PESTS: Persian_English Cross Lingual Corpus for Semantic Textual Similarity

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Abstract

One of the components of natural language processing that has received a lot of investigation recently is semantic textual similarity. In computational linguistics and natural language processing, assessing the semantic similarity of words, phrases, paragraphs, and texts is crucial. Systems for answering questions, semantic search, fraud detection, machine translation, information retrieval, and other applications leverage semantic textual similarity. Calculating the degree of semantic resemblance between two textual pieces, paragraphs, or phrases provided in both monolingual and cross-lingual versions is known as semantic similarity. Cross lingual semantic similarity requires corpora in which there are sentences' pairs in both the source and target languages with a degree of semantic similarity between them. Many existing cross lingual semantic similarity models use a machine translation due to the unavailability of cross lingual semantic similarity dataset, which the propagation of the machine translation error reduces the accuracy of the model. On the other hand, when we want to use semantic similarity features for machine translation the same machine translations should not be used for semantic similarity. For Persian, which is one of the low resource languages, no effort has been made in this regard and the need for a model that can understand the context of two languages is felt more than ever. In this article, the corpus of semantic textual similarity between sentences in Persian and English languages has been produced for the first time by using linguistic experts. We named this dataset PESTS (Persian English Semantic Textual Similarity). This corpus contains 5375 sentence pairs. Also, different models based on transformers have been fine-tuned using this dataset. The results show that using the PESTS dataset, the Pearson correlation of the XLM_ROBERTa model increases from 85.87% to 95.62%.

Keywords: Semantic Similarity; Cross lingual; Persian-English Corpus

1. Introduction

Measuring semantic similarity between textual sections (words, sentences, paragraphs, or even documents) is a very important area of research in natural language processing. Calculating semantic similarity between sentences in many natural language applications such as semantic search (Manjula and Geetha, 2004), Summarization (Aliguliyev, 2009), Question-Answering Systems (De Boni and Manandhar, 2003), document classification (Al-Anzi and AbuZeina, 2017), Sentiment Analysis (Žižka and Dařena, 2010) and plagiarism (Alzahrani *et al.*, 2011) is used. Finding the degree of semantic similarity with the aim of understanding and natural language generation is an attractive research in computer science, artificial intelligence and computational linguistics. Semantic similarity was considered as a two-class classification problem from 2006 to 2012 (determining whether two sentences are semantically similar or not), but from 2012 until now, the degree of similarity expressed in numbers has been calculated (Majumder *et al.*, 2016).

Sentences in different languages can also be semantically similar. For example, the English sentence "He wants to play football" and the Persian sentence "غني تعرين ميكند" can be semantically similar. These two sentences are in two languages with different structures. In many of the researches performed, due to the lack of text corpora and labeled data for training in both languages, they use a machine translation to translate the source language sentence into the target language and then use the semantic similarity models of the target language (in the above example: English) to calculate the semantic similarity; But the main weakness of such systems is the machine translation error propagation and the translation of the source language into the target language may not be done well. One of the aims of the article is to prevent the machine translation errors for finding similarity between Persian and English sentences by producing a dataset. In Table 1, a sample of PESTS with their semantic similarity, which is in the range of 0 to 5, can be seen. A score of 5 indicates the highest degree of similarity and 0 indicates the lowest level of similarity.

