What do you mean, BERT?

Assessing BERT as a Distributional Semantics Model

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Outline of this talk:

1. Motivation
2. Experiments conducted:
   2.1 Word-type cohesion
   2.2 Cross-sentence coherence
   2.3 Sentence-level structure
3. Recap

Introduction

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What is BERT

- BERT (Devlin et al., 2018) is a recent, successful model that uses a new architecture ('Transformer' of Vaswani et al., 2017).
  - has been shown to be widely useful: from QA to NLI to NER

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- BERT is an embedding model that produces **contextualized** word embeddings
  - it maps *tokens* to vectors, rather than *types* to vectors.

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  - has been shown to be widely useful: from QA to NLI to NER
- BERT is an embedding model that produces **contextualized** word embeddings
  - it maps *tokens* to vectors, rather than *types* to vectors.
- How to assess models such as BERT is an open topic
  - existing methods of analysis of Transformers have their limitations (Serrano and Smith, 2019; Hewitt and Liang, 2019)

Introduction

Embeddings and Distributional Semantics

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- Non-neural: LSA (Landauer and Dumais, 1997) transforms cooccurrence counts into vectors
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- Non-neural: LSA (Landauer and Dumais, 1997) transforms cooccurrence counts into vectors
- Neural: W2V (Mikolov et al., 2013) trains model to predict words according to their context of occurrence
- Testing, eg. on formal analogy (Mikolov, Yih, and Zweig, 2013): 74.0% on ‘semantic’ relations, 60.0% on ‘syntactic’ relations (Garten et al., 2015)

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BERT as Distributional Semantics

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Focus: **semantically similar words should lie in similar regions of the vector space.**

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- dataset: NLTK Gutenberg sample
- model: `BERT large uncased`
- input format: 2 running sentences of text per input

  no overlap between 1st and 2nd sentences

Word-Type Cohesion

Word-type cohesion

General Intuition

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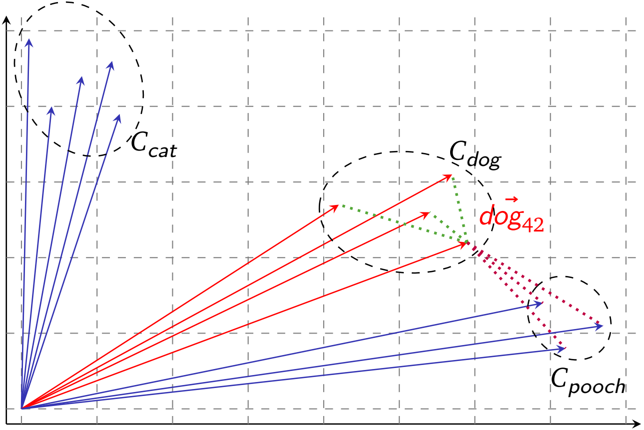
- so **types should describe coherent clusters of similar token embeddings**
- this can be assessed with silhouette scores (Rousseeuw, 1987)



Word-type cohesion

Experimental Setup

Formally, silhouette scores are defined as:

$$\mathit{separation}(\vec{v}, C_i) = \min\{\underset{\vec{v'} \in C_j}{\text{mean}}\ d(\vec{v}, \vec{v'})\ \forall\ C_j \in C - \{C_i\}\}$$

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Example values:

- If $\mathit{cohesion}(\vec{v}, C_i) = 1$ and $\mathit{separation}(\vec{v}, C_i) = 100$,
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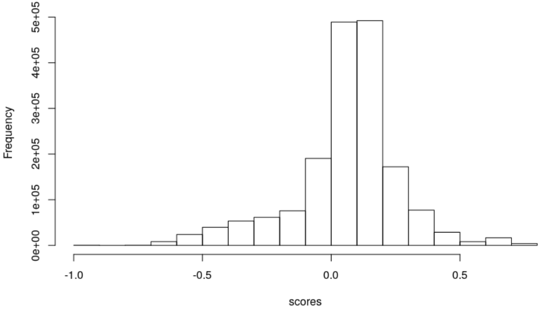

