

Graded word similarity in context by composing static and contextual embeddings

Tim Lawson

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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 meaning¹ 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 may obstruct its use in modelling context-dependent phenomena.

Prior to the widespread availability of pre-trained word embeddings (e.g., Mikolov, Chen, et al. 2013; Pennington et al. 2014) and their successors, 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 (*word-sense disambiguation*); or secondly, by composing the representation of the target word with the representations of the words in its context (*contextualisation*). 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 human judgment of similarity of the same pair of words in two different contexts (Section 2). I elected to focus on the first subtask, which is to predict the *change* in similarity, rather than the absolute similarity in each context. Specifically, I evaluated the results obtained by computing the cosine similarity between static and contextual embeddings and the composition of these embeddings within a fixed-size context window.

2 Task definition

The first subtask of SemEval-2020 Task 3 is to predict the direction and magnitude of the change in the human judgment of similarity of the same pair of target words in two different contexts. The task is unsupervised: the submissions were evaluated on the CoSimLex dataset (Armendariz, Purver, Ulčar, et al. 2020, pp. 39–42) but only a minimal ‘practice kit’ of fewer than ten instances was provided in advance. CoSimLex is an extension of SimLex-999 (Hill et al. 2015) that consists of pairs of target words and their contexts in four languages: English ($n = 340$), Finnish ($n = 24$), Croatian ($n = 112$), and Slovene ($n = 111$).

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

The score for the first subtask was computed by the uncentered (zero-mean) Pearson correlation coefficient between the predicted changes in similarity and the human judgments represented in the CoSimLex dataset (Armendariz, Purver, Ulčar, et al. 2020, p. 42). This metric is equivalent to the cosine similarity between the two vectors of results:

$$\text{score}(\vec{y}, \vec{y}) = \frac{\sum_{i=1}^n \hat{y}_i y_i}{(\sum_{i=1}^n \hat{y}_i^2) (\sum_{i=1}^n y_i^2)} = \frac{\vec{y} \cdot \vec{y}}{\|\vec{y}\| \|\vec{y}\|} \quad (1)$$

A consequence of this choice of evaluation metric is that composing representations by addition or the arithmetic mean produces the same results; hence, I elected to only evaluate addition between them.

3 Related work

Many context-based approaches to word-sense disambiguation have been proposed since the advent of count-based models of word meaning. In Landauer and Dumais (1997)’s introduction of Latent Semantic Analysis (LSA), the authors argued that taking the average of the high-dimensional representation of a word with those of its immediate context may be sufficient to determine the word’s contextual meaning (ibid., pp. 229–230). The contextualisation of representations of word meanings is intimately related to their composition to form representations of phrase and sentence meanings. This connection is evident in Kintsch (2001), who proposed a procedure to modify the vector of a predicate according to the argument in its context, and the adaptation by Mitchell and Lapata (2008) of Kintsch’s evaluation methodology to alternative composition operations. Vector addition and averaging continue to be ‘surprisingly effective’ means to compose word embeddings (Boleda 2020, p. 10), and addition produces plausible results for the word-analogy task (e.g. Mikolov, Sutskever, et al. 2013).

Nevertheless, models that produce contextual embeddings have achieved widespread success on benchmarks that involve language understanding. As Arora et al. (2020) point out, this comes at a significant computational cost, and static embeddings may be sufficient for many tasks. Furthermore, Gupta et al. (2019) and Bommasani et al. (2020) have shown that static embeddings can be obtained from contextual-embedding models, which outperform the embeddings of static models while retaining their computational advantages.

4 Methodology

Originally, it would not have been possible to optimise a parameterised model for the task except by reference to a separate dataset; therefore, I chose to focus on the application of pre-trained static and contextual embeddings. The basic procedure of the methods that I evaluated is as follows. For each pair of target words and each of the two contexts in which they appear, I obtained a contextualised representation of a target word by: finding the index of the target word’s first sub-word token within the tokens of the target word’s context; finding the tokens within a fixed-size window around the target word’s first token; obtaining the embeddings of the tokens in the window; and combining the the embeddings to produce a single representation of the target word.

