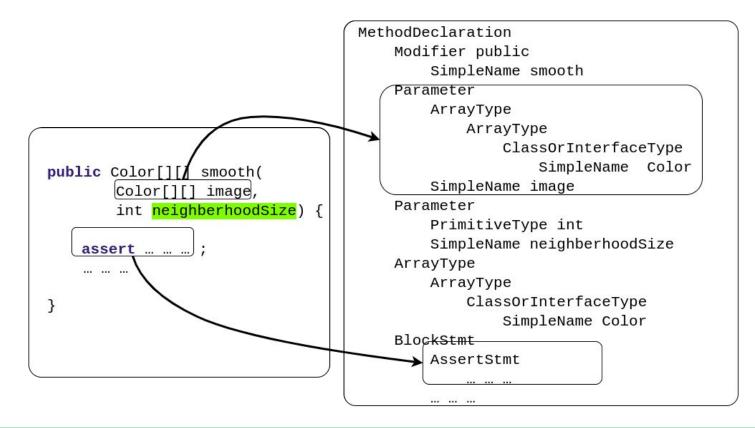
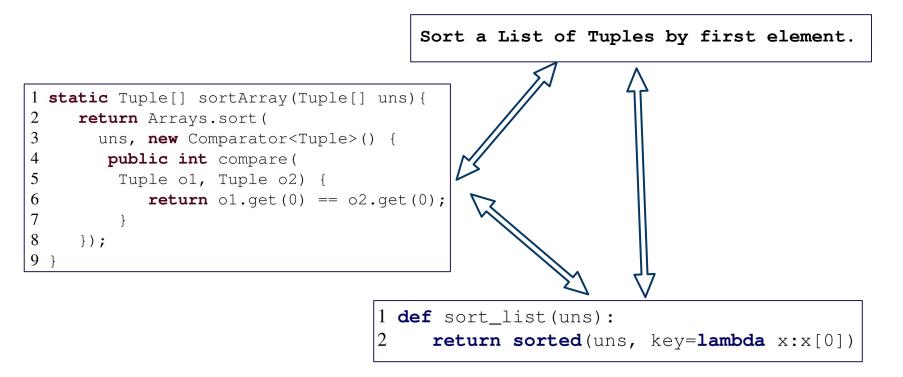
ARiSE Lab Columbia University Computer Science

Research effort in Machine Learning for Source Code Analysis

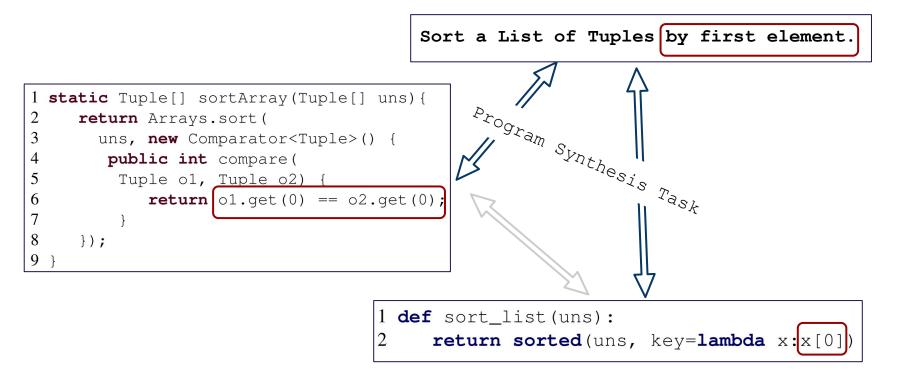
Do we really need AI/ML for code analysis?



