Securing Large Cellular Networks via A Data Oriented Approach: Applications to SMS Spam and Voice Fraud Defenses

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Dedication

I dedicate this dissertation to my husband Yu Jin for years of encouragement and support each step of the way; to our lovely daughter Amy, for the cheer and happiness she brings to the family; to my parents, Wenyi Jiang and Meili Zhao, for their unconditional love and care; to my sister Yao Jiang, who is willing to help whenever I need; to my parents-in-law, Shengxue Jin and Huizhen Liang, who help taking care of Amy.

Abstract

With widespread adoption and growing sophistication of mobile devices, fraudsters have turned their attention from landlines and wired networks to cellular networks. While security threats to wireless data channels and applications have attracted the most attention, attacks through mobile voice channels, such as *Short Message Service (SMS) spam* and *voice-related fraud activities* also represent a serious threat to mobile users. In particular, it has been reported that the number of spam messages in the US has risen 45% in 2011 to 4.5 billion messages, affecting more than 69% of mobile users globally. Meanwhile, we have seen increasing numbers of incidents where fraudsters deploy malicious apps, e.g., disguised as gaming apps to entice users to download; when invoked, these apps automatically – and without users' knowledge – dial certain (international) phone numbers which charge exorbitantly high fees. Fraudsters also frequently utilize social engineering (e.g., SMS or email spam, Facebook postings) to trick users into dialing these exorbitant fee-charging numbers.

Unlike traditional attacks towards data channels, e.g., Email spam and malware, both SMS spam and voice fraud are not only annoying, but they also inflict financial loss to mobile users and cellular carriers as well as adverse impact on cellular network performance. Hence the objective of defense techniques is to restrict phone numbers initialized these activities quickly before they reach too many victims. However, due to the scalability issues and high false alarm rates, anomaly detection based approaches for securing wireless data channels, mobile devices, and applications/services cannot be readily applied here.

In this thesis, we share our experience and approach in building operational defense systems against SMS spam and voice fraud in large-scale cellular networks. Our approach is data oriented, i.e., we collect real data from a large national cellular network and exert significant efforts in analyzing and making sense of the data, especially to understand the characteristics of fraudsters and the communication patterns between fraudsters and victims. On top of the data analysis results, we can identify the best predictive features that can alert us of emerging fraud activities. Usually, these features represent *unwanted communication patterns* which are derived from the original feature space. Using these features, we apply advanced machine learning techniques to train accurate detection models. To ensure the validity of the proposed approaches, we build and deploy the defense systems in operational cellular networks and carry out both extensive off-line evaluation and long-term online trial. To evaluate the system performance, we adopt both direct measurement using known fraudster blacklist provided by fraud agents and indirect measurement by monitoring the change of victim report rates. In both problems, the proposed approaches demonstrate promising results which outperform customer feedback based defenses that have been widely adopted by cellular carriers today.

More specifically, using a year (June 2011 to May 2012) of user reported SMS spam messages together with SMS network records collected from a large US based cellular carrier, we carry out a comprehensive study of SMS spamming. Our analysis shows various characteristics of SMS spamming activities. and also reveals that spam numbers with similar content exhibit strong similarity in terms of their sending patterns, tenure, devices and geolocations. Using the insights we have learned from our analysis, we propose several novel spam defense solutions. For example, we devise a novel algorithm for detecting related spam numbers. The algorithm incorporates user spam reports and identifies additional (unreported) spam number candidates which exhibit similar sending patterns at the same network location of the reported spam number during the nearby time period. The algorithm yields a high accuracy of 99.4% on real network data. Moreover, 72% of these spam numbers are detected at least 10 hours before user reports.

From a different angle, we present the design of Greystar, a defense solution against the growing SMS spam traffic in cellular networks. By exploiting the fact that most SMS spammers select targets randomly from the finite phone number space, Greystar monitors phone numbers from the gray phone space (which are associated with data only devices like data cards and modems and machine-to-machine communication devices like point-of-sale machines and electricity meters) to alert emerging spamming activities. Greystar employs a novel statistical model for detecting spam numbers based on their footprints on the gray phone space. Evaluation using five month SMS call detail records from a large US cellular carrier shows that Greystar can detect thousands of spam numbers each month with very few false alarms and 15% of the detected spam numbers have never been reported by spam recipients. Moreover, Greystar is much faster than victim spam reports. By deploying Greystar we can reduce 75% spam messages during peak hours.

To defend against voice-related fraud activities, we develop a novel methodology for detecting voice-related fraud activities using only call records. More specifically, we advance the notion of *voice call graphs* to represent voice calls from domestic callers to foreign recipients and propose a Markov Clustering based method for isolating dominant fraud activities from these international calls. Using data collected over a two year period from one of the largest cellular networks in the US, we evaluate the efficacy of the proposed fraud detection algorithm and conduct systematic analysis of the identified fraud activities. Our work sheds light on the unique characteristics and trends of fraud activities in cellular networks, and provides guidance on improving and securing hardware/software architecture to prevent these fraud activities.

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Chapter 1

Introduction

The past decade has witnessed the rapid deployment and evolution of mobile cellular networks, which now support billions of users and a vast diverse array of mobile devices from smartphones, tablets, to e-readers and smart meters. It was reported [1] that in 2010 there were over 5 billion mobile phones in operation, in comparison to the total world population of 6.8 billion. Mobile phones and tablets are gradually replacing traditional wire-lines as well as personal computers, and are becoming an indispensable component in our daily life [2, 3]. With breath-taking advances in smart mobile devices and the growing sophistication in the mobile applications (apps) and services (e.g., location services and cloud services) they spur, we are now entering in a new era of mobile computing.

With their wide adoption, smartphones, while providing valuable utility and convenience to mobile users, also bring with them new security threats. As smartphones function both as phones as well as mobile computers, smartphone users not only face the usual Internet security threats (e.g., malware and botnets [4]) through their web browsing and other data activities (albeit such data-related security threats are mitigated by the perhaps markedly improved hardware and software platforms compared to conventional desktop platforms); they may also encounter unsolicited SMS (Short Message Service) spam, as well as a variety of *voice-related* security threats.

SMS Spam are unsolicited SMS messages sent by SMS spammers to a vast number of victims. The explosion of mobile devices in the past decade has brought with it an onslaught of such unwanted SMS) spam [5]. It has been reported that the number of spam messages in the US has risen 45% in 2011 to 4.5 billion messages [6]. In 2012, there were 350K variants of SMS spam messages accounted for globally [7] and more than 69% of the mobile users claimed to have received text spam [8]. The sheer volume of spam messages not only inflicts an annoying user experience, but also incur significant costs to both cellular service providers and customers alike. As the increasingly rich functionality provided by smart mobile devices, these SMS spam often entice users to visit certain (fraud) websites for other illicit activities, e.g., to steal personal information or to spread malware apps, which can inflict financial loss to the users. At the same time, the huge amount of spam messages also concerns the cellular carriers as the messages traverse through the network, causing congestion and hence degraded network performance. In contrast to email spam where the number of possible email addresses is unlimited - and therefore the spammer generally needs a seed list beforehand, SMS spammers can more easily reach victims by, e.g., simply enumerating all numbers from the *finite* phone number space. This, combined with wide adoption of mobile phones, makes SMS a medium of choice among spammers.

Voice Spam ranges from conventional voice scams similar to those on landlines, e.g., stealing customers privacy information or defrauding users of money through various social engineering techniques, to new forms of voice fraud that utilize the data functionality of smartphones for voice-related trickeries. For instance, we have seen increasing numbers of incidents where fraudsters deploy malicious apps, disguised as interesting games and other applications to entice users to download them; when invoked, these apps automatically – and without users' knowledge – dial certain (international) phone numbers which charge exorbitantly high fees. Fraudsters also frequently utilize other social engineering trickeries to deceive users, e.g., through SMS or email spam, Twitter tweets, or fake online postings to lure users into clicking on malicious URL links, resulting in automatic dialing of exorbitant fee-charging international numbers. Compared to malware apps that focus primarily on smartphone users, voice-related fraud activities can have a much wider impact in cellular networks, as potentially all mobile users can be victims of such activities. Furthermore, unlike data traffic, mobile international voice calls often follow the pay-per-call compensation model, and are far more expensive; hence voice-related fraud activities involving international phone numbers can bring direct and significant financial losses to both mobile users and cellular service providers. Detecting and rooting out such voice-related fraud activities, especially those that target users through the data plane triggered voice fraud, is not an easy task, due to the large user population, the vast phone number space and limited data.

1.1 Existing Defenses

Because both SMS spam and voice fraud are not only annoying, but they also inflict financial loss to mobile users and cellular carriers as well as adverse impact on cellular network performance, the objective of defense techniques is to restrict phone numbers initialized these activities quickly before they reach too many victims. To this end, many existing solutions in defending against other threats like email spam are not applicable here. For example, anomaly detection based approaches for securing wireless data channels, mobile devices, and applications/services [9, 10, 11, 12, 13] can potentially lead to an unacceptable false alarm rate, which can disturb normal users' activities by incorrectly restricting their services. Meanwhile, content inspection/classification based techniques which are commonly used for detecting email spam often cannot scale up with the huge number of SMS messages traversing the network within seconds.

Due to these reasons, cellular carriers often seek help from their customers to alert them of emerging spamming and fraud activities. More specifically, for SMS spam, cellular carriers deploy reporting mechanism for spam victims to report received spam messages and then examine and restrict these reported spam numbers accordingly. After receiving a spam message, a victim can report it via a text message forward. For voice fraud, a victim can report suspicious voice transactions to the fraud agents by calling the cellular carrier's support line. To increase the accuracy of detection and to avoid malicious users from gaming the reporting system, fraud agents can crowdsource reports from multiple users regarding the same phone numbers. Such detection techniques based on victim reports are very accurate, thanks to the human intelligence added while submitting these reports. However, these methods can suffer from significant delay due to the low report rate and slow user responses, rendering them inefficient in controlling SMS spam and voice fraud.

1.2 Our Approach

To attack these problems, we adopt a data oriented approach which we illustrate below:

1. **Large-scale data analysis and profiling**. In both problems, we are facing a huge volume of data records (e.g., billions of SMS messages and voice calls each day) but only a small number of features. For example, we use only Call Detail Records (CDRs) as our input in both problems, which only contain limited features, like the originating phone number, the terminating phone number, the communication time, etc. Building an accurate detection model directly on top of these features is often infeasible. Therefore, we collect real data from a large national cellular network and exert significant efforts in analyzing and making sense of the data, especially to understand the characteristics of fraudsters and the communication patterns between fraudsters and victims.

2. **Predictive Feature Identification**. On top of the data analysis results, we can identify the best predictive features that can alert us of emerging fraud activities. Usually, these features represent *unwanted communication patterns* which are derived from the original feature space. Legitimate users are very unlikely involved in such communication patterns and hence these derived features serve as good indicators of fraud activities.

3. **Building Statistical Detection Model**. Even with the identified predictive features, fraudster behaviors usually cannot be separated from legitimate user behaviors using simple threshold based method. We therefore apply statistical learning techniques to build the detection models, which provides more accurate detection using sophisticated decision rules learned automatically from training samples.

4. **Off-line Evaluation and On-line Trial**. Given the objective of our work is to design defense solutions that are applicable to a real large-scale cellular network environment, we carry out both extensive off-line evaluation and long-term online trial in operational networks. To evaluate the system performance, we adopt both direct measurement using known fraudster blacklist provided by fraud agents and indirect measurement by monitoring the change of victim report rates.

5. **Post-analysis of Fraud Activities**. Building a defense solution is not the end of our work. Instead, we carry out post-analysis of fraud activities detected by the proposed algorithms which are later confirmed by auxiliary information sources. Such analysis enables us to better understand the evolving techniques adopted by fraudsters, which also shed lights on the future trend of fraud activities as well as potential new defenses.

1.3 SMS Spam Defenses

Following the aforementioned approach, in Chapter 4 and Chapter 5, we present two algorithms developed for fast and accurate detection of SMS spam.

Taking advantage of this SMS spam reporting mechanism, we collect spam messages reported to one of the largest cellular carriers in the US from May 2011 to June 2012 – which contains approximately 543K spam messages – and carry out an extensive analysis of spamming activities using these user reported spam messages together with their associated SMS network records. Our objectives are three-fold: 1) to characterize the spamming activities in today's large cellular networks; 2) to infer the intent and strategies of spammers; and 3) to develop effective spam detection methods based on lessons learned from our analysis.

To achieve these goals, we first identify more than 78K spam numbers from user-submitted SMS spam reports (referred to as user spam reports hereafter) and conduct an in-depth analysis of spamming activities associated with these numbers. We observe strong differences in behaviors between spammers and non-spammers in terms of their voice, data and SMS usage. We find that the tenure of the spam numbers to be less than one week old, and programmable devices are often used to deliver spam messages at various spam sending rates.

In addition to analyzing spamming behaviors of individual spam numbers, we carry out a multi-dimensional analysis of the correlations of spam numbers. More specifically, we apply a text mining tool, CLUTO [14, 15], to cluster spam numbers into various clusters based on similarity of spam content they generate. Our investigation shows strong similarity among the spam numbers contained in each cluster: for instance, the devices associated with these spam numbers are frequently of identical types, the spam numbers used are often purchased at nearly the same time; furthermore, the call records of these numbers also exhibit strong temporal and spatial correlations, namely, they occur at a particular location and close in time. All the evidence suggests that the spam numbers contained in the same cluster are likely employed by a single spammer to engage in the same SMS spam campaign, e.g., at a particular location using multiple devices such as laptops or 3G/4G cellular modems.

Based on the characteristics of spam numbers found in our analysis, we innovative several spam defenses that rely less on user spam reports or do not require users' participation at all. For example, leveraging the strong temporal/spatial correlations among spam numbers employed by the same spammer, we propose a novel *related spam number* detection algorithm. The algorithm consists of two components. First, it maintains a watchlist of all potential spam numbers detected based on the SMS sending patterns of individual phone numbers. Second, upon receiving a user spam report, it identifies additional (unreported) spam number candidates which exhibit similar sending patterns at the same network location during the same or nearby time period. Evaluated on a month long dataset, the algorithm identifies 5.1K spam numbers with an extremely high accuracy of 99.4%, where more than 72% and 40% of the detection results are 10 hours and 1 day before the user reports, respectively. Moreover, 9% of the detected spam numbers have never been reported by users possibly due to the extremely low report rate.

We next take a in-depth look at the target selection strategies adopted by most SMS spammers in Chapter 5. We find that most spammers select targets randomly, either from a few area codes or the entire phone number space. This is plausibly due to the *finite* phone number space which enables spammers to reach victims by simply enumerating their numbers. Meanwhile, we find spammers tend to concentrate at and select targets from densely populated geolocations (e.g., large metro areas), where they have access to more resources (e.g., high speed networks and spamming devices) and can reach live users more easily. As a consequence, at these locations, the huge volume of spam traffic can lead to more than a 20 times increase of SMS traffic at some Node-Bs, and more than 10 times at some RNCs. The sheer volume of spam traffic can potentially have an adverse impact on the experience of normal users in these areas.

Based on such observations, to detect these aggressive random spammers, we advance a novel notion of *grey phone space*. Grey phone space comprises a collection of *grey phone numbers* (or grey numbers in short). Grey numbers are associated with two types of mobile devices: data only devices (e.g., many laptop data cards and data modems, etc.) and machine-to-machine (M2M) communication devices (e.g., utility meters and medical devices, etc.). These grey numbers usually do not participate actively in SMS communication as other mobile numbers do (e.g., those associated with smartphones), they thereby form a grey territory that legitimate mobile users rarely enter. In the mean time, the wide dispersion of grey numbers makes them hard to be evaded by spammers who choose targets randomly.

On top of grey phone space, we propose the design of *Greystar*. Greystar employs a novel statistical model to detect spam numbers based on their interactions with grey numbers and other non-grey phone numbers. We evaluate Greystar using five months of SMS call records. Experimental results indicate that Greystar is superior to the existing SMS spam detection algorithms, which rely heavily on victim spam reports, in terms of both accuracy and detection speed. In particular, Greystar detected over 34K spam numbers in five months while only generating two false positives. In addition, more than 15% of the detected spam numbers have never been reported by mobile users. Moreover, Greystar reacts fast to emerging spamming activities, with a median detection time of 1.2 hours after spamming activities occur. In 50% of the cases, Greystar is at least 1 day ahead of victim spam reports. The high accuracy and fast response time allow us to restrict more spam numbers soon after spamming activities emerge, and hence to reduce a majority of the spam messages in the network. We demonstrate through simulation on real network data that, after deploying Greystar, we can reduce 75% of the spam messages during peak hours. In this way, Greystar can greatly benefit the cellular carriers by alleviating the load from aggressive SMS spam messages on network resources as well as limiting their adverse impact on legitimate mobile users.

1.4 Voice Fraud Defense and Analysis

In Chapter 6, we introduce our work in defending against voice fraud activities. In particular, using voice call records collected over a two year period in one of the largest cellular networks in the US, the goal of our study is two-fold: 1) to develop an effective approach to proactively isolate dominant fraud calls from a myriad of legitimate calls; 2) and to conduct a systematic analysis of the unique characteristics and trends of fraud activities in cellular networks, e.g., techniques for soliciting fraud calls and social engineering. Achieving these goals can provide a means of alerting customers and cellular providers of potential fraud threats to avoid financial loss for both parties, and ultimately improve customers' satisfaction. Moreover, understanding different fraud activities can help gain useful insights in developing better hardware/software architecture for preventing future fraud activities.

Since voice call records only contain limited information, such as call time, originating/terminating numbers, country codes and call durations, we explore the relationship among parties participating in the calls (i.e., "who calls whom") for the fraud detection task. In particular, we advance the notion of *voice call graphs* for representing the call records. A voice call graph is a bi-partite graph, where two independent sets of nodes represent the groups of domestic originating numbers and foreign terminating numbers, respectively, and the edges stand for phone calls between these originating numbers and terminating numbers. By visualizing small scale voice graphs and characterizing large scale voice graphs with classic graph statistics, we find that fraud numbers and victims often exhibit very strong correlation, which results in community structures in the voice call graph. Therefore, the task of isolating fraud calls can be formulated as the problem of extracting dominant community structures from voice graphs. This serves as our basic heuristic for detecting voice-related fraud. Based on this heuristic, we propose a Markov Clustering (MCL) based algorithm to decompose voice call graphs in an iterative manner, which produces millions of disconnected subgraphs on a month-long voice graph. We further rely on the strength of community structures (measured by the number of cliques) and their popularity (measured by the number of callers) as a gauge to isolate fraud activities from these subgraphs.

We validate the proposed detection algorithm using two sources of ground truth: 1) a list of phone numbers that are reported by mobile users to the cellular service provider, which are then manually verified by fraud agents to be involved in international revenue sharing fraud (IRSF); 2) online reports from mobile users that are posted on forums, blogs or social media sites. By matching our detection results against the ground truth, we find that the proposed algorithm is able to isolate from millions of terminating numbers the most dominant IRSF fraud numbers. In particular, these IRSF numbers together have attracted more than 85% of the victims and resulted in 78% of the fraud calls. More importantly, in 60% of the cases, our method is able to detect fraud numbers at least 1 month prior to the earliest online user reports. Such an advantage in early fraud detection allows us to effectively reduce exposure to significant financial loss for both mobile users and cellular network providers. In addition to IRSF activities, our method also identifies a wide variety of other types of fraud, ranging from traditional voice scams to emerging fraud cases committed through mobile devices, smartphone apps and online social media sites. This enables us to gain a comprehensive view of voice-related fraud in today's large cellular networks.

Based on our detection results, we conduct extensive analysis of fraud activities in cellular networks. Our analysis unveils two major types of fraud: 1) IRSF fraud which brings direct revenue to the fraudsters through victims placing calls to premium rate international numbers; and 2) scams that rely on social engineering to defraud victims. For both types of fraud, we observe interesting characteristics that are unique to cellular networks. For example, we find malware apps, unlocked devices and online media sites can serve as new channels for carrying IRSF fraud, and smartphone users are more susceptible to many of these fraud activities. Also, personal information such as email contact lists and online transaction details are becoming popular components of social engineering techniques. In addition, we identify the *heteronym property* of fraud numbers, which take advantage of the fact that most mobile devices lack the ability of distinguishing foreign numbers from domestic ones to solicit calls to fraud numbers. Moreover, we find that the vetting process used by online app marketplace and online media sites plays an important role in effectively preventing fraud activities. All these observations provide us with useful insights in designing better and more secure hardware/software platforms to prevent future fraud activities.

Chapter 2

Background

In this chapter, we first briefly introduce the architecture of the UMTS (Universal Mobile Telecommunication System) network under study. We then review the components that form a phone number in UMTS networks. Lastly, we describe the user reporting mechanism that cellular service providers usually deploy to defense against SMS spam.

2.1 UMTS Network Overview

The cellular network under study utilizes primarily UMTS, a popular 3G mobile communication technology supporting both voice and data services. The key components of a typical UMTS network are illustrated in Fig. 2.1. When making a voice call or accessing a data service, a mobile device directly communicates with a cell tower (or node-B), which forwards the voice/data traffic to a Radio Network Controller (RNC). In the case of mobile voice (also including Short Message Service or SMS), the RNC delivers the voice traffic to the PSTN (Public Switched Telephone Network) or ISDN (Integrated Services Digital Network) telephone network, through a Mobile Switching Center (MSC) server. All voice call records, domestic or international, can be observed at MSCs.

When sending an (text-based) SMS message, as illustrated in 2.2, [1] an end user equipment (UE_A) directly communicates with a cell tower (or node-B), which forwards

[1] Note that we focus on studying text-based SMS messages, which are sent through the control (signaling) channel as opposed to messaging services which deliver content through data channels, like iMessage and Multimedia Message Service (MMS).

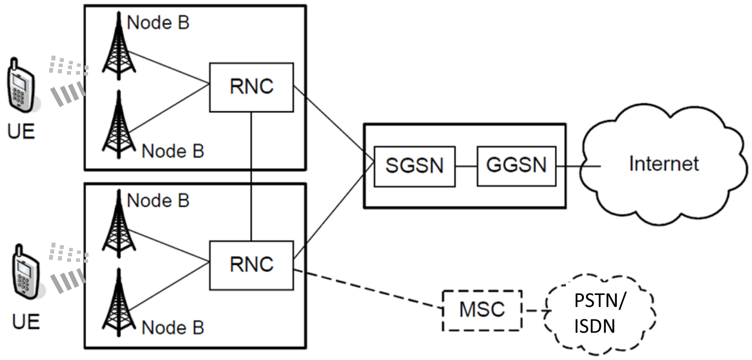


Figure 2.1: UMTS network architecture.

the message to an RNC. The RNC then delivers the message to an MSC server, where the message enters the Signaling System 7 (SS7) network and is stored temporarily at a Short Message Service Center (SMSC). From the SMSC, the message will be routed to the serving MSC of the recipient (UE$_B$), then to the serving RNC and Node-B, and finally reach UE$_B$. The return message will follow a reverse path from UE$_B$ to UE$_A$.

In the case of mobile data, the RNC delivers the data service request to a Serving GPRS Support Node (SGSN), which establishes a tunnel with a Gateway GPRS Support Node (GGSN) using GPRS Tunneling Protocol (GTP), through which the data enters the IP network (and the public Internet) (see [16] for details of the UMTS network). The UMTS network has a hierarchical structure: where each RNC controls multiple node-Bs, and one SGSN serves multiple RNCs. A similar hierarchical structure also exists in the voice channel, where each MSC communicates with multiple RNCs.

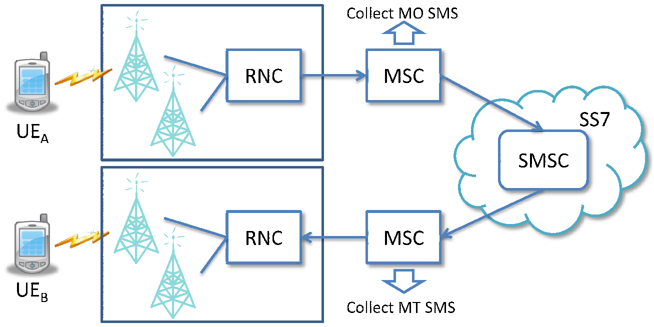


Figure 2.2: SMS architecture in UMTS networks.

