Module 5

Data Security and Privacy

Data Security and Privacy

- Data Security
  - Who has access to the data?
  - Who can change the data?
  - What are the threats to the data?
  - How do we mitigate the threats?
- Data Privacy
  - Who is the data about?
  - How can we share data without threatening people's privacy?

Threats to Data Security

- Random corruption
- Software flaws
- Human errors
- Malicious corruption
- Malicious injection

Protecting Data Security

- Access Control
- Error Checking/Correction
- Backup

Access Control

- Define access control for (legitimate) users
- Mandatory vs Discretionary models
  - Mandatory: Admin controls all r/w/x permissions
    - Includes: Multi-level security
  - Discretionary: Each user decides
    - Includes: Unix file access control

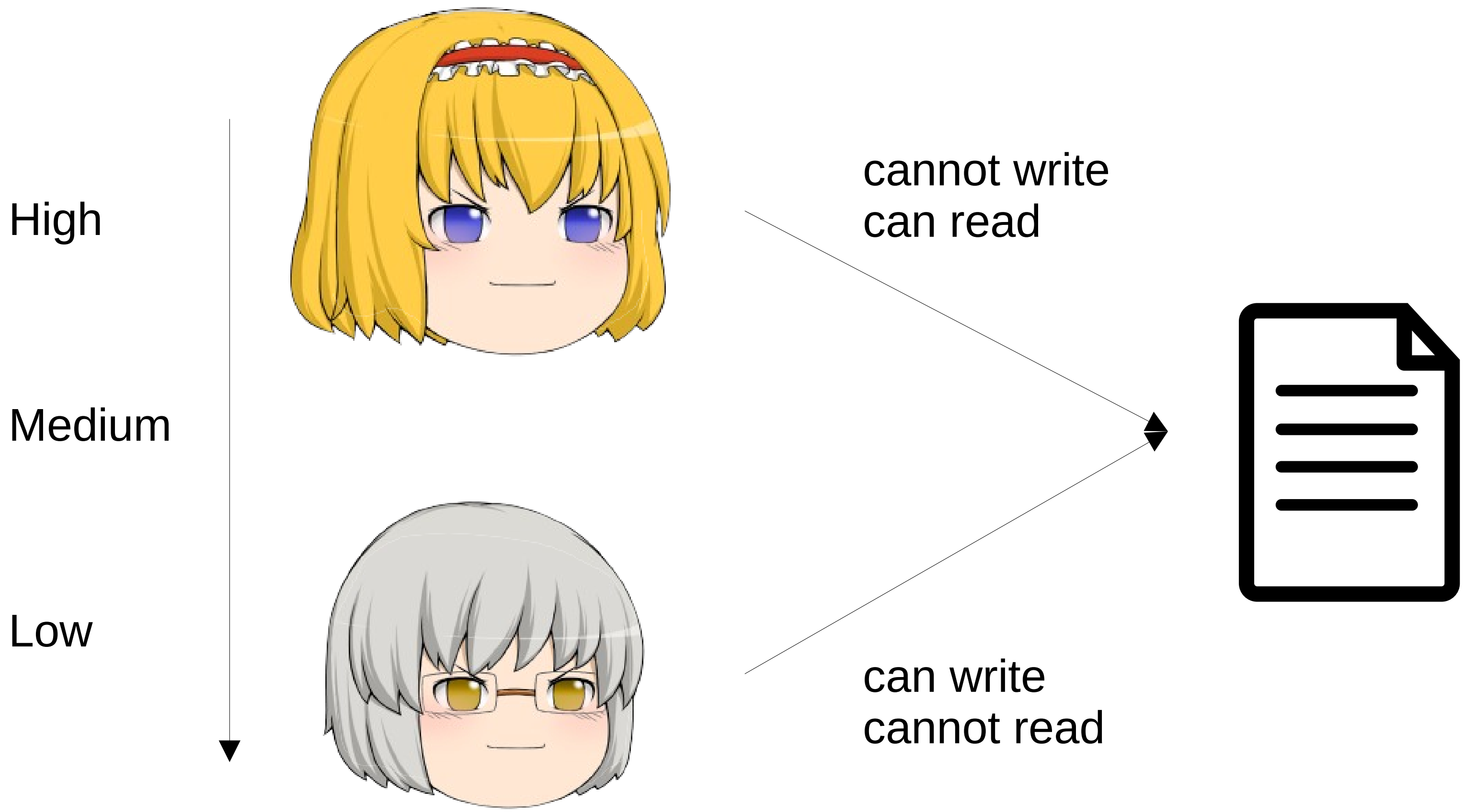
Bell-LaPadula Model

- Example of Multi-Level Security
- Subjects and Objects both have security levels (e.g. High, Low)
- All read/write must follow two rules (next slide)
- Prevents leakage of information (i.e. confidentiality)

Bell-LaPadula Model

1) A lower security subject cannot read a higher security object

2) A higher security subject cannot write to a lower security object



Biba Integrity Model

- Like Bell-LaPadula, but reversed. Two rules:
  1) A higher security subject cannot read from a lower security object
  2) A lower security subject cannot write to a higher security object
- Prevents flow of incorrect information (i.e. integrity)

High-water and Low-water mark

- Replaces rule 2) of each model
- High-water Bell-LaPadula: After higher security subject writes to lower security object, increase security level of object to level of subject
- Low-water Biba Integrity: After high security subject reads from lower security object, decrease security level of subject to level of object

File Access Control

- Access control matrix
- Access control list
- Capabilities
- Role-based

		Objects		
		Data1	Data2	Data3
Subjects	Alice	rw	r	-
	Bob	-	-	r
	Carol	r	r	r

Access Control List

- “Which subjects can read/write/execute this object?”
- e.g. chmod 744 on Unix (what does it mean?)

