THE SCIENCE OF GUESSING
analyzing an anonymized corpus of 70 million passwords

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≈ OAKLAND, CA, USA
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Why do password research in 2012?

Compatible Time-Sharing System, MIT 1961

Research goal

Precisely compute the guessing difficulty of a given population's password distribution

Research goal

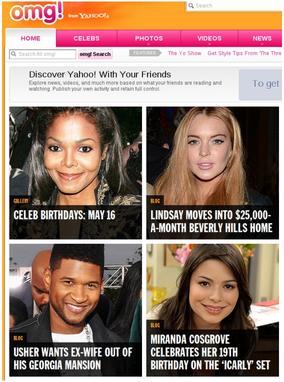
Compare the guessing difficulty of password distributions chosen by different populations

Compare the guessing difficulty of password distributions chosen by different populations

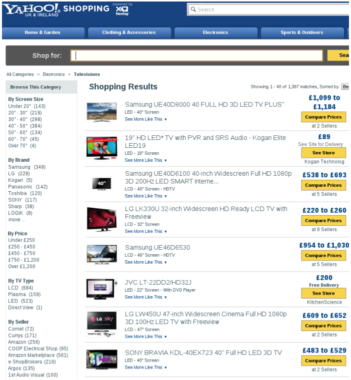
vs.

Research goal

Compare the guessing difficulty of password distributions chosen by different populations



vs.



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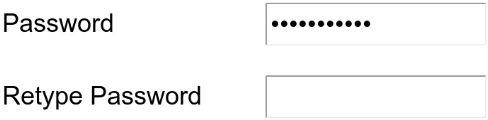

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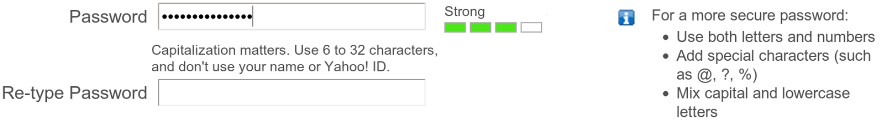
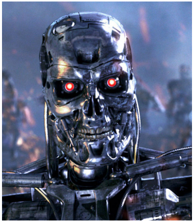
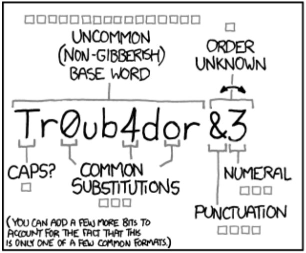


Compare the guessing difficulty of password distributions chosen by different populations





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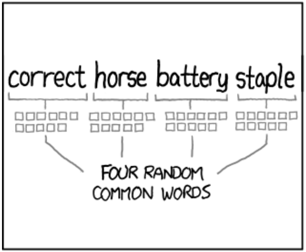

Approach #1: Semantic password evaluation

- How long are the passwords?
- Do they look like English words?
- What kind of characters do they contain?

Approach #1: Semantic password evaluation

	94 Character Alphabet			10 char. alphabet		94 char alphabet
Length Char.	**No Checks**	**Dictionary Rule**	**Dict. & Comp. Rule**			
1	4	-	-	3	3.3	6.6
2	6	-	-	5	6.7	13.2
3	8	-	-	7	10.0	19.8
4	10	14	16	9	13.3	26.3
5	12	17	20	10	16.7	32.9
6	14	20	23	11	20.0	39.5
7	16	22	27	12	23.3	46.1
8	18	24	30	13	26.6	52.7
10	21	26	32	15	33.3	65.9
12	24	28	34	17	40.0	79.0
14	27	30	36	19	46.6	92.2
16	30	32	38	21	53.3	105.4
18	33	34	40	23	59.9	118.5
20	36	36	42	25	66.6	131.7
22	38	38	44	27	73.3	144.7
24	40	40	46	29	79.9	158.0
30	46	46	52	35	99.9	197.2
40	56	56	62	45	133.2	263.4

NIST “entropy” formula

Approach #2: Cracking experiments

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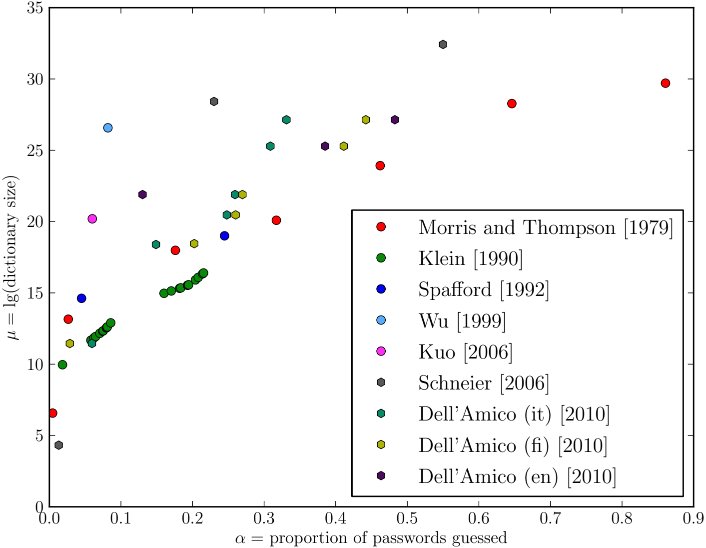


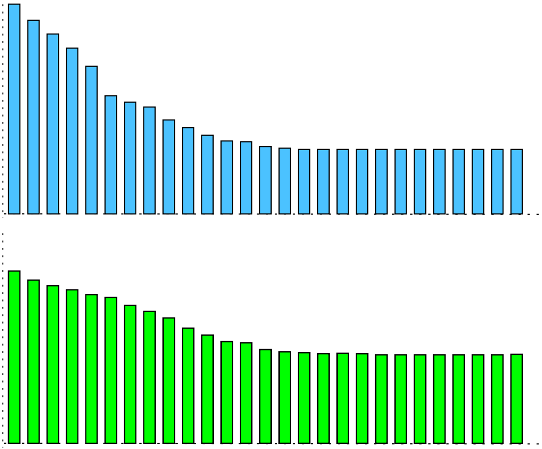
Methodological problems with password analysis

	semantic	cracking
external validity		✓
no operator bias	✓	
no demographic bias	?	
repeatable	✓	?
easy	✓	?

