

Advances in Sentiment Analysis of the Large Mass-Media Documents

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Sentiment Analysis

I LOVEEEE dogs
@beautygirl5 I love you <3
I enjoyed the food.
The game yesterday was intense!
@LOLTrish hey long time no see!
You put smiles on my face.
Today was a good day.
I love this notebook!



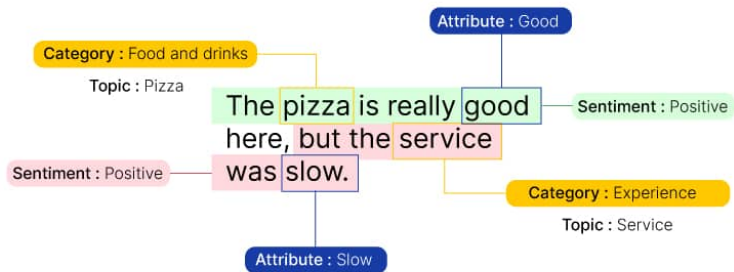
Positive



Negative

@bigdennis4 nobody asked you!
This week is not going as I had hoped
life has been like hell...
Don't force a joke if it ain't funny
I'm learning R programming.
So many homeworks !!!
Ugh. Can't sleep. Its 1:30am.
My Nokia 1110 died..

Detailization of Analysis



Text classification

The first attempt to propose the task^[1]:

$$\langle d \rangle \rightarrow c$$

d – document

c – related class positive, negative

“The picture quality of this camera at night time is amazing”

$$\langle d \rangle \rightarrow \textit{positive}$$

[1] Peter Turney. “Thumbs Up or Thumbs Down? Semantic Orientation Applied to Unsupervised Classification of Reviews”. In: *Proceedings of the 40th Annual Meeting of the Association for Computational Linguistics*. 2002, pp. 417–424.

Targeted sentiment analysis

Considering entity as an input parameter^[2]:

$$\langle d, e_j \rangle \rightarrow c$$

e_j – object, or entity

“The picture quality of this camera_e
at night time is amazing, especially with tripod_e”

$$\langle d, camera \rangle \rightarrow positive \quad \langle d, tripod \rangle \rightarrow ?$$

[2] Long Jiang et al. “Target-dependent twitter sentiment classification”. In: *Proceedings of the 49th annual meeting of the association for computational linguistics: human language technologies*. 2011, pp. 151–160.

Aspect Based Sentiment Analysis

Focusing on two core tasks^[3]:

- 1 Aspect extraction;
- 2 Aspect sentiment analysis:

$$\langle d, e_j, a_k \rangle \rightarrow c$$

a_k – aspect, object characteristics

“The **picture quality** of this **camera_e** is amazing ...”^[3]

$$\langle d, camera, picture\ quality \rangle \rightarrow positive$$

[3] Bing Liu and Lei Zhang. “A survey of opinion mining and sentiment analysis”. In: *Mining text data*. Springer, 2012, pp. 415–463.

Attitude Definition

Opinions between mentioned named entities (e_j, e_m):

$$\langle d, e_j, e_m, a_k, h_t, t_l \rangle \rightarrow c$$

a_k – aspect

e_m – subject

e_j – object

h_t – author

t_l – time

c – sentiment class (pos, neg)

“ ... **Moscow_e** dissatisfied with the **Warsaw's_e** decision ... ”

$$\langle e_m, e_j \rangle \rightarrow \text{neg}$$

Sentiment Attitude Extraction

Input:

- 1 Collection of analytical articles $\langle D_i, E_i \rangle$ (in Russian)
 - Each article includes: document D_i , list of mentioned named entities E_i
- 2 For synonymous mentions: given a collection of synonyms:

Russia_e , RF_e , Russian Federation_e

Task: For each D_i complete the list of sentiment attitudes (pairs $\langle e_i, e_j, l_{i,j} \rangle$)^[4], with label $l_{i,j} \in \{\text{pos}, \text{neg}\}$

[4] Natalia Loukachevitch and Nicolay Rusnachenko. “Extracting sentiment attitudes from analytical texts”. In: *Proceedings of International Conference on Computational Linguistics and Intellectual Technologies Dialogue-2018 (arXiv:1808.08932)* (2018), pp. 459–468.

Task aspects and problems

- 1 Large amount of named entities (NE);
- 2 Text structure complexities:

« Trump_e accused China_e and Russia_e
of “playing devaluation of currencies” »

(Trump_{subj}, China_{obj}) → negative

(Trump_{subj}, Russia_{obj}) → negative

Models

Approach in Large Document Sentiment Analysis

Contexts as the main idea¹

- Retrieval of attitudes – pos and neg labeling among a set *neutrally labeled* contexts

Prediction:

- Structured output: Text Classification
- Non-structured output: Text Generation

¹ Assumption: a relatively short distance between entities in the text

Rule-Based Annotation

Patterns for classification:

- Emoticons^[1], matching words or phrases.

