

Data Integration and Large Scale Analysis

04 Schema Matching and Mapping

Shafaq Siddiqi

Graz University of Technology, Austria



Agenda

- **Project Descriptions**
- **Motivation and Terminology**
- **Schema Detection**
- **Schema Matching**
- **Schema Mapping**

Project Descriptions

Student Projects

- **SystemDS**

- <https://issues.apache.org/jira/browse/SYSTEMDS-3780?filter=12350169>

- **Daphne**

- <https://github.com/daphne-eu/daphne/issues?q=is%3Aissue+is%3Aopen+label%3A%22student+project%22>

- **Contact person: Dr. Lucas Iacono <liacono@know-center.at>**

Team Projects

- **#1 Data Analysis Pipeline for Weather Data and Deploy it on Cloud**
 - Goal: to provide insights about thermal inversion on Austrian Farms using weather data collected with a sensor tower and a weather station (**real data**)
 - Develop a pipeline including data collection, preparation, analysis, modeling, model deployment and results provisioning
 - Use public cloud services (AWS, Google or Azure) to perform the data cleaning and inspection, and to compute the required analytics
 - Detect thermal inversions in the lower layers of the atmosphere above the farm in the frost season
 - Merge the data from the sensor tower with the dataset from the weather station to train and evaluate a DL model to predict minimum temperature in the location of the tower
- **#2 Data Analysis Pipeline for Motor Sports Data and Deploy it on Cloud**
 - F1 data but to predict the fastest lap times from the sector times

Motivation and Terminology

Recap: ETL/EAI Schema Transformations

```
<?xml version="1.0" encoding="UTF-8"?>
<xsl:stylesheet version="2.0" xmlns:xsl="http://www.w3.org/1999/XSL/Transform">
<xsl:template match="/">
  <xsl:element name="suppliers">
    <xsl:for-each select="/resultsets/resultset[@Tablename='Supplier']/row">
      <xsl:element name="supplier">
        <xsl:attribute name="ID"><xsl:value-of select="Suppkey"/></xsl:attribute>
        <xsl:element name="Name"><xsl:value-of select="Suppname"/></xsl:element>
        <xsl:element name="Address"><xsl:value-of select="SuppAddress"/></xsl:element>
      </xsl:element>
    </xsl:for-each>
  </xsl:element>
</xsl:template>
</xsl:stylesheet>
```

Are you kidding me? I have 100s of systems/apps and 1000s* of tables/attributes

```
<resultsets>
  <resultset Tablename="Supplier">
    <row>
      <Suppkey>7</Suppkey>
      <Suppname>MB</Suppname>
      <SuppAddress>1035 Coleman Rd</SuppAddress>
    </row>
    <row> ... </row>
  </resultset>
</resultsets>
```



```
<suppliers>
  <supplier ID="7">
    <Name>MB</Name>
    <Address>1035 Coleman Rd</Address>
  </supplier>
  <supplier> ... </supplier>
</suppliers>
```

* [Rudolf Munz: Datenmanagement für SAP Applikationen, BTW, 2007:
67,000 tables, 700,000 columns, 10,000 views, 13,000 indexes]

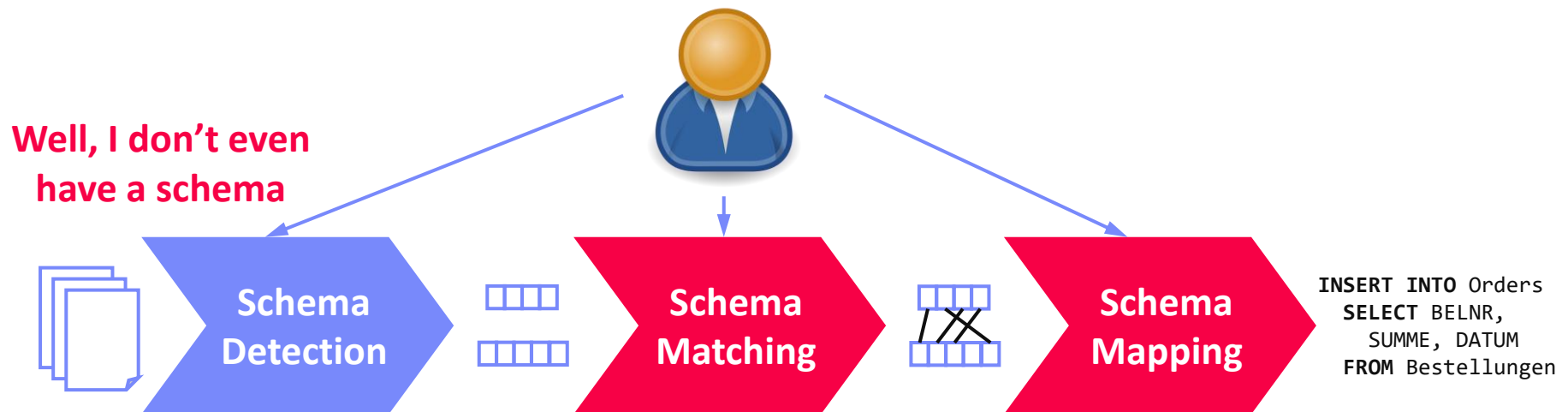
Schema Matching and Mapping

■ Schema Matching

- **Given:** two or more relational/hierarchical schemas (and data)
- Find schema mappings in terms of logical attribute correspondences

■ Schema Mapping

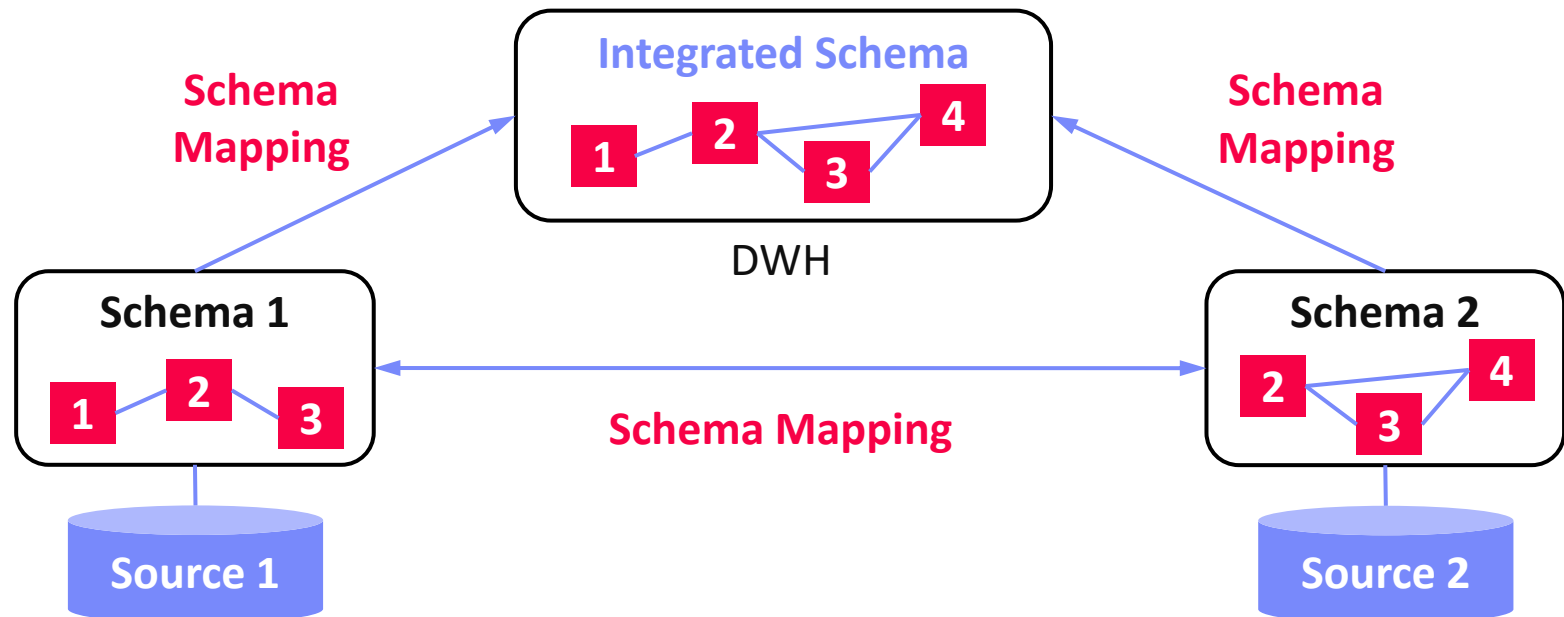
- **Given:** logical attribute correspondences between schemas
- Compile physical schema mapping programs ([SQL](#), [XSLT](#), [XQuery](#), etc)



