Microsoft

Pre-trained Models and Benchmark for Code Intelligence

(from the perspective of an NLP researcher)

Nan Duan (段楠)
Principal Researcher & Research Manager
Natural Language Computing Group
Microsoft Research Asia

Keynote at KDD workshop on Programming Language Processing (PLP), 2021-08-15

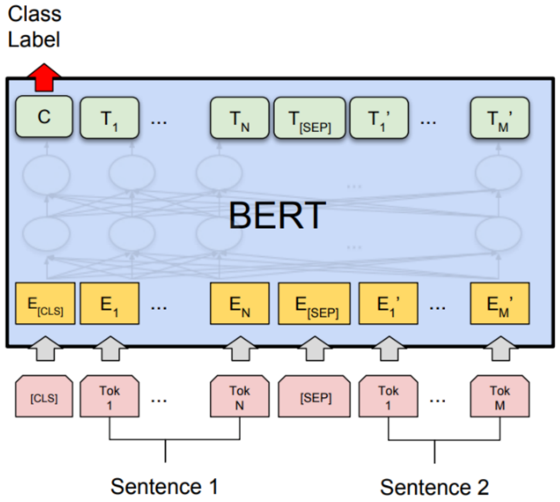
Acknowledge

- I'd like to thank my colleagues/students that contributed to this code intelligence project, including Duyu Tang (Tencent), Shuai Lu (Microsoft), Daya Guo (Sun Yat-sen University), Junjie Huang (Beihang University), Shuo Ren (MSRA), Zhangyin Feng (Harbin Institute of Technology), Long Zhou (Microsoft), Shujie Liu (Microsoft), Ambrosio Blanco (Microsoft), Ming Zhou (Sinovation), Lidong Zhou (Microsoft), Ming Gong (Microsoft), Linjun Shou (Microsoft), Daxin Jiang (Microsoft), Alexey Svyatkovskiy (Microsoft), Shengyu Fu (Microsoft), Colin Clement (Microsoft), Shao Kun Deng (Microsoft), Dawn Drain (Microsoft), Michele Tufano (Microsoft), Neel Sundaresan (Microsoft), Marc Brockschmidt (Microsoft), Miltiadis Allamanis (Microsoft).

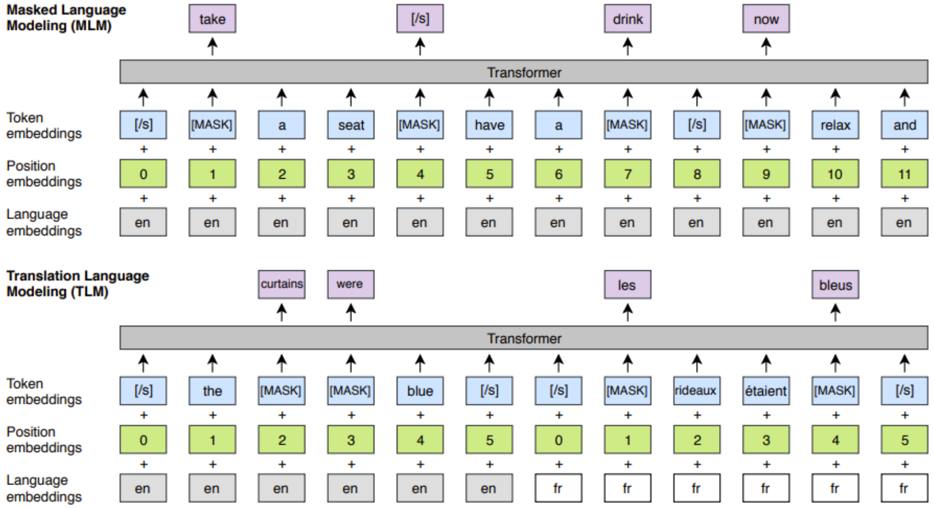
Today's Agenda

- **Background**
- Pre-trained Models for Code Intelligence
- Benchmark for Code Intelligence
- Conclusion & Future Work

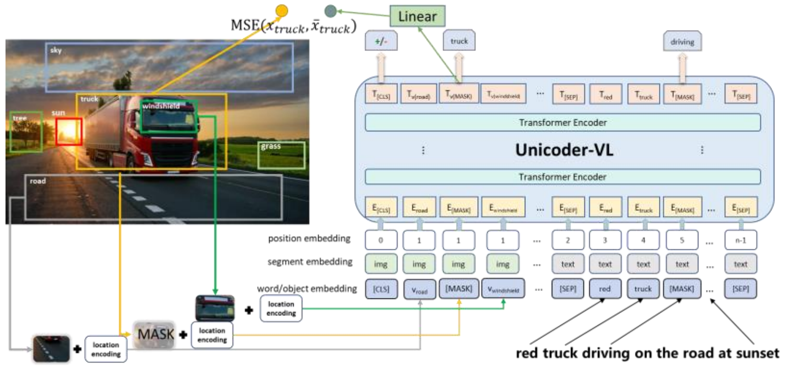
Current NLP Paradigm: Large-scale Pre-trained Models



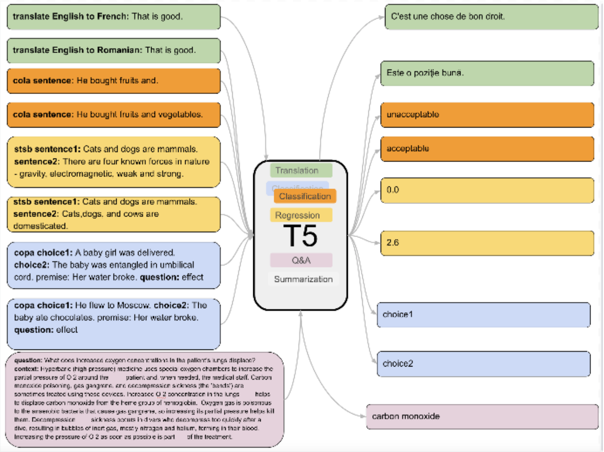
BERT (Devlin et al., 2018)



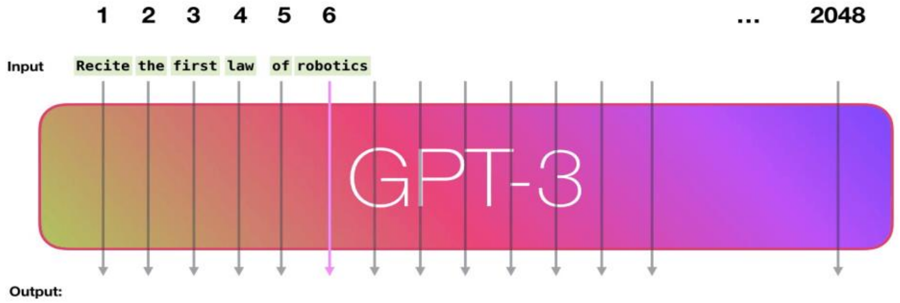
XLM (Lample and Conneau, 2019)



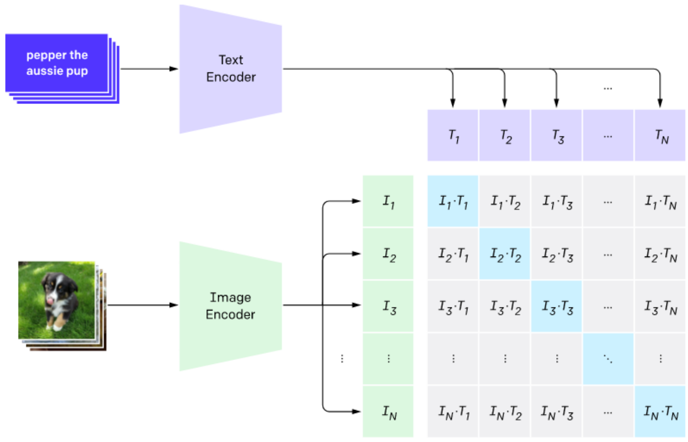
Unicoder-VL (Li et al., 2020)



T5 (Raffel et al., 2020)



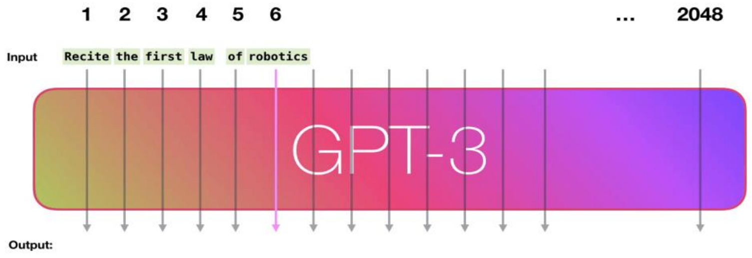
GPT-3 (Brown et al., 2020)



CLIP (Radford et al., 2021)

Self-supervised Learning in Language Pre-training

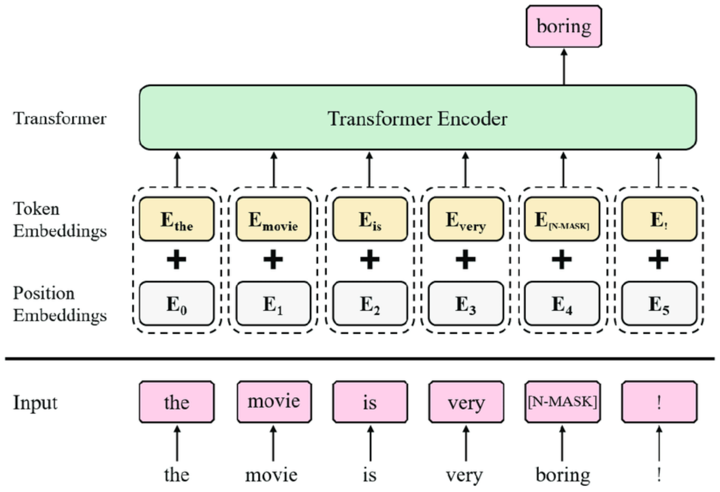
Auto-regressive Decoding



GPT-3 (Brown et al., 2020)

