Module outline

1. Introduction to databases
2. Security requirements
3. Data disclosure and inference
4. Multilevel security databases
5. Designs of secure databases
6. Data mining and data release
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(Relational) Databases

• Structured, queryable collection of data (records)
• Each record consists of fields (elements)
• Structure (schema) set by database administrator
• Database management system (DBMS) provides support for queries and management
• Most popular DBMS is based on relational model
• Stores records in one or multiple tables (relations)
  • Table has named columns (attributes) and rows (tuples)
  • Individual tables can have relationships between them
<table>
<thead>
<tr>
<th>Name</th>
<th>First</th>
<th>Address</th>
<th>City</th>
<th>State</th>
<th>Zip</th>
<th>Airport</th>
</tr>
</thead>
<tbody>
<tr>
<td>ADAMS</td>
<td>Charles</td>
<td>212 Market St.</td>
<td>Columbus</td>
<td>OH</td>
<td>43210</td>
<td>CMH</td>
</tr>
<tr>
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<tr>
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<td>Chicago</td>
<td>IL</td>
<td>60603</td>
<td>ORD</td>
</tr>
<tr>
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<td>411 Elm St.</td>
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</tr>
<tr>
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<tr>
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<tr>
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<td>Mary</td>
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<td>Columbus</td>
<td>OH</td>
<td>43210</td>
<td>CMH</td>
</tr>
</tbody>
</table>
## Relations

### NAME-ZIP

<table>
<thead>
<tr>
<th>NAME</th>
<th>ADDRESS</th>
<th>CITY</th>
<th>STATE</th>
<th>ZIP</th>
</tr>
</thead>
<tbody>
<tr>
<td>ADAMS</td>
<td>212 Market St.</td>
<td>Columbus</td>
<td>OH</td>
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</tr>
<tr>
<td>BENCHLY</td>
<td>501 Union St.</td>
<td>Chicago</td>
<td>IL</td>
<td>60603</td>
</tr>
<tr>
<td>CARTER</td>
<td>411 Elm St.</td>
<td>Columbus</td>
<td>OH</td>
<td>43210</td>
</tr>
</tbody>
</table>

### ZIP-AIRPORT

<table>
<thead>
<tr>
<th>ZIP</th>
<th>AIRPORT</th>
</tr>
</thead>
<tbody>
<tr>
<td>43210</td>
<td>CMH</td>
</tr>
<tr>
<td>60603</td>
<td>ORD</td>
</tr>
</tbody>
</table>

(Attributes are missing)
Database queries

- Most popular query language is SQL
  - SELECT Address FROM NAME-ZIP
    WHERE (Zip = '43210') AND (Name = 'ADAMS')
    - Prints address of family in relation NAME-ZIP whose zip code is 43210 and whose name is Adams
  - SELECT Name, Airport
    FROM NAME-ZIP, ZIP-AIRPORT
    WHERE NAME-ZIP.Zip = ZIP-AIRPORT.Zip
    - Prints each family name and their airport by joining relations NAME-ZIP and ZIP-AIRPORT
  - SELECT COUNT(Name) FROM NAME-ZIP
    WHERE City = 'Columbus'
    - Prints number of families in Columbus
    - Can also do other computations, like SUM, MIN, or AVG
- Result of a query is a subschema
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Security requirements

• Physical database integrity
• Logical database integrity
• Element integrity
• Referential integrity
• Auditability
• Access control
• User authentication
• Availability
Database integrity

- **Logical and physical integrity**
- Protect against database corruption
  - Allow only authorized individuals to perform updates
- Recover from physical problems (Power failures, disk crashes, . . . )
  - Perform periodic backups
  - Keep log of transactions to replay transactions since last backup
Element integrity

- Ensure correctness/accuracy of database elements
- **Access control** to limit who can update element
- **Element checks** to validate correctness
  - Element must be numeric, within a particular range,...
  - Not more than one employee can be president
  - Helps against mistakes by authorized users
  - Typically enforced by **triggers** (procedures that are automatically executed after an INSERT, DELETE,...)
Element integrity (cont.)