Schema Mapping vs. Schema Integration

Schema Integration

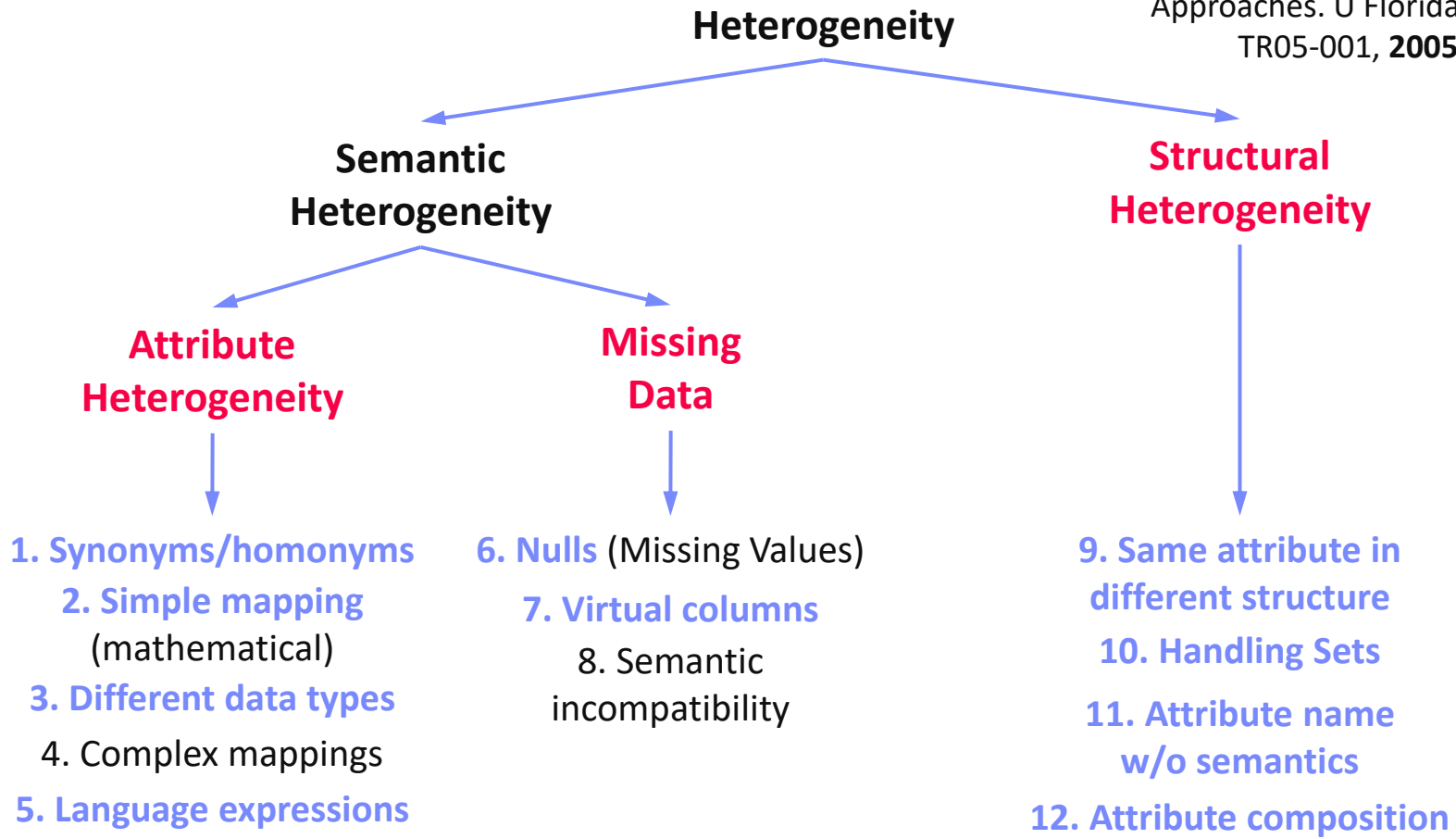
- **Use case:** DWH schema ([lecture 02](#)), virtual/federated DBMS ([lecture 03](#))
- **Schema integration:** map existing schemas into consolidated schema
- **Schema mapping** orthogonal, but both deal with semantic and structural heterogeneity



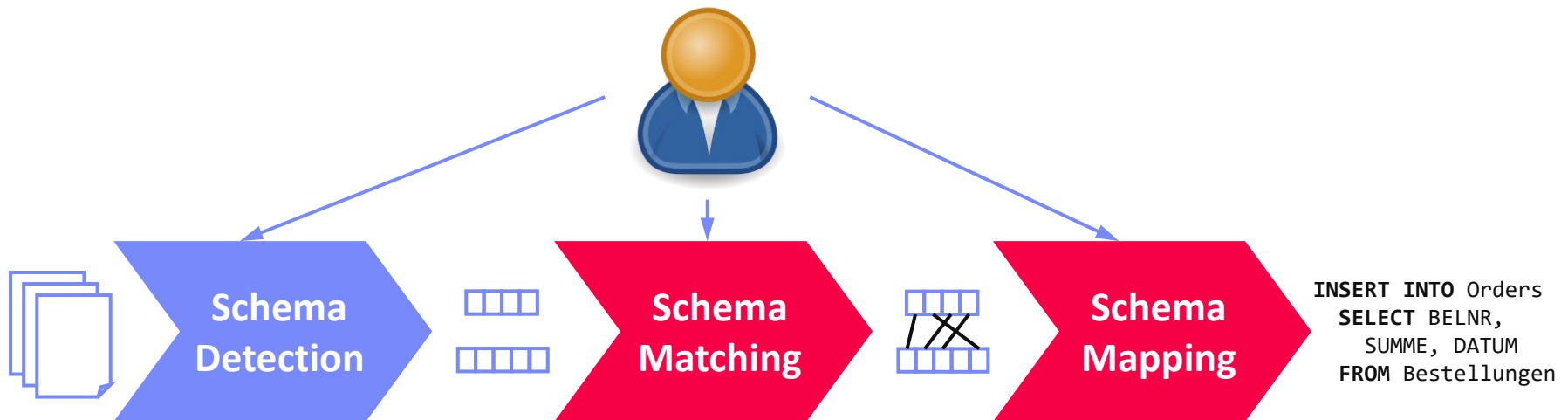
Recap: Types of Heterogeneity

→ Scope

[J. Hammer, M. Stonebraker, and O. Topsakal: THALIA: Test Harness for the Assessment of Legacy Information Integration Approaches. U Florida, TR05-001, 2005]



Schema Detection



Atomic Data Type Detection

Overview

- **Problem:** Given CSV, JSON, XML files, detect data types of attributes
- **Approach:** Basic extraction rules, regular expressions over data sample

Example: Schema Inference

- Infer schema for dataframe/dataset columns from sample
- **Basic types:** Decimal, Boolean, Double, Integer, Long, String
- Infer schema from java objects via class reflection

```
StructType(
  StructField(pid, IntegerType, true),
  StructField(name, StringType, true),
  StructField(pos, StringType, true),
  StructField(jnum, IntegerType, true),
  StructField(ncid, IntegerType, true),
  StructField(tid, IntegerType, true))
```



```
./data/players.csv:
pid,name,pos,jnum,ncid,tid
4614,Hannes Reinmayr,FW,14,1313,258
5435,Miroslav Klose,FW,11,789,144
6909,Manuel Neuer,GK,1,163,308
```



```
Dataset<Row> ds = sc.read()
  .format("csv")
  .option("header", true)
  .option("inferSchema", true)
  .option("samplingRatio", 0.001)
  .load("./data/players.csv");
```



