A New Targeted Password Guessing Model

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Abstract. TarGuess-I is a leading targeted password guessing model using users' personally identifiable information(PII) proposed at ACM CCS 2016 by Wang et al. Owing to its superior guessing performance, TarGuess-I has attracted widespread attention in password security. Yet, TarGuess-I fails to capture popular passwords and special strings in passwords correctly. Thus we propose TarGuess-I$^+$: an improved password guessing model, which is capable of identifying popular passwords by generating top-300 most popular passwords from similar websites and grasping special strings by extracting continuous characters from user-generated PII. We conduct a series of experiments on 6 real-world leaked datasets and the results show that our improved model outperforms TarGuess-I by 9.07% on average with 1000 guesses, which proves the effectiveness of our improvements.

Keywords: TarGuess, Targeted password guessing, Probabilistic context-free grammar(PCFG), Personally identifiable information(PII).

1 Introduction

Password-based authentication is still an essential method in cybersecurity [1]. To understand password security, people have gone through several stages, from the initial heuristic methods with no theoretical basis, to the scientific probabilistic algorithms [2]. Since the emergence of Markov-based [3, 4] and PCFG-based [5, 6] probabilistic password guessing models, trawling password guessing has been intensively studied [7–10]. Recently, several large-scale personal information database leakage events have caused widespread concern in the field of password security [11–14]. With the development of related researches, it has been found that a large part of net-users tend to create passwords with their PII and the targeted password guessing models based on users' PII have emerged [15–17].

Das et al. [15] have studied the threat posed by password reuse and proposed a cross-site password guessing algorithm for the first time. However, due to the lack of popular password recognition, this algorithm is not optimal. Li et al. [16] studied what extent a user's PII can affect password security, and they proposed a targeted password guessing model, personal-PCFG, which adopts a length-based PII matching and substitution. But it could not accurately capture users' PII usage, which greatly hinders the efficiency of password guessing. As a milestone work on password guessing, Wang et al. [17] put forward a targeted password guessing framework, TarGuess, which contains the password reuse behavior analysis and type-based PII semantic recognition, significantly improving the efficiency of the password guessing. Wang et al.'s [17] remarkable achievements have motivated successive new studies on password security [18–21] and even led the revision of the NIST SP800-63-3 [22, 23].

TarGuess framework is proposed after an in-depth analysis of users' vulnerable behaviors such as password construction using PII and password reuse, including four password guessing models for four attacking Scenarios #1 $\sim$ #4. TarGuess-I caters for Scenario #1 where the attacker is equipped with the victim user's PII information such as name, birthday, phone number, which can be easily obtained from the Internet [24]. And the rest three models required user information such as PII attributes that play an implicit role in passwords (e.g., gender and profession) and/or sister passwords that were leaked from the user's other accounts. This work mainly focuses on Scenario #1. As more users' PII is being leaked these days, Scenario #1 becomes more practical.

Wang et al. [17] showed that their TarGuess-I model is more efficient than previous models using users' PII to crack users' passwords, which can gain success rates over 20% with just 100 guesses. However, we find that there is still room for improvement in the analysis of users' vulnerable behaviors after using this model to analyze the real data. Therefore, based on TarGuess-I, we put forward two improvements and proposed an improved model, TarGuess-I$^+$, to make it more consistent with users' vulnerable behavior characteristics and improve the performance of guessing.

Our contributions In this work, we make the following key contributions:

(1) **An improved password guessing model.** After analyses of users' vulnerable behaviors based on a total of 147,877,128 public leaked data and TarGuess-I, we find that the effectiveness of some semantic tags has not been testified and employed in the experiments of Wang et al. [17]. To fill the gap, we make use of the adaptiveness of TarGuess-I PII tags and define two new tags: the Popular Password tag P_1 and the Special String tag X_n. This gives rise to a variant of TarGuess-I, we call it TarGuess-I$^+$.

(2) **An extensive evaluation.** To demonstrate the feasibility of the improvements, we perform a series of experiments on the real-world leaked datasets. The experimental results show that the success rate of the improved model TarGuess-I$^+$ outperforms the original model TarGuess-I by 9.07% on average with 1000 guesses, which proves the feasibility of the improvements.

(3) **A novel method.** We introduce a novel method to the password guessing: parsing the password segments into special strings, such as anniversary days and someone's name, that appeared in user-generated PII, such as e-mail addresses and user names.

2 Preliminaries

This section explicates what kinds of users' vulnerable behaviors are considered in this work and gives a brief introduction to the models.

2.1 Explication of users' vulnerable behaviors

Users' vulnerable behaviors are the key influence factor of password crackability [25]. A series of related studies have been conducted since the pioneering work of Morris and Thompson in 1979 [26]. Part of the studies are based on data analyses, such as [3,12,14,27–30], the others are based on user surveys, such as [15,31–34]. In summary, the discovered users' vulnerable behaviors can be classified into the following three categories:

1. **Popular passwords.** A large number of studies (such as [3,14,29]) have shown that users often choose simple words as passwords or make simple transformed strings to meet the requirements of the website password setting strategy, such as "123456a" meeting the "alphanumeric" strategy. These strings, which are frequently used by users, are called popular passwords. Furthermore, Wang et al. [35] have found that the Zipf distribution is the main cause of the aggregation of popular passwords.
2. **Password reuse.** After a series of interviews to investigate how users cope with keeping track of many accounts and passwords, Stobert et al. [31] point out that users have more than 20 accounts on average and it is fairly impossible for them to create a unique password for each account, so reusing passwords is a rational approach. At the same time, password-reuse is a vulnerable behavior, the key is how to reuse.
3. **Password containing personal information.** Wang et al. [36] note that Chinese users tend to construct passwords with their pinyin name and relevant digits, such as phone number and birthdate, which is quite different from English users. They revealed a new insight into what extent users' native languages influence their passwords and what extent users' personal information plays a role in their passwords.

