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Chapter 11
Information Integration

contributions by Jürgen Göres

Outline

- Information Integration Challenges
  - Distribution
  - Autonomy
  - Heterogeneity
- Schema Matching
  - Classification of Approaches
  - Example: Cupid
- Multidatabase Languages
  - SchemaSQL
  - FIRA/FISQL
- Integration Planning
  - Clio
- Data Integration
  - Data Quality Problems
  - Causes and Consequences
  - Data Cleaning Approaches

Integration Challenges

- Goal of Information Integration:
  Provide a homogeneous, integrated view on multiple, distributed, autonomous and heterogeneous data sources.
- Three fundamental challenges:
  - Distribution
  - Autonomy
  - Heterogeneity
- Orthogonal, but interrelated
- Techniques to handle distribution discussed in previous chapters
- In this chapter we focus on resolving heterogeneity

Distribution

- Physical distribution
  - Data located on (geographically) separated systems
  - Challenges:
    - Addressing data across the globe (URLs)
    - Accessing data in different schemas (Multi-database languages, federated database systems)
    - Optimizing distributed queries (no topic of this lecture)
- Logical distribution
  - Several possible storage locations for a given data item
  - Caused by (partial) redundancy due to overlapping intension of schema elements
  - Challenges:
    - Maintaining consistency among redundant data
    - Provide metadata to enable data localization
    - Detect and resolve duplicates
    - Detect and resolve data inconsistencies and conflicts } Data Cleaning
- Physical and logical distribution are orthogonal:
  - Data can be logically distributed and physically on the same system (and vice versa)

Autonomy

- Design Autonomy
  - Administrators of data sources can freely decide in which way they model data
  - Data model, formats, units, …
  - Leads to heterogeneity among sources
- Interface Autonomy
  - Freedom to decide how technical access is provided
  - Protocols (HTTP, JDBC, SOAP, …), supported query languages (SQL, XQuery, …)
- Access Autonomy
  - Freedom to decide *whom* to allow access to *what* data
  - Mode of Authentication (Certificates, Username/Password)
  - Authorization (boolean, R/W, Access Control Lists, …)
- Judicial Autonomy
  - Freedom to prohibit integration of data by others
  - Intellectual property (IP) issues

⇨ Autonomy is the major cause of integration problems

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Forms of Heterogeneity

Heterogeneity

- Translated from [LeNa07]:
  "Two information systems that do not provide the exact same methods, models and structures to access their data are called heterogeneous."
- Causes for heterogeneity among IS:
  - Specific requirements
  - Independent development
  - Developer preferences
  - ...

  ⇨ All aspects result from autonomy
- Heterogeneity of metadata *and* data
- Two main approaches:
  - Try to resolve heterogeneity when needed
  - Enforce homogeneity/limit heterogeneity by establishing standards (not in this lecture)
    - No real solution to the problem
    - Only creates "spheres of homogeneity", any participants that have existing systems or requirements not conforming to the standards have to resolve heterogeneity locally

Technical Heterogeneity

- Refers to differences in the options to access data, e.g.
  - Communication protocols (HTTP, SOAP, …)
  - Exchange formats (binary, text, XML, …)
  - APIs (JDBC, ODBC, proprietary)
  - Query mechanism
    - Forms, canned queries
    - Query languages
  - Query language
    - SQL, XQuery, …

Data Model Heterogeneity

- Caused by the use of different data models among data sources
  - hierarchical, relational, XML, …
- Data models can have different expressiveness, e.g. support of
  - Inheritance
  - Types and degree of associations between entities/application concepts
  - Multi-valued attributes
  - Different atomic data types
- Mapping from semantically richer to poorer models in general results in a loss of information
- Approaches to bridge data model heterogeneity
  - SQL/XML (see later chapter)
  - Wrappers/Mediators (Chapter 9)

Syntactic Heterogeneity

- Differences in the representation of identical facts
  - Binary representations (little/big endian, number formats)
  - Encodings (ASCII, ISO-8859-1, EBCDIC, Unicode, …)
  - Separators (Tab-delimited vs. CSV)
  - Textual representation
- Not to be mixed up with semantic heterogeneity!
- Usually easy to resolve (if used consistently)
- Examples:
  - "20070201" vs. "Februar 1st, 2007" vs. "02-01-07"
  - "123.45" vs. "1.2345×10^2"

➔ *Data Fusion*

Structural Heterogeneity

- Caused by modeling identical application concepts differently using the *same* elements in the same data model
- Example - denormalized relational schema

Employee

EmpNo	Name	DoB	DeptNo
4711	Bob	1978-03-20	11
0815	Jane	1975-11-05	7
1234	Joe	1954-05-26	11

Department

DeptNo	Name
7	Sales
11	Accounting

⇔

EmpDept

EmpNo	Name	DoB	Deptname	DeptNo
4711	Bob	1978-03-20	Accounting	11
0815	Jane	1975-11-05	Sales	7
1234	Joe	1954-05-26	Accounting	11

- Easily resolved using relational operators:

```
SELECT e.EmpNo, e.Name, e.DoB, d.name as deptname, d.deptno
FROM Employee e, Department d WHERE e.deptno = d.deptno
```


Structural Heterogeneity (cont.)

- Example: inverted hierarchy

```
<bib>
  <book title="a">
     <author name="x"/>
     <author name="y"/>
  </book>
  <book title="b">
     <author name="x"/>
  </book>
</bib>
```

⇔

```
<bib>
  <author name="y">
    <book title="a"/>
  </author>
  <author name="x">
    <book title="a"/>
    <book title="b"/>
  </author>
</bib>
```

- Easily resolved using XQuery

```
<bib> {
  for $a in distinct-values(doc("BookAuthor.xml")//author/@name)
  return <author name="{$a}"> {
    for $b in doc("BookAuthor.xml")//book
    where $b/author/@name = $a
    return <book title="{$b/@title}"/>
    } </author>
} </bib>
```

Schematic Heterogeneity

- Often considered a special case of structural heterogeneity
- Caused by modeling identical application concepts using *different* data model concepts of the same data model
- Example: *attribute value – relation name* conflict

categorical attribute

Person

ID	Name	Gender
1234	Bob	male
4567	Jane	female

Men

ID	Name
1234	Bob

Women

ID	Name
4567	Jane

- Problems of this kind cannot be resolved *generically* with SQL
  - How to handle an unknown/variable number of values for categorical attributes?

➔ *Multi-database languages*

Semantic Heterogeneity

- "Semantics" = interpretation of data and metadata
- Different representation of identical application concepts, (e.g. synonyms)
- Identical representation of different application concepts (e.g. homonyms)
  - e.g. Lotus (the car) vs. Lotus (the flower)
- Ambiguities – unclear whether two elements refer to the same concept (are synonyms) or refer to broader/narrower terms (hypernyms)
  - hypernym or synonym?
    - car – (motor) vehicle
    - person – employee
    - product – item
  - decision depending on context
- Perhaps *the* biggest challenge in II
- Resolving semantic heterogeneity is a prerequisite for many integration tasks
- Many attempts to automate

➔ *Schema Matching*

Bridging/Resolving Heterogeneity

- Real-world integration scenarios suffer from all kinds of heterogeneity
- Techniques and concepts already discussed in previous chapters and the primary issues they address:
  - Wrappers (data model heterogeneity, technical heterogeneity, syntactic heterogeneity)
  - Garlic (technical heterogeneity, structural heterogeneity, distribution)
  - SQL/XML (data model heterogeneity) – *see subsequent chapter*
  - DB Gateways (technical heterogeneity)
  - ETL tools (structural heterogeneity, technical heterogeneity, syntactic heterogeneity)
  - ⇨ focus on data access/transformation infrastructure (i.e., as a runtime platform)
- Further techniques discussed in this chapter
  - Schema Matching and Integration (semantic heterogeneity, structural heterogeneity)
  - Multi-database languages (schematic heterogeneity, technical heterogeneity, distribution)
  - Data Cleaning/Fusion (syntactic heterogeneity, semantic heterogeneity (in data))
  - ⇨ focus on integration planning, resolving schematic heterogeneity

Information Integration Tasks

- Information integration subsumes numerous tasks (and has numerous names for most of them...):
  1. Schema Merging/Schema Integration
  2. Design of the integrated target schema
  3. Schema Matching/Schema Mapping
  4. Integration Planning/Schema Mapping/Schema Integration/Mapping Generation/Mapping Interpretation
  5. Data Cleaning
  6. Data Fusion/Record Matching/Entity Resolution/Instance Disambiguation
  7. Wrapping/Data model transformation

Information Integration Phases [Gö05b]

- Analysis – Determine the requirements on the integrated schema:
  - Desired data model, integration strategy (virtual or materialized)
  - Relevant data (which application concepts should be present)
- Discovery – Find/identify relevant data sources
  - In classical scenarios sources are often known implicitly
  - Challenging aspect of ➔ Dynamic information integration
- Planning – Resolve heterogeneity
  - Technical heterogeneity (enable access to sources)
  - Semantic heterogeneity ➔ Schema Matching
  - Data model, structural and schematic heterogeneity
    ➔ develop data transformation specification (integration plan)
- Deployment
  - Set up integration plan in a runtime environment that provides the integrated data
  - e.g., federated DBMS, data warehouse, stylesheets, scripts
- Runtime
  - React to changes in the data sources/requirements

Information Integration Approaches

- Bottom-up design
  - Used to completely integrate a well-known set of data sources
  - Assumes that changes of the number and properties of the data sources are rare
  - Integrated schema is created based on the data sources (➔ *Schema Merging*)
  - No distinguished discovery and analysis phases
  - Common in enterprise integration scenarios
- Top-down design
  - Used when the available data sources are not known a priori
  - The number and properties of candidate data sources for integration are changing constantly
  - Integrated schema is designed independently from the sources, based only on the application requirements
  - Analysis phase precedes discovery phase
  - ➔ *Dynamic Information Integration*
- Hybrid design
  - Selection of data sources based on requirements
  - Design of integrated schema influenced by requirements and data source schemas
  - Analysis and discovery are intertwined