maximize the likelihood under the forward auto-regressive factorization

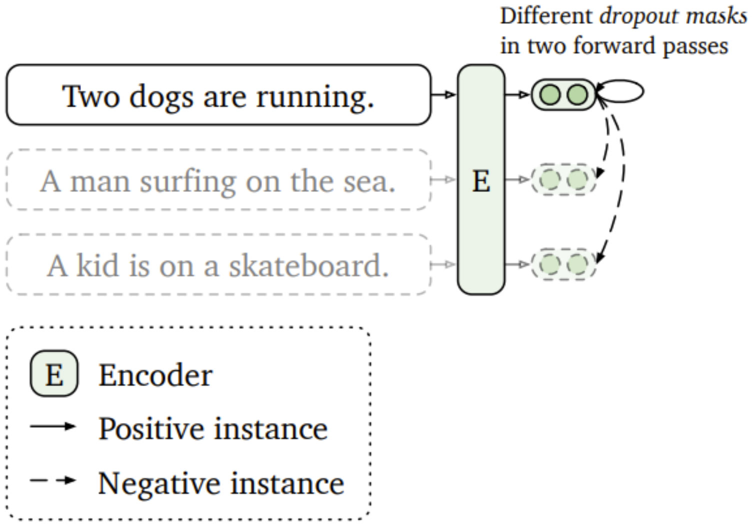
Denoising Auto-encoding



BERT (Devlin et al., 2018)

reconstruct masked words/spans/sentences from corrupted inputs

Contrastive Learning

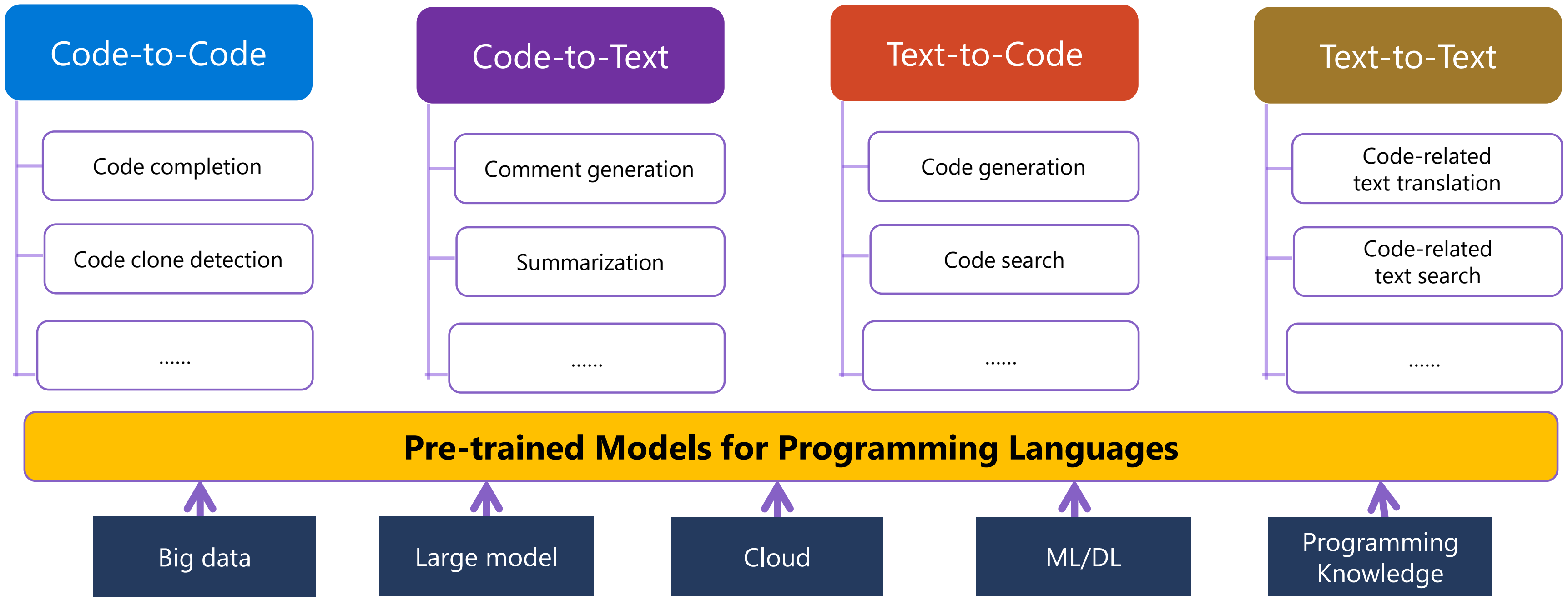


SimCSE (Gao et al., 2021)

learn representations such that similar samples stay close to each other

Large-scale Pre-training for Code Intelligence

To build large-scale pre-trained models for code to help developers to improve their programming productivity.

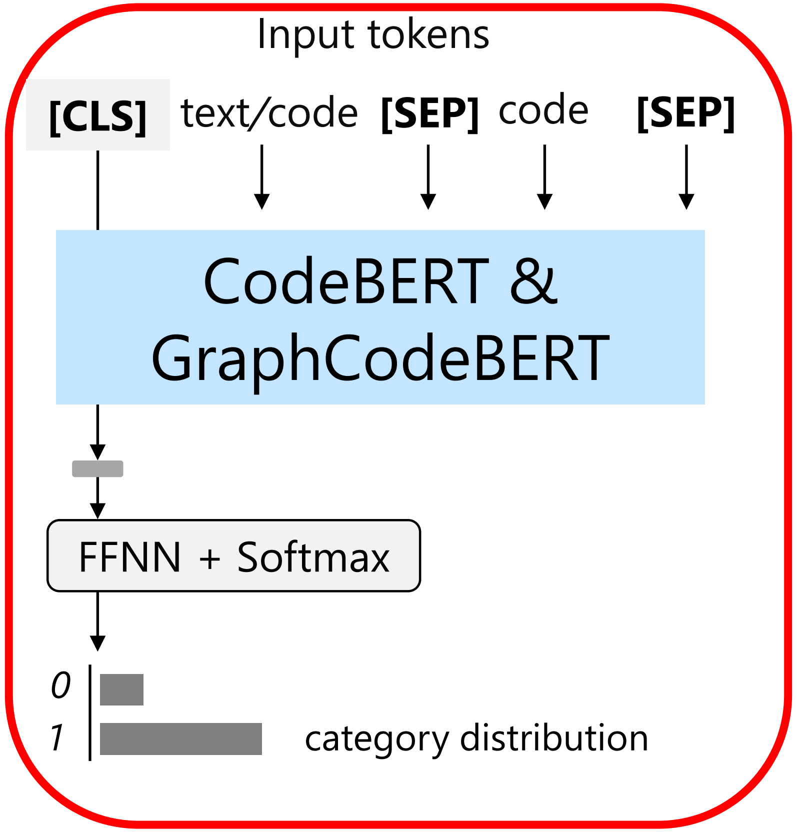


Today’s Agenda

- Background
- **Pre-trained Models for Code Intelligence**
- Benchmark for Code Intelligence
- Conclusion & Future Work

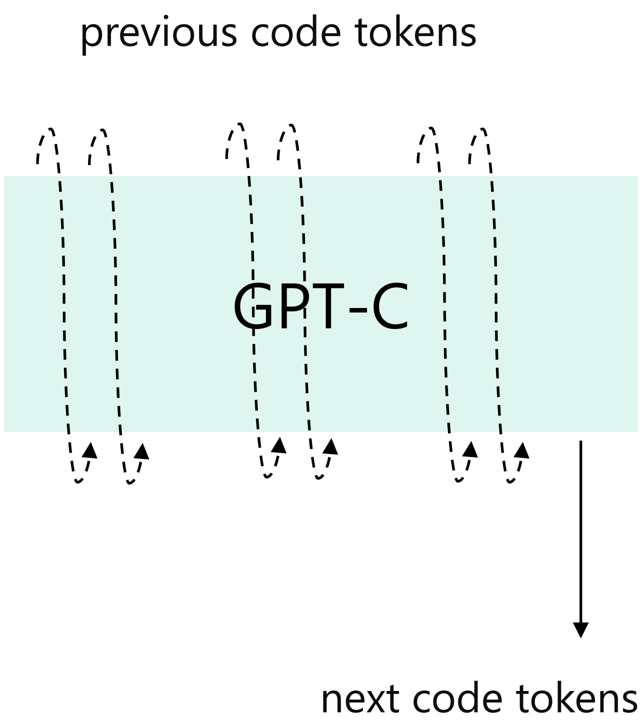
Three Pre-trained Models for Code

Understanding

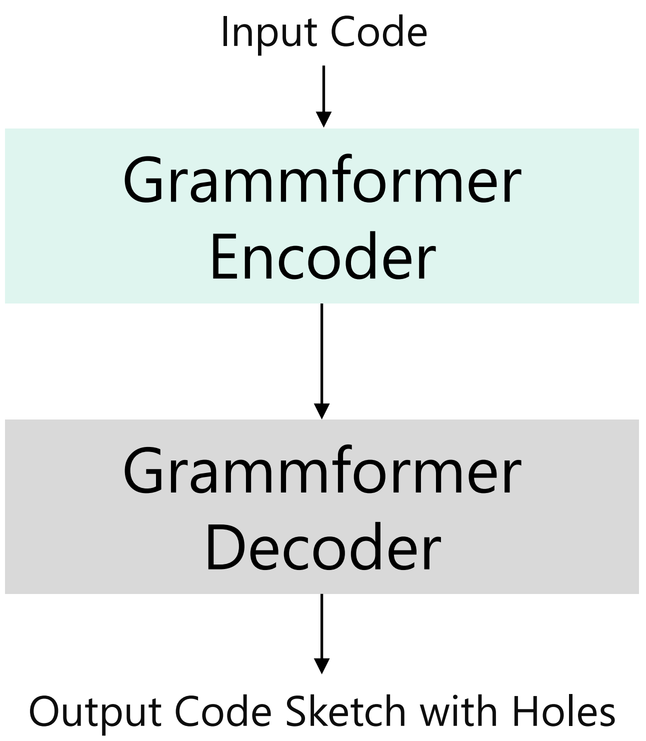


Accepted by EMNLP 2020 and ICLR 2021.

