UNIVERSITY OF MANNHEIM

Web Data Integration

Schema Mapping and Data Translation

The Data Integration Process

Data Collection

Schema Mapping
Data Translation

Identity Resolution

Data Quality Assessment
Data Fusion

Outline

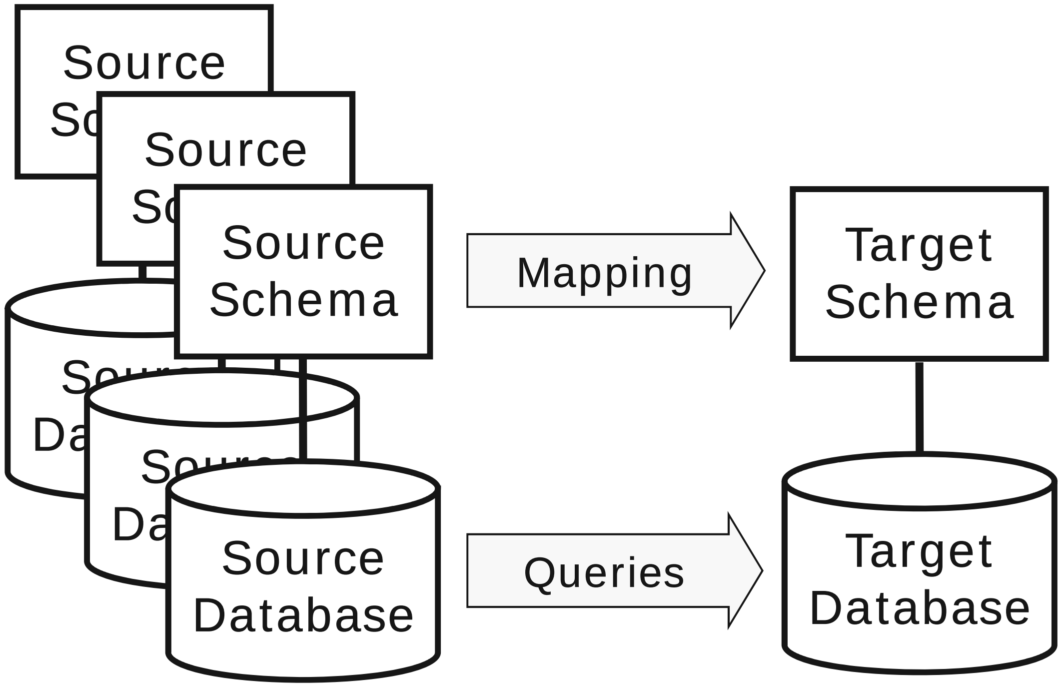
1. Two Basic Integration Situations
2. Correspondences
3. Schema Integration
4. Data Translation
5. Schema Matching
6. Schema Heterogeneity on the Web
7. References

Basic Integration Situation 1: Schema Mapping

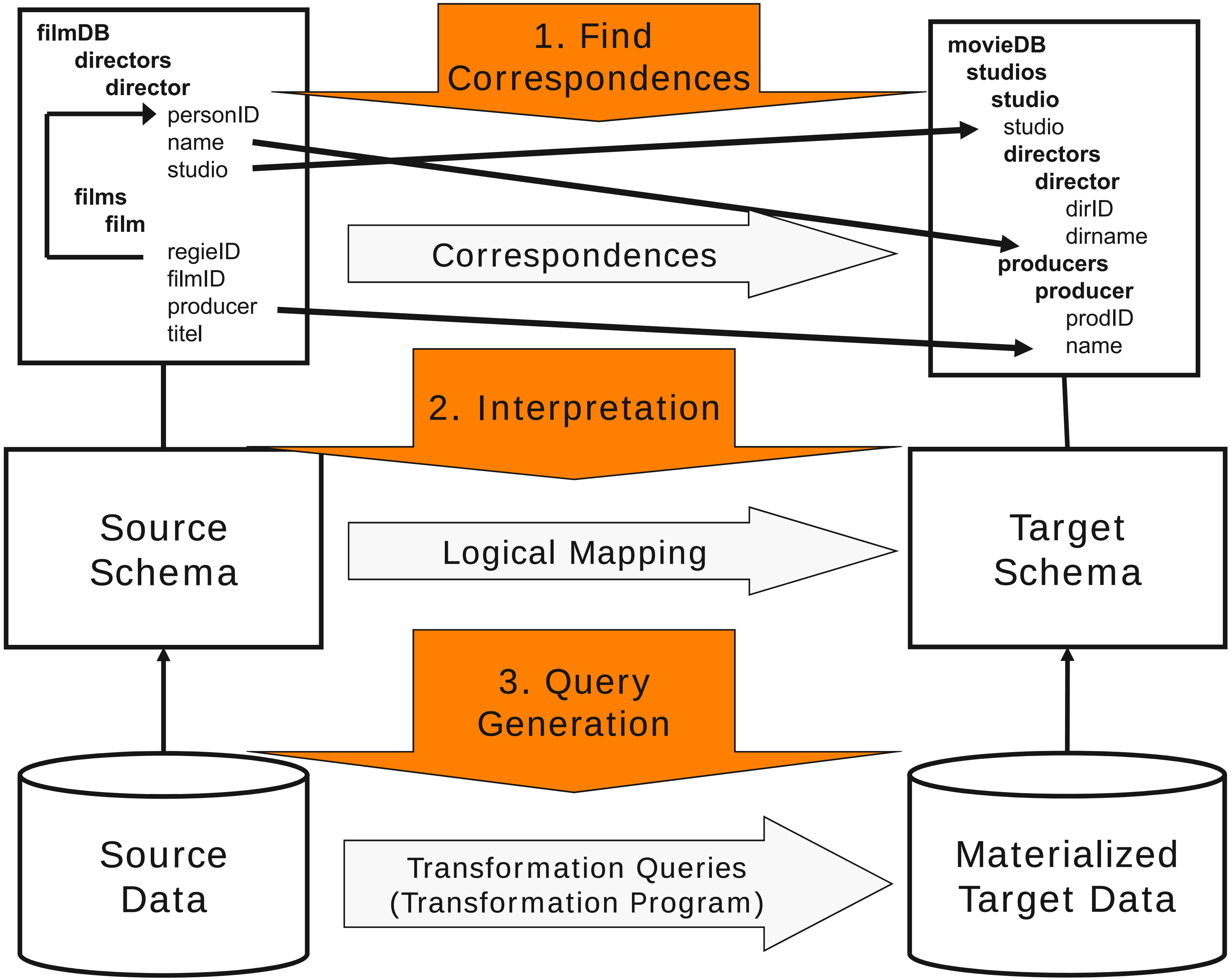
Goal: Translate data from a set of source schemata into a given target schema.

– Top-down integration situation

– Triggered by concrete information need (= target schema)



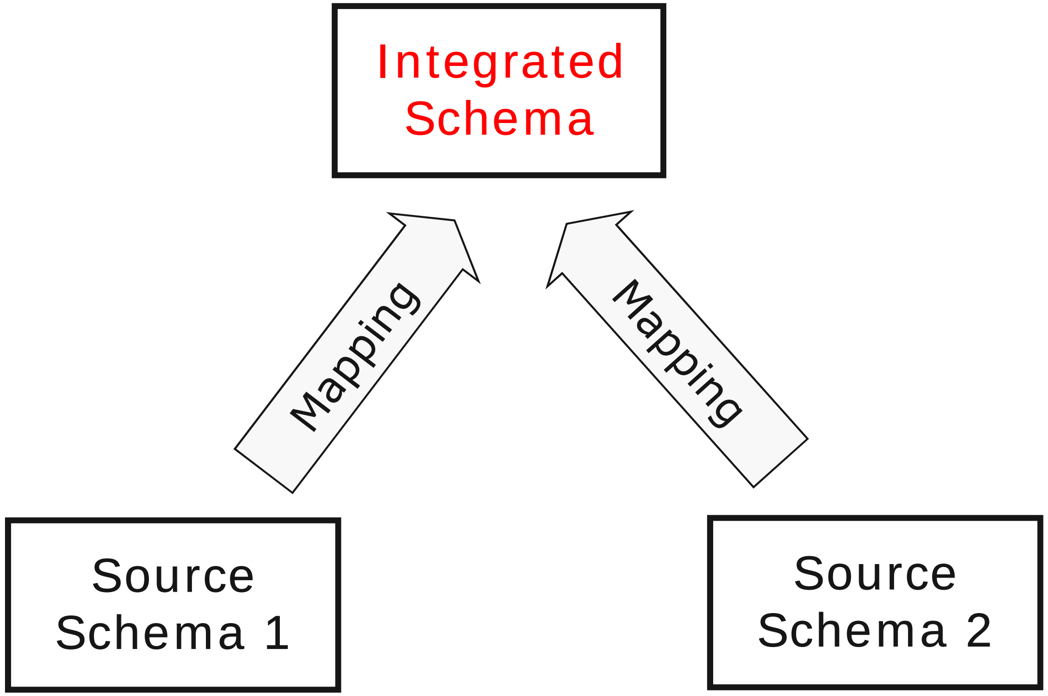
The Schema Mapping Process



Basic Integration Situation 2: Schema Integration

Goal: Create a new integrated schema that can represent all data from a given set of source schemata.

- Bottom-up integration situation
- Triggered by the goal to fulfill different information needs based on data from all sources.



2. Correspondences

A correspondence relates a set of elements in a schema S to a set of elements in schema T.

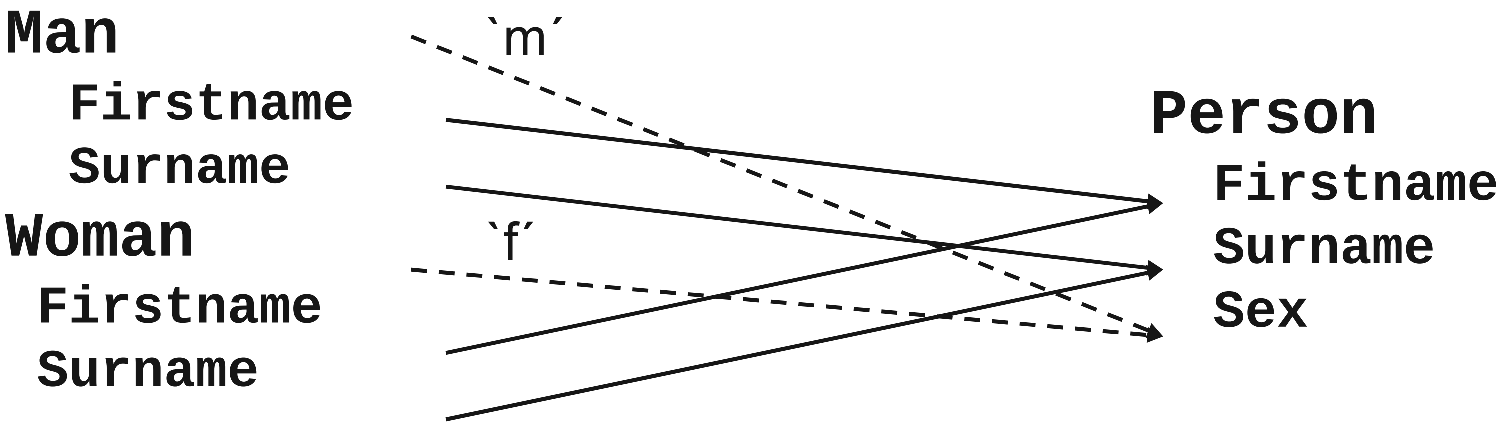
- Mapping = Set of all correspondences that relate S and T
- Correspondences are easier to specify than transformation queries
  - domain expert does not need technical knowledge about query language
  - specification can be supported by user interface
  - step-by-step process with separate local decisions
- Correspondences can be annotated with transformation functions
  - normalize units of measurement (€ to US$, cm and km to meters)
  - calculate or aggregate values (salary * 12 = yearly salary)
  - cast attribute data types (integer to real)
  - translate values using a translation table (area code to city name)

Types of Correspondences

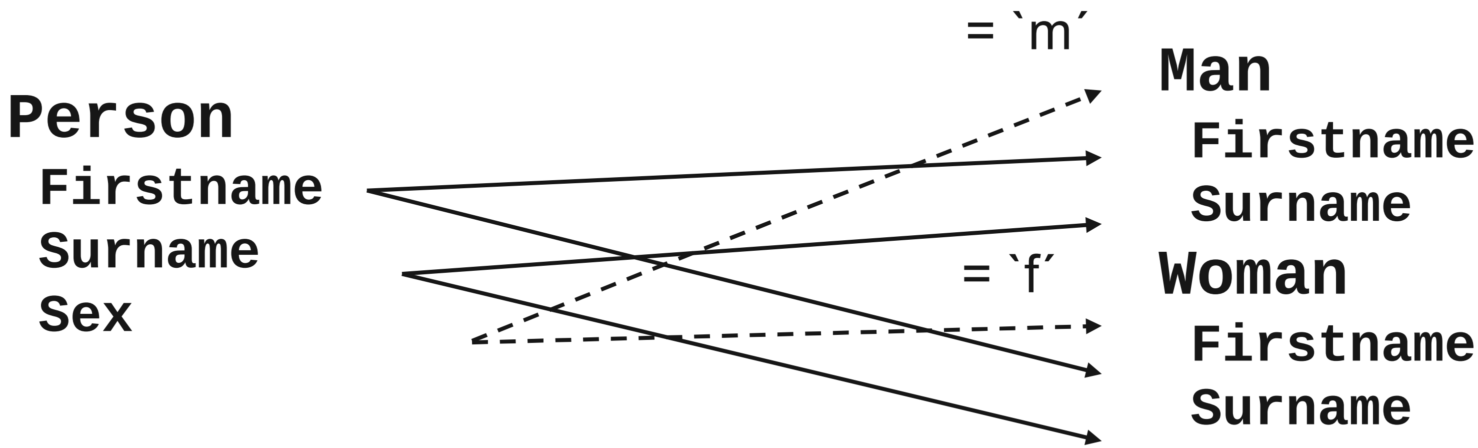
- One-to-One Correspondences
  - Movie.title → Item.name
  - Product.rating → Item.classification
  - Movie ≡ Film (equivalence: Same semantic intention)
  - Athlete ⊆ Person (inclusion: All athletes are also persons)
- One-to-Many Correspondences
  - Person.Name → split() → FirstName (Token 1)
→ Surname (Token 2)
- Many-to-One Correspondences
  - Product.basePrice * (1 + Location.taxRate) → Item.price
- Higher-Order Correspondences
  - relate different types of data model elements
  - for example: Relations (classes) and attributes, see next slide

Examples of Higher-Order Correspondences

Relation-to-Value Correspondences



Value-to-Relation Correspondences



Types of Schema Heterogeneity that can be Captured

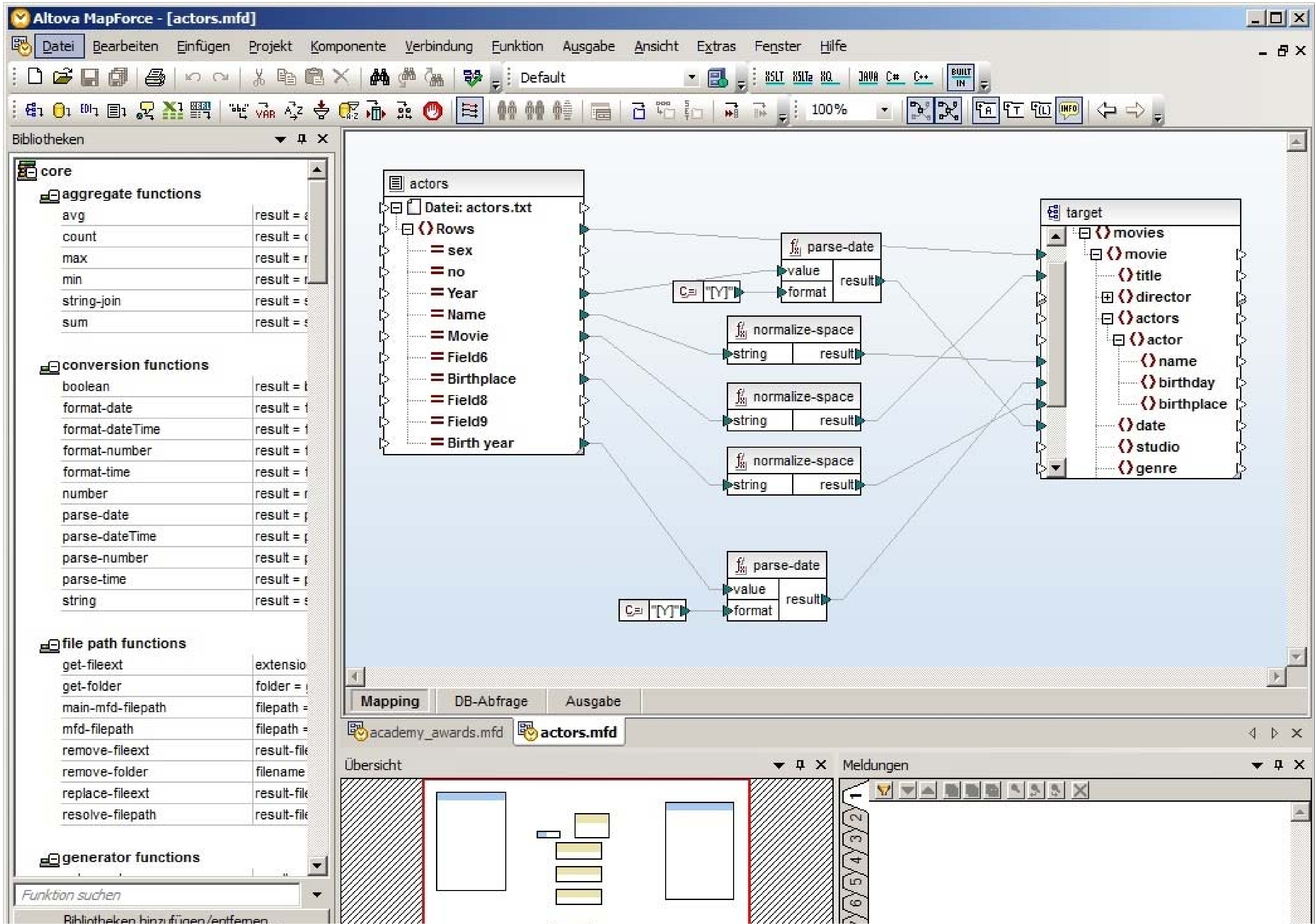
- Naming of
  - Relations
  - Attributes
- Normalized vs. Denormalized
- Nesting vs. Foreign Keys

1:1, 1:n, n:1 Correspondences

- Alternative Modelling
  - Relation vs. Value
  - Relation vs. Attribute
  - Attribute vs. Value

Higher-order Correspondences

Defining Correspondences



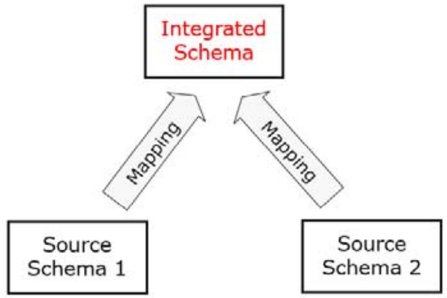
Schema Matching

Schema Matching: Automatically or semi-automatically discover correspondences between schemata.