Any algorithm which allows you to perform this annotation.

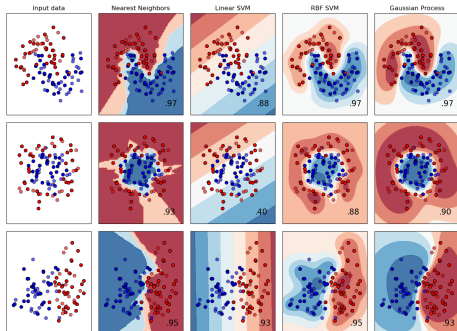
PROS: fast², minimal amount of RAM to launch

CONS: data dynamics

² Relatively in comparison with further methods

Linear Classifiers

- Documents as vectors
- NB, SVM, Random Forest, kNN.
- Given a set of classes, we adopt different **kernels**
- Every word has a scalar value:
 Bag-Of-Words



Bag of words (BoW)

Very good drama although it appeared to have a few blank areas leaving the viewers to fill in the action for themselves. I can imagine it being this way for someone who can neither read nor write. The film simply smacked of the real world: the wife who is suddenly the sole supporter, the lie-in relatives and their quarrels, the troubled child who gets knocked up and then, typically, drops out of school, a jealous husband who takes the next egg and lays beer with it, 2 turns up... very very very good movie.



{the, 0},
 {, 5},
 {very, 4},
 {drama, 3},
 {good, 2},
 {it, 2},
 {to, 2},
 {the, 2},
 {can, 2},
 {that, 2},
 {of, 2},
 {areas, 1},
 {although, 1},
 {appeared, 1},
 {have, 1},
 {leaving, 1},
 {blank, 1},
 ...

PROS: all text as vector, update.

CONS: no connection between words, vectors sparsity

Neural Networks (NN) (I)

Words as vectors, or *embeddings*:

- One-hot vector model

$$[0 \dots 0, 1, 0 \dots 0]$$

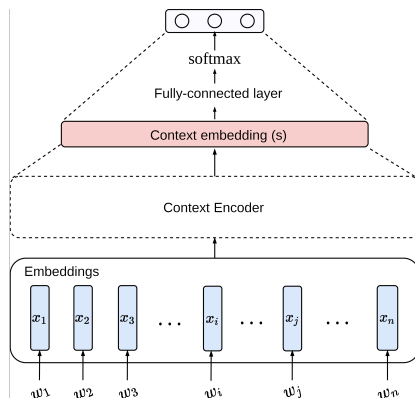
Classification: $o = W \cdot s + b$

Views of input:

- Windowed (Convolutional NN)
- Sequential (Recurrent NN)

PROS: non-linear transformations

CONS: How to establish
connection?



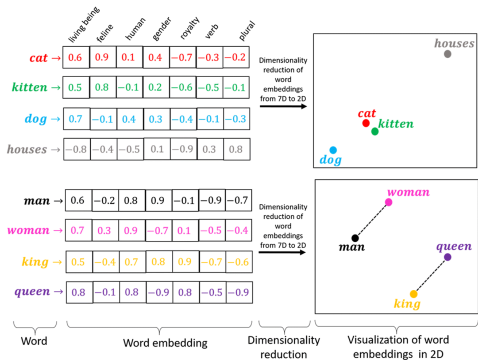
Embeddings

Raw documents could be a source of words in contexts^[5]

PROS: attempt of domain/general knowledge sharing for AI models, replacement of BoW

CONS: time and resources for training on large data

[e] Tomas Mikolov et al. "Efficient estimation of word representations in vector space". In: *arXiv preprint arXiv:1301.3781* (2013).



Neural Networks with Embeddings

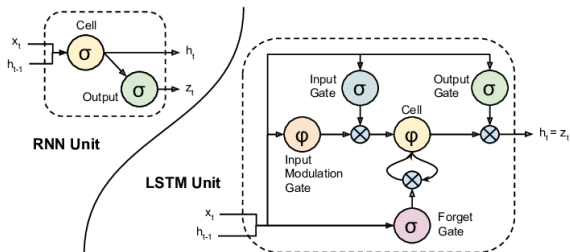
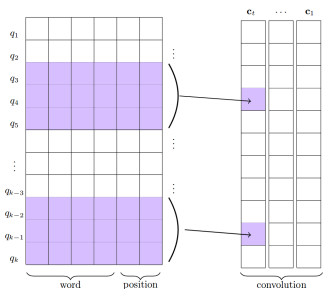


