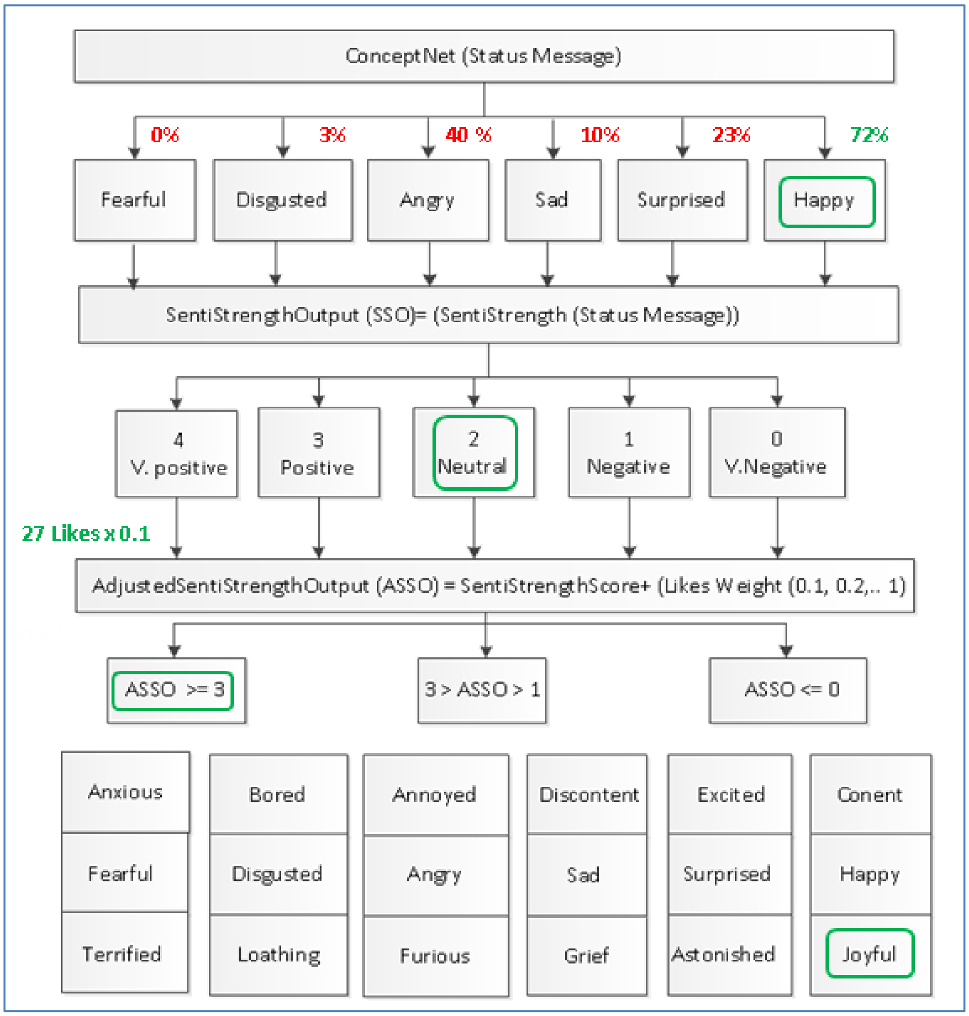

Figure 46: Experiment 3 A - Studying the impact of likes example

In the above example, the status message was tagged by the happy emotion since it has the highest percentage. Then, the output of the SentiStrength was 2. This status message got 27 likes assuming that $\alpha = 0.1$ at this time. The adjusted SentiStrengthScore is 2+2.7 which is greater than 3. Thus, the status message will be assigned to the strong emotion of happy which is joyful.

Results:

We analyzed the results of the various likes Weights (α) and the accuracy. We found out that α=0.2 achieves the maximum accuracy of **70.56**%

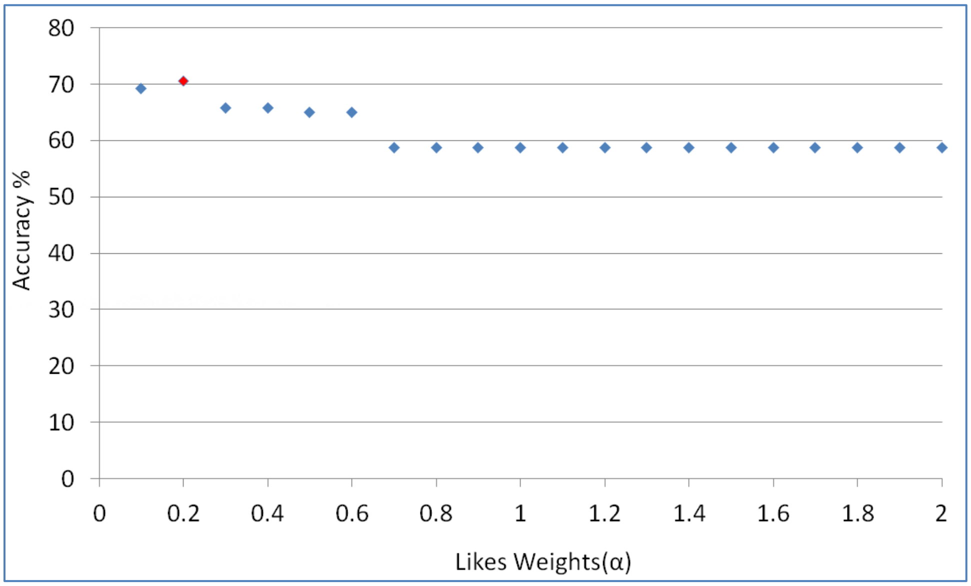

Figure 47: Results of experiment 3 A - Studying the impact of likes

3.3.4 Experiment three B - Studying the impact of the likes of the status message on the emotions of the social network users taking into consideration the relationships

Objective: The objective of this experiment is to study the impact of the increase of number of likes to the status message of the user taking into consideration the relationships of the friends who made the likes and how they can impact the emotions of the users. Then, identify the weights of likes made by friends of different relationships that maximize the number of correctly detected emotions of the Facebook users.

Assumptions:

- The sentiment detected within the comments of the status message and their relationships is not taken into consideration.

DataSet: We asked the participants of our experiment to tag their status messages with one of the 18 emotions as their final emotion that they experience after receiving the likes and comments interactions. We use those tags as our ground truth. We will compare our findings against them to calculate the accuracy

Method:

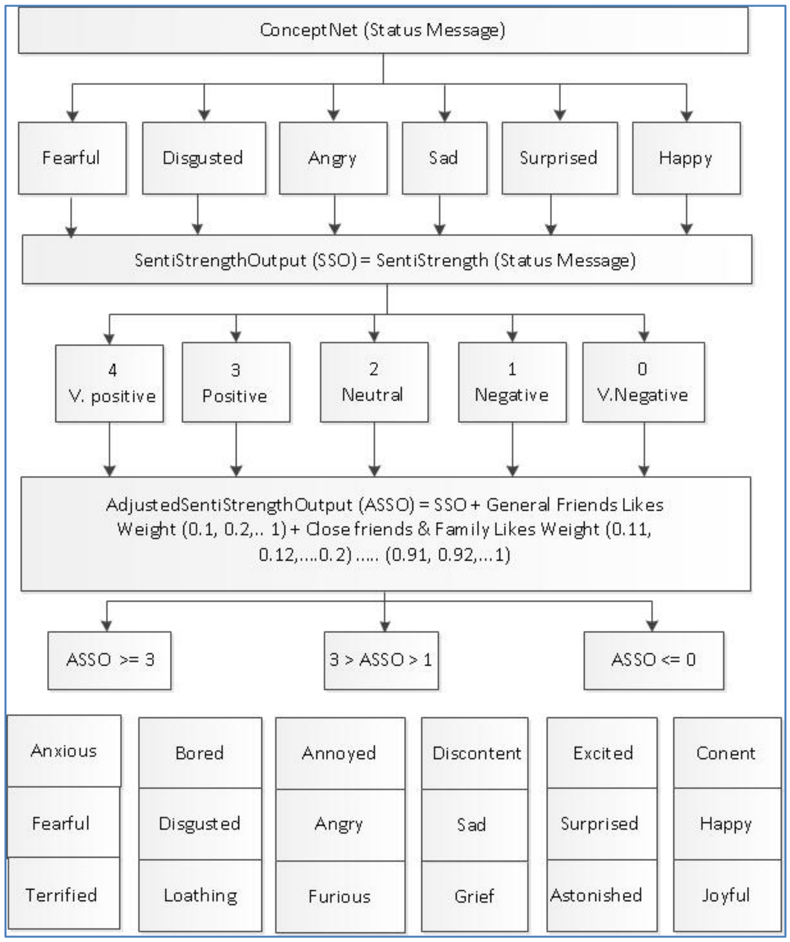

Figure 48: Experiment 3 B - Studying the impact of likes

1. We used GuessMood function (GM) to tag each status message with one of the six Ekman emotions. The status will be tagged with the emotion of the highest %.
2. Then, we ran SentiStrength on the status message. SentiStrength outputs two numbers. We calculated the SentiStrength output (SSO) using the below formula as explained in the previous experiment

$$SentiStrengthOutput\ (SSO) = \begin{cases} Very\ negative\ (0),\ if |Neg| = 5\ and\ Pos\ \in \{1,2\} \\ Negative\ (1),\quad if\ 3\ \leq |Neg| < 5\ and\ |Neg| > Pos \\ Neutral(2), \qquad\qquad otherwise \\ Positive\ (3),\ if\ 3 \leq\ Pos < 5\ and\ pos >\ |Neg| \\ Very\ Positive\ (4),\ if\ Pos = 5\ and\ Neg \in \{-1,-2\} \end{cases}$$

3. As per our survey, the increase in the number of likes on the status message affects the emotions of the users positively.

