AstBERT: Enabling Language Model for Code Understanding with Abstract Syntax Tree

Rong Liang$^1$, Yujie Lu$^1$, Zhen Huang$^1$, Tiehua Zhang$^1$, Yuze Liu$^1$

$^1$Ant Group

{liangrong.liang, lyj272836, hz101346,zhangtiehua.zth, liuyuze.liuyuze} @antgroup.com

Abstract

Using a pre-trained language model (i.e., BERT) to apprehend source codes has attracted increasing attention in the natural language processing community. However, there are several challenges when it comes to applying these language models to solve programming language (PL) related problems directly, the significant one of which is the lack of domain knowledge issue that substantially deteriorates the model’s performance. To this end, we propose the AstBERT model, a pre-trained language model aiming to better understand the PL using the abstract syntax tree (AST). Specifically, we collect a colossal amount of source codes (both java and python) from GitHub and incorporate the contextual code knowledge into our model through the help of code parsers, in which AST information of the source codes can be interpreted and integrated. We verify the performance of the proposed model on code information extraction and code search tasks, respectively. Experiment results show that our AstBERT model achieves state-of-the-art performance on both downstream tasks (with 96.4% for code information extraction task, and 57.12% for code search task).

1 Introduction

Programming language representation and analyzing the source code using deep learning method have been received increasingly attention in recent years. These researches mainly treat source code as a language and make analyzing source code as nature language process (NLP) task. In recent years, pre-trained language model and fine-tuning achieve state-of-the-art performance in various NLP tasks. Large masked pre-trained language models (MLM) such as BERT [Devlin et al., 2018], AIBERT [Lan et al., 2019] and RoBERTA [Liu et al., 2019] have impressively improved the almost all NLP task performance. These pre-trained language models are trained on large unlabeled data by self-supervised task to effectively learn contextual representations. The success of the pre-trained model in NLP is reproduced in other related fields, such as VideoBERT [Sun et al., 2019] in video-language and VisualBERT [Li et al., 2019b] in picture-language. Inspired by the success of the pre-trained model, some researchers attempt to apply this technique to source code. More recently, [Kanade et al., 2019] trained CuBERT using a massive corpus of Python programs collected from GitHub, and compare its task performance with different embedding techniques, such as Word2Vec embeddings [Mikolov et al., 2013]. [Hellendoorn et al., 2019] propose a new hybrid model using a gated graph neural network and Transformers to combine local information and global information to learn representations of source code. [Feng et al., 2020] presented CodeBERT and trained it using source code of six programming languages from GitHub. [Huang et al., 2021] propose a novel contrastive learning method using CodeBERT and develop a large-scale query-code matching dataset.

The pre-trained language model like BERT have made a great progress in multiple NLP tasks and other related filed such as video reorganization and code search. These pre-trained models are often pre-trained over large-scale open-domain corpora and then fine-tuned in downstream tasks. However, there is often knowledge-domain difference between pre-trained corpora and downstream task, which makes these pre-trained models do not perform well on some knowledge-driven tasks. One way to solve this problem is to pre-train a model using specific domain corpora from scratch. However, pre-training a model is time-consuming and computationally expensive, and domain corpora is often not enough for pre-training task. To address this problem, [Xu et al., 2021] propose a knowledge-enabled language representation model (K-BERT) with knowledge graphs (KGs), which uses triples(entity and its relation) in KGs to bring domain knowledge for the original sentence. As we known, source code is different to natural language, because it has structure information which plays an important role to triples in KGs. So we can believe that bringing structure information into source code when it comes to do code understanding tasks will improve the performance.

In this work, we propose AstBERT model, a pre-trained language model aiming to better understand the code using abstract syntax tree (AST). As we know, AST is an tree construction description for the code. Instead of source code, we use AST as input when we train and fine-tune AstBERT. Here, there are two challenges in using AST:(1) Token Explosion: In general, AST is much longer than the code and
too much information incorporation may divert the meaning of code. (2) How To Represent Tree Construction: As we know, the input for language model is a string sequence. To overcome these challenges, this paper use a pruning method to avoid token explosion and AST-Embedding Layer to encode tree construction. And, we adapt the “Don’t stop pre-train in domains and tasks” [Gururangan et al., 2020] suggestion, use public pre-trained language model “bert-base-uncased” [Devlin et al., 2018] as our initialization and continue pre-train on AST corpus. In this way, AstBERT can capture the semantic information for nature language (NL) and programming language (PL).

