Stateless Puzzles for Real Time Online Fraud Preemption

Mizanur Rahman
Florida Int'l University, USA
mrahm031@fiu.edu

Ruben Recabarren
Florida Int'l University, USA
recabarren@gmail.com

Bogdan Carbunar
Florida Int'l University, USA
carbunar@gmail.com

Dongwon Lee
Penn State University, USA
dongwon@psu.edu

ABSTRACT

The profitability of fraud in online systems such as app markets and social networks marks the failure of existing defense mechanisms. In this paper, we propose **FraudSys**, a real-time fraud preemption approach that imposes Bitcoin-inspired computational puzzles on the devices that post online system activities, such as reviews and likes. We introduce and leverage several novel concepts that include (i) stateless, verifiable computational puzzles, that impose minimal performance overhead, but enable the efficient verification of their authenticity, (ii) a real-time, graph based solution to assign fraud scores to user activities, and (iii) mechanisms to dynamically adjust puzzle difficulty levels based on fraud scores and the computational capabilities of devices. FraudSys does not alter the experience of users in online systems, but delays fraudulent actions and consumes significant computational resources of the fraudsters. Using real datasets from Google Play and Facebook, we demonstrate the feasibility of FraudSys by showing that the devices of honest users are minimally impacted, while fraudster controlled devices receive daily computational penalties of up to 3,079 hours. In addition, we show that with FraudSys, fraud does not pay off, as a user equipped with mining hardware (e.g., AntMiner S7) will earn less than half through fraud than from honest Bitcoin mining.

KEYWORDS

Stateless Puzzle, Online Fraud Preemption

1 INTRODUCTION

The social impact of online services built on information posted by their users has also turned them into a lucrative medium for fraudulently influencing public opinion [8, 17, 21, 24]. The need to aggressively promote disinformation has created a black market for social network fraud, that includes fake opinions and reviews, likes, followers and app installs [4–6, 18, 22, 23, 25]. For instance, in § 3.1, we show that in fraud markets, a fake review can cost between $0.5 and $3 and a fake social networking "like" can cost

WebSci'17, June 25–28, 2017, Troy, NY, USA

DOI: http://dx.doi.org/10.1145/3091478.3091507

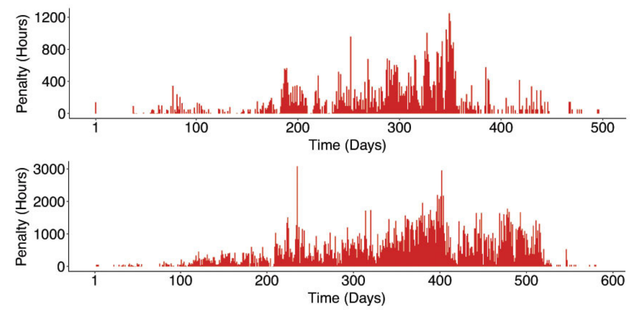


Figure 1: Timeline of daily penalties (in hours) assigned by FraudSys to the Google Play activities of two fraudsters we identified in Freelancer.com. FraudSys imposes daily penalties of up to 1,247 hours to the fraudster at the top and 3,079 hours for the fraudster at the bottom. As a result, the fraudsters need to consume significant computational resources, while their fraud is significantly delayed. This in turn reduces the number of payments they would receive, and impacts their profitability.

$2. The profitability of fraud suggests that current solutions that focus on fraud detection, are unable to control organized fraud.

In this paper we introduce the concept of *fraud preemption systems*, solutions deployed to defend online systems such as social networks and app markets. Instead of reacting to fraud posted in the past, fraud preemption systems seek to discourage fraudsters from posting fraud in the first place. We propose FraudSys, the first real-time fraud preemption system that reduces the profitability of fraud from the perspective of both crowdsourced fraud workers and the people who hire them. FraudSys imposes computational penalties: the activity of a user (e.g., review, like) is posted online only after his device solves a computational puzzle. Puzzles reduce the profitability of fraud by (i) limiting the amount of fraud per time unit that can be posted for any subject hosted on the online system, and (ii) by consuming the computational resources of fraudsters. For instance, Figure 1 shows the timelines of daily penalties assigned by FraudSys to two fraudsters detected in Google Play. Based only on the recorded activities, FraudSys frequently assigned hundreds of hours of daily computational penalties to a single fraudster.

Challenges. Implementing a fraud preemption system raises several challenges. First, FraudSys needs to detect fraud in real-time, whenever a user performs an online system activity. Once assigned, a puzzle cannot be rescinded. This is in contrast to existing systems (e.g., Yelp) that detect fraud retroactively and can update previous decisions when new information surfaces. Second, FraudSys needs to impose difficult puzzles on fraudsters, but minimally impact the experience of honest users. This is made even more complex by the fact that fraudsters can attempt to bypass detection and even obscure their true ability to solve puzzles. Third, a stateful FraudSys service that maintains state for millions of issued and active puzzles is expensive and vulnerable to DoS attacks.

Our Contributions. Through FraudSys, we introduce several innovative solutions. To address the first challenge, we exploit observations of fraudulent behaviors gleaned from crowdsourcing sites and online systems, to propose a real-time graph based algorithm to infer an *activity fraud score*, the chance that a user activity is fraudulent [§ 4.2]. More specifically, we introduce features that group fraudulent activities according to their human creator: FraudSys identifies densely connected components in the co-review graph of the subject targeted by the user activity, each presumably controlled by a different fraudster. It then quantifies the connectivity of the user account performing the action, to each component, and uses the highest connectivity as features that may indicate that the user account and the corresponding component are controlled by the same fraudster. FraudSys then leverages supervised learning algorithms trained on these features to infer the activity fraud score.

To address the second challenge, we develop adaptive hashrate inference techniques to detect the computational capabilities of even adversarial controlled devices to solve puzzles [§ 4.3], and devise mechanisms to convert fraud scores to appropriate temporal penalty and puzzle difficulty values [§ 4.3]. The puzzles assigned by FraudSys do not alter the online experience of users, as they are solved on their devices, in the background. However, the puzzles (1) significantly delay detected fraudulent activities, posted only when the device returns the correct puzzle solutions and (2) consume the computational resources of the fraudsters who control the devices.

To address the third challenge, we propose the notion of *stateless computational puzzles*, computational tasks that impose no storage overhead on the fraud preemption system provider, but enable it to efficiently verify their authenticity and the correctness of their solutions [§ 4.1]. Thus, the fraud preemption system can assign a puzzle to a device from which an activity was performed on the online system, without storing any state about this task. The device can return the results of the puzzle in 5 seconds or 1 day, and the provider can verify that the task is authentic, and its results are correct. This makes our approach resistant to DoS attacks that attempt to exhaust the provider's storage space for assigned puzzles.

We show that the computational penalty imposed by FraudSys on a fraudulent activity is a function of the capabilities of the device from which it is performed, and the probability that the activity is fraudulent. We introduce and prove upper bounds on the profitability of fraud and the amount of fraud that can be created for a single subject, per time unit [§ 5] . We evaluate FraudSys on 23,028 fraudulent reviews (posted by 23 fraudsters from 2,664 user accounts they control), and 1,061 honest reviews we collected from Google Play, as well as 274,297 fake and 180,400 honest likes from Facebook. Even with incomplete data, FraudSys imposes temporal penalties that can be as high as 3,079 hours per day for a single fraudster. We also show that fraud does not pay off. At today's fraud payout, a fraudster equipped with an AntMiner S7 (Bitcoin mining hardware) will earn through fraud less than half the payout of honest Bitcoin mining.

