CE 815 – Secure Software Systems

ML-Based Vulnerability Detection Methods (Vulchecker)

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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.

Review

- Automated vulnerability detection
- Code graph representation
- Word2Vec
- GNN
- Hand-selected dataset

- Problem?

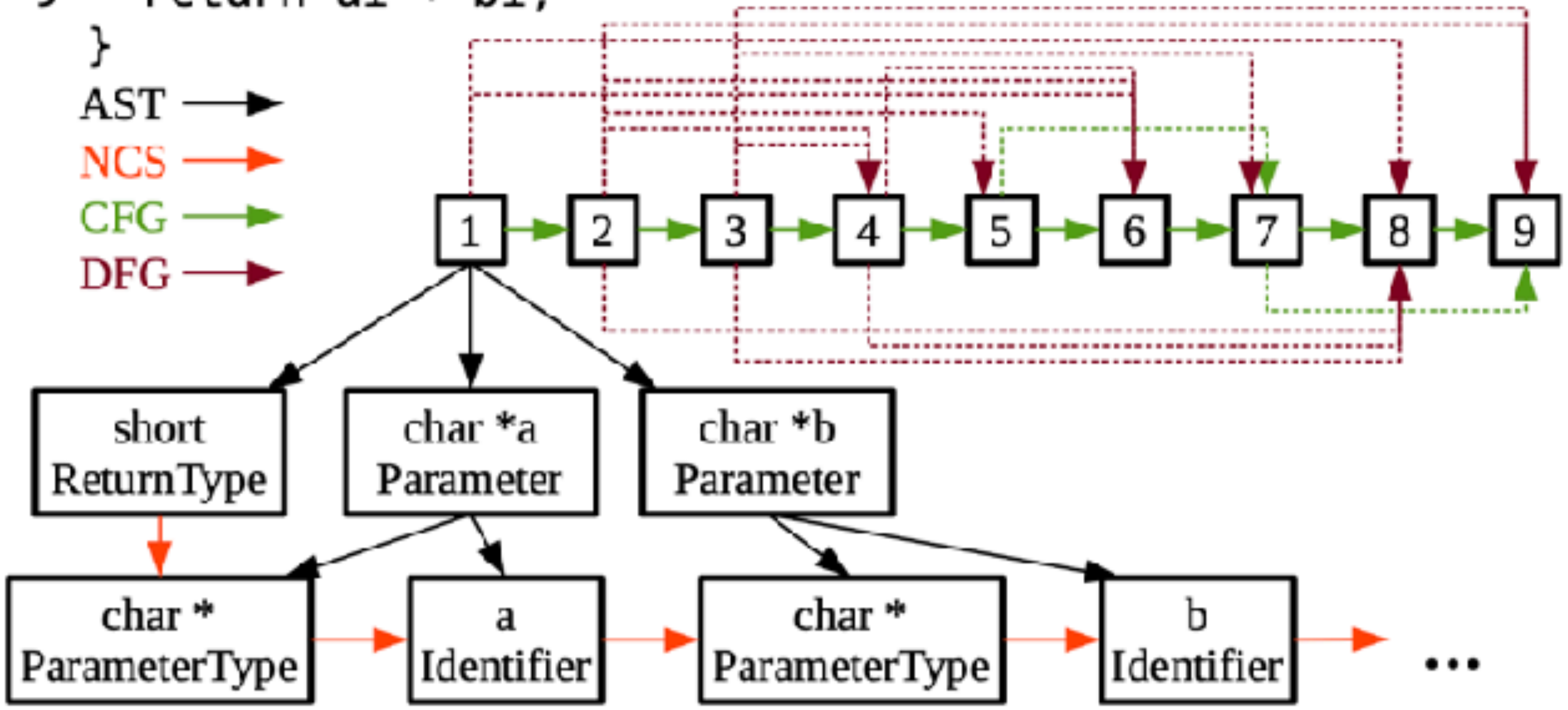
Prior Works Limitations

- Detects vulnerability at function level
- Can’t find vulnerability type

VulChecker

- Precisely locate vulnerabilities in source code (down to the exact instruction)
- Classify vulnerabilities type
- Low-cost dataset augmentation
- Manifestation distance
- Level of program representation

```c
short concat(char *a, char *b, char **out) {
  short al = strlen(a);
  short bl = strlen(b);
  *out = (char *) malloc(al+bl);
  if (al)
    memcpy(*out, a, al);
  if (bl)
    memcpy(*out+al,b,bl);
  return al + bl;
}
```



