# Using Probabilistic Context-Free Grammar to Create Password Cracking Tools

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#### Introduction

- Text-based password
  - Most common form of authentication
  - Passwords are reused or use common patterns and word
- Database leaks or hacks
- Guessing models
  - Data-driven
  - Exploits regualities seen in samples
- Probabilistic Context-Free Grammar Guessing Models
  - O Are they efficient?

#### Outline

- Background
  - Password data leaks
  - Probabilistic context-free grammar
  - Other password cracking models
- Semantic PCFG
  - Definition
  - Password modeling example
  - Testing and results
- Chunk-Level PCFG
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- Conclusion

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## Background - Password Data Leaks (English)

#### RockYou

- Data breach in 2009
- o 32 million passwords

#### LinkedIn

- Originally hacked in 2012, more information was released in 2016
- 162 million passwords

#### 000webhost

- Hacked in 2015
- 13 million passwords

#### CitOday

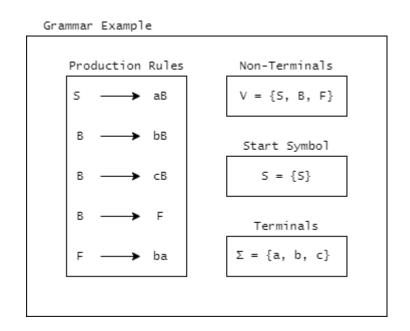
- Data breach in 2020
- o 200 million passwords

## Background - Password Data Leaks (Chinese)

- CSDN
  - Hacked in 2011
  - o 6 million passwords
- 178
  - Hacked in 2011
  - o 9 million passwords

## Background - Context-Free Grammar

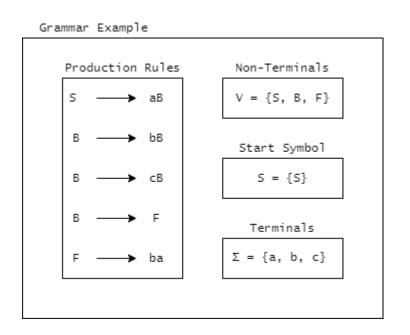
- Generates strings from given language
  - Sentences from English language



## Background - Context-Free Grammar

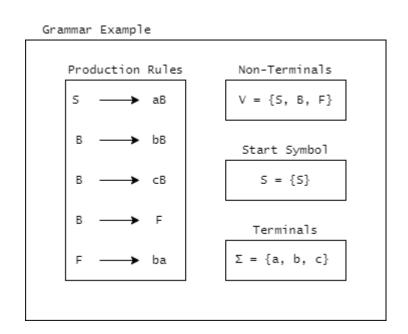
- Generates strings from given language
  - Sentences from English language
- Example:

String	PR
S → aB	
→ abB	(B → bB)
→ abcB	(B → cB)
→ abcbB	(B → bB)
→ abcbF	(B → F)
→ abcbba	(F → ba)



## Background - Probabilistic Context-Free Grammar

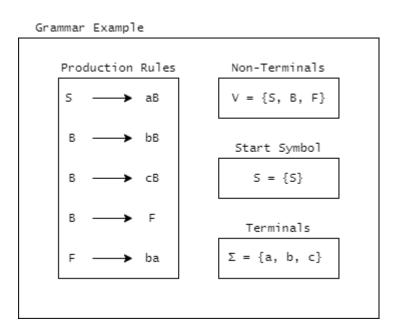
- Extension of Context-Free Grammar
- Adds probability factor to production rules
- Production rules and probability are determined by a training data set



## Background - Probabilistic Context-Free Grammar

#### Example:

String	PR	Probability		
S → aB		1.00		
→ abB	(B → bB)	0.50		
→ abcB	$(B \rightarrow cB)$	0.25		
→ abcbB	(B → bB)	0.50		
→ abcbF	$(B \rightarrow F)$	0.25		
→ abcbba	(F → ba)	1.00		



