Context Aware Password Guessability via Multi-Dimensional Rank Estimation

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Abstract—Password strength estimators are used to help users avoid picking weak passwords. Existing probabilistic estimators use various approaches to predict how many attempts a password cracker would need until it finds a given password.

In this paper we present the first method for estimating the strength of human-chosen text passwords that is able to tweak the estimation according to each user’s personal context, without retraining its model.

Our method is able to incorporate context such as the user’s name, preferred suffix, or previously cracked passwords (if available) when estimating the current password’s strength. Based on a corpus of 1.4 billion leaked passwords, we demonstrate that there is significant correlation between the user’s name and the chosen password, and that users’ likelihood of reusing a password is as high as 22%. Since our method’s context-aware tweaking only takes a few seconds per password, our strength estimations show that many passwords are in fact much weaker than previously estimated, once context is taken into account.

Our idea is to cast the question in a probabilistic framework used in side-channel cryptography. We view each password as a point in a \( d \)-dimensional search space, and learn the probability distribution of each dimension separately. The a-priori probability of a given password is the product of the \( d \) probabilities of its sub-passwords.

After a detailed evaluation of leaked password corpora we found that an effective choice is to use \( d = 5 \) dimensions: base word, prefix, suffix, shift-pattern, and l33t transformation. We coupled this decomposition with a state-of-the-art rank estimation algorithm to create our new PESrank estimator.

We show that PESrank is more powerful than previous methods: it can crack more passwords, with fewer attempts, than the password crackers we compared it to. Even without using per-user context, PESrank is more accurate than previous methods for crackable passwords whose rank is smaller than \( 10^{12} \). Furthermore, its training time is drastically shorter than previous methods, taking minutes, rather than days, to train on comparably-sized training sets, and taking a few hours to train on 905 million passwords, which is 8 times more passwords than previously used.

1. Introduction

1.1. Background

Text passwords are currently the most popular authentication and are still in widespread use specially for online authentication on the Internet. Unfortunately, users often choose predictable and easy passwords, enabling password guessing attacks. Password strength estimators are used to help users avoid picking weak passwords. The most precise definition of password’s strength is the number of attempts that an attacker would need in order to guess it [9].

A common way to evaluate the strength of a password is by running or simulating password-guessing techniques. Methods such as counts of lower- and uppercase characters, digits, and symbols (LUDS) have been used to measure the strength of passwords. Despite it being well-known that these do not accurately capture password strength [55], they are still used in practice. More sophisticated password strength estimators have been proposed e.g., based on Markov models [27], [23], [11], probabilistic context-free grammars (PCFGs) [36], [21], neural networks [26], [33] and others [38], [16].

1.2. Related Work

Password strength measurement often takes one of two conceptual forms: pure-estimator approaches, and cracker-based approaches. In the latter, either an actual password cracker is utilized to evaluate the password strength—or the meter uses an accurate model of the number of attempts a particular cracker would use until reaching the given password. In pure-estimator approaches, the model provides a strength estimate directly from attributes of the password, without an accompanying passwords cracker that can achieve the predicted number of attempts.

1.2.1. Pure-Estimator Approaches. The earliest and probably the most popular methods of password strength estimation are based on LUDS: counts of lower- and uppercase letters, digits and symbols. The de-facto standard for this type of method is the NIST 800-63 standard [8], [15]. It proposes to measure password strength in entropy bits, on
the basis of some simple rules such as the length of the password and the type of characters used (e.g., lower-case, upper-case, or digits). These methods are known to be quite inaccurate since simple, easily compressible heuristics.

In 2012 Wheeler proposed an advanced password strength estimator [37], that extends the LUDS approach by including dictionaries, considering list speak transformations, keyboard walks, and more. Due to its easy to integrate design, it is deployed on many websites. The meter’s accuracy was later backed up by scientific analysis [38].

In 2018 Guo et al. [16] proposed a lightweight client-side meter. It is based on cosine-length and password-edit distance similarity. It transforms a password into a LUDS vector and compares it to a standardized strong-password vector using the aforementioned similarity measures.

Such pure-estimator approaches have the advantage of very fast estimation—typically in fractions of a second—which makes them suitable for online client-side implementation. However, they do not directly model adversarial guessing so their accuracy requires evaluation.

1.2.2. Cracker-Based Approaches. Software tools are commonly used to generate password guesses [14]. The most popular tools transform a wordlist using mangling rules, or transformations intended to model common behaviors in how humans craft passwords. Two popular tools of this type are Hashcat [17] and John the Ripper [28].

These tools typically run until a timeout is triggered. If they crack the given password before the timeout then their accuracy is perfect: they can report exactly how many attempts they used. However, if they fail to crack the password by the timeout, they do not estimate how many more attempts would have been necessary. Since they generally take a long time to run (minutes to hours, depending on the timeout setting) their usefulness as online strength estimators is limited.

A probabilistic cracker method, based on a Markov model, was first proposed in 2005 [27], and studied more comprehensively subsequently [5, 23, 11]. Conceptually, Markov models predict the probability of the next character in a password based on the previous characters, or context characters. In 2009 Weir et al. [36] proposed a method which uses probabilistic context-free grammars (PCFGs). The intuition behind PCFGs is that passwords are built with template structures (e.g., 6 letters followed by 2 digits) and terminals that fit into those structures. A password’s probability is the probability of its structure multiplied by those of its terminals. In 2015 the PCFGs method was integrated with the technique reported by Komanduri in his PhD thesis [21]. In 2016 Melicher et al. [26] proposed to use a recurrent neural network for probabilistic password modeling.

The basic Markov, PCFGs, and neural-network approaches generate a long sequence of passwords, and assign each password with an a-priori probability. This one-dimensional sequence is then sorted in decreasing order of probability, and stored in a password-candidate DB. Given a password to crack, the cracker attempts all the passwords in the DB, in their order, until a match is found. Building the password-candidate DB can be very time consuming, and the DB can grow very large. However, if the password-candidate DB is prepared in advance and indexed, then measuring the strength of a given password is very fast, and perfectly accurate.

In [26] the authors also describe a Monte-Carlo method to sample the password DB and store only the sample for online password strength measurement. They suggested a probabilistic calculation to estimate the number of guessing attempts needed to crack a given password, based on its a-priori probability calculated by the neural-network, in combination with the stored sample. This Monte-Carlo approach significantly reduces the DB size, making it suitable for client-side implementation. However, with the Monte-Carlo sampling, the neural-network method can be viewed as a strength estimator, whose accuracy needs to be evaluated.

