

## Studying Attention Models in Sentiment Attitude Extraction Task

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# Introduction

## Microblogging posts (Twitter)

- Mostly user reviews  $\Rightarrow$  considered a single object for analysis.

## Analytical articles:

- Large amount of named entities ( $NE$ ):  $Ukraine_e$ ,  $Russia_e$ ,  $Russian\ Federation_e$  ;

- Has complicated structure:

$Trump_e$  accused  $China_e$  and  $Russia_e$  of "playing devaluation of currencies"

## Related:

- Text Analysis Conference (TAC), Knowledge Base Population (KBP) track<sup>1</sup>;
- MPQA 3.0: sentiment attitudes towards entities and events;

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<sup>1</sup> <https://tac.nist.gov/2014/KBP/Sentiment/index.html>

# Sentiment Attitude Extraction

## ① Input (Context):

«As is apparent in Washington<sub>subj</sub>, there is no place for objectivity on the subject of Russia<sub>obj</sub>, irrespective of facts and events»

## ② Output (Extract):

Washington → Russian, negative

## Resources

# RuSentRel: Contents

- 73 large analytical articles;
- **Text attitudes** – manual annotation, sentiment towards *named entities* (*NE*) as triplets  $\langle \text{Object}, \text{Subject}, \text{Label} \rangle$ , where:
  - Subject – *NE* or “author”
  - Object – *NE*
  - Label  $\in \{\text{pos}, \text{neg}\}$
- **Named Entities** – automatic (CRF based recognizer);
- List *S* of synonymous *NE* – manually implemented.

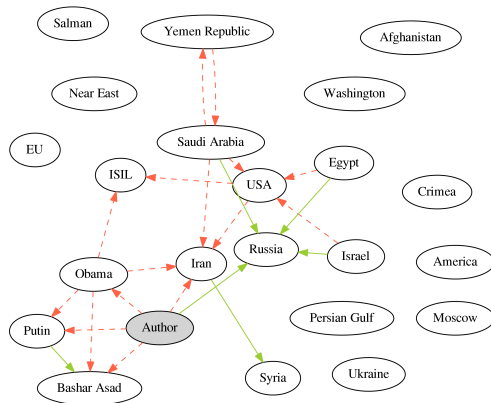


Figure 1: Document opinions

# RuSentiFrames Lexicon Structure

Describes sentiments and connotations conveyed with a predicate in a verbal or nominal form.

## ① Role Designation:

- A0 is an argument exhibiting features of a Prototypical Agent;
- A1 is a Theme.

## ② Dimensions:

- the attitude of the author of the text towards mentioned participants;
- **polarity** – sentiment between participants ;
- **effects** to participants;
- mental **states** of participants related to the described situation.

Frame	"Одобрить" (Approve)
roles	A0: who approves A1: what is approved
polarity	A0 → A1, pos, 1.0 A1 → A0, pos, 0.7
effect	A1, pos, 1.0
state	A0, pos, 1.0 A1, pos, 1.0

**Table 1:** Example description of frame "Одобрить" (Approve) in RuSentiLex lexicon.

# Attention Models

# Sentiment Attitude Extraction

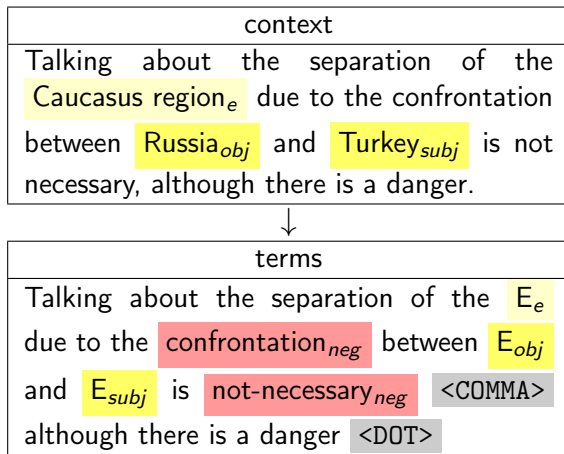
- 1 Introducing **context attitude** – a pair  $\langle \text{Subject}, \text{Object} \rangle$  its named entities within a context:  
«Talking about the separation of the **Caucasus region<sub>e</sub>** due to the confrontation between **Russia<sub>obj</sub>** and **Turkey<sub>subj</sub>** is not necessary, although there is a danger»
- 2 We predict a sentiment label of a pair in **three-scale** format – positive, negative or *neutral* (extraction).