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Schema Matching

Schema Matching

- Goal: Identify semantically related elements across different schemas
- Schema element: table, column, element, attribute, class, etc.
- Result: set of *matches* or *(value) correspondences* (a *mapping*)
- Essential preparation step for most subsequent integration tasks
- Different expressiveness of correspondences
  - Match Degree (also: *local cardinality*)
    - 1:1 semantic relationship of one element of schema A with one element of schema B
    - 1:n semantic relationship of one element of schema A with a set of elements of schema B
    - n:m semantic relationship between sets of elements from schemas A and B
  - Match Semantics
    - Basic matches do not carry additional semantics, they only indicate "some relationship"
    - Advanced matches can indicate abstraction concepts (inheritance, composition, etc.) or functions (e.g., "A is equivalent to the sum of B_1 and B_2")
- "Higher order" correspondences
  - Connect different types of schema elements (e.g. a department table corresponding to a department attribute)
  - Connect metadata with data (e.g., categorical attributes)
- Does *not* refer to the relationship between the instances of the matched concepts (e.g. instances are identical/subsumed/disjoint/overlap)

Schema Matching – Terminology Disambiguation

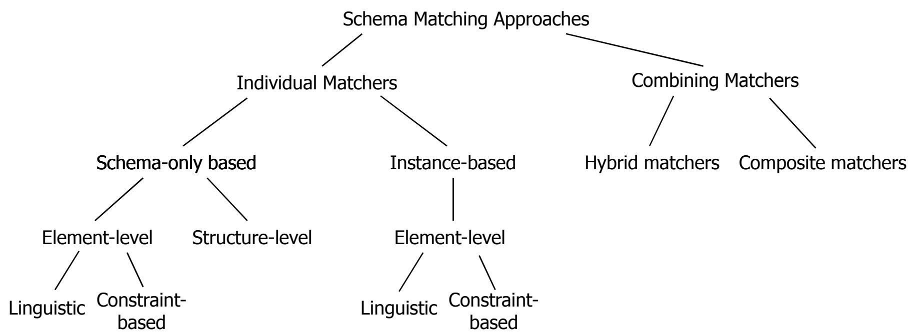
- Mapping
  - **A set of correspondences between two schemas**
  - The process of creating a set of correspondences (→ schema matching, see below)
  - But also
    - A function or transformation describing how data is transformed (→ Integration plan)
    - The process to create a function/transformation (→ Integration planning)
- Schema Matching
  - **The process of obtaining a mapping**
  - An *automatic* process to obtain a mapping

Schema Matching – Challenges

- Identification of matches difficult
  - Very large schemas (10^2-10^3 relations, 10^3-10^4 attributes)
  - Complex schemas
  - Initially unknown and undocumented schemas
  - Ambiguities (Synonyms, Hypernyms, Abbreviations, …)
  - Foreign languages
  - Cryptic identifiers
- Time-consuming and expensive
  - Element-wise "comparing" a schema A with *n* elements with a schema B with *m* elements requires $n \cdot m/2$ comparisons
  - For $n \approx m$: $O(n^2)$
  - Even higher complexity if sets of elements are compared ($O(2^{2n})$), e.g. to obtain 1:n/n:m matches → practical approaches limit sets to a maximum size k

→ Numerous approaches to automate schema matching
  - Error-prone (false-positives and false-negatives)
  - At best semi-automatic (for good results, domain experts must review, amend and revise matches)
  - → Used as a preparation step for a human domain expert to reduce search space

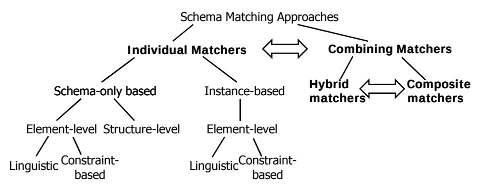
Schema Matching – Classification of Approaches



based on [RaBe01]

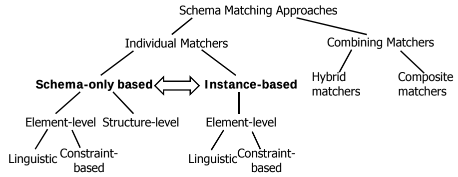
Individual vs. Combining Matchers

- Individual matchers exploit only one kind of information for identifying matches
- Combining matchers use several:
  - Hybrid:
    - Different approaches "hard-wired" into one (parameterizable) component to create a single mapping between the schemas
    - Reuse of individual elements in combination with other matchers or extension with new concepts and approaches to matching is difficult
  - Composite
    - Retroactively combine mappings from different (individual and combining) matchers
    - Common methods: (weighted) average, max, min



Schema-only vs. instance-based matching

- Schema-only techniques operate solely on metadata:
  - table/column/element/attribute/… identifiers and comments or annotations
  - data types
  - constraints
  - element structuring
- Instance-based techniques also consider properties of the data
  - Can only be used *among* data sources
  - In order to use with target schema, sample data can be provided
  - Uses statistical information on data values
    - Actual value ranges of attribute values (e.g., ints in the interval [0,120])
    - Enumeration of values actually present in the data
    - Histograms (Number of occurrences of individual attribute values)
    - Regular expressions describing value patterns (e.g. `[0..9]{5}` for German zip codes)



Linguistic Matching – String Similarity

- String distance or similarity measures [CRF03]
- Based on the lexical similarity of schema element identifiers
- Often used after applying string preprocessing techniques
  - Tokenization: split identifiers based on case, punctuation, etc.
  - Stemming: reduce identifiers to word stem (e.g. "computer" ➔ "comput")
    Note: Stemming algorithms are language-dependent (for English: Porter's algorithm)
  - Stopword elimination
- Edit-distance-like functions, e.g.
  - Levenshtein distance:
    - Count the number of edit operations (insert, modify, delete) to turn string a into string b
    - Example:
      `kitten`
      `sitting`
      ➔ 2 replacements, 1 insertion LevenshteinDist("kitten","sitting") = 3
    - Weighting of operations possible (e.g. replace more expensive than delete)
    - Normalization to interval [0,1] by dividing result through max(length(String A), length(string B))
  - Other measures: Monge-Elkan, Jaro-Winkler, ...

Linguistic Matching – String Similarity (cont.)

- Token-based functions, e.g.
  - Applied on sets of tokens of identifiers
    - Tokenization based on word separators (white space, punctuation, special characters, case)
      - e.g. "Web-of-trust" ➔ {"Web", "of", "trust"}, "CamelCaseIdentifier" ➔ {"Camel", "Case","Identifier"}
    - Tokenization based on n-grams
      - Tokens created by sliding a window of size n over the string
      - e.g. 3-grams for "Information" ➔ {"Inf", "nfo", "for", "orm", "rma", "mat", "ati", "tio", "ion"}
  - Jaccard similarity – describes the similarity of two sets

$$\mathrm{JaccardSimilarity}(A,B)=\frac{|A\cap B|}{|A\cup B|}$$

    - Example:
      ProductPrice ➔ A= {Product, Price}, PriceOfProduct ➔ B = {Price, Product, Of}
      JaccardSimilarity(A,B) = 2/3
  - TFIDF (Term frequency/inverse document frequency) methods
    - Measure originally developed for information retrieval
    - Here: document = (tokenized) identifier, term = token
    - Determines a weight $w_s(t)$ for each token t of a string S based on its frequency in the identifier (term frequency, $tf_S(t)$) and the inverse of its frequency in all identifiers (inverse document frequency, idf(t))
    - Idea: Tokens occurring frequently in the string S have a high weight, while tokens occurring in almost every string receive a low weight
    - Basic weight formula: $w_s(t) = tf_s(t) \cdot idf(t)$

Linguistic Matching – String Similarity (cont.)

  - TFIDF (continued)
    - Many different approaches to calculate $tf_S(t)$ and idf(t)
    - e.g., with $n_{S,x}$ being the number of occurrences of term x in document S, T being the set of all terms in S, N being the total number of documents, and N_t being the number of documents that contain term t (at least once):

$$tf_s(t)=\frac{n_{S,t}}{\max_{i\in T}(n_{S,i})} \qquad idf_s(t)=\log_e\left(1+\frac{N}{N_t}\right)$$

    - Identifiers can be interpreted as vectors in n-dimensional space (with n being the number of different tokens), with the term weights $w_s(t)$ as vector components/elements
    - The similarity between the identifiers is the similarity of the direction (ignoring length) of their respective vectors, i.e., the greater the angle between their vectors, the smaller the similarity
    - Applying the cosine on the angle, we normalize the difference in angle to [0,1]: for an angle of 0°, the cosine is 1 (maximum similarity), for an angle of 90° the cosine is 0
    - Then the similarity function between two identifiers S_1 and S_2 is defined using the cosine measure

$$\mathrm{cosine}(S_1,S_2)=\frac{\sum_{t=1}^{n} w_{S1}\cdot w_{S2}}{\sqrt{\sum_{t=1}^{n} w_{S1}(t)^2}\cdot\sqrt{\sum_{t=1}^{n} w_{S2}(t)^2}}$$

- Hybrid approaches
  - use a secondary similarity function to determine similarity between tokens
- Problem of all approaches based on lexical similarity:
  - Lexical similarity does not necessarily indicate semantic similarity! (and v.v.)

