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Chapter 4
Information Integration

Outline

- Information Integration Tasks
- Schema Matching
  - Classification of Approaches
  - Example: Cupid
- Schema Merging
  - Example: Rondo
- Integration Planning
  - Example: Clio
- Deployment
  - Example: Orchid
  - Incremental loading of DW
- Data Integration
  - Data Quality Problems
  - Causes and Consequences
  - Data Cleaning Approaches

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)
  - Multi-database languages (schematic heterogeneity, technical heterogeneity, distribution)
  - SQL/XML (data model heterogeneity)
  - 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)
  - Data Cleaning/Fusion (syntactic heterogeneity, semantic heterogeneity (in data))
  - ⇨ focus on integration planning

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
  8. Deployment/Integration Plan Implementation

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)

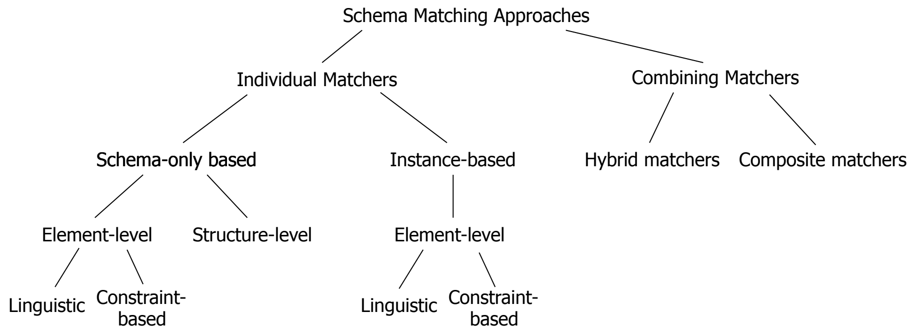
Schema Matching – Terminology Disambiguation

- 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

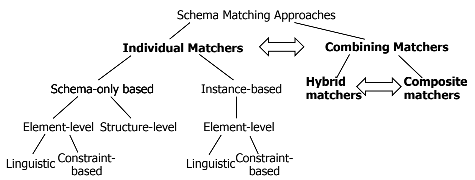
Schema Matching – Classification of Approaches



based on [RaBe01]

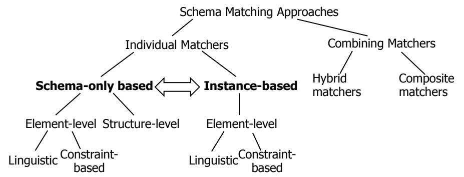
Individual vs. Combining Matchers

- 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

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

    - 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):

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

    - 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

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

- 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"

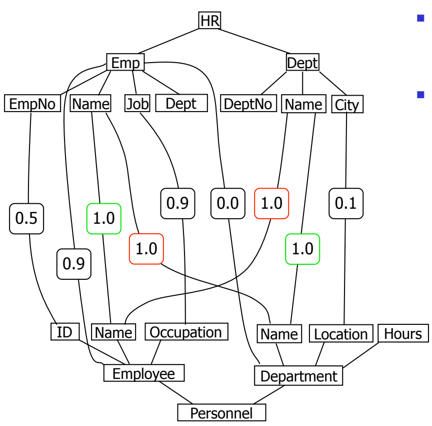
Cupid Linguistic Matching (cont.)

- 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

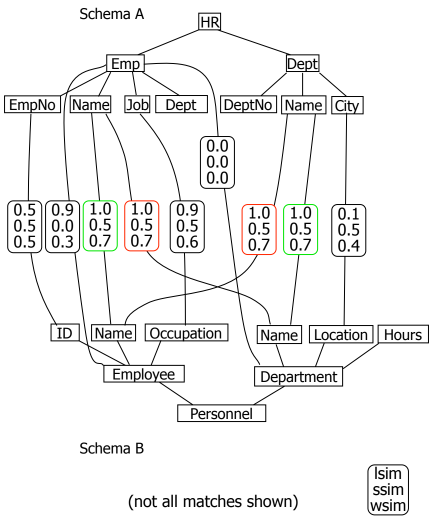
Cupid Structural Matching

- 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 weighted similarity (see next chart)

Cupid Structural Matching (cont.)

