### 46th International Conference on Software Engineering

# Coca: Improving and Explaining GNN-Based **Vulnerability Detection**

**Sicong Cao**<sup>1</sup>, Xiaobing Sun<sup>1</sup>, Xiaoxue Wu<sup>1</sup>, David Lo<sup>2</sup>, Lili Bo<sup>1</sup>, Bin Li<sup>1</sup>, and Wei Liu<sup>1</sup>

<sup>1</sup> Yangzhou University <sup>2</sup> Singapore Management University





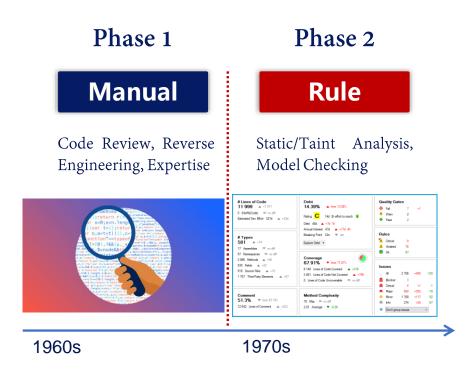
### Phase 1

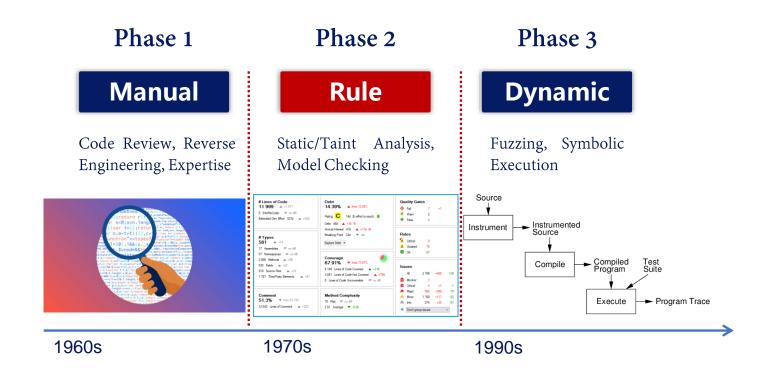
## Manual

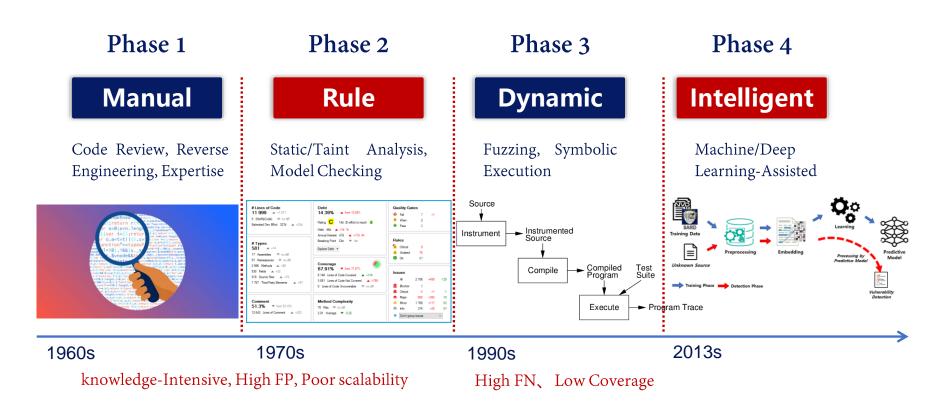
Code Review, Reverse Engineering, Expertise