Linguistic Matching – Ontology-based approaches

- Use a Dictionary/Thesaurus/Ontology[1] to store knowledge about application domain terms and concepts and their relationships, e.g.
  - Synonymy
  - Hypo/hypernymy, sub/superclasses
  - Aggregation
  - Opposite terms/concepts
- Can contain alternative forms for terms (word stem, abbreviations)
- Distance of two terms within the thesaurus is translated to similarity value
- Can be extended to handle different languages
- Ontologies can be domain-specific or generic and vary in the level of detail
  - Design of a good ontology is a daunting task
  - Depending on their specific point of view and their level of detail, ontologies will often disagree on terms and their relationships, e.g.:
    Is "car" a special type of "vehicle" (hyponym), or are the terms synonyms?

1 These and similar terms are not used consistently throughout the literature. See e.g. http://www.metamodel.com/article.php?story=20030115211223271 for an attempt at a definition of these terms.

Structural Schema Matching

- Exploit the relationships (structure) among schema elements to improve the quality of matches
- Usually require an initial set of correspondences provided by (non-structural) schema matchers

  ➔ Practical implementations are usually hybrid matchers (although they could be built as combining matchers)
- Examples:
  - Cupid [MBR01]
  - Similarity Flooding [MGR02]

Cupid

- Developed by Microsoft Research [MBR01]
- Hybrid approach:
  - Element-based: linguistic and data type similarity
  - Structure-based: *TreeMatch* algorithm
- Three phases
  - Linguistic matching
    - Determine initial matches based on schema element identifiers
  - Structure matching
    - Modify initial values based on element structure
  - Creation of mappings/matches
    - Choose the matches to return as result
    - Method depends on the intended use for the matches, e.g.
      - Prune matches below a given threshold
      - Return only leaf-level matches

Cupid Linguistic Matching

1. Normalization
   - Tokenization: split identifiers into tokens based on punctuation, case, etc.
     e.g. POBillTo ⇨ {PO, Bill, To}
     five token types: number, special symbol, common word, concept, content
   - Expansion: expand acronyms with the help of a thesaurus/dictionary
     e.g. Qty ⇨ Quantity
   - Elimination: discard prepositions, articles, etc. with the help of a stop word list
     e.g. {PO, Bill, To} ⇨ {PO, Bill}
   - Tagging: identifiers related to a known application concept are tagged with the concept
     e.g. identifiers *Price*, *Cost* and *Value* are tagged with the concept *Money*
2. Categorization
   - Clusters elements into categories (= a group of elements identified by a set of keywords)
   - Goal: reduce comparisons to only those elements within compatible categories
   - One category for each:
     - Concept tag
     - Data type (coarse grained, e.g., number, string, date, ...)
     - Container (e.g., address contains city, state, and street)
   - Elements can belong to multiple categories
   - Categories are compatible, if their respective sets of keywords are "name similar"

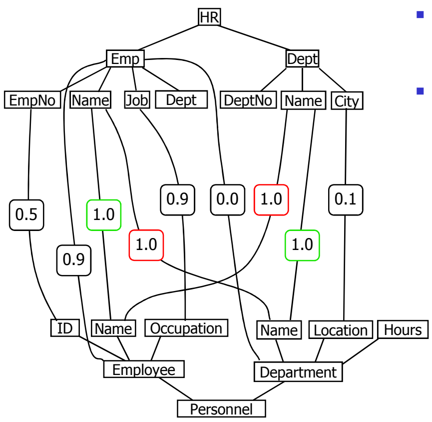
Cupid Linguistic Matching (cont.)

- Name similarity:
  - The *name similarity* of two token sets T_1 and T_2 is the average of the best similarity of each token in set T_1 with a token in set T_2
  - To determine the similarity of two tokens t_1 and t_2, a thesaurus lookup is performed
  - If no thesaurus entry is present for a pair of tokens, substring matching is used to identify common pre- and suffixes

3. Comparison
   - Determines the linguistic similarity coefficient $lsim(s,t)$ $s \in S$, $t \in T$, for pairs of elements of the two schemas S and T
   - For each pair of elements s, t from compatible categories
     1. Calculate the name similarity of the element tokens *per token type*
     2. Calculate the weighted mean of the per-token-type name similarity (concept and content tokens are assigned a higher weight)
     3. Calculate lsim for the pair by scaling the result of 2. with the maximum name similarity of the categories of s and t

- Result: a table of linguistic similarity coefficients $lsim(s,t)$ in the range [0,1]

Cupid Linguistic Matching – Problems



(not all matches shown)

- Linguistic matching does not consider context: e.g., false positive: Emp/Name is as similar to Employee/Name as it is to Department/Name
- Linguistically dissimilar, but semantically related elements are underrated (caused by missing or incomplete thesaurus)
  e.g. Dept/City – Department/Location

Cupid Structural Matching

- Based on a tree representation of the structure of the schema
- *TreeMatch* algorithm
- Basic intuitions
  1. A pair of leaves from two trees is similar, if
     a) they are individually similar (linguistic, data type, …)
     b) their neighbors (ancestors and siblings) are similar
  2. A pair of non-leaves is similar, if
     a) they are linguistically similar
     b) their subtrees are similar
  3. A pair of non-leaves is structurally similar, if their respective leaves are highly similar (not necessarily their direct children)
- Initialize *ssim* for all leaves using a data type compatibility matrix (range [0,0.5])
- *Stronglink:* similarity between two leaves is above threshold th_{accept}
  - based on wheighted similarity (see next chart)

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Cupid Structural Matching (cont.)

- Iterate over the tree nodes in post-order (bottom-up calculation)
- For each pair s,t:
  - Calculate ssim(s,t) as the fraction of leaves in the two subtrees below s and t that have at least one stronglink to a leaf in the other subtree
  - Calculate a weighted similarity measure wsim(s,t):
    $wsim(s,t) = w_{struct} \cdot ssim(s,t) + (1-w_{struct}) \cdot lsim(s,t)$
  - If wsim(s,t) is above threshold th_{high}, increase the similarity of each pair of leaves in the subtrees of s and t by a factor c_{inc} (not exceeding 1)
  - If wsim(s,t) is below threshold th_{low}, decrease the similarity of each pair of leaves in the subtrees of s and t by a factor c_{dec} (but never below 0)

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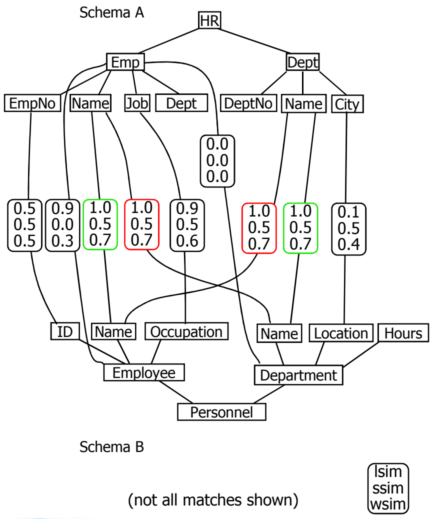
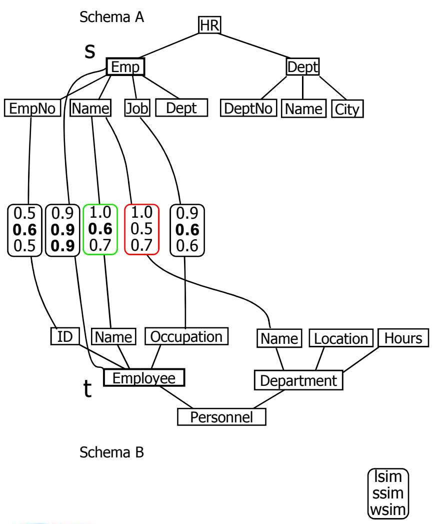
Cupid Structural Matching – Example



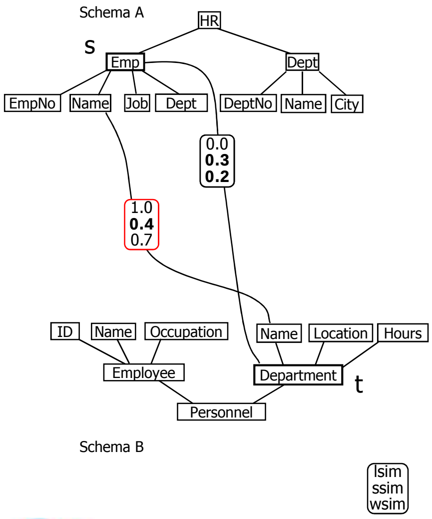
- Initialization:
  - ssim set to 0.0 for all non-leaf nodes
  - ssim set to data type similarity for leaves
- Parameters:
  - $th_{accept} = 0.5$
  - $w_{struct} = 0.7$
  - $th_{high} = 0.7$, $c_{inc} = 1.2$
  - $th_{low} = 0.3$, $c_{dec} = 0.8$

Cupid Structural Matching – Example (cont.)



- Iteration for
  s = Emp, t = Employee:
  - Calculate ssim:
    3 out of 4 leaves of Emp have stronglinks to leaves of Employee, 3 out of 3 leaves of Employee have stronglinks to Emp
    ssim(s,t) = 6/7 ≈ 0.9
  - Calculate wsim:
    $wsim(s,t) = w_{struct} \cdot ssim(s,t) + (1-w_{struct}) \cdot lsim(s,t)$
    $= 0.7 \cdot 0.9 + 0.3 \cdot 0.9 = 0.9$
  - Modify structural similarity for leaves of s and t:
    $wsim(s,t) = 0.9 > th_{high} = 0.7$
    ⇨ increase ssim for each pair (l_s, l_t),
    $l_s \in$ leaves(s) and $l_t \in$ leaves(t):
    $ssim_{new}(l_s, l_t) = ssim_{old}(l_s, l_t) \cdot c_{inc} = 0.5 \cdot 1.2 = 0.6$
    (wsim for leaf-pairs is left unchanged)
- Result:
  - Similarity between s and t increased, because children are similar (intuitions 2b and 3)
  - Similarity between the child nodes increased, because their neighbors (here: ancestors) are similar (intuition 1b)

Cupid Structural Matching – Example (cont.)



