

A Syntactic Neural Model for General-Purpose Code Generation

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Abstract

We consider the problem of parsing natural language descriptions into source code written in a general-purpose programming language like Python. Existing data-driven methods treat this problem as a language generation task without considering the underlying syntax of the target programming language. Informed by previous work in semantic parsing, in this paper we propose a novel neural architecture powered by a grammar model to explicitly capture the target syntax as prior knowledge. Experiments find this an effective way to scale up to generation of complex programs from natural language descriptions, achieving state-of-the-art results that well outperform previous code generation and semantic parsing approaches.

1 Introduction

Every programmer has experienced the situation where they know what they want to do, but do not have the ability to turn it into a concrete implementation. For example, a Python programmer may want to “*sort my_list in descending order*,” but not be able to come up with the proper syntax `sorted(my_list, reverse=True)` to realize his intention. To resolve this impasse, it is common for programmers to search the web in natural language (NL), find an answer, and modify it into the desired form (Brandt et al., 2009, 2010). However, this is time-consuming, and thus the software engineering literature is ripe with methods to directly generate code from NL descriptions, mostly with hand-engineered methods highly tailored to specific programming languages (Balzer, 1985; Little and Miller, 2009; Gvero and Kuncak, 2015).

In parallel, the NLP community has developed methods for data-driven semantic parsing, which attempt to map NL to structured logical forms executable by computers. These logical forms can be general-purpose meaning representations (Clark and Curran, 2007; Banarescu et al., 2013), formalisms for querying knowledge bases (Tang and Mooney, 2001; Zettlemoyer and Collins, 2005; Berant et al., 2013) and instructions for robots or personal assistants (Artzi and Zettlemoyer, 2013; Quirk et al., 2015), among others. While these methods have the advantage of being learnable from data, compared to the programming languages (PLs) in use by programmers, the *domain-specific* languages targeted by these works have a schema and syntax that is relatively simple.

Recently, Ling et al. (2016) have proposed a data-driven code generation method for high-level, *general-purpose* PLs like Python and Java. This work treats code generation as a sequence-to-sequence modeling problem, and introduce methods to generate words from character-level models, and copy variable names from input descriptions. However, unlike most work in semantic parsing, it does not consider the fact that code has to be well-defined programs in the target syntax.

In this work, we propose a data-driven syntax-based neural network model tailored for generation of general-purpose PLs like Python. In order to capture the strong underlying syntax of the PL, we define a model that transduces an NL statement into an Abstract Syntax Tree (AST; Fig. 1(a), § 2) for the target PL. ASTs can be deterministically generated for all well-formed programs using standard parsers provided by the PL, and thus give us a way to obtain syntax information with minimal engineering. Once we generate an AST, we can use deterministic generation tools to convert the AST into surface code. We hypothesize that such a structured approach has two benefits.

Production Rule	Role	Explanation
$\text{Call} \mapsto \text{expr}[\text{func}] \text{expr}^*[\text{args}] \text{keyword}^*[\text{keywords}]$	Function Call	$\triangleright \text{func}$: the function to be invoked $\triangleright \text{args}$: arguments list $\triangleright \text{keywords}$: keyword arguments list
$\text{If} \mapsto \text{expr}[\text{test}] \text{stmt}^*[\text{body}] \text{stmt}^*[\text{orelse}]$	If Statement	$\triangleright \text{test}$: condition expression $\triangleright \text{body}$: statements inside the If clause $\triangleright \text{orelse}$: elif or else statements
$\text{For} \mapsto \text{expr}[\text{target}] \text{expr}^*[\text{iter}] \text{stmt}^*[\text{body}] \text{stmt}^*[\text{orelse}]$	For Loop	$\triangleright \text{target}$: iteration variable $\triangleright \text{iter}$: enumerable to iterate over $\triangleright \text{body}$: loop body $\triangleright \text{orelse}$: else statements
$\text{FunctionDef} \mapsto \text{identifier}[\text{name}] \text{arguments}^*[\text{args}] \text{stmt}^*[\text{body}]$	Function Def.	$\triangleright \text{name}$: function name $\triangleright \text{args}$: function arguments $\triangleright \text{body}$: function body