My approach

1. Collect password data on a huge scale
2. Compare populations as probability distributions
3. Test hypotheses using different populations

My approach



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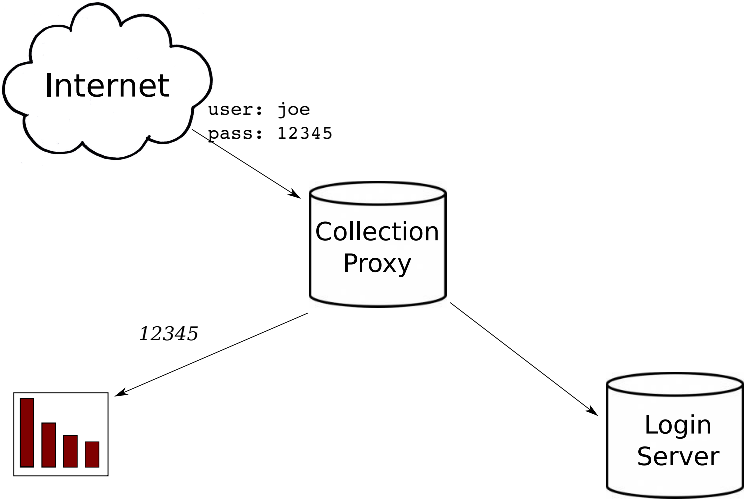
Goal #1: collect a massive data set

- with cooperation from Yahoo!
- privacy-preserving collection ☺
  - histograms only
- demographic splits collected

Collecting large-scale data at Yahoo!



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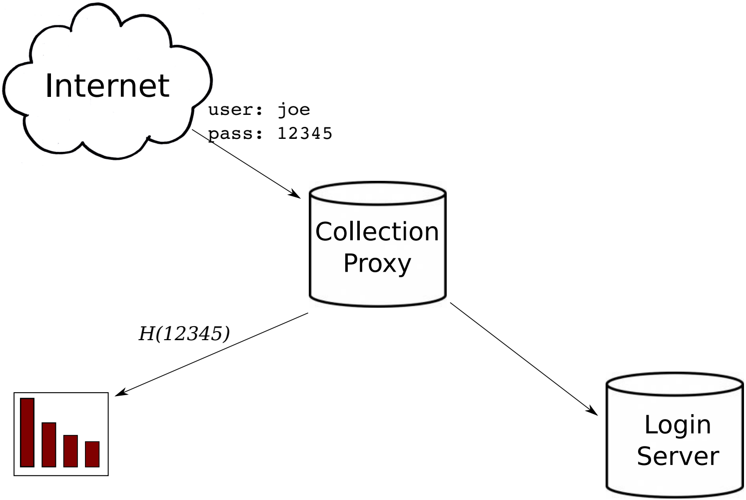

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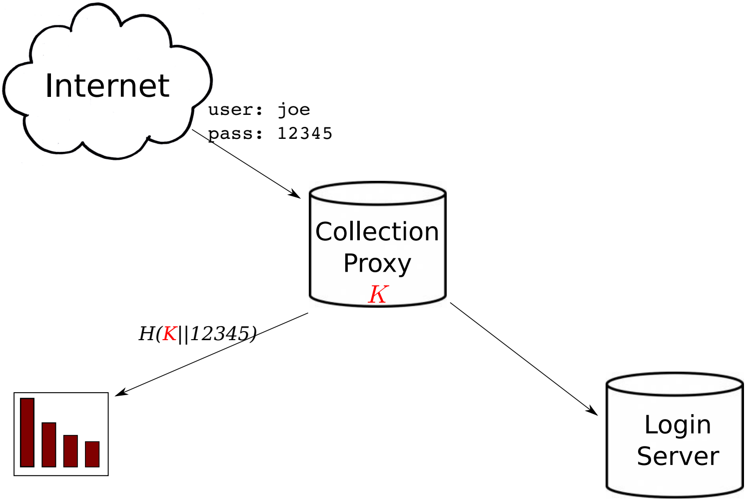

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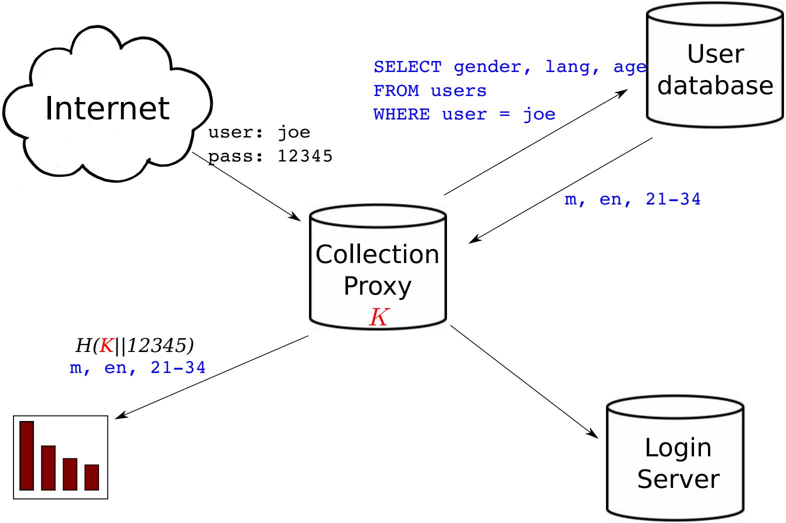

