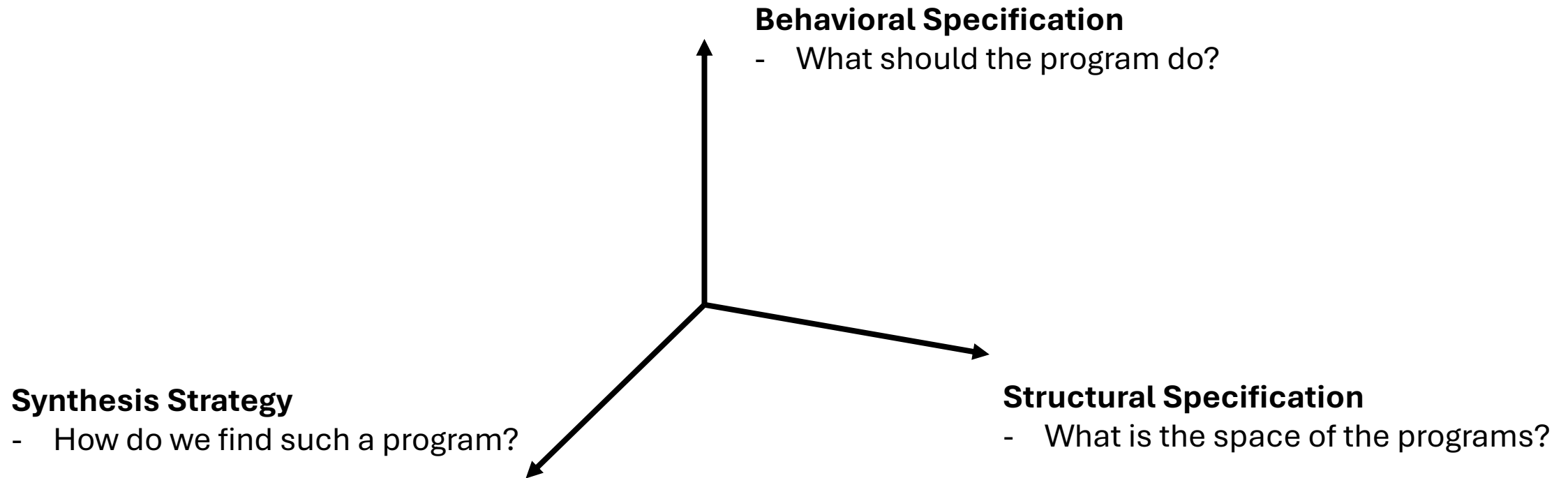


Machine Programming

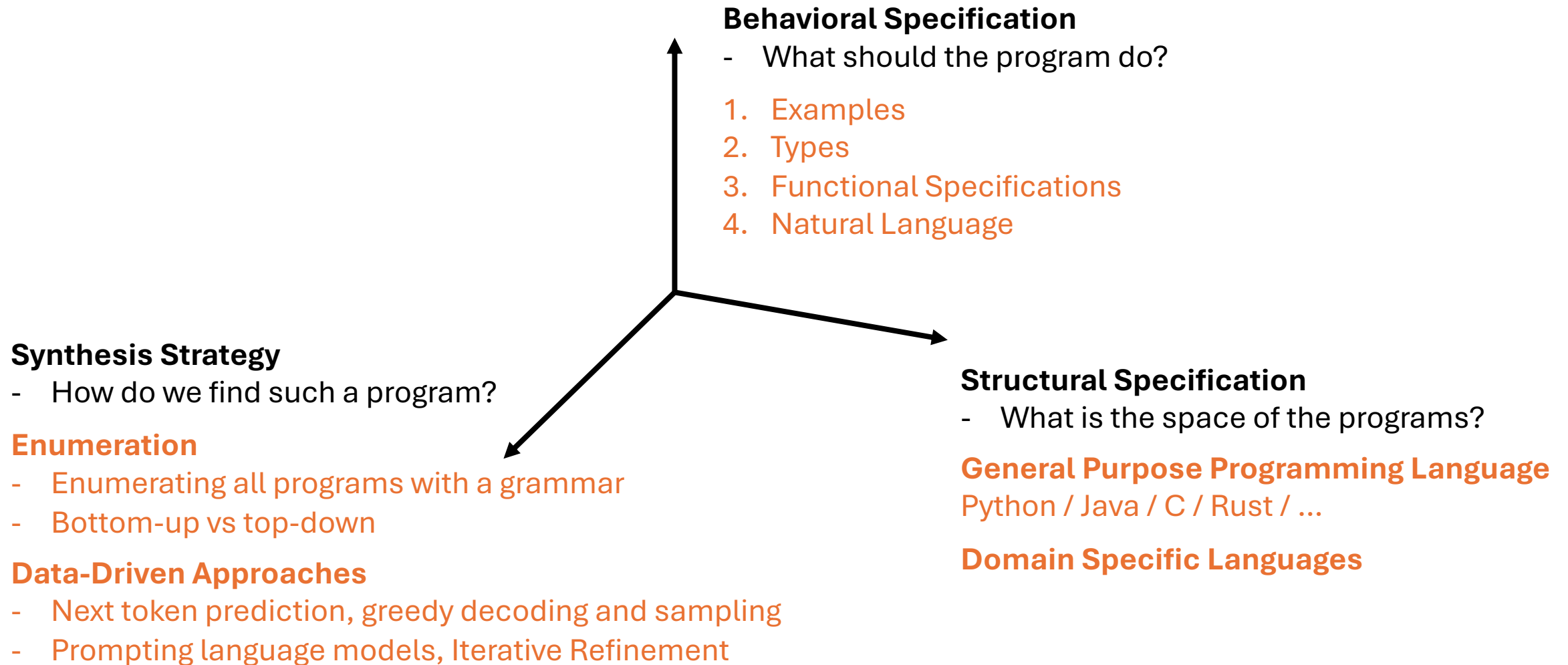
Lecture 8 – Controlled Decoding and Steering

Ziyang Li

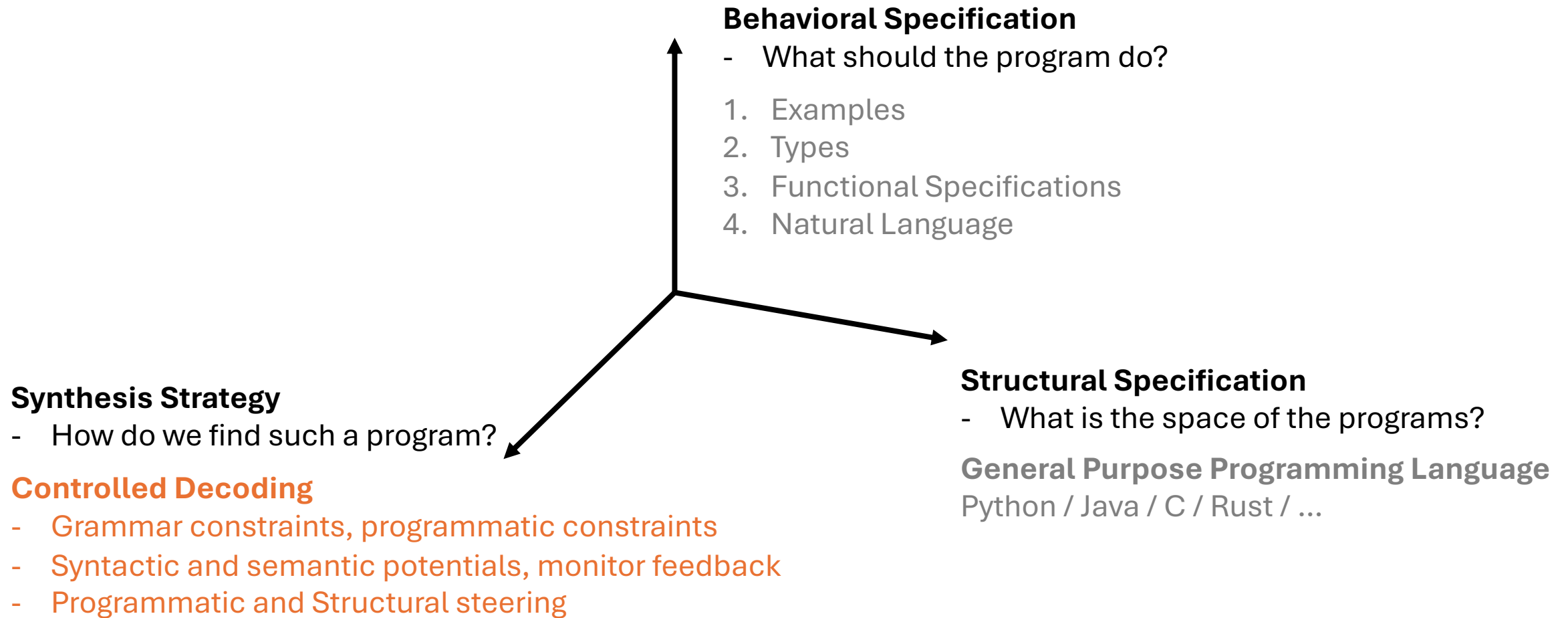
Dimensions in Program Synthesis



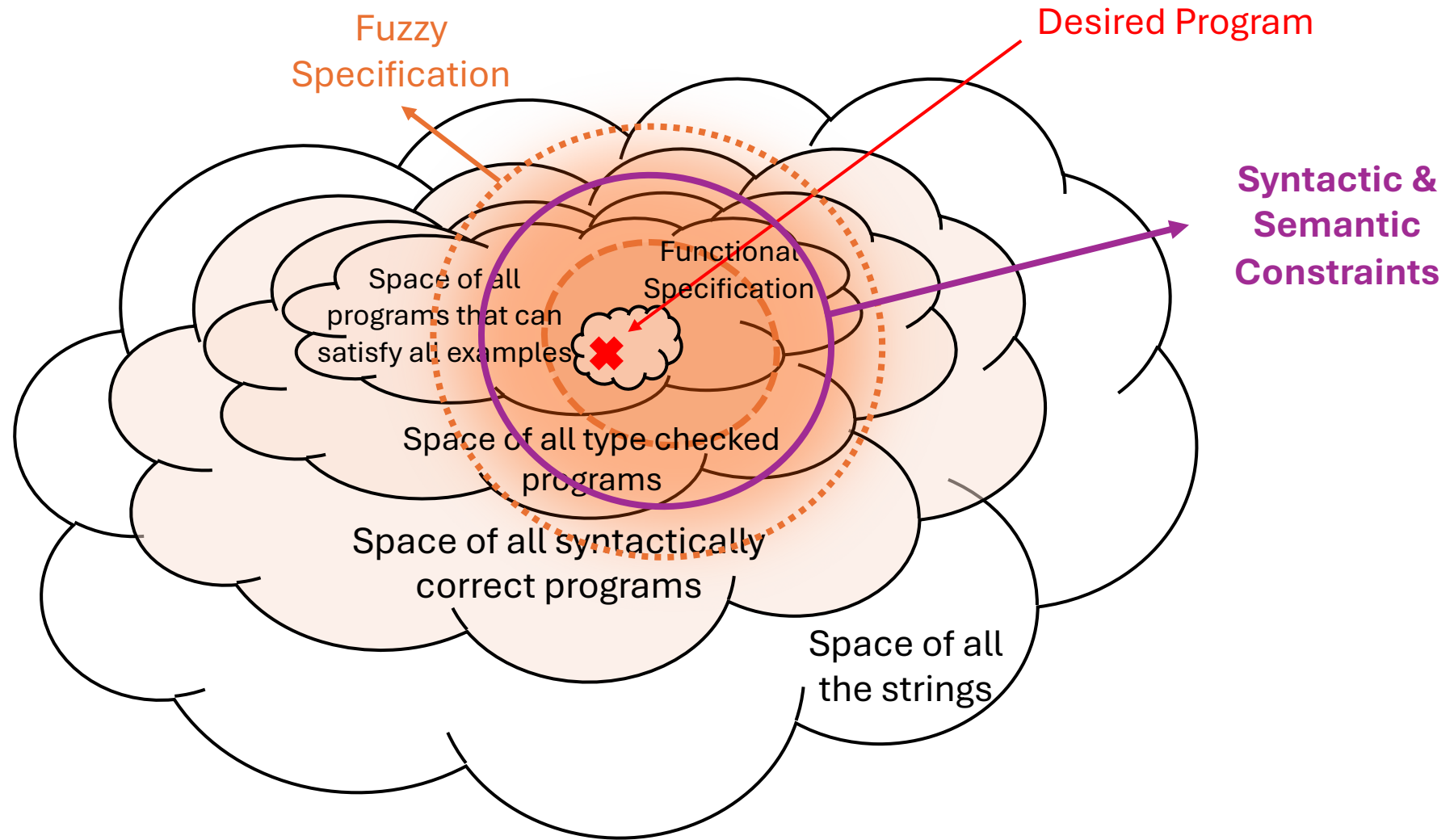
The Course So Far



Today



High Level Picture



High Level Picture

- We studied foundations of programming languages and synthesis
 - Syntax (regular tree grammar), Semantics (denotational, operational)
 - Enumeration (top-down, bottom-up) that searches within grammar
- We studied basic usage of language models
 - Purely neural: next token prediction → sequential decoding
 - Prompting and iterative refinement: elicit better programs from LLM
- Question:
 - Can we inject more **structure** during **neural** generation process

Review: Syntax in Regular Tree Grammar

```
(Program) P ::= L | N
(List) L ::= input
           | empty
           | single(N)
           | concat(L, L)
(Number) N ::= len(L)
            | min(L)
            | add(N, N)
            | 0 | 1 | 2 | ...
```

Review: Syntax in Regular Tree Grammar

(Program) $P ::= L \mid N$
(List) $L ::= \text{input}$
 $\mid \text{empty}$
 $\mid \text{single}(N)$
 $\mid \text{concat}(L, L)$
(Number) $N ::= \text{len}(L)$
 $\mid \text{min}(L)$
 $\mid \text{add}(N, N)$
 $\mid 0 \mid 1 \mid 2 \mid \dots$



(Program) $P ::= L \mid N$
(List) $L ::= \text{input}$
 $\mid []$
 $\mid [N]$
 $\mid L ++ L$
(Number) $N ::= \text{len}(L)$
 $\mid \text{min}(L)$
 $\mid N + N$
 $\mid 0 \mid 1 \mid 2 \mid \dots$

Review: Syntax in Context Free Grammar

```
(Program) P ::= L | N
(List) L ::= input
           | empty
           | single(N)
           | concat(L, L)
(Number) N ::= len(L)
            | min(L)
            | add(N, N)
            | 0 | 1 | 2 | ...
```



```
(Program) P <- L | N
(List) L <- 'input'
           | '[' ']'
           | '[' N ']'
           | L '++' L
(Number) N <- 'len' '(' L ')'
            | 'min' '(' L ')'
            | N '+' N
            | '0' | '1' | '2' | ...
```

From Program to Abstract Syntax Tree

Concrete Program

```
min(input ++ [0])
```

Concrete Grammar (Context Free Grammar)

```
(Program) P <- L | N
(List) L <- 'input'
          | '[' ']'
          | '[' N ']'
          | L '++' L
(Number) N <- 'len' '(' L ')'
            | 'min' '(' L ')'
            | N '+' N
            | '0' | '1' | '2' | ...
```

Abstract Grammar (Regular Tree Grammar)

```
(Program) P ::= L | N
(List) L ::= input
          | empty
          | single(N)
          | concat(L, L)
(Number) N ::= len(L)
            | min(L)
            | add(N, N)
            | 0 | 1 | 2 | ...
```

From Program to Abstract Syntax Tree

Concrete Program

`min(input ++ [0])`



Token Sequence

`['min', '(', 'input', '++', '[', '0', ']']`

Concrete Grammar (Context Free Grammar)

```
(Program) P <- L | N
(List) L <- 'input'
          | '[' ']'
          | '[' N ']'
          | L '++' L
(Number) N <- 'len' '(' L ')'
            | 'min' '(' L ')'
            | N '+' N
            | '0' | '1' | '2' | ...
```

Abstract Grammar (Regular Tree Grammar)

```
(Program) P ::= L | N
(List) L ::= input
          | empty
          | single(N)
          | concat(L, L)
(Number) N ::= len(L)
            | min(L)
            | add(N, N)
            | 0 | 1 | 2 | ...
```

From Program to Abstract Syntax Tree

Concrete Program

`min(input ++ [0])`

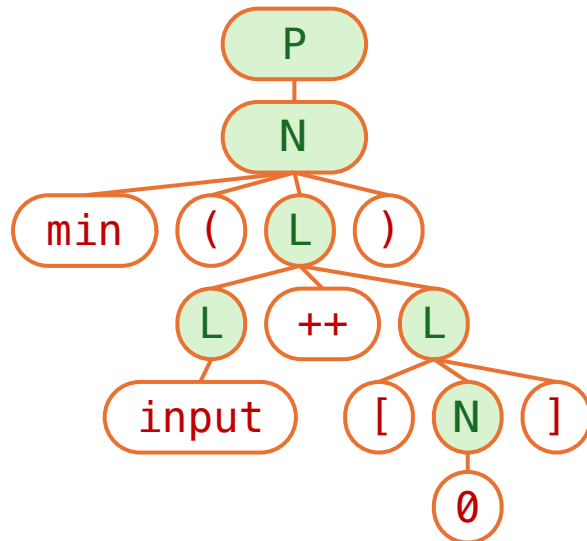


Token Sequence

`['min', '(', 'input', '++', '[', '0', ']']`



Concrete Syntax Tree



Concrete Grammar (Context Free Grammar)

```
(Program) P <- L | N
(List) L <- 'input'
          | '[' ']'
          | '[' N ']'
          | L '++' L
(Number) N <- 'len' '(' L ')'
            | 'min' '(' L ')'
            | N '+' N
            | '0' | '1' | '2' | ...
```

Abstract Grammar (Regular Tree Grammar)

```
(Program) P ::= L | N
(List) L ::= input
          | empty
          | single(N)
          | concat(L, L)
(Number) N ::= len(L)
           | min(L)
           | add(N, N)
           | 0 | 1 | 2 | ...
```