In all cases, the tokenization was performed by and the embeddings were obtained from pre-trained models available via the HuggingFace *Transformers* library (Wolf et al. 2020). The models that I evaluated for each language are given in Table ?? . For the static-embedding variants of the procedure, I used the models’ input embeddings; for the contextual-embedding variants, I used the models’ outputs. Several of the submissions to SemEval–2020 Task 3 used a combination of the weights of a Transformer model’s hidden states (e.g., Gamallo 2020, p. 276; Pessutto et al. 2020, p. 3; Hettiarachchi and Ranasinghe 2021, p. 4); a thorough comparison of the performance of variants of this approach is beyond the scope of this paper.

Notably, the use of a sub-word vocabulary by these models (e.g., Devlin et al. 2019, p. 4174) dictates that a target word may be represented by a different number of tokens in each context. As a

...from the Isenj. He accepts their offer but knows that ...

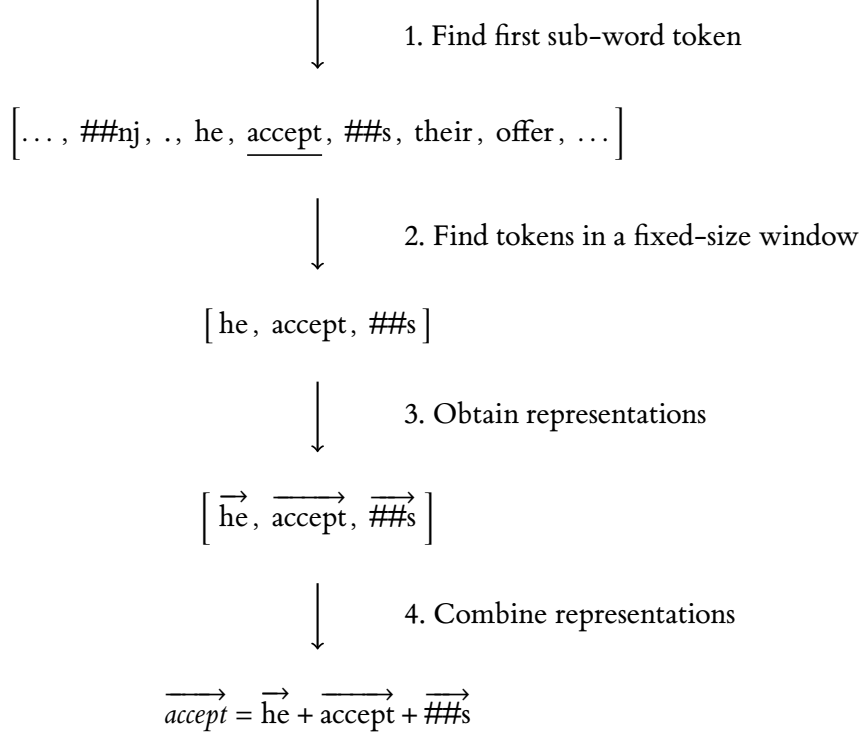


Figure 1: A schematic of the procedure used to obtain a contextualised representation of a target word from pre-trained static or contextual embeddings. In this example, the target word is “accept”, the window size is one (either side of the target word), and the composition operation is addition.

