Abusing Phone Numbers and Cross-Application Features for Crafting Targeted Attacks

Srishti Gupta
Indraprastha Institute of Information Technology Delhi
srishtig@iiitd.ac.in

Payas Gupta
New York University Abu Dhabi
payasgupta@nyu.edu

Mustaque Ahamad
Georgia Institute of Technology New York University Abu Dhabi
mustaq@cc.gatech.edu

Ponnurangam Kumaraguru
Indraprastha Institute of Information Technology Delhi
pk@iiitd.ac.in

ABSTRACT
With the convergence of Internet and telephony, new applications (e.g., WhatsApp) have emerged as an important means of communication for billions of users. These applications are becoming an attractive medium for attackers to deliver spam and carry out more targeted attacks. Since such applications rely on phone numbers, we explore the feasibility, automation, and scalability of phishing attacks that can be carried out by abusing a phone number. We demonstrate a novel system that takes a potential victim’s phone number as an input, leverages information from applications like Truecaller and Facebook about the victim and his/her social network, checks the presence of phone number’s owner (victim) on the attack channels (over-the-top or OTT messaging applications, voice, email, or SMS), and finally targets the victim on the chosen channel. As a proof of concept, we enumerate through a random pool of 1.16 million phone numbers. By using information provided by popular applications, we show that social and spear phishing attacks can be launched against 51,409 and 180,000 users respectively. Furthermore, voice phishing or vishing attacks can be launched against 722,696 users. We also found 91,487 highly attractive targets who can be attacked by crafting whaling attacks. We show the effectiveness of one of these attacks, phishing, by conducting an online roleplay user study. We found that social (69.2%) and spear (54.3%) phishing attacks are more successful than non-targeted phishing attacks (35.5%) on OTT messaging applications. Although similar results were found for other mediums like email, we demonstrate that due to the significantly increased user engagement via new communication applications and the ease with which phone numbers allow collection of information necessary for these attacks, there is a clear need for better protection of OTT messaging applications. We propose some recommendations in this direction.

Keywords
Phone number, Over-The-Top, Phishing, Roleplay, Facebook, Truecaller, WhatsApp, Vishing.

1. INTRODUCTION
We are being constantly targeted by cyber criminals who rely on a variety of online attacks to victimize users and enterprises. Phishing, which is a form of social engineering attacks, is often used by such criminals to fraudulently gain access to sensitive information or systems by impersonating a trusted party [35]. In the past, phishing attacks have used the email and web channels to reach their victims. However, recently, there has been a tremendous growth of similar phishing attempts over the telephony channel. New forms of phishing attacks have emerged exploiting traditional text messaging services, i.e., SMS (smishing [11]) and voice phishing (vishing [14]).

Several factors make the telephony channel attractive for cyber criminals. The convergence of telephony with the Internet has resulted in an unprecedented growth of new forms of online communication, especially mobile communication due to the advent of Over-The-Top (OTT) messaging applications (like WhatsApp, Viber, and WeChat [6]). Because of the growing popularity of OTT messaging applications, particularly WhatsApp, malicious actors are now abusing it for illicit activities like delivering spam and phishing messages. Unsolicited messages like investment advertisements, adult conversation ads (random contacts requests) were seen to propagate on the channel in early 2015 [7].

Vishing attacks are also increasing due to 1) low mobile-mobile calling plans with the advent of services like Skype and Google Voice. This allows spammers to pump out huge volumes of voice calls at a marginal cost, and 2) easy caller ID spoofing due to Voice over IP phone technology that allows spammers to pick an area code and even the prefix
number they want when they set up a new phone number. These numbers can be used to disguise where calls originate. To avoid falling victim to such vishing attacks and know more about the incoming phone number, cloud-based caller identification services are emerging to help in getting additional information about the caller. Millions of people are using such applications, namely Truecaller [12], Facebook's Hello [4], and Whitepages Caller ID applications and Block [17].

OTT messaging applications and caller ID applications use a phone (mobile) number, a personally identifiable piece of information with which an individual can be associated uniquely, in most cases [50]. OTT messaging applications use it to uniquely identify users and allow them to find their friends who also use the same application and caller ID applications provide additional information about the calling phone number. Prior research has shown that other Internet resources like e-mail addresses can be exploited as an identifier to launch targeted phishing attacks [35, 47], distributed phishing attacks [37], and to correlate user identities across social networking platforms [21]. In this paper we demonstrate how attackers can exploit phone number as a unique identifier and use cross-application features for launching spear [17] and social phishing attacks [35].

A challenge spammers face when using an e-mail address is that this medium is heavily defended and spammers often cannot ensure that a spam message has been delivered and seen by the target user. Furthermore, unlike e-mail addresses that come from an unlimited pool and can be freely created, phone numbers are a limited and controlled resource. People generally retain the same number for a long period due to the cost associated with it [10]. Also, phone numbers are a finite pool with a defined numbering plan. They can be easily enumerated by looping through the entire pool of number space. However, it is possible that not all phone numbers are currently allocated to users and some of them may be unassigned. Thus, determining if a phone number is currently assigned and its owner can be reached is a challenge that needs to be overcome before such applications can be targeted.

In this paper, we demonstrate how a phone number can be used across multiple applications to aggregate private and personal information about the owner of the phone number. Such information can then be used for targeted attacks. For example, reverse-lookup contact feature used by caller ID applications like Truecaller [12] can be exploited to find more details (name) about the phone number’s owner. Moreover, by correlating this with the public information present on online social networking platforms (e.g., Facebook), attackers can determine the social circle (friends) of the victim. Such information can then be used to launch a variety of phishing attacks.

