Using Convolutional Neural Networks for Sentiment Attitudes Extraction from Analytical Texts

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ABSTRACT

We present an application of the specific neural network model for sentiment attitude extraction without handcrafted NLP features implementation. Given a mass-media article with the list of named entities mentioned in it, the task is to extract sentiment relations between these entities. The problem considered for the whole documents as a three-class machine learning task. The modified architecture of the Convolutional Neural Networks (CNN) was used. The latter exploits positions of named entities in text for emphasizing aspects of related contexts for a given relation. The RuSentRel v1.0 corpus was used for experiments.

Keywords: sentiment analysis, relation extraction, convolutional neural networks

1 INTRODUCTION

Automatic sentiment analysis, i.e. the identification of the author's opinion on the subject discussed in the text, is one of the most popular applications of natural language processing during the last years. Approaches to extracting sentiment positions from a text depends on the genre of the text being analyzed.

One of the most studied text genres in the sentiment analysis task is users' reviews about products or services [13, 15]. Such texts usually discuss a single entity (but, perhaps in its various aspects), and the opinion is expressed by author of review [1, 3, 14, 17].

One of the most complicated document genres for sentiment analysis are analytical articles that analyze a situation in some domain: politics or economy. These texts contain opinions conveyed by different subjects, including the author(s)' attitudes, positions of cited sources, and relations of the mentioned entities between each other [6]. Analytical texts usually contain a lot of named entities, and only a few of them are subjects or objects of sentiment attitudes.

In this paper we describe a problem of sentiment attitudes extraction related to large mass-media analytical articles written in Russian. The model proposed in this paper is not depends on manually implemented features.

2 RELATED WORK

The task of extracting sentiments towards aspects of an entity in reviews has been studied in numerous works [7, 8]. Also extraction of sentiments to targets, stance detection was studied for short texts such as Twitter messages [2, 9, 11]. But the recognition of sentiments toward named entities including opinion holder identification from full texts have been attracted much less attention.

In [5], MPQA 3.0 corpus is described. In the corpus, sentiments towards entities and events are labeled. The annotation is sentence-based. For example, in the sentence "When the Imam issued the fatwa against Salman Rushdie for insulting the Prophet...", Imam is negative to Salman Rushdie, but is positive to the Prophet.

The paper [4] studied the approach to the recovery of the documents attitudes between subjects mentioned in the text. The approach considers such features as relatedness between entities, frequency of a named entity in the text, direct-indirect speech, and other features. The best quality of opinion extraction obtained in the work was 36% F-measure, i.e. task still remains complicated and has not been sufficiently studied.

For a model and trainable features the CNN model were chosen as a framework, where the input convolved by different *filters*. However original architecture does not cover attitude aspects: entities position, relation direction. To emphasize such aspects, the Piecewise CNN architecture [18] was implemented[1].

3 CORPUS AND ANNOTATION

We use RuSentRel v1.0 corpus[2] consisted of analytical articles from Internet-portal inosmi.ru [10]. These are translated into Russian texts in the domain of international politics obtained from foreign authoritative sources. For the documents, the manual annotation of the sentiment attitudes towards the mentioned named entities have been carried out and divided into two subtypes:

(1) The author's relation to mentioned named entities;
(2) The relation of subjects expressed as named entities to other named entities.

These opinions were recorded as triples: (*Subject of opinion, Object of opinion, attitude*). The *attitude* can be negative (*neg*) or positive (*pos*), for example: (*Author, USA, neg*), (*Moscow, Beijing, pos*). Neutral opinions or lack of opinions are not recorded. Attitudes are described for the whole documents, not for each sentence. In some texts, there were several opinions of the different sentiment orientation of the same subject in relation to the same object.

For automatic analysis, the texts were processed by the automatic NE recognizer, based on CRF method [12]. Preliminary analysis showed that the F-measure of determining the correct entity boundaries exceeds 95%.

An analytical document can refer to an entity with several variants of naming, synonyms (*Russia – Russian Federation*), or lemma

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[1]https://github.com/nicolay-r/sentiment-pcnn/tree/russir-2018
[2]https://github.com/nicolay-r/RuSentRel/tree/v1.0

variants generated from different wordforms. For correct inference of attitudes between named entities in the whole document, corpora provides the list of variant names for the same entity found in our corpus (contains 83 sets of name variants). It allows to separate the sentiment analysis task from the task of named entity coreference.

The collection was divided into the *training* and *test* parts. Table 1 contains statistics for corresponding parts[3].

Table 1: Statistics of RuSentRel v1.0 corpus

Parameter	Training	Test
documents	44	29
sentences (avg/doc)	74.5	137
mentioned NE (avg/doc)	194	300
unique NE (avg/doc)	33.3	59.9
positive pairs of NE (avg/doc)	6.23 (4.5%)	14.7 (4.7%)
negative pairs of NE (avg/doc)	9.33 (7.0%)	15.6 (5.3%)
neutral pairs of NE (avg/doc)	120 (88.5%)	276 (90.0%)

4 SENTIMENT ATTITUDES EXTRACTION

We compose attitudes *between entities of the same sentences.* It allows to cover up to 76.5% and 74% of sentiment attitudes for train and test collections respectively.