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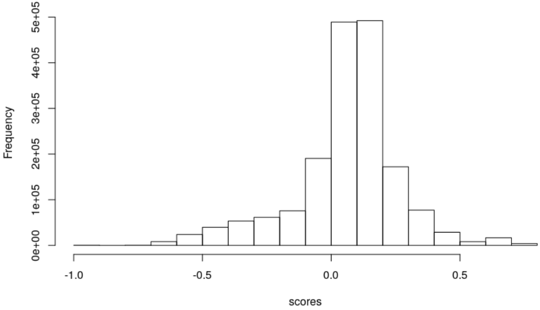

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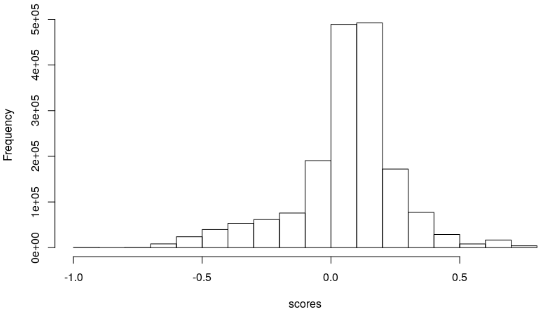

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- Significant difference between cohesion and separation scores $(p < 2 \cdot 2^{-16})$, but rather small effect size $(d = -0.121)$.

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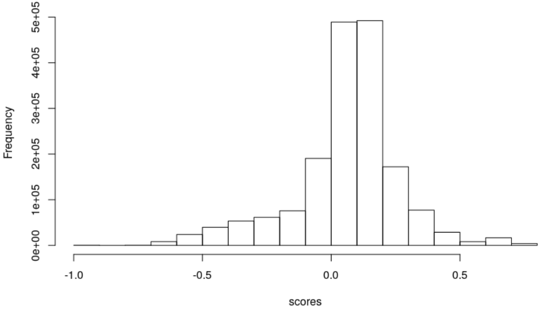

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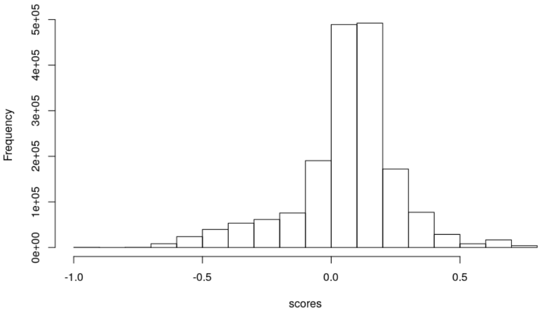

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- Consistently, monosemous word types yield higher silhouette scores than polysemous word types ($d = 0.236$)
- Centroids for word types are consistent with human similarity judgment (MEN (Bruni, Tran, and Baroni, 2014): $\rho = 0.705$)

Word-type cohesion
Recap

Overall, word-types are coherently described

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- The vector space seems consistent with lexical semantics

Word-type cohesion

Recap

Overall, word-types are coherently described

- The vector space seems consistent with lexical semantics
- Some details are not entirely satisfactory

Cross-Sentence Coherence

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General Intuition

- BERT embeddings for tokens are largely semantically cohesive.

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- **Does BERT encode non-semantic information?**

Cross-Sentence Coherence

General Intuition

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- **Does BERT encode non-semantic information?**
- For example, BERT architecture suggests that **segment** information could also be encoded.

Cross-Sentence Coherence

Formal Approach: BERT input format

BERT is a Transformer, trained on the "next sentence prediction" objective (viz. '*does the 2^{nd} sentence of the input follow the 1^{st}?*')

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4. 2 special tokens: `[SEP]` for sentence boundaries, `[CLS]` for performing the actual prediction

Cross-Sentence Coherence

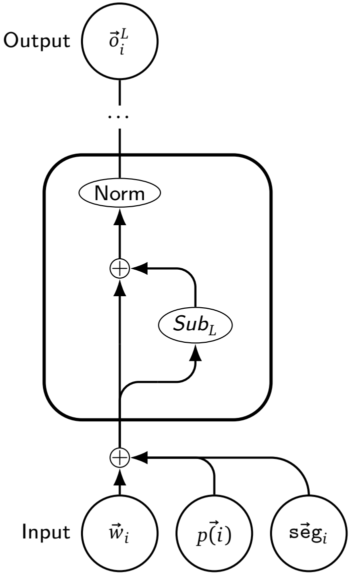
Formal Approach: BERT input format illustrated