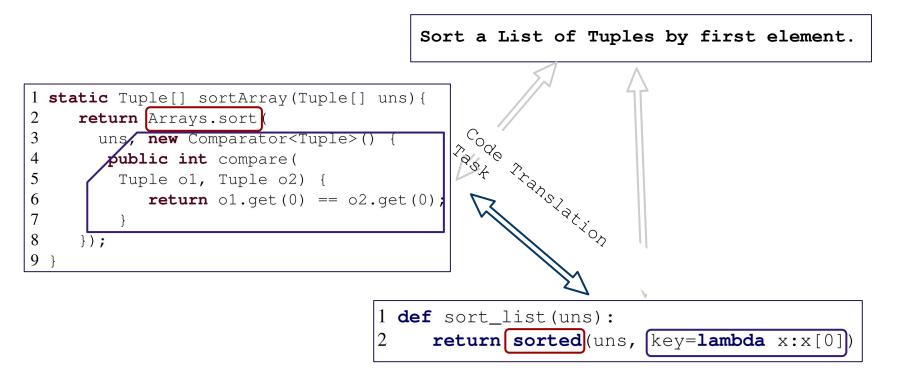
Perhaps we DO need AI/ML in SE



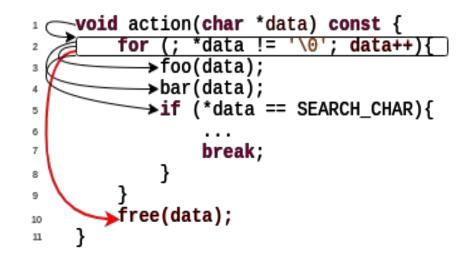
Perhaps we DO need AI/ML in SE.



Perhaps we DO need AI/ML in SE.



Perhaps we DO need AI/ML in SE.

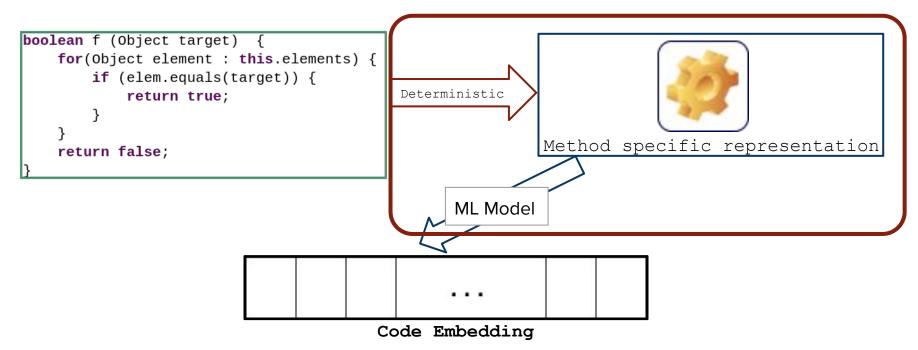


Vulnerability Detection Task

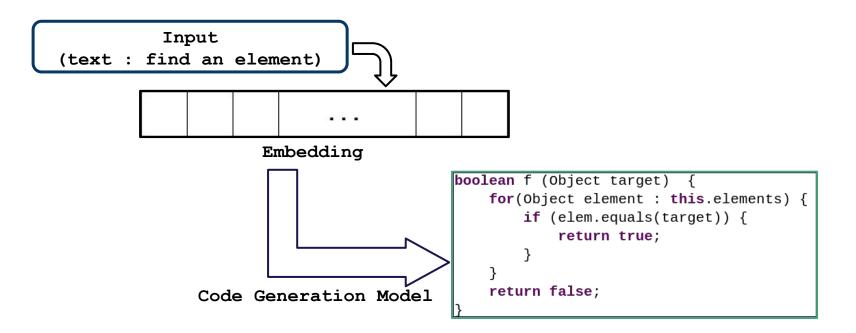
Our Effort in AI for Source Code Analysis

- 1. Understanding Source Code
 - a. Code Completion.
 - b. Vulnerability Detection.
- 2. Learning to Represent Source Code
 - a. Code Comprehension/Summarization.
 - b. Code generation.
 - c. Code translation.
- 3. Learning to Edit Code
 - a. Automated Code Change.
 - b. Program Repair.

Source Code Representation (understanding)

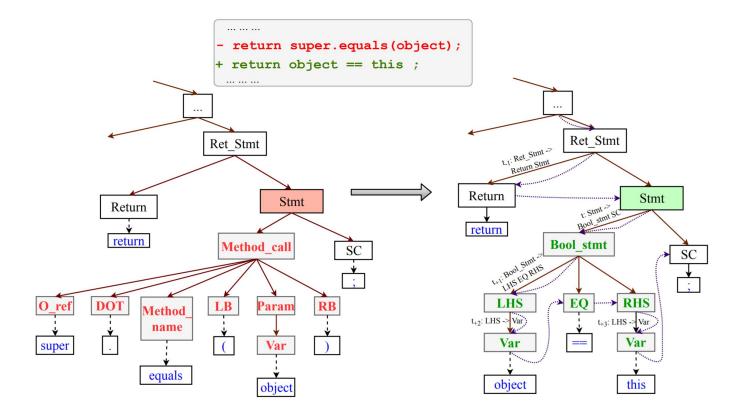


Source Code Generation

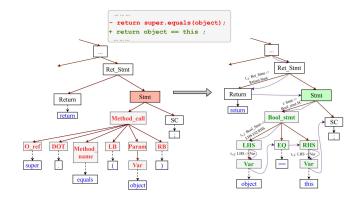


Learning to Edit Code

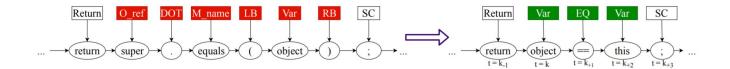
Application - 1 (Code Editing) (CODIT - TSE'20)



