Side-Channel Attack

CS463/ECE424 University of Illinois



Side Channel Attacks: Two Case Studie

- Keyboard spy via acoustic side channels
- Information leakage via hardware side channels





Extracting Information from Side Channels

• Inferring words typed on the keyboard by analyzing the sound





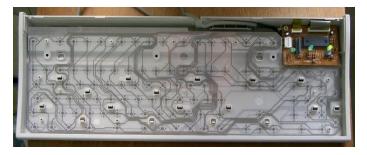
Keyboard Acoustic Emanations Revisited, Li Zhuang, Feng Zhou, J. D. Tygar, CCS 2005

Intuition: Why could this possibly work?

- Different keystrokes make different sounds
 - Locations
 - Underlying hardware







Threat Model and Challenges

- Attacker has a microphone recording the victim's typing
 - Assumptions: typing English text, no labeled input
 - Goals: recovering the English text, inferring random text (e.g., password)
- Challenges
 - Hard to obtain labeled training data --- no cooperation from the victim
 - Typing patterns can be keyboard specific
 - Typing patterns can be user specific

Threat Model and Challenges

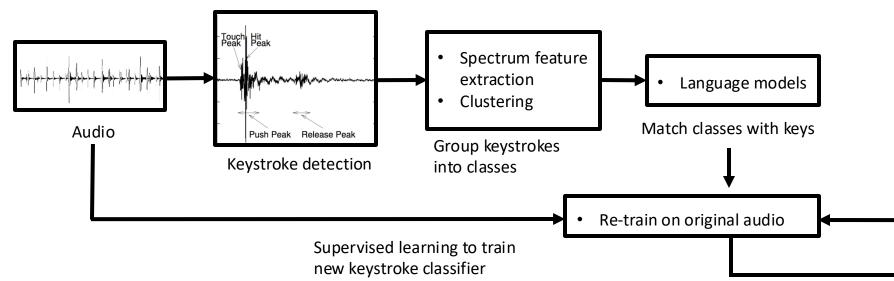
- Attacker has a microphone recording the victim's typing
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- Challenges

Key Intuition: the typed text is often not random.

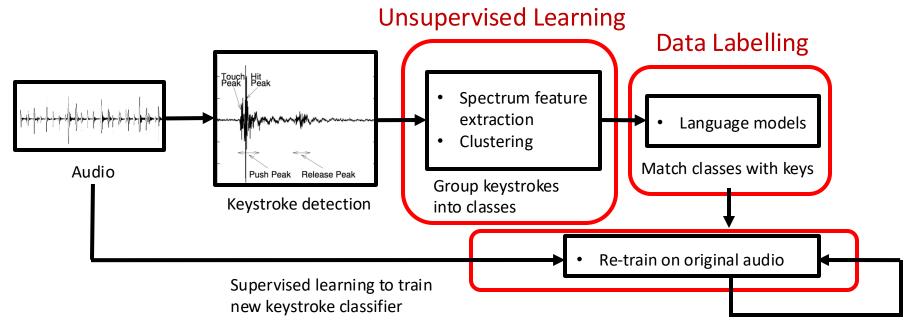
- English words limits the possible temporal combinations of keys
- English grammar limits the word combinations.

How The Attack Works

- Key idea: generating training data automatically
 - Labelling the audio of a key stroke with the actual key



A Combination of Different Learning Methods



Supervised Learning

Step1: Unsupervised Learning

- Unsupervised clustering
 - Feature generation
 - Cepstrum features
 - Clustering into K classes
 - K > N (actual number of keys used)
- Output
 - K unlabeled classes

- Spectrum feature extraction
- Clustering

Group keystrokes into classes

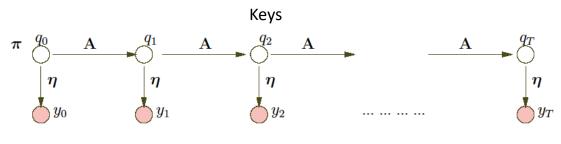
this is the best pizza in town this is the best pizza in town