Given the example "*My dog barks. It is a pooch.*", the actual input would be:

$$
\begin{aligned}
\vec{\texttt{[CLS]}} + p(\vec{0}) + \vec{\texttt{seg}}_A, &\quad \vec{My} + p(\vec{1}) + \vec{\texttt{seg}}_A, \\
\vec{dog} + p(\vec{2}) + \vec{\texttt{seg}}_A, &\quad \vec{barks} + p(\vec{3}) + \vec{\texttt{seg}}_A, \\
\vec{.} + p(\vec{4}) + \vec{\texttt{seg}}_A, &\quad \vec{\texttt{[SEP]}} + p(\vec{5}) + \vec{\texttt{seg}}_A, \\
\vec{It} + p(\vec{6}) + \vec{\texttt{seg}}_B, &\quad \vec{is} + p(\vec{7}) + \vec{\texttt{seg}}_B, \\
\vec{a} + p(\vec{8}) + \vec{\texttt{seg}}_B, &\quad \vec{pooch} + p(\vec{9}) + \vec{\texttt{seg}}_B, \\
\vec{.} + p(\vec{10}) + \vec{\texttt{seg}}_B, &\quad \vec{\texttt{[SEP]}} + p(\vec{11}) + \vec{\texttt{seg}}_B
\end{aligned}
$$

Cross-Sentence Coherence

Formal Approach: BERT architecture



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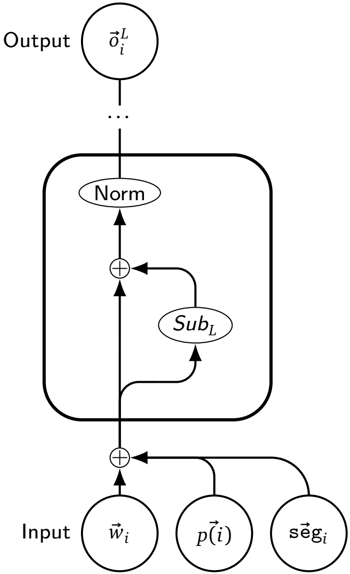

- Let $\vec{i}_i = \vec{w}_i + p(\vec{i})$. The output of the first sublayer of a Transformer (given the input sequence) is:

$$\begin{aligned}
\vec{o}_i^1 &= Norm(Sub_1(\vec{i}_i + \vec{seg}_i) + \vec{i}_i + \vec{seg}_i) \\
&= \vec{b}_l + \vec{g}^1 \odot \frac{1}{\sigma_i^1} Sub_1(\vec{i}_i + \vec{seg}_i) + \vec{g}^1 \odot \frac{1}{\sigma_i^1} \vec{i}_i \\
&\quad - \vec{g}^1 \odot \frac{1}{\sigma_i^1} \mu(Sub_1(\vec{i}_i + \vec{seg}_i) + \vec{i}_i + \vec{seg}_i) \\
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&= \tilde{\vec{o}}_i^1 + \vec{g}^1 \odot \frac{1}{\sigma_i^1} \vec{seg}_i
\end{aligned}$$

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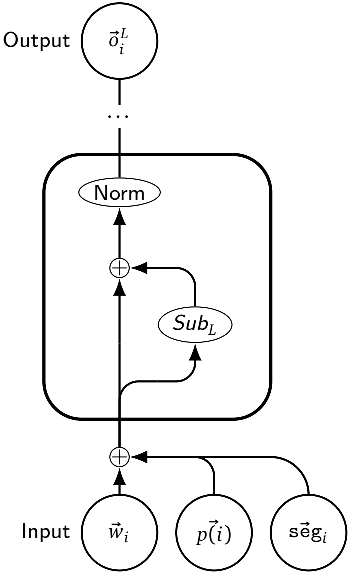

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&\quad + \vec{g}^1 \odot \frac{1}{\sigma_i^1} \vec{\text{seg}}_i \\
&= \vec{\tilde{o}}_i^1 + \vec{g}^1 \odot \frac{1}{\sigma_i^1} \vec{\text{seg}}_i
\end{aligned}$$

