Guessing and Passwords

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16 January 2014

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## How to Guess a Password?

Passwords are everywhere.

If you don't know the password, can you guess it?

- 1. Make a list of passwords.
- 2. Assess the probability that each was used.
- 3. Guess from most likely to least likely.
- A *dictionary attack*, but with optimal ordering.

Want to tell you a bit about the theory of guessing, and what this game looks like.

#### How long will that take?

If we knew probability  $P_i$  of  $i^{\text{th}}$  password. Rank the passwords from 1 (most likely) to N (least likely). Average number of guesses is:

$$G=\sum_{i=1}^{N}iP_{i}.$$

Applies to computers and keys too. sci.crypt FAQ:

We can measure how bad a key distribution is by calculating its entropy. This number E is the number of "real bits of information" of the key: a cryptanalyst will typically happen across the key within  $2^E$  guesses. E is defined as the sum of  $-p_K \log_2 p_K$ , where  $p_K$  is the probability of key K.

### Relationship to Entropy?

Could guesswork be the same as entropy?

$$G(P) = \sum_{i=1}^{N} iP_i \stackrel{?}{\approx} 2^{-\sum P_i \log_2 P_i} = 2^{H(P)}$$

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The answer is no (Massey '94), Entropy underestimates.

# G = H Asymptoticly?

Asymptotic Equipartition: Look at i.i.d sequences of *typical* passwords of length *n* with probability within  $\epsilon$  of  $2^{-nH(P)}$ .

As  $n \to \infty$  these typical words have all the mass and are roughly equally likely. Does  $G(P^n) \approx H(P^n)$ ?

You can get asymptotic result:

$$G(P^n) \asymp \left( \left( \sqrt{p_1} + \sqrt{p_2} + \ldots \right)^2 \right)^n$$

Family of asymptotic results (Arikan '96, Malone and Sullivan 2004, Christiansen and Duffy 2012, ...).

# Twenty Questions

- Suppose we can ask "Is the password one of X, Y, ...?".
- We still want to identify the exact password.
- Basically building binary tree, based on yes/no.
- Want minimise expected leaf depth.

Same problem as encoding a message into minimal number of bits.

H(P) is a lower bound. Huffman Encoding (Huffman '52) optimal.

 $H(P) \leq \mathbb{E}(\text{set guesses}) \leq H(P) + 1.$ 

(Use  $H(P^n) = nH(P)$  for Source Coding Theorem.)

# Questions

- Does this P<sub>i</sub> really make sense?
- Is there a distribution with which passwords are chosen?

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• How would we find out?

(Mainly from Malone and Maher, WWW'12)

# How are Passwords Stored?

Passwords are usually *hashed*. Storage:

- 1. Ask user for password, choose random unique salt.
- 2. Calculate hash = h(salt.password).
- 3. Store username, salt and hash.

Verify

- 1. Ask for username and password.
- 2. Look up salt and hash for username.
- 3. Check if hash = h(salt.password).

h maps strings to fixed length.

Preimages should be hard. h should slow, but not too slow<sup>1</sup>

# Getting data

Want a collection of passwords to study distribution. Asked Yahoo, Google.

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Crackers eventually obliged.

- 2006: flirtlife, 98930 users, 43936 passwords, 0.44.
- 2009: hotmail, 7300 users, 6670 passwords, 0.91.
- 2009: computerbits, 1795 users, 1656 passwords, 0.92.
- 2009: rockyou, 32603043 users, 14344386 passwords, 0.44.
- 2013: adobe, 129576416 users, 55855039 passwords, 0.43.
  First four in clear text!
  Had to clean up data.

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# Top Ten

Rank	hotmail	#users	flirtlife	#users	computerbits	#users	rockyou	#users
1	123456	48	123456	1432	password	20	123456	290729
2	123456789	15	ficken	407	computerbits	10	12345	79076
3	111111	10	12345	365	123456	7	123456789	76789
4	12345678	9	hallo	348	dublin	6	password	59462
5	tequiero	8	123456789	258	letmein	5	iloveyou	49952
6	000000	7	schatz	230	qwerty	4	princess	33291
7	alejandro	7	12345678	223	ireland	4	1234567	21725
8	sebastian	6	daniel	185	1234567	3	rockyou	20901
9	estrella	6	1234	175	liverpool	3	12345678	20553
10	1234567	6	askim	171	munster	3	abc123	16648

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(c.f. Imperva analysis of Rockyou data, 2010)

# Adobe

- Adobe encrypted data instead of hashing.
- 3DES ECB mode.
- Key unknown, but includes password hints.
- No hashing, lots of fun.

Rank	Cyphertext	indicative hint	inferred password	#users
1	EQ7fIpT7i/Q=	One to six in numeral form	123456	1905308
2	j9p+HwtWWT86aMjgZFLzYg==	1234567890 ohne 0	123456789	445971
3	L8qbAD3j13jioxG6CatHBw==	answer is password	password	343956
4	BB4e6X+b2xLioxG6CatHBw==	adbeandonetwothree	adobe123	210932
5	j9p+HwtWWT/ioxG6CatHBw==	123456789 minus last number	12345678	201150
6	5djv7ZCI2ws=	1st 123456 letters	qwerty	130401
7	dQiOasWPYvQ=	1234567 is the password	1234567	124177
8	7LqYzKVeq8I=	6 number 1s	111111	113684
9	PMDTbP0LZxu03SwrFUvYGA==	adobe photo editing software	photoshop	83269
10	e6MPXQ5G6a8=	one two three one two three	123123	82606

HACKERS RECENTLY LEAKED 153 MILLION ADOBE USER EMAILS, ENCRYPTED PASSWORDS, AND PASSWORD HINTS.

