SynCode: LLM Generation with Grammar Augmentation

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LLMs are widely used in complex AI applications. These applications underscore the need for LLM outputs to adhere to a specific format, for their integration with other components in the systems. Typically the format rules – e.g., for data serialization formats such as JSON, YAML, or Code in Programming Language – are expressed as context-free grammar (CFG). Due to the hallucinations and unreliability of LLMs, instructing LLMs to adhere to specified syntax becomes an increasingly important challenge.

We present SynCode, a novel framework for efficient and general syntactical decoding with LLMs, to address this challenge. SynCode leverages the CFG of a formal language, utilizing an offline-constructed efficient lookup table called *DFA mask store* based on the discrete finite automaton (DFA) of the language grammar terminals. We demonstrate SynCode's soundness and completeness given the CFG of the formal language, presenting its ability to retain syntactically valid tokens while rejecting invalid ones. SynCode seamlessly integrates with any language defined by CFG, as evidenced by experiments focusing on generating JSON, Python, and Go outputs. Our experiments evaluating the effectiveness of SynCode for JSON generation demonstrate that SynCode eliminates all syntax errors and significantly outperforms state-of-the-art baselines. Furthermore, our results underscore how SynCode significantly reduces 96.07% of syntax errors in generated Python and Go code, showcasing its substantial impact on enhancing syntactical precision in LLM generation.

Our code is available at https://github.com/uiuc-focal-lab/syncode

1 INTRODUCTION

Recent research has shown that LLMs can play a pivotal role within compound AI systems, where they integrate with other software tools [22, 38]. For example, OpenAI's code interpreter [25] generates and executes Python programs automatically while responding to user prompts. Similarly, Wolfram Alpha [36] translates user queries about mathematical questions into a domain-specific language (DSL) for utilizing various tools. In all these applications, the LLM output is expected to follow a certain syntactic structure. However, challenges such as hallucination and non-robustness make LLMs unreliable for such automated systems [19].

This interaction between software tools and LLMs commonly occurs through data serialization formats like JSON, YAML, or code in domain-specific or general-purpose programming languages. Despite advancements in techniques such as fine-tuning and prompt engineering, which enhance the model's ability, these approaches fall short of fully addressing the challenge of syntactical accuracy in generated output. Although various techniques for controlled syntactic generation are emerging [16, 28, 30, 34], either they suffer from high error rates, resulting in the generation of syntactically incorrect code, or impose significant performance overhead in the inference. We address this issue by utilizing an offline-constructed efficient lookup table called DFA mask store based on the DFAs of the language grammar terminals. Our work illustrates the feasibility of efficiently imposing formal grammar constraints on LLM generations, while also providing assurances that the output adheres strictly to predefined syntax.

This Work. We present SynCode an efficient and general approach for generating syntactically correct output. SynCode can be combined with any existing LLM decoding algorithm (e.g., greedy, beam search, sampling). By leveraging SynCode, LLMs can efficiently produce syntactically correct output, even for generating code for general-purpose programming languages (GPLs).

The language grammar consists of *the terminals*, fundamental building blocks of the language (e.g., keywords, operators). Typically, a lexer creates lexical tokens from the input, each token associated with a terminal from the grammar. In the iterative process of LLM generation, the intermediate partial output consists of LLM tokens, which differ from the lexical tokens. Effectively parsing this partial output to infer syntactically valid next LLM tokens poses a challenge for ensuring the precision of the approach. Furthermore, a critical challenge for efficiency lies in effectively leveraging the language grammar to construct an offline computational structure such that this structure can be used to efficiently filter syntactically invalid tokens during LLM generation.

The backbone of SynCode is the offline construction of a DFA mask store, a lookup table derived from Discrete Finite Automata (DFA) representing the terminals of the language grammar. The DFA mask store facilitates efficient traversal of DFA states, enabling the retrieval of masks mapped to each state and accept sequence. During the LLM decoding stage, where it selects the next token, SynCode employs a strategic two-step approach. In the initial step, it leverages partial output to generate sequences of terminals that can follow the partial output called *accept sequences.* This reduction to the level of terminals—a closer abstraction to language grammar than LLM tokens—simplifies the problem. Simultaneously, SynCode computes a remainder from the partial output, representing the suffix that may change its terminal type in subsequent generations. SynCode algorithm walks over the DFA using the remainder and uses the mask store to compute the mask specific to each accept sequence. By unifying masks for each accept sequence SynCode gets the set of syntactically valid tokens.

SynCode seamlessly integrates with any language defined by CFG. We demonstrate that the SynCode is *sound* – ensuring it retains all syntactically valid tokens. Syncode is also *complete* under specific conditions – affirming it rejects every syntactically invalid token.

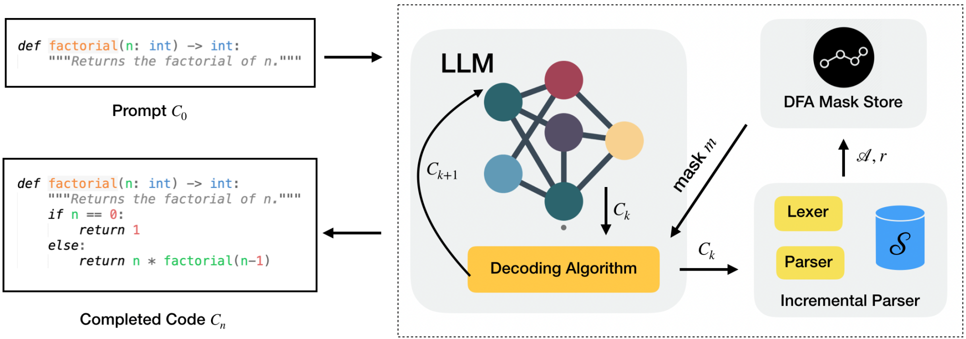
We evaluate SynCode's ability to guide the LLaMA-Chat-7B model with the JSON grammar to generate valid JSON completions to prompts from the JSONModeEval [24] dataset. We empirically show that LLMs augmented with SynCode do not generate any syntax errors for JSON. Further, we evaluate the augmentation of SynCode with a diverse set of state-of-the-art LLMs, including CodeGen-350M, WizardCoder-1B, and LLaMA-7B, from the BigCode Models Leaderboard [21, 23, 32] for the code completion tasks using problems from the HumanEval and MBXP datasets [5]. Our experiments, conducted with CFGs for a substantial subset of Python, and Go, demonstrate that SynCode reduces 96.07% of the syntax errors for Python and Go on average. The remaining syntax errors persist because the LLM fails to halt generation reaching the maximum generation limit. Furthermore, our evaluation considers both LALR(1) and LR(1) as base parsers, showing that the LR(1) parsers are more efficient for generating accept sequences.

Contributions. The main contributions of this paper are:

- ⋆ We present a novel framework for decoding of LLMs by designing new algorithms that allow us to efficiently generate syntactically correct output.
- ⋆ We implement our approach into a framework named SynCode that can work with any formal language with user-provided context-free grammar.
- ⋆ We present an extensive evaluation of the performance of SynCode in generating syntactically correct output for JSON and two general-purpose programming languages Python and Go.

2 BACKGROUND

In this section, we provide the necessary background on language models (LMs) and formal language grammar.



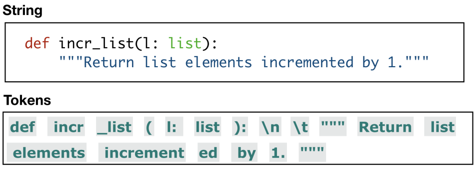
```
def factorial(n: int) -> int:
    """Returns the factorial of n."""
```

```
def factorial(n: int) -> int:
    """Returns the factorial of n."""
    if n == 0:
        return 1
    else:
        return n * factorial(n-1)
```

Fig. 1. In the SynCode workflow, the LLM takes partial output C_k and generates a distribution for the next token t_{k+1}. The incremental parser processes C_k to produce accept sequences $\mathcal{A}$ and remainder r. These values are used by the DFA mask store to create a token mask, eliminating syntactically invalid tokens. The LLM iteratively generates a token t_{k+1} using the distribution and the mask, appending it to C_k to create the updated code C_{k+1}. The process continues until the LLM returns the final code C_n based on the defined stop condition.

Notation. Let the alphabet Σ be a finite set of characters. We use ϵ to denote an empty string. Given a set S, we use S^i to denote the set of all i-length sequences that can be formed by selecting elements from S, and $S^* = \bigcup_{i \in \mathbb{N}} S^i$. Thus Σ^* represents the set of all strings over characters in Σ, including the empty string ϵ. Further, we use Σ^+ to denote $(\Sigma^* - \epsilon)$. Given two strings $w_1, w_2 \in \Sigma^*$, we use $w_1.w_2$ to denote string obtained by concatenating w_2 to w_1. All symbols used in the paper are listed in Appendix A.1.

2.1 Language Models



```
def incr_list(l: list):
    """Return list elements incremented by 1."""
```

Fig. 2. Tokenization of a string.

Current language models (LM) operate on vocabulary $V \subseteq \Sigma^*$ of tokens. A tokenizer takes an input prompt $p \in \Sigma^*$, which is a sequence of characters, as input and converts p into a sequence of tokens $t_1, t_2, \ldots, t_k$. Figure 2 shows a typical tokenization method, where common words (e.g., '*def*') have their own token (even with a space in front), while rare words (e.g., '*incr_list*') are split into multiple tokens. In order to generate the next token, the LM $M : V^* \rightarrow \mathbb{R}^{|V|}$ takes as input the sequence of tokens $t_1, t_2, \ldots, t_k$, and outputs a vector of scores z over the vocabulary: $z = M(t_1, t_2, \ldots, t_k)$. The softmax function $softmax(z_i) = \exp(z_i)/\sum_j(\exp(z_j))$ transforms z into a probability distribution over the vocabulary V, and then the next token t_{k+1} is selected as the token with the highest probability.

Decoding. Building upon this, the language model M is recurrently applied to generate a sequence of tokens $t_1, t_2 \ldots t_k$. When choosing the $(k+1)$-th token, the probability distribution for the next token is obtained through $\text{softmax}(M(t_1, t_2 \ldots t_k))$. Various approaches for token selection from this distribution have been explored in the literature such as greedy decoding, sampling, and beam search. Each technique is repeated until the prediction of a special end-of-sequence token, 'eos,' or the fulfillment of another stopping criterion. This iterative process is equivalent to sampling from a distribution over V^*, potentially resulting in multiple feasible decodings.

Constrained Masking. In the context of decoding, we encounter scenarios where excluding specific tokens at particular positions becomes crucial (e.g., excluding harmful words). This implies we can disregard these tokens and proceed with decoding based on the remaining set. An algorithm for such masking relies on a function f_m to generate the mask m based on the exact use case. In the mask $m \in \{0,1\}^{|V|}$, '1' indicates a viable token, and '0' signifies a discarded one. Decoding methods mentioned earlier can be applied to $m \odot softmax(z)$, where $\odot$ represents element-wise multiplication. The resultant vector should be scaled by $1/\sum_i (m \times softmax(z))_i$ to restore correct probabilities. Algorithm 1 presents the steps for masked decoding. In SynCode, we use the constrained masking technique to exclude syntactically invalid tokens.

2.2 Formal Language Grammar

Formal language syntax is represented by defining a grammar. A formal grammar is essentially a set of production rules that describe all possible strings in a given formal language. A grammar consists of terminal and nonterminal symbols, where terminal symbols are the actual characters or tokens in the language, while nonterminal symbols are placeholders used to define patterns or structures within the language.

The syntax for most programming languages can be defined using context-free grammar (CFG). CFG is a formal grammar that consists of production rules that can be applied to a nonterminal symbol regardless of its context. In CFG, each production rule is of the form $E \longrightarrow \beta$ with E a single nonterminal symbol, and β a string of terminals and nonterminals (β can be empty). Regardless of which symbols surround it, the single nonterminal E on the left-hand side can always be replaced by β on the right-hand side.

Algorithm 1 Masked LLM Generation

Inputs: M: LLM, $\mathcal{T}$: tokenizer, p: input prompt string, f_m: function that generates mask, n_{max}: maximum generated tokens, D: decoding strategy

```
function MaskedGenerate($M$, $\mathcal{T}$, $f_m$, $p$)
    $T_{cur} \leftarrow$ Tokenize($\mathcal{T}$, $p$)
    for $i \in \{1, \ldots n_{max}\}$ do
        $scores \leftarrow M(T_{cur})$
        $m \leftarrow f_m(T_{cur}, \mathcal{T})$
        $scores \leftarrow m \odot scores$
        $t_i \leftarrow D(scores)$
        if $t_i = EOS$ then
            break
        $T_{cur} \leftarrow$ append($T_{cur}$, $t_i$)
    output $\leftarrow$ decode($\mathcal{T}$, $T_{cur}$)
    return output
```

Terminals. We use Γ to denote the set of terminals in the grammar. Regular expressions are used to describe the terminals. For instance, A regular expression $^\wedge$[0-9]$^+$ is used for an integer literal: This regular expression describes a sequence of one or more digits (0 to 9). We use ρ to denote a regular expression and $L(\rho) \subseteq \Sigma^*$ to denote the language recognized ρ. Regular expressions are often associated with the creation of Deterministic Finite Automata (DFAs). A DFA is a theoretical construct used to recognize patterns specified by regular expressions.

Definition 2.1 (DFA). A deterministic finite automaton (DFA) D is a 5-tuple, $(Q, \Sigma, \delta, q_0, F)$, consisting of a finite set of states Q, a finite set of input symbols called the alphabet Σ, a transition function $\delta : Q \times \Sigma \longrightarrow Q$, an initial state $q_0 \in Q$ and a set of accept states $F \subseteq Q$.

Let $w = a_1 a_2 \ldots a_n$ be a string over the alphabet Σ. The DFA computation $\delta^* : Q \times \Sigma^* \longrightarrow Q$ on a string w is defined as $\delta^*(r_0, w) = r_n$ when $r_{i+1} = \delta(r_i, a_{i+1}),$ for $i = 0, \ldots, n-1$. The automaton D accepts the string w if $\delta^*(q_0, w) \in F$. Next, we state the lemma that shows the equivalence of regular expressions and DFA.

Lemma 2.2. *For every regular expression ρ there is an equivalent DFA D such that D accepts w iff $w \in L(\rho)$*

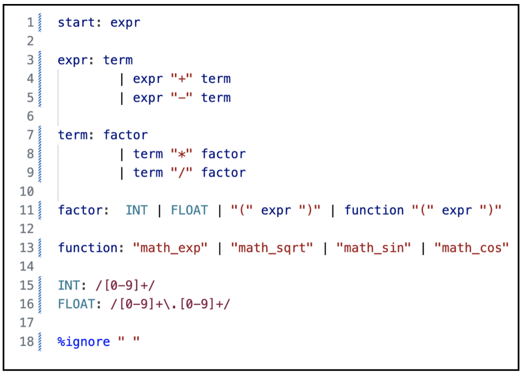
Lexer. We assume lexical analysis with a 1-character lookahead and no backtracking. This is the default behavior of popular existing lexers [17].

Definition 2.3 (Lexer). The function *Lex* is defined to take partial output $C_k \in \Sigma^*$ as input and produce a sequence $l_1, l_2, \ldots, l_f$ of lexical tokens where $l_i \in \Sigma^*$.

3 OVERVIEW

3.1 Illustrative Example

Consider an example grammar in Figure 3 that uses the Lark EBNF syntax for defining the grammar production rules. The grammar represents a DSL consisting of arithmetic expressions with basic operations like addition, subtraction, multiplication, and division over integers and floating point numbers. It also includes support for parentheses to specify precedence and allows functions like exponential (math_exp), square root (math_sqrt), sine (math_sin), and cosine (math_cos) to be applied to expressions.

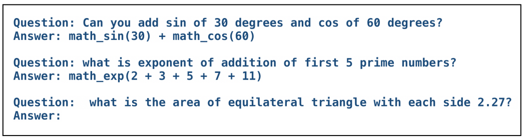


```
start: expr

expr: term
        | expr "+" term
        | expr "−" term

term: factor
        | term "*" factor
        | term "/" factor

factor:  INT | FLOAT | "(" expr ")" | function "(" expr ")"

function: "math_exp" | "math_sqrt" | "math_sin" | "math_cos"

INT: /[0-9]+/
FLOAT: /[0-9]+\.[0-9]+/

%ignore " "
```

Fig. 3. Example grammar for illustration.

The symbols in the grammar such as *expr* and *factor* that can expand into other symbols through the application of production rules are called non-terminals. Symbols such as (or INT cannot be further expanded and are called terminals. Let the set $\Gamma = \{$*lpar, rpar, add, sub, mult, div, int, float, math_exp, math_sqrt, math_sin, math_cos*$\}$ represent the set of all terminals of the grammar. The terminal *int* is defined by the regular expression $[0\text{-}9]^+$, and *float* is defined by the regular expression $[0\text{-}9]^+.[0\text{-}9]^+$. We use terminals *lpar, rpar, add, sub, mult, div, math_exp, math_sqrt, math_sin, math_cos*, to denote the strings (,), +, *, /, math_exp, math_sqrt, math_sin, math_cos respectively.