In our evaluation study we used Ur et al.’s Password Guessability Service [4] (PGS), which provides access to the Hashcat [17] and John the Ripper [28] crackers, and the Markov [27] and PCFGs [36] the neural-network method [26] using Monte-Carlo methods.

1.3. Contributions

In this paper we present the first method for estimating the strength of human-chosen text passwords that is able to tweak the estimation according to each user’s personal context, without retraining its model.

Our method is able to incorporate context such as the user’s name, preferred suffix, or previously cracked passwords (if available) when estimating the current password’s strength. Based on the Jason corpus of leaked passwords [18], which contains 1.4 billion usernames and passwords, we demonstrate that there is significant correlation between the user’s name and the chosen password, and that users’ likelihood of reusing a password is as high as 22%. Since our method’s context-aware tweaking only takes a few seconds per password, our strength estimations show that many passwords are in fact much weaker than previously estimated, once context is taken into account.

Our idea is to cast the question in a probabilistic framework used in side-channel cryptography. We view each password as a point in a $d$-dimensional search space, and learn the probability distribution of each dimension separately. This learning process is based on empirical password frequencies extracted from leaked password corpora, that are projected onto the $d$ dimensions. Once the $d$ probability distributions are learned, the a-priori probability of a given password is the product of the $d$ probabilities of its sub-passwords.

Using this model, optimal-order password cracking is done by searching the space in decreasing order of a-priori password probability, which is analogous to side-channel key enumeration; likewise, password strength estimation is analogous to side-channel rank estimation. There is exten-
sive research and well known algorithms for both problems in the side-channel cryptanalysis literature.

After a detailed evaluation of leaked password corpora we found that an effective choice is to use \( d = 5 \) dimensions: base word, prefix, suffix, shift-pattern, and \( 133t \) transformation. We coupled this decomposition with the rank estimation algorithm of [2] to create our new, tweakable, PESrank estimator.

We compared the ranks calculated by PESrank to the ranks obtained by five password crackers using the PGS service [4]. We show that PESrank is more powerful than previous methods: it can crack more passwords, with fewer attempts, than the password crackers we compared it to. Even without using per-user context, PESrank is more accurate than previous methods for crackable passwords whose rank is smaller than \( 10^{12} \).

Furthermore, its training time is drastically shorter than previous methods, taking minutes, rather than days, to train on comparably-sized training sets, and taking a few hours to train on 905 million passwords, which is 8 times more than previously used.

We plan to make our Python code implementing PESrank publicly-available.

**Organization:** In the next section we introduce the background on side-channel key enumeration and rank estimation. In Section 5 we describe our multi-dimensional password model. In Section 4 we describe the dimension selection process we applied. In Section 5 we discuss the benefit of using personal context when estimating the password strength. In Section 6 we discuss modeling password reuse in the model. In Section 7 we compare PESrank to other existing methods and discuss our findings. In Section 8 we discuss the lookup time of our PESrank both with and without using context. We conclude with Section 9.

## 2. Rank Estimation and Key Enumeration

Cryptographic Side-Channel Attacks

Side-channel attacks (SCA) represent a serious threat to the security of cryptographic hardware products. As such, they reveal the secret key of a cryptosystem based on leakage information gained from physical implementation of the cryptosystem on different devices. Information provided by sources such as timing [20], power consumption [19], electromagnetic emulsion [30], electromagnetic radiation [11], [12] and other sources, can be exploited by SCA to break cryptosystems.

A security evaluation of a cryptographic device should determine whether an implementation is secure against such an attack. To do so, the evaluator needs to determine how much time, what kind of computing power and how much storage a malicious attacker would need to recover the key given the side-channel leakages. The leakage of cryptographic implementations is highly device-specific, therefore the usual strategy for an evaluation laboratory is to launch a set of popular attacks, and to determine whether the adversary can break the implementation (i.e., recover the key) using “reasonable” efforts.

Most of the attacks that have been published in the literature are based on a “divide-and-conquer” strategy. In the first “divide” part, the cryptanalyst recovers multi-dimensional information about different parts of the key, usually called subkeys (e.g., each of the \( d = 16 \) AES key bytes can be a subkey). In the “conquer” part the cryptanalyst combines the information all together in an efficient way via key enumeration.

### 2.1. The Key Enumeration Problem

The cryptanalyst obtains \( d \) independent subkey spaces \( k_1, \ldots, k_d \), each of size \( n \), and their corresponding probability distributions \( P_{k_1}, \ldots, P_{k_d} \). The problem is to enumerate the full-key space in decreasing probability order, from the most likely key to the least, when the probability of a full key is defined as the product of its subkey’s probabilities.

A naive solution for key enumeration would be to take the Cartesian product of the \( d \) dimensions, and sort the \( n^d \) full keys in decreasing order of probability. However this approach is generally infeasible due to both time and space complexity. Therefore several algorithms offering better time/space tradeoffs have been devised. The currently best optimal-order key enumeration is \([33]\), with an \( O(n^{d/2}) \) space complexity, and near-optimal-order key enumeration algorithms with drastically lower space complexities are those of \([6], [25], [2], [29], [24]\).

### 2.2. The Rank Estimation Problem

Unlike a cryptanalyst trying to extract the secret key, a security evaluator knows the secret key and aims to estimate the number of decryption attempts the attacker needs to do before he reaches the correct key, assuming the attacker uses the SCA’s multi-dimensional probability distributions. Formally:

*The rank estimation problem:* Given \( d \) independent subkey spaces of sizes \( n_i \) for \( i = 1, \ldots, d \) with their corresponding probability distributions \( P_1, \ldots, P_d \) such that \( P_i \) is sorted in decreasing order of probabilities, and given a key \( k^* \) indexed by \( (k_1, \ldots, k_d) \), let \( p^* = P_1(k_1) \cdot P_2(k_2) \cdot \ldots \cdot P_d(k_d) \) be the probability of \( k^* \) to be the correct key. Estimate the number of full keys with probability higher than \( p^* \), when the probability of a full key is defined as the product of its subkey’s probabilities.

In other words, the evaluator would like to estimate \( k^* \)’s *rank*: the position of the key \( k^* \) in the sorted list of \( n^d \) possible keys when the list is sorted in decreasing probability order, from the most likely key to the least.

