A Simple Approach for Handling Out-of-Vocabulary Identifiers in Deep Learning for Source Code

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Abstract

There is an emerging interest in the application of deep learning models to source code processing tasks. One of the major problems in applying deep learning to software engineering is that source code often contains a lot of rare identifiers resulting in huge vocabularies. We propose a simple yet effective method based on identifier anonymization to handle out-of-vocabulary (OOV) identifiers. Our method can be treated as a preprocessing step and therefore allows an easy implementation. We show that the proposed OOV anonymization method significantly improves the performance of the Transformer in two code processing tasks: code completion and bug fixing.

1 Introduction

Natural language processing (NLP) is widely used for source code processing (SCP), e.g. for learning meaningful vector representations of code (Feng et al., 2020; Alon et al., 2019; Azcona et al., 2019) that can be used in downstream tasks, code summarization (Iyer et al., 2016; Shiv and Quirk, 2019), code completion (Kim et al., 2020), or bug fixing (Hellendoorn et al., 2020).

Textual data usually contains many rare tokens, which are hard to learn meaningful representations for because of a low number of token occurrences in the dataset. This problem is even more urgent for source code where arbitrary complex identifiers are allowed and actually used by the developers. Karampatsis et al. (2020) underline that modern source code datasets incorporate millions of unique identifiers, of which less than 1% occur in the dataset frequently, e.g. more than 5 times. To avoid huge embedding matrices and the meaningless embeddings of rare tokens, the common practice is to crop the vocabulary based on top-N identifiers and replace all occurrences of out-of-vocabulary (OOV) identifiers with UNK identifier.

But can one process rare identifiers in a better way? A popular solution for processing rare tokens in NLP is to use character-based encodings or byte-pair encoding (BPE) (Sennrich et al., 2016). In SCP, this toolkit is complemented with splitting identifiers into subtokens based on snake_case or CamelCase. All mentioned approaches encode the input sequence computing the embeddings.

Vocabulary: \{np, sin\}
Input: my_y = np.sin(my_x) + my_x
Standard OOV processing procedure:
UNK = np.sin(UNK) + UNK
Proposed OOV anonymization procedure:
VAR1 = np.sin(VAR2) + VAR2

Figure 1: Illustration of the proposed OOV anonymization procedure. OOV identifiers sin_my_var and my_var are replaced with anonymized identifiers VAR1 and VAR2, while in-vocabulary identifiers np and sin preserve their names.

\[ \text{Joint accuracy} = \frac{\text{true positives}}{\text{true positives} + \text{false negatives}} \]

Figure 2: Results for Transformer in variable misuse task: joint bug localization and repair accuracy, mean value ± standard deviation. Models with the proposed OOV anonymization significantly outperform the standard model (vocabulary size 50K, all OOV identifiers are replaced with UNK token) and the model trained on the data with all identifiers being anonymized (zero vocabulary size).
of rare tokens using some aggregation function of the embeddings of the token’s parts, and for the decoding, these approaches generate tokens by parts. In generation tasks, another popular solution is to use pointer mechanism (Gulcehre et al., 2016) for copying rare words from the input sequence.

We propose a new simple yet effective approach for processing OOV identifiers in source code, namely OOV anonymization. Anonymization implies replacing rare identifiers with unique placeholders, i.e. var1, var2, var3 etc., while preserving the names of frequent identifiers. An example of OOV anonymization is shown in figure 1. The intuition behind using anonymization is that it preserves the semantics of the algorithm that the code snippet implements, i.e. renaming all user-defined identifiers does not change the underlying algorithm. In contrast, replacing all rare identifiers with UNK identifier changes the algorithm. We underline that we propose anonymizing only rare identifiers and not frequently used ones, because frequently used identifier names may serve as an additional source of information about what algorithm the code snippet implements, and neural networks are indeed capable of capturing this source of information.

The proposed OOV anonymization strategy allows an easy implementation as a preprocessing step, so no modification of model code or training code is needed. In addition, OOV anonymization can be used in both the encoder and the decoder. We show the proposed approach significantly outperforms the model with all rare identifiers being replaced with UNK, in code completion and bug fixing tasks, with the Transformer (Vaswani et al., 2017) architecture being used, see example comparison in fig. 2.

The rest of the work is organized as follows. In section 2, we review the existing works in the field of rare identifiers processing. In section 3 we formally describe the proposed anonymization-based approach of handling rare identifiers. Finally, in section 4 we empirically test the proposed method on two tasks, namely, code completion and bug fixing.

2 Related Work

Handling OOV tokens in NLP. Handling OOV tokens is a long-standing problem in NLP. (Gulcehre et al., 2016) proposed a pointer attention mechanism for the task of neural machine translation to copy unknown words from a source sentence. A line of works accounts for subword and character patterns. (Sennrich et al., 2016) introduced a byte pair encoding, which is currently the most popular approach for natural language modeling. (Bhatia et al., 2016) utilized morphological prior knowledge for rare words.

