Code Representation for Neural Networks and Applications

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SiDNN – 10.05.2022

Outline

Relevant Tasks

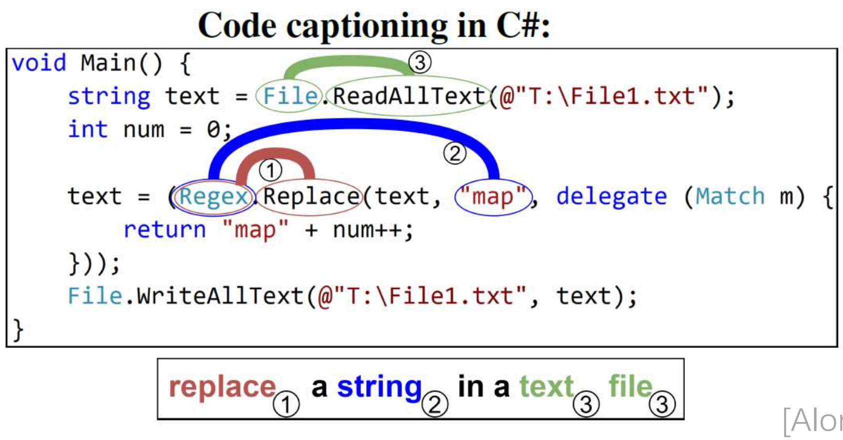
AST Code Representations

AST-based Models

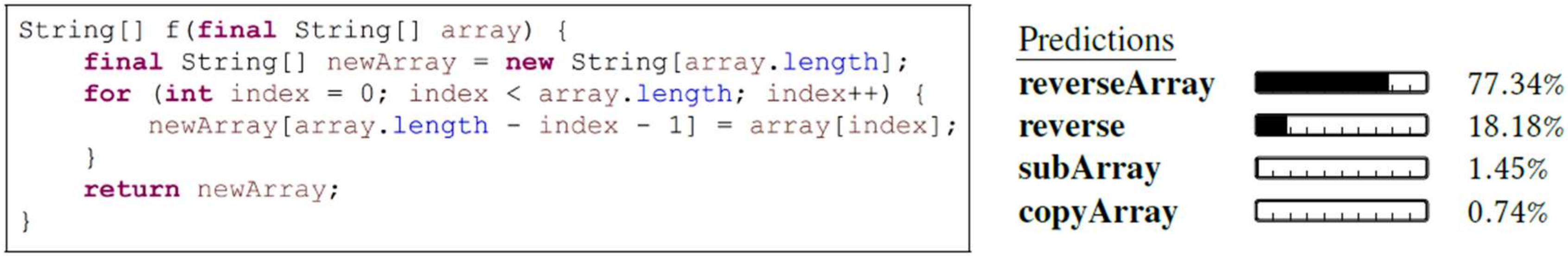
Possible Research Directions

Relevant Tasks

Task Category	Input	Output
Explanation Tasks (code captioning, code summary)	Code snippet	Natural language sequence



[Alon et al. 2018]



Relevant Tasks

Task Category	Input	Output
Explanation Tasks (code captioning, code summary)	Code snippet	Natural language sequence
Information Retrieval Tasks (identifier name search, code search)	Query String (e.g., key-word-to-find, code summary)	Relevant code (e.g., relevant identifiers, relevant code snippets)

A	≈B
size	getSize, length, getCount, getLength
active	isActive, setActive, getIsActive, enabled
done	end, stop, terminate
toJson	serialize, toJsonString, getJson, asJson,
run	execute, call, init, start

Figure from
[Alon et al. 2018]

```
swap two elements in the list
```

(a) Query q

```
void swapElementInList(List<Integer> list, int i, int j) {
    int element = list.get(i);
    list.set(i, list.get(j));
    list.set(j, element);
}
```

(b) Code Snippet s_1

```
void swapElementInList(List<Integer> list, int i, int j) {
    Collections.swap(list, i, j);
}
```

(c) Code Snippet s_2

2022, Sun et al., Code Search based on Context-aware Code Translation, https://arxiv.org/abs/2202.08029

Relevant Tasks

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Generation Tasks (code completion, comment to code)	Code snippet (incomplete) or natural language	Code snippet (e.g., a single identifier, a code block)

```
class Operator(Employee):
  def __init__(self, name, employee_id):
    super(Operator, self).__init__(name, Rank.OPERATOR)
    self.employee_id = employee_id

  def _dispatch_call(self, call, employees):
    for employee in employees:
      employee.take_call(call)

  def record_path(self, base_name):
    return os.path.join(base_name, str(self.___?___))
```

Figure from [Li et al. 2017]

Code Representation

Central problem

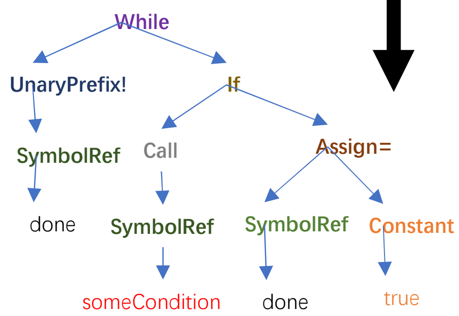
Question: how to feed code to neural networks?

Option 1: NLP approach

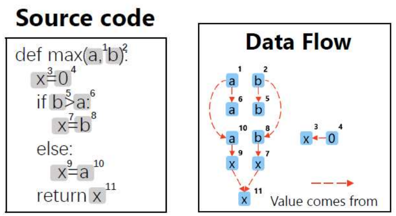
```
while (!done) {
    if (someCondition()) {
        done = true;
    }
}
```

[while, (, !, done,), {, \n, \t, if, (, someCondition, (,),), …]

Option 2: code as syntactic parse tree



Option 3: extract features



Code Representation

Central problem

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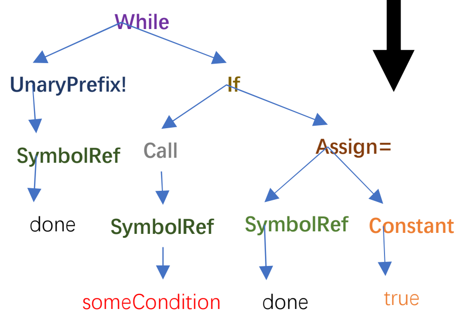
Option 2: code as syntactic parse tree



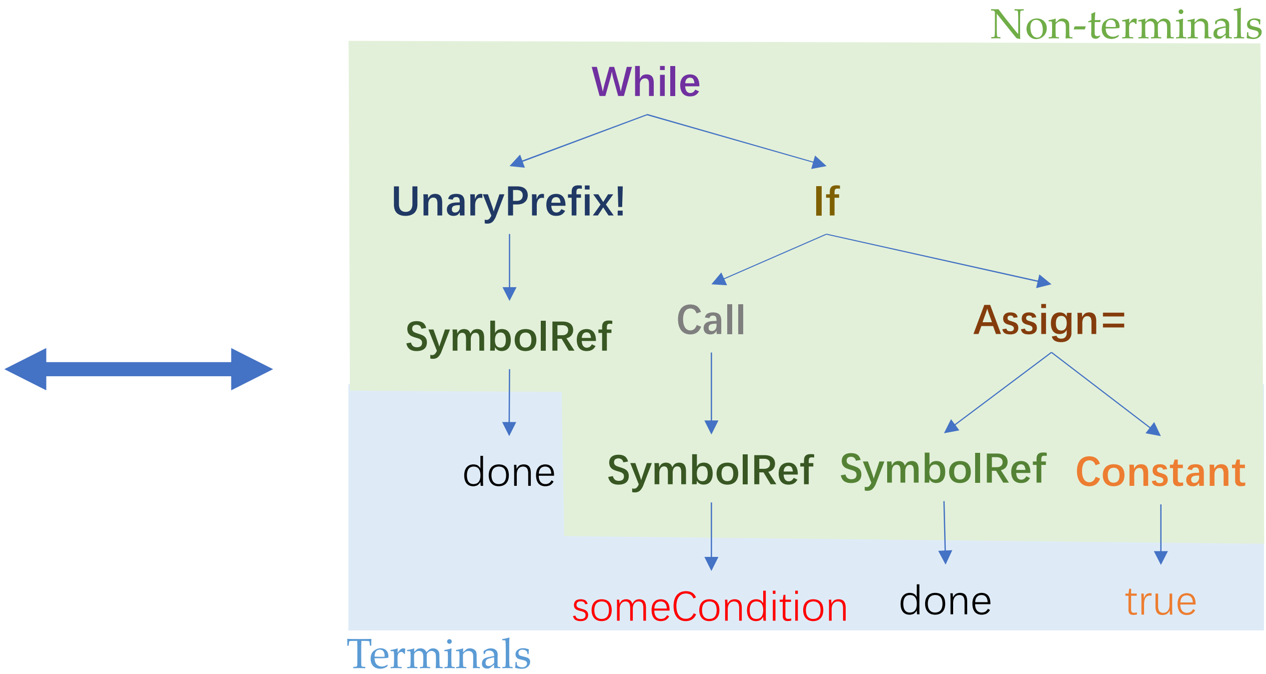
Option 3: extract features from parse tree