Considering the scenario on which TarGuess-I is based, we only analyze the users' vulnerable behaviors of using popular passwords and making use of personal information.

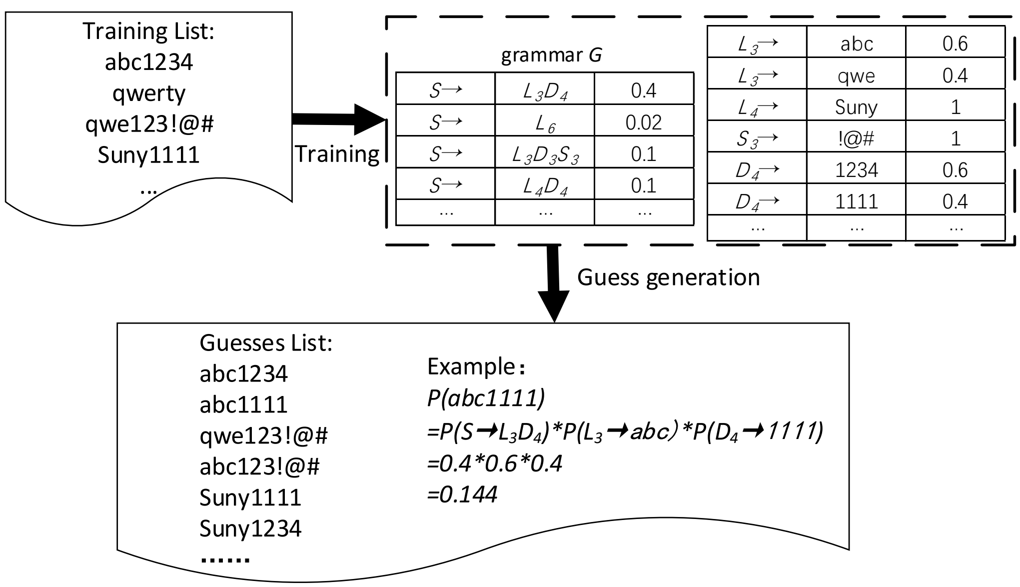


Fig. 1. An illustration of PCFG-based model

2.2 The PCFG-based password guessing model [5]

TarGuess-I model is built on Weir et al.'s PCFG-based model, which has shown great success in dealing with trawling guessing scenarios [17]. The Context-free grammar in [17] is defined as $\mathcal{G} = (\mathcal{V}, \Sigma, \mathcal{S}, \mathcal{R})$, where:

- $\mathcal{V}$ is a finite set of variables;
- Σ is a finite set disjoint from $\mathcal{V}$ and contains all the terminals of $\mathcal{G}$;
- $\mathcal{S}$ is the start symbol and $\mathcal{S} \in \mathcal{V}$;
- $\mathcal{R}$ is a finite set of productions of the form: $\alpha \to \beta$, where α & $\beta \in \mathcal{V} \cup \Sigma$.

The core assumption of the model is the segments of letters, numbers, and symbols in a password were independent of each other, so in the $\mathcal{V}$ except for the $\mathcal{S}$ start symbol, only to join L_n letters, D_n digits and S_n symbols tag sets, where n represents the segment length, such as L_3 represents 3-letter segments, D_4 represents 4-digit segments.

There are two phases in the model, the training phase and the guess generation phase, as shown in Fig. 1. In the training phase, the password is parsed into the LDS segments based on the length and the type to generate the corresponding password base structure (the start symbol $\mathcal{S}$). Then, it counts the segments frequency table in each tag set, and it outputs the context-free grammar $\mathcal{G}$. In the guess generation phase, passwords are derived by the grammar $\mathcal{G}$ and the segments frequency table. The final output set is arranged based on the probability multiplied by all the frequency of segments in the password.

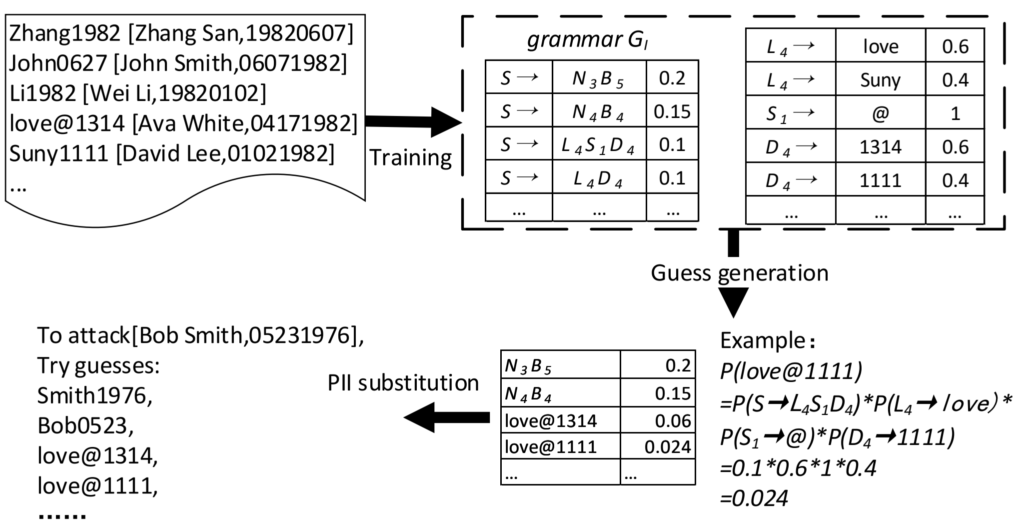


Fig. 2. An illustration of TarGuess-I [17]

2.3 The targeted password guessing model TarGuess-I [17]

TarGuess-I adds 6 PII tags (N_n name, U_n username, B_n birthday, T_n phone number, I_n id card, E_n mailbox) to the three basic tags of LDS in the PCFG-based model. For each

PII tag, its index number n is different from the LDS tag, which represents the type of generation rule for this PII. For example, N stands for name usage, while N_1 stands for the full name, and N_2 stands for the abbreviation of the full name (such as "Zhang San" abbreviated as "zs"). B stands for birthday usage, while B_1 stands for the use of birthday in the format of month/year (e.g., 19820607), B_2 stands for the use of birthday in the format of month/day/year. For a specific description, see Fig. 4.

