

# Do Not Give A Dog Bread Every Time He Wags His Tail: Stealing Passwords through Content Queries (CONQUER) Attack

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**Abstract**—Android accessibility service was designed to assist individuals with disabilities in using Android devices. However, it has been exploited by attackers to steal user passwords due to design shortcomings. Google has implemented various countermeasures to make it difficult for these types of attacks to be successful on modern Android devices. In this paper, we present a new type of side channel attack called content queries (CONQUER) that can bypass these defenses. We discovered that Android does not prevent the content of passwords from being queried by the accessibility service, allowing malware with this service enabled to enumerate the combinations of content to brute force the password. While this attack seems simple to execute, there are several challenges that must be addressed in order to successfully launch it against real-world apps. These include the use of lazy query to differentiate targeted password strings, active query to determine the right timing for the attack, and timing- and state-based side channels to infer case-sensitive passwords. Our evaluation results demonstrate that the CONQUER attack is effective at stealing passwords, with an average one-time success rate of 64.91%. This attack also poses a threat to all Android versions from 4.1 to 12, and can be used against tens of thousands of apps. In addition, we analyzed the root cause of the CONQUER attack and discussed several countermeasures to mitigate the potential security risks it poses.

## I. INTRODUCTION

Even with the adoption of biometric authentication methods such as fingerprint scanning and facial recognition, as well as additional hardware authentication methods like USB keys and IC cards, passwords remain an important means of authenticating a user in mobile security. As the first line of defense against unauthorized access, passwords protect valuable user data, making them an attractive target for attackers. While traditional attacks like brute-force attempts are not impossible, they often come with significant drawbacks, like a high time cost. As a result, attackers are seeking more practical methods to obtain user passwords, such as distributing malware (e.g., keyloggers) onto mobile devices, or guessing passwords based on personal information [34].

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On Android devices, malware often uses the accessibility service to steal user passwords. The accessibility service was originally designed to assist users with disabilities in using Android apps, but it can be easily exploited by malware to collect sensitive information such as passwords. This is because the accessibility service has the ability to interact with victim apps and obtain information such as the content of foreground windows and app life cycles without involving the user. Attackers can use the accessibility service to passively collect user credentials through accessibility events or actively hijack input or output channels to intercept user credentials. Previous research has demonstrated the potential of abusing the accessibility service for malicious purposes, including the collection of user credentials (e.g., [11], [18], [8]) and the interception of user input (e.g., [21], [17], [11], [18]).

Google is aware of the risks posed by accessibility-service-based attacks and has implemented various defenses to mitigate them. One defense strategy is to remove passwords from accessibility events (e.g., [18]). Other defenses aim to increase user awareness by sending warning messages or requiring user confirmation before allowing the accessibility service to access certain information (e.g., [35]). These measures make it difficult to exploit the accessibility service to steal passwords on newer versions of Android.

However, in this paper, we show that existing defenses against password stealing attacks can be bypassed and passwords can still be stolen by exploiting a new query-based side channel — using `findAccessibilityNodeInfosByText(text)` to query the content of the foregrounds. Particularly, this allows users to locate user interface (UI) elements containing specific text by returning a list of such elements. For example, consider an Android app that has a login button with the text “Login”. Using this API, an assistive app can quickly identify the login button and automatically click it for the user. While it is intended to help users navigate and use apps more easily, we have found that it can also be exploited to steal passwords: password fields are also UI elements that can be located by searching for a string that exists within the password. Surprisingly, Android neither prevents searches of password fields (it returns the password input box as usual if the searched string hits the real password) nor alerts users to this potential security risk. To make matters worse, even if only bullet points are displayed in the password field (which is a type of defense enabled by Android), this API can still search the given text in the real password.

Based on this observation, we introduce the **Content Queries** (CONQUER) attack, a new query-based side channel method for stealing passwords. CONQUER exploits the side channel by repeatedly querying the latest password character entered using the API as the users types their passwords, by setting the parameter to all possible characters. If the API returns results indicating that the queried string is in the password field, we can determine what the user has just entered and update our collected password accordingly (essentially, we are performing a brute-force attack to query each newly entered password character).

While CONQUER may seem straightforward to launch, there are three challenges that must be addressed in order to make it practical. First, query results can be ambiguous due to the existence of content descriptions (which are configured by the developers) and do not necessarily indicate the presence of specific strings or characters in a password. Second, some apps have implemented defenses to mitigate previous attacks (e.g., [18], [8]). As a side effect, these defenses may hinder an attacker’s ability to determine when to perform queries. For instance, these defenses may block outgoing password-related accessibility events (through which the malware can determine when to launch the queries), and malware can no longer receive them. Third, the API being exploited does not require the specified text to be case-sensitive. As such, the malware can only collect a case-insensitive password by default.

Fortunately, we have addressed these challenges and successfully implemented CONQUER. To address the first challenge, we propose a lazy query algorithm: we can combine and query the characters not in the content description but in the password (i.e., lazy queries) to eliminate side effects caused by the text in the content description. To deal with the second challenge, we actively query the password length, and whenever it changes, we know that the user has entered a new character. For the third challenge, we use the time and typing speed as side channels (i.e., pressing the case-switch button will cause more time to enter a character) and set up a state machine that tracks the input state of the user (e.g., pressing the case-switch button) to recover case-sensitive passwords.

We evaluated the effectiveness of CONQUER by conducting extensive experiments. The experimental results on 108 real-world passwords show that CONQUER can recover the original passwords based on the collected case-insensitive passwords and input timing information with an average one-time success rate of 64.91%. We show that CONQUER works against all popular Android versions (ranging from Android 4.1 to Android 12), and all apps that use system-provided password input boxes are therefore vulnerable to our attack. Through our large-scale analysis on 13,786 Android apps that use custom password input boxes, we also identified 13,001 (94.30%) apps that are subject to our attack. We responsibly disclosed our findings to Google, who acknowledged our findings but decided not to fix the issue at this time because the accessibility service requires this behavior to function as intended. We therefore believe that there is no easy fix for CONQUER.

Our major contributions are summarized as follows.

- **New Findings.** We are the first to propose CONQUER, a novel password-stealing attack that exploits the content query side channel in the Android accessibility

service. Though Android currently has multiple countermeasures in place to defend against accessibility-service-based attacks, CONQUER can go around them and steal user passwords.

- **New Techniques.** To ensure the practicality of CONQUER, we have introduced several new techniques: the lazy query technique eliminates the side effects caused by content descriptions, the length-based side channel allows us to determine if the user is entering the password, and the temporal side channel and state machine enable us to handle case-sensitive passwords.
- **Extensive Experiments.** We evaluate the performance and security implications of CONQUER through real-world experiments. Our results show that CONQUER can recover case-sensitive passwords with an average one-time success rate of 64.91%. In addition, CONQUER affects system-provided password input boxes on all popular Android versions, and our large-scale analysis of Android apps revealed that 13,001 out of 13,786 (94.3%) apps using customized password input boxes are also vulnerable to our attack.

## II. BACKGROUND

In this section, we first introduce the Android accessibility service in §II-A. Next, we discuss existing accessibility-service-based attacks as well as the defenses in §II-B.

### A. Android Accessibility Service

The Android accessibility service provides user interface enhancements in assisting users with disabilities (e.g., visual or hearing impairment) [12]. The accessibility service allows apps to be notified of accessibility events triggered by UI actions, such as clicking buttons or scrolling the screen. For example, TalkBack [14] can provide real-time spoken feedback to users while they are interacting with their devices. In order to use the accessibility service, app developers must configure the service to tell the system when and how accessibility service should be invoked, and which event types (e.g., clicking a button or scrolling the screen) the service should respond to. To achieve this, developers need to extend the `AccessibilityService` class and override the callback method `onAccessibilityEvent(event)` to handle received accessibility events and take corresponding actions (i.e., specifying how the app deals with accessibility events).

Being an important service that is open to all developers, the Android accessibility service has offered various APIs. One such API is `findAccessibilityNodeInfosByText(text)`. The API takes a specific text as input and returns a list of `AccessibilityNodeInfo` objects, each representing a foreground UI component containing the specified text. Therefore, this API is typically used to automatically locate UI components that have specific names or contain specific texts. For example, an assistive Android app might use this API to facilitate automatic login. To this end, the app can first get the root node of the currently active window in its target via `getRootInActiveWindow()` (Android organizes UI components in a tree structure, with each active window having a root node [13]). The app can then invoke `findAccessibilityNodeInfosByText("login")`

Attacks	Study	Passive?	Determining Timing?	Solely Using Ally?	Easily Noticeable?	Mitigation?	Feasible?
Keystroke Sniffing	Fratantonio et al. [11]	✓	✗	✓	✗	✓	✗
Password Sniffing	Kalysch et al. [18]	✓	✗	✓	✗	✓	✗
App Hijack	Kraunelis et al. [21]	✗	✓	✗	✓	✗	✗
Draw and Destroy Overlay	Wang et al. [35]	✗	✓	✗	✓	✗	✓
Overlay Hijack	Fratantonio et al. [11]	✗	✓	✗	✓	✗	✓
IME Hijack	Kalysch et al. [18]	✗	✓	✗	✓	✗	✗
TTS Hijack	Jang et al. [17]	✗	✓	✗	✓	✓	✗

TABLE I: Comparison of existing accessibility-services-based password stealing attacks. Ally is short for the accessibility services.

on the root node to acquire all UI components within the window containing the string “login” (e.g., the text of the login button is usually “login”). By enumerating and testing each of the returned UI components, the app can finally locate the login button and automatically click it through the `performAction(action)` API.

