Evaluating Multilingual Sentence Representation Models in a Real Case Scenario

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Abstract

In this paper, we present an evaluation of sentence representation models on the paraphrase detection task. The evaluation is designed to simulate a real-world problem of plagiarism and is based on one of the most important cases of forgery in modern history: the so-called “Protocols of the Elders of Zion”. The sentence pairs for the evaluation are taken from the infamous forged text “Protocols of the Elders of Zion” (Protocols) by unknown authors; and by “Dialogue in Hell between Machiavelli and Montesquieu” by Maurice Joly. Scholars have demonstrated that the first text plagiarizes from the second (Cohn, 1967; Taguieff, 2004), indicating all the forged parts on qualitative grounds. Following this evidence, we organized the rephrased texts and asked native speakers to quantify the level of similarity between each pair. We used this material to evaluate sentence representation models in two languages: English and French, and on three tasks: similarity correlation, paraphrase identification, and paraphrase retrieval.

Our evaluation aims at encouraging the development of benchmarks based on real-world problems, as a means to prevent problems connected to AI hypes, and to use NLP technologies for social good. Through our evaluation, we are able to confirm that the infamous Protocols are actually a plagiarized text but, as we will show, we encounter several problems connected to the convoluted nature of the task, that is very different from the one reported in standard benchmarks of paraphrase detection and sentence similarity. Code and data available at https://github.com/roccotrip/protocols

Keywords: sentence representation, sentence similarity, paraphrase detection, real-world evaluation

1. Introduction

Paraphrase detection is the task of analyzing two segments of text and determining if they have the same meaning despite the differences in structure and wording (Wieting et al., 2015). This definition, like that of synonymity for words, is hard to apply in real case scenarios, since each lexical form has a definite connotation (Bloomfield, 1933). To this end, in this work, we use the denotation by Bhagat and Hovy (2013) of (quasi-) paraphrases, i.e., sentences or phrases that convey approximately the same meaning using different words.

Paraphrase detection is an application of compositional semantics, a discipline that studies how lexical semantics units combine to generate complex thoughts, and therefore it is based on the principle of compositionality: the meaning of the whole is a function of the meaning of its parts (Frege, 2002). The first compositional semantics models were based on formal semantics (Montague, 1973), while the most recent models are based on distributional semantics (Mitchell and Lapata, 2008; Baroni and Lenci, 2010; Zanzotto et al., 2010; Ji and Eisenstein, 2013) and in particular on neural network models (Socher et al., 2011a; Yin et al., 2016; Liu et al., 2019a). Unfortunately, the evaluation of these models is conducted on datasets composed of short and grammatically simple sentences in most cases. This is because constructing more challenging benchmarks requires a vast amount of time. Therefore, semi-automatic procedures have been employed for creating these datasets. Furthermore, most of them are in English only, limiting the evaluation of models on other languages. Only recently, multilingual datasets have been released (Yang et al., 2019; Hu et al., 2020), which however, employ the characteristics of the existing datasets in English, i.e., are automatically constructed and contain short and highly overlapping sentence pairs.

In this work, we collected a small but challenging set of sentences for paraphrase detection based on a well-known forgery and plagiarism case. Historians (Cohn, 1967; Taguieff, 2004) have definitively established that several segments of the book “Dialogue in Hell between Machiavelli and Montesquieu” (henceforth, Dialogue) by Maurice Joly have been used to assemble the infamous booklet “The Protocols of the Elder of Zion” by unknown authors (henceforth, Protocols). Indeed, we choose this specific case study due to the fact that Protocols can be considered as one of the most famous – and pernicious – cases of plagiarism in modern history. For this reason, we decided to test whether an automatic analysis can effectively discover the plagiarized texts identified using the specialized knowledge of scholars in the field, aiming at developing technologies that can be used for social good.

From a more technical point of view, our evaluation is tailored to alleviate some of the drawbacks observed in the current evaluation benchmarks, which: i. are mainly in English; ii. comprise short sentences; iii. consist of paraphrase pairs with high word overlap; iv. have simple

We want to underline here that the publication and the spread of Protocols contributed to the rise of antisemitism during the first decades of Twentieth century and still today the text has a large circulation and following despite being a forgery (see Section 3 for more detailed discussion on the origin of Protocols).
syntactic structures; v. are mostly formulated as binary classification; vi. do not provide retrieval tasks. The evaluation conducted in this paper is, in fact, conducted on two languages and involve long sentences with low word overlap. Indeed, many of our paraphrases are abstract and involve similarities at concept level that can be conveyed using elliptical constructions. We use this textual material to formulate three different tasks with increasing level of sophistication, in order to effectively simulate a real-world scenario.

