

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!



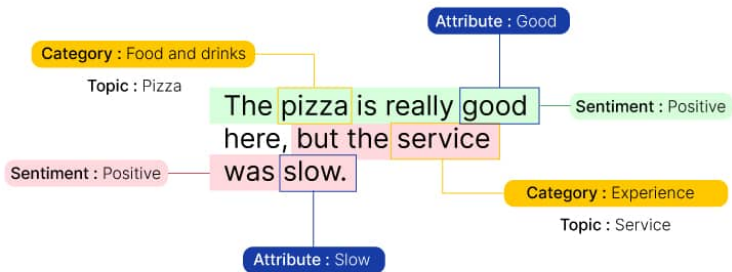
Positive



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:

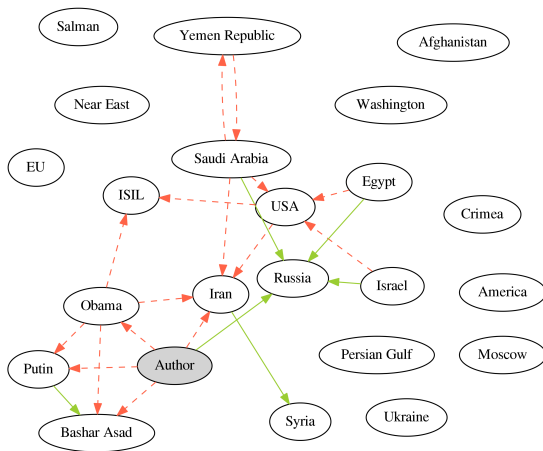
- 1 Collection of analytical articles $\langle D_i, E_i \rangle$ (in Russian)
 - Each article includes: document D_i , list of mentioned named entities E_i
- 2 For synonymous mentions: given a collection of synonyms:

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.

Document-Level Attitude Representation



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

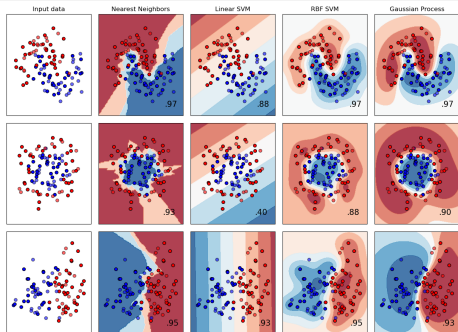
² Relatively in comparison with further methods

Conventional Classifiers

- Documents as vectors
- NB, SVM, Random Forest, kNN.
- We can adopt different **kernels** (for the non-linear transformations)
- Every word has a scalar value:
Bag-Of-Words

PROS: all text as vector, update.

CONS: no connection between words, vectors sparsity



Bag of words (BoW)

Very good drama although it appeared to have a few blank areas leaving the viewers to fill in the actor to themselves. I can imagine life being this way for someone who can neither read nor write. This film simply smacked of the real world: the wife who is suddenly the sole supporter, the low-in relatives and their quarrels, the troubled child who gets knocked up and then, typically, drops out of school, a jolted husband who loses the nest egg and buys beer with it. 2 thumbs up... very very very good movie.



{the: 8},
{: 5},
{very: 4},
{: 4},
{they: 4},
{and: 3},
{good: 3},
{it: 2},
{to: 2},
{for: 2},
{can: 2},
{the: 2},
{of: 2},
{: 2},
{: 1},
{although: 1},
{appeared: 1},
{have: 1},
{: 1},
....

Neural Networks (NN) (I)

Words as vectors, or *embeddings*:

- One-hot vector model

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

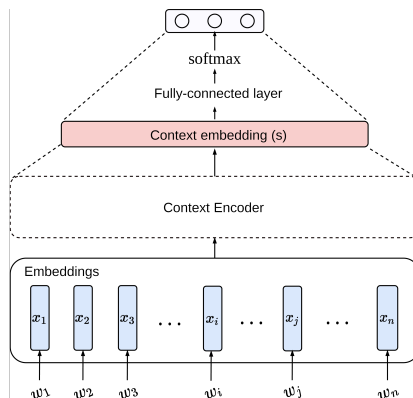
Classification: $o = W \cdot s + b$

Views of input:

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

PROS: non-linear transformations

CONS: How to establish
connection?



