Reducing Bias in Modeling Real-world Password Strength via Deep Learning and Dynamic Dictionaries

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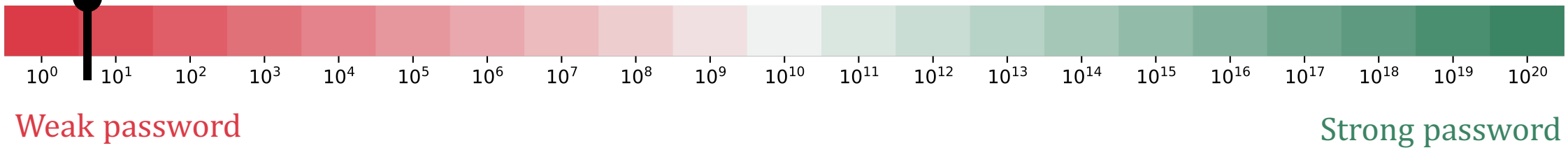
Password Security in a slide:

Adversary model

Guess number

(how many guesses A has to perform to guess it)

$$A(\text{"}pa\$\$w0rd!\text{"}) = 1123$$



Weak password

Strong password

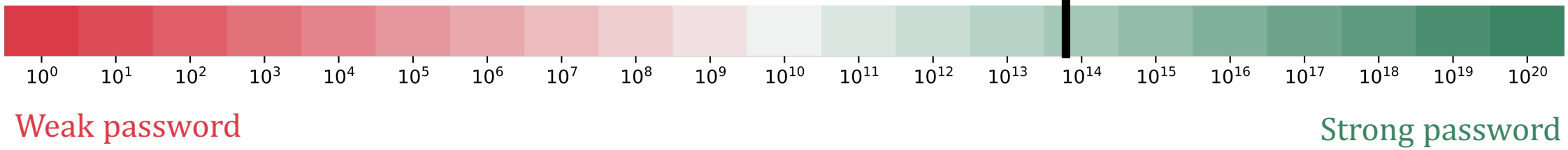
Password Security in a slide:

Adversary model

Guess number

(how many guesses ***A*** has to perform to guess it)

$$\boldsymbol{A}(\text{"}7H1d6{\sim}3.qA\text{"}) = \mathbf{10^{14}}$$

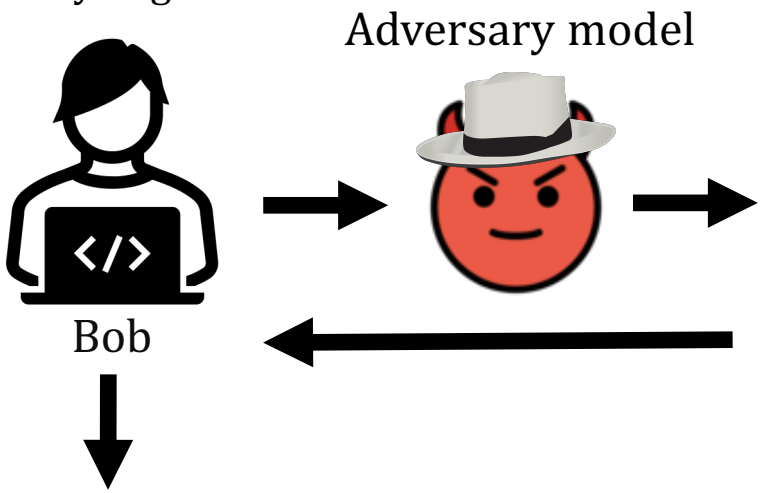


Weak password

Strong password

Why measuring password strength?

e.g., system administrator/
security engineer:



Questions Bob must answer:

- Should I make the hash function more expensive? (e.g., increasing the work–factor)
- Should I impose a different password composition policy?
- Is this new password composition policy making users choose stronger passwords?
- etc..

Real password cracker:

Reality check:

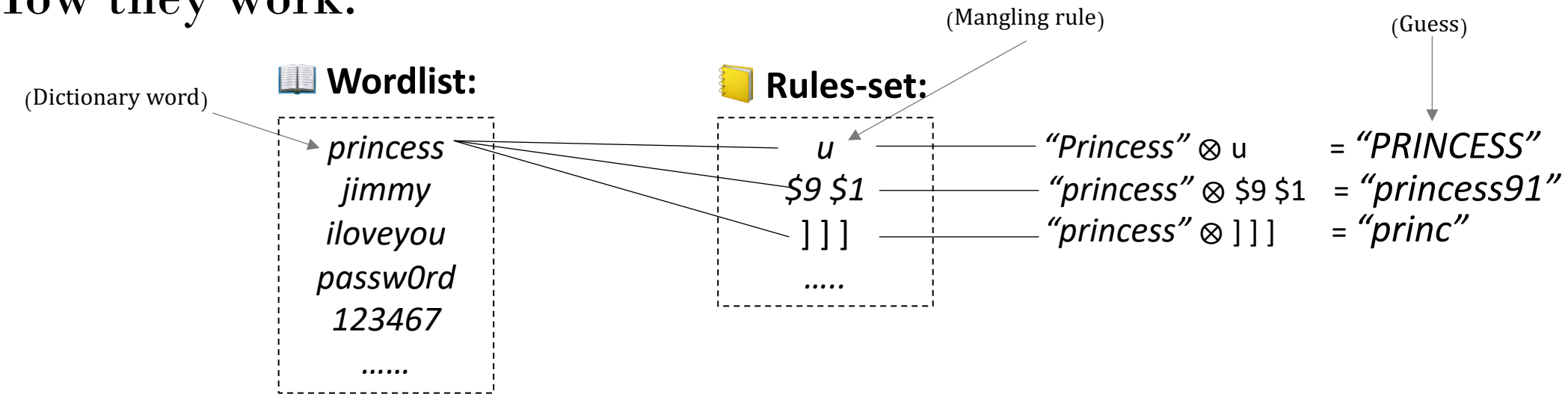
Our model of the **real-world password cracker**