We focus on exploring how cross-application features can be exploited to harvest information that can facilitate targeted and non-targeted attacks on different channels viz., OTT messaging applications, voice, e-mail, or SMS. First, we demonstrate how to craft targeted spear and social phishing attacks against a random pool of phone numbers on OTT messaging applications. OTT messaging applications allow attackers to find relevant information about targets by exploiting address book syncing feature which helps to discover friends on a given OTT messaging application (e.g., WhatsApp). Second, we demonstrate a novel targeted vishing attack that can be carried out by compromising the integrity of caller ID applications; an attacker can create a convincing profile to gain victim’s trust. Also, because the information (e.g., name) provided to these applications during registration is not verified fully, it is relatively easy to add accounts with false information and impersonate trusted entities such as banks. By making a call appear to come from such entities, it is easy to deceive people into giving out their personal information like bank account number, credit card number etc. The success rate of vishing attacks can be increased by making them more personalized and targeted by collecting information about the victim from Truecaller and Facebook. Third, we provide early evidence of the feasibility of crafting whaling attacks [15], attacks that are targeted against the owners of vanity numbers [9], phone numbers generally owned by people with high influence or high-net-worth individuals, who are very attractive targets for criminals.

By developing an automated and scalable system that allows such attacks to be crafted at scale and evaluating the effectiveness of phishing attacks on OTT messaging applications (as a proof of concept) with a roleplay user study, we make the following contributions on three different fronts:

- **Feasibility**: This is the first attempt to systematically understand the threat posed by the ease of correlating user information across caller ID lookup application (Truecaller), and social networking application (Facebook). This was executed using phone numbers as unique identifiers. We show the attack is feasible with easily available computational resources, and poses a significant security and privacy threat. An attacker can use these cross-application features to launch highly targeted attacks on multiple channels like OTT messaging applications, voice, e-mail, or SMS.

- **Automation**: We design and implement an automated system that takes a phone number as an input, collects necessary information about the victim (owner of the phone number). It can automatically determine the target attack channel (OTT messaging applications, voice, e-mail, or SMS), and finally crafts an attack vector (both targeted and non-targeted) to launch an attack against the victim on the chosen channel.

- **Scalability**: For 1,162,696 random pool of Indian phone numbers that we enumerated, it is possible to launch social and spear phishing attacks against 51,409 and 180,000 users respectively. Vishing attacks can be launched against 722,696 users. We also found 91,487 highly influential victims who can be attacked by crafting whaling attacks against them.

To demonstrate the effectiveness of phishing attacks on OTT messaging applications, we present results by conducting a roleplay user study with 314 participants recruited from Amazon Mechanical Turk (MTurk). Our results are consistent with prior research on e-mail and online social networks [21, 35] and confirm empirically that social phishing (69.2%) is the most successful attack on OTT messaging applications, as compared to spear (54.3%) and non-targeted phishing (35.5%) attacks.

To the best of our knowledge, this is the first exploration of large-scale targeted attacks abusing phone numbers along with an evaluation of the effectiveness of the attacks. Given
that telephony medium is not as well defended as e-mail, we believe that these contributions offer a promising new direction and demonstrate the urgent need for better security for such applications.

2. RELATED WORK

In this section, we briefly outline some of the prior research related to abusing phone numbers; vishing attacks and Spam over Internet Telephony (see Section 2.1) and abusing address book syncing feature of smartphones for user profiling (see Section 2.2). We also discuss some of the related work on launching targeted attacks on online social media (see Section 2.3).

2.1 Vishing Attacks and SPIT

Due to low cost and scalability of VoIP based calling systems, scammers are using the telephony channel to make millions of call and expand the vishing ecosystem. Prior work has explored the detection and ways to combat scams on VoIP. Griffin et al. demonstrated that vishing attacks can be carried out using VoIP [30]. They illustrated how several vishing attacks can be crafted in order to increase information security awareness. Chiappetta et al. analyzed VoIP CDRs (Call Detail Records) to build features that can classify normal or malicious users during voice communication [26]. The features were built using mutual interactions and communication patterns between the users. Past literature demonstrates detection of spam over VoIP through semi-supervised clustering [49], constructing multi-stage spam filter based on trust and reputation of callers [27], comparing human communication patterns with hidden Turing tests to detect botnets [44], building a system using features like call duration, social networks, and global reputation [19], proposing protection model based on user-profile framework such as users’ habits [45], placing telephone honeypots to collect intelligence about telephony attacks [31], and using call duration and traffic rate [39]. Caller ID spoofing is being used by scammers to hide their real identity and make fraudulent calls. Researchers have implemented various solutions to detect caller ID spoofing, using covert channels built on timing estimation and call status for verification [43], identifying the caller by tracing the calls to the corresponding SIP-ISUP interworking gateway [48], using customer’s phonebook feature for storing white and black lists for filtering unwanted voice calls [21], and detecting audio codecs in call path, calculating packet loss and noise profiles to determine source and path of the call [20].

In this work, we present first evidence of feasibility of targeted vishing attacks by exploiting the integrity of the information provided by caller ID applications e.g., Truecaller.

2.2 Abusing Address Book Syncing in OTT Messaging Applications

Recent work shows that collection of user profiles can be automated and yields a lot of personal information like phone numbers, display names, and profile pictures [25, 35]. Schrittwieser et al. analyzed popular OTT messaging applications like WhatsApp, Viber, Tango etc. and evaluated their security models with a focus on authentication mechanisms [49]. They also highlighted the enumeration and privacy-related attacks that are possible due to address book syncing feature of these applications. Antonatos et al. proposed HoneyBuddy, an active honeypot infrastructure designed to detect malicious activities in Instant Messaging applications like MSN [18]. It automatically finds people using a particular messaging service and adds them to its contacts. These findings confirmed the ineffectiveness of existing security measures in Instant Messaging services.

In our research, we further demonstrate how cross-application features can be abused to launch targeted attacks; address book sync feature in OTT messaging applications and exploiting integrity of information in caller ID applications.

2.3 Targeted Attacks and User Profiling

Bilge et al. launched automated identity theft attacks via profiling users on SNS (Social Networking Services) by employing friend relationship with the victims [22]. The authors showed that people tend to accept friend requests from strangers on social networks. Balduzzi et al. presented experiments conducted on “social phishing” [21]. They crawled social networking sites to obtain publicly available information about users and manually crafted phishing e-mails containing certain information about them. This study showed that victims are more likely to fall for phishing attempts if some information about their friends or about themselves is included in the phishing e-mail. Jagatic et al. showed that Internet users might be over four times more likely to become victims if the sender is an acquaintance [35]. Gupta et al. showed that inference attacks can be employed to harvest real interests of people and subsequently break mechanisms that use such personal information for user authentication [32]. Huber et al. presented friend-in-the-middle-attack on Facebook which could leverage social information about users in an automated fashion [34]. They further pointed out the possibility of context-aware spam and social phishing attacks, where attacks were found to be cheap in terms of cost and hardware. Boshmaf et al. highlighted vulnerabilities that can be exploited by social bots to infiltrate OSNs [23]. They showed that social bots can mimic real users and exploit friendship network leading to strong privacy implications. Kurowski showed a manual attack on WhatsApp to retrieve personal information about victims and proposed the feasibility of social phishing attacks against victims [42].