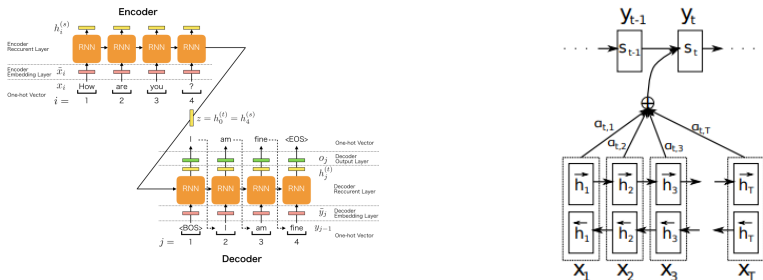
Figure: CNN, Convolution

Figure: RNN/LSTM Cell

CONS: limit of window, forgetting information, limit of input in words/tokens

Attention mechanism for Machine Translation (MT)

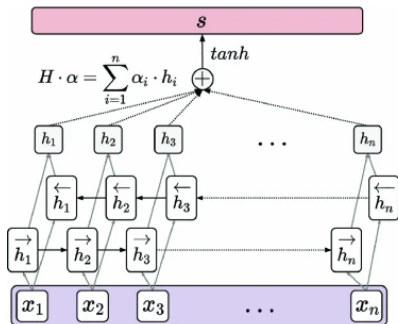
Mechanism for assessing weights of input information, originally for MT^[6]



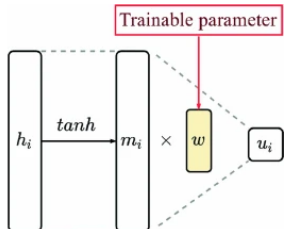
PROS: widely distributed in other NLP domains, including sentiment analysis

[6] Dzmitry Bahdanau, Kyunghyun Cho, and Yoshua Bengio. "Neural machine translation by jointly learning to align and translate". In: *arXiv preprint arXiv:1409.0473* (2014).

Attention for Text Classification [7]



(a) Context encoder architecture



(b) Quantification of h_j with respect to parameter w [17]; w represents a hidden vector which modifies during model training process

[7] Nicolay Rusnachenko and Natalia Loukachevitch. "Studying Attention Models in Sentiment Attitude Extraction Task". In: *Proceedings of the 25th International Conference on Natural Language and Information Systems*. 2020. url: https://doi.org/10.1007/978-3-030-51310-8_15.

Self-Attention

Proposed for the Machine Translation problem^[8]

PROS: Affect on other NLP tasks with different conception of models training, knowledge about language

CONS: Computation cost $O(N^2)$, where N is an input sequence length

[8] Ashish Vaswani et al. "Attention is all you need". In: *Advances in neural information processing systems* 30 (2017).

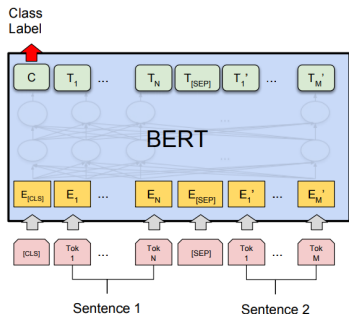
BERT for text classification^[9]

- Pre-training on large amount of data gives us a deep generalized understanding of the language, or **language model**.
- **Text classification**: FC-layer application towards the averaged embedded vectors
- Variations: RoBERTa, DistilBERT

PROS: Backbone with general knowledge

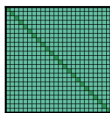
CONS: Input limitation of 512 tokens

[9] **Jacob Devlin et al.** "Bert: Pre-training of deep bidirectional transformers for language understanding". In: *arXiv preprint arXiv:1810.04805* (2018).

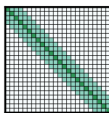


Decoder and Attention Sparsity^[11]

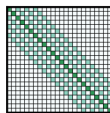
- Generative based: GPT, T5, Longformer, LongT5, BigBIRD
- Text classification: classification layer
- Serialized input/output^[10]



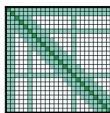
(a) Full n^2 attention



(b) Sliding window attention



(c) Dilated sliding window



(d) Global+sliding window

PROS: options to train long input with 4K, 8K, 16K

[10] Gaku Morio et al. “Hitachi at SemEval-2022 Task 10: Comparing Graph- and Seq2Seq-based Models Highlights Difficulty in Structured Sentiment Analysis”. In: *Proceedings of the 16th International Workshop on Semantic Evaluation (SemEval-2022)*. Association for Computational Linguistics, 2022, pp. 1349–1359.

[11] Iz Beltagy, Matthew E Peters, and Arman Cohan. “Longformer: The long-document transformer”. In: *arXiv preprint arXiv:2004.05150* (2020).

