Effects and Mitigation of Out-of-vocabulary in Universal Language Models

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Abstract: One of the most important recent natural language processing (NLP) trends is transfer learning – using representations from language models implemented through a neural network to perform other tasks. While transfer learning is a promising and robust method, downstream task performance in transfer learning depends on the robustness of the backbone model’s vocabulary, which in turn represents both the positive and negative characteristics of the corpus used to train it. With subword tokenization, out-of-vocabulary (OOV) is generally assumed to be a solved problem. Still, in languages with a large alphabet such as Chinese, Japanese, and Korean (CJK), this assumption does not hold. In our work, we demonstrate the adverse effects of OOV in the context of transfer learning in CJK languages, then propose a novel approach to maximize the utility of a pre-trained model suffering from OOV. Additionally, we further investigate the correlation of OOV to task performance and explore if and how mitigation can salvage a model with high OOV.

Keywords: Natural language processing, Machine learning, Transfer learning, Language models

1. Introduction

Using a large-scale neural language model as a pre-trained backbone and transferring to a multitude of downstream tasks\textsuperscript{[6], [7], [21]} has been one of the most significant advancements in the field of natural language processing (NLP). This approach has been commonly used with convolutional neural networks trained against the ImageNet dataset and is commonly referred to as transfer learning. Language models used in this form do not yet have an official name but have been canonically called universal language models\textsuperscript{[11]}, due to its universal applicability. Unlike the domain of images or audio, pre-training language models for natural language processing do not require any annotated data due to various self-supervising training methods which have been recently proposed. This allows models to be pre-trained at scale, as there is a nearly infinite supply of training data from text data on the internet and through centuries worth of book corpora, given that one can efficiently digitize this into textual data and afford the amount of compute power needed as the training data is scaled up.

However, these methods still depend on a vocabulary bound to an embedding matrix. Due to the unavoidable growth of computational budget required as the vocabulary size increases, many methods have been proposed to reduce the vocabulary size to a manageable size, notably through subword based methods. Subword based methods, such as Byte-Pair Encoding (BPE)\textsuperscript{[23]}, WordPiece\textsuperscript{[30]}, SentencePiece\textsuperscript{[13]}, which break the lexicons into smaller subwords, have shown to be effective when applied to languages that utilize Latin-like alphabets in their writing system to reduce the size of the vocabulary while increasing the robustness against out-of-vocabulary (OOV) in downstream tasks. This is especially powerful when combined with transfer learning.

As these tokenizers still operate at Unicode character levels – contrary to the names suggesting byte-level (which would completely mitigate OOV, as studied in Ref.\textsuperscript{[10]}). Hence, the vocabulary’s minimum size is twice the size of all unique characters in the corpus, as subword tokenizers store each character in prefix and suffix form in the vocabulary. In commonly investigated languages, this still provides significantly more flexibility over lexicons. For these reasons, OOV issues have not been actively studied as it simply does not surface. However, this problem is yet to be solved in Chinese, Japanese, and Korean (CJK) languages due to the complex alphabets. We recognize that these unsolved problems make the applicability of neural language models for tasks in the context of CJK languages less universal than that of other languages.

The high-level idea of our method is illustrated in Fig.\textsuperscript{1}, where i, a token missing from the vocabulary, is substituted with i. This work expands on our our existing work\textsuperscript{[20]}, which adds an OOV vocabulary learning step before fine-tuning for a downstream task. This is done by re-assigning OOV subwords to existing subwords. Through experiments, we demonstrate the effects of OOV in a downstream task setup and compare the OOV mitigation scheme’s efficacy with and without additional pre-training. We further investigate how OOV contributes to task contribution by artificially inducing OOV in a pre-trained model and verify our proposed method can recover the model to a useable state even in moderately extreme OOV conditions.

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This work is an extension of our work in the Proceedings of Empirical Methods in Natural Language Processing, 2020\textsuperscript{[20]}. 
2. Related Work

This work builds on the foundation of multiple natural language processing developments, which we will explain in the sections below. First, we disambiguate the concept of a language model, subword tokenization, then explain how it was combined to build a backbone model for different tasks and discuss the limitations.

2.1 Neural Language Models

A language model is formally defined as a probability distribution over a sequence of tokens. Given a sequence of length \( m \), a probability \( P(w_1, \ldots, w_m) \) is assigned to the whole sequence. A neural language model is a sequence prediction model, commonly implemented as a classifier that predicts a sequence based on the past context. In the example above, given a current time step \( t \) which satisfies \( t < m \), it can predict \( P(w_t|w_1, \ldots, w_{t-1}) \) up to the \( P(w_{t+m}|w_1, \ldots, w_{t-1}) \). This is done by training such a neural network with unlabeled text corpora. This is possible because natural language can use coherently written sentences as a form of labeled data, unlike many other modalities. In the past, neural language models have been implemented using recurrent neural networks (RNN) such as long short-term memory networks (LSTM), but recent trends have shifted towards Transformer [26] based models due to the discovery of its applicability in other tasks, which we will discuss in Section 2.3.

2.2 Subword Tokenization

Tokenization is the process of breaking a sequence into smaller units for an algorithm to consume. In an NLP context, the most common practice is to tokenize at the whitespace level, which generally results in tokens becoming words in languages such as English. However, when the algorithm that is expected to consume this is a neural network, the possible conjugations and permutations (such as numbers) become computationally intractable for the network to process. For these reasons, traditional methods used forms of preprocessing, such as stemming or lemmatization or sample the vocabulary to a consumable size. This results in information loss, which can result in lost performance during evaluation.