In this paper, we demonstrate how phone numbers can be used for automated cross-application targeted attacks where people are attacked on one application by leveraging information from multiple other applications i.e., using Truecaller and Facebook to launch targeted phishing, vishing, and whaling attacks on OTT messaging applications, voice, e-mail, or SMS.

3. SYSTEM OVERVIEW: FEASIBILITY AND AUTOMATION

In this section, we demonstrate the feasibility and the case with which different targeted attacks can be crafted by abusing phone numbers. To automate the whole process, we build a system that exploits cross-application features to collect information about a phone’s user and determines the attack channel (OTT messaging applications, voice, e-mail, or SMS) and targeted or non-targeted attack vectors (see Figure 1). Specifically, the system has four main steps. a) Based on a numbering plan, phone numbers are randomly generated and inserted into an address book of a smartphone. This address book is on a device that is under the
control of the attacker. b) The system fetches data from Truecaller and Facebook applications to determine any additional information about the owners of those phone numbers. c) After the information is aggregated, the system determines the attack channel viz. OTT messaging applications, voice, e-mail, or SMS, and d) finally crafts an attack vector and targets the victim with the best possible attack (based on the information collected).

Figure 1: System for Cross-Application Information Gathering and Attack Architecture.

3.1 Step 1: Setting Up Attack Device

This section elaborates phone number generation and setting up the device under attacker’s control, once phone numbers are generated. The system generates a large pool of phone numbers which could be exploited by an attacker to launch targeted attacks. There are several methods to obtain a pool of phone numbers; consolidating white-pages directory or any other public online directories, or scraping the Internet using regex patterns. We chose the easiest method for an attacker; taking random phone numbers as initial seeds, incrementing the digits by one to obtain a sufficient pool. Unlike e-mail addresses, the phone number set is finite, therefore, an entire range can be enumerated and inserted into the address book. This may give a few misses as some phone numbers may not be allocated for general use. Once phone numbers are generated, attacker initializes the address book of the device under his control. The phone numbers added in the address book are now his potential victims for carrying out various kinds of targeted attacks as demonstrated in this paper.

3.2 Step 2: Collecting Information for an Attack Vector

In this step, the system aggregates all the available information to launch an attack against the victim. To obtain information about the victim, we used Truecaller, an application that enables searching contact information using a phone number. Its legitimate use is to identify incoming callers and block unwanted calls. It is a global collaborative phone directory that keeps data of more than one billion people around the globe. We used Truecaller as an example, but any such application can be used to determine this information. Truecaller also maintains data from social networking sites and correlates this information to create a large dataset for people who register on it. Also, due to its address book syncing feature, it retrieves information about contacts (friends) of the “owner of the phone number” who installed it too. The ‘search’ endpoint of Truecaller application provides details of an individual like:

name, address, phone number, country, Twitter ID, e-mail, Facebook ID, Twitter photo URL, and photo URL.

However, the private information obtained is according to the privacy settings of users.

We automated the whole process of fetching information about phone numbers from Truecaller. We exploited the search end-point (used to search information about a random phone number) to obtain the registration ID corresponding to a particular phone number 1. This was necessary to make authenticated requests and retrieve the information from their servers. We extracted the registration ID from the network packet sent while searching a random phone number on Truecaller application installed on our iPhone as shown in Figure 2. Once the registration ID was obtained, we programmatically fetched information for phone numbers in our dataset. Multiple instances of the process were initiated, on a 2.5 GHz Intel i5 processor, 4GB RAM at the rate of 3000 requests / min. We worked with only one registration ID for not abusing the Truecaller servers and effecting its services, however, it is easy for an attacker to scale the process by collecting multiple registration IDs to bypass rate limits imposed by Truecaller.

Figure 2: Screenshot of a network packet which is used to obtain the registration ID from Truecaller to fetch information from its servers.

To obtain the social network of the victim, we used Facebook, the largest social network of family and friends 1. We assume that friends obtained will be related to the person in some way or the other which can increase the probability of success of a social phishing attack. However, we do not differentiate between the affinity of a friend Alice with the victim as compared to another friend Charlie. Though, there may be greater affinity with one friend as compared to the other in the real-world, however, in this paper, we treat all friends equal and leave affinity determination as future work. Truecaller aggregates data from various social networking websites and sometimes provides a link to the public profile picture of the victim on Facebook. We extracted Facebook ID from these links to retrieve friends of the victim on Facebook.

Extracting friends from victim’s profile is a non-trivial task, since everyone does not have their friendlist set as public. Therefore, we decided to use public sources like victim’s public feed, victim’s public photo albums, and victim’s public posts on Facebook to obtain friends information 3, assuming users liking / commenting on any of these public sources are friends of the victim. To validate the above

1We used this phone number only for research purposes and nothing else.
hypothesis, we performed a small experiment to determine if friends obtained from public sources on Facebook are a subset of public friendlist. Even though normal access token from Facebook does not provide these details, we were able to fetch the information using a never-expiring mobile OAuth token obtained from iPhone’s Facebook application. We monitored the data packet sent while launching Facebook application on our iPhone device and extracted the authentication token to make further requests.

We collected a random sample of 122,696 Facebook IDs and obtained 95,756 friends from public sources and 80,979 friends from public friendlist (see Figure 3). There were only 62,574 users for whom we were able to find friends from both public sources and public friendlist. Out of which, we found that 42,552 (68%) user-IDs liking and commenting on public sources were part of victim’s friendlist with more than 95% matching rate. As observed in Figure 3, in some cases friends from public sources were not a complete subset of friends from public friendlist. We obtained 5,881 friends with 90 - 95% matching, 3,754 friends with 85 - 90% matching, and 10,387 friends with less than 85% matching. This could be because some users might have disabled all platform applications from accessing their data. In this case, they might not appear anywhere in any Facebook API. To launch attacks using friends information, friends can be picked from public friendlist, if available, else, the attacker can rely on public sources to extract friends. Therefore, we extracted the Facebook ID from the photo URL (using regular expression) obtained from Truecaller JSON response, and obtained public sources using Facebook Graph API to find friends on Facebook to craft social phishing attack vectors.