Model name	English	Finnish	Croatian	Slovene
bert-base-multilingual-cased	✓	✓	✓	✓
bert-base-multilingual-uncased	✓	✓	✓	✓
EMBEDIA/crosloungual-bert ¹	✓	✓	✓	✓
bert-base-cased	✓			
bert-base-uncased	✓			
bert-large-cased	✓			
bert-large-uncased	✓			
bert-large-cased-whole-word-masking	✓			
bert-large-uncased-whole-word-masking	✓			
classla-bcms-bertic ²			✓	
TurkuNLP/bert-base-finnish-cased-v1 ³		✓		
TurkuNLP/bert-base-finnish-uncased-v1 ³		✓		
TurkuNLP/bert-large-finnish-cased-v1 ³		✓		

Figure 2: The pre-trained models available via the HuggingFace *Transformers* library (Wolf et al. 2020) that I chose to evaluate for each language. The corresponding references are ¹Ulčar and Robnik-Šikonja (2020), ²Ljubešić and Lauc (2021), ³Virtanen et al. (2019), and Devlin et al. (2019) otherwise.

result, the representations of a pair of target words may be different in each context, even if they are static and the window size is zero. This is the cause of the non-zero scores obtained by models of this kind (Section 8.2), particularly for the Finnish language.

Inspired by Landauer and Dumais (1997), Kintsch (2001), and Mitchell and Lapata (2008), I predominantly investigated the application of element-wise addition and multiplication as composition operations. However, preliminary experiments indicated that multiplication performed poorly across all languages, models, and window sizes; hence, it was discarded before the final analysis. Additionally, I chose to evaluate the concatenation (‘stacking’) of embeddings. In the case that the number of embeddings was fewer than the context-window size, i.e., the target word was close to the beginning or the end of its context, I right-padded the concatenated embedding with zeros to obtain contextual embeddings of equal length.

5 Results

5.1 Cost-benefit analysis of contextual embeddings

5.2 Language-specificity of window-size effects

Generally, I found that the scores obtained by both static- and contextual-embedding models were maximised by a non-zero context-window size. Due to the computational expense of exhaustively searching the possible window sizes, I applied a heuristic to constrain the search space. A naïve estimation of the average number of words in each context, i.e., segmenting on whitespace, gave a result of between 40 and 60 for the different languages. Therefore, for the static-embedding models, I chose 50 as an upper bound on the window size. The motivation to choose a smaller maximum window size for contextual-embedding models was similarly economical (Section 5.1); however, as the window size approaches the length of the sequence, one would expect a combination of token representations to be superseded by the sequence-level representation of the model, e.g., the special CLS token of BERT variants (Devlin et al. 2019, p. 4174). These heuristics were largely vindicated by the results of the evaluation, which demonstrated that the scores decrease as the window size approaches the maximum.

The influence of the window size is intuitive in the case of static embeddings. Without a context window, the representations of a target word only differ between expressions if the word is represented by different sub-word tokens in the different expressions. A similar argument applies to contextual embeddings, in that a target word may be represented by multiple sub-word tokens. The window sizes that maximise the score for each language and model are given in Table ??.

6 Discussion

Batchkarov et al. (2016) critically analyse word similarity as an evaluation methodology for distributional semantic models. In particular, the notion of ‘similarity’ manifested by these models encompasses a broad range of semantic relations (e.g., Padó and Lapata 2003, p. 2), with the consequence that performance on an intrinsic word-similarity task does not necessarily translate to extrinsic downstream tasks (Batchkarov et al. 2016, pp. 7–8). Moreover, inter-annotator agreement is generally poor for word-similarity tasks in comparison to more specific downstream tasks (ibid., pp. 8–9).

7 Conclusion

In this paper, I have presented the results of a hypothetical submission to SemEval-2020 Task 3, “Graded Word Similarity in Context”. The purpose of this evaluation was to compare the performance of static and contextual embeddings and their composition within a fixed-size context window on the task of predicting the change in the human judgment of similarity of a pair of words in two different

contexts. I found that contextual embeddings generally outperformed static embeddings, but at a significant computational cost, and that composition benefited both static and contextual embeddings of sub-word tokens, with highly language-specific dependence on the window size.

