

Fast Dictionary Attacks on Passwords Using Time-Space Tradeoff

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April 14, 2015

Overview

Introduction

- Introduction

- Time-Space Tradeoff

- Smart Dictionary Attack

Filtering

- Markovian

- Finite Automaton

Indexing Algorithms

Experiment

Conclusions

Analysis

Introduction

- ▶ Humans tend to generate passwords that are easy to remember
- ▶ Common defense: *composition rules* require passwords to include digits and special characters
- ▶ Even with the addition of digits and special characters, Humans are not too random

Introduction

- ▶ Consider a string “abababababababab” 16 characters long
- ▶ Although the string is long and hard to brute-force, it is not very random
- ▶ This can be modeled by the *Kolmogorov complexity* (K-Complexity)
 - ▶ Kolmogorov complexity: The length of the shortest Turing Machine that outputs a string and then halts

Introduction

- ▶ Iterate over all strings with $K\text{-Complexity} \leq \text{some threshold}$
- ▶ Can't be done
 - ▶ $K\text{-Complexity}$ is uncomputable
 - ▶ Human randomness is different than computational randomness
- ▶ Solution: Use techniques from natural language processing, such as "Markovian Filters" to generate strings that are phonetically similar to the user's natural language

Goal

Ultimate goal: given a cipher text c recover the password k such that $H(k) = c$

Time-Space Tradeoff

Full look up table

Time

$O(1)$

?????

Space

$O(|\mathcal{K}|)$

Brute-force attack

Time

$O(|\mathcal{K}|)$

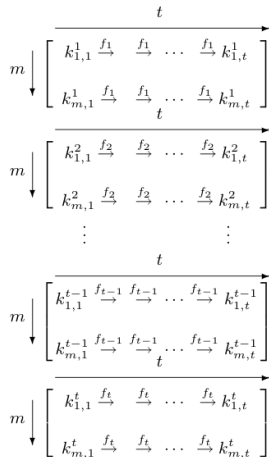
Space

$O(1)$

Time-Space Tradeoff

In 1980 Martin Hellman answers this question by contributing a Time-Space tradeoff for the problem of cryptanalysis.

- ▶ Precompute: m “chains” of length t
- ▶ Store only the first and last items in each chain



Chain Generation

The function $f(k)$ maps from one key to another. Where:

$$f(k) = R[H(k)]$$

where

- ▶ $H(k)$ is a hash function that maps from key k to ciphertext c
- ▶ $R(c)$ is a Reduction function mapping from a ciphertext c back to a value $k \in \mathcal{K}$
- ▶ Example reduction function: drop last n characters/bits

$$\begin{array}{c}
 \xrightarrow{t} \\
 m \downarrow \left[\begin{array}{ccccccc} k_{1,1}^1 & \xrightarrow{f_1} & & \xrightarrow{f_1} & \dots & \xrightarrow{f_1} & k_{1,t}^1 \\ k_{m,1}^1 & \xrightarrow{f_1} & & \xrightarrow{f_1} & \dots & \xrightarrow{f_1} & k_{m,t}^1 \end{array} \right] \\
 \xrightarrow{t} \\
 m \downarrow \left[\begin{array}{ccccccc} k_{1,1}^2 & \xrightarrow{f_2} & & \xrightarrow{f_2} & \dots & \xrightarrow{f_2} & k_{1,t}^2 \\ k_{m,1}^2 & \xrightarrow{f_2} & & \xrightarrow{f_2} & \dots & \xrightarrow{f_2} & k_{m,t}^2 \\ \vdots & & & & & & \vdots \end{array} \right] \\
 \xrightarrow{t} \\
 m \downarrow \left[\begin{array}{ccccccc} k_{1,1}^{t-1} & \xrightarrow{f_{t-1}} & & \xrightarrow{f_{t-1}} & \dots & \xrightarrow{f_{t-1}} & k_{1,t}^{t-1} \\ k_{m,1}^{t-1} & \xrightarrow{f_{t-1}} & & \xrightarrow{f_{t-1}} & \dots & \xrightarrow{f_{t-1}} & k_{m,t}^{t-1} \end{array} \right] \\
 \xrightarrow{t} \\
 m \downarrow \left[\begin{array}{ccccccc} k_{1,1}^t & \xrightarrow{f_t} & & \xrightarrow{f_t} & \dots & \xrightarrow{f_t} & k_{1,t}^t \\ k_{m,1}^t & \xrightarrow{f_t} & & \xrightarrow{f_t} & \dots & \xrightarrow{f_t} & k_{m,t}^t \end{array} \right]
 \end{array}$$

