CS520 - Course Info

0) Course Info
1) Introduction
2) Data Preparation and Cleaning
3) Schema mappings and Virtual Data Integration
4) Data Exchange
5) Data Warehousing
6) Big Data Analytics
7) Data Provenance

About me

Hi, I am Boris Glavic, Assistant Professor in CS
I am a database guy!
I will teach you: database stuff

What is information integration?
• Combination of data and content from multiple sources into a common format
  – Completeness
  – Correctness
  – Efficient

Why Information Integration?
• Data is already available, right?
• …, but
• Heterogeneity
  – Structural
    • Data model (relational, XML, unstructured)
    • Schema (if there)
  – Semantic
    • Naming and identity conflicts
    • Data conflicts
  – Syntactic
    • Interfaces (web form, query language, binary file)

Why Information Integration?
• Autonomy
  – Sources may not give you unlimited access
    • Web form only support a fixed format of queries
    • Does not allow access to unlimited amounts of data
  – Source may not be available all the time
    • Naming and identity conflicts
    • Data conflicts
  – Data, schema, and interfaces of sources may change
    • Potentially without notice
“Real World” Examples?

- Portal websites
  - Flight websites (e.g., Expedia) gather data from multiple airlines, hotels
- Google News
  - Integrates information from a large number of news sources
- Science:
  - Biomedical data source
- Business
  - Warehouses: integrate transactional data

Example Integration Problem [1]

- Integrate stock ticker data from two web services A and B
  - Service A: Web form (Company name, year)
  - Service B: Web form (year)

Example Integration Problem [2]

- Service A:

  ```xml
  <Stock>
  <Company>IBM</Company>
  <DollarValue>155.8</DollarValue>
  <Month>12</Month>
  </Stock>
  ```

- Service B:

  ```xml
  <Stock>
  <Company>International Business Machines</Company>
  <Date>2014-08-01</Date>
  <Value>106.8</Value>
  <Currency>Euro</Currency>
  </Stock>
  ```

Example Integration Problem [2]

- Service A:

  ```xml
  <Stock>
  <Company>IBM</Company>
  <DollarValue>155.8</DollarValue>
  <Month>12</Month>
  </Stock>
  ```

- Service B:

  ```xml
  <Stock>
  <Company>IBM</Company>
  <Date>2014-08-01</Date>
  <Value>155.8</Value>
  <Currency>Euro</Currency>
  </Stock>
  ```

Example Integration Problem [2]

- SQL interface for integrated service

  ```sql
  SELECT month, value
  FROM ticker
  WHERE year = 2014
  AND cmp = 'IBM'
  ```

- Service A: (IBM, 2014)
- Service B: (2014)
Example Integration Problem [4]

- For web service A we can either
  - Get stocks for **IBM** in **all years**
  - Get stocks for **all companies** in **2014**
  - Get stocks for **IBM in 2014**
- Trade-off between amount of processing that we have to do locally, amount of data that is shipped, …

Example Integration Problem [5]

- **Service A**: (IBM, 2014)
- **Service B**: (2014)

Example Integration Problem [6]

