EmotiNet: A Knowledge Base for Emotion Detection in Text Built on the Appraisal Theories

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Abstract. The automatic detection of emotions is a difficult task in Artificial Intelligence. In the field of Natural Language Processing, the challenge of automatically detecting emotion from text has been tackled from many perspectives. Nonetheless, the majority of the approaches contemplated only the word level. Due to the fact that emotion is most of the times not expressed through specific words, but by evoking situations that have a commonsense affective meaning, the performance of existing systems is low. This article presents 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. The core of the resource is built from a set of self-reported affective situations and extended with external sources of commonsense knowledge on emotion-triggering concepts. The results of the preliminary evaluations show that the approach is appropriate for capturing and storing the structure and the semantics of real situations and predict the emotional responses triggered by actions presented in text.

Keywords: EmotiNet, emotion detection, emotion ontology, knowledge base, appraisal theories, self-reported affect, action chain.

1 Introduction

The study of human affect-related phenomena has always been a challenge. Different scientific theories of emotion have been developed along the last century of research in philosophy, psychology, cognitive sciences or neuroscience. In Natural Language Processing (NLP), although different approaches to tackle the issue of emotion detection in text have been proposed, the complexity of the emotional phenomena led to a low performance of the systems implementing this task [1]. The main issue related to the present approaches is that they only contemplate the word level, while expressions of emotion are most of the times not present in text in specific words (e.g. "I am angry.") [2]. Most of the times, the affect expressed in text results from the interpretation of the situation presented therein [3,4]. Psychological theories of emotion give various explanations as to why certain episodes lead to a specific affective state [5]. Among them, the so-called "appraisal theories" [6] 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 result is based on the person's experience, goals and opportunities for action.

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In the light of the appraisal theories, the aim of this research is to:

1) Propose a method for modelling affective reaction to real-life situations described in text, based on the psychological model of the appraisal theory.
2) Design and populate a knowledge base of action chains called EmotiNet, based on the proposed model. We subsequently extend the resource to include appraisal criteria, either by automatic extraction, extension with knowledge from other sources, such as ConceptNet [7] or VerbOcean [8].
3) Propose, validate and evaluate a method to detect emotion in text based on EmotiNet.

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 Artificial Intelligence (AI), the term *affective computing* (AC) was first introduced by Rosalind Picard [9]. Previous approaches to spot affect in text include the use of models simulating human reactions according to their needs and desires [10], fuzzy logic [11], lexical affinity based on similarity of contexts – the basis for the construction of WordNet Affect [12] or SentiWordNet [13], detection of affective keywords [14] and machine learning using term frequency [15], or term discrimination [16]. Other proposed methods include the creation of syntactic patterns and rules for cause-effect modelling [17]. Significantly different proposals for emotion detection in text are given in the work by [18] and the recently proposed framework of *sentic* computing [19], whose scope is to model affective reaction based on commonsense knowledge. For a survey on the affect models and their AC applications, see [5].

The set of models in psychology known as the appraisal theories claim that emotions are elicited and differentiated on the basis of the subjective evaluation of the personal significance of a situation, object or event [20, 21, 22]. These theories consider different elements in the appraisal process (see [6]), which are called appraisal criteria (e.g. familiarity, expectation). Scherer [24] 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 [25].

As far as knowledge bases are concerned, many NLP applications have been developed using manually created knowledge repositories such as WordNet [26], CYC (http://cyc.com/cyc/opencyc/overview), ConceptNet or SUMO (http://www.ontologyportal.org/index.html). Some authors tried to learn ontologies and relations automatically, using sources that evolve in time - e.g. Yago [27], which employs Wikipedia to extract concepts. Other approaches to knowledge base population were by Pantel and Ravichandran [28], and for relation learning [29]. DIPRE [30] and Snowball [31] create hand-crafted patterns to extract ontology concepts. Finally, Grassi [32] proposes a model of representing emotions using ontologies.

