

Don't Skype & Type!

Acoustic Eavesdropping in Voice-Over-IP

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- Side Channels
 - *Eavesdropping physical emanations*
 - *Keyboard acoustic eavesdropping*

- Skype&Type Attack
 - *Design and setup*
 - *Evaluation*

- Conclusions and Future Work

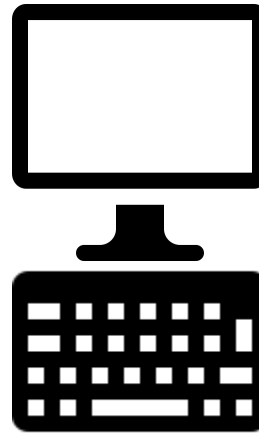
Physical Emanations



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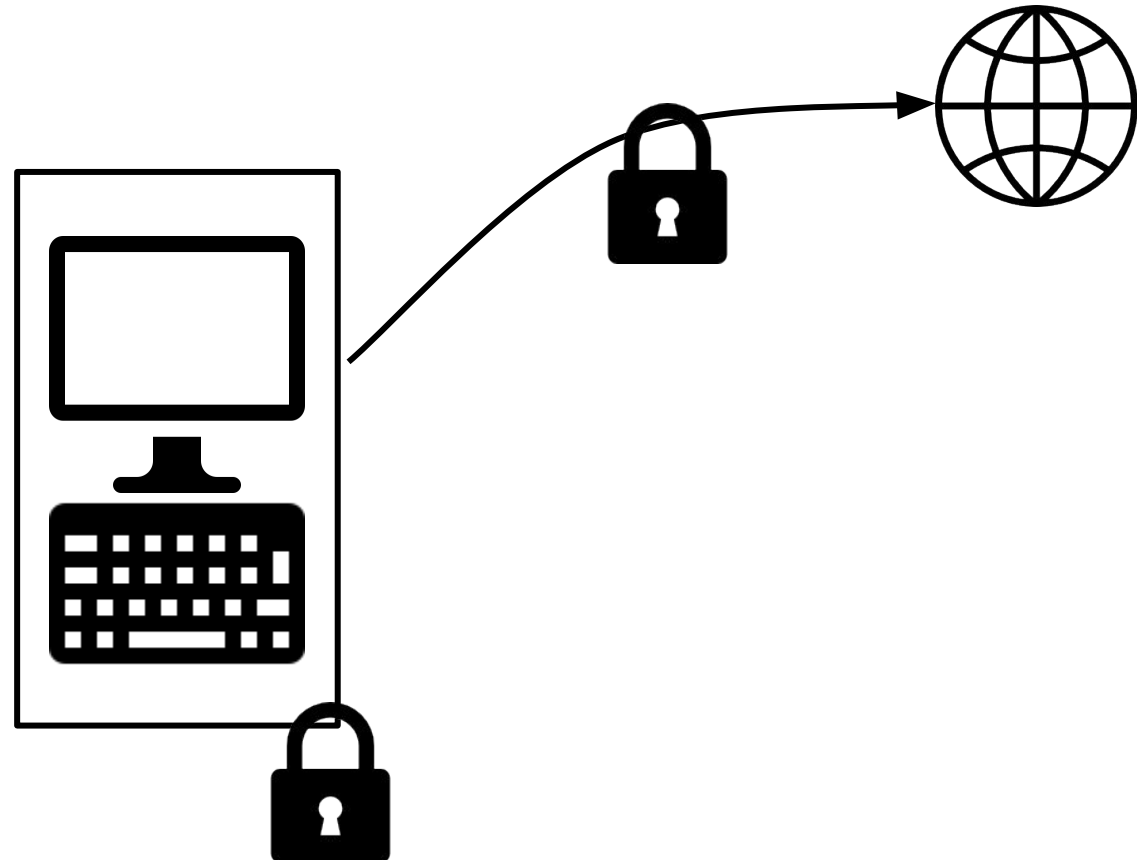
Physical Emanations



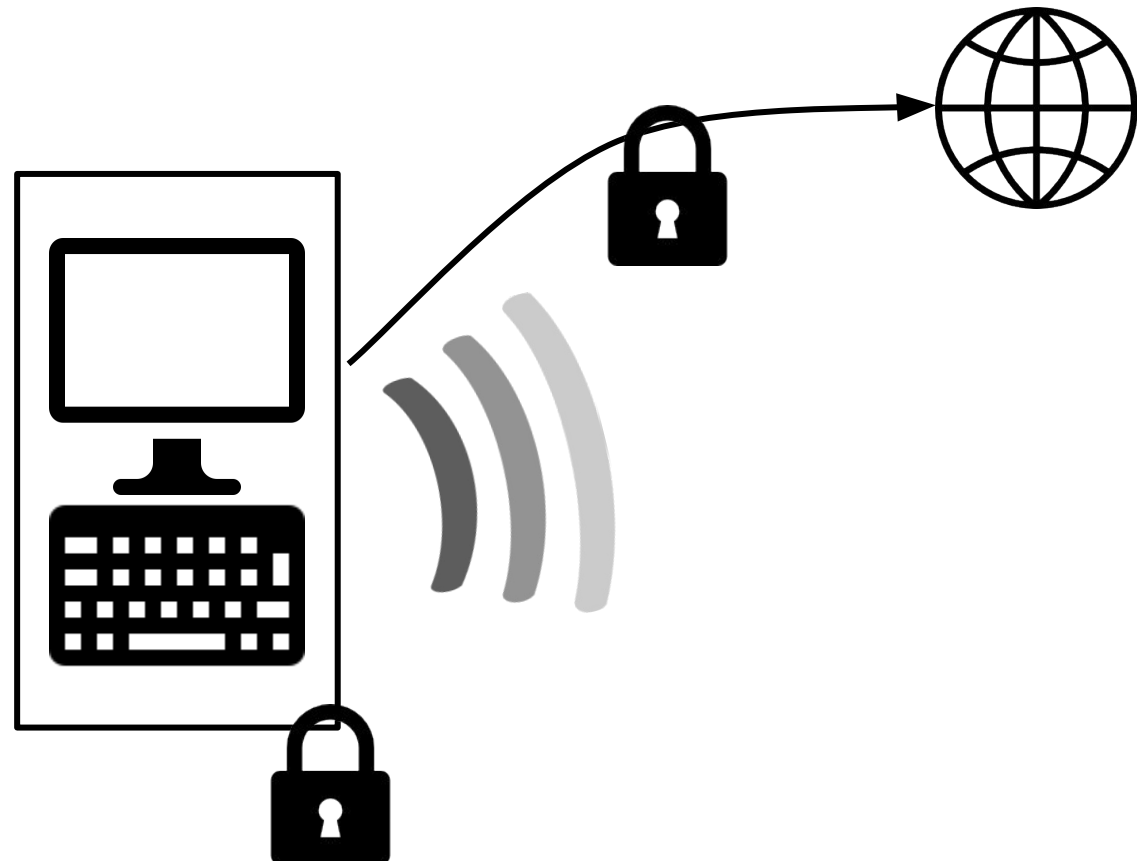
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- **Electromagnetic**
Data transmission
- **Visual**
Videos, reflections
- **Acoustic**
Hardware sounds
- **Tactile**
Motion sensors