## Background - Password Cracking Models

- Controls models for testing the efficiency
  - First PCFG model (Weir et al.)
    - Breaks down passwords in to character classes
    - Does not use word segmentation
  - Enhanced PCFG (Komanduri)
    - Word segmentation
    - Learn fulls passwords as terminals
  - Neural Network (Melicher et al)
    - Long short-term memory

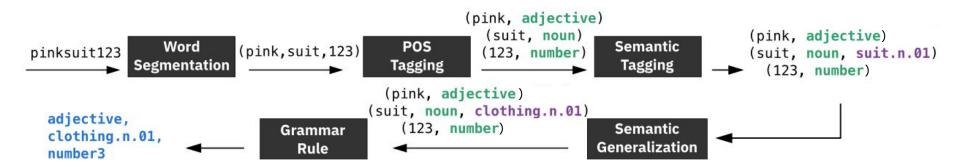
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#### Semantic Definition

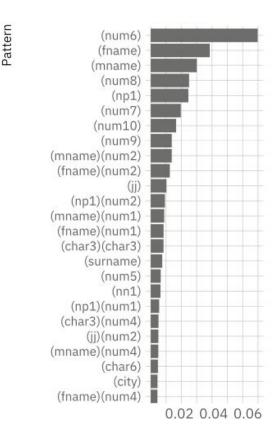
- Parts-of-speech and semantics
- Training the grammar
  - Text processing pipeline
  - Semantic generalization
  - Does not classify misspellings or substitutions
- Probability
  - Maximum length estimation (MLE)
    - The more frequent a production rule is seen, the higher the probability
  - Terminal smoothing to deter overfitting
    - Laplace formula

## Semantic - Password Modeling Example



## Semantic - Password Modeling

- Top grammar rules from RockYou
- Parts of speech tags (CLAWS7)
  - o **np** singular proper noun
  - o **ii** adjective
  - o mname/fname male/female name
  - o **char** unidentified words or symbols
  - o **num** number
  - -# amount of objects
    - Ex: (num6) = 123456, 132436