2.2 A Primer on Phone Numbers

A telephone number consists of a sequence of digits for reaching a particular phone line in a public switched phone network. The phone line that initiates the call is associated with an *originating number* and the number of the targeting phone line is called the *terminating number*. In a UMTS network, the phone number is also referred to as a MSISDN (Mobile Subscriber Integrated Services Digital Network Number). A MSISDN comprises three components: a country code followed by an area code (also called a national destination code), then by the subscriber number. A majority of phone numbers within the same geographical area share the same country code and area code. Depending on the specific country, phone numbers vary in length. Under certain circumstances, phone numbers from two different countries can be exactly the same (see Section 6.6.4). An international dialing prefix (also referred to as an exit code) is attached in front of the country code to distinguish these numbers. The specific exit code is determined by both the originating country and the terminating country and is provided directly by the cellular service provider. Users need to explicitly dial the exit code in order to initiate an international phone call. However, when receiving a phone call from a foreign party, the exit code is already contained in the incoming foreign number. Therefore, when returning such a call, the exit code is often attached automatically by the mobile device without the user's knowledge.

2.3 User Spam Report

Cellular service providers deploy an SMS spam reporting service for their users: when a user receives an SMS text and deems it as a spam message, s/he can forward the message to a *spam report number (7726 usually)* designated by cellular service providers. Once the spam is forwarded, an acknowledgment message is returned, which asks the user to reply with the spammer's phone number (referred to as the *spam number*[2] hereafter). Once the above two-stage process is completed within a predefined time interval, a

[2] We use the term "spam numbers" here to differentiate from spammers, where the latter term refers to the human beings who are in control of these phone numbers that initiate SMS spam. It will be shown later chapters, spammers often employ multiple spam numbers for an SMS spam campaign. In contrast, a non-spammer (e.g., an airline notification service) typically uses only a single phone number when "broadcasting" an SMS notification to many recipients.

record is created in the user spam report. However, if the user fails to report the spam number or the second SMS response is sent outside the time interval, an incomplete spam record is created, leaving an empty entry for the spam number.

Chapter 3

Related Work

3.1 Spam Analysis and Detection

There is a large volume of literature on analyzing spam activities and on spam detection.

Spam Analysis: In a related study [17], the authors characterized the demographic features and network behaviors of individual SMS spam numbers. Though we also conduct network-level analysis of SMS spam, our purpose is to infer the intents and strategies of SMS spammers, and to identify and explain the correlation among different spam numbers. [18] investigated the security impact of SMS messages and discussed the potential of denying voice service by sending SMS to large and accurate phone hitlists at a high rate. Meanwhile, [18] also discussed several ways of harvesting active phone numbers, which can potentially be employed by SMS spammers to generate accurate target number lists to launch spam campaign more efficiently and to evade detection. [19, 20] studied talkback spam on weblogs. Meanwhile, akin to SMS spammers, the behaviors of email spammers were characterized in [21, 22, 23, 24]. As online social media sites become popular, many studies focus on understanding spam activities on these sites. For example, [25] quantified and characterized spam campaigns from "wall" messages between Facebook users. [26] studied link farming by spammers on Twitter. [27] analyzed the inner social relationships of spammers on Twitter. [28] characterized spam on Twitter. In comparison, we not only study the strategies of SMS spammers but also propose an effective spam detection solution based on our analysis.

Behavior based detection: Network behaviors of spammers, e.g., sending patterns, have been used in SMS spam detection, such as [29]. Similar network statistics based methods designed for email spam detection were also applied for identifying SMS spam, such as[30, 31, 32, 33]. Content-based SMS spam filters using machine learning techniques were also proposed in [34, 35]. However, the application of these methods is limited due to either the unacceptable false alarm rate associated or the large computation overhead on the end user devices, because many legitimate customers can exhibit SMS sending patterns similar to those of spammers. such as the numbers employed by schools, churches and other organization for informing their employees or subscribers important information. In contrast, Greystar utilizes a novel concept of grey phone space to detect spam numbers, which yields an extremely low false alarm rate.

User end solutions: Some systems have been developed in the form of smartphone apps to classify spam messages on user mobile devices[34, 35, 36]. However, not all mobile devices support executing such apps. Furthermore, from a user's perspective, this method is a late defense as the spam message has already arrived on his/her device and the user may already be charged for the spam message. Moreover, the high volume of spam messages that have already traversed the cellular network may have resulted in congestion and other adverse network performance impacts. Greystar is deployed inside the carrier network and hence do not have these drawbacks. As we have seen in Section 5.7, Greystar can quickly detect spam numbers once they start spamming and hence significantly reduce spam traffic volume in the network.

Leveraging unwanted traffic: Similar to our work, many works have leveraged unwanted traffic for anomaly detection, such as Internet dark space [37, 38], grey space [39], honeynet [40, 41] and failed DNS traffic [12], etc. We are the first to advance the notion of grey phone space and propose a novel statistical method for identifying SMS spam using grey phone space.

3.2 Voice Fraud

Our work is related to many research topics as follows.

Fraud detection: There is a rich body of literature on detection of various Internet fraud activities. [42] studied the one click fraud by analyzing public reports of fraudulent websites. [43] designed NetProbe, a system to detect fraud in online auction networks. [44] detected fraud in web advertising networks. [45] used a spectrum based framework for fraud detection in social networks. [46] also studies fraud detection in wireless and landline networks. However, they focused on detecting subscription fraud (account holders who have no intention to pay for any bill) by assessing the similarity between accounts. In comparison, we focus on fraud that employ foreign fraud numbers and target mobile customers inside the cellular network. To the best of our knowledge, our work is the first to present a comprehensive study of voice fraud in large cellular networks and we have discovered many emerging attacks carried by mobile devices, smartphone apps and other channels in mobility networks.

Cellular network security: Due to the increasing popularity of cellular networks, security in cellular networks is becoming an important research area. There are many works which focus on detecting malware, botnets and other anomalous activities in cellular networks. For example, [9] studied 25 distinct families of mobile viruses and worms targeting the Symbian OS and developed a machine learning based malware detection algorithm using behavioral statistics of these malware. [10] designed a mobile botnet called *Andbot* which infects Android mobile devices and utilizes URL flux for the command and control channel. [11] proposed to use process state transitions and user operational patterns to differentiate behaviors of malware and human users. [47] studied the security of feature phones and designed attacks using SMS messages against end-users as well as mobile operators. Most of the existing works focus on securing the mobile data channel. In comparison, our focus in chapter 6 is on fraud activities through voice channels, which have potentially a much wider influence and can bring direct financial loss to both mobile users and cellular network providers.

Graph based anomaly detection: Many recent works focus on anomaly detection by representing the data as graphs and detecting suspicious activities by extracting community structures from these graphs. For example, [48] studied properties of community structures in different application traffic graphs, [12] proposed to utilize DNS failure graphs to identify suspicious network activities, [49] presented a data mining technique for detecting anomalies in various bi-partite social graphs, [13] detected malware by mining file relation graphs. [50] designed a method to capture graph evolution over time and applied the method to detect subscription fraud in telecom networks. Motivated by these works, we propose to use voice call graphs to isolate fraud activities in cellular networks.

Chapter 4

Understanding SMS Spamming Activities

4.1 Introduction

As we have introduced in the previous chapter, service providers adopt user reports to help them defense against SMS spam. which produces much fewer false alarms, thanks to the human intelligence added while submitting these reports. In this Chapter, we collect spam messages reported to one of the largest cellular carriers in the US from May 2011 to June 2012, and carry out an extensive analysis of spamming activities using these user reported spam messages together with their associated SMS network records.

Our objectives are three-fold: 1) to characterize the spamming activities in today's large cellular networks; 2) to infer the intent and strategies of spammers; and 3) to develop effective spam detection methods based on lessons learned from our analysis. Achieving these objectives enables us to gain a better understanding of SMS spamming activities and hence to develop more effective approaches to detect and reduce SMS spams. Based on the characteristics of spam numbers found in our analysis, we pinpoint the inefficacy of existing spam defenses based solely on user spam reports due to the associated low report rate and long delay. By leveraging the strong temporal/spatial correlations among spam numbers employed by the same spammer, we propose and evaluate a novel *related spam number* detection algorithm.

The remainder of this chapter is organized as follows. We briefly introduce the datasets in Section 4.2. In Section 4.3 we analyze user spam reports and extract spam numbers, which we use to study the characteristics of SMS spammers in Section 4.4 and their network behaviors in Section 4.5. In Section 4.6, we cluster spam numbers based on the spam content and further investigate correlations of spam numbers contained in each cluster. Analysis of existing solutions and proposal of new spam defenses are presented in Section 4.7. Section 4.8 concludes the chapter.

4.2 Datasets

In this section, we describe the datasets collected from the UMTS network introduced in 2.1 for our analysis.

4.2.1 User Spam Report Dataset

As we have introduced in Section 2.3, cellular service providers usually deploy an SMS spam reporting service for their users, and user spam reports will be generated when users choose to report spams they received. The dataset used in our study contains spam messages reported by users over a one-year period (from June 2011 to May 2012). The dataset contains approximately 543K complete spam records and all the spam numbers reported are inside the said UMTS network (i.e., for whom we have access to complete service plan information and can hence observe all the SMS network records originated from these numbers). Each spam record consists of four features: the spam number, the reporter's phone number, the spam forwarding time and the spam text content.

4.2.2 SMS Spam Call Detail Records

To assist our analysis of spamming activities from multiple dimensions, we also utilize the SMS (network) records – SMS Call Detail Records (referred to as CDRs hereafter) – associated with the reported spam numbers over the same one year time period. These CDRs are collected at MSCs primarily for billing purposes: depending on the specific vantage point where call records are collected, there are two types of SMS CDRs (see Fig. 2.2): whenever an SMS message sent by a user reaches the SS7 network, a Mobile Originating (MO) CDR is generated at the MSC serving the sender (even when the terminating number is inactive); once the recipient is successfully paged and the message is delivered, a Mobile Terminating (MT) CDR is generated at the MSC serving the recipient. We note that unlike the user-generated SMS spam reports, these SMS CDRs do *not* contain the text content of the original SMS messages. Instead, they contain only limited network related information such as the SMS sending time, the sender's and receiver's phone numbers, the serving cell tower and the device International Mobile Equipment Identity (IMEI) number for the sender (in MO CDRs) or the receiver (in MT CDRs). Using SMS spam numbers identified from spam reports, we extract all CDRs associated with these spam numbers during the same one-year period, and use them to study the network characteristics of spam numbers and hence to infer the intents and strategies of the spammers. Recall that all the focused spam numbers are inside the cellular network under study, we only utilize MO CDRs for our studies, which cover the complete spamming history of each spam number.

We would like to emphasize that no customer personal information was collected or used in our study, and all customer identities were *anonymized* before any analysis was carried out. In particular, for phone numbers, only the area code (i.e., the first 3 digits of the 10 digit North American numbers) was kept; the remaining digits were hashed. Similarly, we only retained the first 8-digit Type Allocation Code (TAC) of the IMEIs in order to identify device types and hashed the remaining 8 digits. In addition, to adhere to the confidentiality under which we have access to the data, in places we only present normalized views of our results while retaining the scientifically relevant magnitudes.

4.3 Analyzing User Spam Reports

In this section, we study the user reported spam messages. We first describe the data preprocessing step and explain how to extract spam numbers from these messages. We then illustrate statistics derived from the spam text content.

4.3.1 Data Preprocessing

Human users, unfortunately, may introduce noise and/or biases in the rather cumbersome SMS spam reporting process. For instance, a user may mistype a spam number in the second step, leave it blank, or simply enter an arbitrary alphanumeric string, say, xxxxxx, due to lack of patience. In addition, users may apply differing criteria in deciding what is considered as spam. To address these issues, we take a rather *conservative* approach and employ several preprocessing mechanisms to filter out the noise and potential biases introduced by human users during the reporting process.

To remove noise, we first filter out all spam reports that do not contain legitimate and valid 10-digit phone numbers[1] . In addition, we use the SMS CDRs to cross-validate the remaining spam numbers, i.e., we remove those that either have no corresponding SMS CDRs (within a week window of the user reporting). This filtering process removes roughly 15.6% of the spam reports from further consideration.

To address the potential biases introduced by users in reporting spam, we match the spam messages in the spam reports against a set of regular expressions defined by anti-fraud/anti-abuse human agents of the cellular carrier (e.g., "*.*you have won a XXX $1,000 giftcard.**"). These regular expressions are generated by these agents over time in a conservative manner based on manual inspection of spam reports and other user complaints, with the aim to restrict the offending spam numbers from further abuse. Hence these regular expressions have been tracked over years to ensure no false positives (the agents are notified of false alarms when legitimate customers call the customer care to complain about their SMS services being restricted). We obtain 384K spam reports after removing all reports that do not match any of the regular expressions.

4.3.2 Spam Number Extraction and Spam Report Volume

During a one year observation period, a phone number can be deactivated, e.g., abandoned by users or shut down by cellular providers, and can be recycled after a predefined time period. In other words, a phone number can be owned by some users for legitimate communication and by some others for launching SMS spam during the observation period. To address this issue, we consult the service plans of the phone numbers and

[1] In fact, 12.2% of the user spam reports contain (valid) so-called *short code* numbers with fewer than 10 digits. The short codes are generally used as gateways between mobile networks and other (computer) networks and services. For instance, they are used for computer users (e.g., via Google voice or Yahoo messenger service) to send SMS messages to other mobile users, or for mobile users to send tweets to Twitter, or to vote for American Idol (in latter two cases, the messages are received by computers for further processing). Since this study focuses on SMS spam sent/received by mobile users, we remove these short code related reports from further consideration, leaving analysis of them as our future work.

identify their service starting times and ending times, which help uniquely identify each phone number. For instance, even with the same 10-digit sequence, a phone number which has a service plan that ends in January and is reopened in May will be counted as two different numbers in these two months. Hereafter we shall follow this definition to identify spam numbers.

After preprocessing, from the one-year user-generated spam reports, we extract a total of 78.8K spam numbers. Fewer than 1,000 spam messages were reported daily in 2011, and since 2012 this number has increased steadily and reached above 5K after April 2012. Furthermore, the number of new spam numbers reported has also increased over time (albeit not as significant). These increases are likely due to two factors: i) SMS spam activities have grown considerably over time; and ii) more users have become aware of – and started using – the spam reporting service. We also observe a clear day-of-week effect because spamming activities are more significant during week days.

4.3.3 Analyzing Spam Text Content

Our initial analysis on the text content of the reported spam messages reveals many interesting observations which we summarize as follows. We find among all the user reported spam messages, 23% of them contain reply phone numbers and 75.1% of them contain at least one valid URL, where 7.4% of these URLs used URL shortening service like TinyURL [51]. This is likely due to the limited SMS message length and spammers' intention of hiding the real phishing sites, which are much easier to be identified by mobile users. We find that 74.6% of the domain names associated with the embedded URLs are lookupable, i.e., they can be resolved to a total of 595 unique IP addresses. For these 595 IP addresses, 443 (74.4%) are associated with one domain name, while the rest of the 152 IP addresses are corresponding to multiple domain names. We find each of these 152 IP addresses is usually associated with a relatively large number of domain names. For example, the largest one is associated with 50 domain names. Moreover, these IPs tend to come from similar subnets.

We further examine the domain names mapped to the same IP address. By looking at the keywords within these domain names, we find clusters of domain names belonging to different topics. For example, we find an IP address that hosts domain names related to free rewards and free electronic devices, where the corresponding domain names look very similar, such as *1k-reward.xxx* and *1krewards.xxx*, and *cell-tryouts.xxx* and *celltryout.xxx*. These observations imply that spammers are likely to rent hosting servers from certain IP ranges that are managed with loose policies. On each hosting server, they tend to apply for multiple domain names and create a separate website for each domain name. In this way, spammers can maximize the utilization of the phishing sites.

An interesting observation is that most spam messages are customized. Over 60% of the messages contain random numbers or strings. These random numbers or strings are often claimed as identification codes or are part of the URLs inside the spam messages. We suspect these random contents are used to differentiate spam victims for two purposes. First, when victims access the phishing sites through the URLs, such random content helps the spammer estimate the effectiveness of the spamming activities. We believe some spammers are paid based on how many unique victims are attracted to the phishing sites by the spam messages. Second, by recording the victims who reply to the spammers or access the phishing sites, spammers can obtain a list of active (or vulnerable in some sense) mobile phone numbers to increase the success rate of future spam activities.

4.4 Characterizing Spam Numbers

Using spam numbers extracted from the user spam reports, we gather various other sources of data associated with these numbers, such as account and device profiles, network and traffic level data and statistics (voice, SMS and data usage patterns, geolocations, and so forth). By analyzing and correlating these data sources, we study the various characteristics of individual spam numbers.

4.4.1 Device and Tenure

Device: In order to identify the devices employed by spammers, we extract the first 8-digit TAC from each IMEI associated with spam numbers and match it against a TAC lookup table. The table was created by the carrier in January 2013, which covers the most popular mobile devices in the cellular network under study.

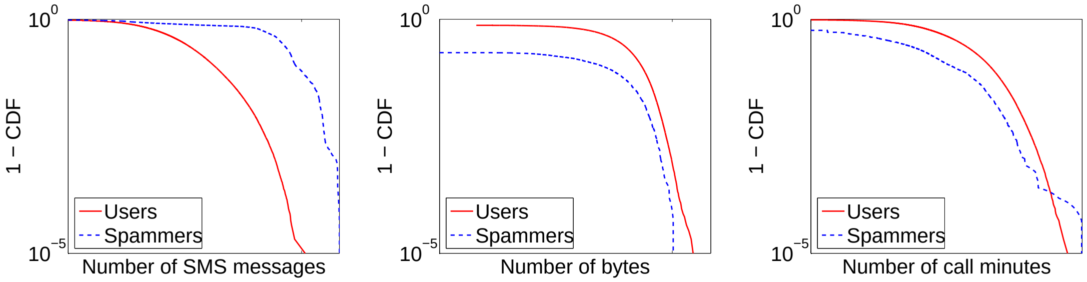
We find that nearly half of the devices are smartphones (44.5%). The rich functionality of these devices enables spammers to create apps to automate SMS spamming activities. There are 20.3% of the devices that have an *unknown* TAC type – this is likely due to either unpopular spam devices or random IMEI numbers generated by SIM boxes. Programmable devices such as 3G data modems, laptops/netbooks, data cards, etc. account for a total of 11.7% devices used in SMS spam. Interestingly, many "M2M" (machine-to-machine) devices (e.g., used for vehicle tracking and vending machines) are also employed by spammers for sending SMS spam. Costs (both in terms of the devices and the account contracts/payment methods available to them) likely play a role in determining what types of devices are deployed for SMS spam campaigns.

Tenure. Here *tenure* is defined as the time from when the account of the spam number is first enrolled in the service until the first spam message from that spammer is reported. We find that a majority of the spammers hold new accounts. In particular, over half of spam numbers have a tenure of only one day and more than 60% of them have a tenure less than a week (similar observation was made in [17]).

4.4.2 SMS, Voice and Data Usage Patterns

We now study the overall SMS, voice and data usage patterns of spam numbers, and compare them with the rest of legitimate numbers [2] . For data usage patterns, only those spam numbers with data activities are used. Figs. 4.1[a-c] display the comparison in terms of the number of SMS messages [a], the number of bytes of data [b] , and the total call duration [c] over the same one month observation period. Not surprisingly, spam numbers initiated far more SMS messages than legitimate ones (Fig. 4.1[a]). In fact, we observe that 80% of the spam numbers send more than 10K SMS's, and half of the spam numbers send more than 100K SMS's. In comparison to SMS usage, spam numbers consume very little data as represented by the much fewer number of bytes (Fig. 4.1[b]). However, among the spam numbers which do initiate data communications, the data activities more often than not involve financial sites such as banks. Further investigation of whether such data traffic is associated with security attacks or other illicit financial transactions is left to future work.

[2] Though we have checked the tenure and device information of the legitimate numbers to remove likely spam numbers, there is still a chance that a few spam numbers are included in these legitimate numbers. However, we believe this does not affect our analysis of the usage behaviors of legitimate numbers given their large population size.



(a) Number of SMS's (b) Number of data bytes (c) Total call minutes

Figure 4.1: Monthly SMS/data/voice usage.

The total call minutes of spam numbers are generally shorter than those of legitimate ones (Fig. 4.1[c]). However, we find some spam numbers may initiate even far more (though generally short) voice calls than legitimate ones do. We count the out-going voice calls from spam numbers and find 10 spam numbers which have initiated more than 10K voice calls. All of them were reported by users on popular online forums [52] as being involved in telemarketing and other voice related fraud activities [53]. It is possible that these spam numbers harvest live mobile numbers through voice calls in order to increase the efficiency of spamming.

4.5 Network Characteristics of Spam Numbers

Using the SMS CDRs, we next study the network characteristics of spam numbers.

4.5.1 Spam Sending Rate

We measure the SMS spamming rate using the average number of SMS messages sent from each identified spam number per hour. We assess the variability of spamming rates using the *coefficient of variation*, which is defined as $c_v = \sigma/\mu$, where σ and μ represent the standard deviation and mean spamming rate of each spam number, respectively. The coefficient of variation shows the extent of variability relative to the mean sending rate. Fig. 4.2 displays the mean spamming rate and the corresponding coefficient of variation for individual spam numbers. For ease of visualization, we illustrate the marginal densities along both axes using rug plots. We observe that the

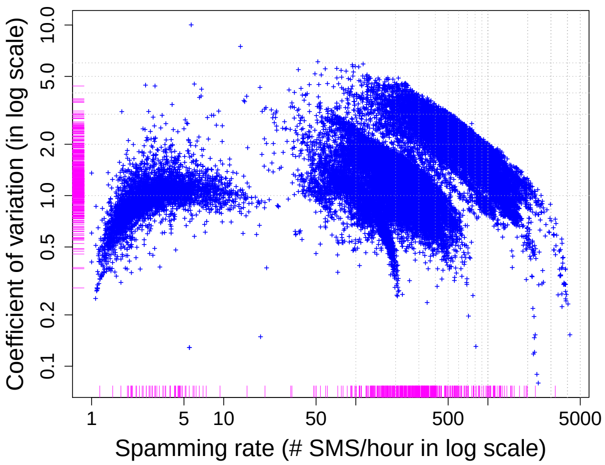


Figure 4.2: Spamming rate and variability in terms of number of messages.

spamming rate varies from a few to over 5,000 spam messages per hour. In addition, while the majority of spamming activities are at a constant rate (i.e., with a low c_v close to the x-axis), some numbers exhibit more bursty spamming behaviors, i.e., with a c_v greater than 3. From these two metrics, we observe three distinct regions, which we refer to as "slow," "moderate," and "fast" spammers (i.e., three clusters from left to right in Fig. 4.2). "Moderate" spammers cover 63% of all spam numbers, while "fast" spammers and "slow" spammers account for 20% and 17%, respectively. Further investigation shows that the spamming rates often depend on the devices used and the network locations of the spammers.

4.5.2 Spamming Locations and Impact on the Cellular Network

We end this section by an assessment of the sending locations of spam messages and the potential impact of spamming traffic on the cellular network. We define the location of a spam number as the serving node-B from which a spam message is sent by that spam number. We find there are a few spam numbers (4.9%) which are highly mobile, i.e., they utilize more than 10 node-B's and distribute their workload among these node-B's (i.e., with the proportion of spam messages from the most dominant node-B less than 40%). However, most spam numbers initiate spam at less than 5 node-B's (78.2% spam numbers) and the most dominant node-B carry more than 60% of the traffic (74.5%). We hence refer to these dominant node-B's as the *primary spamming locations* for spam numbers. In fact, many of these node-Bs reside in densely populated metro areas (e.g., New York City and Los Angeles). We suspect that concentrating on densely populated urban areas enables spammers to easily obtain resources, like used phone numbers. In addition, spammers can take the advantage of the high-speed 3G/4G network at these locations to spam in much higher rates.

