ScrawlD: A Dataset of Real World Ethereum Smart Contracts Labelled with Vulnerabilities

Chavhan Sujeet Yashavant
Indian Institute of Technology Kanpur
Kanpur, India
sujeetc@cse.iitk.ac.in

Saurabh Kumar
Indian Institute of Technology Kanpur
Kanpur, India
skmtr@cse.iitk.ac.in

Amey Karkare
Indian Institute of Technology Kanpur
Kanpur, India
karkare@cse.iitk.ac.in

ABSTRACT
Smart contracts on Ethereum handle millions of U.S. Dollars and other financial assets. In the past, attackers have exploited smart contracts to steal these assets. The Ethereum community has developed plenty of tools to detect vulnerable smart contracts. However, there is no standardized data set to evaluate these existing tools, or any new tools developed. There is a need for an unbiased standard benchmark of real-world Ethereum smart contracts. We have created ScrawlD: an annotated data set of real-world smart contracts taken from the Ethereum network. The data set is labelled using 5 tools that detect various vulnerabilities in smart contracts, using majority voting.

KEYWORDS
Ethereum, Smart contracts, Annotated dataset, Vulnerabilities

1 INTRODUCTION
Permissionless blockchains like Ethereum have tens of millions of smart contracts [11]. A smart contract is a code that resides on the Ethereum network and executes when predetermined conditions get satisfied. Smart contracts on Ethereum handle financial assets worth millions of U.S. Dollars (USD). Attacking smart contracts can provide monetary benefits to the attackers or cause other damages [1]. Therefore, the attacks on Ethereum smart contracts have increased rapidly over the last few years [2].

To detect the attacks on Ethereum smart contracts, the Ethereum community has developed plenty of tools [3, 8, 10, 12, 16, 18]. These tools analyze smart contracts and produce vulnerability reports. The authors of these tools use datasets of smart contracts to evaluate the tools’ efficiency, correctness, and other parameters. However, datasets used by the authors to evaluate their tools vary significantly [14]. The type of dataset has an impact on the tool’s performance. Therefore it is necessary to evaluate tools using multi-type integrated benchmark suite [14].

Ren et al. [14] have created a dataset having two types of smart contracts: annotated and non-annotated. However, the number of annotated smart contracts in the database is very small (less than a thousand). Further, most of these annotated smart contracts not real-world contracts. The dataset created by Ferreira et al. [9] the same issues. Hence, these datasets cannot be considered representatives for the real-world Ethereum smart contracts. There is a need for a benchmark suite containing real world smart contracts labelled with vulnerabilities.

We present ScrawlD: a dataset of real-world Ethereum smart contracts labelled with vulnerabilities. The Ethereum community can use ScrawlD for an unbiased evaluation of new and existing tools to analyse vulnerabilities. ScrawlD contains 6.7K labelled real-world Ethereum smart contracts. Our methodology to label the smart contracts is based on the work by Ren et al. [13]. This paper describes our solution that uses various tools (such as [3, 8, 10, 16, 17]) to find and catalog the vulnerabilities in the smart contracts. The resulting data set, ScrawlD, is released at https://github.com/sujeetc/ScrawlD.

2 RELATED WORK
Ren et al. [14] crafted a benchmark suite that integrates labeled and unlabeled Smart Contracts. The unlabeled dataset has 45,622 Real-World Ethereum Smart Contracts having more than one transaction on the Ethereum blockchain. The labeled dataset has artificially constructed contracts (350 contracts) and confirmed vulnerable contracts (214 contracts).

Durieux et al. [6] crafted a dataset of annotated and non-annotated smart contracts. The annotated part contains 69 contracts tagged with 115 vulnerabilities. The annotated part has ten categories of vulnerabilities. In contrast, the non annotated part contains 47,518 unique contracts, each with at least one transaction on the Ethereum network.

Researchers can’t use the unlabeled dataset to evaluate the tool as there is no ground truth associated with it. Moreover, the labeled dataset doesn’t have more than a thousand smart contracts.

Many vulnerability analysis tools used unlabelled datasets to evaluate the tool. Due to huge number of contracts in these datasets, either the dataset is not annotated or a very small subset is annotated with the vulnerabilities present. To the best of our knowledge, there is no fully annotated dataset released publicly. We describe existing efforts in this area. Smartcheck [16] authors evaluate the tool’s accuracy by using three annotated smart contracts. These annotated smart contracts do not represent the diverse smart contracts from Ethereum. Moreover, the authors used 4,600 verified contracts from Ethereum to evaluate the tool’s efficiency. However, the issues found in these 4,600 smart contracts are not manually verified.

