Guessing human-chosen secrets

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Are passwords a thing of the past?

Compatible Time-Sharing System, MIT 1961

Evaluating popular password replacement proposals

There is no clear alternative to passwords...

Category	Scheme	Described in section	Reference	*Memory-wise-Effortless*	*Scalable-for-users*	*Nothing-to-Carry*	*Manually-Effortless*	*Easy-to-Learn*	*Efficient-to-Use*	*Infrequent-Errors*	*Easy-Recovery-from-Loss*	*Accessible*	*Negligible-Cost-per-User*	*Server-Compatible*	*Browser-Compatible*	*Mature*	*Non-Proprietary*	*Resilient-to-Physical-Observation*	*Resilient-to-Targeted-Impersonation*	*Resilient-to-Throttled-Guessing*	*Resilient-to-Unthrottled-Guessing*	*Resilient-to-Internal-Observation*	*Resilient-to-Leaks-from-Other-Verifiers*	*Resilient-to-Phishing*	*Resilient-to-Theft*	*No-Trusted-Third-Party*	*Requiring-Explicit-Consent*	*Unlinkable*
(Incumbent)	Web passwords	III	[13]	○	●	●	○	●	●	○	●	●	●	●	●	●	●	○	○	●	●	●	●	●	●	●	●	●
Password managers	Firefox	IV-A1		○	●	○	○	●	●	○	●	●	●	●	●	●	●	○	○	●	●	●	●	●	●	●	●	●
	LastPass	IV-A2		○	●	○	○	●	●	○	●	●	●	●	●	●	●	○	○	●	●	●	●	●	●	●	●	●
Proxy	URRSA	IV-B1	[5]	●	●	●	○	●	●	○	●	●	●	●	●	●	●	●	○	●	●	●	●	●	●	●	●	●
	Impostor	??	[21]		●	●	○	●	●	○	●	○	●	○	●	●	●	○	○	●	●	●	●	●	●	●	●	●
Federated	OpenID	IV-C1	[25]	○	●	●	○	●	●	○	●	●	●	●	●	●	●	○	○	●	●	●	●	●	●	●	●	●
	MS Passport	IV-C2	[29]	○	●	●	○	●	●	○	●	●	●	●	●	●	●	○	○	●	●	●	●	●	●	●	●	●
	FBConnect	IV-C3	[31]	○	●	●	○	●	●	○	●	●	●	●	●	●	●	○	○	●	●	●	●	●	●	●	●	●
	BrowserID	IV-C4	[33]	○	●	●	○	●	●	○	●	●	●	●	●	●	●	○	○	●	●	●	●	●	●	●	●	●
	OTP over email	IV-C5	[37]	○	●	●	○	●	●	○	●	●	●	●	●	●	●	○	○	●	●	●	●	●	●	●	●	●
Graphical	PCCP	IV-D1	[7]	●	●	●	○	●	●	○	●	●	●	●	●	●	●	○	○	●	●	●	●	●	●	●	●	●
	PassGo	IV-D2	[93]	●	●	●	○	●	●	○	●	●	●	●	●	●	●	○	○	●	●	●	●	●	●	●	●	●
Cognitive	GridSure	IV-E1	[51]	●	●	●	○	●	●	○	●	●	●	●	●	●	●	○	○	●	●	●	●	●	●	●	●	●
	Weinshall	??	[47]	●	●	●	○	●	●	○	●	●	●	●	●	●	●	○	○	●	●	●	●	●	●	●	●	●
	Hopper Blum	??	[48]	●	●	●	○	●	●	○	●	●	●	●	●	●	●	○	○	●	●	●	●	●	●	●	●	●
	Word Association	??	[50]	●	●	●	○	●	●	○	●	●	●	●	●	●	●	○	○	●	●	●	●	●	●	●	●	●
Paper tokens	OTPW	IV-F1	[54]	●	●	●	○	●	●	○	●	●	●	●	●	●	●	○	○	●	●	●	●	●	●	●	●	●
	S/KEY	IV-F2	[53]	●	●	●	○	●	●	○	●	●	●	●	●	●	●	○	○	●	●	●	●	●	●	●	●	●
	PIN+TAN	IV-F3	[56]	●	●	●	○	●	●	○	●	●	●	●	●	●	●	○	○	●	●	●	●	●	●	●	●	●
Visual crypto	PassWindow	IV-G1	[61]	●	●	●	○	●	●	○	●	●	●	●	●	●	●	○	○	●	●	●	●	●	●	●	●	●
Hardware tokens	RSA SecurID	IV-H1	[63]	○	●	●	○	●	●	○	●	●	●	●	●	●	●	○	○	●	●	●	●	●	●	●	●	●
	Yubikey	IV-H2	[65]	○	●	●	○	●	●	○	●	●	●	●	●	●	●	○	○	●	●	●	●	●	●	●	●	●
	Ironkey	IV-H3	[67]	○	●	●	○	●	●	○	●	●	●	●	●	●	●	○	○	●	●	●	●	●	●	●	●	●
	CAP reader	IV-H4	[68]	○	●	●	○	●	●	○	●	●	●	●	●	●	●	○	○	●	●	●	●	●	●	●	●	●
	Pico	IV-H5	[8]	○	●	●	○	●	●	○	●	●	●	●	●	●	●	○	○	●	●	●	●	●	●	●	●	●
Phone-based	Phoolproof	IV-I1	[70]	○	●	●	○	●	●	○	●	●	●	●	●	●	●	○	○	●	●	●	●	●	●	●	●	●
	Cronto	IV-I2		○	●	●	○	●	●	○	●	●	●	●	●	●	●	○	○	●	●	●	●	●	●	●	●	●
	MP-Auth	IV-I3	[6]	○	●	●	○	●	●	○	●	●	●	●	●	●	●	○	○	●	●	●	●	●	●	●	●	●
	OTP over SMS	IV-I4		○	●	●	○	●	●	○	●	●	●	●	●	●	●	○	○	●	●	●	●	●	●	●	●	●
	Google 2-Step	IV-I5	[73]	○	●	●	○	●	●	○	●	●	●	●	●	●	●	○	○	●	●	●	●	●	●	●	●	●
Biometric	Fingerprint	IV-J1	[75]	●	●	●	○	●	●	○	●	●	●	●	●	●	●	○	○	●	●	●	●	●	●	●	●	●
	Iris	IV-J2	[76]	●	●	●	○	●	●	○	●	●	●	●	●	●	●	○	○	●	●	●	●	●	●	●	●	●
	Voice	IV-J3	[77]	●	●	●	○	●	●	○	●	●	●	●	●	●	●	○	○	●	●	●	●	●	●	●	●	●
Recovery	Personal knowledge	IV-K1	[83]	○	●	●	○	●	●	○	●	●	●	●	●	●	●	○	○	●	●	●	●	●	●	●	●	●
	Preference-based	IV-K2	[91]	○	●	●	○	●	●	○	●	●	●	●	●	●	●	○	○	●	●	●	●	●	●	●	●	●
	Social re-auth.	??	[94]		●	●	○	●	●	○	●	○	●	○	●	●	●	○	○	●	●	●	●	●	●	●	●	●

Table I
COMPARATIVE EVALUATION OF THE VARIOUS SCHEMES WE EXAMINED

●= offers the benefit; ○= almost offers the benefit; *no symbol* = no benefit.
▥= better than passwords; ▥= worse than passwords; *no background* = no change.
We group related schemes into categories. For space reasons, our Oakland paper [1] describes at most one scheme f
category, but this tech report discusses them all.

Joseph Bonneau, Cormac Herley, Paul van Oorschot, and Frank Stajano.

"The Quest to Replace Passwords: A Framework for Comparative Evaluation of Web Authentication Schemes", *IEEE Security & Privacy*, 2012.

The “last mile” of authentication

What's harder to guess?

1. A teenager's password or a senior citizen's?
2. A human-chosen 4-digit PIN or a random 3-digit PIN?
3. A password or a stranger's surname?

Semantic password evaluation

year	study	length	% digits	% special
1989	Riddle et al.	4.4	3.5	—
1992	Spafford	6.8	31.7	14.8
1999	Wu	7.5	25.7	4.1
1999	Zviran and Haga	5.7	19.2	0.7
2004	Campbell and Bryant	8.0	78.0	3.0
2006	Cazier and Medlin	7.4	35.0	1.3
2010	Devillers et al.	7.9	54.0	3.4
2009	RockYou data	7.9	44.4	2.6

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

Evaluating passwords via cracking tools

Secure Purchase Accent Password Recovery Software

Purchase Accent software securely **online** and **offline**. To purchase, choose a product title and a type of license you'd like to pay for, then just follow the instructions.

Pay with credit cards, checks, money orders, PayPal, or bank transfers.

Read Terms and Conditions.

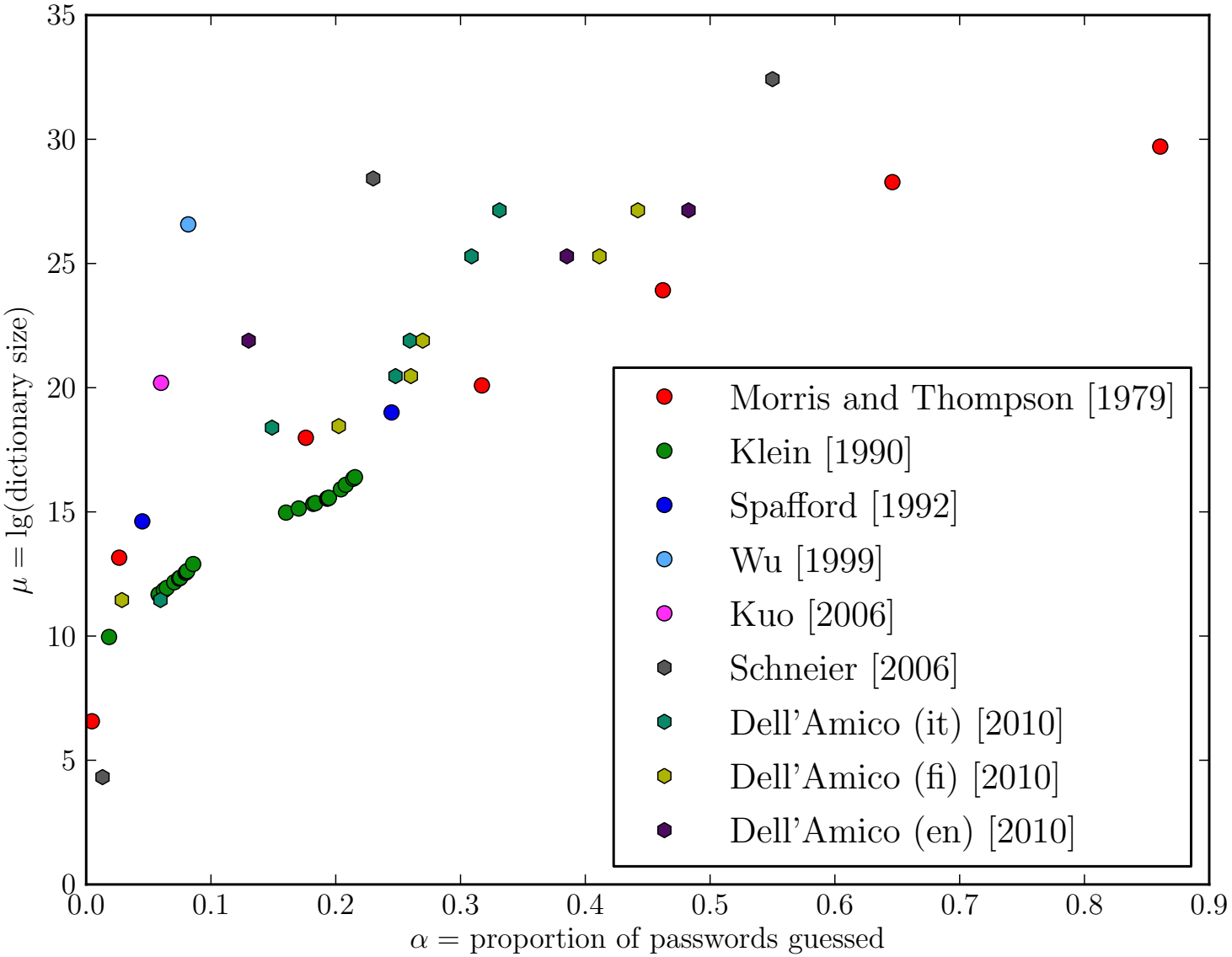
Prices:

Standard Edition - **£1,399**
(you save £396)

Forensic Edition - **£3,995**
(you save £1,895)

Business Edition - **£13,995**
(you save £5,177)

Evaluating passwords via cracking tools



Desiderata for evaluating human-chosen secrets

- sound
- repeatable
- no operator bias
- no demographic bias
- practical

Massive password data sets available for the first time

290729	123456
79076	12345
76789	123456789
59462	password
49952	iloveyou
33291	princess
21725	1234567
20901	rockyou
20553	12345678
16648	abc123

Dissertation: Guessing human-chosen secrets

1. Develop statistical guessing metrics
2. Collect large-scale data in a privacy-preserving manner
3. Approximate metrics using a random sample
4. Analyse data!