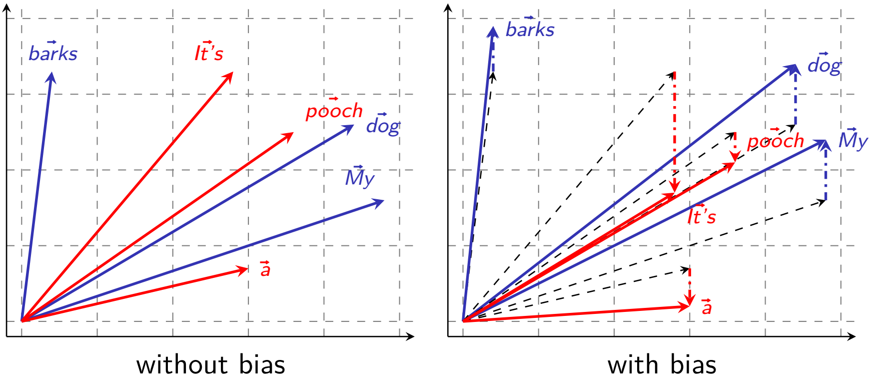
- By recurrence, we get that the final output contains a 'sentence bias':

$$\vec{o}_i^L = \vec{\tilde{o}}_i^L + \left(\bigodot_{l=1}^{L} \vec{g}^l \right) \odot \left(\prod_{l=1}^{L} \frac{1}{\sigma_i^l} \right) \times \vec{\text{seg}}_i$$

Cross-Sentence Coherence

Visualisation

- Each embedding is shifted by a scaled segment encoding



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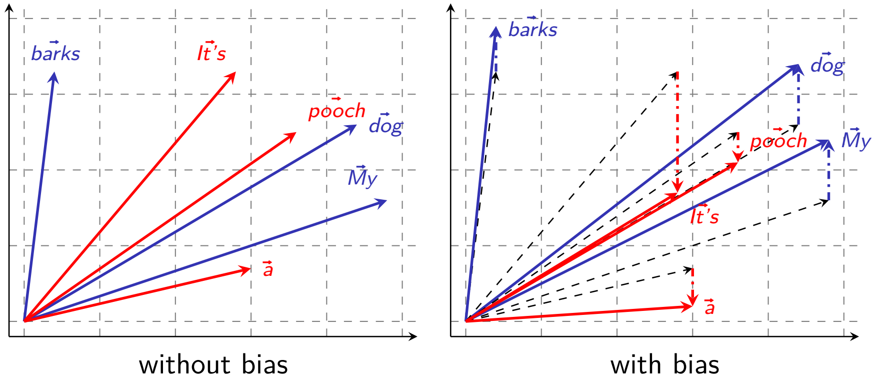

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Cross-Sentence Coherence

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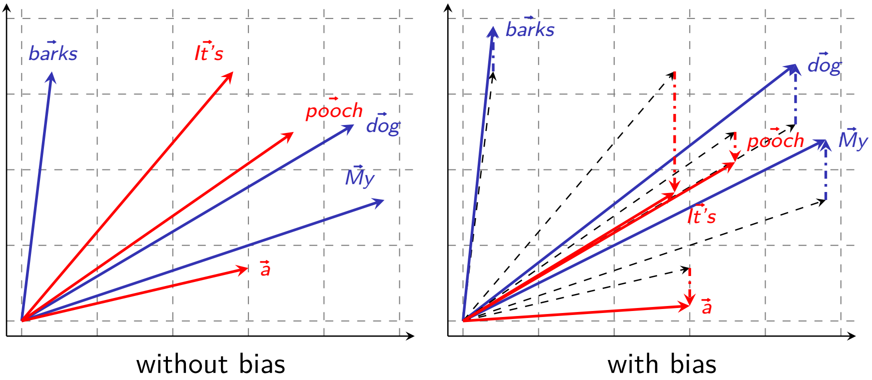

- The bias *may* alter the global characteristics of the embedding space
- **Is this bias noticeable?**

Cross-Sentence Coherence

Experimental Setup

- For a given word type w, we constitute two groups:
  1. $w_{\mathtt{seg}_A}$, the set of tokens for this type w belonging to 1st sentences in the inputs
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$$\mathrm{MSE}(E, \vec{\mu}) = \frac{1}{\#E} \sum_{\vec{v} \in E} \sum_{d} (\vec{v}_d - \vec{\mu}_d)^2$$