### B. Accessibility Service Abuse and Defense

The accessibility service has been exploited to design malware [21], [11], [18], [10], [1], [39] and to power various practically feasible attacks, such as automatic permission granting, silent app installation, and password stealing. For example, the use of the accessibility service for password stealing has been widely discussed [21], [17], [11], [18], [8], and has significant impacts. We group existing accessibility-service-related password stealing attacks into two categories based on how passwords get leaked. As illustrated in Table I, we summarize the attacks as follows:

- Passive Attacks.** In this type of attacks, attackers passively sniff accessibility events and collect leaked user credentials. User credentials can be leaked by keyboard sniffing [11] (attackers extract passwords from keystrokes), or password fields sniffing [18], [8] (attackers directly extract passwords from the entered password). Although there are currently no system-level defenses against keyboard sniffing, developers can enforce security mechanisms on keyboards (e.g., disabling the accessibility event propagation) to prevent keystrokes from being leaked [18]. Password fields sniffing can be defended at the system level if users have configured the Android OS securely. To this end, users need to turn off the “Make passwords visible” option in `Settings` to prevent just-entered password characters from being displayed on the screen. Consequently, the most recent character of a password will not be leaked through accessibility events. In summary, the feasibility of passive password stealing attacks highly depends on the environment the victim is in, resulting in limited generality.
- Active Attacks.** In this type of attack, attackers directly intercept user inputs by actively hijacking the input or output channels of user credentials. In these attacks, the accessibility service is used to determine when to launch the attacks. For example, an attacker

launches a phishing app when the victim attempts to launch the real app [21] and logs the entered username and password. Through the accessibility service, the malware knows when the victim launches the real app based on the collected accessibility events (which contains the information of interest such as the package name of the real app). Other than the full-window hijacking, malware can also use overlays to hijack specific UI components [11] and, again, accessibility services can be used to determine the timing of such attacks. For instance, malware can place well-crafted visible overlays above credential input boxes, thus tricking victims into entering their passwords into attacker-controlled widgets. However, this type of attacks have been mitigated, as Android now notifies users when an overlay stays in the foreground [35]. There is also an attack that switches the default input method (IME) used by the system to a malicious third-party IME [18]. However, the attacker has to perform several UI operations using APIs provided by the accessibility service, which the victim can easily notice. Finally, malware can programmatically set the system-level default text-to-speech (TTS) engine, which can intercept all user inputs by design [17]. However, this attack no longer works on newer versions of Android. In summary, the stealthiness of active password stealing attacks cannot be well guaranteed due to system-enforced defenses (e.g., the overlay hijack attack) or the limitation of the attack itself (e.g., TTS hijack).

## III. OBSERVATION AND THREAT MODEL

### A. Key Observation

While Android has introduced countermeasures to prevent the accessibility service from stealing user passwords, we find that there is still a side channel: recall that `findAccessibilityNodeInfosByText(text)` accepts a specific string and returns a list of UI components containing the string. However, the password input box is also a UI component, and theoretically, it can be identified by `findAccessibilityNodeInfosByText(text)` as long as it contains the specified string. To our surprise, Android currently does not prevent password input boxes from being searched by `findAccessibilityNodeInfosByText(text)`, and Android does not even raise alerts to users. As such, assume that a user enters his or her password into the password input box, and being an attacker, we can query whether a specific string is in the user’s password by invoking `findAccessibilityNodeInfosByText(text)` and checking whether the returned list contains the password input box. As the user continually enters his or her password, the text within the password input box will change accordingly, and the attacker may need to query multiple times in order to completely derive the password.

As an example, consider a user who needs to enter the password “password” character by character into the password input box. When the user enters “p”, the attacker is notified by an accessibility event signaling that the password text has changed. The attacker then uses `findAccessibilityNodeInfosByText(text)` to enumerate all possible letters, numbers and symbols (e.g.,

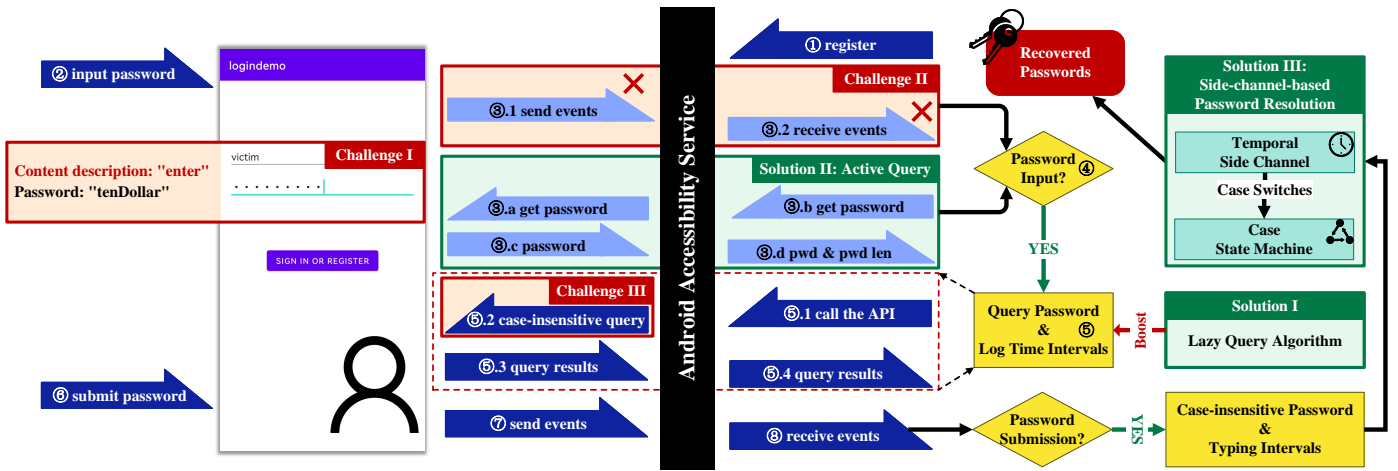


Fig. 1: Overall design of the CONQUER attack

“a”, “b”, “1”). Consequently, when the attacker feeds the character “p” into `findAccessibilityNodeInfosByText(text)`, the function returns a list of UI components including the input box. The attacker then knows “p” is the first character of the user’s password. Similarly, when the user enters the second character of the password, the password text becomes “pa”. If the attacker feeds this string (i.e., “pa”) into `findAccessibilityNodeInfosByText(text)`, the input box will be returned. Please note that before this round of enumeration, the attacker had already determined that the first character of the password is “p”, and he or she only needs to attach a single character to the first character to assemble the password string. By using the same method repeatedly, the attacker is able to recover each remaining character of the password.

### B. Threat Model and Assumptions

The objective of our attack is to steal passwords from regular users. We exclude individuals who rely on the accessibility service (e.g., visually-impaired individuals), because they often use the touch exploration mode. In this mode, passwords are directly leaked through accessibility events and our attack is not necessary. We make four assumptions for our attack. First, we assume that victims have installed the malware on their Android mobile devices and granted it the accessibility service permission. This assumption is reasonable because many prior studies that target or abuse the accessibility service (e.g., [11]) had similar assumptions. Besides, recent research [7] has revealed that users are willing to grant whatever permissions the apps request if they wish to use them. Therefore, we believe that malware can lure users into granting such permissions unsuspectingly. Second, we assume that victims are using the latest Android phones, as older versions of Android are easier to compromise using attacks introduced in previous efforts [17], [11], [18]. Third, we assume that victims have turned off the “Make Passwords Visible” option in order to prevent characters of the password from being directly extracted through accessibility events. Finally, although the techniques we introduced can be used to deploy other attacks (e.g., obtaining users’ keystrokes beyond just their passwords), we particularly focus on password stealing attacks given their high security implications.

## IV. OVERVIEW OF CONTENT QUERIES (CONQUER) ATTACK

Based on the observations and assumptions outlined in §III-A, we propose **Content Queries (CONQUER)** attack, which can be leveraged by the malware to steal user passwords. In the following, we first present the basic workflow of the CONQUER attack, then introduce challenges and the solutions, followed by the overall design of the CONQUER attack as shown in Figure 1.

### A. Basic Workflow

At a high level, the basic workflow of CONQUER attack can be broken into four steps: (i) The malware registers (①) for the accessibility service to receive the intended events (e.g., events triggered by inputting the password). We have omitted the details of these techniques for brevity as they are well-known. (ii) When the user enters the password (②), the malware will get notified (③.1-2) and be able to determine relevant events by inspecting the types of the incoming events (④). (iii) When the malware determines that the user has entered a specific character of the password, it then extravagantly enumerates possible combinations to infer that character (⑤) using the observation introduced in §III-A. (iv) When the user hits the login button (⑥), the malware gets notified (⑦-⑧) and knows that the user has finished entering the password. At this point, the malware has learned the entered password, which forms the output of the malware.

### B. Challenges and Solutions

While the attack is theoretically easy to deploy, it still faces various challenges in practice. Generally speaking, there are at least three challenges that attackers must overcome to successfully launch the CONQUER attack. Below, we explain each challenge in greater detail:

**(C-I) Differentiating Passwords and Descriptions.** The accessibility service has provided content labels to assist users in understanding the meaning of UI elements, and the `android:contentDescription` attribute is one of these labels. For example, app developers can set the `android:contentDescription` attribute to “Password”

for a password input box to help users understand that they need to enter their passwords into this field. However, when issuing queries using `findAccessibilityNodeInfosByText(text)`, for UI components such as password input boxes, the content of the `android:contentDescription` attribute will also be searched along with the actual text (e.g., the entered password). As a consequence, if the content description is set for the password, we cannot determine whether the searched string is in the content description or the password text. For example, assume the password to be entered is “passport”, then the strings “p”, “pa”, and “pas” will exist in both the password (i.e., “passport”) and the content description (i.e., “password”). As a result, the password node will be returned in all queries made on these searched texts. Being the attacker, we cannot know whether these strings are part of the password or just part of the content description.

To address this challenge, one intuitive solution is to simply keep all strings indicated to be contained in the password box by the query results, and use these strings as the basis for subsequent queries. For example, queries for each letter in “password” will succeed during the first round of queries. Therefore, we save all these letters as password candidates of length 1 (e.g., “p”, “a”, “s”). During the second round of queries, multiple enumerations are carried out based on the saved 1-character password candidates respectively, and we further get multiple new password candidates of length 2 (e.g., “pa”, “as”, “ss”). However, this solution requires more rounds of character enumeration since multiple strings are saved as candidates (instead of only one string under normal cases), which can be extremely time-consuming and the queries cannot finish in time (e.g., before the next character is entered). Our preliminary experiments using this naive method have confirmed this drawback: it can take several seconds to finish one round of queries after a single character input.

#### Differentiating Passwords via Lazy Queries (§V-A)

This challenge only limits our knowledge of whether characters present in the content description are also present in the password. However, it does not prevent us from querying characters that are only present in the actual password. When we query a character that is not in the content description and it returns the password node, the influence of the content description is eliminated and we can then begin querying the rest of the password (using lazy queries).