Goal #1

Develop statistical guessing metrics

Framework

- Assume a completely-known 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 $X \xleftarrow{R} \mathcal{X}$

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)

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

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

```
1,ed65e09b98bdc70576d6c5f5e2ee38a9
1,e54d409c55499851aeb25713c1358484
1,dee489981220f2646eb8b3f412c456d9
1,c4df8d8e225232227c84d0ed8439428a
1,bd9059497b4af2bb913a8522747af2de
1,b25d6118ffc44b12b014feb81ea68e49
1,aac71eb7307f4c54b12c92d9bd45575f
1,9475d62e1f8b13676deab3824492367a
1,92965710534a9ec4b30f27b1e7f6062a
1,80f5a0267920942a73693596fe181fb7
1,76882fb85a1a8c6a83486aba03c031c9
1,6a60e0e51a3eb2e9fed6a546705de1bf
1,6843b9efec36f428deabce22c0fc1805
1,5dfbcd6390b77d06df9027c8d7d4fe84
1,4374968e935a9a0f8d56785ea682eb5f
1,0753929001291091112580111091991a
1,0410412e7194adc1b419a87a47979c36
...
```

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

G_1 fails badly for real password distributions

Lemma: For a mixture distribution

$$\mathcal{Z} = p \cdot \mathcal{X} + q \cdot \mathcal{Y}$$

we have

$$G_1(\mathcal{Z}) \geq p \cdot G_1(\mathcal{X}) + q \cdot G_1(\mathcal{Y})$$

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Therefore, for real passwords $\mathcal{P}$, we have:

$$G_1(\mathcal{P}) \geq p \cdot G_1(\mathcal{X}) + 2^{-20} \cdot G_1(\mathcal{U}_{2^{128}})$$

$$\boxed{G_1(\mathcal{P}) > 2^{107}}$$

Optimal attacks will give up on the hardest values

New goal: Correctly guess k of m values $X_1, X_2 \ldots X_M \xleftarrow{R} \mathcal{X}$

Name #1	Name #2	Name #3	...	Name #m
Smith	Smith	Smith	...	Smith
Jones	Jones	Jones	...	Jones
Johnson	Johnson	Johnson	...	Johnson
...	...	...	...	...
Ytterock	Ytterock	Ytterock	...	Ytterock
Zdrzynski	Zdrzynski	Zdrzynski	...	Zdrzynski

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...	...	...	...	...
Ytterock	Ytterock	Ytterock	...	Ytterock
Zdrzynski	Zdrzynski	Zdrzynski	...	Zdrzynski

α-work-factor—attackers with a limited dictionary

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

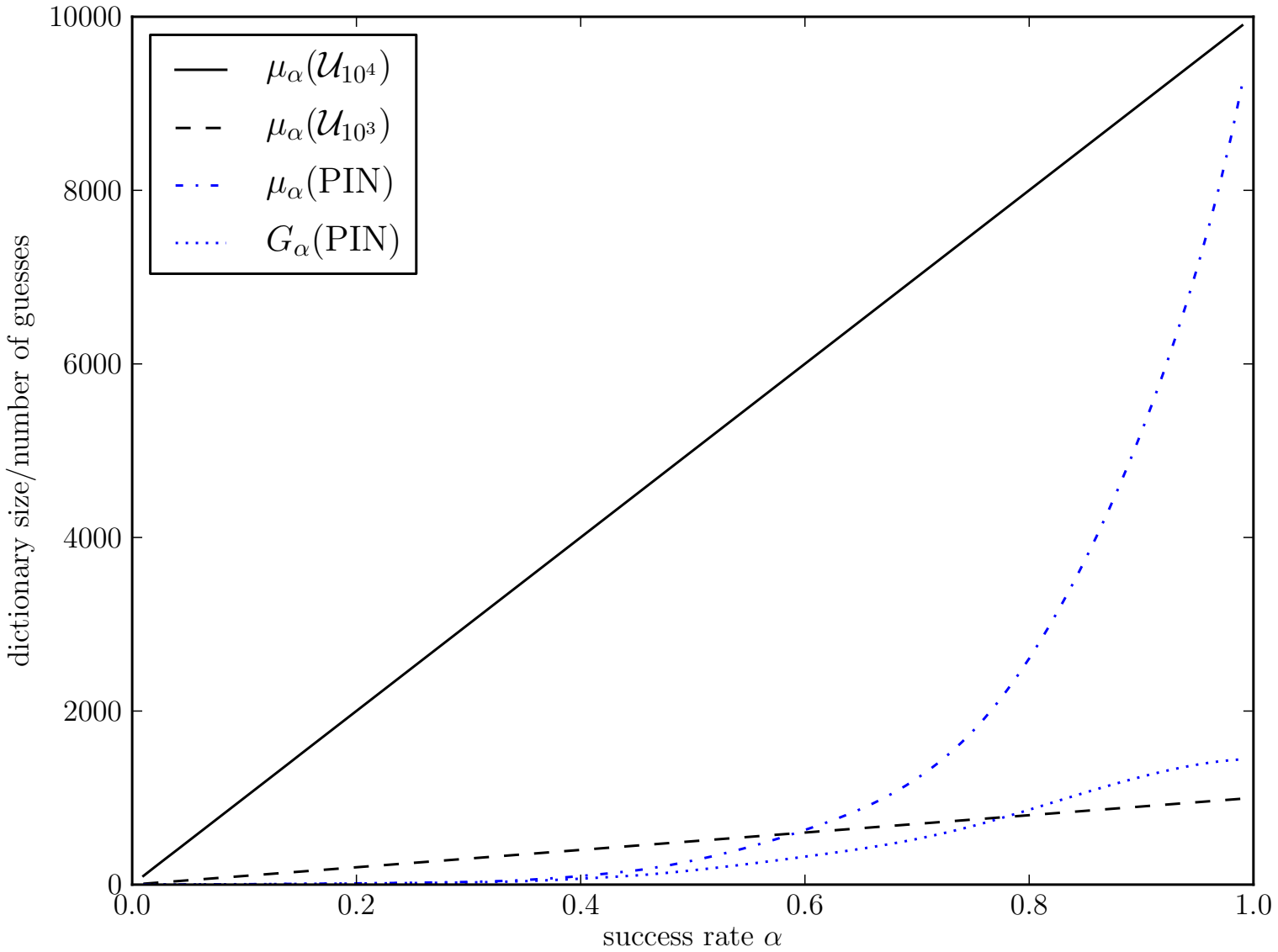
Intepretation: Dictionary size required to succeed with probability α

α-guesswork—attackers get to quit early

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

Intepretation: Expected # of guesses to succeed with probability α

Guessing curves visualise all possible attacks



All metrics convertible to bits

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

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

- More complicated:

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

- Sanity check:

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

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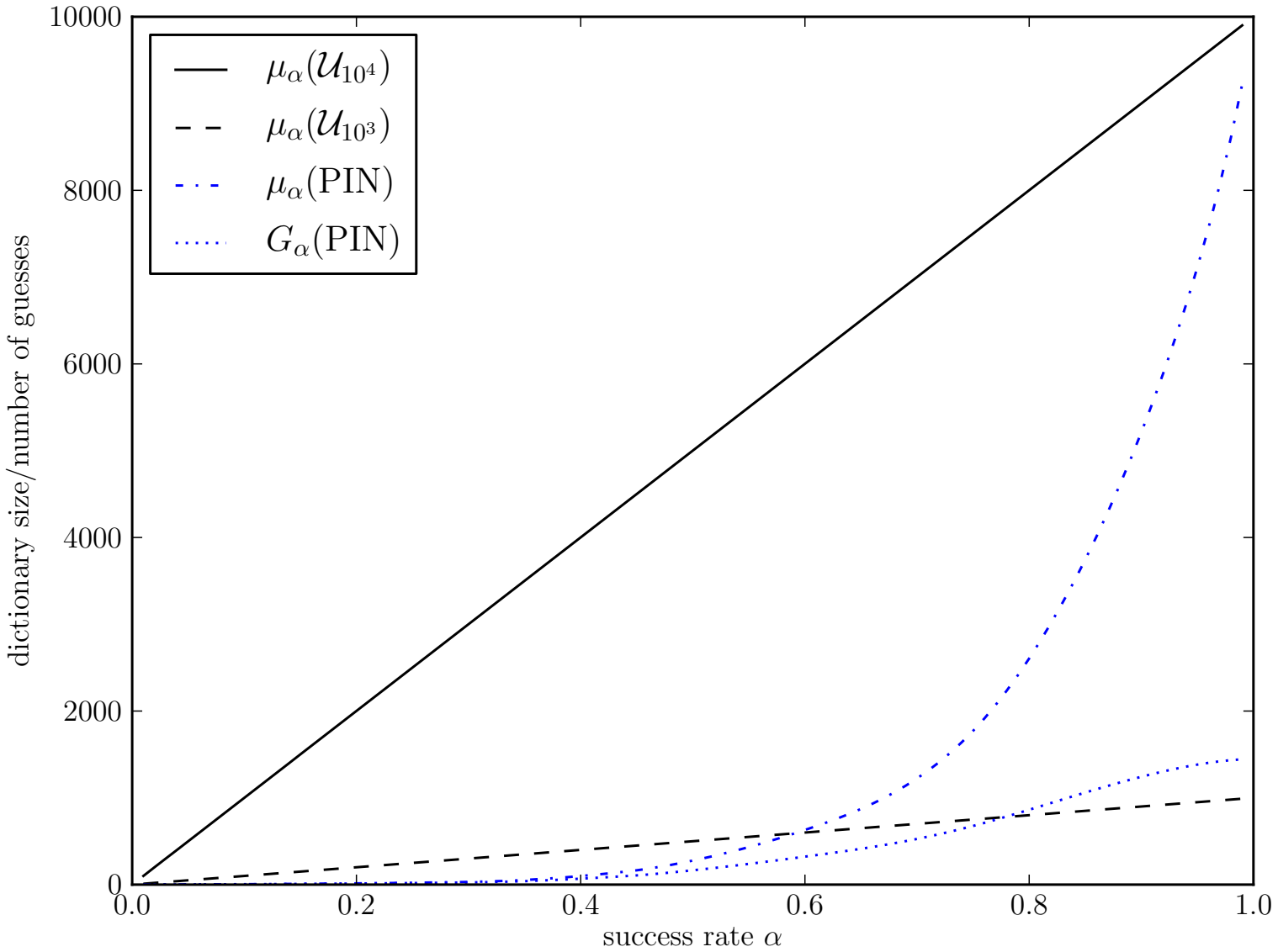

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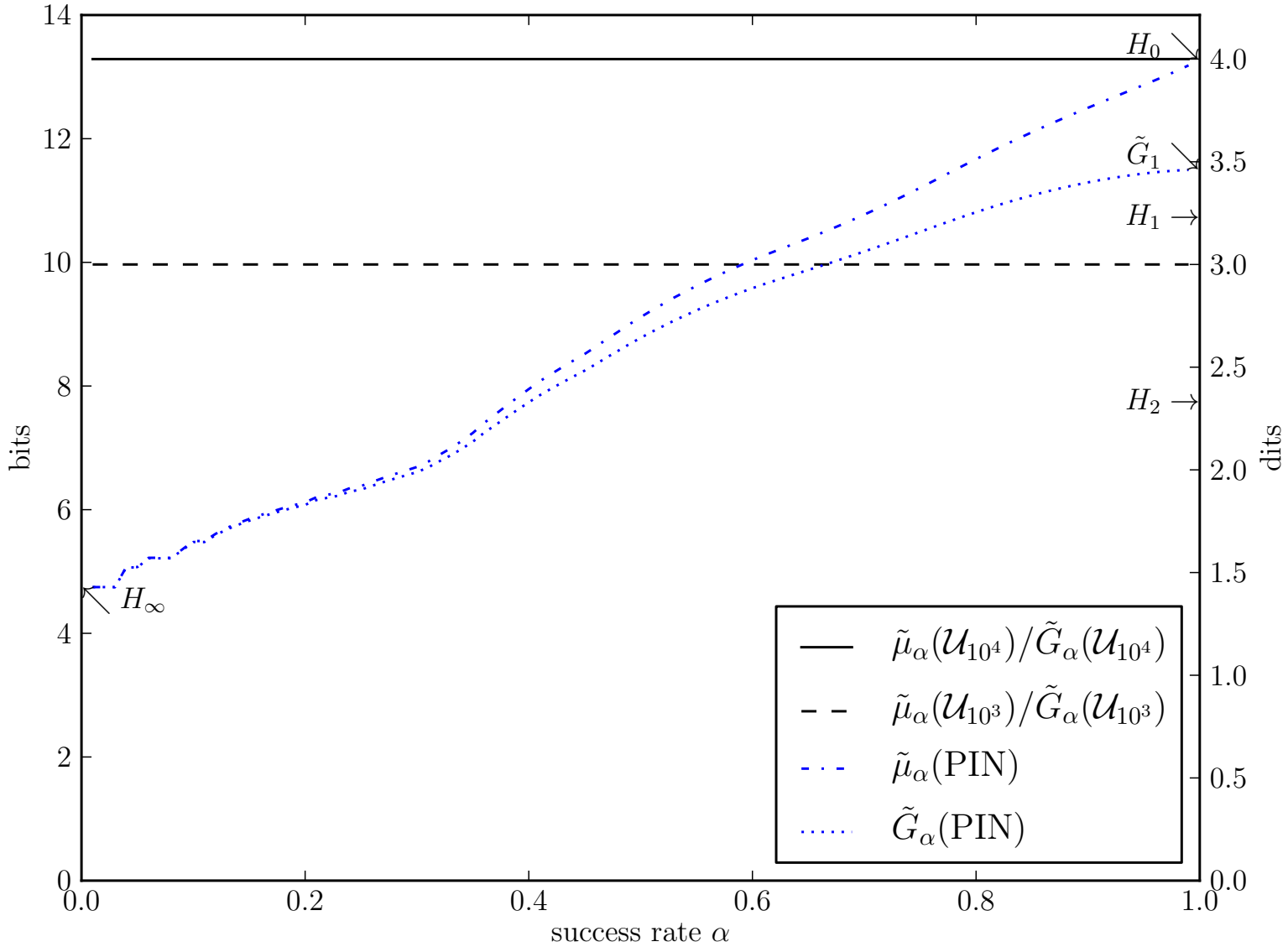

