Learning to Generate Code Sketches

Daya Guo  
Microsoft Research  
Beijing, China  
t-dayaguo@microsoft.com

Alexey Svyatkovskiy  
Microsoft  
Redmond, WA, USA  
alsvyatk@microsoft.com

Jian Yin  
School of Data and Computer Science  
Sun Yat-sen University, China  
isjyin@mail.sysu.edu.cn

Nan Duan  
Microsoft Research  
Beijing, China  
nanduan@microsoft.com

Marc Brockschmidt  
Microsoft Research  
Cambridge, UK  
mabrocks@microsoft.com

Miltiadis Allamanis  
Microsoft Research  
Cambridge, UK  
miallama@microsoft.com

Abstract

Traditional generative models are limited to predicting sequences of terminal tokens. However, ambiguities in the generation task may lead to incorrect outputs. Towards addressing this, we introduce GRAMMFORMERS, transformer-based grammar-guided models that learn (without explicit supervision) to generate sketches — sequences of tokens with holes. Through reinforcement learning, GRAMMFORMERS learn to introduce holes avoiding the generation of incorrect tokens where there is ambiguity in the target task.

We train GRAMMFORMERS for statement-level source code completion, i.e. the generation of code snippets given an ambiguous user intent, such as a partial code context. We evaluate GRAMMFORMERS on code completion for C# and Python and show that it generates 10-50% more accurate sketches compared to traditional generative models and 37-50% longer sketches compared to sketch-generating baselines trained with similar techniques.

1 Introduction

While machine learning models and tools often aim for fully autonomous operation, often they need to collaborate with their (human) users towards helping them achieve some goal. While recent advent of language models (LM) has shown that Transformer-based LMs generate realistic text, it is often hard to guide them towards a specific goal, especially when providing the intent is impossible or more costly than manually generating the target output.

One such scenario are LMs of source code (LMC). Since Hindle et al. [13] increasingly sophisticated LMCs have been built, including transformer-based ones, such as those of Svyatkovskiy et al. [34], Feng et al. [9] and various similar unpublished models such as TabNine and SourceAI. These models generate full sequences of code tokens left-to-right with any prefix acting as the (partial) user intent. While LMs generate realistic-looking outputs, they are known to occasionally “hallucinate” [27, 22, 23, 19], i.e. generate plausible but incorrect content. Avoiding hallucinations is useful when models need to cooperate with humans: mistakes confuse users, worsening their experience [14], and potentially mislead them in introducing erroneous code.
Towards addressing this, we create GRAMMFORMER, a transformer-based grammar-guided code generation model that generates code sketches, i.e. sequences of code tokens with holes (denoted as ‘■’). We train GRAMMFORMER to insert holes when it is uncertain about the actual tokens of the code. Holes allow GRAMMFORMER to better handle ambiguity in the user’s intent (e.g. partial code context, or ambiguous natural language description) resulting in more accurate but partial/abstract predictions, i.e. holes act as an “escape hatch” from generating incorrect tokens. For example, in Fig. 1(left) a developer has typed some code and is about to type the next line. Within this context, the developer’s intent is ambiguous, but GRAMMFORMER correctly suggests a sketch (Fig. 1 bottom right) — reasonably guessing that the developer wants to declare a third flag. However, any guess about the name of the flag would be premature and hence a hole is introduced. The developer can then fill-in the hole based on their actual intent, which has been latent to the model. Note here that GRAMMFORMER generated multiple tokens but generated a hole in a location where there was no sufficient certainty about the actual expression, resulting in a useful sketch. This is in contrast to traditional generative models (e.g. Fig. 1 top right) that would need to “hallucinate” incorrect tokens at the location of the introduced hole. To achieve this, GRAMMFORMER uses grammar-driven generation (Fig. 2) which allows to naturally structure the decision space for sketch generation.

Contributions (a) We present GRAMMFORMER, a transformer-based model that generates code based on the programming language grammar, instead of generating code tokens left-to-right or a linearized form of a syntax tree. (2) We endow GRAMMFORMER with the ability to generate sketches, i.e. code snippets with holes, by allowing the model to pick the non-terminals it expands in any order, while allowing it to stop code generation creating holes at arbitrary positions in the generated output. We train GRAMMFORMER using reinforcement learning techniques. (3) Finally, we evaluate GRAMMFORMER on large corpora of Python and C# code and show that it can make longer and more precise statement-level sketch completions compared to left-to-right token-level models.

2 GRAMMFORMER

GRAMMFORMER generates text by following a context-free grammar (CFG) and iteratively deciding which non-terminal to expand (if any should be expanded), and how to expand it (Fig. 2). Most programming languages are context-free. In traditional grammar-based generation of text [7] or code [21, 38, 2, 5], the CFG is followed by sequentially expanding the left-most, bottom-most non-terminal symbol, using one of the production rules in \( R \). GRAMMFORMER changes this and instead selects which (if any) non-terminal symbol to expand. Similar to recent works [38, 5, 16], GRAMMFORMER loosens the CFG assumptions but retains many aspects, discussed next. Alg. 1 contains a high-level description of GRAMMFORMER. Fig. 2 shows a sample generation.

Probabilistic Model A CFG is defined as a tuple \((\Sigma, \mathcal{N}, S, R)\) where \(\Sigma\) is a set of terminal symbols, \(\mathcal{N}\) is a set of non-terminal symbols, \(S \in \mathcal{N}\) is the root symbol and \(R\) is a set of productions (or production rules). We denote a concrete non-terminal as “\((\text{NonTerminalName})\)”. GRAMMFORMER accepts as input a sequence \(x_0 = x_{0,1}, x_{0,2}, \ldots, x_{0,n}\) where \(x_{0,i} \in \Sigma \cup \mathcal{N}\), i.e. \(x_0\) is a sequence of terminal and non-terminal symbols. An example \(x_0\) is shown at the top of Fig. 2. Let \(\mathcal{N}(x_i) = \)
Algorithm 1: GRAMFORMER generative process, given an input sequence $x_0$.

```plaintext
for $t = 0, 1, 2, \ldots$ do
  $i_t \sim P_s(i|x_t, N(x_t))$  \hspace{1cm} $\triangleright$ Sample non-terminal position from $N(x_t)$ to expand
  if $i_t = \emptyset$ then
    $\triangleright$ if $x_t$ does not contain non-terminals or none was selected by $P_s$
    break
  $\triangleright$ Stop generation
  $\hat{y}_{t,i_t} \sim P_e(y|x_t,i_t)$  \hspace{1cm} $\triangleright$ Sample expansion of non-terminal at position $i_t$
  $x_{t+1} \leftarrow x_{t,<i_t}; \hat{y}_{t,i_t}; x_{t,>i_t}$  \hspace{1cm} $\triangleright$ Create $x_{t+1}$ by expanding non-terminal at $i_t$ to $\hat{y}_{t,i_t}$
  $x_{\text{out}} \leftarrow \text{NONTERMINALSTOHOLE}(x_t)$  \hspace{1cm} $\triangleright$ Convert any remaining non-terminals to holes
return $x_{\text{out}}$
```

$\{i | x_{t,i} \in \mathcal{N} \} \cup \{\emptyset\}$, i.e. the set of all the positions of non-terminal symbols in $x_t$ and a special “$\emptyset$” symbol. GRAMFORMER is made of two submodels: the non-terminal expansion model $P_e(y|x_t,i)$, and the non-terminal selector model $P_s(i|x_t)$.