Most importantly, the ultimate aim of this work is to encourage researchers to test models on highly challenging real case problems with a social impact.

2. Related Work

We divide this Section in two parts: Section 2.1 describes several datasets for paraphrase detection and sentence similarity; Section 2.2 introduces recent approaches to create sentence representations.

2.1. Datasets

Classification datasets. The most popular benchmark for sentence understanding tasks is GLUE (Wang et al., 2019b). It consists of nine datasets: i. Corpus of Linguistic Acceptability (Warstadt et al., 2018, CoLA); ii. Stanford Sentiment Treebank (Socher et al., 2013, SST-2); iii. Microsoft Research Paraphrase Corpus (Dolan et al., 2004, MRPC); iv. Quora Question Pairs; v. Semantic Textual Similarity Benchmark (Cer et al., 2017, STS); vi. The Stanford Question Answering Dataset (Rajpurkar et al., 2016, QNLI) vii. Multi-Genre NLI corpus (Dolan et al., 2018, MNLI); viii. Recognizing Textual Entailment ix. Winograd Schema Challenge (Dagan et al., 2005) Bar-Haim et al., 2006, Giampiccolo et al., 2007, Bentivogli et al., 2009, RTE); (Levesque et al., 2012, WNLI). The first two are single sentence tasks; the datasets iii, iv, v are sentence similarity and paraphrase detection tasks; the other are natural language inference tasks. Most of them are formulated as binary classification problems, except STS, which is evaluated using regression, and MNLI with three classes. More recently, Wang et al. (2019a) introduced SuperGLUE, a set of more challenging tasks than GLUE. It was necessary since recent pre-trained models proved to solve GLUE tasks easily.

Sentence similarity/relatedness datasets. Semantic relatedness tasks consist of learning to predict a score between two sentences ranging from 0 to 5. The benchmarks for this task are SICK (Marelli et al., 2014) and STS (Cer et al., 2017). Sentences in these datasets are concise and constructed following the same template. This might allow simple models, that deal only with the identification of common words, to obtain high results. For example, The young boys are playing outdoors and the man is smiling nearby, and The kids are playing outdoors near a man with a smile have a relatedness score of 4.7; A group of friends are riding the current in a raft and This group of people is practicing water safety and wearing preservers have a relatedness score of 3.1; A person is wearing a hat and is sitting on the grass and A man is running in a field have a relatedness score of 1.4.

As we can see from all these examples, sentence pairs have similar length, high scores correspond to sentences that have key words replaced by synonyms, and low scores correspond to sentences that have words with contrasting meanings (running vs sitting).

The sentence similarity task consists in evaluating how a similarity measure between the representation of two sentences correlates with human judgments. Several datasets have been proposed in the SemEval shared task (Agirre et al., 2011) (Agirre et al., 2013, Agirre et al., 2014) (Agirre et al., 2015) (Agirre et al., 2016). Their limitations consist in the short length of the sentences, the limited vocabulary, the simplicity of the syntactic structure of the sentences, and the overlap of the words used in the sentence pairs.

Retrieval datasets. The task of finding comparable sentences in multiple corpora is gaining momentum, in particular, because of the success of transfer learning approaches in multilingual tasks (Ruder et al., 2019). Examples of such datasets include Bucc (Zweigeb; baum et al., 2018), which has been released with the shared task organized in the workshop Building and Using Parallel Corpora consisting of parallel texts in 5 languages, and Tatoeba (Artetxe and Schwenk, 2019), which has been recently released for sentence retrieval, consisting of up to 1000 English sentence pairs aligned with 122 languages. While these datasets retrieve comparable sentences across languages, in our tackled task, we retrieve sentences written in the same language but which have been plagiarized.

