

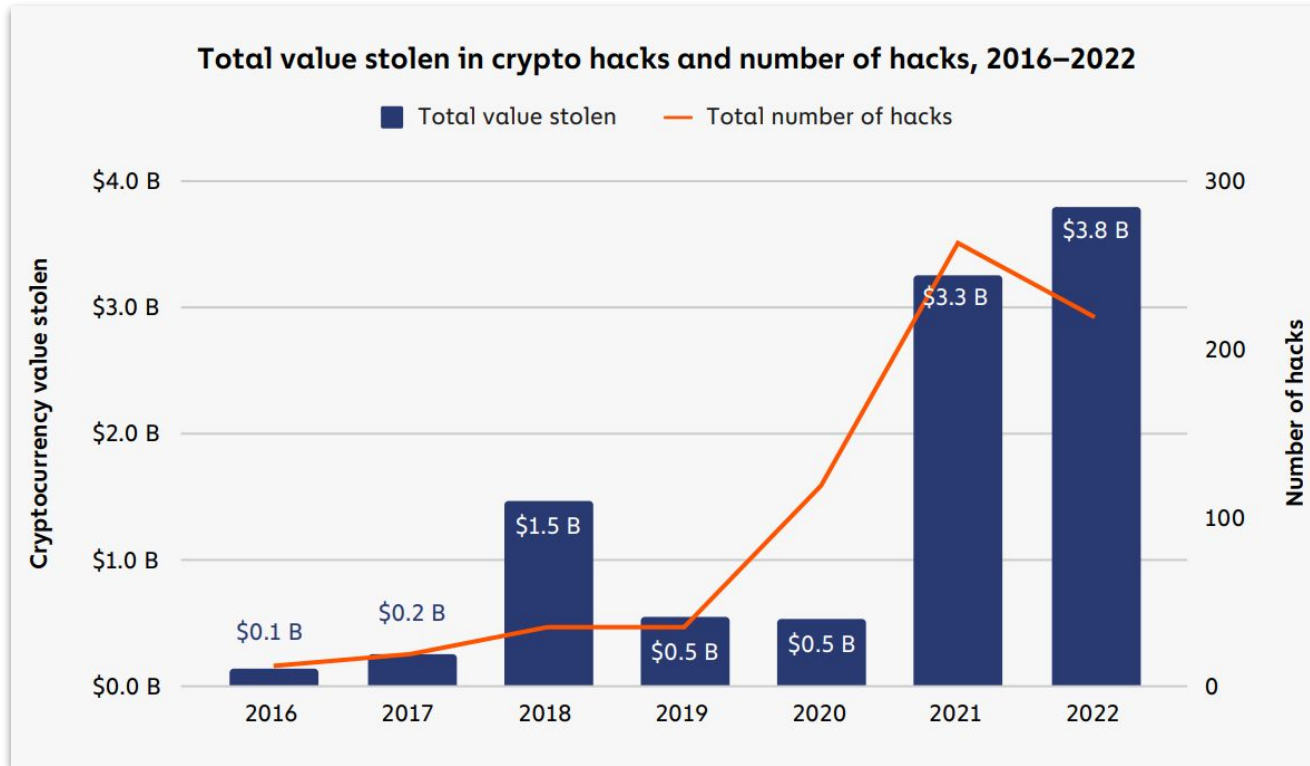


Smart Learning to Find Dumb Contracts

Tamer Abdelaziz and [Aquinas Hobor](#). "[Smart Learning to Find Dumb Contracts](#)".
The 32nd USENIX Security Symposium ([USENIX Security 23](#)).



Bugs in Cryptocurrency have been Expensive



Source: The Chainalysis 2023 Crypto Crime Report

Existing Smart Contract Vulnerability Detection Frameworks

Static Program Analysis

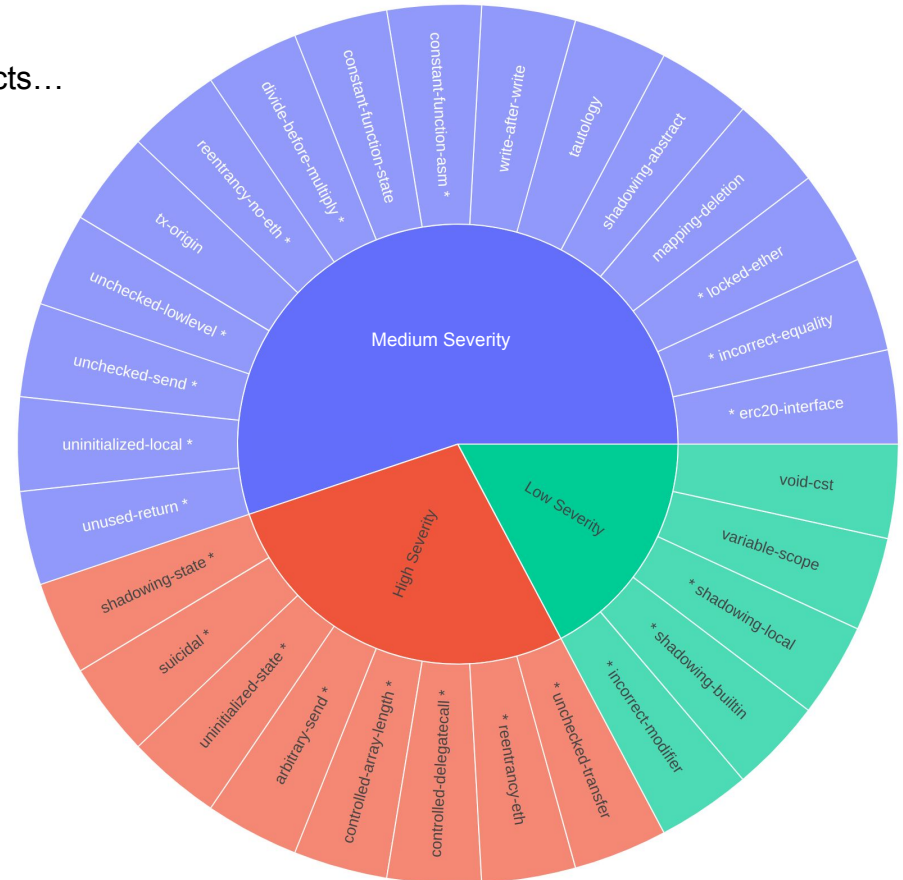


- + Impressive tools
- Difficult to maintain and extend
- Require expert rules
- Mostly need access to the source code
- Slow for large-scale analysis

Can deep learning help address these challenges?

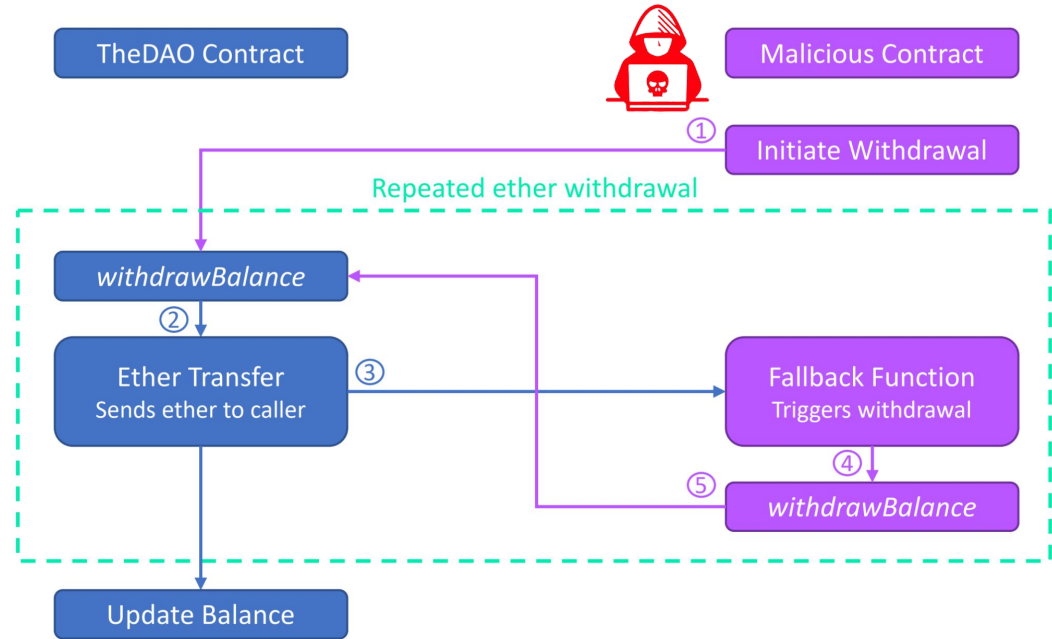
DLVA: Deep Learning Vulnerability Analyzer

