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Recognizing emotions in short texts

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Objective

Emotion detection is increasingly used in Embodied Conversational Agents to create an adapted reply channel to the user's affective state. In this context, we propose a method to detect emotions in short texts (i.e. in texts whose size is similar to dialog utterances). Our goal is to design a model to detect the dominant affective state produced by short texts onto a reader and to classify them into six clusters, corresponding to Ekman's psychological theory.

In the current paper, the corpus consists of newspaper headlines, from SemEval 2007, task 14 [SM08] The corpus was chosen because of the appropriate size of its elements and their high emotional content. Since the methods presented in the paper, related to the corpus do not offer a good accuracy, we introduce a new classification mechanism based on the Self Organizing Maps. Also, our approach can be easily transposed to other contexts such as chat logs, forums or oral transcripts.

Related work

Psychological approaches:
- Charles E. Osgood : emotions induction through text [OMM75]

Approaches based on ontology and WordNets:
- WordNet Affect [SV04], WordNet annotated with 6 emotion (Ekman's annotation scheme)
- ConceptNet [LS04], mainly used for semantic disambiguation
- SentiWordNet[BES10], automatically annotated WordNet with the degrees of positivity and negativity

Specialized approaches:
- Word presence based on WordNet Affect [VSS05] or chat logs [MPI05]
- Corpus based methods: SentEval 2007, task 14 [SM08]

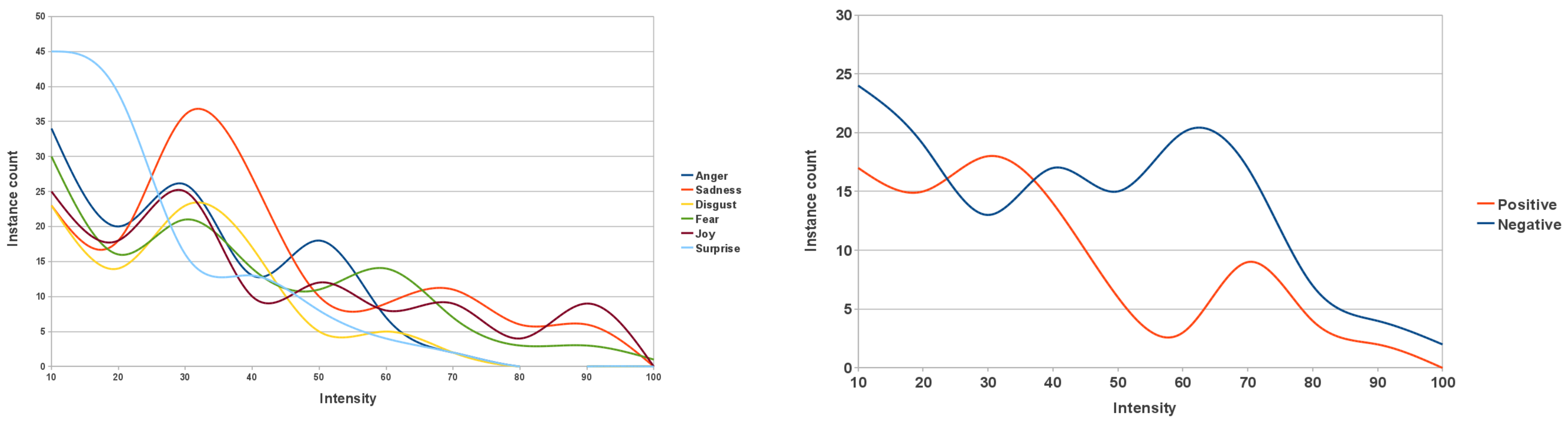
- Machine Learning approaches based on different feature extractors and classifiers: [ARS05], [DA08], or [DCSG06]

Corpus examples

A	D	F	J	Sad.	Sur.	Headline
-	-	-	0.15	0.25	-	Bad reasons to be good
-	-	-	-	-	0.36	Martian Life Could Have Evaded Detection by Viking Landers
-	-	0.68	-	-	-	Hurricane Paul nears Category 3 status
-	-	-	0.75	-	0.57	Three found alive from missing Russian ship - report
0.52	0.64	0.50	-	0.43	-	Police warn of child exploitation online

Anger=**A**, Disgust=**D**, Fear=**F**, Joy=**J**, Sadness=**Sad.**, Surprise=**Sur.**

Table 1: Headlines from the training corpus, presented with dominant emotions



(a) Intensity distribution for emotions
(b) Intensity distribution for valence

Figure 1 Distributions of values in the training corpus.