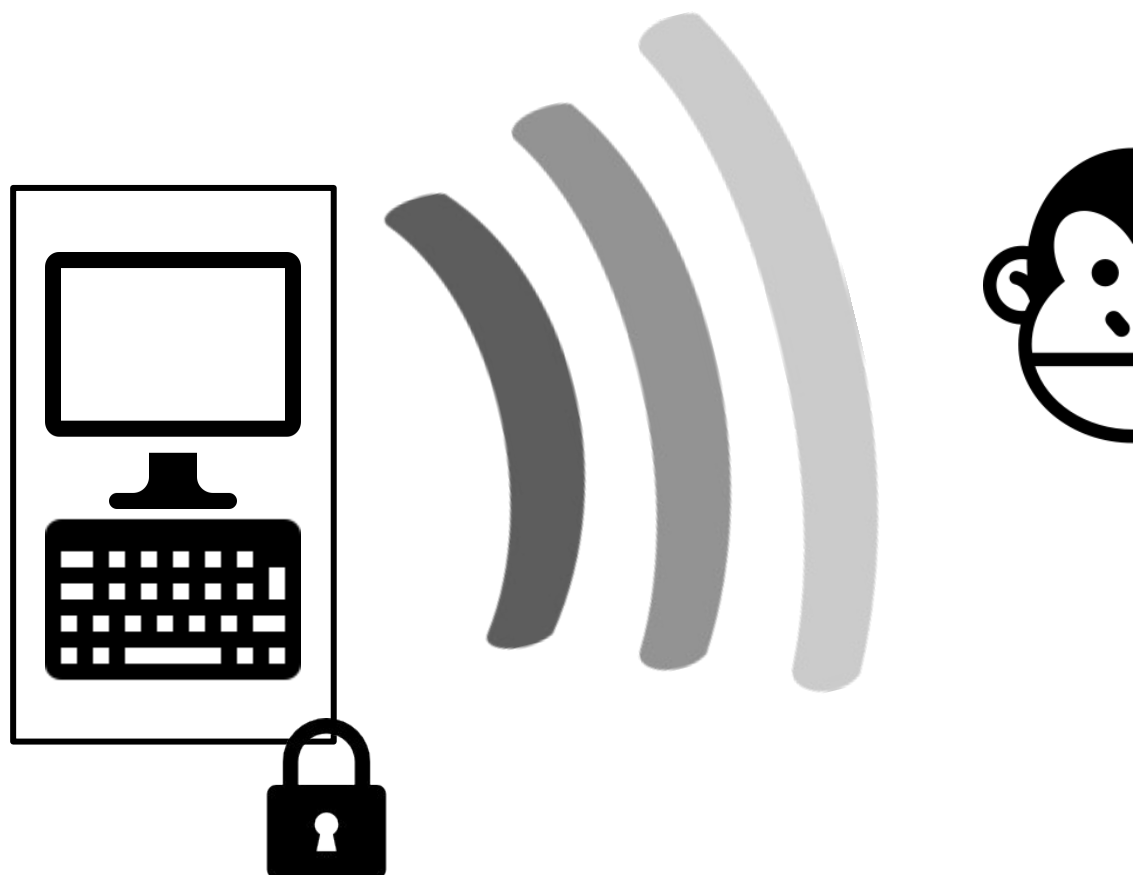
Physical Emanations Eavesdropping



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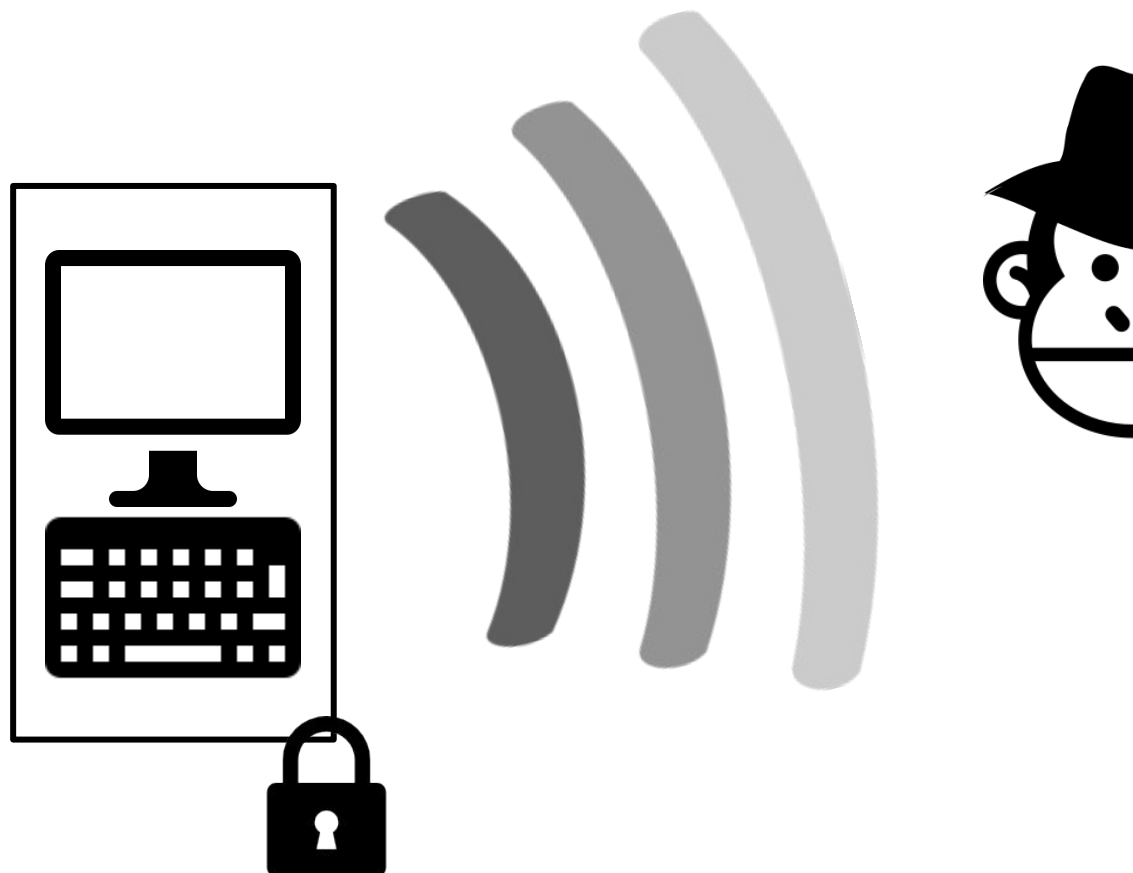
Physical Emanations Eavesdropping



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A convenient means to steal sensitive data

- Transmitting medium

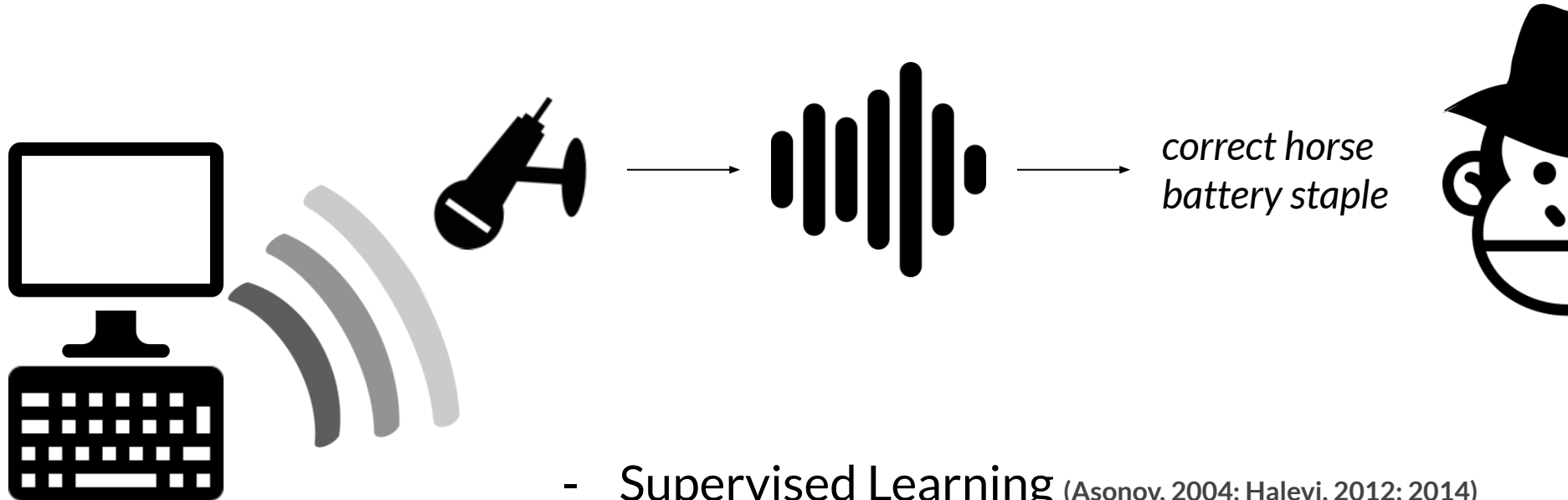
Network cables, wireless emanations, peripherals buses