- Iteration for s = Emp, t = Department:
  - Calculate ssim:
    ssim(s,t) = 2/7 ≈ 0.3
    (1 out of 4 leaves of Emp have stronglinks to leaves of Department, 1 out of 3 leaves of Department have stronglinks to leaves of Emp)
  - Calculate wsim:
    $wsim(s,t) = w_{struct} \cdot ssim(s,t) + (1-w_{struct}) \cdot lsim(s,t)$
    $= 0.7 \cdot 0.3 + 0.3 \cdot 0.0 = 0.21 \approx 0.2$
  - Modify structural similarity for leaves of s and t:
    $wsim(s,t) = 0.2 < th_{low} = 0.3$
    ⇨ decrease ssim for each pair (l_s,l_t),
    $l_s \in$ leaves(s) and $l_t \in$ leaves(t):
    $ssim_{new}(l_s,l_t) = ssim_{old}(l_s,l_t) \cdot c_{dec}$
    (wsim for leaf-pairs is left unchanged)
- Result:
  - Similarity between Emp/Name and Department/Name decreased, because their ancestors are not similar

Cupid – Summary

- TreeMatch exploits a schema element's context to modify similarity values
- Helps to discern between pairs that were rated identical by linguistic matching:
  - Confidence of false positives reduced:
    - Match confidence between leaves with dissimilar ancestors decreases
    - Match confidence of linguistically similar non-leaves with different children decreases
  - Confidence of false negatives or uncertain matches increased
    - Match confidence of leaf-pairs with similar ancestor increases
    - Match confidence of linguistically dissimilar non-leaves with similar children increases

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Multi-database languages/ Schematic Query Languages

Limitations of SQL

- Standard SQL is unable to generically solve most forms of schematic heterogeneity
- Comp. Person – Men/Women example

Schema A

Person

ID	Name	Gender
1234	Bob	male
4567	Jane	female

⟺

Schema B

Men

ID	Name
1234	Bob

Women

ID	Name
4567	Jane

- Can be solved with relational view(s)...

A to B

```
CREATE VIEW Men AS
SELECT ID, Name
FROM Person
WHERE Gender='male'

CREATE VIEW Women AS
SELECT ID, Name
FROM Person
WHERE Gender='female'
```

⟺

B to A

```
CREATE VIEW (ID, Name, Gender)
AS
SELECT ID, Name, 'male'
FROM Men
UNION
SELECT ID, Name, 'female'
FROM Women
```

- … but only because the number of different "categories" (here: genders) is known a priori (and fixed)

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Limitations of SQL (cont.)

- e.g., replace gender with department:

Schema A

Person

ID	Name	Department
1234	Bob	Accounting
4567	Jane	Sales
9876	**Joe**	**Service**

Schema B

Accounting

ID	Name
1234	Bob

Sales

ID	Name
4567	Jane

Service

ID	**Name**
9876	**Joe**

  - Departments might change over time
  - When using static views as before
    - Each new department in A requires its own view definition to transform to schema B
    - Each new department in B requires a modification of the view to transform to schema A
  - ➔ Expensive maintenance

A to B

```
CREATE VIEW Accounting AS
…
CREATE VIEW Sales AS
…
CREATE VIEW Service AS
SELECT ID, Name
FROM Person
WHERE Department ='Service'
```

B to A

```
CREATE VIEW (ID, Name, Department)
AS
SELECT ID, Name, 'Accounting'
FROM Accounting
UNION
SELECT ID, Name, 'Sales'
FROM Sales
UNION
SELECT ID, Name, 'Service'
FROM Service
```

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Schematic Query Languages

- Solution: Extend SQL to be able to transform data to metadata (and v.v.)
- ➔ Schematic Query Languages (a.k.a. Multi-database QLs)
- Examples
  - SchemaSQL
  - FIRA/FISQL
- Challenge:
  - The schema of the result of a query is now dependent on the data actually present in the input relations
  - To allow such *dynamic schemas*, schematic query languages have to extend the relational model
- In addition, schematic query languages provide mechanism to access different databases in a single query

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Example Databases

Kaiserslautern (KL)

Sales

Store	Department	AvgSales
Innenstadt	TV	139000
Innenstadt	Computer	156000
Innenstadt	Hifi	118000
Gewerbegbt	TV	112000
Gewerbegbt	Computer	180000
Gewerbegbt	Hifi	57000

Mannheim (MA)

AvgSales

Store	TV	Computer	Hifi
Quadrate	205000	234000	108000
Kaefertal	90000	76000	87000
Sandhofen	73000	81000	98000

Trier (TR)

Eisenbahnstr

Dept	AvgSales
TV	67000
Computer	51000
Hifi	78000

Hauptstr

Dept	AvgSales
TV	74000
Computer	103000
Hifi	89000

SchemaSQL

- Lakshmanan, Sadri & Subramanian [LSS96, LSS01]
- First approach addresses the issue of schematic heterogeneity with SQL
- Built on top of SQL by providing an extended FROM clause:
  - Specify range variables ("aliases") not only over tuples of relations, but also over
    - the databases of the (M)DBMS `->`
    - the relation names of a database `db->`
    - attribute names of a relation `db::rel->`
    - tuples of a relation (-> SQL) `db::rel`
    - distinct values of an attribute `db::rel.attr`
  - Elements of the FROM clause can be nested, e.g.
    `FROM xdb-> xdbtables, xdbtables-> atts`
    to iterate over the relations of database xdb and then over the relations' attributes
  - Variables in the FROM clause can be used in view definitions for dynamic result schemas

SchemaSQL – Example

- Transform KL database to MA format:

```
CREATE VIEW KL2MA::AvgSales(Store, KD) AS
SELECT KS.Store, KS.AvgSales
FROM KL::Sales KS, KS.Department KD
```

1. Dynamic result schema: number of attributes depends on number of attribute values in the source relation's department attribute
2. Nesting of sets in FROM clause
3. A source tuple's value for AvgSales is placed in the result column depending on the value of the tuple's Department attribute (merge into one result tuple is implicit)

- Problem: Operation (the merge) is not well-defined for all source relations
  - What happens if there was an additional tuple ("Innenstadt","Hifi", 97500) in the KL database? Which value (11800 or 97500) to place into the "Hifi" column?
  - SchemaSQL does not answer this question

SchemaSQL – Example (cont.)

- Aggregation over a variable number of columns
- e.g. "What are the average sales of the Mannheim stores, across all departments?"
- Number of departments cannot assumed to be fixed!

```
SELECT MS.Store, AVG(MSAtts)
FROM MA::AvgSales MS, MA::AvgSales-> MSAtts
WHERE MSAtts<>'Store'
GROUP BY MS.Store
```

- Use of attribute set in aggregate function

Mannheim (MA)

AvgSales

Store	TV	Computer	Hifi
Quadrate	205000	234000	108000
Kaefertal	90000	76000	87000
Sandhofen	73000	81000	98000

SchemaSQL – Criticism

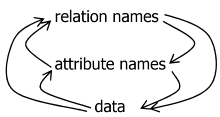
- Semantics of a SchemaSQL SELECT statement differs depending on context:
  - e.g., query from Example 2, placed in a view definition:

```
CREATE VIEW MA::PerDeptAvgs(Store, MSAtts) AS
    SELECT MS.Store, AVG(MSAtts)
    FROM MA::AvgSales MS, MA::AvgSales-> MSAtts
    WHERE MSAtts<>'Store'
    GROUP BY MS.Store
```

- Query now computes the averages for each department *individually*!

FIRA/FISQL

- Presented by Wyss and Robertson [WyRo05]
- Extends the relational model to the *federated relational model*
  - Number of output relations and their attributes is fully dynamic
- Provides an extended SQL syntax (Federated Interoperable SQL, FISQL)
- Provides a sound theoretical foundation by specifying the underlying algebra operators (Federated Interoperable Relational Algebra, FIRA)
- FIRA/FISQL is *transformationally complete*:
  - Transform any form of relational metadata to data and v.v.



- FISQL allows nesting of queries

FIRA/FISQL Data Model

- *Federated* relational data model:
  - Extends the relational model to incorporate metadata
    - A federated tuple is a mapping from a finite set of names S (=attribute names) to values; S is known as the schema of the tuple.
    - A federated relation has a name and contains a finite set of federated tuples
    - A federated database has a name and consists of a finite set of federated relations
    - A federation consists of a finite set of federated databases
    - The schema of a federated relation is the union of the schemas of the tuples
      - → Operations that add/change/delete tuples may modify the relation schema
- Defines federated counterparts of the six standard relational operators, e.g.
  - Renaming of relations (in addition to attributes)
  - Cartesian product/union/difference of databases
- Introduces six new operators
- Most operators defined on federated relations and on federated databases, i.e. operators take a relation/database as input and produce a relation/database as output

FIRA/FISQL – Operators

- Drop-projection $\not\pi_A(R)$, $\not\pi_A(D)$
  - Two variants: one for relations, one for federated databases
  - Parameter A is the set of attributes to be *removed* from the relation/fed. DB
  - Required to generically handle relations/fed. DBs with variable schema
- Down $\downarrow_I(R)$, $\downarrow_I(D)$
  - Two variants: one for relations, one for federated databases
  - "Demotes" a table R's metadata to data by creating a relation *metadata$_i$* and forming its crossproduct with R.
  - For a relation R with name N and attributes $A_1 \dots A_n$, the relation *metadata$_i$* is defined as:
  - Ignores metadata columns: $\downarrow_i(R) = metadata_i(R) \times \not\pi_{r_i,a_i}(R)$

metadata$_i$(R)=

r_i	a_i
N	A_1
N	A_2
…	…
N	A_n

- Attribute Dereference $\Delta_A^B(R)$
  - The value of attribute B of the target tuple t is determined by using the value found in the attribute named equal to t's value in column A, values of all other attributes of t are equal to the respective value of those in source tuple s
  - Let t[X] denote the value of attribute X of tuple t. The attribute values of a result tuple t are obtained from the values of its respective source tuple s like this:

$$t[X] = \begin{cases} s[s[A]] \text{ if } X = B \\ s[X] \text{ otherwise} \end{cases}$$

FIRA/FISQL – Operators (cont.)

