HOPPITY: LEARNING GRAPH TRANSFORMATIONS TO DETECT AND FIX BUGS IN PROGRAMS

Elizabeth Dinella*, Hanjun Dai*, Ziyang Li, Mayur Naik, Le song, Ke Wang

Presenter: Liunian Li, Ruochen Wang

Motivation

- Sheer size and complexity of modern codebases are difficult to debug
- Automated debugging tools to the rescue



99 little bugs in the code

Existing Methods

- Rule-based
- Data-driven

Existing Methods

- Rule-based Example
 - ErrorProne (part of Google Tricorder Analysis Tool)
 - find bug patterns based on AST matching
 - Consists a list of bug patterns, and these will be used to match against a query code

On by default : ERROR AndroidInjectionBeforeSuper AndroidInjection.inject() should always be invoked before calling super.lifecycleMethod() ArrayEquals Reference equality used to compare arrays ArrayFillIncompatibleType Arrays.fill(Object[], Object) called with incompatible types. ArravHashCode hashcode method on array does not hash array contents ArrayToString Calling toString on an array does not provide useful information Arrays.asList does not autobox primitive arrays, as one might expect. AsyncCallable should not return a null Future, only a Future whose result is null. AsyncFunctionReturnsNull AsyncFunction should not return a null Future, only a Future whose result is null. **AutoValueConstructorOrderChecker** Arguments to AutoValue constructor are in the wrong order Classes that implement Annotation must override equals and hashCode. Consider using AutoAnnotation instead of implementing Annotation by hand BadShiftAmount Shift by an amount that is out of range Deserializing user input via the Serializable API is extremely dangerous **BundleDeserializationCast** Object serialized in Bundle may have been flattened to base type. ChainingConstructorIgnoresParameter

This paper

- Propose a learning-based for detecting and fixing bugs in Javascript (JS)
- Hypothesis: A code snippet is buggy if it deviates from common practices.
 (pattern matching -> learning-based)
- Contribution:
 - A single model to deal with a wide range of bugs
 - Fixing JS bugs is challenging due to anti-human syntactic designs
 - Can handle complex bugs: adding/removing statements from a program
 - o End-to-End in the sense that:
 - propose bug location
 - propose fixes
 - implement fixes

