Empirical Analysis of Password Reuse and Modification across Online Service

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ABSTRACT
Leaked passwords from data breaches can pose a serious threat to users if the password is reused elsewhere. With more online services getting breached today, there is still a lack of large-scale quantitative understanding of the risks of password reuse across services. In this paper, we analyze a large collection of 28.8 million users and their 61.5 million passwords across 107 services. We find that 38% of the users have reused exactly the same password across different sites, while 20% have modified an existing password to create new ones. In addition, we find that the password modification patterns are highly consistent across different user demographics, indicating a high predictability. To quantify the risk, we build a new training-based guessing algorithm, and show that more than 16 million password pairs can be cracked within just 10 attempts (30% of the modified passwords and all the reused passwords).

1. INTRODUCTION
The widespread of data breaches (e.g., Yahoo, Myspace, Office of Personnel Management, Ashley Madison) are posing significant threats to users and organizations. In 2016 alone, there were more than 2000 confirmed breaches causing a leakage of billions of user records [1]. Many of the leaked datasets contain sensitive information such as user passwords, which are often made publicly available on the Internet by attackers [2, 3, 4, 5].

A leaked password incurs serious risks if the user reuses the password across different services. Reusing the same or even slightly modified passwords allows attackers to further compromise the user’s accounts in other “un-breached” services [6, 7]. Even worse, if the target user happens to be the administrator of another service, password reuse may lead to new massive data breaches (e.g., Dropbox [7]).

With more passwords leaked everyday [1, 4], there is still a lack of large-scale quantitative understanding on password usage across online services. Existing work studies password reuse and transformation either through a user survey [8, 9, 10] or small-scale data analytics (6-7K users) [8, 9]. The limited scope of the data (sample size, service type, user demographics) makes it challenging to comprehensively quantify the risks to see the bigger picture.

In this paper, we conduct a large-scale measurement on 28,836,775 users on their password reuse and modification patterns across 107 online services. By analyzing publicly available password datasets, we seek to empirically measure the common ways in which users reuse/modify passwords. In addition, to quantify the security risks introduced by password reuse and modification, we develop a training-based algorithm to guess a target user’s password based on her leaked one. Our study reveals several key findings.

How often do users reuse or modify existing passwords?
Among the 28.8 million users, we find that 38% of users have once reused the same password in two different services and 21% of the users once modified an existing password to sign up a new service. Particularly, passwords of email services (e.g., Gmail) have a noticeably high reuse rate (60.4%). Given the sensitivity of email accounts, reusing the password of email accounts incurs serious risks.

What are the common ways of modifying passwords?
We empirically measure 8 high-level categories of password transformation rules. We find that users prefer using simple rules to modify passwords. More importantly, the password transformation patterns are highly consistent across users of different professions (military, government, education) and countries. The low variance of the transformation patterns is likely to make the modified passwords predictable.

How likely can attackers guess a modified password?
Our training-based algorithm can guess 30% of the modified passwords within 10 attempts (46.5% within 100 attempts). Together with the identical passwords (reused), more than 16 million password pairs can be cracked within 10 guesses. In addition, the algorithm achieves a similar performance even if it is trained with only 0.1% of the data. This confirms the low-variance of password modification patterns, indicating that attackers can learn the basic patterns with minimal training to crack massive passwords in an online fashion.

This work is the first large-scale measurement on the password reuse and modification patterns across online services. Our result sheds light on the emerging security threats introduced by massive data breaches, and calls for more effective tools to secure users’ online accounts and digital assets.

1Our study has received IRB approval (Protocol #17-393).
| Category     | #Plain PWs (#Datasets) | Top 3 Largest Datasets                     |
|--------------|------------------------|--------------------------------------------|
| Adult        | 72.2M (9)              | Zoosk, Mate1, YouPorn                      |
| Email        | 9.6M (3)               | Gmail, Mail.ru, Yandex                     |
| Game         | 40.8M (13)             | Neopets, 7k7k, Lhsq                        |
| Shopping     | 340K (12)              | RedBox, 1394store, Myaribags               |
| Business     | 10K (9)                | Movatiahtletic, Hsappotoren, 99Fame       |
| Total        | 460M (107)             | Myspace, VK, LinkedIn                      |

Table 1: Categories and statistics of collected datasets.