Code Representation AST

Abstract Syntax Tree (AST): parse tree for program codes

Example:

```
while (!done) {
    if (someCondition()) {
        done = true;
    }
}
```

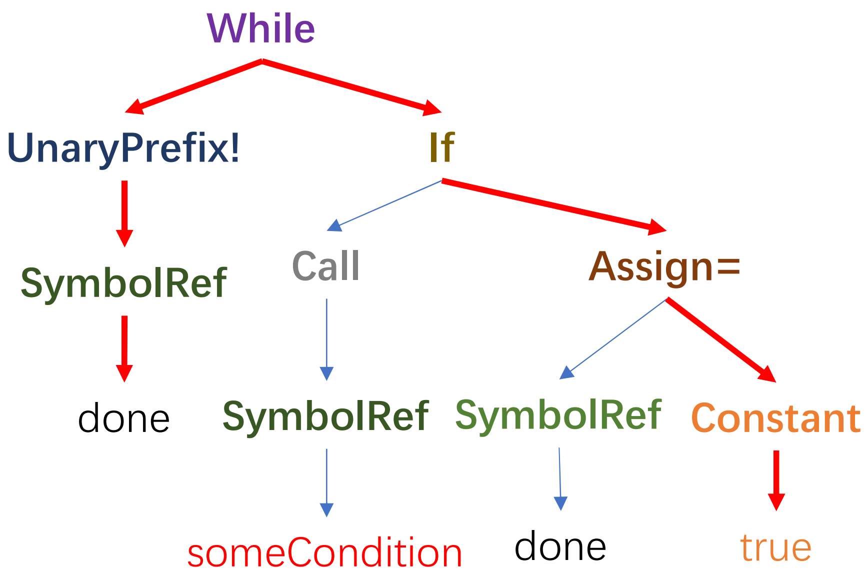


Code Representation

Bag of AST path contexts

- **How to feed parse tree to neural network?**

AST path example:



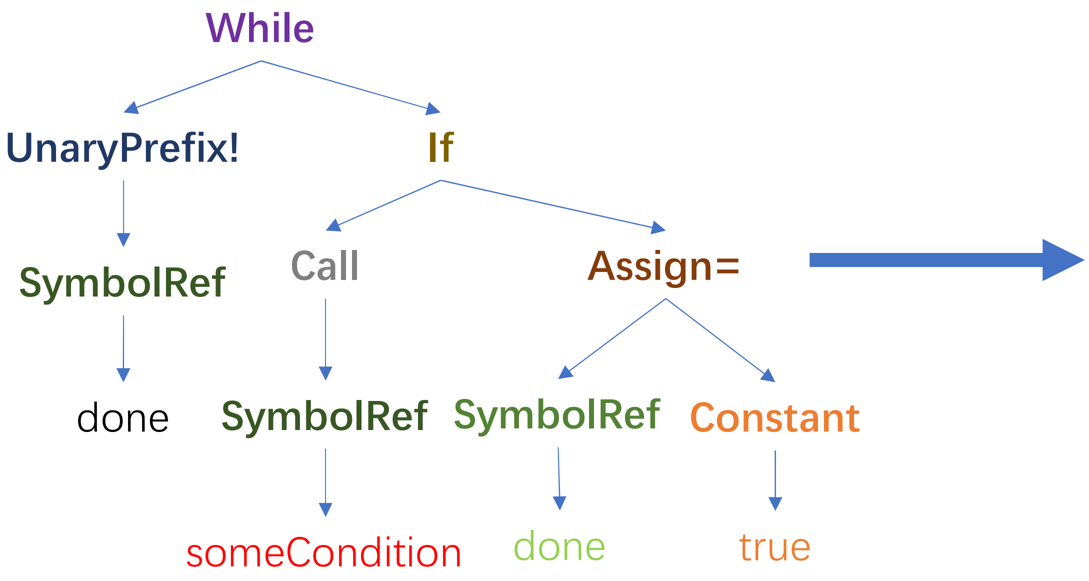
The red-marked path

$p = \langle$done, (**SymbolRef** $\uparrow$ **UnaryPrefix!** $\uparrow$ **While** $\downarrow$ **If** $\downarrow$ **Assign=** $\downarrow$ **Constant**), true$\rangle$

Code Representation

Bag of AST path contexts

- **How to feed parse tree to neural network?**



$$C = \left\{ \begin{array}{c} \langle \text{done}, p_1, \text{someCondition} \rangle, \\ \langle \text{done}, p_2, \text{done} \rangle, \\ \langle \text{done}, p_3, \text{true} \rangle, \\ \langle \text{someCondition}, p_4, \text{done} \rangle, \\ \langle \text{someCondition}, p_5, \text{true} \rangle, \\ \langle \text{done}, p_6, \text{true} \rangle \end{array} \right\}$$

Proposed in code2vec [Alon et al. 2018].

Code Representation

Bag of AST path contexts

Embedding for Bag of AST path contexts:

Basic idea: maintain 2 embedding vocabularies: $V_{\text{value}}, V_{\text{path}}$

$$C = \left\{ \begin{array}{c} \langle \text{done}, p_1, \text{someCondition} \rangle, \\ \langle \text{done}, p_2, \text{done} \rangle, \\ \langle \text{done}, p_3, \text{true} \rangle, \\ \langle \text{someCondition}, p_4, \text{done} \rangle, \\ \langle \text{someCondition}, p_5, \text{true} \rangle, \\ \langle \text{done}, p_6, \text{true} \rangle \end{array} \right\}$$

$$\text{Emb}(\langle x_s, p, x_t \rangle) = [V_{\text{value}}(x_s), V_{\text{path}}(p), V_{\text{value}}(x_t)]$$

Proposed as code2vec [Alon et al. 2018], further used in code2seq [Alon et al. 2019].