- **Service A**:
  ```xml
  <Stock>
  <Company>IBM</Company>
  <DollarValue>155.8</DollarValue>
  <Month>12</Month>
  </Stock>
  ...
  ``

- **Service B**:
  ```xml
  <Stock>
  <Company>International Business Machines</Company>
  <Date>2014-12-01</Date>
  <Value>106.8</Value>
  <Currency>Euro</Currency>
  </Stock>
  ...
  ```

Example Integration Problem [7]

- IBM vs. Integrated Business Machines

Example Integration Problem [8]

- Granularity of time attribute
  - Month vs. data
- What if both services return different values (after adapting granularity)
  - Average?
  - Median?
  - Trust-based?

Example Integration Problem [9]

- Return final results:
  ```xml
  <Stock>
  <Month>01</Month>
  <Value>105</Value>
  </Stock>
  ...
  <Stock>
  <Month>12</Month>
  <Value>107</Value>
  </Stock>
  ```
Why hard?

- System challenges
  - Different platforms (OS/Software)
  - Efficient query processing over multiple heterogeneous systems
- Social challenges
  - Find relevant data
  - Convince people to share their data
- Heterogeneity of data and schemas
  - A problem that even exists if we use same system


- Often called AI-complete
  - Meaning: “It requires human intelligence to solve the problem”
  - Unlikely that general completely automated solutions will exit
- So why do we still sit here
  - There exist automated solutions for relevant less general problems
  - Semi-automated solutions can reduce user effort (and may be less error prone)

AI completeness

- Yes, but still why is this problem really so hard?
  - Lack of information: e.g., the attributes of a database schema have only names and data types, but no computer interpretable information on what type of information is stored in the attribute
  - Undecidable computational problems: to decide whether a user query can be answered from a set of sources that provide different views on the data requires query containment checks which are undecidable for certain query types

Relevant less general problems

- Data cleaning:
  - Clean dirty data before integration
  - Conformance with a set of constraints
  - Deal with missing and outlier values
- Entity resolution
  - Determine which objects from multiple dataset represent the same real world entity
- Data fusion
  - Merge (potentially conflicting) data for the same entity

Relevant less general problems

- Schema matching
  - Given two schemas determine which elements store the same type of information
- Schema mapping
  - Describe the relationships between schemas
    - Allows us to rewrite queries written against one schema into queries of another schema
    - Allows us to translate data from one schema into

Relevant less general problems

- Virtual data integration
  - Answer queries written against a global mediated schema by running queries over local sources
- Data exchange
  - Map data from one schema into another
- Warehousing: Extract, Transform, Load
  - Clean, transform, fuse data and load it into a data warehouse to make it available for analysis
Relevant less general problems

• Integration in Big Data Analytics
  – Often "pay-as-you-go":
    • No or limited schema
    • Engines support wide variety of data formats

• Provenance
  – Information about the origin and creation process of data
  – Very important for integrated data
    • E.g., “from which data source is this part of my query result”

Webpage and Faculty

• Course Info
  – Course Webpage: http://cs.iit.edu/~cs520
  – Google Group: https://groups.google.com/d/forum/cs520-2015-spring-group
    • Used for announcements
    • Use it to discuss with me, TA, and fellow students

• Faculty
  – Boris Glavic (http://cs.iit.edu/~glavic)
  – Email: bglavic@iit.edu
  – Phone: 312.567.5205
  – Office: Stuart Building, room 226C
  – Office Hours: Mondays, 12pm-1pm (and by appointment)

TAs

• TAs
  – TBA

Workload and Grading

• Exams (60%)
  – Final

• Homework Assignments (preparation for exams!)
  – Practice theory for final exam
  – Practice the tools we discuss in class

• Literature Review (40%)
  – In groups of 2 students
  – Topics will be announced soon
  – You have to read a research paper
  – Papers will be assigned in the first few weeks of the course
  – You will give a short presentation (15min) on the topic in class
  – You will write a report summarizing and criticizing the paper (up to 4 pages)

Course Objectives

• Understand the problems that arise with querying heterogeneous and autonomous data sources
• Understand the differences and similarities between the data integration/exchange, data warehouse, and Big Data analytics approaches
• Be able to build parts of a small data integration pipeline by “glueing” existing systems with new code

Course Objectives cont.

• Have learned formal languages for expressing schema mappings
• Understand the difference between virtual and materialized integration (data integration vs. data exchange)
• Understand the concept of data provenance and know how to compute provenance
Fraud Policies

- All work has to be original!
  - Cheating = 0 points for review/exam
  - Possibly E in course and further administrative sanctions
  - Every dishonesty will be reported to office of academic honesty

- Late policy:
  - -20% per day
  - You have to give your presentation to pass the course!
  - No exceptions!

Fraud Policies cont.

- Literature Review:
  - Every student has to contribute in both the presentation and report!
  - Don’t let others freeload on you hard work!
    - Inform me or TA immediately

Reading and Prerequisites

- **Textbook:** Doan, Halevy, and Ives.
  - Principles of Data Integration, 1st Edition
  - Morgan Kaufmann
  - Publication date: 2012
  - Prerequisites:
    - CS 425

Additional Reading

- Papers assigned for literature review
- Optional: Standard database textbook

Outline

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- 2) Data Preparation and Cleaning
- 3) Schema mappings and Virtual Data Integration
- 4) Data Exchange
- 5) Data Warehousing
- 6) Big Data Analytics
- 7) Data Provenance
Overview

- Topics covered in this part
  - Heterogeneity and Autonomy
  - Data Integration Tasks
  - Data Integration Architectures (Methods)
  - Some Formal Background (sorry!)

1.1 System Heterogeneity

- Hardware/Software
  - Different hardware capabilities of sources
  - Different protocols, binary file formats, …
  - Different access control mechanism

- Interface Heterogeneity
  - Different interfaces for accessing data from a source
    - HTML forms
    - XML-Webservices
    - Declarative language

1.1 System Heterogeneity

- Hardware/Software
  - Different hardware capabilities of sources
    - Mobile phone vs. server: Cannot evaluate cross-product of two 1GB relations on a mobile phone
  - Different protocols, binary file formats, …
    - Order information stored in text files: line ending differs between Mac/Window/Linux, character encoding
  - Different access control mechanism
    - FTP-access to files: public, ssh authentication, ..
1.1 System Heterogeneity

• Interface Heterogeneity
  – Different interfaces for accessing data from a source
    • HTML forms
    • Services (SOA)
    • Declarative language
    • Files
    • Proprietary network protocol
  …

• Interface Heterogeneity – Expressiveness
  – Keyword-search vs. query language
  – **Predicates**: equality (=), inequality (<, !=)
  – **Logical connectives**: conjunctive (AND), disjunctive (OR), negation
  – **Complex operations**: aggregation, quantification
  – **Limitations**: restriction to particular tables, predicates, fixed queries with parameters, …

• Interface Heterogeneity – Examples
  – Google search (+/-, site:, intitle:, filetype:)

• Interface Heterogeneity – Examples
  – SQL

• Interface Heterogeneity – Examples
  – Web-form (with DB backend?)
1.1 System Heterogeneity

• Interface Heterogeneity – Examples
  – Email-client

- Name Query
- Disjunctive or conjunctive
- Comparison operator

• Problems with interface heterogeneity
  – Global query language is more powerful
    • User queries may not be executable
    • Integration system has to evaluate part of the query
  – Bound parameters are incompatible with query
    • User query may not be executable

- Example: more expressive global language
  – SQL with one table
    • books (title, author, year, isbn, genre)
  – Web form for books about history shown below
  – What problems do may arise translating user queries?

- SELECT title
  FROM books
  WHERE author = 'Steven King'
  AND year = 2012;

- Query requires multiple requests

- Query cannot be answered

Web form is for history book only!
1.1 Heterogeneity + Autonomy

- Taxonomy of Heterogeneity

1.1 Structural Heterogeneity

- **Data model**
  - Different semantic/expressiveness
  - Different structure

- **Schema**
  - Integrity constraints, keys
  - Schema elements:
    - use attribute or separate relations
  - Structure:
    - e.g., normalized vs. denormalized relational schema

1.1 Structural Heterogeneity

- **Data model**
  - Relational model
  - XML model
  - Object-oriented model
  - Ontological model
  - JSON
  - ...

1.1 Structural Heterogeneity

- **Example: data model**
  - Relational model
  - XML model
  - JSON
  - OO

- Person and their addresses

1.1 Structural Heterogeneity

- **Schema**
  - Modeling choices
    - Relation vs. attribute
    - Attribute vs. value
    - Relation vs. value
  - Naming
  - Normalized vs. denormalized (relational concept)
  - Nesting vs. reference
1.1 Structural Heterogeneity

- Relation-relation conflicts
  - Naming conflicts
    - Relations with different name representing the same data (synonym)
    - Relations with same name representing different information (homonym)
  - Structural conflicts
    - Missing attributes
    - Many-to-one
    - Missing, but derivable attributes
  - Integrity constraint conflicts

Example: Conflicts between relations
Person(Id, firstname, lastname, male, female)
Person(Id, name, gender, birthday)
Manager(Id, name, gender, age)

- Attribute-attribute conflicts
  - Naming conflicts
    - Attributes with different name representing the same data (synonym)
    - Attributes with same name representing different information (homonym)
  - Default value conflict
  - Integrity constraint conflicts
    - Datatype
    - Constraints restricting values

Example: Conflicts between attributes and attributes

<table>
<thead>
<tr>
<th>SSN</th>
<th>FirstName</th>
<th>LastName</th>
<th>Age</th>
</tr>
</thead>
<tbody>
<tr>
<td>333-333-3333</td>
<td>Peter</td>
<td>Schmeter</td>
<td>30</td>
</tr>
<tr>
<td>333-333-9999</td>
<td>Hans</td>
<td>Glanz</td>
<td>NULL</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>SSN</th>
<th>FirstName</th>
<th>LastName</th>
<th>Age</th>
</tr>
</thead>
<tbody>
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<td>3333333333</td>
<td>Peter</td>
<td>Schmeter</td>
<td>30</td>
</tr>
<tr>
<td>3333339999</td>
<td>Hans</td>
<td>Glanz</td>
<td>-1</td>
</tr>
</tbody>
</table>
1.1 Structural Heterogeneity

- **Normalized vs. denormalized**
  - E.g., relational model: Association between entities can be represented using multiple relations and foreign keys or one relation

**Example**

- Person
  - Name
  - Address
  - City
  - Zip

- Person
  - Name
  - City
  - Zip

1.1 Structural Heterogeneity

- **Nested vs. flat**
  - Association between entities can be represented using nesting or references (previous slides)

**Example**

- Person
  - Value
  - (Address
    - Id
    - City
    - Zip)

- Person
  - Value
  - City
  - Zip

1.1 Structural Heterogeneity

- **Problems caused by schema heterogeneity**
  - Unified access to multiple schemas or integrate schemas into new schema
    - **Schema level**: schema mapping, model management operators, schema languages
    - **Data Level**: virtual data integration, data exchange, warehousing (ETL)

1.1 Heterogeneity + Autonomy

- **Taxonomy of Heterogeneity**

1.1 Semantic Heterogeneity

- **Semantic Heterogeneity**
  - Naming Conflicts
  - Identity Conflicts (Entity resolution)
  - Value Conflicts (Data Fusion)

1.1 Semantic Heterogeneity

- **Naming Conflicts**
  - Ontological (concepts)
    - Birds vs. Animals
  - Synonyms
    - Surname vs. last name
  - Homonyms
  - Units
    - Gallon vs. liter
  - Values
    - Manager vs. Boss
1.1 Semantic Heterogeneity

- Ontological concepts
  - Relationships between concepts
    - $A = B$ - Equivalence
    - $A \subseteq B$ - Inclusion
    - $A \cap B$ - Overlap
    - $A \neq B$ - Disjunction

- Naming concepts (synonyms)
  - Different words with same meaning

- Naming concepts (homonyms)
  - Same words with different meaning

- Naming concepts (units)

- Identity Conflicts
  - What is an object?
    - E.g., multiple tuples in relational model
  - Central question:
    - Does object A represent the same entity as B
  - This problem has been called
    - Entity resolution
    - Record linkage
    - Deduplication
    - …
1.1 Semantic Heterogeneity

• Identity Conflicts

Example

([IBM, 3010000000, JSA])
(International Business Machines Corporation, $10000)

• Value Conflicts
  – Objects representing the same entities have conflicting values for semantically equivalent attributes
  – We have to identified that these objects are represent the same entity first!
  – Resolving such conflicts require **Data Fusion**
    • Pick value from conflicting values
    • Numerical methods: e.g., average
    • Preferred value
    • …

1.2 Data integration tasks

• Cleaning and preparation
• Entity resolution
• Data Fusion
• Schema matching
• Schema mapping
• Query rewrite
• Data translation

1.3 Data integration architectures

• Virtual data integration
• Data Exchange
• Peer-to-peer data integration
• Datawarehousing
• Big Data analytics

1.4 Formal Background

• Query Equivalence
  – Complexity for different query classes
• Query Containment
  – Complexity for different query classes
• Datalog
  – Recursion + Negation
• Integrity Constraints
  – Logical encoding of integrity constraints
• Similarity Measures/Metrics
1.4 Integrity constraints

- You know some types of integrity constraints already
  - Functional dependencies
    - Keys are a special case
  - Foreign keys
    - We have not really formalized that

- Other types are
  - Conditional functional dependencies
    - E.g., used in cleaning
  - Equality-generating dependencies
  - Multi-valued dependencies
  - Tuple-generating dependencies
  - Join dependencies
  - Denial constraints
  - ...

- How to manage all these different types of constraints?
  - Has been shown that these constraints can be expressed in a logical formalism.
  - Formulas which consist of relational and comparison atoms. Variables represent values
    - \( R(x,y,z) \)
    - \( x = y \)

- Types of constraints we will use a lot
  - Tuple-generating dependencies (tgds)
    - Implication with conjunction of relational atoms
    - Foreign keys and schema mappings (later)
      \( \forall \vec{x} : \phi(\vec{x}) \rightarrow \exists \vec{y} : \psi(\vec{x}, \vec{y}) \)
  - Equality-generating dependencies (egds)
    - Generalizes keys, FDs
      \( \forall \vec{x} : \phi(\vec{x}) \rightarrow \land_{k=1}^{n} x_{i_k} = x_{j_k} \)

- What is datalog?
  - Prolog for databases (syntax very similar)
  - A logic-based query language
  - Queries (Program) expressed as set of rules
    \( Q(\vec{x}) : - R_1(x_1), \ldots, R_n(x_n). \)
  - One Q is specified as the answer relation (the relation returned by the query)
1.4 Datalog - Intuition

- A Datalog rule
  \[ Q(\overline{x}) : \neg R_1(\overline{x}_1), \ldots, \neg R_n(\overline{x}_n). \]

- For all bindings of variables in the right-hand side (RHS) that makes the RHS true (conjunction) return bindings of \( \overline{x} \)

Example:
\[ Q(\text{Name}) : \text{Person}(\text{Name}, \text{Age}). \]
Return names of persons

1.4 Datalog - Syntax

- A Datalog program is a set of datalog rules
- Optionally a distinguished answer predicate
- A Datalog rule is
  \[ Q(\overline{x}) : \neg R_1(\overline{x}_1), \ldots, \neg R_n(\overline{x}_n). \]

- \( \overline{x} \)'s are lists of variables and constants
- \( R_i \)'s are relation names
- \( Q \) is a relation name

1.4 Datalog - Terminology

- Left-hand side of a rule is called it’s head
- Right-hand side of a rule is called it’s body
- Relation are called predicates
- \( R(\overline{x}) \) is called an atom
- An instance \( I \) of a database is the data
- The active domain \( \text{adom}(I) \) of an instance \( I \) is the set of all constants that occur in \( I \)
  \[ Q(\overline{x}) : \neg R_1(\overline{x}_1), \ldots, \neg R_n(\overline{x}_n). \]

Example:

<table>
<thead>
<tr>
<th>Name</th>
<th>Age</th>
</tr>
</thead>
<tbody>
<tr>
<td>peter</td>
<td>34</td>
</tr>
<tr>
<td>bob</td>
<td>45</td>
</tr>
</tbody>
</table>

Activate domain
\( \text{adom}(I) = \{ \text{peter, bob, 34, 45} \} \)

1.4 Datalog - Terminology

- Intensional vs. extensional
  - Extensional database (\( \text{ed} \))
    - What we usually call database
  - Intensional database (\( \text{id} \))
    - Relations that occur in the head of rules (are populated by the query)
    - Usually we assume that these do not overlap
  \[ Q(\overline{x}) : \neg R_1(\overline{x}_1), \ldots, \neg R_n(\overline{x}_n). \]

1.4 Datalog - Safety

- A datalog program is safe if all its rules are safe
- A rule is safe if all variables in \( \overline{x} \) occur in at least one \( \overline{x}_i \)
  \[ Q(\overline{x}) : \neg R_1(\overline{x}_1), \ldots, \neg R_n(\overline{x}_n). \]

Example:
\[ Q(\text{Name}) : \text{Person}(\text{Name}, \text{Age}). \quad \text{(safe)} \]
\[ Q(\text{Name}, \text{Sal}) : \text{Peron}(\text{Name}, \text{Age}). \quad \text{(unsafe)} \]
1.4 Datalog - Semantics

- The instance of an idb predicate \( Q \) in a datalog program for an edb instance \( I \) contains all facts that can be derived by applying rules with \( Q \) in the head.
- A rule derives a fact \( Q(c) \) if we can find a binding of variables of the rule to constants from \( \text{adom}(I) \) such that \( x \) is bound to \( c \) and the body is true

\[
Q(\overline{x}) : \neg \bigwedge_{i=1}^{n} R_i(\overline{x}_i) .
\]

1.4 Datalog

- Different flavors of datalog
  - Conjunctive query
    - Only one rule
    - Expressible as Select-project-join (SPJ) query in relational algebra
  - Union of conjunctive queries
    - Also allow union
    - SPJ + set union in relational algebra
    - Rules with the same head in Datalog
  - Conjunctive queries with inequalities
    - Also allow inequivalences, e.g., \(<\)

Example

\[
Q_1(x, y) : R(x, y), R(x, z) .
\]

1.4 Datalog

Example

\[
Q_2(x, y) : R(x, y) .
\]

1.4 Datalog

Example

\[
Q_3(x, x) : R(x, x) .
\]

1.4 Datalog

Example

\[
Q_4(x, y) : R(x, y) .
\]

1.4 Datalog

Example

\[
Q_5(x, x) : R(x, y), R(x, x) .
\]

1.4 Datalog

Example

\[
Q_6(x, z) : R(x, y), R(y, z) .
\]

Example

\[
Q_{\text{hop}}(x, z) : \text{hop}(x, y), \text{hop}(x, z) .
\]

Example

\[
Q_{\text{reach}}(x, y) : \text{hop}(x, y) .
\]

Example

\[
Q_{\text{cycle}}(x) : \text{hop}(x, y) .
\]

Example

\[
Q_{\text{node}}(x) : \text{hop}(y, x) .
\]
1.4 Datalog

Example
Relation \textit{hops}(A, B) storing edges of a graph.
\begin{itemize}
\item \textit{Q\_node}(x): \text{hop}(x, y).
\item \textit{Q\_node}(x): \text{hop}(y, x).
\item \textit{Q\_notReach}(x, y): \textit{Q\_node}(x), \textit{Q\_node}(y), not \textit{Q\_reach}(x, y).
\end{itemize}

1.4 Containment and Equivalence

Definition: Query Equivalence
Query \textit{Q} is equivalent to \textit{Q'} if for every database instance \textit{I} both queries return the same result
\[ Q \equiv Q' \iff \forall I : Q(I) = Q'(I) \]

Definition: Query Containment
Query \textit{Q} is contained in query \textit{Q'} if for every database instance \textit{I} the result of \textit{Q} is contained in the result of \textit{Q'}
\[ Q \subseteq Q' \iff \forall I : Q(I) \subseteq Q'(I) \]

1.4 Equivalence

- The problem of checking query equivalence is of different complexity depending on the query language and whether we consider set or bag semantics

1.4 Containment and Equiv.

Example
Relation \textit{hops}(A, B) storing edges of a graph.
\begin{itemize}
\item \textit{Q\_2hop}(x, z): \text{hop}(x, y), \text{hop}(x, z).
\item \textit{Q\_op2hop}(x, z): \text{hop}(x, y), \text{hop}(x, z).
\item \textit{Q\_sym}(x, y): \text{hop}(x, y).
\item \textit{Q\_sym}(x, y): \text{hop}(y, x).
\item \textit{Q\_sym2hop}(x, y): \textit{Q\_sym}(x, y), \textit{Q\_sym}(y, z).
\end{itemize}

1.4 Containment and Equiv.

Example
Relation \textit{hops}(A, B) storing edges of a graph.
\begin{itemize}
\item \textit{Q\_2hop}(x, z): \text{hop}(x, y), \text{hop}(x, z).
\item \textit{Q\_op2hop}(x, z): \text{hop}(x, y), \text{hop}(x, z).
\item \textit{Q\_sym}(x, y): \text{hop}(x, y).
\item \textit{Q\_sym}(x, y): \text{hop}(y, x).
\item \textit{Q\_sym2hop}(x, y): \textit{Q\_sym}(x, y), \textit{Q\_sym}(y, z).
\end{itemize}

1.4 Complexity of Eq. and Cont.

<table>
<thead>
<tr>
<th>Set semantics</th>
<th>Relational Algebra</th>
<th>Conjunctive Queries (CQ)</th>
<th>Union of Conjunctive Queries (UCQ)</th>
<th>Monotone Queries/ CQ*</th>
</tr>
</thead>
<tbody>
<tr>
<td>Query Evaluation (Combined Complexity)</td>
<td>PSPACE-complete</td>
<td>NP-complete</td>
<td>NP-complete</td>
<td>NP-complete</td>
</tr>
<tr>
<td>Query Evaluation (Data Complexity)</td>
<td>LOGSPACE (that means in P)</td>
<td>LOGSPACE (that means in P)</td>
<td>LOGSPACE (that means in P)</td>
<td>LOGSPACE (that means in P)</td>
</tr>
<tr>
<td>Query Equivalence</td>
<td>Undecidable</td>
<td>NP-complete</td>
<td>NP-complete</td>
<td>#P-complete</td>
</tr>
<tr>
<td>Query Containment</td>
<td>Undecidable</td>
<td>NP-complete</td>
<td>NP-complete</td>
<td>#P-complete</td>
</tr>
</tbody>
</table>
1.4 Complexity of Eq. and Cont.

<table>
<thead>
<tr>
<th>Bag semantics</th>
<th>Relational Algebra</th>
<th>Conjunctive Queries (CQ)</th>
<th>Union of Conjunctive Queries (UCQ)</th>
<th>Monotone Queries/CDQ</th>
</tr>
</thead>
<tbody>
<tr>
<td>Query Equivalence</td>
<td>Undecidable</td>
<td>Equivalent to graph isomorphism</td>
<td>It is in PSPACE, lower-bound unknown</td>
<td></td>
</tr>
<tr>
<td>Query Containment</td>
<td>Undecidable</td>
<td>Open Problem</td>
<td>Undecidable</td>
<td>( \Pi_2 )-complete</td>
</tr>
</tbody>
</table>

1.4 Containment Mappings

- NP-completeness for set semantics CQ and UCQ for the containment, evaluation, and equivalence problems is based on reducing these problems to the same problem
  - [Chandra & Merlin, 1977]
- Notational Conventions:
  - head(Q) = variables in head of query Q
  - body(Q) = atoms in body of Q
  - vars(Q) = all variable in Q

1.4 Boolean Conjunctive Queries

- A conjunctive query is boolean if the head does not have any variables
  - Q() :- hop(x,y), hop(y,z)
  - We will use Q :- … as a convention for Q() :- …
  - What is the result of a boolean query
    - Empty result \{\} e.g., no hop(x,y), hop(y,z)
    - If there are tuples matching the body, then a tuple with zero attributes is returned \{()\}
