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Time-Aware SentenceBert to analyse discourse dynamics

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Extended Abstract

Content analysis often involves comparing texts over time to study discourse dynamics [4]. In our study, we aim to assess the similarity of narratives represented in texts, establish links between time and narratives, and train a model capable of understanding time relations. These efforts are crucial for gaining insights into discourse dynamics and studying how language use evolves because they allow us to understand how language use changes over time and how various factors influence it. By comparing texts, we can identify patterns in language use and track how certain narratives evolve. One of the ways to do that is by using text encoding methods to compare many text pieces. Embeddings are one of the most newest ways to make text encoding into a numeric representation of its sense. Word embeddings have proven valid; however, they may only partially satisfy our goal of performing sentence or text-level comparisons, as with other BoW-based methods. Nevertheless, some promising efforts have been made to develop time-aware word embeddings, allowing the comparison of meanings over time:
1. TWEC [1] - Temporal Word Embeddings with a Compass - a new heuristic for training temporal word embeddings based on word2vec, using atemporal vectors as a reference. Experimental results demonstrate that this approach surpasses or equals other methods and exhibits greater robustness with respect to corpus size. However, this method has disadvantages, mainly the need to train a separate model for each period we want to compare.
2. DCWE [3] - Dynamic contextualized word embeddings, which represent words as a function of both linguistic and extralinguistic context. These embeddings jointly model time and social space using a pretrained language model. However, this method is limited due to its computational resource needs.
We address these limitations by proposing a new method for time-aware similarity detection. Our method is based on the well-known transformer-model BERT [2], and its variant working on sentences called SentenceBert [6]. Although the main task of this model is paraphrase detection, it generally estimates the similarity between any two input sequences, which we can convert into tokens using BERT tokenizer [7]. We prepare a dataset with pairs of sentences and labels to train it, indicating whether the two sentences have the same content. We propose a more elegant solution using a relatively compact model to distinguish between messages on different days instead of scale-inefficient TWEC and DCWE. The proposed solution relies on appropriately preparing the dataset using our algorithm for labelling input data and establishing the semantic relationship between texts and corresponding dates. Our approach draws inspiration from the word2vec model, based on analyzing word co-occurrences in sentences. The model deems words in close proximity as semantically related and vice versa, thereby obviating the need for explicit labelling [5]. We introduce a way to encode relations in the text-text, date-text, and date-date pairs, allowing us to train the model to understand the relation between text and time entities. We give more details of our approach to encode input on the Figure 1. The approach assigns higher values to similar word pairs and lower values to dissimilar ones, aiding the model in understanding similar narratives and temporal relationships. We also train

the model to comprehend the relationship between dates and text by assigning one to matching pairs and zero to non-matching ones. This strategy enhances the model's ability to make sense of the text's context and temporal references. Usually, the training of the proposed model would entail a vast collection of labelled pairs of sentences, denoting their content similarity. However, our new labelling approach allows us to bypass manual labelling. To illustrate the effectiveness of this approach, we conducted a case study involving the analysis of news articles sourced from Russian pro-government online media.

Using a multilanguage pretrained model [7], we trained an embedding model on a dataset to generate a 768-dimensional vector representing the semantic position of text or date within the Russian pro-government media. Our dataset contained 567 840 pairs of text-text, date-text, and date-date. It allowed us to train a model to reveal substantive similarities and relate them to the temporal context. Using these vectors, we can measure the cosine similarity between texts and dates and thus say which semantic narratives (represented as complete sentences) in the Russian media are close and for which dates these narratives are more typical.

The analysis suggests synchronicity in Russian propaganda media's anti-Western and anti-Ukrainian rhetoric, with a significant increase in such narratives observed since 2014. It could be interpreted as Russia's informational preparation for a confrontation with NATO, as well as a new round of aggression against Ukraine. The aggregated results are presented in Figure 2, depicting the general trend derived from the analysis of 20 anti-Ukraine and anti-West statements. Our method overperforms other methods because this model can be applied to more periods without model enlargement. Also, it allows us to compare even big text entities and applies to other types of text and languages.

