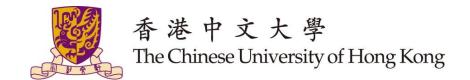


Code Completion with Neural Attention and Pointer Networks

Jian Li, Yue Wang, Michael R. Lyu, Irwin King {jianli, yuewang, lyu, king}@cse.cuhk.edu.hk IJCAI 2018, Stockholm, Sweden





Code Completion

An example:

```
public static void main(String[] args) {
    int firstNumber = 1;
    int secondNumber = 3;
    int i =
            firstNumber
                                                            int
£
            secondNumber
                                                            int
            Integer. MAX VALUE
                                                            int
            Integer.MIN VALUE
                                                            int
          🕅 Integer.SIZE
                                                            int
          Integer.bitCount(int i)
                                                            int
          Integer.decode(String nm)
                                                        Integer
          Integer.getInteger(String nm)
                                                        Integer
          🕼 Integer.getInteger(String nm, Integer val) Integer
          Integer.getInteger(String nm, int val)
                                                        Integer
```

- Static programming languages: compile-time type information
- Dynamic programming languages: learning-based language models

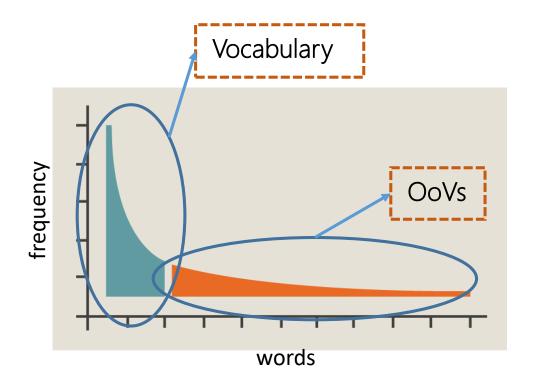
Code Completion with Language Models

 Simplified problem: given a sequence of code tokens, our task is to predict the next one token.

Method: adapt neural language models for code completion.

Challenges

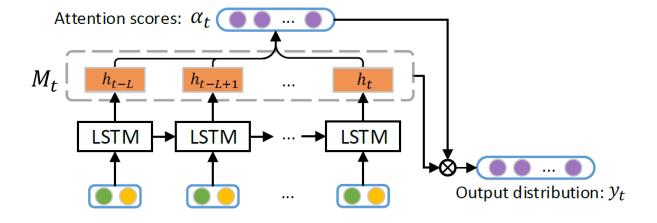
- 1. Long-range dependencies
- 2. Out-of-Vocabulary (OoV) words



OoVs cannot be correctly predicted!

Attention Mechanisms

- Deal with long-range dependencies:
 - Context attention



$$A_{t} = v^{T} \tanh(W^{m} M_{t} + (W^{h} h_{t}) 1_{L}^{T})$$

$$\alpha_{t} = softmax(A_{t})$$

$$c_{t} = M_{t} \alpha_{t}^{T}$$

$$G_{t} = \tanh(W^{g}[h_{t}; c_{t}])$$

$$y_{t} = softmax(W^{v} G_{t} + b^{v})$$

Attention Mechanisms

- Deal with long-range dependencies:
 - Abstract Syntax Tree (AST)

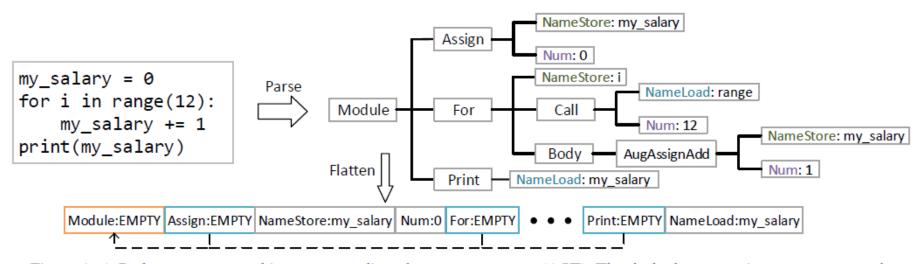
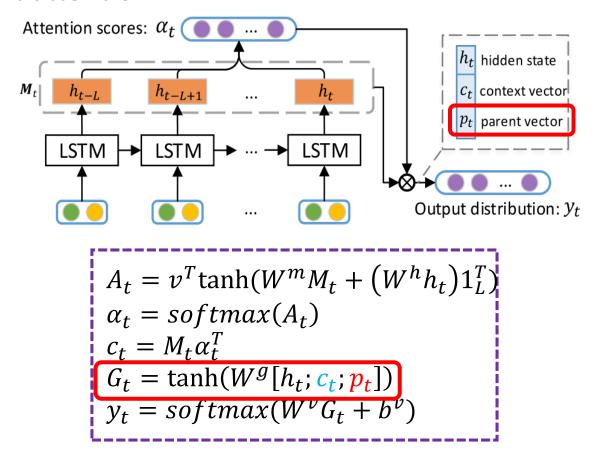


Figure 1: A Python program and its corresponding abstract syntax tree (AST). The dashed arrow points to a parent node.