Paraphrase detection datasets. The most popular benchmark for paraphrase detection is presented by Dolan et al. (2004, MRPC), which is organized as a binary classification task. Barrón-Cedeño et al. (2013) proposed a selection of MRPC annotated with paraphrases types. More recently, Zhang et al. (2019) presented the PAWS dataset, which examples are generated through an automatic process of word scrambling and back translation via language models. It is designed for the paraphrases to have a high word overlap, and, similar to MRPC, it is a binary classification task. Yang et al. (2019) instead, extend the PAWS dataset to six other languages, consisting of paraphrase pairs with high word overlap, similar to its English version. These features make the PAWS and PAWS-X dataset less challenging than our task, which, in contrast, consists of challenging sentence pairs that contain few overlapping words and are not automatically created. Furthermore, while these datasets might be suitable for the evaluation of a classifier, in real-world scenarios a paraphrase has to be found in a large document or a collection of documents, and it should produce a ranking of retrieved sentences, therefore identifying the degree of rephrasing.
1. we show the statistics regarding the above-mentioned word embedding models based on deep neural networks. White space was used as token delimiter.

2.2. Sentence Representation Approaches

Word embedding models based on deep neural networks have received significant attention, especially due to the success of distributional semantics models (Mikolov et al., 2013) and are nowadays the main building block for NLP applications. Over the years, different approaches have been exploited to derive sentence embeddings starting from these word vectors, following the principle of compositionality. In fact, for many years, unsupervised models, reminiscent of the bag-of-words (BoW) approach and based on the construction of sentence vectors as a linear combination of word vectors, were very popular. Among them, we cite Smooth Inverse Frequency (Arora et al., 2017, SIF) that extends the BoW model and connects with the TF-IDF weighting schema. It uses a weighted average of the words composing a sentence, and then, modifies it using PCA. This simple model has demonstrated to be beneficial in many downstream tasks, providing an effective way of obtaining sentence representations compositionally.

Beside compositional models for sentence embeddings, several approaches have emerged to directly encode the semantics of a sentence based on: recurrent neural networks (Kalchbrenner and Blunsom, 2013, Sutskever et al., 2014); attention mechanisms (Bahdanau et al., 2015), where instead of using indiscriminately all the words in a sentence to construct its final representation, the relations among the words are weighted; recursive neural networks (Socher et al., 2011b), which use external knowledge about the structure of the sentence, e.g., syntactic structure; structured LSTM (Zhu et al., 2015); autoencoders (Socher et al., 2011c), to name a few. In the recent years, several strong baseline models have been proposed, especially tailored for sentence representation learning and knowledge transfer to several downstream NLP tasks. Universal Sentence Encoder (Cer et al., 2018, USE) uses an attention mechanism to produce context-aware representations of words that are then averaged to obtain a sentence-level representation. LASER (Artetxe and Schwenk, 2019) is another language-agnostic sentence encoder trained in parallel sentences with the aim of producing similar representations for sentences expressing the same meaning in different languages. More recently, motivated by the performance of contextualized models (Devlin et al., 2019), Reimers and Gurevych (2019) developed a modification of the pre-trained BERT network for representing sentences (SBERT), using siamese and triplet network structures, which have proven to be more efficient and better performing in several sentence similarity tasks. As regards formal semantics, there have been several attempts in representing text as a structured meaning representation. Abstract Meaning Representation (Banarescu et al., 2013, AMR) is a formalism for representing the meaning of sentences into semantic graphs, which has been previously exploited in the context of the paraphrase detection task (Issa et al., 2018) and multilingual sentence representation (Biloshim et al., 2020, Procopio et al., 2021). AMR aims at abstracting away from its surface form, therefore, sentences expressing the same meaning should be represented by the same or close structures. Based on these features, AMR appears to be suitable for representing paraphrase sentences. In this paper we collect and evaluate the performance of several approaches to sentence encoding in a challenging real case scenario of plagiarism, thus providing an exhaustive comparison of NLP tools.

3. The Textual Material

3.1. History of the Books

The Protocols were drafted in Russia at the beginning of the Twentieth century (De Micheli, 2004). They describe an imaginary meeting between a group of senior members of the Jewish community – represented as if it had really happened – discussing the conquest and ruling of international society, governments, and

Table 1: Dataset statistics. Average sentence length expressed as the average number of tokens; Average word overlap expressed as the % of common tokens. White space was used as token delimiter.