Data and Finetuning Advances

Supervised Learning

By default for AI methods, we consider a training based on manually annotated data by experts

PROS: Correct annotated data

CONS: Few samples, low resource domain

Supervised Learning Experiments

Trump_e accused China_e and Russia_e of “playing devaluation of currencies”

(Trump_{subj}, China_{obj}) → negative

(Trump_{subj}, Russia_{obj}) → negative

Supervised Learning Experiments

RuSentRel³: articles about Russia's international relations

Documents	73
Sentences per document	105.8
Entities per document	247
pos and neg pairs per document	11.47

³ <https://github.com/nicolay-r/RuSentRel/tree/v1.1>

RuSentRel^[13] Supervised Learning Results, 3-fold cv

Model	$F_1(P, N)$
SentRuBERT	33.4
AttPCNN _{ends}	29.9
PCNN	29.6
Experts agreement	55.0

For MPQA-3.0, $F_1 = 36.0$ ^[12]

[12] Eunsol Choi et al. “Document-level sentiment inference with social, faction, and discourse context”. In: *Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*. 2016, pp. 333–343.

[13] Nicolay Rusnachenko. “Language Models Application in Sentiment Attitude Extraction Task”. Russian. In: *Proceedings of the Institute for System Programming of the RAS (Proceedings of ISP RAS), vol.33. 3.* 2021, pp. 199–222.

Distant Supervision

Using external knowledge with rule-based or AI pre-trained methods to perform annotation.

<i>emotion</i>	<i>emojis</i>
anger	😡
joy	😄😍❤️😁💖😘😏😌😇🙏
sadness	😭😞😓
surprise	😱

PROS: Quick data annotation for further fine-tuning

CONS: Noisy labeling

Distant Supervision Experiments

- 1 **News collection**: Russian articles from mass-media sources (**8.8M**);
- 2 Knowledge Base **RuSentiFrames**⁴: describes sentiment association, conveyed by *predicate* in a form of a verb on noun (311 frames)
 - **roles**: A0 (agent), A1 (theme);
 - **dimensions**: authors attitude towards the participants mentioned in text; **polarity** – score between participants;

Frame (bragging)	Description
entries	bragging, boasting
roles	A0: those who bragging A1: the object of bragging
polarity	A0→A1, pos author→A0, neg

⁴ <https://github.com/nicolay-r/RuSentiFrames>

Distant Supervision Application II

Main assumption: news title has a simple structure.

... **Subject_e** ... $\{frame_{A0 \rightarrow A1}\}_k$... **Object_e** ...

Distant supervision performed in two steps^[14]:

- 1 Collect the list A of the *most-sentiment attitudes* ($subject \rightarrow object$) from news titles using frame $A0 \rightarrow A1$ polarity across all news titles
- 2 Filter news titles and sentences, which contains at least one pair with $A0 \rightarrow A1$ score as in A

[14] Nicolay Rusnachenko, Natalia Loukachevitch, and Elena Tutubalina. "Distant supervision for sentiment attitude extraction". In: *Proceedings of the International Conference on Recent Advances in Natural Language Processing (RANLP 2019)*. 2019, pp. 1022–1030.

Frame Title

Title

Tillerson_e : USA_e won't remove *sanctions*_{neg} from Russia_e before the return of Crimea_e

↓ USA→Russia_{neg}, USA→Crimea_{neg}

Most sentiment attitudes

Query	Search results
-------	----------------

USA→Russia _{neg}	pair found, scores match; pos: 32%, neg: 68%
---------------------------	---

USA→Crimea _{neg}	pair not found
---------------------------	----------------

↓ USA→Russia_{neg}

Sentence

Secretary of State USA_e Rex Tillerson_e, speaking in Brussels_e at a meeting Foreign_e heads of NATO_e affiliates stated that the sanctions from Russians_e will only be removed after the return of Crimea_e, according to CNN_e.

Datasets

RuAttitudes – automatically marked up collection of texts using the Distant Supervision approach over a large amount of mass-media short news per 2017 year.

Documents	134442
Attitudes per document	2.26

RuSentRel^[13] distant-supervision results, 3-fold cv

Model	$F_1(P, N)$
SentRuBERT (pretrain + ft)	37.9
AttPCNN _{ends}	32.2
SentRuBERT	33.4
AttPCNN _{ends}	29.9
PCNN	29.6
Experts agreement	55.0

Prompts, prompts, prompts!

Provide additional information that mimicking the expected class or region of text to consider.

- Predefined template: QA, NLI
- Sequence of words mimicking the class^[15]
- With abstract tokens serializing a particular task^[16]

[15] Taylor Shin et al. “Autoprompt: Eliciting knowledge from language models with automatically generated prompts”. In: *arXiv preprint arXiv:2010.15980* (2020).

[16] Xiang Lisa Li and Percy Liang. “Prefix-tuning: Optimizing continuous prompts for generation”. In: *arXiv preprint arXiv:2101.00190* (2021).