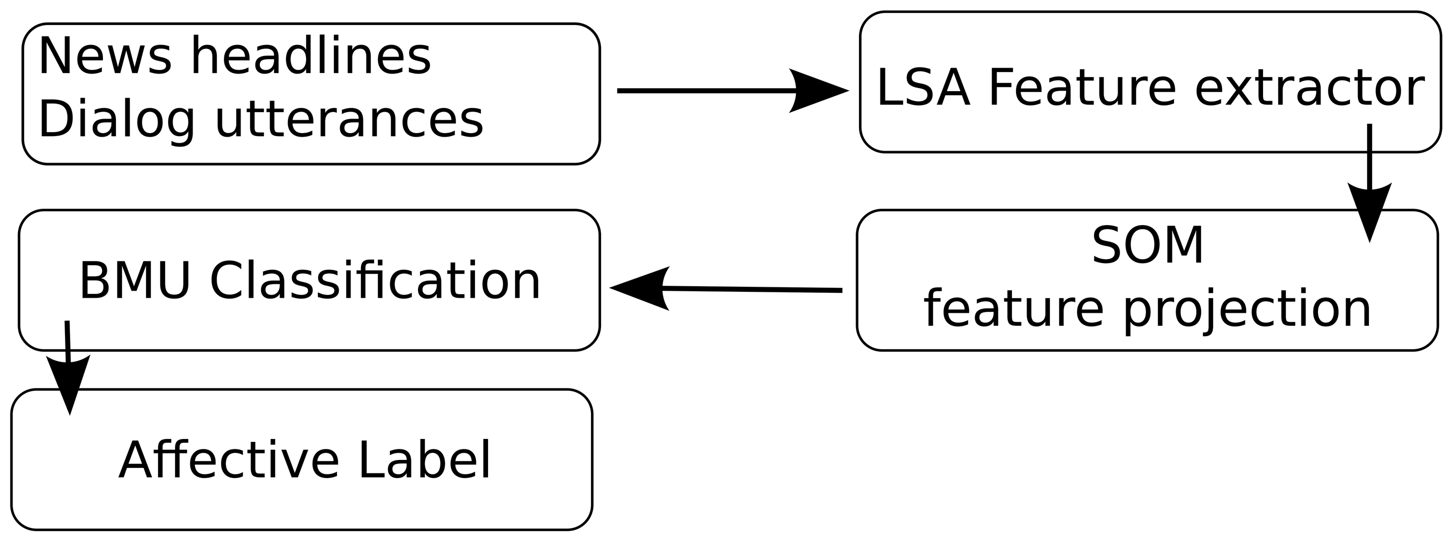
Corpus description

The chosen corpus for our experiment is the one from SemEval 2007, task 14 [SM08], proposed at the conference with the same name. The data set contains headlines (newspaper titles) from major websites, such as New York Times, CNN, BBC or the search engine Google News.

The corpus was manually annotated by 6 different persons. They were instructed to annotate the headlines with emotions according to the presence of affective words or group of words with emotional content. The annotation scheme used for this corpus is the basic six emotions set, presented by Ekman: Anger, Disgust, Fear, Joy(Happiness), Sadness, Surprise. In situations were the emotion was uncertain, they were instructed to follow their first feeling. The data is annotated with a 0 to 100 scale for each emotion.

The authors of the corpus proposed a double evaluation, for both valence and emotion annotated corpus, on a fine-grained scale and on coarse-grained scale. For the fine-grained scale, for values from 0 to 100 (-100 to 100, for valence), the system results are correlated using the Pearson coefficients computed in the inter-annotator agreement. The second proposition was a coarse-grained encoding, where every value from the 0 to 100 interval is mapped to either 0 or 1 (0 =[0,50) , 1=[50,100]). Considering the coarse-grained evaluation, a simple overlap was performed in order to compute the precision, recall and F-measure for each class.