The results that I have given must be interpreted in context: the original submission authors did not have access to the evaluation dataset prior to submitting their results, only the ‘practice kit’ of very few instances, and were therefore unable to optimise a parameter such as the window size prior to submission. Additionally, the models that I used were not necessarily available to the authors. With these caveats, I achieved several notable results:

- The contextual embeddings of `EMBEDDIA/croslengual-bert` with a window size of three would have placed second among the Croatian submissions (0.708).
- The contextual embeddings of `TurkuNLP/bert-base-finnish-uncased-v1` with a window size of zero would have placed fourth among the Finnish submissions (0.679).
- The *static* embeddings of `TurkuNLP/bert-base-finnish-uncased-v1` with a window size of zero outperform several of the Finnish submissions, including the baseline (0.564).

Given the significant expense of applying contextual-embedding models, these results highlight the importance of analysing the complexity of the task at hand and considering the possibility that a simpler model produces adequate results.

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8 Appendix

8.1 Cost-benefit analysis of contextual embeddings

8.2 Language-specificity of window-size effects

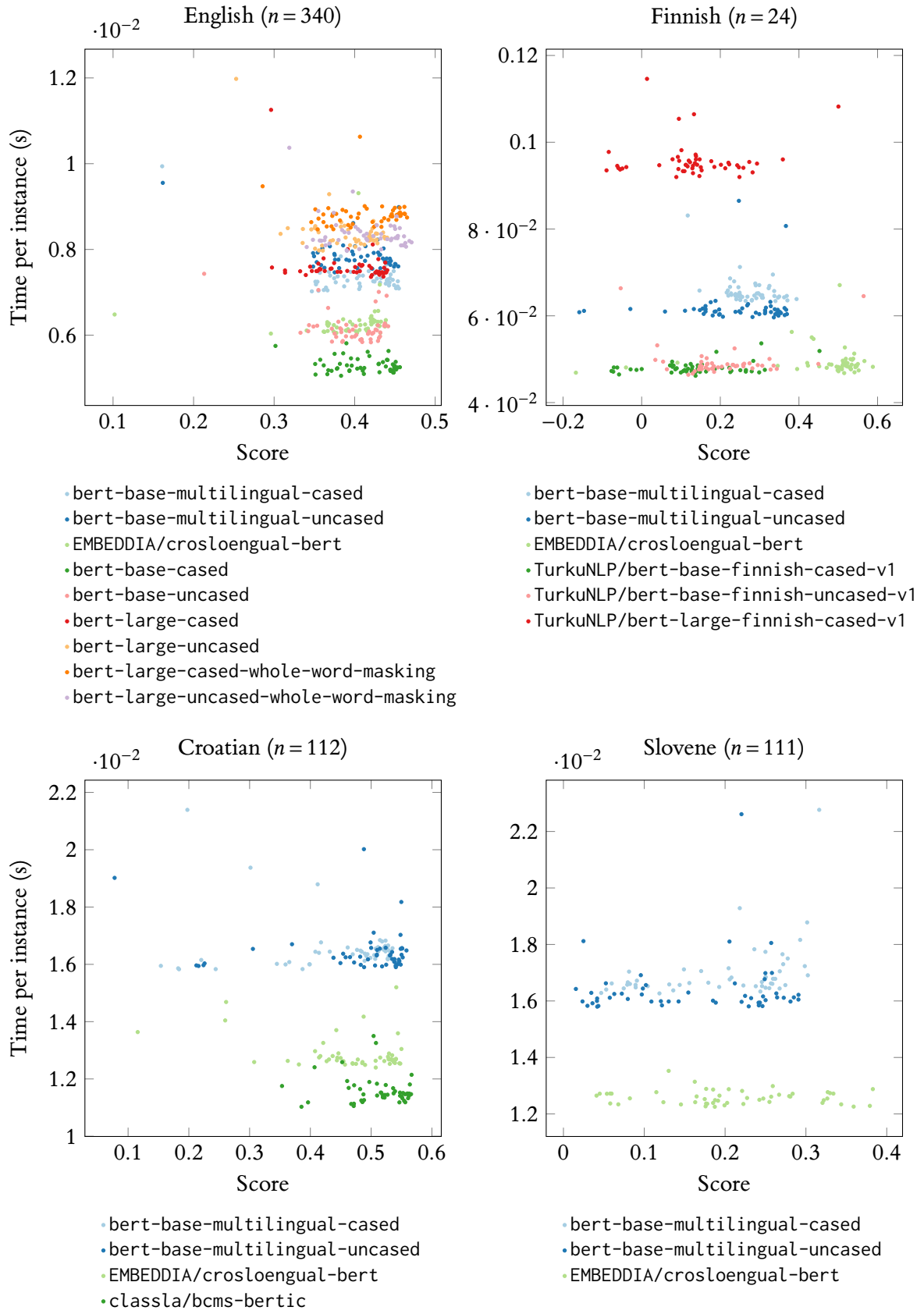


Figure 3: The time per target word pair against score for static-embedding models with the additive composition operation.