Step 2: Context-based Language Model

- Need to label the clusters: which key they represent?
- Assume the victim is typing English text
 - Characters follow certain frequency
 - Actual content follows English spelling and grammar
- Advantages:
 - Use 2-character combination frequency to match classes to keys
 - Use language model (spelling, grammar) to correct mistakes

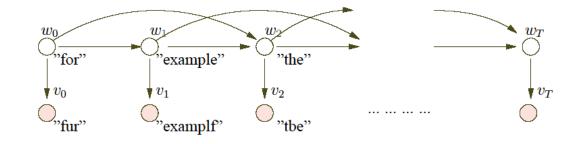
Details: Context-based Language Model

- Character-level mapping:
 - Hidden Markov Model
 - Produce a probability of keys assigned to classes.
 - Example: "th" vs. "tj"



Unlabeled clusters

- Word-level correction:
 - 1. Spell check
 - 2. Grammar
 - Tri-gram



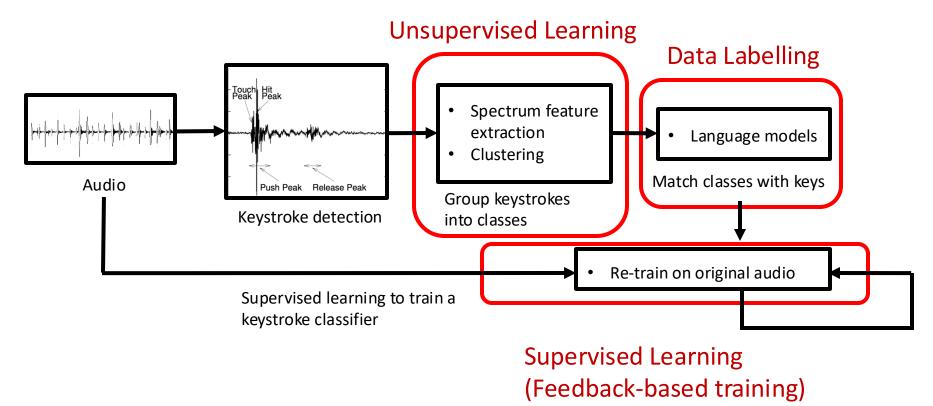
Details: Context-based Language Model

Before spelling and grammar correction

After spelling and grammar correction the big money fight has drawn the <u>shoporo</u> <u>od dosens</u> of companies in the entertainment industry as well as attorneys <u>gnnerals</u> on states, who fear the <u>fild shading softwate</u> will encourage illegal <u>acylvitt</u>, <u>srem</u> the <u>grosth</u> of small <u>arrists</u> and lead to lost <u>cobs</u> and dimished sales <u>tas</u> revenue.

the big money fight has drawn the support of dozens of companies in the entertainment industry as well as attorneys generals in states, who fear the <u>film</u> sharing software will encourage illegal activity, stem the growth of small artists and lead to lost jobs and <u>finished</u> sales tax revenue.

A Combination of Different Learning Methods



Feedback based Training



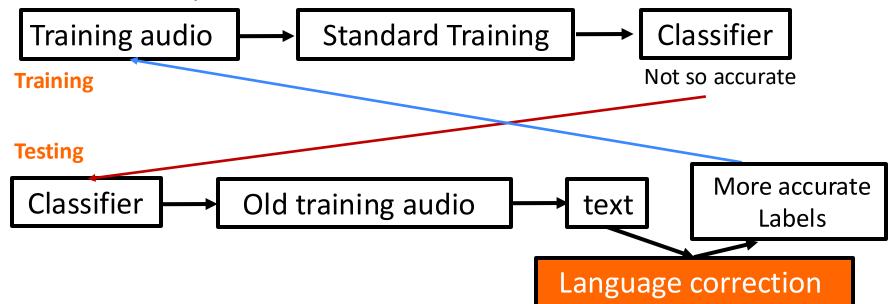
- A keystroke classifier (for inferring random text)
 - Given a keystroke, produce the label of the key

Training

- Input: noisy training data
 - Only a subset of labeled data from the language models
 - Choose those with fewer corrections by the language model (quality indicator)
- Output: a not so accurate keystroke classifier
- Testing
 - Use the trained classifier to classify the training data again
 - Use the language model to correct the classification result
 - Use the corrected label for re-training