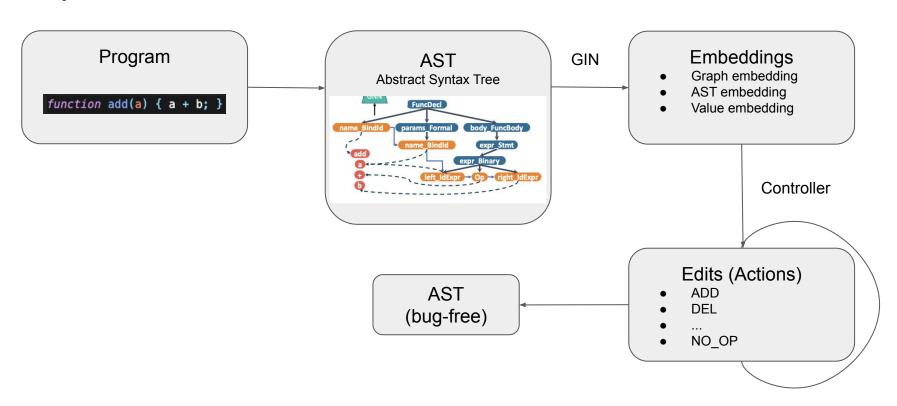


Existing Methods

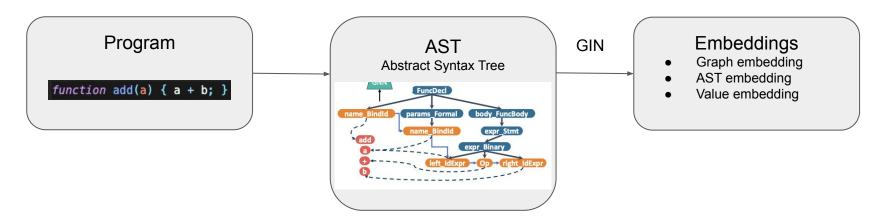
- Data-driven (Example)
 - LEARNING TO REPRESENT PROGRAMS WITH GRAPHS
 - o Idea:
 - Construct a graph of code based on AST (Abstract Syntax Tree)
 - Utilize the learned node embedding for downstream tasks
 - Tasks:
 - VarNaming: predict the name of a variable given its usage
 - VarMisuse: infer which variable should be used for a given location

```
var clazz=classTypes["Root"].Single() as JsonCodeGenerator.ClassType;
Assert.NotNull(clazz);
var first=classTypes["RecClass"].Single() as JsonCodeGenerator.ClassType;
Assert.NotNull(clazz);
Assert.Equal("string", first.Properties["Name"].Name);
Assert.False(clazz.Properties["Name"].IsArray);
```

Pipeline Overview



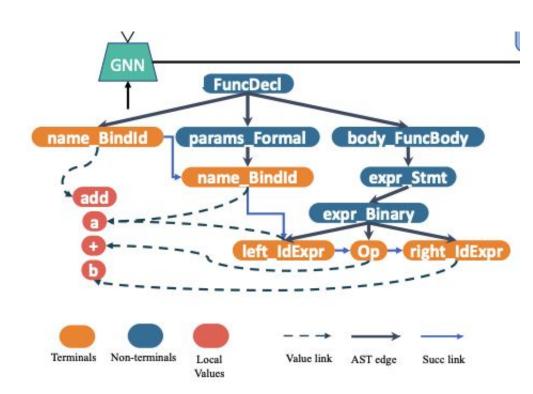
Method Part I: Embedding



Program

function add(a) { a + b; }

- Abstract Syntax Tree (AST):
 - Nodes: motifs of a program
 - Terminal nodes
 - Non-terminal nodes
 - Local values
 - Edges:
 - AST edge
 - Succ link (SuccToken)
 - Value link



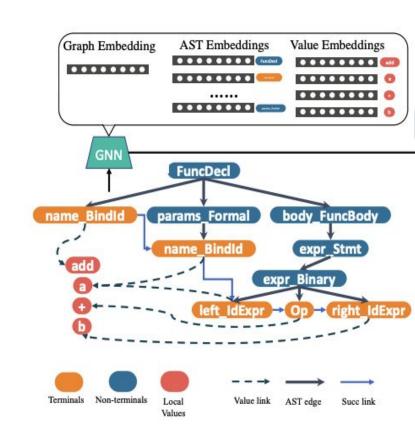
- GIN (graph isomorphism network)
- GIN vs GNN: GIN uses sum() as aggregation function
 - They argue that sum aggregation is better than mean and max aggregation in terms of distinguishing graph structure.
 - o Proved to be as powerful as WL (Weisfeiler-Lehman) test.

$$h_v^{(k)} = \text{MLP}^{(k)} \left(\left(1 + \epsilon^{(k)} \right) \cdot h_v^{(k-1)} + \sum_{u \in \mathcal{N}(v)} h_u^{(k-1)} \right)$$

- Update rule:
 - Extend GIN to Multi-graph setting (multiple types of edges)
 - AST edge
 - Succ link (SuccToken)
 - Value link

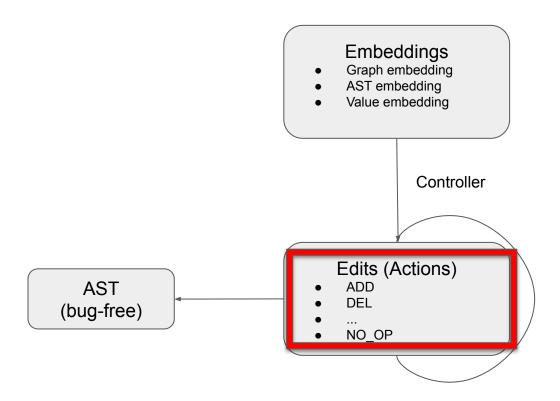
$$h_v^{(l+1),k} = \sigma(\sum_{u \in \mathcal{N}^k(v)} \mathbf{W}_1^{l,k} h_u^{(l)}), \forall k \in \{1, 2, \dots, K\}$$
 $h_v^{(l+1)} = \sigma(\mathbf{W}_2^l[h_v^{(l+1),1}, h_v^{(l+1),2}, \dots, h_v^{(l+1),K}] + h_v^{(l)})$
 $\vec{q} = AVG_l(MAXPOOL_v(h_v^l))$

