Code Prediction by Feeding Trees to Transformers

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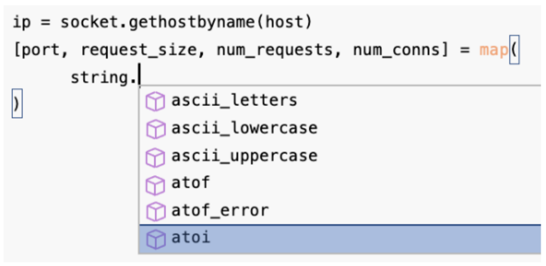
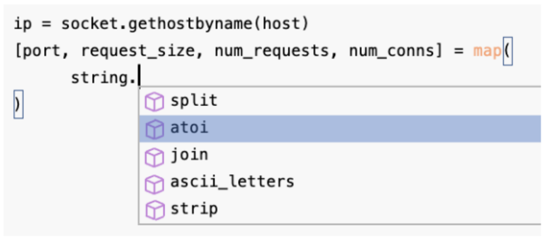
1 Introduction

Code prediction is a technology that is primarily used in autocomplete techniques in intelligent IDEs. Autocomplete is very useful to developers as it serves to ease their effort in writing good code, one important use case being the prediction of the next code token that the developer could potentially use. Another use case is that it does away with the requirements for developers to remember API calls and function names.[3]
These techniques are enabled by a machine learning model: Popular ones include Type-based alphabetical (such as Jedi[2]), SeqRNN[4] and Transformers. These models enable next token prediction in different ways. As can be seen from Fig 1[3], the Transformer-based model is that which not only predicts the next token *atoi*, but additionally offers this up at the top of the list of next token predictions. The other options require one to utilize more keystrokes to navigate to the desired token. It is then no coincidence that the focus of this paper is this: **next token prediction using Transformer-based models.**



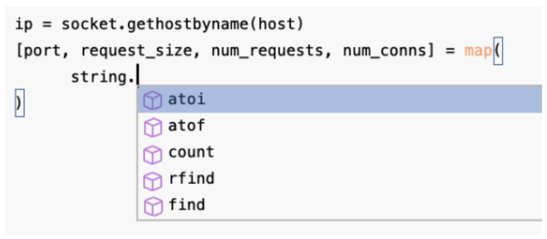
```
ip = socket.gethostbyname(host)
[port, request_size, num_requests, num_conns] = map(
      string.
)               ascii_letters
                ascii_lowercase
                ascii_uppercase
                atof
                atof_error
                atoi
```

(a) Type-based, alphabetical



```
ip = socket.gethostbyname(host)
[port, request_size, num_requests, num_conns] = map(
      string.
)               split
                atoi
                join
                ascii_letters
                strip
```

(b) SeqRNN



```
ip = socket.gethostbyname(host)
[port, request_size, num_requests, num_conns] = map(
      string.
)               atoi
                atof
                count
                rfind
                find
```

(c) TravTrans

Figure 1. Comparison of different next token prediction outcomes

2 Limitations of existing methods and improvements

2.1 Limitations

As mentioned previously, the most popular autocomplete techniques utilize popular machine learning models such as Type-based inference or sequential Recurring Neural Network (SeqRNN) ones. However, this paper points major limitations in the those two: Type-based models such as Jedi[1] or Eclipse[2] recommended and rank the next token in a very naive way (usually alphabetically), while their research has showed very clearly that popular machine learning based code prediction models such as SeqRNN recommends the next token in such a way that the correct result is present in approximately the top 2.7 results, leaving a definite margin for improvement.[3]

2.2 Improvements

While the SeqRNN ML model yields impressive results in terms of next token recommendation, this paper's research found that using Transformer-based models for code prediction (instead of RNN) improved the ranking statistics: Correct results were displayed to developers within the first 1.5 - 2 results, an improvement of about 0.5 to 1 ranks higher.[3]
A Transformer is a machine learning model first introduced by **GoogleBrain**.[3] It is a type of model which processes input as a whole (for instance an entire sentence) and does not depend on past hidden states to retain past information (like Recurrent Neural Networks (RNN) do).[6] This has the advantage that Transformers don't risk losing past information.
An abstract syntax tree (AST) is generally defined as the abstract syntactic representation of source code.[1] Within this representation, each node of the AST represents a construct/token of the source code. The research in this paper postulates the above mentioned improvement in accuracy by feeding ASTs into Transformers. However, since Transformers are sequential models, only partial structures of the AST can be fed in at one point in time. Their solution to this was to explore three different methods to this end:[3]

- Decompose source code into partial programs and consequently each partial program into a sequential stream of source code tokens (SeqTrans)
- Decompose the AST into multiple paths and subsequently feed each path into the Transformer (PathTrans)
- Decompose the AST into its various traversal orders and subsequently feed each traversal into the Transformer (TravTrans)

2.3 SeqTrans

Since a Transformer is designed to take only sequential input, the input for this particular method works out of the box with the