**(C-II) Breaking Defenses enabled on Victim Apps.** Some real-world Android apps do not actively send accessibility events when users enter passwords (i.e., ③.1 in Figure 1 is blocked), even though the app will still respond to inquiries from other apps. This can be achieved by extending the `AccessibilityDelegate` class and overriding the `SendAccessibilityEvent()` method. When victim apps block outgoing password-related accessibility events, no app using the accessibility service can receive password-related accessibility events passively. We speculate that this design is intended to protect against previous accessibility-based password-stealing attacks (e.g., [18], [8]). As a result, when targeting these apps, we cannot receive notifications when a victim is entering the password and the associated

password node cannot be directly acquired from accessibility events. For example, when users try to log in to Alipay, no password-related accessibility events are sent while they are entering their passwords.

#### Thwarting Defenses via Active Queries (§V-B)

This challenge only prevents us from knowing when and which object to query passively. However, being an attacker, we can first try to locate the password input box to be queried, then actively query the password length to see if the victim has already started entering the password.

**(C-III) Recovering Password from Case-Insensitive Strings.** Initially, `findAccessibilityNodeInfosByText(text)` is designed to assist users with disabilities and has the requirements of being robust. As such, the match is case insensitive containment (e.g., `findAccessibilityNodeInfosByText(text)` identifies buttons that contain “login” regardless of whether the text “login” is in upper or lower case). This is reasonable: if someone is using TalkBack to receive real-time spoken feedback, he or she will likely not care the case of the letters. However, being a piece of malware that attempts to steal user passwords, it must have the capability of knowing whether the password is in upper or lower case. Intuitively, the malware can enumerate all the combinations of upper and lower case letters in a case-insensitive string (e.g., “Password”, “PAssword”, etc.). However, it is very costly. For a password that has 8 letters, there could be 64 (i.e.,  $2^8$ ) combinations. While the attacker can still enumerate those combinations, it is not particularly practical (e.g., many apps will block accounts after several failed login attempts).

#### Inferring Passwords via Side Channels (§V-C)

We can still try to recover user actions (e.g., switching between cases) by exploiting other side channels. For example, since it usually takes longer to enter the next letter if a user switches case, this temporal side channel can be exploited to detect case switches.

## V. DETAIL DESIGN OF CONQUER

### A. Lazy Query for Password Differentiation

**The Lazy Query Algorithm.** Since content descriptions are usually short phrases, it is rare for them to cover all characters in the password. Based on this intuition, C-I can be handled by *lazy query*: the content of the password is not queried until users have entered a character that is not in the content description into the password box. As an advantage of this strategy, we can completely eliminate the side effects brought by the content description. The complete lazy query algorithm is shown in Algorithm 1. Let  $S_c$  be the set of all (case-insensitive) characters in the content description, and  $S$  be the set of all characters that can be used in a password. Initially, we have  $S_c \subset S$ . During the lazy query process, every time a character is entered, we first check if the character is not present in the content description by applying single-character

queries on  $\overline{S_c}$  (line 7-13). If we fail to get a match, the value of the queried character is ignored. However, the number of ignored characters are recorded (line 25-26). Once we get a match, the password and the content description can be differentiated starting from this character. We then perform backward queries to determine the value of all previously ignored characters by repeatedly performing queries on  $S_c$  (line 14-24), and the collected password is finally returned. With the result from the differentiation process, subsequent queries can be handled easily using the normal query method.

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**Algorithm 1: The Lazy Query Algorithm**

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**Data:** set of characters presented in content description  $S_c$ , set of all possible characters in passwords  $S$ , the password node  $N_p$

**Result:** case-insensitive password  $P$

```

1 Function main ( $N_p, S_c, S$ ):
2    $cnt \leftarrow 0$ ;
3    $P \leftarrow ""$ ;
4    $belazy \leftarrow \text{True}$ ;
5   while  $belazy$  do
6     if a character is entered then
7       for  $ch \in (S - S_c)$  do
8         if  $\text{Query}(N_p, ch)$  then
9            $belazy \leftarrow \text{False}$ ;
10           $P \leftarrow P + ch$ ;
11          break
12        end
13      end
14      if  $\neg belazy$  then
15        while  $cnt > 0$  do
16          for  $ch \in S_c$  do
17            if  $\text{Query}(N_p, ch + P)$  then
18               $P \leftarrow ch + P$ ;
19               $cnt \leftarrow cnt - 1$ ;
20              break
21            end
22          end
23        end
24        break
25      else
26         $cnt \leftarrow cnt + 1$ ;
27      end
28    end
29  end
30  return  $P$ ;
31
32 Function Query ( $Node, Text$ ):
33    $flag \leftarrow \text{False}$ ;
34    $qr \leftarrow \text{Node.findAccessibilityNode-}$ 
35      $\text{InfosByText}(Text)$ ;
36   if  $Node \in qr$  then
37      $flag \leftarrow \text{True}$ ;
38   end
39   return  $flag$ ;

```

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For example, consider a scenario where the password we want to query is “tendollar” and the target app is `com.infonow.bofa`, whose password field has the content description “enter”. We first obtain the set  $S_c = \{‘e’, ‘n’, ‘r’, ‘t’\}$  from the content description. After the user enters

“t”, we perform single-character queries on  $\overline{S_c}$  and no match is found. The same process is repeated after the user enters “e” and “n”, and no match is found as well. However, after the user enters “d”, we get a match through single-character queries. We then perform backward queries on  $S_c$  to determine previously entered characters: “ed”, “nd”, “rd” and “td” are queried and we can get a match on “nd”. The same steps are repeated until we obtain “tend”.

It is worth noting that, although it is very rare, the lazy query algorithm may fail if: 1) the password happens to be a sub-string of the content description; or 2) the content description includes a significant portion of the characters in a password. We cannot handle the first scenario. However, the second scenario can still be handled. The basic idea is to record sub-strings that are only present in the content description, and combine them with characters within the content description to derive new sub-strings that are only possible to be present in the password and query them using the API. Once such a sub-string is found, the password can be quickly identified.

Specifically, we start by defining  $S_{cj}$  as the set of all sub-strings in the content description with length  $j$ , specifically, we define  $S_{c0} = \emptyset$ . By definition, it is clear that  $S_{c1} = S_c$ . We further define  $S_{nj} = S_{c(j-1)} \times S_c - S_{cj}$ , where the Cartesian product symbol represents string concatenation. Whenever a character is entered, single-character queries will first be performed on  $\overline{S_c}$  in case a character not in the content description is entered. If it is not the case, assume the current length of the password is  $k$ , strings in  $S_{nk}$  are enumerated and queried. Since  $S_{nk} \cap S_{ck} = \emptyset$  by definition, if we get a match, the queried string must be the current password and we can fall back to the normal query strategy since then. Otherwise, we know the current password lies within  $S_{ck}$ , but the specific value needs to be determined by subsequent queries. If we cannot decide the actual value of the password until password submission, we can only make an assertion that the password is in  $S_{cl}$ , where  $l$  is the final length of the password. However, since extra queries are needed compared to lazy query, and the size of  $S_{nj}$  is large (think about a content description that covers all characters), this algorithm comes with a higher time cost. For example, assume the content description is “enter”, but the password is “teren”, we first obtain  $S_{c1} = \{‘e’, ‘n’, ‘r’, ‘t’\}$ ,  $S_{c2} = \{‘en’, ‘nt’, ‘te’, ‘er’\}$ ,  $S_{n1} = \overline{S_c}$ , and  $S_{n2} = \{‘ee’, ‘et’, \dots, ‘tt’\}$ , etc. When “t” is entered, no match will be found on  $\overline{S_c}$  and  $S_{n1}$ . The same procedure repeats for the second and the third character. When the fourth character “e” is entered, the current password is “tere” and a match will be found on  $S_{n4}$ , and we hence know “tere” only exists in the password.

### B. Active Queries for Breaking Enabled Defenses

Even though we will not be passively notified by these apps, we can actively query the victim apps to monitor their status changes. To this end, we first locate the password node. This can be done by first identifying the view ID of the password input box (e.g., by reverse engineering or debugging), then invoking `findAccessibilityNodeInfosByViewId(id)` on the root node of the active window of the victim app with the previously acquired view id. Once the password node  $N_p$  is located and acquired, we can repeatedly query the victim app to obtain the current length of the

password via  $N_p.getText().length()$  (i.e., ③.a-d in Figure 1). As such, we can successfully gather information about when the user has entered a character into his or her password and perform queries accordingly.

We now demonstrate this process using the aforementioned Alipay example (whose package name is `com.eg.android.AlipayGphone`). First, we locate the password input box and obtain its view ID, which is `com.ali.user.mobile.security.ui:id/content`. After that, the corresponding `AccessibilityNodeInfo` object of the password input box can be obtained by invoking `findAccessibilityNodeInfosByViewId(id)` on the root node of the active window (obtained via `getRootInActiveWindow()` as discussed earlier) with the parameter set to the acquired view ID. With the collected password node  $N_p$ , we can repeatedly request updates on the current length of the password via  $N_p.getText().length()$  and determine when we need to perform queries based on the increase of the password length.

### C. Side Channels for Passwords Resolution

Intuitively, it may take the users longer to enter the next letter if they switch between upper and lower case letters. This temporal difference can be used as a side channel to detect when the user is switching between cases. However, relying solely on this temporal side channel is not reliable under real-world scenarios for two reasons. First, most keyboards provide two ways to switch cases: using caps-lock or shift, but such information cannot be effectively derived through the temporal side channel. Second, the user may need to switch between different keyboard layouts to enter a more complex password, which, like case switching, also takes longer and hence can be indistinguishable for the temporal side channel. To address the limitations of the standalone time-based side channel and further improve the robustness of the password resolution process, we additionally exploit a state-machine-based side channel to recover characters with better precision (e.g., most keyboards share the same operation logic for case switching, therefore a general state machine can be built to mimic the case switching process). The details of the two side channels are discussed below.