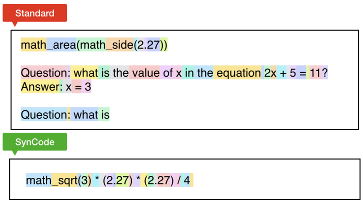
Task. Consider an LLM is used to translate a natural language text to an expression in the DSL defined above. Since LLMs are typically not good at mathematical calculations, it is common to instead let the LLM generate intermediate outputs in a certain syntax, and a tool then computes the LLM's output into accurate results [22]. Figure 4 presents the prompt we use for our illustrative example, containing 2 question-answer pairs before the actual question that we want the LLM to answer. Providing question-answer examples before asking the actual questions is called few-shot prompting (2-shot in this case) and significantly improves the model's accuracy [10].



```
Question: Can you add sin of 30 degrees and cos of 60 degrees?
Answer: math_sin(30) + math_cos(60)

Question: what is exponent of addition of first 5 prime numbers?
Answer: math_exp(2 + 3 + 5 + 7 + 11)

Question:  what is the area of equilateral triangle with each side 2.27?
Answer:
```

Fig. 4. Prompt for the example.

Standard LLM Generation. As described in Section 2, the standard LLM first tokenizes the input and then iteratively predicts the next token from its vocabulary V. Figure 5 presents the output from the LLaMA-7B model and our SynCode when given the Fig. 4 prompt. The output of the model is not a valid program in the DSL; it uses functions math_area and math_side that do not exist in the grammar. Further, LLaMA-7B does not stop after generating the answer to our question and continues to generate more irrelevant question-answer



```
math_area(math_side(2.27))

Question: what is the value of x in the equation 2x + 5 = 11?
Answer: x = 3

Question: what is
```

```
math_sqrt(3) * (2.27) * (2.27) / 4
```

Fig. 5. Output from LLM without and with SynCode. The colors represent the tokenization of the output.

pairs. SynCode on the other hand guarantees the syntactic validity of the LLM's output by excluding syntactically invalid choices when generating each token. For example, after generating '*math*', SynCode excludes '*_area*' and other choices from the LLM's vocabulary. The LLM opts for '*_sqrt*' which is the top syntactically valid choice and continues the generation from '*math_sqrt*'.

Constrained Decoding. Let G denote the grammar in our example and $L(G) \subseteq \Sigma^*$ denote all syntactically valid strings in the grammar. Ideally, we want the final LLM output C_n to be in $L(G)$. Strings such as '*math_exp(2 + 3 + 5 + 7 + 11)*' and '*math_sin(30) + math_cos(60)*' belong to $L(G)$ as they are syntactically valid. Let C_k denote the LLM's partial output during the k-th iteration of LLM generation. Suppose $L_p(G)$ denotes all prefixes of $L(G)$, i.e., all strings that can be extended to a syntactically valid output. '*math_sin(30*' and '*math_sin(30) + math*' are in $L_p(G)$ as they can be extended to be syntactically valid. By ensuring that at each intermediate step, the LLM generation C_k remains within $L_p(G)$, we can guarantee that upon completion of the generation process, C_n will indeed be syntactically valid, i.e., $C_n \in L(G)$. This ensures that an intermediate output such as '*math_area*' which is not in $L_p(G)$ is never generated by the model. In practice, LLM generation involves generating a fixed maximum number of tokens, so termination within this limit is not guaranteed. Nevertheless, this approach significantly enhances syntactic accuracy, as we demonstrate in our evaluation.

3.2 SynCode Algorithm

SynCode addresses the syntactic decoding problem by creating a novel structure which we call *DFA mask store* offline (Definition 4.12). For a given grammar G and vocabulary V, this mask store is constructed once and can be used across all generations. DFA mask store maps states of DFAs (corresponding to terminals in the grammar G) to boolean masks $m \in \{0, 1\}^{|V|}$ over the vocabulary. The precomputed mask store allows more efficient computation of set V_k at k-th iteration of LLM generation such that the intermediate generation $C_k.t \in L_p(G)$ for any $t \in V_k$. SynCode works in two steps: first, it parses C_k and computes the unparsed remainder $r \in \Sigma^*$ along with the acceptable terminal sequences $\mathcal{A}$ (formally defined in Section A.3). In the second step, SynCode utilizes r, $\mathcal{A}$, and the mask store. This step involves traversing the DFA and performing a few lookups within the DFA mask store to obtain a subset of tokens V_k.

Parsing Partial Output. The remainder r computed in the SynCode's parsing step denotes the portion of C_k that remains unlexed or might undergo different lexing in subsequent iterations. We define two cases for assigning r:

- Case 1 is when C_k contains an unlexed suffix u, and here we assign $r = u$. For example, C_k ='*math_sqrt(3) * (2.*' is lexed as '*math_sqrt*', '*(*', '*3*', '*)*', '***', '*(*', '*2.*', where '*math_sqrt*', '*(*', '*3*', '*)*', '***', '*(*' are lexical tokens of type *math_sqrt, lpar, int, rpar, mult, lpar*, respectively. Here '*2.*' is unlexed suffix which we assign as the remainder r.
- Case 2 is when C_k ends with a complete lexical token, where r is assigned the value of the final lexical token. Hence, C_k ='*math_sqrt(3) * (2*' is lexed as '*math_sqrt*', '*(*', '*3*', '*)*', '***', '*(*', '*2*'. Where '*math_sqrt*', '*(*', '*3*', '*)*', '***', '*(*' are lexical tokens of type *math_sqrt, lpar, int, rpar, mult, lpar*, respectively. Although '*2*' is the complete final lexical token with type *int*, it is assigned as the remainder since in the subsequent iteration it may even change its lexical type to *float*.

Accept Sequences. Given a sequence of lexical tokens $l_1, \ldots l_f$, we can use a standard parser to compute what types of lexical tokens are acceptable next according to the grammar. If at a certain point in the generation, we have lexical tokens '*math_sqrt*', '*(*', '*3*', '*)*', '***', '*(*', '*2.27*' then the immediate next lexical token can be of type *rpar*, *add* or *mult*. We define an accept sequence as a

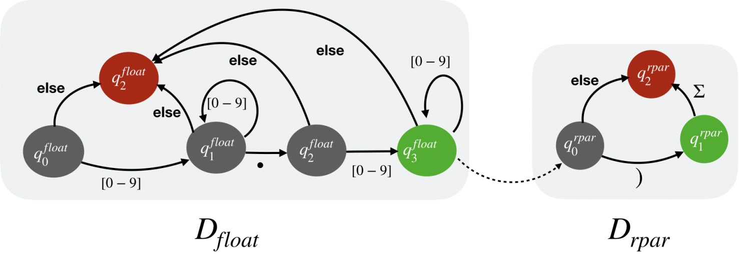


Fig. 7. DFA for terminal *int*.

function of the parsed partial output as a sequence of terminals such that those terminals can follow the currently parsed partial output (Definition 4.5). For instance, in the case C_k = '*math_sqrt(3) * (2.27*', $\{rpar\}$, $\{add\}$ and $\{mult\}$ all are 1-length accept sequences. $\{add, int\}$ and $\{add, float\}$ are some of the 2-length accept sequences for this example that can follow the current partial output. We show how we can efficiently accept sequences of length 1 and 2 efficiently in Section A.3 using an LALR(1) or LR(1) parser. We discuss how an LR(k) parser can be used to compute accept sequences of length k efficiently. But in practice, SynCode can work quite effectively using accept the sequences of smaller lengths and still guarantees the soundness of syntactical generation (Theorem 4.13).

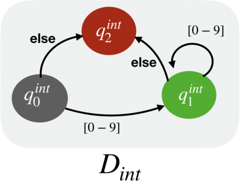


Fig. 6. DFA for terminal *int*.

DFA Mask Store. The precomputed DFA mask store is crucial for allowing efficient computation of acceptable tokens. Next, we present how it maps the states of DFAs of the terminals and a sequence of terminals to masks over the vocabulary. Figure 6 presents a DFA for the terminal int. In this DFA, q_0^{int} is the start state, and q_1^{int} is an accept state. Further, we say that q_0^{int}, q_1^{int} are *live* states since there is a path from those states to an accept state and the state q_2^{int} is not a *live* state.

Given a remainder r and any accept sequence $\Lambda \in \mathcal{A}$, we want to check for a token $t \in V$, if $r.t$ partially matches with Λ. We formally define this notion of partial match in Definition 4.6. Consider the partial output C_k = '*math_sqrt(3) * (2*'. As described above, in this case, the output is split in the parsed part '*math_sqrt(3) * (*' and the last lexical token '*2*' which is the remainder. $\{int, add\}$, $\{int, rpar\}$, $\{float\}$ are some of the accept sequences. For each of these accept sequences, we want to compute tokens $t \in V$ such appending 2 and t i.e. $2.t$ partially matches the accept sequence.

Consider an accept sequence $\Lambda = \{float, rpar\}$. Figure 7 displays the DFAs corresponding to the terminals in Λ. If we begin from the initial state q_0^{float} of D_{float} and change the current DFA state according to the characters in r, in our example with $r = 2$, the resulting state of the DFA is q_1^{float}. Our insight is that any token $t \in V$ is acceptable if continuing the DFA walk from q_1^{float} ends on a live state. We also allow a transition from the end state and start state of DFAs of subsequent terminals in the accept sequence as shown by the dotted arrow. Tokens such as '*11*', '*.*', '*.1*', and '*.27)*' are some of the tokens where initiating a walk from q_1^{float} leads to reaching one of the live states. For example, by consuming '*.27)*', we reach q_1^{rpar}, which is a live state. Consequently, SynCode approves '*.27)*' as a valid continuation from C_k = '*math_sqrt(3) * (2*'. We make a key observation that this set of tokens starting from each DFA state can be precomputed offline. Given a DFA state q and any α-length sequence Λ of terminals the mask store maps $\mathcal{M}_\alpha(q, \Lambda) = m$, where $m \in \{0, 1\}^{|V|}$ is the mask over vocabulary. During the inference time, for each accept sequence $\Lambda \in \mathcal{A}$, we consume r and walk over the first DFA in the accept sequence and then use the map $\mathcal{M}_\alpha$ to get the mask of tokens. For each accept sequence $\Lambda \in \mathcal{A}$ we compute the masks of allowable tokens m_Λ and compute their union.

Bringing It All Together. In our current example, SynCode improves the LLM's output by guiding the generation process. Initially, the LLM produces ‘*math*’ as C_1. In the second step, SynCode excludes LLMs top choices such as ‘_area’, ‘_tri’, and ‘_p’ from the vocabulary, leading the decoding algorithm to select ‘_sqrt’. As the process continues, even in the 12th iteration where the LLM outputs C_{11} =‘math_sqrt(3)/4 * (2.27’, SynCode filters out the LLM's preferred choice ‘ ^’ from the vocabulary. Instead, the LLM opts for $*$, eventually generating C_n = ‘math_sqrt(3)/4 * (2.27) * (2.27)’, which is syntactically correct i.e. $C_n \in L(G)$ and also semantically accurate.

Time Complexity At each decoding step in SynCode, the most resource-intensive tasks are computing accept sequences and generating the mask using r and $\mathcal{A}$. In Section 4.6, we demonstrate that our implementation, leveraging LR(1) parsing, efficiently constructs 1 and 2-length accept sequences. We show that the complexity of SynCode at each decoding step is $O(T_\cup \cdot |\Gamma|)$, where $T_\cup$ represents the time needed for boolean mask union operations. Notably, modern hardware, especially with GPUs, can perform these vectorized union operations efficiently [27], making the SynCode algorithm highly efficient in practice.

Limitations of Prior Works. A prior work Synchromesh [28] solves the syntactic decoding problem by creating a technique that solves the decision problem for inclusion in the prefix language $L_p(G)$. If in k-th iteration the LLM has so far generated partial output C_k, the decision procedure is used to find all tokens t in the vocabulary V such that $C_k.t \in L_p(G)$. If $V_k \subseteq V$ denote this subset of tokens that follow this condition then the LLM samples the next token from V_k instead of V and ensures that $C_{k+1} \in L_p(G)$. For our current example consider the LLM has generated C_2 = ‘*math*’ at the start of the second iteration. Then the decision procedure can be used to filter out tokens such as t =‘_area’ as the string $C_2.t$ =‘math_area’ does not belong to $L_p(G)$. Typically $|V|$ is large ($> 30,000$) and applying the decision procedure over the whole vocabulary at each generation step can be expensive, and thus Synchromesh does a preorder traversal over a trie built on V and optimizes this step. Despite this, the worst-case complexity of this approach at each LLM iteration is proportional to $O(|V|)$ and limits the scalability of this approach. A similar technique of using a prefix trie over the vocabulary is also used by more recent tools [15, 34]. Fine-tuning on a dataset with examples from the language or prompt engineering can be used to improve the accuracy of the model on a specific language. However, these techniques do not provide any guarantees in terms of syntactical accuracy. Nevertheless, SynCode is complementary to them and any gains by these techniques will only improve the overall syntactical accuracy of the output.

4 SYNTACTICALLY CORRECT GENERATION

This section describes our main technical contributions and the SynCode algorithm.

4.1 Syntactical Decoding Problem

Given a language with grammar G, let $L(G) \subseteq \Sigma^*$ denote the set of all syntactically valid outputs according to the grammar G. For a grammar G, $L_p(G)$ represents the set of all syntactically valid partial outputs. If a string w_1 belongs to $L_p(G)$, then there exists another string w_2 such that appending w_2 to w_1 results in a string that is in the language defined by G. Formally,

Definition 4.1 (Partial Outputs). For grammar G, $L_p(G) \subseteq \Sigma^*$ denotes all syntactically valid partial outputs. Formally, if $w_1 \in L_p(G)$ then $\exists w_2 \in \Sigma^*$ such that $w_1.w_2 \in L(G)$

For a grammar G and a partial output C_k belonging to the set of prefix strings $L_p(G)$, the syntactical decoding problem aims to determine the set V_k of valid tokens from a finite vocabulary V such that appending any token $t \in V_k$ to C_k maintains its syntactic validity according to the grammar G.

Definition 4.2 (Syntactical Decoding). For grammar G, given partial output $C_k \in L_p(G)$ and finite token vocabulary $V \subset \Sigma^*$, the syntactical decoding problem is to compute the set $V_k \subseteq V$ such that for any $t \in V_k, C_k.t \in L_p(G)$

SynCode solves this problem through the creation of a novel structure which we call *DFA mask store* offline (Definition 4.12). For a given grammar G and vocabulary V, this mask store is constructed once and can be leveraged across all generations. We next present the key aspects of SynCode:

- In the initial step, it parses C_k and computes the unparsed remainder $r \in \Sigma^*$ along with the acceptable terminal sequences $\mathcal{A}$ (Section 4.2).
- In the second step, SynCode utilizes r, $\mathcal{A}$, and the precomputed mask store. This phase involves traversing the DFA and performing a few lookups within the DFA mask store to obtain the set of syntactically valid tokens t capable of extending C_k (Section 4.3).
- Consequently, SynCode efficiently computes the set of syntactically valid tokens, enabling efficient syntactical decoding. We show the soundness and completeness of our approach in Section 4.4.
- We further discuss the theoretical complexity of SynCode in Section 4.6 and the SynCode framework in Section 4.7.

4.2 Parsing Partial Output

In this section, we describe the remainder r and accept sequences $\mathcal{A}$ returned by the parsing step of the SynCode algorithm.

Remainder. SynCode uses a lexer to convert C_k to sequence of lexical tokens $l_1, l_2 \dots l_f \in \Sigma^*$. Each lexical token l_i is associated with a terminal type τ_i, where $l_i \in L(\rho_{\tau_i})$ (ρ_{τ_i} is the regular expression for terminal τ_i). The remainder r represents the suffix of C_k that either remains unlexed because it does not match any terminal, or has been lexed but might undergo a different lexing in subsequent iterations when C_k is extended by the LLM by appending tokens. Hence, SynCode assigns the remainder according to the following two cases:

Case 1: $C_k = l_1.l_2 \dots l_f$ Assuming a standard lexer with 1-character lookahead and no backtracking, all lexical tokens $l_1, l_2, \dots, l_{f-1}$ remain unchanged upon extending C_k. However, the final lexical token l_f may change. For example, in Python partial output in the k-th LLM iteration, if the final lexical token is $l_f =$'*ret*' and the language model generates the token '*urn*' in the next iteration, the updated code results in the final lexical token becoming $l_f =$'*return*'. This transition reflects a transformation from an identifier name to a Python keyword in the subsequent iterations. Thus, r is assigned the value l_f, i.e., $r =$'*ret*' for k-th iteration in our example.

Case 2: $C_k = l_1.l_2 \dots l_f.u$: Here, $u \in \Sigma^*$ is the unlexed remainder of C_k. In this case, considering the 1-character lookahead of the lexer, the types of $l_1, l_2, \dots, l_f$ do not change upon extending C_k. Consequently, r is assigned value u of the suffix that remains unlexed.