The **real-world password cracker**

[1] *Measuring Real-World Accuracies and Biases in Modeling Password Guessability*, Ur et al. USENIX Sec 15

Dictionary attacks with Mangling rules:

- How they work:



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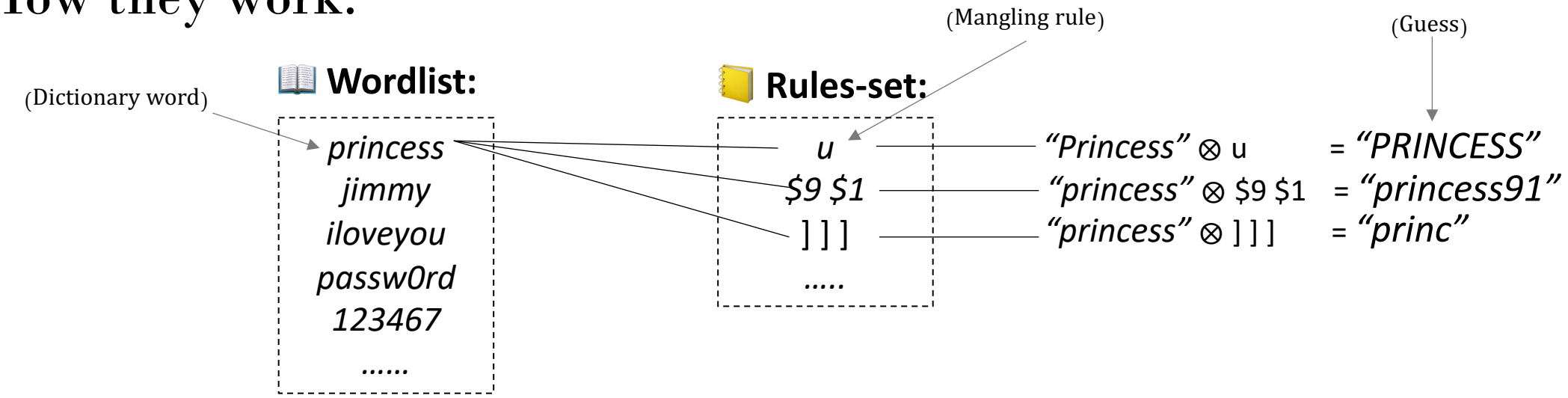
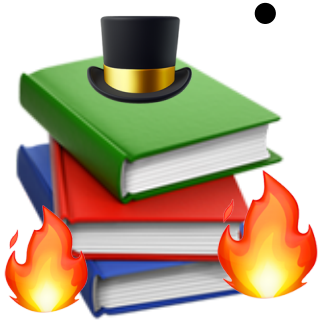


- Why Dictionary attacks are so important:
  - **Password crackers use Dictionary Attacks:**
    - **Dictionary Attacks** are fast (offline attacks are also about time)
    - **Dictionary Attacks** are flexible (every target is different)

A real Dictionary Attack:

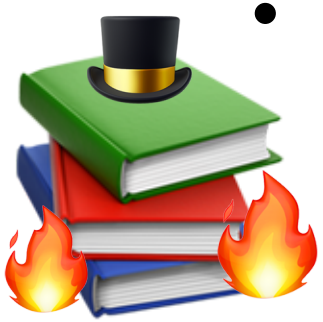


- Real-world password crackers:
  1. Use **optimized setups:**
     - Carefully chosen Word-lists
     - Carefully crafted Rules-sets

Manual processes that require a profound domain knowledge.

  2. **Manually tailor** the setup for the very **target:**
     - Collect information on the target before the attack
     - Tune in consideration of the initial passwords guessed during the attack

A real Dictionary Attack:



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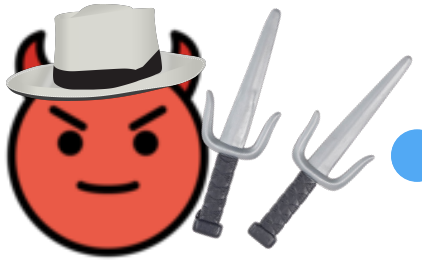
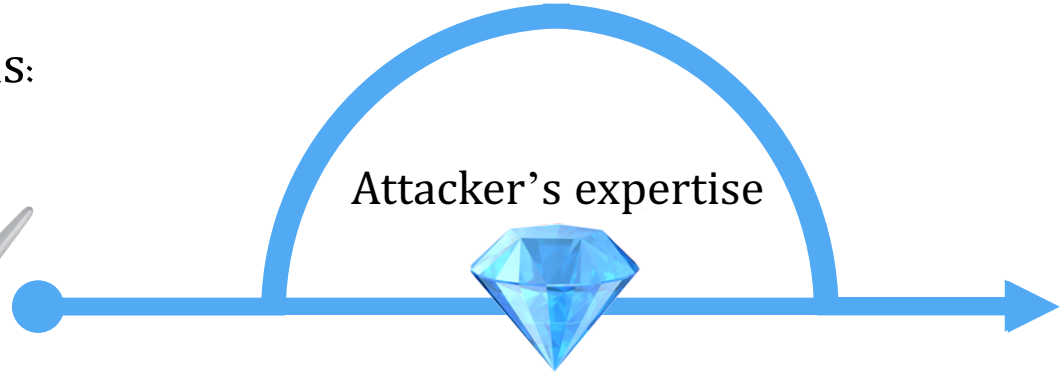
UNDERESTIMATION