#### (I) Time-based Side Channel for Case Switch Detection.

In order to use the time-based side channel to detect case switches, two challenges must be overcome: First, typing speed varies significantly among people [26], making it difficult to create a universal model that works for everyone. Second, the complexity of passwords can also vary widely, with some requiring users to switch between different keyboards in addition to changing cases. This makes it harder to distinguish between case switches and keyboard switches, as the time intervals between characters may be similar in both cases. For example, consider the password “dot#COm”. To enter this password, the user must switch to the symbols keyboard to enter “#”, then switch back to the letters keyboard and change the case to enter “c”. However, it is difficult to determine whether the user changed the case before entering “c”, as the time interval between “#” and “c” may be large due to the keyboard switch and indistinguishable from a large interval caused by a case

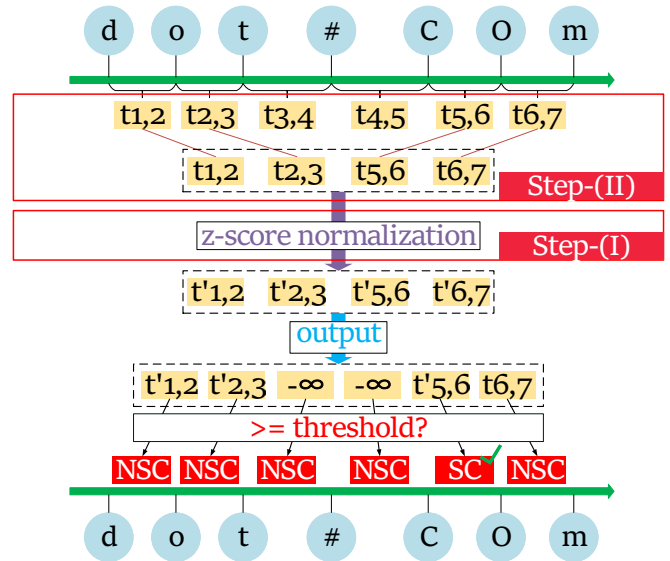


Fig. 2: Workflow of the time-side-channel-based case switch detection

switch. As shown in Figure 2, we tackle the two challenges through a two-step process:

#### Step-(I): Detecting Case Switches Using Normalized Typing Intervals.

To address the first challenge, instead of trying to determine an absolute-time-based model, we build a relative-time-based model using normalized time interval sequences. Normalization can help to reduce individual differences and increase the generality of our model, making it more effective at detecting case switches. Assume the input time interval sequence  $t$  for a password with length  $n$  is given as  $t = (t_{1,2}, t_{2,3}, \dots, t_{n-1,n})$ , where  $t_{i,i+1}$  represents the time interval between entering the  $i$ th and the  $(i+1)$ th character. Then  $t$  is first normalized with z-score:

$$t_{norm} = \frac{t - \mu_t}{\sigma_t} \quad (1)$$

where  $\mu_t$  is the average of  $t$ , and  $\sigma_t$  is the standard deviation of  $t$ . We further define the true positive rate for detecting case switches and non-case-switches as  $TPRCS$  and  $TPRNCS$ , respectively. With the normalized  $t_{norm}$ , a universal optimal threshold value that maximizes  $TPRCS \times TPRNCS$  can be obtained to detect potential case switches.

#### Step-(II): Improving Robustness by Ignoring Keyboard Switches.

To handle the second challenge, our key idea is to only normalize the time intervals between letters. In contrast, all other intervals are discarded before the normalization, and reassigned to the value  $-\infty$  afterwards. The rationale behind this solution is that by only considering time intervals between letters, we can eliminate the influence of keyboard switching, which can help to create a more robust model. Take the previous password “dot#COm” as an example, the time intervals between “t” and “#”, and “#” and “c” will be discarded during normalization and reassigned the value  $-\infty$ . Formally, assume  $D = \{t_{i_1, i_1+1}, t_{i_2, i_2+1}, \dots, t_{i_k, i_k+1}\}$  is the set of all discarded time intervals, then the original time interval sequence  $t = (t_{1,2}, \dots, t_{i_1, i_1+1}, \dots, t_{i_k, i_k+1}, \dots, t_{n-1,n})$

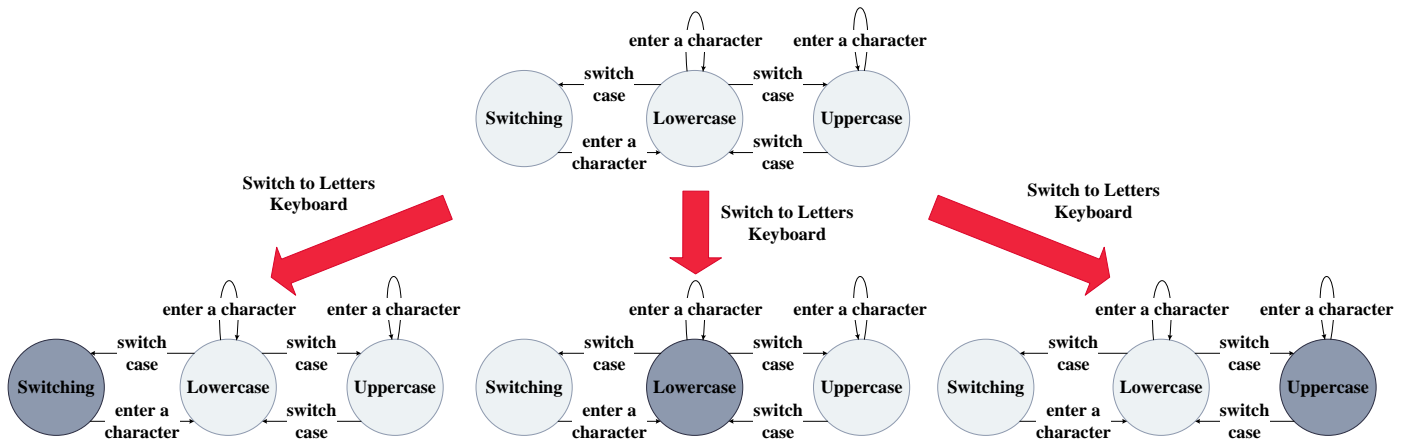


Fig. 3: Case state NFA and state forking

is first transformed to  $\mathbf{t}' = (t_{1,2}, \dots, t_{n-1,n})$ , where all intervals in  $\mathbf{D}$  are removed. We then apply the normalization in Equation (1) on  $\mathbf{t}'$  to obtain the normalized sequence  $\mathbf{t}'_{norm} = (t'_{1,2}, \dots, t'_{n-1,n})$ . After the normalization, all discarded time intervals are reassigned the value  $-\infty$  and we finally get  $\tilde{\mathbf{t}} = (t'_{1,2}, \dots, -\infty, \dots, -\infty, \dots, t'_{n-1,n})$ . By acquiring an optimal threshold value on  $\tilde{\mathbf{t}}$  using the same method as discussed previously, we can detect case switches more precisely.

It is important to ensure that the threshold value obtained is generally applicable in order to successfully launch our attack. In fact, as an attacker, our goal is to steal and recover the original user passwords. However, it is unlikely that we will have sufficient prior knowledge about all potential victims to compute an optimal threshold suitable for the entire population. Instead, we may need to collect data (either from ourselves or from others) in advance to compute a threshold that can be used in future attacks. We will show the generality of our method in §VI by computing a threshold based on the MOBIKEY [4] public dataset, and reuse this threshold throughout our experiment.

**(II) State-Machine-based Side Channel for Characters Recovery.** As discussed, one way to potentially recover user actions, such as switching between cases, is to utilize other sources of information as side channels. For instance, it typically takes longer to type the next letter after switching cases. This time delay can be used as a side channel to detect when a case switch has occurred. However, even with the time-based case switch detection method, there are still several vital pieces of information that cannot be inferred. To tackle these problems, we first build a non-deterministic finite automaton (NFA) to recover passwords that contain only case switches. We then build upon this NFA by designing a state forking mechanism to recover passwords that also include keyboard switches:

**Step-(I): Dealing with Case States Using Non-deterministic Finite Automaton (NFA).** First, we do not know whether the user is switching cases using caps-lock or shift. As a consequence, we cannot determine the case of the next letter to be entered, which we refer to as the case state. Second, since our method only considers the time intervals between letters, and discards all other intervals (such as those between symbols and letters) during normalization, we cannot accurately determine

whether case switches occurred when the user switched back to the letters keyboard. For example, if the original password is “dot#COM”, we are unable to know that the user has switched cases before entering the letter “c”.

To address these drawbacks, we have implemented a keyboard case state machine as shown in Figure 3. This machine includes a non-deterministic finite automaton (NFA) driven by case switches to recover possible case states for the first drawback and a state forking mechanism to recover possible case states after the user switches back to the letters keyboard for the second drawback. The three states and the transition conditions in the case state NFA are described as listed below:

- **Lowercase State:** Lowercase state models the normal keyboard state. In the lowercase state, the next entered letter is assumed to be in lowercase. The NFA will transition to either the switching state or the uppercase state until a case-switching action is detected.
- **Switching State:** Switching state models the keyboard state after the shift key is pressed. In the switching state, the next entered letter is assumed to be in uppercase. The NFA will transition back to the lowercase state immediately after a character is entered.
- **Uppercase State:** Uppercase state models the keyboard state after the shift key is pressed twice (i.e., caps-lock). In the uppercase state, the next entered letter is also assumed to be in uppercase. However, unlike the switching state, the NFA will only transition to the lowercase state after a case-switching action is detected.

During the password recovery process, the case state NFA is used to determine the case of each character in the case-insensitive password. To this end, the NFA processes each character in the password and its corresponding input time interval in order. Once a case-switching action is detected, the current case state will change according to Figure 3. Since the next state may be diverse, we generate a new copy of the currently recovered password with different case states and recover the corresponding character according to the case state within each copy. Moreover, since the time interval sequence starts with the interval between the first and the second input character, the initial state of the password is

unknown. Therefore, we will have three copies of the initial password (i.e., an empty string) with the case state set to lowercase, switching, and uppercase, respectively.