4. We assigned weights to the each general friends likes, close friends and family likes which the status message received and added those weights to the SentiStrengthOutput to calculate the adjustedSentiStrengthOutput. Let α be the weight of each general friends like and Let β be the weight of each close friends and family like.

$$Adjusted\ SentiStrengthOutput\ (ASSO) = SSO + \text{\# of general friends likes} * \alpha + \text{\# of close friends and family likes} * \beta$$

5. We ran our experiment with the various weights of α ∈ {0.1, 0.2 …2 } and β ∈ { α +0.01, α+0.02,… α+1} to identify which weights of α and β maximizes the percentage of the correctly detected status messages. We computed all possible pairs of α and β and we selected the pair that maximizes the accuracy following the factorial design model in [73].

6. To map the results of the positive emotions of happy and surprised we used the below formula

$$Porisitve\ Extended\ Emotion\ (ASSO, positive\ emotion) = \begin{cases} Strong\ positive\ emotion, if\ ASSO >= 3 \\ positive\ emotoin,\ \ if\ 3 > ASSO > 1 \\ Weak\ positive\ emotion,\ \ \ \ if\ \ ASSO =< 1 \end{cases}$$

7. To map the results of the negative emotions of sad, angry, fearful and disgusted we used the below formula

$$Negative\ Extended\ Emotion\ (ASSO, negative\ emotion) = \begin{cases} Weak\ negative\ emotion, if\ ASSO >= 3 \\ negative\ emotoin,\ \ \ \ if\ \ 3 > ASSO > 1 \\ Strong\ negative\ emotion,\ \ if\ ASSO =< 1 \end{cases}$$

8. To validate the tags produced by this process, we compare the automatically generated tags to the manual tags given by the users to their Facebook statues and we calculate the accuracy of our tags. We will calculate the Accuracy= $\frac{\#\ of\ correctly\ detected\ emotions}{\#\ of\ status\ messages}$

Example:

In the below example, the status message was tagged by the angry emotion and was detected as neutral. This status message received 6 general friends' likes and 4 closefriends and family likes. The SSO = 2 now the ASSO =3 thus the final emotion will be annoyed.

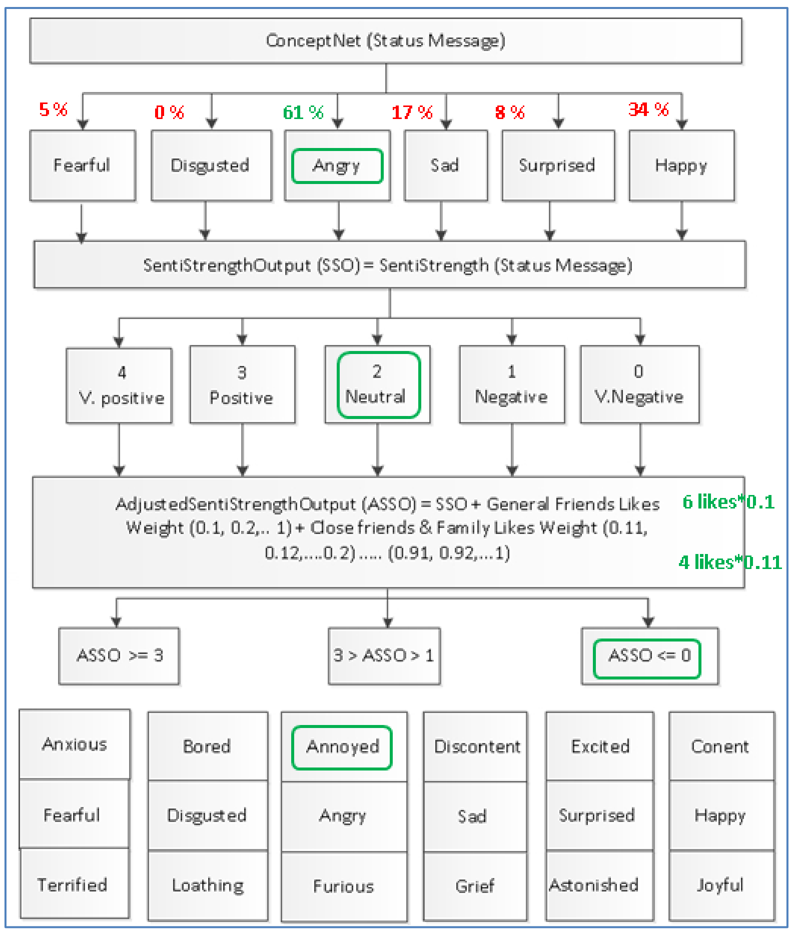

Figure 49: Experiment 3 B - Studying the impact of likes example

Results:

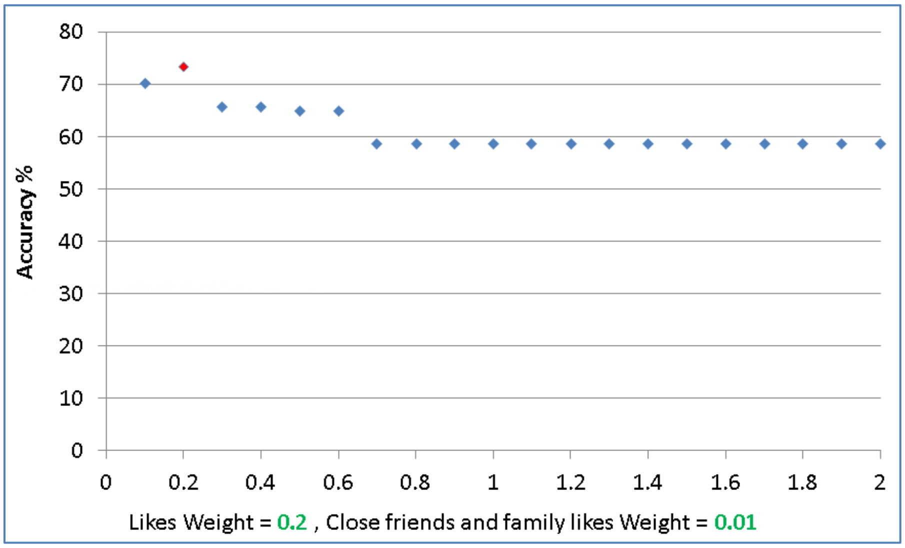

Figure 50: Results of experiment 3 B - Studying the impact of likes

We analyzed the results of the various general friends likes Weights (α), close friends and family likes weights (β) and the accuracy. We found out that α=0.2 and β = 0.21 achieves the maximum accuracy of **73.36**%.

For simplicity the above graph does not show the third axis of the β and the point of 0.21.

3.3.5 Experiment four A - Studying the impact of the comments on the emotions of the social network users

Objective: The objective of this experiment is to study the impact of receiving comments to the status message of the user and how they can impact the emotions of the users. Then, identify the weight of comments that maximizes the number of correctly detected emotions of the Facebook users after receiving comments on their status messages

Assumptions:

- The likes of the status messages and the relationship of the friends who made the likes are not taken into consideration
- The relationships of the friends who made the comments are not taken into consideration

DataSet: We asked the participants of our experiment to tag their status messages with one of the 18 emotions as their final emotion that they experience after receiving the likes and comments interactions. We use those tags as our ground truth. We will compare our findings against them to calculate the accuracy

Method:

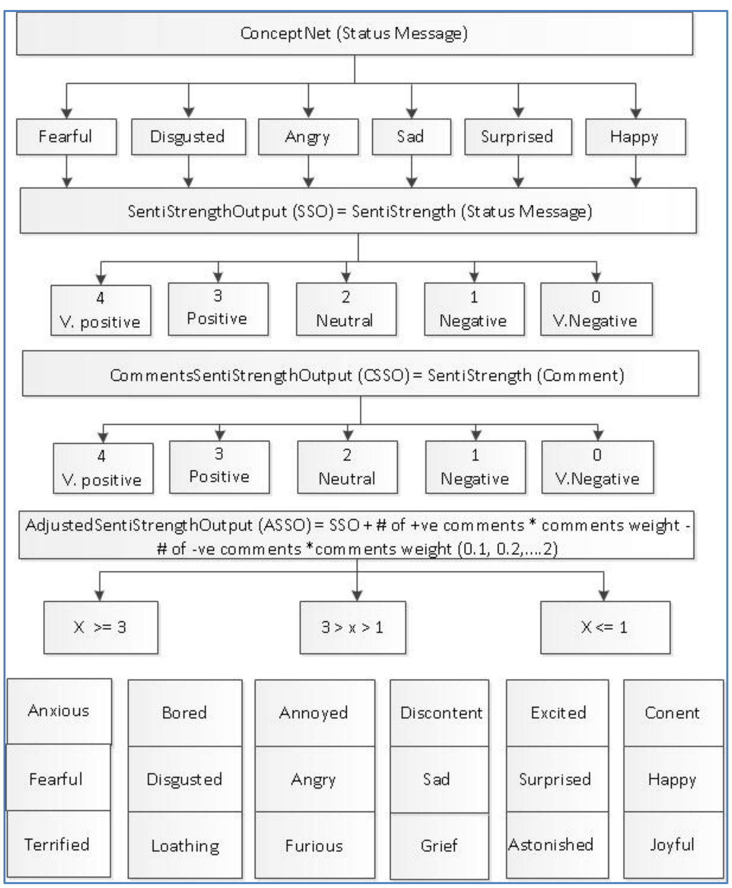

Figure 51: Experiment four A - Studying the impact of comments

1. We used GuessMood function (GM) to tag each status message with one of the six Ekman emotions. The status will be tagged with the emotion of the highest %.
2. Then, analyzed the sentiment detected in the status message. SentiStrength outputs two numbers. We calculated the SentiStrength output (SSO) using the below formula as explained in the previous experiment

$$SentiStrengthOutput\ (SSO) = \begin{cases} Very\ negative\ (0),\ if |Neg| = 5\ and\ Pos\ \in \{1,2\} \\ Negative\ (1),\quad if\ 3\ \leq |Neg| < 5\ and\ |Neg| > Pos \\ Neutral(2),\qquad otherwise \\ Positive\ (3),\ if\ 3 \leq\ Pos < 5\ and\ pos >\ |Neg| \\ Very\ Positive\ (4),\ if\ Pos = 5\ and\ Neg \in \{-1,-2\} \end{cases}$$

3. To investigate how the sentiment within the comments impacts the emotion of the user, we detected the sentiment of each comment by using SentiStrength. We calculated the CommentSentiStrengthOutput (CSSO) as per the below formula

$$CSSO = \begin{cases} Very\ negative\ (0),\quad if |Neg| = 5\ and\ Pos\ \in \{1,2\} \\ Negative\ (1),\quad if\ 3\ \leq |Neg| < 5\ and\ |Neg| > Pos \\ Neutral(2),\qquad otherwise \\ Positive\ (3),\quad if\ 3 \leq\ Pos < 5\ and\ pos >\ |Neg| \\ Very\ Positive\ (4),\quad if\ Pos = 5\ and\ Neg \in \{-1,-2\} \end{cases}$$

4. We added a weight (γ) for each positive comment to the SSO of the status message, for each neutral comment we did not add a weight and we subtracted the same weight (γ) if the sentiment of the comment is negative.

