Syntax-Aware On-the-Fly Code Completion

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Abstract—Code completion aims to help improve developers’ productivity by suggesting the next code tokens from a given context. Various approaches have been proposed to incorporate abstract syntax tree (AST) information for model training, ensuring that code completion is aware of the syntax of the programming languages. However, existing syntax-aware code completion approaches are not on-the-fly, as we found that for every two-thirds of characters that developers type, AST fails to be extracted because it requires the syntactically correct source code, limiting its practicality in real-world scenarios. On the other hand, existing on-the-fly code completion does not consider syntactic information yet. In this paper, we propose PyCoder to leverage token types, a kind of lightweight syntactic information, which is readily available and aligns with the natural order of source code. Our PyCoder is trained in a multi-task training manner so that by learning the supporting task of predicting token types during the training phase, the models achieve better performance on predicting tokens and lines of code without the need for token types in the inference phase. Comprehensive experiments show that PyCoder achieves the first rank on the CodeXGLUE leaderboard with an accuracy of 77.12% for the token-level predictions, which is 0.43%-24.25% more accurate than baselines. In addition, PyCoder achieves an exact match of 43.37% for the line-level predictions, which is 3.68%-84.73% more accurate than baselines. These results lead us to conclude that token type information (an alternative to syntactic information) that is rarely used in the past can greatly improve the performance of code completion approaches, without requiring the syntactically correct source code like AST-based approaches do. Our PyCoder is publicly available on HuggingFace and GitHub.

Index Terms—Code Completion, Multi-Task Learning

1 INTRODUCTION

Code completion, or AutoCompletion, is one of the most essential features in modern Integrated Development Environments (IDEs) (e.g., GitHub’s Copilot, Intellisense in Visual Studio Code [1]). The goal of code completion is to automatically recommend source code based on a given context, which could help developers reduce the amount of typing and coding iteration time and eliminate the number of typo errors. A recent study conducted by Google found that the current code completion feature could reduce developers’ effort by 6% and context switching by 7% [2].

Recent code completion approaches often leverage modern deep learning architectures (e.g., Recurrent Neural Network, Transformer architecture) to exploit their strong representation power. More specifically, state-of-the-art code completion models (e.g., CodeGPT [3], GPT-2 [4], GPT-C [5], TravTrans [6], CodeFill [7]) are based on code-focused large language models (LLMs) that are trained from large codebase and natural language corpora (e.g., the CodeSearchNet corpus with 2 million GitHub repositories). These LLMs are fine-tuned on a specific dataset to perform specific tasks (e.g., code completion). However, existing code completion approaches have the following limitations.

Limitation 1: On-the-fly code completions approaches do not consider syntactic information. On-the-fly code completion approaches are designed to generate code tokens based on a given context without requiring the completeness of prior context. Represent techniques include GPT-2 [4], a Transformer-based decoder model for generative tasks pre-trained on English webpage datasets; CodeGPT [3], a GPT-2 model architecture pre-trained on source code datasets; and GPT-C [5], a GPT-2 model architecture pre-trained on multi-language source code. In their pre-training, these models learn to complete the next code tokens. In doing so, the performance of these on-the-fly code completion approaches is limited by their lack of consideration of syntactic information.

Limitation 2: Existing syntax-aware code completion approaches are not on-the-fly. To ensure that the generated source code is syntactically correct [8], researchers proposed to leverage the Abstract Syntax Tree (AST) information [9], [10], [6], [11], [7], [12]. For example, Kim et al. [6] proposed TravTrans, a Transformer-based architecture consuming syntactic information from a variety representations of ASTs traversal; Izadi et al. [7] proposed CodeFill, a multi-task, Transformer-based architecture consuming source code and AST types. While existing AST-based code completion approaches may generate code that is more syntactically correct, the application scenario remains limited. In particular, the existing AST-based code completion approaches [9], [10], [6], [11], [7], [12] require source code to be completed (i.e., all the previous tokens are valid and parsable) at the inference time so the AST information can be obtained from the source code. However, our motivating analysis found that in practice, two thirds of the source code characters is incomplete and not parsable (e.g., containing syntax errors), making the existing AST-based code completion approaches inapplicable in real-world scenarios.

In this paper, we propose PyCoder, an automated code completion approach that can generate source code at any time regardless of the completeness of the source code, i.e., syntax-aware on-the-fly code completion. Our approach is
designed to consider the syntactic information of the source code during the learning phase, but does not require syntactic information during the inference phase. Instead of using the AST information like in previous works [6], [7], [9], [10], [11], [12], we propose to leverage the token type information (e.g., String, Number, Name, Keyword), which is a readily-available and light-weight syntactic information without requiring the completeness of the source code. During the learning process, we design our approach to carry out two prediction tasks, i.e., the token prediction task and the type prediction task. To ensure that our model captures both syntactic and semantic information during the training process, we leverage Multi-Task Training (MTT) techniques to learn both the token prediction task and the type prediction task. Given a sequence of code tokens, our approach performs the following steps: (1) extract the token type information of each token, (2) perform the sub-word tokenization on each token, (3) align token type data with sub-word source code data, and (4) build a code completion model using a GPT-2 architecture based on a pre-trained CodeGPT language model with a multi-task training technique.

In our experiment, we compare our PyCoder with five existing state-of-the-art models (i.e., Pointer Mixture Network [9], TravTrans [6], GPT-2 [4], CodeGPT [3], and UniXcoder [13]). During the inference phase, we evaluate our approach based on the token-level and line-level prediction tasks. Through an extensive evaluation on the PY150 [14] standard benchmark Python dataset for the code completion task that is used in Microsoft’s CodeXGLUE benchmark [3], we answer the following research questions:

RQ1) What is the performance of our PyCoder for the token-level and line-level code completion tasks when compared to state-of-the-art models? 

Results. PyCoder achieves the first rank on the CodeXGLUE leaderboard with an accuracy of 77.12% for the token-level predictions, which is 0.43%-24.25% more accurate than baselines. In addition, PyCoder achieves an exact match of 43.37% for the line-level predictions, which is 3.63%-84.73% more accurate than baselines.

RQ2) What is the impact of the training strategies on the performance of our PyCoder? 

Results. Multi-task training strategies have an impact on PyCoder for both token-level and line-level predictions. We find that PyCoder-Hard performs best; followed by PyCoder-IFN and PyCoder-Soft.

RQ3) What is the impact of the task weighting parameters in multi-task learning on the performance of our PyCoder? 

Results. PyCoder is generally robust to the task weighting parameters, achieving comparative (without task weighting) or better (with task weighting) performance when compared to the baselines.

RQ4) What is the impact of the decoding methods on the performance of our PyCoder? 

Results. Decoding methods have an impact on the performance of PyCoder with an exact match varying from 33.80% to 41.52% for line-level predictions. Beam Search performs best, while Sampling performs worst.

Novelty. The key novelty of our work is as follows:

- PyCoder is the first to leverage the standard token type information for code completion with a variety of multi-task training techniques, which is different from existing work that leverages AST token type information.
- PyCoder is the first to extensively explore the sensitivity of the task weighting parameter and decoding methods in code completion.
- PyCoder surpasses five state-of-the-art code completion techniques in our setting and the CodeXGLUE Benchmark setting, achieving the highest performance in both token-level and line-level predictions.
- PyCoder is publicly available on HuggingFace together with the code dataset and token type dataset. Our source code also available on GitHub.

Paper Organization. The paper is organized as follows. Section 2 describes the background, motivation, and limitations of the state-of-the-art approaches. Section 3 presents our PyCoder approach. Section 4 describes the experimental setup and state-of-the-art baselines. Section 5 presents the experimental results and discussions. Section 6 discusses the results of our PyCoder. Section 7 describes related work to code completion. Section 8 discloses the threats to validity. Section 9 draws the conclusion.

2 BACKGROUND AND MOTIVATION

In this section, we discuss related work about automated code completion to situate the problems and present a motivating analysis.