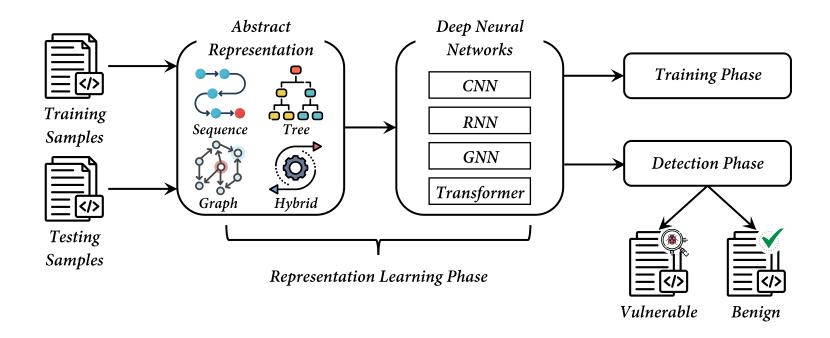
1960s



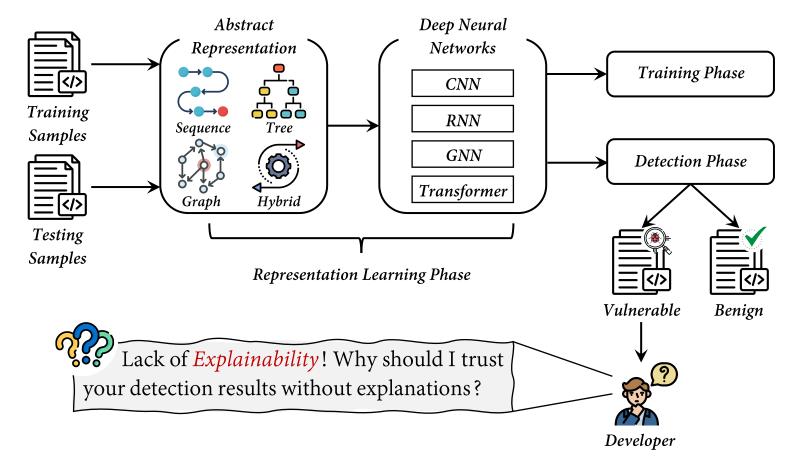




## DL-based VD Workflow



### DL-based VD Workflow



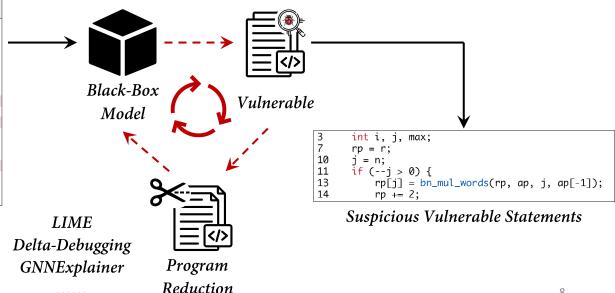
## Explainable VD Workflow

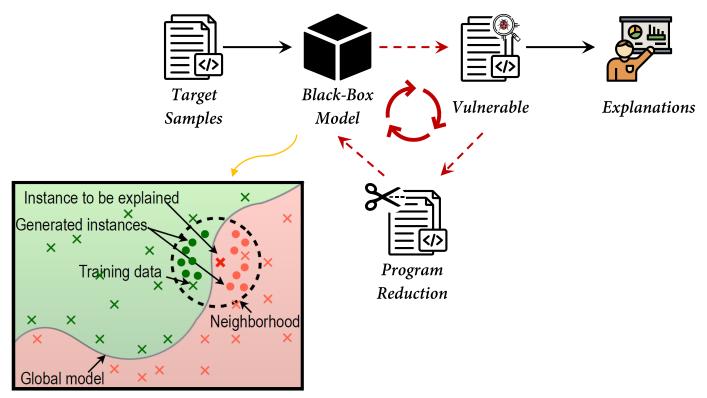
#### Definition 1

Given an input program  $P = \{s_1, \dots, s_m\}$  which is detected as vulnerable, the explanation is a set of crucial statements  $\{s_i, \dots, s_i\}$  that are most relevant to the decision of the model.

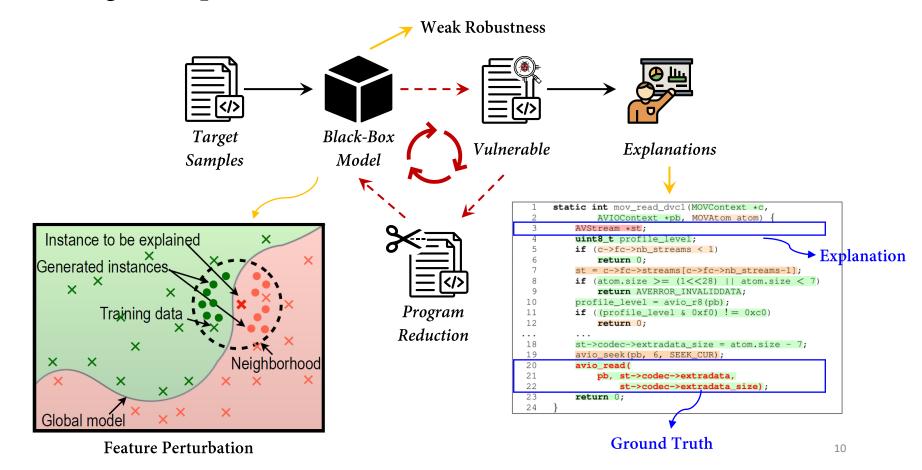
```
File: openssl/crypto/asnl/asnl lib.c
Commit: https://github.com/openssl/openssl/blob/9b10986d7742a5105ac8c5f4cba8b103caf57ac9/
Vulnerability Type: Buffer Overrun
1 void bn_sqr_normal(BN_ULONG *r, const BN_ULONG *a,
                           int n, BN_ULONG *tmp)
       int i, j, max;
       const BN_ULONG *ap;
       BN_ULONG *rp;
       ap = a;
       rp = r:
       rp[0] = rp[max - 1] = 0;
       rp++;
       j = n;
       if (--i > 0) {
11
12
13
            rp[j] = bn_mul_words(rp, ap, j, ap[-1]);
14
            rp += 2;
15
16 }
```