Chain Generation

Example (Chain Generation)

4-character passwords

6-character password sets

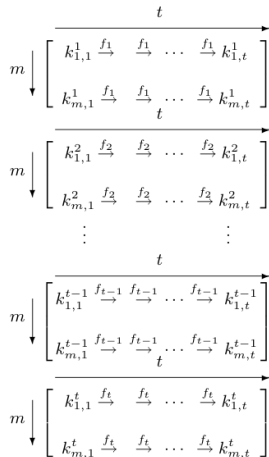
$$\text{pass} \rightarrow^H \text{FE4gT6} \rightarrow^R \text{ofie} \rightarrow^H$$

$$\text{FP03u2} \rightarrow^R \text{ueyf} \dots \rightarrow^R \text{lswq}$$

$$\begin{array}{c}
 \begin{array}{c} m \\ \downarrow \end{array} \begin{array}{c} \xrightarrow{t} \\ \left[\begin{array}{ccccccc} k_{1,1}^1 & \xrightarrow{f_1} & & \xrightarrow{f_1} & \dots & \xrightarrow{f_1} & k_{1,t}^1 \\ k_{m,1}^1 & \xrightarrow{f_1} & & \xrightarrow{f_1} & \dots & \xrightarrow{f_1} & k_{m,t}^1 \end{array} \right] \end{array} \\
 \begin{array}{c} m \\ \downarrow \end{array} \begin{array}{c} \xrightarrow{t} \\ \left[\begin{array}{ccccccc} k_{1,1}^2 & \xrightarrow{f_2} & & \xrightarrow{f_2} & \dots & \xrightarrow{f_2} & k_{1,t}^2 \\ k_{m,1}^2 & \xrightarrow{f_2} & & \xrightarrow{f_2} & \dots & \xrightarrow{f_2} & k_{m,t}^2 \end{array} \right] \end{array} \\
 \vdots \\
 \begin{array}{c} m \\ \downarrow \end{array} \begin{array}{c} \xrightarrow{t} \\ \left[\begin{array}{ccccccc} k_{1,1}^{t-1} & \xrightarrow{f_{t-1}} & & \xrightarrow{f_{t-1}} & \dots & \xrightarrow{f_{t-1}} & k_{1,t}^{t-1} \\ k_{m,1}^{t-1} & \xrightarrow{f_{t-1}} & & \xrightarrow{f_{t-1}} & \dots & \xrightarrow{f_{t-1}} & k_{m,t}^{t-1} \end{array} \right] \end{array} \\
 \begin{array}{c} m \\ \downarrow \end{array} \begin{array}{c} \xrightarrow{t} \\ \left[\begin{array}{ccccccc} k_{1,1}^t & \xrightarrow{f_t} & & \xrightarrow{f_t} & \dots & \xrightarrow{f_t} & k_{1,t}^t \\ k_{m,1}^t & \xrightarrow{f_t} & & \xrightarrow{f_t} & \dots & \xrightarrow{f_t} & k_{m,t}^t \end{array} \right] \end{array}
 \end{array}$$

Key Recovery

- ▶ Given any cipher text c , use the reduction function R to generate a key k_i
- ▶ Generate a new chain of length t (where t is the length of chains in the stored table)
- ▶ Search the *last* elements of the precomputed table for every key generated from the given ciphertext c



Key Recovery

- ▶ Because we found the chain our ciphertext belongs to, we can recover the key that generates the ciphertext
- ▶ Time-Space Tradeoff comes from the length of the chains

Example (On Board)