- Various schema matching methods exist (we will cover them later)
- Automatically finding a complete high-quality mapping is not possible in most real-world cases. Halevy: „It‘s plain hard.“ :-(
- In practice, schema matching is used to create candidate correspondences that are verified by domain experts afterwards
- Realistic goal: Reduce the effort required from domain experts

3. Schema Integration

Create a new integrated schema that can represent all data from a given set of source schemata.



– Goals:
  - Completeness: All elements of the source schemata should be covered
    - not always necessary
  - Correctness: All data should be represented semantically correct
    - cardinalities, integrity constraints, …
  - Minimality: The integrated schema should be minimal in respect to the number of relations and attributes
    - redundancy-free
  - Understandability: The schema should be easy to understand

– Various schema integration „procedures“ have been proposed in literature (see Leser/Naumann, Chapter 5.6)

Schema Integration Steps

1. Pre-Integration
   - Convert sources into single data model (relational, XML, RDF, object-oriented)
   - If more than two schemata, decide in which order to integrate the schemata
2. Schema Comparison
   - Find correspondences (manually or using schema matching)
   - Identity conflicts (normalization, nesting, relation vs. attribute vs. value, …)
3. Schema Normalization
   - Change structure of individual schemata in order to resolve conflicts (normalization, nesting, relation vs. attribute vs. value, …)
4. Schema Fusion
   - Generate integrated schema that can represent all data
     - Merge equivalent relations and attributes
     - Add relations and attributes that only exist in a single schema to integrated schema

Example of a Schema Integration Method

- Spaccapietra, et al.: Model Independent Assertions for Integration of Heterogeneous Schemas. VLDB 1992
- Input
  1. Two source schemata in Generic Data Model
     - classes, attributes, and relationships
     - similar to Entity Relationship Model
  2. Correspondence Assertions
     - correspondences between classes, attributes, and relationships
     - correspondences between paths of relationships
- Output: Integrated Schema

Integration Rules

Include into the target schema S:

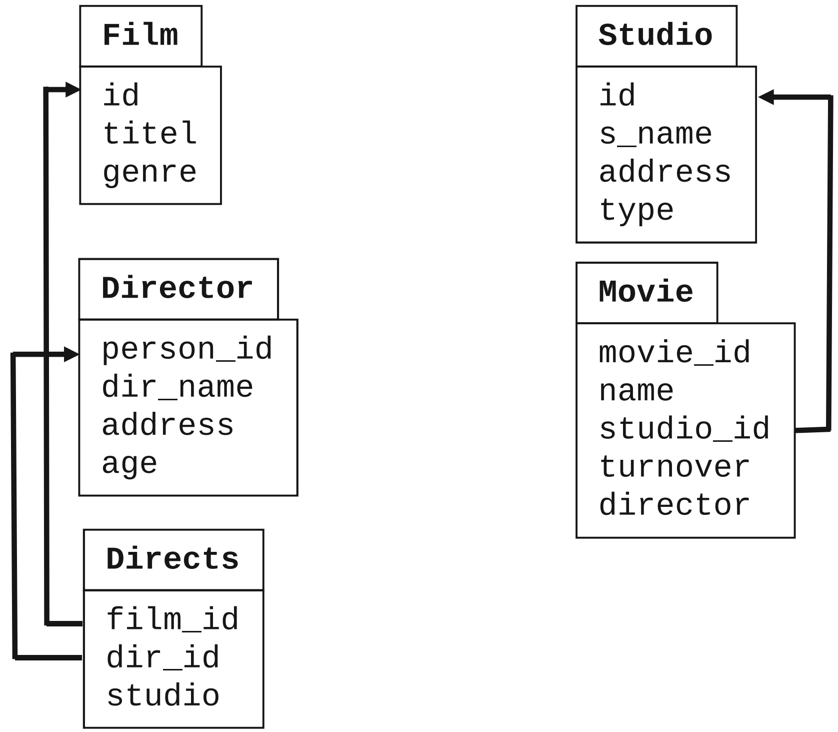
1. Classes with their attributes that are not part of any class-class correspondence (classes without direct equivalent)
2. Equivalent classes and merge their attribute sets
   - Pick class / attribute names of your choice for equivalent classes / attributes
3. Direct relationships between equivalent classes
   - If $A \equiv A'$, $B \equiv B'$, $A\text{-}B \equiv A'\text{-}B'$ then include A-B
4. Paths between equivalent attributes and classes
   a) If $A \equiv A'$, $B \equiv B'$, $A\text{-}B \equiv A'\text{-}A_1'\text{-}\ldots\text{-}A_m'\text{-}B'$ then include the longer path
      - as the length one path is subsumed by the longer path
      - as the longer one is more expressive with respect to cardinality

   b) If $A \equiv A'$, $B \equiv B'$, $A\text{-}A_1\text{-}\ldots\text{-}A_n\text{-}B \equiv A'\text{-}A_1'\text{-}\ldots\text{-}A_m'\text{-}B'$ then include both paths
      - as they represent different relationships to B
5. Equivalences between classes and attributes are included as relationships
   - again, prefer more expressive solution with respect to cardinality

Example: Two Schemata about Films

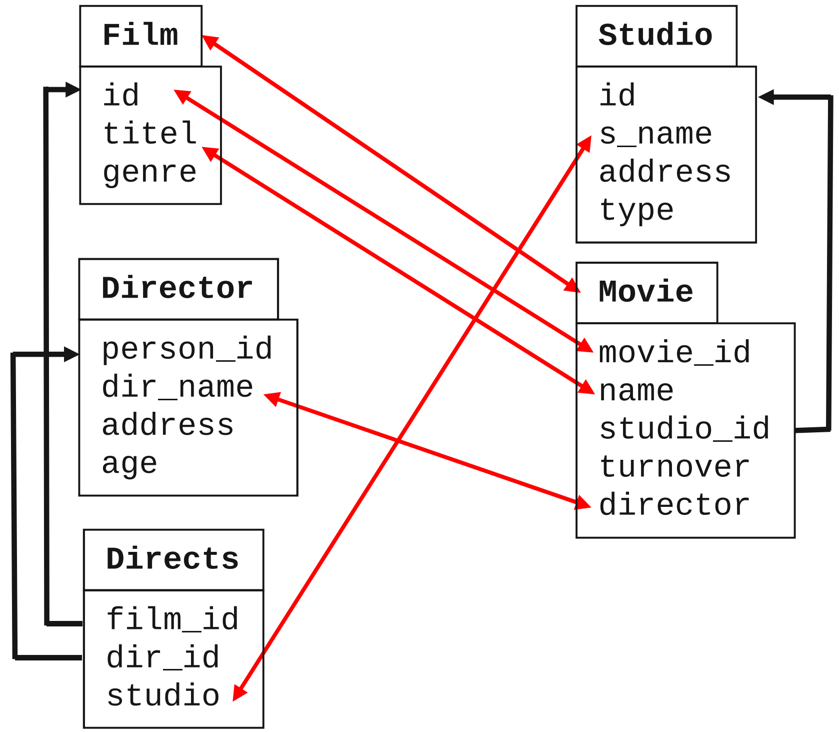
Different focus and level of detail

- Schema 1: Who are the directors of a movie?
- Schema 2: What are the details about the studio in which the movie was shot?



Example: Class and Attribute Correspondences

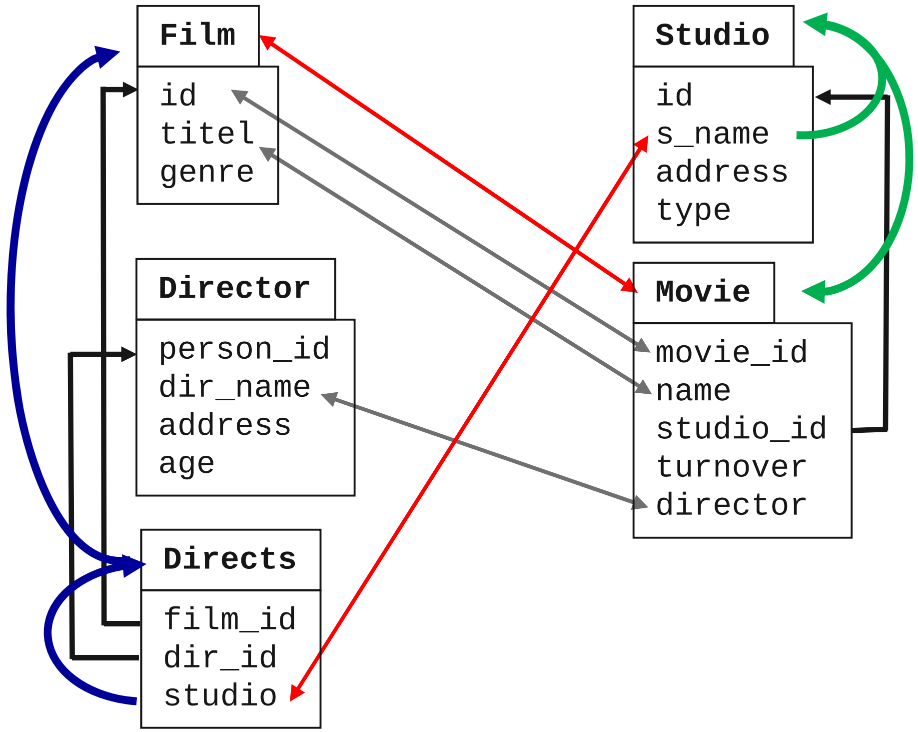
- Film ≡ Movie
  - id ≡ movie_id
  - titel ≡ name
- dir_name ≡ director
- studio ≡ s_name



Example: Relationship Path Correspondence 1

- studio-Directs-Film ≡ s_name-Studio–Movie

- Film ≡ Movie
- studio ≡ s_name

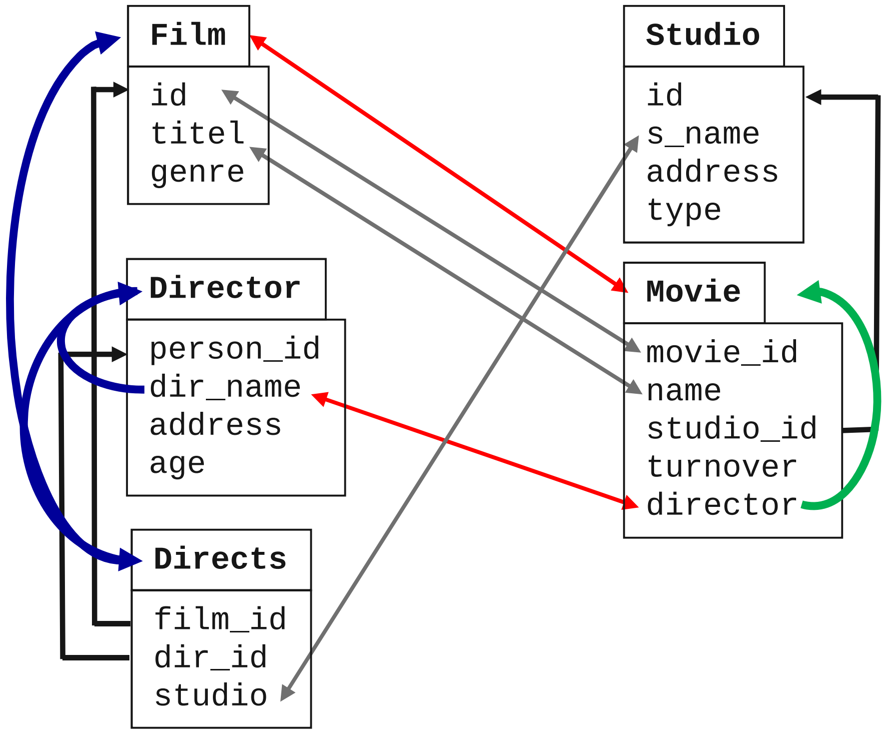


Example: Relationship Path Correspondence 2

– dir_name-Director-Directs-Film ≡ director-Movie

– Film ≡ Movie

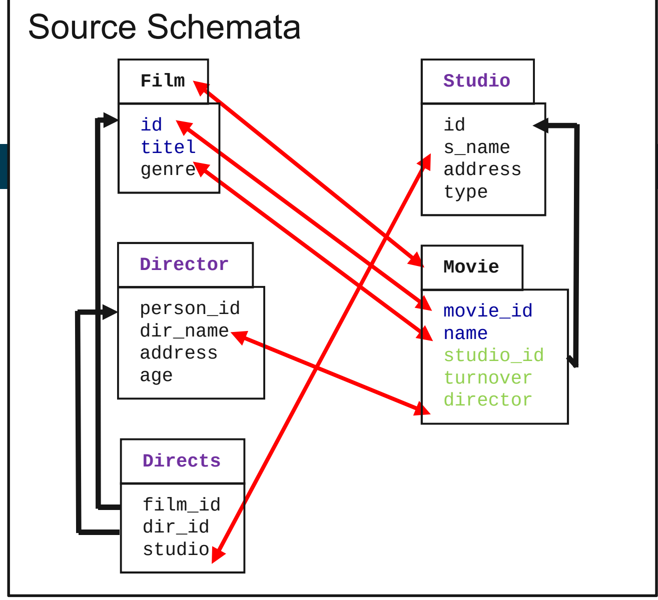
– dir_name ≡ director

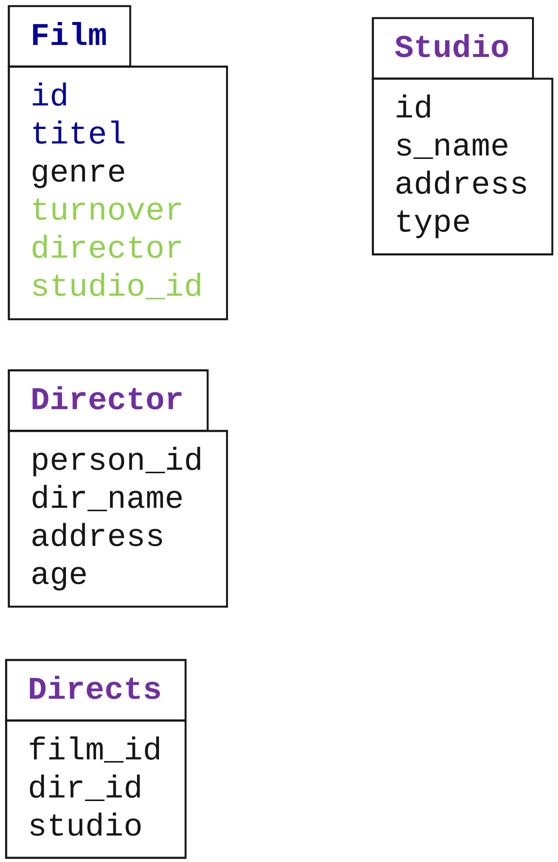


Creation of the Integrated Schema 1

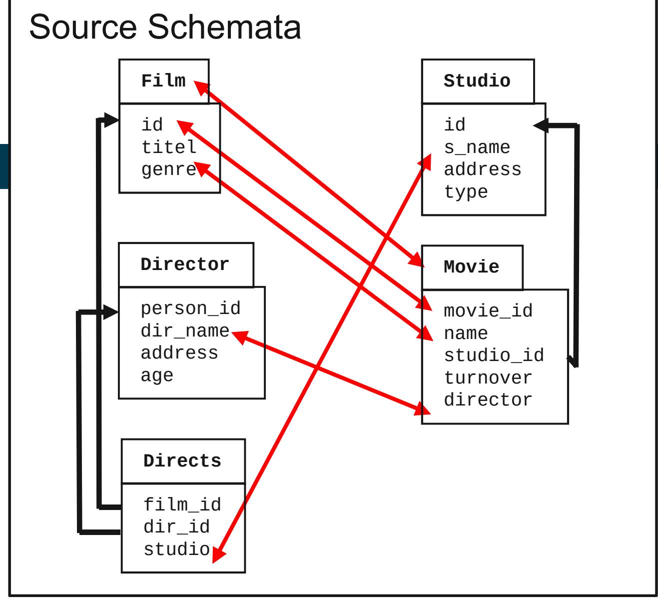
– Correspondences
  - **Film ≡ Movie**
    - **id ≡ movie_id**
    - **titel ≡ name**

