
Multi-armed bandit approach to password guessing

— Hazel Murray & David Malone —
Maynooth university, Ireland

Who Are You?! Adventures in Authentication Workshop (WAY) 7th August 2020

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Motivation



Facebook 13

Facebooku

computerispowerfacebook

Linked  linkedin
LinkedIn
jobsearch

Motivation



- Ibare, J., Musungu, J. and Kigali, R., A comparison of common passwords in East Africa against common passwords in the United States.
- AlSabah, M., Oligeri, G. and Riley, R., 2018. Your culture is in your password: An analysis of a demographically-diverse password dataset. *Computers & security*, 77, pp.427-441.

Goals

Identify whether a learning algorithm can recognise characteristics of a password set

Multi-armed bandit

Can this aid an a

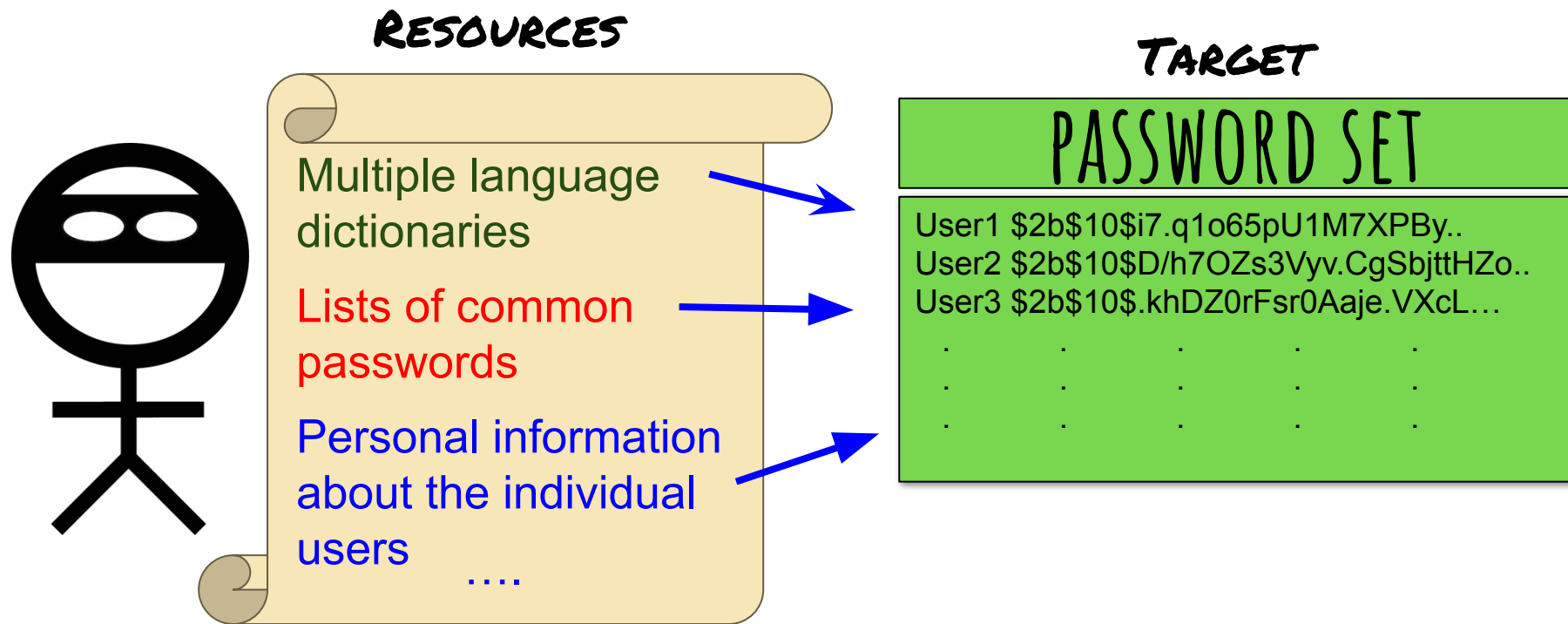
passwords?