Generation



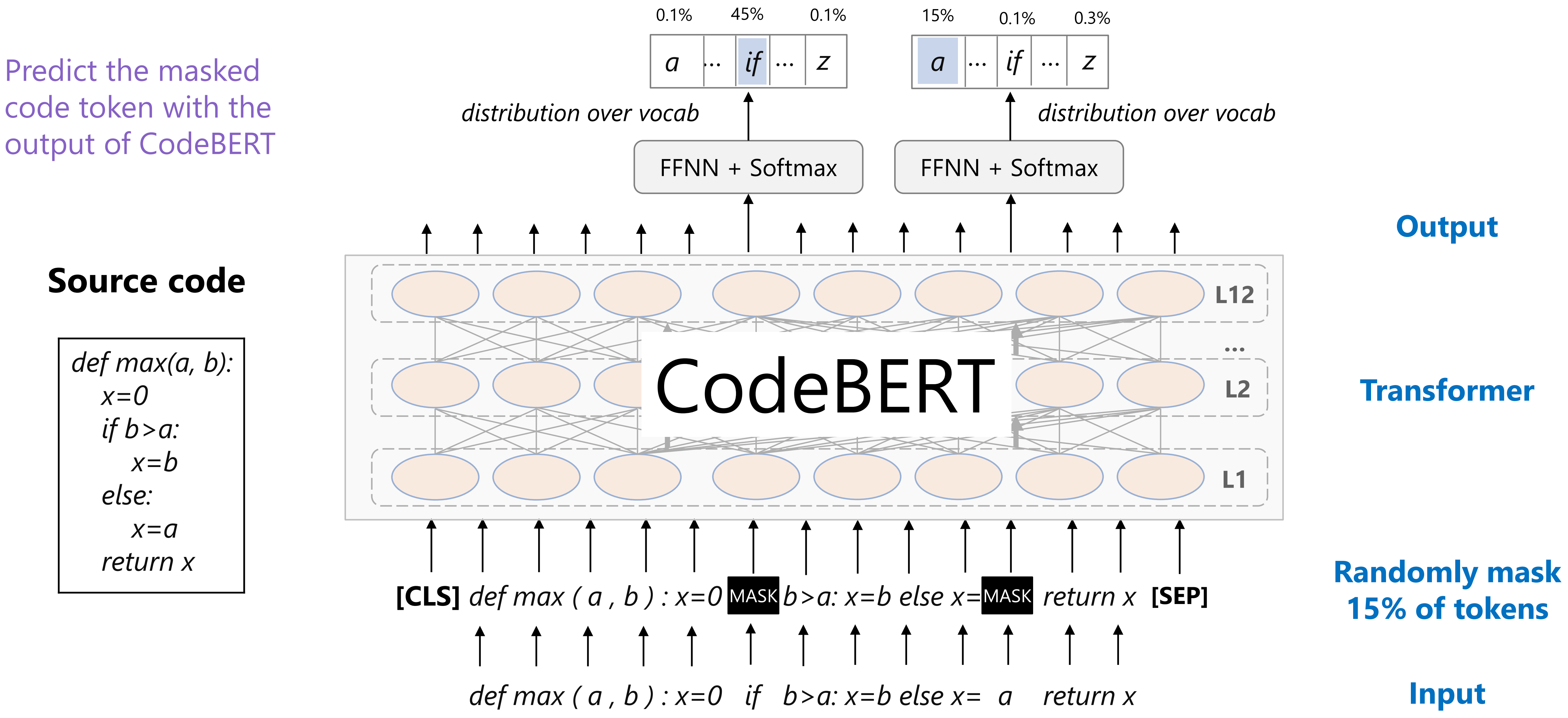
Submitted to EMNLP 2021.



Submitted to NeurIPS 2021.

accepted by EMNLP 2020

CodeBERT: Pre-Train with Code



accepted by EMNLP 2020

CodeBERT: Pre-Train with Code+Text

Predict the masked code/text tokens with the output of CodeBERT

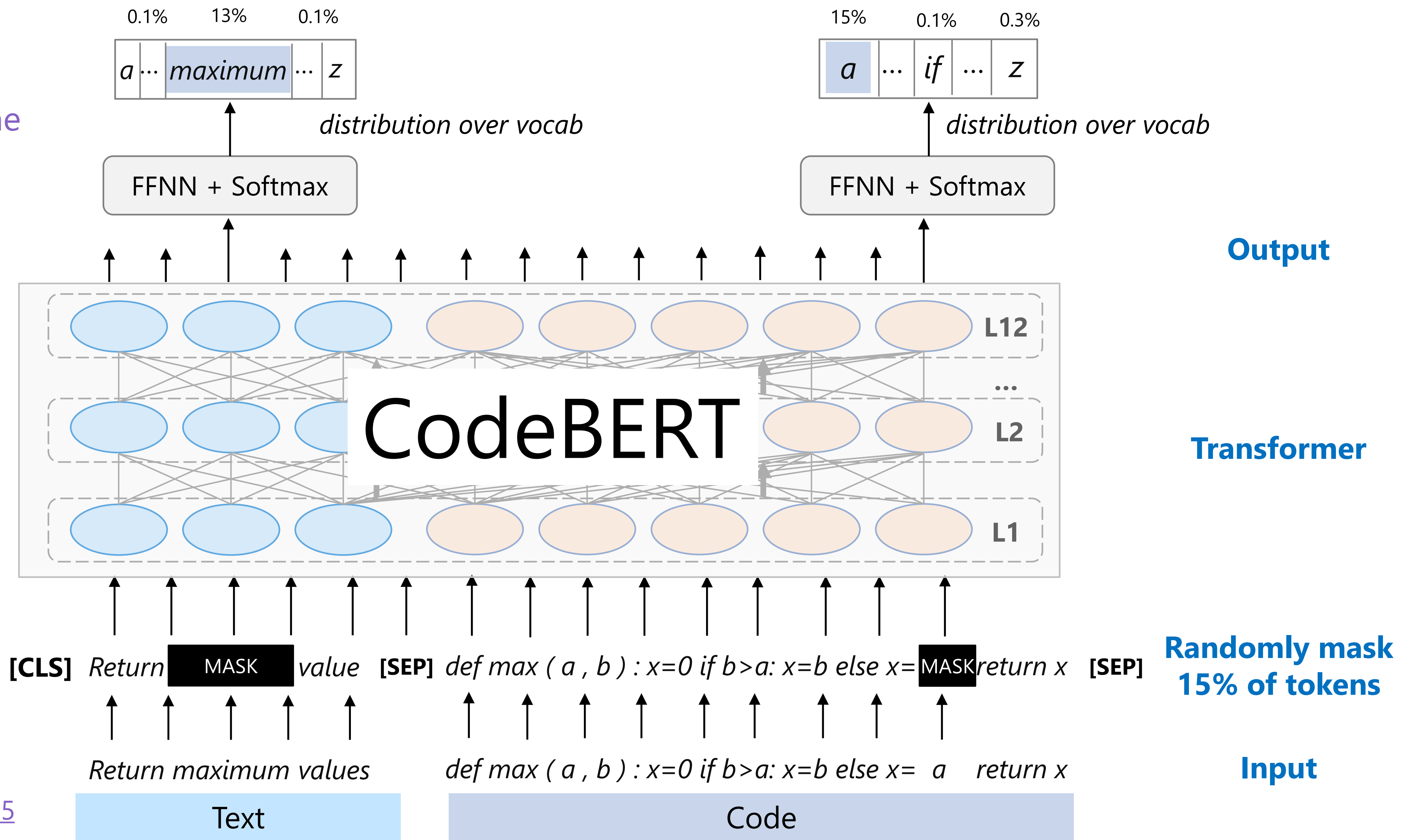
Source code

```
def max(a, b):
    x=0
    if b>a:
        x=b
    else:
        x=a
    return x
```