For example, following JSON object was obtained for one of the phone numbers in the dataset –

```
{
  "NAME": "XXXXX",
  "NUMBER": "+91 XX000000X",
  "COUNTRY": "India",
  "PHOTO_URL": "http://graph.facebook.com/XXXXX/picture?width=320&height=320",
  "e-mail": "",
}
```

The Facebook ID was parsed from PHOTO_URL and used to make further requests. E-mail addresses for some users were also available which can be used to target them.

An attacker can utilize the information, as obtained in this step and craft attack vectors described in step 4. The attacker can craft non-targeted attacks, in case no information about the victim is obtained.

Apart from applications like Truecaller and Facebook that we explored in this paper, attackers can exploit CNAM (Caller ID Name) database, a database that is linked to names of calling number. The service operational in US, provides information associated with a landline number. Attackers can use this to obtain basic information about their targets. This is out of scope of current work.

3.3 Step 3: Formulating Attacker’s Profile and Attack Channel

\(^2\)We are not sure if this is an additional feature provided by Facebook or a bug in their system. At the time of writing this paper, we did not find any official Facebook documentation about it.

\(^3\)http://www.voip-info.org/wiki/view/CNAM

Once the data is collected about phone number’s owner, the system determines the channel (OTT messaging applications, voice, e-mail, or SMS) to phish the victim. This entirely depends on whether the victim is present on that particular channel.

OTT messaging applications.

If the attacker decides to choose OTT messaging applications like WhatsApp, Viber, or Snapchat, he needs to ensure if the victim is using one of these applications. This is achieved by exploiting the address book syncing feature in OTT messaging applications. Once a user registers himself on these applications, his contacts in the address book are uploaded (automatically, for some applications) to the OTT messaging applications’ service provider and are matched against the users of the application to find already existing contacts. Only the information about the owners of the phone numbers present in the address book is retrieved. Unlike Facebook and Twitter, these applications make no suggestions/recommendations for people who might be using these OTT messaging applications. While this makes it easy and convenient for users to discover friends on these applications rather than adding them manually, it poses a security threat as well as, an attacker can use this to find the presence or absence of the victim on these applications (i.e., the attack channel). The attacker can himself create a convincing profile (profile picture and local phone number) on WhatsApp to make sure the victim feels that attacker is legitimate.

Voice.

In addition, an attacker can choose voice as an attack channel to target their victims. Similar to OTT messaging applications, to target victims on this channel, an attacker needs to gather relevant information without checking the presence of the victim beforehand. An attacker can devise a strategy to make himself look like a trusted or legitimate organization, to gain victim’s trust. Specifically, attackers can exploit the integrity of information provided by caller ID applications like Truecaller, Facebook’s Hello, and Whitepages Caller ID and Block. These applications are emerging to help in getting additional information about the incoming caller. In general, these applications al-
low an individual to register using his / her phone number and help in identifying the caller by showing the information (like name) from their respective databases. Caller ID applications also gather information from social networking sites to collect more information about the caller. Attackers can undermine such an application to gain trust of their victims. Specifically, a) attackers can register a phone number (controlled by him / her) as a trusted bank / company / organization in which a user is interested in or is dealing with; b) spoof one of the already registered phone numbers with the caller ID applications and call victims such that the call appears to come from a real entity. We describe each of them in detail.

- **Fake Registration**: An attacker can add spurious information in caller ID applications fairly easily, thus compromising the integrity of the information provided by them to gain victim’s trust. Associating an identity with a phone number increases the trust of an individual and likelihood to pick a call. Since caller ID applications do not have a mechanism for verification of the users’ details, and rely on the information provided by the user while registering, it is easy for an attacker to abuse this trust. For example, an attacker can register as multiple fake banks on caller ID applications as shown in Figure 4. We only use HDFC Bank as an example, but any name / entity can be used.

For registration, he needs a smartphone device with working phone connection. It is a manual process where a short SMS code is sent from caller ID applications to verify the phone number. Since the number of banks are limited, it is not difficult for the attacker to do this manually. Attacker does not know the bank of all these victims, therefore, the attacker can target a large user population to achieve a good success rate. As millions of automated VoIP calls can be generated at low cost, as shown in the past, at-tacker does not need to worry about picking only the victims whose banks are known [30]. To make the profile look more authentic, fake social media profiles can be created and linked to caller ID applications while registering an account on it. Top five most popular applications (Truecaller, Whitepages caller ID and Block, Facebook’s Hello, Whoscall-Caller ID and Block, and Contactive) with fake registrations as HDFC bank by exploiting caller ID applications has been shown in Appendix.

- **Caller ID spoofing**: Another trick to deceive victims uses caller ID spoofing which can be carried out by imitating already registered phone numbers or other phone numbers whose details were uploaded by caller ID applications exploiting address book syncing feature. As a user must have entered some details about him / her while registering, it makes the attacker look genuine, than an unknown phone number flashing on the screen.

**SMS**.

An attacker can choose SMS as the attack channel to phish their victims. He needs to gather relevant information about the victim without checking his / her presence on the attack channel. As the victim does not see any profile of the attacker, he can choose using a local phone number to gain victim’s confidence.

**E-mail**.

Since so many people around the world depend on e-mail, it is a lucrative channel for attacks. Attackers lure people in giving away their information or entice them to take some action. If there is a non-empty field in the JSON object received from the Truecaller, e-mail can be used to phish users. Attackers can craft these e-mails to look convincing, sending them out to literally millions of people around the world [8]. As attacker’s profile is visible to the victim, he can carefully choose an e-mail address and name to convince victim about his authenticity.

### 3.4 Step 4: Crafting Attack Vector

After the attack channel is determined, attacker can craft appropriate attack vector to phish the victim. We describe the attack vector generation details for each of the attacks below.