- Generalized Union $\Sigma(D)$
  - Creates a relation holding the outer union of all relations in the database D
- Transpose τ_A^B (R)
  - For each distinct value of the parameter column B in the input relation R, create a column in the result relation (whose name is the respective value of B)
  - For each tuple t of the result relation, obtain the value of column X (denoted t[X]) from the respective source tuple s like this:

$$t[X] = \begin{cases} s[A] \text{ if } X = s[B] \\ s[X] \text{ if } X \in \text{schema}(s) \\ \text{NULL otherwise} \end{cases}$$

  - i.e.: for each new attribute N_i, its value is that of the source tuple's A attribute if the source tuple's B attribute value is equal to the name of attribute N_i, NULL otherwise
  - other attributes remain unchanged
- Partition operator $\wp_A$(R)
  - Roughly the opposite of Generalized Union
  - Creates a federated database with one relation for each distinct value in column A of input relation R

FIRA/FISQL example – KL2TR

- Transform the Kaiserslautern database to the format of the Trier database
- Requires the Partition operator $\wp_A$(R) and (drop) projection

Kaiserslautern (KL)

Sales

Store	Department	AvgSales
Innenstadt	TV	139000
Innenstadt	Computer	156000
Innenstadt	Hifi	118000
Gewerbegbt	TV	112000
Gewerbegbt	Computer	180000
Gewerbegbt	Hifi	57000

KL2TR'= $\wp_{Store}$(KL)

KL2TR'

Innenstadt

Store	Department	AvgSales
Innenstadt	TV	139000
Innenstadt	Computer	156000
Innenstadt	Hifi	118000

Gewerbegbt

Store	Department	AvgSales
Gewerbegbt	TV	112000
Gewerbegbt	Computer	180000
Gewerbegbt	Hifi	57000

KL2TR= $\mathcal{U}_{Store}$(KL2TR')
OR
KL2TR= $\pi_{Department,\ AvgSales}$(KL2TR')

KL2TR

Innenstadt

Department	AvgSales
TV	139000
Computer	156000
Hifi	118000

Gewerbegbt

Department	AvgSales
TV	112000
Computer	180000
Hifi	57000

- FISQL statement:

```
SELECT KS.Department AS Dept, KS.AvgSales INTO KS.Store
FROM KL.Sales KS
```

A

FIRA/FISQL example – MA2KL

- Transform the Mannheim database to the format of the Kaiserslautern database
- Requires a combination of the down and attribute deference operator

Mannheim (MA)

AvgSales

Store	TV	Computer	Hifi
Quadrate	205000	234000	108000
Kaefertal	90000	76000	87000
Sandhofen	73000	81000	98000

$S = \downarrow_1 (MA.AvgSales)$

S

r_1	a_1	Store	TV	Computer	Hifi
AvgSales	Store	Quadrate	205000	234000	108000
AvgSales	TV	Quadrate	205000	234000	108000
AvgSales	Computer	Quadrate	205000	234000	108000
AvgSales	Hifi	Quadrate	205000	234000	108000
AvgSales	Store	Kaefertal	90000	76000	87000
AvgSales	TV	Kaefertal	90000	76000	87000
…	…	…	…	…	…
AvgSales	Hifi	Sandhofen	73000	81000	98000

$S' = \sigma_{a_1 <> \text{'Store'}}(S)$

S'

r_1	a_1	Store	TV	Computer	Hifi
AvgSales	TV	Quadrate	205000	234000	108000
AvgSales	Computer	Quadrate	205000	234000	108000
AvgSales	Hifi	Quadrate	205000	234000	108000
AvgSales	TV	Kaefertal	90000	76000	87000
…	…	…	…	…	…
AvgSales	Hifi	Sandhofen	73000	81000	98000

FIRA/FISQL – MA2KL (cont.)

$S'' = \Delta_{a_1}^{AvgSales}(S')$

S''

r_1	a_1	Store	TV	Computer	Hifi	**AvgSales**
AvgSales	**TV**	Quadrate	**205000**	234000	108000	**205000**
AvgSales	**Computer**	Quadrate	205000	**234000**	108000	**234000**
AvgSales	**Hifi**	Quadrate	205000	234000	**108000**	**108000**
AvgSales	**TV**	Kaefertal	**90000**	76000	87000	**90000**
…	…	…	…	…	…	
AvgSales	**Hifi**	Sandhofen	73000	81000	**98000**	**98000**

- Cleanup:
  $MA2KL = \pi_{\text{Store, Department, AvgSales}}\ \rho_{\text{a1->Department}}(S'')$

MA2KL

Store	Department	AvgSales
Quadrate	TV	205000
Quadrate	Computer	234000
Quadrate	Hifi	108000
Kaefertal	TV	90000
…	…	
Sandhofen	Hifi	98000

FIRA/FISQL example – TR2KL

- Use Down (on DB) with Generalized union, renaming and projection:
  TR2KL= $\rho^{\varepsilon\text{->}Sales}\pi_{Store,\ Dept,\ AvgSales}\ \rho_{r1\text{->}Store}\ \Sigma(\downarrow_1 (TR))$

Trier (TR)

Eisenbahnstr

Dept	AvgSales
TV	67000
Computer	51000
Hifi	78000

Hauptstr

Dept	AvgSales
TV	74000
Computer	103000
Hifi	89000

$TR' = \downarrow_1 (TR)$

TR'

Eisenbahnstr

r_1	a_1	Dept	AvgSales
Eisenbahnstr	Dept	TV	67000
Eisenbahnstr	AvgSales	TV	67000
Eisenbahnstr	Dept	Computer	51000
...	...	...	...
Eisenbahnstr	AvgSales	Hifi	78000

Hauptstr

r1	a
Hauptstr	D
Hauptstr	A
...	.

$TR'' = \Sigma (TR')$

TR''

ε

r_1	a_1	Dept	AvgSales
Eisenbahnstr	Dept	TV	67000
Eisenbahnstr	AvgSales	TV	67000
Eisenbahnstr	Dept	Computer	51000
...	...	...	...
Hauptstr	AvgSales	Hifi	89000

TR2KL= $\rho^{\varepsilon\text{->}Sales}\ \pi_{Store,\ Dept,\ AvgSales}\ \rho_{r1\text{->}Store}\ (TR'')$

TR2KL

Sales

Store	Dept	AvgSales
Eisenbahnstr	TV	67000
Eisenbahnstr	TV	67000
Eisenbahnstr	Computer	51000
...	...	...
Hauptstr	Hifi	89000

FIRA/FISQL example – KL2MA

- Transform the Kaiserslautern database to the format of the Mannheim database
- Requires the transpose and drop-projection operators:

Kaiserslautern (KL)

Sales

Store	Department	AvgSales
Innenstadt	TV	139000
Innenstadt	Computer	156000
Innenstadt	Hifi	118000
Gewerbegbt	TV	112000
Gewerbegbt	Computer	180000
Gewerbegbt	Hifi	57000

$S = \tau_{\substack{Department\\AvgSales}} (Sales)$

KL

S

Store	Department	AvgSales	TV	Computer	Hifi
Innenstadt	TV	139000	139000	-	-
Innenstadt	Computer	156000	-	156000	-
Innenstadt	Hifi	118000	-		118000
Gewerbegbt	TV	112000	112000	-	-
Gewerbegbt	Computer	180000	-	180000	-
Gewerbegbt	Hifi	57000	-	-	57000

$S' = \upsilon_{Department,\ AvgSales}(S)$

KL

S'

Store	TV	Computer	Hifi
Innenstadt	139000	-	-
Innenstadt	-	156000	-
Innenstadt	-		118000
Gewerbegbt	112000	-	-
Gewerbegbt	-	180000	-
Gewerbegbt	-	-	57000
Innenstadt	-	-	97500

Merge

S''

Store	TV	Computer	Hifi
Innenstadt	139000	156000	$\boxed{118000}$?
Gewerbegbt	112000	180000	57000

FIRA/FISQL – Merging

- Merging of tuples required
  - Merging is simple if no "conflicts" arise
  - Merge not uniquely defined if tuples conflict
  - Two tuples t_1, t_2 of a relation with n attributes are mergeable if either
    - $t_1[A_i] = t_2[A_i]$ or
    - one of $t_1[A_i]$ or $t_2[A_i]$ is a null value

    holds for $1 \leq i \leq n$
  - The merge t of two mergeable tuples t_1, t_2 (denoted $t = t_1 \odot t_2$) is defined as

$$t[A_i] = \begin{cases} t_1[A_i] \text{ if } t_1[A_i] \text{ not null} \\ t_2[A_i] \text{ otherwise} \end{cases} \quad \text{for } 1 \leq i \leq n$$

- Optimal tuple merge
  - For a relation schema R and two relations r_1 and r_2 that are instances of R, r_2 is a tuple merge of r_1, if it can be obtained from r_1 by a finite sequence of merge operations of mergeable tuples
  - A tuple merge r_2 of r_1 is an optimal tuple merge, if for every r_3 that is also a tuple merge of r1