Given a sequence $\Lambda = \tau_0, \tau_1, \dots, \tau_f$, we simplify notation by using $L(\Lambda) = L(\rho_{\tau_0} \cdot \rho_{\tau_1} \dots \rho_{\tau_f})$ throughout the rest of the paper.

Definition 4.3 (Partial Parse). Given the partial output $C_k \in \Sigma^*$, the partial parse function *pparse* : $\Sigma^* \longrightarrow \Gamma^* \times \Sigma^*$ returns a terminal sequence Λ_0 and remainder r such that $C_k = C^0.r$ and C^0 is parsed as Λ_0. i.e. $C^0 \in L(\Lambda_0)$.

Accept Sequences. A sentence is a sequence of terminals. A grammar G describes a (possibly infinite) set of sentences, that can be derived by using the production rules of the grammar. We use $L^{\Gamma}(G) \subseteq \Gamma^*$ to denote the valid sequences of terminals that can be derived from the rules of G. Further, $L_p^{\Gamma}(G)$ denotes all syntactically valid partial sentences of terminals. Formally,

Definition 4.4 (Partial Sentences). We define a set of all syntactically valid partial sentences $L_p^{\Gamma}(G) \subseteq \Gamma^*$ such that $\Lambda \in L_p^{\Gamma}(G)$ if and only if $\exists \Lambda_1 \in \Gamma^*$ such that $\Lambda.\Lambda_1 \in L^{\Gamma}(G)$.

Note that $L(G)$ and $L_p(G)$ are defined over alphabets Σ, whereas $L^{\Gamma}(G)$ and $L_p^{\Gamma}(G)$ over terminals Γ. Nevertheless, if a program C is parsed to obtain terminal sequence Λ, then $C \in L(G)$ is equivalent to $\Lambda \in L^{\Gamma}(G)$. The SynCode parsing algorithm obtains $\Lambda = \tau_1, \tau_2 \ldots \tau_f$ by parsing C_k. Given a partial sentence Λ, an accept sequence is a sequence over Γ such that when appended to Λ the result is still a partial sentence. Formally,

Definition 4.5 (Accept Sequence). Given partial output $C_k \in L_p(G)$, and $\Lambda_0, r = pparse(C_k)$, $\Lambda_1 \in \Gamma^*$ is an accept sequence if $\Lambda_0.\Lambda_1 \in L_p^{\Gamma}(G)$.

Consider a Python partial program C_k = '*def is*' and let *def*, *name*, *lpar* and *rpar* be the terminals in Python grammar. we get $\{def\}$,'*is*' = $pparse$('*def is*'), where $\Lambda_0 = \{def\}$ and r ='*is*'. $\Lambda = \{name, lpar, rpar\}$ is an accept sequence in this case as the sequence of terminals $\Lambda_0.\Lambda_1 = \{def, name, lpar, rpar\}$ is a valid partial sentence. The parser state on parsing the partial output C_k can be directly utilized to compute a set of accept sequences denoted as $\mathcal{A}$. The soundness and completeness of the SynCode algorithm depend on the length of these accept sequences in $\mathcal{A}$. In theory, using longer accept sequences enhances the precision of the SynCode algorithm. However, this improvement comes at the cost of increased computational complexity. In Section 4.5, we show our method for obtaining 1 and 2-length accept sequences that are efficient and precise in practice.

4.3 Grammar Mask

This section outlines the utilization of the set of acceptable terminal sequences $\mathcal{A}$ and the remainder r in the creation of a boolean mask using the DFA mask store which is subsequently used for constraining the LLM output. The DFA mask store is constructed offline and makes SynCode efficient during the LLM generation. Given partial output C_k, our objective is to identify tokens $t \in V$ such that appending them to C_k leads to syntactical completion. Given remainder r and set of sequences $\mathcal{A}$, the goal is to determine whether $r.t$ partially matches the regular expression derived from any of the sequences in $\mathcal{A}$. To characterize the notion of strings partially matching a regular expression, we next introduce the function *pmatch*.

Definition 4.6 (pmatch). The function *pmatch* takes a word $w \in \Sigma^*$, a regular expression ρ and returns a boolean. $pmatch(w, \rho) = true$ if either of the following conditions holds:

(1) $\exists w_1 \in \Sigma^*, w_2 \in \Sigma^+$ such that $w = w_1.w_2$ and $w_1 \in L(\rho)$ or
(2) $\exists w_1 \in \Sigma^*$ such that $w.w_1 \in L(\rho)$

Thus $pmatch(w, \rho)$ is true when either a prefix of w matches ρ or w can be extended to match ρ. The consequence of allowing *pmatch* to be defined such that it is true even when prefix matches, is that SynCode will conservatively accept all tokens for which the prefix matches the accept sequence. Hence, we overapproximate the precise set of syntactically valid tokens. We make this choice to ensure that SynCode is sound for any length of accept sequences. Next, we give definitions related to DFAs. These definitions are useful for describing the construction of the DFA mask store and proving properties related to its correctness in the SynCode algorithm. In particular, we first define the live states of DFA. We say state q is live if there is a path from q to any final states in F. Formally,

Definition 4.7 (DFA live states). Given a DFA $D(Q, \Sigma, \delta, q_0, F)$, let $live(Q) \subseteq Q$ denote the set of live states such that

$$q \in live(Q) \text{ iff } \exists w \in \Sigma^* \text{ s.t. } \delta^*(w, q) \in F$$

We use $D_\tau(Q_\tau, \Sigma_\tau, \delta_\tau, q_0^\tau, F_\tau)$ to denote a DFA corresponding to a terminal $\tau \in \Gamma$. Next, we establish the definition of *dmatch* for DFA, which is an equivalent concept to *pmatch* with regular expressions. *dmatch* is recursively defined such that its computation can be performed by walking over the DFAs of a sequence of terminals.

Definition 4.8 (dmatch). Given a DFA $D(Q, \Sigma, \delta, q_0, F)$, a string $w \in \Sigma^*$, a DFA state $q \in Q$ and any sequence of terminals $\Lambda = \{\tau_{f+1}, \tau_{f+2} \ldots \tau_{f+d}\}$, $dmatch(w, q, \Lambda) = true$, if either of the following conditions hold:

(1) $\delta^*(w, q) \in live(Q)$ or
(2) $\exists w_1 \in \Sigma^*, w_2 \in \Sigma^+$ such that $w_1.w_2 = w$, $\delta^*(w_1, q) \in F$ and $\Lambda = \{\}$ or
(3) $\exists w_1 \in \Sigma^*, w_2 \in \Sigma^*$ such that $w_1.w_2 = w$, $\delta^*(w_1, q) \in F$, and $dmatch(w_2, q_0^{\tau_{f+1}}, \{\tau_{f+2} \ldots \tau_{f+d}\}) = true$ where $q_0^{\tau_{f+1}}$ is the start state corresponding to the DFA for τ_{f+1}

Given an accept sequence $\Lambda = \{\tau_{f+1}, \tau_{f+2} \ldots \tau_{f+d}\} \in \mathcal{A}$, our objective is to compute the set of tokens $t \in V$ such that $pmatch(r.t, \rho_\Lambda)$ holds, where $\rho_\Lambda = (\rho_{f+1}.\rho_{f+2}.\ldots.\rho_{f+d})$ is the regular expression obtained by concatenating regular expressions for terminals. If Λ^p denotes the sequence $\{\tau_{f+2}, \ldots \tau_{f+d}\}$, Lemma 4.9 simplifies this problem to finding $dmatch(r.t, q_0^{\tau_1}, \Lambda^p)$. Furthermore, utilizing Lemma 4.10, this can be further reduced to computing $q = \delta^*_{\tau_1}(r, q_0^{\tau_1})$ and $dmatch(t, q, \Lambda^p)$. It's important to note that $dmatch(t, q, \Lambda^p)$ does not depend on C_k and can be computed offline. While the computation of q for $dmatch(t, q, \Lambda^p)$ is relatively inexpensive, evaluating $dmatch(t, q, \Lambda^p)$ can be computationally expensive both offline and online, as it requires considering numerous potential accept sequences offline, and where it needs to iterate over all tokens in V online. We observe that if we consider sequences of smaller lengths, we can efficiently precompute the set of tokens satisfying $dmatch(t, q, \Lambda^p)$ for all q, t and Λ^p offline. We later establish the soundness of Syncode when using accept sequences of length at least 1 (Theorem 4.13) and completeness for accept sequences of the length greater than maximum length of tokens in the vocabulary (Theorem 4.16). Typically, LLM tokens are small in size, allowing us to obtain these guarantees.

Lemma 4.9. *Given* $\Lambda = \{\tau_{f+1}, \tau_{f+2} \ldots \tau_{f+d}\}$, $\Lambda^p = \{\tau_{f+2} \ldots \tau_{f+d}\}$ *and* $\rho_\Lambda = (\rho_{f+1}, \rho_{f+2}, \ldots, \rho_{f+d})$, $dmatch(w, q_0^{\tau_1}, \Lambda^p) \iff pmatch(w, \rho_\Lambda)$.

Lemma 4.10. *If* $q = \delta^*_\tau(r, q_0^\tau)$ *and no prefix of* r *is in* $L(\tau)$ *i.e.* $\nexists w_1 \in \Sigma^*, w_2 \in \Sigma^*$ *such that* $w_1.w_2 = r$ *and* $\delta^*_\tau(w_1, q_0^\tau) \in F_\tau$ *then* $dmatch(t, q, \Lambda) \iff dmatch(r.t, q_0^\tau, \Lambda)$.

The proofs of both the lemmas are in Appendix A.2.

Illustrative Example: Consider the scenario with C_k = '*def is*', r ='*is*', and an accept sequence $\Lambda = \{name, lpar, rpar\}$ in $\mathcal{A}$, where *name*, *lpar*, and *rpar* are terminals in Γ. Our objective is to determine all $t \in V$ such that '*def is*'.t forms a valid partial program. This can be

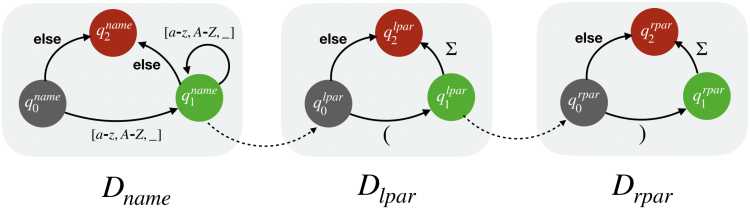


Fig. 8. DFAs in accept sequence $\Lambda = \{name, lpar, rpar\}$ for example. The start state, final states, and dead states are in gray, green, and red respectively. The dashed arrows link the final states of one DFA to the starting state of the next DFA, adhering to condition 3 in Definition 4.8. This illustrates the sequential traversal across DFAs during the computation of *dmatch*.

achieved by finding tokens t that satisfy $pmatch(\text{'}is\text{'}.t, \rho_\Lambda)$, where $\rho_\Lambda = [a\text{-}z, A\text{-}Z, \_]^*()$. Let's consider a token t = '*_prime():*'. We observe that $r.t$ ='*is_prime():*' can be decomposed into '*is_prime*' (*name*), '*(*' (*lpar*), '*)*' (*rpar*), and '*:*'. Consequently, it partially matches ρ_Λ as defined by *pmatch*. In Figure 9, we present the DFAs for Λ used in computing *dmatch*. The reduction $dmatch(r.t, q_0^{name}, lpar, rpar) = dmatch(\text{'}is\_prime():\text{'}, q_0^{name}, lpar, rpar)$ simplifies successively to $dmatch(\text{'}():\text{'}, q_0^{lpar}, rpar)$, then to $dmatch(\text{'}):\text{'}, q_0^{rpar},)$, and finally to $dmatch(\text{'}:\text{'}, q_1^{rpar},)$. As q_1^{rpar} is a final state, according to condition 2 of Definition 4.8, $dmatch(\text{'}:\text{'}, q_1^{rpar},)$ holds true. Next, we define a mask over vocabulary

Definition 4.11 (Vocabulary mask). Given vocabulary $V \subseteq \Sigma^*$, $m \in \{0, 1\}^{|V|}$ is a mask over the vocabulary. We also use $set(m) \subseteq V$ to denote the subset represented by m.

For an integer α, we define a DFA table $\mathcal{M}_\alpha$ as the mask store over the DFA states with α lookahead. Given the set of all DFA states $Q_\Omega = \bigcup_{\tau \in \Gamma} Q_\tau$, the table stores binary masks of size $|V|$, indicating for token string t, for any DFA state $q \in Q_\Omega$ and a sequence of α terminals Λ_α if $dmatch(t, q, \Lambda_\alpha) = true$. The lookahead parameter α signifies the number of subsequent terminals considered when generating the mask stored in the table. Choosing a larger value for α enhances the precision of SynCode algorithm, but it comes at the cost of computing and storing a larger table. We next formally define the DFA mask store,

Definition 4.12 (DFA mask store). For an integer α, the DFA mask store $\mathcal{M}_\alpha$ is a function defined as $\mathcal{M}_\alpha : Q_\Omega \times \Gamma^\alpha \longrightarrow \{0, 1\}^{|V|}$, where $Q_\Omega = \bigcup_{\tau \in \Gamma} Q_\tau$ represents the set of all DFA states and Γ^α is a set of α-length terminal sequences. Then $\mathcal{M}_\alpha(q, \Lambda) = m$ is a binary mask such that $t \in set(m)$ if $dmatch(t, q, \Lambda)$

For our illustrative example if $m = \mathcal{M}_2(q_1^{name}, \{lpar, rpar\})$ then t ='*_prime():*' should be contained in $set(m)$. The grammar mask for a set of accept sequences $\mathcal{A}$ can be computed by combining masks for each $\Lambda \in \mathcal{A}$.

Computing Grammar Mask The DFA mask store $\mathcal{M}_0$ maps each DFA state to all tokens such that they *pmatch* without considering any following accept sequence (0-length sequence). In this case, the table maps each state with a single mask denoting the tokens that match the regular expression of the corresponding DFA. This approach is equivalent to the one used by [34] for regular expression guided generation. The current parsers can easily compute acceptable sequences of terminals with a length of 2 from partial output. We note that *pmatch* $r.t$ with a 2-length sequence is equivalent to *dmatch* with a 1-length sequence, as stated in Lemma 4.9. Consequently, in our work, we opt for $\mathcal{M}_0$ and $\mathcal{M}_1$ since we have observed empirically that this combination is sufficient for producing syntactically valid outputs. The table is constructed offline by enumerating all DFA states Q_Ω, considering all possible terminals in Γ, and all tokens in V. The DFA mask store depends on the set of terminals Γ and the model's vocabulary V. As a result, a unique mask store is created for each grammar and tokenizer combination, and to enhance efficiency, we cache and reuse this table for future inferences.

Algorithm 2 presents our approach for computing the grammar mask during LLM generation. It computes a grammar mask based on the sets of current accept sequences $\mathcal{A}$, and the remainder string (r). It iterates over $\mathcal{A}$, considering each sequence Λ. The algorithm initializes an empty mask m. It iterates over each acceptable sequence, considering the first terminal τ_1 in each. It computes the resulting state q_r by processing τ_1 from an initial state $q_0^{\tau_1}$ and the remainder string r. If q_r is in a live state, the algorithm updates the grammar mask by unifying the mask cached in $\mathcal{M}_\alpha$.

4.4 Soundness and Completeness

Algorithm 2 Computing Grammar Mask

```
Inputs: $\mathcal{A}$: set of accept sequences, $r$: remainder string
function GrammarMask($\mathcal{A}$, $r$)
    $m \leftarrow \{\}$
    for $\Lambda \in \mathcal{A}$ do
        $\tau_1 \leftarrow \Lambda[0]$
        $q_r \leftarrow \delta^*(q_0^{\tau_1}, r)$
        if $q_r \in live(Q_{\tau_1})$ then
            $\Pi \leftarrow len(\Lambda) - 1$
            $m \leftarrow m \cup \big(\mathcal{M}_\Pi(q_r, \Lambda[1:])\big)$
    return $m$
```

This section establishes the soundness and completeness of the SynCode algorithm. Algorithm 3 presents the LLM generation algorithm with SynCode. It takes as inputs an LLM represented by M, a tokenizer denoted by $\mathcal{T}$, an input prompt string C_0, the maximum number of generated tokens n_{max}, and a base decoding strategy D. The algorithm begins by tokenizing the input prompt using the tokenizer. It then iteratively generates tokens using the LLM, decodes the current token sequence, and performs parsing to obtain acceptable terminal sequences $\mathcal{A}$, and a remainder r (line 6). A grammar mask is applied to the logit scores based on these values (line 7). The algorithm subsequently selects the next token using the decoding strategy, and if the end-of-sequence token (EOS) is encountered, the process terminates. The final decoded output is obtained, incorporating the generated tokens, and is returned as the result of the MaskedGenerate algorithm.

Given partial output $C_k \in L_p(G)$ and SynCode generates a corresponding mask m. If, for a token $t \in V$, the concatenation $C_k.t$ results in a syntactically valid partial output, i.e. $C_k.t \in L_p(G)$, our soundness theorem ensures that t is indeed a member of the set defined by the generated mask m. The subsequent theorem formally states this soundness property.

