Early Detection of Smart Ponzi Scheme Contracts Based on Behavior Forest Similarity

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Abstract—Smart contracts empowered by blockchains often manage digital assets in a distributed and decentralized environment. People believe in smart contracts based on these new technologies. Unfortunately, malicious smart contracts, such as smart Ponzi scheme contracts (ponzitracts, for short), pose risk. Existing techniques detect ponzitracts by analyzing the code as well as a large amount of transaction data after time-consuming deployment. However, a conclusion based on transaction data can only be gotten after the damage has been caused. This paper proposes PonziDetector, a ponzitract detection technique that does not rely on transaction data. Behavior forest is introduced into PonziDetector to capture dynamic behaviors of smart contracts during interacting with them, which makes it possible to early detect ponzitracts. The empirical study demonstrates that PonziDetector, without transaction data, can improve the precision and the recall of the state-of-the-art to 94.6% and 93.0% respectively. This means that PonziDetector can avoid potential losses by early detecting ponzitracts.

Index Terms—Smart contract, Smart Ponzi scheme, Behavior tree, Behavior forest, Ponzitract detection

I. INTRODUCTION

The advent of Bitcoin makes it possible for anonymous participants to exchange value securely without the intermediation of trusted authorities [1]. The blockchain technology behind in Bitcoin enables decentralized financial activities and has become a hotspot in both academia and industry [2], [3]. After Bitcoin, Ethereum [4] ushered in the second-generation blockchain [5] that supports the execution of smart contracts. To make it possible, Ethereum implements Ethereum Virtual Machine (EVM) which provides a smart contract execution environment and defines a contract-oriented high-level scripting language called Solidity [6] to unambiguously describe smart contracts.

Smart contracts are self-executing programs with the terms of the agreement among stakeholders. Since a smart contract enables reliable transactions between mutually distrusting participants [7], it has become widely used for a broad spectrum of financial applications [8]. Unfortunately, malicious financial applications emerged to exploit technical innovations and people’s trust in smart contracts. Among which is blockchain implementation of the notorious Ponzi scheme [9] — a classic scam originated in the offline world at least 150 years ago. A Ponzi scheme is a fraudulent investing and disguised as promising a high rate of returns to investors. The Ponzi scheme generates returns for early investors by acquiring new investors. This is similar to a pyramid scheme in that both are based on using new investors’ funds to pay the earlier backers. Ponzi schemes eventually bottom out when the flood of new investors dries up and there isn’t enough money to go around. At that point, the schemes unravel.

A smart contract implementation of the Ponzi scheme is called a ponzitract (smart Ponzi scheme contract) [9], [10]. Such implementation is very attractive because it inherits the inherent properties of smart contracts and blockchains: decentralized, anonymous and immutable. These properties are the cornerstones of many legit financial applications. But at the same time, they make smart Ponzi schemes more dangerous than traditional Ponzi schemes:

- The initiator of ponzitracts can stay anonymous, which apparently provides protection against incrimination of the people who started the scheme.
- The deployed ponzitracts are hard to modify and stop. Once an investor participates there is no easy way out. In order to avoid loss, the investor has to continually invite new investors. This exactly matches the malicious intention of the creators.
- Decentralization gives investors the illusion that ponzitracts are reliable and credible.

To the best of our knowledge, the first feasible detection technique of ponzitracts is proposed by Weili et al. [7]. They present a classification model trained with two kinds of features (i.e., “Account” and “Opcode” features) extracted from the transaction history data and operation codes (opcodes) of smart contracts to detect ponzitracts. “Account” features, such as Known rate (the proportion of receivers who have invested before payment) and Balance (the balance of the smart contract), are collected through analyzing the transaction history data. So their technique relies partly on transaction data which however are not available in the early days of ponzitract deployment. It means detection based on transaction data occurs only after the damage has been done. In the absence of transaction data, the existing approach gives a much less satisfactory result.

In this paper, we propose a novel ponzitracts detection technique according to our speculation that an accurate model...
of the opcodes will reveal the behavior of a smart contract and thus identify whether it is a ponzi contract. Based on the hypothesis we have implemented PonziDetector that does not rely on transaction data. Behavior trees built on the Ethereum Testnet are introduced in PonziDetector to fully characterize the dynamic behaviors of smart contracts. Specifically, at first, PonziDetector employs the traditional testing techniques to mining the complete behaviors (i.e., opcodes) of smart contracts during interacting with them by using tests. We regard the opcodes as the behaviors of the smart contract, explained in detail in Section II-B. Secondly, these behaviors are leveraged to build behavior graphs, and we further use the pruning technology to eliminate the cyclic edges in that to produce comparable behavior trees. Then, the adapted All Path Tree Edit Distance (AP-TED) [11] algorithm is employed to calculate the similarities among weighted behavior trees. A behavior forest is constructed on all behavior trees in a smart contract. Behavior forest similarity is introduced to analyze the smart contract under detection. Finally, PonziDetector combines with the threshold analysis to detect ponzi contracts. Note that the entire process does not rely on transaction data.

We utilize a publicly available smart contract dataset [7] to evaluate our approach. The evaluation results show that the behaviors mined by PonziDetector are more completely, thereby can effectively improve the recall (increased by nearly 15%) of early detection of ponzi contracts while maintaining precision is no less than that of a previous study [7].

In summary, we make the following contributions:

- PonziDetector detects ponzi contracts from the perspective of the behavior described by the smart contracts themselves. It does not rely on anything else except for the smart contract itself and can detect the ponzi contract that is just deployed.
- The experiments are conducted on a public dataset 1 and the experimental results show that PonziDetector can apparently improve the performance of ponzi contract detection, i.e., high precision and recall.
- We released all our experimental results and a behavior forest database of known ponzi contracts at the website 2 for other researchers to conduct related research.

The rest of this paper is organized as follows. Section II describes two basic concepts. The details of our methodology are given in Section III. We introduce the experiment in detail in Section IV. Threats to validity and related work are given in Section V and Section VI respectively. The conclusion is in Section VII.

