

Emotion models for textual emotion classification

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Abstract. This paper deals with textual emotion classification which gained attention in recent years. Emotion classification is used in user experience, product evaluation, national security, and tutoring applications. It attempts to detect the emotional content in the input text and based on different approaches establish what kind of emotional content is present, if any. Textual emotion classification is the most difficult to handle, since it relies mainly on linguistic resources and it introduces many challenges to assignment of text to emotion represented by a proper model. A crucial part of each emotion detector is emotion model. Focus of this paper is to introduce emotion models used for classification. Categorical and dimensional models of emotion are explained and some more advanced approaches are mentioned.

1. Introduction

Emotion detector is software used for detection and recognition of emotion from the input. Its goal is to help with improving customer experience, removing inappropriate posts from social networks, discover opinions about products and many other applications. One of the most recent applications being human-agent interaction [1].

Textual emotion recognition is the youngest branch of affective computing which should be able to recognize emotions mainly from text. The present textual emotion detectors developed from facial [2]–[4] and voice analysis of emotions as a branch of natural language processing.

This tool has grown in importance in the last years, where computer mediated communication plays greater role than ever before. Textual recognition can be applied to statuses, posts from social networks, microblogs, blogs, online newspapers, forums, reviews, and many others. It can help with removal of inappropriate or abusive content of social network, recognition of blog post author stands in certain matter, gathering negative opinions of users about specific product. Information gained from these sources can serve as a starting point to improving services, providing feedback, fixing errors and avoiding mistakes.

Emotion recognition is very challenging since the information in text can be very limited, extremely ambiguous, and largely depends on context and common sense. Therefore there are resources with information about the word's purpose and meaning in different contexts. Along them there are many different emotion models. There does not seem to be a consensus on how to distinguish these models and some ambiguity in terms of labeling emotions. This papers aims to provide an overview of existing approaches. Emotion models are divided into three categories and explained one by one with

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examples of use. This paper distinguished three major areas of emotion models – categorical, dimensional and extended, which are described in the chapter two.

2. Classifying emotions

Ekman found evidence for a group of six basic emotions [3], [5] and since then there were other researchers taking this approach and creating new emotion categories [6]. Nevertheless, Ekman's basic six emotions remain the most popular ones in terms of use in natural language processing [7], [8]. Based on this thought the emotions can be classified according to two main branches:

- Categorical
- Dimensional
- Extended

Categorical divides emotions into several groups and assigns the emotion into a proper discrete category. These methods are based on works of Ekman, who introduced this concept [3].

Dimensional methods see emotions as a place in two or even multi-dimensional space, where the emotion is expressed as a point in the plane or space defined by variables taken into account.

To determine the emotion from a textual input, it is crucial to have some framework to use. In order to assess one's emotion, lexicons are used where each of the records is marked with proper emotional content or a classifier is trained with a database of well annotated data stating the nature of emotions. What emotions are used, and how they are treated is not standardized. There are many different approaches to define and classify emotions. Next two sections will focus on describing available models for emotion classification used in related works.

2.1. Categorical Emotion Models

Categories which are used in the research of textual emotion recognition are based on the idea of discrete emotion theory. This theory argues that there is only a limited set of emotion which a person can experience.

The simplest categorical classification is to decide whether the emotion is positive or negative one. Some of the papers are working with similar idea, but use "happy" and "sad" state instead, as can be seen for example in the work of J.T. Hancock [9]. They have based their emotional recognition on leveraging the Social Information Processing model (SIP).

These models are also used in linguistic resources. To annotate the records with the emotional information, very simple categorical labels were used: positive, negative, objective for SentiWordNet. Labels positive, negative, ambiguous, and neutral were used for WordNet-Affect.

Table 1. Categories of emotions.

Author	Count	Emotions
Ekman	6	anger, disgust, fear, joy, sadness, surprise
Parrot	6	anger, fear, joy, love, sadness, surprise
Frijda	6	desire, happiness, interest, surprise, wonder, sorrow
Plutchik	8	acceptance, anger, anticipation, disgust, joy, fear, sadness, surprise
Tomkins	9	desire, happiness, interest, surprise, wonder, sorrow
Izard	12	interest, joy, surprise, sadness, anger, disgust, contempt, self-hostility, fear, shame, shyness, guilt
Extended Ekman	18	anger, disgust, fear, joy, sadness, surprise, amusement, contempt, contentment, embarrassment, excitement, guilt, pride in achievement, relief, satisfaction, sensory pleasure, and shame

Many works are building up on a research done by prof. Ekman. His work is based on recognizing emotions from facial expressions. Cross-cultural study was conducted concluding that in case of facial

expressions there are six basic emotions expressed the same way regardless of the subject place of origin [3], [2]. Emotions recognized by Ekman are happiness, sadness, anger, fear, disgust, and surprise.

For the purposes of textual emotion recognition, there is also a neutral state considered as one of the categories to reflect neutral statements, such as newspaper headlines. Some of the models based on Ekman's basic six also distinguish between positive and negative surprise [10].

Similar approach is taken by prof. Izard from the University of Delaware in [11] where he considers 12 basic emotions: interest, joy, surprise, sadness, anger, disgust, contempt, self-hostility, fear, shame, shyness, and guilt. Summary of possible emotional labels, which were used in other works is in Table 1. Using two emotional categories is very often used to examine novel designs and test that the algorithm operates as expected. Decision on a specific emotion can be then perceived as a selection from the category of positive or negative emotions.