Let's fill the gap

Trying to get from this:





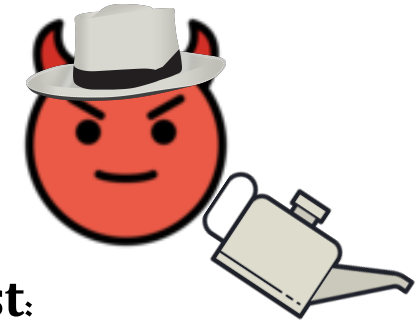
To this:

How we do it:

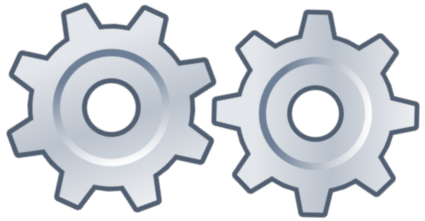
1. **Adaptive Mangling Rules**
(simulate high-end configurations)
2. **Dynamic Dictionary** (hits-recycling)
(simulates customized setups for the target)

On the functional interaction between rules-set and dictionary:

Adaptive Mangling Rules:



Wordlist:

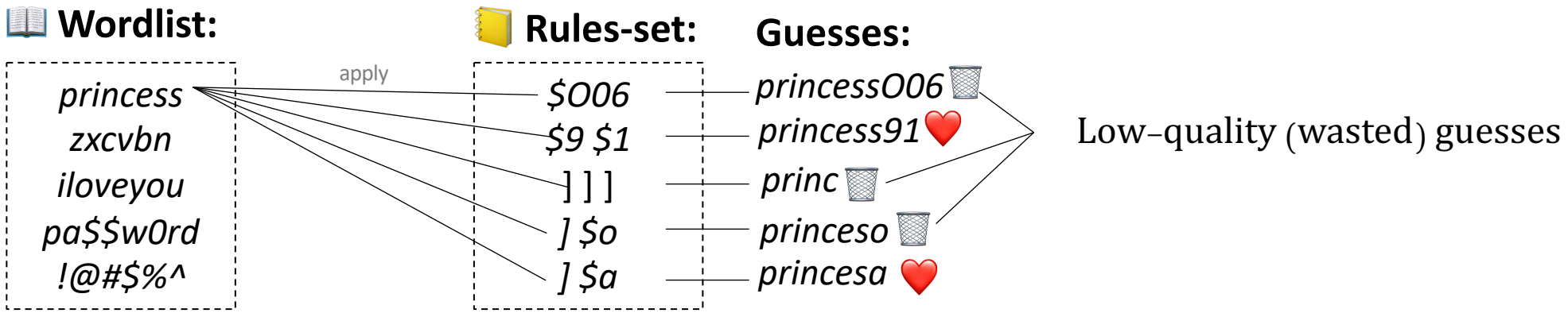


Rule-set:

The idea: It is a good attack if the **wordlist and the rule-set work well together**

Optimizing compatibility between Wordlist and Rule-set

- Not all the rules equally interact with all the dictionary words:



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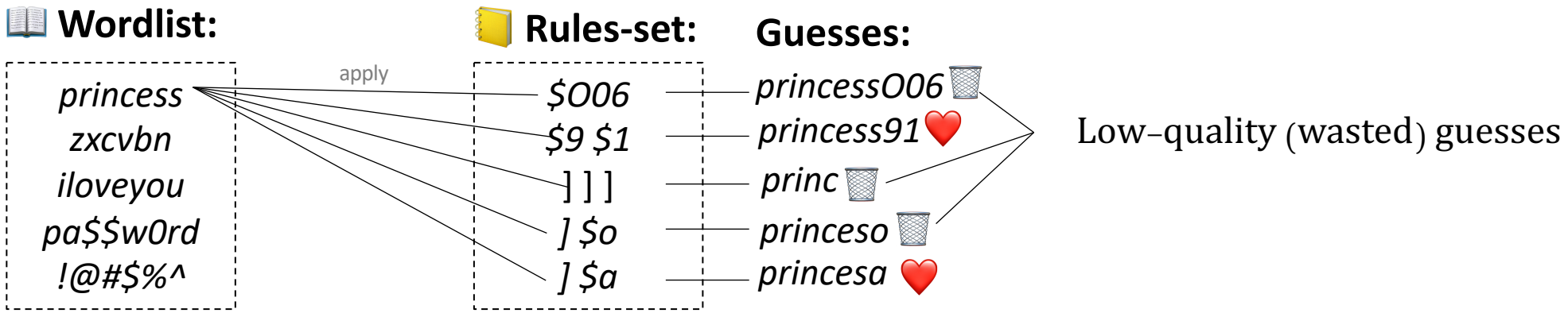
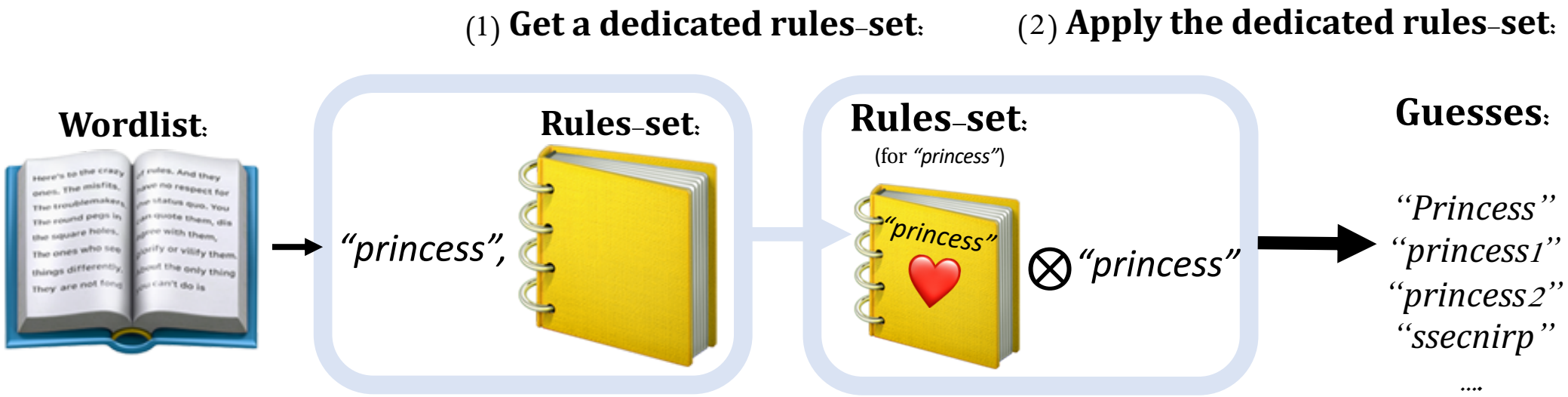