We train AstBERT on corpus collected from Github code repositories in Python and Java and evaluate it on two down-stream tasks, including natural language code search and code parsing. Experiments results show that on two tasks AstBERT has better ability for understanding code. The main contributions of this work can be summarized as follows:

- We propose a simple and effective way to enhance pre-trained language model’s ability for understanding programming language with the help of abstract syntax tree information.
- Empirical results show that AstBERT is effective in both on code search and code information extraction tasks.
- We created a dataset for the name entity recognition (NER) task in code, which, to our knowledge, is the first NER dataset in code.

2 Related Work

In this part, we describe existing pre-trained models and datasets in language-code in detail.

2.1 Datasets in language-code

[Nie et al., 2016] collect questions and answers from Stack Overflow and form text-code pairs for the purposes of code search. Also, a large-scale unlabeled text-code pairs are extracted and formed from GitHub by [Husain et al., 2019]. [Heyman and Van Cutsem, 2020] build three benchmark datasets, each of which is consisted of a code snippet collection and a set of queries. [Li et al., 2019] present an evaluation dataset consisting of natural language question and code snippet pairs. They manually check whether the questions meet the requirements and filter out the ambiguous pairs. [Yin et al., 2018] train a model on a human-annotated dataset to automatically mine massive natural language and code pairs from Stack Overflow. Recently, [Huang et al., 2021] construct CoSQA dataset that includes 20,604 labels for pairs of natural language queries and code. CoSQA is annotated by human annotators and it is obtained from real-world queries and Python functions.

From the above we can know, most of the datasets in language-code are about code search task which belongs to sequence classification task. We propose a new dataset for named entity reorganization (NER) task in code.

2.2 Models in language-code

Using deep learning network to solve language-code task has been studied for years, [Wan et al., 2019] is a Multi-Modal Attention Network for code search. It is developed for representing unstructured and structured features of source code with two LSTM. [Kanade et al., 2019] uses massive Python code obtained from GitHub to train a masked language model and obtain a high-quality embedding for source code. [Karampatissis and Sutton, 2020] train a set of embeddings based on ELMo [Peters et al., 2018] and conduct bug detection task. The results prove that even a low-dimensional embedding trained on a small corpus of programs is very useful for downstream task. [Svyatkovskiy et al., 2020] use GPT-2 framework and train it from scratch on source code data to support code generative task like code completion. CodeBERT [Feng et al., 2020] is a multi-PL (programming language) pretrained model for code and natural language, and it is trained with the new learning objective based on replaced token detection. [Buratti et al., 2020] propose C-BERT pretrained from C language source code collected from GitHub to do AST node tagging task. Different with previous work, AstBERT is a simple and effective way to use pre-trained model in language-code field. Instead of pre-training a language from scratch, it only needs continue pre-train the language model using AST corpus and the model will have ability to understand the language and code.

3 AstBERT

In this part, we describe the details about AstBERT, including model architecture, input and output representations, the data used for continue pre-training, and how to use AstBERT when it comes to downstream tasks.

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![Figure 1: The model structure of AstBERT: A easy and effiective way to enhance pre-trained language model’s understanding PL](image-url)
Figure 2: The explanation of AST enhancing the representation for Java code

3.1 Model Architecture

Figure 1 shows the main architecture of AstBERT, instead of source code, the input of AstBERT is AST information from source code after pruning. For each token of source code, the AST information is inserted in the front and the position index shows clearly the order of the input. In embedding layer, token embedding is consistent with BERT [Devlin et al., 2018], the difference is that the vocabulary used is added AST keywords. Each token after token embedding is converted to a vector via a trainable lookup table. Additionally, in AstBERT there are AST-segment and AST-position to tell which token is AST information and which token is source code, the detail of their function will be introduced in subsection 3.3. After embedding layer, the embedding vectors are encoded by multi-layer bidirectional transformer encoder [Vaswani et al., 2017] in BERT to generate hidden vectors and here we will not present the details about BERT [Devlin et al., 2018]. After this sequence encoded by transformer encoder, we use AST-Selection layer to mask the hidden vector from tokens of AST information and retain the hidden vector from tokens of original source code. In output layer, if the task is classification, the hidden vectors after AST-Selection layer pass average pooling layer to predict class label; If the task is named entity reorganization, each hidden vector after AST-Selection layer will be used to predict tag directly.