Table 1. Sample Persian-English sentence with semantic similarity

English Sentences	Persian Sentences	Degree of similarity
This is not a request hard to meet.	او درباره دلیل رسیدن به چنین تصمیمی توضیح نداد.	0
A transmission phase of the torch includes Mount Everest, located on the border of Tibetan and Nepal.	وی میگوید صعود به بلندترین قله در جهان برایش آرزوئی بوده که سرانجام تحقق یافته است.	1
Six people lost their lives in the attacks and more than one hundred were wounded.	سه نفر از کسانی که جان خود را از دست دادند، ماموران پلیس بودند.	2
The Space Infrared Telescope Facility's mission is to search for the beginnings of the universe.	ناسا قرار است از صبح دوشنبه تاسیسات تلسکوپ مادون قرمز فضایی را راهاندازی کند.	2.5
The official death toll from this acute and chronic disease of the SARS respiratory has increased in 26 countries to 293 people.	این بیماری مرموز که عوارضی نظیر آنفلونزا دارد تاکنون در سطح جهانی موجب مرگ ۴۴۸ نفر شده است.	3
Both materials stimulate circulation and help reduce cholesterol levels.	دارچین و عسل گردش خون را تحریک کرده و به کاهش سطح کلسترول کمک میکنند.	4
Only a decade ago, companies mainly paid attention to research on consumers.	تنها یک دهه است که شرکتها عمدتاً به نتایج تحقیقات بر روی مصرفکنندگان توجه میکنند.	5

In this paper, the Persian English cross lingual Similarity corpus is introduced and then by using it, different models based on transformers are fine-tuned, and finally, these models are evaluated using the test dataset. The innovations of this article can be listed as follows:

- 1- Production of Persian-English cross-lingual dataset
- 2- Generating a model with the highest degree of correlation to identify the degree of semantic similarity between Persian and English sentences
- 3- Remove machine translation phase for measuring Persian-English cross lingual semantic textual similarity.

The purpose of this article is to create a semantic similarity dataset between Persian and English. Here, semantic similarity refers to the semantic distance between two sentences, that is, how similar or different the two sentences are in terms of lexical content and general subject matter. The evaluation results show that by using the semantic similarity corpus between Persian and English, the semantic richness of the models (performance of the models to determine the degree of similarity) can be increased.

In the continuation of this article, we will first describe the related works in the semantic textual similarity field. Then we will explain how to choose sentence pairs and annotate them. In the following, the statistics related to the corpus will be described and at the end, the semantic textual similarity models produced, introduced and have been tested. The dataset for non-commercial usage has been publicly available¹.

2. Related works

Semantic similarity is one of the important tasks that various researchers around the world have done, but their main focus is on English and few corpora have been produced in cross lingual semantic similarity. In order to promote the progress of cross lingual semantic similarity in other languages, in 2017, special emphasis was placed on the semantic similarity of English with Arabic, Spanish and Turkish (Cer *et al.*, 2017). Various semantic similarity corpora have been produced since 2005, some of which we will mention.

Lee et al. (Lee, Pincombe and Welsh, 2005) Their data set consists of 65 sentence pairs based on the word similarity dictionary (Mayank, 2020). Human experts have been used to score sentence pairs that have scored in the range 0 (minimum similarity) to 4 (maximum similarity). Their corpus is too small to train, develop and test machine learning based systems. Li et al. (Li *et al.*, 2006) Their data set includes 50 news documents with a number of words ranging from 51 to 126 words. In order to produce this statue, the taggers were asked to rate the degree of similarity between each document pair in the range of 1 (lowest similarity) to 5 (highest similarity). This data set has more pairs of documents than the first data set, but it goes beyond the similarity of the sentence and is more similar to the similarity of the document. After that, semantic textual similarity datasets were not published until 2012.

The data set published in 2012 (Agirre *et al.*, 2012) uses various sources such as Microsoft Research Data (MSR), which includes two datasets. One of them (MSRpar) consists of 5,801 sentence pairs and has been collected from thousands of news sources on the web over an 18-month period that 67% of the pair of sentences were labeled as equal and in this dataset the inter annotator agreement is between 82% and 84%. Another dataset of Microsoft Research (MSR) datasets is the MSR Video Paraphrase Corpus, in which the authors show brief video segments to the annotators and ask them to provide a one-sentence description of the main action or event in the video. Based on this, nearly 120,000 sentences were collected for 2,000 videos.

In 2013, Agirre et al. (Agirre *et al.*, 2013b) presented a corpus that consists of two tasks: the main task, which is similar to SemEval 2012 but differs in the genre of sentence pairs, and the other is the typed similarity task, which indicates how two sentences are similar to each other. In both tasks, the correlation between the annotator is 62% to 87%.