References

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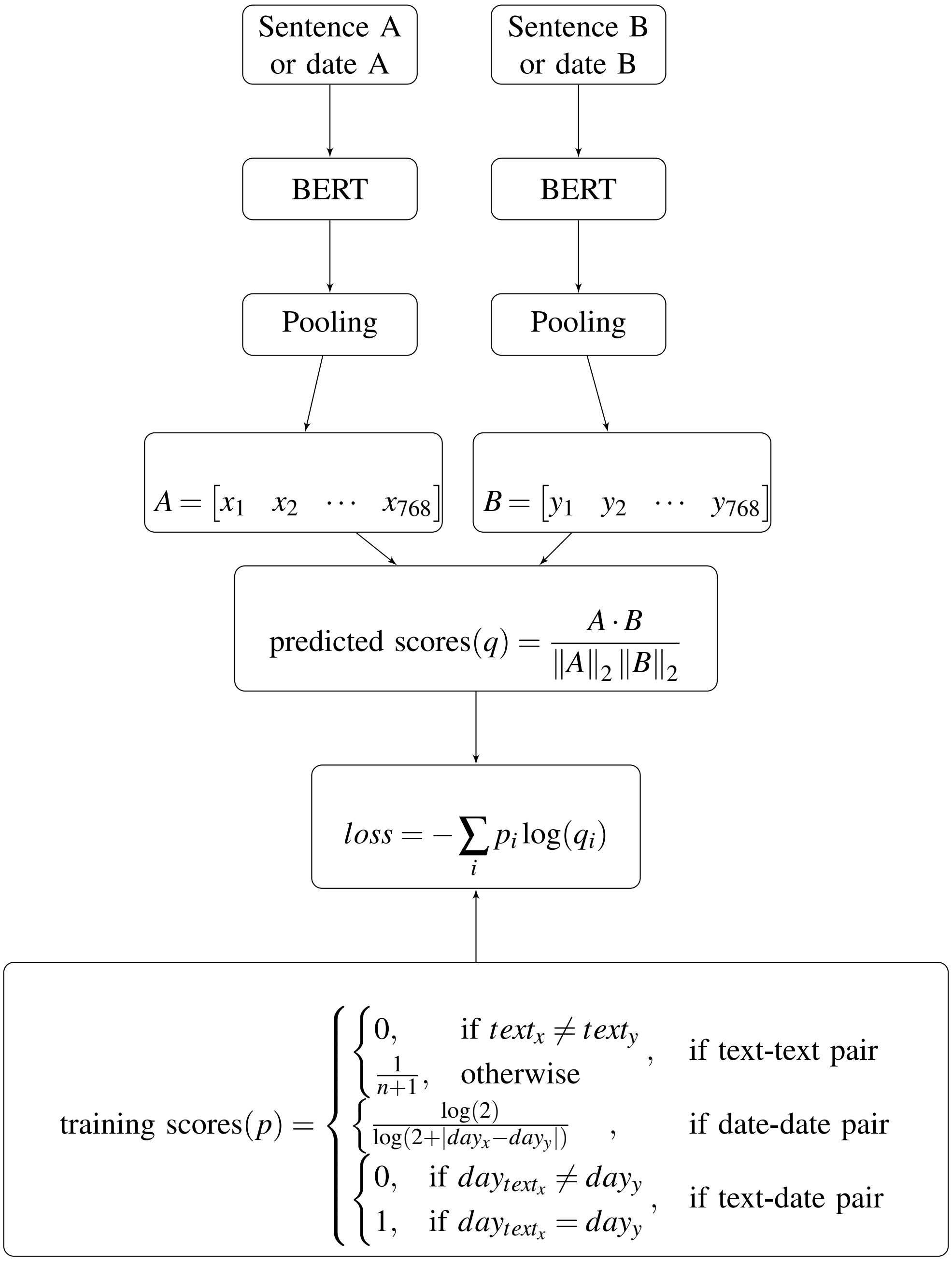

Note: $text_x$ and $text_y$ are the two sentences being compared, and n is the number of other sentences between them in the same news piece.