Table 1: Example production rules for common Python statements (Python Software Foundation, 2016)

First, we hypothesize that structure can be used to constrain our hypothesis space, ensuring generation of well-formed code. To this end, we propose a syntax-driven neural code generation model. The backbone of our approach is a *grammar model* (§ 3) which formalizes the generation story of a derivation AST into sequential application of *actions* that either apply production rules (§ 3.1), or emit terminal tokens (§ 3.2). The underlying syntax is therefore encoded in the grammar model *a priori* as the set of possible actions. Our approach frees the model from recovering the underlying grammar from limited training data, and instead enables the system to focus on learning the compositionality among existing grammar rules. Xiao et al. (2016) have noted that this imposition of structure on neural models is useful for semantic parsing, and we expect this to be even more important for general-purpose PLs where the syntax trees are larger and more complex.

Second, we hypothesize that structural information helps to model information flow within the network, which naturally reflects the recursive structure of PLs. To test this, we extend a standard recurrent neural network (RNN) decoder to allow for additional neural connections which reflect the recursive structure of an AST (§ 4.2). As an example, when expanding the node \star in Fig. 1(a), we make use of the information from both its parent and left sibling (the dashed rectangle). This enables us to locally pass information of relevant code segments via neural network connections, resulting in more confident predictions.

Experiments (§ 5) on two Python code generation tasks show 11.7% and 9.3% absolute improvements in accuracy against the state-of-the-art system (Ling et al., 2016). Our model also gives competitive performance on a standard semantic parsing benchmark.

2 The Code Generation Problem

Given an NL description x , our task is to generate the code snippet c in a modern PL based on the in-

tent of x . We attack this problem by first generating the underlying AST. We define a probabilistic grammar model of generating an AST y given x : $p(y|x)$. The best-possible AST \hat{y} is then given by

$$\hat{y} = \arg \max_y p(y|x). \quad (1)$$

\hat{y} is then deterministically converted to the corresponding surface code c .¹ While this paper uses examples from Python code, our method is PL-agnostic.

Before detailing our approach, we first present a brief introduction of the Python AST and its underlying grammar. The Python abstract grammar contains a set of production rules, and an AST is generated by applying several production rules composed of a head node and multiple child nodes. For instance, the first rule in Tab. 1 is used to generate the function call `sorted(.)` in Fig. 1(a). It consists of a head node of type `Call`, and three child nodes of type `expr`, `expr*` and `keyword*`, respectively. Labels of each node are noted within brackets. In an AST, non-terminal nodes sketch the general structure of the target code, while terminal nodes can be categorized into two types: *operation terminals* and *variable terminals*. Operation terminals correspond to basic arithmetic operations like `AddOp`. Variable terminal nodes store values for variables and constants of built-in data types². For instance, all terminal nodes in Fig. 1(a) are variable terminal nodes.

3 Grammar Model

Before detailing our neural code generation method, we first introduce the grammar model at its core. Our probabilistic grammar model defines the generative story of a derivation AST. We factorize the generation process of an AST into sequential application of *actions* of two types:

- `APPLYRULE[r]` applies a production rule r to the current derivation tree;

¹We use `astor` library to convert ASTs into Python code.

²`bool`, `float`, `int`, `str`.