Fig. 2 shows an illustration of the model. For each user, the element set of each PII tag is first generated through the user's PII to match with the password, and the rest of the segments are parsed into LDS segments. Then the frequency of the elements of each set will be calculated as with PCFG. Finally, the context-free grammar $\mathcal{G}_{\mathcal{I}}$ containing the PII tags will be output.

3 Analysis of real password data and TarGuess-I model

This section analyzes the real-world leaked password data and TarGuess-I to provide the basis for the improvement of the model. We dissect 146,570,537 leaked user passwords from 6 websites (see Table 1) to find out the disadvantages of TarGuess-I.

Table 1. Basic information about our personal-info datasets

Dataset	Web service	When leaked	Total	With PII
Duduniu	E-commerce	2011	16,258,891	
Tianya	Social forum	2011	29,020,808	
CSDN	Programmer	2011	6,428,277	
renren	Social forum	2011	2,185,997	
12306	Train ticketing	2014	129,303	✓
youku	Video entertainment	2016	92,547,261	

3.1 Analysis of popular passwords

According to the frequency of occurrence, the top-10 popular passwords in 6 password databases with the proportion of them were calculated, and the results are shown in Table 2. Table 2 shows that 1.10% to 5.27% of users' passwords could be guessed successfully by just using top-10 popular passwords. Chinese users prefer simple combinations of numbers, such as "123456", "111111", "000000", and the strings with the meaning of love, such as "5201314" and "woaini1314".

There are also some unique passwords in the top-10 list, such as "111222TIANYA" in Tianya, "dearbook" and "147258369" in CSDN, "7758521" in Renren and "xuanchuan" in Youku. These passwords may come from the name or the culture of the website, or they maybe come from a large number of "ghost accounts" held by a particular user of the website. Besides, "1qaz2wsx" and "1q2w3e4r" in the top-10 of 12306 is the password constructed with the QWERTY keyboard pattern.

By analyzing the list of popular passwords, we find that there is one missing item in the password recognition of the TarGuess-I model: the popular passwords.

Table 2. Ranking and proportion of top-10 popular passwords

Rank	**Duduniu**	**Tianya**	**CSDN**	**Renren**	**12306**	**Youku**
1	123456	123456	123456789	123456	123456	123456
2	111111	111111	12345678	123456789	a123456	123456789
3	123456789	000000	11111111	111111	123456a	xuanchuan
4	a123456	123456789	dearbook	12345	woaini1314	111111
5	123123	123123	00000000	5201314	5201314	123123
6	5201314	121212	123123123	123123	111111	000000
7	12345	123321	1234567890	12345678	qq123456	5201314
8	aaaaaa	111222TIANYA	88888888	1314520	1qaz2wsx	1234
9	12345678	12345678	111111111	123321	1q2w3e4r	a123456
10	123456a	5201314	147258369	7758521	123qwe	123321
%	5.27%	1.17%	3.34%	4.91%	1.10%	3.89%

Popular password The statistical results of the distribution of base structures analyzed by the PCFG-based model for top-10000 popular passwords are shown in Table 3.

Table 3. Form distribution of the top-10000 popular passwords

Form	**Duduniu**	**Tianya**	**CSDN**	**Renren**	**12306**	**Youku**
Letter	11.47%	10.93%	15.56%	10.67%	4.56%	12.46%
Digit	39.18%	63.37%	65.66%	66.27%	32.29%	63.77%
Symbol	0.02%	0.03%	0.04%	0.02%	0.00%	0.08%
Composite	49.34%	25.67%	18.74%	23.05%	63.15%	23.69%

Table 3 illustrates that the majority of popular passwords are pure numbers. Besides, composite passwords (that is, the structure includes multiple types of character) also account for a considerable part, especially 63.15% in the 12306 data set. Since the grammar $\mathcal{G}_{\mathcal{II}}$ of TarGuess-I does not contain tags related to the popular passwords, while TarGuess-I is based on data-driven probabilistic statistical PCFG algorithm, which generates passwords based on the existing base structures in the data and the set of elements in various tags. Therefore, in the training phase, the model parses the password into LDS segments, an illusion is shown in Fig. 1. Due to the guess generation phase of the PCFG algorithm, it might generate many invalid outputs at last.

For example, "adbc1234" is the 28th most popular password in 12306, which is divided into L_4D_4 syntax using PCFG algorithm. In the element set of L_4, "love" ranks the first, while "1234" ranks the first in D_4. Therefore, in the guessing stage, the first output password with the base structure L_4D_4 is "love1234". This password occupies a relatively small proportion in the actual password distribution but ranks much higher in the model guessing list due to the high probability, thus reducing the overall password guessing success rate.

3.2 Analysis of passwords containing personal information

We adopt the improved TarGuess-I^+P model, which contains the popular password tag P_1, to analyze the passwords. The results of the top-10 password base structures and the proportion of the password containing PII have been shown in Table 4. Due to the lack of datasets containing users' PII, we choose the unique PII(such as e-mail, phone, ID number) in 12306 to match passwords in other datasets. The sizes of the password sets are shown in Table 5.

