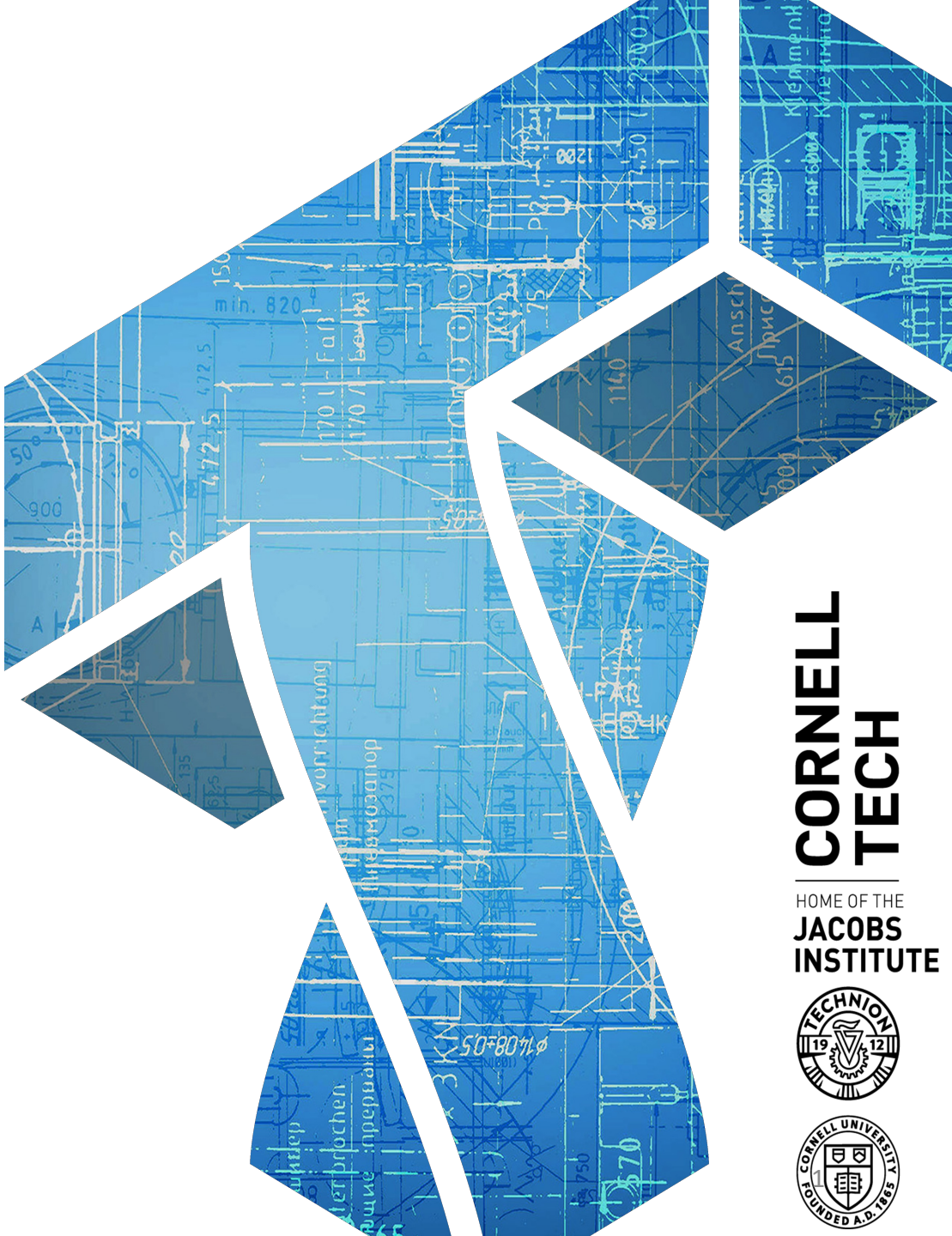
CS 5435: Microarchitectural vulnerabilities Data protections

Instructor: Tom Ristenpart

https://github.com/tomrist/cs5435-fall2024



CORNELL TECH

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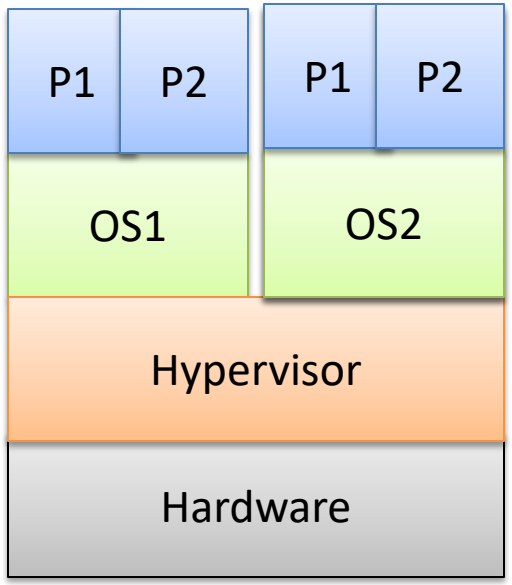
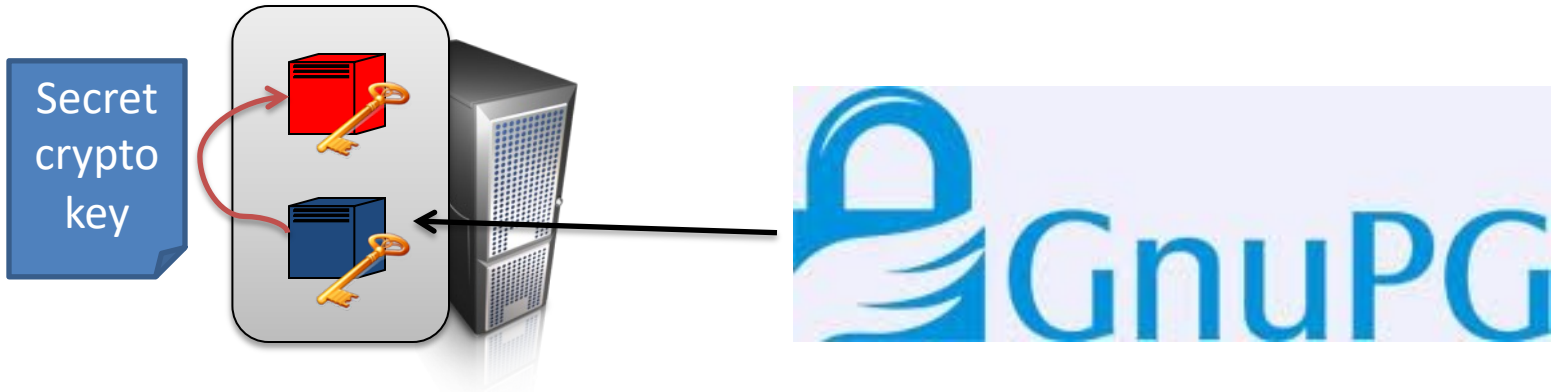
Server consolidation

- Consolidation
  - Use VMs to optimize use of hardware
  - Pack as many VMs onto each server as possible
  - Turn off other servers
- Threat model?
  - Containment
  - Isolation
  - Assume guests are/can be compromised



Cross-VM cryptographic side-channel attacks

[Zhang, Juels, Reiter, R. – CCS `12]



Target is 4096-bit ElGamal secret key e

Modular Exponentiation (x, e, N):

let $e_n \ldots e_1$ be the bits of e

$y \leftarrow 1$

for e_i in $\{e_n \ldots e_1\}$

- $y \leftarrow$ **Square**(y) **(S)**
- $y \leftarrow$ **Reduce**(y, N) **(R)**
- if $e_i = 1$ then
  - $y \leftarrow$ **Multi**(y, x) **(M)**
  - $y \leftarrow$ **Reduce**(y, N) **(R)**

return y // $y = x^e \bmod N$

$e_i = 1 \rightarrow$ "SRMR"