		Objects		
		Data1	Data2	Data3
Subjects	Alice	rw	r	-
	Bob	-	-	r
	Carol	r	r	r

ACL for Data1

Capabilities

- A transferable "reference" that gives a subject permissions to an object
- "Which objects can this subject read/write/execute?"
- f = open("filename", r);

		Objects		
		Data1	Data2	Data3
Subjects	Alice	rw	r	-
	Bob	-	-	r
	Carol	r	r	r

Alice's capabilities

Biometrics

- Visual, sound, fingerprint, gait
- Can be mimicked – photos, recordings, etc.
- Also suffers from base rate fallacy

Token devices

- For key K and time T, output is:

$$h(K \oplus T)$$

- Only device owner and authorization checker have the key K

Physical Security

- Preventing damage: Rain, Bug, Storm, Electricity, Earthquake, Tornado, etc.
- Access: Fencing, Walls, Windows
- Monitoring: Guards, Cameras

Error detection

- Small number of bit errors should be detectable
- Append a tag to a file:
  - Parity
  - Checksums, e.g. CRC32
  - Hashes; a weak cryptographic hash may be a good error detection hash (e.g. MD5)
- Input can be any size, output is fixed (32-bit for CRC32, 128-bit for MD5)
- Cannot fix an error

Error correction

- Error Correcting Codes (ECC)
- Used in memory, storage, etc.
- Hamming code example:
  - For 2^k-1 bits of transmission, use k bits of parity
  - parity k is in location 2^k
  - There are 2^k-k-1 bits of data in all other locations
  - parity k covers all locations with 1 in the *k*th bit except itself
  - Can correct any 1 bit error
  - Can detect any 2 bit error if we add a parity bit covering all other bits

Error correction

Data is:

$$d_1 d_2 d_3 ... d_{11}$$

Add parity bits in the right places:

$$\mathbf{p_1 p_2} d_1 \mathbf{p_3} d_2 d_3 d_4 \mathbf{p_4} d_5 d_6 d_7 d_8 d_9 d_{10} d_{11}$$

Compute parity bits:

$$\mathbf{p_1 = H_3 \oplus H_5 \oplus H_7 \oplus H_9 \oplus H_{11} \oplus H_{13} \oplus H_{15} = d_1 \oplus d_2 \oplus d_4 \oplus d_5 \oplus d_7 \oplus d_9 \oplus d_{11}}$$

$$\mathbf{p_2 = H_3 \oplus H_6 \oplus H_7 \oplus H_{10} \oplus H_{11} \oplus H_{14} \oplus H_{15} = d_1 \oplus d_3 \oplus d_4 \oplus d_6 \oplus d_7 \oplus d_{10} \oplus d_{11}}$$

...

Let's say d_6 was flipped. Which parity bits will seem “wrong”?

d_4 is H_{10}, and 10 = $(1010)_2$, so p_2 and p_4 will seem “wrong”

Let's say the receiver notices parity bits 2 and 3 seem wrong.
Which bit should they correct?

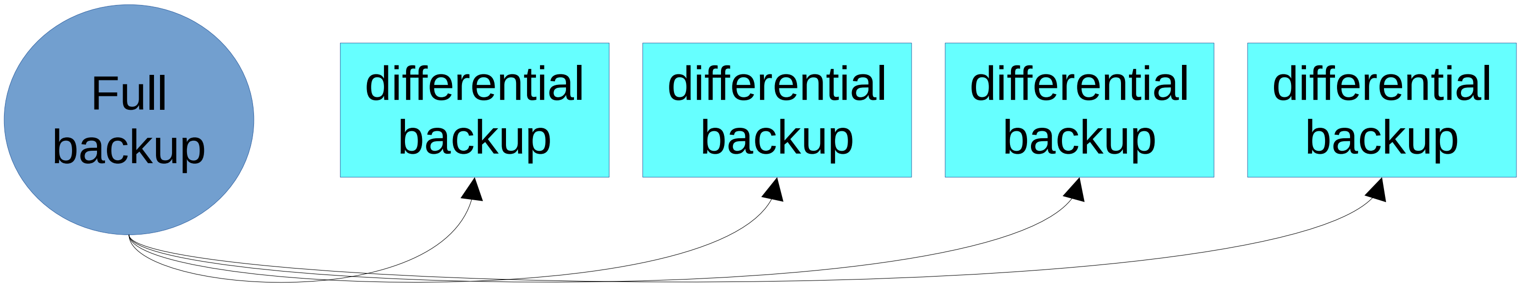
$(0110)_2$ is 6, and H_6 is d_3, so they should correct d_3

Backup

- Used for disaster recovery – we want to recover our data after corruption
- Full backups store all data, but we cannot store too many
- We need to use differential and incremental backups

