AST-Transformer: Encoding Abstract Syntax Trees Efficiently for Code Summarization

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Abstract—Code summarization aims to generate brief natural language descriptions for source code. As source code is highly structured and follows strict programming language grammars, its Abstract Syntax Tree (AST) is often leveraged to inform the encoder about the structural information. However, ASTs are usually much longer than the source code. Current approaches ignore the size limit and simply feed the whole linearized AST into the encoder. To address this problem, we propose AST-Transformer to efficiently encode tree-structured ASTs. Experiments show that AST-Transformer outperforms the state-of-arts by a substantial margin while being able to reduce \(90 \sim 95\%\) of the computational complexity in the encoding process.

Index Terms—tree-based neural network, source code summarization

I. INTRODUCTION

The summary of source code is a brief natural language description explaining the purpose of the code \([1]\). The code to be summarized can be with different units. In this work, we focus on summarizing the subroutines or defined methods in a program.

Current state-of-the-arts all follow the encoder-decoder architecture \([2\)–\(4]\) and can be trained end-to-end with code-summary pairs. Since the source code is highly structured and follows rigid programming language grammars, a common practice is to also leverage the Abstract Syntax Tree (AST) to help the encoder digest the structured information. The AST is usually linearized by different algorithms like pre-order traversal \([5]\), structure-based traversal (SBT) \([6]\) and path decomposition \([7]\), then fed into the encoder. Several works also proposed architectures specific for tree encoding like tree-LSTM \([8]\, [9]\).

However, the linearized ASTs, as containing additional structured information, are much longer than their corresponding source code sequence. Some linearization algorithms can further increase the length. For example, linearizing with SBT usually doubles the size of original AST. This makes the model extremely difficult to accurately detect useful dependency relations from the overlong input sequence. Moreover, it brings significant computational overhead, especially for those state-of-the-art Transformer-based models where the number of self-attention operations grows quadratically with the sequence length. Encoding ASTs with tree-based models like tree-LSTM will incur extra complexity as they need to traverse the whole tree to obtain the state of each node.

In this work, we argue that it is unnecessary to model the dependency between every single node pair. Our intuition is that the state of a node in the AST is affected most by its (1) ancestor-descendent nodes, which represent the hierarchical relationship within one operation, and (2) sibling nodes, which represent the temporal relationship across different operations. Based on this intuition, we propose AST-Transformer, a simple variant of the Transformer model to efficiently handle the tree-structured AST.

II. APPROACH

This section details our proposed AST-Transformer, i.e., a simple yet effective Transformer variant to deal with the tree-structured AST. The overall architecture of AST-Transformer has two main parts, i.e., AST Encoder and Decoder respectively. The particularity of the proposed AST-Transformer lies in the three special components in the Encoder, namely, AST Linearization, Relation Matrices, and Tree-Structure Attention. First, in subsection §II-A three different linearization methods for transforming input AST into a sequence are introduced. Then, two matrices for encoding the ancestor-descendent and sibling relationships in the tree are defined in subsection §II-B as well as concrete methods for constructing the matrices. Eventually, the proposed self-attention mechanism based on relation matrix for generating code summaries is illustrated in subsection §II-C.

A. AST Linearization

In order to make the tree-shaped AST suitable as the input of the neural network model, it first needs to be converted into a sequence with a linearization method. Technically, the proposed AST-Transformer is orthogonal to the linearization and can be build upon any concrete approach. In this paper, the three most representative methods are selected for conducting experiments to test which one can achieve the best effect in combination with the self-attention based on the relation matrix, and they are: Pre-order Traversal (POT), Structure-based Traversal (SBT) \([6]\) and Path Decomposition (PD) \([7]\).

We find that the performances of using SBT and PD have no big differences with using POT in AST-Transformer through experiments. However, generating POT saves almost \(90 \sim 95\%\) time costs compared with generating SBT or PD for the entire dataset. And fortunately, using the simplest POT has been able to achieve the state-of-the-art performance.
B. Relationship Matrices

We define two kinds of relationships between nodes in the tree that we care about: the ancestor-descendant relationship and the sibling relationship. The former represents the hierarchical information within one operation, and the latter represents the temporal information across different operations. Specifically, two nodes have the ancestor-descendant relationship if there exists a directed path from root node that can traverse through them. Two nodes have the sibling relationship if they share the same parent node.

We use two matrices, i.e., $A_{N \times N}$ and $S_{N \times N}$, to represent the ancestor-descendent and sibling relationships respectively. $N$ is the total number of nodes. We denote the $i$th node in the linearized AST as $n_i$, $A_{i,j}$ is the distance of the shortest path between $n_i$ and $n_j$ in the AST. $S_{i,j}$ is horizontal sibling distance between $n_i$ and $n_j$ in the AST if they satisfy the sibling relationship. If one relationship is not satisfied, its value in the matrix will be infinity.

By taking the advantages of these two matrices, the model can find related nodes in parallel and efficiently by scanning the matrices instead of traversing the initial tree.

C. Tree-Structure Attention

For incorporating with the relationship matrices in self-attention, we combine the practices of Shaw et al. [14] and He et al. [15]. Similar to the vanilla Transformer, we use multi-head attention to jointly attend to information from different relationship matrices. Then the outputs of the self-attention with the ancestor-descendant and the sibling relationship matrices are concatenated and once again projected, resulting in the final values.

III. EXPERIMENTS

The overall result of AST-Transformer and the baselines are proposed in Table I. Results show that AST-Transformer obviously outperforms all the baselines in all three metrics. AST-Transformer outperforms the nearest baseline using code token sequence as input by 2.06, 1.3 BLEU, 2.04, 2.19 METEOR and 0.45, 0.41 ROUGE-L in the Java and Python datasets respectively. And the improvement is more obvious compared with baselines using AST or linearized AST as input. We think there are two main reasons for the improvement of AST-Transformer. Firstly, top two approaches (AST-Transformer and Transformer(CODE)) both use the Transformer architecture. As the length of code or AST is much longer than the natural language, self-attention mechanism is conducive to help the model catch long distance meaningful word pair or node pair, and then learn some characters related to the code function. Secondly, though we say that AST contains more information than code token sequence, as AST not only has the semantic information (which is stored in leaf nodes), but also has the structural information (which is stored in non-leaf nodes), the performances of most approaches based on AST are inferior to Transformer(Code), a model just using code token sequence as input. It may be illustrated by that there are many very general structures, such as MethodDeclare → MethodBody, in AST. These structures basically occur in every code, and they are noisy information for models, just like the pause words in nature language. This is exactly why Transformer(SBT) has hardly improved compared to DeepCom, as SBT has around 4 times more nodes than AST. In AST-Transformer, we only allow the node exchanges information with other nodes that are no more than $K$ away from it. This can effectively ensure the specificity of each node without being assimilated by the overall structure.

IV. CONCLUSION

In this paper, we have presented a new Transformer-based model that can encode AST effectively. By using two relationship matrices, AST-Transformer can encode AST without suffering from the computational complexity. Comprehensive experiments show that AST-Transformer outperforms other competitive baselines and achieves the state-of-art performance on several automatic metrics.

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