– Integration Steps
  1. Rule 2: Equivalent classes **Film** and **Movie** are merged to **Film**. Attributes are either merged (**id, title**) or simply copied (**turnover, director, studio_id**).
  2. Rule 1: Classes without direct equivalent are included into the integrated schema (**Director, Directs, Studio**)

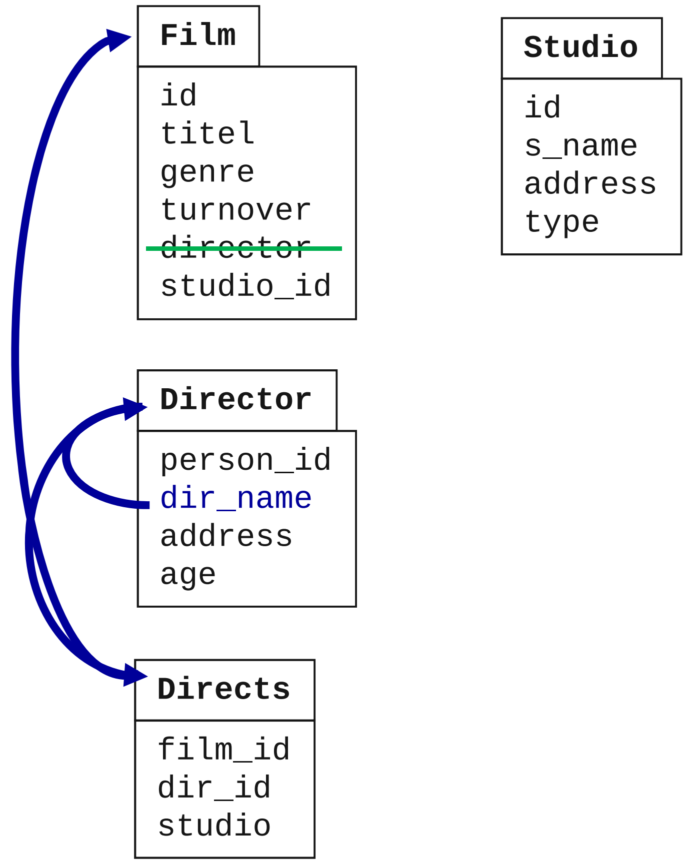




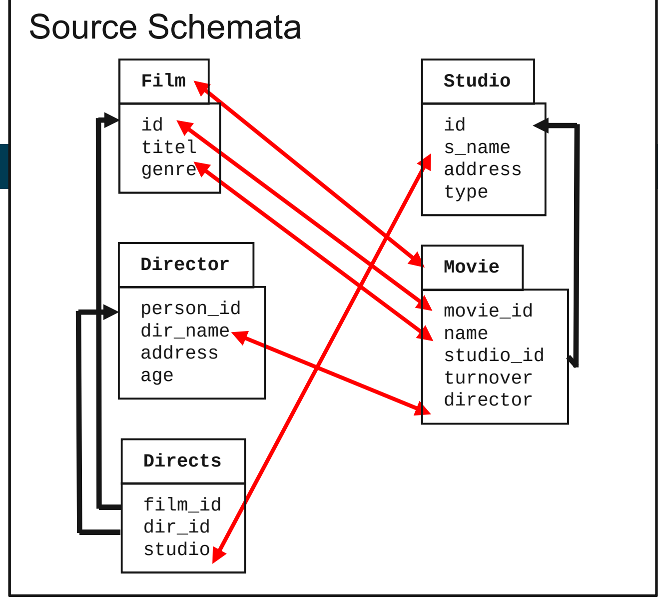
Creation of the Integrated Schema 2



- Correspondence
  - **dir_name–Director–Directs–Film** ≡ **director-Movie**
- Integration Steps
  3. Rule 4a: The path **dir_name–Director–Directs–Film** is included. The path **director-Movie** is left out as it is less expressive (allows only one director per movie)
  4. Thus, **dir_name** is kept and **director** removed.

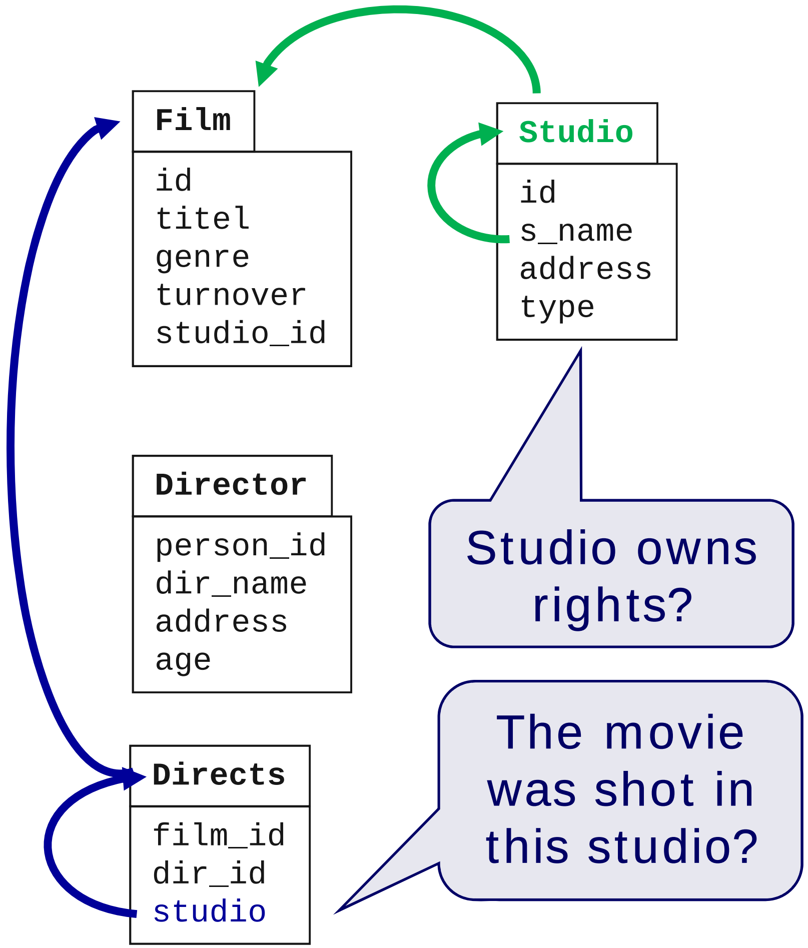


Creation of the Integrated Schema 3



– Correspondence
  - studio-Directs-Film ≡ s_name-Studio–Movie

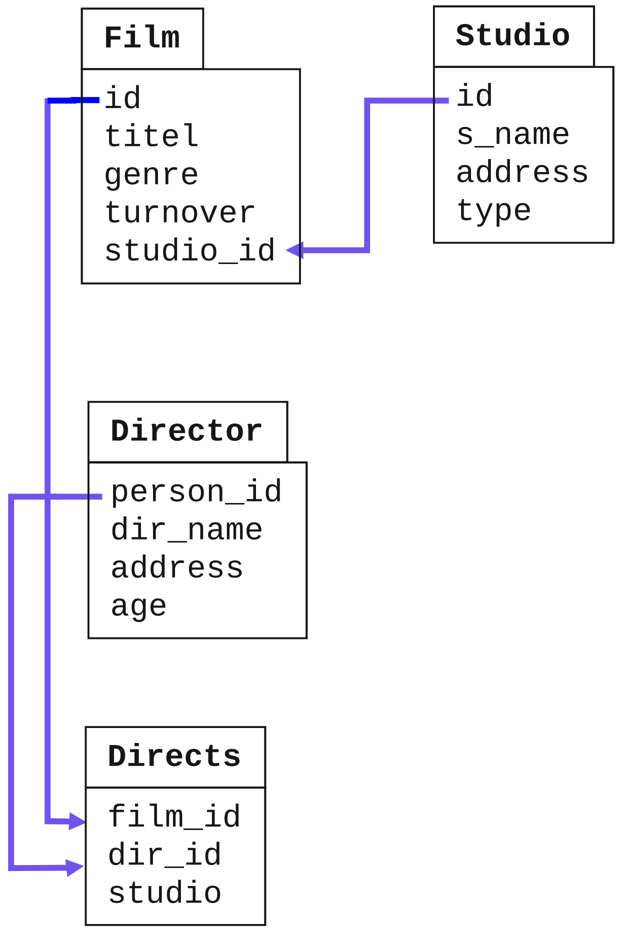
– Integration Step
  5. Rule 4b: Both paths are included.
     - **Studio** and **studio** are not merged as they have a different relationship to the surrounding classes and might thus mean different things.



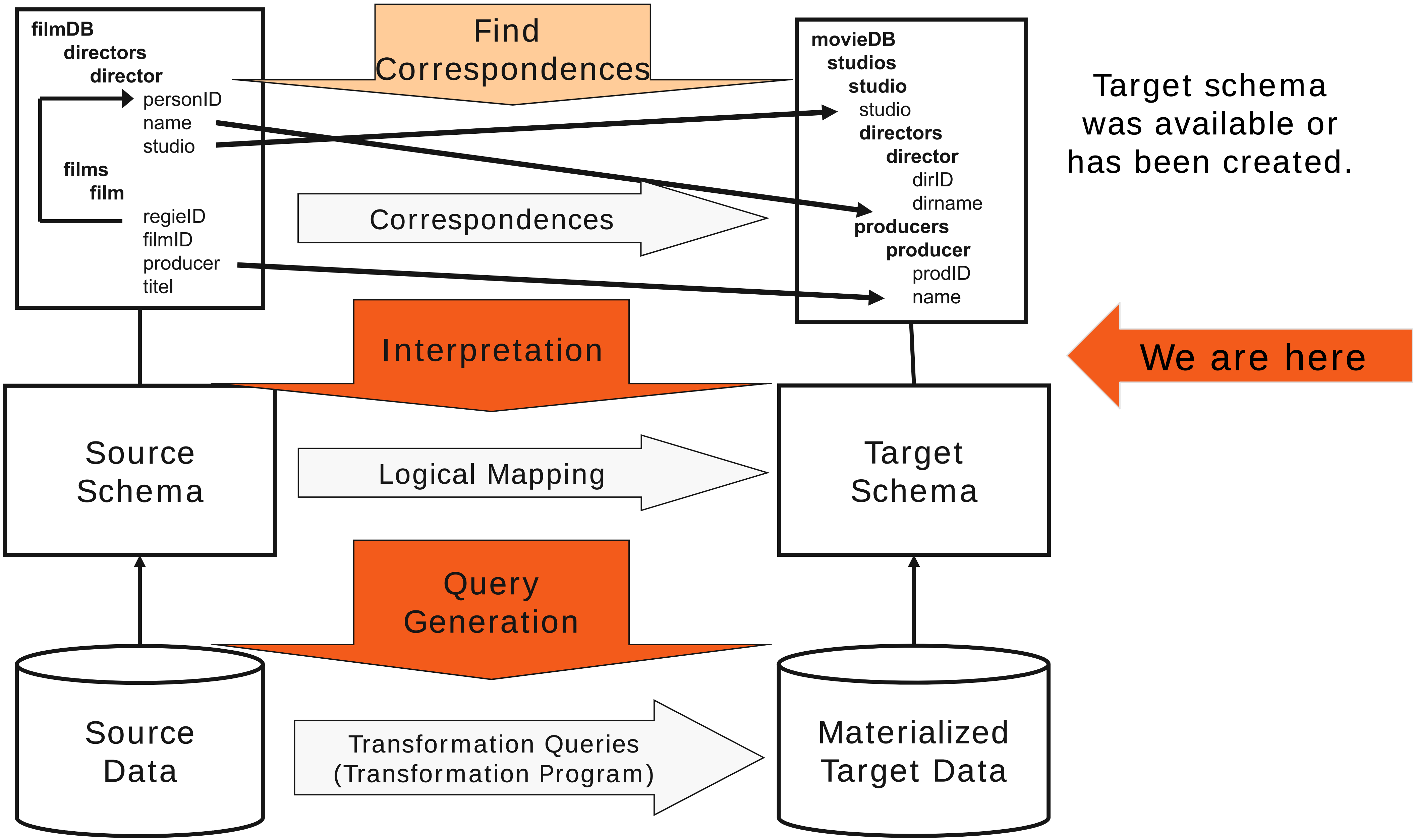
Final Integrated Schema

- Schema Integration Goals
  - Completeness: All elements of the source schemata covered
  - Correctness: All data can be represented semantically correct
  - Minimality: The integrated schema is minimal in respect to the number of relations and attributes
  - Understandability: The schema is easy to understand

- Schema Integration Rules of Thumb
  1. Merge all classes with equivalent classes in other schema (Film)
  2. Add all classes without equivalent (other classes)
  3. Add relationships with highest cardinality in order to be expressive (multiple directors per film)



4. Data Translation



Target schema was available or has been created.

Interpretation and Query Generation

Goal: Interpret correspondences in order to generate suitable data translation queries (or programs).

– Query types: SQL Select Into, SPARQL Construct, XSLT

– Example of a data translation query:

```
ARTICLE              PUBLICATION
  • artPK    ——→   • pubID
  • heading  ——→   • title
                   • date
```

```
SELECT artPK AS pubID
       heading AS title
       null AS date
INTO   PUBLICATION
FROM   ARTICLE
```

– Challenges for more complex schemata
- Correspondences are not isolated but embedded into context (tables, relationships)
- How to join tables in order to overcome different levels of normalization?
- Which join paths to choose if there are different possibilities?
- How to combine data from multiple source tables (horizontal partitioning)?

Normalized → Denormalized

ARTICLE
- artPK
- title
- pages

AUTHOR
- artFK
- name

PUBLICATION
- pubID
- title
- date
- author

Naïve approach with one query per source table does not work.

```
SELECT artPK AS pubID     UNION   SELECT null AS pubID
       title AS title                    null AS title
       null AS date                      null AS date
       null AS author                    name AS author
FROM   ARTICLE                    FROM   AUTHOR
```

Normalized → Denormalized

ARTICLE
- artPK
- title
- pages

AUTHOR
- artFK
- name

PUBLICATION
- pubID
- title
- date
- author

Better approach: Use foreign key relationship to join tables.

```
SELECT   artPK AS pubID
         title AS title
         null AS date
         name AS author
FROM     ARTICLE, AUTHOR
WHERE    ARTICLE.artPK = AUTHOR.artFK
```

INNER JOIN vs. OUTER JOIN

ARTICLE
- artPK
- title
- pages

AUTHOR
- artFK
- name

PUBLICATION
- pubID
- title
- date
- author

Interpretation: Do we want publications without author?

```
SELECT      artPK AS pubID
            title AS title
            null AS date
            name AS author
FROM        ARTICLE LEFT OUTER JOIN AUTHOR
ON          ARTICLE.artPK = AUTHOR.artFK
```

Denormalized ➔ Normalized

PUBLICATION
- title
- date
- author

ARTICLE
- artPK
- title
- pages

AUTHOR
- artFK
- name

DISTINCT

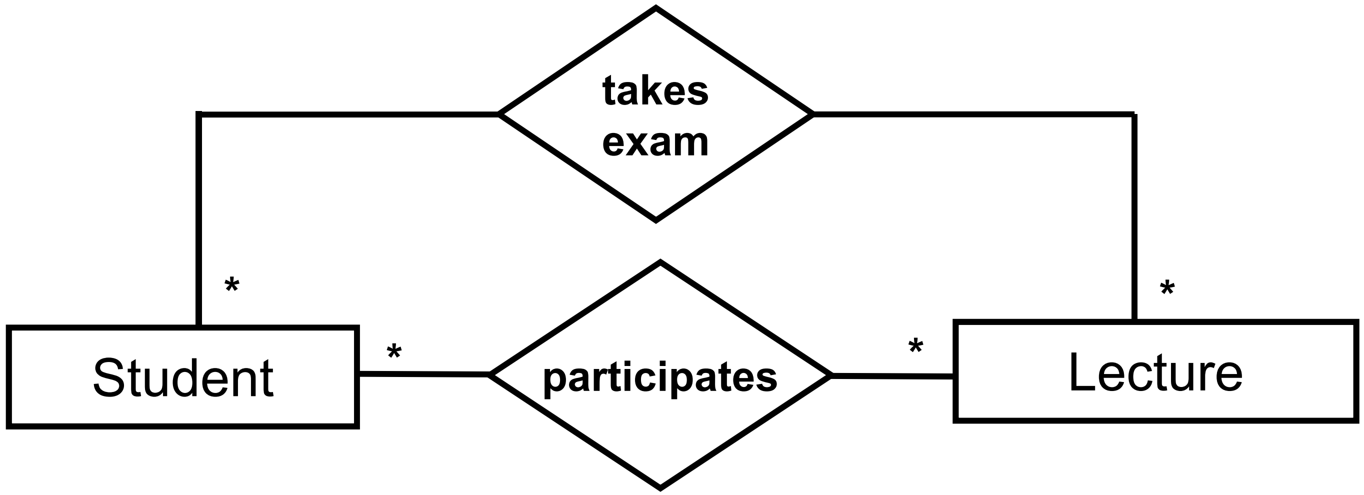
```
SELECT SK(title) AS artPK
       title AS title
       null AS pages
FROM   PUBLICATION
```

```
SELECT SK(title) AS artFK
       author AS name
FROM   PUBLICATION
```

SK(): Skolem function used to generate unique keys from distinct values.

