# Using CNN for Sentiment Attitudes Extraction from Analytical Texts

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# Sentiment Analysis: genres of documents

A lot of studies are devoted to sentiment analysis of users' reviews or short posts in social networks (Twitter)

- Posts are limited and short in length;
- Mostly user reviews $\Rightarrow$ considered a single object for analysis.

News or analytical reports

- Large amount of named entities (*NE*):

  *Ukraine, Russia, Russian Federation, ...*

- Large amount of attitudes between *NE*;
- Has complicated structure.

# Example

*As is apparent in Washington, there is no place for objectivity on the subject of Russia, irrespective of facts and events*[1]

- Washington is negative to Russia
- Author is negative to Washington
- Autor attitude to Russia?

[1] `https://www.counterpunch.org/2017/05/26/ukraine-and-the-nato-military-alliance/`

# Outline

- Corpus of analytical articles **RuSentRel** annotated with sentiment attitudes;
- Experiments on extracting sentiments with machine-learning methods
  - Baselines
  - Features
  - Human performance in the same task
- Analysis of errors and future research

# New sentiment-annotated collection RuSentRel

- **RuSentRel 1.0**[2][LR18] consisted of analytical articles from Internet-portal `inosmi.ru`;
- Text attitudes – manual annotation, as triplets:

$$\langle Object, Subject, Label \rangle$$

  - Object – named entity (NE) or "author"
  - Subject – *NE*
  - Label $\in$ {pos, neg}
- Named entities – automatic, recognizer based on CRF [ML16];
- List of synonymous *NE* – manually implemented.

[2] `https://github.com/nicolay-r/RuSentRel/tree/v1.0`

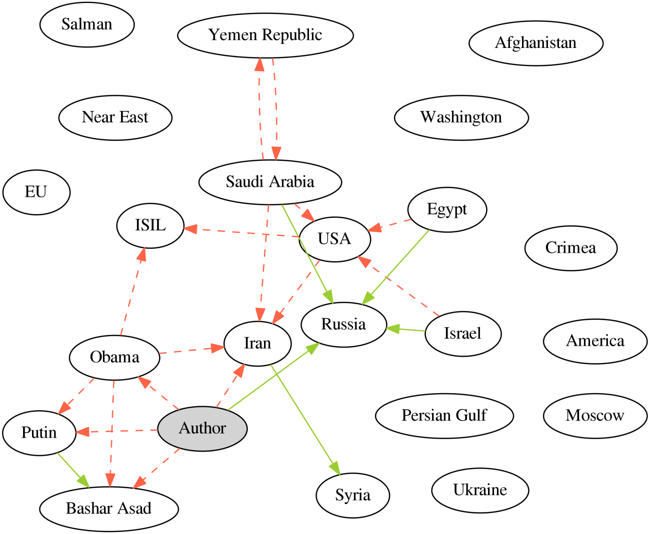
Отношения Финляндии и Швеции можно считать хорошими. Ведь входили же страны в состав одного королевства до 1809 года. Страны объединяет также и то, что они не входят в НАТО, но являются партнерами альянса. Кроме того, Финляндия и Швеция укрепляют двустороннее сотрудничество в области обороны.

Несмотря на все это, в ходе обсуждений в Култаранте возникли разногласия. Бывший министр обороны Швеции Карин Энстрём возмутилась тем, что президент Финляндии встречается в следующем месяце с президентом России в Хельсинки. По мнению второго шведского участника дискуссий, Владимиру Путину не были бы рады в Швеции.

# Whole Text Labeling

Обама, Асад, neg (Obama, Asad, neg)
США, ИГИЛ, neg (USA, ISIL, neg)
Иран, Асад, pos (Iran, Asad, pos)
США, Ирак, neg (USA, IRAK, neg)
США, Афганистан, neg (USA, Afganistan, neg)
Япония, США, pos (Japan, USA, pos)
Южная Корея, США, pos (South Korea, USA, pos)
Австралия, США, pos (Australia, USA, pos)
author, Обама, pos (Author, Obama, pos)

# Picture of whole text



# Task

- Classification of attitudes between named entities into three classes: positive, negative, neutral
- Measure: averaged sum of F-measure of positive class and negative class
- The first attempt
  - Summer School "Natural Language Processing and Data mining" (2017)
  - Higher School of Economy

# Context attitudes equality

Two context attitudes $a_1 = \langle NE_1, NE_2 \rangle$ and $a_2 = \langle NE_3, NE_4 \rangle$ are *equal up to synonyms* $a_1 \simeq a_2$ when both ends related to the same synonym group $S(\cdot)$:

$$S(NE_1) = S(NE_3) \textit{ and } S(NE_2) = S(NE_4) \tag{1}$$

# Context attitude set

- Consider context attitudes extraction within a single sentence

| Avg. per doc. | Training collection | Test collection |
|---|---|---|
| unique positive | 6.23 | 14.7 |
| unique negative | 9.33 | 15.6 |
| unique neutral | **120** | **276** |