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¹ https://github.com/mohammadabdous/PESTS

In STS 2014, presented by Agirre et al. (Agirre *et al.*, 2014), there are two subtasks: English and Spanish. For English sub-task, the score between sentence pairs is between 0 and 5, and five test datasets are presented: two datasets that extend the genres published in previous datasets. These collections include ontoNotes-WordNet Sense mappings (750 sentence pairs) and News headlines (750 sentence pairs). Also, the three new genres include image descriptions (750 sentence pairs), DEFT discussion forum data and newswire (300 sentence pairs for news and 450 sentence pairs for the forum data) and tweet-newswire headline mappings (750 sentence pairs); Also, all datasets published in 2012 and 2013 are used as train data.

For Spanish subtask, the score between the sentence pairs is between 0 and 4, and two diverse datasets on different genres are introduced, namely encyclopedic descriptions extracted from the Spanish Wikipedia (324 sentence pairs) as well as the contemporary Spanish newswire (480 sentence pairs). For the Spanish subtask, there was a limited amount of labeled data, consisting of 65 sentence pairs, for training, indicating that the dataset in Spanish has a small number of sentence pairs to perform the training operation.

STS 2015, presented by Agirre et al. (Agirre *et al.*, 2015), defines three subtasks: English, Spanish and the interpretable pilot subtask. For English, there have been sentence pairs from news headlines (750 sentence pairs) and image descriptions (750 sentence pairs), and new genres have been introduced, including answer pairs from a tutorial dialogue system (750 sentence pairs) and from Q&A websites (375 sentence pairs), pairs from a committed belief dataset (375 sentence pairs). For Spanish, sentence pairs were selected from Spanish Wikipedia (251 sentences) and contemporary news articles collected from news media in Spanish (500 sentences). The label of each sentence pair is obtained by averaging expert's scores. Finally, with an interpretable pilot subtask, it is examined whether systems can explain why two sentences are related / unrelated, and in fact an explanatory layer is added to the similarity score.

In SemEval 2015, in English, the similarity of sentences is evaluated with numbers between 0 and 5, but in Spanish, this evaluation is done with numbers between 0 and 4, and in fact, it is evaluated in such a way that points 3 and 4 for English are point 3 for Spanish.

Agirre et al. (Agirre et al., 2016) In their dataset, cross lingual test data is divided into two test sets: news and multi sources. News datasets are manually collected from multilingual news sources, while multi source datasets are extracted from different sources in the English text, But the sentences that are from another language are obtained by translating English sentences into that language by human translators. This dataset includes datasets for Spanish-English language pairs and has English-English datasets to assess monolingual semantic similarity. News evaluation datasets include 301 sentence pairs and multi-source datasets contain 2973 sentence pairs that are used to evaluate models and methods.

Marelli et al. (M. Marelli et al., 2014) their dataset consists of 10,000 pairs of English sentences and each pair of sentences is annotated for two important semantic tasks, one is the semantic relationship of two sentences marked with a score between 1 and 5 and the other is the entailment relation, which is characterized by 3 labels: entailment, contradiction and neutral. This dataset is made up of two existing datasets: the imageFlickr dataset and the video description dataset in SemEval 2012. To generate sentence pairs for Sick dataset, a number of sentence pairs are randomly selected from each source dataset and pre-processed in 3 steps. First the main sentences are normalized to eliminate unwanted linguistic phenomena, then the normalized sentences are extended to obtain a maximum of three new sentences with special features suitable for evaluating systems, and finally as a last step, all generated sentences in the

expansion step, they are paired as normalized sentences to obtain the final data set. The gold label of each pair of sentences for the semantic similarity task was obtained by averaging the points of 10 participants, which showed that, on average, participants' judgments varied by as much as 0.76% of the points around the final score assigned to each pair.