At each iteration of the loop in Alg. 1, $P_s$ yields a probability distribution over $N(x_t)$ sampling the index $i_t$ of the non-terminal to be expanded next or the special stop symbol. Given $i_t$, $P_e$ generates the expansion sequence $y = y_1, y_2, \ldots$ of the selected non-terminal $x_{t,i_t}$, and $y_t \in \Sigma \cup \mathcal{N}$. Finally, by concatenating the prefix $x_{t,<i_t}$ before the expanded non-terminal $x_{t,i_t}$, the generated expansion $y$ and the suffix $x_{t,>i_t}$ after the expanded non-terminal $x_{t,i_t}$, we retrieve the next sequence $x_{t+1}$. In practice, we define $P_s$ and $P_e$ as a (joint) neural model, discussed next. Note that factorizing GRAMFORMER into two models ($P_s$, $P_e$) is an important modeling decision: the probability of correctly expanding a non-terminal does not “compete” with the probability of deciding if a hole should be introduced (which are disjoint events). However, this would have been the case if we used a standard (sequence) decoder.

Given the last sequence $x_t$ of Alg. 1, NONTERMINALSTOHOLE(·) replaces all remaining non-terminal symbols with a hole “$\_\_\_\_\_\_$” and present $x_{\text{out}}$ to the user. Fig. 2 shows $x_t$ across loop iterations for a potential (synthetic) generation of a small snippet of code. At each step, a non-terminal symbol — not necessarily the left-most one — is expanded to a sequence of terminals and non-terminals, which replace the expanded symbol (underlined in Fig. 2). Note that GRAMFORMER is not context-free, taking into account the whole input sequence when expanding a non-terminal. Second, in contrast to many grammar-based methods [38, 5], any non-terminal can be expanded at each time. Finally, the rule set $R$ is not a discrete set of rules, but is instead implicitly modeled by $P_e$.

**Neural Model** GRAMFORMER combines a standard encoder-decoder model with a few important modifications. First, a transformer encoder $E$ encodes the input sequence $x_t$ into a $n \times D$ matrix $E(x_t)$, where $D$ is the hidden dimension of the transformer [35]. $E$ is then used within both $P_s$ and $P_e$. The expansion model $P_e$ follows a standard autoregressive formulation, i.e. $P_e(y_j|x_t, i_t) = \prod_{j=1}^m P_{\text{dec}}(y_j|E(x_t), i_t, y_{<j})$, but additionally uses $i_t$, the position of the non-terminal being expanded. We implement $P_{\text{dec}}(y_j|E(x_t), i_t, y_{<j})$ with a (causal) relational transformer decoder,
similar to Wang et al. [36]. Relational transformers augment the attention mechanism by incorporating predefined relationships among elements. In GRAMMFORMER, we define a relation to indicate the encoded representation of the currently expanded non-terminal \( x_{t,i} \), i.e. for each head \( h \), the cross-attention matrix is

\[
\text{Attention}(Q, K, V) = \text{softmax} \left( \frac{1}{\sqrt{d_K}} Q (W_K E(x) + \left[ \begin{array}{c} i_{t-1}^{-1} \\ 0, \cdots, 0, r_h, 0, \cdots \end{array} \right] )^T \right),
\]

\( i.e. \) we add a learnable bias \( r_h \) to the encoding of the non-terminal \( x_i \). Thus between an input token \( x_{t,m} \) and an output token \( y_t \), the cross-attention is \( \alpha_{t,m}^{(h)} \propto q_h (W_K E(x)_m + \mathbb{I}(m = i_t) \cdot r_h)^T \).

Finally, we define \( P_s \) as a pointer-like network over all encoded non-terminals, i.e.

\[
P_s(i|x_t) = \text{softmax}_{i \in N(x_t)} \left( f(E(x_t)), i \right),
\]

where \( f \) is a feed-forward neural network, and \( E(x_t) \) is the encoded representation of the non-terminal at position \( i \). We set \( E(x_t)_0 = E(x_t)_{|x_t|} since x_{t,0} is the representation of the special start symbol \([CLS]\).

Note, that we opted for using “standard” transformers for \( E \) and the decoder \( P_c \), given the impressive results of transformer-based models in NLP and code [9]. However, other encoder-decoder models such as a biGRU encoder and a GRU decoder [3] or efficient transformer variants, such as Longformers [4], can be employed here. We leave that to future work.

**Loss**

To train GRAMMFORMER, we employ reinforcement learning, due to the discrete, choice of \( i_t \), for which we have no supervision. To compute the loss of the probabilistic model defined in [Alg. 1] we assume we have a — potentially non-differentiable — reward function \( r(x, \hat{x}^*) \) measuring the quality of a sketch \( \hat{x} \) given a ground truth sequence of terminals \( x^* \). We discuss such a function in Sec. 3. Inspired by Paulus et al. [26] we use self-critical policy gradient training [28] and minimize

\[
L_{\text{train}}(x_0, x^*) = (r(x_{\text{out}}, x^*) - \hat{r}(x_0)) \sum_{t=0}^T \left( -\log P_s(i_t | x_t) - \mathbb{I}(i_t \neq \odot) \log P_c(\hat{y}_{t \in \Theta_i} | x_t, i_t) \right),
\]

where \( t \) are the indices at the iterations of the loop in [Alg. 1], \( \mathbb{I}(\cdot) \) is the indicator function, \( x_0 \) is the input sequence, \( x^* \) is the ground-truth sequence of terminals, and \( \hat{r}(x_0) \) is the reward achieved by the prediction from the snapshots of \( P_s \) and \( P_c \), that achieved the best score so far. Essentially, this loss rewards models that improve upon the previous best policy with respect to \( r \). Note that during training, we provide exact supervision for \( P_c(\hat{y}_{t \in \Theta_i} | x_t, i_t) \) since the expansion of the non-terminal at \( i_t \) is known given parsed training examples. At test time, no parsing is required.