- Input/output devices

Keyboards, touchscreens, monitors, printers

- Processing medium

CPUs, hard drives, RAM



- Supervised Learning (Asonov, 2004; Halevi, 2012; 2014)
Less input assumptions, more specific
- Unsupervised Learning (Berger, 2006; Zhuang, 2009)
More input assumptions, more general

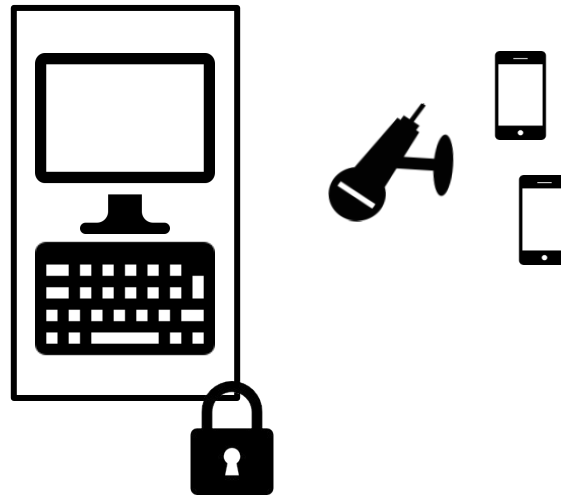
1) Precise training data - how?

vs.

Generic training data - *a lot, or in a known language (no passwords)*

2) Need physical proximity → unrealistic scenario

To place microphones / mobile phones





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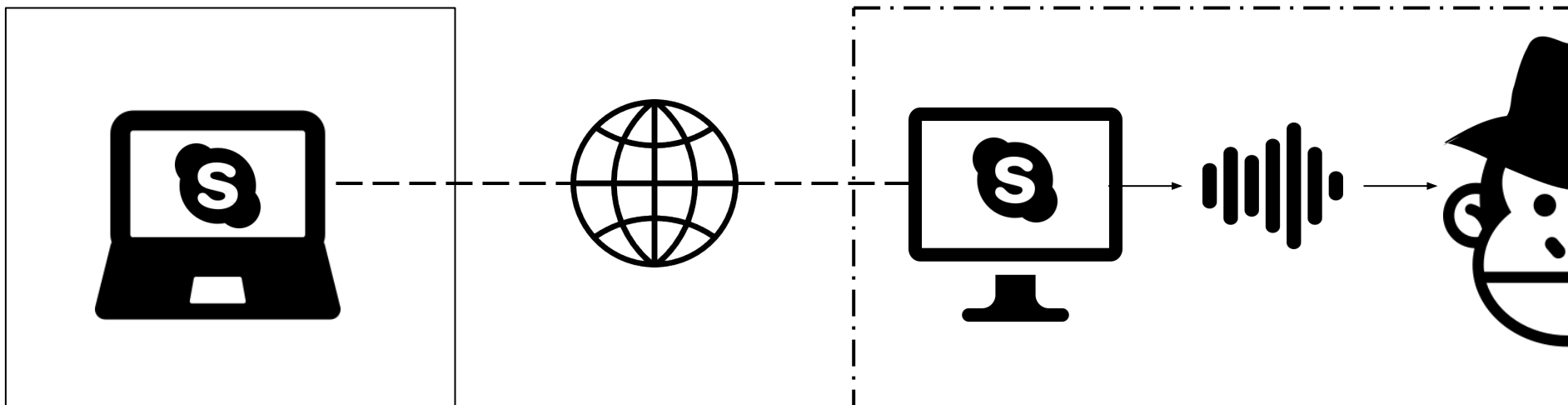
VoIP → one of the most used software: in academia, industry, at home

People type private stuff during Skype calls - it happens!

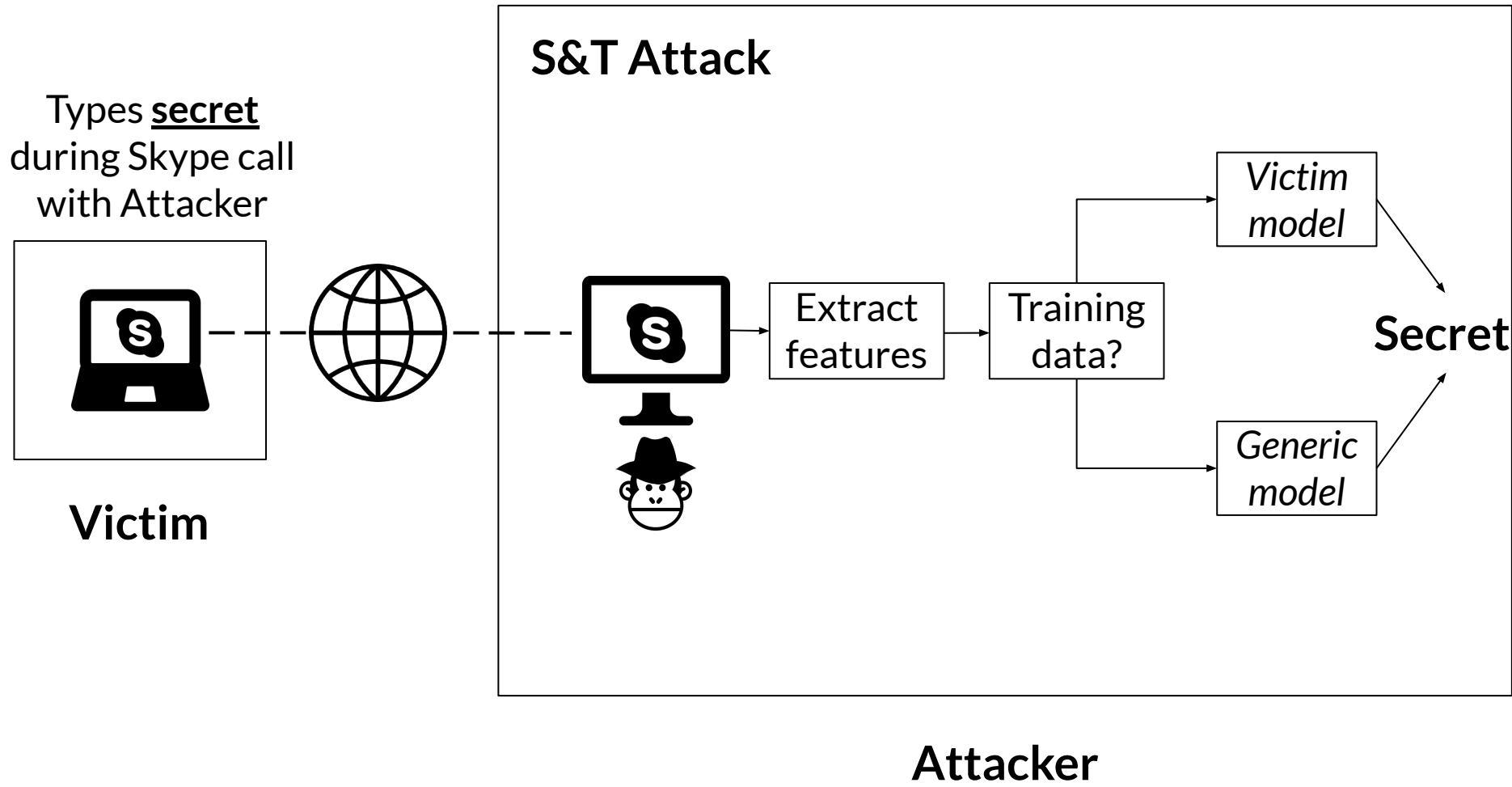
- *Login to websites*
- *Write a sensitive email*
- *Take notes*