Structure Extraction from Nested Documents

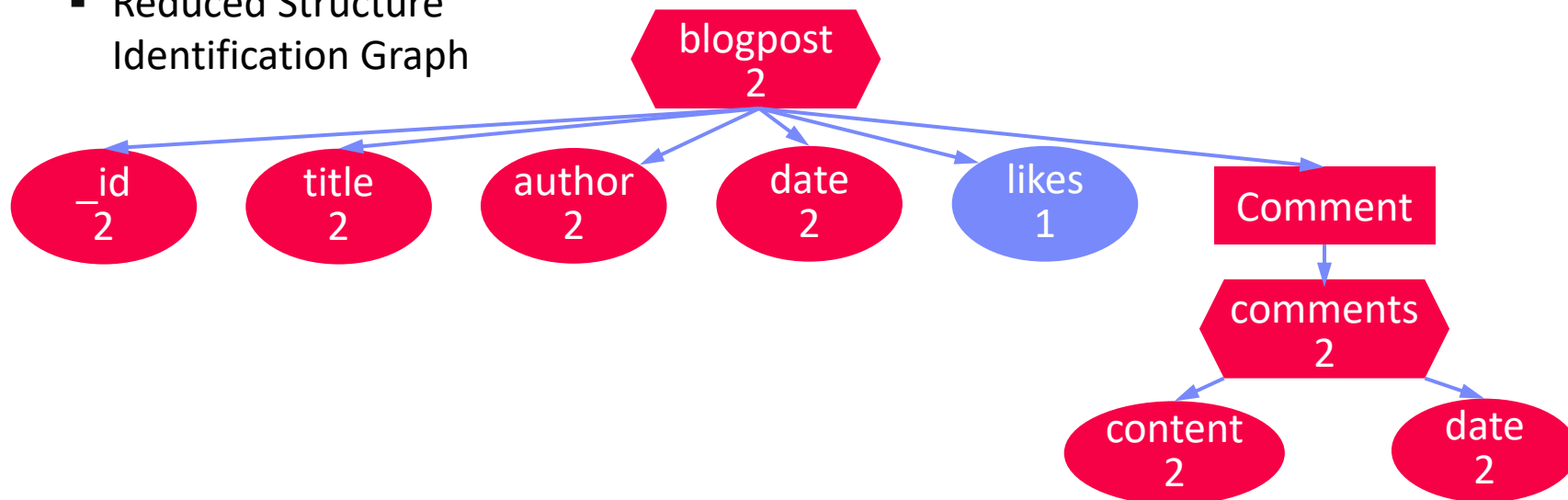
Structure Extraction Overview

- **Problem:** JSON/JSONL, XML documents with optional attributes, subtrees
- **Approach:** Scan data, build maximum tree w/ attached meta data
- Meta data := counts or appearances (e.g., document/line IDs)

Example JSON Schema Extraction

- Structure Identification Graph (appearances, data types, etc)
- Reduced Structure Identification Graph

[Meike Klettke, Uta Störl, Stefanie Scherzinger: **Schema Extraction and Structural Outlier Detection** for JSON-based NoSQL Data Stores. **BTW 2015**]



Data Profiling

#1 Inclusion Dependency (ID) Discovery

- ID from $R[X]$ to $S[Y]$ indicates that all values in $R[X]$ must appear in $S[Y]$ → potential indication of **FK relationship** from $R[X]$ to $S[Y]$
- Robust inclusion dependency:**
 $|R[X] \in S[Y]| / |R[X]| > \delta$
- PK-FK candidate refinement
(e.g., coverage, similarity, value ranges)

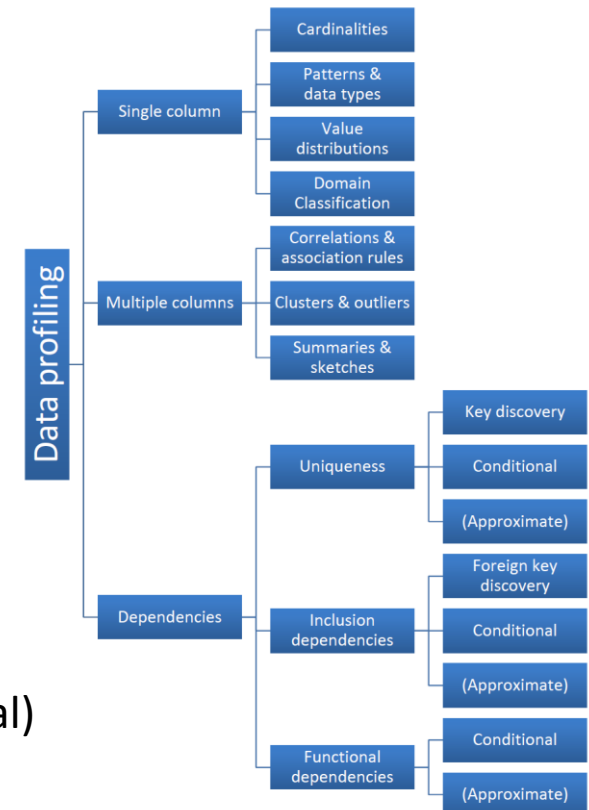
#2 Functional Dependency (FD) Discovery

- FDs indicative of relational schema
(**key candidates**, **normalization**)
- Discover minimal, non-trivial dependencies
- Extend candidates along **set containment lattice**
 - $A \rightarrow C$ allows pruning $\{AB\} \rightarrow C$ (non-minimal)
 - $\text{NOT}(A \rightarrow B)$ allows pruning $A \rightarrow BC$

[Ziawasch Abedjan, Lukasz Golab, Felix Naumann: Data Profiling: A Tutorial. **SIGMOD 2017**]



[Dong Deng et al: The Data Civilizer System. **CIDR 2017**]



Semantic Data Type Detection

[Madelon Hulsebos et al:
Sherlock: A Deep Learning
Approach to Semantic Data
Type Detection. **KDD 2019**]



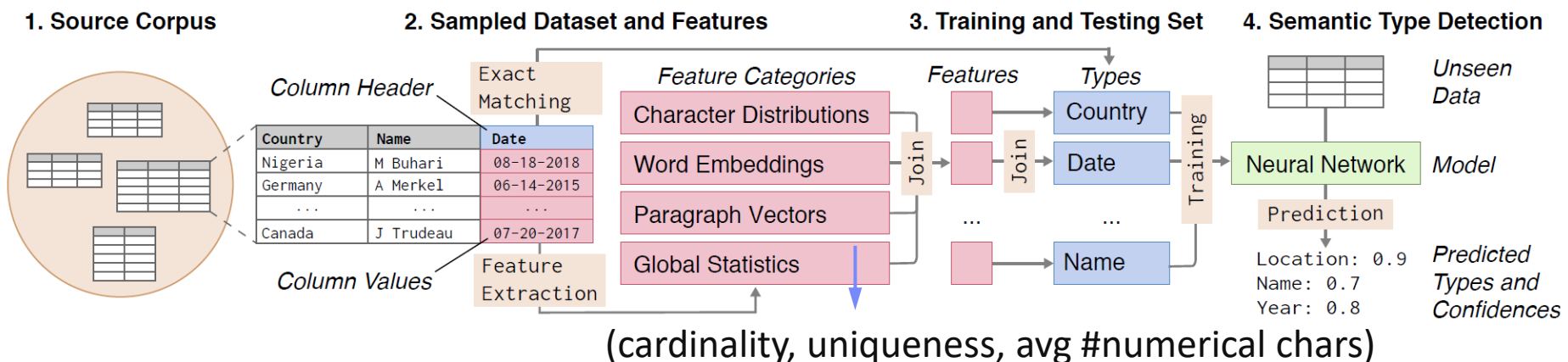
Problem

- Detect semantic types of columns (e.g., location, date, name)
- **Use cases:** improved data cleaning, schema matching via semantic types

Sherlock: DNN-based Type Detection

- Trained on 686,765 data columns
- 78 semantic types from T2Dv2 → VizNet extraction
- 1,588 features from each column, incl global stats
- Formulation of type detection as multi-class classification problem

<http://webdatacommons.org/webtables/goldstandardV2.html>
(DBPedia, Webtables)



Semantic Data Type Detection

[Dan Zhang et al:

Sato: Contextual Semantic Type Detection in Tables. **PVLDB 2020**]

