

PAVUDI:

Patch-based vulnerability discovery using Machine Learning

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AISec '23

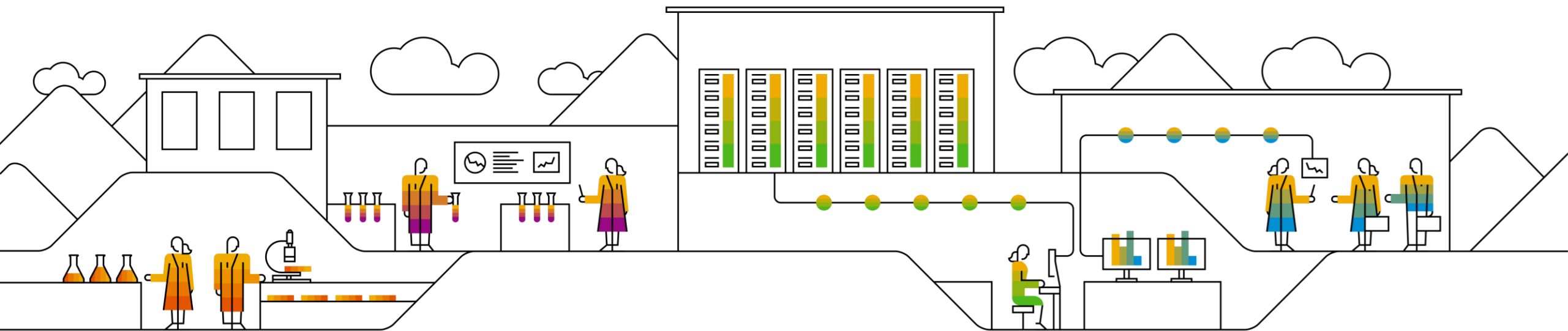


¹ SAP Security Research

² TU Berlin



Introduction



Vulnerability Discovery

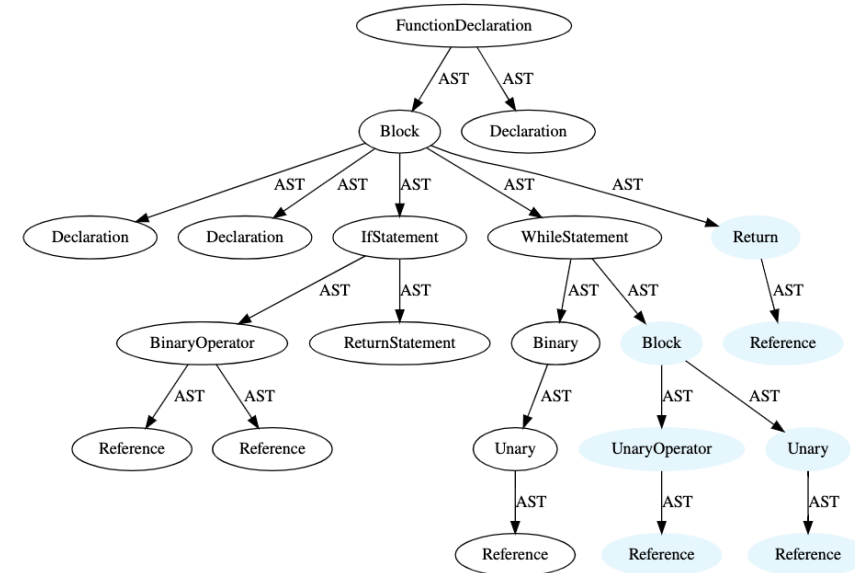
- Classical Static Vulnerability Detection
 - Manually crafted rules
 - Often high false positive rate
 - For example
 - Flawfinder, CPPCheck
 - Coverity, Clang Analyzer
- Definition of a Vulnerability Detector

A method for **static vulnerability discovery** is a decision function $f: x \mapsto P(\text{vuln} | x)$ that maps a piece of code x to its probability of being vulnerable.

Learning-based Vulnerability Discovery

- Learning-based Static Vulnerability Detection
 - Learns rules
 - Requires dataset
 - Adjustable threshold
 - Representation learning

```
1 ...  
2 value = *name;  
3 value <=<= 5;  
4 if (len > 10) {  
5     value += name[len - (plen + 1 + 1)];  
6 ...
```



- Definition of a Learning-based Vulnerability Detector

A static **learning-based vulnerability discovery method** is a parametrized hypothesis function $f_\theta : x \rightarrow P(vuln|x)$ that extracts a representation x and maps it to a probability of being vulnerable.