Additionally, these methods are not robust to rare words, which in evaluation can result in out-of-vocabulary. Subword tokenization was proposed as a mitigation for the out-of-vocabulary problem. Byte-Pair Encoding (BPE) [23], WordPiece [30], and SentencePiece [14] are all subword tokenization methods, which break the lexicons into smaller subwords. These methods have been shown to make the vocabulary robust to rare words while minimizing information loss.

2.3 Universal Language Models

The term Universal Language Model was first coined in ULMFiT [11], which uses a pre-trained LSTM language model’s [18] hidden state to perform a multitude of tasks and achieve significant performance gains over per-task trained models. Around the same time, it was also discovered that such language model pretraining applied to a Transformer [26] based model, which was originally proposed for machine translation. The main difference of this Transformer based language model, BERT [7], is that it used significantly more compute power, was trained with a much larger pre-train dataset, and used subword tokenization.

With the advent of BERT, numerous other Transformer based architectures have been proposed and have shown to be extremely effective at being scaled up in terms of both increasing the amount of training data while also increasing the model capacity. Recent work such as GPT-3 [2] demonstrated substantial performance gains by scaling up both the model and data and validated that larger models are competitive in both zero-shot and few-shot settings.

Generally, the amount of pre-train data and model capacity is inversely proportional to the amount of downstream task data needed [2]. A pre-trained model also acts as a better initialization [1] as it also converges faster, reducing the amount of computation budget needed to achieve high performance on a given task. Due to this, state-of-the-art research employs transfer learning in some form.

While not all of the proposed backbone networks provide multilingual models or evaluations, work such as Ref. [6] shows that pre-training these models with multilingual corpora transferring with language models is also effective in a multilingual setup. However, a multilingual model’s downside over a monolingual model is that multilingual models tend to suffer from pre-train data imbalance. This reflects the real world since different languages differ in the number of users the language has. Generally, the amount of textual data one can acquire tends to be proportional to the number of users of each language and is also affected by socio-economic factors contributing to a lower deployment..
rate of digital technology, resulting in fewer data.

3. Preliminaries

3.1 CJK Tokenization in Universal Language Models

Out-of-vocabulary (OOV) in a subword tokenization context typically happens when a character was never seen in a pre-train context. These missing words can be introduced either by setting an upper limit on the character coverage or the vocabulary size. Here, the latter is tied to the former – if the character itself has been pruned from the initial set of characters to be covered, it is naturally infeasible to form a subword since the character is missing. This issue tends to be more significant in languages with a diverse alphabet, such as Chinese, Japanese, or Korean.

Chinese and Japanese use a large set of ideographs; some of which are rarely used, hence will not be statistically significant enough to be selected for inclusion but can be crucial in specific tasks such as named entity recognition (NER) since rare ideographs have moderate usage in names of people or locations.

Korean, on the other hand, has a large alphabet for somewhat artificial reasons. While the modern Korean alphabet can be expressed with 41 characters, the encoding of Korean in a computational context is done in a way that it is expressed through a combination of the underlying alphabet to form a composite character, and has been standardized in Unicode as these composite characters instead of its native form.

For these reasons, when trained against a diverse set of languages, the vocabulary size increases proportionally to the number of languages supported and needs to factor in the number of characters needed to express the language. For example, expressing English requires 26 characters, which results in 52 with both upper and lower cases. To express this in character level subwords, this results in 104 subwords, as both prefix and suffix forms are required in a vocabulary. To express French using the same vocabulary, the initial 26 can be re-used, and only 16 new characters specific to French are needed.

However, in the context of CJK languages, the initial character count is much larger, starting at approximately 2000 for common characters. Full coverage for the CJK ideographs requires 92,856 characters and 11,172 characters. While doubling the budget is not necessary, there are no cases in CJK languages which are written without spaces. Chinese and Japanese qualify as scriptio continua, while Korean is a special case where spacing rules are liberal and can be expressed without spaces in colloquial writing.

3.2 BERT Tokenizer

The multilingual BERT model bert-base-multilingual-cased [7] we used performs two-phase tokenization, first with whitespace (token) followed by WordPiece [30] tokenization (subword token). An example output of the tokenizer is explained in Fig. 1. The prefix forms of the subwords are expressed in their original form, while suffix forms are expressed by appending a ## prefix.

If either form of the subword is missing in a token, the tokenization fails, and the token surface is treated as OOV. Using the example in Fig. 1, the suffix form of is not in the vocabulary, hence the entire surface of the token 플랫 becomes OOV. This is due to the greedy merging nature of the WordPiece algorithm and is not universal to all subword-based methods.

Due to the dependency on initial whitespace tokenization, BERT’s tokenization is not expected to work well with scriptio continua languages, especially if it has a diverse alphabet. To workaround this limitation, BERT’s tokenizer implements special...
handing \footnote{https://github.com/google-research/bert/blob/master/tokenization.py#L251} which artificially injects whitespace before and after CJK ideographs. This mechanism is not enabled for Korean.

### 3.3 OOV Mitigation

As OOV was a much more prevalent problem in the context of word-based methods, it has been investigated further than OOV in subword-based methods.

In the context of word-based models, pre-processing the input with stemming and lemmatization was a common practice, both to reduce OOV and the size of the vocabulary. Additionally, novel methods such as dictionary-based post-processing \cite{17} and distributional representation based substitution \cite{12} have been proposed.

However, in the context of subword tokenization this has not been actively investigated, aside from Ref. \cite{27}, which proposes adding new words to the vocabulary, and Ref. \cite{20}, which is our work.