While enumerating the keys in the optimal SCA-predicted order is a correct strategy for the evaluator, it is limited by the computational power of the evaluator. Hence using algorithms to estimate the rank of a given key, without enumeration, is of great interest. Multiple rank estimation algorithms appear in the literature, the best of which are currently \([2], [13], [25]\). They all work in fractions of a second and generally offer sub 1-bit accuracy (so up to a multiplicative factor of 2).
3. Multi-Dimensional Models for Passwords

3.1. Overview

The starting point in producing a password strength estimator is a leaked password corpus. The frequency of appearance of each leaked password provides an a-priori probability distribution over the leaked passwords. Given a hash of an unknown password, trying the leaked passwords in decreasing frequency order, is the optimal strategy for a password cracker—if the password at hand is in the corpus. To crack passwords that are not in the leaked corpus as-is, password crackers rely on the observation that people often take a word, which we shall call the base word, and mutate it using various transformations such as adding digits and symbols before or after the base word, capitalizing some of the base word’s letters, or replacing letters by digits or symbols that are visually similar using “1337” translations.

Our main observation is that if we can represent the list of base words as a dimension, and represent each possible class of transformations as another independent dimension, we can pose the password cracking problem as a key enumeration problem, and similarly, pose the password strength estimation as a rank estimation problem. Each dimension should have its own probability distribution: e.g., as we shall see, for the “suffix” dimension, the most probable in our training set is the “empty” suffix, with $Pr = 0.49$, followed by that of appending a digit ‘1’ ($Pr = 0.062$) etc. Once we pose the password strength estimation question this way, we can use existing algorithms. A multi-dimensional password cracker would enumerate combinations of base word plus a transformation in every dimension, in decreasing order of the product of per-dimension a-priori probabilities. For each combination it would apply all the transformations to the base word, and test the password. The matching multi-dimensional password strength estimator decomposes a given password into its base word and a transformation in every dimension, uses the model to calculate the a-priori probability of the password, and then estimates its rank.

Thus, we arrive at the following framework: First, identify meaningful classes of transformations, and find a suitable representation for each as a dimension. Next, build a probability distribution for each dimension using the training corpus, to create a model. Finally, use a good rank estimation algorithm with the model and evaluate its performance.

3.2. The Data Corpus

To study the statistical properties of passwords, and then to train our method, we used Jason’s corpus of leaked passwords [18]. This corpus contains 1.4 billion pairs of username and password, compiled from multiple leaked corpora: Yahoo, Target, Facebook, Hotmail, Twitter, MySpace, hacked PHPBB instances, and many, many more places. We believe that Jason’s corpus is a superset of the corpora used to train previous methods.

The “username” field in Jason’s corpus is generally an email address, e.g., adaml234@gmail.com. It should be noted that the passwords provided in the corpus are not necessarily the passwords of the email accounts themselves (although they could be). Rather, the email addresses provided were harvested as the username for the breached entity in question, and the password provided is the password that was used with that username at the time of the breach.

We eliminated passwords that contain non-ASCII characters. We also eliminated passwords of fewer than 8 characters, in order to make our training comparable to that of the methods accessible via PGS [4]—in particular, the PGS implementation of the neural method [26] is trained on passwords of length 8 or more. The result was a corpus of 905 million passwords.

From this corpus we sampled 300,000 username-password pairs, to serve as a test set. We split the test set into 10 separate samples, of 30,000 passwords each, and submitted all the sample sets to PGS for evaluation. Of the remaining passwords, we down-sampled the corpus into 5 different-size training sets, to explore the effect of the training-set size on the training time and the strength estimations. We used the following sizes for the smaller training sets: (1) 41 million username-passwords pairs (2) 113 million username-passwords pairs (3) 226 million username-passwords pairs (4) 452 million username-passwords pairs (5) and finally, 905 million username-passwords pairs.

4. Selecting the Dimensions

Our main goal in selecting the dimensions is generalization. For instance, if we recognize that a suffix of ‘1’ has probability $p_1$, and that the base word ‘iloveyou’ has probability $p_2$, a 2-dimensional model will implicitly incorporate the password ‘iloveyou1’, with probability $p_1 \cdot p_2$, even if it does not appear as-is in the training corpus.

4.1. The Basic 3D model

In our simplest model we divide each password into 3 sub-passwords: prefix, base word and suffix. The prefix consists of all the digits and symbols that appear to the left of the leftmost letter. The suffix consists of the digits and symbols that appear to the right of the rightmost letter. The base word is the string starting with the leftmost letter and ending with the rightmost letter. The base word can consist of letters, digits and/or symbols. For example if the password is the string ‘123abc45!’ the prefix is ‘123’, the base word is ‘abc’ and the suffix is ‘45!’. In case there are no letters in the password, the password itself is considered to be the base word, and the prefix and suffix are the empty strings. In case the password starts with a letter, the prefix is the empty string, and similarly, if the password ends with a letter, the suffix is the empty string.

4.2. Using The Model

We use this basic 3D model description to demonstrate the process we followed in training and evaluating it. We followed the same process with the other, more sophisticated, models we describe in subsequent sections.
4.2.1. The Learning Phase. We first learn the distributions of the prefix, the base word and the suffix, using one of the training set sampled from the Jason corpus [18]—recall Section 3.2. For each password in the training set, we divide the password into its three sub-passwords, as described above, and increment the dimensional-frequency of each sub-password by 1. Finally we normalize the three lists of frequencies into probability distributions, and sort them in decreasing order. For instance, in the 3D model, using the 41 million password training set, the two most popular base words are ‘a’ (Pr = 0.0046) and ‘password’ (Pr = 0.0035), the two most popular prefixes are the empty string (Pr = 0.910) and ‘1’ (Pr = 0.0090), and the most popular suffixes are also the empty string (Pr = 0.497) and ‘.’ (Pr = 0.062).

4.2.2. The Estimation Phase. Given that we know the order in which a model-based cracker goes over the password candidates, we can use it to estimate the password guessability. Given a password $P$, we split into its sub-passwords $P = p^*|b^*|s^*$ where $p^*$ is a prefix, $b^*$ is a base word, and $s^*$ is a suffix. With this, using the three probability distributions $P_1$, $P_2$, $P_3$, we can apply a rank estimation algorithm such as [7]. The algorithm estimates the number of 3-part passwords $p_i||b_j||s_k$ (split in the same way), whose probabilities obey

$$P_1(i) \cdot P_2(j) \cdot P_3(k) \geq P_1(p^*) \cdot P_2(b^*) \cdot P_3(s^*).$$

In other words, it estimates the number of guesses a model-based cracker would attempt before reaching the given password $P$.