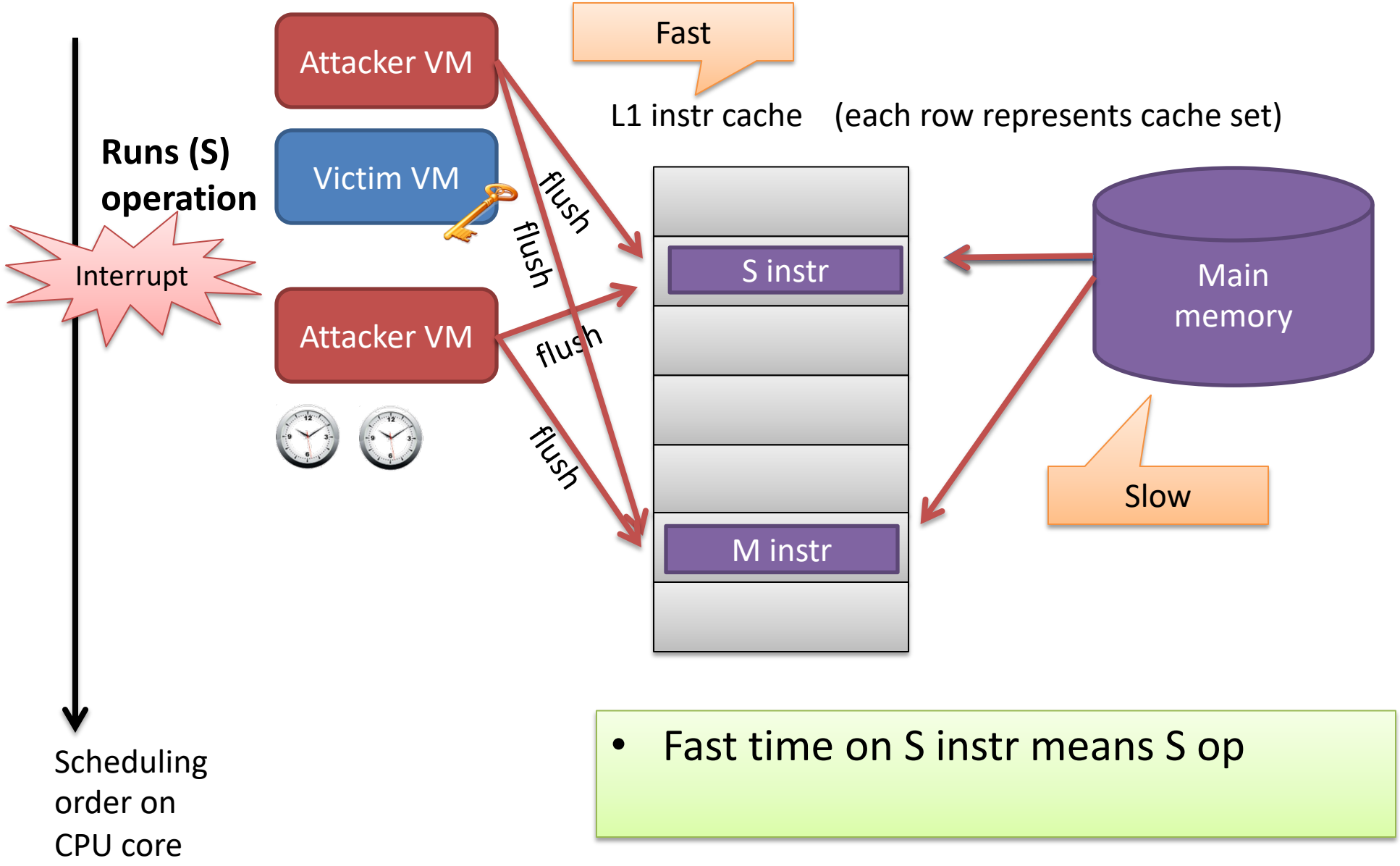
$e_i = 0 \rightarrow$ "SR"

Sequence of function calls reveals secret key

Microarchitectural side-channels

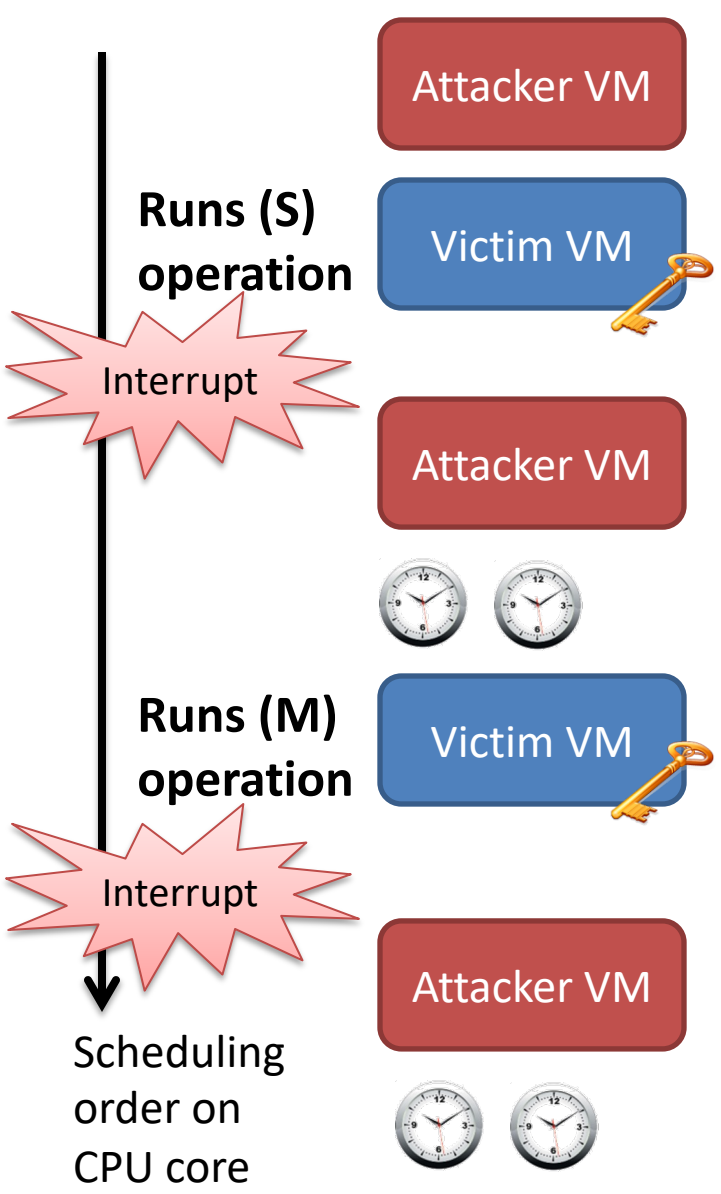
- Lots of research on exploiting microarchitectural side-channels
- Improved cross-VM Prime+Probe attacks :
  - Sinan Inci et al. 2016 “Cache Attacks Enable Bulk Key Recovery on the Cloud”
- Flush+Reload (F+R) more robust side-channel in shared memory settings [Yarom, Falkner 2013]
  - Spy process flushes memory shared with victim from caches
  - Idles
  - Times how long it takes to read shared memory