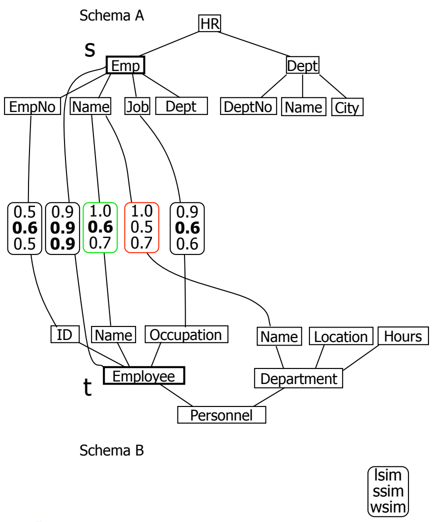
- Iterate over the tree nodes in post-order (bottom-up calculation)
- For each pair s,t:
  - Calculate ssim(s,t) as the fraction of leaves in the two subtrees below s and t that have at least one stronglink to a leaf in the other subtree
  - Calculate a weighted similarity measure wsim(s,t):
    $wsim(s,t) = w_{struct} \cdot ssim(s,t) + (1-w_{struct}) \cdot lsim(s,t)$
  - 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)

Cupid Structural Matching – Example



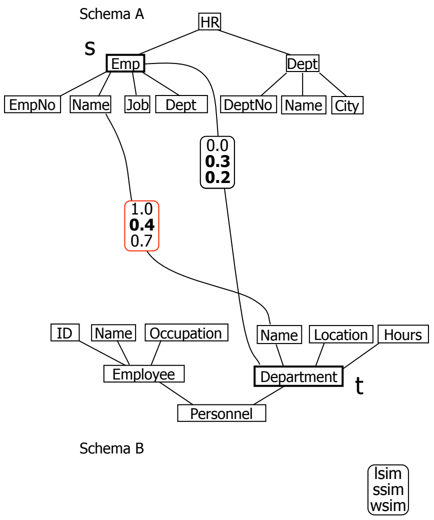
- Initialization:
  - ssim set to 0.0 for all non-leaf nodes
  - ssim set to data type similarity for leaves
- Parameters:
  - $th_{accept} = 0.5$
  - $w_{struct} = 0.7$
  - $th_{high} = 0.7$, $c_{inc} = 1.2$
  - $th_{low} = 0.3$, $c_{dec} = 0.8$

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
    $ssim(s,t) = 6/7 \approx 0.9$
  - 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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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

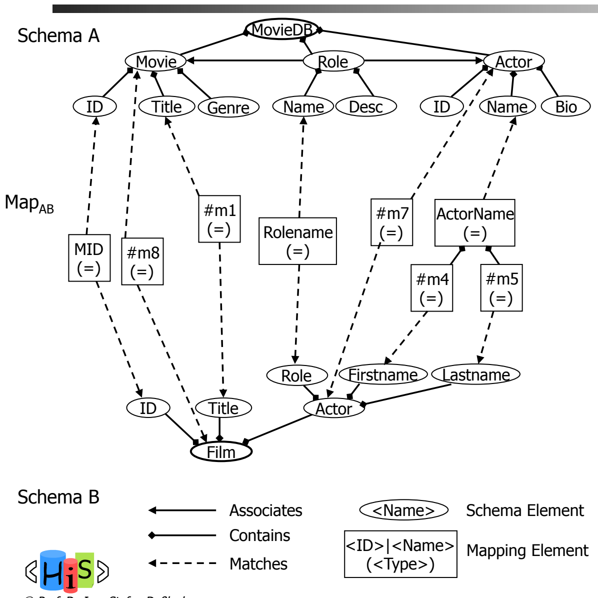
Rondo Merge Operator Requirements

- 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

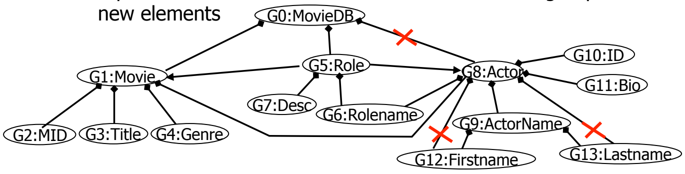


Groups:

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.)