2.1 Code Completion

Code completion is a task to suggest the next code token from a given context. More formally, given a sequence of $m$ tokens $x_1...x_m$, as a context, code completion aims to predict the next $n$ tokens to complete a sentence $x_1...x_{m+n}$. The learning objective of a language model for code completion is to minimize a conditional probability distribution of the following function:

$$ P(x_{1:m+n}) = \prod_{i=1}^{m+n} P(x_i|x_1...x_{i-1}) $$

Statistical language models. Previously, several studies proposed code completion approaches using various types of techniques (e.g., heuristic, statistical, and deep learning). Heuristic-based approaches aim to recommend source code based on rules [15], program history [16], and code examples [17]. However, heuristic-based approaches are heavily based on rules and patterns that researchers need to develop, which is time-consuming and expensive. Therefore, statistical language models have been proposed to automatically learn the naturalness of source code based on a probabilistic of the occurrence of source code. For example, Hindle et al. [18], [19] argued that source code

1. https://huggingface.co/Wannita/PyCoder
2. https://huggingface.co/datasets/Wannita/PyCoder
3. https://huggingface.co/datasets/Wannita/PyCoder-Type
4. https://github.com/awsm-research/pycoder
is natural and repetitive (similar to natural language) and found that an n-gram approach can accurately predict the next code token based on a given context. Raychev et al. [14] proposed TGEN, a probabilistic-based learning approach with decision tree structures. However, the statistical language models are able to learn only the limited number of n consecutive tokens (according to the n-gram algorithm), which does not reflect the nature of the source code that is usually long (i.e., long-term dependencies).

**LSTM-based language models.** To address the limitation of the statistical language models, Long Short-Term Memory (LSTM)-based deep learning approaches are applied to the code completion task. However, existing LSTM-based language models can only learn the semantic information of the source code, without considering its syntactic structure. Thus, to ensure that the LSTM-based code completion models recognize the syntactic information, Abstract Syntax Tree (AST) is widely used by the previous work. For example, Li et al. [9] proposed Pointer Mixture Networks, which is an LSTM-based architecture for predicting the AST node. Similarly, Svyatkovskiy et al. [10] proposed Pythia, which is an LSTM-based approach that incorporates ASTs information through the Word2Vec embedding approach. While such RNN-based and LSTM-based are able to handle longer sequences of source code than statistical language models, the approach remain inaccurate due to the sequential nature of source code processing, the limited ability to capture long-term dependencies, and the limited ability to recognize the importance of different code tokens.

**Transformer-based language models.** To address the limitations of LSTM-based language models, the Transformer architecture is introduced for the code completion task. Generally, the development of Transformer-based language models consists of two steps: pre-training and fine-tuning. Pre-training is a process to train a Transformer-based language model in a self-supervised manner (i.e., without labels), allowing the language models to self-understand given data by itself (i.e., natural language or programming languages). Normally, the language models for code completion are trained using a Causal Language Model (CLM) (i.e., predicting the unknown token after a sequence of known tokens). Once a language model is pre-trained, the model is then fine-tuned on a specific dataset (e.g., PY150 [14]) with the same learning objective as the pre-training process (i.e., CLM). For example, Lu et al. [3] proposed CodeGPT-based models, which is based on a GPT-2 architecture [4] that is pre-trained on both Natural Language (NL) corpus (i.e., WebText) and/or Programming Language (PL) corpus (i.e., CodeSearchNet)—i.e., PL only for CodeGPT, and NL+PL for CodeGPT-adapter.

To ensure that the Transformer-based language models recognize the syntactic structure of source code, Kim et al. proposed TravTrans [6], a vanilla Transformer-based language model that incorporates ASTs information through different encoding styles. Similarly, Wang et al. [20] leverages AST information with a vanilla Transformer-based language model, but using a different AST encoding technique (i.e., by flattening the ASTs nodes). However, these AST-based code completion approaches also leverage AST information at the inference phase, which requires source code to be completed at the inference time so the AST information can be parsed and obtained from the source code. Therefore, in practice, source code is often incomplete and not compilable (e.g., syntax errors), making the existing AST-based code completion approaches not applicable in real-world scenarios.

![Fig. 1: The comparison between AST and Token Type representations and the ideal deployment scenarios.](image)

### 2.2 A Motivating Example

Let’s consider a code snippet `logging.getLogger()` as an example (see Figure 1). `logging` is the input code token, while `getLogger()` is the code token to be predicted. Below, we illustrate two key limitations of the AST-based code completion approach by using TravTrans [6] as an example, which makes the existing AST-based code completion not able to predict next code tokens on-the-fly.

**First,** the learning objective of TravTrans does not reflect the natural order of typing source code sequences. Since representing the source code as AST node sequence by traversing the AST, the order of the node sequence are inconsistent with the token sequence [12]. For example, at the learning phase, TravTrans [6] represents the input code tokens as a sequence of an AST node structure (i.e., `[AttributeLoad, NameLoad, logging, Attr]`) in order to predict the next AST node (i.e., `[getLogger]`). However, this learning objective does not mimic the natural sequence of code tokens (i.e., `[logging, ., ., ., ., ., .]`, meaning that the programming language-specific characters (e.g., dot [.] and parenthesis [()]]) are currently ignored. Therefore, in many cases at the deployment scenarios, such AST node information needs to be post-processed in order to successfully perform code completion in practice (e.g., add missing tokens [(),], convert `[Attr]` to [.]).

**Second,** in order to use AST information as an input, TravTrans [6] requires source code to be completed at the inference time so the AST information can be parsed and obtained from the source code. For example, in Figure 1, if developers type `logging.`, TravTrans can successfully recommend the next token (e.g., `getLogger`). However, source code is often incomplete and not compilable. For example, in Figure 1, if developers type `logging.get`, TravTrans cannot correctly recommend the next token, due to the syntax errors during the AST parsing step.

### 2.3 A Motivating Analysis

To demonstrate the significance of the problem of the AST-based code completion approaches, we perform a motivat-
ing analysis to investigate how often AST information could be provided at the inference phase, making AST-based code completion can be executed at the inference phase.

Let’s assume that a developer is typing a Python program character-by-character, we aim to analyze how often an AST parser can/cannot successfully parse a Python program at each character. To do so, we select a statistical representative sample of 383 syntactically correct Python files from the PY150 dataset (with a confidence level of 95% and a confidence interval of 5%). Since we simulate the application of AST-based code completion at the character level, we execute a Python AST parser at each character incrementally. In total, we execute a Python AST parser for 1,263,296 times according to the total of 1,263,296 characters. We find that 33.96% of the executions can be successfully parsed, while 66.04% of the executions fail to parse due to syntax errors.

TABLE 1: The percentage of the successful/failed executions of the Python AST parser from the 1,263,296 executions.

| AST Parsable? | Percentage |
|--------------|------------|
| Successful executions | 33.96% |
| Failed executions | 66.04% |

Finding: For every two out of three characters that developers type, AST-based code completion cannot be performed at all due to the failed execution of the Python AST parser, limiting its ability to perform code completion on-the-fly at the inference time. Since existing syntax-aware code completion is not on-the-fly and existing on-the-fly code completion is not syntax-aware, this paper aims to address these significant gaps by proposing a syntax-aware on-the-fly Python code completion approach.

3 Syntax-Aware On-the-Fly Code Completion

In this section, we present an overview of our syntax-aware on-the-fly Python code completion approach (PyCoder).

Conceptually, PyCoder aims to generate source code at any time regardless of the completeness of the source code, while considering the syntactic and semantic information of the source code during the learning phase, but do not require syntactic information during the inference phase. To ensure that the learning process considers both semantic and syntactic information, we design our approach to focus on two prediction tasks, i.e., the code token prediction task and the token type prediction task. In particular, we leverage a Multi-Task Training technique (MTT) to cooperatively learn both the code token prediction task (Task 1: Predict the next code token, considered as a Target Task) and the token type prediction task (Task 2: Predict its token type, considered as a Supporting Task). For the type prediction task, we propose to leverage the standard Python token type information (e.g., String, Number, Name, Keyword), which is readily available and lightweight, instead of using the AST information [6], [7], [9], [10], [11], [12] where we found not available for the two-third of the executions (see our finding in Section 2.3), limiting its ability to perform on-the-fly code completion. In contrast, our PyCoder does not require syntactic information at the inference phase. Thus, the completeness of the source code at the inference time is not required.