3 Motivation and Contribution

To illustrate the need to build a more robust model for emotion detection, we will start with series of examples.

Given a sentence such as (1) "I am happy", an automatic system should label it with "joy". Given this sentence, a system working at a lexical level would be able to detect the word "happy" (for example using WordNet Affect) and would correctly identify the emotion expressed as "joy". But already a slightly more complicated example – (2) "I am not happy" – would require the definition of "inverse" emotions and the approach would no longer be straightforward. In the second example, although emotion words are present in the text, additional rules have to be added in order to account for the negation. Let us consider another example: (3) "I'm going to a party", which should be labelled with "joy" as well. A system working at a lexical level would find in the text no word that is directly related to this emotion. A method to overcome this issue is proposed by Liu et al. [18] and Cambria et al. [19]. The main idea behind these approaches is to acquire knowledge on the emotional effect of different concepts. In this manner, the system would know that "going to a party" is something that produces "joy". These approaches solve the problem of indirectly mentioning an emotion by using the concepts that are related to it instead. However, they only spot the emotion contained in separated concepts and do not integrate their interaction or the context in which they appear. If the example we considered is extended as in (4) "I'm going to a party, although I should study for my exam", the emotion expressed is no longer "joy", but most probably "guilt". As it can be noticed, even if there are concepts that according to our general knowledge express a certain emotion, their presence in the text cannot be considered as a mark that the respective sentence directly contains that emotion. Finally, the same situations are associated with distinct emotion labels depending on properties of the actor, action or object (e.g. "The man killed the mosquito." versus "The man killed his wife"; or "The kitten climbed into my lap" versus "The pig climbed into my lap."; or "The dog started barking as I approached" versus "The dog started wagging his tail as I approached".) The properties of the actors, actions and objects, as we can see, are very important at the time of determining the emotional label of a situation. These properties actually translate into the different values of the appraisal criteria. Therefore, a resource aimed for emotion detection must include this information. The quantity of commonsense knowledge required is tremendous. However, most of it is already present in existing commonsense knowledge bases (e.g. CYC, SUMO or ConceptNet). Given a sufficiently flexible model of representation for action chains, the underlying ontology can be enriched with such knowledge from external sources, resulting in a deep semantic representation of the situations, from which emotion can be detected in a more precise way. In the light of these considerations, our contribution relies in proposing and implementing a framework for modelling affect based on the appraisal theories, which can support:

a) The automatic processing of texts to extract:

- The components of the situation presented (which we denote by "action chains") and their relation (temporal, causal etc.)
- The elements on which the appraisal is done in each action of the chain (agent, action, object);

- The appraisal criteria that can automatically be determined from the text (modifiers of the action, actor, object in each action chain);

b) The inference on the value of the appraisal criteria, extracted from external knowledge sources (characteristics of the actor, action, object or their modifiers that are inferable from text based on common-sense knowledge);

c) The manual input of appraisal criteria of a specific situation.

4 Building a Knowledge Base of Action Chains: EmotiNet

The general idea behind our approach is to model situations as chains of actions and their corresponding emotional effect using an ontological representation. According to the definition provided by Studer et al. [33], an ontology captures knowledge shared by a community that can be easily sharable with other communities. These two characteristics are especially relevant if we want the recall of our approach to be increased. Knowledge managed in our approach has to be shared by a large community and it also needs to be fed by heterogeneous sources of common knowledge to avoid uncertainties. However, specific assertions can be introduced to account for the specificities of individuals or contexts. In this manner, we can model the interaction of different events in the context in which they take place and add inference mechanisms to extract knowledge that is not explicitly present in the text. We can also include knowledge on the appraisal criteria relating to different concepts found in other ontologies and knowledge bases (to account for the different properties of the actor, action and object). At the same time, we can define the properties of emotions and how they combine. Such an approach can account for the differences in interpretation, as the specific knowledge on the individual beliefs or preferences can be easily added as action chains or properties of concepts.