- Change log or shadow fields to undo erroneous changes
  - In case access control or element checks fail
  - Require additional space in the database
- Error detection codes to protect against OS or hard disk problems
Integrity: two-phase update

• For a set of operations, either all of them or none of them should be performed
  • Integrity violation if only some are performed
  • E.g., money is withdrawn from an account, but not deposited to another account

• First phase: gather information required for changes, but don’t perform any updates, repeat if problem arises (shadow fields)

• Second phase: make changes permanent, repeat if problem arises

• See text for example
Integrity: concurrency control

• Concurrent modifications can lead to integrity violation
  • Two operations A and B read variable X
  • A then writes new value of X
  • B then writes new value of X
  • A’s update gets lost

• Need to perform A and B as atomic operations
• Take CS 454 for more about this
Referential integrity

- Each table has a primary key, which is a minimal set of attributes that uniquely identifies each tuple
  - User ID or social insurance number
  - First name and last name (maybe not)
- A table might also have a or multiple foreign keys, which are primary keys in some other table
  - Zip is (likely) a primary key in ZIP-AIRPORT
  - Zip is a foreign key in NAME-ZIP
- Referential integrity ensures that there are no dangling foreign keys
  - For each zip in NAME-ZIP, there is an entry in ZIP-AIRPORT
Auditability

- Keep an audit log of all database accesses
  - Both read and write
- Access control can be difficult (see later), audit log allows to retroactively identify users who accessed forbidden data
  - Police officer looking at somebody’s criminal record as a favor to a friend, unauthorized medical personnel looking at Britney Spears’ medical records
- Maybe combination of accesses resulted in disclosure, not a single one (see later)
- Must decide about granularity of logging
  - Should results of a SELECT query be logged?
Access control

- More difficult than OS access control
- Might have to control access at the relation, record or even element level
- Many types of operations, not just read/write
  - SELECT, INSERT, UPDATE, CREATE, DROP, ...
- Relationships between database objects make it possible to learn sensitive information without directly accessing it
  - Inference problem (see later)
- Efficiency problem in presence of thousands of records, each consisting of dozens of elements
Access control (cont.)

- Access control might consider past queries
  - Current query, together with past ones, could reveal sensitive information
    - Iteratively querying whether element is in set ultimately leaks set
- Or type of query
  - `SELECT lastname, salary FROM staff WHERE salary > 50000` might be forbidden, but not
  - `SELECT lastname FROM staff WHERE salary > 50000`
User authentication / Availability

- Database might do its own authentication
- Additional checks possible
  - E.g., time of day
- Databases facilitate sharing, but availability can suffer if multiple users want to access the same record
  - Block access until other user finishes updating record
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Types of data disclosure

- Exact data
- Bounds
  - Sensitive value is smaller than \( H \), but bigger than \( L \)
  - Might iteratively decrease range (binary search)
- Negative result
  - Knowing that a person does not have zero felony convictions is sensitive, even if actual number is hidden
- Existence
  - Knowing of existence of some data can be sensitive
- Probable value
  - Sensitive data has value \( x \) with probability \( y \)
Security vs. precision

- Security: Forbid any queries that access sensitive data, even if (aggregated) result is no longer sensitive
- Precision: Aggregated result should reveal as much non-sensitive data as possible
Data inference

- Derivation of sensitive data from (supposedly) non-sensitive data
- Direct attack
  - Attacker issues query that directly yields sensitive data
  - Might obfuscate query to fool DBMS
    - SELECT SUM(salary) FROM staff
      WHERE lastname = 'Adams'
      OR (sex = 'M' AND sex = 'F')
- Indirect attack
  - Infer sensitive data from statistical results
    - As released by governments or pollers
  - Tracker attack
Statistical inference attacks

- **Sum**
  - Leaks sensitive data if sum covers only one record or if attacker can control set of covered records
    - SELECT SUM(salary)
    - SELECT SUM(salary) WHERE lastname != 'Adams'

