

# CE 815 – Secure Software Systems

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ML-Based Vulnerability Detection Methods (Hoppity)

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Acknowledgments: Some of the slides are fully or partially obtained from other sources. A reference is noted on the bottom of each slide, when the content is fully obtained from another source. Otherwise a full list of references is provided on the last slide. Thanks to Mohammad Haddadian for the help on the slides.



# Introduction

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- Vulnerability detection as first step
  - Then, Vulnerability repair
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- Compiler VS Interpreter
  - Vulnerability VS Bug
  - Security VS non-Security

**HOPPITY: Learning Graph Transformations to Detect and Fix Bugs in Programs, ICLR 2020.**



# Problem

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Source-code analysis is:

- Undecidable
- Noisy
- Rules are hand written
- Tailored to specific code bases / bug patterns



# Javascript Challenges

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- Incorrect operators
- Incorrect identifiers
- Accessing undefined properties
- Mishandling variable scopes
- Type incompatibilities

# Example



```
function clearEmployeeListOnLinkClick(){
  document.querySelector("a").addEventListener("click",
    function(event){
      document.querySelector("ul").InnerHTML = "";
    }
  );
}
```

(a) InnerHTML should have been innerHTML.

```
if (matches) {
  return {
    episode: Number(matches.groups.episode),
    hosts: matches.groups.hosts.split(/([, &]+|\sand\s)/).
      map(el => S(el).trim().s)
  };
}
```

(b) Highlighted parentheses should have been removed.

```
module.exports = function (grunt) {
  grunt.initConfig({
    execute: {...}, copy: {...}, checktextdomain: {...}
    wp_readme_to_markdown: {...}, makepot: {...}}
  ...
  grunt.registerTask('default', ['wp_readme_to_markdown',
    'makepot', 'execute', 'checktextdomain'])
};
```

(c) copy function should have also been included in the highlighted list.

```
export default {
  computed: {
    level () {
      return dictMap.skillLevel[
        parseInt((this.value === 0 ? 1 : this.value)/20)];
    }, ...
  }
}
```

(d) parseInt should have been removed because == implies this.value is an integer.

# Solution



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Leverage large amounts of Javascript fixes on Github to locate and repair bugs

# Steps

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- Represent source code
- Represent fixes
- Learning





# Model

- Problem of detecting and repairing bugs in programs is a structured prediction problem on a graph-based representation of programs.

$$p(g_{fix} | g_{bug}; \theta) = p(g_1 | g_{bug}; \theta) p(g_2 | g_1; \theta) \dots p(g_{fix} | g_{T-1}; \theta)$$



# Goal

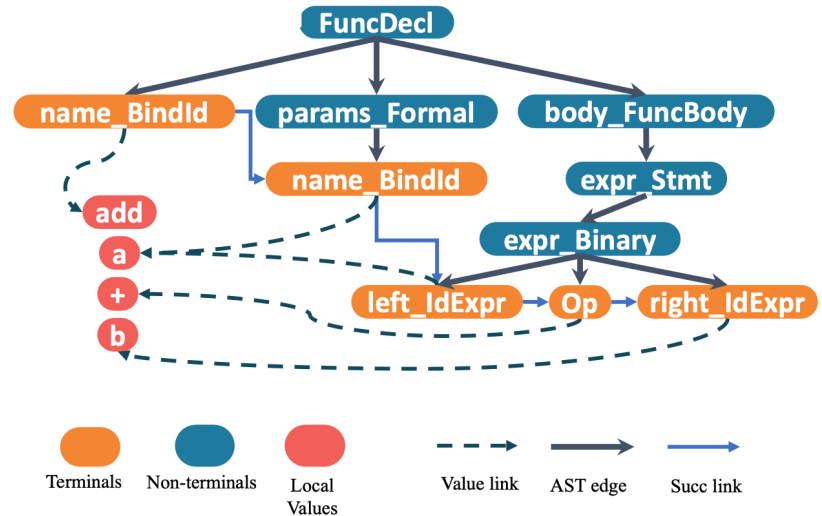
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- 1- function `add (a) {a + b;}` Buggy
- 2- function `add (a, b) {a + b;}` Step 1
- 3- function `add (a, b) { return a + b;}` Step 2