II. BASIC CONCEPTS

In this section, we introduce two basic concepts on smart Ponzi scheme and program behavior.

A. Smart Ponzi Scheme

For ease of comprehension, we use a practical example to illustrate the smart Ponzi scheme. As shown in Fig.1, “StackyGame” 3 is a smart contract which implements the Ponzi scheme. It declares a participant array used to records all investors’ information (line s0). The function enter() is a core function where the investment and Ponzi scheme occur (lines s16 – s40). The functions $\text{msg.sender}$ and $\text{msg.value}$ are transaction properties 4 used to record the address and investment amount of the investor (lines s23 – s24). When the investment amount of the new investor meets certain conditions (line s17), “StackyGame” firstly collects some fees (lines s25 – s30). Then, to encourage former investors to invite more new investors, it also automatically send high rewards to former investors (lines s35 – s36) when the balance of the contract account (i.e., balance declared at line s9) is sufficient (line s31). The number of rewards also depends on the former’s investment amount (lines s42 – s44), and the higher the investment, the higher the reward. Finally, the function collectFees() which can only be accessed by the owner of “StackyGame” makes it easier to reap without spending a cent (lines s41 – s45). Note that the former investors have income only based on new investors falling into the scam and all of them can not withdraw their investments by themselves. Obviously, it is a classic smart Ponzi scheme.

B. Program Behavior

There are many studies on program behavior related to program executions and operations [12]–[18]. A smart contract is a special program running on EVM. With the guide of the work [17], we employ opcodes to capture behaviors of the smart contract. In Ethereum, the opcode is the mnemonic form of EVM bytecode, and the type of operations corresponding to opcodes is fixed [4]. For example, the opcode corresponding to the bytecode ‘0x01’ is ‘ADD’, i.e., representing addition operation. Therefore, the opcode is more readable while containing all the information contained in the bytecode.

For easy to understand, we use a simple smart contract with a loop instruction (i.e., while instruction), as shown in Fig. 2, to illustrate the smart contract behavior. After deploying the smart contract “SimpleSC” into Ethereum Testnet, we can interact with it by invoking the function “rewardPlay()”. For example, a testing input (amount = 3, balance = 4) can be used to interact with it, and then we can collect opcodes shown in Fig. 3-(a). Further, as shown in Fig. 3-(b), directed edges are used to connect these opcodes to represent continuous behaviors of the smart contract. To improve the efficiency of analysis, the cyclic edge would be pruned to produce a behavior tree, as shown in Fig. 3-(c). Formally, we define a behavior tree as follows.

**DEFINITION 1 (Behavior Tree $\mathcal{B}T$):** A behavior tree of a function $f$ in a smart contract is a labeled tree defined by

$$\mathcal{B}T(f) = \langle v_0, V, E \rangle$$

- $v_0$ is the entrance of $f$, as the root vertex of the tree;
- $V$ is the set of vertices of $\mathcal{B}T$;
- $E$ is the set of edges of $\mathcal{B}T$.

[1] base.site/scamedb
[2] github.com/wssun/PonziDetector

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3 etherscan.io/address/0x8f13ad43088b64ddd10e161361386f5952d665
4 The msg variable is a special global variable that contains properties (e.g., msg.sender) which allow access to the blockchain.
• $V$ is a non-empty finite set of vertices, in which each vertex has two labels: opcode and execution times.

• $E \subseteq V \times V$ is a set of unlabeled undirected edges.

All directed edges of smart contract execution is simplified as undirected edges in a tree. For each function, a behavior tree is constructed. In practice, we only construct the behavior tree for the function that is explicitly claimed in smart contract. In Fig. 2-(a), four basic blocks $b_1$–$b_4$ are remarked: $b_1$ at line $s_4$, $b_2$ at line $s_5$, $b_3$ at line $s_6$, and $b_4$ at line $s_7$. In particular, $b_1$ is the “entry block”, $b_4$ the “exit block”. The Fig. 2-(b) shows a control flow graph (CFG) [19] that consists of these four blocks. Fig. 2-(b) and Fig. 3-(c) are compared to illustrate the difference between two ways. $BT$ not only contains the syntax (logic structure) the program that CFG mainly focuses on but also takes the semantics of the smart contract into account.

The state-of-art [7] experimental results show that opcodes can be more critical and valuable for detecting ponzitracts. These inspires us to introduce $BT$ to detect ponzitracts.

### III. Methodology

Our methodology PonziDetector, as shown in Fig. 4, has the following parts: generating simulation data for transaction properties, generating tests by fuzzing, constructing behavior trees using tests, calculating behavior forest similarity and detecting ponzitracts using behavior forest similarity. The solid blue line (labeled ‘3’ in Fig. 4) indicates the deployment of smart contracts, and the other solid black lines represent the flow of various data.

#### A. Data Generation

Given a smart contract $X$, before interacting with it, we firstly need to prepare data for transaction properties. The property $msg.sender$ is an address type and refers to the sender of the message (current caller). In our Ethereum Testnet, there are many simulated account addresses that can be used as external callers of $X$, i.e., senders of the message.

For the property $msg.value$, it is a uint type and refers to the number of wei sent with the message. Ether units consist of wei, finney, szabo and ether, among which wei is the minimum unit [6]. To dig out the complete smart contract behavior as much as possible, it is necessary to generate reasonable data for $msg.value$. We employ the seeding strategy [20] to generate candidate data. Specifically, we firstly extract numeric values along with ether units from code statements related to $msg.value$. For example, the numeric 1 ether would be extracted from the statement $s_{17}$ in Fig. 1. We consider these seeds as boundaries. Further, with the guidance of mutation operation from genetic algorithms [20], for each boundary, we generate two new values (known as offsprings) that less and larger than the boundary respectively through two simplest mutation operators (i.e., $+$ and $-$). For example, given the boundary 1 ether, we firstly transfer it to minimum unit (1 ether = $10^{18}$ wei); then automatically generate two offsprings, e.g., $10^{18} \pm \Delta$. In practice, $\Delta$ usually set as the minimum disturbance. In our case, the input space of
**msg.value** is `uint` thereby 1 is the minimum disturbance. All seeds and offsprings are saved to a constant pool for subsequent interaction with `X`.