Feedback based Training (Con't)

Not 100% accurately labeled



Evaluation

		Sel 1		Set 2		Set 3		Set 4	
		words	chars	words	chars	words	chars	words	chars
unsupervised	keystrokes	34.72	76.17	38.50	79.60	31.61	72.99	23.22	67.67
learning	language	74.57	87.19	71.30	87.05	56.57	80.37	51.23	75.07
1st supervised	keystrokes	58.19	89.02	58.20	89.86	51.53	87.37	37.84	82.02
feedback	language	89.73	95.94	88.10	95.64	78.75	92.55	73.22	88.60
2nd supervised	keystrokes	65.28	91.81	62.80	91.07	61.75	90.76	45.36	85.98
feedback	language	90.95	96.46	88.70	95.93	82.74	94.48	78.42	91.49
3rd supervised	keystrokes	66.01	92.04	62.70	91.20	63.35	91.21	48.22	86.58
feedback	language	90.46	96.34	89.30	96.09	83.13	94.72	79.51	92.49

Table 2: Text recovery rate at each step. All numbers are percentages.

Other Key Results

- Works for random text
 - Inferring passwords that contain English letters only
 - 90% of 5-character random passwords: < 20 attempts</p>
 - 80% of 10-character random passwords: <75 attempts</p>
- Works for multiple types of keyboards

• Even "low-quality" microphones can do the job

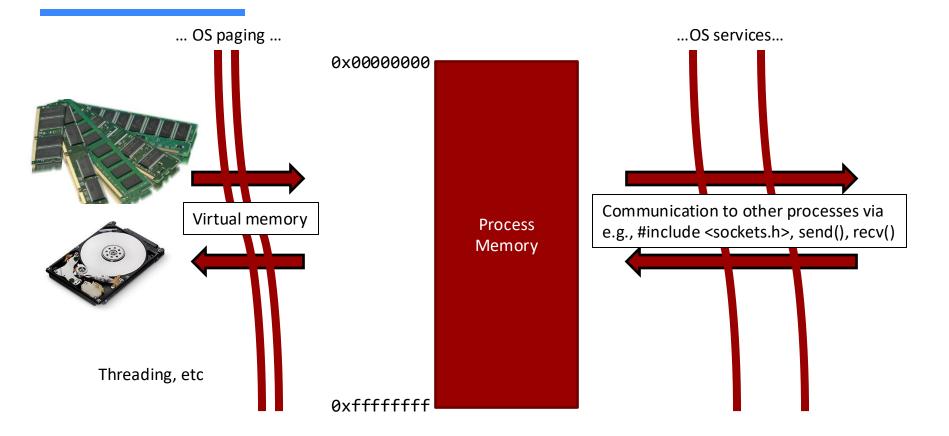
Possible Defenses

- Introduce noise into the system
 - Add (random) background noise to keystrokes
 - $_{\circ}\,$ Remove the unique pattern for each key
 - Use quieter keyboards
- Other defenses
 - Two factor authentication (not just typing a password)
 - No microphone in your room?

Microarchitectural covert and side channels (how to share a secret)

Credit: Chris Fletcher (UIUC)

Process isolation + OS (CS 233)



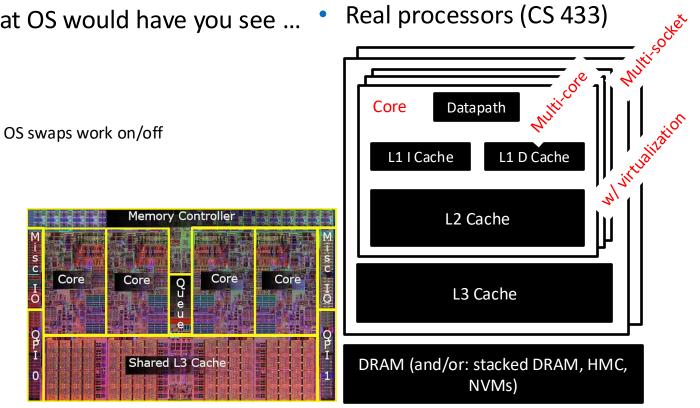
Programs run on processors

Processor that OS would have you see ...