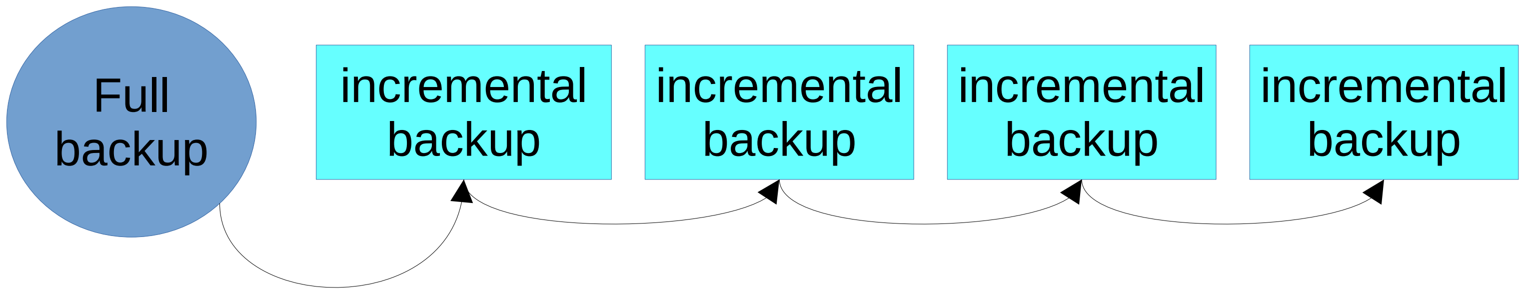
Differential backup

- Stores all changes between current time and last full backup
- How can we find changes?
  - e.g. rsync in Unix: Divide file into chunks, then hash each chunk, and compare the hash for each chunk with stored MD5 hashes
  - Only updates chunks with changed hashes



Incremental backup

- Stores all changes between current time and last backup (not necessarily full backup)
- Smallest storage space
- Hard to recover (if full backup was a long time ago)
- What happens if we combine differential and incremental backups?



Replication

- Different from backups: replication keeps no historical state
- Synchronous replication: All file updates should happen (almost) immediately
- Asynchronous replication: Small delay when pushing to replicas is acceptable
- Shadowing for databases

Data Privacy

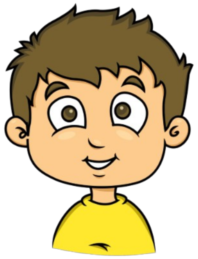
Data has sensitive attributes and personally identifiable information

How can the data owner allow a data user to utilize the data without compromising privacy?

Idea: Restrict queries by data user
But this leads to *inference attacks!*

Inference Attack

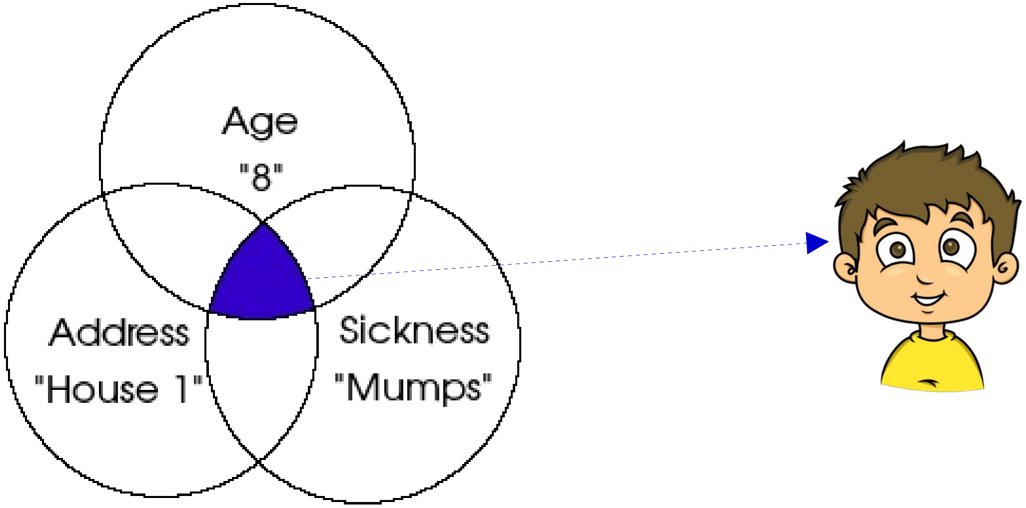
- Use restricted queries to infer sensitive attributes
- Example: A hospital has a database of patients and their sicknesses, and wants to allow queries on it for research
- For simplicity: Database includes Age, Address, Sickness
- The hospital restricts all queries to COUNT queries
- Bob is the only boy who is 8 and lives in House 1
- Can the data user (who knows Bob’s Age and Address) figure out if Bob has mumps?