- In unoptimized setups, most of the guesses are generated by low-compatibility pairs (rule/word).
- **Most of the generated guesses have very low-quality!**

Adaptive Mangling Rules: The idea

- Every word from the dictionary gets its own rules-set:



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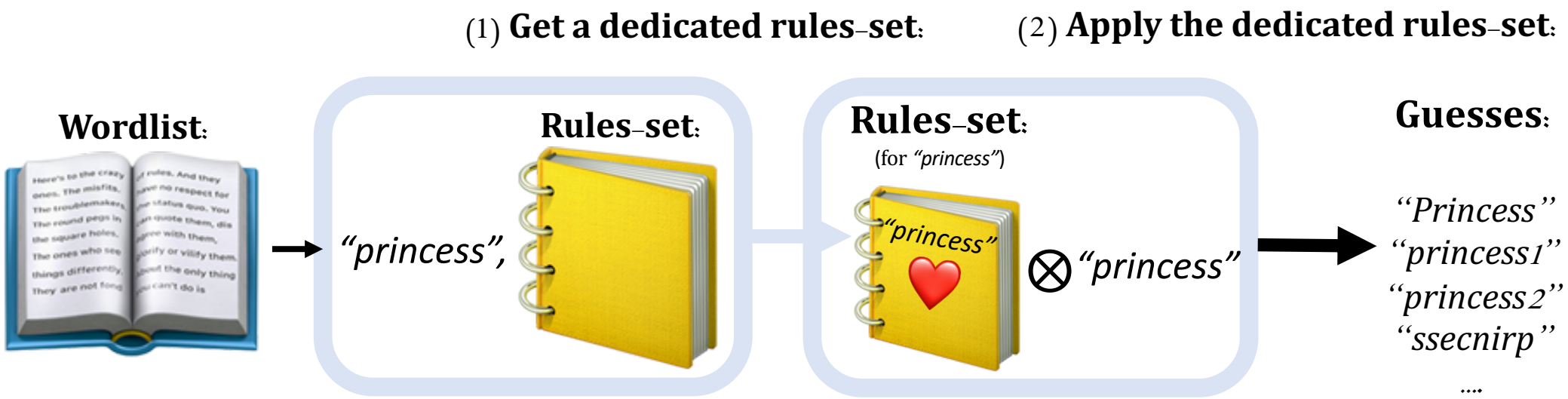
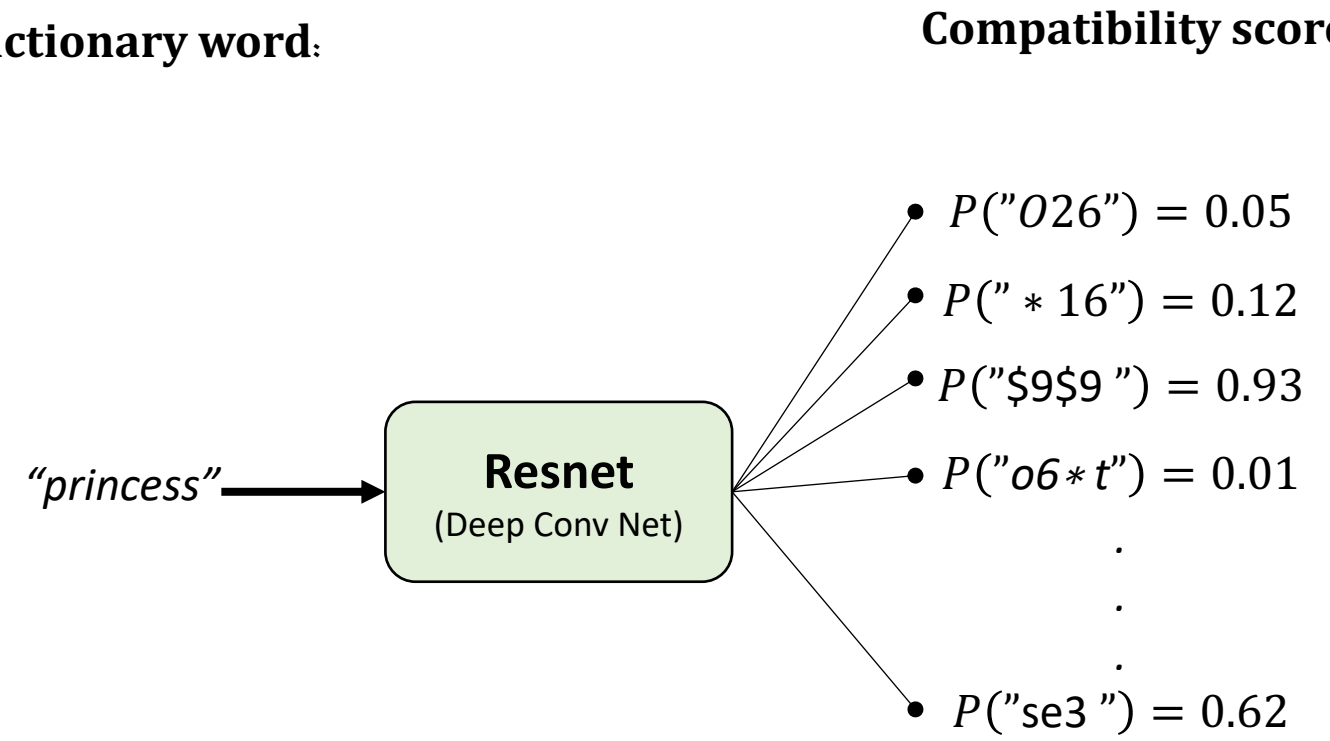