Ferrero et al. (Ferrero et al., 2016) provided a dataset to assess the similarity of cross lingual texts that can be very useful in fraud detection. This dataset is multilingual (French, English and Spanish) and provides cross lingual alignment of information at different levels of the document, sentence and fragment, and includes human texts or using a machine translation. This dataset also includes a variety of documents written by a variety of mid-level to high level writers. This dataset has overcome many of the limitations of previous datasets, one of which is the ability to align only at a certain level (for example, the sentence level).

In cross lingual semantic similarity, the goal is to calculate the degree of similarity between sentences in two different languages. There is no problem in calculating semantic similarity in high resource languages, but in some languages that do not have a suitable source, calculating similarity is a serious challenge. One of the available solutions to solve this challenge is to use machine translation-based approaches to convert sentences from low-source language such as Persian to high-source language such as English. The main problem of such approaches is the existence of errors in machine translation and it is highly dependent on the quality of translation (Bjerva and Ostling, 2017).

In their study, Tang et al. (Tang *et al.*, 2018) developed a model for low-resource languages such as Spanish, Arabic, Indonesian, and Thai. Using a monolingual semantic similarity model framework, they extended it to multilingual mode and showed that by using a common multilingual encoder, each sentence could show different embeddings according to the target language.

Brychcin (Brychcín, 2020) proposed the idea that multilingual semantic spaces are placed in a common space using a bilingual dictionary. They showed that common semantic spaces could be improved by weighting words. Their results show Pearson correlation criterion of 61.8% in Arabic-English sentences.

At the 2017 Semantic Evaluation Conference (Cer *et al.*, 2017), the main focus was on cross lingual and multilingual semantic textual similarity. In this conference, 17 participants competed in 31 teams and in this conference, the STSBenchMark dataset was presented. Some cross lingual datasets including Arabic-English, Spanish-English and Turkish-English were also introduced and evaluated by the participants.

Important work done in the field of cross lingual semantic similarity is based on cross lingual embeddings (Klementiev, Titov and Bhattarai, 2012)(Zou et al., 2013)(Mikolov, Le and Sutskever, 2013)(Gouws, Bengio and Corrado, 2015)(Ammar et al., 2016). Chidambaram et al. (Chidambaram et al., 2018) have generated cross lingual vector space using a model based on dual encoder. Their goal is to train a model that produces the maximum similarity between sentence pairs in a paraphrase corpus. The resulting embeddings are improved by the use of monolingual datasets and simultaneous multitasking training. They use the common vector space obtained in many tasks and have a comparative advantage compared to other tasks. At the core of their proposed method is modeling the tasks which is based on ranking sentence pairs using dual encoders and producing cross lingual embeddings by using machine translations. In shared encoder architecture, there are three transformers, each with feed forward sublayers and multi head attention. The output of the transformer is a variable length sequence that by averaging them, the

embedding of the sentences is obtained. The embeddings created in the feed forward layers are then used to fine-tune each task.

Conneau et al. (Conneau et al., 2018) have developed a cross lingual dataset called XNLI. Because data collection in all languages is a costly process, the interest in Cross-Lingual Language Understanding and transmission in low-resource languages has increased. In this paper, a test dataset for Cross-Lingual Language Understanding has been developed and the test datasets have been expanded to 15 languages, including low resource languages such as Swahili and Urdu. Labels in the generated corpus are premise and hypothesis. To prove the value of the data set, they tested it on several tasks, such as machine translation, multilingual bag of words, and LSTM encoder.

Conneau et al. (Conneau and Lample, 2019) have proposed a cross lingual model called XLM. They used two methods to learn cross lingual models. The first method is unsupervised, which relies only on monolingual data, and the second method is supervised, which uses a paraphrase corpus with the aim of modeling the target language. Their proposed method performs best on supervised and unsupervised machine translation tasks and XNLI.