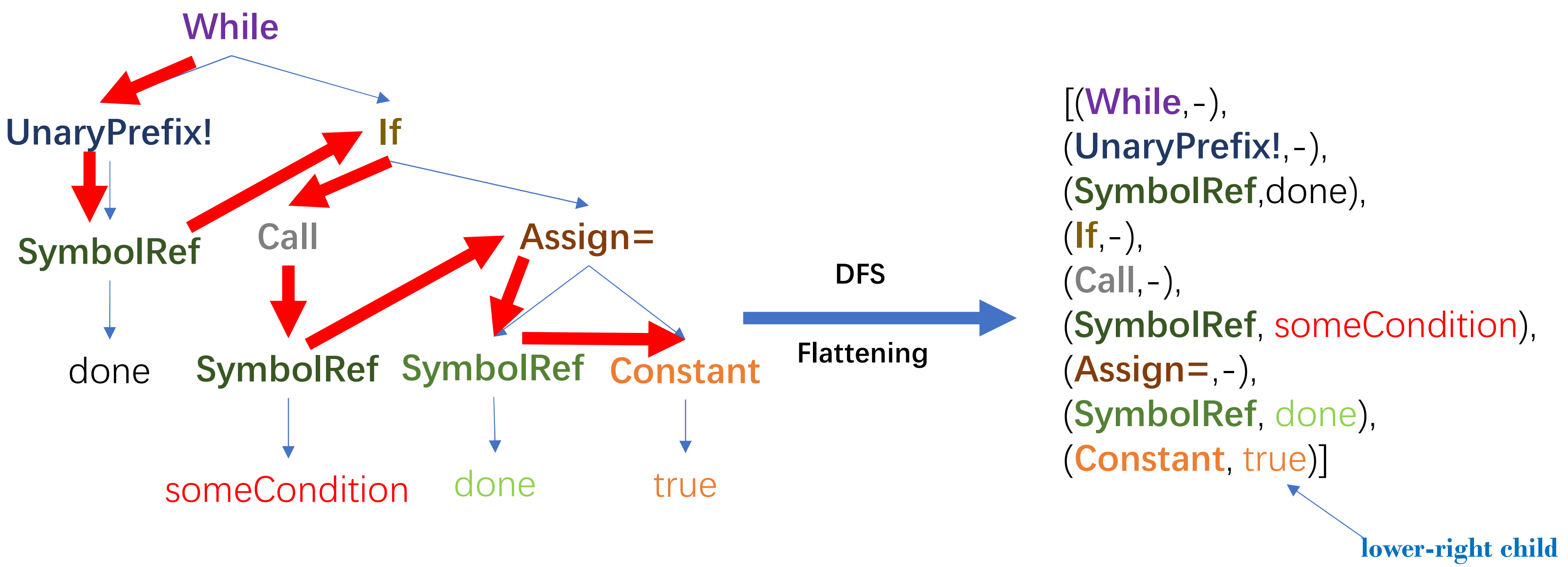
Afraid of large vocabulary size?

- Tokenize (e.g., `list_of_hash` = [`list, of, hash`])
- Use RNN encoder for paths [Alon et al. 2018]

Code Representation

AST as sequence of (non-terminal, terminal) pairs

- Another idea to feed parse tree to neural network



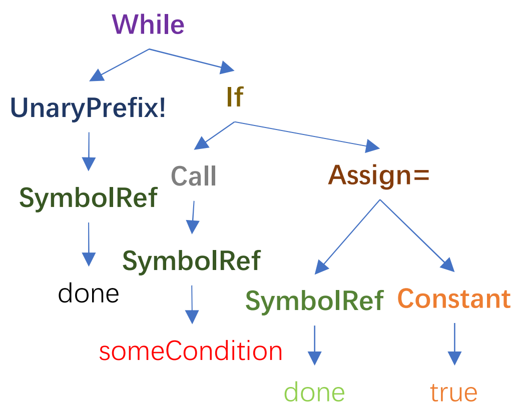
What is the benefit?

Tokenized AST is a suitable representation for code completion [Li et al. 2017]

Code Representation

AST graph

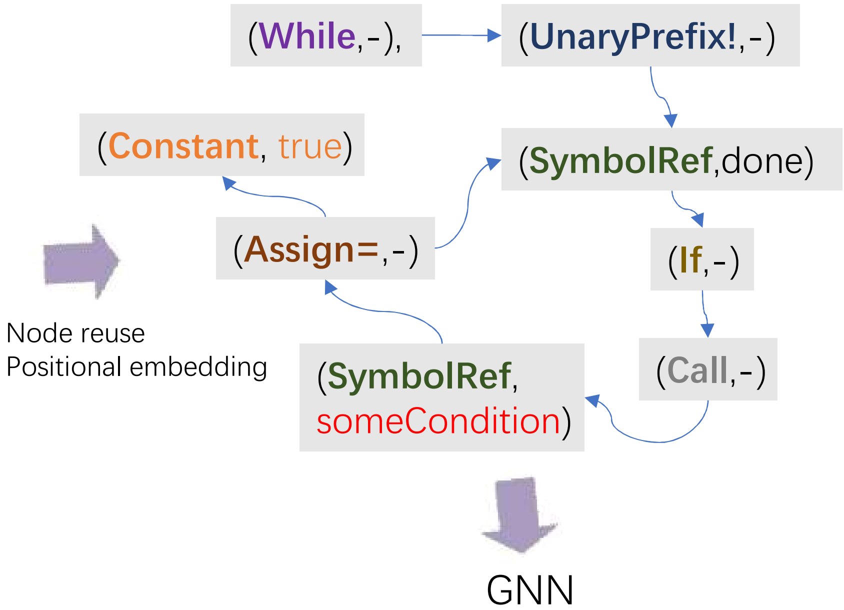
- **AST is a graph!**



[(**While**,-),
(**UnaryPrefix!**,-),
(**SymbolRef**,done),
(**If**,-),
(Call,-),
(**SymbolRef**, someCondition),
(**Assign=**,-),
(**SymbolRef**, done),
(**Constant**, true)]

Code Completion method by modeling flattened ASTs as Graphs

CCAG, [Wang et al. 2021]



Question: why not feed AST directly to GNN?

Reasoning of [Wang et al. 2021]: "in original AST, sequential information is missing"

Really?

Code Representation

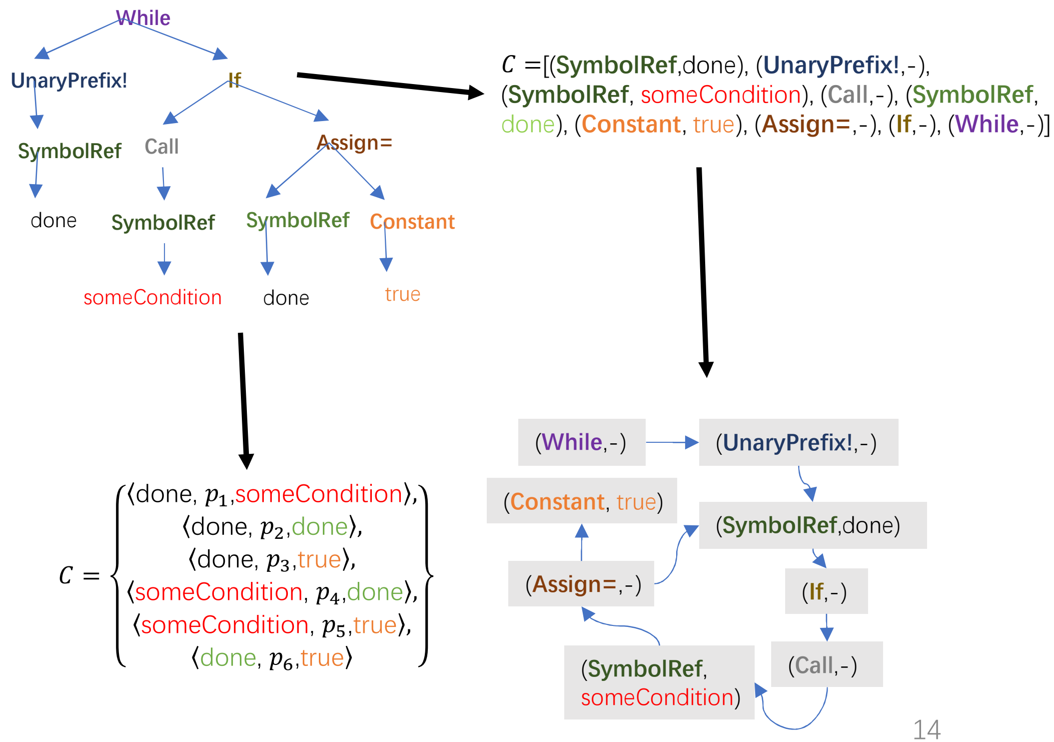
Summary

Level 1: natural-language-like representations

Level 2: AST (syntax-level representation)