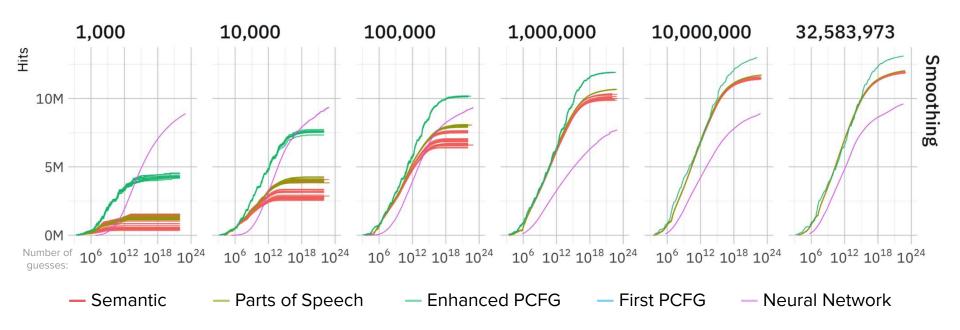


Source: Veras et al, 2021

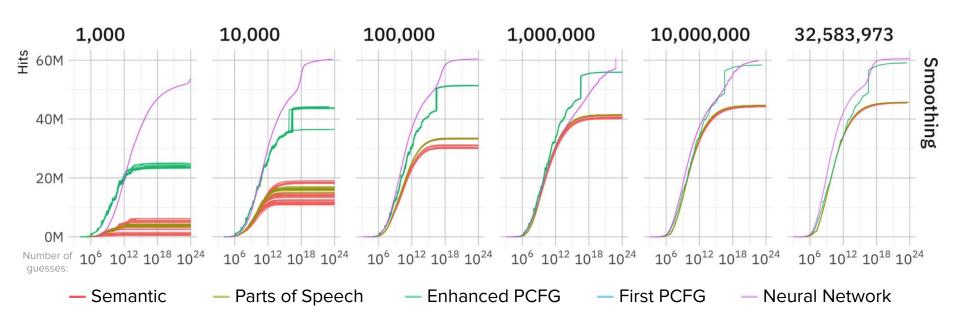
## Semantic - Testing

- Models trained on multiple size samples
  - 0 1,000 | 10,000 | 100,000 | 1,000,000 | 10,000,000 | 32,583,973
- Tested the model with different levels semantic accuracy
- Tested the model without semantic tagging (parts of speech)
- Tested the model with and without terminal smoothing

#### Semantic - Results from 000webhost



#### Semantic - Results from LinkedIn



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#### Chunk-Level - Definition

- Password specific segmentation
  - Extend the Byte-Pair-Encoding algorithm
  - Merges character pairs, then creates vocabulary
- Probability
  - Maximum length estimation

## Chunk-Level - Password Modeling Example

#### Input

password: frequency



#### Merge operation

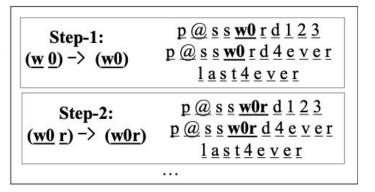
repeat the step iteratively until avg  $len \ge threshold$ 



#### Vocabulary

 $avg\_len = 4.5$ 

p@ssw0rd123:4 p@ssw0rd4ever:3 last4ever:2



<u>4ever</u> : 5	<u>1</u> : 2	<u>t</u> : 2	
p@ssw0rd123: 4	<u>a</u> : 2		
p@ssw0rd:3	<u>s</u> : 2		

# Chunk-Level - Password Modeling

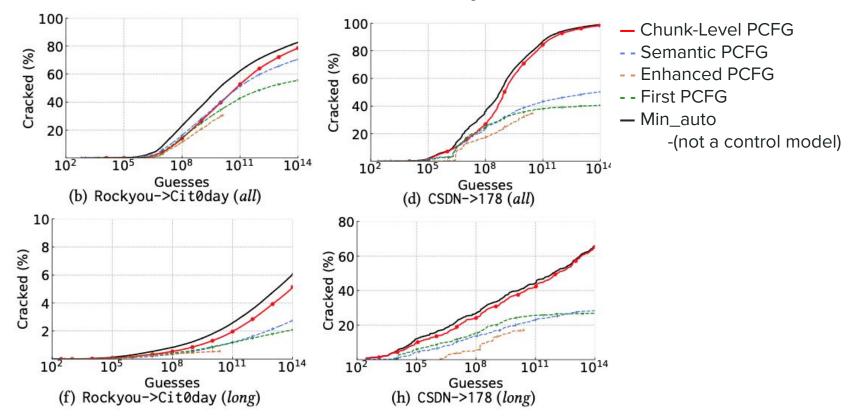
Rank	Rockyou		Cit0day		CSDN	
1	4ever	16,787	4ever	1,023	p@ssw0rd	356
2	love4ever	1,486	4me2	71	P@ssw0rd	353
3	2cute4u	1,145	s4me	67	4ever	289
4	4EVER	1,105	l0ve	61	l0ve	71
5	2hot4u	949	w00d	54	w0rd	30
6	sk8er	811	10v3	54	just4you	26
7	l0ve	764	w0rd	44	il0ve	19
8	il0ve	687	4Ever	42	p@ss	18
9	10v3	534	P@ssw0rd	40	pa\$\$w0rd	16
10	love4u	528	L0ve	39	P@ss	16

Top chunks with misspellings or substitutions

## Chunk-Level - Testing

- Trained on English and Chinese passwords
  - English passwords from RockYou leak
  - Chinese passwords from CSDN leak
- Models were ran on two samples
  - First test: all passwords leaked from CitOday and 178
  - Second test: passwords equal or longer to 16 characters from CitOday and 178