Table 4. Ranking of top-10 base structure, proportion of the passwords containing PII and proportion of popular passwords

Rank	**Duduniu**	**Tianya**	**CSDN**	**Renren**	**12306**	**Youku**
1	E_1	D_6	P_1	D_7	P_1	P_1
2	D_7	D_7	D_8	D_6	D_6	D_6
3	P_1	P_1	E_1	P_1	D_7	D_7
4	D_6	D_8	B_1	D_8	N_2D_6	D_8
5	D_8	E_1	D_9	E_1	U_1	N_2D_6
6	N_2D_6	D_{10}	N_2D_6	U_3	D_8	U_1
7	A_1D_7	B_1	U_1	D_9	E_1	U_3
8	N_2D_7	B_8	D_{11}	B_1	N_2D_7	E_1
9	U_1	D_9	N_2D_7	B_8	U_3	B_1
10	A_2D_6	N_2D_6	D_{10}	D_{11}	A_2D_6	N_1D_3
% of PII	41.54%	35.43%	39.64%	36.85%	42.78%	40.65%
% of P_1	3.99%	5.91%	8.91%	6.27%	4.14%	5.58%

The results indicate that nearly 50% of users generally construct passwords using PII or choose popular passwords. And we find that the top-10 password base structures contain several base structures with base tags that are not relevant to users' PII. Based on the above analysis of the users' behavior in constructing the password, we can speculate that the top-10 base structures of passwords should be related to the strings which are accessible for the user to memorize.

The strings which are accessible to memorize include users' PII conversions and popular passwords. They also include user-generated strings (hereinafter referred to as the special strings) that have special meaning for the user but are of no equal importance to other users. For $\mathcal{A}$ user, for example, "080405" is $\mathcal{A}$'s particular date, but for another user $\mathcal{B}$, "080405" is just a very ordinary day, then the probability of $\mathcal{A}$'s password containing this string is different from that of $\mathcal{B}$'s. Meanwhile, we can not find the string "080405" in $\mathcal{A}$'s and $\mathcal{B}$'s demographic information (such as name, ID number, telephone number, etc.). The special string cannot be extracted from the user's demographic information but may appear in strings which are generated by the user, such as e-mail address and user name, or it may appear in passwords on other servers of the user. Therefore, we found another lack of recognition in TarGuess-I: the special string.

The special string The analyses of the user data in TarGuess-I also include the user-generated strings, such as e-mail address E_n and user name U_n. However, the analyses of these 2 user-generated strings are not accurate enough. Only three parse type (Entire E_1&U_1, the first letter segments E_2&U_2 and the first digit segments E_3&U_3) are proposed.

The probability distribution of special strings for each user is different. If we use the original TarGuess-I model for password recognition, because of the lack of recognition of the special string, most of these segments will be parsed into typical LDS segments, merging the users' behavior characteristics, thus they hinder the effectiveness of the model. Therefore, we consider adding the special string tags X_n to the set $\mathcal{V}$ of TarGuess-I.

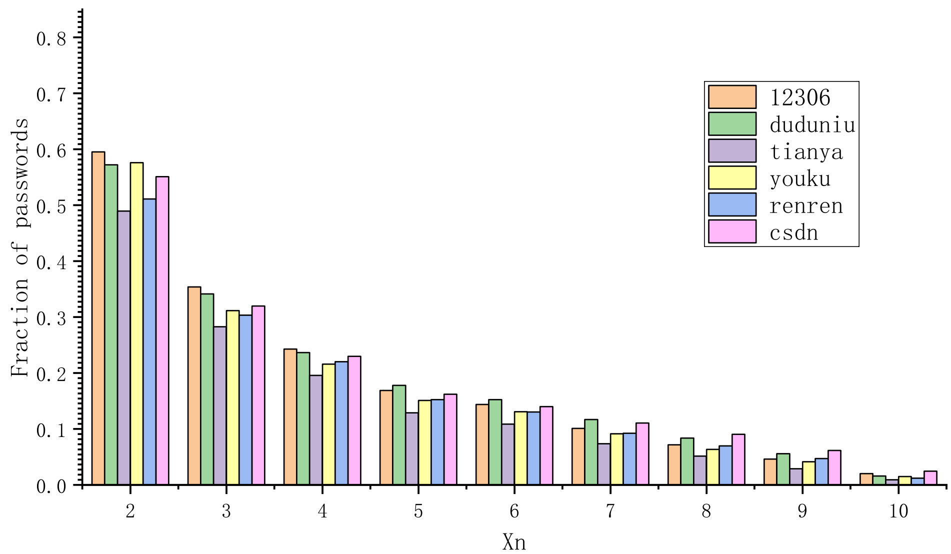


Fig. 3. The probability of the occurrence of the special string X_n in the password

Considering that only two user-generated PII are needed in TarGuess-I, the e-mail address and the user name, we employ the sliding window algorithm to analyze the coverage of consecutive substrings of the e-mail address and user name in the password to verify the validity of the special string improvement. The result is shown in Fig. 3. Note that, to differ from TarGuess-I, we only consider substrings with $len \geq 2$, and we ignore the full strings of e-mail address prefix and user name.

Fig. 3 shows that a significant number of user passwords do overlap user-created strings. It gives us a new hint that when an attacker obtains information about a user that is not public or very useful, they may turn that information into a special string to participate in password guessing.

3.3 Brief summary

We find two improvements of TarGuess-I model in this section:

– Add the popular password tag P_1 to the set $\mathcal{V}$ of probability context $\mathcal{G}_{\mathcal{II}}$ and apply the popular password list generated from a data set similar to the target website or server type.
– Add the special string tag X_n to the set $\mathcal{V}$ of probability context $\mathcal{G}_{\mathcal{II}}$, and add the special string associated with the user for password guessing.