CODIT(contd.)







CODIT (contd.)

Method		Code Change Data			Pull Request Data			
		Num	ber of examples	: 5143	Number of examples : 613			
		Top-1	Top-2	Top-5	Top-1	Top-2	Top-5	
	Seq2Seq	107 (2.08%)	149 (2.9%)	194 (3.77%)	45 (7.34%)	55 (8.97%)	69 (11.26%)	
Token Based	Tufano <i>et al</i> .	175 (3.40%)	238 (4.63%))	338 (6.57%)	81 (13.21%)	104 (16.97%)	145 (23.65%)	
	SequenceR	282 (5.48%)	398 (7.74%)	502 (9.76%)	39 (6.36%)	137 (22.35%)	162 (26.43%)	
	Tree2Seq	147 (2.86%)	355 (6.9%)	568 (11.04%)	39 (6.36%)	89 (14.52%)	144 (23.49%)	
Tree Based	Code2seq	58 (1.12%)	82 (1.59%)	117 (2.27%)	4 (0.65%)	7 (1.14%)	10 (1.63%)	
	CODIT	201 (3.91%)	571 (11.10%)	820 (15.94%)	57 (9.3%)	134 (21.86%)	177 (28.87%)	
IR based	\mathscr{B}_{ir}	40 (0.77%)	49 (0.95%)	61 (1.18%)	8 (1.30%)	8 (1.30%)	9 (1.46%)	

CODIT - Examples

```
void visit(JSession * session , ...) throws Exception
{
    visit (((JNode) (* session)), ...);
}
```



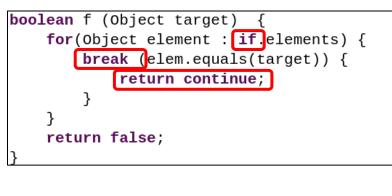
```
public void copyFrom( java.lang.Object arr){
    try{
        android.os.Trace.traceBegin (...);
    finally{
        android.os.Trace.traceEnd(...);
    }
}
```

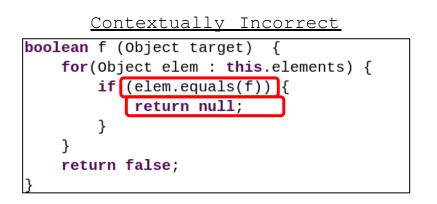
CODIT - Takeaway

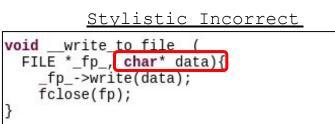
- 1. Neural Machine Translation is really useful for learning code change patterns.
- 2. Tree can be generated by sampling from CFG.
- 3. A tree is syntactically correct.
- 4. CODIT builds tree instead of code.

Example of Invalid code.