2. RELATED WORK

Password Reuse & Transformation. Password guessing attacks become a major concern as data breaches are increasingly frequent. The attack is immediately effective if the user reuses the same password for different services [5,10]. Even if non-identical passwords are used, users may follow simple transformation patterns to modify their passwords, which makes their passwords predictable [8,38]. Existing work investigated this problem based on user surveys or small-scale data analytics (6–7K users) [8,15,25,38]. In this work, we perform the first large-scale measurement to understand cross-site password usage and quantify the risk of leaked passwords (28.8 million users, 107 websites).

Online & Offline Password Guessing. Online password guessing requires attackers to guess the password within a limited number of attempts. Trawling based approach simply guesses the most popular passwords chosen by users [20]. More targeted guessing exploits the fact that users may reuse the same/similar passwords across services [8,38]. Existing work investigated this problem based on user surveys or small-scale data analytics (6–7K users) [8,15,25,38]. In this work, we perform the first large-scale measurement to understand cross-site password usage and quantify the risk of leaked passwords (28.8 million users, 107 websites).

A larger body of work focuses on offline guessing [12,14,21,22,33,36], where the number of attempts is unlimited. A common scenario is that given a hashed password dataset, offline guessing seeks to recover the plaintext passwords. A number of approaches have been proposed, including Markov Models [18,22], Mangled Wordlist methods [21], Probabilistic Context-Free Grammars (PCFGs) [14,22,33,36], and Neural Networks [21]. Offline guessing has also been used to measure password strength [9,13,30].

3. DATASET

To analyze password usage across services, we gathered a large collection of publicly available password datasets. In January 2017, we searched through online forums and public data archives for candidate datasets using two criteria. First, the dataset should contain email addresses to link a user’s passwords across services. Second, we exclude datasets with only salted hashes since it is difficult to massively recover their passwords.

We collected 107 datasets leaked between 2008–2016, which contain 497,789,976 passwords and 428,199,842 unique users (email addresses). 14 datasets contain hashed passwords, and we spent a week to recover the plaintext using offline guessing tools [2,13,31]. In total, we obtained 460,874,306 plaintext passwords (93% of all passwords). The rest 7% are difficult to recover, and we will use them to test our guessing algorithm later. Figure 1 shows the number of passwords in each dataset. In Table 1 we classify the datasets into 10 categories. The “others” category contains 7 datasets with generic file names (difficult to label). We have made sure that the 7 datasets did not overlap with any existing ones.

Primary Dataset (28.8 Million Users). To study cross-site password usage, we need users who appear on at least two websites. To this end, we construct a primary dataset of 28,836,775 users who have at least two plaintext passwords (61,552,446 passwords in total). Our analysis in the paper will focus on this primary dataset. Note that users outside of the primary dataset are not necessarily risk-free: they might still have accounts in services that we didn’t cover.

Ethic Guidelines. Our work involves analyzing leaked datasets that contain sensitive information. We have worked closely with our local IRB and obtained the approval for our research. Our study is motivated by the following considerations. First, we only analyze datasets that are already publicly available. Analyzing such data does not add additional risks other than what already exist. Second, these datasets are also publicly available to potential attackers. Failure to include the data for research may give attackers an advantage over researchers that work on defensive techniques. In the past decades, leaked password datasets have been extensively used in academic research [8,9,13,17,32,34] to develop security mechanisms to protect users in the long run.

4. PASSWORD REUSE ACROSS SERVICES

We start by analyzing how often users reuse exactly the same password for different services. Out of the 28.8 million users in the primary dataset, we extract 37,301,406 password pairs where both passwords are from the same user. If a user has more than two passwords, then all possible pairs are considered (e.g., 4 passwords means 6 pairs). We find that 34.3% of the pairs are identical pairs. At the user level, 38% of the users (10.9 million) have at least one identical pair, indicating that the user sets the same password for different services. This ratio is slightly lower than the self-reported result (51%) from a user study [8].