Handling OOV identifiers in source code. Code processing often borrows ideas from NLP. Source code can be represented as a sequence of identifiers. In this case, identifiers can be further split into subtokens using BPE (Karampatsis et al., 2020) resulting in an open vocabulary model. This approach has several drawbacks. Firstly, splitting breaks one-to-one alignment between identifiers and the nodes in the parsing tree, e.g. abstract syntax tree, which can make it harder to apply structure-aware models such as (Hellendoorn et al., 2020). If we wish to account for the tree-based syntactic structure of the code, an identifier should be treated as a single and complete syntactic element.

An orthogonal direction for handling OOV identifiers in source code is the modification of the computational graph. For the task of code generation, the pointer mechanism is widely adapted (Li et al., 2018). Cvitkovic et al. (2019) propose a graph-structured cache for inferring the representations of the rare identifiers in source code. The major drawback of the mentioned approaches is that they are quite hard to implement while our approach can be implemented as a simple preprocessing step. In addition, our approach can be easily combined with the pointer mechanism and the graph-structured cache.

Identifier anonymization in source code. Chirkova and Troshin (2020) conduct an empirical study of Transformers in a setting with all identifiers being anonymized and show that Transformers are able to make meaningful predictions in this setting. In contrast, we propose anonymizing only OOV identifiers and show that it boosts the performance of the model in the setting with frequent identifier names being present in the data. The anonymization of all identifiers has also been used in (Gupta et al., 2017) and (Xu et al., 2019) for training recurrent neural networks. Ahmed et al. (2018) replace variables with their types, loosing information about identifier repetition.
3 Proposed method

We describe the OOV anonymization procedure in the setting when the input code snippet is treated as a sequence of identifiers \( x = [x_1, \ldots, x_L] \). The same procedure can be straightforwardly used for other code representations as well, for example, when the sequence also includes language keywords and punctuation marks, or when the code snippet is represented as a graph.

We propose an elegant way of tackling OOV identifiers based on anonymization, i.e. replacing all OOV identifiers with placeholders vari1, var2, vari3 etc. Example OOV anonymization is presented in figure 1. We underline that all occurrences of one identifier are replaced with the same placeholder (anonymized identifier), but different identifiers are replaced with different placeholders. One identifier may be replaced with different placeholders in different input sequences. In practice, to ensure the frequencies of all placeholders are approximately equal and to avoid occasional data leak in code completion task, we fix placeholder vocabulary size to 1000 and for each code snippet, select a subset of the random permutation of placeholders vari1, \ldots, vari1000. The snippet from fig. 1 then can be transformed into \( \text{VAR}38 = \text{np.sin} (\text{VAR}801) + \text{VAR}801 \).

To ensure that we can always encode identifiers in a code snippet injectively, the size of the placeholder vocabulary can be chosen as the maximum number of tokens per snippet.

More formally, for each code example \( x \), we gather an ordered set of all unique OOV identifiers \( U(x) = \{u_1, \ldots, u_{K(x)}\} \). We randomly map this set into the randomly chosen subset of anonymized identifier names \{vari1, \ldots, vari1000\}:

\[
anon(u_i) = \text{var}_{\sigma(i)}
\]

\[i = 1, \ldots, K(x), \quad \sigma \in S(1000)
\]

where \( S(1000) \) are all permutations of 1000 elements. Finally, the code snippet is represented with a sequence \( \tilde{x} = [\tilde{x}_1, \ldots, \tilde{x}_L], \tilde{x}_i = x_i \text{ if } x_i \notin U(x) \text{ else } \text{anon}(x_i) \).

The proposed OOV anonymization can be seen as a preprocessing step, so no other parts of the model change. For example, in the encoder, the embedding matrix contains embeddings for both anonymized and in-vocabulary identifiers: \( \{e_v\}_{v \in V} \cup \{e_{\text{VAR}i}\}_{i=1}^{1000} \). In the decoder, when generating the next identifier, the softmax is computed over all anonymized and in-vocabulary identifiers.

4 Experiments

4.1 Experimental setup

We conduct experiments with Transformer (Vaswani et al., 2017) architecture on the code completion task (Python150k (Raychev et al., 2016a) and JavaScript150k (Raychev et al., 2016b) datasets) and variable misuse task (Python150k dataset). We follow the experimental setup of Chirkova and Troshin (2020). We do not consider the function naming task of Chirkova and Troshin (2020) because, in their experiments, anonymization did not help in this task.

Chirkova and Troshin (2020) converted each input code snippet to the depth-first traversal of the abstract syntax tree (AST), obtaining a sequence of pairs (node type, node value). The node types denote syntactic units of the programming language, e.g. If or For, and come from a small dictionary (up to 100 types), while the node values denote user-defined identifiers, language-specific identifiers, e.g. None in Python, and constants. The authors showed that ablating types results in worse performance in code completion and variable misuse tasks, and that using relative attention (Shaw et al., 2018) with the depth-first traversal leads to high performance. We use the same setup and anonymize OOV node values. Chirkova and Troshin (2020) also emphasize the importance of the thoughtful splitting data into training and testing parts, which includes splitting by repositories and removing duplicate code. We follow the same strategy in our experiments (later referred to as custom train-test split).