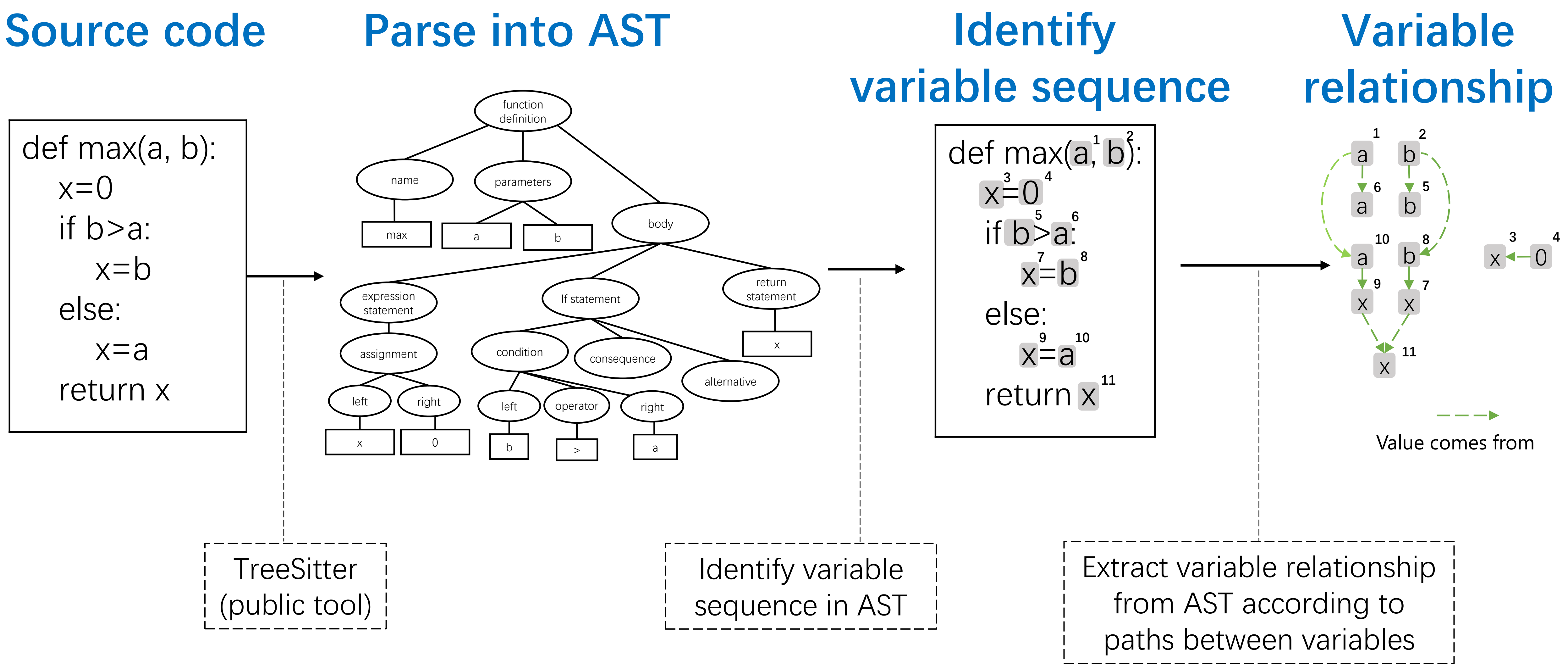
Comment

Return maximum value

https://arxiv.org/abs/2002.08155

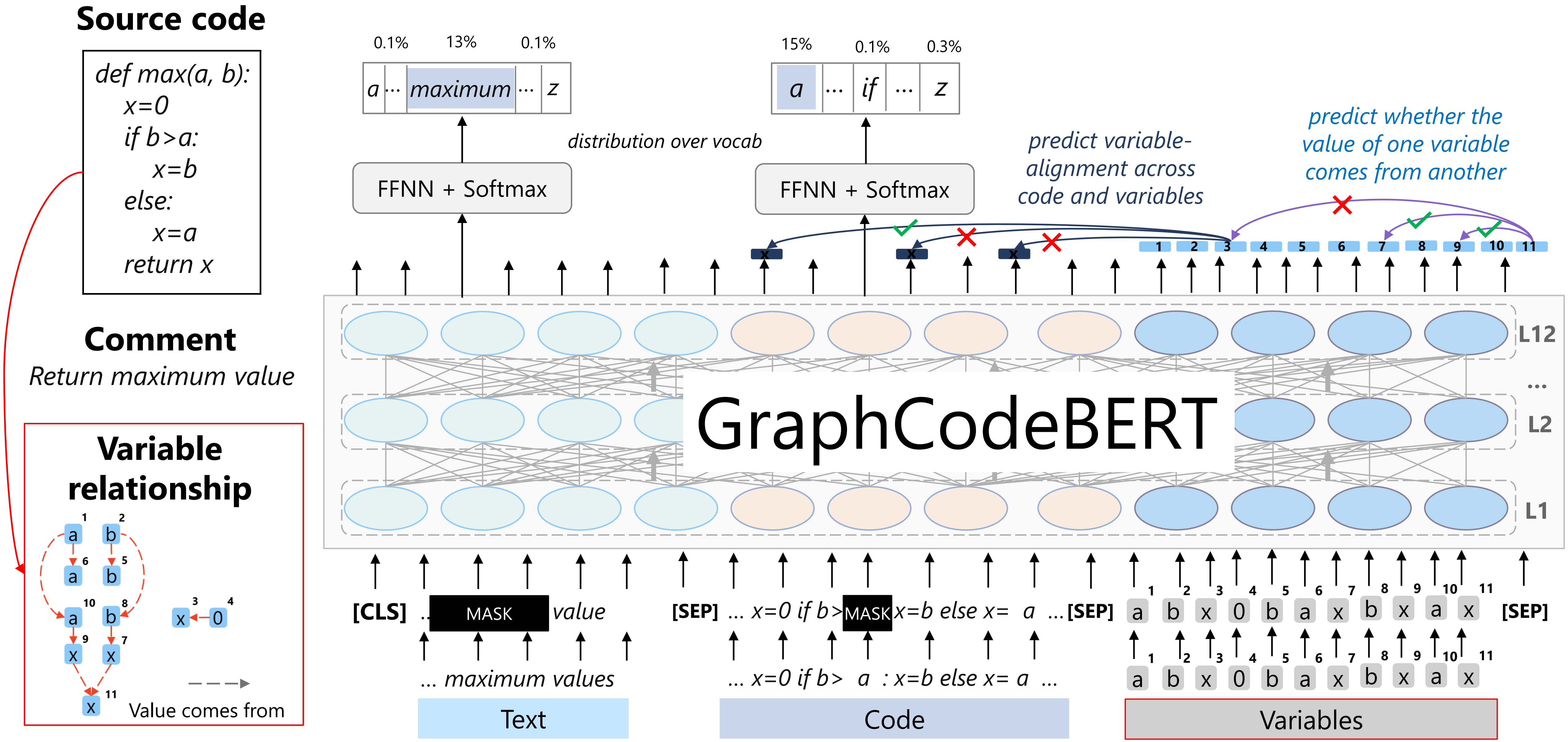


Code Structure



accepted by ICLR 2021

GraphCodeBERT: Pre-Train with Code+Text+Structure



Understanding Results

Results on code search.

Model	Ruby	JavaScript	Go	Python	Java	PHP	Overall
BiRNN	0.213	0.193	0.688	0.290	0.304	0.338	0.338
RoBERTa	0.587	0.517	0.850	0.587	0.599	0.560	0.617
RoBERTa (code)	0.628	0.562	0.859	0.610	0.620	0.579	0.643
CodeBERT	0.679	0.620	0.882	0.672	0.676	0.628	0.693
GraphCodeBERT	**0.703**	**0.644**	**0.897**	**0.692**	**0.691**	**0.649**	**0.713**

Input: *How to read text file in Python?*

Output:

```python
def read_text_file(filename, encoding="utf-8"):
    """
    Reads a file under python3 with encoding (default UTF-8).
    Also works under python2, without encoding.
    Uses the EAFP (https://docs.python.org/2/glossary.html#term-eafp)
    principle.
    """
    try:
        with open(filename, 'r', encoding) as f:
            r = f.read()
    except TypeError:
        with open(filename, 'r') as f:
            r = f.read()
    return r
```

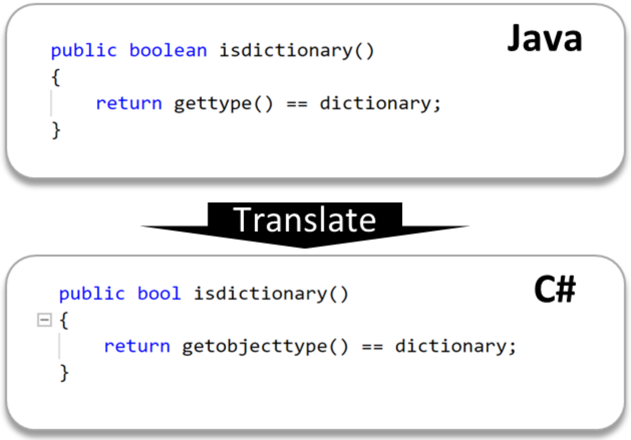
code source from GitHub

https://github.com/microsoft/CodeBERT

Generation Results

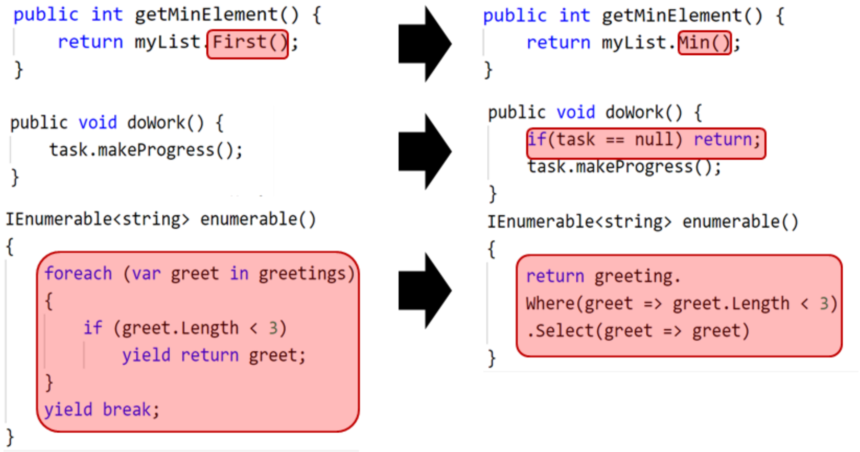
Results on code translation.

Model	Java->C#		C#->Java	
	BLEU	Accuracy	BLEU	Accuracy
Naïve	18.54	0.0	18.69	0.0
PBSMT	43.53	12.5	40.06	16.1
RoBERTa (code)	77.46	56.1	71.99	57.9
CodeBERT	79.92	59.0	72.14	58.0
GraphCodeBERT	**80.58**	**59.4**	**72.64**	**58.8**

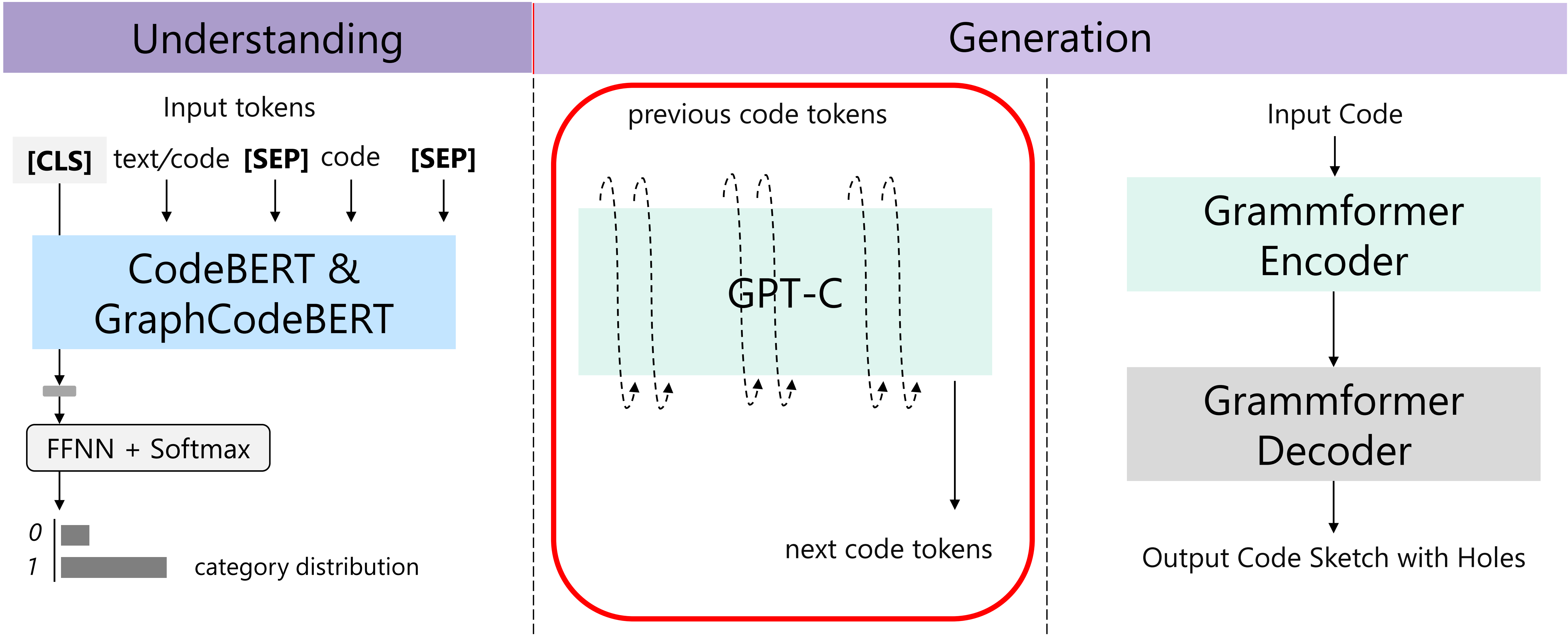


Results on code refinement.