Prior Works

			(1) Code Representation								(2) Sample Selection							(3) Feature Extraction					(4) Model induction				(5) Application				
											Code Slicing																				
			Level		Structure						Plane			PoI		Cut		Node				Edge	Input		Model	Utilizes Edge Type	Detection level				
Year	Cite	Name	Source Code	IR	Linear	CFG	PDG	CPG	ncsCPG	ePDG	Function	Control-flow	Data-flow	Generic	Manifestation	Region	Scoped	One-hot Enc.	Word2Vec	Doc2Vec	Explicit features	Dtype feature	Sequence	Graph			Function	Code Region	Line	Instruction	Classifies Vuln. Type?
2018	[28]	Russle'18	●		●						●					●		●					●		CNN,RF		●				●
2018	[23]	Vuldeepecker	●		●								●	●		●		●					●		BiLSTM			●			●
2019	[40]	µVulDeePecker	●		●								●	●		●		●					●		BiLSTM			●			●
2019	[39]	Devign	●						●		●					●			●					●	GCN,DNN	●	●				
2019	[14]	VGDetector	●			●					●					●				●				●	GCN,DNN			●			
2019	[31]	NW-LCS	●			●					●					●		●						●	LCS Scores		●				●
2020	[19]	Li'20	●		●							●		●		●			●				●		CNN			●			●
2020	[38]	Zagane'20	●		●							●		●		●		○					●		DNN			●			
2020	[32]	Funded	●						●		●					●			●					●	GNN,GRU	●	●				●
2020	[30]	AI4VA	●					●			●			●		●			●					●	GNN,GRU	●	●				
2021	[22]	SySeVR	●		●							●		●		●		●					●		BiRNN			●			
2021	[20]	Li'21		●	●							●		●		●		●					●		CNN+RNN,DNN			●			
2021	[21]	Vuldeelocator		●	●							●			●	●		●					●		BiRNN				●		
2021	[13]	DeepWukong	●				●					●		●		●				●				●	GCN,DNN			●			●
2021	[35]	Wu'21	●				●				●					●			●					●	GNN,DNN	●	●				
2021	[9]	BGNN4VD	●					●			●			●		●			●					●	GNN,GRU	●	●				
2021	[11]	Reveal	●					●			●			●		●			●					●	GCN,DNN	●	●				
		VulChecker		●						●		●			●		●	○			●	●		●	GN (S2V)	●			●	●	●