Problem Setting

- Apply vulnerability detector on each patch (CI/CD)
- Problems with patches:
 - Context-sensitive changes
 - Non-coherent changes
 - Evolution of Software

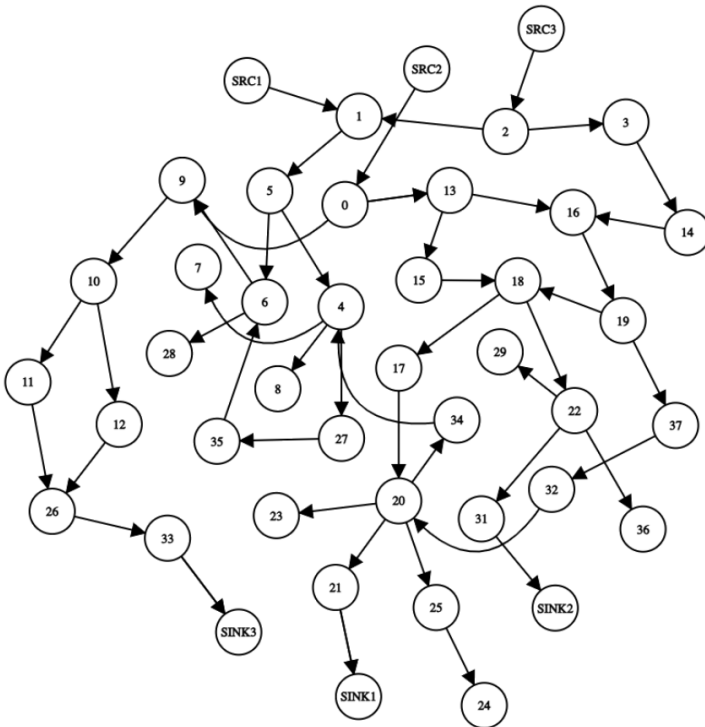
- Example: Heartbleed Bug
- Commit introducing the bug:
 - Touches 12 Files
 - 5 Header Files
 - In 2 different packages

```
1 if (hbtype == TLS1_HB_REQUEST)
2   {
3     unsigned char *buffer, *bp;
4     int r;
5
6     /* Allocate memory for the response, size is 1 byte
7      * message type, plus 2 bytes payload length, plus
8      * payload, plus padding
9      */
10    buffer = OPENSSL_malloc(1 + 2 + payload + padding);
11    bp = buffer;
12
13    /* Enter response type, length and copy payload */
14    *bp++ = TLS1_HB_RESPONSE;
15    s2n(payload, bp);
16    memcpy(bp, pl, payload);
```

Naive Solution

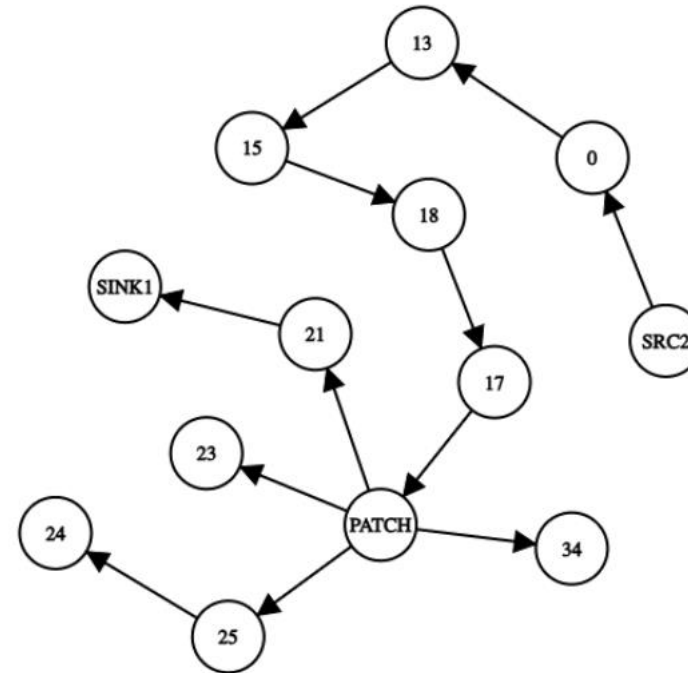
Use Existing Learning-based Discovery Methods:

- Feed them Inputs with Patch Context
- Problem: Feature Space explodes

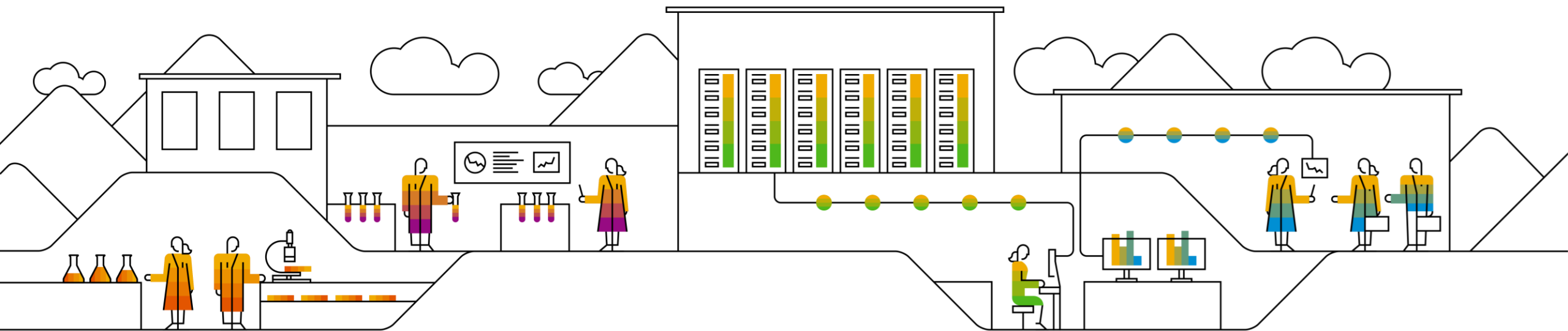


Better Idea:

- Identify security relevant Paths
- Only consider those intersecting Changes



Methodology

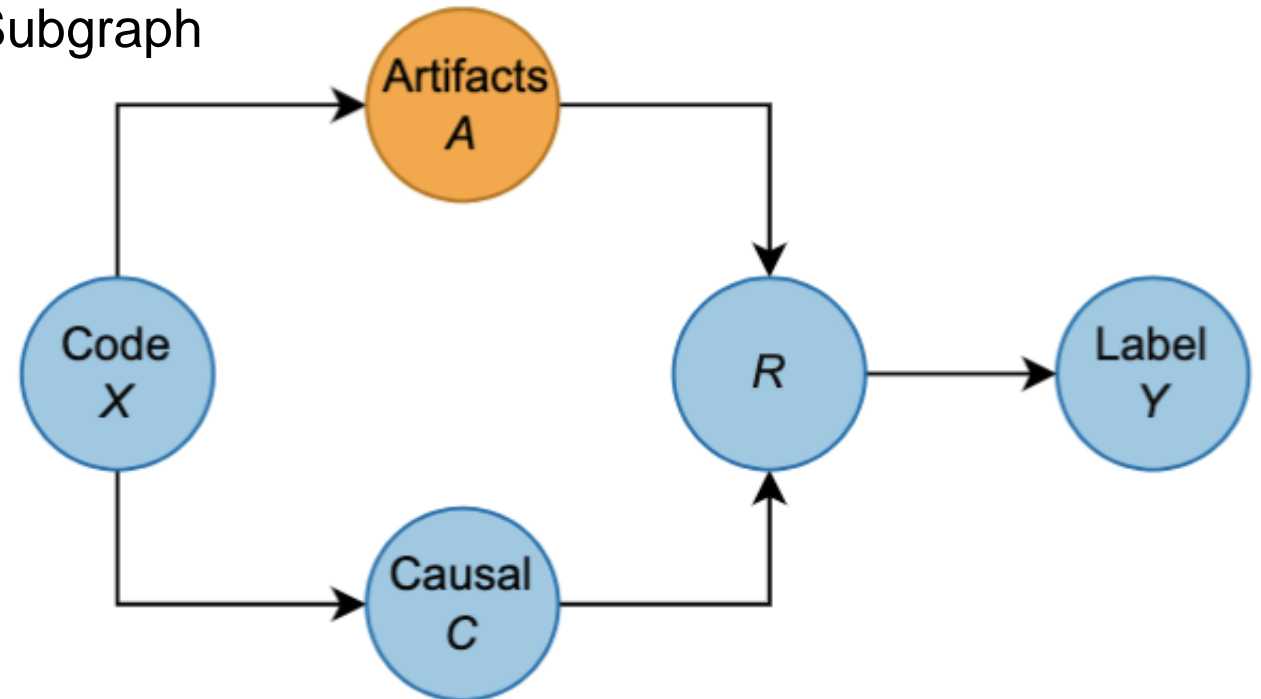


Representation

1. Obtain composite code graph
2. Insert call edges
3. Insert interprocedural data flow
4. Perform value-set analysis
5. Create security-relevant slices

Causal Graph Neural Network

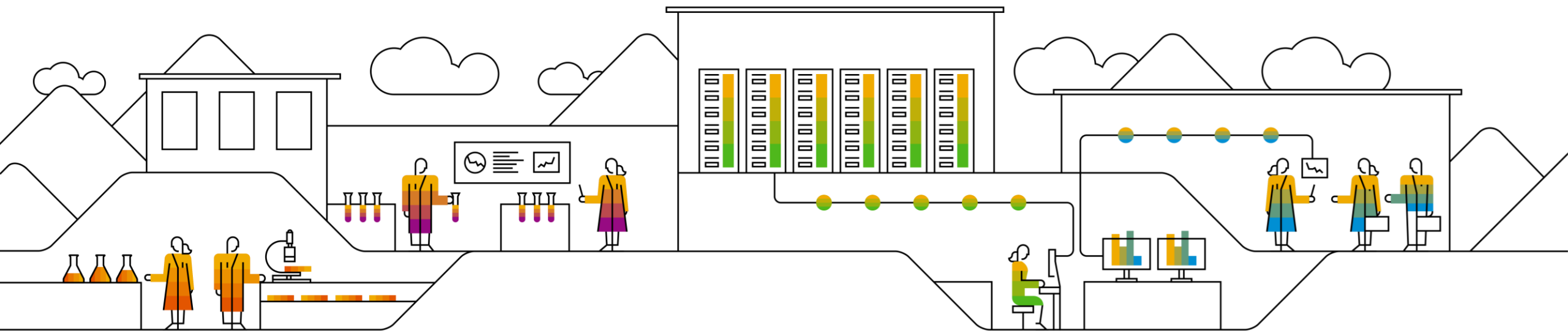
- Graph separated into Artifacts and causal Subgraph
- Separation learned by network
- Prediction only on causal Subgraph



Training dataset

- Previous datasets contain only vulnerability-fixing patches
- We try to find vulnerability-introducing patches
 - Very difficult to collect
- Instead: Find patches that touch vulnerable code
 - From vulnerability-fixing patches, go back in time
 - Patches on same methods are vulnerable
 - Patches on other methods are assumed to be clean

Experiments



Research Questions

- **RQ1** How do other strategies compare to PAVUDI?
- **RQ2** How does the size of a commit affect the performance?
- **RQ3** How does PAVUDI behave after training and deployment?
- **RQ4** How do the individual components of PAVUDI contribute to the detection capability?