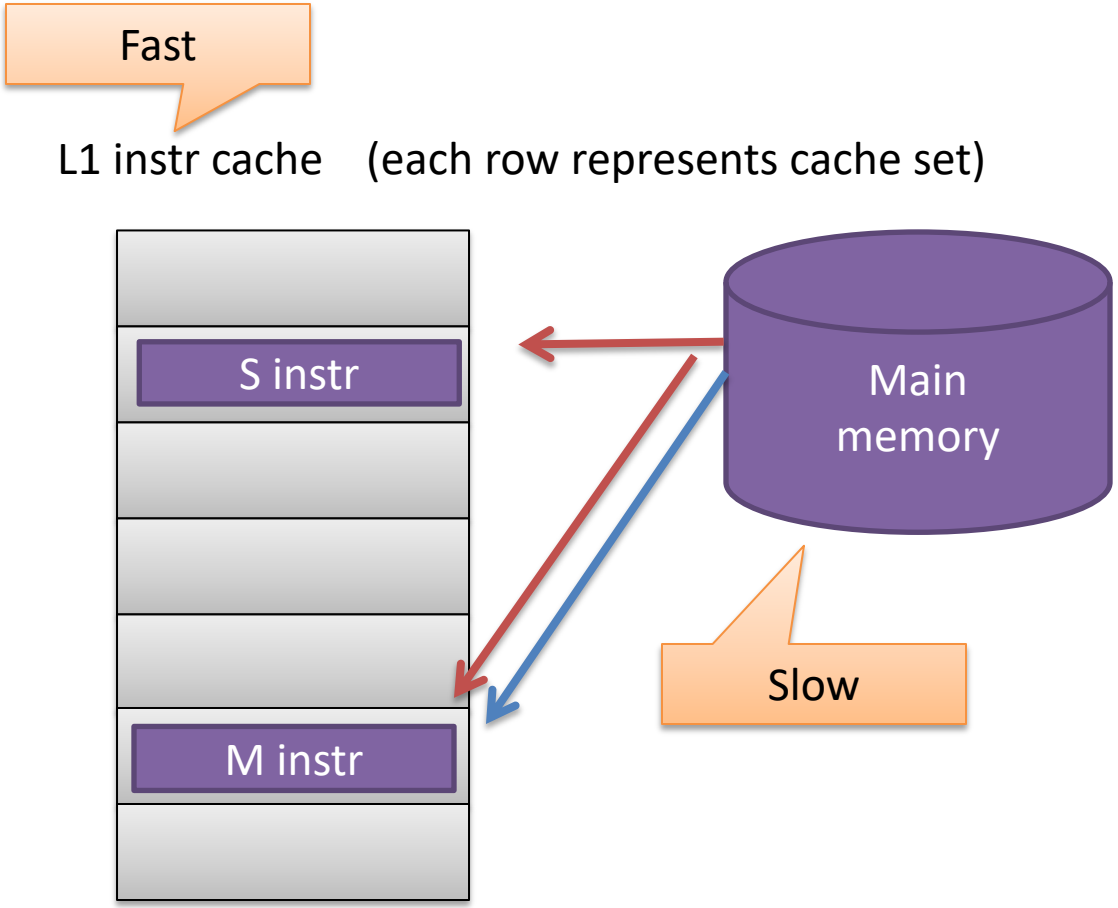
Flush+Reload protocol



- Fast time on S instr means S op

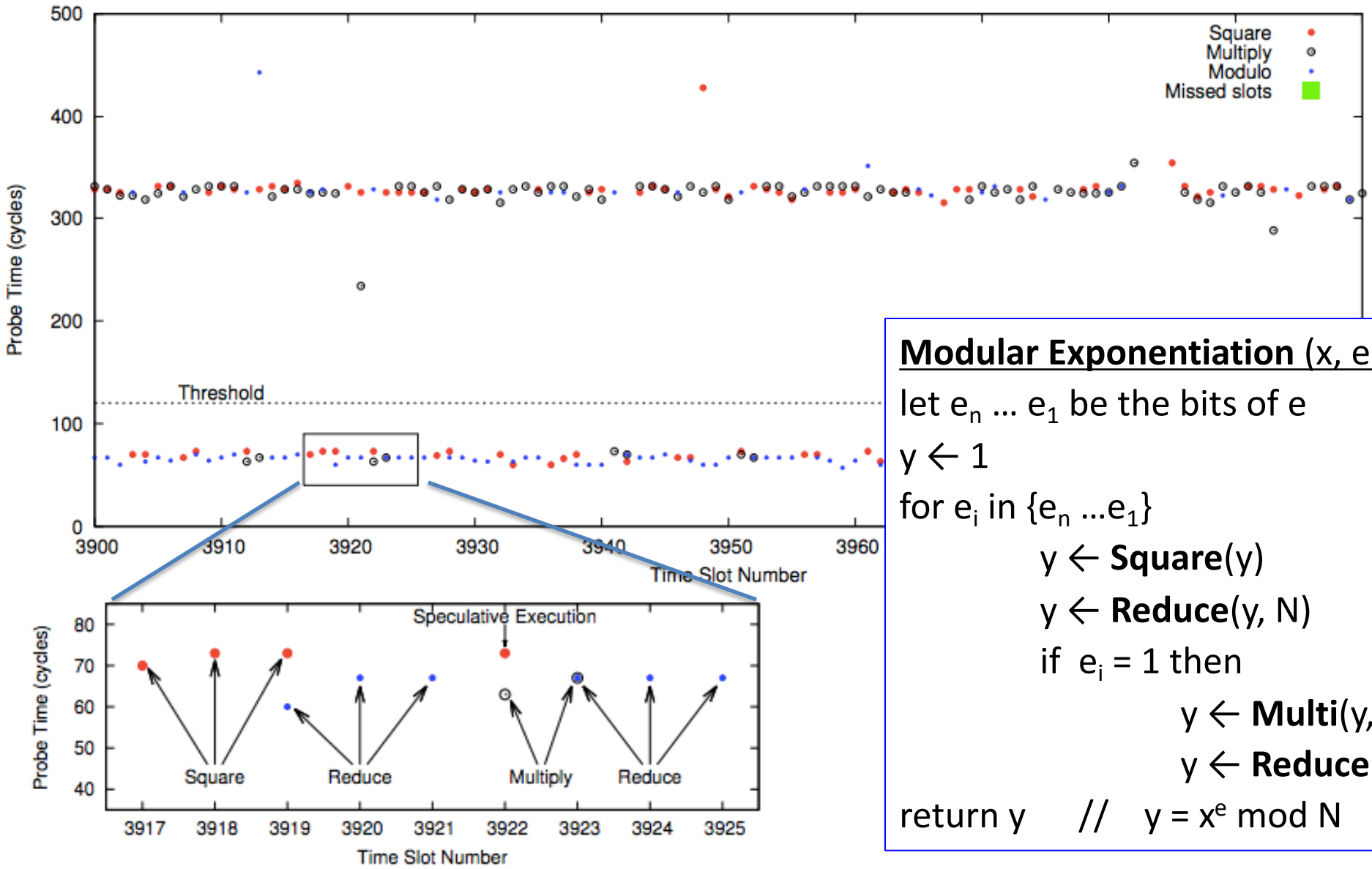
Flush+Reload protocol





- Fast time on S instr means S op
- Fast time on M instr means M op

Attacking Square and Multiply



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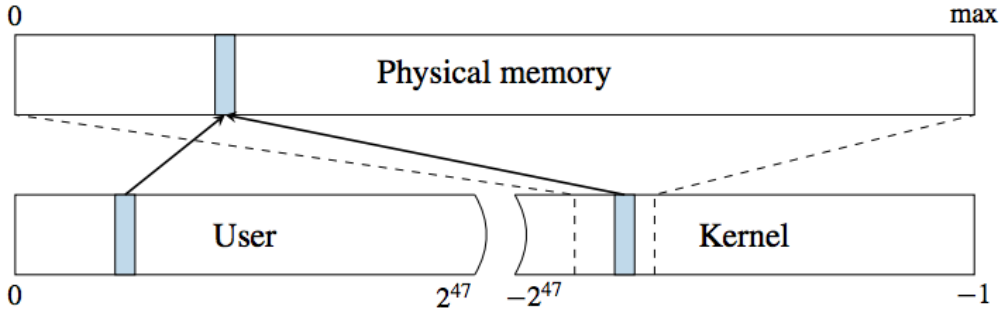
Flush+Reload widely applicable side-channel

- Useful anywhere code is shared across processes / VMs / containers
- Cross-tenant attacks in platform-as-a-service (PaaS) clouds
  - [Zhang, Juels, Reiter, R. 2014]
- Used as building block for Meltdown, Spectre vulnerabilities

Meltdown and Spectre

- Speculative execution bugs in Intel x86, ARM, IBM processors + cache-based side-channels (I
  - Allows reading kernel (or hypervisor, other VM) memory



