04. Passwords

Blase Ur and Mainack Mondal

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CMSC 23210 / 33210

THE UNIVERSITY OF CHICAGO

UCHICAGO SUPER GROUP

Security, Usability, & Privacy Education & Research


12345
password
123456789
princess
iloveyou
rockyou
1234567
12345678
monkey
jessica
babygirl
654321
michelle
tigger
nicole
liverpool
purple
shadow
michael
andrea
tinkerbell
ashley
daniel
password1
anthony
lovely
jordan
football
qwerty
abc123
basketball
butterfly
superman
sunshine
chocolate
jennifer
angel
carlos
soccer
flower
eminem
hottie
cookie
bubbles
dragon
rangers
whatever
hannah
samantha
melissa
christian
summer
softball
matthew
chelsea
pretty
secret
andrew
angels
justin
hello
playboy
jasmine
brandon
elizabeth
jesus
mickey
000000

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Google security exec: 'Passwords are dead'

Speaking at TechCrunch Disrupt, Google's Heather Adkins says startups should look beyond passwords to secure users and their data.

PCWorld

Yahoo wants to kill the password one text message at a time

COMPUTERWORLD FROM IDG INSIDER

NEWS

Russian credential theft shows why the password is dead

It's way past time for companies to implement strong authentication measures

theguardian

US world opinion sports soccer tech arts lifestyle fashion business

Google aims to kill passwords by the end of this year

GIZMODO

The Tech That Will Kill Passwords

Adam Clark Estes

12/04/14 2:30pm · Filed to: PASSWORDS

Why Passwords?

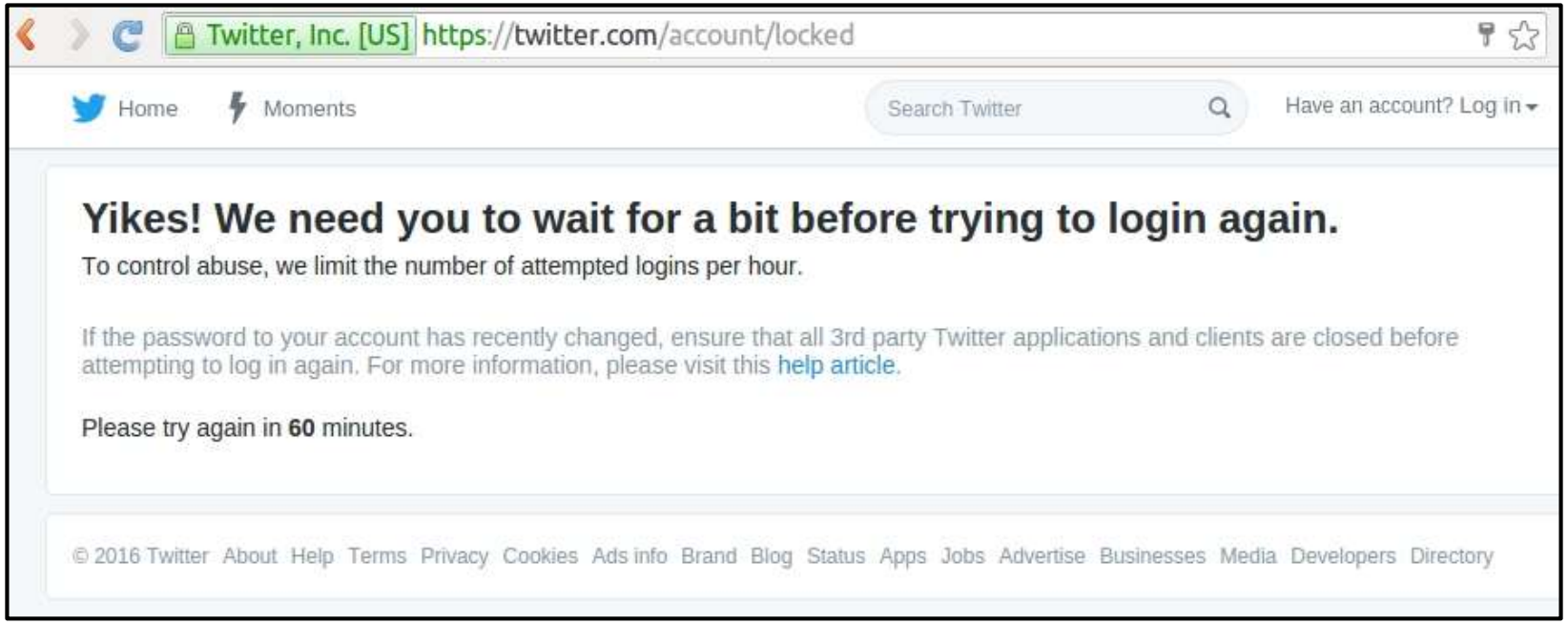
- Familiar to people
- Nothing to carry
- Difficult to coerce
- Easy to deploy, revoke, and replace

Threats to Password Security

- Online attack against live system

Threats to Password Security

- Online attack against live system
  - Rate-limiting



Threats to Password Security

- Online attack against live system
- Attack against password-protected file
- Offline attack against stolen database

Anatomy of an Offline Attack

- Attacker compromises database
  - hash(“Blase”) =

`$2a$04$iHdEgkI681VdDMc3f7edau9phRwORvhYjqWAIb7hb4B5uFJO1g4zi`

- Attacker makes and hashes guesses
- Finds match → try on other sites

Problem 1: Absurd Advice

Carnegie Mellon University

Password Requirements

Must Contain

- At least 8-characters.
- At least one uppercase alphabetic character (e.g., A-Z).
- At least one lowercase alphabetic character (e.g., a-z).
- At least one number (e.g., 0-9).
- At least one special character (e.g., []~!@#$%^&*()?<>./_-+=).

Cannot Contain

- Known information (i.e., first name, last name, Andrew userID, date of birth, 9-digit Carnegie Mellon ID number, SSN, job title).
- Four or more occurrences of the same character (e.g., aaaa, 2222, a123a345a678a).*
- A word that is found in a standard dictionary.* (after removing non-alpha characters).

***This requirement does not apply to Andrew account passwords that are more than 19 characters in length (e.g., passphrase).**

Additional Policies

- Last five passwords cannot be used.
- Cannot be changed more than four times in a day.

Problem 2: Inaccurate Feedback

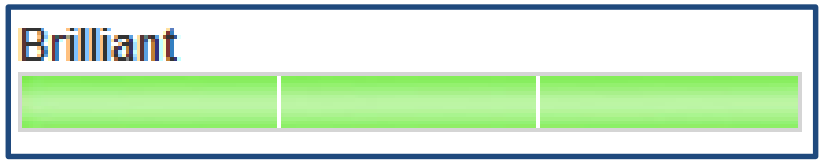
Problem 3: Unhelpful Feedback

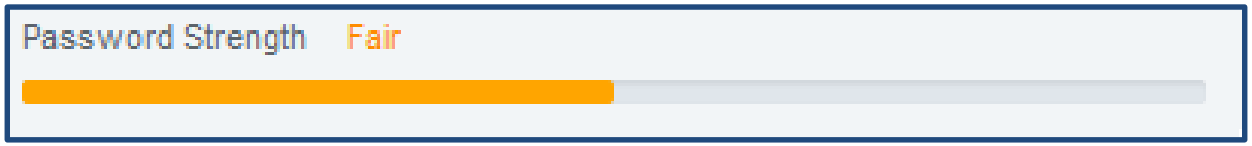
1. Impact of password meters
2. Modeling password cracking
3. Password perceptions
4. Neural-network-based guessing
5. Building a data-driven meter

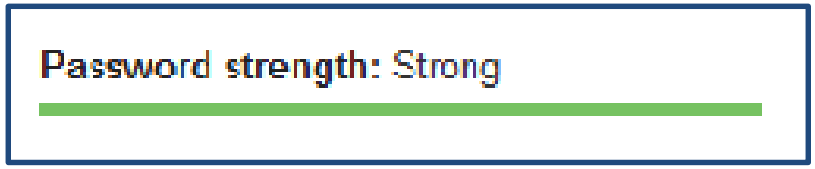
Meters' Security & Usability Impact

Blase Ur, Patrick Gage Kelley, Saranga Komanduri, Joel Lee, Michael Maass, Michelle Mazurek, Timothy Passaro, Richard Shay, Timothy Vidas, Lujo Bauer, Nicolas Christin, Lorrie Faith Cranor. How Does Your Password Measure Up? The Effect of Strength Meters on Password Creation. In *Proc. USENIX Security Symposium*, 2012.

Meters Are Ubiquitous



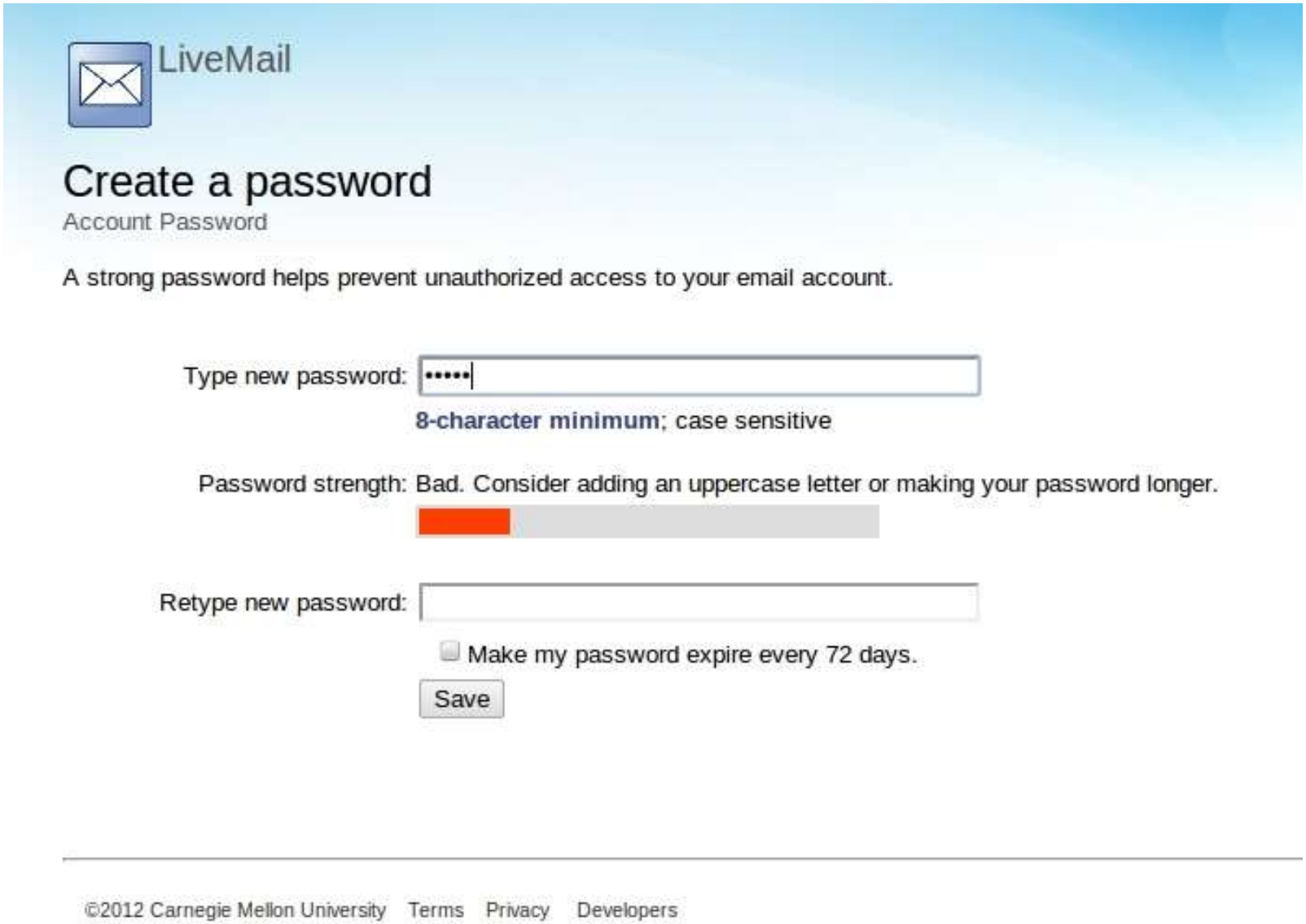




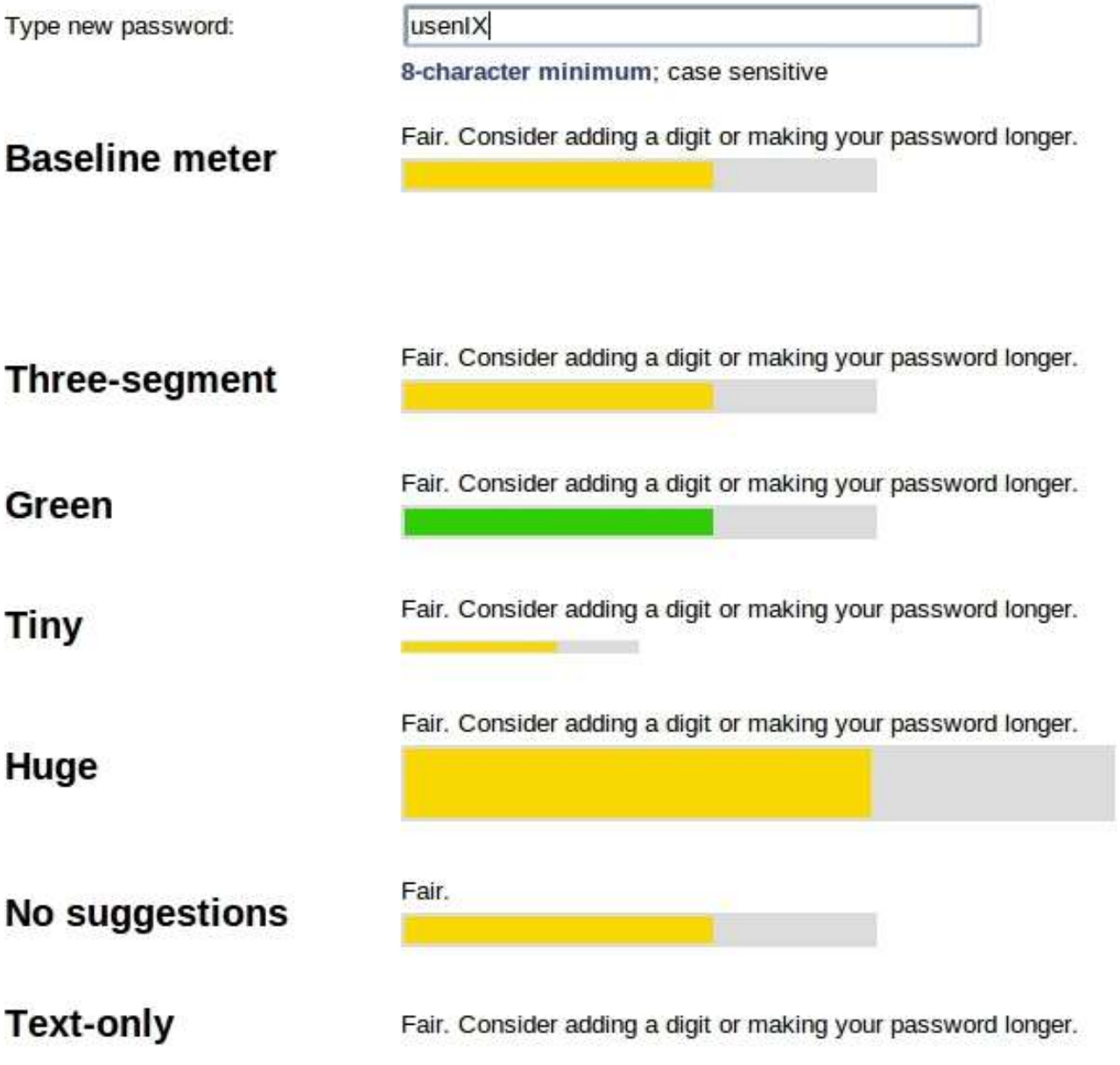
Test Meters' Impact

- How do meters impact password security?
- How do meters impact usability?
  - Memorability
  - User sentiment
  - Timing
- What meter features matter?
- 2,931-participant online study

Baseline Password Meter



Visual Differences



Visual Differences

Type new password: usenIX

8-character minimum; case sensitive

Baseline meter

Fair. Consider adding a digit or making your password longer.

Three-segment

Fair. Consider adding a digit or making your password longer.

Green

Fair. Consider adding a digit or making your password longer.

Tiny

Fair. Consider adding a digit or making your password longer.

Huge

Fair. Consider adding a digit or making your password longer.

No suggestions

Fair.

Text-only

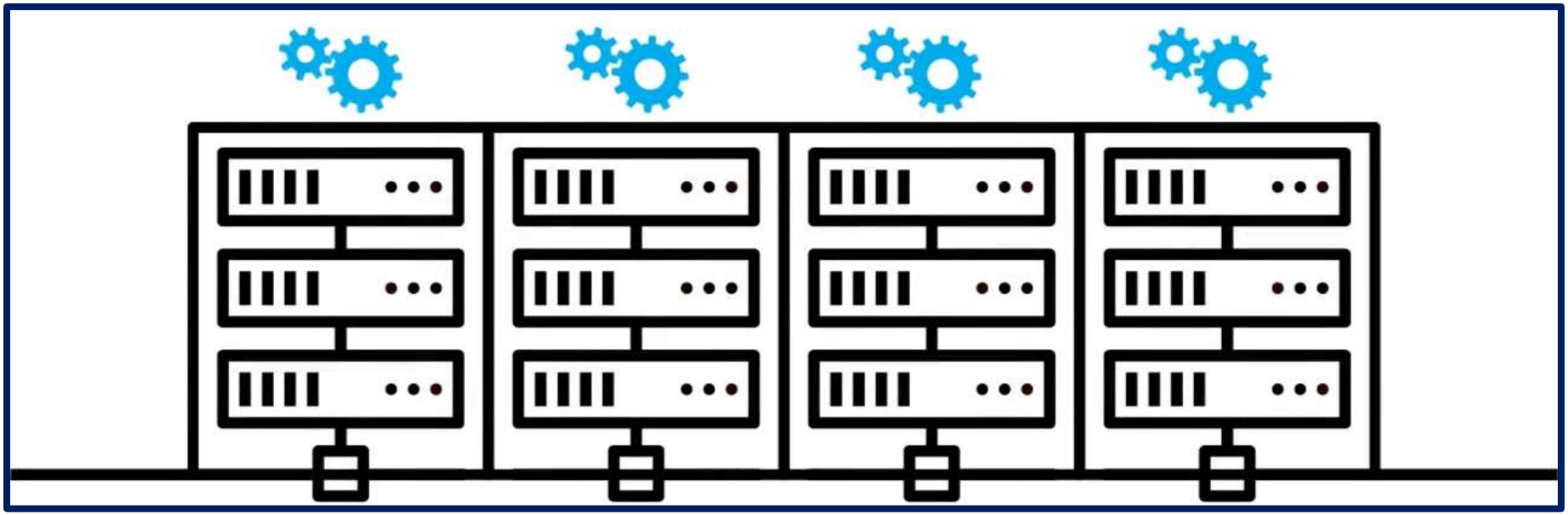
Fair. Consider adding a digit or making your password longer.

Scoring Differences

Key Results

- Stringent meters with visual bars increased resistance to guessing
- Visual differences did not significantly impact resistance to guessing
- No significant impact on memorability

Modeling Password Cracking



Blase Ur, Sean M. Segreti, Lujo Bauer, Nicolas Christin, Lorrie Faith Cranor, Saranga Komanduri, Darya Kurilova, Michelle L. Mazurek, William Melicher, Richard Shay. Measuring Real-World Accuracies and Biases in Modeling Password Guessability. In *Proc. USENIX Security Symposium*, 2015.

Password-Strength Metrics

- Statistical approaches
  - Traditionally: Shannon entropy
  - Recently: α-guesswork
- Disadvantages for researchers
  - Usually no per-password estimates
  - Huge sample required
  - Not real-world attacks

Parameterized Guessability

- How many guesses a particular cracking algorithm with particular training data would take to guess a password

j@mesb0nd007!

