# Chapter 1

# Introduction

The ultimate goal of the computer scientists is to build an *intelligent* machine. In most of the definitions, *intelligence* has been thought of as mental ability to reason, solve problem, take rational decisions and learn. Thus, the foundation of computer science has classically been logic, rationality and decidability. According to the western philosophy, emotion has been perceived as the antithesis of reason or logic. This has motivated the computer scientists to restrict their thoughts in the realm of logic keeping emotional aspects out of consideration. With the introduction of *multiple intelligences* (Gardner, 1983), the traditional notion of intelligence started to be reshaped in order to account for the influence of non-cognitive aspects like emotion.

Over the recent past, several researchers (Payne, 1985) have advocated that emotion has to be taken into account for appropriately describing or measuring intelligence. In this context, a new paradigm of intelligence, called *emotional intelligence*, was proposed. Emotional intelligence is defined as follows:

> *"Emotional Intelligence (EI) describes the ability, capacity, skill or, in the case of the trait EI model, a self-perceived ability, to identify, assess, and manage the emotions of one's self, of others, and of groups"* (Bradberry and Greaves, 2009)

Furthermore, emotion has been regarded as an information cue in decision making process (Hsee and Hastie, 2006; Hsee and Kunreuther, 2000). It has been proposed that the decision making process takes into account ‘anticipatory emotions’ Loewenstein et al. (2001). Damasio (1994) also suggested that emotion plays an important role in decision making. Johnson-Laird and Shafir (1993) pointed out that given a set of facts, logic alone is unable to choose a sensible one from an infinite number of conclusions. Motivated by the findings regarding the dependence between the rational (decision making, problem solving, planning, learning etc) and non-rational behavior (emotion, feeling etc.), several computer scientists advocated for developing emotionally intelligent machine (Turing, 1950; Minsky, 2007).

With the present day computer usage in all spheres of life, human computer interaction methods have gained utmost importance for designing interactive environments. The users expect these interactive frameworks to behave as close as human behavior. *Affective Computing* (Picard, 1997) is an emerging area that casts a computational aspect to the emotional behavior of human beings in order to make design of emotionally intelligent interfaces feasible.

For designing emotionally intelligent interfaces, it is required to recognize or identify the emotional behaviors of the users by analyzing the implicit or explicit feedbacks provided by them. The recognition or identification of users’ emotional behaviors can be performed by classifying the users’ responses into emotion categories with respect to some of their behavioral features related to the expression of emotions.

There are different modes through which emotions are expressed or communicated. For example, emotions are often expressed through deformation or modulation of different facial and vocal features. Emotion recognition in facial and vocal expressions has shown promising results and has been deployed in different emotion sensitive interfaces.

Language is another mode through which emotions are expressed. In the present days, there are several interfaces that use natural language as a mode for interaction. For example, chat, blog etc. use natural language interfaces for communication. Thus, there is a need to perform emotion classification of natural language text in order to make there interfaces emotionally intelligent. In this thesis, we intend to perform some studies on emotion classification in natural language text by identifying different discriminating features and techniques for classification.

In section 1.1, we provide the role of affective computing in human computer interaction. In section 1.2, we discuss about different modes through which emotions are expressed. In section 1.3, we focus on affective or emotion analysis of natural language text and discuss issues related to emotion classification. In section 1.4, motivation behind the the present work and objectives of it are enumerated. The overview of our work has been provided in section 1.5. Finally, in section 1.6, we enumerate the specific contributions of these thesis.

## 1.1 Affective Computing and Human-Computer Interaction (HCI)

Human life is getting more and more digital as they need to interact with different computing devices from cell phones to personal computers. The computing devices are accessed by people through some interfaces. The area of HCI deals with effective deployment of these interfaces in order to minimize the efforts of the end users. As emotion or affect is an important signature of human behavior, efforts are being put forward in order to make these interfaces process human emotions. Below a list of example cases have been provided where the emotion or affect aware interfaces may help.