#### 3.4.1 Social Phishing Attacks

Although phishing is a social engineering attack, here we discuss social phishing [35], i.e., how phishing attacks can be better targeted by making them appear to be coming from a friend within victim’s own network. Friends’ information can be conveniently chosen to gain trust, therefore, the attacker uses victim’s name and one of his friend’s information (i.e., friend’s name) to craft the attack vector. This information is obtained from Facebook, as discussed earlier in this section.

#### 3.4.2 Whaling attacks

Whaling attacks [15] that are directed specifically at senior executives or other high-profile individuals within a business, government, or other organization. It uses the same technique as above mentioned targeted phishing, vishing, or whaling attacks but the intended victims are people with high influence or high-net-worth individuals. In India, there is a particular set of phone numbers reserved by mobile operators for politicians, bureaucrats, and people willing to invest large amount of money to get these special phone numbers. They are called Vanity / VIP / Fancy numbers.
and follow a specific pattern [13]. It could be one digit repeated several times, 99999-xxxxx or xx-8888-xxxxx; two digits, xx-85-85-85-xx; or in different orders, xx-123-123-xx or xx-11-112233. The main advantage of vanity phone numbers over standard phone numbers is increased memorability. Since they are bought at higher price, owners of these phone numbers can be assumed as people, or high influence who likely are more attractive targets for attackers [9]. For very special numbers, network providers host auctions online where people can purchase these numbers [2]. Using only vanity numbers in the address book, attackers can launch whaling attacks that only targets HNIs (High-net-worth individuals) by sending them targeted or non-targeted phishing messages or initiating vishing calls.

3.4.3 Spear Phishing Attacks
Spear phishing attacks are directed at specific individuals or companies. These attacks are crafted using some a-priori knowledge of either victim’s name, location, or interests to make it more believable and increase the likelihood of its success. We focus on generating spear phishing attack vectors using victim’s name, as obtained from Truecaller.

3.4.4 Non-targeted Attacks
Non-targeted attacks are undirected attacks which are aimed to target as many users as possible. The goal is to reach out to a large audience and not to target a particular individual. Since it only requires the knowledge whether the victim is present on the channel, this can be achieved by crafting a non-targeted phishing, vishing, or whaling attack, even if no information about the victim is available. With low VoIP calls, non-targeted vishing attacks are cost-effective for attackers.

All the targeted and non-targeted attacks described in this step can be launched on either channels viz., OTT messaging applications, voice, e-mail, or SMS.

4. SCALABILITY
To define scalability, we assume that an attacker starts with no information about its potential targets. The attack method’s scalability can be characterized by the fraction of people who can be reached over an attack channel, and targeted attacks can be launched against them. To demonstrate the scalability of our attacks, we enumerated through a list of 1,162,696 random Indian phone numbers. Since these numbers are chosen randomly, no additional information is available about their owners at the beginning. We demonstrate the scale at which each of the proposed attacks can be carried out with the techniques described earlier.

4.1 Phishing Attacks
We forged the address book of an Android device by inserting all these phone numbers in multiple phases. The next step was to collect attributes associated with the owner of the phone number (victim). Truecaller (TC) was used to collect more information about the victims. Detailed information for 722,696 (62%) users was collected using Truecaller; name was obtained for all the users as shown in Figure 5. For rest of the users whose information cannot be obtained from Truecaller, non-targeted phishing attacks can be launched against them. To craft more targeted and personalized attacks, i.e., social phishing attacks, friends information was leveraged from Facebook (FB). Social circle information was obtained for 114,161 (93%) out of 122,696 users; 80,979 from public friendlist and 33,182 friends from public sources. To check the presence of these numbers on an attack channel, they were synced with WhatsApp application (WA) using address book syncing feature. About 51,409 users were present on WA. Social phishing attacks can be launched against these users whereas spear phishing attacks can be launched against other 180,000 users whose social circle was not obtained, but were present on WA. Numbers which were not found on WhatsApp either may not be allocated to any user or may not be registered on it.

Spear phishing attacks can be launched against 600,000 users on voice or SMS. In addition, 122,696 users can be social phished on voice or SMS. E-mail address for 81,389 can be spear phished on voice or SMS.

4.2 Vishing Attacks
Personal information for 722,696 users was found on Truecaller against 1,162,696 phone numbers searched. Vishing attacks can be crafted against the owners of these phone numbers. We could extract Facebook ID’s for 122,696 users. Using Facebook Graph API, we obtained following details for these users: gender (112,880), relationship status (57,755), work details (92,352), school information (110,426), employer details (106,746), birthday (9,728), and hometown (80,979). The collated information can be used to increase the success rate of targeted vishing attacks.

4.3 Whaling Attacks
As owners of vanity numbers might belong to elite members of the society, they can be of particular interest to attackers. We looped through the “patterns” available from an e-auction website to enumerate vanity numbers pool [2]. We initialized our smartphone’s address book with 171,323 vanity numbers. We found 91,487 vanity numbers on Truecaller and 11,286 on Facebook. They were synced with WhatsApp and 5,756 (51%) were found on it. Out of 11,286 vanity numbers that were found on Truecaller and Facebook; we obtained personal information (using Facebook) about owners as follows: gender (10,246), relationship status (3,733), birthday (726), work details (6,729), school details (10,994), employer details (9,801), and hometown (6,952). We manu-

Figure 5: Data collection to demonstrate scalability of phishing attacks of the system choosing OTT messaging applications as the attack channel, WA–WhatsApp, TC–Truecaller, FB–Facebook.
ally analyzed Facebook profiles of 100 random vanity number owners to find their occupation details and found director / CEO / chairman (10), student (10), engineer (12), consultants (2), business (5), accountant / officer (8), lecturer (5), manager (8), bank officials (12) for 70 user profiles.

Whaling attacks with social information was obtained for 11,286 users which could be attacked on voice or SMS. However, only name was obtained for 80,201 users, using Truecaller, who can be made targets on voice or SMS. E-mail address for 11,013 users was obtained; 1,354 users with social information. Attacks can be made more targeted and personalized against these users.

