Multilingual Universal Sentence Encoder for Semantic Retrieval

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Abstract

We present easy-to-use retrieval focused multilingual sentence embedding models, made available on TensorFlow Hub. The models embed text from 16 languages into a shared semantic space using a multi-task trained dual-encoder that learns tied cross-lingual representations via translation bridge tasks (Chidambaram et al., 2018). The models achieve a new state-of-the-art in performance on monolingual and cross-lingual semantic retrieval (SR). Competitive performance is obtained on the related tasks of translation pair bitext retrieval (BR) and retrieval question answering (ReQA). On transfer learning tasks, our multilingual embeddings approach, and in some cases exceed, the performance of English only sentence embeddings.

1 Introduction

We introduce three new multilingual members in the universal sentence encoder (USE) (Cer et al., 2018) family of sentence embedding models. The models target performance on tasks that involve multilingual semantic similarity and achieve a new state-of-the-art in performance on monolingual and cross-lingual semantic retrieval (SR). One model targets efficient resource usage with a CNN model architecture (Kim, 2014). Another targets accuracy using the Transformer architecture (Vaswani et al., 2017). The third model provides an alternative interface to our multilingual Transformer model for use in retrieval question answering (ReQA). The 16 languages supported by our multilingual models are given in Table 1.\textsuperscript{1}

\begin{table}[h]
\centering
\begin{tabular}{|l|l|}
\hline
Languages & Family  \\
\hline
Arabic (ar) & Semitic  \\
Chinese (PRC) (zh) & Sino-Tibetan  \\
Chinese (Taiwan) (zh-tw) & Sino-Tibetan  \\
Dutch (nl) English (en) & Germanic  \\
German (de) & Germanic  \\
French (fr) Italian (it) & Latin  \\
Portuguese (pt) Spanish (es) & Latin  \\
Japanese (ja) & Japonic  \\
Korean (ko) & Koreanic  \\
Russian (ru) Polish (pl) & Slavic  \\
Thai (th) & Kra–Dai  \\
Turkish (tr) & Turkic  \\
\hline
\end{tabular}
\caption{Multilingual universal sentence encoder’s supported languages (ISO 639-1). Multilingual sentences are mapped to a shared semantic space.}
\end{table}

2 Model Toolkit

Our multilingual models are implemented in TensorFlow (Abadi et al., 2016) and made publicly available on TensorFlow Hub.\textsuperscript{2} Listing 1 illustrates the easy-to-use generation of multilingual sentence embeddings. The models conveniently only rely on TensorFlow without requiring additional libraries or packages. Listing 2 demonstrates using the question answering interface. Responses are encoded with additional context information such that the resulting context aware embeddings have a high dot product similarity score with the questions they answer. This allows for retrieval of indexed candidates using efficient nearest neighbor search.\textsuperscript{3}

3 Encoder Architecture

3.1 Multi-task Dual Encoder Training

Similar to Cer et al. (2018) and Chidambaram et al. (2018), we target broad coverage using a
import tensorflow_hub as hub

module = hub.Module("https://tfhub.dev/google/universal-sentence-encoder-multilingual/1")
multilingual_embeddings = module(["Hola Mundo!", "Bonjour le monde!", "Ciao mondo!",
"Hello World!", "Hallo Welt!", "Hallo Wereld!",
"你好世界!", "Привет, мир!", "مرحبا بالعالم!"])

Listing 1: Python code mapping multilingual sentences into a shared semantic embedding space.

module = hub.Module("https://tfhub.dev/google/universal-sentence-encoder-multilingual-qa/1")
query_embeddings = module(dict(text=["What is your age?"], signature="question_encoder", as_dict=True)
candidate_embeddings = module(dict(text=["I am 20 years old."], context=["I will be 21 next year."],
signature="response_encoder", as_dict=True)

Listing 2: Python code embedding a question and an answer for retrieval Question-Answering (ReQA).

3.2 SentencePiece
SentencePiece tokenization (Kudo and Richardson, 2018) is used for all of the 16 languages supported by our models. A single 128k SentencePiece vocabulary is trained from 8 million sentences sampled from our training corpus and balanced across the 16 languages. For validation, the vocab is used to process a development set, separately sampled from the sentence encoding model training corpus. We find the development set character coverage is higher than 99% for all languages, with less than 1% out-of-vocabulary tokens. Each token in the vocab is mapped to a fixed length embedding vector.