Slither [8] does two types of experiments to evaluate the tool. The first experiment contains DAO [4] and SpankChain [15] smart contracts. DAO and SpankChain are two famous reentrancy attacks on Ethereum. The second experiment contains 1000 most used smart contracts from the Ethereum network. This dataset is unlabelled. The authors manually reviewed the results of detecting reentrancy vulnerability for 50 random smart contracts to evaluate the accuracy of Slither. Thus, their validation is not representative of the possible vulnerabilities in a dataset having large number of smart contracts.
Table 1: Vulnerabilities Description and SWC-ID as per SWC Registry

| Vulnerability Type | SWC-ID       | Description                                      |
|--------------------|--------------|--------------------------------------------------|
| ARTHM              | SWC-101      | Arithmetic (Integer Overflow and Underflow)      |
| DOS                | SWC-113, SWC-128 | Denial of Service                              |
| LE                 | –            | Locked Ether                                     |
| RENT               | SWC-107      | Reentrancy                                       |
| TimeM              | SWC-116      | Block values as a proxy for time                |
| TimeO              | SWC-114      | Transaction Order Dependence                     |
| UE                 | SWC-104      | Unchecked Call Return Value                      |
| TX-Origin          | SWC-115      | Authorization through tx.origin                  |

Table 2: Vulnerabilities Supported by Selected Tools.

✓ indicates that the tool supports the vulnerability.
× indicates that the tool doesn’t support the vulnerability.
_ indicates Unknown.

| Tool Name | Vulnerability Type |
|-----------|-------------------|
|           | ARTHM | DOS | LE | RENT | TimeM | TimeO | TX-Origin |
| Slither   | ×      | ✓   | ✓  | ✓    | ✓     | X     | ✓         |
| Smartcheck| ✓      | ✓   | ✓  | X    | ✓     | X     | ✓         |
| Mythril   | ✓      | ✓   | –  | ✓    | ✓     | ✓     | ✓         |
| Oyente    | ✓      | ✓   | X  | ✓    | ✓     | X     | –         |
| Osiris    | ✓      | X   | X  | X    | X     | X     | X         |

Table 3: Threshold for each Vulnerability Type

| Vulnerability Type | #Tools that can detect the Vulnerability | Threshold |
|--------------------|------------------------------------------|-----------|
| ARTHM              | 4                                        | 2         |
| DOS                | 3                                        | 2         |
| LE                 | 2                                        | 1         |
| RENT               | 3                                        | 2         |
| TimeM              | 4                                        | 2         |
| TimeO              | 2                                        | 1         |
| UE                 | 3                                        | 2         |
| TX-Origin          | 3                                        | 2         |

3 METHODOLOGY
This section explains the data source, tools used, and process to label the dataset with an example.

3.1 Data Source
We took 45,622 addresses belonging to smart contracts from the dataset of the paper by Ren et. al. [14] The dataset contains all unique smart contracts with more than one transaction on the Ethereum network. Moreover, these smart contracts’ source code is publicly available. We crawled the source codes of these 45,622 smart contracts through Etherscan’s API [7]. However, we released 6780 smart contracts in SCRAWD due to challenges given in Section 6.

3.2 Tools Used
The following points explain the criteria to select the tools as used in the paper by Durieux et. al. [6]

- **Available and CLI:** The tool is released publicly and has a command-line interface (CLI).
- **Compatible Input:** The tool requires input as Solidity smart contract. We do not consider the tools that require only EVM bytecode.
- **Only Source:** The tool runs on only Solidity source code. We do not consider the tools that require a test suite or smart contract labelled with assertions.
- **Vulnerability Finding:** The tool finds vulnerabilities in smart contracts.

The following tools are selected based on the above criteria.

- **Slither:** Slither [8] is a static analysis tool designed to analyze Ethereum smart contracts. It has four prominent use cases: automated detection of vulnerabilities, automated detection of code optimization opportunities, improvement of users’ understanding of the contracts, and assistant with code review.
4 RESULTS

Table 3 shows the number of tools that support each vulnerability. The threshold column in the table shows the majority rule. For example, consider Unhandled Exception (UE) vulnerability. Three tools support it. Its threshold is two. Hence, if two or more tools say that the contract is vulnerable for UE at the same location, we report it as a real vulnerability. We show the vulnerability only if greater than or equal to 50% of the tools report that it is present.