As the number of case switches in the password grows, the maximum number of possible passwords recovered through the NFA can be shown to form a Fibonacci sequence. To prove this, we first define  $n_s$  as the number of detected case switches, and  $a_n^l$  as the number of passwords with the case state set to lowercase after  $n$  case switches. Similarly, we define  $a_n^s$  and  $a_n^u$  respectively for the switching and uppercase state. The initial condition is defined by Equation (2). According to Figure 3, the uppercase state will transition to the lowercase state on a case switch, the lowercase state will transition to either the switching or uppercase state on a case switch, and the switching state is temporary, which will transition to the lowercase state once the next character is entered. Therefore, we have the relationship between  $a_n^l$ ,  $a_n^s$  and  $a_n^u$  as shown in Equation (3).

$$a_0^l = 1, a_0^s = 1, a_0^u = 1 \quad (2)$$

$$\begin{aligned} a_{n+1}^l &= a_n^u \\ a_{n+1}^s &= a_n^l + a_n^s \\ a_{n+1}^u &= a_n^l + a_n^s \end{aligned} \quad (3)$$

Let  $Q_n$  be the number of passwords after  $n$  case switches. Through a series of derivations as shown in Equation (4), we can see that  $\{Q_n\}$  is a Fibonacci sequence with  $Q_0 = 3$  and  $Q_1 = 5$ .

$$\begin{aligned} Q_{n+2} &= a_{n+2}^l + a_{n+2}^s + a_{n+2}^u \\ &= a_{n+1}^u + a_{n+1}^l + a_{n+1}^s + a_{n+1}^l + a_{n+1}^s \\ &= Q_{n+1} + a_n^u + a_n^l + a_n^s \\ &= Q_{n+1} + Q_n \end{aligned} \quad (4)$$

While the Fibonacci numbers will increase exponentially, it is important to note that  $Q_n$  can be guaranteed to be small in most cases. In fact, previous research [20], [23] has shown that even when password composition policies require the inclusion of at least one uppercase letter, the average number of uppercase letters used in passwords is typically no more than 2. With this assumption, even in the worst-case scenario, in which a password contains two non-adjacent uppercase letters that are both located in the middle of the password (therefore 2 case switches are needed), the number of possible combinations is limited to 8 at most given that  $Q_2 = 8$ .

**Step-(II): Dealing with Extraordinary Cases Using State Forking Handler.** While the case state NFA is effective at handling continuous letter input, complex passwords may require the user to switch keyboards from and back to the letters keyboard. We handle this situation by proposing a state forking mechanism. The state forking mechanism is activated whenever the user switches back to the letters keyboard (referred to as keyboard switches for brevity), which can be easily detected from the already collected case-insensitive password. During state forking, three copies of the current password with three different case states are created, corresponding to the

three different possibilities respectively: lowercase, switching, and uppercase.

To analyze the theoretical password recovery performance with state forking enabled, we further assume that the number of detected keyboard switches is  $m_s$ . The number of passwords with the lowercase state after  $m$  keyboard switches and  $n$  case switches is defined to be  $a_{n,m}^l$ . Similarly,  $a_{n,m}^s$  and  $a_{n,m}^u$  are defined for the switching and uppercase state respectively. Now let  $Q_{n,m}$  be the number of passwords after  $m$  keyboard switches and  $n$  case switches. According to Equation (4), we immediately have Equation (5). For every keyboard switch detected, 3 new copies of the password with 3 different case states are generated, therefore Equation (6) holds.

$$Q_{n+2,m} = Q_{n+1,m} + Q_{n,m} \quad (5)$$

$$Q_{n,m+1} = 3Q_{n,m} \quad (6)$$

As shown in our theoretical analysis, the number of guessed passwords heavily depends on the number of case switches and keyboard switches. If the number of case switches and keyboard switches is large, the total number of recovered possible passwords may be up to dozens or hundreds. However, according to our statistical analysis (see §VI-A) on the RockyOU password dataset [28], which consists of 14,344,356 unique passwords and their use counts leaked from a real-world website, shows that for passwords used by 99.65% of the users, the number of case switches and keyboard switches is small. Therefore, the theoretical password recovery performance of our model is sufficient in most scenarios. Our analysis also shows that among users who have passwords with at least one letter, 99.55% of these passwords follow one of three simple patterns: all letters are lowercase, all letters are uppercase, or the first character is the only uppercase letter. Hence, we include these three patterns in the recovered possible passwords to increase the robustness of our attack.

TABLE II: Vendors, device names and OSs of mobile phones used by participants

Vendor	Device Name	OS
Xiaomi	Mi 11	Android 12
	Mi 10 Pro	Android 12
	Mi 10	Android 12
	Redmi K30 Pro Zoom Edition	Android 11
Vivo	IQOO Neo5	Android 12
	IQOO Z1	Android 11
OPPO	Reno5	Android 12
Meizu	16T	Android 9
OnePlus	5T	Android 9
Samsung	Galaxy S8	Android 8.0
	Mate 20	HarmonyOS 2.0.0
	Mate 30	HarmonyOS 2.0.0
	Mate 40 Pro	HarmonyOS 2.0.0
	P40 Pro	HarmonyOS 2.0.0
	Nova 4	HarmonyOS 2.0.0
Huawei	Nova 5	HarmonyOS 2.0.0
	30 Pro	HarmonyOS 2.0.0
	10 Lite	HarmonyOS 2.0.0
Honor		

\* **Note:** duplicated (vendor, device name, OS) tuples are ignored.

## VI. EVALUATION

In this section, we conduct an experimental evaluation of CONQUER. We first illustrate the experiment setup, then

TABLE III: Selected Passwords. “x” represents the number of case switches, and “y” represents the number of keyboard switches.

Category (x, y)	Passwords					
(0, 0)	chocolate tinkerbell	password1 spongebob	butterfly alexandra	liverpool beautiful	basketball alexander	elizabeth christian
(0, 1)	love4ever friends4ever	1password 1truelove	123456789a 1babygirl	1princess love4life	hotmail.com c.ronaldo	yahoo.com 4everlove
(0, 2)	i love you 2gether4ever	2cute4you 1life2live	2bornot2b 11verp00l	ch0c0late 2pac4life	@hotmail.com i love me	2hot2handle TEXT ONLY AD
(1, 0)	HarryPotter TokioHotel	JesusChrist BettyBoop	ChrisBrown CyoiydgTv	HelloKitty JohnnyDepp	LinkinPark SpongeBob	iloveJesus HannahMontana
(1, 1)	iydgTvmujl6f okiu9oN	iydgTvgl,v Lbibiy9oN	glk;jydKIN vkiuiy9oN	123qweASD iydgTv,kd	ry=ibomiN OydidAKIN	Tbfkiy9oN Ibibi9oN
(1, 2)	16fk9oN 06Rkiy9oN	iydgTvm6d;yo 8ow,jrbgLK	iy9ok4iIN 06iuiy9oN	The RockYou Team v6[[jiy9oN	OyomiN0bik 164kiy9oN	4ymik4iIN JOHNY_exstasy_nemis
(2, 0)	FallOutBoy JesseMcCartney	diiIbdkiN IchLiebeDich	MyChemicalRomance CrashIntoMe99	AaBbCc123 dHgTvojkiyd	WinnieThePooh TeQuieroMucho	TaeKwonDo SuzieAndRocco
(2, 1)	iydotgHdF`j mbrpN;iii	dyPPkiy9oN db99bLydfbN	iydotgHdF`\\j vii5lbnTbN	16iLydfbN oyomNiyd.kiN8	v4blbmTbN m5vulbsTd8	obLkiy9oN gfHd,uxyPsk
(2, 2)	ob9bLk19iN xXx-rebecca-xXx	Mje4nGq6vL45 xAlvp`jLbJx	JaY14\$PrBoricua pacS*ptt-*KnKA*	2KaEle4cxK 16mTkiy9oN	*mZ?9%`jS 16mTbjydKIN	y712xC61vIHc k6kgWW7WuM

explain the experiment results by answering several research questions.

### A. Experiment Setup

**Volunteers and Testing Environment.** We recruited 20 volunteers to participate in the experiment, which is a typical setup used in previous research (e.g., [11]). The volunteers were recruited from our college campus and were all students. The vendors, device names and OSs of the mobile phones used by the participants are listed in Table II. The experiment was approved by the IRB. The volunteers were instructed to install the provided malware and victim app on their own mobile phones, and to give the malware access to the accessibility service. They were then asked to input several pre-selected real-world passwords into the victim app using their usual keyboards. The case-insensitive passwords and the input time interval sequences collected by the malware during the experiment are later processed to evaluate the efficiency of CONQUER in recovering passwords.

**Password Selection.** The real-world passwords used in the experiment are selected from the ROCKYOU password dataset. As discussed in §V-C, the number of case switches and keyboard switches are two main factors that influence the ability to recover passwords. Therefore, we first categorize these passwords by the number of case switches and keyboard switches, then select passwords from different categories. Based on our analysis of the ROCKYOU dataset, we found that among all users using passwords containing at least one letter, passwords used by 99.65% of them have a case switch and keyboard switch count of no more than 2 times. Therefore, we focused our experiment on the 9 categories of passwords that fall within this range. Within each category, we sorted passwords that are longer than 8 characters and contain only English keyboard characters based on their popularity (i.e., the number of users), and selected the top 12 passwords for the experiment. In total, we selected 108 (9×12) real-world passwords. The selected passwords are listed in Table III.

**Experiment Guidelines.** The selected 108 passwords were randomly distributed to the 20 volunteers, with 8 volunteers being assigned 6 passwords and 12 volunteers being assigned

5 passwords. To simulate the real attack scenario, we assumed that different people use different passwords and therefore each password was only assigned to one volunteer. Furthermore, to simulate the fact that people are typically familiar with their own passwords, each password was entered 20 times during the experiment. To ensure that the volunteers were familiar with the assigned passwords, we heuristically omitted data collected during the first 10 inputs of a password and only considered the last 10 user inputs of each password as valid data for the experiment.

**Metrics.** We define three metrics for our experiment:  $TPRCS$ ,  $TPRNCS$  and one-time password recovery success rate.  $TPRCS$  and  $TPRNCS$  are previously defined in §V-C and are introduced to evaluate the effectiveness of the time-side-channel-based switch detection method. We define a password recovery process as successful if the real password is included in the set of recovered possible passwords. In real-world scenarios, attackers generally only have one chance to steal user passwords. Therefore, we propose to use the one-time password recovery success rate as a metric, which is defined as the ratio of successfully recovered passwords (out of the selected 108 passwords) in a single round of password input. Note that similar to the one-time password recovery success rate,  $TPRCS$  and  $TPRNCS$  are also independently calculated between rounds.