Core

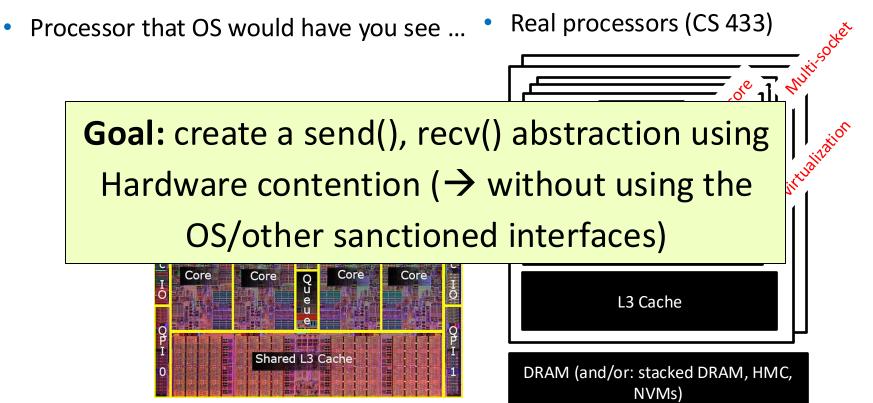
Memory

Cache = on-chip memory, faster to access than DRAM



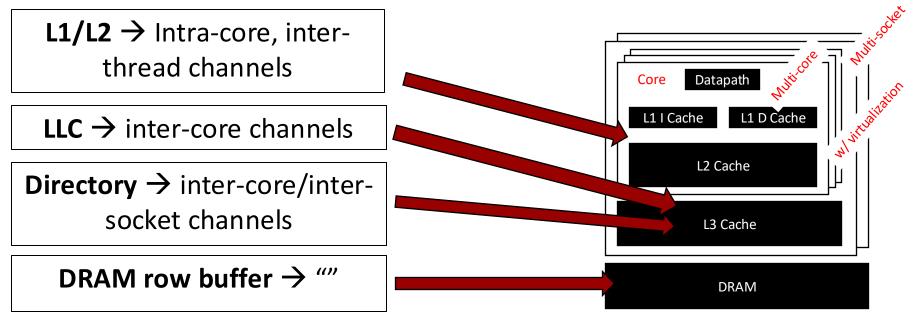
Programs run on processors

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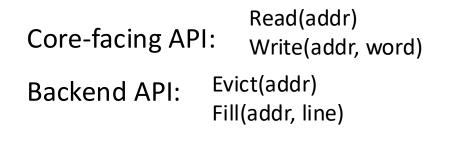
Covert Channels 101: Through the cache

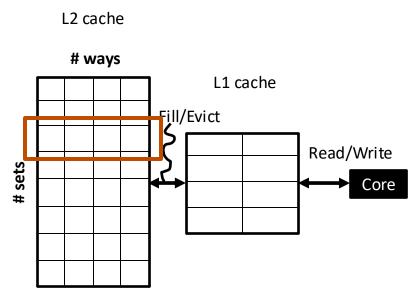
- Cache fill for line A may cause another line B to be evicted
- Various mechanisms for owner of B to detect a hit or miss
- We like the cache: easy to measure, many types of sharing



Processor caches

- Motivation
 - Programs have locality
 - Memory access cost \propto memory size
- Block placement/replacement policies tell us where blocks can live and when