At these node-B's, we find that the sheer volume of spamming traffic is astonishing. The spamming traffic can exceed normal SMS traffic by more than 10 times. Even at the RNC's, which serve multiple node-B's, the traffic from spamming may account for 80% to 90% of total SMS traffic at times. Such a high traffic volume from spammers can exert excessive loads on the network, affecting legitimate SMS traffic. Furthermore, since SMS messages are carried over the voice control channel, excessive SMS traffic can deplete the network resource, and thus can potentially cause dropped calls and other network performance degradation. These observations also emphasize the necessity of restricting spam numbers earlier before they reach many victims and inflict adverse impact on the cellular network.

4.6 Investigating Correlations between Spam Numbers

So far we have focused on the characteristics of *individual* spam numbers. In this section we will cluster spam numbers based on the content similarity of the spam messages they generate, and characterize and explain the correlations between spam numbers.

4.6.1 Clustering Spam Messages with CLUTO

Recall that, through our initial manual content inspection, we have observed that many spam numbers are reported to have generated the same or similar spam messages. We hence apply a text mining tool–CLUTO [14, 54]–to cluster spam messages with similar content into spam clusters. CLUTO contains many different algorithms for a variety of text-based clustering problems, which have been widely applied in research domains like analyzing botnet activities [55]. After testing different clustering algorithms implemented in CLUTO, we choose the most scalable k-way bisecting algorithm, which yields comparable clustering results to other more sophisticated algorithms.

Raymond you won ... Go To apple.com.congratsuwon.xxx/*codelrkfxxxxxx*
Laurence you won ... Go To apple.com.congratsuwon.xxx/*codercryxxxxxx*
You have been chosen ... Goto ipad3tests.xxx. Enter: *68xx* on 3rd page
You have been chosen ... Goto ipad3tests.xxx. Enter: *16xx* on 3rd page

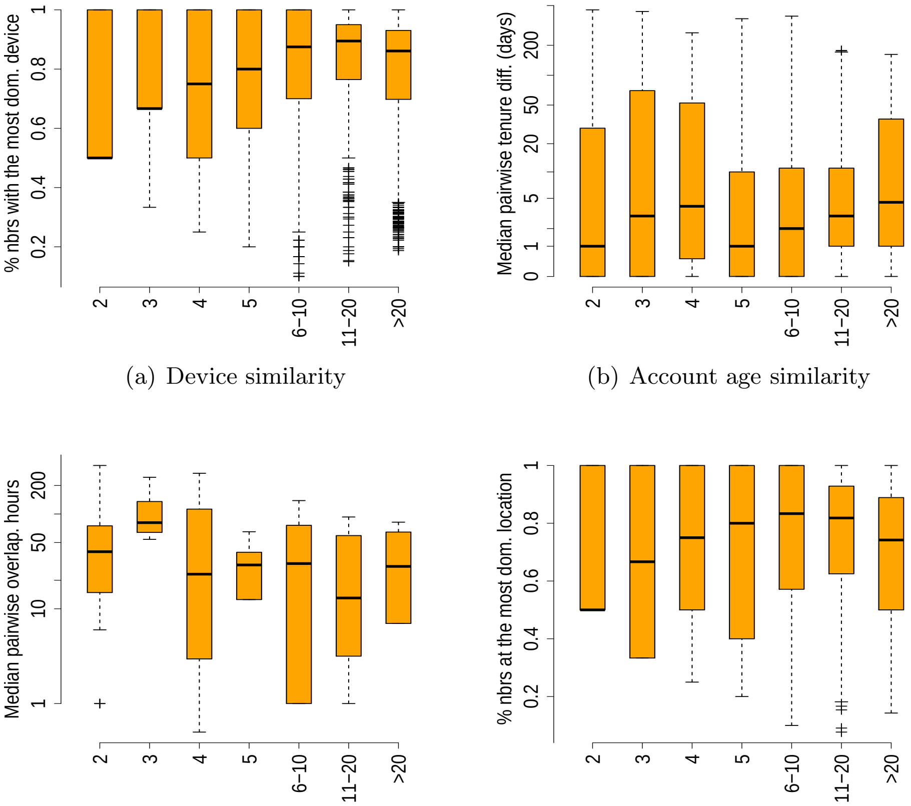
Table 4.1: Example spam messages from the same clusters.

Before applying CLUTO, we first compute a similarity matrix for all the spam messages, using the *tf-idf* term weighting and the cosine similarity function. Operating on the similarity matrix, the k-way bisecting algorithm repeatedly selects one of the existing clusters and bi-partitions it in order to maximize a predefined criterion function. The algorithm stops when K clusters are formed. We explore different choices of K's and select the largest K such that trivial clusters (i.e., which contain only one message) start to appear after further increasing K. Details regarding how to apply CLUTO for clustering spam messages can be found in [56].

We manually investigate and validate the clusters identified by CLUTO. Not surprisingly, we find that spam messages within the same cluster are generally similar except for one or two words. Table 4.1 demonstrates examples of spam messages that belong to two different clusters, where the variant text content is highlighted in blue italics. We suspect that such variant content is specific to each spam victim. Spammers rely on such content to distinguish and track responses from different victims and possibly get paid according to the number of unique responses. In the end, we obtain 2,540 spam clusters that cover all the spam messages. We observe that most of the clusters (92%) contain multiple spam numbers and 48% can cover more than 10 spam numbers. In the follow-up analysis, we focus on the top 1,500 clusters which exhibit an intra-cluster similarity greater than 0.8, and investigate the correlations of the spam numbers inside these clusters. These clusters cover totally over 85% of the reported spam messages.

4.6.2 Correlations of Spam Numbers

Device similarity. We start by comparing the device types associated with individual spam numbers. We define the *device similarity* as the proportion of spam numbers within each cluster that use the most dominant device of that cluster. Fig. 4.3[a] shows the distribution of device similarities. For ease of comparison, we bin spam clusters based on their sizes with the purpose of ensuring enough samples in each bin. We note that in the rest of our analysis, we shall follow the same binning scheme for consistency. We observe that all the bins exhibit strong device similarities, i.e., all with a median similarity greater than 0.5. Meanwhile, device similarity strengthens as the spam clusters become larger. For example, the median device similarity is above 0.8 for clusters with more than 5 spam numbers. This suggests that spam numbers within each cluster tend to be associated with the same cellular device for launching spam.



(a) Device similarity

(b) Account age similarity

(c) Spamming time similarity

(d) Spamming location similarity

Figure 4.3: Correlation of spam numbers belonging to the same spam clusters.

Account age difference. We next consult the account information of the spam numbers and identify their most recent account initiation dates prior to the occurrence of spam traffic. We note that after purchasing a spam number, a spammer may spend some time preparing for spamming by sending out a few test messages. Taking this into consideration, we refer to the *account age* of a spam number as the time span from the account initiation date to the first date with observed active spamming behaviors (i.e., the first date with a spamming rate above 50 messages per hour based on Fig. 4.2).

We measure the *account age difference* of spam numbers in each cluster using the their median pairwise absolute account age difference (in days). From Fig. 4.3[b], we see the median values of such difference in all the bins are below 5 days. Such a small difference indicates that most spam clusters employ spam numbers acquired within a short time period, e.g., purchased from the same retailer at the same time. In fact, for 30% of the clusters, spammers start spamming actively at the same date when all the spam numbers are initiated, 73% within 3 days and 82% within one week. This implies that monitoring and tracking purchases of bulks of phone numbers by the same user can be an effective way of alerting potential spam clusters.

Spamming time similarity. After investigating the similarity of demographic features, we next compare the spamming patterns of spam numbers. We first explore whether spam numbers within each cluster tend to send spam actively during the same time period. We define the time similarity as the median pairwise overlapping time (in hours) with active spamming behaviors (i.e., more than 50 messages per hour), which is displayed in Fig. 4.3[c]. In most of the bins, the median values are above 20 hours, which implies a strong temporal correlation among these spam numbers.

Spamming location similarity. Another spamming pattern we investigate is the spamming locations of spam numbers. We define the *location similarity* as the proportion of spam numbers within a cluster with primary spamming locations being the most dominant one in that cluster. Fig. 4.3[d] displays the distribution of the location similarity, which again appears to be very significant. The similarity reaches 0.8 when the cluster size equals 5 and drops slightly as cluster size further increases. We investigate the clusters with more than 20 spam numbers and find that many of these phone numbers have primarily locations in closeby node-B's. We suspect that this is because spammers want to increase the spamming speed by deploying multiple numbers at nearby locations.

To summarize, various independent evidences from our analysis above of the spam clusters demonstrate that spam numbers within the same cluster are strongly correlated. We believe that the spam numbers contained in the same clusters are very likely employed by the same spammers. These spammers purchase a bulk of spamming devices and phone numbers and program them to initiate spam. These spam numbers thus exhibit strong spatial and temporal correlations. Meanwhile, we observe that for more than 80% of the clusters, the spam numbers in the cluster employ similar spamming rates and target selection strategies. It implies that spammers often program their spamming devices in a similar way (often at the maximum speed allowable for the devices at the locations of the network). In comparison, spam numbers exhibit little correlation across clusters, indicating that different clusters are likely caused by different spammers (likely) from different locations.

4.7 Implications on Building Effective SMS Spam Defenses

Based on our previous analysis on various aspects of SMS spam numbers, in this section, we pinpoint the inefficacy of existing solutions solely replying on user spam reports. We then propose several novel and effective spam defense methods.

4.7.1 Are User Spam Reports Alone Sufficient?

As we have mentioned, many cellular carriers today rely primarily on user spam reports for detecting and restricting spam numbers. Unfortunately, such a user-driven approach inevitably suffers from significant delay. For example, the black solid curve in Fig. 4.4 measures how long it takes for a spam number to be reported after spam starts (i.e., *report delay*). We consider a spam number starts spamming when it first reaches at least 50 victims in an hour. From Fig. 4.4, we observe that only less than 3% of the spam numbers are reported within 1 hour after spam starts. More than 50% of the spam numbers are reported 1 day after. This is likely due to the extreme low spam report rate. Compared with the huge volume of spam messages, less than 1 in 10,000 of spam messages were reported by users in the 1-year observation period.

While most of the report delay is due to the extremely low spam report rate, even users who do report spam may also introduce delay on their side, partly due to the inconvenient two-stage reporting method. The red dotted curve in Fig. 4.4 shows how fast a user reports a spam message after receiving it. Since each user can receive multiple spam messages from the same spammer and can report the same report number multiple times, we define *user delay* as the time difference between when the user reports a spam message and the *last* time that the user receives spam from that particular spammer before the report. We observe in Fig. 4.4, among the users who report spam, half of their reports arrive more than 1 hour after they receive the spam messages. Around 20% of the spam messages occur after one day. In fact, even for those users who report spam, we find around 16.8% of them stop at the first stage and fail to supply the corresponding spam numbers, not to mention the inaccurate spam records caused by users mistyping spam numbers.

Such report delay is amplified when used for detecting multiple spam numbers employed by the same spammers. For example, we measure the earliest report times of all spam numbers in each of the clusters which we identified in Section 4.6 that contain at least 5 spam numbers. Fig. 4.5 demonstrates the total time (in hours) required for users to report 50%, 80% and all spam numbers in each cluster, respectively. We again observe a significant delay in user reports. In particular, for 80% of the clusters, it takes 20 hours for users to report half of the spam numbers in them. It takes even more than 38 hours for users to report 80% of the spam numbers in them.

Therefore, spam defenses relying solely on the current user spam reports can be late and can miss many spam numbers due to both the low report rate and report delay. Advertising can be useful to increase the users' awareness of the spam reporting service and hence can help increase the report rate. Meanwhile, incentives (e.g., credits) provided by cellular carriers can encourage more users to report spam they have received. In addition, an enhancement of the existing cumbersome two-stage reporting method is also important to prevent mistakes during spam reporting and ultimately increase spam report rate. As an example, on smartphones, we are currently developing a mobile-app based solution which enables users to report spam via one single click.

4.7.2 Detecting Spam Numbers using Spatial/Temporal Correlations

In addition to improving the existing spam reporting, we can also design more efficient spam defenses that are less dependent on user spam reports. For instance, although it

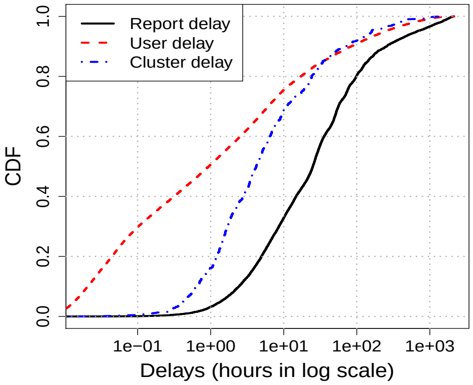


Figure 4.4: Different kinds of delays associated with user reported spam messages.

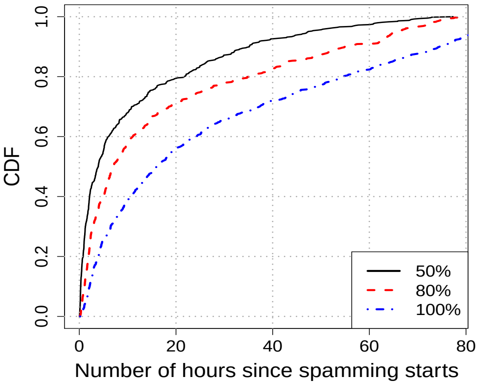


Figure 4.5: Time for users taking to report multiple spam numbers in each cluster.

takes a long time for a majority of the spam numbers in each cluster to be reported by users, the first report regarding a particular spam number often comes much faster. In Fig. 4.4, we show for the top 1500 clusters in Section 4.6, how long it takes for the first number in each cluster to be reported after any number in the cluster starts spamming (i.e., *cluster delay*). For 15% of the top 1500 clusters, we find the earliest report comes within an hour and for 70% of them the first report comes within 10 hours. Given our observation that spammers often employ multiple spam numbers, once a number has been reported, we can detect other related numbers earlier by exploring their temporal and spatial correlations with the reported number, instead of waiting for users to report them.

We illustrate our idea in Algorithm 1, which consists of two components. First, we continuously monitor all SMS senders in the network and maintain a watchlist of phone numbers at different geolocations (node-B's) that have sent SMS messages to more than β recipients in each time interval of length T^3 . Second, the detection part

[3] We note that, the process of maintaining watchlists is similar as running a real-time spam detection purely based on behavioral statistics associated with individual phone numbers. Here we only utilize SMS volume (fan-out) as the feature and apply a hard threshold for detecting suspicious phone numbers. However, more sophisticated features, e.g., SMS message inter-arrival time, entropy based features, etc., and more intelligent thresholds [57, 32], can be applied to further improve the accuracy of the watchlists.

is triggered by a confirmed spam number (e.g., from user spam reports). In particular, when a spam number in the watchlist is confirmed, we look for all the other numbers from the watchlist whose primary spamming locations (i.e., node-B's) is the same as the confirmed number and report them as spam number candidates.

Algorithm 1 Detecting correlated spam numbers.

```
Input: $T$, $\beta$
//Maintaining a watchlist
**for all** Locations $l$ **do**
    Within the observation window $T$, identify $W_l$={$nbr$: $nbr$ at location $l$ has sent
    SMS's to more than $\beta$ recipients}, and $W := \cup W_l$;
**end for**
//Detecting spam numbers by geo/temporal correlations;
**loop**
    **if** A spam number $x$ is confirmed and $x \in W$ **then**
        Obtain the location $l$ associated with $x$;
        Output spam number candidates $W_l - \{x\}$;
    **end if**
**end loop**
```

We simulate the detection process on a month long dataset consisting of CDRs and spam reports received during that month. The proposed algorithm detects 5,121 spam number candidates, 4,653 (90.9%) of which were reported later by mobile users via spam reports. We have the remaining unreported candidates investigated by fraud agents. The investigation combines information sources such as spam reports from online forums (e.g., [58]), service plans, devices as well as the expert knowledge. In the end, 465 of them have been validated to be spam numbers. In other words, the proposed algorithm is highly accurate, with only 3 (less than 0.06%) candidates not yet verified. In addition, we observe that in more than 93% of the cases, the proposed algorithm detects spam numbers an hour ahead of user reports. More than 72% and 40% of the detection results are 10 hours and 1 day before user reports arrive. In fact, more than half of the spam messages can be reduced by detecting and restricting spam numbers using our method. From the perspective of spammers, the proposed method can only be evaded by either reducing the spamming speed, employing a single number for spamming or distribute numbers at different network locations. Nevertheless, any of

For proprietary reasons, the specific choices of parameters β and T will not be released here.

them will either limit the impact of spamming or significantly increase the management cost.

4.8 Summary

In this chapter, we carried out extensive analysis of SMS spam activities in a large cellular network by combining user reported spam messages and spam network records. Using thousands of spam numbers extracted from these spam reports, we studied in-depth various aspects of SMS spamming activities, including spammer's device type, tenure, voice and data usage, spamming patterns and so on. We found that spam numbers sending similar text messages exhibit strong similarities and correlations from various perspectives. Based on these facts, we proposed several novel spam detection methods which demonstrated promising results in terms of detection accuracy and response time.

Chapter 5

Greystar: Detecting SMS Spam using Grey Phone Space

5.1 Introduction

In Chapter 4, we performed extensive analysis on SMS spam, and proposed a novel related spam number detection algorithm based on the strong temporal/spatial correlations among spam numbers employed by the same spammer, as well as user spam report. However, this algorithm still relies on user spam reports, which, as we also pointed out in Section 4.7, inevitably suffers from significant delay. To address this issue, in this chapter, we study popular target selection strategies adopted by spammers and find that a majority of spammers choose targets randomly from a few area codes or the entire phone number space, and initiate spam traffic at high rates.

To detect such aggressive random spammers, we advance a novel notion of *grey phone space*. On top of grey phone space, we propose the design of *Greystar*. Greystar employs a novel statistical model to detect spam numbers based on their interactions with grey numbers and other non-grey phone numbers. We evaluate Greystar using five months of SMS call records. Experimental results indicate that Greystar is superior to the existing SMS spam detection algorithms, which rely heavily on victim spam reports, in terms of both accuracy and detection speed.

The remainder of this chapter is organized as follows. We introduce the datasets used in our study in Section 5.2. We then motivate the design of Greystar in Section 5.3. In

Section 5.4 we study the SMS activities of spammers and legitimate users. The definition of grey numbers is presented in Section 5.5. In Section 5.6, we explain in detail the design of Greystar. Evaluation results are presented in Section 5.7. Section 5.8 summarizes this chapter.

5.2 Datasets

In this section, we describe the datasets and our ground truth used for identifying spam phone numbers in this chapter. We used the same datasets as in Chapter 4, namely user spam reports and SMS call detail records. The CDR dataset spans 5 months from Jan 2012 to May 2012 for the study in this chapter. We also employ six months of spam reports from Jan 2012 to June 2012 in order to cover spam numbers observed between Jan and May but are reported after May due to the delay of the spam reports (see Section 5.3.2).

5.2.1 Obtaining Ground Truth

Although victim spam reports provide us with ground truth for some spam numbers, they are by no means comprehensive and can be noisy (see Section 5.3.2). Therefore, in this paper, we employ a more reliable source of ground truth. In particular, we request the fraud agents from the said UMTS carrier to manually verify spam number candidates detected by us. These fraud agents are exposed to much richer (and more expensive) sources of information. For example, fraud agents can investigate the ownership and the price plan information of the candidates, examine their SMS sending patterns and correlate them with known spam numbers in terms of their network locations and active times, etc. The final decision is made conservatively by corroborating different evidence.

Admittedly, fraud agents can make mistakes during their investigation. Meanwhile, their breadth may be limited by not being able to inspect all mobile numbers in the network. Nevertheless, fraud agents provide us with the most authoritative ground truth available for our study. It is worth mentioning that such investigation by fraud agents has been deployed independently for SMS spam number detection and restriction for more than one year and no false alarm has yet been observed (e.g., no user complaint is observed so far regarding incorrectly restricted phone numbers). Therefore, in our study, we will treat fraud agents as a black box authority, i.e., we submit a list of spam number candidates to fraud agents and they return a list of confirmed spam numbers.

5.3 Objectives and Existing Solutions

In this section, we discuss the objectives of developing an effective defense against SMS spam by comparing the difference between SMS spam and traditional email spam. We then review the most widely adopted SMS spam detection method based on crowdsourcing victim spam reports and point out its inefficacy. In the end, we present the rationale of the proposed Greystar system.

5.3.1 SMS Spam Defense Objectives

In a conventional SMS spamming scenario, an SMS spammer (note that we refer to an SMS *spammer* as the person who employs a set of spam numbers to launch SMS spam campaigns) first invests in a set of phone numbers and special high-speed devices, such as 3G modems and SIM boxes [17]. Using these devices, s/he then initiates unsolicited SMS messages to a large number of mobile phone numbers. Akin to traditional email spam, the objective of SMS spam is to advertise certain information to entice further actions from the message recipients, e.g., calling a fraud number or clicking on a URL link embedded in the message which points to a malicious site. However, SMS spamming activities exhibit unique characteristics which shift the focus of the defense mechanisms and hence render inapplicable or inefficient existing solutions for defending against traditional email spam.

Email service providers usually detect and filter email spam at their mail servers, to which they have full access. There they can build accurate spam filters by exploiting rich features in emails including the text content. Spam filters at end user devices are also a common choice, where email clients (apps) filter spam while retrieving emails from remote mail servers. Though blacklist of email spammers are sometimes used to assist spam classification [59, 60, 61], restricting email spam senders is usually not the main focus of the defense, since it requires close collaboration between email providers and network carriers. Moreover, it is observed that many spam emails are originated from legitimate hosts due to botnet activities [62], which makes restricting spam originators an inapplicable solution.

In comparison to emails which are generally stored on servers and wait for users to retrieve them, SMS messages are delivered instantly to the recipients through the SS7 network. Along the path, SMS messages are only cached temporarily at SMSC (only when the recipients are offline), leaving little time for cellular carriers to react to them. The task becomes even more challenging especially when the SMS traffic volume peaks during busy hours. Filtering SMS spam at end user devices (e.g., using mobile apps) is also not applicable given many SMS capable devices (e.g., feature phones) do not support running such apps. In addition, for a user with a pay-per-use SMS plan, she is already charged for the spam message once it arrives at her device. More importantly, even when SMS spam filters are deployed at SMSC's and end user devices, SMS spammers can still inflict significant loss to the carrier and other mobile users. This is because the huge number of spam messages can lead to a significant increase in the SMS traffic volume at the cell towers serving the spam senders, possibly causing congestion and hence deteriorating voice/data usage experience of nearby users. For example, we have found the SMS traffic volume at cell towers can easily get multiplied by more than 10 times due to the activities of spammers. Therefore, the focus of the SMS spam defense is to *control spam numbers as soon as possible before they reach a large number of victims.*

An efficient SMS spam detection algorithm is hence expected to react quickly to emerging spamming activities. Meanwhile, the focus on restricting spam numbers places a strong emphasis on the accuracy of the algorithm. First, it requires a spam detection algorithm to limit false alarms, because false alarms can lead to incorrect restriction of legitimate users from accessing SMS services. Second, it demands the algorithm detect as many spam numbers as possible so as to minimize the impact of SMS spam activities on the network. Such high accuracy requirements are hard to achieve solely based on the SMS sending patterns of the spammers. For example, it is difficult to separate spam campaigns from legitimate SMS campaigns, such as a school sending messages to its students to alert adverse weather conditions. These legitimate senders can exhibit characteristics that are common to SMS spammers[1] . Spammers may also alter their

[1] Maintaining a whitelist of such legitimate intensive SMS users can be challenging. First, we have little information to identify the white list if the users are outside the network. Second, even for the users inside the network, the whitelist can still be dynamic, with new businesses/organizations

sending patterns to mimic legitimate users to avoid detection. As a result, cellular carriers often seek the assistance from their customers to alert them of emerging SMS spam activities.

5.3.2 Spam Detection by Crowdsourcing Victim Spam Reports

The emphasis on high accuracy gives rise to the wide adoption of spam detection methods based on victim spam reports which were introduced in Section 5.2. Victim spam reports represent a more reliable and cleaner source of SMS spam samples, as all the spam messages contained in the reports have been vetted and classified by mobile users (using human intelligence). To further mitigate the possible errors caused during the two-step reporting process, cellular carriers often crowdsource spam reports from different users. For example, a simple yet effective strategy is to identify a spam number after receiving reports from K distinct users. Meanwhile, defense mechanisms based on victim spam reports are also of low cost, because only numbers reported by users need to be further analyzed. Due to this reason, spam reports are usually a trigger for more sophisticated investigation on the senders, such as their sending patterns, service plans, etc..