Syntactically Incorrect

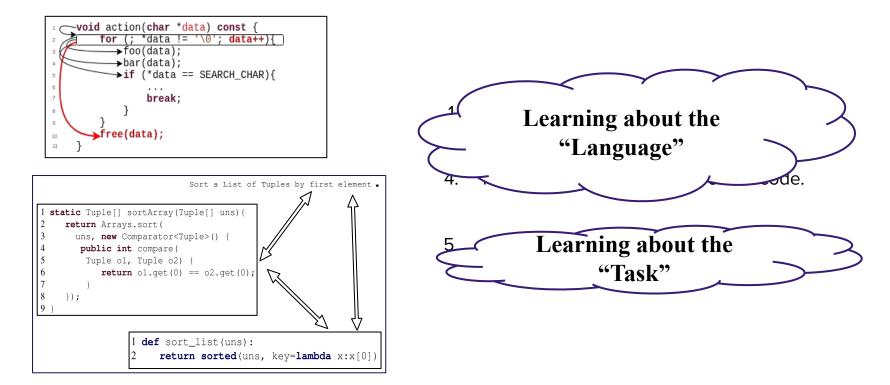




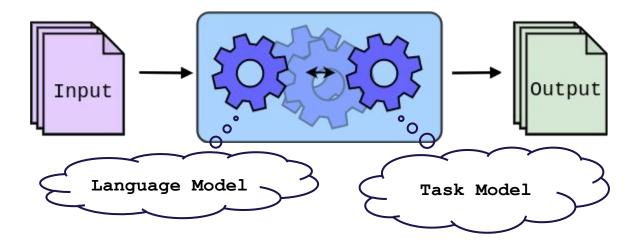


Learning to Represent Source Code

Some Interesting Points to note



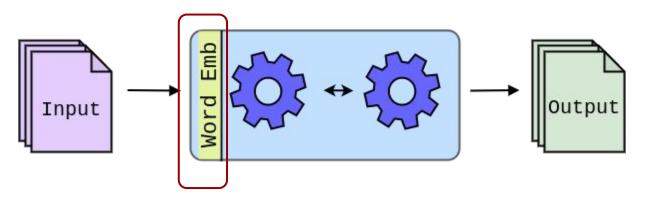
Some Interesting points to note



Can we lessen the burden for model?

Can we transfer any knowledge from elsewhere?

- 1. Word2Vec in code (used by VulDeePecker, SySeVR, Devign) can be a way.
- 2. Code2Vec; another way.

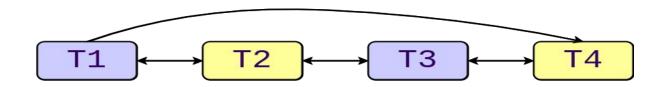


Related topic - Different Models

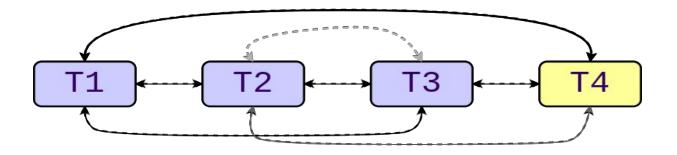
1. Sequence Based Models

T1
$$\leftarrow$$
 T2 \leftarrow T3 \leftarrow T4

2. Graph Based Models

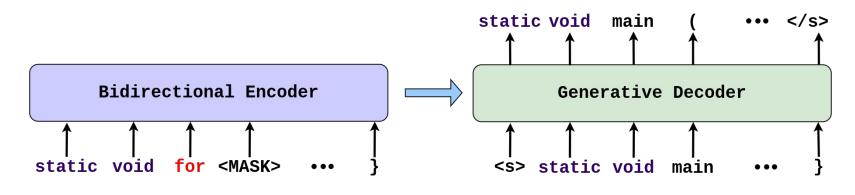


Related topic - Transformer



- 1. Implicitly learns non-linear structure in the input data.
- 2. Often very large/deep models with very high capabilities.
- 3. Learns the syntactic and semantic relationship very well.

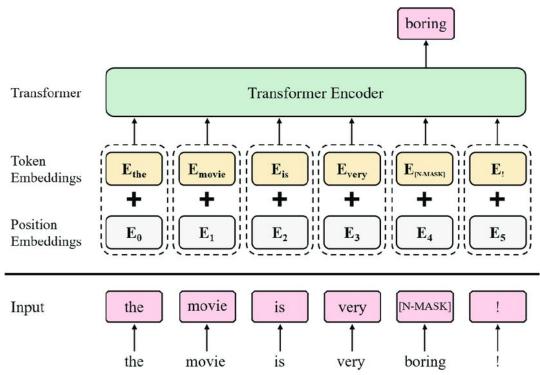
PLBART - NAACL'21



PLBART:

- 1. Trained on 470M Java code, 210M Python Code, 47M Stackoverflow posts.
- 2. Multiple languages for **pre-training** one model for different SE tasks.