**Pretraining**

Directly optimizing [Eq. 2] is computationally intensive due to the in-CPU loop, the discrete choice of \( i_t \), and expensive transformer-based model. To speed-up training, we pretrain \( P_c \) and \( P_s \), in two steps. First, we pretrain \( P_c \) to expand every non-terminal, independently of the expansion strategy learned in \( P_s \). To do this, we use the input training examples and follow [Alg. 1] but instead of \( P_s(\cdot) \), (line 2) we sample \( i_t \) from a uniform distribution over \( N(x_t) = N(x_t) \setminus \{ \odot \} \), i.e. all non-terminals in \( x_t \) except from the special stop symbol. This yields inputs \( x_t \) along with their ground-truth expansions \( y_{t \in \Theta_i}^* \) for every non-terminal position \( i \in N(x_t) \). Then, for each sample we pretrain the encoder and decoder by minimizing

\[
L_{\text{pre-enc}}(x_t; \{ y_{t \in \Theta_i}^* \}_{i \in N(x_t)}) = \frac{1}{|N(x_t)|} \sum_{i \in N(x_t)} -\log P_c(y_{t \in \Theta_i}^* | x_t, i),
\]

\( i.e. \) the negative log-likelihood of the correct expansion for all non-terminals in \( x_t \). This computation is more computationally efficient compared to the one in [Eq. 2] since the cost of encoding \( x_t \) is amortized across all expansions \( \{ y_{t}^* \} \) and no reinforcement learning is used. Once \( P_c \) is pretrained, we pretrain \( P_s \) by fixing the encoder \( E \) — pretrained in the previous step — and optimizing the remaining parameters of \( P_s \) through [Eq. 2]. This includes only the parameters \( \theta \) of \( f \). Once we have a pretrained \( P_c \) and \( P_s \), we then fine-tune all the model weights end-to-end, using [Eq. 2].
2.1 Practical Considerations

Reducing the Expansion Steps Following the formal grammar of a programming language commonly introduces tedious expansions. For example, the Python non-terminal (Call) is always expanded to \( \langle \text{Expr} \rangle \langle \text{ArgumentList} \rangle \) or the C# non-terminal (NotEqualOp) is always expanded to the terminal \(!=\). We manually “flatten” the grammar by replacing non-terminals such as (Call) and (NotEqualOp) with all their possible expansions. In Appendix C we provide the list of the flattened non-terminals. Note that if we repeated this process for all non-terminals except from the starting symbol \( S \), GRAMMFORMER would degenerate into a standard encoder-decoder model.

Beam Search At test time, we employ a two-step beam search, and replace sampling from \( P_γ \) (line 2 in Algorithm 1) and \( P_e \) (line 5 in Algorithm 1) with their top-\( ν \) outputs, keeping a beam of size \( k \). First, for each \( x_i \) in the beam, we compute \( P_s \) and get the top-\( m \) non-terminal positions to expand. For each of those \( m \) positions, we sample the top-\( n \) expansions from \( P_e \) using a standard beam search. Finally, for all the \( k \cdot n \cdot m \) we compute their likelihood and keep only the top-\( k \). This process (detailed in Appendix C) is similar to a standard beam search but takes into account that two models \( P_s \) and \( P_e \) are involved in the generation.

Computational Cost GRAMMFORMER’s ability to predict sketches comes with additional computational cost compared to standard transformer encoder-decoder models: since at each iteration of the loop in Algorithm 1 \( x_i \) changes, \( P_s \) and \( P_e \) must be recomputed. This means that the encoder-decoder needs to run as many times as the number of expansions required until the stopping condition is met. Future work might consider selecting more than one element from those \( 1 \) in the loop in Algorithm 1) and \( \mathbb{P} \) in the beam, we compute \( \mathbb{P}_ω \) and get the top-\( m \) non-terminal positions to expand. For each of those \( m \) positions, we sample the top-\( n \) expansions from \( P_e \) using a standard beam search. Finally, for all the \( k \cdot n \cdot m \) we compute their likelihood and keep only the top-\( k \). This process (detailed in Appendix C) is similar to a standard beam search but takes into account that two models \( P_s \) and \( P_e \) are involved in the generation.

3 Evaluation

Evaluating generation of sketches is an interesting problem, since there is a trade-off between the concreteness and correctness of a generation: as sketches become less concrete, their accuracy will be higher but their usefulness will diminish. Since, to our knowledge, we are the first to perform evaluation of automatic sketch generation, we take special care in defining evaluation metrics but acknowledge that more research may be required for tuning evaluation metrics.

Metrics Our goal is to predict sketches that (a) can be completed into the correct output and (b) are as precise as possible. We define a new metric REGEXACC which combines these two desiderata: For (a), we use toRegex(\( \hat{a} \)) to turn a predicted sketch \( \hat{a} \) into a regular expression by replacing all holes with the wildcard matching any non-empty sequence (“\.*” in Perl Compatible Regular Expression syntax). If the regex matches the ground truth, matches(\( \cdot \cdot \cdot \)) returns a score of 1 otherwise it returns 0. To implement (b), we set the maximum REGEXACC to the proportion of terminal tokens predicted, by defining nTerm(a) as the function that returns the number of terminal symbols in a. More formally, assume an output sketch \( \hat{s} \) and a ground-truth sequence \( s^* \), where \( s^* \) does not contain any holes. REGEXACC is defined as

\[
\text{REGEXACC}(\hat{s}, s^*) = \frac{n\text{Term}(\hat{s})}{n\text{Term}(s^*)} \cdot \text{matches(toRegex(\hat{s}), s^*)}.
\]

Beyond REGEXACC, we also report ROUGE \cite{lin2004rouge}, since the sketch can be thought as a form of a “summary” of the original text. ROUGE is more lenient to errors than REGEXACC and gives partial credit to non-matching but plausible sketch predictions. We also report the average length of the generated output in number of terminal tokens to show the size of the predicted sketches.

Note that we measure REGEXACC and ROUGE only over the portion of the generated sequence, i.e. ignore any context tokens that appear in \( x_0 \), which remain unchanged and are thus not predicted by our model. In the example of Figure 1, REGEXACC will be computed with the arguments \( \hat{s} = \text{“ap.add_argument(\( \square \), action=\"store_true\")”} \) and \( s^* = \text{“ap.add_argument(\"--experimental", action=\"store_true\")”} \), i.e. the context tokens “\( \... \) --prerelease“, action = “store_true“)“ are ignored, since they were part of the input.

Datasets To create a dataset, we clone all non-fork repositories with more than 20 stars in GitHub that have C# or Python as their top language. Then, we deduplicate the corpus using the method
of Allamanis [1], Lopes et al. [20]. Finally, we parse all files into a syntax tree using Tree-sitter ignoring any files that cannot be parsed using the v0.19.0 grammar definitions. Finally, we split the files into 70-10-20 train-validation-test. To create (pre-)training and test examples, i.e. inputs to [Alg. 1] we search the syntax tree of each file and for each ⟨SimpleStatement⟩ non-terminal create an example. For each example, x₀ is the 200 terminal tokens before the ⟨SimpleStatement⟩ non-terminal. The syntax tree rooted at the ⟨SimpleStatement⟩ non-terminal is then used to get the ground-truth expansions during pre-training and the ground-truth expansion s*. More details about the dataset can be found in Appx. B.

