Graded Similarity in Context

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1 Introduction

In his *Foundations of Arithmetic*, Frege promises "never to ask for the meaning of a word in isolation, but only in the context of a proposition" (1980, p. xvii). This 'context principle' is intuitive: words are frequently polysemous, or assume different connotations and emphasis within different expressions. Historically, however, contextuality has been a problem for distributional meaning representations. Founded on the distributional hypothesis (Harris 1954; Firth 1957), both count-based and predictive models of word meaning[1] originally produced a single representation for each word in the model's vocabulary. One of these *static* representations must, therefore, encode all of a word's senses and connotations, which precludes its use in modelling context-dependent phenomena.

Prior to the widespread availability of pre-trained word embeddings (e.g., Mikolov et al. 2013; Pennington et al. 2014), this problem was generally addressed by one of two approaches: firstly, by producing a representation for each sense of a target word and disambiguating between them in the given context; or secondly, by composing the representation of the target word with the representations of the words in its context. These approaches have been largely overshadowed by the advent of model architectures that take sequences as inputs and naturally produce *contextual* representations of the items in the sequence, such as transformers (Vaswani et al. 2017).

To my knowledge, however, there has been scant direct comparison of the performance of these contextual representations with the application of prior methods of contextualisation to static representations. SemEval-2020 Task 3, *Graded Word Similarity in Context* (Armendariz, Purver, Pollak, et al. 2020), presents an opportunity to make such a comparison. Briefly, the task is to predict the change in the human judgment of similarity between the same pair of words in two different contexts. This objective is both context-dependent and continuous, i.e., not limited to discrete word-sense disambiguation. I elected to focus on the first subtask, which is to predict the *change* in similarity, rather than the similarity in each context. Specifically, I compared the results of computing the similarity between both kinds of representation of the target words and their composition with the representations of the words in a fixed-size context window, inspired by Kintsch (2001) and Mitchell and Lapata (2008).

2 Task definition

The CoSimLex dataset (Armendariz, Purver, Ulčar, et al. 2020), which served to evaluate the task submissions, extends the SimLex-999 dataset (Hill et al. 2015) to include multiple contexts for each pair of words.

3 Related work

4 Methodology

5 Results

6 Conclusion

- Language-specific models perform better on their target language(s).
- A small context window improves the outcomes for both static and contextualised embeddings.

[1] This terminological distinction is due to Baroni et al. (2014).

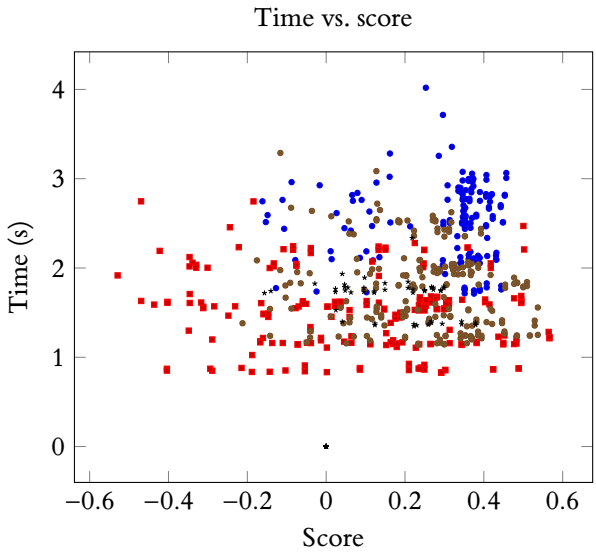

Figure 1: The elapsed time for each static-embedding model against its score.

Model	Window size	Operation	Score
bert-large-cased-whole-word-masking	20	mean	0.457
bert-large-uncased-whole-word-masking	20	sum	0.453
bert-large-uncased-whole-word-masking	20	mean	0.453
bert-base-multilingual-cased	20	sum	0.448
bert-base-multilingual-cased	20	mean	0.448

Figure 2: The top five results in English with static embeddings.

Model	Window size	Operation	Score
EMBEDDIA/crosloengual-bert	20	sum	0.567
TurkuNLP/bert-base-finnish-uncased-v1	0	none	0.564
TurkuNLP/bert-large-finnish-cased-v1	2	prod	0.502
TurkuNLP/bert-large-finnish-cased-v1	0	none	0.500
bert-large-uncased-whole-word-masking	50	mean	0.495

Figure 3: The top five results in Finnish with static embeddings.

Model	Window size	Operation	Score
classla/bcms-bertic	20	sum	0.537
EMBEDDIA/crosloengual-bert	20	sum	0.529
EMBEDDIA/crosloengual-bert	20	mean	0.529
classla/bcms-bertic	5	sum	0.517
classla/bcms-bertic	5	mean	0.517

Figure 4: The top five results in Croatian with static embeddings.

Model	Window size	Operation	Score
EMBEDDIA/crosloengual-bert	10	sum	0.379
EMBEDDIA/crosloengual-bert	1	mean	0.344
EMBEDDIA/crosloengual-bert	1	sum	0.344
bert-base-multilingual-cased	10	sum	0.299
bert-base-multilingual-cased	10	mean	0.299

Figure 5: The top five results in Slovakian with static embeddings.

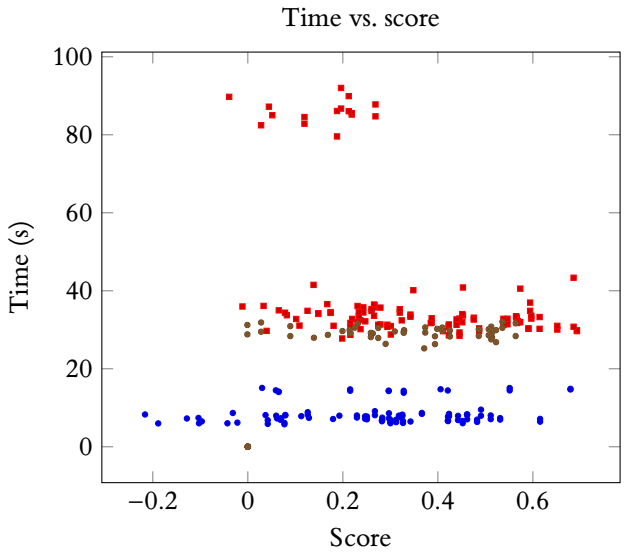

Figure 6: The elapsed time for each contextual-embedding model against its score.

- The contextualised embeddings outperform the static embeddings.
- However, the static embeddings are much quicker to compute.

References

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