3.2 Input and Pruning

As shown in Figure 2, the AST contains the complete information of the source code and provide the more description for each token. For example, the getValueAsDouble is the name for MethodCallExpr (an AST node type) and the TEST_var is an argument for MethodCallExpr. Also we can know the Double is a type of the variable var from AST. These information provided from the AST bring the domain knowledge for the source code.

In general, AST is much longer than source code, as shown in Figure 3, the AST from Python standard library contains some nodes such as lineno, end_lineno and so on. Taking the code result = test1 + 1 as an example, this code will be presented as an assign node in AST. From the Figure 3 we can see, the AST for this code contains information about which line the code appears on, and every child node contains this line number information. Here, after generating AST, we will prune this tree by removing the meaningless and uninformed node to avoid longer and noise input for model.

3.3 Embedding Layer

Instead of source code, we use AST (after pruning) as input for model and it will pass embedding layer firstly. Figure 4 shows the embedding layer in AstBERT, it is consisted of token-embedding, AST-segment embedding, AST-position embedding and segment embedding. Taking the code in Figure 2 as an example, the AST for this code is described in subsection 3.2, we can see the additional AST information account for most of tokens in the input, which can lead changes in the meaning of the original code. To prevent this from happening, we use AST-segment embedding to distinguish between AST tokens and source code tokens. As we known, in BERT all the order information for input sequence is contained in the position embedding, which allows us to add dif-
3.4 AST-Selection Layer

As shown in Figure 5, after this sequence encoded by transformer encoder, we use AST-Selection layer to mask the hidden vector from tokens of original source code. This is because, even after pruning, among the all tokens in input, the tokens from AST information account for most of them. In the output layer, if we use all hidden vectors to finetune the downstream task, it will weaken the meaning of source code tokens. On other hand, transformer encoder has already fused the AST information for each source code token by attention mechanism. So here, we extract the hidden vectors of source code tokens by using AST-Selection layer. In output layer, if the task is classification, the hidden vectors after AST-Selection layer will pass average pooling layer to predict class label; If the task is named entity reorganization, each hidden vector after AST-Selection layer will be used predict tag directly.

We curate massive Python and Java code from GitHub and generate the AST for these source code (Python code uses standard AST API, Java code use javaparser). Then, instead of source code, we use AST to continue pre-train the BERT. Meanwhile, we bring keywords in AST into BERT vocabulary and make the tokenizer can recognize these AST keywords. The objective of pre-training is masked language modeling (MLM), which is proposed by [Devlin et al., 2018] and has proven effective.

4 Task

4.1 Code Name Entity Recognition

In this section, we introduce the construction of the CoNER dataset. As we known, it is the first work to construct the dataset for named entity recognition (NER) task in code. We study the Java in this work, and we plan to extend to more
programming language in the future. As can be seen in Figure 6, in this code snippet, we need to according with our practical rules to recognize different parts of code as different entities. The aim of this task is driven from our practical work. Taking the condition inf.getValAsString("Test_variable_1") != null in if statement as an example, the argument "Test_variable_1" of getValAsString function is labelled as splitpot_entity, the operation of this condition != is labelled as splitpot_oper entity and the right expression of this condition null is labelled as splitpot_value entity. The same rule is applicable to the condition writeinfo ObtainValAsInt("Test_variable_2") > 100 and the condition "TRUE".equals(status_result). But when it comes to the condition previous_num >= current_num, the left expression previous_num is labelled as ifeq_left, the operation >= is labelled as ifeq_oper and the right expression is labelled as ifeq_right. This is because that the left and right expression in the last condition are both variable and the condition "TRUE".equals(status_result), the left expression "TRUE" is labelled as splitpot_entity, the operation of this condition == is labelled as splitpot_oper entity and the right expression of this condition status_result is labelled as splitpot_value entity.

In CoNER dataset, there is a total of 17 different entities including splitpot_entity, splitpot_oper, splitpot_value, contain_entity, default_value_entity, default_value_value, getvar2var_entity, getvar2var_value, ifeq_left, ifeq_oper, ifeq_right, outputvar2var_entity, outputvar2var_value, outputvar_entity, reasonvar_entity, reasonvar_value. We build CoNER dataset from Java code and check it by human. The average number of tokens in the sample is 136 and there are 5000 samples in CoNER.

### 4.2 Code Search

We use CoSQA (Junjie Huang et al. 2021) dataset to do code search task. In this task, the sample is query-code pair and the label is "1" or "0" which means whether the code can answer the query. These query-code pairs are collected from Microsoft Bing search engine and annotated by human. Both in real world and in this dataset, it is often the case that a code can completely or partially meet the demands of the query.