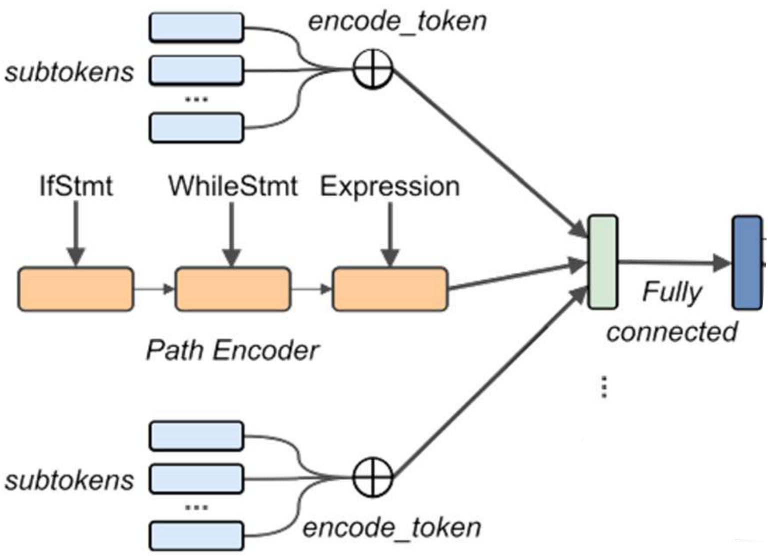
Level 3: extracted features (from AST)

Bag of AST paths,
Sequence of AST nodes (flattened AST),
AST graph



Models

Utilizing AST Paths



Embedding
z_i

Figure adapted from
code2seq [Alon et al. 2019]

Task Category	Input	Output
Explanation Tasks	Code snippet	Natural language sequence
Information Retrieval Tasks	Query String	Relevant code
Code completion	Code snippet	Code snippet

Models

Utilizing AST Paths – researches by Alon et al.

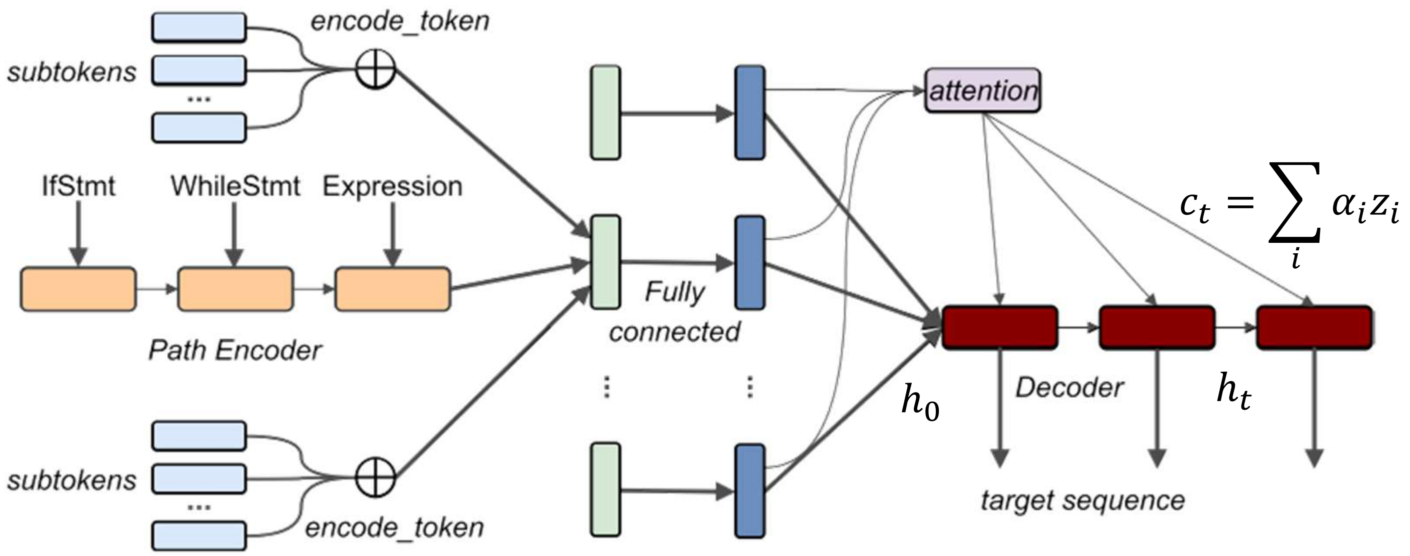


Figure adapted from code2seq [Alon et al. 2019]

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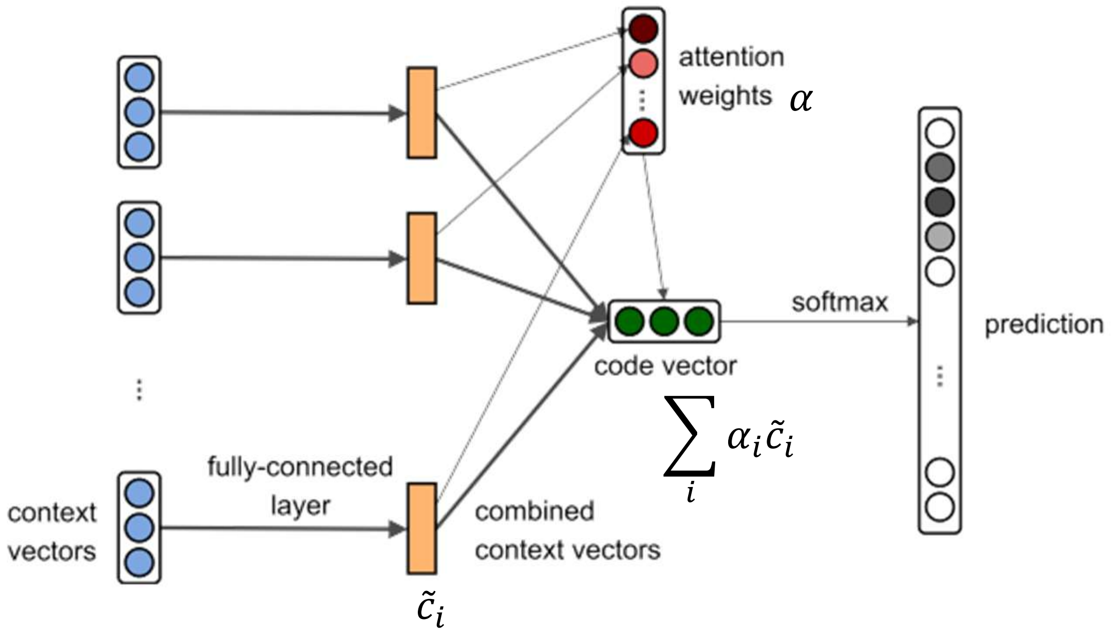

Figure adapted from
code2vec [Alon et al. 2018]

$\tilde{c}_i$ attention with what?

A global vector a maintained as a parameter:

$\alpha_i = \text{softmax}(\tilde{c}_i^T a)$

Task Category	Input	Output
Explanation Tasks	Code snippet	~~Natural language sequence~~ A single word
Information Retrieval Tasks	Query String	Relevant code
Code completion	Code snippet	Code snippet

Models

Utilizing AST Paths – researches by Alon et al.

DEMO: https://code2seq.org/

DEMO
https://code2vec.org/ -> “most similar”, “analogy”

Task Category	Input	Output
Explanation Tasks	Code snippet	Natural language sequence
Information Retrieval Tasks	Query String	Relevant code
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Models

Utilizing AST Paths – researches by Alon et al.

How to?