- GIN produces three types of embeddings
 - Graph Embedding (g)
 - AST Embedding
 - Value Embedding
- Those embeddings will be used to determine how to edit the code



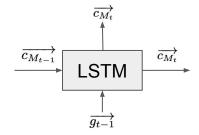
Method Part II: Controller

Pipeline Overview



Method - Controller - context embedding

- Context embedding "c"
 - encodes edit history and graph info
 - Provide information for how to edit the graph
- Two types:
 - \circ Macro: $\overrightarrow{c_{M_t}}' = \text{LSTM}(\overrightarrow{g_{t-1}}|\overrightarrow{c_{M_{t-1}}})$



 $\qquad \text{Micro:} \qquad \overrightarrow{c_{m_t}} = \text{LSTM}(\overrightarrow{e_t}|\text{LSTM}(\overrightarrow{v_t}|\overrightarrow{c_{M_t}}))$

CMT: typo in the update rule of Micro: missing "prime" sign

- Five in total
 - ADD: add a new node to the graph
 - DEL: delete a node from graph
 - REP_VAL: replace the value of a terminal node
 - REP_TYPE: replace the type of a non-terminal node
 - NO_OP: no operation needed, program fixed
- These actions can be constructed using "Edit Primitives"

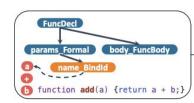
Method - Controller - Edit Primitives

- Three primitives that can be used to construct high level edits
 - Location
 - Determine the location (node) of bug
 - $loc(\vec{c}, g) = \arg\max_{v \in V} \vec{v}^{\top} \vec{c}$
 - Value
 - Assign a value to a terminal node
 - Possible values = local values (cur file) + global values (common for a language)
 - $extbf{val}(ec{c},g) = \operatorname{argmax}_{t \in D_{val} \cup V_{val}} ec{t}^{ op} ec{c}.$
 - Type
 - Determine the type of the non-terminal nodes

CMT: error in the main text: {Type} determines the type for all nodes

- Multi-class Classification
- e.g.

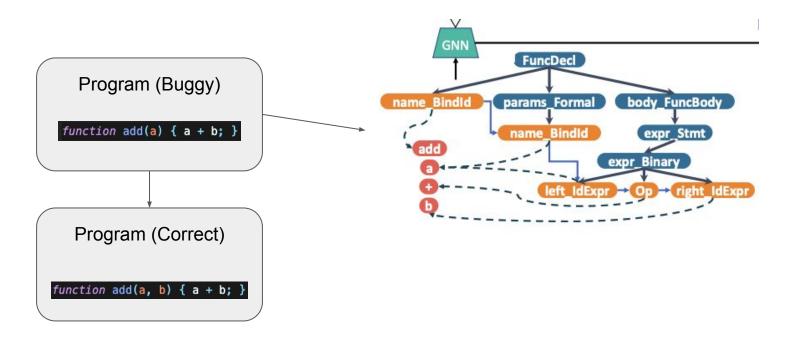




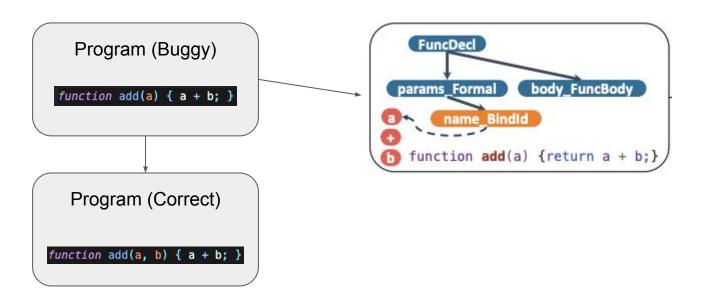
Method - Controller - Example

- Let's use a concrete example to understand the entire pipeline
- Consider the previous buggy program "add"