Theorem 4.13. *Let $C_k \in L_p(G)$ be the partial output and any integer $d \geq 1$, let $\mathcal{A}_d \subseteq \Gamma^d$ contain all possible accept terminal sequences of length d and $r \in \Sigma^*$ denote the remainder. If $m = GrammarMask(\mathcal{A}, r)$ then for any $t \in V$, if $C_k.t \in L_p(G)$ then $t \in set(m)$*

The proof of the theorem is in Appendix A.2.

Next, we give a definition that establishes a partial order on sets of terminal sequences, where one set is considered greater than another if every sequence in the second set has a prefix in the first set.

Definition 4.14 ($\preccurlyeq$). We define a partial order $\preccurlyeq$ on set of terminal sequences $\mathcal{P}(\Gamma^*)$ such that $\mathcal{A}_1 \preccurlyeq \mathcal{A}_2$ when $\forall \Lambda_2 \in \mathcal{A}_2 \exists \Lambda_1 \in \mathcal{A}_1 \exists \Lambda_3 \in \Gamma^*$ s.t. $\Lambda_2 = \Lambda_1.\Lambda_3$

We further state the lemma that shows the relation in the grammar masks generated by two accept sequences satisfying relation $\preccurlyeq$.

Lemma 4.15. *Given $\mathcal{A}_1$ and $\mathcal{A}_2$ are set of accept sequences such that $\mathcal{A}_1 \preccurlyeq \mathcal{A}_2$ and $m_1 = GrammarMask(\mathcal{A}_1, r)$ and $m_2 = GrammarMask(\mathcal{A}_2, r)$ then $set(m_2) \subseteq set(m_1)$*

The proof of the lemma is in Appendix A.2.

Theorem 4.13 establishes soundness for accept sequences $\mathcal{A}_d$ of length d, while Lemma 4.15 extends this proof to any set of accept sequences $\mathcal{A}$ such that $\mathcal{A} \preccurlyeq \mathcal{A}_d$. Our implementation, employing sequences of varying lengths, can be proven sound based on this extension.

The completeness theorem ensures that, under specified conditions, each token $t \in set(m)$ guarantees $C_k.t$ as a syntactically valid partial output. An implementation of SynCode with a short length of accept sequences although sound, may not guarantee completeness. To illustrate, let's take the example where $\Lambda = \tau_{f+1}, \tau_{f+2} \in \mathcal{A}$ with simple singleton regular expressions $\rho_{\tau_{f+1}} =$ '*(*' and $\rho_{\tau_{f+2}} =$ '*(*'. In this case, our algorithm conservatively treats all tokens $t \in V$ as syntactically valid, whenever '*((*' is a prefix of those tokens (e.g., '*(((*', '*(()*')) even though some tokens may not meet syntactic validity.

However, by assuming that the accept sequences are long enough, we can establish the completeness of the approach.

Theorem 4.16. *Let $C_k \in L_p(G)$ be the partial output, let $\mathcal{A}_d \subseteq \Gamma^d$ contain all possible accept terminal sequences of length d and $r \in \Sigma^*$ denote the remainder. Suppose for any $t \in V, d > len(t)$ and $m = GrammarMask(\mathcal{A}_d, r)$ such that $t \in set(m)$ then $C_k.t \in L_p(G)$*

The proof of the theorem is in Appendix A.2. While our completeness theorem ensures the SynCode consistently extends syntactically correct partial outputs, it does not guarantee termination with a correct and complete output. The focus of the theorem is on generating syntactically valid partial outputs, and the theorem does not address whether the process converges to a syntactically correct whole output. Termination considerations go beyond the completeness theorem's scope.

Algorithm 3 SynCode Generation

Inputs: M: LLM, $\mathcal{T}$: tokenizer, C_0: input prompt string, n_{max}: maximum generated tokens, D: decoding strategy

```
function MaskedGenerate($M$, $\mathcal{T}$, $C_0$, $n_{max}$, $D$)
    $T_{cur} \leftarrow$ Tokenize($\mathcal{T}$, $C_0$)
    for $i \in \{1, \ldots n_{max}\}$ do
        $scores \leftarrow M(T_{cur})$
        $C_k \leftarrow$ decode($\mathcal{T}$, $T_{cur}$)
        $\mathcal{A}, r \leftarrow$ Parse($C_k$)
        $m \leftarrow$ GrammarMask($\mathcal{A}, r$)
        $scores \leftarrow m \odot scores$
        $t_i \leftarrow D(scores)$
        if $t_i = EOS$ then
            break
        $T_{cur} \leftarrow$ append($T_{cur}, t_i$)
    output $\leftarrow$ decode($\mathcal{T}$, $T_{cur}$)
    return output
```

4.5 SynCode Implementation

In our implementation, we focus on generating accept sequences of length 1 or 2, as they can be efficiently obtained from existing parsers. While this approach incurs some loss of precision, it leads to sound but incomplete syntactical decoding. Further, our evaluation demonstrates that this strategy is efficient and precise in practical scenarios. We note that *pmatch* $r.t$ with a 2-length sequence is equivalent to *dmatch* with a 1-length sequence, as stated in Lemma 4.9. Consequently, in our work, we precompute mask stores $\mathcal{M}_0$ and $\mathcal{M}_1$. On parsing the partial output C_k, the parser state can be used to directly obtain syntactically acceptable terminals for the current completion (A_0) and the next completion (A_1). We utilize A_0 and A_1 to construct the accept sequences $\mathcal{A}$, considering two cases:

Case 1: $C_k = l_1.l_2 \ldots l_f$**:** Let τ_f represent the type of the final lexical token. In many instances, a token may be extended in the subsequent generation step, such as when an identifier name grows longer or additional words are appended to a comment. In those cases if $A_1 = \tau_1^1, \tau_2^1, \ldots, \tau_n^1$, we include all 2-length sequences $\{\tau_f, \tau_i^1\}$ for each i. As previously discussed, the type of the final lexical token may change from τ_f. Consequently, when $A_0 = \{\tau_1^0, \tau_2^0, \ldots, \tau_n^0\}$, we add 1-length sequences Λ_i for each terminal sequence $\{\tau_i\}$ from A_0, excluding τ_f. This method ensures the generation of sequences accounting for potential extensions of the same token and changes in the type of the final lexical token.

Case 2 $C_k = l_1.l_2 \ldots l_f.u$**:** In this scenario, the current terminal is incomplete, leading to a lack of information about subsequent terminals. Consequently, when $A_1 = \{\tau_1, \tau_2, \ldots, \tau_n\}$, we define $\mathcal{A}$ as a set of sequences: $\{\Lambda_1, \Lambda_2, \ldots, \Lambda_n\}$, where each Λ_i corresponds to a single terminal sequence $\{\tau_i\}$ from A_1. Specifically, $\Lambda_1 = \{\tau_1\}$, $\Lambda_2 = \{\tau_2\}$, and so forth. This approach ensures the generation of accept sequences based on the available information for subsequent terminals when the current one is incomplete.

We discuss how the implementation of how parsing is performed *incrementally* to obtain the accept sequences and remainder in the Appendix A.3.

4.6 Time Complexity

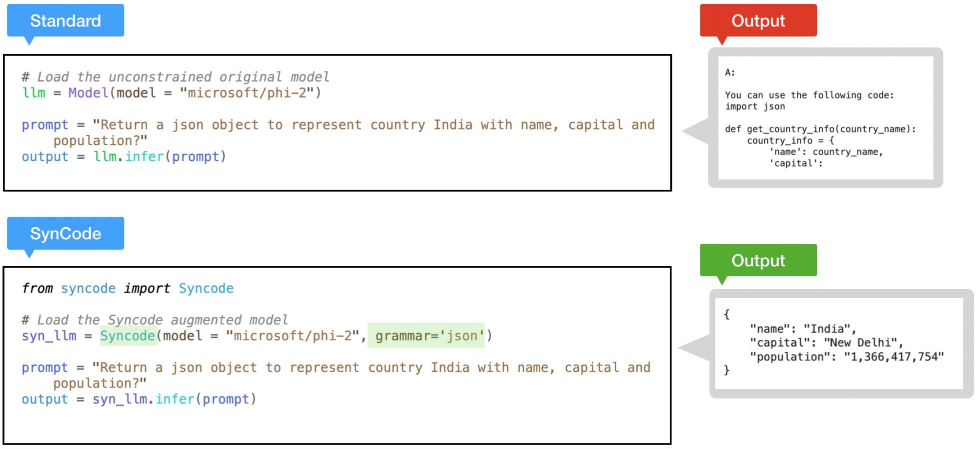
In this section, we analyze the time complexity of the SynCode algorithm. We focus on the cost of creating the mask at each iteration of the LLM generation loop. The key computations involved in this process are the parsing carried out by the incremental parser to compute $\mathcal{A}$ and the lookup/unification operations performed through the DFA mask store.

The incremental parser parses $O(1)$ new tokens at each iteration and computes $\mathcal{A}$. Let T_A represent the time taken by the parser to compute the accepted terminals and T_P denote the time the parser takes to parse a new token and update the parser state. Hence, in each iteration, the parser consumes $O(T_A + T_P)$ time to generate $\mathcal{A}$. The DFA mask store lookup involves traversing $|\mathcal{A}|$ DFA sequences, with the number of steps in this walk bounded by the length of the remainder r. As $\mathcal{A}$ can have a maximum of $|\Gamma|$ sequences, the DFA walk consumes $O(|\Gamma| \cdot len(r))$ time. We employ a hashmap to facilitate efficient lookups at each DFA node, ensuring that all lookups take constant time. Consequently, this step takes $O(|\Gamma|)$ time. Let $T_\cup$ denote the time taken for computing the union of binary masks. With potentially $|\Gamma|$ union operations to be performed, the mask computation takes $O(T_\cup \cdot |\Gamma|)$ time. Therefore, the overall time complexity at each step during generation is given by $O(T_A + T_P + |\Gamma| \cdot len(r) + T_\cup \cdot |\Gamma|)$.

Choice of base parser: Bottom-up LR parsers, including LR(1) and LALR(1) parsers, process terminals generated from the lexical analysis of the code sequentially and perform shift or reduce operations [3]. LR(1) parsers have the immediate error detection property, ensuring they do not perform shift or reduce operations if the next input terminal is erroneous [2]. This property allows us to use LR(1) parsing tables to efficiently compute acceptable terminals at any intermediate point, making them preferable for SynCode applications. Thus, computing acceptable terminals with LR(1) parsers has a complexity of $O(|\Gamma|)$. Although LALR(1) parsers are more commonly used due to their smaller memory requirements and faster construction, computing acceptable terminals with them requires iterating over all terminals leading to a complexity of $O(T_P \cdot |\Gamma|)$ due to the need for multiple reduce operations before confirming the validity of each terminal. Furthermore, while for $k > 1$, LR(k) parsers can compute accept sequences of length k immediately, they incur extremely high memory requirements. Additionally, while we can use LL(k) parsing tables to compute the next k accept terminals, LR(k) parsers offer a higher degree of parsing power. Therefore, we employ LR parsers in SynCode. Our evaluation indicates that LR(1) parsers suffice for effectively eliminating most syntax errors, making them a practical choice for SynCode.

As a consequence, the complexity of our SynCode implementation for syntactic decoding at each step of LLM token generation is $O(|\Gamma| \cdot len(r) + T_\cup \cdot |\Gamma|)$. Typically, the remainder r is small, allowing us to further simplify our complexity analysis to $O(T_\cup \cdot |\Gamma|)$ by treating $len(r)$ as constant. Additionally, all these computations have the potential for parallelization during LLM generation, but this aspect is deferred to future work.

Offline cost: The cost of computing the mask store $\mathcal{M}_\alpha$ offline involves considering all DFA states $q \in Q_\Omega$, all possible terminal sequences of length α, and all tokens $t \in V$. Given that we need to traverse the DFA for $len(t)$ steps for each entry in the store, the time complexity for computing the mask store is $O(max_{t \in V}(len(t)).|Q_\Omega|.|V|.|\Gamma|^\alpha)$. Typically, $len(t)$ is small, allowing us to simplify this to $O(|Q_\Omega|.|V|.|\Gamma|^\alpha)$. In our implementation, the use of $\mathcal{M}_0$ and $\mathcal{M}_1$ results in a cost of $O(|Q_\Omega|.|V|.|\Gamma|)$. The size of $|Q_\Omega|$ depends on the complexity of regular expressions for the terminals, which may vary for each grammar. However, as demonstrated in our evaluation section, these mask stores can be computed within 10 minutes for each combination of grammar and LLM.



```
# Load the unconstrained original model
llm = Model(model = "microsoft/phi-2")

prompt = "Return a json object to represent country India with name, capital and
    population?"
output = llm.infer(prompt)
```

```
A:

You can use the following code:
import json

def get_country_info(country_name):
    country_info = {
        'name': country_name,
        'capital':
```

```
from syncode import Syncode

# Load the Syncode augmented model
syn_llm = Syncode(model = "microsoft/phi-2", grammar='json')

prompt = "Return a json object to represent country India with name, capital and
    population?"
output = syn_llm.infer(prompt)
```

```
{
    "name": "India",
    "capital": "New Delhi",
    "population": "1,366,417,754"
}
```

Fig. 9. The upper section displays erroneous output from a standard LLM generation, failing to produce the intended JSON format. The lower segment showcases the fix achieved through the use of the SynCode library.

This computation is a one-time cost that can be amortized over all generations performed for the given LLM and grammar.

4.7 SynCode Framework

Figure 9 shows how SynCode framework can be used in practice by selecting a grammar. We next discuss other important features of the framework.

Adding a New Grammar. Our SynCode library is shipped with several built-in grammars such as JSON, Python, Go, etc. A user can apply SynCode for arbitrary grammar by providing the grammar rules in EBNF syntax with little effort. The grammar needs to be unambiguous LALR(1) or LR(1) grammar for using the respective base parsers. The power of the LALR(1) parser is sufficient for most mainstream formal languages [11].

Ignore Terminals. Our EBNF syntax adopted from Lark allows one to provide *ignore terminals* as part of the grammar. Lark ignores those terminals while parsing. In the case of Python, this includes *comments* and *whitespaces*. SynCode handles these ignore terminals by adding a trivial 1-length accept sequence for each of these ignore terminals.

Parsers. SynCode supports both LALR(1) and LR(1) as base parsers. We adapt Lark's [17] LALR(1) parser generator for SynCode. Since Lark does not implement the LR(1) parser generator, we implemented the LR(1) parser generator on top of the Lark. The generation of LR(1) parser which is performed offline may take longer time compared to the LALR(1) parser (e.g., up to 2 mins for our Python grammar), however, it is more efficient at inference time in computing the accept sequences. Further, since the Lark-generated parser is non-incremental, we build the incremental parser on top of it by caching the parser state as described in Appendix A.3.

Non-CFG Fragments of PLs. SynCode can handle non-context-free fragments of PLs, such as *indentation* in Python and end-of-scope markers in Go. To support languages with indentation, such as Python and YAML, SynCode has a mechanism that tracks acceptable indentation for the next token, effectively masking tokens that violate indentation constraints at a given point. This indentation constraint feature can be enabled with any new grammar. Similarly, for handling other custom parsing rules beyond CFGs, users can add additional constraints to the generation by overriding specific SynCode functions. For instance, in Go, semicolons are optional and may be automatically inserted at the end of non-blank lines under certain conditions. Implementing such constraints in SynCode programmatically requires minimal effort. However, SynCode currently does not support addition of semantic constraints. (e.g, if a variable in a program is defined before it is used.)

5 EXPERIMENTAL METHODOLOGY

Models. For our evaluation, we select a diverse range of state-of-the-art LLMs with different sizes, tokenizer vocabularies, and training objectives. We select the state-of-the-art chat model LLaMA-Chat-7B [32] for our JSON evaluation. Furthermore, we chose models such as LLaMA-7B [32], WizardCoder-1B [21], and CodeGen-350M [23] for code completion. These models were chosen since they were the top-performing small models featured on the BigCode Models Leaderboard [9]. We give more detail about these models in Appendix A.4.

Datasets. We focus our evaluation on generating JSON, Python, and Go outputs. We choose JSON as it is supported by the baselines [16, 34], which allows us to compare against them. We selected Python since it is extensively present in the training data employed for LLM training and fine-tuning. Conversely, we opted for Go due to its lower standard LLM accuracy and a relatively smaller presence in the training data. We consider JSON-Mode-Eval [24] dataset for text to JSON generation and HumanEval and MBXP [5] dataset for evaluating Python and Go code generation. We display examples of prompts from these datasets in Appendix A.7.

- **JSON-Mode-Eval [24].** It consists of 100 zero-shot problems. Each problem prompt follows the chat format with a system prompt specifying a JSON schema and a user prompt requesting the LLM to generate a JSON object that contains specified contents.
- **Multilingual HumanEval [5].** It is an extension of the original HumanEval collection [13], which comprises 164 Python programming problems, to include other languages like Go. Each problem in the dataset consists of a function definition, and text descriptions of the function as a part of the function docstring.
- **MBXP [5].** It is extended from the MBPP [6] dataset for Python to support other languages such as Go. The dataset consists of 974 problems, each of which follows the same format as those of HumanEval.