The masked language model has a similar purpose as introduced by Davlin in Bert paper (Devlin et al., 2018), except that in this model we are faced with a continuous flow of sentence pairs. In the machine translation language model, like the masked language model, pairs of parallel sentences are given to the machine. To predict an English word, this model can look at both English and French translations, and it seeks to align English and French embeddings. XLM uses Byte Pair Encoding (BPE) method and Bert language learning mechanism to learn the relation between words in different languages. Byte Pair Encoding is a data compression method that consistently replaces the most frequently repeated character pairs (essentially bytes) in a particular data set with a non-event symbol in the text. In each iteration, the algorithm finds the most frequent pairs of characters and merges them to create a new symbol. In the XLM model, instead of using the word or characters as input to the model, it uses byte Pair Encoding, which divides the input into the most common sub word in all languages, thus increasing common cross lingual vocabulary. The XLM model enhances Bert's architecture in two ways:

in the Bert model, each train instance consists of one language, while in the XLM model, each train instance consists of two languages. As in the prediction of masked words in Bert's model, this model uses the context of the source sentence to predict the masked words of the destination sentence. This model also receives the language identifier and word order in each language separately as a position encoder. This new metadata helps the model learn the relation between related words in different languages. Table 6 in the appendix summarizes the generated semantic textual similarity datasets.

In this article, a semantic similarity between Persian and English sentences was created. In the following, we will explain how to produce the dataset.

3. Corpus production process

As mentioned before, for creating the cross lingual corpus we first create a Persian - persian semantic similarity corpus. Because in Persian we can find expert linguists that can distinguish the semantic between sentences but finding the linguistic expert in both English and Persian simultaneously is more challengeable.

In order to produce the Persian-Persian corpus, first 20,000 pairs of suitable Persian sentences were selected and the semantic scores between them were presented by the annotators; after that, a part of the whole corpus was used to make a Persian-English corpus. In the following, the details of corpus production will be described.

When building our datasets, collecting pairs of natural sentences with varying scores of semantic similarities was itself a challenge. If we consider a pair of sentences at random, the majority of them will be completely unrelated, and only a very small fragment will show some kind of semantic equivalent.

One of the major challenges is to find similar sentence pairs. If such an important point is not observed in the production of the corpus, most of the sentence-based corpora have a score of 0 or a maximum of 1, and thus the corpus has not sufficient quality for machine learning models and cannot be used in practice. To solve this challenge, we used multiple textual sources and different text corpus so that we could extract sentence pairs from these corpora that are 7 to 25 words long. Of course, there are other preprocesses for selecting a pair of sentences, which are described below.

3.1. Sentence preprocessing

One of the most important problems that can be seen in large text corpora such as Ferdowsi², Persica (Eghbalzadeh *et al.*, 2012), Wikipedia and the like, is the existence of several problems that occur due to lack of pre-processing of its sentences. The various sentences and texts that exist in these corpora should be examined and in order to use it practically, its shortcomings should be eliminated. In the following, we will describe the various preprocesses performed.

- 1. From the text corpus, sentences were selected that have a number of words between 7 and 25.
- 2. In the corpus, some sentences, some of which (for example, one or more words of it) are in other languages, have been removed so that the models that want to be produced in the future using this corpus have the desired quality.
 - 3. Sentences are checked using the spell correction tool and corrected if they are misspelled.
- 4. The sentence pairs selected from the corpora should semantically similar, which has been done using human experts.
 - 5. The characters of the words in the sentences have been examined using the normalizer tool.
- 6. If the sentence has a quote, the part that is placed after ":" (quote section) is selected as the main sentence
 - 7. The difference in sentence length can be up to 5 words.

3.2. Selection of sentence pairs

After pre-processing the sentences and applying the relevant rules, sentence pairs were extracted by the discretion of the human expert from the corpus so that the distribution of similarity scores in the generated corpus is desirable and from all scores (0 to 5) have a suitable pair of sentences. If we randomly select sentence pairs from a set of pre-processed sentences, more than 99% of them have a score of 0 or a final 1, and in fact most of these sentence pairs have little semantic similarity and their distribution of similarity degrees is not uniform.

