## Building Better Passwords using Probabilistic Techniques

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## Outline

- Introduction
- Problems with passwords
- Probabilistic password cracking using grammars
- Training
- Cracking
- Our approach - analysis and modification
- The AMPs system
- Estimating strength of password
- Modifying the password
- Updating AMPs over time
- Entropy measures in updating the system


## Introduction

- Passwords are still the most common means of securing computer systems and websites.
- Most users do not have the information to ensure that they are using a "strong" password.


Why great care and consideration should be taken when selecting the proper password

## Existing problems with passwords

- Rule-based password creation policies
- Inconsistent
- Confusing
- Frustrating

| Website | Length | Digit |
| :---: | :---: | :---: |
| Chase.com | $7-32$ | 1 |
| Special char |  |  |
| Bank of America | $8-20$ | 1 |
| Ets.org allowed |  |  |
| Banana Republic | $5-16$ | 1 |

## Microsoft <br> Safety \& Security Centre

Check your password-is it strong?
Test the strength of your passwords: Type a password into the box.

## - Password checkers

- No scientific basis


## alice123!

| Services | Strength scores |  |
| :---: | :---: | :---: |
| Apple | Moderate | $2 / 3$ |
| Dropbox | Very Weak | 1/5 |
| Drupal | Strong | 4/4 |
| eBay | * | -/5 |
| FedEx | Very Weak | 1/5 |
| Google | Good | 4/5 |
| Intel | Oh No! | 1/2 |
| Microsoft (v1) | Strong | $3 / 4$ |
| Microsoft (v2) | Weak | 1/4 |
| Microsoft (v3) | Medium | $2 / 4$ |
| PayPal | Strong | 4/4 |
| QQ | Strong | 4/4 |
| Skype | Medium | $2 / 3$ |
| Twitter | Perfect | 6/6 |
| Yahoo! | Very Strong | 4/4 |
| 12306.cn | Average | $2 / 3$ |

## Analyze and Modify Passwords

Abstract


## Probabilistic password attack

[Weir, Aggarwal and De Medeiros]

- Infer a probabilistic context-free grammar from datasets
- Some words are more likely than others
- Password, monkey, football
- Some mangling rules are more likely than others
- Capitalize the first letter, add the digits at the end
- Assign probability to dictionary words, digits, symbols, mangling rules



## Probabilistic password attack

- Training
- Construct the context-free grammar
- Parse every password into base structures and count their frequency.
- Base structures consist of L (alpha sequences), D (digits), S (symbols), M(capitalization)
- Base structure also includes length information



## Probabilistic password attack Training


tiny99
1pass! this2! star99
.
-
tree99
burn1!
1star!
down11

| $\mathrm{S} \rightarrow$ | $\mathrm{L}_{4} \mathrm{D}_{2}$ | 0.5 |
| :---: | :---: | :---: |
| $\mathrm{S} \rightarrow$ | $\mathrm{D}_{1} \mathrm{~L}_{4} \mathrm{~S}_{1}$ | 0.25 |
| $\mathrm{S} \rightarrow$ | $\mathrm{L}_{4} \mathrm{D}_{1} \mathrm{~S}_{1}$ | 0.25 |
| $\mathrm{D}_{2} \rightarrow$ | 99 | 0.7 |
| $\mathrm{D}_{2} \rightarrow$ | 11 | 0.3 |
| $\mathrm{D}_{1} \rightarrow$ | 1 | 0.8 |
| $\mathrm{D}_{1} \rightarrow$ | 2 | 0.2 |
| $\mathrm{S}_{1} \rightarrow$ | ! | 1.0 |
| $\mathrm{L}_{4} \rightarrow$ | alex | 0.1 |
| $\mathrm{S} \rightarrow$ * alex2! With probability$0.25 \times 0.1 \times 0.2 \times 1.0=0.005$ |  |  |

Note: Alpha sequence probabilities come from dictionaries and are equal to $1 / n_{L}$, where $\mathrm{n}_{\mathrm{L}}$ is the number of words in the dictionary of length L .