- **Count**
  - Useful in attack above

- **Mean**
  - \( \text{sum} = \text{count} \times \text{mean} \)

- **Median**
  - Intersecting medians might leak sensitive data
  - See text for example
Tracker attacks

- Assume that there is a query $C$ that DBMS refuses to answer since it matches fewer than $k$ or more than $N - k$ (but fewer than $N$) records
  - $N$: number of records in database
  - Why the more than $N - k$ restriction?
- A tracker $T$ is a query whose result matches between $2k$ and $N - 2k$ records
  - DBMS will answer query $T$ and the query not $T$
Tracker attacks (cont.)

- Let $q()$ be the result of a query (e.g., a COUNT or SUM query) and let $S$ be the set of all records.
- Using Venn diagrams, we can show that
  - $q(C) = q(C \text{ or } T) + q(C \text{ or } \neg T) - q(S)$
  - Use right-hand side for computing $q(C)$ if $q(C)$ matches fewer than $k$ records.
  - $q(C) = 2 \times q(S) - q(\neg C \text{ or } T) - q(\neg C \text{ or } \neg T)$
  - Use right-hand side for computing $q(C)$ if $q(C)$ matches more than $N - k$ records.
- In general, simple logic or linear algebra might allow an attacker to convert a forbidden query into multiple, allowed queries.
Controls for statistical inference attacks

- Apply control to query or to data items
  - As seen, former is difficult
- **Suppression and concealing** are two controls applied to data items
- Suppression
  - Suppress sensitive data from result
- Concealing
  - Answer is close to actual value, but not exactly
Controls (cont.)

- **n-item k-percent rule**
  - For the set of records that were included in the result, if there is a subset of n records that is responsible for over k percent of the result, omit the n records from result.
  - However, omission itself might leak information or omitted value could be derived with other means.

- **Combined results**
  - Report set or range of possible values.

- **Random sample**
  - Compute result on random sample of database.
  - Need to use same sample for equivalent queries.
Controls (cont.)

- Random data perturbation
  - Add or subtract small random error to/from each value before computing result
  - Expectation is that statistical properties are maintained

- Query analysis
  - Maintain history of user’s queries and observe possible inferences
  - Costly, fails for colluding users
Differential Privacy

- The response to a query should not depend on an individual (not) being part of the dataset
- A query $K$ has $\epsilon$-differential privacy if for all datasets $D$ and $D'$, where $D$ and $D'$ differ in at most one row, the probability that $K(D)$ has a particular output is at most $e^\epsilon \times$ the probability that $K(D')$ has this output ($0 \leq \epsilon \leq 1$)
- Typically differential privacy is achieved by adding noise to the result of a query before releasing it
- Differential privacy is an active topic of research and has been incorporated into MapReduce and SQL databases
Data aggregation

- Data aggregation is related to data inference
- Building sensitive results from less sensitive inputs
- Aggregation can take place outside of a DBMS, which makes it difficult to control
  - People with different access rights talking to each other
- Closely related to data mining (see later), where information from different databases is combined
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Multilevel Security (MLS) Databases

- Support classification/compartamentalization of information according to its confidentiality
  - E.g., two sensitivity levels (sensitive and not sensitive)
- At element level if necessary
  - Salary might be sensitive only for some employees
  - Other information in employee’s record might not be sensitive
- In an MLS database, each object has a sensitivity classification and maybe a set of compartments
  - Object can be element, aggregate, column, or row
*-Property

- Implementing the *-property (no read up, no write down) in an MLS database is difficult
  - User doing a write-up, even though the user cannot read the data having higher sensitivity (Blind writes)
  - Write-downs need a sanitization mechanism
  - Trusted processes that can do anything
- DBMS must have read and write access at all levels to answer user queries, perform back-ups, optimize database,
  - Must trust DBMS
Confidentiality