Exploit the parent-children information on program's AST!

Attention Mechanisms

- Deal with long-range dependencies:
 - Parent attention



 p_t is the parent vector storing the hidden state of the parent node.

Pointer Mixture Network

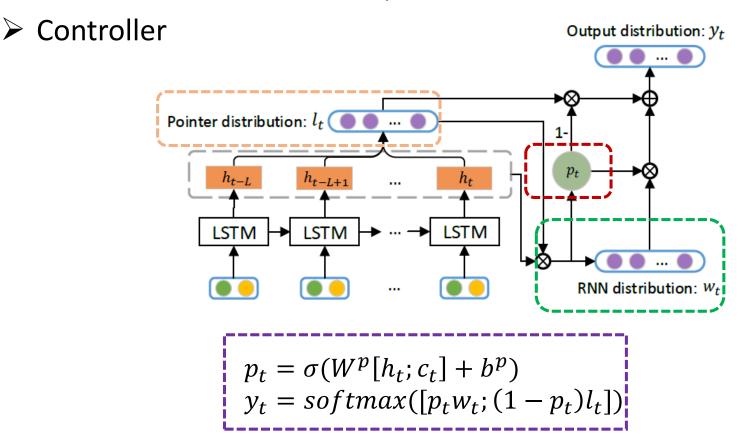
- Deal with OoV words:
 - > Locally repeated terms are prevalent.

```
my_salary = 0
for i in range(12):
    my_salary += 1
print(my_salary)
```

- > Copy from local context to predict OoVs.
- > Learn when and where to copy.

Pointer Mixture Network

- Deal with OoV words:
 - Global RNN component
 - Local pointer component
 - ☐ Reuse the attention scores as the pointer distribution



Experiments

- Dataset
 - JavaScript (JS) and Python (PY)
 - Query: remove the AST node (plus all the nodes to the right) from the node sequence and then attempt to predict the node.

Table 1: Dataset Statistics					
	JS	PY			
Training Queries	$10.7 * 10^7$	$6.2*10^{7}$			
Test Queries	$5.3 * 10^7$	$3.0*10^{7}$			
Type Vocabulary	95	329			
Value Vocabulary	$2.6 * 10^6$	$3.4 * 10^6$			

OoV problem!

Experiments

Accuracies on next value prediction with different vocabulary sizes

Vocabulary Size	JS_1k	JS_10k	JS_50k	PY_1k	PY_10k	PY_50k
OoV Rate / Localness	20% / 8%	11% / 3.7%	7% / 2%	24% / 9.3%	16% / 5.2%	11% / 3.2%
Vanilla LSTM	69.9%	75.8%	78.6%	63.6%	66.3%	67.3%
Attentional LSTM (ours)	71.7%	78.1%	80.6%	64.9%	68.4%	69.8%
Pointer Mixture Network (ours)	73.2%	78.9 %	81.0%	66.4%	68.9%	70.1%

- OoV Rate denotes the percentage of AST nodes whose value is beyond the global vocabulary.
- Localness is the percentage of values who are OoV but occur in the context window, which is the upper-bound of the performance gain.

Vocabulary size \uparrow , OoV rate \downarrow , accuracy \uparrow , performance gain \downarrow

Experiments

- Comparisons against the state-of-the-arts
 - Pointer Mixture Network only for predicting VALUE node

	JS		PY	
	TYPE	VALUE	TYPE	VALUE
Vanilla LSTM	87.1%	78.6%	79.3%	67.3%
Attentional LSTM (no parent attention)	88.1%	80.5%	80.2%	69.8%
Attentional LSTM (ours)	88.6%	80.6%	80.6%	69.8%
Pointer Mixture Network (ours)	-	81.0%	-	70.1%
LSTM [Liu et al., 2016]	84.8%	76.6%	-	-
Probabilistic Model [Raychev et al., 2016]	83.9%	82.9%	76.3%	69.2%

- Our model outperforms the state-of-the-art in almost all cases
- The proposed parent attention is also effective

Conclusion

- 1. Propose a parent attention mechanism for AST-based code completion.
- 2. Propose a pointer mixture network which learns to either generate a new value or copy an OoV value from local context.
- 3. Demonstrate the effectiveness of our model via experiments.