Intel didn't warn US government about CPU security flaws until they were public

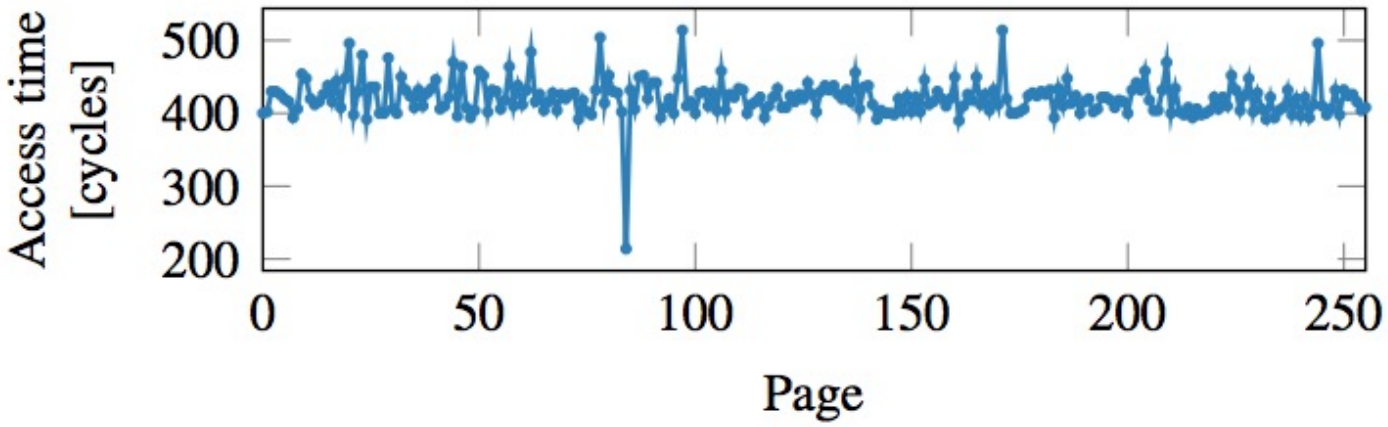
Meltdown and Spectre were kept secret

Researchers find malware samples that exploit Meltdown and Spectre

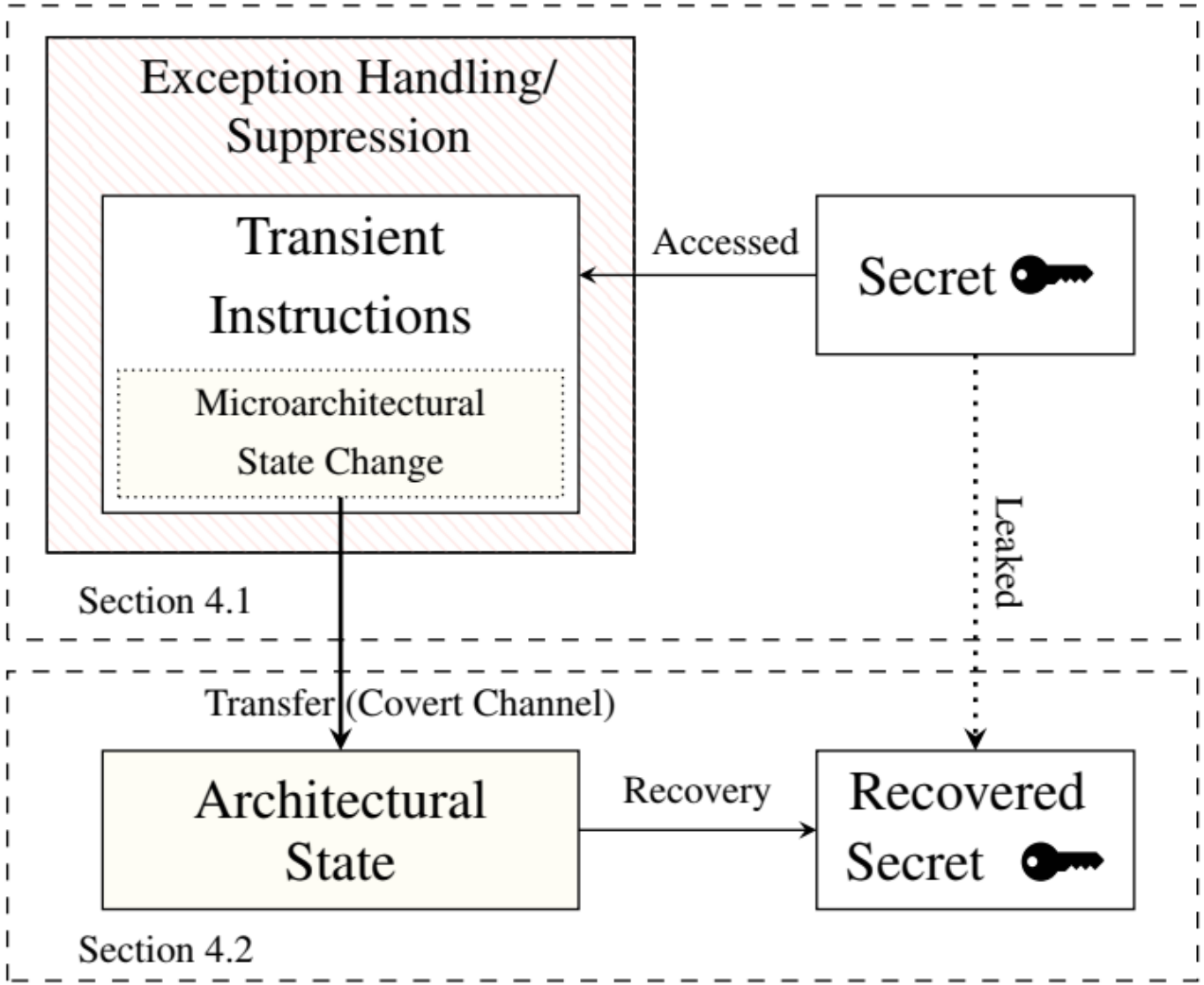
As of Feb. 1, antivirus testing firm AV-TEST had found 139 malware samples that exploit Meltdown and Spectre. Most are not very functional, but that could change.

Meltdown: intuition

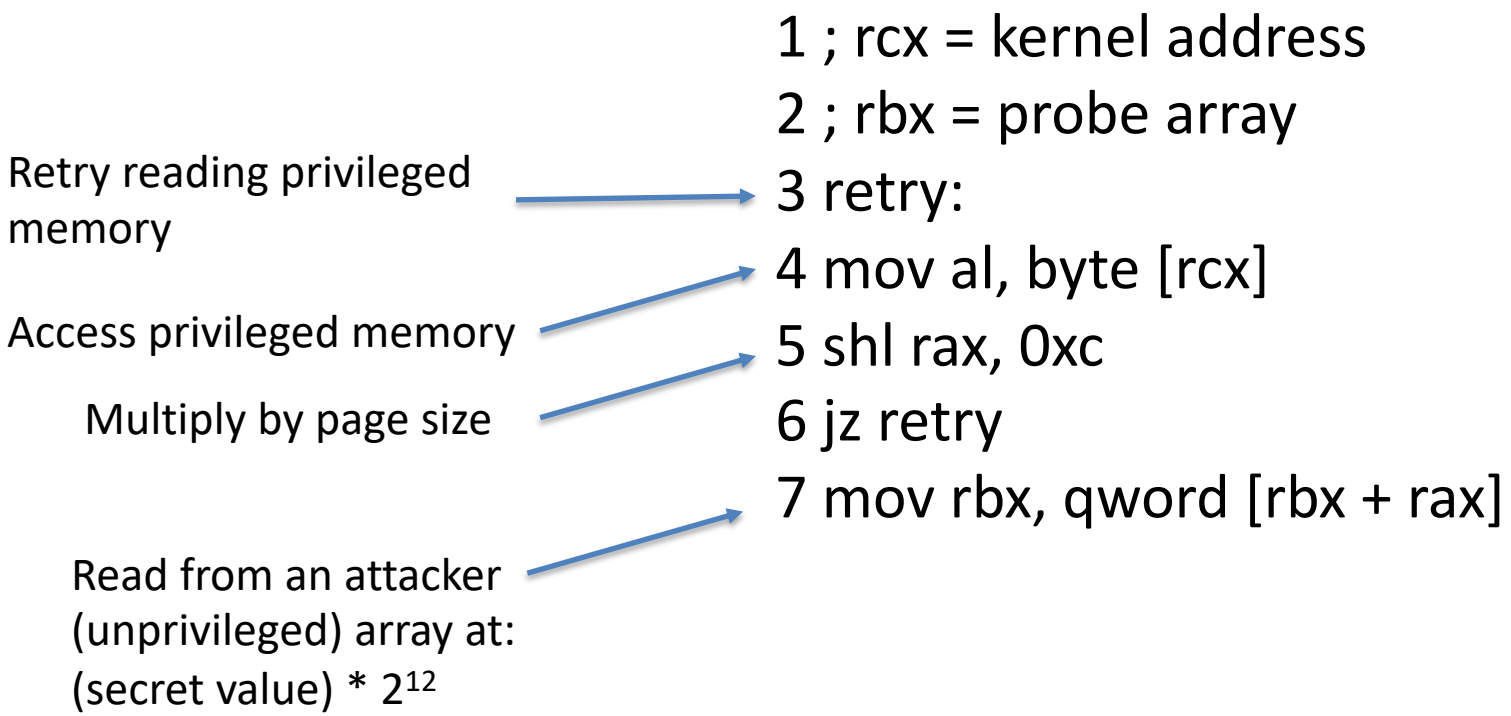
```
1  raise_exception();
2  // the line below is never reached
3  access(probe_array[data * 4096]);
```



