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A Grammar-Based Structural CNN Decoder for Code Generation

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INTRODUCTION

- Generating code from natural language description.
  - Open the file, F1 → f = open(‘F1’, ‘r’)
- Automatically code generation is beneficial in various scenarios.
  - Similar code snippets can be generated from another.
  - It takes a long time for a programmer to learn a new implement.

INTRODUCTION

- Previous works with neural network are all based on RNN.
  - Researchers [1, 2, 3] have proposed several approach based on AST using LSTM.

- A program is much larger than a natural language sentence and that RNNs suffer from the long dependency problem [4].
  - A program is made up of a large number of AST nodes.

1. Dong, L., and Lapata, M. 2016. Language to logical form with neural attention. In ACL, 33–43.
2. Yin, P., and Neubig, G. 2017. A syntactic neural model for general-purpose code generation. In ACL, 440–450.
3. Rabinovich, M.; Stern, M.; and Klein, D. 2017. Abstract syntax networks for code generation and semantic parsing. In ACL, 1139–1149.
4. Bengio, Y.; Simard, P.; and Frasconi, P. 1994. Learning long-term dependencies with gradient descent is difficult. IEEE Transactions on Neural Networks 5(2):157–166.

INTRODUCTION

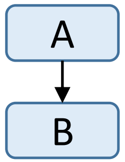
- Researchers are showing growing interest in using the CNN as the decoder.
  - QANet [1], a CNN encoder-decoder, achieves a significant improvement in SQuAD dataset for question answering.

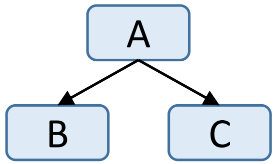
- To address the question, we apply a CNN encoder-decoder.

1. Yu, A. W.; Dohan, D.; Luong, M.-T.; Zhao, R.; Chen, K.; Norouzi, M.; and Le, Q. V. 2018. QANet: Combining local convolution with global self-attention for reading comprehension. In ICLR.

INTRODUCTION

- Programs contain rich structural information, which is important to program modeling.
  - We designed several components for the CNN encoder-decoder.

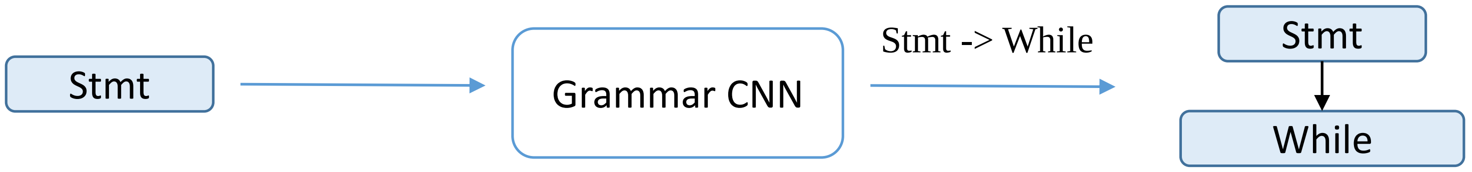




- We design several distinct components for the CNN encoder-decoder.

TO GENERATE A ENTIRE CODE

- The key step of generation is to predict the grammar rule, which will be applied to expand the AST.