$$\begin{array}{c}
 \xrightarrow{t} \\
 \begin{array}{c} m \downarrow \\ \left[\begin{array}{ccccccc} k_{1,1}^1 & \xrightarrow{f_1} & & \xrightarrow{f_1} & \dots & \xrightarrow{f_1} & k_{1,t}^1 \\ k_{m,1}^1 & \xrightarrow{f_1} & & \xrightarrow{f_1} & \dots & \xrightarrow{f_1} & k_{m,t}^1 \end{array} \right] \\ \xrightarrow{t} \end{array} \\
 \begin{array}{c} m \downarrow \\ \left[\begin{array}{ccccccc} k_{1,1}^2 & \xrightarrow{f_2} & & \xrightarrow{f_2} & \dots & \xrightarrow{f_2} & k_{1,t}^2 \\ k_{m,1}^2 & \xrightarrow{f_2} & & \xrightarrow{f_2} & \dots & \xrightarrow{f_2} & k_{m,t}^2 \end{array} \right] \\ \vdots \qquad \qquad \qquad \vdots \end{array} \\
 \xrightarrow{t} \\
 \begin{array}{c} m \downarrow \\ \left[\begin{array}{ccccccc} k_{1,1}^{t-1} & \xrightarrow{f_{t-1}} & & \xrightarrow{f_{t-1}} & \dots & \xrightarrow{f_{t-1}} & k_{1,t}^{t-1} \\ k_{m,1}^{t-1} & \xrightarrow{f_{t-1}} & & \xrightarrow{f_{t-1}} & \dots & \xrightarrow{f_{t-1}} & k_{m,t}^{t-1} \end{array} \right] \\ \xrightarrow{t} \end{array} \\
 \begin{array}{c} m \downarrow \\ \left[\begin{array}{ccccccc} k_{1,1}^t & \xrightarrow{f_t} & & \xrightarrow{f_t} & \dots & \xrightarrow{f_t} & k_{1,t}^t \\ k_{m,1}^t & \xrightarrow{f_t} & & \xrightarrow{f_t} & \dots & \xrightarrow{f_t} & k_{m,t}^t \end{array} \right] \end{array}
 \end{array}$$

Problem

Chains can merge. The reduction function can produce the same key for two different ciphertexts

- ▶ If the merge happens early in the chain generation, the table will not cover as many passwords
- ▶ Hard to detect because the chains will still have different end points (Unless the merge happens at the same position in the two chains)

Solution

Rainbow Tables

- ▶ Use different related reduction functions R_1 to R_n where n is the length of the chain
- ▶ If a collision happens, It has to be at the same position in chain generation and collisions can be detected
- ▶ Key recovery changes because we are using a different reduction function each time.
 - ▶ assume generate chain starting at position $n - 1$ use reduction function R_{n-1} and move backwards through the chain

Smart Dictionary Attacks

- ▶ Rainbow tables and the classical space-time tradeoff make **no assumptions** about the keyspace other than its size
- ▶ Narayanan and Shmatikov use Markov chains and Regular expressions to make some assumptions about the keyspace. This means that we can search only a “smart” portion of the keyspace.

Markov Chains

- ▶ Markov chains are commonly used in natural language processing. Most notably speech recognition systems.
- ▶ Markov models have been used to generate passwords for users.
- ▶ Given a set of states $S = \{s_1, s_2, \dots, s_n\}$ there is some probability p_{ij} that denotes the probability of transitioning from state s_i to state s_j
- ▶ The probability of transitioning to the next state depends only on the current state

Markov Chains

The order of a Markov chain of order n is defined as:

$$P(X_n = x_n | X_{n-1} = x_{n-1}, X_{n-2} = x_{n-2}, \dots, X_1 = x_1) = \\ P(X_n = x_n | X_{n-1} = x_{n-1}, \dots, X_{n-m} = x_{n-m})$$

Zero-order Markov Chain:

$$P(X_n = x_n | X_{n-1} = x_{n-1}, X_{n-2} = x_{n-2}, \dots, X_1 = x_1) = \\ P(X_n = x_n)$$

First-order Markov Chain:

$$P(X_n = x_n | X_{n-1} = x_{n-1}, X_{n-2} = x_{n-2}, \dots, X_1 = x_1) = \\ P(X_n = x_n | X_{n-1} = x_{n-1})$$

Zero-order Markov Model

In a zero-order Markov model, each character is generated given its underlying probability distribution. This is based on the frequency of the letter in the users natural language. Formally the zero-order model can be written as:

$$P(\alpha) = \prod_{x \in \alpha} \mathcal{V}(x)$$

where: where

- ▶ $P(\cdot)$ is the markovian probability distribution
- ▶ α is a string of characters
- ▶ $\mathcal{V}(\cdot)$ is the frequency of a letter occurring in English
- ▶ x is an individual character