Meltdown: design



Meltdown: core spy code



Attacker times accessing [rbx + rax] for different values of rax

When finds one that loads fast, learns sensitive byte

Microarchitectural vulnerabilities

- Meltdown
- Spectre
- Foreshadow
- Downfall
- Retbleed
- Zombieload
- **Pacman**
- …

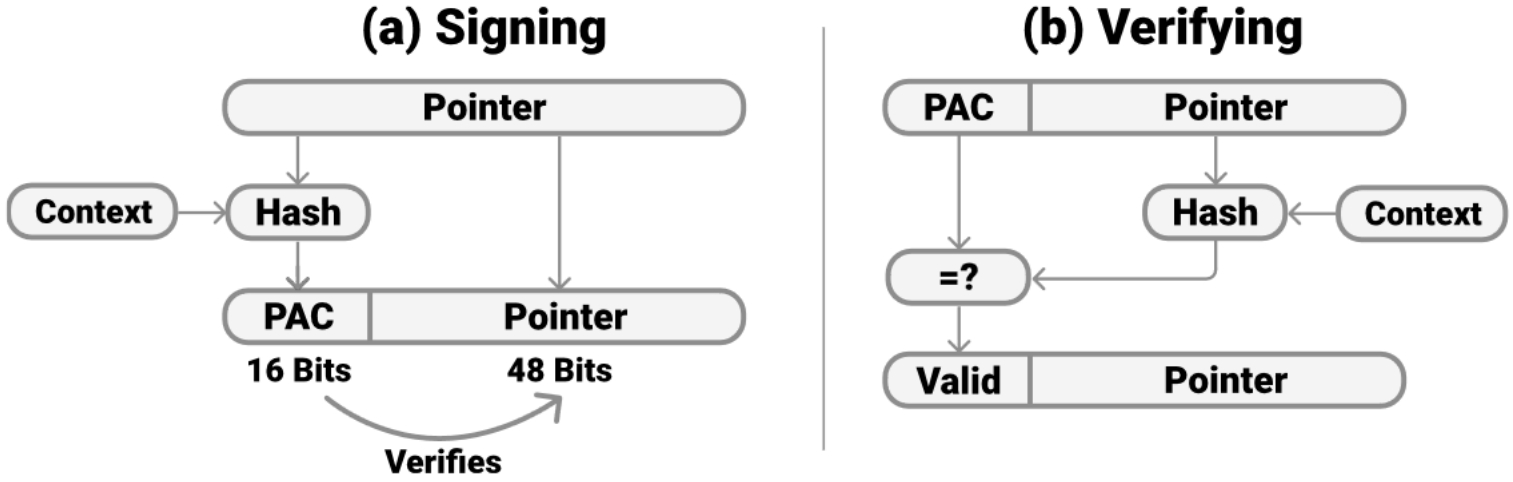


Figure 1: Signing and verifying pointers.

1. Use speculative execution to leak correct PAC for an adversarial target address
2. Exploit memory corruption to (e.g.) overwrite a return address

Lessons

- Isolation/containment useful for defense-in-depth
- VMs great for isolation/containment, but issues with:
  - VMM transparency
  - Containment (exploitable hypervisor bugs rare but happen)
  - Strong isolation (side channels exist)
  - Securing guest OS and host OS needed for defense-in-depth
- Side-channels are perennial problem
- Microarchitectural vulnerabilities like Meltdown new frontier
  - Spectre, ForeShadow, Fallout, Zombieload, …

Attacks that can expose sensitive data?

Client devices
with web browser
or app

Network
(the internet)

Virtual machine (VM)

Web backend
(Python scripts)

Support utilities
(Shell scripts,
programs)

Network or
local

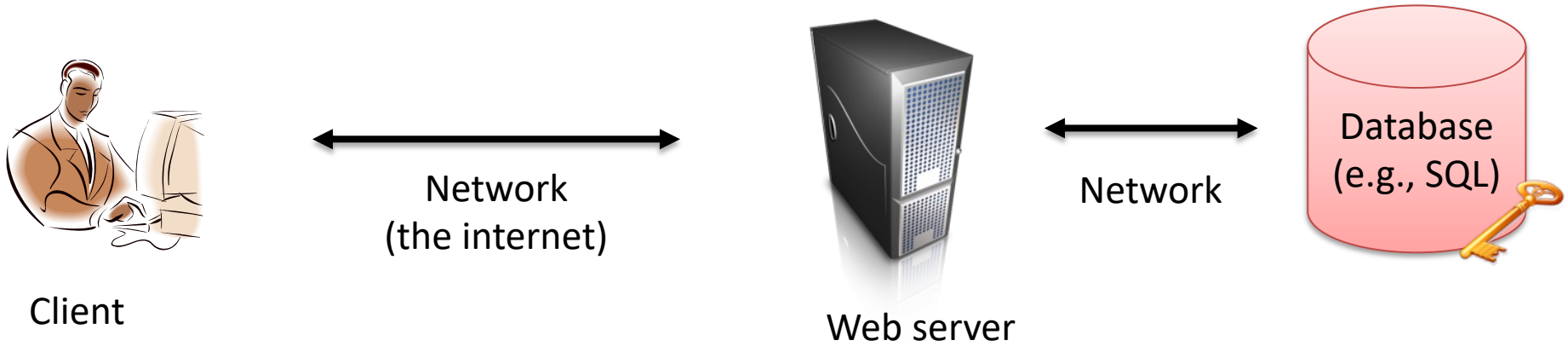
Database
(e.g., SQL)

Today: how do we minimize damage of breach?

- Access controls
  - Least privilege principle applied to database
  - Monitoring & logging accesses
- Encrypted databases
  - Encryption at rest
  - Property-revealing encryption
- Data privacy protections
  - De-identification
  - K-anonymity
  - Differential privacy

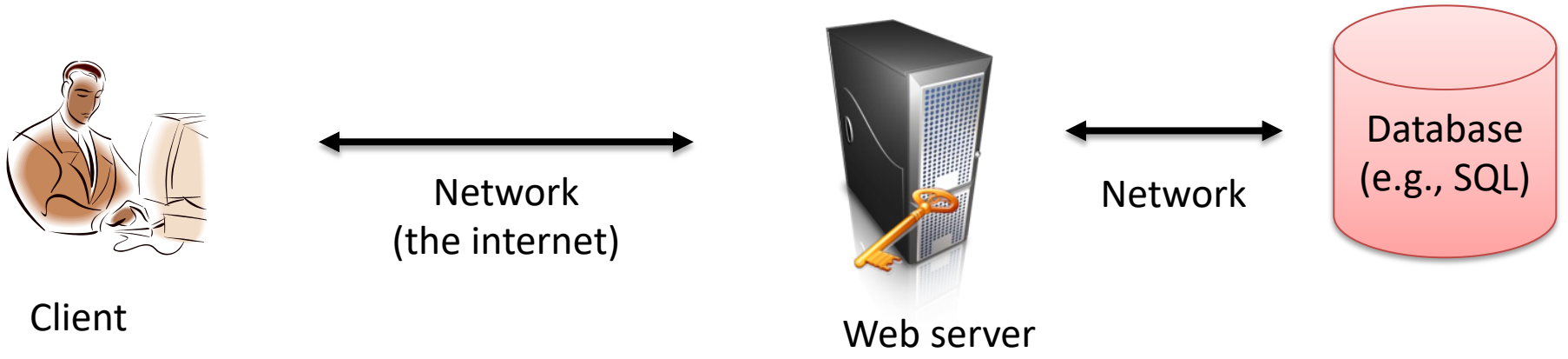
Encrypted databases

- Encrypting data-at-rest
  - Encrypt before storing to persistent storage (keys in software)
  - Encrypted hard drives (keys stored in hard drive)



Encrypted databases

- Encrypting data-at-rest
  - Encrypt before storing to persistent storage (keys in software)
  - Encrypted hard drives (keys stored in hard drive)
- Encrypting *before* insertion into DB
- What attacks could these prevent?