The task treated as follows: given an attitude as a pair of related named entities, we predict attitude sentiment label, which could be *positive*, *negative* or *neutral*. Figure 1 illustrates classifier architecture. Next, we select only those of them which were predicted as sentiment, i.e. labeled as non neutral.

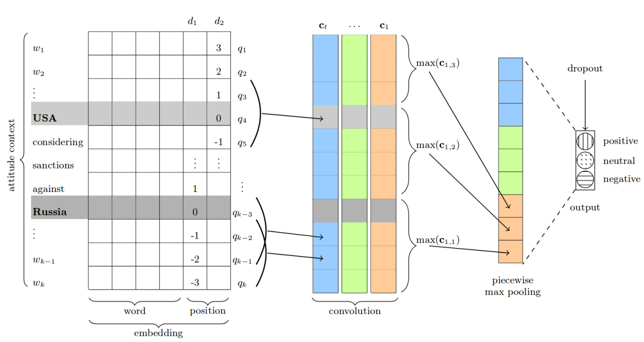

Figure 1: Piecewise CNN architecture [16]

4.1 Piecewise Max Pooling

Given an attitude ends as a borders, we divide each $\mathbf{c}_i$ (convolution result by i'th filter) into *inner*, *left* and *right* segments $\{\mathbf{c}_{i,j}\}$. Then *max* pooling applied per each segment of $\{c_i\}$ (see Figure 1):

$$p_{i,j} = max(\mathbf{c}_{i,j}), \quad i \in \overline{1 \ldots k} \quad j \in \{1, 2, 3\} \tag{1}$$

Thus per each convolved layer i we have a set $\mathbf{p}_i = \{p_{i,1}, p_{i,2}, p_{i,3}\}$. Concatenation of these sets $\mathbf{p}_{i:j}$ results in $\mathbf{p} \in \mathbb{R}^{3k}$ and is a result of pooling operation.

[3]Neutral attitudes were additionaly composed between entity pairs of the same sentences; pairs that belong sentiment attitudes were discarded

4.2 Training

Training process organized as follows:

(1) Split T into list of batches b with fixed size of m, and therefore $b_s = \{t_1, \ldots, t_m\}, t_i \in T$;
(2) An output of the forward propagation for b_s is an o_s;
(3) Compute *cross entropy loss* for o_s;
(4) Update hidden variables: filters $\{\mathbf{c}_i\}$, fully connected layer;
(5) Repeat steps 2-4 until the necessary epochs count will not be reached.

5 EXPERIMENTS

Table 2 contains experiment results. The proposed approach[4] significantly outperforms the baselines and performs better than conventional feature-based approaches[5] [10]. Comparing CNN and PCNN (see Figure 2), the latter trains and reaches $F_1(P, N) \geq 0.30$ faster. Overall, we may conclude that this task still remains complicated. It should be noted that the authors of the [4], who worked with much smaller documents written in English, reported F-measure 36%.

Table 2: Experiment results

Method	Precision	Recall	$F_1(P, N)$
Baseline negative only	0.03	0.39	0.05
Baseline positive only	0.02	0.40	0.04
Baseline distr	0.05	0.23	0.08
KNN	0.18	0.06	0.09
SVM (GRID)	0.09	**0.36**	0.15
Random forest (GRID)	0.41	0.21	0.27
CNN	0.41	0.23	**0.31**
PCNN	**0.42**	0.23	**0.31**
Expert agreement	0.62	0.49	0.55

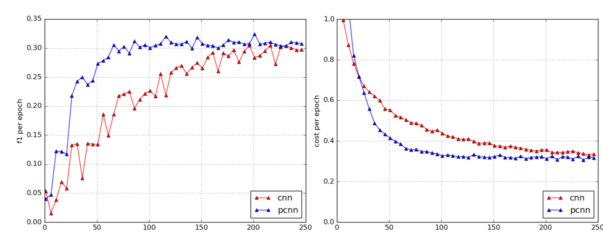

Figure 2: CNN vs. PCNN model training comparison within 250 epochs; left: $F_1(P, N)$**, right:** *cost values*

CONCLUSION

This paper introduces the problem of sentiment attitudes extraction from mass-media articles. The keypoint of proposed model that it is not depends on handcrafted NLP features implementation.

Due to the dataset limitation and manual annotating complexity, in further works we plan to discover unsupervised pre-training techniques based on automatically annotated articles of external sources.

[4]https://github.com/nicolay-r/sentiment-pcnn/tree/russir-2018
[5]https://github.com/nicolay-r/sentiment-relation-classifiers/tree/dialog_2018

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