Figure 7 shows some samples in CoSQA described from (Junjie Huang et al. 2021), if the code function can completely answer the query (Case 1 in Figure 7), this query-code pair is annotated with label "1". From the case 2, we can see this code function meets and exceeds the demands of the query, because it also has the function to do with tuple and set, so this case is also annotated with label "1". In case 3, query is about measuring distance between 2 points, but the code function is about calculating the distance about 2 vectors. In this case, this code function only meet a certain category of the query demands, in this dataset it is also annotated with label "1". From the case 4, we can see the code function is only to read a file, but the query is to read and write in file. When code function satisfies 50% of the demand, it is annotated with label "0". In case 5 and case 6, only small part of code is relevant to the query and can not answer, these samples are annotated with label "0".

### 5 Experiments

#### 5.1 Experiments Settings

We train the models on the CoNER dataset and CoSQA dataset and evaluate them on two tasks: code named entity recognition and code question answering. On code named entity recognition, we random divide the CoNER into training, validation and tests sets in the number of 4000:500:500. On code question answering task, we use the 20,000 training and 604 validation examples split by Microsoft Bing search engine and annotated by human. Both of comparing with the result from public works, we directly evaluate the models on two tasks: code named entity recognition task and code question answering task. AstBERT outperforms the existing baseline approaches.

| Model                  | Data   | Code NER |
|------------------------|--------|----------|
| CRF                    | CoNER  | 0.923    |
| CRF (with AST info)    | CoNER  | 0.929    |
| BERT + CRF             | CoNER  | 0.932    |
| AstBERT + CRF          | CoNER  | 0.964    |

Table 1: Performance of different model on code named entity recognition task. AstBERT outperforms the existing baseline approaches.
Table 2: Evaluation of different pre-trained language models on code question answering.

| Model    | Data    | Code Question Answering |
|----------|---------|-------------------------|
| BERT     | CoSQA   | 39.92                   |
| RoBERTA  | CoSQA   | 42.12                   |
| CodeBERT | CoSQA   | 52.65                   |
| AstBERT  | CoSQA   | 57.12                   |

AST information. This demonstrates the importance of AST information in named entity recognition task. Meanwhile, the performance of the BERT without AST information is better than the CRF++ with AST information, which indicates the pre-trained language model can better understand the source code. Comparing with the augmentations from CRF++ and pre-trained language model, we can see that the latter achieves more performance gain than the former (0.6% versus 3.2%). This demonstrates that our AstBERT can better take advantage of AST information to understanding the source code.

Results of Code Search

In addition to code NER task, we also conduct another code search experiment using CoSQA dataset which is proposed by [Huang et al., 2021]. We train the models and evaluate them on code question answering by the following settings: (i) using BERT proposed by [Devlin et al., 2018], (ii) using RoBERTA proposed by [Liu et al., 2019], (iii) CodeBERT proposed by [Feng et al., 2020], and (iv) AstBERT. From the Table 2, we can see the BERT and RoBERTA achieve a similar and relative low accuracy in this task. This is because that these two models are pre-trained by natural language corpus and are not integrated with programming language. Comparing with the augmentation from RoBERTA and CodeBERT, the latter achieves more performance gain than the former (10.53%) and this accuracy is similar with the results published by [Huang et al., 2021]. This demonstrates that CodeBERT can better understand code. And, our AstBERT achieves better performance than the CodeBERT by 4.47%. This demonstrates that AstBERT by integrating AST information as domain knowledge can further improve the ability for understanding programming language.

6 Conclusion

In this paper, we propose AstBERT, a simple and effective way to enable pre-trained language model for code understanding by integrating with abstract syntax tree (AST). Specifically, AstBERT injects structural information from AST into source code as input. In order to encode structural information, AstBERT uses AST-Segment and AST-position to make model recognize AST construction. We use public pre-trained language model BERT(BERT-base-uncased) [Devlin et al., 2018] as initialization and continue pre-train AstBERT on AST corpus. We also develop a new dataset CoNER for code named entity recognition (NER) task, which to the best of our knowledge is the first dataset for code NER task. Then, we conduct two experiments to evaluate the performance of AstBERT. We find that AstBERT outperforms baseline models on code NER and code search tasks and perform detailed analysis to investigate the effects of AstBERT on code understanding.
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