Fake News Detection

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Problem Statement

Task Formalization

Input: text

All Skoltech students like writing reports	Lectures have online format
Fake → 0	True → 1

Steps

1. Methodology
2. Datasets
3. Data preprocessing. Metrics
4. Experiments
5. Results
6. Conclusion

Methodology

Transformers

[CLS] and [SEP]

Models Description

BERT(bert-base-uncased)	Bidirectional Encoder Representations from Transformers
BERT-Tiny(google/bertuncasedL-2H-128A-2)	BERT-Tiny is the smallest of several pre-trained language models that follow the same pre-training procedure as BERT.
RoBERTa(roberta-base)	RoBERTa is like BERT but removes the next-sentence prediction pre-training objective while making the masking procedure dynamic by regenerating the mask for example every time and leverage larger batch sizes and increased training iterations to improve performance.
ALBERT `(albert-large-v2)`	ALBERT adds an additional pre-training objective while incorporating two methods that reduce the number of parameters in the model, factoring the embedding layer and tying weights across hidden layers.
BERTweet `(vinai/bertweet-base)`	BERTweet follows an identical training procedure to RoBERTa, and is pre-trained on 850 million tweets.

Models Description

COVID-Twitter-BERT (covid-twitter-bert-v2)	COVID-Twitter-BERT follows an identical training procedure to BERT, and the latest version is pre-trained on 1.2 billion training examples generated from 97 million tweets.
DeCLUTR (declutr-base)	Transformer-based language model that proposes a contrastive, self-supervised method for learning general purpose sentence embeddings.
Funnel Transformer (funnel-transformer/small-base)	The Funnel Transformer improves the efficiency of bidirectional transformer models by applying a pooling operation after eachlayer, akin to convolutional neural networks,to reduce the length of the input.
ELMo	It uses bidirectional LSTMs to perform autoregressive language modelling in both the forward and backward directions
Longformer **(**allenai/longformer-base-4096)	The Longformer was introduced with an attention mechanism that scales linearly with sequence length, making it easy to process documents of thousands of tokens or longer.Longformer's attention mechanism is a drop-in replacement for the standard self-attention and combines a local windowed attention with a task motivated global attention.

Datasets

Datasets

FakeNews

1. 240 fake
2. 240 legit news

Celebrity

1. 250 fake
2. 250 legit news

ReCOVery

1. 2029 articles on coronavirus

FakeNewsNet

1. 187014 fake
2. 415645 legit news

NELA-GT-2018

1. 713534 articles

Data Preprocessing

500 symbols

We take only 500 symbols of each sample text.

many splits

➔ We split each article on pieces and get several samples corresponding to one piece of news.

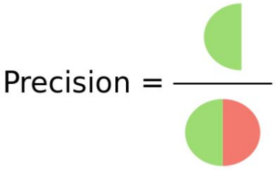
get the larger dataset

➔ During the test phase we use the majority vote strategy. If majority of fragments of the sample text is classified as legit, we treat this article as legit, and fake otherwise.

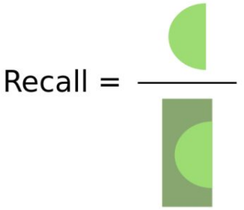
Metrics

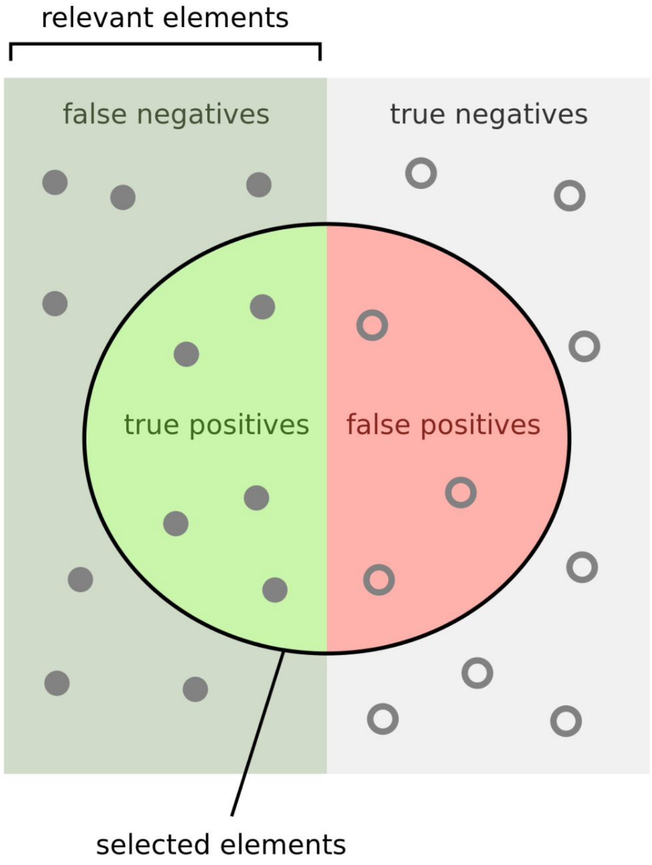
$$F_1 = 2 \cdot \frac{\text{precision} \cdot \text{recall}}{\text{precision} + \text{recall}}$$