However, there are some drawbacks. Simple discrete categories are unable to reflect the valence or arousal of a particular emotion, unless somehow modified. The labels given to emotions may have a slightly different meaning when translated into other language, hence reducing its information value. Therefore dimensional emotion models are used. Table 2 shows how often were specific models used in studied literature. Table suggests that there is so far no unified way of assigning labels to emotions.

Table 2. Overview of used models

Paper	Data	Input granularity	Emotional model
[12]	SentiFul, WordNet-Affect	fine-grained	Anger, Disgust, Fear, Guilt, Interest, Joy, Sadness, Shame, and Surprise
[13]	OMCS, WordNet-Affect	N/A	Ekman
[14]	N/A	N/A	Ekman
[15]	Blog posts annotated with Ekman's model, sentences	Sentences	Ekman, 2 states
[16]	WordNet-based Lexicon, Lexicon of Emoticons, Abbreviations	Sentence-Level	Ekman
[17]	N/A	N/A	Ekman - only 5 emotions
[18]	Aman 2007, Twitter - hashtag annotated	N/A	Ekman
[19]	WordNet-Affect, Twitter annotated by hashtags	N/A	Ekman + neutral
[20]	WordNet-Affect	Word, Sentence	Ekman
[21]	BAWE Corpus	N/A	Anger, Fear, Joy, Sadness
[22]	Ren-CECps	Sentence, fine-grained	Positive emotions: expect, joy, love, surprise; Negative emotions: anxiety, sorrow, anger, hate. <expect, joy, love, surprise, anxiety, sorrow, anger, hate> range 0.0 to 1.0
[23]	N/A	Sentence-Level	Ekman + neutral extended of three intensity states.
[24]	Political articles	Sentence-Level, Document-Level	Binary: Palestinian, Israeli
[25]	AutoTutor Log Files	Sentence-Level, Chat exchange level	boredom, confusion, eureka, frustration
[26]	AutoTutor Log Files, Video annotated by trained judges, Experiment participants cross annotation	Sentence-Level, Chat exchange level	boredom, flow/engagement, confusion, frustration
[27]	LiveJournal Blog posts, YouTube Videos (tagged like/dislike)	Blog Level, Video level	Hourglass model (10 emotions effectively)

2.2. Dimensional Emotion Models

In dimensional classification methods emotions are presented as a point or a region within a two-dimensional or multi-dimensional space. Emotions are therefore not a subject of assignment to a single category, but to many variables. Consider Ekman's basic six emotions. The categorical principle would assign to a particular word one single emotion label. Extending the categorical classification by adding a scale to each of the emotions and the result is a more flexible emotion vector. With emotion scales for each category, the final classification forms a vector, where each item corresponds to a certain emotion and each value corresponds to emotion intensity.

Another transformation of categorical to dimensional is that instead of using positive or negative emotion categories, a single emotion classification with the range from -1 to 1 is used. Less than zero refers to negative emotions and above zero refers to positive emotions. The value expresses the arousal.

Some special approaches were also developed to suit the needs of affective computing. The examples of such approaches are positive activation and negative activation model (PANA), Circumplex model (Valence, Arousal, Power), Plutchik emotion model, Hourglass model.

Each model has its own advantages and disadvantages in terms of use or implementation. PANA and Circumplex mode are very powerful and simple tools to evaluate emotional state. Emotion is modelled as a point in a plane where axis are assigned to a variable of interest (e.g. arousal, valence). Such approach is easy to navigate and understand. Plutchik and Hourglass model use similar method, with the difference being the number of variables. There are more axis along which the emotion is modelled. On top of it, authors explicitly assign specific labels to certain regions, providing some sort of compatibility with categorical models. These models are more advanced than categorical in terms of complexity and ability to express complex emotions. Despite their complexity, mentioned models do not take into account the context and personal typology of the reader or author. Therefore there is a third group, which is within this paper recognized as extended models.

2.3. Extended Models

On top of above mentioned models, there are additional models considered in the field of textual emotion recognition. Two examples are Ortony, Clore and Collins model and Five Factors Model. Both take a little bit different approach than previous ones. Firstly, these models are used in papers, where the personality, targets and desires of the presenting or receiving the text are taken into account. For example in the work of Kao et al. is used a FFM and in the paper from Li et al. is used OCC together with FFM [28], [29], [30]. OCC's main features are a decision tree to determine emotion, considering the event triggering the emotion, and evaluating the relation between the feeling and the situation. In work of Li et al. the FFM is used to establish a personal typology of the reader/writer of the text. This model is employed to improve the efficiency of the emotion recognition for a particular individual.

3. Conclusions

This paper presented the emotion models, which are used for emotion recognition. Emotion detectors will play a significant role in the future and therefore it is important to provide an overview of existing approaches and to understand their tradeoffs.

The models presented here were categorical, dimensional, and extended. Categorical models, summarizes in table 1, are extensively used for their simplicity and unique output. Dimensional models are used less (for comparison see table 2), but provide more flexibility in assigning emotions, where there are no labels. The process is harder to calculate. Extended models build on top of two previous categories and aim to provide a better assignment of emotions based on i.e. personal typology.

Especially the ability to use personal traits seem to be very important in upcoming years, where the human computer interaction may get extremely personal and the computer may need to extend its field of situation awareness to be emotion aware. Thanks to ability to recognize, model, and understand

human emotions, the use, communication, and overall efficiency when dealing with electronic device might improve.

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5. References

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