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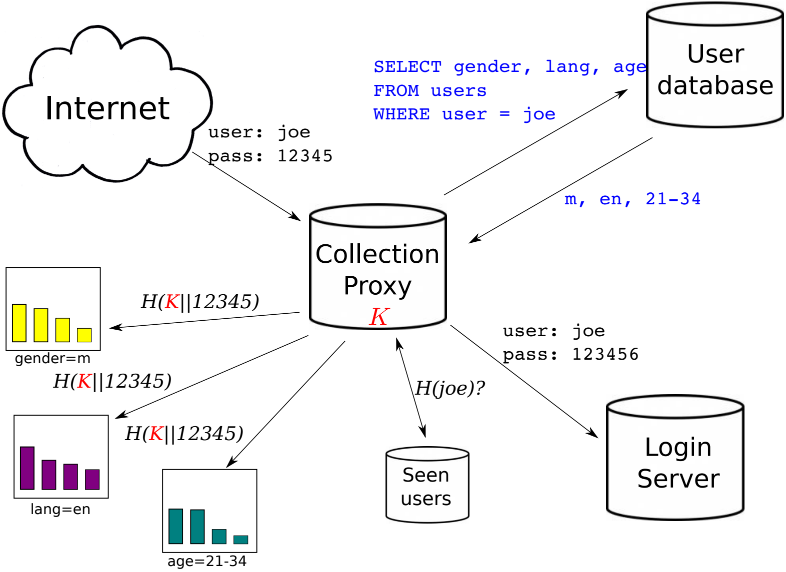

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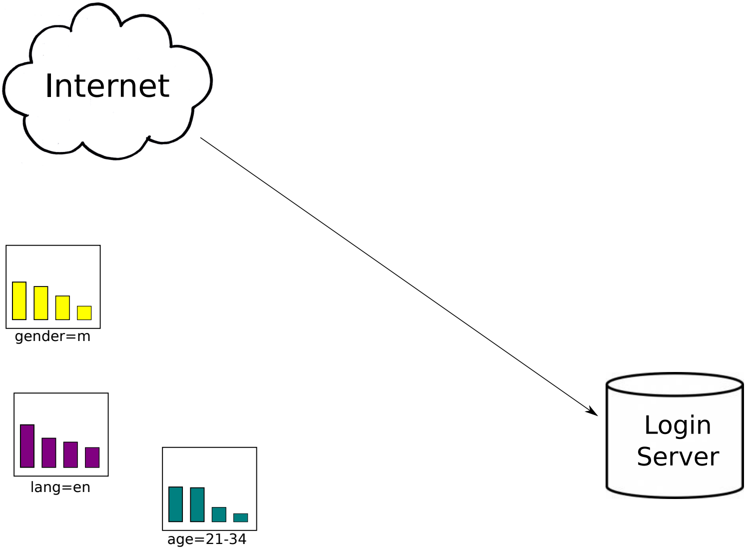


Collecting large-scale data at Yahoo!

- Experiment run May 23–25, 2011
- 69,301,337 unique users
- 42.5% unique
- 328 different predicate functions

Goal #2: model guessing as a probability problem

- Assume perfect knowledge of the distribution $\mathcal{X}$
- $\mathcal{X}$ has N *events* (passwords) $x_1, x_2, \ldots$
- Events have probability $p_1 \geq p_2 \geq \ldots \geq p_N \geq 0$
- Each user chooses at random $X \stackrel{R}{\leftarrow} \mathcal{X}$

Question: How hard is it to guess X?

Shannon entropy

$$H_1(\mathcal{X}) = -\sum_{i=1}^{N} p_i \lg p_i$$

Interpretation: Expected number of queries "Is $X \in \mathcal{S}$?" for arbitrary subsets $\mathcal{S} \subseteq \mathcal{X}$ needed to guess X. (Source-Coding Theorem)

Guesswork (guessing entropy)

$$G_1(\mathcal{X}) = E\left[\#_{\text{guesses}}\right] = \sum_{i=1}^{N} p_i \cdot i$$

Intepretation: Expected number of queries "Is $X = x_i$?" for $i = 1, 2, \ldots, N$ (optimal sequential guessing)

G_1 fails badly for real password distributions

Random 128-bit passwords in the wild at RockYou ($\sim 2^{-20}$)

```
ed65e09b98bdc70576d6c5f5e2ee38a9
e54d409c55499851aeb25713c1358484
dee489981220f2646eb8b3f412c456d9
c4df8d8e225232227c84d0ed8439428a
bd9059497b4af2bb913a8522747af2de
b25d6118ffc44b12b014feb81ea68e49
aac71eb7307f4c54b12c92d9bd45575f
9475d62e1f8b13676deab3824492367a
92965710534a9ec4b30f27b1e7f6062a
80f5a0267920942a73693596fe181fb7
76882fb85a1a8c6a83486aba03c031c9
6a60e0e51a3eb2e9fed6a546705de1bf ...
```

$$\Rightarrow \quad G_1(\text{RockYou}) > 2^{107}$$

Attackers might be happy ignoring the hard values

α-work-factor

$$\mu_\alpha(\mathcal{X}) = \min \left\{ \mu \in [1, N] \,\middle|\, \sum_{i=1}^{\mu} p_i \geq \alpha \right\}$$