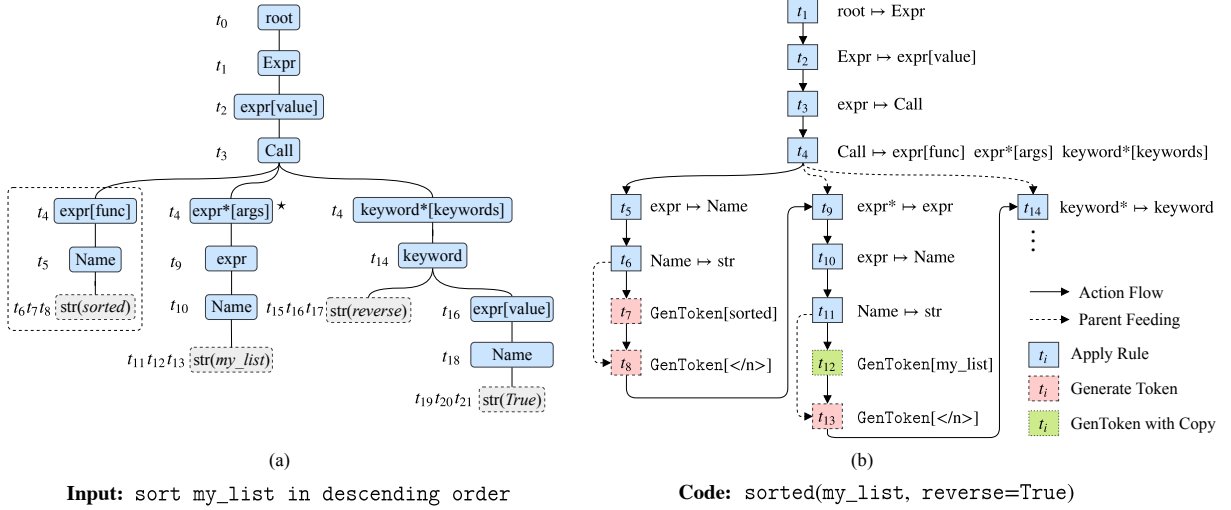


Figure 1: (a) the Abstract Syntax Tree (AST) for the given example code. Dashed nodes denote terminals. Nodes are labeled with time steps during which they are generated. (b) the action sequence (up to t_{14}) used to generate the AST in (a)

- `GENTOKEN[v]` populates a variable terminal node by appending a terminal token v .

Fig. 1(b) shows the generation process of the target AST in Fig. 1(a). Each node in Fig. 1(b) indicates an action. Action nodes are connected by solid arrows which depict the chronological order of the action flow. The generation proceeds in depth-first, left-to-right order (dotted arrows represent parent feeding, explained in § 4.2.1).

Formally, under our grammar model, the probability of generating an AST y is factorized as:

$$p(y|x) = \prod_{t=1}^T p(a_t|x, a_{<t}), \quad (2)$$

where a_t is the action taken at time step t , and $a_{<t}$ is the sequence of actions before t . We will explain how to compute Eq. (2) in § 4. Put simply, the generation process begins from a root node at t_0 , and proceeds by the model choosing `APPLYRULE` actions to generate the overall program structure from a closed set of grammar rules, then at leaves of the tree corresponding to variable terminals, the model switches to `GENTOKEN` actions to generate variables or constants from the open set. We describe this process in detail below.

3.1 APPLYRULE Actions

`APPLYRULE` actions generate program structure, expanding the current node (the *frontier node* at time step t : n_{f_t}) in a depth-first, left-to-right traversal of the tree. Given a fixed set of production rules, `APPLYRULE` chooses a rule r from the subset that has a head matching the type of n_{f_t} , and uses r to expand n_{f_t} by appending all child nodes specified by the selected production. As an

example, in Fig. 1(b), the rule `Call \mapsto expr...` expands the frontier node `Call` at time step t_4 , and its three child nodes `expr`, `expr*` and `keyword*` are added to the derivation.

`APPLYRULE` actions grow the derivation AST by appending nodes. When a variable terminal node (e.g., `str`) is added to the derivation and becomes the frontier node, the grammar model then switches to `GENTOKEN` actions to populate the variable terminal with tokens.