## Context as a sequence of «terms»

Terms:

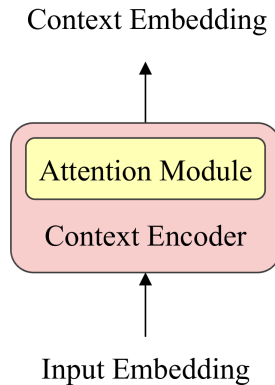
- Words;
- Entities (Masked);
- Frames;
- Tokens;



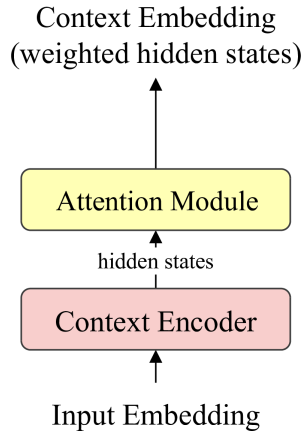
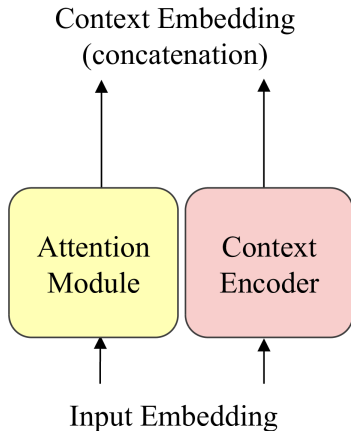
# Input embedding

- ① Pretrained Word2Vec model (size of 1000);
- ② Additional parameters (size of 5 each):
  - **Distance embedding** – is vectorized distance in terms from attitude participants of entry pair ( $E_{obj}$  and  $E_{subj}$  respectively) to a given term;
  - **Closest to synonym** distance embedding – is a vectorized abs. distance in terms from a given term towards the nearest entity, synonymous to  $E_{obj}$  and  $E_{subj}$ ;
  - **Part-of-speech** embedding;
  - A0→A1 **polarity** embedding – is a vectorized «positive» or «negative» value for frame entries in RuSentiFrames

# What is Attention?



## Attention embed options



## Attention Modules (Types and References)

- Based on input embedding: AttCNN<sup>[1]</sup> (PCNN<sup>[2]</sup>);
- Based on hidden states: IAN<sup>[3]</sup>; Att-BLSTM<sup>[4]</sup> (BiLSTM as an encoder);

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[1] [Yatian Shen and Xuanjing Huang](#). “Attention-Based Convolutional Neural Network for Semantic Relation Extraction”. In: *Proceedings of COLING 2016, the 26th International Conference on Computational Linguistics: Technical Papers* (Dec. 2016), pp. 2526–2536.

[2] [Nicolay Rusnachenko and Natalia Loukachevitch](#). “Using convolutional neural networks for sentiment attitude extraction from analytical texts”. In: *EPiC Series in Language and Linguistics 4* (2019), pp. 1–10.

[3] [Dehong Ma et al.](#) “Interactive attention networks for aspect-level sentiment classification”. In: *arXiv preprint arXiv:1709.00893* (2017).

[4] [Peng Zhou et al.](#) “Attention-based bidirectional long short-term memory networks for relation classification”. In: *Proceedings of the 54th Annual Meeting of the ACL (Volume 2: Short Papers)* (2016), pp. 207–212.

# Multi-Layer Perceptron (MLP) Based Attention (AttCNN)

- 1 Feature  $f$ : attitude ends, frames;

$$h_i = [x_i, f]$$

- 2 Weight calculation:

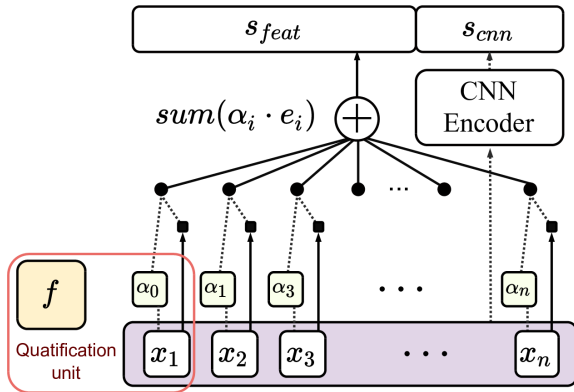
$$u_i = W_a (\tanh(W_{we} \cdot h_i + b_{we})) + b_a$$