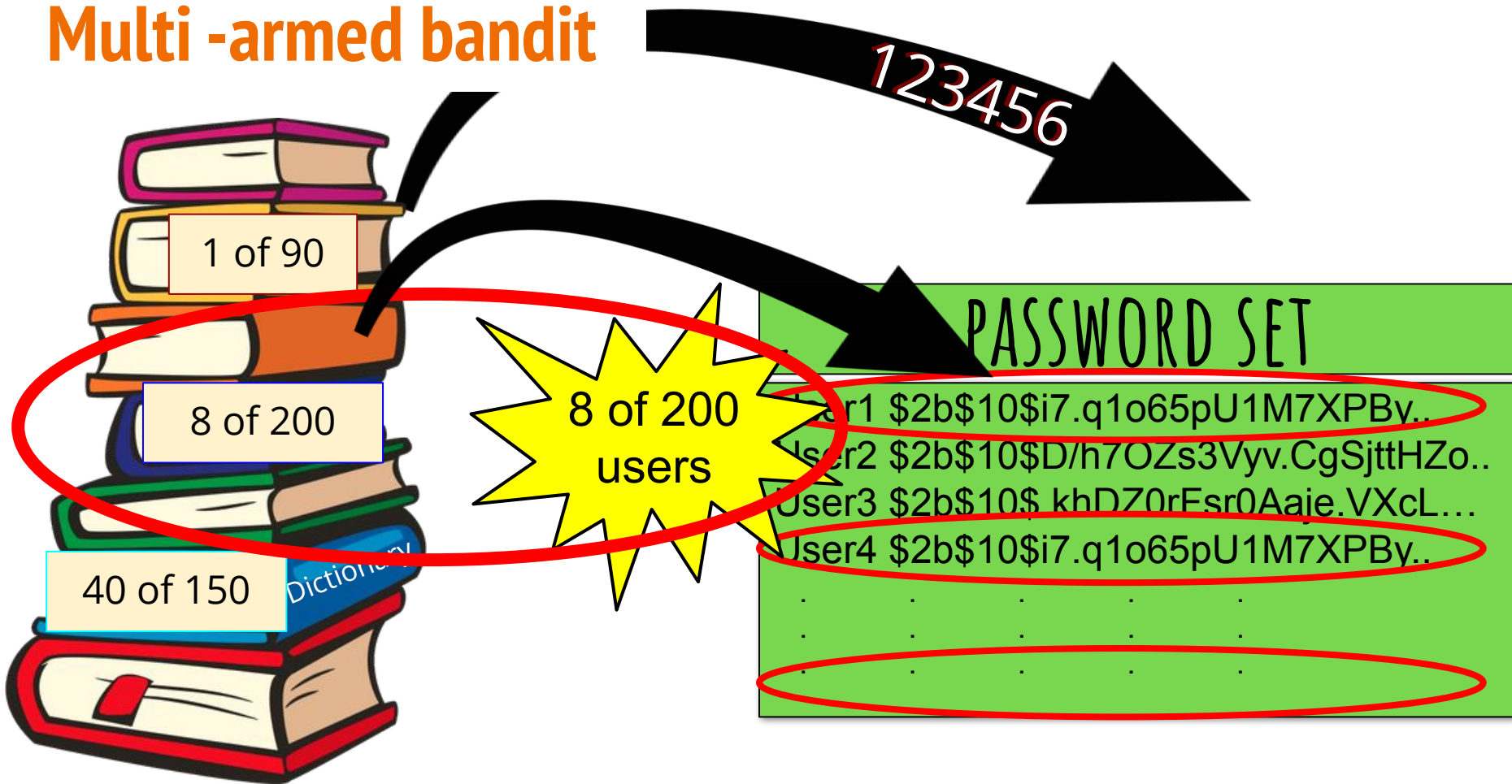
Multi-armed bandit



A multi-armed bandit password attacker



Multi-armed bandit



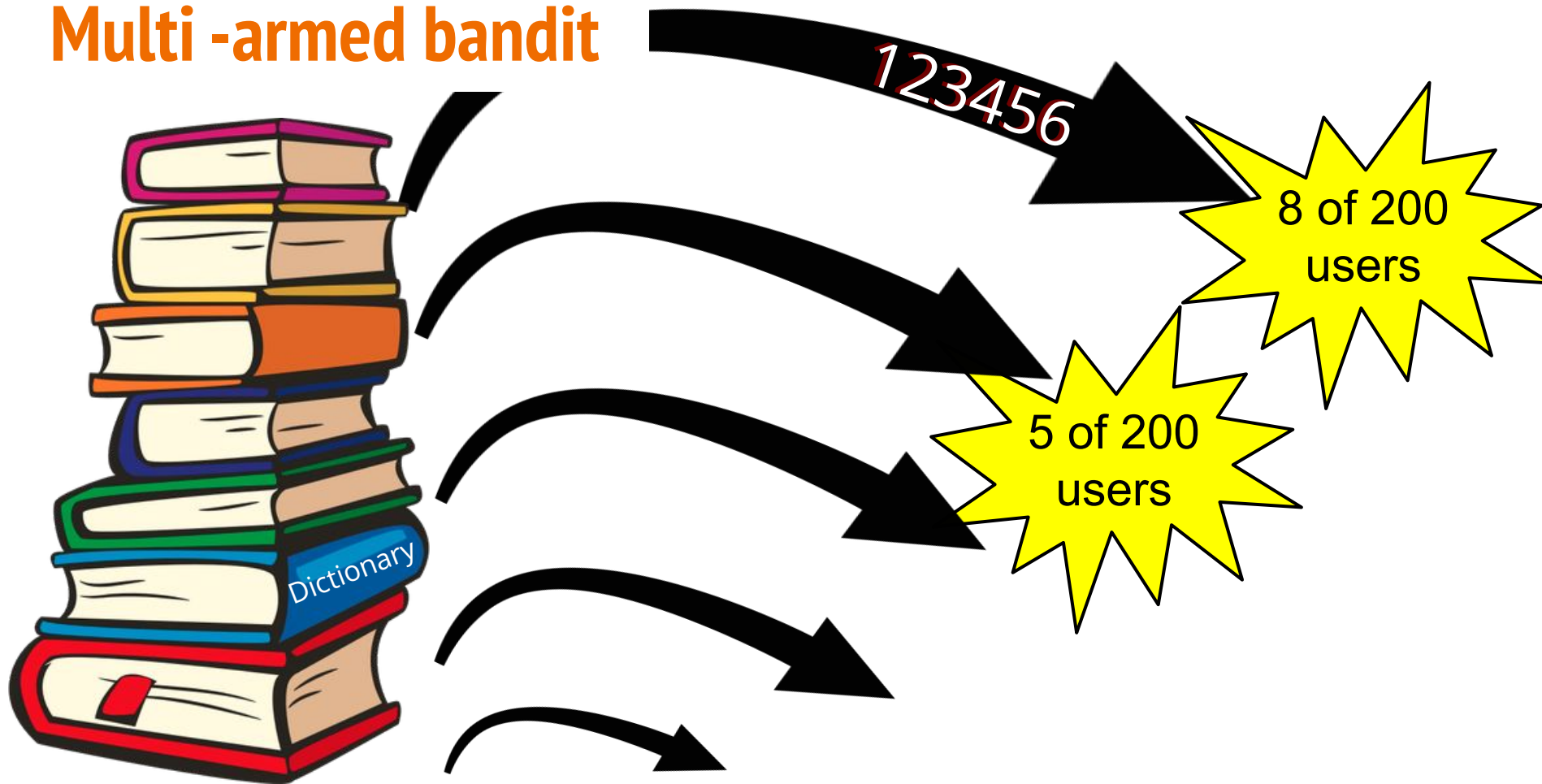
Multi-armed bandit



8 of 200
users

PASSWORD SET			
User1	\$2b\$10\$	i7.q1o65pU1M7XPBy..	
User2	\$2b\$10\$	D/h7OZs3Vyv.CgSjttHZo..	
User3	\$2b\$10\$	khD70rEsr0Aaie.VXcL...	
User4	\$2b\$10\$	i7.q1o65pU1M7XPBy..	
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Multi-armed bandit

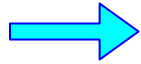


Learning Techniques

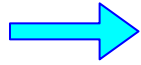
There are two learning techniques we are employing here:

- Matching the proportions seen to those in the dictionaries we have
- Making informed guesses based on this information.