### References

[1] Ren, J., Wang, W., & Sun, L. (2019). A dataset of real world Ethereum smart contracts labelled with vulnerabilities. In Proceedings of the 18th ACM International Conference on Information and Knowledge Management (pp. 331-340). ACM.

[2] Mythril: Mythril is a tool that does security analysis of Ethereum smart contracts. It detects various security issues [3].

[3] Smartcheck: Smartcheck [16] is an extensible static analysis tool that detects vulnerabilities in smart contracts. It converts Solidity code into XML-based intermediate representation and checks it with XPath patterns.

[4] Oyente: Oyente [10] is a symbolic execution tool to find security bugs in smart contracts.

[5] Osiris: Osiris [17] is a framework comprising symbolic execution and taint analysis. It detects integer bugs in Ethereum smart contracts.

These tools are neither sound nor complete. They can miss vulnerabilities (False Negatives) or detect them when they are not present (False Positives).

#### 3.3 Vulnerabilities

Table 1 shows vulnerabilities selected for evaluation. The column “Vulnerability type” indicates the acronym used in the paper for a particular vulnerability, while the column “SWC-ID” shows the ID provided by the SWC Registry for the vulnerability where available.

Table 2 shows vulnerabilities supported by selected tools. Symbol ✓ indicates that the tool can detect a particular vulnerability, whereas symbol ✗ indicates that the tool can’t detect the vulnerability. Symbol – indicates that we don’t know whether the tool has detection capability of the particular vulnerability or not. Due to improper documentation of the tool, it is hard to find whether it supports this vulnerability or not.

#### 3.4 Process to Label the Dataset

We use the methodology given in the paper by Ren et al. [13] to find vulnerabilities in smart contracts. To understand the process of labeling the dataset, consider the example shown in Listing 1. It shows a code snippet of a vulnerable contract from the SWC registry. Here, the constructor name should be “Missing”. However, accidentally, the smart contract developer writes it as “IamMissing”. Now, any node on the Ethereum blockchain can create a transaction that calls this function named “IamMissing” and can become the owner of this contract. This type of bug is known as incorrect constructor name.

Due to the presence of false positives in the reports generated by the tools, we cannot depend on just one tool. We use majority voting, that is, at least 50% of the tools must report the same vulnerability at the same location. For example, assume that tools T1, T2, and T3 can detect incorrect constructor name vulnerability. Suppose, at least two tools report that incorrect constructor name vulnerability is present at Line 4. Then we say that the contract is vulnerable for incorrect constructor name; otherwise, we say that the contract is not vulnerable.

Algorithm 1 shows the methodology to label the dataset. The following steps explain the methodology given in the algorithm 1:

1. First, collect the output of the selected tools for the smart contract to be analyzed (line 2).
2. Note the vulnerability name and line number for the vulnerability per tool (line 4).
3. For the same vulnerability, if different tools show different locations, consider them as different warnings. We consider two warnings as the same only if the vulnerability name and location match for different tools (line 5).
4. The methodology says that the vulnerability exists at a location if more than 50% tools confirm the same vulnerability at the exact location. In that case, label the location with the vulnerability (line 8 to 12).

---

**Table 4: Total Contracts with Unique Vulnerabilities**

| #Unique Vulnerabilities | #Contracts |
|-------------------------|-----------|
| NONE                    | 2688      |
| 1                       | 2912      |
| 2                       | 1082      |
| 3                       | 86        |
| 4                       | 12        |

---

**Algorithm 1 Process to Label the Dataset**

1. for `tool ← tool_1 to tool_n do`
2. Collect the output of `tool`
3. for `vuln ← vuln_1 to vuln_n do`
4. 1. Note the `line_number` for `vuln` detected by `tool`
5. 2. Increase the `tool_count` for `vuln` for `line_number` detected
6. end for
7. end for
8. for `vuln ← vuln_1 to vuln_n do`
9. if `tool_count` ≥ n/2 for `line_number` then
10. Vulnerability: `vuln` is present at `line_number`
11. end if
12. end for
The idea of marking the vulnerability as real or not is taken from the paper by Ren et al. [13].

Figure 1 shows the number of smart contracts with at least one occurrence of particular vulnerability according to the majority vote. For example, consider Reentrancy vulnerability. Table 3 shows that Slither, Mythril, and Oyente support the detection reentrancy vulnerability. We say that the contract contains reentrancy only if two of these three tools report that it is present at the same location.