Inference Attack

Queries only including Bob

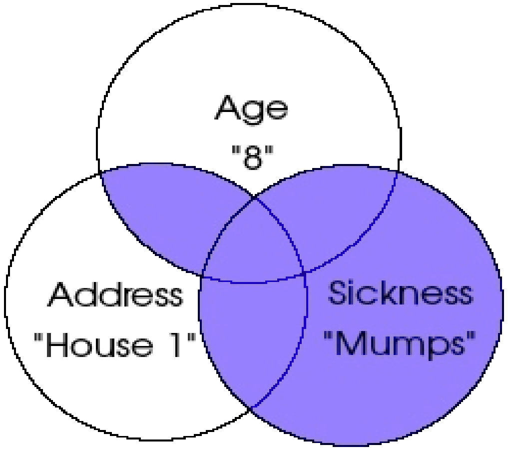
- Data user makes a query returning 0 or 1 result:
  - COUNT(Age=”8” and Address=”House 1” and Sickness=”mumps”)
- Such queries should also be restricted
- But this does not solve difference and intersection inference attacks (next)



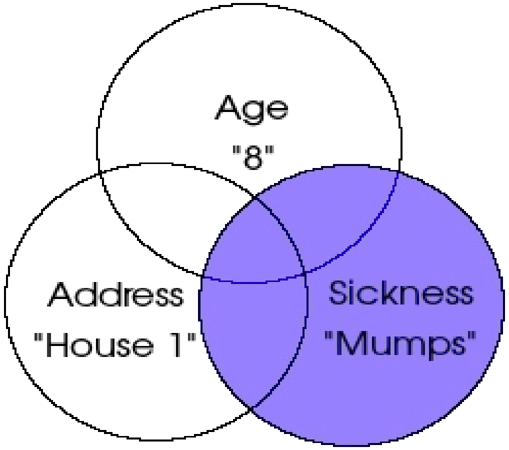
Inference Attack

Difference of queries

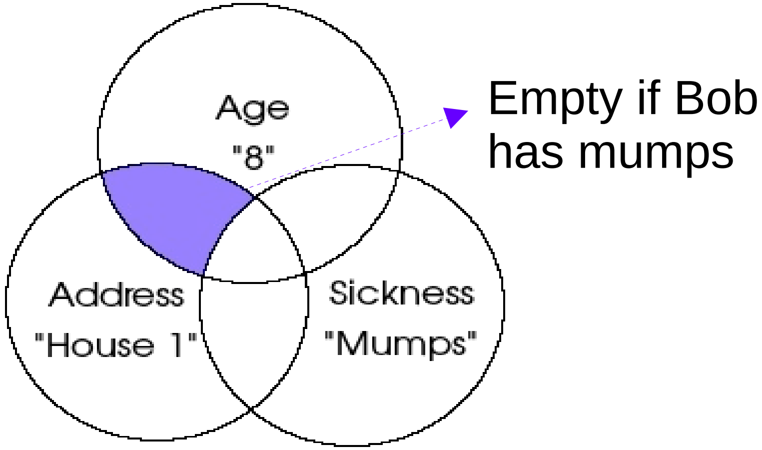
- Data user makes two queries, and takes their difference:
  - Q1 = COUNT(Sickness=”mumps”)
  - Q2 = COUNT((Age=”8” and Address=”House 1”) or Sickness=”mumps”)
- Q2-Q1 = 0 if Bob has mumps, and 1 if not



Q2



Q1

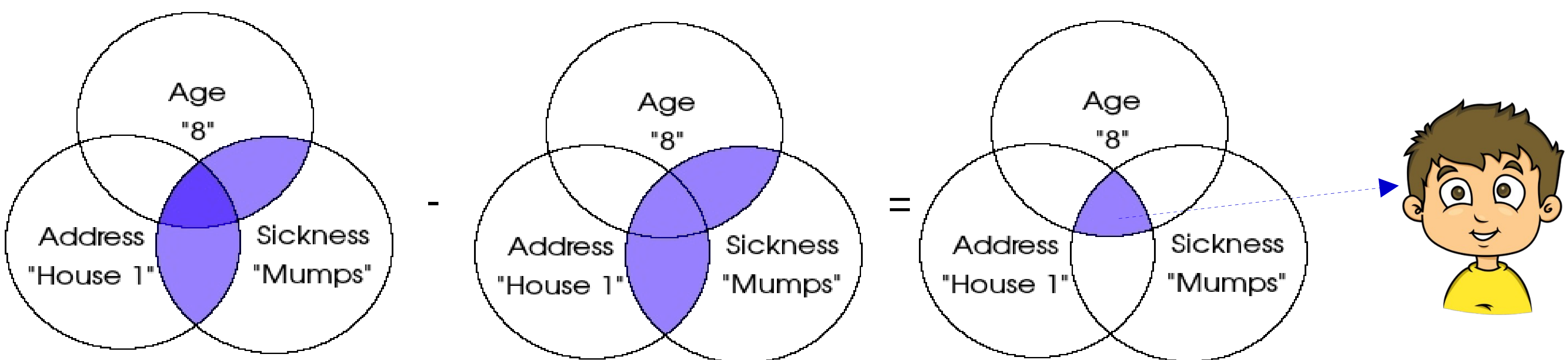


Q2-Q1

Inference Attack

Intersection of queries

- Data user makes three queries:
  - Q1 = COUNT(Age="8" and Sickness="mumps")
  - Q2 = COUNT(Address="House 1" and Sickness="mumps")
  - Q3 = COUNT((Age="8" or Address="House 1") and Sickness="mumps")
- Q1+Q2-Q3 is 1 if Bob has mumps, and 0 if not