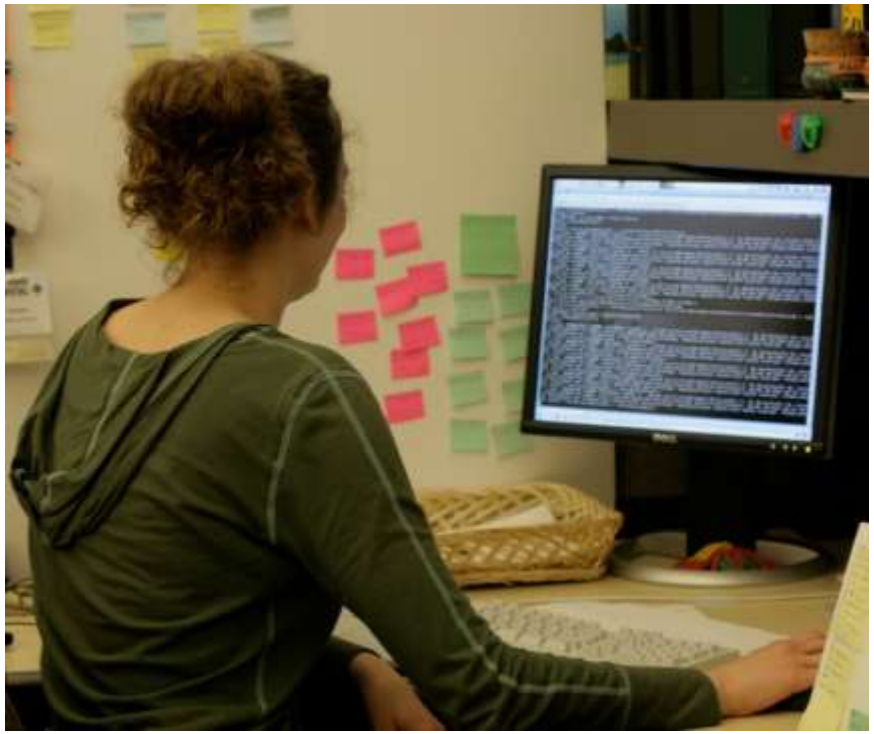
Guess # 366,163,847,194

n(c$JZX!zKc^bIAX^N

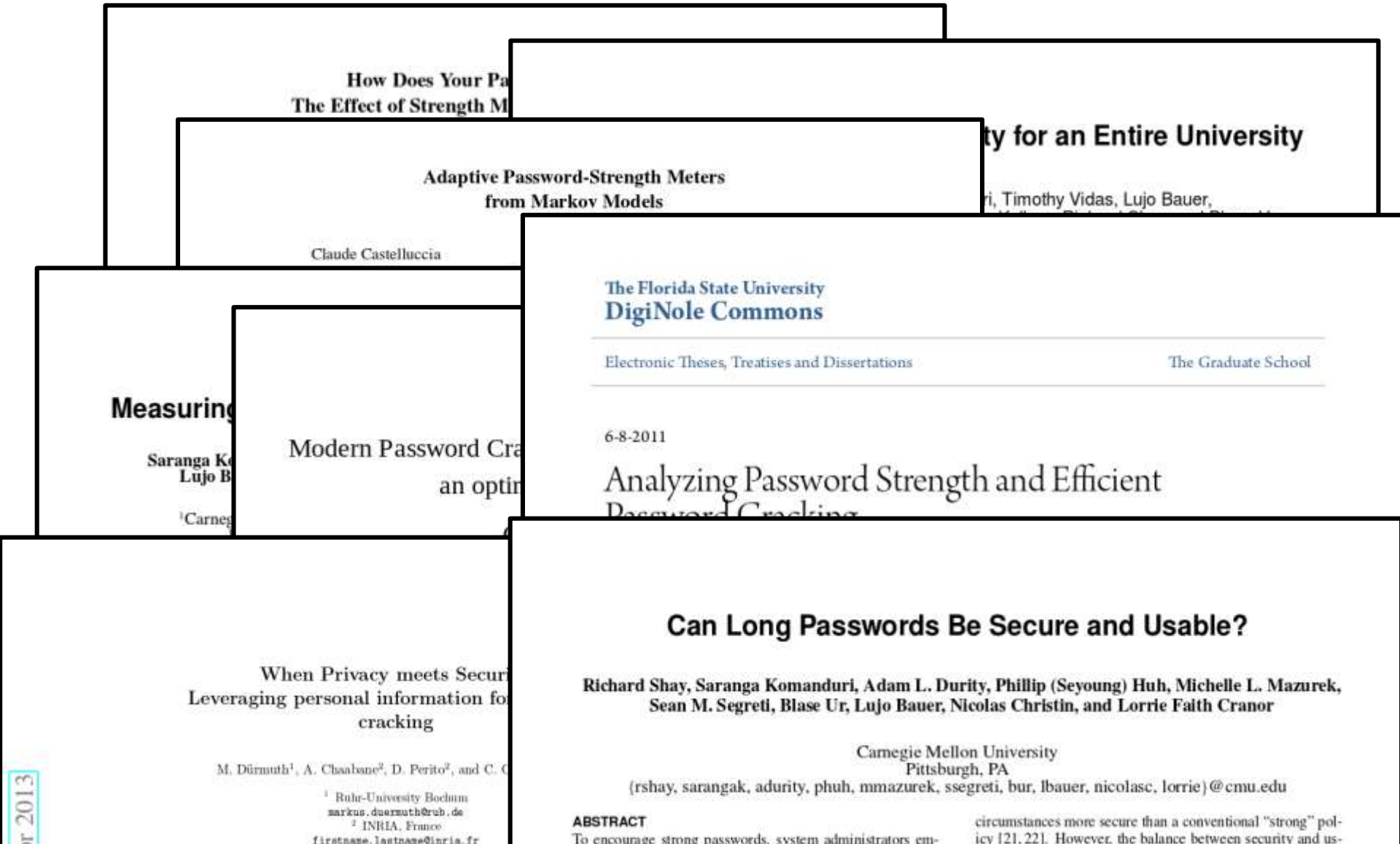
Guess # past cutoff

Guessability in Practice

Guessability in Practice



Single Cracking Approach



Default Configuration

Of Password
Measuring the Effect of Pas

Saranga Komanduri[1], Richard Shay[1], Pa

On The Ecological Validi

Sascha Fahl, Marian Harbach, Y
Usable Security and P
versity Ha
smith@

Improving Text Passwords Through Persuasion

Alain Forget[1,2], Sonia Chiasson[1,2], P.C. van Oorschot[1], Robert Biddle[2]
[1]School of Computer Science & [2]Human Oriented Technology Lab
Carleton University, Ottawa, Canada
{aforget, chiasson, paulv}@scs.carleton.ca, robert_biddle@carleton.ca

A Study of User Password Strategy for Multiple Accounts

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Department of C
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Arlington,TX USA
eresh03@gmail

Matthew Wright
Department of CSE

Shannon Scielzo
Department of Psychology

topic
pass-
study

ABSTRACT

Despite advances in biometrics
words remain the most common
tion in computer systems. User
levels for different passwords.
the degree of similarity among
rity levels of a user. We conduc
with 80 students from a public
United States. We asked the su

The Tangled Web of Passw

Anupam Das*, Joseph Bonneau†, Matthew Caesar*, Nikita Boris
*University of Illinois at Urbana-Champaign
{das17, caesar, nikita}@illinois.edu

From *Very Weak* to *Very Strong*:
Analyzing Password-Strength Meters

Xavier de Carné de Carnavalet and Mohammad Mannan
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Concordia University, Montreal, Canada

International Journal of Innovative Computing, Information and Control
Volume 9, Number 2, February 2013

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PASSWORD CRACKING BASED ON LEARNED PATTERNS FROM DISCLOSED PASSWORDS

Hsien-Cheng Chou[1], Hung-Chang Lee[2], Hwan-Jeu Yu[1], Fei-Pei Lai[1,3]
Kuo-Hsuan Huang[4] and Chih-Wen Hsueh[1]

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Analyzing Password Strength and Efficient Password Cracking

Shiva Houshmand Yazdi
Florida State University

Questions About Guessability

1) How does guessability used in research compare to an attack by professionals?
2) Would substituting another cracking approach impact research results?

Approach

4 password sets

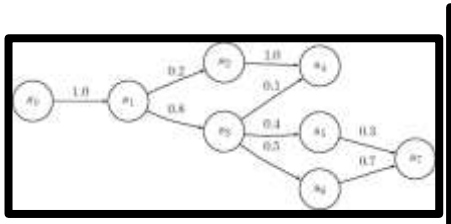
```
password
iloveyou
teamo123
…
```

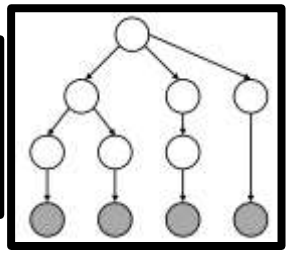
```
passwordpassword
12345678123456 78
!1@2#3$4%5^6&7*8
…
```

```
Pa$$w0rd
iLov3you!
1QaZ2W@x
…
```

```
pa$$word1234
12345678asDF
!q1q!q1q!q1q
…
```

✖ 5 approaches





KoreLogic SECURITY

Key Results

- Configuration is critical
- Considering single approach insufficient
  - Multiple approaches proxy for pros
- Analyses of password sets robust
  - More granular analyses not robust

Per-Password Highly Impacted

P@ssw0rd!

Per-Password Highly Impacted

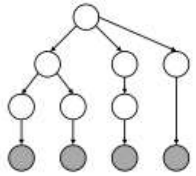
- JTR guess # 801 


```
P@ssw0rd!
```

Per-Password Highly Impacted

- JTR guess # 801

- Not guessed in 10^{14} PCFG guesses



P@ssw0rd!

Per-Password Highly Impacted

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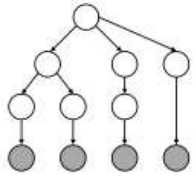


P@ssw0rd!

Password Guessability Service

- Guessability of plaintext passwords

```
asdfF123#
P@ssw0rd!
Qwertyuiop!1
…
```

https://pgs.ece.cmu.edu


```
"Guess #", "Password"
"127188816", "Qwertyuiop!1"
"1853004462", "asdfF123#"
"2251762491", "P@ssw0rd!"
...
```

The Art of Password Creation

Blase Ur, Saranga Komanduri, Lujo Bauer, Lorrie Faith Cranor, Nicolas Christin, Adam L. Durity, Phillip (Seyoung) Huh, Stephanos Matsumoto, Michelle L. Mazurek, Sean M. Segreti, Richard Shay, Timothy Vidas. The Art of Password Creation: Semantics, Strategies, and Strategies. Image Creative Commons by Lasya J on Flickr.

Reverse-Engineering Passwords

~Cowscomehom3

“till the cows come home”

Key Results

- Character substitutions both infrequent and predictable
- Words and phrases frequently used
  - Wikipedia excellent source of training data
- Composition policy detrimental for some

Understanding Password Creation

Blase Ur, Fumiko Noma, Jonathan Bees, Sean M. Segreti, Richard Shay, Lujo Bauer, Nicolas Christin, Lorrie Faith Cranor. “I Added ‘!’ at the End to Make It Secure”: Observing Password Creation in the Lab. In *Proc. SOUPS*, 2015.

Understand Origin of Passwords

`LEFTbrown8!`

Understand Origin of Passwords

`LEFTbrown8!`

Understand Origin of Passwords

LEFTbrown8!

Understand Origin of Passwords

LEFTbrown8!

Key Results

- Important misconceptions
  - Digits and symbols
  - Keyboard patterns
  - Dictionary words
- Misallocation of effort in password creation

Perceptions of Password Security

Blase Ur, Jonathan Bees, Sean M. Segreti, Lujo Bauer, Nicolas Christin, Lorrie Faith Cranor. Do users' perceptions of password security match reality? In *Proc. CHI*, 2016.

Perception vs. Reality

Compare actual strength of passwords to users' perceptions

Measuring Perceptions

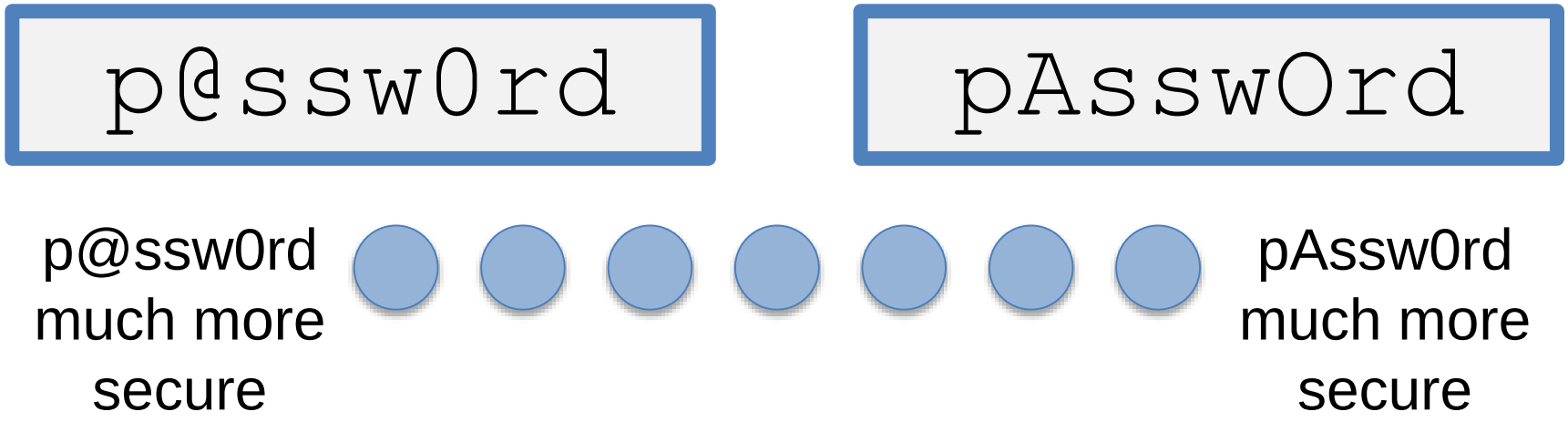
- Online study
  - Compensated $5 for ~30 minutes
- 165 participants from Mechanical Turk
  - Age 18+, live in United States
  - Median age 33
  - 49% female, 51% male
  - 16% CS or related degree or job
  - 4% student/professional in computer security

Study Tasks

1. Evaluating password pairs

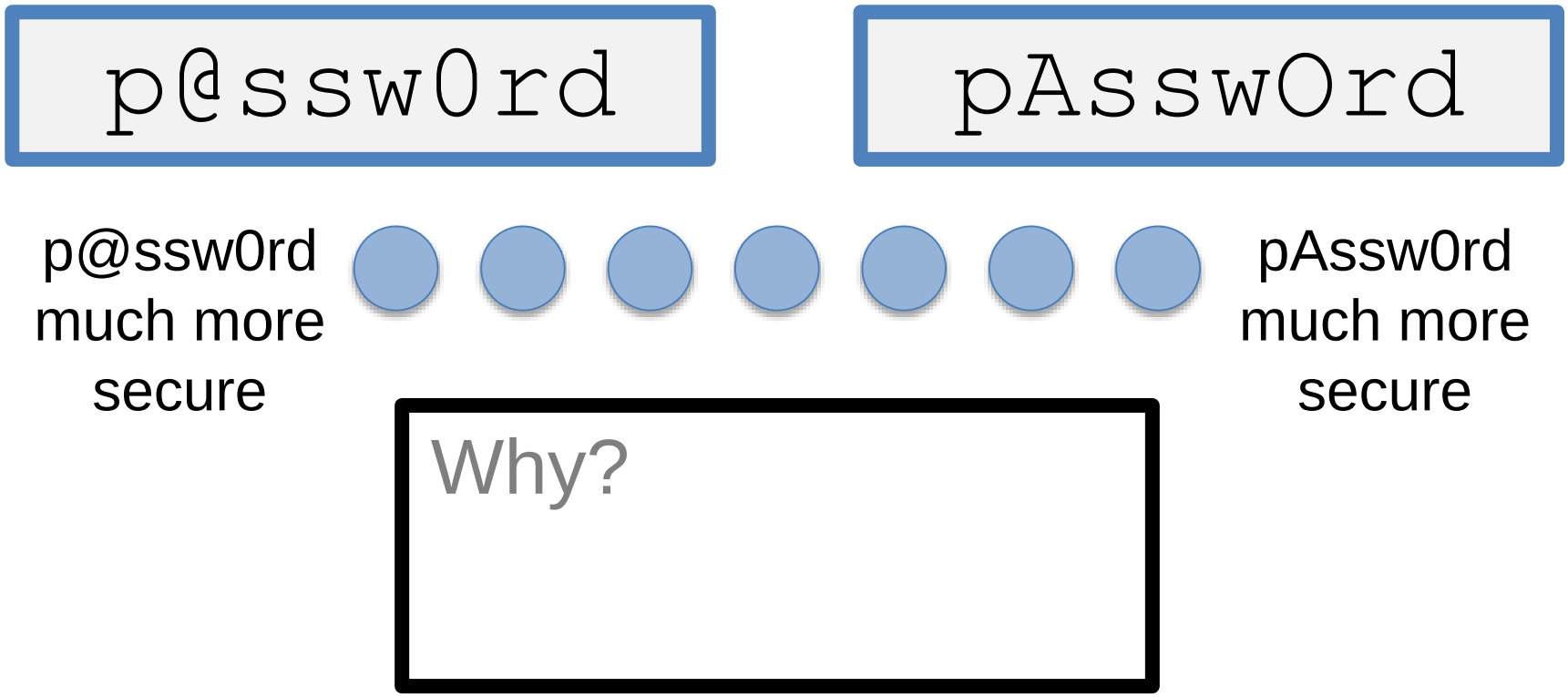
Study Tasks

1. Evaluating password pairs



Study Tasks

1. Evaluating password pairs



Task 1 Hypotheses

- 25 common characteristics, e.g.,
  - Capitalization
  - Letters vs. digits vs. symbols
  - Choice of words and phrases

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- Created 3 pairs per hypothesis
  - Randomly chose 1 pair per participant

Task 1 Hypotheses

- 25 common characteristics, e.g.,
  - Capitalization
  - Letters vs. digits vs. symbols
  - Choice of words and phrases
- Created 3 pairs per hypothesis
  - Randomly chose 1 pair per participant
  - At least one password per pair from rockyou

Study Tasks

1. Evaluating password pairs
2. Rating selected passwords

Study Tasks

1. Evaluating password pairs
2. Rating selected passwords

Please rate the **security** of the following password: `rolltide`

Please rate the **memorability** of the following password: `rolltide`

Study Tasks

1. Evaluating password pairs
2. Rating selected passwords
3. Rating creation strategies

Study Tasks

1. Evaluating password pairs
2. Rating selected passwords
3. Rating creation strategies
4. Describing attackers
   - Who, why, how

Results

1. Evaluating password pairs
2. Rating selected passwords
3. Rating creation strategies
4. Describing attackers

Evaluating Password Pairs

`iloveyou88`

`ieatkale88`

Evaluating Password Pairs

`iloveyou88`

`ieatkale88`

Evaluating Password Pairs

`iloveyou88`

`ieatkale88`

Evaluating Password Pairs

`iloveyou88`

`ieatkale88`

4,000,000,000 × more secure!

Evaluating Password Pairs

`brooklyn16`

`brooklynqy`

Evaluating Password Pairs

`brooklyn16`

`brooklynqy`

Evaluating Password Pairs

`brooklyn16`

`brooklynqy`

Evaluating Password Pairs

`brooklyn16`

`brooklynqy`

300,000 ×
more secure!

Ways People Were Wrong

- Overstated security benefits of:
  - Digits
  - Character substitutions (e.g., a→@)
  - Keyboard patterns (e.g., 1qaz2wsx3edc)
- Did not recognize common words/phrases

Many Ways People Were Right

- Capitalize letters other than the first
- Put digits and symbols in middle, not end
- Use symbols rather than digits
- Avoid:
  - Common first names
  - Words related to account
  - Years and sequences

If perceptions of many individual characteristics are correct, then why do people make bad passwords?

Perceptions of Attackers

Perception: How Many Guesses?

Perception: How Many Guesses?

- 2 guesses (Min)

Perception: How Many Guesses?

- 2 guesses (Min)
- 100,000,000,000,000,000,000,000,000,000,000,000,000,000,000,000,000,000,000,000,000,000 guesses (Max)

Perception: How Many Guesses?

- 2 guesses (Min)
- 100,000,000,000,000,000,000,000,000,000, 000,000,000,000,000,000,000,000,000,000, 000,000 guesses (Max)
- 34% ≤ 50 guesses (manual attack)

Perception: How Many Guesses?

- 2 guesses (Min)
- 100,000,000,000,000,000,000,000,000,000,000,000,000,000,000,000,000,000,000,000,000,000,000,000 guesses (Max)
- 34% ≤ 50 guesses (manual attack)
- 67% ≤ 50,000 guesses (small-scale)

Perception: How Many Guesses?

- 2 guesses (Min)
- 100,000,000,000,000,000,000,000,000,000,000,000,000,000,000,000,000,000,000,000,000,000,000,000 guesses (Max)
- 34% ≤ 50 guesses (manual attack)
- 67% ≤ 50,000 guesses (small-scale)
- 7% ≥ 10^{14} guesses (large-scale)

Reality: How Many Guesses?

Reality: Small-Scale Guessing

Reality: Small-Scale Guessing

- Targeted guessing by someone you know

Reality: Small-Scale Guessing

- Targeted guessing by someone you know
- Automated attack by a stranger

Reality: Small-Scale Guessing

- Targeted guessing by someone you know
- Automated attack by a stranger
  - Online: 1 – 1,000,000 guesses

Reality: Large-Scale Guessing

Reality: Large-Scale Guessing

- Against stolen database of passwords

Reality: Large-Scale Guessing

- Against stolen database of passwords
- Against password-protected file

Reality: Large-Scale Guessing

- Against stolen database of passwords
- Against password-protected file
- 1,000,000 guesses (best practices)

Reality: Large-Scale Guessing

- Against stolen database of passwords
- Against password-protected file
- 1,000,000 guesses (best practices)
- 10^{14} or more (common reality)

Perception

Small-scale

67% ≤ 50,000

Reality

Small-scale…

…and large-scale

≥ 10^{14} guesses

Conclusions

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- Perceptions of individual characteristics
  - Often consistent with current attacks
  - Some crucial differences

Conclusions

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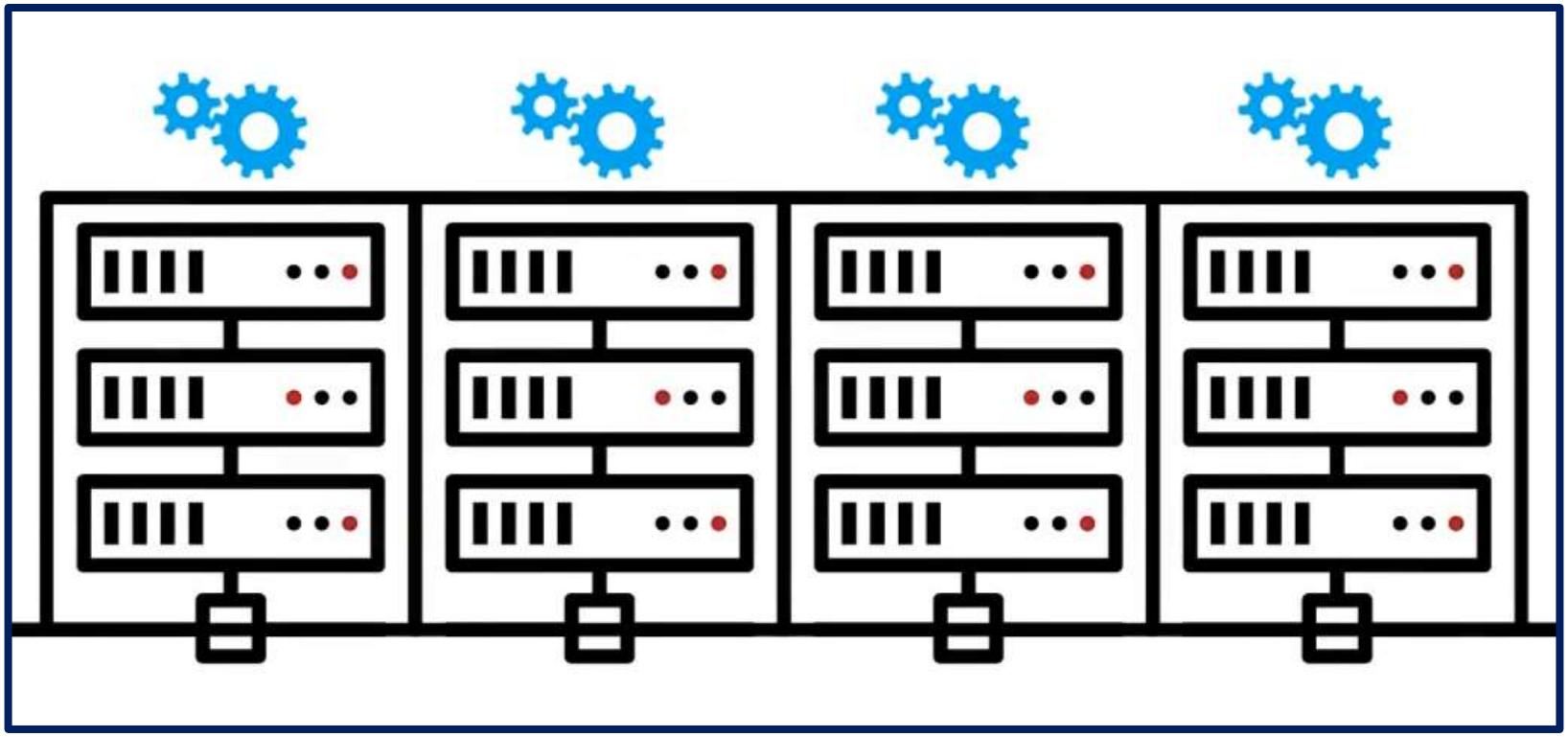
  - Often consistent with current attacks
  - Some crucial differences
- Huge variance in perceptions of attackers

Conclusions

- Perceptions of individual characteristics
  - Often consistent with current attacks
  - Some crucial differences
- Huge variance in perceptions of attackers
- Current user feedback is insufficient

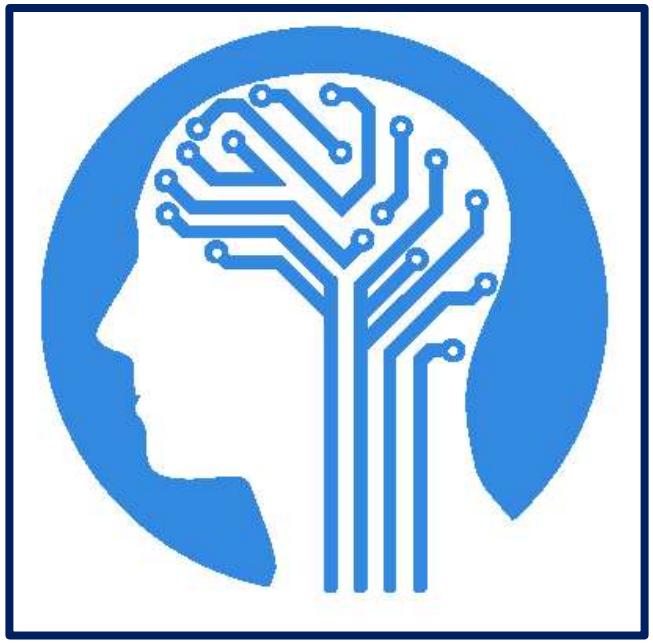
Better Password Scoring



William Melicher, Blase Ur, Sean M. Segreti, Saranga Komanduri, Lujo Bauer, Nicolas Christin, Lorrie Faith Cranor. Fast, Lean, and Accurate: Modeling Password Guessability Using Neural Networks. In *Proc. USENIX Security Symposium*, 2016.