$$\text{precision} = \frac{tp}{tp + fp}$$



$$\text{recall} = \frac{tp}{tp + fn}$$





Scores

General models 500 symbols

Model	F1	Precision	Recall
Bert	0.927	0.909	0.951
BERT-Tiny	0.870	0.863	0.884
RoBERTa	0.975	0.960	0.992
ALBERT	0.905	0.898	0.928
BERTWeet	0.949	0.935	0.964
COVID Twitter	0.966	0.949	0.986
DeCLUTR	0.966	0.961	0.974
Funnel Transf.	0.942	0.942	0.946

Recovery Dataset

*other dataset results – in the report

General models Large datasets

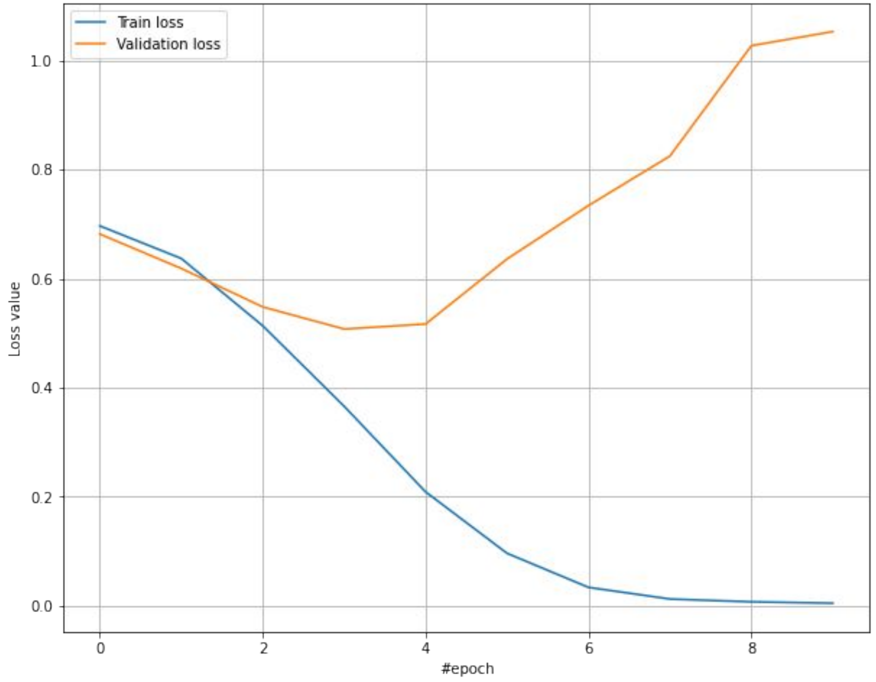
Scores

Model	F1	Recall	Precision
BERT-Tiny	0.894	0.904	0.796
BERTWeet	0.940	0.817	0.901
Funnel Transf.	0.917	0.823	0.823