From Program to Abstract Syntax Tree

Concrete Program

`min(input ++ [0])`

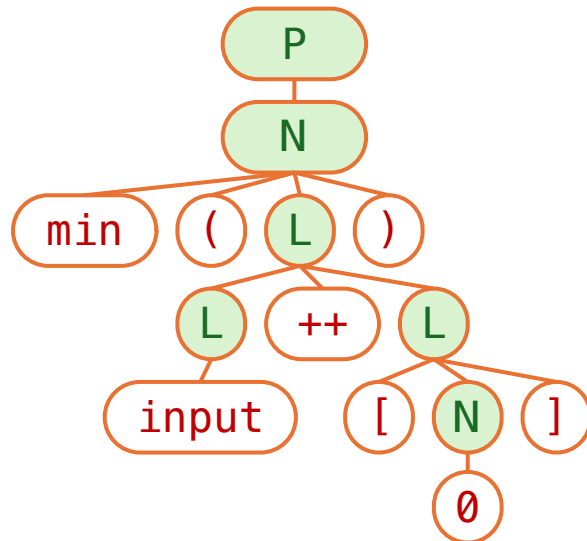


Token Sequence

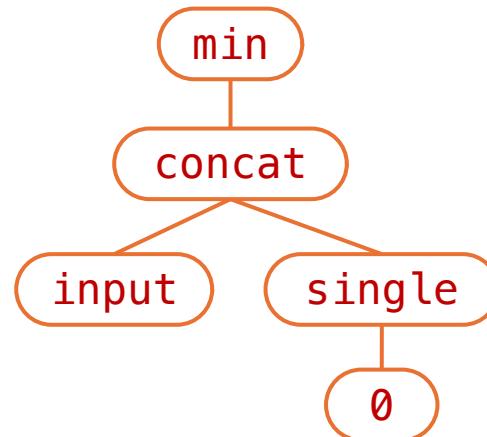
`['min', '(', 'input', '++', '[', '0', ']']`



Concrete Syntax Tree



Abstract Syntax Tree



Concrete Grammar (Context Free Grammar)

```
(Program) P <- L | N
(List) L <- 'input'
          | '[' ']'
          | '[' N ']'
          | L '++' L
(Number) N <- 'len' '(' L ')'
            | 'min' '(' L ')'
            | N '+' N
            | '0' | '1' | '2' | ...
```

Abstract Grammar (Regular Tree Grammar)

```
(Program) P ::= L | N
(List) L ::= input
          | empty
          | single(N)
          | concat(L, L)
(Number) N ::= len(L)
            | min(L)
            | add(N, N)
            | 0 | 1 | 2 | ...
```

From Program to Abstract Syntax Tree

Concrete Program

`min(input ++ [0])`

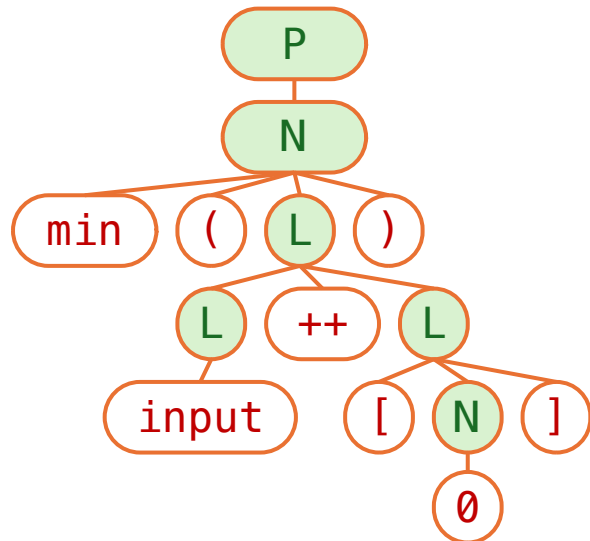
↓ **Lexer**

Token Sequence

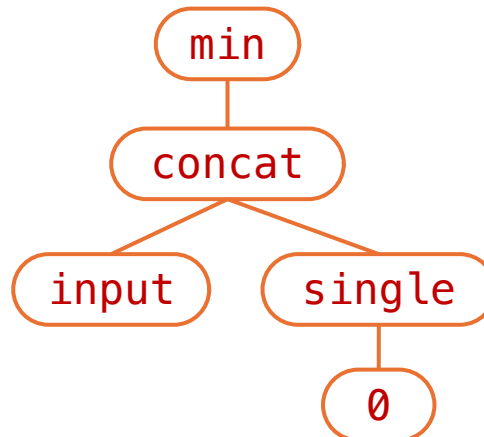
`['min', '(', 'input', '++', '[', '0', ']']`

↓ **Parser**

Concrete Syntax Tree



Abstract Syntax Tree



Concrete Grammar (Context Free Grammar)

```
(Program) P <- L | N
(List) L <- 'input'
          | '[' ']'
          | '[' N ']'
          | L '++' L
(Number) N <- 'len' '(' L ')'
          | 'min' '(' L ')'
          | N '+' N
          | '0' | '1' | '2' | ...
```

Abstract Grammar (Regular Tree Grammar)

```
(Program) P ::= L | N
(List) L ::= input
          | empty
          | single(N)
          | concat(L, L)
(Number) N ::= len(L)
          | min(L)
          | add(N, N)
          | 0 | 1 | 2 | ...
```

Lexer and Parser

Concrete Program

`min(input ++ [0])`

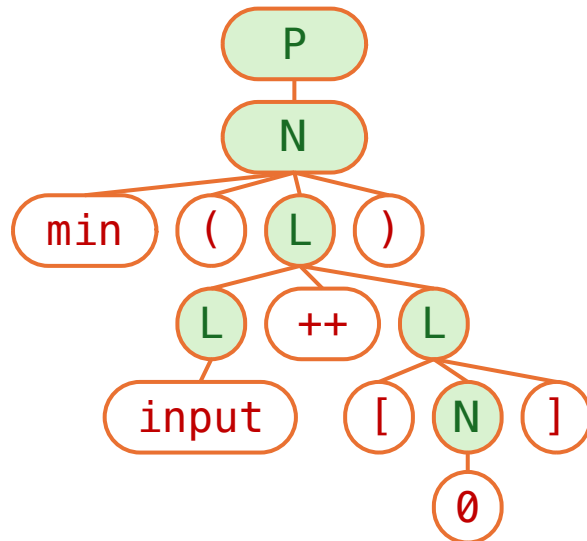
↓ **Lexer**

Token Sequence

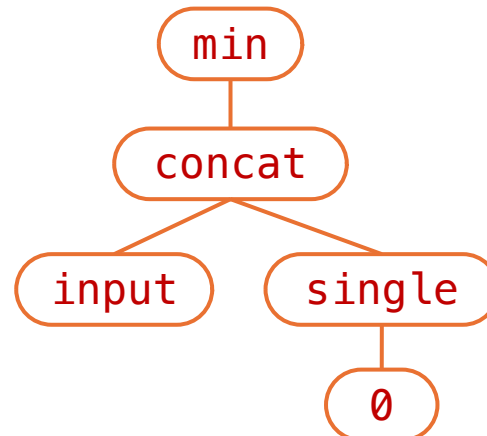
`['min', '(', 'input', '++', '[', '0', ']']`

↓ **Parser**

Concrete Syntax Tree



Abstract Syntax Tree



I have a concrete grammar in CFG

(Program) $P \leftarrow L \mid N$

(List) $L \leftarrow \text{'input'}$

$\mid \text{'[' ']'}$

$\mid \text{'[' N ']'}$

$\mid L \text{'++' } L$

(Number) $N \leftarrow \text{'len' '(' L ')')}$

$\mid \text{'min' '(' L ')')}$

$\mid N \text{'+' } N$

$\mid \text{'0' } \mid \text{'1' } \mid \text{'2' } \mid \dots$

Corresponding to it there is an abstract grammar

(Program) $P ::= L \mid N$

(List) $L ::= \text{input}$

$\mid \text{empty}$

$\mid \text{single}(N)$

$\mid \text{concat}(L, L)$

(Number) $N ::= \text{len}(L)$

$\mid \text{min}(L)$

$\mid \text{add}(N, N)$

$\mid 0 \mid 1 \mid 2 \mid \dots$

Can you help me write a treesitter parser in javascript?

Lexer and Parser

Concrete Program

`min(input ++ [0])`

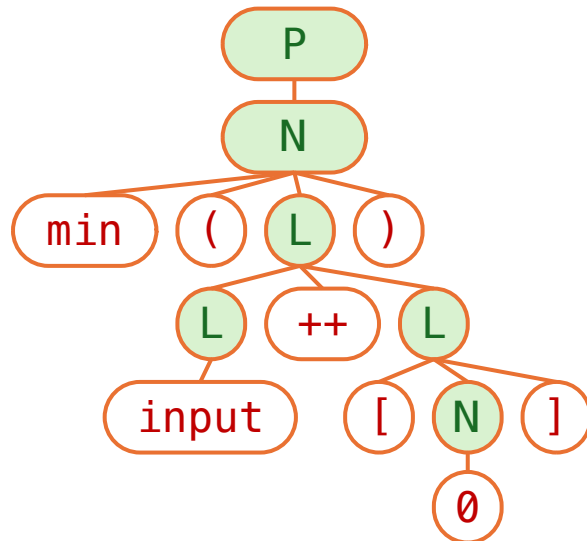
↓ **Lexer**

Token Sequence

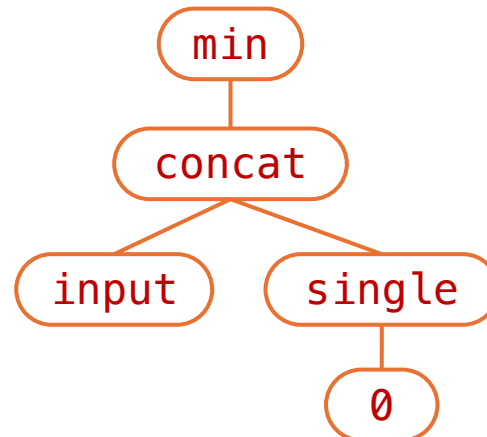
`['min', '(', 'input', '++', '[', '0', ']']`

↓ **Parser**

Concrete Syntax Tree



Abstract Syntax Tree



I have a concrete grammar in CFG

```
(Program) P <- L | N
(List) L <- 'input'
| '(' L ')'
| '(' L 'N' ')'
| L '++' L
(Number) N <- 'len' '(' L ')'
| 'min' '(' L ')'
| N '++' N
| '0' | '1' | '2' | ...
```

Corresponding to it there is an abstract grammar

```
(Program) P ::= L | N
(List) L ::= input
| empty
| single(N)
| concat(L, L)
(Number) N ::= len(L)
| min(L)
| add(N, N)
| 0 | 1 | 2 | ...
```

Can you help me write a treesitter parser in javascript?

```
1 module.exports = grammar({
2   name: 'listnum',
3   rules: {
4     program: $ => choice($.list, $.number),
5
6     list: $ => choice($.input, $.empty_list, $.single, $.concat),
7     input: _ => 'input',
8     empty_list: _ => seq('[', ']'),
9     single: $ => seq('[', $.number, ']'),
10    concat: $ => prec.left(1, seq($.list, '++', $.list)),
11
12    number: $ => choice($.len, $.min, $.add, $.int_lit),
13
14    len: $ => seq('len', '(', $.list, ')'),
15    min: $ => seq('min', '(', $.list, ')'),
16    add: $ => prec.left(2, seq($.number, '+', $.number)),
17    int_lit: $ => alias($.int, 'int'),
18    int: _ => /[0-9]+/,
19  }
20 });
```

Lexer and Parser

Concrete Program

`min(input ++ [0])`

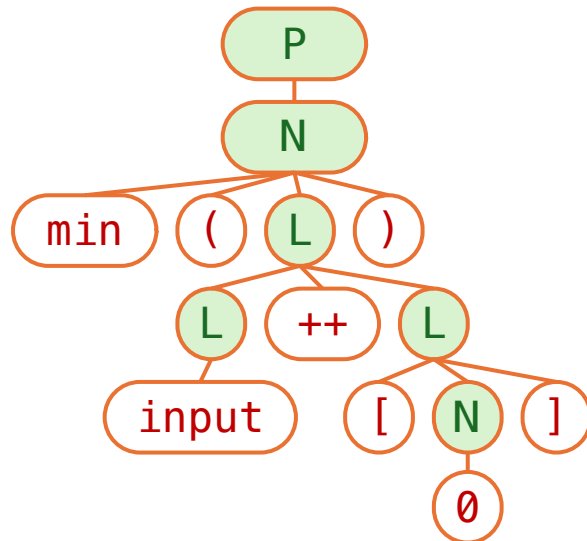
↓ **Lexer**

Token Sequence

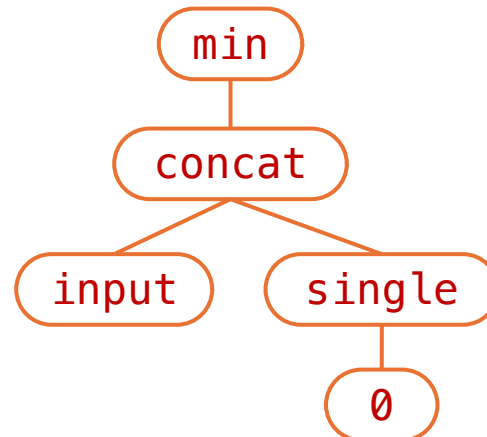
`['min', '(', 'input', '++', '[', '0', ']']`

↓ **Parser**

Concrete Syntax Tree



Abstract Syntax Tree



```
1 module.exports = grammar({
2   name: 'listnum',
3   rules: {
4     program: $ => choice($.list, $.number)
5   },
6   list: $ => choice($.input, $.empty_list),
7   input: _ => 'input',
8   empty_list: _ => seq('[', ']'),
9   single: $ => seq('[', $.number, ']'),
10  concat: $ => prec.left(1, seq($.list,
11    $.number: $ => choice($.len, $.min, $.add
```

I have a concrete grammar in CFG

```
(Program) P <- L | N
(List) L <- 'input'
| '[' ']'
| '[' N ']'
| L '+' L
(Number) N <- 'len' | 'L' | 'N'
| 'min' | 'L' | 'N'
| 'N' '+' N
| '0' | '1' | '2' | ...
```

Corresponding to it there is an abstract grammar

```
(Program) P ::= L | N
(List) L ::= input
| empty
| single(N)
| concat(L, L)
(Number) N ::= len(L)
| min(L)
| add(N, N)
```

`> echo "min(input ++ [0])" | npx tree-sitter parse`

```
(program [0, 0] - [1, 0]
 (number [0, 0] - [0, 17]
  (min [0, 0] - [0, 17]
   (list [0, 4] - [0, 16]
    (concat [0, 4] - [0, 16]
     (list [0, 4] - [0, 9]
      (input [0, 4] - [0, 9]))
     (list [0, 13] - [0, 16]
      (single [0, 13] - [0, 16]
       (number [0, 14] - [0, 15]
        (int_lit [0, 14] - [0, 15])))))))))))
```

Lexer and Parser in the Wild

JSON (json.l)

```
%{
#include "y.tab.h"
}%

%%

"true"      return TRUE;
"false"     return FALSE;
"null"      return NULLVAL;
[0-9]+      { yylval = atoi(yytext); return NUMBER; }
\"([^\"]*)\" { yylval = strdup(yytext); return STRING; }
[ \t\n]+    ; /* skip */
"{"         return '{';
"}"         return '}';
"["         return '[';
"]"         return ']';
":"         return ':';
","         return ',';
%%
```

JSON (json.y)

```
%token TRUE FALSE NULLVAL NUMBER STRING

%%
value: STRING
    | NUMBER
    | object
    | array
    | TRUE
    | FALSE
    | NULLVAL
    ;

object: '{' '}'
    | '{' members '}'
    ;

members: pair
    | members ' ' pair
    ;

pair: STRING ':' value ;

array: '[' ']'
    | '[' elements ']'
    ;

elements: value
    | elements ' ' value
    ;
```

Python (python.lalrpop)

```
Parser / parser / src / python.lalrpop

Code Blame 1796 lines (1644 loc) · 60.4 KB

123         ast::Stmt::Assign(
124             ast::StmtAssign { targets, value, type_comment: None, range: (location..end_location).into() }
125         )
126     },
127 },
128 <location:@L> <target:TestOrStarExprList> <op:AugAssign> <rhs:TestListOrYieldExpr> <end_location:@R> => {
129     ast::Stmt::AugAssign(
130         ast::StmtAugAssign {
131             target: Box::new(set_context(target, ast::ExprContext::Store)),
132             op,
133             value: Box::new(rhs),
134             range: (location..end_location).into()
135         },
136     )
137 },
138 <location:@L> <target:Test<"all">> ":" <annotation:Test<"all">> <rhs:AssignSuffix?> <end_location:@R> => {
139     let simple = target.is_name_expr();
140     ast::Stmt::AnnAssign(
141         ast::StmtAnnAssign {
142             target: Box::new(set_context(target, ast::ExprContext::Store)),
143             annotation: Box::new(annotation),
144             value: rhs.map(Box::new),
145             simple,
146             range: (location..end_location).into()
147         },
148     )
149 },
150 };
```

High Level Picture

- We studied foundations of programming languages and synthesis
 - Syntax (regular tree grammar), Semantics (denotational, operational)
 - Enumeration (top-down, bottom-up) that searches within grammar
- We studied basic usage of language models
 - Purely neural: next token prediction → sequential decoding
 - Prompting and iterative refinement: elicit better programs from LLM
- Question:
 - Can we inject more **structure** during **neural** generation process

Possible Next Token by Parser

Partial Program

```
min(input ++ [0])
```

Token Sequence

```
['min', '(', 'input', '++', '[', '0', ']']
```

```
(Program) P <- L | N
(List) L <- 'input'
          | '[' ']'
          | '[' N ']'
          | L '++' L
(Number) N <- 'len' '(' L ')'
          | 'min' '(' L ')'
          | N '+' N
          | '0' | '1' | '2' | ...
```

Possible Next Token by Parser

Partial Program

`min(input ++ [0])`

Token Sequence

`['min', '(', 'input', '++', '[', '0', ']']`



Step 1

```
(Program) P <- L | N
(List) L <- 'input'
          | '[' ']'
          | '[' N ']'
          | L '++' L
(Number) N <- 'len' '(' L ')'
          | 'min' '(' L ')'
          | N '+' N
          | '0' | '1' | '2' | ...
```