- Depending on a user’s clearance, he/she might get different answers for a query
  - Less precision for low-clearance users
- Existence of a record itself could be confidential
- Keeping existence hidden can lead to having multiple records with the same primary key, but different sensitivity (polyinstantiation)
  - Admin notices that there is no record for employee Bob Hill and creates one
  - However, Bob Hill is a secret agent, so there already is a record, which admin cannot see
  - DBMS must allow admin’s request, else admin would get suspicious
Partitioning

- Have separate database for each classification level
- Simple, often used in practice
- Might lead to data stored redundantly in multiple databases
- Doesn’t address the problem of a high-level user needing access to low-level data combined with high-level data
Encryption

- Separate data by encrypting it with a key unique to its classification level
- Must be careful to use encryption scheme in the right way
  - E.g., encrypting the same value in different records with the same key should lead to different ciphertexts
- Processing of a query becomes expensive, many records might have to be decrypted
  - Doing the processing directly on the encrypted data is an active research area (homomorphic encryption)
Integrity lock

- Provides both integrity and access control
- Each data item consists of
  - The actual data item
  - An integrity level (maybe concealed)
  - A cryptographic signature (or MAC) covering the above plus the item’s attribute name and its record number
- Signature protects against attacks on the above fields, such as attacks trying to modify the sensitivity label, and attacks trying to move/copy the item in the database
- This scheme does not protect against replay attacks
Integrity lock (cont.)

• Any (untrusted) database can be used to store data items and their integrity locks
  • Locks can consume lots of space (maybe multiple locks per record)
• (Trusted) procedure handles access control and manages integrity locks
  • E.g., updates integrity level to enforce *-property or re-computes signature after a write access
  • Expensive
• Have to encrypt items and locks if there are other ways to get access to data in database
  • Makes query processing even more expensive
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Trusted front end

- Front end authenticates a user and forwards user query to old-style DBMS
- Front end gets result from DBMS and removes data items that user is not allowed to see
- Allows use of existing DBMS and databases
- Inefficient if DBMS returns lots of items and most of them are being dropped by front end
Commutative filters

- Front end re-writes user query according to a user’s classification
  - Remove attributes that user is not allowed to see
  - Add constraint expressing user’s classification
- Benefits from DBMS’ superior query processing capabilities and discards forbidden data items early on
- Front end might still have to do some post processing
Distributed/federated databases

- Based on partitioning
- Front end forwards user query only to databases that user can access based on classification
- Front end might have to combine the results from multiple databases
  - Complex process, front end essentially becomes a DBMS
- Doesn’t scale to lots of classification labels
Views

- Many DBMS support views
- A view is logical database that represents a subset of some other database
  - `CREATE VIEW foo AS SELECT * FROM bar WHERE...`
- Element in view can correspond to an element in underlying database or be a combination of multiple elements
  - E.g., their sum
- Views can be used for access control
  - A user’s view of a database consists of only the data that the user is allowed to access
  - Hide attribute/row unless user is allowed to access at least one element, set to UNDEFINED any elements that user can’t access
Truman vs. non-Truman semantics

- **Truman semantics**: the DBMS pretends that the data the user is allowed to access is all the data there is
  - Like “The Truman Show”
  - All queries will succeed, even if they return incorrect results
- **Non-Truman semantics**: the DBMS can reject queries that ask for data the user is not allowed to access
  - Any queries that succeed will produce precise answers
  - Some queries will fail
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Data mining

- Multilevel databases weren’t a commercial success
  - Mainly military clients, finding all possible inferences is NP-complete
- However, the combination of (sensitive) information, stored in multiple (maybe huge) databases, as done for data mining, raises similar concerns and has gotten lots of attention recently
- So far, a single entity has been in control of some data
  - Knows what kind of data is available
  - Who has accessed it (ignoring side channels)
- No longer the case in data mining, data miners actively gather additional data from third parties
Data mining (cont.)