Next, we are curious whether users with more passwords are more likely to reuse the same password. The intuition
is that it is difficult to memorize many completely different passwords. Our result in Table 2 shows that this hypothesis is true for users with less than 5 passwords. However, the trend is reversed for users with even more passwords. A careful examination shows that users with more passwords are more likely to “modify” an existing password for new services. Based on the results in [9] users with more than 4 passwords have a higher chance of modifying existing passwords (64.0%) compared with the overall ratio (21.0%).

As a case study, we specifically analyze the passwords for “email” services. Email accounts are sensitive due to the fact that emails can be used to reset the password for various online services. Many online accounts will be in danger if the user’s email account is compromised. As shown in Table 1 we have 3 leaked email datasets from Gmail, Mail.ru and Yandex. We identify 4,033,847 password pairs involving 3 million users that contain an email password. We find that 2,440,232 of the pairs are identical, which yields a much higher reuse ratio (60.4%) than the overall ratio (34.3%). This indicates users are more likely to use their email password for another service, a practice that incurs serious risks.

5. PASSWORD TRANSFORMATION

In addition to reusing the same password, users may also modify an existing password when signing up for a new service. Given a password pair of the same user, our goal is to infer the “transformation rule” (if there is one) that the user follows to modify the password. Then, we seek to understand how much the transformation patterns differ across users from different demographics.

5.1 Transformation Rules
Our measurement workflow is shown in Figure 2. In total, we construct 8 rules for password transformation based on our manual examinations of 1000 random password pairs and results from prior studies [8, 38, 39]. We test these rules against the password pairs in the primary dataset, and the results are shown in Table 3.

| #PWs per User | # of Users | % of Users w/ PW Reuse |
|---------------|------------|------------------------|
| 2             | 25,355,516 | 34.6%                  |
| 3             | 2,877,322  | 63.4%                  |
| 4             | 370,990    | 78.8%                  |
| 5             | 54,258     | 74.6%                  |
| 6             | 11,112     | 51.5%                  |
| 7             | 3,701      | 29.6%                  |
| ≥8            | 3,876      | 22.6%                  |

Table 2: Password reuse rate vs. # of passwords per user.

| Rule            | # Pairs of Passwords | Ratio (%) |
|-----------------|----------------------|-----------|
| 1. Identical    | 12,780,722           | 34.3%     |
| 2. Substring    | 3,748,258            | 10.0%     |
| 3. Capitalization| 478,233              | 1.3%      |
| 4. Leet         | 93,418               | 0.3%      |
| 5. Reversal     | 5,938                | <0.1%     |
| 6. Sequential keys| 12,118               | <0.1%     |
| 7. Common Substring| 2,103,888          | 5.7%      |
| 8. Combination of Rules | 754,393          | 2.0%      |
| Can Not Find A Rule | 17,324,438        | 46.4%     |

Table 3: Distribution of password transformation rules.

The majority of the password pairs (55.6%) can be explained by one of the transformation rules. To translate the numbers to the user level, 38% of the users have reused the same password at least once, and 21% of the users have once modified an existing password to create a new one. Collectively, these users count for 52%. The rest 48% of the users are likely to create a new password from scratch for each service. Below, we discuss each rule in details and further analyze the unmatched passwords.

**Identical.** The most common rule is reusing the same password (12 million password pairs, 34.3%).

**Substring.** This rule indicates that one password is a substring of the other one (e.g., abc and abc12). This rule matches 3.7 million password pairs (10%), indicating that users have inserted/deleted a string to/from an existing password to make a new one. As shown in Table 3, most insertions/deletions happened at the tail (87.2%). Most inserted/deleted strings are pure digits (74%) and short (1–2 characters), e.g., “1”, “2”, and “12”.

**Capitalization.** Users may simply capitalize certain letters in a password. Even though the ratio of matched pairs is not high (1.3%), the absolute number is still significant (478,233 pairs). We observe that users commonly capitalize letters in the beginning of the password (73%), particularly the first letter (68.6%).

**Leet.** 93,418 password pairs match the leet rule (0.3%). Leet transformation refers to replacing certain characters with other similar-looking ones. Our analysis shows the top 10 most common transformations are: 0→o, 1→i, 3→e, 4→a, 1→!, 1+1, 5+5, @, & and $+$. These 10 transformations already cover 96.6% of the leet pairs.