Possible Next Token by Parser

Partial Program

`min(input ++ [0])`

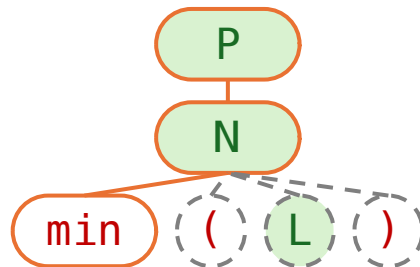
Token Sequence

`['min', '(', 'input', '++', '[', '0', ']']`



Step 1: Goal is P

`'min'` only appears in the rule `N <- 'min' '(' L ')'`



```
(Program) P <- L | N
(List) L <- 'input'
          | '[' ']'
          | '[' N ']'
          | L '++' L
(Number) N <- 'len' '(' L ')'
          | 'min' '(' L ')'
          | N '+' N
          | '0' | '1' | '2' | ...
```

Possible Next Token by Parser

Partial Program

`min(input ++ [0])`

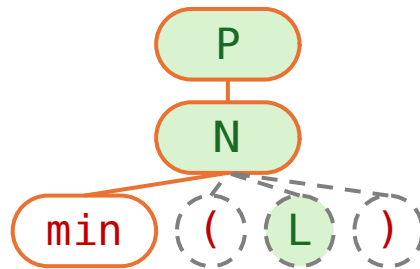
Token Sequence

`['min', '(', 'input', '++', '[', '0', ']']`



Step 1: Goal is P

`'min'` only appears in the rule `N <- 'min' '(' L ')'`



The next token could only be `'('`

```
(Program) P <- L | N
(List) L <- 'input'
          | '[' ']'
          | '[' N ']'
          | L '++' L
(Number) N <- 'len' '(' L ')'
            | 'min' '(' L ')'
            | N '+' N
            | '0' | '1' | '2' | ...
```

Possible Next Token by Parser

Partial Program

`min(input ++ [0])`

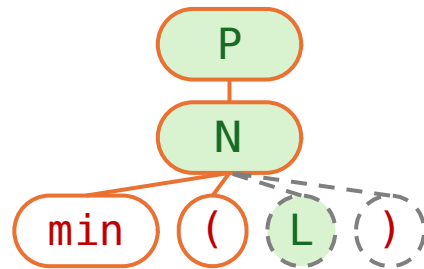
Token Sequence

`['min', '(', 'input', '++', '[', '0', ']']`



Step 2: Goal is P

`'min' '('` only appears in the rule `N <- 'min' '(' L ')'`



```
(Program) P <- L | N
(List) L <- 'input'
          | '[' ']'
          | '[' N ']'
          | L '++' L
(Number) N <- 'len' '(' L ')'
            | 'min' '(' L ')'
            | N '+' N
            | '0' | '1' | '2' | ...
```

Possible Next Token by Parser

Partial Program

`min(input ++ [0])`

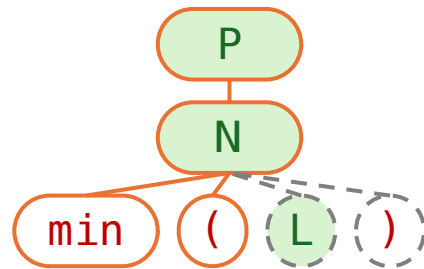
Token Sequence

`['min', '(', 'input', '++', '[', '0', ']']`



Step 2: Goal is P

`'min' '('` only appears in the rule `N <- 'min' '(' L ')'`



The next token could only be the first token expanded from L: `'input', '['`

```
(Program) P <- L | N
(List) L <- 'input'
          | '[' ']'
          | '[' N ']'
          | L '++' L
(Number) N <- 'len' '(' L ')'
            | 'min' '(' L ')'
            | N '+' N
            | '0' | '1' | '2' | ...
```

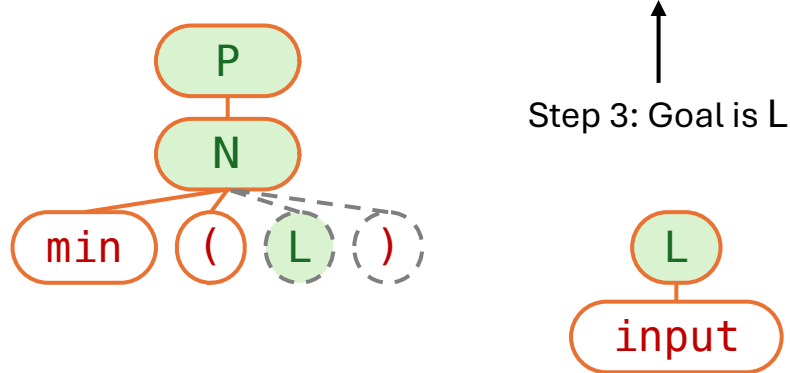
Possible Next Token by Parser

Partial Program

`min(input ++ [0])`

Token Sequence

`['min', '(', 'input', '++', '[', '0', ']']`



```
(Program) P <- L | N
(List) L <- 'input'
          | '[' ']'
          | '[' N ']'
          | L '++' L
(Number) N <- 'len' '(' L ')'
            | 'min' '(' L ')'
            | N '+' N
            | '0' | '1' | '2' | ...
```

We can expand `L` into `input`, matching the third token

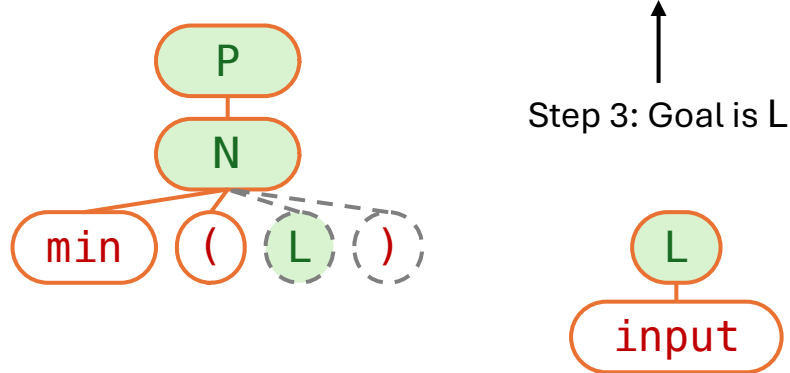
Possible Next Token by Parser

Partial Program

`min(input ++ [0])`

Token Sequence

`['min', '(', 'input', '++', '[', '0', ']']`



```
(Program) P <- L | N
(List) L <- 'input'
          | '[' ']'
          | '[' N ']'
          | L '++' L
(Number) N <- 'len' '(' L ')'
            | 'min' '(' L ')'
            | N '+' N
            | '0' | '1' | '2' | ...
```

We can expand `L` into `input`, matching the third token

➔ Finishing `L`, next token is `)`

Possible Next Token by Parser

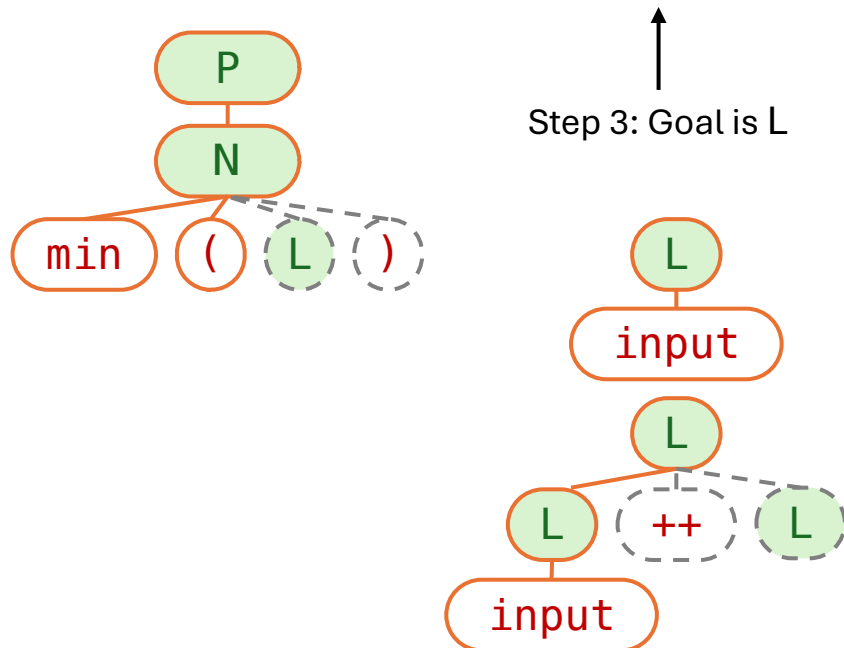
Partial Program

`min(input ++ [0])`

Token Sequence

`['min', '(', 'input', '++', '[', '0', ']']`

```
(Program) P <- L | N
(List) L <- 'input'
          | '[' ']'
          | '[' N ']'
          | L '++' L
(Number) N <- 'len' '(' L ')'
            | 'min' '(' L ')'
            | N '+' N
            | '0' | '1' | '2' | ...
```



We can expand **L** into **input**, matching the third token

➔ Finishing L, next token is **)**

We can expand **L** into **L + L**, where the first **L** can be expanded into **input**, matching the third token

Possible Next Token by Parser

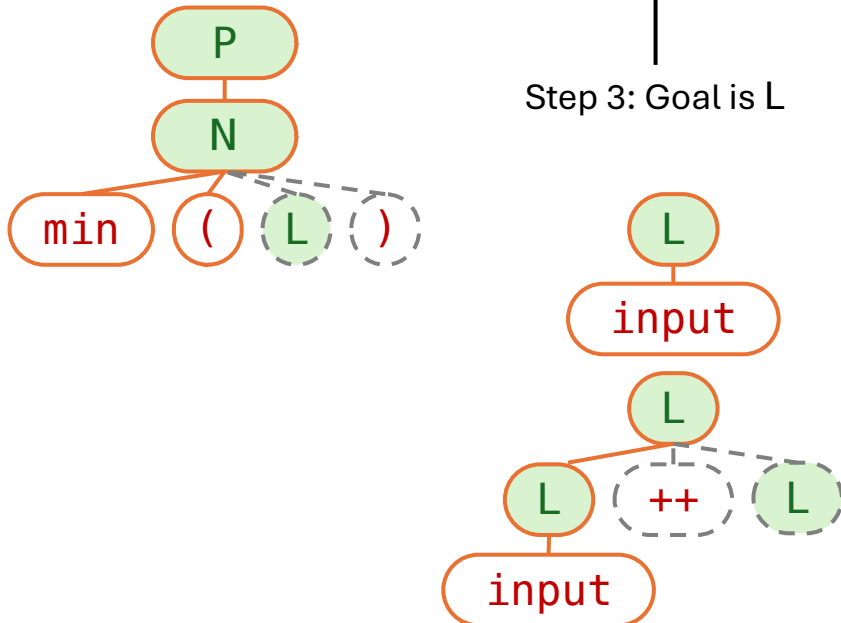
Partial Program

```
min(input ++ [0])
```

Token Sequence

```
['min', '(', 'input', '++', '[', '0', '']
```

Step 3: Goal is L



```
(Program) P <- L | N
(List) L <- 'input'
        | [' ']'
        | [' N ']'
        | L '++' L
(Number) N <- 'len' '(' L ')'
        | 'min' '(' L ')'
        | N '+' N
        | '0' | '1' | '2' | ...
```

We can expand L into **input**, matching the third token

➔ Finishing L, next token is ') '

We can expand **L** into **L + L**, where the first **L** can be expanded into **input**, matching the third token

→ Finishing the left L, next token is '++'

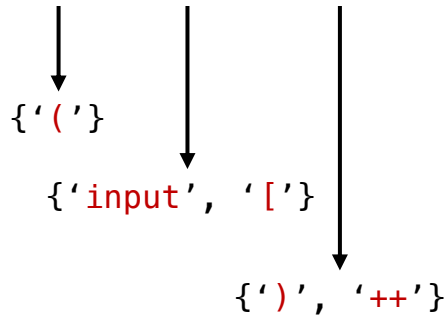
Possible Next Token by Parser

Partial Program

```
min(input ++ [0])
```

Token Sequence

```
['min', '(', 'input', '++', '[', '0', ']']
```



```
(Program) P <- L | N
(List) L <- 'input'
          | '[' ']'
          | '[' N ']'
          | L '++' L
(Number) N <- 'len' '(' L ')'
            | 'min' '(' L ')'
            | N '+' N
            | '0' | '1' | '2' | ...
```

Alternatives of Next Token Filtering

- Problem:
 - Given a **prefix**, find the **set of tokens** that could be the **next**
- Alternative problem:
 - Given a prefix and **a predicted next token**, check if the next token is a **plausible completion**
 - Prefix viability problem / Prefix membership problem
 - Given a grammar G and a prefix w , does there exist x s.t. $wx \in L(G)$

Algorithms for parsing

- Basic parsing
 - **Earley parsing**: maintains a set of items that implicitly answer the “prefix membership” question at each position
 - **CKY (Cocke–Younger–Kasami) parsing**: bottom-up finding substrings that can be turned into abstract syntax trees
 - **Automaton**: convert the grammar into an Automaton, keep an active state, reject the string if the next token leads to an error state

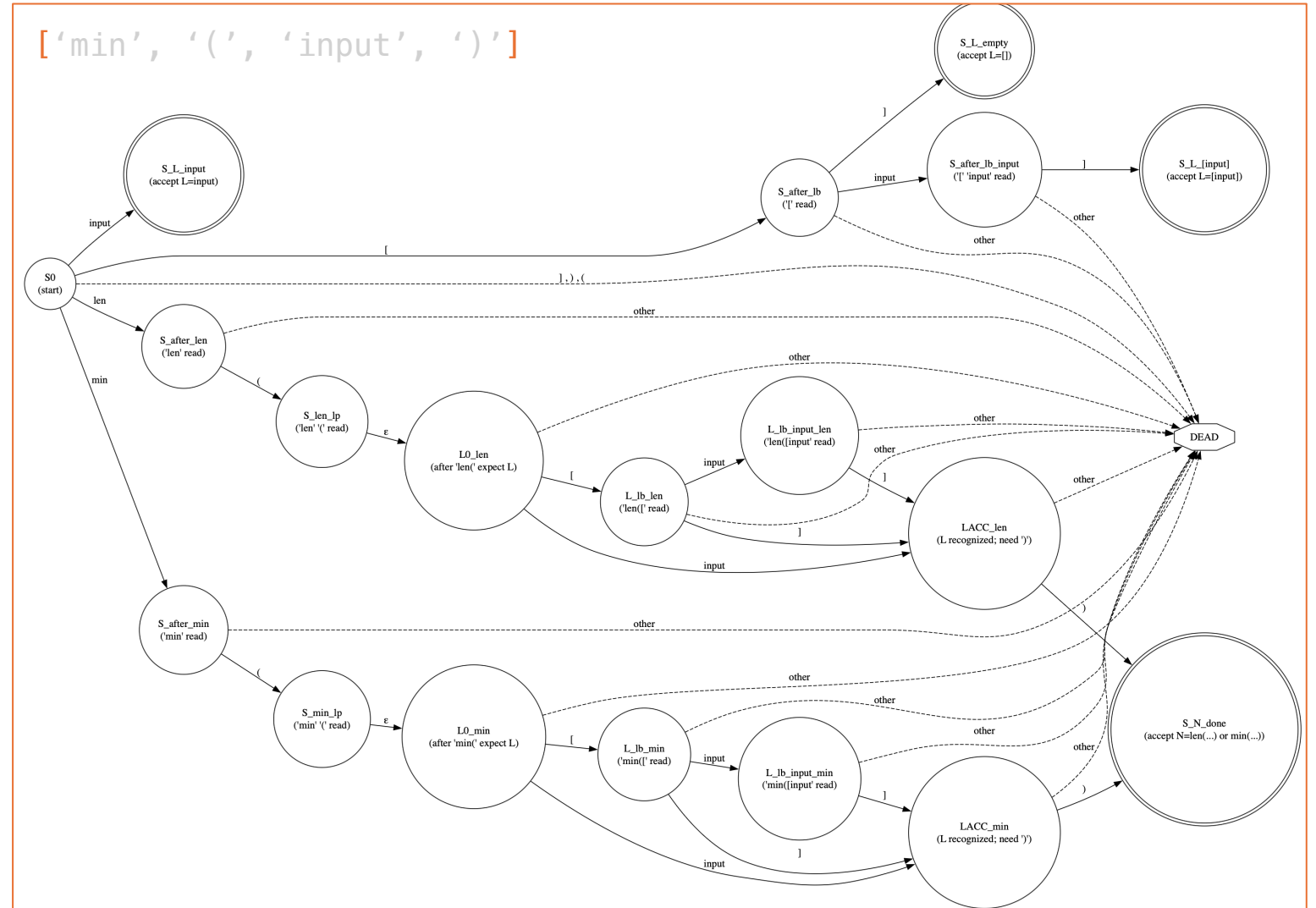
Constrained Decoding with Automaton

```
state = start_of_automaton(grammar)
current_sequence = input_tokens
output_sequence = []
for step in 1 .. max_length:
    logits = predict_next_token(current_sequence) / temperature
    for (token_id, logit) in enumerate(logits):
        if not allowed_by(state, token_id):
            logits[token_id] = -inf
    probs = softmax(logits)
    next_token = nucleus_sample_from(probs, P)
    current_sequence += [next_token]
    output_sequence += [next_token]
    if next_token == <EOS>: break
    state = advance(state, next_token)
return output_sequence
```

Constrained Decoding with Automaton

```
(Program) P <- L | N
(List) L <- 'input'
| '[' ']'
| '[' N ']'
(Number) N <- 'len' '(' L ')'
| 'min' '(' L ')'
```