If the password $P = p^*|b^*|s^*$ is not in the model, which means that at least one of the sub-passwords does not appear in the corresponding distribution, then we return -5 (following the behavior of PGS [4] under analogous conditions).

4.3. 4D: Adding the Shift Pattern

The next level of sophistication is to add another dimension, to represent the “shift pattern”: the pattern of upper-case and lower-case letters in the passwords.

To begin with we split a password into its 3D sub-passwords as in Section 4.1. We only consider the shift pattern within the base word. Given a base word, it is clear which of its letters are shifted (upper case) and which are not. However, we have a choice how to represent the pattern. The obvious option is to represent the pattern as a binary string, with a ‘1’ bit in position $j$ indicating that the $j$’th letter is capitalized. However, this representation is closely tied to the word’s length: e.g., position 5 could indicate the last letter in a 5-letter word, or the before-last letter in a 6-letter word, etc. Our intuition, and a preliminary inspection of the Jason [18] corpus, show that people tend to associate significance to the distance from the word’s end: e.g., capitalizing the last letter is fairly common (Pr = 0.0011). Therefore we elected to represent the shift pattern as a list of positive and negative indices at which capital letters appear. The negative indices count from the word end, with -1 representing the rightmost letter. The positive indices count from the word start, with 0 representing the leftmost letter. To avoid ambiguity, both the negative and the positive indices do not exceed the middle index.

We augment the 3D learning phase as follows. As in the 3D case, we divide each password into three sub-passwords: prefix, base word and suffix. Then, we find the indices at which there are upper case letters in base word, and represent their pattern using our positive/negative index representation. We increment the frequency of the pattern in the fourth dimension by 1.

Furthermore, before incrementing the base word’s frequency, we “unshift” it, i.e., we ensure that all the base word letters are in lower case. If there is no letter in the base word, the password itself is the base word and the shift pattern is empty. Examples of the 4D decomposition appear in Table 1.

The two most popular shift patterns we found in our training set are the empty transformation (Pr = 0.923) and ‘[0]’, representing capitalizing the first letter (Pr = 0.034).

Note that the shift-pattern dimension is not strictly independent of the base-word dimension: e.g., a shift pattern $t$ may refer to indices that are outside a short base word $b$, or $b$’s characters at the indexed positions may be symbols or digits (which do not have a capitalized form). In such cases the transformation $t$ degenerates into the null transformation. For a model-based password cracker, this dependence implies some inefficiency, since the cracker will test the same password multiple times, once for each shift-pattern that is equivalent to the null transformation for the current base word. The rank estimation, which assumes an independence between the dimensions, accounts for the cracker’s inefficiency. This means that the estimated rank of a password using the 4D model can actually be viewed as an over-estimate: a more sophisticated cracker could skip null transformations and save itself time. As we shall see in Section 7, despite this structural tendency to over-estimate, in the experimental evaluation the resulting PESrank algorithm actually under-estimates the “ground-truth” ranks fairly often—which means that a model-based password cracker may perform even better.

4.4. 5D: 133t

As observed by [38], it is well documented that people sometimes mutate passwords using “133t” transformations: replacing base-word letters by digits and symbols that are visually similar. We elected to add the 133t transformation as a fifth dimension to our model. The 133t transformations we considered are shown in Table 2.

As in the 4D case (Section 4.3), we need to devise a representation for the 133t pattern. In principle the 133t

| password | prefix | base word | suffix | shift pattern |
|----------|--------|-----------|--------|---------------|
| 123      |        |           |        |               |
| 1234567890 | empty | 1234567890 | empty |               |
| 123qweASD | 123    | qweasd    | empty | [-3,-2,-1]    |

### Table 1. 4D Decomposition Examples
The two most popular l33t patterns in our training set are the empty transformation (Pr = 0.900) and the l33t pattern ‘4’ → ‘a’ (Pr = 0.007). The total number of l33t patterns we detected in the corpus is 1596.

4.5. Model Enrichment

As we shall see, using a 5D model gives us good generalization capabilities beyond the training data. However, following [22], [32], [10], we know that people have a tendency to choose passwords that contain dates and meaningful numbers. To take this observation into account, we enriched the probability distributions of the prefix, base word, and suffix dimensions, by adding strings that are not present in the training corpus. Every string that is added to a given dimension is added with a frequency $\epsilon = 0.5$, to account for the fact that it didn’t appear in the corpus. The resulting frequencies: those computed from the corpus (with values $\geq 1$), together with all enriched $\epsilon$ values, are then normalized into a probability distribution. We tested other values $\epsilon \neq 0.5$ but they all performed similarly as long as $\epsilon < 1$. If the current enrichment string exists in the corpus with an empirical frequency $f$, we update its frequency to $f + \epsilon$. We enriched the model in two ways:

- All the digit sequences of up to 4 digits were added to the prefix and suffix distributions.
- All the digit sequences of length exactly 6 were added to the base word distribution.

Note that this enrichment gives good coverage of many date patterns: adding all the 6-digit strings to the base words covers all the dates that have patterns of ddmmyy or yymmdm or mmdy, and most of the dates with a 4-digit year, such as 98 or 2003. An 8-digit date, e.g., with a ddmmymmm format, as a stand-alone password, is also included in the model as both a 2-digit prefix plus a 6-digit base word, and as a 6-digit base word plus a 2-digit suffix.

Now for a given password which is composed only of digits, the enriched model may include several options to reach this password by the model-based password cracker. As we saw with an 8-digit date example, a numeric password can be divided into prefix, base word, and suffix, in different ways, and the enriched model may include all the sub-passwords in the respective distributions. To account for this condition in the rank estimation, we added special handling of numeric passwords. For such a password, the PESRank algorithm iterates over all its possible divisions into 3 sub-passwords (of any length): for an $\ell$-digit password there are exactly $\binom{\ell + 1}{\ell - 2}$ possibilities. For each division whose 3 sub-passwords appear in the model we calculate the password’s probability. Finally, we return the rank of the division with the highest probability, since this is the division that will be encountered first by the optimal enumeration algorithm.
4.6. Basic Model Evaluation

In order to evaluate our 4 models we computed for each model:

1) The percentage of passwords that would be cracked after a particular number of guesses: in other words, the Cumulative Distribution Function (CDF) of each model. More powerful guessing methods guess a higher percentage of passwords in our test set, and do so with fewer guesses: hence a better model has a CDF that rises more sharply and ultimately reaches a higher percentage.