2 RELATED WORK

Computation Based Fraud Preemption. Dwork and Naor [12] were the first to propose the use of computation to prevent fraud, in particular spam, where the sender of an e-mail needs to include the solution to a "moderately hard function" computed over a function of the e-mail. Juels and Brainard [15] proposed to use puzzles to prevent denial of service attacks, while Borisov [11] introduced puzzles that deter Sybils in peer-to-peer networks. In Borisov [11], newly joined peers need to solve a puzzle to which all the other peers have contributed.

FraudSys not only seeks to adapt computational puzzles to prevent online system fraud, but also needs to solve the additional challenges of building puzzles whose difficulty is a function of the probability that an activity is fraudulent, while handling heterogeneous user devices (e.g., ranging from smartphones to machines that specialize in such puzzles).

Graph Based Fraud Detection. Graphs have been used extensively to model relationships and detect fraudulent behaviors in online systems. Ye and Akoglu [26] quantified the chance of a subject to be a spam campaign target, then clustered spammers on a 2-hop subgraph induced by the subjects with the highest chance values. Lu et al. [16] proposed a belief propagation approach implemented on a review-to-reviewer graph, that simultaneously detects fake reviews and spammers (fraudsters).

Mukherjee et al. [19] proposed a suite of features to identify reviewer groups, as users who review many subjects in common but not much else, post their reviews within small time windows, and are among the first to review the subject. Hooi et al. [14] have recently shown that fraudsters have evolved to hide their traces, by adding spurious reviews to popular items. To identify "camouflaged" fraud, Hooi et al. [14] introduced "suspiciousness" metrics that apply to bipartite user-to-item graphs, and developed a greedy algorithm to find the subgraph with the highest suspiciousness. Akoglu et al. [2] survey graph based online fraud detection. [13] provide a survey of community detection methods, evaluation scores and techniques for general networks.

Unlike previous work, FraudSys assigns fraud scores to individual user activities in *real time*, thus uses only partial information. To achieve this, FraudSys develops and leverages features that quantify the connectivity of the user activity to other groups of activities *previously* performed by other fraudsters on the same subject. Further, FraudSys also imposes computation and temporal penalties to discourage fraud creation.

3 SYSTEM AND ADVERSARY MODEL

Figure 2 illustrates the three main components of the system model. First, the online service (the *service*) hosts the system functionality, and stores information about user accounts and featured *subjects*. Subjects can be apps in stores like Google Play, or pages for businesses, accounts and stories in social networks like Facebook.

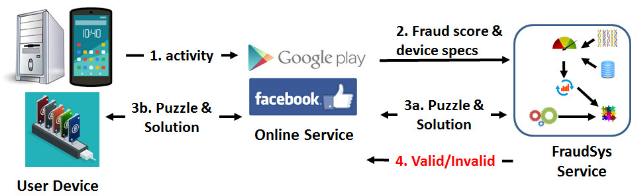


Figure 2: System model. The user performs actions on the online service, from a device that can range from a smartphone to a Bitcoin miner. The online service implements and posts the activity only if and after the FraudSys service validates it. The FraudSys functionality can be implemented by the online service or by a third party provider.

Second, the users: they register with the service, record profile information (e.g., name) and receive initial service credentials, including a unique id. Users can access the online service from a variety of devices. For this, they need to install a client (e.g., app) on each device they use. The online service stores and maintains information about each device that the user has used, e.g., to provide compatibility information on Google Play apps.

Users are encouraged to *act* on existing subjects. The activities include posting reviews, comments, or likes, installing mobile apps, etc. The online service associates statistics over the activities performed for each supported subject. The statistics have a significant impact on the popularity and search rank of subjects [1, 7], thus are targets of manipulation by fraudsters (see § 3.1).

The third component of the system model is the FraudSys service, whose goal is to validate user activities. For increased flexibility, Figure 2 shows FraudSys as an independent provider. However, FraudSys can also be a component of the online service.

3.1 Adversary Model

We consider two types of adversaries – adversarial owners and crowdsourced fraud workers.

Adversarial owners. Adversarial behaviors start with the subject owners. Adversarial owners seek to fraudulently promote their subjects (or demote competitor subjects) in order to bias the popularity and public opinion of specific subjects. For instance, fraudulent promotions seek to make subjects more profitable [3, 17], increase the "reachability" of malware (through more app installs), and boost the impact of fake news.

Fraud workers (= fraudsters). We assume that adversarial owners crowdsource this promotion task (also known as search rank fraud) to *fraud workers*, or fraudsters. In this paper we focus on two types of fraudulent activities: writing fake reviews in Google Play and posting fake "Likes" in Facebook. We have studied fraudster recruitment jobs in crowdsourcing sites and fraud posted in Google Play and Facebook. This has allowed us to collect fraud data (see § 6.1) and to identify several fraud behaviors: (i) more than one fraudster can target the same subject; (ii) user accounts controlled by a fraudster tend to have a significant history of common activities, i.e., performed on the same subjects; and (iii) accounts controlled by different fraudsters tend to have few common past activities.

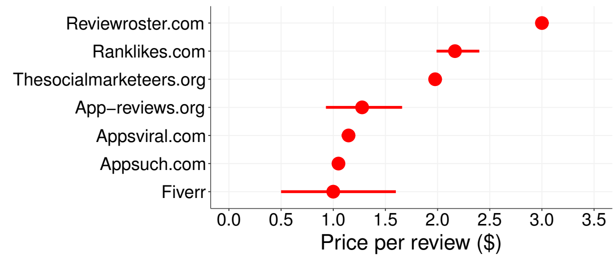


Figure 3: Price per review (minimum, average and maximum), for crowdsourcing sites that focus on app market fraud. The sites offer "fraud packages" and even discounts for bulk fake review purchases. A fake review costs between $0.5-$3.

Fraud incentives. We assume that fraud workers are rational, motivated by financial incentives. That is, given an original investment in expertise and equipment, a fraud worker seeks to maximize his revenue achieved per time unit. Figure 3 shows the minimum, average and maximum cost per fraudulent activity, as advertised by several crowdsourcing and fraud-as-a-service (FAAS) sites: a fake review for an app is worth between $0.5-$3, while a fake social networking "like" can cost $2. In contrast, an adversarial owner may have both financial incentives (e.g., increased market share for his subject, thus revenue), and external incentives (e.g., malware or fake news distribution).