Proposed method



Our method consists in multiple processing steps:

> **Pre-processing step**: we eliminate any non-functional word or special character

> **Feature extractor**: based on the **Latent Semantic Analysis** (**LSA** or **meta-LSA** [VSS05], as a variance for the classic algorithm) and it is used to project the document space (the News headlines, in our case) into the words space.

> **Feature projection**: done with an implementation of **Self-Organizing Maps** (**SOM** [K90]), based on a grid of 50x50 units and used to project the feature space into the Label Space

> **Classification**: based on **Best Matching Unit** (**BMU**), where the discrete label is choosed accoring to the similarity between two continous labels

Results

	LSA training			LSA Gutenberg		
	Prec.	Rec.	F1	Prec.	Rec.	F1
Anger	10.00	11.86	10.85	**18.52**	15.38	**16.80**
Disgust	3.33	4.17	3.70	**8.33**	7.69	**8.00**
Fear	19.01	17.76	18.36	28.39	27.67	**28.03**
Joy	36.75	36.75	36.75	40.49	64.62	**49.79**
Sadness	24.14	40.00	30.11	27.08	19.60	22.74
Surprise	**29.73**	6.92	11.23	22.50	4.95	8.11

Table 2: Results for each emotional class

	LSA All emotional			UA			UPAR7		
	Prec.	Rec.	F1	Prec.	Rec.	F1	Prec.	Rec.	F1
Anger	6.20	**88.33**	11.59	12.74	21.60	16.03	16.67	1.66	3.02
Disgust	1.98	**94.12**	3.88	0.00	0.00	-	0.00	0.00	-
Fear	12.55	**86.44**	21.92	16.23	26.27	20.06	**33.33**	2.54	4.72
Joy	18.60	**90.00**	30.83	40.00	2.22	4.21	**54.54**	6.66	11.87
Sadness	11.69	**87.16**	20.62	25.00	0.91	1.76	**48.97**	22.02	**30.38**
Surprise	7.62	**95.31**	14.11	13.70	16.56	**14.99**	12.12	1.25	2.27

Table3 : The systems presented in the SemEval competition

	Precision	Recall	F1
LSA training	20.50	19.57	20.02
LSA Gutenberg	24.22	23.31	**23.76**
LSA All emotion	9.77	**90.22**	17.63
UA	17.94	11.26	13.84
UPAR7	**27.60**	5.68	9.42

Table 4 Overall results

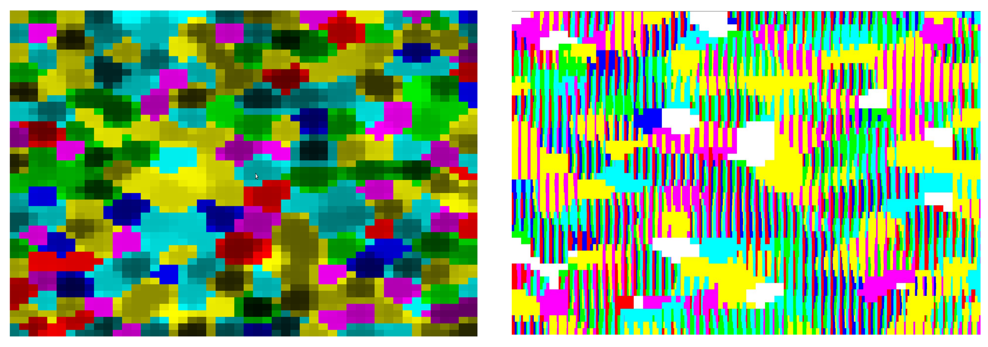


Figure 2 The two visualization options for the SOM results. Darker zones represent stronger emotion in (a) and larger areas of the same color represent the equivalent in the (b) representation.
Color legend: Anger, Disgust, Fear, Joy, Sadness, Surprise and white represents No Emotion

Conclusion

The results are not surprising, because the LSA All emotions offers a good coverage over the emotional words, but its synonym expansion algorithm introduces a lot of noise in the method, and therefore offers a very poor precision. UPAR7 leads in some cases to a good precision, due to its analytical nature, but it lacks in recall. Our system is a good compromise between precision and recall, as F1 measure shows.

We present a method for recognizing emotions in short texts, designed to be integrated into an Embodied Conversational Agent. In other words, the length of the analyzed texts corresponds to the length of utterances during a dialog.

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