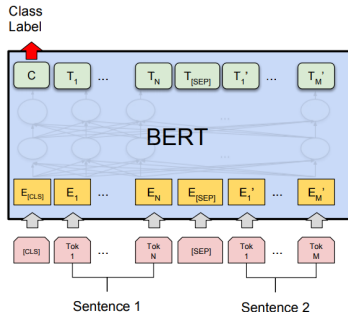
BERT with prompts^[17]

Input sequences:

- TextA: Input context terms
- TextB: (Optional), as prompt:

E_{-subj} towards E_{-obj} in « $E_{-subj} \dots E_{-obj}$ » is NEG

Context labeling: FC-layer application towards the averaged embedded vectors



[17] Chi Sun, Luyao Huang, and Xipeng Qiu. "Utilizing BERT for aspect-based sentiment analysis via constructing auxiliary sentence". In: *arXiv preprint arXiv:1903.09588* (2019).

RuSentRel^[13] distant-supervision results, 3-fold cv

Model	$F_1(P, N)$
SentRuBERT (pretrain + ft) + NLI _{prompt}	39.0
SentRuBERT (pretrain + ft)	37.9
AttPCNN _{ends}	32.2
SentRuBERT	33.4
AttPCNN _{ends}	29.9
PCNN	29.6
Experts agreement	55.0



Official RuSentRel leaderboard

ChatGPT

Illustrates state-of-the art results in **zero-shot learning!**^[18]

We use the following prompt template (NLI format)⁵:

*What's the attitude of the sentence "[S]" from "[X]" to the target "[Y]".
positive or negative.*

Experiments with RuSentRel: classification of sentiment labels

- We receive 1% of unknown answers
- 27% of Neutral classes
- F1 = 68.46 (Complarable with prior results in 2 scale format)

[18] Bowen Zhang, Daijun Ding, and Liwen Jing. "How would Stance Detection Techniques Evolve after the Launch of ChatGPT?". In: *arXiv preprint arXiv:2212.14548 (2022)*.

Unknown Response⁶

Q: What's the attitude of the sentence: "She has in Syria two strongest allies Israel and Iran ." from "Israel" to the target "Syria". positive or negative.

ChatGPT: It is not possible to determine the attitude of the sentence towards Syria from the perspective of Israel as the sentence does not express any sentiment or opinion about the relationship between Israel and Syria. It simply states that Israel is one of two allies of Syria

⁶ whether we should consider "allies" as sentiment?

Unknown Response⁷

Q: What's the attitude of the sentence: "Russia waging a hybrid war against Europe without the military component that is on Ukraine", - believes Klimkin. from "Klimkin" to the target "Ukraine". positive or negative

ChatGPT: It is difficult to determine the specific attitude of the speaker, "Klimkin," towards Ukraine based on the provided sentence alone. The statement is primarily focused on describing Russia's actions towards Europe, and mentions Ukraine in relation to that. Without more context it is not possible to know the attitude of Klimkin towards Ukraine.

⁷ Unknown position of the speaker

Neutral Examples with Explanation

Q: What's the attitude of the sentence: "Iran and Syria are in the same group for the 2018 World Cup qualifying round to be held in Russia : thus , the new mentor of the Syrian team hossam-al-saed to compete for a ticket to Russia with a Portuguese specialist carlos-queiros leading the team iran , the publication" from "iran" to the target "Syria". positive or negative.

ChatGPT: It is neutral, as it is simply stating a fact about the groups for the 2018 World Cup qualifying round and the coaches for the teams of Iran and Syria. It does not express a positive or negative attitude towards Syria.

Neutral Examples with Explanation ⁸

Q: What's the attitude of the sentence: "Belarus included in Customs-Union together with Russia , Kazakhstan , armenia and kyrgyzstan ." from "Belarus" to the target "Russia". positive or negative.

ChatGPT: The attitude of the sentence towards Russia is neutral. It simply states that Belarus is included in a Customs-Union with Russia, Kazakhstan, Armenia, and Kyrgyzstan, without expressing any positive or negative sentiment.

⁸ Different way it treats the expression, however we convey the presence of positive attitude due to the «union»

ChatGPT alternatives

[TBA] **Google Bard**⁹ based on LaMDA^[19]

- Transformer pretrained on large amount of chat dialogs

⁹ <https://blog.google/technology/ai/bard-google-ai-search-updates/>

[19] **Romal Thoppilan et al.** "Lamda: Language models for dialog applications". In: *arXiv preprint arXiv:2201.08239* (2022).

Frameworks and Toolset

AREkit – Text Opinion Sampler



AREkit – Document level **A**ttitude and **R**elation
Extraction toolkit for sampling mass-media news into
datasets for your ML-model training and evaluation



github.com/nicolay-r/AREkit

AREnets – attention based neural networks



AREnets* – Tensorflow-based framework which lists attentive implementation of the CNN, RNN-based, applicable for Relation Extraction classification tasks as well as API for custom model implementation



github.com/nicolay-r/AREnets

Awesome Sentiment Attitude Extraction



A curated list of works devoted to sentiment attitude extraction of large mass-media documents



`github.com/nicolay-r/awesome-...`

Conclusion

- The informative analysis of the large Mass-media texts is a granular analysis:
 - Text Classification → Targeted Sentiment Analysis → Aspect-based Analysis → Attitude Extraction
- Attitude extraction is considered as text classification problem of small text parts¹⁰
- The latest advances is self-attention which lead us to transformers that can memorize information from massive amount of the pretrained texts

¹⁰ Generative transformers with the largest input of 16K tokens.