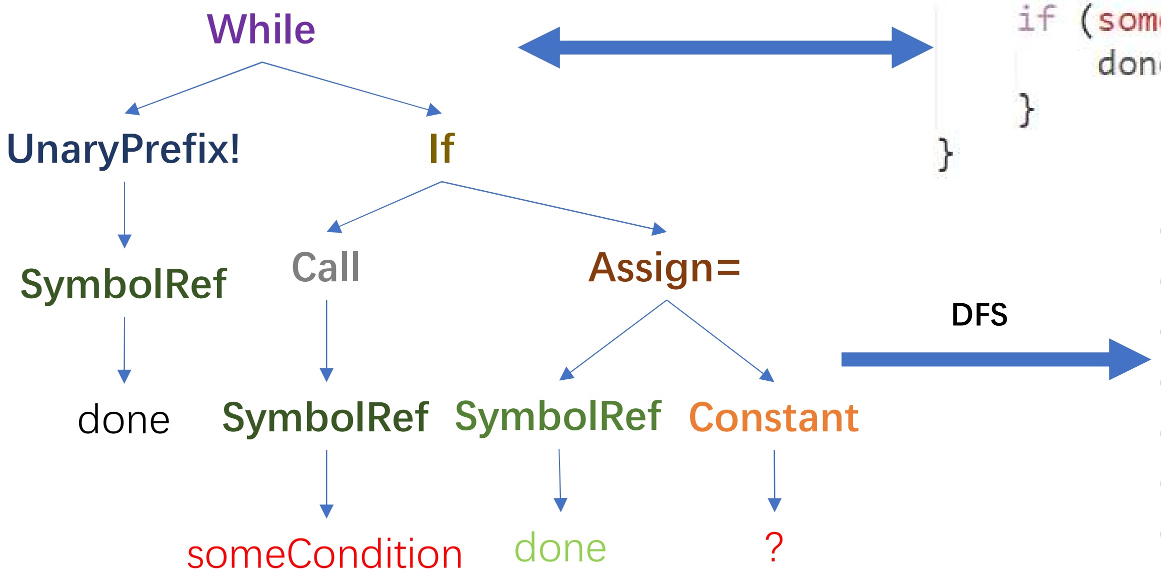
Task Category	**Input**	**Output**
Explanation Tasks	Code snippet	Natural language sequence
Information Retrieval Tasks	Query String	Relevant code
Code completion	Code snippet	Code snippet

Models

Single-token Code Completion Utilizing AST Token Sequences

Recall: converting code into AST token sequence

```
while (!done) {
    if (someCondition()) {
        done = _____;
    }
}
```



[(While,-),
(UnaryPrefix!,-),
(SymbolRef,done),
(If,-),
(Call,-),
(SymbolRef, someCondition),
(Assign=,-),
(SymbolRef, done),
(Constant, ?)]

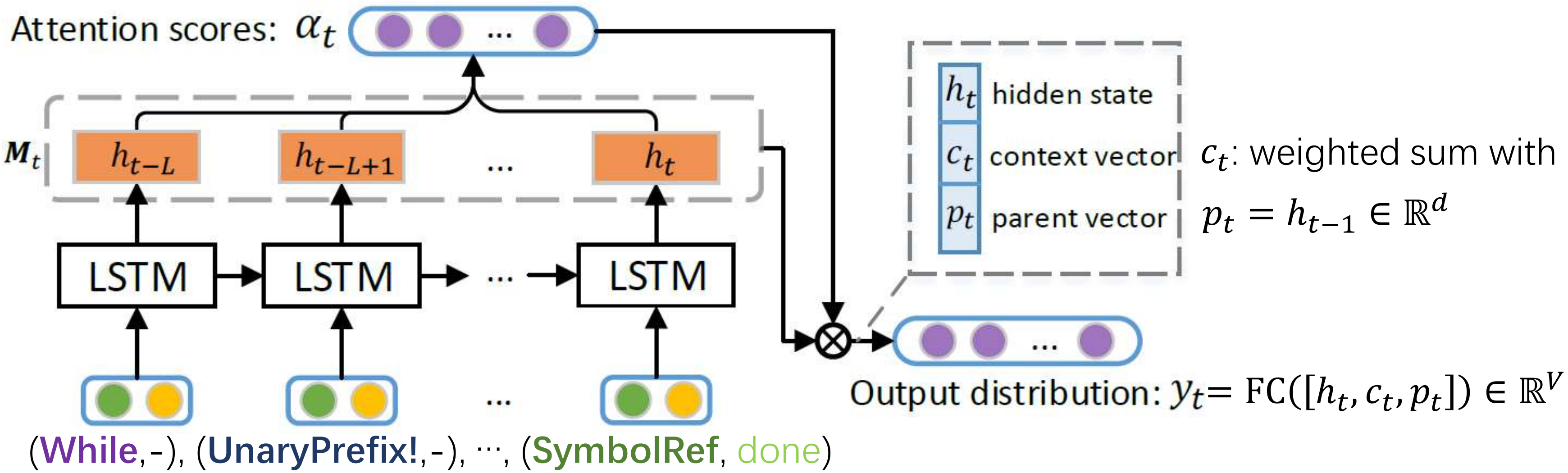
Single-token code completion:
Predict the last token (which is exactly the end of DFS).

Models

Single-token Code Completion Utilizing AST Token Sequences

Basic model: LSTM (with attention)

Figure from [Li et al. 2017]



c_t: weighted sum with attention scores

$p_t = h_{t-1} \in \mathbb{R}^d$

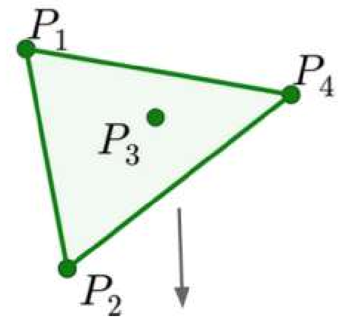
Question: what if the desired prediction is not in the vocabulary?