### B. Test Generation

Given a smart contract `X`, the Adapted Compiler module integrating multiple versions of the `solc` compiler is responsible for compiling it. Some smart contracts specified the version number of the compiler in the first line of code by using the instruction "pragma solidity ***", and "****" will be replaced by the specific version number of `solc` compiler, such as the first line `s1` in Fig. 2. The Adapted Compiler automated scans the `X`’s source code statically to find the best matching version of the `solc` compiler. If the target compiler version is not found, the Adapted Compiler will try to compile it using multiple versions of the `solc` compiler, from high to low versions until `X` is compiled successfully.

The ABI Parser module analyzes and extracts all functions information from the compilation results of `X`. For each function, the name and parameters of this function are extracted. This module employs the fuzzing [21] technique and aims at generating one set of candidate tests for each function that requires inputs. Specifically, the test generation module equipped with the tool ContractFuzzer [22] receives types of parameters as inputs and outputs some specific values against specific types. ContractFuzzer [22] takes different strategies to generate inputs for fixed-size inputs (e.g., `uint`) and non-fixed-sized inputs (e.g., `string`). For example, in Fig. 2, the function "rewardPay()" with two `uint` parameters, our generator may generate tests like `(amount = 3, balance = 4)` for it. Considering the expensive runtime cost of the execution of test cases on smart contracts, our test generator creates 10 test cases for each input. Finally, all tests are saved to test set `T`, so that we can leverage them to interact with the more smart contracts in the next step.

### C. Behavior Forest Construction

**DEFINITION 2 (Behavior Forest `BF`):** A behavior forest of a smart contract `X = \{f_1, f_2, \cdots, f_m\}` is defined by

\[
BF(X) = \cup_{i=1}^m BT(f_i)
\]  

Algorithm 1 describes the construction process of behavior forest for a given smart contract. The inputs are a smart contract `X` with a set of functions `\{f_i\}`, a test set `T = \{t_j\}` generated by fuzzing and a set of simulated account address `A = \{msg.address_k\}` from Ethereum Testnet. The output is a behavior forest `BF(X)` with respect to `T`.

**Algorithm 1 Construction of `BF`**

**Input:** `X = \{f_i\}`, `T = \{t_j\}`, `A = \{msg.address_k\}`;

**Output:** `BT`;

1. Set `BF = \emptyset`;
2. Set `V = simulateMV(X)`;
3. var `comResult = compile(X)`;
4. var `xAddr = deploy(comResult)`;
5. var `funcList = ABIParser(comResult)`;
6. for each function `f_i \in X` do
7. \hspace{1em} var `BT(f_i) = NULL`;
8. \hspace{1em} for each `msg.value v_m \in V` do
9. \hspace{2em} for each test `t_j \in T` do
10. \hspace{3em} `op = interact(xAddr, msg.address_k, v_m, f_i, t_j)`;
11. \hspace{3em} \hspace{1em} `var BT = buildBT(op)`;
12. \hspace{3em} `BT(f_i) = mergeAndPrune(BT(f_i), BT)`;
13. \hspace{1em} end for
14. \hspace{1em} `BF(X) = BF(X) \cup \{BT(X, f_i)\}`;
15. end for
16. end for
17. output `BF(X)`;

For a smart contract `X`, it is firstly statically analyzed to produce simulation data for the transaction property `msg.value` (line 2). Then, it is compiled and deployed by invoking the interfaces of `compile()` and `deploy()` respectively (lines

![Fig. 4: Framework of PonziDetector](image-url)
Then, the function information is extracted from the compilation results and the opcodes are produced for each function \( f_i \) by invoking the interface `interact()` (line 10). In essence, an interaction is a transaction. The elements required to complete a transaction include: address of \( X \), `xAddr`, address of the transaction initiator `msg.address`, transaction amount of `msg.value`, `v_m`, the function for executing the transaction \( f_i \) and its parameters \( t_j \). The interface `buildBT()` is used to generate a partial behavior tree (line 11). These partial behavior trees are merged and pruned to produce a behavior tree for each function (line 12). The merging operation is responsible for merging partial behavior trees generated under different \( v_m \) and \( t_j \) into a complete behavior tree or behavior graph. (as shown in Fig. 3-(b)). The pruning operation is responsible for eliminating the cyclic edge so that producing the easy-to-analyze behavior tree (as shown in Fig. 3-(c)). Finally, for each \( X \), a behavior forest \( BT(X) \) is the output (line 17).

**Behavior Tree Filtering:** Obviously, some functions in a ponzitract present normal program behavior. Hence, we need to filter these normal behavior trees in a ponzitract. Given a ponzitract \( Y^P \) and a non-Ponzi smart contract \( Y^N \), Algorithm 1 is used to generate two sets of behavior trees, \( BT(Y^P) \) and \( BT(Y^N) \), respectively. In order to improve the performance of ponzitract detection, \( BT(Y^N) \) is used to filter \( BT(Y^P) \). That is, we use \( BT(Y^P) - BT(Y^N) \) for ponzitract detection in practice.

**D. Behavior Forest Similarity Measurement**

In order to introduce behavior forest similarity, we first define behavior tree similarity based on the tree edit distance [23], i.e., \( D(BT(f_i), BT(f'_i)) \). The edit distance is the minimal-cost sequence of vertex edit operations that transforms one tree into another via insertion, deletion and relabeling operations. An efficient method AP-TED [11] is used for tree edit distance calculation in this paper. Please note that each vertex in a behavior tree has two labels: specific opcode and its execution times. For example, in Fig. 3-(c), there is a vertex with the label ‘DUP1:3’ where 3 is execution times of the opcode ‘DUP1’. That is one label is counted into 0.5 for relabeling in our methodology.