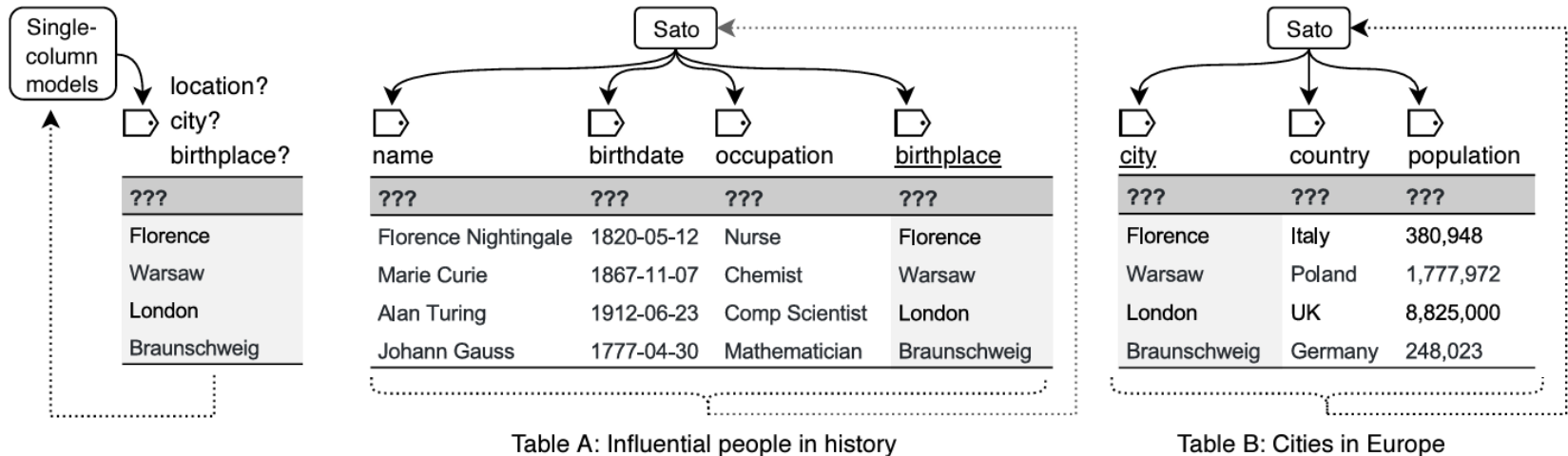


Problem

- Detect semantic types of columns with context
- **Use cases:** improved data cleaning, schema matching via semantic types

SATO: LDA + DNN-based Type Detection

- LDA model to estimate a table's intent (global context)
- Co-occurrence of columns (local context)
- Sherlock for single column type prediction



Schema Enforcement and Evolution

■ Schema Enforcement

- Given schema of syntactic and semantic types
- **#1 Raise errors** on invalid data ingestion (ACID consistency and atomicity)
- **#2 Leverage schema constraints** for automatic data cleaning

■ Schema Evolution

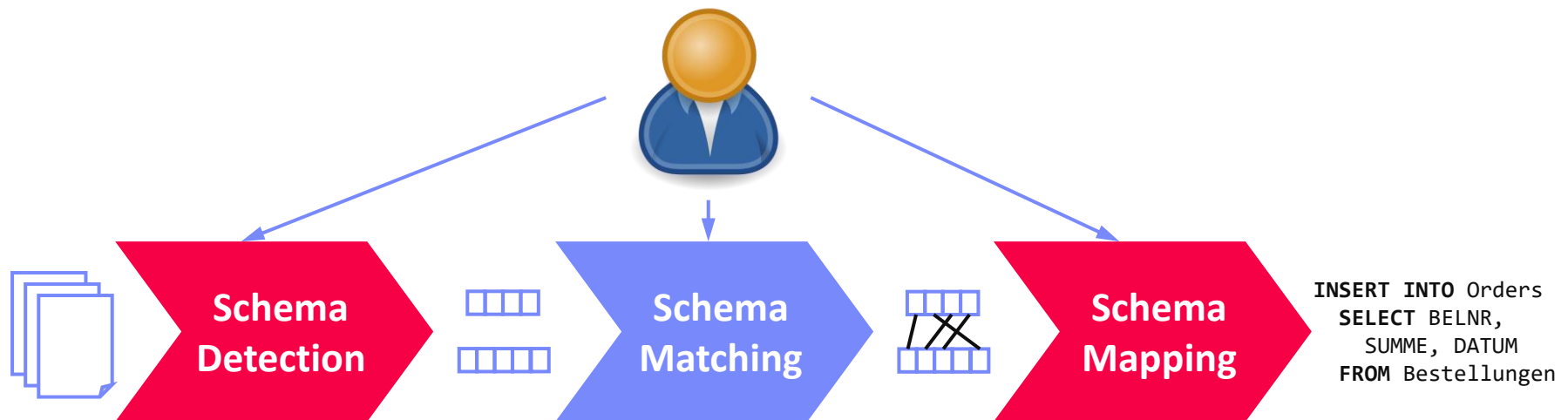
- Incremental modification of schema
- Handle changes of source data (additional columns, different data types)
- Copy vs. in-place modifications (e.g., data type int → string)
- Example: **Delta Lake**

[Andreas Neumann, Denny Lee: Enforcing and Evolving the Schema – Diving into Delta Lake Series,

<https://www.databricks.com/blog/2019/09/24/diving-into-delta-lake-schema-enforcement-evolution.html> , 2019]



Schema Matching



Overview Schema Matching

[Philip A. Bernstein, Jayant Madhavan, Erhard Rahm: Generic Schema Matching, Ten Years Later. PVLDB 2011 (test of time award)]



Motivation

- Large and convoluted schemas (# tables, # attributes, structure)
- Goal:** generation of matching candidates (refined by user)

S2

Problem Definition

- Given:** two schemas **S1** and **S2**
- Goal:** Generate correspondences between **S1** and **S2**
- Correspondence:** relationship between M elements in S1 and N elements in S2
- Mapping expression:** function how elements are related (directional or non-directional)