We hear the keys' noise and use it to understand typed text

- *Victim is willingly giving us access to his microphone*



Skype&Type Attack



- Data windowing and segmentation

To extract sound samples

- Mel frequency cepstral coefficients

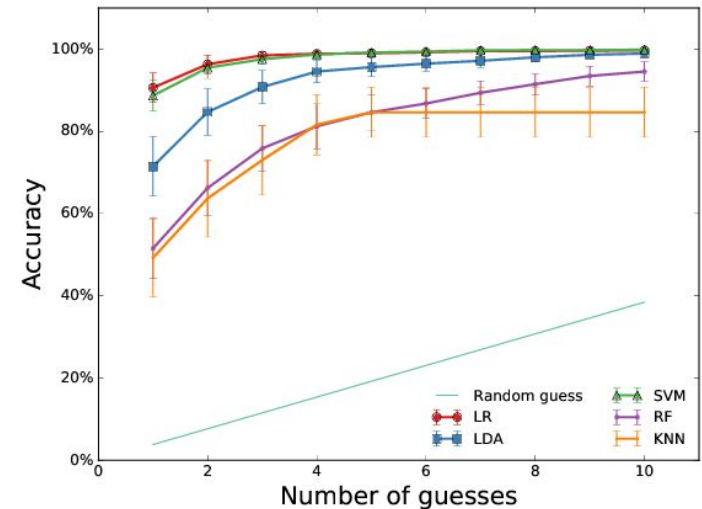
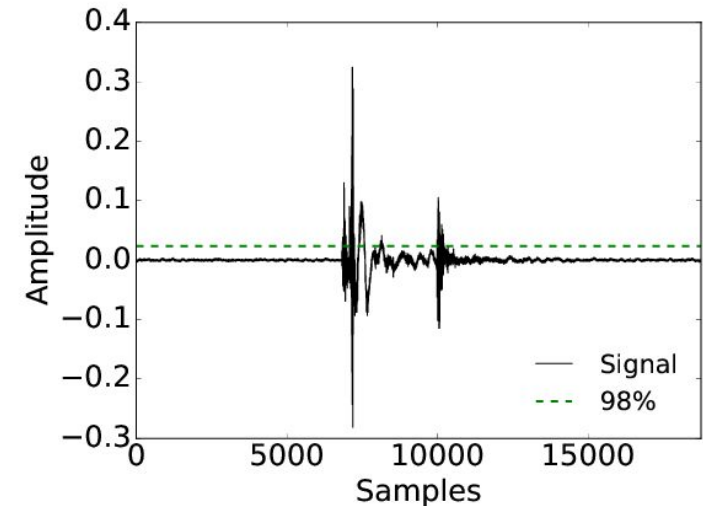
Best performing and robust

- Supervised learning paradigm

Target text can be possibly:

- *Short (no clustering)*
- *Random (no dictionary)*

- Logistic Regression classifier





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- Try S&T in many scenarios
 - With 5 different users over **Skype** (Google Hangouts also vulnerable)
 - Using 3 different common laptops: Macbook Pro, Lenovo, Toshiba
 - With 2 typing styles: single finger, and natural “touch” typing
- Evaluate top-n accuracy of character recognition
 - as a function of the number of guesses, focus on top-1 and top-5 accuracy*
- Against a “dumb” random guess
 - Might be a random password -- we can not use “smarter” approaches*

Evaluate the attack on two realistic scenarios

- **Complete Profiling Scenario** (Asonov, 2004; Halevi, 2012; 2014)
 - *Profiled the user on his laptop → specific training set*
 - *Ground truth disclosure, e.g., a short chat message*

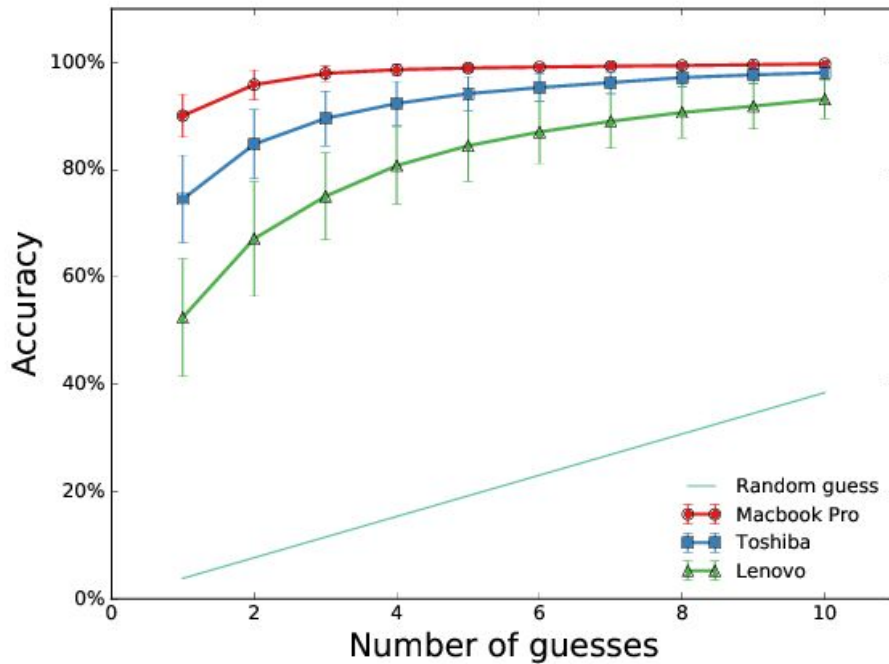
- **Model Profiling Scenario**
 - *Profiled a laptop of the same model on some users*
 - ***Victim is/can be unknown!***