Model	Small		Medium	
	BLEU	Accuracy	BLEU	Accuracy
Naïve	78.06	0.0	90.91	0.0
LSTM	76.76	10.0	72.08	2.5
RoBERTa (code)	77.30	15.9	90.07	4.1
CodeBERT	77.42	16.4	90.07	5.2
GraphCodeBERT	**80.02**	**17.3**	**91.31**	**9.1**



Three Pre-trained Models for Code



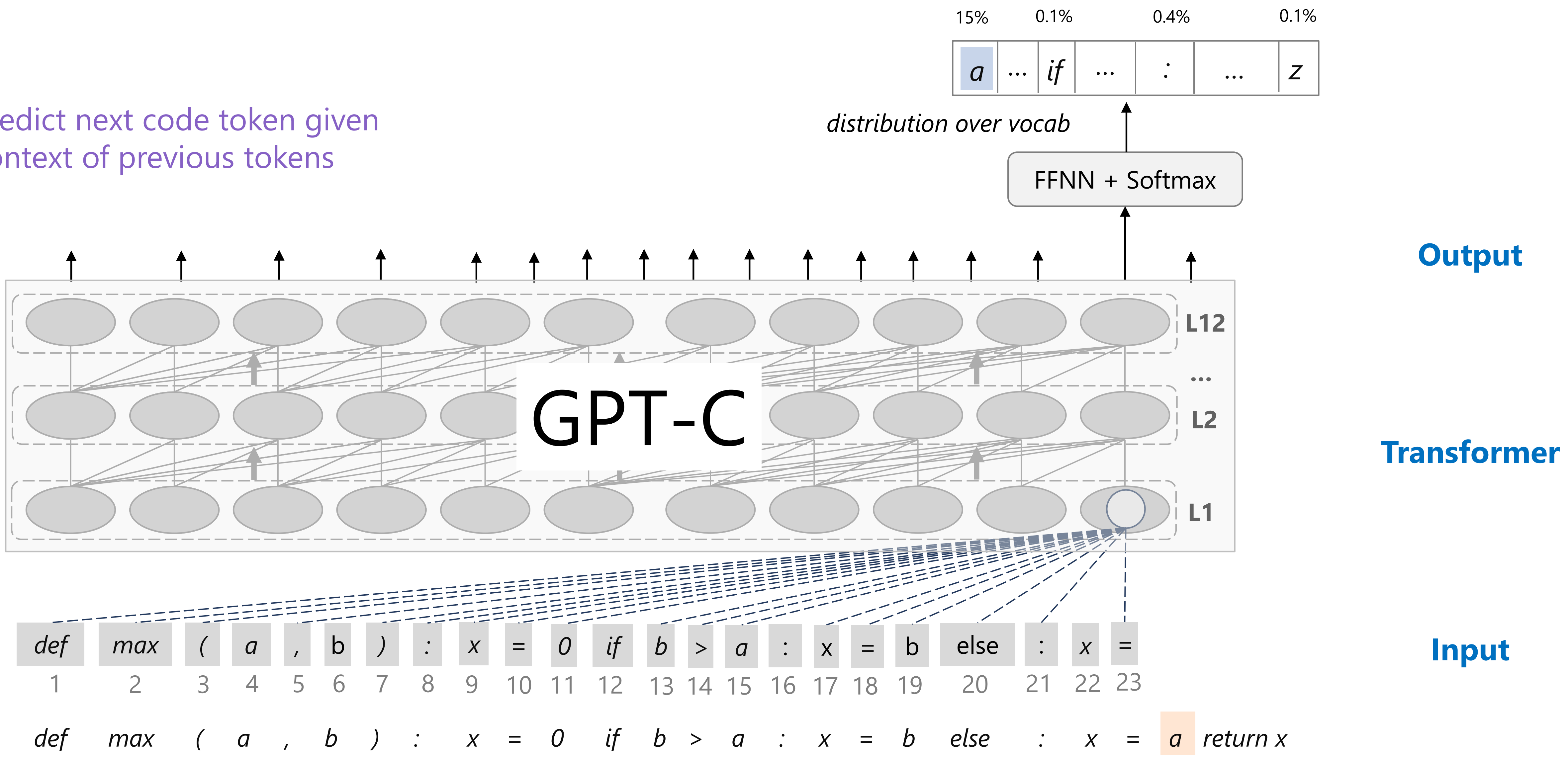
Accepted by EMNLP 2020 and ICLR 2021.

Submitted to EMNLP 2021.

Submitted to NeurIPS 2021.

GPT-C: Multilingual Pre-trained Model

Predict next code token given context of previous tokens



Trained for 10 PLs: JavaScript, C, Java, Go, PHP, Python, C++, C#, Ruby, TypeScript

Evaluation on Code Completion

- Corpus
  - 10 programming langauges
  - 354K code projects
  - 18B code lines
  - Split 8:1:1 as Train/Dev/Test

Programming language	#Projects	#Files (↓)	#Lines
JavaScript	113,890	15,330,706	4,226,121,235
C	19,900	13,462,890	7,253,471,852
Java	46,921	10,385,540	1,491,132,997
Go	17,922	5,720,219	1,997,845,604
PHP	24,625	4,691,140	653,891,761
Python	71,343	4,465,808	854,503,198
C++	20,958	4,293,413	1,400,309,370
C#	17,387	3,765,835	550,267,681
Ruby	17,804	1,663,262	137,558,948
TypeScript	3,801	466,924	64,671,728

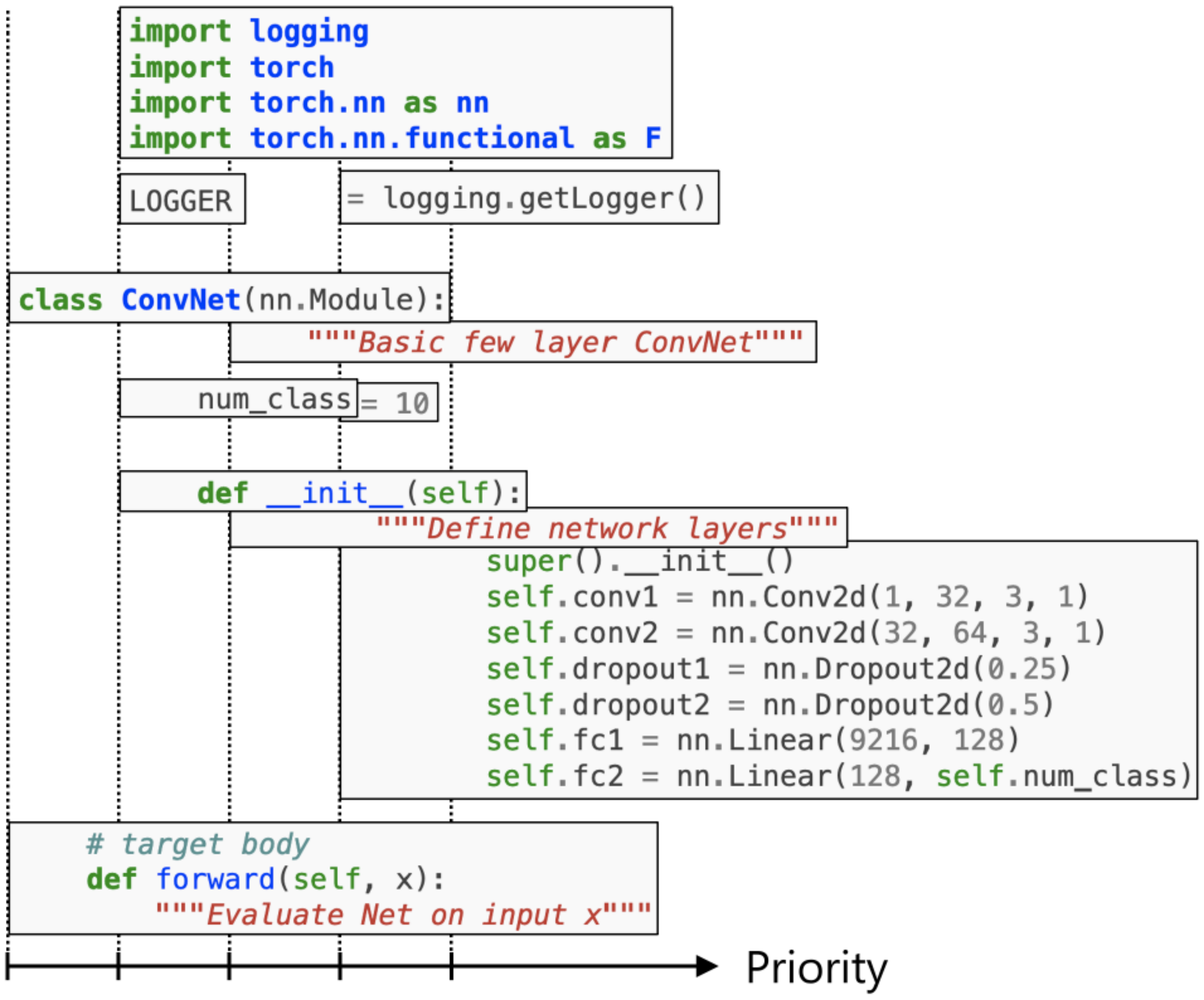
Model	Test language	ROUGE-L			Average edit similarity (Levenshtein, %)
		Precision	Recall	F1	
GPT-C (12L)	Python	0.72	0.80	0.76	83.0
	C#	0.56	0.75	0.64	77.5
	JavaScript	0.71	0.81	0.76	92.2
	Go	0.65	0.72	0.68	81.0
	Scala **(zero-shot)**	0.41	0.54	0.47	64.2

Extended Context for Code Completion

1. Take the concrete syntax tree of the source file;

2. Prioritize the syntactic elements;
   i. signature and docstring of the focal method;
   ii. global import statements and assigned values;
   iii. class attributes, peer class method signatures, class docstring, peer class method docstrings;
   iv. global expressions and code bodies of peer class methods.