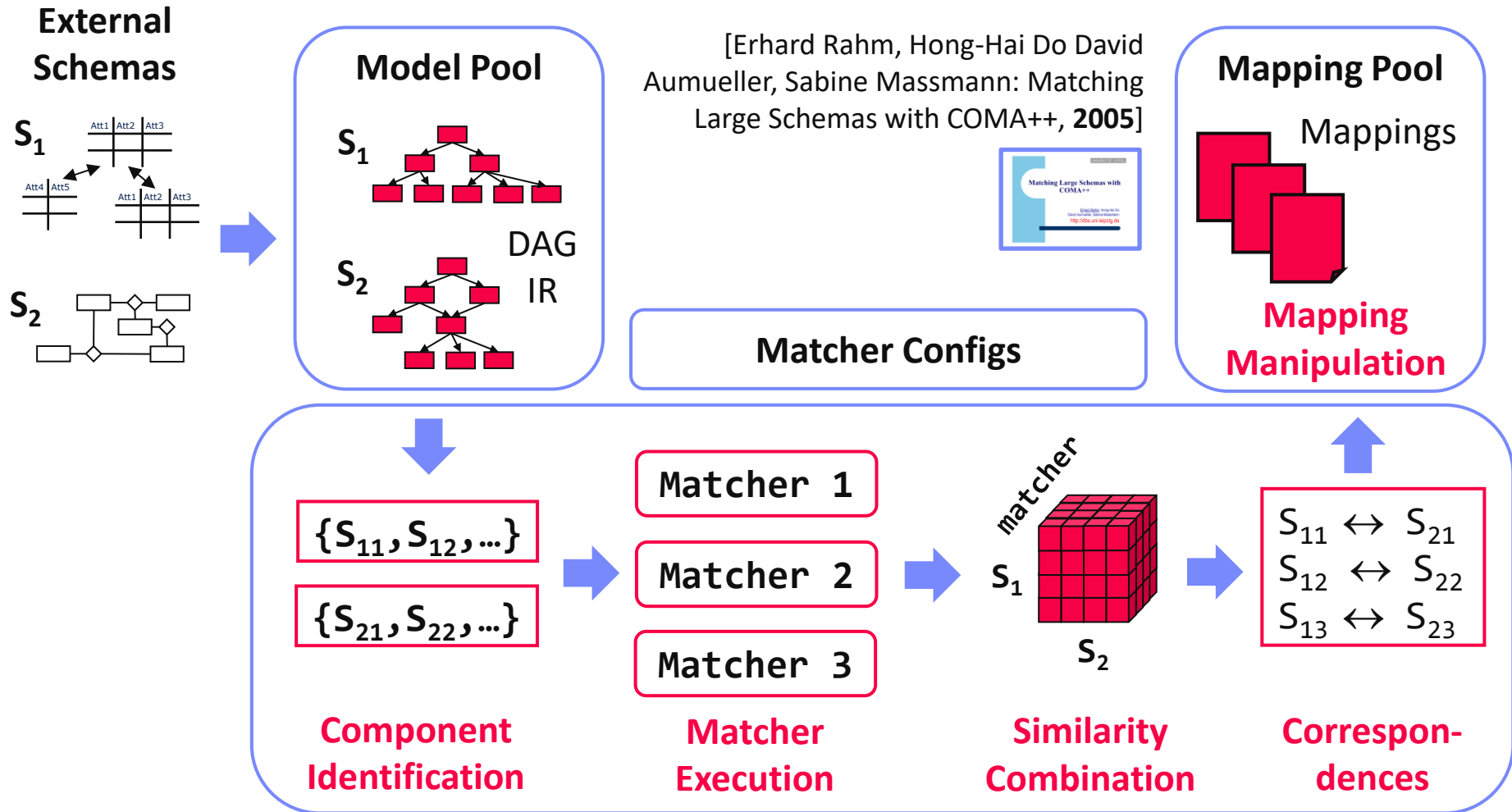
S1

Books	
ISBN	CHAR(15) PK
Title	VARCHAR(96)
Author	VARCHAR(64)
Price	FLOAT

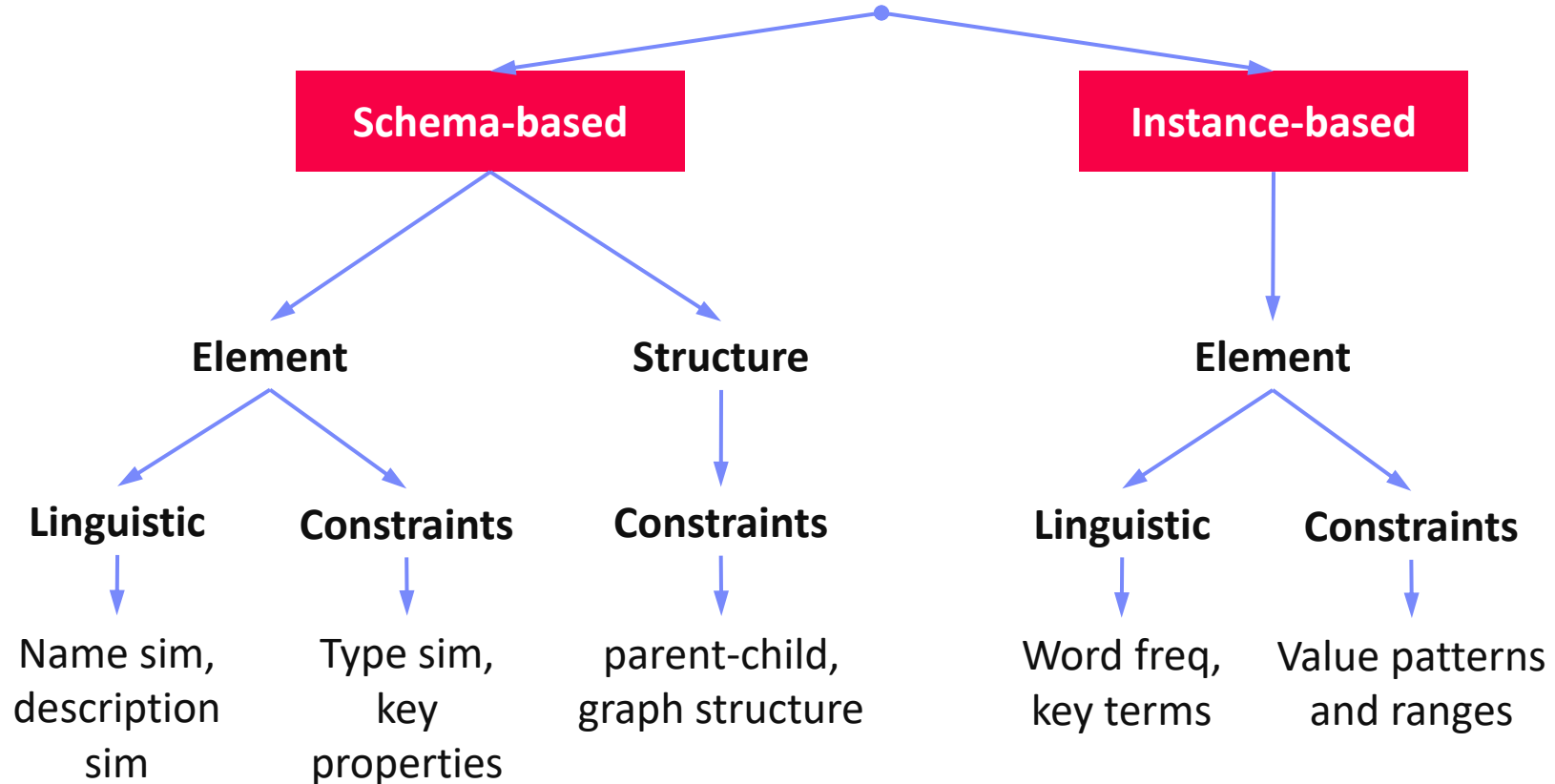
BookInfo	
ID	CHAR(15) PK
AuthorID	INT REF AuthorInfo
BookTitle	VARCHAR(128)
ListPrice	FLOAT
DiscPrice	FLOAT

AuthorInfo	
AuthorID	INT PK
LastName	VARCHAR(32)
FirstName	VARCHAR(32)

System Architecture and Matching Process



Classification of Matching Techniques

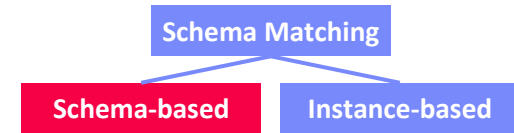


- **Cardinalities: 1:1, 1:N, N:M**
- **Combined Matchers (hybrid, composite)**

[Erhard Rahm, Philip A. Bernstein: A survey of approaches to automatic schema matching. *VLDB J.* 2001]



Selected Matchers



Linguistic Approaches

- Syntactic
 - Affix (suffix, prefix)
 - N-grams
 - EditDistance
- Semantic
 - Synonyms
 - Hierarchy → taxonomies
 - Language → dictionaries

Name	Street	City
Emma Schmidt	Luisenstrasse 90	Munich, 80333
Klaus Schumann	Koenigsstrasse 7	Dresden, 01199

Firstname	Lastname	Street	Num	ZIP	City
Susanne	Froehlich	Weststrasse	2	01187	Dresden
Thomas	Kunze	Dammweg	45	12437	Berlin

Example Trigram

- Similarity

$$= 2 | \text{S1} \cap \text{S2} | / (| \text{S1} | + | \text{S2} |)$$

$$= 8/16 = 0.5$$

Name					__N	_Na	Nam	ame	me_	e__
Lastname	__L	_La	Las	ast	stn	tna	nam	ame	me_	e__

(alignment irrelevant)

Selected Matchers, cont.

Schema Matching

Schema-based

Instance-based

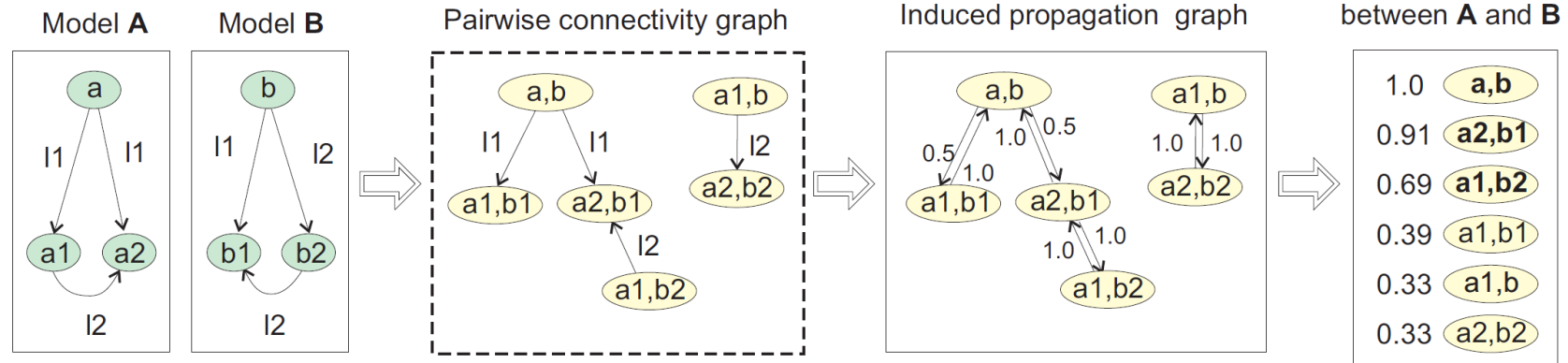
■ Constraint-Based Approaches

- **Elements:** data types, domains, key attributes, constraints
- **Structure:** relationships between elements, combinations of data types, neighborhood, specialization and composition

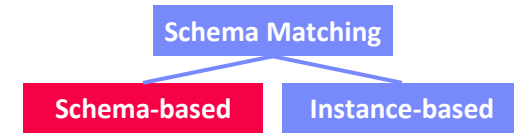
■ Example Similarity Flooding

- Create map pairs $A \times B$ (PCG)
- Propagation coefficients: $1/|\text{out}(v)|$ (IPG)
- Initial sim, adjusted by neighborhood sim until fixpoint (converged)