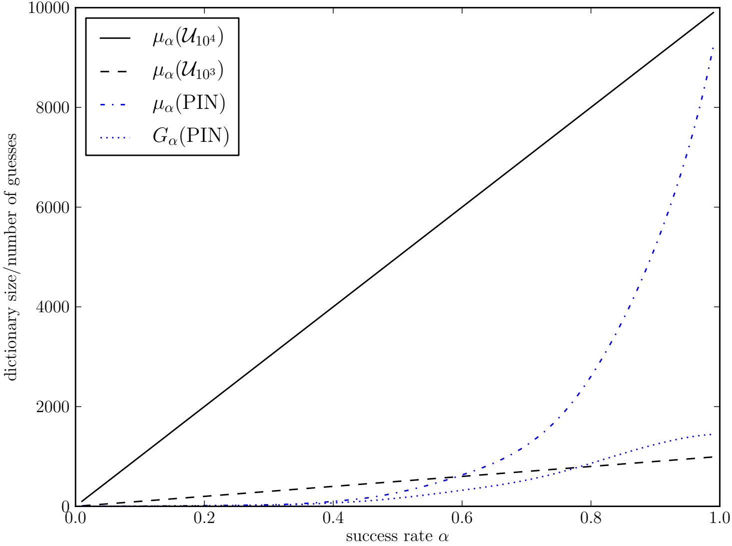
Intepretation: Minimal dictionary size to succeed with probability α

α-guesswork

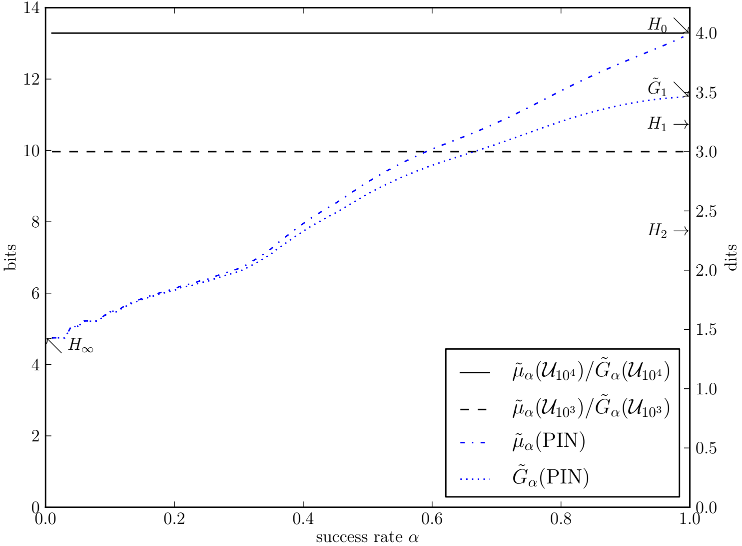
$$G_\alpha(\mathcal{X}) = (1 - \lceil \alpha \rceil) \cdot \mu_\alpha(\mathcal{X}) + \sum_{i=1}^{\mu_\alpha(\mathcal{X})} p_i \cdot i$$

Intepretation: Mean number of guesses to succeed with probability α

Guessing curves visualise all possible attacks



More intuitive after converting to bits



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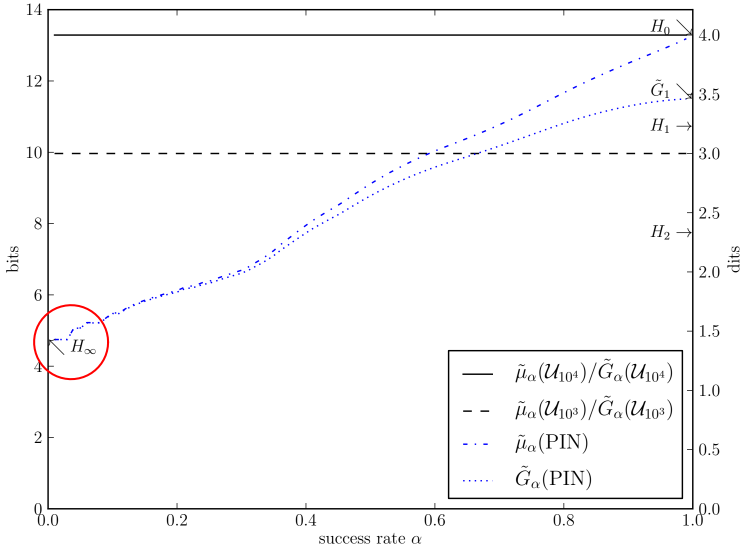

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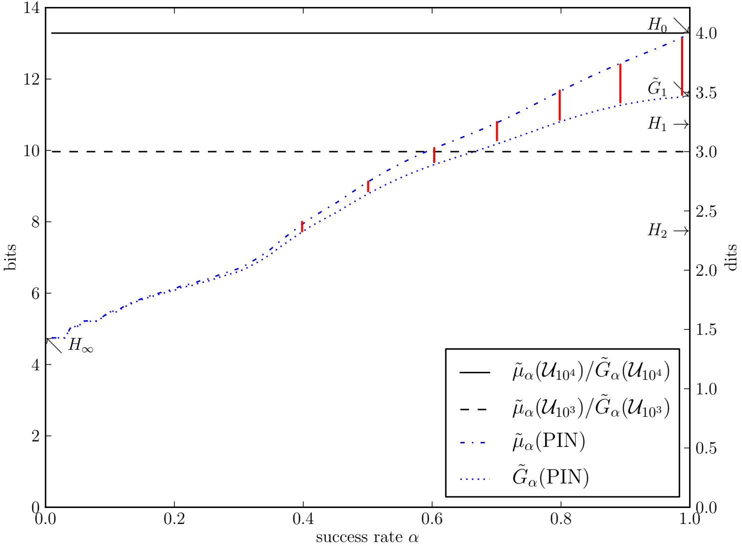