3.2 Fraud Preemption System Definition

We introduce the concept of *fraud preemption systems*, that seek to restrict the profitability of fraud for both fraudsters and the people who hire the fraudsters (i.e., adversarial owners). Specifically, let $Sys = (\mathcal{U}, \mathcal{S}, \mathcal{F}, P)$ be a system that consists of finite sets of users ($\mathcal{U}$), subjects ($\mathcal{S}$) and fraudsters ($\mathcal{F}$) that interact through a set of procedures P. In the adversary model of § 3.1, we say that Sys is a (p,a)-*fraud preemption system* if it satisfies the following two conditions:

(1) **Fraudster deterrence**: The average payout per time unit of any fraudster in $\mathcal{F}$ does not exceed p.
(2) **Adversarial owner deterrence**: The average number of fraudulent activities allowed for any subject in $\mathcal{S}$ per time unit does not exceed a.

In addition, a puzzle-based fraud preemption system needs to satisfy the following requirements:

(1) **Real-time fraud detection**. Detect fraud at the time it is created, with access to only limited information (i.e., no knowledge of the future).
(2) **Penalty accuracy**. Impose difficult puzzles on fraudsters, but minimally impact the online experience of honest users.
(3) **Device heterogeneity**. Both honest and fraudulent users may register and use multiple devices to access the online service. Malicious users may obfuscate the computational capabilities of their devices.
(4) **Minimize system resource consumption**. The high number of issued, active puzzles will consume the resources of the FraudSys provider, and open it to DoS attacks.

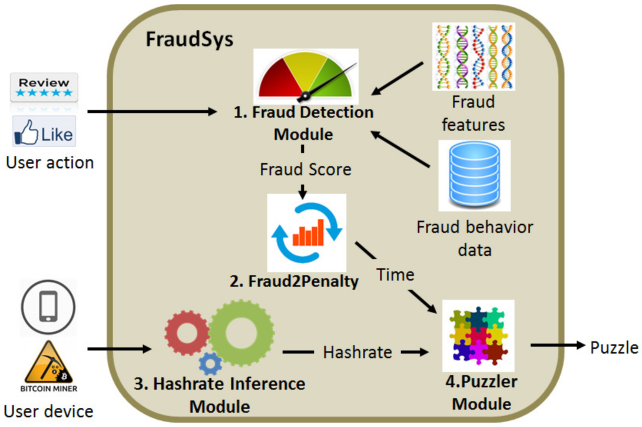


Figure 4: FraudSys architecture. The Fraud Detector module uses supervised learning to assign a fraud score to user activities. The Fraud2Penalty module converts the fraud score to a *time penalty*. The Hashrate Inference module estimates the computational capabilities of the user device. Finally, the Puzzler module generates a puzzle that the device should take approximately the time penalty to solve.

4 FRAUDSYS

We introduce FraudSys, a real-time fraud preemption system that requires users to verify commitment through an imposed resource consumption action for each activity they perform on the online system. Specifically, FraudSys requires the device from which the activity was issued, to solve a *computational puzzle*. FraudSys consists of the modules illustrated in Figure 4: The Fraud Detection module takes as input a user activity and the current state of the subject, and outputs a *fraud score*. The Fraud2Penalty module converts the fraud score to a *time penalty*: the time that the user's device will need to spend working on a computational puzzle. The Hashrate Inference module interacts with the user device in order to learn its puzzle solving capabilities. Finally, the Puzzler module uses the inferred device capabilities to generate a puzzle that the device will take a time approximately equal to *time penalty* to solve.

To address requirement #1, the Fraud Detection module exploits the fraudulent behaviors described in § 3.1. It builds *co-activity graphs* and extracts features that model the relationships between the user performing the activity and other users that have earlier performed similar activities for the same subject.

We address requirement #2 through a two-pronged approach. First, the Fraud Detection and Fraud2Penalty modules ensure that the difficulty of a FraudSys puzzle will be a function of the detected probability of fraud: activities believed to be honest will be assigned trivial puzzles, while increasingly fraudulent activities will be assigned increasingly difficult puzzles. Second, FraudSys does not change the experience of the user on the online system: the user writes the review or clicks on the like button, then continues browsing or quits the app. The assigned puzzle is solved in the background by the device on which the activity was performed. However, FraudSys delays the publication of the activity, until the device produces the correct puzzle solution.

Notation	Definition
U, D, S, A	user, device, subject, activity
T	time of puzzle issue
r	activity fraud score
Δ	puzzle difficulty
η_D	hashrate of device D
Γ	puzzle cookie
Π	puzzle
$target$	puzzle target value
τ	temporal penalty
q	number of shares (puzzle solutions)
K	secret key of FraudSys

Table 1: FraudSys symbol table.

To address requirement #3, the Hashrate Inference module estimates the hashrate of the device performing the activity, and provides the tool to punish devices that cheat about their puzzle solving capabilities. To solve requirement #4, the Puzzler module generates puzzles that outsource the storage constraints from the FraudSys service to the user devices that solve the puzzles. In the following we detail each FraudSys module, starting with the central puzzle creation module.

4.1 The Puzzler Module: Stateless Puzzles

Let U be a user that performs an activity A from a device D, on a subject S hosted by the online service. Table 1 summarizes the notations we use. The FraudSys service stores minimal state for each registered user, and *serializes* his activities, see Figure 5: the devices from which a user performs a sequence of activities on the online service, are assigned one puzzle per activity, each with its own timeout. The device needs to return the puzzle solutions before the associated timeout. To implement this, for each user U, the FraudSys service stores the following entry:

$$U, [\langle D_i, \eta_i \rangle]_{i=1..d}, timeout,$$

where, for each of the $i = 1..d$ devices registered by U, D_i is the device identifier and η_i is its hashrate (puzzle solving capabilities measure, see following), and $timeout$ is the latest time by which one of these devices needs to return puzzle solutions.

FraudSys builds on the computational puzzles of Bitcoin, see [20]. Let $H^2(M)$ denote the double SHA-256 hash of a message M. Then, the FraudSys puzzle issued to device D consists of a $target$ value and a fixed string F. We detail F shortly. To solve the puzzle, D needs to randomly choose 32 byte long *nonce* values until it finds at least one that satisfies:

$$H^2(nonce||F) < target \quad (1)$$

That is, the double hash of the *nonce* concatenated with F, needs to be smaller than the $target$ value, another 32 byte long value. A smaller $target$ implies a harder puzzle. The largest $target$ acceptable by the system is called $target\_1$, or *target of difficulty 1*.

Bitcoin has two drawbacks. First, the current difficulty of Bitcoin puzzles requires computational capabilities that greatly exceed those of devices used to access online services. Second, Bitcoin requires the network to maintain state about issued puzzles. State storage exposes FraudSys to attacks, while not storing state

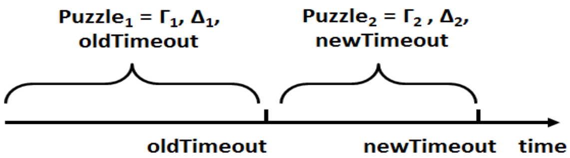


Figure 5: Puzzle serialization: a user can perform multiple activities, but each receives a different puzzle with its own timeout, authenticated through the cookie Γ.

can enable adversaries to lower the difficulty of their assigned puzzles. To address these problems we (i) change the $target\_1$ difficulty to allow trivial puzzles, and (ii) introduce *puzzle cookies*, special values that authenticate puzzles with minimal FraudSys state, see following.