- ★ Detects 29 vulnerabilities in Ethereum smart contracts...
... without any predefined patterns or expert rules
- ★ Analyzes EVM bytecode (no source required)
- ★ High accuracy...
... and low false positive rate
- ★ Almost always answers...
... very quickly (10x-1,000x faster than competitors)
- ★ Extensively benchmarked
- ★ Available for immediate download and use



Reentrancy Attack Example

```
contract TheDAO {  
  
    mapping(address => uint) balances;  
  
    function deposit() public payable {  
        uint amount = balances[msg.sender];  
        balances[msg.sender] = amount + msg.value;  
    }  
  
    function withdrawBalance() public {  
        if (msg.sender.call.value(balances[msg.sender]))  
            { balances[msg.sender] = 0; }  
    }  
  
}
```



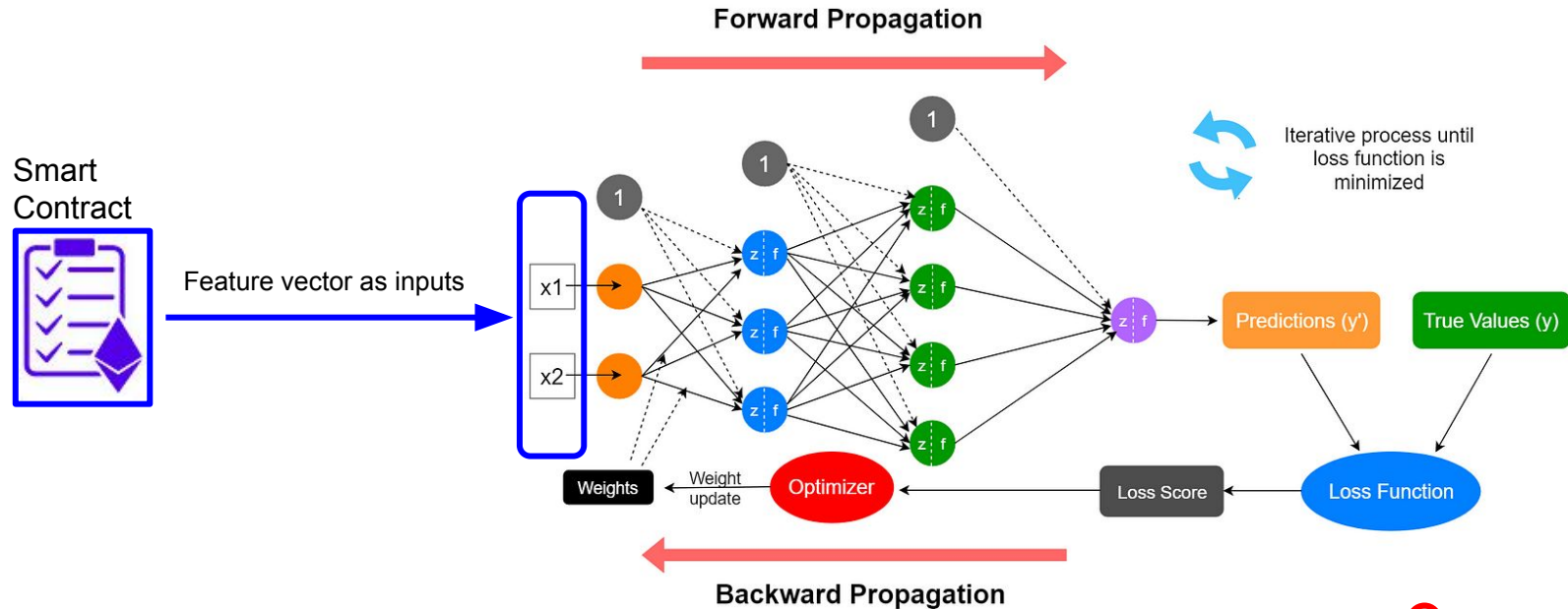
In TheDAO hack, the attacker stole over 3.6 million Ether!

Next: Designing DLVA

1. Motivation and Introduction
2. Designing DLVA
3. Training DLVA
4. Benchmarking DLVA



Neural Network's Training Process



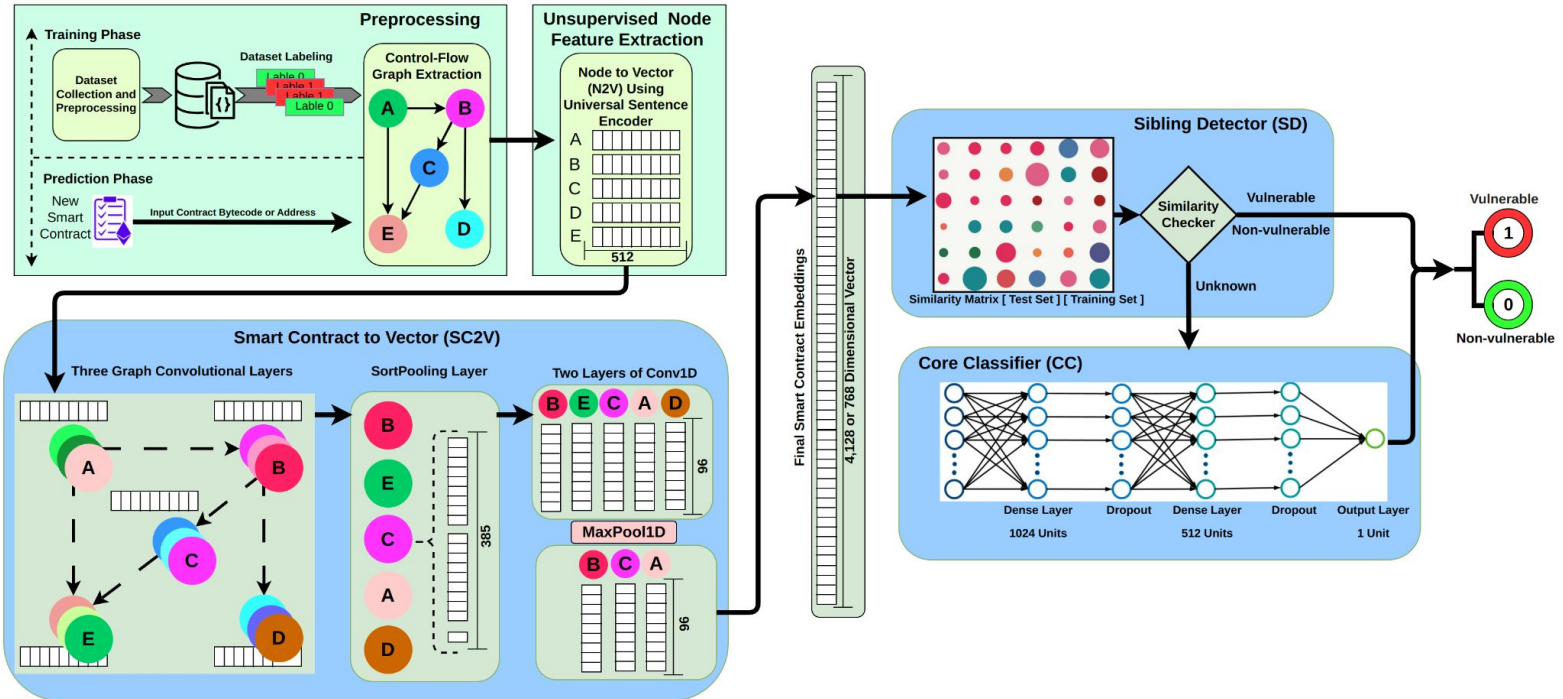
Main Challenge:

Representing smart contracts as feature vectors suitable for NN inputs

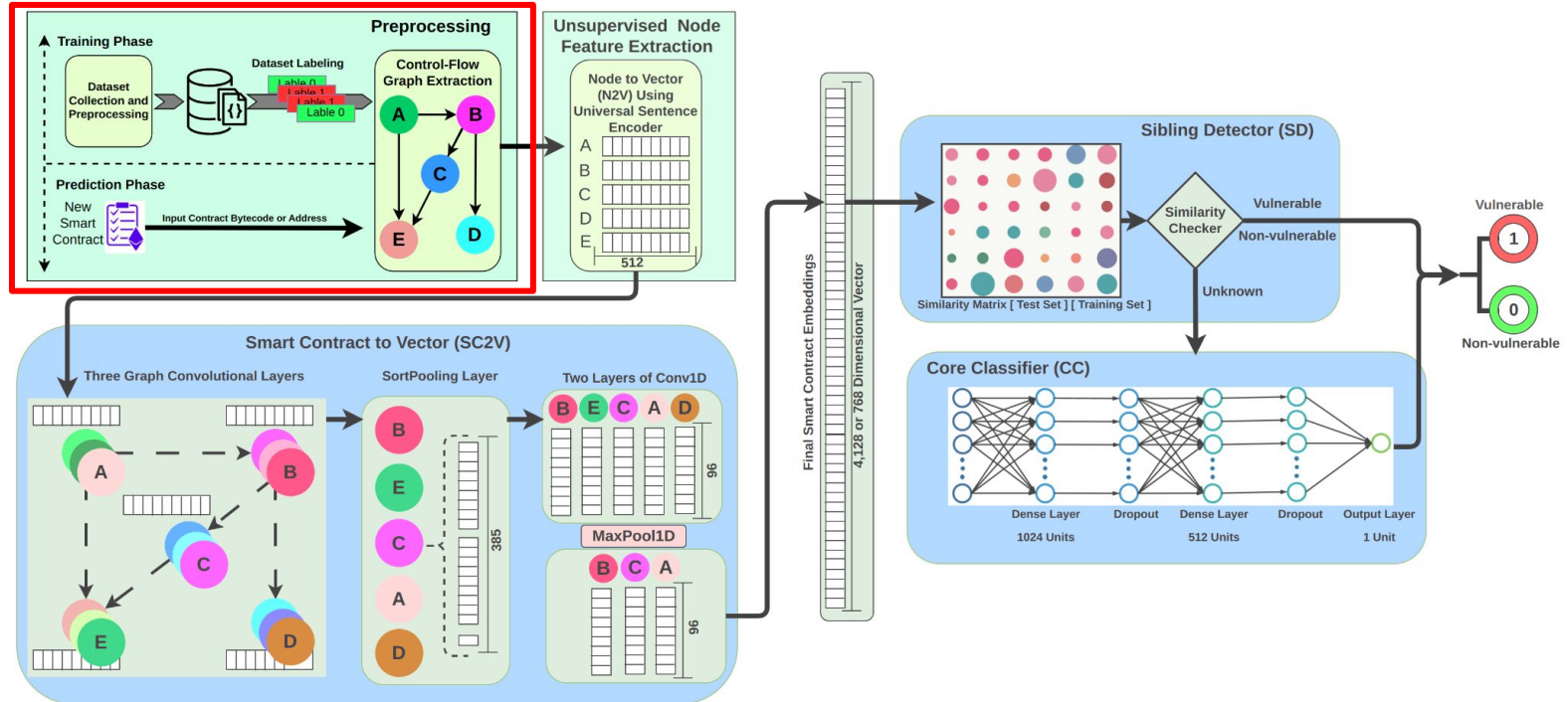
Our Solution: **DLVA's Smart Contract to Vector (SC2V) engine**

Architecture of DLVA

- 🔑: Neural networks learn from feature vectors to classify contracts
- 🔑: Use graph convolution NN to extract semantic structure

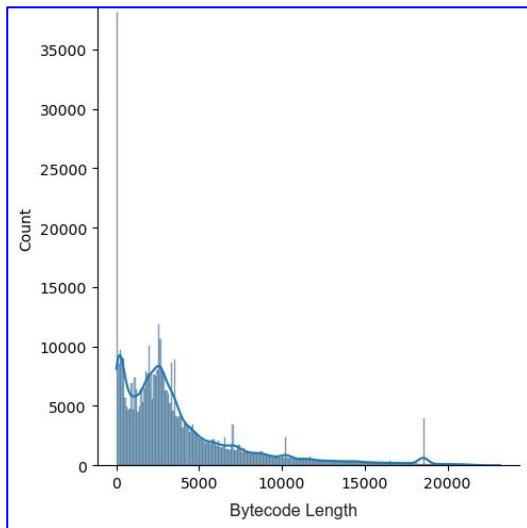


Preprocessing



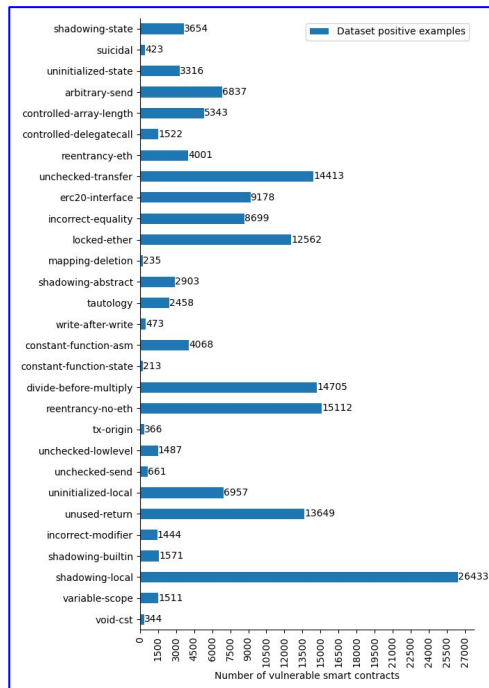
Preprocessing

1. Dataset Collection



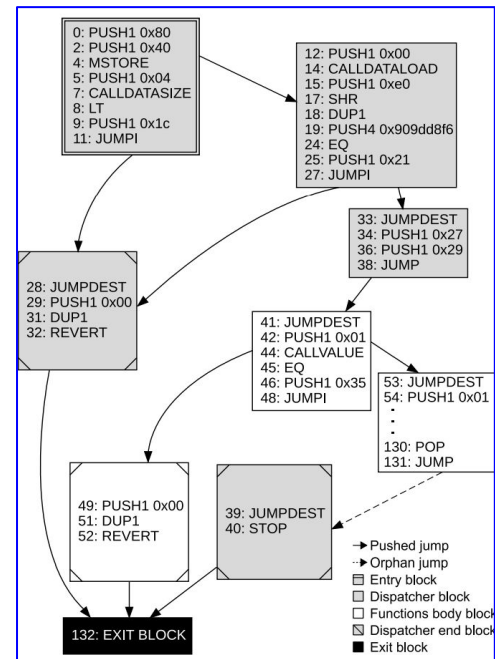
- **51,913,308** real-world contracts
- Remove redundant **99.3%**
- Only **368,438** are unique contracts