Better Password Scoring

- Real-time feedback
- Runs entirely client-side
- Accurately models password guessability



Generating Passwords

Generating Passwords

`passw`  o or maybe 0 or O or ...

Generating Passwords

`passw` 

Next char is:

A: 3%

B: 1%

C: 0.6%

…

O: 55%

…

Z: 0.01%

0: 20%

1: …

Generating Passwords

“”

Prob: 100%

Next char is:

A:	3%
B:	2%
C:	5%
…	
O:	2%
…	
Z:	0.2%
0:	1%
1:	…
END:	2%

Generating Passwords

“”

Prob: 100%

Next char is:

A:	3%
B:	2%
C:	5%
…	
O:	2%
…	
Z:	0.2%
0:	1%
1:	…
END:	2%

Generating Passwords

“C”

Prob: 5%

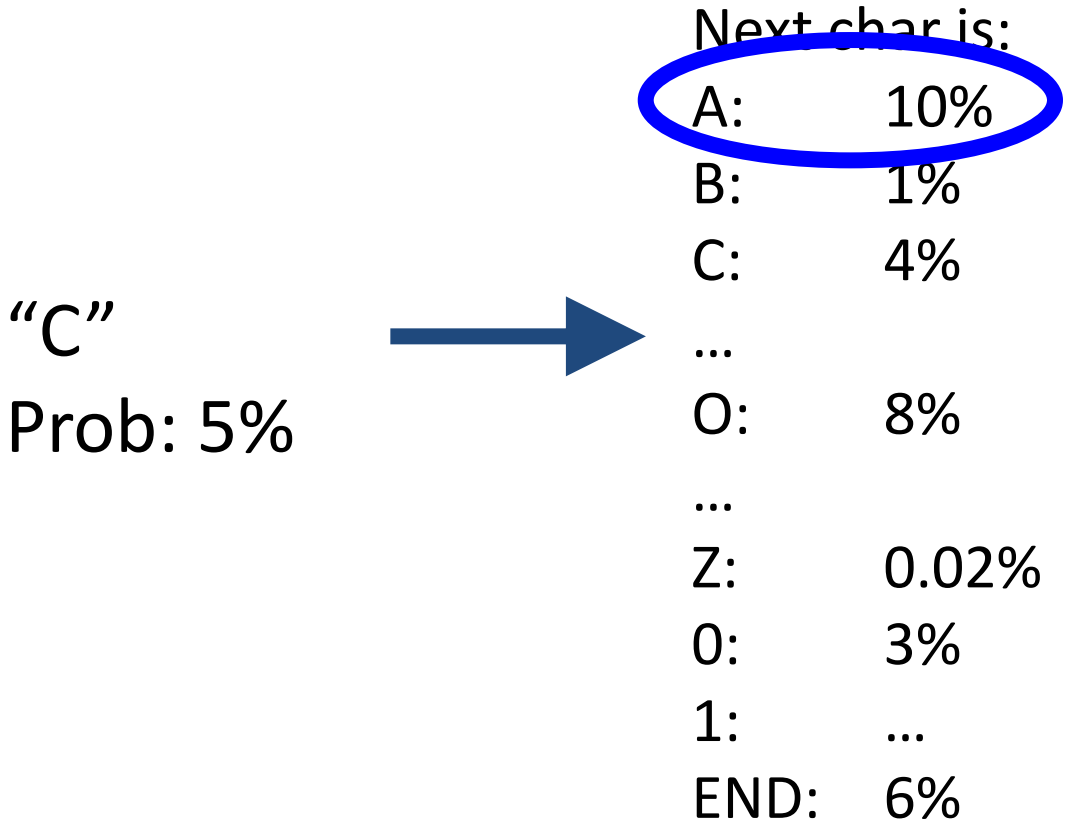
Generating Passwords

"C"
Prob: 5%

Next char is:

A:	10%
B:	1%
C:	4%
…	
O:	8%
…	
Z:	0.02%
0:	3%
1:	…
END:	6%

Generating Passwords



Generating Passwords

"CA"
Prob: 0.5%

Next char is:

A:	3%
B:	10%
C:	7%
…	
O:	1%
…	
Z:	0.03%
0:	2%
1:	…
END:	12%

Generating Passwords

"CAB"

Prob: 0.05%

Next char is:

A:	3%
B:	10%
C:	7%
…	
O:	1%
…	
Z:	0.03%
0:	2%
1:	…
END:	3%

Generating Passwords

"CAB"

Prob: 0.05%

Next char is:

A:	4%
B:	3%
C:	1%
…	
O:	2%
…	
Z:	0.01%
0:	4%
1:	…
END:	12%

Generating Passwords

"CAB"

Prob: 0.05%

Next char is:

A:	4%
B:	3%
C:	1%
…	
O:	2%
…	
Z:	0.01%
0:	4%
1:	…
END:	12%

Generating Passwords

“CAB”

Prob: 0.006%

Generating Passwords

CAB - 0.006%
CAC - 0.0042%
ADD1 - 0.002%
CODE - 0.0013%
…

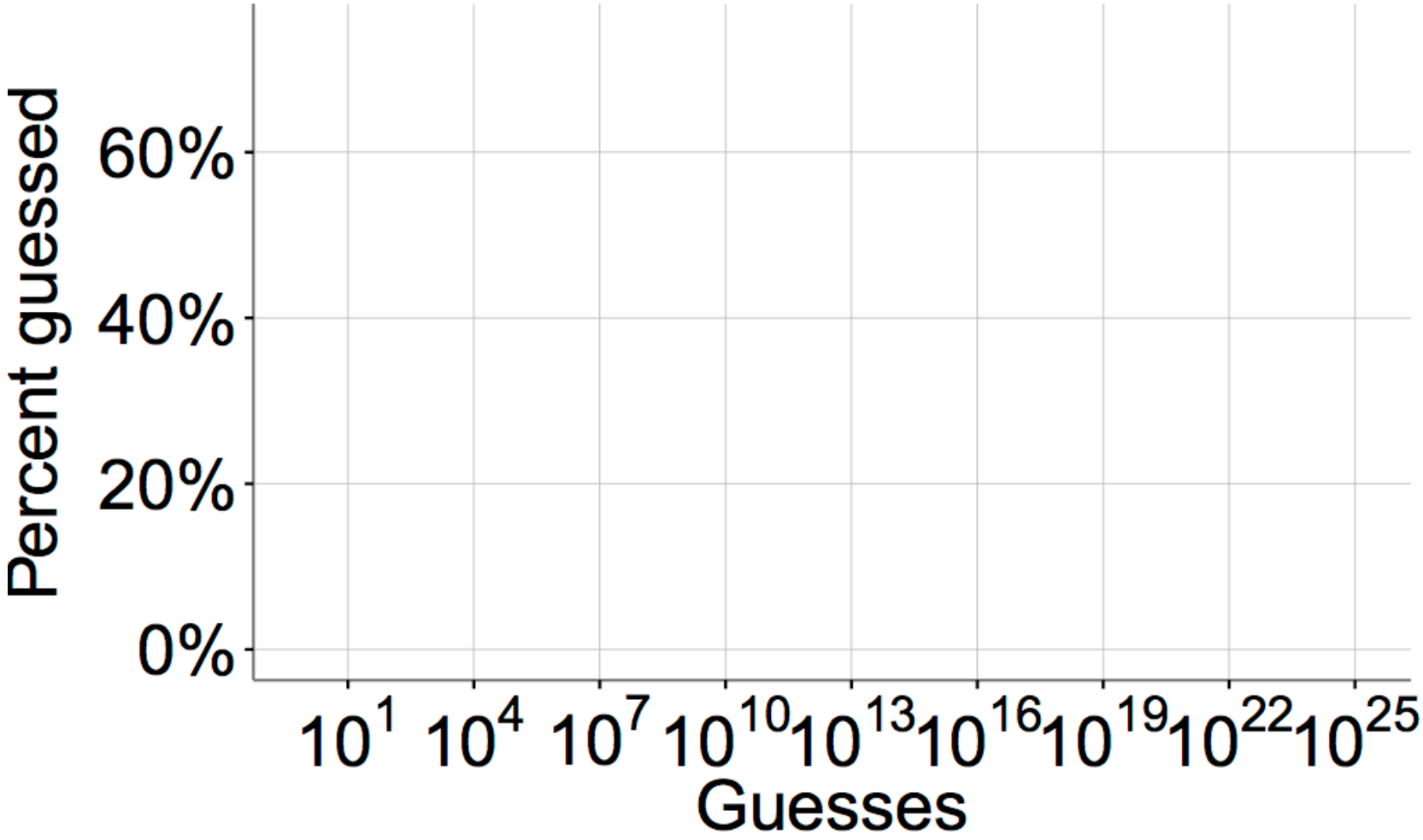
Design Space

- Model size: 3mb (browser) vs. 60mb (GPU)
- Transference learning
  - Novel password-composition policies
- Training data
  - Natural language
- (Many others)

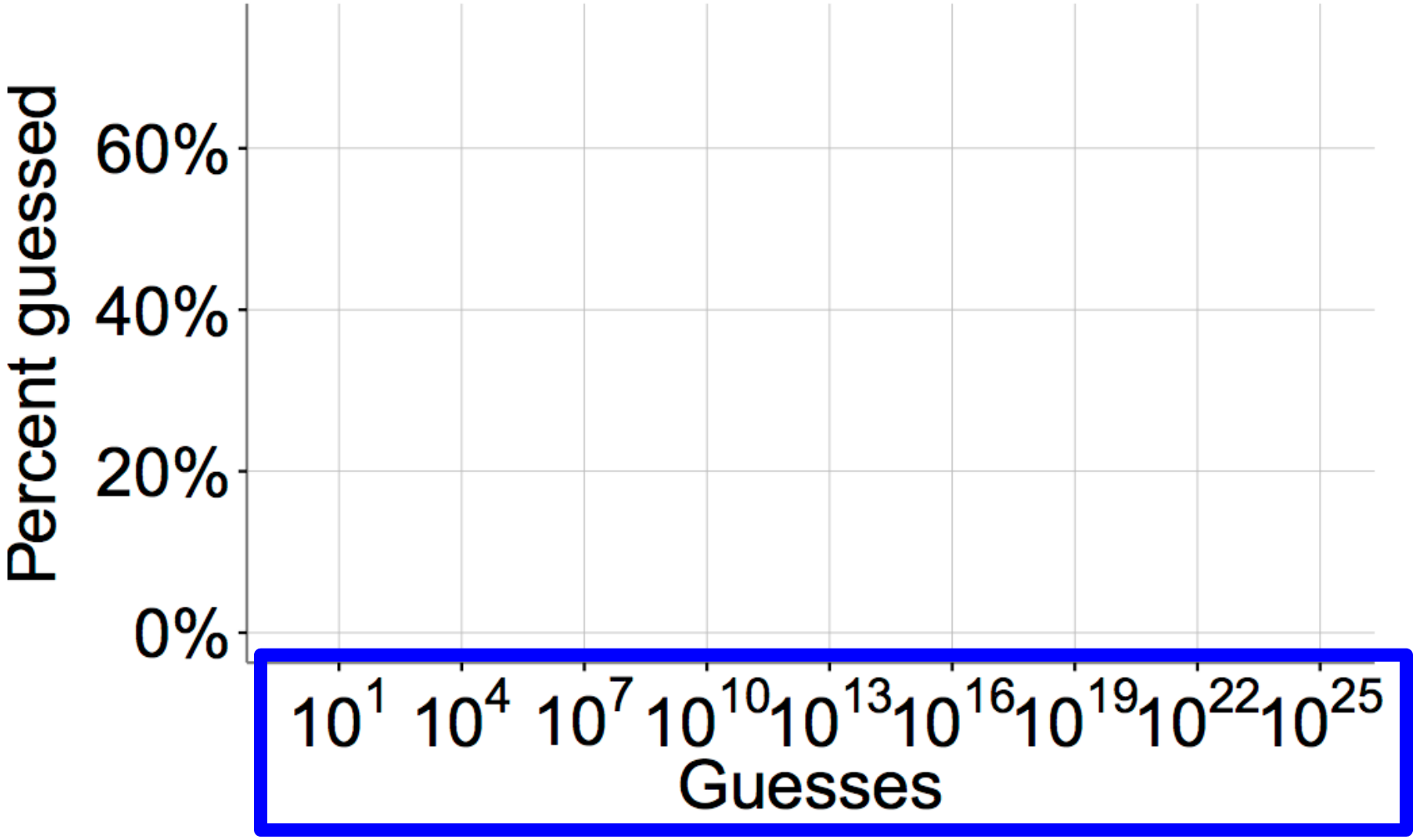
Method

- Test on many password sets
- Monte Carlo methods to estimate guess #

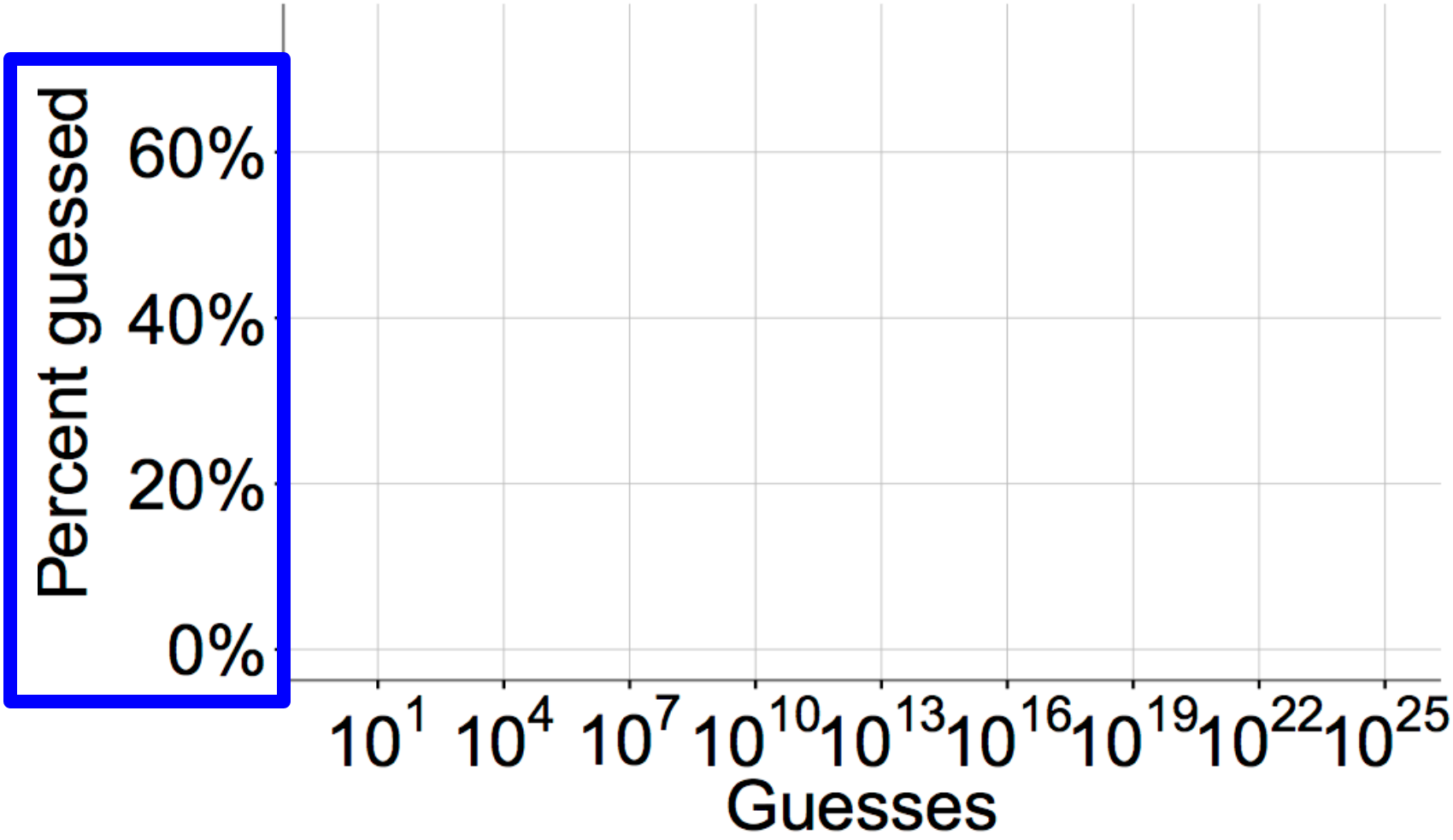
Results


Percent guessed
60%
40%
20%
0%
10^1 10^4 10^7 10^{10} 10^{13} 10^{16} 10^{19} 10^{22} 10^{25}
Guesses

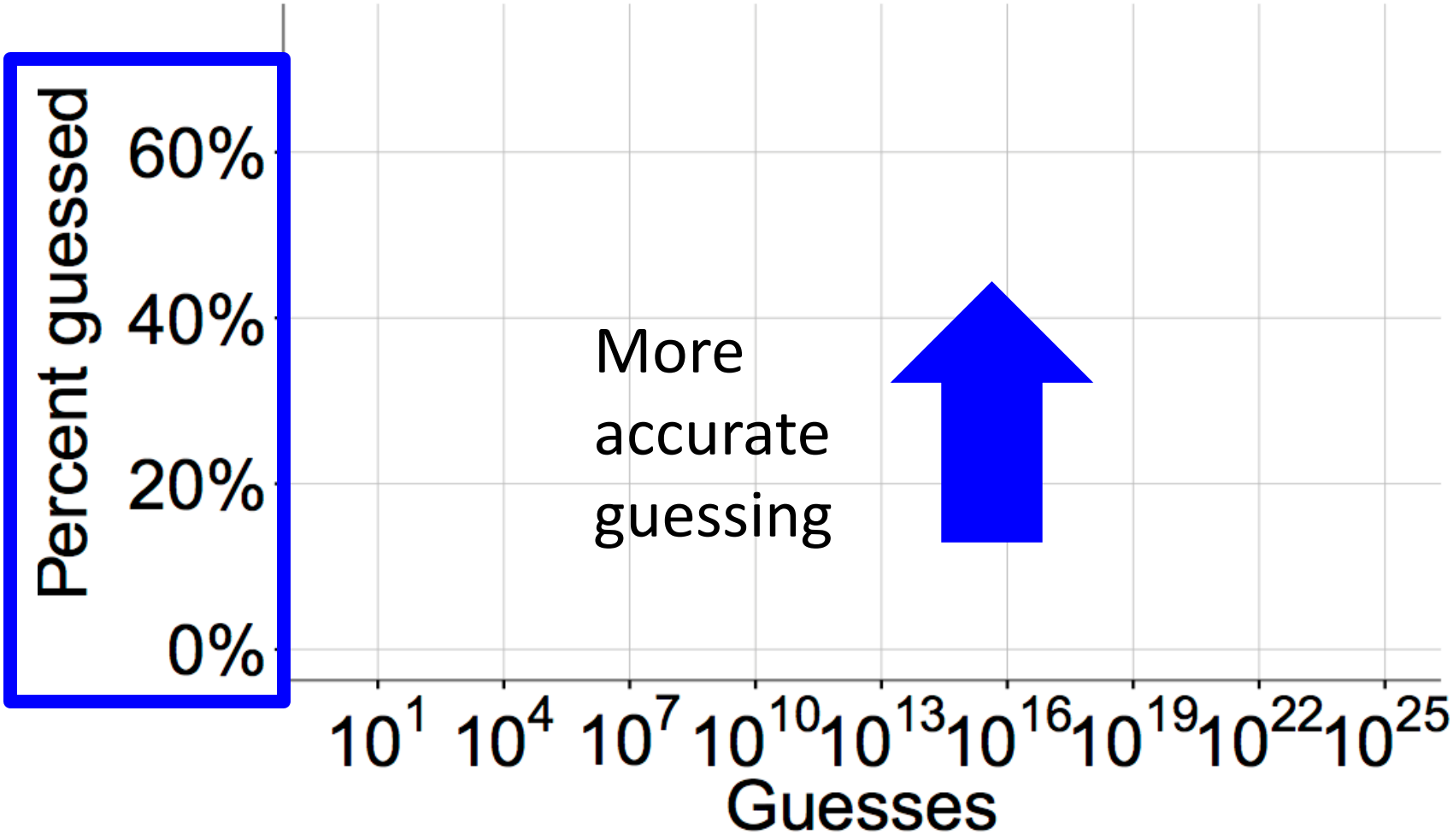
Results


Percent guessed
60%
40%
20%
0%
10^1 10^4 10^7 10^{10} 10^{13} 10^{16} 10^{19} 10^{22} 10^{25}
Guesses