3.3 Shared Encoder
Two distinct architectures for the sentence encoding models are provided: (i) transformer (Vaswani et al., 2017), targeted at higher accuracy at the cost of resource consumption; (ii) convolutional neural network (CNN) (Kim, 2014), designed for efficient inference but obtaining reduced accuracy.

Transformer The transformer encoding model embeds sentences using the encoder component of the transformer architecture (Vaswani et al., 2017). Bi-directional self-attention is used to compute context-aware representations of tokens in a sentence, taking into account both the ordering and the identity of the tokens. The context-aware token representations are then averaged together to obtain a sentence-level embedding.

CNN The CNN sentence encoding model feeds the input token sequence embeddings into a con-
Table 2: Training tasks for the multilingual sentence encoder. For better coverage across languages, we combine native text with machine translated (MT) data. For NLI, native data is only used for English (en).

| Task Name                                      | Task Type | Data Source | Native or Not |
|-----------------------------------------------|-----------|-------------|---------------|
| Retrieval Question-Answering (ReQA)           | Ranking   | Web Crawled | Native + MT   |
| Translation Ranking                           | Ranking   | Web Crawled | Native        |
| Natural Language Inference (NLI)              | 3 way classification | Human Written | Native (en) + MT |

Table 3: Training examples by task for each of the 16 languages understood by our models.

Table 4: MAP@100 on SR (English). Models are compared with the best models from Gillick et al. (2018) that exclude in-domain training data.

4 Training and Configuration

4.1 Training Corpus

Training data consists of mined question-answer pairs, mined translation pairs, and the Stanford Natural Language Inference (SNLI) corpus (Bowman et al., 2015). SNLI only contains English data. The number of mined questions-answer pairs also varies across languages with a bias toward a handful of top tier languages. To balance training across languages, we use Google’s translation system to translate SNLI to the other 15 languages.

We also translate a portion of question-answer pairs to ensure each language has a minimum of 60M training pairs. For each of our datasets, we use 90% of the data for training, and the remaining 10% for development/validation. Table 2 and 3 lists the details of data used for each task / language.

4.2 Model Configuration

Input sentences are truncated to 256 tokens for the CNN model and 100 tokens for transformer. The CNN encoder uses 2 CNN layers with filter width of [1, 2, 3, 5] and 256 filters per width. The Transformer encoder employs 6 transformer layers, with 8 attentions heads, hidden size 512, and filter size 2048. Similar to our prior work (Cer et al., 2018), we configure our models with the intention of making them small and fast enough to be used directly within many downstream applications without the need for model distillation. Model hyperparameters are tuned on development data sampled from the same sources as the training data. We export sentence encoding modules for our two encoder architectures: USE_Trans and USE_CNN. We also export a larger graph for QA tasks from our Transformer based model that includes QA specific layers and support providing context information from the larger document as USE_QA_Trans+Cxt.

5 Experiments on Retrieval Tasks

In this section we evaluate our multilingual encoding models on semantic retrieval, bitext and...
Table 5: P@1 on UN translation pair bitext retrieval (BR). Yang et al. (2019) is a specialized translation retrieval model and the current state-of-the-art.

### 5.1 Semantic Retrieval (SR)

Following Gillick et al. (2018), we construct semantic retrieval (SR) tasks from the Quora question-pairs (Hoogeveen et al., 2015) and AskUbuntu (Lei et al., 2016) datasets. The SR task is to identify all sentences in the retrieval corpus that are semantically similar to a query sentence.\(^{11}\)

For each dataset, we first build a graph connecting each of the positive pairs, and then compute its transitive closure. Each sentence then serves as a test query that should retrieve all of the other sentences it is connected to within the transitive closure. Mean average precision (MAP) is employed to evaluate the models. More details on the constructed datasets can be found in Gillick et al. (2018). Both datasets are English only.

Table 4 shows the MAP@100 on the Quora and AskUbuntu retrieval tasks. We use Gillick et al. (2018) as the baseline model, which is trained using a similar dual encoder architecture. The numbers provided here are for models without focused in-domain training data.\(^{12}\) Both USE\(_{CNN}\) and USE\(_{Trans}\) outperform the prior state-of-the-art. USE\(_{Trans}\) and USE\(_{CNN}\) perform comparably on Quora. However, USE\(_{Trans}\) performs notably better than USE\(_{CNN}\) on AskUbuntu, suggesting the AskUbuntu data could be more challenging.