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- MSE measures how much observations $\vec{v} \in E$ deviate from the mean value $\vec{\mu}$

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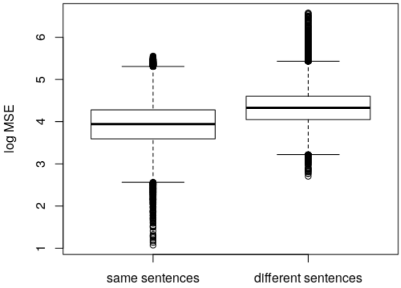
- Null hypothesis: segment shift is negligible.
- If so, $w_{\mathtt{seg}_A}$ and $w_{\mathtt{seg}_B}$ contain equivalent embeddings,
- If so, $\forall \vec{w} \in w_{\mathtt{seg}_i}, \quad \mathrm{MSE}(\{\vec{w}\}, \overline{w_{\mathtt{seg}_i}}) \approx \mathrm{MSE}(\{\vec{w}\}, \overline{w_{\mathtt{seg}_j}})$.

Cross-Sentence Coherence

Results



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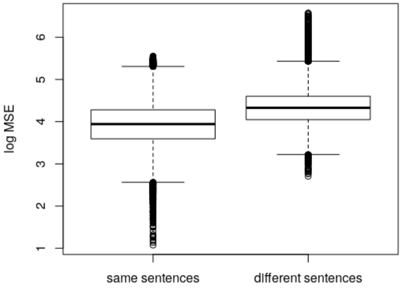

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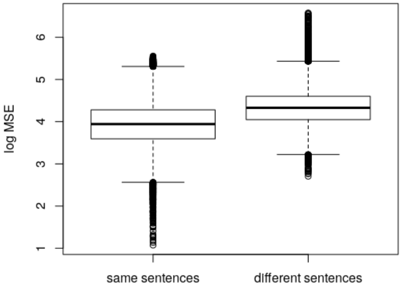

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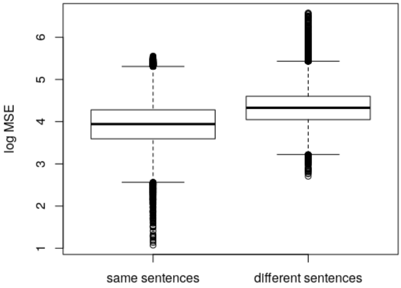

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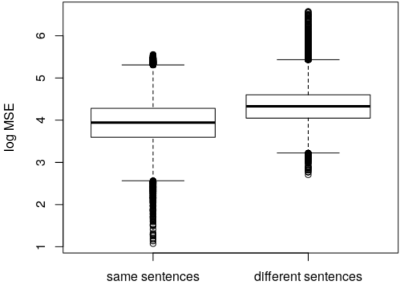

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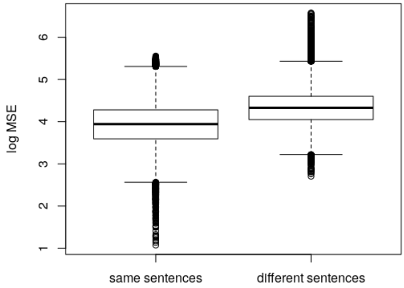

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Frequency plays a role, though it's not the only factor

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Recap

- BERT's architecture encodes a segment based shift, or 'sentence bias'

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- **This bias is statistically significant and noticeable**

Cross-Sentence Coherence

Recap

- BERT's architecture encodes a segment based shift, or 'sentence bias'
- **This bias is statistically significant and noticeable**
- BERT embeddings encode at least segment information in addition to semantic information

Sentence-Level Structure

Does the segment bias affect the similarity structure of the embedding space?

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General Intuition

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- Semantic similarity scores in 1st and 2nd sentences should be equivalent

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  Cosines for any two words in the sentence "I walk my dog." should be more or less equal to cosines for any two words in the sentence "It is a pooch."