Summary of guessing metrics

- H_1 doesn't apply to guessing
- G_1 is unrealistic
- $\tilde{G}_\alpha$ for $\alpha < 1$ is the best metric
  - No single value of α is sufficient
- $\tilde{\mu}_\alpha$ can be compared directly to cracking results

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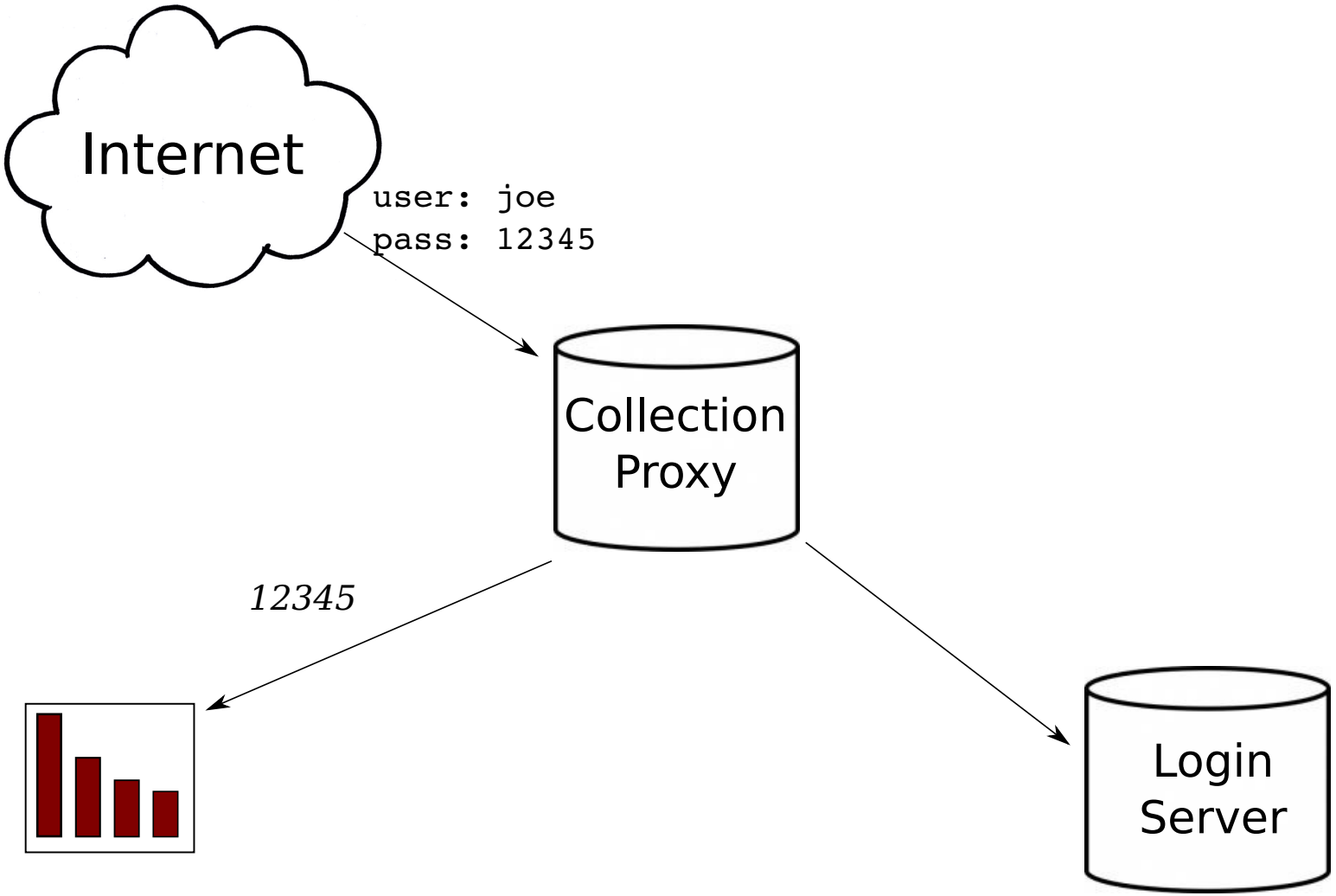
Goal #2

Collect data in a privacy-preserving manner

Collecting large-scale data at Yahoo!



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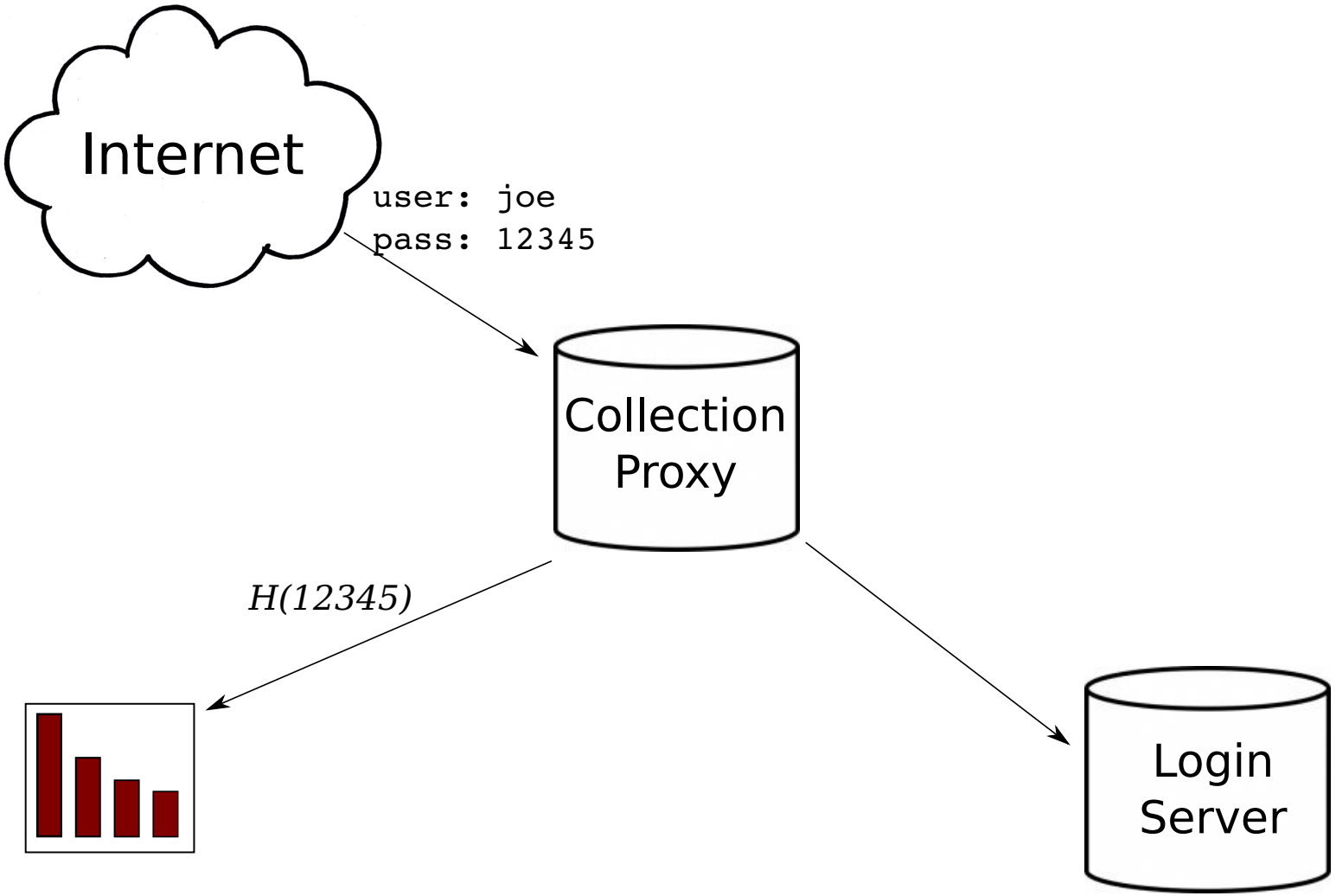

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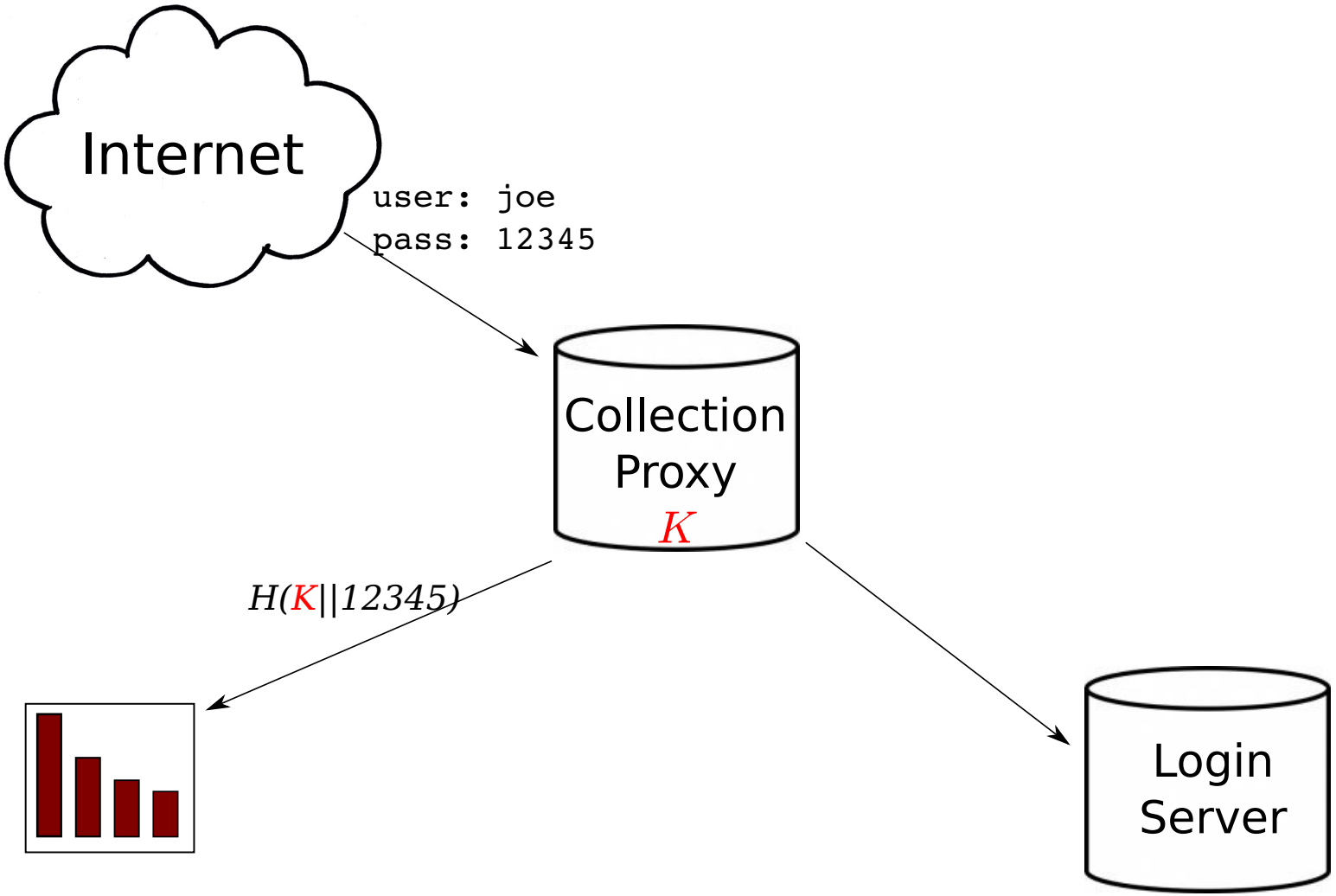

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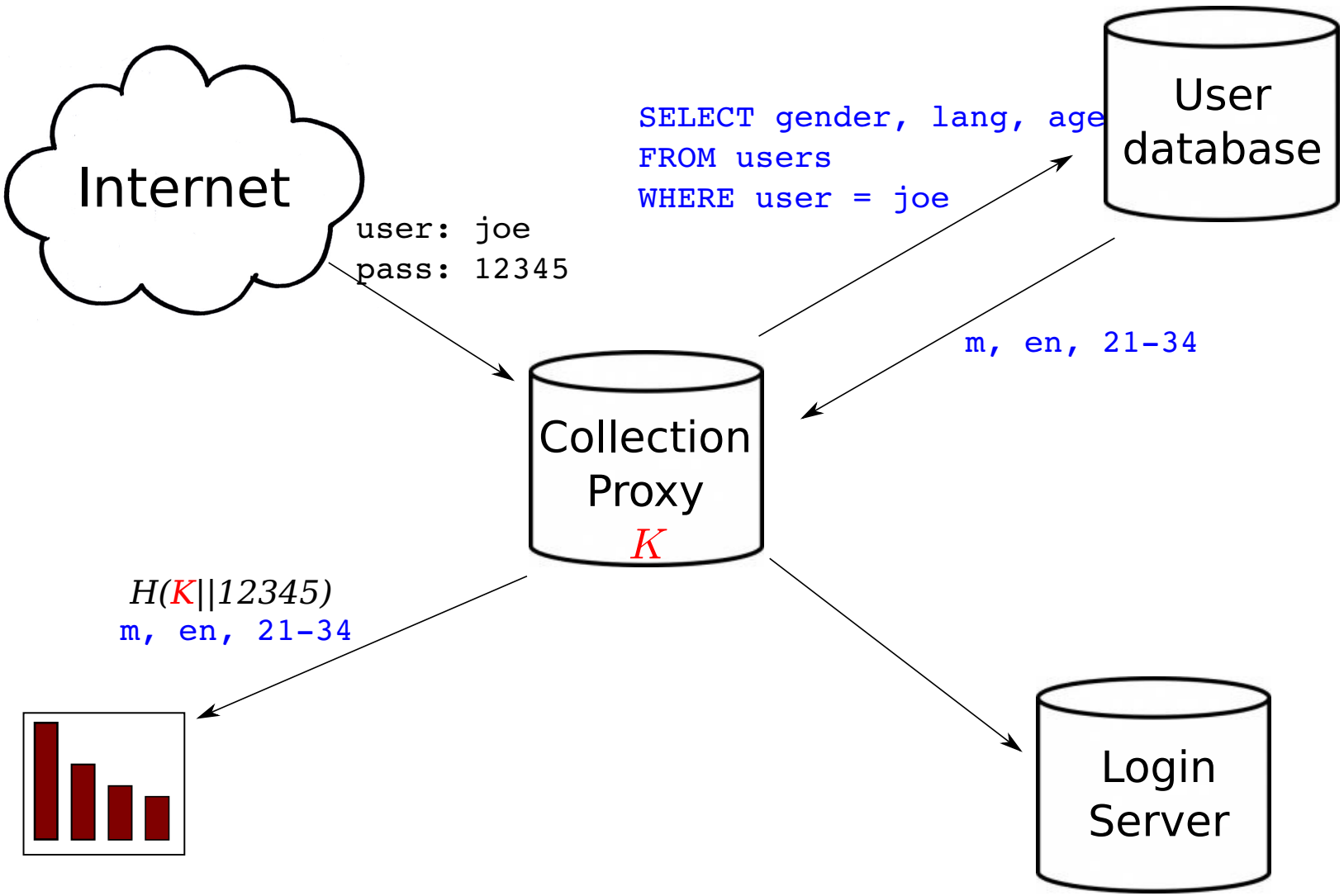