4 The improved model TarGuess-I$^+$

We now propose TarGuess-I$^+$, which is capable of identifying the popular passwords and the special strings. The context-free grammar $\mathcal{G}_{\mathcal{II}} = (\mathcal{V}, \Sigma, \mathcal{S}, \mathcal{R})$ in the model is described as below:

1. $\mathcal{S} \in \mathcal{V}$ is the start symbol;
2. $\mathcal{V} = \{\mathcal{S}; L_n, D_n, S_n; N_n, B_n, U_n, E_n, I_n, T_n; P_1, X_n\}$ is a finite set of variables, where:
   (a) Letters(L_n), Digits(D_n), Symbols(S_n) are the basic tag of the PCFG algorithm, we rename them in case to differ from other improvement tags;
   (b) Name(N_n), Birthday(B_n), User name(U_n), E-mail address(E_n), ID number(I_n), and Phone number(T_n) are the PII tags created in TarGuess-I model, see Fig. 4 for an example of generation;
   (c) Popular password(P_1) and Special string(X_n) are proposed in this paper, the implementation detail have been shown in subsection 4.1.
3. $\Sigma = \{95 \text{ printable ASCII codes}, Null\}$ is a finite set disjoint from $\mathcal{V}$ and contains all the terminals of $\mathcal{G}_{\mathcal{II}}$;
4. $\mathcal{R}$ is a finite set of rules of the form $A \to \alpha$, with $A \in \mathcal{V}$ and $\alpha \in \mathcal{V} \cup \Sigma$.

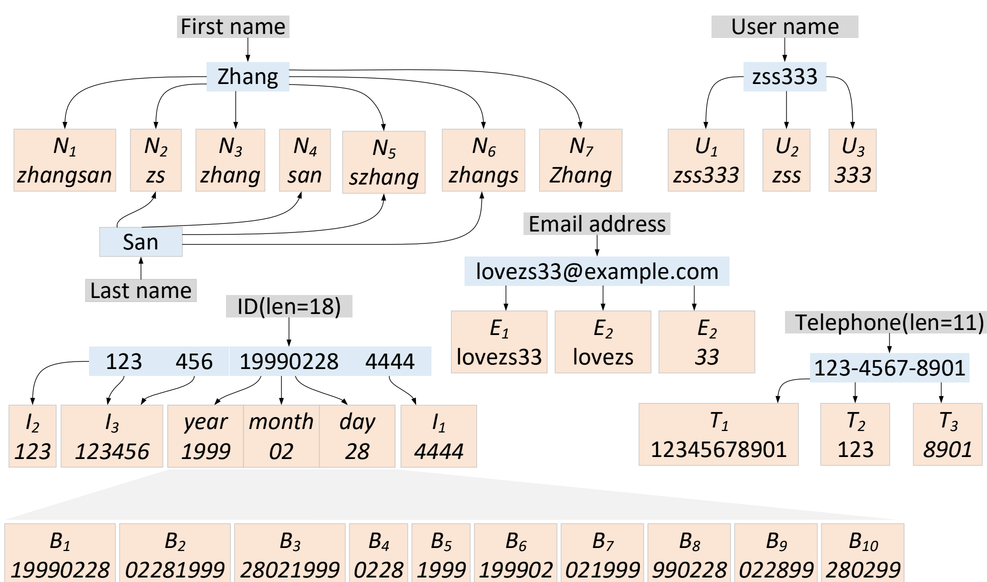


Fig. 4. An illustration of PII tags generation

4.1 Model implementation

Popular password P_1 Add the popular password tag P_1 to $\mathcal{V}$ set of the grammar $\mathcal{G}_{\mathcal{I}}$, and the element set in P_1 tag is a top-N popular password list based on the data statistics of relevant websites. The index 1 in P_1 has no meaning just to conform to the overall format. The parse of P_1 tag is shown in Fig. 5.

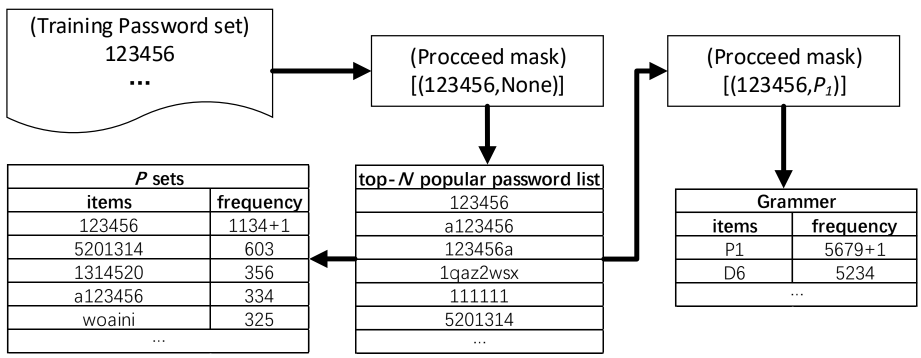


Fig. 5. An illustration of P_1 tag parse

In the training phase, the top-N list is matched with the password data by a regular expression. If the match occurs, the occurrence of the corresponding password in P_1 set is increased by 1. In the guess generation phase, the probability of containing P_1 password structures is multiplied by the frequency of the corresponding password in the element set of P_1 as the final probability of output password.

Fig. 6 shows the similarity between the top-k list of the popular passwords compiled by six websites and the top-k list of the popular passwords of each website (k represents the first k pieces of password ranking). It can be seen from the figure that when k value is around 300, the similarity tends to a stable peak, and then the similarity continues to decrease. Therefore, the size of the popular password list should be limited to about $N = 300$ to improve the success rate of cross-site guessing.

Special string X_n The element sets of the special string X_n tag are generated from the e-mail address prefix and user name. Since there are various and different ways for each user to generate special strings, it is difficult to categorize the generation methods of special strings uniformly and may cause sparse data. Therefore, n is only classified according to the length of the string. To avoid generating too many conventional strings with excessive extraction granularity, which results in invalid recognition, we only consider strings with $len \geq 4$. An illustration of special string X_n parse is shown in Fig. 7. The second number in $X_{n,m}$ tags represents the generation type in the element sets, which means the starting position of the substrings.