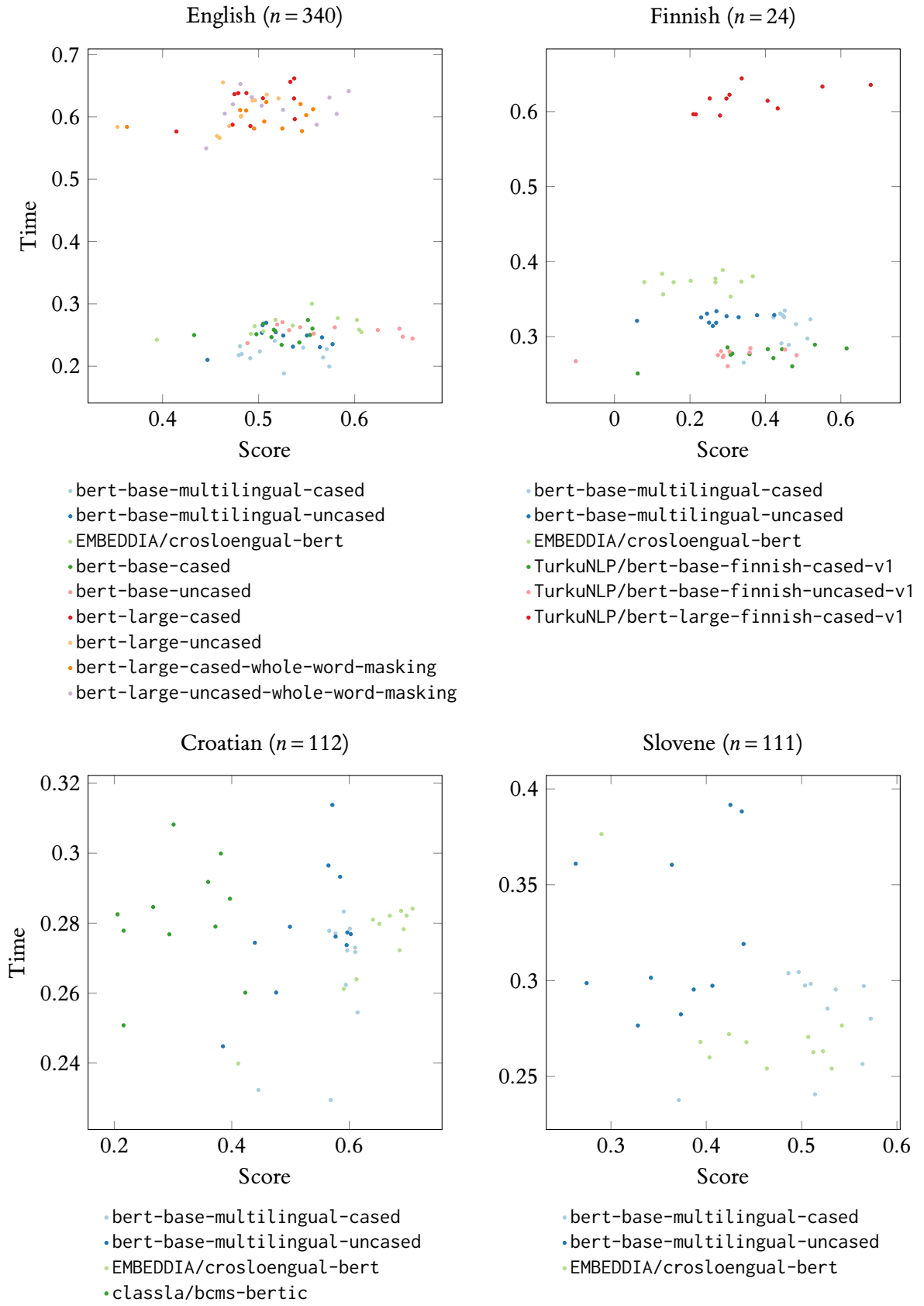


Figure 4: The time per target word pair against score for contextual-embedding models with the additive composition operation.

Model name	Window size	Score
EMBDDIA/crosloengual-bert	17	0.439
bert-base-cased	18	0.456
bert-base-multilingual-cased	18	0.455
bert-base-multilingual-uncased	19	0.455
bert-base-uncased	14	0.442
bert-large-cased	18	0.441
bert-large-cased-whole-word-masking	18	0.465
bert-large-uncased	16	0.440
bert-large-uncased-whole-word-masking	16	<u>0.471</u>

(a) English

Model name	Window size	Score
EMBDDIA/crosloengual-bert	21	<u>0.588</u>
TurkuNLP/bert-base-finnish-cased-v1	0	0.452
TurkuNLP/bert-base-finnish-uncased-v1	0	0.564
TurkuNLP/bert-large-finnish-cased-v1	0	0.500
bert-base-multilingual-cased	3	0.394
bert-base-multilingual-uncased	29	0.369

(b) Finnish

Model name	Window size	Score
EMBDDIA/crosloengual-bert	31	0.550
bert-base-multilingual-cased	32	0.535
bert-base-multilingual-uncased	31	0.558
classla/bcms-bertic	31	<u>0.567</u>

(c) Croatian

Model name	Window size	Score
EMBDDIA/crosloengual-bert	11	<u>0.383</u>
bert-base-multilingual-cased	8	0.316
bert-base-multilingual-uncased	10	0.291

(d) Slovene