Model Training We provide the training details for all experiments. GRAMMFORMER uses 6 layers of Transformer encoder and 6 layers of Transformer decoder with 768 dimensional hidden states and 12 attention heads. The vocabulary is constructed using byte-pair encoding [29] and the vocabulary size is 25,000. We set max length of input and output sequences as 512 and 64, respectively. We train the model with Adam optimizer using a learning rate of 2e-5 and 4,096 batch size. We used automatic mix precision. Training was performed on 64 NVIDIA Tesla P100 with 16GB memory size is 25,000. We set max length of input and output sequences as 512 and 64, respectively. We

| Table 1: Performance of GRAMMFORMER compared to baselines for Python and C#. |
|-----------------|-----------------|-----------------|-----------------|-----------------|
|                | REGEXACC        | ROUGE           | Avg Gen         | REGEXACC        | ROUGE           | Avg Gen         |
|                | Top 1 | Top 5 | Length | Top 1 | Top 5 | Length |
| L → R      | 0.42  | 0.47  | 77.0   | 7.1  | 0.17  | 0.20  | 53.2   | 5.8  |
| L → R + ◦   | 0.45  | 0.54  | 69.1   | 5.3  | 0.20  | 0.29  | 39.3   | 3.0  |
| GRAMMFORMER | 0.47  | 0.59  | 77.4   | 7.5  | 0.21  | 0.30  | 51.6   | 6.1  |

By construction, L → R cannot generate sketches. We create “L → R + ◦”, which has the same encoder-decoder architecture as L → R but additionally learns to stop generation inserting a hole that captures any suffix. L → R + ◦ maximizes the reward function r(·). Note that L → R + ◦ can only generate sketches that are prefixes of the target completion, i.e. it is a standard token-level language model with a learnable stopping ability. To train this model, we use the self-critical policy gradient training [Eq. 2] with the reward function of [Eq. 3]

Both baselines’ architectures (number of layers, heads, etc.) are identical to GRAMMFORMER, but both do not have the relational biases rᵦ of [Eq. 1] and L → R does not have a model Pₙ and thus no associated parameters.

Results ([Tbl. 1] shows the comparison of GRAMMFORMER to the baselines. For both Python and C#, GRAMMFORMER outperforms the baseline methods in terms of REGEXACC, showing that the
grammar-based generation can create better sketches compared to previous methods. Note that although $L \to R$ has a comparable or better ROUGE score, it severely underperforms GrammFormer with respect to REGEXACC, meaning that the predictions are “similar” but the sketches contain errors (i.e. do not match the ground-truth). This means that if a code completion system suggested the full output of $L \to R$, the user would have to pause and correct the suggestion more frequently. On the other hand, $L \to R + \ominus$ improves over $L \to R$ in terms of REGEXACC but has a worse ROUGE and generates significantly shorter suggestions (5.3 vs. 7.5 tokens-long for C#). This is expected since $L \to R + \ominus$ is trained to be more “conservative” (i.e. avoid incorrect suggestions) but is also unable to introduce holes beyond the last generated token. However, as one would expect, for very short ground-truth utterances “traditional” $L \to R$ models perform better, given their simpler nature and thus for short sequences GrammFormer should not be used.

Since REGEXACC represents a single view on the trade-off between sketch correctness and length, in Fig. 3 we plot the length of the generated sketch compared to the length of the ground-truth code. Here, it is clear that for both languages, GrammFormer generates longer sketches, whereas $L \to R + \ominus$ is limited to significantly shorter outputs. Of course, since these outputs are shorter, they also tend to be more accurate (Fig. 4).

Table 2: Performance for GrammFormer ablations (C#), for different $P_s$ and loss functions.

| Loss Function                        | REGEXACC Top 1 | REGEXACC Top 5 | ROUGE Top 1 | ROUGE Top 5 | Avg Gen Length |
|--------------------------------------|----------------|----------------|-------------|-------------|----------------|
| Random Expansion w/o $\ominus$       | 0.42           | 0.54           | 78.3        | 8.1         |
| Fixed Threshold                      | 0.45           | 0.57           | 71.6        | 5.8         |
| $r(\cdot) = \text{ROUGE}_{F_1}$     | 0.42           | 0.54           | 78.2        | 8.1         |
| Eq. 3 (Default $r(\cdot)$)          | 0.47           | 0.59           | 77.4        | 7.5         |
| $r(\cdot) = \text{REGEXACC}$        | 0.51           | 0.62           | 70.8        | 5.8         |
Table 3: Performance of different methods to train $P_e$ and $P_s$ in GRAMMFORMER.

|            | C# | Python |
|------------|----|--------|
|            | REGEXACC | ROUGE | Avg Gen | Length | REGEXACC | ROUGE | Avg Gen | Length |
| Pre-training only | 0.45 | 0.57 | 77.0 | 7.2 | 0.20 | 0.29 | 50.2 | 5.7 |
| Full training | **0.47** | **0.59** | **77.4** | **7.5** | **0.21** | **0.30** | **51.6** | **6.1** |

**Code Context:**

```python
1 import sys
2 target = sys.argv[1]
3 I
```

**Suggested Code Completions**

```
L → R                  target = target.replace("\\\", "/")
L → R + ⪭              target = □
```

**Ground-Truth:**

```
GRAMMFORMER □ = sys.argv[2]
```

Figure 5: A sample snippet (left; abbreviated from Fig. 14 in Appx. A), illustrating the importance of sketch generation. A developer has just typed the code and their cursor (in blue) is at line 3. GRAMMFORMER correctly introduces a hole at the left-hand side of the assignment and correctly predicts that the developer’s intent is to read-in a second argument (Fig. 7 in Appx. C shows the generation process). In contrast left-to-right methods fail to generate correct suggestions.

Note that the performance of the models on C# is generally better compared to the performance in Python. We believe that this has to do with the grammar of each language and the patterns it induces within the developer’s code. Casalnuovo et al. [6], Karampatsis et al. [15] have observed a similar phenomenon on the perplexity across (standard left-to-right) language models for different programming languages.

**Ablations** Next, we look into ablations of GRAMMFORMER and reason about how its components perform. First, we discuss the effect of the policy $P_s$ and the reward function $r$. Tbl. 2 shows how different methods used in the C# dataset. First, we create a “random expansion” model, a model that samples uniformly at random the next expansion $i_t$ until there is no non-terminal left. This model achieves the best ROUGE score, but a relatively bad REGEXACC. This is expected, as this ablated model can only generate a full sequence of terminal tokens.

The “fixed threshold” model (Tbl. 2) is a GRAMMFORMER model similar to the “random expansion” model but the expansion is stopped when the probability of the generated $x_t$ reaches a certain threshold. We tune this threshold in the validation set. This model makes shorter but more accurate sketch predictions, compared to the “random expansion”, but it is still worse compared to GRAMMFORMER’s default policy. These two ablations demonstrate the usefulness of $P_s$ and the need for reinforcement learning methods in sketch generation.

**Tbl. 2** also shows the results when using different reward functions $r(\cdot, \cdot)$. As it would be expected, when optimizing Eq. 2 for a single metric, this metric improves. However, this is at the cost of the other metric. Using REGEXACC as the reward directly, improves over the default reward function at the cost of creating significantly shorter predictions with a low ROUGE score. We believe that this is because REGEXACC is a strict metric, returning 0 if the sketch does not match which leads to sparser rewards, and makes the resulting model more conservative at expanding non-terminals.