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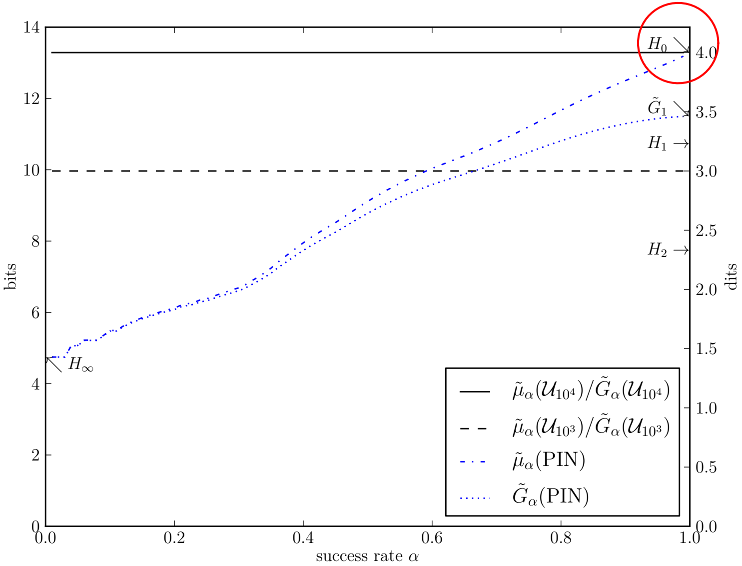

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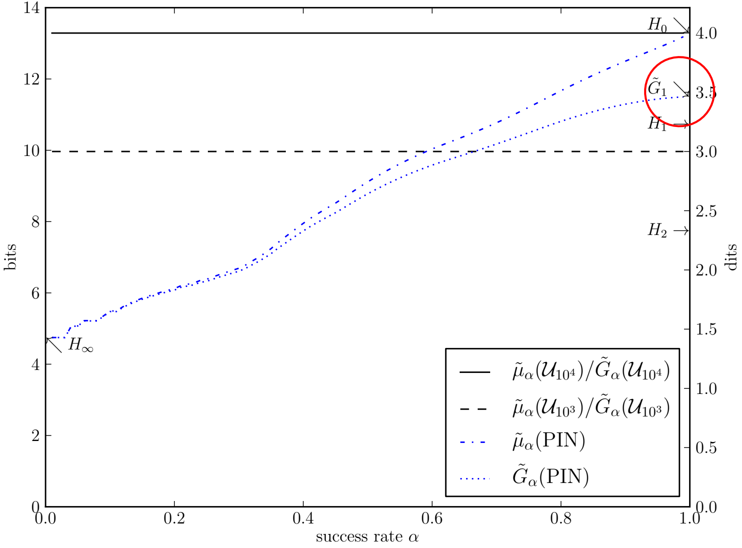

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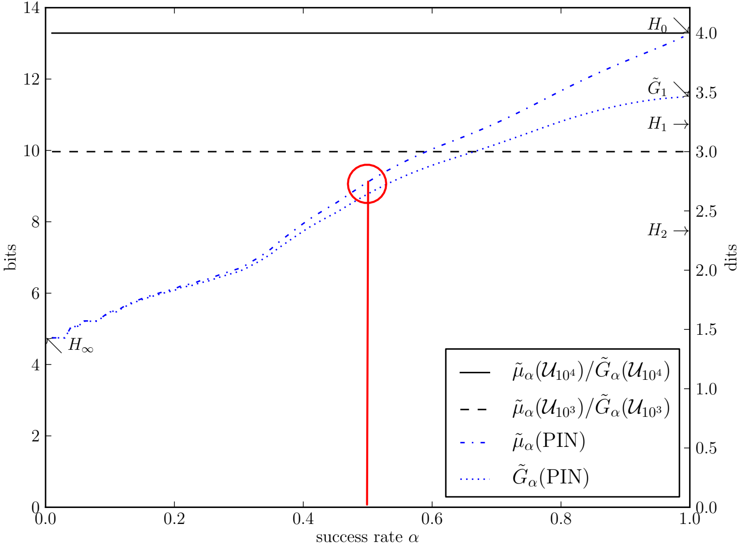
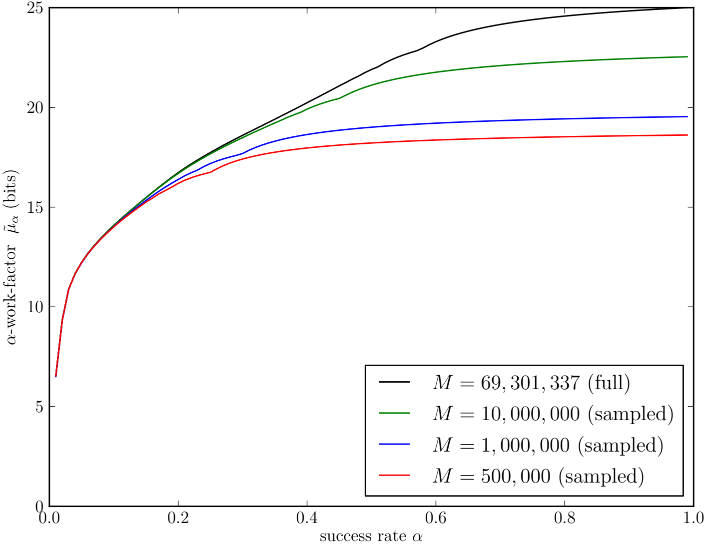
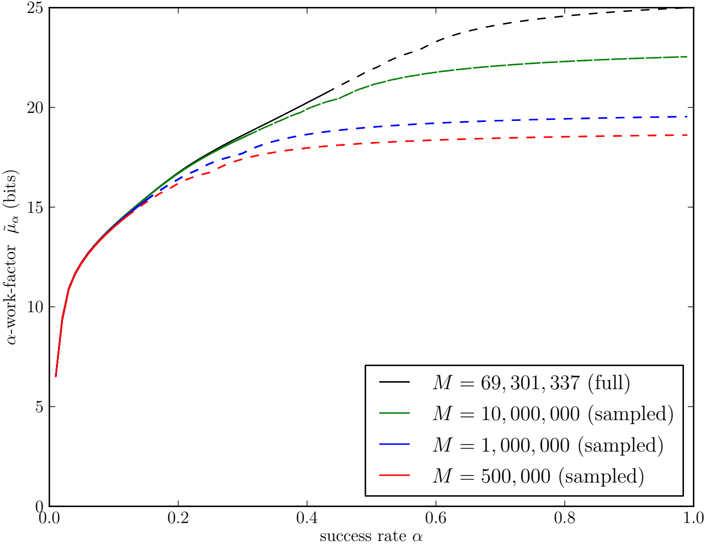