Parsers. Our evaluation considers the LR(1) base parser as the default and considers the LALR(1) parser for the ablation.

Grammars. For Python, we used the readily available grammar from the Lark repository. For Go, we converted an existing LL(*) grammar implementation to LALR(1) grammar for our use [4]. We write the CFG for these languages using the Extended Backus-Naur Form (EBNF) syntax. We use a substantial subset of grammar for Python and Go syntactic generation with SynCode. The grammar has commonly used features of the language such as control flow, and loops, and excludes some features such as Python's support for lambda functions. Adding support for more features would require more engineering effort but it will not change the overall technique. The grammars we used are available in Appendix A.8. The JSON grammar consists of 19 rules and 12 terminals. The Python grammar we used contains 520 production rules and 94 terminals, whereas the Go grammar comprises 349 rules and 87 terminals.

Evaluating Syntax Errors. For evaluating the errors in the generated output in each of the languages, we use their respective standard compilers.

Hyperparameter Values. We use temperature = 0.2, top $p = 0.95$ to make the model's predictions more consistent and set max new tokens $n_{max} = 400$ unless stated otherwise. We use these same hyperparameter values for our baselines.

Experimental Setup. We run experiments on a 48-core Intel Xeon Silver 4214R CPU with 2 NVidia RTX A5000 GPUs. SynCode is implemented using PyTorch [26], HuggingFace transformers library [35] and Lark library [17].

6 EXPERIMENTAL RESULTS

6.1 Effectiveness of SynCode for JSON Generation

Table 1. Effectiveness of SynCode in generating JSON with original and explicit prompts from JSONEval dataset.

Tool	Syntax Errors		Validation Accuracy (%)		Generation Time (s)	
	Original	Explicit	Original	Explicit	Original	Explicit
SynCode	**0**	**0**	**66%**	**84%**	**3.07**	**3.02**
Standard	98	41	2%	58%	3.58	3.11
llama.cpp	23	23	63%	68%	21.91	20.84
Outlines	71	46	4%	6%	7.14	12.46

We evaluate the effectiveness of SynCode in guiding LLMs with the JSON grammar to generate syntactically correct JSON. We run the inference with LLaMA-Chat-7B with SynCode, llama.cpp,Outlines, and standard generation on the 100 zero-shot problems from the JSON-Mode-Eval dataset. We chose llama.cpp and Outlines as they have JSON grammars that work with their frameworks. We run llama.cpp on CPU as it requires a specific CUDA version not compatible with our machine. We set max new tokens $n_{max} = 400$. We also report an evaluation of augmenting the prompts with an explicit request to output only JSON. We present an example of these explicit prompts in Appendix A.7. We evaluate the correctness of JSON generated by an LLM by first evaluating whether the JSON string can be parsed and converted to a valid JSON object. We further evaluate whether the generated JSON is valid against the schema specified in the system prompt. Although the SynCode with the JSON grammar does not enforce the corresponding schema to the JSON output for each task, we believe that it is an important research question to check whether the reduced syntax errors due to SynCode can also lead to improved schema validity of JSON.

Table 1 presents our evaluation results. We report results for both the prompts taken directly from the dataset (denoted as "Original") and after augmenting these prompts with an explicit request to output JSON (denoted as "Explicit"). In the "Validation Accuracy" column, we compute the percentage of completions that are valid against their respective schemas. In the "Generation Time (s)" column, we report the average time taken to generate a completion to a prompt from the dataset. Guiding LLaMA-Chat-7B with the JSON grammar via SynCode eliminates syntax errors in generated JSON. On the other hand, LLaMA-Chat-7B with standard generation generates syntactically incorrect JSON for 98% of completions to the original prompts, a majority of which are due to the generation of natural language before and after the JSON. While prompting LLaMA-Chat-7B with standard generation with explicit prompts eliminates the generation of output other than JSON in many cases, the LLM generates syntactically invalid outputs to 41% of the explicit prompts, primarily due to errors such as unmatched braces and unterminated string literals. llama.cpp faces similar problems with closing braces and terminating strings for original prompts and even explicit prompts. Augmenting LLaMA-Chat-7B with Outlines, results in the generation of nonsensical output, such as numbers, empty braces, empty strings, and incomplete JSON, that does not align with the prompts.

SynCode significantly improved the JSON schema validation accuracy over standard generation, from 2% to 66% and 58% to 84% for original and explicit prompts respectively. SynCode outperforms llama.cpp and Outlines in validation accuracy by 3% and 62% respectively for original prompts and 16% and 78% for explicit prompts. The remaining schema validation errors with SynCode are semantic errors, including data type mismatch between the generation JSON and schema, missing fields required by the schema, and adding extra fields not allowed by the schema. SynCode is 4.13x faster than Outlines for explicit prompts and 2.33x faster for original prompts. llama.cpp runs slower than the other approaches as it was run in CPU. We observed that JSON grammar-guided generation in llama.cpp reduces the average time to generate a completion by between 6.4% to 10.9% over standard llama.cpp generation. Interestingly, we observe that SynCode reduces the average generation time over standard generation. We attribute this finding to the fact that without grammar-guided generation, the model generates syntactically invalid output, such as natural language, in addition to JSON and thus generates more tokens in response to the same prompt than with SynCode. Thus, augmenting LLMs with SynCode can significantly improve syntactical correctness and runtime efficiency when structured output is needed.

6.2 Effectiveness of SynCode for Code

We run inference with CodeGen-350M, WizardCoder-1B, and LLaMA-7B with SynCode and with the standard no-masking approch. We do not compare SynCode with the other baselines as none of these works support general-purpose programming language grammars. Our experimentation encompassed both Python and Go programming languages, evaluating performance on zero-shot problems from the HumanEval and MBXP datasets. For each dataset, we generate $n = 20$ and $n = 1$ samples per problem with the LLM, respectively. We run the LLM-generated code completion against a predefined set of unit tests. For each unit test, we record the error type when running the generated program against that test case.

Table 2 presents our results for Python and Go. The columns standard and SynCode represent the total number of generated programs with syntax errors for the respective approaches. The column ↓ designates the percentage reduction in syntax errors from the standard generation to the SynCode generation. In this evaluation, across both HumanEval and MBXP datasets, we generate a total of 4154 samples for each language. On average, of all standard generated samples, 6% and 25% have syntax errors for Python and Go, respectively.

Notably, our experiments reveal that SynCode reduces the number of syntax errors by over 90% over the baseline in most experiments. Moreover, SynCode reduces the number of syntax errors to less than 1% of the total samples. Interestingly, we observe significantly more Syntax errors in standard LLM-generated Go code than in Python code, likely because the LLMs are trained more

Table 2. Number of programs with syntax errors for standard and SynCode generation (↓ shows how much SynCode reduces the occurrence of the syntax errors compared to 'Standard'.

Dataset	Architecture	Python			Go		
		Standard	SynCode	↓	Standard	SynCode	↓
HumanEval	CodeGen-350M	271	**15**	95%	573	**49**	91%
	WizardCoder-1B	36	**3**	92%	1031	**50**	95%
	LLaMA-7B	291	**2**	99%	725	**10**	99%
MBXP	CodeGen-350M	78	**4**	95%	212	**2**	99%
	WizardCoder-1B	28	**2**	93%	243	**14**	94%
	LLaMA-7B	148	**5**	97%	414	**1**	99%

Table 3. Avg. time taken for a single prompt generation

Model	Python(s)		Go(s)	
	Standard	SynCode	Standard	SynCode
CodeGen-350M	4.36	4.88	4.35	5.12
WizardCoder-1B	1.49	1.74	1.42	1.99
LLaMA-7B	4.88	6.07	5.35	6.67

Table 4. Functional correctness on HumanEval problems

Metric	Architecture	Python		Go	
		Standard	SynCode	Standard	SynCode
pass@1	CodeGen-350M	6.8%	**6.9%**	3.6%	3.6%
	WizardCoder-1B	20.0%	20.0%	9.3%	**9.5%**
	LLaMA-7B	11.2%	**11.5%**	3.8%	**4.25%**
pass@10	CodeGen-350M	10.6%	10.6%	5.6%	**6.1%**
	WizardCoder-1B	27.6%	**28.4%**	12.5%	**13.7%**
	LLaMA-7B	17.1%	**18.9%**	8.8%	8.8%

extensively on Python code than Go. Thus, SynCode can be especially effective for Go and more underrepresented programming languages, where LLMs are more likely to generate syntax errors due to a limited understanding of the language. SynCode can bridge this gap by guiding the LLM to sample only the syntactically valid tokens during decoding.

We further analyze the errors in Python and Go code generated by the LLMs augmented with SynCode, an example of which is presented in Appendix A.6. All of the errors were because the LLM failed to generate a complete program within the maximum token limit. Recall, SynCode provides guarantees of completeness for syntactically correct partial programs. However, it does not provide any guarantees as to whether the process will converge to a syntactically correct complete program.

Runtime Comparison. We compare the runtime of code generation with and without SynCode. We used Python and Go prompts from the HumanEval dataset. For each example, we generate a single sample ($n = 1$) per problem, with the max new tokens parameter set to 200. Table 3 reports the average time taken to generate a code completion to a prompt from the HumanEval dataset. Our results reveal that SynCode increases the generation time by 1.22x on average. Despite these slight time increases, the benefits of SynCode in reducing syntax errors outweigh the incurred overhead. As highlighted earlier, LLMs augmented with SynCode generate code with significantly fewer syntax errors.

Functional Correctness for Code Generation. We investigate whether augmenting LLMs with SynCode improves the functional correctness of the generated code. We evaluate functional correctness using the pass@k metric, where k samples are generated per problem, and a problem is considered solved if any sample passes a set of unit tests, and the fraction of solved problems is calculated. Table 4 reports our results for pass@1 and pass@10 for generated code completions to problems from the HumanEval dataset. We observe that augmenting LLMs with SynCode has a slight improvement in functional correctness over standard generation. This observation indicates that for these state-of-the-art models, syntactic correction is not sufficient to improve their ability to generate logically correct code that passes the unit tests for these tasks.

Table 5. DFA Mask store creation time and memory

		Python		Go	
Model	$\|V\|$	Time(s)	Memory	Time(s)	Memory
CodeGen-350M	51200	602.26	1.87GB	603.03	1.58GB
WizardCoder-1B	49153	588.28	1.83GB	588.84	1.54GB
LLaMA-7B	32000	382.26	1.17GB	380.49	1.06GB

6.3 Mask Store Overhead

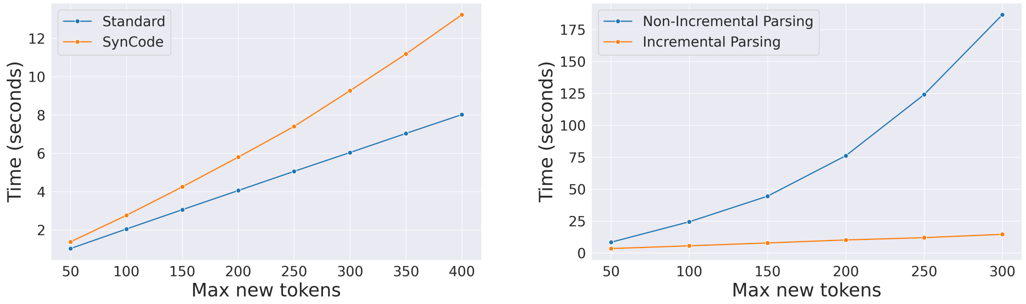
We analyze the time and memory overhead involved in generating a DFA mask store using SynCode. The DFA mask store for LLaMA-Chat-7B took 113.72 seconds to create and consumes 181 MB of memory. Additionally, we report the creation time and memory overhead of DFA mask stores for models used for Python and Go in Table 5. Each row shows the SynCode store generation time in seconds, and memory in GBs, for a particular LLM and grammar. The $|V|$ column represents the total vocabulary size of the tokenizer of the particular LLM. We see that generating the store requires less than 2GB of memory and several minutes across the evaluated models and grammars. Importantly, this overhead is minimal for practical SynCode use cases, as the mask store is a one-time generation task. Thereafter, the mask store can be efficiently loaded into memory and used for repeated inference. Furthermore, we see smaller generation time and memory with LLaMA-Chat-7B and JSON grammar as opposed to LLaMA-7B, WizardCoder-1B, and CodeGen-350M with Python and Go grammars since the size of the mask store is proportional to the number of terminals in the grammar.

6.4 Ablation Studies

Incremental Parsing. We compare the runtime efficiency of utilizing incremental parsing over re-running parsing from scratch in SynCode. We run inference on CodeGen-350M with SynCode using incremental parsing and parsing from scratch on Python prompts from the HumanEval dataset. We generate $n = 1$ samples and control the max new tokens in the code completion. Our results are presented in Figure 10b, where the x-axis represents the max new tokens and the y-axis represents the average generation time, in seconds, with and without incremental parsing. As shown in the figure, the average generation time when re-parsing from scratch increases significantly as the maximum length of code that the LLM can generate increases. On the other hand, the average generation time increases slowly with incremental parsing. For max new tokens = 300, SynCode with incremental parsing achieves 9x speedup over running parsing from scratch. Our results collectively demonstrate that augmenting SynCode with incremental parsing dramatically improves generation time, especially when generating longer completions.

Max New Tokens. We conduct an ablation study into the relationship between the maximum length of code that the LLMs can generate and generation times. We used Python prompts from the HumanEval dataset and leveraged CodeGen-350M to generate the code completions, both with and without the augmentation of the SynCode. As shown in Figure 10a, as we increase the max new tokens, we observe a corresponding increase in generation time.

LR(1) and LALR(1). We compare the runtime efficiency of utilizing LR(1) and LALR(1) parsing in SynCode. We run inference on CodeGen-350M, WizardCoder-1B, and LLaMA-7B with SynCode with LALR(1) parser and with LR(1) parser for Python and Go on the HumanEval dataset. We generate a single sample ($n = 1$) per prompt with the max new tokens parameter set to 200. Table 6 reports the average time taken to generate each prompt from the datasets. As shown in Table 6, we



(a) Average generation time for different max new tokens

(b) Average generation time with and without incremental parser

Fig. 10. Ablation studies on CodeGen-350M model.

Table 6. Avg. time taken for a single prompt generation with LR(1) and LALR(1)

Model	Python(s)		Go(s)	
	LALR(1)	LR(1)	LALR(1)	LR(1)
CodeGen-350M	6.06	**4.88**	6.79	**5.12**
WizardCoder-1B	3.00	**1.74**	3.69	**1.99**
LLaMA-7B	7.26	**6.07**	7.97	**6.67**

observe that SynCode with LR(1) parser outperforms the LALR(1) parser with respective overheads of 1.22x on average and 1.76x on average compared to the standard generation result from 3.

7 RELATED WORK

There are several recent works on constrained LLM generation [1, 7, 8, 15, 16, 20, 28, 30, 33, 34]. We focus our comparison to the techniques that constrain LLM for structured generation according to a formal language.

Structured LLM Generation. Table 7 presents the various recent techniques for structured LLM generation. The columns "Regex" and "CFG" indicate regular expression and CFG constraining features, respectively. The "Precomputed" column denotes techniques that precompute certain structures to enhance generation efficiency. "Sound" indicates whether these techniques provide soundness guarantees. The "GPL" column specifies if the tools support general-purpose PLs. "Max CFG" displays the number of production rules in the largest supported Grammar by these techniques. Finally, the "Input Format" column indicates the format used to specify generation constraints.

Recent works such as Outlines [34], guidance [20], and lmql [7] mitigate the unpredictability of LLM responses by using template or constraint-based controlled generation techniques. These libraries feature a templating engine where prompts are expressed with holes for the generation to fill. They support general regular expression constraints, allowing the generated content to be bound to the template, thereby guiding their outputs.

Synchromesh [28] is a proprietary [1] tool from Microsoft that supports CFG-guided syntactic decoding of LLMs. It goes further, using techniques like Target Similarity Tuning for semantic example selection and Constrained Semantic Decoding to enforce user-defined semantic constraints

[1] While there exists a publicly available unofficial reimplementation of Synchromesh [14] that operates on a non-incremental Lark parser, it has bugs and did not work with our grammar despite reasonable efforts to fix the issues.