[Sergey Melnik, Hector Garcia-Molina, Erhard Rahm: Similarity Flooding: A Versatile Graph Matching Algorithm and Its Application to Schema Matching. **ICDE 2002**]



Selected Matchers



Pre-Trained Language Models

- **Standard Practice**: Customer's data to a known industry-specific schema (ISS)
- **Limitations**: Data privacy (no access to data records), Large ISSs
- Active learning for labeled input
- Use pre-trained language model BERT to extract features

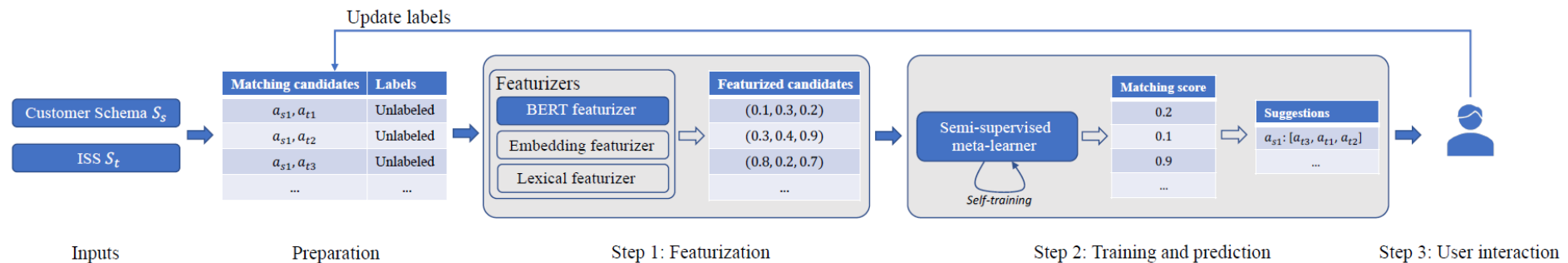
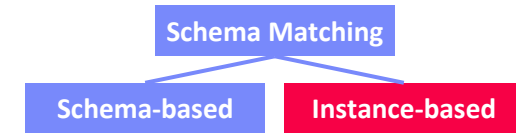


Fig. 2: The Matching Pipeline of the Learned Schema Matcher

Selected Matchers, cont.



■ Problem Schema-based

- Attribute names might differ vastly (CustNa vs Name, CustSt vs Street)

→ **Instance-based matching**, but need for data

■ Linguistic Approaches

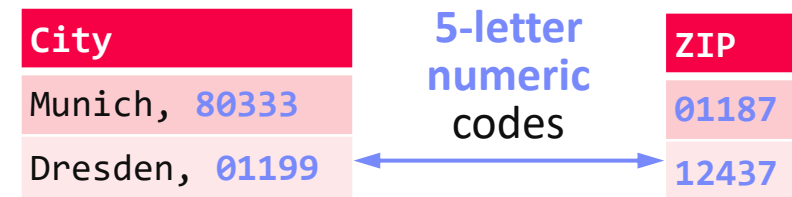
- Word frequencies, bigrams, trigrams, etc
- Keywords, abbreviations

Street	City
Luisenstrasse 90	Munich, 80333
Koenigsstrasse 7	Dresden, 01199

Street	Num	ZIP	City
Weststrasse	2	01187	Dresden
Dammweg	45	12437	Berlin

■ Constraint-based Approaches

- Elements:** data types and lengths, value domains, patterns
- Structure:** combinations of element constraints



Combination of Matchers

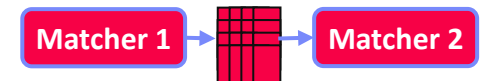
#1 Reuse

- Exploitation of transitive similarity
- Fast and efficient matching, but potential for lost mappings (e.g., S3 misses attributes)

$$S1 \cong S3 \wedge S3 \cong S2 \\ \rightarrow S1 \cong S2$$

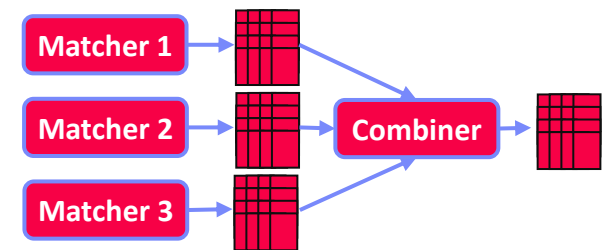
#2 Refinement

- Chaining:** matcher M_{n+1} works on mappings of M_n
 \rightarrow efficiency but potential for lost mappings
- Context-sensitive matching:** Matching context of schema components, matching elements within components



#3 Composite Matchers

- Select combination of complementary matchers in form of **ensemble**
- Aggregation** of similarity (e.g., trigram, synonym \rightarrow avg/min/max)



Efficiency and Scalability

[Philip A. Bernstein, Jayant Madhavan, Erhard Rahm: Generic Schema Matching, Ten Years Later. **PVLDB 2011**]



■ Problem

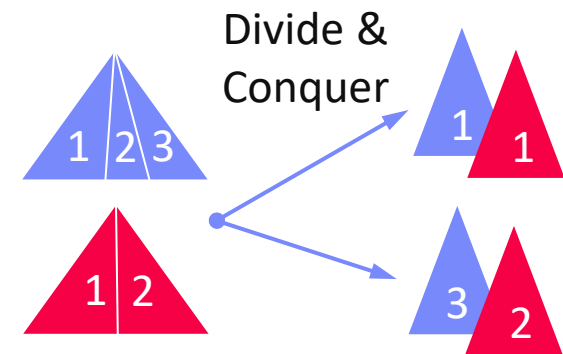
- **Large schemas and matching complexity**; all-pair problem $O(n*m)$

■ #1 Early Search Space Pruning

- Faster matchers used to eliminate unlikely matches
- Reduce schema sizes for expensive matchers

■ #2 Partition-based Matching

- Blocking into independent fragments
- Match elements of similar fragment



■ #3 Parallel Matching

- Process different steps/fragments in parallel

■ #4 Custom Similarity Matrices

- Sparse matrices (adjacency lists) w/ nesting

[Philip A. Bernstein, Sergey Melnik, Michalis Petropoulos, Christoph Quix: Industrial-Strength Schema Matching. **SIGMOD Record 2004**]



Schema Matching Tools

Commercial Tools

- Most **message-oriented middleware**, **EAI**, **ETL** tools provide mapping UIs (w/ basic string similarity for matching)
- Many data modeling tools also support matching/mapping

Academic Prototypes



[Erhard Rahm: Towards Large-Scale Schema and Ontology Matching. Schema Matching and Mapping 2011]

		COMA++	Falcon	Rimom	Asmov	AM	Harmony
year of introduction		2002/2005	2006	2006	2007	2007	2008
Input	<i>relational</i>	✓	-	-	-	-	✓
schemas	<i>XML</i>	✓	-	-	-	(✓)	✓
	<i>ontologies</i>	✓	✓	✓	✓	✓	✓
compreh. GUI		✓	(✓)	?	?	✓	✓
Matchers	<i>linguistic</i>	✓	✓	✓	✓	✓	✓
	<i>structure</i>	✓	✓	✓	✓	✓	✓
	<i>Instance</i>	✓	-	✓	✓	✓	-
use of ext.dictionaries		✓	?	✓	✓	✓	✓

Schema Matching Tools, cont.

COMA system for combining match algorithms in a flexible way)



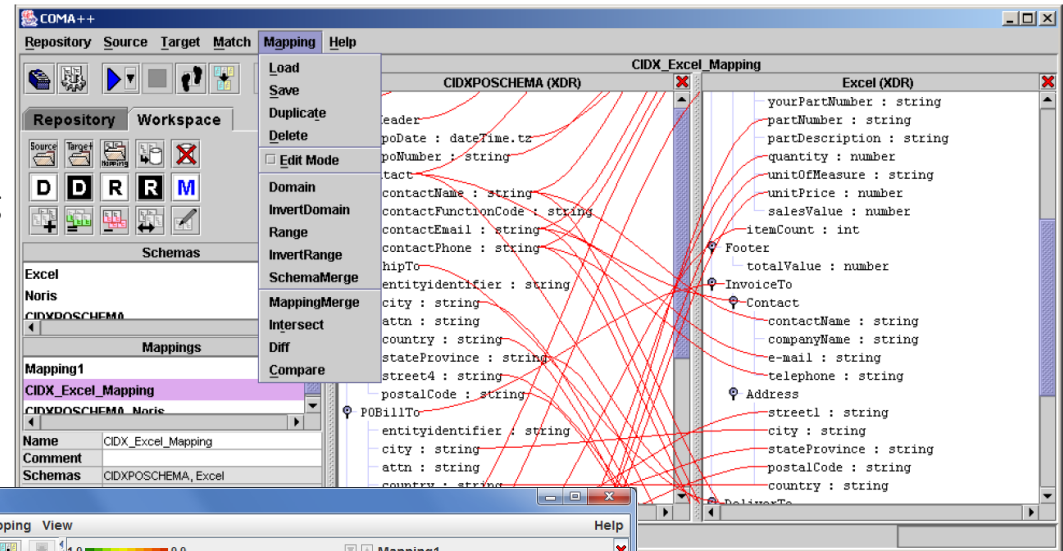
COMA ++



[Hong Hai Do, Erhard Rahm: COMA - A System for Flexible Combination of Schema Matching Approaches. **VLDB 2002**]