5. ETHICAL AND LEGAL CONSIDERATIONS

Crawling data is an ethically sensitive area. We did the data collection just to demonstrate the feasibility and scalability of targeted attacks by abusing a phone number. The goal of this work was not to collect personal information about individuals, but to explore how such applications can be abused to collect personal information. As a proof of concept, we collected information about owners of random phone numbers ensuring that the collected information is not made available to any other organization or individual. All the conducted experiments were approved by the Institutional Review Board (IRB) of our institution. Data collected from the participants was anonymized and protected according to the procedures described in the corresponding IRB submission documents. At the end of our experiments and analysis, phone numbers of all the profiles were delinked to maintain privacy and confidentiality of data. Phone numbers and Facebook IDs were hashed to preserve privacy. We collected only the public information available on Facebook using it’s Graph API.

6. STUDY DESIGN

In this paper, we only focus on demonstrating the effectiveness of phishing attacks on OTT messaging applications. Thus, we do not address effectiveness of the other attacks and channels as demonstrated in previous sections.

To demonstrate the effectiveness of phishing attacks on OTT messaging applications, we chose to conduct an online roleplay user study on Amazon Mechanical Turk (MTurk). We chose this over a real-world study because conducting a real-world study would involve user deception. To launch attacks as proposed in this paper would require us to gather personalized against these users.

6.1 Briefing

Susceptibility to phishing attacks was measured with response to a roleplay task which was built on Javascript and showed multiple screens as WhatsApp screenshots. This phase of the study was common across all participants to familiarize them with the real-world scenario. A hypothetical situation for the participant to assume himself as “Dave”, and has friends “Alice”, “Bob” and “Charlie”. We used Facebook as a medium to bootstrap this and to let the participant familiarize with the roles. An attacker can extract this information from Facebook and create a social phishing attack vector to phish the victim, which is modeled in this step. Next screen shows the registration on WhatsApp, as “Dave”, using a random phone number. The aim is to make the participant understand that the user (i.e., Dave) has an account on WhatsApp. Once registered, WhatsApp syncs Dave’s address book and found only Charlie. Note that other Facebook friends of Dave (i.e., Alice and Bob) were not present on WhatsApp. There could be two reasons, either Dave does not have Alice’s and Bob’s number in his smartphone or Alice and Bob do not have an account on WhatsApp. The primary idea is to introduce Charlie as the only friend who is present on WhatsApp and other friends (Alice and Bob) are not present on WhatsApp. This is to mimic the attack model when an attacker might not know which of victim’s friends is present on WhatsApp. Therefore, the success of the attack should be independent of this knowledge: who provided wrong answers to any of the following two questions asked, “Who was your friend on Facebook?”, and “Who was your friend on WhatsApp?”. Since correct answers to these questions were provided during course of the experiment, participants who did not provide correct answers were filtered out.

6.2 The Play

In this phase of the user study, participants were exposed to one of the three phishing: non-targeted, spear, and social. Each of the case was randomly assigned to the participants. In all three cases, the legitimate case was shown to the participant to ensure that his responses were as expected as in a real-world scenario i.e., given a message m and a trust function T,

\[ T(m) \text{ from known no.} \geq T(m) \text{ from an unknown no.} \]  

The order of phishing and legitimate messages was randomized to avoid learning bias during the course of the experiment. Some participants were removed from the analysis due to unexpected behavior as discussed in Section 6.3. At
the end of each WhatsApp message shown to the participant, the participant was asked the following question and corresponding options: “What would you like to do with the message?” with following options: click, reply, delete, or do nothing. Now we describe the three experiments to test the success of phishing attacks. Since the names and message content were kept same in all the three experiments, we do not foresee any bias.

**e1:** Testing non-targeted phishing attack’s success.

Non-targeted phishing is defined as an attack scenario where no additional information about the victim is known beforehand, except the phone number. In the play phase, participants were exposed to two scenarios in a random order to avoid learning bias; probably phishing message (C1) and legitimate message (C0). In C1, the sender is a random phone number, whereas, in C0, the message is from Dave’s friend Charlie. The former scenario is probable phishing because from Dave’s perspective, the sender could be one of his friends who is not present in his WhatsApp contacts. However, the latter case is legitimate because Charlie was already in Dave’s address book, as mentioned during the briefing phase (see Section 6.1).

**e2:** Testing spear phishing attack’s success.

Spear phishing is defined as an attack where some information about the victim is known beforehand, in addition to his phone number. In our experiment, name of the participant was “Dave”, as described in the briefing phase. This information was used to craft a spear phishing attack vector. Similar to non-targeted phishing, participants were exposed to two scenarios; probably phishing message (C2) and legitimate message (C0). In C2, the sender is a random phone number, whereas in C0, the message appears to be coming from the friend Charlie. However, with one notable difference, that the name of the victim (Dave) was added to the message to make it more personalized as compared to e1.

**e3:** Testing social phishing attack’s success.

Social phishing is defined as an attack where social information (friends, acquaintances, colleagues, etc.) associated with the victim is gathered, in addition to known basic information about the victim (name and phone number). In this part of the experiment, participants were exposed to three scenarios (as compared to two in e1 and e2) in a random order; probably phishing message (C3), legitimate message (C0), and phishing message (C1). In C3, the sender is a random phone number; however, mentioning the name of “Alice” (one of Dave’s friend on Facebook but not in the WhatsApp contacts, see Section 6.1). From Dave’s perspective, this could probably be a legitimate message because Alice is not in Dave’s address book and plausibly in real-world scenario Alice is trying to initiate a conversation with Dave. On the other hand, this could be a phishing message, because friend’s name (Alice) could be forged and an attacker could imitate Alice and send a message to Dave. In C0, the message appears to be coming from the friend Charlie and in C1, the message is coming from a random phone number having Charlie as the friend’s name. Since, Charlie is anyways a friend of Dave on WhatsApp, this is definitely a phishing attack because the sender phone number should have shown Charlie and not a random number.

### 6.3 Effectiveness of Attacks

In this section, we demonstrate the effectiveness of phishing attacks performed during our user study. In total, 460 participants completed the entire user study, out of which 129 participants were filtered out based on answers to two questions asked from the participants during the briefing phase (see Section 6.1). We present the results based on remaining 331 participants. We used Kruskal Wallis and Mann Whitney statistical tests to check the behavior of population subject to different order of messages shown to them. We did not find statistical difference between the random groups in failing victims to all three kinds of phishing attacks.

