Slides Credit: Matthias Boehm

Data Integration and Large Scale Analysis
04 Schema Matching and Mapping

Shafaq Siddiqi

Graz University of Technology, Austria

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Agenda

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

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

```
<resultssets>
  <resultset Tablename=“Supplier”>
    <row>
      <Suppkey>7</Suppkey>
      <SuppName>MB</Suppname>
      <SuppAddress>1035 Coleman Rd</SuppAddress>
    </row>
    <row> … </row>
  </resultset>
</resultsets>
```

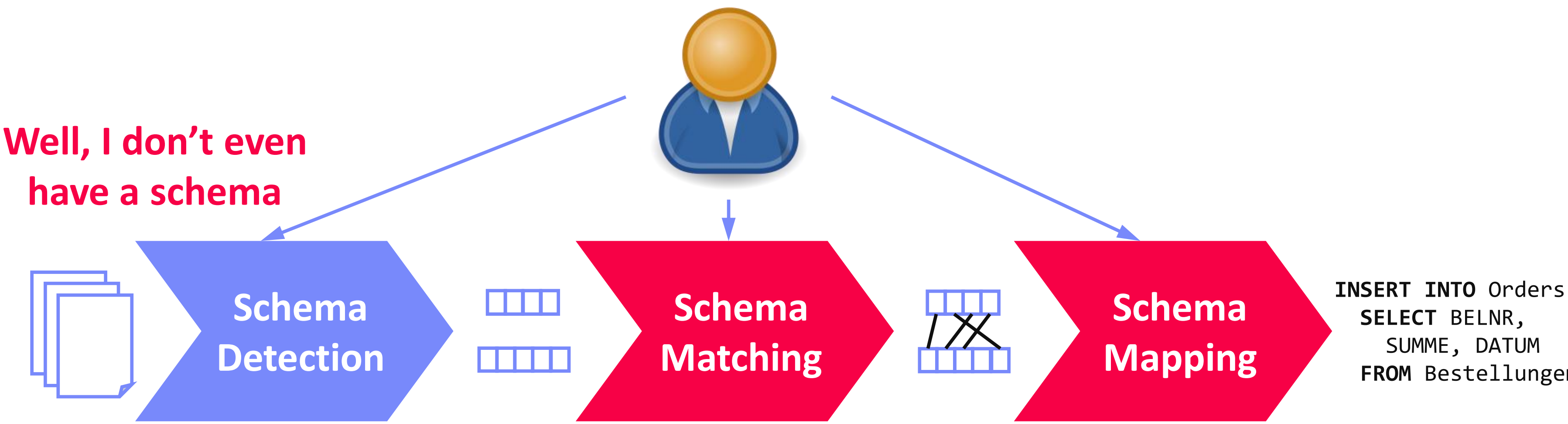
→

```
<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]

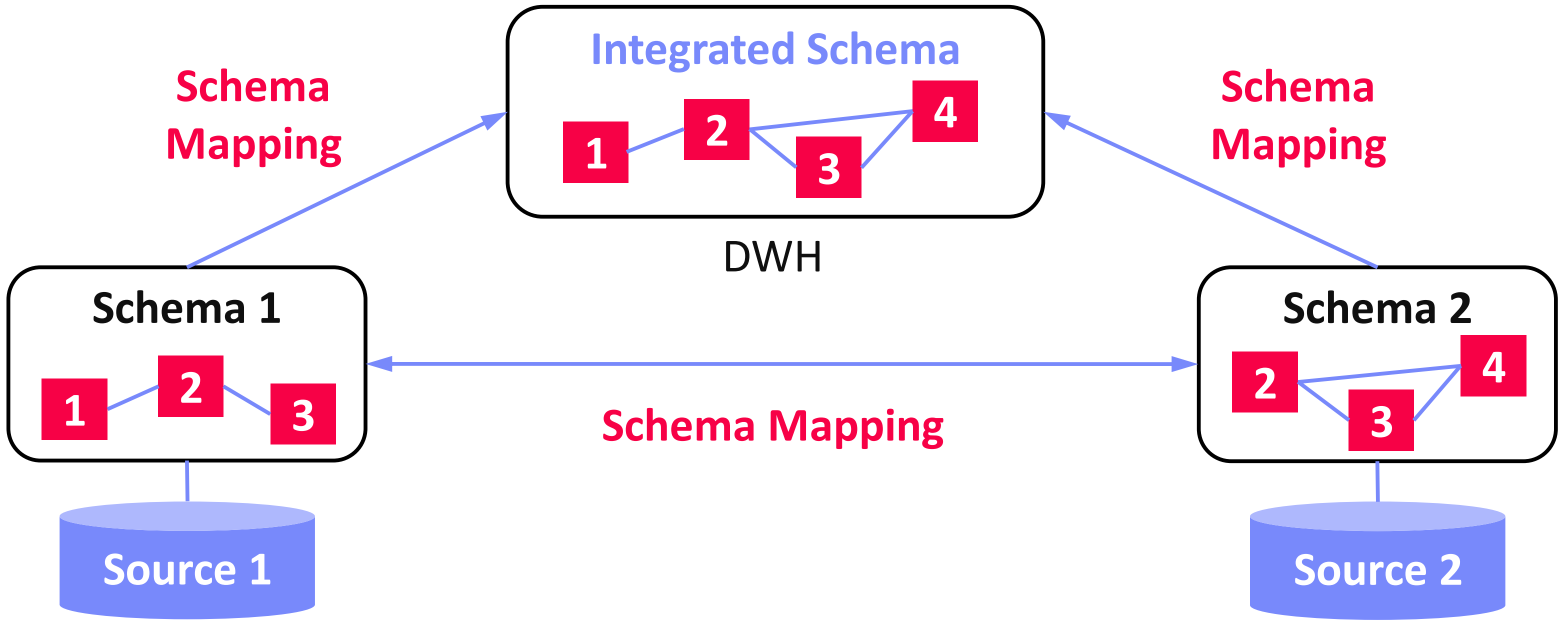
Schema Matching and Mapping

