KorNLI and KorSTS:
New Benchmark Datasets for Korean Natural Language Understanding

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Abstract

Natural language inference (NLI) and semantic textual similarity (STS) are key tasks in natural language understanding (NLU). Although several benchmark datasets for those tasks have been released in English and a few other languages, there are no publicly available NLI or STS datasets in the Korean language. Motivated by this, we construct and release new datasets for Korean NLI and STS, dubbed KorNLI and KorSTS, respectively. Following previous approaches, we machine-translate existing English training sets and manually translate development and test sets into Korean. To accelerate research on Korean NLU, we also establish baselines on KorNLI and KorSTS. Our datasets are made publicly available via our GitHub repository.

1 Introduction

Natural language inference (NLI) and semantic textual similarity (STS) are considered as two of the central tasks in natural language understanding (NLU). They are not only featured in GLUE (Wang et al., 2018) and SuperGLUE (Wang et al., 2019), which are two popular benchmarks for NLU, but also known to be useful for supplementary training of pre-trained language models (Phang et al., 2018) as well as for building and evaluating fixed-size sentence embeddings (Reimers and Gurevych, 2019). Accordingly, several benchmark datasets have been released for both NLI (Bowman et al., 2015; Williams et al., 2018) and STS (Cer et al., 2017) in the English language.

When it comes to the Korean language, however, benchmark datasets for NLI and STS do not exist. Popular benchmark datasets for Korean NLU typically involve question answering [2] and sentiment analysis [3], but not NLI or STS. We believe that the lack of publicly available benchmark datasets for Korean NLI and STS has led to the lack of interest for building Korean NLU models suited for these key understanding tasks.

Motivated by this, we construct and release KorNLI and KorSTS, two new benchmark datasets for NLI and STS in the Korean language. Following previous work [Conneau et al., 2018], we construct our datasets by machine-translating existing English training sets and by translating English development and test sets via human translators. We then establish baselines for both KorNLI and KorSTS to facilitate research on Korean NLU.

2 Background

2.1 NLI and the {S,M,X}NLI Datasets

In an NLI task, a system receives a pair of sentences, a premise and a hypothesis, and classifies their relationship into one out of three categories: entailment, contradiction, and neutral.

There are several publicly available NLI datasets in English. [Bowman et al., 2015] introduced the Stanford NLI (SNLI) dataset, which consists of 570K English sentence pairs based on image captions.

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https://github.com/kakaobrain/KorNLUDatasets
https://korquad.github.io/ (Lim et al., 2019)
http://www.aihub.or.kr/aidata/84
https://github.com/e9t/nsmc

https://arxiv.org/abs/2004.03289v2 [cs.CL] 8 Apr 2020
Figure 1: Data construction process. MT and PE indicate machine translation and post-editing, respectively. We translate original English data into Korean using an internal translation engine. For development and test data, the machine translation outputs are further post-edited by human experts.

(Williams et al., 2018) introduced the Multi-Genre NLI (MNLI) dataset, which consists of 455K English sentence pairs from ten genres. (Conneau et al., 2018) released the Cross-lingual NLI (XNLI) dataset by extending the development and test data of the MNLI corpus to 15 languages. Note that Korean is not one of the 15 languages in XNLI.

2.2 STS and the STS-B Dataset

STS is a task that assesses the gradations of semantic similarity between two sentences. The similarity score ranges from 0 (completely dissimilar) to 5 (completely equivalent). It is commonly used to evaluate either how well a model grasps the closeness of two sentences in meaning, or how well a sentence embedding embodies the semantic representation of the sentence.

The STS-B dataset consists of 8,628 English sentence pairs selected from the STS tasks organized in the context of SemEval between 2012 and 2017 (Agirre et al., 2012; Agirre et al., 2013; Agirre et al., 2014; Agirre et al., 2015; Agirre et al., 2016). The domain of input sentences covers image captions, news headlines, and user forums. For details, we refer readers to (Cer et al., 2017).

3 Data

3.1 Data construction

We explain how we develop two new Korean language understanding datasets: KorNLI and KorSTS. The KorNLI dataset is derived from three different sources: SNLI, MNLI, and XNLI, while the KorSTS dataset stems from the STS-B dataset. The overall construction process, which is applied identically to the two new datasets, is illustrated in Figure 1.