  - We interpret \{\} as false and \{()\} as true
  - Boolean query is essentially an existential check

1.4 Boolean Conjunctive Queries

- BCQ in SQL

  Example
  ```
  Hop relation: Hop(A,B)
  Q := hop(x,y)
  SELECT EXISTS (SELECT * FROM hop)
  Note: in Oracle and DB2 we need a from clause
  ```

1.4 Boolean Conjunctive Queries

- BCQ in SQL

  Example
  ```
  Q := hop(x,y), hop(y,z)
  SELECT EXISTS (SELECT * FROM hop l, hop r
  WHERE l.B = r.A)
  ```

Notes:
- Oracle and DB2 FROM not optional
- Oracle has no boolean datatype
1.4 Containment Mappings

- How to check for containment of CQs (set)

**Definition: Variable Mapping**
A variable mapping $\psi$ from query $Q$ to query $Q'$ maps the variables of $Q$ to constants or variables from $Q'$.

**Definition: Containment Mapping**
A containment mapping from query $Q$ to $Q'$ is a variable mapping $\psi$ such that:

$\psi(\text{head}(Q)) = \text{head}(Q')$

$\forall R(x_i) \in \text{body}(Q) : \psi(x_i) \in \text{body}(Q')$

---

**Theorem: Containment Mapping and Query Containment**
Query $Q$ is contained in query $Q'$ if there exists a containment mapping $\psi$ from $Q'$ to $Q$.

**Example**

$Q_1(u, z) : R(u, z)$.
$Q_2(x, y) : R(x, y)$.

Can we find a containment mapping?

$Q_1 \rightarrow Q_2 : \psi(u) = x, \psi(z) = y$
$Q_2 \rightarrow Q_1 : \psi(x) = u, \psi(y) = z$

---

**Example**

$Q_1(a, b) : R(a, b), R(c, b)$.
$Q_2(x, y) : R(x, y)$.

Do containment mappings exist?

$Q_1 \rightarrow Q_2 : \text{none exists}$
$Q_2 \rightarrow Q_1 : \psi(x) = a, \psi(y) = b$
1.4 Containment Background

- It was shown that query evaluation, containment, equivalence as all reducible to homomorphism checking for CQ
  - Canonical conjunctive query \( Q^C \) for instance \( I \)
    - Interpret attribute values as variables
    - The query is a conjunction of all atoms for the tuples
    - \( I = \{ \text{hop}(a,b), \text{hop}(b,c) \} \rightarrow Q^C : \text{hop}(a,b), \text{hop}(b,c) \)
  - Canonical instance \( I^O \) for query \( Q \)
    - Interpret each conjunct as a tuple
    - Interpret variables as constants
    - \( Q : \text{hop}(a,a) \rightarrow I^O = \{ \text{hop}(a,a) \} \)

1.4 Containment Mappings

Example

- \( Q_1() : \text{R}(a,b), \text{R}(c,b) . \)
- \( Q_1() : \text{R}(x,y) . \)
- \( Q_2 \rightarrow Q_1 : \Psi(x)=a, \Psi(y)=b \)
- \( D = \{ \text{R}(1,1), \text{R}(1,2) \} \)
- \( Q_1(D) = \{ (1,1), (1,2) \} \)
- \( \phi(a)=1, \phi(b)=2, \phi(c)=1 \)
- \( \Psi \phi(x)=1, \Psi \phi(y)=2 \)

1.4 Containment Background

- Containment Mapping <-> Containment
- Proof idea (boolean queries)
  - (if direction)
    - Assume we have a containment mapping \( Q_1 \) to \( Q_2 \)
    - Consider database \( D \)
    - \( Q_2(D) \) is true then we can find a mapping from \( \text{vars}(Q_2) \) to \( D \)
    - Compose this with the containment mapping and prove that this is a result for \( Q_1 \)

1.4 Containment Mappings

Example

- \( Q_1() : \text{R}(a,b), \text{R}(c,b) . \)
- \( Q_1() : \text{R}(x,y) . \)
- \( Q_2 \rightarrow Q_1 : \Psi(x)=a, \Psi(y)=b \)
- \( I^{Q_1} = \{ (a,b), (c,b) \} \)
- \( Q_2(I^{Q_1}) = \{ () \} \)
- \( \phi(x)=a, \phi(y)=b \)
- \( \phi \) is our containment mapping \( \Psi \)

1.4 Containment Background

- If you are not scared and want to know more:
  - Look up Chandra and Merlins paper(s)
  - The text book provides a more detailed overview of the proof approach
  - Look at the slides from Phokion Kolaitis excellent lecture on database theory
    - https://classes.soecs.ucsc.edu/cmps277/Winter10/
1.4 Containment Background

- A more intuitive explanation why containment mappings work
  - Variable naming is irrelevant for query results
  - If there is a containment mapping Q to Q’
    - Then every condition enforced in Q is also enforced by Q’
    - Q’ may enforce additional conditions

1.4 Containment Mappings

Example

\[Q_1: R(a,b), R(c,b)\]
\[Q_2: R(x,y)\]
\[Q_2 \rightarrow Q_1: \Psi(x) = a, \Psi(y) = b\]

If there exists tuples \(R(a,b)\) and \(R(c,b)\) in \(R\) that make \(Q_1\) true, then we take \(R(a,b)\) to fulfill \(Q_2\)

1.4 Similarity Measures

- Problem faced by multiple integration tasks
  - Given two objects, how similar are they
  - E.g., given two attribute names in schema matching, given two values in data fusion/entity resolution, ...

1.4 Similarity Measures

- Object models
  - Multidimensional (feature vector model)
    - Object is described as a vector of values - one for each dimension out of a given set of dimensions
    - E.g., Dimensions are gender (male/female), age (0-120), and salary (0-1,000,000). An example object is [male, 80, 70, 000]
  - Strings
    - E.g., how similar is “Poeter” to “Peter”
  - Graphs and Trees
    - E.g., how similar are two XML models
1.4 Similarity Measures

**Definition: Similarity Measure**

Function \( d(p,q) \) where \( p \) and \( q \) are objects, that returns a real score with

- \( d(p,p) = 0 \)
- Interpretation: the lower the score the "more similar" the objects are
- We require \( d(p,p)=0 \), because nothing can be more similar to an object than itself
- Note: often scores are normalized to the range \([0,1]\)

---

**Example**

- **String equality:** \( d(p,q) = 0 \) if \( p=q \) strings
  \( d(p,q) = 1 \) else

- **Euclidean distance:** \( d(p,q) = \sqrt{\sum_{i=1}^{N} (p[i]-q[i])^2} \) in \( N \)-dimensional space

- **Edit distance:** \( d(p,q) = \) minimum number of single character insertions, deletions, replacements to transform \( p \) into \( q \)

---

**Definition: Metric**

Function \( d(p,q) \) where \( p \) and \( q \) are objects, that returns a real score with

- **Non-negative** \( d(p,q) \geq 0 \)
- **Symmetry** \( d(p,q) = d(q,p) \)
- **Identity of indiscernibles** \( d(p,q) = 0 \) if \( p=q \)
- **Triangle inequality** \( d(p,q) + d(q,r) \geq d(p,r) \)

- Metric is a stricter definition
- Which of the previous similarity measure is a metric?
  - All of them!

---

**Why do we care whether \( d \) is a metric?**

- Some data mining algorithms only work for metrics
  - E.g., some clustering algorithms such as k-means
  - E.g., clustering has been used in entity resolution

- Metric spaces allow optimizations of some methods
  - E.g., Nearest Neighborhood-search: find the most similar object to an object \( p \). This problem can be efficiently solved using index structures that only apply to metric spaces

---

**Summary**

- **Heterogeneity**
  - Types of heterogeneity
  - Why do they arise?
  - Hint at how to address them
- **Autonomy**
- **Data Integration Tasks**
- **Data Integration Architectures**
- **Background**
  - Datalog + Query equivalence/containment + Similarity + Integrity constraints
Outline

0) Course Info
1) Introduction
2) Data Preparation and Cleaning
   3) Schema matching and mapping
   4) Virtual Data Integration
   5) Data Exchange
   6) Data Warehousing
   7) Big Data Analytics
   8) Data Provenance
2. Data Preparation and Cleaning

**Boris Glavic**

http://www.cs.iit.edu/~glavic/

http://www.cs.iit.edu/~cs520/

http://www.cs.iit.edu/~dbgroup/

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**2. Overview**

- Topics covered in this part
  - Causes of Dirty Data
    - Constraint-based Cleaning
    - Outlier-based and Statistical Methods
    - Entity Resolution
    - Data Fusion

**2. Causes of “Dirty” Data**

- Manual data entry or result of erroneous integration
  - Typos:
    - “Peter” vs. “Pteer”
  - Switching fields
    - “FirstName: New York, City: Peter”
  - Incorrect information
    - “City: New York, Zip: 60616”
  - Missing information
    - “City: New York, Zip: ”

- Redundancy:
  - (ID:1, City: Chicago, Zip: 60616)
  - (ID:2, City: Chicago, Zip: 60616)

- Inconsistent references to entities
  - Dept. of Energy, DOE, Dep. Of Energy, …

**2. Cleaning Methods**

- Enforce Standards
  - Applied in real world
  - How to develop a standard not a fit for this lecture
  - Still relies on no human errors
- Constraint-based cleaning
  - Define constraints for data
  - “Make” data fit the constraints
- Statistical techniques
  - Find outliers and smoothen or remove
    - E.g., use a clustering algorithm
2. Overview

- Topics covered in this part
  - Causes of Dirty Data
  - Constraint-based Cleaning
  - Outlier-based and Statistical Methods
  - Entity Resolution
  - Data Fusion

2.1 Cleaning Methods

- Constraint-based cleaning
  - Choice of constraint language
  - Detecting violations to constraints
  - Fixing violations (automatically?)

2.1 Constraint Languages

- First work focused on functional dependencies (FDs)
- Extensions of FDs have been proposed to allow rules that cannot be expressed with FDs
  - E.g., conditional FDs only enforce the FD is a condition is met
    - : finer grained control, e.g., zip -> city only if country is US
- Constraints that consider master data
  - Master data is highly reliable data such as a government issued zip, city lookup table

2.1 Example Constraints

<table>
<thead>
<tr>
<th>SSN</th>
<th>zip</th>
<th>city</th>
<th>name</th>
<th>boss</th>
<th>salary</th>
</tr>
</thead>
<tbody>
<tr>
<td>333-333-3333</td>
<td>60616</td>
<td>New York</td>
<td>Peter</td>
<td>Gert</td>
<td>50,000</td>
</tr>
<tr>
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- expressible as functional dependency
- e.g., denial constraint
- e.g., denial constraint
- Sometimes use logic based notation introduced previously

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- expressible as functional dependency
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2.1 Example Constraints

Example: Constraints Languages

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- **C1**: The zip code uniquely determines the city
- **C2**: Nobody should earn more than their direct superior
- **C3**: Salaries are non-negative

### 2.1 Constraint Repair Problem

**Definition: Constraint Repair Problem**

Given set of constraints $\Sigma$ and an database instance $I$ which violates the constraints find a clean instance $I'$ so that $I'$ fulfills $\Sigma$

- This would allow us to take any $I'$
  - E.g., empty for FD constraints
- We do not want to loose the information in $I$
  (unless we have to)
- Let us come back to that later

### 2.1 Constraint based Cleaning Overview

- Define constraints
- Given database $D$
  - 1) Detect violations of constraints
    - We already saw example of how this can be done using queries. Here a bit more formal
  - 2) Fix violations
    - In most cases there are many different ways to fix the violation by modifying the database (called **solution**)
      - What operations do we allow: insert, delete, update
      - How do we choose between alternative solutions

### 2.1 Example Constraints

Example: Constraint Violations

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- **FD1**: Zip code -> city

### 2.1 Constraint based Cleaning Overview

- Study 1) + 2) for FDs
- Given database $D$
  - 1) Detect violations of constraints
    - We already saw example of how this can be done using queries. Here a bit more formal
  - 2) Fix violations
    - In most cases there are many different ways to fix the violation by modifying the database (called **solution**)
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2.1 Example Constraints

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How to repair:

**Deletion:**
- remove some conflicting tuples
- quite destructive

**Update:**
- modify values to resolve the conflict
- equate RHS values (city here)
- disequate LHS value (zip)

2.1 Constraint based Cleaning Overview

- How to repair?
- **Deletion:**
  - remove some conflicting tuples
  - quite destructive
- **Update:**
  - modify values to resolve the conflict
    - equate RHS values (city here)
    - disequate LHS value (zip)
- **Insertion?**
  - Not for FDs, but e.g., FKs

2.1 Detecting Violations

- **Given FD A -> B on R**
  - Recall logical representation
  - For all X, X': R(X) and R(X') and A=A' -> B=B'
  - Only violated if we find two tuples where A=A', but B != B'
  - In datalog:
    - `Q(): R(X), R(X'), A=A', B!=B'`
  - In SQL:
    - `SELECT EXISTS (SELECT * FROM R x, R y WHERE A=A' AND B!=B')`

2.1 Detecting Violations

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    - `SELECT EXISTS (SELECT * FROM R x, R y WHERE A=A' AND B!=B')`
2.1 Example Constraints

Example: SQL Violation Detection

Relation: Person(name, city, zip)
FD: zip -> city
Violation Detection Query
SELECT EXISTS (SELECT * FROM Person x, Person y WHERE x.zip = y.zip AND x.city <> y.city)
To know which tuples caused the conflict:
SELECT * FROM Person x, Person y WHERE x.zip = y.zip AND x.city <> y.city

2.1 Fixing Violations

• Principle of minimality
  – Choose solution that minimally modifies the database
  – Updates:
    • Need a cost model
    – Deletes:
      • Minimal number of deletes

2.1 Constraint Repair Problem

Definition: Constraint Repair Problem (restated)
Given set of constraints \( \Sigma \) and an database instance \( I \) which violates the constraints find a clean instance \( I' \) (does not violate the constraints) with \( \text{cost}(I, I') \) being minimal

• Cost metrics that have been used
  – Deletion + Insertion
    \[ \Delta(I, I') = (I - I') \cup (I' - I) \]
    – S-repair: minimize measure above under set inclusion
    – C-repair: minimize cardinality
  – Update
    • Assume distance metric \( d \) for attribute values

2.1 Cost Metrics

• Deletion + Insertion
  \[ \Delta(I, I') = (I - I') \cup (I' - I) \]
  • S-repair: minimize measure above under set inclusion
  • C-repair: minimize cardinality

• Update
  • Assume single relation \( R \) with uniquely identified tuples
  • Assume distance metric \( d \) for attribute values
  • Schema(\( R \)) = attributes in schema of relation \( R \)
  • \( t' \) is updated version of tuple \( t \)
  • Minimize:
    \[ \sum_{r \in R} \sum_{A \in \text{schema}(R)} d(t.A, t'.A) \]

• We focus on this one
• This is NP-hard
  – Heuristic algorithm

2.1 Naïve FD Repair Algorithm

• FD Repair Algorithm: 1. Attempt
  – For each FD \( X \rightarrow Y \) in \( \Sigma \) run query to find pairs of tuples that violate the constraint
  – For each pair of tuples \( t \) and \( t' \) that violate the constraint
    • update \( t.Y \) to \( t'.Y \)
    – choice does not matter because cost is symmetric, right?
2.1 Constraint Repair

Example: Constraint Repair

SSN	 zip	 city	 name
333-333-3333	 60616	 New York	 Peter
333-333-9999	 60615	 Chicago	 Gert
333-333-5599	 60615	 Schaumburg	 Gertrud
333-333-6666	 60616	 Chicago	 Hans
333-355-4343	 60616	 Chicago	 Malcom

2.1 Problems with the Algorithm

• FD Repair Algorithm: 1. Attempt
  – For each FD X -> Y in Σ run query to find pairs of tuples that violate the constraint
  – For each pair of tuples t and t' that violate the constraint: t.X = t'.X and t.Y != t'.Y
    • update t.Y to t'.Y
      – choice does not matter because cost is symmetric, right?
      – Our updates may cause new violations!

• FD Repair Algorithm: 2. Attempt
  – I' = I
    – 1) For each FD X -> Y in Σ run query to find pairs of tuples that violate the constraint
    – 2) For each pair of tuples t and t' that violate the constraint: t.X = t'.X and t.Y != t'.Y
      • update t.Y to t'.Y
        – choice does not matter because cost is symmetric, right?
      – 3) If we changed I' goto 1)

• FD Repair Algorithm: 3. Attempt
  – I'' = I
    – 1) For each FD X -> Y in Σ run query to find pairs of tuples that violate the constraint
    – 2) For each pair of tuples t and t' that violate the constraint: t.X = t'.X and t.Y != t'.Y
      • update t.Y to t'.Y
        – choice does not matter because cost is symmetric, right?
      – 3) If we changed I'' goto 1)

• FD Repair Algorithm: 4. Attempt
  – I''' = I
    – 1) For each FD X -> Y in Σ run query to find pairs of tuples that violate the constraint
    – 2) For each pair of tuples t and t' that violate the constraint: t.X = t'.X and t.Y != t'.Y
      • update t.Y to t'.Y
        – choice does not matter because cost is symmetric, right?
      – 3) If we changed I''' goto 1)

• FD Repair Algorithm: 5. Attempt
  – I'''' = I
    – 1) For each FD X -> Y in Σ run query to find pairs of tuples that violate the constraint
    – 2) For each pair of tuples t and t' that violate the constraint: t.X = t'.X and t.Y != t'.Y
      • update t.Y to t'.Y
        – choice does not matter because cost is symmetric, right?
      – 3) If we changed I'''' goto 1)

• FD Repair Algorithm: 6. Attempt
  – I''' = I
    – 1) For each FD X -> Y in Σ run query to find pairs of tuples that violate the constraint
    – 2) For each pair of tuples t and t' that violate the constraint: t.X = t'.X and t.Y != t'.Y
      • update t.Y to t'.Y
        – choice does not matter because cost is symmetric, right?
      – 3) If we changed I''' goto 1)

• FD Repair Algorithm: 7. Attempt
  – I'''' = I
    – 1) For each FD X -> Y in Σ run query to find pairs of tuples that violate the constraint
    – 2) For each pair of tuples t and t' that violate the constraint: t.X = t'.X and t.Y != t'.Y
      • update t.Y to t'.Y
        – choice does not matter because cost is symmetric, right?
      – 3) If we changed I'''' goto 1)

• FD Repair Algorithm: 8. Attempt
  – I''''' = I
    – 1) For each FD X -> Y in Σ run query to find pairs of tuples that violate the constraint
    – 2) For each pair of tuples t and t' that violate the constraint: t.X = t'.X and t.Y != t'.Y
      • update t.Y to t'.Y
        – choice does not matter because cost is symmetric, right?
      – 3) If we changed I''''' goto 1)
2.1 Problems with the Algorithm

- **FD Repair Algorithm: 2. Attempt**
  - Even if we succeed the repair may not be minimal. There may be many tuples with the same X values
    - They all have to have the same Y value
    - Choice which to update matters!

2.1 Problems with the Algorithm

- **FD Repair Algorithm: 3. Attempt**
  - **Equivalence Classes**
    - Keep track of sets of cells (tuple.attribute) that have to have the same values in the end (e.g., all Y attribute values for tuples with same X attribute value)
    - These classes are updated when we make a choice
    - Choose Y value for equivalence class using minimality, e.g., most common value
  - **Observation**
    - Equivalence Classes may merge, but never split if we only update RHS of all tuples with same X at once
    - \(\rightarrow\) we can find an algorithm that terminates

2.1 Problems with the Algorithm

- **FD Repair Algorithm: 3. Attempt**
  - **Initialize**:
    - Each cell in its own equivalence class
    - Put all cells in collection unresolved
  - **While** unresolved is not empty
    - Remove tuple \(t\) from unresolved
    - Pick FD \(X \rightarrow Y\) (e.g., random)
    - Compute set of tuples \(S\) that have same value in \(X\)
    - Merge all equivalence classes for all tuples in \(S\) and attributes in \(Y\)
    - Pick values for \(Y\) (update all tuples in \(S\) to \(Y\))

2.1 Consistent Query Answering

- As an alternative to fixing the database which requires making a choice we could also leave it dirty and try to resolve conflicts at query time
  - Have to reason over answers to the query without knowing which of the possible repairs will be chosen
  - **Intuition**: return tuples that would be in the query result for every possible repair
2.1 Constraint Repair

Example: Constraint Repair

<table>
<thead>
<tr>
<th>ID</th>
<th>age</th>
<th>city</th>
<th>name</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>333-333-3333</td>
<td>New York</td>
<td>Peter</td>
</tr>
<tr>
<td>2</td>
<td>333-333-9999</td>
<td>Chicago</td>
<td>Gert</td>
</tr>
<tr>
<td>3</td>
<td>333-333-5599</td>
<td>Schaumburg</td>
<td>Gertrud</td>
</tr>
<tr>
<td>4</td>
<td>333-333-6666</td>
<td>Chicago</td>
<td>Hans</td>
</tr>
<tr>
<td>5</td>
<td>333-355-4343</td>
<td>Chicago</td>
<td>Malcom</td>
</tr>
</tbody>
</table>

Changes: 1.city = Chicago
Not so cheap: set 4.city and 5.city = New York

2.2 Statistical and Outlier

- Assumption
  - Errors can be identified as outliers
- How do we find outliers?
  - Similarity-based:
    - Object is dissimilar to all (many) other objects
    - E.g., clustering, objects not in cluster are outliers
  - Some type of statistical test:
    - Given a distribution (e.g., fitted to the data)
    - How probable is it that the point has this value?
    - If low probability -> outlier

2.3 Entity Resolution

- Entity Resolution (ER)
- Alternative names
  - Duplicate detection
  - Record linkage
  - Reference reconciliation
  - Entity matching
  - …

### Definition: Entity Resolution Problem

Given sets of tuples A compute equivalence relation (E(,) which denotes that tuple t and t' represent the same entity.

- Intuitively, E should be based on how similar t and t' are
  - Similarity measure?
- E should be an equivalence relation
  - If t is the same as t' and t' is the same as t''
    then t should be the same as t''
2.3 Entity Resolution

Example: Two tuples (objects) that represent the same entity

<table>
<thead>
<tr>
<th>SSN</th>
<th>zip</th>
<th>city</th>
<th>name</th>
</tr>
</thead>
<tbody>
<tr>
<td>333-333-3333</td>
<td>60616</td>
<td>Chicago</td>
<td>Peter</td>
</tr>
<tr>
<td>3333333333</td>
<td>IL</td>
<td>60616</td>
<td>Petre</td>
</tr>
</tbody>
</table>

Similarity based on similarity of attribute values
- Which distance measure is appropriate?
- How do we combine attribute-level distances?
- Do we consider additional information?
  - E.g., foreign key connections
  - How similar should duplicates be?
  - E.g., fixed similarity threshold
- How to guarantee transitivity of \( E \)
  - E.g., do this afterwards

2.3 Entity Resolution – Distance Measures

- Edit-distance
  - Measures similarity of two strings
  - \( d(s, s') = \) minimal number of insert, replace, delete operations (single character) that transform \( s \) into \( s' \)
  - Is symmetric (actually a metric)
  - Why?

Definition: Edit Distance

Example:

NEED -> STREET

Trivial solution: Delete all chars in NEED, then insert all chars in STREET
- gives upper bound on distance \( l(s) + l(s') \)

Example:

NEED -> STREET

Minimal solution:
- insert S
- replace N with R
- replace D with T

\( d(NEED, STREET) = 4 \)
2.3 Entity Resolution

**Principal of optimality**
- Best solution of a subproblem is part of the best solution for the whole problem

**Dynamic programming algorithm**
- \( D(i,j) \) is the edit distance between prefix of len \( i \) of \( s \) and prefix of len \( j \) of \( s' \)
- \( D(\text{len}(s),\text{len}(s')) \) is the solution
- Represented as matrix
- Populate based on rules shown on the next slide

---

**Recursive definition**
- \( D(i,0) = i \)
  - Cheapest way of transforming prefix \( s[i] \) into empty string is by deleting all \( i \) characters in \( s[i] \)
- \( D(0,j) = j \)
  - Same holds for \( s'[j] \)
- \( D(i,j) = \min \{ \)
  - \( D(i-1,j) + 1 \)
  - \( D(i,j-1) + 1 \)
  - \( D(i-1,j-1) + d(i,j) \) with \( d(i,j) = 1 \) if \( s[i] \neq s[j] \) and 0 else

---

Example:

```
NEED -> STREET
```

```
S T R E E T
0 1 2 3 4 5 6
N 1 1 2 1 3
E 2 2 2 2 3
D 4 4 4 4 4
```
2.3 Entity Resolution

Example:

NEED -> STREET

<table>
<thead>
<tr>
<th></th>
<th>S</th>
<th>T</th>
<th>R</th>
<th>E</th>
<th>E</th>
<th>T</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>5</td>
<td>6</td>
</tr>
<tr>
<td>N</td>
<td>1</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>5</td>
</tr>
<tr>
<td>E</td>
<td>2</td>
<td>2</td>
<td>2</td>
<td>3</td>
<td>3</td>
<td>4</td>
</tr>
<tr>
<td>D</td>
<td>4</td>
<td>4</td>
<td>4</td>
<td>4</td>
<td>4</td>
<td>4</td>
</tr>
</tbody>
</table>

2.3 Entity Resolution

Example:

NEED -> STREET

<table>
<thead>
<tr>
<th></th>
<th>S</th>
<th>T</th>
<th>R</th>
<th>E</th>
<th>E</th>
<th>T</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>5</td>
<td>6</td>
</tr>
<tr>
<td>N</td>
<td>1</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>5</td>
</tr>
<tr>
<td>E</td>
<td>2</td>
<td>2</td>
<td>2</td>
<td>3</td>
<td>3</td>
<td>4</td>
</tr>
<tr>
<td>D</td>
<td>4</td>
<td>4</td>
<td>4</td>
<td>4</td>
<td>4</td>
<td>4</td>
</tr>
</tbody>
</table>

2.3 Entity Resolution

Other sequence-based measures for string similarity

- Needleman-Wunsch
  - Missing character sequences can be penalized differently from character changes

- Affine Gap Measure
  - Limit influence of longer gaps
  - E.g., Peter Friedrich Mueller vs. Peter Mueller

- Smith-Waterman Measure
  - More resistant to reordering of elements in the string
  - E.g., Prof. Franz Mueller vs. F. Mueller, Prof.
2.3 Entity Resolution – Distance Measures

- **Token-set based measures**
  - Split string into tokens
    - E.g., single characters
    - E.g., words if string represents a longer text
  - Potentially normalize tokens
    - E.g., word tokens replace word with its stem
      - Generating, generated, generates are all replaced with generate
    - Represent string as set (multi-set) of tokens

Example:
- **Tokenization**

Input string: $S =$ "the tokenization of strings is commonly used in information retrieval"

Set of tokens: $\text{Tok}(S) = \{\text{commonly, in, information, is, of, retrieval, strings, the, tokenization, used}\}$

Bag of tokens: $\text{Bag}(S) = \{\text{commonly, in, information, is, of, retrieval, strings, the, tokenization, used}\}$

- **Jaccard-Measure**
  - $B_S = \text{Tok}(s) =$ token set of string $s$
  - Jaccard measures relative overlap of tokens in two strings
    - Number of common tokens divided by total number of tokens
    - $d_{jacc}(s, s') = \frac{|B_s \cap B_{s'}|}{|B_s \cup B_{s'}|}$

Example:
- **Tokenization**

Input string: $S =$ "nanotubes are used in these experiments to…"

$S' =$ "we consider nanotubes in our experiments…"

$S'' =$ "we prove that P=NP, thus solving …"

$\text{Tok}(S) = \{\text{are, experiments, in, nanotubes, these, to, used}\}$

$\text{Tok}(S') = \{\text{consider, experiments, in, nanotubes, our, we}\}$

$\text{Tok}(S'') = \{\text{P=NP, prove, solving, that, thus, we}\}$

$d_{jacc}(S, S') = \frac{3}{10} = 0.3$

$d_{jacc}(S, S'') = 0 / 13 = 0$

$d_{jacc}(S', S'') = 1 / 11 = 0.0909$

- **Other set-based measures**
  - **TF/IDF**: term frequency, inverse document frequency
    - Take into account that certain tokens are more common than others
    - If two strings (called documents for TF/IDF) overlap on uncommon terms they are more likely to be similar than if they overlap on common terms
      - E.g., the vs. carbon nanotube structure
2.3 Entity Resolution

- **TF/IDF**: term frequency, inverse document frequency
  - Represent documents as feature vectors
  - One dimension for each term
  - Value computed as frequency times IDF
  - Inverse of frequency of term in the set of all documents
  - Compute cosine similarity between two feature vectors
  - Measure how similar they are in term distribution (weighted by how uncommon terms are)
  - Size of the documents does not matter
  - See textbook for details

2.3 Entity Resolution

- **Entity resolution**
  - Concatenate attribute values of tuples and use string similarity measure
  - Loose information encoded by tuple structure
  - E.g., [Gender: male, Salary: 9000]
    - “Gender: male, Salary: 9000”
    - or “male, 9000”
  - Combine distance measures for single attributes
  - Weighted sum or more complex combinations
    - E.g., $d(t, t') = w_1 \times d_A(t.A, t_0.A) + w_2 \times d_B(t.B, t_0.B)$
  - Use quadratic distance measure
    - E.g., earth-movers distance

2.3 Entity Resolution

- **Weighted linear combination**
  - Say tuples have $n$ attributes
  - $w_i$: predetermined weight of an attribute
  - $d_i(t, t')$: similarity measure for the $i$th attribute
  - Tuples match if $d(t, t') > \beta$ for a threshold $\beta$

Example: Weighted sum of attribute similarities

<table>
<thead>
<tr>
<th>SSN</th>
<th>zip</th>
<th>city</th>
<th>name</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>10</td>
<td>07</td>
<td>0.6</td>
</tr>
<tr>
<td>2</td>
<td>10</td>
<td>10</td>
<td>0.6</td>
</tr>
</tbody>
</table>

Assumption: SSNs and names are most important, city and zip are not very predictive

$w_{SSN} = 0.4$, $w_{zip} = 0.05$, $w_{city} = 0.15$, $w_{name} = 0.4$

$d(t, t') = 0.4 \times 1 + 0.05 \times 0.8 + 0.15 \times 0 + 0.4 \times 0.6$

$= 0.4 + 0.04 + 0 + 0.24$

$= 0.68$
2.3 Entity Resolution

- **Entity resolution**
  - Rule-based approach
  - Learning-based approaches
  - Clustering-based approaches
  - Probabilistic approaches to matching
  - Collective matching

- **Rule-based approach**
  - Collection (list) of rules
  - If $d_{name}(t,t') < 0.6$ then unmatched
  - If $d_{zip}(t,t') = 1$ and $t.country = USA$ then matched
  - If $t.country 
eq t'.country$ then unmatched

- **Advantages**
  - Easy to start, can be incrementally improved

- **Disadvantages**
  - Lot of manual work, large rule-bases hard to understand

- **Learning-based approach**
  - Build all pairs $(t,t')$ for training dataset
  - Represent each pair as feature vector from, e.g., similarities
  - Train classifier to return {match, no match}

- **Advantages**
  - Automated

- **Disadvantages**
  - Requires training data

- **Clustering-based approach**
  - Apply clustering method to group inputs
  - Typically hierarchical clustering method
  - Clusters now represent entities
    - Decide how to merge based on similarity between clusters

- **Advantages**
  - Automated, no training data required

- **Disadvantages**
  - Choice of cluster similarity critical
2.3 Entity Resolution

- Entity resolution
  - Rule-based approach
  - Learning-based approaches
  - Clustering-based approaches
  - Probabilistic approaches to matching
  - Collective matching
    - See textbook

2.4 Data Fusion

- Data Fusion = how to combine (possibly conflicting) information from multiple objects representing the same entity
  - Choose among conflicting values
    - If one value is missing (NULL) choose the other one
    - Numerical data: e.g., median, average
    - Consider sources: have more trust in certain data sources
    - Consider value frequency: take most frequent value
    - Timeliness: latest value

Outline

0) Course Info
1) Introduction
2) Data Preparation and Cleaning
3) Schema matching and mapping
4) Virtual Data Integration
5) Data Exchange
6) Data Warehousing
7) Big Data Analytics
8) Data Provenance
3. Why matching and mapping?

- **Problem: Schema Heterogeneity**
  - Sources with different schemas store overlapping information
  - Want to be able to translate data from one schema into a different schema
    - Data warehousing
    - Data exchange
  - Want to be able to translate queries against one schema into queries against another schema
    - Virtual data integration

- **Why both mapping and matching**
  - Split complex problem into simpler subproblems
    - Determine matches and then correlate with constraint information into mappings
  - Some tasks only require matches
    - E.g., matches can be used to determine attributes storing the same information in data fusion
  - Mappings are naturally a generalization of matchings

3. Overview

- **Topics covered in this part**
  - Schema Matching
  - Schema Mappings and Mapping Languages
3.1 Schema Matching

- **Problem: Schema Matching**
  - Given two (or more schemas)
  - For now called *source* and *target*
  - Determine how elements are related
  - Attributes are representing the same information
    - name = lastname
  - Attribute can be translated into an attribute
    - MonthlySalary * 12 = YearlySalary
  - 1-1 matches vs. M-N matches
    - name to lastname
    - name to concat(firstname, lastname)

- Why is this hard?
  - Insufficient information: schema does not capture full semantics of a domain
  - Schemas can be misleading:
    - E.g., attributes are not necessarily descriptive
    - E.g., finding the right way to translate attributes not obvious

- What information to consider?
  - Attribute names
    - or more generally element names
  - Structure
    - e.g., belonging to the same relation
  - Data
    - Not always available
  - Need to consider multiple types to get reasonable matching quality
    - Single types of information not predictable enough

- Typical Matching System Architecture
  - Matcher
  - Constraint Enforcer
  - Combiner
  - Match Selector
  - Determine actual matches
  - Use constraints to modify similarity matrix
  - Combine individual similarity matrices
  - Each matcher uses one type of information to compute similarity matrix
3.1 Schema Matching

- **Matcher**
  - **Input:** Schemas
  - Maybe also data, documentation
  - **Output:** Similarity matrix
  - Storing value [0,1] for each pair of elements from the source and the target schema

**Example:**

<table>
<thead>
<tr>
<th>Name</th>
<th>Address</th>
<th>Office-phone</th>
<th>Office-address</th>
<th>Home-phone</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>0</td>
<td>0</td>
<td>0.5</td>
<td>0.5</td>
<td>0</td>
</tr>
</tbody>
</table>

3.1 Schema Mapping

**Example:** Types of Matching

- **Name-Based Matchers**
  - String similarities measures
    - E.g., Jaccard and other measures we have discussed
  - **Preprocessing**
    - Tokenization?
    - Normalization
      - Expand abbreviations and replace synonyms
    - Remove stop words
      - In, and, the

- **Data-Based Matchers**
  - Determine how similar the values of two attributes are
  - Some techniques
    - **Recognizers**
      - Dictionaries, regular expressions, rules
    - **Overlap matcher**
      - Compute overlap of values in the two attributes
    - **Classifiers**

- **Recognizers**
  - Dictionaries
    - Countries, states, person names
  - Regular expression matchers
    - **Phone numbers:** `\d\d?\d{3}\d{3}\d{4}`

- **Overlap of attribute domains**
  - Each attribute value is a token
  - Use set-based similarity measure such as Jaccard

- **Classifier**
  - Train classifier to identify values of one attribute A from the source
    - Training set are values from A as positive examples and values of other attributes as negative examples
  - Apply classifier to all values of attributes from target schema
    - Aggregate into similarity score
3.1 Schema Matching

- **Combiner**
  - **Input**: Similarity matrices
  - **Output**: Similarity matrix

- **Constraint Enforcer**
  - **Input**: Similarity matrix
  - **Output**: Similarity matrix

**Example: Constraints**

Constraint 1: An attribute matched to `source.cust-phone` has to get a score of 1 from the phone regexpr matcher.

Constraint 2: Any attribute matched to `source.fax` has to have fax in its name.

Constraint 3: If an attribute is matched to `source.firstname` with score > 0.9 then there has to be another attribute from the same target table that is matched to `source.lastname` with score > 0.9.

3.1 Schema Matching

- **Combiner**
  - **Input**: Similarity matrices produced by the matchers into single matrix
  - **Output**: Single Similarity matrix

- **Constraint Enforcer**
  - **Input**: Similarity matrix
  - **Output**: Similarity matrix

- **How to search match combinations**
  - **Full search**
    - Exponentially many combinations potentially
  - **Informed search approaches**
    - **A* search**
    - **Local propagation**
    - Only local optimizations
3.1 Schema Matching

- **A* search**
  - Given a search problem
  - Set of states: start state, goal states
  - Transitions about states
  - Costs associated with transitions
  - Find cheapest path from start to goal states
  - Need admissible heuristics \( h \)
    - For a path \( p \), \( h \) computes lower bound for any path from start to goal with prefix \( p \)
  - Backtracking best-first search
    - Choose next state with lowest estimated cost
    - Expand it in all possible ways

- **Algorithm**
  - Data structures
    - Keep a priority queue \( q \) of states sorted on \( f(n) \)
    - Initialize with start state
  - Keep set \( v \) of already visited nodes
    - Initially empty
  - While \( q \) is not empty
    - pop state \( s \) from head of \( q \)
    - If \( s \) is goal state return
    - Foreach \( s' \) that is direct neighbor of \( s \)
      - If \( s' \) not in \( v \)
        - Compute \( f(s') \) and insert \( s' \) into \( q \)

- **Application to constraint enforcing**
  - Source attributes: \( A_1 \) to \( A_n \)
  - Target attributes: \( B_1 \) to \( B_m \)
  - States
    - Vector of length \( n \) with values \( B_i \) or * indicating that no choice has not been taken
    - Initial state
      - \([*, *, *, *] \)
    - Goal states
      - All states without *

- **Match Selector**
  - **Input**: Similarity matrix
    - Output of the individual matchers
  - **Output**: Matches

- **Match Selection**
  - Merge similarity matrices produced by the matchers into single matrix
  - Typical strategies
    - Average, Minimum, Max
    - Weighted combinations
    - Some script
3.1 Schema Matching

- Many-to-many matchers
  - Combine multiple columns using a set of functions
    - E.g., concat, +, currency exchange, unit exchange
  - Large or even unlimited search space
  - Need method that explores interesting part of the search space
  - Specific searchers
    - Only concatenation of columns (limit number of combinations, e.g., 2)

3.2 Schema Mapping

Example: Matching Result

<table>
<thead>
<tr>
<th>Person</th>
<th>Address</th>
<th>Id</th>
<th>City</th>
<th>Office-contact</th>
</tr>
</thead>
<tbody>
<tr>
<td>Peter</td>
<td>1</td>
<td>1</td>
<td>Chicago</td>
<td>(312) 123-4567</td>
</tr>
<tr>
<td>Alice</td>
<td>3</td>
<td>2</td>
<td>Chicago</td>
<td>(312) 555-7890</td>
</tr>
<tr>
<td>Bob</td>
<td>3</td>
<td>3</td>
<td>New York</td>
<td>(901) 123-4567</td>
</tr>
</tbody>
</table>

Assume: We have data in the source as shown above. What data should we create in the target? Copy values based on matches?

3.2 Schema Mapping

- Matches do not determine completely how to create the target instance data! (Data Exchange)
  - How do we choose values for attributes that do not have a match?
  - How do we combine data from different source tables?
- Matches do not determine completely what the answers to queries over a mediated schema should be! (Virtual Data Integration)

3.2 Schema Mapping

- Schema mappings
  - Generalize matches
  - Describe relationship between instances of schemas
  - Mapping languages
    - LAV, GAV, GLAV
    - Mapping as Dependencies: tuple-generating dependencies
- Mapping generation
  - Input: Matches, Schema constraints
  - Output: Schema mappings
3.2 Schema Mapping

- **Instance-based definition of mappings**
  - Global schema $G$
  - Local schemas $S_1$ to $S_n$
  - Mapping $M$ can be expressed as for each set of instances of the local schemas what are allowed instances of the global schema
    - Subset of $(I_G \times I_1 \times \ldots \times I_n)$
    - Useful as a different way to think about mappings, but not a practical way to define mappings

3.2 Schema Mapping

- **Languages for Specifying Mappings**
- **Describing mappings as inclusion relationships between views:**
  - Global as View (GAV)
  - Local as View (LAV)
  - Global and Local as View (GLAV)
- **Describing mappings as dependencies**
  - Source-to-target tuple-generating dependencies (st-tgds)

3.2 Schema Mapping

- **Excursion Virtual Data Integration**
  - More in next section of the course

3.2 Schema Mapping

- **Certain answers**
  - Given mapping $M$ and $Q$
  - Instances $I_1$ to $I_n$ for $S_1$ to $S_n$
  - Tuple $t$ is a certain answer for $Q$ over $I_1$ to $I_n$
    - If for every instance $I_G$ so that $(I_G \times I_1 \times \ldots \times I_n)$ in $M$ then $t$ in $Q(I_G)$

3.2 Schema Mapping

- **Describing mappings as inclusion relationships between views:**
  - Global as View (GAV)
  - Local as View (LAV)
  - Global and Local as View (GLAV)
- **Terminology stems from virtual integration**
  - Given a global (or mediated, or virtual) schema
  - A set of data sources (local schemas)
  - Compute answers to queries written against the global schema using the local data sources

3.2 Schema Mapping

- **Global-as-view (GAV)**
  - Express the global schema as views over the local schemata
  - What query language do we support?
    - CQ, UCQ, SQL, …?
  - **Closed vs. open world** assumption
    - Closed world: $R = Q(S_1, \ldots, S_n)$
      - Content of global relation $R$ is defined as the result of query $Q$ over the sources
    - Open world: $R \supseteq Q(S_1, \ldots, S_n)$
      - Relation $R$ has to contain the result of query $Q$, but may contain additional tuples
3.2 Schema Mapping

Example: Types of Matching

Local Schema
Person
Name
Address
City
Office-contact
Global Schema
Person
Name
Address
Office-phone
Office-address
Home-phone

Person(X', Y', Z', A', B')
= Q(X, Z, A, NULL, NULL) :- Person(X, Y), Address(Y, Z, A)

Since heads of LHS and RHS have to be the same we can use simpler notation without the head of the view expression:

Person(X, Z, A, NULL, NULL) = Person(X, Y), Address(Y, Z, A)

Consider switching local and global schema

Person(X, NULL) = Person(X, Y, Z, A, B)
Address(NULL, Y, Z) = Person(X, Y, Z, A, B)

3.2 Schema Mapping

• Global-as-view (GAV)

• Solutions (mapping M)
  – Unique solutions (1 solution!)
  – Intuitively, execute queries over local instance that produced global instance

3.2 Schema Mapping

• Global-as-view (GAV)

• Answering Queries
  – Simply replace references to global tables with the view definition

Map R(X, Y) = S(X, Y), T(Y, Z)
Q(X) :- R(X, Y)
Rewrite into
Q(X) :- S(X, Y), T(Y, Z)

3.2 Schema Mapping

• Global-as-view (GAV)

• Discussion

– Hard to add new source
  • have to rewrite the view definitions

– Does not deal gracefully with missing values

– Easy query processing
  • view unfolding

• Local-as-view (LAV)

– Express the local schema as views over the global schemata

– What query language do we support?
  • CQ, UCQ, SQL, ...?

– Closed vs. open world assumption

  • Closed world: S_q = Q(G)
    – Content of local relation S_q is defined as the result of query Q over the sources

  • Open world: S_q ⊇ Q(G)
    – Local relation S_q has to contain the result of query Q, but may contain additional tuples
3.2 Schema Mapping

Example: Types of Matching

Local Schema
Person
Name
Address

Global Schema
Person
Name
Address
Office-phone
Office-address
Home-phone

Person(X, NULL) = Person(X, Y, Z, A, B)
Address(NULL, Y, Z) = Person(X, Y, Z, A, B)

• Local-as-view (LAV)
• Solutions (mapping M)
  – May be many solutions

• Global-Local-as-view (GLAV)
  – Express both sides of the constraint as queries
  – What query language do we support?
    • CQ, UCQ, SQL, …?
  – Closed vs. open world assumption
    • Closed world: Q'(G) = Q(S)
    • Open world: Q'(G) \supseteq Q(S)
3.2 Schema Mapping

• **Local-as-view (GLAV) Discussion**
  -- Kind of best of both worlds (almost)
  -- Complexity of query answering is the same as for LAV
  -- Can address the lost correlation and missing values problems we observed using GAV and LAV

• **Source-to-target tuple-generating dependencies (st-tgds)**
  -- Local way of expressing GLAV mappings
  \[ \forall x : \phi(x) \rightarrow \exists y : \psi(x, y) \]
  -- Equivalence to a containment constraint:
  \[ Q'(G) \supseteq Q(S) \]

• **Generating Schema Mappings**
  -- **Input**: Schemas (Constraints), matches
  -- **Output**: Schema mappings
  -- **Ideas**:
    -- Schema matches tell us which source attributes should be copied to which target attributes
    -- Foreign key constraints tell us how to join in the source and target to not loose information

• **Clio**
  -- Clio is a data exchange system prototype developed by IBM and University of Toronto researchers
  -- The concepts developed for Clio have been implemented in IBM InfoSphere Data Architect
  -- Clio does matching, mapping generation, and data exchange
    -- For now let us focus on the mapping generation

---

**Example: Types of Matching**

<table>
<thead>
<tr>
<th>Source Scheme</th>
<th>Global Schema</th>
</tr>
</thead>
<tbody>
<tr>
<td>Person</td>
<td>Person</td>
</tr>
<tr>
<td>Name</td>
<td>Name</td>
</tr>
<tr>
<td>Address</td>
<td>Address</td>
</tr>
<tr>
<td>City</td>
<td>City</td>
</tr>
<tr>
<td>Office-contact</td>
<td>Office-address</td>
</tr>
</tbody>
</table>

Source: \( Q(X,Y,Z) :- Person(X',Y'), Address(Y',Z',A') \)
Target: \( Q(X',Y',Z') :- Person(X',Y',Z',A',B') \)
3.2 Schema Mapping

- **Clio Algorithm Steps**
  - 1) Use foreign keys to determine all reasonable ways of joining data within the source and the target schema
    - Each alternative of joining tables in the source/target is called a logical association
  - 2) For each pair of **source-target logical associations**: Correlate this information with the matches to determine candidate mappings

- **Chase step**
  - Works on tableau: set of relational atoms
  - A chase step takes one tgd t where the LHS is fulfilled and the RHS is not fulfilled
    - We fulfill the tgd t by adding new atoms to the tableau and mapping variables from t to the actually occurring variables from the current tableau
  - Chase
    - Applying the chase until no more changes
    - Note: if there are cyclic constraints this may not terminate

- **Clio Algorithm: 2) Generate Candidate Mappings**
  - For each pair of logical association \( A_S \) in the source and \( A_T \) in the target produced in step 1
  - Find the matches that are covered by \( A_S \) and \( A_T \)
    - Matches that lead from an element of \( A_S \) to an element from \( A_T \)
  - If there is at least one such match then create mapping by equating variables as indicated by the matches and create st-tgd with \( A_S \) in LHS and \( A_T \) in RHS

3.2 Schema Mapping

- **Clio Algorithm: 1) Find logical associations**
  - This part relies on the chase procedure that first introduced to test implication of functional dependencies (’77)
  - The idea is that we start use a representation of foreign keys are **inclusion dependencies** (tgd's)
    - There are also chase procedures that consider edges (e.g., PKs)
  - Starting point are all single relational atoms
    - E.g., \( R(X,Y) \)

**Outline**

0) Course Info
1) Introduction
2) Data Preparation and Cleaning
3) Schema matching and mapping
4) **Virtual Data Integration**
5) Data Exchange
6) Data Warehousing
7) Big Data Analytics
8) Data Provenance
4. Virtual Data Integration

Virtual Data Integration

Problems:
- How to create mappings?
  - Discussed in previous part of the course
- How to compute query Q
  - This is the main focus of this part

4. Query Answering with Views

How to compute query Q over global schema based on source schemas only?
- What language is used to express mappings?
- What language do we allow for Q?
- What language(s) can we use to query local sources?
- What language can we use to compute Q from query results returned by local sources?
- How to deal with incompleteness?
4. Query Answering with Views

- **Problems**
  - How to determine whether query can be answered at all?
  - Given a rewriting of the query using views, how do we know it is correct?
  - What to do if views can only return some of the query results?

**Motivating Example (Part 1)**

\[
Q(T,Y,D) := \neg \text{Movie}(I,T,Y,G) \land G \geq 1950, G \neq \text{"comedy"}
\]

\[
\text{Director}(I,D), \text{Actor}(I,D)
\]

\[
V_1(T,Y,D) := \neg \text{Movie}(I,T,Y,G) \land G \geq 1940, G \neq \text{"comedy"}
\]

\[
\text{Director}(I,D), \text{Actor}(I,D)
\]

**Containment** does not hold, but intuitively, \(V_2\) and \(V_3\) are useful for answering \(Q\).

\[
Q^*(T,Y,D) := V_2(T,Y,D) \land V_3(I,D)
\]

**Motivating Example (Part 2)**

\[
Q(T,Y,D) := \text{Movie}(I,T,Y,G) \land G \geq 1950, G = \text{"comedy"}
\]

\[
\text{Director}(I,D), \text{Actor}(I,D)
\]

\[
V_2(I,T,Y) := \text{Movie}(I,T,Y,G) \land G \geq 1950, G = \text{"comedy"}
\]

\[
\text{Director}(I,D), \text{Actor}(I,D)
\]

**Containment** does not hold, but intuitively, \(V_2\) and \(V_3\) are useful for answering \(Q\).

\[
Q^*(T,Y,D) := V_2(I,T,Y) \land V_3(I,D)
\]

**Problem Definition**

**Input:** Query \(Q\)

View definitions: \(V_1, \ldots, V_n\)

A rewriting: a query \(Q'\) that refers only to the views and interpreted predicates (comparisons)

An equivalent rewriting of \(Q\) using \(V_1, \ldots, V_n\): a rewriting \(Q'\), such that \(Q' \Leftrightarrow Q\)
**Naïve approach**

- **Given Q and views**
  - Randomly combine views into a query Q’
  - Check equivalence of Q’ and Q
  - If Q’ is equivalent we are done
  - Else repeat

- **Why is this not good?**
  - There are infinitely many ways of combining views
    - E.g., V, V x V, V x V x V, ...
  - We are not using any information in the query

**Motivating Example (Part 3)**