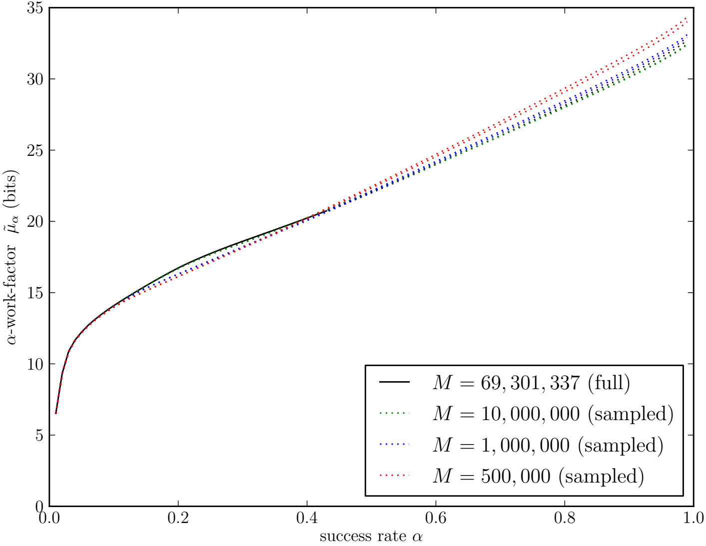
Sample size is a major problem for passwords...



Predict our confidence range by *bootstrapping*



Extrapolation w/ truncated Sichel-Poisson distribution



Goal #3: Analyze Yahoo! passwords

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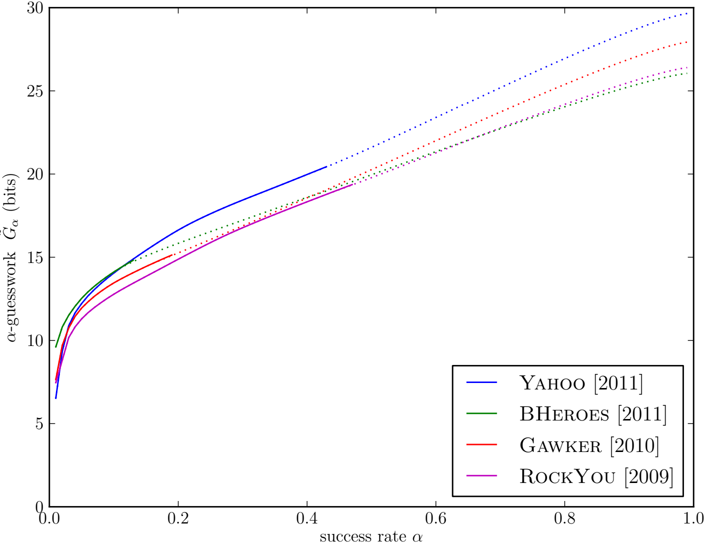

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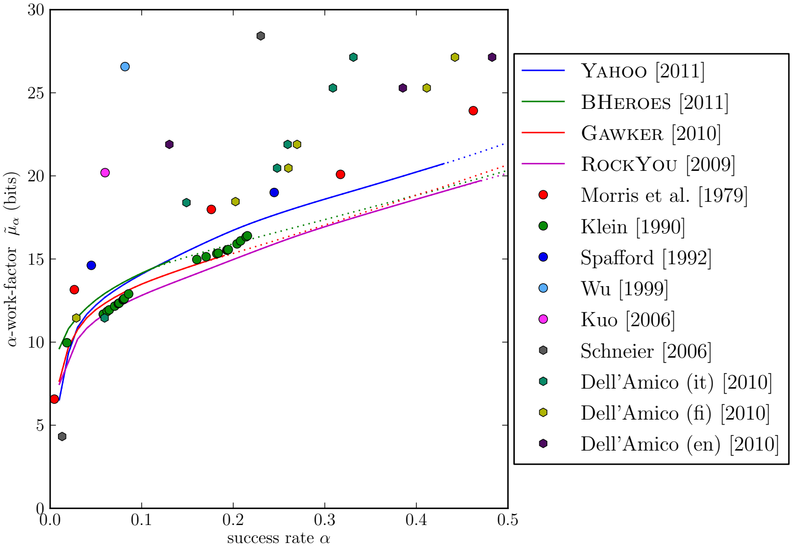
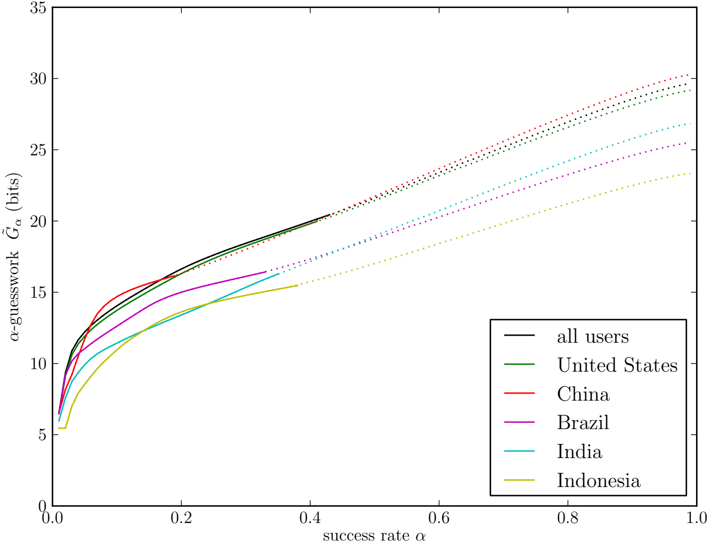
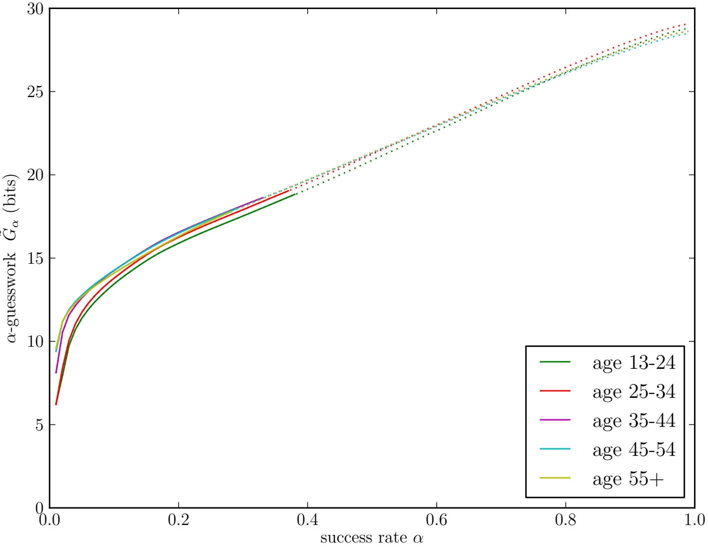