Which Join Path to Choose?

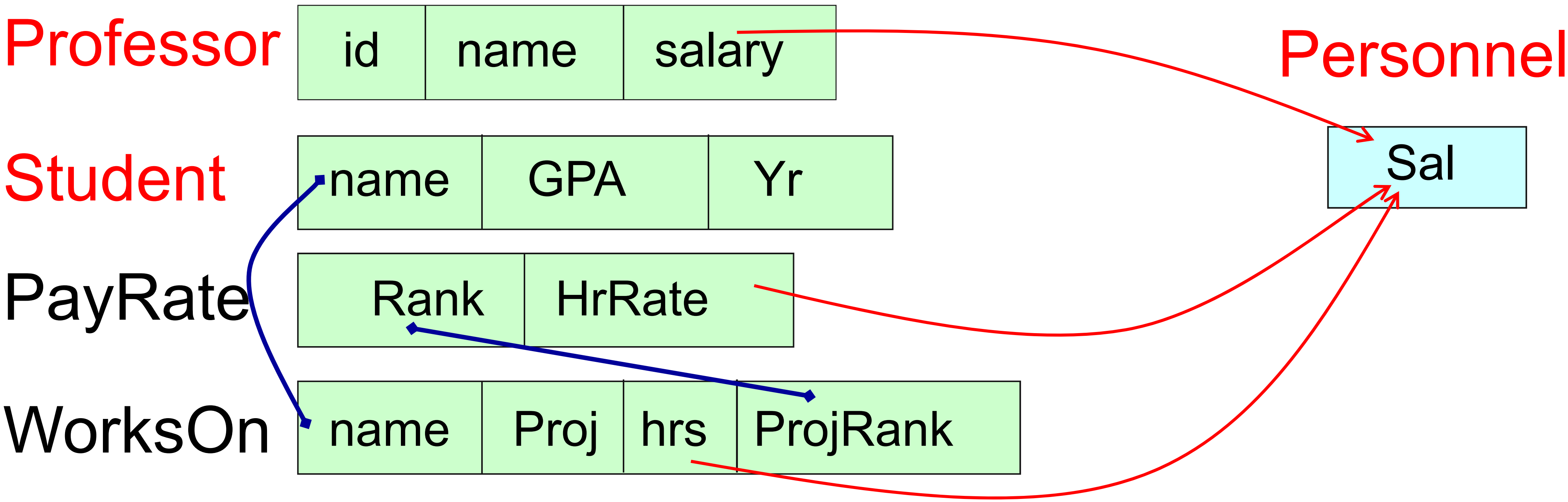
Source Schema:



Target Schema:

Interpretation: Do we only want students that took the exam in the list?

Horizontal Partitioning



c1: Professor(Sal) $\rightarrow$ Personnel(Sal)

*c2: PayRate(HrRate) * WorksOn(Hrs) = Personnel(Sal)*

UNION the Salaries of Professors and Students

```
SELECT P.HrRate * W.hrs
FROM PayRate P, WorksOn W
WHERE P.Rank = W.ProjRank

UNION

SELECT salary
FROM Professor
```

Complete Algorithms for Generating Translation Queries

- Relational Case
  - Doan, Halevy, Ives: Principles of Data Integration. Pages 152-158.
- XML Case
  - Leser, Naumann: Informationsintegration. Pages 137-143.
- MapForce
  - implements another one which we will try out in the exercise.

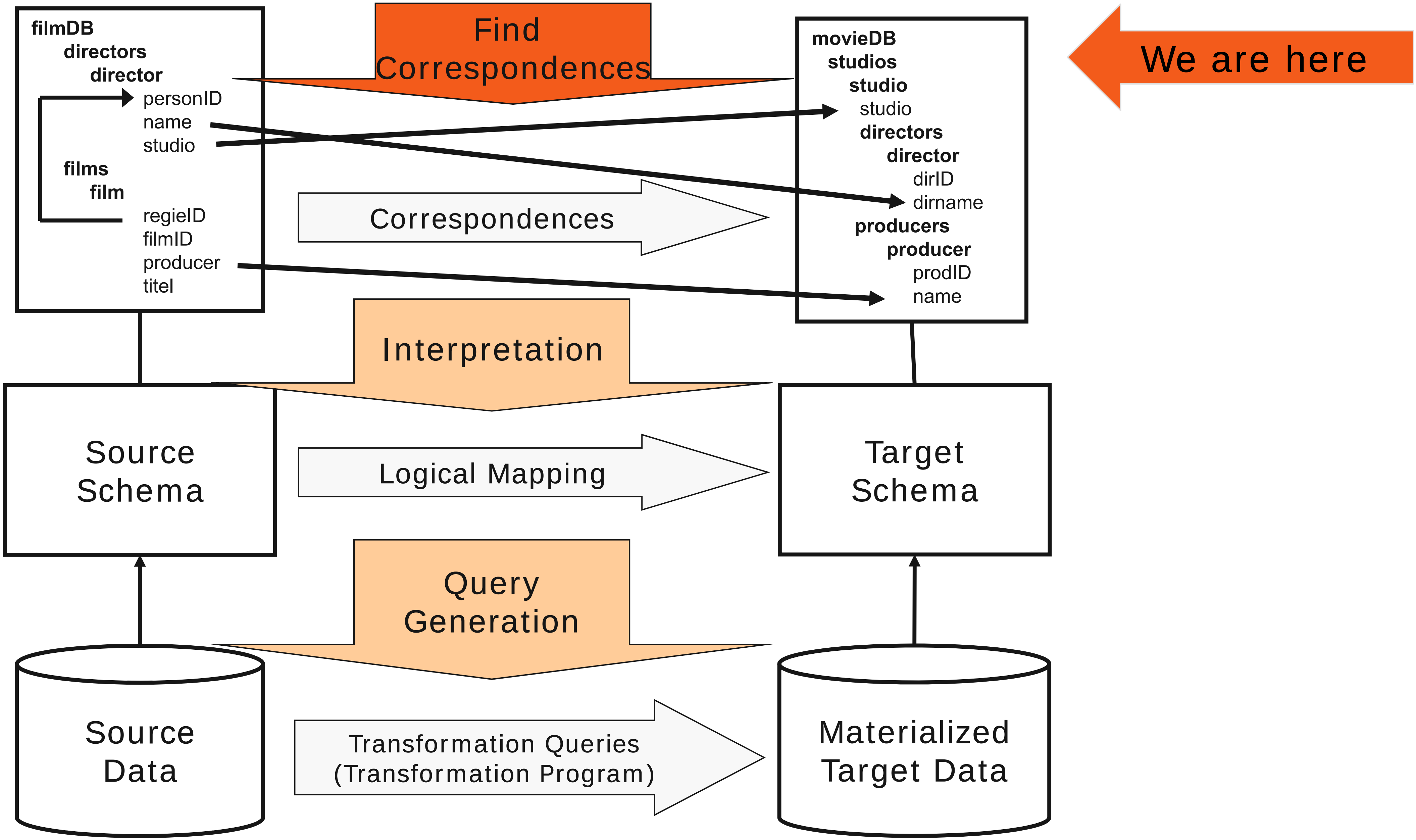
The algorithms can not do the interpretation and thus need to be guided by the user.

5. Schema Matching

Schema Matching: Automatically or semi-automatically discover correspondences between schemata.

- Automatically finding a complete high-quality mapping (= set of all correspondences) is not possible in many real-world cases.
- In practice, schema matching is used to create candidate correspondences that are verified by domain experts afterwards.
- Schema matching methods focus on finding 1:1 correspondences.
  - we restrict ourselves to 1:1 for now and speak about 1:n and n:1 later.

Schema Matching



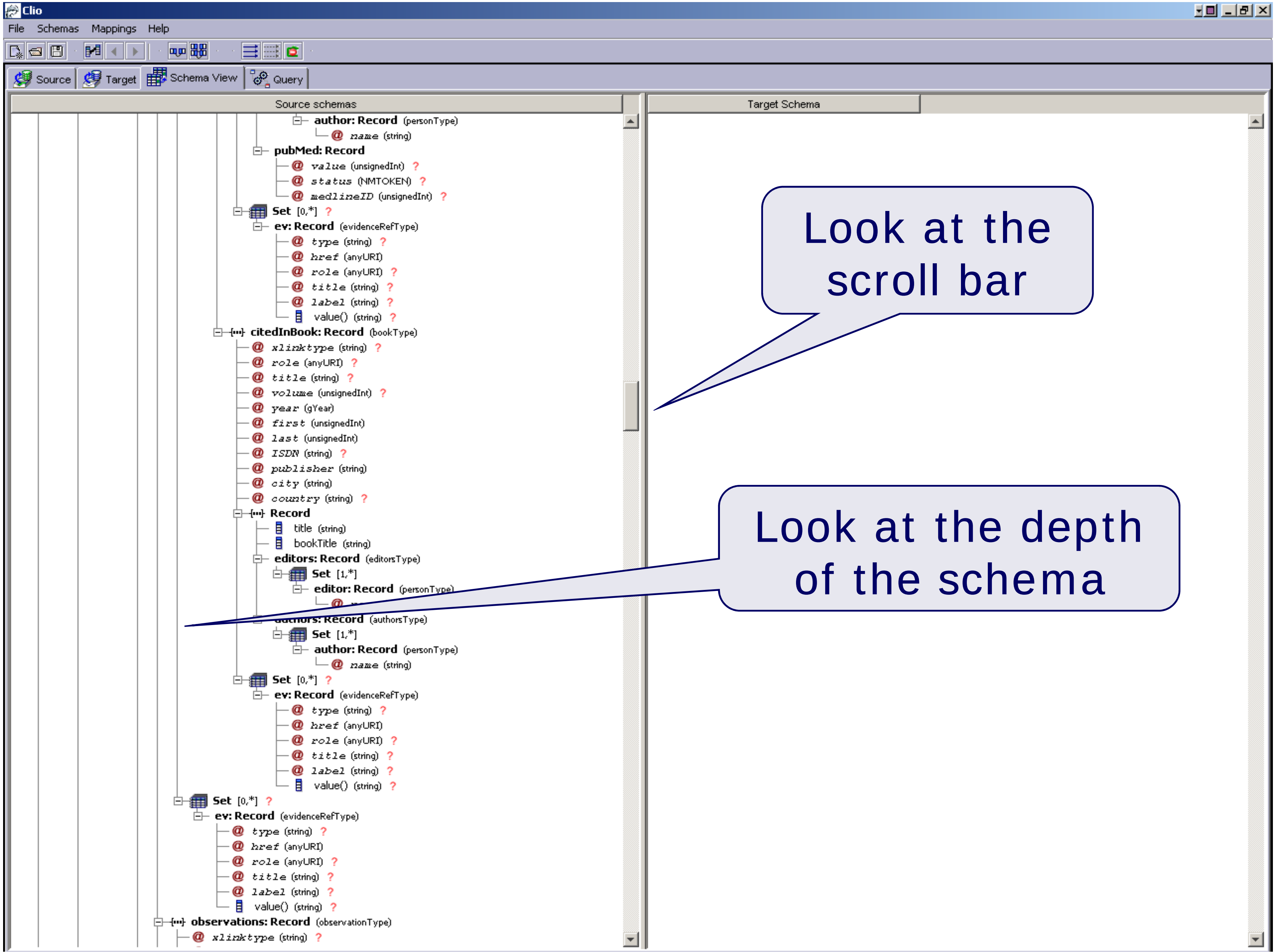
Outline: Schema Matching

1. Challenges to Finding Correspondences
2. Schema Matching Methods
   1. Label-based Methods
   2. Instance-based Methods
   3. Structure-based Methods
   4. Combined Approaches
3. Generating Correspondences from the Similarity Matrix
4. Finding n:1 and 1:n Correspondences
5. Example Schema Matching System
6. Summary and Current Trends

5.1 Challenges to Finding Correspondences

1. Large schemata
   - >100 tables and >1000 attributes
2. Esoteric naming conventions and different languages
   - 4 character abbreviations: SPEY
   - city vs. ciudad vs. مدينة
3. Generic, automatically generated names
   - attribute1, attribute2, attribute3 (used for product features in Amazon API)
4. Missing documentation
5. „Strange" schemata
   - denormalization, redundancies, …
6. Semantic heterogeneity
   - synonyms, homonyms, …

Problem Space: Large Schemata



Problem Space: Different Languages and Strange Names

Männer	
Vorname	**Nachname**
Felix	Naumann
Jens	Bleiholder

Frauen	
Vorname	**Nachname**
Melanie	Weis
Jana	Bauckmann

Persons			
firstname	**name**	**male**	**female**
Felix	Naumann	1	0
Jnes	Bleiho.	1	0
Melanie	Weiß	0	1
Jana	baukman	0	1

Pers		
FN	**NN**	**S**
F.	Naumann	M
J.	Bleiholder	M
M.	Weis	F
J.	Bauckmann	F

How do humans know?

– We recognize naming conventions and different languages

– use table context

– values look like first names and surnames

– values look similar

– if there is a first name, there is usually also a surname

– persons have first- and surnames

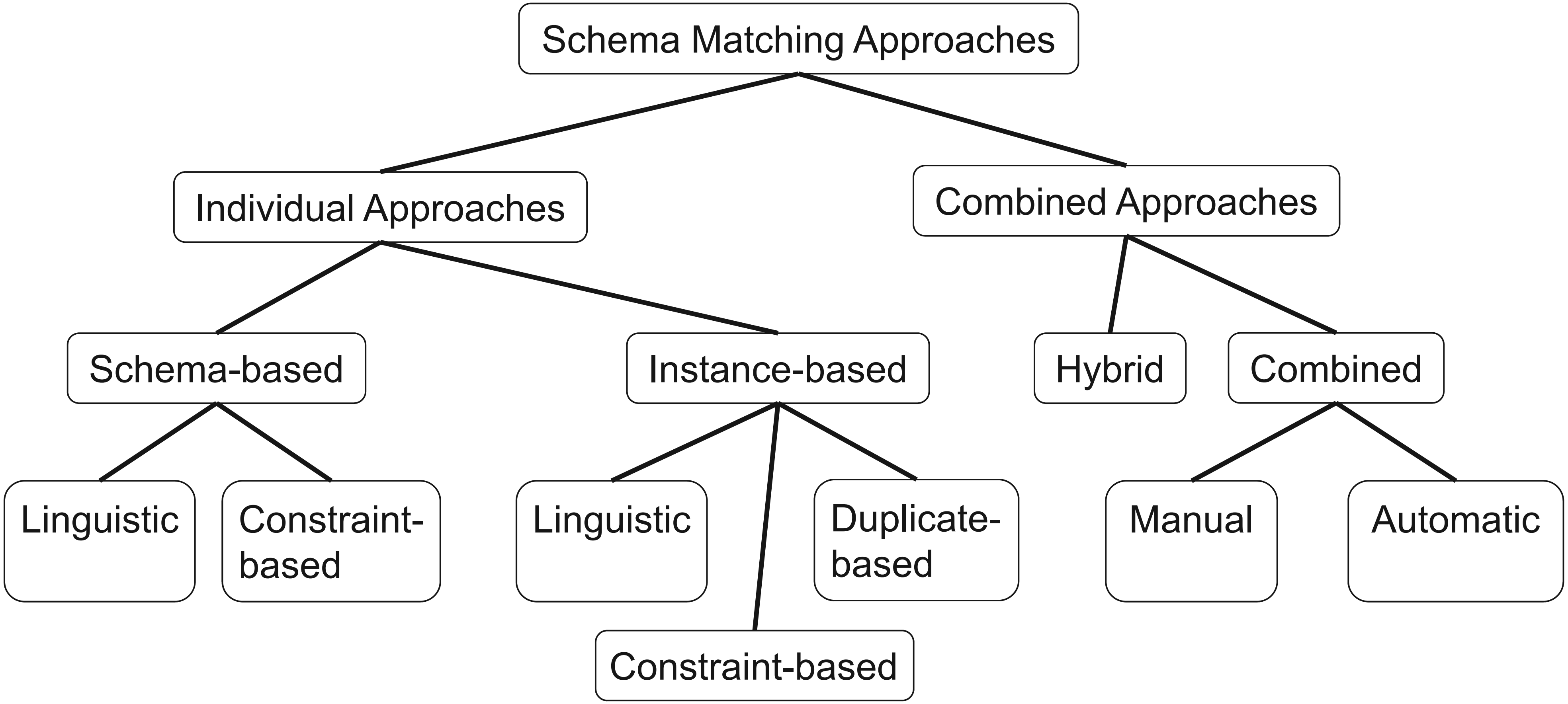
– man are persons

➔ Recognizing these clues is hard for the computer.