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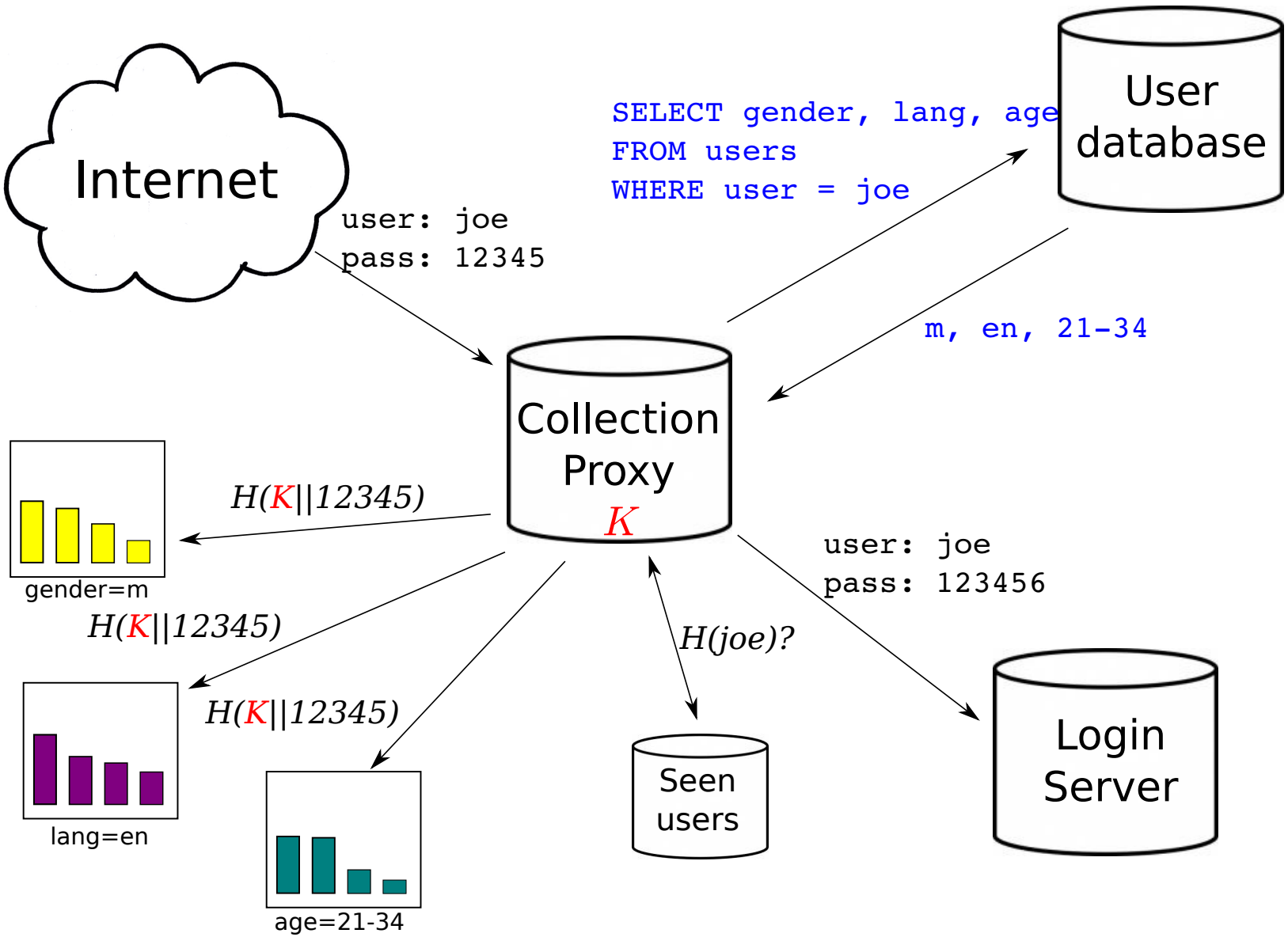

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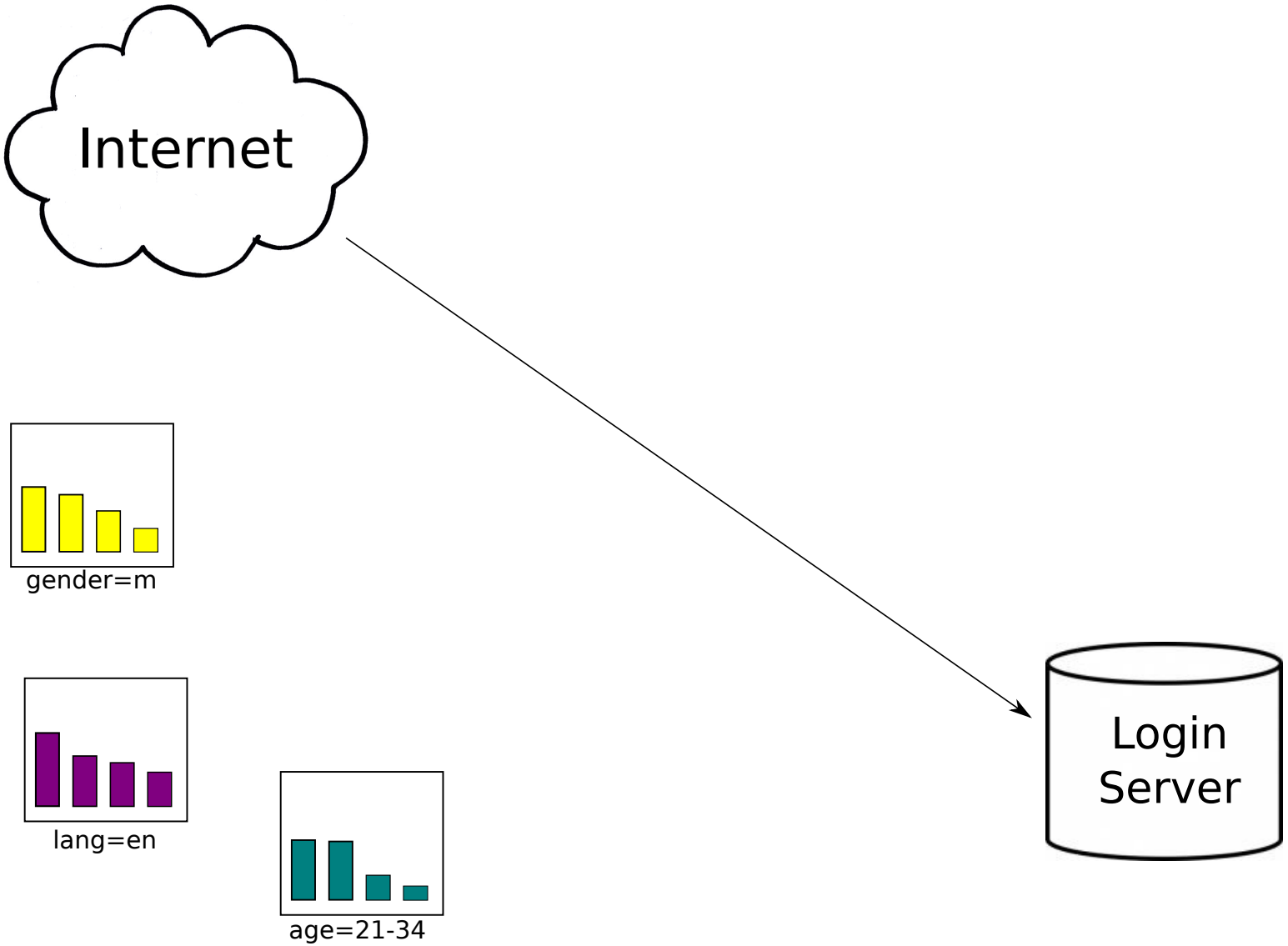

Collecting large-scale data at Yahoo!

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

Goal #3

Approximate metrics using a random sample

Theoretical results

Negative:

- Can't estimate N (non-parametrically)
- Can't estimate H_1
  - requires $O(\frac{N}{\ln N})$ samples (Valiant & Valiant, 2011)
- General: *Low-Frequency Blindness* property (Valiant)
  - Can't estimate G_1

Positive:

- Canonical Testing Theorem (Valiant)
  - Pretend the rare stuff isn't there and compute away

Theoretical results

Negative:

- Can't estimate N (non-parametrically)
- Can't estimate H_1
  - requires $O(\frac{N}{\ln N})$ samples (Valiant & Valiant, 2011)
- General: *Low-Frequency Blindness* property (Valiant)
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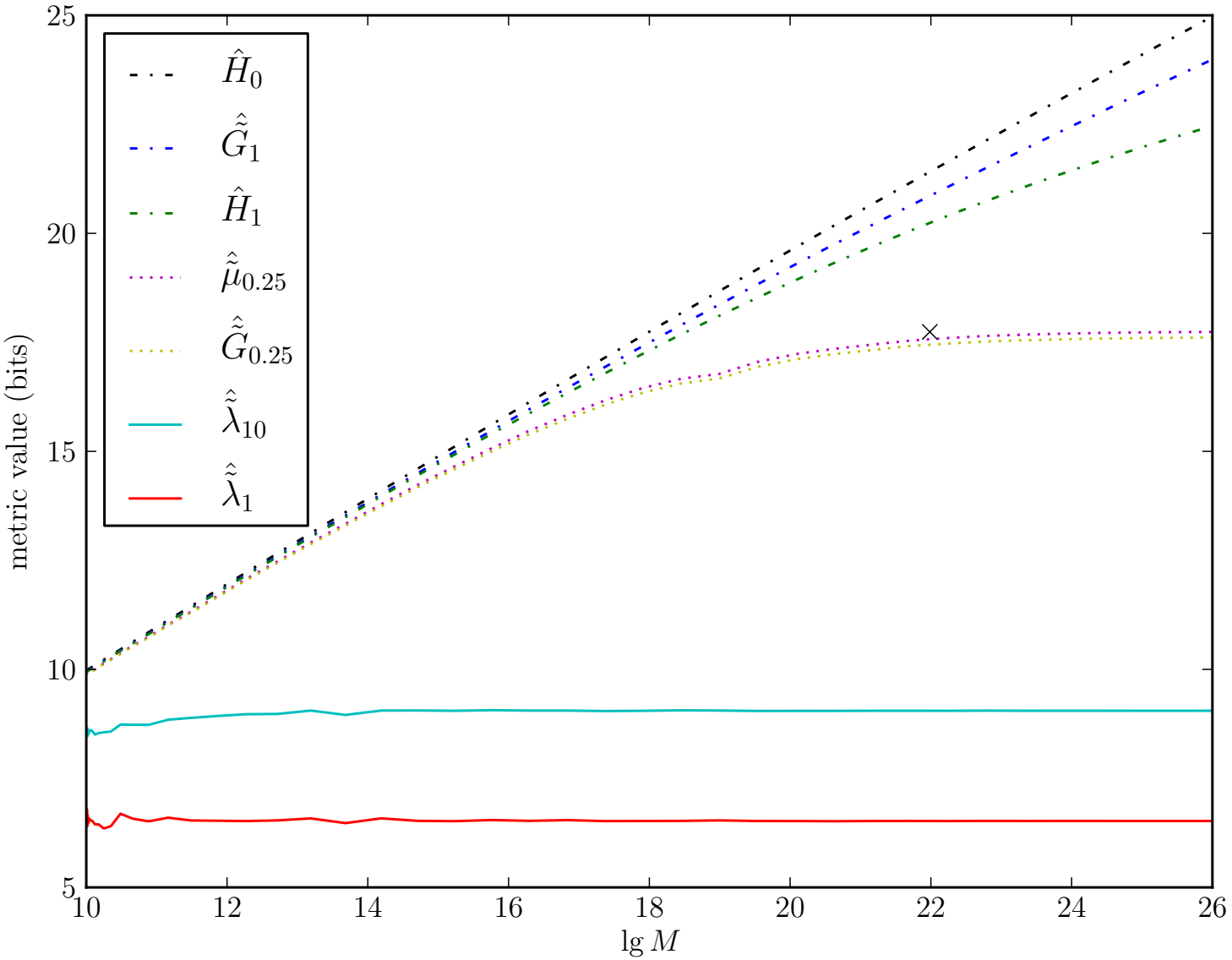
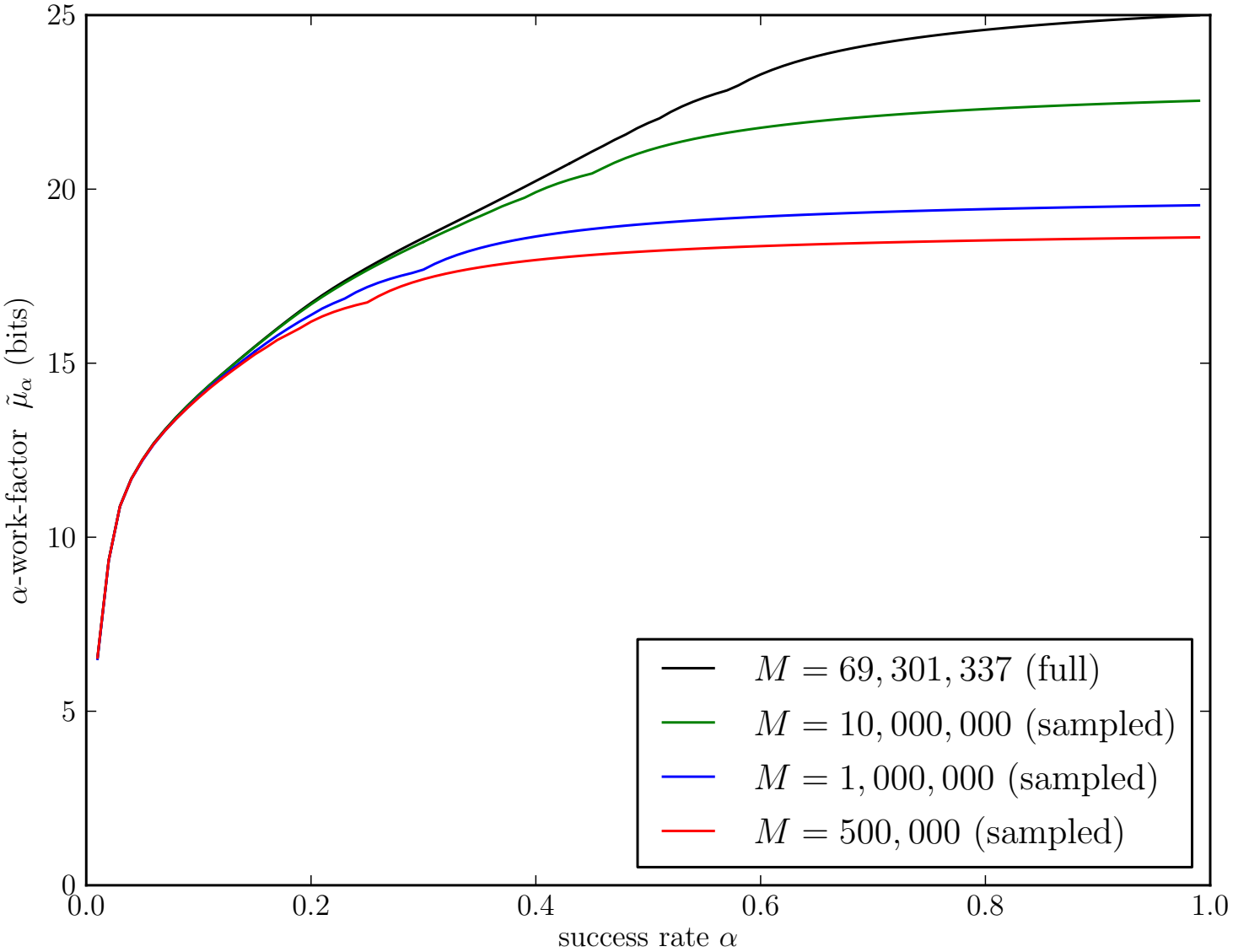
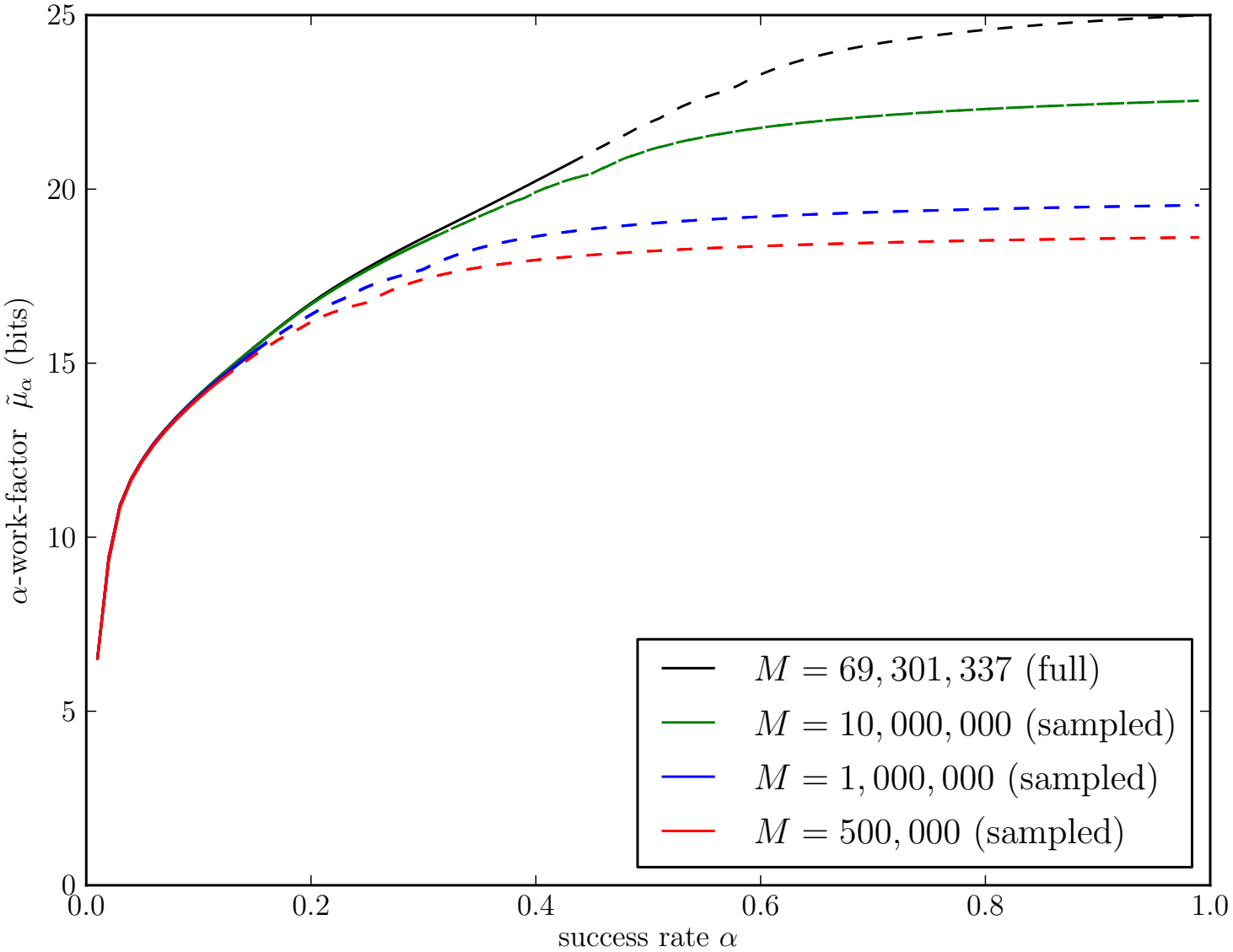
Naive metric estimates



Predicting the confidence interval by bootstrapping



Predicting the confidence interval by bootstrapping



We can parametrically extend our approximation

- Generalized inverse-Gaussian Poisson (Sichel) distribution[a]:

$$\psi(p|b,c,g) = \frac{2^{g-1}p^{g-1}e^{\frac{p}{c}-\frac{b^2c}{4p}}}{(bc)^g \cdot K_g(b)}$$

- Probability of k observations given pdf ψ:

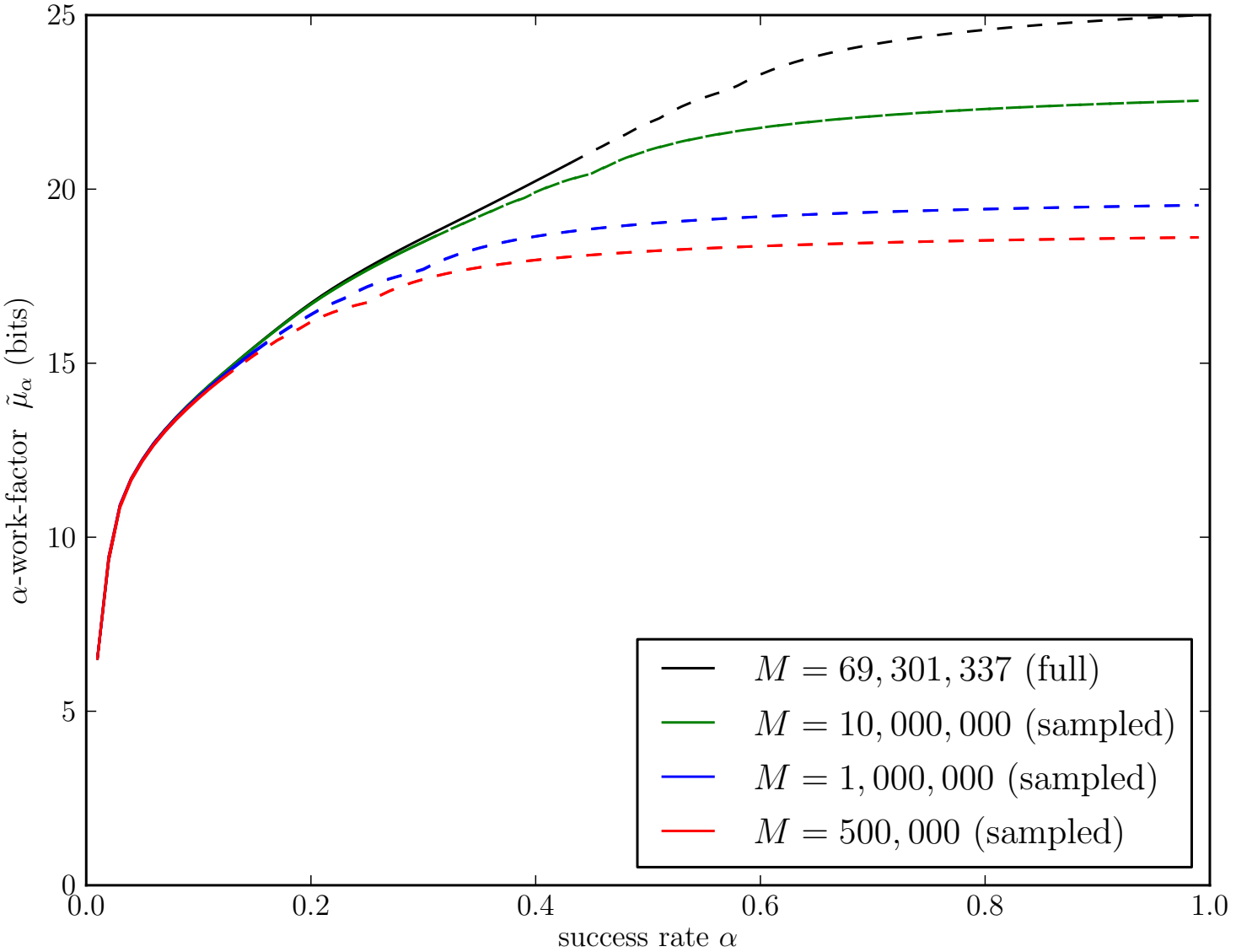
$$\Pr[k \text{ obs.}] = \frac{\int_0^1 \frac{(p\cdot M)^k \cdot e^{-p\cdot M}}{k!}\psi(p)\mathrm{d}p}{1-\int_0^1 e^{-p\cdot M}\psi(p)\mathrm{d}p}$$

- optimize b, c, g by maximizing:

$$\text{Likelihood} = \prod_{i=1}^{\hat{N}} \Pr[f_i \text{ obs.}]$$

[a] K_g is the modified Bessel function of the second kind.