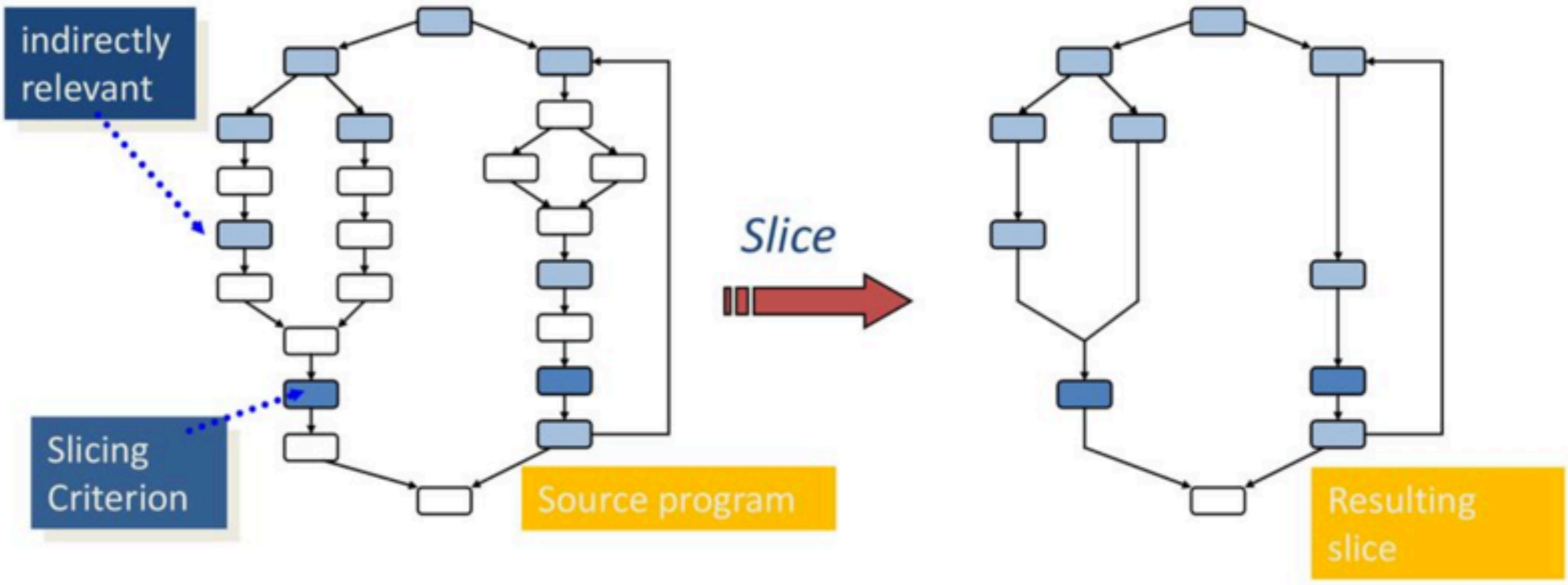
Embedding

- Some embeddings include one hot encodings and pre-processed embeddings (e.g., Word2Vec)
- In some cases entire portions of code are summarized using Doc2Vec
- The issue with these representations:
  - nodes in G_i would likely capture multiple operations in a single line of source code resulting in a loss in semantic precision
  - the use of pre-processed embeddings prevents the model from learning the best representation to optimize the learning objective

ePDG

- ePDGs are graph structures in which nodes represent atomic machine-level instructions and edges represent control- and data-flow dependencies between instructions

Program Slicing



Program Slicing (cont.)

```
public class SimpleExample {
   static int add(int a, int b){
              return(a+b);
              }
              public static void main(final String[] arg){
                                   int i = 1;
                                   int sum = 0;
                                   while (i < 11) {
                                      sum = add(sum, i);
                                      i = add(i, 1);
                                   }
                                   System.out.println("sum = " + sum);
                                   System.out.println("i = " + i);
              }
}
```

Slicing Criterion

```
public class SimpleExample {
   static int add(int a, int b){
              return(a+b);
              }
              public static void main(final String[] arg){
                              int i = 1;
                              int sum = 0;
                              while (i < 11) {
                                 sum = add(sum, i);
                                 i = add(i, 1);
                              }
                              System.out.println("sum = " + sum);
                              System.out.println("i = " + i);
              }
}
```

Slicing Criterion

VulChecker

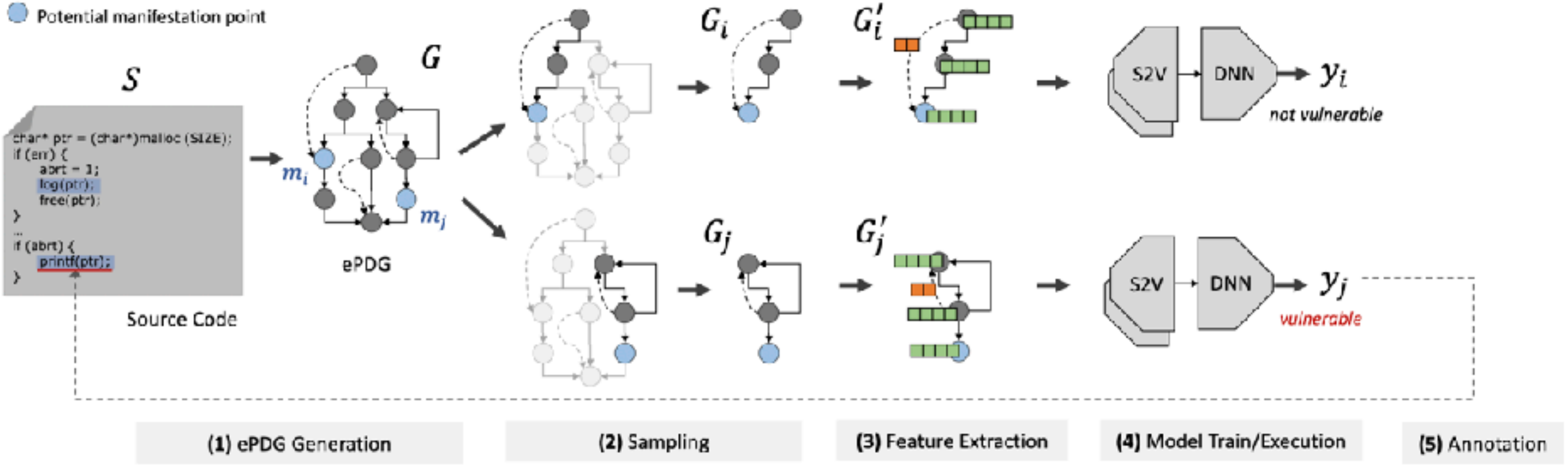


Figure 2: A diagram showing the steps of VulChecker's pipeline for one CWE. Note that the real graphs are significantly larger than what is visualized (e.g., projects like `libgit2-v0.26.1` have over 18 million nodes in G). Solid edges represent control-flow and dashed edges are data dependencies.