[1]https://github.com/davidhalter/jedi
[2]https://www.eclipse.org/pdt/help/html/working with code assist.htm
[3]https://research.google/teams/brain/

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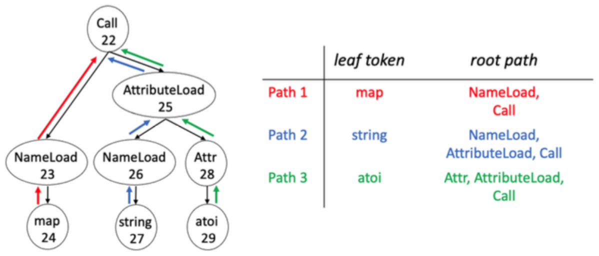
2021.

Transformer. A partial program (which is effectively a sequence of source code tokens) is fed as input to the Transformer, which in turn is expected to yield a single source code token as output.This method was already proven to be better than SeqRNN, as well as provided a platform for the following two AST based methods.

2.4 PathTrans

This method works on the concept of root paths: A root path is the path from a leaf node of an AST to to its root. Such an example is depicted in Fig 2 If an AST has multiple leaf nodes, there will



	leaf token	*root path*
Path 1	map	NameLoad, Call
Path 2	string	NameLoad, AttributeLoad, Call
Path 3	atoi	Attr, AttributeLoad, Call

Figure 2. Rootpath concept

be multiple root paths. Since each root path forms a sequence of internal nodes of the AST to each leaf token, it would ideally capture all the syntactical information along this path. Consequently, the root paths help in leaf token prediction when they are fed into the Transformer.

2.5 TravTrans

This method works on the concept of tree traversals;ie;feeding a sequence of nodes of the AST in a certain tree traversal order. The popular tree traversal methods include pre-order, post-order and in-order and can be applied to tree structures such as AST. The method involves feeding code token sequences which are obtained from pre-order traversals (in Depth First Search order since pre-order traversal is a kind of DFS) of the AST to optimize leaf token prediction. Fig 3 represents an AST. If we consider node 29 for example (atoi), the the node chain in DFS order preceding it would be:
Call -> NameLoad -> Map -> AttributeLoad -> NameLoad -> string -> Attr

3 Implementation and Datasets

The project mainly used two types of datasets:[3]

- External dataset comprising of 150k Python 2 source code files across several external GitHub repositories decomposed into ASTs. This resulted in a overall count of roughly 16 million leaf nodes.
- Internal dataset from GitHub repositories internal to Facebook. These also consisted of similar Python 2 source code files decomposed into ASTs. However, since the coding style was distinct, the main aim here was to ascertain consistency in prediction across disjoint projects. This also resuted in additional 1 million leaf nodes.

As for the implementation of the Transformers(SeqTrans, PathTrans and TravTrans), the project mainly used the GPT-2 small

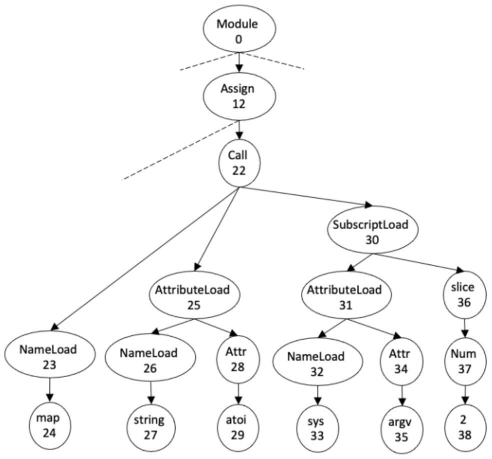


Figure 3. AST as input to TravTrans

implementation[5] based on the PyTorch library[4]. The schematic of a GP2 Transformer is depicted in Fig 4

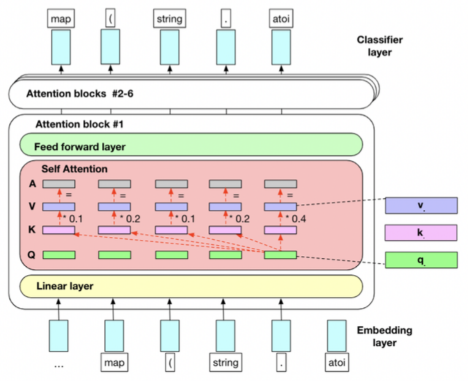


Figure 4. GP2 Transformer

4 Result

The token prediction results are generally expressed in terms of **mean reciprocal rank** percentages. As mentioned earlier, for typical RNN based methods, this percentage is about **37**.However, their most efficient method, **TravTrans**, which functions on feeding AST tree traversal sequences to Transformers, was found to increase this percentage by about **18**. Since 37 roughly equates to the correct token being present in the first 2.7 results, this 18 percent increase meant that now the correct token could be present anywhere between the first 1.5 and 2 results.

[4]https://github.com/graykode/gpt-2-Pytorch

References

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