**Reversal.** Reversal rule is rarely used (5938 pairs, <0.1%), which means reversing the order of the characters in a password, e.g., abcd→dcba. Intuitively, reversed password is hard to memorize.
Table 4: Substring rule: insertion/deletion patterns.

| Insert/Delete Type | Length Ratio | Inserted/Deleted Length Ratio |
|--------------------|--------------|------------------------------|
| Tail               | 87.2%        | 1                            |
| Head               | 11.0%        | 2                            |
| Both Ends          | 1.8%         | 3                            |
| Insert/Delete Type |              |                              |
| Digit              | 74.0%        | “1”                          |
| Letter             | 17.8%        | “2”                          |
| Combined           | 4.5%         | “1.2”                        |
| Special Char       | 3.7%         | “1.23”                       |

Table 5: Common substring rule: longest common substring and transformation patterns.

Sequential Keys. Sequential keys include alphabetically-ordered letters (abcd), sequential numbers (1234) and adjacent keys on the keyboard (qwert, asdfg, !@#$%). The matched pairs (i.e., both passwords are sequential keys) are also below 0.1%.

Common Substrings. When a user modifies an existing password to create a new one, we assume the majority of the password remains the same. As shown in Figure 2, we extract the longest common substrings from the two passwords to learn how they transform the rest parts. To avoid accidental character overlaps, we require the longest common string to be >2 characters, and all the common substrings should cover >50% characters of a password (i.e., the majority).

This rule matches 2.1 million password pairs (5.7%). To make sure the thresholds make sense, we manually examine a random sample of 1000 matched pairs. 44 pairs look like to have accidental overlaps, which projects a false positive rate of 4.4%. We can tolerate false negatives for now since we have one more rule left. Based on the false positive rate, we estimate that the common substring rule should count for at least 5.4% of all password pairs.

Table 5 shows that the longest common substrings are often pure letters (63.8%) or pure digits (22%). 56.7% of the pure-letter strings are English words/names (based on NLTK corpus [6]). Table 5 also shows the typical transformations. Note that one password pair may have multiple transformations (total exceeds 100%).

Combination of Rules. As a final step, we combine possible rules to find a match. Note that rule3–6 modify the characters (or the sequence) in a password, while rule2 and rule7 operate on substrings. Our approach is to use a combination of rule3–6 to modify the password first, and then test if rule2 or rule7 can declare a match. In this way, we further matched another 754,000+ pairs (2.0%). Table 6 shows the most common ways of combining rules.

Unmatched Password Pairs. After testing all the above rules, there are 46.4% of password pairs remain unmatched. To make sure we did not miss any major rules, we randomly sample 1000 unmatched pairs for manual examination. We did not find any password pair that still exhibited a meaningful transformation. We regard the 46.4% of password pairs as the result of users “making new passwords from scratch”.

5.2 Impact of User Demographics

Next, we seek to understand how much the transformation patterns differ across different user demographics. We infer user demographics from their email addresses.

Profession. Certain email domains are exclusive to people of special organizations. For example, “.edu” is limited to higher educational institutions, “.mil” is exclusively to military, and “.gov” represents government agencies. In total, we identify 128,036 users from educational institutions, 7,376 users from military, and 3,384 users from the government. As shown in Figure 3(a), we find that their password transformation patterns are surprisingly consistently: about 30% password pairs are identical, followed by those that apply the substring rule (about 10%), common substring rule (about 5%) and capitalization rule (about 3%). Rules such as leet, reversal and sequential key are consistently below 1%.

Country. Similar results are observed in Figure 3(b) where we divide users based on their countries. More specifically, we identify email domains that contain a country code (e.g., “.ru” stands for Russia). This returns 233 country
codes and 5,892,528 users. In Figure 3(b), we plot the distributions of the transformation rules for the top 10 countries (counting for 90.5% of the users with a country code). Again, the transformation patterns are very similar for users from different countries.

Our result demonstrates a high-level of consistency (low variance) for password transformation patterns across different user populations. This, however, could make the attacker’s job easier. Even using a small dataset, it is possible for the attacker to learn the basic transformation patterns that apply to broader user populations. In the next section, we develop a training-based algorithm to validate this hypothesis.