- Data mining tries to automatically find interesting patterns in data using a plethora of technologies
  - Statistics, machine learning, pattern recognition, ...
  - Still need human to judge whether pattern makes sense (causality vs. coincidence)
- Data mining can be useful for security purposes
  - Learning information about an intrusion from logs
Security problems of data mining

- Confidentiality
  - Derivation of sensitive information
- Integrity
  - Mistakes in data
- Availability
  - (In)compatibility of different databases
Confidentiality

- Data mining can reveal sensitive information about humans (see later) and companies.
  - Problem started to occur in 1995, and each company individually had some evidence of the problem.
  - However, data about product quality is sensitive, which makes sharing it with other companies difficult.
- Supermarket can use loyalty cards to learn who buys what kind of products and sell this data, maybe to manufacturers’ competitors.
Data correctness and integrity

- Data in a database might be wrong
  - E.g., input or translation errors
- Mistakes in data can lead to wrong conclusions by data miners, which can negatively impact individuals
  - From receiving irrelevant mail to being denied to fly
- Privacy calls for the right of individuals to correct mistakes in stored data about them
  - However, this is difficult if data is shared widely or if there is no formal procedure for making corrections
- In addition to false positives, there can also be false negatives: don’t blindly trust data mining applications
Availability

- Mined databases are often created by different organizations
  - Different primary keys, different attribute semantics, . . .
    - Is attribute “name” last name, first name, or both?
    - US or Canadian dollars?

- Makes combination of databases difficult
- Must distinguish between inability to combine data and inability to find correlation
Privacy and data mining

• Data mining might reveal sensitive information about individuals, based on the aggregation and inference techniques discussed earlier

• Avoiding these privacy violations is active research

• Data collection and mining is done by private companies
  - Privacy laws (e.g., Canada’s PIPEDA or U.S.’ HIPAA) control collection, use, and disclosure of this data
  - Together with PETs

• But also by governments
  - Programs tend to be secretive, no clear procedures
  - Phone tapping in U.S., no-fly lists in U.S. and Canada
Privacy-preserving data release

- Anonymize data records before releasing them
  - E.g., strip names, addresses, phone numbers
  - Unfortunately, such simple anonymization might not be sufficient
- Anonymized NYC Taxi trip logs release due to FOIA request by Chris Whong
  - 173 million trips
  - Each includes information about driver licence number (anon.), taxi number (anon.), pick up and drop off times and locations and other information
Privacy-preserving data release

- The structure is the following:

```
medallion, hack_license, vendor_id, rate_code, store_and_fwd_flag, pickup_datetime, dropoff_datetime, passenger_count, trip_time_in_secs, pickup_longitude, pickup_latitude, dropoff_longitude, dropoff_latitude
```

- An example record looks like this:

```
6B111958A39B24140C973B262EA9F8A5, D3B035A03C8A34DA17488129DA581EE
7, VTS, 5, 2013-12-03 15:46:00, 2013-12-03 16:47:00, 1, 3660, 22.71, -73.813927, 40.698135, -74.093307, 40.829346
```

- The medallion and license is anonymized using a hash function (MD5)
  - What is the problem with this?
Privacy-preserving data release

• Turns out the identifiers have structures:
  • License numbers are 6 or 7 digit numbers.
  • Medallion numbers are either:
    • [0–9] [A–Z] [0–9] [0–9] [0–9] or
    • [A–Z] [A–Z] [0–9] [0–9] [0–9] [0–9] or
    • [A–Z] [A–Z] [A–Z] [0–9] [0–9] [0–9] [0–9]

• What’s the problem?
  • How many unique identifiers?
  • How would you attack this?
  • What’s a possible defence?
AOL Search Data Set

- August 6, 2006: AOL released 20 million search queries from 658,000 users
- To protect users’ anonymity, AOL assigned a random number to each user
  - 4417749 “numb fingers”
  - 4417749 “landscapers in Lilburn, GA”
  - 17556639 “how to kill your wife”
- August 9: New York Times article re-identified user 4417749
  - Thelma Arnold, 62-year old widow from Lilburn, GA
Another example (by L. Sweeney)

