Computers Capable of Distinguishing Emotions in Text

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Abstract. Detecting human emotions is an important reserach task in intelligent systems. This paper in the following sections outlines the issue of sentiment analysis with emphasis on recent research direction in emotion detection in text. Firstly, we describe emotions from a psychological point of view. We depict accepted and most used emotional models (categorical, dimensional and appraisal-based). Next, we describe what sentiment analysis is and its interconnection with emotions. We take a closer look at methods used in sentiment analysis taking into consideration emotion detection. Each method will be covered by a few studies. At the end, we propose utilization of emotion detection in the text in human-machine interaction.

1 Introduction

Detecting emotions is an interesting and nowadays popular research topic. It connects together the field of humanities with computer science. Affective computing is an interdisciplinary field spanning over computer science, psychology and cognitive science. Psychologists and cognitive scientists supply us with theories behind emotion, such as: What is emotion? What role does it play in thinking? What is the reason behind emotion? Does everybody feel the same about a certain thing? How does emotion affect us in everyday life? On the other hand, researchers from computer science, especially in the field of artificial intelligence, are trying to take advantage of gained knowledge.

What is emotion? Even today the answer for this question is unclear. The problem is that emotion has many rather disparate and often unspecified meanings [9]. However, all modern theorists agree that emotions influence what people perceive, learn and remember and that they play an important part in personality development. We cannot be mistaken by saying that people are driven by emotions to do something or make activities to experience emotions. Such emotional behaviour is a perfect ground for research. Regarding this, a lot of work has been done on emotion analysis in speech and video ([14] (robust speech-based happiness recognition), [23] (speech emotion recognition based on multilinear principal component analysis), [19] (modular neural-SVM scheme for speech emotion recognition using the ANOVA feature selection method), [21]). Speech and video emotion detection together with text emotion detecting could be an interesting cross-connection. We see a great potential in using such contribution in human-machine interaction. Human-machine interaction has got a lot of attention in recent years. It studies a human and a machine in conjunction [17].

The paper is organized as follows. In section 2 we describe widely used emotional models. Subsequently, we describe what sentiment analysis is and its connection to

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emotion detection. Next, we depict three basic approaches to detecting emotion and describe works done in each. In section 3 we describe our approach to the emotion detection in the text in the field of robotics and human-computer interaction. Section 4 concludes the paper.

2 Sentiment Analysis and Emotion

Sentiment analysis is one of the hot topics in the field of natural language processing. It incorporates emotion detection as one of its research tasks besides subjectivity detection, classification of polarity and intensity classification. To detect emotion, researchers use a generally known algorithm created for sentiment analysis. To be able to tell which emotion is in a text, we need to know emotion models according to which we can estimate emotion.

2.1 Emotion Models

Let's look at emotions from a psychological point of view. According to [7], three major directions to affect computing could be distinguished: categorical/discrete, dimensional and an appraisals-based approach. Despite the existence of various other models, the categorical and dimensional approaches are the most commonly used models for automatic analysis and prediction of affect in continuous input [8].

Categorical Approach

The categorical approach claims that there is a small number of basic emotions which are hard-wired in our brains and recognized across the world. Each affective state is classified into a single category Table 1. However, a couple of researchers proved that people show non-basic, subtle and rather complex affective states such as thinking, embarrassment or depression which could be impossible to handle [8]. Assigning text to a specific category can be done manually or by using learning-based techniques.

Table 1. Emotion classes according to psychologists

	Ekman (1973)	Izard (1977)	Plutchik (1980)	Tomkins (1984)	Epstein (1984)	Shaver et al. (1987)	Frijda et al. (1995)	Oatley and Johnson - Laird (1987)
negative	fear	fear	fear	fear	fear	fear	fear	fear
	anger	anger	anger	anger	anger	anger	anger	anger
	sadness	distress	sadness	distress	sadness	sadness	sadness	sadness
	disgust	disgust	disgust	disgust	-	-	-	disgust
	-	contempt	-	contempt	-	-	-	-
	-	shame	-	shame	-	-	-	-
	-	guilt	-	-	-	-	-	-
positive or negative	surprise	surprise	surprise	surprise	-	surprise	-	-
positive	joy	joy	joy	joy	joy	joy	happiness/joy	happiness
	-	-	acceptance	-	love	love	love	-
	-	interest	-	interest	-	-	-	-
	-	-	anticipation	-	-	-	-	-

Dimensional Approach

The dimensional approach is based on Wundt's proposal that feelings (which he distinguished from emotions) can be described by the dimensions of pleasantness–unpleasantness, excitement–inhibition and tension–relaxation, and on Osgood's work on the dimensions of affective meaning (arousal, valence, and potency). Most recent models have concentrated on only two dimensions - valence and arousal. Valence (pleasure-displeasure) depicts how positive or negative an emotion is. Arousal (activation-deactivation) depicts how excited or apathetic an emotion is [3].