Overview. Figure 2 presents the overview of our PyCoder, which consists of two phases: training and inference. During the training phase, PyCoder performs 6 main steps: Step 1 Type Extraction, to extract the token type information from source code; Step 2 Tokenization, to perform subword tokenization on the source code; Step 3 Data Alignment, to align the type information which is word level to the code information which is currently subword level; Step 4 Multi-task Training Architecture with 3 training techniques: hard parameters sharing (MTL), soft parameters sharing (MTL), and intermediate fine-tuning (IFN); then in Step 5 Hyperparameter Task Weighing and Step 6 Decoding Methods are the exploration steps to maximize the performance. For the inference phase, we describe in Step 7 Code Generation step in the details of token-level prediction and line-level prediction.

3.1 (Step 1) Type Extraction

Syntactic information can be represented in many forms, e.g., Abstract Syntax Tree (AST) which is widely used in the previous work, and Token Type information which remains largely unexplored. In fact, both AST and token type information have their own advantages and disadvantages. While AST provides a formal representation of syntactic information of source code, it requires syntactically correct source code in order to be successfully parsed by a Python AST parser. Since our finding in Section 2.3 shows that the Python AST parser failed to execute for every two out of three characters that developers type, the usage scenarios of the existing AST-based code completion approach are still limited in practice.

To address this challenge, we leverage a standard Python token type information, offering a more abstract representation of the syntactic structure of source code (e.g., Name, String, Number), which (1) is more lightweight, (2) follows the natural order of code sequences; and (3) can be successfully parsed at any times without requiring the complete and syntactically correct source code. Generally, the standard Python token consists of two pieces of information i.e., (1) the token type, which provides syntactic meaning, and (2) the token value, which provides semantic meaning. For example, given a logging token, the token type is NAME and its value is logging. Since the token type information is not available in the existing code completion benchmark, we describe the steps to extract the type information below.

To extract type information, we use the tokenizer function provided by the standard Python tokenizer library with an option exact_type in order to extract the most fine-grained type for each token. For the Python tokenizer (Python 3.7 version), there will be a total of 58 different types. In particular, we focus on the 12 primary types of code tokens as follows: <NAME>, <NUMBER>, <STRING>,

5. https://www.surveysystem.com/sscalc.htm
6. https://docs.python.org/3/library/ast.html
7. https://docs.python.org/3/library/tokenize.html
The following token types [NAME, DOT, NAME, LPAR, RPAR].

3.2 (Step 2) Tokenization
Tokenization is an important step in automated code completion, aiming to split the source code into meaningful units. There are three general levels of granularity, i.e., a word level, a subword level, and a character level. While the word-level representation is the simplest tokenization approach, it may produce a massive vocabulary size. However, limiting the vocabulary size based on its frequency may cause an Out-of-Vocabulary words (OOV) problem. While the character-level representation can diminish the OOV problem with the limited vocabulary size (e.g., English characters), models may not be able to handle an excessively long sequence of source code (i.e., each character has its own vector). Instead, we use sub-word tokenization with the Byte-Pair Encoding (BPE) algorithm [21], as prior studies found that BPE can substantially reduce the vocabulary size [22], [23], while being able to generate new identifiers that never appear in the dataset [24]. First, BPE splits source code into characters. Then, BPE iteratively merges the characters into subwords based on the frequency of the occurrences to create the vocabulary until the desired size. In this paper, we use the CodeGPT tokenizer, which has a vocabulary size of 50,000 subwords. To ensure that the CodeGPT tokenizer can recognize the token types, we represent the token types in the bracket parenthesis form (...), which are included in the special token vocabulary for the BPE tokenizer to avoid any subword tokenization on these token types.

3.3 (Step 3) Data Alignment
Data alignment is an important step to ensure that the sequence of code tokens and their corresponding token
types are correctly matched and aligned. With the use of BPE, some words may be tokenized as subwords, while their type is not tokenized into the subword level, making the sequence of code tokens and the corresponding token types not correctly matched. For example, as shown in Figure 2, BPE splits logging into [logg, ing] with a single corresponding <NAME> token type. To address this problem, we repeat the token type for any word that is split by BPE. Therefore, in Figure 2, the token type <NAME> is repeated twice in order to match the subword-level code sequence of [logg, ing]. This data alignment step will produce a sequence of code tokens and their corresponding token types with the same length, which is ready to be fed into our code completion approach to learn both syntactic and semantic meanings of source code.

3.4 (Step 4) Multi-Task Training Architectures

Our PyCoder leverages a Multi-Task Training (MTT) paradigm, which is a set of techniques designed to learn multiple tasks, allowing the model to capture multiple sources of information. Traditionally, deep learning is designed for one single learning objective (e.g., only predicting the next code token), limiting its ability to capture other important and useful sources of information (e.g., syntactic information of source code). Instead of training a model with one single learning objective, the MTT paradigm aims to provide a generalist model with multiple learning objectives, providing a more robust vector representation. For our PyCoder approach, we design the target task to predict the next token, while the supporting task (aka. an auxiliary task or additional related non-target task) is to predict the token type. In addition, we build three variants of PyCoder, with three different MTT techniques, according to two learning styles [25] as follows.

3.4.1 Multi-Task Learning (MTL)

Multi-Task Learning (MTL) learns multiple tasks simultaneously instead of learning them separately. Normally, during the learning process, the model aims to optimize a loss function for one single learning objective (e.g., only predicting the next code token), limiting its ability to capture other important and useful sources of information (e.g., syntactic information of source code). Instead of training a model with one single learning objective, the MTT paradigm aims to provide a generalist model with multiple learning objectives, providing a more robust vector representation. For our PyCoder approach, we design the target task to predict the next token, while the supporting task (aka. an auxiliary task or additional related non-target task) is to predict the token type. In addition, we build three variants of PyCoder, with three different MTT techniques, according to two learning styles [25] as follows.

3.4.2 Intermediate Fine-Tuning (IFT)

Intermediate Fine-Tuning (IFT) [25] adapts a transfer learning concept (i.e., pre-training then fine-tuning) where the goal is to learn multiple tasks sequentially. First, the model is fine-tuned on the supporting task (token type prediction) followed by the target task (code token prediction), respectively. Thus, the fine-tuned step on the supporting task can be considered the second stage of the model pre-training. Therefore, the Intermediate Fine-Tuning (IFT) model (PyCoder-IFT) is first trained based on an intermediate self-supervised task (token type prediction), then trained on the target task (code token prediction), allowing the model to gain knowledge on the token type prior to predicting the next code tokens.

GPT-2 Model Architecture

Among the three variants of the MTT techniques (i.e., PyCoder-Hard, PyCoder-Soft, and PyCoder-IFT), we use the GPT-2 architecture as a base model. GPT-2 [4] is a decoder-only Transformer model. The GPT-2 architecture for code completion consists of three main components: the embedding layer, the decoder block, and the language model head. First, the embedding layer embeds the input tokens into vectors with positional encoding, allowing the model to learn the semantic meaning and the position of each code token. Then, the embedding vectors are fed into the decoder block which contains decoder layers. Each decoder layer includes masked self-attention layers, feed-forward neural
network layers, and normalization layers. The masked self-attention layer indicates which tokens to focus on, while the masking approach prevents the attention mechanism [28] to see the unseen tokens in the future. The feed-forward neural network layer is a sophisticated network with hidden nodes to capture the related information between each data point. The normalization layer makes the learning process more effective by enabling smoother gradients and generalized accuracy. After $L$ layers of decoder, an output of the last layer is fed to the language model head, i.e., a linear layer, which converts the output to a vector whose dimensions are the same as the vocabulary size. Lastly, the vector is converted to a probability distribution by the softmax activation function. Formally, to predict the next token $x_t$ based on a given input sequence, GPT-2 can be represented as follows:

$$h_0 = W_e \cdot C + W_p$$

$$h_i = decoder\_layer(h_{i-1}), \forall l \in [1, L]$$

$$P(x_t) = y_t = \text{softmax}(h_n \cdot W^T_e), t \in [0, N]$$

where $W_e$ is the tokens embedding matrix, $C$ denotes the context vector of tokens, $W_p$ is the position embedding matrix, $L$ is a number of decoder layers, and $N$ is the length of the sequence. We follow the traditional language models by maximizing the log-likelihood of:

$$L(x_t) = \sum_i \log P(x_t | x_1...x_{t-1}, \omega)$$

, where $\omega$ is the model parameters that are learned during the optimization process. Particularly, PyCoder uses the pre-train CodeGPT [3] that is pre-trained on the CodeSearchNet dataset [29] as a starting checkpoint.