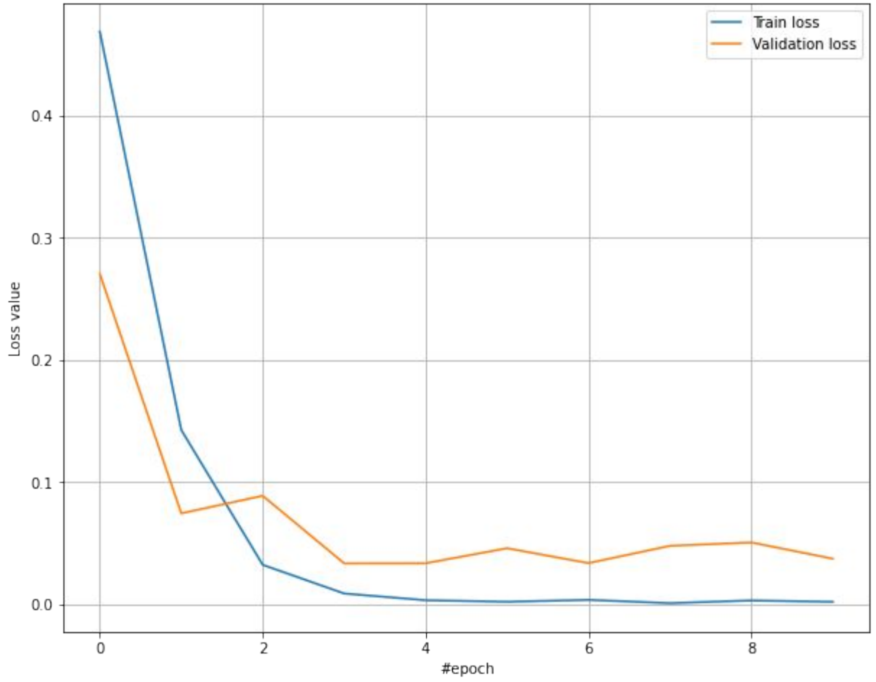
Many splits

Loss comparison

500 symbols



Many splits



General models Cross tests (500 symbols)

Scores

Model	F1	Recall	Precision
Bert	0.757	0.891	0.667
BERT-Tiny	0.766	0.921	0.620
RoBERTa	0.830	0.967	0.782
ALBERT	0.759	0.894	0.675
BERTWeet	0.811	0.890	0.745
COVID Twitter	0.818	0.962	0.718
DeCLUTR	0.827	0.976	0.722
Funnel Transf.	0.763	0.867	0.697

Recovery Dataset

*other dataset results - in the report

General models Cross tests (many splits)

Scores

Model	F1	Recall	Precision
Bert	0.756	0.784	0.784
BERT-Tiny	0.768	0.842	0.707
RoBERTa	0.831	0.967	0.728
ALBERT	0.712	0.703	0.737
BERTWeet	0.811	0.891	0.745
COVID Twitter	0.829	0.989	0.713
DeCLUTR	0.820	0.929	0.735
Funnel Transf.	0.779	0.808	0.751