Q1+Q2 Q3 Q1+Q2-Q3

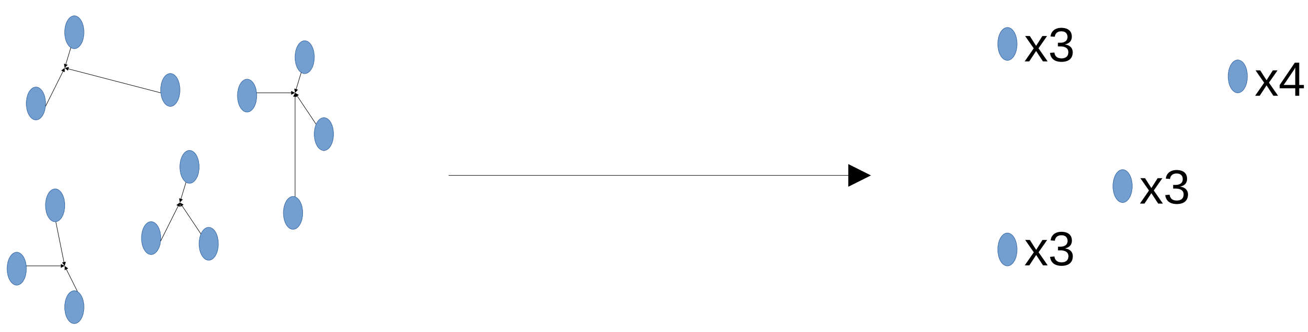
Data Privacy

How can the data user compute Q on data owner's D without compromising privacy?

- <u>k-Anonymity</u>: (D sensitive, Q possibly sensitive) Publish distorted D
- <u>Differential Privacy</u>: (D sensitive) Allow only special queries with mathematical error guarantees
- <u>Secure Multiparty Computation</u>: (D1, D2 sensitive) jointly compute Q without revealing D1, D2 to each other
- <u>Private Information Retrieval</u>: (Q sensitive) Retrieve some information from D without revealing Q

k-Anonymity

- Remove link between identifiers (PII) and sensitive attribute
- Anonymization function is usually deterministic
- After anonymization, each **set** of identifiers in the table must appear at least *k* times (= anonymity sets have at least k elements)



(data points)

k-Anonymity

	Quasi-identifiers		
	Age	Weight (kg)	Heart disease?
Hospital Subjects	23	86	N
	15	65	Y
	34	123	Y
	55	95	N
	32	63	Y
	45	89	Y
	59	112	N
	61	81	Y
	15	73	Y

→

	Quasi-identifiers		
	Age	Weight (kg)	Heart disease?
Hospital Subjects	25	100	N
	25	50	Y
	25	100	Y
	50	100	N
	25	50	Y
	50	100	Y
	50	100	N
	50	100	Y
	25	50	Y

"Round Age to nearest 25, Weight to nearest 50" → k = 2
(There are three anonymity sets: Size 2, Size 3, Size 4.
We take the minimum to be k.)

k-Anonymity

	Quasi-identifiers		
	Age	Weight (kg)	Heart disease?
Hospital Subjects	25	100	N
	25	50	Y
	25	100	Y
	50	100	N
	25	50	Y
	50	100	Y
	50	100	N
	50	100	Y
	25	50	Y

- A flaw in k-anonymity: All members of an anonymity set may have the same sensitive attribute
  - e.g. If your friend is around age 25 and weight 50kg, and you know they're in the table, you know they have heart disease
- To fix this, we can also enforce *l*-diversity: Every anonymity set must have at least *l* different sensitive attributes

k-Anonymity

- Another weakness is that completentary releases can compromise k-anonymity:

	Quasi-identifiers	
	Weight (kg)	Sickness
Hospital Subjects	30-60	A
	30-60	B
	30-60	C
	30-60	D
	30-60	E
	60-150	F
	60-150	G
	60-150	H
	60-150	I

$k = 4$

	Quasi-identifiers	
	Weight (kg)	Sickness
Hospital Subjects	25-55	A
	25-55	B
	25-55	C
	25-55	D
	55-150	E
	55-150	F
	55-150	G
	55-150	H
	55-150	I

$k = 4$

Different rounding schemes will weaken k - if your friend has weight 56 kg, you know they have E

k-Anonymity

- Knowing the anonymization scheme can also compromise the scheme. Suppose Age is the only QID. If you know the anonymization scheme is the following:
  - Sort patients by age, start with an anonymity set containing only the smallest age.
  - Add patients in order to the current anonymity set until desired *k* and *l* have been achieved. Then start a new anonymity set with the next person that has not been added.
  - Repeat until all patients added; if final anonymity set is too small, merge it with the previous completed anonymity set.
- Suppose the hospital want to achieve *k = 3, l* = 2. It releases two anonymity sets {Age}:{Heart Disease} as follows:

  - {0-40}: {N, Y, Y, Y, Y}   {40-80}: {Y, N N}

- If you know that your friend is the youngest person in the database, then they definitely have heart disease, otherwise the first set would not be so large!

Differential privacy

- Ensures privacy of data items using a *differential* mathematical formulation
- Hard to understand, easy to implement
- Anonymization function is random
- Used in iOS 10 (2016)

Motivation: Differencing attack

- Suppose you query the mean salary of a company M_1 with 500 people, then someone joins, and you query it again to obtain M_2
- What is the salary of the person who joined?
- Similar: Query for total count of people with a certain condition, ethnicity, etc.
- What about sequential queries?

Differential privacy

Two databases are *neighboring* if they are the same except for one element (one person's data).

