# BERTScore

Marek Kadlčík, 485294

### Problem statement

Given: machine translation output and reference translation

**Compute**: reasonable similarity score between the two

(This problem appears also in automatic image captioning, generative question answering...)

# Reminder of existing solutions

- BLEU score
- word error rate
- precision and recall (or f1) of individual words
- METEOR

. . .

What makes a metric good?

- agreement with human judgement
- computational speed

# **BERTScore** algorithm

- 1. embeddings\_1 ← BERT(reference translation)
- 2. embeddings\_2 ~ BERT(machine-translated sentence)
- 3. C ← cosine similarity matrix, i.e.: C[i, j] = cos\_similarity(embeddings\_1[i], embeddings\_2[j])
- 4. recall  $\leftarrow$  take max in each row and compute average
- 5. precision  $\leftarrow$  take max in each column and compute average
- 6. return F1(recall, precision)

# Example

#### **Reference translation:**

The weather is cold today.

#### Machine translation:

It is freezing today.



recall = avg(0.713, 0.515, 0.858, 0.796, 0.913)
precision = avg(...)

(Authors also try a variant with word weighting - not all words are equally important)

## Properties

- not as fast as simple metrics (BERTScore requires evaluating BERT)
- has high agreement (~0.95 correlation) with human judgement

For detailed analysis of agreement with human judgement see the original paper, sections *Experimental setup* and *Results*.

# Implementations

Author's implementation (pytorch):

- github: <u>https://github.com/Tiiiger/bert\_score</u>
- pypi: <u>https://pypi.org/project/bert-score/</u>

Huggingface transformers:

<u>https://huggingface.co/metrics/bertscore</u>

# Sources

https://arxiv.org/pdf/1904.09675.pdf

https://jlibovicky.github.io/2019/05/01/MT-Weekly-BERTScore.html