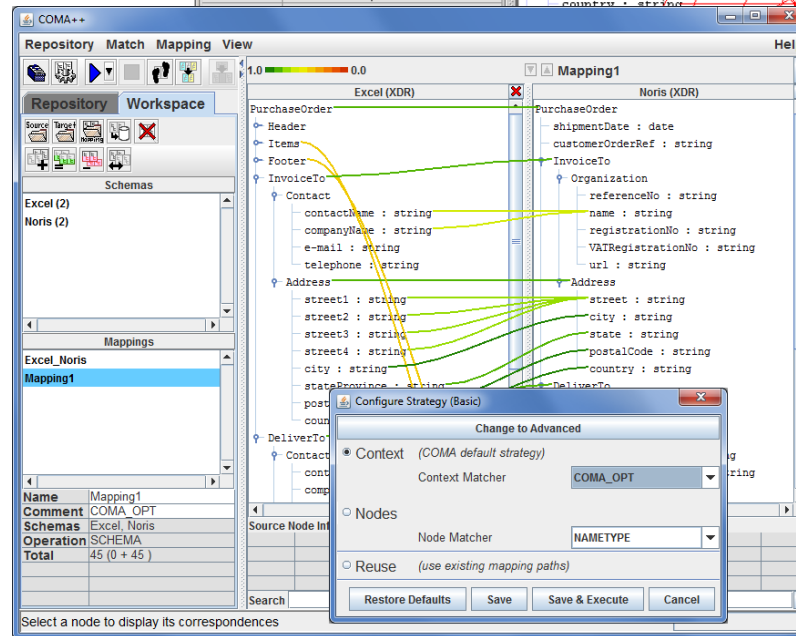


[David Aumüller, Hong Hai Do, Sabine Massmann, Erhard Rahm: Schema and ontology matching with COMA++. **SIGMOD 2005**]



COMA 3.0

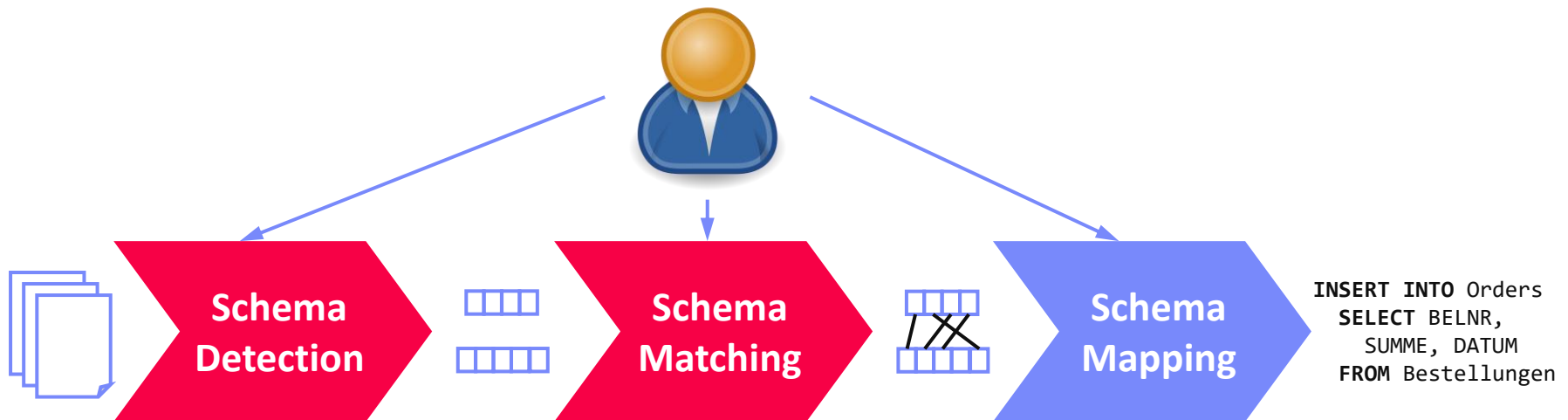
- 2011/2012
- Ontology Merging
- Workflow Management



[Credit:

<https://dbs.uni-leipzig.de/de/Research/coma.html>]

Schema Mapping



Schema Mapping Overview

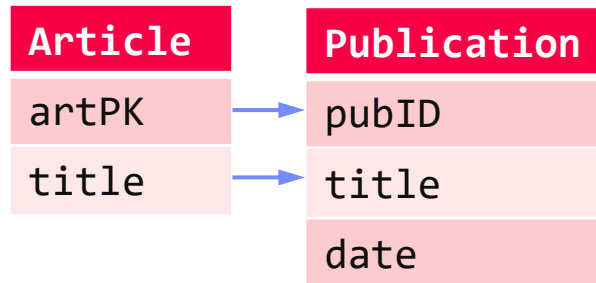
■ Problem

- **Given:** two schemas w/ high-level mapping
- Generate concrete transformation program/query (SQL, XSLT, XQuery)

■ Schema Mapping Process (systematic lowering)

- **High-level mapping:** intra- and inter-schema correspondences
- **Low-level mapping:** mapping that ensures consistency with constraints of target schema and user intend (interpretation)
- **Transformation query:** transformation program from one into the other schema, backend-specific (query generation)

■ Example

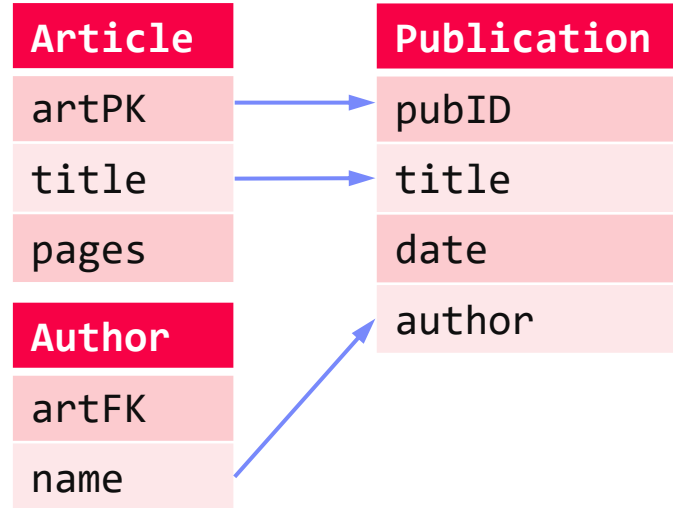


Transformation Query:

```
INSERT INTO Publication
SELECT artPK, title, NULL
FROM Article
```

Mapping Interpretations

Without Intra-Schema Correspondences



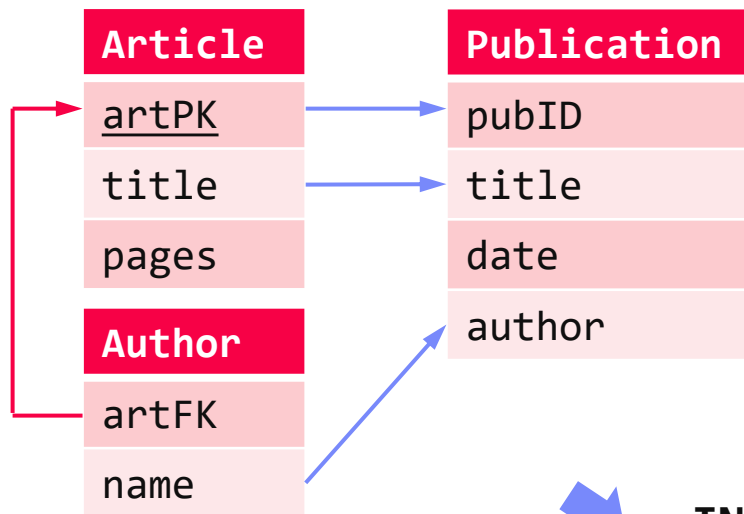
```

INSERT INTO Publication
  (SELECT artPK AS pubID,
    title AS title,
    NULL AS date,
    NULL AS author
  FROM Article)
UNION ALL
  (SELECT NULL AS pubID,
    NULL AS title,
    NULL AS date,
    name AS author
  FROM Author)
  
```



Mapping Interpretations, cont.