Given these requirements, our approach defines a new knowledge base, called EmotiNet, to store action chains and their corresponding emotional labels from several situations in such a way that we will be able to extract general patterns of appraisal. From a more practical viewpoint, our approach defines an action chain as a sequence of action links, or simply actions that trigger an emotion on an actor. Each specific action link can be described with a tuple (actor, action type, patient, emotional reaction). Specifically, the EmotiNet KB was built by means of an iterative process that extracts the action chains from a document and adds them to the KB. This process is divided in a series of steps, explained in the subsequent sections.

4.1 ISEAR – Self-reported Affect

In the International Survey of Emotional Antecedents and Reactions (ISEAR) – [35], http://www.unige.ch/fapse/emotion/databanks/isear.html, the respondents were asked to report situations in which they had experienced all of 7 major emotions (*joy*, *fear*, *anger*, *sadness*, *disgust*, *shame*, and *guilt*). In each case, the questions covered the way they had appraised the situation and how they reacted. An example of entry in the ISEAR databank is: “I felt anger when I had been obviously unjustly treated and had no possibility to prove they were wrong.” Each example is attached to one single emotion. In order to have a homogenous starting base, we selected from the 7667 examples in the ISEAR database only the 1081 cases that contained descriptions of situations involving kinship relationships. Subsequently, the examples were POS-tagged using TreeTagger. Within each emotion class, we then computed the similarity of the examples with one another, using the implementation of the Lesk distance in Ted Pedersen's Similarity Package. This score was used to split the examples in each emotion class into six clusters using the Simple K-Means implementation in Weka. The idea behind this approach, confirmed by the output of the clusters, was to group examples that are similar, in vocabulary and structure.

4.2 Modelling Situations with Semantic Roles

The next step was to extract, from each of the examples, the actions described. For this, we employed the semantic role labelling (SRL) system introduced by Moreda et al. [34]. In order to build the core of knowledge in the EmotiNet KB, we chose a subset of 175 examples (25 per emotion), which we denote by T. The criteria for choosing this subset were the simplicity of the sentences and the variety of actions described. In the case of these examples, we manually extracted the agent, the verb and the patient from the output of the SRL system (the remaining examples are used for testing). For example, if we use the situation "I borrowed my brother's car and I crashed it. My brother was very angry with me", we can extract three triples (or action links) with the main actors and objects of the sentences: (I, borrow, brother's car), (I, crash, brother's car) and (brother, feel, angry).

Further on, we resolved the anaphoric expressions automatically, using a heuristic selection of the family member mentioned in the text that is closest to the anaphoric reference and whose properties (gender, number) are compatible with the ones of the reference. The replacement of the references to the speaker, e.g. 'I', 'me', 'myself', is resolved by taking into consideration the entities mentioned in the sentence. Following the last example, the subject of the action is assigned to the daughter of the family and the triples are updated: (daughter, borrow, brother's car), (daughter, crash, brother's car) and (brother, feel, angry). Finally, the action links are grouped and sorted in action chains. This process of sorting is determined by the adverbial expressions that appear within the sentence, which actually specify the position of each action on a temporal line (e.g. "although", "because", "when"). We defined pattern rules according to which the actions introduced by these modifiers happen prior to or after the current context.