6. PASSWORD GUESSING

Based on the measurement results, we then evaluate the security risks introduce by users modifying an existing password for different services. We perform password guessing experiments using a training-based algorithm to answer two key questions: First, how quickly can attackers guess a modified password based on a known one? Second, given the low variance of password transformation patterns, can attackers use a small training data (e.g., 0.1%) to achieve effective guessing?

6.1 Guessing Algorithm

We build a new password guessing algorithm by addressing the weaknesses in DBCBW [6]. DBCBW is a popular algorithm to guess a target user’s password by transforming a known password of the same user. DBCBW’s design goal is simplicity, but has two weaknesses: First, due to the lack of training data, the algorithm uses hand-crafted transformation rules. Second, it applies these rules in a fixed order, which may not be optimal for individual passwords. For example, “l0ve” should try the leet rule first (0→ö), even though the substring rule is overall more popular.

Our algorithm overcomes these drawbacks by introducing a training phase. Using ground-truth password pairs as the training data, we learn two things: (1) the transformation procedure for each rule, and (2) a model to customize the ordering of the rules for each password.

Training: Transformation Procedures. For each rule $R_i$, we seek to learn a list of password transformations $T_i = [t_{i1}, t_{i2}, ... t_{iN}]$ where $t_{ij}$ represent one transformation under this rule. $T_i$ is sorted by the frequency of each transformation’s appearance in the training dataset. During password guessing, we will test each transformation independently. For example, in the “substring rule”, $t$ is characterized by $\langle \text{insert/delete}\rangle \langle \text{position}\rangle \langle \text{string}\rangle$. In “capitalization rule”, $t$ is characterized by $\langle \text{position}\rangle \langle \#\text{chars}\rangle$. In a similar way, we learn the transformation list $T$ for “leet”, “sequential keys” and “reversal”.

Common substring rule is special. During training, we learn the sorted transformation list (insert, delete, replace, substitute, switch orders). However, when applying the transformation to a given password, we need to first split the password to detect potential common substrings. In our design, we test 3 types of candidate: (1) substrings of pure digits/letters/special characters, (2) English words/names, and (3) popular common substrings in the training data. For the “combined rule”, $T$ is a sorted list of rule-combinations where each rule-combination has a sorted list of transformations to be tested.

Training: Rule Ordering. For a given password, we learn which rule should be applied first using a Bayesian model. We treat this as a multiple-class classification problem. Given a password, we train a model to estimate the likelihood that the password can be transformed by each rule. To achieve a quick training, we choose the Naive Bayes classifier (multinomial model) [19], which produces the probability that a data point (password) belong to a class (rule). Based on the probability, we customize the ordering of the rules for this password. Table 7 shows the 18 features used in the Bayesian model.

| 18 Features Extracted from a Password |
|---------------------------------------|
| PW (password) length, # Lowercase letters, # Uppercase letters, # Digits, # Special chars, Letter-only pw?, Digit-only pw?, # Repeated chars, Max # consec. letters, Max # consec. digits, Max # sequential keys, Englishword-only pw?, # Consec. digits (head), # Consec. digits (tail), # Consec. letters (head), # Consec. letters (tail), # Consec. special-chars (head), # Consec. special-chars (tail) |

Password Guessing. For a given password pair $(pw_1, pw_2)$, we test how many attempts are needed to guess $pw_2$ by transforming a known $pw_1$. We first use the Bayesian model to generate a customized order of rules for $pw_1$. Following the ordered rule list, we have two options for guessing:

- **Sequential**: testing one rule at a time. After testing all the transformations under a rule, we move to the next rule. Since certain rules have a significantly longer list than others, we set a threshold $M$ as the maximum number of guesses under each rule ($M = 800$ for our experiment).
- **Rotational**: testing one rule and one transformation at a time. After testing one transformation under a rule, we move to the next rule to test another transformation. We rotate to test each rule for just one guess.

Sequential guessing requires a higher accuracy of the predicted order. If the predicted order is wrong, it will waste many guesses on the wrong rule before moving on. Rotational method is more tolerable to the prediction errors.