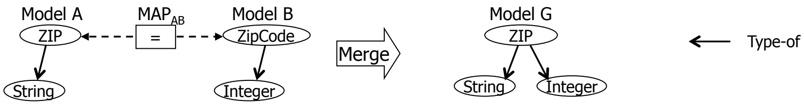
- Merge(A,B, Map_{AB}) with A as the preferred schema
  - One element for each group
  - replicate all associations between members of the groups as associations between the new elements



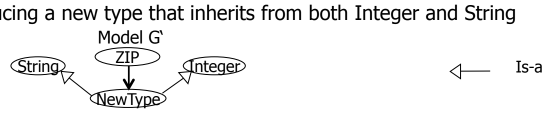
- Remove implied relationships to obtain minimum coverage of associations

Conflict resolution

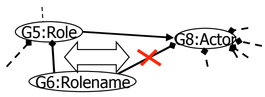
- Fundamental conflicts (shared across all metamodels)
  - e.g. One-type restriction violated



  - 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]

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: $dom(A_1) \times dom(A_2) \times \ldots dom(A_q) \rightarrow dom(B)$
    - a *filter* p_i indicating which source values should be used:
      p_i: $dom(A_1) \times dom(A_2) \times \ldots dom(A_r) \rightarrow boolean$
  - 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

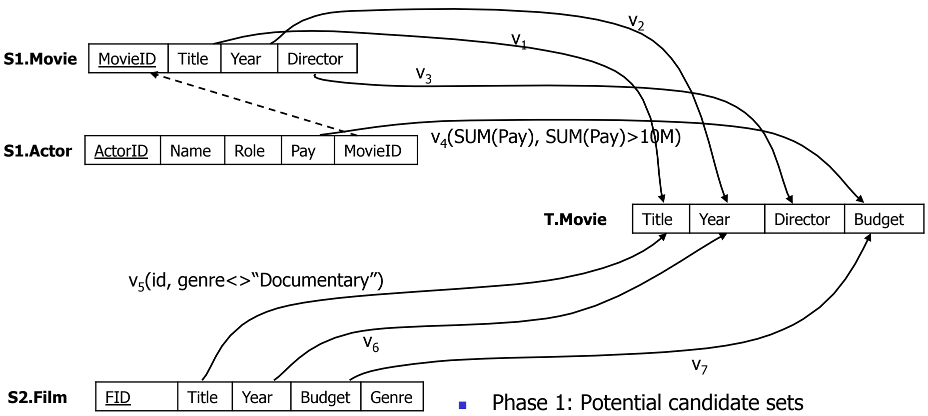
Clio Query Discovery – Algorithm

- 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 paths 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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Deployment

Information Integration Middleware

- Multitude of middleware systems and architectures
  - Major approaches:
    - logical (virtual) integration
      - federated DBMS, multi-database systems
      - data processing specified using SQL, XQuery, …
    - physical (materialized) integration
      - data replication, data warehousing, ETL (extract-transform-load), XML transformations, message brokering
      - utilizes ETL "scripts" based on (product-specific) dataset processing operators
- Technologies
  - differ in terms of
    - functional properties (data processing specification, expressive power)
    - non-functional properties (target response times, data currency)
  - are often used in combination, involving several product platforms
- Complex development /deployment tasks!

  No common language for platform-independent integration plan!

An Abstract Data Set Processing Model

- Idea: provide a generic model for describing data set processing
  - abstract data set model
    - structural properties (schema): flat & nested relations, XML
    - data access properties: associative vs. sequential, persistent vs. transient, sorting/grouping properties, update properties …
    - should also cover data streams, XML feeds
  - abstract processing model
    - platform-independent data processing operators
    - starting point: extended relational algebra
    - should also cover XML processing, data cleansing operations, propagation of source updates
    - used to specify an integration plan in a platform-independent manner