- 3 Attention Embedding:

$$\alpha = \text{softmax}(u)$$

$$\hat{s} = \sum_{i=1}^n x_i \cdot \alpha_i$$

$$s_{feat} = \text{avg}_{j=1..k}(\hat{s})$$



# Interactive Attention Network (IAN)

❶ Feature ( $p$ ): avg. pooling across:

- Context ( $p_c$ );
- Aspects (Features) ( $p_f$ );

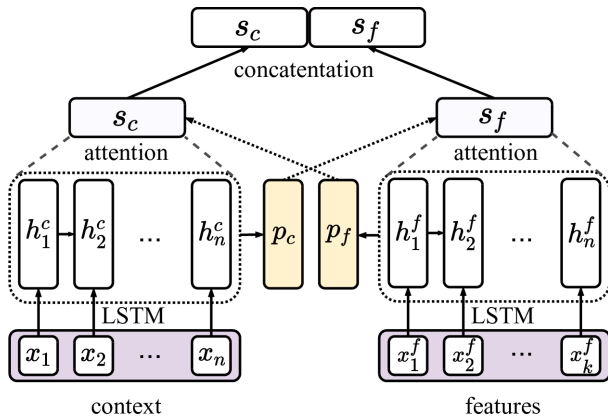
❷ Weight calculation:

$$u_i^c = \tanh(h_i^c \cdot W_f \cdot p_f + b_f)$$

$$u_j^f = \tanh(h_j^f \cdot W_c \cdot p_c + b_c)$$

❸ Result Embedding:

$$s_c = \sum_{i=1}^n \alpha_i^c \cdot h_i^c \quad s_f = \sum_{j=1}^k \alpha_j^f \cdot h_j^f$$



# Self-Based Attention

- 1 Hidden state  $\mathbf{w}$ .

$$h_i = \vec{h}_i + \overleftarrow{h}_i, \quad i \in \overline{1..n}.$$

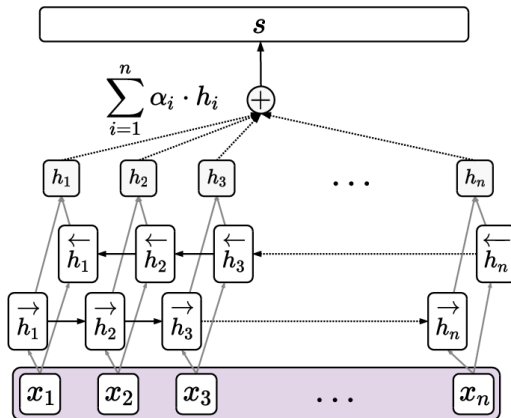
- 2 Attention (Att-BLSTM):

$$m_i = \tanh(h_i)$$

$$u_i = m_i^T \cdot \mathbf{w}$$

$$\alpha = \text{softmax}(u)$$

$$s = \tanh(H \cdot \alpha)$$





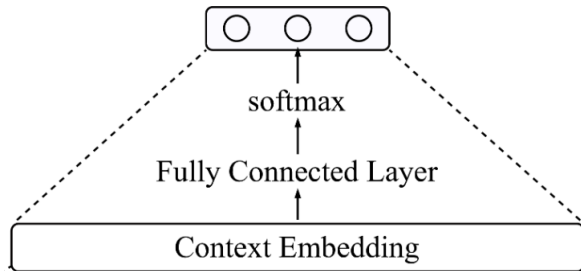
# Output Class Probabilities

- $s$  – is a context embedding;

$$r = W_r \cdot \tanh(s) + b_r$$

$$o = \text{softmax}(r)$$

$$\text{label} = \text{argmax}(o)$$



# Experiments

## Experiment Details

- ① Experiment format:
  - Three-scale – positive, negative or *neutral* (extraction).
- ② Output: document level opinions ;
- ③ Evaluation formats:
  - Measure: F1-score;
  - 3-Fold CV average results ( $F_{avg}$ );
  - Fixed Test separation of RuSentRel<sup>2</sup> ( $F_{test}$ ).
- ④ Model groups: AttPCNN, IAN, Att-BLSTM;

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2 <https://miem.hse.ru/clschool/results>