Figure 1: Modified Sentence-BERT

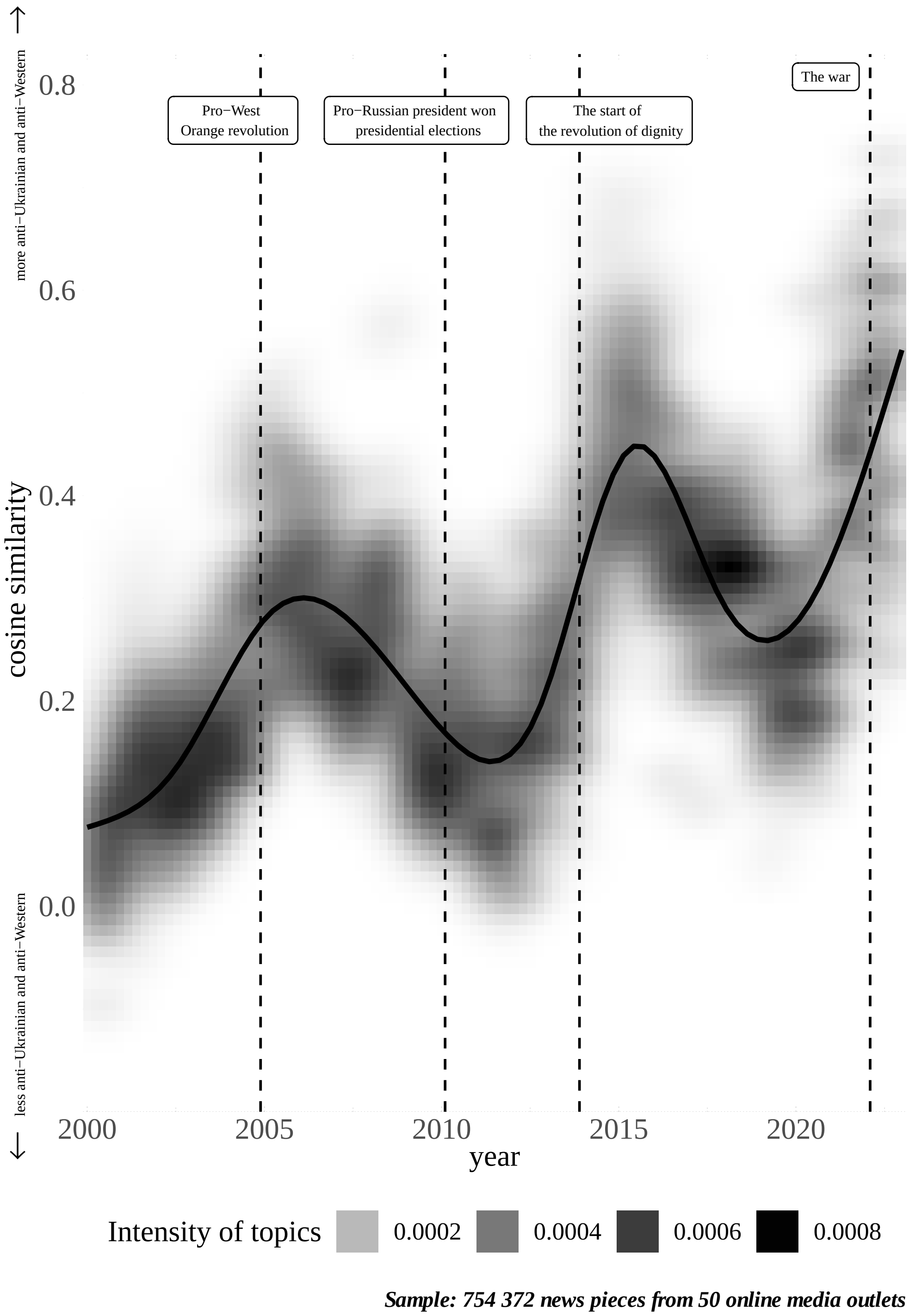

Figure 2: Dependence between the sample of anti-Ukrainian and anti-Western narratives in the sample of Russian pro-government online media