3.3. Annotation process

² https://github.com/Text-Mining/Ferdowsi-Annotated-Academic-Linguistic-Corpus

In the production process of large corpora, different systems are used for annotation. With the use of annotating systems, the quality of the production corpus is increased and its production speed is also increased. In producing the semantic textual similarity corpus, a web-based system has been used, which we will describe in the following.

The annotating system for sentence pairs consists of two parts. In the first part each annotator can view sentence pairs related to himself / herself using the available user ID and assign a score of -1 to 5 to each pair of sentences. Because, in addition to the reviews and preprocessing done, the sentence pairs may still have misspellings or other semantic flaws, a score of -1 is assigned to it by the annotator, and finally, another expert reviews the scores of -1 and if the sentence pair cannot be corrected, it will be removed from the data set; otherwise, the sentence pair is corrected and resent for annotation.

In the second part of the system, the production of the corpus is managed. By entering this system, the admin user can see the sentence pairs that have been annotated by all annotators so far according to different filters such as hours, number of annotator users, average score of three annotators, and so on. Users can also use this system to modify or edit sentence pairs that have been annotated yet. For annotating each pair by experts, the below Instruction that is described in Table 2 is used.

Table 2. Similarity scores with explanations and English examples from (Agirre et al., 2015)

score	definition
5	The two sentences are completely equivalent, as they mean the same thing.
4	The two sentences are mostly equivalent, but some unimportant details differ.
3	The two sentences are roughly equivalent, but some important information differs/missing.
2	The two sentences are not equivalent, but share some details.
1	The two sentences are not equivalent, but are on the same topic.
0	The two sentences are completely dissimilar

3.4. Experts specification

For the purpose of scoring sentence pairs, three linguists with a Ph.D. degree in linguistics and highly experienced in the field of linguistic and textual data analysis have been used. All annotators follow the same basis and guidelines for scoring. The correlation between annotators is important and causes the corpus to be more accurate. Table 3 also shows the degree of correlation between annotators based on the degree of score they gave to the sentence pairs. As you can see in Table 3, the Pearson correlation rate between the labels is over 90%, which is a very good amount.

Table 3. The degree of correlation between annotators' scores

Between Annotators' scores	Pearson correlation
Annotator1 & annotator 2	90.32
Annotator 1 & average scores of annotators 2 and 3	92.66

Annotator1 & annotator 3	90.80
Annotator 2 & average scores of annotators 1 and 3	92.86
Annotator2 & annotator 3	92.05
Annotator 3 & average scores of annotators 1 and 2	93.21

3.5. Review of sentence pairs by an expert

Despite the same scoring basis, annotators usually assign different scores to a single pair, which can have several reasons: First, a person may score incorrectly due to fatigue, lack of concentration, or speed; The second reason is that semantic similarity does not have a clear and uniform definition, and in many cases the degree of semantic similarity depends on the personal opinion of individuals; And third, the scores we are looking for (0 to 5) have definite boundaries, while the exact numerical score may be between two scores. For example, if the score is around 2.5, one person may score 2 and another may score 3. In the final corpus, the final score of the semantic similarity of the sentence pair is obtained from the average score of the three annotators. Accordingly, if the difference in scores is due to an individual mistake, it must be corrected. If it is related to two other reasons (i.e., the concept of similarity is unclear or the boundary of scores is definite), it is acceptable as long as the difference of scores is only one unit. Therefore, if the score difference is large (i.e. more than one unit), it often indicates that a score error has occurred and should be checked.

3.6. Creating a Persian-English corpus

In order to construct a data set that reflects the uniform distribution of similarity score ranges, a smaller data set consisting of 5,374 pairs of sentences was extracted and sampled from more than 20,000 scored Persian sentence pairs. The first sentence of this collection has been translated into English by fluent linguists and has replaced the Persian sentence. Thus, a corpus was obtained in which the first side of the sentence pairs is English and the second side is Persian sentences, and in the third column, the degree of similarity between the two sentences of Persian and English is stated.