| Dataset          | Sent. length | Word overlap |
|------------------|--------------|--------------|
| SemEval2017T1    | 8.7 ± 3.34   | 23.8 ± 11.8  |
| SICK             | 9.6 ± 3.69   | 29.2 ± 12.1  |
| SemEval2015T2    | 11.5 ± 6.38  | 15.0 ± 11.8  |
| SemEval2016T1    | 14.3 ± 19.45 | 26.2 ± 11.9  |
| MRPC             | 19.7 ± 16.03 | 28.0 ± 8.1   |
| PAWS             | 21.5 ± 5.42  | 40.1 ± 4.7   |
| Our work         | 23.5 ± 13.64 | 10.3 ± 6.4   |
The most relevant source is with a title and a summary. After discarding all summaries and titles, we collect the remaining sentence pairs. In Table 2 we provide one example for each similarity score in our grading model (see Table 2). As seen from these examples, our chosen scoring range is necessary given the heterogeneity of paraphrases present in the collections, and to account for quasi-paraphrases (Bhagat and Hovy, 2013). Similarly to what was observed by Barrón-Cedeño et al. (2010) in different datasets, low similarity scores correspond to more abstract paraphrases in which a few concepts are maintained in the two sentences, while the highly scored pairs share the same meaning and also overlapping lexical units. The distributions of the dataset scores are presented in Figure 1.

3.2. The Books in Numbers

Protocols is made up of 24 chapters, each introduced with a title and a summary. After discarding all summaries and titles, we collect the remaining 294 paragraphs, each of which comprising 3.5 sentences of 26.3 tokens, on average. Thus, Protocols consists of a total of 1031 sentences. Cohn (1967) and, more recently, Taguieff (2004) manually identified the pieces of text in Protocols that have been plagiarized from Dialogue. This collection of forged text covers 110 of the Protocols paragraphs, comprising 11731 tokens in total. In our work, we collect and annotate the plagiarized texts of the books in French and English. As regards the French collection, similarly to Taguieff (2004), we used the 1921 edition of the Protocols (Anonymous, 1921) and the 1864 edition of Dialogue (Joly, 1864). Initially, a native French speaker manually selected the pieces of corresponding texts, starting from the Protocols sources, and judged the similarity between them using grades in a 1–5 range, following the scoring model in Table 2. Then, we asked three other native French speakers to annotate 50 randomly sampled sentence pairs from the resulting dataset each, with samples being different for every new annotator. This allows for computing the agreement among them and the first annotator using the Krippendorff’s alpha (\( \alpha \)) coefficient (Hayes and Krippendorff, 2007), which in turn ignores missing data entries, handles different sample sizes, and applies to any measurement type. Therefore, we believe it is an appropriate agreement measure for our case. Finally, the Krippendorff’s alpha coefficient for the French dataset is 0.73. The same process has been applied for English, identifying the corresponding French sentences in the two respective translations of the books, i.e., Marsden (1934) for Protocols and Joly (2003) for Dialogue. Similarly to French, the annotator agreement for the English dataset is 0.71. Generally, values of \( \alpha \) between 0.667 and 0.8 are considered acceptable.

In summary, the collected French text consists of 110 paragraphs comprising 353 sentence pairs, while the English one consists of 123 paragraphs consisting of 315 sentence pairs. In Table 3 we provide one example for each similarity score in our grading model (see Table 2). As seen from these examples, our chosen scoring range is necessary given the heterogeneity of paraphrases present in the collections, and to account for quasi-paraphrases (Bhagat and Hovy, 2013). Similarly to what was observed by Barrón-Cedeño et al. (2010) in different datasets, low similarity scores correspond to more abstract paraphrases in which a few concepts are maintained in the two sentences, while the highly scored pairs share the same meaning and also overlapping lexical units. The distributions of the dataset scores are presented in Figure 1.

4. Experimental Setup

4.1. Sentence Representations

We evaluate the performance of four different techniques to building sentence representations, based on:
We create sentence representations as a combination of embeddings using TF-IDF, and then, when using static word embeddings, we build sentence embeddings using the TF-IDF weighting schema, i.e., we first average all the word vectors.

Static word embedding models. We use the pre-trained word2vec model via skip-gram on a corpus of 30,813 French books (Levis Sullam et al., 2021). We create sentence representations as a combination of embeddings of words appearing in the sentence, by using the weighted mean according to the TF-IDF and SIF weighting schemata. Throughout our experiments, we denote these combinations as model\textsubscript{AVG}, model\textsubscript{TF-IDF} and model\textsubscript{SIF}, respectively, where model is a variable.