- *Sensing user frustration:* The technology or the interface may frustrate the users for several reasons and sometimes the users express it explicitly. The affect aware interface may sense the user frustration and dynamically reconfigure itself in a better way or communicate control signals (Klein et al., 1999) to change the emotion state of the user. Fernandez and Picard (1997) made use of two physiological signals together with mouse clicks in order to characterize user behavior during interaction.

- *Medical informatics (Luneski et al., 2008):* The emotional state has been observed to affect the mental and physical health of a person. For example, positive emotion help in improving the functioning of immune system. The negative emotions like depression and anxiety are often related to blood pressure disorder and heart risks. Tele-Home Health Care (THHC) is an Internet based emergent communication technology that provide medical assistance to the patients without the physical presence of the doctor. In this setting, the affective computing technology help in sensing the patients emotional state so that the doctor in the remote end can take necessary diagnostic actions.

- *Addressing Social-skill impairment:* Some segment of population cannot interact with the outer world due to different types of impairment. For example, the autistics persons with neuro-motor disorder finds it very hard to communicate with other people. As they are socially detached, the emotional skills are less developed. Picard (1999) proposed a system to help the autistic children to learn associating emotions and their expressions to appropriate situations.

In order to sense emotion, the interfaces need to monitor actively of passively some verbal and non-verbal signals. These signals are communicated through different channels that have been discussed in the next section.

## 1.2 Modes of Emotion Communication

There are different channels through which the emotions are expressed.

- *Facial expression:* In this channel, the specific facial muscles are activated in order to portray a particular emotion. Ekman and Rosenberg (1998) were first to propose *Facial Action Coding System (FACS)*, a detailed categorization of the facial expressions based the activation of facial muscles. The FACS represents the facial behavior in terms of activation of 46 *Action Units (AU)*. Several works (Cohen et al., 2000; Valstar and Pantic, 2006; Cohn, 2006; Pantic and Rothkrantz, 2004) use image processing techniques in order to perform emotion recognition through facial expression analysis. These works focus on identifying facial deformations for each emotion by analyzing the action units.

- *Speech expression:* Speech is another media for communicating emotions. People sometimes express emotions by adjusting certain acoustic cues like pitch, intensity and voice quality and these cues have been observed to posses evolutionary significance in communication of emotions (Fernald, 1989). Studies (Banse and Scherer, 1996; Juslin and Laukka, 2003) have been performed in order to distinguish between the emotions in terms of specific patterns of various acoustic cues. For instance, anger, happiness, and fear are associated with high mean pitch and voice intensity, whereas sadness is correlated with low mean pitch and intensity. These cues have been used in different automatic emotion recognition systems (Yu et al., 2001; Pierre-Yves, 2003; Bhatti et al., 2004; Morrison et al., 2007).

- *Bio-signals:* According to the James-Lange theory (James, 2007)[1], emotions happen as a result of certain autonomic nervous system activities like muscular tension, sweating, dryness of mouth, increasing skin temperature, change in heart rate etc. in response to some stimuli.

Though emotion is not intrinsically a linguistic entity (Kovecses, 2003), language is one of the most common modes for expressing emotion whether it is day-to-day communication(spoken language) or published communication(written language). Emotion or affect recognition from text is a recent sub-area of natural language processing (NLP) and has drawn a substantial amount of attention from the NLP researchers.

## 1.3 Affect or Emotion Analysis in Natural Language Text

Works related to subjective analysis of text focus on two different aspects of language: emotion and sentiment or opinion.

People sometimes provide positive or negative feedbacks about an entity. For example in movie or product review, the communicator may possess a positive or negative opinion regarding a particular movie or product. The central task

[1] http://en.wikipedia.org/wiki/James-Lange_theory

of *sentiment analysis* or *opinion mining* is to determine whether one particular review is positive or negative.

On the other hand, text may be classified into positive or negative emotion class or into distinct emotion classes like happy, sad, anger etc. This sub-area is termed as *emotion analysis* of text.