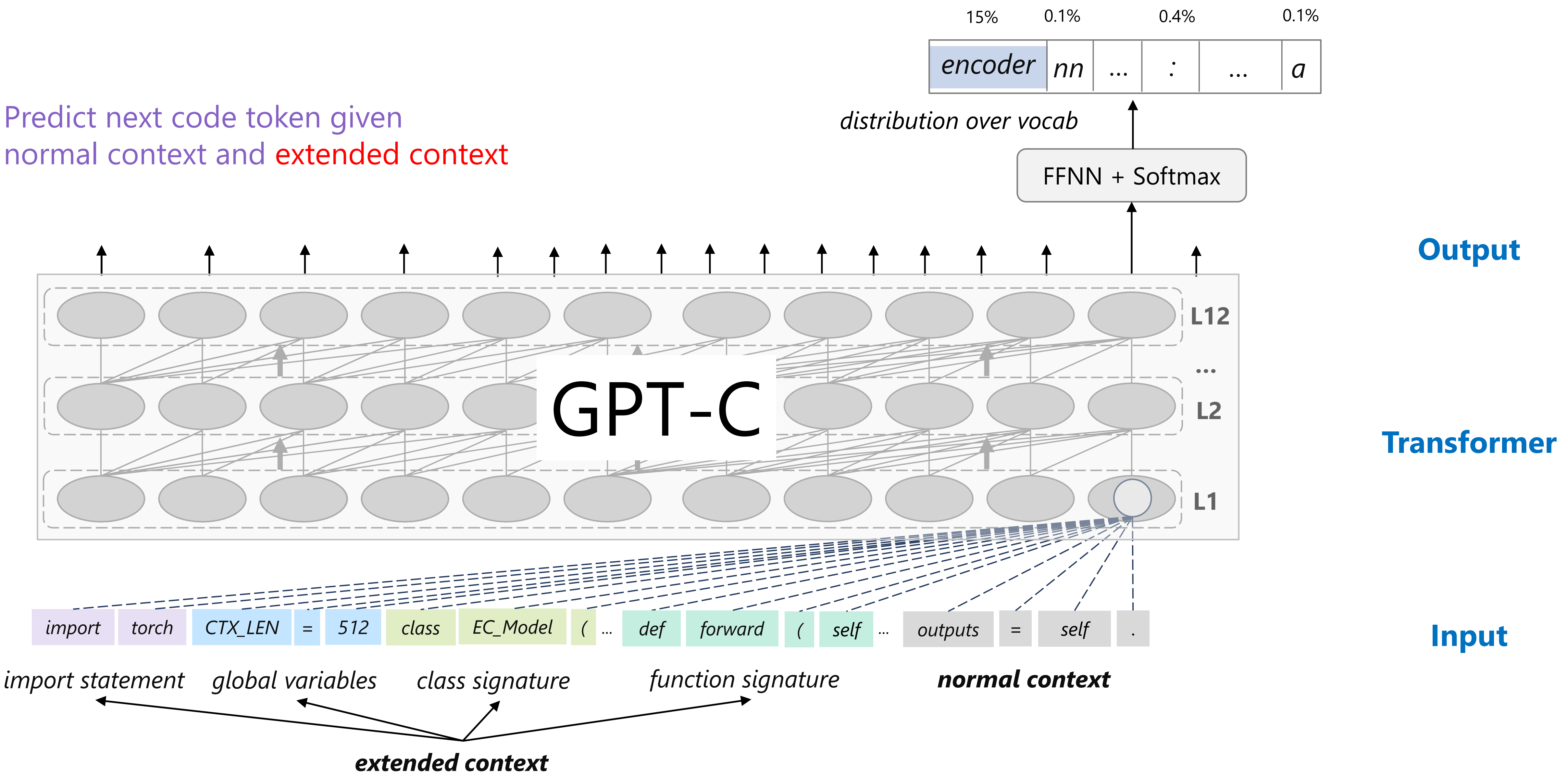
3. Take elements based on their priorities until the context window has been filled.



We reserve 3/4 (768/1,024) tokens for the extended context and 1/4 (256/1024) tokens for the local context.

GPT-C with Extended Context

Predict next code token given
normal context and extended context

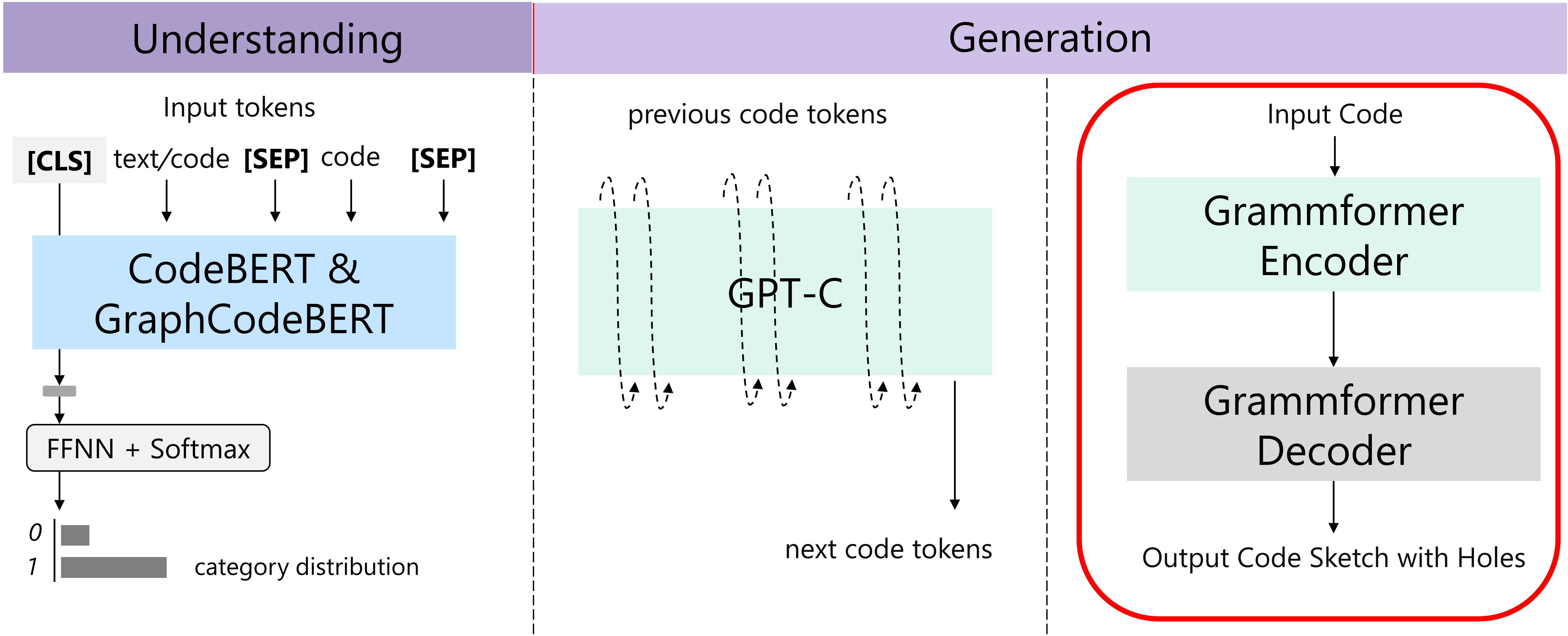


Evaluation on Code Completion

- Pre-training data
  - Python dataset used in multilingual GPT-C pre-training
- Evaluation data
  - PY150 test set in CodeXGLUE

Model	Test language	ROUGE-L			Average edit similarity (Levenshtein, %)
		Precision	Recall	F1	
GPT-C (12L)	Python	0.81	0.94	0.87	89.0
GPT-C with Extended Context (12L)	Python	**0.90**	**0.96**	**0.93**	**93.7**

Three Pre-trained Models for Code



Accepted by EMNLP 2020 and ICLR 2021.

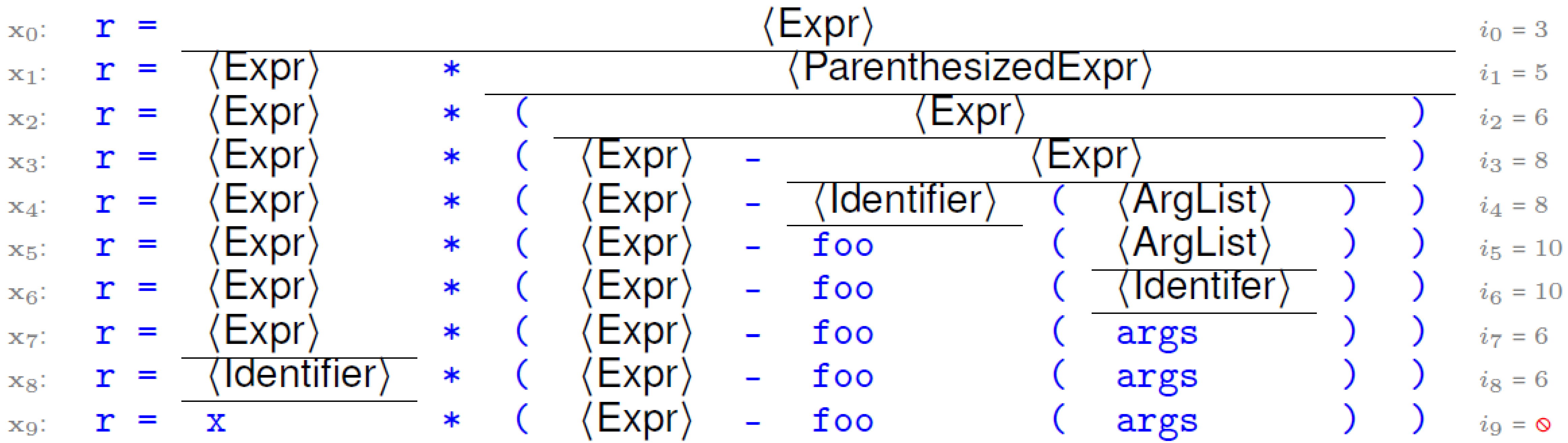
Submitted to EMNLP 2021.