Table 1 summarizes the results obtained in three experiment scenarios e1, e2 and e3 as mentioned in Section 6.2. In this work, we define the success of a phishing attack if either a participant decided to click the link or reply to the message, whereas, attack is unsuccessful if the participant decided to delete or do nothing about the message. Note that these are potential victims who may fall for phishing attacks. Actual phishing attack happens when the participant goes through all the steps in the phishing attack i.e. by providing his / her personal details like credit card information, passwords etc. on the phishing web page. However, previous studies have established that a very high percentage of participants who click on the link continue to provide information to the phishing websites [40, 41, 47]. We believe that users who choose to reply to the message are potential victims too, as the attacker can verify active usage of the phone number. Also, attacker can lure the victim to give out personal information in subsequent messages. Extra cautious users would have preferred to either delete / do nothing with the message received. We denote,

\[
\begin{align*}
\odot \to \odot \to \odot & \implies \text{clicked / replied to the message, and} \\
\odot \to \odot \to \odot & \implies \text{deleted / did nothing about the message}
\end{align*}
\]

For example, \(\odot\) means participant chose to click or reply to a probably phishing message, while \(\odot\) means participant chose to delete or do nothing about the probably phishing message. We remove those participants from our further analysis who chose to click on phishing / vulnerable message but not on the legitimate message. Because according to equation (1), \(T(\odot) \geq T(\odot)\) and \(T(\odot) \geq T(\odot)\). We denote these participants as Unknown (see Table 1).

| Case | Vulnerable | Cautious | Unknown |
|------|------------|----------|---------|
| e1   | \(\odot\)  | \(\odot\) | \(\odot\) |
|      | (37)       | (24)     | (7)     |
|      | \(\odot\)  | \(\odot\) | \(\odot\) |
|      | (46)       |          |         |
| e2   | \(\odot\)  | \(\odot\) | \(\odot\) |
|      | (56)       | (19)     | (4)     |
|      | \(\odot\)  | \(\odot\) | \(\odot\) |
|      | (28)       |          |         |
| e3   | \(\odot\)  | \(\odot\) | \(\odot\) |
|      | (54)       | (12)     | (2)     |
|      | \(\odot\)  | \(\odot\) | \(\odot\) |
|      | (20)       |          | (1)     |
|      | \(\odot\)  | \(\odot\) | \(\odot\) |
|      | (9)        |          | (3)     |

We denote those participants who chose to click / reply
on either phishing (●) or probably phishing messages (○) or both as Vulnerable (i.e., falling for phishing attacks). All other participants were part of Cautious group, i.e., who chose to delete or do nothing about both phishing (●) and probably phishing messages (○).

We define the success rate of phishing attack as:

\[
\text{Success}(\%) = \frac{V_{\text{Vulnerable}} + C_{\text{Cautious}}}{V_{\text{Vulnerable}} + C_{\text{Cautious}}} \times 100
\]

In total, we have 314 out of 331 participants who were either vulnerable or cautious. We rest our analysis on these 314 participants. We found that phishing attacks on OTT messaging applications were successful as, \(c_1 = 34.5\% (37\) out 107), \(c_2 = 54.3\% (56\) out of 103), and \(c_3 = 69.2\% (72\) out of 104). This is consistent with prior work that social phishing is the most effective out of the three. Furthermore, in social phishing as observed from Table 1, equal number of participants (63 = 54+9) fell for phishing when the name mentioned in the message text was Charlie (i.e., it is coming from a friend who is in Dave’s WhatsApp contacts) and when the name was Alice (i.e., it is coming from a friend who is not in Dave’s WhatsApp contacts). This shows that including friend’s name in the message (irrespective of whether the friend is present or absent on WhatsApp) increases the success rate of phishing attacks. We repeated the analysis for random 25%, 50%, and 75% of the total participant population and found the success results to be consistent. Hence, we can establish that the participant pool size is sufficient for our analysis.

## 6.4 Limitations

There are a few limitations to the current study. First, the sample was drawn from MTurk users and is not expected to be a complete representative of people using OTT messaging applications. Our sample of MTurk users tend to be younger, more educated, and more tech-savvy than the general public. A second limitation of this study is the lack of direct consequences for user behavior. Participants might be more willing to engage in risky behavior in this roleplay if they feel immune to any negative outcomes that may follow. However, the factors used to determine phishing susceptibility would not differ as observed in the real-world behavior.

## 7. MITIGATING RISKS

Based on the exploits we found as described in Section 3.4, we present recommendations on how to alleviate (if not eliminate) the security risks created by these exploits. We communicated with a number of service providers highlighting the security issues; they considered it to be a serious problem and ensured prompt redressal. To combat the abuse, there have been services in place, for instance, CNAM lookup databases\(^4\) for landlines numbers. Also, initiatives like Secure Telephone Identity Revisited (STIR) working group\(^5\) aim to provide a more secure telephony identity by limiting the ability to spoof phone Caller ID. However, this relied on PKI that is currently not implemented. Recently, some services have put some defensive measures in place. WhatsApp incorporated spam blocker feature as a first step in this direction\(^6\), though their effectiveness need to be studied. Facebook patched the mobile OAuth token which enabled us to obtain personal public information, which was otherwise unavailable via Graph API.

### 7.1 OTT Messaging Applications

Given the plausibility of phishing attacks on OTT messaging applications, this medium needs to be better defended. OTT messaging applications can put certain checks; restrict address book sync features, where people can be added only based on requests (like Facebook). End-to-end encryption poses a major challenge to identify a phishing message at zero hour. In order to effectively defend against phishing message, one solution could be assigning crowd-sourced score (phishing) to the source of a phishing message. OTT messaging applications can filter messages with high phishing score. However, introducing noise in the dataset, remains a challenge. To this end, we are currently investigating a defense from our side. It involves building cross platform intelligence from existing Internet infrastructure to associate history with a given phone number which can help in modeling potentially bad phone numbers.