- 🏃 **It works at run-time!** (we'll see why later)

- Let's model rule/word compatibility with a **Deep Neural Network**
  - It's a multi-label classification task (each mangling rule is a class)
  - A rule-set is fixed (e.g., *generated2.rule*) and the network outputs a "*compatibility score*" for each rule in the set with a single inference.



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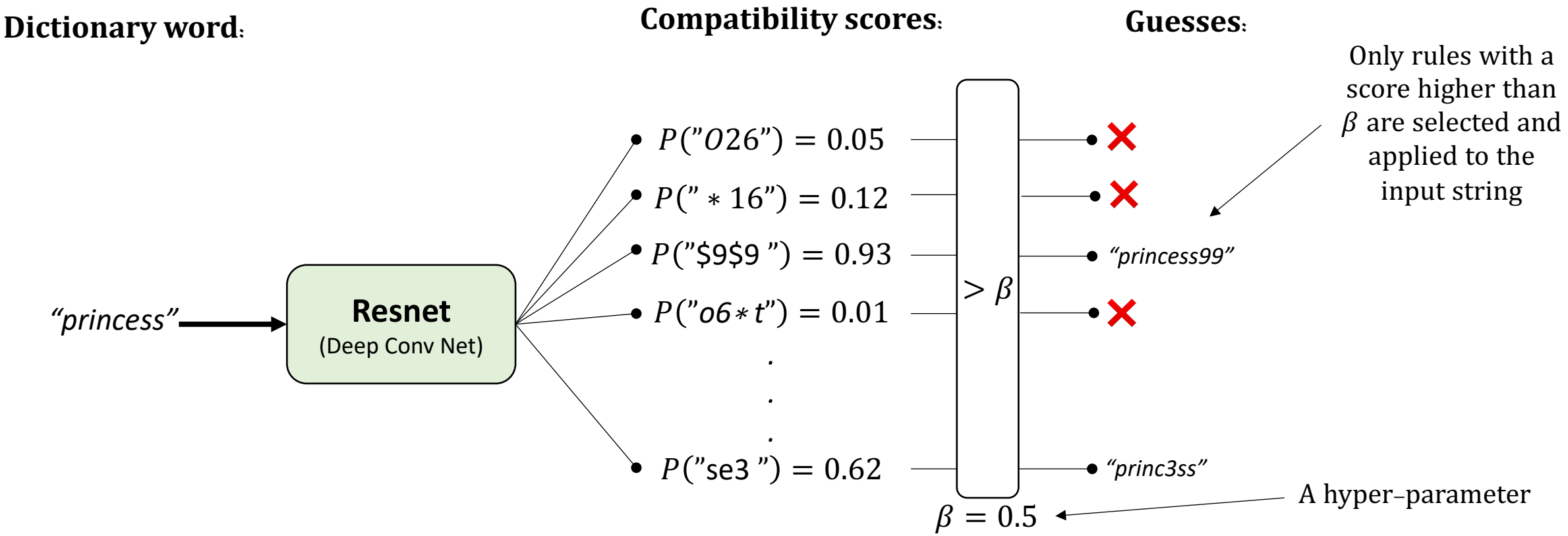
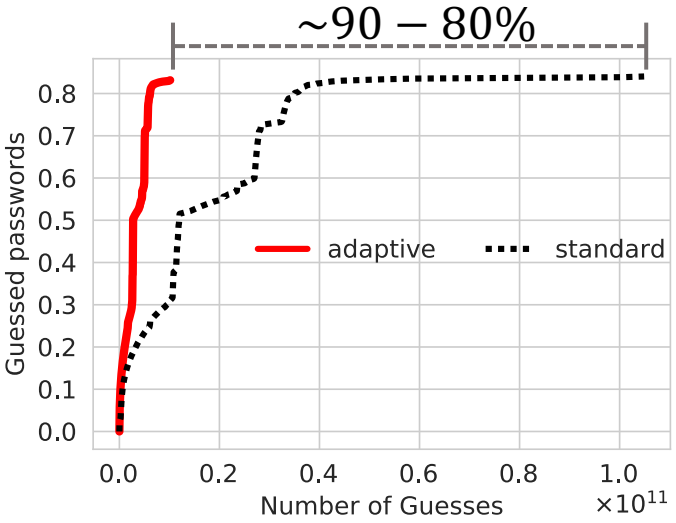


Is it Effective? An example:

Setup:

- **Rule engine**: *HashCat*
- **Wordlist**: *MyHeritage.com*
- **Rules-set**: *InsidePro-PasswordsPro* (3120 rules)
- **Target**: *animoto.com*