For our experiments, we used four CJK datasets for evaluation. For all tasks, we first learn OOV words, perform fine-tuning, then evaluate. The OOV rates noted for each dataset is the ratio of sentences containing at least one OOV token. We intentionally chose sentiment analysis datasets, as the pre-trained model used (bert-base-multilingual-cased) was trained on Wikipedia and book corpora, and a domain shift to user-written content had a higher likelihood of suffering from OOV due to words that are unlikely to appear in well-formed content. Theoretically, Korean is expected to suffer the most, as the BERT tokenizer does not have special case handling, hence is susceptible to the greedy merging of the underlying WordPiece tokenizer.

### 4. Proposed Method

In this section, we propose a method to mitigate OOV without training a new model. This is based on a hypothesis that OOV has adversarial effects on task performance, which we also verify through experiments in Section 5.2. Our method is implemented as a modification of the BERT tokenizer. In all mitigation experiments, we compare with and without additional pre-training.

The BERT tokenizer is modified to support a secondary vocabulary which points new words to existing words for our experiments. This modified tokenizer is used instead of the original tokenizer in a BERT model. The approach consists of three steps.

First, we perform a complete corpus analysis and search for all OOV surfaces by tokenizing the task corpus. An OOV surface in the context of BERT is an entire space tokenized token. Whenever OOV occurs, we keep a record of the entire OOV surface, along with the context.

For each OOV surface, we brute-force search to find the maximally specific OOV subword surface. An OOV subword surface is an actual subword missing in an OOV surface. In this step, we compute a frequency table for both OOV and in-vocabulary subwords for a preference mechanism in the mitigation strategy. We observed that most OOV subword surface cases were caused by one character missing in the vocabulary during our experiments, which is a result of incomplete character coverage from the corpora used for pre-training.

Finally, we use this information to build a mitigation strategy for the OOV subwords. Whenever applicable, we use the previously computed frequency of the OOV tokens to prioritize frequent OOV tokens over rare cases. Here, we evaluate different algorithms for OOV mitigation, each of which we discuss in the individual method sections below. After applying OOV mitigation, we then optionally perform additional pre-training and evaluate against the baseline.

Additional pre-training is the process of using the task corpus to train the model under a masked language modeling task, which is a form of additional pre-training, but against domain corpora. Here, the model is trained to fill in a masked portion of a given passage, given the context. Formally, this is called a cloze task and is the same process used to train BERT initially.

This additional pre-training intends to adapt the model so that it learns the changes in the vocabulary introduced by our mitigations, as the model has never seen the new subwords. This also helps the model better learn adequate representations that are better suited for the task domain. If the surrogate is assigned to a subword from a different language, for example, when using unseen subwords, this process is crucial. As this does not require an annotated corpus, it is also possible to make the model more robust by providing extra corpora.

Substitution to mitigate OOV has been studied in Ref.\cite{12}. This method depends on part-of-speech tagging or a secondary corpus and model for similarity computation, challenging to apply in a subword model. Our approach’s significance is that it works for subword models and its practical applicability, as only a downstream task corpus and a pre-trained model is required.

#### 4.1 Surrogated Tokens

Surrogates, simply put, map a subword missing from the vocabulary to a subword that is already in the vocabulary of a pre-trained model. There are intuitive ways to find substitute words in a word-level setup, the most obvious being choosing a semantically similar word from a thesaurus. In a subword context, this is not as straightforward, as a subword generally has no meaning. In our work, we discuss different surrogate selection processes.

The surrogate selection process assigns multiple subwords to the same embedding, which is a trade-off that limits the utility of the proposed method for generation tasks. As surrogates are only assigned once, to perform generation tasks when a subword is polysemic, one would need to use an auxiliary binary classifier to determine which subword the prediction actually is. This is not required for tasks that do not require generation, such as classification.

The embeddings between the newly added subword and the surrogate are shared and updated together in the fine-tuning process. The OOV subword frequency table we constructed in the second step of the process above is used to break ties and minimize conflicts. For example, token A and B, both of which are OOV subwords, can end up with the same proposals \{X, Y\} in preference order. In this case, given A has a higher frequency, it gets precedence over B, so the surrogate map becomes $A \rightarrow X$. 

\[\text{surrogated tokens} \rightarrow \text{model's vocabulary} \]

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exploit are different codepoints as seen in function. We perform an exhaustive search, formulated as the following.

- Select tokens from the in-vocabulary token frequency table, which were never seen in the current task as surrogates.

4.1.1 Character Distance

This method selects the surrogate with the shortest Unicode codepoint distance from the OOV subword, limited to subword tokens within the vocabulary of the same length. In this process, we perform an exhaustive search, formulated as the following.

$$\text{argmin}_{w \in W} |\text{ord}(v) - \text{ord}(u)|$$

In the formula above, $v$ is the OOV subword, and $W$ is a subset of the vocabulary $W$ which satisfies UTF-8 character level length equality $|v| = |u|$ for $u \in W$. $\text{ord}$ is the Unicode ordinal conversion function.

The intuition of this method builds on the characteristics of the CJK Unicode blocks, which allow us to cheaply approximate text or semantic similarity through the scalar values of the Unicode codepoints as seen in Fig. 3. The properties which we intend to exploit are different depending on the target language. In CJK ideographs, adjacent characters tend to share a radical, hence has a bias towards semantic similarity.

On the other hand, in Korean, phonetically similar characters are adjacent. This approximates edit distance, as it tends to disallow edits on the first two components of the character. In the event of a distance tie, we used the candidate with a lower codepoint.

Frequent subword tokens get preferential treatment and hence get surrogates with closer distance to an infrequent token. Once a token has been assigned, it is held out. Therefore, less frequent words are assigned to ones that the model has not seen in the context.

We use the same frequency preference as character distance, which allows frequent OOV subwords to have precedence when selecting surrogates. As with other methods, once a surrogate is assigned, it is held out. Therefore, less frequent words are assigned to the next most locally frequent surrogate. After the entire process, OOV subwords that were not assigned a surrogate are assigned to the candidate with the lowest frequency. This method has the highest computation cost, as it requires inference on the model.