2) The model size: we calculated the Total Dimension Length—the sum of all the dimensions length i.e., \( \sum_{i=1}^{d} n_i \). This metric counts the total number of (password-fragment, probability) pairs in the model. We also calculated the models’ file sizes (uncompressed and compressed).

3) volume: this is the total number of passwords that can be reached using our model. When the model has \( d \) dimensions, whose sizes are \( n_i \) for \( i = 1, \ldots, d \), then volume \( = \prod_{i=1}^{d} n_i \).

We trained the four models using the 41 million password training set, and evaluated them using 10 different test sets (recall Section 3.2). The results are shown in Figure 1. The 10 graphs of the different test sets look similar, therefore we show only one of them.

In Figure 1, the x-axis represents the number of guesses (log scale) and the y-axis shows the corresponding percentage of passwords in the test set that can be guessed in that number of guesses. As we can see, the method becomes more powerful with each added dimension, successfully cracking a greater fraction of the passwords, with fewer attempts. We also see that adding the enrichment by numeric strings as described in Section 4.5 is very effective.

In Table 3, we can see the model sizes of the different models. The table shows that the model size decreases with the added dimensions, Table 3 shows that the volume grows dramatically, from a raw corpus of about \( 10^8 \) passwords to a password volume of \( 10^{19} \) in the 3D model, and by another 8 orders of magnitude reaching about \( 10^{27} \) with the 5D+ model.

We conclude that the enriched 5D+ model is superior to the simpler alternatives, and it’s size is well within the capabilities of modern computers. In the remainder of this paper we use this enriched 5D+ model.

4.7. Training Time

We tested our Python implementation of PESrank’s training on a 3.40GHz core 7 PC running Windows 8.1 64-bit with 32GB RAM. Figure 2 shows the time to train PESrank as a function of the training set size. The figure shows that the PESrank training phase is quite fast—much faster than reported for previous methods. It takes only 12 minutes to train PESrank on a corpus of 41 million passwords, in comparison to the days of training reported for the Markov [23] or PCFG [36] methods, that were trained on the similarly-sized “PGS training set”. To train our method on 113 million passwords, it took only 34.5 minutes, in comparison to the days it took to train the neural method [26] on the similarly-sized “PGS++ training set” (see more details in Section 7.1). Because the PESrank training time is fast, we are able to train PESrank on a corpus of roughly 8 times the size of the “PGS++ training set”, with 905 million passwords, and even on this corpus the training only took 4.5 hours.
4.8. Storage Requirements

Beyond Table 3, Figure 3 shows the effect of the training set size on the storage requirements. As we can see, the required storage grows sub-linearly with the training set size, reaching 7.5GB with the 905 million passwords training set: significantly less than the 40GB of the raw Jason corpus, and well within the capabilities of modern computers.

5. Adding Context

A large corpus such as the Jason corpus [18] includes passwords obtained from multiple sources. Therefore training a password model from such a corpus constructs a general-purpose model that is suitable to estimate the password strength of many suggested passwords. However, if additional information is available to the password cracker, or the strength estimator, about the user owning the password, it is advantageous to customize the general-purpose model. In general we call the additional per-user information the context. If the password cracking is part of a targeted attack against an individual, then detailed context information can come from many sources such as social media or social engineering. However, we argue that context is often available even to a general purpose password strength estimator—and that a good estimator should use it. We highlight two easy-to-obtain sources of context:

1) Site context: In some cases, the password strength estimator is embedded in a site, to assist users of that site to pick strong passwords. We hypothesize that some users tend to use the name of the site, or a meaningful part of it, as the base word in their selected password. Therefore, a password model customized for such a site should include the site name and its meaningful parts, with increased probabilities.

2) Personal context: In many cases, the password cracker and the password strength estimator have access to the username or email address associated with the password—e.g., this data would appear in a leaked /etc/passwd + /etc/shadow corpus. One could imagine additional context associated with the password, such as first and last name, etc. Again, we hypothesize that some users tend to use their names and other personal context as base words of their passwords, and if they tend to use prefixes or suffixes in their username—they may tend to use the same prefixes or suffixes in their passwords.

Thus, it may be beneficial to personalize a general-purpose password model for each suggested password, by introducing the known context about the password owner into the model, with elevated probability.

In order to customize a password model, the method must allow efficient tweaking: adding a few base words, prefixes or suffixes, with updated a-priori probabilities, that better model the password choices of the user at hand. Retraining the whole system with the personal information for each new password is impractical: e.g., PCFG [36] and neural [26] report training times measured in days, and even our PESrank takes minutes-to-hours to train (depending on the corpus size, recall Figure 2). Conveniently, since PESrank uses a very simple model representation—essentially a sorted probability list of password elements per dimension—it’s model is efficient to tweak, without the need to retrain.

5.1. Is per-user context present?

We conducted an evaluation of the above-mentioned hypotheses using the Jason corpus [18]. The corpus comprises of pairs of “username”+password: recall Section 3.2. However, the usernames in this corpus look like email addresses: “name@domain.tld”. We used this information to test both the “Personal context” hypothesis, that the username provides information about the password, and the “Site context” hypothesis—assuming that the domain part of the email address is related to the site from which the passwords were leaked.

For each username-password pair in the corpus, we divided the “username” into its name part (the text before the ‘@’ in the username), which we denoted by name, and its domain part (the text between the ‘@’ and the
We then split the name into its 3D dimensions, as described in Section 3: prefix, base word, and suffix. We split the password into its 3D dimensions as well. For example, for the username adam123@myspace.com and the password ‘!adam!’, the name is ‘adam123’, its base word is ‘adam’, which is equal to the password base word. For the username aaaa111@myspace.com and the password myspace111 the domain ‘myspace’ is equal to the password base word, and the name suffix ‘111’ is equal to the password suffix. We then counted the number of passwords with:

1) prefix equal to the name prefix.
2) base word equal to the name base word.
3) suffix equal to the name suffix.
4) base word equal to the domain.
5) full password identical to the full username.