Existing Approach - BERT

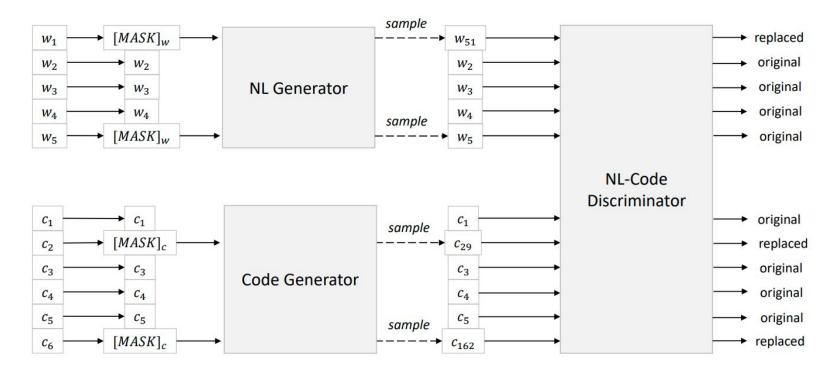


Pre-training:

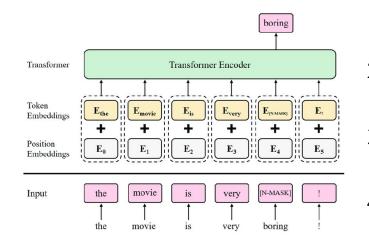
Task agnostic Masked Language Model.

Fine Tuning: Task Specific Objective.

CodeBERT - BERT for Code



BERT - Any Problem?



- 1. Just a Transformer encoder.
- 2. Works very well for

Understanding/Descriminative tasks.

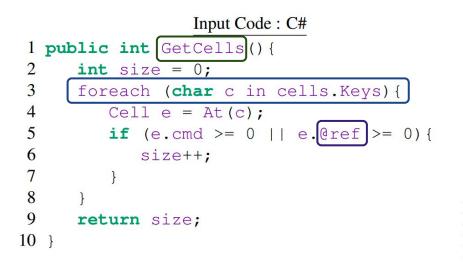
- 3. Must be accompanied with a decoder (trained from scratch during fine-tuning).
- 4. Decoder itself may demand high volume of data.

PLBART - Take Away points.

- 1. Transformer (specially very large architectured) are powerful enough to learn syntactic and contextually correct code.
- 2. Pre-training a model to understand and generate code simultaneously enables the model to learn the language as well as engineering constructs.
- 3. Denoising task in PLBART enables the model to understand the code syntax and semantics.
- 4. Auto-encoding task in PLBART enables it to correctly generate code.

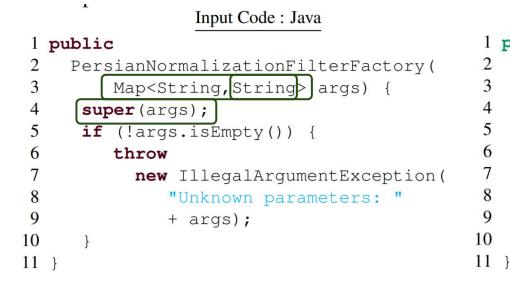
Some Interesting examples of PLBART

Example 1 : ✔



	Generated Code : Java
1	<pre>public int getCells() {</pre>
2	Iterator <character> i =</character>
3	<pre>cells.keySet().iterator();</pre>
4	<pre>int size = 0;</pre>
5	<pre>for (; i.hasNext();) {</pre>
6	Character c = i.next();
7	Cell $e = at(c);$
8	if (e.cmd >= 0 e.ref >= 0) {
9	size++;
0	}
1	}
2	return size;
3	}

Some Interesting examples of PLBART



Generated Code : C#

1 public

PersianNormalizationFilterFactory(
 IDictionary<string, string) args)
 : base(args){
 if (args.Count > 0) {
 throw new System.ArgumentException(
 "Unknown parameters: "
 + args
);
 }
}

Some Interesting examples of PLBART

Input : Returns the count to which the specified key is mapped in this frequency counter , or 0 if the map contains no mapping for this key .

Reference Code	Generated Code
<pre>1 Integer function (T arg0) { 2 Integer loc0 = counter.get(arg0); 3 if (loc0 == null) { 4 return 0;</pre>	<pre>1 int function (T arg0) { 2 Integer loc0 = counter.get(arg0); 3 if (loc0 == null) { 4 return 0; 5 }</pre>
5 } 6 return loc0; 7 }	6 else { 7 return loc0; 8 } 9 }

Some Interesting results from PLBART (generative)

Methods	Ruby	Javascript	Go	Python	Java	PHP	Overall
Seq2Seq	9.64	10.21	13.98	15.93	15.09	21.08	14.32
Transformer	11.18	11.59	16.38	15.81	16.26	22.12	15.56
RoBERTa	11.17	11.90	17.72	18.14	16.47	24.02	16.57
CodeBERT	12.16	14.90	18.07	19.06	17.65	25.16	17.83
PLBART	14.11	15.56	18.91	19.30	18.45	23.58	18.32