Variable misuse task. In the variable misuse task, given the code of a function, the task is to output two positions (using two pointers): in what position a wrong variable is used and which position a correct variable can be copied from (any such position is accepted). If a snippet is non-buggy, the first pointer should select a special no-bug position. We obtain two pointers by applying two position-wise fully-connected layers and softmax over positions on top of Transformer outputs.

We use the joint localization and repair accuracy metric of (Hellendoorn et al., 2020) to assess the quality of the model. This metric estimates the portion of buggy examples for which the model
The code completion task implies predicting the type and value of the next node based on the prefix of the depth-first AST traversal. We predict the next type and value using two fully-connected heads on top of the Transformer decoder and optimize the sum of cross-entropy losses for types and values.

For the next identifier prediction task, we add the pointer mechanism to the Transformer for comparison. We re-implement pointer mechanism mostly following the design choice of (Deaton, 2019). Given an input sequence \([x_1, \ldots, x_\ell]\) of length \(\ell\), Transformer outputs two distributions: the distribution over the fixed vocabulary \(V\), \(p_{\text{model}}(t_i), t_i \in V\), and the probability of copying an input from position \(j\), \(p_{\text{copy}}(j), j = 1, \ldots, \ell\). Then both distributions are combined to obtain the final distribution over the extended vocabulary: \(p(x_{\ell+1} = a) = p_{\text{gen}}p_{\text{model}}(a) + (1 - p_{\text{gen}}) \sum_{j=1}^{\ell} p_{\text{copy}}(j)[x_j = a]\). The switcher is computed given the current input and the output of the decoder as \(p_{\text{gen}}(x_\ell, h_\ell) = \sigma(w_h^T h_\ell + w_x^T x_\ell + b_{\text{gen}})\). The cross entropy loss is computed over the extended vocabulary.

We use mean reciprocal rank (MRR) to measure the quality of the model: \(\text{MRR}(\text{rank}) = \frac{1}{n-1} \sum_{i=1}^{n-1} \frac{1}{\text{rank}_i}\), where \(\text{rank}_i\) is a position of the true token in the model ranking. As in (Kim et al., 2020), we assign zero score if the true token is not in the top 10 predicted tokens. For the baseline model, we assign zero score if the true token is UNK.

In this task, we split the large files into the overlapping chunks of maximum length 500, as described in (Kim et al., 2020). Limiting the maximal length allows us to also limit the placeholder vocabulary size, which we set to 500.

**Hyperparameters.** We list hyperparameters for variable misuse / code completion tasks using slashes. Our Transformer model has 6 layers, 8 / 6 heads, \(d_{\text{model}}\) equals to 512 / 384. We limit vocabulary size for values up to 50K / 100K tokens and preserve all types. We train all Transformers using Adam with a starting learning rate of 0.00001 / 0.0001 and the batch size of 32 for 20 epochs. In the code completion task, we use cosine learning rate schedule (Loshchilov and Hutter, 2017) with warmup step of 2000 and zero minimal learning rate, and gradient clipping of 0.2. In variable misuse task, we use a constant learning rate. We use residual, embedding and attention dropout with \(p = 0.2 / 0.1\). We use relative attention (Shaw et al., 2018) with the maximum distance between elements of 32.
4.2 Results

We compare the proposed anonymization of OOV identifiers with the following baseline approaches: (1) the standard approach with the vocabulary containing the top of the most frequent identifiers, and with OOV identifiers being replaced with \texttt{<UNK>} identifier; (2) training on fully anonymized data, i.e. zero-size vocabulary and all identifiers being anonymized. For the code completion task, we also include the baseline with the pointer mechanism.

The results for the variable misuse task are presented in figure 2. We observe that the proposed approach with the anonymization of OOV identifiers (blue circles) performs significantly better than the baseline models, particularly than the standard approach with rare identifiers being replaced with \texttt{<UNK>} (orange square).

The results for code completion are presented in the figure 3. In this task, the proposed approach also significantly outperforms the standard baseline and the baseline with full anonymization. Moreover, the proposed OOV anonymization surpasses the strong pointer baseline (with no anonymization) for all vocabulary sizes except the largest one. The advantage of the proposed OOV anonymization approach is that it helps Transformer to distinguish OOV identifiers not only at the output layer but also at the input one, while the pointer mechanism enhances only the output layer. Also, in contrast to the pointer mechanism, OOV anonymization is much easier to implement.

For the JavaScript150k dataset, the gap between OOV anonymization-based approach and standard approach is slightly less than for Python150 dataset. We hypothesize this is because 100k vocabulary covers the higher fraction of the unique identifiers in the JavaScr ipt150k dataset: 95.7% for JS vs 90.7% for PY.

5 Conclusion

In this work, we propose the effective anonymization-based encoding of out-of-vocabulary identifiers. Our preprocessing technique is easy to implement and outperforms the widely used standard approach by a significant margin. We argue that the proposed simple technique should always be used when training neural networks on source code data. The proposed approach can also be combined with the existing approaches for handling out-of-vocabulary identifiers, i.e. the pointer mechanism.

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