   $\text{AdjustedSentiStrengthOutput (SSO)} = \text{SSO} + \text{\# of positive comments} * \gamma - \text{\# of negative comments} * \gamma$
5. We ran our experiment with the various weights of γ =0.1, 0.2 …2 to identify which weights of γ maximizes the percentage of the correctly detected status messages.

6. To map the results of the positive emotions of happy and surprised we used the below formula

$$Poisitve\ Extended\ Emotion\ (ASSO, positive\ emotion)$$

$$= \begin{cases} Strong\ positive\ emotion, if\ ASSO >= 3 \\ positive\ emotoin,\ \ if\ 3 > ASSO > 1 \\ Weak\ positive\ emotion, \qquad if\ \ ASSO =< 1 \end{cases}$$

7. To map the results of the negative emotions of sad, angry, fearful and disgusted we used the below formula

$$Negative\ Extended\ Emotion\ (ASSO, negative\ emotion)$$

$$= \begin{cases} Weak\ negative\ emotion, if\ ASSO >= 3 \\ negative\ emotoin, \qquad if\ \ 3 > ASSO > 1 \\ Strong\ negative\ emotion,\ \ \ if\ ASSO =< 1 \end{cases}$$

8. To validate the tags produced by this process, we compare the automatically generated tags to the manual tags given by the users to their Facebook statues and we calculate the accuracy of our tags. We will calculate the Accuracy= $\frac{\#\ of\ correctly\ detected\ emotions}{\#\ of\ status\ messages}$

__Example__:

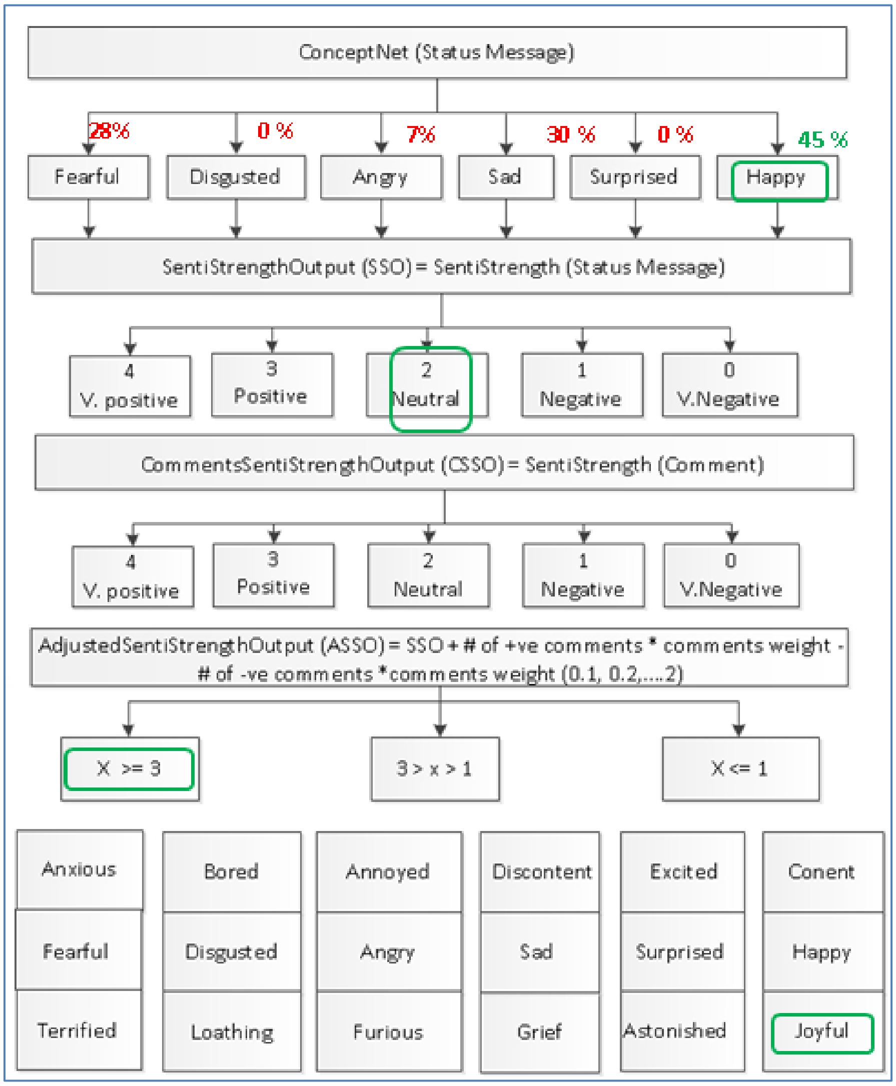

Figure 52: Experiment four A - Studying the impact of comments example

In the above example, the status message was tagged as happy initially. The sentiment detected in the status message was neutral since the output of SentiStrength is 2. Then, it received 16 positive comments and 5 negative comments. The overall comments weight made the ASSO > 3 thus the status message was assigned to the strong emotion which is Joyful

Results:

We analyzed the results of the various comments Weights (γ), and the accuracy. We found out that γ=0.6 achieves the maximum accuracy of **67.31**%.

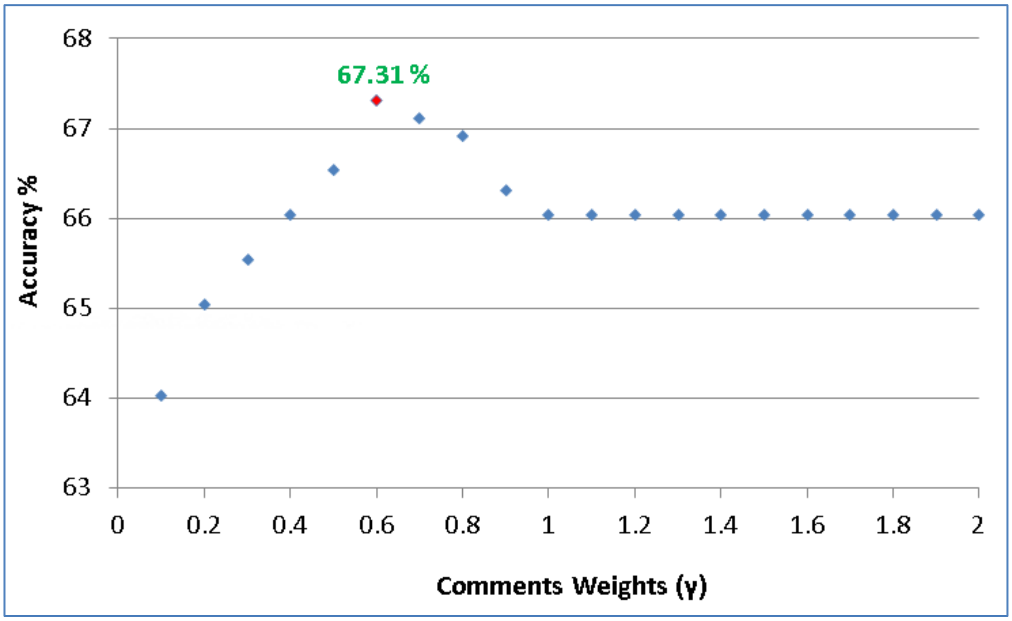

Figure 53: Results of experiment four A - Studying the impact of comments

3.3.6 Experiment four B - Studying the impact of the comments on the emotions of the social network users taking into consideration the relationships

Objective: The objective of this experiment is to study the impact of receiving comments to the status message of the user taking into consideration the relationships of who made the comments and how they can impact the emotions of the users. Then, identify the weight of comments that maximizes the number of correctly detected emotions of the Facebook users after receiving comments on their status messages

Assumptions:

- The likes of the status messages and the relationship of the friends who made the likes are not taken into consideration

DataSet: We asked the participants of our experiment to tag their status messages with one of the 18 emotions as their final emotion that they experience after receiving the likes and comments interactions. We use those tags as our ground truth. We will compare our findings against them to calculate the accuracy