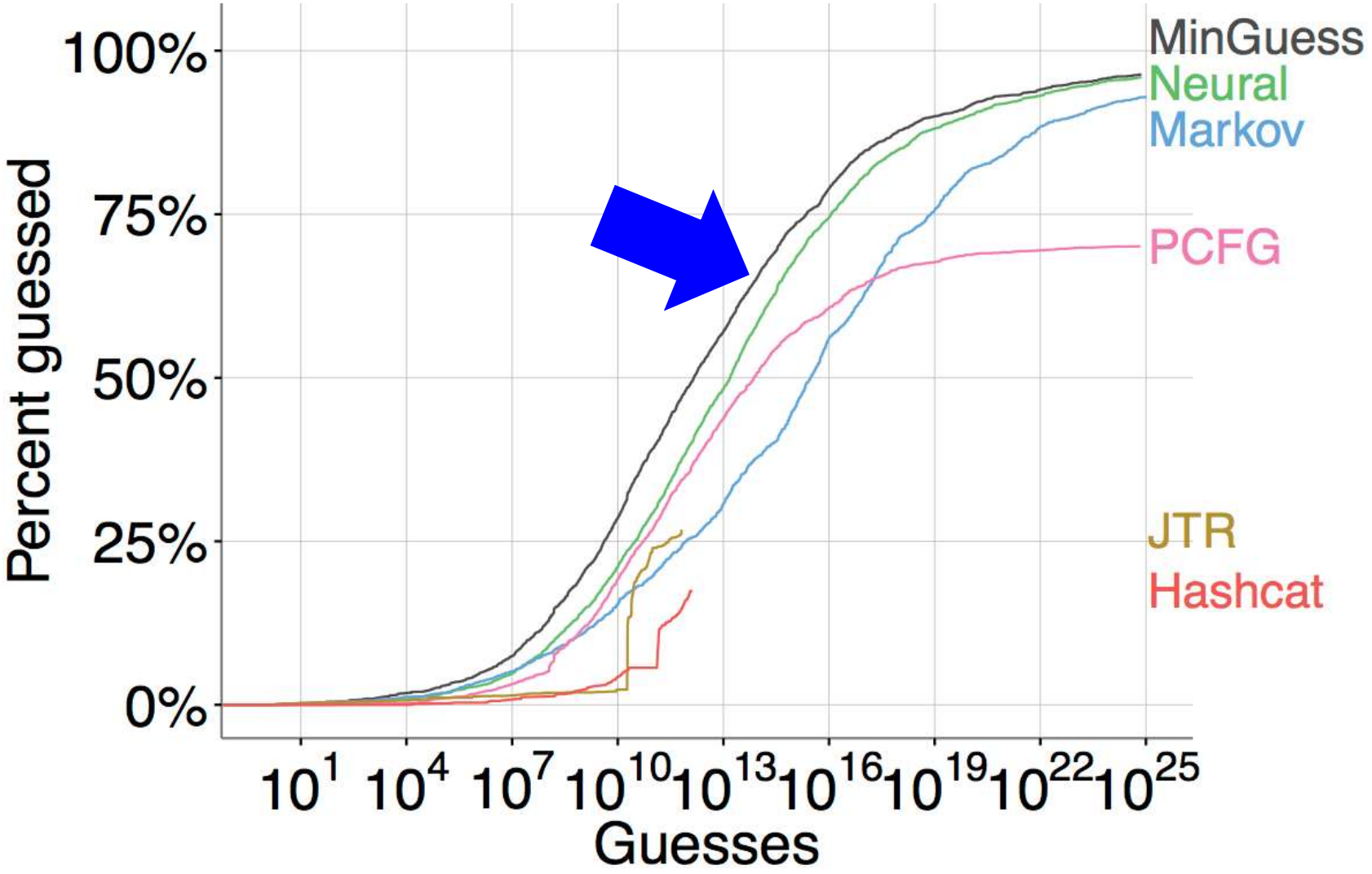
Results


Percent guessed
60%
40%
20%
0%
10^1 10^4 10^7 10^{10} 10^{13} 10^{16} 10^{19} 10^{22} 10^{25}
Guesses

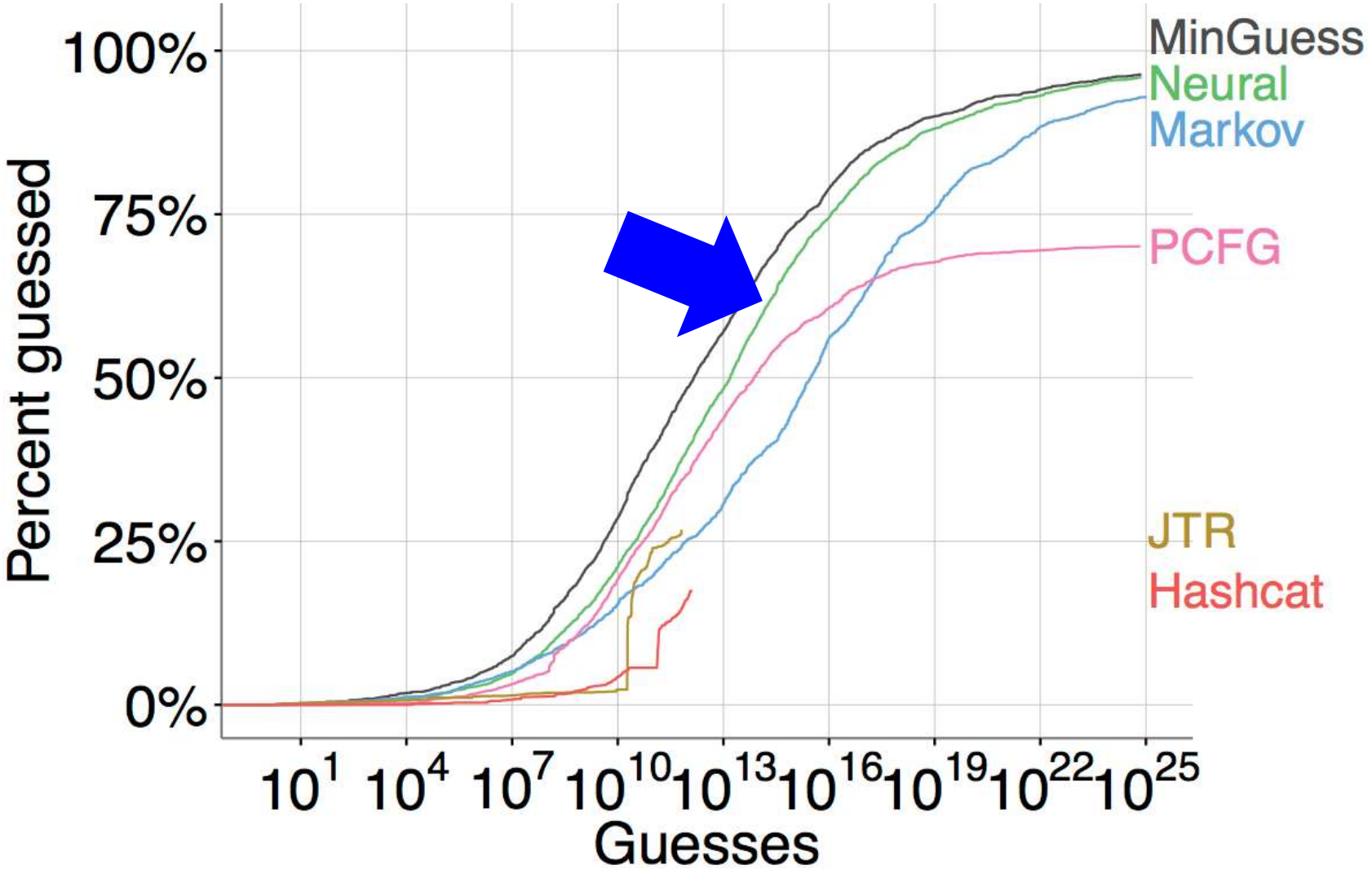
Results


Percent guessed
60%
40%
20%
0%
More
accurate
guessing
10^{1} 10^{4} 10^{7} 10^{10} 10^{13} 10^{16} 10^{19} 10^{22} 10^{25}
Guesses