4.3 Models of Emotion

In order to describe the emotions and the way they relate and compose, we employ Robert Plutchik's wheel of emotion [36] and Parrot's tree-structured list of emotions [37]. These models are the ones that best overlap with the emotions comprised in the ISEAR databank. Moreover, they contain an explicit modelling of the relations between the different emotions. Plutchik's wheel of emotions contains 8 basic emotions and a set of advanced, composed emotions. The model described by Parrot comprises primary, secondary and tertiary emotions. Our approach combines both models by adding the primary emotions missing in the first model and adding the secondary and tertiary emotions as combinations of the basic ones. Using this combined model as a reference, we manually assigned one of the seven most basic emotions, i.e. *anger, fear, disgust, shame, sadness, joy or guilt*, or the *neutral* value to all the action links in the B_T set, thus generating 4-tuples *(subject, action, object, emotion)*, e.g. (daughter, borrow, brother's car, joy), (daughter, crash, brother's car, fear) and (brother, feel, angry, anger). This annotation was done in parallel by two annotators, obtaining a kappa value of 0.83. The cases where the annotators disagreed were discussed and a common decision was taken.

4.4 Designing the EmotiNet Ontology

The process of building the core of the EmotiNet knowledge base (KB) of action chains started with the design of the core of knowledge, in our case an ontology, whose design process was divided in three stages:

1) *Establishing the scope and purpose of the ontology.* The ontology we propose has to be capable of defining the concepts required in a general manner, which will allow it to be expanded and specialised by external knowledge sources. Specifically, the EmotiNet ontology needs to capture and manage knowledge from three domains: kinship membership, emotions (and their relations) and actions (characteristics and relations between them).

2) *Reusing knowledge from existing ontologies.* In a second stage, we searched for other ontologies on the Web that contained concepts related to the knowledge cores we needed. At the end of the process, we located two ontologies that would be the basis of our ontological representation: the ReiAction ontology (www.cs.umbc.edu/~lkagal1/rei/ontologies/ReiAction.owl), which represents actions between entities in a general manner, and the family relations ontology (www.dlsi.ua.es/~jesusmhc/emotinet/family.owl), which contains knowledge about family members and the relations between them.

3) *Building our own knowledge core from the ontologies imported.* This third stage involved the design of the last remaining core, i.e. emotion, and the combination of the different knowledge sources into a single ontology: EmotiNet. In this case, we designed a new knowledge core from scratch based on a combination of the models of emotion presented in Section 4.3 (see Fig.1). This knowledge core includes different types of relations between emotions and a collection of specific instances of emotion (e.g. anger, joy). In the last step, these three cores were combined using new classes and relations between the existing members of these ontologies (Fig. 1).

4.5 Extending and Populating EmotiNet with Real Examples

After designing the ontology core, we extended EmotiNet with new types of action and action chains (as instances of the ontology) using real examples from the ISEAR corpus. For this, we employed the T set. Once we carried out the processes described in sections 4.2 and 4.3 on the chosen documents, we obtained 175 action chains (ordered lists of tuples). In order to be included in the EmotiNet knowledge base, all their elements were mapped to existing concepts or instances within the KB. When these did not exist, they were added to it.

We would like to highlight that in EmotiNet, each "4-tuple" (actor, action, object, emotion) extracted from the process of action extraction and emotion assignation has its own representation as an instance of the subclasses of Action. Each instance of Action is directly related to an instance of the class Feel, which represents the emotion felt in this action. Subsequently, these instances (action links) were grouped in sequences of actions (class Sequence) ended by an instance of the class Feel, which, as mentioned before, determine the final emotion felt by the main actor(s) of the chain. In our example, we created two new classes Borrow and Crash (subclasses of DomainAction) and three new instances of them: instance “act1” (“Borrow”, “daughter”, “brother’s car”, “Joy”); instance “act2” (“Crash”, “daughter”, “brother’s car”, “Fear”). The last action link already existed within EmotiNet from another chain so we reused it: instance “act3” (Feel, “brother”, “Anger”).