Target Sample





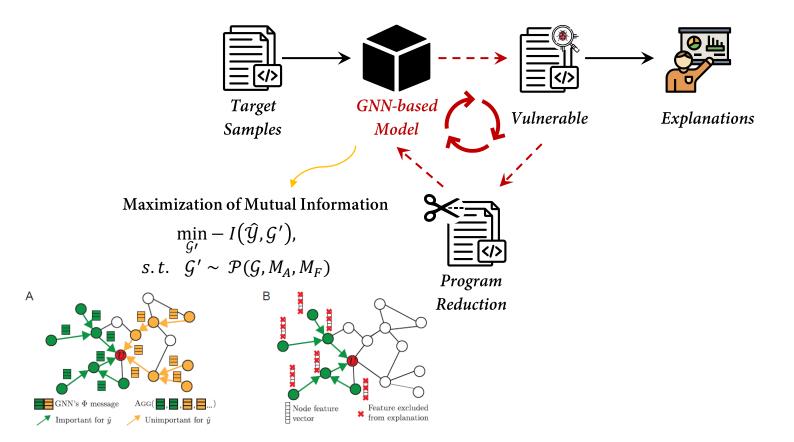
**Feature Perturbation** 

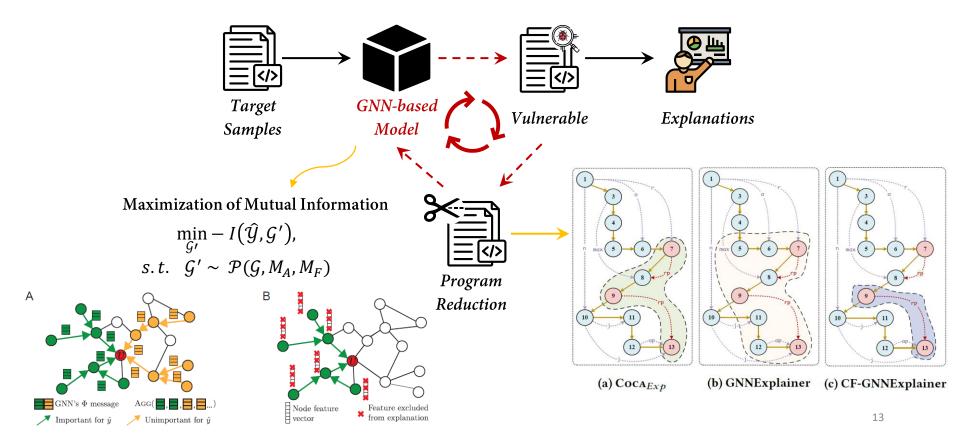




Due to the weak robustness of existing DL-based vulnerability detectors, their explanations are easy to be altered due to small perturbations, or even random noise. As a result, explanations built on top of the detection results from such weakly-robust models just reveal spurious correlations, which are hard to be tolerated by security applications.

Program Reduction

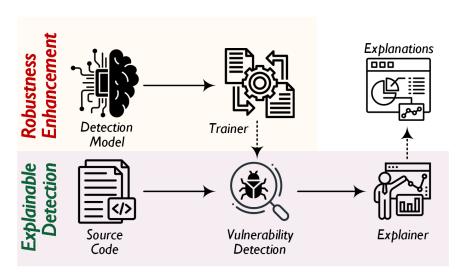






Factual reasoning-based techniques favor a sufficient subset which contains enough information to make the same prediction as they do for the original program, while counterfactual explanations may only cover a small subset of the ground truth. As a result, existing GNN-specific explanation approaches fail to balance the effectiveness and conciseness.