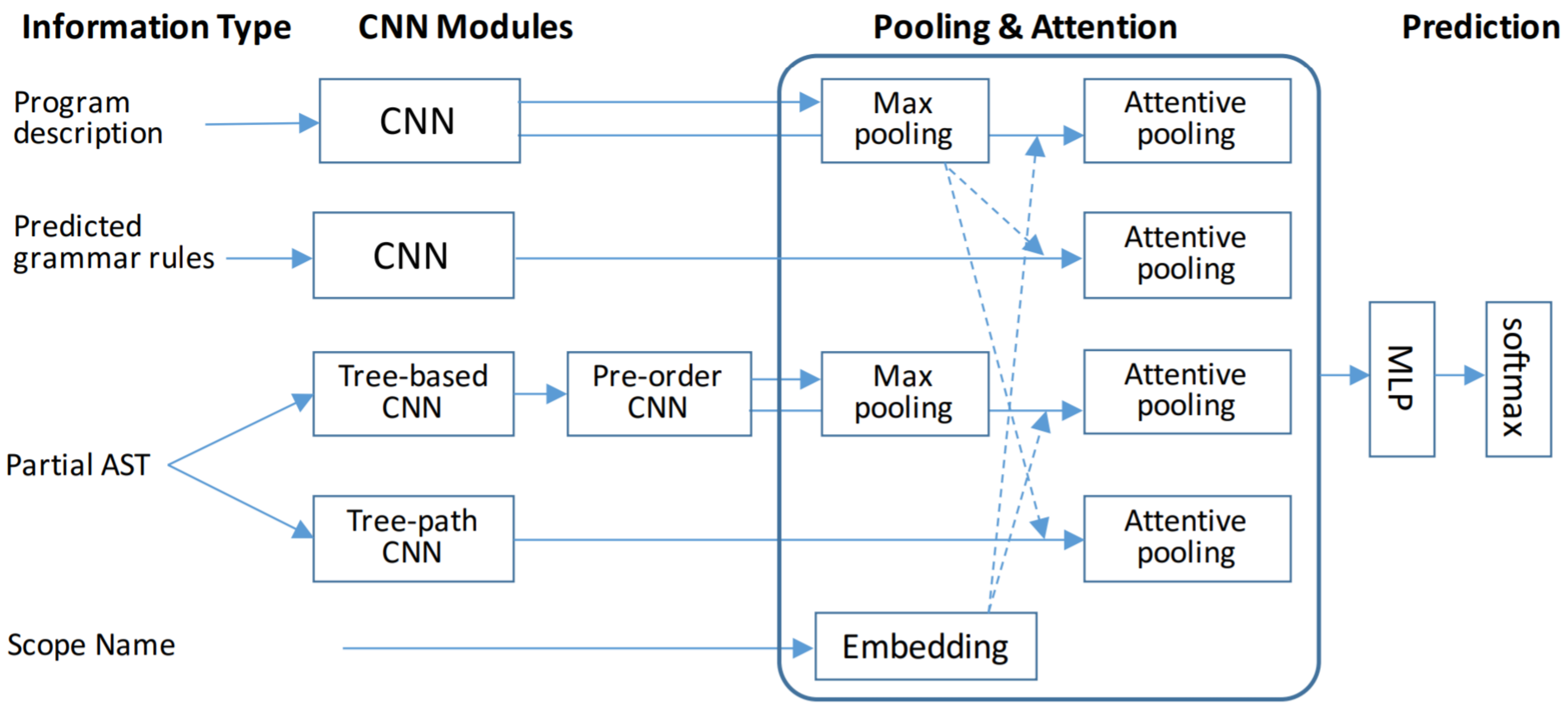
- The probability of an entire code is decomposed as

$$p(\text{program}) = \prod_{n=1}^{N} p(\mathrm{r}_n | \mathrm{r}_1 \cdots, \mathrm{r}_{n-1})$$

TO PREDICT GRAMMAR RULES

- The prediction is mainly based on three types of information:
  - the source input(e.g. a natural language)
  - the previously predicted grammar rules.
  - the partial AST that has been generated.

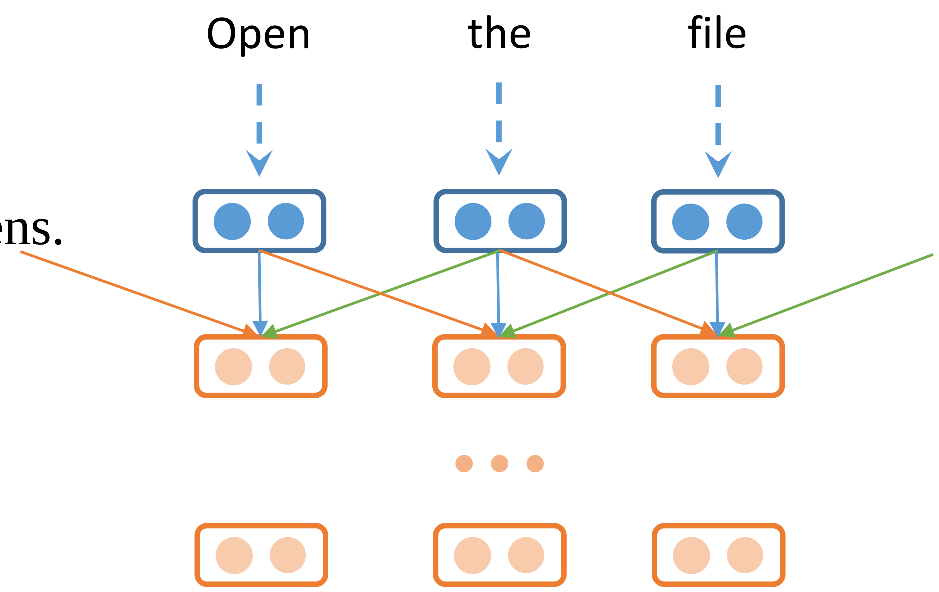
OVERVIEW



Information Type
CNN Modules
Pooling & Attention
Prediction
Program description
CNN
Max pooling
Attentive pooling
Predicted grammar rules
CNN
Attentive pooling
Tree-based CNN
Pre-order CNN
Max pooling
Attentive pooling
MLP
softmax
Partial AST
Tree-path CNN
Attentive pooling
Scope Name
Embedding

