Neural Code Completion with Anonymized Variable Names

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Abstract

Source code processing heavily relies on the methods widely used in natural language processing (NLP), but involves specifics that need to be taken into account to achieve higher quality. An example of this specificity is that renaming variables does not change the semantics of what the code does. In this work, we develop a recurrent architecture that processes code with all variable names anonymized, i.e. replaced with unique placeholders. The proposed architecture outperforms standard NLP baselines on code completion task by a large margin in the anonymized setting, and improves the base model in the non-anonymized setting, being ensembled with it.

1 Introduction

Natural language processing (NLP) methods are widely used in source code processing (SCP) for solving a variety of tasks, e.g. code completion (Li et al., 2018), generating code comments (Alon et al., 2019) or fixing errors in code (Vasic et al., 2019). A lot of modern SCP approaches are based on recurrent neural networks, other popular architectures are transformers, convolutional and graph neural networks (Le et al., 2020). The tree-based architectures (Chen et al., 2018; Shiv and Quirk, 2019) allow utilizing the native structure of code.

LeClair et al. (2019) point out that existing SCP models heavily rely on information contained in used-defined variable names. As an example, the quality of source code summarization dramatically drops when variable names are removed from the data (LeClair et al., 2019; Alon et al., 2019). However, the semantics of what the code implements, does not depend on particular variable names, and may be potentially inferred from the source code with all variables renamed. In some applications, e.g. in decompiled code processing (Lacomis et al., 2019), the data naturally lacks variable names, but does not lose any semantics. The described property of source code is an important difference between NLP and SCP that needs to be taken into account in SCP architectures.

The goal of this work is to develop a recurrent architecture for processing code with anonymized variables, i.e. with all user-defined variables being replaced with unique placeholders. The main property of this architecture is that it is invariant to any change of variable names: if all user-defined variable names are replaced with arbitrary unique names, the output of the network does not change. Existing approaches either lose some semantic information, erasing all variable names (LeClair et al., 2019) or replacing them with their types (Hu et al., 2018), or use standard embedding layer to treat anonymized variables (Xu et al., 2019). In the latter scenario, the invariance property is not satisfied, as different placeholders have different embeddings.

The principled problem of using the standard embedding layer for treating anonymized variables is that it stores global, same for all programs, semantics of the variables, while in the anonymized setting, there are no global semantics of the variables, only equal-or-not-equal relation. However, the anonymized variable may have local, specific to a particular program, semantics if it is used several times in the program. Our main idea consists of introducing so-called dynamic embeddings that capture these local semantics. At the beginning of a program processing, all anonymized variables have the same initial embedding. When some anonymized variable repeatedly occurs in the program, its embedding updates to reflect the variable’s role in the program. In this work, we focus on the code completion problem, but the method we propose is general and may
be straightforwardly applied to other tasks. We empirically show that the proposed dynamic embeddings significantly improve the quality of code completion in the anonymized setting, compared to standard embeddings, called static embeddings in our work, and to removing variable names.

Based on the described results, we further investigate whether the proposed dynamic embeddings may improve the quality of the standard model in the setting with full data, i.e. with present variable names. We find that ensembling the proposed model trained on the anonymized data, and the standard model trained on the full data, significantly outperforms the standard model alone.

2 Proposed method

In order to make the description of the proposed model more comprehensive, we firstly describe the base model that we use in our experiments, and then describe our approach. The proposed approach is general and may be easily utilized in other recurrent architectures or for other tasks.

2.1 Pointer-LSTM for code completion

We first describe the base model we rely on, it is also referred as a standard model. In this work, we treat the code completion system as a language model of the source code, where given the prefix of the program, the task is to predict the next token.