First, we translate the training sets of the SNLI, MNLI, and STS-B datasets, as well as the development and test sets of the XNLI and STS-B datasets, into Korean using an internal machine translation engine from Kakao. Then, the translation results of the development and test sets are post-edited by professional translators in order to guarantee the quality of evaluation. This multi-stage translation strategy aims not only to expedite the translators’ work, but also to help maintain the translation consistency between the training and evaluation datasets. To assure the quality of human translation, we split the machine translation outputs into halves, and have two human experts post-edit them. It is worth noting that the post-editing procedure does not simply mean proofreading. Rather, it refers to human translation...
based on the prior machine translation results, which serve as first drafts. After their work is done, we request the translators cross-check each other. Finally, we check spelling and grammar with Microsoft Word™ and correct errors manually.

### 3.2 KorNLI

| Source | Total | Train | Dev. | Test |
|--------|-------|-------|------|------|
| - SNLI, MNLI | - Machine | XNLI | Human | XNLI |
| # Examples | 950,354 | 942,854 | 2,490 | 5,010 |
| Avg. # words (premise) | 13.6 | 13.6 | 13.0 | 13.1 |
| Avg. # words (hypothesis) | 7.1 | 7.2 | 6.8 | 6.8 |

Table 1: Statistics of the KorNLI dataset.

| Example | English Translation | Label |
|---------|---------------------|-------|
| P: 저는, 그날 알아내려고 거기 있었어요. | I was just there just trying to figure it out. I was trying to understand. | Ent. |
| H: 이해하려고 노력하고 있었어요. | | |
| P: 저는, 그날 알아내려고 거기 있었어요. | I was just there just trying to figure it out. I understood it well from the beginning. | Contr. |
| H: 나는 처음부터 그것을 잘 이해했다. | | |
| P: 저는, 그날 알아내려고 거기 있었어요. | I was just there just trying to figure it out. I was trying to understand where the money went. | Neutr. |
| H: 나는 돈이 어디로 갔는지 이해하려고 했어요. | | |

Table 2: Examples from the KorNLI dataset. P and H denote Premise and Hypothesis, respectively. Ent., Contr., and Neutr. are contractions of Entailment, Contradiction, and Neutral, respectively.

Table 1 shows the statistics of the KorNLI dataset. There are 942,854 training examples translated automatically and 7,500 evaluation (development and test) examples translated manually. The premises are almost twice as long as the hypotheses, as reported in (Conneau et al., 2018). We present a few examples in Table 2.

### 3.3 KorSTS

As provided in Table 3, the KorSTS dataset comprises 5,749 training examples translated automatically and 2,879 evaluation examples translated manually. On average, a sentence has 7.5 words. Examples are shown in Table 4.

### 4 Baselines

In this section, we provide baselines for the Korean NLI and STS tasks using our newly created benchmark datasets. Because both tasks receive a pair of sentences as an input, there are two different approaches depending on whether the model encodes the sentences jointly (“cross-encoding”) or separately (“bi-encoding”).

#### 4.1 Cross-Encoding Approaches

As illustrated with BERT (Devlin et al., 2019) and many of its variants, the de facto standard approach for NLU tasks is to pre-train a large language model and fine-tune it on each task. In the cross-encoding approach, the pre-trained language model takes each sentence pair as a single input for fine-tuning. These cross-encoding models typically achieve the state-of-the-art performance over bi-encoding models, which encode each input sentence separately.

For both KorNLI and KorSTS, we consider two pre-trained language models. We first pre-train a Korean RoBERTa (Liu et al., 2019), both base and large versions, on a collection of internally collected

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7These nomenclatures (cross-encoding and bi-encoding) are adopted from (Humeau et al., 2020).
Table 3: Statistics of KorSTS dataset.

| Source          | Total | Train | Dev. | Test |
|-----------------|-------|-------|------|------|
| Translated by   | -     | Machine | Human | Human |
| # Examples      | 8,628 | 5,749 | 1,500 | 1,379 |
| Avg. # words    | 7.7   | 7.5   | 8.7  | 7.6  |

Table 4: Examples of KorSTS dataset.

| Example                                                                 | English Translation                                      | Label |
|-------------------------------------------------------------------------|-------------------------------------------------------|-------|
| 한 남자가 음식을 먹고 있다.                                             | A man is eating food.                                   | 4.2   |
| 한 남자가 뜨거운 음료를 먹고 있다.                                        | A man is eating something.                              |       |
| 한 비행기가 착륙하고 있다.                                              | A plane is landing.                                     | 2.8   |
| 애니메이션화된 비행기 하나가 착륙하고 있다.                               | A animated airplane is landing.                         |       |
| 한 여성이 고객을 요리하고 있다.                                         | A woman is cooking meat.                                 | 0.0   |
| 한 남자가 말하고 있다.                                                 | A man is speaking.                                      |       |