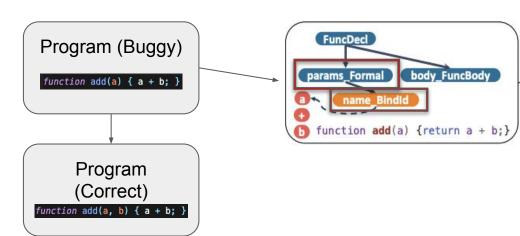
Consider the previous buggy program "add" (simplify next)



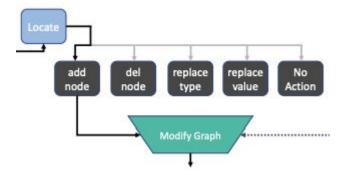
Consider the previous buggy program "add"



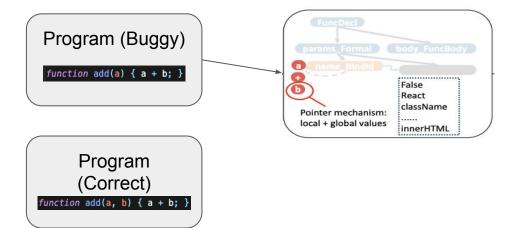
- Step 1: locate the buggy node (location primitives)
 - \circ locate the <u>parent node</u> of the bug $loc(ec{c},g) = rg \max_{v \in V} ec{v}^ op ec{c}$
 - locate the <u>sibling node</u> of the bug (so that we can add SuccToken link)
 - Not mentioned in the paper
 - Our guess: also use the above equation, but this time search over child nodes
 - Update micro-context embedding
 - $c_{m1} = \text{LSTM}(\overrightarrow{v_{sibling}} | \overrightarrow{c_m})$



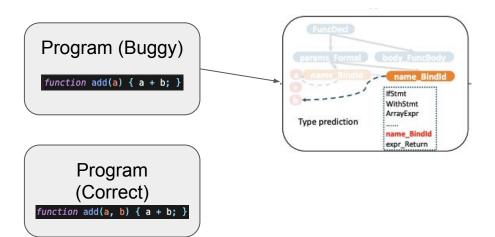
- Step 2: Determine the edit action (e.g. ADD, DEL)
 - Classification (input: node embedding)



- Step 3: Assign a value to the newly added node (Value)
 - $\circ \quad val(\vec{c},g) = \operatorname{argmax}_{t \in D_{val} \cup V_{val}} \vec{t}^{\top} \vec{c}.$
 - Update micro-context embedding
 - $\vec{c_{m2}} = \text{LSTM}(val(\vec{c_{m1}}, g) | \vec{c_{m1}})$



- Step 4: Assign a type to the newly added node (Type)
 - Classification (input: micro-context and graph embedding)
 - Update micro-context embedding

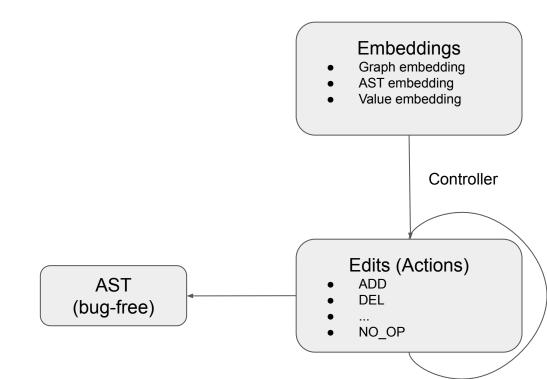


- Step 5: Complete the links for AST
 - Connect Parent with newly added node via AST Link
 - Connect newly added node with assigned value via ValueLink
 - Connect sibling node with newly added node via SuccToken (Link)

- Step 6: Update macro contents
 - Graph embeddings g (refit the edited graph with GIN)
 - Macro-context embeddings (paper does not discuss how)

$$\overrightarrow{c_{M_t}} \longleftarrow \overrightarrow{c}_{ADD}$$

Repeat Step 1 - 6 until "NO_OP" is selected.