Figure 5: The window size that maximises the score for static-embedding models with the additive composition operation. The best score for each language is underlined.

Model name	Window size	Score
EMBDDIA/crosloengual-bert	3	0.607
bert-base-cased	1	0.556
bert-base-multilingual-cased	1	0.574
bert-base-multilingual-uncased	3	0.577
bert-base-uncased	1	<u>0.660</u>
bert-large-cased	3	0.538
bert-large-cased-whole-word-masking	2	0.557
bert-large-uncased	1	0.521
bert-large-uncased-whole-word-masking	1	0.594

(a) English

Model name	Window size	Score
EMBDDIA/crosloengual-bert	10	0.366
TurkuNLP/bert-base-finnish-cased-v1	1	0.615
TurkuNLP/bert-base-finnish-uncased-v1	1	0.483
TurkuNLP/bert-large-finnish-cased-v1	1	<u>0.679</u>
bert-base-multilingual-cased	3	<u>0.519</u>
bert-base-multilingual-uncased	2	0.423

(b) Finnish

Model name	Window size	Score
EMBDDIA/crosloengual-bert	3	<u>0.708</u>
bert-base-multilingual-cased	5	0.614
bert-base-multilingual-uncased	6	0.603
classla/bcms-bertic	10	0.423

(c) Croatian

Model name	Window size	Score
EMBDDIA/crosloengual-bert	3	0.542
bert-base-multilingual-cased	3	<u>0.572</u>
bert-base-multilingual-uncased	9	0.439

(d) Slovene

Figure 6: The window size that maximises the score for contextual-embedding models with the additive composition operation. The best score for each language is underlined.