4.2 Additional Tokens

Here, we add new tokens to the vocabulary and increase the model size, motivated by prior work [29]. As this increases the network parameters, these are used as a secondary baseline to be compared with surrogates.

4.2.1 Random Initialization

After adding the missing subword to the vocabulary, then the corresponding embedding is randomly initialized. This is analogous to how a model is commonly initialized, and also how new tokens are added to an existing vocabulary.

4.2.2 Transfer Initialization

Transfer initialization is done by following the first step of the masked language model task to generate a list of surrogates. We then initialize by copying the embedding vector of the topmost probable candidate of the OOV subword into the newly added OOV subword’s slot in the embedding matrix. These two tokens share the same initial embeddings but are expected to diverge through fine-tuning.
5. Datasets

5.1 Naver Sentiment Movie Corpus

The Naver Sentiment Movie Corpus *5 (NSMC) [3] is a Korean sentiment analysis task, containing 200,000 user comments and a corresponding binary label which indicates positive or negative sentiment. The OOV rate on the pre-trained BERT model was 30.1% due to a large number of typos and the domain gap.

5.2 Japanese Twitter Sentiment Analysis

As a second validation target language, we used a subset *6 of a Japanese Twitter dataset [25] *7, which is a sentiment analysis task with five possible labels. The subset contains 20 K Tweets and 2 K Tweets, respectively, for training and test. We observed that a large portion of the OOV was from emojis during analysis, resulting in an OOV rate of 25.1% on the pre-trained BERT model.

5.3 Chinese News Sentiment Analysis

The INEWS dataset is part of the ChineseGLUE *8 dataset. The input is a short sentence from a news article, and the label is one of three labels denoting the tone of the sentence. This is also a sentiment analysis task, with a split of 5 K train and 1 K validation, and an OOV rate of 20.1% on the pre-trained BERT model.

5.4 KorQuAD 1.0

KorQuAD 1.0 *9 is a Korean version of the SQuAD [22] reading comprehension task. The task involves answering a question given a passage of text, and consists of 10 K passages with 66 K questions. The passages are from Wikipedia, which is commonly used as a part of large-scale training corpora. The result of this is a low OOV rate of 5.9% on the pre-trained BERT model. For this task, additional pre-training was omitted to prevent the model from memorizing answers. We added this additional task to validate our method against a low-OOV task.

6. Experiments

To validate the effectiveness of our method proposed in the previous section, we perform multiple experiments against multiple CJK datasets in the upcoming sections. To thoroughly evaluate the effects of our proposed scheme, we validate against both real and synthetic setups, using the different mitigation schemes explained in Section 4. The high-level flow of all experiments we do here work is explained in Fig. 4. We compare the effects of different methods using a pre-trained multilingual BERT (bert-base-multilingual-cased). Each method was tested with fine-tuning, including a masked language modeling (additional pre-training) task, or by fine-tuning only against the task. Task-level fine-tuning was included in every experiment to ensure fairness and is done by attaching a task head and training the downstream task model. This allows the model to learn how to accomplish the task while adapting itself to produce better representations for the task. For our experiments, we limited additional pre-training to the task corpus to make the experiments reproducible with only the task datasets.

All experiments that involved training the model were trained for three epochs. The full list of hyperparameters used for the experiments is listed in Table A·1, in this paper’s appendix. Every experiment in the upcoming section was run five times each, with the random seed fixed to an integer value of the run number in the range of [1..5]. The runs are then compared to the baseline scores to observe the statistical significance of the different scores for each method. For the significance test, we performed a dependent t-test for paired samples, following the guidelines in Ref. [9]. We used a p-value of $p < 0.05$ to determine statistical significance and a fixed seed (42) for any random algorithm to make the results deterministic, which guarantees reproducibility, as can be seen in Table 2. The evaluation was done with the reference implementation *10 from Ref. [9].

6.1 Results on Task Datasets

The evaluation was done through the SST-2 GLUE task metrics [28] for the sentiment analysis tasks, and EM/F1 evaluation from the SQuAD metrics for KorQuAD, as the two tasks are com-

*5 https://github.com/e9t/nsmc
*6 https://github.com/cynthia/japanese-twitter
*7 http://www.db.info.gifu-u.ac.jp/data/Data_5d832973308d57446583ed9f
*8 https://github.com/chineseGLUE
*9 https://korquad.github.io/
*10 https://github.com/rjmmarr/testSignificanceNLP
The results of these experiments are in Table 2. compatible. Each model used the same dataset and training parameters as the baseline, only with different OOV mitigation methods. The results of these experiments are in Table 2.

Additionally, while Chinese and Japanese are both scriptio continua languages, BERT’s tokenizer treats CJK ideograph text differently and breaks at every character by artificially injecting whitespaces. This makes the affected surface from OOV significantly smaller, resulting in less information loss. We expect to see more considerable gains in Korean for these reasons, as the per-character break is not enabled.

### 6.1.1 Naver Sentiment Movie Corpus

Due to the larger OOV surface and frequency, we expect to observe a modest increase in the best case compared to the baseline. As seen in Table 2, we can indeed observe that regardless of the mitigation method, OOV mitigation, in general, improves accuracy and the improvements are statistically significant. The OOV tokens we observed here were from casual writing in user comments, which shifts from the book corpus like domain used for pre-train. This suggests that even without robust, representative embeddings, it is still better than losing information during tokenization. We also hypothesize that performance improves by domain adaptation through additional pre-training because the initial embeddings are not representative of the subword in context. As this dataset had the most significant gains in performance, we investigated the positive and negative examples in Fig. 5. As we have observed in Table 3, there were more cases which improved with our method. However, we also observed that negative cases emerge from additional pre-training, such as the samples in Fig. 5, some of which we suspect can be attributed to surrogates being assigned to a different language’s Unicode page.