# Source code representation

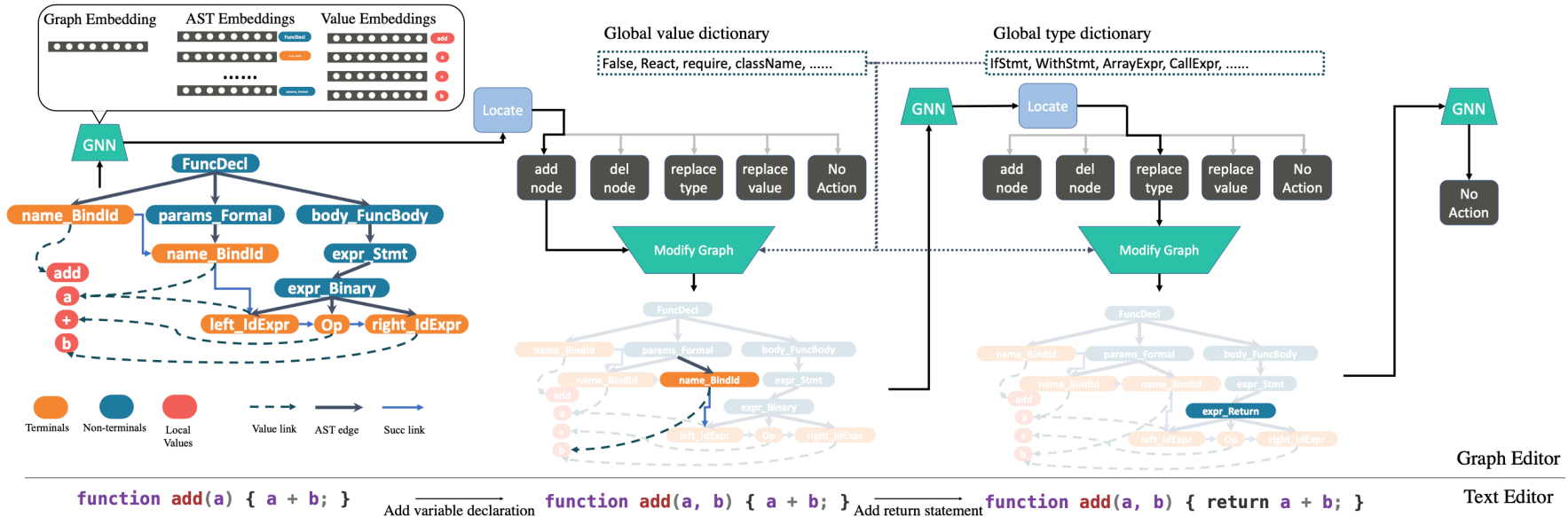
- AST
- ValueLink



```
function add(a) { a + b; }
```