### 5.2 Bitext Retrieval (BR)

Bitext retrieval performance is evaluated on the United Nation (UN) Parallel Corpus (Ziemski et al., 2016), containing 86,000 bilingual document pairs matching English (en) documents with their translations in five other languages: French (fr), Spanish (es), Russian (ru), Arabic (ar) and Chinese (zh). Document pairs are aligned at the sentence-level, which results in 11.3 million aligned sentence pairs for each language pair.

Table 5 shows sentence-level retrieval precision@1 (P@1) for the proposed models as well as the current state-of-the-art results from Yang et al. (2019), which uses a specialized translation pair retrieval model. USE\(_{Trans}\) is generally better than USE\(_{CNN}\), performing lower than the SOTA but not by too much with the exception of en-zh.\(^{13}\)

| Model            | en-es | en-fr | en-ru | en-zh |
|------------------|-------|-------|-------|-------|
| USE\(_{Trans}\)  | 86.1  | 83.3  | 88.9  | 78.8  |
| USE\(_{CNN}\)    | 85.8  | 82.7  | 87.4  | 79.5  |
| Yang et al. (2019)| **89.0**| **86.1**| **89.2**| **87.9**|

Table 6: P@1 for SQuAD ReQA. Models are not trained on SQuAD. Dev and Train only refer to the respective sections of the SQuAD dataset.

### 5.3 Retrieval Question Answering (ReQA)

Similar to the data set construction used for the SR tasks, the SQuAD v1.0 dataset (Rajpurkar et al., 2016) is transformed into a retrieval question answering (ReQA) task.\(^{14}\) We first break all documents in the dataset into sentences using the sentence splitter distributed with the ReQA evaluation suite.\(^{15}\) Each question of the (question, answer spans) tuples in the dataset is treated as a query. The task is to retrieve the sentence designated by the tuple answer span. Search is performed on a retrieval corpus consisting of all of the sentences within the corpus. We contrast sentence and paragraph-level retrieval using our models, with the later allowing for comparison against a BM25 baseline (Jones et al., 2000).\(^{16}\)

| Model            | SQuAD Dev | SQuAD Train |
|------------------|-----------|-------------|
| **Paragraph Retrieval** |          |             |
| USE\(_{QA Trans+Cxt}\) | 63.5      | 53.3        |
| BM25 (baseline)  | 61.6      | 52.4        |
| **Sentence Retrieval** |          |             |
| USE\(_{QA Trans+Cxt}\) | 53.2      | 43.3        |
| USE\(_{Trans}\) | 47.1      | 37.2        |

\(^{11}\)The task is related to paraphrase identification (Dolan et al., 2004) and Semantic Textual Similarity (STS) (Cer et al., 2017), but with the identification of meaning similarity being assessed in the context of a retrieval task.

\(^{12}\)The model for Quora is trained on Paralex (http://knowitall.cs.washington.edu/paralex) and AskUbuntu data. The model for AskUbuntu is trained on Paralex and Quora.

\(^{13}\)Performance is degraded from Yang et al. (2019) due to using a single sentencepiece vocabulary to cover 16 languages. Languages like Chinese, Korean, Japanese have much more characters. To ensure the vocab coverage, sentencepiece tends to split the text of these languages into single characters, which increases the difficulty of the task.

\(^{14}\)The retrieval question answering task was suggested by Chen et al. (2017) and then recently explored further by Cakaloglu et al. (2018). However, Cakaloglu et al. (2018)’s use of sampling makes it difficult to directly compare with their results and we provide our own baseline based on BM25.