Table 4 provides the results. According to Table 4, there is significant context information in the name’s base word, and in the name’s suffix: 2.478% and 2.570% respectively. The prefix dimension of the username seems to carry much less context, with less than 0.1% of records in the corpus showing a match.

We therefore conclude that the username in the email address carries significant contextual information, specifically in its base word and suffix, and we argue that the “Personal context” hypothesis is validated.

Conversely, we find that “Site context” is weak in the Jason corpus: less that 0.1% of the passwords matched the domain. A possible reason is that the domain part of the email address is not a good indicator to the site at which the password was used. However, we feel that people tendency to use the site name in their passwords is still a valid hypothesis, which can be tested with corpora whose origin is more clear.

For the purposes of password cracking and password strength estimation, it is reasonable to assume that a-priori, the password suffix has a 2.570% probability of matching the name’s suffix, and the a-priori probability the password’s base word matching name’s base word is 2.478%.

### 5.2. Using Context in PESrank

Recall that PESrank uses a very simple model representation: it keeps a sorted probability list of password elements per dimension. Therefore, all that is required to tweak one of its dimensions (e.g., adding a base word \( w \) with a-priori probability \( p \)) is:

\[
p_w = p \cdot \Delta p^w
\]

where \( p_w \) is the post-tweaking probability of \( w \) in the dimension’s probability distribution, and \( \Delta p = p - p_w \).

- Let \( p_0 \) be the pre-tweaking probability of \( w \) in the dimension’s probability distribution, and let \( \Delta p = p - p_0 \). Normalize the probabilities of all the other words in that dimension by multiplying each with \( 1 - \Delta p \).
- Insert \( w \) into its correct place in the sorted order, with probability \( p \). If \( w \) was already present in the distribution, update its probability to be \( p \).

Note that since the dimension’s list is already sorted, both insertion and normalization can be done very efficiently, within seconds, in a single pass of the list, without need to re-sort.

Beyond its superior training time in comparison to earlier works, the “tweakability” of PESrank makes using personal context very practical. It can be done on-line, as part of the strength estimation of a suggested password: waiting a some extra seconds during password registration is not excessive. And certainly using context can be done during an evaluation study such as ours.

To evaluate the advantages of the username context contribution we used 11,880 password-username pairs from our test set. First we calculated the strength of each password using the 5D+ enrichment model using the 41 million training corpus. Then, for each password, we tweaked the base word dimension with the name’s base word at probability 2.478%, tweaked the suffix dimension with the name’s suffix at probability 2.570%, and calculated the strength of the password using the tweaked model.

Figure 4 shows the results. In general we can see that adding context improves the estimation, and rank estimates are provided for 65.5% of the passwords with context, 1.1% more than without context. However, importantly, the improvement is most noticeable in the left side of the CDF curves: we can see that, with context, a significant number of passwords are discovered to be very weak: 20.6% of the passwords can be cracked with fewer than \( 10^6 \) attempts when using context, in comparison to 18.4% without context. We conclude that incorporating even the very limited context present in the username can greatly benefit the
password cracker, and deserves to be included in the strength estimate of a proposed password.

6. Modeling Password Reuse

It is well documented that people tend to reuse their previous passwords, either exactly, or with some variations. Therefore we hypothesize that knowledge of a user’s previous passwords can be a powerful source of context when cracking her current new password. Conveniently, the Jason corpus [18] allows us to quantify the amount of information a password cracker gains from such historical knowledge.

By a simple search of the Jason corpus [18] we discovered that many users reuse their password exactly. Specifically, as in Section 5.1, we extracted the name part of each username, and we found that for 22% of the records in the corpus there exists at least one more record with the same name and the same current password. In this search we made the plausible assumption that all the email addresses of the form adaml23@domain.tld belong to the same person. This 22% statistic may actually be an underestimate, since it does not take into account the manipulations that users employ (e.g., retaining the base word and changing the prefix or suffix when setting passwords on different sites).

Therefore, when cracking, or evaluating the strength of a user’s password, if we know previous passwords belonging to a user with the same name, it is reasonable to assume that one of her known passwords or their variants is being reused with an a-priori probability of 22%.

We used this information as a personal context to customize PESrank in the following way: For each user in the test set:

1) Let $L$ denote the list of all the passwords (whose length is greater than 8 and contain only ASCII) in the Jason corpus [18] that belong to usernames with the same name, excluding the current password.
2) Calculate the frequency $f$ of each unique password in $L$.
3) Split each password in $L$ into its 3D dimensions.
4) Add or update the context of each prefix/base word/suffix dimension so its corresponding probability will be $0.22 \cdot f$ (as in Section 5.2), and normalize the distributions.

We sampled 5,000 username-password pairs from our test set, and evaluated their strength with the context-aware PESrank using both the username context of Section 5.2 and the password-reuse context (if such context was available), when our model is trained on 41 million passwords. Figure 5 compares its CDF to that of the 5D+ model (as in Figure 1). The figure clearly shows that when using both username and password-reuse context, there is a dramatic improvement in the cracking power (and conversely, a dramatic decrease in password strength). Again, the most important improvement is on the left side of the CDF: 42.8% of the passwords can be cracked with fewer than $10^6$ attempts when using password-reuse context.

We draw several conclusion from this experiment. First, we find that indeed knowing the user’s previous passwords provides the password cracker with very valuable information. Second, that a good password strength estimator should use such history as context, to accurately model the cracker’s capability—and that resources such as Jason’s corpus [18] already provide a wealth of historical data on millions of users. And third, that the PESrank algorithm is well suited to use such context.

7. Comparison with Existing Methods

7.1. Overview

In order to test the power and accuracy of our method, we compared it to multiple approaches. We first compared its guessing power, and its storage requirements, to those of five accurate cracker-based methods offered in PGS [4]: (1) the Markov model [23]; (2) the PCFGs model [36] with Komanduri’s improvements [21]; (3) Hashcat [17]; (4) John the Ripper [28] mangled dictionary models; and (5) the neural network-based model of Melicher et al. (with Monte-Carlo estimation) [26]. Then we tested the accuracy of PESrank as an estimator, versus the currently best heuristic estimator, zxcvbn [37, 38].