Table 2 : RuSentRel text attitudes

| Total | Training set | Test set |
|---|---|---|
| positive | 571 | — |
| negative | 735 | — |
| neutral | **6584** | **8024** |

Table 3 : Context attitudes amount

# Attitudes classification

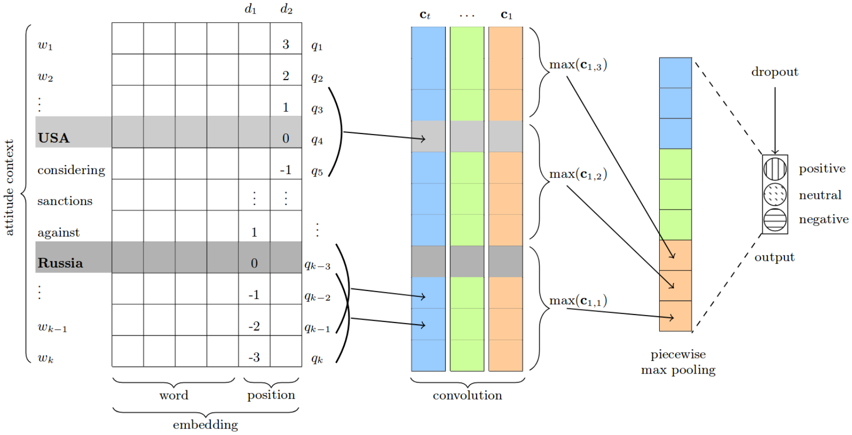



Figure 1 : PCNN[4] [ZLCZ15]