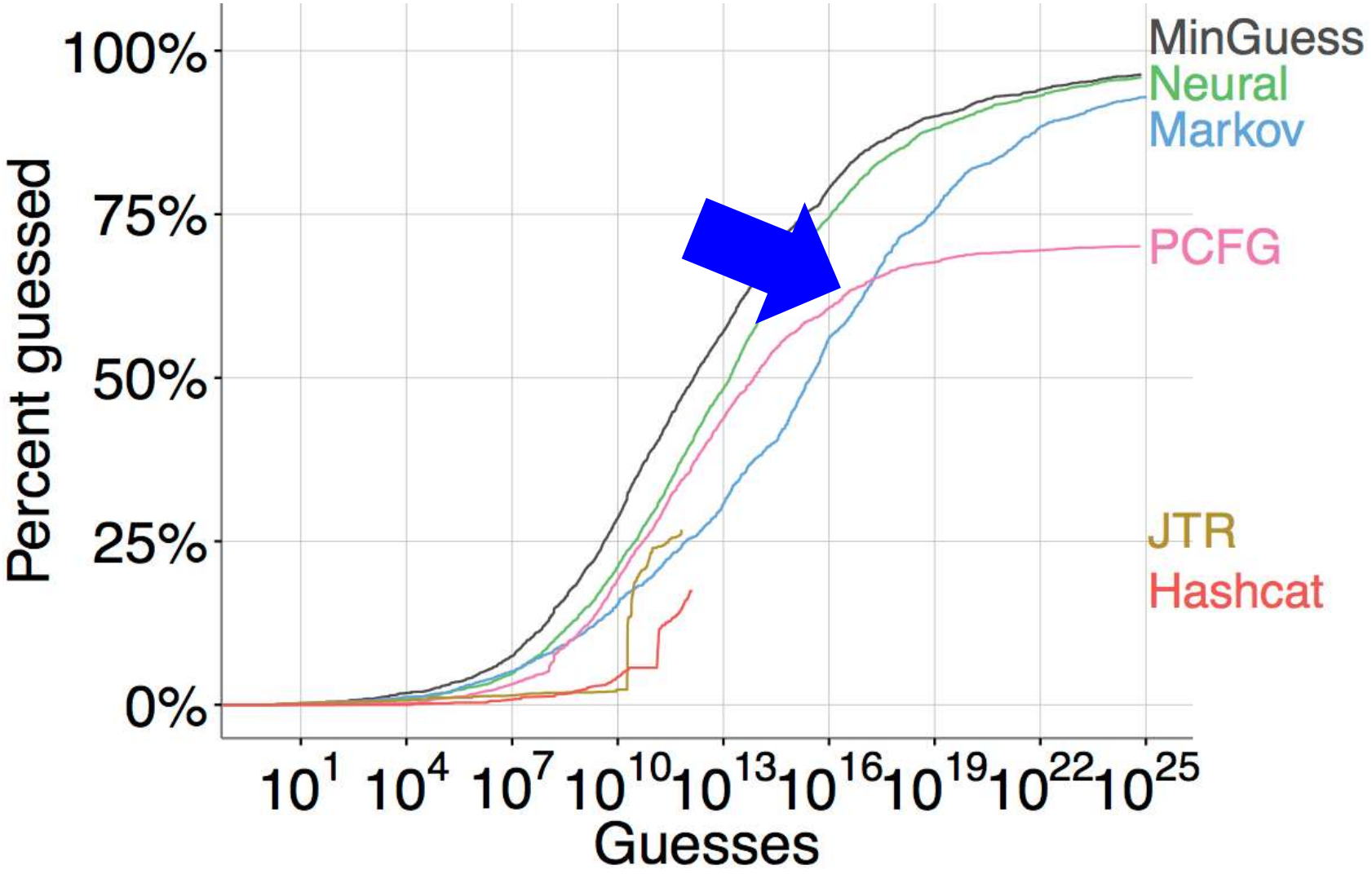
Neural Networks Guess Better



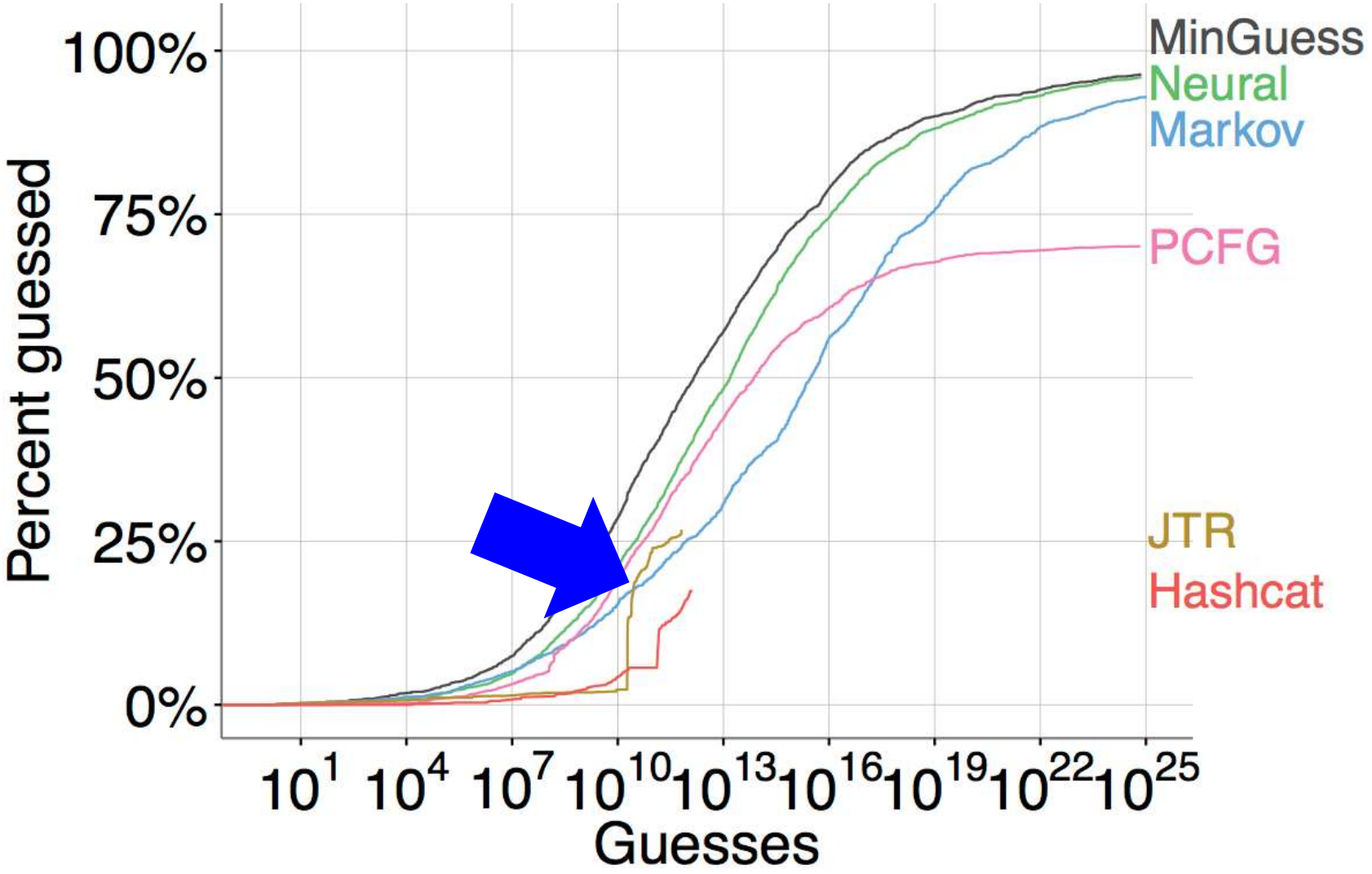
Neural Networks Guess Better



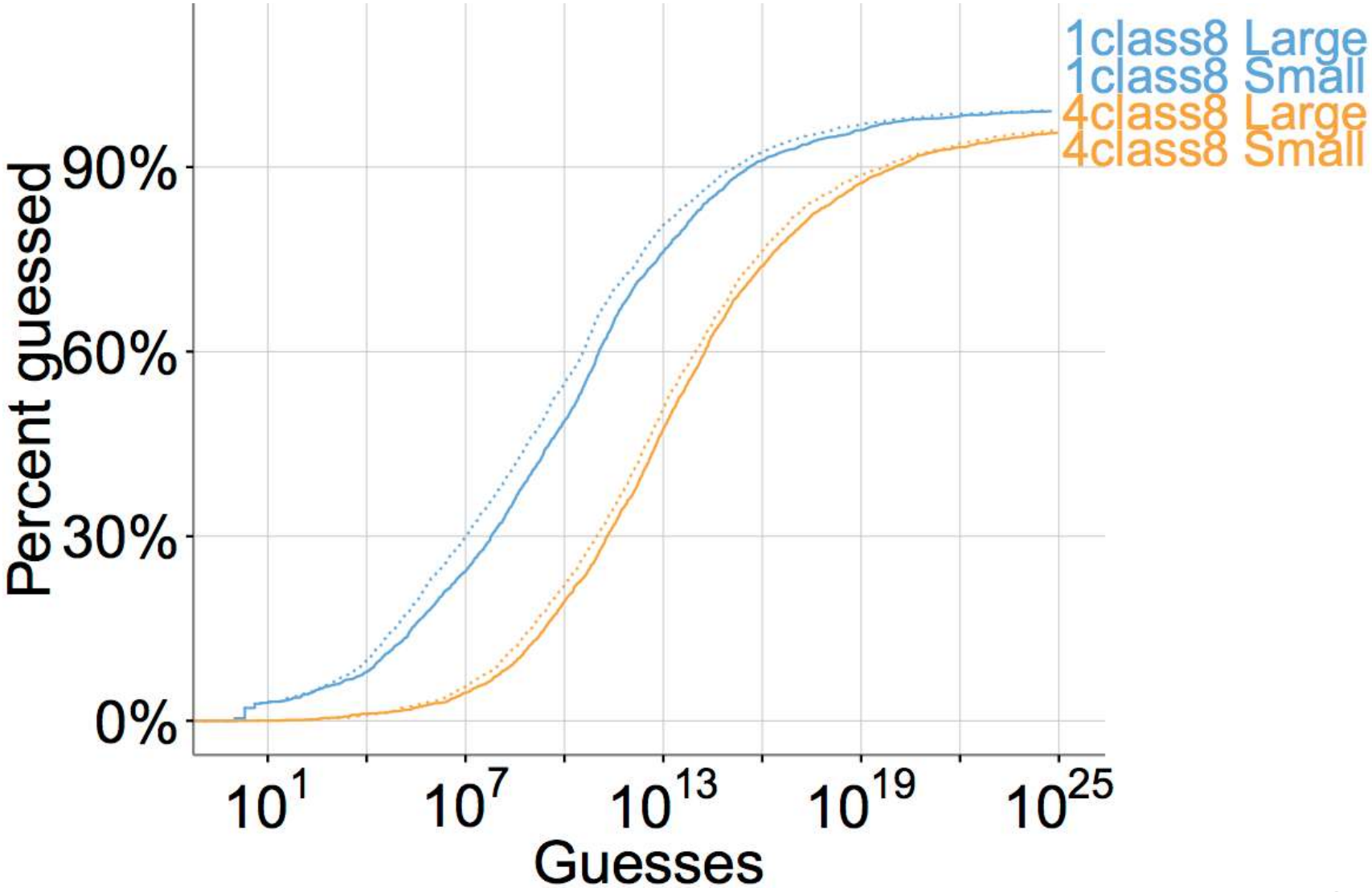
Neural Networks Guess Better



Neural Networks Guess Better



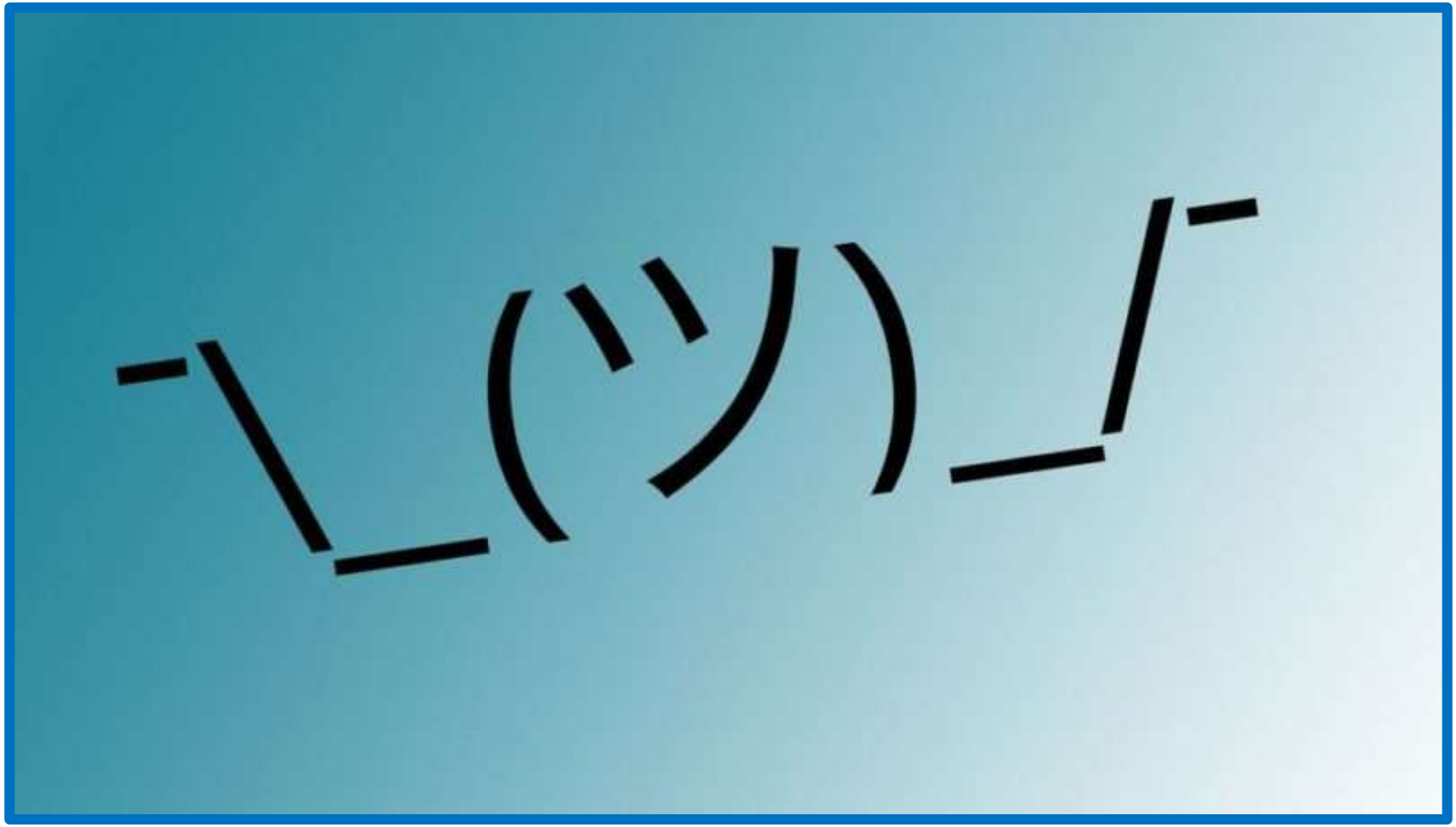
Larger Model Not Major Advantage



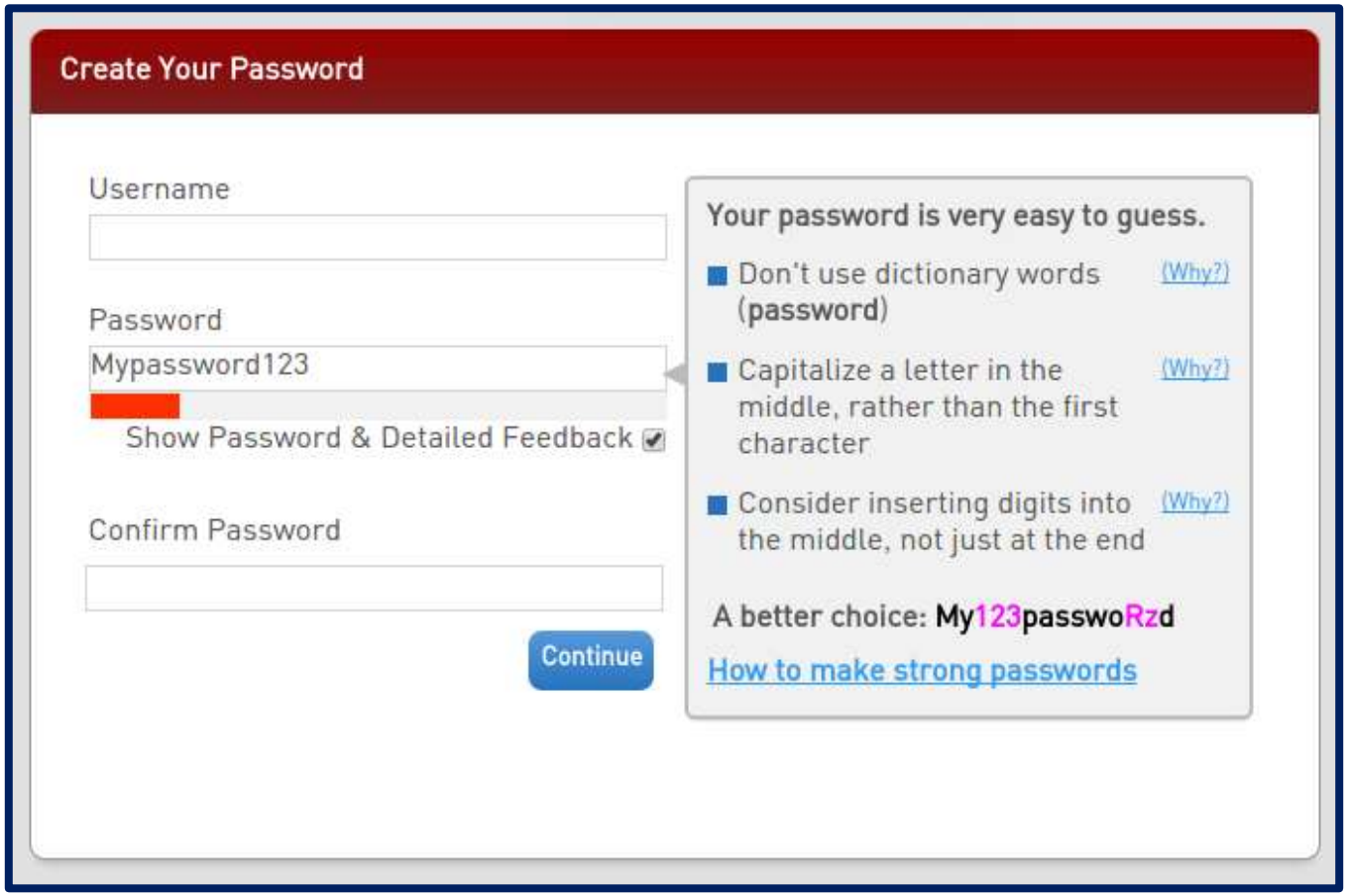
Browser Implementation

- Start with smaller model
- Quantize parameters
- Lossless compression
- Pre-compute inexact mapping of probabilities → guess #
- Cache intermediate results
- <1mb, ~ 17ms per character

Intelligibility



Building a Data-Driven Meter



Blase Ur, Felicia Alfieri, Maung Aung, Lujo Bauer, Nicolas Christin, Jessica Colnago, Lorrie Faith Cranor, Henry Dixon, Pardis Emami Naeini, Hana Habib, Noah Johnson, William Melicher. Development and Evaluation of a Data-Driven Password Meter. In *Proc. CHI*, 2017.

We designed & tested a meter with:

1) Principled strength estimates

2) Data-driven feedback to users

We designed & tested a meter with:

1) Principled strength estimates

2) Data-driven feedback to users

We designed & tested a meter with:

1) Principled strength estimates

2) Data-driven feedback to users

Provide Intelligible Explanations

`Unic0rns`

Don't use simple transformations of words or phrases (**unicorns** → **Unic0rns**)

Capitalize a letter in the middle, rather than the first character

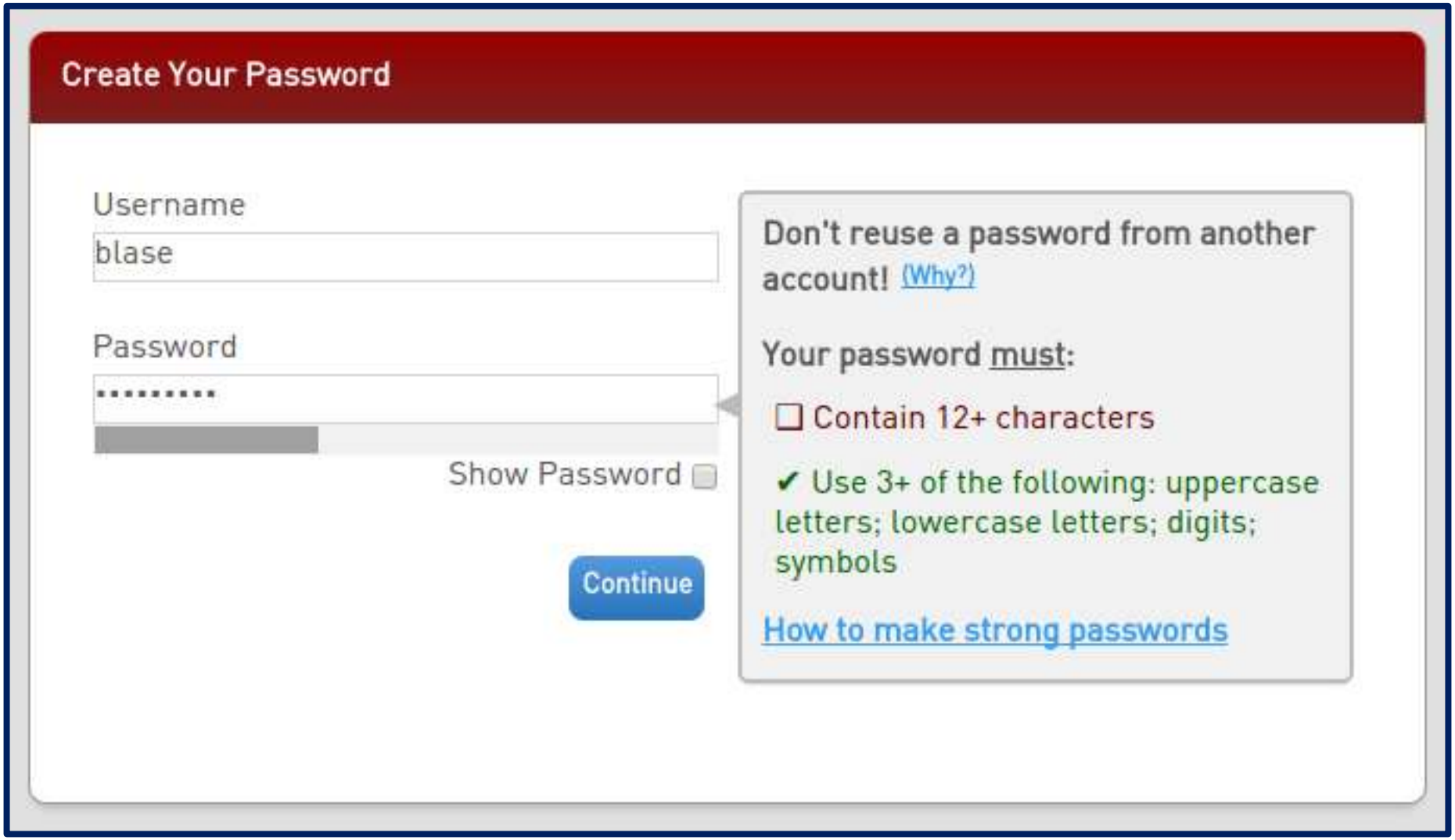
- 21 characteristics
- Weightings determined with regression

We designed & tested a meter with:

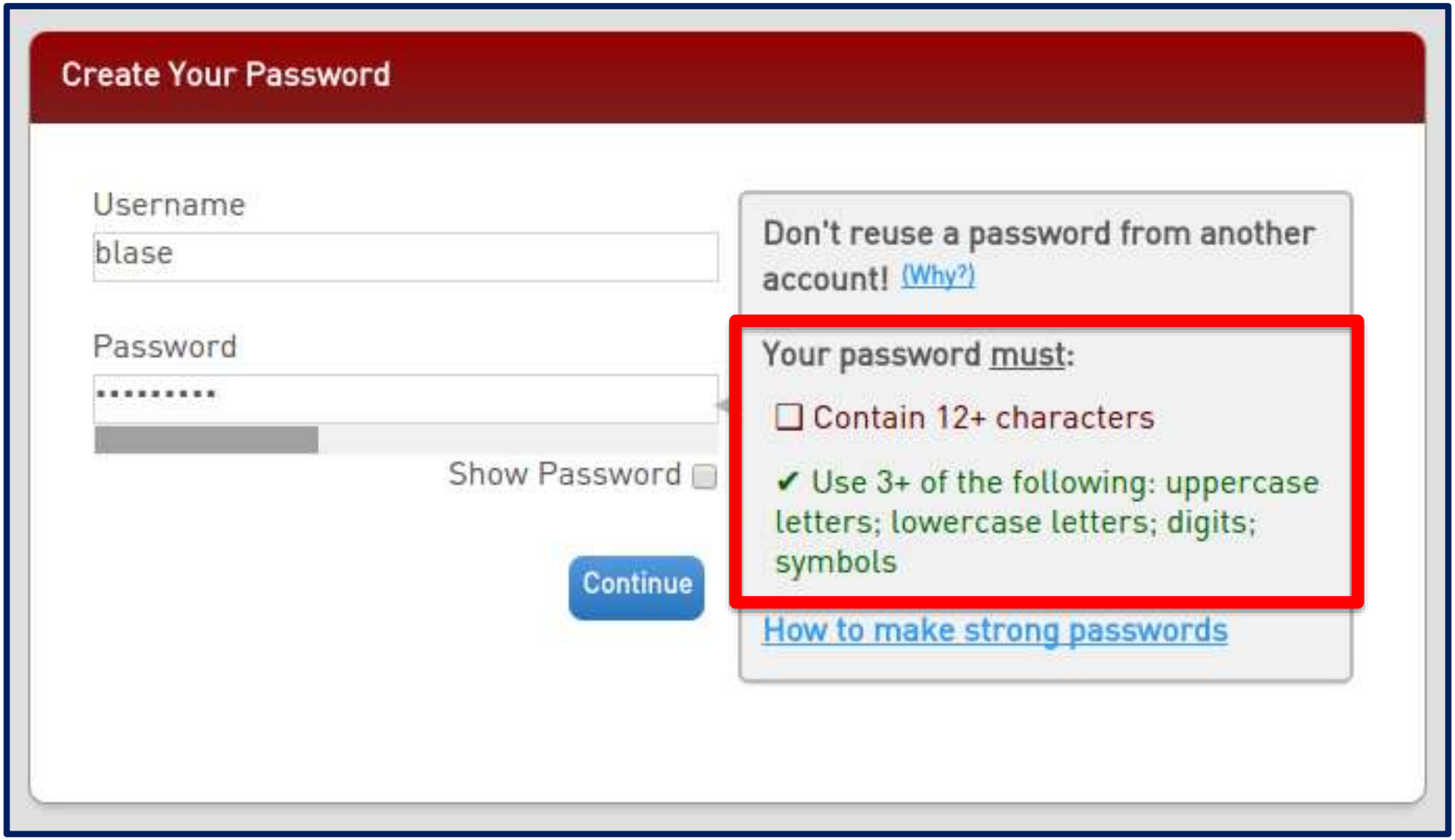
1) Principled strength estimates

2) Data-driven feedback to users

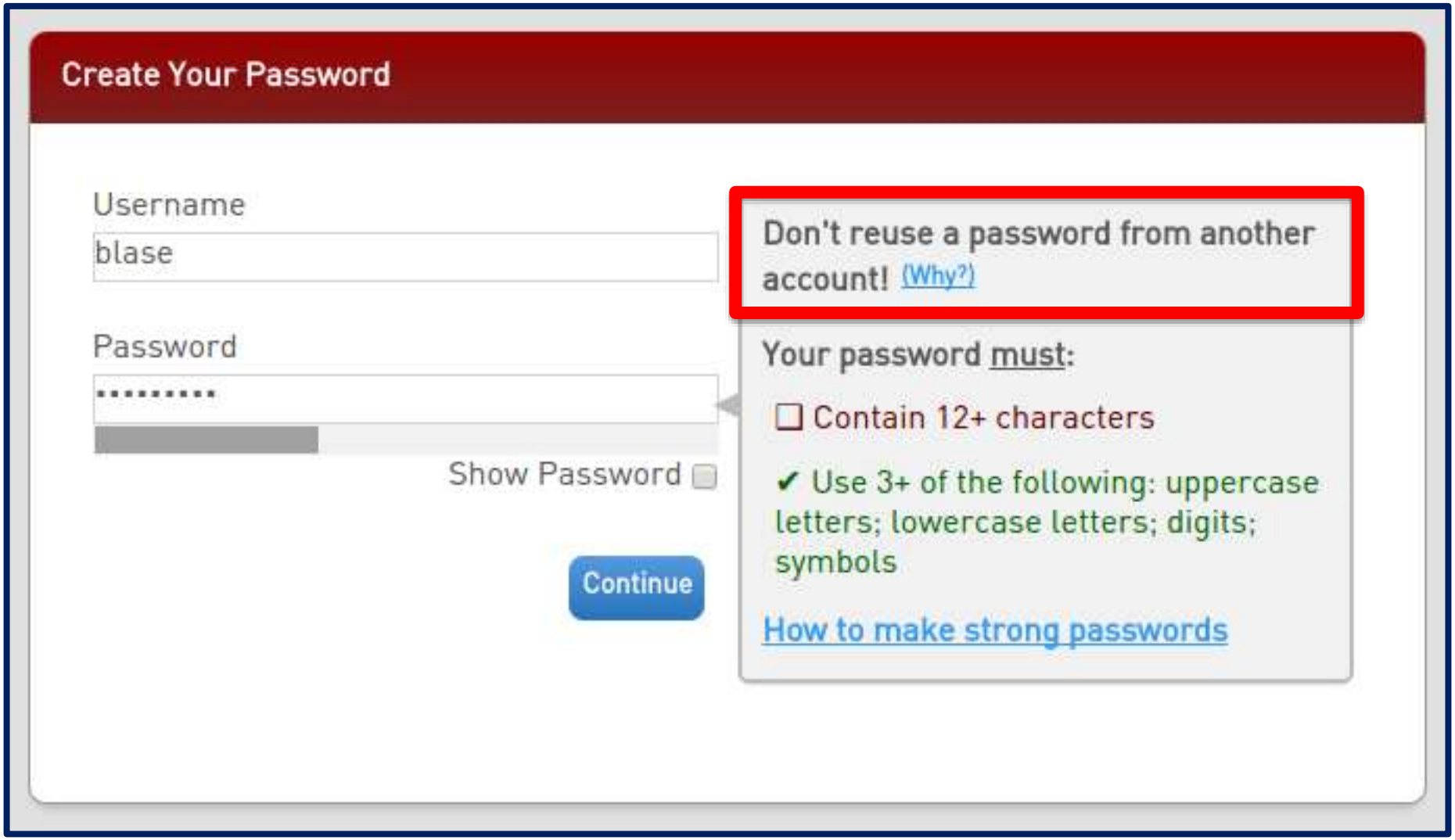
Main Screen…


Create Your Password
Username
blase
Password
Show Password
Continue
Don't reuse a password from another account! (Why?)
Your password must:
Contain 12+ characters
Use 3+ of the following: uppercase letters; lowercase letters; digits; symbols
How to make strong passwords