\(^{15}\)https://github.com/google/retrieval-qa-eval

\(^{16}\)BM25 is a strong baseline for text retrieval tasks. Paragraph-level experiments use the BM25 implementa-
| Model | en | ar | de | es | fr | it | ja | ko | nl | pt | pl | ru | th | tr | zh / zh-t |
|-------|----|----|----|----|----|----|----|----|----|----|----|----|----|----|-----------|
| **Cross-lingual Semantic Retrieval (cl-SR)** | | | | | | | | | | | | | | | |
| Quora | USETrans | 89.1 | 83.1 | 85.5 | 86.3 | 86.7 | 86.8 | 85.1 | 82.5 | 83.8 | 86.5 | 82.1 | 85.7 | 85.8 | 82.5 | 84.8 |
| USECNN | 89.2 | 79.9 | 83.7 | 85.0 | 85.0 | 85.5 | 82.4 | 77.6 | 81.3 | 85.2 | 78.3 | 83.8 | 83.5 | 79.9 | 81.9 |
| LASER | 79.7 | 82.2 | 83.5 | 83.1 | 83.7 | - | 73.4 | 82.8 | 83.6 | 82.3 | 82.6 | 78.6 | - | | |
| AskUbuntu | USETrans | 42.3 | 38.2 | 40.0 | 39.9 | 39.3 | 40.2 | 40.6 | 40.3 | 39.5 | 39.8 | 38.4 | 39.6 | 40.3 | 37.7 | 40.1 |
| USECNN | 39.9 | 33.0 | 35.0 | 35.6 | 35.2 | 36.1 | 35.5 | 35.1 | 34.5 | 35.0 | 32.2 | 35.2 | 32.2 | 34.6 |
| LASER | 24.5 | 26.1 | 26.4 | 26.5 | 27.0 | - | 22.0 | 26.2 | 26.2 | 25.7 | 25.6 | 23.8 | 25.0 | - | |
| **Average** | USETrans | 65.7 | 60.7 | 62.8 | 63.1 | 63.0 | 63.5 | 63.8 | 62.4 | 61.7 | 63.2 | 60.7 | 62.7 | 63.1 | 60.1 | 62.5 |
| USECNN | 64.6 | 56.5 | 59.4 | 60.3 | 60.1 | 60.8 | 59.0 | 56.4 | 57.9 | 60.4 | 55.6 | 59.5 | 59.4 | 56.4 | 58.3 |
| LASER | 52.1 | 54.2 | 55.0 | 54.8 | 55.4 | - | 47.7 | 54.5 | 54.9 | 54.0 | 54.6 | 51.2 | 52.5 | - | |

| Model | en | ar | de | es | fr | it | ja | ko | nl | pt | pl | ru | th | tr | zh / zh-t |
|-------|----|----|----|----|----|----|----|----|----|----|----|----|----|----|-----------|
| **Cross-lingual Retrieval Question Answering (cl-ReQA)** | | | | | | | | | | | | | | | |
| SQuAD train | USEQA Trans+Cxt | 43.3 | 33.2 | 35.2 | 37.2 | 37.0 | 37.0 | 32.9 | 31.1 | 36.6 | 37.7 | 34.5 | 33.2 | 36.9 | 32.3 | 32.7 |

Table 7: Cross-lingual performance on Quora/AskUbuntu cl-SR (MAP) and SQuAD cl-ReQA (P@1). Queries/questions are machine translated, while retrieval candidates remain in English.

We evaluated ReQA using the SQuAD dev and train sets and without training on the SQuAD data. The sentence and paragraph retrieval P@1 are shown in table 6. For sentence retrieval, we compare encodings produced using context from the text surrounding the retrieval candidate, USEQA Trans+Cxt, to sentence encodings produced without contextual cues, USETrans. Paragraph retrieval contrasts USEQA Trans+Cxt with BM25.

### 5.4 Cross-lingual Retrieval

Our English retrieval experiments are extended to explore cross-lingual semantic retrieval (cl-SR) and cross-lingual retrieval question answering (cl-ReQA). SR queries and ReQA questions are machine translated into other languages, while keeping the retrieval candidates in English. Table 7 provides our cross-lingual retrieval results for our transformer and CNN multilingual sentence encoding models. We compare against the state-of-the-art LASER multilingual sentence embedding library (Artetxe and Schwenk, 2019). On both the Quora and AskUbuntu cl-SR tasks, USETrans outperforms USECNN and LASER on all datasets, except the Polish (pl) Quora data where LASER achieves slightly better performance. USECNN tends to outperform LASER on Quora and always outperforms LASER by a sizable margin on AskUbuntu. We note that our CNN based model not only outperforms LASER, but also relies on simpler model architecture than LASER's LSTM based architecture. Given the similar level of performance on Quora between USECNN and LASER, we suspect the notably better performance on AskUbuntu over LASER is due to differences in the training data provided to encoding models.