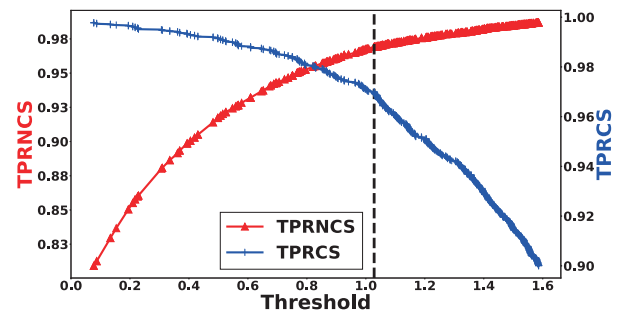


Fig. 4: Calculated  $TPRNCS$ -threshold and  $TPRCS$ -threshold curve on the MOBIKEY dataset

**General Threshold Calculation.** To calculate a general threshold for detecting case switches as discussed in §V-C, we

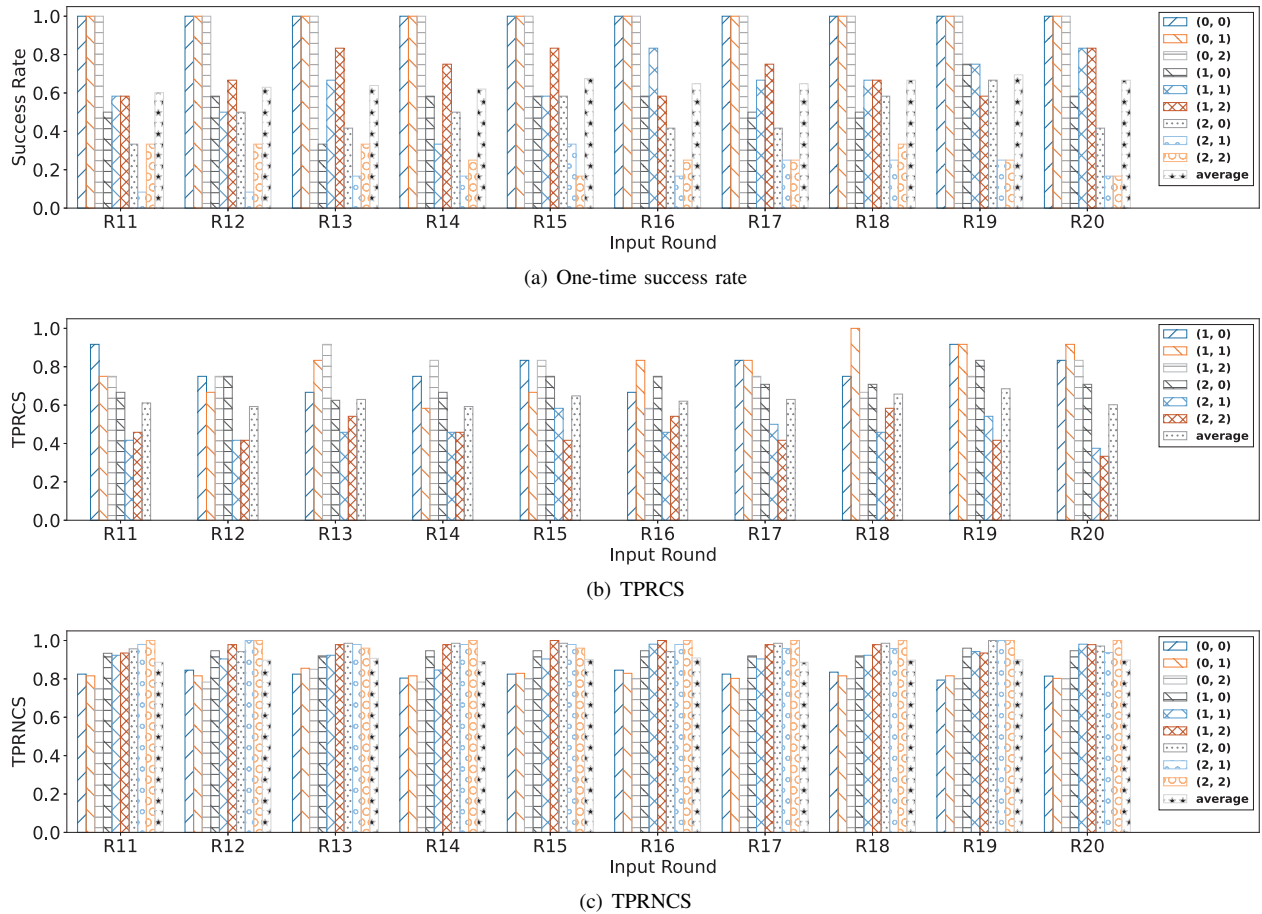


Fig. 5: Experiment results of the CONQUER attack

conducted a preliminary experiment on the strong password (*tie5Roanl*) dataset of the MOBIKEY keystroke dynamics password database [4]. This dataset includes 3303 records and provides many different features of keystroke dynamics when entering the password, including time intervals between keystrokes. Using the time intervals between keystrokes, we can collect the time intervals between entering two letters. As discussed in §V-C, the time interval between entering “e” and “5” was discarded during normalization. However, we did keep the time interval between entering “5” and “R” because “R” is the only uppercase letter in the password. This specific time interval was calculated as the summation of keystroke intervals between “abc” and “shift”, and “shift” and “R”, while the interval between “5” and “abc” was ignored to minimize the impact of keyboard switching. After that, the optimal threshold that maximizes  $TPRCS \times TPRNCS$  was calculated as previously discussed.

Figure 4 describes the relationship between  $TPRNCS$  and the threshold, as well as the relationship between  $TPRCS$  and the threshold on the MOBIKEY dataset. Using the metric mentioned above, the threshold was calculated to be 1.028, resulting in  $TPRCS$  and  $TPRNCS$  values of 0.9700 and 0.9692, respectively. To validate the effectiveness and generality of the time-and-model-based password recovery method, we adopted this optimal threshold (i.e., 1.028) derived from the MOBIKEY dataset throughout our experiment.

## B. Experiment Results

### RQ1. How does the pre-calculated threshold perform in detecting case switches?

We measure  $TPRCS$  and  $TPRNCS$  to answer this question.  $TPRCS$  and  $TPRNCS$  were calculated for the entire set of 108 selected passwords, as well as for each category of passwords, using the data collected from the last 10 rounds of password inputs. The threshold used to detect case switches was set to 1.028 as previously discussed. The results are shown in Figure 5(b) and Figure 5(c), where the notion “( $a$ ,  $b$ )” represents a category of passwords with  $a$  case switches and  $b$  keyboard switches. Note that for  $TPRCS$ , passwords in categories (0, 0), (0, 1), and (0, 2) do not have case switches and are therefore omitted in the figure. The overall  $TPRCS$  and  $TPRNCS$  within the last 10 rounds ranges from 59.26% to 68.51% and 88.69% to 90.87%, respectively. Interestingly, we observed two diametrically opposite trends for  $TPRCS$  and  $TPRNCS$ . For  $TPRCS$ , the value decreases as the number of case switches increases, and the negative impact of the number of keyboard switches on  $TPRCS$  becomes greater as the number of case switches increases. However, when it comes to  $TPRNCS$ , the value increases as the number of case switches increases, and the increase in the number of keyboard switches has a positive impact on this value. We believe that

this phenomenon occurs because the increase of these two numbers may make passwords more difficult to enter, thereby violating the common input pattern exploited by the proposed temporal-side-channel-based case switch detection method.

**RQ2. Can CONQUER effectively steal user passwords exploiting the two side channels?**

To answer this question, we first measure the one-time password recovery success rate. Similarly, the success rate was calculated for all 108 selected passwords and for each category of passwords within the last 10 rounds of input. Figure 5(a) shows the obtained one-time success rate. The overall one-time success rate ranges from 60.18% to 69.44%, with an average of 64.91%. For passwords in categories (0, 0), (0, 1) and (0, 2), the success rate is 100% because they follow the three most common patterns described in §V-C. For other categories of passwords, the one-time recovery success rate is related to *TPRCS* and therefore follows the same pattern as *TPRCS*. The one-time recovery success rate is relatively low for passwords in categories (2, 1) and (2, 2) due to their high complexity. However, such cases are rare in real-world, because among all users who use passwords with at least one letter, only 0.02041% of them have deployed passwords in these two categories. Additionally, we did not observe the impact of smartphones keyboard layouts on our experiment of 20 subjects, as our method of detecting case switches utilizes normalized typing intervals between letters, which will not be affected by keyboard layouts. Finally, we evaluated the stealthiness of CONQUER. CONQUER does not necessitate any foreground UI operations, instead, it only executes background queries. Therefore, except for possible delays caused by the queries, victims should not detect any unusual behavior. Our experiment validated this point: we explicitly asked the volunteers if they had observed any anomalies (including delays), and none of them did. To demonstrate the high query efficiency of CONQUER, we randomly generated 20 passwords of length 16 and recorded the time it took to successfully query them. The results show that on average, it only takes 174ms to query a password of length 16, including the time for inter-process communication (IPC) and the time for actually processing the query on the victim side (see §VII-B). In summary, CONQUER is robust and can effectively recover passwords in most real-world scenarios.

**RQ3. Which Android versions are affected and how many apps are subject to CONQUER attack?**

Through manual verification, all Android versions from 4.1 to 12 (i.e., all currently officially supported versions) are subject to CONQUER, which means that all system-provided password field UI components and apps using these components are vulnerable. However, Android apps may use custom password input boxes, which could potentially avoid this vulnerability. As such, we have designed and implemented a framework for detecting vulnerable custom password input boxes used by Android apps. Our framework is built on top of Jadx [16] and Soot [30] to decompile Android apps, extract layout files, and perform static analysis. We look for self-defined elements whose

`android:inputType` attributes represent password input boxes and check if they follow two rules based on our root cause analysis (see §VII-B) : (i) the class of the custom password input box must be a subclass of `TextView`. (ii) the class and its superclasses (excluding `TextView`) must not override the `findViewsWithText()` method, and either the `getAccessibilityNodeProvider()` method is not overridden by these superclasses or it is overridden but no class in the app has extended `AccessibilityNodeProvider`.

To measure the impact of CONQUER on these apps, we collected 324,125 Android apps from AndroZoo[3] and performed a large-scale security analysis on these apps using our framework. We were able to successfully test 324,080 apps, while 45 apps were unable to be tested because Jadx failed to decompile them. Out of the 324,080 apps that we successfully tested, 13,786 have custom password input boxes, and 13,001 out of the 13,786 apps (94.30%) implement their own custom password input boxes based on `TextView`. By applying our detection rules on these `TextView`-based custom password input boxes, we found that all of them (100%) are vulnerable to CONQUER. The evaluation results show that the vulnerability has not been previously recognized by the community and has a huge security impact.