ePDG Generation

- Lowering the source code S to LLVM IR
- Extracting G based on the structure and flows it contains

Lowering Code to LLVM IR

- Simplifies the program representation:
  - Control-flow: complicated branching constructs in source code are reduced to conditional jumps that test a single condition
  - Data-flow: definition-use chains are shorter and less complex as they are based on virtual register values rather than source code variables
- During lowering, VulChecker instructs Clang to embed debug information in the IR, which enables traceability of IR instructions back to source code instructions

Lowering Code to LLVM IR (cont.)

- Using semantic-preserving compiler optimizations provided by LLVM to simplify and better express the code in *G:*
  - Function inlining to replace function call sites in the IR with a concrete copy of the called function body
  - Indirect branch expansion to eliminate indirect branching constructs
  - Dead code elimination to reduce the size of the output graph

Generating the ePDG

- C is the set of all types of instructions in the LLVM instruction API (e.g., return, add, allocate, etc.) and A_c is the set of all possible attributes for instruction $v \in V$ of type c.
- D is the set of edge types (i.e., control-flow or data-flow) and A_d is the set of flow attributes for a flow type d (e.g., the data type of the data dependency)

$$G := (\mathcal{V}, \mathcal{E}, q, r)$$

$$q : \mathcal{V} \to \{\{c, a\} : c \in C, a \in A_c\}$$

$$r : \mathcal{E} \to \{\{(x, y), d, b\} : x, y \in \mathcal{V}, d \in D, b \in A_d\}$$

Sampling

- PoI Criteria
- Program Slicing
  - Crawls G backwards from m_i using breadth first search (BFS)
- Labeling

Feature Extraction

- Operational Node Features
- Structural Node Features
  - Distance from the nearest potential root cause
  - Betweeness centrality measure (BEC)
- Semantic Node Features
- Edge Features

Table 2: Summary of Features used in G_i'

	Name	Bool	Num.	Categ.	Count
Vertex	Has static value?	•			1
	Static value		•		1
	Operation {+, *, %, ...}			•	54
	Basic function {malloc, read, ...}			•	1228
	Part of IF clause	•			1
	Number of data dependents		•		1
	Number of control dependents		•		1
	Betweeness centrality measure		•		1
	Distance to m_i		•		1
	Distance to nearest r		•		1
	Operation of nearest r			•	54
	Output dtype {int, float, ...}			•	6
	Node tag {r, m, none}	•			2
				Total	1352
Edge	Output dtype {float, pointer ...}				6
	Edge type {CFG, DFG}				2
				Total	8

Data Augmentation

- Data augmentation is a technique for creating new training examples from existing ones. VulChecker augments its training dataset by adding synthetic vulnerabilities to "clean" projects.
- Validity: Since augmentation process splices multiple ePDGs, it may produce samples where a vulnerability ePDG subgraph lies on an infeasible path in the augmented ePDG

Data Augmentation (cont.)