### 3.5 (Step 5) Hyperparameter Task Weighting

Since our PyCoder leverages MTL training techniques to learn multiple different tasks simultaneously, some tasks may have a higher influence than others, which later may produce an unsatisfactory accuracy for the other tasks (called a conflicting gradient problem). To prevent such conflicting gradients between tasks, it is important to find the most optimal task weights by minimizing the loss. Therefore, we optimize the hyperparameters $(\alpha_i)$ to adjust the task weights to find optimal task weights for our architecture. Specifically, we aim to minimize the loss of the code prediction task along with the type prediction task using the following loss function.

$$L_{\text{MTL}} = \arg\min_{\omega} \left( \sum_i \alpha_i \cdot L_i(d, \omega) \right)$$

### 3.6 (Step 6) Decoding Methods

Decoding is a method to select the next token from the potential vocabulary when generating a sequence. Although selecting only the highest probable token is suitable for a single step, it might be sub-optimal for the sequence. Since the search space of the next tokens is large, different decoding methods will have different mechanisms, providing different predictions of the next tokens. Thus, the selection of the decoding methods may have an impact on the overall performance of our PyCoder. In the code completion literature, we found that Beam Search is one of the most commonly used decoding methods. However, Holtzman et al. [30] found that there exist other decoding methods that are widely used in the NLP area, yet remain largely explored in the code completion literature. Thus, we aim to experiment with the six following decoding methods.

- **Greedy** is a method to select the maximum probable vocabulary to be the next tokens. This method assumes that the model already outputs the best probability in every timestep.
- **Beam Search** applies a search algorithm to generate all possible tokens in the vocabulary; then, it selects the top $b$ (i.e., beam size) probable tokens to continue. The Beam Search method is one of the most commonly used decoding methods in text generation tasks [31], [32].
- **Sampling** is a method to randomly select the next token from the actual probability distribution assigned by the model. Different from Greedy and Beam search methods which in some cases may recommend only the same probable next tokens at different timesteps, the sampling method may recommend different next tokens at different timesteps (i.e., non-deterministic).
- **Sampling with Temperature** applies a temperature parameter to shape the probability distribution [33], which is different from the original sampling method where the randomness is arbitrary. The temperature is used to increase the probability of the most probable next tokens, while decreasing the probability of the others. We note that the probability of the least probable next tokens is only decreased, but they are not removed from the recommendation. The range of the temperature value is usually at $0 < temp \leq 1$, where $temp = 1$ is a normal sampling.
- **Top-K Sampling** aims to truncate the probability distribution by choosing the top-$k$ probable next tokens from the vocabulary, then, re-scale the distribution and perform sampling based on the new distribution. This method ensures that the less probable next tokens will not be generated, while only the top-$k$ probable next tokens are only considered during the sampling process.
- **Top-P Sampling (Nucleus Sampling)** is similar to the Top-k sampling method where the Top-P sampling method also truncates the probability distribution, but with different criteria. Top-P sampling prunes the distribution by the cumulative probability of the current step $\geq p$ [30]; then, re-scale and perform sampling. Formally, given the probability $P$, we can define the smallest summation of the probability as $V_p$ in

$$\sum_{x \in V_p} P(x | x_{1:t-1}) \geq p$$

The benefit of this method is that it can dynamically adjust the number of $k$ depending on the certainty of the model. If the model is very certain on some tokens, the search space is small, and vice versa.

### 3.7 (Step 7) Code Completion

PyCoder performs predictions at two granularity levels, i.e., at the token level and at the line level.
Token-level code completion is a process to predict the next token (the right side), given the prior code tokens as a context (the left side).

Line-level code completion is similar to the token-level prediction, but the model aims to predict the next tokens until completing the whole line of code (i.e., not just only one single next token). For the line-level prediction, we leverage the same model used for the token-level code completion task to iteratively generate the next token, where the newly generated token is used as a context for the next step of the prediction. This process is repeated iteratively until the model generates a \(EOL\) token, or until it reaches a certain \(n\) threshold (\(n = 100\), following the CodeXGlue [3]).

4 EXPERIMENTAL SETUP

In this section, we present the goal of our experiment, along with the research questions, followed by the experimental setup in detail.

4.1 Goal and Research Questions

The goal of this paper is to empirically evaluate our PyCoder and compare with the state-of-the-art approaches according to the token-level and line-level code completion tasks and to provide a better understanding of the impact of the components of our PyCoder. To achieve this goal, we present the motivation and the research questions below.

RQ1) What is the performance of our PyCoder for the token-level and line-level code completion tasks when compared to state-of-the-art models?

**Motivation.** As motivated earlier, existing syntax-aware code completion are not on-the-fly, while existing on-the-fly code completions are not syntax-aware. To address this important gap, we introduce PyCoder (a syntax-aware on-the-fly code completion). Thus, we formulate this RQ to investigate how well our PyCoder perform when compared to the state-of-the-art approaches for both token-level and line-level code completion tasks based on the CodeXGlue Benchmark.

RQ2) What is the impact of the training strategies on the performance of our PyCoder?

**Motivation.** There exist various training strategies for multi-task learning used in code completion. For example, Liu et al. [12] found that hard parameter sharing performs best, while Izadi et al. [7] found that soft parameter sharing performs better than hard parameter sharing for code completion. This contradictory finding motivates us to investigate the impact of training strategies on the performance of PyCoder.

RQ3) What is the impact of the task weighting parameters in multi-task learning on the performance of our PyCoder?

**Motivation.** Our PyCoder relies on two prediction tasks, i.e., code prediction and token type prediction tasks. It could be possible that these two tasks may be conflicting with each other or one task has a higher influence than the other task during the learning process. Thus, prior studies [34], [35] raised concerns that the conflicting issue (aka. conflicting gradient) may degrade the performance of multi-task learning. Therefore, task weighting parameters are used to weigh the importance of each task to achieve optimal accuracy. However, PyCoder may be sensitive to the task weighting parameters. Thus, we set out this RQ to investigate the impact of the task weighting parameters on the performance of PyCoder.

RQ4) What is the impact of the decoding methods on the performance of our PyCoder?

**Motivation.** Decoding methods are an important component of code completion used to generate the next probably code tokens. Recently, only a few methods are used for code completion (e.g., Beam Search, Greedy) [5], [6], [7], [9]. However, there are other decoding methods that have been used for text generation in the natural language processing field, yet have never been explored in software engineering. Thus, there is a lack of understanding of whether decoding methods widely used in code completion are the best.

4.2 Dataset

We use the ETH PY150 python dataset (the standard code completion benchmark) provided by Raychev et al. [14] to ensure a fair comparison with prior studies [6], [7], [9], [36]. The dataset is collected from open-source software projects in GitHub repositories with non-viral licenses (e.g., MIT, Apache, and BSD)—a license that an owner gives permission for freely use under specific terms; thus mitigating potential licensing issues. Note that this dataset is also used in Microsoft’s CodeXGlue benchmark [3]—a worldwide competition for the AI4Code area. As any duplicated codes have been removed by Raychev et al. [14], arriving at a total of 150,000 Python files, we confirm that there is no exact code duplication between the training set and the testing set, thus mitigating several potential biases like code duplication in our experiment. Following CodeXGLUE, for token-level predictions, the dataset is split into 95,000 files for the training set, 5,000 files for the validation set, and 50,000 files for the testing set, with the number of tokens of 72.1M, 4.4M, and 37.3M, respectively. For line-level predictions, it’s a common practice to reuse the same model trained for token-level predictions. Thus, only a testing set is required, but a training set and a validation set are not required. Therefore, we use the 10,000 Python files provided by CodeXGLUE [3] as a testing set for line-level predictions.