5.2. Schema Matching Methods

1. Label-based Methods: Rely on the names of schema elements
2. Instance-based Methods: Compare the actual data values
3. Structure-based Methods: Exploit the structure of the schema
4. Combined Approaches: Use combinations of above methods

Classification of Schema Matching Methods



Source: Erhard Rahm and Philip Bernstein: A survey of approaches to automatic schema matching., VLDB Journal 10(4), 2001.

5.2.1 Label-based Schema Matching Methods

- Given two schemata with the attribute (class) sets A and B
  - A={ID, Name, Vorname, Alter}, B={No, Name, First_name, Age}
- Approach
  1. Generate cross product of all attributes (classes) from A and B
  2. For each pair calculate the similarity of the attribute labels
     - using some similarity function: Edit distance, Jaccard, Soundex, etc.
     - we will cover similarity functions in detail in the chapter on identity resolution
  3. The most similar pairs are the matches

	ID	Name	Vorname	Alter
No	0.8	0.6	0.4	0.4
Name	0.1	1.0	0.6	0.3
First_name	0.2	0.6	0.5	0.3
Age	0.4	0.3	0.2	0.7

Levenshtein Distance (aka Edit Distance)

- Measures the dissimilarity of two strings
- Measures the minimum number of edits needed to transform one string into the other
- Allowed edit operations
  - insert a character into the string
  - delete a character from the string
  - replace one character with a different character
- Examples
  - levensthein('Table', 'Cable') = 1 (1 Substitution)
  - levensthein('Table', 'able') = 1 (1 Deletion)
- Converting Levenshtein distance into a similarity

$$sim_{Levenshtein} = 1 - \frac{LevenshteinDist}{\max(|s_1|, |s_2|)}$$

Problems of Label-based Schema Matching

1. Semantic heterogeneity is not recognized
   - the labels of schema elements only partly capture their semantics
   - synonyms und homonyms
2. Problems with different naming conventions
   - Abbreviations: pers = person, dep = department
   - Combined terms and ordering: id_pers_dep vs. DepartmentPersonNumber
   - Different languages: city vs. ciudad vs. مدينة

– We need to apply smart, application-specific tweaks:
  1. Preprocessing: Normalize labels in order to prepare them for matching
  2. Matching: Employ data-specific similarity functions

Pre-Processing of Labels

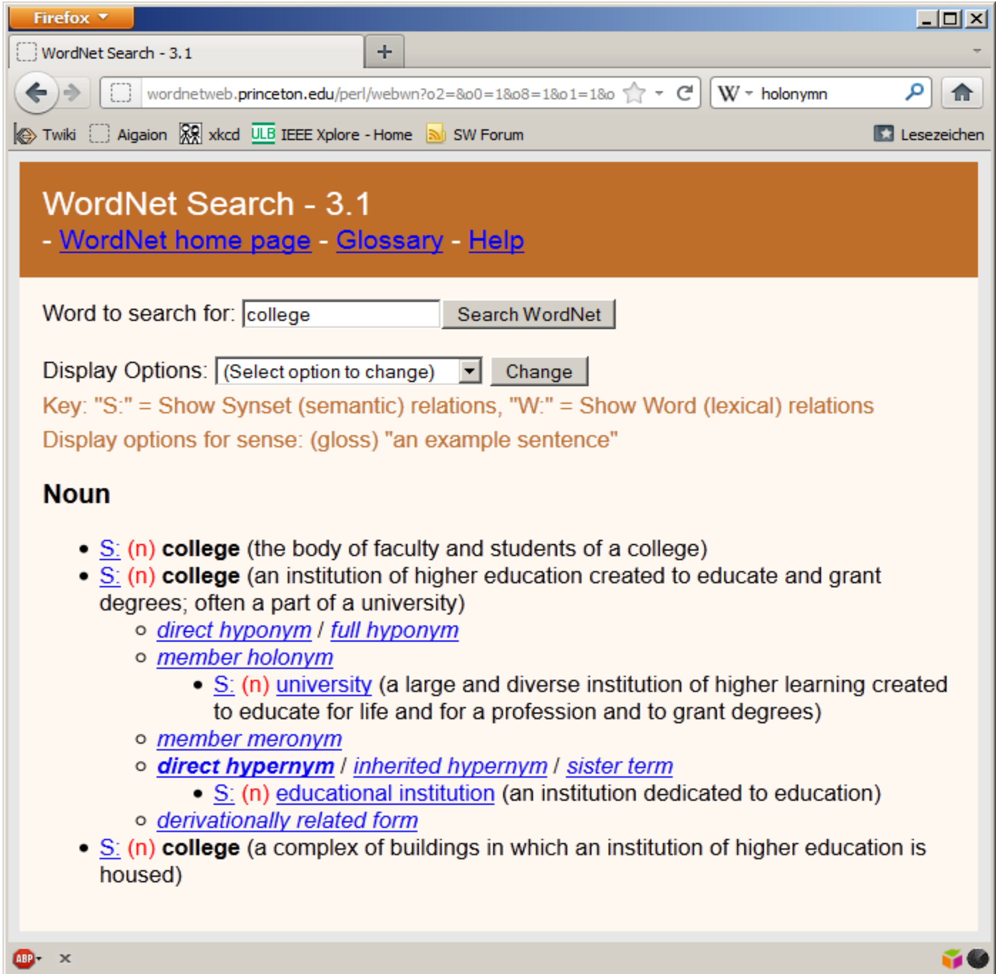
- Case and Punctuation Normalization
  - ISBN, IsbN, and I.S.B.N → isbn
- Explanation Removal
  - GDP (as of 2014, US$) → gdp
- Stop Word Removal
  - in, at, of, and, …
  - ex1:locatedIn → ex1:located
- Stemming
  - ex1:located, ex2:location → both stemmed to ‚locat‘
  - but: ex1:locationOf, ex2:locatedIn (Inverse Properties!)
- Tokenization
  - ex1:graduated_from_university → {graduated,from,university}
  - ex2:isGraduateFromUniversity → {is,Graduate,from,University}
  - tokens are then compared one-by-one using for instance Jaccard similarity

Use Linguistic Resources for Pre-Processing

- Translate labels into target language
  - ciudad and مدينة ➔ city
- Expand known abbreviations or acronyms
  - loc ➔ location, cust ➔ customer
  - using a domain-specific list of abbreviations or acronyms
- Expand with synonyms
  - add cost to price, United States to USA
  - using a dictionary of synonyms
- Expand with hypernyms (is-a relationships)
  - expand product into book, dvd, cd
- Use taxonomy/ontology containing hypernyms for matching
  - similarity = closeness of concepts within taxonomy/ontology

Useful External Resources

- Google Translate
  - recognizes languages and translates terms
- WordNet
  - provides synonyms and hypernyms for English words
- Wikipedia/DBpedia
  - provides synonyms, concept definitions, category system, cross-language links
  - see Paulheim: WikiMatch. 2012.
- The Web
  - google for terms, if result are similar then terms are similar
  - see Paulheim: WeSeE-Match. 2012.



5.2.2 Instance-based Schema Matching Methods

- Given two schemata with the attribute sets A and B and
  - all instances of A and B or
  - a sample of the instances of A and B
- Approach
  - Determine correspondences between A and B by examining which attributes in A and B contain similar values
  - as values often better capture the semantics of an attribute than its label
- Concrete Methods
  1. Use Attribute Recognizers
  2. Calculate Value Overlap
  3. Feature-based Methods
  4. Duplicate-based Methods

Table A	
A1	**A2**
Felix	Naumann
Jens	Bleiholder

Table B	
VN	**NN**
Felix	Naumann
Jens	Bleiholder

Attribute Recognizers and Value Overlap

1. Attribute Recognizers
   - employ dictionaries, regexes or rules to recognize values of a specific attribute
     - Dictionaries fit attributes that only contain a relatively small set of values (e.g. age classification of movies (G, PG, PG-13, R), country names, US states
     - Regexes or rules fit attributes with regular values (e.g. area code – phone number).
   - similarity = fraction of the values of attribute B that match dictionary/rule of attribute A

2. Value Overlap
   - calculate the similarity of attribute A and B as the the overlap of their values using the Jaccard similarity measure (or Generalized Jaccard):

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

Feature-based Methods

– Given two schemata with the attribute sets A and B and instances of A and B

– Approach

1. For each attribute calculate interesting features using the instance data, e.g.
   - attribute data type
   - average string length of attribute values
   - average maximal and minimal number of words
   - average, maximal and minimal value of numbers
   - standard derivation of numbers
   - does the attribute contain NULL values?
2. generate the cross product of all attributes from A and B
3. for each pair compare the similarity of the features

Example: Feature-based Matching

ID	Name	Loc
1	Müller	Danziger Str, Berlin
2	Meyer	Boxhagenerstr, Berlin
4	Schmidt	Turmstr, Köln

Nr	Adresse	Telefon
1	Seeweg, Berlin	030-3324566
3	Aalstr, Schwedt	0330-1247765
4	Rosenallee, Kochel	0884-334621

- Features: Attribute data type, average string length
  - Table1 = {(ID, NUM, 1), (Name, STR, 6), (Loc, STR, 18)}
  - Table1 = {(Nr, NUM, 1), (Adresse, STR, 16), (Telefon, STR, 11)}
- Similarity measure: Euclidean Distance (NUM=0, STR=1)

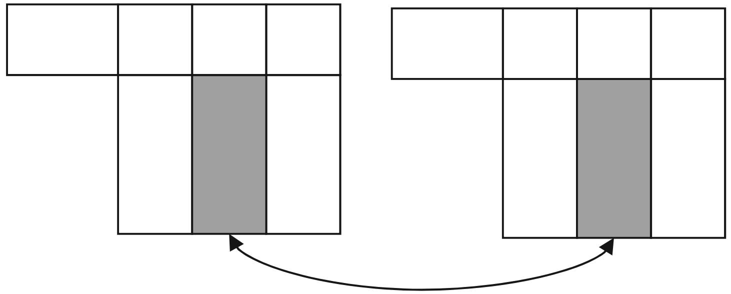
	ID	Name	Loc
Nr	d(<0,1>,<0,1>)	d(<1,6>,<0,1>)	d(<1,18>,<0,1>)
Adresse	d(<0,1>,<1,16>)	d(<1,6>,<1,16>)	d(<1,18>,<1,16>)
Telefon	d(<0,1>,<1,11>)	d(<1,6>,<1,11>)	d(<1,18>,<1,11>)

Discussion: Feature-based Methods

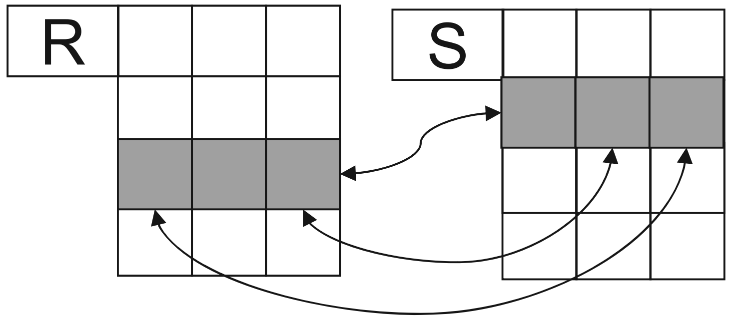
1. Requires decision which features to use
   - good features depend on the data type and application domain
2. Requires decision how to compare and combine values
   - e.g. Cosine similarity, Euclidian distance (of normalized values), …
   - different features should have different weights
3. Similar attribute values do not always imply same semantics
   - phone number versus fax number
   - employee name versus customer name

Duplicate-based Methods

– Classical instance-based matching in vertical
  - Comparison of complete columns
  - Ignores the relationships between instances



– Horizontal duplicate-based matching
  1. Find (some) potential duplicates or
     use previous knowledge about duplicates
  2. Check which attribute values closely match
     in each duplicate
  3. Result: Attribute correspondences per duplicate
  4. Final matching: Use majority voting



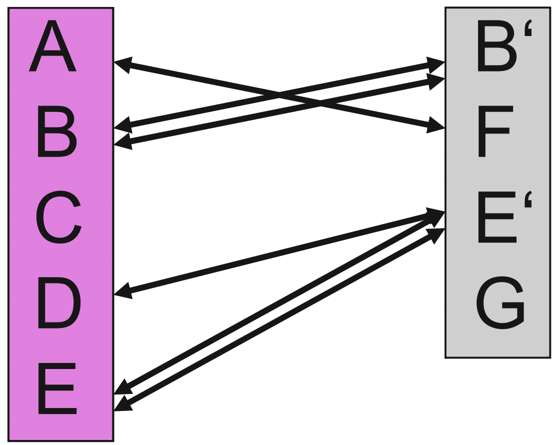
Example: Vote of Two Duplicates

A	B	C	D	E
Max	Michel	m	601- 4839204	601- 4839204
Sam	Adams	m	541- 8127100	541- 8121164

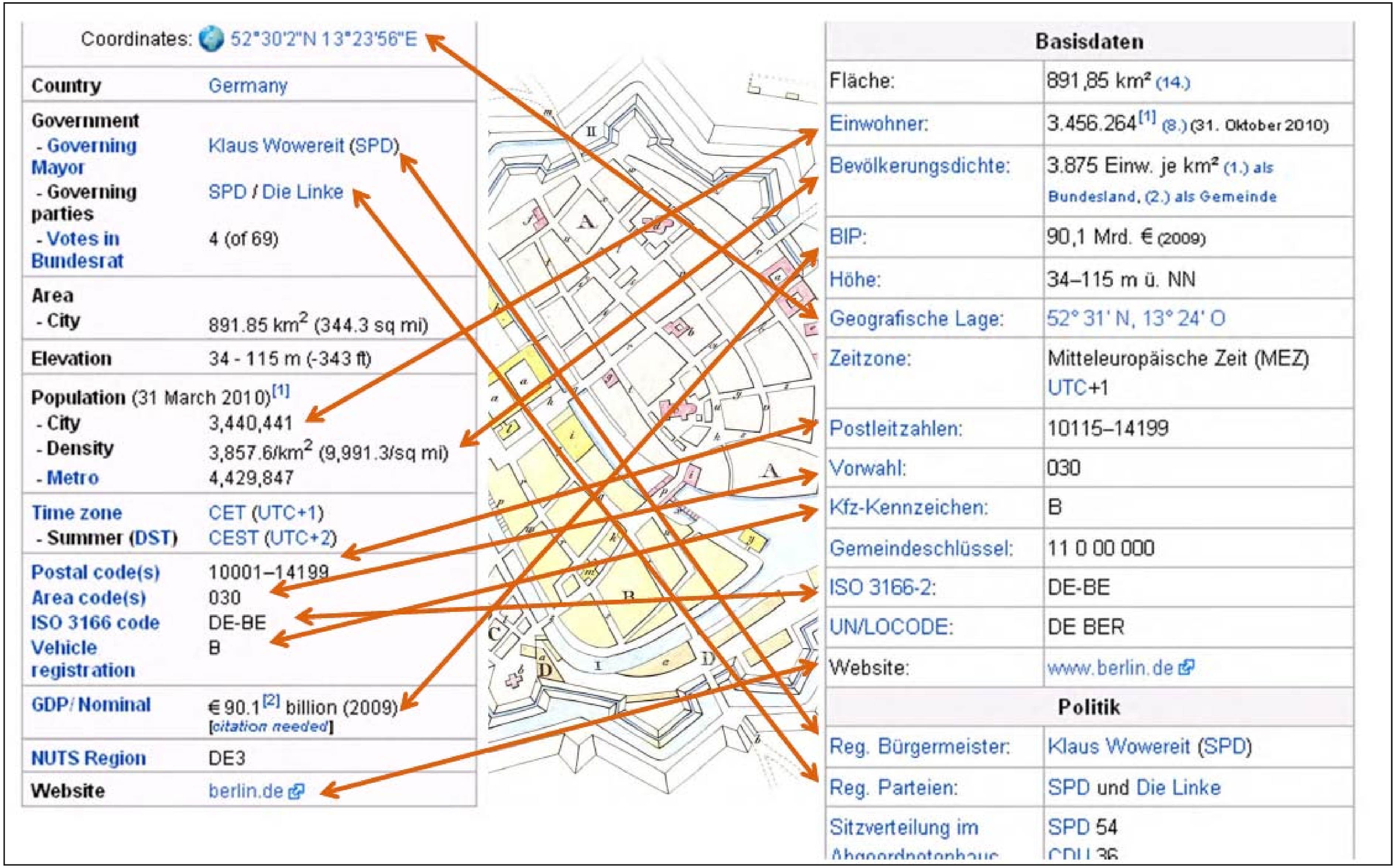
=

B‵	F	E‵	G
Michel	maxm	601- 4839204	UNIX
Adams	beer	541- 8127164	WinXP

Vote of the two duplicates:



Using Duplicates for Cross-Language Infobox Matching



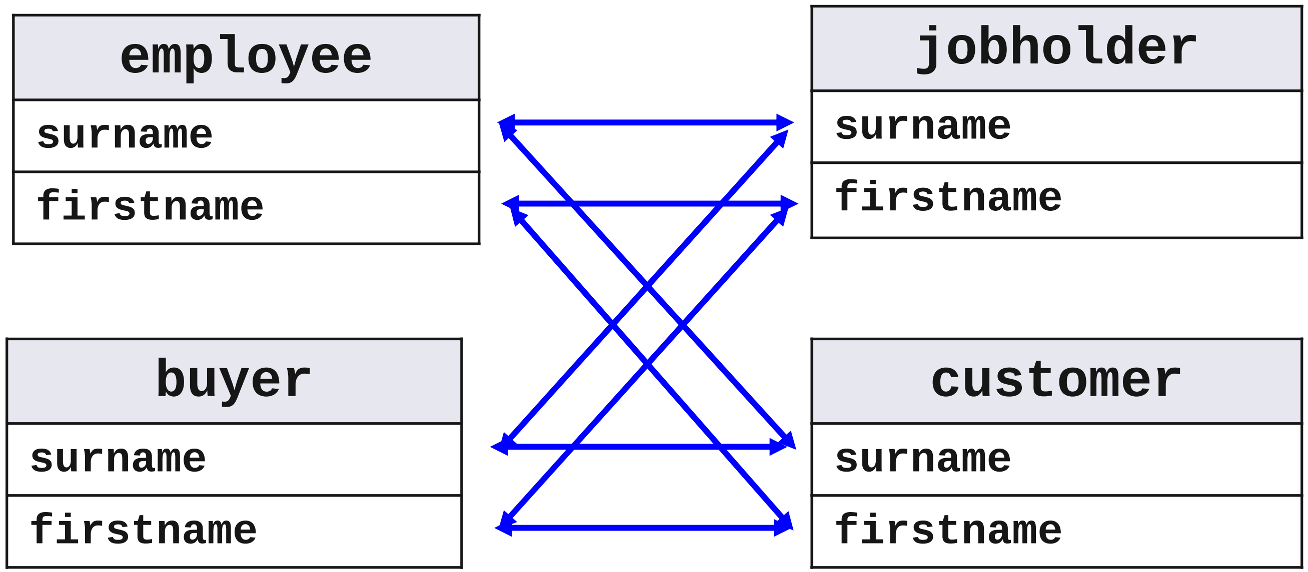
Source: Felix Naumann, ICIQ 2012 Talk

Discussion: Duplicate-based Methods

- Work well if duplicates are known or easy to find
  - owl:sameAs statements in LOD cloud
  - shared IDs like ISBN or GenID
- Can correctly distinguish very similar attributes
  - Telephone number <> fax number, Surname<>Maiden name
- In general, duplicate detection is tricky and computationally expensive
  - we will discuss this later in the chapter on identity resolution

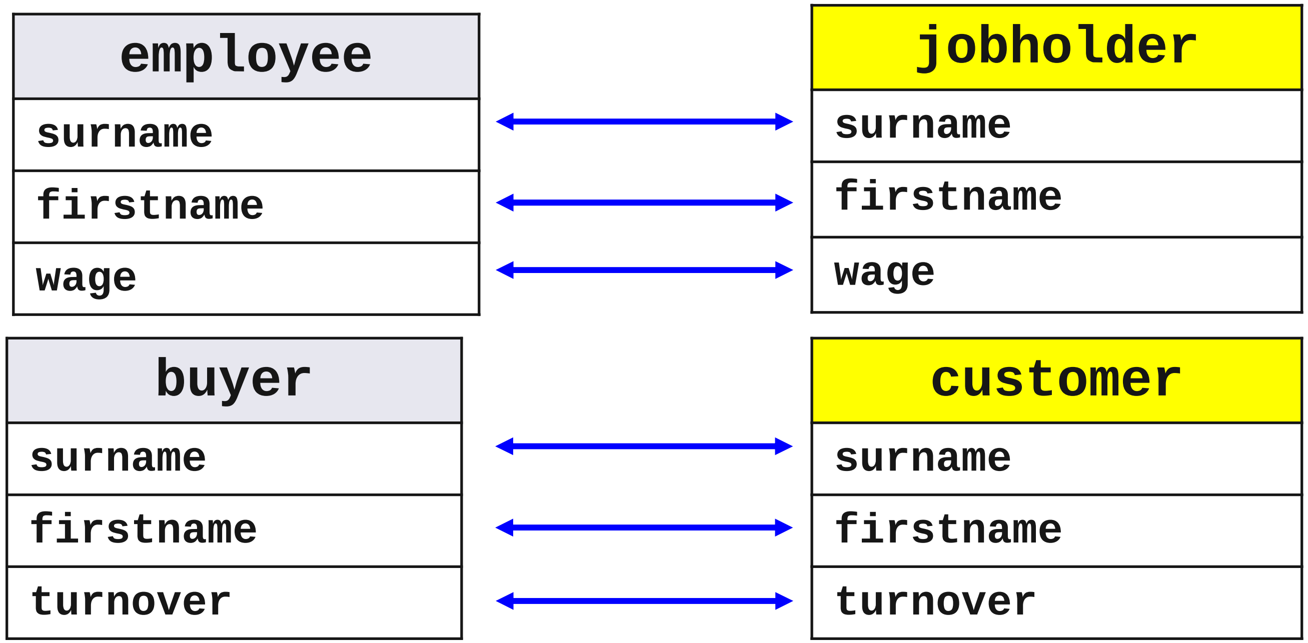
5.2.3 Structure-based Schema Matching Methods

– Addresses the following problem:



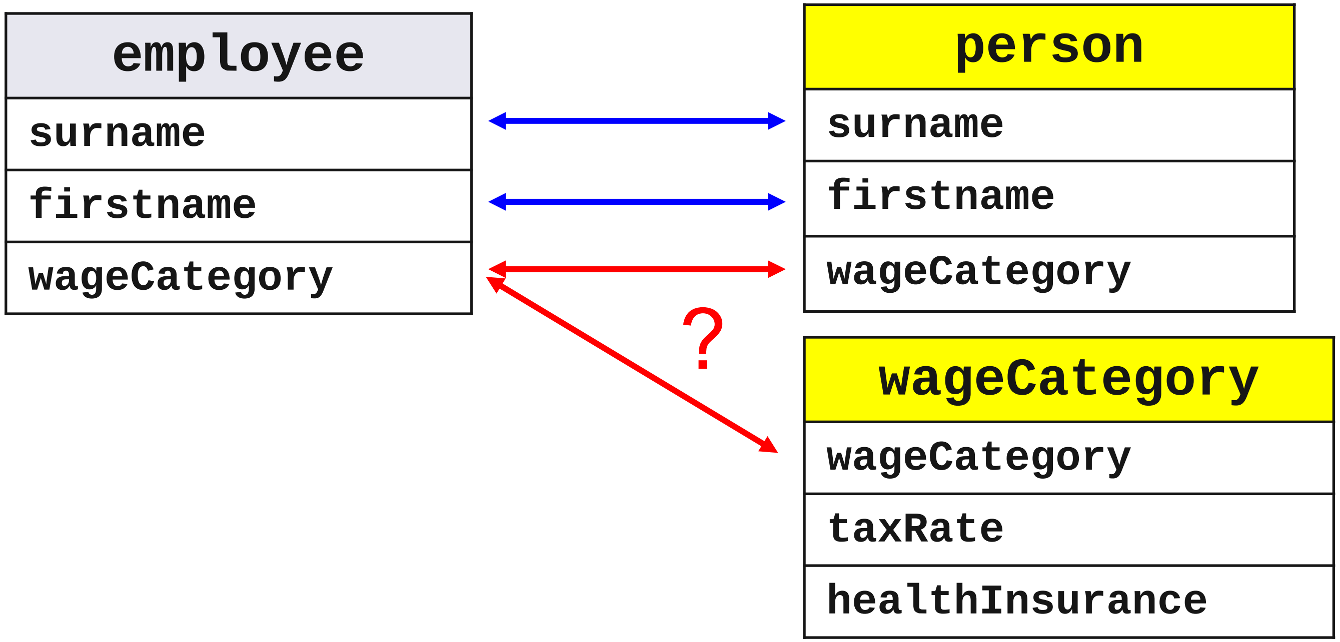
– Attribute-Attribute-Matching
  - Instance-based: Values of all attributes rather similar
  - Label-based: Labels of all attributes rather similar
  - All matchings are about equally good ☹

Better approach: Exploit the Attribute Context



– Attributes that co-occur in one relation often (but not always) also co-occur in other relations.

Approach: Spread Similarity to Neighbors

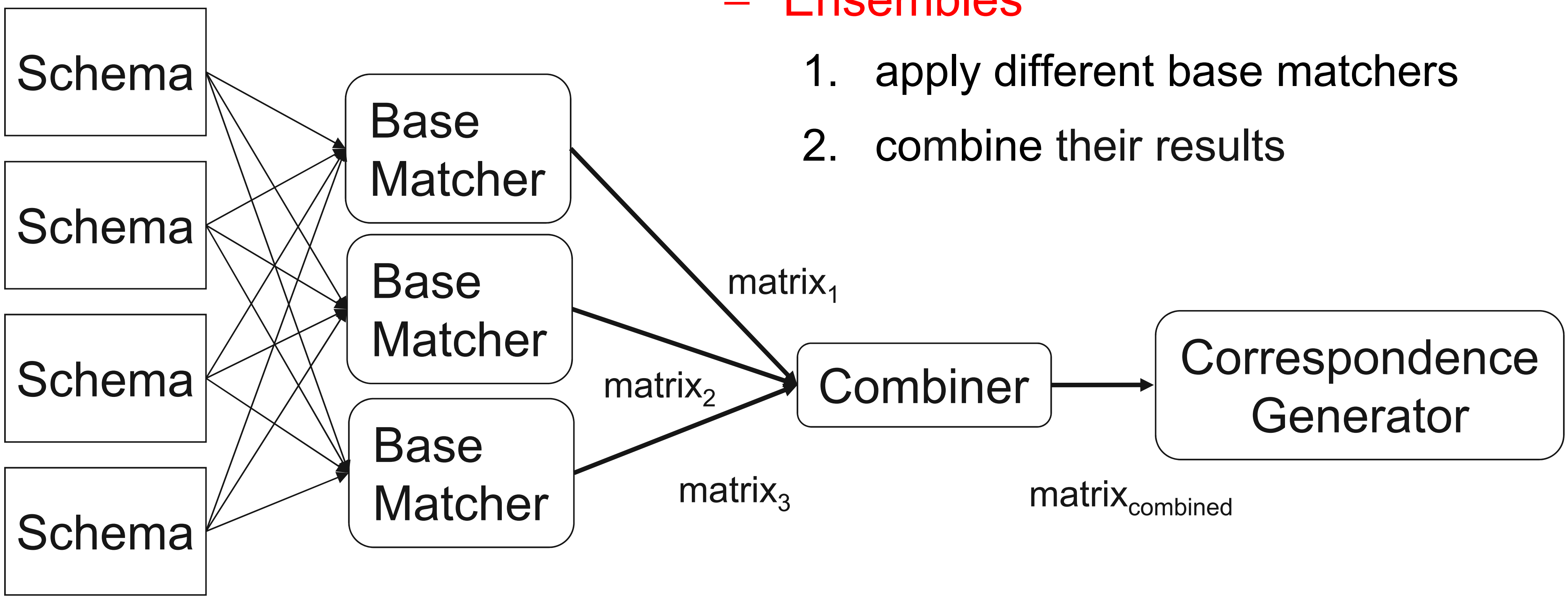


– Idea: High similarity of neighboring attributes and/or name of relation increases similarity of attribute pair
– Base similarities: Label-based and/or instance-based
– Simple calculation: Weight attribute similarity with average similarity of all other attributes in same relation and similarity of relation names
– Alternative calculation: Similarity Flooding algorithm (see references)

5.2.4 Combined Approaches

– Hybrid Approaches
  - integrate different clues into single similarity function
  - clues: labels, structure, instance data

– Ensembles
  1. apply different base matchers
  2. combine their results



Example of the Need to Exploit Multiple Types of Clues

realestate.com

listed-price	contact-name	contact-phone	office	comments
\$250K \$320K	James Smith Mike Doan	(305) 729 0831 (617) 253 1429	(305) 616 1822 (617) 112 2315	Fantastic house Great location

homes.com

sold-at	contact-agent	extra-info
\$350K \$230K	(206) 634 9435 (617) 335 4243	Beautiful yard Close to Seattle

- If we use only labels
  - contact-agent matches either contact-name or contact-phone
- If we use only data values
  - contact-agent matches either contact-phone or office
- If we use both labels and data values
  - contact-agent matches contact-phone

How to Combine the Predictions of Multiple Matchers?

- Simple approaches: Use avg(), min(), or max() function.
- When to use which combiner?
  - average combiner : when we do not have any reason to trust one matcher over the others
  - maximum combiner: when we trust a strong signal from matchers, i.e., if a matcher outputs a high value, we are relatively confident that the two elements match
  - minimum combiner: when we want to be more conservative

More complex Types of Combiners

- Weighted-sum combiners
  - give weights to each matcher, according to its quality
  - you may learn the weights using
    - known correspondences as training data
    - linear regression or decision tree learning algorithms
    - we will cover learning weights in detail in chapter on identity resolution
- Use hand-crafted rules
  - e.g., if $\mathbf{s}_i$ is address, return the score of the data-based matcher otherwise, return the average score of all matchers

5.3 Generating Correspondences from the Similarity Matrix

– Input: Matrix containing attribute similarities

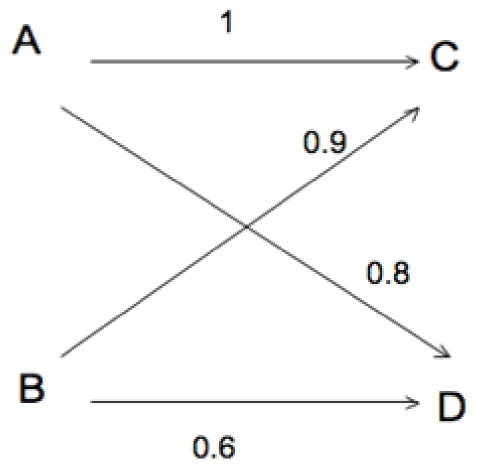
– Output: Set of correspondences

Local Single Attribute Strategies:

1. Thresholding
   - all attribute pairs with sim above a threshold are returned as correspondences
   - domain expert checks correspondences afterwards and selects the right ones
2. TopK
   - give domain expert TopK correspondences for each attribute
3. Top1
   - directly return the best match as correspondence
   - very optimistic, errors might frustrate domain expert

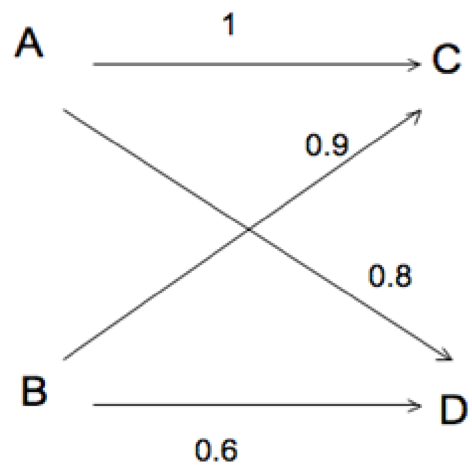
Alternative: Global Matching

- Looking at the complete mapping (all correct correspondences between A and B) gives us the additional restriction that one attribute in A should only be matched to one attribute in B.
- Goal of Global Matching
  - Find optimal set of disjunct correspondences
  - avoid correspondence pairs of the form A ≡ C and B ≡ C
- Approach:
  - find set of bipartite pairs with the maximal sum of their similarity values
- Example:
  - A ≡ D and B ≡ C have the maximal sum of their similarity values
  - Ignores that sim(A,C) = 1