TO ENCODE THE INPUT

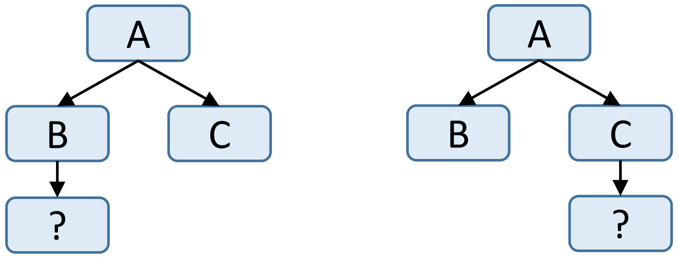
- The input of our model is a piece of description.
- We first tokenize the input, and obtain a sequence of tokens.
- Then, a set of convolutional layers are applied.
    - We adopt shortcut connections every other layer parallel to linear transformation, as in ResNet [1].



[1] He, K.; Zhang, X.; Ren, S.; and Sun, J. 2016. Deep residual learning for image recognition. In CVPR, 770–778.

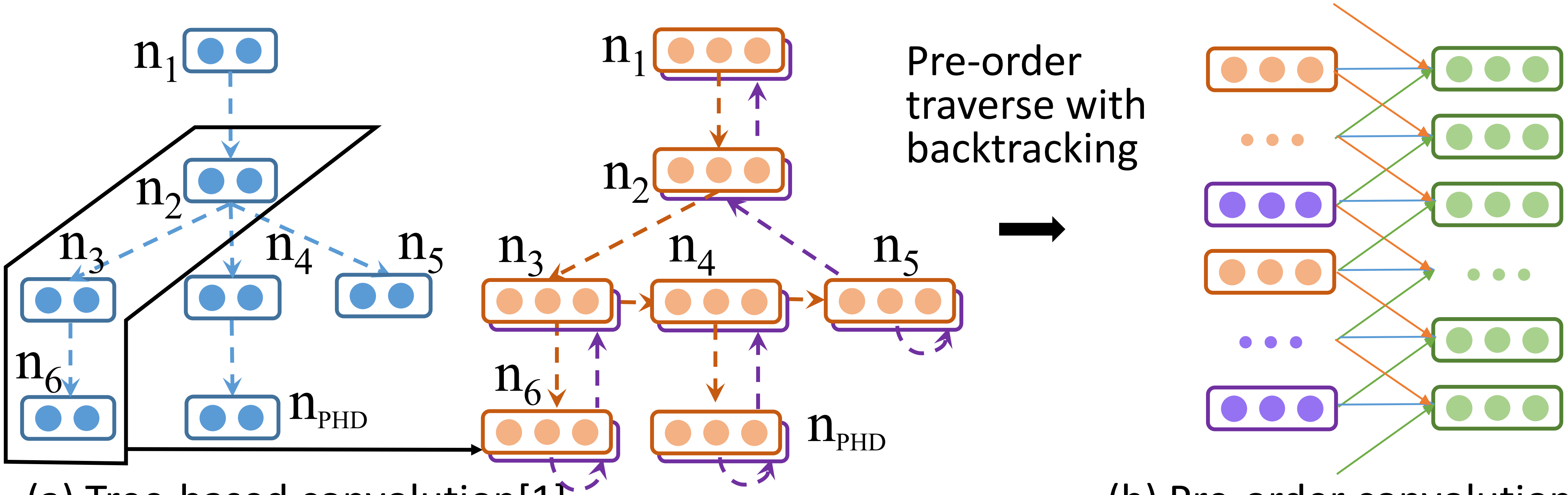
TO DECODE

- The main difficulties for the decoder are as follows:
  - To capture the structural information of the AST.
  - To tell the where the next grammar rule is applied.



TO CAPTURE THE STRUCTURAL INFORMATION

- We split each node into two nodes.