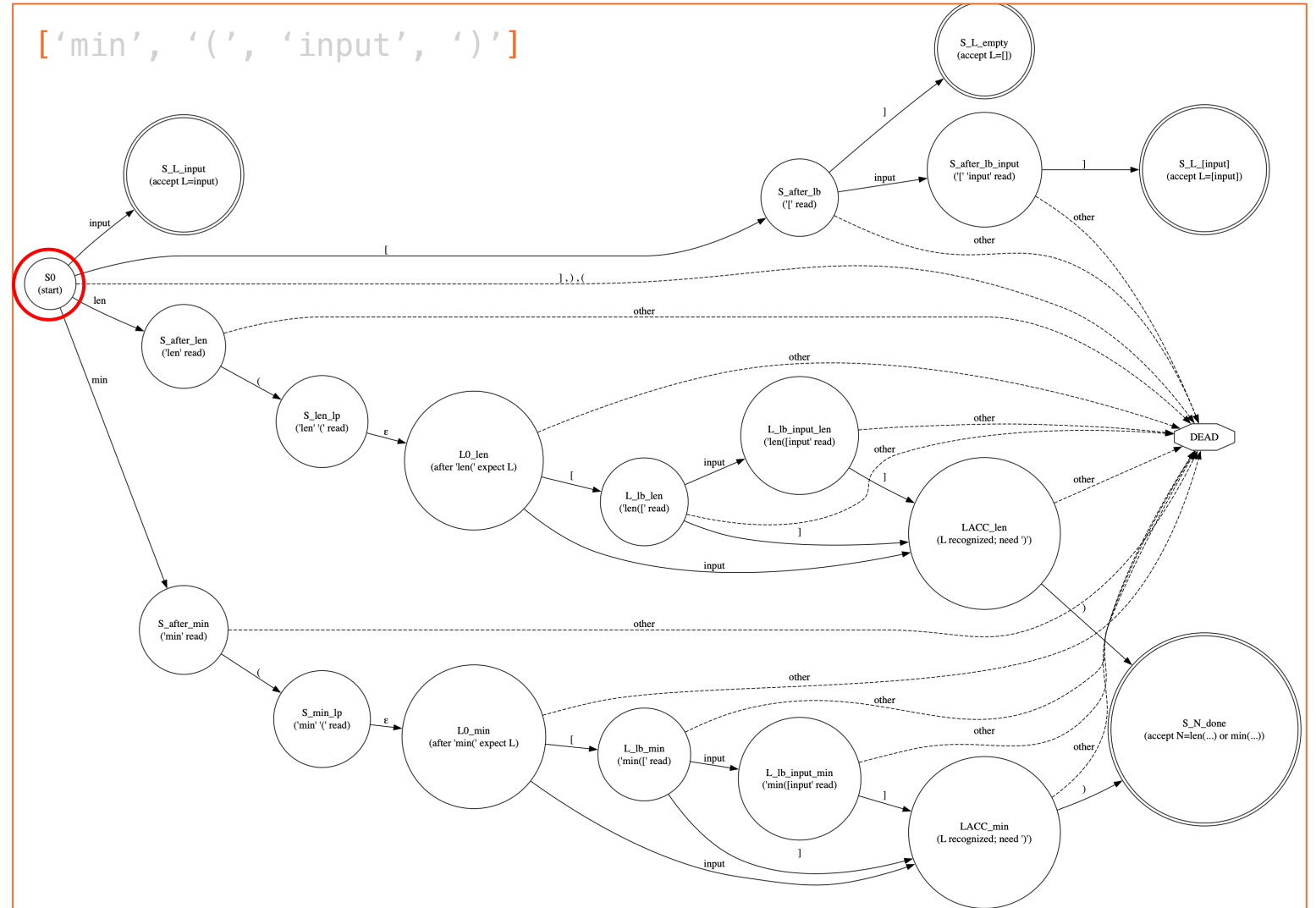
```
state = start_of_automaton(grammar)
current_sequence = input_tokens
output_sequence = []
for step in 1 .. max_length:
    logits = predict_next_token(current_sequence)...
    for (token_id, logit) in enumerate(logits):
        if not allowed_by(state, token_id):
            logits[token_id] = -inf
    probs = softmax(logits)
    next_token = nucleus_sample_from(probs, P)
    current_sequence += [next_token]
    output_sequence += [next_token]
    if next_token == <EOS>: break
    state = advance(state, next_token)
return output_sequence
```



Constrained Decoding with Automaton

```
(Program) P <- L | N
(List) L <- 'input'
| '[' ']'
| '[' N ']'
(Number) N <- 'len' '(' L ')'
| 'min' '(' L ')'
```

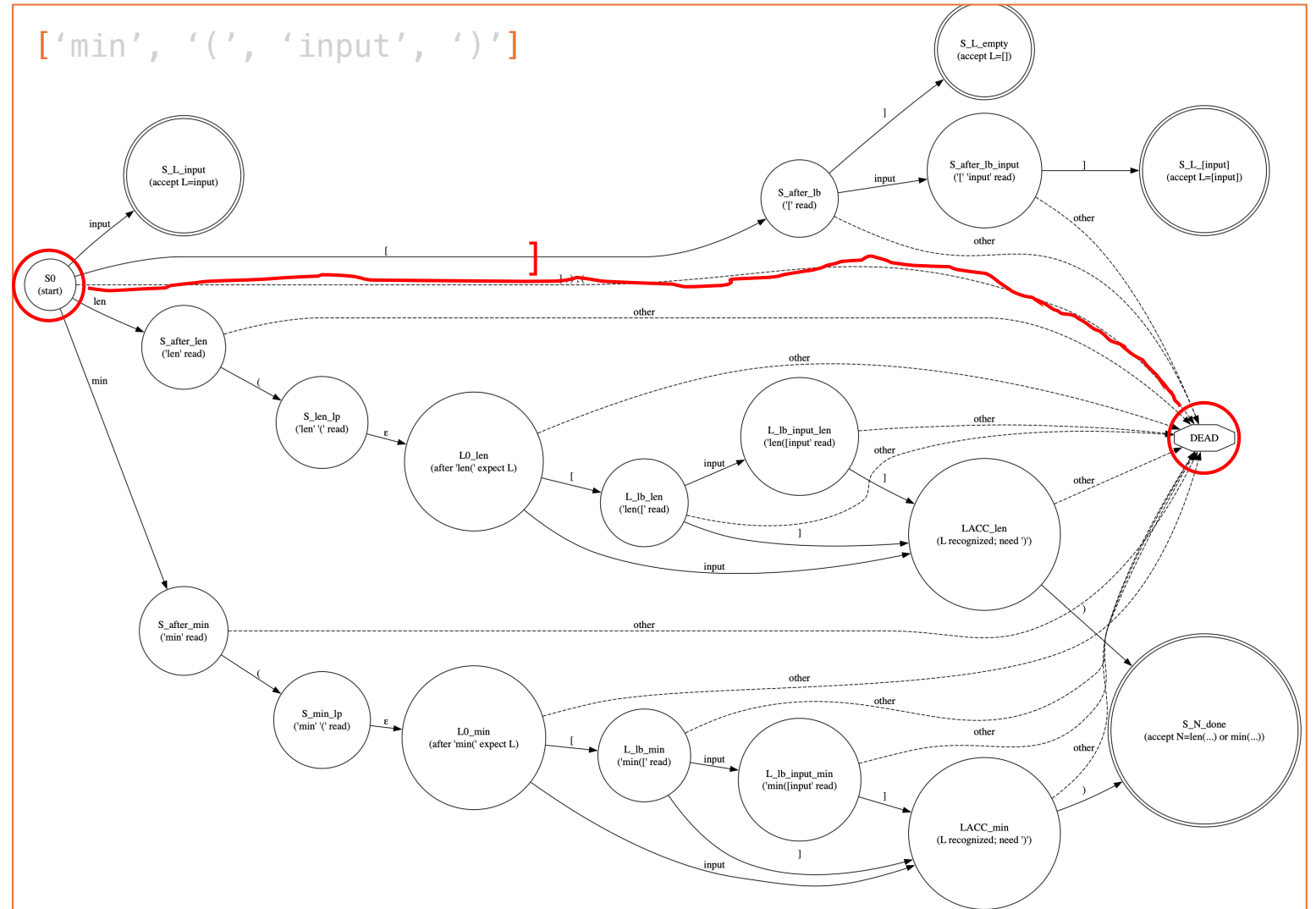
```
state = start_of_automaton(grammar)
current_sequence = input_tokens
output_sequence = []
for step in 1 .. max_length:
    logits = predict_next_token(current_sequence)...
    for (token_id, logit) in enumerate(logits):
        if not allowed_by(state, token_id):
            logits[token_id] = -inf
    probs = softmax(logits)
    next_token = nucleus_sample_from(probs, P)
    current_sequence += [next_token]
    output_sequence += [next_token]
    if next_token == <EOS>: break
    state = advance(state, next_token)
return output_sequence
```



Constrained Decoding with Automaton

```
(Program) P <- L | N
(List) L <- 'input'
          | [' '],
          | [' N '],
(Number) N <- 'len' (' L '),
          | 'min' (' L ')
```

```
state = start_of_automaton(grammar)
current_sequence = input_tokens
output_sequence = []
for step in 1 .. max_length:
    logits = predict_next_token(current_sequence)...
    for (token_id, logit) in enumerate(logits):
        if not allowed_by(state, token_id):
            logits[token_id] = -inf
    probs = softmax(logits)
    next_token = nucleus_sample_from(probs, P)
    current_sequence += [next_token]
    output_sequence += [next_token]
    if next_token == <EOS>: break
    state = advance(state, next_token)
return output_sequence
```



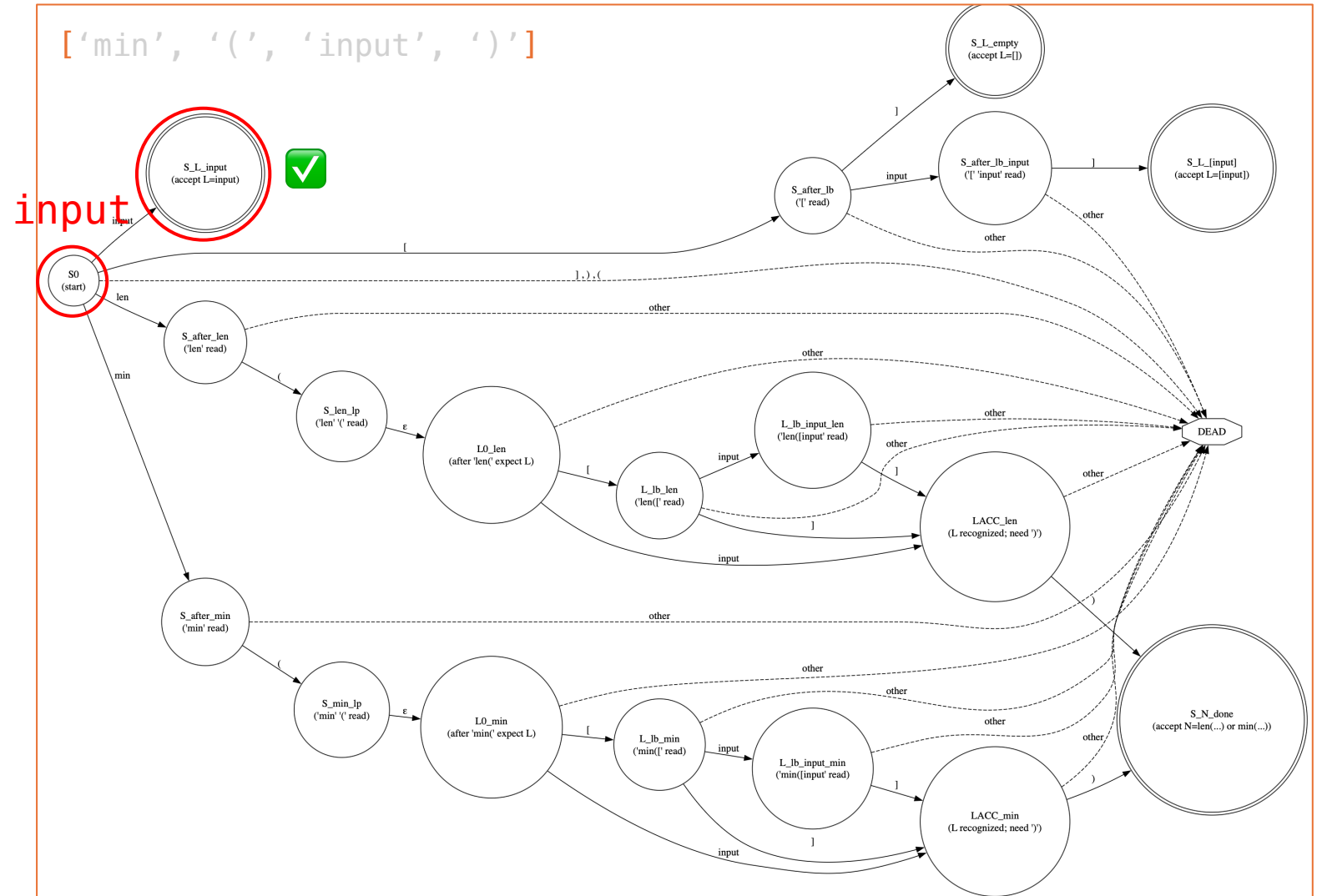
Constrained Decoding with Automaton

```

(Program) P <- L | N
(List) L <- 'input'
| '[' ']'
| '[' N ']'
(Number) N <- 'len' '(' L ')'
| 'min' '(' L ')'
    
```

```

state = start_of_automaton(grammar)
current_sequence = input_tokens
output_sequence = []
for step in 1 .. max_length:
    logits = predict_next_token(current_sequence)...
    for (token_id, logit) in enumerate(logits):
        if not allowed_by(state, token_id):
            logits[token_id] = -inf
    probs = softmax(logits)
    next_token = nucleus_sample_from(probs, P)
    current_sequence += [next_token]
    output_sequence += [next_token]
    if next_token == <EOS>: break
    state = advance(state, next_token)
return output_sequence
    
```



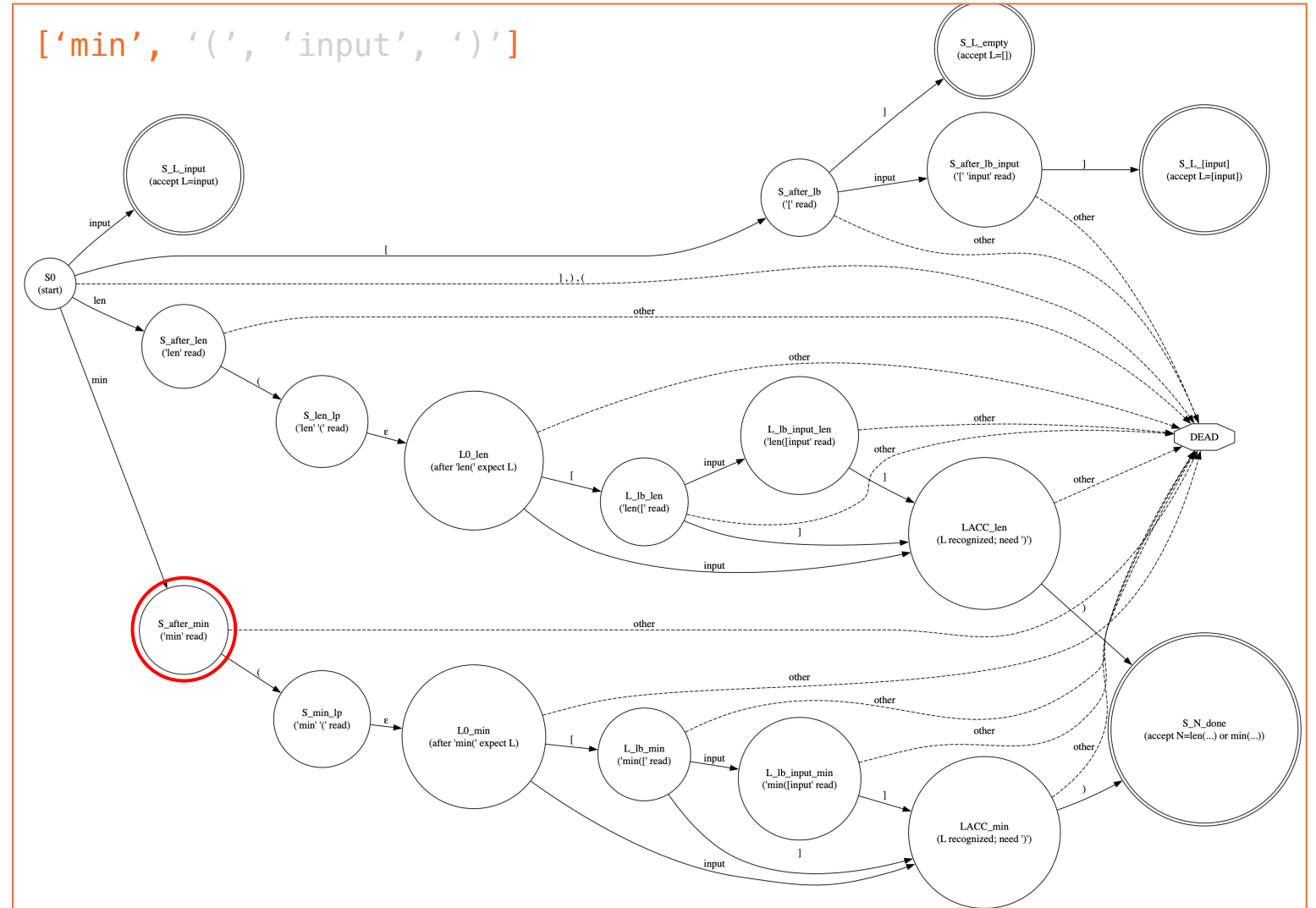
Constrained Decoding with Automaton

```

(Program) P <- L | N
(List) L <- 'input'
| '[' ']'
| '[' N ']'
(Number) N <- 'len' '(' L ')'
| 'min' '(' L ')'
    
```

```

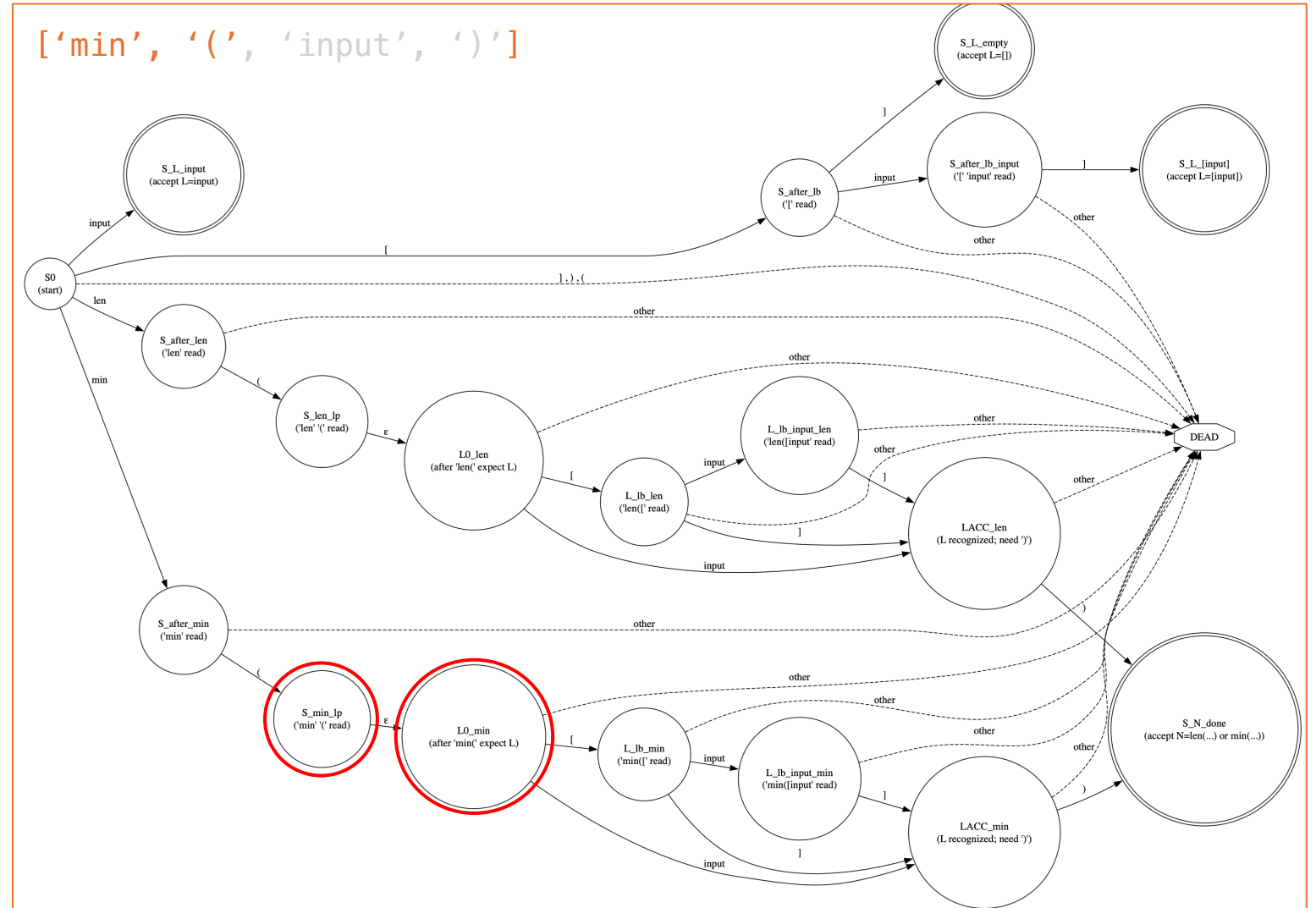
state = start_of_automaton(grammar)
current_sequence = input_tokens
output_sequence = []
for step in 1 .. max_length:
    logits = predict_next_token(current_sequence)...
    for (token_id, logit) in enumerate(logits):
        if not allowed_by(state, token_id):
            logits[token_id] = -inf
    probs = softmax(logits)
    next_token = nucleus_sample_from(probs, P)
    current_sequence += [next_token]
    output_sequence += [next_token]
    if next_token == <EOS>: break
    state = advance(state, next_token)
return output_sequence
    
```