Unary Closure Sometimes, generating an AST requires applying a chain of unary productions. For instance, it takes three time steps ($t_9 - t_{11}$) to generate the sub-structure `expr* \mapsto expr \mapsto Name \mapsto str` in Fig. 1(a). This can be effectively reduced to one step of `APPLYRULE` action by taking the closure of the chain of unary productions and merging them into a single rule: `expr* \mapsto str`. Unary closures reduce the number of actions needed, but would potentially increase the size of the grammar. In our experiments we tested our model both with and without unary closures (§ 5).

3.2 GENTOKEN Actions

Once we reach a frontier node n_{f_t} that corresponds to a variable type (e.g., `str`), `GENTOKEN` actions are used to fill this node with values. For general-purpose PLs like Python, variables and constants have values with one or multiple tokens. For instance, a node that stores the name of a function (e.g., `sorted`) has a single token, while a node that denotes a string constant (e.g., `a='hello world'`) could have multiple tokens. Our model copes with both scenarios by firing `GENTOKEN` actions at one or more time steps. At each time

4.2.2 Calculating Action Probabilities

In this section we explain how action probabilities $p(a_t|x, a_{<t})$ are computed based on s_t .

APPLYRULE The probability of applying rule r as the current action a_t is given by a softmax⁵:

$$p(a_t = \text{APPLYRULE}[r]|x, a_{<t}) = \frac{\exp(\mathbf{W}_R \cdot g(\mathbf{s}_t))^\top \cdot \mathbf{e}(r)}{\sum_r \exp(\mathbf{W}_R \cdot g(\mathbf{s}_t))^\top \cdot \mathbf{e}(r)} \quad (4)$$

where $g(\cdot)$ is a non-linearity $\tanh(\mathbf{W} \cdot \mathbf{s}_t + \mathbf{b})$, and $\mathbf{e}(r)$ the one-hot vector for rule r .

GENTOKEN As in § 3.2, a token v can be generated from a predefined vocabulary or copied from the input, defined as the marginal probability:

$$p(a_t = \text{GENTOKEN}[v]|x, a_{<t}) = p(\text{gen}|x, a_{<t})p(v|\text{gen}, x, a_{<t}) + p(\text{copy}|x, a_{<t})p(v|\text{copy}, x, a_{<t}).$$

The selection probabilities $p(\text{gen}|\cdot)$ and $p(\text{copy}|\cdot)$ are given by $\text{softmax}(\mathbf{W}_S \cdot \mathbf{s}_t)$. The probability of generating v from the vocabulary, $p(v|\text{gen}, x, a_{<t})$, is defined similarly as Eq. (4), except that we use the embedding matrix of **GENTOKEN**, \mathbf{W}_G . To model the copy probability, we follow recent advances in modeling copying mechanism in neural networks (Gu et al., 2016; Jia and Liang, 2016; Ling et al., 2016), and use a pointer network (Vinyals et al., 2015) to compute the probability of copying the i -th word from the input by attending to input representations $\{\mathbf{h}_i\}$:

$$p(w_i|\text{copy}, x, a_{<t}) = \frac{\exp(\omega(\mathbf{h}_i, \mathbf{s}_t, \mathbf{c}_t))}{\sum_{i'=1}^n \exp(\omega(\mathbf{h}_{i'}, \mathbf{s}_t, \mathbf{c}_t))},$$

where $\omega(\cdot)$ is a DNN with a single hidden layer.

4.3 Training and Inference

Given a dataset of pairs of NL descriptions x_i and code snippets c_i , we parse c_i into its AST y_i and decompose y_i into a sequence of oracle actions under the grammar model. The model is then optimized by maximizing the log-likelihood of the oracle action sequence. At inference time, we use beam search to approximate the best AST \hat{y} in Eq. (1). See supplementary materials for the pseudo-code of the inference algorithm.

5 Experimental Evaluation

5.1 Datasets and Metrics

HEARTHSTONE (HS) dataset (Ling et al., 2016) is a collection of Python classes that implement

tioning on the hidden states of parent non-terminals, while our parent feeding uses the states of parent actions.