We can parametrically extend our approximation



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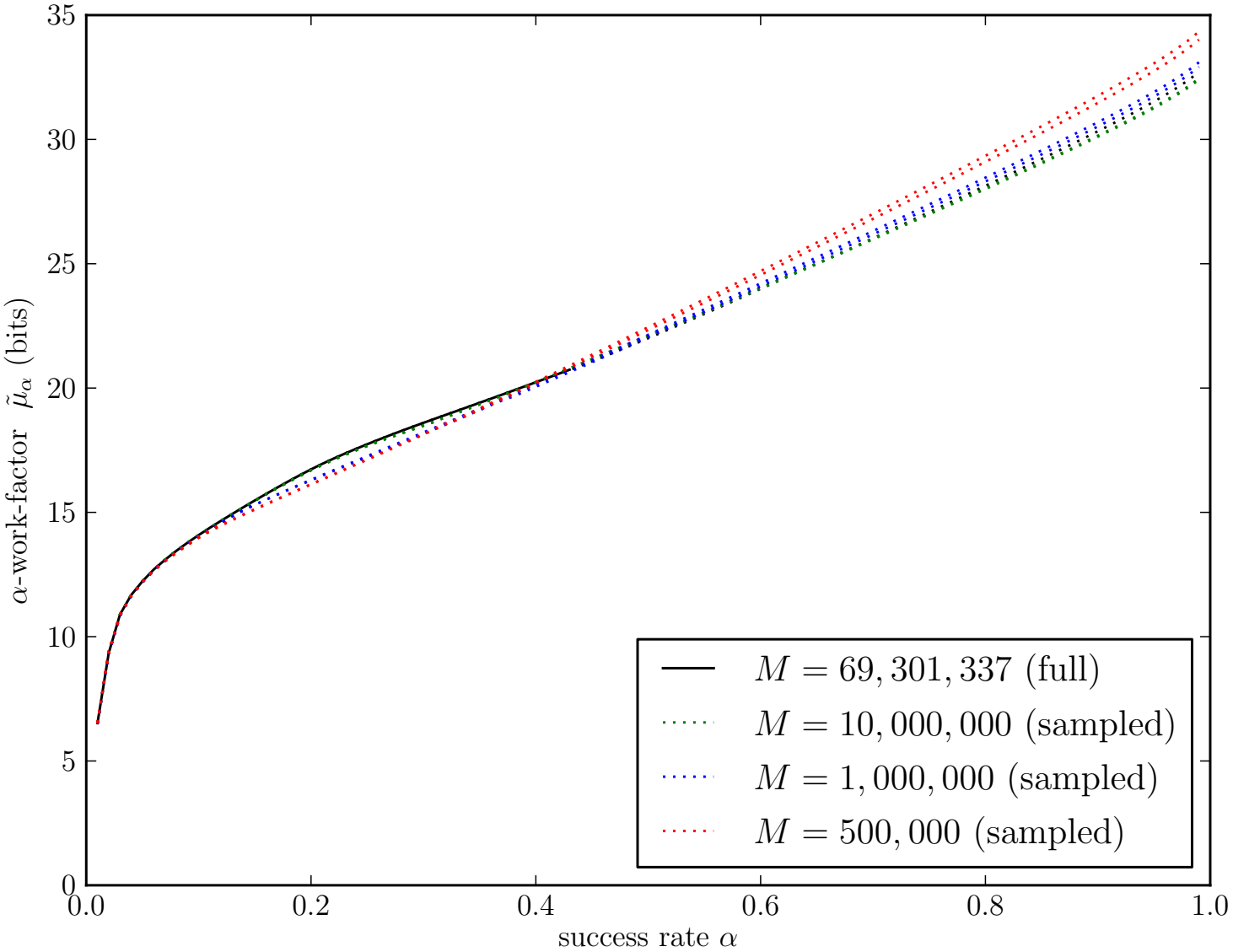
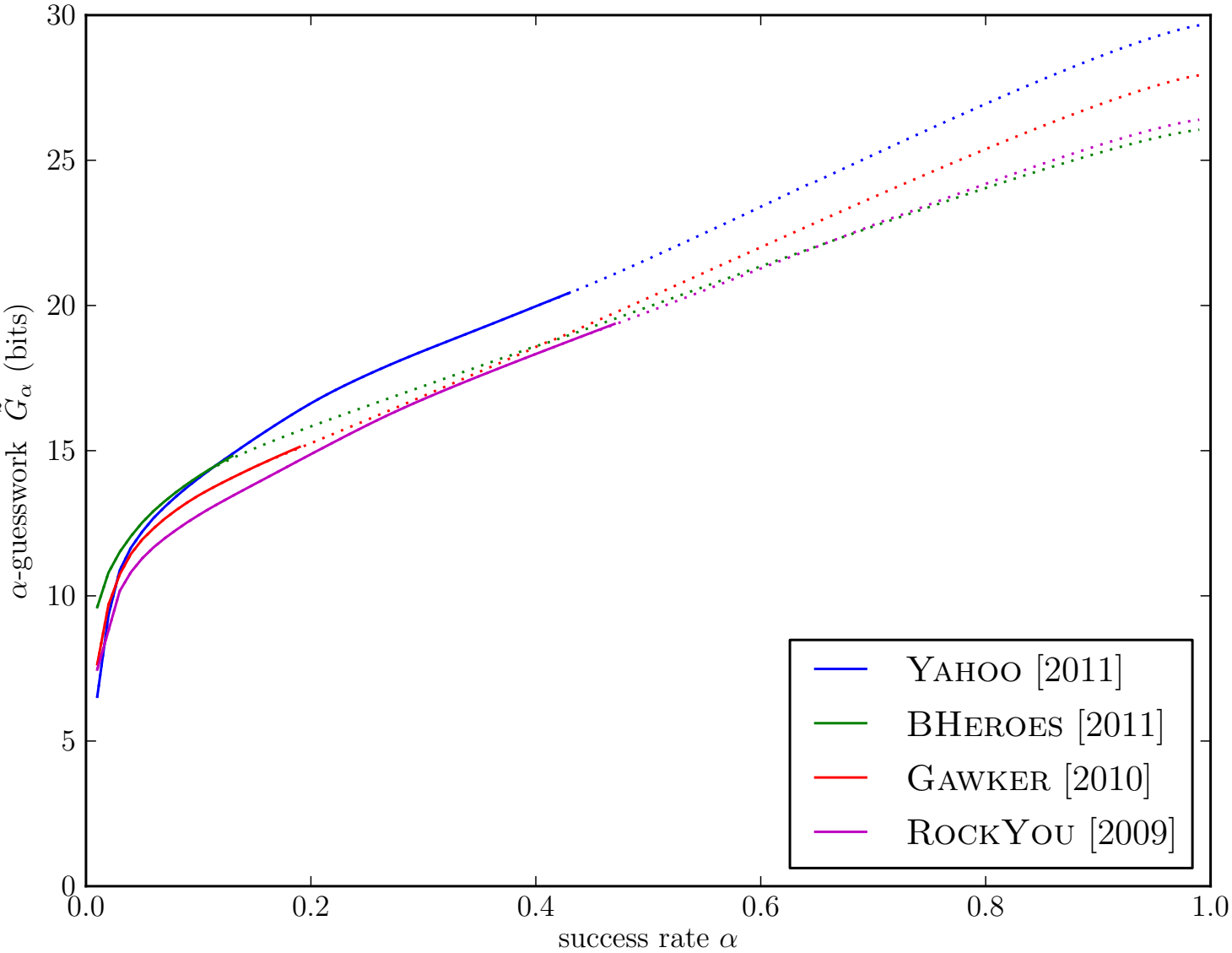


Goal #4

Analyse data

How secure are Yahoo! passwords



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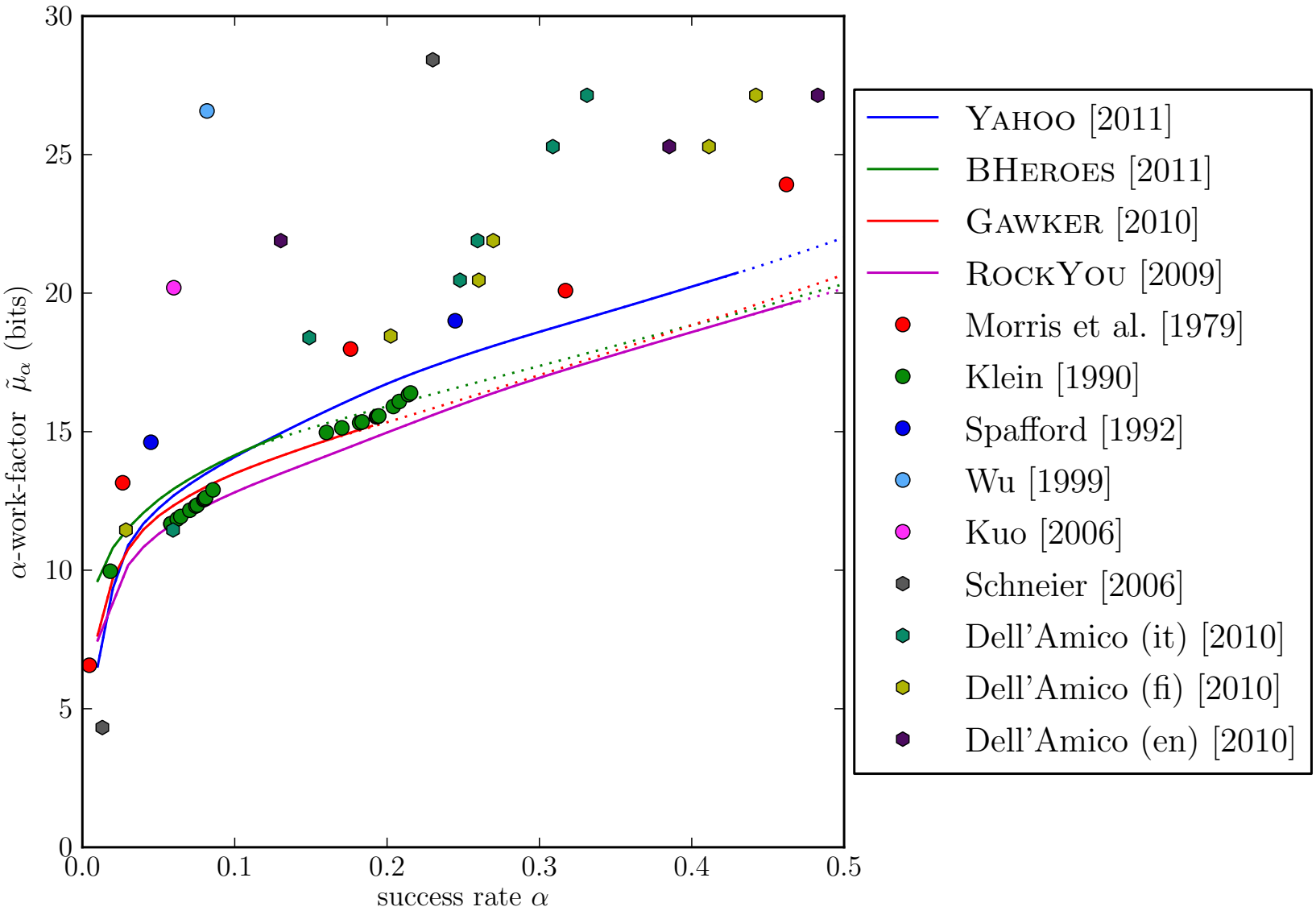