In all cases we used the algorithms’ default settings and training data. We implemented PESrank in Python. Since we used the implementations of Neural, PCFG, Markov, hashcat and JtR, as made publicly available through the PGS service, we had no control over the corpora the PGS administrators used to train all these algorithms—nor do we have the precise set of corpora that they used. According to the PGS site, they trained the PCFG, Markov, hashcat and JtR algorithms on 6 corpora, totalling 33 million passwords, plus 6 million natural language words, collectively called the “PGS training set”. The Neural algorithm was trained on passwords from 26 corpora, totalling 105 million passwords plus 6 million natural language words, called the “PGS++ training set”. As far as we can tell the Jason [18] corpus
Figure 6. The CDFs of PESrank versus PCFG, Markov, Hashcat and JtR, when PESrank is trained on 41 million passwords and the other methods are trained on the PGS training set.

Figure 7. The CDFs of PESrank versus Neural, when PESrank is trained on 113 million passwords and Neural is trained on the PGS++ training set.

includes all the passwords that are in the PGS++ training set.

Therefore, to have a fair comparison, we trained PESrank on two training sets: one containing 41 million passwords, for comparison with the PCFG, Markov, hashcat and JtR algorithms, and one containing 113 million passwords for comparison with the Neural algorithm. We also trained PESrank method on larger training sets (226 million, 452 million and 905 million passwords) in order to see how the training set size affects its method performance.

7.2. Comparison to Cracker-based Methods

Figure 6 shows the CDFs comparing PESrank, trained on 41 million passwords with PCFG, Markov, hashcat and JtR algorithms, that are trained on the same corpus size (PGS).

The figure shows that PESrank outperforms other approaches for "practically crackable" passwords. Up to ranks around $10^{11}$, PESrank is able to crack a higher percentage of passwords in the test set, and do it with fewer attempts than the other methods. While PCFG is able to provide lower ranks for passwords beyond rank $10^{11}$, we argue that it is more valuable to the user to learn that her password is crackable, versus just how uncrackable it is (e.g. for a PCFG rank of $10^{14}$).

Figure 7 shows the results comparing PESrank, trained on 113 million passwords, with the Neural method which is trained on a similar corpus size (PGS++). Again, we see that PESrank outperforms the Neural method for "practically crackable" passwords, while Neural is able to better estimate the strengths of the very strong passwords.

As a side note, the Neural algorithm is apparently able to provide a rank for every possible password, and its CDF always reaches 100%: we tested it on 20-character passwords, including letters, digits and symbols, generated uniformly at random by the “Random.pw - Random Password Generator” [31]. On such passwords Neural returned strength estimations of about $10^{41} ≈ 2^{120}$, which is a fair estimate assuming 6-bits of entropy per password character. Thus Neural will always surpass PESrank on the right-hand side of the CDF, since PESrank will never return a rank that exceeds the password volume in the model (recall Table 3).

Figure 8 shows the CDFs of all the methods we compared, each trained on the maximal training set available to it. When PESrank is trained on a 905 million password training set, its advantage over the other methods, as provided by the PGS service [4], grows, and only Neural surpasses PESrank, for ranks beyond $10^{12}$. While this figure mostly demonstrates the advantage of using a larger training set, it also shows that PESrank is actually able to digest such a large training set, due to its fast training time, whereas the other methods’ ability to do so in reasonable time is currently unknown.

7.3. Storage Requirements

Table 5 summarizes the storage space of the different methods, as reported by [26]—where, unlike in the PGS
service [4], the authors trained the earlier methods on the PGS++ training set. For comparison we provide the PESrank storage for the training set of size 113 million passwords. The table shows that the Neural network requires the lowest amount of storage (60MB) on the server-side, while PESrank requires a larger, yet very reasonable 1.4GB storage, and significantly less than PCFG.

### 7.4. Comparison to a Heuristic Estimator

We also compared the accuracy of PESrank with that of the zxcvbn [38], [37] heuristic. We used the open source Python code of zxcvbn [38].

As a ground truth for this comparison, for each password, we used the minimum number of attempts needed to guess a password by running PGS [4], in its MIN AUTO configuration mode. In this mode PGS returns the minimum number of guesses among (1) the Markov model [23], (2) the PCFG model [36] with Komanduri’s improvements [21], (3) Hashcat [17], (4) John the Ripper [28] mangled dictionary models; and (5) Neural Networks [26] (with Monte-Carlo estimation).

#### 7.4.1. Estimator Quality Metrics

We used several metrics to evaluate the quality of the estimator. Following [38], given a test set $S$, on each sampled password $x_i \in S$ we measure an algorithm’s estimation error by computing its order-of-magnitude difference $\Delta_i$ from the ground-truth:

$$\Delta_i = \log_{10} \frac{g_{alg}(x_i)}{g_{pks}(x_i)}$$

where $g_{alg}$ is the rank estimate of the algorithm and $g_{pks}$ is the minimum rank of the five PGS methods. Note that $\Delta_i$ can be positive (if the algorithm over-estimates the ground truth) or negative if it under-estimates.

We also define the following three metrics: over-estimation, accurate and under-estimation, which give a sense of how frequently an estimated rank is significantly above or below the ground-truth and how frequently it is close to the ground truth. Specifically, over-estimation is the fraction of passwords for which the estimated rank is two orders of magnitude ($\times 100$) more than ground-truth, and similarly for under-estimation. accurate is the fraction of passwords for which the estimated rank is within two orders of magnitude from the ground truth. Using the definition of $\Delta_i$ we obtain the following expressions:

$$\text{over-estimation} = \frac{1}{|S|} \left| \{x_i \in S : \Delta_i > 2\} \right|$$

$$\text{accurate} = \frac{1}{|S|} \left| \{x_i \in S : -2 \leq \Delta_i \leq 2\} \right|$$

#### 7.4.2. Accuracy Comparison

In Figure 9 we see the over- and under-estimation of PESrank and zxcvbn using the metrics defined in Section 7.4.1. The figure shows that the PESrank method is more accurate than the zxcvbn: our model has the highest total number of passwords correlated with the ground truth.

Moreover, the figure shows that zxcvbn under-estimates 43.87% of the passwords: i.e., significant numbers of unsafe errors. In contrast, PESrank is more aligned with the ground-truth, only over-estimating 4.56% of the passwords and under-estimating 21.21% of them. Notice that PESrank under-estimation is actually advantageous, since PESrank is backed by a model-based password cracking algorithm that can achieve its predictions. It means that such a cracker can do better than the “ground-truth”.