# Results

Model	$F1_{avg}$	$F1_{cv}^1$	$F1_{cv}^2$	$F1_{cv}^3$	$F1_{test}$
Att-BLSTM	<b>0.314</b>	<b>0.35</b>	0.27	<b>0.32</b>	<b>0.35</b>
BiLSTM	0.286	0.32	0.26	0.28	0.34
IAN <sub>ef</sub>	0.289	0.31	0.28	0.27	0.32
IAN <sub>ends</sub>	0.286	0.31	0.26	0.29	0.32
LSTM	0.284	0.28	0.27	0.29	0.32
AttPCNN <sub>e</sub>	0.297	0.32	<b>0.29</b>	0.28	<b>0.35</b>
AttPCNN <sub>ef</sub>	0.289	0.31	0.25	0.31	0.31
PCNN	0.285	0.29	0.27	0.30	0.32

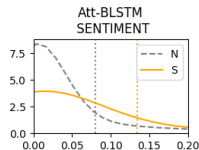
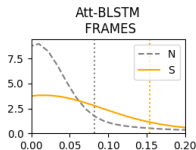
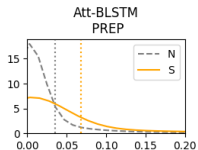
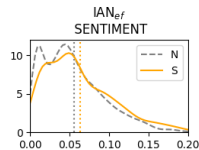
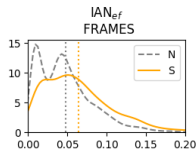
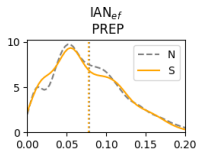
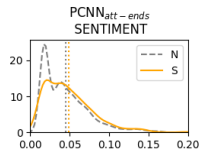
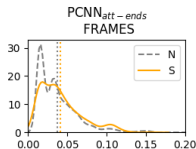
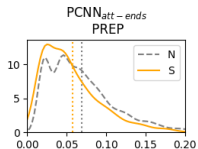
# Weight Distribution Analysis

- ① **Term groups** presented in analysis:
  - Frames;
  - Words  $\rightarrow$  Prepositions, Sentiment<sup>3</sup>;
- ② **Context-level weight** of a particular term group is a weighted sum of terms which both appear in the context and belong to the corresponding term group.
- ③ We utilize distributions  $(\rho_S, \rho_N)$  of context-levels weights across:
  - Sentiment contexts (S) – contexts labeled with positive or negative labels;
  - Neutral contexts (N) – contexts labeled as neutral;

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3 Contains words and expressions of the Russian language with sentiment labels

# Weight Distribution Analysis



# Weight distribution visualization on sentiment contexts

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## Att-BLSTM

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$\underline{E}_{subj}$  также должный предоставлять дополнительный экономический **помощь**  $\underline{E}_{obj}$

$\underline{E}_{subj}$  also should provide additional economic **assistance**  $\underline{E}_{obj}$

...

$\underline{E}_{subj}$  , в свою очередь , **приходиться** идти на силовой демонстрация , чтобы **принуждать**  $\underline{E}_{obj}$  к **поиск** компромисс

$\underline{E}_{subj}$  , in turn , **have to** go to military demonstration , to **force**  $\underline{E}_{obj}$  to **seek** compromises

...

Е **спасать**  $\underline{E}_{obj}$  от  $\underline{E}_{subj}$  и Е , но ее больше не **ждать** за европейский **стол** для почетный **гость**

Е **saves**  $\underline{E}_{obj}$  from  $\underline{E}_{subj}$  and Е , but she is no longer **waiting** at the European **table** for honored **guest**

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## Conclusion

- ① We consider sentiment attitude extraction task as three-scale classification onto the following classes: positive, negative, neutral.
- ② We study the attention-based neural networks. The application of attentive context encoders illustrates the classification improvement in 1.5-5.9% range by F1;
- ③ Model with self-attentive encoders (Att-BLSTM) illustrates the greatest discrepancy in weight distributions on sentiment and neutral contexts across all the term groups presented in the analysis;



## Links

- RuSentRel: <https://github.com/nicolay-r/RuSentRel/tree/v1.1>
- RuSentiFrames: <https://github.com/nicolay-r/RuSentiFrames/tree/v1.0>
- Experiments:  
<https://github.com/nicolay-r/attitude-extraction-with-attention>
- Word2Vec News embedding<sup>4</sup>;

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<sup>4</sup> [http://rusvectors.org/static/models/rusvectors2/news\\_mystem\\_skipgram\\_1000\\_20\\_2015.bin.gz](http://rusvectors.org/static/models/rusvectors2/news_mystem_skipgram_1000_20_2015.bin.gz)