## Probabilistic password attack

 Generating the guesses| $\mathrm{S} \rightarrow$ | $\mathrm{L}_{4} \mathrm{D}_{2}$ | 0.5 |
| :--- | :--- | :--- |
| $\mathrm{~S} \rightarrow$ | $\mathrm{D}_{1} \mathrm{~L}_{4} \mathrm{~S}_{1}$ | 0.25 |
| $\mathrm{~S} \rightarrow$ | $\mathrm{~L}_{4} \mathrm{D}_{1} \mathrm{~S}_{1}$ | 0.25 |
| $\mathrm{D}_{2} \rightarrow$ | 99 | 0.7 |
| $\mathrm{D}_{2} \rightarrow$ | 11 | 0.3 |
| $\mathrm{D}_{1} \rightarrow$ | 1 | 0.8 |
| $\mathrm{D}_{1} \rightarrow$ | 2 | 0.2 |
| $\mathrm{~S}_{1} \rightarrow$ | $!$ | 1.0 |
| $\mathrm{~L}_{4} \rightarrow$ | alex | 0.1 |


| alex 99 <br> andy 99 <br> beta 99 <br> $\ldots$ | 0.035 |
| :--- | :---: |
| 1 alex ! <br> 1 andy ! <br> $\ldots$ <br> alex 1! <br> andy 1! <br> $\ldots$ | 0.02 |
| alex 11 <br> andy 11 <br> $\ldots$ | 0.015 |
| 2 alex ! <br> 2 andy ! <br> $\ldots$ |  |
| alex 2 <br> andy 2 ! <br> $\ldots$ | 0.005 |

## AMP System Overview

 Analyzer and Modifier for Passwords

## AMP Analyzing

Estimate the password strength

- Train the system on real user passwords and produce the context-free grammar.
- Using the context-free grammar, we calculate the probability of the user-chosen password.



## AMP

## Setting the Threshold

- Threshold: is a probability value thp

| Total_Guesses: | 69491415 | Probability: | $3.1716 \mathrm{e}-10$ |
| :--- | :--- | :--- | :--- |
| Total_Guesses: | 69744266 | Probability: | $3.14529 \mathrm{e}-10$ |
| Total_Guesses: | 70000775 | Probability: | $3.12015 \mathrm{e}-10$ |
| Total_Guesses: | 70602451 | Probability: | $3.09261 \mathrm{e}-10$ |
| Total_Guesses: | 71121270 | Probability: | $3.06813 \mathrm{e}-10$ |
| Total_Guesses: | 71519812 | Probability: | $3.04416 \mathrm{e}-10$ |
| Total_Guesses: | 71799637 | Probability: | $3.02051 \mathrm{e}-10$ |
| Total_Guesses: | 72097254 | Probability: | $2.9943 \mathrm{e}-10$ |
| Total_Guesses: | 72304253 | Probability: | $2.97314 \mathrm{e}-10$ |
| Total_Guesses: | 72508371 | Probability: | $2.95322 \mathrm{e}-10$ |
| Total_Guesses: | 72969956 | Probability: | $2.92856 \mathrm{e}-10$ |
| Total_Guesses: | 73582269 | Probability: | $2.90398 \mathrm{e}-10$ |
| Total_Guesses: | 74074952 | Probability: | $2.87881 \mathrm{e}-10$ |
| Total_Guesses: | 74277559 | Probability: | $2.85883 \mathrm{e}-10$ |
| Total_Guesses: | 74826737 | Probability: | $2.83975 \mathrm{e}-10$ |
| Total_Guesses: | 75329839 | Probability: | $2.81662 \mathrm{e}-10$ |
| Total_Guesses: | 75667418 | Probability: | $2.79658 \mathrm{e}-10$ |
| Total_Guesses: | 76191974 | Probability: | $2.77426 \mathrm{e}-10$ |
| Total_Guesses: | 76346168 | Probability: | $2.75369 \mathrm{e}-10$ |

- Converting to time: $\frac{\text { Total_number_of_guesses }}{\text { Calculations_per_hour }}=$ Expected_time(hour)