⁵We do not show bias terms for all softmax equations.

Dataset	HS	DJANGO	IFTTT
Train	533	16,000	77,495
Development	66	1,000	5,171
Test	66	1,805	758
Avg. tokens in description	39.1	14.3	7.4
Avg. characters in code	360.3	41.1	62.2
Avg. size of AST (# nodes)	136.6	17.2	7.0

Statistics of Grammar			
w/o unary closure			
# productions	100	222	1009
# node types	61	96	828
terminal vocabulary size	1361	6733	0
Avg. # actions per example	173.4	20.3	5.0
w/ unary closure			
# productions	100	237	–
# node types	57	92	–
Avg. # actions per example	141.7	16.4	–

Table 2: Statistics of datasets and associated grammars

cards for the card game HearthStone. Each card comes with a set of fields (e.g., name, cost, and description), which we concatenate to create the input sequence. This dataset is relatively difficult: input descriptions are short, while the target code is in complex class structures, with each AST having 137 nodes on average.

DJANGO dataset (Oda et al., 2015) is a collection of lines of code from the Django web framework, each with a manually annotated NL description. Compared with the HS dataset where card implementations are somewhat homogenous, examples in DJANGO are more diverse, spanning a wide variety of real-world use cases like string manipulation, IO operations, and exception handling.

IFTTT dataset (Quirk et al., 2015) is a domain-specific benchmark that provides an interesting side comparison. Different from HS and DJANGO which are in a general-purpose PL, programs in IFTTT are written in a domain-specific language used by the IFTTT task automation App. Users of the App write simple instructions (e.g., `If Instagram.AnyNewPhotoByYou Then Dropbox.AddFileFromURL`) with NL descriptions (e.g., “Autosave your Instagram photos to Dropbox”). Each statement inside the `If` or `Then` clause consists of a channel (e.g., Dropbox) and a function (e.g., `AddFileFromURL`)⁶. This simple structure results in much more concise ASTs (7 nodes on average). Because all examples are created by ordinary Apps users, the dataset is highly noisy, with input NL very loosely con-

⁶Like Beltagy and Quirk (2016), we strip function parameters since they are mostly specific to users.

nected to target ASTs. The authors thus provide a high-quality filtered test set, where each example is verified by at least three annotators. We use this set for evaluation. Also note IFTTT’s grammar has more productions (Tab. 2), but this does not imply that its grammar is more complex. This is because for HS and DJANGO terminal tokens are generated by GENTOKEN actions, but for IFTTT, all the code is generated directly by APPLYRULE actions.

Metrics As is standard in semantic parsing, we measure **accuracy**, the fraction of correctly generated examples. However, because generating an exact match for complex code structures is non-trivial, we follow Ling et al. (2016), and use token-level **BLEU-4** with as a secondary metric, defined as the averaged smoothed BLEU (Lin and Och, 2004) scores over all examples.

5.2 Setup

Preprocessing All input descriptions are tokenized using NLTK. We perform simple canonicalization for DJANGO, such as replacing quoted strings in the inputs with place holders. See supplementary materials for details. We extract unary closures whose frequency is larger than a threshold k ($k = 30$ for HS and 50 for DJANGO).

Configuration The size of all embeddings is 128, except for node type embeddings, which is 64. The dimensions of RNN states and hidden layers are 256 and 50, respectively. Since our datasets are relatively small for a data-hungry neural model, we impose strong regularization using recurrent dropouts (Gal and Ghahramani, 2016), together with standard dropout layers added to the inputs and outputs of the decoder RNN. We validate the dropout probability from $\{0, 0.2, 0.3, 0.4\}$. For decoding, we use a beam size of 15.