Despite the high accuracy and low cost, detecting SMS spam based on spam reports is analogous to performing spam filtering at user devices. The major drawback is detection delay, which we have illustrated in Section 4.7. In addition to the problem of detection delay, the current two-stage reporting method is error-prone. We find around 10% reporters fail to provide a valid spam number at the second stage. Moreover, spam report based methods are vulnerable to attacks, as attackers can easily game with the detection system by sending bogus reports to Denial-of-Service (DoS) legitimate numbers. All these drawbacks render spam detection using victim spam reports an insufficient solution.

5.3.3 Overview of Greystar

Recognizing the drawbacks of existing victim report based solutions, we introduce the rationale behind Greystar. The objective of Greystar is to accurately detect SMS spam

initiating/stopping SMS broadcasting services every day. More importantly, users are not obliged to report to the carrier when they intend to start such services.

while at the same time being able to control spam numbers as soon as possible before they reach too many victims. To this end, we advance a novel notion of grey phone numbers. These grey numbers usually do not communicate with other mobile numbers using SMS, they thereby form a grey territory that legitimate mobile users rarely enter. On the other hand, as we shall see in Section 5.4, it is difficult for spammers to avoid touching these grey numbers due to the random target selection strategies that they usually adopt. Greystar then passively monitors the footprints of SMS senders on these grey numbers to detect impending spam activities targeting a large number of mobile users.

Greystar addresses the problems in existing spam report based solutions as follows. First, the population of grey numbers is much larger and widely distributed (see Section 5.5), providing us with more "spam alerts" to capture more spam numbers more quickly. Second, by passively monitoring SMS communication with grey numbers, we avoid the user delay and errors introduced when submitting spam reports. Last, Greystar detects spammers based on their interactions with grey phone space. This prevents malicious users from gaming the Greystar detection system and launching DoS attacks against other legitimate users.

In the following, we first study the difference of spamming and legitimate SMS activities in Section 5.4, which lays the foundation of the Greystar system. In Section 5.5 we introduce our methodology for identifying grey numbers. We then present the design of Greystar in Section 5.6 and evaluate it in Section 5.7.

5.4 Analyzing SMS Activities of Spammers and Legitimate Users

We first formally define SMS spamming activities. During a spamming process, a spammer selects (following a certain strategy) a sequence of *target phone numbers*, $X := \{x_1, x_2, \cdots, x_i, \cdots\}$ $(1 \leq i \leq n)$, to send SMS messages to over a time window T. Each target phone number is a concatenation of two components, the 3-digit area code x_i^a, which is location specific, and the 7-digit subscriber number x_i^s. Note that we only examine US phone numbers (which have 10 digits excluding the leading country code "1"). Phone numbers of SMS senders from other countries which follow the same North

American Numbering Plan (NANP) are removed before the study. All the statistics in this section are calculated based on a whole month data from January 2012. To compare the activities of spam numbers and legitimate numbers, we obtain an equal amount of samples from both groups. In particular, the spam numbers are identified from victim spam reports and the legitimate numbers are randomly sampled from the remaining SMS senders appearing in the month-long CDR data set. Both samples of phone numbers are checked by fraud agents before the analysis to remove false positives and false negatives.

5.4.1 Spammer Target Selection Strategy

We next study how spammers select spamming targets. Let $X = \{x_t\}, 1 \leq t \leq T$, denote the sequence of phone numbers that a spam number sends messages to over time. Given the fact that each phone number is a concatenation of two components: the 3-digit area code x_t^a, which is location specific, and the 7-digit subscriber number x_t^s, we also characterize the target selection strategies at two levels, i.e., how spammers choose area codes and phone numbers within each area code.

We use the metric *area code relative uncertainty* (ru_a) to measure whether a spammer favors phone numbers within certain area codes. The ru_a is defined as:

$$ru_a(X) := \frac{H(X^a)}{H_{max}(X^a)} = \frac{-\sum_{q \in Q} P(q) \log P(q)}{log|Q|},$$

where $P(q)$ represents the proportion of target phone numbers with the same area code q and $|Q|$ is the total number of area codes in the phone number space. Intuitively, a large ru_a (e.g., greater than 0.8) indicates that the spammer uniformly chooses targets across all the area codes. In contrast, a small ru_a means the targets of the spammer are concentrated by sharing only a few area codes.

We next define a metric *random spamming ratio* to measure how spammers select targets within each area code. Let P^a be the proportion of active phone numbers [2] with area code a. For a particular spamming target sequence X^a of a spam number, if

[2] The active phone numbers are identified as all registered phone numbers inside the carrier's billing database who have unexpired service plans. We find that the active numbers are uniform across all area codes, possibly due to frequent phone number recycling within carrier networks (e.g., phone numbers originally used by landlines are reassigned to mobile phones) and users switching between cellular carriers while retaining the same phone numbers.

the spammer randomly choose targets, the proportion of active phone numbers in X^a should be close to P^a. Otherwise, we believe the spammer has some prior knowledge (e.g., with an obtained target list) to select specific phone numbers to spam. Based on this idea, we carry out a one sided Binomial hypothesis test for each spammer and each area code to see if the corresponding target selection strategy is random within that area code. The random spamming ratio is then defined as the proportion of area codes with random spamming strategies (i.e., when the test fails to reject the randomness hypothesis with P-value=0.05). Note that, for each spam number, only area codes with more than 100 victims are tested to ensure the validity of the test.

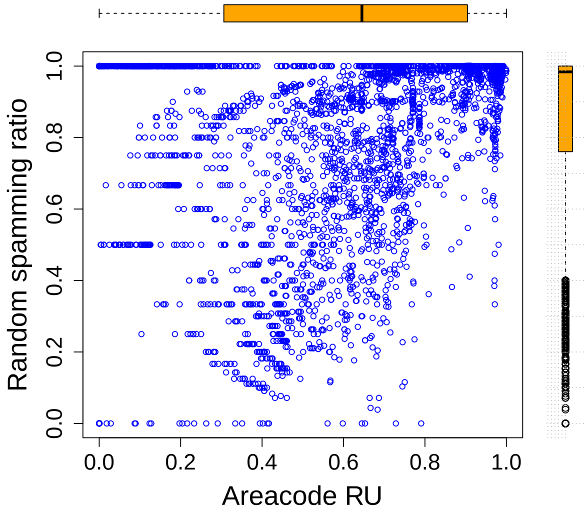
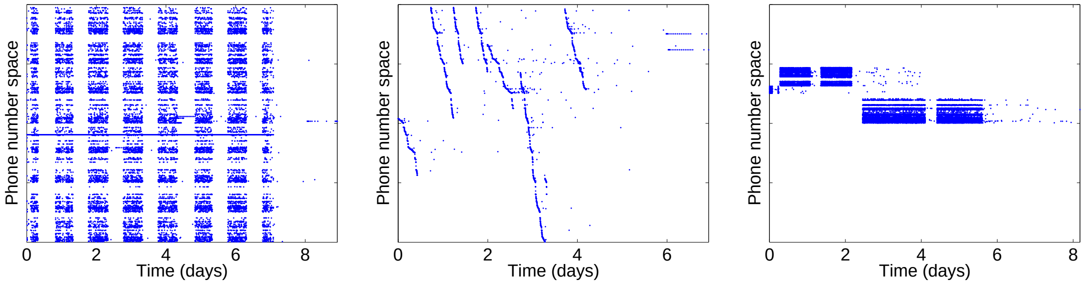


Figure 5.1: Target selection strategies.

Fig. 5.1 plots the ru_a (the x-axis) and the random spamming ratio (the y-axis) for individual spam numbers. For ease of visualization, we illustrate the marginal densities along both axes. Based on the marginal density of ru_a, we find that a majority of spam numbers (78%, using $ru_a = 0.8$ as a cut-off threshold) concentrate on phone numbers within certain area codes. We refer to such a spamming strategy as *block spamming*. In comparison, the remaining 22% spam numbers adopt a *global spamming* strategy, i.e., selecting targets from the entire phone number space. We rank area codes by their popularity among spam numbers, i.e., how many spam numbers select the most target numbers from a particular area code. In fact, we investigate the top 20 popular area code among spammers and find that most of them correspond to large cities and metro areas, e.g., New York City (with 3 area codes) , Chicago (2), Los Angeles (2), Atlanta, and so on.

Based on the y-axis, we find that, no matter how a spam number chooses area codes, a predominant portion of them select targets randomly within each area code. We refer to these spammers as *random spammers* hereafter. This is likely accredited to the finite phone number space, which enables spammers to enumerate phone numbers to send spam messages to. Such random spamming strategies are of almost zero cost and hence are the most economic strategies for spammers. Furthermore, this explains why spammers favor large metro areas, because they are likely to reach more active mobile users by randomly selecting numbers from these area codes.



(a) Global random

(b) Global sequential

(c) Block random

Figure 5.2: Foot prints of most representative target selection strategies.

We illustrate in Fig. 5.2 the “footprints” of three most popular target selection strategies, where the x-axis represents time and the y-axis stands for numbers in the phone number space. The *global random spamming* is shown Fig. 5.2[a], where a spammer randomly chooses phone numbers from the entire phone number space [3] . In comparison, in the *global sequential spamming* strategy (Fig. 5.2[b]), a spammer enumerates

[3] Note that most spam numbers are programmed to avoid well known area codes that are unlikely to contain active mobile users or inflict extra cost when sending SMS to, e.g., 900 area codes and area codes of foreign countries which adopt the North American Numbering Plan (NANP). This results in ranges of phone numbers never assessed by the spam number (i.e., shown as the blank horizontal regions in Fig. 5.2[a]).

numbers in the phone number space in an ascending order and sends spam messages to each phone number sequentially. Different from the above two strategies, *block random spamming* only focuses on victims within certain area codes, and selects victims from each area code randomly; see Fig. 5.2[c] for an example (the *block sequential spamming* strategy, observed less frequently, is omitted due to space limit).

In summary, due to the finite phone space, spammers can simply enumerate phone numbers to send spam messages. Compared to having a target phone number list before spamming, this random target selection strategy is effective and of low cost, and hence has been adopted by most SMS spammers. Due to their predominance, in this chapter, we focus on detecting these random spammers. Meanwhile, the spammers who utilize non-random target selection strategies (e.g., the points at the bottom of Fig. 5.1) will be discussed in Section 5.7.3.

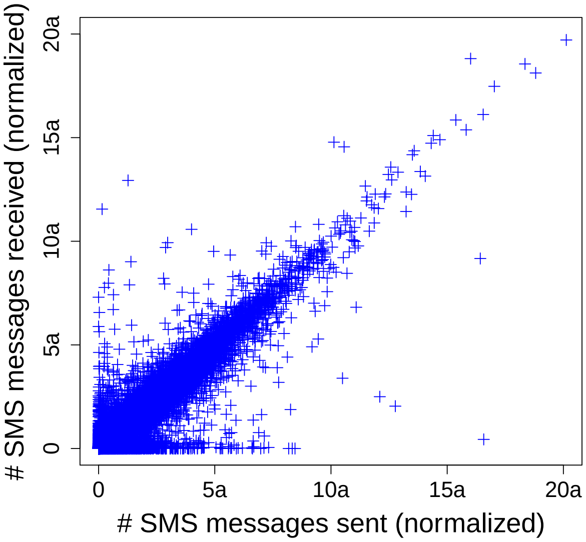


Figure 5.3: SMS sent vs. received.

5.4.2 Mobile User SMS Activities

Since many SMS spammers adopt random target selection strategies, mobile users (within the same area code) have the same exposure to spam. In other words, given a fixed (long enough) observation period, these mobile users are expected to receive an equal amount of spam messages. In this section, we study the SMS activities of legitimate mobile users and demonstrate that certain users can be used for detecting spam activities.

We first obtain a general understanding on the volume of SMS activities from legitimate mobile users in the network. Fig. 5.3 shows the number of messages sent (x-axis) and received (y-axis) by each user over a month[4] . We observe that a majority of users send and receive a similar amount of SMS messages and thereby form an approximate diagonal line. However, there are mobile users who deviate from such a pattern noticeably. For example, the points close to the x-axis represent users who send far more SMS messages than the ones they receive. These users consist of senders who own a large subscriber base, e.g., cellular providers, university emergency contact lines, political campaign lines, etc. In contrast, we observe quite a few points that reside near the y-axis. Investigation shows that they are phone numbers which receive periodic updates (e.g., electricity readings) from machine-to-machine (M2M) devices through SMS messages (see Section 5.5.2 for discussion of M2M devices).

Fig. 5.3 implies the different magnitude that mobile users engaged in SMS communication. To quantify the intensity of SMS activities from mobile users, we define (SMS) *activeness* as the number of messages sent from a mobile user during the observation period. Intuitively, for users who are less active, the spam messages tend to account for a more dominant proportion of their overall SMS communication. We illustrate this point in Fig. 5.4, where we bin all users based on their activeness (x-axis, in log scale), and calculate the distribution of the proportion of spam messages out of all SMS messages received by each user within each bin. Note that spam messages are identified as the SMS messages originated from spam numbers contained in victim spam reports. From Fig. 5.4, we observe an upward shift of spam message proportions as the activeness decreases. Interestingly, we find quite a few numbers which have sent no more than 1 SMS message during the one month period. For a majority of these numbers, all the messages they have received are spam (as indicated by the fact that most probability mass is squeezed to a small region close to 1). This implies that these SMS inactive

[4] We note that the constants used for normalization (denoted as a and b) vary across individual figures.

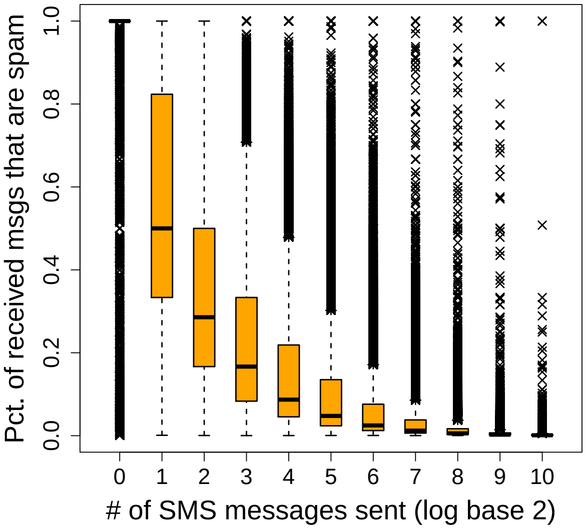


Figure 5.4: Activeness vs. spam prop.

numbers are good indicators of spamming activities, i.e., SMS senders who communicate with them are more likely to be spammers.

5.5 SMS Grey Phone Number Space

In order to utilize these SMS inactive numbers for spam detection, we want to first answer the following questions. Why do these numbers have a low volume of SMS activity? Is there an inexpensive way to identify a stable set of such numbers for building the detection system? To answer these questions, we carry out an in-depth analysis of SMS inactive users. We then define grey phone space and propose a method for identifying the grey phone space using CDR records. In the end, we study properties of grey phone space and show the potential of using it to detect spamming activities.

5.5.1 Investigating Service Plans

Cellular carriers often provide their customers with a rich set of features to build their personal service plans. Users are free to choose the best combination of features to balance their needs and the cost. For example, a frequent voice caller often opts in an unlimited voice plan and a user who watches online videos a lot can choose a data plan with a larger data cap. Therefore, service plans encode demographic properties of the associated users. We hence study the correlations between different service plan features and SMS activeness to understand these SMS inactive users.

More specifically, we extract all the service plans associated with the legitimate user samples, which include features related to voice, data and SMS services. We calculate the Pearson correlation coefficients of the SMS activeness and individual plan features (treated as binary variables). The features are then ranked according to the correlation values. We summarize the top 5 features that are positively and negatively correlated with SMS activeness in Table 5.1.

Top 5 negatively correlated	Top 5 positively correlated
Text restricted	Monthly unlimited voice/text
Voice restricted	Messaging unlimited
Text msg pay per use	Rollover family plan
Voice/data prepaid	Unlimited SMS/MMS
Large cap data plans	Small cap data plans

Table 5.1: Corr. of activeness and plan features.

The top 5 features with negative correlations are in the first column of Table 5.1. Many of these SMS inactive users are enrolled in the pay-per-use SMS plan, a common economical choice for users who rarely access SMS services. Interestingly, a large number of SMS inactive users have restrictions on their voice/text plans and have been simultaneously enrolled in large cap data plans. Such restrictions only apply for mobile users with data only devices, such as tablets and laptop data cards, etc. In contrast, the top 5 features with positive correlations are summarized in the second column. Most of SMS active users have unlimited SMS plans, a favorable choice of frequent SMS communicators. Many of them have also enrolled in small cap data plans and unlimited MMS plans, which are dedicated for smartphone users.

Though service plans demonstrate clear distinctions between SMS inactive and active users, relying on service plans to identify SMS inactive users is not effective in practice due to two reasons. First, service plans change frequently, especially when users upgrade their devices. Second, query service plan information persistently during run time can be very expensive. Fortunately, our analysis above also reveals that service plans are strongly correlated with the device types, e.g., data only device users are less active compared to smartphone users. Can we use device types as a proxy to identify SMS inactive users instead? We shall explore such possibilities in the following section.

SMS towards data only devices. Like phones, laptops and other data only devices are also equipped with SIM cards and hence, once connected to the network, are able to receive SMS messages. We therefore can capture CDR records to these devices at MSCs. However, manufacturers often restrict text usage on these devices by masking the APIs related to SMS functions. Meanwhile, at the billing stage, text messages to these data only devices (with a text restricted plan) are not charged by the carrier. There are exceptions such as laptops enrolled in regular text messaging plans, however, such cases are rare based on our observations.

5.5.2 Identifying Grey Phone Space

The device associated with each phone number can be found in the CDR data based on the first eight-digit TAC of the IMEI. We use the most updated TAC to device mapping from the UMTS carrier in January 2013 and have identified 27 mobile device types (defined by the carrier) which we summarize in Table 5.2. We note that finer grained analysis at individual device level is also feasible. However, we find that, except for the vehicle tracking devices which we shall see soon, devices within each category have strong similarity in their SMS activeness distributions. Hence we gain little by defining grey numbers at the device level.

Type	Examples
Data-only	Laptop data cards, tablets, netbooks, eReaders, 3G data modems, etc.
M2M	Security alarms, telematics, vehicle tracking devices, point-of-sale terminals, medical devices, etc.
Phone	Smartphones, feature phones, quick messaging phones, PDAs, etc.

Table 5.2: Device categories and examples.

Fig. 5.5 shows the CDF distributions of SMS activeness of phone numbers associated with different device types. We observe three clusters of CDF curves. The first one consists of curves concentrating at the top-left corner, representing devices with very low

SMS activeness. This cluster covers all data only devices and a majority of machine-to-machine devices (see [63] for more discussions of M2M devices). The second cluster lies in the middle of the plot, which includes all phone devices. The third cluster contains only one M2M device type, which covers all vehicle tracking devices. Interestingly, the curve of such devices shows a bi-modal shape, where some devices communicate frequently using SMS while other devices mainly stay inactive. Based on Fig. 5.5, we define grey numbers as the ones that are associated with devices in the first cluster, i.e., data only devices and M2M devices excluding the vehicle tracking device category. The collection of all grey number are referred to as the grey phone space. The grey numbers are representatives of a subset of SMS inactive users[5] . Meanwhile, the grey phone space defined in this way is stable because it is tied to mobile devices instead of specific phone numbers, whose behaviors can change over time (e.g., when a user upgrades the device). Furthermore, grey numbers can be identified directly based on the IMEIs in the CDR data with little cost, as opposed to querying and maintaining service plan information for individual users.

5.5.3 Characterizing Grey Phone Space

We next study the distribution of grey numbers and show how grey phone space can help us detect spamming activities.

Fig. 5.6 shows the size of each area code in the phone space (the x-axis, in terms of the number of active phone numbers) and the proportion of grey phone numbers out of all active phone numbers in that area code (the y-axis). The correlation coefficient of two dimensions is close to 0, indicating that grey numbers exist in both densely and sparsely populated areas. The wide distribution of grey numbers ensures a better chance of detecting spam numbers equipped with random spamming strategies. To illustrate this point, we calculate the proportion of grey numbers out of all the numbers accessed by spam numbers (red solid curve) and legitimate users (blue dotted curve). We observe

[5] We use devices in the first cluster as our definitions of grey space, however, as we have seen in Fig. 5.5, even within the grey number categories there are still (a very few) numbers that are highly active in SMS communication. The proposed beta-binomial classification model (discussed in detail in Section 5.6) will take into account this fact. Intuitively, the model detects a spam number only when it is observed to have significant interaction with the grey space. Given a majority of the grey numbers that are SMS inactive, the chance that a phone number is misclassified as a spam number due to its interaction with these outliers in the grey space is very small.

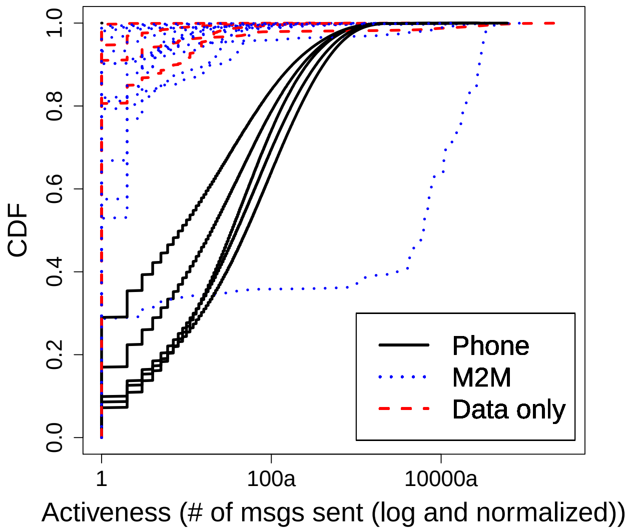


Figure 5.5: Device activeness (log).

that a predominant portion of legitimate users never touch grey phone space. In fact, less than 1% of the users have ever accessed grey numbers in the 1 month observation period. In addition, we show the same distribution for legitimate users (who have sent to at least 50 recipients in a month) conditioned on having touched at least one grey number. Compared to the spam numbers which tend to access more grey numbers (red solid curve), these legitimate users communicate with much fewer grey numbers. In most cases, the access of grey numbers is triggered by users replying to spam numbers who usually use M2M devices to launch spam.

5.5.4 Discussion: Greyspace vs. Darkspace

In addition to the grey phone space, the "dark" phone space (i.e., formed by unassigned phone numbers) can also be a choice for detecting spam activities using the same technique proposed in this chapter. Analogous concepts of grey IP addresses and dark IP addresses for detecting anomalous activities have been explored in [39, 37]. However, unlike IP addresses which are often assigned to organizations in blocks (i.e., sharing the same IP prefix), the phone number space is shared by different cellular service providers,

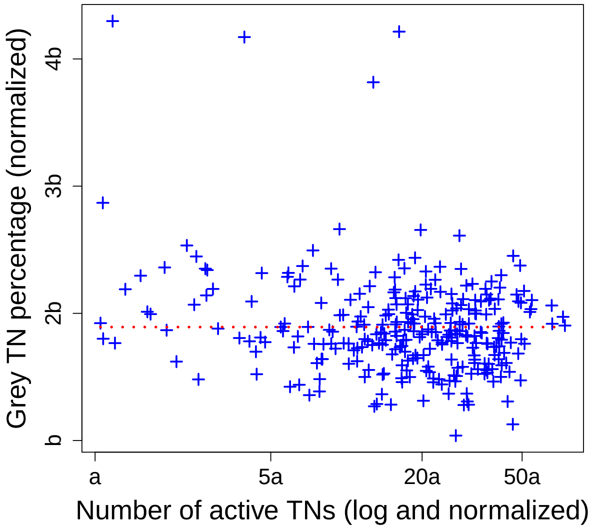


Figure 5.6: Grey number distribution.

landline service providers and even (IP) TV providers. Even if some phone numbers are assigned in blocks initially to a certain provider, the frequent phone number assignment changes caused by new user subscription, old user termination, recycling of phone numbers and phone number porting in/out between different providers will ultimately result in the shared ownership of the phone number space as we have seen today. For example, different cellular and landline providers can have phone numbers under the same legitimate area code. It is difficult to tell which phone number belongs to which provider without inquiring the right provider.