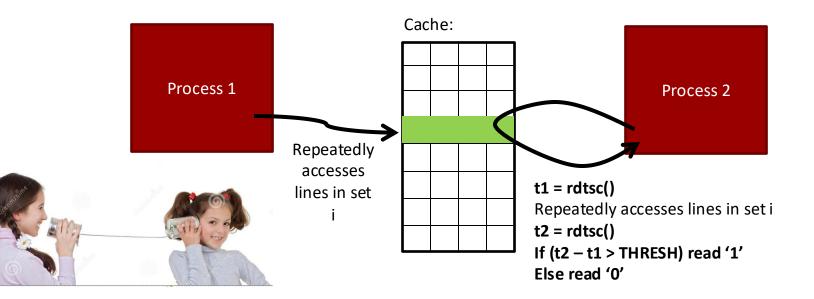




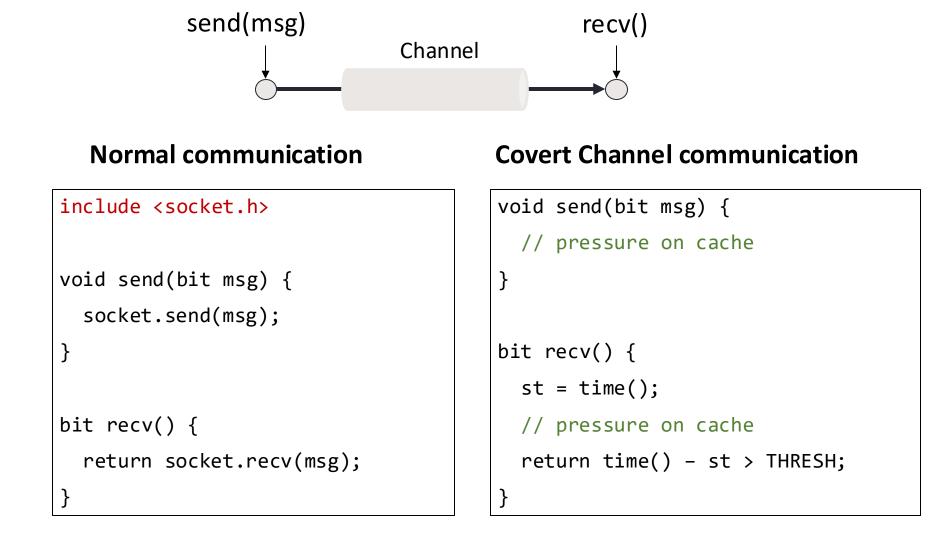
Why is cache design relevant?



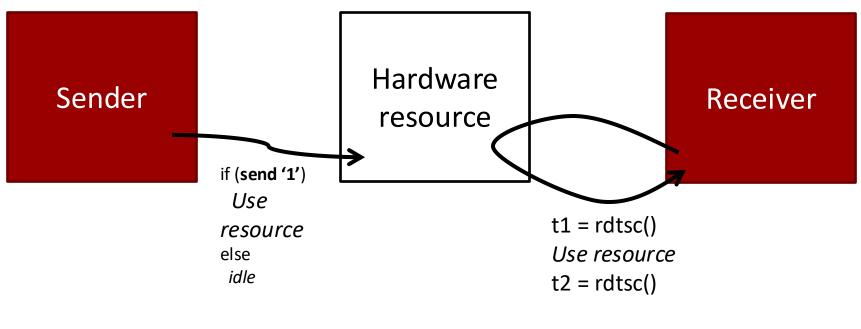
 Two processes can agree on "dead drops" on the processor hardware, to pass information under the OS's nose



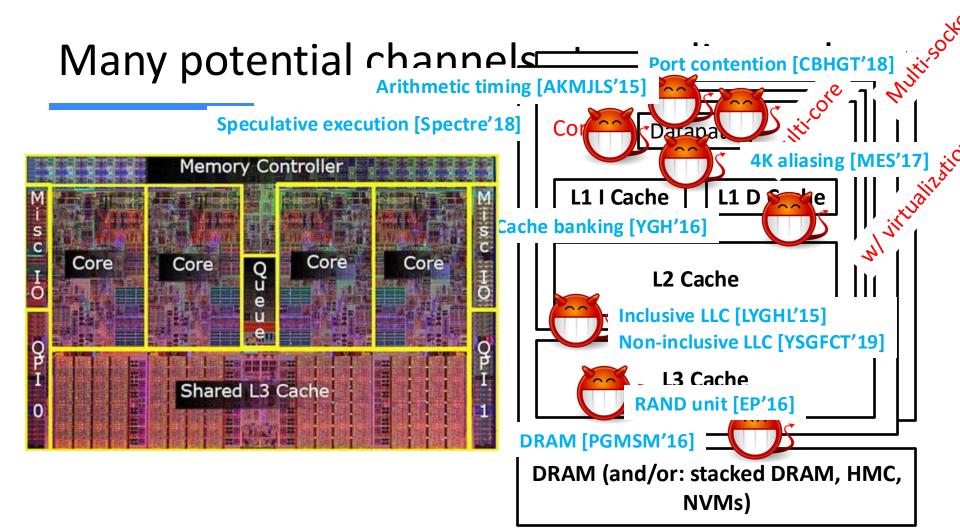
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Fun! How else can I do this?