Method Part III: Learning & Inference

Method - Learning

- Dataset: pairs of buggy code and fixed code $\mathcal{D} = \{(g_{bug}^{(i)}, g_{fix}^{(i)})\}_{i=1}^{|\mathcal{D}|}$
- Objective:

$$\max_{\theta} \mathbb{E}_{(g_{bug}, g_{fix}) \sim \mathcal{D}} p(g_{fix} | g_{bug}; \theta)$$

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

We can obtain supervision for the factorized graph transformation sequences:

Parse the source code using the SHIFT AST format, and utilize a JSON diff toolbox to compile the code differences into a sequence of AST edits

(Training is similar to how we train a forward language model)

Method - Inference

ullet Goal: $rg \max_{g_{fix}} p(g_{fix}|g_{bug}; heta)$

Problem: combinational search space

Solution: beam search

Method - Inference - Beam Search

- Maintain a pool of B partially fixed programs, which starts with simply the single buggy program
- For every program in the pool, we propose B locations, B operators, or B primitives, depending on the current state of the program
- Rank solutions based on the joint log-likelihood and keep top B partially fixed programs

Method - Inference - Beam Search

- Maintain a pool of B partially fixed programs, which starts with simply the single buggy program
- For every program in the pool, we propose B locations, B operators, or B primitives, depending on the current state of the program
- Rank solutions based on the joint log-likelihood and keep top B partially fixed programs

Experiments

Dataset

- Automatically mined from Github
- How to determine if a commit is a bug fix or not?

Heuristic: a commit with a smaller number of AST differences is more likely to be a bug fix

 The program before a bug-fix commit is the buggy program and after the bug-fix commit is the correct program

Dataset

Three datasets:

OneDiff, ZeroOneDiff, ZeroOneTwoDiff

	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

	To	tal	Loca	ation	Operator	Va	lue	Ty	ре
	Top-3	Top-1	Top-3	Top-1	Top-1	Top-3	Top-1	Top-3	Top-1
TOTAL	26.1	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 (%).

- A model will be penalized in Value and Type if it predict the Operator wrong
- Random baseline shows the large search space of the problem

Evaluation - Compare with GGNN

Value	GGNN-Rep	GGNN-RNN	Норріту
Top-1	63.8%	60.3%	69.1%
Top-3	67.6%	63.6%	73.4%

Table 4: REF	_VAL	accuracies	with	location+op.
--------------	------	------------	------	--------------

Туре	GGNN-Rep	GGNN-Cls	Норріту
Top-1	53.2%	99.6%	90.0%
Top-3	85.8%	99.6%	94.8%

Table 3: REP_TYPE accuracies with location+op.

- GGNN-Rep: from Allamanis et al. 2018
- GGNN-Cls: muti-class classification with target node and graph embedding
- GGNN-RNN: predict the value as a character-level language model

Evaluation - Compare with SequenceR

	Top-1	Top-3
Норріту	67.7%	73.3%
SequenceR	64.2%	68.6%

Table 5: Overall OneDiff accuracy with location.

 Sequence R: predict a sequence of tokens given a buggy line (similar to machine translation)

Evaluation - Compare with TAJS

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

- Static analysis tool
- Only support part of the evaluation set; Need manual setup for its control options;

Related Work - Static analysis for bug detection

Advantage

- Targets a broad range of programming errors
- Not only localize bugs but also fixes them
- Significantly higher sigal-to-noise ratio

Potential drawback: longer run time; scalability to long code sequence?

Related Work - Learning-based bug detection

Allamanis et al. (2018): use GNN to predict correct variable name given a buggy location

Vasic et al. (2019): pointer network on top of RNN

DeepBugs: only supports three classes of bugs

SequenceR: seq2seq bug fixing

Getafix: hierarchical clustering to sort fix patterns

All need the bug location as input.

Related Work - Graph learning and optimization

The local value table and pointer mechanism inspired by prior work

Related to auto-regressive graph modeling

Some work model graph modification in latent space but lack fine-grained control (graph-to-graph transformation)

Conclusion

End-to-end learning-based approach to detect and fix bugs in Javascript

Correctly predicts 9490 out of 36361 code changes in real programs on Github

Future work

Bugs spanning multiple files

Deploy in IDE

Other languages