- **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



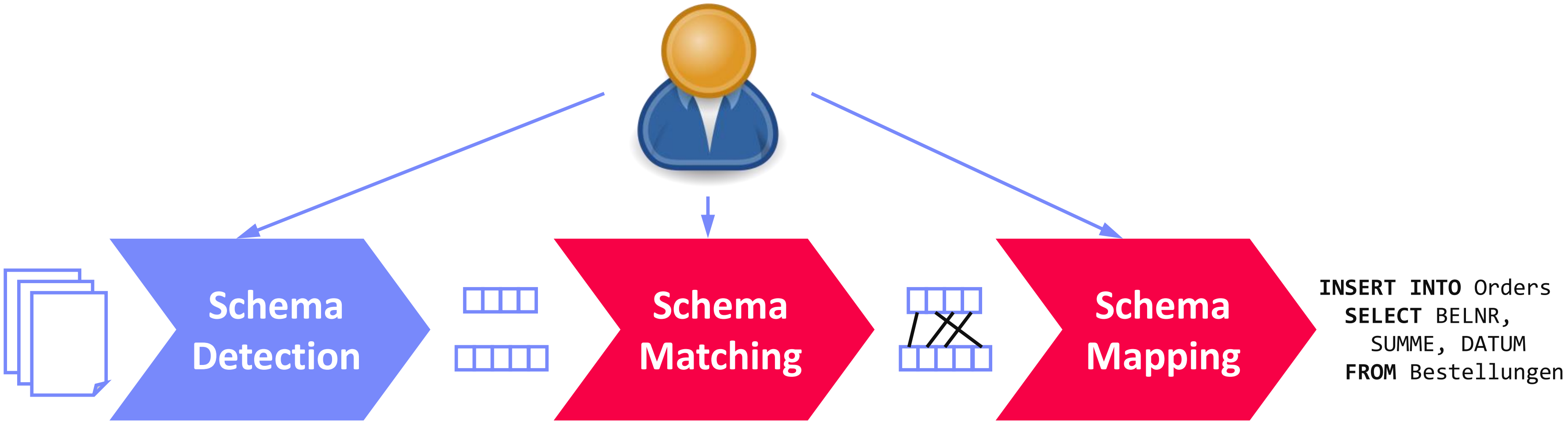
Recap: Types of Heterogeneity → Scope

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

Heterogeneity

- **Semantic Heterogeneity**
  - **Attribute Heterogeneity**
    1. **Synonyms/homonyms**
    2. **Simple mapping** (mathematical)
    3. **Different data types**
    4. Complex mappings
    5. **Language expressions**
  - **Missing Data**
    6. **Nulls** (Missing Values)
    7. **Virtual columns**
    8. Semantic incompatibility
- **Structural Heterogeneity**
  9. **Same attribute in different structure**
  10. **Handling Sets**
  11. **Attribute name w/o semantics**
  12. **Attribute composition**

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