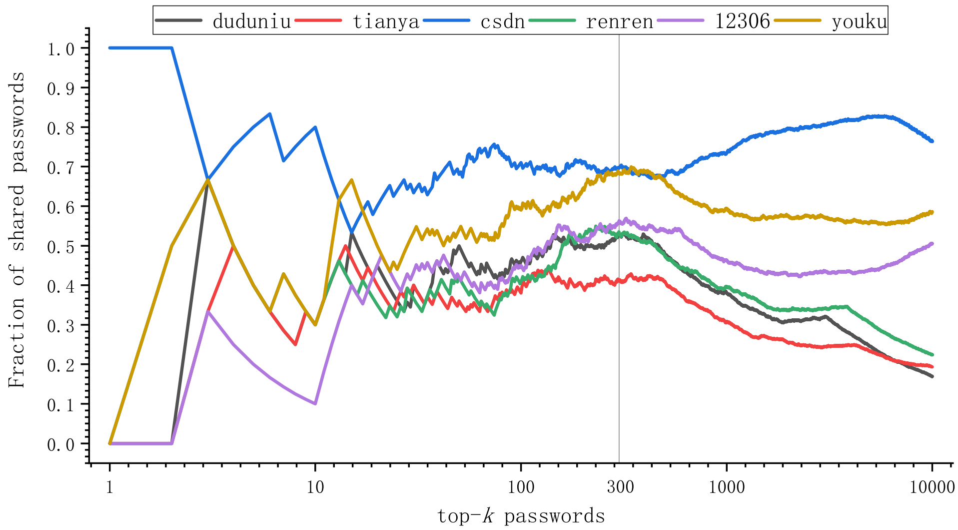


Fig. 6. The similarity of the popular passwords

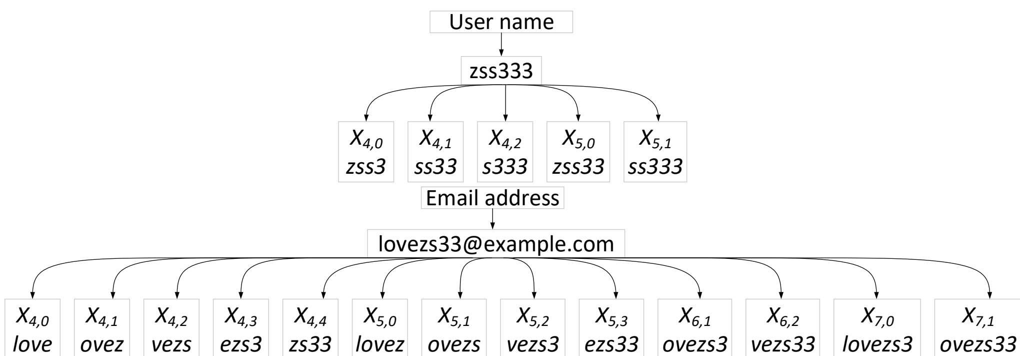


Fig. 7. An illustration of X_n tags parse

5 Experiments

TarGuess-I is mainly used in online guessing scenarios, where the guess number allowed is the most scarce resource, while computational power and bandwidth are not essential [17]. Therefore, we mainly evaluate the availability of the model by guess-number graphs.

5.1 Experiment setup

Our experiments need various types of users' PII. Because of the limited experimental resources and the lack of original datasets associated with PII, we only employed 10^5

pieces of 12306 data containing users' PII to match the rest of datasets using e-mail addresses, and the obtained data size is shown in Table 5.

Table 5. The size of experiment datasets

	Duduniu	**Tianya**	**CSDN**	**Renren**	**12306**	**Youku**	**Total**
Training set	-	-	-	-	25,372	11,554	36,926
Testing set	7,539	6,792	2,998	1,062	74,516	27,278	120,185
Total	7,539	6,792	2,998	1,062	99,888	38,832	157,091

Note that, to make our experiments as scientific as possible, we follow 4 rules:

1. Training sets and testing sets are strictly separated;
2. The comparison experiments of the two models are based on the same training sets and testing sets;
3. The base structures of password sets for the experiments are evenly distributed;
4. The training sets and testing sets shall be as large as possible.

To follow the rules 3 and 4, we first filtrate the password data by analyzing the base structure of the passwords using TarGuess-I. We store the passwords which have their base structure with more than 10 occurrences. And we choose the **12306** set and **Youku** set as training sets and testing sets at a ratio of 7:3, the other data sets have been entirely used for testing.

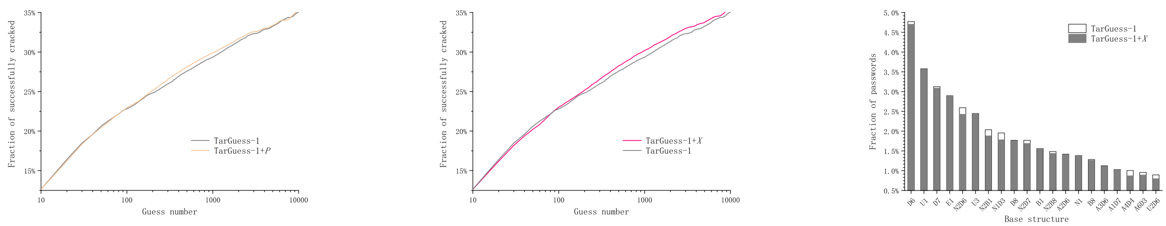
5.2 Experiment 1: Validation of the improvements

We adopted two improvement methods to generate two models: TarGuess-I+P with popular password tag P_1, and TarGuess-I+X with special string tag X_n, then we chose **12306** training data and **Youku** training data to generate the context-free grammars $\mathcal{G}_{\mathcal{I}}$ and $\mathcal{G}_{\mathcal{II}}$. At last, we implemented comparison experiments with the corresponding testing data. The results are shown in Fig. 8 and Table 6.