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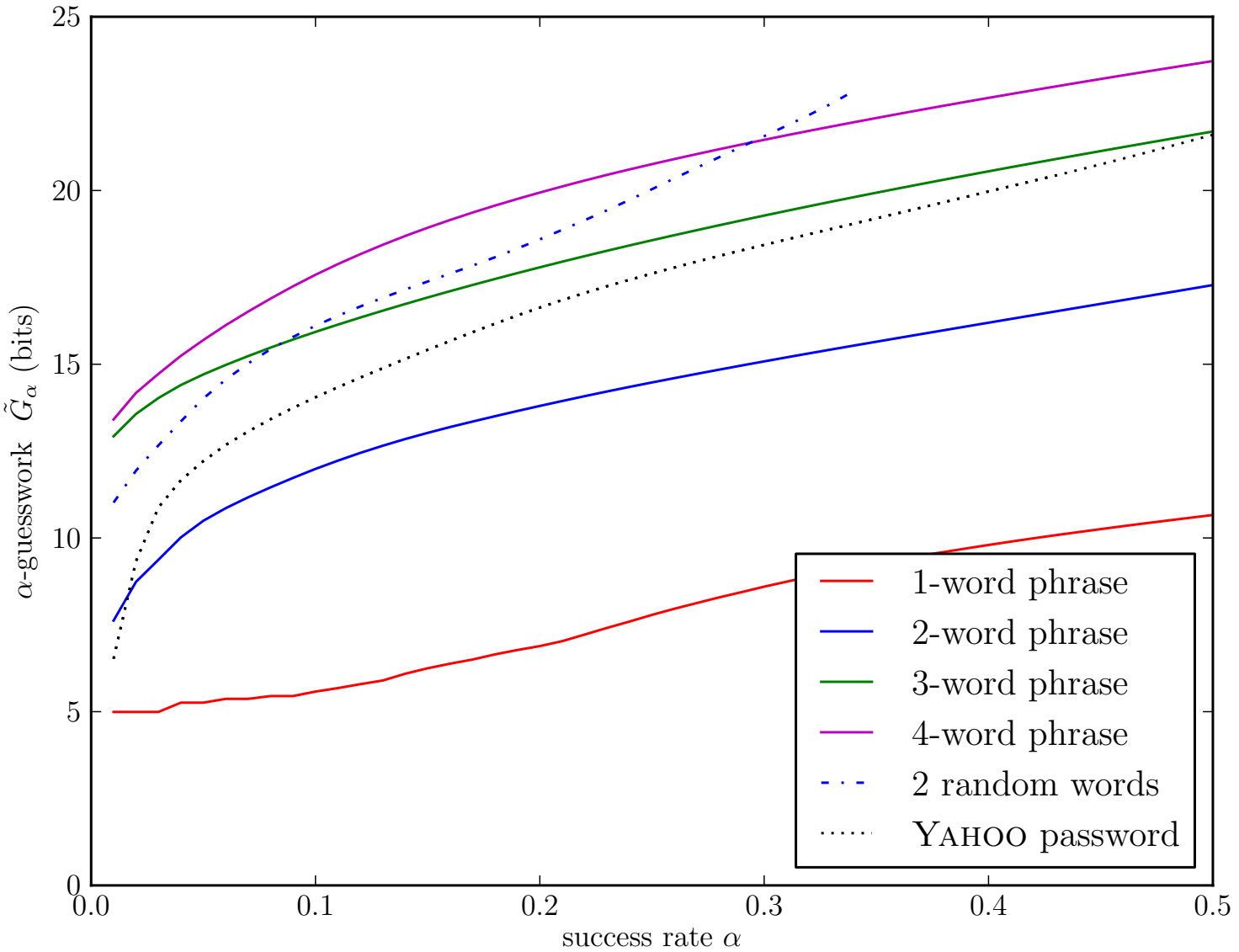
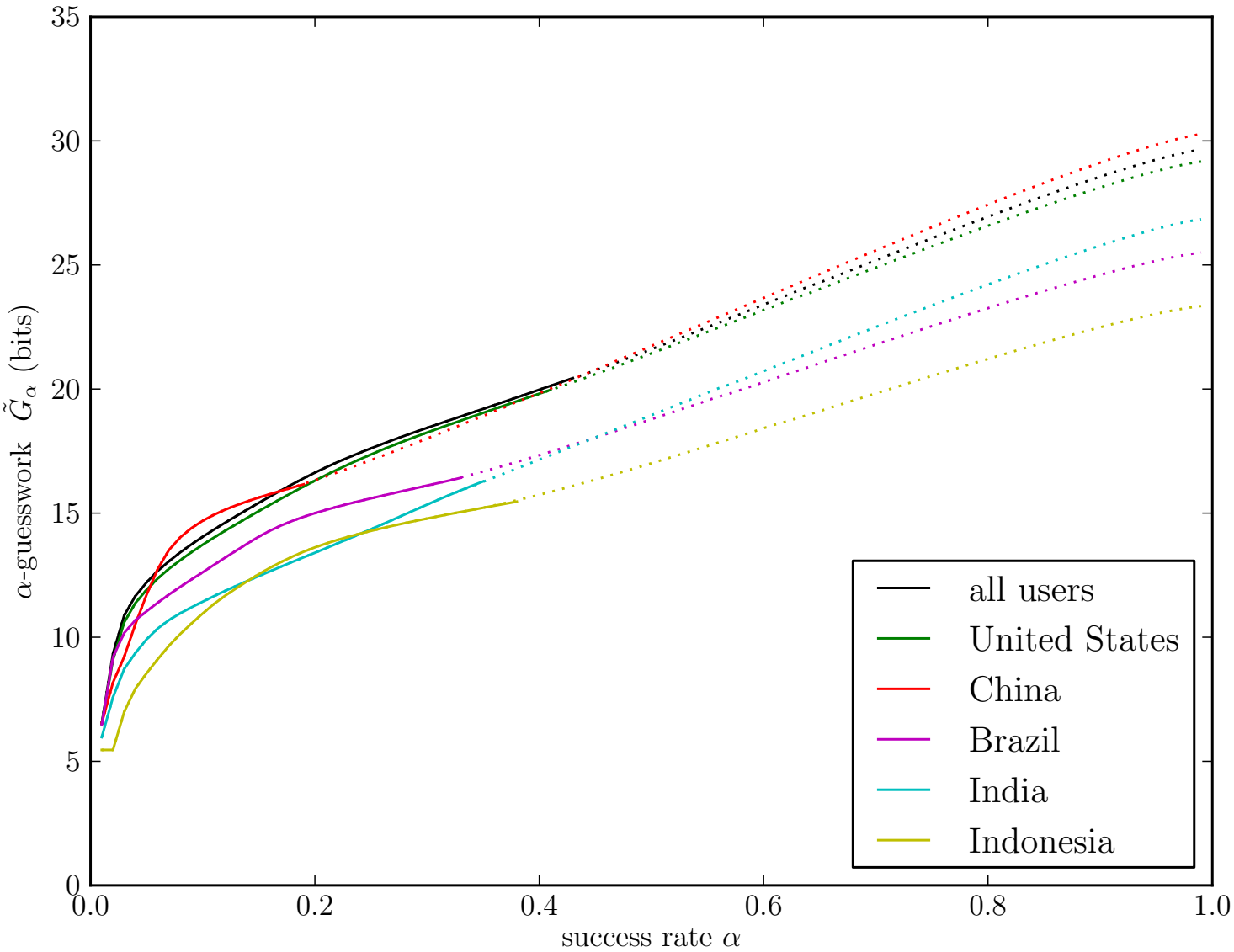
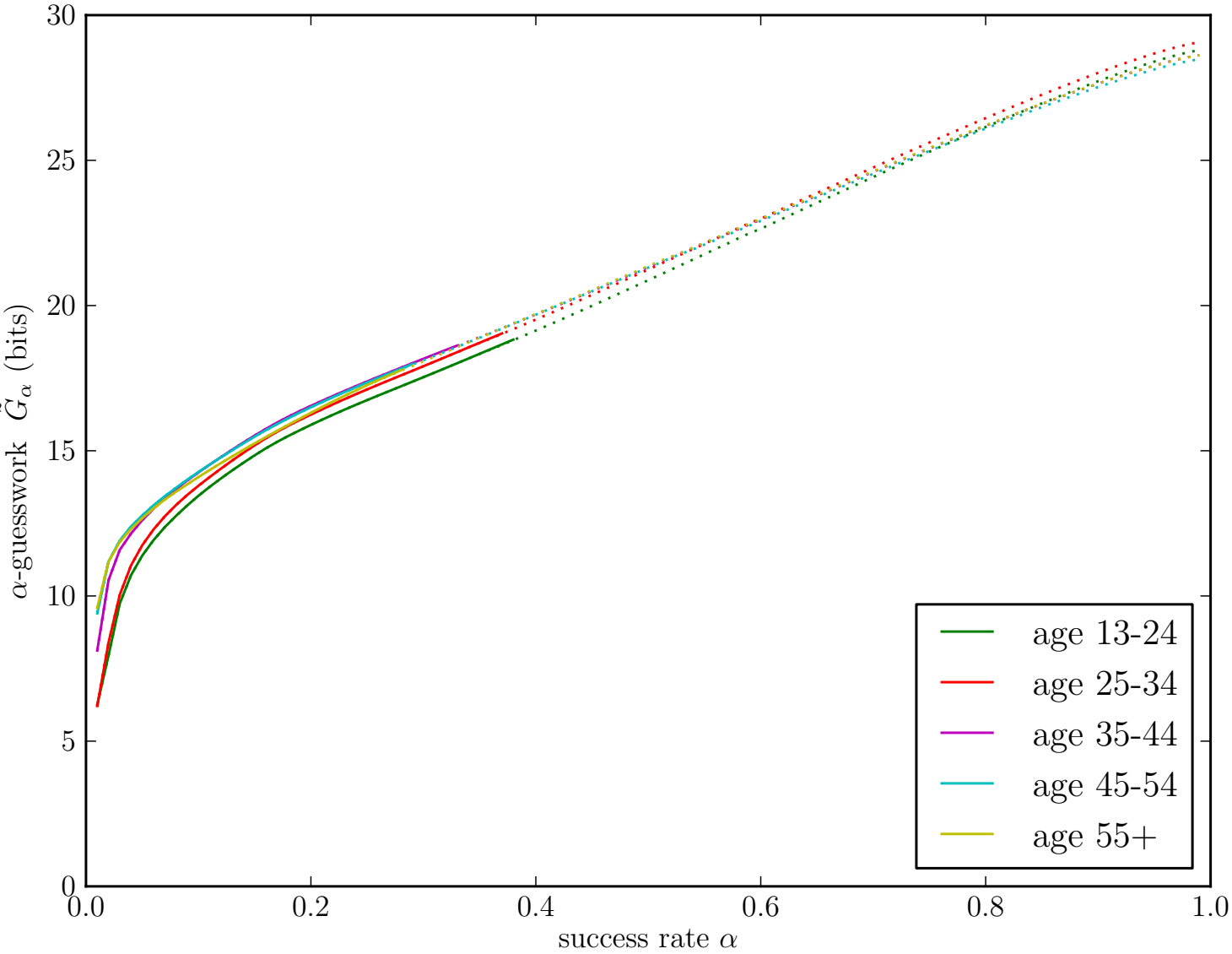


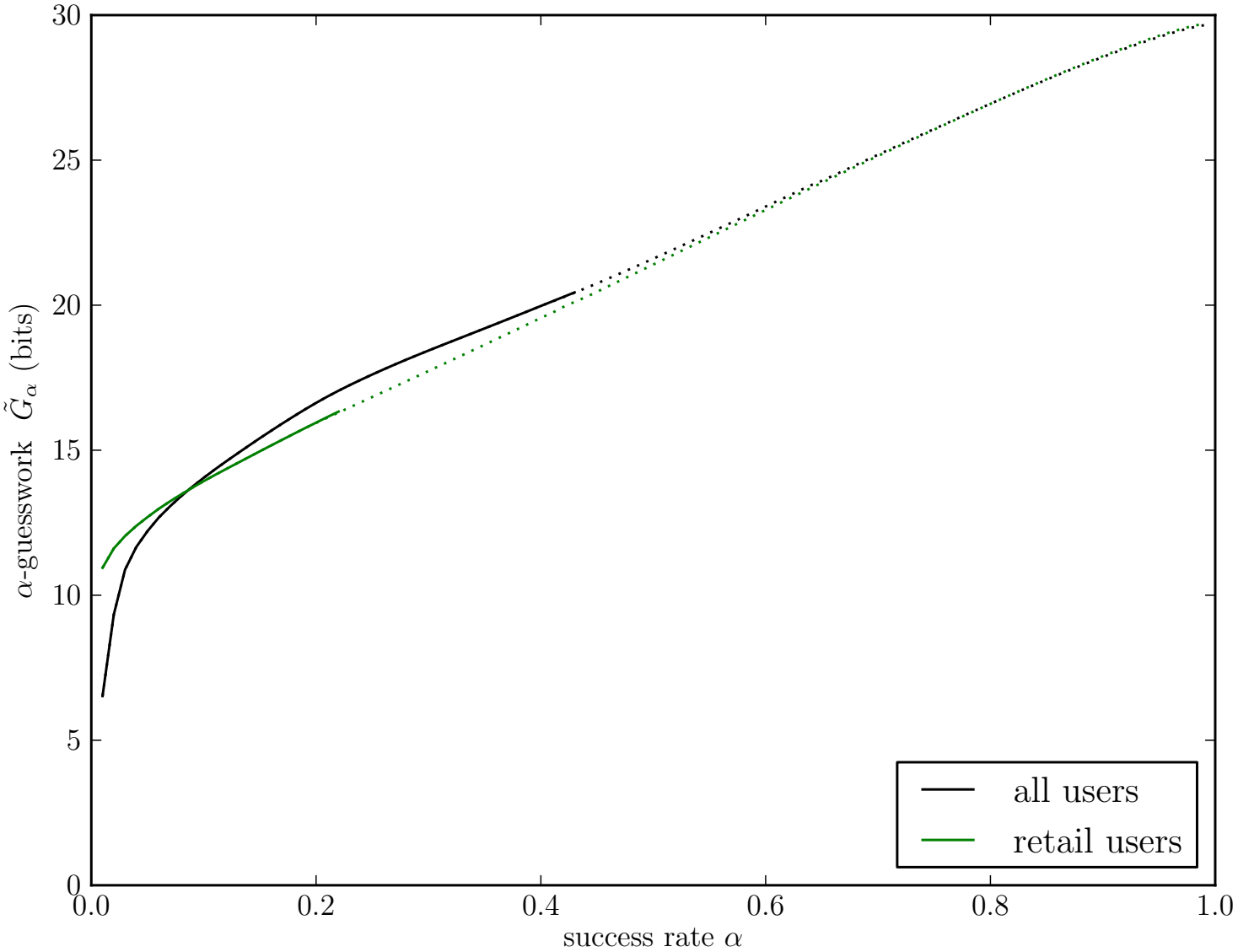
Demographic trends



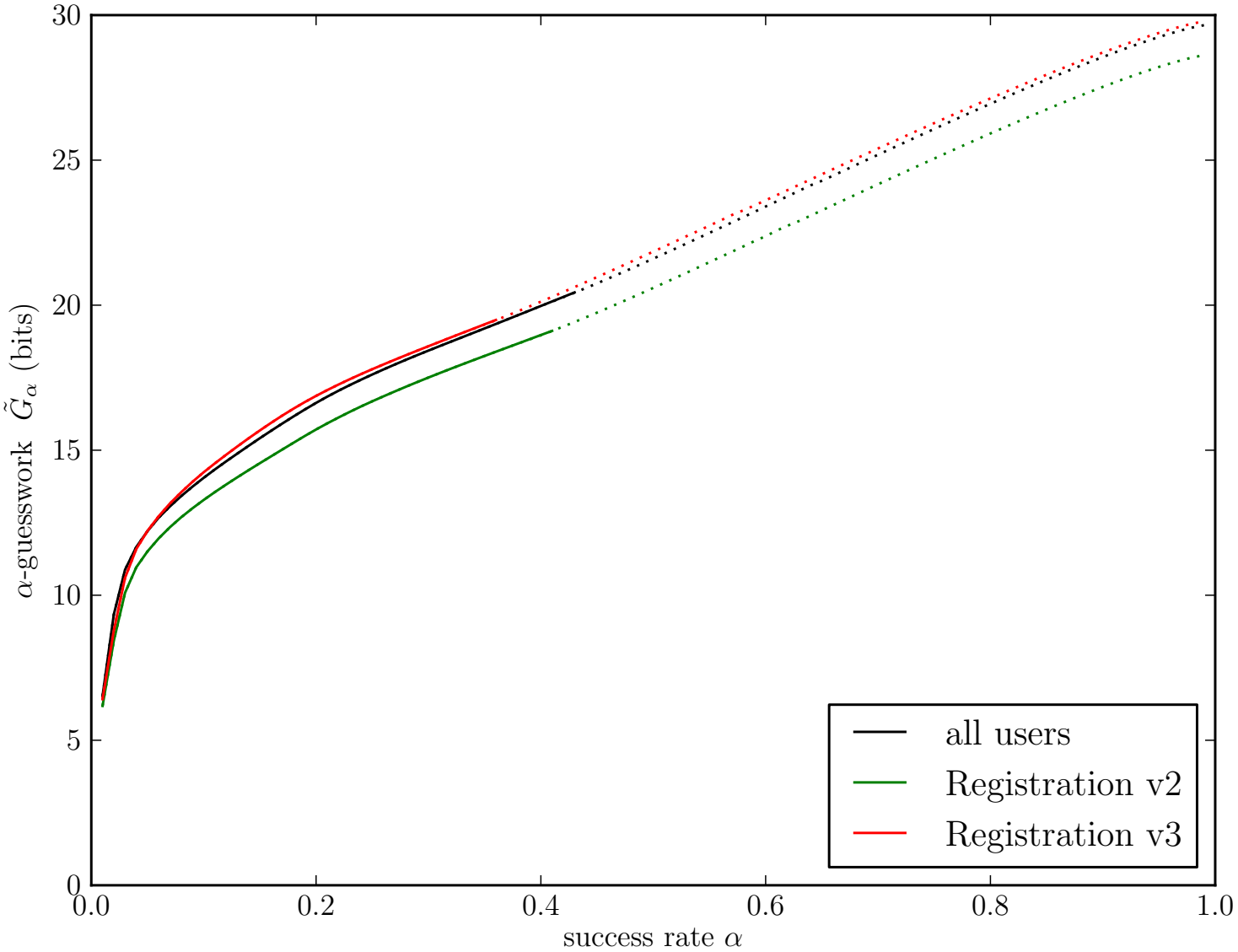
Demographic trends



Demographic trends



Demographic trends



Demographic summary

- Differences small but detectable
- Online attack $\tilde{\lambda}_{10}$ = 6–9 bits
- Offline attack $\tilde{G}_{0.5}$ = 15–25 bits
- There is no “good group” of users

Surprisingly little lanuage variation

target	dictionary: de	en	es	fr	id	it	ko	pt	zh	vi	global
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%

For $\beta = 1000$, 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.