Contextualized word embedding models. We use BERT (Devlin et al., 2019) for English and CamemBERT (Martin et al., 2019) for French, a model based on the RoBERTa (Liu et al., 2019b) architecture trained on French texts. We also employ two multilingual models: the multilingual version of BERT (BERT-M) and XLM-RoBERTa (Conneau et al., 2020) XLM-R for encoding both English and French sentences. Similarly to when using static word embeddings, we build sentence representations from the contextualized word embeddings using the TF-IDF weighting schema, i.e., we first weight each token of a sentence using TF-IDF, and then, average all the word vectors.

Sentence embedding models. To directly create latent sentence representations, we use the following pre-trained sentence encoders: i. LASER (Artetxe and Schwenk, 2019) multilingual model, trained on parallel corpora, for both English and French; ii. USE for English and its multilingual extension (mUSE) for both languages; and iii. multilingual SBERT (Reimers and Gurevych, 2019) for both English and French.

Explicit Semantic Representation. As we mention in Section 2.2, the ability to abstract away from the sentence makes AMR adequate for representing paraphrase sentences. We follow (Issa et al., 2018), and use a pre-trained AMR parsing model, i.e., AMREager (Dazmonte et al., 2016), to represent the English sentences as structured representations.

4.2. Tasks

In this Section we present a set of experiments on three different tasks. As a first task we evaluate the correlation between the paraphrase similarity scores calculated using different representation models, and that assigned by human annotators. We formulate the second task as a retrieval task, i.e., given an input sentence from the Protocols marked as a paraphrase by the annotators, find the corresponding sentence in the full text of the Dialogue book. The third task consists of using the full text of both books to find how many paraphrases a model is able to detect, based on various similarity thresholds. We use the cosine similarity among all the dense representations, while for AMR, we measure the similarity between sentence AMR graphs via the Smatch (Cai and Knight, 2013) metric.
We compute the Pearson ($\rho$), XLM-R, and monolingual model, i.e., camemBERT. Interestingly, the performance of the multilingual contextualized model, i.e., BERT-M and XLM-R, is relatively low. This might be due to the tendency of these models to produce representations with high similarity. In fact, the starting (sub) token embeddings are anisotropic, occupying a narrow cone in the vector space (Ethayarajh, 2019). These aspects are particularly evident from the heatmaps of the similarity matrices between the sentence representations produced with XLM-R and mUSE, that we show in Figure 2. Evidently, higher similarity values appear mostly on the main diagonal of the mUSE matrix, while values in the XLM-R matrix are very close to 1. However, there is a noticeable performance gap between the multilingual contextualized models, i.e., BERT-M and XLM-R, and monolingual model, i.e., camemBERT. Indeed, the fact that it has been trained to model French text only, might be the reason to its significantly better performance than the multilingual models.

### 4.2.1. Correlation Experiment

We compute the Pearson ($\rho$) and Spearman ($r_s$) correlation between the similarity scores given by human annotators and those we compute automatically via the above-listed representation models.

#### French

In Table 4 we report the correlation scores on the French dataset. The highest correlation scores are reached by the multilingual sentence encoders, i.e., LASER, mUSE, and SBERT, with mUSE performing best as it surpasses the other models by more than 0.06 points. Furthermore, we observe the remarkable performance of SG$_{SIF}$, which, despite its simplicity, can compete with more sophisticated systems such as LASER. This result suggests that the SIF weighting schema, originally developed and tested only in English, can also be used in other languages. Moreover, compared to SG$_{AVG}$, SG$_{SIF}$ obtains a significantly higher performance, confirming the importance of weighting each word’s contribution in the sentence. Surprisingly, the performance of the multilingual contextualized embedding models (BERT-M and XLM-R) is relatively low. This might be due to the tendency of these models to produce representations with high similarity. In fact, the starting (sub) token embeddings are anisotropic, occupying a narrow cone in the vector space (Ethayarajh, 2019). These aspects are particularly evident from the heatmaps of the similarity matrices between the sentence representations produced with XLM-R and mUSE, that we show in Figure 2. Evidently, higher similarity values appear mostly on the main diagonal of the mUSE matrix, while values in the XLM-R matrix are very close to 1. However, there is a noticeable performance gap between the multilingual contextualized models, i.e., BERT-M and XLM-R, and monolingual model, i.e., camemBERT. Indeed, the fact that it has been trained to model French text only, might be the reason to its significantly better performance than the multilingual models.