Device hashrate and puzzle difficulty. We set the $target\_1$ value to be a 32 byte long value with one zero at the beginning, e.g., $2^{255} - 1$. In addition, the *hashrate* η_D of a device D is a measure that describes the ability of the device to solve puzzles. Since the puzzles need to be solved in a brute force approach, the hashrate is measured in hashes per second. A relevant concept is the notion of *difficulty*, denoted by Δ, a measure of how difficult it is to solve a puzzle whose input values hash below a given target. Its relationship to the above $target$ value is given by:

$$\Delta = \frac{target\_1}{target} = \frac{2^{255} - 1}{target} \tag{2}$$

Given η_D, we derive the time τ taken by D to solve a puzzle with difficulty Δ, as follows. First, the number of hashes smaller than a given target is equal to the target. For instance, the number of hashes smaller than $target\_1$ is $2^{255} - 1$. Then, the probability p of finding an input that hashes to a value smaller than the target is equal to the target divided by the total number of hashes (2^{256}). Furthermore, the expected number of hashes, E, before achieving the target is given by $1/p$. Thus:

$$E = \eta_D \times \tau = \frac{2^{256}}{target} = \frac{2^{256}}{target\_1} \times \frac{target\_1}{target} \approx 2 \times \Delta$$

and conclude that

$$\tau = \frac{2 \times \Delta}{\eta_D} \tag{3}$$

For instance, the lowest puzzle difficulty is 1, which occurs when the $target$ has a prefix of one zero and the device is expected to generate 2 hashes before solving the puzzle. Similarly, the maximum difficulty is ($2^{255} - 1$), for a $target = 1$, when the device is expected to perform $\frac{2^{255}-1}{1} \times 2 \approx 2^{256}$ hashes.

The FraudSys puzzle and cookies. To minimize the storage imposed on the FraudSys service (see above), we leverage the cookie concept [10]. Algorithm 1 illustrates the puzzle creation, verification and computation components. The FraudSys service generates and stores a secret key K (line 2). When a user U performs an activity A from a device D on a subject S of the online service, the online service calls the BuildCookie function of the FraudSys service (lines 3-11). BuildCookie retrieves the hashrate of the device D from the record stored by FraudSys for U (line 4). It then computes the fraud score associated to the activity (line 5) then converts it to a time penalty τ (line 6). We describe this functionality in the

Algorithm 1 FraudSys puzzle creation, verification and computation components.

1. Object **FraudSysService**
2. K: key;
3. Function **BuildCookie**(U, D, S, A, q)
4. η_D := getHashrate(U, D);
5. r := computeFraudScore(U, S, A);
6. τ := fraud2Penalty(r);
7. Δ := $\eta_D \times \tau / 2q$
8. $oldT$:= getTimeout(U);
9. $newT$:= $oldT + \tau$;
10. Γ := HMAC(K, U, D, S, $newT$, Δ, A);
11. setTimeout(U, $newT$);
12. return Γ, Δ, $newT$;
13. Function **VerifyPuzzle**(U, D, S, A, $timeout$, Γ, σ: share[q])
14. **if** (Γ != HMAC(K, U, D, S, A, $timeout$, Δ) return -1;
15. $target$:= getTarget(Δ);
16. **for** (i := 0; $i < q$; i++)
17. **if** ($H^2(\sigma[i] \mid\mid \Gamma) > target$) return -1;
18. waitUntil($timeout$); post A;
19. $\tau' := T_c - T$;
20. **if** (($\eta_D := 2\Delta/\tau') \geq \eta_{min}$)
21. updateHashrate(U, D, η_D);
22. Object **UserDevice**
23. Function **SolvePuzzle**(Γ, Δ, $timeout$, q)
24. $target$:= getTarget(Δ);
25. σ := new share[q]; i := 0;
26. **while** ($i < q$) **do**
27. $nonce$:= getRandom();
28. **if** ($H^2(nonce \mid\mid \Gamma) < target$)
29. $\sigma[i] := nonce$;
30. i := i+1;
31. return U, D, S, A, $timeout$, Γ, σ;

next subsections. BuildCookie then uses a modified Equation 3 to compute the difficulty Δ that the puzzle should have (line 7). Δ is q times smaller than in Equation 3, as the puzzle solution consists of q shares, see SolvePuzzle. BuildCookie gets the current timeout *oldT* of U, and updates it to *newT* by adding the penalty τ to it (lines 8-9). It then computes the puzzle cookie Γ,

$$\Gamma = HMAC_K(U, D, S, A, timeout, \Delta)$$

as a keyed HMAC [9] over the user and device id, subject, activity, new timeout and puzzle difficulty (lines 9-10). BuildCookie sets U's timeout value to the updated *newT* value (line 11), then returns the following puzzle (line 12) to the online service that forwards it to device D (see Figure 2):

$$\Pi = \Gamma, \Delta, timeout.$$

The puzzle cookie ensures that an adversary that modifies the puzzle's difficulty or timeout, will be detected: the adversary does not know the key K, which is a secret of the FraudSys service. Puzzle cookies are unique with high probability, due to collision resistance properties of the HMAC, whose input is non-repeating.

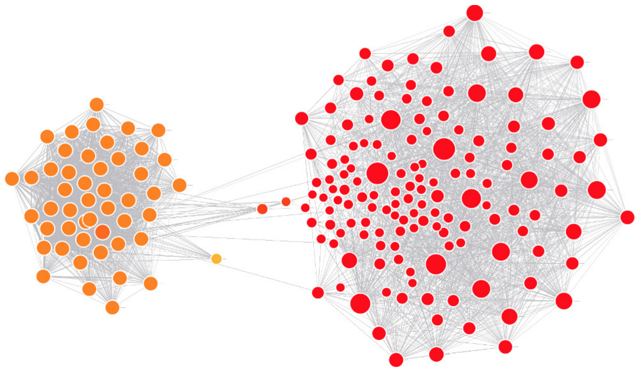


Figure 6: Visualization of the co-review graph of a fraudulent Google Play app. The nodes represent user accounts; edges connect nodes corresponding to accounts with common, past review activities. The nodes in each of the 2 clusters correspond to accounts controlled by the same fraudster.

Solving the puzzle. When the device D receives the puzzle, it needs to solve it: search for q *nonce* values that satisfy the inequality $H^2(nonce \mid\mid \Gamma) < target$, for a *target* corresponding to the difficulty Δ. Specifically, D invokes the SolvePuzzle function (lines 23-31), that needs to identify q *shares*, i.e., nonce values that satisfy the puzzle. q is a system parameter. The function first uses Equation 2 to retrieve the *target* value corresponding to the difficulty Δ (line 24). Then, it generates random *nonce* values until it identifies q values that satisfy the puzzle condition (lines 25-30). SolvePuzzle returns the identified shares (in the σ array), which are then sent to the online service and forwarded to the FraudSys server, along with the user, device and subject ids, activity, timeout and cookie of the received puzzle (see line 12 and Figure 2).