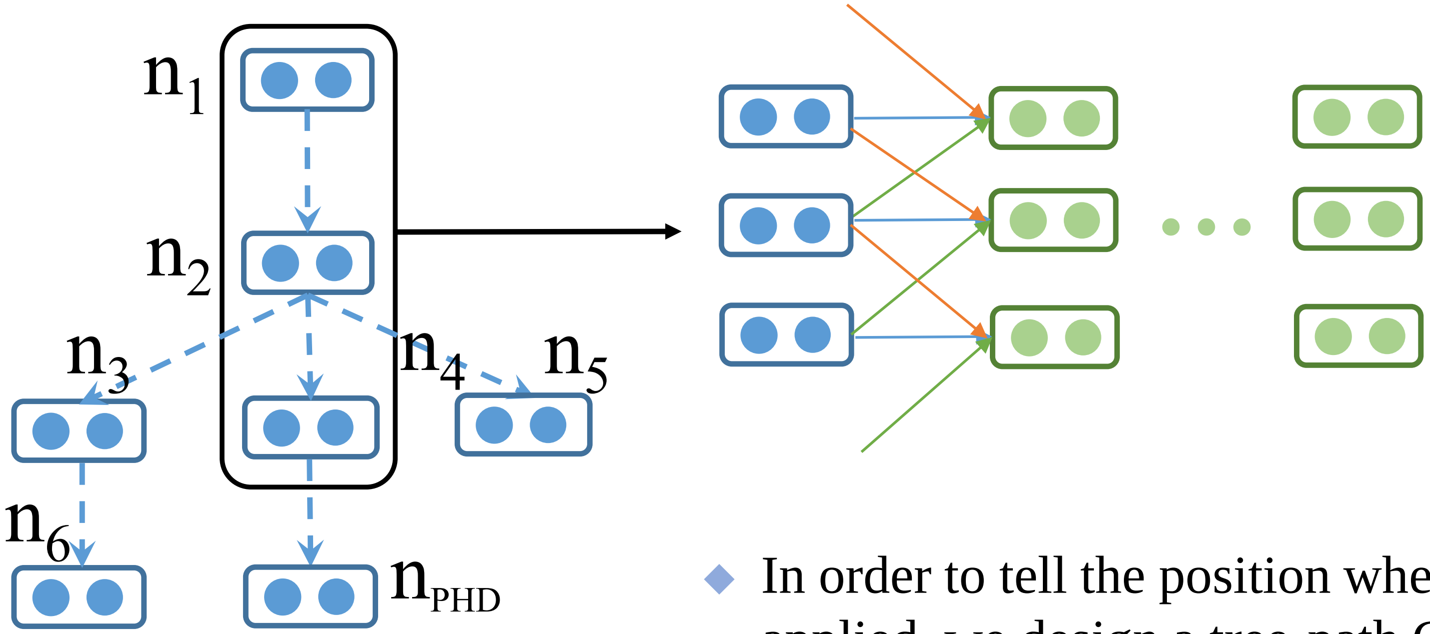
(a) Tree-based convolution[1]

(b) Pre-order convolution

- A local feature detector of a fixed depth, sliding over a tree to extract structural feature.
- We put a placeholder to indicate where the next grammar rule is applied.

[1] Mou, L.; Li, G.; Zhang, L.; Wang, T.; and Jin, Z. 2016. Convolutional neural networks over tree structures for programming language processing. In AAAI, 1287–1293

TO TELL THE POSITION



- In order to tell the position where the next grammar rule is applied, we design a tree-path CNN to catch this information.
- We extract the path from the root to the node to expand.

TO DECODE

- Moreover, we also design several components for code generation.
    - The CNN for predicted.
    - The attentive pooling.

EXPERIMENT: HEARTHSTONE

- Our main experiment is based on an established benchmark dataset, HearthStone (HS) [1]
- The dataset comprises 665 different cards of the HearthStone game.
- We use StrAcc (exact match), Acc+ and BLEU-4 score as metrics.
  - Acc+ is a human-adjusted accuracy.


```
[NAME]
Acidic Swamp Ooze
[ATK] 3
[DEF] 2
[COST]  2
[DUR]  -1
[TYPE]  Minion
[CLASS] Neutral
[RACE] NIL
[RARITY] Common
[DESCRIPTION]
"Battlecry: Destroy Your Opponent's Weapon"
```

```python
class AcidicSwampOoze(MinionCard):
    def __init__(self):
        super().__init__("Acidic Swamp Ooze", 2,
            CHARACTER_CLASS.ALL, CARD_RARITY.COMMON,
            battlecry=Battlecry(Destroy(), WeaponSelector(EnemyPlayer())))

    def create_minion(self, player):
        return Minion(3, 2)
```


[1] Ling, W.; Blunsom, P.; Grefenstette, E.; Hermann, K. M.; Kocisk ˇ y, T.; Wang, F.; and Senior, A. 2016. Latent predictor ` networks for code generation. In ACL, 599–609.