Finally, in **Tbl. 3** we show how pretraining and fine-tuning works. Just by pretraining, GRAMMFORMER can reach a competitive performance, but — as one would expect — training on the full objective of Eq. 2 boosts the performance. We believe that this is because when $P_e$ and $P_s$ are trained jointly, they co-adapt: some of the capacity of the encoder $E$ that is used to make predictions for hard-to-expand non-terminals is “freed” since $P_s$ decides to not expand them.

### 3.1 Qualitative Evaluation
Having observed the quantitative results, we now turn our attention to a qualitative look at the results and show some cherry-picked examples that illustrate desired and undesired behaviors of GRAMMMFORMER and the baselines. Fig. 5 shows an example and eleven more are shown in Appx. A. Fig. 5 illustrates the importance of generating sketches instead of concrete sequences of terminal tokens: oftentimes, the code context does not provide sufficient information about the user’s intent. Sketch-generating models can offer more informative suggestions given the partial intent.

Of course, GRAMMMFORMER also makes mistakes. For example, GRAMMMFORMER and \( L \rightarrow R + \) can sometimes be “too” conservative (e.g. Fig. 16 in Appx. A) generating holes where \( L \rightarrow R \) can generate full concrete completions. This suggests that there are opportunities for future research in better methods for calibrating \( P_s \).

Finally, a pure language modeling approach to code completion will always be insufficient. For example, user-defined types and rare APIs cannot be predicted by a language model, since the correct names of the APIs cannot be known at training time (Fig. 8 and Fig. 18 in Appx. A). Researching methods to scalably introduce information from static analyses and additional context will most probably alleviate this problem.

4 Related Work

One of the most successful applications of LMCs is code completion [33, 15] and transformer language models have been recently shown exceptional performance at the task being able to predict relatively long sequences of code tokens [34]. Grammar-based code completion and generation has been researched with neural [21, 38, 16] and non-neural models [5], always expanding the left-most, bottom-most non-terminal. In contrast to GRAMMMFORMERS, all these code completion models target the generation of complete code without the ability to create sketches. R3NN [25] can only generate complete programs of a simple functional DSL for string transformations but expands the non-terminal with the highest confidence score, instead of the left-most, bottom-most one, similar to GRAMMMFORMER. In contrast to all the aforementioned models, GRAMMMFORMER does not maintain an explicit tree representation of the generation but instead uses the sequences of leaves in the generation tree.

Most left-to-right language models can generate sequences of terminal tokens, but not holes. One exception is the work of Nye et al. [24] who use a left-to-right sequence-based model to generate small functional programs of a simple DSL towards speeding-up enumerative program synthesis from input-output examples. In contrast to GRAMMMFORMER, Nye et al. [24] train a sketch generator by listing all possible sketches and providing supervision for the highest-probability one within a heuristically computed time budget. However, for general-purpose programming language such a method is prohibitive. Recently, sequence generation approaches that go beyond the left-to-right paradigm have been proposed [37, 32, 11, 10, 17, 30], usually by considering generation as an iterative refinement procedure that changes or extends a sequence in every iteration. These models often aim in speeding-up inference or allowing models to figure a better order for generating a full sentence (of terminal tokens). However, since these models focus on natural language and since its grammar is not defined a priori, these methods do not follow a language grammar which effectively limits the space for sketch generation. Additionally, these work generate full utterances of text, rather than sketches. Future work may consider combining ideas in GRAMMMFORMER with those models. Sketch-like ideas appear in NLP such as the coarse-to-fine semantic parsing of Dong and Lapata [8] and chat-bots of Shum et al. [31]. However, sketches are extracted deterministically to create a supervised dataset.

A related concept is learning to abstain [39] where a model learns to predict a “don’t know” when it is uncertain about the outcome of a classification task. This resembles the stop symbol “\(\diamond\)” with the difference that GRAMMMFORMER employs reinforcement learning to learn \(P_s\) for a sequential problem rather than learning to abstain for a single-step classification problem.

5 Discussion & Conclusions

In this work, we presented GRAMMMFORMER, a generative model of code that goes beyond standard left-to-right generation and is able to generate sketches, i.e. snippets of code with holes. Designing
generative machine learning models with such abilities is important towards facilitating better collaboration between machine learning models and their human users.

While we have shown that GRAMMFORMER performs better than other alternatives in the sketch generation task, there are still many opportunities for improvement in the future. First, larger transformer models will most probably yield better results, as shown in the relevant literature. Second, although we used REGEXACC as a plausible evaluation metric, human studies for evaluating the trade-off between sketch correctness and concreteness are needed. Such studies, similar to those conducted for machine translation and summarization metrics, can yield more informed reward functions $r(\cdot)$ and improved user experiences.

Second, although we focused on programming languages, modeling natural language also seems possible. However, training such a model would require large corpora of parsed text. Finally, we have treated programming languages as a sequence of terminal and non-terminal symbols, ignoring the structure imposed by code’s strict semantics, such as data and control flow. Explicitly providing information about the code’s (deterministic) structure, e.g. with relational transformer encoders similar to Hellendoorn et al. \[12\] may further improve GRAMMFORMER’s performance.

Acknowledgments and Disclosure of Funding

The authors would like to thank Alex Polozov for interesting discussions and useful feedback. M. Allamanis would like also to thank Patrick Fernandes, Szymon Malik, and Guilherme Ilunga for early experimentation on sketch generation ideas which provided the inspiration for this work.

References

[1] M. Allamanis. The adverse effects of code duplication in machine learning models of code. In Proceedings of the 2019 ACM SIGPLAN International Symposium on New Ideas, New Paradigms, and Reflections on Programming and Software, pages 143–153, 2019.

[2] M. Allamanis and C. Sutton. Mining idioms from source code. In Proceedings of the International Symposium on Foundations of Software Engineering (FSE), 2014.

[3] D. Bahdanau, K. Cho, and Y. Bengio. Neural machine translation by jointly learning to align and translate. In Proceedings of the International Conference on Learning Representations (ICLR), 2015.

[4] I. Beltagy, M. E. Peters, and A. Cohan. Longformer: The long-document transformer. arXiv preprint arXiv:2004.05150, 2020.

[5] P. Bielik, V. Raychev, and M. Vechev. PHOG: Probabilistic model for code. In Proceedings of the International Conference on Machine Learning (ICML), 2016.

[6] C. Casalnuovo, K. Sagae, and P. Devanbu. Studying the difference between natural and programming language corpora. Empirical Software Engineering, 24(4):1823–1868, 2019.

[7] S. B. Cohen, K. Stratos, M. Collins, D. Foster, and L. Ungar. Spectral learning of latent-variable PCFGs. In Proceedings of the 50th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 223–231, 2012.

[8] L. Dong and M. Lapata. Coarse-to-fine decoding for neural semantic parsing. arXiv preprint arXiv:1805.04793, 2018.

[9] Z. Feng, D. Guo, D. Tang, N. Duan, X. Feng, M. Gong, L. Shou, B. Qin, T. Liu, D. Jiang, et al. CodeBERT: A pre-trained model for programming and natural languages. arXiv preprint arXiv:2002.08155, 2020.

[10] N. Ford, D. Duckworth, M. Norouzi, and G. E. Dahl. The importance of generation order in language modeling. arXiv preprint arXiv:1808.07910, 2018.