#### English

In Table 5 we show the correlation results in the English dataset. Similarly to French, the models that achieve higher performances are the sentence encoders, except for LASER, which is not among the top-ranked models. In fact, LASER degrades with more than 0.1 points in English when compared to French. The best performing model is the monolingual USE model, which outperforms even its multilingual version by more than 0.07 points. SBERT instead, has stable performances across languages and is the second best model across the board. The performance of contextualized embedding is low even in English, from which the monolingual BERT model obtains the highest results. Moreover, the static word embeddings aggregated using SIF obtain competitive results, especially the ConceptNet embeddings. Indeed, the latter encode also the word meanings derived from the ConceptNet semantic network (Speer et al., 2017b), which might motivate their competitive performance. Finally, representing sentences with AMR, achieves a performance that is in line with static embeddings weighted using SIF, despite the drastically different approach, i.e., distributional versus explicit semantics.

#### 4.2.2. Retrieval Using an Input Sentence

The experiments in this Section consist in analyzing the ability of different sentence embedding models to identify paraphrases of specific target sentences. We use the paraphrased sentences in Protocols as the source and the Dialogue full text as target sentences and compute precision at $k$ (P@$k$) with $k \in \{1, 5, 10\}$ to evaluate the performance of the models.

#### French

We present the retrieval performance of models in French in Figure 3. The patterns that emerge from these results are: i. no system is able to achieve a P@1 higher than 0.4 if we consider the performance on all the sentences, regardless of their gold annotation; ii. the best performing models are the sentence encoders, specifically LASER, mUSE, and SBERT; iii. only SBERT can detect all the paraphrases with similarity score 5 (starting from P@5); iv. the gap between precision computed on 5 relatedness scores and those computed on lower scores is large, suggesting that the models detect

|                  | SG$_{AVG}$ | SG$_{SIF}$ | camemBERT$_{TF-IDF}$ | BERT-M$_{TF-IDF}$ | XLM-R$_{TF-IDF}$ | LASER | mUSE | SBERT | AMR |
|------------------|-----------|-----------|----------------------|------------------|------------------|-------|------|-------|-----|
| $\rho$           | 0.30      | 0.55      | 0.44                 | 0.38             | 0.28             | 0.57  | 0.66 | 0.59  |     |
| $r_s$            | 0.33      | 0.54      | 0.45                 | 0.40             | 0.19             | 0.58  | 0.66 | 0.60  |     |

Table 4: Pearson ($\rho$) and Spearman ($r_s$) correlation for each model on the French dataset.

|                  | ConceptNet$_{SIF}$ | SG$_{SIF}$ | BERT-M$_{TF-IDF}$ | XLM-R$_{TF-IDF}$ | LASER | USE | mUSE | SBERT | AMR |
|------------------|---------------------|-----------|------------------|------------------|-------|-----|------|-------|-----|
| $\rho$           | 0.54                | 0.51      | 0.35             | 0.26             | 0.41  | 0.64| 0.56 | 0.62  | 0.50|
| $r_s$            | 0.32                | 0.48      | 0.38             | 0.27             | 0.49  | 0.61| 0.54 | 0.59  | 0.44|

Table 5: Pearson ($\rho$) and Spearman ($r_s$) correlation for each model on English texts.

![Figure 2: Heatmaps of the similarity matrices obtained using XLM-R (left) and mUSE (right).](image-url)
well highly similar pairs, but fail when the rephrasing is more abstract; v. P@5 and P@10 do not change much, suggesting that some paraphrases are very difficult to be discovered, and even more sophisticated models would not be able to handle these cases in a real-world application; vi. only a few models (camemBERT and BERT-M) can detect paraphrases with score 1 when evaluated with P@1; vii. sentence encoders perform well on sentences with scores above 3, which might be because they have been trained on parallel sentences with high similarity; viii. sentence encoders do not retrieve paraphrases with similarity score 1, while contextualized word embedding models detect some of them.

The low performance of all the models, when evaluated for the pairs with low relatedness scores, suggests that it is challenging to find abstract similarities. For example, the sentences with gold similarity score of 1, In certain regions of Europe, there are people incapable of moderation in the exercise of liberty and The idea of freedom is impossible of realization because no one knows how to use it with moderation, are not detected even when evaluated with P@10.