There have been a number of studies on sentiment analysis of product reviews or movie reviews (Pang and Lee, 2004). However, the research in emotion recognition from text is relatively in its infancy (Cho and Lee, 2006).

### Issues in Emotion Classification

The central task in emotion classification is to assign emotion labels like anger, happiness etc. to an input text segment. In emotion classification from writer's perspective, the task is to classify the input text into emotion labels that the writer has intended to express. On the other hand, the task in emotion classification from reader's perspective is to classify the text into emotion classes that will be evoked in reader in response to it. Existing works adopted different techniques to perform emotion classification from both the perspectives. The major issues of the classification task addressed in this thesis are:

- *Single label vs. multi-label classification:* In single label (or multi-class) classification, one text segment may be classified into at most one emotion category from a set of emotion categories. On the other hand, one text segment may be classified into more than one emotion category simultaneously. This type of classification is called multi-label classification.

- *Crisp vs. fuzzy Classification:* Emotion classification may be crisp, where the membership of one text segment in an emotion class is binary or it may be fuzzy, where the labels will indicate degrees of membership of a text segment to different emotion classes.

## 1.4 Motivation and Objectives of Our Work

Most of the earlier works in emotion labeling of text have dealt with sentence level classification. This is due to the fact that word or phrase level analysis is too fine and document level analysis is too coarse. In many applications like emotional speech synthesis, emotional dialog management etc. sentence level emotion processing is required.

In earlier works, emotion classification of text has been addressed in two different perspectives: writer perspective, where the task is to identify the emotions that are expressed in text by the writer and reader perspective, where the task is to recognize emotions that are evoked in a reader. There are a few works that have addressed the problem of identifying the emotion evoked in reader at document level. However, no work encountered so far has performed reader emotion classification in sentence level.

For a text segment, evocation of multiple emotions is very natural. Furthermore, as emotion is a subjective feeling, the emotions are evoked with varying degrees. Thus, contrary to the single-label and crisp approaches, it is more natural to perform emotion classification in multi-label and fuzzy classification setting. However, most of the existing works are restricted to single label and crisp classification of emotion.

The specific objective of the present work is to perform sentence level classification of emotion in fuzzy and multi-label classification setting. To achieve this, it is necessary to identify the features of text and classification techniques required for determining the emotions that will be evoked in reader. Thus, the objective identifies the following subtasks to be achieved.

- *Corpus creation and annotation:* The previous studies on reader emotion classification considered documents as corpus unit. Since, our objective is to classify emotion at sentence level, the available corpora on emotion classification do not meet our requirement. Hence, it is required to select a suitable data source to collect sentences for performing emotion classification. The collected sentences has to be annotated with emotion labels by the human judges or annotators for preparing ground truth data. This requires a proper annotation scheme to be defined.

- *Corpus reliability assessment:* Prior to performing emotion classification with a data set, it has to be ensured that the data annotation is reliable or consistent. In fact, in any data driven NLP task, estimation of corpus reliability is a standard practice. As emotion is a subjective entity, the perception of emotion may vary with different readers. Consequently, corpus labeled by a single annotator may not be reliable. Agreement of multiple annotators regarding labeling of sentences with emotion categories has to be measured to determine the reliability of annotation. Finally, the ground truth or gold standard corpus has to be generated before using it for developing emotion classifiers.

- *Identification of features:* To develop emotion classifier, the features that are more discriminating for the task have to be identified. To perform automatic analysis, the extraction procedures of these features from the sentences should be provided.

- *Emotion classification:* Our objective is to adopt a supervised technique for emotion classification. In order to do that, each sentence has to be represented in the form of a vector of extracted features. There is a need for exploration of a repertoire of machine learning techniques and select the suitable methods for multi-label and fuzzy emotion classification. Detailed analysis of the efficacy of the classification methods have to be performed for choosing the best method.

## 1.5 Overview of our work

In this section, we provide a brief overview of our work a schematic of which is shown in Figure 1.1.