Model Baselines

- Learning-based Graph Vulnerability Detectors
 - DeepWuKong
 - ReVeal
 - Devign
 - BGNN4VD
- Learning-based Token Vulnerability Detectors
 - SySeVR
 - VulDeePecker
- Heuristics-based Vulnerability Detector
 - VUDDY

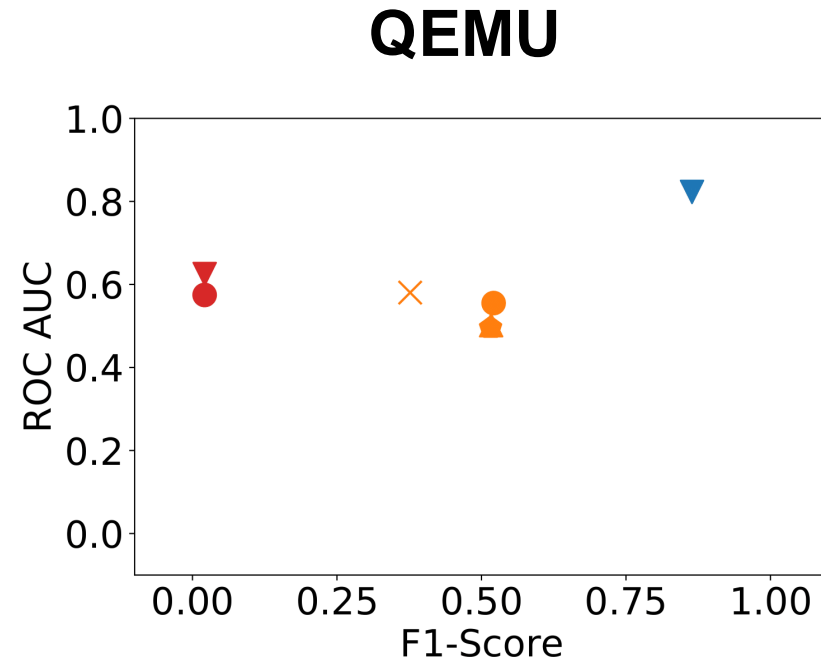
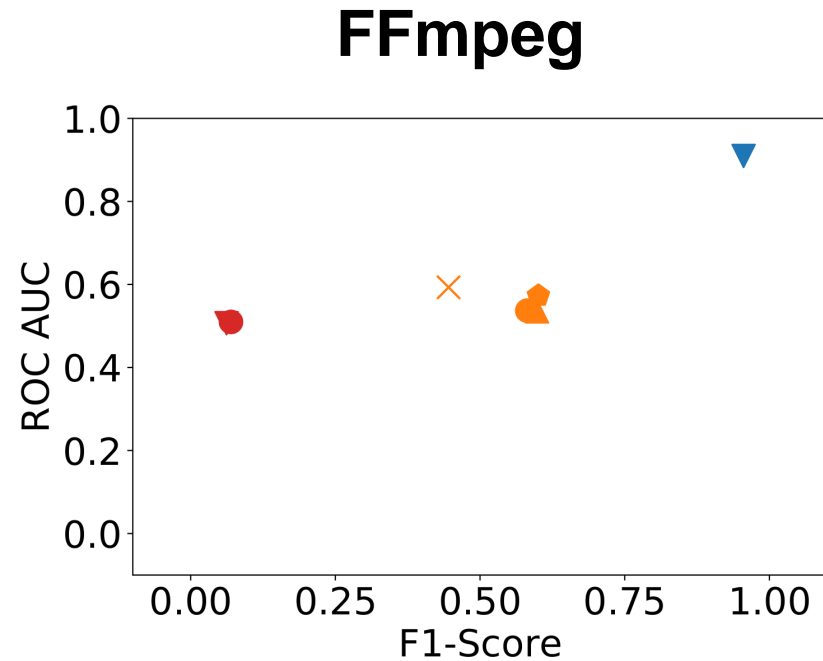
Not Applicable to Patches!