We use the recurrent model of (Li et al., 2018) as a base model, as it includes several components that are important in the anonymized setting. To take into account the tree structure of the source code when applying LSTM, Li et al. (2018) convert the Abstract Syntax Tree (AST) of the program into a sequence \( [(n_1, v_1), \ldots, (n_T, v_T)] \) of pairs (node type \( n_i \), node value \( v_i \)) via the depth-first traversal of the tree. Node type stores information about the syntactic unit (e.g. ForCycle, VariableDeclaration etc.), while node value (NV) stores the variable name for the leaf nodes of the tree, and <EMPTY> value for the non-leaf nodes. To predict the next NV \( v_i \) given the prefix \( [(n_1, v_1), \ldots, (n_{i-1}, v_{i-1})] \), the authors use LSTM with attention. The input of the LSTM is the concatenation of the embeddings of the node and NV. To simplify the implementation, the input sequence is split into chunks of length 50, and attention is applied only over last 50 positions. Since the vocabulary of NVs is limited, some rare NVs are replaced with <UNK> value. To improve the prediction of these rare NVs, the authors apply pointer mechanism that can copy NVs from previous 50 positions. The pointer reuses attention scores \( l_i \), and to make the final prediction, the predicted distribution \( w_i \) over NVs and distribution \( l_i \) over last 50 positions are concatenated into one distribution using switcher \( s_i \in (0, 1): [s_i w_i; (1 - s_i) l_i] \). The target is represented by the true NV for NV contained in the vocabulary, and the last occurrence of the same NV, for NV <UNK> that occurred in the last 50 positions. Other occurrences of NV <UNK> are ignored in the target.

2.2 Dynamic embeddings for anonymized variable names

We use the same problem setup as (Li et al., 2018), but with anonymized variable names. We select the anonymized vocabulary size \( K \) so that approximately 99% of programs in the training data contain not more than \( K \) different NVs (different variable names), and map the set of all NVs in the program (except dummy NVs, e.g. <EMPTY>) to the random subset of anonymized node values (ANVs) \( \text{var1...varK} \). All occurrences of the same NV in the program, e.g. \( \text{sum} \), are replaced with one ANV, but NV \( \text{sum} \) may be replaced with different ANVs in different programs. If the program contains more than \( K \) different NVs, extra NVs are replaced with ANV <UNK>. After anonymization, the training data is represented by the corpus of the sequences \( [(n_1, \tilde{v}_1), \ldots, (n_T, \tilde{v}_T)] \) of pairs (node type \( n_i \), ANV \( \tilde{v}_i \)). Given the prefix of the sequence, the task is to predict the next ANV.

If we applied the architecture of (Li et al., 2018) straightforwardly, each ANV would have the same embedding in all sequences, while the role of the corresponding anonymized variable may be different. For example, ANV \( \text{var1} \) may replace NV \( \text{sum} \) in one program and NV \( \text{array} \) in another program. These straightforwardly applied embeddings are called static embeddings in the paper. We develop approach that captures the changing role of ANVs. Informally, when the ANV appears in the sequence the first time, its role in the program is unclear, but we collect more and more
We now describe the mechanism of dynamic embeddings more formally. At the beginning of the processing of a program, we set the dynamic embeddings of all ANVs $e_{\tilde{v}, 0} = e_{\text{init}}$, and hidden state $h_0 = h_{\text{init}}$. At each timestep $i = 1, \ldots, T$, we update the dynamic embedding $e_{\tilde{v}, i}$ of the current ANV $\tilde{v}_i$, and hidden state $h_i$ using two LSTMs:

$$e_{\tilde{v}, i} = \text{LSTM}_{\text{dyn}}(h_{i-1}, e_{n_i}, e_{\tilde{v}, i-1}) \tag{1}$$

$$e_{\tilde{v}, i} = e_{\tilde{v}, i-1}, \quad \tilde{v} \neq \tilde{v}_i \tag{2}$$

$$h_i = \text{LSTM}_{\text{main}}(e_{\tilde{v}, i-1}, e_{n_i}, h_{i-1}) \tag{3}$$

Here $e_{n_i}$ denotes the embedding of the node type $n_i$, responsible for storing information about the syntax. LSTM$_{\text{main}}$ implements the recurrence over the hidden state, while LSTM$_{\text{dyn}}$ implements the recurrence over dynamic embeddings, and the same LSTM$_{\text{dyn}}$ is used to update the dynamic embeddings of different ANVs at different timesteps. An attention mechanism in LSTM$_{\text{main}}$ is omitted in formulas for brevity.