### 6 Experiments on Transfer Tasks

For comparison with prior USE models, English task transfer performance is evaluated on SentEval (Conneau and Kiela, 2018). For sentence classification transfer tasks, the output of the sentence encoders are provided to a task specific DNN. For the pairwise semantic similarity task, the similarity of sentence embeddings $u$ and $v$ is assessed using $-\arccos\left(\frac{\langle u, v \rangle}{||u|| \cdot ||v||}\right)$, following Yang et al. (2018). In table 8, our multilingual models show competitive transfer performance when compared to state-of-the-art sentence embedding models. USETrans performs better than USECNN on all tasks. Our new

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17For sentences, the resulting retrieval task for development set consists of 11,425 questions and 10,248 candidates, and the retrieval task for train set is consists of 87,599 questions and 91,703 candidates. For paragraph retrieval, there are 2,067 retrieval candidates in the development set and 18,896 in the training set. To retrieve paragraphs with our model, we first run sentence retrieval and use the retrieved nearest sentence to select the enclosing paragraph.

18Poor translations are detected and rejected when the original English text and English back translation have a cosine similarity $< 0.5$ according our previously released English USETrans model (Cer et al., 2018).

19https://github.com/facebookresearch/LASER

20Results are not presented for LASER on ja and zh due to unicode errors.
Table 8: Performance on English transfer tasks from SentEval (Conneau and Kiela, 2018).

| Model                                    | MR  | CR  | SUBJ | MPQA | TREC | SST  | STS Bench (dev / test) |
|------------------------------------------|-----|-----|------|------|------|------|------------------------|
| USE multilingual models                  |     |     |      |      |      |      |                        |
| USE\textsubscript{CNN}                   | 73.8| 83.2| 90.1 | 87.7 | 96.4 | 78.1 | 0.829 / 0.809          |
| USE\textsubscript{Transformer}           | 78.1| 87.0| 92.1 | 89.9 | 96.6 | 80.9 | 0.837 / 0.825          |
| The state-of-the-art English embedding models |     |     |      |      |      |      |                        |
| InferSent (Conneau et al., 2017)         | 81.1| 86.3| 92.4 | 90.2 | 88.2 | 84.6 | 0.801 / 0.758          |
| Skip-Thought LN (Ba et al., 2016)        | 79.4| 83.1| 93.7 | 89.3 | –    | –    | –                      |
| Quick-Thought (Logeswaran and Lee, 2018) | 82.4| 86.0| 94.8 | 90.2 | 92.4 | 87.6 | –                      |
| USE\textsubscript{DAN} for English (Cer et al., 2018) | 72.2| 78.5| 92.1 | 86.9 | 88.1 | 77.5 | 0.760 / 0.717          |
| USE\textsubscript{Transformer} for English (Cer et al., 2018) | 82.2| 84.2| 95.5 | 88.1 | 93.2 | 83.7 | 0.802 / 0.766          |

Figure 2: Resource usage for the multilingual Transformer and CNN encoding models.

multilingual USE\textsubscript{Trans} model outperforms our best previously released English only model, USE\textsubscript{Trans} for English (Cer et al., 2018), on some tasks.

7 Resource Usage

Figure 2 provides compute and memory usage benchmarks for our models.\textsuperscript{21} Inference times on GPU are 2 to 3 times faster than CPU. Our CNN models have the smallest memory footprint and are the fastest on both CPU and GPU. The memory requirements increase with sentence length, with the Transformer model increasing more than twice as fast as the CNN model.\textsuperscript{22} While this makes CNNs an attractive choice for efficiently encoding longer texts, this comes with a corresponding drop in accuracy on many retrieval and transfer tasks.

8 Conclusion

Easy-to-use retrieval focused multilingual models for embedding sentence-length text are made available on TensorFlow Hub. Our models embed text from 16 languages into a shared semantic embedding space and achieve a new state-of-the-art in performance on monolingual and cross-lingual semantic retrieval (SR). The models achieve good performance on the related tasks of translation pair bi-text retrieval (BR) and retrieval question answering (ReQA). Monolingual transfer task performance approaches, and in some cases exceeds, English only sentence embedding models. Our models are freely available under an Apache license with additional documentation and tutorial colabary notebooks at:

https://tfhub.dev/s?q=universal-sentence-encoder-multilingual

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