2. Dataset Labeling



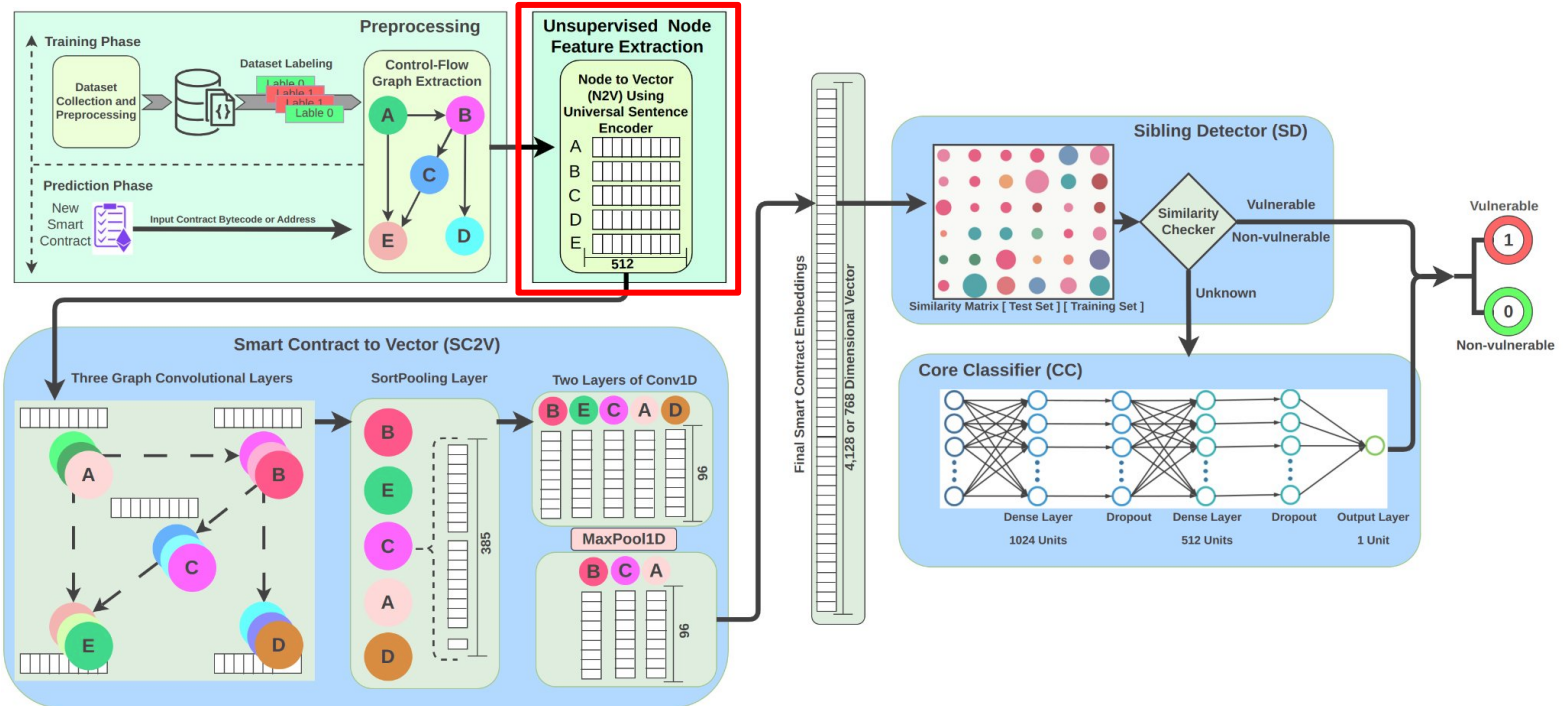
- Slither requires source code available
- Only $\frac{1}{3}$ of unique contracts are labeled

3. CFG extraction



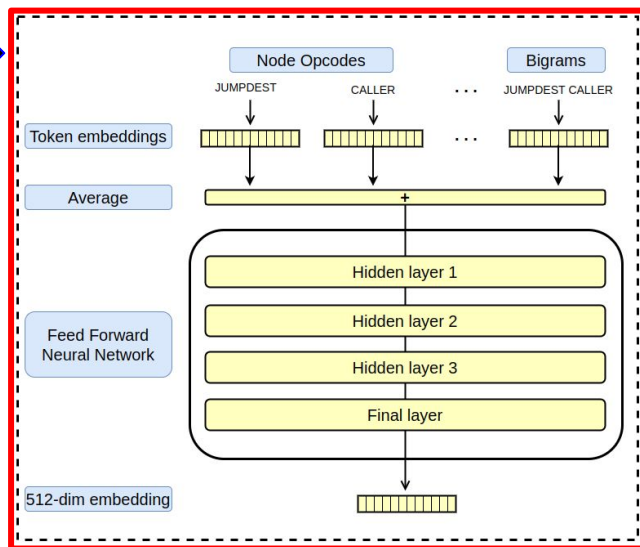
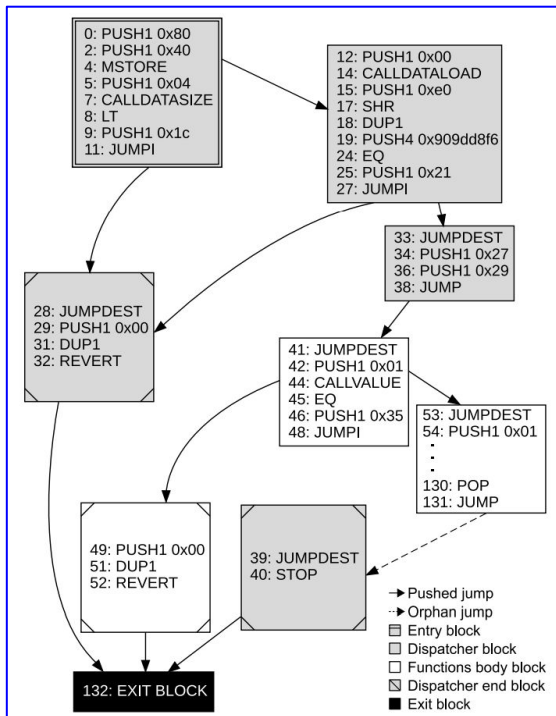
- CFG captures important semantics structures

Node to Vector (N2V)

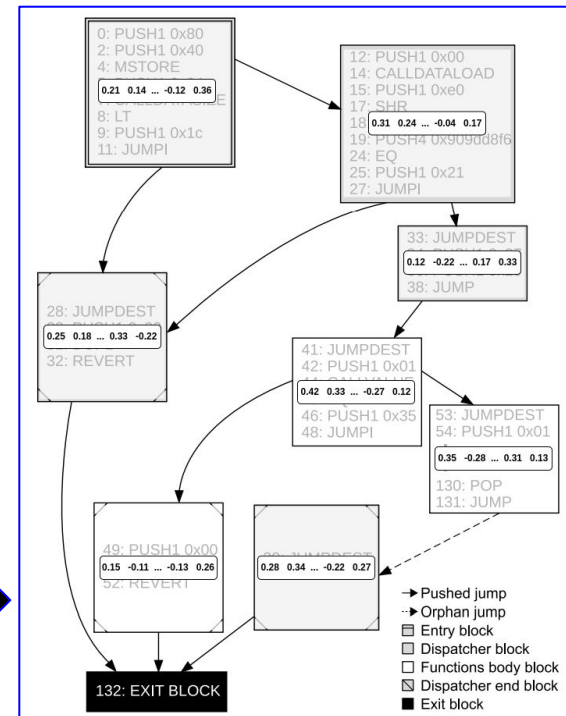


Node to Vector (N2V)