Constrained Decoding with Automaton

```
(Program) P <- L | N
(List) L <- 'input'
| '[' ']'
| '[' N ']'
(Number) N <- 'len' '(' L ')'
| 'min' '(' L ')'
```

```
state = start_of_automaton(grammar)
current_sequence = input_tokens
output_sequence = []
for step in 1 .. max_length:
    logits = predict_next_token(current_sequence)...
    for (token_id, logit) in enumerate(logits):
        if not allowed_by(state, token_id):
            logits[token_id] = -inf
    probs = softmax(logits)
    next_token = nucleus_sample_from(probs, P)
    current_sequence += [next_token]
    output_sequence += [next_token]
    if next_token == <EOS>: break
    state = advance(state, next_token)
return output_sequence
```



Constrained Decoding with Automaton

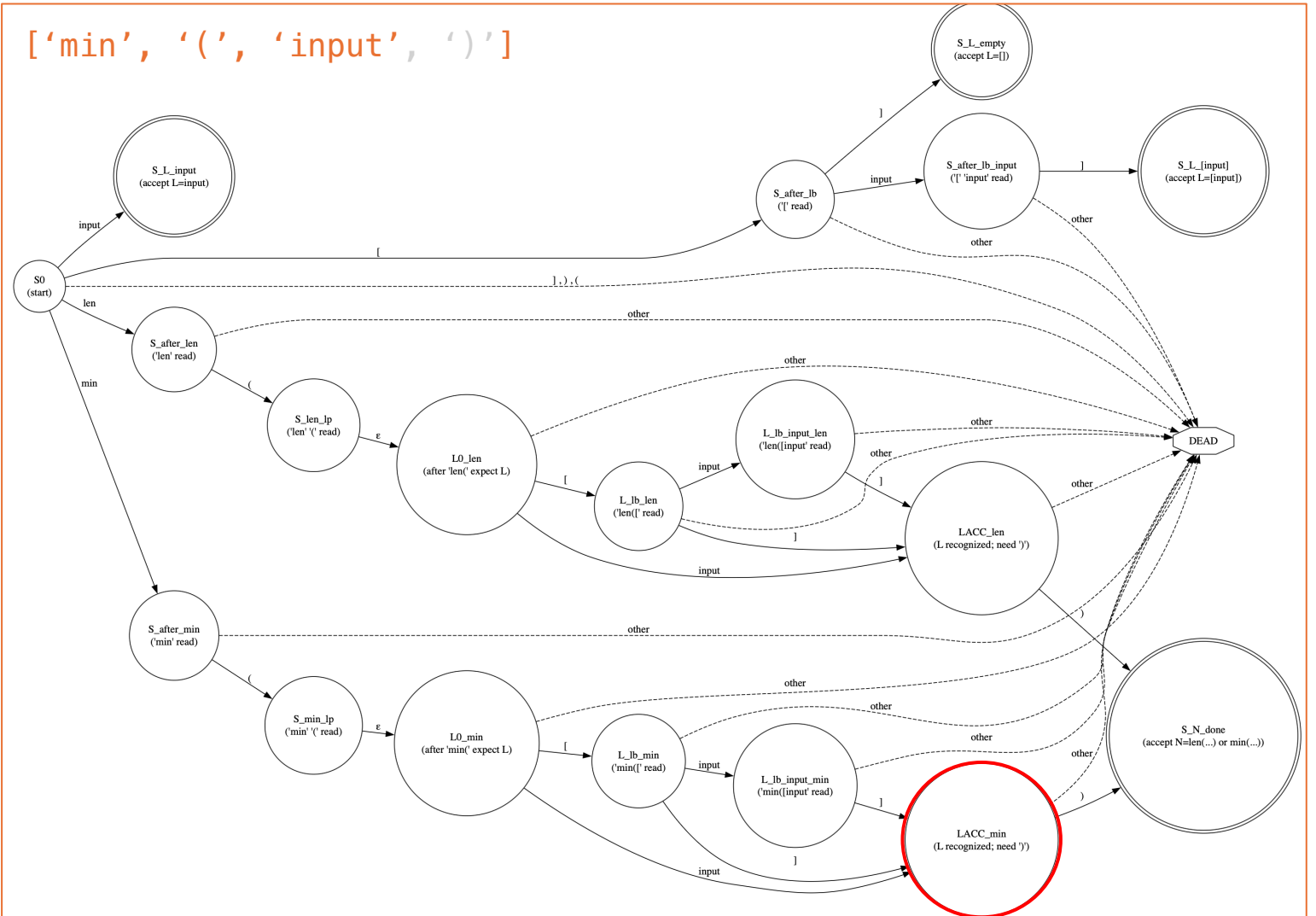
```

(Program) P <- L | N
(List) L <- 'input'
| '[' ']'
| '[' N ']'
(Number) N <- 'len' '(' L ')'
| 'min' '(' L ')'
    
```

```

state = start_of_automaton(grammar)
current_sequence = input_tokens
output_sequence = []
for step in 1 .. max_length:
    logits = predict_next_token(current_sequence)...
    for (token_id, logit) in enumerate(logits):
        if not allowed_by(state, token_id):
            logits[token_id] = -inf
    probs = softmax(logits)
    next_token = nucleus_sample_from(probs, P)
    current_sequence += [next_token]
    output_sequence += [next_token]
    if next_token == <EOS>: break
    state = advance(state, next_token)
return output_sequence
    
```

['min', '(', 'input', ')']



Constrained Decoding with Automaton

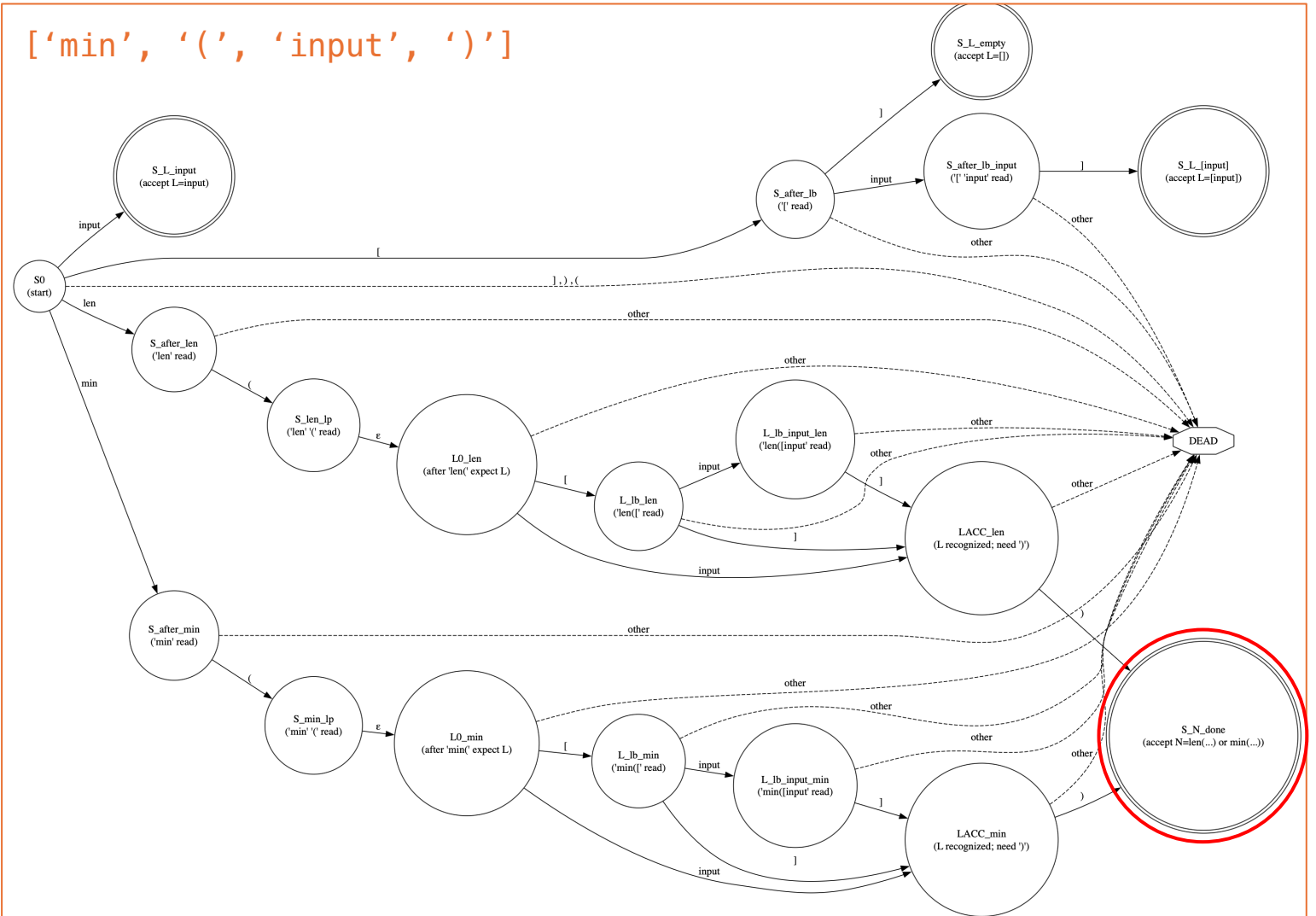
```

(Program) P <- L | N
(List) L <- 'input'
| '[' ']'
| '[' N ']'
(Number) N <- 'len' '(' L ')'
| 'min' '(' L ')'
    
```

```

state = start_of_automaton(grammar)
current_sequence = input_tokens
output_sequence = []
for step in 1 .. max_length:
    logits = predict_next_token(current_sequence)...
    for (token_id, logit) in enumerate(logits):
        if not allowed_by(state, token_id):
            logits[token_id] = -inf
    probs = softmax(logits)
    next_token = nucleus_sample_from(probs, P)
    current_sequence += [next_token]
    output_sequence += [next_token]
    if next_token == <EOS>: break
    state = advance(state, next_token)
return output_sequence
    
```

['min', '(', 'input', ')']



Algorithms for parsing

- Basic parsing
 - **Earley parsing**: maintains a set of items that implicitly answer the “prefix membership” question at each position
 - **CKY (Cocke–Younger–Kasami) parsing**: bottom-up finding substrings that can be turned into abstract syntax trees
 - **Automaton**: convert the grammar into an Automaton, keep an active state, reject the string if the next token leads to an error state
- Compiler Parsing
 - Batched parsing: takes the entire program and parses
- Interactive / Incremental parsing
 - Error-tolerant / resilient parsers; skip until synchronizing symbols (like ;,})
 - Keeps tree of interactions; maintain the global AST structure and only create bad subtrees when there is error