Example: outsourced storage settings

Salesforce stores customer records for companies

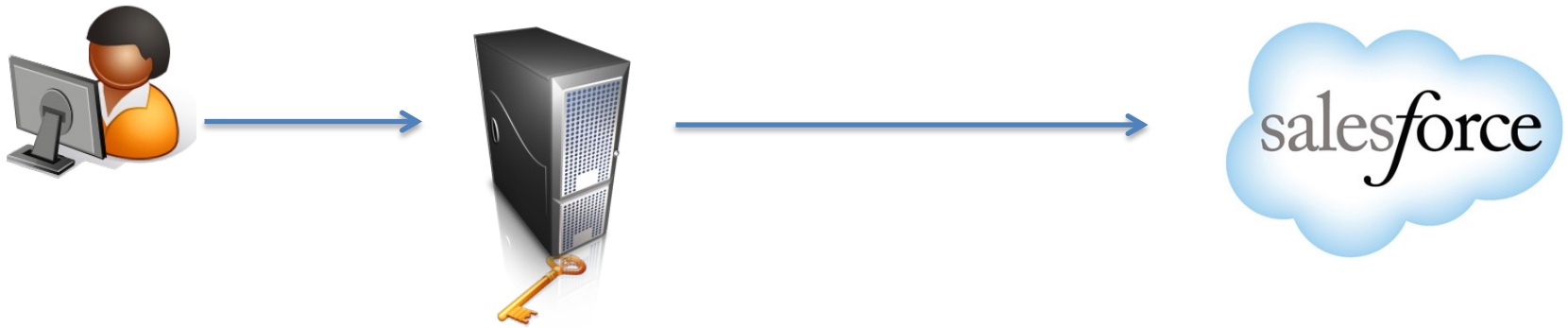
Name:	Clarisse	Comments:	Works in NYC office
Age:	22	Gender:	Female
Salary:	100,000	SSN:	555-31-4325

Much value-add server-side functionality

- Keyword search (find all records with name “Clarisse”)
- Range queries (all records with 20 <= Age <= 30)
- Sorted lists (return records orderered by salary)

What security threats would one worry about?

Example: outsourced storage settings



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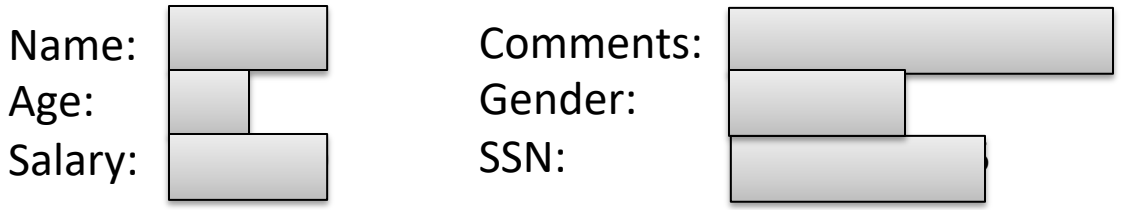
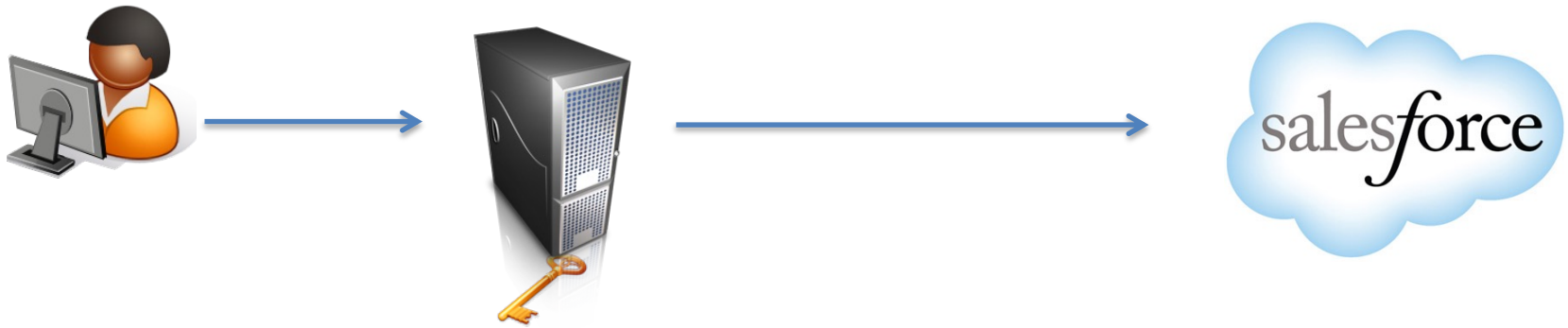


What DB functionalities broken if we use standard authenticated encryption?

- Field search (Find all records with Name = Alice)
- Keyword search
- Range queries (Find all people who make between 90k and 120k)
- Format problems (Age must be integer between 0 and 130)
- …

Example: outsourced storage settings



Salesforce stores customer records for companies

Name:
Age:
Salary:

Comments:
Gender:
SSN:

One approach:

Encrypt data with special ***property-revealing encryption (PRE)*** schemes that leak just enough about plaintexts to perform some operations

CipherCloud™ Trust in the Cloud

PerspecSys Making the Public Cloud Private

skyhigh

Cloud access security brokers (CASB)

Property-revealing encryption (PRE)

Problem	Crypto primitive	Description	Literature
Keyword search	Searchable symmeric encryption	Perform search over ciphertexts given encrypted search token	[Dawn, Song, Wagner 2000] [Curtmola et al. 2006] …
Equality search	Deterministic encryption	X = Y implies DET(X) = DET(Y)	[Rogaway Shrimpton 06]
Range queries	Order-preserving encryption	X > Y implies OPE(X) > OPE(Y)	[Boldyreva et al. 2009]
Range queries	Order-revealing encryption	X > Y implies Cmp(ORE(X),ORE(Y)) = 1	[Boldyreva et al. 11], [Boneh et al. 15]
Deduplication	Message-locked encryption (Convergent encryption)	Different user's encryptions of same plaintext give same ciphertext	[Douceur et al. 2002] [Bellare et al. 2013]
Format restrictions	Format-preserving encryption	Ciphertext has same format as plaintext	[Bellare et al. 2009]

PREs in databases

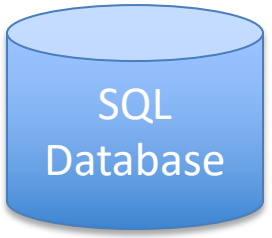
DET(K1, “Alice”)	OPE(K2, “22”)	OKE(K3,“100,000”)
DET(K1, “Bob”)	OPE(K2, “29”)	OPE(K3,“80,000”)
DET(K1, “Alice”)	OPE(K2, “31”)	OPE(K3,“130,000”)

Encrypt by column

Name: DET(K1, “Alice”)
Age: OPE(K2, “22”)
Salary: OPE(K3, “100,000”)

PREs in databases

DET(K1, “Alice”)