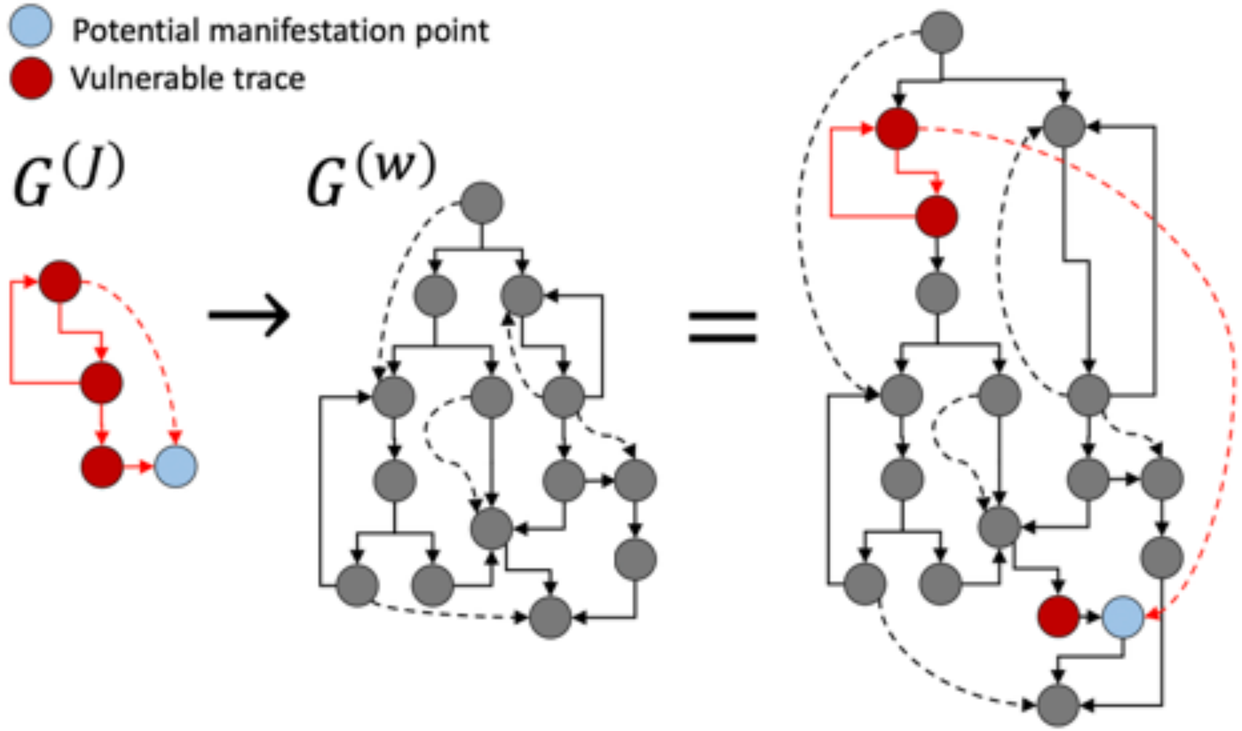
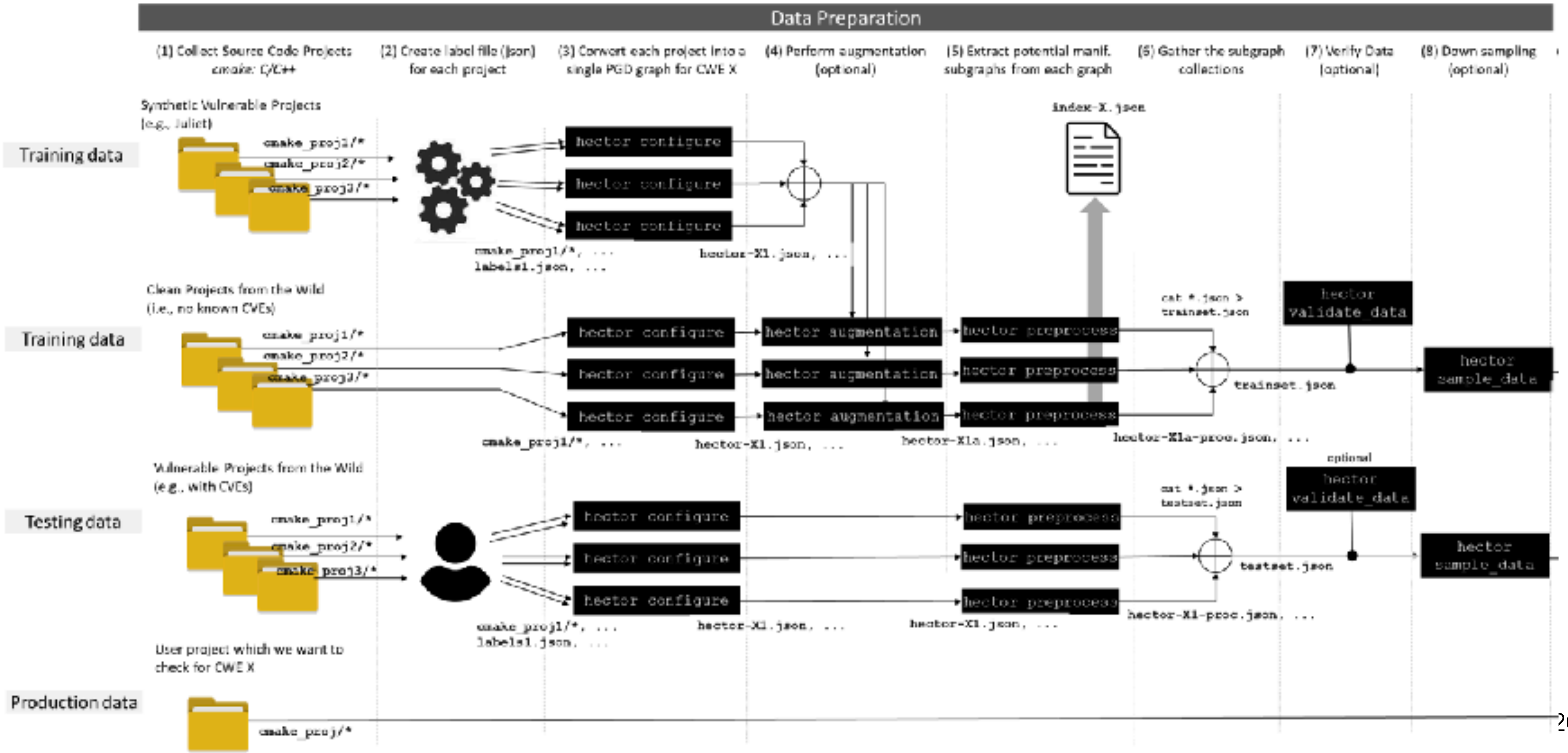