TRANSFORMER EXPLAINER

Examples ▾

min(input ++

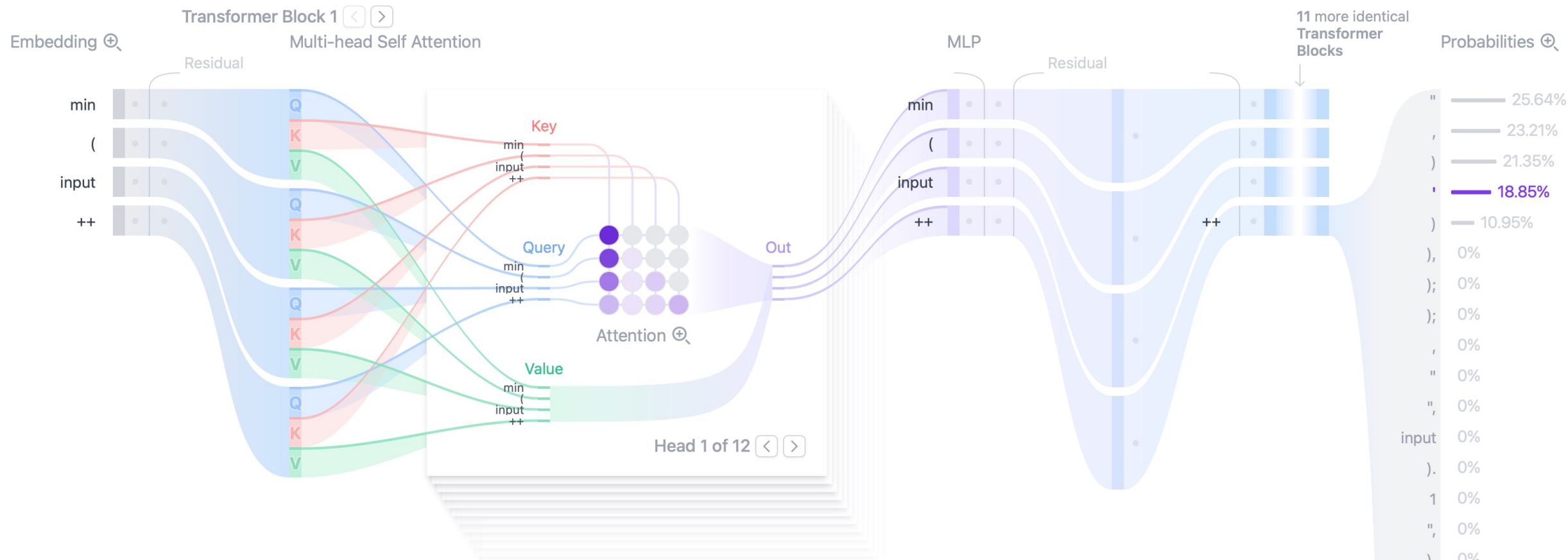
Generate

Temperature

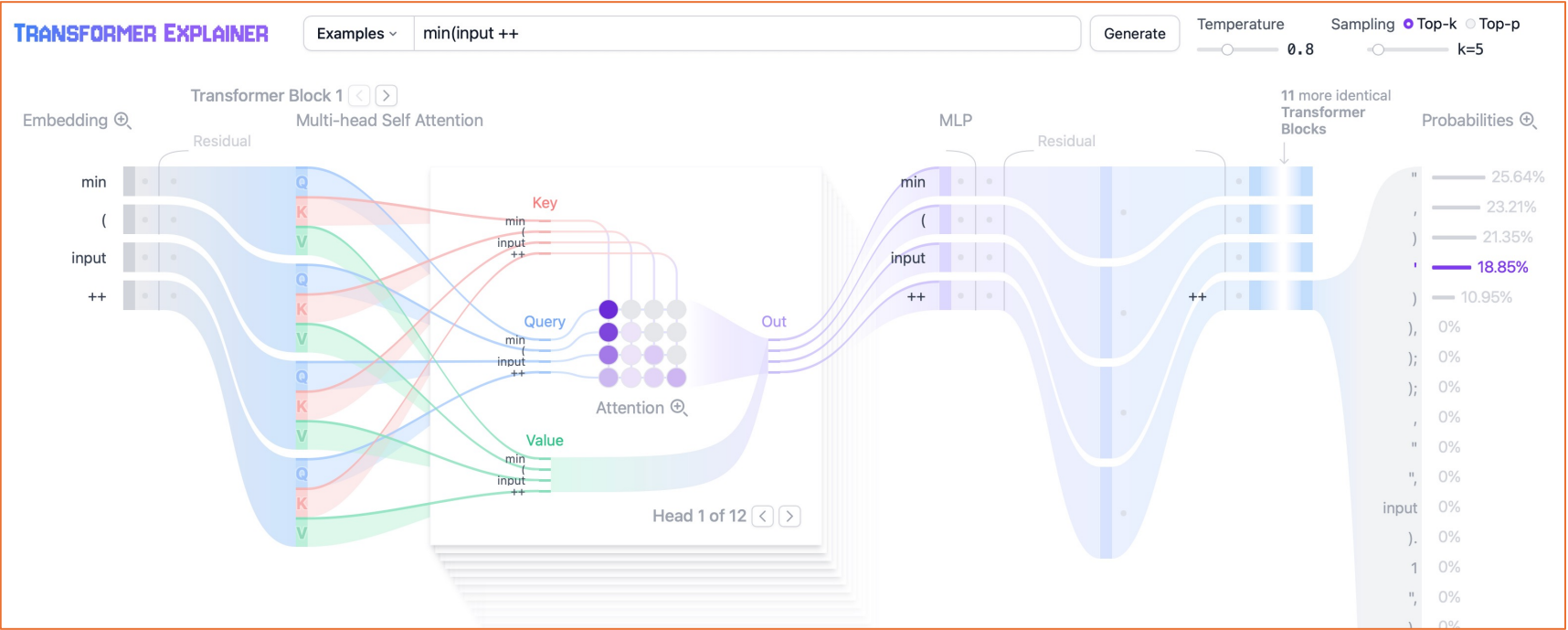
0.8

Sampling ● Top-k ● Top-p

k=5



Prefix: min(input ++



LLM Predicted
Next Token

Prefix Viability
Mask

input	0.01	1
)	0.21	0
'	0.19	0
"	0.26	0
;	0.01	0
[	0.02	1

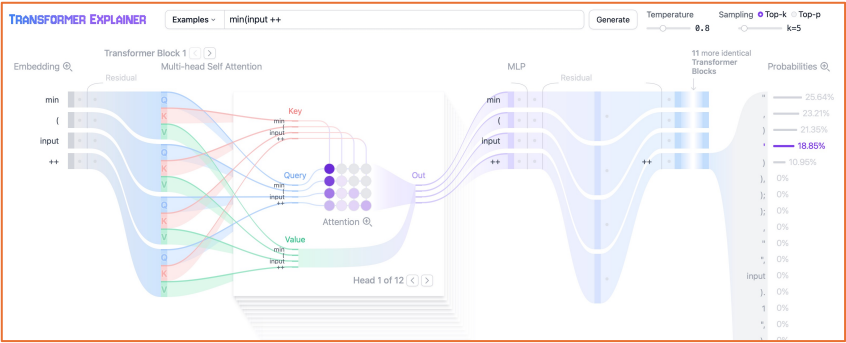
	LLM Predicted Next Token	Prefix Viability Mask		
Prefix: <code>min(input ++</code>	<code>input</code> 0.01	1	×	=
	<code>)</code> 0.21	0		
	<code>'</code> 0.19	0		
	<code>"</code> 0.26	0		
	<code>;</code> 0.01	0		
	<code>[</code> 0.02	1		

	LLM Predicted Next Token	Prefix Viability Mask		
Prefix: <code>min(input ++</code>	<code>input</code> 0.01	1		0.01
	<code>)</code> 0.21	0		0
	<code>'</code> 0.19	0	×	0
	<code>"</code> 0.26	0		0
	<code>;</code> 0.01	0		0
	<code>[</code> 0.02	1		0.02
			=	

		LLM Predicted Next Token	Prefix Viability Mask			
Prefix: <code>min(input ++</code>	<code>input</code>	0.01	1	0.01		0.49
	<code>)</code>	0.21	0	-inf		0.0
	<code>'</code>	0.19	0	-inf		0.0
	<code>"</code>	0.26	0	-inf	softmax	0.0
	<code>;</code>	0.01	0	-inf		0.0
	<code>[</code>	0.02	1	0.02		0.51

Prefix: min(input ++

```
(Program) P <- L | N
(List) L <- 'input'
          | [' ']'
          | [' N ']'
          | L '++' L
(Number) N <- 'len' '(' L ')'
             | 'min' '(' L ')'
             | N '+' N
             | '0' | '1' | '2' | ...
```



LLM Predicted Next Token	Prefix Viability Mask			
input	0.01	1	0.01	0.49
)	0.21	0	-inf	0.0
'	0.19	0	-inf	0.0
"	0.26	0	-inf	0.0
;	0.01	0	-inf	0.0
[	0.02	1	0.02	0.51

×

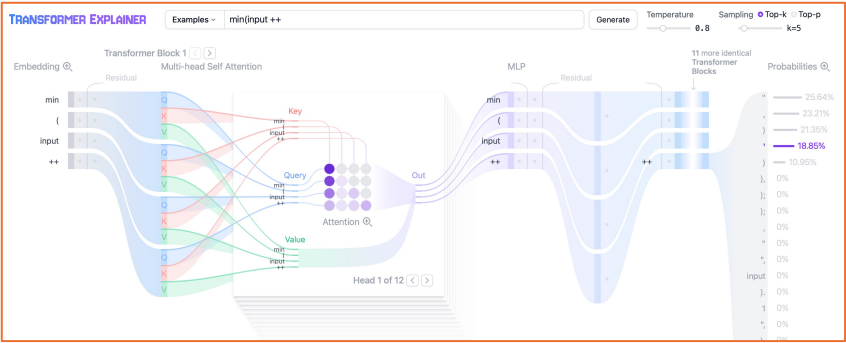
→

→

softmax

Prefix: min(input ++

```
(Program) P <- L | N
(List) L <- 'input'
          | [' ']'
          | [' N ']'
          | L '++' L
(Number) N <- 'len' '(' L ')'
             | 'min' '(' L ')'
             | N '+' N
             | '0' | '1' | '2' | ...
```



LLM Predicted Next Token	Prefix Viability Mask			
input	0.01	1	0.01	0.49
)	0.21	0	-inf	0.0
'	0.19	0	-inf	0.0
"	0.26	0	-inf	0.0
;	0.01	0	-inf	0.0
[	0.02	1	0.02	0.51

×

→

→

softmax

Constrained Decoding in the Wild

A Syntactic Neural Model for General-Purpose Code Generation

Pengcheng Yin

Language Technologies Institute
Carnegie Mellon University
pcyin@cs.cmu.edu

Graham Neubig

Language Technologies Institute
Carnegie Mellon University
gneubig@cs.cmu.edu

A Syntactic Neural Model for General-Purpose Code Generation

Pengcheng Yin

Language Technologies Institute

Carnegie
Pittsburgh

Graham Neubig

Language Technologies Institute

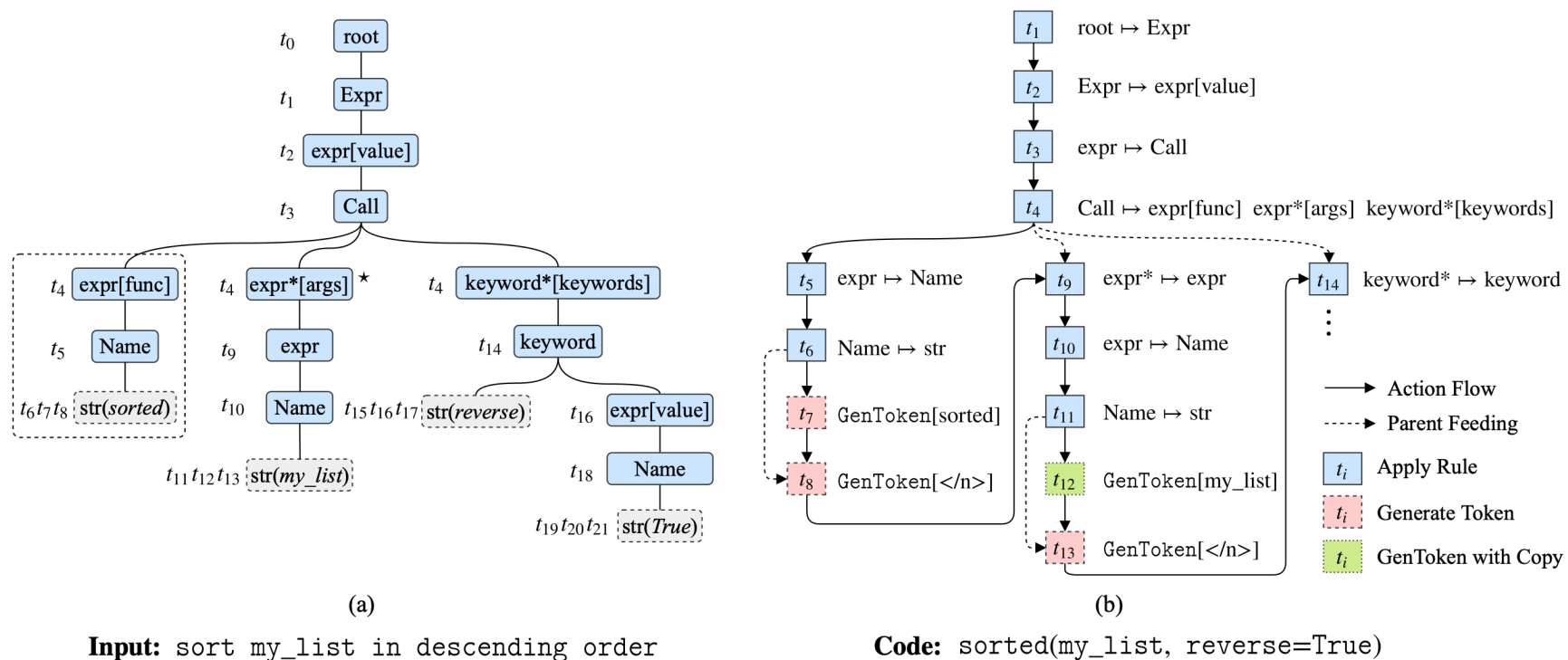


Figure 1: (a) the Abstract Syntax Tree (AST) for the given example code. Dashed nodes denote terminals. Nodes are labeled with time steps during which they are generated. (b) the action sequence (up to t_{14}) used to generate the AST in (a)

A Syntactic Neural Model for General-Purpose

Language
Code

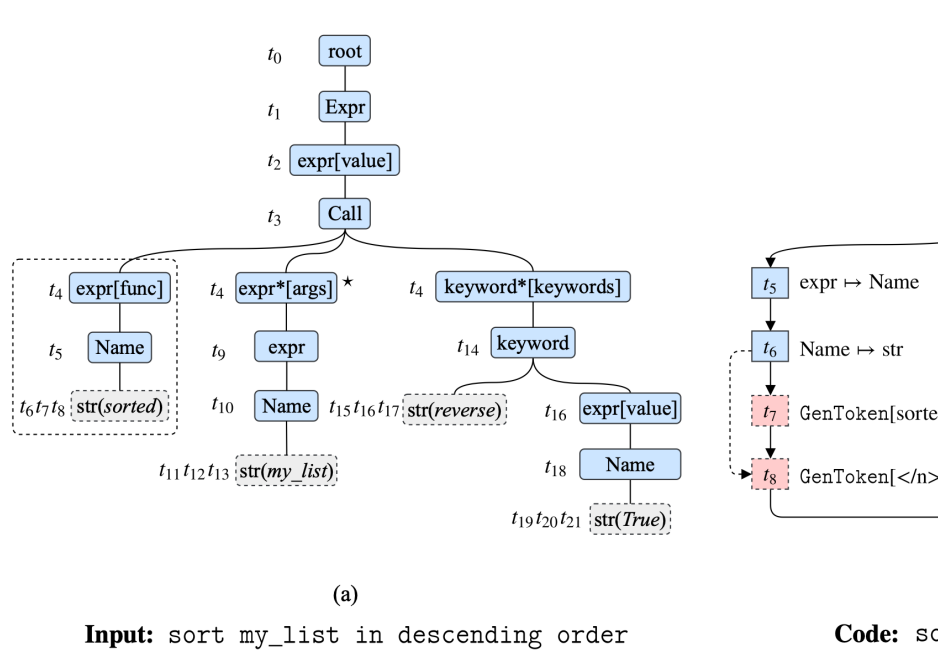


Figure 1: (a) the Abstract Syntax Tree (AST) for the given example code. Dashed boxes indicate time steps during which they are generated. (b) the action sequence (up to t8).

4.2.2 Calculating Action Probabilities

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

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

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

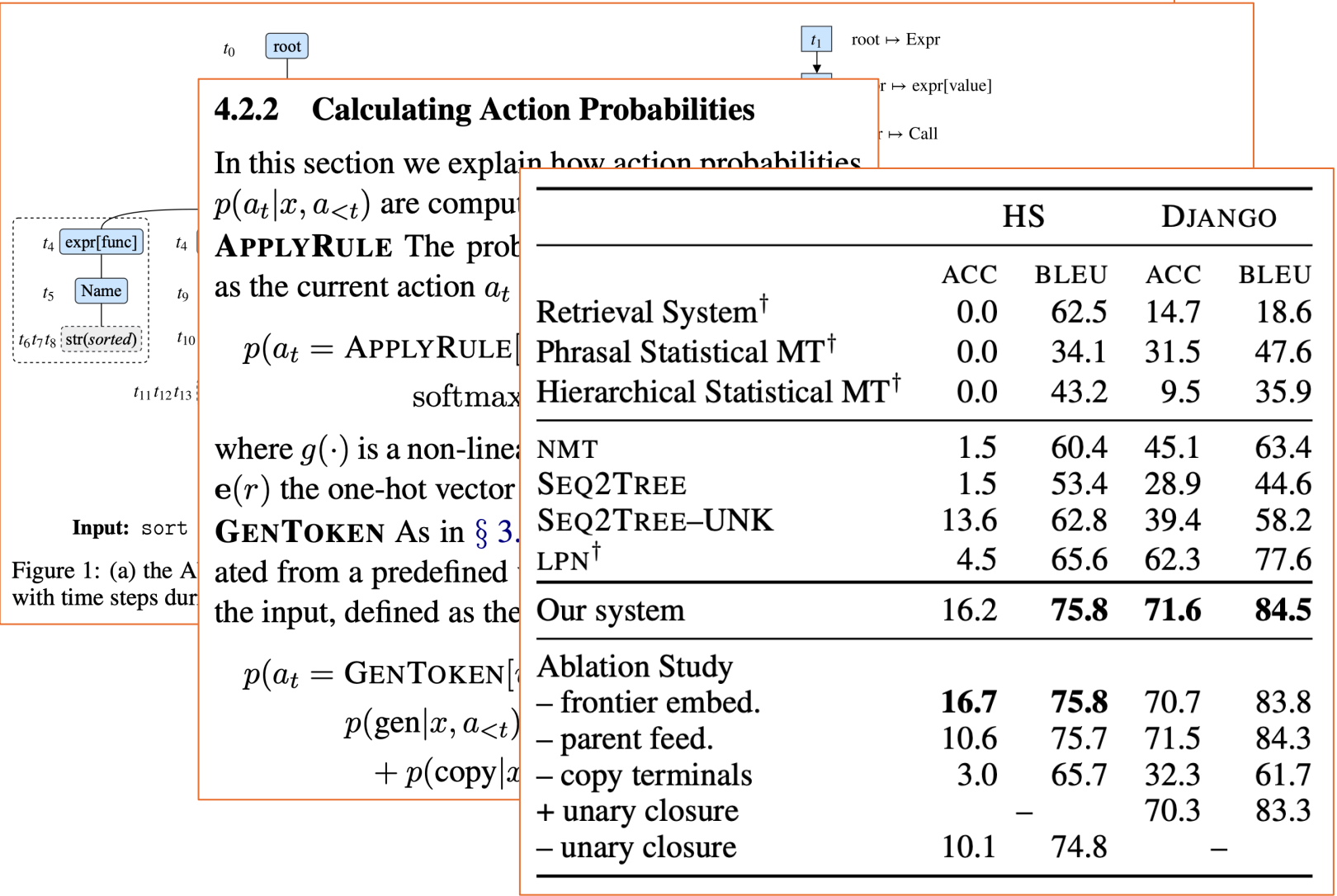
where $g(\cdot)$ is a non-linearity $\tanh(\mathbf{W} \cdot \mathbf{s}_t + \mathbf{b})$, and $\mathbf{e}(r)$ the one-hot vector for rule r .

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

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

A Syntactic Neural Model for General-Purpose Code Generation

Language
Context



Constrained Decoding in the Wild

Abstract Syntax Networks for Code Generation and Semantic Parsing

Maxim Rabinovich* **Mitchell Stern*** **Dan Klein**

Computer Science Division

University of California, Berkeley

`{rabinovich,mitchell,klein}@cs.berkeley.edu`

Abstract Syntax Networks for Code Generation and Semantic Pa

Maxim Rabinovich* Mitchell Stern* Dan Klein

Computer Science Division

University of California, Berkeley

{rabinovich,mitchell,klein}@cs.berkeley.edu



```
class DireWolfAlpha(MinionCard):
    def __init__(self):
        super().__init__(
            "Dire Wolf Alpha", 2, CHARACTER_CLASS.ALL,
            CARD_RARITY.COMMON, minion_type=MINION_TYPE.BEAST)
    def create_minion(self, player):
        return Minion(2, 2, auras=[
            Aura(ChangeAttack(1), MinionSelector(Adjacent()))
        ])
```

Figure 1: Example code for the “Dire Wolf Alpha” Hearthstone card.

```
show me the fare from ci0 to ci1

lambda $0 e
  ( exists $1 ( and ( from $1 ci0 )
                    ( to $1 ci1 )
                    ( = ( fare $1 ) $0 ) ) ) )
```

Figure 2: Example of a query and its logical form from the ATIS dataset. The *ci0* and *ci1* tokens are entity abstractions introduced in preprocessing (Dong and Lapata, 2016).