In this work, we chose to build a corpus of *news items*. The reason for this decision is the fact that news items are written in such a way that they are capable of evoking certain emotions in reader's mind. This idea is known as *emotional framing* (Corcoran, 2006; Goffman, 1986; Shah et al., 2009) which is very popular in news media for writing emotionally charged news articles.

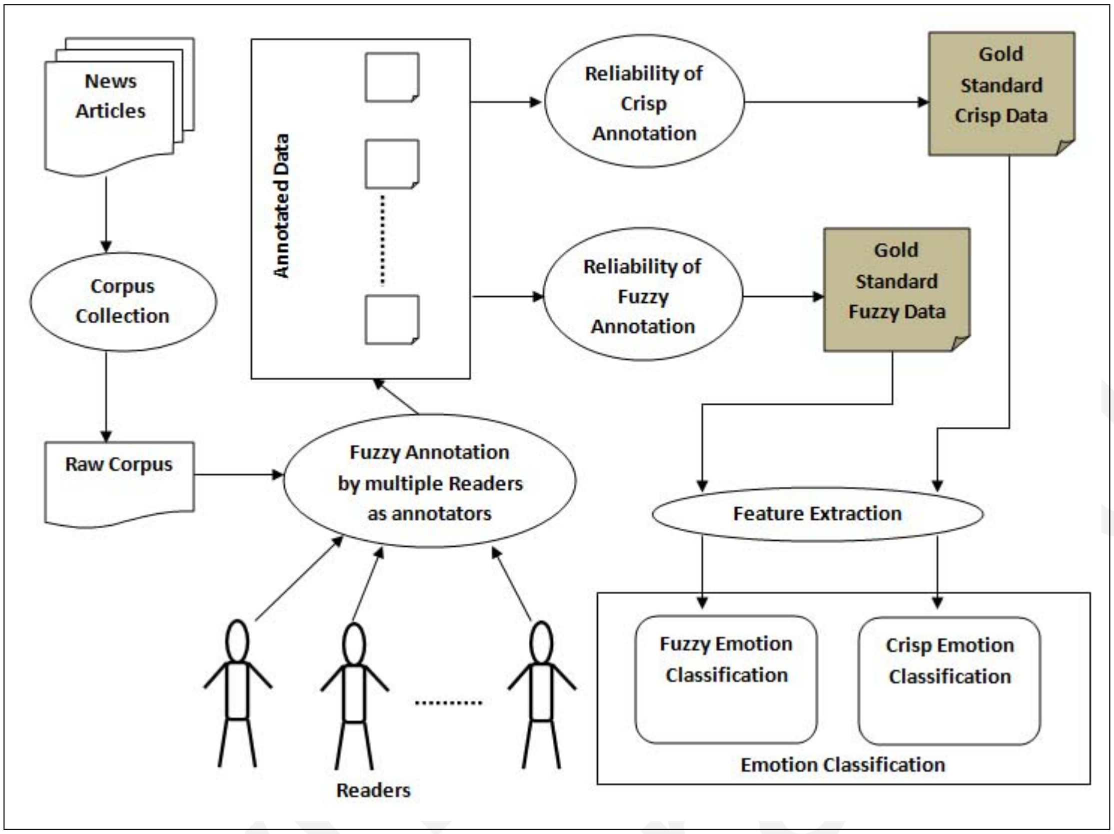


Figure 1.1: The overview of our work.

The sentences are collected from news articles to compile our raw emotion corpus manually. The annotation scheme applies fuzzy annotation, that is, each emotion class is considered to be a fuzzy set and for a sentence, an annotator can provide a degree of membership to different emotion classes.

In the present work, we focus on two types of emotion analysis task. In the first task, it is to determine whether a sentence evokes a particular emotion or not. Thus, in this task, the emotion classes are considered to be crisp sets and sentences are considered to have binary memberships in each of the emotion classes. The second task is to predict the degree of membership of a sentence in the emotion classes, considering them as fuzzy classes as in actual corpus.