[11] J. Gu, C. Wang, and J. Zhao. Levenshtein transformer. arXiv preprint arXiv:1905.11006, 2019.
[12] V. J. Hellendoorn, C. Sutton, R. Singh, P. Maniatis, and D. Bieber. Global relational models of source code. In International conference on learning representations, 2019.

[13] A. Hindle, E. T. Barr, Z. Su, M. Gabel, and P. Devanbu. On the naturalness of software. In Proceedings of the International Conference on Software Engineering (ICSE), 2012.

[14] E. Horvitz. Principles of mixed-initiative user interfaces. In Proceedings of the SIGCHI conference on Human Factors in Computing Systems, pages 159–166, 1999.

[15] R.-M. Karampatsis, H. Babii, R. Robbes, C. Sutton, and A. Janes. Big code!= big vocabulary: Open-vocabulary models for source code. In Proceedings of the International Conference on Software Engineering (ICSE), 2020.

[16] S. Kim, J. Zhao, Y. Tian, and S. Chandra. Code prediction by feeding trees to transformers. In Proceedings of the International Conference on Software Engineering (ICSE), pages 150–162. IEEE, 2021.

[17] J. Lee, E. Mansimov, and K. Cho. Deterministic non-autoregressive neural sequence modeling by iterative refinement. arXiv preprint arXiv:1802.06901, 2018.

[18] C.-Y. Lin. ROUGE: A package for automatic evaluation of summaries. In Text summarization branches out, pages 74–81, 2004.

[19] T. Liu, Y. Zhang, C. Brockett, Y. Mao, Z. Sui, W. Chen, and B. Dolan. A token-level reference-free hallucination detection benchmark for free-form text generation. arXiv preprint arXiv:2104.08704, 2021.

[20] C. V. Lopes, P. Maj, P. Martins, V. Saini, D. Yang, J. Zitny, H. Sajnani, and J. Vitek. Déjàvu: a map of code duplicates on github. Proceedings of the ACM on Programming Languages, 1(OOPSLA):84, 2017.

[21] C. Maddison and D. Tarlow. Structured generative models of natural source code. In Proceedings of the International Conference on Machine Learning (ICML), 2014.

[22] E. Malmi, S. Krause, S. Rothe, D. Mirylenka, and A. Severyn. Encode, tag, realize: High-precision text editing. arXiv preprint arXiv:1909.01187, 2019.

[23] J. Maynez, S. Narayan, B. Bohnet, and R. McDonald. On faithfulness and factuality in abstractive summarization. arXiv preprint arXiv:2005.00661, 2020.

[24] M. Nye, L. Hewitt, J. Tenenbaum, and A. Solar-Lezama. Learning to infer program sketches. In International Conference on Machine Learning, pages 4861–4870. PMLR, 2019.

[25] E. Parisotto, A.-r. Mohamed, R. Singh, L. Li, D. Zhou, and P. Kohli. Neuro-symbolic program synthesis. In Proceedings of the International Conference on Learning Representations (ICLR), 2017.

[26] R. Paulus, C. Xiong, and R. Socher. A deep reinforced model for abstractive summarization. arXiv preprint arXiv:1705.04304, 2017.

[27] R. Puduppully, L. Dong, and M. Lapata. Data-to-text generation with content selection and planning. In Proceedings of the AAAI conference on artificial intelligence, volume 33, pages 6908–6915, 2019.

[28] S. J. Rennie, E. Marcheret, Y. Mroueh, J. Ross, and V. Goel. Self-critical sequence training for image captioning. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 7008–7024, 2017.

[29] R. Sennrich, B. Haddow, and A. Birch. Neural machine translation of rare words with subword units. arXiv preprint arXiv:1508.07909, 2015.

[30] H. Shah, B. Zheng, and D. Barber. Generating sentences using a dynamic canvas. In Proceedings of the AAAI Conference on Artificial Intelligence, volume 32, 2018.
[31] M. Shum, S. Zheng, W. Kryściński, C. Xiong, and R. Socher. Sketch-Fill-AR: A persona-grounded chit-chat generation framework. *arXiv preprint arXiv:1910.13008*, 2019.

[32] M. Stern, W. Chan, J. Kiros, and J. Uszkoreit. Insertion transformer: Flexible sequence generation via insertion operations. *arXiv preprint arXiv:1902.03249*, 2019.

[33] A. Svyatkovskiy, Y. Zhao, S. Fu, and N. Sundaresan. Pythia: AI-assisted code completion system. In *Proceedings of the 25th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining*, pages 2727–2735, 2019.

[34] A. Svyatkovskiy, S. K. Deng, S. Fu, and N. Sundaresan. IntelliCode Compose: Code generation using transformer. In *Proceedings of the 28th ACM Joint Meeting on European Software Engineering Conference and Symposium on the Foundations of Software Engineering*, pages 1433–1443, 2020.

[35] A. Vaswani, N. Shazeer, N. Parmar, J. Uszkoreit, L. Jones, A. N. Gomez, Ł. Kaiser, and I. Polosukhin. Attention is all you need. In *Advances in Neural Information Processing Systems*, pages 5998–6008, 2017.

[36] B. Wang, R. Shin, X. Liu, O. Polozov, and M. Richardson. RAT-SQL: Relation-aware schema encoding and linking for text-to-SQL parsers. *arXiv preprint arXiv:1911.04942*, 2019.

[37] S. Welleck, K. Brantley, H. Daumé III, and K. Cho. Non-monotonic sequential text generation. *arXiv preprint arXiv:1902.02192*, 2019.

[38] P. Yin and G. Neubig. A syntactic neural model for general-purpose code generation. 2017.

[39] L. Ziyin, Z. Wang, P. P. Liang, R. Salakhutdinov, L.-P. Morency, and M. Ueda. Deep gamblers: Learning to abstain with portfolio theory. *arXiv preprint arXiv:1907.00208*, 2019.
A Generated Samples

Fig. 6 and Fig. 7 show two examples from our dataset along with the ground-truth and the sequence of expansions performed by Grammformer. Fig. 8-14 show example generations by Grammformer and the baseline models $L \rightarrow R$ and $L \rightarrow R + \infty$. The parentheses in red indicate the REGEXACC score for each suggestion. For the $L \rightarrow R + \infty$ baseline the special non-terminal <suffix> is added to indicate that a hole is introduced at the end of the left-to-right generation. Finally Fig. 16-18 show example generations where Grammformer make mistakes. A discussion for each of those sample is found at the caption of each figure.