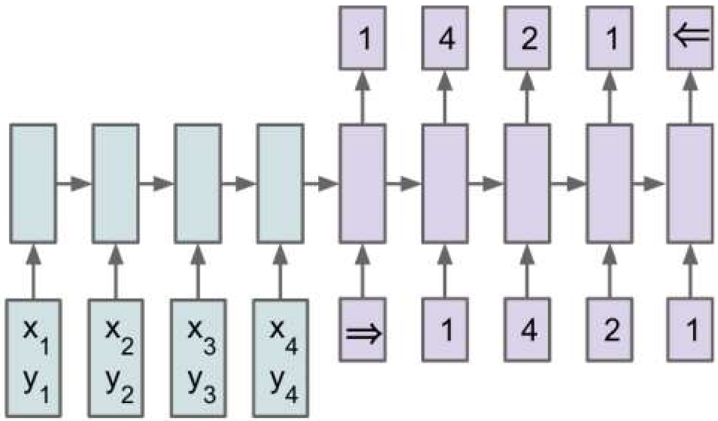
Pointer Network

Models

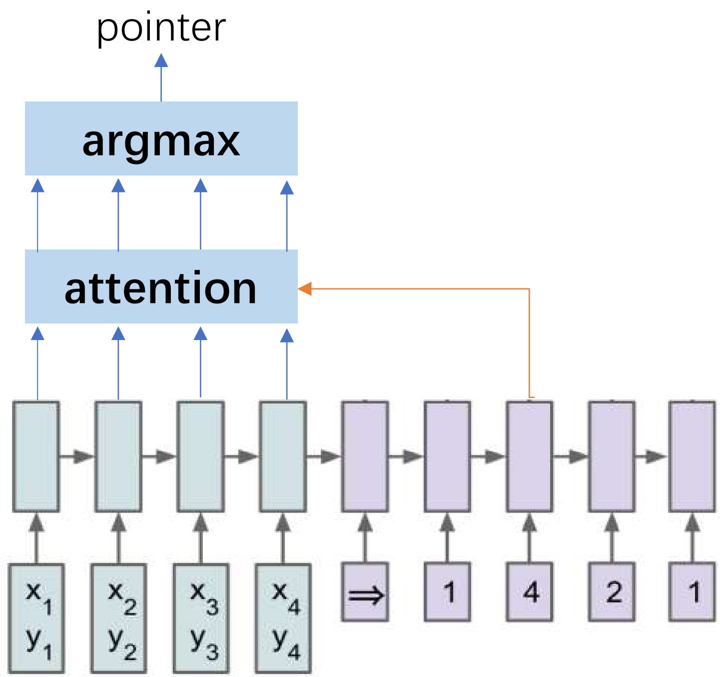
Pointer Network

2015, Vinyals et al., Pointer Network, https://arxiv.org/abs/1506.03134v2





Vanilla Seq2seq



Pointer network

Models

Single-token code completion utilizing AST Token Sequences

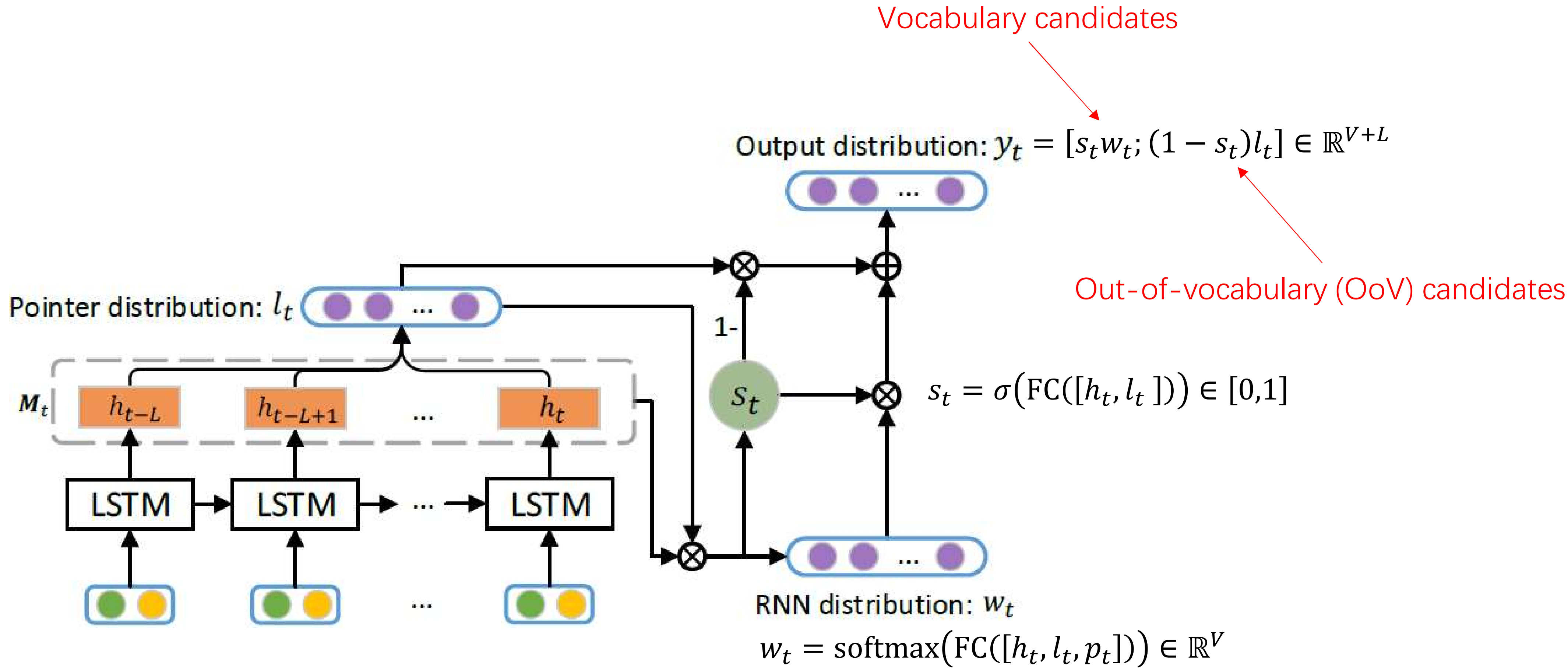


Figure from [Li et al. 2017]

Models

Single-token code completion utilizing AST Token Sequences

Example of OoV

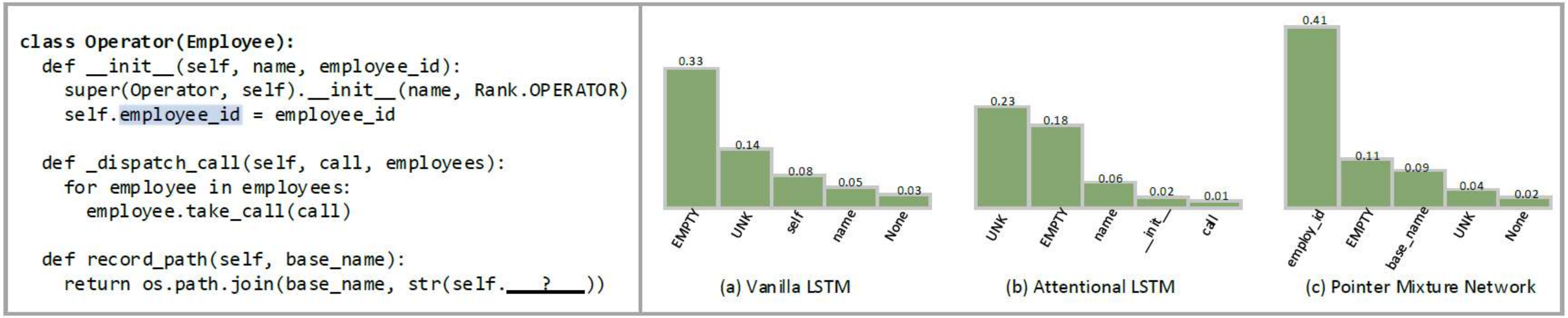


Figure from [Li et al. 2017]

Models

Single-token code completion using GNN

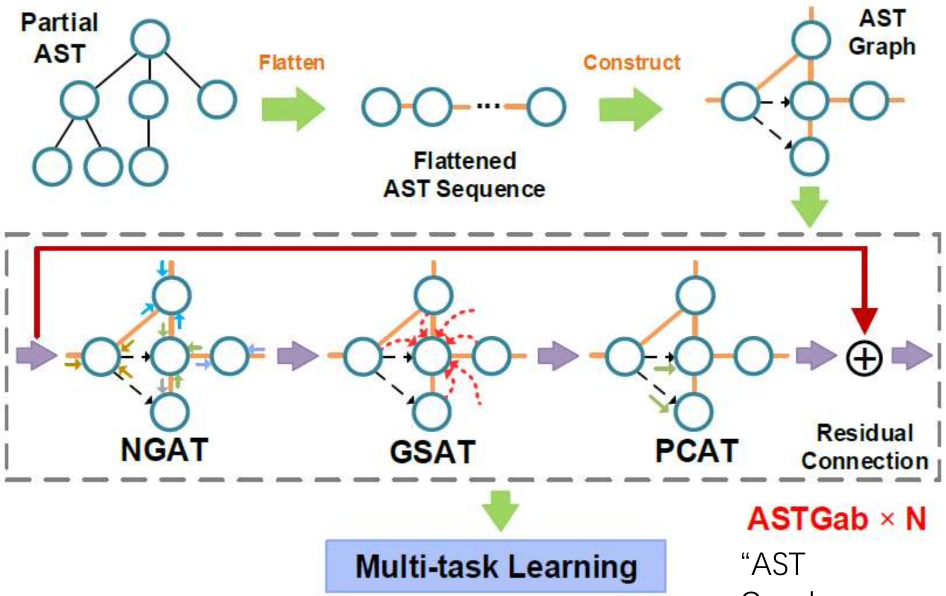


Figure from [Wang et al. 2021]

“AST Graph Attention Block”

Aggregation 1. Neighbor Graph Attention (NGAT)
Aggregation 2. Global Self-Attention (GSAT)
Aggregation 3. Parent-Child Attention (PCAT)
Aggregation 4. Residual connection

-> Get the final hidden state $\mathbf{H}$

Summarization:

$$s = \text{weighted\_pool}(\mathbf{H})$$
$$y^{(\text{nt})} = \text{FC}(s),$$
$$y^{(\text{t})} = \text{FC}(s)$$