Code Summarization

	Methods	EM	BLEU	CodeBLEU
	Seq2Seq	3.05	21.31	17.61
Sis	Guo et al. (2019)	10.05	24.40	20.99
Synthesis	Iyer et al. (2019)	12.20	26.60	-
Ę	GPT-2	17.35	25.37	22.79
Ň	CodeGPT-2	18.25	28.69	25.69
с, U	CodeGPT-adapted	20.10	32.79	27.74
Code	PLBART	18.75	36.69	38.52
Ŭ	$PLBART_{10K}$	17.25	31.40	33.32
	$PLBART_{20K}$	18.45	34.00	35.75
	$PLBART_{50K}$	17.70	35.02	37.11

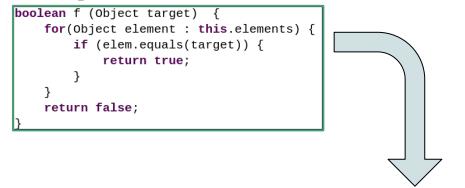
_	Methods	Java to C#			C# to Java		
lation	<u>o</u> Methods		EM	CodeBLEU	BLEU	EM	CodeBLEU
lat	Naive Copy	18.54	0	34.20	18.69	0	43.04
JS	PBSMT	43.53	12.50	42.71	40.06	16.10	43.48
Transl	Transformer	55.84	33.00	63.74	50.47	37.90	61.59
	RoBERTa (code)	77.46	56.10	83.07	71.99	57.90	80.18
de	CodeBERT	79.92	59.00	85.10	72.14	58.80	79.41
Code	GraphCodeBERT	80.58	59.40	-	72.64	58.80	-
0	PLBART	83.02	64.60	87.92	78.35	65.00	85.27

Some Interesting results from PLBART (understanding)

Tasks	Vulnerability	Clone
Tasks	Detection	Detection
Transformer	61.64	-
CodeBERT	62.08	96.5
GraphCodeBERT	-	97.1
PLBART	63.18	97.2

How things are done in literature (Encoding)

1. Sequence of tokens



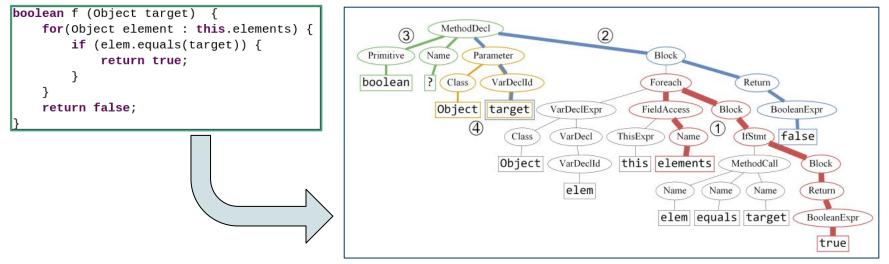
boolean f (Object target) { for (Object element ... return false ; }

Russell et. al. boolean ID (ID ID) { for (ID ID ... return false ; }

Used models : RNN, LSTM, CNN, etc.

How things are done in literature (Encoding)

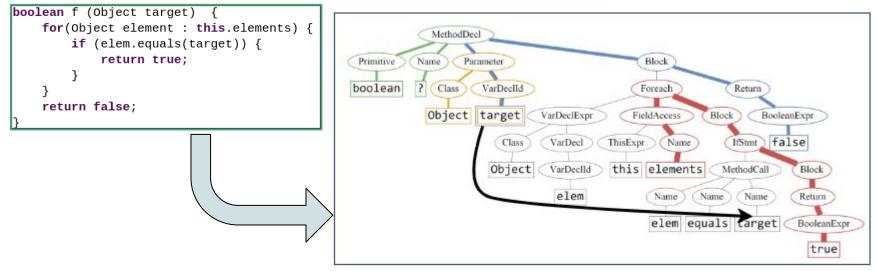
2. AST



Used models : ASTNN (Zhang et. al.), Hierarchical RNN (Code2Vec)

How things are done in literature (Encoding)