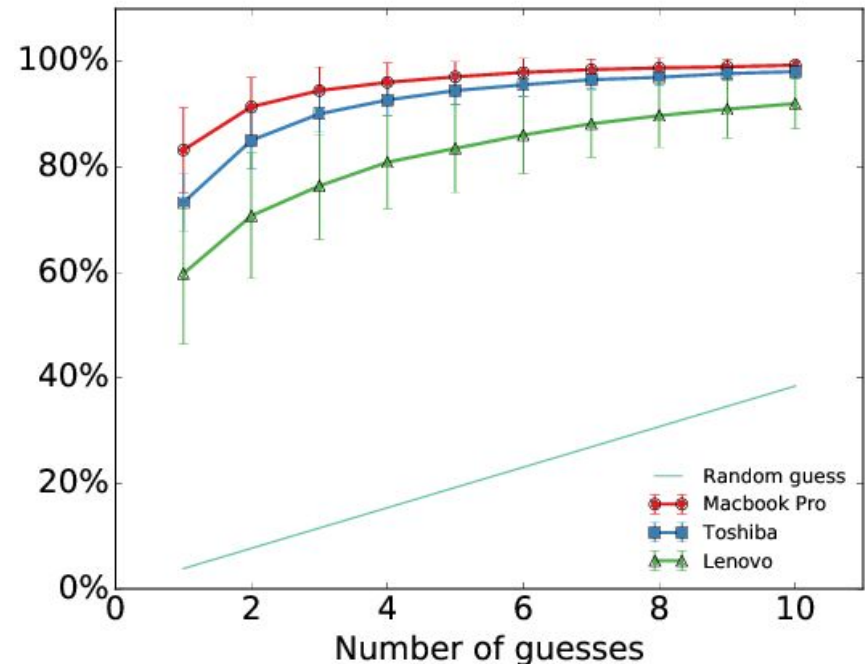
Complete Profiling



Training set with the data the user disclosed



Hunt&Peck typing, unfiltered data

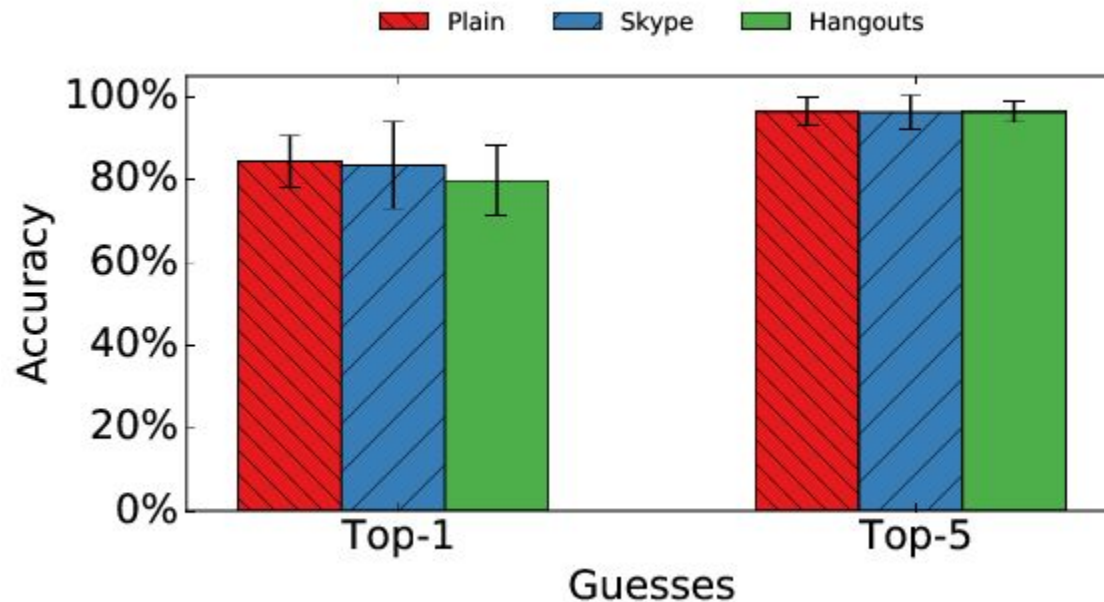


Touch typing, Skype filtered data

Complete Profiling



Is only Skype vulnerable to our attack?



No! It looks like a common problem for VoIP software



On the *Model Profiling* Scenario, the victim can be unknown
Someone the attacker does not know personally



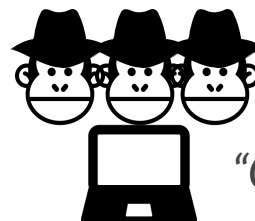
First need to understand the laptop of the victim
→ match it with a database of model signatures

- Guess correctly **93%** of the times if the model is known
- Statistical measures if the model is unknown

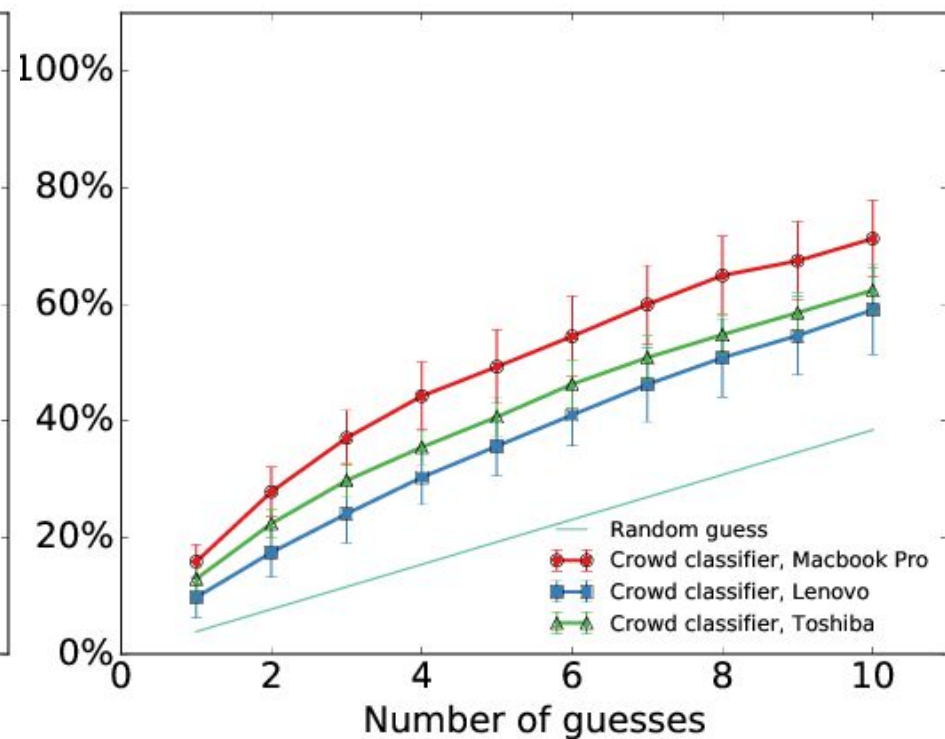
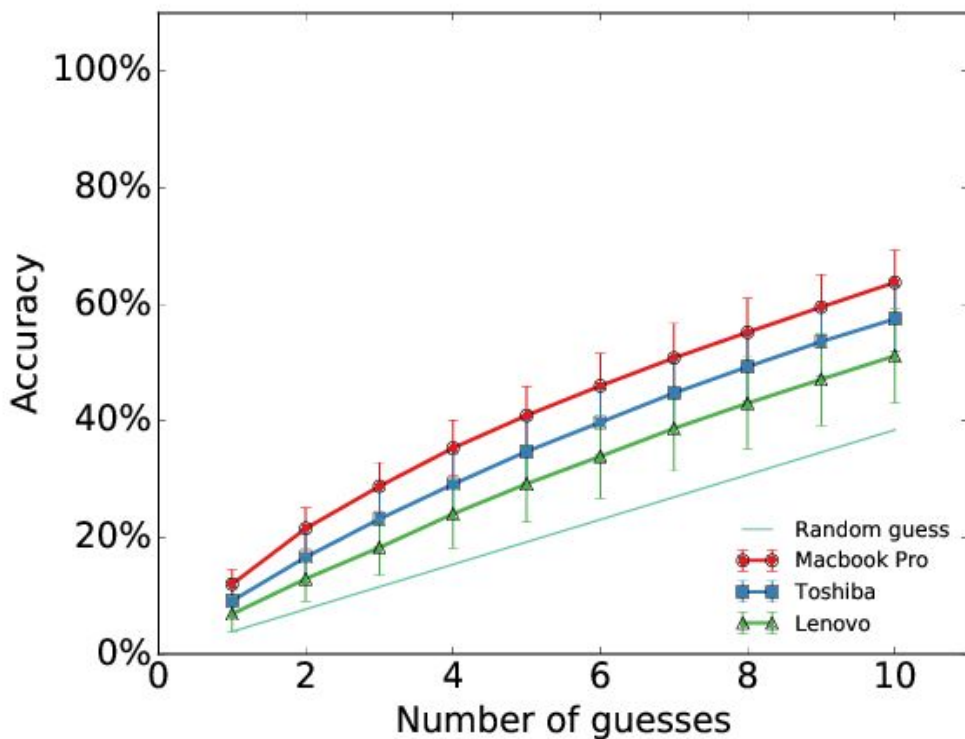
Model Profiling