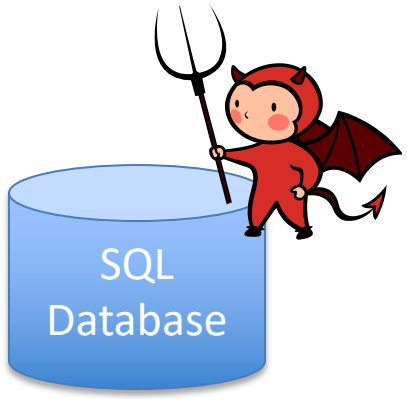
DET(K1, “Alice”)	OPE(K2, “22”)	OKE(K3,“100,000”)
DET(K1, “Bob”)	OPE(K2, “29”)	OPE(K3,“80,000”)
DET(K1, “Alice”)	OPE(K2, “31”)	OPE(K3,“130,000”)

Perform *equality search* by querying DET encryption of keyword

$$DET(K1,X) = DET(K1,Y) \Leftrightarrow X = Y$$

PREs in databases

OPE(K2, 10) , OPE(K2, 30)



DET(K1, “Alice”)	OPE(K2, “22”)	OKE(K3,“100,000”)
DET(K1, “Bob”)	OPE(K2, “29”)	OPE(K3,“80,000”)
DET(K1, “Alice”)	OPE(K2, “31”)	OPE(K3,“130,000”)

Perform *equality search* by querying DET encryption of keyword

$$DET(K1,X) = DET(K1,Y) \Leftrightarrow X = Y$$

Perform *range search* by querying OPE encryption of end points

$$OPE(K2,X) < OPE(K2,Y) \Leftrightarrow X < Y$$

What is revealed to adversarial server?

Frequency analysis

DET(K1, “Alice”)
DET(K1, “Bob”)
DET(K1, “Alice”)
DET(K1, “Alice”)
DET(K1, “Alice”)
DET(K1, “Bob”)

Auxiliary data is plaintext dataset distributed similarly to target. Histogram:

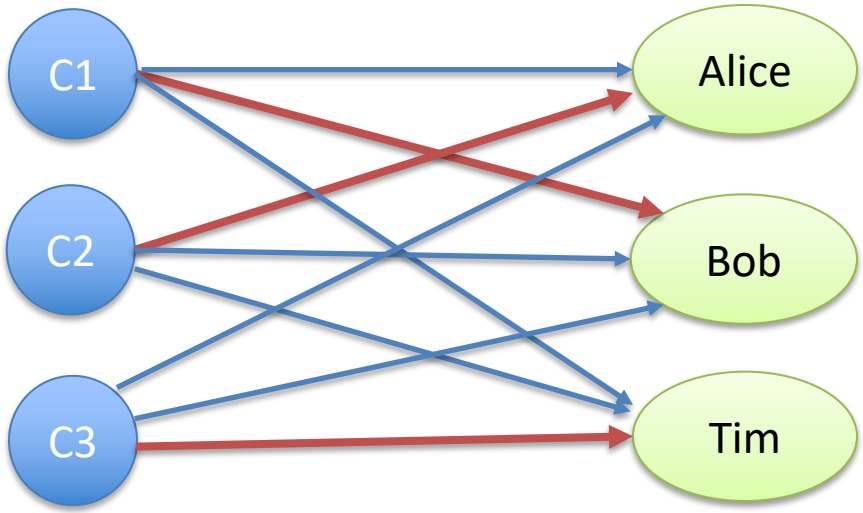
Alice 15
Bob 3
…

p(Name) = Freq(Name)/N
p(Alice) = 15/100000, p(Bob) = 3/10000, …

Match most frequent ciphertext to most frequent auxiliary value
Match next most frequent to next most frequent, etc.

Technique is thousands of years old; applied most often to substitution ciphers
But: DET is just a substitution cipher over large alphabet

Graph viewpoint for attacking DET

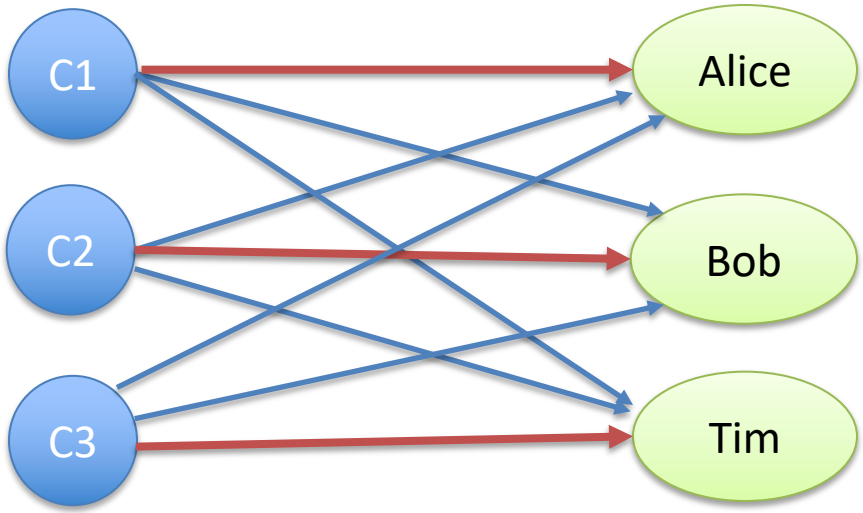


Bipartate graph problem: find matching of ciphertexts, names that maximizes total weight

$$\text{Weight}(C,\text{Name}) = \text{Freq}(C) * \log p(\text{Name})$$

Equivalent to frequency analysis

Graph viewpoint for attacking ORE



Bipartate graph problem: find *non-crossing* matching of ciphertexts, names that minimizes total weight

$$\text{Weight}(C,\text{Name}) = \text{Freq}(C) * \log p(\text{Name})$$

This takes into account ordering constraints

Dynamic programming algorithm efficiently finds non-crossing matching

Leakage-abuse attacks (LAAs)

Question: what can attackers learn from leakage of PRE schemes?

Searchable encryption	[Islam, Kuzu, and Kantarcioglu 2012] [Cash, Grubbs, Perry, R. 2015] [Zhang, Katz, Papamanthou 2016] [Wright, Kamara 2016] …	DET, OPE, ORE	[Naveed, Kamara, Wright 2015] [Durak, DuBuisson, Cash 2016] [Grubbs et al. 2016] …

[Grubbs et al. 2016] recovery rates (percent of DB recovered) for ORE schemes:

Scheme(s)	First names	Last names
Kerschbaum [27]	26%	6%
Popa et al. [36], Kerschbaum [28]	**84%**	38%
BCLO [12, 13]	**99%**	**97%**
CLWW [18]	**98%**	**75%**
BCLO + CLWW [18]	**85%**	44%
Baseline Guessing	4%	1%

Today: how do we minimize damage of breach?

- Access controls
  - Least privilege principle applied to database
  - Monitoring & logging accesses
- Encrypted databases
  - Encryption at rest
  - Property-revealing encryption
- Data privacy protections
  - De-identification
  - K-anonymity
  - Differential privacy

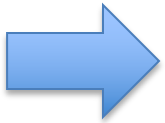
Can we limit the damage of leaking data by lowering its sensitivity?

De-identification

https://nvlpubs.nist.gov/nistpubs/ir/2015/NIST.IR.8053.pdf

Remove identifiers from a database

Name	Age	Salary
Alice	22	100,000
Bob	29	80,000
Charlie	31	130,000

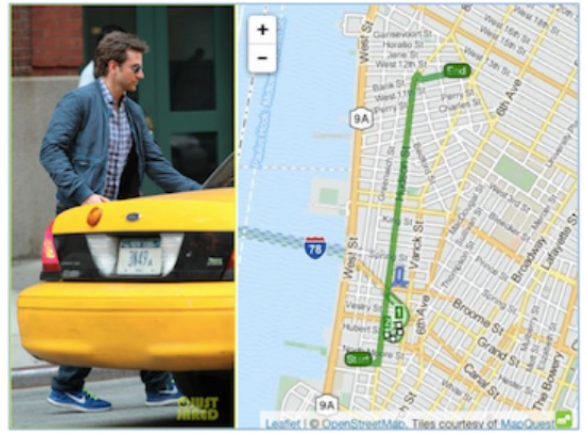


Pseudonym	Age	Salary
7412	22	100,000
8192	29	80,000
3841	31	130,000

How should pseudonym be generated?