ADOBE ENCRYPTED THE PASSWORDS IMPROPERLY, MISUSING BLOCK-MODE 3DES. THE RESULT IS SOMETHING WONDERFUL:



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# Questions for Data

- Is there password distribution?
   Is knowing it better than a crude guess?
- Are there any general features?
   Do different user groups behave in a similar way?
- Some distributions better than others. Can we help users make better decisions?

#### Distribution?



Others?



SAC

#### Log-log Plots

Is everything a straight line on a log-log plot?



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# Zipf?

- A straight line on a log-log plot points towards heavy tail.
- Zipf?

$$P_r \propto rac{1}{r^s}$$

- Slope gives *s*.
- Can also do MLE and check p-values (Clauset '09).
- s is small, less than 1.

	hotmail	flirtlife	c-bits	rockyou	adobe
s	0.246	0.695	0.23	0.7878	0.7927
MLE					
S	0.009	0.001	0.02	< 0.0001	< 0.0001
stderr					
p-value	< 0.01	0.57	< 0.01	< 0.01	< 0.01

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#### **Guesswork** Predictions



flirtlife



rockyou



#### hotmail



computerbits

## Who cares?

- 1. Algorithm Design exploit heavy tail?
- 2. Can we get close to optimal dictionary attack?
- 3. Can we make dictionary attack less effective?

2 and 3 are questions about common behavior and helping users.

Can use the clear text data to study.

### Dictionary Attack

Suppose we use one dataset as a dictionary to attack another.



## Dictionary Attack — Same Story



# Dictionary Attack Gawker

December 2010, Gawker, 748090 Unix crypt Hashes, well salted.



Dell'Amico'10 review smart generators. This looks A10 + ( = ) = oac

# Helping Users

User is biased 'random' password generator. Can we make them a better generator?

- Banned list (e.g. twitter),
- Password rules (e.g. numbers and letters).
- Act like a cracker (e.g. cracklib),
- Cap peak of password distribution (e.g. Schechter'10),
- Aim for uniform?

In WWW'12 paper, looked at Metropolis-Hastings algorithm. We'll look at rejection sampling here.

# Helping with Rejection

If we know  $P_i$ , then we could use rejection sampling.

- 1. Have a probability  $r_i$  for each password that it is chosen.
- 2. Ask user for a new password x'.
- 3. With probability  $r_{x'}$  accept the password, otherwise go to 2.

If users choices are i.i.d with distribution  $P_i$ :

- Resulting distribution is proportional to  $q_i = r_i P_i$ .
- $r_i = C/P_i$  results in a uniform distribution.
- Take  $C = P_N$  to give least number of rejections.

## How does this do?

- Generate 1000000 users.
- Rockyou-based i.i.d password choices.
- Learns F(x) as it goes, uses 1/F(x).



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How annoying? Mean tries 1.29, variance 0.63.

## Limiting Mean Rejections

Suppose we want to make guesswork as large as possible, but bound  $\mathbb{E}[R] \leq L$ . Note, if  $a = \sum q_i$ , then  $\mathbb{E}[R] = 1/a - 1$ .

**Optimisation Problem:** Maximise

$$G=\sum irac{q_i}{a},$$

given

 $\mathbb{E}[R] \leq L,$ 

where

$$q_i=r_iP_i, 0\leq r_i\leq 1, q_i\geq q_{i+1}.$$

**Solution:** Guessed to level high probability ones. Finalising proof with van Wijk.

# Conclusions

- Idea of distribution of password choices seems useful.
- Zipf is OK, but not perfect match.
- Different user groups have a lot in common (not peak).
- Dictionaries not great for dictionary attacks.
- Treat users as random password generators?
- Banned lists are not optimal<sup>2</sup>.
- Future: Look at Bonneau's data?
- Future: Generalise beyond web passwords?
- Future: Field test Metropolis-Hastings or Rejection?

## Metropolis-Hastings for Uniform Passwords

Keep a frequency table F(x) for requests to use password x.

- 1. Uniformly choose x from all previously seen passwords.
- 2. Ask user for a new password x'.
- 3. Generate a uniform real number u in the range [0, F(x')] and then increment F(x'). If  $u \le F(x)$  go to step 4 (accept), otherwise return to step 2 (reject).
- 4. Accept use of x' as password.

Rockyou-based test, 1000000 users, mean tries 1.28, variance 0.61.

Could be implemented using min-count sketch. Doesn't store actual *use* frequencies. No parameters, aims to flatten whole distribution.

## Rejection Sampling: Sketch Proof

- 1. Show  $q_i \ge q_{i+1}$  doesn't make things worse.
- 2. Show the  $r_i^*$  have to be positive.
- 3. Show that  $r_m^* = 1$  then  $r_n^* = 1$  for  $n \ge m$ .
- 4. Show that if  $r_m^* < 1$  then  $q_1^* = q_2^* = \ldots q_m^*$ .

Shows that if you can afford to, make it uniform. Otherwise clip the probability of most likely passwords.