This poses significant challenges when we want to identify dark (unassigned) phone numbers. As dark phone numbers can be anywhere in the phone number space (within legitimate area codes) and can belong to any provider, it is rather difficult to determine a dark number, at least from the perspective of a single provider. For instance, just because a phone number is not assigned to any user/device belonging to a particular provider, it does not necessarily mean that such a number is dark. In other words, accurate detection of dark numbers requires the collaboration of all the owners of the phone number space, which is an intractable task. Meanwhile, such dark number repository needs to be updated frequently to reflect the changes of phone number assignments.

In comparison, grey numbers can be defined easily with respect to a particular provider: these are phone numbers assigned to devices belonging to customers of that provider where there are usually less SMS activities originated from these numbers (devices). Meanwhile, whether a number is grey is readily available to us (based on the existing the IMEI numbers inside CDR records) without any extra work.

5.6 System Design

In this section, we first present an overview of Greystar. We then introduce the detection model and how we choose parameters for the model.

5.6.1 System Overview

The logic of Greystar is illustrated in Alg. 2, which runs periodically at a predefined frequency. In our experiment, we run Greystar hourly. Greystar employs a time window of W (e.g., W equals 24 hours in our studies). The footprint of each SMS originating number s, e.g., the sets of grey and non-grey numbers accessed by s (denoted as G_s and N_s, respectively), are identified from the CDR data within W. After that, a filtering process is conducted which asserts two requirements on originating numbers to be classified, i.e., in the past 24 hours: i) the sender is active enough (which has sent messages to no less than $M = 50$ recipients. Recall the high sending rates of known spam numbers in Fig. 4.2); and ii) the sender has touched at least one grey number. These two criteria, especially the second one, can help significantly reduce the candidates to be classified in the follow-up step. In fact, we find that, on average, less than 0.1% of users send SMS to grey numbers in each day. More importantly, these users cover a majority of active SMS spammers in the network as we shall see in Section 5.7. As a consequence, this filtering step can noticeably reduce the system load as well as potential false alarms.

Once a sender passes the filtering process, the function *detect_spamnbr* is called to classify the sender into either a spam number or a legitimate number based on G_s and N_s associated with that sender. In this chapter, we propose a novel Beta-Binomial model for building the classifier, which we explain in detail next.

Algorithm 2 Greystar algorithm.

```
Input: CDR records $D$ from the past $W = 24$ hours, $M$=50;
Output: Spam number candidates $C$;
From $D$, extract all SMS senders $Orig$;
for each $s \in Orig$ do
    Extract the CDR records associated with $s$: $D_s \subset D$;
    From $D_s$, identify the grey numbers $G_s$ and non-grey numbers $N_s$ accessed by $s$;
    if $|G_s| + |N_s| \geq M$ and $|G_s| > 0$ then
        if $detect\_spamnbr(G_s, N_s)$=1 then
            $C := C \cup \{s\}$;
        end if
    end if
end for
```

5.6.2 Classifier Design

We assume a random SMS spammer selects spamming targets following a two-step process. First, the spammer chooses a specific target phone number block. Second, the spammer uniformly chooses target phone numbers from that block. Let θ denote the density of grey numbers in the target block and $X := \{x_i\}, 1 \leq i \leq n$ be the sequence of target phone numbers selected. Meanwhile, let k be the number of grey numbers in X. The target selection process can then be formulated as the following generative process.

1. Choose a target block with grey number density θ;
2. Choose $x_i \sim Bernoulli(\theta)$, $1 \leq i \leq n$;

We note that θ varies as a spammer chooses different phone number blocks. The choice of phone number blocks is arbitrary. For example, A spammer can choose a large phone block across multiple area codes or a small one consisting of only a fraction of phone numbers within one area code. Therefore, θ itself can be considered as a random variable. We assume θ follows a Beta distribution[6] , i.e., $\theta \sim Beta(\alpha, \beta)$, with

[6] In Bayesian inference, the Beta distribution is the conjugate prior probability distribution for the Bernoulli and binomial distributions. Instead of using the Bernoulli model, we can model the second stage of the target selection process as sampling from a multinomial distribution corresponding to different device types. In this case, the conjugate prior distribution of the multinomial parameters is the Dirichlet distribution. However, our preliminary experiments show little performance gain from applying the more sophisticated model in comparison to the increased computation cost.

a probability density function as:

$$P(\theta|\alpha, \beta) = \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)}\theta^{\alpha}(1-\theta)^{\beta},$$

where Γ is the gamma function. Therefore, the random variable k follows a Beta-Binomial distribution:

$$P(k|n, \alpha, \beta) = \binom{n}{k}\frac{\Gamma(k+\alpha)\Gamma(n-k+\beta)}{\Gamma(n+\alpha+\beta)}\frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)}$$

The target selection process of legitimate users can be expressed using the same process. Because legitimate users tend to communicate less with grey numbers, their corresponding θ^*'s are usually much smaller. Let α^* and β^* be the parametrization of the Beta distribution associated with θ^*. For a phone number that has accessed n targets, out of which k are grey numbers, we classify it as a spam number (i.e., *detect_spamnbr* returns 1) if

$$\frac{P(spammer|k, n)}{P(legitimate|k, n)} = \frac{P(k|n, \alpha, \beta)P(spammer)}{P(k|n, \alpha^*, \beta^*)P(legitimate)} > 1,$$

where the first equation is derived using the Bayes theorem. It is equivalent to

$$\frac{P(k|n, \alpha, \beta)}{P(k|n, \alpha^*, \beta^*)} > \frac{P(legitimate)}{P(spammer)} = \eta$$

In practice, it is usually unclear how many spammers are in the network, therefore, to estimate η directly is challenging. We instead choose η through experiments.

5.6.3 Parameter Selection

There are five parameters to be estimated in the classifier, $\hat{\alpha}, \hat{\beta}, \hat{\alpha^*}, \hat{\beta}^*$ and η. We use the data from January 2012 to determine these parameters. To obtain ground truth, we submit to the fraud agents a list of all the SMS senders that i) have sent to more than 50 recipients in a 24 hour time window; and ii) at least one of the recipients is grey (recall the filtering criteria in Algorithm 2). Fraud agents carry out investigation on these numbers for us and label spam numbers in the list. We then divide the January data into two subsets, the first two weeks of data for fitting the Beta-binomial models (i.e., to determine the first four parameters) and the rest of data is reserved for testing the classifier to estimate η.

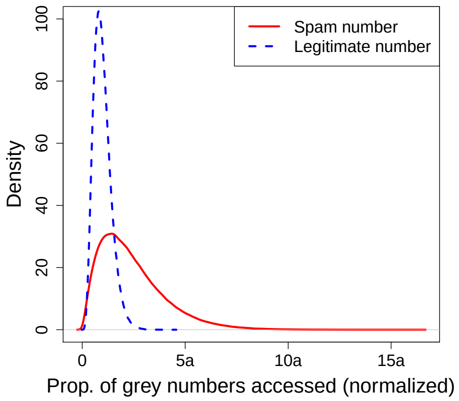


Figure 5.7: Distr. of θ and θ^*.

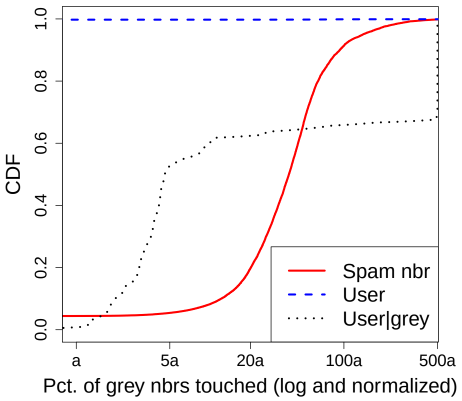


Figure 5.8: Grey ratio.

In particular, using the training data set, we estimate the parameters for two Beta-binomial models using maximum likelihood estimation. With the estimated parameters, we illustrate the probability density function $\theta \sim Beta(\alpha, \beta)$ and $\theta^* \sim Beta(\hat{\alpha^*}, \hat{\beta^*})$ in Fig. 5.7. The density functions agree with our previous observations in Fig. 5.8. The mass of the probability function corresponding to the legitimate users concentrates on a narrow region close to 0, implying that legitimate users communicate much less with grey numbers than non-grey numbers. In contrast, the density associated with spam numbers widely spreads out, indicating more grey numbers are touched by spam numbers due to their random target selection strategies.

We evaluate the accuracy of the classifier given different choices of η on the test data set and the Receiver Operating Characteristic (ROC) curve is displayed in Fig. 5.9. The x-axis represents the false alarm rate (or the false positive rate) and the y-axis stands for the true detection rate (or the true positive rate). From Fig. 5.9, with a certain η, Greystar can detect more than 85% spam numbers without producing any false alarm. We will choose this η value in the rest of our experiments[7] .

[7] Note that the exact parameter values used in Greystar are proprietary and we are not able to release them in the thesis. We have also tested the choice of η using different partitioning of the training/test data. The η remains stable across experiments.

5.7 Greystar Evaluation

In this section, we conduct an extensive evaluation of Greystar using five months of CDR data and compare it with the methods based on victim spam reports in terms of accuracy, detection delay and the effectiveness in reducing spam traffic in the network.

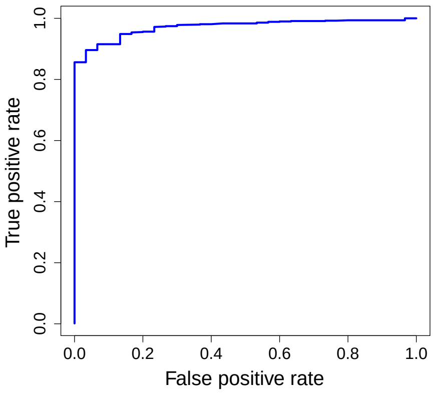


Figure 5.9: ROC curve (false positive rate vs. true positive rate).

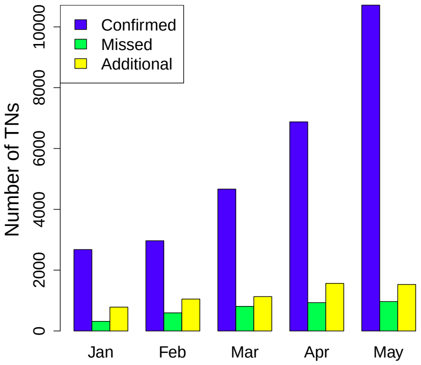


Figure 5.10: Accuracy evaluation (in comparison to victim spam reports).

5.7.1 Accuracy Evaluation

To estimate the accuracy and the false alarm rate, we again consult with the fraud agents to check the numbers from Greystar detection results. False negatives (or missed detections), on the other hand, are more difficult to identify. Given the huge number of negative examples classified, we are unable to have all of them examined by the fraud agents to identify all missed detections because of the high manual investigation cost. As an alternative solution, we compare Greystar detection results with victim spam reports to obtain a lower bound estimate of the missed detections.

More formally, let S_g denote the detection results from Greystar and S_c be the spam numbers contained in the victim spam reports received during the same time period. We define *missed detections* of Greystar as $S_c - S_g$. In addition, we define *additional detections* of Greystar as $S_g - S_c$ to measure the value brought by Greystar to the existing spam defense solution. The monthly accuracy evaluation results are displayed in Fig. 5.10.

The blue bars in Fig. 5.10 illustrate the spam numbers validated by fraud agents in each month. Greystar is able to detect thousands of spam numbers per month. The ascending trend of detected spam numbers coincides with the increase of victim spam reports in the five-month observation window. This implies that Greystar is able to keep up with the increase of spam activities. In addition to the large number of true detections, Greystar is highly accurate given only two potential false alarms are identified by fraud agents in 5 months. Interestingly, these two numbers are associated with tenured smartphone users who suddenly behave abnormally and initiate SMS messages to many recipients whom they have never communicated with in the past. We suspect these users have been infected by SMS spamming malware that launch spam campaigns from the users' devices without their consent. To identify SMS spamming malware and hence removing such false alarms will be our future work.

In comparison to the victim spam reports, Greystar detects over 1000 addition spam numbers that were not reported by spam victims while missing less than 500 monthly. Meanwhile, although a majority of the spam numbers detected by Greystar are also reported by spam victims, Greystar can detect these numbers much faster than methods based on victim reports, and consequently can suppress more spam messages in the network. We illustrate this point in the next section.

5.7.2 Detection Speed and Benefits to Cellular Carriers

We note that, to reduce noise, cellular carriers often rely on multiple spam reports (e.g., K reports) from different victims to confirm a spam number. We refer to such a crowdsourcing method as the $K+$ algorithm. To evaluate the speed of Greystar, we compare it with two versions of the $K+$ algorithms, namely, 1+ and 3+. Comparing with 1+ supplies us with the lower bound of the time difference and comparison with 3+ illustrates the real benefit brought by Greystar to practical spam defense solutions. More specifically, we measure how many hours Greystar detects a spam number ahead of 1+ and 3+, respectively. Fig. 5.11 shows the CDF curves of the comparison results, where we highlight the location on the x-axis corresponding to 24 hours with a green vertical line. We observe that Greystar is much faster than $K+$ algorithms. For example, Greystar is one day ahead of 1+ in 50% of the cases and is one day before 3+ in more

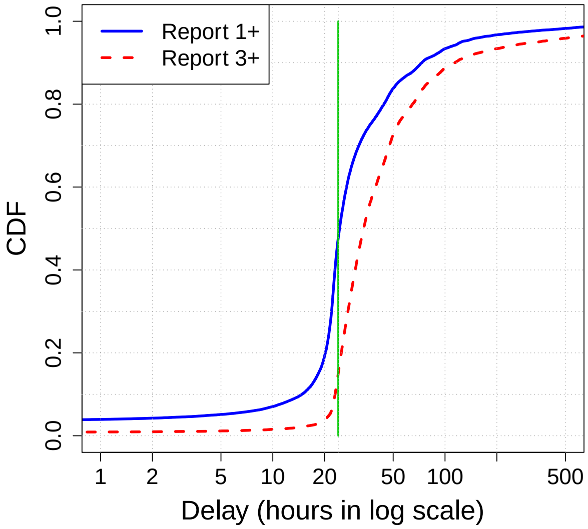


Figure 5.11: Detection speed compared to spam report based methods.

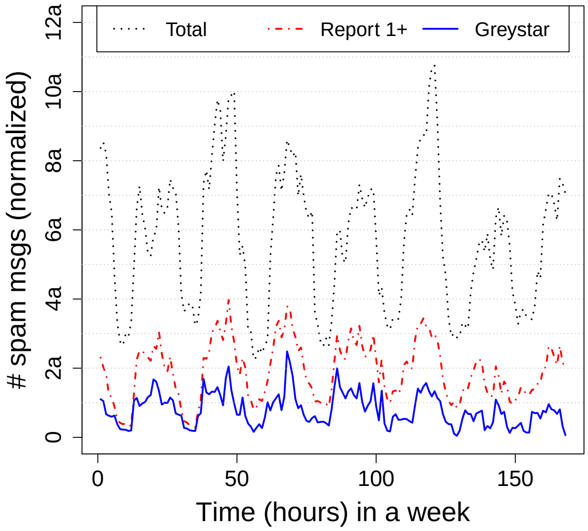


Figure 5.12: Number of spam messages after restriction.

than 90% of the times.

We find that, on average, it takes less than 1.2 hours for Greystar to detect a spam number after it starts spamming (i.e., starts sending messages to more than 50 victims in an hour). The fast response time of Greystar is accredited to the much larger population of grey numbers, from which Greystar can gather evidence to detect more spam numbers more quickly. In addition, collecting evidence passively from grey numbers eliminates the delay during the human reporting process (recall Fig. 4.4). Therefore, Greystar is characterized with a much faster detection speed than the $K+$ algorithm. Such a gain in the detection speed can lead to more successful reduction of spam traffic in the network. We illustrate this point next.

For simplicity, we assume a spam number can be instantly restricted after being detected. We run simulation on a one week dataset (the first week of January 2012) and calculate the number of spam messages appearing in each hour assuming a particular spam detection algorithm is deployed exclusively in the network. The results are illustrated in Fig. 5.12. The total spam messages are contributed by known spam numbers observed in that week. We observe that Greystar can successfully suppress the majority of spam messages. During peak hours when the total number of spam messages exceeds 600K, only around 150K remains after Greystar is deployed. In other words, Greystar leads to an overall reduction of 75% of spam messages during peak hours. In comparison, 1+ only guarantees a spam reduction of 50% due to long detection delay. We note that, due to the noise in the spam reports, cellular providers often employ $K+$ ($K \geq 3$) instead of 1+ to avoid false alarms. In this case, the benefit from Greystar is even more substantial.

5.7.3 Analysis of Missed Detections

In this section, we investigate the missed detections (false negatives) from Greystar, i.e., the spam number candidates that were not detected by Greystar but have been reported by spam victims. There are around 500 such numbers in each month and totally around 27K missed detections. We note that we focus only on a subset of the candidates who are customers of the cellular network under study, for whom we have access to a much richer set of information sources to carry out the investigation. We believe the conclusions from analyzing this subset of candidates also apply for other candidates outside the network.

We classify these candidates into three groups based on the volume of the associated CDR records.

No volume. We do not observe any CDR record for 19.5% of the numbers. We inquiry the SMS billing records for these numbers and find that many of them initiate a vast amount of SMS traffic to foreign countries, such as Canada and Jamaica, etc., and hence no CDR record has been collected to trigger Greystar detection.

Low volume. We find around 27% of the missed detections have accessed less than 50 recipients during the observation period. We study the text content inside the victim spam reports to understand the root cause of these missed detections. The most popular text content are party advertisements and promotions from local restaurants. Users are likely to have registered with these merchants in the past and hence received ads from them. For the rest of the numbers, we find many send out spam messages to advertise mobile apps and premium SMS services. From the users' comments posted on online forums and social media sites [58, 52], we find two of the advertised apps are messenger/dating apps which have issues with their default personal settings. Without manual correction, these apps, once initiated, will send out friend requests to a few random users of the apps. Spam messages from the remaining numbers are also likely to be sent out without users' consent, especially the ones that broadcast premium SMS services. We suspect they are caused by apps abusing permissions or even behaviors of malware apps. For example, one app advertised by spam is reported to contain malware that sent SMS text to the contact list on the infected device, where the text contains a URL for downloading that malware.

High volume. The rest of the phone numbers send SMS to a large number of recipients. From the reported spam text, we find 7.1% of them belong to legitimate advertiser who broadcast to registerred customers and are somehow reported by the recipients. For the rest of numbers, we find their spam topics are quite different from those of the detected ones. In particular, 11% of these numbers are associated with adult sites or hotlines, in comparison to only 0.06% among the detected numbers. Meanwhile, 17.6% of them advertise local shopping deals, as opposed to only 2.1% among the detected ones. Such difference suggests that these spam victims somehow gave out their phone numbers to spammers, e.g., while visiting malicious sites to register services or to purchase products. In addition, we extract the voice call history associated with these high volume candidates. Interestingly, we find that about 4% of these numbers have initiated phone calls to many terminating numbers in the past. We suspect that these spammers employ auto-dialers to harvest active phone numbers (i.e., the ones that have answered the calls) from the phone number space. With the list of active phone numbers, spammers can send spam more effectively and avoid detection in the mean time.

Admittedly, there are spam numbers in these three categories that are missed by Greystar because they are equipped with a target number list obtained through auto-dialing or social engineering techniques (for example, accurate target lists can potentially be obtained by applying techniques discussed in [18]). SMS traffic from these users is not differentiable from that of the legitimate users. However, we emphasize that these missed detections only account for less than 9% of all the spam numbers detected and they will not have a significant impact on the efficacy of Greystar for reducing the overall spam traffic. In fact, we find that, on average, the missed detections sent 37% less spam messages in comparison to the spam numbers detected by Greystar. On the other hand, we do see the needs of combining Greystar and other methods to build a more robust defense solution. For example, many malicious activities can be better detected by correlating different channels (e.g., voice, SMS and data). Meanwhile, cellular carriers can collaborate with mobile marketplace to detect and control suspicious apps that can potentially initiate spam.

5.8 Summary

In this chapter, we presented the design of Greystar, an innovative system for fast and accurate detection of SMS spam numbers. Greystar monitors a set of grey phone numbers, which signify impending spam activities targeting a large number of mobile users, and employs an advanced statistical model for detecting spam numbers according to their interactions with grey phone numbers. Using five months of SMS call detail records collected from a large cellular network in the US, we conducted extensive evaluation of Greystar in terms of the detection accuracy and speed, and demonstrated the great potential of Greystar for reducing SMS spam traffic in the network.

Chapter 6

Voice Graph

6.1 Introduction

In the previous Chapters, we have studied extensively SMS spam and proposed effectively defenses to reduce the adverse impact of SMS spammers. In this Chapter, we study another major threat to mobile users through voice channels – voice fraud, especially when *international* phone numbers are involved.

Using voice call records collected over a two year period in one of the largest cellular networks in the US, the goal of our study is two-fold: 1) to develop an effective approach to proactively isolate dominant fraud calls from a myriad of legitimate calls; 2) and to conduct a systematic analysis of the unique characteristics and trends of fraud activities in cellular networks, e.g., techniques for soliciting fraud calls and social engineering. Achieving these goals can provide a means of alerting customers and cellular providers of potential fraud threats to avoid financial loss for both parties, and ultimately improve customers' satisfaction. Moreover, understanding different fraud activities can help gain useful insights in developing better hardware/software architecture for preventing future fraud activities.

we advance the notion of *voice call graphs* for representing the call records. A voice call graph is a bi-partite graph, where two independent sets of nodes represent the groups of domestic originating numbers and foreign terminating numbers, respectively, and the edges stand for phone calls between these originating numbers and terminating numbers. By visualizing small scale voice graphs and characterizing large scale voice graphs with classic graph statistics, we find that fraud numbers and victims often exhibit very strong correlation, which results in community structures in the voice call graph. Therefore, the task of isolating fraud calls can be formulated as the problem of extracting dominant community structures from voice graphs. This serves as our basic heuristic for detecting voice-related fraud. Based on this heuristic, we propose a Markov Clustering (MCL) based algorithm to decompose voice call graphs in an iterative manner, which produces millions of disconnected subgraphs on a month-long voice graph. We further rely on the strength of community structures (measured by the number of cliques) and their popularity (measured by the number of callers) as a gauge to isolate fraud activities from these subgraphs.

We validate the proposed detection algorithm using two sources of ground truth: 1) a list of phone numbers that are reported by mobile users to the cellular service provider, which are then manually verified by fraud agents to be involved in international revenue sharing fraud (IRSF); 2) online reports from mobile users that are posted on forums, blogs or social media sites. By matching our detection results against the ground truth, we find that the proposed algorithm is able to isolate from millions of terminating numbers the most dominant IRSF fraud numbers.

Based on our detection results, we conduct extensive analysis of fraud activities in cellular networks. Our analysis unveils two major types of fraud: 1) IRSF fraud which brings direct revenue to the fraudsters through victims placing calls to premium rate international numbers; and 2) scams that rely on social engineering to defraud victims. For both types of fraud, we observe interesting characteristics that are unique to cellular networks.

The remainder of this Chapter is organized as follows. The datasets studied are introduced in Section 6.2. In Section 6.3, we formally define voice call graphs and motivate the heuristics for fraud detection. We then propose a MCL based algorithm in Section 6.4 to decompose voice call graphs and isolate fraud related subgraphs. Using ground truth from two sources, we evaluate the detection results in Section 6.5 and conduct systematic analysis of detected fraud activities in Section 6.6. Section 6.7 concludes the Chapter.

