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Editorial

Detecting implicit expressions of affect in text using EmotiNet and its extensions

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ABSTRACT

In the past years, an important volume of research in Natural Language Processing has concentrated on the development of automatic systems to deal with affect in text. The different approaches considered dealt mostly with explicit expressions of emotion, at word level. Nevertheless, expressions of emotion are often implicit, inferrable from situations that have an affective meaning. Dealing with this phenomenon requires automatic systems to have "knowledge" on the situation, and the concepts it describes and their interaction, to be able to "judge" it, in the same manner as a person would. This necessity motivated us to develop the EmotiNet knowledge base — a resource for the detection of emotion from text based on commonsense knowledge on concepts, their interaction and their affective consequence. In this article, we briefly present the process undergone to build EmotiNet and subsequently propose methods to extend the knowledge it contains. We further on analyse the performance of implicit affect detection using this resource. We compare the results obtained with EmotiNet to the use of alternative methods for affect detection. Following the evaluations, we conclude that the structure and content of EmotiNet are appropriate to address the automatic treatment of implicitly expressed affect, that the knowledge it contains can be easily extended and that overall, methods employing EmotiNet obtain better results than traditional emotion detection approaches.

1. Introduction

Anger, fear, sadness, disgust, happiness, surprise. Any human being is able to relate to these emotions, give examples of situations when they can be felt and the possible manners in which they can be expressed. In many cases, such expressions contain little or no affect-related word [30]; they simply describe the experience, in a way in which it can be "deciphered" by the audience [3,4].

Using the common knowledge about the emotions felt in such a situation, the audience can "understand" and "infer" the affective value of the experience. For human beings, this process is simple; the mechanism governing the functioning of emotions (i.e. how and why certain situations trigger certain emotions) is natural. However, automatically detecting emotions from such contexts is difficult task. The process involved explains in part the low performance of the systems that have been implemented to deal with this task [39].

Bearing these considerations in mind, we can see that in order to detect affect from text, it is important to a) employ mechanisms to model the semantics of the situation it describes; and b) implement the mechanism governing the cause–effect in affect-eliciting situations.

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For the first task, we chose ontologies. Until not long ago, to gather and model such knowledge on situations (in a manner in which it can gradually be enriched and new knowledge can be inferred based on it) was almost impossible. However, today, the information existent in knowledge bases and on the web can be flexibly modelled using structures that allow data storage, easy extension and give the possibility to perform inferences on the data they contain: ontologies [25,11,22].

For the second task, among the different psychological theories of emotion explaining the causes of affective states (see for example [7]), we chose the "Appraisal Theories" [36]. They state that an emotion can only be experienced by a person if it is elicited by an appraisal of an object that directly affects them and that the affective result is based on the person's experience (knowledge of the meaning of the situation, its implications), as well as on their goals and opportunities for action.

Employing these mechanisms, we created EmotiNet, a knowledge base that:

1. Can be used to model affective reaction to real-life situations described in text, based on the psychological model of the Appraisal Theories.
2. Contains a collection of action chains, storing the components of situations, their properties, their affective values and their interaction, based on the proposed model.
3. Can be further extended to include appraisal criteria, either by automatic extraction or extension with knowledge from other sources — lexical (e.g., "Core WordNet", "VerbOcean" [9], "WordNet Affect"), onto-lexical (e.g., ConceptNet [21]), or textual (e.g., new examples of situations that trigger emotion, such as the ones gathered by the "wefeelfine.org" portal).
4. Can be employed to propose, validate and evaluate a method to detect emotion in texts that contain little or no explicit expressions of emotion, such as the situations described in the International Survey of Emotion Antecedents and Reactions ([37], ISEAR).

In this article, we describe the manner in which we gradually built EmotiNet, the different stages in which it was extended, with various types of external knowledge resources and describe three methods to detect affect from text using the resulting KB. Additionally, we comparatively analyse the performance of employing other existing methods on such data, to demonstrate the usefulness of our new resource. Results of the evaluations show that our approach to detecting emotion from texts based on EmotiNet outperforms existing methods, demonstrating its validity and the usefulness of the created resource for the emotion detection task.

2. State of the art

In Psychology, the major theories of emotion can be grouped into different categories. Traditionally, these categories are: physiological, neurological and cognitive. Physiological theories state that emotions are felt as a consequence of responses within the body. Neurological theories argue that emotional responses are due to the activity within the brain. Finally, cognitive theories state that the most important role in the formation of emotions is held by thoughts and other mental activity.

In Artificial Intelligence (AI), the term affective computing (AC) was first introduced by [31].

Previous approaches to spot affect in text include the use of models simulating human reactions according to their needs and desires [13], fuzzy logic [41], lexical affinity based on similarity of contexts — the basis for the construction of WordNet Affect [40] or SentiWordNet [14], detection of affective keywords [34] and machine learning using term frequency [27], or term discrimination [10]. Other proposed methods include the creation of syntactic patterns and rules for cause–effect modelling [35]. Significantly different proposals for emotion detection in text are given in the work by [20] and the framework of sentic computing [8], whose scope is to model affective reaction based on commonsense knowledge. For a survey on the affect models and their AC applications, see [7].

The set of models in psychology known as the "Appraisal Theories" claims that emotions are elicited and differentiated on the basis of the subjective evaluation of the personal significance of a situation, object or event [12,16,26]. These theories consider different elements in the appraisal process ([36], see), which are called appraisal criteria (e.g., familiarity, expectation). [38] later used the values of such criteria in self-reported affect-eliciting situations to construct the vectorial model in the expert system GENESIS. The appraisal models have also been studied and employed in systemic functional linguistics [23].

As far as knowledge bases are concerned, many NLP applications have been developed using manually created knowledge repositories such as WordNet [15], CYC,[1] ConceptNet or SUMO.[2] Some authors tried to learn ontologies and relations automatically, using sources that evolve in time — e.g., Yago [42] or [19], which employs Wikipedia to extract concepts. Other approaches to knowledge base population were by [28,17], and for relation learning [5]. DIPRE [6] and Snowball [1] create hand-crafted patterns to extract ontology concepts. Finally, [18] proposes a model of representing emotions using ontologies.

3. Motivation and contribution

Existing models of emotion detection are able to spot mainly direct expressions of affect. The use of knowledge-rich methods (such as dictionaries) can lead to the correct classification of examples, such as (1) "*I am happy*", (2) "*I am angry*", (3) "*This is great!*", etc., because such dictionaries contain words like "happy", "sad", "great" with corresponding affective meaning.

[1] http://cyc.com/cyc/opencyc/overview.
[2] http://www.ontologyportal.org/index.html.