## VII. DISCUSSION

### A. Responsible Disclosure and Ethical Considerations

We take ethics into the highest consideration. First, we responsibly disclosed our findings to Google. However, Google decided not to fix this vulnerability for two main reasons: 1) this behavior is required for the accessibility service to function as intended, and 2) potential security risks of granting the accessibility service permission have been informed to users in an alert window before they make the final decision. We agree that the accessibility service depends on this API to function normally, and there is no easy fix for the vulnerability. We also argue that users often ignore security warnings for convenient features [7], simply warning users of potential risks cannot effectively defend against CONQUER. Second, the IRB of our university approved all experiments involving volunteers in this work. All attacks were carried out with the full knowledge and consent of the participants, and no malicious acts were performed throughout the experiments. Third, we have never exploited this vulnerability to create or distribute malware, nor have we disclosed any related information to unrelated people or organizations.

### B. Root Cause Analysis

We analyze the root cause of CONQUER to help summarize the vulnerability scan rules proposed in VI-A and to identify possible countermeasures that could reduce the potential security risk of this vulnerability. Generally speaking, the root cause of this vulnerability is that the abused API does not perform any security checks or restrictions when the object to be queried is actually a password input box. As a result, an attacker can continuously leak information from this vulnerability and eventually obtain user passwords. To further understand CONQUER, we referred to the Android source code (see Listing 1) to investigate the issue at the code level. When `findAccessibilityNodeInfosByText(text)` is invoked

```

1 private void findAccessibilityNodeInfosByTextUiThread(
  ↳ ead(Message message)
  ↳ {
2     final int flags = message.arg1;
3     ...
4     ...
5     final int accessibilityViewId = args.arg1;
6     final int virtualDescendantId = args.arg2;
7     ...
8     List<AccessibilityNodeInfo> infos = null;
9     try {
10        ...
11        final View root = findViewByAccessibilityId(ac_
  ↳ cessibilityViewId);
12        if (root != null && isShown(root)) {
13            AccessibilityNodeProvider provider =
14                root.getAccessibilityNodeProvider();
15            if (provider != null) {
16                infos = provider.findAccessibilityNodeInfo_
  ↳ sByText(text,
  ↳ virtualDescendantId);
17            } else if (virtualDescendantId ==
  ↳ AccessibilityNodeProvider.HOST_VIEW_ID) {
18                ArrayList<View> foundViews =
19                    mTempArrayList;
20                foundViews.clear();
21                root.findViewsWithText(foundViews, text,
22                    View.FIND_VIEWS_WITH_TEXT
23                    | View.FIND_VIEWS_WITH_CONTENT_DESCRIPTION
24                    | View.FIND_VIEWS_WITH_ACCESSIBILITY_NODE_
  ↳ PROVIDERS);
25                ...
26            }
27        } finally {
28            ...
29        }
30    }

```

Listing 1: Client-side `findAccessibilityNodeInfosByText()` request handler in the Android source code

by an app with the accessibility service permission, the call is forwarded via IPC and the request is finally handled by the `View` object to be searched. A `View` object has two ways to handle the request: First, the method `getAccessibilityProvider()` is called. If an `AccessibilityProvider` object is returned, the request is finally handled by the `findAccessibilityNodeInfosByText(text)` method of the returned object. Second, if `getAccessibilityProvider()` returns `null`, the request is handled by the `findViewsWithText()` method of the `View` object itself.

By default, the `getAccessibilityProvider()` method in `View` will return `null`, and hence `findViewsWithText()` will be invoked to handle the request. However, the `findViewsWithText()` method in `View` only searches the given text in the content description of the `View` object and hence is not vulnerable to the proposed attack. `TextView` is a subclass of `View`. In `TextView`, the `findViewsWithText()` method is overridden to search the given text in the object's own text, while the `get-`

`AccessibilityProvider()` method is not overridden. Therefore, `TextView` and all Android-provided `TextView`-based classes, including those that are widely used as password input boxes (e.g., `EditText`), are vulnerable to CONQUER because they do not override the two methods.

### C. Possible Mitigation

While CONQUER is hard to be defended as it is powered by the normal functionalities of the accessibility service, there are still possible mitigation measures. There are two possible ways to mitigate the attack based on the discussion in §VII-B: either at the system level, before the `findAccessibilityNodeInfosByText(text)` request is handled by the client, or at the application level, after the request is dispatched to the client.

- **System level mitigation** There are several ways to fix this vulnerability at the system level. One option is to enforce security checks inside the server-side accessibility service API `findAccessibilityNodeInfosByText(text)` to ensure that a password node is not allowed to be searched. However, identifying password nodes could be challenging in general due to the existence of custom password input boxes. Another way is to make the API only search the given text inside content descriptions but not the contained texts. However, this approach may hinder the functionalities of the accessibility service.
- **Application level mitigation** To mitigate this vulnerability, Android app developers should always adopt custom password fields instead of system-provided `TextView`-based classes as password fields. Custom password fields inherited directly or indirectly from `TextView` should either override the `findViewsWithText()` method to make sure the password text is not searched, or override the `getAccessibilityNodeProvider()` method to return a custom `AccessibilityNodeProvider`-based object.

### D. Limitations

Our CONQUER is not perfect, and it has the following limitations. First, though the range of possible passwords is greatly reduced to make the attack more practical, the remaining number of possible passwords could still be too large to perform a successful login attempt when there is a limitation on failed login attempts. Second, the time-and-model-based password recovery method is not reliable for long or complex passwords due to accidental input errors or different typing habits (e.g., using keyboard pop-ups to choose characters). However, smartphone sensors can accurately detect touch events (e.g., [36]). Future research can use sensors to more accurately distinguish case changes based on the number of touches between letters. Additionally, passwords may have semantic features [31], [33]. Future research can also apply these semantic patterns to recover passwords. Third, if victims use password managers to automatically fill in their passwords, CONQUER can only steal case-insensitive passwords by actively issuing content queries. As discussed in §VI-B, querying passwords is efficient and if the victim does

not press the login button within a very short period after the password is filled in, the case-insensitive password can still be obtained. However, original passwords cannot be efficiently recovered due to the lack of input timing information. Previous research has shown that the use of password managers is not common, particularly on mobile phones [27], [2].

## VIII. RELATED WORK

**Android Accessibility Service Abuses.** The Android accessibility service has been proven to have exploitable design shortcomings by previous research. Kraunelis *et al.* [21] demonstrated that the Android accessibility service can be exploited by malware to perform malicious actions such as gaining control of the screen and stealing user credentials through phishing. Jang *et al.* [17] studied the security of accessibility support on four popular platforms and identified several vulnerabilities. Fratantonio *et al.* [11] proposed the famous “cloak and dagger” attack exploiting both overlay and the accessibility service. Interestingly, the “cloak and dagger” attack can be executed even without the overlay permission before Android 8.0 [37]. Aonzo *et al.* [5] showed that it is possible to conduct phishing attacks against password managers by exploiting the accessibility service. Kalysch *et al.* [18] discovered several security flaws in the accessibility service and discussed corresponding countermeasures. Diao *et al.* [9] conducted a systematic study of the Android accessibility framework through code review and app scanning, and discussed several shortcomings as well as corresponding attacks exploiting these weaknesses. Evidence has proven that various real-world malware [10], [1], [39] have exploited the attacks mentioned above. However, none of these works have discovered the query-based side channel in the Android accessibility service.

**Accessibility Service Assisted Password Stealing Attacks.** Kraunelis [21] *et al.* pointed out that the accessibility service can be exploited to steal user passwords through phishing, but the malware has to completely disguise itself as a benign app, which could be hard for complex closed-source apps. Jang *et al.* [17] demonstrated that an Android malware exploiting the accessibility service can alter system settings programmatically without user consent and register a malicious text-to-speech (TTS) application to steal passwords. However, this approach no longer works on newer versions of Android. Instead, a series of UI operations are needed to accomplish the same goal. Fratantonio *et al.* [11] proposed three password stealing attacks, two of which require the assistance of overlay. This results in the display of an alert window on Android 8.0 or later, which makes it less practical these days. The other attack that only uses the accessibility service is achieved by inferring keystrokes from keyboards, but this requires the keyboard used by the victim to be vulnerable. However, some keyboards have addressed this vulnerability [18]. Kalysch *et al.* [18] found that by exploiting screen recording or accessibility events sniffing, the most recently entered password character can be acquired, as the character is displayed on the screen for a short period of time. However, this can be easily defended by turning off the “Make passwords visible” option in *Settings*. Therefore, all existing accessibility-service-assisted password stealing attacks are much less practical or feasible nowadays than when they were first proposed. In

contrast, our proposed attack is more stealthy, general, and practical.

**Android Accessibility Service Defenses.** Compared with attacks against the accessibility service, defenses on the framework are rarely focused. Naseri *et al.* [25] proposed a framework to help developers automatically detect and fix Android apps that may leak passwords through the accessibility service. Huang *et al.* [15] recently proposed a privacy-enhanced accessibility framework to strike a balance between the regular functionality of the accessibility framework and its security mechanisms. While this is not the focus of this work, more comprehensive security mechanisms should be studied in the future.

**Side-Channel-based Keystroke Inference.** Previous research has studied the feasibility of inferring keystrokes through various side channels. The temporal side channel is one of the most commonly exploited methods for keystroke inference [29], [6]. Smartphone sensors are also used to infer user keystrokes [38], [32], [19], [36], [24], [22] due to the vast amount of information they provide. We also exploit the temporal side channel, but unlike previous works, it is used to detect case switches rather than inferring keystrokes.

## IX. CONCLUSION

In this work, we propose CONQUER: a novel content query assisted password stealing attack. CONQUER breaks existing Android defenses against password stealing attacks by exploiting a query-based side channel in the Android accessibility service, and can be abused to launch password stealing attacks in real-world scenarios. To make CONQUER practical, we introduce the *lazy query* technique to disambiguate query results, the *active query* technique to determine query timing, and the temporal side channel and state machine to recover case-sensitive passwords. Our experiment shows that CONQUER can steal user passwords with a high success rate. The attack has affected all Android versions from 4.1 and 12 and many Android apps. CONQUER has not been recognized by the community and poses a significant security risk.