4.3 Pre-processing Methods

Sensitive data information (e.g., name, number, credential, IP address) could appear in the source code. To avoid the models unnecessarily paying attention to this information, we mask these sensitive data by creating a placeholder for any string and numeric literals in the source code. Partic-ularly, following CodeXGLUE [3], we first identify tokens based on their STRING and NUMBER types. Then, in the top-200 most frequent strings and the top-30 most frequent numeric literals, we replace the string with \(\langle STR\_LIT:value\rangle\) and replace the number with \(\langle NUM\_LIT:value\rangle\). Note that we use similar frequent numbers to CodeXGLUE [3]. The rest of the uncommon literals are masked by \(\langle STR\_LIT\rangle\) or \(\langle NUM\_LIT\rangle\). Finally, these placeholders are also added to the special tokens of the tokenizer, avoiding any subword tokenization for these special tokens.
### Table 2: Model Hyperparameters

| Hyperparameter               | Value       |
|-----------------------------|-------------|
| Learning rate               | 8e-5        |
| Weight decay                | 0.01        |
| Batch size                  | 2           |
| Gradient accumulation steps | 4           |
| Block size for token-level  | 1024        |
| Block size for line-level   | 924         |

In addition, we preserve the original indentation of the source code that is ignored by CodeXGLUE’s pre-processing step. Indentation plays an important role as part of the Python syntax grammars, as it is used to indicate a group of statements that belongs to a particular code block, assisting a Python interpreter to decide the execution of the next statement. To do so, for any positions of the indentation, we use (INDENT) and (DEDENT) special tokens. (INDENT) denotes the indentation, which appears once at the beginning of a code block, not once per line, while (DEDENT) denotes the denotation at the end of the code block.

#### 4.4 Model Training

We use PyTorch\(^9\) [37] and HuggingFace\(^10\) [38] libraries for the implementation of our GPT-2 based model with the pre-trained checkpoint of CodeGPT. The base model is the default GPT-2 small configuration [4], consisting of 12 layers of Transformer decoders, 12 attention heads, \(n_{\text{position}} = 1024\), \(n_{\text{ctx}} = 1024\), and \(n_{\text{embd}} = 768\). We train our models for 200,000 steps with an Adam optimizer [39]. The hyperparameters setting is shown in Table 2. We do not fine-tune the hyperparameters due to limited resources. Therefore, our results could serve as a lower bound, but the optimization may improve the accuracy of our model. Overall we train 12 variants of PyCoder (3 multi-task training techniques + 9 task weighing parameters) for a total of more than 850 training hours. For the baseline, we use all the best hyperparameters described in their papers. Our experiments is run on one NVIDIA GeForce RTX 3090 GPU with 24 GB memory, an Intel(R) Core(TM) i9-9980XE CPU @ 3.00GHz with 36 core processors, and 64G RAM.

#### 4.5 Evaluation Measurement

We evaluate our models based on the following evaluation measures: Accuracy (Acc) for token-level predictions; Exact Match (EM), Edit Similarity (ES), Mean Reciprocal Rank (MRR), BLEU, METEOR, and ROUGE for line-level predictions.

**Accuracy (Acc)** is the proportion of correctness between predicted code tokens to the ground-truth tokens.

**Exact Match (EM)** is similar to Accuracy, but is evaluated at the line level, meaning that the whole predicted lines must be exactly matched with the ground-truth lines.

**Edit Similarity (ES)** uses a Levenshtein distance [40] to measure the edit distance between the predicted lines and ground-truth lines. The Levenshtein distance is the minimum number of edits in characters (either an insertion, a deletion, or a replacement of a character) between the predicted line and the ground-truth line.

**Mean Reciprocal Rank (MRR)** evaluates the top-\(R\) possible results using the multiplicative inverse of the rank of the first correct prediction. Formally, MRR is defined as:

\[
MRR = \frac{1}{|Q|} \sum_{i=1}^{|Q|} \frac{1}{\text{rank}_i}
\]

where \(Q\) is the number of samples, and \(\text{rank}_i\) is the rank of the correct prediction given by the model. If the correct prediction exceeds rank \(R\), then the reciprocal rank is 0. In this paper, we use \(R = 5\).

**BLEU** evaluates how similar the predicted lines to the ground-truth lines using n-gram [41]. In this paper, we use the cumulative 4-gram BLEU score (i.e., BLEU-4) from NLTK library\(^11\), with the weight of 0.25 for each of the 1-gram, 2-gram, 3-gram, and 4-gram score.

**METEOR** evaluates how similar the the predicted lines to the ground-truth lines based on the harmonic mean of unigram precision and recall [42].

**ROUGE** measures the quality of the summary by counting the number of overlapping units such as n-gram, token sequences and token pairs between the predicted lines and the ground-truth lines [43]. In this paper, we use ROUGE-L, which is the Longest Common Subsequence (LCS) [44] based statistics.

#### 4.6 Baselines

There exist various non-AST-based code completion approaches in CodeXGLUE [3], [4] and AST-based code completion approaches [6], [7], [9] in the literature. To ensure that our evaluation is reasonably comprehensive, we consider a total of eight (8) baselines with respect to two evaluation settings: (1) externally evaluate the prediction results through the CodeXGLUE leaderboard,\(^12\) and (2) internally evaluate the prediction results within our own setting.

For the CodeXGLUE evaluation setting, we compare our approach with CodeGPT-adapt, CodeGPT, GPT-2, Transformer (12L), and LSTM+BPE. To do so, we apply our PyCoder to the testing set provided by CodeXGLUE for both token-level and line-level predictions. Then, the prediction results are submitted to the CodeXGLUE team to obtain the results based on their evaluation setting. Additionally, we also include the results from UniXcoder [13] for a comprehensive comparison, as the authors experimented on the same CodeXGLUE benchmark setting.

For our own evaluation setting, we consider two AST-based approaches (i.e., Pointer Mixture Network [9] and TravTrans [6]); two non AST-based approaches (i.e., GPT-2 and CodeGPT); and a multi-modal pretrain model (i.e., UniXcoder). We do not consider CodeFill [7], since the available replication package is not executable. We also do not consider Codex (i.e., a descendant of GPT-3 for source code) in our experiment due to the different levels of model parameter size. GPT-3, a base model of Codex, has 175B model parameters, which is 100x larger than the size of our GPT-2 based model which has only 117M model parameters. Below, we describe the details of each approach.