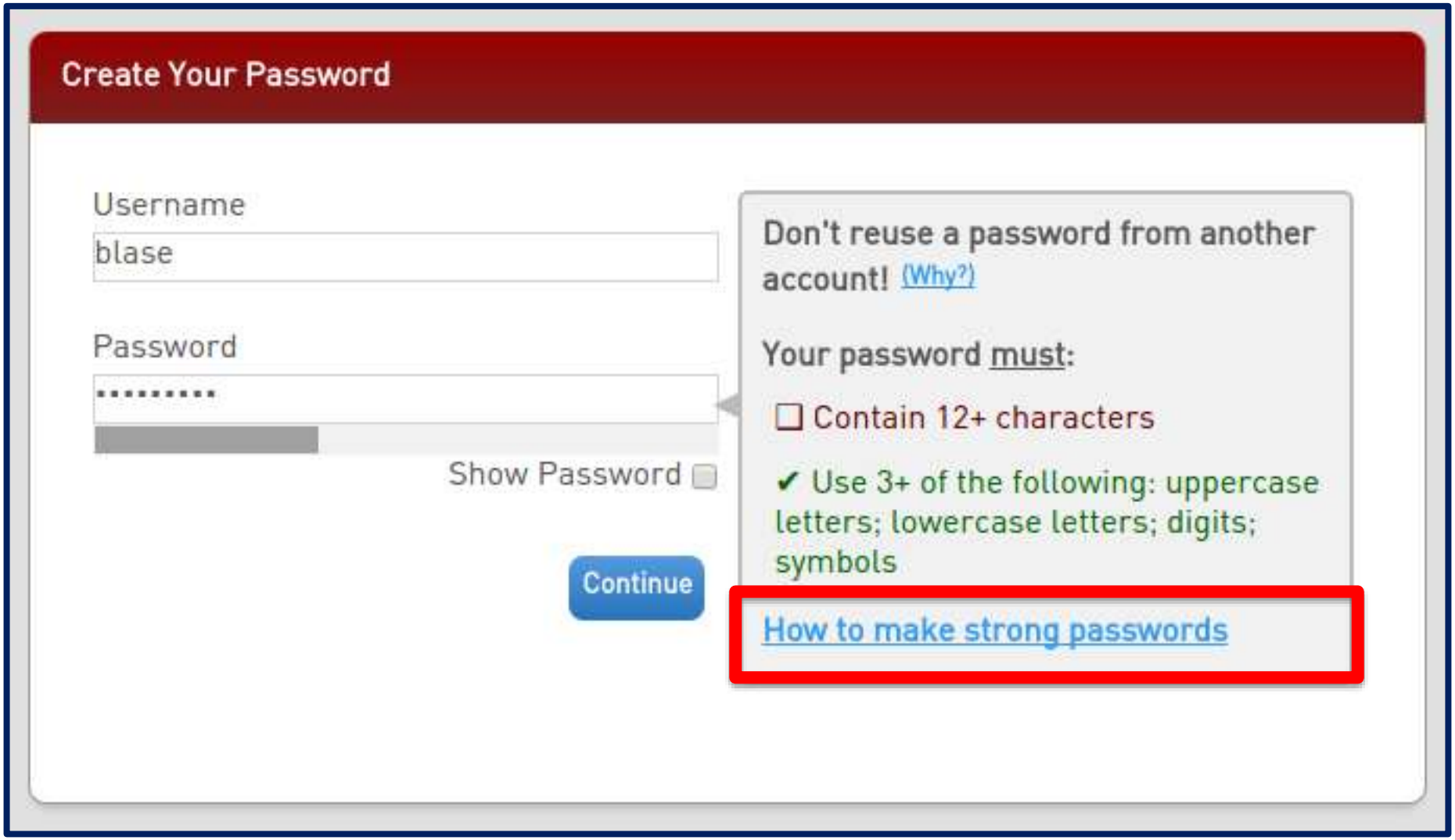
…Shows Requirements



…Emphasizes Avoiding Reuse



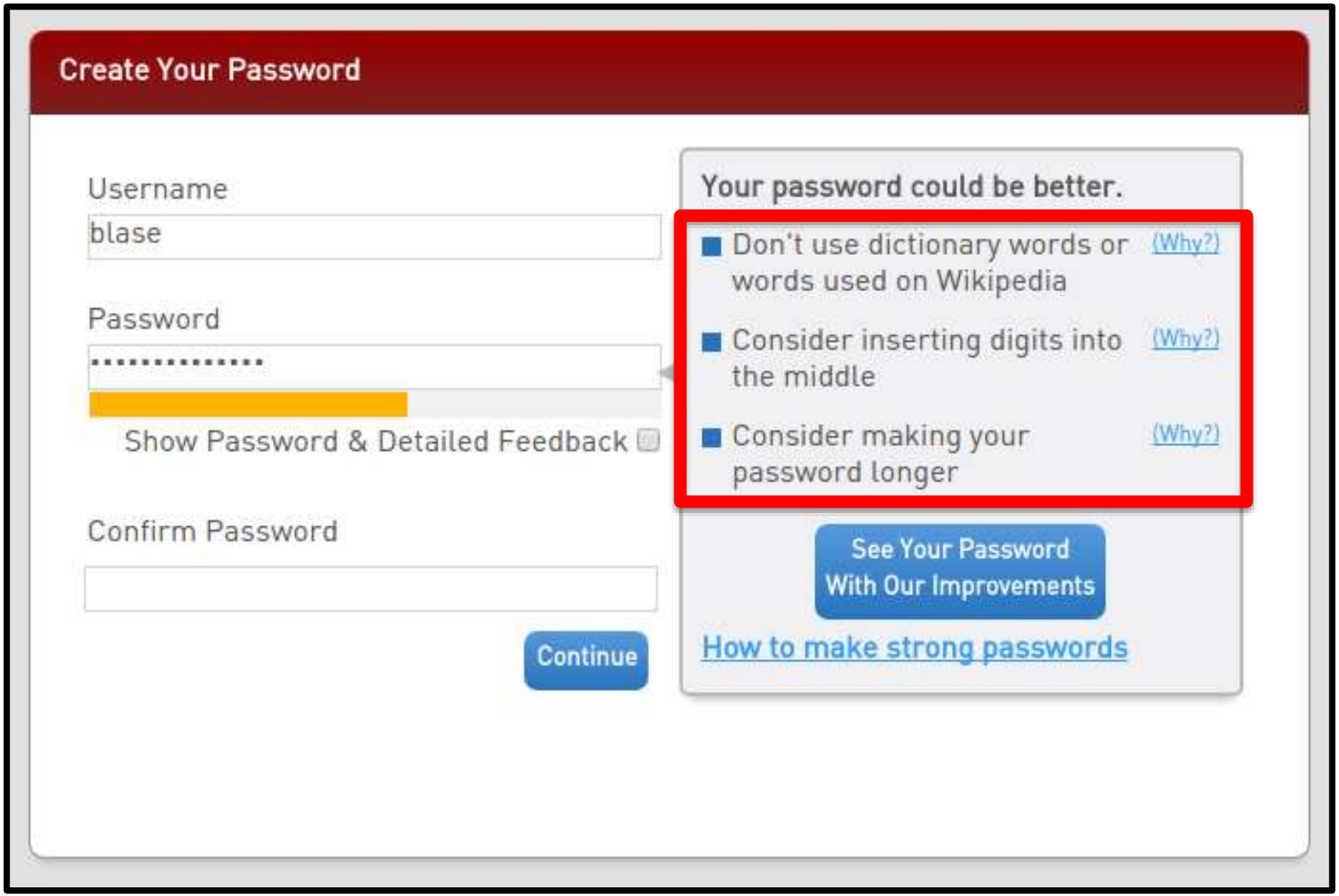
…Provides Abstract Advice



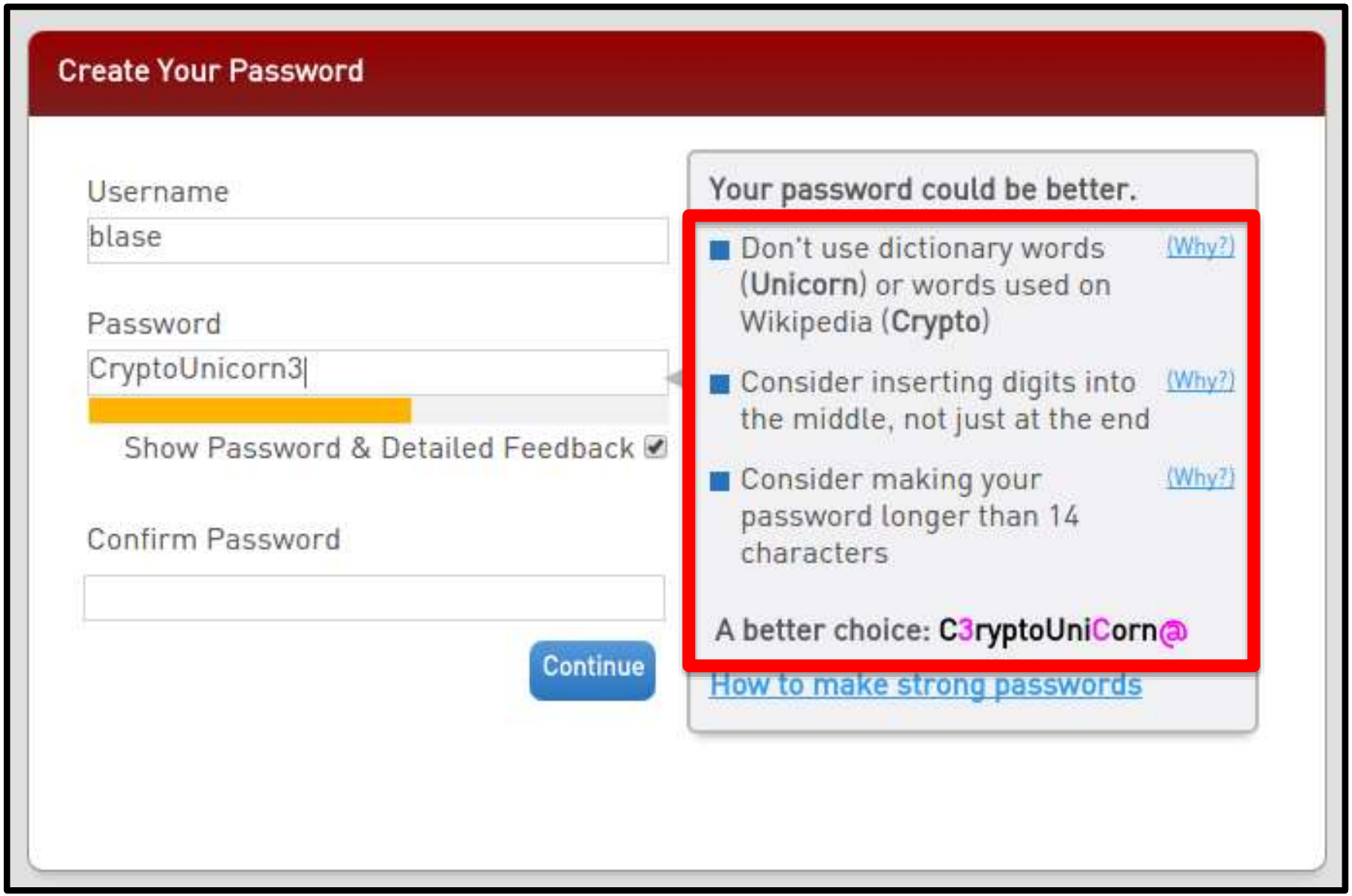
After Requirements Are Met…

…Displays Score Visually

…Provides Text Feedback

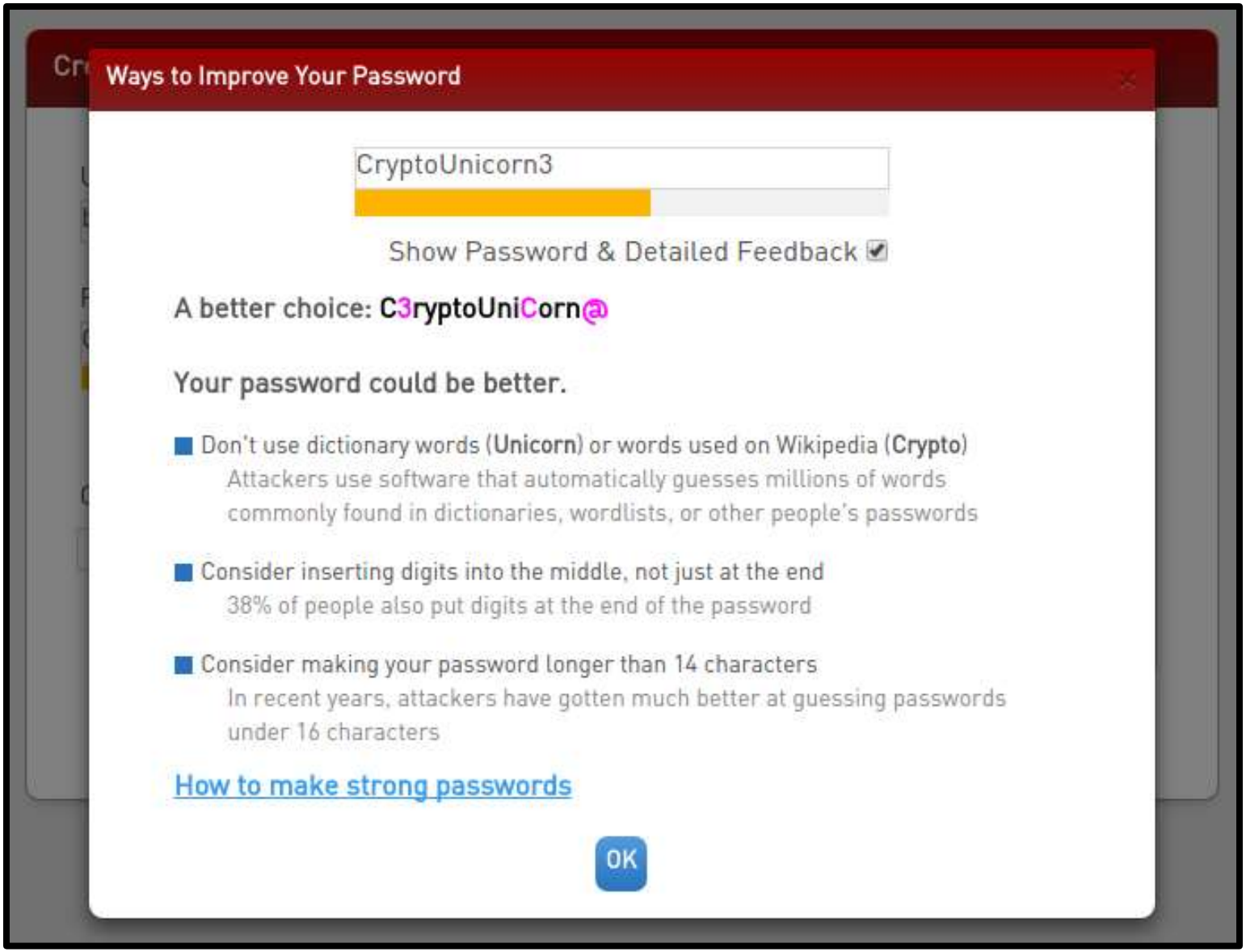


…Gives Detail (Password Shown)



…Offers Explanations

Explanations Shown in Modal



We designed & tested a meter with:

1) Principled strength estimates

2) Data-driven feedback to users

Evaluation

- 2-part online study

  1) Create password; survey; recall password

  (48 hours later, send automated email)

  2) Recall password; survey

- 4,509 Mechanical Turk participants
  - Between-subjects
  - Full-factorial design along three dimensions

Dimension 1: Composition Policy

- 8+ characters (1class8)

```
password
```

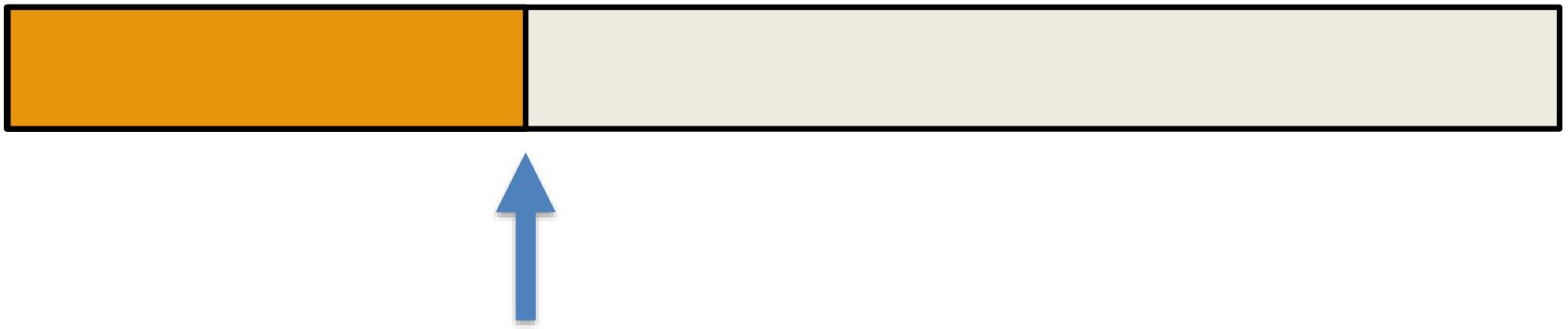
- 12+ characters, 3+ classes (3class12)

```
Password1234
```

Dimension 2: Stringency

- Low
- Medium
- High

Dimension 2: Stringency



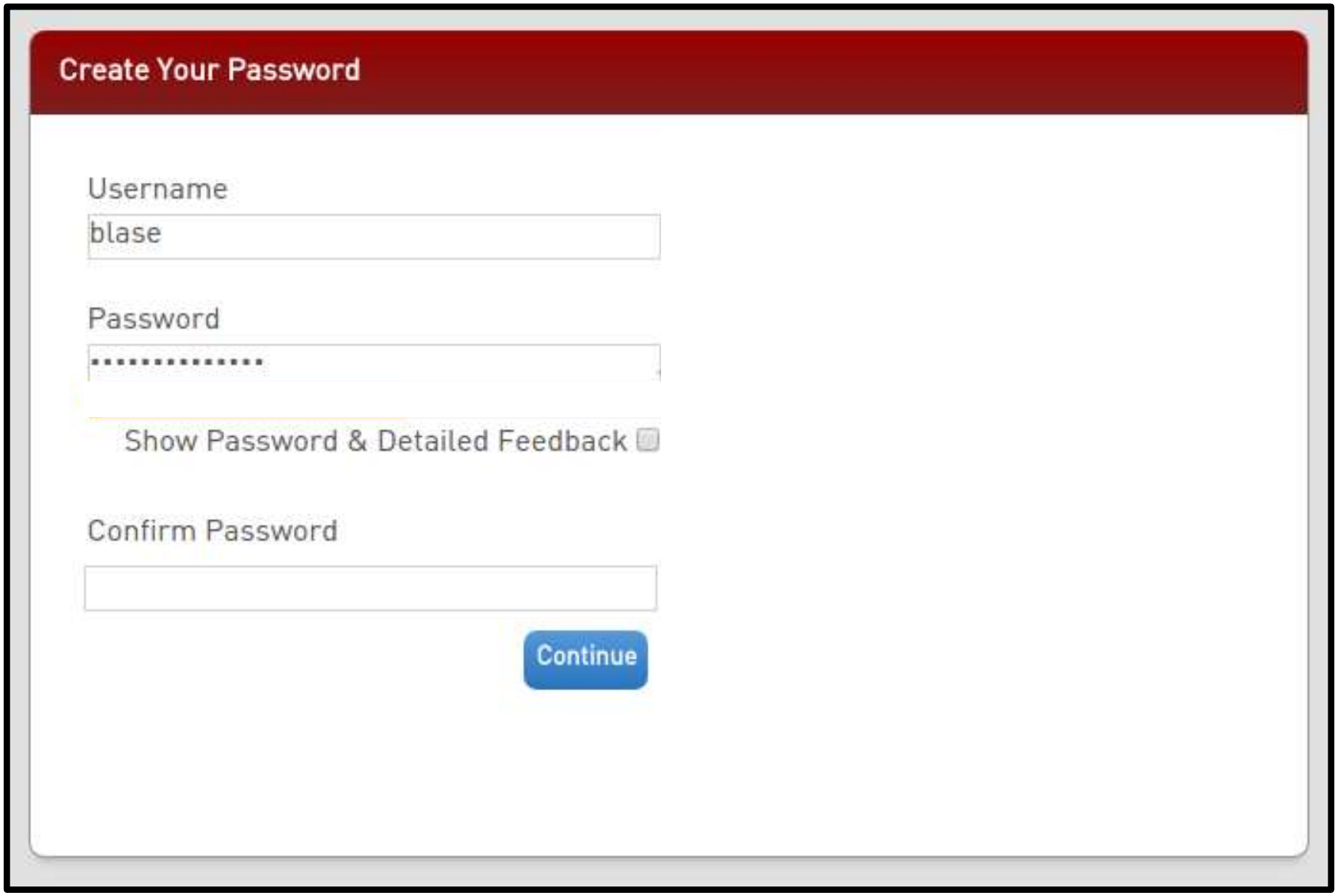
- Low 10^4 guesses
- Medium 10^6 guesses
- High 10^8 guesses

Dimension 2: Stringency

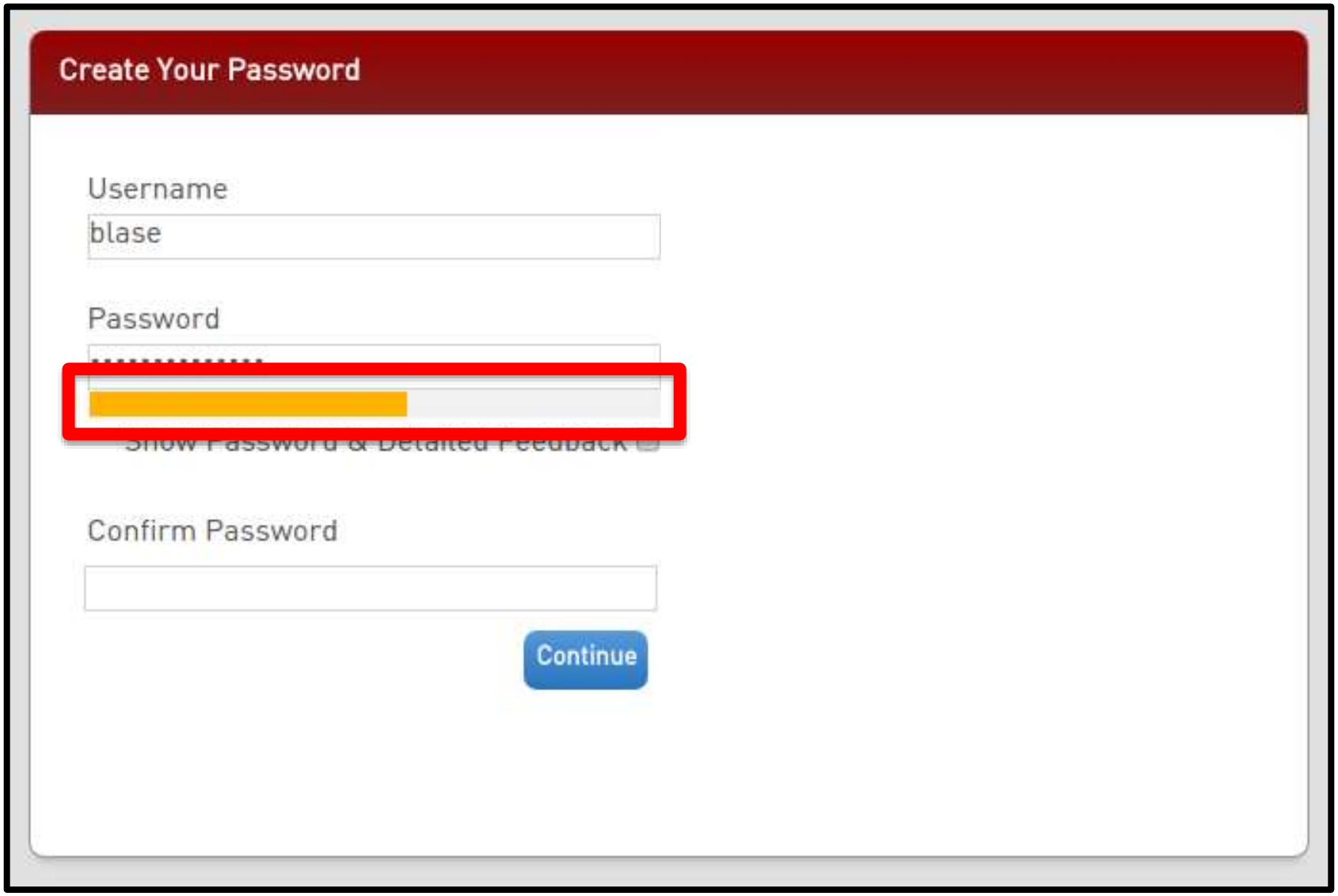
- Low 10^4 guesses 10^8 guesses
- Medium 10^6 guesses 10^{12} guesses
- High 10^8 guesses 10^{16} guesses