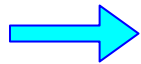
Maximum likelihood



q_1



q_2

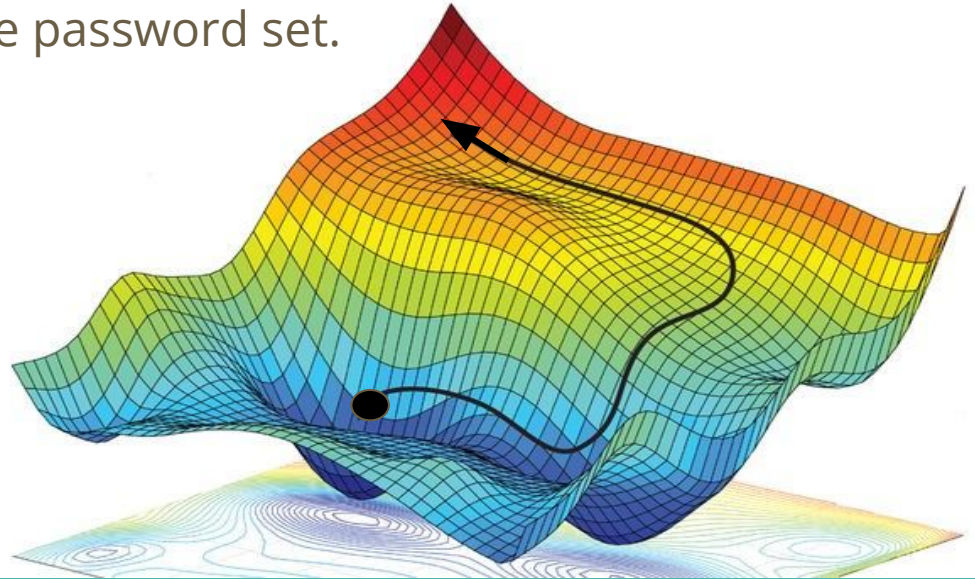


q_3

- Maximum likelihood estimation is a method of estimating the parameters of a probability distribution using observed data.

Maximum likelihood

- Except in limited cases, the likelihood cannot be solved explicitly to find the maximum.
- We used a technique called gradient descent to converge towards the q values that best describe the password set.



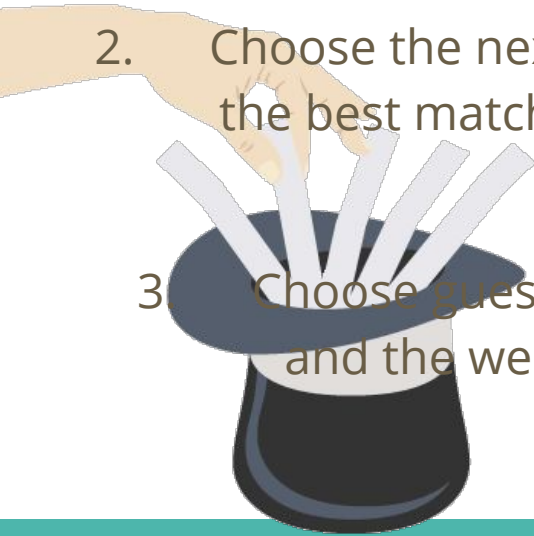
Informing our guesses

We have three ways of choosing our guesses:

1. Randomly choose a dictionary to guess from and choose the next most probable word from that dictionary. (exploring)

2. Choose the next best password from the dictionary which seems to be the best match for the password set we are guessing (exploiting)

3. Choose guesses based on information about the frequency of words and the weightings of all the dictionaries we have:



Q method

$$q_1 = 0.3$$

Dictionary 1:

Bye Password Hello 123456 Bye Bye LetMeIn qwerty

$$q_2 = 0.7$$

Dictionary 2:

qwerty Hello trustno1 123456 password1 Hello Bye 123456789

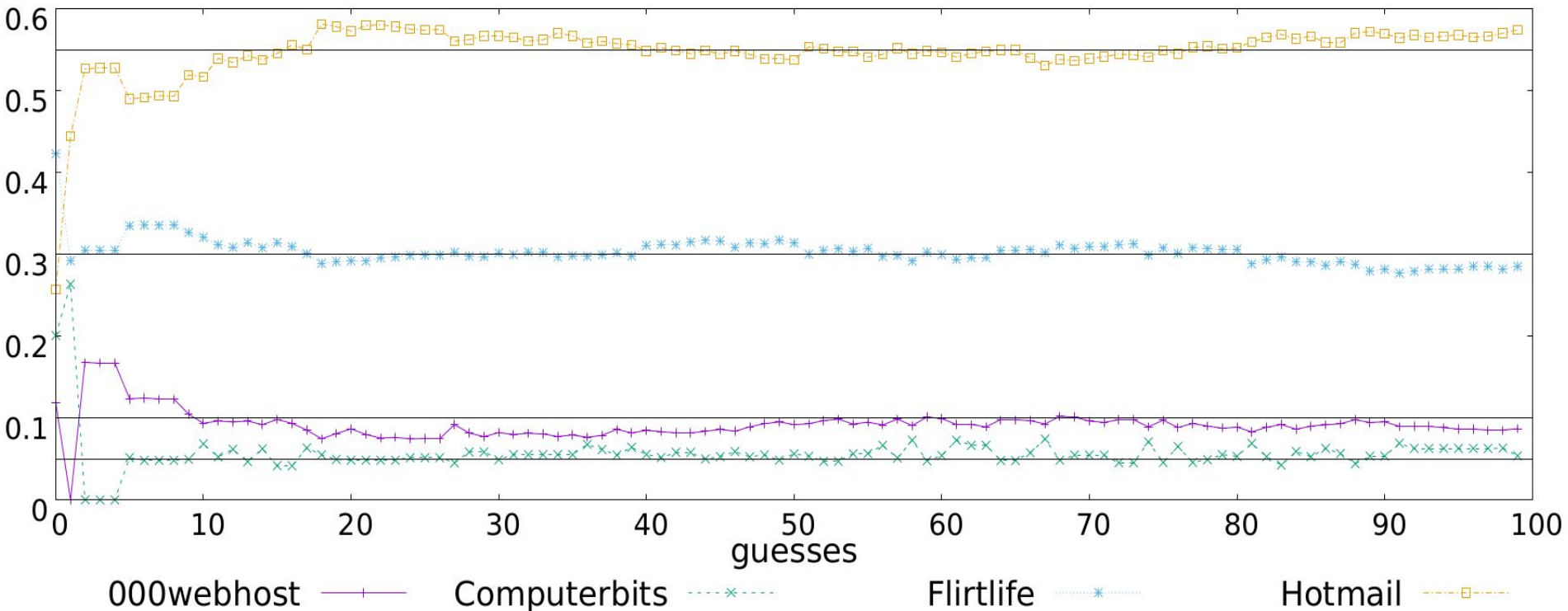
$$Q(\text{"Hello"}) = (1/8)(0.3) + (2/8)(0.7) = 0.2125$$

Multi-armed Bandit Results.