Models

Code-block completion

Codex

Evaluating Large Language Models Trained on Code

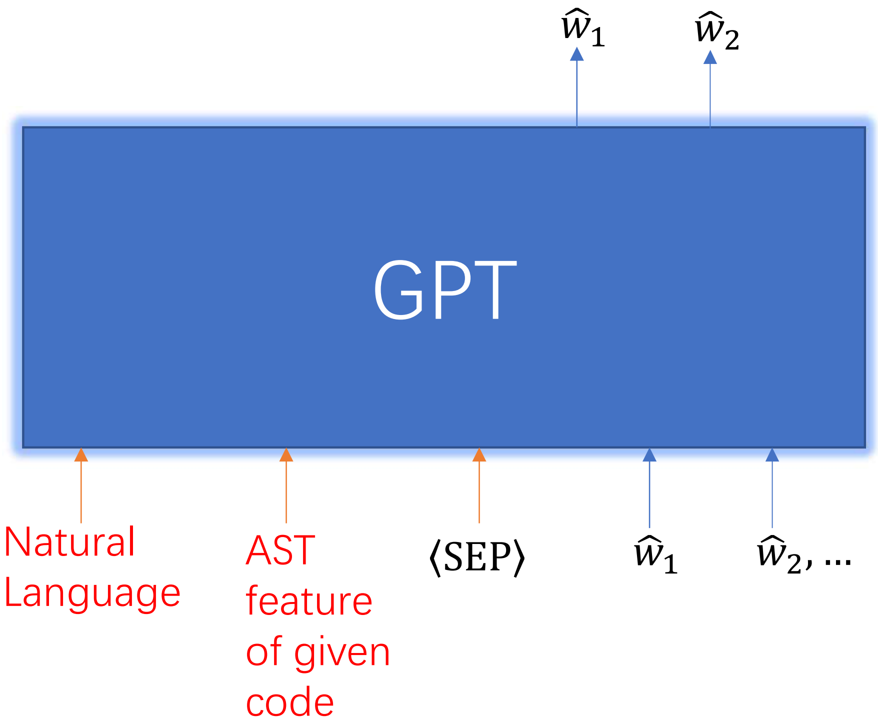
Mark Chen [*1] Jerry Tworek [*1] Heewoo Jun [*1] Qiming Yuan [*1] Henrique Ponde de Oliveira Pinto [*1]
Jared Kaplan [*2] Harri Edwards [1] Yuri Burda [1] Nicholas Joseph [2] Greg Brockman [1] Alex Ray [1] Raul Puri [1]
Gretchen Krueger [1] Michael Petrov [1] Heidy Khlaaf [3] Girish Sastry [1] Pamela Mishkin [1] Brooke Chan [1]
Scott Gray [1] Nick Ryder [1] Mikhail Pavlov [1] Alethea Power [1] Lukasz Kaiser [1] Mohammad Bavarian [1]
Clemens Winter [1] Philippe Tillet [1] Felipe Petroski Such [1] Dave Cummings [1] Matthias Plappert [1]
Fotios Chantzis [1] Elizabeth Barnes [1] Ariel Herbert-Voss [1] William Hebgen Guss [1] Alex Nichol [1] Alex Paino [1]
Nikolas Tezak [1] Jie Tang [1] Igor Babuschkin [1] Suchir Balaji [1] Shantanu Jain [1] William Saunders [1]
Christopher Hesse [1] Andrew N. Carr [1] Jan Leike [1] Josh Achiam [1] Vedant Misra [1] Evan Morikawa [1]
Alec Radford [1] Matthew Knight [1] Miles Brundage [1] Mira Murati [1] Katie Mayer [1] Peter Welinder [1]
Bob McGrew [1] Dario Amodei [2] Sam McCandlish [2] Ilya Sutskever [1] Wojciech Zaremba [1]

- Details?

https://copilot.github.com/

Models

Codex **Guesses on its inferencing**



Want-to-knows:

- **Representation of $\hat{w}_t$**
  - Problems of predicting natural-language-level tokens?
  - Problems of predicting AST token pairs?
- **OoV?**

Summary

Contents covered

- AST-based representations
- Code2Seq, Single-token code completion

Work	Code Representation	Task	Model
Code2vec [Alon et al. 2018]	AST Path Embedding	Code summary	Embedding + Attention + FC
Code2seq [Alon et al. 2019]	AST Path Embedding	Code captioning	Embedding + Attention + RNN decoder
[Li et al. 2017]	AST Token Sequence	Code completion	Pointer Mixture Network
CCAG [Wang et al. 2021]	AST Graph	Code completion	GNN
GraphCodeBERT [Guo et al. 2021]	Text + Code Text + Variable Flow	Universal	BERT + Downstream-specific Models
SynCoBERT [Wang et al. 2021]	Text + Code Text + AST Token Sequence	Universal	BERT + Downstream-specific Models
CodeBERT [Feng et al. 2020]	Text + Code Text	Universal	BERT + Downstream-specific Models

Tensors are universal

Possible Research Directions

A tentative list of relevant topics for research

GNN-related open questions and "combination of techniques" (which is not done yet)

- AST vs. flattened AST graph: does "sequential information" really matter?
- OoV (graph pointer neural network)
- More GNN architectures

Code-block completion

- How did Codex achieve this?
- Is it possible to generate code in a natural-language-like manner?
- How to generate AST using neural network?

More application scenarios

- e.g., code maintenance: given description (e.g., "plot the output") and modify the original code
- …

References

Uri Alon, Meital Zilberstein, Omer Levy, and Eran Yahav. 2018. A General Path-based Representation for Predicting Program Properties. 39th ACM SIGPLAN Conference on Programming Language Design and Implementation (PLDI 2018). ACM, New York, 404–419. https://doi.org/10.1145/3192366.3192412

Uri Alon, Meital Zilberstein, Omer Levy, and Eran Yahav. 2018. Code2Vec: Learning Distributed Representations of Code. Proc. ACM Program. Lang. http://doi.acm.org/10.1145/3290353

Uri Alon, Meital Zilberstein, Omer Levy, and Eran Yahav. 2019. Code2Seq: Generating Sequences from Structured Representations of Code. https://arxiv.org/abs/1808.01400

Jian Li, Yue Wang, Michael R Lyu, and Irwin King. 2017. Code completion with neural attention and pointer networks. https://arxiv.org/abs/1711.09573

Yanlin Wang and Hui Li. 2021. Code Completion by Modeling Flattened Abstract Syntax Trees as Graphs. https://arxiv.org/abs/2103.09499

Zhangyin Feng et al. 2020. CodeBERT: A Pre-Trained Model for Programming and Natural Languages. https://arxiv.org/abs/2002.08155

Daya Guo et al. 2021. GraphCodeBERT: Pre-training Code Representations with Data Flow. https://arxiv.org/abs/2009.08366

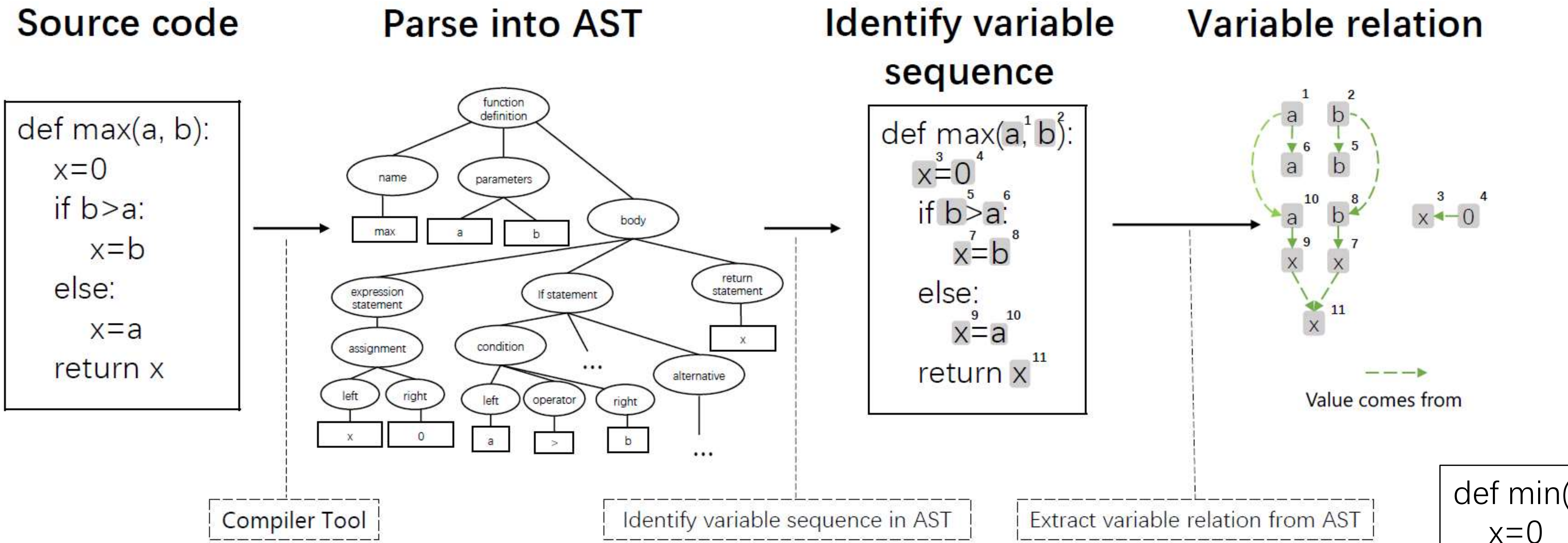
Xin Wang et al. 2021. SynCoBERT: Syntax-Guided Multi-Modal Contrastive Pre-Training for Code Representation. https://arxiv.org/abs/2108.04556