Table 7. Overview of various constrained decoding methods

	Regex	CFG	Precomputed	Sound	GPL	Max CFG	Input format
lmql [7]	✓	✗	✗	✗	✗	✗	LMQL DSL
guidance [20]	✓	✓	✗	✓	✗	50-100	Python DSL
Outlines [34]	✓	✓	✓	✗	✗	50-100	Lark EBNF
Picard [30]	✓	✓	✗	✗	✗	50-100	Haskell
Synchromesh [28]	✓	✓	✗	✓	✗	‡	ANTLR
llama.cpp [16]	✓	✓	✗	†	✗	50-100	GBNF DSL
gcd [15]	✓	✓	✗	✓	✗	20-50	GF
Domino [8]	✓	✓	✓	✓	✗	50-100	GBNF DSL
SynCode (ours)	✓	✓	✓	✓	✓	500+	Lark EBNF

† Implementation issues ‡ Synchromesh is closed-source and the information about DSL grammars is unavailable
GF: Grammatical Framework, GBNF is a DSL defined by LLAMA.CPP

and works on DSLs. More recently, libraries such as llama.cpp [16] and Outlines [34] have added support for CFG-guided LLM generation. All of these approaches produce comparatively high inference overhead, since, in the worst case, they have to check the entire model vocabulary at each step. In contrast, our work, SynCode focuses exclusively on syntactic generation. As demonstrated in our evaluation, SynCode is more efficient and results in significantly fewer syntax errors and scales to large GPL grammars. Picard [30] uses a specific decoding strategy that maintains a beam of multiple candidate outputs and promptly rejects the candidates that violate the syntax. It utilizes an incremental monadic parser and was developed specifically to support SQL generation. Introducing a new grammar into Picard necessitates considerable effort, as it lacks support for a grammar-defining language to provide grammar rules.

Concurrent to our work, Domino [8] does CFG-guided LLM generation. It avoids traversing the whole vocabulary during inference by precomputing a prefix tree corresponding to each NFA state of the terminals of the grammar. The purpose of creating this structure is similar to SynCode's DFA mask store. We believe that SynCode's mask store is more efficient than Domino's prefix tree since on modern machines (especially with GPUs) the union of the boolean masks from mask store can be performed quite efficiently in practice [27]. Domino defines the *minimally invasive* property which is equivalent to SynCode's soundness property. One key difference between SynCode and Domino is that Domino applies under-approximation, permitting only tokens that align with the lookahead of the parser, while SynCode adopts a conservative over-approximation approach, allowing tokens as long as their prefixes match the parser lookahead. Due to the under-approximation, they claim that it requires ∞ parser lookahead to get this soundness, whereas SynCode ensures soundness for any lookahead. Further, the largest grammar that Domino can support currently is highly simplified C grammar with 70 rules with roughly 25% overhead. Domino's code is not available yet to experimentally compare it with SynCode.

Fixed Schema Generation. Many recent works perform constrained decoding LLM to ensure that the generated output follows a fixed schema of JSON or XML [8, 31, 34, 39]. When employing a fixed schema, many intermediate points in the generation process offer either a single syntactical choice (e.g., key in the JSON schema) or present only a handful of distinct options. In cases where only one choice exists, the generation of the next token through the LLM can be entirely skipped. Alternatively, when there are multiple but limited choices, techniques like speculative decoding can be used to expedite the generation process [12]. SynCode does not focus on generation problems with fixed schema, it solely focuses on grammar-guided generation for any language that can be defined with a CFG. We made the same observation as in [8], techniques such as speculation are not useful for complex grammars where the schema is not fixed.

8 CONCLUSION

Existing methods for guiding LLMs to produce syntactically correct output have been notably slow and restrictive, primarily applied to small DSLs. In this paper, we present SynCode, the first efficient and general framework to enhance LLMs' ability to generate syntactical output for various formal languages. During decoding, SynCode incrementally parses the partially generated code, computes the unparsed remainder and acceptable terminal sequences, and then leverages the remainder, accept sequences, and pre-computed DFA mask store to compute a mask to constrain the LLM's vocabulary to only syntactically valid tokens. We evaluated SynCode on generating syntactically correct JSON, Python, and Go code with different combinations of datasets, models, and prompt engineering tasks. SynCode eliminates syntax errors in JSON completions and significantly improves JSON schema validation over the baselines. Furthermore, SynCode reduces the number of syntax errors in generated Python and Go code by 96.07% on average compared to standard generation. We believe that our approach will pave the way for more efficient and higher-quality structured LLM generation in real-world applications.

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A APPENDIX

A.1 List of Symbols

G	Formal Grammar
$L(G)$	Language of a grammar
$L_p(G)$	Prefix language of a grammar
l	lexical tokens
l_i	i-th lexical token in the parsed output
τ	A terminal in the grammar
τ_i	Terminal type of i-th lexical token
Γ	Set of all terminals in the grammar
$L^\Gamma(G)$	Language of terminals for grammar G
$L_p^\Gamma(G)$	Prefix language of terminals
P	Parser
Λ	Sequence of terminals
$\mathcal{T}$	Tokenizer in an LLM
V	Vocabulary of an LLM
V_k	Subset of vocabulary containing acceptable tokens at k-th LLM generation iteration
ρ_τ	Regular expression for a terminal τ
ρ_i	Regular expression corresponding to i-th lexical token
$\preccurlyeq$	Partial order over set of terminal sequences
r	Remainder from SynCode parsing the partial output
C_k	Partial output at k-th iteration of LLM generation
$\mathcal{A}$	Set of accept sequences
$\mathcal{M}_\alpha$	DFA lookup store function for terminal sequences of length α
$dmatch$	Match with DFA walk as defined in Section 4
$pmatch$	Partial match with regular expression
$pparse$	Partial parsing function
m	Boolean mask
D	Discrete finite automaton
Q	States in a DFA
Σ	Set of characters i.e. alphabet for DFA
δ	Transition function in a DFA
δ^*	Extended transition function in a DFA
q_0	Start state of a DFA
F	Set of final states in DFA
$live$	Live states of the DFA
Q_Ω	Set containing all DFA states for DFAs of all terminals in the grammar
A_0	Set of terminals acceptable for current lexical token
A_1	Set of terminals acceptable as for next lexical token
Lex	Lexer function
len	Length of a sequence
T_{cur}	Current set of tokens
$\mathcal{S}$	Map for storing parser state

A.2 Proofs for Theorems

LEMMA 4.9. *Given* $\Lambda = \{\tau_{f+1}, \tau_{f+2} \dots \tau_{f+d}\}$, $\Lambda^p = \{\tau_{f+2} \dots \tau_{f+d}\}$ *and* $\rho_\Lambda = (\rho_{f+1}, \rho_{f+2}, \dots, \rho_{f+d})$, $dmatch(w, q_0^{\tau_1}, \Lambda^p) \iff pmatch(w, \rho_\Lambda)$.

PROOF. (a) First we prove $dmatch(w, q_0^{\tau_{f+1}}, \Lambda^p) \implies pmatch(w, \rho_\Lambda)$ We prove this using induction on the length i of w.

For $i = 0$, $pmatch(w, \rho_\Lambda)$ is trivially true.

Now, we assume that for w of length $i < k$, $dmatch(w, q_0^{\tau_{f+1}}, \Lambda^p) \implies pmatch(w, \rho_\Lambda)$.

We consider w of length k and $dmatch(w, q_0^{\tau_{f+1}}, \Lambda^p)$.

We consider 3 conditions from Definition 4.8.

If condition 1 is true, $\delta^*_{\tau_{f+1}}(w, q_0^{\tau_{f+1}}) \in live(Q_{\tau_{f+1}})$. Let $q_1 = \delta^*(w, q_0^{\tau_{f+1}})$. By Definition 4.7, $\exists w_1$ s.t. $\delta^*_{\tau_{f+1}}(w_1, q_1) \in F_{\tau_{f+1}}$. Hence,

$$\delta^*(w.w_1, q_0^{\tau_{f+1}}) \in F_{\tau_{f+1}} \implies w.w_1 \in L(\rho_{\tau_{f+1}})$$

We assume that each terminal $L(\tau_i)$ is non-empty. Hence,

$$\exists w_2 \in L(\rho_{\Lambda^p}) \implies w.w_1.w_2 \in L(\rho_\Lambda)$$

Hence, by condition 2 from Definition 4.6, $pmatch(w, \rho_\Lambda)$.

If condition 2 is true, $\exists w_1, w_2$ such that $w_1.w_2 = w$, $\delta^*_{\tau_{f+1}}(w_1, q_0^{\tau_{f+1}}) \in F$ and $\Lambda^p = \{\}$. Here, $w_1 \in L(\rho_{\tau_{f+1}})$. Since $\Lambda^p = \{\}$, $\rho_\Lambda = \rho_1$, and hence, $w_1 \in L(\rho_\Lambda)$. Hence by condition 1 from Definition 4.6, $pmatch(w, \rho_\Lambda)$.

If condition 3 is true, $\exists w_1, w_2$ such that $w_1.w_2 = w$, $\delta^*_{\tau_{f+1}}(w_1, q_0^{\tau_{f+1}}) \in F_{\tau_{f+1}}$, and $dmatch(w_2, q_0^{\tau_{f+2}}, \{\tau_{f+3} \dots \tau_{f+d}\}) = true.$

$$\delta^*_{\tau_{f+1}}(w_1, q_0^{\tau_{f+1}}) \in F_{\tau_{f+1}} \implies w_1 \in L(\rho_{\tau_{f+1}})$$

Since length of $w_2 < k$, by our induction hypothesis, $pmatch(w_2, \rho_{\Lambda^p}) = true.$ By Definition 4.6, there are two possibilities. Suppose $\exists w_2 = w_3.w_4$ such that $w_3 \in L(\rho_{\Lambda^p})$.

$$w_1.w_3 \in L(\rho_\Lambda) \implies pmatch(w, \rho_\Lambda) = true$$

Alternatively, if $\exists w_3$ such that $w_2.w_3 \in L(\rho_{\Lambda^p})$

$$w_1.w_2.w_3 \in L(\rho_\Lambda) \implies pmatch(w, \rho_\Lambda) = true$$

Hence, our induction proof is complete and $pmatch(w, \rho_\Lambda) = true$

(b) Next we prove $pmatch(w, \rho_\Lambda) \implies dmatch(w, q_0^{\tau_{f+1}}, \Lambda^p)$ We prove this using induction on the length i of w.

For $i = 0$, $dmatch(w, q_0^{\tau_{f+1}}, \Lambda^p)$ is trivially true.

Now, we assume that for w of length $i < k$, $pmatch(w, \rho_\Lambda) \implies dmatch(w, q_0^{\tau_{f+1}}, \Lambda^p)$

Now we consider w of length k and $pmatch(w, \rho_\Lambda)$.

By Definition 4.6, there are two possible conditions

Case 1: $\exists w_1 \in \Sigma^*, w_2 \in \Sigma^+$ such that $w = w_1.w_2$ and $w_1 \in L(\rho_\Lambda)$

Hence, $\exists w_3, w_4$ such that $w_1 = w_3.w_4$ and $w_3 \in L(\rho_{\tau_{f+1}})$ and $w_4 \in L(\rho_{\Lambda^p})$. By induction hypothesis,

$$pmatch(w_4.w_2, \rho_{\Lambda^p}) \implies dmatch(w_4 w_2, \{\tau_{f+2}, \tau_{f+3} \dots \tau_{f+d}\})$$

Since $w = w_3.w_4.w_2$ and

$$w_3 \in L(\rho_{\tau_{f+1}}) \implies \delta^*_{\tau_{f+1}}(w_3, q_0^{\tau_{f+1}}) \in F_{\tau_{f+1}}$$

Hence, by condition 3 in Definition 4.8, $dmatch(w, q_0^{\tau_{f+1}}, \Lambda^p)$
Case 2: $\exists w_1$ such that $w.w_1 \in L(\rho_\Lambda)$
Hence, $\exists w_2, w_3$ s.t $w.w_1 = w_2.w_3$ and $w_2 \in L(\rho_{\tau_{f+1}})$ and $w_3 \in L(\rho_\Lambda)$
Now there are two possibilities, either w is prefix of w_2 or w_2 is prefix of w_2
Supoose w is prefix of w_2, then $\delta^*_{\tau_{f+1}}(w, q_0^{\tau_{f+1}}) \in live(Q_{\tau_{f+1}})$ and hence by Definition 4.8, $dmatch(w, q_0^{\tau_{f+1}}, \Lambda^p)$ Alternatively, if w_2 is prefix of w then $\exists w_4$ s.t. $w = w_2 w_4$
Hence, $w_4.w_1 = w_3 \in L(\rho_{\tau_{f+1}})$ and thus $pmatch(w_4, \rho_{\Lambda^p})$
By induction hypothesis $dmatch(w_4, q_0^{\tau_{f+2}}, \{\tau_{f+3}, \tau_4 \dots \tau_{f+d}\})$
and since $w = w_2.w_4$ and $\delta^*_{\tau_{f+1}}(w_2, q_0^{\tau_{f+1}}) \in F_{\tau_{f+1}}$. We get $dmatch(w, q_0^{\tau_{f+1}}, \Lambda^p)$

□

Lemma 4.10. *If* $q = \delta^*_\tau(r, q_0^\tau)$ *and no prefix of* r *is in* $L(\tau)$ *i.e.* $\nexists w_1 \in \Sigma^*, w_2 \in \Sigma^*$ *such that* $w_1.w_2 = r$ *and* $\delta^*_\tau(w_1, q_0^\tau) \in F_\tau$ *then* $dmatch(t, q, \Lambda) \iff dmatch(r.t, q_0^\tau, \Lambda)$.

Proof. (a) First, we prove $dmatch(t, q, \Lambda) \implies dmatch(r.t, q_0^\tau, \Lambda)$.
From Definition 4.8, either of the 3 conditions hold true for $dmatch(t, q, \Lambda)$.

If condition 1 is true then

$$\delta^*_{\tau_1}(t, q) \in live(Q_\tau) \implies \delta^*_\tau(r.t, q_0^\tau) \in live(Q_\tau) \implies dmatch(r.t, q_0^\tau, \Lambda)$$

If condition 2 is true, $\exists w_1, w_2$ such that $w_1.w_2 = t$, $\delta^*_\tau(w_1, q) \in F$ and $\Lambda = \{\}$. Therefore,

$$\delta^*_\tau(r.w_1, q) \in F \implies dmatch(r.t, q_0^\tau, \Lambda)$$

If condition 3 is true, $\exists w_1, w_2$ such that $w_1.w_2 = t$, $\delta^*_\tau(w_1, q) \in F$
and $dmatch(w_2, q_0^{\tau_1}, \{\tau_2 \dots \tau_d\}) = true$. Therefore,

$$\delta^*_\tau(r.w_1, q) \in F \implies dmatch(r.t, q_0^\tau, \Lambda)$$

Therefore, in all cases, $dmatch(rt, q_0^\tau, \Lambda)$ must hold.

(b) Now, we prove $dmatch(rt, q_0^\tau, \Lambda) \implies dmatch(t, q, \Lambda)$.
From Definition 4.8, either of the 3 conditions hold true for $dmatch(r.t, q_0^\tau, \Lambda)$.

If condition 1 is true then

$$\delta^*_{\tau_1}(r.t, q_0^\tau) \in live(Q_\tau) \implies \delta^*_\tau(t, q) \in live(Q_\tau) \implies dmatch(t, q, \Lambda)$$

If condition 2 is true, $\exists w_1, w_2$ such that $w_1.w_2 = r.t$, $\delta^*_\tau(w_1, q_0^\tau) \in F$ and $\Lambda = \{\}$. Since no prefix of r is accepted by $L(\tau)$, $\exists w_3$ s.t. $w_3 w_4 = t$ and

$$\delta^*_\tau(w_3, q) \in F \implies dmatch(t, q, \Lambda)$$

If condition 3 is true, $\exists w_1, w_2$ such that $w_1.w_2 = r.t$, $\delta^*_\tau(w_1, q_0^\tau) \in F$
and $dmatch(w_2, q_0^{\tau_1}, \{\tau_2 \dots \tau_d\}) = true$. Since no prefix of r is accepted by $L(\tau)$, $\exists w_3$ s.t. $w_3 w_4 = t$ and

$$\delta^*_\tau(w_3, q) \in F \implies dmatch(t, q, \Lambda)$$

Therefore, in all cases, $dmatch(t, q, \Lambda)$ must hold.