Program
Reduction



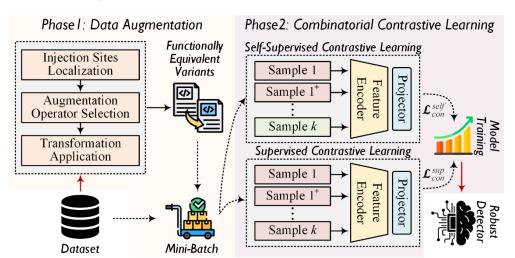
Workflow of Coca

# A General Optimization Framework for GNN-based Explainable Vulnerability Detection

- ☐ Combinatorial Contrastive Learning-based Robustness Enhancement
- ☐ Vulnerability Explanation via Dual-View Causal Inference

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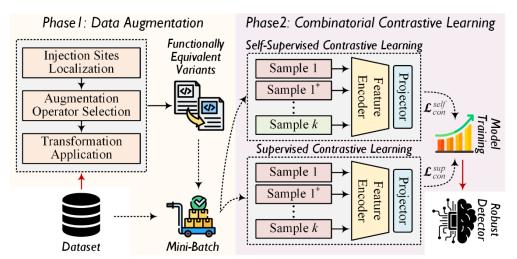
How to enhance the robustness of Classifier against random perturbations?

Perform data augmentation to construct functionally-equivalent variants.

No.	Name	Description
1	Identifier Renaming	Substitute the function/variable name with a random token.
2	Operand Swap	Swap the operands of binary logical operations.
3	Statement Permutation	Swap two lines of statements that have no dependency.
4	Loop Exchange	Replace for loops with while loops or vice versa.
5	Block Swap	Swap then block of a chosen if statement with its corresponding else block.
6	Switch to If	Replace a switch statement with its equivalent if statement.

# A General Optimization Framework for GNN-based Explainable Vulnerability Detection

- ☐ Combinatorial Contrastive Learning-based Robustness Enhancement
- Vulnerability Explanation via Dual-View Causal Inference



How to enhance the robustness of Classifier against random perturbations?

- ➤ Perform data augmentation to construct functionally-equivalent variants.
- Combine self-supervised contrastive learning with supervised contrastive learning to optimize the learned feature representations.

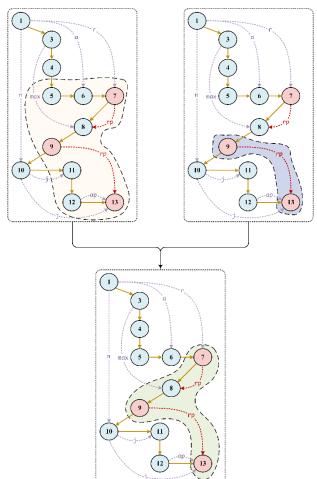
$$\mathcal{L}_{total} = (1 - \lambda)\mathcal{L}_{con}^{self} + \lambda\mathcal{L}_{con}^{sup}$$

# A General Optimization Framework for GNN-based Explainable Vulnerability Detection

- Combinatorial Contrastive Learning-based
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How to make a trade-off between effectiveness and conciseness?

Combine factual inference with counterfactual inference to search the explanation subgraph.

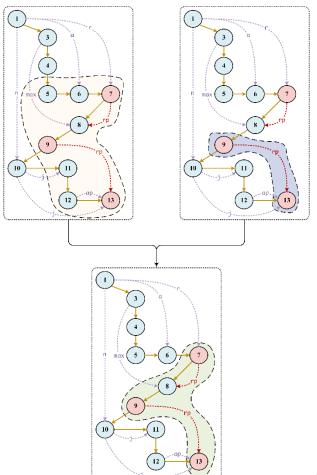


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- Combinatorial Contrastive Learning-based
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How to make a trade-off between effectiveness and conciseness?

minimize  $C(M_k, F_k)$  Factual Inference subject to  $S_f(M_k, F_k) > P(\hat{y}_{k,s} | A_k \odot M_k, X_k \odot F_k)$   $S_c(M_k, F_k) > -P(\hat{y}_{k,s} | A_k - A_k \odot M_k, X_k - X_k \odot F_k)$ 



#### **Dataset**

Dataset	# Vul	# Non-vul	# Total	% Ratio
Devign	11,888	14,149	26,037	45.66
ReVeal	1,664	16,505	18,169	9.16
Big-Vul	11,823	253,096	264,919	4.46
CrossVul	6,884	127,242	134,126	5.13
<b>CVEFixes</b>	8,932	159,157	168,089	5.31
Merged	29,844	305,827	335,671	8.89

### **Baselines**

- Devign (NeurIPS'19)
- ReVeal (TSE'21)
- DeepWuKong (TOSEM'21)