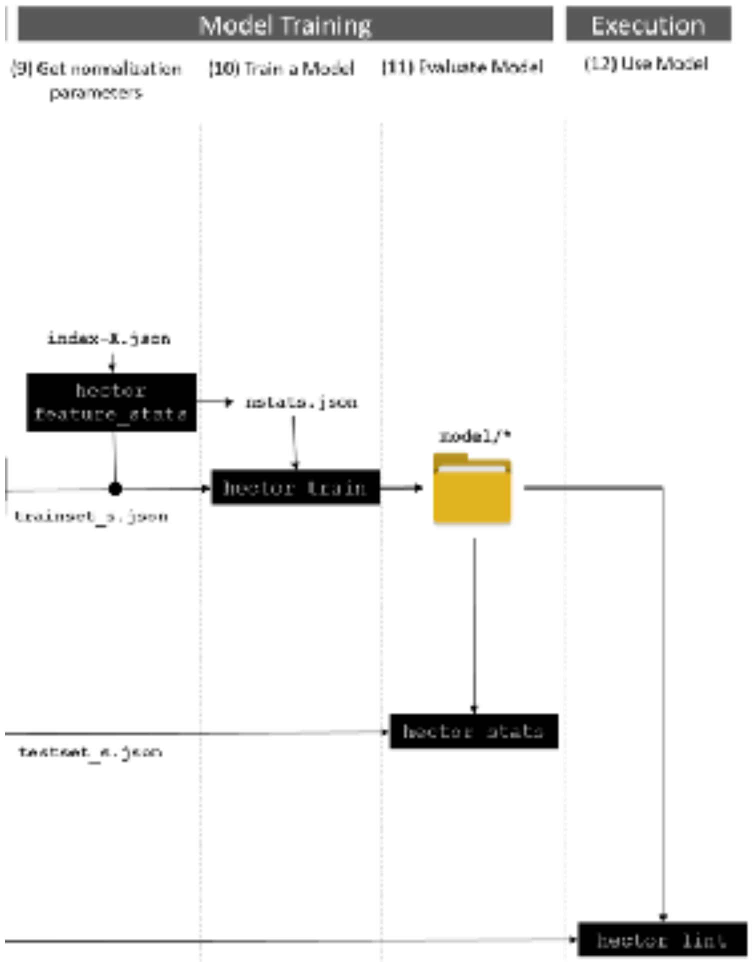
Figure 3: An illustration of an ePDG from the wild $G^{(w)}$ being augmented with a synthetic vulnerability trace from Juliet $G_i^{(J)}$.