__Method__:

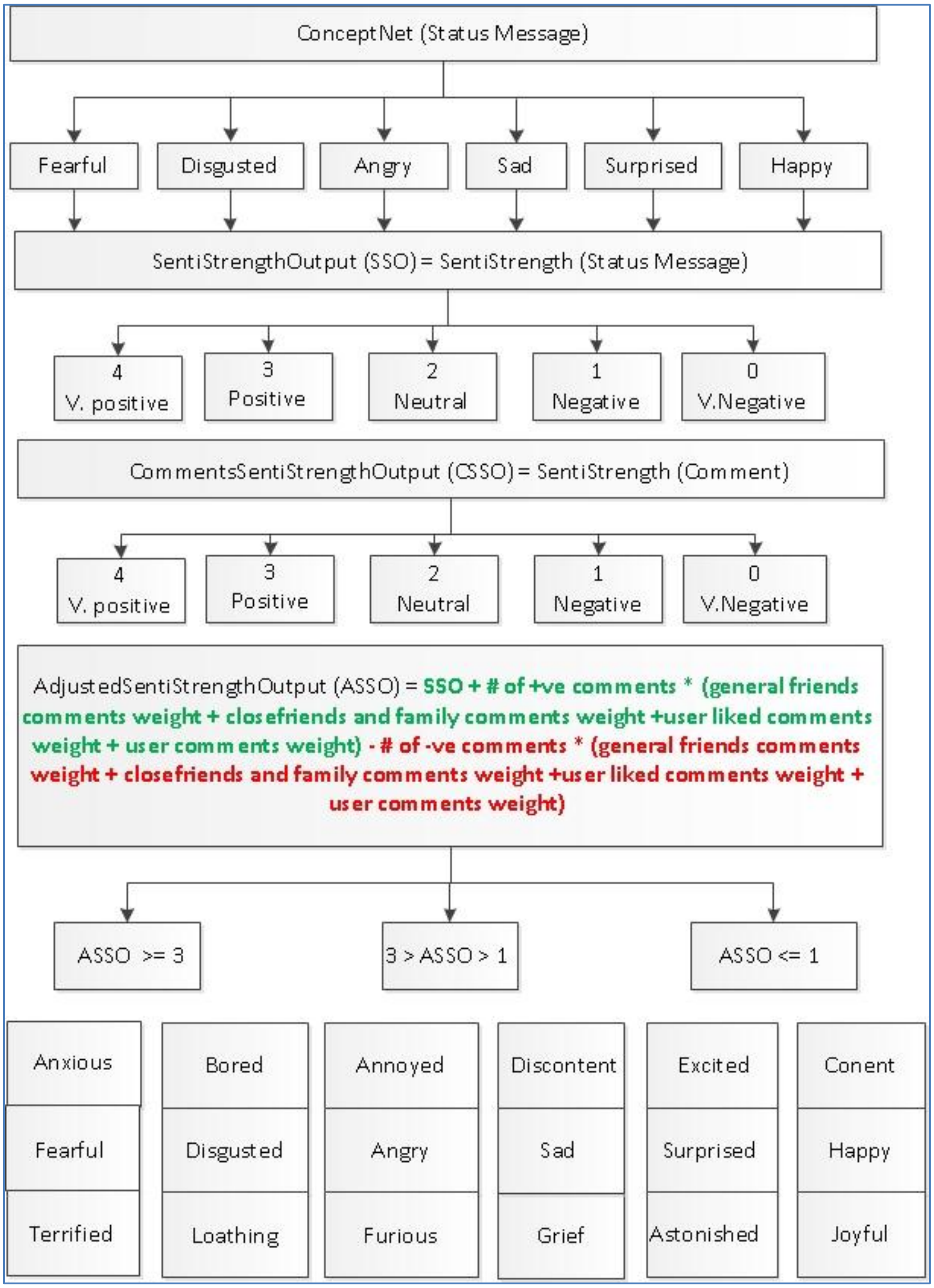

Figure 54: Experiment 4 B - studying the impact of comments

1. We used GuessMood function (GM) to tag each status message with one of the six Ekman emotions. The status will be tagged with the emotion of the highest %.
2. Then, analyzed the sentiment detected in the status message. SentiStrength outputs two numbers. We calculated the SentiStrength output (SSO) using the below formula as explained in the previous experiment

$$SentiStrengthOutput\ (SSO) = \begin{cases} Very\ negative\ (0), & if |Neg| = 5\ and\ Pos\ \in \{1,2\} \\ Negative\ (1), & if\ 3\ \leq |Neg| < 5\ and\ |Neg| > Pos \\ Neutral(2), & otherwise \\ Positive\ (3), & if\ 3 \leq\ Pos < 5\ and\ pos >\ |Neg| \\ Very\ Positive\ (4), & if\ Pos = 5\ and\ Neg \in \{-1,-2\} \end{cases}$$

3. To investigate how the sentiment within the comments impacts the emotion of the user, we detected the sentiment of each comment by using SentiStrength. We calculated the CommentSentiStrengthOutput (CSSO) as per the below formula

$$CSSO = \begin{cases} Very\ negative\ (0), & if |Neg| = 5\ and\ Pos\ \in \{1,2\} \\ Negative\ (1), & if\ 3\ \leq |Neg| < 5\ and\ |Neg| > Pos \\ Neutral(2), & otherwise \\ Positive\ (3), & if\ 3 \leq\ Pos < 5\ and\ pos >\ |Neg| \\ Very\ Positive\ (4), & if\ Pos = 5\ and\ Neg \in \{-1,-2\} \end{cases}$$

4. We added a weight (γ) for each positive comment by a general friend to the SSO of the status message, for each neutral comment we did not add a weight and we subtracted the same weight (γ) if the sentiment of the comment is negative.
5. We added additional weight (δ) for each positive comment by a close friend or family to the SSO of the status message, for each neutral comment we did not add a weight and we subtracted the same additional weight of (δ) if the sentiment of the comment is negative.
6. We added additional weight (ε) for each positive comment by the users themselves to the SSO of the status message, for each neutral comment we did not add a weight and we subtracted the same additional weight of (ε) if the sentiment of the comment is negative.

7. We added additional weight (ζ) for each positive comment liked by the users themselves to the SSO of the status message, for each neutral comment we did not add a weight and we subtracted the same additional weight of (ζ) if the sentiment of the comment is negative.

AdjustedentiStrengthOutput (SSO) $=$ SSO $+$ # of positive comments * (γ+δ+ε+ζ) - # of negative comments * (γ+δ+ε+ζ)

8. To map the results of the positive emotions of happy and surprised we used the below formula

$$Porisitve\ Extended\ Emotion\ (ASSO) = \begin{cases} Strong\ positive\ emotion, if\ ASSO >= 3 \\ positive\ emotoin,\ \ if\ 3 > ASSO > 1 \\ Weak\ positive\ emotion,\ \ \ \ if\ ASSO =< 1 \end{cases}$$

9. To map the results of the negative emotions of sad, angry, fearful and disgusted we used the below formula

$$Negative\ Extended\ Emotion\ (ASSO) = \begin{cases} Weak\ negative\ emotion, if\ ASSO >= 3 \\ negative\ emotoin,\ \ \ \ if\ \ 3 > ASSO > 1 \\ Strong\ negative\ emotion,\ \ if\ ASSO =< 1 \end{cases}$$

10. We ran our experiment with the various weights of γ Є {0.1, 0.2 …2}, δ Є {γ+0.01, γ+0.02,… γ+1}, ε Є γ+0.01, γ+0.02,… γ+1} and ζ Є {γ+0.01, γ+0.02,… γ+1} to identify which weights of γ, δ, ε and ζ maximizes the percentage of the correctly detected status messages.

11. To validate the tags produced by this process, we compare the automatically generated tags to the manual tags given by the users to their Facebook statues and we calculate the accuracy of our tags. We calculated the Accuracy= $\frac{\#\ of\ correctly\ detected\ emotions}{\#\ of\ status\ messages}$

Example:

The status message was initially tagged as happy in the below example. The sentiment of the status message was detected as neutral by SentiStrength. We detected the sentiment of each comment by SentiStrength. We assigned the weight of 0.1 for each positive comment of the general friends and -0.1 for each negative comment of the general friends. We assigned the weight of -0.11 for negative closefriends and family comments. We assigned the weight of 0.11 to the comments by the users themselves and the comments liked by the users. This resulted in having the adjusted SentiStrength output to be less than one. Therefore, the emotion of the status message moved from initially being happy to the weak state of the emotion which is content.

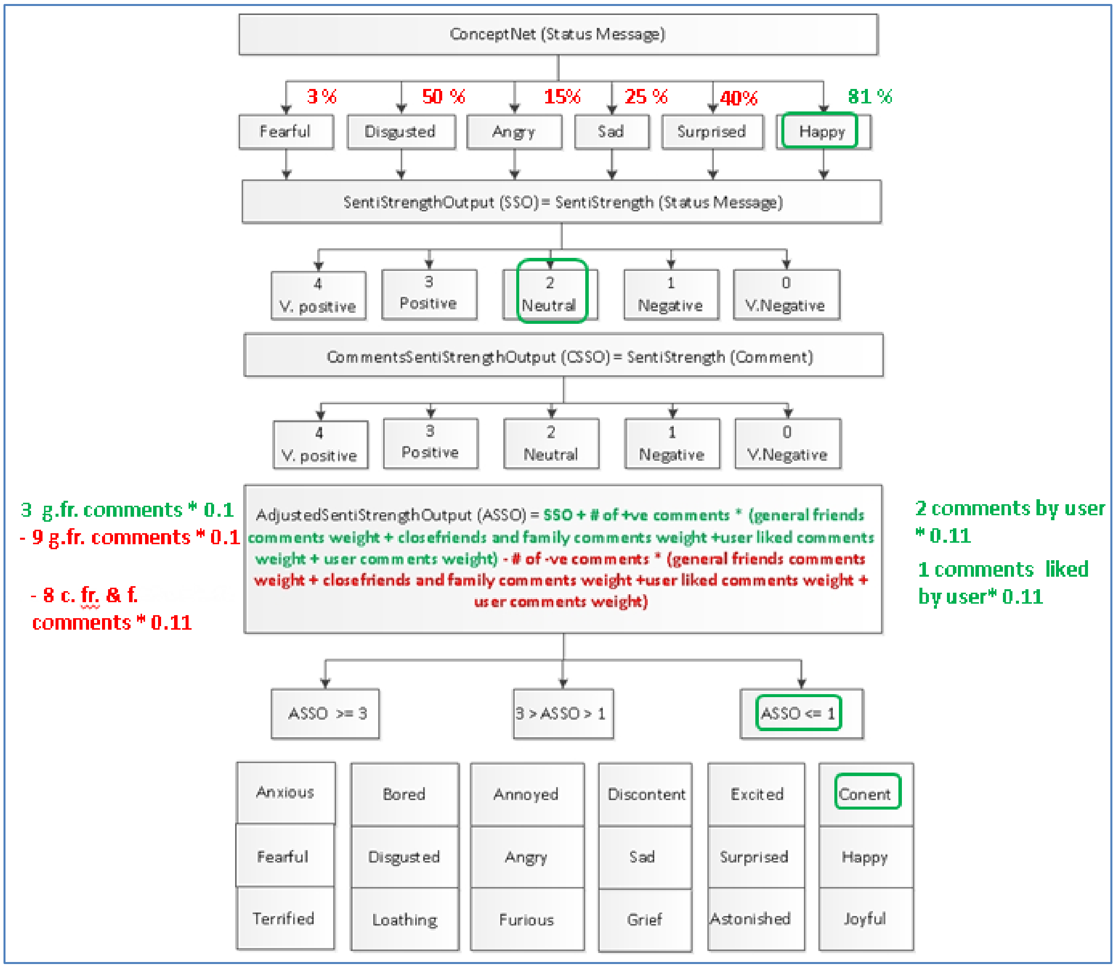

Figure 55: Experiment 4 B - studying the impact of comments example

Results:

We investigated the results of the comments Weights (γ), close friends and family comments weights (δ), user comments weights (ε), user-liked comments weights (ζ) and the accuracy. We found out that Comment Weight (γ) = 0.5, Close friends and family weight (δ) = 0.01, user comments weight (ε) = 0.02 and user liked (ζ) 0.01achieves the maximum accuracy of **72.035**%.

For simplicity the above graph does not show the axis of the δ, ε and ζ.

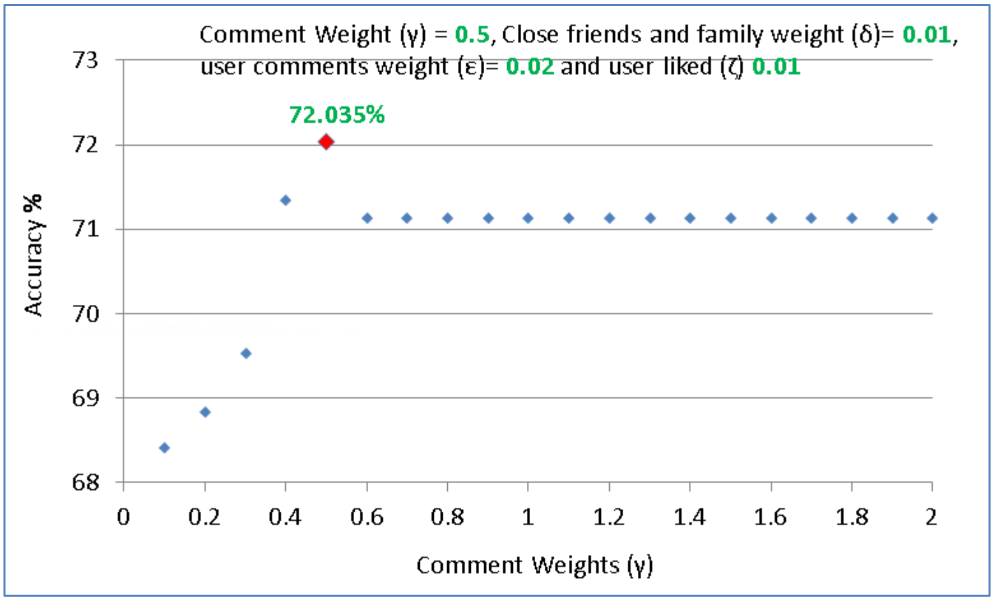

Figure 56: Results of experiment 4 B - studying the impact of comments

3.3.7 Experiment five - Studying the impact of both likes and comments on the emotions of the social network users taking into consideration the relationships

Objective: The objective of this experiment is to study the impact of receiving likes and comments to the status message of the user taking into consideration the relationships of who made the likes and comments and how they can impact the emotions of the users. Then, identify the weight of likes and comments that maximizes the number of correctly detected emotions of the Facebook users after receiving comments on their status messages

Assumptions:

- The likes of the status messages and the relationship of the friends who made the likes are taken into consideration
- The comments of the status messages and the relationships of the friends who made the comments are taken into consideration

DataSet: We asked the participants of our experiment to tag their status messages with one of the 18 emotions as their final emotion that they experience after receiving the likes and comments interactions. We use those tags as our ground truth. We will compare our findings against them to calculate the accuracy

Method:

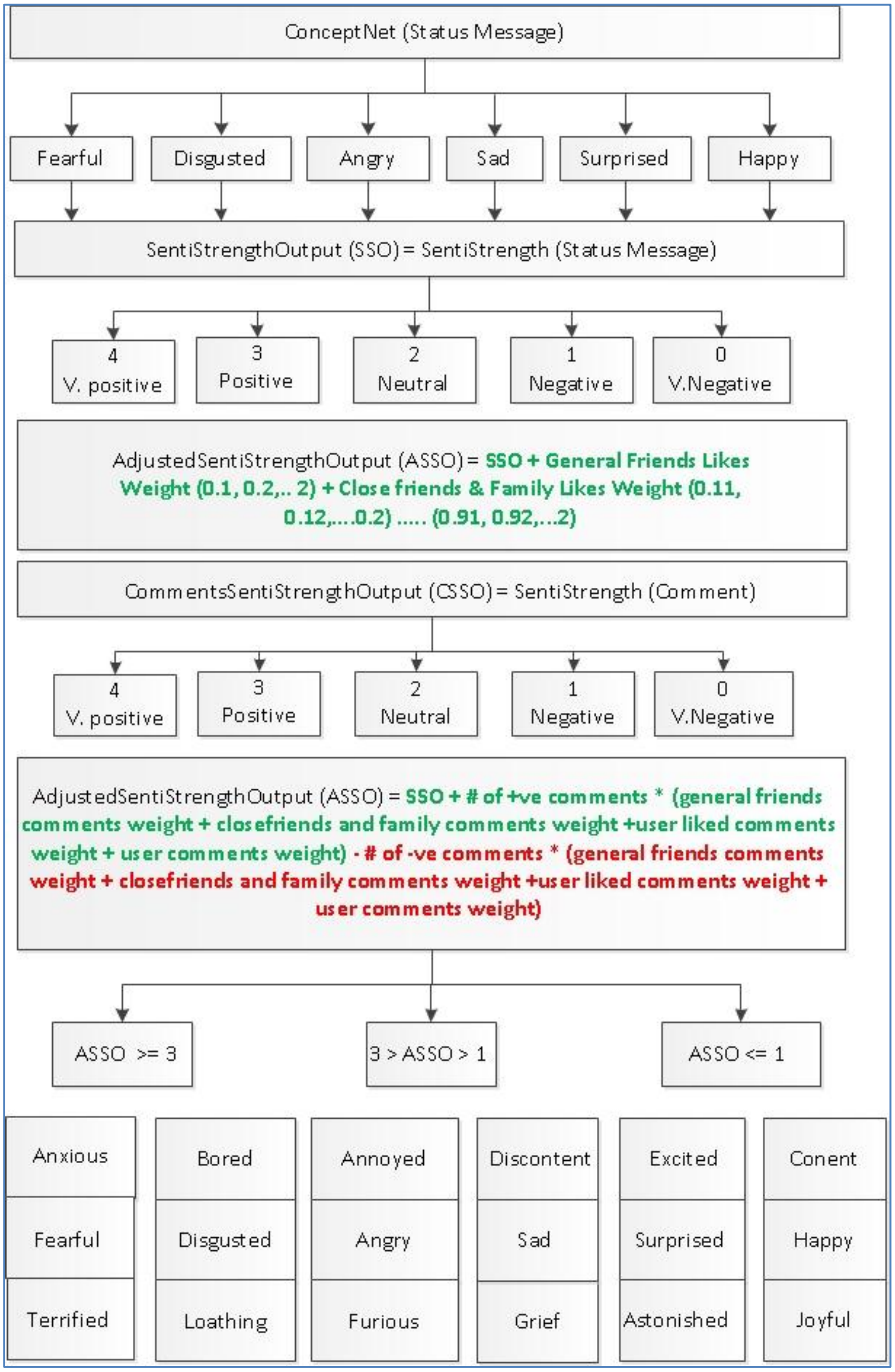

Figure 57: Experiment 5 - studying the impact of both likes and comments

1. We used GuessMood function (GM) to tag each status message with one of the six Ekman emotions. The status will be tagged with the emotion of the highest %.
2. Then, analyzed the sentiment detected in the status message. SentiStrength outputs two numbers. We calculated the SentiStrength output (SSO) using the below formula as explained in the previous experiment

$$SentiStrengthOutput\ (SSO) = \begin{cases} Very\ negative\ (0), & if |Neg| = 5\ and\ Pos\ \in \{1,2\} \\ Negative\ (1), & if\ 3\ \leq |Neg| < 5\ and\ |Neg| > Pos \\ Neutral(2), & otherwise \\ Positive\ (3), & if\ 3 \leq\ Pos < 5\ and\ pos >\ |Neg| \\ Very\ Positive\ (4), & if\ Pos = 5\ and\ Neg \in \{-1,-2\} \end{cases}$$

3. We assigned various weights to the each general friends likes, close friends and family likes which the status message received and added those weights to the SentiStrengthOutput to calculate the adjustedSentiStrengthOutput. Let α be the weight of each general friends like and Let β be the weight of each close friends and family like.
4. We detected the sentiment of each comment by using SentiStrength. We calculated the CommentSentiStrengthOutput (CSSO) as per the below formula

$$CSSO = \begin{cases} Very\ negative\ (0), & if |Neg| = 5\ and\ Pos\ \in \{1,2\} \\ Negative\ (1), & if\ 3\ \leq |Neg| < 5\ and\ |Neg| > Pos \\ Neutral(2), & otherwise \\ Positive\ (3), & if\ 3 \leq\ Pos < 5\ and\ pos >\ |Neg| \\ Very\ Positive\ (4), & if\ Pos = 5\ and\ Neg \in \{-1,-2\} \end{cases}$$

5. We added a weight (γ) for each positive comment by a general friend to the SSO of the status message, for each neutral comment we did not add a weight and we subtracted the same weight (γ) if the sentiment of the comment is negative.
6. We added additional weight (δ) for each positive comment by a close friend or family to the SSO of the status message, for each neutral comment we did not add a weight and we subtracted the same additional weight of (δ) if the sentiment of the comment is negative.