3.7. Statistics of corpus

In the generated corpus, 5374 sentence pairs have been scored by three annotators, and using the training set, which constitutes 90% of 5374 sentence pairs, a semantic similarity model has been created. Statistics of the generated corpus are described in Table 4, which can be used for various tasks in the field of natural language processing.

Table 4. Statistics of the corpus

	Train (80%)	Dev (10%)	Test (10%)	All (100%)
Number of Pairs				
	4298	538	538	5375
all score				
	920	130	131	1181
scores between 0 to 1				

scores between 1 to 2	488	60	60	608
scores between 2 to 3	1087	136	136	1359
scores between 3 to 4	640	80	80	800
scores between 4 to 5	1163	132	131	1427
Average number of words in a persian sentence	14.17	13.88	13,88	14.1
Average number of words in an English sentence	14	13.84	13.84	13.97

4. experiments

In this paper, we have used several transformer-based language models to perform experiments on the corpus. The performance of these models using the created corpus is examined and compared for semantic textual similarity tasks.

Transformers are designed to solve the problem of sequencing in a neural network, meaning that they take a string (like words in a sentence) and after processing it regularly, output it in a specific sequence and will not be allowed to leave until the entire string is finally approved. Transformers are made up of encoders that are used to consider meanings and concepts in vectors and to obtain semantic vectors. Some of these transformers are multilingual (multilingual Bert, XLM etc.) and are actually trained in different languages and can be used to represent vector representations in different languages However, their performance also improves when these transformers are fine-tuned using cross lingual corpora. It should be noted that during the fine-tuning operation, the weight of the last layer of the transformers is updated using the training data.

In these experiments, we have fine-tuned the models used using the training data of the Persian-English semantic similarity corpus and we have also shown an improvement in their performance compared to the non-fine-tuned mode, which can be seen in Table 5.

The fine-tuning operation in our experiments was performed in 4 epochs and in batch size 32 and the Cosine similarity loss function was used.

The cosine similarity criterion has been used to measure the semantic similarity between the two sentences. The criterion of cosine similarity between two vectors is one of the most widely used criteria in measuring semantic similarity between sentences.

Pearson correlation coefficient (Benesty *et al.*, 2009) and Spearman (SPEARMAN, 1910) are used to evaluate the output of semantic textual similarity systems. The purpose is to calculate the correlation between the score of similarity detected by the system and its true score of similarity. How to calculate Pearson correlation coefficient according to Equation 1:

$$I_{XY} = \frac{\sum_{i=1}^{n} (x_i - \underline{x})(y_i - \underline{y})}{\sqrt{\sum_{i=1}^{n} (x_i - \underline{x})} \sqrt{\sum_{i=1}^{n} (y_i - \underline{y})}}$$
(1)

In the above formula x_i indicates first (or predicted) score and y_i indicates the second (or gold) score. \underline{x} indicate the average of first(or predicted) scores and \underline{y} indicate the average of second(or gold) scores. Predicted or gold score is used in the testing phase.

If Pearson correlation coefficient is near to one, then the obtained model is more accurate. In the following, the results related to the implementation of the model on the test data of semantic textual similarity between English-Persian languages are expressed.

In order to measure the performance of the produced model, we tested and evaluated it using test data for cross lingual semantic textual similarity. Cosine similarity criteria were used to calculate the score of semantic similarity between the two sentence vectors and Pearson and Spearman criteria were used to measure the correlation between model scores and gold scores. The results of the models are as shown in Table 5 and show that by using the generated corpus, the percentage of correlation of transformer-based models can be increased to measure the semantic similarity between English and Persian, for example, the paraphrase-xlm-r-multilingual-v1 model has a Pearson correlation of 85.87 in the non-fine-tuning mode and Pearson correlation of 95.62 in the fine-tuned mode, which has increased the correlation rate by approximately ten percent using the generated corpus. It should also be noted that in the results obtained, the test data for evaluation and the training data for fine-tuning are fixed in all experiments.