Calculations_per_hour

## Example table for threshold

| Total number of <br> guesses g(t) | Probability t | Time (on my laptop for <br> MD5 hash) |
| :---: | :---: | :---: |
| $1,800,000,000$ | $1.31 \times 10^{-11}$ | 1 hour |
| $14,400,000,000$ | $1.59 \times 10^{-12}$ | 8 h |
| $21,600,000,000$ | $1.20 \times 10^{-12}$ | 12 h |
| $28,800,000,000$ | $6.37 \times 10^{-13}$ | 16 h |
| $43,200,000,000$ | $2.96 \times 10^{-13}$ | 24 h |
| $86,400,000,000$ | $9.94 \times 10^{-14}$ | 48 h |
| $129,600,000,000$ | $6.7 \times 10^{-14}$ | 72 h |
| $172,800,000,000$ | $5.29 \times 10^{-14}$ | 96 h |

## AMP

Setting the Threshold approaches

1. Using password guesser

- Accurate
- Straightforward
- Takes a long time

2. Using the context-free grammar

- Gives a lower bound for the number of guesses
- Faster


## AMP-Setting the Threshold

 Running password guesser| Total_Guesses: | 69491415 | Probability: | 3.1716e-10 | base_struct: | 000Ue12 |
| :---: | :---: | :---: | :---: | :---: | :---: |
| Total_Guesses: | 69744266 | Probability: | 3.14529e-10 | base_struct: | 00Le\$\$ |
| Total_Guesses: | 70000775 | Probability: | 3.12015e-10 | base_struct: | ! Le2Le- |
| Total_Guesses: | 70602451 | Probability: | 3.09261e-10 | base_struct: | 2Le12\# |
| Total_Guesses: | 71121270 | Probability: | 3.06813e-10 | base_struct: | 9.3. |
| Total_Guesses: | 71519812 | Probability: | 3.04416e-10 | base_struct: | Le2Ue143 |
| Total_Guesses: | 71799637 | Probability: | 3.02051e-10 | base_struct: | 93.2 |
| Total_Guesses: | 72097254 | Probability: | $2.9943 \mathrm{e}-10$ | base_struct: | Le63Le07 |
| Total_Guesses: | 72304253 | Probability: | $2.97314 \mathrm{e}-10$ | base_struct: | 0000.. |
| Total_Guesses: | 72508371 | Probability: | 2.95322e-10 | base_struct: | Ue5Ue4 |
| Total_Guesses: | 72969956 | Probability: | 2.92856e-10 | base_struct: | 1Le95Le3 |
| Total_Guesses: | 73582269 | Probability: | 2.90398e-10 | base_struct: | 93.3 |
| Total_Guesses: | 74074952 | Probability: | 2.87881e-10 | base_struct: | 1213 |
| Total_Guesses: | 74277559 | Probability: | 2.85883e-10 | base_struct: | 27Le2001 |
| Total_Guesses: | 74826737 | Probability: | 2.83975e-10 | base_struct: | Le3Ue1Ue7 |
| Total_Guesses: | 75329839 | Probability: | 2.81662e-10 | base_struct: | Le58Le8Le |
| Total_Guesses: | 75667418 | Probability: | 2.79658e-10 | base_struct: | . Le2Le0 |
| Total_Guesses: | 76191974 | Probability: | 2.77426e-10 | base_struct: | 5_007 |
| Total_Guesses: | 76346168 | Probability: | 2.75369e-10 | base_struct: | Le@Le! 2 |
| Total_Guesses: | 76964953 | Probability: | 2.73163e-10 | base_struct: | 4Le9Le5 |
| Total_Guesses: | 77380282 | Probability: | 2.71075e-10 | base_struct: | 1@2-1 |
| Total_Guesses: | 77947787 | Probability: | 2.69186e-10 | base_struct: | 9Le |
| Total_Guesses: | 78858297 | Probability: | 2.67563e-10 | base_struct: | 1991+ |
| Total Guesses: | 78913486 | Probabilitv: | $2.65541 \mathrm{e}-10$ |  | 1138 |

## AMP-Setting the Threshold Using the Grammar

- Estimating the number of guesses before threshold (thp).
- Starting from the first base structure, for example $\mathrm{b}_{1}=\mathrm{L}_{5} \mathrm{D}_{3} \mathrm{~S}_{1}$ with probability $\mathrm{p}_{1}$, we need to find the elements in each component so that the product of their probabilities is $>$ thp.