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9. https://pytorch.org
10. https://huggingface.co
11. https://www.nltk.org/api/nltk.translate.bleu_score.html
12. https://microsoft.github.io/CodeXGLUE/
TABLE 3: (RQ1) The results that appear in the CodeXGLUE leaderboard (https://microsoft.github.io/CodeXGLUE/).

| Rank | Model          | Team name       | Date              | Line-level | Token-level |
|------|----------------|-----------------|-------------------|------------|-------------|
| 1    | PyCoder-Hard   | Monash University | 2022-10-13        | 43.91      | 71.74       | 76.93       |
| 2    | UniXcoder      | Guo et al.      | 2022-03-08 (publish data) | 43.12      | 72.00       | -           |
| 3    | CodeGPT-adapt  | CodeXGLUE Team  | 2020-08-30        | 42.37      | 71.59       | 76.60       |
| 4    | CodeGPT        | CodeXGLUE Team  | 2020-08-30        | 42.18      | 71.23       | 75.58       |
| 5    | GPT-2          | CodeXGLUE Team  | 2020-08-30        | 41.73      | 70.60       | 75.90       |
| 6    | Transformer (12L) | CodeXGLUE Team | 2020-08-30        | 38.51      | 69.01       | 74.48       |
| 7    | LSTM + BPE     | CodeXGLUE Team  | 2020-08-30        | 33.37      | 56.26       | 61.39       |

TABLE 4: (RQ1) The results of PyCoder when compared to existing approaches through our internal evaluation.

| Model          | Line-level | Token-level |
|----------------|------------|-------------|
|                | EM  | ES  | MRR | BLEU-4 | METEOR | ROUGE-L | Acc  |
| PyCoder-Hard   | 43.37 | 73.20 | 48.82 | 46.03 | 40.42 | 59.97 | 77.12 |
| UniXcoder      | 40.68 | 71.99 | 45.85 | 43.31 | 39.26 | 58.36 | 75.69 |
| CodeGPT        | 40.03 | 70.61 | 46.64 | 42.12 | 38.53 | 56.96 | 75.50 |
| TravTrans      | -   | -   | -   | -   | -   | -   | 75.50 |
| GPT-2          | 37.64 | 68.44 | 43.85 | 39.23 | 36.89 | 54.32 | 73.89 |
| PMN            | -   | -   | -   | -   | -   | -   | 69.02 |

- Pointer Mixture Network (PMN), proposed by Li et al. [9], is an LSTM-based code completion leveraging AST information for syntactic structures. The model is designed with pointer networks to mitigate the OOV problems in code completion. Their replication package is available on Github and also in Pytorch version.
- TravTrans, proposed by Kim et al. [6], is a transformer-based model that considers the syntactical structure of source code via AST information. Their replication package is available on GitHub.
- GPT-2, proposed by Radford et al. [4], is a GPT-2-based model for text generation tasks. The GPT-2 model is first pre-trained on millions of English web pages (the WebText corpus) to build a language model through self-supervision learning without any explicit labels. The model is available on HuggingFace.
- CodeGPT, proposed by Lu et al. [3], is a GPT-2-based model for source code generation. The CodeGPT model is a GPT-2 model that is pre-trained on a monolingual python source code from CodeSearchNet [29] dataset. The model is available on HuggingFace.
- UniXcoder, proposed by Guo et al. [13], is a Transformers-based unified cross-modal pre-trained model for source code generation. The UniXcoder model is pretrained on three types of language model tasks: masked language model, unidirectional language model, and denoising objective, and two types of inputs: comment and flattened AST. The pretrain datasets are six programming languages from CodeSearchNet dataset [29], and natural text from C4 dataset [45]. Their replication package is available on Github.

5 Experimental Results

In this section, we present the experimental results according to our four research questions (RQs).

(RQ1) What is the performance of our PyCoder for the token-level and line-level code completion tasks when compared to state-of-the-art models?

PyCoder achieves the first rank on the CodeXGLUE leaderboard for the code completion task (as of 13 October 2022, see Table 3). We find that PyCoder achieves an accuracy of 76.93% for the token-level predictions, while achieving an exact match of 43.91% for the line-level predictions. The evaluation results confirm that PyCoder is more accurate than other baselines by 0.43%-24.25% for token-level predictions and 3.63%-84.73% for line-level predictions.

Similarly, PyCoder outperforms existing AST-based and non-AST-based code completion approaches, according to our own setting. Table 4 shows that PyCoder achieves an accuracy of 77.12% for the token-level predictions, while achieving an exact match of 43.37% for the line-level predictions. For the token-level predictions (Acc), we find that PyCoder is more accurate than Pointer Mixture Network by 11.74%, GPT-2 by 4.37%, TravTrans by 2.15%, and CodeGPT by 1.89%. This finding indicates that PyCoder that is syntax-aware and on-the-fly performs better than a code completion approach that is either syntax-aware alone or on-the-fly alone. It is worth noting that the accuracy of PyCoder-Hard, CodeGPT, and GPT-2 achieved for the CodeXGLUE leaderboard is slightly different from the accuracy of those that are run in our experimental setup. The difference that we observed has to do with the dataset used in CodeXGLUE and our experiment. In CodeXGLUE, they removed the indentation, while the dataset used in our experiment preserved the original indentation. To mimic the practical deployment
In addition, the token-type information can improve the line-level code completion task by 6.61%-15.22%. For the line-level predictions (EM), we find that PyCoder is more accurate than GPT-2 by 15.22%, CodeGPT by 8.34%, and UniXcoder by 6.61%. This finding indicates that the use of token-type information that is largely ignored by the literature can also improve line-level predictions by 6.61% to 15.22%, confirming that the token-type information is useful to improve the performance of line-level code completions.

Finally, when comparing PyCoder with the existing AST-based code completions (i.e., TravTrans and Pointer Mixture Network), we find that the existing AST-based code completions are designed for the token-level predictions only. Thus, the line-level predictions cannot be performed, highlighting the limitations of the AST-based approaches that require AST information at the inference time, while demonstrating the benefits of our approach that consider the token-type information (i.e., syntax-aware), while can still predict code at any points of time (i.e., on-the-fly).

**RQ1 Summary.** PyCoder achieves the first rank on the CodeXGLUE leaderboard with an accuracy of 77.12% for the token-level predictions, which is 0.43%-24.25% more accurate than baselines. In addition, PyCoder achieves an exact match of 43.37% for the line-level predictions, which is 3.63%-84.73% more accurate than baselines.

(RQ2) What is the impact of the training strategies on the performance of our PyCoder?

Table 5 presents the results of PyCoder when using various multi-task training strategies. Hard parameter sharing (PyCoder-Hard) as a multi-task training strategy performs the best. Table 5 shows that different multi-task training strategies have an impact on the performance of PyCoder for both token-level and line-level predictions. Particularly, we observe that PyCoder with hard parameter sharing achieves an exact match of 42.83%, while PyCoder with software parameter sharing achieves an exact match of 38.29%. The 4.54% difference (i.e., max-min) confirms the impact that the training strategies have on the performance of PyCoder. In addition, our results are contradictory to Izadi et al. [7] who found that soft parameter sharing performs best for code completion. This finding highlights the importance of investigating various choices of multi-task training strategies for code completions, instead of following prior suggestions or practices.

Different from Izadi et al. [7], our PyCoder-Hard is designed to take both sequences of code tokens and their types as inputs one-by-one at a time and simultaneously learn with the same loss functions that are optimized together within the same model. With this method, the inputs can be detached from each other at the inference phase, resulting in better performance confirmed by our results. Nonetheless, the high-performing hard parameter-sharing training strategy (PyCoder-Hard) has to do with the benefits of the tight relationship between the learning tasks (i.e., code predictions and type predictions). Since token types are directly aligned with the same sequence of code tokens, these two pieces of information have a tight relationship. Therefore, PyCoder-Hard, which completely shares the model’s weights and parameters between tasks, gains the most benefit from the shared relationship between the code and type information. However, the soft parameter sharing model (PyCoder-Soft) learns each task separately, making the learning process between two related tasks harder, resulting in sub-optimal performance.

**RQ2 Summary.** Multi-task training strategies have an impact on PyCoder for both token-level and line-level predictions. We find that PyCoder-Hard performs best; followed by PyCoder-IFN and PyCoder-Soft.
(RQ3) What is the impact of the task weighting parameters in multi-task learning on the performance of our PyCoder?

Table 6 presents the results of different task weighting parameters for PyCoder-Hard.

PyCoder is generally robust to the task weighting parameters, achieving comparative (without task weighting) or better (with task weighting) performance when compared to the baselines. Table 6 shows that when varying the task weighting parameters (Type:Code) from 1:9 to 9:1, our PyCoder achieves an exact match between 41.19% to 43.37%, which is still greater than the existing approaches (i.e., 40.03% for CodeGPT and 37.64% for GPT-2) with an exception for the weighting of 9:1. Although the task parameters are not weighted (cf. No Weight), our PyCoder still achieves an exact match of 42.83%, which also outperforms the existing approaches. In line with the other measures for both line-level and token-level predictions, this finding confirms that by adding token-type information by at least a small weighting of 10%, our PyCoder often performs better than the existing approaches. This means that the task objectives of PyCoder rarely suffered from conflicting gradients (i.e., the gradients of different task objectives are not aligned leading to the sub-optimal performance in the average gradient) showing that type prediction and code prediction are correspondent and beneficial to each other. In our setting, the best task’s weight is 1:9 for the type prediction task to the code prediction task.