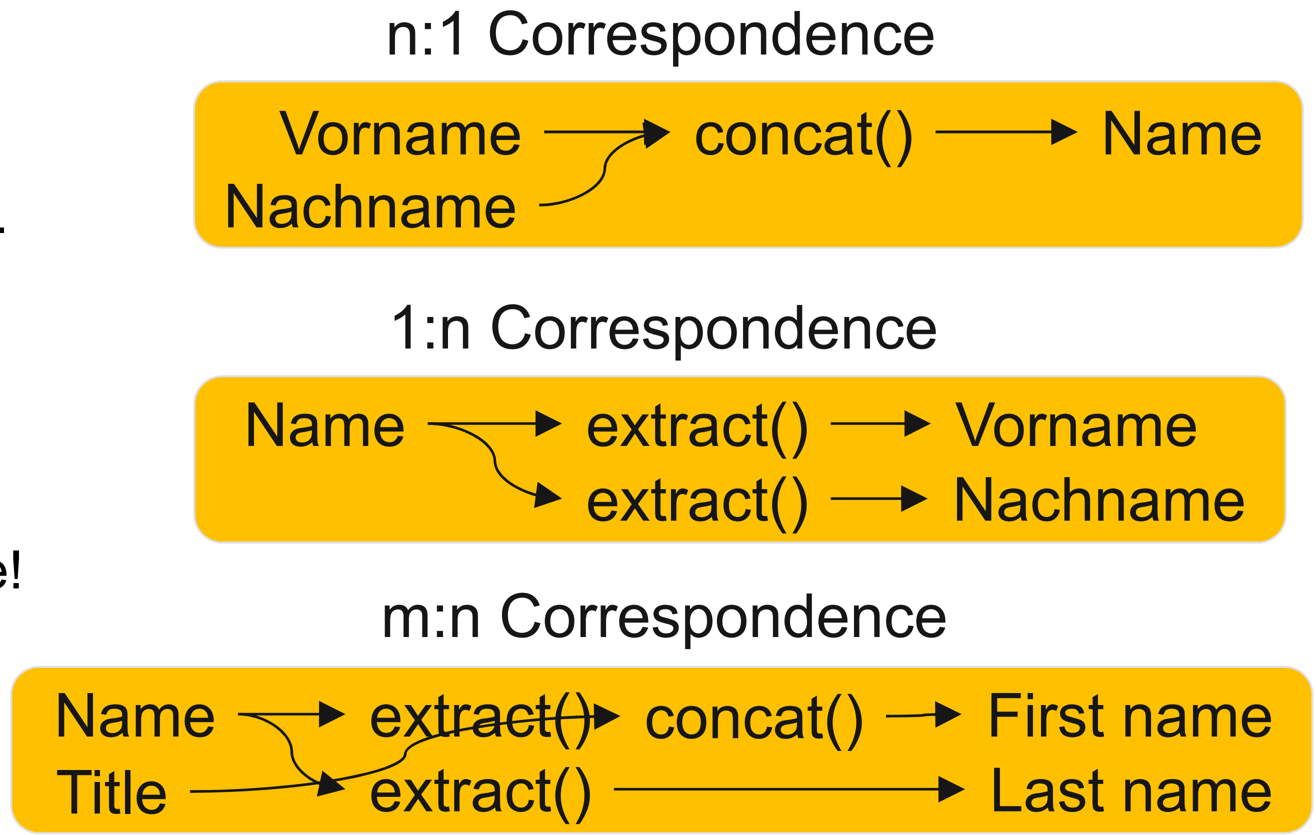
Alternative: Stable Marriage

- Elements of S = men, elements of T = women
- Sim(i,j) = degree to which $\mathbf{A}_i$ and $\mathbf{B}_j$ desire each other
- Goal: Find a stable match combination between men and women
- A match combination would be unstable if
  - there are two couples $\mathbf{A}_i = \mathbf{B}_j$ and $\mathbf{A}_k = \mathbf{B}_l$ such that $\mathbf{A}_i$ and $\mathbf{B}_l$ want to be with each other, i.e., sim(i,l) > sim(i, j) and sim(i,l) > sim(k,l)
- Algorithm to find stable marriages
  - Let match={}
  - Repeat
    - Let (i,j) be the highest value in sim such that A_i and B_j are not in match
    - Add $A_i = B_j$ to match
- Example: A = C and B = D form a stable marriage



5.4 Finding Many-to-One and One-to-Many Correspondences

- Up till now all methods only looked for 1:1 correspondences
- But real-world setting might require n:1 and 1:n or even n:m correspondences
- Question:
  - How to combine values?
  - Lots of functions possible.
- Problem:
  - Should we test
    1.2 * A + 2 * B - 32 ≡ C
  - … unlimited search space!



Search for Complex Correspondences

- Paper: Doan, et al.: iMAP: Discovering complex Semantic Matches between Database Schemas. SIGMOD, 2004.
- Employs specialized searchers:
  - text searcher: uses only concatenations of columns
  - numeric searcher: uses only basic arithmetic expressions
  - date searcher: tries combination of numbers into dd/mm/yyyy pattern
- Key challenge: Control the search.
  - start searching for 1:1 correspondences
  - add additional attributes one by one to sets
  - consider only top k candidates at every level of the search
  - termination based on diminishing returns

An Example: Text Searcher

Mediated-schema

price	num-baths	address

homes.com

listed-price	agent-id	full-baths	half-baths	city	zipcode
320K	532a	2	1	Seattle	98105
240K	115c	1	1	Miami	23591

concat(agent-id,city)
532a Seattle
115c Miami

concat(agent-id,zipcode)
532a 98105
115c 23591

concat(city,zipcode)
Seattle 98105
Miami 23591

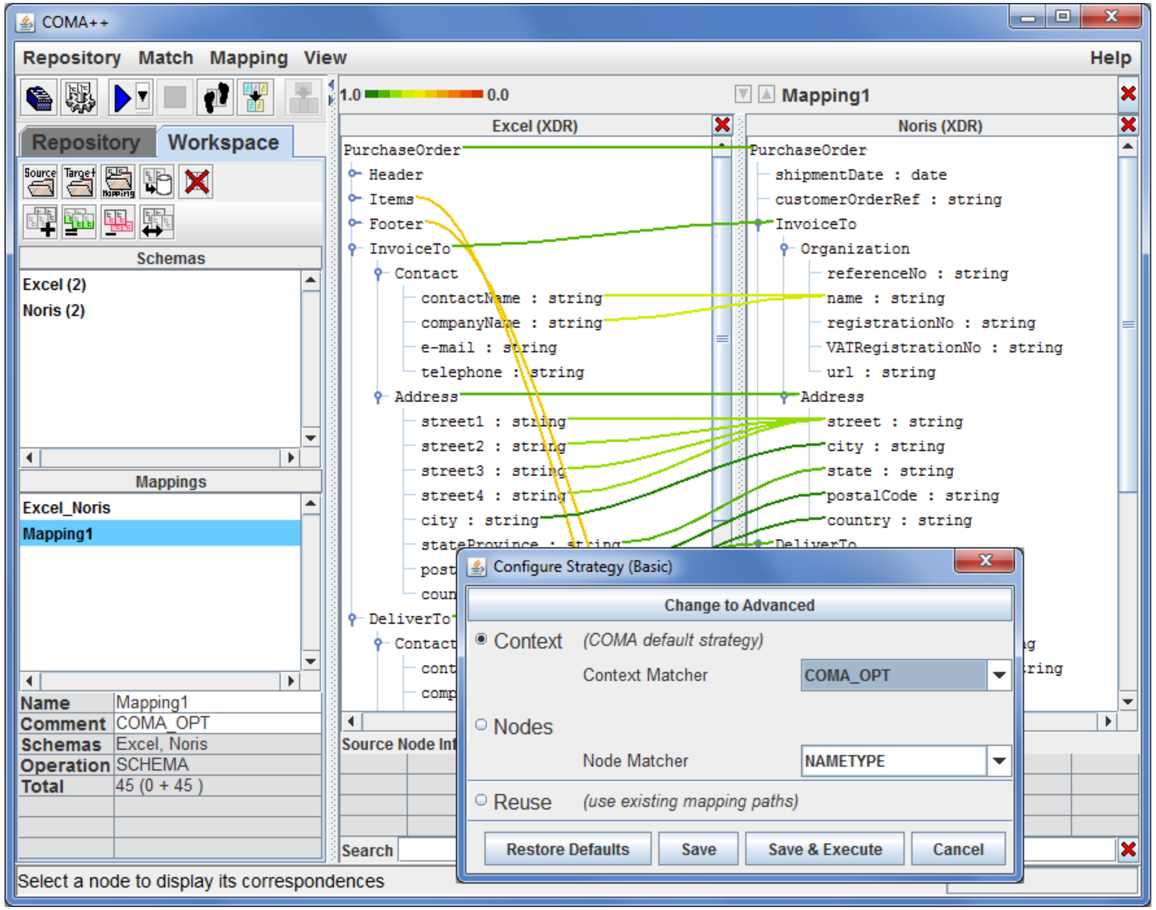
– Best match candidates for address

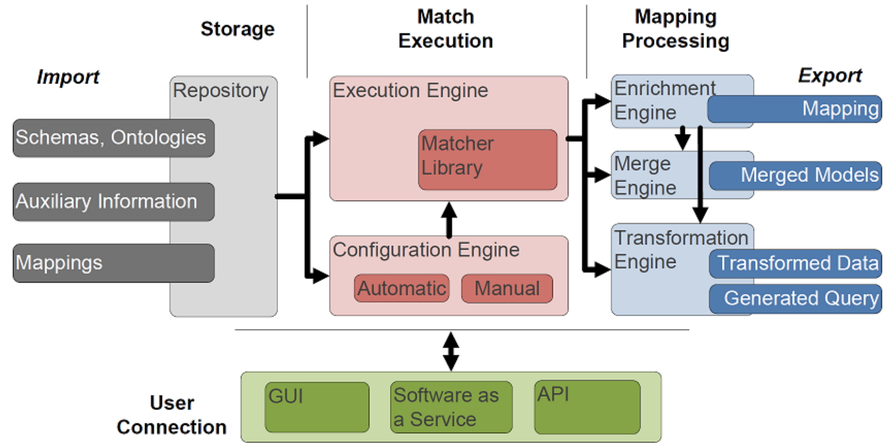
- (agent-id,0.7), (concat(agent-id,city),0.75), (concat(city,zipcode),0.9)

5.5. Example Matching System: COMA V3.0

Developed by Database Group at University of Leipzig since 2002

- provides wide variety of matchers (label, instance, structure, hybrid)
- provides user interface for editing correspondences.
- provides data translation based on the correspondences.





http://dbs.uni-leipzig.de /de/Research/coma.html

5.6. Summary

- Schema Matching is an active research area with lots of approaches
  - Yearly competition: Ontology Alignment Evaluation Initiative (OAEI)
- Quality of found correspondences depends on difficulty of problem
  - Many approaches work fine for toy-problems, but fail for larger schemas
  - Hardly any commercial implementations of the methods
- Thus it is essential to keep the domain expert in the loop.
  - Active Learning
    - learn from user feedback while searching for correspondences
  - Leveraging the Crowd
    - mechanical turk
    - click log analysis of query results
    - DBpedia Mapping Wiki
  - Spread the manual integration effort over time
    - pay-as-you-go integration in data spaces (see next slide)

The Dataspace Vision

Alternative to classic data integration systems in order to cope with growing number of data sources.

Properties of dataspaces

- may contain any kind of data
  (structured, semi-structured, unstructured)
- require no upfront investment into a global schema
- provide for data-coexistence
- provide give best effort answers to queries
- rely on pay-as-you-go data integration

Franklin, M., Halevy, A., and Maier, D.: From Databases to Dataspaces
A new Abstraction for Information Management, SIGMOD Rec. 2005.

Madhavan, J., et al.: Web-scale Data Integration: You Can Only Afford to Pay As You Go, CIDR 2007.

6. Schema Heterogeneity on the Web

1. Role of Standards
   1. RDFa/Microdata/Microformats
   2. Linked Data

2. Self-Descriptive Data on the Web

6.1 Role of Standards

For publishing data on the Web, various communities try to avoid schema-level heterogeneity by agreeing on standard schemata (also called vocabularies or ontologies).

- Schema.org
  - 600+ Types: Event, local business, product, review, person, place, …
- Open Graph Protocol
  - 25 Types: Event, product, place, website, book, profile, article
- Linked Data
  - various widely used vocabularies.
  - FOAF, SKOS, Music Ontology, …

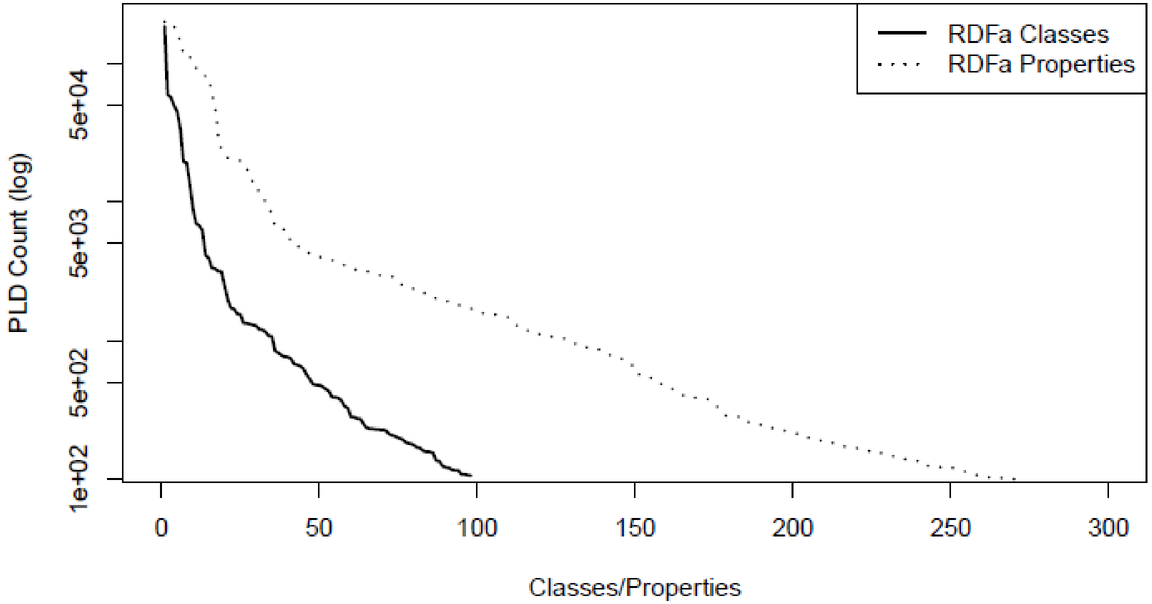
Microdata Vocabularies (CC 2012)

Only two vocabularies are used!

1. schema: Schema.org
2. datavoc: Google's Rich Snippet Vocabulary

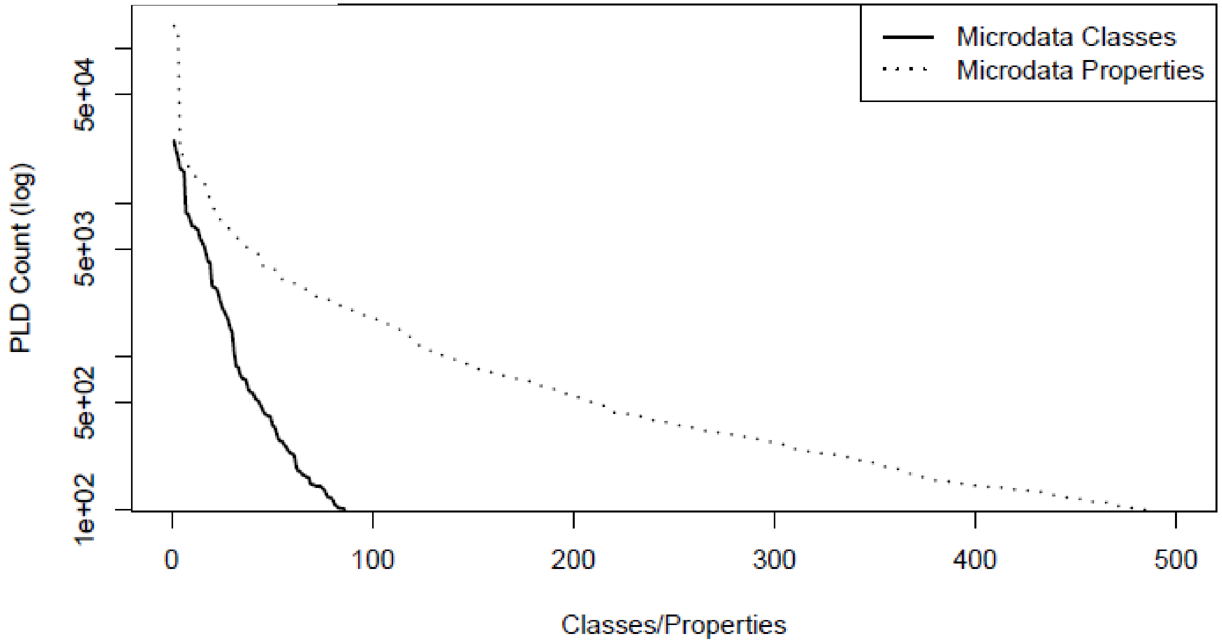
	Class	PLDs Total #	PLDs Total %	PLDs in Alexa #	PLDs in Alexa %
1	*schema:BlogPosting*	25,235	17.98	1,502	6.63
2	*datavoc:Breadcrumb*	21,729	15.49	5,244	23.13
3	*schema:PostalAddress*	19,592	13.96	1,404	6.19
4	*schema:Product*	16,612	11.84	3,038	13.40
5	*schema:LocalBusiness*	16,383	11.68	845	3.73
6	*schema:Article*	15,718	11.20	3,025	13.35
7	*datavoc:Review-aggregate*	8,517	6.07	2,376	10.48
8	*schema:Offer*	8,456	6.03	1,474	6.50
9	*datavoc:Rating*	7,711	5.50	1,726	7.61
10	*schema:AggregateRating*	7,029	5.01	1,791	7.90
11	*schema:Organization*	7,011	5.00	1,270	5.60
12	*datavoc:Product*	6,770	4.82	1,156	5.10
13	*schema:WebPage*	6,678	4.76	2,112	9.32
14	*datavoc:Organization*	5,853	4.17	654	2.89
15	*datavoc:Address*	5,559	3.96	654	2.89
16	*schema:Person*	5,237	3.73	890	3.93
17	*schema:GeoCoordinates*	4,677	3.33	312	1.38
18	*schema:Place*	4,131	2.94	488	2.15
19	*schema:Event*	4,102	2.92	659	2.91
20	*datavoc:Person*	2,877	2.05	523	2.31
21	*datavoc:Review*	2,816	2.01	783	3.45

Class / Property Distribution (CC 2012)



➔ Only a small set of the defined classes and properties is actually used.