Submitted to NeurIPS 2021.

Challenge in Code Completion: Ambiguities

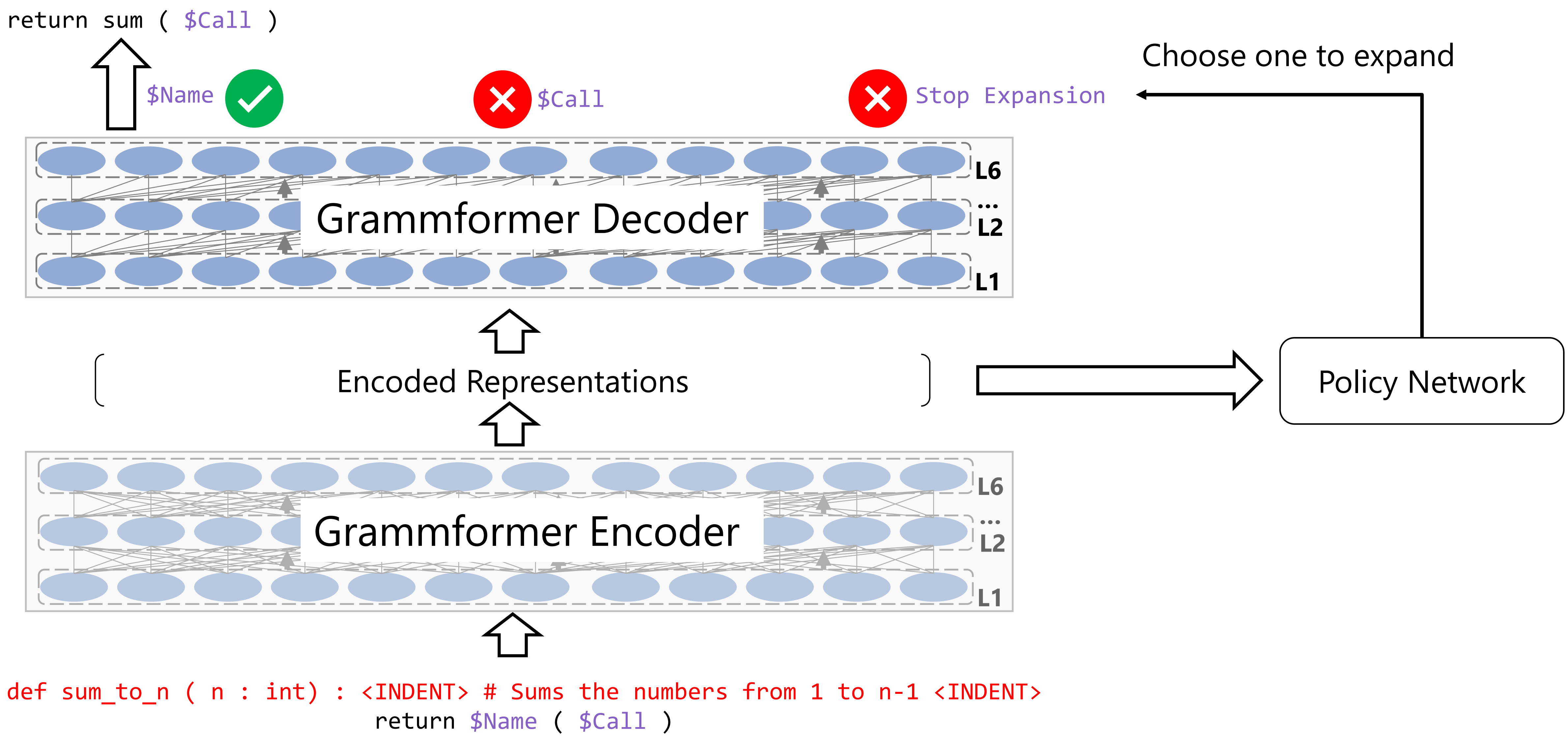
```python
import argparse
ap = argparse.ArgumentParser()
ap.add_argument("--release",
                action="store_true")
ap.add_argument("--prerelease",
                action="store_true")

```

Grammformer Example



[2106.10158] Learning to Generate Code Sketches (arxiv.org)

Grammformer Inference



Grammformer Training

Algorithm 1 GRAMMFORMER generative process, given an input sequence $\mathbf{x}_0$.

for $t = 0, 1, 2, \ldots$ **do**
- $i_t \sim P_s(i|\mathbf{x}_t, N(\mathbf{x}_t))$ ▷ Sample non-terminal position from $N(\mathbf{x}_t)$ to expand
- **if** $i_t = \oslash$ **then** ▷ if $\mathbf{x}_t$ does *not* contains non-terminals or none was selected by P_s
  - **break** ▷ Stop generation
- $\hat{\mathbf{y}}_{t \circledcirc i_t} \sim P_e(\mathbf{y}|\mathbf{x}_t, i_t)$ ▷ Sample expansion of non-terminal at position i_t
- $\mathbf{x}_{t+1} \leftarrow \mathbf{x}_{t,<i_t} :: \hat{\mathbf{y}}_{t \circledcirc i_t} :: \mathbf{x}_{t,>i_t}$ ▷ Create $\mathbf{x}_{t+1}$ by expanding non-terminal at i_t to $\hat{\mathbf{y}}_{t \circledcirc i_t}$

$\mathbf{x}_{\text{out}} \leftarrow \textsc{NonTerminalsToHoles}(\mathbf{x}_t)$ ▷ Convert any remaining non-terminals to holes

return $\mathbf{x}_{\text{out}}$

$$\mathcal{L}_{\text{train}}(\mathbf{x}_0, \mathbf{x}^*) = \left(r(\mathbf{x}_{\text{out}}, \mathbf{x}^*) - \tilde{r}(\mathbf{x}_0)\right) \sum_{t=0}^{T} \left(-\log P_s(i_t|\mathbf{x}_t) - \mathbb{I}(i_t \neq \oslash) \log P_e(\hat{\mathbf{y}}_{t \circledcirc i_t}|\mathbf{x}_t, i_t)\right)$$

REGEXACC as Reward Function

return 1 if the regex matches the ground truth, and 0 otherwise

$$\textsc{RegexAcc}(\hat{s}, s^*) \triangleq \frac{\mathtt{nTerm}(\hat{s})}{\boxed{\mathtt{nTerm}}(s^*)} \cdot \boxed{\mathtt{matches}}(\boxed{\mathtt{toRegex}}(\hat{s}), s^*)$$

return the number of terminal symbols

turn a predicted sketch into a regular expression by replacing all non-terminals with the wildcard matching any non-empty sequence

Experiment

Dataset

More than 20 stars in GitHub that contain C# and Python Code.
Including 3.8M and 4.5 M files for C# and Python, respectively.

Results

	C#				Python			
	REGEXACC		ROUGE	Avg Gen Length	REGEXACC		ROUGE	Avg Gen Length
	Top 1	Top 5			Top 1	Top 5		
$L \rightarrow R$	0.42	0.47	77.0	7.1	0.17	0.20	**53.2**	5.8
$L \rightarrow R + \oslash$	0.45	0.54	69.1	5.3	0.20	0.29	39.3	3.0
GRAMMFORMER	**0.47**	**0.59**	**77.4**	**7.5**	**0.21**	**0.30**	51.6	**6.1**

Today's Agenda

- Background
- Pre-trained Models for Code Intelligence
- **Benchmark for Code Intelligence**
- Conclusion & Future Work