**RQ3 Summary.** PyCoder is generally robust to the task weighting parameters, achieving comparative (without task weighting) or better (with task weighting) performance when compared to the baselines.

(RQ4) What is the impact of the decoding methods on the performance of our PyCoder?

Since decoding methods are specially designed for generating code predictions as a sequence (i.e., not an individual code token), the rest of this RQ will focus on the line-level predictions only, not the token-level predictions. We note that some decoding methods (i.e., Beam Search and Sampling with a probability shaping function) require parameter settings to be specified. Thus, we experiment with the following parameters: a beam size \( b \) of \( \{3, 5, 10, 16, 50\} \) for Beam Search, a temperature \( \text{temp} \) of \( \{0.05, 0.1, 0.3, 0.5, 0.7, 0.9\} \) for Sampling with Temperature, a top-k \( k \) of \( \{3, 5, 10, 50, 100\} \) for Top-K Sampling, and a top-p \( p \) of \( \{0.05, 0.1, 0.3, 0.5, 0.7, 0.9\} \) for Top-P Sampling. For the Sampling approaches, we repeat the experiment five (5) times with different seed numbers to ensure the robustness of the results. Thus, we present the results using the average of the distribution and its standard deviation (SD). Since Beam Search and Greedy methods are available in both CodeXGLUE and HuggingFace libraries with different implementations, we also evaluate decoding methods using both libraries. Finally, we experiment with a total of 102 variants of 6 decoding methods, i.e., \( (2\text{libraries} \times (1\text{Greedy} + 5\text{BeamSearch}) + 5 \text{repeats} \times (1\text{Sampling}, 6\text{Temp}, 5\text{k}, 6\text{p})) \).

Beam Search performs the best, while Sampling performs the worst. Table 7 shows that there is a great performance difference of PyCoder when different decoding methods are used. For example, Beam Search (CodeXGLUE) generally achieves an exact match of 43.37%, while Sampling achieves an exact match of 33.80%, confirming that the decoding methods have a substantial impact on the performance of PyCoder for line-level code completion. In addition, we find that not only the methods but different libraries with different implementations also produce different results. In particular, when comparing Beam Search between CodeXGLUE and HuggingFace libraries (see Table 7), we find that Beam Search from the CodeXGLUE library achieves an exact match of 43.37% (used by PyCoder), which is greater than that from the HuggingFace library. This finding suggests that future studies should use Beam Search (CodeXGLUE) for code completion and should report the library used for decoding methods for better reproducibility and replicability details.

We find that Sampling is the lowest-performing decoding method, while advanced Sampling (i.e., Sampling with Probability Shaping) tends to perform better, depending on the specified parameter settings. Through the comprehensive investigation, Top-P Sampling performs best when \( p = 0.1 \), and Sampling with Temp performs best when \( \text{temp} = 0.1 \). These optimal parameter settings are domain and context-specific to code completion, which are different from Holtzman et al. [30] who recommend \( \{0.5, 1\} \), \( k \in [1, 100] \), \( p \in [0.9, 1] \) for the text generation tasks. The optimal setting that we achieved for code completion is different from the recommendations in the NLP text generation field suggests that researchers should experiment with various parameter settings for the problem that tackle, instead of solely relying on suggestions or recommendations from prior work.
Fig. 3: The chart of the token-level code prediction accuracy in token type granularity sorted by the type frequency from small (left) to large (right). The tokens related to syntax types is represented in blue color.

**RQ4 Summary.** Decoding methods have an impact on the performance of PyCoder with an exact match varying from 33.80% to 41.52% for line-level predictions. Beam Search performs best, while Sampling performs worst.

### 6 Discussion

#### 6.1 How many line-level predictions that our PyCoder can correctly predict while others cannot?

To answer this question, we perform additional analysis on the line-level predictions between PyCoder and the state-of-the-art approaches (i.e., CodeGPT and GPT2 that PyCoder built upon). We use a Venn diagram to visualize the number of correct (i.e., exact match) and incorrect predictions at the line level for each of the three approaches (see Figure 4).

We find that 11.5% (\(\frac{499}{4337}\)) of the line-level predictions can be correctly predicted by PyCoder while others cannot. Figure 4 shows that, among the 10,000 line-level samples in the testing set, there are 4,878 samples that can be correctly predicted by one of the approaches, meaning that 5,122 samples cannot be correctly predicted by any of these three approaches. Among the correct predictions, PyCoder can correctly predict the majority of the samples (i.e., 4,337), accounting for 88.9% of the total correct predictions. Most importantly, among these, 11.5% (\(\frac{499}{4337}\)) of samples can be accurately predicted by PyCoder while others cannot, highlighting the various key strengths of our approach that others do not have.

#### 6.2 Does PyCoder predict syntax-related tokens more accurately than the others?

The key strength of PyCoder is based on the multi-task learning that combines token type information, while others (e.g., CodeGPT and GPT-2) don’t. Since PyCoder is specifically designed to incorporate token-type information, it is likely that PyCoder can predict syntax-related tokens more accurately than the others. To answer this question, we perform additional analysis to investigate the relationship between the accuracy of code token predictions for each token type and the frequency of each token type that appears in the training and testing dataset (see Figure 3).

We find that syntax-related types of tokens tend to be more accurate than other types of tokens (e.g., operational tokens, boolean and logical expressions, strings, and numbers). The difference in accuracy could be due to the amount of data in the training/testing dataset. Figure 3 shows that tokens related to syntax types (i.e., LPAR, RPAR, COLON, KEYWORD, INDENT, DEDENT, EOL) generally achieve an accuracy of 68.35%-100.00%, where these types account for 58.50% and 58.33% of the training and testing datasets, respectively. On the other hand, operation-related tokens (e.g., PLUS, STAR, GREATER, NOTEQUAL) tend to be less accurate than syntax-related tokens, since these operation-related tokens tend to have less amount of tokens in the dataset. The relationship between the code token accuracy and its frequency is also confirmed by Spearman’s Rank Correlation of 0.85 (high, \(p\)-value \(= 1.59 \times 10^{-15}\)), suggesting that more data in the training dataset may improve the code token predictions that are less frequent in the dataset. This suggests that the performance of PyCoder may be dependent on the amount of dataset (could be either training or testing).

Figure 4 presents an example line-level prediction that
is correctly predicted by PyCoder, but not by the others. Example 1 is a Python code snippet where the input line is an attribute call (h = cosmo.h), expecting to complete () according to the ground truth. When analyzing the output from the other approaches, we find that they may generate incomplete code tokens, causing syntax errors. On the other hand, our PyCoder that learns with token types can accurately complete the attribute call with () while others cannot, demonstrating the effectiveness of PyCoder that considers token type information during multi-task learning.

6.3 Why some predictions of our PyCoder are incorrect?

To answer this question, we perform an error analysis to investigate the predictions of PyCoder that are incorrect when compared to the ground truth. We first start from the group of incorrect predictions (i.e., 5,122 samples in Figure 4). After a manual analysis of the random samples, we found the following two patterns of incorrect predictions.

PyCoder can generate syntactically correct code, but still incorrect due to the endless possibilities (e.g., after a new line). Example 2 demonstrates an example of syntactically correct generated code by PyCoder, but still incorrect due to the endless possibilities (e.g., after a new line). For Example 2, the input is extensions = [1,2,0] with a new line, where the model is expected to complete the line after. As the model is expected to predict a new line, the possibility is endless. The ground truth is related to a variable declaration (servicePacks = ...), while PyCoder generates a new method name (def setUp). While both recommendations are syntactically correct, but the recommended line from PyCoder still does not match the ground truth. Therefore, it remains difficult for a model to complete the next line that is independent of the line before.