A query Q is *ε-differentially private if for all neighbouring databases D_1 and D_2 and for all q:*

$$\frac{Pr(Q(D_1)=q)}{Pr(Q(D_2)=q)} \leq e^{\varepsilon}$$

Intuitively, changing one person's data is unlikely to change the result (distribution) of a differentially private query => the query result does not reveal that person's existence!

Hypothesis Testing

Differential privacy is closely related to hypothesis testing. Suppose that two hypotheses are:

H_0: The underlying dataset is D which does contain Alice
H_1: The underlying dataset is D remove {Alice}

We use the definition of differential privacy:

$$\frac{Pr\left(Q\left(D_1\right)=q\right)}{Pr\left(Q\left(D_2\right)=q\right)} \leq e^{\varepsilon}$$

The probability of rejecting the null hypothesis H_0 at significance level *a* is no higher than $e^{\varepsilon}a$ ~= *a*, i.e. any test cannot be powerful

Achieving differential privacy

In many cases, differential privacy is easily achieved with *Laplacian* noise, with pdf defined as follows:

$$f(x,b)=\frac{1}{2b}\exp\left(\frac{-|x|}{b}\right)$$

Consider two neighboring databases query results $Q(D_1) > Q(D_2)$, then for any k *we can write* $k = Q(D_1) + x_1$ *and* $k = Q(D_2) + x_2$

$$\frac{Pr(Q(D_1)=k)}{Pr(Q(D_2)=k)}=\frac{\frac{1}{2b}\exp\left(\frac{-|x_1|}{b}\right)}{\frac{1}{2b}\exp\left(\frac{-|x_2|}{b}\right)}\leq\exp\left(\frac{|Q(D_1)-Q(D_2)|}{b}\right)$$

Sensitivity

The sensitivity of a query is the maximum amount it can change between neighboring datasets:

$$S(Q) = max_{neighbours} |Q(D_1) - Q(D_2)|$$

Therefore, Laplacian noise with mean 0 and sensitivity b achieves *ε-DP* where *ε* = *S(Q)/b*

Sensitivity of common queries:

- Count (including conditional count): 1
- Summation: *m* where *m* is the largest possible element
- Mean: *m/n* where *m* is as above and *n* is the smallest possible dataset

Intuition of differential privacy

- A small amount of noise on a query output can be equivalent to a large amount of noise on each individual element
- We are anonymizing a *query*, not a database
  - It will work on any database
- If a query output is possible for a database but not for a neighboring database, there is no DP

Usefulness of differential privacy

<u>Composition theorem</u>

- If Q_1 and Q_2 are differentially private at levels ε_1 and ε_2, $(Q_1(x), Q_2(x))$ is $(\varepsilon_1 + \varepsilon_2)$-differentially private
  - This protects against sequential release