6.2 Datasets

In this section, we discuss the datasets and ground truth used in our fraud analysis. We use datasets consisting of a complete set of international voice calls collected at the MSCs of the UMTS network under study. Theses phone calls are initiated by mobile users in the cellular network (i.e., domestic users) to international terminating numbers. We emphasize here that no customer private information is used in our analysis and we have *anonymized* all customer identities (domestic originating numbers). In particular, the anonymization process keeps the area code intact and only anonymizes the remaining 7 digits in the originating numbers. More importantly, the distance between two originating numbers[1] is also preserved after anonymization. In addition to protecting users' privacy, this type of anonymization enables us to study the relationship among phone numbers that participate in the same fraud activities. Similarly, to adhere to the confidentiality under which we have access to the data, in places, we only present normalized views of our results while retaining the scientifically relevant magnitudes.

6.2.1 Obtaining Ground Truth

To evaluate the efficacy of the proposed fraud detection algorithm and to understand different fraud activities, we utilize two sources of user reports as our ground truth.

IRSF list: This list contains phone numbers associated with *international revenue share fraud* activities. In the scenarios of IRSF, an international revenue share provider designates a set of numbers as *premium rate service (PRS)* numbers, which are often priced much higher than normal calls terminating to the same foreign country[2] . The profit generated from calls to these PRS numbers are shared by the revenue share provider and the content provider. By serving as the content provider and attracting victims to call these PRS numbers, the attackers gain direct revenue from these IRSF calls. Cellular service providers are directly impacted by IRSF fraud because they will suffer from monetary loss when their customers refuse to pay for the cost due to IRSF calls. The IRSF list in our study is created from customer reports to the care center of a large cellular service provider regarding suspicious IRSF activities observed from

[1] We treat two phone numbers on_i, on_j as two integers, and the distance between them defined as $|on_i - on_j|$.

[2] In a few countries, revenue sharing numbers can have similar rates as regular calls.

their monthly bill statements. Manual validation then follows up by placing phone calls to the reported IRSF candidates before adding these numbers to the list. If such numbers are of premium rates, provider-specific strategies will be applied to prevent future customers' calls to these numbers. Some agents may even check the numbers that are adjacent to the reported numbers to see if they are also premium-rate. Even though these numbers may not be involved in any reported fraud activities so far, they can be acquired by fraudsters in future. We refer to the phone numbers identified in this way as *premium rate number ranges* in the rest of this Chapter.

Online feedback: This list contains phone numbers regarding which we have found customer complaints posted on forums, blogs and other online media sites, such as [64, 52], through popular search engines. This data source covers a wide variety of fraud activities, such as voice calls related to scams and malware, etc. We note that a small fraction of the IRSF numbers identified from the online feedback overlap with the IRSF list. However, there are also many IRSF numbers which are not covered by the IRSF list, possibly because no one has complained about them yet. In addition, to understand different fraud activities and their associated social engineering techniques, we assign labels to the fraud numbers by distilling and summarizing keywords from user comments describing these numbers (see Section 6.6.3).

We note that since there is no guarantee that users will report all fraud activities they encounter, not to mention that many users lack the knowledge to identify fraud activities, these two data sources only cover a subset of all fraud activities in the network. Moreover, there is often a lag between fraud activities and user feedback. For example, users may only start to notice the IRSF activity when they observe unexpected charges on their monthly bills. As we shall see in Section 6.5.2, such a lag can last weeks to even months, rendering much less effective the widely used reactive fraud detection method based on user feedback.

6.3 Voice Call Graphs

In this section, we advance the notion of *voice call graphs* as a means to represent the communication patterns exhibited in the mobile voice channel. After characterizing voice graphs constructed from different time spans, we propose our key heuristic in identifying fraud activities.

6.3.1 Definition of Voice Call Graphs

In this Chapter, we only study a single direction of phone calls, i.e., the outbound phone calls placed by domestic phone numbers to international numbers. This choice not only helps reduce the volume of the data, but also enables us to observe both fraud calls initiated by domestic numbers and returned calls solicited by incoming fraud calls (e.g., random scanning, see Section 6.6).

In our dataset, each voice record contains the domestic originating number and the targeted international terminating number (note that we drop the terms "domestic" and "international" in the rest of the Chapter for simplicity). By depicting each record as an edge, all voice records can be readily captured by a bi-partite graph, which we refer to as a *voice call graph*, or a *voice graph* in short. Formally, we define a voice call graph $\mathcal{G} := \{\{\mathcal{ON}, \mathcal{TN}\}, \mathcal{E}\}$, where $\mathcal{ON}$ and $\mathcal{TN}$ stand for the set of originating numbers and the set of terminating numbers appearing within the observation time window T, respectively. An edge e_{ij} is drawn between $on_i \in \mathcal{ON}$ and $tn_j \in \mathcal{TN}$ if at least one voice call is made from on_i to tn_j within T. Note that since we only look at phone calls on one direction (i.e., from domestic numbers to international numbers), we treat edges as undirected[3] .

6.3.2 Voice Call Graph Properties

Fig. 6.1 shows a call graph plotted using the Graphviz tool [65], which represents voice calls from 1,000 randomly sampled originating numbers in one single day, where the blue/red nodes represent originating/terminating numbers, respectively. At a glance, the voice graph in Fig. 6.1 is extremely sparse and contains a large number of disconnected components (subgraphs), with a majority of the subgraphs containing only one single edge. For those subgraphs with more than one edge, most of them exhibit a star structure centered on originating numbers, representing one originating number placing phone calls to a few terminating numbers. In comparison, most terminating numbers only have degree 1. As we extend the observation time period and the originating

[3] The definition of voice call graphs can be easily extended to weighted graphs or directed graphs. For instance, the weight on an edge represents the number of calls associated with each edge.

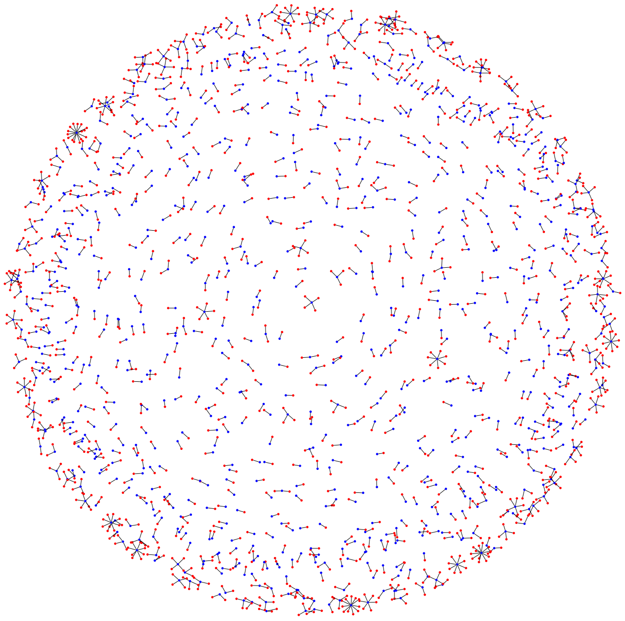
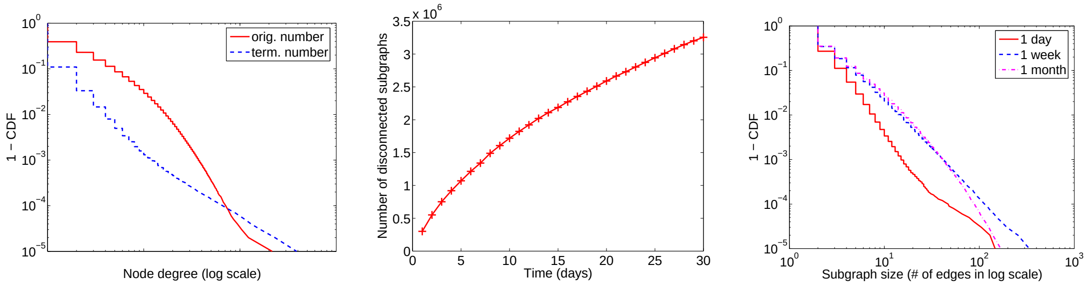


Figure 6.1: A voice graph from 1,000 randomly sampled originating numbers.

number population, the voice graph grows significantly and renders direct visualization inapplicable. Instead, we characterize larger voice graphs using popular graph statistics. Fig. 6.2[a] shows the log-log plot of the node degree distribution in a one-day voice graph. We observe that the degrees of both the originating numbers and terminating numbers display a power-law shape. The power-law shape of the originating numbers implies that a majority of domestic customers rarely call foreign numbers from their cell phones. In addition, the power-law shape of the terminating numbers indicates that, except for a few very popular terminating numbers (on the low end of the curve) associated with hotlines of popular hotels and resorts or foreign agencies like embassies, etc., most terminating numbers receive calls from a very small number of originating numbers.

Similarly to what we observed in Fig. 6.1, originating numbers tend to have a higher degree than terminating numbers. The low popularity of terminating numbers also reflects the lack of correlation among originating numbers. This is not surprising, due to the much larger space of foreign terminating numbers, in general, two mobile customers are unlikely to call the same international number(s). Therefore, voice graphs often



(a) Node degrees in a one-day graph

(b) Number of subgraphs over time

(c) Subgraph size distribution

Figure 6.2: Voice call graph properties.

consist of a large number of small disconnected subgraphs. Fig. 6.2[b] shows the increase in the number of subgraphs over time, which ranges from 0.3 million in a one-day graph to more than 3 million in a one-month graph. The growth is sublinear, plausibly due to the expansion of a giant connected component, which we will discuss in section 6.3.4. In addition, Fig. 6.2[c] demonstrates the distribution of the sizes of subgraphs from voice graphs spanning different time periods (in terms of the number of edges within each subgraph). The subgraph sizes display again a power-law shape, indicating the dominance of small subgraphs in voice graphs. The same observation holds for the voice graphs from one day, one week, and one month data, though we do observe that the number of subgraphs grows during a longer observation period. The extremely low connectivity in a voice graph distinguishes it from other types of widely studied graphs, such as network traffic activity graphs [48] and online social network graphs [66], which often exhibit much stronger connectivity and correlations among nodes.

We note that, since the objective of this Chapter is to identify and analyze fraud activities in cellular networks, we want to identify as many fraud activities as possible. As we shall see in Section 6.6.4, fraud activities can take days to become noticeable. To cover such cases, we need to extend our observation period. Therefore, in the rest of this Chapter, *by default we choose one month as the observation window for constructing voice graphs.*

6.3.3 Heuristic for Detecting Voice-related Fraud

Based on our analysis of voice graphs, we propose our heuristic for detecting fraud activities from these graphs. We utilize two properties of voice graphs. First, in comparison to most legitimate terminating numbers that have low degrees, fraudsters intend to attract more victims to call fraud numbers and hence fraud numbers often appear to be much more popular (also referred to as heavy hitters). We note that detecting heavy hitters is a common approach used for identifying anomalous activities [67, 68]. However, the popularity of terminating numbers alone is not enough in this scenario. We find that the most popular terminating numbers are associated with hotel hotlines, traveling agencies, embassies, and so on. In comparison, as we shall see in Section 6.5, the most popular fraud activities only attract hundreds of victims during a month-long period, which are not among the top high degree terminating numbers. We need additional features to help identify fraud numbers.

The second property we utilize is the low connectivity of voice graphs. Based on our experience, fraudsters often employ several foreign numbers to increase the chance of reaching victims and to avoid detection and regulation. As we shall see in Section 6.6, these numbers can even come from different countries. Therefore, we are alerted with a potential fraud activity while observing many domestic users start placing phone calls to the same set of foreign numbers. The communication patterns exhibiting the above two properties are often referred to as *community structures* in voice call graphs, where a set of originating numbers place phone calls to a set of terminating numbers. This serves as our key heuristic for detecting voice fraud in cellular networks.

Based on this heuristic, we formulate the fraud detection problem as finding the community structures from voice graphs[4] . We note that a community structure can also originate to legitimate activities, for example, due to tourists calling hotlines in a popular resort or companies communicating with foreign branches. However, as we shall see in Section 6.5, this heuristic can help successfully isolate a large number of popular fraud activities from millions of phone calls. In addition, we shall discuss in Section 6.6 that certain types of fraud activities can be detected in a more accurate way

[4] We have also explored other call features such as call duration and call time. However, none of them exhibit significant difference between fraud numbers and legitimate numbers. In future work, we will investigate other features like user calling history to improve detection accuracy.

by investigating properties of the community structures.

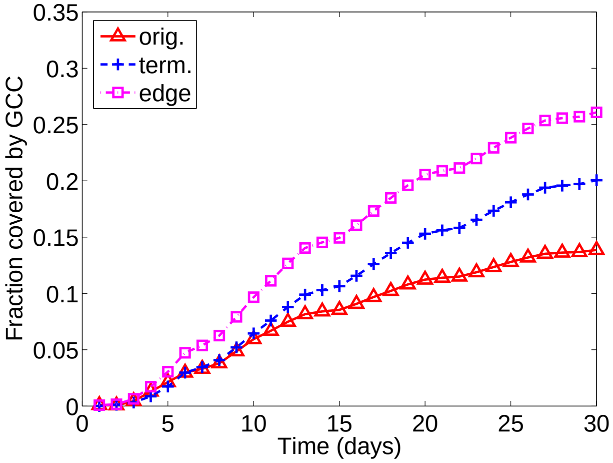


Figure 6.3: Evolution of GCC's in voice call graphs spanning different time intervals.

6.3.4 Challenges

Identifying all community structures is still a challenging task. This is mainly due to the appearance of random edges or weak connections which connect different communities, thereby forming large subgraphs mixed with different fraud activities. For example, Fig. 6.3 shows the evolution of the largest subgraph (a.k.a. giant connected component or GCC) in the voice call graph over a month-long time period. In Fig. 6.3, three curves display the coverage of GCC at a particular time in terms of originating numbers, terminating numbers and edges, respectively. We observe the GCC becomes significant from 10 days onwards and covers up to 25% edges in a 30-day voice graph. Since the voice graphs used in this Chapter are constructed using month-long data, with such a long observation period, the GCC and other large subgraphs can grow to thousands or millions of edges. To separate different fraud activities within GCC and other large subgraphs, it is necessary to decompose them first. Therefore, we next propose a Markov clustering based method for decomposing large subgraphs and then identifying community structures from the decomposition results.

6.4 A Markov Clustering based Fraud Detection Algorithm

In this section, we propose a Markov Clustering (MCL) [69] based algorithm for decomposing voice graphs and identifying potential fraud activities.

6.4.1 Decomposing Voice Graphs using MCL

Alg. 3 shows the proposed algorithm, where we iteratively apply the MCL algorithm to large subgraphs which contain more than N edges ($N = 2,000$). For subgraphs with fewer than 2K edges, we can extract community structures with little cost (see Section 6.4.2).

Algorithm 3 Decomposing voice call graphs with MCL.

```
 1: Input: $\mathcal{G}$, $N = 2,000$, $\beta = 2$;
 2: Extract disconnected subgraphs $\mathbf{G} := \{\mathcal{G}_i\}$ from $\mathcal{G}$, where $\mathcal{ON} = \cup_i \mathcal{ON}_i$, $\mathcal{TN} = \cup_i \mathcal{TN}_i$
    and $\mathcal{E} = \cup_i \mathcal{E}_i$;
 3: for each $\mathcal{G}_i \in \mathbf{G}$ do
 4:   if $\mathcal{E}_i > N$ then
 5:     Construct symmetric adjacency matrix $A$ from $\mathcal{G}_i$;
 6:     repeat
 7:       Normalize rows in $A$;
 8:       $A := A^2$; //expansion
 9:       $a_{ij} := a_{ij}^{\beta}$, for all entries in $A$;//inflation
10:     until $A$ converges
11:     Extract disconnected subgraphs $\mathbf{G}_A$ from $A$;
12:     $\mathbf{G} = \mathbf{G} \cup \mathbf{G}_A - \{\mathcal{G}_i\}$;
13:   end if
14: end for
```

Introduction to MCL algorithm. The MCL algorithm is developed for graph partitioning, which is based on the assumption that random walks tend to stay within the same cluster for a longer time rather than traversing across clusters. MCL iterates two processes: expansion and inflation (line 8 and 9 in Algorithm 3). Expansion takes the power of the Markovian matrix using regular matrix product. For instance, taking the square of the matrix will compute random walks of length two. Since higher length paths are more common within clusters than between different clusters, expansion will increase the probabilities of intra-cluster walks. Inflation is the element-wise power to

β followed by a diagonal scaling (to make the resulting matrix Markovian). Inflation changes the probabilities associated with the collection of random walks departing from one particular edge by favoring more probable walks. MCL terminates when the two processes converge. Cluster memberships can be identified by extracting connected components from the MCL result. We select MCL to decompose voice graphs for two reasons. First, in MCL, we do not need to specify the expected number of clusters. Second, MCL can scale up to large graphs consisting of millions of edges.

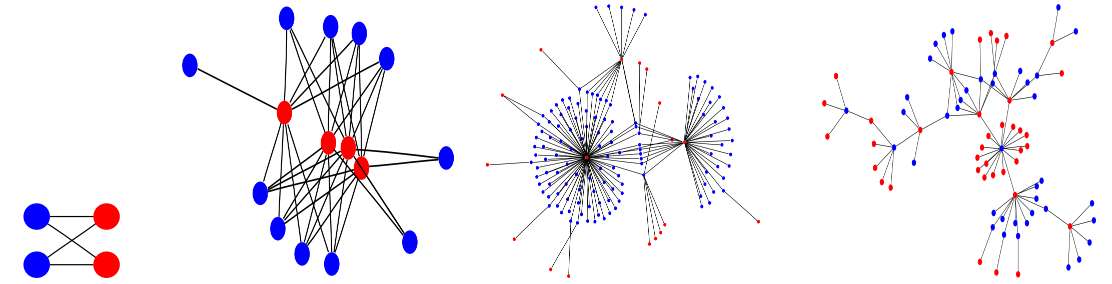
The standard MCL algorithm only takes regular (non bi-partite) undirected graphs as input. However, voice call graphs are bi-partite undirected graphs. Therefore, for each subgraph up to decomposition, before feeding it to MCL, we need to create its corresponding non bi-partite version. For example, let A_{asym} be the adjacency matrix corresponding to a voice graph $\mathcal{G}$, we construct a symmetric adjacency matrix A from A_{asym} as follows:

$$A = \begin{pmatrix} 0 & A_{asym} \\ A^T_{asym} & 0 \end{pmatrix}$$

The MCL algorithm then operates on A and finally decomposes G into a series of subgraphs after iterating the expansion and inflation steps. We have tested different selections of β and $\beta = 2$ yields the most stable and interpretable results, which is the default parameter setting that we use throughout this Chapter. By the end of the algorithm, all voice graphs larger than N will be decomposed and the remaining subgraphs are of less than N edges. We next isolate fraud activities from these subgraphs.

6.4.2 Isolating Fraud Activities

Recall that we have formulated the task of detecting fraud activities as the problem of identifying dense community structures in call (sub)graphs. In a bipartite graph, we refer to the atomic community structure as a *clique*, which represents the smallest complete (2-by-2 bi-partite) subgraph in the original graph. Fig. 6.4[a] shows the structure of a clique, which contains four edges, connecting two originating numbers and two terminating numbers. The total number of cliques varies across different voice graphs. For example, Fig. 6.4[b-d] shows three voice graphs corresponding to three different types of fraud activities identified using the proposed method (Please refer to



(a) A clique.

(b) Win mobile malware (11 orig. nbrs, 4 term. nbrs, 177 cliques)

(c) Random scanning (126 orig. nbrs, 18 term. nbrs, 74 cliques)

(d) Email scam (40 orig. nbrs, 38 term. nbrs, 16 cliques)

Figure 6.4: Voice graphs of a single clique and three different fraud activities.

Section 6.6 for detailed descriptions and analysis of these fraud activities). Fig. 6.4[d] exhibits a much denser community structure, and, as a consequence, is characterized by a large number of cliques[5] . In other words, the number of cliques serves as an indicator of the significance of the community structure in a subgraph. Therefore, in this Chapter, we only consider *subgraphs with at least one clique* as the candidates for fraud activities. After this filtering step, we isolate approximately 30K candidates from millions of call subgraphs every month. For the rest of the subgraphs which contain no clique, the originating numbers show little correlation and hence our heuristic does not apply. In Section 6.5.1, we will discuss those fraud activities that fall into subgraphs without any clique.

After filtering out subgraphs without cliques, we further reduce the number of candidates for investigation based on the graph properties. Based on the heuristic presented in Section 6.3.3, we differentiate subgraphs representing fraud activities from legitimate ones through two features: the popularity of terminating numbers (in terms of the number of originating numbers forming the community structure) and the connectivity of the community structure (in terms of the number of cliques in the subgraph). By matching the first month data against two sources of ground truth, Fig. 6.5 displays how

[5] In fact, the community structure in Fig. 6.4[b] is formed by the return calls in response to three fraud numbers sequentially pinging the same set of victims. The community structure is not significant since victims may not necessarily respond to the same fraud numbers. In Fig. 6.4[c], the fraudster advertised fraud numbers through emails and the loose community structure is due to victims calling multiple fraud numbers. In comparison, Fig. 6.4[d] shows the fraud activity caused by a malware. A victim is programmed to call all the fraud numbers coded in the malware, and thereby showing a very strong community structure.

the detection rate changes while we tune these two parameters. In Fig. 6.5, the x-axis represents the percentile of subgraphs extracted after we change each of the parameters, and the y-axis stands for the proportion of fraud activities that are *not* covered by the x percentile of subgraphs. We observe in Fig. 6.5 that 1) the top 5% subgraphs with no less than 5 cliques account for more than 90% of fraud activities; 2) the top 20% subgraphs with no less than 10 originating numbers also cover around 90% of fraud activities. These observations also validate our heuristic that fraud numbers are often associated with a higher popularity and fraud activities tend to exhibit dense community structures in their corresponding subgraphs. We note that in practice, we prefer to choose higher values for these two parameters. Though this limits the number of fraud activities identified, it can help reduce the workload of manual investigation by eliminating many false alarms. However, since one of our main objectives in this Chapter is to understand the diversity of voice fraud activities in cellular networks, we want to include as many fraud activities as possible. Therefore, in the rest of this Chapter we choose 5 cliques and 10 originating numbers as the thresholds, i.e., only subgraphs with at least 5 cliques and 10 originating numbers will be considered as containing potential fraud activities. Investigation based on the ground truth shows that such thresholds are able to help filter out 98% of these subgraphs, while still capturing more than 90% of the fraud activities.

We note that a limitation of the proposed algorithm is that it relies on strong community structures in voice call graphs to detect fraud activities. Therefore, fraudsters can potentially evade detection by eliminating the correlation among fraud numbers, e.g., by employing only one fraud number or by defrauding a different subset of victims with each individual fraud number. The proposed algorithm also fails to detect stealthy fraud activities that attract less than 10 victims in a month. However, as we shall see in Section 6.5.1, both strategies are not dominant and are only adopted in less than 10% of the observed fraud cases. Moreover, these strategies limit the impact of fraud activities and hence they attract far fewer victims than other fraud activities that employ multiple correlated phone numbers.

In the remainder of this Chapter, for each remaining subgraph, we call the terminating numbers within cliques *potential fraud numbers*. The originating numbers that phone these fraud numbers are referred to as *victims* and the associated calls are called

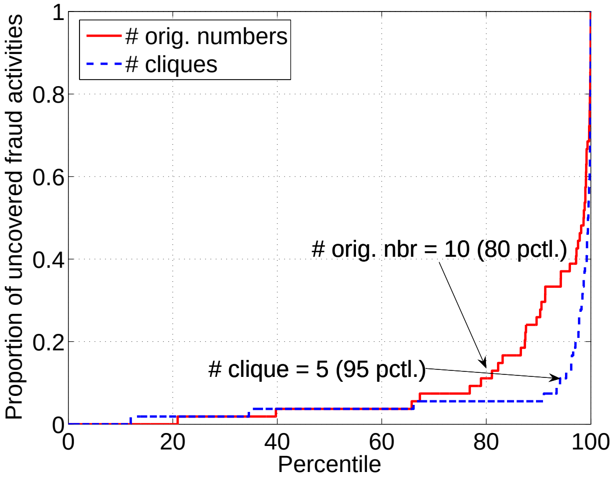


Figure 6.5: Determining thresholds for identifying suspicious clusters.

fraud calls. Fraud numbers, victims, and fraud calls collectively form a *fraud activity*. The remaining nodes and edges in the subgraph are omitted in our studies. Next, we will evaluate our fraud detection results.