Abstract Syntax Networks for Code Generation and Semantic Parsing

Maxim Rabinovich*

Mitchell Stern*

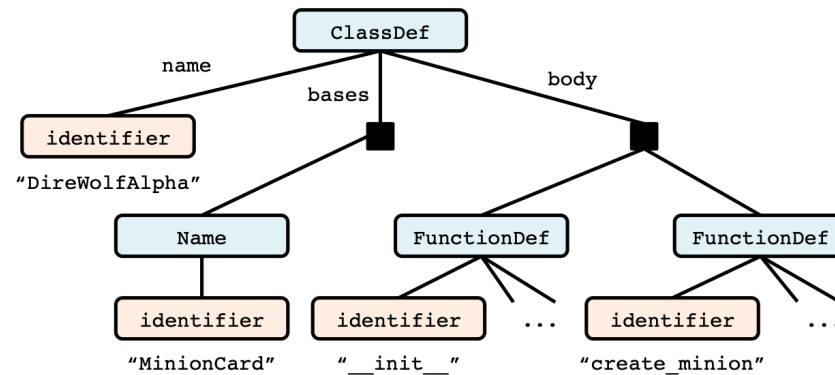
Dan Klein

Computer Science Division

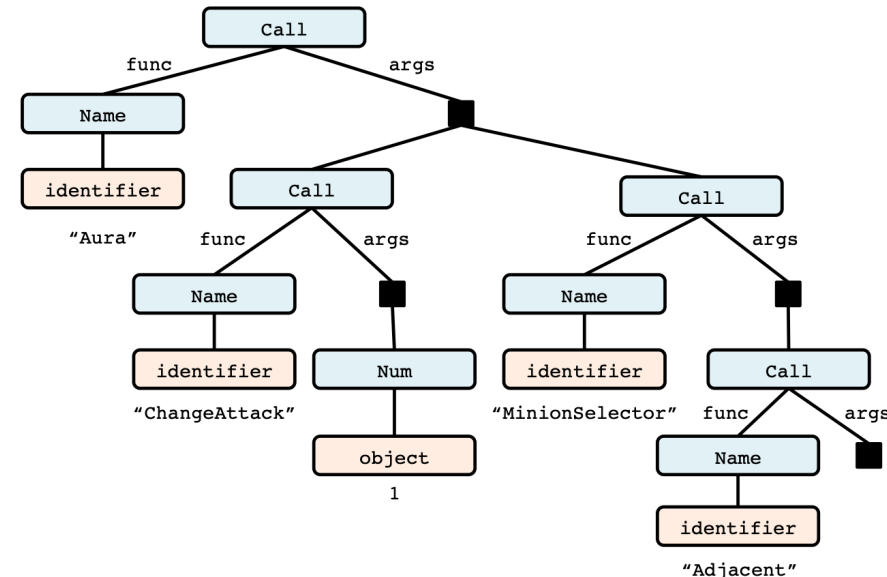
University of California, Berkeley



```
name: [
  'D', 'i', 'r', 'e', ' ',
  'W', 'o', 'l', 'f', ' ',
  'A', 'l', 'p', 'h', 'a']
cost: ['2']
type: ['Minion']
rarity: ['Common']
race: ['Beast']
class: ['Neutral']
description: [
  'Adjacent', 'minions', 'have',
  '+', '1', 'Attack', '.']
health: ['2']
attack: ['2']
durability: ['-1']
```



(a) The root portion of the AST.



(b) Excerpt from the same AST, corresponding to the code snippet `Aura (ChangeAttack (1), MinionSelector (Adjacent (ci1)))`.

Figure 2. Example of a query and its logical form from the ATIS dataset. The `ci0` and `ci1` tokens are entity abstractions introduced in preprocessing (Dong and Lapata, 2016).

Abstract Syntax Networks for Code Generation and Semantic Parsing



```
name: [
  'D', 'i', 'r', 'e', ' ',
  'W', 'o', 'l', 'f', ' ',
  'A', 'l', 'p', 'h', 'a']
cost: ['2']
type: ['Minion']
rarity: ['Common']
race: ['Beast']
class: ['Neutral']
description: [
  'Adjacent', 'minions', 'have',
  '+', '1', 'Attack', '.']
health: ['2']
attack: ['2']
durability: ['-1']
```

```
(MinionCard):
):
- (
  pha", 2, CHARACTER_CLASS.ALL,
  COMMON, minion_type=MINION_TYPE.BEAST)
(self, player):
  2, auras=[
    attack(1), MinionSelector(Adjacent()))
```

code for the “Dire Wolf Alpha”

e from ci0 to ci1

```
and ( from $1 ci0 )
  ( to $1 ci1 )
  ( = ( fare $1 ) $0 ) ) )
```

e of a query and its logical form
dataset. The ci0 and ci1 tokens
introduced in preprocess-
data, 2016).

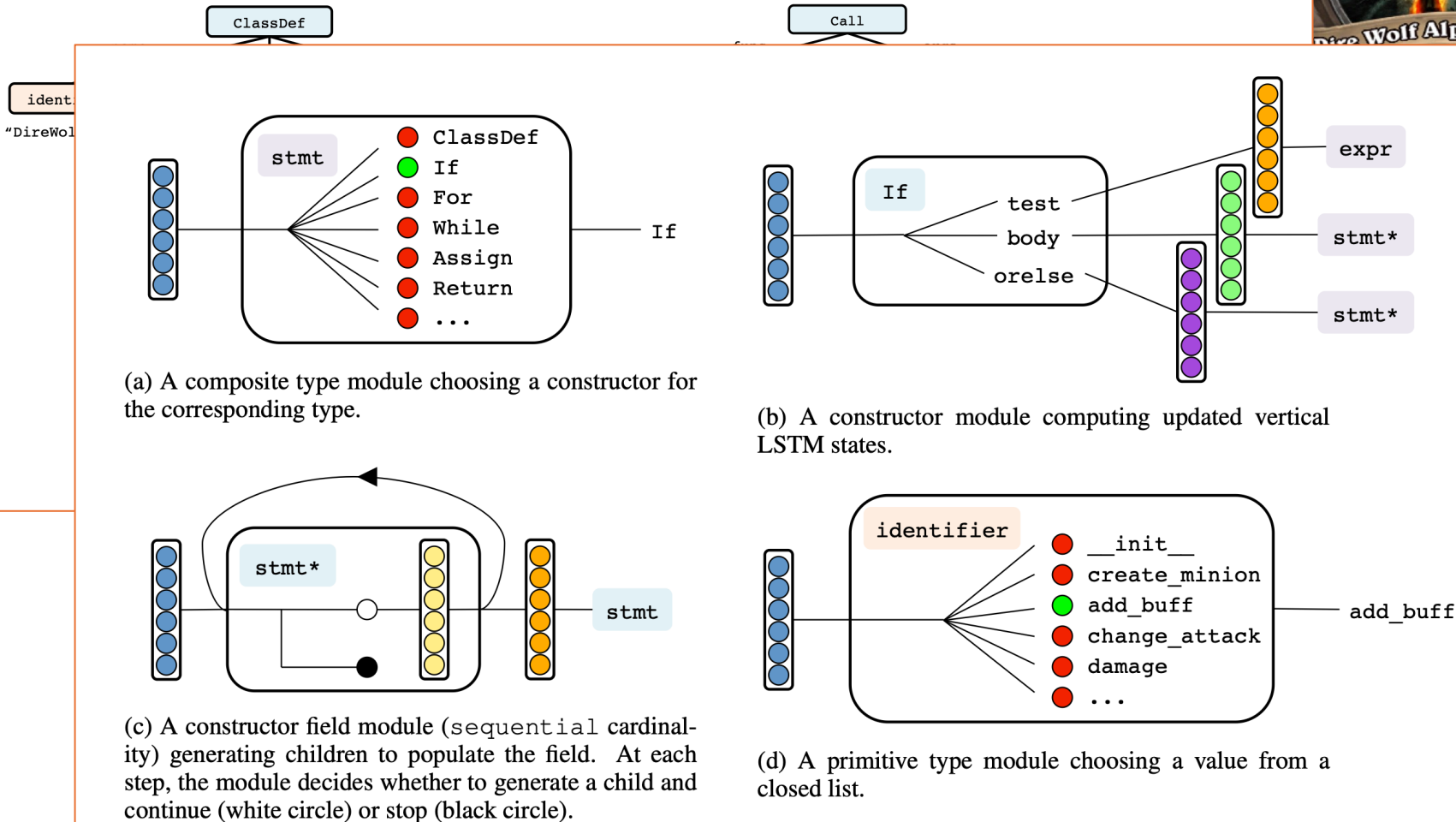


Figure 5: The module classes constituting our decoder. For brevity, we omit the cardinality modules for singular and optional cardinalities.

Constrained Decoding in the Wild

Grammar-Aligned Decoding

Kanghee Park^{1*} Jiayu Wang^{1*} Taylor Berg-Kirkpatrick²

Nadia Polikarpova² Loris D'Antoni¹

¹University of Wisconsin-Madison

²University of California San Diego

{kpark247, jwang2782, ldantoni}@wisc.edu, {tberg, npolikarpova}@ucsd.edu

Grammar-Aligned Decoding

Kanghee Park^{1*} Jiayu Wang^{1*} Taylor Berg-Kirkpatrick²

Constrained decoding addresses the inefficiency of rejection sampling by greedily “forcing” the LLM output to satisfy the given constraint. Specifically, when the constraint is given as a grammar, *grammar-constrained decoding* (GCD) [7, 27, 28], can build automata that allow for on-the-fly masking of tokens that will provably lead to outputs outside of the grammar during decoding.

Grammar-Aligned Decoding Given a model distribution P and a CFG $\mathcal{G}$, *grammar-aligned decoding* (GAD) is the task of sampling from the distribution $Q^{P,\mathcal{G}}$ that is *proportional* to P but *restricted* to sentences in $\mathcal{G}$:

$$Q^{P,\mathcal{G}}(w) = \frac{\mathbb{1}[w \in \mathcal{L}(\mathcal{G})] \cdot P(w)}{\sum_{w'} \mathbb{1}[w' \in \mathcal{L}(\mathcal{G})] \cdot P(w')}$$

Grammar-Aligned Decoding

Kanghee Park^{1*} Jiayu Wang^{1*} Taylor Berg-Kirkpatrick²

Constrained decoding addresses the inefficiency of rejection sampling by greedily “forcing” the LLM output to satisfy the given constraint. Specifically, when the constraint is given as a grammar, *grammar-constrained decoding* (GCD) [7, 27, 28], can build automata that allow for on-the-fly masking of tokens that will provably lead to outputs outside of the grammar during decoding.

Grammar-Aligned Decoding Given a model distribution P and a CFG $\mathcal{G}$, *grammar-aligned decoding* (GAD) is the task of sampling from the distribution $Q^{P,\mathcal{G}}$ that is *proportional* to P but *restricted* to $\mathcal{G}$.

```
Start ::= S
S ::= name | " " | "."
      | str.++ S S | str.at S I
      | str.replace S S S
      | str.substr S I I
I ::= 0 | 1 | 2 | + I I | - I I
      | str.len S | str.indexof S S I
```

(c) Grammar for f

```
Start ::= BV
BV ::= s | t
      | #x0 | #x7 | #x8
      | bvneg BV | bvnot BV
      | bvadd BV BV | bvsub BV BV
      | bvand BV BV | bvlor BV BV
      | bvlshl BV BV | bvlshr BV BV
```

(d) Grammar for inv

Constrained Decoding in the Wild

Monitor-Guided Decoding of Code LMs with Static Analysis of Repository Context

Lakshya A Agrawal

Microsoft Research

Bangalore, India

t-lakagrawal@microsoft.com

Aditya Kanade

Microsoft Research

Bangalore, India

kanadeaditya@microsoft.com

Navin Goyal

Microsoft Research

Bangalore, India

navingo@microsoft.com

Shuvendu K. Lahiri

Microsoft Research

Redmond, United States

shuvendu.lahiri@microsoft.com

Sriram K. Rajamani

Microsoft Research

Bangalore, India

sriram@microsoft.com

Monitor-Guided Decoding of Code LMs with Static Analysis of Repository Context

Lakshya A Agrawal

Microsoft Research

Bangalore, India

lakshya@microsoft.com

Aditya Kanade

Microsoft Research

Bangalore, India

kanadeaditya@microsoft.com

Method to be completed

```
private ServerNode parseServer(String url) {
    Preconditions.checkNotNull(url);
    int start = url.indexOf(str:"/") + 2;
    int end = url.lastIndexOf(str:"?") == -1 ?
        url.length() : url.lastIndexOf(str:"?");
    String str = url.substring(start, end);
    String [] arr = str.split(regex:":");

    return ServerNode.Builder
        .newServerNode()
        .
}
```



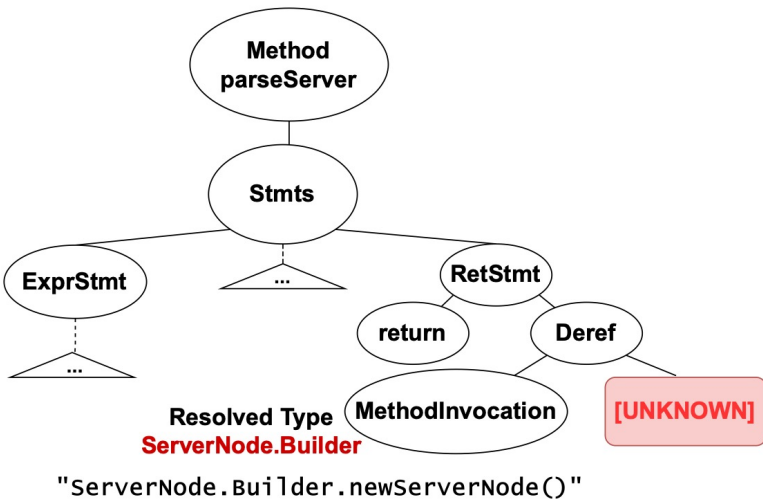
text-davinci-003 and SantaCoder

```
host(arr[0])
.port(Integer.parseInt(arr[1]))
.build();
```



SantaCoder with monitor guided decoding

```
withIp(arr[0])
.withPort(Integer.parseInt(arr[1]))
.build();
```



(a) Example where text-davinci-003 and SantaCoder generate wrong identifiers, but SantaCoder with MGD generates correct identifiers. (b) Annotated partial AST for the code to the left.

Monitor-Guided Decoding of Code LMs with Static



(a) Editor interface

Integrated development environments (IDEs) have been at the forefront of assisting developers. Our inspiration is the use of static analysis by IDEs to bring the global context at the fingertips of developers. Many analyses are integrated in IDEs (Fuhrer, 2013) to infer and enforce semantic constraints on the code under development, e.g., resolving def-use, symbol references, and type hierarchies. Recently, there has been a rise in the use of Language Server Protocol (LSP) (lsp), which is an open industry standard of communication between IDEs and programming language specific tools like static analyzers and compilers, called Language Servers. There are a large number of Language Servers available, targetting most programming languages (lan, 2023), and providing a variety of syntactic and semantic information. In this work, we focus on the type-directed code completion analysis available through LSP in a language-agnostic manner, to provide guidance to an LM.

Monitor-Guided Decoding of Code LMs with Static



(a) E
iden

Integrated development environments (IDEs) have been at the forefront of assisting developers.