Figure 2 shows the total warnings reported for each vulnerability according to the majority of tools. Please note that there can be multiple warnings in a single file for each vulnerability.

Table 4 shows contracts having exclusive number of vulnerabilities. According to our evaluation methodology, 2688 contracts have no vulnerabilities. 2912 contracts have only one type of vulnerability. Similarly, 1082 contracts have two vulnerabilities each.

5 APPLICATIONS OF THE DATASET

5.1 Evaluation of New Tools

The Ethereum community can use our dataset for evaluating correctness and other parameters of newly designed tools. SCRAWLD comprises a diverse set of real-world annotated smart contracts. Hence, researchers can use SCRAWLD for evaluating new tools.

5.2 Machine Learning based Tools

Vulnerability analysis tools based on Machine Learning needs dataset for training. SCRAWLD has 6.7K labelled smart contracts. Hence, researchers can use SCRAWLD as a basis for learning or training of ML-based tools.

5.3 Empirical Analysis of existing Tools

There are plenty of tools that analyze Ethereum smart contracts and detect different vulnerabilities. Smart contract developers face difficulty choosing the tool to analyze their smart contracts. There should be an empirical study that compares various tools and suggest which tools are better. Previous works [6, 14] use dataset where the annotation is limited to a few thousand smart contracts. The effectiveness of these studies can be improved with SCRAWLD.

6 CHALLENGES IN CREATING THE ANNOTATED DATASET

Each tool depends on different packages, specific versions of these packages. Most of the time, different tools are not compatible with each other. That’s why we create docker [5] containers for these tools and run our experiments.

Mythril tool is memory-intensive. It consumes more than 10 GB RAM, and hence we cannot run it in parallel. It is cumbersome to get results from Mythril.

7 THREATS TO VALIDITY

Each tool selected for evaluation is neither sound nor complete. There can be a lot of false positives or false negatives generated by a specific tool. However, we used the majority approach to say whether a vulnerability is present or not. But, this approach may fail if majority of the tools generate false positives or false negatives.

We can solve these issues by integrating more tools or manually reviewing detected vulnerabilities through crowdsourcing or other means. However, these approaches are time and resource-intensive, and we can do it incrementally.

8 CONCLUSION AND FUTURE WORK

We collected 46K Ethereum smart contracts from Etherscan. However, due to challenges in section 6, we could not label them all. We are working on labeling more contracts, and SCRAWLD will be updated regularly.

We will add more tools to SCRAWLD and do a manual inspection of detected vulnerabilities in smart contracts through crowdsourcing or some other means in the future.
REFERENCES

[1] Nicola Atzei, Massimo Bartoletti, and Tiziana Cimoli. 2017. A Survey of Attacks on Ethereum Smart Contracts (SoK). In Principles of Security and Trust, Matteo Maffes and Mark Ryan (Eds.). Springer Berlin Heidelberg, Berlin, Heidelberg, 164–186.

[2] Huashan Chen, Marcus Pendleton, Laurent Njilla, and Shouhuai Xu. 2020. A Survey on Ethereum Systems Security: Vulnerabilities, Attacks, and Defenses. ACM Comput. Surv. 53, 3, Article 67 (Jan 2020), 43 pages. https://doi.org/10.1145/3399195

[3] ConsenSys. 2022. Mythril. https://github.com/ConsenSys/mythril-classic

[4] Phil Daian. 2022. Analysis of the dao exploit. http://hackingdistributed.com/

[5] Docker. Initial Release: 2013. Empowering App Development for Developers. https://www.docker.com

[6] Thomas Durieux, João F. Ferreira, Rui Abreu, and Pedro Cruz. 2020. Empirical Review of Automated Analysis Tools on 47,587 Ethereum Smart Contracts. In Proceedings of the ACM/IEEE 42nd International Conference on Software Engineering (Seoul, South Korea) (ICSE ’20). Association for Computing Machinery, New York, NY, USA, 530–541. https://doi.org/10.1145/3377811.3380364

[7] Etherscan. 2022. The Ethereum Blockchain Explorer. https://etherscan.io

[8] Josselin Feist, Gustavo Greico, and Alex Groce. 2019. Slither: A Static Analysis Framework for Smart Contracts. In Proceedings of the 2nd International Workshop on Emerging Trends in Software Engineering for Blockchain (Montreal, Quebec, Canada) (WETSEB ’19). IEEE Press, 8–15. https://doi.org/10.1109/WETSEB.2019.00008