Context:
using System.Collections;
using System.Collections.Generic;
using UnityEngine;
public class BottleFlipAcademy: Academy{
    public float MaxDistance;
    public float MinScale;
    public bool IsRandomDirection;
    public override void AcademyReset(){
        MaxDistance = resetParameters["max_distance"];<expression_statement>
        MinScale = resetParameters["min_scale"];<expression_statement>
        Prediction:
        MinScale = resetParameters[<string_literal>];<expression_statement>

Generation Process:
<expression_statement>
<left> <assignment_operator> <right> ;
<left> = <right> ;
<identifier> = <right> ;
<identifier> = <expression> [ <argument> ] ;
<identifier> = <identifier> [ <argument> ] ;
<identifier> = resetParameters [ <argument> ] ;
<identifier> = resetParameters [ <string_literal> ] ;
MinScale = resetParameters [ <string_literal> ] ;

Figure 6: An example Grammformer generation for C#. Each line in the generation process shows subsequent states of $x_i$ in Alg. 1. Here, Grammformer predicts a sketch that matches the ground-truth expansion, but places a hole at the key of the dictionary lookup, instead of predicting a low-likelihood string literal.

B Dataset Statistics

Some statistics about the datasets used throughout this work are shown in Tbl. 4.

C Flattened Non-Terminals

The non-terminals in Tbl. 5 are always expanded and are not considered as non-terminals. Most of these non-terminals have always the same children (terminals or non-terminals), representing a single CFG rule. By flattening those non-terminals the depth of tree is reduced (and hence the number of loops needed in Alg. 1).
import sys
import os
import platform

if platform.system() == "Linux":
    os.system('clear')
elif platform.system() == "Windows":
    os.system('cls')
target = sys.argv[1]

Figure 7: An example GRAMMFORMER generation for Python. Each line in the generation process shows subsequent states of $x_t$ in Alg. 1. GRAMMFORMER here predicts that the user’s intent is to read-in a second argument and store it in a variable. However, within the current context, the name of the variable storing the second argument would be impossible to predict. GRAMMFORMER—reasonably—places a hole at the given location and generates a matching sketch. In this example, any traditional left-to-right model would need to first predict an accurate target variable name (which seems unlikely in the given context) before predicting the right-hand side of the assignment.

D Understanding REGEXACC

Since REGEXACC is a new metric, we include two deterministic ways of introducing sketches in Tbl. 6. First, if all literals (strings, numeric) are replaced with a hole, we see that a high REGEXACC is achieved. In contrast, replacing both identifiers and literals (leaving “just” parentheses, brackets, dots, etc.) we get an easy “lower-bound”. Note how C#—which is syntactically more verbose—achieves a better score, compared to Python. In Tbl. 7, we show some example sketches and their associated REGEXACC score.

E Beam search

Alg. 2 presents the beam search used in GRAMMFORMER.
Context:
...
exchangeActivity = (ExchangeActivity) Singleton<ActivitySys>.GetInstance().GetActivity(
    COM_WEAL_TYPE.COM_WEAL_EXCHANGE,
    msg.stPkgData.stWealExchangeRes.dwWealID);

if ( exchangeActivity != null ){
    exchangeActivity.IncreaseExchangeCount(
        (int) msg.stPkgData.stWealExchangeRes.bWealIdx,
        msg.stPkgData.stWealExchangeRes.dwDrawCnt);
    <expression_statement>
}

Ground Truth:
exchangeActivity.UpdateView();

Prediction:
\[ L \rightarrow R \]
Singleton<CUIManager>.GetInstance().CloseSendMsgAlert(); (0.000)

\[ L \rightarrow R + \varnothing \]
Singleton<suffix> (0.000)

GrammFormer:
exchangeActivity.<identifier>(); (0.833)

Figure 8: A C# example and completion outputs from different models. REGEXACC score reported in red. Here, GrammFormer correctly identifies that a method should be invoked on exchangeActivity, but does not predict the concrete method. If GrammFormer was extended with information from a static analysis about the ExchangeActivity (potentially a user-defined type) then an accurate suggestion could have potential been made.

|                      | Python | C#   |
|----------------------|--------|------|
| Num Training Files/Trees | 1973400 | 1948516 |
| Num Validation Files/Trees | 218398 | 216299 |
| Num Test Files/Trees   | 460874 | 480166 |
| Avg num tokens of \( x_t \) | 194.5  | 201.4 |
| Median num tokens of \( x_t \) | 205    | 206   |
| 99 percentile num tokens of \( x_t \) | 250    | 260   |
| Avg num tokens of \( y \)  | 1.9    | 1.9   |
| Median num tokens of \( y \)  | 1      | 1     |
| 99 percentile num tokens of \( y \)  | 9      | 7     |

Table 4: Statistics of the datasets used.
**Context:**
...
[Test] public void CanPassTwoProviders(){
// arrange
var expectedLength = 100;
var input1 = new TestSampleProvider(44100, 2, 50);
var input2 = new TestSampleProvider(44100, 2, 50);
var concatenator = new ConcatenatingSampleProvider(new[]{input1, input2});
var buffer = new float[2000];
var read = concatenator.Read(buffer, 0, buffer.Length);
Assert.AreEqual(expectedLength, read, "read == expectedLength");
Assert.AreEqual(49, buffer[49]);
}

**Ground Truth:**
Assert.AreEqual(0, buffer[50]);

**Prediction:**

$L \rightarrow R$:
Assert.AreEqual(50, buffer[50]); (0.000)

$L \rightarrow R + \epsilon$:
Assert.AreEqual(<suffix> (0.333)

**GrammFormer:**
Assert.AreEqual(<argument>, buffer[50]); (0.917)

Figure 9: A C# example and completion outputs from different models. REGEXACC score reported in red. Here, GRAMMFORMER correctly predicts that an Assert statement should be made, checking the value of buffer[50]. However, within this context, the correct concrete expected value (0) would be hard to predict, even for a human. GRAMMFORMER places a hole there and generates a correct line-level sketch. In contrast, $L \rightarrow R$ introduces a wrong completion and $L \rightarrow R + \epsilon$ creates a correct, but much shorter sketch.

**Python**
block, tuple, and, or, +, -, *, /, ||, //, %, +=, -=, *=, /=,
//=, @=, &=, |=, call, keyword_argument, name, binary_operator,
for_in_clause, unary_operator, **, true, not_operator, none,
false, boolean_operator, augmented_assignment, await, >>, pair,
|, parameters, <<, dictionary_comprehension, ellipsis, arguments,
assignment, ~,

**C#**
block, tuple, and, or, +, -, *, /, &l, //, %, @,
+=, -=, *=, /=, //=, %=, &=, |=, **, >>, |, <<,
~, ~, assignment_expression, invocation_expression,
arguments, member_access_expression, try_statement,
catch_clause, conditional_expression, ==, array_type,
rank, base_expression, conditional_access_expression,
member_binding_expression, initializer, null_literal, >,
element_access_expression, subscript, ??, this_expression,
imPLICIT_array_creation_expression, cast_expression, !=,
variable_declaration, implicit_type, &&, as_expression,
as, <, local_declaration_statement, if_statement,
>=, <=, throw_expression, default_expression,
pattern, is_pattern_expression, binary_expression,
bracketed_argument_list, name, object_creation_expression,
await_expression,

Table 5: Non-terminals that are always expanded in the Tree-Sitter grammar for the two languages considered.