□

Theorem 4.13. *Let* $C_k \in L_p(G)$ *be the partial output and any integer* $d \geq 1$, *let* $\mathcal{A}_d \subseteq \Gamma^d$ *contain all possible accept terminal sequences of length* d *and* $r \in \Sigma^*$ *denote the remainder. If* $m = GrammarMask(\mathcal{A}, r)$ *then for any* $t \in V$, *if* $C_k.t \in L_p(G)$ *then* $t \in set(m)$

Proof. Let $r, \Lambda_0 = pparse(C_k)$ where $\Lambda_0 = \tau_1, \tau_2 \dots \tau_f$ and let $r_1, \Lambda_1 = pparse(C_k.t)$ where $\Lambda_1 = \tau_1, \tau_2 \dots \tau_f \dots \tau_{f+g}$
Hence, we can split $r.t$ such that for $w \in \Sigma^*$, $r.t = w.r_1$ and $w \in L(\tau_{f+1} \dots \tau_{f+g})$
There are two possible cases:
Case 1: $g < d$

$$w \in L(\tau_{f+1} \dots \tau_{f+g})$$
$$\implies w \in L_p(\tau_{f+1} \dots \tau_{f+g})$$

By our assumption on $\mathcal{A}_d$ there must exist $\Lambda_2 = \tau_{f+1} \dots \tau_{f+d}$ s.t. $\tau_{f+1} \dots \tau_{f+g}$ is prefix of Λ_2. Hence,

$$\implies w \in L_p(\Lambda_2)$$
$$\implies pmatch(r.t, \Lambda_2)$$

Case 2: $g \geq d$
Since we assume that $\mathcal{A}_d$ contains all possible accept sequence of length d, $\Lambda_2 = \tau_{f+1} \dots \tau_{f+d}$ must be contained in $\mathcal{A}_d$
Hence, $\exists w_1, w_2 \in \Sigma^*$ such that $w = w_1.w_2$ and

$$w_1 \in L(\Lambda_2)$$
$$\implies w \in L_p(\Lambda_2)$$
$$\implies pmatch(r.t, \Lambda_2)$$

In both cases, $pmatch(r.t, \Lambda_2)$. Using Lemma 4.9,

$$\implies dmatch(r.t, q_0^{\tau_{f+1}}, \{\tau_{f+2} \dots \tau_{f+d}\})$$

Using Lemma 4.10 if $q = \delta^*_{\tau_{f+1}}(r, q_0^{\tau_{f+1}})$

$$dmatch(r.t, q_0^{\tau_{f+1}}, \{\tau_{f+2} \dots \tau_{f+d}\}) \implies dmatch(t, q, \{\tau_{f+2} \dots \tau_{f+d}\})$$

Here from Definition 4.12, if $\mathcal{M}_{d-1}(q, \{\tau_{f+2} \dots \tau_{f+d}\}) = m_2$ then $t \in set(m_2)$.
Since $m_2 \subseteq m$, we have our result $t \in set(m)$.

□

Lemma 4.15. *Given $\mathcal{A}_1$ and $\mathcal{A}_2$ are set of accept sequences such that $\mathcal{A}_1 \preccurlyeq \mathcal{A}_2$ and $m_1 = GrammarMask(\mathcal{A}_1, r)$ and $m_2 = GrammarMask(\mathcal{A}_2, r)$ then $set(m_2) \subseteq set(m_1)$*

Proof. Since $\forall \Lambda_2 \in \mathcal{A}_2 \exists \Lambda_1 \in \mathcal{A}_1 \exists \Lambda_3 \in \Gamma^*$ s.t. $\Lambda_2 = \Lambda_1.\Lambda_3$, Hence

$$pmatch(w, \rho_{\Lambda_2}) \implies pmatch(w, \rho_{\Lambda_1})$$

Hence, for the mask $set(m_2) \subseteq set(m_1)$ □

Theorem 4.16. *Let $C_k \in L_p(G)$ be the partial output, let $\mathcal{A}_d \subseteq \Gamma^d$ contain all possible accept terminal sequences of length d and $r \in \Sigma^*$ denote the remainder. Suppose for any $t \in V, d > len(t)$ and $m = GrammarMask(\mathcal{A}_d, r)$ such that $t \in set(m)$ then $C_k.t \in L_p(G)$*

For the simplicity of presenting the proof, we assume that $d > 2$.
Since $t \in set(m)$ for some $\Lambda_1 = \{\tau_{f+1}, \tau_{f+2} \dots \tau_{f+d}\} \in \mathcal{A}$

$$\implies dmatch(t, q, \{\tau_{f+2} \dots \tau_{f+d}\}) \implies dmatch(r.t, q_0^{\tau_{f+1}}, \{\tau_{f+2} \dots \tau_{f+d}\})$$
$$\implies pmatch(r.t, \{\rho_{\tau_{f+1}}.\rho_{\tau_{f+2}} \dots \rho_{\tau_{f+d}}\})$$

By Definition 4.6, there are two possible cases:

(1) $\exists w_1 \in \Sigma^*, w_2 \in \Sigma^+$ such that $r.t = w_1.w_2$ and $w_1 \in L(\rho_{\tau_{f+1}}.\rho_{\tau_{f+2}} \dots \rho_{\tau_{f+d}})$
We show that this case is not possible since our terminal sequence Λ_1 is long enough that no prefix of $r.t$ cannot be in $L(\rho_{\tau_{f+1}}.\rho_{\tau_{f+2}} \dots \rho_{\tau_{f+d}})$
We can infer that $len(w_1) < len(r.t) \implies len(w_1) < len(r) + len(t)$
Further, from the assumption $d > len(t)$, we have

$$len(w_1) < d + len(r)$$

Firstly, note that $r \notin L(\rho_{\tau_{f+1}}.\rho_{\tau_{f+2}})$ by the definition of remainder r
Note that we assume no terminal contains empty string i.e. $\epsilon \notin L(\rho_{\tau_i})$
Hence, every string in $L(\rho_{\tau_{f+2}} \dots \rho_{\tau_{f+d}})$ should have length at least $d - 1$

Clearly, r is prefix of w_1. Let $w_3 \in \Sigma^*$, $r.w_3 = w_1$ and hence $len(w_3) > d - 1$
Hence,

$$len(r) + d - 1 < len(w_1)$$
$$len(r) + d - 1 < len(w_1) < d + len(r)$$

This is not possible and hence such w_1 cannot exist.

(2) $\exists w_1 \in \Sigma^*$ such that $r.t.w_1 \in L(\rho_{\tau_{f+1}}.\rho_{\tau_{f+2}} \dots \rho_{\tau_{f+d}})$
By Definition 4.3, we have $\Lambda_0, r = pparse(C_k)$ s.t $C_k = C^0.r$, $\Lambda_0 = \tau_1, \tau_2 \dots \tau_f$ $C^0 \in L(\rho_{\tau_1}.\rho_{\tau_2} \dots \rho_{\tau_f})$.
Let $\Lambda_1 = \tau_{f+1}, \tau_{f+2} \dots \tau_{f+d}$
Since, $C_k.t = C^0.r.t$, $C^0 \in L(\Lambda_0)$ and $r.t.w_1 \in L(\Lambda_1)$, we have

$$C^0.r.t.w_1 \in L(\Lambda_0.\Lambda_1)$$
$$C_k.t.w_1 \in L(\Lambda_0.\Lambda_1)$$

By Definition 4.5 of accept sequence, $\Lambda_0.\Lambda_1 \in L_p^\Gamma(G)$, Hence

$$C_k.t.w_1 \in L_p(G) \implies C_k.t \in L_p(G)$$

Thus, our proof is complete and $C_k.t \in L_p(G)$

A.3 Incremental Parsing Algorithm

Our parsing algorithm achieves incrementality in LLM generation by utilizing a map $\mathcal{S}$ to store the parser state. This map associates a list of lexical tokens with the corresponding parser state after parsing those tokens. Frequently, in subsequent LLM generation iterations, the count of lexical tokens remains the same—either the next vocabulary token is appended to the final lexical token, or it increases. Although uncommon, there are cases where the number of parsed lexical tokens may decrease during iterations. For example, in Python, an empty pair of double quotes, "", is recognized as a complete lexical token representing an empty string. On the other hand, """ serves as a prefix to a docstring, constituting an incomplete parser token. Consequently, the addition of a single double quote " reduces the overall count of lexical tokens in these iterations. We observe that while the total count of lexer tokens at the end may undergo slight changes during these iterations, the majority of prefixes of the parsed lexical tokens remain consistent. Hence, we establish a mapping between lists of prefixes of lexical tokens and the corresponding parser state after parsing those tokens. Subsequently, when parsing a new list of lexer tokens, we efficiently determine the maximum length prefix of the lexer token list that is already present in $\mathcal{S}$. This incremental approach significantly reduces the complexity of our parsing algorithm.

Algorithm 4 Incremental Parsing

```
Inputs: $C_k$: partial output, $\mathcal{S}$: state map
function PARSE($C_k$)
    $l_1, l_2 \dots l_f \leftarrow Lex(C_k)$
    $\gamma, S_\gamma \leftarrow \text{RestoreState}(\mathcal{S}, L)$
    $P \leftarrow \text{Initialize}(S_\gamma)$
    $parsed \leftarrow l_1.l_2 \dots l_{\gamma-1}$
    for $l_i \in l_\gamma, l_{\gamma+1} \dots l_f$ do
        $Next(P, l_i)$
        if $P.state = Error$ then
            break
        $parsed \leftarrow parsed + l_i$
        $A_0 \leftarrow A_1$
        $A_1 \leftarrow Follow(P)$
        $S_i \leftarrow P.state$
        $\text{Store}(\mathcal{S}, parsed, S_i)$
    if $C_k = parsed$ then
        $r = l_f$
        $\mathcal{A} \leftarrow \{\tau_f, A_1[0]\}, \{\tau_f, A_1[1]\} \dots\}$
            $\cup\{A_0[0]\}, \{A_0[1]\} \dots\}$
    else
        $r = C_k - parsed$
        $\mathcal{A} \leftarrow \{A_1[0]\}, \{A_1[1]\} \dots$
    return $\mathcal{A}, r$
```

While it could be feasible to introduce incrementality in the lexing operation, our experiments revealed that lexing consumes insignificant time in comparison to parsing. As a result, we opted to focus only on performing parsing incrementally.

Our incremental parsing algorithm uses a standard non-incremental base parser P that maintains a parser state and supports two functions *Next* and *Follow*. The *Next* function accepts the next lexer token and then updates the parser state. The *Follow* function returns a list of acceptable terminals at the current parser state. These functions are present in common parser generator tools [4, 17].

The Algorithm 4 presents our incremental parsing algorithm. The algorithm utilizes a lexer to tokenize the partial output. The function RestoreState is used to restore the state of the parser to the maximal matching prefix of lexical tokens that exist in $\mathcal{S}$. The main loop iterates through the tokens and maintains a parser state map. For each token, it updates the parser state, stores the mapping in $\mathcal{S}$, and retrieves the next set of acceptable terminals. The process continues until the end of the partial output. The algorithm returns accept sequences $\mathcal{A}$ and remainder r.

Table 8. SynCode on few-shot prompting

Architecture	Error Type	Standard	SynCode	↓
CodeGen-350M	Syntax	53	0	100%
	Indentation	15	3	80%
WizardCoder-1B	Syntax	40	2	95%
	Indentation	22	1	95%
Llama-7B	Syntax	110	0	100%
	Indentation	40	5	88%

A.4 Evaluation Models

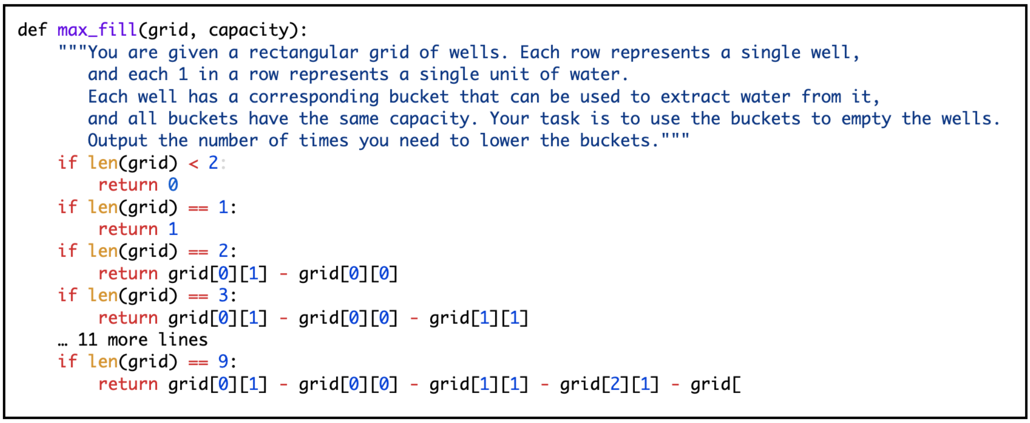
CodeGen-350M-multi [23]. It is a member of the CodeGen series. With its 28-layer architecture, it has 350M parameters, a hidden state size of 4096, 16 attention heads, and a diverse vocabulary of 50400 tokens. It is pre-trained on the BigQuery dataset [23], which encompasses open-source code from six programming languages, including C, C++, Java, JavaScript, Go, and Python.
WizardCoder-1B [21]. It is fine-tuned from StarCoder[18]. It employs the Evol-Instruct [37] methodology for refining the training dataset, ensuring simpler and more consistent prompts. The model features 24 transformer layers, 2048-dimensional hidden states, 16 attention heads, over 1B parameters, and a vocabulary count of 49153.
Llama-7B [32]. It is from the Llama model family and engineered for advanced natural language processing tasks, including code synthesis. The model is structured with 32 transformer layers, 4096-dimensional hidden states, 32 attention heads, 7 billion parameters, and a diverse vocabulary of 32000 tokens. Its pre-training regime encompasses a diverse set of data sources such as CommonCrawl, C4, Github, Wikipedia, Books, ArXiv, and StackExchange.

A.5 Few-Shot Prompting

Few-shot prompting [29] refers to the idea that language models do not need to be specifically trained for a downstream task such as classification or question answering. Rather, it is sufficient to train them on broad text-sequence prediction datasets and to provide context in the form of examples when invoking them. We study the performance of utilizing SynCode on few-shot prompting code generation tasks. We selected Python few-shot examples from the MBXP dataset and generated code completions with CodeGen-350M, LLaMA-7B, and WizardCoder-1B with SynCode and the standard no-masking generation. We present our results in Table 8. The columns standard and SynCode represent the total number of errors of a particular Error Type of LLM-generated code completions to problems in a particular dataset when utilizing that respective generation approach. The column ↓ represents the percentage reduction from the standard column to the SynCode column. As shown in the table, SynCode exhibits effectiveness not only in zero-shot but also in the context of few-shot prompting tasks. This signifies the versatility of SynCode in enhancing code generation across different prompt engineering techniques.

A.6 SynCode Syntax Errors

Figure 11 presents an example of when the SynCode augmented LLM fails to generate a complete program within the maximum token limit for a problem from the HumanEval dataset. While the code is a syntactically correct partial program, it is not a syntactically correct complete program. Recall, that SynCode guarantees completeness for syntactically correct partial programs but does not guarantee termination with a syntactically correct complete program.



```
def max_fill(grid, capacity):
    """You are given a rectangular grid of wells. Each row represents a single well,
       and each 1 in a row represents a single unit of water.
       Each well has a corresponding bucket that can be used to extract water from it,
       and all buckets have the same capacity. Your task is to use the buckets to empty the wells.
       Output the number of times you need to lower the buckets."""
    if len(grid) < 2:
        return 0
    if len(grid) == 1:
        return 1
    if len(grid) == 2:
        return grid[0][1] - grid[0][0]
    if len(grid) == 3:
        return grid[0][1] - grid[0][0] - grid[1][1]
    … 11 more lines
    if len(grid) == 9:
        return grid[0][1] - grid[0][0] - grid[1][1] - grid[2][1] - grid[
```

Fig. 11. Syntactically Incorrect SynCode Program

A.7 Prompts Used in the Evaluation

```
<s>[INST] <<SYS>>
You are a helpful assistant that answers in JSON. Here's the json schema you must
     adhere to:
<schema>
{'title': 'Person', 'type': 'object', 'properties': {'firstName': {'type': 'string
     ', 'description': "The person's first name."}, 'lastName': {'type': 'string',
      'description': "The person's last name."}, 'age': {'description': 'Age in
     years which must be equal to or greater than zero.', 'type': 'integer', '
     minimum': 0}}, 'required': ['firstName', 'lastName', 'age']}
</schema>

<</SYS>>

Please generate a JSON output for a person's profile that includes their first
     name, last name, and age. The first name should be 'Alice', the last name '
     Johnson', and the age 35. [/INST]
```

Listing 1. Example original JSON Prompt from the JSON-Mode-Eval dataset [24]. The prompt consists of a system message that specifies a schema and a user message requesting JSON output given certain parameters.

```
<s>[INST] <<SYS>>
You are a helpful assistant that answers in JSON. Here's the json schema you must
     adhere to:
<schema>
{'title': 'Person', 'type': 'object', 'properties': {'firstName': {'type': 'string
     ', 'description': "The person's first name."}, 'lastName': {'type': 'string',
      'description': "The person's last name."}, 'age': {'description': 'Age in
     years which must be equal to or greater than zero.', 'type': 'integer', '
     minimum': 0}}, 'required': ['firstName', 'lastName', 'age']}
</schema>

<</SYS>>

Please generate a JSON output for a person's profile that includes their first
     name, last name, and age. The first name should be 'Alice', the last name '
     Johnson', and the age 35. Output only JSON. [/INST]
```

Listing 2. Example JSON prompt from the JSON-Mode-Eval dataset [24] after augmentation with an explicit request to only output JSON.

```
def has_close_elements(numbers: List[float], threshold: float) -> bool:
    """ Check if in given list of numbers, are any two numbers closer to each
         other than
    given threshold.
    >>> has_close_elements([1.0, 2.0, 3.0], 0.5)
    False
    >>> has_close_elements([1.0, 2.8, 3.0, 4.0, 5.0, 2.0], 0.3)
    True
    """
```

Listing 3. Example Python prompt from the HumanEval dataset [5]

```
package main

import (
  "encoding/json"
  "reflect"
)
// You're an expert Golang programmer
// Check if in given list of numbers, are any two numbers closer to each other
     than
// given threshold.
// >>> has_close_elements([1.0, 2.0, 3.0], 0.5)
// False
// >>> has_close_elements([1.0, 2.8, 3.0, 4.0, 5.0, 2.0], 0.3)
// True
//
func has_close_elements (numbers []float64, threshold float64) bool {
```