Our inspiration is the use of static analysis by IDEs to bring the global context of the fingerprinting

Eq. (1) states that whenever the monitor is in the wait state s_0 , we sample x_{n+1} as per the logits ℓ determined by the LM (Eq. (2)). Otherwise, the logits are combined with a mask m using a function $\oplus$ such that if $m[x] = 0$ then $\ell[x]$ is reset to a large negative value $-K$ and is left unchanged otherwise. This mask is computed by the function `maskgen` in Eq. (3) guided by the current state s of the monitor. Eq. (4) defines how the state of the monitor evolves. When the pre-condition $\text{pre}(s; x_1, \dots, x_n)$ evaluates to true, the next state s' of the monitor is determined by the suggestions returned by the static analysis A_φ . Otherwise, it is determined by the update function.

$$(L_\theta || M_\varphi)(x_{n+1} | x_1, \dots, x_n; C, p, s) = \begin{cases} \text{softmax}(\ell)[x_{n+1}] & \text{if } s = s_0 \text{ is the wait state} \\ \text{softmax}(\ell \oplus m)[x_{n+1}] & \text{otherwise} \end{cases} \quad (1)$$

$$\ell = L_\theta(\cdot | x_1, \dots, x_n; p) \quad (2)$$

$$m = \text{maskgen}(s, V) \quad (3)$$

$$s' = \begin{cases} A_\varphi(x_1, \dots, x_n; C) & \text{if } s = s_0 \wedge \text{pre}(s; x_1, \dots, x_n) \\ \text{update}(s, x_{n+1}) & \text{otherwise} \end{cases} \quad (4)$$

SYNTACTIC AND SEMANTIC CONTROL OF LARGE LANGUAGE MODELS VIA SEQUENTIAL MONTE CARLO

**João Loula^{*1} Benjamin LeBrun^{*5} Li Du^{*6} Ben Lipkin¹ Clemente Pasti² Gabriel Grand¹
Tianyu Liu² Yahya Emara² Marjorie Freedman⁸ Jason Eisner⁶ Ryan Cotterell²
Vikash Mansinghka^{‡1} Alexander K. Lew^{‡1,7} Tim Vieira^{‡2} Timothy J. O'Donnell^{‡3,4,5}
¹MIT ²ETH Zürich ³McGill ⁴Canada CIFAR AI Chair ⁵Mila ⁶Johns Hopkins ⁷Yale ⁸ISI
genlm@mit.edu**

SYNTACTIC AND SEMANTIC CONTROL OF LARGE LANGUAGE MODELS VIA SEQUENTIAL MONTE CARLO

João Loula^{*1} Be
Tianyu Liu² Yah
Vikash Mansingh
¹MIT ²ETH Zürich
genlm@mit.edu

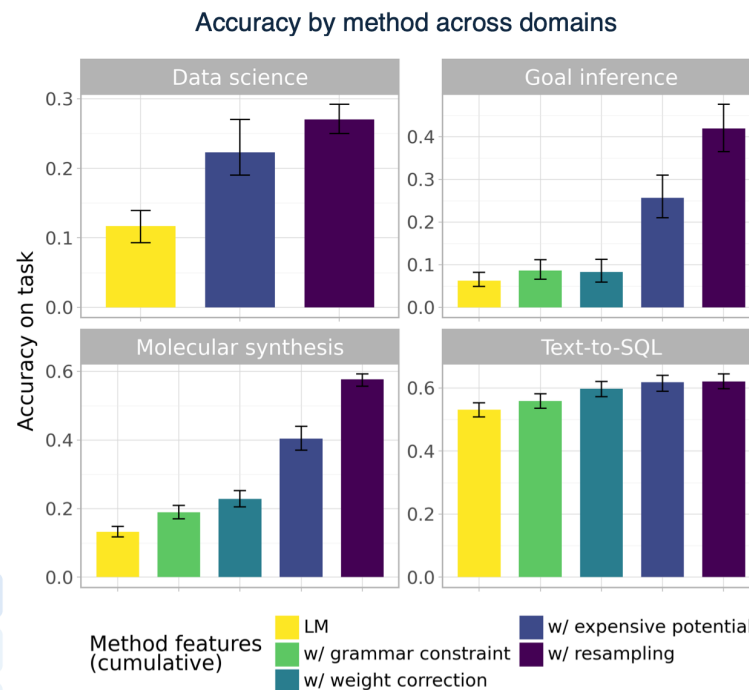
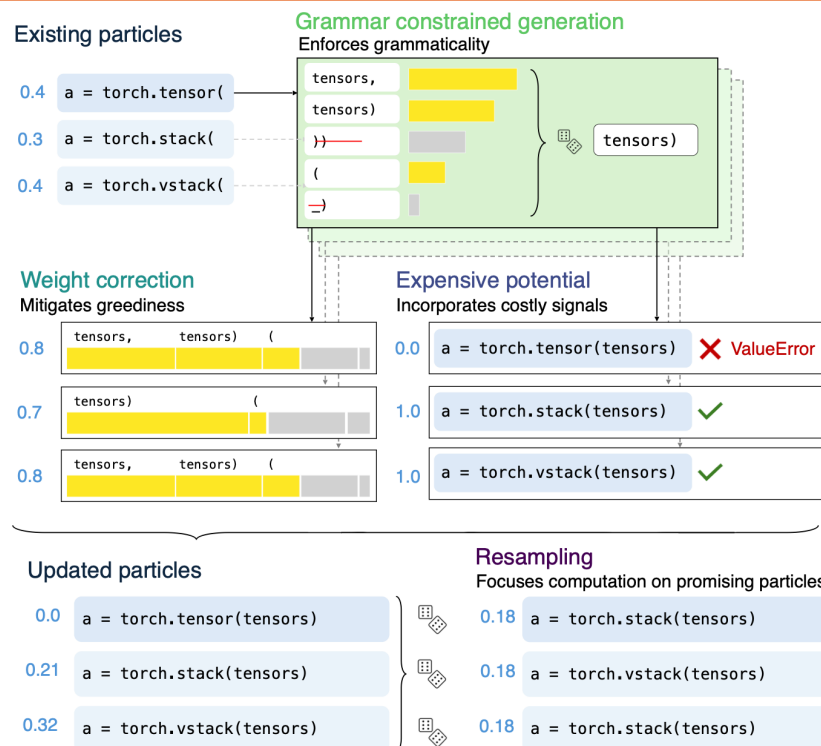


Figure 1: *Controlled generation from LMs via sequential Monte Carlo.* Left: We use sequential Monte Carlo to sample from high-quality approximations to posteriors over LM outputs. Partial sequences are repeatedly extended via **grammar-constrained generation**. We then apply **weight corrections** to mitigate the greediness of locally constrained decoding, as well as **expensive potentials** to encode rich information that cannot be included in logit masks. Finally, **resampling** focuses computation on promising particles. Right: Accuracy gains from these innovations on challenging data science, text-to-SQL, goal inference, and molecule synthesis benchmarks.

SYNTACTIC AND SEMANTIC CONTROL OF LARGE LANGUAGE

João Loula*¹ Bo
Tianyu Liu² Yal
Vikash Mansingh
¹MIT ²ETH Zürich
genlm@mit.edu

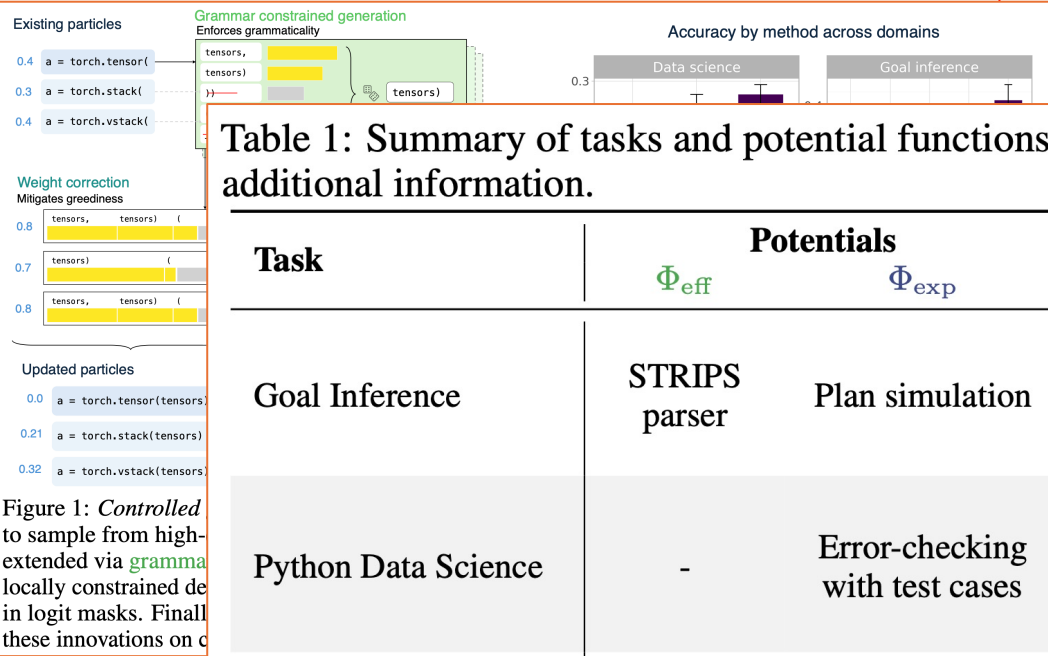


Table 1: Summary of tasks and potential functions. Examples are truncated for brevity. Full prompts include additional information.

Task	Potentials		Prompt	Output
	Φ_{eff}	Φ_{exp}		
Goal Inference	STRIPS parser	Plan simulation	Write the STRIPS goal condition for the planning problem described below [...]. The STRIPS initial condition is: [...]	(:goal (and (arm-empty) (on-table b1) [...]
Python Data Science	-	Error-checking with test cases	Here is a sample dataframe: [...] I'd like to add inverses of each existing column to the dataframe [...]	result = df.join(df.apply(lambda x: 1/x) [...]
Text-to-SQL	SQL parser	Alias and table-column checking	Here is a database schema: [...] For each stadium, how many concerts are there?	SELECT T2.name, COUNT(*) FROM concert AS T1 [...]
Molecular Synthesis	SMILES parser	Incremental molecule validation	Given the following list of molecules in SMILES format, write an additional molecule [...]	CC1=CC2(OC=N)C(=O) [...]

SYNTACTIC AND SEMANTIC CONTROL OF LARGE LANGUAGE

João Loula*¹ Be
Tianyu Liu² Ya
Vikash Mansingh
¹MIT ²ETH Zür
genlm@mit.edu

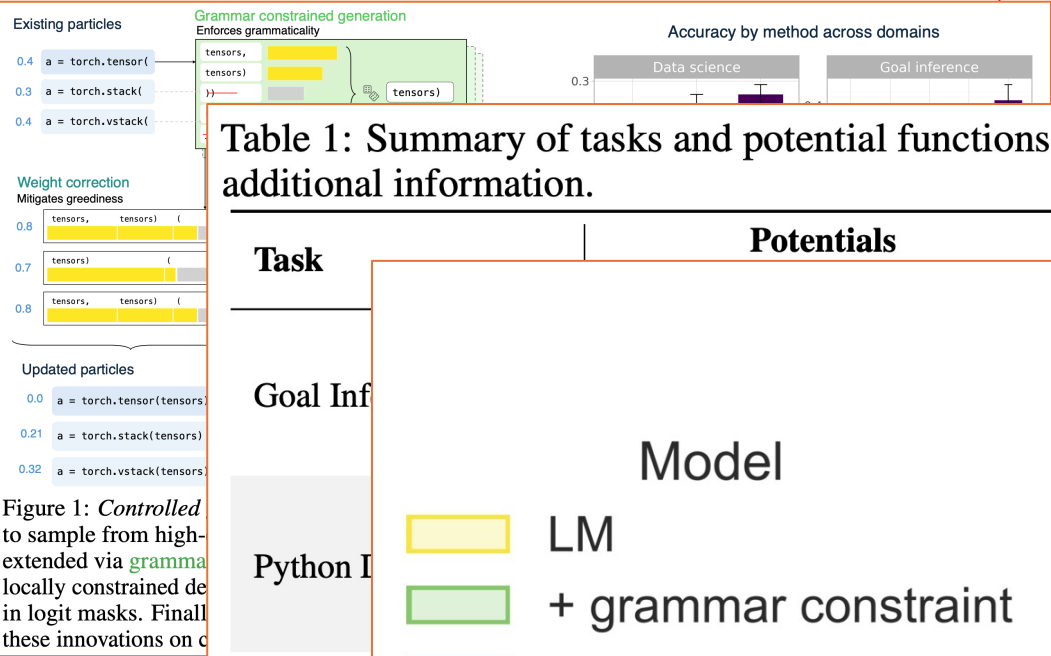
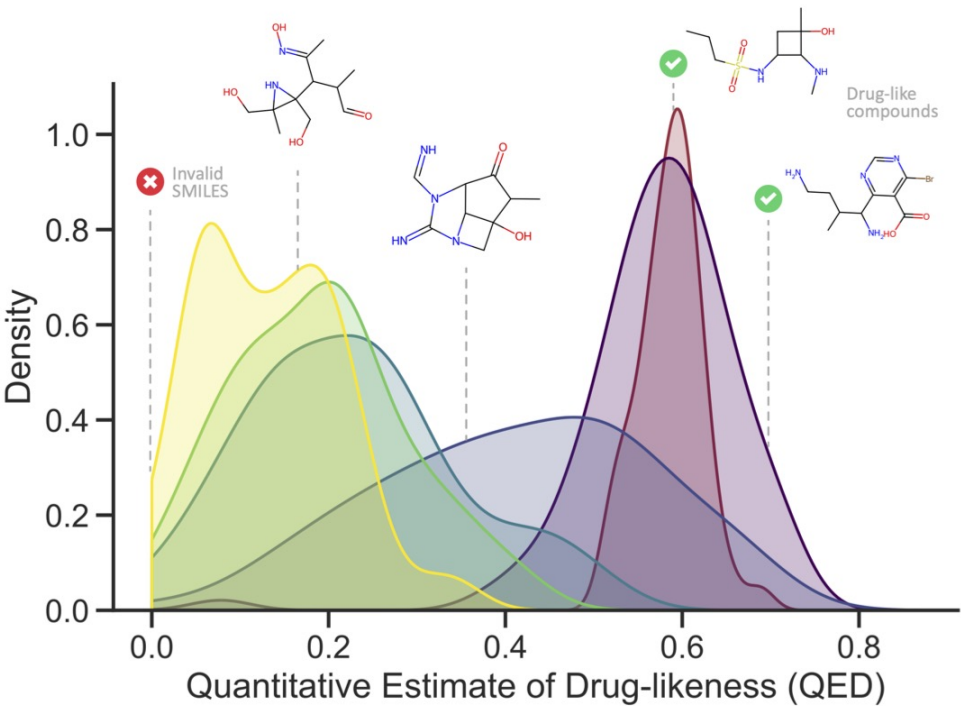


Table 1: Summary of tasks and potential functions. Examples are truncated for brevity. Full prompts include additional information.

Task	Potentials	Examples
Goal Inf		
Python I		
Text-to-S		
Molecul		

Model

- LM
- + grammar constraint
- + weight correction
- + expensive potential
- + resampling
- Target distribution



Beyond Constrained Decoding

Programmatic Structured Steering



LMQL

A programming language for large language models.

[Documentation »](#)

[Explore Examples](#) · [Playground IDE](#) · [Report Bug](#)

 chat 78 online

 package 0.7.3

 Watch 21 ▾

 Fork 210 ▾

 Star 4.1k ▾

Prompting Is Programming: A Query Language for Large Language Models

1

Prompting Is Programming: A Query Language for Large Language Models

LUCA BEURER-KELLNER, MARC FISCHER, and MARTIN VECHEV, ETH Zurich, Switzerland

```
1 argmax
2   "A list of things not to forget when "
3   "travelling:\n"
4   things = []
5   for i in range(2):
6     "- [THING]\n"
7     things.append(THING)
8   "The most important of these is [ITEM]."
```

9 **from** "EleutherAI/gpt-j-6B"

10 **where**

```
11   THING in ["passport",
12             "phone",
13             "keys", ...] // a longer list
14   and len(words(THING)) <= 2
```

{guidance}

Guidance is an efficient programming paradigm for steering language models. With Guidance, you can control how output is structured and get high-quality output for your use case—*while reducing latency and cost vs. conventional prompting or fine-tuning*. It allows users to constrain generation (e.g. with regex and CFGs) as well as to interleave control (conditionals, loops, tool use) and generation seamlessly.

👁 Watch 123 ▾

🔗 Fork 1.1k ▾

★ Star 20.7k ▾

```
from guidance.library import one_or_more

@guidance(stateless=True)
def _gen_heading(lm: Model):
    lm += select(
        options=[_gen_text_in_tag("h1"), _gen_text_in_tag("h2"), _gen_text_in_tag("h3")]
    )
    lm += "\n"
    return lm

@guidance(stateless=True)
def _gen_para(lm: Model):
    lm += "<p>"
    lm += one_or_more(
        select(
            options=[
                _gen_text(),
                _gen_text_in_tag("em"),
                _gen_text_in_tag("strong"),
                "<br />",
            ],
        )
    )
    lm += "</p>\n"
    return lm
```

```
import guidance

from guidance.models import Model

ASCII_OFFSET = ord("a")

@guidance
def zero_shot_multiple_choice(
    language_model: Model,
    question: str,
    choices: list[str],
):
    with user():
        language_model += question + "\n"
        for i, choice in enumerate(choices):
            language_model += f"{chr(i+ASCII_OFFSET)} : {choice}\n"

    with assistant():
        language_model += select(
            [chr(i + ASCII_OFFSET) for i in range(len(choices))], name="string_choice"
        )

    return language_model
```

Sequential Monte Carlo Steering of Large Language Models using Probabilistic Programs

Alexander K. Lew
MIT
alexlew@mit.edu

Tan Zhi-Xuan
MIT
xuan@mit.edu

Gabriel Grand
MIT
grandg@mit.edu

Vikash K. Mansinghka
MIT
vkm@mit.edu

```
# The step method is used to perform a single 'step' of generation.
# This might be a single token, a single phrase, or any other division.
# Here, we generate one token at a time.
async def step(self):
    # Condition on the next token *not* being a forbidden token.
    await self.observe(self.context.mask_dist(self.forbidden_tokens), False)

    # Sample the next token from the LLM -- automatically extends `self.context`.
    token = await self.sample(self.context.next_token())

    # Check for EOS or end of sentence
    if token.token_id == self.eos_token or str(token) in ['.', '!', '?']:
        # Finish generation
        self.finish()
```

Sequential Monte Carlo Steering of Large Language Models using Probabilistic Programs

Alexander K. Lew
MIT
alexlew@mit.edu

Tan Z
xuan@

LLaMPPL

docs passing Codebase tests passing codecov 65%

```
# The step method is used to
# This might be a single tok
# Here, we generate one token
async def step(self):
    # Condition on the next
```

```
    await self.observe(self.context.mask_dist(self.forbidden_tokens), False)
```

```
# Sample the next token from the LLM -- automatically extends `self.context`.
token = await self.sample(self.context.next_token())
```

```
# Check for EOS or end of sentence
if token.token_id == self.eos_token or str(token) in ['.', '!', '?']:
    # Finish generation
    self.finish()
```

LLaMPPL is a research prototype for language model probabilistic programming: specifying language generation tasks by writing probabilistic programs that combine calls to LLMs, symbolic program logic, and probabilistic conditioning. To solve these tasks, LLaMPPL uses a specialized sequential Monte Carlo inference algorithm. This technique, SMC steering, is described in [our recent workshop abstract](#).

Summary

- We are building an arsenal of tools to generate good **symbolic** code from **neural** language models
 - Natural (Magical) strategies
 - Prompting
 - Prompt tuning
 - Mechanical strategies
 - Controlled decoding
 - Structural strategies
 - Iterative refinement
 - Programmatic steering
 - Agentic strategies
 - External tool use

We have not discussed...

- Syntactic constraints
 - Context free grammar
 - Regular expressions (Regex)
 - Finite state machine; Automaton; how to compile an automaton from CFG
 - Algorithms for lexing, parsing, compile a parsing, how to write AST
- Steering libraries
 - LMQL
 - Guidance
 - Langchain
 - DSPY

Week 4

- Assignment 1
 - <https://github.com/machine-programming/assignment-1>
 - Accepting late submissions
- Assignment 2
 - <https://github.com/machine-programming/assignment-2>
 - Due in two weeks; sending out another set of API keys; autograders
- Oral presentation starting from week 7
 - Sign-up sheet going out this week
- Feedback Questionnaire
 - Sending out this week
 - +0.5% of your overall grade