16
using System;
using System.Collections.Generic;
using System.Linq;
using System.Web;
using System.ComponentModel;
namespace Bug604053.Prueba{
    public class Data{
        public int M1{get; set;}
        public string M2{get; set;}
        public Data(int m1, string m2){M1 = m1; M2 = m2;}
    }
    [DataObject(true)] public class DataSource{
        public Data[] Retrieve()
        {
            Data[] data = new Data[10];
            for (int i = 0; i < 10; i++){
                <expression_statement>
            }
        }
    }
}

Ground Truth: data[i] = new Data(i, i.ToString());

Prediction:
L → R:
data[i] = new Data( ); (0.000)
L → R + Ø:
data[i] = new Data( ); (0.000)
GrammFormer:
data[i] = new Data(i, <string_literal>); (0.706)

Figure 10: A C# example and completion outputs from different models. REGEXACC score reported in red. While all models predict that an assignment needs to be made to each data[i], the exact form of the constructor is hard to predict. GrammFormer seems to be looking at the constructor definition and predicts that some ⟨StringLiteral⟩ needs to be used as the second argument, although it is uncertain about its concrete form, hence introducing a hole.

| Replace all literals with holes | C# | Python |
|--------------------------------|----|--------|
|                               | 0.865 | 0.608  |
| Replace all literals and identifiers with holes | 0.126 | 0.060 |

Table 6: REGEXACC when deterministically introducing holes at specific location.

Table 7: Example REGEXACC scores for a variety of sketches.

| Ground-truth | REGEXACC |
|--------------|----------|
| ap.add_argument("--experimental", action="store_true") |  |
| ap.add_argument("", action="store_true") | 0.9 |
| ap.add_argument("", action="") | 0.8 |
| ap.add_argument("", "") | 0.6 |
| ap.add_argument("", action="store_false") | 0.0 |
| ap.add_argument("", required="") | 0.0 |
def htmlWidth(sIn):
    iBr = indexOfBr(sIn)
    if (-1 == iBr):
        s = sIn
    else:
        s = sIn[:iBr]
    return len(s)

Figure 11: A Python example and completion outputs from different models. REGEXACC score reported in red. Here both \( L \rightarrow R \) and GRAMMFORMER predict the full line correctly, but \( L \rightarrow R + \bigcirc \) seems to return a more conservative (but correct) sketch.

Figure 12: A Python example and completion outputs from different models. REGEXACC score reported in red. See main text in the introduction for a description.
Figure 13: A Python example and completion outputs from different models. REGEXACC score reported in red. Generation steps of GRAMMFORMER shown in Fig. 7. $L \rightarrow R$ and $L \rightarrow R + \emptyset$ cannot generate correct sketches since the first token would be impossible to guess within this code context.

Figure 14: A Python example and completion outputs from different models. REGEXACC score reported in red. GRAMMFORMER completes the line creating a correct sketch with two holes at locations avoiding to make the mistakes that $L \rightarrow R$ and $L \rightarrow R + \emptyset$ makes.
public void setSize(MainMenuConfig mainMenuConfig) {
    props = PropertiesSingleton.instance;
    int width = mainMenuConfig.actualWidth;
    int height = mainMenuConfig.actualHeight;
    left = right = new Rect(0, 0, config.borderSize, height);
    right.x = width - config.borderSize;
    top = bottom = new Rect(config.borderSize, 0, width-config.borderSize*2, config.borderSize);
    Color32 previousColor;
    public override void OnGUI() {
        if (!props.wrongActionShowFrame)
            return;
        previousColor = GUI.color;
        GUI.color = config.borderColor;
        GUI.DrawTexture(left, config.texture);
        GUI.DrawTexture(right, config.texture);
    }
}

Figure 15: A C# example and incorrect completion outputs from different models. REGEXP ACC score reported in red. The prediction from GRAMMFOMER is almost right but should have created a hole at the first argument for the user to fill-in. This shows that improved methods for training the policy network may improve results in the future.

Algorithm 2 GRAMMFOMER beam search, given an input sequence $x_0$.

$b \leftarrow \{(x_0, 0, false)\}$ ▷ Initialize Beam (state, logprob, isDone)

while $\exists (x, p, isDone) \in b$ with $isDone = false$ do ▷ While beam contains incomplete generations

$b' \leftarrow \{}$

for $(x, p, isDone) \in b$ do ▷ For each sample in beam

    if $isDone$ then
        $b' \leftarrow b' \cup \{(x, p, isDone)\}$ ▷ No operation, beam is complete
        continue
    for $i \in \text{TOP}\{P_e(i|x, N(x))\}$ do ▷ Get top-$m$ non-terminal positions
        $p_s \leftarrow \log P_s(i|x, N(x))$
        if $i = \emptyset$ then
            $b' \leftarrow b' \cup \{(x, p + p_s, true)\}$ ▷ Stop Expansion
        else
            for $y \in \text{TOP}\{P_e(y|x, i)\}$ do ▷ Beam search on $y$ yields $n$ candidates
                $p_e \leftarrow P_e(y|x, i)$
                $b \leftarrow b \cup \{(x_{<i} :: y :: x_{>i}), p + p_s + p_e, false\}$ ▷ Expand $x_i$
            $b \leftarrow \text{TOP}\{b'\}$ ▷ Prune Candidates and keep top $k$

return $b$
using System;
using System.Collections.Concurrent;
using System.Collections.Generic;
using System.Linq;
using System.Net.Http;
using System.Threading;

namespace AspNetMvcCorePerformance{
    public class Program{
        public static int Main(string[] args){
            try {
                string urlBase = "http://localhost:54562/";
                var threadCount = 1;
                var iterationsPerThread = 50;
                if (args?.Length > 0){
                    urlBase = args[0];
                    threadCount = int.Parse(args[1]);
                }
            }
        }
    }
}

Ground Truth:
iterationsPerThread = int.Parse(args[2]);

Prediction:
L → R:
iterationsPerThread = int.Parse(args[2]); (1.000)
L → R +⦸:
iterationsPerThread = int.Parse(args[2]); (1.000)
GrammFormer:
iterationsPerThread = <integer_literal>; (0.250)

Figure 16: A C# example and completion outputs from different models. REGEXACC score reported in red. GRAMMFORMER suggests a correct sketch but the right-hand side of the assignment has to stop expansion since ⟨IntegerLiteral⟩ cannot generate int.Parse(args[2]). This suggests some of the limitations that the grammar-based generation of GRAMMFORMER may have, especially for shorter sequences.

Context:
import multiprocessing
from os import getenv
bind = '127.0.0.1:8001'

Ground Truth:
workers = multiprocessing.cpu_count() * 3

Prediction:
L → R:
workers = 2 (0.000)
L → R +⦸:
workers = <suffix> (0.222)
GrammFormer:
<identifier> = <string> (0.111)

Figure 17: A Python example and completion outputs from different models. REGEXACC score reported in red. Although the sketch of the prediction from GRAMMFORMER is typically correct, it is not useful. Researching better evaluation metrics may improve GRAMMFORMER.
Figure 18: A Python example and completion outputs from different models. REGEXACC score reported in red. All model fail to invoke the correct API of the library. A potential future direction to mitigate the problem is to incorporate definitions of the external or system classes.