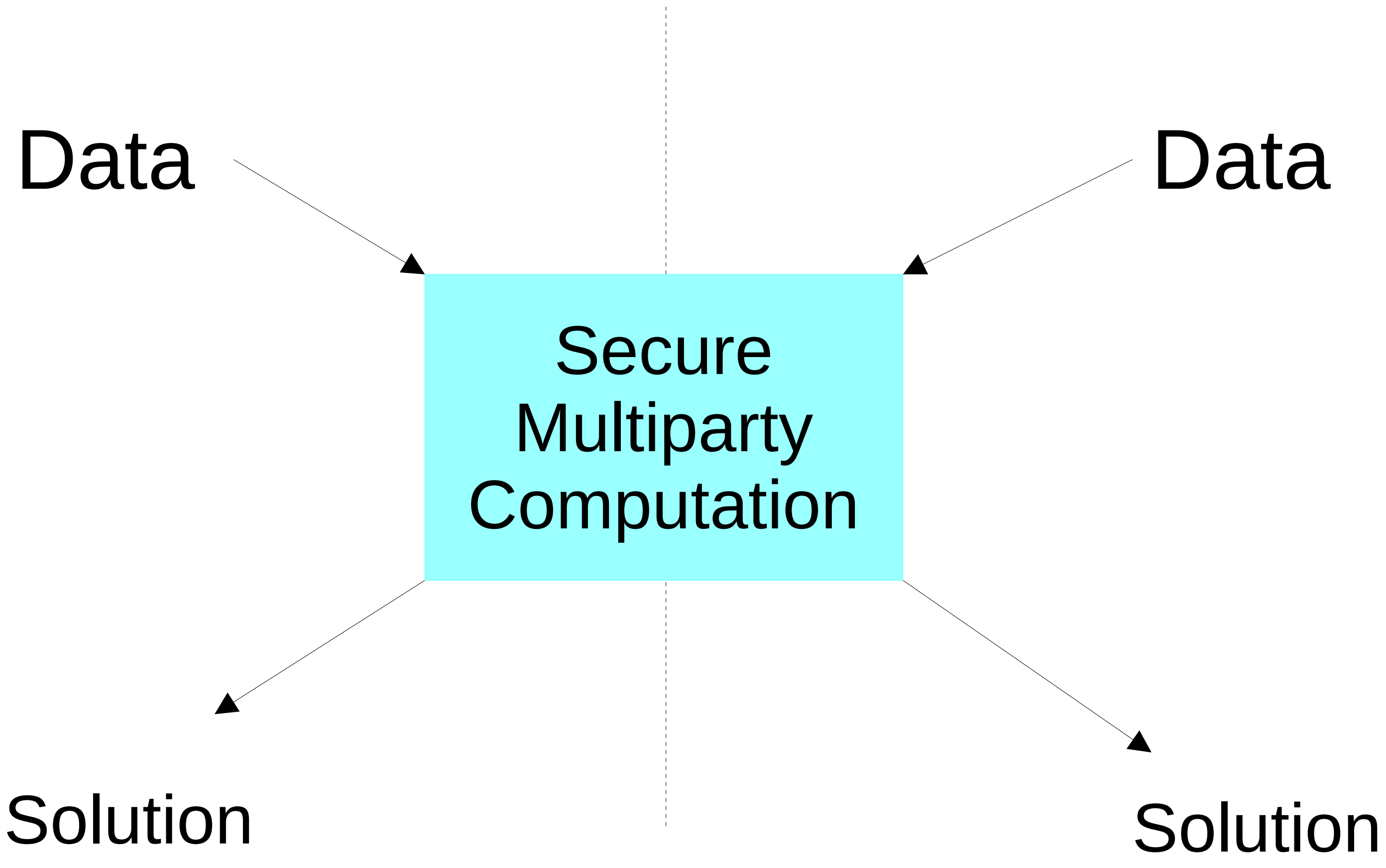
<u>Post-processing theorem</u>

- If Q is ε-differentially private, $g(Q)$ is ε-differentially private for any function g
  - Any operation on the output is safe

Differential privacy for data aggregation

- Scenario: Each individual has (private) data, we want to compute aggregate without compromising privacy
- DP intuition: Large noise for each person = small noise on result
- Example: Count Mean Sketch for identifying energy-hungry websites
  - Energy-hungry website is first mapped to a one-hot vector using a hash function
  - Each bit of the vector is then randomly flipped with some probability to introduce noise
  - Summing all users' vectors still produces a number close to the true value
- Also possible to jointly train a ML model

Secure Multiparty Computation



Useful for research, data analytics, collaboration, etc.

Secure Multiparty Computation

- Two parties with different data can jointly compute a known function on the union of their data while sharing no data at all
  - e.g. “Who has more customers on this day?”
- Generally (much) slower than directly running the algorithm
  - e.g. 20 minutes on 2 cores to complete one AES encryption of 128 bits under SMPC
- Guaranteed correctness without noise

Secure Multiparty Computation

Yao’s garbled circuit

- Construct a boolean circuit representing the problem
- Suppose A is the “garbler”, and B is the “evaluator”
- For each boolean gate, A will compute a *garbled* table and share all garbled tables with Bob

Secure Multiparty Computation

Yao's garbled circuit

- For each boolean gate, A computes a garbled table:
  - Generate random garbled strings I_0, J_0, I_1, J_1 representing input bits being 0 or 1
  - Generate random garbled strings O_0, O_1 representing output bits being 0 or 1
  - Encrypt the four possible outputs (random strings) of the table using its inputs as keys, with some long public string A (e.g. 128 bits of 0)
  - Randomize the order of the table, share this table

Input 1 (I)	Input 2 (J)	Output (O)
0	0	0
0	1	1
1	0	1
1	1	0

→

Encrypted Output (O)
$Enc_{I1, J0}(O_1 \| \| A)$
$Enc_{I0, J0}(O_0 \| \| A)$
$Enc_{I1, J1}(O_0 \| \| A)$
$Enc_{I0, J1}(O_1 \| \| A)$

This table is shared with Bob

Secure Multiparty Computation

Yao's garbled circuit

- What does Bob do with the table?

Encrypted Output (O)
$Enc_{I1, J0}(O_1\|\|A)$
$Enc_{I0, J0}(O_0\|\|A)$
$Enc_{I1, J1}(O_0\|\|A)$
$Enc_{I0, J1}(O_1\|\|A)$

- Suppose Alice's input is I (and it is 0) and Bob's bit is J (and it is 1)
- Alice sends Bob I_0, Bob requests J_1 from Alice
- Using those two strings as a key, Bob tries to decrypt all 4 rows of this table
- Only one row will succeed (Bob knows it succeeds if A shows up)
- Bob will then obtain O_1 (without knowing the meaning of O_1)
- This can be used in the next gate, or if it is the final output, its meaning can be determined by asking Alice

Secure Multiparty Computation

Yao's garbled circuit

- We achieve these desired properties:
  - Bob can compute the gate without knowing the real inputs
  - The output is unknown to Bob until Alice reveals what the output means
  - Alice does not see the output garbled string until Bob reveals it
- Bob's request from Alice needs to be protected: Bob can't take both J_0 and J_1 (otherwise he can cheat), but Bob can't say "I want J_1" (otherwise Alice knows Bob's input is 1)
- This can be done with oblivious transfer

A different scenario

- What if the data holder’s data is not sensitive, but the data user’s query is sensitive?
- For example:
  - Searching for a patent
  - Searching for attributes of a sickness
  - Searching for darknet sites
- We want to use Private Information Retrieval in these cases

Private Information Retrieval

- Mechanisms to hide query from data owner
- Data returned is accurate
- Trivial solution: Let data user download entire database, but this is not efficient
- Multi-database PIR can be information-theoretically secure (and efficient)
- Single-database PIR is possible (see notes)

4-Database Information-Theoretic PIR

- First, represent the database as a 2-dimensional table; Alice wants to obtain one of these elements