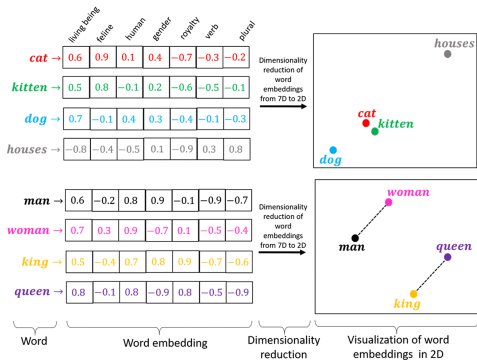
Embeddings

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

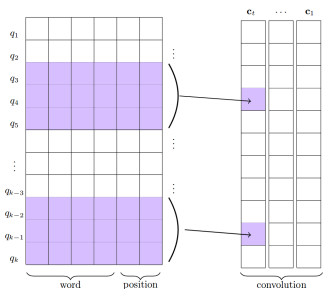


Figure: CNN, Convolution

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

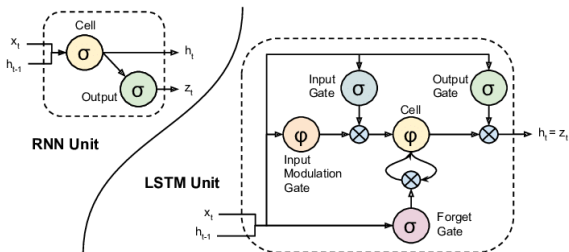
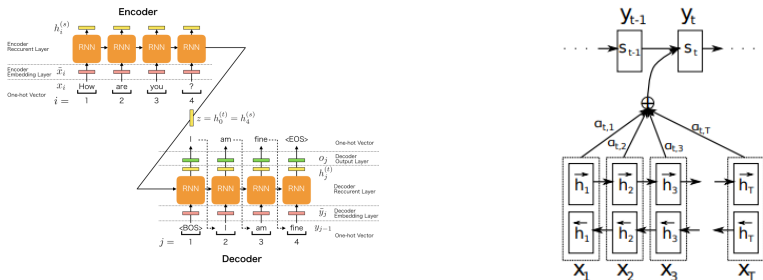


Figure: RNN/LSTM Cell

Attention mechanism for Machine Translation (MT)

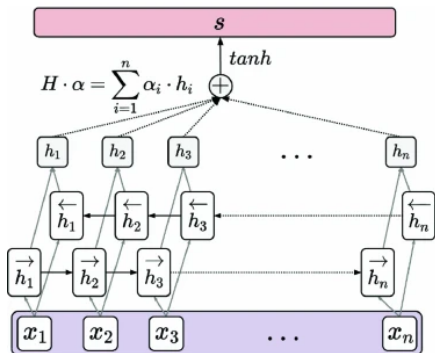
Mechanism for assessing weights of input information, originally for MT^[6]



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]



$$m_i = \tanh(h_i)$$

$$u_i = m_i^T \cdot w$$

trainable vector

Figure: Weight calculation

[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).

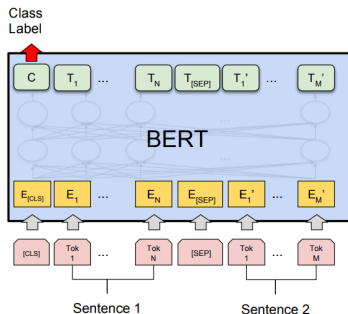
BERT for text classification^[9]

- 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).



Long-Range Input Transformers

Main limitation for input $X \in \mathbb{R}^N$:

- $O(N^2)$ original self-attention^[8] computation complexity;

Solution:

- 1 **Sparse self-attention**^{[10][11]}: ETC, Longformer
- 2 #1 with Global Attention
- 3 **Structurization** – limit attention within sentences, paragraphs, etc. via *masking*

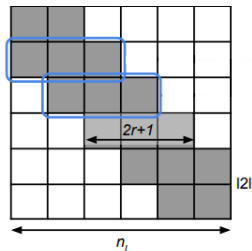
[10] Iz Beltagy, Matthew E Peters, and Arman Cohan. “Longformer: The long-document transformer”. In: *arXiv preprint arXiv:2004.05150* (2020).