### 7.2 Caller ID Applications

There is also a necessity to ensure the integrity of the information provided by caller ID applications, as people rely heavily on them to know about the incoming call and trust the information provided by these services.

**Verification.**

One of the biggest challenge that caller ID applications have to face is to implement verification of the information

---

\(^4\)http://www.voip-info.org/wiki/view/CNAM

\(^5\)https://datatracker.ietf.org/wg/stir/charter/
provided by users. Currently, at the time of registration, only phone numbers are verified, and neither the entity behind these phone numbers nor the details of owners of these phone numbers is verified. Caller ID applications can check the integrity of specific business organizations with appropriate authority, listing them as verified users, and routinely scan for any malicious activity in these accounts. Similar techniques can be implemented by caller ID applications to maintain the integrity of the information stored in their databases.

Additional Information About Callers.

Additional information can be provided about the caller / the owner of the phone number. For instance, applications can record the timestamp when the account was registered and call frequency patterns. These details can be provided to the user so that he / she can make an informed decision about the caller. In addition, social information about the caller can be displayed, like number of mutual friends, presence on social networks etc. Caller ID applications can design several metrics like social rank based on the information aggregated across social networks. If the same name appears across multiple networks and the user is found to be active, he / she can be assigned a higher score than a passive user.

Delinking information.

Caller ID applications like Truecaller serve as a reservoir of information, by collating information from multiple sources. The data from different sources should not be aggregated and stored at the same place, it serves as a goldmine reservoir. Some parts of the information can be even encrypted to ensure unnecessary information leakage.

8. CONCLUSION

OTT messaging and Voice over IP applications are gaining popularity worldwide. These applications have millions of registered users. As much as these applications attract users, spammers find them attractive as well. In this paper, we demonstrated the feasibility, automation, scalability of targeted phishing, vishing, and whaling attacks by abusing phone numbers. We investigated how easy it would be for a potential attacker to launch automated targeted and non-targeted attacks on different channels viz., OTT messaging applications, voice, e-mail, or SMS. We presented a novel, scalable system which takes a phone number as an input, leverages information from Truecaller (to obtain victim’s details) and Facebook (to obtain social circle), checks for the presence of phone number’s owner on the attack channel (OTT messaging applications, voice, e-mail, or SMS), and finally targets the victim. We collected information for 1,162,696 Indian phone numbers and show how non-targeted and targeted phishing, vishing, and whaling attacks can be launched against the owners of these phone numbers by exploiting cross-application features. Social and spear phishing attacks can be launched against 51,409 and 180,000 users respectively. Vishing attacks can be launched against 11,026 and 57,869 users. We also found 91,487 highly influential victims who can be attacked by crafting whaling attacks. To evaluate the effectiveness of one of our attacks, phishing attacks, we conducted an online roleplay study with 314 participants on Amazon MTurk. Our results show that social phishing (69.2%) is the most successful phishing attack on OTT messaging applications, followed by spear (54.3%), and non-targeted phishing (35.5%). To mitigate the attacks demonstrated in this paper, we also suggest some recommendations for OTT messaging applications and caller ID applications which can prevent their users falling prey to targeted attacks.

9. REFERENCES

[1] 91 Leading Social Networks Worldwide. http://www.practicalecommerce.com/articles/96284-91-Leading-Social-Networks-Worldwide
[2] BSNL auction for Vanity Numbers. http://eauction.bsnl.co.in/auction1/index.aspx?id=74
[3] Facebook Graph API. https://developers.facebook.com/docs/graph-api
[4] Facebook Hello. http://www.engadget.com/2015/04/22/facebook-hello/
[5] Fetching friends from Graph API. http://stackoverflow.com/questions/1135053/fetching-list-of-friends-in-graph-api-or-fql-appears-to-be-missing-some-friend
[6] Four Of The Top Six Social Networks Are Actually Chat Apps. http://marketingland.com/four-top-six-social-networks-actually-chat-apps-115168
[7] HeadsUp for WhatsApp. http://www.adaptivemobile.com/blog/headup-for-whatsapp
[8] How to send 5 million spam emails without even noticing. https://nakedsecurity.sophos.com/2014/08/05/how-to-send-5-million-spam-emails/
[9] Price for Vanity Numbers. http://articles.economictimes.indiatimes.com/2007-10-13/news/27675454_1_digit-numbers-mukul-khanna-minimum-price
[10] SIM card cost, India. http://prepaid-data-sim-card.wikia.com/wiki/India
[11] SMS Phishing. https://en.wikipedia.org/wiki/SMS_phishing
[12] Truecaller. http://truecaller.com/
[13] Vanity Numbers. http://www.openthemagazine.com/article/real-india/calling-9999999999
[14] Voice Phishing. https://en.wikipedia.org/wiki/Voice_phishing
[15] Whaling? These Scammers Target Big Phish. http://www.scambusters.org/whaling.html
[16] WhatsApp Spam Block Feature. http://www.ibtimes.co.uk/whatsapp-rolls-out-new-spam-blocker-feature-1497715
[17] Whitepages Caller ID and Block. http://www.whitepages.com/caller-id
[18] S. Antonatos, I. Polakis, T. Petsas, and E. P. Markatos. A systematic characterization of IM threats using honeypots. In Proceedings of the 17th Annual Network and Distributed System Security Symposium (NDSS), San Diego, CA, 2010.
[19] V. Balasubramaniyan, M. Ahamed, and H. Park. CallRank: Combating SPIT Using Call Duration, Social Networks and Global Reputation. In Conference on Email and Anti-Spam, CEAS, 2007.
[48] J. Song, H. Kim, and A. Gkelias. iVisher: Real-Time Detection of Caller ID Spoofing. *ETRI Journal*, 36(5):865–875, 2014.

[49] Y.-S. Wu, S. Bagchi, N. Singh, and R. Wita. Spam detection in voice-over-ip calls through semi-supervised clustering. In *Dependable Systems & Networks, 2009. DSN’09.*, pages 307–316. IEEE, 2009.

[50] E. Zheleva and L. Getoor. Privacy in social networks: A survey. In *Social network data analytics*, pages 277–306. Springer, 2011.

10. APPENDIX
Figure 7: Incoming call showing fake HDFC bank (example in our case) on various caller ID applications.