Korean corpora (65GB). We construct a byte pair encoding (BPE) (Gage, 1994; Sennrich et al., 2016) dictionary of 32K tokens using SentencePiece (Kudo and Richardson, 2018). We train our models using fairseq (Ott et al., 2019) with 32 V100 GPUs for the base model (25 days) and 64 for the large model (20 days).

We also use XLM-R (Conneau and Lample, 2019), a publicly available cross-lingual language model that was pre-trained on 2.5TB of Common Crawl corpora in 100 languages including Korean (54GB). Note that the base and large architectures of XLM-R are identical to those of RoBERTa, except that the vocabulary size is significantly larger (250K), making the embedding and output layers that much larger.

In Table 5, we report the test set scores for KorNLI (accuracy) and KorSTS (Spearman correlation). For KorNLI, we only train on the MNLI portion of the KorNLI dataset to ensure comparability with XNLI. Overall, despite being smaller, the Korean RoBERTa models outperform the XLM-R models for their respective sizes (base and large). For each model, the larger variant outperforms the base one, consistent with the findings in (Liu et al., 2019). The large version of Korean RoBERTa performed the best for both KorNLI (83.67) and KorSTS (85.27) among all models tested.

4.2 Bi-Encoding Approaches

We also report the KorSTS scores of bi-encoding models. The bi-encoding approach bears practical importance in applications such as semantic search, where computing pairwise similarity among a large set of sentences is computationally expensive with cross-encoding.

Here, we first provide two baselines that do not use pre-trained language models: Korean fastText and the multilingual universal sentence encoder (M-USE). Korean fastText (Bojanowski et al., 2017) is a pre-trained word embedding model trained on Korean text from Common Crawl. To produce sentence embeddings, we take the average of fastText word embeddings for each sentence. M-USE (Yang et al., 2019), is a CNN-based sentence encoder model trained for NLI, question-answering, and translation ranking across 16 languages including Korean. For both Korean fastText and M-USE, we compute the cosine similarity between two input sentence embeddings to make an unsupervised STS prediction.

Pre-trained language models can also be used as bi-encoding models following the approach of SentenceBERT (Reimers and Gurevych, 2019), which involves fine-tuning a BERT-like model with a Siamese network structure on NLI and/or STS. We use the SentenceBERT approach for both Korean RoBERTa (“Korean SRoBERTa”) and XLM-R (“SXLM-R”). We adopt the MEAN pooling strategy, i.e. computing the sentence vector as the mean of all contextualized word vectors.

8 https://dl.fbaipublicfiles.com/fasttext/vectors-crawl/cc.ko.300.bin.gz
9 https://tfhub.dev/google/universal-sentence-encoder-multilingual/3
10 https://tfhub.dev/google/universal-sentence-encoder-multilingual-large/3
Table 5: Test set scores for fine-tuned cross-encoding language models. KorNLI scores are accuracy (%) and KorSTS scores are $100 \times$ Spearman correlation. †To ensure comparability with XNLI, we only use the MNLI portion of the KorNLI dataset.

| Model                | # Params. | KorNLI† | KorSTS |
|----------------------|-----------|---------|--------|
| Korean RoBERTa (base)| 111M      | 82.75   | 83.00  |
| Korean RoBERTa (large)| 338M      | **83.67** | **85.27** |
| XLM-R (base)         | 270M      | 80.56   | 77.78  |
| XLM-R (large)        | 550M      | 83.41   | 84.68  |

Table 6: KorSTS test set scores ($100 \times$ Spearman correlation) of bi-encoding models. Note that the first two columns of results are unsupervised w.r.t. KorSTS, and the latter two are supervised w.r.t. KorSTS. †Trained on machine-translated SNLI only.

| Model                | # Params. | Unsupervised | Supervised |
|----------------------|-----------|--------------|------------|
| Korean fastText      | -         | -            | -          |
| M-USE\textsubscript{CNN} (base) | 68.9M      | 47.96       | -          |
| M-USE\textsubscript{CNN} (large) | 85.2M      | -           | †72.74     |
| Korean SRoBERTa (base) | 111M      | 48.96       | 74.19      |
| Korean SRoBERTa (large) | 338M      | 51.35       | 75.46      |
| SXLM-R (base)        | 270M      | 45.05       | 73.99      |
| SXLM-R (large)       | 550M      | 39.92       | 77.01      |