Recovery Dataset

*other dataset results - in the report

Long Transformer

Scores

Transforms large sentences

F1	Recall	Precision
0.965	0.946	0.991

Recovery Dataset

*other dataset results – in the report

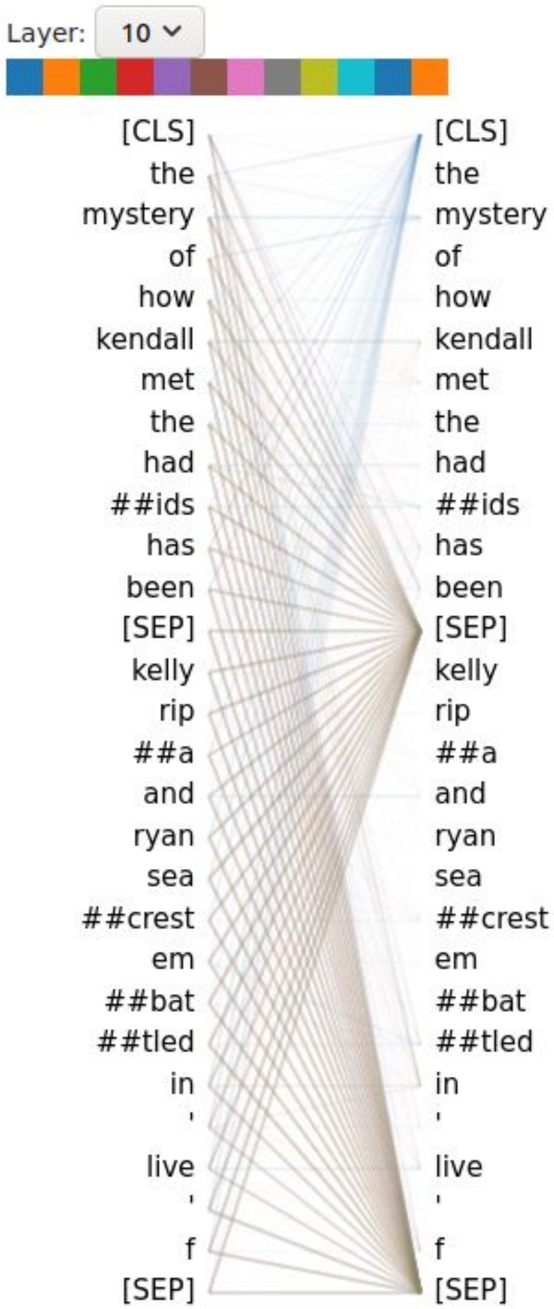
Elmo

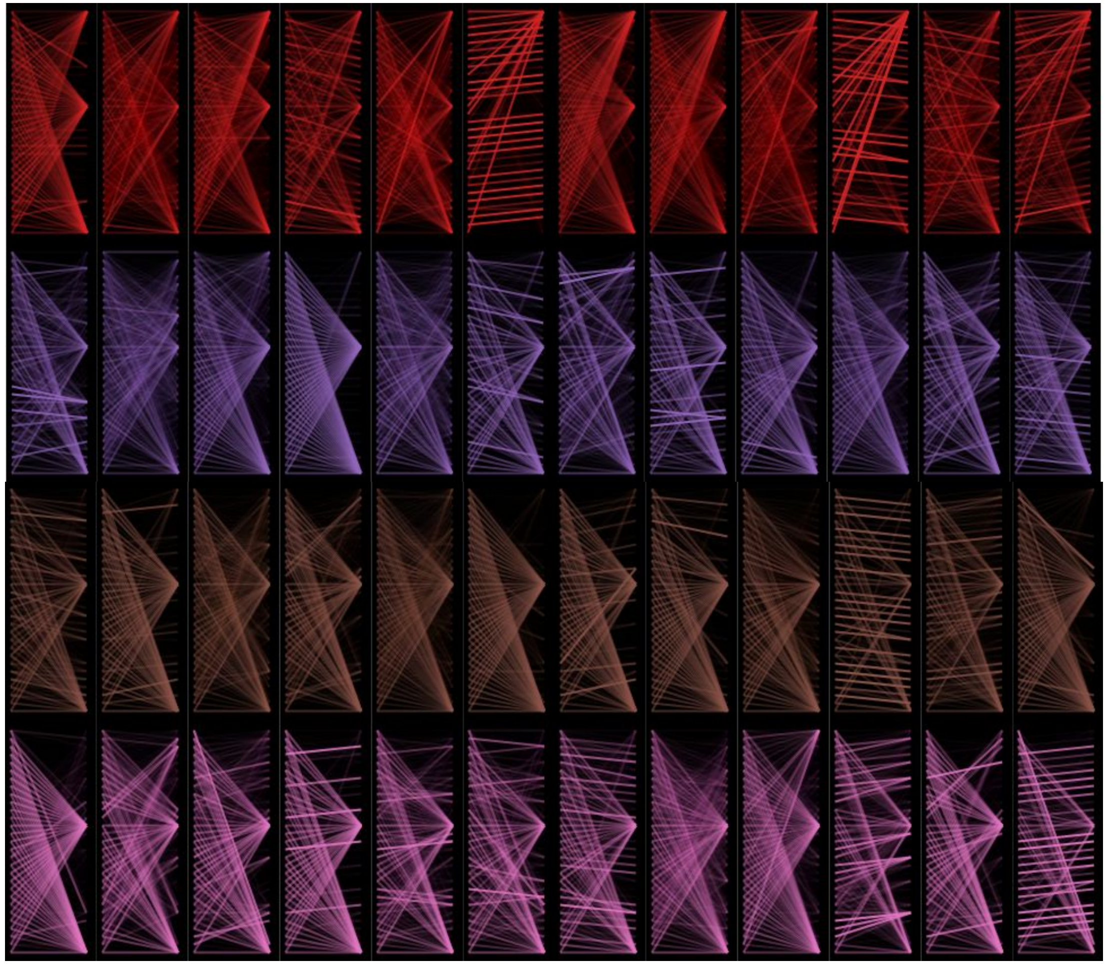
Scores

With vocabulary from Bert model

Dataset	Celebrity	FakeNews	Recovery
F1	1.0	1.0	1.0

Attention Visualization





Final conclusion

- Transformers are good for the task
- Many splits method is worth using
- ELMo is very powerful

Future work

- Test on larger batch sizes
- Use better hardware for large transformers
- Test other approaches for data preprocessing

Thank you for attention,
cause...
Attention is all we need!