Verification of puzzle correctness. Upon receiving these values, the FraudSys server invokes the VerifyPuzzle function (lines 13-21), to verify its correctness as follows: (1) Reconstruct the puzzle cookie Γ based on the received values and the secret key K. Verify that this cookie is equal to the received Γ value (line 14). This ensures that all values, including the *timeout* have not been altered by an adversary; and (2) Verify that each of the q shares satisfy the puzzle (lines 15-17). If these verifications succeed, FraudSys waits until *timeout* expires to confirm the user action A, for posting by the online service (line 18). It then uses the time required by the device to solve the puzzle, to re-evaluate the hashrate of the device (lines 19-20). It updates the stored hashrate only if the new value is above a minimally accepted hashrate value (lines 20-21).

4.2 The Fraud Detection Module

To assign a fraud score to a user activity in real-time, the fraud detection module can only rely on the existing history of the user and of the subject on which the activity is performed. We propose an approach that builds on the *co-activity graphs* of subjects, where nodes correspond to user accounts that performed activities on the subject, and edges connect nodes whose user accounts have a history of activities that targeted the same subjects. Edge weights denote the size of that history. Figure 6 shows the co-review (where activities are reviews) graph of a fraudulent Google Play app, that received fake reviews from 2 fraud workers. Each cluster is formed by accounts controlled by one of the workers.

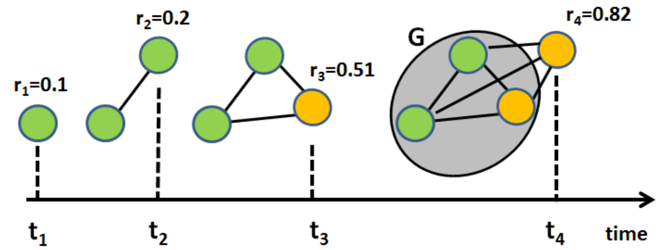


Figure 7: Fraud detection illustration: temporal evolution of the co-activity graph of a subject. The nodes represent user accounts that have performed an activity on the subject. Edges connect accounts with common past activities. As a new user account posts an activity, FraudSys assigns the activity a fraud score (the $r_1..r_4$ values), based on its connectivity to previous activities. Yellow nodes are considered fraudulent ($r > 0.5$).

The fraud detection module leverages the adversary model findings (§ 3.1) that a fraudster-controlled user account that performs a new activity on a subject, is likely to be well connected to the co-activity graph of the subject, or at least one of its densely connected sub-graphs. Figure 7 illustrates this approach: Let U be a user account that performs an activity A for a subject S at time T. Let $G = (V, E)$ be the co-activity graph of S before time T. Let $G_T = (V_T, E_T)$ be the new co-activity graph of S, that also includes U, i.e., $V_T = V \cup U$. Given U, S and G, FraudSys extracts the following features, that model the relationship of U with S:

- **Connectivity features**. The percentage of nodes in V to whom U is connected. The average weight of the edges between U and the nodes in V. The average weight of those edges divided by the average weight of the edges in E. This feature will indicate if U increases or decreases the overall connectivity of G. The number of triangles in G_T that have U as a vertex. The average edge weight of those triangles.

- **Best fit connectivity features**. Since U may be controlled by one of multiple fraudsters who target S, U may be better connected to the subgraph of G controlled by that fraudster. Then, use a weighted min-cut algorithm to partition G into components $G_1, .., G_k$, such that any node in a component is more densely connected to the nodes in the same component than to the nodes in any of the other components. $G_1, .., G_k$ may contain user accounts controlled by different fraudsters, see Figure 6. Identify the component G_b, $b \in \{1, ..k\}$ to which U is the most tightly connected (according to the above connectivity features). Output the connectivity features between U and G_b.

- **Account based features**. The number of activities previously performed by U. The age of U: the time between U's creation and the time when activity A is performed on S. The *expertise* of U: the number of actions of U for subjects similar to S. Similarity depends on the online service, e.g., same category apps in Google Play, pages with similar topics in Facebook.

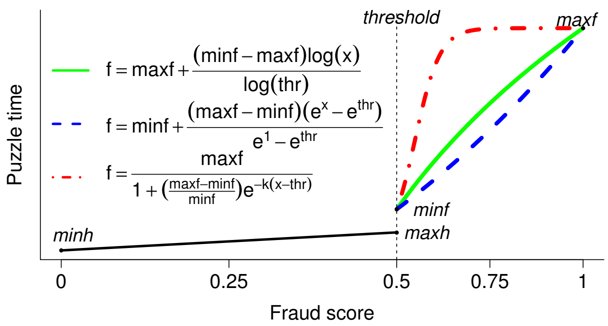


Figure 8: Comparison of functions to convert fraud scores (x axis) to time penalties (y axis). The logistic function (red dot-line) exhibits the required exponential increase.

The Fraud Detection module trains a probabilistic supervised learning algorithm on these features and uses the trained model to output the probability that a given activity is fraudulent. We detail the performance of various algorithms, over data that we collected from Google Play and Facebook, in § 6.

Per-fraudster timeout. We exploit the ability of the fraud detection module to identify accounts controlled by the same fraudster, to further restrict fraud. Specifically, instead of storing a *timeout* timestamp for each user account, FraudSys can store a single *timeout* per detected fraudster. Thus, FraudSys will accumulate penalties in a single, per-fraudster account. This facilitates Claim 2.

4.3 The Fraud2Penalty Module

Given the fraud score r of an activity of user U (output by the Fraud Detection module), performed from a device D associated with the account of U (see the model section), the Puzzler module generates a puzzle whose difficulty is a function of both r and the computational capability of D. We now describe the Fraud2Penalty module, that converts r into a time penalty. We have explored several functions to convert the fraud score r of a user activity to a time penalty. Let $minh$ and $maxh$, and $minf$ and $maxf$, denote the minimum and maximum times imposed on the device from which an honest, respectively fraudulent activity is performed. Let thr denote the threshold fraud score above which we start to consider a user activity as being fraudulent. We propose a conversion function that increases linearly when $r < thr$, and exponentially when $r > thr$. Specifically, we propose a flexible generalization of the logistic function (when $r > thr$), where the parameter k is the *growth rate*:

$$\begin{cases} \frac{maxh-minh}{thr}r + minh & 0 \le r \le thr \\ \frac{maxf}{1+(\frac{maxf-minf}{minf})e^{-k(r-thr)}} & thr \le r \le 1 \end{cases} \tag{4}$$

We have compared this logistic increase function with other functions, with the same linear increase in the honest region, but exponential ($(maxf - minf)\frac{e^r - e^{thr}}{e^1 - e^{thr}} + minf$) and logarithmic ($(minf - maxf)\frac{logr}{log(thr)} + maxf$) increase in the fraudulent regions. Figure 8 compares the logistic, exponential and logarithmic functions. It shows that unlike the exponential and logarithmic functions, the logistic function exhibits the desired rapid increase for fraud probability values above the threshold value. In § 6 we detail parameter values for the logistic conversion function,

4.4 The Hashrate Inference Module

New device registration. When a user registers a new device, the device sends its specs to the online service that forwards them to FraudSys. FraudSys leverages its list of profiled devices (see Table 2) to retrieve the hashrate of the profiled device with the most similar capabilities. FraudSys stores the new device along with this initial hashrate estimate under the id of the user that registers it (see the Puzzle module). Given this hashrate and the above time penalty, FraudSys uses Equation 3 to compute an initial puzzle difficulty.