Application Strategies

Apply Models to Fragments of the Patch and aggregate prediction score

- Max
- Mean
- Probability
- Isotonic
- Commit

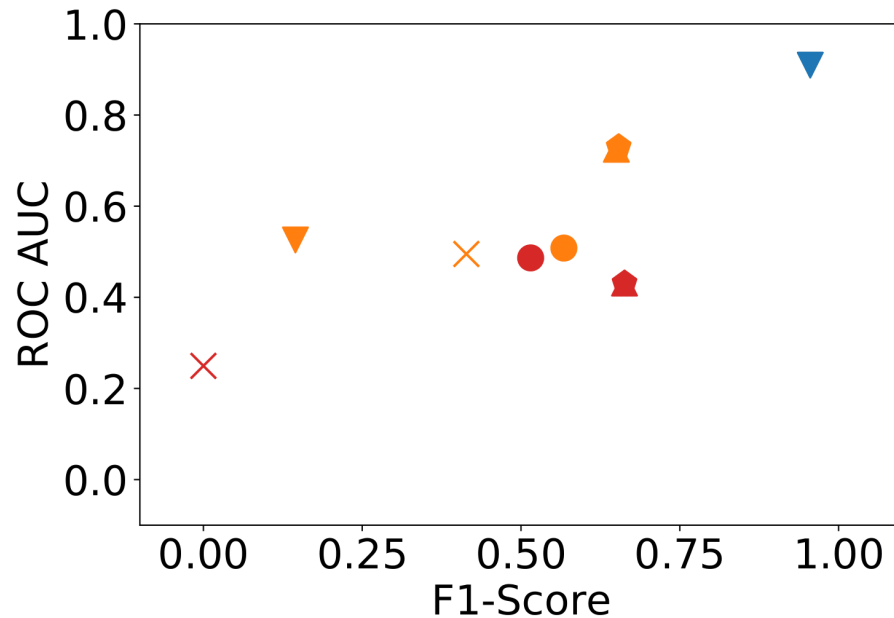
RQ1 How do other strategies compare to PAVUDI?



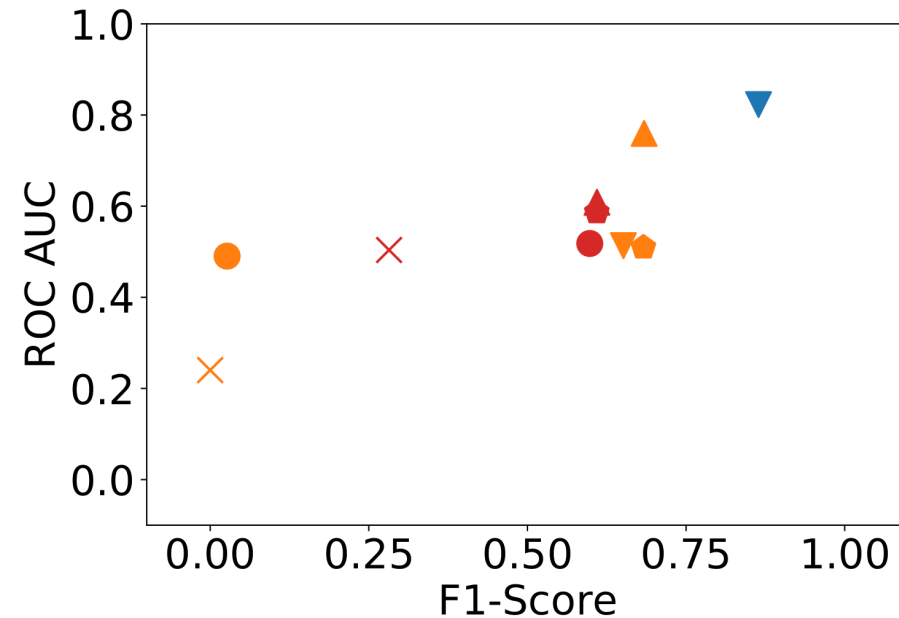
- | | | | |
|------------------|--------------------|-----------------------|-------------|
| ▼ TaintGraph | ▲ DeepWukong Proba | ◆ DeepWukong Isotonic | ● Vuddy Max |
| ● DeepWukong Max | × DeepWukong Mean | ▼ Vuddy Commit | |

RQ1 How do other strategies compare to PAVUDI?