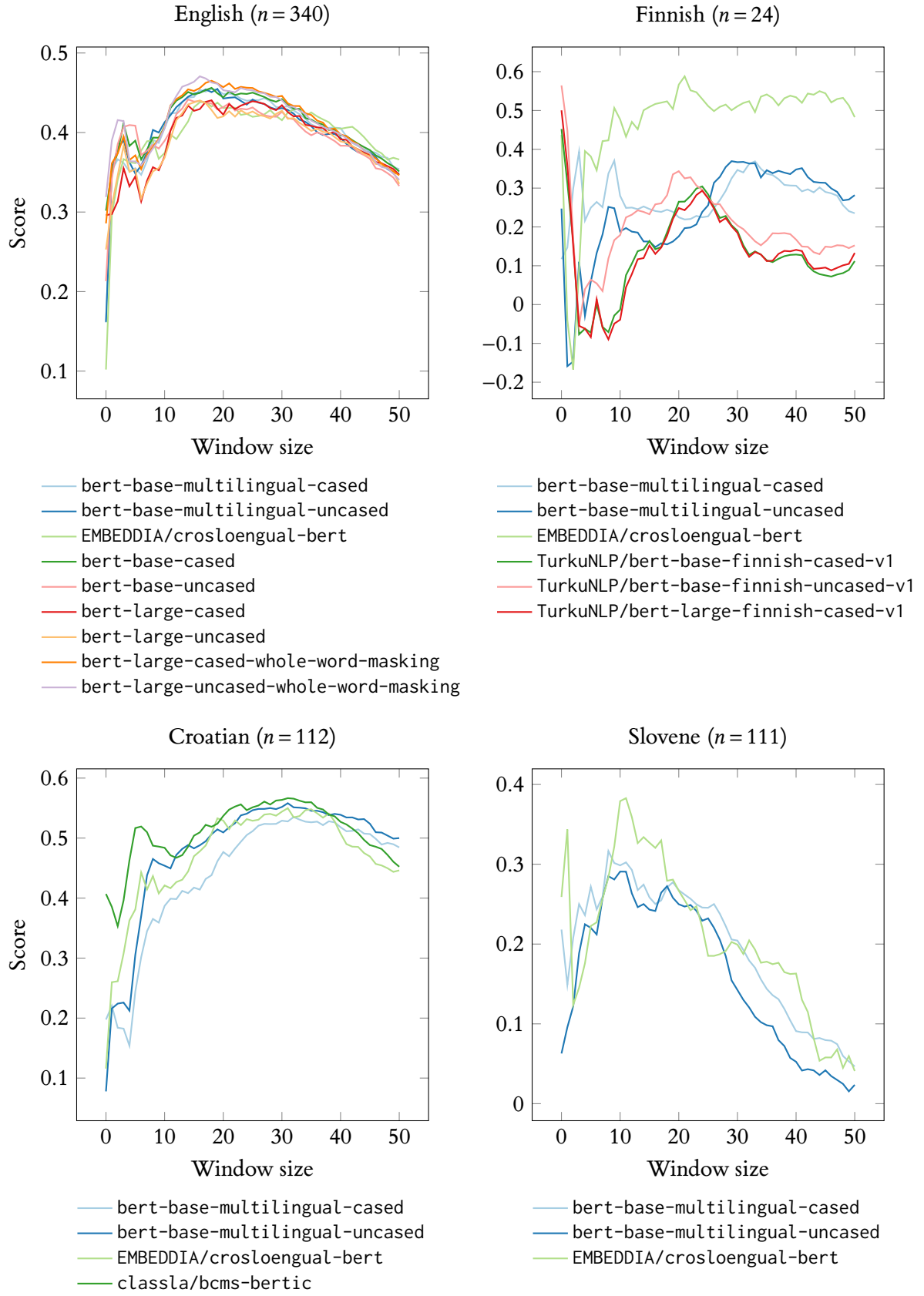


Figure 7: The score against window size for static-embedding models with the additive composition operation.