In Table 6 we present the KorSTS test set scores (Spearman correlation) for the bi-encoding models. We categorize each result based on whether the model was additionally trained on KorNLI and/or KorSTS. Note that models that are not fine-tuned at all or only fine-tuned to KorNLI can be considered as unsupervised w.r.t. KorSTS. Also note that M-USE is trained on a machine-translated version of SNLI, which is a subset of KorNLI, as part of its pre-training step.

First, given each model, we find that supplementary training on KorNLI consistently improves the KorSTS scores for both unsupervised and supervised settings, as was the case with English models (Conneau et al., 2017; Reimers and Gurevych, 2019). This shows that the KorNLI dataset can be an effective intermediate training source for bi-encoding approaches. When comparing the baseline models in each setting, we find that both M-USE and the SentenceBERT-based models trained on KorNLI achieve competitive unsupervised KorSTS scores. Both models significantly outperform the average of fastText embeddings model and the Korean SRoBERTa and SXLM-R models without fine-tuning. Among our baselines, large SXLM-R trained on KorNLI followed by KorSTS achieves the best score (81.84).

5 Conclusion

We introduced KorNLI and KorSTS—new datasets for Korean natural language understanding. Using these datasets, we also established baselines for Korean NLI and STS with both cross-encoding and bi-encoding approaches. We hope that our datasets and baselines will facilitate future research on improving Korean NLU systems.

References

Eneko Agirre, Daniel Cer, Mona Diab, and Aitor Gonzalez-Agirre. 2012. Semeval-2012 task 6: A pilot on semantic textual similarity. In * SEM 2012: The First Joint Conference on Lexical and Computational Semantics–
Yinhan Liu, Myle Ott, Naman Goyal, Jingfei Du, Mandar Joshi, Danqi Chen, Omer Levy, Mike Lewis, Luke Zettlemoyer, and Veselin Stoyanov. 2019. RoBERTa: A robustly optimized bert pretraining approach. arXiv preprint arXiv:1907.11692.

Myle Ott, Sergey Edunov, Alexei Baevski, Angela Fan, Sam Gross, Nathan Ng, David Grangier, and Michael Auli. 2019. fairseq: A fast, extensible toolkit for sequence modeling. In Proceedings of NAACL-HLT 2019: Demonstrations.

Jason Phang, Thibault Févry, and Samuel R. Bowman. 2018. Sentence encoders on stilts: Supplementary training on intermediate labeled-data tasks.

Nils Reimers and Iryna Gurevych. 2019. Sentence-BERT: Sentence embeddings using Siamese BERT-networks. In Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP), pages 3982–3992, Hong Kong, China, November. Association for Computational Linguistics.

Rico Sennrich, Barry Haddow, and Alexandra Birch. 2016. Neural machine translation of rare words with subword units. In Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 1715–1725, Berlin, Germany, August. Association for Computational Linguistics.

Alex Wang, Amanpreet Singh, Julian Michael, Felix Hill, Omer Levy, and Samuel Bowman. 2018. GLUE: A multi-task benchmark and analysis platform for natural language understanding. In Proceedings of the 2018 EMNLP Workshop BlackboxNLP: Analyzing and Interpreting Neural Networks for NLP, pages 353–355, Brussels, Belgium, November. Association for Computational Linguistics.

Alex Wang, Yada Pruksachatkun, Nikita Nangia, Amanpreet Singh, Julian Michael, Felix Hill, Omer Levy, and Samuel R Bowman. 2019. Superglue: A stickier benchmark for general-purpose language understanding systems. arXiv preprint arXiv:1905.00537.

Adina Williams, Nikita Nangia, and Samuel Bowman. 2018. A broad-coverage challenge corpus for sentence understanding through inference. In Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long Papers), pages 1112–1122. Association for Computational Linguistics.

Yinfei Yang, Daniel Cer, Amin Ahmad, Mandy Guo, Jax Law, Noah Constant, Gustavo Hernandez Abrego, Steve Yuan, Chris Tar, Yun-Hsuan Sung, Brian Strope, and Ray Kurzweil. 2019. Multilingual universal sentence encoder for semantic retrieval.