```
./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");
```

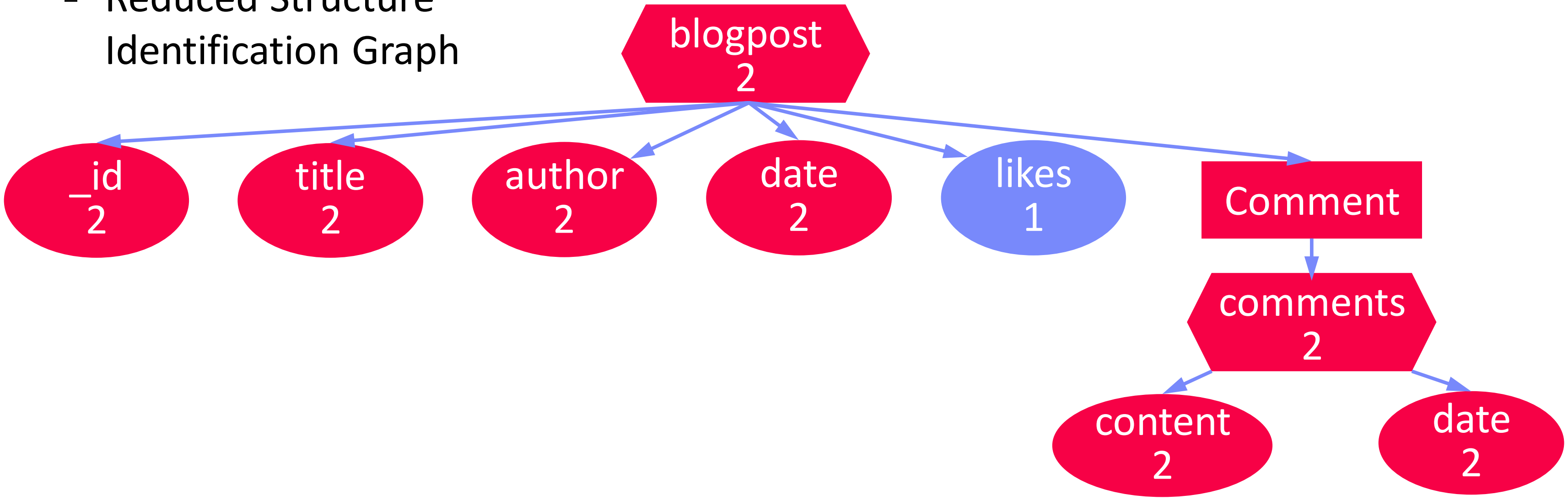
```
StructType(
  StructField(pid,IntegerType,true),
  StructField(name,StringType,true),
  StructField(pos,StringType,true),
  StructField(jnum,IntegerType,true),
  StructField(ncid,IntegerType,true),
  StructField(tid,IntegerType,true))
```

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**]



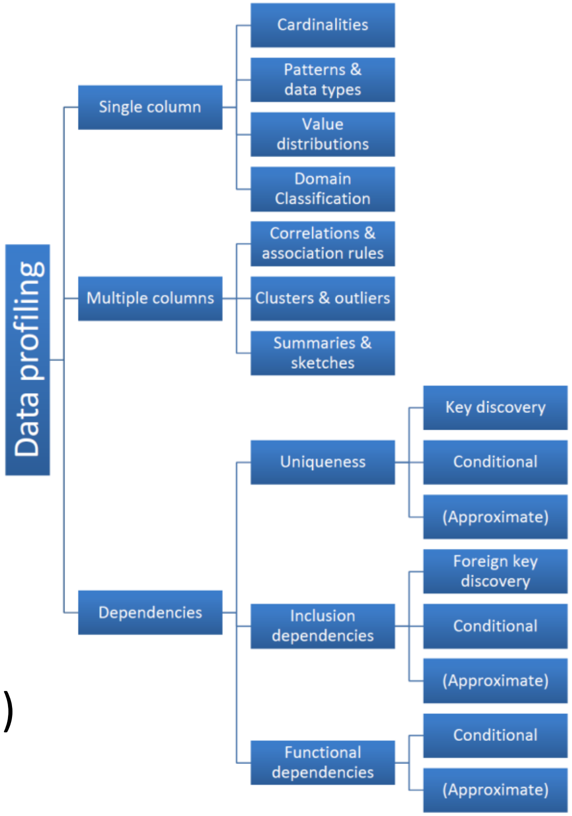
Data Profiling

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