FFmpeg

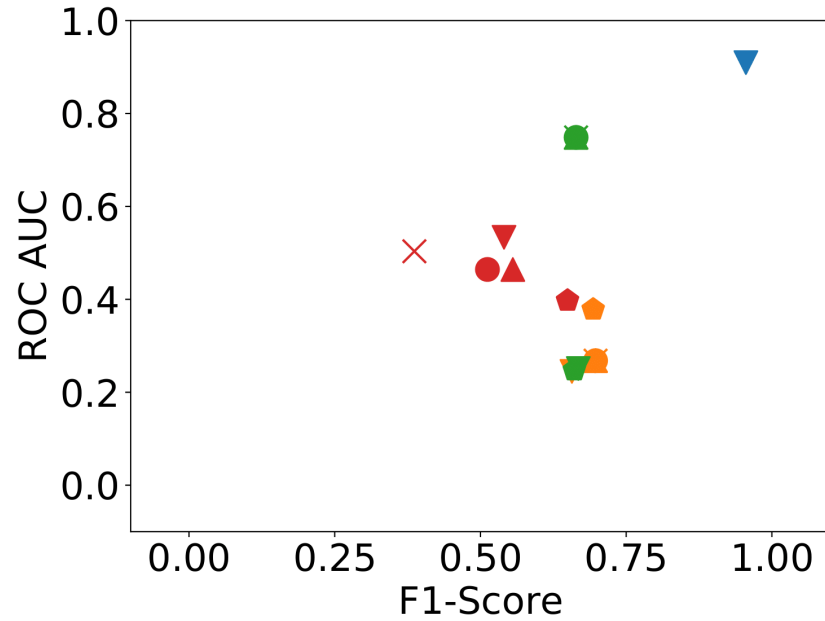


QEMU

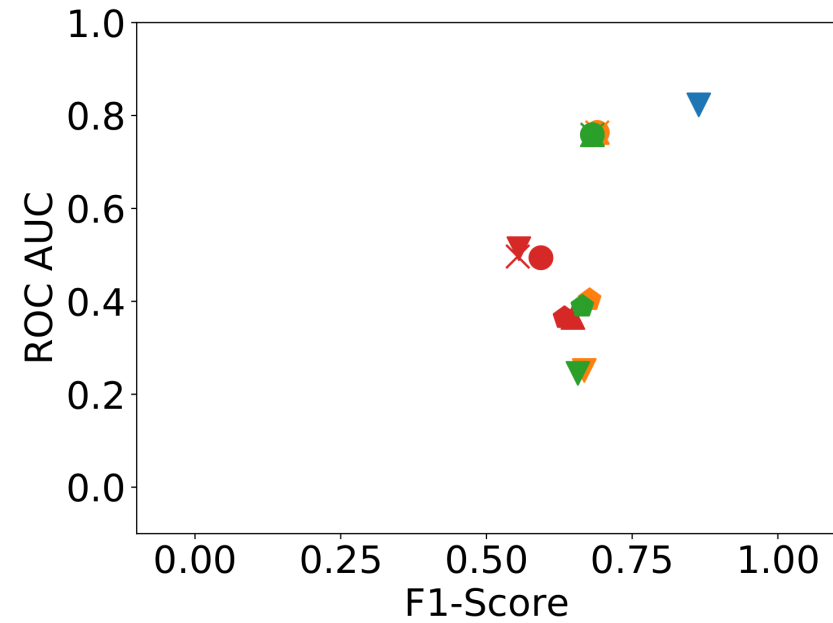


RQ1 How do other strategies compare to PAVUDI?

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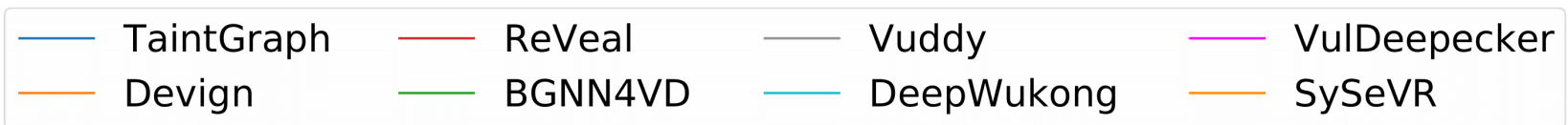
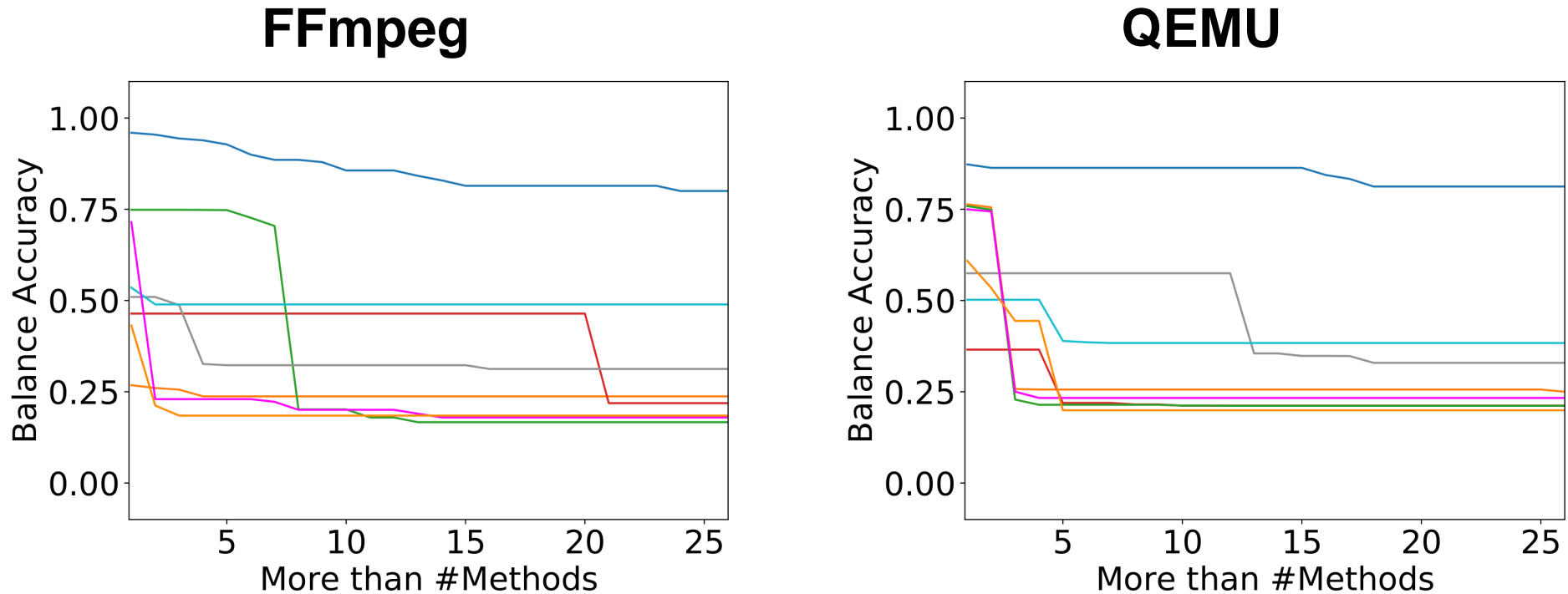