Config	Loss	Approach	Acc	Pre	Rec	F1
Default	CE	Devign   ReVeal   DeepWuKong	89.74 86.05 87.21	32.59 31.43 28.55	31.40 38.45 26.04	31.98 34.59 27.24
	Ours	Devign ReVeal DeepWuKong	88.15 87.42 88.30	34.68 <b>35.96</b> 30.07	37.12 <b>40.61</b> 34.79	35.86 <b>38.14</b> 32.26
$COCA_{Tra}$	InfoNCE	Devign ReVeal DeepWuKong	86.33 84.95 86.20	28.38 29.64 25.99	30.11 34.27 24.83	29.22 31.78 25.40
	NCE	Devign ReVeal DeepWuKong	83.97 81.52 83.06	26.15 26.73 22.40	27.69 31.76 21.46	26.90 29.03 21.92

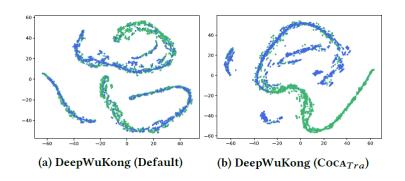
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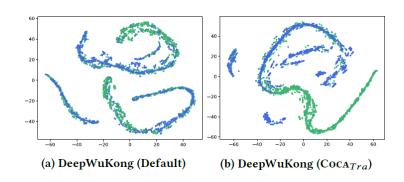
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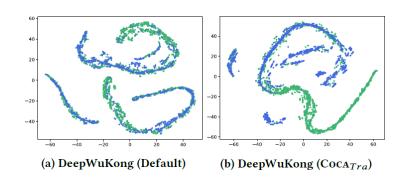
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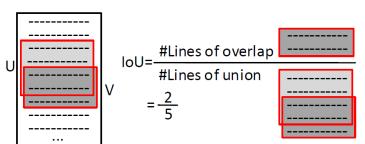


#### **Baselines**

- mVulPreter (TDSC'22)
- IVDetect (ESEC/FSE'21)
- P2IM (ESEC/FSE'21)

#### **Evaluation Metrics**

- Mean Statement Precision (MSP)
- Mean Statement Recall (MSR)
- Mean Intersection over Union (MIoU)



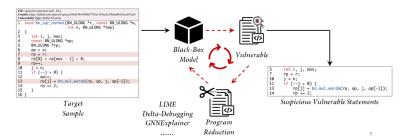
### **Explanation Performance**

Config	Approach	MSP	MSR	MIoU
Default	mVulPreter IVDetect P2IM (Devign) P2IM (ReVeal) P2IM (DeepWuKong) CocA <sub>Exp</sub> (Devign) CocA <sub>Exp</sub> (ReVeal) CocA <sub>Exp</sub> (DeepWuKong)	25.86 32.54 27.99 31.04 26.57 33.84 35.61 29.77	29.01 23.79 43.85 46.10 38.12 44.06 52.94 40.16	22.88 17.06 22.56 28.94 23.11 30.89 34.36 25.83
CocATra	IVDetect   P2IM (Devign)   P2IM (ReVeal)   P2IM (DeepWuKong)   Coca <sub>Exp</sub> (Devign)   Coca <sub>Exp</sub> (ReVeal)   Coca <sub>Exp</sub> (DeepWuKong)	39.81 33.01 40.62 32.97 43.61 <b>49.52</b> 40.33	31.64 48.33 55.73 44.85 52.98 <b>58.39</b> 47.61	25.19 29.27 36.29 28.10 39.64 <b>44.97</b> 34.22

### Conclusion

#### Explainable VD Workflow





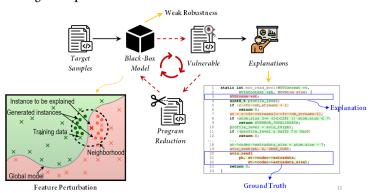
#### Our approach: COCA



Injection Sites	Functionally Equivalent	Self-Supervised Contrastive Learning
Localization	Variants	Sample 1
Augmentation		Sample 1* Projection   Leaf
Operator Selection		
Transformation Application		Supervised Contrastive Learning
Application		Sample 1
1	+	Sample 1* → E F P
	. TA	Sample 1 Projecto
	lalala	Sample k

No.	Name	Description			
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#### Challenge of Explainable VD



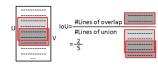
#### Performance of COCA

#### Baselines

- mVulPreter (TDSC'22)
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- Mean Statement Precision (MSP)
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#### **Explanation Performance**

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Default	mVulPreter	25.86	29.01	22.88
	IVDetect	32.54	23.79	17.06
	P2IM (Devign)	27.99	43.85	22.56
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	CocaExp (Devign)	33.84	44.06	30.89
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	Coca <sub>Exp</sub> (DeepWuKong)	40.33	47.61	34.22
		1		<b>N</b>

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# Thanks for listening!

- **Sicongcao1996@gmail.com**
- https://github.com/CocaVul/Coca