Let \( |BT(f_i)| \) be the number of vertices in \( BT(f_i) \). It is not difficult to see that \( D(BT(f_i), BT(f'_i)) \) is not larger than \( \max(|BT(f_i)|, |BT(f'_i)|) \). Intuitively, two trees are more similar if the tree edit distance is lower. In this paper, we use \( \phi(BT(f_i), BT(f'_i)) \) to represent the behavior tree similarity and \( \phi \in [0, 1] \) is calculated by the following equation:

\[
\phi(BT(f_i), BT(f'_i)) = 1 - \frac{D(BT(f_i), BT(f'_i))}{\max(|BT(f_i)|, |BT(f'_i)|)}
\]

Given two smart contracts \( X = \{f_1, f_2, \cdots, f_m\} \) and \( Y = \{f_1', f_2', \cdots, f_n'\} \), the behavior forests can be constructed from Algorithm 1 with filtering and denoted by \( BT(X) = \{BT(f_1), BT(f_2), \cdots, BT(f_m)\} \), \( BT(Y) = \{BT(f_1'), BT(f_2'), \cdots, BT(f_n')\} \), respectively. The similarity of two sets is normally defined by the maximum similarity between two elements in the two sets. In order to balance each behavior tree \( BT(f_i) \) in a forest, a weight \( \omega_i = \frac{|BT(f_i)|}{\sum_{i=1}^{m}|BT(f_i)|} \) is introduced. Formally, the behavior forest similarity is defined as follows.

**DEFINITION 3 (Behavior Forest Similarity):** Given two behavior forests \( BT(X) \) and \( BT(Y) \), the behavior forest similarity \( \Phi \) is defined as,

\[
\Phi(BT(X), BT(Y)) = \sum_{i=1}^{m} \omega_i \times \max_{j\in[1,n]} \{\phi(BT(f_i), BT(f'_j))\}
\]

It is not difficult to see that \( \Phi(BT(X), BT(Y)) \in [0, 1] \) for any \( X \) and \( Y \), because each \( \phi \in [0,1] \) and the result is the average. Please note that \( \Phi(BT(X), BT(Y)) \) is asymmetrical, i.e., \( \Phi(BT(X), BT(Y)) \neq \Phi(BT(Y), BT(X)) \) in some cases. In our methodology, \( X \) is a smart contract under detection and \( Y \) is a known ponzitract. The asymmetric can work well on the one-way comparison in ponzitract detection.

**Ponzitract Detection:** Given a smart contract \( X \) under detection, Algorithm 1 is used to construct a behavior forest \( BT(X) \). Please note that a large number of known ponzitracts and non-Ponzi smart contracts have been collected. All the behavior forests will be constructed in advance to generate a *PonziBF* database. For each ponzitract \( Y \in PonziBF \), we calculate the behavior forest similarity between \( X \) and \( Y \), i.e., \( \Phi(BT(X), BT(Y)) \). If \( \Phi(BT(X), BT(Y)) > \delta \), \( X \) will be classified as a ponzitract, in which \( \delta \) is a threshold, which will be discussed in Section 4. All \( Y \) with \( \Phi(BT(X), BT(Y)) > \delta \) will also be collected for manually inspecting \( X \) in further.

**IV. EVALUATION**

In this section, we present the details of our experiments as well as the results analysis. To evaluate the performance of *PonziDetector*, we applied it to a public smart contracts dataset and investigated the following research questions:

- **RQ1**: How effective is *PonziDetector* for ponzitract detection?
- **RQ2**: How efficient is *PonziDetector* for ponzitract detection?
- **RQ3**: What prompts *PonziDetector* to employ the behavior forest similarity (behavioral similarity for short) instead of common textual similarity to detect ponzitract?

**A. Experimental Setup**

**Experimental Environment.** All the experiments were performed on 64-bits Ubuntu 16.04.4 desktop with Intel i5-3470 CPU and 8GB of memory. We setup a private blockchain as the Ethereum Testnet with the geth client version 1.8.21. We used web3.js in our node.js program to interact with the geth client and used JSON-RPC to gain the results of runtime opcodes. In order to deploy smart contracts with different versions, we built a solc.js compiler with binaries of soljson from v0.1.1-nightly to v0.6.0-nightly.

**Experimental Design.** To answer our three research questions, we designed the following two experiments:

The first experiment is to evaluate the effectiveness and efficiency of *PonziDetector* by comparing the precision and
recall of ponzitract detection achieved by PonziDetector with a previous work [7] under the same dataset of smart contracts.

The second experiment is to compare the textual and behavioral similarity among smart contracts, aiming at proving that, in the application scenario of ponzitract detection, it is more accurate to use the behavioral similarity rather than the textual similarity to represent the similarity among smart contracts. In this comparison, we used Difflib [24] to compare two smart contracts’ codes, then calculated the textual similarity.

B. Experimental Subjects and Evaluation Metrics

In this paper, we utilized a public dataset of smart contracts released by [7] as our experimental subjects, and downloaded 3,972 smart contracts with verified source code from ibase.site, of which 132 were labeled as ponzitracts. 129 ponzitracts were deployed successfully. Three ponzitracts deployed failed for two reasons: (1) two of them failed due to a wrong compilation of the source code; (2) the remaining one prompted “This contract does not implement all functions and thus cannot be created.”. Then, we tried to interact with 129 ponzitracts, one of which 5 can’t be interacted with because its code specifies two specific addresses that do not exist in our Ethereum Testnet. In this study, we temporarily ignore this ponzitract, and will explore this issue further in future research.

We randomly split 128 ponzitracts into two groups, one group containing 96 ponzitracts is used to build a PonziBF database, and the remaining 32 ponzitracts is used to verify the performance of PonziDetector (corresponding to the $SC^P$ column in Table I). Furthermore, we randomly selected 192 out from 3,840 non-Ponzi smart contracts, and all of them can be successfully deployed and interacted with. 96 of 192 non-Ponzi smart contracts were used to filter behavior trees (i.e., normal program behaviors) that are also appearing in the behavior forest database of non-Ponzi smart contracts from PonziBF (corresponding to the G1’s $SC^N$ column in Table I). The remaining 96 non-Ponzi smart contracts were randomly divided into three groups. All groups were combined with 32 ponzitracts respectively to get three test datasets (corresponding to G2, G3, G4 in Table I). The ratio of ponzitracts to non-Ponzi smart contracts in each group is 1:1. It should be noted that we used the same 32 ponzitracts in G2, G3, and G4, that is, among which ponzitracts are identical, but the other 32 non-Ponzi smart contracts are entirely different. In summary, four groups of datasets as shown in Table I are used in our experiments.