Hashrate correction. The initial hashrate estimate of FraudSys may be incorrect. In addition, as discussed in the System Model, the user may be adversarial, thus attempt to provide an inaccurate view of the puzzle solving capabilities of his device. To address these problems, FraudSys employs an adaptive hashrate correction process. Specifically, an adversary with a more capable device than advertised (see e.g., Table 2) will solve the assigned puzzle faster. The incentive for this is a shorter wait time for his activity to post on the online service. If this occurs, FraudSys increases its device hashrate estimate to reflect the observed shorter time required by the device to solve the puzzle (see Algorithm 1, lines 19-20).

5 FRAUDSYS PROPERTIES

Claim 1. *A fraudster that performs a fraudulent activity with fraud score r from a device with hashrate η, is expected to compute $\frac{\eta \times maxf}{1+(\frac{maxf-minf}{minf})e^{-k(r-thr)}}$ double hashes.*

Proof. According to Equation 4, the time penalty assigned to a fraudulent activity with score r is $\tau = \frac{maxf}{1+(\frac{maxf-minf}{minf})e^{-k(r-thr)}}$. Then, Equation 3 ensures that the number of expected hashes that the device needs to perform to solve the puzzle of Equation 1 is $\eta \times \tau$, which concludes the proof. □

Let f be the number of fraud workers in the system (i.e., $f = |\mathcal{F}|$), τ be the average temporal penalty assigned by FraudSys to a fraudulent activity, and let p be the expected payout for a single fraudulent activity. We introduce then the following claim:

Claim 2. *FraudSys is a $(p/\tau, f/\tau)$-fraud preemption system.*

Proof. The best fit connectivity features of the Fraud Detection module (see § 4.2) enable FraudSys to detect activities performed from accounts controlled by the same fraudster. This, coupled with an extension of the *timeout* concept applied at the fraudster level (see § 4.2) ensures a serialization of fraudster activities. Then, the average number of fraudulent activities that a fraudster can post per time unit in FraudSys is $1/\tau$. This implies that, per time unit, the expected payout of a fraudster is p/τ, and a subject can be the target of at most f/τ fraudulent activities. This, according to the definition of § 3.2, completes the proof. □

5.1 Security Discussion and Limitations

The FraudSys puzzle not only ties the penalty computation to the user activity, but also addresses pre-computation, replay and guessing attacks: the adversary cannot predict the cookie value of its actions, thus cannot pre-compute puzzles and cannot reuse old cookies. It also offloads significant work from the FraudSys service, which no longer needs to keep track of puzzle assignments.

Device deception. An adversary with a specialized puzzle solving device (e.g., AntMiner) will be assigned puzzles with large difficulty values (see, e.g., Table 2), thus consume the same amount of time as when using a resource constrained device (e.g., a smartphone). The adversary can exploit this observation to avoid the implications of Claim 1: register a resource constrained device, but rely on a powerful back-end device to solve the assigned puzzles faster. The adversary has two options. First, report the solutions as soon as the back-end device retrieves them. In this case however, the adversary leaks his true capabilities, as FraudSys will update the adversary hashrate (Algorithm 1, line 20). Thus, subsequently, his assigned puzzles will have a significantly higher difficulty value. In a second strategy, the adversary estimates the time that his front-end device would take to complete the puzzle, then waits the remaining penalty time. In this case, the adversary incurs two penalties, the long wait time and the underutilized back-end device investment.

Adversary strategies: new user accounts. To avoid the implications of Claim 2, the adversary registers new user accounts. While new accounts are cheap, their freshness and lack of history will enable the account based features of the Fraud Detection module to label them as being likely fraudulent. As the adversary reuses such accounts, the connectivity features start to play a more important role in labeling their activities as fraudulent. Thus, the adversary has a small usable window of small penalties for new accounts.

While new honest accounts may also be assigned larger penalties for their first few activities, they will not affect the user experience: the user can continue her online activities, while her device solves the assigned puzzle in the background.

6 EMPIRICAL EVALUATION

6.1 Datasets

We have collected the following datasets of fraudulent and honest behaviors from Google Play and Facebook.

Google Play: fraud behavior data. We have identified 23 workers in Freelancer, Fiverr and Upwork, with proven expertise on performing fraud on Google Play apps. We have contacted these workers and collected the ids of 2,664 Google Play accounts controlled by them. We have also collected 640 apps heavily reviewed from those accounts, with between 7 and 3,889 reviews, of which between 2% and 100% (median of 50%) were written from accounts controlled by the workers. These apps form our gold standard *fraud app* dataset. We have also collected the 23,028 fake reviews written from the 2,664 fraudster controlled accounts for the 640 apps. Figure 6 shows the co-review graph of one of these apps, that received fake reviews from 2 of the identified 23 workers.

Device	Hashrate	Diff (5s)	(12hr)	(7 day)
Nexus 4	6.53 KH/s	16.32K	141.04M	1.97G
Nexus 5	13.26 KH/s	33.15K	286.41M	4.00G
LG Leon LTE	10.1 KH/s	25.25K	218.16M	3.05G
NVS 295	1.7MH/s	4.25M	36.72G	514.08G
Server	80 MH/s	200M	1.72T	24.19T
AntMiner	4.72 TH/s	11.8T	101.95P	1427P

Table 2: Hashrate profiling table for various device types (smartphone, tablet, PC and Bitcoin miner), along with difficulty values for penalty times of 5s, 12 hours and 7 days.

Google Play: honest behavior data. We have selected 925 candidate apps that have been developed by Google designated "top developers". We have removed the apps whose apks (executables) were flagged as malware by VirusTotal. We have manually investigated 601 of the remaining apps, and selected a set of 200 apps that (i) have more than 10 reviews and (ii) were developed by reputable media outlets (e.g., NBC, PBS) or have an associated business model (e.g., fitness trackers). We call these the gold standard *benign app dataset*.

We have identified 600 reviewers of these 200 benign apps and 140 reviewers of the 640 fraud apps (see above), such that each has reviewed at least 10 paid apps, i.e., paid to install the app, then reviewed it, and had at least 5 posts on their associated Google Plus (social network) accounts. These 740 user accounts form our gold standard *honest user dataset*. We have then retrieved and manually vetted 854 reviews written by the 600 honest reviewers for the 200 benign apps, and 207 reviews written by the 140 honest reviewers of the 640 fraud apps. Each selected review is informative, containing both positive and negative sentiment statements. We call the resulting dataset, the *honest review dataset*, with 1,061 reviews.