## AMP

Set the threshold - Using the context free grammar


## MODIFYING A WEAK PASSWORD

## Modifying a weak password

- There are certain numbers or words that are easy to remember for each individual.
- Edit distance: The minimum number of operations used to transform a string to another one.
- We only change within edit distance of 1.



## Modifying a weak password

 distance function- Operations on the base structure
- Insertion
- Deletion
- Transposition
$\mathrm{L}_{5} \mathrm{D}_{3} \mathrm{~S}_{1}$
L5S 1 D3S1
$\mathrm{L}_{5} \mathrm{D}_{3} \mathrm{~S}_{4}$
$\mathrm{D}_{3} \mathrm{~L}_{5} \mathrm{~S}_{1}$
$\mathrm{D}_{3}: 123$
1263
423
- Substitution

129
$\mathrm{L}_{5}$ : alice
aLice

- Case (only for alpha part)



## Modifying a weak password Example

| Input password to AMP | Output of modifier |
| :--- | :--- |
| trans2 | \%trans2 |
| colton00 | 8colton00 |
| 789pine | 789pinE |
| mitch8202 | mitch=8202 |
| callfero | cal8fero |
| KILLER456 | KILlER456 |
| violin22 | violin^22 |
| ATENAS0511 | 0511AETENAS |
| *zalena6 | *3zalena6 |
| KYTTY023 | KYTTY023r |

## Testing

## Testing the AMP System

## Experiment Setup



## Testing the AMP System

Some results
Cracked by John the Ripper - 1 day threshold

|  | Originally Strong passwords | Originally Weak passwords (Not able to make stronger) | Originally Weak passwords (Able to make stronger) | Strengthened passwords Modified from weak ones |
| :---: | :---: | :---: | :---: | :---: |
| Hotmail | $\begin{gathered} \frac{2}{325} \\ (\mathbf{0 . 6 1 \%}) \end{gathered}$ | $\begin{gathered} \frac{49}{53} \\ \text { (92.45\%) } \end{gathered}$ | $\begin{gathered} \frac{988}{2059} \\ (\mathbf{4 7 . 9 8 \%}) \end{gathered}$ | $\begin{gathered} \frac{2}{2059} \\ (\mathbf{0 . 0 9 7 \%}) \end{gathered}$ |
| cracked |  |  |  |  |
| total |  |  |  |  |
| Percentage |  |  |  |  |
| MySpace | $\begin{aligned} & \frac{23}{1484} \\ & (1.55 \%) \end{aligned}$ | $\begin{gathered} \frac{104}{149} \\ \text { (69.80\%) } \end{gathered}$ | $\begin{aligned} & \frac{5,343}{13,866} \\ & \mathbf{( 3 8 . 5 3 \% )} \end{aligned}$ | $\begin{array}{r} \frac{71}{13,866} \\ (\mathbf{0 . 5 1 \% )} \end{array}$ |
| cracked |  |  |  |  |
| total |  |  |  |  |
| Percentage |  |  |  |  |
| RockYou | 281 | 22,248 | 235,302 | 1,186 |
| cracked |  |  |  |  |
| total | $\begin{gathered} 32,794 \\ (\mathbf{0 . 8 6 \%}) \end{gathered}$ | $\begin{gathered} 24,745 \\ \mathbf{( 8 9 . 9 0 \% )} \end{gathered}$ | $\begin{gathered} 442,461 \\ \mathbf{( 5 3 . 1 8 \%} \end{gathered}$ | $\begin{gathered} 442,461 \\ (\mathbf{0 . 2 7 \% )} \end{gathered}$ |
| Percentage |  |  |  |  |