### 6.1.2 Japanese Twitter Sentiment Analysis

This corpus showed a high OOV rate due to the frequent occurrence of emoji in the text, and improper normalization of Unicode punctuation. We observe similar patterns with the results from NSMC. Generally, we see only minor improvements, except for character distance – which was statistically significant. We observed that character distance assigned surrogates to Korean characters *11.

### Table 2

| Model        | Dataset         | Score | p-value | Improvement | Delta |
|--------------|-----------------|-------|---------|-------------|-------|
| BERT (Baseline) | NSMC (ko)       | 0.8824 | 0.8785  | 0.7284      | 0.7192 | 0.138  | 0.8074 | 0.7037 | 0.9005 |
|               | Twitter (ja)    | 0.8916 | 0.8844  | 0.7319      | 0.7223 | 0.116  | 0.8082 | 0.7097 | 0.9030 |
|               | INEWS (zh)      | 0.0002 | 0.0000  | 0.1091      | 0.1623 | 0.2599 | 0.4437 | 0.0091 | 0.0041 |
|               | KorQuAD (ko)    | 0.8928 | 0.8848  | 0.7310      | 0.7211 | 0.8186 | 0.8106 | 0.7098 | 0.9029 |
| Char. Distance | NSMC (ko)       | 0.8926 | 0.8855  | 0.7304      | 0.7238 | 0.8122 | 0.8092 | 0.7094 | 0.9031 |
|               | Twitter (ja)    | 0.0002 | 0.0000  | 0.0046      | 0.0041 | 0.0049 | 0.0065 | 0.0034 | 0.0018 |
|               | INEWS (zh)      | 0.0000 | 0.0000  | 0.2263      | 0.1639 | 0.1280 | 0.0601 | 0.0128 | 0.0248 |
| Masked LM     | NSMC (ko)       | 0.8915 | 0.8842  | 0.7307      | 0.7225 | 0.8100 | 0.8090 | 0.7089 | 0.9027 |
|               | Twitter (ja)    | 0.0002 | 0.0002  | 0.1103      | 0.1219 | 0.1451 | 0.2801 | 0.0177 | 0.0614 |

### Table 3

| Dataset     | Regressed | Improved | Delta |
|-------------|-----------|----------|-------|
| NSMC        | 392       | 528      | 136   |
| KorQuAD     | 64        | 79       | 15    |
| Twitter     | 21        | 32       | 11    |
| INEWS       | 11        | 11       | 0     |

*11 This would have been appropriate to demonstrate with examples, but due to the Twitter license agreement, reproducing the original text in this paper was not possible.
Positive, positive (with bad patches) and negative examples with the proposed method applied.

Negative cases are surrogate assignments which had adversarial effects on performance, and positive is the opposite. Positive with bad patches is a special case where the assignment looks incorrect, but contributed positively to performance. The OOV surfaces have been marked in bold.

In the next section, we explore if our method can recover performance in high-OOV models, which we have synthetically created through initial OOV and performance correlation experiments.

6.2 Effects of OOV on Task Performance

In the previous section, we demonstrated the effects of our method on different tasks and languages. These experiments were conducted based on the hypothesis that OOV has an adversarial impact on task performance. In this section, we artificially induce OOV on a pre-trained model through vocabulary pruning and correlate the OOV rate to task performance. With these synthetic OOV models, we use one of the tasks to investigate how OOV affects task performance in a BERT model. Following this, we apply our scheme to these synthetic models to verify if our proposed method is effective at recovering the performance of a broken model.

In this section, we investigate the correlation between OOV and task performance by evaluating task performance using the baseline BERT (bert-base-multilingual-cased) model, then compare the results of that to models with varying OOV rates. We use the three methods to eliminate the most frequent words, the least frequent words, and random sampling. We compare different methods to ensure fairness, as the different methods exhibit different scenarios of how an OOV can be introduced in a downstream task. NSMC was chosen because it was the largest dataset we had for our experiments, and we assumed that the larger the task corpus is, the more likely it will have a diverse vocabulary, hence being more susceptible to OOV.

For the frequency computation, we used two datasets. The first dataset we used is the kobert12 corpus. This corpus is a Korean corpus cleansed of Wiki markup from multiple publicly available Wiki dumps. As we only use the Wikipedia part of kobert, we refer to the corpus as KoWiki in this paper. We considered this to be a good approximation of what the backbone model (bert-base-multilingual-cased) was initially trained with. This is because almost every large-scale pre-train corpus contains Wikipedia in some form. For this case, the frequency table was initialized with every Korean subword in the model, and the frequencies against the KoWiki corpus were updated on the frequency table. Subwords in the model’s vocabulary, but not in the KoWiki corpus, were kept at a 0. The second dataset used was the actual task corpus, as using the task corpus is the most effective way to introduce OOV artificially.

This experiment intends to correlate the relation between OOV rate and task performance to confirm our initial hypothesis. It is worth noting that as we do not train a model from scratch, this is an approximation and not an accurate representation of what a pre-trained model’s vocabulary would have due to the properties of subword tokenization depending on the character level n-gram distribution. This trade-off was made for computational efficiency reasons, as pre-training a new model requires a significant amount of computing power, and for our experiments, we will need to train 42 models, which was computationally infeasible.