PyCoder can generate syntactically correct code, but semantically incorrect (e.g., incomplete input parameter, incorrect method name). Examples 3 and 4 demonstrate an example of syntactically correct generated code by PyCoder, but semantically incorrect. For Example 3, the input is return self where the model is expected to complete this line as (self, txt):. However, PyCoder incorrectly completes this line as (self): due to the missing of an input parameter (txt). For Example 4, the input is def make_reserved_names where the model is expected to complete this line as .sortedListToBST_dfs (NUM_LIT:0, length=<NUM_LIT:1>). However, PyCoder incorrectly completes this line as .sortedListToBSTRecu(head, length) due to the incorrect method name (i.e., sortedListToBSTRecu).

7 RELATED WORK

In this section, we mainly discuss related work in multi-task learning for code completion and highlight the novelty of PyCoder with respect to the existing work.

Multi-task learning has been applied in the code completion tasks. Table 8 summarizes the difference between PyCoder and the existing multi-task learning code completion. Similar to the existing work, PyCoder leverages multi-task learning for code completion. However, there are three aspects that PyCoder is different from prior work, namely, the training/testing mechanism, types of multi-task learning, and the sources of information.

1) Training/testing mechanism: Prior studies [11], [12], [7] generally used code+AST for both fine-tuning and inference. As mentioned in the Motivation section, AST information requires the completeness of source code, limiting its practical application in various real-world scenarios. Instead, PyCoder leverages code+token type in the training, but only code for the inference, making our PyCoder can perform on-the-fly code completion, while existing AST-based code completion cannot.

2) Types of multi-task learning: Similar to prior studies [46], [11], [12], [7], our PyCoder leverages multi-task learning for code completion. However, prior studies only investigated a few types of multi-task learning (e.g., hard parameter sharing alone or with soft parameter sharing). Instead, this paper conducted a systematic comparison to confirm which types of multi-task learning perform the best (see RQ2). We found that...
TABLE 8: The difference between PyCoder and the existing multi-task learning code completion.

| Approach      | Training/Testing Mechanism | Inference | Hard share (Training Objectives) | Soft share | IFN | Semantic | Syntactic |
|---------------|----------------------------|-----------|----------------------------------|------------|-----|----------|-----------|
| PyCoder (ours) | Code + Token Type          | Code Only | Two tasks: (1) Next Token Code prediction (2) Next Token Type prediction | Code       | Standard Token Type | |
| CugLM [46]    | Code Only                  | Code Only | Three tasks: (1) Masked bidirectional LM (2) Next code segment prediction (3) Unidirectional LM | N/A        | N/A | Code     | N/A       |
| UMTLM [11], [12] | Code + AST                | Code + AST | Two tasks: (1) Next AST node type prediction (2) Next AST node value prediction | N/A        | N/A | Code     | AST       |
| CodeFill [7]  | Code + AST                 | Code + AST | Three tasks: (1) Next AST token-type prediction (2) Next token-level prediction (3) statement-level prediction | N/A        | Code | Code     | AST       |

3) The types of syntactic information: There are various forms that can be used to represent syntactic information, e.g., AST and standard token types. Prior studies [11], [12], [7] mainly focus on AST information. As discussed in the Motivation section, such AST token types are formal and required the completeness of source code, limiting their applicability. Instead, we are the first to leverage the standard token type information, which (1) is more static, abstract, and lightweight information, (2) follows the natural order of code sequences, and (3) can be extracted at any time without requiring the completeness and syntactically correct of the code snippets as AST does. These benefits allow PyCoder to perform on-the-fly code completion, while being syntax-aware.

Based on the empirical results from RQ1, we confirm that PyCoder performs the best. In addition, the ablation studies from RQ2-4 also confirm that the design architecture of our PyCoder plays a significant role in performance improvement, highlighting the significant advancement and novelty of our contributions to the code completion literature.

8 Threats to Validity

Threats to construct validity relate to the selection of baseline approaches. In this paper, we select the publicly accessible approach, which could reduce biases and increase the transparency of the comparison of the experimental results. Therefore, we select the competitive state-of-the-art approaches which are publicly available by the authors as the baselines. We run all the experiments using the replication package and the best hyperparameter settings in their papers.

Additionally, regarding the computational cost, there will be some additional computation costs related to token type data extraction and the model training time. However, the inference cost remains the same as the state-of-the-art models like CodeGPT and GPT-2 that PyCoder built upon (i.e., same model size, model parameters, inference time). Given the fact that the model is trained once based on a snapshot of datasets without the need for model retraining, the additional cost will not directly impact the end users and should not be a major concern.

Threats to internal validity relate to the impact of the hyperparameters on the performance of PyCoder. To mitigate this threat, we conduct experiments with various hyperparameter settings (see RQ3 and RQ4). However, we find that PyCoder is generally robust to the model task weights. Thus, we suspect that hyperparameters will have a minimal impact on the performance of PyCoder. Nevertheless, optimizing the hyperparameters of the Transformer model could be expensive and is not the main goal of this paper. Due to the limited access to premium GPU computing resources, our results serve as a minimum bound, which could be further improved after optimization and with premium GPU access. Nevertheless, to mitigate this threat, we report the hyperparameter settings in our replication package.

Threats to external validity relate to the generalizability of our approach. The evaluation of our approach is limited to the PY150 dataset, where the testing set consists of 50,000 python files. The PY150 dataset is a standard benchmark dataset for code completion, which has been used in prior studies and Microsoft’s CodeXGlue [3], [6], [7], [9], [11], [12], [36], ensuring a fair comparison of our work with the prior studies. However, the results may not be generalized to other programming languages, projects and contexts. Although we could potentially collect a larger size of the dataset, a comparison of our approach with our own collected dataset may pose various potential threats to validity, e.g., obtaining different results reported in CodeXGLUE, unfair comparison with the existing work, etc.

In addition, our results are limited to the Python programming language only. Nevertheless, it is also possible to extend our approach to other programming languages. For example, researchers can apply Java’s tokenizer library to extract the token type information. For Java, researchers could use the standard “javalang” library. Therefore, other languages can be explored in the future.

Finally, our evaluation is limited to line-level and token-level accuracy measures. Such measures only evaluate the model performance (which is the goal of this work), but it does not reflect user satisfaction and its impact on developer productivity. This is also the key important limitation that applies to the existing code completion studies. To answer the research question (How do the right/wrong predictions of PyCoder impact developer productivity?), we believe that

19. https://github.com/c2nes/javalang/blob/master/javalang/tokenizer.py
an actual tool must be developed and must be used by actual developers. Unfortunately, PyCoder is still at the early stage of development, not yet ready to be a prototyping tool, preventing us to conduct a rigorous and comprehensive analysis of how the predictions from PyCoder impact developer productivity. Then, human-centric research must be used, for example, an observational study, an intervention study, and an ethnographic study. Given the fact that this is an open-challenge research question that requires specific research methodologies, we suggest that multi-disciplinary research (i.e., human-centered computing, AI, and Software Engineering) is required in order to address this challenging research question.

9 CONCLUSION
In this work, we propose PyCoder to leverage token types, a kind of lightweight syntactic information, with a multi-task training strategy that learning on the supporting task of predicting token types during the training phase. We intensively train and test our PyCoder on different multi-task training techniques, task weighing parameters, and decoding methods to find the best suitable architecture. Our study underline the following conclusion:

- PyCoder surpasses all the state-of-the-art models in our setting and also receives the first place in CodeXGLUE’s python code completion benchmark. The results indicate that the token type syntactic information can be beneficial in code completion.
- In our setting, MTL: Hard Parameter Sharing – PyCoder-Hard with task's weight (TypeCode) 1:9 and Beam Search performs the best.
- Our study highlights the importance of investigating various choices of setting (e.g., multi-task training strategies, parameter setting) instead of solely relying on suggestions from prior work.

Our PyCoder has extended the feature of on-the-fly code completion with lightweight syntactic-aware information. However, we acknowledge that there is still a space to develop the fully syntactically correct code completion model with on-the-fly feature. We leave this exploration for the future research study.

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