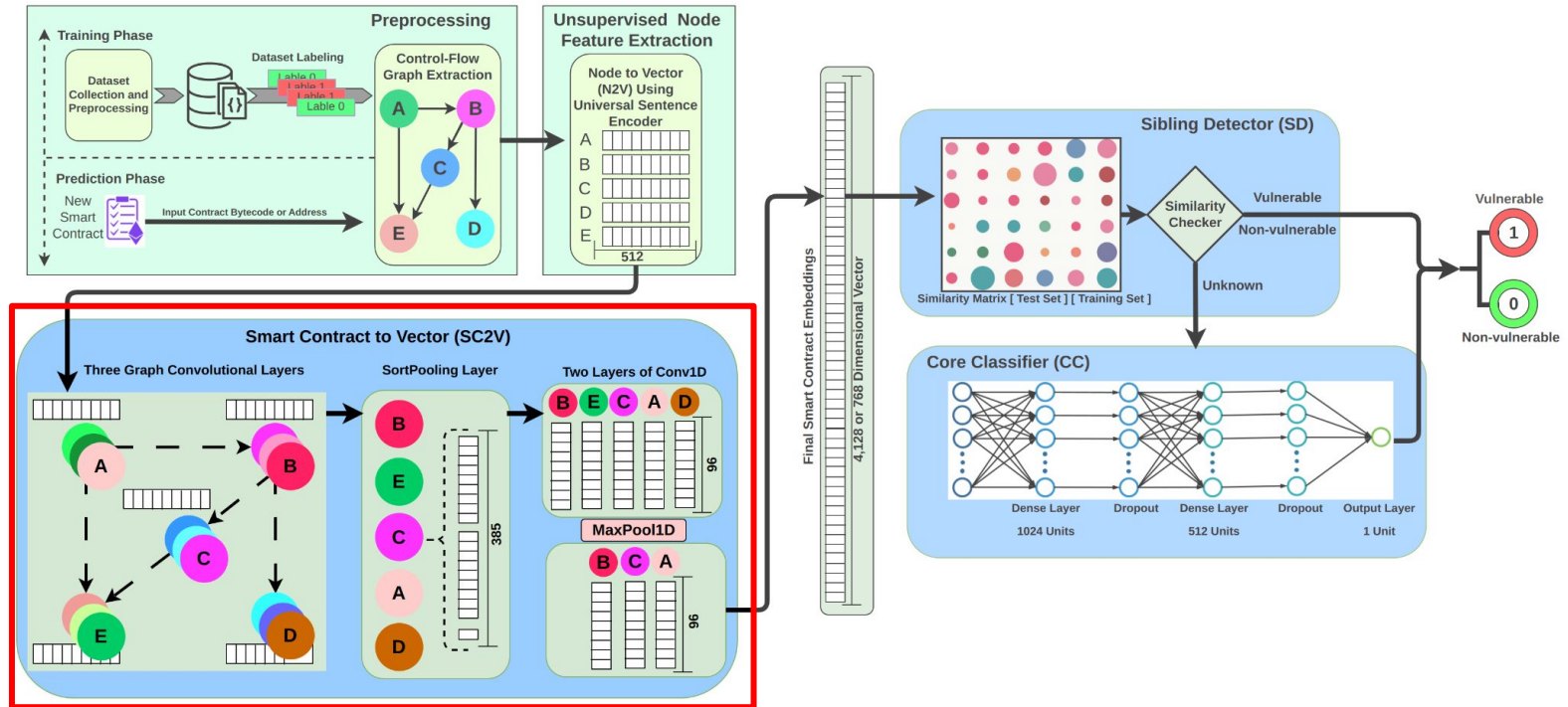
🔑: Similar basic blocks/nodes → Similar vectors in embedding space




Deep Averaging Network of the Universal Sentence Encoder

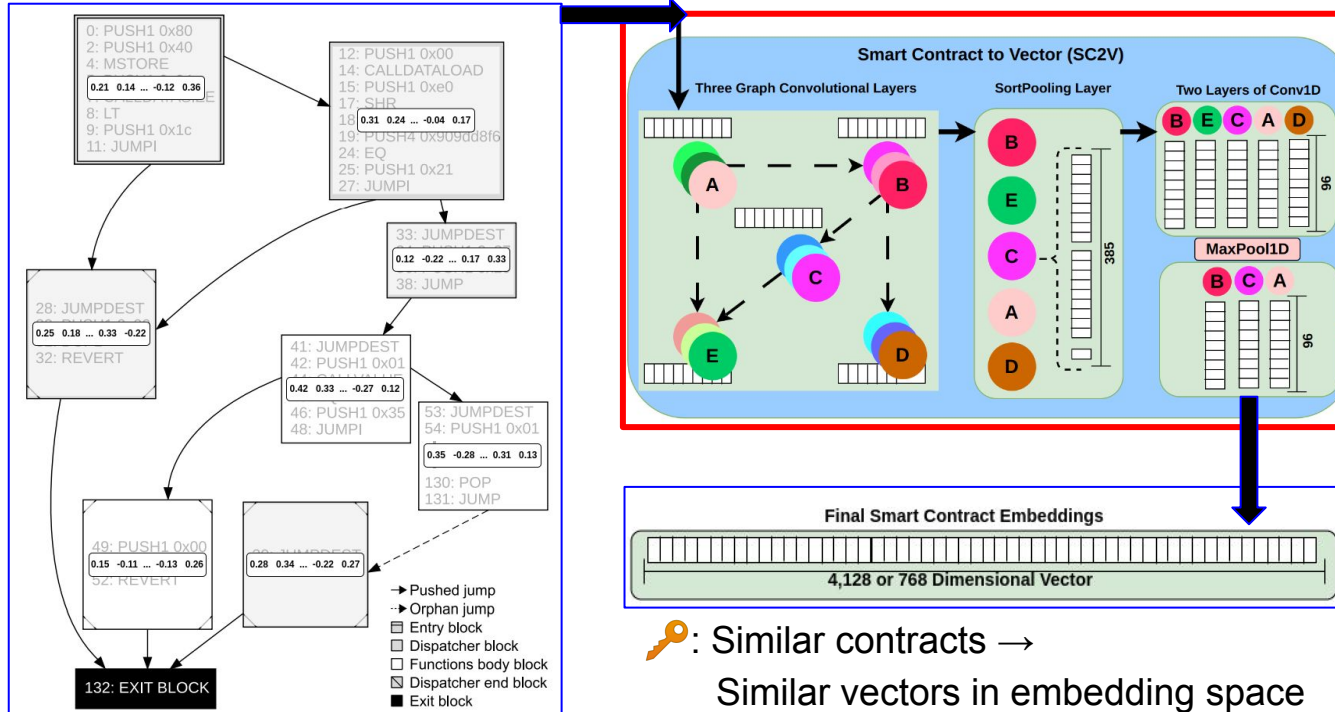


Smart Contract to Vector (SC2V)