To evaluate the performances of PonziDetector, three measure metrics: precision ($P = TP/(TP + FP)$), recall ($R = TP/(TP + FN)$), and $F_1$-measure ($F_1 = 2 \times P \times R/(P + R)$) are employed. The $TP$ and $FP$ values are the number of ponzitracts and non-Ponzi smart contracts among the detected results respectively; and the $TN$ and $FN$ values are the number of non-Ponzi smart contracts and ponzitracts among the rest results respectively. The precision corresponds to the proportion of ponzitracts in all smart contracts detected by the threshold, which indicates how useful the detected results are. The recall corresponds to the proportion of ponzitracts detected by the threshold in all ponzitracts labeled manually, which indicates how complete the detected results are. Since both precision and recall are important in ponzitract detection, we further use the $F_1$-measure to evaluate PonziDetector. The $F_1$-measure is the harmonic average of the precision and recall, where an $F_1$-measure reaches its best value at 1 (perfect precision and recall) and worst at 0.

C. Experimental Results and Analysis

This part of the experimental study is mainly used to answer RQ1 and RQ2.

PonziDetector employs threshold analysis to classify smart contracts. When the behavior forest similarity between the smart contract under detection X and the ponzitract Y is greater than a given threshold $\delta$ (i.e., $\Phi(BF(X), BF(Y)) > \delta$), we classify X as the ponzitract. Therefore, the performance of the PonziDetector is affected by the choice of threshold. To find an optimal threshold or a suitable threshold interval, we experimented with several different thresholds. Specifically, the initial threshold was set to 0.05, and each time the increase was 0.05 to the end of 1.00, a total of 20 experiments were performed.

Table II lists the experimental results of PonziDetector on test datasets G2, G3 and G4 with different thresholds. Due to the limited space, for the experimental results on the PonziBF database after filtering, we only list its $F_1$-measure (corresponding to the $F_1$ column in the G2, G3, and G4 columns) and average of each metric results (corresponding to the $P$, $R$ and $F_1$ columns in “Average” column) to represent the performance of PonziDetector, without showing precision and recall details. When the threshold is 0.75, PonziDetector has achieved a precision of 1.0 on every test dataset, so we didn’t list the experimental data after 0.75.

1) PonziDetector’s Effectiveness: In order to better illustrate the effectiveness of PonziDetector, we directly compared the experimental results of PonziDetector with that shown in the paper [7] reported by Weili et al. The reason for comparing with them are: (1) the smart contract dataset we used is public by them; (2) we all tried to solve the same problem, that is, ponzitract detection; and (3) the opcodes of smart contracts were used in both two methodology. The best performance of their methodology presented in their paper as follows: the precision is 0.94, the recall is 0.81, and the $F_1$-measure is 0.86. Compared with their methodology, as shown in Table II,

<table>
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<th>$SC^N$</th>
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<tr>
<td>0.35</td>
<td>0.698</td>
<td>0.938</td>
</tr>
<tr>
<td>0.40</td>
<td>0.789</td>
<td>0.938</td>
</tr>
<tr>
<td>0.45</td>
<td>0.857</td>
<td>0.938</td>
</tr>
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<td>0.50</td>
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<td>0.938</td>
</tr>
<tr>
<td>0.55</td>
<td>0.968</td>
<td>0.938</td>
</tr>
<tr>
<td>0.60</td>
<td>0.967</td>
<td>0.906</td>
</tr>
<tr>
<td>0.65</td>
<td>0.966</td>
<td>0.875</td>
</tr>
<tr>
<td>0.70</td>
<td>0.963</td>
<td>0.813</td>
</tr>
<tr>
<td>0.75</td>
<td>1.000</td>
<td>0.813</td>
</tr>
</tbody>
</table>

**PonziDetector** achieves the best performance on the G2, G3, G4 test datasets when the threshold $\delta = 0.55$. At this time, except for the precision on the G4 is less than 0.94, the values of other metrics are higher than their methodology.

In addition, if only the “Opcode” features are considered, regardless of the “Account” features, the performance of their methodology is as follows: the precision is 0.90, the recall is 0.80, the $F_1$-measure is 0.84. It is worth noting that there may not be enough “Account” features available in the early stages of a ponzitract release. Fortunately, **PonziDetector** does not rely on the “Account” features, so it is not limited by how long the contract has been deployed on Ethereum blockchain and can be used for early detection of ponzitracts.

We suspect that some behavior trees in **PonziBF** may also exist in some non-Ponzi smart contracts. However, the existence of them may not only reduce the accuracy of ponzitract detection but also reduce the detection efficiency. To improve the effectiveness and efficiency of **PonziDetector**, we tried to filter the database **PonziBF**. It is well known that a decrease in recall usually accompanies the increase in precision. In our scenario, when the threshold is 0.55, **PonziDetector** achieves the best performance, and the corresponding $F_1$ value is the largest. From Fig. 5 (a) - (c), combining with the detailed data in Table II, we can find two phenomena:

1. When $\delta \in (0.00, 0.55)$, the $F_1$ and $F_1'$ value will increase as the $\delta$ increases, and in the case of the same $\delta$, the $F_1'$ value is greater than or equal to the value $F_1$ (i.e., $F_1' \geq F_1$);
2. When $\delta \in (0.55, 1.00)$, the $F_1$ and $F_1'$ value will decrease as the $\delta$ decreases, and in the case of the same $\delta$, the $F_1'$ value is less than or equal to the value $F_1$ (i.e., $F_1' \leq F_1$).