```
Movie(ID,title,year,genre)
Director(ID,director)
Actor(ID,actor)
```

Q

- Movie(I,T,Y,G), Y ≥ 1950, G = "comedy"
  Director(I,D)
- V₃(I,D)
- V₄(I,T,Y)

Q’

- MAXIMALLY-CONTAINED REWRITING

**Maximally-Contained Rewritings**

**Input:** Query Q

**Rewriting query language L**

**View definitions:** V₁, ..., Vₙ

Q’ is a maximally-contained rewriting of Q given V₁, ..., Vₙ and L if:

1. Q’ ∈ L,
2. Q’ ⊆ Q, and
3. there is no Q”’ in L such that Q”’ ⊆ Q and Q’ ⊂ Q”’

**Why again?**

```
Query
Global Schema

Local Schema 1
Local Schema 2

MAPINGS
LAV/LGAV
```

**Other use-cases**

- Query optimization with materialized views
  - Need equivalent rewritings
  - Implemented in many commercial DBMS
  - Here interest is cost: how to speed-up query processing by using materialized views

**Exercise: which of these views can be used to answer Q?**

```
Q(T,Y,D) : ¬Movie(I,T,Y,G), Y ≥ 1950, G = "comedy"
  Director(I,D), Actor(I,D)
V₃(I,D) : ¬Movie(I,T,Y,G), Y ≥ 1950, G = "comedy"
V₄(I,D) : ¬Director(I,D), Actor(ID,D)
V₅(T,Y) : ¬Movie(I,T,Y,G), Y ≥ 1950, G = "comedy"
V₆(I,T,Y) : ¬Movie(I,T,Y,G), Y ≥ 1950, G = "comedy"
  Award(I,W)
V₇(I,T) : ¬Movie(I,T,Y,G), Y ≥ 1940, G = "comedy"
```
Algorithms for answering queries using views

- **Step 1**: we'll bound the space of possible query rewritings we need to consider (no comparisons)
- **Step 2**: we'll find efficient methods for searching the space of rewritings
  - Bucket Algorithm, MiniCon Algorithm
- **Step 2b**: we consider “logical approaches” to the problem:
  - The Inverse-Rules Algorithm

Bounding the Rewriting Length

**Theorem**: if there is an equivalent rewriting, there is one with at most \( n \) subgoals.

Query: \( Q(X) : - p_1(X_1), ..., p_n(X_n) \)

Rewriting: \( Q'(X) : - V_1(X_1), ..., V_m(X_m) \)

Expansion: \( Q''(X) : - g_1^{i_1}, ..., g_k^{i_k} \)

Proof: Only \( n \) subgoals in \( Q \) can contribute to the image of the containment mapping \( \varphi \)

Complexity Result

[LMSS, 1995]

- Applies to queries with no interpreted predicates.
- Finding an equivalent rewriting of a query using views is \( \text{NP-complete} \)
  - Need only consider rewritings of query length or less.
- Maximally-contained rewriting:
  - Union of all conjunctive rewritings of length \( n \) or less.

The Bucket Algorithm

**Key idea**:
- Create a bucket for each subgoal \( g \) in the query.
  - The bucket contains views that contribute to \( g \).
  - Create rewritings from the Cartesian product of the buckets (select one view for each goal)

- **Step 1**: assign views with renamed vars to buckets
- **Step 2**: create rewritings, refine them, until equivalent/all contained rewriting(s) are found

The Bucket Algorithm

**Step 1 Intuition**
- A view can only be used to provide information about a goal \( R(X) \) if it has a goal \( R(Y) \)
  - \( Q(X) : - R(X,Y) \)
  - \( V(X) : - S(X,Y) \)
- If the query goal contains variables that are in the head of the query, then the view is only useful if it gives access to these values (they are in the head)
  - \( Q(X) : - R(X,Y) \)
  - \( V(X) : - S(X,Y), R(Y,Z) \)
Cuts down the number of rewritings that need to be considered, especially if views apply many interpreted predicates.

The search space can still be large because the algorithm does not consider the interactions between different subgoals.

See next example.

**The MiniCon Algorithm**

\[
\text{Q(title, year, dir)}: \neg \text{Movie(ID, title, year, genre), Director(ID, dir), Actor(ID, dir)}
\]

\[
V_5(D, A) : \neg \text{Director(I, D), Actor(I, A)}
\]

**Intuition:** The variable \( I \) is not in the head of \( V_5 \), hence \( V_5 \) cannot be used in a rewriting.

**MiniCon** discards this option early on, while the Bucket algorithm does not notice the interaction.
MinCon Algorithm Steps

• 1) Create MiniCon descriptions (MCDs):
  – Homomorphism on view heads
  – Each MCD covers a set of subgoals in the query with a set of subgoals in a view

• 2) Combination step:
  – Any set of MCDs that covers the query subgoals (without overlap) is a rewriting
  – No need for an additional containment check!

MiniCon Descriptions (MCDs)
An atomic fragment of the ultimate containment mapping

\[ Q(\text{title}, \text{act}, \text{dir}) : \neg \text{Movie}(\text{ID}, \text{title}, \text{year}, \text{genre}), \]
\[ \quad \text{Director}(\text{ID}, \text{dir}), \text{Actor}(\text{ID}, \text{act}) \]
\[ V(I,D,A) : \neg \text{Director}(I,D), \text{Actor}(I,A) \]

MCD:
\[ \begin{align*}
  & \text{ID} \rightarrow I \\
  & \text{dir} \rightarrow D \\
  & \text{act} \rightarrow A
\end{align*} \]
covered subgoals of \( Q \): \{2,3\}

MCDs: Detail 1

\[ Q(\text{title}, \text{year}, \text{dir}) : \neg \text{Movie}(\text{ID}, \text{title}, \text{year}, \text{genre}), \]
\[ \quad \text{Director}(\text{ID}, \text{dir}), \text{Actor}(\text{ID}, \text{dir}) \]
\[ V(I,D,A) : \neg \text{Director}(I,D), \text{Actor}(I,A) \]

Need to specialize the view first:
\[ V'(I,D,D) : \neg \text{Director}(I,D), \text{Actor}(I,D) \]

MCD:
\[ \begin{align*}
  & \text{ID} \rightarrow I \\
  & \text{dir} \rightarrow D
\end{align*} \]
covered subgoals of \( Q \): \{2,3\}

MCDs: Detail 2

\[ Q(\text{title}, \text{year}, \text{dir}) : \neg \text{Movie}(\text{ID}, \text{title}, \text{year}, \text{genre}), \]
\[ \quad \text{Director}(\text{ID}, \text{dir}), \text{Actor}(\text{ID}, \text{dir}) \]
\[ V(I,D,D) : \neg \text{Director}(I,D), \text{Actor}(I,D), \]
\[ \quad \text{Movie}(I,T,Y,G) \]

Note: the third subgoal of the view is not included in the MCD.

MCD:
\[ \begin{align*}
  & \text{ID} \rightarrow I \\
  & \text{dir} \rightarrow D
\end{align*} \]
covered subgoals of \( Q \) still: \{2,3\}

Inverse-Rules Algorithm

• A “logical” approach to AQUV
• Produces maximally-contained rewriting in polynomial time
  – To check whether the rewriting is equivalent to the query, you still need a containment check.
• Conceptually simple and elegant
  – Depending on your comfort with Skolem functions...

Inverse Rules by Example

Given the following view:
\[ V_e(I,T,Y,G) : \neg \text{Movie}(I,T,Y,G), \text{Director}(I,D), \text{Actor}(I,D) \]

And the following tuple in \( V_e \):
\[ V_e(79, \text{Manhattan}, 1979, \text{Comedy}) \]

Then we can infer the tuple:
\[ \text{Movie}(79, \text{Manhattan}, 1979, \text{Comedy}) \]

Hence, the following “rule” is sound:
\[ \text{IN}_1 : \text{Movie}(I,T,Y,G) :: V_e(I,T,Y,G) \]
Skolem Functions

\[ V_7(I, T, Y, G) : \text{Movie}(I, T, Y, G), \text{Director}(I, D), \text{Actor}(I, D) \]

Now suppose we have the tuple \( V_7(79, \text{Manhattan}, 1979, \text{Comedy}) \)

Then we can infer that there exists some director. Hence, the following rules hold (note that they both use the same Skolem function):

\[ \text{IN}_2: \text{Director}(I, f_1(I, T, Y, G)) \leftarrow V_7(I, T, Y, G) \]
\[ \text{IN}_3: \text{Actor}(I, f_1(I, T, Y, G)) \leftarrow V_7(I, T, Y, G) \]

Inverse Rules in General
Rewriting = Inverse Rules + Query

\[ Q_2(title, year, genre) : \text{Movie}(ID, title, year, genre) \]

Given \( Q_2 \), the rewriting would include:

\[ \text{IN}_1, \text{IN}_2, \text{IN}_3, Q_2. \]

Given input: \( V_7(79, \text{Manhattan}, 1979, \text{Comedy}) \)

Inverse rules produce:

\( \text{Movie}(79, \text{Manhattan}, 1979, \text{Comedy}) \)
\( \text{Director}(79, f_1(79, \text{Manhattan}, 1979, \text{Comedy})) \)
\( \text{Actor}(79, f_1(79, \text{Manhattan}, 1979, \text{Comedy})) \)

(Inv. rls. produc. to. last tuple produced by applying \( Q_2 \).

Comparing Algorithms

- **Bucket algorithm:**
  - Good if there are many interpreted predicates
  - Requires containment check. Cartesian product can be big
- **MiniCon:**
  - Good at detecting interactions between subgoals

Algorithm Comparison (Continued)

- **Inverse-rules algorithm:**
  - Conceptually clean
  - Can be used in other contexts (see later)
  - But may produce inefficient rewritings because it “undoes” the joins in the views (see next slide)
- Experiments show MiniCon is most efficient.
- Even faster:
  Konstantinidis, G. and Ambite, J.L, Scalable query rewriting: a graph-based approach. SIGMOD ’11

Inverse Rules Inefficiency Example

Query and view:

\[ Q(X, Y) : \neg e_1(X, Z), e_2(Z, Y) \]
\[ V(A, B) : \neg e_1(A, C), e_2(C, B) \]

Inverse rules:

\[ e_1(A, f_1(A, B)) : \neg V(A, B) \]
\[ e_2(f_1(A, B), B) : \neg V(A, B) \]

Now we need to re-compute the join…

View-Based Query Answering

- Maximally-contained rewritings are parameterized by query language.
- More general question:
  - Given a set of view definitions, view instances and a query, what are all the answers we can find?
- We introduce certain answers as a mechanism for providing a formal answer.
Consider the two views:

\[ V_8(\text{dir}) : \neg \text{Movie}(\text{ID,dir,actor}) \]
\[ V_9(\text{actor}) : \neg \text{Movie}(\text{ID,dir,actor}) \]

And suppose the extensions of the views are:

\[ V_8 : \{\text{Allen, Copolla}\} \]
\[ V_9 : \{\text{Keaton, Pacino}\} \]

Possible Databases

There are multiple databases that satisfy the above view definitions: (we ignore the first argument of Movie below)

DB1. \{\{Allen, Keaton\}, \{Coppola, Pacino\}\}
DB2. \{\{Allen, Pacino\}, \{Coppola, Keaton\}\}

If we ask whether Allen directed a movie in which Keaton acted, we can’t be sure. Certain answers are those true in all databases that are consistent with the views and their extensions.

Certain Answers

Certain Answers: Formal Definition

[Open-world Assumption]

- Given:
  - Views: \( V_1, \ldots, V_n \)
  - View extensions \( v_1, \ldots, v_n \)
  - A query \( Q \)
- A tuple \( t \) is a certain answer to \( Q \) under the open-world assumption if \( t \in Q(D) \) for all databases \( D \) such that:
  - \( V_i(D) \subseteq v_i \) for all \( i \).

Certain Answers: Example

\[ V_8(\text{dir}) : \neg \text{Director}(\text{ID,dir}) \quad V_8 : \{\text{Allen}\} \]
\[ V_9(\text{actor}) : \neg \text{Actor}(\text{ID,actor}) \quad V_9 : \{\text{Keaton}\} \]
\[ Q(\text{dir,actor}) : \neg \text{Director}(\text{ID,dir}), \text{Actor}(\text{ID,actor}) \]

Under closed-world assumption:
- single DB possible \( \Rightarrow \) \{Allen, Keaton\}

Under open-world assumption:
- no certain answers.

The Good News

- The MiniCon and Inverse-rules algorithms produce all certain answers
  - Assuming no interpreted predicates in the query (ok to have them in the views)
  - Under open-world assumption
  - Corollary: they produce a maximally-contained rewriting
In Other News…

• Under closed-world assumption finding all certain answers is co-NP hard!

Proof: encode a graph - G = (V,E)

\[ v_1(X) : \neg \text{color}(X,Y) \quad h(V_1) = V \]
\[ v_2(Y) : \neg \text{color}(X,Y) \quad h(V_2) = \{ \text{red}, \text{green}, \text{blue} \} \]
\[ v_3(X,Y) : \neg \text{edge}(X,Y) \quad h(V_3) = E \]

\[ q() : \neg \text{edge}(X,Y), \text{color}(X,Z), \text{color}(Y,Z) \]

q has a certain tuple iff G is not 3-colorable

Interpreted Predicates

• In the views: no problem (all results hold)
• In the query Q:
  – If the query contains interpreted predicates, finding all certain answers is co-NP-hard even under open-world assumption
  – Proof: reduction to CNF.

Outline

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3) Schema matching and mapping
4) Virtual Data Integration
5) Data Exchange
6) Data Warehousing
7) Big Data Analytics
8) Data Provenance
5. Data Exchange

- **Virtual Data Integration**
  - Never materialize instances for the global schema
  - Data of global schema only “visible” through queries

- **Data Exchange**
  - Materialize instance of global instance
  - Based on information from an instance of the local schema
  - We call this the “source schema”

**Data Exchange Problem Statement**

- **Input:**
  - Given a source and a target schema
  - + instance of the source schema
  - + set of schema mappings (here st-tgds)

- **Output:**
  - Instance of the target schema that fulfills constraints

*Example: Types of Matching*

<table>
<thead>
<tr>
<th>Source</th>
<th>Target</th>
</tr>
</thead>
<tbody>
<tr>
<td>Name</td>
<td>Name</td>
</tr>
<tr>
<td>Address</td>
<td>Address</td>
</tr>
<tr>
<td>City</td>
<td>City</td>
</tr>
<tr>
<td>Office-contact</td>
<td>Office-contact</td>
</tr>
</tbody>
</table>

∀x, y, z, a : Person(x, y) ∧ Address(x, y, a) → ∃b, c : Person(x, z, a, b, c)
5.1 Data Exchange Setting

Definition: Data Exchange Setting
Data Exchange setting is a tuple \((S, T, I, \Sigma)\)
• Schema \(S\)
• Schema \(T\)
• Instance \(I\) of \(S\)
• Mappings \(\Sigma\) from \(S\) to \(T\)

5.1 Data Exchange Solutions

Example: Solutions

<table>
<thead>
<tr>
<th>Person</th>
<th>Name</th>
<th>Address</th>
<th>Id</th>
<th>City</th>
<th>Office-contact</th>
</tr>
</thead>
<tbody>
<tr>
<td>Peter</td>
<td>1</td>
<td>Chicago</td>
<td>(312) 123 4343</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Alice</td>
<td>2</td>
<td>Chicago</td>
<td>(312) 555 7777</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Bob</td>
<td>3</td>
<td>New York</td>
<td>(465) 123 1234</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

\[ \forall x, y, z, a : Person(x, y) \land Address(y, z, a) \rightarrow \exists b, c : Person(x, z, a, b, c) \]

Can we come up with a solution?

5.1 Number of Solutions

• How many solutions exist?
  – Depends on whether we use existentially quantified variables in the mappings?
    • i.e., do we have attributes for which we have to invent values?
  – What attribute values do we allow?
    • Surely values from the source instance (active domain)
    • NULL?
      – Need multiple NULL values as placeholders for missing values that have to be the same
    – Note that this is the open-world assumption
      • There are infinitely many solutions (if domains infinite)

5.1 Data Exchange Setting

Definition: Data Exchange Setting
Given data exchange setting \((S, T, I, \Sigma)\)
• Find instance \(J\) of \(T\) so that \((I, J)\) fulfills mappings \(\Sigma\)
• \(J\) uses values from a universe \(U\) and set of labeled nulls \(N\)

5.1 Data Exchange Solutions

Example: Solutions

<table>
<thead>
<tr>
<th>Person</th>
<th>Name</th>
<th>Address</th>
<th>Office-phone</th>
<th>Office-address</th>
<th>Home-phone</th>
</tr>
</thead>
<tbody>
<tr>
<td>Peter</td>
<td>1</td>
<td>Chicago</td>
<td>(312) 123 4343</td>
<td>NULL</td>
<td>NULL</td>
</tr>
<tr>
<td>Alice</td>
<td>2</td>
<td>Chicago</td>
<td>(312) 555 7777</td>
<td>NULL</td>
<td>NULL</td>
</tr>
<tr>
<td>Bob</td>
<td>3</td>
<td>New York</td>
<td>(465) 123 1234</td>
<td>NULL</td>
<td>NULL</td>
</tr>
</tbody>
</table>

\[ \forall x, y, z, a : Person(x, y) \land Address(y, z, a) \rightarrow \exists b, c : Person(x, z, a, b, c) \]

5.1 Number of Solutions

• Target instance domain
  – Consider a universe \(U\)
    • Source instance can only use values from \(U\)
  – Consider an infinite set \(N\) of labeled nulls
    • Target instance can use these as placeholders for missing values
5.1 Data Exchange Solutions

Example: Multiple Solutions

<table>
<thead>
<tr>
<th>Name</th>
<th>Address</th>
<th>Office phone</th>
<th>Office address</th>
<th>Home phone</th>
</tr>
</thead>
<tbody>
<tr>
<td>Peter</td>
<td>Chicago</td>
<td>(312) 123-4567</td>
<td>Y</td>
<td></td>
</tr>
<tr>
<td>Alice</td>
<td>Chicago</td>
<td>(312) 909-8765</td>
<td>A</td>
<td></td>
</tr>
<tr>
<td>Bob</td>
<td>New York</td>
<td>(465) 131-2345</td>
<td>C</td>
<td>D</td>
</tr>
</tbody>
</table>

5.1 Certain answers (... again)

- Have multiple solutions
  - Define certain answers for queries as before
  - Every tuple t so that t is in the result of query Q over any valid solution J
- What’s new?
  - Want to materialize an instance so that computing certain answers over this instance is easy
    - Not immediately clear that this actually possible

5.1 Universal solutions

- Universal solution
  - Want a solution that is as general as possible
  - We call such most general solutions universal solutions
  - How do we know whether it is most general
    - We can map the tuples in this solution to any other less general solution by replacing unspecified values (labelled nulls) with actual data values

5.1 Data Exchange Solutions

Example: Solution generality

<table>
<thead>
<tr>
<th>Name</th>
<th>Address</th>
<th>Office phone</th>
<th>Office address</th>
<th>Home phone</th>
</tr>
</thead>
<tbody>
<tr>
<td>Peter</td>
<td>Chicago</td>
<td>(312) 123-4567</td>
<td>Y</td>
<td></td>
</tr>
<tr>
<td>Alice</td>
<td>Chicago</td>
<td>(312) 909-8765</td>
<td>A</td>
<td></td>
</tr>
<tr>
<td>Bob</td>
<td>New York</td>
<td>(465) 131-2345</td>
<td>C</td>
<td>D</td>
</tr>
</tbody>
</table>

How general is solution (in terms of certain answers)?

Consider query:

\[ Q(n) :- P(n,a,op,oa,hp), oa = \text{Hometown} \]

5.1 Universal Solutions

Definition: Homomorphism

A homomorphism \( h \) from instance \( J \) to instance \( J' \) maps the constants and nulls of \( J \) to the constants and nulls of \( J' \) and fulfills the following conditions:

- Constants are mapped onto themselves: \( h(c) = c \)
- Every tuple \( R(a_1, \ldots, a_n) \) in \( J \) is mapped to a tuple in \( J' \):
  \[ h(R(a_1, \ldots, a_n)) = R(h(a_1), \ldots, h(a_n)) \]

Definition: Universal solution

Given data exchange setting (\( S, T, I, \Sigma \)). An instance \( J \) of \( T \) is called a universal solution for a source instance \( I \) if \( J \) is a solution and for every other solution \( J' \) hold that:

- There exists a homomorphism from \( J \) to \( J' \)
5.1 Data Exchange Solutions

Example: Solution generality

<table>
<thead>
<tr>
<th>Name</th>
<th>Address</th>
<th>Office phone</th>
<th>Home phone</th>
</tr>
</thead>
<tbody>
<tr>
<td>Peter</td>
<td>Chicago</td>
<td>(312) 123-456</td>
<td>111-322-3454</td>
</tr>
<tr>
<td>Alice</td>
<td>Chicago</td>
<td>(312) 555-777</td>
<td>A</td>
</tr>
<tr>
<td>Bob</td>
<td>New York</td>
<td>(465) 123-123</td>
<td>D</td>
</tr>
</tbody>
</table>

Above is universal solution.

Replace generic labeled Nulls with values:

<table>
<thead>
<tr>
<th>Name</th>
<th>Address</th>
<th>Office phone</th>
<th>Home phone</th>
</tr>
</thead>
<tbody>
<tr>
<td>Peter</td>
<td>Hometown</td>
<td>111-322-3454</td>
<td></td>
</tr>
<tr>
<td>Alice</td>
<td>A</td>
<td>A</td>
<td></td>
</tr>
<tr>
<td>Bob</td>
<td>Other town</td>
<td>D</td>
<td></td>
</tr>
</tbody>
</table>

Example: Solution generality

<table>
<thead>
<tr>
<th>Name</th>
<th>Address</th>
<th>Office phone</th>
<th>Home phone</th>
</tr>
</thead>
<tbody>
<tr>
<td>Peter</td>
<td>Hometown</td>
<td>111-322-3454</td>
<td></td>
</tr>
<tr>
<td>Alice</td>
<td>A</td>
<td>A</td>
<td></td>
</tr>
<tr>
<td>Bob</td>
<td>Other town</td>
<td>D</td>
<td></td>
</tr>
</tbody>
</table>

5.2 Computing Solutions

• Can we use a database system to compute solutions?
  – Yes, systems such as Clio generate queries that compute universal solutions!
    • SQL
    • Java
    • XSLT (for XML docs)

• Generating Executable Transformations
  – How to preserve semantics of labeled nulls
    • n = n’ is true if we have the same labeled null only
    • n = n’ if one is a constant and the other one is a labeled null

5.2 Skolem Functions

• Skolem functions for labeled nulls
  – For each existential variable in a tgd we create a new skolem function
  – What should be the arguments of the function?
    • Naïve: all universally quantified variables
    • Better: only relevant ones