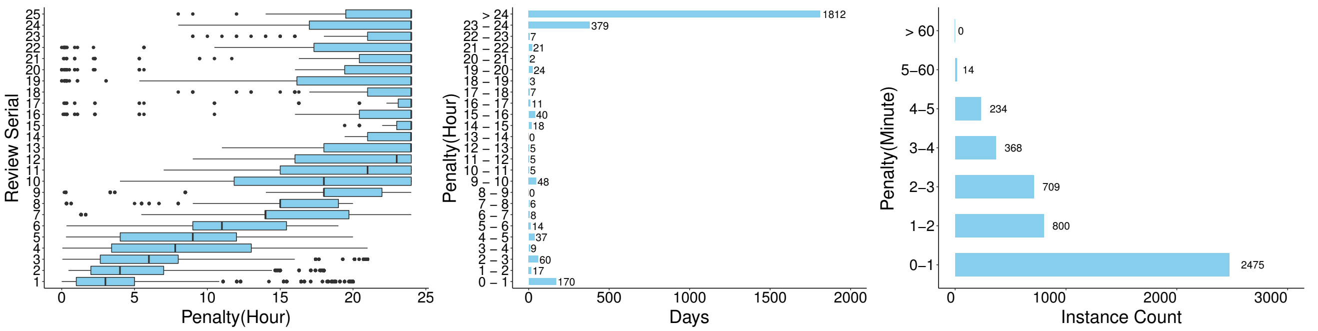
Facebook Like dataset. We have used a subset of the dataset from [8], consisting of 15,694 Facebook pages, that each has received at least 30 likes. The pages were liked from 13,147 user accounts, of which 6,895 are fraudster controlled, and 6,252 are honest. In total, these fraudsters have posted 274,297 fake likes, and the honest accounts have posted 180,400 honest likes.

6.2 Device Hashrate Profile

Strategy	FPR%	FNR%	Accuracy%
k-NN	1.41	4.45	97.92
SVM	5.8	11.3	92.40
Random Forest	3.44	6.46	95.69

Table 3: 10-fold cross validation results of supervised learning algorithms in fraud vs. honest Google Play review classification. k-NN achieves the lowest FPR and FNR.

We have profiled the hashrate of several devices, ranging from smartphones to a Bitcoin mining hardware (AntMiner S7: ARMv7 CPU, 254 Mb of RAM, 135 BM1385 chips @ 700MHz). Since Bitcoin mining requires capabilities far exceeding those of smartphones, we have implemented an Android app to evaluate the hashrate of several Android devices. Table 2 shows the hashrate values for the profiled devices, along with the corresponding difficulty (Δ) values for puzzles required to impose 5 second, 12 hour and 7 day



(a) (b) (c)

Figure 9: Stats over the Google Play data when $maxf$ = 24h, $minh$ = 2s, $maxh$ = $minf$ = 5min. (a) Evolution of average, 1st and 3rd quartile of the penalty imposed on the i-th fraud activity of a fraudster for the same subject. It shows a steep increase: the average penalty of the first three fraud activities for a subject sums to 15.34h, while the average penalty of the 12th activity exceeds 24h. (b) Distribution of per-fraudster daily penalties, over data from 23 fraudsters: in 1,812 days out of 2,708 days, the penalty assigned to a single fraudster exceeds 24 hours. (c) Distribution of penalties assigned to an honest review. Only 14 out of 4,600 honest review instances received a penalty exceeding 5 minutes, but still below 1 hour.

time penalties on such devices. We observe the significant gap between the hashrate of a smartphone (10-15 KH/s) and a specialized device (4.72 TH/s). This motivates the need for the puzzles issued by FraudSys to have different Δ values for various user devices. FraudSys maintains a similar table in order to be able to build appropriate puzzles for newly registered devices.

6.3 Fraud Penalty Evaluation: Google Play

Supervised learning algorithm choice. We first used 10 fold cross-validation to evaluate the ability of the Fraud Detection module to correctly classify the 23,028 fraudulent vs. 1,061 honest reviews of the Google Play dataset previously described. Table 3 shows the false positive (FPR) and negative (FNR) rates, as well as the accuracy achieved by the top 3 performing supervised algorithms. k-NN has the lowest FPR and FNR, for an accuracy of 97.92%. Thus, in the following experiments we use only k-NN.

Parameter evaluation. We have used the fraud and honest review datasets described earlier, to compute the temporal penalties imposed by FraudSys on fraudsters and honest users. We have performed the following experiments. In each experiment, we use the data of 22 fraud workers and 200 randomly chosen honest reviews (out of 1,061) to train the supervised learning algorithm (k-NN) then test the model on the data of the remaining fraud worker and on the remaining 861 honest reviews. Thus, we have performed 23 experiments, one for each worker.

We set the $maxf$ parameter such that the average daily payout of a fraudster is below the average Bitcoin mining payout with a last generation AntMiner device. Thus, this ensures that even such a powerful adversary has more incentive to do Bitcoin mining instead of search rank fraud. Specifically, the above AntMiner's current (Jan. 2017) average daily payout is 0.0037 BTC. At the current BTC to USD rate, this means $3.67 per day [1]. In addition, we have experimented with $maxf$ values ranging from 12 to 48 hours. The average penalty assigned by FraudSys to a fraudulent review is 8.01 hours when $maxf$=12h, 15.34h when $maxf$=24h, and 29.33h when $maxf$=48h. Figure 9a shows the median, first and third quartiles for the time penalty (in hours) imposed on the i-th fraudulent activity performed by a fraudster for a subject, when $maxf$= 24h: the 12th fake activity receives a median penalty of 24h.

Thus, we set $maxf$=24h, which is sufficient for Google Play reviews: A fraudster would be able to post on average less than 2 fake reviews per day, thus, even with a reward of $2 per fraud activity (see Figure 3), achieve a payout of around $3.15 per day, below the Bitcoin mining payout. In addition, we have set $minh$ = 2s. Figure 1 shows the penalty timelines of two workers when $minh$ = 2s, $maxh$ = $minf$ = 5 min, $maxf$ = 24 hours, thr = 0.5, and k = 30 (for a steep increase of time penalty with fraud score). We note that a $maxh$ = 5 min is not excessive: this penalty is not imposed on the user, but on his device. The user experience remains the same in the online service.

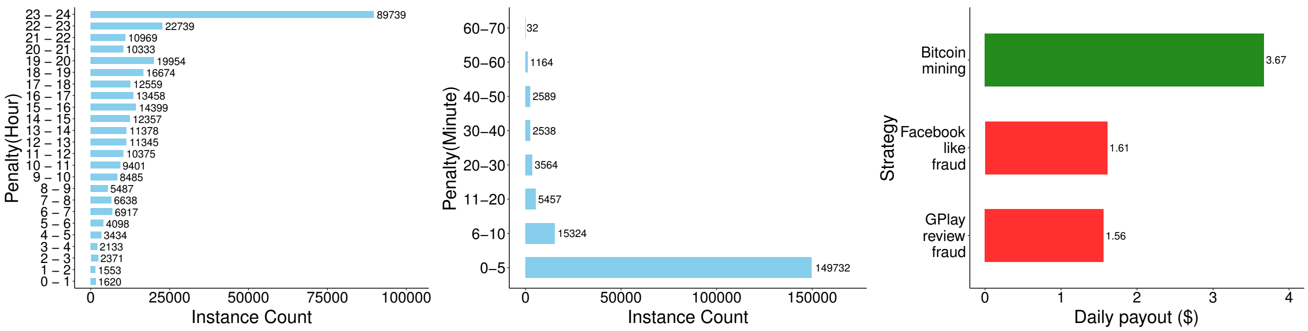
Each vertical bar shows the daily temporal penalty assigned to a single worker, over reviews posted from multiple accounts. The maximum daily penalty of the two workers is 1,247 hours and 3,079 hours respectively. We observe that each worker has many days with a daily penalty exceeding 24 hours.