Overview

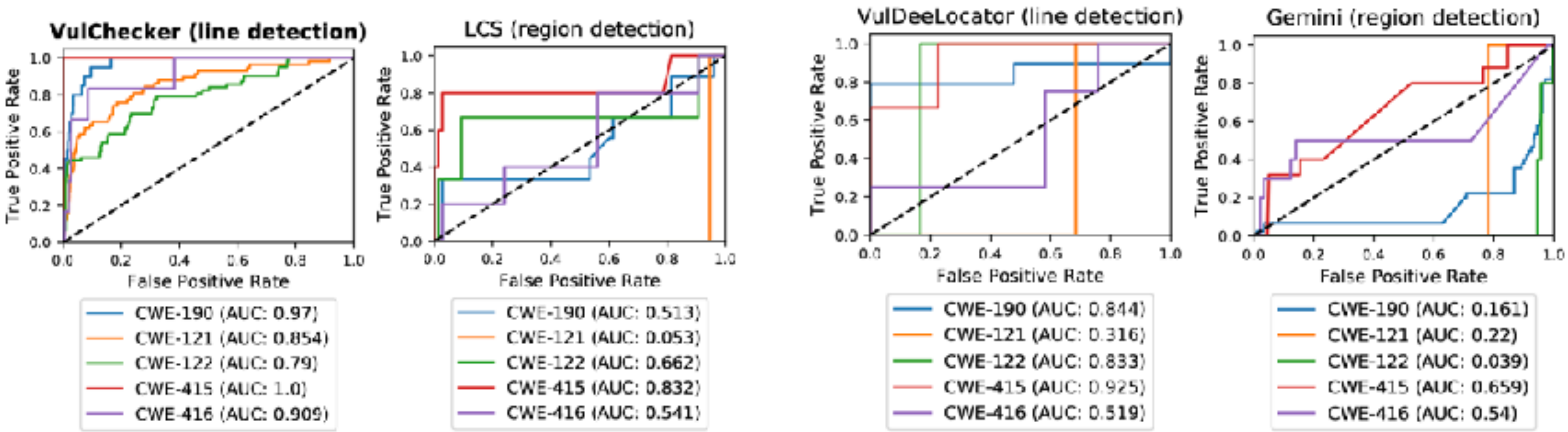


Data Preparation
(1) Collect Source Code Projects
cmake: C/C++
(2) Create label file (json) for each project
(3) Convert each project into a single PGD graph for CWE X
(4) Perform augmentation (optional)
(5) Extract potential manif. subgraphs from each graph
(6) Gather the subgraph collections
(7) Verify Data (optional)
(8) Down sampling (optional)
Training data
Synthetic Vulnerable Projects (e.g., Juliet)
cmake_proj1/*
cmake_proj2/*
cmake_proj3/*
hector configure
cmake_proj1/*, ...
labels1.json, ...
hector-X1.json, ...
index-X.json
Training data
Clean Projects from the wild (i.e., no known CVEs)
hector augmentation
hector preprocess
hector-X1a.json, ...
hector-X1a-proc.json, ...
cat *.json > trainset.json
trainset.json
hector validate_data
hector sample_data
optional
Testing data
Vulnerable Projects from the Wild (e.g., with CVEs)
cat *.json > testset.json
testset.json
hector-X1-proc.json, ...
User project which we want to check for CWE X
Production data
cmake_proj/*

Overview (cont.)



Evaluation


VulChecker (line detection)
True Positive Rate
False Positive Rate
CWE-190 (AUC: 0.97)
CWE-121 (AUC: 0.854)
CWE-122 (AUC: 0.79)
CWE-415 (AUC: 1.0)
CWE-416 (AUC: 0.909)
LCS (region detection)
True Positive Rate
False Positive Rate
CWE-190 (AUC: 0.513)
CWE-121 (AUC: 0.053)
CWE-122 (AUC: 0.662)
CWE-415 (AUC: 0.832)
CWE-416 (AUC: 0.541)
VulDeeLocator (line detection)
True Positive Rate
False Positive Rate
CWE-190 (AUC: 0.844)
CWE-121 (AUC: 0.316)
CWE-122 (AUC: 0.833)
CWE-415 (AUC: 0.925)
CWE-416 (AUC: 0.519)
Gemini (region detection)
True Positive Rate
False Positive Rate
CWE-190 (AUC: 0.161)
CWE-121 (AUC: 0.22)
CWE-122 (AUC: 0.039)
CWE-415 (AUC: 0.659)
CWE-416 (AUC: 0.54)

Evaluation (cont.)

Table 3: Baseline comparison against a commercial SAST tool in detecting CVEs in the wild.

	VulChecker @ FPR 0.05			VulChecker @ FPR 0.1			Helix QAC		
	Lines		CVEs	Lines		CVEs	Lines		CVEs
CWE	**TP**	**FP**	**TP**	**TP**	**FP**	**TP**	**TP**	**FP**	**TP**
190	9	55	3	12	112	6	1	2	1
121	7	33	7	9	112	9	4	230	1
122	1	6	1	1	6	1	4	241	1
415	3	0	2	3	0	2	0	5	0
416	4	6	4	6	228	6	0	0	1
Total	**24**	**100**	**17**	**31**	**458**	**24**	**9**	**478**	**4**

Evaluation (cont.)