    $|r_2| \leq |r_3|$ holds

FIRA/FISQL – Merge Operator

- (Unique optimal tuple) Merge Operator $\mu(R)$ [WyRo05b]
  - Let R be a relational schema, and r an instance of R
  - Let $Ø^R$ denote the empty relation of schema R
  - Then the unique optimal tuple merge of r is

$$\mu(r) := \begin{cases} Ø^R \text{if there is more than one optimal tuple merge of r} \\ \text{the unique optimal tuple merge otherwise} \end{cases}$$

- Merge was not part of the original FIRA/FISQL
  - ➔ No FISQL syntax specified
- FISQL statement (without merge):

```
    SELECT DROP (KS1.Department, KS1.Avgsales)
    FROM    (SELECT KS.*, KS.Avgsales ON KS.Department
             FROM KL.Sales AS KS)   A                 B
           S
S'          AS KS1
```

FIRA/FISQL example – KL2MA continued

KL

S'

Store	TV	Computer	Hifi
Innenstadt	139000	-	-
Innenstadt	-	156000	-
Innenstadt	-		118000
Gewerbegbt	112000	-	-
Gewerbegbt	-	180000	-
Gewerbegbt	-	-	57000

$S'' = \mu_{Store}(S')$

S''

Store	TV	Computer	Hifi
Innenstadt	139000	156000	118000
Gewerbegbt	112000	180000	57000

KL

S'

Store	TV	Computer	Hifi
Innenstadt	139000	-	-
Innenstadt	-	156000	-
Innenstadt	-		118000
Gewerbegbt	112000	-	-
Gewerbegbt	-	180000	-
Gewerbegbt	-	-	57000
Innenstadt	-	-	97500

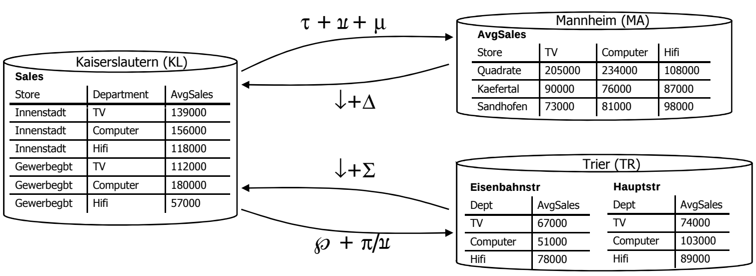
$S'' = \mu_{Store}(S')$

S''

Store	TV	Computer	Hifi

FIRA/FISQL – Summary

- Theoretically sound approach to resolve schematic heterogeneity
- Open questions:
  - How does grouping/aggregation fit into the model?
    - Group by/aggregate over an unknown set of attributes ?
    - Could allow the user to solve the merge problem for relations with conflicting tuples by explicitly specifying the desired merge semantics (using an aggregate function)
  - What does transformational completeness mean in the XML data model?



Kaiserslautern (KL) – Sales

Store	Department	AvgSales
Innenstadt	TV	139000
Innenstadt	Computer	156000
Innenstadt	Hifi	118000
Gewerbegbt	TV	112000
Gewerbegbt	Computer	180000
Gewerbegbt	Hifi	57000

Mannheim (MA) – AvgSales

Store	TV	Computer	Hifi
Quadrate	205000	234000	108000
Kaefertal	90000	76000	87000
Sandhofen	73000	81000	98000

Trier (TR) – Eisenbahnstr

Dept	AvgSales
TV	67000
Computer	51000
Hifi	78000

Trier (TR) – Hauptstr

Dept	AvgSales
TV	74000
Computer	103000
Hifi	89000

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Schema Integration

Schema Integration

- Goal: Create an integrated schema T from a set S of schemas that is:
  - complete (contains all concepts of S)
  - minimal (contains semantically equivalent concepts only once)
  - correct (each concept must correspond to a concept of at least one source)
  - intelligible (humans can understand the schema, e.g., names of concepts and their attributes should be preserved where possible)
- Schema Integration is *not* about transforming data from one schema to another (➔ Information integration, data fusion)
- Also known as schema (or ontology) merging
- Can be separated into four phases [BLN86]:
  - Preintegration
    - Choose schemas to integrate
    - Collect additional information (e.g., documentation of data sources)
  - Comparing the schemas
    - Schema Matching
    - Identify conflicts

Schema Integration (cont.)

- "Conforming" the schemas
  - Resolve conflicts, e.g., by renaming attributes, restructuring (e.g., (de-)normalization))
  - At the end of the phase, identical concepts are represented identically in all schemas
- Schema Merging and Restructuring
  - Superimpose schemas
  - Restructure to meet the four goals
- Two main categories:
  - Binary approaches integrate exactly two schemas
  - n-ary approaches integrate an arbitrary number of schemas in one step
- For binary approaches, the sequence in which they are applied to the n input schemas can make a difference
- Most approaches are not algorithms, but guidelines
  - Even algorithms require manual conflict resolution
  - ➔ At best semi-automatic
- Examples:
  - Rondo Merge Operator [PoBe03]
  - Generic Integration Model (GIM) [ScSa05]

Rondo Merge Operator – Schema Representation

- A model L is a triple (*E*, *Root*, *Re*), with *E* being a set of elements, *Root* ∈ *E* being the root element of the model, and *Re* being the set of relationships of the model
- Elements with required properties *name* and an internal *ID*
- Binary, directed relationships R(x,y) with cardinality constraints and five different kinds:
  - Associates A(x,y) – elements x and y are associated in a (not further specified) manner
  - Contains C(x,y) – element x (container) contains element y (containee) (Containment)
    - Containees cannot exist on their own (i.e., delete on the container cascades to the containees)
    - transitive and acyclic
  - Has-a H(x,y) – element x has a subelement y (Aggregation)
    - weaker than contains: no cascading of deletes, cycles allowed
  - Is-a I(x,y) – x is a specialization of y (Specialization/Generalization)
    - transitive and acyclic
  - Type-of T(x,y) – x is of type y
    - an element can be of at most one type (*one-type restriction*)

Rondo Merge Operator (cont.)

- Metamodel-specific *relationship implication rules* to infer implicit relations based on explicit relations, e.g.
  - If T(q,r) and I(r,s), then T(q,s) – an element q of type r is implicitly also an instance of any of r's superclasses s
  - If I(p,q) and H(q,r), then H(p,r) and If I(p,q) and C(q,r), then C(p,r) – an element inherits aggregates and components from its superclasses
- Mappings (=sets of correspondences) are themselves models
  - Contain mapping elements (two kinds: equality and similarity)
  - Contain mapping relationships M(x,y), indicating that mapping element x represents element y
  - All model elements y represented by a single mapping element via M(x,y) are said to *correspond* to one another

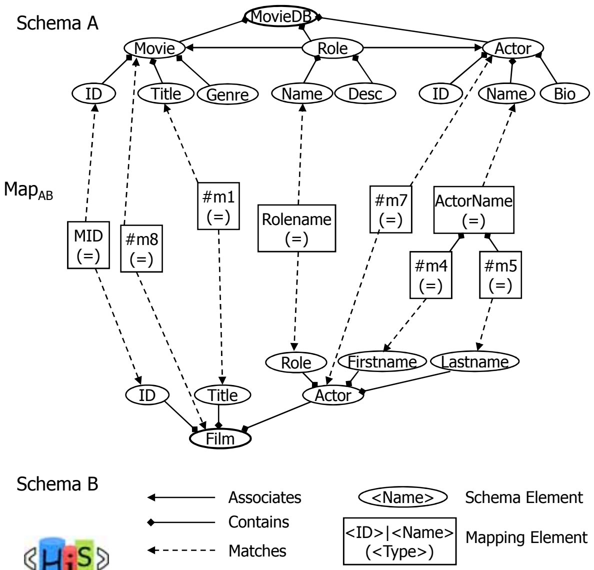
Rondo Merge Operator Requirements

- Inputs:
  - Two models A and B
  - A mapping Map_{AB} (=set of correspondences) between A and B
  - Optional: an indication which model is the preferred one
- Output: a merged model G
- Merge semantics based on *Generic Merge Requirements*
  1. Each element e with $e \in A \cup B \cup Map_{AB}$ corresponds to exactly one element e' in G (Element preservation)
  2. Two input elements are only mapped to the same element in G if the mapping indicates that they are equal (Equality preservation)
  3. Each input relationship is represented directly in G or implied by G (according to the rules of the metamodel) (Relationship preservation)
  4. Elements which are similar (but not equal) according to Map_{AB}, remain separate in G and are related by a relationship (Similarity preservation)
  5. No other elements besides those specified in rules 1-4 exist (Extraneous item prohibition)
  6. An element e in G has a property p if it has a corresponding element e' in A or B that has property p (Property Preservation)

Rondo Merge Algorithm

- Form groups of elements for which an equality mapping exists (directly or transitively)
  - Groups include the mapping elements themselves
- For each group I, create an element e in G:
  - ID(e) is set to an unused ID value
  - For other properties p of e, p's value v is in order of precedence:
    1. the value of property p of a mapping element in I for which property p is defined, otherwise
    2. the value of property p of an element in I of the preferred model for which p is defined, otherwise
    3. the value of property p of any element of I for which p is defined.
    - If more than one value is possible in 1-3, one is chosen arbitrarily
    - ➔ Values of mappings take precedence over those of the preferred model over those of the other model
- For each pair of elements e' and f' in G that correspond to different groups E and F
  - if for any two e ∊ F and f ∊ F a relationship R(x,y) of kind t exists in A resp. B
  - create a relationship R(e',f') of kind t in G
  - Relationships between elements of the same group are ignored
  - Remove implied relationships until a mincover remains
- Resolve conflicts

Merging Example

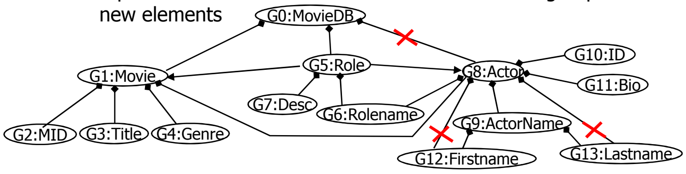


Groups:

G0	{MovieDB}
G1	{A.Movie,B.Film, Map_{AB}.#m8}
G2	{A.Movie.ID, B.Film.ID, Map_{AB}.MID}
G3	{A.Movie.Title, B.Film.Title, Map_{AB}.#m1}
G4	{A.Movie.Genre}
G5	{A.Role}
G6	{A.Role.Name, B.Film.Actor.Role, Map_{AB}.Rolename}
G7	{A.Role.Desc}
G8	{A.Actor, B.Film.Actor, Map_{AB}.#m7}
G9	{A.Actor.Name, Map_{AB}.ActorName}
G10	{A.Actor.ID}
G11	{A.Actor.Bio}
G12	{B.Film.Actor.Firstname, Map_{AB}.#m4}
G13	{B.Film.Actor.Lastname, Map_{AB}.#m5}

Merging Example (cont.)