Back-up Contents

Code Representation

Variable flow

Proposed in GraphCodeBERT [Guo et al. 2021]



Figures adapted from [Guo et al. 2021], GraphCodeBERT

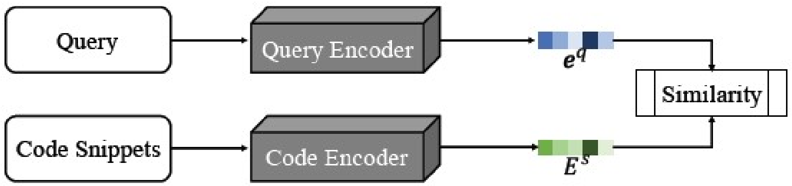
same variable flow

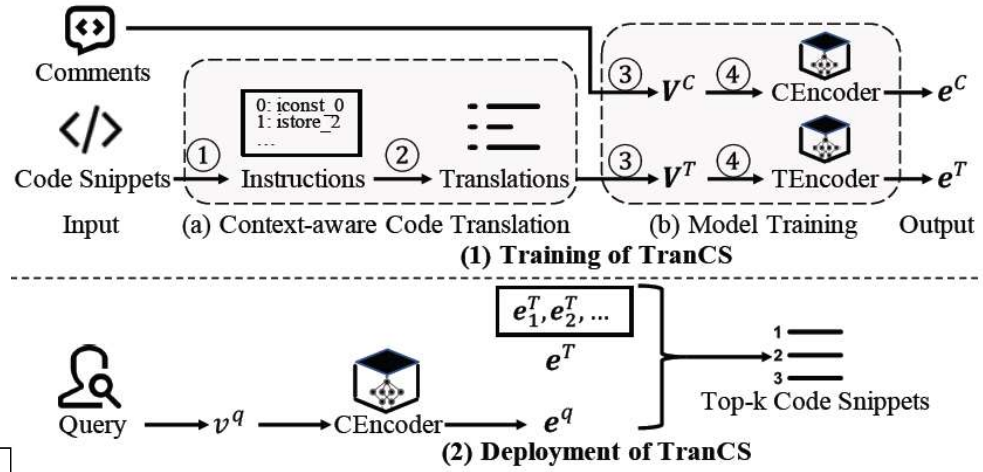
```
def min(a, b):
    x=0
    if b<a:
        x=b
    else:
        x=a
    return x
```

How does low-resolution feature help?

Code Search

Sun et al. 2022. Code Search based on Context-aware Code Translation. https://arxiv.org/abs/2202.08029





②

```java
// calculate the sum of an int array
public int calArraySum(int[] array) {
    int sum = 0;
    int i = 0;
    for (; i < array.length; i++) {
        sum = sum + array[i];
    }
    return sum;
}
```

(a) Code Snippet s_a

0: push int constant **0**.
1: store int **0** into local variable **sum**/**result**.
2: push int constant **0**.
3: store int **0** into local variable **i**/**index**.
4: load int **value** from local variable **i**/**index**.
5: load reference **array**/**array** from local variable **array**/**array**.
6: get length of array **array**/**array**.
7: if and only if int **value** is greater or equal to int **length** then go to **22**.
10: load int **value_1** from local variable **sum**/**result**.
11: load reference **array**/**array** from local variable **array**/**array**.
12: load int **value_2** from local variable **i**/**index**.
13: load int **value_3** from **array**/**array**[**value_2**].
14: int result is int **value_1** add int **value_3**; push result into **value_4**.
15: store int **value_4** into local variable **sum**/**result**.
16: increment local variable **i**/**index** by constant **1**.
19: goto **4**.
22: load int **value_5** from local variable **sum**/**result**.
23: return int **value_5** from method.

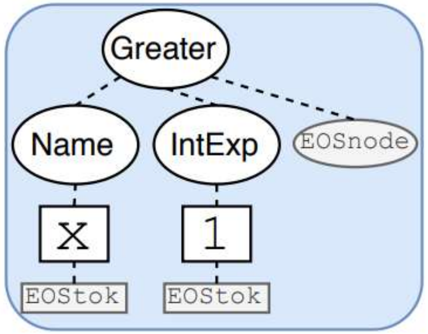
Code-block Completion

Anycode

2020, Alon et al., Structural Language Models of Code, https://arxiv.org/pdf/1910.00577.pdf

```
public static Path[] stat2Paths(
    FileStatus[] stats) {
  if (stats == null) return null;
  Path[] ret = new Path[stats.length];
  for (int i = 0; i < stats.length; ++i){
    ret[i] = [                    ];
  }
  return ret;
}
```

```
public static string Camelize(
    this string input)
{
    var word = input.Pascalize();
    return word.Length > 0 ?
        [                    ].ToLower()
            + word.Substring(1)
        : word;
}
```



Filling in the blank given a partial AST.

The output space in each generation step is determined by the previous token.

Generation ends when sampling EOS_token or EOS_node.

Datasets

For code completion:
JS (JS50K etc.),PY (PY50K etc.) Datasets: https://www.sri.inf.ethz.ch/research/plml

For code summary:
Java (Java Large etc.) Datasets: https://groups.inf.ed.ac.uk/cup/codeattention/
CodeNN C# dataset: https://github.com/sriniiyer/codenn/

For code search:
CodeSearchNet Data Corpus: https://github.com/github/CodeSearchNet#data-details

Model Performances

Single-token code completion
Metric: accuracy

	JS1k		JS10k		JS50k		PY1k		PY10k		PY50k	
	value	type	value	type	value	type	value	type	value	type	value	type
VanillaLSTM	53.19%	69.52%	58.04%	71.16%	59.70%	72.08%	49.99%	68.08%	52.67%	68.86%	53.66%	69.09%
ParentLSTM	56.45%	71.99%	61.54%	73.46%	63.39%	74.24%	52.57%	70.10%	55.87%	76.25%	56.93%	71.00%
PointerMixtureNet	56.49%	71.95%	62.33%	74.28%	64.14%	76.01%	52.98%	69.98%	56.91%	**76.94%**	57.22%	70.91%
Transformer	58.40%	**73.29%**	**63.93%**	**74.78%**	65.31%	75.89%	53.49%	70.63%	57.52%	71.45%	59.05%	71.91%
Transformer-XL	**59.23%**	72.11%	62.82%	74.09%	**66.41%**	**76.23%**	**55.13%**	**72.45%**	**58.21%**	73.19%	**60.00%**	**72.42%**
CCAG	**62.79% (6.01%)**	**75.72% (3.32%)**	**66.69% (4.32%)**	**78.55% (5.04%)**	**68.19% (2.68%)**	**80.14% (5.13%)**	**61.92% (12.32%)**	**76.71% (5.88%)**	**63.24% (8.64%)**	**80.90% (5.15%)**	**64.22% (7.03%)**	**75.31% (3.99%)**

Code Summary

Model	Full Test Set (413915 methods) Precision	Recall	F1
CNN+Attention [Allamanis et al. 2016]	-	-	-
LSTM+Attention [Iyer et al. 2016]	33.7	22.0	26.6
Paths+CRFs [Alon et al. 2018]	53.6	46.6	49.9
PathAttention (this work)	**63.1**	**54.4**	**58.4**

On Java dataset