### 8. Lookup Time Optimizations

The basic lookup time of the PESrank includes: (1) reading the five distributions lists from the five files into memory (2) mapping the given password string into the corresponding probability (3) calculating the estimated strength using the ESrank algorithm [7]. The ESrank algorithm [7] receives as input $d$ distribution lists and a password probability, uses exponential sampling to merge the $d$ lists into two, and then calculates the upper and the lower bounds of the rank of the given probability using these two merged lists.

Figure 6 summarizes the PESrank 5D+ lookup time, when trained with 41 million passwords, in three modes: basic, amortized and with context.

In its basic mode it took 40 seconds to read the 5 files into the RAM and 6.5 seconds to map the password into probability and calculate the estimations.

However, in a large scale test such as ours, it is possible to perform the main parts of the PESrank calculations once
for a batch of passwords to speed up the evaluation. Clearly reading the 5 distribution lists in memory can be done once for the entire password batch. Further, the ESrank merge step (from 5 lists into 2 lists) does not depend on the probability of the given password, but only on the 5 distribution lists, thus it can be pre-computed once and be kept in the memory. Amortizing the one-time computations over 30,000 passwords in a test set we get that the PESrank look up time per password, when trained with 41 million passwords, is 0.002 seconds.

We cannot use the full pre-computation when using context, since the context changes the dimension distribution lists for each password. Therefore we need to read the 5 distribution lists (once), tweak them, and run the full ESrank for each password. The tweaking time when trained on 41 million passwords is 2.5 seconds, leading to an amortized time of PESrank with context to be 8.5013 seconds.

The ESrank algorithm [7] uses exponentially sampling, which depends on a tunable parameter $\gamma$ that effects the accuracy of the rank estimation and the memory footprint of the two lists. In [7] the authors showed that the ratio between the upper bound estimation and the lower bound estimation of a given password is bounded by $\gamma^2d^{-2}$; therefore with $d = 5$ we chose $\gamma$ to be 1.09 to achieve an estimation accuracy of less than 1 bit. As a result of this choice, the memory we need for these two final merged lists is $\sum_{i=1}^{d} \log_2(n_i) = \log_2(\prod_{i=1}^{d} n_i)$. For example, using the 41 million password training set, the volume of the 5d-enrichment model, from table 3, is $1.28 \cdot 10^{27}$, therefore the memory requirement of the two ESrank lists is $\log_{1.09}(1.28 \cdot 10^{27}) \cdot 8$byte$=5.8$KB, which is negligible.

### 9. Conclusions

In this paper we presented the first method for estimating the strength of human-chosen text passwords that is able to tweak the estimation according to each user’s personal context, without retraining its model.

Our method is able to incorporate context such as the user’s name, preferred suffix, or previously cracked passwords (if available) when estimating the current password’s strength. Based on the Jason corpus of leaked passwords [19], which contains 1.4 billion usernames and passwords, we demonstrated that there is significant correlation between the user’s name and the chosen password, and that users’ likelihood of reusing a password is as high as 22%. Since our method’s context-aware tweaking only takes a few seconds per password, our strength estimations show that many passwords are in fact much weaker than previously estimated, once context is taken into account.

Our idea is to cast the question in a probabilistic framework used in side-channel cryptography. We view each password as a point in a $d$-dimensional search space, and learn the probability distribution of each dimension separately. The a-priori probability of a given password is the product of the $d$ probabilities of its sub-passwords.

After a detailed evaluation of leaked password corpora we found that an effective choice is to use $d = 5$ dimensions: base word, prefix, suffix, shift-pattern, and l33t transformation. We coupled this decomposition with a state-of-the-art rank estimation algorithm to create the tweakable PESrank estimator.

We showed that PESrank is more powerful than previous methods: it can crack more passwords, with fewer attempts, than the password crackers we compared it to. Even without using per-user context, PESrank is more accurate than previous methods for crackable passwords whose rank is smaller than $10^{12}$. Furthermore, its training time is drastically shorter than previous methods, taking minutes, rather than days, to train on comparably-sized training sets, and taking a few hours to train on 905 million passwords, which is 8 times more than previously used.

Since PESrank can estimate a password strength in seconds, is tweakable and able to incorporate context, and uses storage and memory that is easily available on a standard computer, we believe that PESrank can be a useful password strength estimator.

### References

[1] D. Agrawal, B. Archambeault, J. Rao, and P. Rohatgi, “The EM side-channel(s),” in *Cryptographic Hardware and Embedded Systems* CHES 2002, 2003, pp. 29–45.

[2] A. Bogdanov, I. Kizhvatov, K. Manzoor, E. Tischhauser, and M. Wittenmann, “Fast and memory-efficient key recovery in side-channel attacks,” in *Selected Areas in Cryptography (SAC)*, 2015.

[3] W. Burr, D. Dodson, and W. Polk, “Electronic authentication guideline,” National Institute of Standards and Technology, Tech. Rep., 2004.

[4] Carnegie Mellon University Password Research Group, “Password guessability service (pgs),” 2019, https://pgs.ece.cmu.edu/ [Online]. Available: https://pgs.ece.cmu.edu/

[5] C. Castelluccia, M. Dürmuth, and D. Perito, “Adaptive password strength meters from markov models.” in NDDSS, 2012.

[6] L. David and A. Wool, “A bounded-space near-optimal key enumeration algorithm for multi-subkey side-channel attacks,” in *Proc. RSA Conference Cryptographers’ Track (CT-RSA’17)*, *LNCS 10159*. San Francisco: Springer Verlag, Feb. 2017, pp. 311–327.

[7] ———, “Poly-logarithmic side channel rank estimation via exponential sampling,” in *Proc. RSA Conference Cryptographers’ Track (CT-RSA’19)*, *LNCS 11405*. San Francisco: Springer Verlag, Mar. 2019, pp. 330–349.

[8] X. D. C. De Carnavalet, M. Mannan *et al.*, “From very weak to very strong: Analyzing password-strength meters.” in *NDSS*, vol. 14, 2014, pp. 23–26.

[9] M. Dell’Amico and M. Filipponi, “Monte carlo strength evaluation: Fast and reliable password checking,” in *Proceedings of the 22nd ACM SIGSAC Conference on Computer and Communications Security*. ACM, 2013, pp. 158–169.

[10] M. Dell’Amico, P. Michiardi, and Y. Roudier, “Password strength: An empirical analysis,” in *2010 Proceedings IEEE INFOCOM*. IEEE, 2010, pp. 1–9.