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## REFERENCES

- [1] 0x1c3n, “Anubis android malware analysis,” 2021. [Online]. Available: <https://0x1c3n.tech/anubis-android-malware-analysis>
- [2] N. Alkaldi and K. Renaud, “Why do people adopt, or reject, smartphone password managers?” in *Proceedings of the 1st European Workshop on Usable Security (EuroUSEC)*, 2016.
- [3] K. Allix, T. F. Bissyandé, J. Klein, and Y. Le Traon, “Androzo: Collecting millions of Android apps for the research community,” in *Proceedings of the 13th International Conference on Mining Software Repositories (MSR)*, 2016, pp. 468–471.
- [4] M. Antal and L. Nemes, “The MOBIKEY keystroke dynamics password database: Benchmark results,” in *Software Engineering Perspectives and Application in Intelligent Systems: Proceedings of the 5th Computer Science Online Conference (CSOC)*, R. Silhavy, R. Senkerik, Z. K. Oplatkova, P. Silhavy, and Z. Prokopova, Eds. Cham: Springer International Publishing, 2016, pp. 35–46.
- [5] S. Aonzo, A. Merlo, G. Tavella, and Y. Fratantonio, “Phishing attacks on modern Android,” in *Proceedings of the 25th ACM SIGSAC Conference on Computer and Communications Security (CCS)*, 2018, pp. 1788–1801.
- [6] L. Cai and H. Chen, “TouchLogger: Inferring keystrokes on touch screen from smartphone motion,” in *Proceedings of the 6th USENIX Workshop on Hot Topics in Security (HotSec)*, 2011.
- [7] W. Cao, C. Xia, S. T. Peddinti, D. Lie, N. Taft, and L. M. Austin, “A large scale study of user behavior, expectations and engagement with Android permissions,” in *Proceedings of the 30th USENIX Security Symposium (USENIX Security)*, 2021, pp. 803–820.
- [8] E. Cebuc, “How are we doing with Android’s overlay attacks in 2020?” 2020. [Online]. Available: <https://labs.f-secure.com/blog/how-are-we-doing-with-androids-overlay-attacks-in-2020/>
- [9] W. Diao, Y. Zhang, L. Zhang, Z. Li, F. Xu, X. Pan, X. Liu, J. Weng, K. Zhang, and X. Wang, “Kindness is a risky business: On the usage of the accessibility APIs in Android,” in *Proceedings of the 22nd International Symposium on Research in Attacks, Intrusions and Defenses (RAID)*, 2019, pp. 261–275.
- [10] T. Fabric, “The rage of Android banking trojans,” 2021. [Online]. Available: <https://www.threatfabric.com/blogs/the-rage-of-android-banking-trojans.html>
- [11] Y. Fratantonio, C. Qian, S. P. Chung, and W. Lee, “Cloak and dagger: From two permissions to complete control of the UI feedback loop,” in *Proceedings of the 38th IEEE Symposium on Security and Privacy (S&P)*, 2017, pp. 1041–1057.
- [12] Google, “Create your own accessibility service,” 2021. [Online]. Available: <https://developer.android.com/guide/topics/ui/accessibility/service>
- [13] Google, “Accessibilitynodeinfo,” 2022. [Online]. Available: <https://developer.android.com/reference/android/view/accessibility/AccessibilityNodeInfo>
- [14] Google, “Talkback,” 2022. [Online]. Available: [https://support.google.com/accessibility/android/answer/6283677?hl=en&ref\\_topic=10601571](https://support.google.com/accessibility/android/answer/6283677?hl=en&ref_topic=10601571)
- [15] J. Huang, M. Backes, and S. Bugiel, “A11y and privacy don’t have to be mutually exclusive: Constraining accessibility service misuse on Android,” in *Proceedings of the 39th IEEE/IFIP International Conference on Dependable Systems & Networks (DSN)*, 2019, pp. 3631–3648.
- [16] JADX, “Dex to Java decompiler,” 2022. [Online]. Available: <https://github.com/skylot/jadx>
- [17] Y. Jang, C. Song, S. P. Chung, T. Wang, and W. Lee, “A11y attacks: Exploiting accessibility in operating systems,” in *Proceedings of the 21st ACM SIGSAC Conference on Computer and Communications Security (CCS)*, 2014, pp. 103–115.
- [18] A. Kalysch, D. Bove, and T. Müller, “How Android’s UI security is undermined by accessibility,” in *Proceedings of the 2nd Reversing and Offensive-oriented Trends Symposium (ROOTS)*, 2018, pp. 1–10.
- [19] K. S. Killourhy and R. A. Maxion, “Comparing anomaly-detection algorithms for keystroke dynamics,” in *Proceedings of the 39th IEEE/IFIP International Conference on Dependable Systems & Networks (DSN)*, 2009, pp. 125–134.
- [20] S. Komanduri, R. Shay, P. G. Kelley, M. L. Mazurek, L. Bauer, N. Christin, L. F. Cranor, and S. Egelman, “Of passwords and people: Measuring the effect of password-composition policies,” in *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI)*, 2011, pp. 2595–2604.
- [21] J. Kraunelis, Y. Chen, Z. Ling, X. Fu, and W. Zhao, “On malware leveraging the Android accessibility framework,” in *Proceedings of the 10th International Conference on Mobile and Ubiquitous System: Computing, Networking and Services (MobiQuitous)*, 2013, pp. 512–523.
- [22] X. Liu, Z. Zhou, W. Diao, Z. Li, and K. Zhang, “When good becomes evil: Keystroke inference with smartwatch,” in *Proceedings of the 22nd ACM SIGSAC Conference on Computer and Communications Security (CCS)*, 2015, pp. 1273–1285.
- [23] M. L. Mazurek, S. Komanduri, T. Vidas, L. Bauer, N. Christin, L. F. Cranor, P. G. Kelley, R. Shay, and B. Ur, “Measuring password guessability for an entire university,” in *Proceedings of the 20th ACM SIGSAC Conference on Computer and Communications Security (CCS)*, 2013, pp. 173–186.
- [24] E. Miluzzo, A. Varshavsky, S. Balakrishnan, and R. R. Choudhury, “Tapprints: your finger taps have fingerprints,” in *Proceedings of the 10th International Conference on Mobile Systems, Applications, and Services (MobiSys)*, 2012, pp. 323–336.
- [25] M. Naseri, N. P. Borges Jr, A. Zeller, and R. Rouvoy, “Accessleaks: Investigating privacy leaks exposed by the Android accessibility service,” in *Proceedings of the 19th Privacy Enhancing Technologies (PETs)*, 2019, pp. 291–305.
- [26] K. Palin, A. M. Feit, S. Kim, P. O. Kristensson, and A. Oulasvirta, “How do people type on mobile devices? Observations from a study with 37,000 volunteers,” in *Proceedings of the 21st International Conference on Human-Computer Interaction with Mobile Devices and Services (MobileHCI)*, 2019.
- [27] S. Seiler-Hwang, P. Arias-Cabarcos, A. Marín, F. Almenares, D. Díaz-Sánchez, and C. Becker, “‘I don’t see why I would ever want to use it’: Analyzing the usability of popular smartphone password managers,” in *Proceedings of the 26th ACM SIGSAC Conference on Computer and Communications Security (CCS)*, 2019, pp. 1937–1953.
- [28] Skull Security Wiki, “Rockyou password dataset,” 2015. [Online]. Available: <https://wiki.skullsecurity.org/Passwords>
- [29] D. X. Song, D. Wagner, and X. Tian, “Timing analysis of keystrokes and timing attacks on SSH,” in *Proceedings of the 10th USENIX Security Symposium (USENIX Security)*, 2001.
- [30] R. Vallée-Rai, P. Co, E. Gagnon, L. Hendren, P. Lam, and V. Sundaresan, “Soot - a Java bytecode optimization framework,” in *Proceedings of the 1999 Conference of the Centre for Advanced Studies on Collaborative Research (CASCON)*, 1999, p. 13.
- [31] R. Veras, C. Collins, and J. Thorpe, “On semantic patterns of passwords and their security impact,” in *Proceedings of the 21st Annual Network and Distributed System Security Symposium (NDSS)*, 2014.
- [32] M. Vuagnoux and S. Pasini, “Compromising electromagnetic emanations of wired and wireless keyboards,” in *Proceedings of the 18th USENIX Security Symposium (USENIX Security)*, 2009, pp. 1–16.
- [33] D. Wang, P. Wang, D. He, and Y. Tian, “Birthday, name and bifacial-security: Understanding passwords of chinese web users,” in *Proceedings of the 28th USENIX Security Symposium (USENIX Security)*, 2019, pp. 1537–1554.
- [34] D. Wang, Z. Zhang, P. Wang, J. Yan, and X. Huang, “Targeted online password guessing: An underestimated threat,” in *Proceedings of the 23rd ACM Conference on Computer and Communications Security (CCS)*, 2016, pp. 1242–1254.
- [35] S. Wang, Z. Ling, Y. Zhang, R. Liu, J. Kraunelis, K. Jia, B. Pearson, and X. Fu, “Implication of animation on Android security,” in *Proceedings of the IEEE 42nd International Conference on Distributed Computing Systems (ICDCS)*, 2022, pp. 1122–1132.
- [36] Z. Xu, K. Bai, and S. Zhu, “Taplogger: Inferring user inputs on smartphone touchscreens using on-board motion sensors,” in *Proceedings of the 5th ACM Conference on Security and Privacy in Wireless and Mobile Networks (WISEC)*, 2012, pp. 113–124.
- [37] C. Zheng, W. Hu, X. Zhang, and Z. Xu, “Android toast overlay attack: ‘Cloak and dagger’ with no permissions,” 2017. [Online]. Available: <https://unit42.paloaltonetworks.com/unit42-android-toast-overlay-attack-cloak-and-dagger-with-no-permissions/>

- [38] L. Zhuang, F. Zhou, and J. D. Tygar, "Keyboard acoustic emanations revisited," in *Proceedings of the 12th ACM Conference on Computer and Communications Security (CCS)*, 2005, pp. 373–382.
- [39] E. Y. Şahin, "When your phone gets sick: Flubot abuses accessibility features to steal data," 2021. [Online]. Available: <https://www.srlabs.de/bites/flubot-abuses-accessibility-features-to-steal-data>