3. Graph



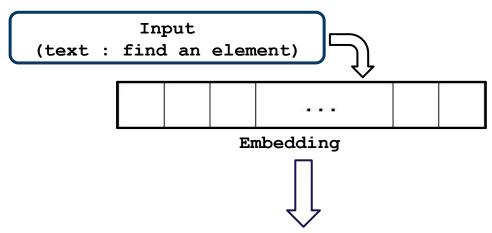
Used models : Gated Graph Neural Network (Allamanis et. al., Devign)

Pros. and Cons. (Encoding)

	Sequence	Tree	Graph	
Pros	- Faster and Simpler methods.	 Capture syntax. Can reason about the syntactic dependencies. 	 Captures both syntax and semantic dependencies. Good for reasoning about semantic relationship between tokens. 	
Cons	 Not merely a sequence of tokens. Lacks Syntax info. Lacks Semantic info. 	 Slightly more complicated models. Still lack the semantic dependencies (data flow). 	 Very complex models. Sometimes the yield is not so much worth the complexity. 	

How things are done in literature (Generation)

1. Sequence based generation

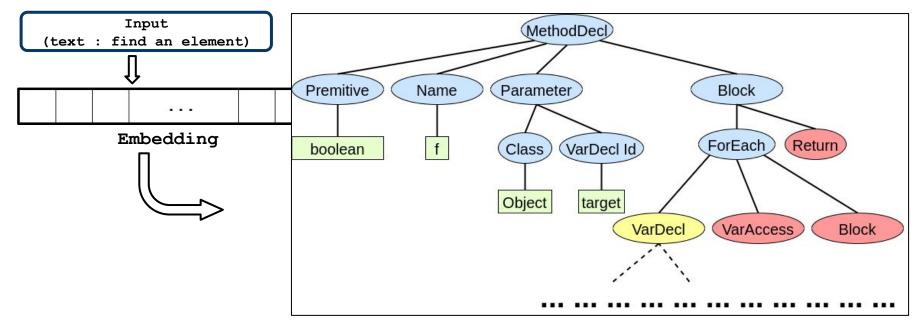


boolean f (Object target) { for (Object element ... return false ; }

Used models : RNN, GRU, LSTM (all with beam search)

How things are done in literature (Generation)

1. Tree/Grammar based generation



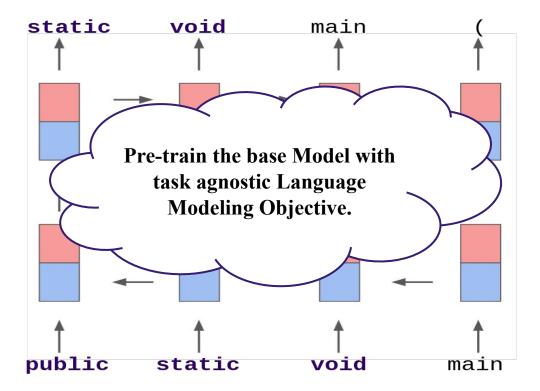
Pros. and Cons. (Decoding/Generation)

	Sequence	Tree	
Pros	 Easier to implement. Off the shelf models can be used directly. 	 Generates Syntactically correct code. Easier when the goal is to generate template rather the full code. 	
Cons	 May generate syntactically invalid code. Might also create semantically wrong code. 	 More complex models. Often difficult to model because of the large grammar. Modeling tokens/identifiers still remains a challenge Semantic correctness is still not guaranteed. 	

What are the challenges in joint learning?

- 1. Most of the task needs annotation/objective to update the model.
- 2. Demand for data increases with the complexity of the task.
- 3. Data is highly demanded by more complex models.

Task agnostic "Pre-Training" (ELMo)



ELMo (pros and cons)

- Pros:
 - Reduces burden on learning task specific reasoning.
- Cons:
 - Uses (Bidirectional)LSTM as base model.
 - Cannot capture the non-linear language constructs in code.

- Prospective Solution :
 - Pretrain tree of graph based models.

Take Away Points

- 1. Machine learning in source code analysis showed a lot of promise over the years.
- 2. Source code exhibit different information through different input modalities, such as identifier names, syntax, semantic interaction between identifiers.
- 3. A good model for a particular task should exploit appropriate information modality.
- 4. Code synthesis is fundamentally different and more challenging than code understanding.
- 5. Annotated data scarcity can be overcome by unsupervised pre-training of a model.
- 6. A pretrained model should contain multiple modality (implicit/explicit), since pre-training is very expensive.