Baselines. We use two baselines for comparison. First, instead of customizing the order for each password, we apply the rules with a fixed order for “sequential guessing” (similar to DBCBW). The fixed order is based on the overall rule popularity in the training data. Our second baseline is a popular off-the-shelf password cracking tool John the Ripper (JtR) [2]. We use the “single” mode of JtR and keep the default setting. Given a password, JtR applies a list of mangling rules to transform the password. The guessing stops when all the mangling rules are exhaustively tested.
6.2 Password Guessing Results

We use the proposed algorithm to evaluate the risks of modified passwords. For this experiment, we exclude identical password pairs (34.3%) since they only take one guess, and 46.4% of pairs that did not match a rule (i.e., new passwords created from scratch). This leaves us 7,196,242 password pairs that represent password modifications (exp dataset).

We conduct two experiments. First, we split the exp dataset to use 50% for training and the other 50% for testing. Second, to validate the “low-variance” assumption we try to use much smaller training data.

**Training on 50% of the Data.** During password guessing, we test both directions for each password pair ($pw_1 \rightarrow pw_2$ and $pw_2 \rightarrow pw_1$), which doubles the testing data. As shown in Figure 4, our best algorithm guessed 46.5% of the passwords within just 100 attempts. Figure 4(b) shows that 10 guesses already cracked 30% of the passwords. In comparison, the JtR baseline almost got nothing in the first 10 attempts and exhausted all the mangling rules after 1081 guesses. Since we evaluate an online-guessing scenario, we stopped our algorithm after 5000 guesses for each password.

Comparing different algorithms, we show that the Bayesian model outperforms the fixed ordering method. This confirms the benefits to prioritize the more likely rules for each password. In addition, rotational guessing is better than sequential guessing. Sequential guessing has a clear stair-step increase of the hit rate after switching to a new rule. This indicates that the first few transformations under each rule are the most effective ones. Sequential guessing’s advantage is in the first 5 guesses (Figure 4(b)) — if the Bayesian prediction is correct, sticking to the right rule helped to guess the password quicker. Rotational guessing has an overall better performance by switching the rules more frequently.

**Using Smaller Training Data.** To validate the low-variance assumption of the transformation patterns, we use even smaller datasets to train our algorithm (Bayesian+rotational). We vary the size of the training data from 0.01% to 10% of the exp dataset. To be consistent, we use the same 50% as the testing data (training and testing data has no overlap). As shown in Figure 5, the 0.1%-training curve is still overlapped with the 50%-curve, suggesting that extremely small training data can achieve a comparable performance. This confirms the low-variance in password transformation patterns. Intuitively, users modify a password for the ease of remembering. This is likely to introduce easy-to-predict passwords.

To measure the number of vulnerable password pairs, we use the 0.1%-trained model to guess the rest 99.9% of the password pairs. Since we guess both directions, the testing data essentially has 14 million passwords. Within 10 attempts, we guessed 30% (4.2 million passwords) — 3.8 million password pairs are cracked for at least one direction. Together with the identical password pairs (12.8 million), over 16.6 million pairs can be cracked within 10 attempts.

**Cracking the Remaining Hashes.** Finally, we perform a quick experiment on the uncracked hashes in Section 3. In total, we have 6,218,778 password pairs where one password is an uncracked hash, and the other one is in plaintext. Our algorithm successfully recovered 939,400 (15.1%) of the hashes within 5000 attempts, which demonstrates the value of our algorithm over existing offline cracking tools. As a future work, we plan to further test our algorithm on salted password hashes.

7. DISCUSSION

After analyzing 28.8 million users’ passwords across 107 services, we find that a majority of users have reused the same password or slightly modified an existing password for different services. Password modification patterns are highly consistent across various user populations, allowing attackers to crack massive passwords online with minimal training.

Moving forward, the challenge is how to effectively mitigate the threat after a service is breached. Given the high reuse rate of passwords, it is necessary to immediately notify users to reset the password, not only for the breached service but also other services with a similar password. The question is who should play the role to notify users, given that not all the breached services would immediately disclose the incident or contact users [16, 27]. In addition, during password reset, it is critical to make sure users don’t modify the already-leaked password to create the new one. A better practice is to use password managers (e.g., 1Password) to set unique and complex passwords for each service without the need to memorize them. Finally, our result shows a concerning high ratio of email password reuse. We argue that more specific warnings should be given to users to avoid reusing the email password when signing up for a service.

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2 Our experiment shows that 50,000 guesses can crack 70%.
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