## Some results

Cracked by Probabilistic Password Cracker - 1 day threshold

|  | Originally Strong passwords | Originally Weak passwords (Not able to make stronger) | Originally Weak passwords (Able to make stronger) | Strengthened passwords Modified from weak ones |
| :---: | :---: | :---: | :---: | :---: |
| Hotmail | $\begin{gathered} \frac{1}{325} \\ (\mathbf{0 . 3 \%}) \end{gathered}$ | $\begin{gathered} \frac{53}{53} \\ (\mathbf{1 0 0 \%}) \\ \hline \end{gathered}$ | $\begin{gathered} \frac{1069}{2059} \\ \text { (51.91\%) } \\ \hline \end{gathered}$ | $\frac{113}{2059}$ <br> (5.48\%) |
| cracked |  |  |  |  |
| total |  |  |  |  |
| Percentage |  |  |  |  |
| MySpace | $\begin{aligned} & \frac{27}{1484} \\ & \text { (1.81\%) } \end{aligned}$ | $\begin{gathered} \frac{135}{149} \\ \text { (90.60\%) } \end{gathered}$ | $\begin{gathered} \frac{8,341}{13,866} \\ (\mathbf{6 0 . 1 5 \% )} \\ \hline \end{gathered}$ | $\begin{gathered} \frac{698}{13,866} \\ (5.03 \%) \end{gathered}$ |
| cracked |  |  |  |  |
| total |  |  |  |  |
| Percentage |  |  |  |  |
| RockYou | 467 | 24,378 | 259,027 | 18,134 |
| cracked |  |  |  |  |
| total | $\begin{array}{r} 32,794 \\ \text { (1.42\%) } \end{array}$ | $\begin{gathered} \overline{24,745} \\ \mathbf{( 9 8 . 5 1 \% )} \end{gathered}$ | $\begin{aligned} & 442,461 \\ & \mathbf{( 5 8 . 5 4 \%} \end{aligned}$ | $\begin{aligned} & \hline 442,461 \\ & (\mathbf{4 . 1 \%}) \end{aligned}$ |
| Percentage |  |  |  |  |

## Some results

Weak and Strengthened passwords cracked by J ohn the Ripper


Number of guesses

## Some results

Beyond 1 day Threshold


## Update the training set

- As we keep using AMP, we suggest more passwords with lower probabilities as strong passwords.
- As people use our suggested passwords more, the probability distribution of passwords changes.
- An attacker might be able to crack passwords using the recent set of real user passwords.


## AMP

Update the training set


## AMP

Update the Context-free Grammar

| Base structures |  |  |
| :--- | :--- | :--- |
| $\mathrm{b}_{1}$ | $\frac{n_{1}}{N}$ | $\frac{n_{1}}{N+1}$ |
| $\mathrm{~b}_{2}$ | $\frac{n_{2}}{N}$ | $\frac{n_{2}}{N+1}$ |
| $\mathrm{~b}_{3}$ | $\frac{n_{3}}{N}$ | $\frac{n_{3}}{N+1}$ |
| $\cdot$ |  |  |
| $\cdot$ | $\frac{n_{i}}{N}$ | $\frac{n_{i}+1}{N+1}$ |
| $\mathrm{~b}_{\mathrm{i}}=\mathrm{S}_{2} \mathrm{D}_{2} \mathrm{~L}_{4}$ |  |  |
| $\cdot$ | $\frac{n_{m}}{N}$ | $\frac{n_{m}}{N+1}$ |
| $\mathrm{~b}_{\mathrm{m}}$ |  |  |


| $\mathrm{S}_{2}$ |  |  |
| :---: | :---: | :---: |
| $\mathrm{S}_{1}$ | $\underline{n_{1}}$ | $n_{1}$ |
|  | $N$ | $\overline{N+1}$ |
| $\mathrm{S}_{2}$ | $\underline{n}$ | $n_{2}$ |
|  | $N$ | $\frac{n_{2}}{N+1}$ |
| $\mathrm{S}_{3}$ | $\frac{n_{3}}{N}$ | $n_{3}$ |
|  |  | $\stackrel{3}{N+1}$ |
| . |  |  |
| $\mathrm{s}_{\mathrm{j}}=$ ! ! | $\frac{n_{j}}{N}$ | $n_{j}+1$ |
|  |  | $N+1$ |
| - |  |  |
| $\mathrm{S}_{\mathrm{m}}$ | $\frac{n_{m}}{N}$ | $\frac{n_{m}}{N+1}$ |