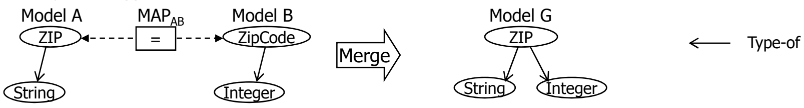
- Merge(A,B, Map_{AB}) with A as the preferred schema
  - One element for each group
  - replicate all associations between members of the groups as associations between the new elements



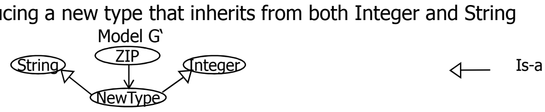
- Remove implied relationships to obtain minimum coverage of associations

Conflict resolution

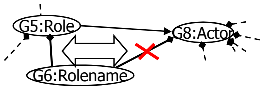
- Fundamental conflicts (shared across all metamodels)
  - e.g. One-type restriction violated



  - Resolve e.g. by introducing a new type that inherits from both Integer and String



- Metamodel conflicts
  - Metamodel-dependent resolution rules
  - e.g., in most data models, an element can be containee in at most one container
    - e.g. Rolename in the example
    - remove one containment relationship



  - SQL92 does not have the concept of subcolumn (as needed for name(firstname, lastname))

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Integration Planning

Integration Planning – Goals

- Creation of an "executable mapping", i.e., a data transformation from source to target schemas
- Inputs
  - Source schemas (and data)
  - Target schema (and sample data)
  - (Correspondences)
- Output
  - An "executable mapping", i.e., a specification for data transformation from the sources to the target schema
  - e.g. SQL(/XML) queries/views, ETL scripts, XQuery statements etc.
  - Usually created manually with tool support
- Many different approaches to partially automate the process
  - Clio Query Discovery [MHH00]
  - Tupelo [FlWy06]
  - Integration Patterns [Gö05a]

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Clio Query Discovery – Overview

- Clio is a combined tool for schema matching and mapping
- Creates executable mappings as SQL/XQuery statements for use in FDBMS
- Uses *value correspondences (VCs):*
  - Essentially complex 1:n matches
  - A value correspondence v_i is a tuple (f_i, p_i) with
    - *a function* f_i describing how to derive a certain target attribute B from a set of source attributes A_k (and possibly from source metadata):
      f_i: dom(A_1) x dom(A_2) x … dom(A_q) $\rightarrow$ dom(B)
    - a *filter* p_i indicating which source values should be used:
      p_i: dom(A_1) x dom(A_2) x … dom(A_r) $\rightarrow$ boolean
  - Note: function and filter of a correspondence can be defined on different sets of attributes
- Idea: Divide the set of value correspondences *V* into subsets each of which determines one way to compute a given target relation T_k

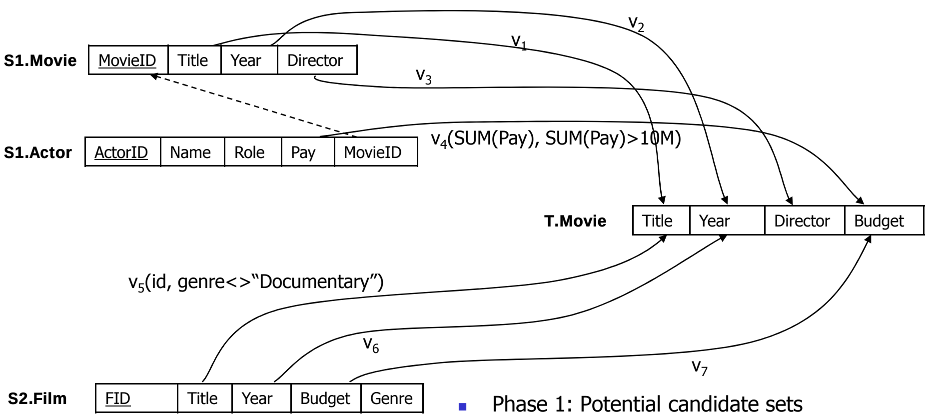
Clio Query Discovery – Algorithm

- Consists of four distinct phases
- For each target relation T_k
  1. Partition V into *potential candidate sets* $\{c_1, \ldots, c_p\}$ that contain *at most* one VC per attribute of T_k:
     - The c_i need not be disjoint
     - A c_i is called *complete* if it includes a VC for *every* attribute in T_k
     - Prefer complete potential candidate sets, and further prefer those that use the smallest set of source relations
     - Prune potential candidate sets that are subsets of another
     - Incomplete candidate sets are considered, as not every target attribute might have a VC
  2. Prune those potential candidate sets that cannot be mapped to a "good" query
     - To create a query, a way of joining the source relations of the potential candidate set is needed
     - Search for *join paths* (i.e. foreign keys) between the relations
     - If several join paths exist, use the one for which the estimated difference in size of an outer and an inner join is smallest, resulting in a minimum number of dangling tuples
     - If no join path exist, request the user to specify them
     - All potential candidate sets without a join path are removed
     - Result: *Candidate sets* for every target relation, representing different ways to obtain the values of the target relation
     - Each candidate set can be mapped to a Select-Project-Join(-Group-by-Aggregate) query

Clio Query Discovery – Algorithm (cont.)

3. Find sets of the candidate sets (*covers*) that contain every VC at least once
   - Determine a minimum cover, i.e., eliminate all covers from which candidate sets can be removed while still containing all VCs
   - Rank the remaining covers according to the inverse number of candidate sets they contain (less candidate sets means less queries)
   - For those with an equal number of candidate sets, choose those that have the largest number of target attributes in all candidate sets (i.e., minimize null values)
   - Present ranked covers as alternative mappings to the user
4. Create the query q for target relation T_k from the selected cover
   - For each candidate set c_i in the cover, create a candidate query q_i such that
     - All correspondence functions f_k mentioned in c_i appear in the SELECT clause
     - All source relations of the VCs in c_i appear in the FROM clause
     - All predicates p_i of the VCs in c_i appear in the WHERE clause
     - All source relations needed for join paths appear in the FROM clause and the join predicates appear in the WHERE clause
     - If c_i contains aggregate functions, all attributes not in the aggregate function are selected as grouping attributes. If the aggregate is in the correspondence function f_k, it is placed in the SELECT clause. If it is in a predicate, it is placed in a HAVING clause.
   - Combine all candidate queries q_i into q by the use of UNION ALL

Clio Query Discovery – Example



- Phase 1: Potential candidate sets

  c1 = {v1, v2, v3, v4}
  c2 = {v5, v6, v7}
  c3 = {v1, v6, v3, v7}
  c4 = {v5, v2, v3, v7}
  …

default for f_i is id, default for p_i is true

Clio Query Discovery – Example (cont.)

- Phase 2: Eliminate potential candidate sets that have no good query
  - e.g. c_3 and c_4 have no join paths, others are subsets
  - Only c_1 and c_2 remain
- Phase 3: Find all minimum cover (sets of candidate sets that contain all VCs)
  - ➔ $\{\{c_1, c_2\}\}$
- Phase 4: Create candidate querys and combined query:

q_1
```
SELECT Title, Year, Director, SUM(Pay)
FROM S1.Movie m, S1.Actor a
WHERE m.MovieID = a.MovieID
GROUP BY Title, Year, Director
HAVING SUM(Pay) >10M
```
```
UNION ALL
```
q_2
```
SELECT Title, Year, null, Budget
FROM S2.Film
WHERE genre <> "Documentary"
```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Data Integration

- Data Quality Problems
- Causes and Consequences
- Data Cleaning

Data Quality

- All approaches discussed so far only resolve heterogeneity regarding the schemas/metadata of the data sources
- Problems in the data itself remain to be resolved:
  - Erroneous data (values outside domain, violated constraints)
  - Data inconsistencies (Contradictions across and within a data source)
  - Duplicates (Are two tuples from different sources refering to the same real world object?)
  - Completeness (Does a data source deliver all data for a concept?)
  - Credibility (Is the source reliable, can the data be trusted?)
  - Timeliness (Is the data up-to-date?)
- Many problems are similar to those for schema integration
  - Synonyms, homonyms ~ semantic heterogeneity
    - Do the tables "Person" and "Pers" refer to the same concept? ≈
    - Do "Gottlieb-Daimler-Straße" and "Gottl.-Daiml.-Str" refer to the same object?
  - Considerable degree of uncertainty
  - Scale of the problem several orders of magnitude larger:
    - ~10^2-10^3 schema elements, but 10^2-10^9++ instances
    - Resolving data quality ("Data Cleaning") problems is extremely expensive
    - Today usually only done in replicating/materialized integration systems

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Classification of Data Quality Problems

- based on [RaDo00, LeNa07]