$x_{1,1}$	$x_{1,2}$	$x_{1,3}$	$x_{1,4}$
$x_{2,1}$	$x_{2,2}$	$x_{2,3}$	$x_{2,4}$
$x_{3,1}$	$x_{3,2}$	$x_{3,3}$	$x_{3,4}$
$x_{4,1}$	$x_{4,2}$	$x_{4,3}$	$x_{4,4}$
$x_{5,1}$	$x_{5,2}$	$x_{5,3}$	$x_{5,4}$

4-Database Information-Theoretic PIR

- Alice randomly picks each row and column with ½ chance (not related to the element she truly wants)
  - R = {Rows 2, 3, 5}
  - C = {Column 3}

$x_{1,1}$	$x_{1,2}$	$x_{1,3}$	$x_{1,4}$
$x_{2,1}$	$x_{2,2}$	$x_{2,3}$	$x_{2,4}$
$x_{3,1}$	$x_{3,2}$	$x_{3,3}$	$x_{3,4}$
$x_{4,1}$	$x_{4,2}$	$x_{4,3}$	$x_{4,4}$
$x_{5,1}$	$x_{5,2}$	$x_{5,3}$	$x_{5,4}$

4-Database Information-Theoretic PIR

- Alice creates R’ and C’ by flipping the rows in R and columns in C corresponding to the element she truly wants. Suppose she wants $x_{2,2}$:
  - Flip row 2, R’ = {Rows 3, 5}
  - Flip column 2, C’ = {Columns 2, 3}
- Then she creates 4 requests to 4 servers. Each request is an XOR of all elements in certain rows and columns:
  - DB1 = XOR all elements in the intersection of R and C
  - DB2 = XOR all elements in the intersection of R’ and C
  - DB3 = XOR all elements in the intersection of R and C’
  - DB4 = XOR all elements in the intersection of R’ and C’

4-Database Information-Theoretic PIR

$x_{1,1}$	$x_{1,2}$	$x_{1,3}$	$x_{1,4}$
$x_{2,1}$	$x_{2,2}$	$x_{2,3}$	$x_{2,4}$
$x_{3,1}$	$x_{3,2}$	$x_{3,3}$	$x_{3,4}$
$x_{4,1}$	$x_{4,2}$	$x_{4,3}$	$x_{4,4}$
$x_{5,1}$	$x_{5,2}$	$x_{5,3}$	$x_{5,4}$

DB1

$x_{1,1}$	$x_{1,2}$	$x_{1,3}$	$x_{1,4}$
$x_{2,1}$	$x_{2,2}$	$x_{2,3}$	$x_{2,4}$
$x_{3,1}$	$x_{3,2}$	$x_{3,3}$	$x_{3,4}$
$x_{4,1}$	$x_{4,2}$	$x_{4,3}$	$x_{4,4}$
$x_{5,1}$	$x_{5,2}$	$x_{5,3}$	$x_{5,4}$

DB2

$x_{1,1}$	$x_{1,2}$	$x_{1,3}$	$x_{1,4}$
$x_{2,1}$	$x_{2,2}$	$x_{2,3}$	$x_{2,4}$
$x_{3,1}$	$x_{3,2}$	$x_{3,3}$	$x_{3,4}$
$x_{4,1}$	$x_{4,2}$	$x_{4,3}$	$x_{4,4}$
$x_{5,1}$	$x_{5,2}$	$x_{5,3}$	$x_{5,4}$

DB3

$x_{1,1}$	$x_{1,2}$	$x_{1,3}$	$x_{1,4}$
$x_{2,1}$	$x_{2,2}$	$x_{2,3}$	$x_{2,4}$
$x_{3,1}$	$x_{3,2}$	$x_{3,3}$	$x_{3,4}$
$x_{4,1}$	$x_{4,2}$	$x_{4,3}$	$x_{4,4}$
$x_{5,1}$	$x_{5,2}$	$x_{5,3}$	$x_{5,4}$

DB4

Yellow = activated Rows, Green = activated Columns, Orange = intersection;
DB replies with XOR of all elements in orange

4-Database Information-Theoretic PIR

- Alice can obtain $x_{2,2}$ just by XORing all 4 responses (XOR sequence: XOR of all orange boxes in the previous slide)
- The desired element is in the intersection of exactly one of R and R’, and exactly one of C and C’, so only once in the XOR sequence
- No other element has the above property:
  - Every other element is in either both R and R’, or both C and C’, or neither R and R’, or neither C and C’
  - In the last two cases it is not in the XOR sequence
  - If it is in R and R’, it appears an even number of times in the XOR sequence depending on if it’s in both C and C’ (4), one of them (2), or neither of them (0) – so it will be cancelled out with XOR
  - Vice-versa for C and C’

4-Database Information-Theoretic PIR

- Information-theoretic privacy follows from each row/column being randomly selected at ½ chance from any database's perspective
  - A database cannot tell which row/column was perturbed, if any
- This is true even if probability of any row/column being perturbed was uneven
- Query length is O(sqrt(n))
- Communication cost is minimum possible – only one bit
- Several other protocols exist with fewer databases/better query length

Which algorithm to use?

- If downloading the entire database solves the problem, PIR is a good solution
  - i.e. data is not private
- If no noise is tolerable, k-anonymity and differential privacy are not acceptable
- k-anonymity is used to hide QIDs
- Differential privacy can also collect data