The reason behind these phenomena is that in the case of the same $\delta$, the number of results searched after filtering may be less than before filtering. And when $\delta \in (0.00, 0.55)$, the number of $FP$ is reduced faster than $TP$, while $\delta \in (0.55, 1.00)$ is the reverse. In summary, the filter improves the accuracy of the behavioral similarity measure, making $F_1$ converge faster, which improves the effectiveness of **PonziDetector**.

To make **PonziDetector** gain better ability of generalization, we do not intend to set the similarity threshold $\delta$ to a fixed value of 0.55. Instead, we hope to find a value interval for the threshold ($TVI$) in which **PonziDetector** can perform satisfactorily. To find such an interval, we first need to find a satisfactory value interval for three metrics (i.e., precision, recall, and $F_1$-measure). In other words, **PonziDetector**'s performance would be satisfactory if the values of three metrics fall within this interval. The value interval of the threshold corresponding to the value interval of metrics ($TVI$) is which we expect to find. As we have described before, we consider that precision and recall are equally crucial for ponzitract detection. $F_1$-measure is the harmonic average of the precision and recall. Therefore, we set the lower bound of the value interval of metrics to the maximum between the precision and the recall. In summary, we set the upper and lower bounds of the value interval of metrics to 0.90 and 1.00, respectively, i.e., $TVI \in [0.90, 1.00]$. The value 0.90 is inspired by the maximum precision and recall that can be achieved by the methodology proposed by Weili et al. [7] in the absence of “Account” features. Fig. 6 shows the performance of **PonziDetector** (i.e., three metrics) with different thresholds. In Fig. 6, we can see a black division line (corresponding to the value of three metrics are 0.9), and the interval $TVI$ corresponds the part above the division line. We can clearly see that the nodes (circles, diamonds, and triangles nodes) used to represent the values of the three metrics appear three times at the same time above the division line, and the corresponding thresholds are 0.5, 0.55, and 0.60, respectively. Therefore, we conclude that the upper and lower bounds of the value of the threshold are 0.5 and 0.6, respectively, i.e.,
**TVI** ∈ [0.50, 0.60].

Moreover, to objectively evaluate the effectiveness of PonziDetector in our limited ponzitract set, we also adopted cross-validation. Cross-validation is any of various similar model validation techniques for assessing how the results of a statistical analysis will generalize to an independent data set [25]. Specifically, we use k-fold cross-validation to evaluate the effectiveness of PonziDetector. For experimental research, 30 subjects per group are often cited as the minimum [26]. 30 is a rule of thumb. Like all rules of thumb it only says something about reasonableness. Thus, to ensure statistical significance, we set the value of k to 4 so that the sample size of ponzitracts is 32 > 30 in each group. Table III shows the experimental results of 4-fold cross-validation.

In Table III, R1, R2, R3 and R4 are the four groups of results for 4-fold cross-validation, respectively. We can get the following observations: (1) PonziDetector still achieved the best performance at δ = 0.55; (2) When δ ∈ [0.55, 1.00], the value of all three evaluation metrics (i.e., precision, recall, F1-measure) are larger than 0.9 (the TVI discussed on the above). Thus, based on these observations, we can conclude that PonziDetector is superior to the state-of-the-art [7]. In addition, the value (including TVI) of threshold our recommended is reasonable and stable so that we can envision PonziDetector to achieve better generalization ability in the future.

2) PonziDetector’s Efficiency: During the evaluation of PonziDetector, most of the time was spent on building a PonziBF database. This is a fundamental and essential work for our approach, but it is a preparation work that does not take up the new smart contract detection time. When detecting a new smart contract X, the time-consuming processes include (1) interaction with X, and (2) searching for the candidate behavior forest set (CBF) in PonziBF.

In the process (1), in order to improve the interaction efficiency, we set the number of tests to 10 instead of more, to limit the times of interactions with the smart contract deployed on Ethereum Testnet.

In the process (2), PonziDetector tries to search for the candidate ponzitract set CBF that used to assist in judging whether X is a ponzitract. To improve search efficiency, we try to filter some behavior trees from PonziBF that are irrelevant to judge whether X is a ponzitract.

Table IV shows the comparison of experimental results before and after filtering PonziBF. Although we only filtered 40 irrelevant behavior trees from PonziBF, the efficiency of search for CBF is still significantly improved (increased by nearly 25%). By optimizing the above two processes, PonziDetector takes an average of 4.8 seconds to detect X.

**D. Textual and Behavioral Similarity**

This part of the experimental study is mainly used to answer RQ3. We have further studied the textual similarity of smart contracts to prove that it is more accurate and reliable for PonziDetector to detect ponzitracts from the perspective of behavioral similarity.

We use Difflib [24], a baseline tool for textual similarity measure, to compare smart contracts, and calculate the textual similarity with the following equations:

$$\text{sim}_D(s_1, s_2) = 1 - \frac{\min(\|s_2\|_{\text{LOC}}, |D(s_1, s_2)|_{\text{LOC}})}{|s_2|_{\text{LOC}}}$$  \hspace{1cm} (5)

$$\text{sim}(s_1, s_2) = \max\{\text{sim}_D(s_1, s_2), \text{sim}_D(s_2, s_1)\}$$  \hspace{1cm} (6)

Difflib relies on the class “difflib.Differ” to compare sequences of lines of text and produce human-readable differences or deltas [24]. It has been used in code similarity analysis [27], [28]. Referring to these papers, given two smart contracts s1 and s2, their textual similarity is calculated by Equation (5), where |s1|_{LOC} and |s2|_{LOC} correspond to the number of lines of code (LOC) in s1 and s2 respectively. D(s1, s2) represents the output of Difflib. Note
that \( \text{sim}_D(s_1, s_2) \) is sensitive to parameter order, and thus \( \text{sim}_D(s_1, s_2) \neq \text{sim}_D(s_2, s_1) \) in most cases. As Equation (6) shows, we regard the maximum in \( \text{sim}_D(s_1, s_2) \) and \( \text{sim}_D(s_2, s_1) \) as the similarity between two smart contracts.