Data Quality Problems
- Single-source Problems
  - Schema Level
  - Instance Level
- Multi-source Problems
  - (Schema Level)
  - Instance Level

- Allocation of problems to categories is not always unambiguous
- Instance level multi-source problems were previously subsumed as syntactic heterogeneity
- Schema level multi-source problems were discussed in previous sections (forms of heterogeneity)

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Single-source schema level problems

- Lack of integrity constraints: data source cannot enforce application constraints that are not made explicit using the facilities of the data model
  - No unique constraints ➔ Duplicate values
  - No enforced referential integrity ➔ inconsistent references
  - Inadequate typing (e.g. String to represent dates) ➔ invalid values
  - Unspecified dependencies ➔ dependency violations
    - e.g. age = $today – birthdate
  - NOT NULL constraint omitted ➔ missing values
- Bad Schema Design
  - e.g., redundancies in schema caused by denormalization

  ➔ Inconsistencies due to insert/delete/update anomalies

Single-source data level problems (I)

- Typos (e.g. "Gremany")
  - can be resolved by spellcheckers or domain experts
- Dummy values to "outwit" constraints
  - e.g. ZIP code 99999 used for "unknown value"
  - "John Doe" for an unidentified person
  - often resolvable for domain experts, but dummy values often not used consistently
- Wrong values – value does not properly represent the real world
  - e.g. Movie(Title="Lord of the Rings", Year="1928")
- Deprecated values
  - e.g. Germany(Founded="1949", Chancelor="Gerhard Schröder")
- Cryptic values
  - encoded or abbreviated data values
- Embedded values
  - values embedded in other fields to compensate for missing fields
  - e.g. Movie(Title="Fight Club, 1999")
- Wrong allocation
  - correct value entered into wrong field/swapped values
  - e.g. Actor(Name="Tyler Durden", Role="Brad Pitt")

Single-source data level problems (II)

- Wrong reference
  - reference to an existing, but the wrong object
- Contradictory values
  - Address(City="Kaiserslautern", ZIP="12345")
  - Student(Name="Christian Meier", Gender="f")
- Transpositions
  - different sequences used for data items within a field
  - Person("Hans Meier"), Person ("Müller, Karl")
- Duplicates
  - two or more data records representing the same real world object
  - techniques for duplicate detection and resolution
  - a problem with many names: record matching, entity resolution, instance disambiguation
  - Data Conflicts
    - Duplicates contradict each other
    - Movie(Title="Lord of the Rings", Year="1978") vs. Movie(Title="Lord of the Rings", Year="2001")
    - How to separate two duplicates with a conflict from two correct entries?

Multi-source data level problems

- Differentiation is difficult – therefore, multi-source data level problems
  - are new kinds of problems that *typically* occur during integration of several source (but can also be present in a single source)
  - include many of the single-source data level problems, e.g. Transpositions, Duplicates when they occur after integration
- Contradictory values
  - data from different sources contradict each other (≠Conflict!)
  - e.g. Source1.Person(ID="1234", Age="47") vs.
    Source2.Person(ID="1234", DoB="1983-06-03")
- Differing representations
  - e.g. Source1.Emp(ID="1234", Job="Sales Mgr.") vs.
    Source2.Emp(ID="1234", Job="S24")
- Different physical units
  - e.g. Source1.Person(Name="Herbert Meier", height="183") [cm] vs.
    Source2.Person(Name="Herbert Meier", height="72") [inches]
- Different precision
  - e.g. Source1.Movie(Title="Fight Club", runtime="2h19min") vs.
    Source2.Movie(Title="Fight Club", runtime="2h19min12sec")
- Different levels of details
  - e.g. "all actors" vs. "only main cast"

Handling Data Quality Problems

- Phase 1: Data Scrubbing (individual records)
  - Resolve errors within individual tuples/data items
  - Normalise data
    - unify case, stemming, stopword removal, acronym expansion
    - Formating: unify date formats, person names ("H. Schmidt" vs. "Schmidt, H."), addresses
  - Conversions: convert numerical values to a single unit
    - simple for physical values (e.g.: length measures: conversion between m, cm, inch etc. is constant)
    - difficult for currencies! (which exchange rate to use? Today's? The rate at the (maybe unknown) insertion date?)
  - Remove outliers
    - test if data conforms to expectations (expressed as constraints, „sanity checks")
    - perform lookup in reference data (e.g., telephone directories)
  - Violated constraints
    - Test referential integrity

Handling Data Quality Problems (II)

- Phase 2: Entity Resolution
  - Resolve problems involving multiple records
  - Detect duplicate entries
    - Pairwise comparison of tuples, calculation of a similarity value
    - If similarity above threshold -> duplicate detected
    - False positives and negatives
    - Determine quality of duplicate detection using
      - precision (percentage of identified duplicates that are really duplicates)
      - recall (percentage of actual duplicates found)
    - Very expensive: $O(n^2)$ (possibly very complex) comparisons
    - Partition data and only compare tuples within a partion
  - Data Fusion
    - Combine detected duplicates into one consistent tuple
      - Equality – tuples agree on all attributes
      - Subsumption – a tuple t_1 subsumes tuple t_2, if it has less null values than t_2 and agrees with t_2 on all non-null values
      - Complementation – two tuples complement each other, if none subsumes the other and if for each non-null value of one tuple, the other tuple either has a null value or the tuples agree on the value
      - Conflict – all other situations represent a conflict, i.e., if two duplicate tuples do not agree on at least one attribute value
    - Subtlety of null value semantics (unknown, inapplicable, withheld …)

Data Cleaning – Summary

- Creation of data cleaning mappings requires human interaction
  - Tools can suggest reasonable mappings
- Many errors can not be resolved "in batch"
  - Either we decide for one source, possibly introducing errors and losing correct data
  - Or we do not make a decision and leave conflicting duplicates in the result
- Duplicate detection and resolution introduces uncertainties
- Actual validity of individual tuples cannot reasonably be checked for all kinds of data
  - Only limited availability of reference data for specific application concepts (e.g. addresses)

References (I)

- [BLN86] Batini, C.; Lenzerini, M. & Navathe, S.B.: A comparative analysis of methodologies for database schema integration *ACM Comput. Surv., ACM Press,* 1986, *18*, 323-364
- [CRF03] Cohen, W.W.; Ravikumar, P. & Fienberg, S.E.: A Comparison of String Distance Metrics for Name-Matching Tasks. *IIWeb,* 2003, 73-78
- [HeSt98] Hernandez, M.A. & Stolfo, S.J.: Real-world Data is Dirty: Data Cleansing and The Merge/Purge Problem Data Mining and Knowledge Discovery, 1998, 2, 9-37
- [FlWy05] Fletcher, G.H.L. & Wyss, C.M.: Relational data mapping in MIQIS *SIGMOD 2005, ACM Press*, 912-914
- [FlWy06] Fletcher, G.H.L. & Wyss, C.M.: Data Mapping as Search. EDBT, 2006, 95-111
- [GoDe07] Göres, J. & Dessloch, S.: Towards an Integrated Model for Data, Metadata, and Operations BTW 2007, to appear
- [Goe05b] Göres, J.: Towards Dynamic Information Integration First VLDB Workshop on Data Management in Grids (DMG05), Trondheim, 2005, 16-29
- [Goe05a] Göres, J.: Pattern-based Information Integration in Dynamic Environments 9th International Database Engineering Applications Symposium (IDEAS 2005), 125-134
- [GPZ01] Greco, S.; Pontieri, L. & Zumpano, E.: Integrating and Managing Conflicting Data PSI '02, Springer-Verlag, 2001, 349-362
- [LeNa07] Leser, U. & Naumann, F.: Informationsintegration *dpunkt Verlag,* 2007
- [LSS96] Lakshmanan, L.V.S.; Sadri, F. & Subramanian, I.N. Vijayaraman, T.M. SchemaSQL: A Language for Interoperability in Relational Multidatabase Systems VLDB 1996, 239-250

References (II)

- [LSS01] Lakshmanan, L.V.S.; Sadri, F. & Subramanian, S.N.
  SchemaSQL: An extension to SQL for multidatabase interoperability
  Database Systems, 2001*, 26*, 476-519
- [RaBe01] Rahm, E. & Bernstein, P.A.
  A survey of approaches to automatic schema matching
  VLDB Journal, 2001*, 10*, 334-350
- [RaDo00] Rahm, E. & Do, H.H.
  Data Cleaning: Problems and Current Approaches.
  IEEE Data Eng. Bull., 2000*, 23*, 3-13
- [PoBe03] Pottinger, R. & Bernstein, P.A.
  Merging Models Based on Given Correspondences.
  VLDB, 2003, 826-873
- [MBR01] Madhavan, J.; Bernstein, P.A. & Rahm, E.
  Generic Schema Matching with Cupid
  The VLDB Journal, 2001, 49-58
- [MGR02] Melnik, S.; Garcia-Molina, H. & Rahm, E.
  Similarity Flooding: A Versatile Graph Matching Algorithm and Its Application to Schema Matching.
  ICDE 2002, 117-128
- [MHH00] Miller, R.J.; Haas, L.M. & Hernández
  Schema Mapping as Query Discovery
  VLDB 2000, Morgan Kaufmann, 2000, 77-88
- [ScSa05] Schmitt, I. & Saake, G.
  A comprehensive database schema integration method based on the theory of formal concepts.
  Acta Inf., 2005*, 41*, 475-524
- [WyRo05] Wyss, C.M. & Robertson, E.L.
  Relational languages for metadata integration
  ACM Trans. Database Syst., ACM Press, 2005*, 30*, 624-660
- [WyRo05b] Wyss, C.M. & Robertson, E.L.
  A formal characterization of PIVOT/UNPIVOT
  CIKM 2005, ACM Press, 602-608