5.3 Results

Evaluation results for Python code generation tasks are listed in Tab. 3. Numbers for our systems are averaged over three runs. We compare primarily with two approaches: (1) Latent Predictor Network (LPN), a state-of-the-art sequence-to-sequence code generation model (Ling et al., 2016), and (2) SEQ2TREE, a neural semantic parsing model (Dong and Lapata, 2016). SEQ2TREE generates trees one node at a time, and the target grammar is not explicitly modeled a priori, but *implicitly* learned from data. We test both the original SEQ2TREE model released by the authors and our revised one (SEQ2TREE-UNK) that uses unknown word replacement to handle rare

	HS		DJANGO	
	ACC	BLEU	ACC	BLEU
Retrieval System [†]	0.0	62.5	14.7	18.6
Phrasal Statistical MT [†]	0.0	34.1	31.5	47.6
Hierarchical Statistical MT [†]	0.0	43.2	9.5	35.9
NMT	1.5	60.4	45.1	63.4
SEQ2TREE	1.5	53.4	28.9	44.6
SEQ2TREE-UNK	13.6	62.8	39.4	58.2
LPN [†]	4.5	65.6	62.3	77.6
Our system	16.2	75.8	71.6	84.5
Ablation Study				
– frontier embed.	16.7	75.8	70.7	83.8
– parent feed.	10.6	75.7	71.5	84.3
– copy terminals	3.0	65.7	32.3	61.7
+ unary closure	–	–	70.3	83.3
– unary closure	10.1	74.8	–	–

Table 3: Results on two Python code generation tasks.

[†]Results previously reported in Ling et al. (2016).

words (Luong et al., 2015). For completeness, we also compare with a strong neural machine translation (NMT) system (Neubig, 2015) using a standard encoder-decoder architecture with attention and unknown word replacement, and include numbers from other baselines used in Ling et al. (2016). On the HS dataset, which has relatively large ASTs, we use unary closure for our model and SEQ2TREE, and for DJANGO we do not.

System Comparison As in Tab. 3, our model registers 11.7% and 9.3% absolute improvements over LPN in accuracy on HS and DJANGO. This boost in performance strongly indicates the importance of modeling grammar in code generation. For the baselines, we find LPN outperforms others in most cases. We also note that SEQ2TREE achieves a decent accuracy of 13.6% on HS, which is due to the effect of unknown word replacement, since we only achieved 1.5% without it. A closer comparison with SEQ2TREE is insightful for understanding the advantage of our syntax-driven approach, since both SEQ2TREE and our system output ASTs: (1) SEQ2TREE predicts one node each time step, and requires additional “dummy” nodes to mark the boundary of a subtree. The sheer number of nodes in target ASTs makes the prediction process error-prone. In contrast, the APPLYRULE actions of our grammar model allows for generating multiple nodes at a single time step. Empirically, we found that in HS, SEQ2TREE takes more than 300 time steps on average to generate a target AST, while our model takes only 170 steps. (2) SEQ2TREE does not directly use productions in the grammar, which possibly leads to grammat-

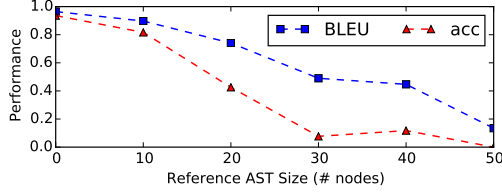


Figure 3: Performance w.r.t reference AST size on DJANGO

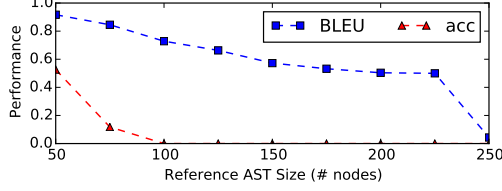


Figure 4: Performance w.r.t reference AST size on HS

ically incorrect ASTs and thus empty code outputs. We observe that the ratio of grammatically incorrect ASTs predicted by SEQ2TREE on HS and DJANGO are 21.2% and 10.9%, respectively, while our system guarantees grammaticality.