Dimension 3: Feedback

No Feedback

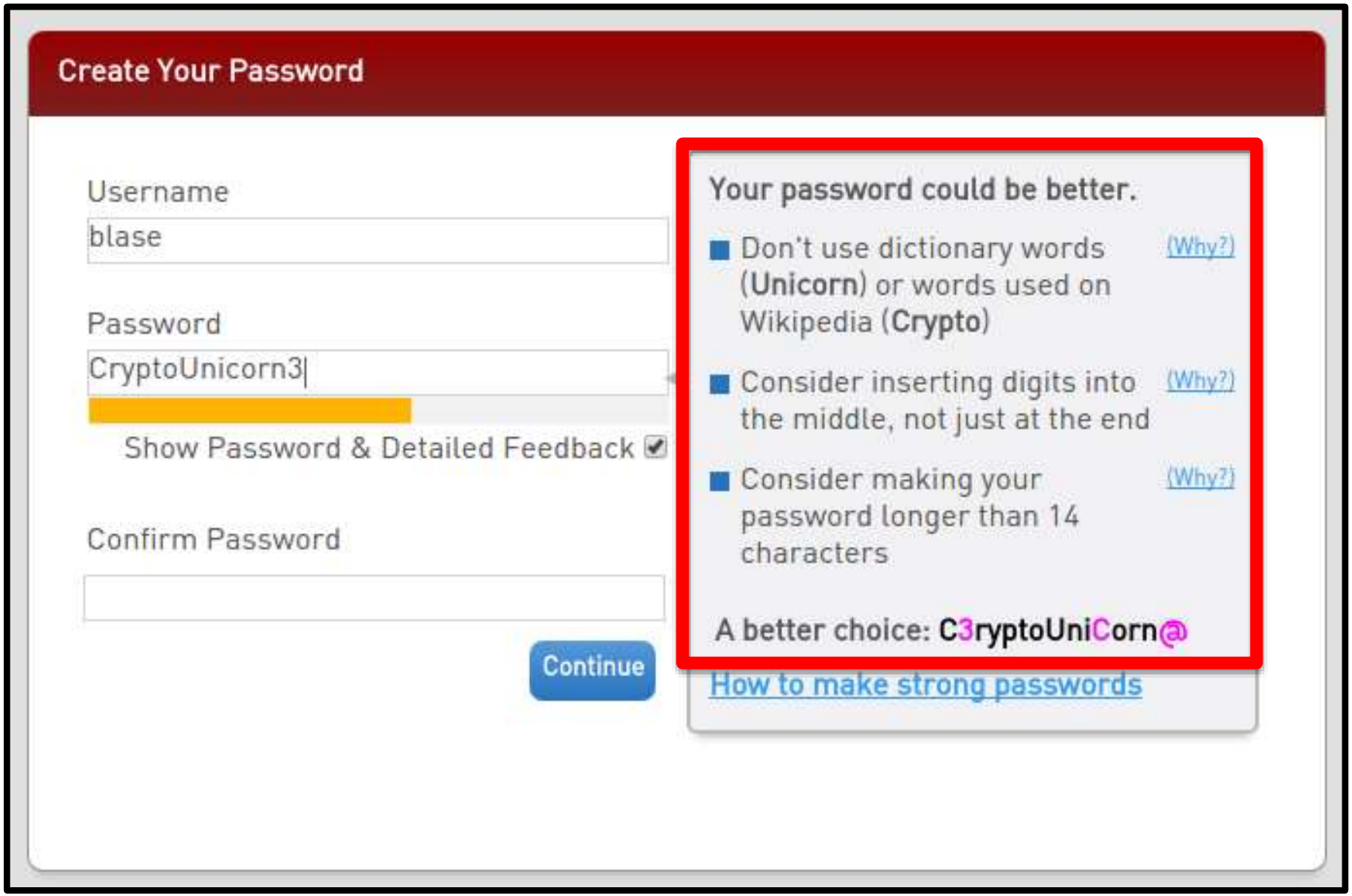

Create Your Password
Username
blase
Password
Show Password & Detailed Feedback
Confirm Password
Continue