In our experiments, we prune subwords from the frequency table in different ratios— for our experiments, we chose 0.1%, 1%, 5%, 10%, 20%, and 50% as the target ratios. 20% and 50% are

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12 https://github.com/cynthia/kosentences
used to test extreme scenarios, to a point where it is likely that the model predictions can be considered equivalent to random choice. We use three different strategies for pruning the vocabulary, which we discuss in the subsections below. The ratio here is the ratio of words of the frequency table’s vocabulary we prune from the vocabulary and should not be mistaken with the OOV ratio discussed in the datasets section.

6.2.1 Common Words
Removing the most frequent words is not a common scenario in any form, especially when it comes to a pre-trained model setup. Ranking the vocabulary in order of frequency, we prune the vocabulary from the top ranking (most frequent) word based on the ratio to be pruned. For example, in a 1,000 word vocabulary with a 5% prune rate, the end result will be a model that is missing 50 of the most frequent words. This was chosen to demonstrate the extreme cases of unusable models, for instance, if a language that was expected to be supported was accidentally omitted from the training data.

6.2.2 Rare Words
This method was chosen to simulate a scenario where the corpus was sampled, or character coverage was reduced due to computational constraints. As least frequent subwords in a corpus will be omitted from the vocabulary, we consider this a rough approximation of what would happen when trade-offs are made due to the computational limitations. The process is the same as common words, but in this case, pruning is in order of least frequent words.

6.2.3 Random Words
In random words, we randomly eliminate subwords from the vocabulary. The subwords list in the frequency table is used to select target subwords to remove from the vocabulary. Based on the target subword list, we randomly choose a word for removal and evaluate the performance.

This is also another approximation of the consequences of computational feasibility trade-offs, as with least frequent words. As the distribution of subword frequency is expected to follow Zipf’s law, even with random removal, we assume that the probability of an infrequent subword being chosen for deletion is inversely proportional to the frequency of the given subword.

6.3 Correlating Task Performance with OOV
The results of these experiments are summarized in **Fig. 6**, accompanied by the full results in Table A.2. An important point to note here is that as this is a balanced, binary classification task, it is unlikely that a model’s accuracy can go significantly below 0.5. As it converges towards 0.5, we can consider the model’s output to be equivalent to an equidistributed binary random number generator, hence a random model.

Based on the experiment results, the first straightforward observation we made is that removing rare words does not affect task performance at all, regardless of how many are removed. Analyzing the removed words, we observed that the removed words were mostly words from a different language, which we suspect will not have substantial contributions to task performance. On the other hand, the other two methods used for pruning affect accuracy, especially as the ratio increases.

We observed that pruning common words had immediate effects, especially using the KoWiki corpus – as the effects are apparent even at 0.1%. This is because the vocabulary of the frequency table of KoWiki is larger than that of NSMC. 0.1% pruned more subwords than the NSMC frequency table, which had a smaller vocabulary. Removal of common words can have devastating effects, as, without a matching suffix form of a subword, the tokenizer’s greedy will fail. In both cases, we can see that starting from around 5%; the model converges towards a random model’s performance. In these worst-case scenarios, we observed that the model’s input had more OOV than actual subwords. In many cases, input to the model exclusively consisted
Random pruning, on the other hand, tended to have a slower effect on task performance. This is expected, as the probability of pruning a common subword is lower than the probability of pruning a less common word. We can still observe noticeable performance decreases on both KoWiki and NSMC starting from 5%. Unlike common, the model did not end up in a state comparable to random choice.

Even when scaled up to 50%, pruning rare subwords did not have significant effects on the performance. This was somewhat unexpected, as we initially hypothesized it to affect the task performance with that many words removed. The reason turned out to be that even at 50%, most of the rare words only appeared once, and only a small portion (less than 5%) of these rare words were Korean – which explains the minimal effect on performance.

We use the models from this experiment with the same protocol we proposed to mitigate OOV for the recovery experiments. Among the multiple methods proposed, we use character distance (CD), as it was shown to be effective while being computationally efficient, which allowed us to experiment with many different configurations.

6.4 Recovery with Proposed Method

The results of this experiment are visualized in Fig. 7, and the full results are in Table A·3. The trends we observed in the original mitigation NSMC experiments repeat here. A model that has been both through additional pre-training and OOV-patching consistently outperformed a model without additional
Table 4  OOV Rate tested on the task datasets used for our experiments with language-specific models. Rates have been rounded the first decimal digit. (0.0% is any value under 0.05%)

| Dataset     | Model          | OOV Tokens | Total Tokens | Token Rate | OOV Sentences | Total Sentences | Sentence Rate |
|-------------|----------------|------------|--------------|------------|---------------|----------------|---------------|
| NSMC        | bert-base-multi| 81,603     | 5,135,891    | 1.5%       | 60,151        | 200,000        | 30.1%         |
| NSMC        | KR-BERT        | 360        | 4,773,732    | 0.0%       | 336           | 200,000        | 0.1%          |
| KorQuAD     | bert-base-multi| 14,159     | 5,134,799    | 2.8%       | 8,569         | 144 K          | 5.9%          |
| KorQuAD     | KR-BERT        | 5,978      | 4,396,060    | 1.4%       | 2,393         | 144 K          | 1.7%          |
| Twitter     | bert-base-multi| 10,310     | 985,345      | 1.0%       | 5,518         | 22,000         | 25.1%         |
| Twitter     | cl-tohoku-base-v2| 26,566  | 951,286      | 2.8%       | 10,165        | 22,000         | 46.2%         |
| INEWS       | bert-base-multi| 2,570      | 158,212      | 1.6%       | 1,278         | 6,355          | 20.1%         |
| INEWS       | bert-base-chinese| 2,338   | 158,065      | 1.5%       | 1,119         | 6,355          | 17.6%         |

Table 4 shows the OOV rates tested on the task datasets used for our experiments with language-specific models. Rates have been rounded to the first decimal digit. (0.0% is any value under 0.05%).