Performance gain:



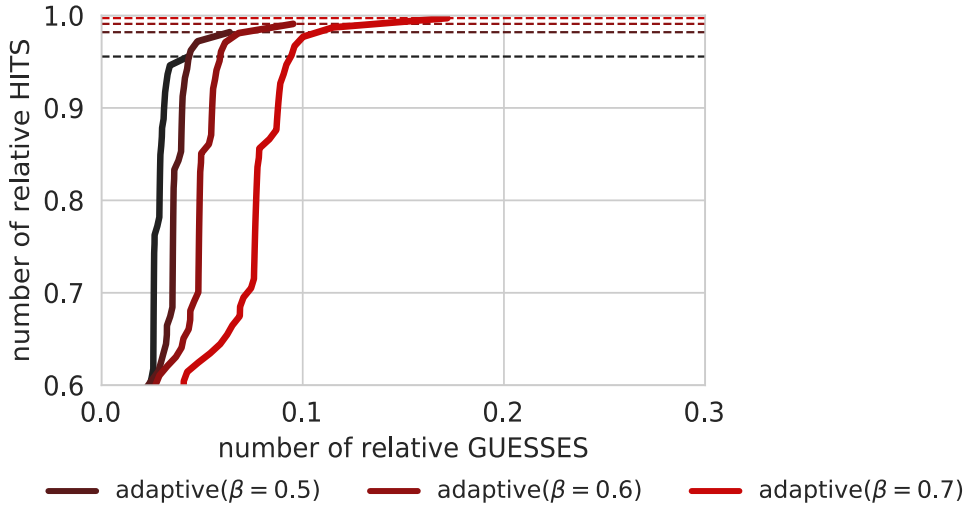
- It's also fast:

Numbers of compatibility scores per second (*On a NVIDIA V100*):

generated2.rule	*generated.rule*	*PasswordPro.rule*
#rules: 64528	#rules: 14424	#rules: 3120
1.528.346.738 c/s	**611.793.885 c/s**	**164.854.041 c/s**

Intrinsic parallel + It can run on tensor cores
(totally idle during the hash computation on GPU).

The effect of β:



♻ Hits-Recycling: Simple, yet effective

- Passwords created under the same environment (e.g., webapp) are not independent from each other.
- Therefore, the passwords you guessed during the attack can easily bring you to guess new related passwords that occur in the target.

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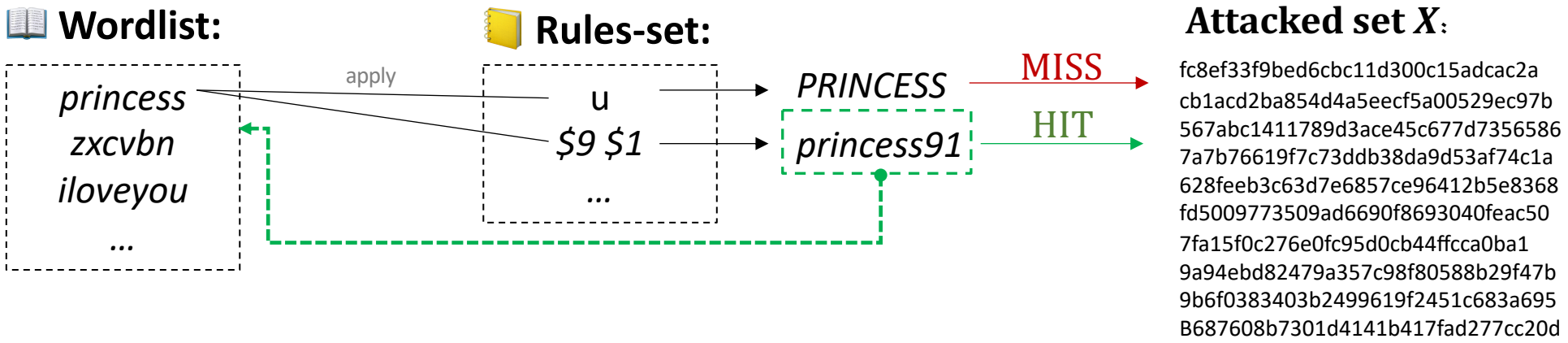
- **Hits-Recycling: The wordlist is dynamically augmented with the passwords guessed during the running attack.**