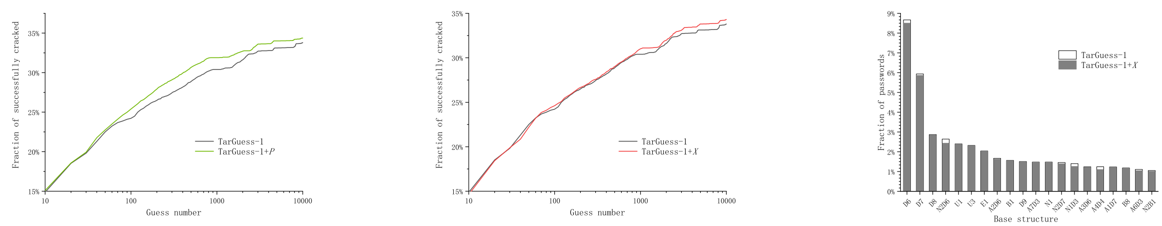
Table 6. The statistics of Fig. 8

Setup	Model	10	10^2	10^3	10^4
12306-train	TarGuess-I	12.655	22.808	29.354	35.085
↓	TarGuess-I+P	12.651	22.954	29.898	35.187
12306-test	TarGuess-I+X	12.643	23.028	32.003	35.668
Youku-train	TarGuess-I	14.877	24.223	30.394	33.795
↓	TarGuess-I+P	15.102	25.392	31.891	34.366
Youku-test	TarGuess-I+X	14.634	24.613	31.008	34.305

Popular password Fig. 8(a) shows that the success rate of TarGuess-I+P is slightly lower than that of TarGuess-I within 100 guesses, but grows higher than the latter from 100 to 10^4 guesses. This maybe due to the largest part of passwords with pure-digits



(a) Improved with P_1 (b) Improved with X_n (c) base structure



(d) Improved with P_1 (e) Improved with X_n (f) base structure

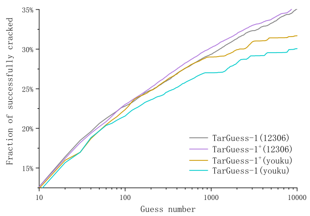
Fig. 8. Figs. 8(a)-8(c) are the results of experiments based on **12306** data set; Figs. 8(d)-8(f) are the results of experiments based on **Youku** data set.

base structures in **12306** set. These types of passwords will be generated more at first by TarGuess-I's grammar $\mathcal{G}_{\mathcal{I}}$, but a few by TarGuess-I+P's grammar $\mathcal{G}_{\mathcal{II}}$. Fig. 8(d) and Table 6 show that TarGuess-I+P significantly outperforms TarGuess-I by 0.28%-6.35% in the **Youku**-based experiment, which proves the effectiveness of the improvement of popular passwords.

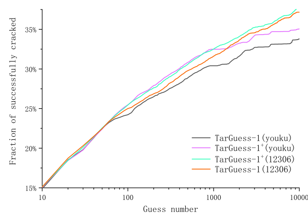
Table 7. The top-5 rank of password base structure with the special string X_n tags

12306			**Youku**		
structure	proportion	rank	structure	proportion	rank
X_8	0.2449%	89	X_6	0.2749%	75
X_9	0.2335%	92	X_8	0.2456%	86
X_6	0.1803%	115	X_7	0.2383%	91
X_{10}	0.1718%	122	X_9	0.2236%	96
X_4D_6	0.1601%	127	X_5D_3	0.1833%	108

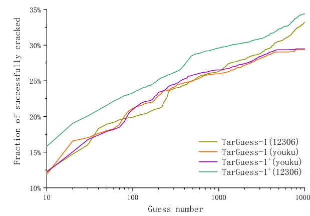
Special string Figs. 8(b) and 8(e) show that TarGuess-I+X is close to TarGuess-I with a slightly lower success rate within 1000 guesses, but gradually outperforms TarGuess-I with the increasing number of guesses. The main reason is that the passwords containing the special strings account for a relatively small proportion of the entire password data, seeing Table 7. And some higher-ranked base structures will be reduced, seeing Figs. 8(c) and 8(f), because some of the passwords, which were originally parsed into these base structures, will be parsed into which contains X_n.



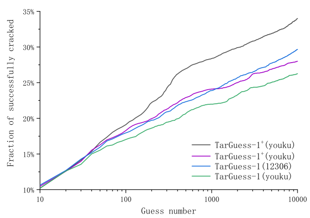
(a) **12306**



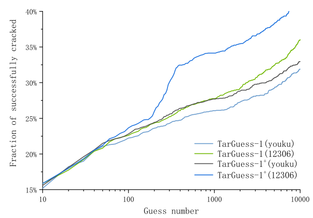
(b) **Youku**



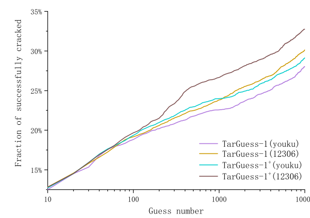
(c) **CSDN**



(d) **Duduniu**



(e) **Renren**



(f) **Tianya**

Fig. 9. Experiment results for comparison with TarGuess-I$^+$ and TarGuess-I based on 6 datasets.

5.3 Experiment 2: Evaluation of TarGuess-I$^+$

We add 2 new tags to the variable set $\mathcal{V}$ of TarGuess-I to generate a new improved model TarGuess-I$^+$, and choose the large datasets **12306** and **Youku** for training to generate the context-free grammar $\mathcal{G}_{\mathcal{II}}$. Then, we perform a series of comparison experiments using the 6 password datasets mentioned at subsection 5.1. Fig. 9 gives 6 graphs for the experiment results, and Table 8 displays the detailed statistics of the 6 graphs.