# Fix representation

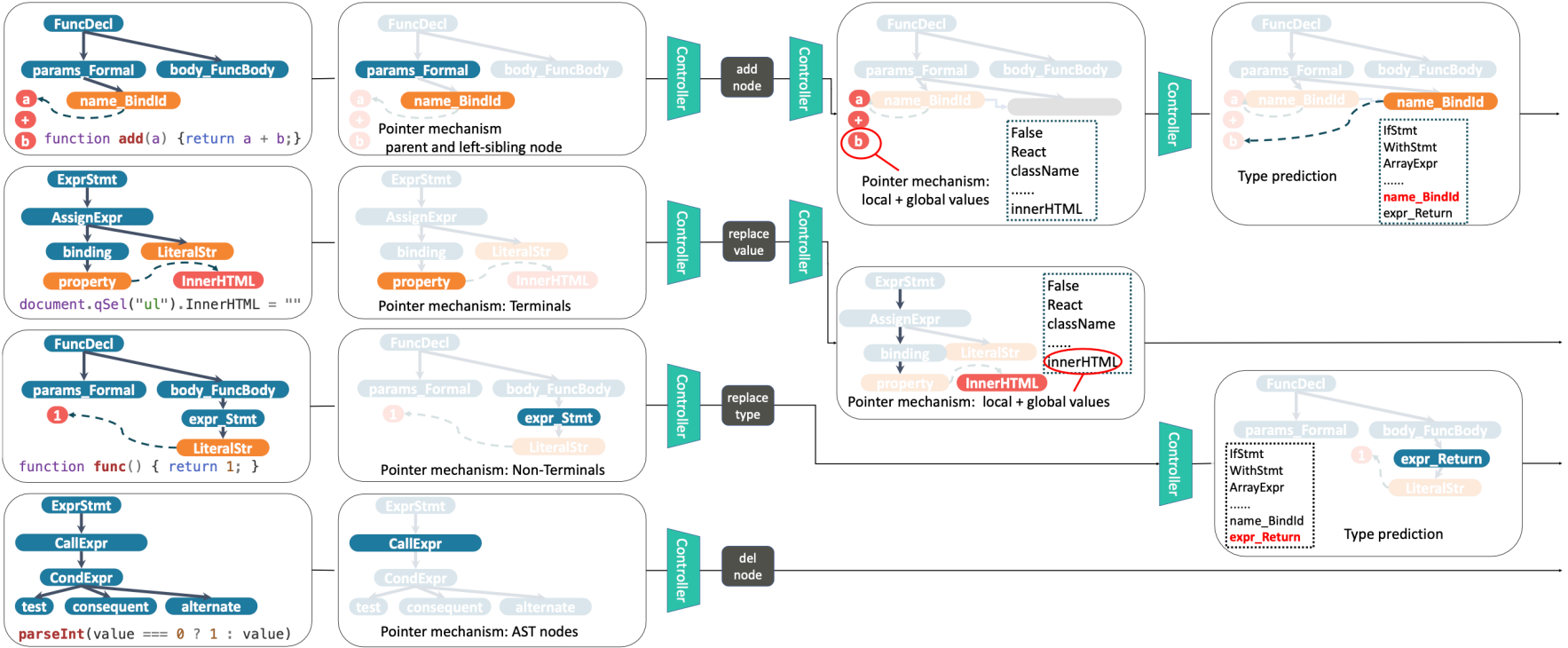
## • Graph Edits



## Location

## Value

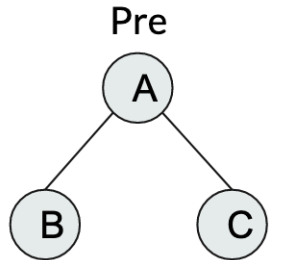
## Type



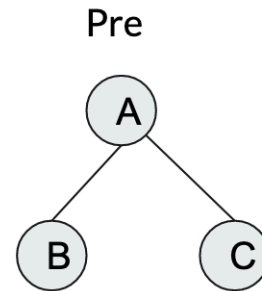
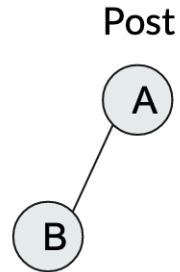


# Low level primitives

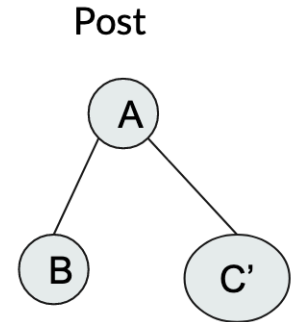
- Location
- Value
- Type



Delete



Replace





# Low level primitives: Value

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Choose from either the values appearing in the current file (local value table), or a collection of global values that are common for the specific language

Let  $D_{\text{val}}$  be the global dictionary of commonly used leaf-node values in the language, where each item  $i \in D$  is associated with a vector representation:

$$\vec{i}_v \in \mathbb{R}^d$$



# Low level primitives: Type

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- As the total possible number of types is finite and fixed for a given language, the type prediction is simply a multi-class classification problem.
- But utilize the AST grammar checker with contextual information to prune the output space.