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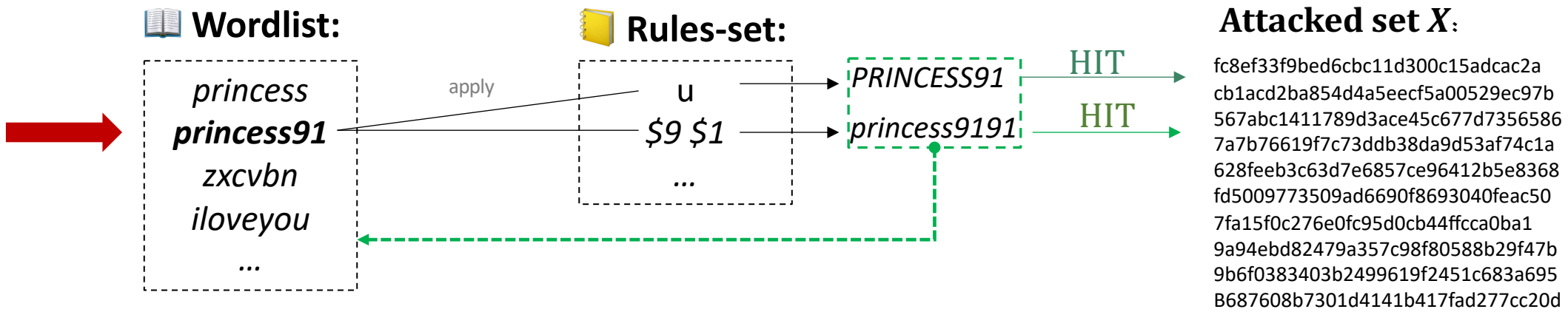
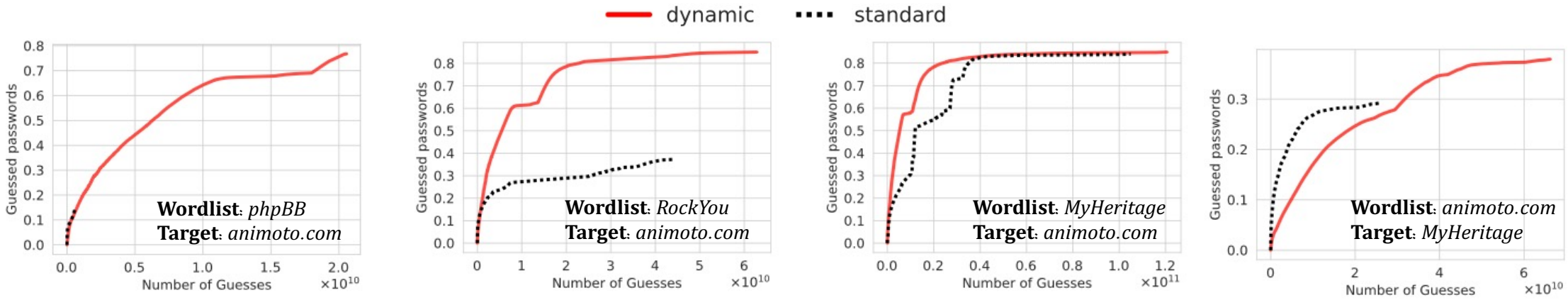


Hits-Recycling: the Effect



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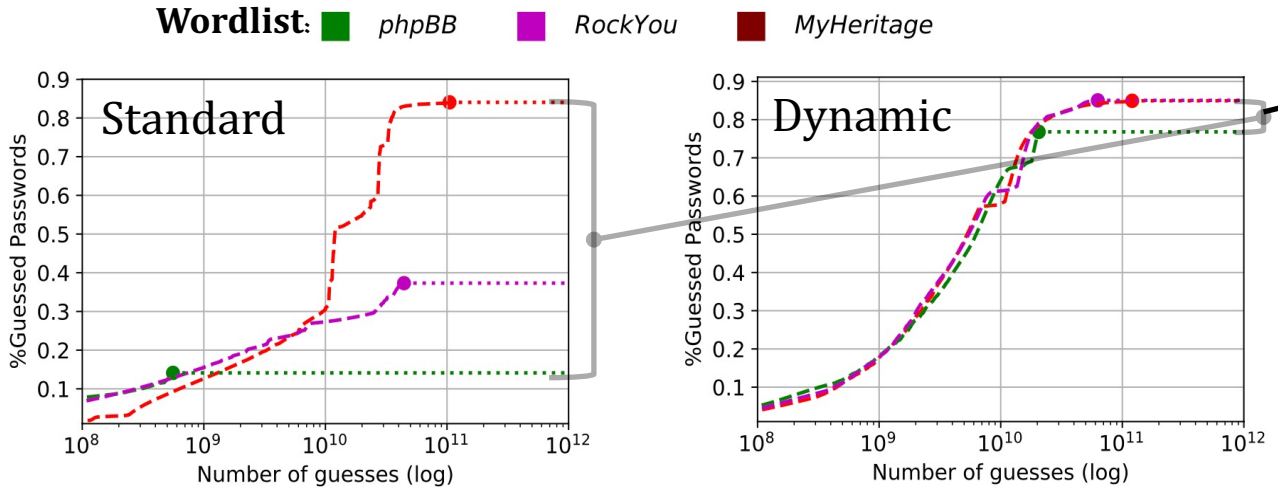

Reduces performance variance.

Setup:

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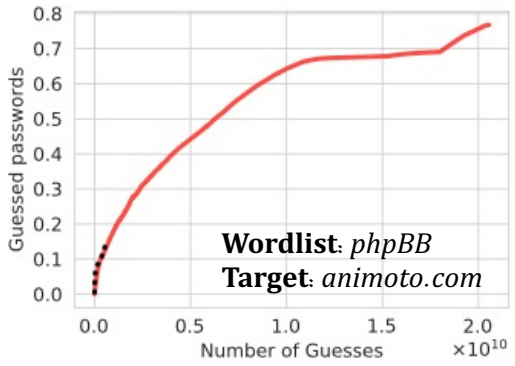
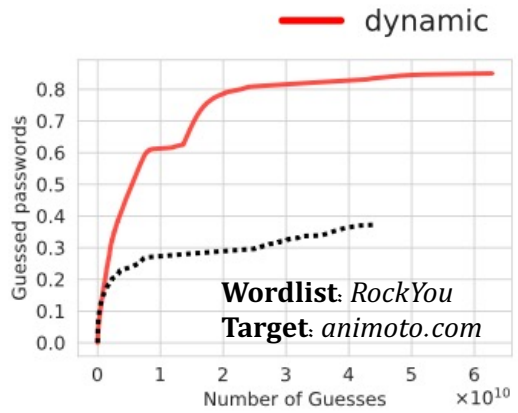
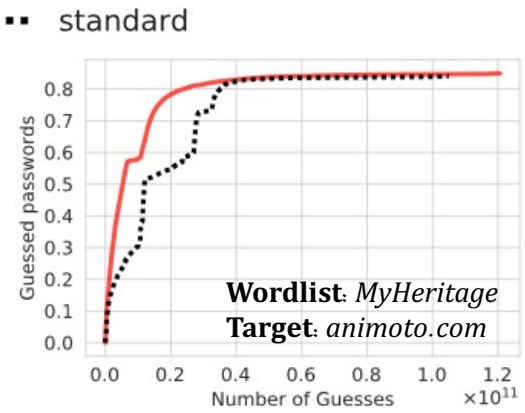
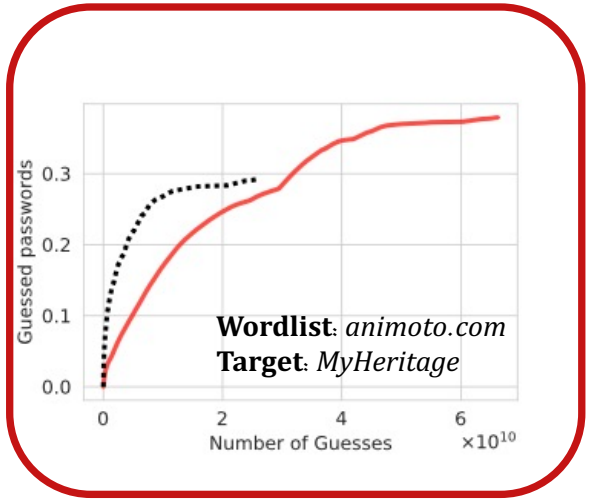
Hits-Recycling: the Effect