Appraisals-Based Approach

Appraisals-based approach view emotion as a dynamic episode in the life of an organism that involves a process of continuous change in all of its subsystems (e.g., cognition, motivation, physiological reactions, motor expressions and feeling—the components of emotion) to adapt flexibly to events of high relevance and potentially important consequences (adopting a functional approach in the Darwinian tradition) [7].

Sentiment Analysis

Let's take an example review:[1]

(1) I am now trying to find words to describe this movie for an hour. (2) I couldn't. (3) You've seen it, or you haven't. (4) It's monumental and outrageously good. (5) The cast is brilliant. (6) The jokes are lovely. (7) The story and the idea behind the movie are beautiful. (8) Especially when you've worked/lived with handicapped people. (9) The music is such a perfect choice, it is unbelievable. (10) I hope this movie makes plenty of people think about how good their life is and how bad it could have been.

Looking closer at the review mentioned above, we get an idea about what sentiment analysis do. We can say sentences (4),(5),(6),(7),(9) express highly positive opinion (explicit opinion) and emotions. Emotions are usually not expressed directly but indirectly, by describing situations (1),(2),(8). At the first sight, sentences (1),(2) seem to depict neutral opinion, but in an emotional level it could be rather disturbing. Sentence (8) implies emotion depending on background knowledge about handicapped people.

There are four major approaches to detecting emotions in text: corpus-based methods, machine learning methods, knowledge-based methods and hybrid methods [3].

Corpus-Based Methods

This approach uses emotion lexicon. Lexicon contains weighted scores from training documents which are then used to build an emotion prediction model. Corpus-based classification uses unigrams (bag-of-words). Its key features are that it employs an emotion lexicon with weighted scores from training documents and uses unigrams (i.e. bag-of-words) [3].

In [11] authors present bootstrapping technique for identifying para phrases. They used LiveJournal blog, Text Affect, Fairy Tales and Annotated blog as datasets. To

[1] We marked every sentence by number for further reference.

pre-process data, they used Stanford part-of-speech tagger and chunker (identifying noun and verb phrases in the sentences). Using k-window algorithm they identify candidates which contain the target seeds (seeds are from WordNet Affect lexicon). Human judges subsequently evaluate results. This method identifies six emotions (proposed by Eckman): happiness, sadness, anger, disgust, surprise and fear.

In [1] authors used corpus of 1000 English words (English dictionary, children stories). Words are afterwards labelled with 34 different emotions (authors did not mention which one). Data was pre-processed using part-of-speech tagger. The rule-based system was used to extract emotions from input (words, sentences).

Detection emotion on newspaper and news web site headlines was a task (called Affective Text") on SemEval 2007. In [20] authors compare their research with three others participants. They used several knowledge-based 2.2.3 and corpus-based methods (variations of Latent Semantic Analysis). They follow the classification of affective words in WordNet Affect. LiveJournal and annotated blogposts were used as dataset. They conducted inter-tagger agreement studies for each of the six emotions. Blogposts were used to train a Naive Bayes classifier 2.2.2. They worked with five emotions: anger, disgust, fear, joy, sadness, surprise and neutral. At the end of the comparison with SWAT [10], UA [12] and UPAR7 [5] system is done.

In comparison with others studies, in [18] authors tried to identify happiness without previous human annotation. They used blogposts from LiveJournal as data set. Naive Bayes was used as a classifier over unigram features and evaluated the classification accuracy in a five-fold cross-validation experiment. This study revealed an interesting fact that certain hours during day and weekdays have higher happiness content than others.

In [15] authors build a system that uses a semantic role labelling tool to detect emotions within textual information. They are validating their research on English based-text with the possibility to extend their emotion detecting on French and Chinese texts. They created a table with emotional rules using publicly available tools: the semantic labelling tool developed by the Cognitive Computation Group of the University of Illinois at Urbana-Champaign and a web mining engine (as Google). Rules are defined as a combination of some selected adjectives and a verb (combination of subjects and objects with verbs). They work with seven emotions: happiness, sadness, anger, fear, disgust, surprise and neutral.

In [13] authors proposed a linguistic-driven rule-based system for emotion cause detection. They constructed a Chinese emotion cause corpus (from Sinica Corpus - corpus of Mandarin Chinese) annotated with emotions and the corresponding cause of events. They work with five emotions: happiness, sadness, fear, anger and surprise (Turners list).

Machine Learning Methods

This approach makes use of an annotated corpus to train an emotion classifier. Its key features are that it employs an annotated corpus to train the emotion classifier. It also uses a supervised or unsupervised method to classify emotions and relies on a classifier for emotion detection, i.e. makes use of a classifier [3].

In [4] authors recognize emotions from Czech newspaper headlines. Several algorithms (SVM method with linear kernel, the SVM method with radial kernel, the SVM method with polynomial kernel with two and three degrees of freedom, k-nearest neighbour algorithm, decision trees using the J48 algorithm, Bayes networks, linear regression and linear discriminated analysis) for learning were assessed and compared according to their accuracy of emotion detection and classification of news headlines. The best results were achieved using the SVM (Support Vector Machine) method with a linear kernel. Data was pre-processed to transform texts into vector space and evaluated using 10-fold cross-validation. They worked with six emotions: fear, joy, anger, disgust, sadness and surprise.