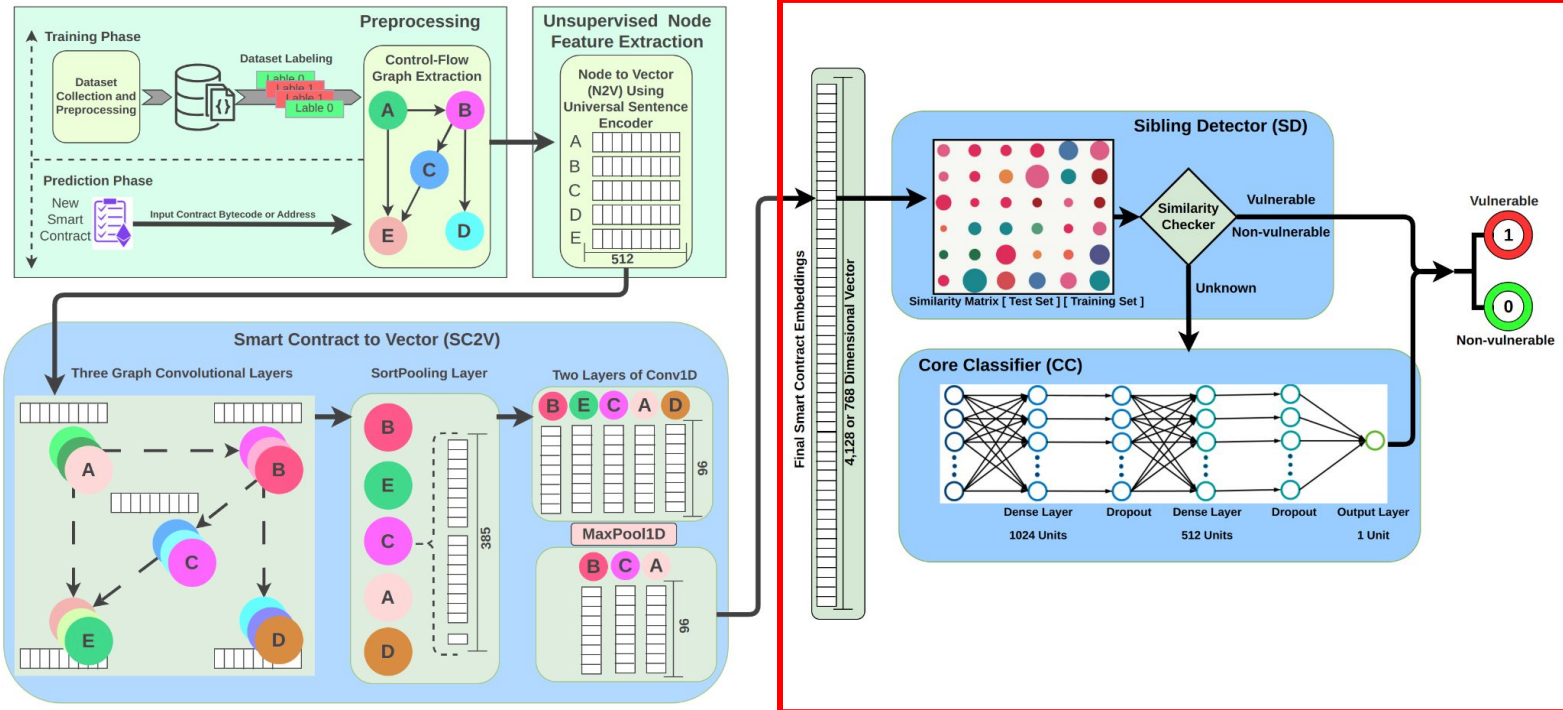


Smart Contract to Vector (SC2V)

- SC2V uses node summaries to make a vector summary of the entire CFG
- : Use graph convolution NN to extract semantic structure from CFG



Sibling Detector (SD) and Core Classifier (CC)

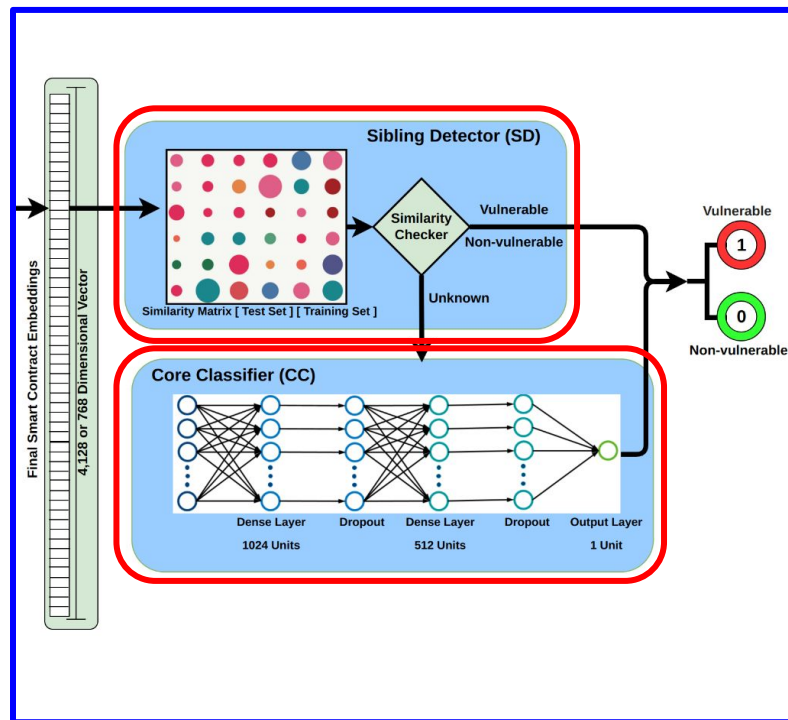


Sibling Detector (SD) and Core Classifier (CC)

- ★ SD tries to find a Euclidean-close neighbor to the target contract from the training data

$$d(\mathbf{p}, \mathbf{q}) = \sqrt{\sum_{i=1}^n (q_i - p_i)^2}$$

- ★ If no close neighbor, SD reports “unknown”
- ★ CC only called when SD reports unknown
- ★ CC uses feedforward neural net to label vulnerable contracts regardless of vector distance.



Next: Training DLVA

1. Motivation and Introduction



2. Designing DLVA




3. Training DLVA

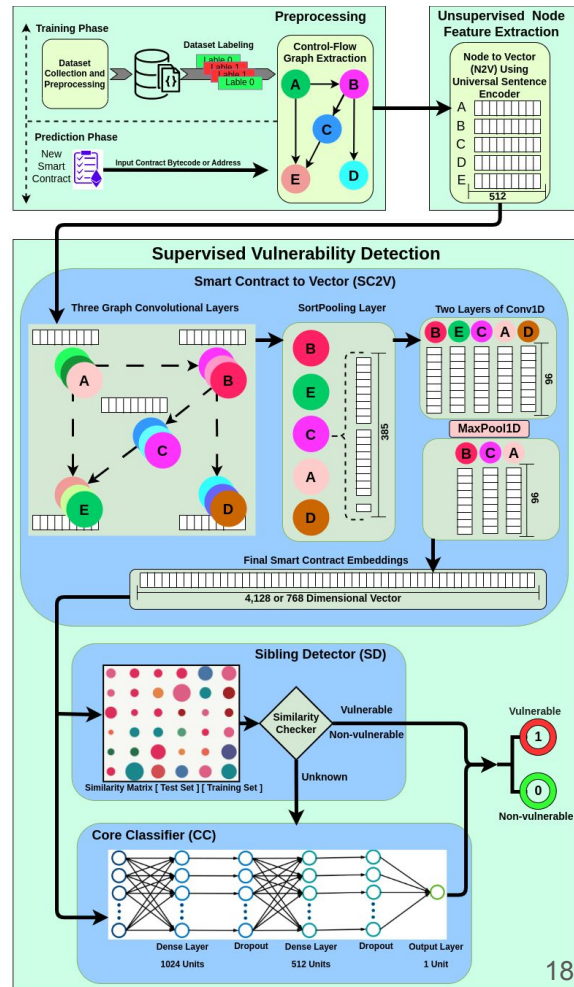
4. Benchmarking DLVA

Training




★ N2V: 21.9 million basic blocks

★  SC2V and CC trained together on 72 thousand contracts

 Slither only labels source code, so we train the bytecode analyzer DLVA using a source code labeller as the oracle