In order to develop robust emotion classifiers, the annotated corpus is tested for reliability, i.e., to what extent the annotators agree in labeling the sentences with emotion classes. Two types of reliability tests are performed in this work. The first test has been carried out to determine the reliability of fuzzy annotations provided by the annotators. If the annotation is reliable, the fuzzy gold standard corpus is generated by aggregating the responses provided by multiple annotators.

The other reliability study assumes the annotation to be crisp. The crisp version of annotation is obtained by setting a threshold on the fuzzy membership value. For an annotator, one sentence is said to evoke a particular emotion if the membership value for that class is above the threshold. The *crisp reliability measure* is then applied over the transformed annotations provided by multiple annotators. If the corpus is reliable enough, the aggregation of the annotations provided by the annotators is performed to obtain gold standard corpus with crisp labels.

The *feature extractor* module extracts the features from sentence to represent it in the form of feature vector. The crisp gold standard corpus is then used to develop *crisp emotion classifier*. The gold standard corpus is used for both training and testing emotion classifiers. The fuzzy labeled gold standard data is employed to build *fuzzy emotion classifier*.

## 1.6 Contributions of the Thesis

In this work, we have identified necessary tools and techniques that are suitable for performing emotion classification in fuzzy and multi-label setting. These techniques have been applied to perform emotion claasification of news sentences. Below we enumerate the specific contributions of our work.

1. **Corpus Performing Fuzzy and Multi-label Emotion Classification**

   Different corpora are available for text based emotion analysis. A detailed discussion of these available corpora are provided in chapter 3. However none of these available resources are suitable for the study of emotion evocation in reader. We have collected a corpus 1350 sentences ( 18K words) from news articles. The corpus has been annotated by 5 annotators with six emotion classes, namely, *anger, disgust, fear, happiness, sadness* and *surprise*. The annotation scheme considers multi-label belongingness with degree of membership in each emotion class.

**2. A new Reliability Measure for Crisp Multi-label Annotation**

As emotion is a subjective experience, the responses of the annotators may vary. Thus, it is needed to measure the agreement of the annotators on labeling one sentence with a set of emotions. As stated earlier, the annotators may annotate one sentence with more than one emotion labels as elicitation of multiple emotions are possible in response to a single stimulus. Thus, the emotion corpus is a multi-label one. The existing reliability measures are applicable to single-label corpus where one data item belongs to at most one category. We have presented a new reliability measure which can be applied to determine the extent of agreement among multiple annotators in multi-label annotation setting.

We have presented an elaborate study on corpus quality through the proposed measure and adopted some corpus cleaning techniques. We have also provided a majority voting based technique to generate aggregated corpus or crisp gold standard corpus which is further used to develop and validate crisp emotion classifier.

**3. Reliability Analysis of Fuzzy Annotation**

The annotation scheme considers the emotion classes to be fuzzy and for a sentence, an annotator provides a membership value into each emotion class. The membership value in an emotion class depends on the extent to which the particular emotion is evoked in the annotator's mind. There is a need to measure how the annotators agree upon the assignment of these membership values. We have used Cronbach's alpha (Cronbach, 1951) in order to perform this kind of reliability test. The reliability test has been performed for individual emotion classes.

We have also provided a method for generation aggregated membership value consulting the membership values provided by the annotators in a single emotion class and sentence for obtaining the fuzzy gold standard corpus that is further used to develop fuzzy emotion classifier.

**4. Feature Extraction for Emotion Classification**

As there has not been much attention to the classification of reader emotion till date, effective features for this task are to be identified. In this work, we have introduced two new features, namely, polarity based feature and semantic level feature.

The evocation of positive or negative emotion for a sentence in sometimes indicated by the polarities of its constituent phrases. For example, when the subject of a sentence performs a negative activity on a negative object, positive emotion may be evoked. For this reason, we have used polarity of the subject, object and verb phrases as the polarity based features.

Understanding the semantics of the text is important for evocation of emotion. The semantics of a sentences may be captured through mapping the words into different semantic categories and establishing relation among them. Semantic frame proposed by Fillmore (1985) is a concept for representing these semantic categories. In this work, we have used semantic frames as the semantic level features.