We reuse the same dynamic embeddings for computing logits $y_{\tilde{v}, i} = e_{\tilde{v}, i}^T \hat{h}_i$, and apply Softmax on the top of $y_{\tilde{v}, i}$ to predict the probability distribution over the next ANV. Here $\hat{h}_i$ denotes the output of the fully-connected layer with input $h_i$, context vector obtained using the attention mechanism, and the hidden state of the parent node (Li et al., 2018).

In practice, several dummy ANVs, e.g. <EMPTY>, <UNK> and <EOF>, do not change their roles in different sequences. We use static, or constant, embeddings for them.

### 3 Experiments

#### Setup and baselines

We conduct experiments on Python150k (Raychev et al., 2016a) and JavaScript150k (Raychev et al., 2016b) datasets. Following (Li et al., 2018), we use test accuracy to measure model quality, and count all predictions of <UNK> as wrong. We compare the proposed model based on dynamic embeddings in the setting with anonymized variables with two baselines: a model based on static embeddings trained on the anonymized data, and a model trained on the data with all non-dummy NVs replaced with NV <UNK>. The latter model does not use variables at all. We consider three variants of the architecture: plain LSTM, and attentional LSTM with and without pointer.

#### Details

We use the same model sizes and training specification as in (Li et al., 2018): node type embeddings have 300 units, NV/ANV embeddings have 1200 units, one-layer LSTM’s hidden state has 1500 units. In the non-anonymized setting, we use the vocabulary of 50000 variable names, and in the anonymized setting, we use the vocabulary size $K = 500$. For the proposed model with dynamic embeddings, static and dynamic ANV embeddings have 500 units, to make the number of parameters approximately the same as in baselines. We initialize all parameters using a uniform distribution over $[-0.05, 0.05]$, except trainable initial hidden states that are initialized with zeros. We train all models for 10 epochs with AdamW (Loshchilov and Hutter, 2019) with an initial learning rate of 0.001, learning rate decay of 0.6 after each epoch, batch size of 128, and using weight decay of 0.01. More details are given

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**Table 1**: Accuracy (%) of three models (without variables, static and dynamic embeddings for anonymized variables) on Python150k (Py) and JavaScript150k (JS) datasets. The last row represents the setting with variable names (Li et al., 2018), for reference. Columns list the three variants of the base architecture: LSTM, attentional LSTM (LSTM+at), attentional LSTM with pointer (LSTM+pt).

| Model        | Py: LSTM | LSTM+at | LSTM+pt | JS: LSTM | LSTM+at | LSTM+pt |
|--------------|----------|---------|---------|----------|---------|---------|
| W/o vars.    | 47.39    | 47.39   | 61.60   | 45.14    | 45.14   | 64.56   |
| Stat. emb.   | 55.95    | 59.91   | 61.08   | 55.46    | 59.36   | 61.82   |
| Dyn. emb.    | **67.02**| **67.45**| **67.61**| **68.24**| **68.99**| **69.00**|
| Standard     | 66.80    | 68.48   | 69.39   | 79.18    | 80.13   | 80.92   |
Results for anonymized setting. Table 1 lists accuracies of the proposed model and baselines, trained on the data with anonymized variables. The first two setups, with plain and attentional LSTM, are designed to compare pure static and dynamic embeddings, without powerful pointer enhancement. In both setups, the baseline with all non-dummy NVs removed, can correctly predict only dummy NVs `<EMPTY>` and `<EOF>`, and is easily outperformed by static embeddings baseline. The proposed dynamic embeddings outperform static embeddings by a large margin in both setups.

| Model                                      | Py  | JS  |
|--------------------------------------------|-----|-----|
| Standard                                   | 69.39 | 80.92 |
| Standard + w/o vars. / st. emb. / dyn. emb. | 68.95 | 78.86 |
| Standard + dyn. emb.                       | 72.50 | 82.23 |
| Dyn. emb. on full data                     | 70.18 | 76.92 |

Table 2: Experiment with full data (with variable names). Accuracy of LSTM with pointer with different modifications: Standard (Li et al., 2018), Standard + w/o vars. / st. emb. / dyn. emb. — ensemble of Standard model and model trained on the data without variable names, Dyn. emb. on full data — model with dynamic embeddings trained on data with variable names. Datasets: Python150k (Py) and JavaScript150k (JS).