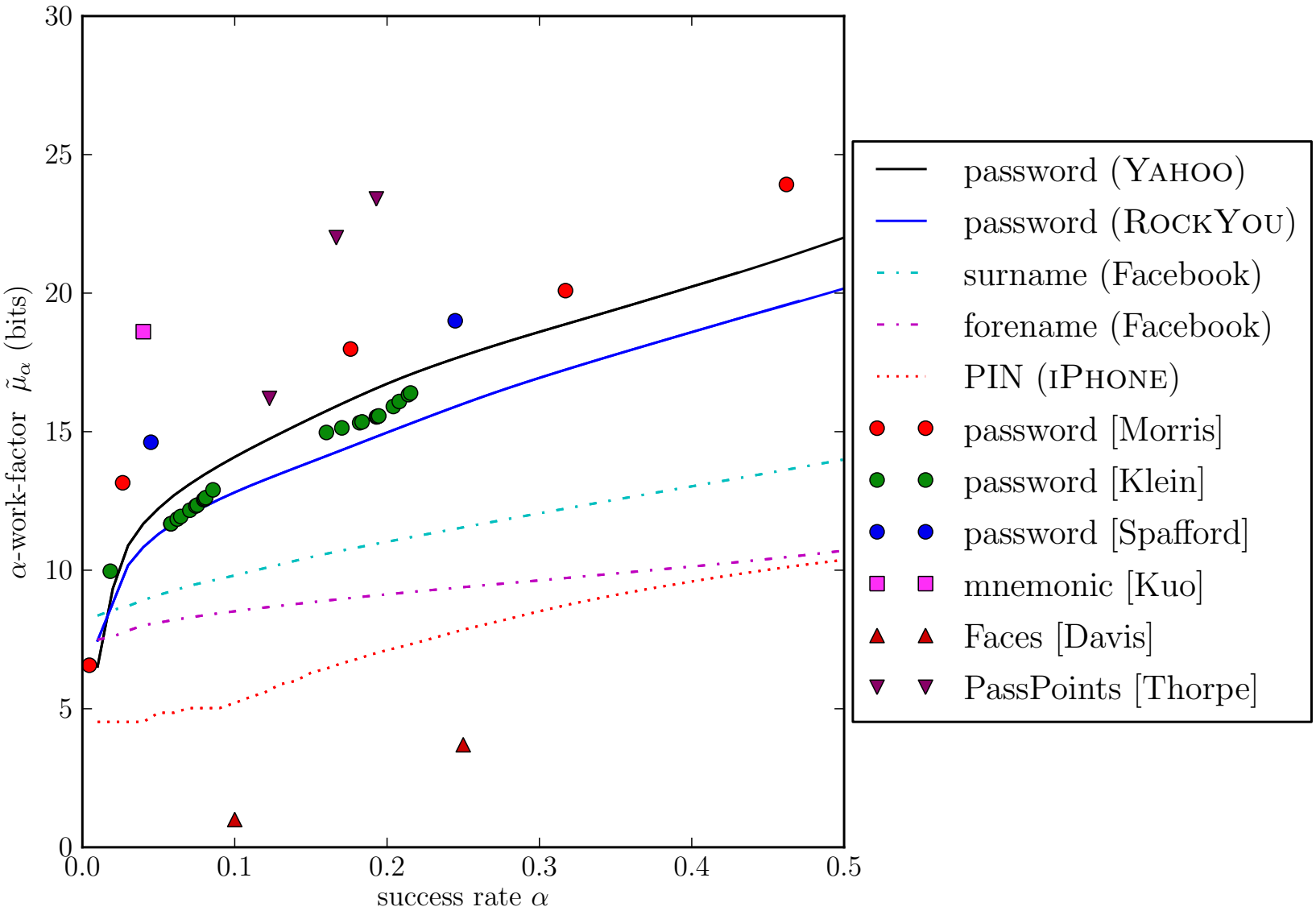
Statistical analysis of passwords

property	semantic	cracking	statistical
sound		●	○
no operator bias	●		●
no demographic bias			●
repeatable	●	○	●
practical	●	○	●
works with small data	●	●	

Joseph Bonneau.

The science of guessing: analyzing an anonymized corpus of 70 million passwords. *IEEE Security & Privacy*, 2012.

Putting it all together



The future of passwords

- Retire passwords from most current roles
- Cease aggregating large databases of credentials
- Figure out what humans can actually remember...

A long road ahead

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.

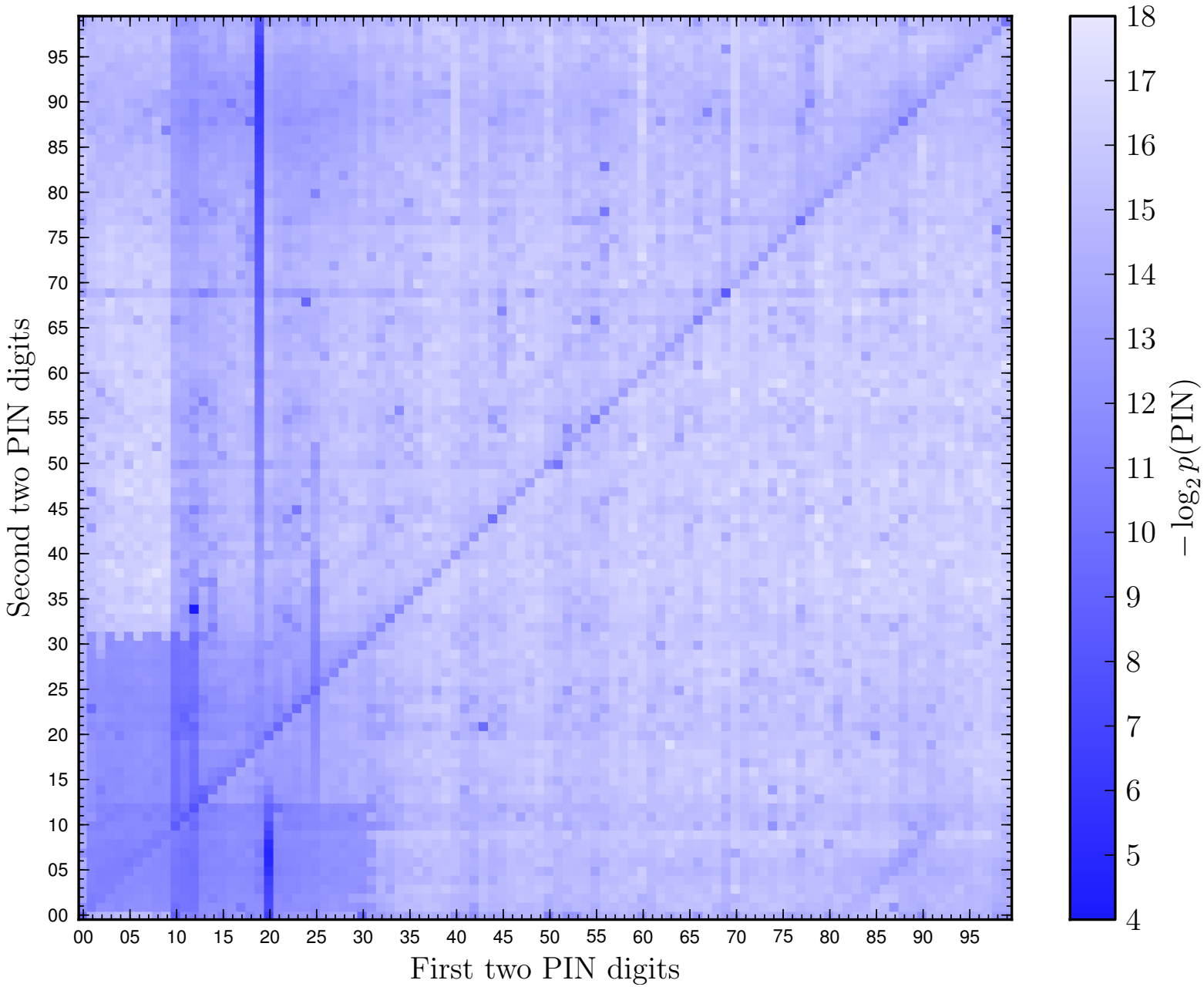
Workshop on the Economics of Information Security, 2010.

Thank you

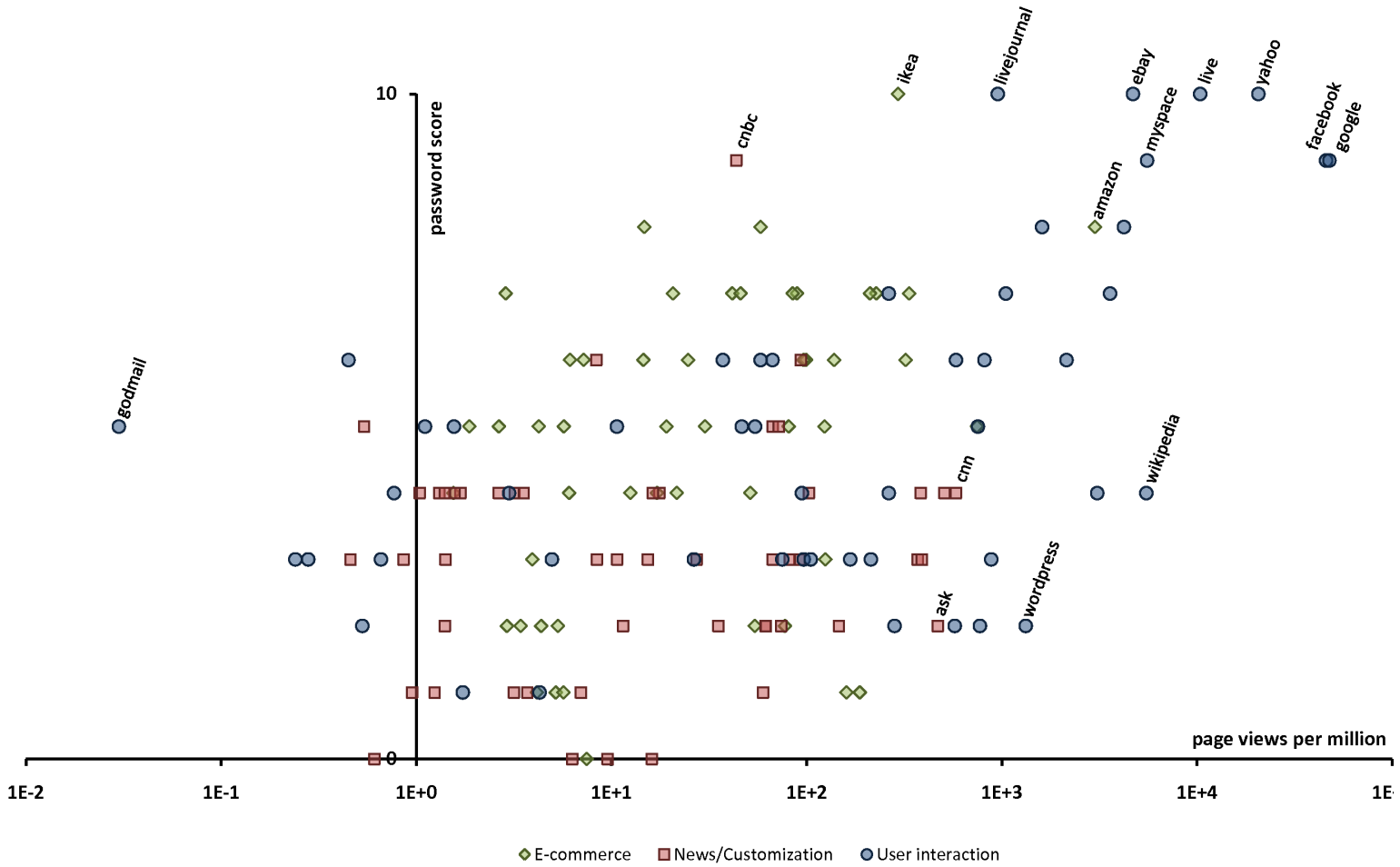
jcb82@cl.cam.ac.uk

Other projects on authentication

Human choice of PINs



The economics of password collection



Passwords and character encoding

пароль

=

пароль

=

%26%231087%3B%26%231072%3B%26%231088%3B
%26%231086%3B%26%231083%3B%26%231100%3B

$6 \rightarrow 42 \rightarrow 78$

Passwords and character encoding

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пароль

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$6 \rightarrow 42 \rightarrow 78$