As word is the most obvious features, it has been used as the baseline feature.

In this work, we have experimented with different combinations of the newly proposed features along with the word feature to observe the relative performance. It has been found that the introduction of the newly proposed feature in combination with traditional word feature enhances performance.

We have provided the extraction procedures for these feature so that the process of emotion analysis can be automated.

**5. Multi-label Classification of Emotion**

Previous studies considered the emotion data to be single label (or multi-class) and the emotion classifiers have been developed with standard multi-class classification algorithms like Support Vector Machine, Naïve Bayes and other algorithms. However, these classification algorithms are not suitable for developing multi-label classification models. We have explored multi-label classification algorithms from different families.

The multi-label classification algorithms can be categorized into two families: crisp multi-label and fuzzy multi-label. The crisp multi-label classifiers are further divided into two categories: algorithm adaptation techniques and problem transformation techniques. The former one adapts the single label or multi-class classification algorithms into multi-label versions whereas the later one converts the multi-label data into single label one and apply the traditional single class classification algorithms. We have selected a representative from each of the mentioned categories to develop crisp emotion classification label.

For developing fuzzy emotion classifier, we have selected fuzzy k nearest neighbor algorithm.

We have performed extensive comparison on the efficacy of the individual features as well as their combinations towards emotion classification. Apart from these comparisons, we have performed some feature selection studies over proposed features to obtain optimal set of features. We have compared the relative performance of the emotion classifiers developed with the mentioned algorithms to find the best one for reader emotion classification.

## 1.7 Organization of the Thesis

The thesis is organized into eight chapters as presented below.

Chapter 2 presents a survey of the existing efforts towards text based emotion analysis as it has direct relevance to our work.

Chapter 3 describes the process of collection of emotion corpus. In this chapter, we justify the selection of news domain for performing reader emotion classification. The annotation scheme for labeling the sentences with emotion classes has been provided. Finally, we present the annotation experiment followed by some statistics regarding annotation.

Chapter 4 is devoted towards the reliability assessment of the emotion corpus considering the annotation scheme to be crisp and multi-label. A new inter-annotator agreement measure has been proposed in order to achieve the task. A detailed study on the corpus quality based on the annotations provided by five annotators has been provided. The behaviors of the annotators has been investigated in the light of psychological theories of emotion. Corpus cleaning and aggregation tasks to generate gold standard corpus have also been provided.

Chapter 5 also concerns corpus reliability but in a fuzzy annotation setting and presents the application of Chronbach's alpha (Cronbach, 1951) for measuring the reliability of the fuzzy membership values assigned to each emotion category for a sentence. Each emotion class has been judged for reliability individually through the application of Chronbach's alpha. A method for aggregating the fuzzy membership values provided by multiple annotators has also been provided.

Chapter 6 is devoted towards the description and extraction procedures of the features for performing emotion classification. We have identified three different features for this task: word based feature, polarity based feature and semantic frame based feature.

Chapter 7 presents the experiments on developing emotion classifiers in multi-label classification setting. Three different multi-label classification algorithms (two for crisp classification and one for fuzzy classification) have been explored in this purpose. The crisp emotion classifiers have been developed with two different multi-label classification algorithms: Multi-Label k Nearest Neighbor (MLkNN) classifier (Zhang and Zhou, 2007) and RAndom k-labEL sets (RAKEL) classifier (Tsoumakas and Vlahavas, 2007). The fuzzy emotion classifier has been developed with Fuzzy k Nearest Neighbor (FkNN) (Keller et al., 1985) algorithm. The experiments have been followed by observations and analysis of efficacy of individual features and their combinations. Effect of statistics based feature selection technique has also been discussed. Finally, the performance of each classifier has been compared to find a suitable one.

Chapter 8 concludes the thesis by summarizing the important findings and suggests some future directions related to the thesis.

Appendix A lists the publications related to this thesis and Appendix B provides the list of other publications by the author.