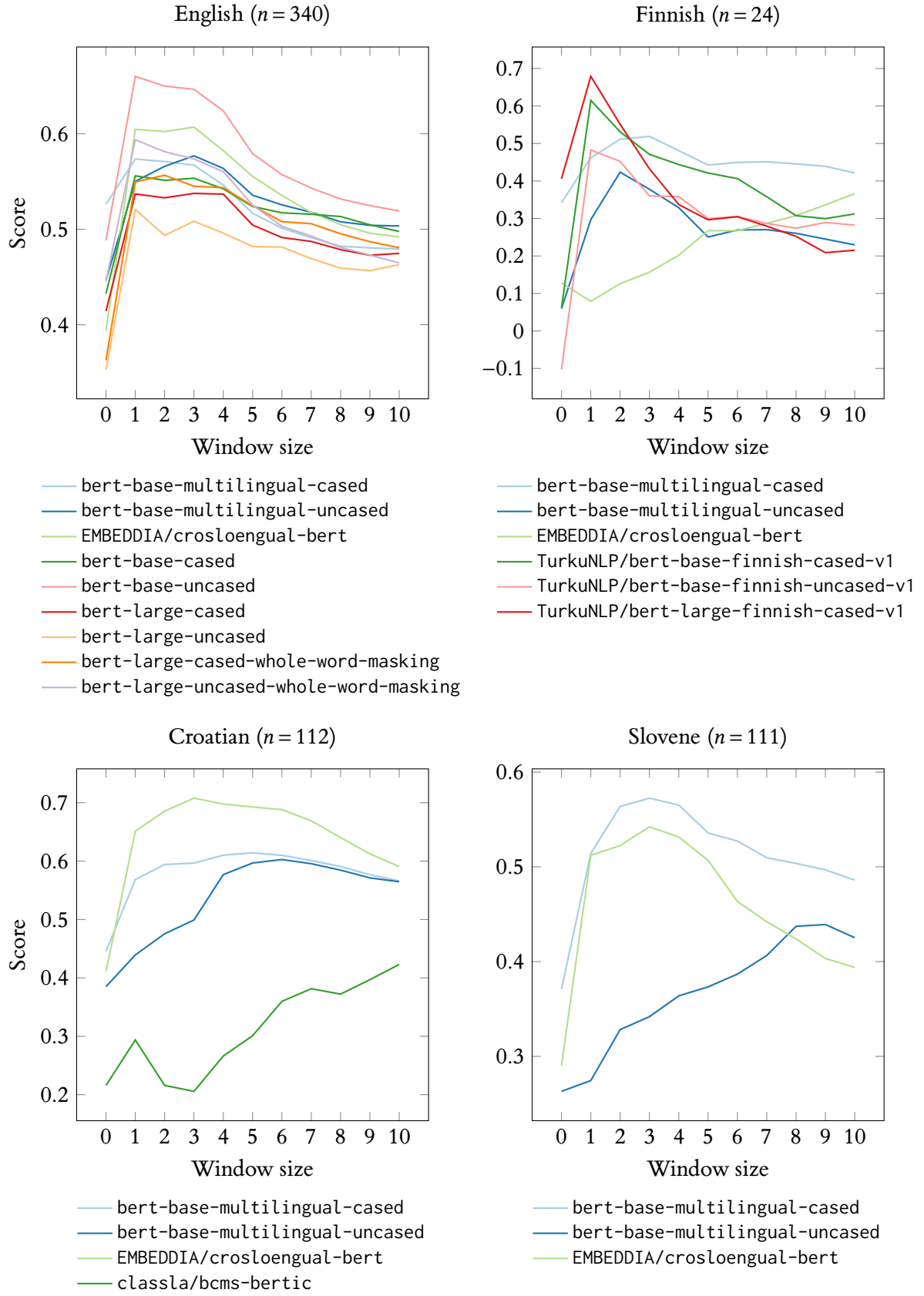


Figure 8: The score against window size for contextual-embedding models with the additive composition operation.