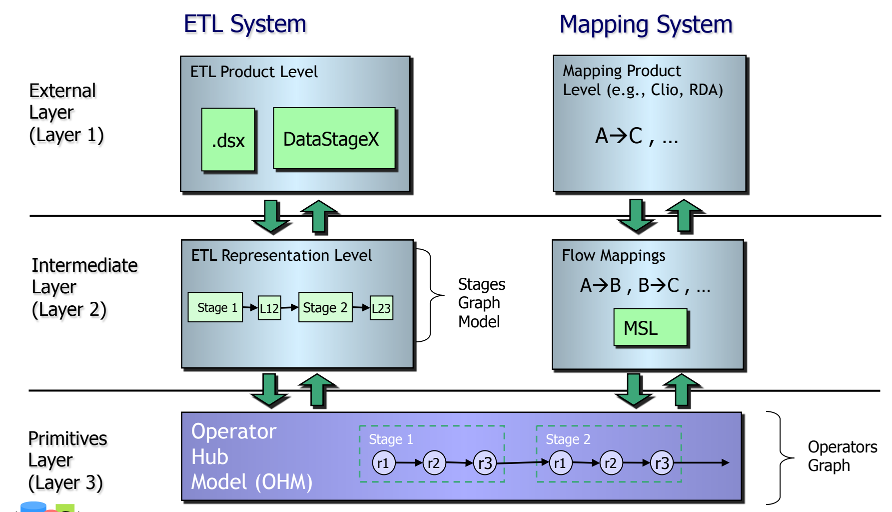
Major Advantages

- Modeling, visualizing, and reasoning about data processing independent of a deployment platform
- Top-down development
  - choice of platform often based on non-functional requirements
    - suggested by system, or determined by user
  - automatic generation of target platform artifacts during deployment
    - ETL scripts, queries and view definitions, replication setup, …
    - initial load vs. incremental load (considering updates, insertions, deletions on data sources)
- Optimization opportunities
  - logical (algebraic) optimization
  - choice of deployment platform(s) for operator subgraphs
    - e.g., push part of processing into the DBMS at the source or target
  - platform-dependent optimization
    - e.g., chose the most suitable ETL operator
- Active area of research

Orchid

- Research project at IBM Almaden [HDWRZ08]
- Links different phases, levels of abstraction in information integration
  - Mappings, mapping interpretations (→ Clio)
  - Abstract data set processing model (OHM – Operator Hub Model)
  - Deployment platforms
    - main focus initially on ETL
- In parts already reflected in IBM products
  - IBM Information Server v8.0.1

Orchid Architecture



OHM Operators

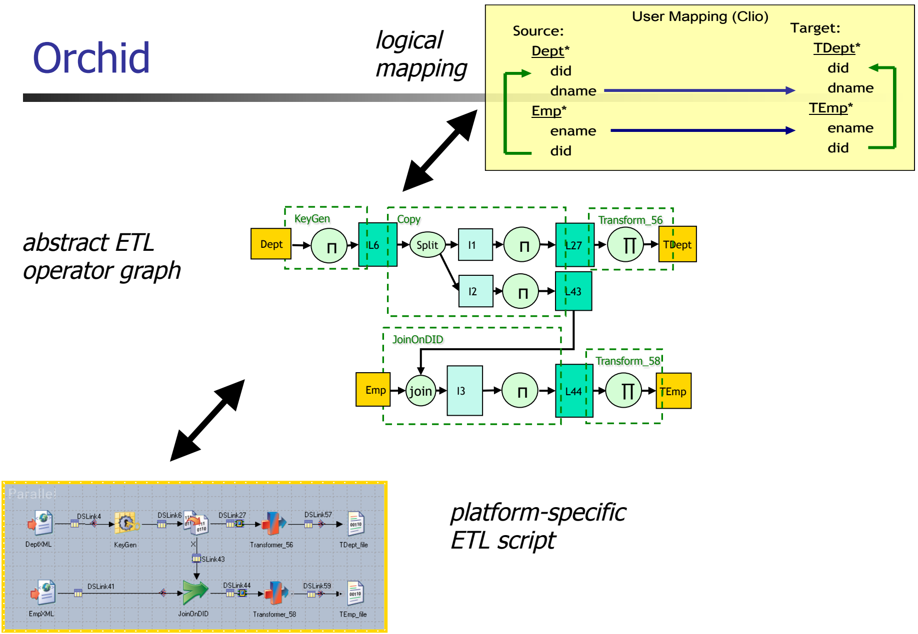
- Based on Relational Algebra operators
  - Initial focus was relational data transformation
  - Simple and well-known semantics (30+ years of history)
  - Plenty of well-known query graph representations, query optimizations, query rewrite techniques.
- Main OHM operators:

FILTER	JOIN	UNION	SPLIT
PROJECT	UNNEST		GROUP

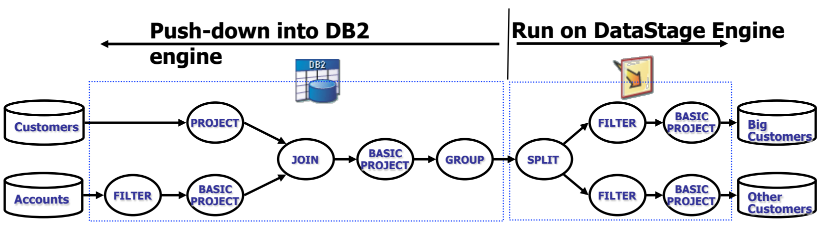
BASIC PROJECT	KEYGEN
COLUMN SPLIT	COLUMN MERGE