NYC Taxi Commission released dataset of 173 million rides in 2014
Pseudonym = MD5(taxi ID)

Trivial to brute-force recover tax IDs



https://research.neustar.biz/author/atockar/

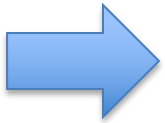
Better approaches:

- Randomly choose pseudonyms
- DET encryption, keyed hash (PRF), and throw away key

De-identification & linkage attacks

Remove identifiers from a database rarely sufficient

Name	Age	Salary
Alice	22	100,000
Bob	29	80,000
Charlie	31	130,000



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7412	22	100,000
8192	29	80,000
3841	31	130,000

What do I need to know to figure out which row corresponds to Alice?

Linkage attacks:

- Determine ***quasi-identifier*** for individuals
- Use pseudoidentifier to look up individuals in another database

[Sweeney 2000]: 87% of Americans uniquely identified by **ZIP code, sex, date of birth**

De-identification & linkage attacks

Remove identifiers from a database rarely sufficient

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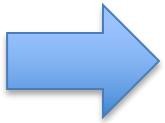

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What do I need to know to figure out which row corresponds to Alice?

[Narayanan, Shmatikov 2008]:

- re-identification attack robust to imprecise background info, perturbations in data
- Case study: re-identify people in de-identified Netflix prize dataset

Countermeasures?

- Try to remove quasi-identifiers
  - Dataset is ***k-anonymous*** if for every combination of quasi-identifiers there are at least k matching records [Samarati, Sweeney 1998]
  - Can: suppress attributes, generalize attributes, add dummy records
  - Various generalizations such as L-diversity
- Generally considered not to provide strong privacy protections
  - Hard to know a priori what can serve as quasi-identifiers
  - Re-identification, other privacy attacks shown to still be possible

Differential privacy

[Dwork, McSherry, Nissim, Smith '06]

Build randomized mechanisms for rendering database (or queries against a database) s.t. adversary can't with high confidence know if any particular individual in data set

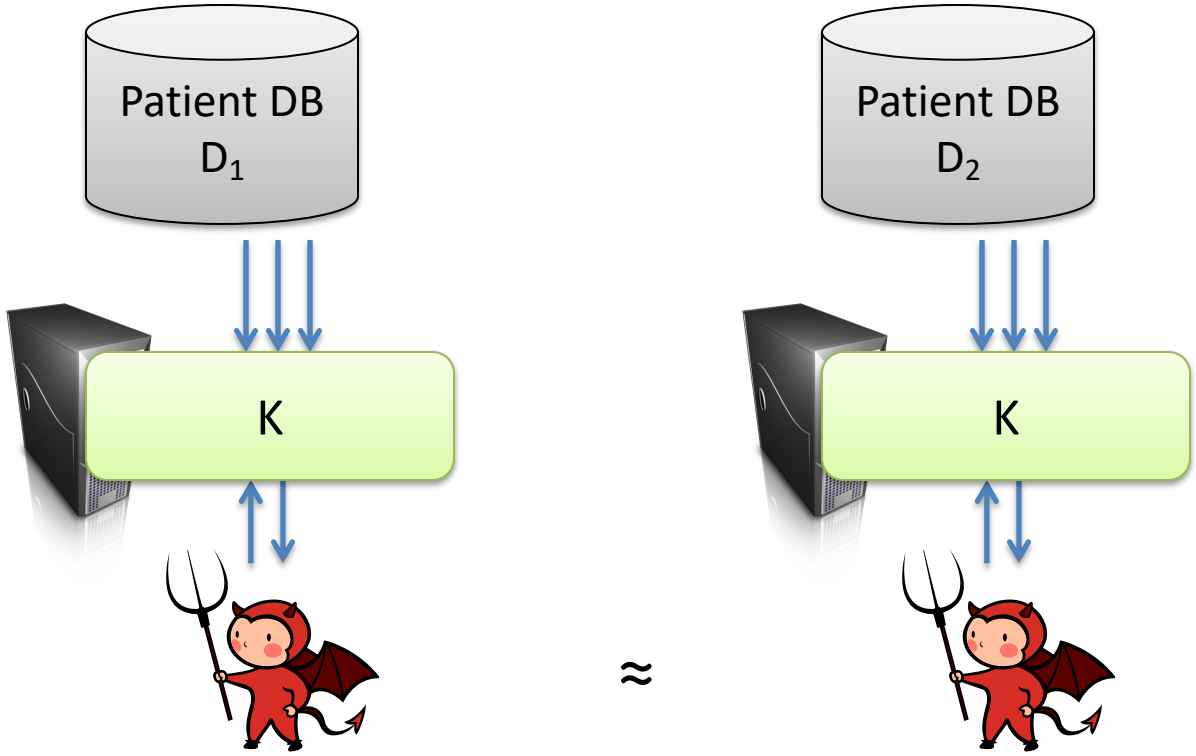
K is randomized algorithm. K is ***ε-differentially private*** if:
for all datasets D_1 , D_2 differing in at most one row and all subsets S of K's range:

$$\Pr[\mathrm{K}(D_1) \in S] \leq e^{\epsilon} \cdot \Pr[\mathrm{K}(D_2) \in S]$$

K *necessarily* adds noise, forcing a utility vs. privacy trade-off

Differential privacy

[Dwork, McSherry, Nissim, Smith '06]



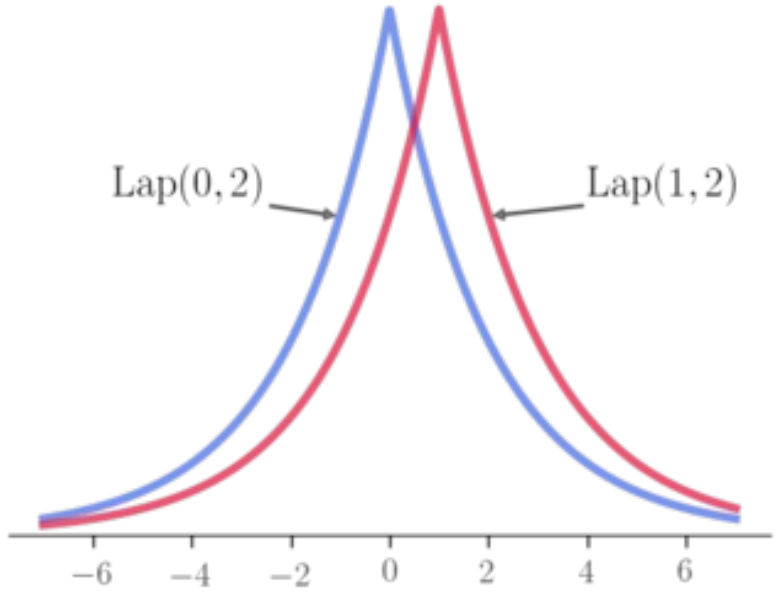
Differential privacy

[Dwork, McSherry, Nissim, Smith '06]

Say we only want to render private some ***statistic*** of DB
Let f be function computing the statistic (e.g., median)

$$K(D,f,\varepsilon) = f(D) + Lap(0,\Delta f/\varepsilon)$$

where $\Delta f = \max|f(D_1) - f(D_2)|$ is sensitivity f and
$Lap(0,\Delta f/\varepsilon)$ is random according to Laplacian distribution



Intuition: add sufficient random noise centered on actual value to ensure uncertainty about which database used

Rappor system in Chrome browser

Google wants to collect information on websites visited by users of Chrome

- [Elringsson et al. 2014] gives DP system for sending reports
- Builds on ***randomized response***. Flip a coin:
  - Heads: report "Visited example.com" no matter what
  - Tails: report whether this user visited example.com
- Uses variant with deniability for both Yes/No answers, long-term private response, short-term private response, …
- Rappor uses $\varepsilon = \ln 3$

- Various limitations, see paper

DP at Apple

Apple deployed DP mechanism for certain user data items collected by iOS

- Proprietary implementation
- [Tang et al. 2017] reverse engineered implementation:
  - Privacy budget epsilon ε not sufficient
  - Re-upped privacy budget each day
- Unclear how much privacy protection really offered

Data protections

- Need multiple layers of defenses
  - ***Minimize sensitive data collected and stored***
  - Deny access to data (access controls + good software security)
  - Encrypt it as much as possible and use best practices for key management
  - Anonymization privacy techniques can be useful, but delicate