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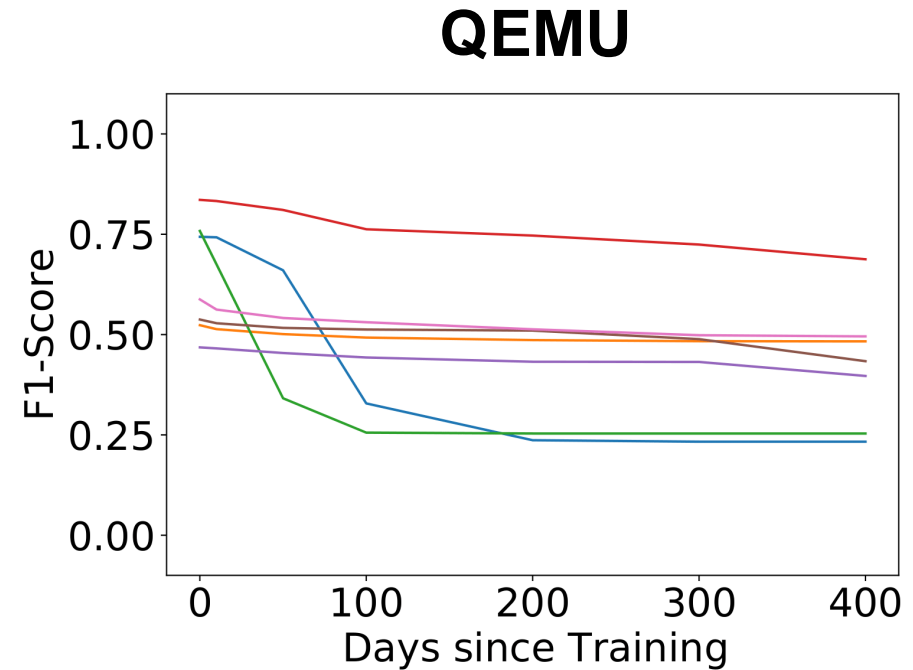
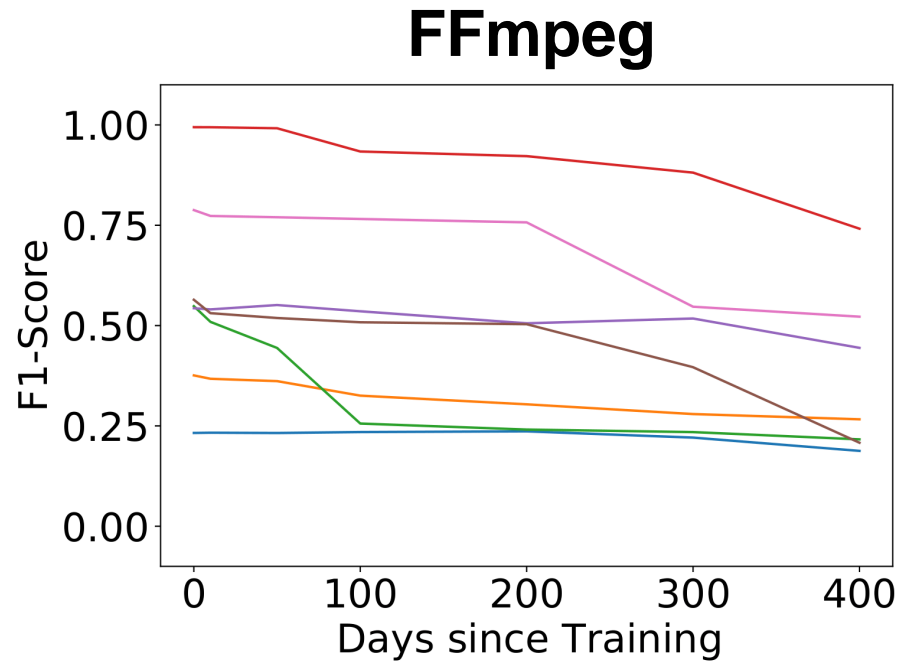


- | | | | |
|----------------|-------------------|-------------------|--------------------|
| ▼ TaintGraph | ◆ Devign Isotonic | × ReVeal Mean | ▲ BGNN4VD Proba |
| ● Devign Max | ▼ Devign Commit | ◆ ReVeal Isotonic | × BGNN4VD Mean |
| ▲ Devign Proba | ● ReVeal Max | ▼ ReVeal Commit | ◆ BGNN4VD Isotonic |
| × Devign Mean | ▲ ReVeal Proba | ● BGNN4VD Max | ▼ BGNN4VD Commit |