6.5 Evaluation

In this section, we compare the detection results against the ground truth. The evaluation shows that proposed algorithm is able to detect most popular fraud activities and our detection results are usually months ahead of user reports.

6.5.1 Evaluation on IRSF Fraud Detection

We run the proposed fraud detection algorithm on five months of data (Jan 2011 to May 2011) Since there is usually an anticipated lag between the occurrence of fraud activities and user reports to the carrier, we use the IRSF list that contains IRSF numbers inserted between Jan 2011 and Oct 2011 by the service provider as the ground truth[6] . Moreover, in Section 6.6, we shall study the evolution of fraud activities using two years of data to track their entire life cycle.

[6] We also have access to the IRSF numbers inserted before Jan 2011. However, most of such numbers show no activity in 2011. This is likely due to the specific strategies exercised by the carrier to prevent users from calling these numbers.

Our first evaluation focuses on detecting IRSF numbers. After decomposing the monthly voice graphs from Jan 2011 to May 2011 and applying the filtering process, we isolate around 24K fraud number candidates in total. Any of the 24K candidates that are covered by the IRSF list is considered as a *true detection* (or a true positive). On the contrary, we consider a *missed detection* when a phone number from the IRSF list appears in the data but not among the 24K candidates. In addition, by searching for feedback on the Internet, we identify a separate set of IRSF numbers outside the IRSF list. Reports of these numbers are often associated with complaints regarding high charges. We refer to this new IRSF number set as *new detections*. We note that the above counting method only provides a lower bound on the detection performance, since some IRSF numbers may be reported after Oct 2011 given the potential lag of user reports (see Section 6.5.2).

To assess the severity and impact of fraud activities, we measure the number of victims and fraud calls attracted by each fraud number. We note that the lifetime of a fraud number determines the quantity of victims and fraud calls associated with that number, which can be affected significantly by user reports. For example, after being reported to the provider, the provider-specific strategies often restrict other users' access to the fraud number. The online user feedback can also prevent other users who read the post from making fraud calls. Therefore, to ensure a fair comparison and to capture the real impact of fraud activities, we count the number of victims and fraud calls of a fraud number only *within a 4-week time window prior to its first report time*. For *true detections* and *missed detections*, we consider the first report time as the time when the fraud numbers were inserted into the IRSF list. For *new detections*, we treat the time of the first online post regarding a fraud number as its first report time.

Table. 6.1 displays the detection results, in terms of the fraud numbers, victims and fraud calls associated with three IRSF number sets. We observe that though the detected and new fraud numbers only account for 11% of all the fraud numbers, together they attract 85% of all the victims and are the root cause of 78% of fraud calls. Fig. 6.6 shows the distribution of the number of victims associated with each IRSF number (note that the x-axis is in log scale). IRSF numbers belonging to the true detection and new detection groups are highly popular and attract a large number of victims, with mean values of 6 and 8, respectively. In comparison, most fraud numbers in the missed detection category are only associated with a single victim. This is plausibly due to two reasons. First, the high popularity of the detected IRSF numbers is actually due to the emergence of new IRSF activities, which utilize malware, unlocked devices, and online social media to draw attention from more victims and hence attract more fraud calls (we shall present case studies of these new IRSF activities in Section 6.6). Second, we find that a majority of the IRSF numbers (more than 90%) that our detection algorithm missed actually belong to the premium rate number ranges. These premium rate numbers were detected proactively by fraud agents exploring the adjacent numbers of confirmed IRSF numbers. However, since no user report is found complaining about these numbers, they may not yet be utilized for fraud activities or the fraudsters have not yet advertised these numbers. In other words, these numbers are *dormant IRSF numbers* in comparison to other *active IRSF numbers* reported by users. By excluding these dormant IRSF numbers, our detection rate on active IRSF numbers can exceed 50%.

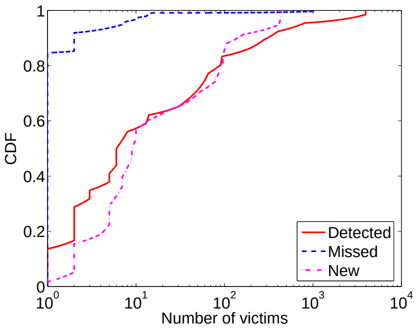


Figure 6.6: Popularity of fraud numbers.

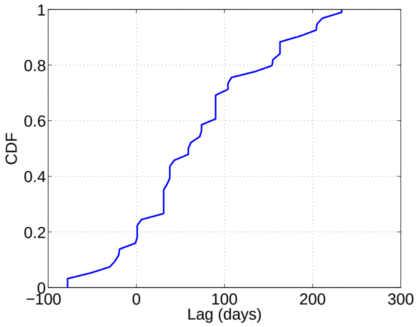


Figure 6.7: Lag of user reported IRSF numbers.

6.5.2 Evaluation on Early Fraud Detection

We have demonstrated that our algorithm can successfully isolate many highly popular IRSF numbers. Taking prompt actions against these IRSF numbers can help both customers and cellular service providers avoid significant financial loss. In fact, one key advantage of our algorithm is the short response time to emerging fraud activities. For the IRSF numbers in the true detection category, we measure the gap between the detection time[7] and the time that they first appear in the IRSF list, which we refer to as the *lag of user reports*. A positive lag value means the detection time goes before the user report time. We demonstrate the cumulative distribution function (CDF) plot of the user report lag in Fig. 6.7. For more than 80% of the IRSF numbers, our detection result precedes user reports and in more than 60% of the cases, we can detect the IRSF numbers at least one month earlier than the user reports! Similar observations are made for the other types of fraud. Early detection of these IRSF numbers provides the cellular service provider with enough time to track and to take actions against these fraud activities to prevent other customers from calling these numbers. On top of our detection results, we are developing tools for alerting customers of potential fraud risk through mobile apps and SMS messages.

Table 6.1: IRSF number detection result.

	Fraud nbrs.	Victims	Fraud calls
Detected	6.7%	66.9%	35.7%
Missed	89.0%	14.6%	22.5%
New	4.3%	18.5%	41.8%

6.5.3 Discussion

False positives. We argue that analyzing voice call graphs alone is not sufficient for identifying fraud activities with high accuracy. By matching the 24K fraud number candidates with the two sources of ground truth, we find that the proposed detection algorithm yields a precision of 9.3%, i.e., around 9.3% out of 24K phone numbers are associated with IRSF or other fraud activities. However, we believe that 9.3% only serves as a precision lower bound. Given the observation of significant delay of user reports in Section 6.5.2, we expect to see more numbers in our detection results to be reported as fraud numbers by mobile users in future.

Practical usefulness. Despite the relatively large number of false positives, the proposed algorithm still provides a valuable “first-line” defense in alerting users and cellular providers of emerging fraud activities. After isolating from millions of voice calls

[7] For IRSF numbers detected using data from one particular month, their detection time is defined as the first day in the following month, e.g., if an IRSF number is detected using the April data, its detection time is considered as May 1st.

a small number of fraud candidates using our method, cellular service providers can allocate resources to track these suspicious numbers and combine with other expensive data sources, like billing information and customer call history, to further confirm the fraud activities. For example, we can investigate the billing records associated with potential IRSF calls to look for exorbitant charges. IRSF numbers can also be confirmed by directly calling these numbers[8] . We believe many of these methods can be automated to reduce the manual cost, e.g., through automated query scripts or using auto-dialing tools, to make post-investigation of our automatic detection results more manageable. More importantly, our analysis using real voice call records shows that, by proactively identifying and restricting potential IRSF numbers based on our detection results, cellular service providers can benefit from a reduction of tens of thousands of fraud calls per month, and subsequently a huge saving in customer care cost and an implicit increase in customer satisfaction, which far outweighs the cost of investigating the detection results.

Other fraud. We note that, unlike IRSF activities, we are unable to assess the detection rate of other types of fraud, since we are not able to query all the numbers to find corresponding user feedback (if any) through online search engines. However, as we shall see in Section 6.6, our method has successfully identified many other types of voice fraud, including emerging fraud cases committed through mobile devices, smartphone apps and online social media sites. This enables us to gain a comprehensive view of voice-related fraud in today's large cellular networks. Understanding these fraud activities, e.g., how are they committed (Section 6.6.2) and what are their popular social engineering techniques (Section 6.6.3), can provide us with unique insights into how to design securer software/hardware architectures to prevent future fraud activities.

6.6 Analysis of Fraud Activities

In this section, we present detailed analysis of the fraud numbers detected using the proposed method.

[8] Once accessing an IRSF number, the callers are often transferred to an interactive voice response, where they are kept on hold with background music, while their airtime is being used.

Table 6.2: Categorization of fraud activities.

Revenue	**Channel**	**Description**	**Pct.(%)**	**RS**
IRSF (dir.)	Malware	Malicious mobile apps with automated dialer to IRSF numbers	13.2	ALL
	Random Scanning	Pinging a range of phone numbers sequentially to solicit return calls	3.3	1.37
	Online Media	Publishing IRSF numbers on blogs, forums and social networks	2.5	1.20
	Unlocked Device	Unlocked devices are pre-configured with IRSF numbers as SMS or MMS access points	2.5	0.53
	Device Exploit	Only certain brand and type of phones are involved	0.8	0.13
Scam (indir.)	Target Scam	Calls users who fraudsters already have information about and attempt to collect more information, to sell products, or to defraud them of money, etc.	55.4	1.04
	Online Media	Post phone numbers online and cheat for money from people who call	10.7	1.44
	Email	Hack somebody's email account, send phishing emails to all the contacts	8.3	1.46
	Malware	Lock users' PCs, force them to call certain numbers to remove the malware	3.3	1.01

6.6.1 Stability of Fraud Activities

Since we use whole month datasets for fraud detection, certain long lasting fraud activities that span several months can appear multiple times. In order to obtain an accurate count of different fraud activities, we first need to remove these duplicated cases. Our approach is as follows.

For any two detected fraud activities i and j, we calculate their similarity using the Jaccard similarity coefficient, defined as $J(i, j) := |\mathcal{FN}_i \cap \mathcal{FN}_j|/|\mathcal{FN}_i \cup \mathcal{FN}_j|$, where $\mathcal{FN}_i$ represents the set of fraud numbers associated with fraud activity i. $J(i, j)$ ranges from 0 to 1, with $J(i, j) = 1$ indicating that two fraud activities are caused by the same fraud numbers. For a fraud activity i, we find its most similar counterpart k from other fraud activities, where $k = argmax_j J(i, j)$. We display the Jaccard similarity between each fraud activity and its most similar counterpart in Fig. 6.8.

We observe that Fig. 6.8 displays a bi-modal shape, where a majority of the fraud activities do not have a counterpart with a similar set of fraud numbers. Based on the plot, we select 0.6 as the threshold and consider a fraud activity i is a duplicate if there exists another activity j such that $J(i, j) > 0.6$.

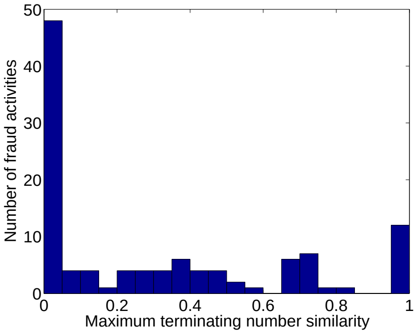


Figure 6.8: Stability of fraud activities measured by term. numbers.

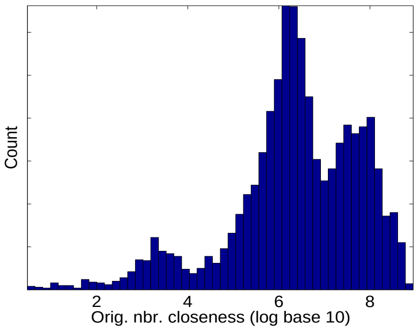
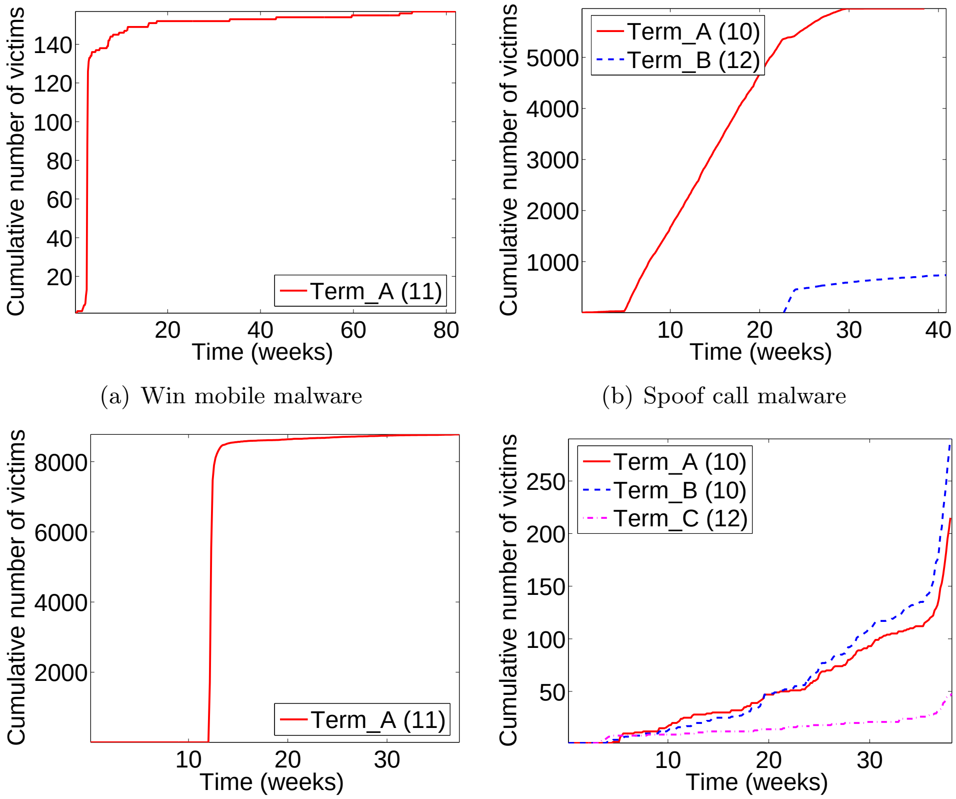


Figure 6.9: Closeness of originating numbers.

6.6.2 Categorization of Fraud Activities

After removing duplicated instances, we match the fraud number candidates from our five months of detection results against the online user feedback to categorize different types of fraud. In particular, we run queries for all fraud number candidates through popular online search engines and extract user comments regarding these numbers based on the search results. Most comments are from online forums, such as *whocallsme.com*[64] and *800notes.com*[52], etc. We manually investigate all the comments and identify different types of fraud activities based on the comments. We note that when we compare user comments regarding different phone numbers within the same fraud activity, we find consistency in terms of the user feedback describing these fraud numbers. This confirms the validity of our detection result, where phone numbers exhibiting strong correlation (e.g., appearing in the same subgraph) are employed for conducting the same fraud activity. In addition, this observation enables us to categorize voice fraud at the level of fraud activities instead of individual phone numbers.

We display the fraud categorization in Table 6.2. Based on whether the fraud activities can bring immediate monetary gain to the fraudsters, we classify them into two major categories: *IRSF* and *Scam* (column 1). Inside each major category, we further group fraud activities into subcategories according to the channels through which different fraud activities are committed (column 2). In the third column of Table 6.2, we present the details of each type of fraud activity. The dominance of each type of fraud in terms of their proportion out of all fraud activities is shown in the fourth column. In the fifth column, we display the *relative significance* (RS) of smartphone devices participating in each type of fraud, which we shall define formally at the end of this section. In the following, we discuss each fraud category in detail and present case studies.



(a) Win mobile malware

(b) Spoof call malware

(c) Scam on Twitter

(d) Voting scam

Figure 6.10: Cumulative number of victims attracted by different fraud activities.

IRSF. IRSF fraudsters devise various approaches to solicit users to make as many phone calls as possible to the fraud numbers to maximize their profit. Though IRSF activities are also common for landlines, we have discovered a number of IRSF activities unique to cellular networks, including:

1) Malware. The most dominant IRSF case, accounting for 13.2% of all fraud activities, is caused by malicious mobile apps. These mobile apps are designed to be able to initiate users' inadvertent phone calls to IRSF numbers. These IRSF numbers employed by the malware can be either static or dynamic. In the former case, we find a malware disguised as a gaming app on windows mobile devices (referred to as windows mobile malware), which has four IRSF numbers hard coded. At night, the app launches many calls to these IRSF numbers automatically. The corresponding voice graph corresponding is depicted in Fig. 6.4[d], which shows a large number of cliques since the app automatically calls all these 4 IRSF numbers.

In the latter case, we identify a series of apps (possibly with the same authorship) which are claimed to be able to spoof the caller's identity or changing the caller's voice (referred to as spoof call malware). However, when a user places a call (e.g., to a domestic number), the call will first pass through an IRSF number (i.e., as a proxy) before reaching the destination. More interestingly, we find that these apps are able to communicate with a remote server to download new lists of IRSF numbers periodically. Due to the employment of dynamic IRSF numbers, it is much harder to detect and disable these apps.

In Fig. 6.10[a-b], we compare the IRSF numbers associated with these two types of malware in terms of the number of victims attracted over time[9] . The x-axis is aligned to the first time when we observe the fraud number, and the y-axis represents the cumulative number of victims over time. In addition, for each terminating number, we display its length (i.e., number of digits) inside the parentheses.

Fig. 6.10[a] demonstrates an IRSF number employed by the Windows mobile malware. We observe that around 140 victims start calling the number within 2 weeks after its debut. However, the number of new victims quickly vanishes after 6 weeks when the malware is taken down from the online marketplace. In comparison, Fig. 6.10[b] shows a similar plot for the spoof call malware. After the malware appears, we observe a linear increase of victims to 50K in around 20 weeks. This is mainly because the malware targets unlocked devices and is hosted by an unofficial website, which lacks a formal process for identifying and removing malicious apps. Meanwhile, when `Term_A` became unavailable somehow at the 20th week, the fraudster acquired a new fraud number `Term_B` and remotely configured the malware to start calling this new number. Therefore, we can see a continuous increase of victims associated with the new number

[9] Because the curves corresponding to the fraud numbers of the same fraud activities in Fig. 6.10[a] and [c] look almost the same, we hence only show one example in each plot.

after 30 weeks, when Term_A stopped acquiring new victims.

2) Random Scanning. In this scenario, fraudsters employ automated calling system to ping a series of adjacent phone numbers and leave no message to attract users to call back. This type of fraud activity can be distinguished by measuring the distance of the originating numbers (recall our datasets contain only the outgoing calls).

In order to measure the relationship of originating numbers, we define the *closeness* as $median_i(\min_j |on_i - on_j|)$, where $on_i, on_j \in \mathcal{ON}$. Essentially, closeness measures the median distance of all originating numbers to their closest counterparts. Fig. 6.9 shows the distribution of closeness of all subgraphs after filtering (note that the x-axis is in log scale). We are able to identify successfully all such random scanning as the instances with a closeness less than 100 (to the left of the x-axis).

3) Online Media IRSF. We find several cases where fraudsters post IRSF numbers on popular online media, e.g., Facebook and Twitter, etc. For example, Fig. 6.10[c] shows the increase of victims corresponding to an IRSF case advertised through Twitter. Around the 12th week, the fraudster posted a tweet disclosing the contact numbers of a famous Puerto Rican singer, which had been retweeted thousands of times within a day. The advertising strategy is so successful that more than eight thousand victims were drawn to make phone calls to these IRSF numbers on the same day. Fortunately, these fraud calls soon disappeared on the following day when many tweets were posted and retweeted shortly to alert other people of this fraud activity.

As another example, we identify a website that advertises IRSF numbers for a public vote of popular scenic locations. Fig. 6.10[d] demonstrates the behaviors of the three IRSF numbers associated with this fraud case. During their lifetime, Term_A and Term_B steadily attracted new victims and number of victims was almost doubled close to the end of the vote. In comparison, the Term_C attracted many fewer victims, plausibly because it has 12 digits instead of 10 digits, which makes it much easier to be identified as an international number (see Section 6.6.4 for the heteronym property of fraud numbers).

4) Unlocked Device. Victims of this fraud activity are users of unlocked mobile devices. Unlocked mobile devices are cell phones that are not tied to a specific carrier. The advantage of purchasing such devices is that it offers the user more choices of voice/data plans and ease of switch between carriers, especially when a user is traveling abroad. There are many ways of acquiring an unlocked device. For example, after the contract with the carrier ends, a user can ask the service provider for a code to unlock her device. It is also possible to purchase unlocked devices through third party retailers. We have identified fraud activities on unlocked devices purchased from online third party retailers, where the fraudsters reconfigured the device and specified IRSF numbers as the access points for Short Message Service (SMS) or Multimedia Messaging Service (MMS). Consequently, sending SMS or MMS messages will trigger calls to IRSF numbers.

5) Device Exploit. This fraud activity only applies for one particular prepaid mobile device. Users complain that they will lose all the remaining credits in their accounts while making phone calls to these fraud numbers. We suspect this is caused by attackers taking advantage of certain vulnerabilities of the device or the operating system. Strictly speaking, this is not a regular IRSF case. However, since fraudsters are likely to gain profit from such activities, we include it here for completeness.

Scam. Scam, sometimes referred to as *phishing fraud*, often involves two stages. At the first stage, fraudsters solicit phone calls from mobile users. At the second stage, when victims call the fraud numbers, fraudsters apply various social engineering techniques to defraud victims of money or acquire private information from them. Scam includes:

1) Target Scam. This is the most common case which accounts for 55.4% of all fraud activities. In this scenario, fraudsters target victims for whom they have certain private information, e.g., their names, phone numbers, addresses, and medical prescription details.

2) Online Media Scam. In this scenario, fraudsters post advertisements on online forums, e.g., craigslist. The advertisements are often about inexpensive house rentals and real estate selling. Several phone numbers are often listed at the end of the posts to entrap victims baited by a low price.

3) Email. In this case, fraudsters hack into personal email accounts and send emails to the contact list disguised as the original account owners. In the email, fraudsters claim an emergency in the foreign country and request phone calls from people in the contact list.

4) Malware. The most interesting means of soliciting phone calls is using malware. We find a particular type of malware called *ransom malware* targeting the Windows operating system. Upon infected by such malware, users' personal computers are locked. The users are unable to execute any command and cannot even enter the safe mode to remove the malware. A dialog box often appears in the center of the screen, informing users to call a list of foreign numbers to obtain a code for unlocking their machines. Often the fraudsters will force the users to pay a ransom for the system restoration. We note that even though the ransom malware we have identified focused only on personal computers, it would not be surprising if such malware appear on mobile devices in the near future. Precaution against such malware (e.g., providing users with a scrutinized set of APIs) is highly suggested for mobile operating systems.

Table 6.3: Social engineering techniques applied by fraudsters.

Techniques	**Description**	**Pct.(%)**
Debt collection	claim the victim has an unpaid bill and threaten for legal actions if full payment is not received.	22.5
Medical	claim a non-existent prescription and ask for payment	17.5
Loan	offer low interest loans for education, auto, etc.	16.3
Credit card	claim to be credit card service representatives and try to collect personal information	12.5
Emergency	fraudsters send emails to the contact lists of hacked email accounts, claim loss of passport or wallet in a foreign country and ask to send money for help	10.0
Rental	post on craigslists or through emails, ask for deposit in order to get free/inexpensive housing	8.8
Computer support	claim to be computer expert who have discovered security issues on the victim's computer. Aim at collecting personal information or leading to downloading malware.	5.0
Fortune	claim to have certain amount of lucky money for you (e.g., winning a lottery, a tax return, or even a heritage).	3.8
Threatening	claim to have smuggled a family member, a relative or a friend and ask for money	2.5
Telemarketing	try to sell prescribed medicines, movies, etc.	1.3

Discussion on Smartphone Penetration. Here we investigate different types of devices involved in the fraud activities above. We identify the model of an end-user device from the first 8-digit Type Allocation Code (TAC) in the associated International Mobile

Equipment Identity (IMEI). The remaining 6-digit serial number has been anonymized to protect customers' privacy. Based on the functionality of devices, we further classify them into *smartphones* and *regular phones*. In comparison to regular phones, smartphones are characterized with high computational power, and support services like video streaming, web browsing, GPS and a variety of mobile apps.