Next: Benchmarking DLVA

1. Motivation and Introduction 
2. Designing DLVA 
3. Training DLVA 
4. Benchmarking DLVA

Datasets used to benchmark DLVA

| Dataset | No. of contracts | No. of vulnerabilities | Contract size | Ground Truth |
|---|------------------|------------------------|---------------|---------------------------------------|
| <i>EthereumSC_{large}</i> [3] | 22,634 | 29 | Large | Slither |
| <i>EthereumSC_{small}</i> [4] | 1,381 | 21 | Small | Slither |
| <i>Elysium_{benchmark}</i> [2] | 900 (57) | 2 | Small | Peer-reviewed |
| <i>Reentrancy_{benchmark}</i> [6] | 473 (472) | 1 | Small | GP: Manual and GN: 2 analyzers |
| <i>SolidiFI_{benchmark}</i> [8] | 444 | 4 | Large | GP: Bug injection and GN: 5 analyzers |

: All datasets are disjoint from DLVA's training sets

: All datasets are publicly available

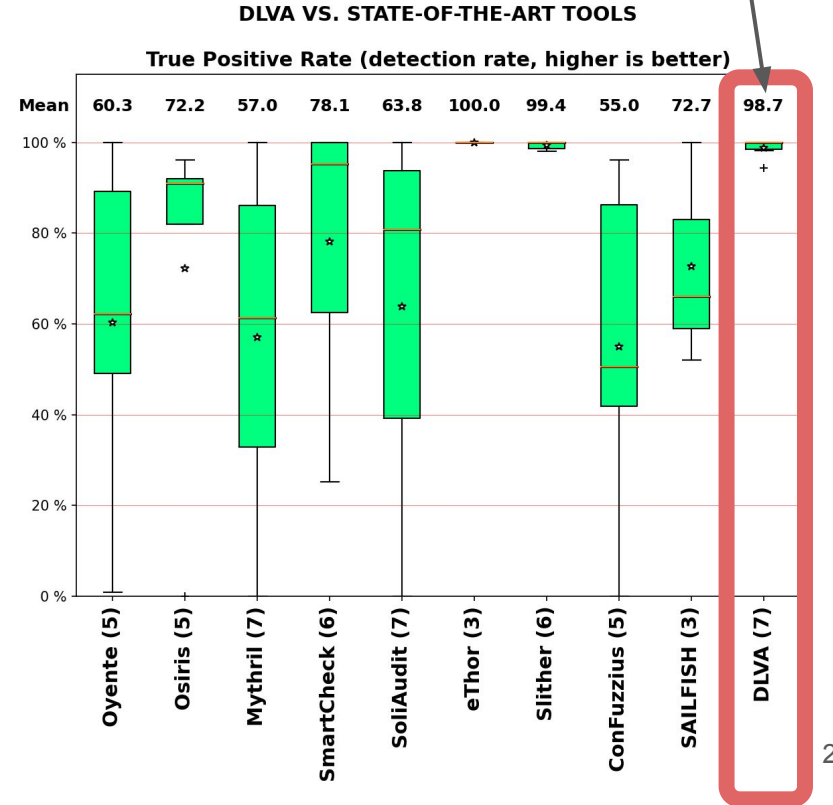
Competitor summary

| Analyzer | Input | Method | Vulnerabilities | Year | Citations |
|-----------------|-------------------|----------------------------|------------------------|-------------|------------------|
| Oyente 0.2.7 | source+ & binary- | static analysis | 4 | 2017 | 1,996 |
| Osiris | source+ & binary- | static analysis | 5 | 2018 | 234 |
| Mythril 0.21.20 | source+ & binary- | static analysis | 13 | 2019 | 127 |
| SmartCheck 2.0 | source | static analysis | 43 | 2019 | 513 |
| SoliAudit | source | machine learning & fuzzing | 13 | 2019 | 76 |
| eThor | binary | static analysis | 1 | 2020 | 80 |
| Slither 0.8.0 | source | static analysis | 74 | 2021 | 292 |
| ConFuzzius | source | static analysis & fuzzing | 10 | 2022 | 19 |
| SAILFISH | source | static analysis | 2 | 2022 | 24 |
| DLVA | binary | deep learning | 29 | 2023 | NA |

DLVA is highly sensitive

| | | |
|------------------|------------------------------------|------------------------------------|
| | <u>P</u> redicted <u>P</u> ositive | <u>P</u> redicted <u>N</u> egative |
| <u>P</u> ositive | <u>T</u> rue <u>P</u> ositive ✓ | <u>F</u> alse <u>N</u> egative ✗ |
| <u>N</u> egative | <u>F</u> alse <u>P</u> ositive ✗ | <u>T</u> rue <u>N</u> egative ✓ |

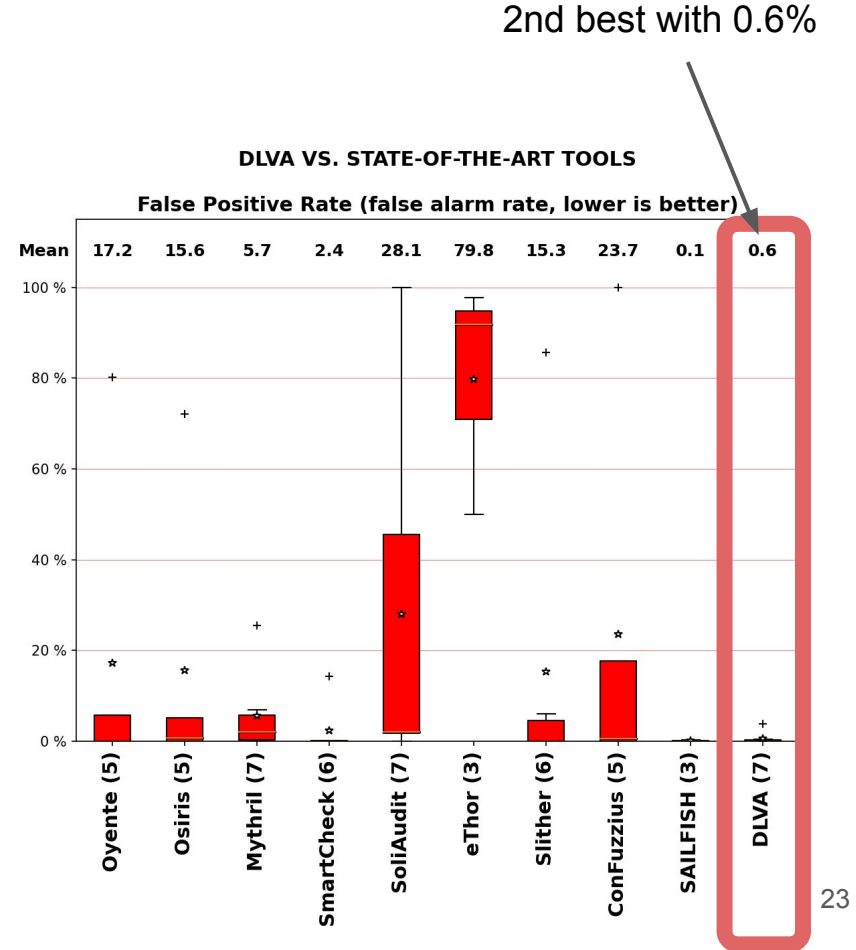
$$\text{True Positive Rate (TPR)} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$