7. We added additional weight (ε) for each positive comment by the users themselves to the SSO of the status message, for each neutral comment we did not add a weight and we subtracted the same additional weight of (ε) if the sentiment of the comment is negative.

8. We added additional weight (ζ) for each positive comment liked by the users themselves to the SSO of the status message, for each neutral comment we did not add a weight and we subtracted the same additional weight of (ζ) if the sentiment of the comment is negative.

$\text{AdjustedentiStrengthOutput (SSO)} = \text{SSO} + \; + \text{\# of general friends likes} * \alpha \; +$ $\text{\# of close friends and family likes} * \beta$ + # of positive comments * (γ+δ+ε+ζ) - # of negative comments * (γ+δ+ε+ζ)

9. To map the results of the positive emotions of happy and surprised we used the below formula

$$Porisitve\ Extended\ Emotion\ (ASSO, positive\ emotion) = \begin{cases} Strong\ positive\ emotion, if\ ASSO >= 3 \\ positive\ emotoin,\ \ if\ 3 > ASSO > 1 \\ Weak\ positive\ emotion,\quad if\ ASSO =< 1 \end{cases}$$

10. To map the results of the negative emotions of sad, angry, fearful and disgusted we used the below formula

$$Negative\ Extended\ Emotion\ (ASSO, negative\ emotion) = \begin{cases} Weak\ negative\ emotion, if\ ASSO >= 3 \\ negative\ emotoin,\quad if\ \ 3 > ASSO > 1 \\ Strong\ negative\ emotion,\ \ if\ ASSO =< 1 \end{cases}$$

11. We ran our experiment with the various weights of γ Є {0.1, 0.2 …2}, δ Є {γ+0.01, γ+0.02,… γ+1}, ε Є γ+0.01, γ+0.02,… γ+1} and ζ Є {γ+0.01, γ+0.02,… γ+1} to identify which weights of γ, δ, ε and ζ maximizes the percentage of the correctly detected status messages.

12. To validate the tags produced by this process, we compare the automatically generated tags to the manual tags given by the users to their Facebook statues and we calculate the accuracy of our tags. We will calculate the Accuracy= $\frac{\#\ of\ correctly\ detected\ emotions}{\#\ of\ status\ messages}$

Example:

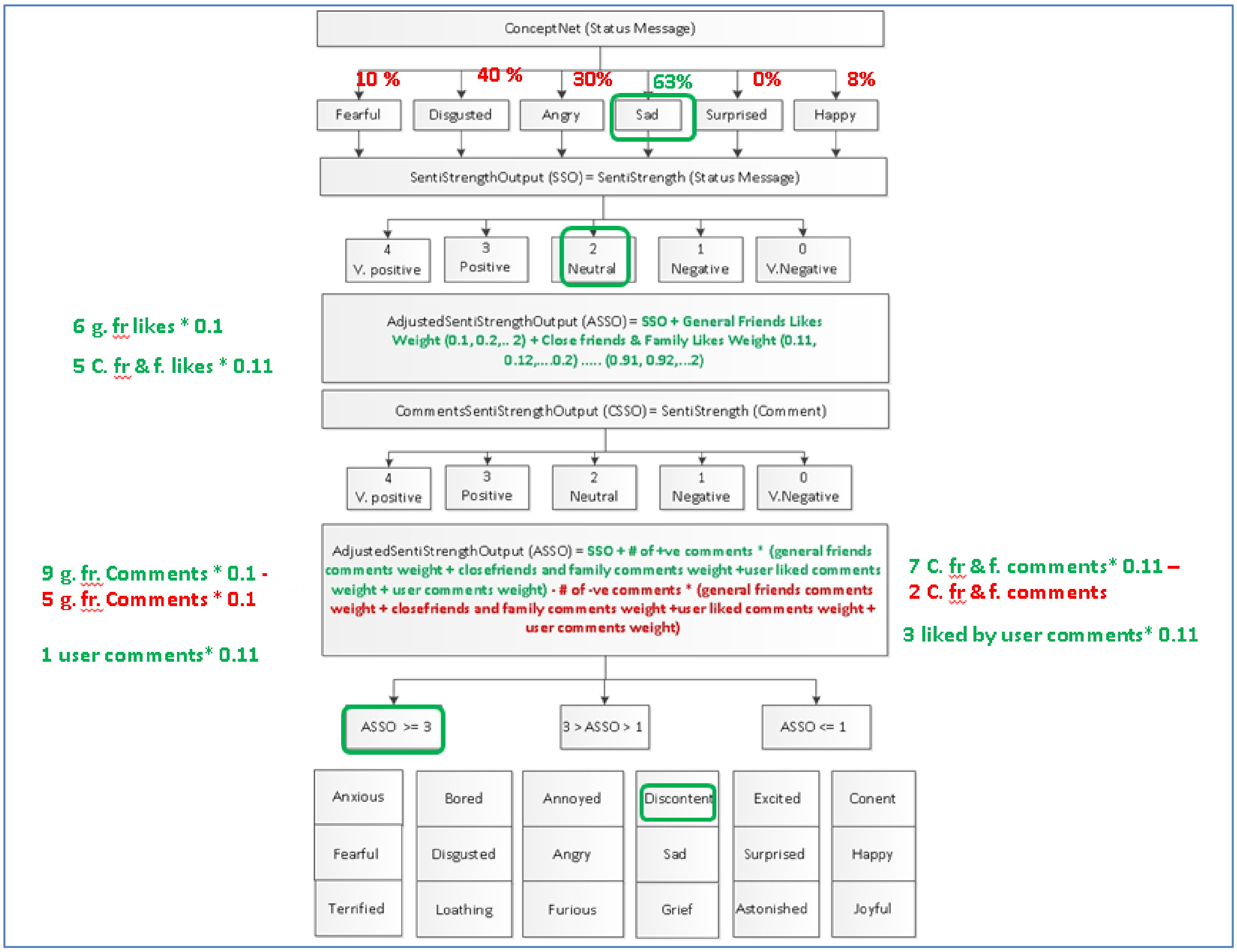

Figure 58: Experiment 5 - studying the impact of both likes and comments example

Results:

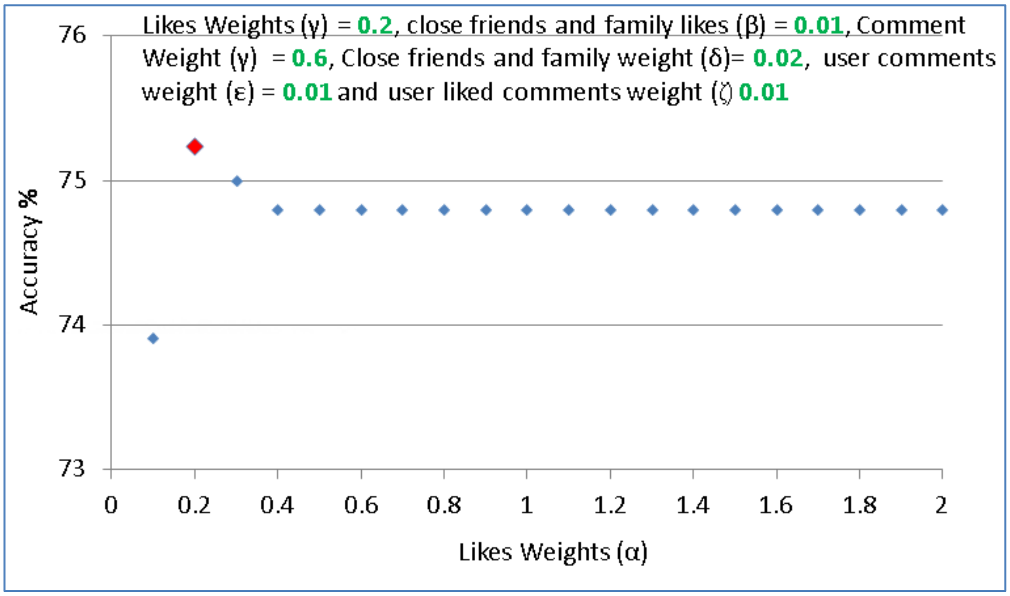

Figure 59: Results of experiment 5 - studying the impact of both likes and comments

We investigated the results of the various general friends likes Weights (α), close friends and family likes weights (β), comments weights (γ), close friends and family comments weights (δ), user comments weights (ε), user liked comments weights (ζ) and the accuracy. We found out that general friends likes Weights (α) = 0.2, close friends and family likes weights (β) =0.01, comments weights (γ) = 0.06, close friends and family comments weights (δ) =0.02, user comments weights (ε) = 0.01, user liked comments weights (ζ) = 0.01 achieves the maximum accuracy of **75.23**%.

For simplicity the above graph does not show the axis of the β, γ, δ, ε and ζ.

4 Conclusion and Future Work

In this section we present our conclusion for our research work and state our main contribution. We also provide details for our future work plan.