In the third, practical, setup, with enabled pointer mechanism, the baseline with all non-dummy NVs removed, is able to either predict dummy NVs or copy NVs from recent positions, and outperforms the baseline with static embeddings. The reason is that, when training the baseline with static embeddings, the mechanism of predicting from vocabulary is trained along with the pointer mechanism, and the pointer loss is included in the final loss more rarely than when training the first baseline. To deal with this effect, we considered several variants of loss for the model with static embedding and pointer, and the best result, reported in table 1, was achieved using the minimum between pointer loss and vocabulary loss, see Appendix A.1 for details. Still, the proposed dynamic embeddings outperform both baselines by a significant margin.

Results for full data. In this paragraph, we investigate, whether the proposed dynamic embeddings can improve the quality of the model on the full data, i.e. with present variable names. We consider two options for incorporating dynamic embeddings. Firstly, inspired by the results of (LeClair et al., 2019), we ensemble the model trained on the full data and the model trained on the anonymized data. As the latter one, we consider all three models compared in the previous experiment. Ensembling is implemented via choosing the highest probability between two models’ predictions. Secondly, we consider a straightforward application: we train the model with dynamic embeddings on the full data, but train an initial embedding for each NV in the vocabulary. In this context, the standard model can be viewed as a simplified version of the described model. We note that the number of parameters in the models trained on the anonymized data is much smaller compared to the number of parameters in the standard model.

The results are given in table 2. Intuitively, the model with dynamic embeddings, trained on the full data, is expected to achieve competitive results, because it combines both concepts of using the global and the local meanings of variable, via the mechanisms of static and dynamics embeddings respectively. However, in practice, this model outperforms the standard model only marginally, i.e. on the Python150k dataset. On the JavaScript150k dataset, this model performs even worse than the standard model, however, we notice that the models with dynamic embeddings are trained with the embedding size of 500, while static models are trained with larger embedding sizes. In contrast, ensembling the standard model and the model with dynamic embeddings, trained on the anonymized data, significantly outperforms the standard model alone, on both datasets. We suggest two reasons for this effect. Firstly, ensembles are known to be a simple and effective technique of improving the quality of a single network (Lakshminarayanan et al., 2017). Secondly, training two models on different variants of the data makes their predictions orthogonal (LeClair et al., 2019), which makes the effect of ensembling even stronger. The ensemble of the standard model and the model with static embeddings also contains models trained on different sources of the data, and marginally outperforms the standard model on the Python150k dataset.
4 Related Work

The possibility of improving deep learning models of source code by taking into account the invariance property of variable names has been superficially discussed in the literature. Ahmed et al. (2018) replace variables with their types, while Gupta et al. (2017) and Xu et al. (2019) use the static embeddings for anonymized variables. However, the existing works did not consider developing a special architecture that fulfills the invariance property. LeClair et al. (2019) and Xu et al. (2019) achieve state-of-the-art results, differentiating two sources of information: syntax represented by the AST-tree with variable names removed or anonymized, and semantics represented by variable names. They train separate models on the two sources and ensemble them. In our work, we further develop this approach, improving the first, syntax-based, model.

Our work is also related to the field of processing out-of-vocabulary (OOV) variable names. The commonly used approaches for dealing with OOV variables are using pointer mechanism (Li et al., 2018) or replacing OOV variables with their types (Hu et al., 2018). As we show in our work, both methods may be successfully combined with the proposed dynamic embeddings.

In the context of NLP, Kobayashi et al. (2017) use similar model with dynamic embeddings to process OOV and anonymized named entities in natural text. In contrast to their approach, we apply dynamic embeddings to the whole vocabulary of NVs, and incorporate dynamic embeddings into the model that relies on the syntactic structure of code, i.e. AST-tree. This results in more meaningful dynamic embeddings. We also an perform empirical study on what is the best way of using dynamic embeddings in the non-anonymized setting.