For ease of exposition, we define $\alpha(g)$ as the proportion of victims involved in fraud activity g who are smartphone users. Similarly, we denote α_0 as fraction of smartphone users out of all mobile users in the network. Therefore, we define the *relative significance* of smartphones associated with fraud activity g as $RS(g) := \alpha(g)/\alpha_0$, which is displayed in the last column of Table 6.2. A higher value of RS (greater than 1) indicates the predominance of smartphones involved in that fraud activity.

Since *IRSF Malware* is propagated in the form of bogus mobile apps, all victims associated with this type of fraud are smartphones. Surprisingly, *Online Media IRSF*, *Online Media Scam* and *Email Scam* (line 3, 7 and 8) attract many more smartphone victims. We conjecture that smartphone users, who are capable of maintaining persistent access to online media sites and email services, are potentially exposed to more fraud activities. Moreover, many smartphone devices support the "click to call" function which allows users to initiate phone calls by clicking on the phone numbers on the web page from the browser. This also increases their chance of responding to fraud activities. In comparison, *Unlocked Device* and *Device Exploit* (line 4 and 5), constrained by a few vulnerable devices, most of which are regular phones, attract a predominant number of regular phone victims. Moreover, since *Target Scam* and *Malware Scam* (line 6 and 9) are migrated unchangeably from landlines and Internet, they do not rely on specific mobile devices. Thus they have an RS value close to 1.

We further explore the fraction of new victims with smartphone devices over a two-year time period, which is depicted as the solid red curve in Fig. 6.11. For comparison, we also display the proportion of smartphone users out of all mobile users over the same time period (the blue dotted curve). The ascending trend of the dotted curve in Fig. 6.11 clearly indicates a sign of smartphone penetration, where the proportion contributed by smartphone users increases steadily, with a few jumps plausibly due to the release of popular smartphone devices and other social events. However, we observe that smartphone users always account for a much higher proportion of new victims (i.e., the solid curve stays above the dotted curve), indicating that smartphone users are more susceptible to fraud activities. In addition, accompanying the fast increase of smartphone popularity, we observe that the proportion of victims with smartphone devices is also increasing significantly, which is indicated by the ascending trend of the red solid curve in Fig. 6.11. This is possibly because of the emerging fraud activities targeting smartphone population, especially the ones carried by malware apps and online media sites, which can be much more effective in acquiring new victims than traditional fraud targeting landlines.

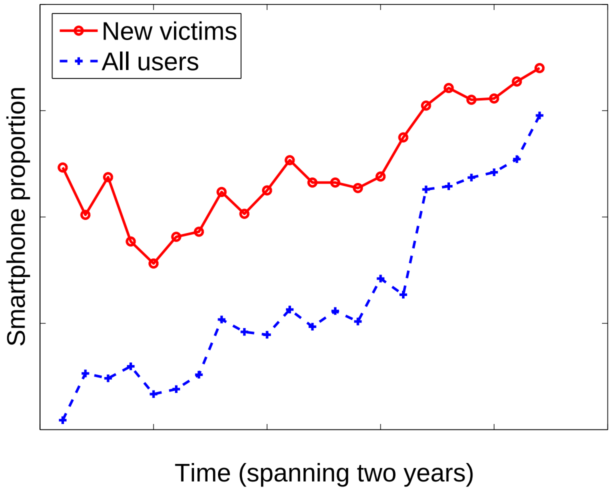


Figure 6.11: Smartphone proportion change over time.

Implications: While mobile users enjoy the advance of smartphone devices, its rich functionality and strong computation power leave more room for fraudsters to carry out more sophisticated attacks on these devices, which makes smartphone devices more susceptible to fraudulent activities. We observe many fraud activities carried by malicious mobile apps targeting smartphones. These malware apps have integrated the functions of voice calls and data transmission and exhibit certain characteristics of modern botnets, e.g., employing dynamic fraud numbers to evade detection and regulation, maintaining connection with a command-and-control (C&C) server, etc. We expect to see in near future that new malware apps incorporate other channels, e.g., SMS and MMS, for fraud activities. Moreover, more techniques used by botnets today are expected to be adopted for developing malware apps, such as fast-flux, domain-flux and

P2P network, etc. Lessons learned from combating botnets can be useful for preventing fraud in cellular networks.

Since all malware infections we have observed are triggered by users actively downloading malware from the online marketplace, detection and removal of malware at the online marketplace has proved to be an effective way of preventing fraud activities. In particular, our analysis suggests that the online marketplace should come up with more advanced vetting process for the apps, especially if it contains code segment involved with voice calls or SMS messages. Similarly, information posted on online media should also be carefully vetted (especially phone numbers appearing on online posts) to avert fraud activities.

6.6.3 Social Engineering Techniques

Given that many fraud activities adopt social engineering to defraud victims, we take a closer look at the social engineering techniques that fraudsters often employ to solicit victims to make phone calls, to disclose sensitive personal information, or even to inflict monetary loss. As mentioned in Section 6.6.2, our analysis of social engineering techniques also relies on descriptions from online feedback provided by the victims based on their conversations with the fraudsters.

We summarize the identified social engineering techniques in Table 6.3, where the first column shows the name of the technique and the second column provides explanation of each technique. The third column displays the popularity of each social engineering technique in terms of the proportion of fraud activities (i.e., subgraphs) that practice it. There are also fraud numbers (less than 10%) that either no one complaints about or the corresponding social engineering technique cannot be distilled from the online feedback. This may be due to the small victim population affected by this fraud activity or the lag in user reports (recall there can be several months of delay of user reports after the fraud activity is detected). We temporarily ignore these numbers and leave them for future investigation.

In Table 6.3, we see various techniques that fraudsters usually adopt. Though these techniques vary from case to case, they generally fall into several categories which are more likely to attract people's attentions. For example, people usually are responsive if they are told that they have an outstanding expense, which may affect their credit rating. Therefore, a very popular social engineering technique is regarding bill or debt, where fraudsters claim fictitious debts owed by the victims in order to acquire private information or defraud victims of money. Similarly, techniques regarding services that are crucial in our daily life, such as personal/car loan and credit cards, are also commonly used by fraudsters. An interesting observation shows that fraudsters applying these techniques often are aware of personal information of the victims, such as their names, addresses, bank account or former prescription information. For example, we observe reports regarding fraudsters pretending to be bank personnel, who mentioned victims' former bank account numbers. In fact, the bank has reported the leak of customer private information due to hacker attacks. Apparently, such information has somehow been acquired to conduct fraud activities. As another example, medical prescription information is adopted frequently by the fraudsters to defraud victims. With personal information, fraudsters often launch targeted scam to increase their success rate. In comparison, when lacking such information, fraudsters usually employ auto dialer to find victims or rely on social media sites, forums or other online media channels. The common social engineering techniques applied by these fraudsters are advertisement for discounted drugs, lottery defraud or even feigning an emergency regarding a family member. However, these fraud activities only account for less than 10%.

Implications: Personal information plays an important role in fraud activities. Based on user reports, fraud activities are more difficult to recognize when personal information is mentioned by fraudsters. We have identified cases where personal information is acquired by fraudsters from bank databases through security attacks. This suggests the importance of correlating fraud activities and network intrusions to understand and track the chain of fraudulent events. In addition, there are also cases where fraudsters are likely to acquire personal information from online sources, like social media sites or personal blogs. Vetting these online sources to avoid information leakage is crucial for combating fraud activities. Moreover, with the increasing functionality of mobile devices, users tend to store personal information, e.g., contact list, emails or even credit card information (for online purchase) in these devices. There is a demanding need for better security on these personal devices.

6.6.4 Originating Countries of Fraud Numbers

To understand the geographical distribution of fraud numbers, we investigate the top originating countries of these numbers. In fact, we find fraud numbers are distributed widely to 58 different countries, where the top countries, UK, Sao Tome and Principe and Russia, collectively contribute to less than 25% of fraud numbers, respectively. More interestingly, we find around 60% of the fraud activities contain phone numbers from multiple countries. All these make tracking and regulating fraud activities a much more challenging task. In addition, we have observed diversity of fraud activities from different countries. For example, the UK is related to a higher number of email related fraud activities, Nigeria is associated with more rental fraud activities, and Sao Tome and Principe has contributed to many malware related fraud numbers.

An interesting observation is made by measuring the length of the fraud numbers. Including country codes, around 60% of the fraud numbers contain 10 digits, the same number of digits as a typical US number excluding the country code "1". We refer to this observation as the *heteronym property* of fraud numbers. Having the same length as a US number, it is very hard for a user to distinguish such a foreign number, and hence increase chances of victims calling that number. In an extreme case, we find a scam activity employing three different foreign numbers looking very similar: 664-133xxxx in Montserrat, 66-4133xxxx in Thailand and 64-4133xxxx in New Zealand[10] . We have tried to initiate international phone calls to mobile devices equipped with four most popular mobile operating systems. Unfortunately, in the default firmware setting, none of the devices has successfully parsed the incoming number and displayed the right country name of the caller. This explains why many users complaining on the forums about high rate US numbers, which are essentially international fraud numbers.

Implications: Though certain mobile apps have started to offer the functionality for parsing incoming phone numbers, it is necessary for the mobile operating systems to provide direct support of such functionality. We believe it is a critical step for preventing fraud activities by presenting more information to the users to help them identify potential fraud calls. Our analysis also indicates that fraudsters often employ numbers

[10] Different international exit codes are used to differentiate calls to these numbers, e.g., 011 for Montserrat, 001 for Thailand, and 00 for New Zealand. However, such exit codes are often attached automatically by the device without informing the user.

from multiple countries to void tracking and regulation. Therefore, a forum for international telecom companies to share knowledge regarding premium rate numbers and known fraud numbers can be useful for detecting and preventing fraudulent activities.

6.7 Summary

In this Chapter, we proposed a graph based method to detect fraud activities of voice calls in a large cellular network, which enables us to efficiently isolate popular fraud numbers from millions of international phone numbers. Using call records spanning a two-year time period, we showed that our method successfully detected a great variety of voice call fraud activities. In addition, we identified unique characteristics of fraud activities in cellular networks, such as new fraud carried by malware apps, unlocked devices and online media sites, social engineering techniques and heteronym property of fraud numbers. Our analysis sheds light on the new characteristics and trends of voice-related fraud activities in current mobile networks.

Chapter 7

Conclusion and Future Work

This dissertation is dedicated to share the experience and our data oriented approach for building operational defense systems against attacks from mobile voice channels in large-scale cellular networks: SMS spam and voice fraud.

In particular, we investigated SMS spam activities in a large cellular network by combining user reported spam messages and spam network records. Using thousands of spam numbers extracted from these spam reports, we studied in-depth various aspects of SMS spamming activities, including spammer's device type, tenure, voice and data usage, spamming patterns and so on. We found that spam numbers sending similar spam messages exhibit strong spacial and temporal correlations, based on which we proposed novel spam detection methods which demonstrated promising results in terms of detection accuracy and response time. In addition, our analysis result also demonstrated that most spammers selected victims randomly. This lead to the design of Greystar, an innovative system for fast and accurate detection of SMS spam numbers.

To defend against voice fraud, we proposed a graph based method to detect fraud activities of voice calls in a large cellular network, which enables us to efficiently isolate popular fraud numbers from millions of international phone numbers. Using call records spanning a two-year time period, we showed that our method successfully detected a great variety of voice call fraud activities. In addition, we identified unique characteristics of fraud activities in cellular networks, such as new fraud carried by malware apps, unlocked devices and online media sites, social engineering techniques and heteronym property of fraud numbers. Our analysis sheds light on the new characteristics and trends of voice-related fraud activities in current mobile networks.

Our future work involves investigating the potential of combining additional features, such as the user calling history, and instant user fraud reports to improve detection accuracy. Our future work will also focus on applying the same approach to detect other suspicious activities in cellular networks, such as telemarketing campaigns. Meanwhile, we will correlate detection results from different methods with cellular data traffic to detect malware engaged in such spamming activities.

References

[1] Over 5 billion mobile phone connections worldwide. http://www.bbc.co.uk/news/10569081.

[2] Data capable cell phones replacing the pc. http://blogs.itbusiness.ca/2011/03/data-capable-cell-phones-replacing-the-pc/.

[3] Report: Cellphones replacing landlines. http://www.upi.com/Top_News/US/2009/11/19/Report-Cellphones-replacing-landlines/UPI-72441258651963/.

[4] iphone virus turns into a mobile botnet. http://www.redmondpie.com/iphone-virus-turns-into-a-mobile-botnet-9140130/.

[5] Federal communications commission. Spam: unwanted text messages and email, 2012. http://www.fcc.gov/guides/spam-unwanted-text-messages-and-email.

[6] Mobile spam texts hit 4.5 billion. http://www.businessweek.com/news/2012-04-30/mobile-spam-texts-hit-4-dot-5-billion-raising-consumer-ire.

[7] C. Baldwin. 350,000 different types of spam sms messages were targeted at mobile users in 2012, 2013. http://www.computerweekly.com/news/2240178681/ 350000-different-types-of-spam-SMS-messages-were-targeted-at-mobile-users-in-2012.

[8] 69% of mobile phone users get text spam, 2012. http://abcnews.go.com/blogs/technology/2012/08/69-of-mobile-phone-users-get-text-spam/.

[9] A. Bose, X Hu, K. Shin, and T. Park. Behavioral detection of malware on mobile handsets. In *MobiSys '08*, 2008.

[10] X. Cui, B. Fang, L. Yin, X. Liu, and T. Zang. Andbot: towards advanced mobile botnets. Proc. of the 4th USENIX Workshop on Large-Scale Exploits and Emergent Threats, 2011.

[11] L. Xie, X. Zhang, J. Seifert, and S. Zhu. pbmds: a behavior-based malware detection system for cellphone devices. In *WiSec '10*, 2010.

[12] N. Jiang, J. Cao, Y. Jin, L. Li, and Z.-L. Zhang. Identifying suspicious activities through dns failure graph analysis. In *Proceedings of the eighteenth IEEE International Conference on Network Protocols (ICNP'10)*, 2010.

[13] Y. Ye, T. Li, S. Zhu, W. Zhuang, E. Tas, U. Gupta, and M. Abdulhayoglu. Combining file content and file relations for cloud based malware detection. In *KDD '11*, 2011.

[14] Cluto - software for clustering high-dimensional datasets. http://glaros.dtc.umn.edu/gkhome/views/cluto.

[15] Y. Zhao and G. Karypis. Criterion functions for document clustering: Experiments and analysis. Technical report, University of Minnesota, 2002.

[16] Y. Jin, N. Duffield, A. Gerber, P. Haffner, W.-L. Hsu, G. Jacobson, S. Sen, S. Venkataraman, and Z.-L. Zhang. Making sense of customer tickets in cellular networks. In *IEEE INFOCOM'11 Mini-Conference*, 2010.

[17] I. Murynets and R. Jover. Crime scene investigation: Sms spam data analysis. IMC'12, 2012.

[18] W. Enck, P. Traynor, P. McDaniel, and T. La Porta. Exploiting open functionality in sms-capable cellular networks. In *Proc. of the 12th ACM Conference on Computer and Communications Security*, 2005.

[19] E. Bursztein, P. Lam, and J. Mitchell. Trackback spam abuse and prevention. In *Proc. of the 2009 ACM workshop on Cloud computing security*, 2009.

[20] E. Bursztein, B. Gourdin, and J. Mitchell. Reclaiming the blogosphere talkback a secure linkback protocol for weblogs. In *Proc. of the 16th European Symposium on Research in Computer Security*, 2011.

[21] C. Kreibich, C. Kanich, K. Levchenko, B. Enright, G. Voelker, V. Paxson, and S. Savage. On the Spam Campaign Trail. In *LEET'08*, 2008.

[22] C. Kreibich, C. Kanich, K. Levchenko, B. Enright, G. Voelker, V. Paxson, and S. Savage. Spamcraft: An inside look at spam campaign orchestration. In *LEET'09*, 2009.

[23] C. Kanich, C. Kreibich, K. Levchenko, B. Enright, G. Voelker, V. Paxson, and S. Savage. Spamalytics: An empirical analysis of spam marketing conversion. *Communications of the ACM*, 52(9):99–107, 2009.

[24] A. Pathak, F. Qian, C. Hu, M. Mao, and S. Ranjan. Botnet spam campaigns can be long lasting: evidence, implications, and analysis. SIGMETRICS '09, 2009.

[25] H. Gao, J. Hu, C. Wilson, Z. Li, Y. Chen, and B. Zhao. Detecting and characterizing social spam campaigns. IMC '10, 2010.

[26] S. Ghosh, B. Viswanath, F. Kooti, N. Sharma, G. Korlam, F. Benevenuto, N. Ganguly, and K. Gummadi. Understanding and combating link farming in the twitter social network. WWW '12, 2012.

[27] C. Yang, R. Harkreader, J. Zhang, S. Shin, and G. Gu. Analyzing spammers' social networks for fun and profit: a case study of cyber criminal ecosystem on twitter. WWW '12, 2012.

[28] C. Grier, K. Thomas, V. Paxson, and M. Zhang. @spam: the underground on 140 characters or less. CCS '10, 2010.

[29] Q. Xu, E. Xiang, Q. Yang, J. Du, and J. Zhong. Sms spam detection using non-content features. *Intelligent Systems, IEEE*, 27(6):44 –51, 2012.

[30] T. Ouyang, S. Ray, M. Rabinovich, and M. Allman. Can network characteristics detect spam effectively in a stand-alone enterprise? PAM'11, 2011.

[31] M. Sirivianos, K. Kim, and X. Yang. Introducing social trust to collaborative spam mitigation. In *Proc. of the 30th IEEE International Conference on Computer Communications*, 2011.

[32] S. Hao, N. Syed, N. Feamster, A. Gray, and S. Krasser. Detecting spammers with snare: spatio-temporal network-level automatic reputation engine. USENIX Security Symposium'09, 2009.

[33] A. Pitsillidis, K. Levchenko, C. Kreibich, C. Kanich, G.M. Voelker, V. Paxson, N. Weaver, and S. Savage. Botnet judo: Fighting spam with itself. In *NDSS'09*, 2010.

[34] K. Yadav, P. Kumaraguru, A. Goyal, A. Gupta, and V. Naik. Smsassassin: crowd-sourcing driven mobile-based system for sms spam filtering. HotMobile '11, 2011.

[35] G. Cormack, J. Hidalgo, and E. Sánz. Feature engineering for mobile (sms) spam filtering. SIGIR '07, 2007.

[36] H. Tan, N. Goharian, and M. Sherr. $100,000 Prize Jackpot. Call now! Identifying the pertinent features of SMS spam. In *Proc. of the 35th Annual ACM SIGIR Conference*, 2012.

[37] R. Pang, V. Yegneswaran, P. Barford, V. Paxson, and L. Peterson. Characteristics of internet background radiation. In *Proc. of the 4th ACM Internet measurement conference*, 2004.

[38] E. Wustrow, M. Karir, M. Bailey, F. Jahanian, and G. Huston. Internet background radiation revisited. In *Proc. of the 10th ACM Internet measurement conference*, 2010.

[39] Y. Jin, G. Simon, K. Xu, Z.-L. Zhang, and V. Kumar. Gray's anatomy: dissecting scanning activities using ip gray space analysis. In *Proceedings of the 2nd USENIX workshop on Tackling computer systems problems with machine learning techniques*, pages 2:1–2:6, 2007.

[40] The honeynet project, 2012. http://project.honeynet.org/.

[41] G. Dunlap, S. King, S. Cinar, M. Basrai, and P. Chen. Revirt: enabling intrusion analysis through virtual-machine logging and replay. In *Proc. of the 2nd USENIX Symposium on Operating Systems Design and Implementation*, 2002.

[42] N. Christin, S. Yanagihara, and K. Kamataki. Dissecting one click frauds. In *CCS '10*, 2010.

[43] S. Pandit, D. Chau, S. Wang, and C. Faloutsos. Netprobe: a fast and scalable system for fraud detection in online auction networks. In *WWW '07*.

[44] A. Metwally, D. Agrawal, and A. Abbadi. Using association rules for fraud detection in web advertising networks. In *VLDB '05*, 2005.

[45] X. Ying, X. Wu, and D. Barbar á. Spectrum based fraud detection in social networks. In *CCS '10*, 2010.

[46] C. Cortes, D. Pregibon, and C. Volinsky. Communities of interest. In *IDA'01*, 2001.

[47] C. Mulliner, N. Golde, and J. Seifert. Sms of death: from analyzing to attacking mobile phones on a large scale. In *SEC'11*, 2011.

[48] Y. Jin, E. Sharafuddin, and Z.-L. Zhang. Unveiling core network-wide communication patterns through application traffic activity graph decomposition. In *Proc. of SIGMETRICS '09*, pages 49–60, 2009.

[49] J. Sun, H. Qu, D. Chakrabarti, and C. Faloutsos. Neighborhood formation and anomaly detection in bipartite graphs. In *ICDM '05*, 2005.

[50] C. Cortes, D. Pregibon, and C. Volinsky. Computational methods for dynamic graphs. *Journal of Computational and Graphical Statistics*, 12, 2003.

[51] Tinyurl. http://tinyurl.com/.

[52] 800notes - Directory of unknown callers. http://www.800notes.com.

[53] N. Jiang, Y. Jin, A. Skudlark, W. Hsu, G. Jacobson, S. Prakasam, and Z.-L. Zhang. Isolating and analyzing fraud activities in a large cellular network via voice call graph analysis. MobiSys'12, 2012.

[54] Y. Zhao, G. Karypis, and U. Fayyad. Hierarchical clustering algorithms for document datasets. *Data Min. Knowl. Discov.*, 2005.

[55] G. Jacob, R. Hund, C. Kruegel, and T. Holz. Jackstraws: picking command and control connections from bot traffic. SEC'11, 2011.

[56] A. Skudlark N. Jiang, Y. Jin and Z.-L. Zhang. Understanding and detecting sms spam through mining customer reports. Technical report, AT&T Labs, 2012.

[57] A. Ramachandran, N. Feamster, and S. Vempala. Filtering spam with behavioral blacklisting. CCS '07, 2007.

[58] Sms watchdog. http://www.smswatchdog.com.

[59] S. Sinha, M. Bailey, and F. Jahanian. Improving SPAM blacklisting through dynamic thresholding and speculative aggregation. In *Proc. of the 17th Annual Network and Distributed System Security Symposium*, 2010.

[60] J. Jung and E. Sit. An empirical study of spam traffic and the use of DNS black lists. In *Proc. of the 4th ACM Internet Measurement Conference*, 2004.

[61] A. Ramachandran, N. Feamster, and D. Dagon. Revealing botnet membership using dnsbl counter-intelligence. In *Proc. of the 2nd Workshop on Steps to Reducing Unwanted Traffic on the Internet*, 2006.

[62] Y. Xie, F. Yu, K. Achan, R. Panigrahy, G. Hulten, and I. Osipkov. Spamming botnets: signatures and characteristics. In *Proc. of the 2008 ACM SIGCOMM Annual Conference*, 2008.

[63] M. Shafiq, L. Ji, A. Liu, J. Pang, and J. Wang. A first look at cellular machine-to-machine traffic: large scale measurement and characterization. In *Proc. of the 2012 ACM International Conference on Measurement and Modeling of Computer Systems*, 2012.

[64] WhoCallsMe - Reverse phone number lookup. http://www.whocallsme.com.

[65] Graphviz. http://www.graphviz.org/.

[66] A. Mislove, M. Marcon, K. Gummadi, P. Druschel, and B. Bhattacharjee. Measurement and analysis of online social networks. In *IMC '07*, 2007.

[67] Y. Zhang, S. Singh, S. Sen, N. Duffield, and C. Lund. Online identification of hierarchical heavy hitters: algorithms, evaluation, and applications. In *Proc. of ACM IMC*, 2004.

[68] A. Mahimkar, Z. Ge, A. Shaikh, J. Wang, J. Yates, Y. Zhang, and Q. Zhao. Towards automated performance diagnosis in a large iptv network. In *SIGCOMM'09*, pages 231–242, 2009.

[69] S. Dongen. *Graph clustering by flow simulation.* PhD thesis, University of Utrecht, 2000.