7. Applicability to Other Models

7.1 Multilingual Models

While our experiments are limited to BERT, the method can be applied to any model. Generally, our proposed method is most effective when applied to greedy merging tokenizers such as WordPiece, which is used by both BERT and ELECTRA [4]. This is due to the fact that greedy merging results in whole chunks of text being lost during tokenization, as we have observed in the Fig. 5 examples.

However, our method is applicable to most subword tokenization methods, such as Byte-pair Encoding (BPE), used by the multilingual model XLM [15], and SentencePiece [14], used by another multilingual model, XLM-R [5] also can benefit from this. The effects will be less significant since both tokenizers are not greedy. The expected effect is a diversification of the UNK token by re-assigning it to different subwords instead of all OOV tokens being mapped to a single embedding. This is expected to make it easier to train. In an actual byte-level subword tokenization, such as used in GPT-2 [21], our method is not expected to have any gains as there will always be a byte-level fallback.

7.2 Monolingual Models

Following the discussion on our method's applicability to different multilingual models, we also investigated whether or not OOV is also a phenomenon in language-specific models. As our method depends on the occurrence of OOV in the first place, if there is a low OOV rate, the contributions of OOV mitigation are also expected to be minor. To investigate this, we used three separate monolingual models for each language.

For Chinese, we used the official BERT Chinese model (bert-base-chinese) released as part of the pre-trained models in Ref. [8], with the BERT tokenizer, and for Japanese we used [14]. Finally, for Korean, we used KR-BERT [16] with Normalization Form Compatibility Decomposition (NFKD) pre-processing. The subcharacter decomposition is similar to the work proposed in Ref. [19] and makes this method much more robust against OOV. Each of the monolingual models was used to tokenize the respective language dataset compared with the multilingual model used in this work. The results are disclosed in Table 4.

We observed that Korean, which is the most effective language to our scheme, we can see that the amount of OOV tokens in this model is extremely low. Due to this, it is unlikely to have adversarial effects on performance. While the OOV token ratio was still above 1% for KorQuAD, most of this turned out to be caused by subwords in a foreign language (e.g., CJK Ideographs), which is unlikely to have severe effects as it is assumed that the reader does not necessarily have to comprehend this from the passage to produce an answer for the task.

Japanese, on the other hand, showed an increase in OOV. This is likely because the pre-training corpus was Wikipedia, which is well-formed text lacking colloquial writing, and Emojis, common in data sourced from social networks. In Chinese, there was very little difference as with the multilingual model, so the effects of applying our method are likely to be the same as a multilingual model.

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*13 Byte-pair Encoding is commonly misrepresented, as while the original method does operate at byte-level, current applications all operate at Unicode character level.
*14 https://github.com/cl-tohoku/bert-japanese
*15 This model does not work if this normalization is omitted.
*16 We confirmed that none of the answers expected an answer in a different language from the dataset.
8. Conclusions

In this work, we investigate the correlation between OOV and task performance in the context of transfer learning. With differing OOV rates, we confirm our hypothesis that OOV directly affects downstream task performance in the context of transfer learning. We demonstrate and compare with no mitigation, mitigation through network modification, and surrogates, which require no network modification, and show how each approach affects downstream tasks. In particular, we show that vocabulary surrogates can provide performance boosts with no additional computation cost at the model level, especially when paired with additional pretraining. Additionally, with the same experiments, we also confirm that tasks with lower OOV suffer less than tasks with higher OOV.

We further explore the applicability of our work in extreme cases and use the high-OOV models we used to test our hypothesis, combined with the proposed mitigation can recover the model’s capabilities and conclude that in a transfer learning setup, tokenization serves a significant role in a pre-trained model’s capabilities.

8.1 Future Work

Additionally, one of our work’s limitations is that most of the surrogate methods cannot be used for generative tasks, as tokens are replaced with other tokens. We expect future work to explore potential solutions for this limitation. Finally, while we provided a hypothesis, the reason why BERT can still perform using unseen subwords for classification is not an answered question and warrants further investigation.

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We ran our experiments as close as possible to the baseline parameters used by the publicly available benchmark scripts for each task type. This means most of the hyperparameters for all of the evaluation was done close to the default values as possible. For the OOV correlation and recovery tasks, we optimized the sequence length and batch size parameter specifically to the task to maximize VRAM usage for faster experimentation. The exact hyperparameters are disclosed in Table A1.17

The masking probability for the MLM task was set to 0.15 for additional pre-training. We did not use whole word masking for our experiments.

A.2 Environment and Computation Cost

The experiments in this paper were run on two different environments. The additional pre-training and accompanied evaluation experiments were executed on a shared rt-G.small instance on the ABCI compute cluster.18 An rt-G.small node has six segregated CPU cores from a Xeon Gold 6148, a Tesla V100 GPU with 16 GB VRAM, and 60 GBs of memory. The training data and experimental code was streamed from a shared GPFS mount. Each experiment requires a different amount of compute budget. The longest-running experiment finished in 10 hours of wall clock time, and the shortest finished in 2 hours of wall clock time. The average runtime for each experiment was approximately 5.5 hours.

The OOV correlation and recovery NSMC experiments were executed on a desktop computer with a Ryzen 9 3900XT 12-core processor, RTX3090 GPU with 24GBs of VRAM, and 64GBs of memory. The training data and experimental code were on a local Pfsense E16 NVMe drive. Both tasks required the same amount of compute budget, and the average runtime for each experiment was approximately 40 minutes with the hyperparameter optimizations used above.