![Fig. 7: Comparison of similarity distribution](image)

Table III: The experimental results of 4-fold cross-validation

<table>
<thead>
<tr>
<th>( \delta )</th>
<th>( P )</th>
<th>( R )</th>
<th>( F_1 )</th>
<th>( P )</th>
<th>( R )</th>
<th>( F_1 )</th>
<th>( P )</th>
<th>( R )</th>
<th>( F_1 )</th>
<th>( P )</th>
<th>( R )</th>
<th>( F_1 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.50</td>
<td>0.919</td>
<td>0.938</td>
<td>0.928</td>
<td>0.923</td>
<td>0.875</td>
<td>0.898</td>
<td>0.893</td>
<td>0.938</td>
<td>0.941</td>
<td>0.921</td>
<td>0.969</td>
<td>0.944</td>
</tr>
<tr>
<td>0.55</td>
<td>0.958</td>
<td>0.938</td>
<td>0.947</td>
<td>0.945</td>
<td>0.875</td>
<td>0.908</td>
<td>0.931</td>
<td>0.938</td>
<td>0.933</td>
<td>0.949</td>
<td>0.969</td>
<td>0.959</td>
</tr>
<tr>
<td>0.60</td>
<td>0.967</td>
<td>0.906</td>
<td>0.935</td>
<td>0.955</td>
<td>0.875</td>
<td>0.913</td>
<td>0.947</td>
<td>0.906</td>
<td>0.926</td>
<td>0.958</td>
<td>0.938</td>
<td>0.947</td>
</tr>
</tbody>
</table>

Table IV: Comparison of PonziDetector’s efficiency before and after filtering the database PonziBF

<table>
<thead>
<tr>
<th>Count_PonziBF</th>
<th>Search_Time_G2 (s)</th>
<th>Search_Time_G3 (s)</th>
<th>Search_Time_G4 (s)</th>
<th>Search_Time_Average (s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Before filtering</td>
<td>318</td>
<td>506.30</td>
<td>403.26</td>
<td>313.01</td>
</tr>
<tr>
<td>After filtering</td>
<td>295</td>
<td>342.84</td>
<td>330.15</td>
<td>244.42</td>
</tr>
</tbody>
</table>

Reduce Improvement | 23 | 163.46 | 73.11 | 68.59 |

2% 32% 18% 22% 25%

The formulas for calculating and \( \text{SCP}^U \) are as follows:

\[
\text{SCP}^U = \begin{cases} 
\frac{\text{SCP} / 100}{\text{IS} / 5} & \text{if LOC Gap} \leq 21 \\
\frac{\text{SCP} / 100}{\text{IS} / 5} & \text{if LOC Gap} > 20 
\end{cases}
\]

where \( \text{IS} \) refers to the interval size of the LOC gap, and the value of \( \text{IS} \) is 5 or 20 when the LOC gap is less than 20 or more than 20.

Table V: The effect of LOC gap on similarity

<table>
<thead>
<tr>
<th>LOC Gap</th>
<th>( \text{AVE}_{TS}^% )</th>
<th>( \text{AVE}_{BS}^% )</th>
<th>( \text{AVE}_{BS}^U )</th>
<th>( \text{SCP} )</th>
<th>( \text{SCP}^U )</th>
</tr>
</thead>
<tbody>
<tr>
<td>0-5</td>
<td>19.9</td>
<td>99.8</td>
<td>9.9</td>
<td>120.0</td>
<td>12.0</td>
</tr>
<tr>
<td>6-10</td>
<td>10.40</td>
<td>99.3</td>
<td>9.93</td>
<td>947.3</td>
<td>9.47</td>
</tr>
<tr>
<td>11-15</td>
<td>6.00</td>
<td>99.1</td>
<td>9.91</td>
<td>581.3</td>
<td>5.81</td>
</tr>
<tr>
<td>16-20</td>
<td>2.10</td>
<td>98.8</td>
<td>9.86</td>
<td>416.1</td>
<td>4.16</td>
</tr>
<tr>
<td>21-25</td>
<td>0.10</td>
<td>98.5</td>
<td>9.85</td>
<td>135.0</td>
<td>1.35</td>
</tr>
<tr>
<td>26-30</td>
<td>0.10</td>
<td>95.3</td>
<td>9.53</td>
<td>651.6</td>
<td>1.65</td>
</tr>
<tr>
<td>31-35</td>
<td>0.00</td>
<td>97.3</td>
<td>9.73</td>
<td>829.3</td>
<td>2.07</td>
</tr>
<tr>
<td>36-40</td>
<td>0.00</td>
<td>96.7</td>
<td>9.67</td>
<td>475.1</td>
<td>1.19</td>
</tr>
<tr>
<td>41-45</td>
<td>0.00</td>
<td>98.5</td>
<td>9.85</td>
<td>390.4</td>
<td>1.48</td>
</tr>
<tr>
<td>46-50</td>
<td>0.00</td>
<td>97.7</td>
<td>9.73</td>
<td>465.1</td>
<td>1.16</td>
</tr>
<tr>
<td>51-55</td>
<td>0.00</td>
<td>97.7</td>
<td>9.73</td>
<td>245.3</td>
<td>0.61</td>
</tr>
<tr>
<td>56-60</td>
<td>0.00</td>
<td>98.5</td>
<td>9.85</td>
<td>50.0</td>
<td>0.13</td>
</tr>
<tr>
<td>61-65</td>
<td>0.00</td>
<td>98.5</td>
<td>9.85</td>
<td>17.0</td>
<td>0.04</td>
</tr>
<tr>
<td>66-70</td>
<td>0.00</td>
<td>95.9</td>
<td>9.59</td>
<td>303.0</td>
<td>0.06</td>
</tr>
<tr>
<td>Total &amp; AVE</td>
<td>2.76</td>
<td>97.9</td>
<td>9.79</td>
<td>8128.0</td>
<td>—</td>
</tr>
</tbody>
</table>