NEST

Orchid

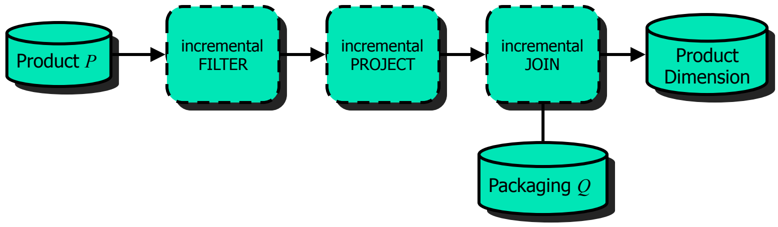


Deployment: Multiple-runtime deployment



- OHM plan can be deployed into multiple runtimes
  - Optimization is an issue

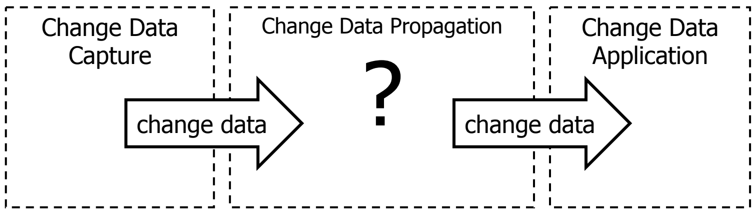
Supporting Incremental Loading [JoDe08]



- OHM instance as starting point
- Replace basic OHM operators with *incremental* variants
- Incremental operators are composed of basic OHM operators
- Leverage Orchid's optimization and deployment facilities

Change Data Propagation

- Interface between Change Data Capture and Change Data Application
- Given CDC limitations, what CDA requirements are satisfiable?
- Given CDA requirements, what CDC limitations are acceptable?
- What data transformations are to be performed for change data propagation?



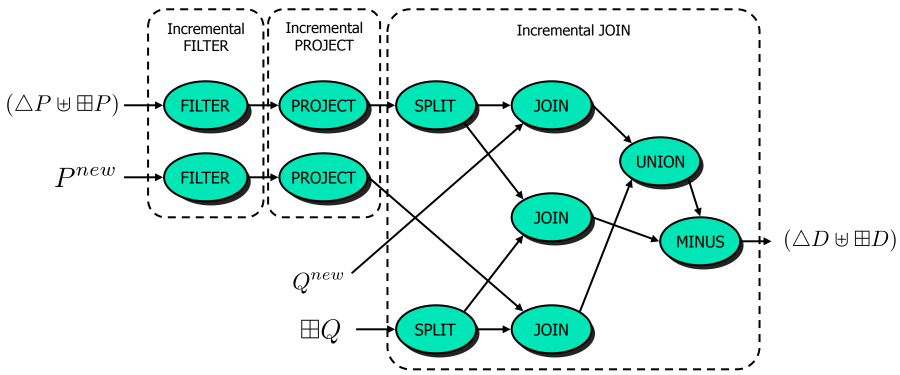
Change Data Model

- Given dataset D
  change data is $(\triangle D, \triangledown D, \boxplus D, \boxminus D)$
  - $\triangle D$ denotes insertions
  - $\triangledown D$ denotes deletions
  - $\boxplus D$ denotes updates (current state)
  - $\boxminus D$ denotes updates (initial state)

- CDC limitations
- *Partial* change data results from CDC limitations
- Missing change data
- Indistinguishable changes

- Audit columns: $(\triangle D \cup \boxplus D)$ or $\triangle D, \boxplus D$
- Snapshot differentials: $\triangle D, \triangledown D, \boxplus D$
- Log-based CDC: $\triangle D, \triangledown D, \boxplus D, \boxminus D$

Incremental OHM Instance



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Summary - Deployment

- Challenge: complexity of implementing an integration solution
  - approaches: virtual vs. materialized – or combinations thereof
  - different middleware platforms
  - complex to use
  - no common language for platform-independent integration plans
- Goal: support an abstract data and transformation model
  - platform-independent, top-down development
  - (cross-platform) optimization
- Orchid
  - Links mapping tools and transformation (ETL) platforms using operator hub model, OHM
  - Generates ETL scripts from mapping specifications (and vice versa)
  - Can deploy to combination of multiple platforms (e.g., DBMS pushdown + ETL)
- Incremental operators
  - Model for (partial) change data
  - Generation of incremental load processes based on
    - CDC limitations , CDA requirements, Source properties and schema constraints
  - Leverage Orchid's deployment facility

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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

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)

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)

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