## Chunk-Level - Results from CitOday and 178



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#### Conclusion

- Newer PCFG models are becoming better at guessing passwords
- PCFG models are intended to identify weak passwords
  - Helps companies and users create stronger passwords
- The data leaks used to train and test these models are outdated

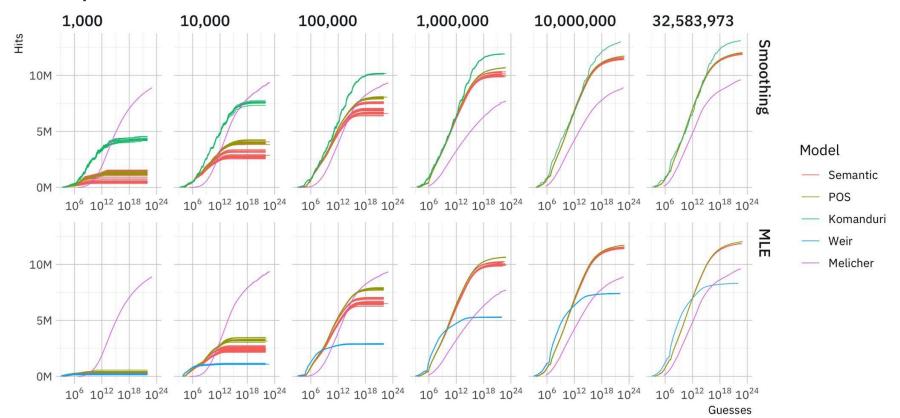
#### References

Rafael Veras, Christopher Collins, and Julie Thorpe. 2021. A Large-Scale Analysis of the Semantic Password Model and Linguistic Patterns in Passwords. ACM Trans. Priv. Secur. 24, 3, Article 20 (apr 2021), 21 pages. <a href="https://doi.org/10.1145/3448608">https://doi.org/10.1145/3448608</a>

Ming Xu, Chuanwang Wang, Jitao Yu, Junjie Zhang, Kai Zhang, and Weili Han. 2021. Chunk-Level Password Guessing: Towards Modeling Refined Password Composition Representations. In Proceedings of the 2021 ACM SIGSAC Conference on Computer and Communications Security (Virtual Event, Republic of Korea) (CCS '21). Association for Computing Machinery, New York, NY, USA, 5–20. <a href="https://doi.org/10.1145/3460120.3484743">https://doi.org/10.1145/3460120.3484743</a>

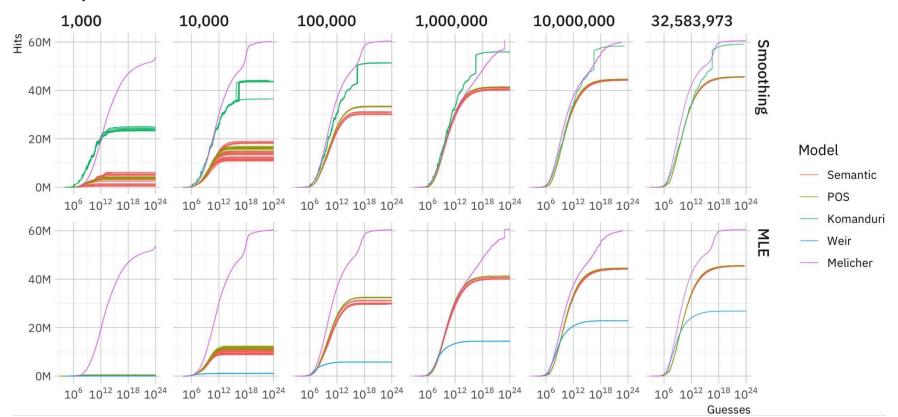
# Questions?

## Complete Results - Semantic PCFG 000webhost



Source: Veras et al, 2021

## Complete Results - Semantic PCFG LinkedIn



## Complete Results - Chunk level PCFG