4.1 Conclusion

In our research we addressed the problem of emotion elicitation of social networks. People tend to use social networks as a mean to express their emotions. Some people for example use a social network like Facebook as an outlet to express their negative emotions like frustration or anger and expect their network of friends to interact with them in a way that might help them deal with such emotions. Through friends' comments and likes people get feedback and support that could help neutralize their negative emotions. In the same manner, people use such networks to express their positive emotions like happiness and excitement. They expect their network of friends to interact with them through comments and likes which usually leads to the amplification of such emotions. Our aim in our research is to study emotion elicitation from social networks interactions. We studied Facebook data; we mainly focused on status updates and the comments and likes on those updates. We devised various experiments that helped use understand more the effect of such social interaction on people's emotion.

We started our research work by reviewing the work done in the literature. We found out that researches have purely dealt with the emotion elicitation problem of social networking from a very limited perspective, and only used the textual features of social networks [5][6]. They ignored the wealth of the other sources of information that could be used to better detect emotions of the users of the social networks, such as social graph of participants, preferences, location, comments, likes, events, images, audio and much more.

We conducted a survey to better understand the social networks features that affect the emotions of users of Facebook. We found out that Facebook users tend to express their emotions using status, comments and likes features more than any other features provided by the social network. The emotions of the Facebook users are positively affected when the numbers of likes to their posts increase. The degree of connection of the person commenting or liking the users' comments makes a difference in the way the users are affected. Users tend to be affected with the posts of close friends the most, then comes the family members after. Gifts and events features of Facebook do not have a great impact on the emotions of Facebook users. Our findings guided us to focus on the likes, comments and degree of connection and the relationships between users and their friends in our study of the use of the various social network features to be used in emotion elicitation.

We started to experiment with ConceptNet GuessMood function and we found that it is limited to only the six basic Ekman emotions which are happy, surprised, sad, angry, disgusted and fearful. Combining different approaches of emotion detection, we managed to expand the six basic emotions to a new set of 18 emotions. We ran an experiment using a labeled dataset to measure the accuracy of the expanded emotions. This hybrid technique resulted in an accuracy of 64.39 %.

After expanding the six basic emotions, we researched the various features of Facebook that affects people emotions namely the likes, comments and the degree of connection. We started with the impact of receiving likes on the status message only on the emotions of the social network users. We aimed at identifying the weight of likes which maximizes the accuracy of the correctly detected emotions. We found out that assigning the likes the weight of 0.2 achieved the best accuracy which is 70.56%. We investigated the impact of the likes of the status message and relationships of the friends who made the likes. We found out that the incorporating different weights to likes by different friend relationships leads to an accuracy of 73.36%. We researched the impact of the comments on the status message only on the where the accuracy turned to be 67.31%. Adding the relationships of the friends i.e. close friends, family and general friends who made the comments to our experiments the accuracy turned to be 72.035 %. Finally, we researched the impact of the likes of the status messages taking into consideration the relationships of the friends who made the likes and comments of the status message taking into consideration the relationships of the friends who made the comments on the emotions of the social networks, We found out that the accuracy turned to be 75.23 %. The below graph summarizes the overall results we got with different variations of the features of the social network.

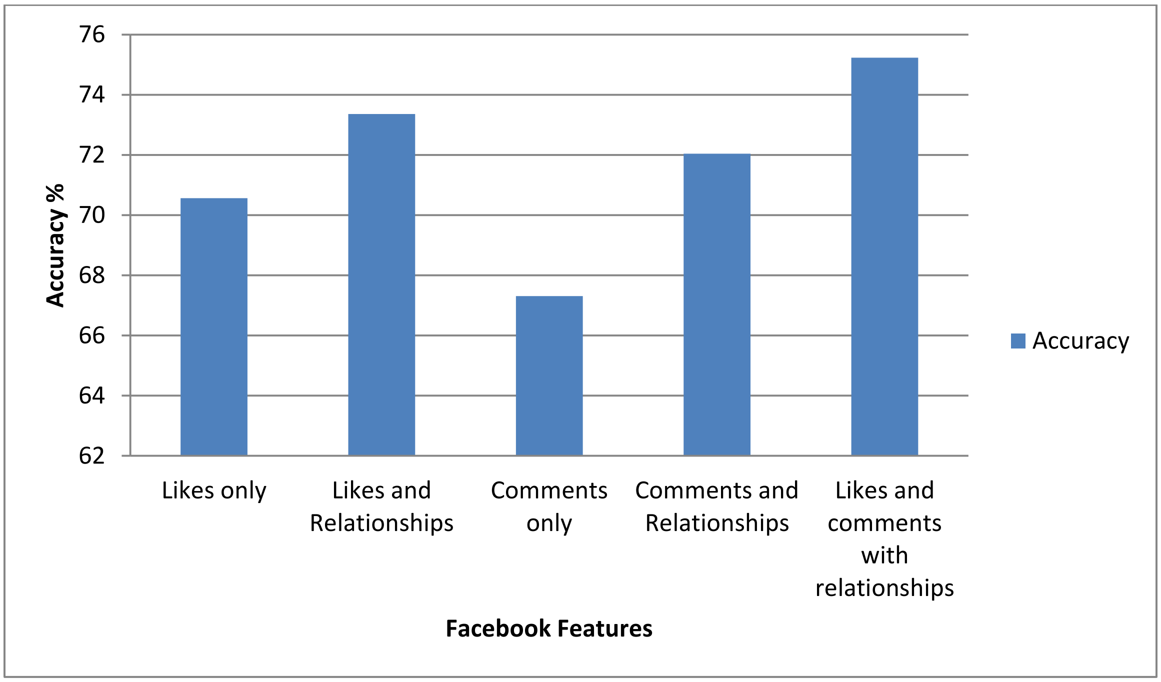

Figure 60: Results of using various Facebook features

4.1.1.1 Main contribution

We identified the top social network features that impact the emotions of the social network users and presented through literature review of the previous work done. We found out that likes, comments and degree of connections are the top features that impact the emotions of the social network users. Our main contribution lies in studying the impact of those features of social networks on the emotions of the social network users. We researched the impact of the social network features and interaction on the emotions of the social network users and identified the weights that maximized the accuracy of the emotions of the social network users. We also introduced an expanded- new set of emotion labels by expanding the six basic Ekman emotions into 18 emotions.

4.2 Future work plan

In this section we will leverage other areas that can be used to enhance the process of detecting mood of social network. Those areas will be part of our future work. There are several areas of research that can enhance detecting emotion of social networks' users. Text, images, audio, video, and mobile activity represent the main pillars under which the Facebook data are classified as the below image illustrates. Each of them represents an area of research that could be used to enhance mood elicitation.

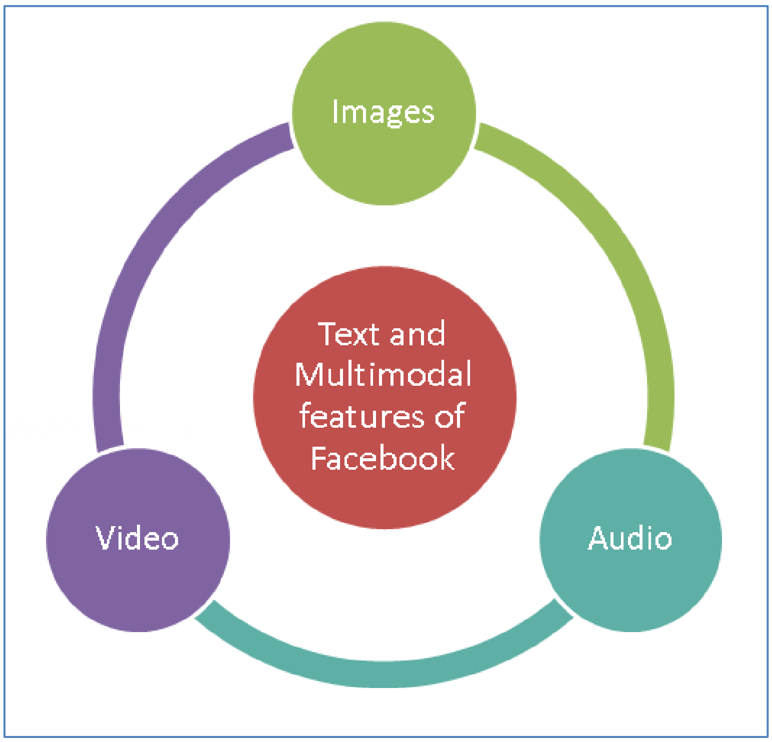

Figure 61: Future plan

4.2.1 Open research areas

In our current experiments, we did not check for sarcasm. Future research is needed to detect the sarcastic status messages or sarcastic comments to the status message and how they impact the emotions of the social network users. Further analysis is also required to study the trending of the spread of emotions i.e. do the users tend to post positive or negative emotions in certain times, such as weekends? How posts of social network users impact their friends' emotions? These are open questions that will require further investigation.

4.2.2 Studying the impact of viewed images on the emotions of the social network users

Facebook provide various images services for its users. Users can set a profile image for themselves. They can create their own albums and post their photos in them. They can tag objects or persons in the photos, share them with friends, like and comment on them. The photos that users share can give us an indication about their mood and feelings. For example, when a user shares, likes or comment on photos of a wedding or birthdays, this may indicate that he or she is experiencing happiness. The following image shows suggestions on how to process images to detect mood of the users.