DLVA is highly selective

| | | |
|------------------|------------------------------------|------------------------------------|
| | <u>P</u> redicted <u>P</u> ositive | <u>P</u> redicted <u>N</u> egative |
| <u>P</u> ositive | <u>T</u> rue <u>P</u> ositive ✓ | <u>F</u> alse <u>N</u> egative ✗ |
| <u>N</u> egative | <u>F</u> alse <u>P</u> ositive ✗ | <u>T</u> rue <u>N</u> egative ✓ |

$$\text{False Positive Rate (FPR)} = \frac{\text{FP}}{\text{FP} + \text{TN}}$$

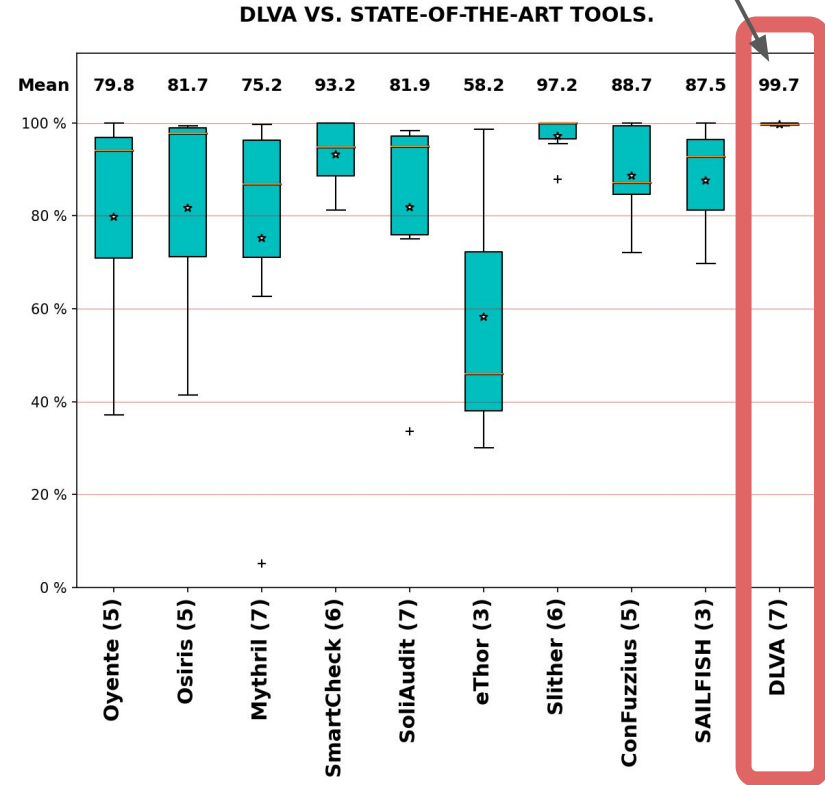


DLVA is highly accurate

| | | |
|------------------|------------------------------------|------------------------------------|
| | <u>P</u> redicted <u>P</u> ositive | <u>P</u> redicted <u>N</u> egative |
| <u>P</u> ositive | <u>T</u> rue <u>P</u> ositive ✓ | <u>F</u> alse <u>N</u> egative ✗ |
| <u>N</u> egative | <u>F</u> alse <u>P</u> ositive ✗ | <u>T</u> rue <u>N</u> egative ✓ |

$$\text{Accuracy} = \frac{(\text{TP} + \text{TN})}{(\text{TP} + \text{FP} + \text{TN} + \text{FN})}$$

Leads the pack with 99.7% accuracy

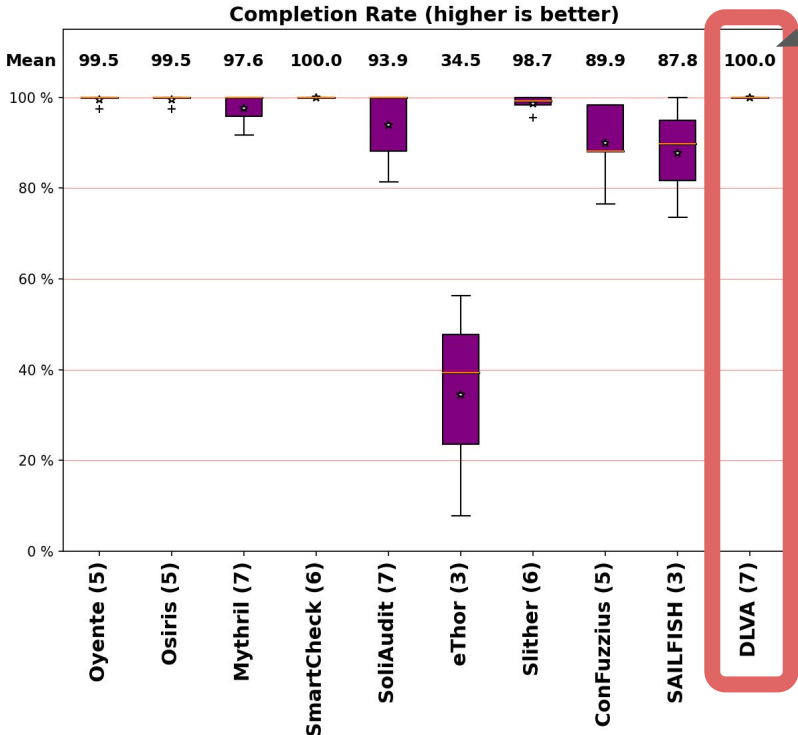


DLVA is 10x – 1000x faster than competitors

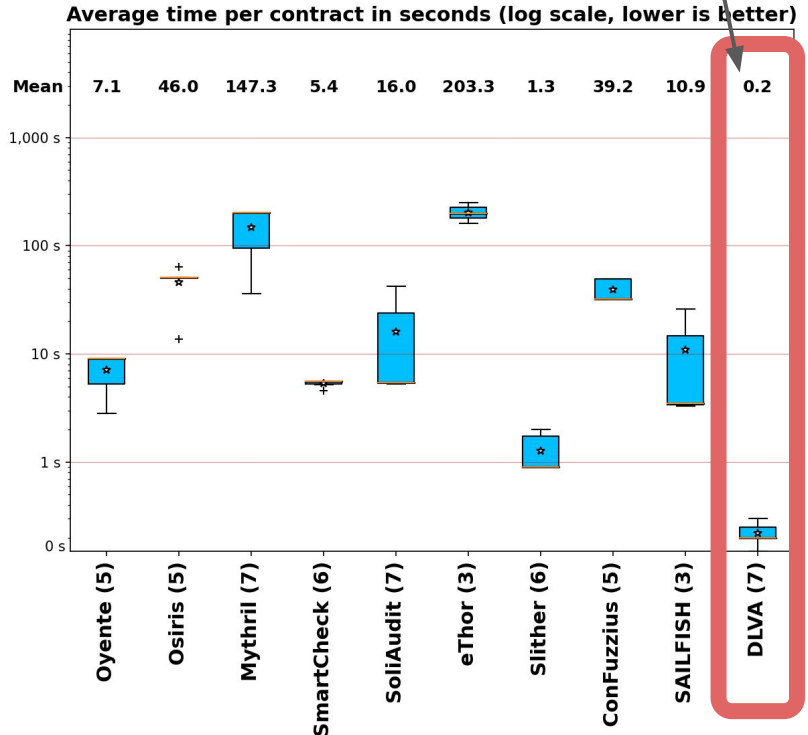
DLVA almost always answers... and very quickly

DLVA is close to 100%

DLVA VS. STATE-OF-THE-ART TOOLS



DLVA VS. STATE-OF-THE-ART TOOLS



Concluding thoughts

Thank you for
your attention!

- ★ Neural nets are surprisingly good at understanding smart contracts
- ★ Incorporating some semantic understanding (CFGs) improved results
- ★ It is hard to pin down why something is flagged
- ★ Finding good datasets is tricky
- ★ Performance is essentially real-time
- ★ DLVA is available as a practical tool for immediate use:

