Birthday, Name and Bifacial-security: Understanding Passwords of Chinese Web Users (Full Version)

Ding Wang, Ping Wang, Debiao He, Yuan Tian

Abstract—While the computer security world has changed a lot over the last two decades, textual passwords remain the dominant authentication mechanism in computer systems and are likely to persist in the foreseeable future. Much attention (e.g., user surveys and empirical analysis) has been paid to passwords chosen by English users, yet relatively little is known about how non-English users select passwords. In this work, we conduct so far the first user survey on the password behaviors of Chinese users, revealing a number of users' basic coping strategies for managing passwords when they are confronted with the demanding tasks of keeping track of many accounts and passwords.

We further perform an empirical analysis of 100 million Chinese web passwords in a comparison with 30 million English ones, a corpus among the largest ones ever studied. We identify a number of interesting structural and semantic characteristics in password usages of Chinese users, and also examine the security of Chinese web passwords by employing two state-of-the-art password cracking techniques (i.e., probabilistic context-free grammars (PCFG) and Markov models). Particularly, our cracking results reveal a *"reversal principle"*: when the guess number allowed is small, Chinese web passwords are much weaker than their English counterparts, yet this relationship will be reversed when the guess number is large. This well reconciles two conflicting claims about the strength of Chinese web passwords made by Bonneau in IEEE S&P'12 and Li et al. in USENIX SEC'14, respectively. At 10^7 guesses, the success rate of our improved PCFG-based attack against the Chinese datasets is from 33.2% to 49.8%, indicating that our improved attack can crack 92% to 188% *more* passwords than the best record reported by Li et al. in 2014. We also discuss the implications of our findings. This work is expected to facilitate both security administrators and users to gain a better understanding of the vulnerability of Chinese passwords, as well as to shed light on future password research.

Index Terms—User authentication, Password security, Semantic pattern, Probabilistic context-free grammar, Markov model.

1 Introduction

Password authentication is the dominant form of access control in distributed systems. Though the security pitfalls of textual passwords were revealed as early as four decades ago [1] and various alternative authentication methods (e.g., graphical passwords [2] and multi-factor authentication [3]) have been proposed since then, they stubbornly survive and reproduce with every new computer system while Internet technologies have advanced by leaps and bounds in other areas. For one reason, textual passwords offer advantages, such as low deployment cost, easy recovery and remarkable simplicity, which cannot always be matched by their alternatives [4], [5]. The matter is further complicated by the shortage of effective methods to quantify the obscure costs of replacing passwords [6], while marginal gains are often insufficient to reach the activation energy that is necessary to overcome the significant transition costs. Thus, passwords remain the primary method for user identification and are likely to persist in the foreseeable future.

Despite its ubiquity, password authentication is stuck with an inherent tension [7]: truly random passwords are hard for users to memorize, while user-memorable passwords may be highly predictable. To deal with this notorious "security-usability" dilemma, researchers have devoted significant efforts [8]–[11] to the following two types of studies. *Type-1* research aims at evaluating the strength of a password dataset by gauging its Shannon entropy as in NIST-800-63 [12], or by measuring its "guessability" [11], [13]. The latter notion characterizes the fraction of passwords that, at a given number of guesses, can be cracked by password cracking algorithms like the probabilistic context-free grammars (PCFG) [14] and Markov-Chain-based attacks [9].

Type-2 research attempts to reduce the use of weak passwords, and mainly two approaches have been utilized: proactive password checking [15] and password strength meter [16]. The former checks the user-selected passwords and only accepts the ones that comply with the system policy (e.g., at least 8 characters long). The latter is typically a visual feedback of password strength, often presented as a colored bar to help users create stronger passwords [17]. Most of today's leading sites employ a combination of these two approaches to restrict users from choosing weak passwords. In this work, though we mainly focus on type-1 research, one can see that our results are also helpful for type-2 research.

1.1 Motivations

Existing literature mainly focuses on passwords chosen by English users, or more precisely, by netizens using the Latin alphabet, yet little attention has been paid to the characteristics and strength of passwords generated by those who use other native languages. For instance, password "`wanglei123`" is currently deemed "Strong" by many high-profile password strength meters like those of AOL, Google, IEEE, and Sina weibo (known as "Chinese Twitter"). However, as shown in [18], this password is highly prone to

- *D. Wang and P. Wang are with the School of Electronics Engineering and Computer Science, Peking University, Beijing 100871, China. Email: {wangdingg, pwang}@pku.edu.cn*
- *Debiao He is with the School of Mathematics and Statistics, Wuhan University, Wuhan 430072, China. Email: hedebiao@whu.edu.cn.*
- *Yuan Tian is with the University of Virginia, VA 22904 USA. Email: yuant@virginia.edu*

guessing, for "wanglei" is a very popular Chinese Pinyin (i.e., the Chinese phonetic alphabet) name but not a random string of length seven. Failing to catch this is equal to blindly overlooking the weaknesses of Chinese passwords, posing the corresponding account at high risks.

Not surprisingly, so far there has been no satisfactory answer to the following fundamental questions: *(i) Are there structural or semantic characteristics that differentiate Chinese web passwords from English web passwords? (ii) What's the security strength of Chinese web passwords? (iii) Are they weaker or stronger than English passwords?* There have been 668 million Chinese netziens in Dec., 2015 [19], which account for over 25% (and also the largest fraction) of the world's Internet population, and it is of great importance to answer theses questions to provide both security engineers and Chinese users with necessary security guidance. For instance, if the answer to the first question is affirmative, then it highly indicates that the password policies (see [18]) and strength meters (e.g., [13]) originally designed for English users cannot be readily applied to Chinese users.

A few studies (e.g., [9]–[11]) have employed some Chinese password datasets, yet they mainly deal with the effectiveness of various probabilistic password models, and relatively little attention is given to the characteristics of Chinese passwords compared to English ones. Besides, to our knowledge, most previous works (e.g., [9]–[11], [20]) about Chinese passwords only employ an empirical approach. Yet, this approach is inherently unable to reveal many important user password behaviors, such as what fraction of users write down their passwords, how many different passwords users have and what's the sentiment (e.g., satisfactory or not) about their own current management of passwords.

To our knowledge, Li et al.'s work [20] may be the closest to the current paper. However, it imprudently renders two of its five Chinese datasets at best useless and at worst negative when performing data cleansing. As a result, the effectiveness of the results reported in [20] will be greatly impaired. Besides, many fundamental characteristics, such as length distribution, frequency distribution and Pinyin-name-based semantic patterns, have not been explored in their work. What's more, they proposed an improved PCFG-based cracking algorithm and at 10^{10} guesses, their best success rate is about 17.3%, while our improved PCFG-based algorithm can achieve achieve success rates from 29.41% to 39.47% at just 10^7 guesses. *Most importantly*, Li et al. invalidated the remarks made in [21] that Chinese passwords are among the strongest ones to guess than that of English users, and concluded that "the strength of the passwords of Chinese and English users is similar". However, we will show that Li et al.'s conclusion is still biased.

1.2 Contributions

To answer the above three fundamental questions, we leverage over 100 million publicly available passwords from six popular Chinese sites and more than 30 million passwords from three English sites, one of the largest corpus of user-chosen passwords ever studied. Benefiting from the plain-text form of these 130M passwords, we seek for fundamental properties of user-chosen passwords and, for the first time, manage to identify several distinct characteristics of Chinese web passwords in comparison to English ones. To complement our empirical analysis, we further conduct an online user survey on the password management behaviors of Chinese users. In summary, we make the key contributions:

- **A user survey**. To reveal user behavior in managing passwords, we carry out a user survey with 442 effective participants. Our survey shows that, among Chinese users, 48.6% have no more than 5 *different* passwords, 81.2% have no more than 10 different passwords, 74.2% have no more than 5 *different types* of passwords; 47.3% have ever recorded passwords on paper or electronic media, 13.8% have ever used a password manager; 41.6% have developed their own coping strategies and 69.0% feel upset about their own management of passwords. This is the first password survey that targets Chinese users and reveals many user behaviors that are otherwise difficult to be explored by an empirical study.
- **An empirical analysis**. By leveraging 100 million real-life Chinese passwords, we for the first time: (1) explore the name semantics in Chinese passwords, and show that there is an *every one in nine* probability that Chinese users insert their Pinyin names into passwords, while the fraction of English passwords that include an English name (with length$\geq$5) reaches 24.3%, i.e., one in four; (2) reveal that *every one in six* Chinese users inserts a 6-digit date (e.g., birthdate) into her password; (3) provide a quantitative measurement of, to what extent, user passwords are influenced by their native language; (4) show that passwords chosen by these two distinct user groups are of quite similar frequency distributions.
- **An reversal principle**. We employ two state-of-the-art password-cracking algorithms (i.e., PCFG-based and Markov-based [9]) to measure the strength of Chinese web passwords. Based on the identified characteristics of Chinese passwords, we improve the PCFG-based algorithm to more accurately capture passwords that are of a monotonically long structure (e.g., "1qa2ws3ed"). At 10^7 guesses, our algorithm can crack 92% to 188% more passwords than the results in [20]. Particularly, we reveal a "*reversal principle*": when the guess number allowed is small, Chinese passwords are much weaker than their English counterparts, yet this relationship is reversed when the guess number is large, thereby reconciling the contradictory claims made in [20], [21].
- **Some insights**. We highlight some useful insights for password cracking, strength meters and creation policies. To our knowledge, we are the first to provide an *empirically grounded evidence* supporting for the hypothesis proposed in [17], [22] that users rationally choose more complex and secure passwords for accounts associated with higher value and knowingly select weak passwords for unimportant accounts.

2 Related work

It has long been an interesting research area to analyze user-generated passwords, dating back at least to Morris and Thompson's work in 1979 [1]. This seminal work is followed by a number of notable studies (e.g., [9], [14], [15], [23]). Before 2009, since real-world password datasets are scare, most research was either based on user survey (e.g., [24]) or small samples (e.g., 150 real-world passwords in [23]). Since the first large-scale dataset (i.e., the 32M Rockyou passwords [25]) were publicly disclosed in 2009, dozens of high-profile sites (e.g., Forbes [26] and Gmail [27]) have been successively hacked and each with millions of passwords leaked. This provides necessary materials for more thorough empirical studies (e.g., [9], [16], [20]).

2.1 Password characteristics

Basic statistics. In 1979, Morris and Thompson [1] analyzed a corpus of 3,000 passwords and reported that 71.12% of passwords are no more than 6 characters long and 13.93% of passwords are non-alphanumeric characters. In 1990, Klein [15] collected 13,797 computer accounts from his friends and acquaintances around US and UK, and observed that users tend to choose passwords that can be easily derived from dictionary words: a dictionary of 62,727 words is able to crack 24.21% of the collected accounts and 51.70% of the cracked passwords are shorter than 6 characters long. In 2004, Yan et al. [7] found that user-chosen passwords are likely to be dictionary words since users have difficulty in memorizing random strings, and that the lengths of passwords in their study (involving 288 participants) are on average between 7 and 8.

In 2012, Bonneau [21] conducted a systematic analysis of 70 million Yahoo passwords. This work examined dozens of subpopulations based on demographic factors (e.g., age, gender and language) and site usage characteristics (e.g., email and retail), and found that "even seemingly distant language communities choose the same weak passwords". Particularly, Chinese passwords are among the most difficult ones to crack. In 2014, however, Li et al. [20] argued that Bonneau's dataset is not representative of general Chinese users, for Yahoo users are those who are familiar with English. Accordingly, Li et al. leveraged a corpus of five datasets from Chinese sites and observed that Chinese users like to use digits when creating passwords, as compared to English users who like to use letters to build passwords. However, as an elementary defect, two of their Chinese datasets have not been cleaned properly (see Section 5.2), which might lead to inaccurate measures and biased comparisons. More importantly, several critical password properties (such as the most popular passwords, the length and frequency distributions of passwords) remain to be explored.

In 2014, Ma et al. [9] investigated password characteristics about the length and the structure of six datasets, three of which are from Chinese websites. Nonetheless, this work mainly focuses on the effectiveness of probabilistic password cracking models and pays little attention to the deeper semantic patterns of passwords (e.g., no information is provided about the role of Pinyins, names or dates).

Semantic patterns. In 1989, Riddle et al. [28] found that birth dates, personal names, nicknames and celebrity names are popular in user-chosen passwords. In 2004, Brown et al. [24] confirmed this by conducting a thorough survey that involved 218 participants and 1,783 passwords, and they reported that the most frequent entity in passwords is the self (accounts for 66.5%), followed by relatives (7.0%), lovers and friends; also, names (32.0%) were found to be the most common information used, followed by dates (7.2%). In 2012, Veras et al. [29] examined the 32 million RockYou dataset by employing visualization techniques and observed that 15.26% of passwords contain sequences of 5-8 consecutive digits, 38% of which could be further classified as dates. They also found that repeated days/months and holidays are popular, and when non-digits are paired with dates, they are most commonly single-characters, or names of months.

In 2014, Li et al. [20] noted that Chinese users tend to insert Pinyins and dates into their passwords. However, many other important semantic patterns (e.g., Pinyin name, place and mobile number) are left unexplored. In addition, due to an imprudent processing of data cleansing and improper tuning of cracking algorithms (see Sec. 7), Li et al.'s measurement of the strength of Chinese passwords will be shown to be biased. In 2015, Ji et al. [10] showed that user-IDs and emails have a great impact on password security. For instance, 53.24% of Dodonew passwords can be guessed by using user-IDs within, on average, 706 guesses. This motivates us to investigate to what extent the Pinyin names and Chinese-style dates impact the security of Chinese passwords.

2.2 Password security

A crucial research area in password cryptography is to study the security strength of user-chosen passwords. To avoid using the brute-force attack, earlier works (e.g., [15], [28]) use a combination of ad hoc dictionaries and mangling rules to model the common password generation practice and see whether user passwords can be successfully rebuilt in a period of time. This technique greatly improves the cracking efficiency and has given rise to automated password cracking tools such as John the Ripper (JTR).

Borrowing the idea of Shannon entropy, the NIST Electronic Authentication Guideline [12] attempts to use the concept of *password entropy* for estimating the strength of password creation policy underlying a password system. Password entropy is calculated mainly according to the length of passwords. Florencio and Herley [30], and Egelman et al. [17] improved this approach by adding the size of the alphabet into the calculation and called the resulting value $log_2((alpha.size)^{pass.len})$ the bit length of a password.

However, previous ad hoc metrics (e.g., password entropy and bit length) have recently been shown far from accurate by Weir et al. [31], and they suggested that the approach based on simulating password cracking sessions is more promising. They also developed a novel method that first automatically derives word-mangling rules from password datasets, and then instantiates the derived grammars by using string segments from external input dictionaries (e.g., the famous Dic-0294 wordlists) to generate guesses in decreasing probability order [14]. This PCFG-based cracking approach is able to crack 28% to 129% more passwords than JTR when given the same number of guesses. It has been considered as one of the state-of-the-art password cracking techniques and used in a number of recent works [9], [32].

Differing from the PCFG-based approach, Narayanan and Shmatikov [23] suggested a template-based model in which the Markov-Chain theory is used for assigning probabilities to letter segments, and it substantially reduces the password search space. This approach was tested in an experiment against 142 real-life user passwords and was able to break 67.6% of them. In 2014, by using various normalization and smoothing techniques from the natural language processing (NLP) domain, Ma et al. [9] systematically evaluated the Markov-based model and found that, in some cases, it performs significantly better than the PCFG-based model at large guesses (e.g., 2^{30}) when parameterized appropriately. Based on [9], [14], some useful automated password analysis tools have been developed in [8], [33]. In this work, we will perform extensive experiments by using both attacking models (combined with the identified characteristics of Chinese passwords) to evaluate the strength of Chinese passwords.

3 A survey on password management behaviors of Chinese users

To reveal Chinese user behaviors and sentiment in the process of password creation and memorization, we carried out an anonymized user survey by using Sojump (sojump.com), the most popular Chinese online survey platform, during June 07 to August 11 in 2015. A copy of our questions can be found at http://www.sojump.com/jq/6443561.aspx, and the third part relates to this work. We got approval from our center's IRB for this survey. The participants are surveyed anonymously and the results are all aggregated such that no user identifiable information can be inferred.

3.1 Survey design

Though our survey is an anonymized one and conducted on a well-known third-party platform, we fear that users may have privacy concerns and refuse to answer our survey or provide untruthfully answers, because passwords are highly sensitive. To minimize such potential adverse effects and ensure ecological validity, we optimize the survey questions before the release of the survey by employing 15 students in other teams of our lab as pilot testers. We get feedbacks from them and revise the questions accordingly. This process is performed in an iterative manner. As a result, a few questions (e.g., "Will you reuse an existing email password for this new email account?" and "How many PIN codes do you maintain?") that are inclined to be offensive are abandoned. In addition, as with [34], we include an "I prefer not to answer" option for questions that might make participants un-comfortable, in order to avoid user drop out.

Our survey is expected to take about 22 to 35 minutes. Each member in our team is requested to invite 10 to 20 reliable friends, relatives or colleagues to fill out the questionnaire. If the participants are willing to further disseminate the survey, they are asked to provide us with the number of invitations they send. In all, a total of 983 invitations are sent and we acquire 442 effective responses.

We initiate our survey by asking participants to create a password for an email account that will be frequently used. The first seven questions aim to explore the transformation rules in password reuse (e.g., "how similar the password created for this new account is similar to that of their existing accounts?", "what transformation rules will be used?" and "what's their popularity?"), and detailed results are referred to Sec. III of [11]. The next thirteen questions are devoted to explore user password behaviors regarding semantics composition, reuse statistics, storage, evolution and sentiment, which are the focus of this work.

3.2 Survey results

Our first question aims to figure out what's the semantics of the letters in the password created for this new email account. As shown in Fig. 1, the most popular choice is "Chinese Pinyin names" (about 40%)[1], followed by "Chinese Pinyin words" (33.71%). These two figures well accord with what we have obtained from real-life datasets, i.e. $\frac{11.24\%}{22.42\%} \approx$50.13% and $\frac{9.73\%}{22.42\%} \approx$30.02% (see Table 5), respectively. Interestingly, many Chinese users also tend to include English words (33.71%) or their English names (22.17%) into their passwords, while these two figures obtained from the large-scale empirical data are 10.74% and 23.86%, respectively. This suggests that users in our survey are two times more likely to use English words than ordinary users do. A plausible reason is that our users are more educated (i.e., 92% have at least a bachelor's degree, see Sec. 4.3), and they are more familiar with English than common user population.

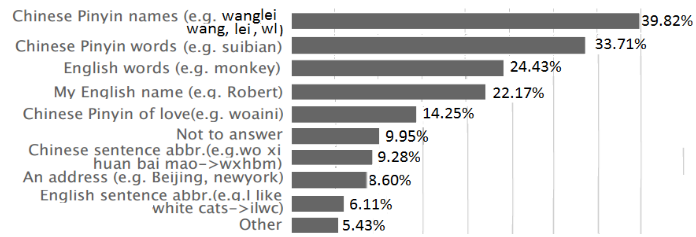


Fig. 1. If you use letters in your password, what are they related to (multiple-choice)? Most users prefer meaningful strings like Chinese names, pinyin words and English words.

It has been shown in [9], [20] that Chinese user like to build passwords with digits. Are there semantics in these digits? Fig. 2 shows that 44.8% of users tend to use dates, which well consists with what we have obtained from real-life datasets, i.e. $\frac{31.60\%}{78.04\%} \approx$40.49% (see Table 5). In addition, 42.3% use phone numbers (either mobile or fixed-line), 16.74% use homophone (e.g., `5201314`) and 3.62% use the time of site registration. What's most interesting is that, 14.03% Chinese users include their personal digit numbers (PINs) of various financial cards into their passwords, unbelievably consistent with Bonneau's PIN survey on English users (i.e., 15%). We, for the first time, provide more than anecdotal evidence of to what extent Chinese users reuse PINs of financial cards in passwords of web accounts. There are also 27.31% users choose random digit sequences. Further considering that there are about 1.5 times more Chinese users include digits in passwords than English users do (see Table 4), this partially explains why Chinese web passwords are more difficult to crack as compared to English passwords (see the "reversal principle" in Sec. 7). Besides dates, the other six semantics are inherently difficult to be captured from empirical datasets, highlighting the superior aspect of user surveys over empirical studies.

Nowadays the number of web accounts we needs to maintain constantly increases, yet human working memory is limited and stable [24]. As a result, users cope by reusing passwords [11], [35]. It is interesting to find out how many *unique passwords* and *different types of passwords* they maintain. Our survey shows that, 81.22% of Chinese users (see Fig. 3) maintain no more than 10 unique passwords. Hopefully, only 20.59% of Chinese users hold fewer than 4 distinct passwords for all their web services, while this figure for English users is as high as 46% [35]; only 48.64% of Chinese users hold less than 6 distinct passwords, while this figure for English users is 72% [35].

1. Chinese Pinyins are made of 26 Latin characters in the Chinese phonetic alphabet, and they are used to latinize the Chinese hieroglyphic characters. For instance, Chinese Pinyin "woaini" means "iloveyou".

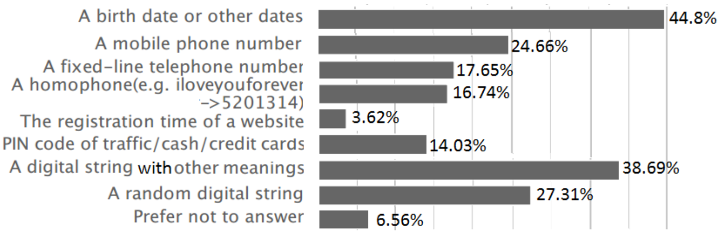


Fig. 2. If you use digits in your password, what are they related to (multiple-choice)? Dates and phone numbers are most prevalent, PINs also show up.

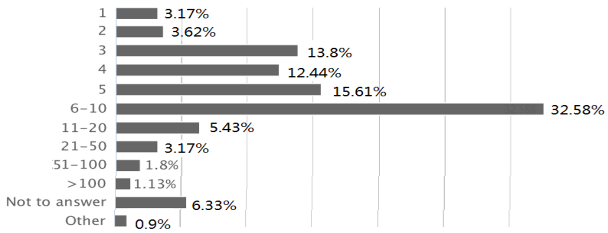


Fig. 3. How many different passwords do you maintain? Note `password1` and `password2` shall be seen as different ones.

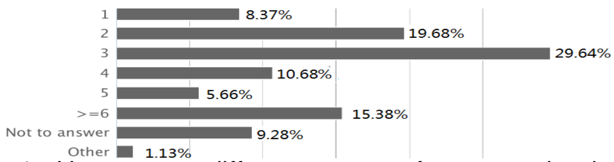


Fig. 4. How many different types of passwords do you maintain? Note that similar passwords fall into the same type.

As our participants are more diversified than that of [35] and our participant number are also two times higher, the above differences in password reuse figures are unlikely due to survey bias. A plausible reason for why Chinese users reuse less may be that, a large number of breached Chinese sites (e.g., over 100 popular sites had leaked passwords during 2011 to 2014 [36]) offer security advices and request users to not reuse passwords. This climax came when China Central Television screened some "best password tips" at peak time in Dec. 2014 [37]. Such advices may increase security consciousness and nudge users towards less *direct* password reuse, yet the rate of *indirect* password reuse is still staggering: 57.69% and 74.05% of Chinese users (see Fig. 4) keep no more than 3 and 5 different types of passwords. In average, each Chinese user keeps 9.74 unique passwords and 3.15 different types of passwords. This is roughly comparable to existing surveys (e.g. 5 unique passwords in [22] and 6.5 unique passwords in [30]).

Fig. 5. Is there any relationship among your different types of passwords? 80% of users admit at least some relationships.

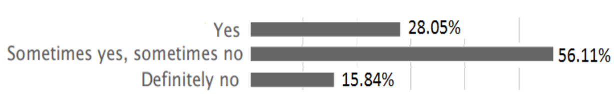


Fig. 6. Do you use different types of passwords for different types of web services? Less than one third say definitely yes.

Fig. 5 illustrates whether there are relationships between users' different types of passwords. As expected, the majority of users acknowledge some relationships. 21.72% show very good practice, while 17.65% are at high risks: all their passwords are created from a single basic password. We further examine whether Chinese users rationally use different types of passwords for different types of online accounts as recommended [37]. Fig. 6 shows that, 28.05% of users conform to the good practice, about half of users report they only sometimes conform to the good practice, while 15.84% acknowledge a "definitely no". This is comparable to Haque et al.'s survey on 80 English students [38]: 19.1% of users reuse (or simple modify) an existing password from a low-value account for a higher-value account.

The next two questions relate to user behaviors in password storage. Regarding how users saving their passwords, Fig. 7 shows that the most popular way is saving passwords in mind (54.3%), successively followed by writing on paper (25.57%), recording electronically (21.72%), saving in browser (12.9%) and using password manager (7.24%). Komanduri et al. [39] found that in their email survey scenario (1000 English participants), about 19% store passwords on paper and 25% store electronically. In comparison, the difference in writing on paper between these two user groups is significant (two-proportion Z-test, p-value $=0.0048 < 0.05$), while the difference in recording electronically is not significant (p-value$= 0.18024 > 0.05$).

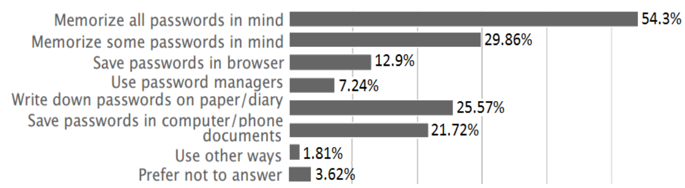


Fig. 7. If you use digits in your password, what are they related to (multiple-choice)? Dates and phone numbers are most prevalent, PINs for financial cards also show up.

While password managers are deemed promising tools for alleviating the password management burden on users by security researchers [5], it remains a question of to what extent they have been accepted by the common users in reality. Fig. 7 shows that, surprisingly, over 50% of Chinese users have not heard about password managers, 22.17% know them yet will not use them because of security concerns, and only 13.8% have used them. What's most staggering is that, only 2.49% of Chinese users have used password managers and also trust their security. Further considering that our participants are more educated and younger than common Chinese users (see Sec. 4.3), the acceptance of password managers in China will be even much lower (probably $< 0.5\%$). In a survey on English users, Stobert and Biddle were also "surprised to find that none of our participants used a dedicated password manager" [22].

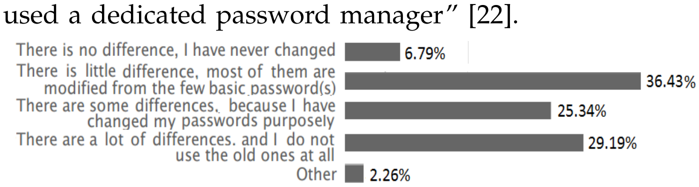


Fig. 8. Please recall. Is there any difference between the passwords you have used before and the ones currently in use? 54.53% of users show there are tangible differences.

The next three questions pay attention to how users' passwords evolve as time goes on. As shown in Fig. 8, 43.22% of users acknowledge little or no difference, while 54.53% show there are tangible differences. The latter well accords with the statistics shown in Fig. 9 that 58.6% of users acknowledge a tangible strength increase in their present

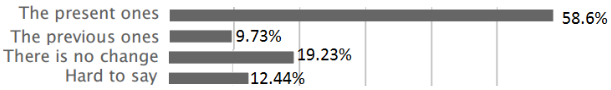


Fig. 9. Whose ones are more secure? Your previous passwords or your present passwords? 58.6% of users acknowledge a tangible strength increase in present ones.

passwords over previous ones. Disturbingly, 28.96% admit no strength increase, while the password cracking techniques (e.g., [9], [40]) are evolving rapidly as time goes by. Fig. 10 illustrates how Chinese users cope with diversified password requirements from various sites: 47.74% of users cope in a temporary manner, while 41.63% have developed their own coping method as time goes by.

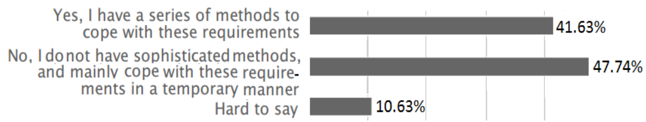


Fig. 10. Have you developed your own method to create passwords to satisfy the varied requirements from various sites? About half of users cope in a temporary manner.

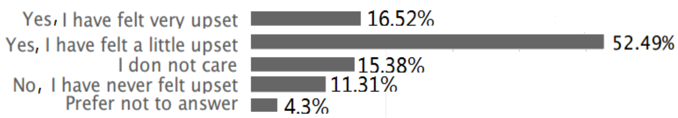


Fig. 11. Have you ever felt upset while managing passwords? (e.g. creation, memorization and change)? 69.01% of users show an unpleasant feeling, while 69.01% do not care.

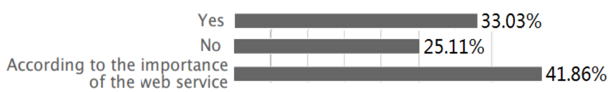


Fig. 12. Suppose you have to create a password with the following constraints: 1) at least 8 characters; and 2) at least one letter, one number and one symbol. Do you think this policy reasonable? 41.86% of users show a rational emotion.

The large fraction of users coping with password requirements in a passive manner partially explains why 69.01% of users (see Fig. 11) feel upset/very upset in their management of passwords. Interestingly, there are also 15.38% of users show a casual emotion and 11.31% show a positive emotion. This is mainly because there are some users who do not care their online security at all [41] and some users are competent in managing security affairs [22].

The final question aims to explore whether Chinese users are rational when confronted with stringent password policies from a site. Fig. 12 illustrates that 41.86% of users are rather rational: the necessity of strict policies depends on the importance of the value (service) to be protected. This implies that, from the user prospective, it is unwise for unimportant sites to impose strict password policies. Unfortunately, our recent investigation (see [18]) into the leading sites show quite the opposite: important services (e.g., email and e-commerce) often impose a loose policy, while unimportant services (e.g., IT corporation and web portal) often enforce a strict policy.

3.3 Demographics of participants

We also obtained some basic demographic information (see Figs. 13∼15) about our participants: two-thirds are male. 80.55% are between 18∼34 years old, and 15.67% are older than 35; 80.55% are pursuing or with at least a bachelor's degree, and 43.44% are pursuing or with at least a master's degree. This is as expected, for the majority of our team members are young PhD candidates and thus their personal relationships are mainly young and educated people. Comparatively, our participants are larger in size and more diversified than that of [22], [35], [38]. For instance, in [35] 93% of its 220 participants are 18∼34 years old and 92% have at least a bachelor's degree. Nevertheless, our participants are younger and more educated than the common population, and they may be more security-conscious and technically savvy. Hence, it is likely that we are underestimating many problems such as password reuse and update.

Fig. 13. What's you gender? About two thirds are male.

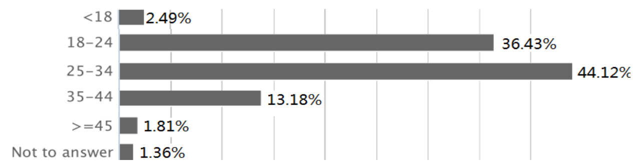


Fig. 14. What's you age? About 80% are between 18 and 34.

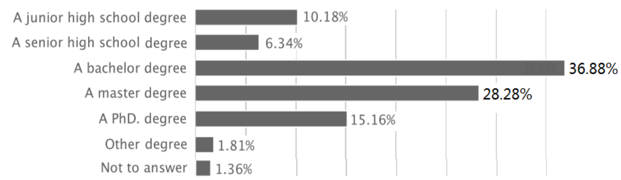


Fig. 15. Which is you highest degree (or you are pursuing)?

Summary. To the best of knowledge, this survey is the first one that targets Chinese users, the world's largest Internet population. Though our participants are superior to earlier related studies (on English users [22], [35], [38]) in terms of size and diversity, yet our survey is subject to the inherent limitation of any password-related survey: users may provide false data and the ecological validity is hard to be assured. Still, in many aspects (e.g., the rate of usages of Chinese Pinyin names and words) our results comply with real-life datasets (see Table 5) and with English users (e.g., the rates of PIN reuse and recording passwords electronically). Particularly, many information on user behaviors (e.g., how many different passwords users maintain and user sentiment) we have gained from the survey is inherently difficult to be obtained from an empirical analysis.

4 Characteristics of Chinese passwords

In this section, we first describe the six Chinese web password datasets and three English password datasets, a total corpus of 130 million passwords that will be used in our analysis and later experiments, and then reveal several important findings about Chinese password characteristics.

4.1 Ethics consideration and dataset descriptions

The nine datasets described here are different in terms of service, size, language and user localization (see Table 1). They were hacked by external attackers or disclosed by anonymous insiders, and were subsequently made public on the Internet. We realize that though publicly available, these datasets are private data. Therefore, we only report the aggregated statistical information, and treat each individual account as confidential such that using it in our

TABLE 1
Data Cleansing of the nine password datasets

Dataset	Web service	Location	Language	Original	Miscellany	Length>30	All removed	After cleansing	Unique passwords
Tianya	Social forum	China	Chinese	31,761,424	860,178	5	2.71%	30,901,241	12,898,437
7k7k	Gaming	China	Chinese	19,138,452	13,705,087	10,078	71.66%*	5,423,287	2,865,573
Dodonew	Gaming&E-commerce	China	Chinese	16,283,140	10,774	13,475	0.15%	16,258,891	10,135,260
178	Gaming	China	Chinese	9,072,966	0	1	0.00%	9,072,965	3,462,283
CSDN	Programmer forum	China	Chinese	6,428,632	355	0	0.01%	6,428,277	4,037,605
Duowan	Gaming	China	Chinese	5,024,764	42,024	10	0.83%	4,982,730	3,119,060
Rockyou	Social forum	USA	English	32,603,387	18,377	3140	0.07%	32,581,870	14,326,970
Yahoo	Portal(e.g., E-commerce)	USA	English	453,491	10,657	0	2.35%	442,834	342,510
Phpbb	Programmer forum	USA	English	255,421	45	3	0.02%	255,373	184,341

*We remove 13M duplicate accounts from 7k7k, because we identify that they are copied from Tianya as we will detail in Section 4.2.

research will not increase risk to the corresponding victim, i.e., no personally identifiable information can be learned. Furthermore, these datasets may be exploited by attackers as training sets or cracking dictionaries, while our use of them is both beneficial for the academic community to understand password choices of Chinese netizens and for security administrators to secure user accounts. Also note that, since the datasets we employed are publicly available, all the results in this work can be reproduced.

The first three datasets are all from US. The Rockyou dataset [25] includes over 32M passwords and was hacked from the social application site rockyou.com in Dec. 2009 by an SQL injection attack. The Phpbb dataset contains around 255K passwords leaked from phpbb.com, a forum on the development of PHP scripting language, in Jan. 2009. The Yahoo dataset [42] consists of about 442K passwords leaked by the hacker group named D33Ds in July 2012.

The following six datasets were all leaked from Chinese sites in Dec. 2011 [43]. The 6.42M CSDN passwords were hacked from csdn.net, a popular community for software developers in China. The 31.76M Tianya passwords were leaked from tianya.cn, an influential Chinese BBS forum. The remaining four datasets are all from popular Chinese gaming websites, of which Dodonew is a site with e-commerce services. As expected, the Dodonew passwords is the strongest one among all datasets (see Section 5). It is revealed that users often rationally choose robust passwords for accounts perceived to be of an important value [22], while knowingly choose weak passwords for unimportant accounts [17]. Since accounts of the same service generally would have the same level of value for a user, we divide datasets into three pairs according to their types of service (i.e., Tianya vs. Rockyou, Dodonew vs. Yahoo, and CSDN vs. Phpbb) when performing strength comparison in Section 5.

4.2 Data cleansing

Before examining the password characteristics, we perform the process of data cleansing. We get rid of email addresses and user names from the original data. We note that the remaining data consists of some strings whose lengths are over 100, which highly indicates that they are junk information. We remove such strings and others that include characters beyond the 95 printable ASCII symbols. We further remove strings whose length is over 30, because after having manually scrutinized the original datasets, we find that these long strings do not seem to be generated by human beings, but more likely by password managers. Moreover, such unusually long passwords are often beyond the scope of attackers who specially care about cost-effectiveness. Though the fraction of excluded passwords is negligible, this step of cleansing unifies the input of cracking algorithms and largely simplifies the later data processing.

Of particular importance is our observation that, the Tianya dataset and 7k7k dataset largely overlap with each other. We were first puzzled by the fact that the password "`111222tianya`" originally lay in the top-10 most popular list of both datasets. We manually scrutinize the original datasets (i.e., before removing the email addresses and user names) and are surprised to find that there are around 3.91 million (actually 3.91*2 million due to a split representation of 7k7k accounts, as we will discuss later) joint accounts in both datasets, and we realize that someone probably have copied these joint accounts from one dataset to the other.

Now, a natural question arises: *From which dataset have these joint accounts been copied?* We believe that these joint accounts were copied from Tianya to 7k7k mainly for two reasons. Firstly, it is unreasonable for 0.34% users in 7k7k to insert the string "`tianya`" into their 7k7k passwords. The following second reason is quite subtle yet convincing. In the original Tianya dataset, we find that the joint accounts are of the form {user name, email address, password}, while in the original 7k7k dataset such a joint account is divided into two parts: {user name, password} and {email address, password}. The password "`111222tianya`" occurs 64822 times in 7k7k and 48871 times in Tianya, and one gets that $64822/2 < 48871$. Therefore, it is more plausible for someone to copy *some* (i.e., 64822/2 of a total of 48871) accounts using "`111222tianya`" as the password from Tianya to 7k7k, rather than to copy all the accounts (i.e., $64822/2$) using "`111222tianya`" as the password from 7k7k to Tianya and further reproduces $16460(= 48871 - 64822/2)$ such accounts.

After removing 7.82 million joint accounts from 7k7k, we found that all of the passwords in the remaining 7k7k dataset occur even times (at least two). This is expected, for we observe that in 7k7k half of the accounts are of the form {user name, password}, while the rest are of the form {email address, password}, and it is likely that both forms are directly derived from the form {user name, email address, password}. For instance, both {wanglei, wanglei123} and {wanglei@gmail.com, wanglei123} are actually derived from the single account {wanglei, wanglei@gmail.com, wanglei123}. Consequently, we further divide 7k7k into two equal parts and discard one part. The detailed information on data cleansing is summarized in Table 1.

As far as we know, Li et al.'s work [20] is the only one that has exploited the datasets Tianya and 7k7k. However, contrary to what we have done in this work, Li et al. think that the 3.91M joint accounts are copied from 7k7k to Tianya.

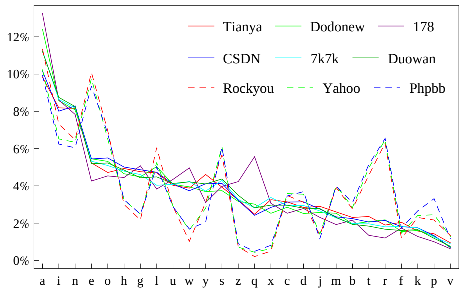


Fig. 16. Letter distributions of passwords

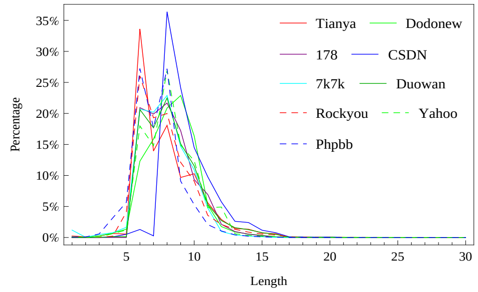


Fig. 17. Length distributions of passwords

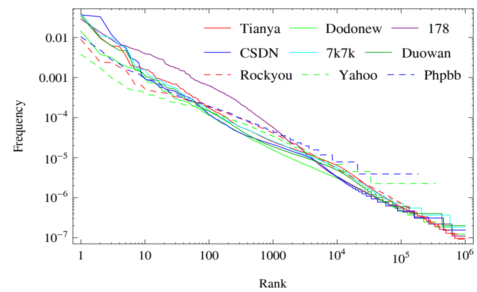


Fig. 18. Frequency distributions of passwords

TABLE 2
Inversion number of the letter distributions (in descending order) between the datasets ("PWs" stands for passwords)

	Tianya	7k7k	178	CSDN	Dodonew	Duowan	All Chinese PWs	Chinese language	Pinyin fullname	Pinyin word	Rockyou	Yahoo	Phpbb	All English PWs	English language
Tianya	0	15	22	42	15	17	14	40	32	37	100	100	113	100	99
7k7k	15	0	23	31	14	10	13	41	39	38	105	101	112	105	96
Dodonew	22	23	0	42	21	15	12	52	40	49	94	92	105	94	99
178	42	31	42	0	41	35	32	56	48	47	134	130	141	134	125
CSDN	15	14	21	41	0	12	15	45	39	42	95	95	106	95	96
Duowan	17	10	15	35	12	0	9	49	39	44	99	97	110	99	98
All_Chinese_PWs	14	13	12	32	15	9	0	44	34	43	104	102	115	104	101
Chinese_language	40	41	52	56	45	49	44	0	38	27	118	114	123	118	113
Pinyin_fullname	32	39	40	48	39	39	34	38	0	31	124	122	135	124	123
Pinyin_word	37	38	49	47	42	44	43	27	31	0	115	113	124	115	112
Rockyou	100	105	94	134	95	99	104	118	124	115	0	12	23	0	47
Yahoo	100	101	92	130	95	97	102	114	122	113	12	0	15	12	39
Phpbb	113	112	105	141	106	110	115	123	135	124	23	15	0	23	44
All_English_PWs	100	105	94	134	95	99	104	118	124	115	0	12	23	0	47
English_language	99	96	99	125	96	98	101	113	123	112	47	39	44	47	0

Their only reason is that, when dividing these two datasets into the reused passwords group (i.e., the joint accounts) and the not-reused passwords group, they find that "the proportions of various compositions are similar between the reused passwords and the 7k7k's not-reused passwords, but different from Tianya's not-reused passwords". However, they have never explained what these "various compositions" are. Such vague statements also cannot answer the critical question: why are there so many 7k7k users using "`111222tianya`" as their passwords? Hence, we believe that they should have removed 3.91*2 million joint accounts from 7k7k but not 3.91 million ones from Tianya. In addition, they fail to note that all the passwords in 7k7k occur even times, which is extremely abnormal. As a result, Li et al. render two of their five Chinese datasets at best useless and at worst negative, because contaminated data would highly lead to inaccurate results and unreliable comparisons.

4.3 Password characteristics

It is widely hypothesized that user-generated passwords are greatly influenced by their native languages, yet so far little empirical evidence has been given. To fill this gap, here we first illustrate the character distributions of the nine password datasets, and then measure the closeness of passwords with their native languages in terms of inversion number of the character distributions (in descending order).

Fig. 16 shows that passwords from different language groups have significantly varied letter distributions. What's quite surprising is that, even though generated and used in vastly diversified web services, passwords among the same language group have quite similar letter distributions. This suggests that, when given a password dataset, one can largely determine what's the native language of its users by investigating its letter distribution. Arranged in descending order, the letter distribution of all Chinese passwords is `aineohglwuyszxqcdjmbtfrkpv`, while this distribution for all English passwords is `aeionrlst mcdyhubkgpjvfwzxq`. While some letters (e.g., '`a`', '`e`' and '`i`') occur frequently in both groups, some letters (e.g., '`q`' and '`r`') only occur frequently in one group. Such information can be exploited by attackers to reduce the search space and optimize their cracking strategies. Note that, all the percentages here are handled case-insensitively (e.g., the percentage of letter '`a`' in Tianya is computed as $\frac{\#\text{of occurences of lower/uppercase letter `a' in Tianya}}{\#\text{of total occurences of all letters in Tianya}} = 11.29\%$).

While users' passwords are greatly affected by their native languages, the letter frequencies in general language usages may not well represent the frequencies of letters that are used in passwords. According to Huang et al.'s work [44], the letter distribution of Chinese language (i.e., written Chinese texts like literary work, newspapers and academic papers), when converted into Chinese Pinyin, is `inauhegoyszdjmxwqbctlpfrkv`. This shows that some letters (e.g., '`l`' and '`w`'), which are popular in Chinese passwords, appear much less frequently in written Chinese texts. A plausible reason may be that '`l`' and '`w`' is the first letter the family name `li` and `wang` (which are the top-2 family names in China), respectively, while Chinese users, as we will show, love to use names to build their passwords.

Similar observation also holds for English passwords, where the letter distribution of English language (i.e., `etaoinshrdlcumwfgypbvkjxqz`) is obtained from www.cryptograms.org/letter-frequencies.php. For instance, '`t`' is common in English texts, but not so in English passwords. A plausible reason may be that '`t`' is used in popular words such as `the`, `it`, `this`, `that`, `at`, `to`, while people are unlikely to use such words in passwords.

To further explore the closeness of passwords with their native languages and with the passwords from other dataset-

TABLE 3
Top-10 most popular passwords of each web service

Rank	Tianya	7k7k	Dodonew	178	CSDN	Duowan	Rockyou	Yahoo	Phpbb
1	123456	123456	123456	123456	123456789	123456	123456	123456	123456
2	111111	0	a123456	111111	12345678	111111	12345	password	password
3	000000	111111	123456789	zz12369	11111111	123456789	123456789	welcome	**phpbb**
4	123456789	123456789	111111	**qiulaobai**	**dearbook**	123123	password	ninja	qwerty
5	123123	123123	**5201314**	123456aa	00000000	000000	**iloveyou**	abc123	12345
6	123321	**5201314**	123123	wmsxie123	123123123	**5201314**	**princess**	123456789	12345678
7	**5201314**	123	a321654	123123	1234567890	123321	123321	12345678	letmein
8	12345678	12345678	12345	000000	88888888	a123456	**rockyou**	sunshine	111111
9	666666	12345678	000000	qq66666	111111111	suibian	12345678	**princess**	1234
10	**111222tianya**	wangyut2	123456a	w2w2w2	147258369	12345678	abc123	qwerty	123456789
Percent of top-10	7.43%	8.12%	3.28%	8.74%	10.44%	6.78%	2.05%	1.01%	2.79%

s, we measure the inversion number of the letter distribution sequence (in descending order) between two password datasets (as well as languages), and the results are summarized in Table 2. “Pinyin_fullname” is a dictionary consisting of 2,426,841 unique Chinese full names (e.g., `wanglei` and `zhangwei`), “Pinyin_word” is a dictionary consisting of 127,878 unique Chinese words (e.g., `chang` and `cheng`), and these two dictionaries will be detailed later. Note that the inversion number of sequence A to sequence B is equal to that of B to A. For instance, the inversion number of `inauh` to `aniuh` is 3, which is equal to that of `aniuh` to `inauh`.

Table 2 shows that, the inversion number of letter distributions between passwords from the same language group is generally *much smaller* than that of passwords from different language groups. This value is also *distinctly smaller* than that of the letter distributions between passwords and their native language (see the bold values in Table 2). All these indicate that passwords from different languages are intrinsically different from each other in letter distributions, and that passwords are close to their native language yet the distinction is still noticeable (measurable).

Fig. 17 depicts the length distributions of passwords. Irrespective of the web service, language and culture differences, the most common password lengths of every dataset are between 6 and 10, among which length-6 or 8 takes the lead. Merely passwords of these five lengths can account for more than 75% of every entire dataset, and this value will rise to 90% if we consider passwords with lengths of 5 to 12. As expected, very few users prefer passwords longer than 15 characters. Notably, people seem to prefer even length over odd length. Another interesting observation is that, CSDN exhibits only one peak in its length distribution curve and has much fewer passwords (i.e., only 2.16%) in lengths below 8. This is likely due to the fact that this site has enforced a minimal length-8 policy since an early stage.

Fig. 18 portrays the frequency vs. the rank of passwords from different datasets in a log-log scale. We first sort each dataset according to the password frequency in descending order, and then each individual password will be associated with a frequency f_r and a rank r. Interestingly, the curve for each dataset closely approximates a straight line, and this trend will be more pronounced if we take all the nine curves as a whole. This well corroborates the Zipf theory [45]: f_r and r follow a relationship of the type $\log f_r = \log C - s \cdot \log r$, where C and s are constants. Particularly, s is the absolute value of slope of the Zipf linear regression line and slightly less than 1.0. The Zipf theory indicates that the popularity of user-generated passwords decreases polynomially with the increase of their rank. This further implies that a few passwords are overly popular, while the majority are sparsely scattered in the password space.

Table 3 illustrates the top-10 most frequent passwords from different services. The most frequent password of all datasets is “`123456`”, with CSDN being the only exception, which is likely due to the CSDN password policy requiring that no password shall be shorter than 8 characters. “`111111`” follows on the heel. Other popular Chinese passwords include “`123123`”, “`123321`”, which are all composed of digits and in simple patterns such as repetition and palindrome, while popular ones in English datasets tend to be meaningful letter strings (e.g., the eternal theme of love — frankly, “`iloveyou`” or euphemistically, “`princess`”). Our results confirm the folklore that “back at the dawn of the Web, the most popular password was `12345`. Today, it is one digit longer but hardly safer: `123456`.”

It is worth noting that, for each digit, there are many Chinese characters that have similar sounds and this makes it easy to obtain digit sequences that sound like meaningful phrases. Hence, it is unsurprising to see that “`5201314`”, which sounds like “I love you forever and ever”, ranks the *7th* and *8th* most popular one in Tianya and Duowan, respectively. Moreover, Chinese passwords are highly concentrated, for only the top-10 most popular ones amount to as high as 6.78%∼10.44% of each entire dataset, with Dodonew being the mere exception. However, even Dodonew achieves 3.24%, while the English datasets are all below 2.80%.

As we have seen that digits are popular in top-10 passwords of Chinese datasets, whether are they popular in the whole datasets? To answer this question, we investigate the frequencies of password patterns that involve *digits*, and results on the top 3 most frequent ones are shown in the left hand of Table 4. More results (i.e., on the top-10 ones) can be found in the supplemental data. The first column of the table denotes the pattern of a password as in [14] (i.e., L denotes a lower-case sequence, D for digit sequence, U for upper-case sequence, S for symbol sequence, and the structure pattern of password “`Wanglei123`” is ULD). We see that an average of more than 50% of Chinese web passwords are only composed of digits, while this value of English datasets is only 11.30%. In contrast, English users prefer the patterns L and LD. Note that, all the percentages hereafter in this work are taken by dividing the corresponding total accounts (e.g., the percentage at the upper-left corner of Table 4 is computed as $\frac{\#\text{of passwords with pattern D}}{\#\text{of total passwords in Tianya}} = \frac{19706174}{30901241} = 63.77\%$).

It is somewhat surprising to see that, the sum of merely the three digit-based patterns (i.e., D, LD and DL) accounts for an average of 81.90% for Chinese datasets. In contrast,

TABLE 4
Top-3 structural patterns in two groups of passwords (The % is taken by dividing the corresponding total accounts.)

Top-3 patterns in Chinese PWs	Chinese password datasets Tianya	7k7k	Dodonew	178	CSDN	Duowan	Average of Chinese PWs	Top-3 patterns in English PWs	English password datasets Rockyou	Yahoo	Phpbb	Average of English PWs
D(e.g., `123456`)	**63.77%**	**59.62%**	30.76%	**48.07%**	**45.01%**	**52.84%**	**52.93%**	L (e.g., `passowrd`)	**41.69%**	33.03%	**50.07%**	**41.59%**
LD (e.g., `a123456`)	14.71%	17.98%	43.50%	31.12%	26.14%	23.97%	23.72%	LD (e.g., `abc123`)	27.70%	38.27%	19.14%	28.37%
DL(e.g., `123456a`)	4.12%	3.91%	7.55%	6.25%	5.88%	5.83%	5.25%	D (e.g., `123456`)	15.94%	5.89%	12.06%	11.30%
Sum of top-3	82.61%	81.51%	81.80%	85.45%	77.03%	82.64%	**81.90%**	Sum of top-3	85.33%	77.19%	81.25%	**81.26%**

English users favor letter-related patterns, and on average, their top-3 patterns (i.e., L, LD and D) also account for slightly over 80%. This indicates that, unlike English users, Chinese users are inclined to employ digits to build their passwords — digits serve the role of letters that play in English passwords, while letters mainly come from Chinese Pinyin words/names. This is probably due in large part to the fact that most Chinese users are unfamiliar with English language (and Roman letters on the keyboard). If this is the case, is there any meaningful (semantic) information underlying these digit sequences?

To gain an insight into the underlying semantic patterns, we construct several dictionaries of different semantic categories and investigate their prevalence (see Table 5). "English_word_lower" is from http://www.mieliestronk.com/wordlist.html and it contains about 58,000 popular lowercase English words. "English_lastname" is a dictionary consisting of 18,839 last (family) names with over 0.001% frequency in the US population during the 1990 census, according to US Census Bureau [46]. "English_firstname" contains 5,494 most common first names (1,219 male and 4,275 female names) in US [46]. "English_fullname" is a cartesian product of "English_firstname" and "English_lastname", consisting of about 1.04 million most common English full names.

To get a Chinese full name dictionary, we make use of the 20 million hotel reservations dataset [47] leaked in Dec. 2013. The Chinese family name dictionary includes 504 family names which are officially recognized in China. Since the first names of Chinese users are widely distributed and can be almost any combinations of Chinese words, we do not consider them in this work. As the names are originally in Chinese, we transferred them into Pinyin without tones by using a Python procedure from `https://pypinyin.readthedocs.org/en/latest/` and removed the duplicates. We call these two dictionaries "Pinyin_fullname" and "Pinyin_familyname", respectively.

"Pinyin_word_lower" is a Chinese word dictionary known as "SogouLabDic.dic", and "Pinyin_place" is a Chinese place dictionary. Both of them are from [48] and also originally in Chinese, and we translate them into Pinyin in the same way as we tackle the name dictionaries. "Mobile_number" consists of all potential Chinese mobile numbers, which are 11-digit strings with the first seven digits conforming to pre-defined values and the last four digits being random. Since it is almost impossible to build such a dictionary on ourselves, we instead write a Python script and automatically test each 11-digit string against the mobile-number search engine http://ku.13131313131.com/.

As for the birthday dictionaries, we use patterns to match digit strings that might be birthdays. For example, "YYYYMMDD" stands for a birthday pattern that the first four digits indicate years (from 1900 to 2014), the middle two represent months (from 01 to 12) and the last two denote dates (from 01 to 31). "PW with a l^+-letter substring" is a subset of the corresponding dataset (see Table 5) and consists of all passwords that include a letter substring *no shorter than* l, and similarly for "PW with a l^+-digit substring".

Table 5 shows the various semantic patterns existing in Chinese and English web passwords. We can see that, a large fraction of English users tend to use raw English words as their password building blocks. More specially, 25.88% English users insert a 5-letter or longer (denoted by 5^+-letter) *word* into their passwords, and this figure accounts for more than a third of the total passwords with a 5^+-letter substring. In contrast, few Chinese users choose raw Pinyin words or English words to build passwords, yet they prefer Pinyin names, especially *full names*. Surprisingly, of all the Chinese passwords (22.42%) that include a 5^+-letter substring, more than half (11.24%) include a 5^+-letter Pinyin full name. There is even a non-negligible proportion (i.e., 4.10%) of English passwords that contain a 5^+-letter full Pinyin name, and a reasonable explanation is that many Chinese users have created accounts in these English sites. For instance, the popular Chinese name "`zhangwei`" appears in both Rockyou and Yahoo. We also note that English names are also widely used in English passwords, yet full names are less popular than last names and first names. As far as we know, *for the first time we have explored name-based semantic patterns in a large-scale empirical password study*.

Equally surprisingly, we find that, on average, 16.99% of Chinese users simply insert a six-digit birthday into their passwords. Besides, about 30.89% of Chinese users employ a 4^+-digit date as their password building blocks, which is 3.59 times higher than that of English users (i.e. 8.61%); there are 13.49% of Chinese users inserting a four-digit year into their passwords, which is about 3.55 times higher than that of English users (3.80%, which is comparable to the results reported in [35]). We note that there might be some overestimates, for there is no way to tell apart whether some digit sequences are dates or not, e.g., `010101` and `520520`. These two sequences may be dates, yet they are also likely to be of other semantic meanings (e.g., `520520` sounds like "I love you$\cdots$"). Nevertheless, it doesn't affect our conclusion that birthdays play a vital role in Chinese user passwords.

Another interesting observation is that, about 3% Chinese users just use their 11-digit mobile numbers as passwords, making up 39.59% of all passwords with a 11^+-digit substring. While there are few passwords longer than 10, if an attacker can determine that the victim uses a long password, she is likely to succeed by just trying the victim's 11-digit mobile number. This reveals a practical attacking strategy against long Chinese passwords.

Note that there are some un-avoidable ambiguities when determining whether a text/digit sequence belongs to a specific dictionary, and improper resolution of these ambiguities would lead to an overestimation or underestimation of

TABLE 5
The prevalence of various dictionary words in user passwords (The percentage is taken by dividing the total accounts.)

Dictionary	Tianya	7k7k	Dodonew	178	CSDN	Duowan	Avg. Chinese	Rockyou	Yahoo	Phpbb	Avg. English
English_word_lower(len $\geq$ 5)	2.08%	2.05%	3.69%	0.83%	3.41%	2.37%	2.41%	**23.54%**	**29.49%**	**24.60%**	**25.88%**
English_firstname(len $\geq$ 5)	1.11%	0.93%	2.23%	0.53%	1.47%	1.19%	1.24%	18.80%	15.21%	9.20%	14.40%
English_lastname(len $\geq$ 5)	2.16%	2.34%	4.48%	1.93%	3.65%	2.77%	2.89%	**20.16%**	**20.82%**	**15.22%**	**18.73%**
English_fullname(len $\geq$ 5)	4.03%	4.30%	6.14%	4.99%	6.58%	5.07%	5.18%	13.05%	11.35%	8.25%	10.88%
English_name_any(len $\geq$ 5)	4.60%	4.65%	6.32%	5.20%	6.87%	5.18%	5.35%	**27.67%**	**26.51%**	**18.71%**	**24.30%**
Pinyin_word_lower(len $\geq$ 5)	7.34%	8.56%	10.82%	10.24%	11.51%	9.92%	9.73%	3.33%	2.99%	2.50%	2.94%
Pinyin_familyname(len $\geq$ 5)	1.35%	1.64%	2.34%	2.24%	2.47%	1.88%	1.99%	0.05%	0.07%	0.07%	0.06%
Pinyin_fullname(len $\geq$ 5)	**8.39%**	**9.87%**	**12.91%**	**11.81%**	**13.14%**	**11.29%**	**11.24%**	4.79%	4.17%	3.35%	**4.10%**
Pinyin_name_any(len $\geq$ 5)	8.56%	10.05%	13.31%	12.11%	13.46%	11.53%	11.50%	4.80%	4.18%	3.36%	4.11%
Pinyin_place(len $\geq$ 5)	1.24%	1.27%	1.64%	1.58%	2.12%	1.48%	1.55%	0.20%	0.18%	0.16%	0.18%
PW_with_a_5$^+$-letter_substring	**18.51%**	**19.99%**	**26.95%**	**19.38%**	**28.03%**	**21.70%**	**22.42%**	**71.69%**	**75.93%**	**68.66%**	**72.09%**
Date_YYYY	14.38%	12.82%	12.45%	10.06%	16.91%	14.33%	13.49%	4.34%	4.30%	2.77%	3.80%
Date_YYYYMMDD	6.06%	5.42%	3.93%	3.94%	8.78%	6.17%	**5.72%**	0.10%	0.05%	0.09%	**0.08%**
Date_MMDD	24.99%	19.97%	17.08%	16.46%	24.45%	22.59%	20.92%	7.53%	4.46%	3.59%	5.20%
Date_YYMMDD	**21.29%**	**15.89%**	**12.70%**	**13.09%**	**20.67%**	**18.28%**	**16.99%**	3.24%	1.23%	1.55%	2.01%
Date_any_above	**36.61%**	**30.39%**	**26.66%**	**27.07%**	**35.30%**	**33.58%**	**31.60%**	11.33%	8.77%	6.45%	8.85%
PW_with_a_digit	89.49%	88.42%	88.52%	90.76%	87.10%	89.26%	88.93%	54.04%	64.74%	46.14%	54.97%
PW_with_a_4$^+$-digit_substring	81.64%	76.98%	71.90%	78.76%	78.38%	80.60%	78.04%	24.72%	21.85%	19.33%	21.97%
PW_with_a_6$^+$-digit_substring	**75.59%**	**68.32%**	**61.16%**	**70.02%**	**69.87%**	**73.10%**	**69.68%**	17.77%	8.48%	11.28%	12.51%
PW_with_a_8$^+$-digit_substring	28.04%	27.56%	26.53%	26.37%	49.73%	31.03%	31.54%	6.88%	2.50%	3.73%	4.37%
Mobile_Phone_Number(11-digit)	**2.90%**	**1.76%**	**2.63%**	**3.97%**	**3.75%**	**2.44%**	**2.91%**	0.07%	0.01%	0.02%	0.03%
PW_with_a_11$^+$-digit_substring	**4.71%**	**2.09%**	**3.39%**	**5.08%**	**7.57%**	**3.35%**	**4.36%**	0.75%	0.17%	0.18%	0.37%

human choices. Here we take the dictionary "YYMMDD" for illustration. For example, both `111111` and `520521` fall into "YYMMDD" and are excessively popular, yet it is more likely that users choose them simply because they are easily memorable repetition numbers or meaningful strings, and considering them as ordinary dates would lead to an *overestimation*. Nevertheless, they can really be dates (e.g., `111111` stands for "Jan. 1th, 2011" and `520521` stands for "May 21th, 1952"), and completely excluding them from "YYMMDD" would result in an *underestimation* of the usages of dates. Thus, assuming that user birthdays are randomly distributed, we assign the expectation of frequency of dates (denoted by E), instead of zero, to the frequency of these abnormal dates. We manually identify 17 abnormal dates each of which is originally with a frequency greater than $10E$ and appears in every top-1000 list of the six Chinese datasets. In this way, the dilemma can be largely resolved. We similarly tackle 21 abnormal items in the dictionary "MMDD". As for the other 19 dictionaries in Table 5, few abnormal items can be identified, and thus they are processed as usual.

We conjecture that, the two characteristics (i.e., excessively high usages of long Pinyin names and birthdays) of Chinese web passwords would pose a potential for an attacker to greatly reduce her search space, for birthdays and popular names generally are drawn from a much smaller space than random strings should be. If this is the case, then it is fair to say that these two characteristics are just two serious weaknesses of Chinese passwords. In the following, we will establish this conjecture by a series of experiments.

5 Strength of Chinese passwords

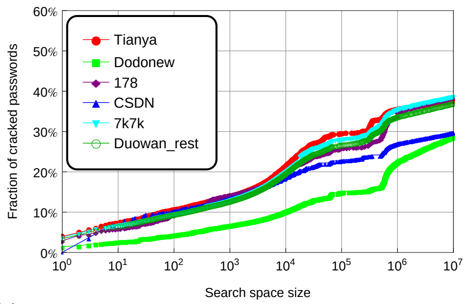
In this section, we employ the state-of-the-art password attacking algorithms (i.e., PCFG-based and Markov-Chain-based [9]) to evaluate the strength of Chinese passwords, for the traditional entropy-based metric has been demonstrated far from accurate [31]. We further investigate whether the characteristics identified in Sec. 4.3 can be practically exploited to reduce password space and facilitate guessing. As with [8], [40], we employ guess-number graphs for measuring the effectiveness of cracking sessions.

5.1 PCFG-based attacks

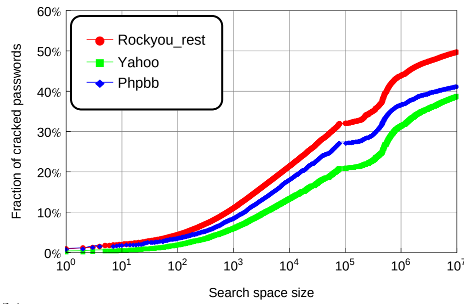
PCFG-based model was first introduced by Weir et al. [14], and it has been revealed to be one of state-of-the-art password cracking algorithms by recent research (e.g., [9], [32]). Unlike JTR that uses ad hoc mangling rules, PCFG-based approach learns the way users create their passwords and automatically derives mangling rules from a training set. Firstly, it divides all the passwords in a training set into segments of similar character sequences and obtains the corresponding base structures and their associated probabilities of occurrence. For example, password "`wanglei@123`" is divided into the L segment "wanglei", S segment "@" and D segment "123", and its base structure is $\mathsf{L}_7\mathsf{S}_1\mathsf{D}_3$. The probability of $\mathrm{L}_7\mathrm{S}_1\mathrm{D}_3$ is $\frac{\#\text{of } \mathrm{L}_7\mathrm{S}_1\mathrm{D}_3}{\#\text{of base structures}}$. Such information is used to generate the probabilistic context-free grammar.

Then, one can derive password guesses in decreasing order of probability, where the probability of any guess is the product of the probabilities of the productions used in its derivation. For instance, the probability of "`liwei@123`" is computed as P("`liwei@123`")= $P(\mathsf{L}_5\mathsf{S}_1\mathsf{D}_3)\cdot$ $P(\mathsf{L}_5 \rightarrow \text{liwei})\cdot$ $P(\mathsf{S}_1 \rightarrow \texttt{@})\cdot$ $P(\mathsf{D}_3 \rightarrow 123)$. In Weir et al.'s proposal [14], the probabilities for digit and symbol segments are learned from the training set by counting, yet letter segments are handled either by also learning from the training set or by using an external input dictionary.

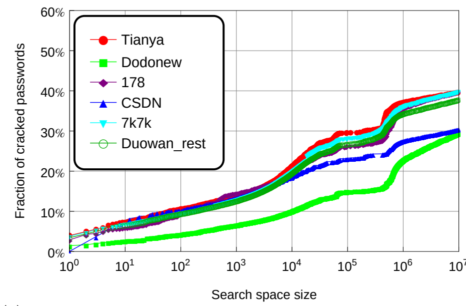
According to the recent works by Ma et al. [9] and Ur et al. [8] and on the basis of our past cracking experience [18], it is revealed that PCFG-based attack using a letter-segment dictionary, which is directly learned from the training set, to instantiate the letter segments of guesses generally performs better than using an external input dictionary. This is largely due to the fact that until now there has been no effective method to measure the quality of an external input dictionary, while an inappropriate input dictionary would greatly reduce the accuracy of guess generations. What's more, using heuristic approaches to choose the input dictionary may defeat the purpose of using PCFG to avoid heuristic approaches when generating guesses in the first place. As a result, we prefer to instantiate the PCFG letter segments of password guesses by using a dictionary directly learned from the training set.



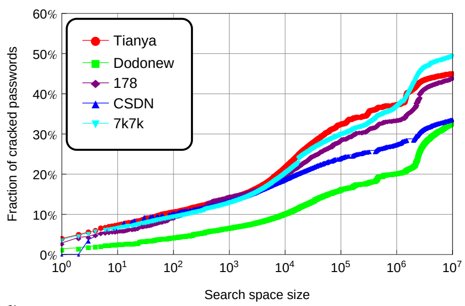
(a) PCFG-based attacks on six Chinese datasets (using 1 million (1M) Duowan passwords as the training set)



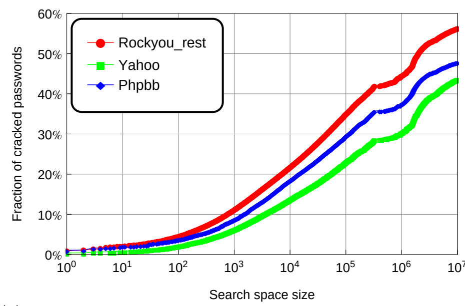
(b) PCFG-based attacks on three English datasets (using 1M Rockyou passwords as the training set)



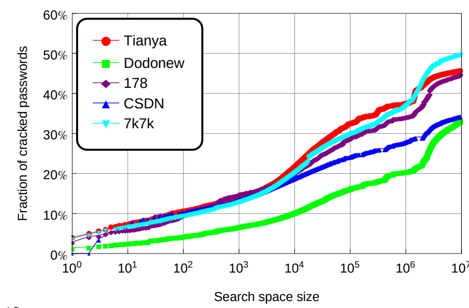
(c) Improved PCFG-based attacks on Chinese datasets (using 1M Duowan passwords as the training set)



(d) PCFG-based attacks on six Chinese datasets (using *all* the Duowan passwords as the training set)



(e) PCFG-based attacks on three English datasets (using 4M Rockyou passwords as the training set)



(f) Improved PCFG-based attacks on Chinese datasets (using *all* the Duowan passwords as the training set)

Fig. 19. General and improved PCFG-based attacks on different groups of datasets

We divide the nine datasets into two groups according to the languages and user locations. For the Chinese group of test sets, we randomly select 1 million passwords from the Duowan dataset [43] as the PCFG training set (denoted by "Duowan_1M"); For the English group of test sets, we similarly select 1M passwords from Rockyou [25] as the PCFG training set. The rationale underlying our choices of training sets is that, passwords in Duowan and Rockyou exhibit more composition varieties than that of other datasets in the same group, which can be seen from Table 3 to 5. Since we have only used part of Duowan and Rockyou, their remaining passwords as well the other seven datasets are used as the test sets. That being said, no external input dictionary is needed in our general PCFG-based attacks. The attacking results about the Chinese group and English group are depicted in Fig. 19(a) and Fig. 19(b), respectively.

From these two figures we can see that, when the guess number (i.e., search space size) allowed is below about 3,000, Chinese web passwords are generally much *weaker* than English web passwords in terms of the same application domain (i.e., Tianya vs. Rockyou, Dodonew vs. Yahoo, and CSDN vs. phpbb). For example, at 100 guesses, the success rate against Tianya, Dodonew and CSDN is 10.2%, 4.3% and 9.7%, respectively, while their English counterparts are 4.6%, 1.9% and 3.7%, respectively. However, when the search space size is above 10,000, Chinese web passwords are generally much *stronger* than their English counterparts. For example, at 10 million guesses, the success rate against Tianya, Dodonew and CSDN is 37.5%, 28.8% and 29.9%, respectively, while their English counterparts are 49.7%, 39.0% and 41.4%, respectively. The strength gap between these two groups of datasets will be even wider when the guess number further increases. This reveals that a *reversal* has occurred: Chinese passwords are more vulnerable to online guessing attacks (i.e., when the guess number allowed is small), especially the trawling attacks, while English passwords are more prone to offline guessing attacks in which the attacker is not subject to the restriction of the guess number. This "reversal principle" well reconciles two obviously conflicting claims (see Section 1.1) about the security strength of Chinese web passwords.

We observe that, the original PCFG-based algorithm [9], [14] inherently gives extremely low probabilities to password guesses (e.g., "`1q2w3e4r`" and "`1a2b3c4d`") that are of a monotonically long structure (e.g., $\mathsf{D_1L_1D_1L_1D_1L_1D_1L_1}$, or $(\mathsf{D_1L_1})_4$ for short). For example, $P(\text{"1q2w3e4r"}) = P((\mathsf{D_1L_1})_4) \cdot P(\mathsf{D_1}{\rightarrow}\mathtt{1}) \cdot P(\mathsf{L_1} \rightarrow \mathtt{q}) \cdot P(\mathsf{D_1} \rightarrow \mathtt{2}) \cdot P(\mathsf{L_1} \rightarrow \mathtt{w}) \cdot P(\mathsf{D_1}{\rightarrow}\mathtt{3}) \cdot P(\mathsf{L_1}{\rightarrow}\mathtt{e}) \cdot P(\mathsf{D_1} \rightarrow \mathtt{4}) \cdot P(\mathsf{L_1} \rightarrow \mathtt{r})$ can hardly be larger than 10^{-9}, for it is a multiplication of nine probabilities. As a result, some guesses (e.g., "`1q2w3e4r`") will never appear in the top 10^7 guesses generated by the original PCFG-based algorithm, even though they are popular (e.g, "`1q2w3e4r`" appears in the top-200 list of every dataset). The essential reason is that the PCFG-based algorithm simply assumes that each segment in a structure is independent. Unfortunately, in many situations this is *not* the case. For instance, the four $\mathsf{D_1}$ segments and $\mathsf{L_1}$ segments in the structure $(\mathsf{D_1L_1})_4$ of password "`1q2w3e4r`" are evidently interrelated with each other.

To address this problem, we specially tackle a few structures that are long but simple alternations of short segments by treating them as short structures, e.g., $(\mathsf{D_1L_1})_4$ and $(\mathsf{D_1L_2})_3$ are converted to $\mathsf{D_4L_4}$ and $\mathsf{D_3L_6}$, respectively. In this way, the probability of "`1q2w3e4r`" now is computed as $P(\text{"1q2w3e4r"}) = P((\mathsf{D_1L_1})_4) \cdot P((\mathsf{D_1L_1})_4 \rightarrow \mathsf{D_4L_4}) \cdot P(\mathsf{D_4} \rightarrow \mathtt{1234}) \cdot P(\mathsf{L_4} \rightarrow \mathtt{qwer})$. Note that, our approach is language-irrelevant and constitutes a *general* improvement over the state-of-the-art PCFG-based algorithm [9].

To further exploit the characteristics of Chinese web passwords, we insert the "Pinyin_name_any" dictionary and the six-digit date dictionary (see Section 4.3) into the L-segment

Algorithm 1: Improved PCFG-based guesses generation

```
Input: A training set S; A name list nameList; A date list
       dateList; A parameter k indicating the desired size of the
       password guess list that will be generated (e.g., k = 10^7)
Output: A password guess list L with the k highest ranked items
Training (with special attention to monotonically long
  passwords):
    for password ∈ S do
        for segment ∈ splitToSegments(password) do
            segmentSet.insert(segment)
        baseStructure ← getBaseStructure(password)
        if monotonicallyLong(baseStructure) then
            transformStructureSet.insert(baseStructure)
            baseStructure ← convertToshort(baseStructure)
        baseStructureSet.insert(baseStructure)
        trainingSet.insert(password)
Append name and date lists to the learned segment list
    for name ∈ nameList do
        correctedCount = totalOverlapNameInSegmentSet ∗
          nameList.getCount(name)/totalOverlapNameInNameList
        if name ∉ segmentSet and correctedCount ≥ 1 then
            segmentSet.insert(name, correctedCount)
    for date ∈ dateList do
        if date ∉ segementSet then
            segementSet.insert(date)
Produce k guesses:
    function guess.calculateProbability()
        guess.probability ←
          baseStructureSet.getProbability(guess.baseStructure)
        if monotonicallyLong(guess.baseStructure) then
            baseStructure ← guess.baseStructure
            guess.probability ← guess.probability ∗
              transformStructureSet.getProbability(baseStructure)
            guess.baseStructure ←
              convertToShort(baseStructure)
        for segment ∈ splitToSegments(guess.password) do
            guess.probability ← guess.probability ∗
              segmentSet.getProbability(segment)
    Initialize heap:
        for baseStructure ∈ baseStructureSet do
            for segmentType ∈ baseStructure.segmentTypeSet
              do
                guess.password +=
                  segmentSet.getFirstSegment(segmentType)
            guess.calculateProbability()
            guess.segmentChangedPosition ← 1
            heap.insert(guess)
    while guessCount ≤ k do
        guess ← heap.pop()
        L.insert(guess)
        guessCount++
        for i ← guess.segmentChangedPosition to
          guess.baseStructure.length do
            guessNew.password ←
              guess.changeToNextHightestSegment(i)
            if guessNew.password = null then
                continue
            guessNew.segmentChangedPosition ← i
            guessNew.caluculateProbability()
            heap.insert(guessNew)
```

dictionary and D-segment dictionary that are learned from the 1 million Duowan passwords using PCFG, respectively. Note that each segment in the L- and D-segment dictionaries is associated with a frequency. As there may have already been some Pinyin names in the original L-segment dictionary and the total frequency of these names (denoted by n_1) largely reflects the tendency that users insert Pinyin names into their passwords, we insert a name (its frequency denoted by f_r) from the "Pinyin_name_any" dictionary into the L-segment dictionary only if: (1) it is not in the original L-segment dictionary and (2) $\frac{n_1 \cdot f_r}{n_2} \geq 1$, where n_2 is the total frequency of names that falls into the intersection of the "Pinyin_name_any" dictionary and the L-segment dictionary. In this way, we manage to only insert a few most frequent ones from an ocean of 2.4M unique names of our name dictionary. On the other hand, as there are only 27.2K items in our six-digit date dictionary, we take all of them into account. More specifically, for any six-digit date that is not in the original D-segment dictionary, we first associate it with a frequency 1 and then insert it into the D-segment dictionary. The resulting changes to the PCFGs learned from the training sets are summarized in Table 6.

TABLE 6
Changes caused to the probabilistic context-free grammars

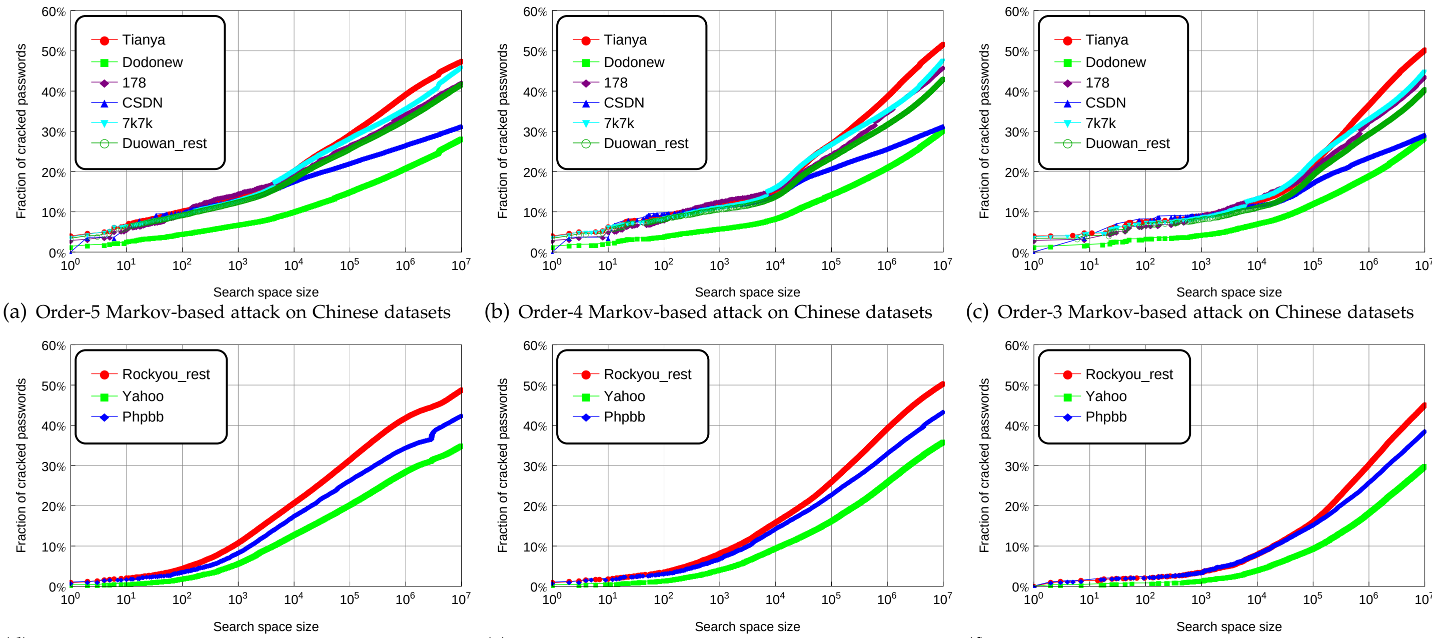
Training set	Base structures	L segments	D segments	S segments
Duowan_1M	8905+0	155693+24416	465157+20341	865+0
Duowan_All	20961+0	559017+98654	1824404+9744	2417+0

Our improved algorithm for the generation of password guesses is illustrated as Algorithm 1. As shown in Fig. 19(c), when the guess number is small (e.g., 10^3), our improved attack exhibits little improvement in success rate; while the guess number grows, the improvement increases substantially. For example, at 10^5 guesses, there is 0.09%∼0.85% improvement in success rate; at 1 million guesses, this figure is 1.32∼4.32%; at 10 million guesses, this figure reaches 1.70%∼4.29%. This indicates that, the excessively high usages of Pinyin names and birthdays facilitate an attacker to reduce the search space, and this vulnerability is especially serious when large guesses are allowed.

In 2014, Li et al. [20] reported that using 2 million Dodonew passwords as the training set and at 10 billion guesses, their best cracking record is about 17.30% (see Fig. 5 of [20]). However, our improved attack, which uses only 1 million passwords as the training set and at merely 10 million guesses, is able to achieve success rate from 29.41% to 39.47%. This means that our improved attack can crack 70% to 128% more passwords than Li et al.'s best record. Alarmingly high success rates highlight the urgency of developing effective countermeasures (e.g., more practical password creation policies and more accurate password meters) to alleviate the situation.

Since the effectiveness of PCFG-based attacks depends on the size of the training set, in the following we increase the size of each training set used in the above three experiments, and attempt to see whether the observations made above still hold. As shown in Fig. 19(d), at 10M guesses, there is an increase in success rate from 3.89% to 10.78% (the avg. is 6.34%) when we increase the training set (i.e., Duowan) from 1M to 4.98M. Similarly, Fig. 19(e) shows that there is an increase in success rate from 4.67% to 6.44% (the avg. is 5.84%) when we quadruple the training set (i.e., Rockyou). As for our improved PCFG-based attack, Fig. 19(f) shows that at 10M guesses, the success rate is from 33.20% to 49.86% when the training set size reaches 4.98M, which means an increase from 3.79% to 10.39% (the avg. is 5.90%). This suggests that, our improved attack with much less guesses is able to crack 92% to 188% more passwords than Li et al.'s best record (i.e., 17.3%, see Fig. 5 of [20]). Remarkably, the "reversal principle" still holds in this series of experiments.

In our improved PCFG-based attacks, external name segments are added into the PCFG L-segment dictionary during training, and we get gladsome increases in success rates over general PCFG-based attacks (see Figs. 19(c) and 19(f)). However, such improvements are still not so prominent as



(a) Order-5 Markov-based attack on Chinese datasets
(b) Order-4 Markov-based attack on Chinese datasets
(c) Order-3 Markov-based attack on Chinese datasets
(d) Order-5 Markov-based attack on English datasets
(e) Order-4 Markov-based attack on English datasets
(f) Order-3 Markov-based attack on English datasets

Fig. 20. Markov-chain-based attacks on different groups of datasets (using *Laplace Smoothing* and *End-Symbol Normalization*). Attacks (a)∼(c) use 1 million Duowan passwords as the training set, while attacks (d)∼(f) use 1 million Rockyou passwords as the training set.

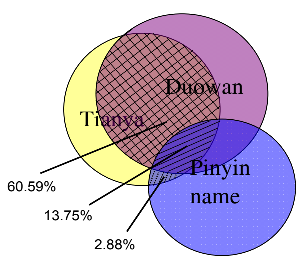


Fig. 21. Coverage of L-segments in the test set Tianya (using Duowan as the training set and Pinyin_name as an extra input dictionary when performing PCFG-based guess generation)

compared to the prevalence of names in Chinese passwords. To explicate this paradox, we scrutinize the internal process of PCFG-based guess generation and manage to identify its crux. Here we take the improved PCFG-based attack against Tianya (using Duowan as the training set) as an example. During training, we have added 98K name segments (see Table 6) into the L-segment dictionary.

However, as shown in Fig. 21, these 98K name segments only cover 2.88% of the total L segments of the Tianya test set, while the original L segments trained from Duowan can cover 3.77(=13.75/2.88-1) times more of the name segments and 60.59% of the non-name L segments in the Tianya test set. This suggests that the training set Duowan is able to *well* cover the name segments in the test set Tianya, and thus the addition of some extra names would be of limited yields. This observation also holds for the other eight test sets and the detailed results are presented in the supplemental data. However, this observation does *not* contradict our findings that Pinyin names are prevalent in Chinese passwords and actually, it *does* suggest that when the training set is selected properly, the name segments in passwords can be well guessed. Still, when there is no proper training set available, our improved attack would show its advantages. Moreover, although our improved PCFG-based algorithm might not be optimal, its cracking results represent a new benchmark that any future algorithm should aim to decisively clear.

5.2 Markov-Chain-based attacks

In our Markov-Chain-based password cracking experiments, as recommended in [9], we consider two smoothing techniques (i.e., Laplace Smoothing and Good-Turing Smoothing) to deal with the data sparsity problem, two normalization techniques (i.e., distribution-based and end-symbol-based) to deal with the unbalanced length distribution problem of passwords. This brings about four attacking scenarios as listed in Table 7. In each scenario we consider three types of markov order (i.e., order-5, 4 and 3) to investigate which order performs best. It is reported in [9] that the other scenario (i.e., backoff with end-symbol normalization) performs “slightly better” than the aforementioned four scenarios, yet it is “approximately 11 times slower, both for guess generation and for probability estimation” [9]. We also investigate this scenario and observe similar results in our experiments. Therefore, attackers, who particularly care about the cost-effectiveness, are highly unlikely to exploit this scenario. Due to space constraints, the detailed password guess generation procedure for Scenario 1 is referred to Algorithm 1 in the supplemental material, and the generation procedures for the other scenarios are quite similar.

TABLE 7
Five Markov-based attacking scenarios

Attacking scenario	Smoothing	Normalization	Markov order
#1	Laplace	End-symbol	3/4/5
#2	Laplace	Distribution	3/4/5
#3	Good-Turing	End-symbol	3/4/5
#4	Good-Turing	Distribution	3/4/5
#5	–	End-symbol	Backoff

As with PCFG-based attacks, in our implementation we use a max-heap to store the interim results to maintain efficiency. To produce $k = 10^7$ guesses, we employ the strategy of first setting a lower bound (i.e., 10^{-9}) for the probability of guesses generated, then sorting all the guesses and finally selecting the top k ones. In this way, we are able to reduce the time overheads by 170% at the cost of about 110% increase in storage overheads, as compared to the strategy of producing exactly k guesses. In Laplace Smoothing, it is required to add δ to the count of each substring and we set $\delta = 0.01$ as suggested by Ma et al. [9]. The cracking results for Scenario #1 are included in Fig. 20. Due to space constraints, the experiments for attacking scenarios #2∼#5 are illustrated in the supplemental data.

There is a subtlety to be noted when implementing the Good-Turing (GT) smoothing technique. We denote f to be the frequency of a password, and N_f to be the number of occurrences of passwords that are with a frequency f. According to the basic GT smoothing formula, the probability of a string "$c_1c_2\cdots c_l$" in a Markov model of order n is denoted by

$$P(\text{“}c_1c_2\cdots c_{l-1}c_l\text{”}) = \prod_{i=1}^{l} P(\text{“}c_i|c_{i-n}c_{i-(n-1)}\cdots c_{i-1}\text{”}), \tag{1}$$

where the individual probabilities in the product are computed empirically by using the training sets. More specifically, each empirical probability is given by

$$P(\text{“}c_i|c_{i-n}\cdots c_{i-1}\text{”}) = \frac{S(count(c_{i-n}\cdots c_{i-1}c_i))}{\sum_{c\in\Sigma} S(count(c_{i-n}\cdots c_{i-1}c))}, \tag{2}$$

where the alphabet Σ includes 95 printable characters on the keyboard plus one special end-symbol (i.e., c_E) that denotes the end of a password, and $S(\cdot)$ is defined as:

$$S(f) = (f+1)\frac{N_{f+1}}{N_f}. \tag{3}$$

It can be confirmed that this kind of smoothing works well when f is small, yet it fails for passwords with a high frequency because the estimates for $S(f)$ are not smooth. For instance, `12345` is the most popular 5-character string in Rockyou, occurring $f = 490,044$ times. As there is no 5-character string that occurs 490,045 times and N_{490045} will be zero, implying the basic GT estimator will give a probability 0 for $P(\text{“12345”})$. There have been various improvements suggested in linguistics to cope with this problem, among which is Gale and Hill's "simple Good-Turing smoothing" [49]. This improvement (denoted by SGT) is famous for its simplicity and accuracy, and we adopt it in this work. SGT takes two steps of smoothing, Firstly, SGT performs a smoothing for N_f:

$$SN(f) = \begin{cases} N(1) & \text{if } f = 1 \\ \dfrac{2N(f)}{f^+ - f^-} & \text{if } 1 < f < \max(f) \\ \dfrac{2N(f)}{2f - f^-} & \text{if } f = \max(f) \end{cases} \tag{4}$$

where f^+ and f^- stand for the next-largest and next-smallest values of f for which $N_f > 0$. Then, SGT performs a linear regression for all values SN_f and obtains a Zipf distribution: $Z(f) = C \cdot (f)^s$, where C and s are constants resulting from regression. Finally, SGT conducts a second smoothing by replacing the raw count N_f from Eq.3 with $Z(f)$:

$$S(f) = \begin{cases} (f+1)\dfrac{N_{f+1}}{N_f} & \text{if } 0 \le f < f_0 \\ (f+1)\dfrac{Z(f+1)}{Z(f)} & \text{if } f_0 \le f \end{cases} \tag{5}$$

where $t(f) = |(f+1)\cdot\frac{N_{f+1}}{N_f} - (f+1)\cdot\frac{Z(f+1)}{Z(f)}|$ and $f_0 = \min\left\{ f \in \mathbb{Z} \,\middle|\, N_f > 0, t(f) > 1.65\sqrt{(f+1)^2\frac{N_{f+1}}{N_f^2}(1+\frac{N_{f+1}}{N_f})} \right\}$.

In 2014, Ma et al. [9] introduced GT smoothing into Markov-based attacks to facilitate more accurate generation of password guesses, yet little attention has been paid to the unsoundness of GT for high frequency events as illustrated above. To the best of our knowledge, *here we for the first time well explicate the combination uses of GT and SGT in Markov-based password cracking*.

Our experiments (see Fig. 20 and the supplemental file) show that for both Chinese and English test sets: (1) At large guesses (i.e., $> 2*10^6$), order-4 markov-chain evidently performs better than the other two orders, while at small guesses (i.e., lower than 10^6) the larger the order, the better the performance will be; (2) There is not much difference in performance between Laplace and GT Smoothing at small guesses, while the advantage of Laplace Smoothing gets greater as the guess number increases; (3) End-symbol-based normalization always performs better than the distribution-based approach, while at small guesses its advantages will be more obvious. This suggests that at large guesses, the attacks preferring order-4, Laplace Smoothing and end-symbol normalization (see Figs. 20(b) and 20(e)) perform best; At small guesses (e.g., $< 10^6$), the attacks preferring order-5, Laplace Smoothing and end-symbol normalization (see Figs. 20(a) and 20(d)) perform best.

It is worth noting that, the "reversal principle" also applies in all the Markov-based experiments. For example, in order-4 Markov-based experiments (see Figs. 20(b) and 20(e)), we can see that, when the guess number is below about 7000, Chinese passwords are generally much *weaker* than their English counterparts. For example, at 1000 guesses, the success rate against Tianya, Dodonew and CSDN is 11.8%, 6.3% and 11.6%, respectively, while their English counterparts (i.e., Rockyou, Yahoo and Phpbb) is merely 8.1%, 4.3% and 7.1%, respectively. However, when the guess number allowed is over 10^4, Chinese passwords are generally *stronger* than their English counterparts. For example, at 1 million guesses, the success rate against Tianya, Dodonew and CSDN is 38.7%, 21.2% and 25.9%, respectively, while their English counterparts is 39.2%, 26.1% and 33.3%, respectively.

6 Some Useful Implications

We now discuss some useful implications that our findings are highly likely to carry. As illustrated in Section 4.3, there is a non-negligible fraction of accounts (see Table 5) in the Internet-scale English sites are created by Chinese users. Thus, the three implications derived below would serve as important password guidance not only for common Chinese users, but also for world-wide security administrators.

6.1 Implications for password cracking

Password cracking algorithms are the necessary tools not only for security administrators to obtain a realistic picture of the password security, but also for law enforcement agencies or forensics analysts to recover encrypted data so as to facilitate information forensics. Our results have three main implications for password cracking. Firstly, our findings in Section 4 show that Chinese passwords have vastly different letter distribution, structure and semantic patterns as compared to English passwords, and thus it is crucial for cracking algorithms to be trained on relevant Chinese password datasets (and may as well including corpus of Pinyin names and Chinese-style dates) when targeting Chinese passwords, otherwise the vulnerability of Chinese passwords is likely to be underestimated.

Secondly, when using PCFG-based attacks, it is better to *mainly* employ the L-segments directly learned from the training set and may *additionally* include some external special dictionaries to instantiate the L-segments of password guesses. This implication accords with the findings in [8], [9]. Its validity can be well established by the fact that, given the same guess numbers and against the same test sets, our PCFG-based attacks can obtain much higher success rates (see Section 5.1) than those of the PCFG-based attacks suggested in [20] where external dictionaries were *mainly* used to instantiate the L-segments of password guesses.

Thirdly, compared to Markov-based attacks, PCFG-based ones are simpler to implement (in terms of both computation and memory cost), and they perform equally well (even better, see Figs. 19 and 20) when the guess number is small (e.g., 10^3). For large guess numbers, order-4 Markov-based attacks are the best choices over order- 3 and 5. As as as we know, these observations have not been previously elucidated. Note that we have only shown the Markov-based results when the guess number is below 10^7, there is a potential that order-3 Markov-based attacks will outperform order-4 and 5 ones at larger guess numbers (e.g., 10^{14}).

6.2 Implications for password strength meters

In Section 1.1 we have shown that the password strength meters (PSMs) of four Internet-scale service providers are highly inconsistent at assessing the security of (weak) Chinese passwords. Failing to provide coherent feedback on user password choices would have great negative effects such as user confusion, frustration and distrust. Carnavalet and Mannan [16] suggested that PSMs "can simplify challenges by limiting their primary goal only to detecting *weak* passwords, instead of trying to distinguish a good, very good, or great password." It follows that the essential step of a PSM would be to identify the characteristics of weak passwords. From our findings in Section 4.3 and Section 5.1, it is evident that for passwords of Chinese users, the incorporation of long Pinyin words or full/family names is a compelling evidence for a "weak" decision. Other signs of weak passwords are the incorporation of birthdates and simple patterns like repetition and palindrome.

The "reverse principle" revealed in Section 5 shows that Chinese passwords are more vulnerable to online guessing attacks, which is highly due to the fact that Chinese passwords are more concentrated (i.e., some passwords are overly popular, see Table 3). Thus, a special blacklist that includes a moderate number (e.g., 50K as suggested in [31]) of most common Chinese passwords (e.g., learned from various leaked Chinese datasets) would be highly helpful for Chinese users to avoid trivial online guessing attacks. Any password falling into this list shall be deemed weak. However, it is well known that if some popular passwords are banned, new popular ones will arise. These new popular passwords may be complex and subtle to detect. Hence, whenever possible, PSMs shall further employ state-of-the-art cracking algorithms and take into consideration of local password characteristics (e.g., service and culture) to assess the real strength that user-generated passwords can provide.

6.3 Implications for password creation policies

Password creation policies are generally used along with PSMs to nudge users towards better passwords. While password creation policies tell a user what constitutes a good (or an acceptable) password, PSMs feedback to a user how her submitted password performs (weak or not?). It is interesting to see that CSDN enforces a minimum length-8 policy (as shown in Fig. 17 and [45], 97.83% passwords in CSDN are of length 8^+), while Dodonew enforces no apparent rule (i.e., neither minimum length nor character set requirement) as is evident from Table 3. However, Figs. 19 and 20 indicate that, given any guess number below 10^7, passwords from CSDN is significantly weaker than passwords from Dodonew. A plausible reason is that Dodonew provides e-commerce services, and most users perceive it as important. As a result, users *rationally* choose more complex passwords for it. As for CSDN, since it is only a technology community, users knowingly choose weak passwords for it.

In 2012, Bonneau [21] cast doubt on the hypothesis that users will rationally select more secure passwords to protect their more important accounts. In 2013 Egelman et al. [17] initiated a field study involving 51 students and confirmed this hypothesis. In 2014, Stobert and Biddle [22] interviewed 27 participants to investigate user behaviour in managing passwords, and their results also corroborate this hypothesis. As far as we know, here we for the first time provide a large-scale *empirical evidence* (i.e., on the basis of 6.43 million CSDN passwords and 16.26 million Dodonew passwords) that supports for this hypothesis.

We also note that though the overall security of Dodonew passwords are higher than passwords from the five other Chinese sites, many popular passwords dwelling in Dodonew also appear in other less sensitive sites (see Table 3 for a concrete example). This might be due to that users inadvertently choose popular passwords and that many users reuse the same password across multiple sites (43%∼51% of users reuse passwords [35]). What's even more dangerous is that many users fail to recognize different categories of accounts, because achieving this goal is not easy [50]. Further considering the "over-constrained nature of authentication" on the Web [4] and the "finite-effort user" [51], we suggest that when designing password creation policies, instead of merely insisting on stringent rules, administrators should put more efforts on helping users gain more accurate perceptions of the importance of the accounts to be protected and on guiding users towards better recognizing different categories of accounts. Both efforts would help enhance user internal impetus and are essential for common users to responsibly allocating (i.e., selecting one candidate from their limited pool of passwords memorized [22], [50]) passwords.

7 Conclusion

In this paper, we have carried out the first user survey on password behaviors of Chinese users. Our survey gets 442 effective responses and reveals a number of users' basic coping strategies for managing passwords as well as user sentiment. Then, we further conducted an extensive empirical study of 130M real-life passwords, including 100M from

China and 30M from US, one of the largest password corpus ever studied. To the best of knowledge, we, for the first time, explore several fundamental properties (e.g., the frequency distribution and the distance between different passwords and languages) that characterize user-chosen passwords. By using a comparative approach, we have identified a number of interesting characteristics of Chinese passwords, such as the common usage of long Pinyin names, birthdays and mobile numbers. We further performed a series of experiments by using the state-of-the-art password cracking algorithms as well as our improved PCFG-based algorithm to evaluate password strength. Our results show that, the identified characteristics can be exploited by an guessing attacker to largely reduce her search space.

Of particular interest is our observation that the "reversal principle" applies: when the guess number allowed is small (e.g., less than 10^4), Chinese passwords are much weaker than their English counterparts, yet this relationship will be reversed when the guess number is large (e.g., larger than 10^5). This indicates that Chinese passwords are more susceptible to *online, trawling attacks*, while English ones are more vulnerable to *offline guessing attacks*, which for the first time well reconciles two conflicting claims [20], [21]. Considering the comprehensiveness of our exploration (and the ampleness of our corpus), it is expected that this work provides a much deeper understanding of Chinese passwords and reveals substantial "ground truth" for better design of future password policies, meters, etc.

References

[1] R. Morris and K. Thompson, "Password security: A case history," *Comm. ACM*, vol. 22, no. 11, pp. 594–597, 1979.

[2] B. Zhu, J. Yan, G. Bao, M. Mao, and N. Xu, "Captcha as graphical passwords–a new security primitive based on hard AI problems," *IEEE Trans. on Inform. Foren. Secur.*, vol. 9, no. 6, pp. 891–904, 2014.

[3] V. Odelu, A. Das, and A. Goswami, "A secure biometrics-based multi-server authentication protocol using smart cards," *IEEE Trans. Inform. Foren. Secur.*, vol. 10, no. 9, pp. 1953–1966, 2015.

[4] J. Bonneau, C. Herley, P. van Oorschot, and F. Stajano, "Passwords and the evolution of imperfect authentication," *Comm. ACM*, vol. 58, no. 7, pp. 78–87, 2015.

[5] J. Bonneau, C. Herley, P. Oorschot, and F. Stajano, "The quest to replace passwords: A framework for comparative evaluation of web authentication schemes," in *Proc. IEEE S&P 2012*. IEEE, pp. 553–567.

[6] C. Herley and P. Van Oorschot, "A research agenda acknowledging the persistence of passwords," *IEEE Secur. Priv.*, vol. 10, pp. 28–36, 2012.

[7] J. Yan, A. F. Blackwell, R. J. Anderson, and A. Grant, "Password memorability and security: Empirical results." *IEEE Secur. Priv.*, vol. 2, no. 5, pp. 25–31, 2004.

[8] B. Ur, S. M. Segreti, L. Bauer, and et al., "Measuring real-world accuracies and biases in modeling password guessability," in *Proc. USENIX SEC 2015*, pp. 463–481.

[9] J. Ma, W. Yang, M. Luo, and N. Li, "A study of probabilistic password models," in *Proc. IEEE S&P 2014*, pp. 689–704.

[10] S. Ji, S. Yang, X. Hu, W. Han, Z. Li, and R. Beyah, "Zero-sum password cracking game: A large-scale empirical study on the crackability, correlation, and security of passwords," *IEEE Trans. Depend. Secur. Comput.*, 2015, doi: 10.1109/TDSC.2015.2481884.

[11] D. Wang, D. He, H. Cheng, and P. Wang, "fuzzyPSM: A new password strength meter using fuzzy probabilistic context-free grammars," in *Proc. DSN 2016*, pp. 1–12.

[12] W. Burr, D. Dodson, R. Perlner, S. Gupta, and E. Nabbus, "NIST SP800-63-2: Electronic authentication guideline," National Institute of Standards and Technology, Reston, VA, Tech. Rep., Aug. 2013.

[13] C. Castelluccia, M. Dürmuth, and D. Perito, "Adaptive password-strength meters from markov models," in *Proc. NDSS 2012*, pp. 1–15.

[14] M. Weir, S. Aggarwal, B. de Medeiros, and B. Glodek, "Password cracking using probabilistic context-free grammars," in *Proc. IEEE S&P 2009*, pp. 391–405.

[15] D. V. Klein, "Foiling the cracker: A survey of, and improvements to, password security," in *Proc. of USENIX SEC 1990*, pp. 5–14.

[16] X. Carnavalet and M. Mannan, "A large-scale evaluation of high-impact password strength meters," *ACM Trans. Inform. Syst. Secur.*, vol. 18, no. 1, pp. 1–32, 2015.

[17] S. Egelman, A. Sotirakopoulos, K. Beznosov, and C. Herley, "Does my password go up to eleven?: the impact of password meters on password selection," in *Proc. ACM CHI 2013*, pp. 2379–2388.

[18] D. Wang and P. Wang, "The emperor's new password creation policies," in *Proc. ESORICS 2015*, pp. 456–477.

[19] C. Custer, *China's Internet users zoom to 668 million*, Jan. 2016, http://www.apira.org/news.php?id=1736.

[20] Z. Li, W. Han, and W. Xu, "A large-scale empirical analysis on chinese web passwords," in *Proc. USENIX SEC 2014*, pp. 559–574.

[21] J. Bonneau, "The science of guessing: Analyzing an anonymized corpus of 70 million passwords," in *IEEE S&P 2012*, pp. 538–552.

[22] E. Stobert and R. Biddle, "The password life cycle: user behaviour in managing passwords," in *Proc. SOUPS 2014*, pp. 243–255.

[23] A. Narayanan and V. Shmatikov, "Fast dictionary attacks on passwords using time-space tradeoff," in *Proc. ACM CCS 2005*, pp. 364–372.

[24] A. S. Brown, E. Bracken, and S. Zoccoli, "Generating and remembering passwords," *Applied Cogn. Psych.*, vol. 18, no. 6, pp. 641–651, 2004.

[25] C. Allan, *32 million Rockyou passwords stolen*, Dec. 2009, http://www.hardwareheaven.com/news.php?newsid=526.

[26] B. Cassie, *Forbes Passwords Leak*, Feb. 2014, https://blog.kaspersky.com/forbes-passwords-leak.

[27] J. Mick, *Russian Hackers Compile List of 10M+ Stolen Gmail, Yandex, Mailru*, Sep. 2014, http://www.dailytech.com/Russian+Hackers+Compile+List+of+10+Million+Stolen+Gmail+Yandex+Mailru/article36537.htm.

[28] B. L. Riddle, M. S. Miron, and J. A. Semo, "Passwords in use in a university timesharing environment," *Computers & Security*, vol. 8, no. 7, pp. 569–579, 1989.

[29] R. Veras, J. Thorpe, and C. Collins, "Visualizing semantics in passwords: The role of dates," in *Proc. ACM VizSec 2012*, pp. 88–95.

[30] D. Florencio and C. Herley, "A large-scale study of web password habits," in *Proc. WWW 2007*, pp. 657–666.

[31] M. Weir, S. Aggarwal, M. Collins, and H. Stern, "Testing metrics for password creation policies by attacking large sets of revealed passwords," in *Proc. ACM CCS 2010*, pp. 162–175.

[32] M. L. Mazurek, S. Komanduri, T. Vidas, L. F. Cranor, P. G. Kelley, R. Shay, and B. Ur, "Measuring password guessability for an entire university," in *Proc. ACM CCS 2013*, pp. 173–186.

[33] S. Ji, S. Yang, T. Wang, and et al., "Pars: A uniform and open-source password analysis and research system." Proc. ACSAC 2015, pp. 1–10.

[34] R. Shay, S. Komanduri, P. G. Kelley, and et al., "Encountering stronger password requirements: user attitudes and behaviors," in *Proc. SOUPS 2010*, pp. 1–20.

[35] A. Das, J. Bonneau, M. Caesar, N. Borisov, and X. Wang, "The tangled web of password reuse," in *Proc. NDSS 2014*, pp. 1–15.

[36] E. Yu, *An incomplete list of Chinese websites that have publichly leaked passwords*, Feb. 2015, http://www.liu16.com/post/476.html.

[37] C. C. Television, *While 12306.cn passwords have been leaked, how to build a secure password?*, Dec. 2014, http://www.aiweibang.com/yuedu/7394854.html.

[38] S. T. Haque, M. Wright, and S. Scielzo, "Hierarchy of users? web passwords: Perceptions, practices and susceptibilities," *Int. J. Human-Comput. Stud.*, vol. 72, no. 12, pp. 860–874, 2014.

[39] 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 *Proc. of CHI 2011*. ACM, 2011, pp. 2595–2604.

[40] W. Li, H. Wang, and S. Kun, "A study of personal information in human-chosen passwords and its security implications," in *Proc. INFOCOM 2016*, pp. 1–9.

[41] S. Riley, "Password security: What users know and what they actually do," *Usability News*, vol. 8, no. 1, pp. 2833–2836, 2006.

[42] V. Katalov, *Yahoo!, Dropbox and Battle.net Hacked: Stopping the Chain Reaction*, Feb. 2013, http://blog.crackpassword.com/tag/yahoo/.

[43] R. Martin, *Amid Widespread Data Breaches in China*, Dec. 2011, http://www.techinasia.com/alipay-hack/.

[44] J. Huang, H. Jin, F. Wang, and B. Chen, "Research on keyboard layout for chinese pinyin ime," *Journal Of Chinese Information Processing*, vol. 24, no. 6, pp. 108–113, 2010.

[45] D. Wang, G. Jian, X. Huang, and P. Wang, "Zipf's law in passwords," Cryptology ePrint Archive, Report 2014/631, pp. 1–33, 2014, http://eprint.iacr.org/2014/631.pdf.

[46] R. A. Butler, *List of the Most Common Names in the U.S.*, Jan. 2014, http://names.mongabay.com/most_common_surnames.htm.

[47] J. Goldman, *Chinese Hackers Publish 20 Million Hotel Reservations*, Dec. 2013, http://www.esecurityplanet.com/hackers/chinese-hackers-publish-20-million-hotel-reservations.html.

[48] *Sogou Internet thesaurus*, Sogou Labs, April 17 2014, http://www.sogou.com/labs/dl/w.html.
[49] W. Gale and G. Sampson, “Good-turing smoothing without tears,” *Journal of Quantitative Linguistics*, vol. 2, no. 3, pp. 217–237, 1995.
[50] R. Nithyanand and R. Johnson, “The password allocation problem: strategies for reusing passwords effectively,” in *Proc. ACM WPES 2013*, pp. 255–260.
[51] D. Florêncio, C. Herley, and P. C. Van Oorschot, “Password portfolios and the finite-effort user: Sustainably managing large numbers of accounts,” in *Proc. USENIX SEC 2014*, pp. 575–590.