Figure 9b shows for $maxh$ = $minf$ = 5min, the overall distribution of daily penalties assigned by FraudSys, over all the 23 fraud workers, in the above experiment. It shows that during most of the active days, fraud workers are assigned a daily penalty exceeding 24 hours. Figure 9c (also for $maxh$ = $minf$ = 5min) shows the distribution of per-review penalty assigned by FraudSys to honest reviews, shown over 4,600 (23×200) honest reviews. Irrespective of the $maxh$ value, only 14 honest reviews were classified as fraudulent, but assigned a penalty below 1 hour. We observed minimal changes in the distribution of penalties of fraudulent reviews when $maxh$ = $minf$ ranges from 5 to 15 minutes.

6.4 Fraud Penalty Evaluation: Facebook

We have performed a similar parameter analysis using the Facebook "like" dataset. Since this dataset lacks information about the fraudsters who control the accounts that posted fake likes, we focus on the penalties assigned by FraudSys to fake and honest likes.

[1] Historically speaking, the BTC to USD rate is increasing. The next generation AntMiner coming up this year is expected to be 3 times more capable.



(a) **(b)** **(c)**

Figure 10: (a) Penalty distribution for the fake Facebook likes. 84% of the likes received a penalty that exceeds 12 hours, and the average fake like penalty is 19.32 hours. (b) Penalty distribution for the honest Facebook likes. 82.97% of the honest likes are assigned a penalty of under 5 min. The maximum penalty assigned to an honest like is 70 minutes. (c) Comparison of daily payouts provided by Bitcoin mining, writing fake reviews in Google Play and posting fake likes in Facebook, under FraudSys. Fraud does not pay off under FraudSys: the fraud payout is less than half the Bitcoin mining payout.

Figure 10a shows the distribution of penalties assigned to fake likes and Figure 10b shows the distribution of the honest likes. Compared to the results over the Google Play data, we observe a higher FPR, i.e., more honest likes with fraud level penalties. We posit that this is due to the fewer features that we can extract for the Facebook likes, as, unlike for Google Play reviews, we lack the time of the activity. Specifically, absence of like sequence information enables us to only extract features based on the last "snapshot" of the page, and not the current page snapshot when the like was posted.

However, 82.97% of the honest likes receive a penalty of under 5 mins and the maximum penalty assigned to an honest review is 70 mins. In addition, 84% of the fake likes receive a penalty that exceeds 12 hours, and the average penalty for a fake like is 19.32 hours. Figure 10c compares the daily payouts received by an AntMiner equipped fraudster who writes fake reviews in Google Play (at $1 per fake review), posts fake likes (at $2 per fake like), or honestly uses his device to mine Bitcoins. It shows that under FraudSys, fraud doesn't pay off: the Bitcoin mining payout is more than double the fraud payout for either fake reviews or likes.

7 CONCLUSION

We have introduced the concept of real-time fraud preemption systems, named as the FraudSys, that seek to restrict the profitability and impact of fraud in online systems. We propose and develop stateless, verifiable computational puzzles, that impose minimal overheads, but enable their efficient verification. We have developed a graph based, real-time algorithm to assign fraud scores to user activities and mechanisms to convert scores to puzzle difficulty values. We used data collected from Google Play and Facebook to show that our solutions impose significant penalties on fraudsters, and make fraud less productive than Bitcoin mining.

8 ACKNOWLEDGMENTS

This research was supported in part by NSF grants CNS-1527153, SES-1450619, CNS-1422215, IUSE-1525601, and Samsung GRO.

REFERENCES

[1] Google I/O 2013 - Getting Discovered on Google Play. www.youtube.com/watch?v=5Od2SuL2igA, 2013.
[2] L. Akoglu, H. Tong, and D. Koutra. Graph based anomaly detection and description: a survey. *Data Mining and Knowledge Discovery*, 29(3):626–688, 2015.
[3] M. Anderson and J. Magruder. Learning from the crowd: Regression discontinuity estimates of the effects of an online review database. *Economic Journal*, 122(563), 2012.
[4] AppReviews. http://www.app-reviews.org, 2016.
[5] AppSuch. http://www.appsuch.com, 2016.
[6] AppsViral. http://www.appsviral.com/, 2016.
[7] Apptamin. Optimize Your Google Play Store App Details Page. http://www.apptamin.com/blog/optimize-play-store-app/, 2016.
[8] P. R. Badri Satya, K. Lee, D. Lee, T. Tran, and J. J. Zhang. Uncovering fake likers in online social networks. In *Proceedings of the ACM CIKM*, 2016.
[9] M. Bellare, R. Canetti, and H. Krawczyk. Keying hash functions for message authentication. In *Proceedings of CRYPTO*, 1996.
[10] D. J. Bernstein. Syn cookies, 1996.
[11] N. Borisov. Computational puzzles as sybil defenses. In *Proceedings of the IEEE P2P*, 2006.
[12] C. Dwork and M. Naor. Pricing via processing or combatting junk mail. In *Proceedings of CRYPTO*, 1992.
[13] S. Fortunato and D. Hric. Community detection in networks: A user guide. arXiv:1608.00163, 2016.
[14] B. Hooi, H. A. Song, A. Beutel, N. Shah, K. Shin, and C. Faloutsos. Fraudar: Bounding graph fraud in the face of camouflage. In *Proceedings of ACM KDD*, 2016.
[15] A. Juels and J. Brainard. Client puzzles: A cryptographic counter-measure against connection depletion attacks. In *Proceedings of ISOC NDSS*, 1999.
[16] Y. Lu, L. Zhang, Y. Xiao, and Y. Li. Simultaneously detecting fake reviews and review spammers using factor graph model. In *Proceedings of the ACM WebSci*, 2013.
[17] M. Luca and G. Zervas. Fake it till you make it: Reputation, competition, and yelp review fraud. *Management Science*, 62(12), 2016.
[18] M. Motoyama, D. McCoy, K. Levchenko, S. Savage, and G. M. Voelker. Dirty jobs: The role of freelance labor in web service abuse. In *Proceedings of USENIX Security*, 2011.
[19] A. Mukherjee, B. Liu, and N. Glance. Spotting fake reviewer groups in consumer reviews. In *Proceedings of ACM WWW*, 2012.
[20] S. Nakamoto. Bitcoin: A peer-to-peer electronic cash system, 2008.
[21] M. Rahman, M. Rahman, B. Carbunar, and P. Chau. Fairplay: Fraud and Malware Detection in Google Play. In *Proceedings of SDM*, 2016.
[22] RankLikes. http://www.ranklikes.com/, 2016.
[23] ReviewRoster. http://www.reviewroster.com/, 2016.
[24] G. Stringhini, G. Wang, M. Egele, C. Kruegel, G. Vigna, H. Zheng, and B. Y. Zhao. Follow the green: growth and dynamics in twitter follower markets. In *Proceedings of ACM IMC*, 2013.
[25] TheSocialMarketeers. http://www.thesocialmarketeers.org/, 2016.
[26] J. Ye and L. Akoglu. Discovering opinion spammer groups by network footprints. In *Proceedings of ML-KDD*. 2015.