5.2 Skolem Functions

Example: Skolem Functions

\[ \forall a, b, c, d, e : \text{Person}(a, b, c, d, e) \rightarrow \exists f, g \text{Person}(a, f, g) \land \text{Address}(f, b, c) \]

Introduce skolem function sk1 and sk2 for f and g.

What arguments to choose for sk1 and sk2?

E.g., f should be fixed for a certain address and should not depend on the person.

Example: Skolem Functions

\[ \forall a, b, c, d, e : \text{Person}(a, b, c, d, e) \rightarrow \exists f, g \text{Person}(a, f, g) \land \text{Address}(f, b, c) \]

Clio Schema Graph Algorithm

- Nodes
  - Create a graph with one node for every target attribute and one node for every target relation
  - Also add nodes for source attribute if they are copied to the target according to the mapping

- Edges
  - Edges between a relation and its attributes
  - Edges between target attributes that use the same variable
  - Edges between source attributes and target attributes if they use the same variable

Annotations

- Annotate each target attribute connected to a source attribute with that source attribute
- Propagate annotations according to the following rules
  - Propagate annotations from attributes to relations
  - Propagate annotations from relations to attributes
    - Only if attribute uses existentially quantified variable
  - Propagate annotations between target attributes connected by equality edges

1) Initialize with source attribute names

2) Propagate to parent and back to children
5.2 Skolem Functions

- Clio Schema Graph Algorithm
  - Derive skolem function arguments from the schema graph annotations of an element

Example: Skolem Functions

\[ \forall a, b, c, d, e : \text{Person}(a, b, c, d, e) \rightarrow \exists f, g \text{Person}(a, f, g) \land \text{Address}(f, b, c) \]

For variable \( f \), assign \( \text{sk1}(a, b, c) \)
For variable \( g \), assign \( \text{sk2}(a, b, c) \)

5.2 Executable Transformations

- SQL Code Generation Example
  - For each tgd mentioning a target relation \( R \) we generate a query fragment
  - All query fragments for \( R \) are “unioned” together
  - A query fragment is
    - A FROM and WHERE clause that is a direct translation of the LHS of a tgd into SQL
    - A SELECT clause corresponding the \( R \) atom in the RHS using attributes from the FROM clause and skolem functions we have determined in the previous step

Example: Skolem Functions

\[ \forall a, b, c, d, e : \text{Person}(a, b, c, d, e) \rightarrow \exists f, g \text{Person}(a, f, g) \land \text{Address}(f, b, c) \]

For Person atom in RHS:

**SELECT** name, address, office-phone AS address
**FROM** Person

For Address atom in RHS:

**SELECT** name, address, office-phone AS address
**FROM** Person

5.3 Recap Data Exchange Steps

- Schema Matching
- Generate Schema Mappings
  - Use constraints
- Generate Executable Transformations
  - SQL, XSLT, XQuery
  - Skolems for missing value
- Run Transformations over source instance to generate target instance
  - Universal solution
5.3 Comparison with virtual integration

- Pay cost upfront instead of at query time
- Making decisions early vs. at query time
  - When generating a solution
  - Caution: bad decisions stick!
- **Universal solutions** allow efficient computation of certain types of queries using, e.g., SQL

Outline

0) Course Info
1) Introduction
2) Data Preparation and Cleaning
3) Schema matching and mapping
4) Virtual Data Integration
5) Data Exchange
6) **Data Warehousing**
7) Big Data Analytics
8) Data Provenance
6. Data Warehousing

• Problem: Data Analysis, Prediction, Mining
  – Example: Walmart
  – Transactional databases
    • Run many “cheap” updates concurrently
    • E.g., each store has a database storing its stock and sales
  – Complex Analysis over Transactional Databases?
    • Want to analyze across several transactional databases
      – E.g., compute total Walmart sales per month
      – Distribution and heterogeneity
    • Want to run complex analysis over large datasets
      – Resource consumption of queries affects normal operations on transactional databases

• Solution: Performance
  – Store data in a different system (the datawarehouse) for analysis
  – Bulk-load data to avoid wasting performance on concurrency control during analysis

• Heterogeneity and Distribution
  – Preprocess data coming from transactional databases to clean it and translate it into a unified format before bulk-loading

6. Data Warehousing Process

1) Design a schema for the warehouse
2) Create a process for preprocessing the data
3) Repeat
  – A) Preprocess data from the transactional databases
  – B) Bulk-load it into the warehouse
  – C) Run analytics

6. Overview

• The multidimensional datamodel (cube)
  – Multidimensional data model
  – Relational implementations

• Preprocessing and loading (ETL)

• Query language extensions
  – ROLL UP, CUBE, ...

• Query processing in datawarehouses
  – Bitmap indexes
  – Query answering with views
  – Self-tuning
6. Multidimensional Datamodel

- Analysis queries are typically aggregating lower level facts about a business
  - The revenue of Walmart in each state (country, city)
  - The amount of toy products in a warehouse of a company per week
  - The call volume per zip code for the Sprint network
  - …

6. Commonality among these queries:
- At the core are facts: a sale in a Walmart store, a toy stored in a warehouse, a call made by a certain phone
- Data is aggregated across one or more dimensions
  - These dimensions are typically organized hierarchically: year – month – day – hour, country – state – zip
- Example
  - The revenue (sum of sale amounts) of Walmart in each state

6. Example 2D

<table>
<thead>
<tr>
<th>Year</th>
<th>1. Quarter</th>
<th>2. Quarter</th>
<th>3. Quarter</th>
<th>4. Quarter</th>
<th>1. Quarter</th>
<th>2. Quarter</th>
</tr>
</thead>
<tbody>
<tr>
<td>2014</td>
<td>3</td>
<td>7</td>
<td>6</td>
<td>4</td>
<td>2</td>
<td>8</td>
</tr>
<tr>
<td>2015</td>
<td>3</td>
<td>9</td>
<td>8</td>
<td>8</td>
<td>6</td>
<td>9</td>
</tr>
</tbody>
</table>

6. Generalization to multiple dimensions

- Given a fixed number of dimensions
  - E.g., product type, location, time
- Given some measure
  - E.g., number of sales, items in stock, …
- In the multidimensional datamodel we store facts: the values of measures for a combination of values for the dimensions

6. Data cubes

- Given \( n \) dimensions
  - E.g., product type, location, time
- Given \( m \) measures
  - E.g., number of sales, items in stock, …
- A datacube (datahypercube) is an \( n \)-dimensional datastructure that maps values in the dimensions to values for the \( m \) measures
  - Schema: \( D_1, ..., D_n, M_1, ..., M_m \)
  - Instance: a function
    \[
    \text{dom}(D_1) \times \ldots \times \text{dom}(D_n) \rightarrow \text{dom}(M_1) \times \ldots \times \text{dom}(M_m)
    \]
6. Dimension Example

- **Location**
  - **Levels**: location, state, city

**Schema**

- location
- state
- city

**Instance**

- Illinois
- Schaumburg
- Madison
- Whitewater

6. Dimension Schema

- **Schema of a Dimension**
  - A set $D$ of category attributes $D_1, ..., D_n$, $\text{Top}_D$
  - These correspond to the levels
  - A partial order $\rightarrow$ over $D$ which represents parent-child relationships in the hierarchy
  - These correspond to upward edges in the hierarchy
  - $\text{Top}_D$ is larger than anything else
    - For every $D_i$: $D_i \rightarrow \text{Top}_D$
  - There exists $D_{\text{min}}$ which is smaller than anything else
    - For every $D_i$: $D_{\text{min}} \rightarrow D_i$

6. Dimension Schema Example

- **Schema of Location Dimension**
  - Set of categories $D = \{\text{location}, \text{state}, \text{city}\}$
  - Partial order
    - $\{\text{city} \rightarrow \text{state}, \text{city} \rightarrow \text{location}, \text{state} \rightarrow \text{location}\}$
  - $\text{Top}_D = \text{location}$
  - $D_{\text{min}} = \text{city}$

6. Cells, Facts, and Measures

- Each cell in the cube corresponds to a combination of elements from each dimension
  - **Facts** are non-empty cells
  - Cells store measures
- Cube for a combination of levels of the dimension

**Fact**

- Items in stock in Jan at Chicago that belong to category Tool

6. Remarks

- In principle there does not have to exist an order among the elements at one level of the hierarchy
  - E.g., cities
- Hierarchies do not have to be linear

6. Facts

- **Targets of analytics**
  - E.g., revenue, #sales, #stock
- A fact is uniquely defined by the combination of values from the dimensions
  - E.g., for dimensions time and location
    - Revenue in Illinois during Jan 2015
- **Granularity**: Levels in the dimension hierarchy corresponding to the fact
  - E.g., state, month
Facts (Event vs. Snapshot)

- **Event Facts**
  - Model real-world events
  - E.g., Sale of an item

- **Snapshot Facts**
  - Temporal state
  - A single object (e.g., a book) may contribute to several facts
  - E.g., number of items in stock

Measures

- **A measure** describes a fact
  - May be derived from other measures

- **Two components**
  - Numerical value
  - Formula (optional): how to derive it
    - E.g., \( \text{avg}(\text{revenue}) = \frac{\text{sum}(\text{revenue})}{\text{count}(\text{revenue})} \)

- We may associate multiple measures to each cell
  - E.g., number of sales and total revenue

Measures - Granularity

- Similar to facts, measures also have a granularity
- How to change granularity of a measure?
- Need algorithm to combine measures
  - **Additive measures**
    - Can be aggregated along any dimension
  - **Semi-additive/non-additive**
    - Cannot be aggregated along some/all dimensions
    - E.g., snapshot facts along time dimension
      - Number of items in stock at Jan + Feb + … + items in stock during year
      - Median of a measure

Design Process (after Kimball)

- **Comparison to classical relational modeling**
  - **Analysis driven**
    - No need to model all existing data and relationships relevant to a domain
    - Limit modeling to information that is relevant for predicted analytics
  - **Redundancy**
    - Tolerate redundancy for performance if reasonable
    - E.g., in dimension tables to reduce number of joins

Design Process – Steps

1. **Select relevant business processes**
   - E.g., order shipping, sales, support, stock management
2. **Select granularity**
   - E.g., track stock at level of branches or regions
3. **Design dimensions**
   - E.g., time, location, product, ...
4. **Select measures**
   - E.g., revenue, cost, #sales, items in stock, #support requests

Design Process Example

- **Coffee shop chain**
  - **Processes**
    - Sell coffee to customers
    - Buy ingredients from suppliers
    - Ship supplies to branches
    - Pay employees
    - HR (hire, advertise positions, …)
  - Which process is relevant to be analysed to increase profits?
Design Process Example

1) Selecting process(es)
   – sell coffee to customers

2) Select granularity
   – Single sale?
   – Sale per branch/day?
   – Sale per city/year?

Relational representation

How to model a datacube using the relational datamodel

We start from
   – Dimension schemas
   – Set of measures
Star Schema

- A data cube is represented as a set of dimension tables and a fact table
- Dimension tables
  - For each dimension schema \( D = (D_1, ..., D_k, Top_D) \) we create a relation
  - \( D \ (PK, D_1, ..., D_k) \)
    - Here \( PK \) is a primary key, e.g., \( D_{\min} \)
- Fact table
  - \( F(FK_1, ..., FK_n, M_1, ..., M_m) \)
  - Each \( FK_i \) is a foreign key to \( D_i \)
  - Primary key is the combination of all \( FK_i \)

Snowflake Schema

- A data cube is represented as a set of dimension tables and a fact table
- Dimension tables
  - For each dimension schema \( D = (D_1, ..., D_k, Top_D) \) we create a relation multiple relations connected through FKs
  - \( D_i \ (PK, A_1, ..., A_l, FK_j) \)
    - \( A_l \) is a descriptive attribute
    - \( FK_j \) is foreign key to the immediate parent(s) of \( D_i \)
- Fact table
  - \( F(FK_1, ..., FK_n, M_1, ..., M_m) \)
  - Each \( FK_i \) is a foreign key to \( D_i \)
  - Primary key is the combination of all \( FK_i \)

Snowflake Schema - Remarks

- Avoids redundancy
- Results in much more joins during query processing
- Possible to find a compromise between snowflake and star schema
  - E.g., use snowflake for very fine-granular dimensions with many levels

Snowflake Schema - Example

- Coffee chain example

6. Extract-Transform-Load (ETL)

- The preprocessing and loading phase is called extract-transform-load (ETL) in datawarehousing
- Many commercial and open-source tools available
- ETL process is modeled as a workflow of operators
  - Tools typically have a broad set of build-in operators:
    - e.g., key generation, replacing missing values, relational operators,
  - Also support user-defined operators
6. Extract-Transform-Load (ETL)

- Some ETL tools
  - Pentaho Data Integration
  - Oracle Warehouse Builder (OWB)
  - IBM Infosphere Information Server
  - Talend Studio for Data Integration
  - CloverETL
  - Cognos Data Manager
  - Pervasive Data Integrator
  - ...

6. Operators supported by ETL

- Many of the preprocessing and cleaning operators we already know
  - Surrogate key generation (like creating existentials with skolens)
  - Fixing missing values
    - With default value, using trained model (machine learning)
  - Relational queries
    - E.g., union of two tables or joining two tables
  - Extraction of structured data from semi-structured data and/or unstructured data
  - Entity resolution, data fusion

6. ETL Process

- Operators can be composed to form complex workflows

6. Typical ETL operators

- Elementizing
  - Split values into more fine-granular elements
- Standardization
- Verification
- Matching with master data
- Key generation
- Schema matching, Entity resolution/Deduplication, Fusion

6. Typical ETL operators

- Control flow operators
  - AND/OR
  - Fork
  - Loops
  - Termination
    - Successful
    - With warning/errors

- Elementizing
  - Split non 1NF data into individual elements
- Examples
6. Typical ETL operators

• **Standardization**
  – Expand abbreviation
  – Resolve synonyms
  – Unified representation of, e.g., dates

  **Examples**
  – “IL” -> “Illinois”
  – “m/w”, “M/F” -> “male/female”
  – “Jan”, “01”, “January”, “january” -> “January”
  – “St” -> “Street”, “Dr” -> “Drive”, ...

6. Typical ETL operators

• **Verification**
  – Same purpose as constraint based data cleaning but typically does not rely on constraints, but, e.g., regular expression matching

  **Examples**
  – Phone matches “[0-9][3-9][3-9][0-9][4]”
  – For all t in Tokens(product description), t exists in English language dictionary

6. Metadata management

• As part of analysis in DW data is subjected to a complex pipeline of operations
  – Sources
  – ETL
  – Analysis queries

• => important, but hard, to keep track of what operations have been applied to data and from which sources it has been derived

• Need metadata management
  • Including provenance (later in this course)

6. Querying DW

• **Targeted model (cube vs. relational)**
  – Design specific language for datacubes
  – Add suitable extensions to SQL

• **Support typical analytical query patterns**
  – Multiple parallel grouping criteria
    • Show total sales, subtotal per state, and subtotal per city
  – Windowed aggregates and ranking
    • Show 10 most successful stores
    • Show cumulative sales for months of 2016
      – E.g., the result for Feb would be the sum of the sales for Jan + Feb

6. Querying DW

• **Targeted model (cube vs. relational)**
  – Design specific language for datacubes
    • MDX

  – **Add suitable extensions to SQL**
    • GROUPING SETS, CUBE, ...
    • Windowed aggregation using OVER(), PARTITION BY, ORDER BY, window specification
    • Window functions
      – RANK, DENSE_RANK()
6. Cube operations

- **Roll-up**
  - Move from fine-granular to more coarse-granular in one or more dimensions of a datacube
  - E.g., sales per (city, month, product category) to sales per (state, year, product category)

- **Drill-down**
  - Move from coarse-granular to more fine-granular in one or more dimensions
  - E.g., phonecalls per (city, month) to phonecalls per (zip, month)

6. SQL Extensions

- **Slice**
  - Select data based on restriction of the values of one dimension
  - E.g., sales per (city, month) -> sales per (city) in Jan

- **Dice**
  - Select data based on restrictions of the values of multiple dimensions
  - E.g., sales per (city, month) -> sales in Jan for Chicago and Washington DC

6. GROUPING SETS

- **GROUP BY GROUPING SETS ((set1), ..., (setn))**
- Explicitly list sets of group by attributes
- Semantics:
  - Equivalent to UNION over duplicates of the query each with a group by clause GROUP BY set,
  - Schema contains all attributes listed in any set
  - For a particular set, the attribute not in this set are filled with NULL values
6. GROUPING SETS

SELECT quarter,
city,
product_typ,
SUM(profit) AS profit
FROM facttable F, time T, location L, product P
WHERE
F.TID = T.TID AND F.LID = L.LID AND F.PID = P.PID
GROUP BY
GROUPING SETS
( (quarter, city), (quarter, product_typ))

<table>
<thead>
<tr>
<th>quarter</th>
<th>city</th>
<th>product_typ</th>
<th>profit</th>
</tr>
</thead>
<tbody>
<tr>
<td>2010Q1</td>
<td></td>
<td>Books</td>
<td>8347</td>
</tr>
<tr>
<td>2012Q2</td>
<td></td>
<td>Books</td>
<td>7836</td>
</tr>
<tr>
<td>2012Q2</td>
<td>Chicago</td>
<td>Gardening</td>
<td>12344</td>
</tr>
<tr>
<td>2012Q2</td>
<td>Seattle</td>
<td></td>
<td>124345</td>
</tr>
</tbody>
</table>

6. GROUPING SETS

• Problem:
  – How to distinguish between NULLs based on grouping sets and NULL values in a group by column?

GROUP BY GROUPING SETS
( (quarter, city), (quarter, product_typ), (quarter, product_typ, city))

<table>
<thead>
<tr>
<th>quarter</th>
<th>city</th>
<th>product_typ</th>
<th>profit</th>
<th>grp_prd</th>
</tr>
</thead>
<tbody>
<tr>
<td>2010Q1</td>
<td></td>
<td>Books</td>
<td>8347</td>
<td>1</td>
</tr>
<tr>
<td>2012Q2</td>
<td></td>
<td>Books</td>
<td>7836</td>
<td>1</td>
</tr>
<tr>
<td>2012Q2</td>
<td>Chicago</td>
<td>Gardening</td>
<td>12344</td>
<td>0</td>
</tr>
<tr>
<td>2012Q2</td>
<td>Seattle</td>
<td></td>
<td>124345</td>
<td>1</td>
</tr>
</tbody>
</table>

6. GROUPING SETS

• Solution:
  – GROUPING predicate
    – GROUPING(A) = 1 if grouped on attribute A, 0 else

GROUP BY GROUPING SETS
( (quarter, city), (quarter, product_typ), (quarter, product_typ, city))

6. GROUPING SETS

• Combining GROUPING SETS

GROUP BY A, B
  = GROUP BY GROUPING SETS ((A,B))

GROUP BY GROUPING SETS ((A,B), (A,C), (A))
  = GROUP BY A, GROUPING SETS ((B), (C), (D))

GROUP BY GROUPING SETS ((A,B), (B,C),
GROUPING SETS ((D,B), (D))
  = GROUP BY GROUPING SETS ((A,B,D,E), (A,B,D), (B,C,D,E), (B,C,D))

6. CUBE

• GROUP BY CUBE (set)
  – Group by all 2\(^n\) subsets of set

GROUP BY CUBE (A,B,C)
  = GROUP BY GROUPING SETS
    ( (), (A), (B), (C), (A,B), (A,C), (B,C), (A,B,C) )
6. CUBE

• GROUP BY ROLLUP (A₁, ..., Aₙ)
• Group by all prefixes
• Typically different granularity levels from single dimension hierarchy, e.g., year-month-day
  – Database can often find better evaluation strategy

GROUP BY ROLLUP (A, B, C)
= GROUP BY GROUPING SETS ((A, B, C), (A, B), (A), ( ), )
6. OVER clause