Bar Only


Create Your Password
Username
blase
Password
Confirm Password
Continue

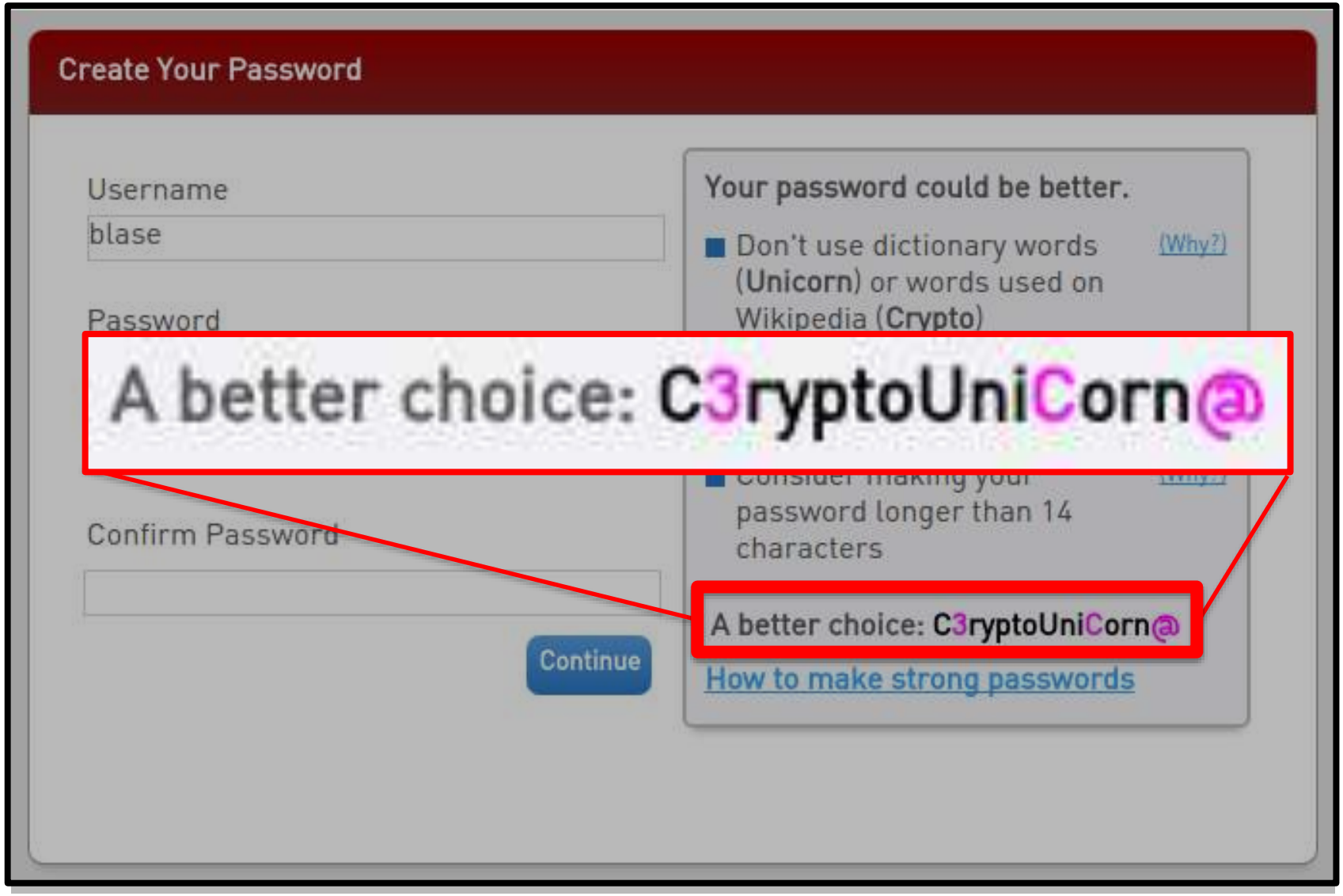
Public (Non-Sensitive) Feedback

Standard Feedback

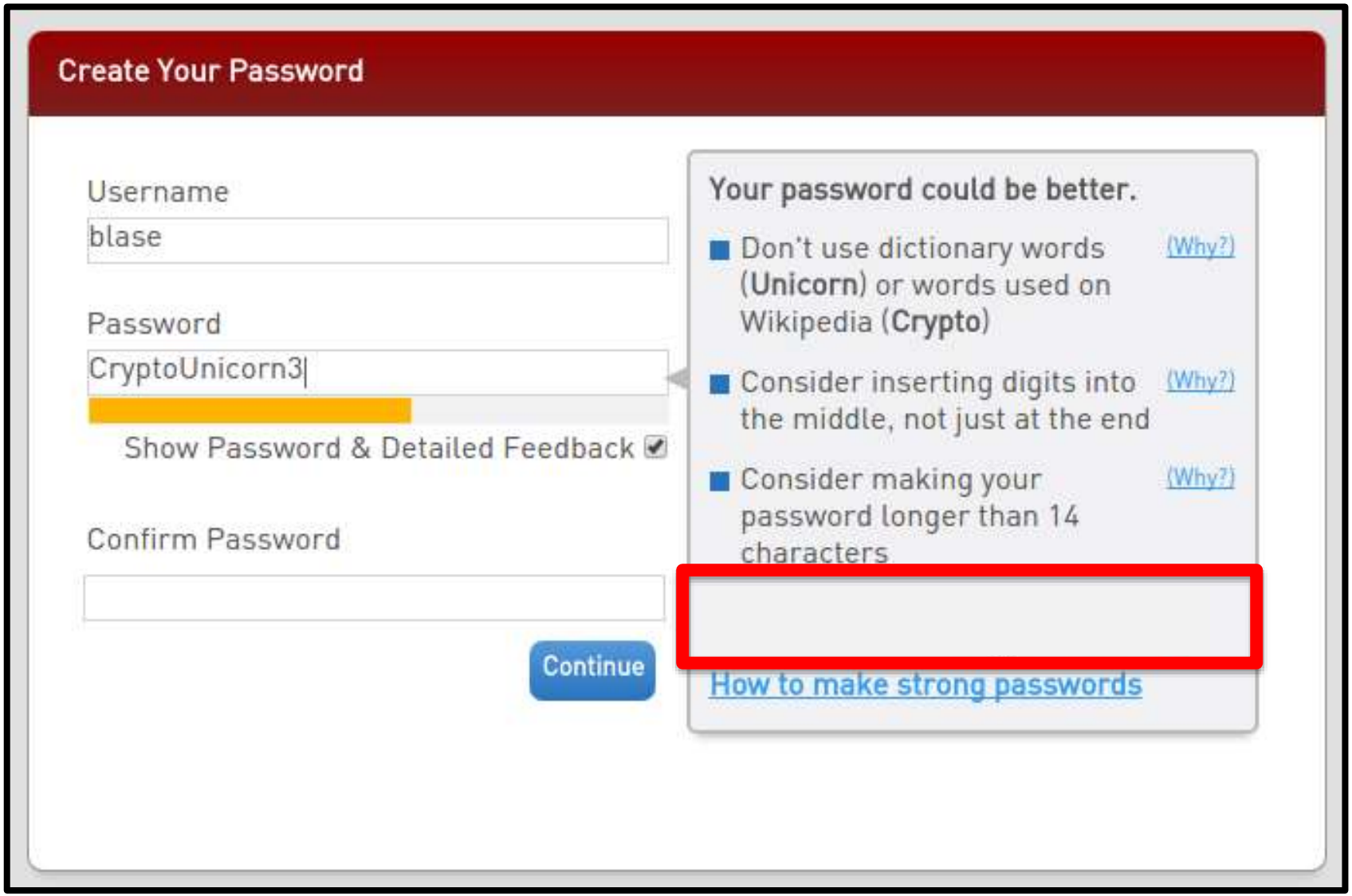


Standard Feedback

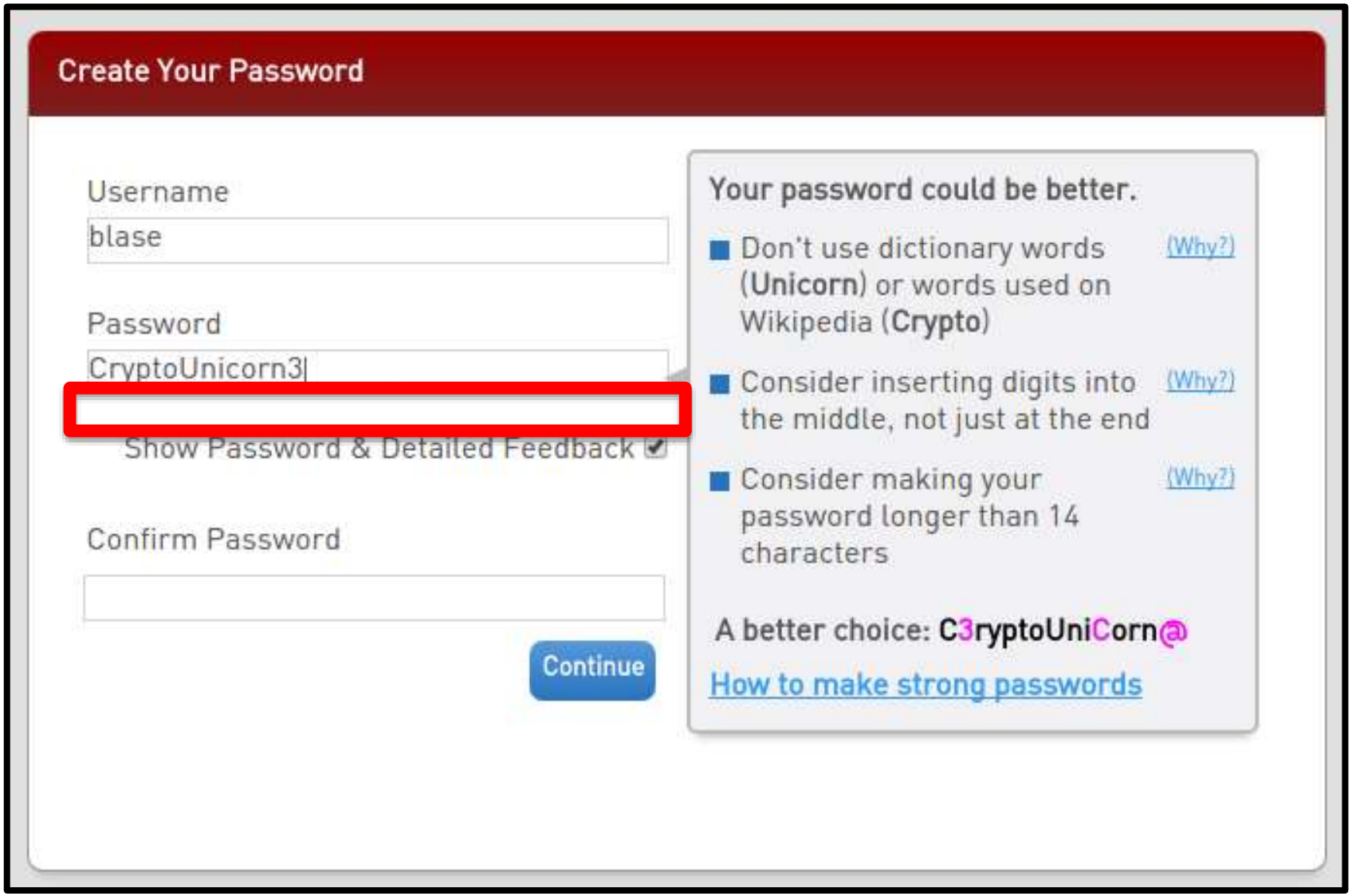
Standard Feedback



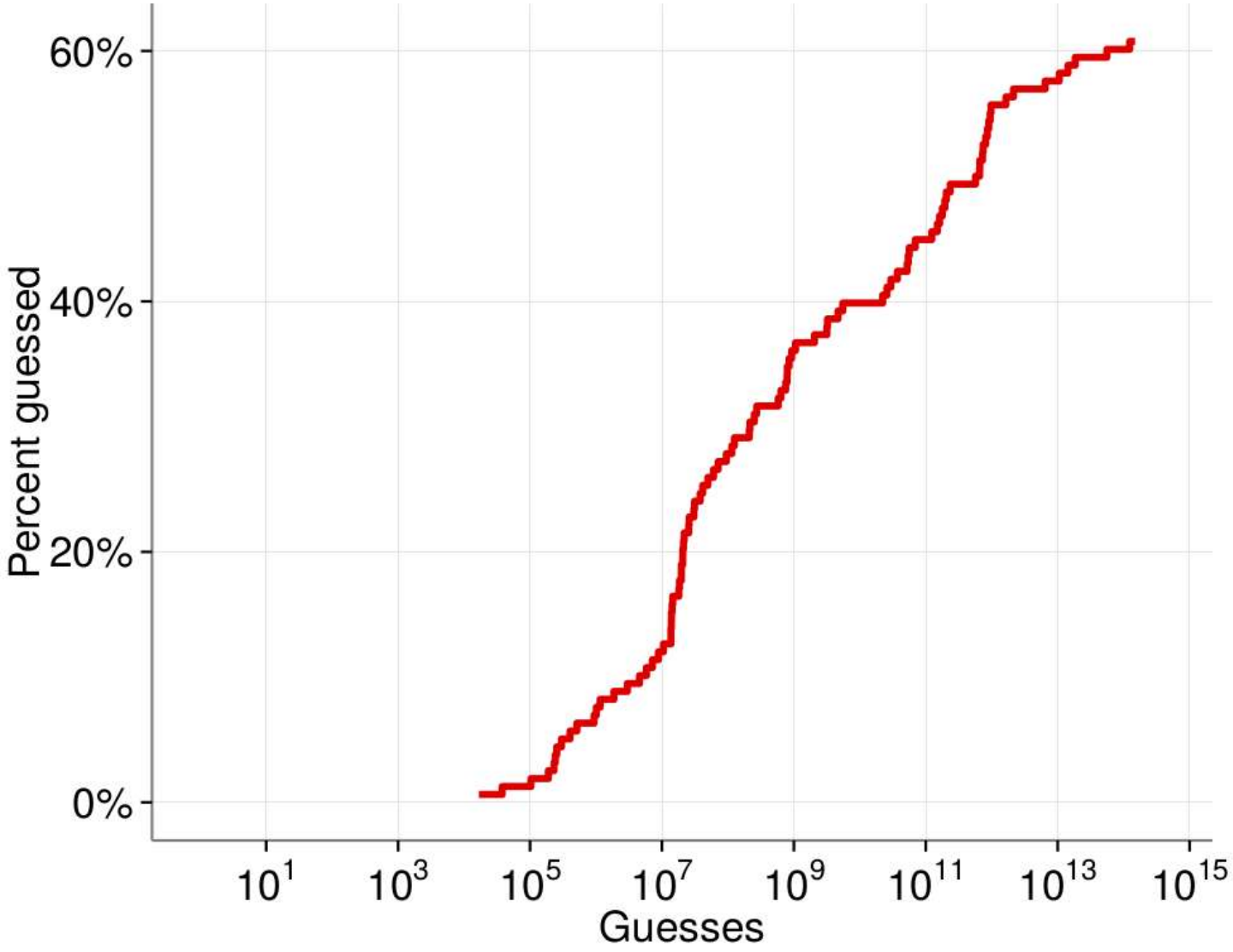
Standard, No Suggested Improvement



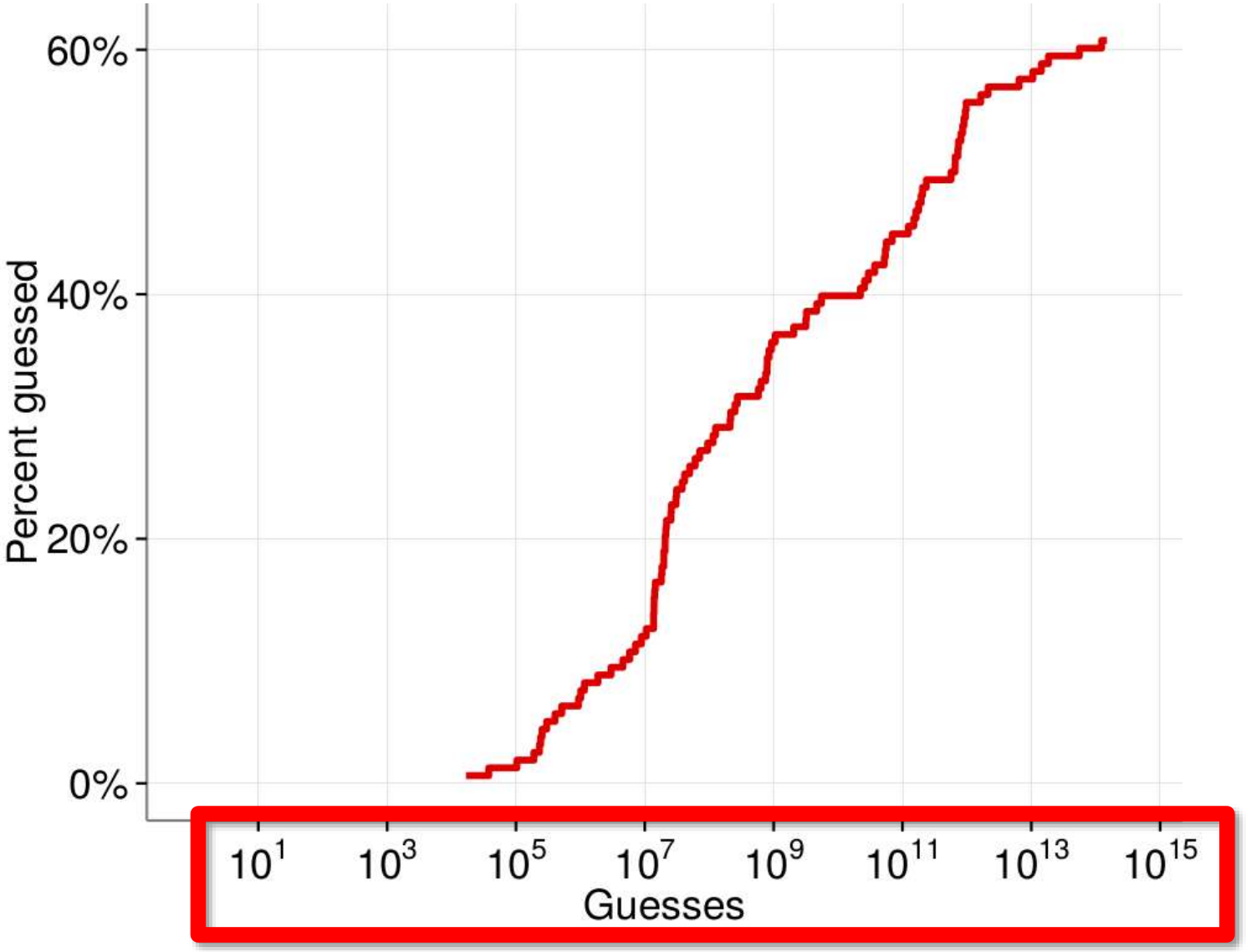
Standard, No Bar



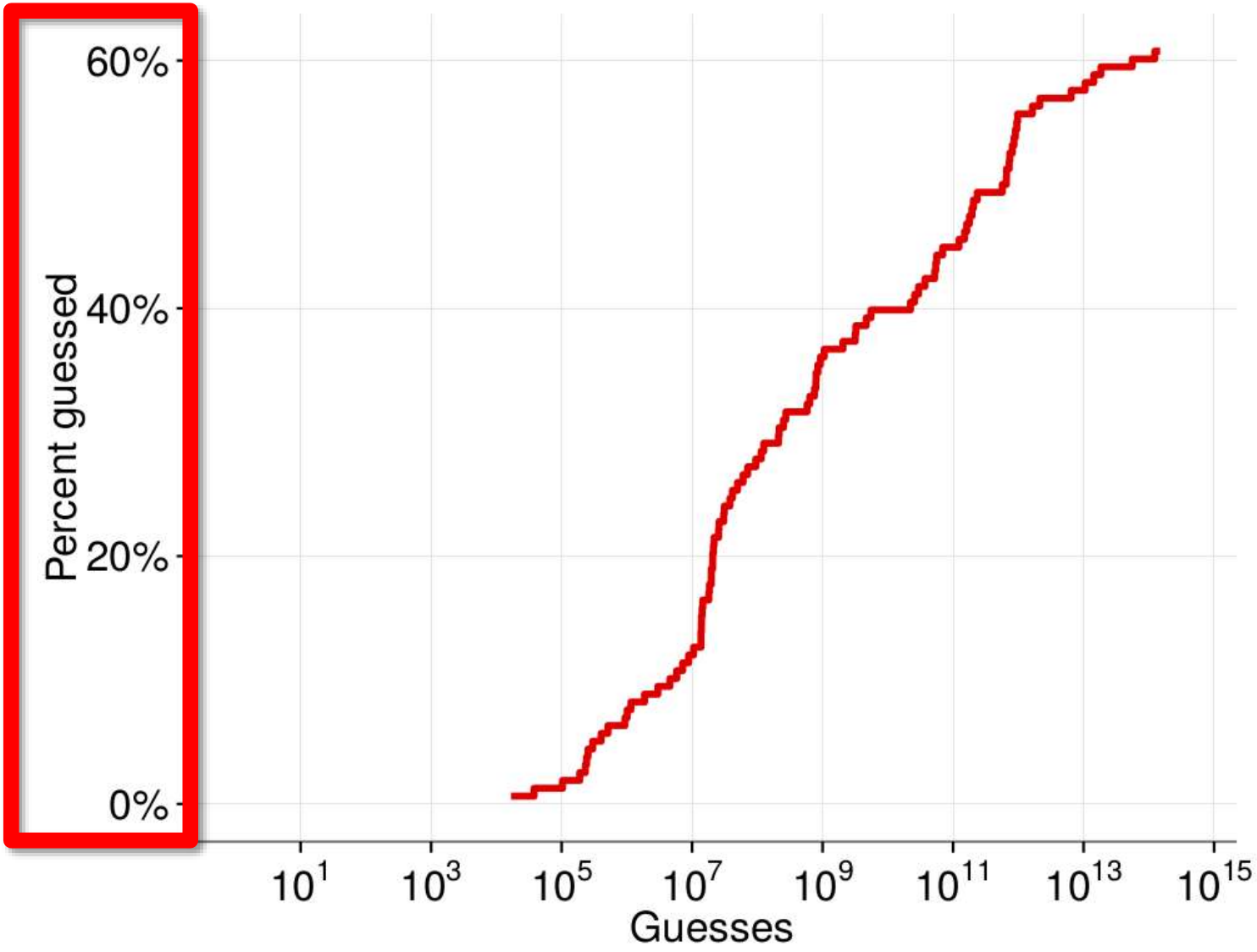
Measure Password Guessability



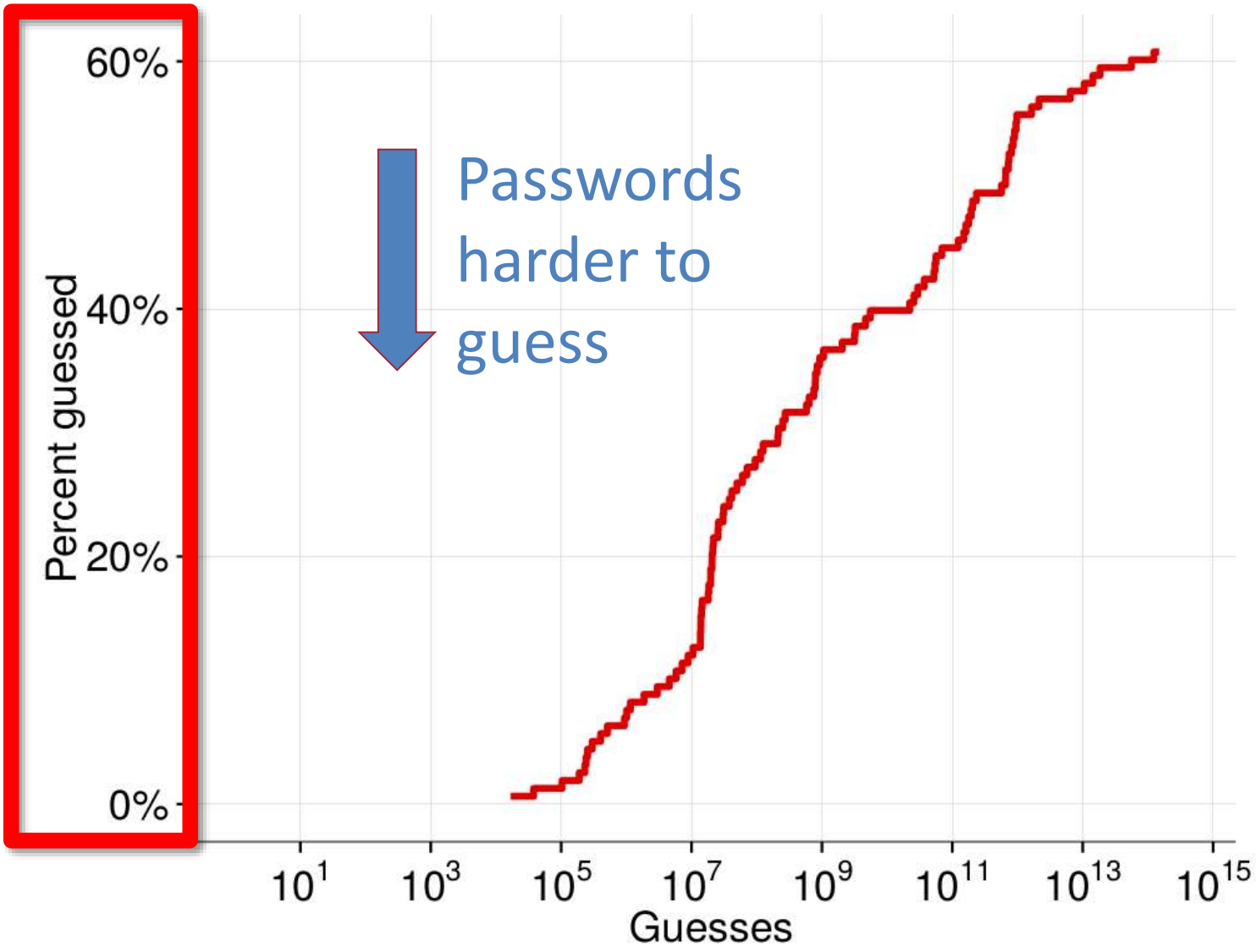
Measure Password Guessability



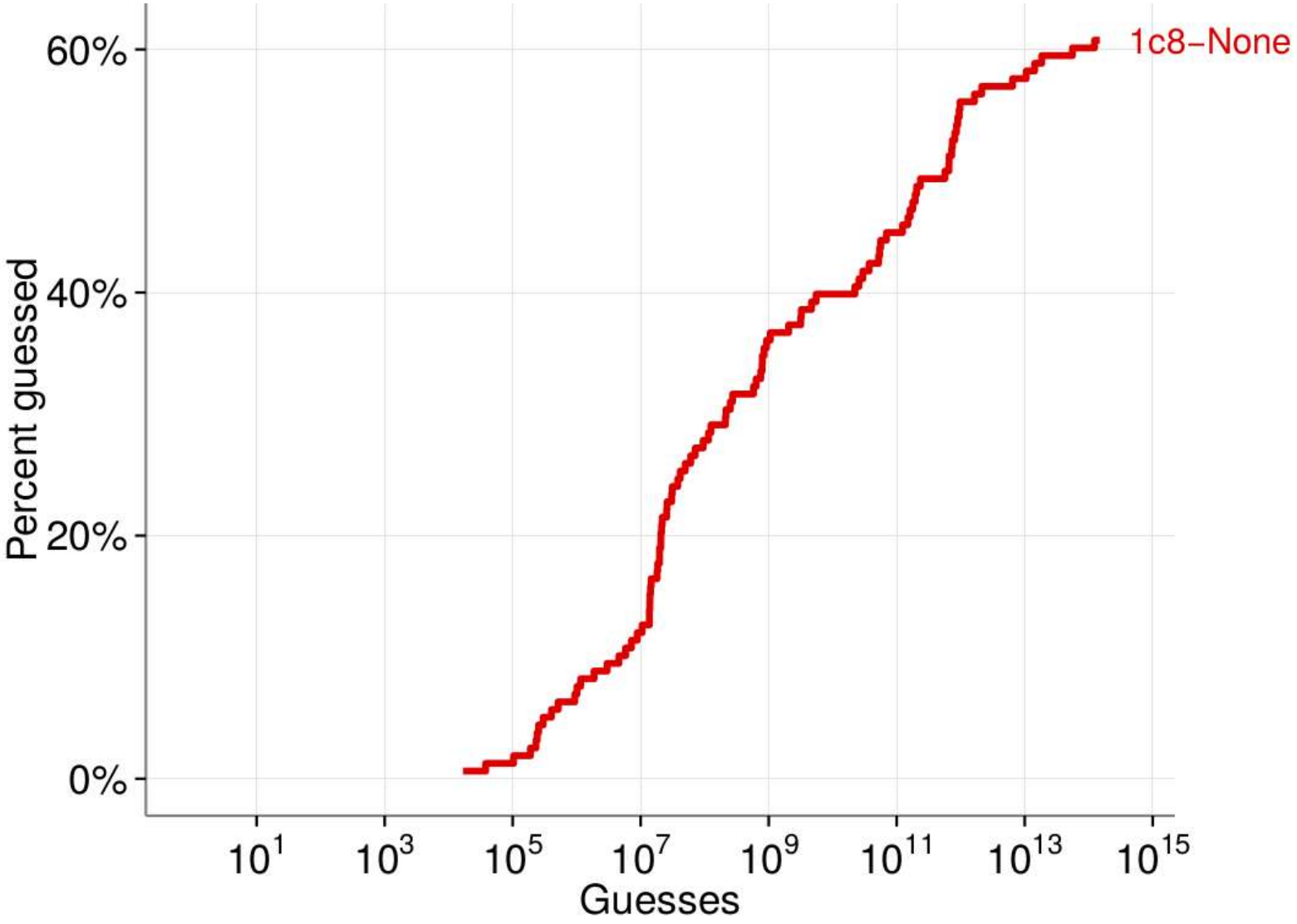
Measure Password Guessability



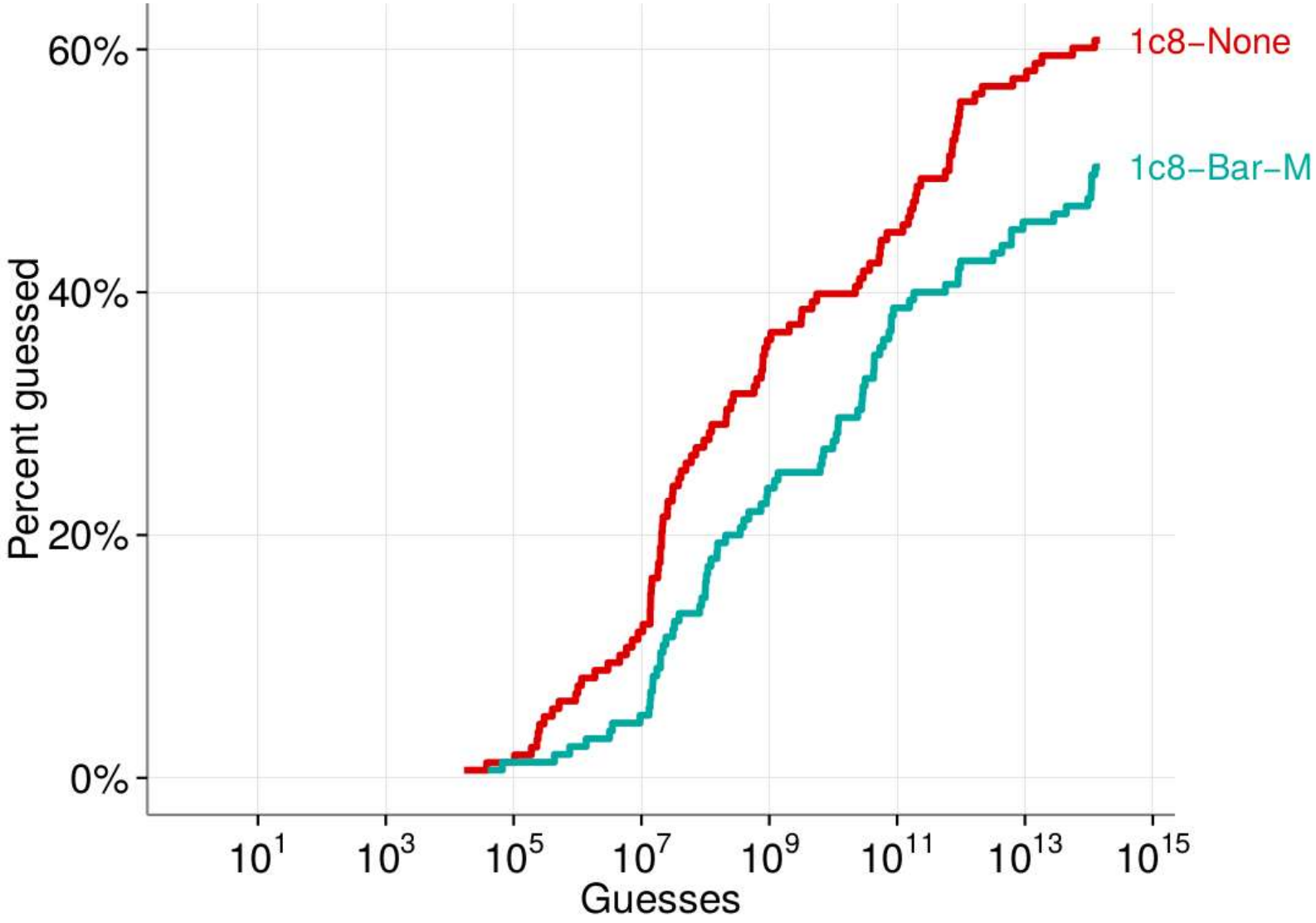
Measure Password Guessability



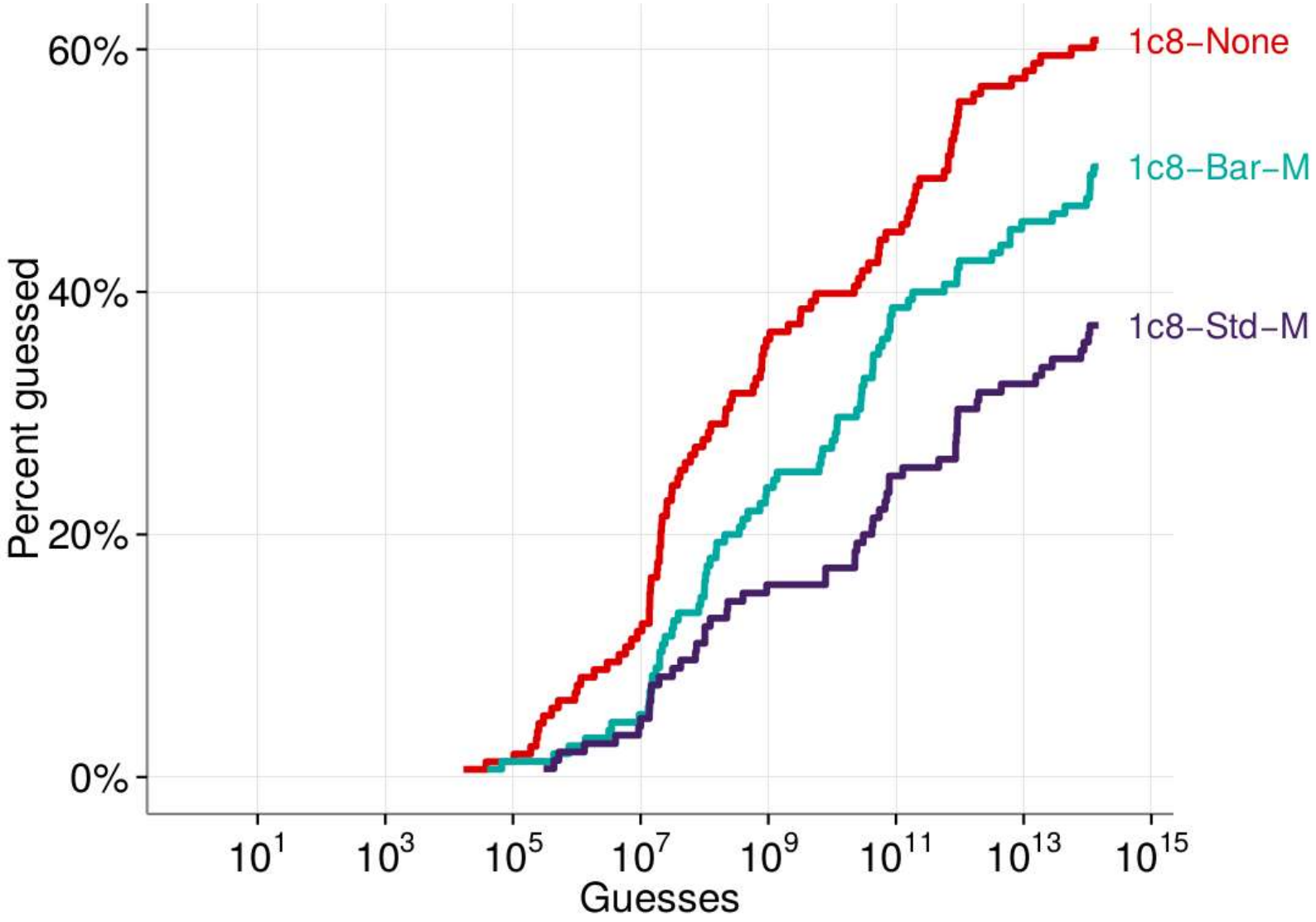
Measure Password Guessability



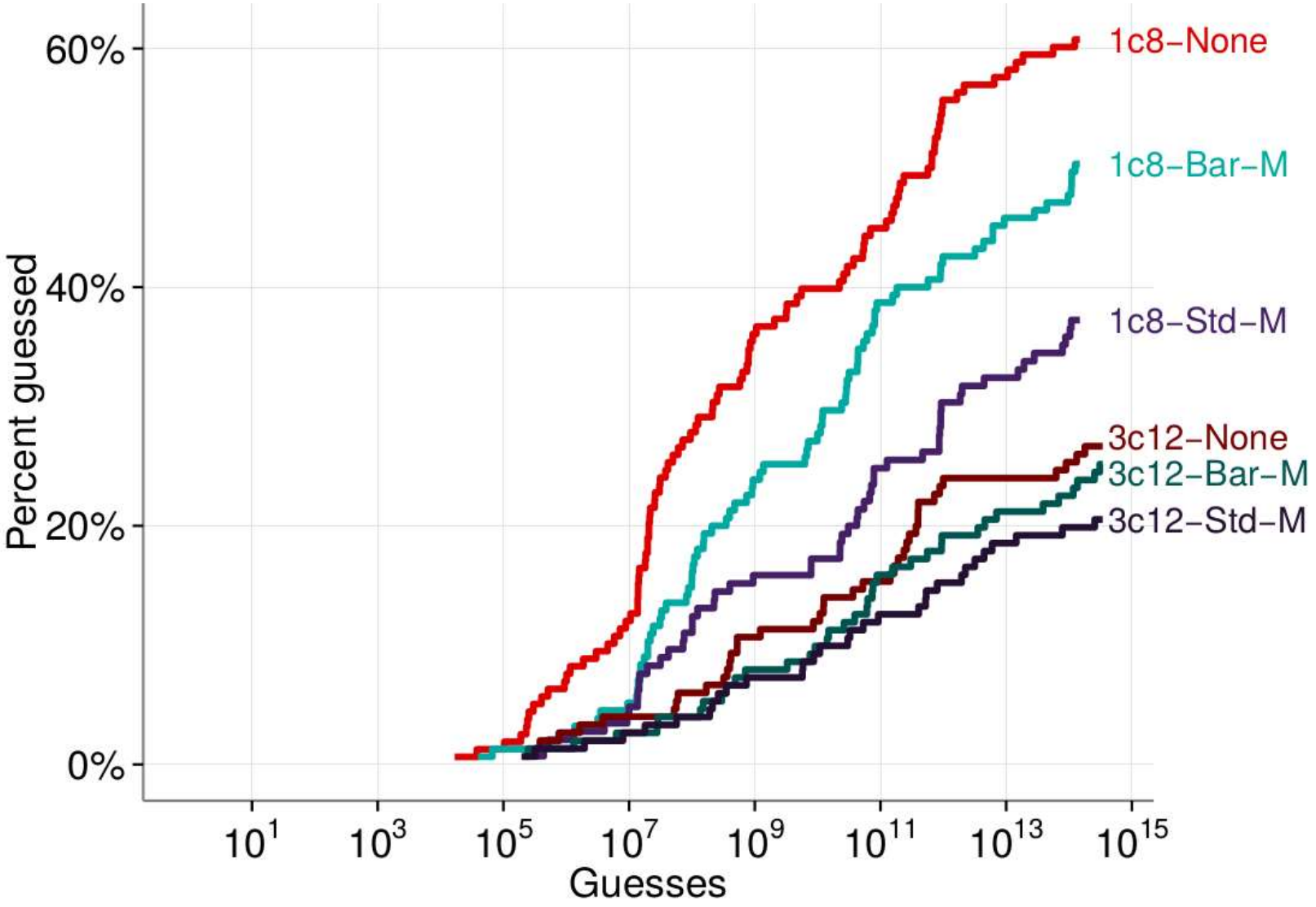
Feedback → More Secure Passwords



Feedback → More Secure Passwords



Feedback → More Secure Passwords



Usability Results

- Feedback did not significantly impact password memorability
- More feedback → more difficult, annoying
- All features had value for some participants

Feedback → More Secure Passwords

https://github.com/cupslab/password_meter

- Help us improve the meter
- Demo: **https://cups.cs.cmu.edu/meter**

Blase Ur, Assistant Professor, University of Chicago

THE UNIVERSITY OF CHICAGO

CyLab Usable Privacy & Security Laboratory
HTTP://CUPS.CS.CMU.EDU

Carnegie Mellon University