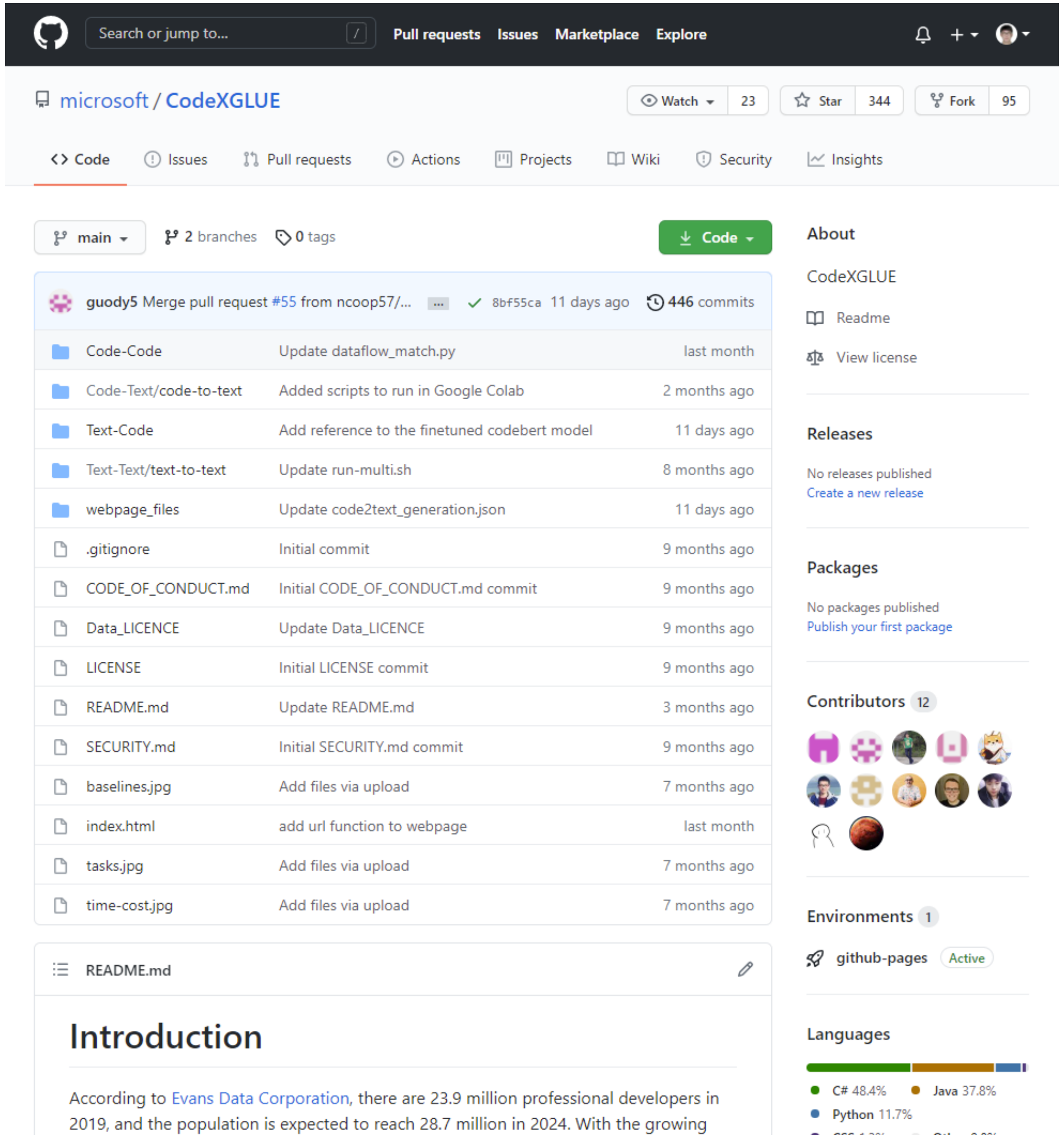
accepted by NeurIPS 2021

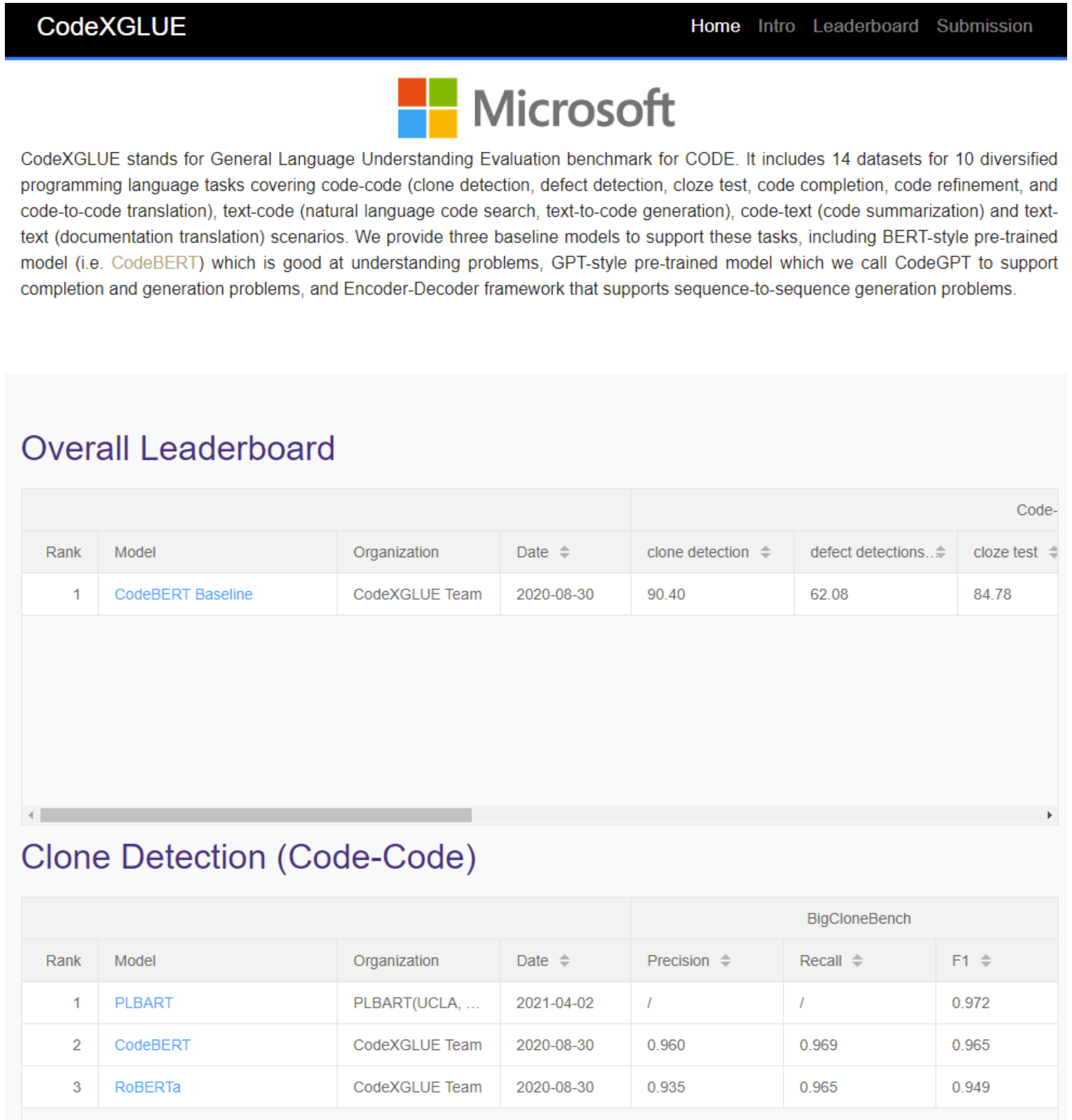
CodeXGLUE: 14 datasets for 10 Code-related tasks

Category	Task	Dataset Name	Language	Train/Dev/Test Size	Baselines	Dataset Provider	Task definition
Code-Code	Clone Detection	BigCloneBench	Java	900K/416K/416K	CodeBERT	Univ. of Saskatchewan	Predict semantic equivalence for a pair of codes.
		POJ-104	C/C++	32K/8K/12K		Peking Univ	Retrieve semantically similar codes.
	Defect Detection	Defects4J	C	21k/2.7k/2.7k		Univ. of Washington	Identify whether a function is vulnerable.
	Cloze Testing	CT-all	Python, Java, PHP, JavaScript, Ruby, Go	-/-/176k		Created by MSRA based on CodeSearchNet	Tokens to be predicted come from the entire vocab.
		CT-max/min	Python, Java, PHP, JavaScript, Ruby, Go	-/-/2.6k		Created by MSRA based on CodeSearchNet	Tokens to be predicted come from {max, min}.
	Code Completion	PY150	Python	100k/5k/50k	CodeGPT	ETH Zurich, line-level data added by MSRA	Predict following tokens given contexts of codes.
		GitHub Java Corpus	Java	13k/7k/8k		Univ. of Edinburgh, line-level data added by MSRA	
	Code Refinement	Bugs2Fix	Java	98K/12K/12K	Encoder-Decoder	The College of William and Mary	Automatically refine codes by fixing bugs.
	Code Translation	CodeTrans	Java-C#	10K/0.5K/1K		MSRA	Translate the codes from one programming language to another programming language.
Text-Code	NL Code Search	CodeSearchnet, AdvTest	Python	251K/9.6K/19K	CodeBERT	GitHub + MSR Cambridge, test provided by MSRA	Given a natural language query as input, find semantically similar codes.
		StacQC, WebQueryTest	Python	2.9k/0.9k/1.9k		The Ohio State Univ, test provided by MSRA	Given a pair of natural language and code, predict whether they are relevant or not.
	Text-to-Code Generation	CONCODE	Java	100K/2K/2K	CodeGPT	Univ. of Washington	Given a natural language docstring/comment as input, generate a code.
Code-Text	Code Summarization	CodeSearchNet*	Python, Java, PHP, JavaScript, Ruby, Go	908K/45K/53K	Encoder-Decoder	Filtered based on CodeSearchNet data	Given a code, generate its natural language docstring/comment.
Text-Text	Documentation Translation	Microsoft Docs	English-Latvian/Danish/Norwegian/Chinese	156K/4K/4K		MSRA	Translate code documentation between human languages (e.g. En-Zh), intended to test low-resource multi-lingual translation.

accepted by NeurIPS 2021

CodeXGLUE: 14 datasets for 10 Code-related tasks





https://github.com/microsoft/CodeXGLUE

https://microsoft.github.io/CodeXGLUE/

Current Submission Status

	Task	Dataset	# of Submissions	Organizations
Code-Code	Clone Detection	BigCloneBench	**2**	UCLA & Columbia University; HNUST;
		POJ-104	**2**	UCLA & Columbia University;
	Defect Detection	Defects4J	**4**	IBM Research; Case Western Reserve University; UCLA & Columbia University; INESC-ID & Carnegie Mellon University;
	Cloze Test	CT-all		
		CT-max/min		
	Code Completion	GitHub Java Corpus		
		PY150		
	Code Repair	Bugs2Fix	**2**	Case Western Reserve University; UCLA & Columbia University;
	Code Translation	CodeTrans	**1**	UCLA & Columbia University;
Text-Code	NL Code Search	AdvTest		
		WebQueryTest		
	Text-to-code Generation	CONCODE	**5**	Wuhan University; Case Western Reserve University; UCLA & Columbia University; UBC Research;
Code-Text	Code Summarization	CodeSearchNet	**4**	USTC & MSRA; Case Western Reserve University; UCLA & Columbia University; UC Davis;
Text-Text	Documentation Translation	Microsoft Docs		
			20 (in total)	

Today’s Agenda

- Background
- Pre-trained Models for Code Intelligence
- Benchmark for Code Intelligence
- **Conclusion & Future Work**

Conclusion & Future Work

- Conclusion
  - Large-scale self-supervised pre-training can be successfully adapted to code scenarios.
  - Considering the uniqueness of code can lead to better pre-trained models for code.
  - CodeXGLUE is a useful benchmark and model evaluation platform for code intelligence.

- Future work
  - Pre-trained models with more code-related knowledge (syntax, structure, etc.) integrated
  - Pre-trained models to deal with downstream tasks with very long code inputs/outputs
  - Efficient training and inference for code completion/generation tasks
  - CodeXGLUE++ with more programming languages and more tasks
  - Serious consideration on privacy and intellectual property when using open-source codes in pre-training and downstream applications (e.g., OpenAI's Copilot ☺)

Thank You
谢谢