Ablation Study We also ablated our best-performing models to analyze the contribution of each component. “-frontier embed.” removes the frontier node embedding n_{f_t} from the decoder RNN inputs (Eq. (3)). This yields worse results on DJANGO while gives slight improvements in accuracy on HS. This is probably because that the grammar of HS has fewer node types, and thus the RNN is able to keep track of n_{f_t} without depending on its embedding. Next, “-parent feed.” removes the parent feeding mechanism. The accuracy drops significantly on HS, with a marginal deterioration on DJANGO. This result is interesting because it suggests that parent feeding is more important when the ASTs are larger, which will be the case when handling more complicated code generation tasks like HS. Finally, removing the pointer network (“-copy terminals”) in GENTOKEN actions gives poor results, indicating that it is important to directly copy variable names and values from the input.

The results with and without unary closure demonstrate that, interestingly, it is effective on HS but not on DJANGO. We conjecture that this is because on HS it significantly reduces the number of actions from 173 to 142 (c.f., Tab. 2), with the number of productions in the grammar remaining unchanged. In contrast, DJANGO has a broader domain, and thus unary closure results in more productions in the grammar (237 for DJANGO vs. 100 for HS), increasing sparsity.

Performance by the size of AST We further investigate our model’s performance w.r.t. the size

	CHANNEL	FULL TREE
Classical Methods		
posclass (Quirk et al., 2015)	81.4	71.0
LR (Beltagy and Quirk, 2016)	88.8	82.5
Neural Network Methods		
NMT	87.7	77.7
NN (Beltagy and Quirk, 2016)	88.0	74.3
SEQ2TREE (Dong and Lapata, 2016)	89.7	78.4
Doubly-Recurrent NN (Alvarez-Melis and Jaakkola, 2017)	90.1	78.2
Our system	90.0	82.0
– parent feed.	89.9	81.1
– frontier embed.	90.1	78.7

Table 4: Results on the noise-filtered IFTTT test set of “>3 agree with gold annotations” (averaged over three runs), our model performs competitively among neural models.

of the gold-standard ASTs in Figs. 3 and 4. Not surprisingly, the performance drops when the size of the reference ASTs increases. Additionally, on the HS dataset, the BLEU score still remains at around 50 even when the size of ASTs grows to 200, indicating that our proposed syntax-driven approach is robust for long code segments.

Domain Specific Code Generation Although this is not the focus of our work, evaluation on IFTTT brings us closer to a standard semantic parsing setting, which helps to investigate similarities and differences between generation of more complicated general-purpose code and and more limited-domain simpler code. Tab. 4 shows the results, following the evaluation protocol in (Beltagy and Quirk, 2016) for accuracies at both channel and full parse tree (channel + function) levels. Our full model performs on par with existing neural network-based methods, while outperforming other neural models in full tree accuracy (82.0%). This score is close to the best classical method (LR), which is based on a logistic regression model with rich hand-engineered features (e.g., brown clusters and paraphrase). Also note that the performance between NMT and other neural models is much closer compared with the results in Tab. 3. This suggests that general-purpose code generation is more challenging than the simpler IFTTT setting, and therefore modeling structural information is more helpful.

Case Studies Finally, we present output examples in Tab. 5. On HS, we observe that most of the time our model gives correct predictions by filling learned code templates from training data with arguments (e.g., cost) copied from input. However, we do find interesting examples indicating that the model learns to generalize beyond trivial copy-