# Graph edit operators

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add  
node

del  
node

replace  
type

replace  
value

No  
Action



# Anatomy of a graph edit

## “replace\_val”

1. Predict **Location**
2. Predict **Value**

## “remove”

1. Predict **Location**

## “replace\_type”

1. Predict **Location**
2. Predict **Type**

## “add”

1. Predict **Location**
2. Predict **Value**
3. Predict **Type**
4. Predict **Child Number**

# Graph transformation

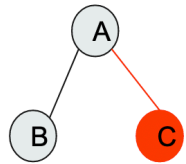


1

2

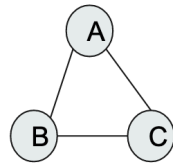
3

# Inference

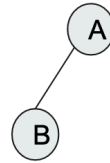
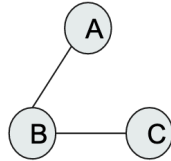
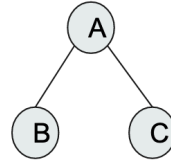


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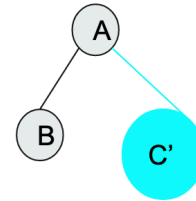
Learn



Request  
Code



Result  
→





# Dataset

- OneDiff (just one change)
- ZeroOneDiff (zero or one edit)
- ZeroOneTwoDiff (zero, one or two edits)

	ADD	REP_TYPE	REP_VAL	DEL	total
train	6,473	1,864	251,097	31,281	290,715
validate	790	245	31,357	3,957	36,349
test	796	233	31,387	3,945	36,361

Table 1: Statistic of `OneDiff` dataset. See appendix for more information of other dataset.

# Evaluation



	<i>Total</i>		<i>Location</i>		<i>Operator</i>	<i>Value</i>		<i>Type</i>	
	Top-3	Top-1	Top-3	Top-1	Top-1	Top-3	Top-1	Top-3	Top-1
<b>TOTAL</b>	<b>26.1</b>	14.2	35.5	20.4	34.4	52.3	29.1	76.1	66.7
ADD	52.9	39.2	69.6	51.4	70.6	65.7	55.1	76.8	68.5
REP_VAL	23.4	11.9	33.3	18.5	31.7	53.0	28.8	-	-
REP_TYPE	71.7	52.4	73.0	52.8	79.4	-	-	74.7	61.0
DEL	39.6	24.8	44.0	27.5	45.8	-	-	-	-
Random	.08	.07	2.28	1.4	27.7	.01	.01	.27	0

Table 2: Evaluation of model on the OneDiff dataset: accuracy (%).

# Evaluation (cont.)



Type	GGNN-Rep	GGNN-Cls	HOPPITY
Top-1	53.2%	<b>99.6%</b>	90.0%
Top-3	85.8%	<b>99.6%</b>	94.8%

Table 3: REP\_TYPE accuracies with location+op.

Value	GGNN-Rep	GGNN-RNN	HOPPITY
Top-1	63.8%	60.3%	<b>69.1%</b>
Top-3	67.6%	63.6%	<b>73.4%</b>

Table 4: REP\_VAL accuracies with location+op.

	Top-1	Top-3
HOPPITY	<b>67.7%</b>	<b>73.3%</b>
SequenceR	64.2%	68.6%

Table 5: Overall OneDiff accuracy with location.

Bug Type	Amount	TAJS	HOPPITY
Undefined Property	7	0	1
Functional Bug	11	0	3
Refactoring	12	0	1
Total	30	0	5

Table 6: Comparison with TAJS.

# Acknowledgments

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- [HOPPITY] HOPPITY: Learning Graph Transformations to Detect and Fix Bugs in Programs, ICLR 2020.