In [6] authors detected emotion from suicide notes. Dataset consists of 900 notes (600 for training, 300 for testing). They used machine learning methodology for fine-grained emotion detection using support vector machines. To differentiate between the 15 different emotions present in the suicide notes, they experimented with lexical and semantic features, viz. bags-of-words of lemmas, part-of-speech tags and trigrams and information from external resources that encode semantic relatedness and subjectivity. They measured performance with micro-averaged F-score.

In [22] were detected emotions from suicide notes using maximum entropy classification, in [16] authors presented experiments in fine-grained emotion detection of suicide notes.

Knowledge-Based Methods

This approach applies linguistic rules through exploiting the knowledge of sentence structures in conjunction with sentiment resources (e.g. Word-Net Affect and SentiWordNet) for emotion classification. Its key features are that it applies linguistic rules and exploits sentence structures in conjunction with sentiment resources like Word-Net Affect and SentiwordNet. Additionally, it employs keyword spotting [3].

In [2] authors proposed a new approach to emotion detection. Their approach defines a new knowledge base called EmotiNet. They extracted descriptions of situations between family members from ISEAR databank for seven emotions: joy, fear, anger, sadness, disgust, shame and guilt. Subsequently, the examples were POS-Tagged using Treeagger. Within each category, they then computed the similarity of the examples with one another using Ted Pedersen Similarity Package. This score is used to split the examples in each emotion class into six clusters using the Simple K-Means implementation in Weka. The next step was to extract action chains from these examples and assign an emotion to them. They use Robert Plutchik's wheel of emotion and Parrot's tree-structured list of emotions.

3 Proposal of System for Detecting Emotions

We propose a system that can detect emotions from text. Data acquisition from social networks, news and blogs is crucial in order to increase our knowledge about what is going on in the world. We propose to employ such a system on social networks and inhuman-machine interaction (Figure 1). As it is depicted on the picture, humans (users) communicate and get information from social networks, rss readers. We propose to program an application which would be able to gather data. Subsequently, the data will be analysed and processed on the cloud. Cloud would be offering the detecting emotion service which would identify following emotions: happiness, sadness, anger, disgust, surprise and fear. After that, users would be able to decide which news they want to know according to the offered emotion. The same principle would work with robots (nao module). Humans would communicate with robots and ask them to tell them news according to the emotion they want. Robots (speech to text) will eventually communicate with an application which acquires information from the web and communicate with the cloud. Finally, the application will send the robot the news depending on the preferences of users. The robot would tell (text to speech) the news and fit motion of its body (motion related to emotion) to the expressed emotion. The last block which we did not describe is learning algorithm. It will be learning habits of each user and, according to that, users would not need to manually do what they used to do. They will become observers on their "personal application".

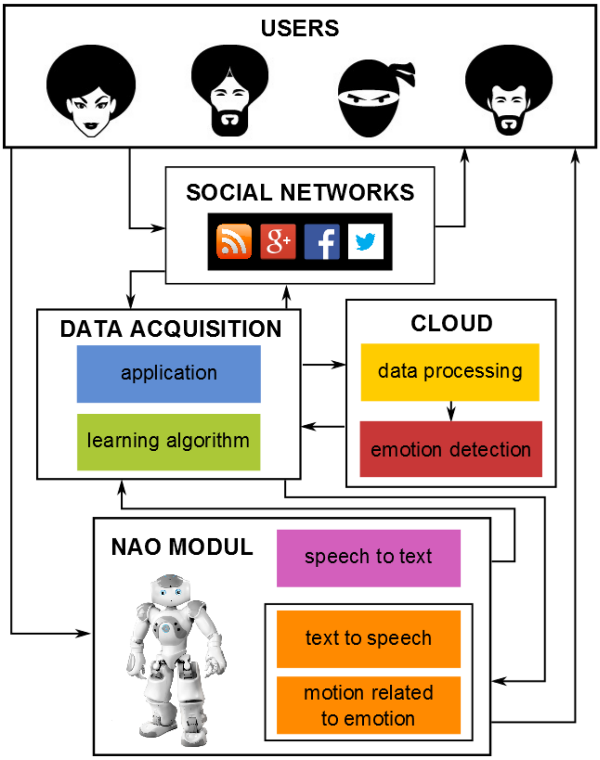

Fig. 1. Proposal of System for Detecting Emotions Using Humanoid Robot

4 Conclusion

We made an overview about emotions in general. We described three approaches to emotion classes: categorical, dimensional and appraisal-based, from which the first and the second are mostly used, respectively. Exploration of the field of emotion detection has become very popular recently. Regarding the emotion detection, a lot of research has been done in video and speech processing and there is some progress in the field of text processing. We introduced four approaches regarding emotion detection in text: corpus-based, machine learning, knowledge approach and hybrid methods. We described the most relevant works done up until today. At the end we propose utilization of detecting emotions in useful application for human-machine interaction.

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