- We shouldn't be able to tell whether some score s corresponds to embeddings drawn from a 1st or a 2nd sentence

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- We compute pairwise cosine for each sentence S:

$$C_S = \{\cos(\vec{v}, \vec{u}) \mid \vec{v} \neq \vec{u} \ \wedge \ \vec{v}, \vec{u} \in S\}$$

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$$C_S = \{\cos(\vec{v}, \vec{u}) \mid \vec{v} \neq \vec{u} \ \wedge \ \vec{v}, \vec{u} \in S\}$$

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Sentence-Level Structure

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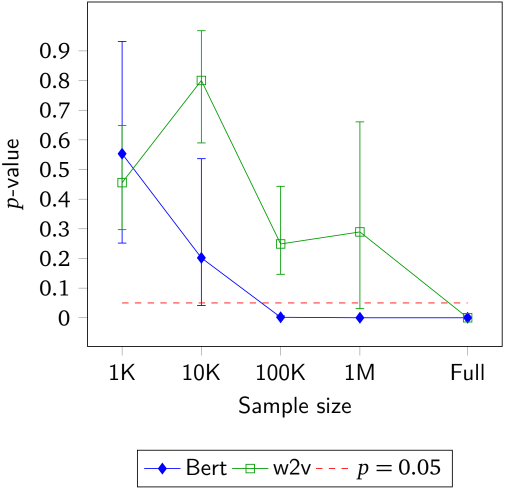
- We also report a W2V baseline

Sentence-Level Structure

Results



Sentence-Level Structure

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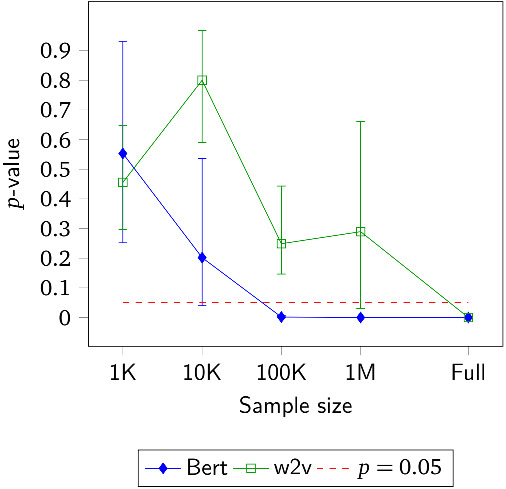

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Sentence-Level Structure

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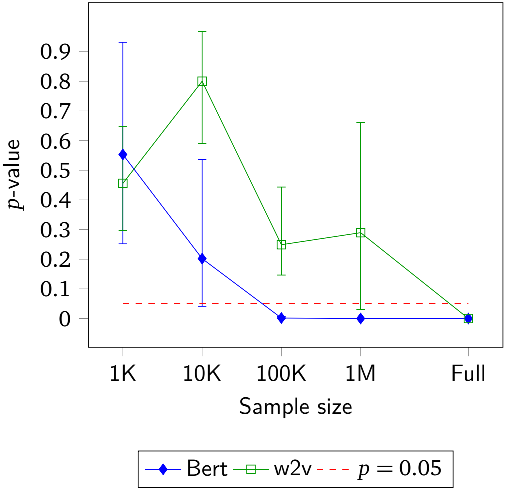

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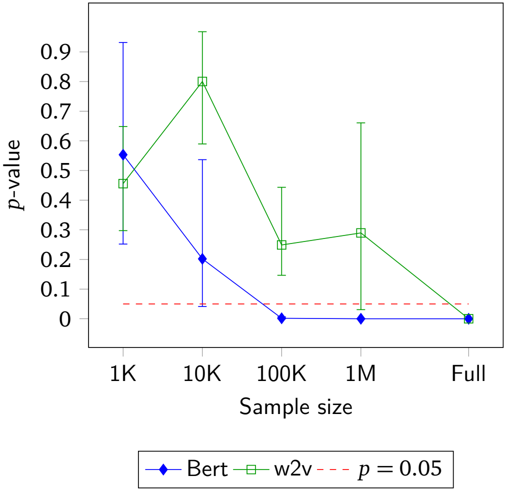

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- p-values for BERT random samples are more often significant
- The effect can't be blamed only on the dataset.

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Recap

There is a difference of semantic similarity between 1st and 2nd sentences.

- On average, similarities of tokens within 1st sentences are greater than similarities of tokens within 2nd sentences.

- This difference cannot be semantic because odd vs. even numbers of segments are essentially arbitrary

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- In future work:
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  2. focus on other potential non-semantic factors (eg. positional encodings)

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