| Base structures |  |  | $\mathrm{S}_{2}$ |  |  | $\mathrm{D}_{2}$ |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| $\mathrm{b}_{1}$ | $\frac{n_{b 1}}{N}$ | $\frac{n_{b 1}}{N_{b}+1}$ | $\mathrm{S}_{1}$ | $\frac{n_{s t}}{N}$ | $\frac{n_{s i}}{N_{s+1}}$ | $\mathrm{d}_{1}$ | $\frac{n_{d 1}}{N}$ | $\frac{n_{d 1}}{N_{d 1}+1}$ |
| $\mathrm{b}_{2}$ | $N_{b}$ <br> $\underline{n_{b 2}}$ <br> $N$ | $\begin{gathered} N_{b}+1 \\ n_{b 2} \\ \hline \end{gathered}$ |  | $N_{s}$ <br> $n_{s 2}$ | $N_{s}+1$ <br> $n_{s 2}$ <br> $N$ |  | $N_{d}$ <br> $n_{d 2}$ <br> $N$ | $N_{d}+1$ <br> $n_{d 2}$ <br> $N$ |
|  | $N_{b}$ | $\overline{N_{b}+1}$ | $\mathrm{S}_{2}$ | $\overline{N_{s}}$ | $\overline{N_{s}+1}$ | $\mathrm{d}_{2}$ | $N_{d}$ | $N_{d}+1$ |
| $\mathrm{b}_{3}$ | $\frac{n_{b 3}}{N}$ | $\frac{n_{b 3}}{N}$ |  | $n_{s 3}$ | $n_{s 3}$ |  | $n_{d 3}$ | $n_{d 3}$ |
| . |  | $N_{b}+1$ | $\mathrm{S}_{3}$ | $\frac{N_{s}}{N_{s}}$ | $\frac{n_{s}}{N_{s}+1}$ | $\mathrm{d}_{3}$ | $\stackrel{N_{d}}{ }$ | $\stackrel{\text { d }}{ }$ |
|  |  |  |  |  |  |  |  |  |
| $\mathrm{b}_{\mathrm{i}}=\mathrm{S}_{2} \mathrm{D}_{2} \mathrm{~L}_{4}$ |  | $\frac{n_{b i}+1}{N}$ |  |  |  |  |  | $n_{\text {dl }}+1$ |
|  | $N_{b}$ | $N_{b}+1$ | $\mathrm{S}_{\mathrm{j}}=$ !! | $\frac{n_{s j}}{N_{s}}$ | $\frac{n_{s j}}{N_{s}+1}$ | $\mathrm{d}_{1}=78$ |  | $\frac{d_{d}}{N_{d}+1}$ |
| $\mathrm{b}_{\mathrm{m}}$ | $n_{b m}$ | $n_{b m}$ |  |  |  |  |  | $n_{d t}$ |
|  |  | $\overline{N_{b}+1}$ | $\mathrm{S}_{\mathrm{k}}$ | $\frac{N_{s}}{N_{s}}$ | $\frac{n_{s}}{N_{s}+1}$ | $\mathrm{d}_{\text {t }}$ | $\overline{N_{d}}$ | $\overline{N_{d}+1}$ |

Preprocessing phase


Metrics for password strength

## Metrics for password strength

- Guessing Entropy G(X):

$$
\begin{gathered}
p_{1} \geq p_{2} \geq \ldots \geq p_{n} \\
G(X)=\sum_{i=1}^{n} i \cdot p_{i}
\end{gathered}
$$

average number of tries for finding the password

- Shannon Entropy:

$$
H(X)=-\sum_{x \in X} p(x) \log p(x)
$$

Where $\mathrm{P}(\mathrm{X}=\mathrm{x})$ is the probability that the variable X has the value x .