EXPERIMENT: HEARTHSTONE

- Our model is compared with previous state-of-the-art results.

Model	StrAcc	Acc+	BLEU
LPN (Ling et al. 2016)	6.1	–	67.1
SEQ2TREE (Dong and Lapata 2016)	1.5	–	53.4
SNM (Yin and Neubig 2017)	16.2	~18.2	75.8
ASN (Rabinovich, Stern, and Klein 2017)	18.2	–	77.6
ASN+SUPATT (Rabinovich, Stern, and Klein 2017)	22.7	–	79.2
Our system	**27.3**	**30.3**	**79.6**

- Ablation tests to analyze the contribution of each component.

Line #	Model Variant	Acc+	BLEU
1	Full model	**30.3**	79.6
2	Pre-order CNN $\rightarrow$ LSTM	21.2	78.8
3	– Predicted rule CNN	24.2	79.2
4	– Pre-order CNN	25.8	**80.4**
5	– Tree-based CNN	25.8	79.4
6	– Tree-path CNN	28.8	**80.4**
7	– Attentive pooling	24.2	79.3
8	– Scope name	25.8	78.6

- Our model outperforms all previous results.
- We have designed reasonable components of the neural architecture, suited to the code generation task.

EXPERIMENT: HEARTHSTONE

```
Generated code:
class Maexxna(MinionCard):
    def __init__(self):
        super().__init__("Maexxna", 6, CHARACTER_CLASS.ALL,
            CARD_RARITY.LEGENDARY, minion_type = MINION_TYPE.BEAST)

    def create_minion(self, player):
        return Minion(2, 8, effects = [Effect(DidDamage(),
            ActionTag(Kill(), TargetSelector(IsMinion())))])

Reference code:
class Maexxna(MinionCard):
    def __init__(self):
        super().__init__("Maexxna", 6, CHARACTER_CLASS.ALL,
            CARD_RARITY.LEGENDARY, minion_type = MINION_TYPE.BEAST)

    def create_minion(self, player):
        return Minion(2, 8, effects = [Effect(DidDamage(),
            ActionTag(Kill(), TargetSelector(IsMinion())))])
```

- The code we successfully generated.

```
Generated Code:
class Gnoll(MinionCard):
    def __init__(self):
        super().__init__("Gnoll", 2, CHARACTER_CLASS.ALL,
                         CARD_RARITY.COMMON, False)

    def create_minion(self, p):
        return Minion(2, 2, taunt = True)

Reference Code:
class Gnoll(MinionCard):
    def __init__(self):
        super().__init__("Gnoll", 2, CHARACTER_CLASS.ALL,
                         CARD_RARITY.COMMON, False)

    def create_minion(self, player):
        return Minion(2, 2, taunt = True)

Reference Code For Anthor Card:
class DefenderMinion(MinionCard):
    def __init__(self):
        super().__init__("Defender", 1, CHARACTER_CLASS.PALADIN,
                         CARD_RARITY.COMMON)

    def create_minion(self, p):
        return Minion(2, 1)
```

- Our model used a different argument name, but implements a correct functionality.

EXPERIMENT: SEMANTIC PARSING

- Semantic parsing aims to generate logical forms given a natural language description.

Input description: list airport in ci0
Output λ-calculus:

```
lambda $0 e ( and ( airport $0 )
                ( loc:t $0 ci0 ) )
```

- We evaluated our model on two semantic parsing datasets (ATIS and JOBS) used in Dong and Lapata (2016) [1] with Accuracy.

[1] Dong, L., and Lapata, M. 2016. Language to logical form with neural attention. In ACL, 33–43.

EXPERIMENT: SEMANTIC PARSING

- The logic form for semantic parsing is usually short, containing only 1/4–1/3 tokens as in HS.

	ATIS		JOBS	
	System	**Accuracy**	**System**	**Accuracy**
Traditional	ZH15	84.2	ZH15	85.0
	ZC07	84.6	PEK03	88.0
	WKZ14	**91.3**	LJK13	90.7
Neural	SEQ2TREE	84.6	SEQ2TREE	90.0
	ASN	85.3	ASN	91.4
	ASN-SUPATT	85.9	ASN-SUPATT	**92.9**
	Our System	85.0	Our System	89.3

- Neural models are generally worse than the WKZ14 system (based on CCG parser).
- Our model achieves results similar to the state-of-the-art neural models.

CONCLUSION

- We propose a grammar-based structural CNN for code generation.
- Our model makes use of the abstract syntax tree (AST) of a program, and generates code by predicting the grammar rules.
- We address the problem that traditional RNN-based approaches may not be suitable to program generation.

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Thank you!

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