English. In Figure 4 we show the results in English. The patterns that emerge from these results are the following: i. the best performing models are the sentence embedding models; ii. the multilingual sentence embedding models perform similarly to the monolingual sentence embedding model and, in fact, USE and mUSE achieve similar P@10 performances of 0.53 and 0.54, respectively. iii. only SBERT can detect all the paraphrases with score 5 (@5), similarly to the French case; iv. contextualized embedding models (BERT, XLM-R) perform poorly, which, as observed in the correlation experiment, tend to produce very similar sentence representations making the selection of candidates challenging; v. sentence embedding models are very good at finding paraphrases with high gold similarity scores, but struggle on low similarity scores, similarly to the French case; vi. only SG and ConceptNet can detect paraphrases with relatedness score 1, with ConceptNet detecting some of them even when evaluated with P@1.

Summary. Overall, we observe better performance of the models in English than in French, with the best model (SBERT) achieving an overall P@10 of 0.54 and 0.51, respectively. However, the search space for English is larger than for French, i.e., Dialogue contains 4684 sentences in English and 3348 in the French version. While this should make the task in English more
difficult, on the other hand, the English sentences are shorter than the French ones. Therefore, it might be easier to embed their content, motivating the better results in English.

4.2.3. Paraphrase Identification in the Full Texts

The final task consists of using the models to embed the full text of the two books and to evaluate how many paraphrases it is possible to find with each approach. This task does not consider the degree of similarity between the paraphrases. Since we do not have a development or training set to tune the threshold parameter above which two sentences are considered paraphrases, we used the Area Under the Receiver Operating Characteristics (AUC) curve, i.e., true-positive rate against the false-positive rate at various threshold settings. AUC is widely used in classification problems to evaluate the ability of a model to rank a random positive example higher than a random negative one, and evaluates the quality of predictions at different thresholds.

French. In Table 6 we show the results in French retrieval task. The best performing model is LASER with an AUC of 0.65. This means that LASER is more suited to discriminate among different similarity scores. It is followed by two other sentence embedding models, i.e., mUSE and SBERT, with slightly lower scores. Instead, contextualized and static word embedding models achieve significantly lower results, i.e., around 0.1 point lower than the sentence encoders, making them inappropriate for resolving this task.

English. Similar to the French case, the best performing models in English are the sentence encoders. Overall, results in Table 7 show that the models cannot achieve an AUC higher than 0.65. ConceptNet performs relatively well considering its simplicity, also confirming the observation in the correlation task (Section 4.2.1), where it is competitive with more complex sentence encoders.

Summary. In general, considering the relatively small search space, the models we analyze perform poorly in both languages. This is because the range of paraphrases is wide, with low scored pairs being significantly more abstract than high scored pairs. For this reason, it is difficult to find a paraphrase threshold which would includes paraphrases of different grades.

5. Conclusions

In this paper we presented an evaluation of sentence embedding models on a small but challenging setting for paraphrase detection, based on a real case of plagiarism. We compared automatic systems for paraphrase detection with the historical analyses that have identified the Protocols as a forgery and the linguistic knowledge of the annotators that scored the sentence pairs. We conducted the evaluation on two languages, and we plan to extend it to German, Italian, and Spanish. Among other insights, we showed that current approaches are good at identifying paraphrases when the sentences are almost identical, and share common words. However, they struggle to detect paraphrases when periphrases are introduced, making the relationship among sentences more abstract, i.e., quasi-paraphrases. Indeed, even if the search space in which we searched for paraphrases is small, the analyzed systems did not achieve good performances. These observations suggest that it would be difficult to use the existing models in real-world scenarios, since they can mainly detect highly similar paraphrase sentences. Furthermore, as much as our presented evaluation represents a real task, it is rather simplified. This is because we already presented to the systems the two books in which the similarities actually exist. In a real case scenario instead, the search space could be broader including an extensive collection of heterogeneous texts to search from. Indeed, this urges the research community to develop more sophisticated tools to deal with pressing issues in modern societies.

Apart from the contribution of providing an evaluation of sentence representations in a real-world scenario, the more noticeable impact of this paper is to encourage the use of language technology in different fields with social impact. We aim to highlight the need to develop more efficient technologies to solve pressing issues, such as plagiarism detection or the spread of misinformation. As the diffusion of the Protocols has had tragic consequences in the past and remains deplorable today, the risk that similar cases emerge and propagate is very high and can be amplified by digital technologies. Finally, empirically verifying the “Protocols of the Elders of Zion” as a case of plagiarism and thus a forgery, remains relevant to fight against the spread of antisemitism, religious hatred, and conspiracy theories: together with the scientific experiments and the proposed technological solution, this has been the ethical aim of this paper.
6. Bibliographical References

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