[9] João F. Ferreira, Pedro Cruz, Thomas Durieux, and Rui Abreu. 2020. SmartBugs: A Framework to Analyze Solidity Smart Contracts. In Proceedings of the 35th IEEE/ACM International Conference on Automated Software Engineering (Virtual Event, Australia) (ASE ’20). Association for Computing Machinery, New York, NY, USA, 1349–1352. https://doi.org/10.1145/3324884.3415298

[10] Lei Lou, Duc-Hiep Chu, Hrishi Olickel, Prateek Saxena, and Aquinas Hobor. 2016. Making Smart Contracts Smarter. In Proceedings of the 2016 ACM SIGSAC Conference on Computer and Communications Security (Vienna, Austria) (CCS ’16). Association for Computing Machinery, New York, NY, USA, 254–269. https://doi.org/10.1145/2976749.2978309

[11] Andrew Müller, Zhicheng Cai, and Somesh Jha. 2018. Smart Contracts and Opportunities for Formal Methods. In Leveraging Applications of Formal Methods, Verification and Validation. Industrial Practice, Tiziana Margaria and Bernhard Steffen (Eds.). Springer International Publishing, Cham, 280–299.

[12] Ivica Nikolosi, Aashish Kolluri, Ilya Sergey, Prateek Saxena, and Aquinas Hobor. 2018. Finding The Greedy, Prodigal, and Suicidal Contracts at Scale. In Proceedings of the 34th Annual Computer Security Applications Conference (San Juan, PR, USA) (ACSAC ’18). Association for Computing Machinery, New York, NY, USA, 653–663. https://doi.org/10.1145/3274694.3274743

[13] Meng Ren, Fuchen Ma, Zijiang Yin, Ying Fu, Huizhong Li, Wanli Chang, and Yu Jiang. 2021. Making Smart Contract Development More Secure and Easier. In Proceedings of the 29th ACM Joint Meeting on European Software Engineering Conference and Symposium on the Foundations of Software Engineering (Athens, Greece) (ESEC/FSE 2021). Association for Computing Machinery, New York, NY, USA, 1360–1370. https://doi.org/10.1145/3468264.3473929

[14] Meng Ren, Zijiang Yin, Fuchen Ma, Zhenyang Xu, Yu Jiang, Chengnian Sun, Huizhong Li, and Yan Cai. 2021. Empirical Evaluation of Smart Contract Testing: What is the Best Choice? In Proceedings of the 30th ACM SIGSOFT International Symposium on Software Testing and Analysis (Virtual, Denmark) (ISSTA 2021). Association for Computing Machinery, New York, NY, USA, 566–579. https://doi.org/10.1145/3460319.3464837

[15] SpankChain. 2022. We got spanked: What we know so far. https://medium.com/spankchain/we-got-spanked-what-we-know-so-far-d5ed3a0f38fe

[16] Sergei Tikhomirov, Ekaterina Vostrukhenskaya, Ivan Ivanitskiy, Ramil Takhaviev, Evgeny Marchenko, and Yaroslav Alexandrov. 2018. SmartCheck: Static Analysis of Ethereum Smart Contracts. In Proceedings of the 1st International Workshop on Emerging Trends in Software Engineering for Blockchain (Gothenburg, Sweden) (WETSEB ’18). Association for Computing Machinery, New York, NY, USA, 9–16. https://doi.org/10.1145/34660319.3464837

[17] Christof Ferreira Torres, Julian Schütte, and Radu State. 2018. Osiris: Hunting for Integer Bugs in Ethereum Smart Contracts. In Proceedings of the 34th Annual Computer Security Applications Conference (San Juan, PR, USA) (ACSAC ’18). Association for Computing Machinery, New York, NY, USA, 664–676. https://doi.org/10.1145/3274694.3274737

[18] Petar Tsankov, Andrei Dan, Dana Drachsler-Cohen, Arthur Gervais, Florian Bunzli, and Martin Vechev. 2018. Security: Practical Security Analysis of Smart Contracts. In Proceedings of the 2018 ACM SIGSAC Conference on Computer and Communications Security (Toronto, Canada) (CCS ’18). Association for Computing Machinery, New York, NY, USA, 67–82. https://doi.org/10.1145/3243734.3243780