[11] Joshua Ainslie et al. “ETC: Encoding long and structured inputs in transformers”. In: *arXiv preprint arXiv:2004.08483* (2020).

Relative Position Encoding

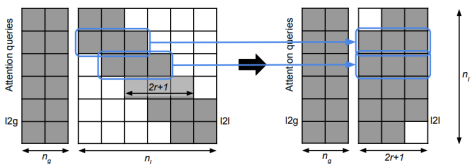
BERT^[9] exploits absolute position encoding
 $X \in \mathbb{R}^N$. ETC proposes **relative**:

- Now position is label $l_{i,j}$ of **connection** of $x_i \in X$ with other X
- **Distance clipping**: k – limit window
 - l_k outside after i ,
 - l_{-k} outside radius k before i .
- **Result** in a_j^K – learnable vectors of relative positions



Local Attention + Global^[11]

- n_l – main input components: **now windowed** (sparse)
- n_g – global input components ($n_g \ll n_l$)



$$z_i^g = \sum_{j=1}^{n_g} \alpha_{ij}^{g2g} x_j^g W^V$$

$$\alpha_{ij}^{g2g} = \frac{\exp(e_{ij}^{g2g})}{\sum_{\ell=1}^n \exp(e_{i\ell}^{g2g})}$$

$$e_{ij}^{g2g} = \frac{x_i^g W^Q (x_j^g W^K + \underbrace{a_{ij}^{K}}_{\text{position}})^T}{\sqrt{d_z}} - \underbrace{(1 - M_{ij}^{g2g}) C}_{\text{masking}}$$

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.

emotion

anger

joy

sadness

surprise

emojis



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 <i>sanctions</i> _{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).

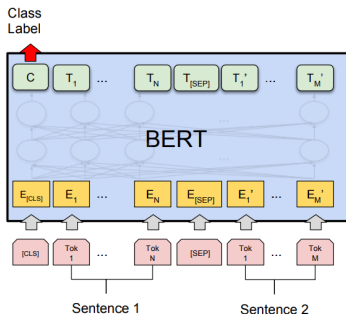
BERT with prompts^[17]

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

Reinforcement Learning from Human Level Feedback⁵

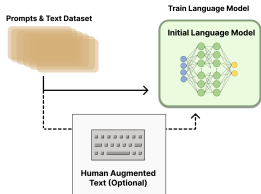


Figure 1.
Prompting+Pre-training

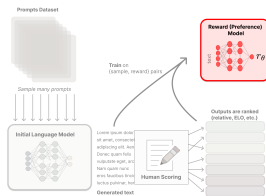


Figure 2. Reward model

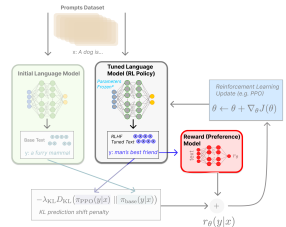
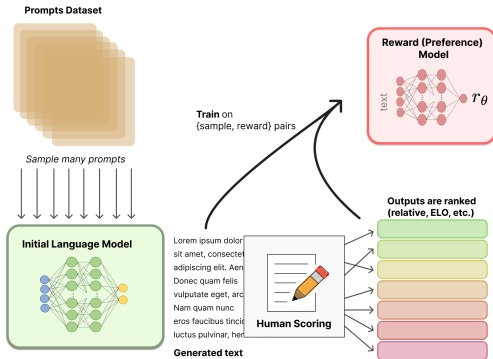


Figure 3. RLHF

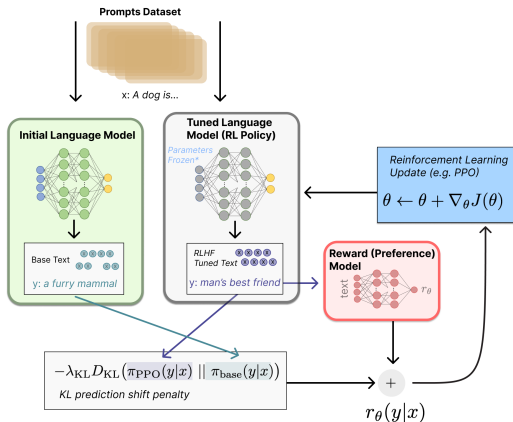
⁵ <https://huggingface.co/blog/rlhf>

Reward Model Training⁶



⁶ <https://huggingface.co/blog/rlhf>

Policy Language Model Prompt Tuning⁷



⁷ <https://huggingface.co/blog/rlhf>

ChatGPT

Illustrates state-of-the art results in **zero-shot learning**!^[18]
We use the following prompt template (NLI format)⁸:

Input

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

[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 Response⁹

Input

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

⁹ whether we should consider "allies" as sentiment?

Unknown Response¹⁰

Input

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.

¹⁰ Unknown position of the speaker

Neutral Examples with Explanation

Input

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.

ChatGPT Results

Model	$F_1(P, N)$
ChatGPT ¹¹	37.7
SentRuBERT (pretrain + ft) + NLI _{prompt}	39.0
SentRuBERT (pretrain + ft)	37.9
AttPCNN _{ends}	32.2
SentRuBERT	33.4
...	



Official RuSentRel leaderboard

¹¹ We did not examine RuSentRel with the provided ChatGPT explanations

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 parts¹²
- The latest advances is self-attention which lead us to transformers that can memorize information from massive amount of the pretrained texts

¹² Generative transformers with the largest input of 16K tokens.

Conclusion

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

*The crucial part of optimizations are **prompts**^[19] ...
early in a form of features and later closer to
output clarification*

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

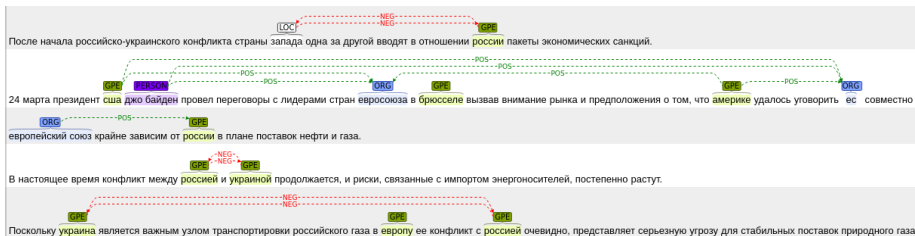
Thank you for attention!



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

ARElight – Inference Attitudes

The complete example is available here¹³.
For SentRuBERT¹⁴:

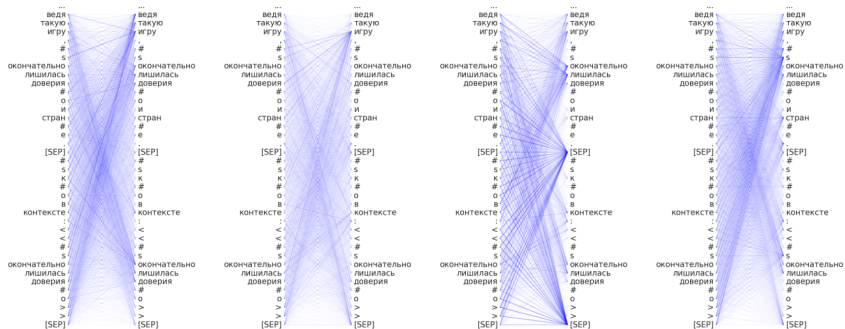


13 <https://raw.githubusercontent.com/nicolay-r/ARElight/main/data/texts-inosmi-rus/e1.txt>

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

SentRuBERT Attention weights analysis

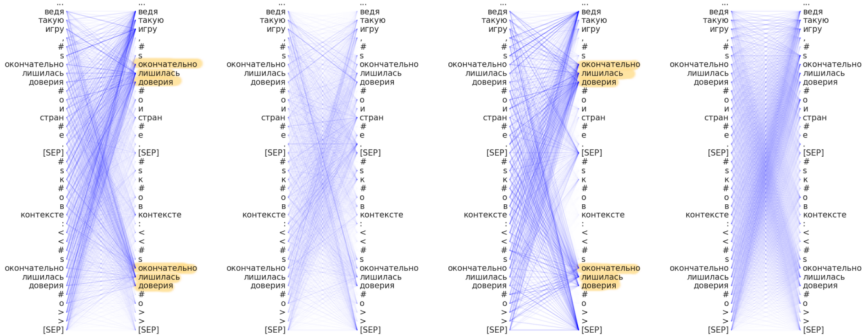
SentRuBERT (head 2, layers from left-to-right: 2, 4, 8, 11)¹⁵



15 ... 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)

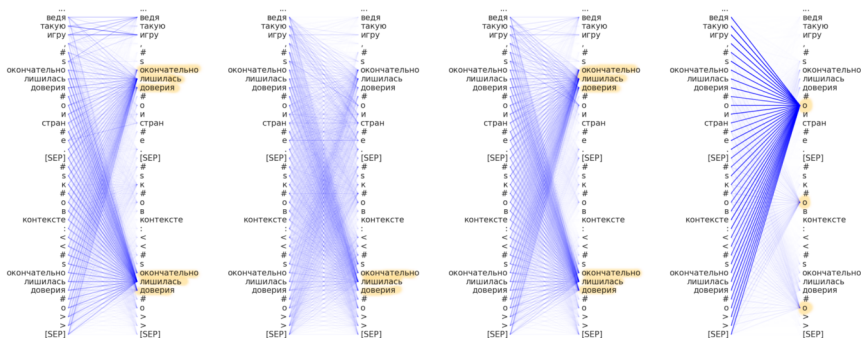
+ 4 epochs on RuAttitudes¹⁶



16 ... 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)

17 + 4 epochs for finetuning on RuSentRel



17 ... 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_subjs	syn_objs	entities	pos_tags
o0_io	0	0	<[> <[> <[> <[> при это subject неоднократно	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 неоднократно	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 неоднократно	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	<[> <[> <[> <[> 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,нато,россии	GPE,ORG,GPE	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	ва,россии	GPE,PERSON	2		2	0	4,0,4	15,12,14,11,15	

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 ие ие провел переговоры с лидерами стран ие ие в контексте	<< ие провел переговоры с лидерами стран ие ие >>	4	10	3	ва,нато,россии	GPE,PERSON,ORG,GPE,GPE,ORG	3,4,10,12,21,24
o0_io	0	0	024 марта президент ие ие провел переговоры с лидерами стран ие ие в контексте	<< ие провел переговоры с лидерами стран ие ие в контексте >>	4	24	3	ва,нато,россии	GPE,PERSON,ORG,GPE,GPE,ORG	3,4,10,12,21,24
o1_io	0	0	024 марта президент ие ие провел переговоры с лидерами стран ие ие в контексте	<< ие провел переговоры с лидерами стран ие ие в контексте >>	4	3	3	ва,нато,россии	GPE,PERSON,ORG,GPE,GPE,ORG	3,4,10,12,21,24
o2_io	0	0	024 марта президент ие ие провел переговоры с лидерами стран ие ие в контексте	<< ие провел переговоры с лидерами стран ие ие в контексте >>	4	21	3	ва,нато,россии	GPE,PERSON,ORG,GPE,GPE,ORG	3,4,10,12,21,24
o4_io	0	0	04е крайне зависе от ие ие в плане поставок нефти и газа.	ие ие в контексте << ие крайне зависе от ие ие >>	0	4	4	ва,нато,россии	ORG,GPE	0,4
o4_io	0	0	Потскау ие является важным узлом транзитероссии ие ие в контексте	<< ие является важным узлом транзитероссии ие ие в контексте >>	9	13	7	ва,нато,россии	ORG,GPE,GPE	1,9,13
o6_io	0	0	024 марта президент ие ие провел переговоры с лидерами стран ие ие в контексте	<< ие провел переговоры с лидерами стран ие ие в контексте >>	10	4	3	ва,нато,россии	GPE,PERSON,ORG,GPE,GPE,ORG	3,4,10,12,21,24
o6_io	0	0	024 марта президент ие ие провел переговоры с лидерами стран ие ие в контексте	<< ие провел переговоры с лидерами стран ие ие в контексте >>	24	4	3	ва,нато,россии	GPE,PERSON,ORG,GPE,GPE,ORG	3,4,10,12,21,24
o8_io	0	0	024 марта президент ие ие провел переговоры с лидерами стран ие ие в контексте	<< ие провел переговоры с лидерами стран ие ие в контексте >>	10	3	3	ва,нато,россии	GPE,PERSON,ORG,GPE,GPE,ORG	3,4,10,12,21,24
o8_io	0	0	024 марта президент ие ие провел переговоры с лидерами стран ие ие в контексте	<< ие в ие вылаз внимание рынка и предположения о т ие >>	10	21	3	ва,нато,россии	GPE,PERSON,ORG,GPE,GPE,ORG	3,4,10,12,21,24
o8_io	0	0	024 марта президент ие ие провел переговоры с лидерами стран ие ие в контексте	<< ие в ие вылаз внимание рынка и предположения о т ие >>	24	3	3	ва,нато,россии	GPE,PERSON,ORG,GPE,GPE,ORG	3,4,10,12,21,24
o12_io	0	0	После начала ие ие конфликта страны ие ие в контексте	<< ие одна за другой вводит ие ие в отношении ие ие >>	5	12	0	ва,россии	LOC,GPE	5,12
o13_io	0	0	08 в настоящее ие ие продолжается, и ие ие в контексте	<< ие ие >>	5	7	6	ва,россии,украине	GPE,GPE	5,7
o13_io	0	0	Потскау ие является важным узлом транзитероссии ие ие в контексте	<< ие является важным узлом транзитероссии ие ие в контексте >>	13	1	7	ва,нато,россии	ORG,GPE	1,9,13
o15_io	0	0	04е крайне зависе от ие ие в плане поставок нефти и газа.	ие ие в контексте << ие крайне зависе от ие ие >>	4	0	4	ва,нато,россии	ORG,GPE	0,4
o15_io	0	0	Потскау ие является важным узлом транзитероссии ие ие в контексте	<< ие является важным узлом транзитероссии ие ие в контексте >>	13	9	7	ва,нато,россии	ORG,GPE,GPE	1,9,13
o17_io	0	0	После начала ие ие конфликта страны ие ие в контексте	<< ие одна за другой вводит ие ие в отношении ие ие >>	12	5	0	ва,россии	LOC,GPE	5,12
o18_io	0	0	024 марта президент ие ие провел переговоры с лидерами стран ие ие в контексте	<< ие провел переговоры с лидерами стран ие ие в контексте >>	3	4	3	ва,нато,россии	GPE,PERSON,ORG,GPE,GPE,ORG	3,4,10,12,21,24
o18_io	0	0	024 марта президент ие ие провел переговоры с лидерами стран ие ие в контексте	<< ие провел переговоры с лидерами стран ие ие в контексте >>	21	4	3	ва,нато,россии	GPE,PERSON,ORG,GPE,GPE,ORG	3,4,10,12,21,24
o20_io	0	0	024 марта президент ие ие провел переговоры с лидерами стран ие ие в контексте	<< ие в ие вылаз внимание рынка и предположения о т ие >>	3	10	3	ва,нато,россии	GPE,PERSON,ORG,GPE,GPE,ORG	3,4,10,12,21,24
o20_io	0	0	024 марта президент ие ие провел переговоры с лидерами стран ие ие в контексте	<< ие в ие вылаз внимание рынка и предположения о т ие >>	3	24	3	ва,нато,россии	GPE,PERSON,ORG,GPE,GPE,ORG	3,4,10,12,21,24
o20_io	0	0	024 марта президент ие ие провел переговоры с лидерами стран ие ие в контексте	<< ие в ие вылаз внимание рынка и предположения о т ие >>	21	24	3	ва,нато,россии	GPE,PERSON,ORG,GPE,GPE,ORG	3,4,10,12,21,24
o24_io	0	0	08 в настоящее время конфликт между ие ие продолжается, и ие ие в контексте	<< ие ие >>	7	5	6	ва,россии,украине	GPE,GPE	5,7
o24_io	0	0	Потскау ие является важным узлом транзитероссии ие ие в контексте	<< ие является важным узлом транзитероссии ие ие в контексте >>	1	13	7	ва,нато,россии	ORG,GPE,GPE	1,9,13

Neutral Examples with Explanation¹⁸

Input

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.

¹⁸ Different way it treats the expression, however we convey the presence of positive attitude due to the «union»