➔ Heterogeneity on schema level is manageable.



Vocabularies in the LOD Cloud (2014)

Data sources mix terms from commonly used and proprietary vocabularies.

- Idea
  - Use common, easy-to-understand vocabularies wherever possible.
  - Define proprietary vocabularies terms only if no common terms exist.
- LOD Cloud Statistics
  - 378 (58.24%) proprietary vocabularies, 271 (41.76%) are non-proprietary
- Common Vocabularies

Vocabulary	Number of Datasets
foaf	701 (69.13%)
dcterms	568 (56.02%)
sioc	179 (17.65%)
skos	143 (14.10%)
void	137 (13.51%)
cube	114 (11.24%)

Source: http://linkeddatacatalog.dws.informatik.uni-mannheim.de/state/

6.2 Self-Descriptive Data

Data sources in the LOD context try to increase the usefulness of their data and ease data integration by making it self-descriptive.

Aspects of self-descriptiveness

1. Reuse terms from common vocabularies / ontologies
2. Enable clients to retrieve the schema
3. Properly document terms
4. Publish correspondences on the Web
5. Provide provenance metadata
6. Provide licensing metadata

Reuse Terms from Common Vocabularies

1. Common Vocabularies
   - **Friend-of-a-Friend** for describing people and their social network
   - **SIOC** for describing forums and blogs
   - **SKOS** for representing topic taxonomies
   - **Organization Ontology** for describing the structure of organizations
   - **GoodRelations** provides terms for describing products and business entities
   - **Music Ontology** for describing artists, albums, and performances
   - **Review Vocabulary** provides terms for representing reviews

2. Common sources of identifiers (URIs) for real world objects
   - **LinkedGeoData** and **Geonames** locations
   - **GeneID** and **UniProt** life science identifiers
   - **DBpedia** wide range of things

Enable Clients to retrieve the Schema

Clients can resolve the URIs that identify vocabulary terms in order to get their RDFS or OWL definitions.

Some data on the Web

```
<http://richard.cyganiak.de/foaf.rdf#cygri>
      foaf:name "Richard Cyganiak" ;
      rdf:type <http://xmlns.com/foaf/0.1/Person> .
```

Resolve unknown term

`http://xmlns.com/foaf/0.1/Person`

RDFS or OWL definition

```
<http://xmlns.com/foaf/0.1/Person>
           rdf:type owl:Class ;
           rdfs:label "Person";
           rdfs:subClassOf <http://xmlns.com/foaf/0.1/Agent> ;
           rdfs:subClassOf <http://xmlns.com/wordnet/1.6/Agent> .
```

Documentation of Vocabulary Terms

The documentation of a vocabulary is published on the Web in machine-readable form and can be used as a clue for schema matching.

- Name of a Vocabulary Term
  - ex1:name rdfs:label "A person's name"@en .
  - ex2:hasName rdfs:label "The name of a person"@en .
  - ex2:hasName rdfs:label „Der Name einer Person"@de .
- Additional Description of the Term
  - ex1:name rdfs:comment "Usually the family name"@en .
  - ex2:name rdfs:comment
    "Usual order: family name, given name"@en .

Publish Correspondences on the Web

Vocabularies are (partly) connected via vocabulary links.

Vocabulary Link

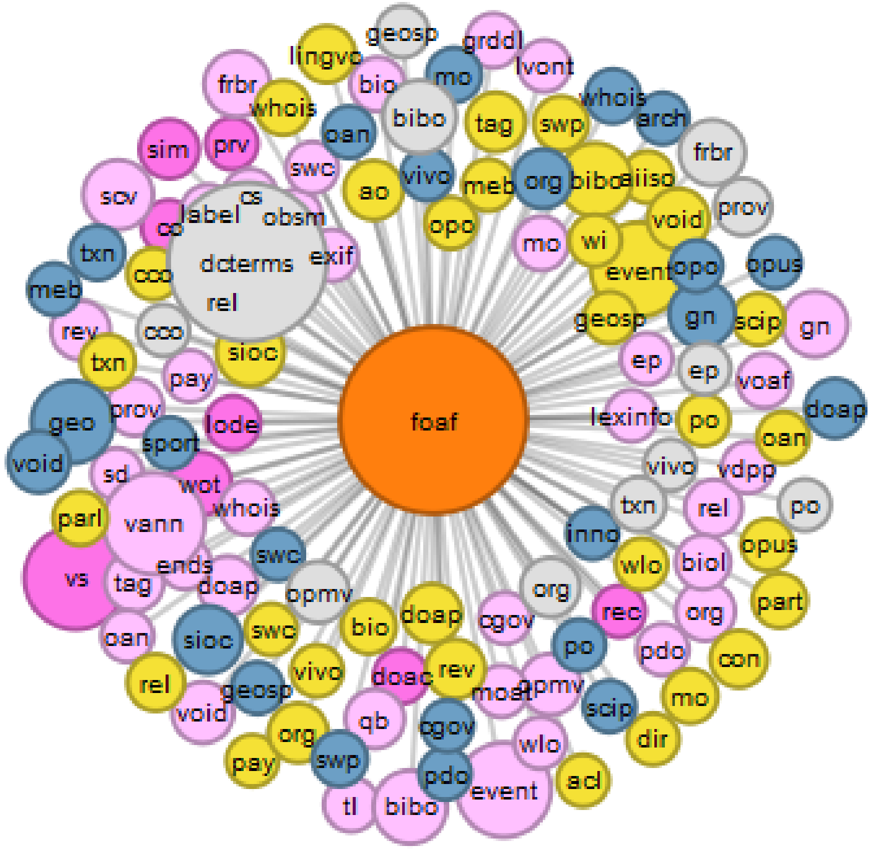
```
<http://dbpedia.org/ontology/Person>
owl:equivalentClass
<http://xmlns.com/foaf/0.1/Person> .
```

– Terms for representing correspondences
  - owl:equivalentClass, owl:equivalentProperty,
  - rdfs:subClassOf, rdfs:subPropertyOf
  - skos:broadMatch, skos:narrowMatch

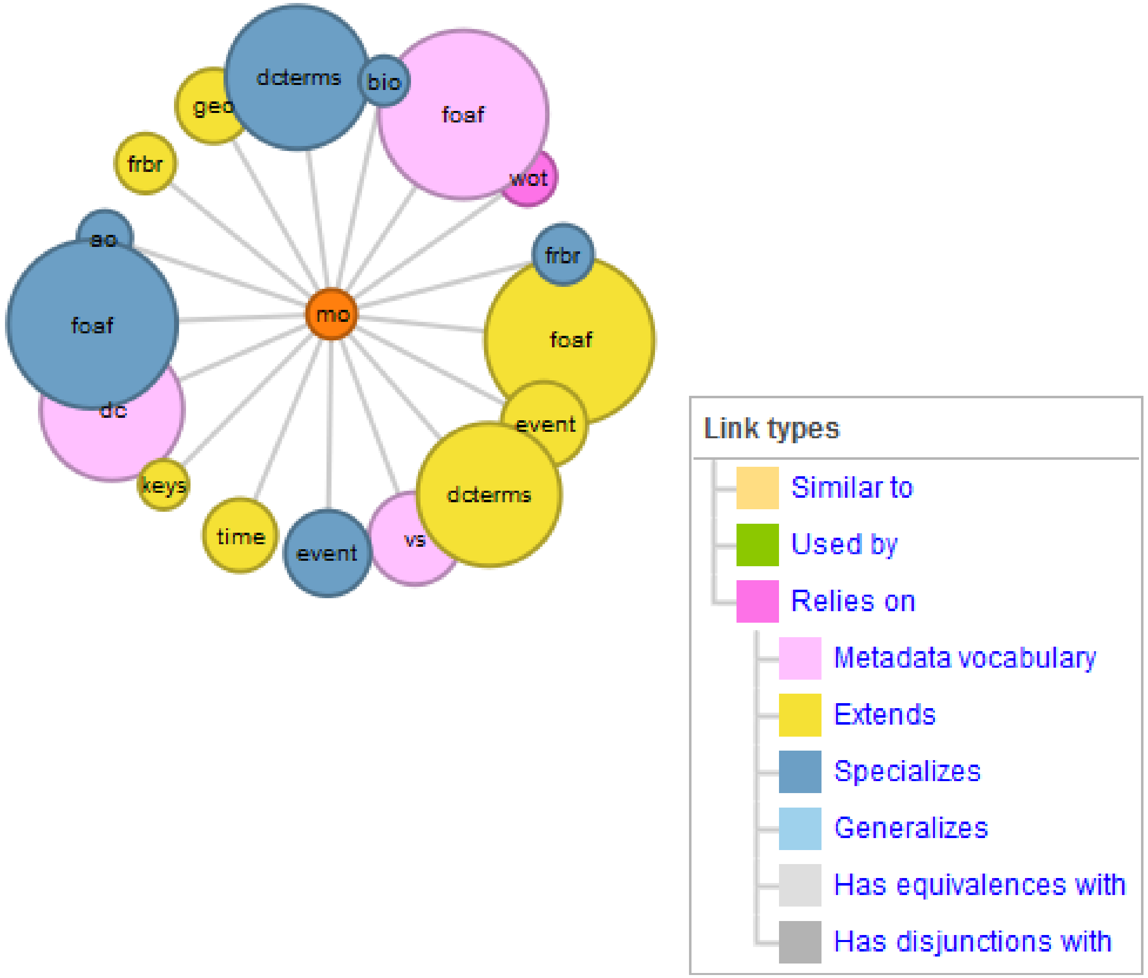
Deployment of Vocabulary Links

Vocabulary links:

Vocabularies referencing "foaf" (119)

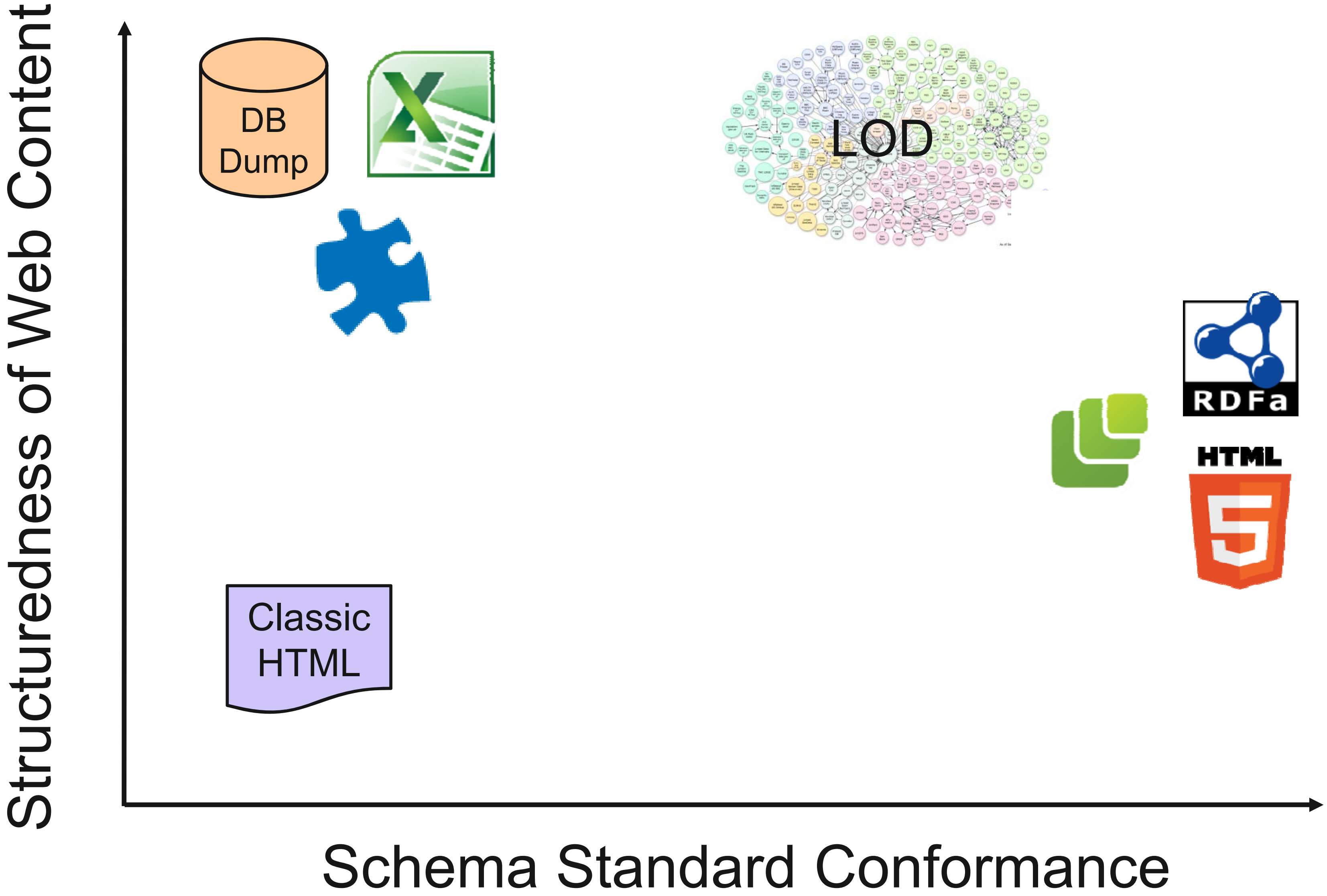


Vocabularies referenced by "mo" (17)



Source: Linked Open Vocabularies, https://lov.linkeddata.es/dataset/lov/

Summary: Structuredness and Standard Conformance



7. References

– Schema Integration

- Leser, Naumann: Informationsintegration. Chapter 5.1, dpunkt Verlag, 2007.
- Spaccapietra, et al.: Model Independent Assertions for Integration of Heterogeneous Schemas. VLDB, 1992.

– Interpretation and Data Translation

- Doan, Halevy, Ives: Principles of Data Integration. Chapter 5.10, Morgan Kaufmann, 2012.
- Leser, Naumann: Informationsintegration. Chapter 5.2, DBunkt Verlag, 2007.
- Ron Fagin, et al.: Translating Web Data. VLDB, 2002.

– Schema Matching

- Doan, Halevy, Ives: Principles of Data Integration. Chapter 5, Morgan Kaufmann, 2012.
- Leser, Naumann: Informationsintegration. Chapter 5.3, DBunkt Verlag, 2007.
- Dong, Srivastava: Big Data Integration. Chapter 2. Morgan & Claypool Publishers, 2015.
- Euzenat, Shvaiko: Ontology Matching. Springer, 2007.
- Rahm, Madhavan, Bernstein: Generic Schema Matching, Ten Years Later. VLDB, 2011.
- Hertling, Paulheim. WikiMatch - Using Wikipedia for Ontology Matching. Proceedings of the 7th International Workshop on Ontology Matching, 2012.
- Doan: iMAP: Discovering complex semantic Matches between Database Schemas. SIGMOD, 2004.

References

– Schema Matching (continued)
  - Rinser, Lange, Naumann: Cross-lingual Entity Matching and Infobox Alignment in Wikipedia. Information Systems (IS) 38(6):887–907, 2013.
  - Melnik, et al.: Similarity Flooding: A Versatile Graph Matching Algorithm and Its Application to Schema Matching. ICDE, 2002.
  - Avigdor Gal: Uncertain Schema Matching. Morgan & Clypool, 2011.

– Data Spaces
  - Franklin, M., Halevy, A., and Maier, D.: From Databases to Dataspaces A new Abstraction for Information Management. SIGMOD Rec., 2005.
  - Madhavan, J., et al.: Web-scale Data Integration: You Can Only Afford to Pay As You Go. CIDR, 2007.

– Heterogeneity/Schema Standardization on the Web
  - Bizer, et al.: Deployment of RDFa, Microdata, and Microformats on the Web – A Quantitative Analysis. 12th International Semantic Web Conference, 2013.
  - Heath, Bizer: Linked Data: Evolving the Web into a Global Data Space. Synthesis Lectures on the Semantic Web. Morgan & Claypool Publishers (also: free online version), 2011.