One user



"Crowd" of multiple users

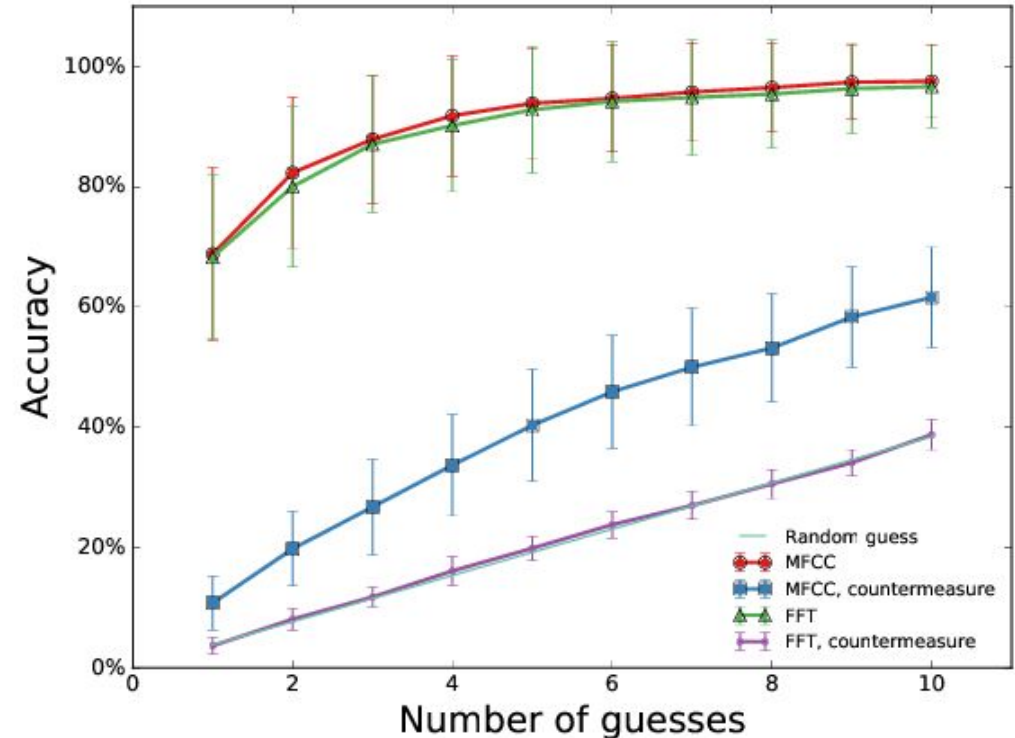


Summing Up Our Results



- Recognize a single character
 - *Complete Profiling: 90%+ accuracy*
 - *Model Profiling: 40%+ accuracy*
- Recognize a single word
 - *Complete Profiling: 98% correct letters*
 - *Model Profiling: 50% correct letters*
- Recognize a random password
 - *Improves 1-5 orders of magnitude time needed to guess the password*
 - *From 50 days to 42 seconds on a domestic PC*

- Don't Skype & Type
- Remove volume when we detect a keypress sound
 - *Impacts voice, greatly degrades call quality*
- Disrupt spectral features with random equalization
 - *Assess impact on voice, real time feasibility*





- VoIP Keyboard acoustic eavesdropping a serious threat
- Feasible and accurate:
 - *Realistic attack scenarios*
 - **91.71% on Complete Profiling scenario**
 - *Halevi (2012; 2014): 85.78%*
 - **41.89% on Model Profiling scenario**
 - *Novel attack vs. unknown victims*
 - *Robust to degradation and to voice*
- Future work:
 - *Try more users and different keyboards, and on more VoIP software*
 - *Try to attack another user in the same room*
 - *Analyze and improve the countermeasures*

Asonov, D., & Agrawal, R. (2004). Keyboard acoustic emanations. In *IEEE Symposium on Security and Privacy*.

Halevi, T., & Saxena, N. (2012). A closer look at keyboard acoustic emanations: random passwords, typing styles and decoding techniques. In *Proceedings of the 7th ACM Symposium on Information, Computer and Communications Security*.

Halevi, T., & Saxena, N. (2014). Keyboard acoustic side channel attacks: exploring realistic and security-sensitive scenarios. *International Journal of Information Security*, Springer.

Berger, Y., Wool, A., & Yeredor, A. (2006). Dictionary attacks using keyboard acoustic emanations. In *Proceedings of the 13th ACM conference on Computer and communications security*.

Zhuang, L., Zhou, F., & Tygar, J. D. (2009). Keyboard acoustic emanations revisited. *ACM Transactions on Information and System Security (TISSEC)*.

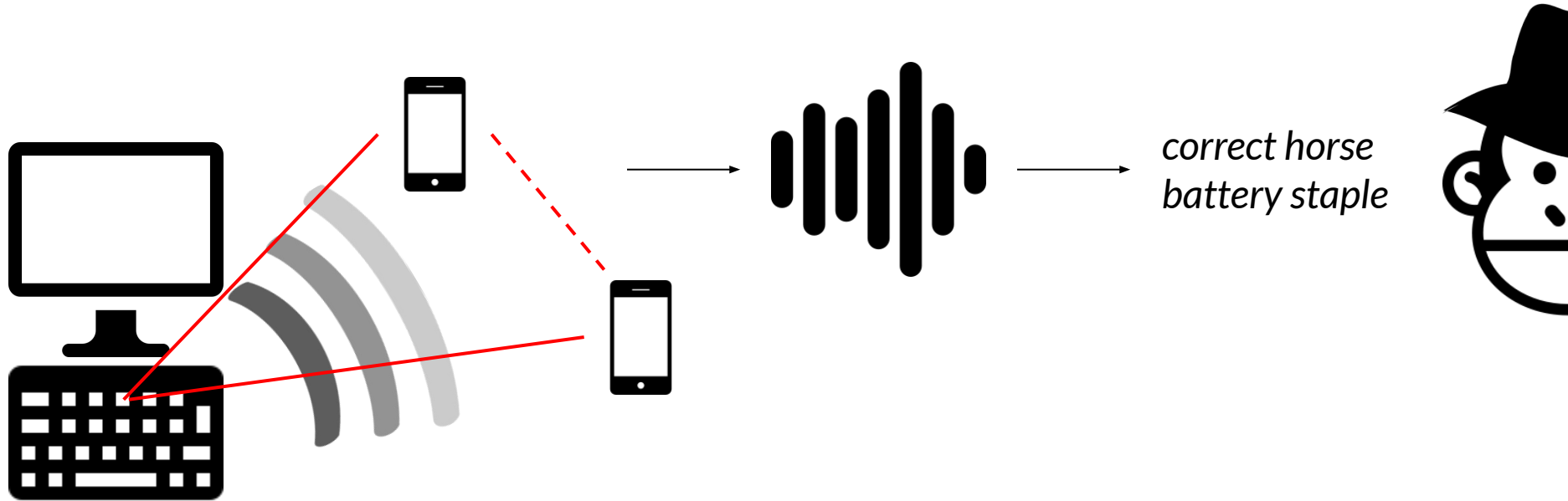
Liu, J., Wang, Y., Kar, G., Chen, Y., Yang, J., & Gruteser, M. (2015). Snooping keystrokes with mm-level audio ranging on a single phone. In *Proceedings of the 21st Annual International Conference on Mobile Computing and Networking*.

Zhu, T., Ma, Q., Zhang, S., & Liu, Y. (2014). Context-free attacks using keyboard acoustic emanations. In *Proceedings of the 2014 ACM SIGSAC Conference on Computer and Communications Security*.