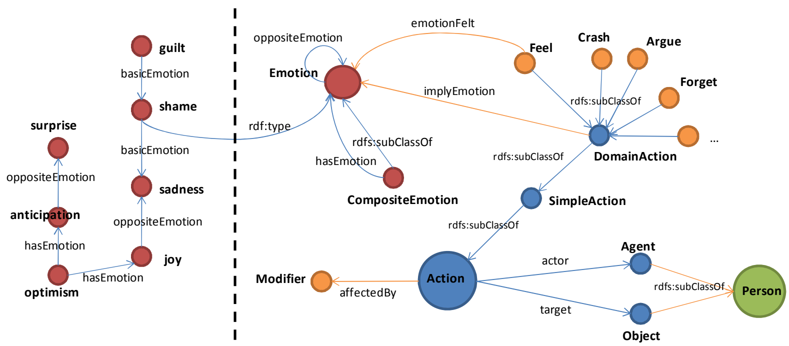

Fig. 1. Main concepts of EmotiNet and instances of the ontology of emotions

The next step consisted in grouping these instances into sequences using instances of the class Sequence, which is a subclass of Action that can establish the temporal order between two actions (which one occurred first). Fig. 2 shows an example of a RDF graph, previously simplified, with the action chain of our example. Following this strategy, we finally obtained a tight net of ontology instances that express different emotions and how actions triggered them. We used Jena (http://jena.sourceforge.net/) and MySQL for the management and storage of EmotiNet.

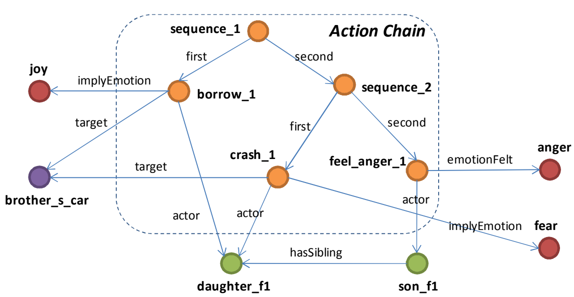

Fig. 2. RDF graph of an action chain

4.6 Expanding EmotiNet with Existing NLP Resources

In order to extend the coverage of the resource, we expanded the ontology with the actions and relations from VerbOcean [8]. In particular, 299 new actions were automatically included as subclasses of DomainAction, which were directly related to any of the actions of our ontology through three new relations: *can-result-in*, *happens-before* and similar. This process of expansion is essential for EmotiNet, since it adds new types of action and relations between actions, which might not have analysed before, thus reducing the degree of dependency between the resource and the initial set of examples. The more external sources of general knowledge added, the more flexible EmotiNet is, thus increasing the possibilities of processing unseen action chains.

5 Experiments and Evaluation

5.1 Experimental Setup

The evaluation of our approach consists in testing if by employing the model we built and the knowledge contained in the core of EmotiNet (which we denote by "training sets"), we are able to detect the emotion expressed in new examples pertaining to the categories in ISEAR.

The first training set (marked with A_T) contains a partial version of the EmotiNet core, with only 4 emotions (anger, disgust, guilt and fear) and 25 action chains per emotion. The second training set (marked with B_T) comprises the final version of the EmotiNet core knowledge base – containing all 7 emotions in ISEAR, and 25 action chains for each. These action chains are the ones obtained in Section 4.5.

The first test set (A) contains 487 examples from ISEAR (phrases corresponding to the anger, disgust, guilt and fear emotions, from which the examples used as core of EmotiNet were removed). The second test set (B) contains 895 examples (ISEAR phrases corresponding to the seven emotions modelled, from which core examples were removed).

In order to assess the system performance on the two test sets, we followed the same process we used for building the core of EmotiNet, with the exception that the manual modelling of examples into tuples was replaced with the automatic extraction of (actor, verb, patient) triples from the output given by the SRL system proposed by Moreda et al. [34]. Subsequently, we eliminated the stopwords in the phrases contained in these three roles and performed a simple coreference resolution (as presented in Section 4.2). Next, we ordered the actions presented in the phrase, using the adverbs that connect the sentences, through the use of patterns (temporal, causal etc.). The resulted action chains for each of the examples in the two test sets will be used in carrying different experiments:

(1). In the first approach, for each of the situations in the test sets (represented as action chains), we search the EmotiNet KB to encounter the sequences in which these actions in the chains are involved and their corresponding subjects. As a result of the search process, we obtain the emotion label corresponding to the new situation and the subject of the emotion based on a weighting function. This function takes into consideration the number of actions and the position in which they appear in the sequence contained in EmotiNet (normalising the number of actions from the new example found within an action chain, stored in the KB, by the number of actions in the reference action chain). The issue in this first approach is that many of the examples cannot be classified, as the knowledge they contain is not present in the ontology. The corresponding results using this approach on test sets A and B were marked with A1 and B1.

(2). A subsequent approach aimed at surpassing the issues raised by the missing knowledge in EmotiNet. In a first approximation, we aimed at introducing extra knowledge from VerbOcean, by adding the verbs that were similar to the ones in the core examples (represented in VerbOcean through the “similar” relation). Subsequently, each of the actions in the examples to be classified that was not already contained in EmotiNet, was sought in VerbOcean. In case one of the similar actions found in VerbOcean was already contained in the KB, the actions were considered equivalent. Further on, each action was associated with an emotion, using the ConceptNet relations and concepts (*EffectOf, CapableOf, MotivationOf, DesireOf*). Action chains were represented as chains of actions with their associated emotion. Finally, new examples were matched against chains of actions containing the same emotions, in the same order, this time, considering the additional knowledge obtained from the VerbOcen and ConceptNet knowledge bases While more complete than the first approximation, this approach was also affected by lack of knowledge about the emotional content of actions. To overcome this issue, we proposed two heuristics:

(2a) In the first one, actions on which no affect information was available, were sought within the examples already introduced in EmotiNet (extended with ConceptNet and VerbOcean) and were assigned the most frequent class of emotion labeling them. The corresponding results are marked with A2a and B2a, respectively.

(2b) In the second approximation, we used the most frequent emotion associated to the known links of a chain, whose individual emotions were obtained from ConceptNet. In this case, the core of action chains is not involved in the process. The corresponding results are marked with A2b and B2b.

5.2 Empirical Results

We performed the steps described in Section 4.1 on the two test sets, A and B. For the first approach, the queries to the test set A led to a result only in the case of 90 examples and for test set B only in the case of 571 examples. For the second approach, using the approximation (2a), 165 examples from test set A and 617 examples from test B were classified. In the case of approximation (2b), the queries obtained results in the case of 171 examples in test set A and 625 examples in test set B. For the remaining ones, the knowledge stored in the KB is not sufficient, so that the appropriate action chain can be extracted. Table 1 presents the results of the evaluations using as knowledge core the training set A_T Table 2 reports the results obtained using as training set the knowledge in B_T. The baselines are random, computed as average of 10 random generations of classes for all classified examples.

5.3 Discussion

From the results in Table 1 and 2, we can conclude that the approach is valid and improves the results of the emotion detection task. Nonetheless, much remains to be done to fully exploit the capabilities of EmotiNet. The model we proposed, based on appraisal theories, proved to be flexible, its level of performance improving – either by percentual increase, or by the fact that the results for different emotional categories become more balanced. We showed that the approach has a high degree of flexibility, i.e. new information can be easily introduced from existing common-sense knowledge bases, mainly due to its internal structure and degree of granularity.