Table 5. Results of the implementation of multilingual transformers based models for cross lingual semantic textual similarity

			Fine-tun	ed model
Models ³	Pearson	Spearman	Pearson	Spearman
Xlm-roberta base (Conneau et al., 2019)	23.80	28.99	89.48	90.40
paraphrase-xlm-r-multilingual-v1	85.87	85.91	95.62	95.17
bert-base-multilingual-cased (Reimers and Gurevych, 2019)	47	45.47	91.88	91.55
distilbert-base-multilingual-cased	45.56	45.18	89.51	89.08
stsb-xlm-r-multilingual	78.37	76.57	94.43	94.02
xlm-r-100langs-bert-base-nli-stsb-mean- tokens	78.37	76.57	94.4	94.03
Twitter-xlm-roberta base	27.94	28.06	90.99	90.28

³ https://huggingface.co/models

5. Conclusion

Nowadays, with the increasing development of textual resources in different languages, the need to produce models that are capable of simultaneously understanding more than one language is felt more than ever. One of the most important tasks used in natural language processing is to understand the meaning of the sentences or phrases, which is called semantic textual similarity. Semantic textual similarity is one of the important tasks of natural language processing that has attracted extensive research that can be used as cross lingual. In this research, a cross lingual semantic textual similarity corpus has been produced. To produce this corpus, first a Persian-Persian corpus has been produced and then the first part of each sentence pair has been translated into English by fluent linguists.

Experiments performed in this study have shown the importance of producing this corpus that can be used to increase the performance of models for semantic textual similarity tasks between Persian-English language and also to evaluate and compare models using the test data of the same corpus.

The produced models can also be used in question answering systems, fraud detection, machine translation, information retrieval and the like in Persian and English.

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Appendix

Table 6. Past semantic textual similarity datasets

Corpus	Language	Dataset	Pairs
		MSRpar	1500

SemEval -2012 Task 6		MSRvid	1500
(Agirre <i>et al.,</i> 2012)	English	OnWN	750
		SMTnews	750
		SMTeuroparl	750
		SUM	5250
	English	HDL	750
SEM 2013 shared task		FNWN	189
(Agirre <i>et al.,</i> 2013a)		OnWN	561
		SMT	750
		SUM	2250
		HDL	750
		OnWN	750
	English	Deft-forum	450
		Deft-news	300
SemEval -2014 Task 10		Images	750
(Agirre <i>et al.,</i> 2014)		Tweet-news	750
		SUM	3750
	Spanish	Wikipedia	324
		News	480
		SUM	804
		HDL	750
		Images	750
	English	Answer-student	750
SemEval -2015 task 2 (Agirre <i>et al.,</i> 2015)		Answer-forum	375
(1.811.0 Ct al., 2013)		Belief	375
		SUM	3000
	Spanish	Wikipedia	251
		News	500
		SUM	751

SemEval -2016 task 1		HDL	249
(Agirre <i>et al.,</i> 2016)	English	Plagiarism	230
		Postediting	244
		AnsAns.	254
		QuestQuest.	209
		SUM	1186
	Spanish-English	Trial	103
		News	301
		Multi-source	294
		SUM	698
SICK (Marco Marelli et		SemEval 2012 MSRvid	9840
al., 2014)	English		
		ImageFlick	
SemEval -2017 task1		evaluation	250
(Cer <i>et al.,</i> 2017)	English	Trial	23
		SUM	273
		evaluation	250
	Spanish	Trial	23
		SUM	273
	Arabic	evaluation	250
		Trial	23
		MSRpar	510
		MSRvid	368
		SMTeuroparl	203
		SUM	1354
	Spanish-English	evaluation	500
		Trial	23
		MT	1000
		SUM	1523

Arabic-English	evaluation	250
	Trial	23
	MSRpar	1020
	MSRvid	736
	SMTeuroparl	406
	SUM	2435
Turkish-English	evaluation	250