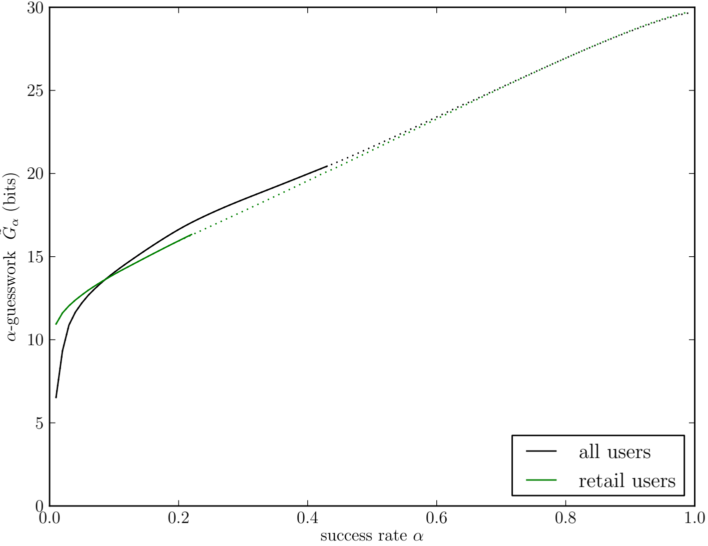
Demographic trends: nationality



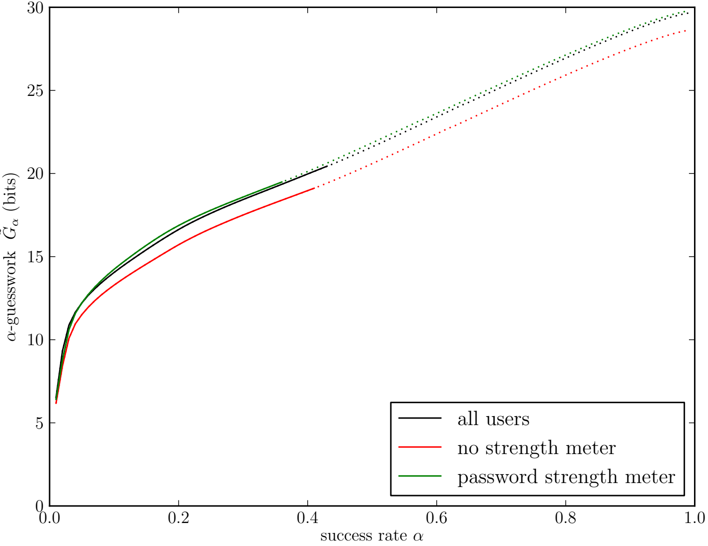
Demographic trends: age



Credit card details make little difference



Password strength meter makes little difference



Demographic summary

- there is no “good group” of users
- differences small but statistically significant
- online attack **6–9** bits ($\tilde{\lambda}_{10}$)
- offline attack **15–25** bits ($\tilde{G}_{0.5}$)

Surprisingly little language variation

		dictionary										
		de	en	es	fr	id	it	ko	pt	zh	vi	global
target	de	**6.5%**	3.3%	2.6%	2.9%	2.2%	2.8%	1.6%	2.1%	2.0%	1.6%	3.5%
	en	4.6%	**8.0%**	4.2%	4.3%	4.5%	4.3%	3.4%	3.5%	4.4%	3.5%	7.9%
	es	5.0%	5.6%	**12.1%**	4.6%	4.1%	6.1%	3.1%	6.3%	3.6%	2.9%	6.9%
	fr	4.0%	4.2%	3.4%	**10.0%**	2.9%	3.2%	2.2%	3.1%	2.7%	2.1%	5.0%
	id	6.3%	8.7%	6.2%	6.3%	**14.9%**	6.2%	5.8%	6.0%	6.7%	5.9%	9.3%
	it	6.0%	6.3%	6.8%	5.3%	4.6%	**14.6%**	3.3%	5.7%	4.0%	3.2%	7.2%
	ko	2.0%	2.6%	1.9%	1.8%	2.3%	2.0%	**5.8%**	2.4%	3.7%	2.2%	2.8%
	pt	3.9%	4.3%	5.8%	3.8%	3.9%	4.4%	3.5%	**11.1%**	3.9%	2.9%	5.1%
	zh	1.9%	2.4%	1.7%	1.7%	2.0%	2.0%	2.9%	1.8%	**4.4%**	2.0%	2.9%
	vi	5.7%	7.7%	5.5%	5.8%	6.3%	5.7%	6.0%	5.8%	7.0%	**14.3%**	7.8%