input	<code><name>Brawl</name><cost>5</cost><desc>Destroy all minions except one (chosen randomly)</desc><rarity>Epic</rarity>...</code>
pred.	<pre>class Brawl(SpellCard): def __init__(self): super().__init__('Brawl', 5, CHARACTER.CLASS. WARRIOR, CARD_RARITY.EPIC) def use(self, player, game): super().use(player, game) targets = copy.copy(game.other_player.minions) targets.extend(player.minions) for minion in targets: minion.die(self)</pre>
ref.	<pre>minions = copy.copy(player.minions) minions.extend(game.other_player.minions) if len(minions) > 1: survivor = game.random.choice(minions) for minion in minions: if minion is not survivor: minion.die(self)</pre>
input	<code>join app.config.path and string 'locale' into a file path, substitute it for localedir.</code>
pred.	<code>localedir = os.path.join(app.config.path, 'locale')</code> ✓
input	<code>self.plural is an lambda function with an argument n, which returns result of boolean expression n not equal to integer 1</code>
pred.	<code>self.plural = lambda n: len(n)</code> ✗
ref.	<code>self.plural = lambda n: int(n!=1)</code>

Table 5: Predicted examples from HS (1st) and DJANGO. Copied contents (copy probability > 0.9) are highlighted.

ing. For instance, the first example is one that our model predicted wrong — it generated code block A instead of the gold B (it also missed a function definition not shown here). However, we find that the block A actually conveys part of the input intent by destroying all, not some, of the minions. Since we are unable to find code block A in the training data, it is clear that the model has learned to generalize to some extent from multiple training card examples with similar semantics or structure.

The next two examples are from DJANGO. The first one shows that the model learns the usage of common API calls (e.g., `os.path.join`), and how to populate the arguments by copying from inputs. The second example illustrates the difficulty of generating code with complex nested structures like lambda functions, a scenario worth further investigation in future studies. More examples are attached in supplementary materials.

6 Related Work

Code Generation and Analysis Most existing works on code generation focus on generating code for domain specific languages (DSLs) (Kushman and Barzilay, 2013; Raza et al., 2015; Manshadi et al., 2013), with neural network-based approaches recently explored (Parisotto et al., 2016; Balog et al., 2016). For general-purpose code gen-

eration, besides the general framework of Ling et al. (2016), existing methods often use language and task-specific rules and strategies (Lei et al., 2013; Raghothaman et al., 2016). A similar line is to use NL queries for code retrieval (Wei et al., 2015; Allamanis et al., 2015). The reverse task of generating NL summaries from source code has also been explored (Oda et al., 2015; Iyer et al., 2016). Finally, there are probabilistic models of source code (Maddison and Tarlow, 2014; Nguyen et al., 2013). The most relevant work is Allamanis et al. (2015), which uses a factorized model to measure semantic relatedness between NL and ASTs for code retrieval, while our model tackles the more challenging generation task.

Semantic Parsing Our work is related to the general topic of semantic parsing, where the target logical forms can be viewed as DSLs. The parsing process is often guided by grammatical formalisms like combinatory categorical grammars (Kwiatkowski et al., 2013; Artzi et al., 2015), dependency-based syntax (Liang et al., 2011; Pasupat and Liang, 2015) or task-specific formalisms (Clarke et al., 2010; Yih et al., 2015; Krishnamurthy et al., 2016; Misra et al., 2015; Mei et al., 2016). Recently, there are efforts in designing neural network-based semantic parsers (Misra and Artzi, 2016; Dong and Lapata, 2016; Nee-lakantan et al., 2016). Several approaches have been proposed to utilize grammar knowledge in a neural parser, such as augmenting the training data by generating examples guided by the grammar (Kociský et al., 2016; Jia and Liang, 2016). Liang et al. (2016) used a neural decoder which constrains the space of next valid tokens in the query language for question answering. Finally, the structured prediction approach proposed by Xiao et al. (2016) is closely related to our model in using the underlying grammar as prior knowledge to constrain the generation process of derivation trees, while our method is based on a unified grammar model which jointly captures production rule application and terminal symbol generation, and scales to general purpose code generation tasks.

7 Conclusion

This paper proposes a syntax-driven neural code generation approach that generates an abstract syntax tree by sequentially applying actions from a grammar model. Experiments on both code generation and semantic parsing tasks demonstrate the effectiveness of our proposed approach.

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