Conclusion

- Rule-based
- Linear classifiers + features
- Neural Networks + embedding + attention + features
- Language Models
- Language Models + **prompts**
- Zero-Shot Language Models + **prompts**

*The crucial part of optimizations are **prompts**^[20] ...
early in a form of features and later closer to
output clarification*

[20] Shuofei Qiao et al. "Reasoning with Language Model Prompting: A Survey". In: *arXiv preprint arXiv:2212.09597* (2022).

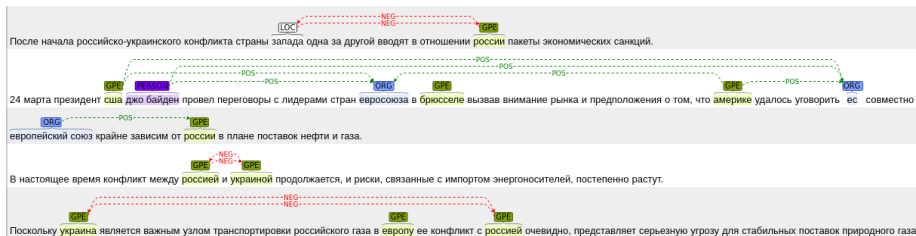
Thank you for attention!



<https://nicolay-r.github.io>

ARElight – Inference Attitudes

The complete example is available here¹¹.
For SentRuBERT¹²:

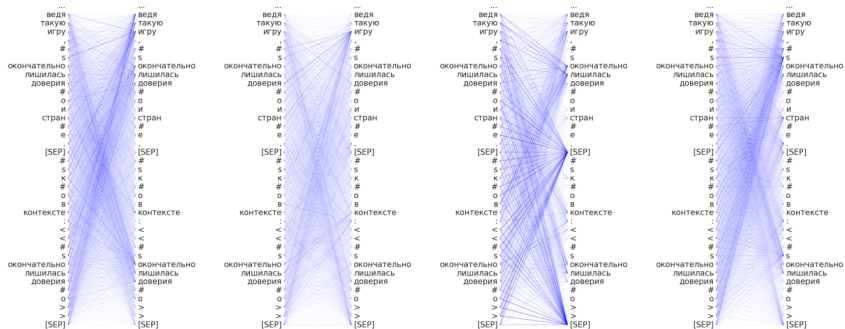


11 <https://raw.githubusercontent.com/nicolay-r/ARElight/main/data/texts-inosmi-rus/e1.txt>

12 http://172.17.0.2/examples/demo/wui_bert.py

SentRuBERT Attention weights analysis

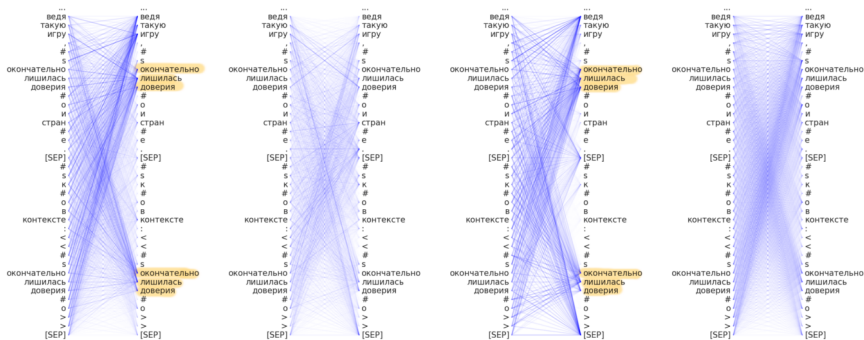
SentRuBERT (head 2, layers from left-to-right: 2, 4, 8, 11)¹³



13 ... playing such a-game, #S finally lost the-trust of #O and countries #E. [SEP] #S to #O in context: “#S has finally lost the-trust of #O” [SEP]

SentRuBERT Attention weights analysis (II)

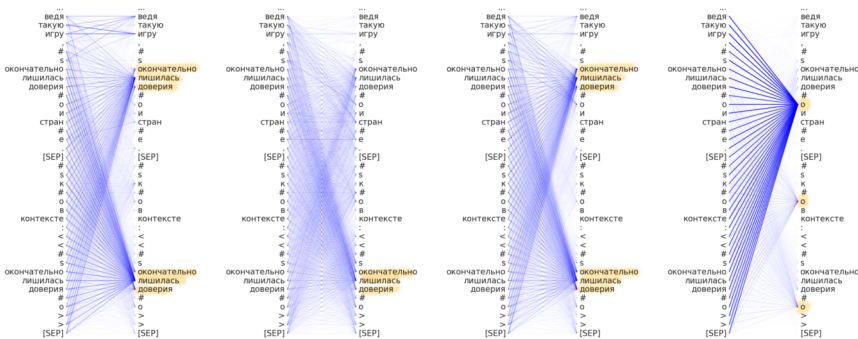
+ 4 epochs on RuAttitudes¹⁴



14 ... playing such a-game, #S finally lost the-trust of #O and countries #E. [SEP] #S to #O in context: "#S has finally_{frame} lost_{frame} the-trust_{frame} of #O" [SEP]

SentRuBERT Attention weights analysis (III)

15 + 4 epochs for finetuning on RuSentRel



15 ... playing such a-game, #S finally lost the-trust of #O and countries #E. [SEP] #S to #O in context: “#S has finally_{frame} lost_{frame} the-trust_{frame} of #O” [SEP]

Sampling

In the case of conventional neural networks (frames, features):

id	doc_id	label	text_a	s_ind	t_ind	sent_ind	entity_values	entity_types	frames	frame_cnnts	uint	syn_subs	syn_objs	entities	pos_tags
o0_io	0	0	<[> <[> <[> <[> при это subject неоднократн	5	19	1	москва,нато,россии	GPE,ORG,GPE				5	19,5,19,25	15,15,15,11,13,15,2,14,15,13	
o1_io	0	0	<[> <[> <[> <[> при это subject неоднократн	5	25	1	москва,нато,россии	GPE,ORG,GPE				5	25,5,19,25	15,15,15,11,13,15,2,14,15,13	
o2_io	0	0	<[> <[> <[> <[> при это object неоднократн	19	5	1	ва,нато,россии	GPE,ORG,GPE				19	5,5,19,25	15,15,15,11,13,15,2,14,15,13	
o3_io	0	0	<[> <[> <[> <[> при это object неоднократно подч	19	25	1	ва,нато,россии	GPE,ORG,GPE				19	25,5,19,25	15,15,15,11,13,15,2,14,15,13	
o4_io	0	0	object намер и против subject	4	0	0	ва,россии	GPE,PERSON	2		2	4	0,0,4	15,12,14,11,15	
o5_io	0	0	<[> <[> <[> <[> при это object неоднократно	25	5	1	москва,нато,россии	GPE,ORG,GPE				25	5,5,19,25	15,15,15,11,13,15,2,14,15,13	
o6_io	0	0	<[> <[> <[> <[> при это e неоднократно подч	25	19	1	москва,нато,россии	GPE,ORG,GPE				25	19,5,19,25	15,15,15,11,13,15,2,14,15,13	
o7_io	0	0	subject намерен ввести-санкции против object	0	4	0	ща,россии	GPE,PERSON	2		2	0	4,0,4	15,12,14,11,15	

Text Entities Frames

In case of BERT-based language models (TextA, TextB):