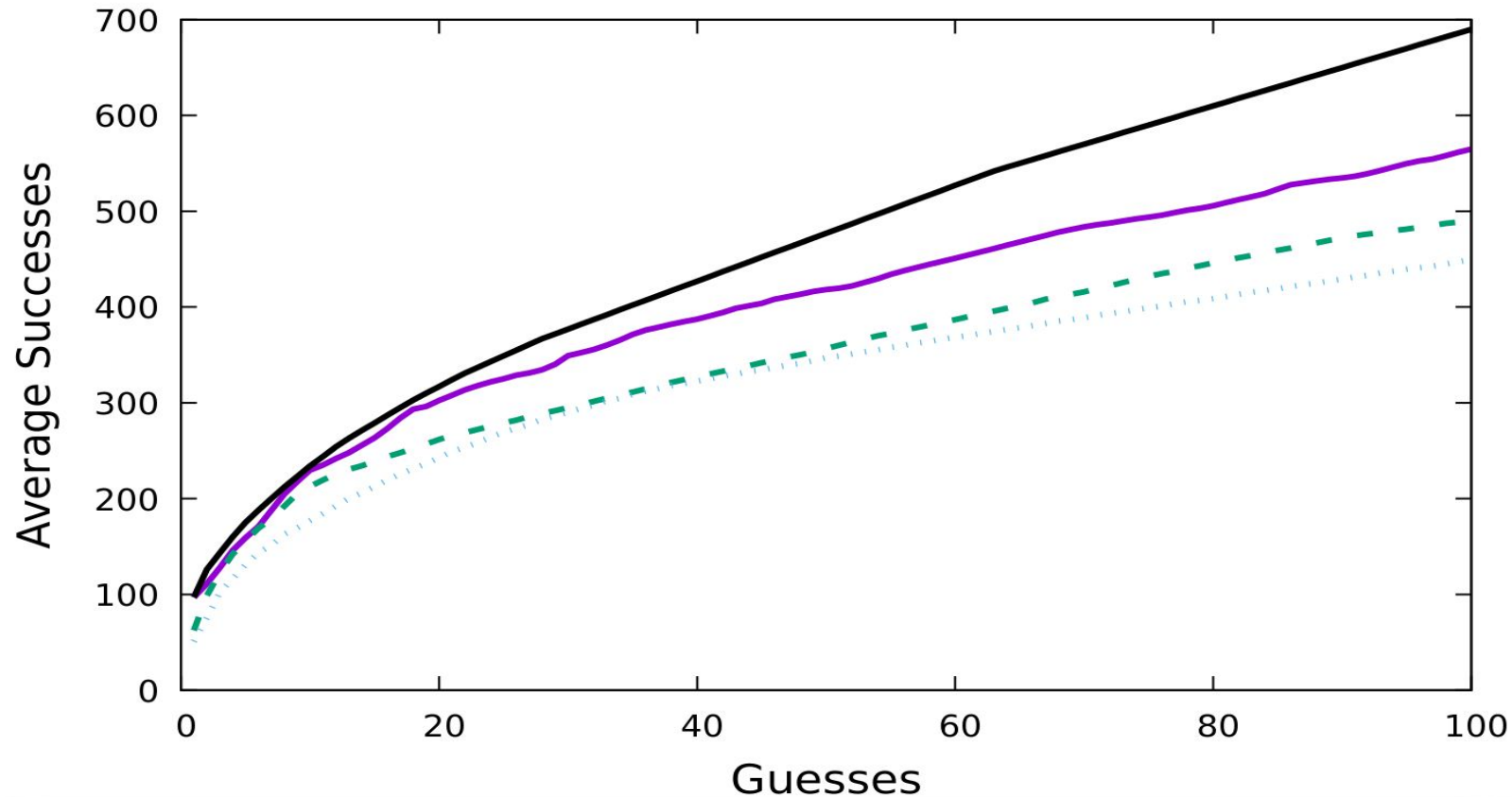
We created a simulated password set which is a sample of 10,000 users where

- 5500 came from hotmail.com
- 3000 came from flirtlife.de
- 1000 came from 000webhost.com
- 500 came from computerbits.ie

Estimation of dictionary weightings



Guessing success



— Optimal

— Q method

- - - Best (exploit)

· · · Random (explore)

Impact

- Guessing improvement - particularly relevant to online attackers who could use the learning in **automated guessing**.
- Discourage **Users** from choosing passwords related to the website name or type.
- Because we can automate the recognition of these patterns, this could be used to inform **password strength meters and blocklists**.

Thank
You



Hazel Murray hazel.murray@mu.ie
David Malone David.malone@mu.ie
Maynooth University, Ireland

Informing our guesses

The multi armed bandit is based on the principle of exploring and exploiting. In that sense we want to learn about all the different dictionaries we have while exploiting the most closely matching dictionary.

One advantage of our multi-armed bandit set up is that when we make a guess we learn something about all the dictionaries because the password we guess will occur with some proportion in all the dictionaries. That proportion could be zero and we have still learnt something.

Testing maximum likelihood