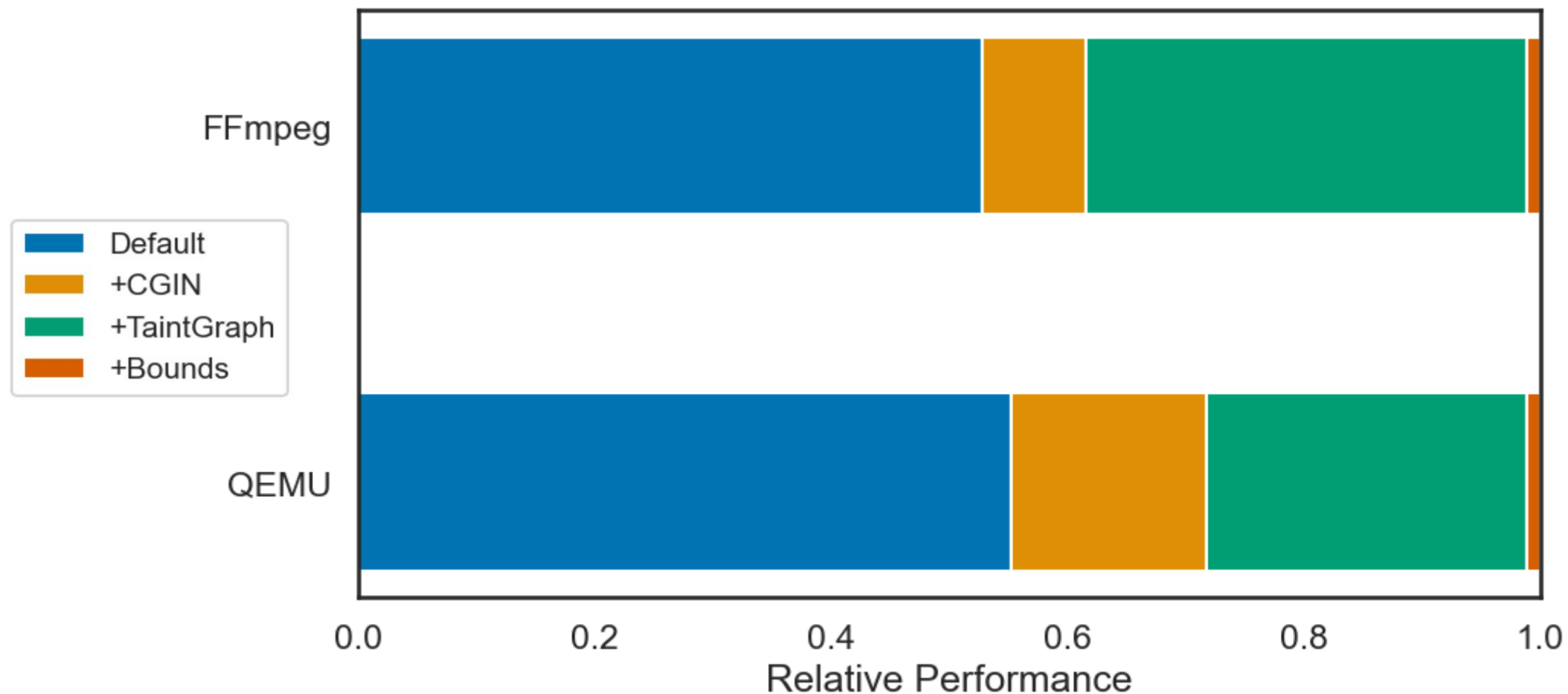
RQ2 How does the size of a commit affect the performance?



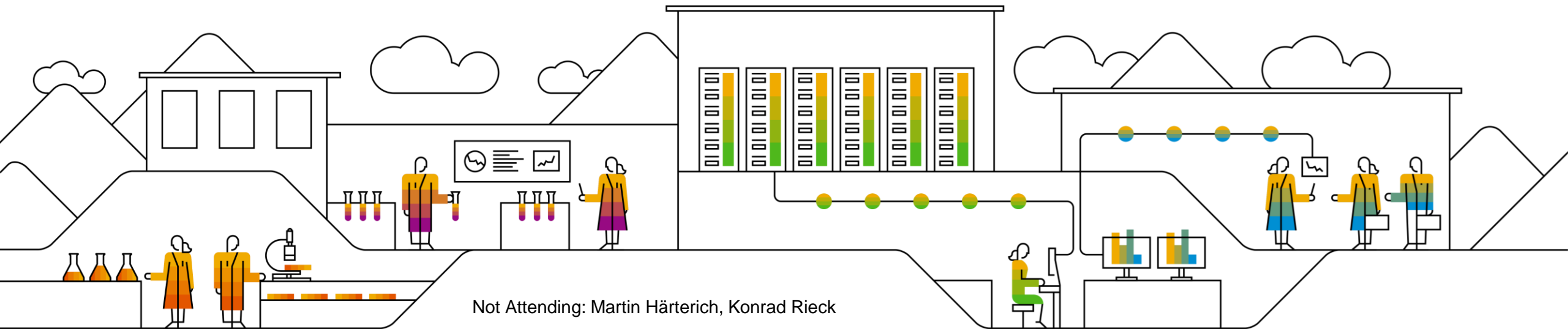
RQ3 How does PAVUDI behave after training and deployment?



RQ4 How do individual components of PAVUDI contribute to its capabilities?



Conclusion



Conclusion

- Patches are the atomic unit of modern software development
- Existing vulnerability detectors are badly suited to patches
- Identified five previously undisclosed bugs
- We introduce a patch-based vulnerability discovery (PAVUDI)
 - With a new interprocedural code representation
 - An explainable graph neural network
- Our solution
 - has more than 50% increased detection performance
 - is twice as robust against concept drift
- Public Implementation: <https://github.com/SAP-samples/security-research-taintgraphs>

Thank you.

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zur Aufdeckung von
Software - Hintertüren



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