if (t2 – t1 > THRESH) read '1' else read '0'



Bandwidth

Error-free bitrate of send() \rightarrow recv()



Depends on what hardware structure is used to build the channel.

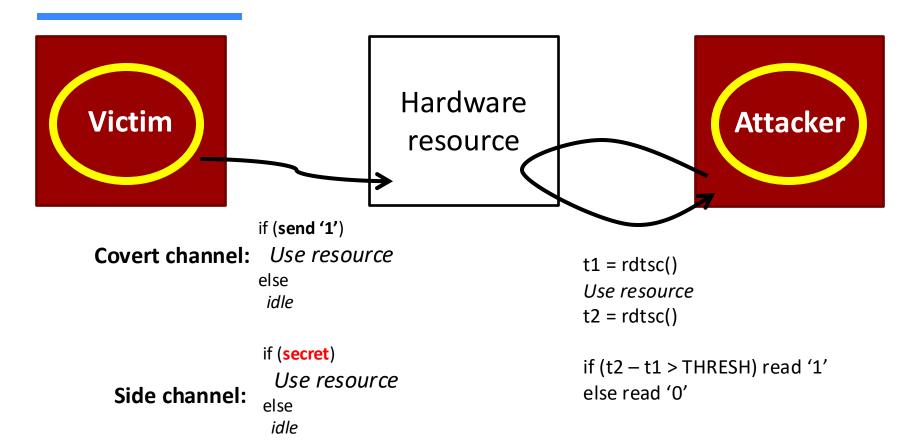
- RDRAND unit: 7-200 Kbps [EP'16]
- Ld/st performance counters: ~75-150 Kbps [HKRVDT'15]
- MemBus/AES-NI contention: ~550-650 Kbps [HKRVDT'15]
- LLC: 1.2 Mbps [MNHF'15]
- Various structures on GPGPU: up to 4 Mbps [NKG'17]

Practical uses

- Talk to your friends for fun
- Malware can inter-communicate w/o OS realizing it
- Different VMs sharing the same box on (e.g.) Amazon AWS can talk

- Side channel attacks
 - Learn private information about co-resident processes

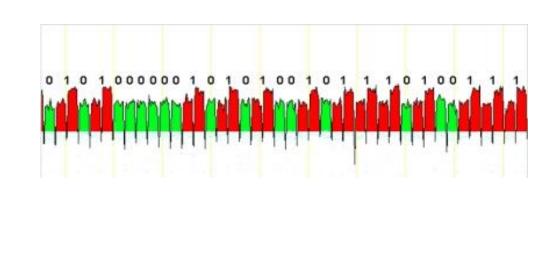
From covert \rightarrow side channels



Side channel attacks

- Shared resource pressure can also lead to side channel attacks
- E.g., RSA encryption msg = Decrypt_{key}(Encrypt_{key}(msg))

```
SquareMult(x, e, N):
let e_n, \ldots, e_1 be the bits of e
y \leftarrow 1
for i = n down to 1 {
                                                   (S)
   y \leftarrow \mathsf{Square}(y)
                                                  (R)
   y \leftarrow \mathsf{ModReduce}(y, N)
    if e_i = 1 then {
                                                 (M)
      y \leftarrow \mathsf{Mult}(y, x)
      y \leftarrow \mathsf{ModReduce}(y, N)
                                                  (R)
 return y
```



Discussion

 Any other examples of side channels you can think of to infer user information / steal data?

 What's your thoughts on the future development of microarchitecture side channels (try to also think from the defender's side of view)?