[4] https://github.com/nicolay-r/sentiment-pcnn

# Attitudes embedding

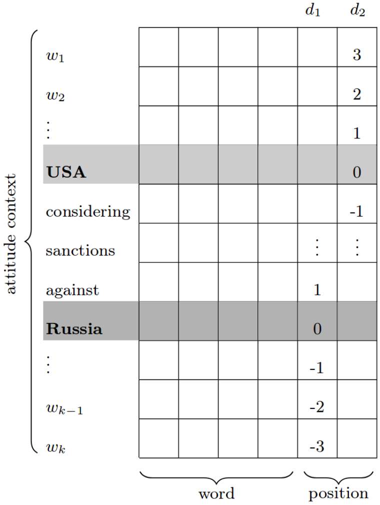



Figure 2 : Attitudes embedding

# Convolution

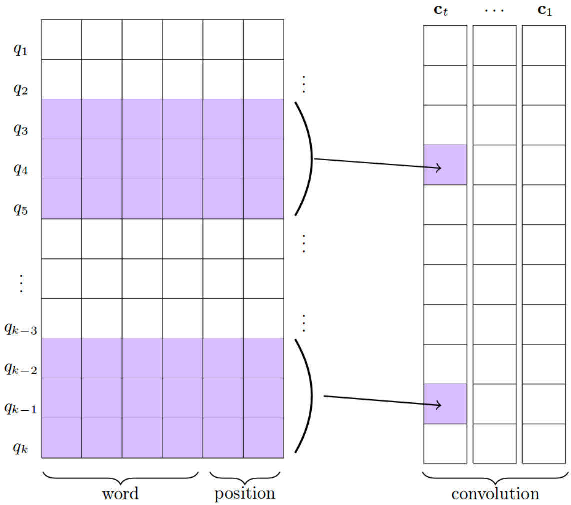



Figure 3 : Convolution

$$w = 3$$

$$m = 4 + 2 = 6$$

$$\mathbf{w} \in \mathbb{R}^{w \cdot m}$$

$$W = \{\mathbf{w_1} \ldots \mathbf{w_t}\}$$

$$c_j = \mathbf{w} q_{j-w+1:j}$$

$$\mathbf{c} = \{c_1, \ldots, c_k\}$$

$$C = \{\mathbf{c}_1, \ldots, \mathbf{c}_t\}$$

# Original vs. Piecewise max pooling

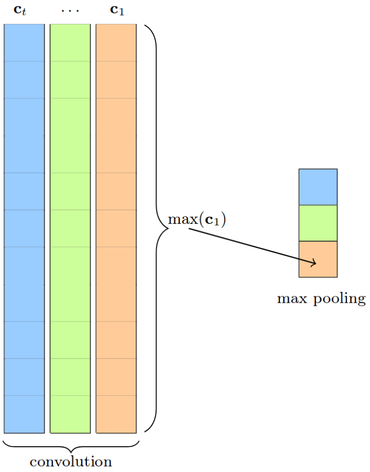



Figure 4 : Original

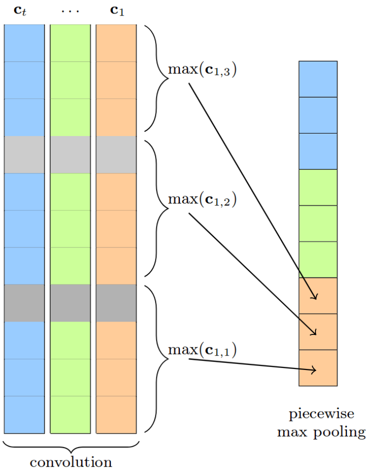



Figure 5 : Piecewise

# Output

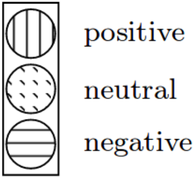



Figure 6 : Output

1. *tanh* maxpool **p** activation:

$$d = tanh(\mathbf{p}),$$

2. **Output**[a]:

$$o = W_1 d + b$$

$W_1$ – hidden layer
$b$ – bias

[a] dropout during training

# Training

- **Input** is a sequence of pairs:

$$\{\langle \mathit{embedding}, \mathit{label} \rangle\}$$

- What to train:

$$\{W, W_1, b\}$$

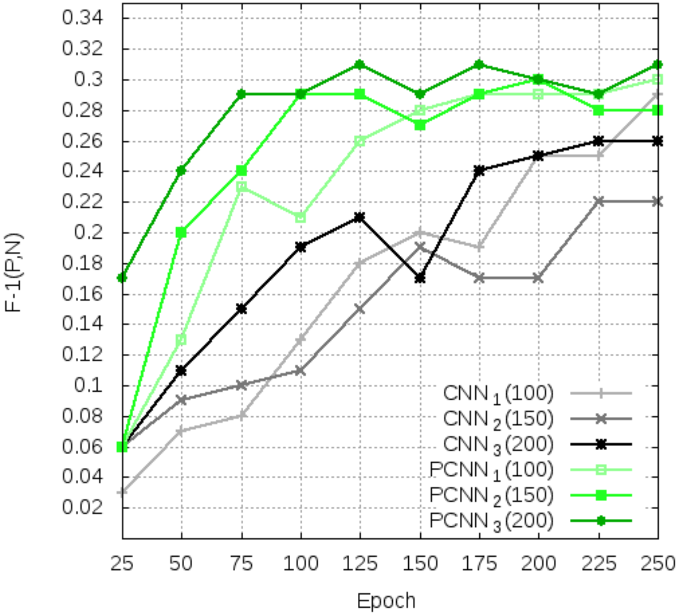
- How to train:
  - Passing batches, $\mathit{size} = 50$
  - Error function: *cross-entropy loss*
  - Optimizer: *Adadelta*, $\rho = 0.95, \ \epsilon = 10^{-6}$
  - Use dropout, $\rho = 0.5$

# Experiments

Table 4 : Results for sentiment attitudes extraction from RuSentRel corpus

| *method* | *precision* | *recall* | $F_1(P, N)$ |
|---|---|---|---|
| Baseline neg | 0.03 | 0.39 | 0.05 |
| Baseline pos | 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 |

# CNN vs. PCNN



F-1(P,N)
0.34
0.32
0.3
0.28
0.26
0.24
0.22
0.2
0.18
0.16
0.14
0.12
0.1
0.08
0.06
0.04
0.02
25
50
75
100
125
150
175
200
225
250
Epoch
CNN $_1$ (100)
CNN $_2$ (150)
CNN $_3$ (200)
PCNN $_1$ (100)
PCNN $_2$ (150)
PCNN $_3$ (200)

# Conclusion

- Proposed CNN-based models significantly outperforms baselines and performs better than NLP-based approaches (Table 4, experiments);
- Best result $F_1(P, N) = 0.31$ is quite low $\Rightarrow$ task still remains significantly complicated;
- Piecewice max pooling prevents from rapid feature reducing $\Rightarrow$ model trains faster (see Figure 16).
- Increasing amount of convolution filters (trainable features) allows model to train faster;

# References I


- L. Deng and J. Wiebe, *Mpqa 3.0: An entity/event-level sentiment corpus*, Proceedings of the 2015 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies (2015), 1323–1328.
- N. Loukachevitch and N. Rusnachenko, *Extracting sentiment attitudes from analytical texts*, Proceedings of International Conference of Computational Linguistics and Intellectual Technologies Dialog-2018 (2018).
- A. Mozharova, V. and V. Loukachevitch, N., *Combining knowledge and crf-based approach to named entity recognition in russian*, International Conference on Analysis of Images, Social Networks and Texts (2016), 185–195.

# References II

Daojian Zeng, Kang Liu, Yubo Chen, and Jun Zhao, *Distant supervision for relation extraction via piecewise convolutional neural networks*, Proceedings of the 2015 Conference on Empirical Methods in Natural Language Processing, 2015, pp. 1753–1762.