- 87% of U.S. population can be uniquely identified based on person’s ZIP code, gender, and date of birth
- Massachusetts’ Group Insurance Commission released anonymized health records
- Records omitted individuals’ names, but gave their ZIP codes, gender, and date of birth (and health information, of course)
- Massachusetts’s voter registration lists contain these three items plus individuals’ names and are publicly available
- Enables re-identification by linking
**$k$-anonymity [2002]**

- Ensure that for each released record, there are at least $k - 1$ other released records from which record cannot be distinguished (where $k \geq 2$)

- For health-records example, release a record only if there are $k - 1$ other records that have same ZIP code, gender, and date of birth
  - Assumption: there is only one record for each individual

- Because of the 87% number, this won’t return many records, need some pre-processing of records
  - Remove ZIP code, gender, or date of birth
  - Reduce granularity of ZIP code or date of birth (domain generalization)
In health-records example, the attributes ZIP code, gender, and date of birth form a “quasi-identifier”

Determining which attributes are part of the quasi-identifier can be difficult

- Should health information be part of it?
- Some diseases are rare and could be used for re-identification

Quasi-identifier should be chosen such that released records do not allow any re-identification based on any additional data that attacker might have

- Clearly we don’t know all this data
Limitations of $k$-anonymity

A 3-anonymized table

<table>
<thead>
<tr>
<th>ZIP</th>
<th>DOB</th>
<th>Disease</th>
</tr>
</thead>
<tbody>
<tr>
<td>902**</td>
<td>196*-*-</td>
<td>Cancer</td>
</tr>
<tr>
<td>902**</td>
<td>196*-*-</td>
<td>Cancer</td>
</tr>
<tr>
<td>902**</td>
<td>196*-*-</td>
<td>Cancer</td>
</tr>
<tr>
<td>902**</td>
<td>195*-*-</td>
<td>Heart disease</td>
</tr>
<tr>
<td>902**</td>
<td>195*-*-</td>
<td>GI disease</td>
</tr>
<tr>
<td>902**</td>
<td>195*-*-</td>
<td>Flu</td>
</tr>
<tr>
<td>904**</td>
<td>195*-*-</td>
<td>Heart disease</td>
</tr>
<tr>
<td>904**</td>
<td>195*-*-</td>
<td>Cancer</td>
</tr>
<tr>
<td>904**</td>
<td>195*-*-</td>
<td>Cancer</td>
</tr>
</tbody>
</table>
\( \ell \)-diversity and \( t \)-closeness

- Homogeneity attack
  - If you know Bob (902**,196*-*-*) is in the table, then Bob has cancer.

- Background knowledge attack
  - If you know Dave (904**,195*-*-*) is in the table, and that his risk for heart disease is very low, then Dave has cancer.

- \( \ell \)-diversity property [2006]:
  - For any quasi-identifier, there should be at least \( \ell \) “well-represented” values of the sensitive fields

- Possibly still not good enough: \( t \)-closeness [2007]
  - Ensure that the distributions of the values for any quasi-identifier are within \( t \) of the distribution for the whole table

⇒ Active research area
Value swapping

- Data perturbation based on swapping values of some (not all!) data fields for a subset of the released records
  - E.g., swap addresses in subset of records
- Any linking done on the released records can no longer considered to be necessarily true
- Trade off between privacy and accuracy
- Statistically speaking, value swapping will make strong correlations less strong and weak correlations might go away entirely
Adding noise

- Data perturbation based on adding small positive or negative error to each value
- Given distribution of data after perturbation and the distribution of added errors, distribution of underlying data can be determined
  - But not its actual values
- Protects privacy without sacrificing accuracy
Sampling / Synthetic data

- Release only a subset of respondents’ data (e.g., a 1% sample) with geographic coarsening and top/bottom coding
  - Geographic coarsening: restrict geographic identifiers to regions containing at least a certain population (e.g., 100,000 people)
  - Top/bottom-coding: for example, if there are sufficiently few respondents over age 90, top-coding would replace all ages $\geq 90$ with the value 90
- Build a distribution model based on gathered data and use the model to generate synthetic data with similar characteristics to original data
  - Release one (or a few) sets of synthetic data
Recap

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