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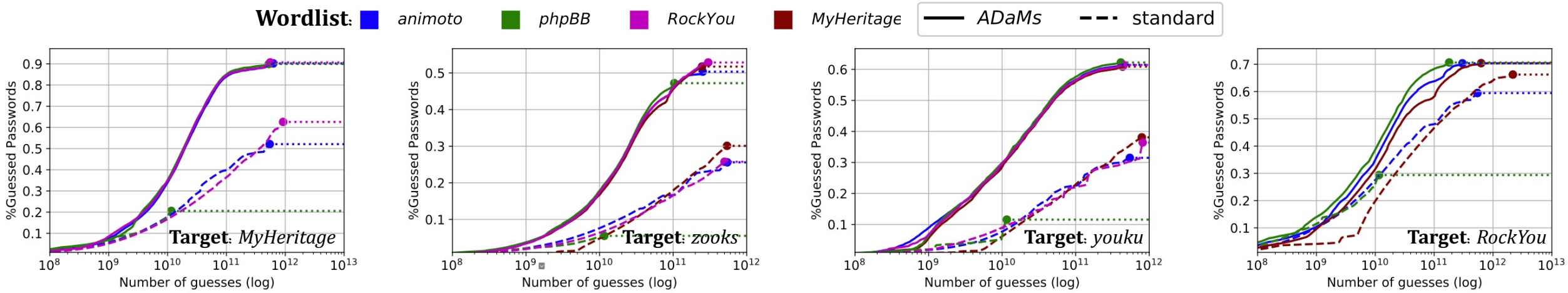
Fixing Hits-Recycling with the **Adaptive rules**

- Hits–recycling + Adaptive Rules = **Adaptive, Dynamic Mangling rules** (***ADaMs***).
- Adaptive mangling rules offers a run–time optimization for the **dynamic created dictionary**.

***ADaMs* vs Standard** attack with same configuration (rules–set/dictionary):

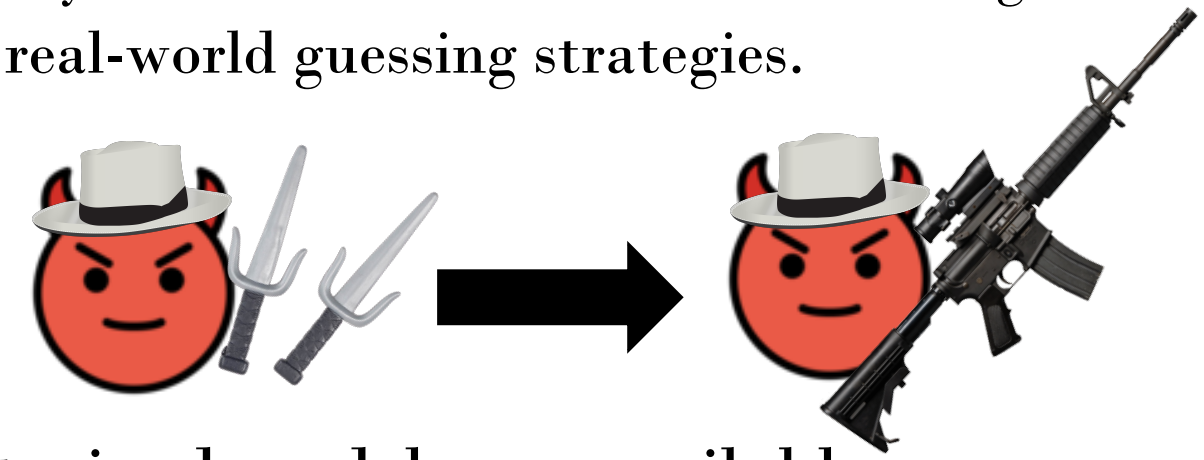


Rules–set: *generated2* (64528 rules)

Conclusion:

The proposed techniques:

- Make dictionary attacks more resilient to misconfigurations.
- Get closer to real-world guessing strategies.



- The code and trained models are available.

Use it instead of plain dictionary attacks in our security analysis!

https://github.com/TheAdamProject/adams

Thanks for your Attention!

For any questions: pasquini@di.uniroma1.it

We are working on a full–fledged (GPU–based) implementation with additional modules:

Adam, The First Cracker