With Intra-Schema Correspondences



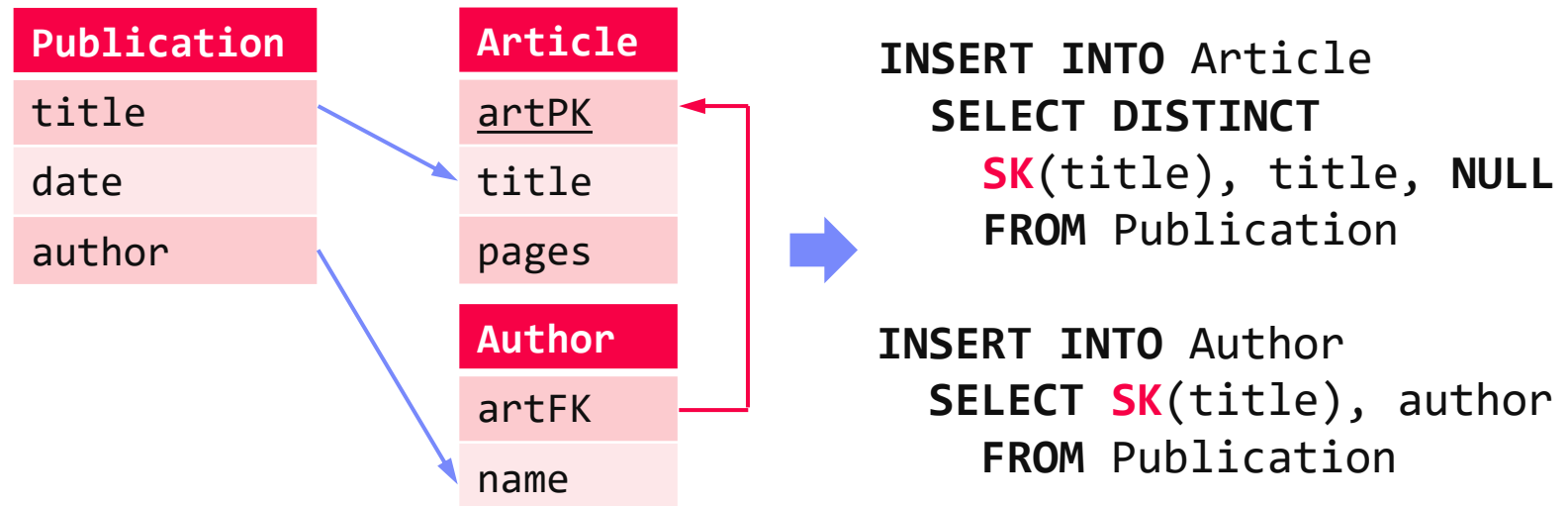
```
INSERT INTO Publication
SELECT artPK, title,
       NULL, name
FROM Article, Author
WHERE artPK = artFK
```

Note: Inner join acts as filter (no articles w/o authors, NOT NULL constraints)

```
INSERT INTO Publication
SELECT artPK, title, NULL, name
FROM Article LEFT OUTER JOIN Author
ON artPK = artFK
```

Mapping Interpretations, cont.

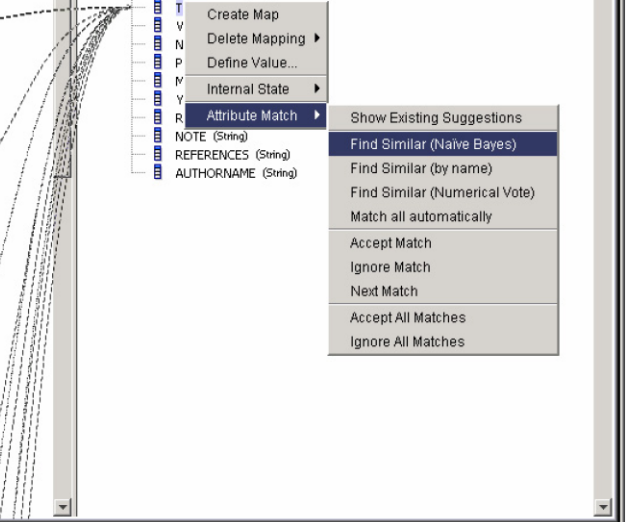
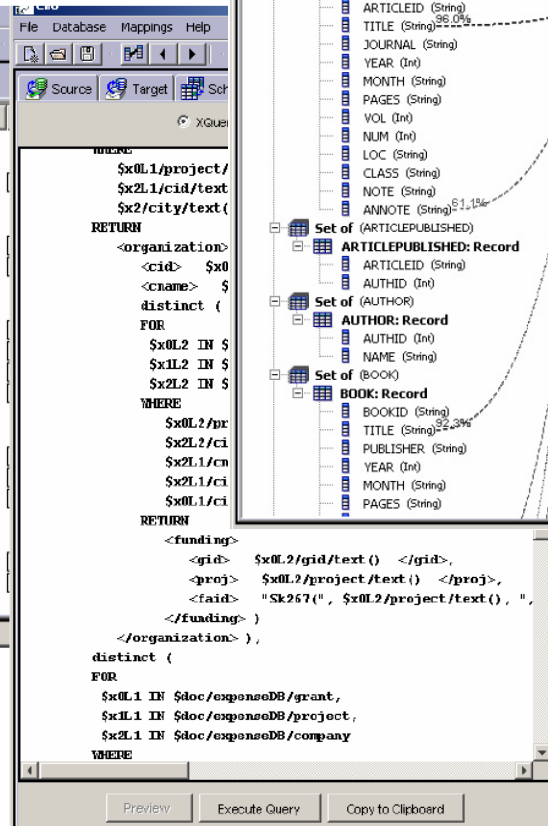
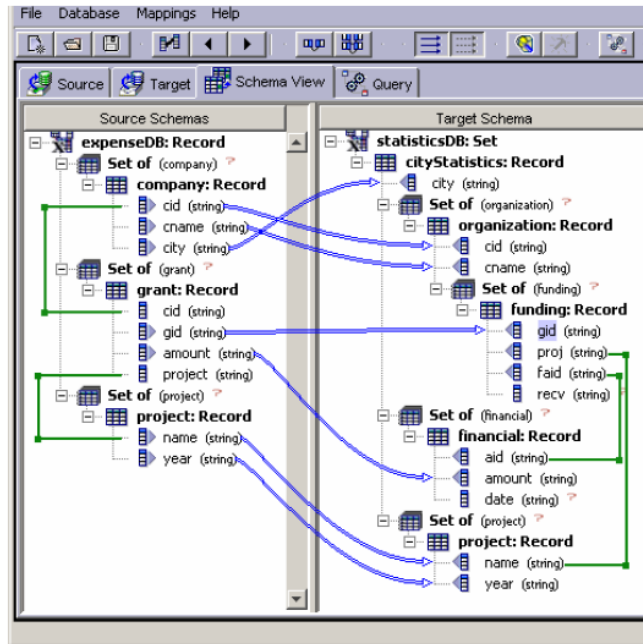
From Denormalized to Normalized Form



- **Skolem Function (SK):** unique key generation from tuple values $t[X]$ of an attribute set X

Schema Matching Tools

■ Clio (IBM Research – Almaden)



[Mauricio A. Hernández, Renée J. Miller, Laura M. Haas: Clio: A Semi-Automatic Tool For Schema Mapping. **SIGMOD 2001**]



[Laura M. Haas, Mauricio A. Hernández, Howard Ho, Lucian Popa, Mary Roth: Clio grows up: from research prototype to industrial tool. **SIGMOD 2005**]

Summary and Q&A

- Schema Detection
- Schema Matching
- Schema Mapping

[Philip A. Bernstein, Sergey Melnik:
Model Management 2.0: Manipulating
Richer Mappings. **SIGMOD 2007**]



“Given the existence of all these tools, **why is it still so labor-intensive to develop engineered mappings?** To some extent, it is an **unavoidable consequence of ambiguity** in the meaning of the data to be integrated. If there is a specification of the schemas, it often says little about integrity constraints, units of measure, data quality, intended usage, data lineage, etc. Given that the specification of meaning is weak and the mapping must be precisely engineered, it seems hopeless to fully automate the process anytime soon. A human must be in the loop.”



**The 80%
Argument**

- Next Lectures
 - 05 Entity Linking and Deduplication [Nov 15]
 - 06 Data Cleaning and Data Fusion [Nov 22]