```
SELECT year, month, city
SUM(profit) OVER (ORDER BY year, month) AS ttl
FROM sales
```

• ORDER BY
  - Order tuples on these expressions
  - Only tuples which are <= to the order as the current tuple belong to the same window

• E.g., can be used to compute an accumulate total

```
year | month | city | profit
--- | --- | --- | ---
2010 1 | Chicago | 10
2010 2 | Chicago | 5
2011 1 | Chicago | 20
2010 1 | New York | 12
```

```
year | month | city | profit |
--- | --- | --- | ---
2010 1 | Chicago | 22
2010 2 | Chicago | 47
2011 1 | Chicago | 47
2010 1 | New York | 47
```

6. OVER clause

```
SELECT year, month, city
SUM(profit) OVER (PARTITION BY year ORDER BY month) AS ttl
FROM sales
```

• Combining PARTITION BY and ORDER BY
  - First partition then order tuples within each partition

6. OVER clause

```
SELECT year, month, city
SUM(profit) OVER (PARTITION BY year ORDER BY month RANGE BETWEEN 1 PRECEDING AND 1 FOLLOWING) AS ttl
FROM sales
```

• Explicit window specification
  - Requires ORDER BY
  - Determines which tuples “surrounding” the tuple according to the sort order to include in the window
6. OVER clause

SELECT year, month, city,
SUM(profit) OVER (ORDER BY year, month
ROWS BETWEEN 1 PRECEDING
AND 1 FOLLOWING) AS ttl
FROM sales

- Explicit window specification
- Requires ORDER BY
- Determines which tuples “surrounding” the tuple according to the sort order to include in the window

<table>
<thead>
<tr>
<th>Year</th>
<th>Month</th>
<th>City</th>
<th>Profit</th>
</tr>
</thead>
<tbody>
<tr>
<td>2010</td>
<td>1</td>
<td>Chicago</td>
<td>10</td>
</tr>
<tr>
<td>2010</td>
<td>2</td>
<td>Chicago</td>
<td>5</td>
</tr>
<tr>
<td>2011</td>
<td>1</td>
<td>Chicago</td>
<td>45</td>
</tr>
<tr>
<td>2010</td>
<td>1</td>
<td>New York</td>
<td>12</td>
</tr>
</tbody>
</table>

6. MDX

- Multidimensional expressions (MDX)
  - Introduced by Microsoft
  - Query language for the cube data model
  - SQL-like syntax
    - Keywords have different meaning
    - MDX queries return a multi-dimensional report
  - 2D = spreadsheet
  - 3D or higher, e.g., multiple spreadsheets

6. MDX Query

- Basic Query Structure
  SELECT <axis-spec>, ..., FROM <cube-spec>, ..., WHERE <select-spec>
- Note!
  - Semantics of SELECT, FROM, WHERE not what you would expect knowing SQL
6. MXD - SELECT

- Specify concepts from dimensions
  - List all values as set, e.g., \{[2010], [2011]\}
  - Not necessarily from same level of hierarchy (e.g., mix years and months)
- Language constructs for accessing parents and children or members of a level in the hierarchy
  - CHILDREN: all direct children
    - E.g., \[2010\].CHILDREN = \{[2010 Jan], …, [2010 Dec]\}
  - PARENT: the direct parent
    - E.g., [2010 Jan].PARENT = [2010]
  - MEMBERS: all direct children
    - E.g., Time.Years.MEMBERS = \{[1990], [1991], …, [2016]\}
  - LASTCHILD: last child (according to order of children)
    - E.g., [2010].LASTCHILD = [2010 Dec]
  - NEXTMEMBER: right sibling on same level
    - E.g., [2010].NEXTMEMBER = [2011]
  - \([a] \{b\} \): all members in interval between a and b

6. MXD - SELECT

- Nesting of sets: CROSSJOIN
  - Project two dimensions into one
  - Forming all possible combinations