Table 1. Results of the emotion detection using EmotiNet on test set A, using A_T as learning set

Emotion	Correct			Total			Accuracy			Recall		
	A1	**A2a**	**A2b**	**A1**	**A 2a**	**A2b**	**A1**	**A2a**	**A2b**	**A1**	**A2a**	**A2b**
disgust	10	28	29	41	52	67	24.39	53.85	43.28	16.95	47.46	49.15
anger	16	39	39	102	114	119	15.69	34.21	32.77	11.03	26.90	26.90
fear	37	43	44	55	74	76	67.27	58.11	57.89	43.53	50.59	51.76
guilt	27	55	59	146	157	165	18.49	35.03	35.76	13.64	27.78	29.80
Total	**90**	**165**	**171**	**344**	**397**	**427**	**26.16**	**41.56**	**40.05**	**18.48**	**33.88**	**35.11**
Recall Baseline	124	124	124	487	487	487	---	---	---	25.46	25.46	25.46

Table 2. Results of the emotion detection using EmotiNet on test set B, using B_T as learning set

Emotion	Correct			Total			Accuracy			Recall		
	B1	**B2a**	**B2b**	**B1**	**B1**	**B1**	**B1**	**B2a**	**B2b**	**B1**	**B2a**	**B2b**
disgust	16	16	21	26	59	63	36.36	38.09	52.50	27.11	27.11	35.59
shame	25	25	26	62	113	113	35.71	32.05	35.62	27.47	27.47	28.57
anger	31	47	57	29	71	73	29.52	40.86	47.11	21.37	32.41	39.31
fear	35	34	37	86	166	160	60.34	52.30	61.67	60.34	52.30	61.67
sadness	46	45	41	26	59	63	41.44	36.58	32.80	17.22	16.85	15.36
joy	13	16	18	62	113	113	52	55.17	51.43	26	32	36.00
guilt	59	68	64	29	71	73	37.34	41.21	37.43	29.79	34.34	32.32
Total	**225**	**251**	**264**	**571**	**617**	**625**	**39.40**	**40.68**	**42.24**	**25.13**	**28.04**	**29.50**
Recall Baseline	126	126	126	895	895	895	---	---	---	14.07	14.07	14.07

From the error analysis we performed, we could determine some of the causes of error in the system. The first important finding is that extracting only the action, verb and patient semantic roles is not sufficient. There are other roles, such as the modifiers, which change the overall emotion in the text (e.g. "I had a fight with my sister" – sadness, versus "I had a fight with my stupid sister" – anger). Therefore, such modifiers should be included as attributes of the concepts identified in the roles, and, additionally, added to the tuples, as they can account for other appraisal criteria. This can also be a method to account for negation. Given that just 3 roles were extracted and the accuracy of the SRL system, there were also many examples that did not make sense when input into the system (~20%). A further source of errors was that lack of knowledge on specific actions. As we have seen, VerbOcean extended the knowledge, in the sense that more examples could be classified. However, given the ambiguity of the resource and the fact that it is not perfectly accurate also introduced many errors. Thus, the results of our approach can be practically limited by the structure, expressivity and degree of granularity of the imported resources. Therefore, to obtain the final, extended version of EmotiNet we should analyse the interactions between the core and the imported resources and among these resources as well.

Finally, other errors were produced by NLP processes and propagated at various steps of the processing chain (e.g. SRL, coreference resolution). Some of these errors cannot be eliminated; others can be partially solved by using alternative NLP tools.

6 Conclusions and Future Work

This article presented our contribution concerning three major topics: the proposal of a method to model real-life situations described in text based on the appraisal theories, the design and population of EmotiNet, a knowledge base of action chains representing and storing affective reaction to real-life contexts and situations described in text and proposing and evaluating a method to detect emotion in text based on EmotiNet, using new texts. We conclude that our approach is appropriate for detecting emotion in text, although additional elements should be included in the model and extra knowledge is required. Moreover, we found that the process of automatic evaluation was influenced by the low performance of the NLP tools used. Thus, alternative tools must be tested in order to improve the output. We must also test our approach on corpora where more than one emotion is assigned per context.

Future work aims at extending the model by adding properties to the concepts included, so that more of the appraisal criteria can be introduced in the model, testing new methods to assign affective value to the concepts and adding new knowledge from sources such as CYC. We also plan to improve the extraction of action chains and adapt the emotion detection process to the persons describing the emotional experiences, by including special attributes to the concepts involved.

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