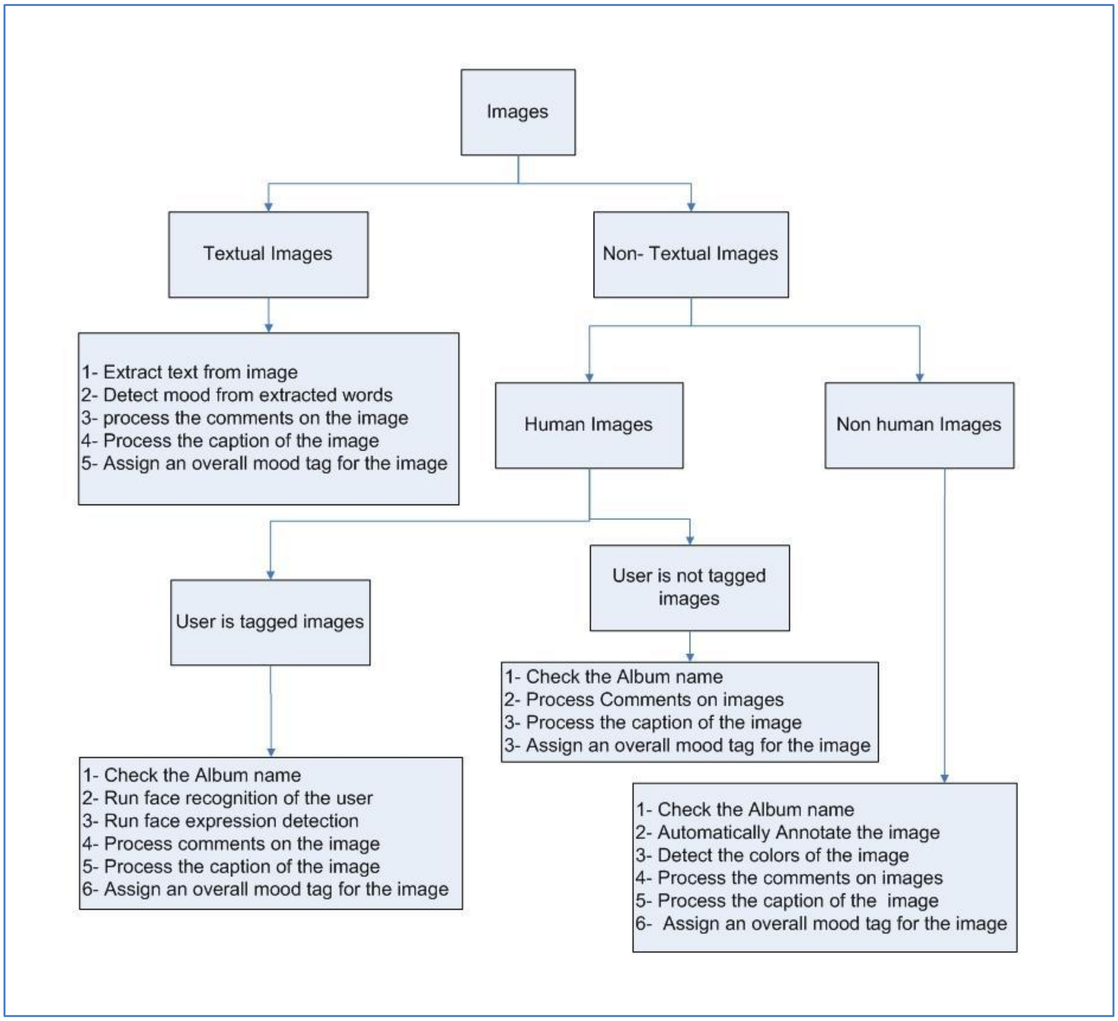

Figure 62: Future work for images multimodal features

Uploaded images by users can be classified into textual and non-textual images. For textual images, we can extract the text from the image, evaluate that mood behind the text of the image and combine it with the output of processing the comments and the caption of the image to assign an overall mood tag for the image. As for non-textual images, they can be divided into images that contain humans and images that do not contain humans. We can process the album name, annotate the images to detect the objects inside it and detect their mood indications, process the comments and the caption of the images for non-human images and assign an overall mood tag for the image. Human images can be divided into images where user is not tagged in and images where user is tagged in. For the images in which the user is not tagged, we can check the album name, caption of the image and comments to assign a mood tag for this image. For images in which they user is tagged in, we can run face and expression recognition techniques to detect the emotion of the user and combine that with the data extracted from the album name, caption, and comments. Then, we assign an overall mood tag for the image. After tagging each image separately we can check all the images in an album and assign a mood tag for each album.

4.2.3 Studying the impact of the audio files on the emotions of the social networks users

Users of Facebook can share personal audio postings, music and any other audio speeches with their friends and the Facebook community. The following image provides a proposed architecture for emotion detection technique from Facebook Audio files. The Audio files will be classified to personal audio postings, which users prepare them with their voices, music, and other audio postings that the Facebook users share with their friends. Emotion recognition techniques from audio can run against the personal audio postings and comments and caption can be processed also to assign a tag for the personal audio postings. Lyrics, comments, and caption of the songs can be used to assign an emotion tag for the song. Any other audio file can be assigned an emotion tag based on caption and comments.

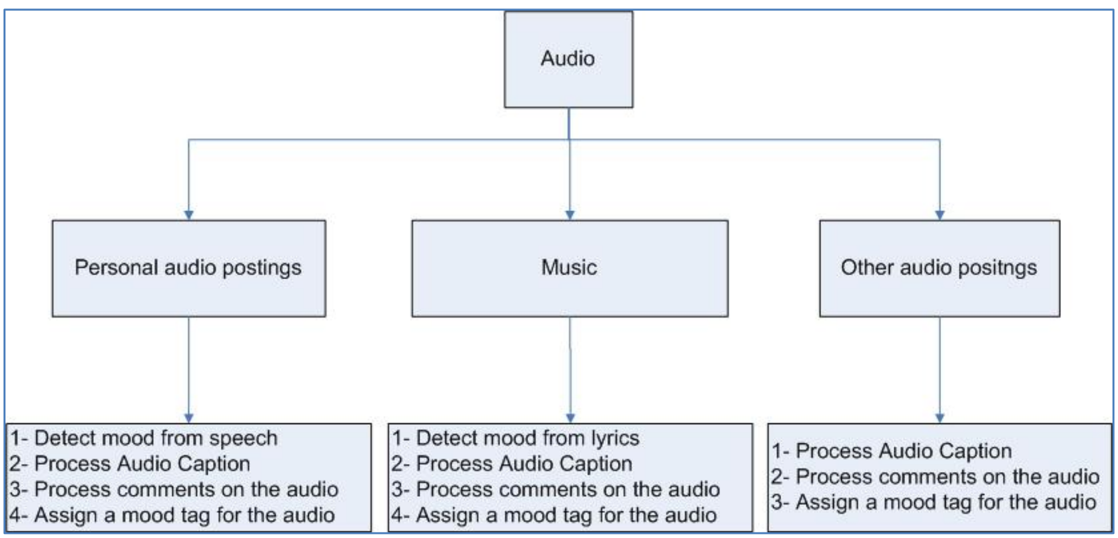

Figure 63: Future work for Audio for multimodal features

4.2.4 Studying the impact of the video files on the emotions of the social network users

Facebook users share their videos with their friends. Some of these videos can be personal. The following image shows the areas of researches that can be included to enhance emotion detection from videos. If the user is not tagged in the video, the video will be automatically annotated, the comments, and the captions will be processed and the video will be assigned an emotion tag. If the user is tagged in the video and it is a video that he made by himself, the emotion of the user can be detected from the speech, the video is automatically annotated and the caption and the comments are processed. Then, based on the results of these operations, the video will be assigned an emotion tag. If the user is tagged in the video and it is a group video, the voice of the user will be detected, emotion of the user will be detected from the speech, the video will be automatically annotated, the comments and caption will be processed. Then, the video will be assigned an emotion tag. If the user is not tagged in the video, the video will be automatically annotated, the comments and caption will be processed and the video will be assigned an emotion tag.

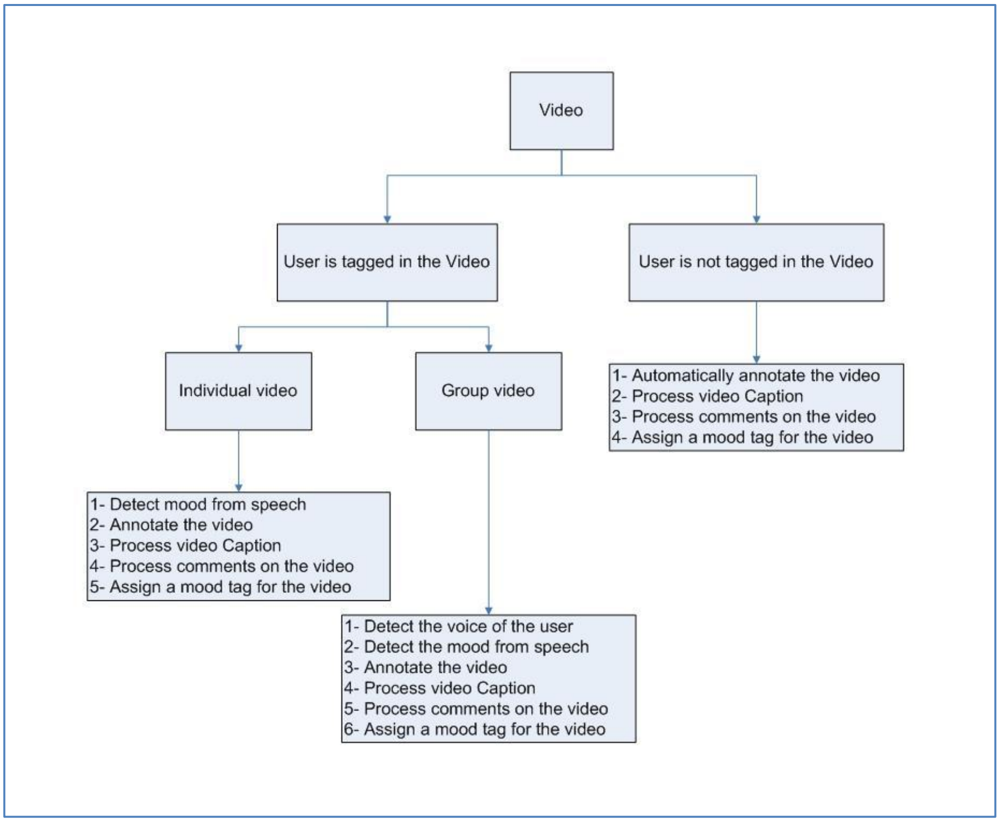

Figure 64: Future work for Video multimodal features

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