BEYOND OUR CONTRADICTIONS

Feature augmentation in large language models for textual entailment detection.

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TEXTUAL ENTAILMENT

A huge part of the meaning of a text is not expressed explicitly, but added to the text by readers through inference.

Given 2 excerpts of texts, can the meaning of one be inferred from the other?

In Moria you will find the remains of a huge Roman aqueduct.



There is something special to see in the village of Moria.

LARGE LANGUAGE MODELS AND FEATURE AUGMENTATION

Large Language Models:

Large data scrapped on the internet

Several pre-trained attention layers + hundreds of millions of parameters



Sentence 2

sentence



Attention layers:

$$x_{n+1} = \operatorname{softmax}\left(\frac{Q^T K}{\sqrt{d}}\right) \cdot V$$

$$Q = \sigma(W^Q \cdot x_n)$$

$$K = \sigma(W^K \cdot x_n)$$

$$V = \sigma(W^V \cdot x_n)$$

Feature augmentation:

cosine similarity



Cosine similarity between:

- The gap

- The mean gap of each class

RESULTS Accuracy with BERT only: 0.60 **BERT** XGBoost classifier Sentences pairs cosine sim distiluse embeddings gap cosine sim paraphembeddings

gap

cosine sim

gap

mpnet BERT training time: 90min

MiniLM

paraph-

New features computation time + XGBoost: 2.3min

embeddings

Whole model accuracy: 0.63

→ +3% accuracy!

DISCUSSION

The classification accuracy remains surprisingly low, even after using different embedding models. have However, we achieved to show that adding our new features significantly increases performance, with additional negligible computation time.