First-order Markov Model

In a First-order Markov model, each ordered pair is assigned a probability and each character is generated by looking at the previous character. The first-order Markov model can be written as:

$$P(x_1 x_2 x_3 \cdots x_n) = \mathcal{V}(x_1) \prod_{i=1}^{n-1} \mathcal{V}(x_{i+1} | x_i)$$

where: where

- ▶ $P(\cdot)$ is the Markovian probability distribution
- ▶ x_i are individual characters
- ▶ $\mathcal{V}(\cdot)$ is the frequency of a letter or ordered pair occurring in English

Markov Dictionary

A probability distribution is not a dictionary. To create a dictionary, discretize the probabilities into two levels using a threshold θ

Zero-order dictionary

$$\mathcal{D}_{\mathcal{V},\theta} = \{\alpha : \prod_{x \in \alpha} \mathcal{V}(x) \geq \theta\}$$

First-order dictionary

$$\mathcal{D}_{\mathcal{V},\theta} = \{x_1 x_2 \cdots x_n : \mathcal{V}(x_1) \prod_{i=1}^{n-1} \mathcal{V}(x_{i+1}|x_i) \geq \theta\}$$

Markov Dictionary

The zero-order model is better for abrivations and acrynms. For example, a user picks their favorite song lyric and the first letter of each word creates their password.

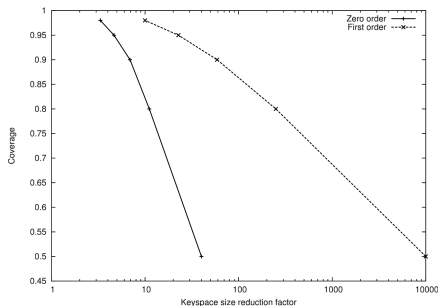


Figure: Convergence vs reduction in Keyspace size ($|\mathcal{K}|$) for 8-character sequences

Deterministic Finite Automaton

- ▶ A DFA or Deterministic Finite Automaton is a finite state machine that accepts or rejects a string
- ▶ A regular expression can be constructed from a DFA
- ▶ Humans are not random with how they use numerals and special characters
 - ▶ Numbers tend to be at the end of a password: password1
 - ▶ Capital letters are typically at the beginning of a password: Password
 - ▶ there are typically more lowercase letters in passwords than uppercase letters, numerals, or special characters

Dictionary using a DFA

An improved dictionary is one where strings are both accepted by a Markovian filter and accepted by at least one DFA from some set of DFA's. The updated dictionary is defined as:

$$\mathcal{D}_{\mathcal{V}, \theta, \langle M_i \rangle} = \{ \alpha : \prod_{x \in \alpha} \mathcal{V}(x) \geq \theta, \text{ and } \exists i : M_i \text{ accepts } \alpha \}$$

where

- ▶ A is the set of 26 uppercase characters
- ▶ a is the set of 26 lowercase characters
- ▶ n is the set of 10 numerals
- ▶ s is the set of 5 special characters
 $\{space, hyphen, underscore, period, comma\}$

Indexing Algorithms

- ▶ The goal is to create an algorithm that will efficiently enumerate the passwords in a given password space. Given i as input return the i^{th}
- ▶ In the rainbow attack the reduction function maps from ciphertext space to $\{0, 1, \dots, |\mathcal{K} - 1|\}$
- ▶ Composed with a mapping from $\{0, 1, \dots, |\mathcal{K} - 1|\}$ to a key in \mathcal{K} .
- ▶ Makes no assumption about keyspace other than its size
- ▶ Use the rainbow attack with a "smart" way to choose the keyspace

Dictionary Modification

Modify the dictionary to only consider fixed length strings. This allows for different threshold values θ for each length.

$$\mathcal{D}_{\mathcal{V},\theta,\ell} = \{\alpha : |\alpha| = \ell \text{ and } \prod_{x \in \alpha} \mathcal{V}(x) \geq \theta\}$$

Discretization

The algorithm also needs to discretize the probability distribution of the strings. First, turn the dictionary into a sum rather than a product.