Backup Slides

Keyboard Acoustic Eavesdropping



- Timing information (Liu, 2015; Zhu, 2014)
Context-free, difficult to setup

Password Cracking



The goal was to crack the victim's random password

→ We need bruteforce techniques

Random password of 10 lowercase letters

- $\log_2(26^{10}) = 47$ bits of entropy

On the Complete Profiling Scenario (high accuracy)

- $\log_2(5^{10}) = 23.22$ bits of entropy

On the other scenarios - entropy is not meaningful

Evaluation - Small Training Set

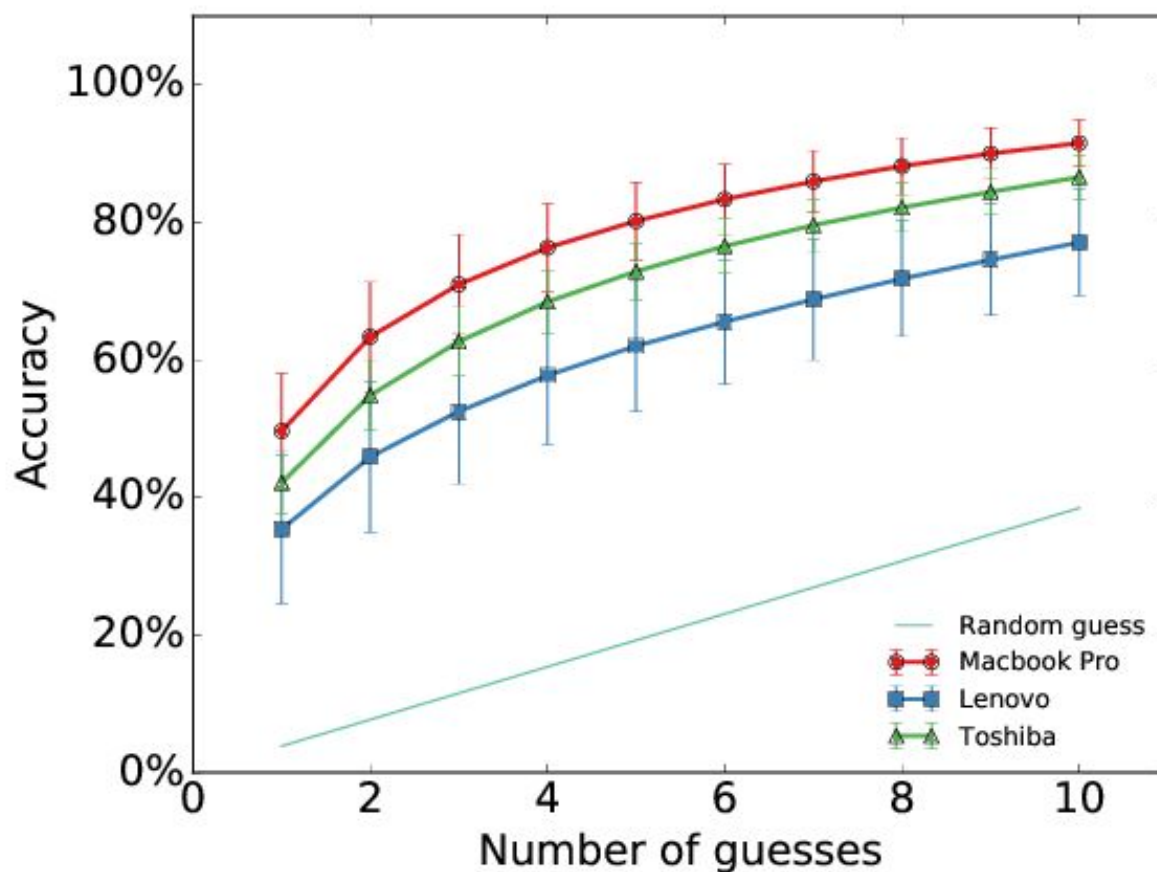


10 samples/character aren't your typical chat message

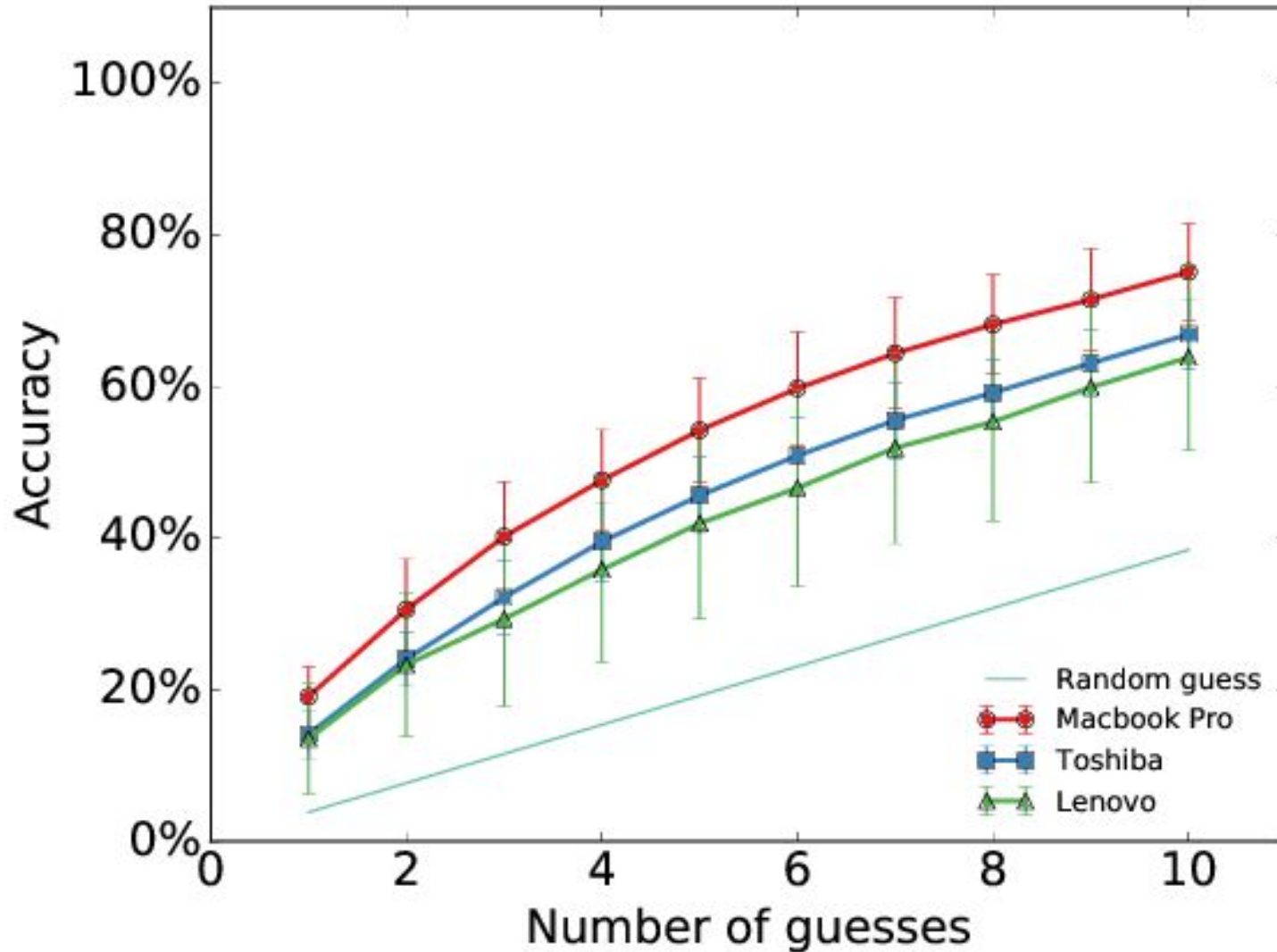
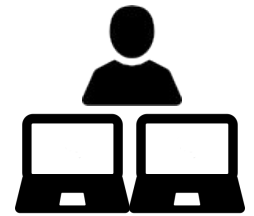
Training set with realistic letter frequencies
Test against random password