5 Conclusion

In this work, we presented a new approach for processing anonymized variable names in source code with RNNs, namely dynamic embeddings. We showed that the using the proposed dynamic embeddings results in a higher quality in the anonymized setting and also helps to achieve higher quality in the standard setting, with full data.
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Appendices

A.1 Training pointer mechanism in anonymized setting

In the anonymized setting, utilizing syntactic and positional information is highly important. In our work, the former one is plugged into the model via the AST-tree traversal, and the latter one is implemented via the pointer mechanism: when predicting the next ANV, the model can either select ANV from a vocabulary of ANVs or copy ANV from one of the recently processed nodes. We train the pointer mechanism in the same way as in the standard model (Li et al., 2018). At each position, we choose between the vocabulary loss and pointer loss. For all in-vocabulary ANVs, we minimize the negative log-likelihood of ANV (vocabulary loss); for out-of-vocabulary ANVs that occur in the last 50 positions, we minimize the negative log-likelihood of the last position of this ANV (pointer loss). Other out-of-vocabulary ANVs are ignored in the loss. This is a reasonable approach, since (1) pointer reuses attention scores, (2) some NVs are replaced with ANV <UNK> in our anonymized data. If the latter were not true, we could randomly select a small portion of NVs to train the pointer loss.

In practice, dynamic embeddings themselves store information about the context of different ANVs, and the pointer mechanism adds only a marginal improvement over the attentional LSTM, see table 1 in the main text. However, for static embeddings, the situation is different.

As can be seen in table 1, in the setting with pointer mechanism, the model with static embeddings performs even worse, than the model trained on the data with only dummy NVs present. The reason is that when training the former model, the pointer loss is included in a total loss much more rarely, than when training the latter model. As an attempt to improve the baseline with static embeddings, we performed experiments with different variants of the total loss: (a) pointer priority: if ANV can be predicted from the context of 50 latest ANVs, minimize pointer loss, otherwise minimize vocabulary loss; (b) vocabulary priority, obtained in the opposite way; (c) minimum between pointer loss and vocabulary loss; (d) the random choice of what loss to minimize for each ANV. Option (c) outperformed other options by approximately one percent on both datasets, so we reported the results in table 1 with the minimum-loss.

A.2 Experimental details

Data. We train models on Python150k (Raychev et al., 2016a) and JavaScript150k (Raychev et al., 2016b) datasets. Each dataset contains 150000 code files. We use the standard split into the training and testing set provided by the authors of the datasets. The detailed dataset statistics may be found in (Li et al., 2018); both datasets are available at https://www.sri.inf.ethz.ch/research/plml.

For training the standard model, we preprocess the data in the same way as in (Li et al., 2018): we flatten the AST-tree into a sequence of (node type, node value) pairs via the depth-first traversal. The vocabulary of node types is full, while the vocabulary of node values is restricted to 50000 most frequent values. For training the model in the anonymized setting, after the standard preprocessing, we apply the anonymization procedure described in section 2.2 of the main text.

Model sizes. We choose the dimension of dynamic embeddings so that, in the anonymized setting, the number of parameters in the proposed model is not larger than in the baseline models: the number of parameters in model without variable names, model with static embeddings and model with dynamic embeddings are 29.27M / 30.62M / 25.17M correspondingly. The standard model incorporates 164M parameters, so the number of parameters in the models trained on the anonymized data is an order smaller compared to the number of parameters in the standard model, and the same holds for the layer of dynamic embeddings.

Computing infrastructure. Experiments were conducted on NVIDIA Tesla P40 GPU, Tesla P100 GPU, and Tesla V100 GPU. The training/prediction time of the model with dynamic embedding in the anonymized setting is approximately 50 hours / 1 hour (10 training epochs, Tesla P40). The training/prediction time of the standard model on the full data is approximately 80 hours / 1.5 hours (10 training epochs, Tesla P40).