Listing 4. Example Go prompt from the HumanEval dataset [5]

A.8 Grammars Used in the Evaluation

A.8.1 JSON Grammar.

```
?start: value

?value: object
| array
| UNESCAPED_STRING
| SIGNED_NUMBER      -> number
| "true"             -> true
| "false"            -> false
| "null"             -> null

array  : "[" [value ("," value)*] "]"
object : "{" [pair ("," pair)*] "}"
pair   : UNESCAPED_STRING ":" value

UNESCAPED_STRING: /\"[^"]*\"/

DIGIT: "0".."9"
HEXDIGIT: "a".."f"|"A".."F"|DIGIT
INT: DIGIT+
SIGNED_INT: ["+"|"-"] INT
DECIMAL: INT "." INT? | "." INT


_EXP: ("e"|"E") SIGNED_INT
FLOAT: INT _EXP | DECIMAL _EXP?
NUMBER: FLOAT | INT
SIGNED_NUMBER: ["+"|"-"] NUMBER
WS: /[ \t\f\r\n]/+

%ignore WS
```

Listing 5. JSON Grammar

A.8.2 Python Grammar.

```
single_input: _NL | simple_stmt | compound_stmt _NL
start: (_NL | stmt)*
eval_input: testlist _NL*

!decorator: "@" dotted_name [ "(" [arguments] ")" ] _NL
decorators: decorator+
decorated: decorators (classdef | funcdef | async_funcdef)

async_funcdef: "async" funcdef
funcdef: "def" NAME "(" parameters? ")" ["->" test] ":" ( suite | _NL)

!parameters: paramvalue ("," paramvalue)* ["," [ starparams | kwparams]]
          | starparams
          | kwparams
starparams: "*" typedparam? ("," paramvalue)* ["," kwparams]
kwparams: "**" typedparam

?paramvalue: typedparam ["=" test]
?typedparam: NAME [":" test]

!varargslist: (vfpdef ["=" test] ("," vfpdef ["=" test])* ["," [ "*" [vfpdef] ("," vfpdef ["=" test])* ["," ["**" vfpdef [","]]] | "**" vfpdef [","]]]
  | "*" [vfpdef] ("," vfpdef ["=" test])* ["," ["**" vfpdef [","]]]
  | "**" vfpdef [","])

vfpdef: NAME

?stmt: (simple_stmt | compound_stmt ) ["eof"]
!?simple_stmt: small_stmt (";" small_stmt)* [";"] _NL
?small_stmt: (expr_stmt | del_stmt | pass_stmt | flow_stmt | import_stmt | global_stmt | nonlocal_stmt | assert_stmt)
?expr_stmt: testlist_star_expr (annassign | augassign (yield_expr|testlist)
         | ("=" (yield_expr|testlist_star_expr))*)
annassign: ":" test ["=" test]
!?testlist_star_expr: (test|star_expr) ("," (test|star_expr))* [","]
!augassign: ("+=" | "-=" | "*=" | "@=" | "/=" | "%=" | "&=" | "|=" | "^=" | "<<=" | ">>=" | "**=" | "//=")
// For normal and annotated assignments, additional restrictions enforced by the interpreter
del_stmt: "del" exprlist
pass_stmt: "pass"
flow_stmt: break_stmt | continue_stmt | return_stmt | raise_stmt | yield_stmt
break_stmt: "break"
continue_stmt: "continue"
return_stmt: "return" [testlist]
yield_stmt: yield_expr
raise_stmt: "raise" [test ["from" test]]
import_stmt: import_name | import_from
import_name: "import" dotted_as_names
// note below: the ("." | "...") is necessary because "..." is tokenized as ELLIPSIS
import_from: "from" (dots? dotted_name | dots) "import" ("*" | "(" import_as_names ")" | import_as_names)
!dots: "."+
import_as_name: NAME ["as" NAME]
dotted_as_name: dotted_name ["as" NAME]
!import_as_names: import_as_name ("," import_as_name)* [","]
dotted_as_names: dotted_as_name ("," dotted_as_name)*
dotted_name: NAME ("." NAME)*
global_stmt: "global" NAME ("," NAME)*
nonlocal_stmt: "nonlocal" NAME ("," NAME)*
assert_stmt: "assert" test ["," test]

compound_stmt: if_stmt | while_stmt | for_stmt | try_stmt | with_stmt | funcdef | classdef | decorated | async_stmt
async_stmt: "async" (funcdef | with_stmt | for_stmt)
if_stmt: "if" test ":" suite ("elif" test ":" suite)* ["else" ":" suite]
while_stmt: "while" test ":" suite ["else" ":" suite]
for_stmt: "for" exprlist "in" testlist ":" suite ["else" ":" suite]
```

```
try_stmt: ("try" ":" suite ((except_clause ":" suite)+ ["else" ":" suite] ["finally" ":" suite] | "finally" ":" suite))
with_stmt: "with" with_item ("," with_item)*  ":" suite
with_item: test ["as" expr]
// NB compile.c makes sure that the default except clause is last
except_clause: "except" [test ["as" NAME]]
suite: simple_stmt | _NL _INDENT stmt+ _DEDENT

?test: or_test ["if" or_test "else" test] | lambdef
?test_nocond: or_test | lambdef_nocond
lambdef: "lambda" [varargslist] ":" test
lambdef_nocond: "lambda" [varargslist] ":" test_nocond
?or_test: and_test ("or" and_test)*
?and_test: not_test ("and" not_test)*

?not_test: "not" not_test -> not
         | comparison
?comparison: expr (_comp_op expr)*
star_expr: "*" expr
?expr: xor_expr ("|" xor_expr)*
?xor_expr: and_expr ("^" and_expr)*
?and_expr: shift_expr ("&" shift_expr)*
?shift_expr: arith_expr (_shift_op arith_expr)*
?arith_expr: term (_add_op term)*
?term: factor (_mul_op factor)*
?factor: _factor_op factor | power

!_factor_op: "+"|"-"|"~"
!_add_op: "+"|"-"
!_shift_op: "<<"|">>"
!_mul_op: "*"|"@"|"/"|"%"|"//"
// <> isn't actually a valid comparison operator in Python. It's here for the
// sake of a __future__ import described in PEP 401 (which really works :-)
!_comp_op: "<"|">"|"=="|">="|"<="|"<>"|"!="|"in"|"not" "in"|"is"|"is" "not"

?power: await_expr ["**" factor]
!await_expr: ["await"] atom_expr

?atom_expr: atom_expr "(" [arguments] ")"      -> funccall
          | atom_expr "[" subscriptlist "]"  -> getitem
          | atom_expr "." NAME               -> getattr
          | atom

?atom: "(" [yield_expr|testlist_comp] ")" -> tuple
     | "[" [testlist_comp] "]"  -> list
     | "{" [dictorsetmaker] "}" -> dict
     | NAME -> var
     | number | string+
     | "(" test ")"
     | "..." -> ellipsis
     | "None"    -> const_none
     | "True"    -> const_true
     | "False"   -> const_false

!?testlist_comp: (test|star_expr) [comp_for | ("," (test|star_expr))+ [","] | ","]
!subscriptlist: subscript ("," subscript)* [","]
subscript: test | [test] ":" [test] [sliceop]
sliceop: ":" [test]
!exprlist: (expr|star_expr) ("," (expr|star_expr))* [","]
!testlist: test ("," test)* [","]
!dictorsetmaker: ( ((test ":" test | "**" expr) (comp_for | ("," (test ":" test | "**" expr))* [","])) | ((test | star_expr) (comp_for | ("," (test | star_expr))* [","])) )

classdef: "class" NAME ["(" [arguments] ")"] ":" suite
!arguments: argvalue ("," argvalue)*  ["," [ starargs | kwargs]]
         | starargs
         | kwargs
         | test comp_for

!starargs: "*" test ("," "*" test)* ("," argvalue)* ["," kwargs]
```

```
kwargs: "**" test

?argvalue: test ["=" test]

comp_iter: comp_for | comp_if | async_for
async_for: "async" "for" exprlist "in" or_test [comp_iter]
comp_for: "for" exprlist "in" or_test [comp_iter]
comp_if: "if" test_nocond [comp_iter]

// not used in grammar, but may appear in "node" passed from Parser to Compiler
encoding_decl: NAME

yield_expr: "yield" [yield_arg]
yield_arg: "from" test | testlist


number: DEC_NUMBER | HEX_NUMBER | OCT_NUMBER | FLOAT_NUMBER

string: STRING | LONG_STRING

// Tokens
NAME: /[a-zA-Z_]\w*/
COMMENT: /#.*(\n[\t ]*)+/ | LONG_STRING
_NL: ( /(\r?\n[\t ]*)+/ | COMMENT)+

LONG_STRING: /[ubf]?r?("""(?<!\\).*?"""|'''(?<!\\).*?''')/is

DEC_NUMBER: /0|[1-9]\d*/i
HEX_NUMBER.2: /0x[\da-f]*/i
OCT_NUMBER.2: /0o[0-7]*/i
BIN_NUMBER.2 : /0b[0-1]*/i
FLOAT_NUMBER.2: /((\d+\.\d*|\.\d+)(e[-+]?\d+)?|\d+(e[-+]?\d+))/i

%import common.WS_INLINE

%declare _INDENT _DEDENT
%ignore WS_INLINE
%ignore /\\[\t \f]*\r?\n/   // LINE_CONT
%ignore COMMENT
```

Listing 6. Python Grammar

A.8.3 Go Grammar.

```

start: package_clause eos (import_decl eos)* ((function_decl | method_decl |
     declaration) eos "eoc"?)*

package_clause: "package" NAME

import_decl: "import"  (import_spec | "(" (import_spec eos)* ")")

import_spec: ("." | NAME)? import_path

import_path: string_

declaration: const_decl | type_decl | var_decl

const_decl: "const"  (const_spec | "(" (const_spec eos)* ")")

const_spec: identifier_list (type_? "=" expression_list)?

identifier_list: NAME ("," NAME)*

expression_list: expression ("," expression)*

type_decl: "type" (type_spec | "(" (type_spec eos)* ")")

type_spec: alias_decl | type_def

alias_decl : NAME "=" type_

type_def : NAME type_parameters? type_

type_parameters : "[" type_parameter_decl ("," type_parameter_decl)* "]"

type_parameter_decl : identifier_list type_element

type_element : type_term ("|" type_term)*

type_term : "~"? type_

// Function declarations

function_decl: "func" NAME type_parameters? signature ("{" statement_list? ("}" |
     "eof"))?

method_decl: "func" receiver NAME signature block?

receiver: parameters

var_decl: "var" (var_spec | "(" (var_spec eos)* ")")

var_spec: identifier_list (type_ ("=" expression_list)? | "=" expression_list)

block: "{" statement_list? "}"

statement_list: ((";"? | EOS?) statement eos)+

statement: declaration | labeled_stmt | simple_stmt | go_stmt | return_stmt |
     break_stmt | continue_stmt | goto_stmt | fallthrough_stmt | block | if_stmt |
      switch_stmt | select_stmt | for_stmt | defer_stmt

simple_stmt: send_stmt | inc_dec_stmt | assignment | expression | short_var_decl

send_stmt: expression  "<-" expression

inc_dec_stmt: expression ("++" | "--")

assignment: expression assign_op expression | expression_list "=" expression_list

assign_op: "+=" | "-=" | "|=" | "^=" | "*=" | "/=" | "%=" | "<<=" | ">>=" | "&=" |
      "&^="
```

```

short_var_decl: expression_list ":=" expression_list

labeled_stmt: NAME ":" statement?

return_stmt: "return" expression_list?

break_stmt: "break" NAME?

continue_stmt: "continue" NAME?

goto_stmt: "goto"  NAME

fallthrough_stmt: "fallthrough"

defer_stmt: "defer" expression

if_stmt: "if"  ( expression | eos expression | simple_stmt eos expression) block
     ("else" (if_stmt | block))?

switch_stmt: expr_switch_stmt | type_switch_stmt

expr_switch_stmt: "switch"  (expression? | simple_stmt? eos expression?) "{"
     expr_case_clause* "}"

expr_case_clause: expr_switch_case ":" statement_list?

expr_switch_case: "case" expression_list | "default"

type_switch_stmt: "switch"  ( type_switch_guard | eos type_switch_guard |
     simple_stmt eos type_switch_guard) "{" type_case_clause* "}"

type_switch_guard: (NAME ":=")? NAME "." "(" "type"  ")"

type_case_clause: type_switch_case ":" statement_list?

type_switch_case: "case" type_list | "default"

type_list: (type_ | "nil" ) ("," (type_ | "nil"  ))*

select_stmt: "select" "{" comm_clause* "}"

comm_clause: comm_case ":" statement_list?

comm_case: "case" (send_stmt | recv_stmt) | "default"

recv_stmt: (expression_list "=" | identifier_list ":=")? expression

for_stmt: "for" [for_clause] block

for_clause: simple_stmt (eos expression eos simple_stmt)? | range_clause

range_clause: (expression_list "=" | expression_list ":=") "range"  expression

go_stmt: "go"expression

type_: literal_type | var_or_type_name type_args? | "(" type_ ")"

channel_type

type_args : "--"

var_or_type_name: NAME "." NAME | NAME | NAME "." "(" type_ ")"

array_type: "[" array_length "]" element_type

array_length: expression

element_type: type_

pointer_type: "*" type_
```

```

interface_type: "interface" "{" ((method_spec | type_element ) eos)* "}"

slice_type: "[" "]" element_type

// It's possible to replace `type` with more restricted type_lit list and also pay attention to nil maps
map_type: "map" "[" type_ "]" element_type

channel_type: ("'chan"  | "chan"   "<-" |  "<-" "chan" ) element_type

method_spec: NAME parameters result | NAME parameters

function_type: "func" signature

signature: parameters result?

result: parameters | type_

parameters: "(" parameter_decl ("," parameter_decl)* ","? ")" | "(" ")"

// a comma-separated list of either (a) name, (b) type, or (c) name and type
// parameter_decl: identifier_list? "..."? type_


// Although following is overapproximate it's an easy way to avoid reduce/reduce conflicts
parameter_decl: (type_ | "..."? type_ | NAME type_)


expression: primary_expr
            | ("+" | "-" | "!" | "^" | "*" | "&" | "<-") expression
            | expression ("*" | "/" | "%" | "<<" | ">>" | "&" | "&^") expression
            | expression ("+" | "-" | "|" | "^") expression
            | expression ("==" | "!=" | "<" | "<=" | ">" | ">=") expression
            | expression "&&" expression
            | expression "||" expression

primary_expr: operand | primary_expr ("." (NAME | "(" type_ ")") | index | slice_ | arguments) | type_

// Giving operand higher precedence than type_ is a hack to avoid reduce/reduce conflicts
operand.3: literal | NAME | "(" expression ")" // removed NAME type_args?

literal: basic_lit | composite_lit | function_lit

basic_lit: "nil" | integer | string_ | FLOAT_LIT | CHAR_LIT

integer: DECIMAL_LIT | BINARY_LIT | OCTAL_LIT | HEX_LIT

DECIMAL_LIT: /0|[1-9]\d*/i
HEX_LIT.2: /0x[\da-f]*/i
OCTAL_LIT.2: /0o[0-7]*/i
BINARY_LIT.2 : /0b[0-1]*/i
FLOAT_LIT.2: /((\d+\.\d*|\.\d+)(e[-+]?\d+)?|\d+(e[-+]?\d+))/i
CHAR_LIT: /'.'/i

composite_lit: literal_type literal_value

literal_type: struct_type | array_type | "[" "..." "]" element_type | slice_type | map_type  | "interface" "{" "}"

literal_value: "{" (element_list ","?)? "}"

element_list: keyed_element ("," keyed_element)*

keyed_element: (key ":")? element

key: expression | literal_value

```

```
element: expression | literal_value

struct_type: "struct" "{" (field_decl eos)* "}"

field_decl: (identifier_list type_ | embedded_field) string_?

string_: RAW_STRING_LIT | INTERPRETED_STRING_LIT

RAW_STRING_LIT: /`.*?`/
INTERPRETED_STRING_LIT: /".*?"/i

embedded_field: "*"? (NAME "." NAME | NAME)  type_args?

function_lit: "func" signature block // function

index: "[" expression "]"

slice_: "[" ( expression? ":" expression? | expression? ":" expression ":"
     expression) "]"

type_assertion: "." "(" type_ ")"

arguments: "(" ( expression_list? "..."? ","?)? ")"

eos: ";" | EOS // | {this.closingBracket()}?

NAME : /[a-zA-Z_]\w*/
EOS: _NL | ";" | "/*' .*? '*/"

COMMENT : /\/\/[^\n]*/
_NL: ( /(\r?\n[\t ]*)+/ | COMMENT)+

%ignore /[\t ]/
%ignore /\\[\t \f]*\r?\n/   // LINE_CONT
```

Listing 7. Go Grammar