With 1000 guesses, greatest efficiency loss is only 4.8 (fr/vi)

Joseph Bonneau and Rubin Xu.

Of contraseñas, סיסמאות and 密码: Character encoding issues for web passwords *Web 2.0 Security & Privacy*, 2012.

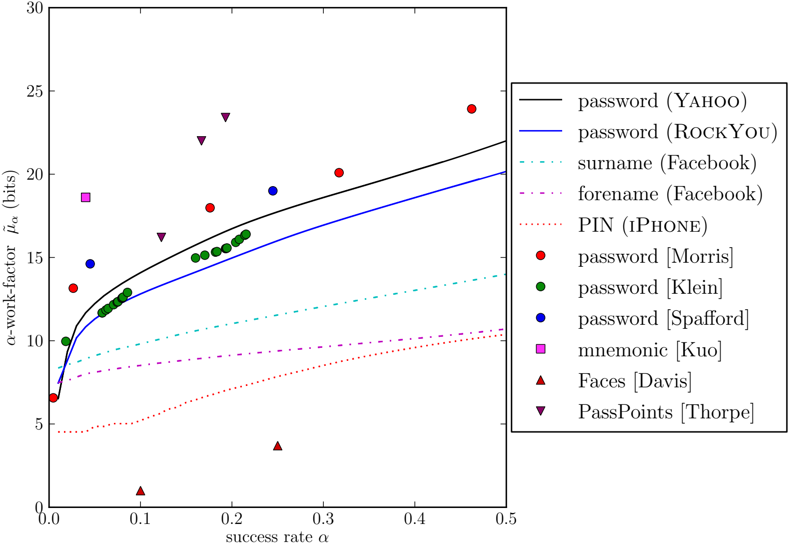
Comparing password analysis methods

	semantic	cracking	statistical
external validity		✓	?
no operator bias	✓		✓
no demographic bias	?		✓
repeatable	✓	?	✓
easy	✓	?	✓

Comparing password analysis methods

	semantic	cracking	statistical
external validity		✓	?
no operator bias	✓		✓
no demographic bias	?		✓
repeatable	✓	?	✓
easy	✓	?	✓
works w/small data	✓	✓	

The picture so far



For more information

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my dissertation

Guessing human-chosen secrets

Acknowledgements

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Andrew Lewis

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Cormac Herley
Arvind Narayanan

Converting metrics to bits

- Find the size of a uniform distribution $\mathcal{U}_N$ with equivalent security
- Easy case:

$$\boxed{\tilde{\mu}_\alpha(\mathcal{X}) = \lg\left(\frac{\mu_\alpha(\mathcal{X})}{\lceil\alpha\rceil}\right)}$$

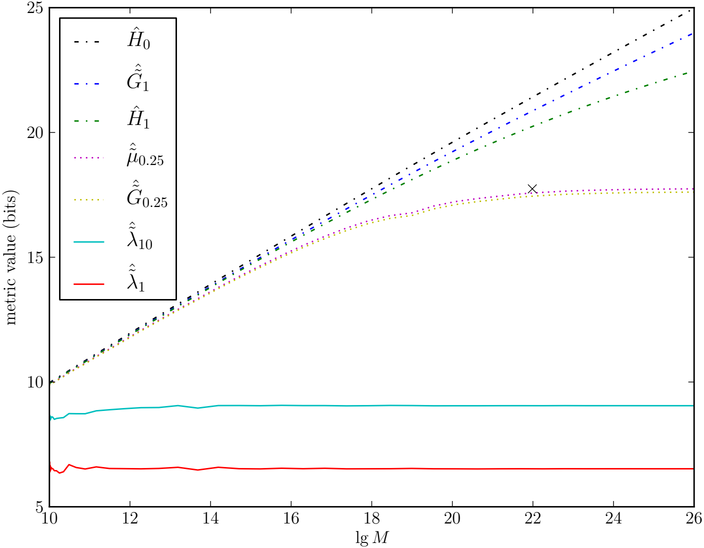
- More complicated:

$$\boxed{\tilde{G}_\alpha(\mathcal{X}) = \lg\left[\frac{2\cdot G_\alpha(\mathcal{X})}{\lceil\alpha\rceil} - 1\right] - \lg(2 - \lceil\alpha\rceil)}$$

- Sanity check:

$$\tilde{\lambda}_\beta(\mathcal{U}_N) = \tilde{\mu}_\alpha(\mathcal{U}_N) = \tilde{G}_\alpha(\mathcal{U}_N) = \lg N$$

Sample size is a major problem for passwords...



Poor password implementations

Results from a study of password authentication in the wild:

- 29–40% of websites don't hash passwords during storage
- 41% of websites don't use any encryption for password submission
    - 22% do so incompletely
- 84% of websites don't rate-limit against guessing attacks
- 97% of websites leak usernames to simple

Joseph Bonneau and Sören Preibusch.

The password thicket: technical and market failures in human authentication on the web.

Workshop on the Economics of Information Security, 2010.