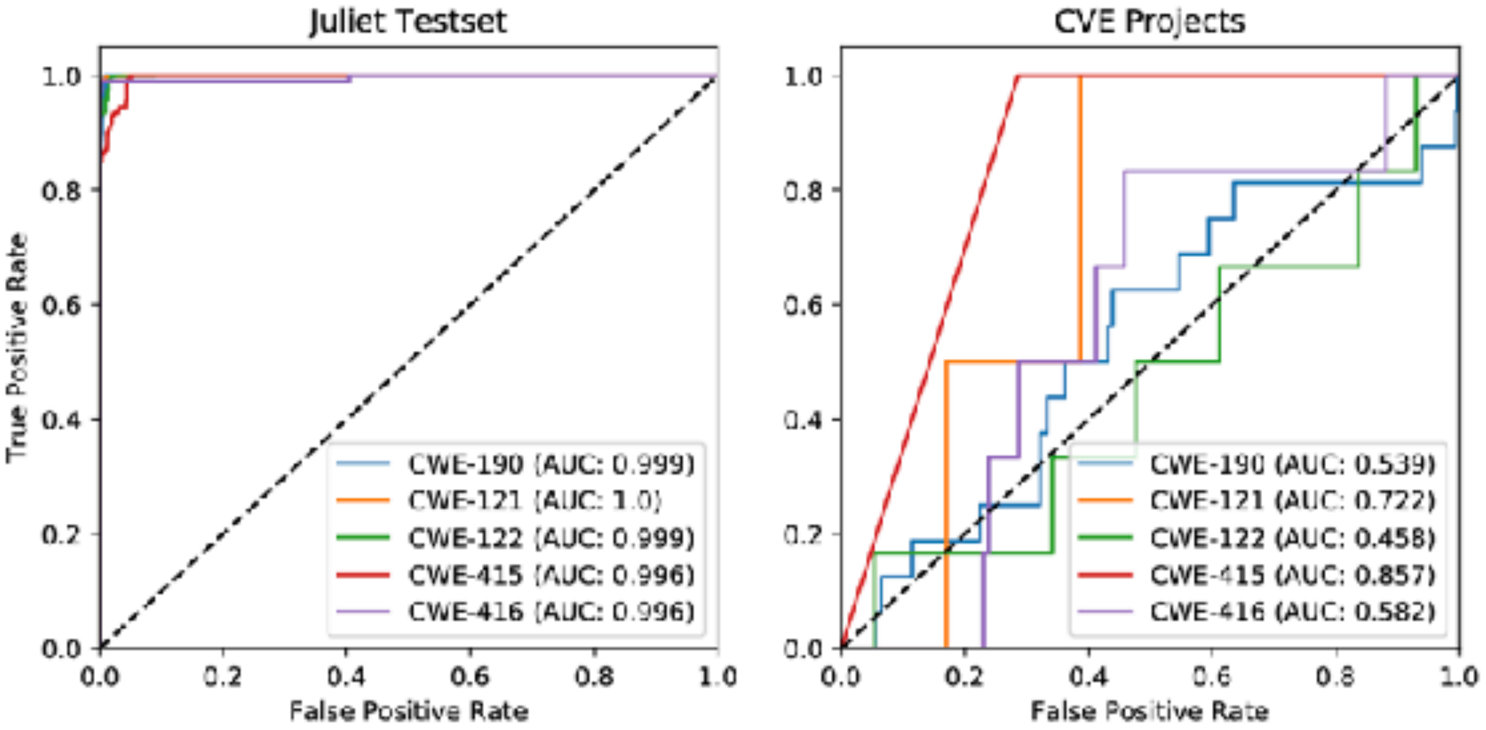


Figure 6: Performance of VulChecker when trained on synthetic data, then either tested on synthetic (left) or tested on real data (right).

Conclusion

- VulChecker precisely locates vulnerabilities in source code down to the exact instruction.
- Classifies vulnerabilities according to the Common Vulnerabilities and Exposures (CVE) taxonomy.
- Employs a novel data augmentation technique to enrich the training dataset and enhance generalization ability.
- Achieves near-zero false positives in vulnerability detection, outperforming commercial tools.
- VulChecker successfully detects a previously unknown zero-day vulnerability, highlighting its ability to identify novel vulnerabilities.

Acknowledgments

- [VulChecker] VulChecker: Graph-based Vulnerability Localization in Source Code, Y. Mirsky, G. Macon, M. Brown, C. Yagemann, M. Pruett, E. Downing, S. Mertoguno, and W. Lee, Usenix Security 2023.
- [Alves] Program Slicing. SwE 455, Alves, E., Federal University of Pernambuco, 2015.