Character	# Samples
E	10
A	9
R	7
J	1
Z	1



Evaluation - User Profiling

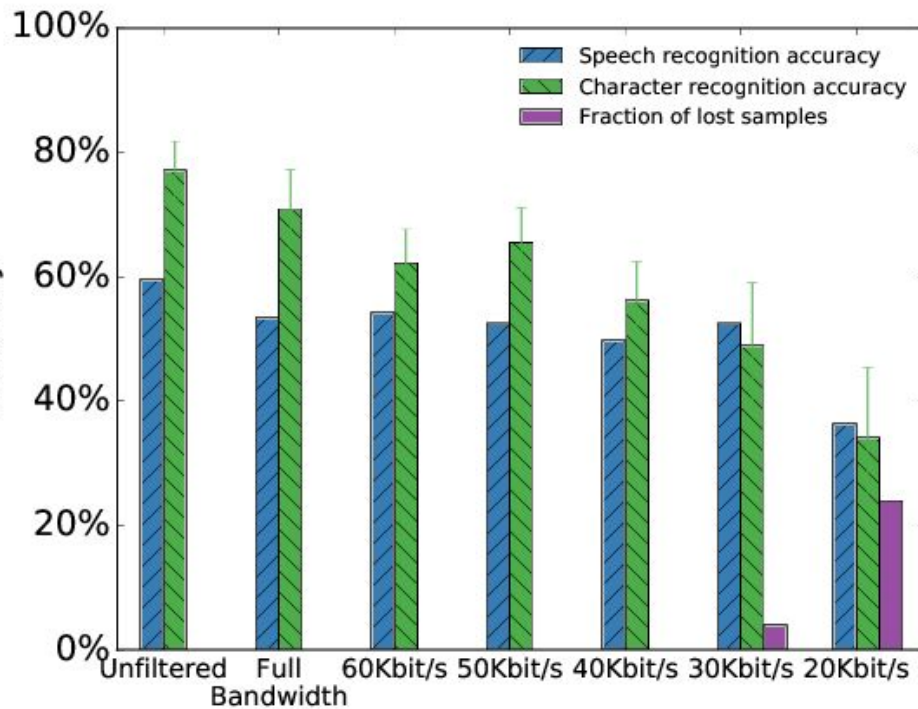


VoIP challenges

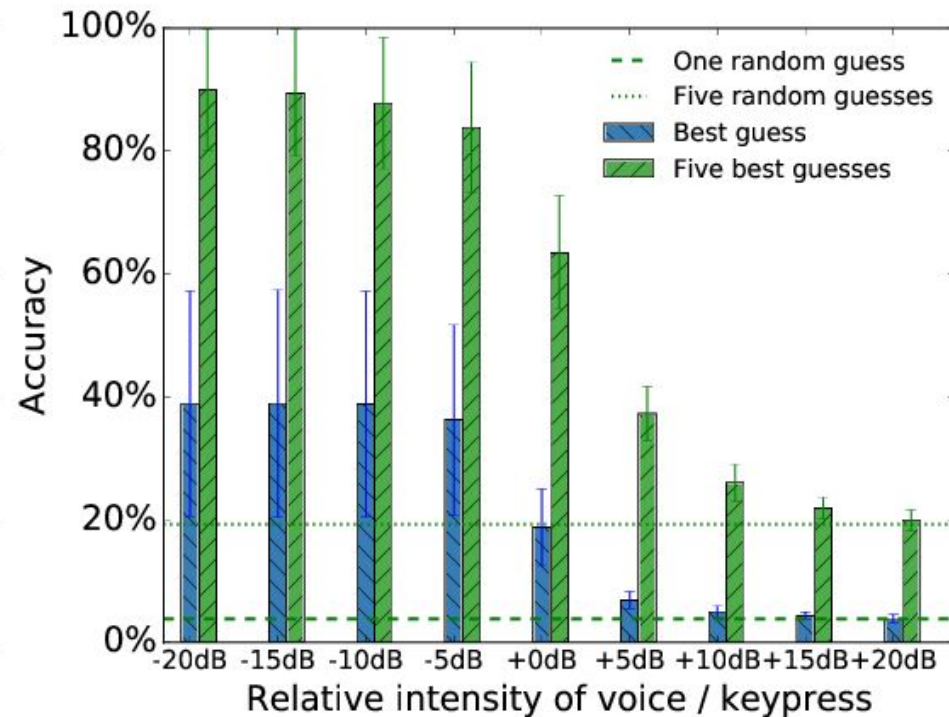


Using Skype poses additional challenges:

Slow Internet degrades call quality



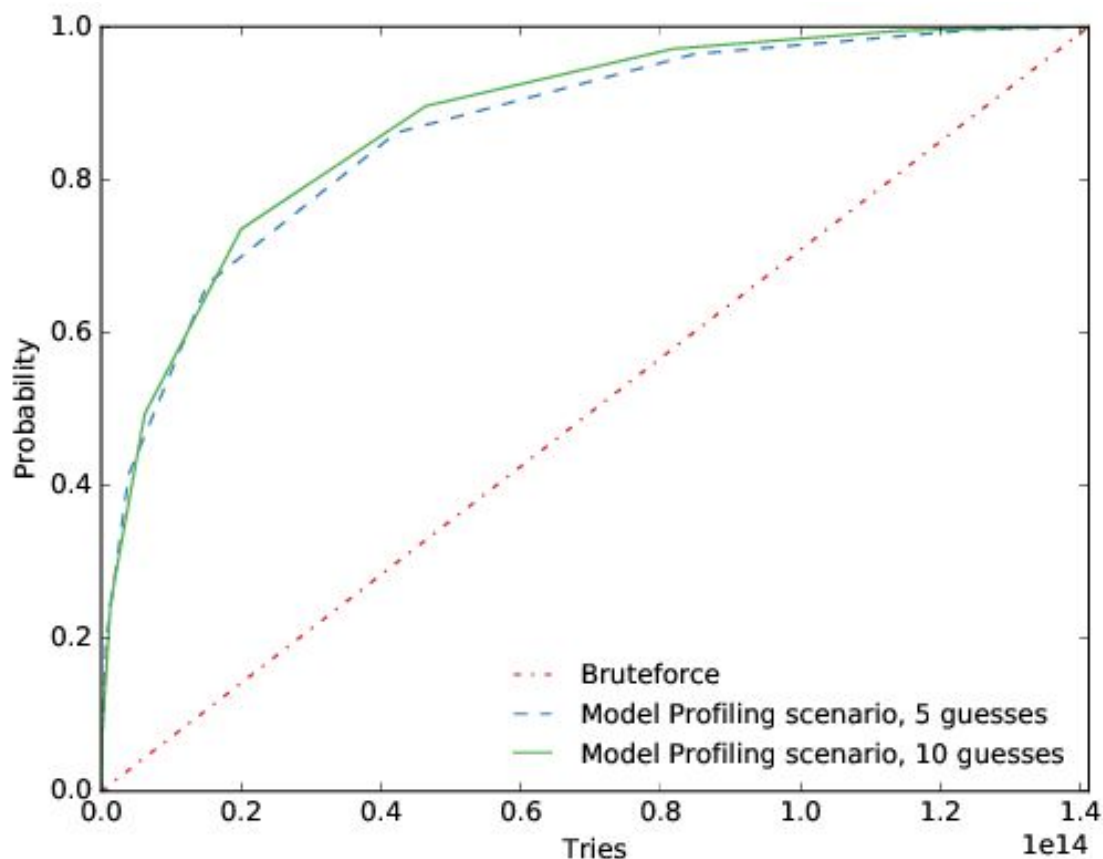
Human voice on top of keypresses



Model Profiling Scenario → improved bruteforce

Take into account character probabilities

Evaluate the reduction of the average number of trials



Fast Fourier Transform coefficients

$$S(f(t)) = 20 \log_{10} (|\mathcal{F}(f(t))|)$$

$f(t)$ = signal

\mathcal{F} = Discrete Fourier Transform function

Cepstrum coefficients

$$C(f(t)) = |\mathcal{F}^{-1}(S(f(t)))|^2$$

Mel frequency cepstral coefficients

$$MFC(f(t)) = DCT(\log_{10}(\text{mel}\{|\mathcal{F}(f(t))|\}))$$

$$\text{mel}(f) = 2595 \log_{10} \left(1 + \frac{f}{700} \right)$$

DCT = Discrete Cosine Transform