From Fig. 8, we can find, obviously, with the increasing of the LOC gap, in addition to a significant decrease in the number of smart contract pairs (\( \text{SCP} \), corresponding to rectangles), the average textual similarity of smart contracts drops rapidly (\( \text{AVE}_{TS} \), corresponding to a curve connected by circles), while change of the average behavioral similarity of them is slight (\( \text{AVE}_{U}^\text{BS} \), corresponding to a curve connected by triangles). Therefore, based on the above experiments, we can conclude that it is more accurate and independent of smart contract size (i.e., the LOC) to use the behavioral similarity.
Threats to Validation

V. Threats to Validation

A. Internal validity

The behaviors extracted by PonziDetector may be incomplete. For example, some branches may require special inputs to achieve. Since each interaction with the smart contract takes a long time, the more interactions, the more complete the mining behavior will be, and of course the longer it takes. So we took a compromise and generated 10 tests for each smart contract to dig out the full smart contract behavior as much as possible. We will further improve and optimize the extraction of behaviors by combining mature test technologies [29], [30], in the future.

We use the similarity threshold to assist in judging whether a smart contract under detection is a ponzitract. Thus, the choice of threshold affects PonziDetector’s performance. In order to reduce the bias of threshold δ, referencing the paper [28], we tried different δ (δ increased from 0 to 1 by 0.05 each time) for many experiments. And we also employ k-fold cross-validation to ensure that we got a reasonable threshold.

B. External validity

Our experiments were conducted on a public dataset that contained smart contracts that were significantly different from the smart contracts we recently observed on Ethereum. Most of the smart contracts observed today are based on specific Ethereum standards (e.g., ERC-20 [31] and ERC-721 [32]), and although the structure is clear, the logic is more complex, which may affect the generalization of our approach. In the future, we are going to experiment on more new datasets.

VI. Related Work

Smart Ponzi Schemes Detection are mainly focused on the two widely used blockchain platforms, i.e., Bitcoin [33], [34] and Ethereum [7], [9], [35]. Massimo et al. [34] and Weili et al. [7] employed a specific method, i.e., data mining and machine learning techniques, to detect Ponzi schemes on Bitcoin and Ethereum respectively. The research most relevant to us is the study by Weili et al. [7]. Both of us think opcodes as one of the critical features for detecting ponzitracts that appear on Ethereum. The opcodes analyzed by [7] are extracted from the compilation results of smart contracts while we collected that by interacting with smart contracts. The dynamically collected opcodes can more accurately describe the complete running-time behaviors of smart contracts. Besides, they only statistic the frequency of opcodes appearing in compilation result but we utilize them to full characterize the semantic information of smart contracts. Because of these, we succeeded in getting rid of the control of trading data.

Behavioral Similarity usually refers to semantic similarity in existing researches [18], [36], [37]. Sihan et al. [18] regard the proportion of inputs producing the same output on both programs over the specific input domain as the behavioral similarity between two programs. They have applied code behavior similarity measure to promote software engineering education. Coen De et al. [37] aim at using a single abstract pattern description to detect multiple concrete pattern instances, in order to achieve this, they take information about a program’s run-time behavior into account. By incorporating a similarity-based unification algorithm like the one in LikeLog [38], they can overcome failures in the refutation process caused by a syntactic difference between parse tree nodes which might actually evaluate to overlapping sets of objects at run-time and are also able to evaluate the confidence our platform has in the discovered software pattern instances. In [36], it divides the types of program similarity into syntactic (also called representational) and semantic or behavioral similarity two categories and details several potential ideas for measuring semantic similarity, such as Input-Output Relation Similarity idea for behavioral similarity measure. After learning these papers, we find, obviously, that utilize behavioral similarity to represent program similarity is more accurate, which also leads us to believe that employ behavioral similarity to detect ponzitracts is feasible.

Malware Detection is a subject of extensive research [39], [40]. Malware authors use obfuscation techniques [41] like dead code insertion, register reassignment, subroutine reordering, instruction substitution, code transposition, and code integration to evade detection by traditional defenses like firewalls, antivirus and gateways which typically use signature based techniques and are unable to detect the previously unseen malicious executables [39]. The initiator of the ponzi-tract conceal malicious scam behavior by implementing Ponzi schemes as smart contracts. However, from the perspective of software program property, the ponzi-tract is also a type of malware. In [17], the authors construct the opcode running tree to simulate the dynamic execution of a program and use the n-gram method [42] to extract executables features to train a classifier to detect malware. The approach of this study is the closest to ours, and we all think the opcode can represent the behavior of the program or smart contract. But there are two clear distinctions: (1) The opcodes our approach used are dynamically collected during interacting with smart contracts
while that in [17] are extracted from executables; (2) Our approach uses complete opcode behaviors to support detection while that used in [17] is partial (i.e., extracting partial features from the opcode running tree). Therefore, even if we can’t directly compare with their methods, we believe that, to a certain extent, our approach should be more accurate.

VII. CONCLUSION

Smart contracts running on Ethereum have become widely used for a broad spectrum of financial applications. Unfortunately, the advantages of blockchain-managed financial assets have also been exploited by criminals, and fraudulent means such as ponzitracts have appeared. To solve this problem in the early days of ponzitract deployment, we developed PonziDetector to supporting detect ponzitracks. More importantly, PonziDetector does not rely on a large number of practical transaction data which indicated that many investors had been deceived. Thus, PonziDetector can detect ponzitracts early. Our experimental results have proven the effectiveness and efficiency of PonziDetector. We are setting up a smart Ponzi schemes detection platform for users to easily detect deployed smart contracts early and prevent to be deceived.

We observed the latest smart contracts on the Etherscan platform [43] that are significantly different from that released by [7]. Most of today’s smart contracts are based on new Ethereum standards (e.g, ERC-20 [31] and ERC-721 [32]). In the future, we are going to further validate and improve PonziDetector against the latest smart contracts. Also, more applicable testing techniques, such as symbolic execution [29], will be explored to support PonziDetector mining more complete behaviors to further improving the performance of ponzitract detection.

ACKNOWLEDGMENT

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