A.3 Experiment Result Tables

The results obtained from all of the experiments, including those omitted from the plots, are in Tables A2 and A3 respectively.
Table A-1 Hyperparameters used to train each of the downstream task models.

| Task                        | Optimizer | Adam $\epsilon$ | LR     | GradAccum | Weight Decay | Length | Batch Size | Epochs |
|-----------------------------|-----------|------------------|--------|-----------|--------------|--------|------------|--------|
| Additional Pre-training     | Adam      | 1e-8             | 5e-5   | 1         | 0.0          | 512    | 6          | 3      |
| OOV Correlation (NSMC)      | Adam      | 1e-8             | 2e-5   | 1         | 0.0          | 160    | 160        | 3      |
| Mitigation (GLUE)           | Adam      | 1e-8             | 2e-5   | 1         | 0.0          | 512    | 10         | 3      |
| Question Answering (KorQuAD) | Adam      | 1e-8             | 3e-5   | 1         | 0.0          | 512    | 12         | 3      |
| OOV Recovery (NSMC)         | Adam      | 1e-8             | 2e-5   | 1         | 0.0          | 160    | 160        | 3      |

Table A-2 Experiment results demonstrating the effects of OOV in an artificial setup. The percentages are the ratio of words removed based on the frequency table computed with different data. Method is the different methods used for pruning.

| Frequency Table | Method       | 0%   | 0.1% | 1% | 5% | 10% | 20% |
|-----------------|--------------|------|------|----|----|-----|-----|
| KoWiki          | Common       | 0.87730 | 0.75882 | 0.64312 | 0.53632 | 0.52584 | 0.50994 | 0.49654 |
| KoWiki          | Rare         | 0.87730 | 0.86772 | 0.86730 | 0.86730 | 0.86842 | 0.86786 | 0.86928 |
| KoWiki          | Random       | 0.87730 | 0.86982 | 0.86456 | 0.85934 | 0.82758 | 0.79182 | 0.70068 |
| NSMC            | Common       | 0.87730 | 0.83650 | 0.70486 | 0.59100 | 0.49656 | 0.52088 | 0.50788 |
| NSMC            | Rare         | 0.87730 | 0.86772 | 0.86918 | 0.86766 | 0.86790 | 0.86762 | 0.86794 |
| NSMC            | Random       | 0.87730 | 0.86784 | 0.86494 | 0.85550 | 0.82104 | 0.70904 | 0.60556 |

Table A-3 Recovery experiment results. Patched is with mitigation, Patched+MLM is with mitigation and additional pre-training.

| Frequency Table | Sampler | Mitigation | 0%   | 0.1% | 1% | 5% | 10% | 20% |
|-----------------|---------|------------|------|------|----|----|-----|-----|
| KoWiki          | Common  | None       | 0.87730 | 0.75882 | 0.64312 | 0.53632 | 0.52584 | 0.50994 | 0.49654 |
| KoWiki          | Rare    | Patched    | 0.88390 | 0.87132 | 0.85702 | 0.85014 | 0.84756 | 0.85146 | 0.85120 |
| KoWiki          | Rare    | Patched (CD) + MLM | 0.88850 | 0.88446 | 0.86514 | 0.86256 | 0.86918 | 0.86662 | 0.86562 |
| KoWiki          | Random  | None       | 0.87730 | 0.86772 | 0.86730 | 0.86730 | 0.86842 | 0.86882 | 0.86928 |
| KoWiki          | Random  | Patched    | 0.88390 | 0.88094 | 0.88017 | 0.88072 | 0.88081 | 0.88124 | 0.88098 |
| KoWiki          | Random  | Patched (CD) + MLM | 0.88850 | 0.88588 | 0.88556 | 0.88572 | 0.88628 | 0.88530 | 0.88464 |
| KoWiki          | Rare    | None       | 0.87730 | 0.86892 | 0.86456 | 0.85934 | 0.82758 | 0.79182 | 0.70068 |
| KoWiki          | Rare    | Patched    | 0.88390 | 0.88092 | 0.88078 | 0.87752 | 0.87452 | 0.87012 | 0.85542 |
| KoWiki          | Rare    | Patched (CD) + MLM | 0.88850 | 0.88582 | 0.88490 | 0.88522 | 0.88380 | 0.88354 | 0.87710 |
| NSMC            | Common  | None       | 0.87730 | 0.88650 | 0.70486 | 0.59100 | 0.49656 | 0.52088 | 0.50788 |
| NSMC            | Common  | Patched    | 0.88390 | 0.87942 | 0.87530 | 0.86340 | 0.85716 | 0.84872 | 0.85000 |
| NSMC            | Common  | Patched (CD) + MLM | 0.88850 | 0.88432 | 0.87788 | 0.86590 | 0.86146 | 0.86122 | 0.86040 |
| NSMC            | Rare    | None       | 0.87730 | 0.86772 | 0.86918 | 0.86766 | 0.86790 | 0.86762 | 0.86794 |
| NSMC            | Rare    | Patched    | 0.88380 | 0.88176 | 0.88208 | 0.88264 | 0.88242 | 0.88248 | 0.88266 |
| NSMC            | Rare    | Patched (CD) + MLM | 0.88850 | 0.88610 | 0.88622 | 0.88648 | 0.88446 | 0.88558 | 0.88490 |
| NSMC            | Random  | None       | 0.87730 | 0.86784 | 0.86494 | 0.85550 | 0.82104 | 0.70904 | 0.60556 |
| NSMC            | Random  | Patched    | 0.86830 | 0.88288 | 0.88112 | 0.88264 | 0.87702 | 0.87506 | 0.86194 |
| NSMC            | Random  | Patched (CD) + MLM | 0.88850 | 0.88488 | 0.88644 | 0.88196 | 0.87882 | 0.87388 | 0.86554 |

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