Transform the product

$$\prod_{x \in \alpha} \mathcal{V}(x) \geq \theta$$

$$\log\left(\prod_{x \in \alpha} \mathcal{V}(x)\right) \geq \log(\theta)$$

$$\log(\mathcal{V}(x_1)\mathcal{V}(x_2) \cdots \mathcal{V}(x_n)) \geq \log(\theta)$$

$$\log(\mathcal{V}(x_1)) + \log(\mathcal{V}(x_2)) + \cdots + \log(\mathcal{V}(x_n)) \geq \log(\theta)$$

Discretization

To arrive at a discrete version of the modified dictionary:

$$\mathcal{D}_{\mathcal{V},\theta,\ell} = \{\alpha : |\alpha| = \ell \text{ and } \sum_{x \in \alpha} \mu(x) \geq \lambda\}$$

Where where

- ▶ $\mu(x) = \log(\mathcal{V}(x))$
- ▶ $\lambda = \log(\theta)$

Discretization

- ▶ $\mu(x) = \log(\mathcal{V}(x))$
- ▶ Discretize the values of the μ function to the nearest multiple of some μ_0
- ▶ Narayanan and Shmatikov use a μ_0 that yields approximately 1000 different discrete values

Partial Dictionary

Define a partial dictionary $\mathcal{D}_{\mathcal{V},\theta,\ell,\theta',\ell'}$ as follows:

- ▶ let α be a string such that $|\alpha| = \ell'$
- ▶ $\prod_{x \in \alpha} \mathcal{V}(x) = \theta'$

Then

$$\mathcal{D}_{\mathcal{V},\theta,\ell,\theta',\ell'} = \{\beta : \alpha\beta \in \mathcal{D}_{\mathcal{V},\theta,\ell}\}$$

Zero-Order Markovian Dictionary

Precompute the size of a partial dictionary (recursively) and store in a 2D-array of size $(\ell, \text{num_levels})$

$$|\mathcal{D}_{\mathcal{V}, \text{threshold}, \text{total_length}, \text{level}, \text{current_length}}|$$

Zero-Order Markovian Dictionary

```
partial_size1(current_length, level)
{
    if level >= threshold: return 0
    if total_length = current_length: return 1
    sum = 0
    for each char in alphabet
        sum = sum + partial_size1(current_length+1,
                                   level+mu(char))
    return sum
}
```

Complexity linear in the product of total length, number of characters in alphabet, and number of levels

Zero-Order Markovian Dictionary

- ▶ For cryptanalysis, given an index i produce the corresponding key k in the dictionary \mathcal{D}
- ▶ Use precomputed partial size to determine the first character by looking up a value from the precomputed matrix.
 - ▶ Adjust the index to a new index relative to the first character
 - ▶ Adjust the threshold based on the frequency of the first character

Zero-Order Markovian Dictionary

Initially call `get_key1(0,0)`

```
get_key1(current_length, index, level)
{
    if total_length = current_length: return ""
    sum = 0
    for each char in alphabet
        new_level = level + mu(char)
        // looked up from precomputed array
        size = partial_size1[
            current_length+1][new_level]
        if sum + size > index
            return char + get_key1(
                current_length+1,
                index-sum, new_level)
    sum = sum + size
```

First-Order Markovian Dictionary

Same as zero order only in `get_key`, we need to keep track of the last character

DFA Dictionary

Similar to zero-order Markov dictionary except instead of a threshold and levels, we have states and transitions

Any Keyspace \mathcal{K}

Assume that we have a superspace $\mathcal{K}' \supset \mathcal{K}$ and we need to decide that given $\alpha \in \mathcal{K}'$ if $\alpha \in \mathcal{K}$

Split \mathcal{K}' into m bins of size t and precompute the number of members in each bin that are in \mathcal{K}

Given an index, quickly figure out what bin it falls into and iterate over all keys in that bin and test each one for membership
 $O(|\mathcal{K}'|)$ precomputation time ... storage and index

Hybrid Markovian/DFA

Multiple Keyspaces

Experiment

- ▶ Measure coverage of rainbow attack vs hybrid attack
- ▶ 142 real user passwords
- ▶ 6-Character alphanumeric sequences for the rainbow attack ($|\mathcal{K}| = 36^6 \approx 2 * 10^9$)
- ▶ 70 regular expressions

Results

Category	Count	Rainbow	Hybrid
Length at most 5	63	29	63
Length 6	21	10	17
Length 7	18	0	10
Length 8, A* or a*	9	0	6
Others	31	0	0
Total	142	39(27.5%)	96(67.6%)
only length ≥ 6	79	10(12.7%)	33(41.8%)

Figure: Passwords recovered in Hybrid attack vs. Rainbow attack

Conclusions

- ▶ One of many attacks targeting human weakness
- ▶ Some possible defences against dictionary attacks for human memorable passwords
 - ▶ Graphical passwords
 - ▶ Biometric information
- ▶ Are these actually safer?

Analysis