- Massey proved the following relationship for discrete distributions:

$$
G(X) \geq\left(\frac{1}{4}\right) 2^{H(X)}+1
$$

## Metric for password strength

- Massey proved the following relationship for discrete distributions:

$$
G(X) \geq\left(\frac{1}{4}\right) 2^{H(X)}+1
$$

Calculation of Entropy basedon Context-free grammars for a password distribution

$$
\mathbf{S} \quad \begin{aligned}
& \mathbf{L}_{2} \mathbf{D}_{3} \\
& \mathbf{D}_{\mathbf{2}} \mathbf{L}_{2} \\
& \mathbf{S}_{1} \mathbf{D}_{2}
\end{aligned}
$$

$$
\mathbf{L}_{2} D_{3} \underset{\text { it999 }}{\mathbf{u p 9 9 9}}
$$

## 10it

$p\left(S \rightarrow L_{2} D_{3}\right)=p\left(B=L_{2} D_{3}\right)$

$$
\begin{array}{ll}
\mathbf{S}_{1} \mathbf{D}_{\mathbf{2}} & \text { \$11 } \\
& \# 11 \\
& \$ 10 \\
&
\end{array}
$$

## Calculation of Entropy

 based on context-free grammar for a password distribution$$
\begin{aligned}
H(B, R) & =H(B)+H(R \mid B) \\
& =H(B)+\sum_{b_{i}} p\left(b_{i}\right) H\left(R \mid B=b_{i}\right)
\end{aligned}
$$

$$
\begin{aligned}
H(B, R) & =H(B)+H(R \mid B) \\
& =H(B)+\sum_{b_{i}} p\left(b_{i}\right) H\left(R \mid B=b_{i}\right) \\
& =-\sum_{b_{i}} p\left(b_{i}\right) \log p\left(b_{i}\right)+\sum_{b_{i}} p\left(b_{i}\right) H\left(R \mid B=b_{i}\right) \\
& =-\sum_{b_{i}} p\left(b_{i}\right) \log p\left(b_{i}\right)+\left[p\left(b_{1}\right) H\left(L_{2} D_{3}\right)+p\left(b_{2}\right) H\left(D_{2} L_{2}\right)+p\left(b_{3}\right) H\left(S_{1} D_{2}\right)\right]
\end{aligned}
$$

## Calculation of Entropy

 based on context-free grammar for a password distribution$$
\begin{aligned}
& H(B, R)=H(B)+\left[p\left(b_{1}\right) H\left(L_{2} D_{3}\right)+p\left(b_{2}\right) H\left(D_{2} L_{2}\right)+p\left(b_{3}\right) H\left(S_{1} D_{2}\right)\right] \\
& H\left(L_{2} D_{3}\right)=-\sum_{l_{2},} \sum_{m_{2}, d_{3}} p\left(l_{2}, m_{2}, d_{3}\right) \log p\left(l_{2}, m_{2}, d_{3}\right) \\
&=-\sum_{l_{2}, m_{2}} \sum_{d_{3}} p\left(l_{2}\right) p\left(m_{2}\right) p\left(d_{3}\right) \log \left(p\left(l_{2}\right) p\left(m_{2}\right) p\left(d_{3}\right)\right) \\
&=-\sum_{l_{2}} \sum_{m_{2}} \sum_{d_{3}} p\left(l_{2}\right) p\left(m_{2}\right) p\left(d_{3}\right)\left[\log p\left(l_{2}\right)+\log p\left(m_{2}\right)+\log p\left(d_{3}\right)\right] \\
&=-\sum_{l_{2}} p\left(l_{2}\right) \log p\left(l_{2}\right)+-\sum_{m_{2}} p\left(m_{2}\right) \log p\left(m_{2}\right)+-\sum_{d_{3}} p\left(d_{3}\right) \log p\left(d_{3}\right) \\
&=H\left(L_{2}\right)+H\left(M_{2}\right)+H\left(D_{3}\right)
\end{aligned}
$$

## Increasing Shannon Entropy

- User enters their chosen password
- If it is not strong enough, it will be rejected
- We suggest a new password with probability less than $1 / n, n$ being the total number of passwords in the distribution.
- We update the probabilities by adding the new password to the training set.


## Increasing Shannon entropy



## Conclusion

- We developed a technique to measure password strength based on the distribution.
- We developed a model and built a system to help users have strong passwords which are resistant to real attacks.
- We developed dynamic modification techniques to maintain the security of our system and also showed that our updating algorithm drives the grammar to higher Shannon entropy.
- We developed a way to calculate realistic entropy values for password distributions.


## Questions/ Comments?



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