From the results, we can see that there is an obvious difference in Fig. 9(c) of the **CSDN**-based experiment. The success rate of TarGuess-I$^+$ based on **12306** data is significantly higher than that of TarGuess-I, but the same comparison based on **Youku** data is not so clear like the former. We conjecture that this difference maybe because the grammar $\mathcal{G}_{\mathcal{II}}$ generated by TarGuess-I$^+$ based on **12306** data is more suitable for **CSDN** data. Table 9 shows that the **12306**-based grammar $\mathcal{G}_{\mathcal{II}}$ generated by TarGuess-I$^+$ has the largest proportion of base structures with PII tags, and the pure-digits base structures rank lower than others, which may satisfy the distribution of **CSDN** data.

It is interesting to find that the success rates of TarGuess-I$^+$ grow dramatically during a short period of the growing guess number. One is based on **Youku**-train data in **Duduniu**-based experiment, and two are based on **12306**-train data in **Renren**-based and **Tianya**-based experiments. We attribute this to the contribution of popular password tag P_1, which outputs the popular passwords concentrated in a certain period of the guess number.

Table 10 calculates the percentage of improvements of TarGuess-I$^+$ in the password guessing success rate compared to TarGuess-I with 1000 guesses based on 6 test datasets. The results show that TarGuess-I$^+$ outperforms TarGuess-I by 2.11%-23.05% and 9.07%

Table 8. The statistics of Fig. 9

Training set	Testing set	Model	10	10^2	10^3	10^4
12306-train	**12306-test**	TarGuess-I	12.655	22.808	29.354	35.085
		TarGuess-I^+	12.643	23.028	30.182	35.668
	Youku-test	TarGuess-I	15.119	25.002	31.614	37.161
		TarGuess-I^+	15.145	25.444	32.505	37.810
	Duduniu	TarGuess-I	10.639	17.957	23.892	29.671
		TarGuess-I^+	10.203	19.109	28.383	34.008
	Tianya	TarGuess-I	12.832	19.173	23.814	30.134
		TarGuess-I^+	12.812	19.678	26.666	32.743
	CSDN	TarGuess-I	12.341	19.902	26.308	33.222
		TarGuess-I^+	15.808	23.291	29.598	34.417
	Renren	TarGuess-I	15.873	22.607	27.754	36.027
		TarGuess-I^+	15.873	23.665	34.151	41.751
Youku-train	**12306-test**	TarGuess-I	12.032	21.558	27.013	30.067
		TarGuess-I^+	12.438	22.366	29.015	31.691
	Youku-test	TarGuess-I	14.877	24.223	30.394	33.795
		TarGuess-I^+	15.076	25.469	32.488	35.05
	Duduniu	TarGuess-I	10.223	17.028	21.985	26.254
		TarGuess-I^+	10.484	18.287	24.105	27.996
	Tianya	TarGuess-I	12.509	18.829	22.571	28.041
		TarGuess-I^+	12.731	19.355	23.996	29.133
	CSDN	TarGuess-I	11.890	21.136	25.994	29.422
		TarGuess-I^+	12.204	20.979	26.543	29.481
	Renren	TarGuess-I	15.200	22.222	26.070	31.890
		TarGuess-I^+	15.584	22.799	27.706	32.949

Table 9. The top-10 rank of base structures and proportion of that with additional tags (PII tags and popular password tag)

Rank	**12306-train**				**Youku-train**			
	TarGuess-I		TarGuess-I^+		TarGuess-I		TarGuess-I^+	
1	D_6	4.70235	P_1	5.46191	D_6	8.50502	P_1	8.15309
2	U_1	3.5697	U_1	3.57776	D_7	5.8582	D_6	6.2028
3	D_7	3.08793	D_6	3.32009	D_8	2.83745	D_7	5.40362
4	E_1	2.90005	E_1	2.90005	N_2D_6	2.4342	D_8	2.68715
5	U_3	2.42767	D_7	2.75646	U_1	2.39387	U_1	2.36088
6	N_2D_6	2.42767	U_3	2.3807	U_3	2.31689	U_3	2.23623
7	N_2B_1	1.88013	N_2B_1	1.89087	E_1	2.04194	E_1	2.03461
8	N_1D_3	1.78217	N_1D_3	1.78217	L_2D_6	1.63135	N_2D_6	1.8843
9	D_8	1.75801	N_2D_6	1.71373	B_1	1.5617	B_1	1.55803
10	N_2D_7	1.68823	D_8	1.66944	N_1	1.47249	N_1	1.45905
% of additional tag		63.51863	70.12532		49.49045		60.6011	

on average. Though the effectiveness of each improvement fluctuates wildly because of the suitableness of grammar $\mathcal{G}_{\mathcal{II}}$ for each data set, it does prove that our improvements are effective. The results of this paper also show the necessity of multi-factor authentication in critical information systems (e.g., military systems, medical systems) [37, 38].

Table 10. The improvements of TarGuess-I$^+$ compared with TarGuess-I within 1000 guesses

Training set	Testing set						
	Duduniu	**Tianya**	**CSDN**	**Renren**	**12306**	**Youku**	**Average**
12306	18.80%	11.98%	12.51%	23.05%	2.82%	2.82%	11.69%
Youku	9.64%	6.31%	2.11%	6.28%	7.41%	6.89%	6.44%

6 Conclusion

Based on the well-known password guessing model TarGuess-I, an improved password guessing model TarGuess-I$^+$ was proposed. After an in-depth analysis and a series of experiments of TarGuess-I based on 6 public leaked password datasets, we have found 2 improvements in TarGuess-I, which are popular passwords and the special strings. Experimental results show that our improved model outperforms the original model by 9.07% on average with 1000 guesses, suggesting the feasibility of our improvements. However, due to the lack of experimental data, the improvements will be further verified in the coming future. Our improvement of special strings sheds new light on password guessing.

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