```
SELECT CROSSJOIN ( { Chicago, Schaumburg }, 
                    { [2010], [2011] } ) 
ON ROWS 
( [2010], [2011] ).CHILDREN ) 
ON COLUMNS 
FROM PhoneCallsCube 
WHERE ( Measures.numCalls )
```

```
<table>
<thead>
<tr>
<th></th>
<th>2010</th>
<th>2011</th>
</tr>
</thead>
<tbody>
<tr>
<td>Chicago</td>
<td>1234</td>
<td>5678</td>
</tr>
<tr>
<td>Schaumburg</td>
<td>9012</td>
<td>3456</td>
</tr>
</tbody>
</table>
```

6. MXD - SELECT

- Conditional selection of members: FILTER
  - One use members that fulfill condition
    - E.g., condition over aggregation result

```
SELECT FILTER ( [2010].CHILDREN, 
                 (Sprint, numCalls) > (ATT, numCalls) ) 
ON ROWS 
( Chicago ) 
ON COLUMNS
FROM PhoneCallsCube 
WHERE ( Measures.numCalls )
```

6. Query Processing in DW

- Large topic, here we focus on two aspects
  - Partitioning
  - Query answering with materialized views

6. Partitioning

- Partitioning splits a table into multiple fragments that are stored independently
  - E.g., split across X disks, across Y servers
- Vertical partitioning
  - Split columns across fragments
    - E.g., \(R = \{A,B,C,D\}\), fragment \(F1 = \{A,B\}\), \(F2 = \{C,D\}\)
    - Either add a row id to each fragment or the primary key to be able to reconstruct
- Horizontal partitioning
  - Split rows
- Hash vs. range partitioning
6. Partitioning

- **Why partitioning?**
  - Parallel/distributed query processing
  - Optimize reads and writes in parallel
  - Distribute storage load across disks/servers
  - Avoid reading data that is not needed to answer a query

- **Vertical Partitioning**
  - Only read columns that are accessed by query

- **Horizontal Partitioning**
  - Range partitioning on attribute A
    - Split domain of A into intervals representing fragments
    - E.g., tuples with A = 15 belong to fragment (0,20]
  - Hash partitioning on attribute A
    - Split domain of A into N buckets using hash function
    - E.g., tuples with h(A) = 3 belong to fragment F

- **Virtual Data Integration**
  - Distribute source data across disks/servers
  - Avoid reading data that is not needed to answer a query
7. Big Data Systems and Integration

IIT DBGroup

Boris Glavic
http://www.cs.iit.edu/~glavic/
http://www.cs.iit.edu/~cs520/
http://www.cs.iit.edu/~dbgroup/

Outline

0) Course Info
1) Introduction
2) Data Preparation and Cleaning
3) Schema matching and mapping
4) Virtual Data Integration
5) Data Exchange
6) Data Warehousing
7) Big Data Analytics
8) Data Provenance

3. Big Data Overview

• 1) How does data processing at scale (read using many machines) differ from what we had before?
  – Load-balancing
  – Fault tolerance
  – Communication
  – New abstractions
  • Distributed file systems/storage

• 2) Overview of systems and how they achieve scalability
  – Bulk processing
    • MapReduce, Shark, Flink, Hyracks, …
    • Graph: e.g., Giraph, Pregel, …
  – Key-value/document stores = NoSQL
    • Cassandra, MongoDB, Memcached, Dynamo, …

3. Big Data Analytics

• Big Topic, big Buzzwords ;-) 
• Here
  – Overview of two types of systems
    • Key-value/document stores
    • Mainly: Bulk processing (MR, graph, …)
  – What is new compared to single node systems?
  – How do these systems change our approach to integration/analytics
    • Schema first vs. Schema later
    • Pay-as-you-go
3. Big Data Overview

• 3) New approach towards integration
  – Large clusters enable directly running queries over semi-structured data (within feasible time)
    • Take a click-stream log and run a query
    – One of the reasons why **pay-as-you-go** is now feasible
    • **Previously:** designing a database schema upfront and designing a process (e.g., ETL) for cleaning and transforming data to match this schema, then query
    • **Now:** start analysis directly, clean and transform data if needed for the analysis

• Advantage of **pay-as-you-go**
  • More timely data (direct access)
  • More applicable if characteristics of data change dramatically (e.g., yesterdays ETL process no longer applicable)

• Disadvantages of **pay-as-you-go**
  • Potentially repeated efforts (everybody cleans the click-log before running the analysis)
  • Lack of meta-data may make it hard to
    – Determine what data to use for analysis
    – Hard to understand semantics of data

3. Big Data Overview

• **Scalable systems**
  – Performance of the system scales in the number of nodes
    • Ideally the per node performance is constant independent of how many nodes there are in the system
    • This means: having twice the number of nodes would give us twice the performance
  – Why scaling is important?
    • If a system scales well we can “throw” more resources at it to improve performance and this is cost effective

• What impacts scaling?
  – Basically how parallelizable is my algorithm
    • **Positive example:** problem can be divided into subproblems that can be solved independently without requiring communication
      – E.g., array of 1-billion integers \([i_1, \ldots, i_{1,000,000}]\) add 3 to each integer. Compute on a node, split input into a equally sized chunks and let each node process one chunk
    • **Negative example:** problem where subproblems are strongly intercorrelated
      – E.g., Context Free Grammar Membership: given a string and a context free grammar, does the string belong to the language defined by the grammar.

3. Big Data – Processing at Scale

• **New problems at scale**
  – DBMS
    • running on 1 or 10’s of machines
    • running on 1000’s of machines
  – Each machine has low probability of failure
    – If you have many machines, failures are the norm
    – Need mechanisms for the system to cope with failures
      • Do not loose data
      • Do not use progress of computation when node fails
    – This is called **fault-tolerance**
  – Need to **evenly** distribute data and computation across nodes
    • Often most overloaded node determine processing speed
    – This is called **load-balancing**
3. Big Data – Processing at Scale

- Building distributed systems is hard
  - Many pitfalls
    - Maintaining distributed state
    - Fault tolerance
    - Load balancing
  - Requires a lot of background in
    - OS
    - Networking
    - Algorithm design
    - Parallel programming

- Hard to debug
  - Even debugging a parallel program on a single machine is already hard
    - Non-determinism because of scheduling: Race conditions
    - In general hard to reason over behavior of parallel threads of execution
  - Even harder when across machines
    - Just think about how hard it was for you to first program with threads/processes

3. Big Data – Why large scale?

- Datasets are too large
  - Storing a 1 Petabyte dataset requires 1 PB storage
    - Not possible on single machine even with RAID storage
  - Processing power/bandwidth of single machine is not sufficient
    - Run a query over the facebook social network graph
      - Only possible within feasible time if distributed across many nodes

3. Big Data – User’s Point of View

- How to improve the efficiency of distributed systems experts
  - Building a distributed system from scratch for every store and analysis task is obviously not feasible!
- How to support analysis over large datasets for non distributed systems experts
  - How to enable somebody with some programming but limited/no distributed systems background to run distributed computations

3. Big Data – Abstractions

- Solution
  - Provide higher level abstractions
- Examples
  - MPI (message passing interface)
    - Widely applied in HPC
    - Still quite low-level
  - Distributed file systems
    - Make distribution of storage transparent
  - Key-value storage
    - Distributed store/retrieval of data by identifier (key)
- More Examples
  - Distributed table storage
    - Store relations, but no SQL interface
  - Distributed programming frameworks
    - Provide a, typically, limited programming model with automated distribution
  - Distributed databases, scripting languages
    - Provide a high-level language, e.g., SQL-like with an execution engine that is distributed
3. Distributed File Systems

- Transparent distribution of storage
  - Fault tolerance
  - Load balancing?

- Examples
  - HPC distributed filesystems
    - Typically assume a limited number of dedicated storage servers
    - GPFS, Lustre, PVFS
  - “Big Data” filesystems
    - Google file system, HDFS

3. HDFS

- Hadoop Distributed Filesystem (HDFS)

- Architecture
  - One nodes storing metadata (name node)
  - Many nodes storing file content (data nodes)

- Filestructure
  - Files consist of blocks (e.g., 64MB size)

- Limitations
  - Files are append only

3. HDFS

- Name node
  - Stores the directory structure
  - Stores which blocks belong to which files
  - Stores which nodes store copies of which block
  - Detects when data nodes are down

- Clients communicate with the name node to gather FS metadata

3. HDFS

- Data nodes
  - Store blocks
  - Send/receive file data from clients
  - Send heart-beat messages to name node to indicate that they are still alive

- Clients communicate data nodes for reading/writing files

3. Distributed FS Discussion

- What do we get?
  - Can store files that do not fit onto single nodes
  - Get fault tolerance
  - Improved read speed (caused on replication)
  - Decreased write speed (caused by replication)

- What is missing?
  - Computations
3. Frameworks for Distributed Computations

- **Problems**
  - Not all algorithms do parallelize well
  - How to simplify distributed programming?

- **Solution**
  - Fix a reasonable powerful, but simple enough model of computation for which scalable algorithms are known
  - Implement distributed execution engine for this model and make it fault tolerant and load-balanced

3. MapReduce

- **Data Model**
  - Sets of key-value pairs \( \{(k_1, v_1), \ldots, (k_n, v_n)\} \)
  - **Key** is an identifier for a piece data
  - **Value** is the data associated with a key

- **Programming Model**
  - We have two higher-level functions map and reduce
    - Take as input a user-defined function that is applied to elements in the input key-value pair set
    - Complex computations can be achieved by chaining map-reduce computations

3. MapReduce Datamodel

- **Data Model**
  - Sets of key-value pairs \( \{(k_1, v_1), \ldots, (k_n, v_n)\} \)
  - **Key** is an identifier for a piece data
  - **Value** is the data associated with a key

- **Examples**
  - Document \( d \) with an id
    - \((\text{id}, d)\)
  - Person with name, salary, and SSN
    - \((\text{SSN}, \text{"name, salary"})\)

3. MapReduce Computational Model

- **Example**
  - **Input**: Set of \((\text{city, population})\) pairs
  - **Task**: multiply population by 1.05

- **Map function**
  - \( f : (\text{city, population}) \rightarrow \{(\text{city, population} \times 1.05)\} \)

- **Application of f through map**
  - Input: \{\((\text{chicago}, 3)\), \((\text{nashville}, 1)\)\}
  - Output: \{\((\text{chicago}, 3.15)\), \((\text{nashville}, 1.05)\)\} = \{\((\text{chicago}, 3.15)\), \((\text{nashville}, 1.05)\)\}

- **Reduce**
  - Takes as input a key with a list of associated values a user-defined function
    - \( g : (k, \text{list}(v)) \rightarrow \{(k, v)\} \)
  - Reduce groups all values with the same key in the input key-value set and passes each key and its list of values to \( g \), and returns the union of the outputs produced by \( g \)
    - \( g((k_1, v_1), \ldots, (k_m, v_m)) \) \( \rightarrow \) \( g((k_1, v_1)) \cup \ldots \cup g((k_m, v_m)) \)
3. MapReduce Computational Model

- **Example**
  - **Input**: Set of (state, population) pairs one for each city in the state
  - **Task**: compute the total population per state

- **Reduce function**
  - $f: \{\text{state},[p_1,\ldots,p_n]\} \rightarrow \{\text{state},\text{SUM}(p_1,\ldots,p_n)\}$

- **Application of $f$ through map**
  - **Input**: $\{\text{illinois}, 3\}, \{\text{illinois}, 1\}, \{\text{oregon}, 15\}$
  - **Output**: $\{\text{illinois}, 4\}, \{\text{oregon}, 15\}$

3. MapReduce Workflows

- **Workflows**
  - Computations in MapReduce consists of map phases followed by reduce phases
    - The input to the reduce phase is the output of the map phase
    - Complex computations may require multiple map-reduce phases to be chained together

3. MapReduce Implementations

- **MapReduce**
  - Developed by google
  - Written in C
  - Runs on top of GFS (Google’s distributed filesystem)

- **Hadoop**
  - Open source Apache project
  - Written in Java
  - Runs on-top of HDFS

3. Hadoop

- **Anatomy of a Hadoop cluster**
  - **Job tracker**
    - Clients submit MR jobs to the job tracker
    - Job tracker monitors progress
  - **Task tracker aka workers**
    - Execute map and reduce jobs

- **Job**
  - **Input**: files from HDFS
  - **Output**: written to HDFS
  - **Map/Reduce UDFs**

- **Fault tolerance**
  - **Handling stragglers**
    - Job tracker will reschedule jobs to a different worker if the worker falls behind too much with processing
  - **Materialization**
    - Inputs are read from HDFS
    - Workers write results of map jobs assigned to them to local disk
    - Workers write results of reduce jobs to HDFS for persistence

3. Hadoop – MR Job

[Diagram of Hadoop MR Job]
3. Hadoop – MR Job

- Each mapper reads its chunk from HDFS, translates the input into key-value pairs and applies the map UDF to every (k,v).
- Outputs are written to disk with one file per reducer (hashing on key).
- Job tracker may spawn additional mappers if mappers are not making progress.

3. Hadoop – MR Job

- Mappers send files to reducers (scp) - Called shuffle.
- Reducers merge and sort these input files on key values.
- External merge sort where runs already exist.
- Reducer applies reduce UDF to each key and associated list of values.

3. Combiners

- Certain reduce functions lend themselves to pre-aggregation
  - E.g., SUM(revenue) group by state
    - Can compute partial sums over incomplete groups and then sum up the pre-aggregated results
    - This can be done at the mappers to reduce amount of data send to the reducers
  - Supported in Hadoop through a user provided combiner function
    - The combiner function is applied before writing the mapper results to local disk

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    - The combiner function is applied before writing the mapper results to local disk
3. Example code – Word count

- [https://hadoop.apache.org/docs/r1.2.1/mapred_tutorial.html](https://hadoop.apache.org/docs/r1.2.1/mapred_tutorial.html)

```java
public static void main(String[] args) throws Exception {
    System.out.println("wordCount();");
    // MapReduce job input

    // Map function
    java.lang.String word;
    int cnt = 0;
    for (word = input.split(new String[] { "\t" }); word != null; word = input.split(new String[] { "\t" })) {
        cnt = cnt + 1;
        System.out.println("\t" + word + " occurrence: " + cnt);
        // Reduce function
    }
}
```

3. Systems/Languages on top of MapReduce

- **Pig**
  - Scripting language, compiled into MR
  - Akin to nested relational algebra
- **Hive**
  - SQL interface for warehousing
  - Compiled into MR
  - Executed on Hadoop cluster

```sql
FROM (SELECT word, COUNT(*) AS cnt FROM docs GROUP BY word)
WHERE cnt > 0
```

3. Hive

- **Hive**
  - SQL dialect with support for directly applying given Map+Reduce functions as part of a query
  - HiveQL is compiled into MR jobs
  - Executed on Hadoop cluster

```sql
FROM (SELECT word, COUNT(*) AS cnt FROM docs GROUP BY word) AS wordCount
WHERE cnt > 0
```

3. Hive Architecture

- [Hadoop Apache](https://hadoop.apache.org/docs/r1.2.1/mapred_tutorial.html)
3. Hive Datamodel

- **Tables**
  - Attribute-DataType pairs
  - User can instruct Hive to partition the table in a certain way
- **Datatypes**
  - Primitive: integer, float, string
  - Complex types
    - Map: Key->Value
    - List
    - Struct
  - Complex types can be nested
- **Example**:
  ```sql
  CREATE TABLE t1(st string, fl float, li list<map<string, struct<p1:int, p2:int>>);
  ```
- **Implementation**
  - Tables are stored in HDFS
  - Serializer/Deserializer - transform for querying

3. Hive - Query Processing

- Compile HiveQL query into DAG of map and reduce functions.
  - A single map/reduce may implement several traditional query operators
    - E.g., filtering out tuples that do not match a condition (selection) and filtering out certain columns (projection)
    - Hive tries to use the partition information to avoid reading partitions that are not needed to answer the query
      - For example
        - table instructor(name, department) is partitioned on department
        - SELECT name FROM instructor WHERE department = 'CS'
      - This query would only access the partition of the table for department 'CS'

3. Operator implementations

- **Join implementations**
  - **Broadcast join**
    - Send the smaller table to all nodes
    - Process the other table partitioned
      - Each node finds all the join partners for a partition of the larger table and the whole smaller table
  - **Reduce join (partition join)**
    - Use a map job to create key-value pairs where the key is the join attributes
    -Reducer output joined rows

3. Example plan

Spark

- MR uses heavy materialization to achieve fault tolerance
  - A lot of I/O
- **Spark**
  - Works in main memory (where possible)
  - Inputs and final outputs stored in HDFS
  - Recomputes partial results instead of materializing them - resilient distributed datasets (RDD)
  - **Lineage**: Need to know from which chunk a chunk was derived from and by which computation

Summary

- Big data storage systems
- Big data computation platforms
- Big data “databases”
- How to achieve scalability
  - Fault tolerance
  - Load balancing
- Big data integration
  - Pay-as-you-go
  - Schema later
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