id	doc_id	label	text_a	text_b	s_ind	t_ind	sent_ind	entity_values	entity_types	entities
o0_io	0	0	024 марта президент АЕ АС провел переговоры с лидерами стран АС	АС в контексте << АС провел переговоры с лидерами стран АС >>	4	10	3	ща,дио баден,евросоюза, А GPE, PERSON, ORG, GPE, GPE, ORG А	3,4,10,12,21,24	
o0_1i	0	0	024 марта президент АЕ АС провел переговоры с лидерами стран АС	АС в контексте << АС провел переговоры с лидерами стран АС в АЕ >>	4	24	3	ща,дио баден,евросоюза, А GPE, PERSON, ORG, GPE, GPE, ORG А	3,4,10,12,21,24	
o2_1i	0	0	024 марта президент АЕ АС провел переговоры с лидерами стран АС	АС в контексте << АС провел переговоры с лидерами стран АЕ в АЕ >>	4	21	3	ща,дио баден,евросоюза, А GPE, PERSON, ORG, GPE, GPE, ORG А	3,4,10,12,21,24	
o4_io	0	0	045 крайние зависии от АС в плане поставок нефти и газа.	АС в АС в контексте << АС крайние зависии от АС >>	0	4	4	европейский союз,россии ORG, GPE	0,4	
o4_1i	0	0	Поскольку АЕ является важным узлом транзитной России АС	АС в АС в контексте << АС е конфликт с АС >>	9	13	7	украина,европу,россии GPE, GPE, GPE	1,9,13	
o6_io	0	0	024 марта президент АЕ АС провел переговоры с лидерами стран АС	АС в АС в контексте << АС провел переговоры с лидерами стран АС >>	10	4	3	ща,дио баден,евросоюза, А GPE, PERSON, ORG, GPE, GPE, ORG А	3,4,10,12,21,24	
o6_1i	0	0	024 марта президент АЕ АС провел переговоры с лидерами стран АС	АС в АС в контексте << АС провел переговоры с лидерами стран АС в АЕ >>	10	3	3	ща,дио баден,евросоюза, А GPE, PERSON, ORG, GPE, GPE, ORG А	3,4,10,12,21,24	
o8_1i	0	0	024 марта президент АЕ АС провел переговоры с лидерами стран АС	АС в АЕ >> вылез внимание рынка и предположения о т	10	21	3	ща,дио баден,евросоюза, А GPE, PERSON, ORG, GPE, GPE, ORG А	3,4,10,12,21,24	
o8_12	0	0	024 марта президент АЕ АС провел переговоры с лидерами стран АС	АС в АЕ >> провел переговоры с лидерами стран АС в АЕ	24	3	3	ща,дио баден,евросоюза, А GPE, PERSON, ORG, GPE, GPE, ORG А	3,4,10,12,21,24	
o8_13	0	0	024 марта президент АЕ АС провел переговоры с лидерами стран АС	АС в АС в контексте << АС удалось уговорить АС >>	24	21	3	ща,дио баден,евросоюза, А GPE, PERSON, ORG, GPE, GPE, ORG А	3,4,10,12,21,24	
o12_io	0	0	0Тотле начал АС-украинец это конфликта страны АС	АС в АС в контексте << АС одна за другой вводит в отношении АС >>	5	12	0	апада,россии LOC, GPE	5,12	
o13_io	0	0	0В настоящее АС провадятся, и АС в АС в контексте << АС >>	АС в АС в контексте << АС >>	5	7	6	россий,украины GPE, GPE	5,7	
o13_1i	0	0	Поскольку АС является важным узлом транзитной России АС	АС в АС в контексте << АС является важным узлом транзитной России АС >>	13	1	7	украина,европу,россии ORG, GPE	1,9,13	
o15_io	0	0	045 крайние зависии от АС в плане поставок нефти и газа.	АС в АС в контексте << АС крайние зависии от АС >>	4	0	4	европейский союз,россии ORG, GPE	0,4	
o15_1i	0	0	Поскольку АЕ является важным узлом транзитной России АС	АС в АС в контексте << АС е конфликт с АС >>	13	9	7	украина,европу,россии GPE, GPE, GPE	1,9,13	
o17_io	0	0	0Тотле начал АС-украинец это конфликта страны АС	АС в АС в контексте << АС одна за другой вводит в отношении АС >>	12	5	0	апада,россии LOC, GPE	5,12	
o18_io	0	0	024 марта президент АЕ АС провел переговоры с лидерами стран АС	АС в АС в контексте << АС >>	3	4	3	ща,дио баден,евросоюза, А GPE, PERSON, ORG, GPE, GPE, ORG А	3,4,10,12,21,24	
o18_1i	0	0	024 марта президент АЕ АС провел переговоры с лидерами стран АЕ	АС в АЕ >> в АЕ >>	21	4	3	ща,дио баден,евросоюза, А GPE, PERSON, ORG, GPE, GPE, ORG А	3,4,10,12,21,24	
o20_io	0	0	024 марта президент АЕ АС провел переговоры с лидерами стран АС	АС в АС в контексте << АС провел переговоры с лидерами стран АС >>	3	10	3	ща,дио баден,евросоюза, А GPE, PERSON, ORG, GPE, GPE, ORG А	3,4,10,12,21,24	
o20_1i	0	0	024 марта президент АЕ АС провел переговоры с лидерами стран АС	АС в АС в контексте << АС провел переговоры с лидерами стран АС >>	3	24	3	ща,дио баден,евросоюза, А GPE, PERSON, ORG, GPE, GPE, ORG А	3,4,10,12,21,24	
o20_12	0	0	024 марта президент АЕ АС провел переговоры с лидерами стран АС	АС в АЕ >> вылез внимание рынка и предположения о т	21	10	3	ща,дио баден,евросоюза, А GPE, PERSON, ORG, GPE, GPE, ORG А	3,4,10,12,21,24	
o20_13	0	0	024 марта президент АЕ АС провел переговоры с лидерами стран АС	АС в АС в контексте << АС удалось уговорить АС >>	21	24	3	ща,дио баден,евросоюза, А GPE, PERSON, ORG, GPE, GPE, ORG А	3,4,10,12,21,24	
o24_io	0	0	0В настоящее время конфликт между АС и АС продолжается, и АС в АС в контексте << АС и АС >>	АС и АС в АС в контексте << АС и АС >>	7	5	6	россий,украины GPE, GPE	5,7	
o24_1i	0	0	Поскольку АЕ является важным узлом транзитной России АС	АС в АС в контексте << АС является важным узлом транзитной России АС >>	1	13	7	украина,европу,россии GPE, GPE, GPE	1,9,13	

TextA TextB Entities