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

- **#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)
    - NOT($A \rightarrow B$) allows pruning $A \rightarrow BC$



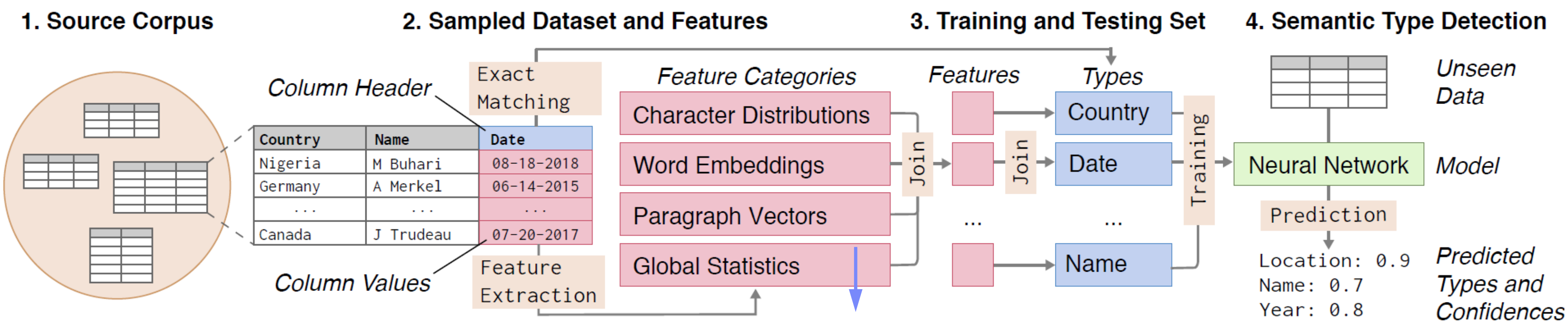
Semantic Data Type Detection

[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)



(cardinality, uniqueness, avg #numerical chars)

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

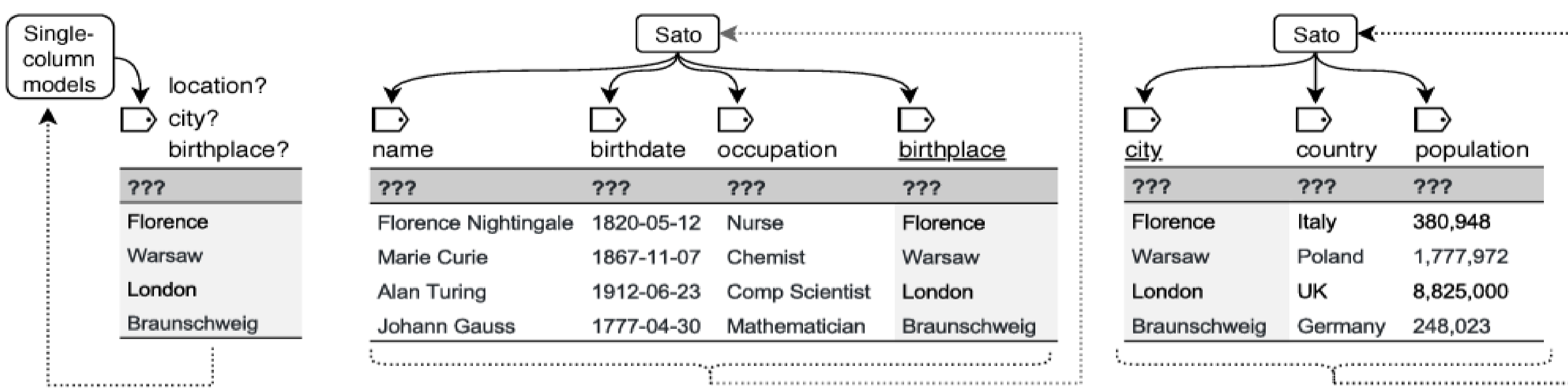


Table A: Influential people in history

Table B: Cities in Europe

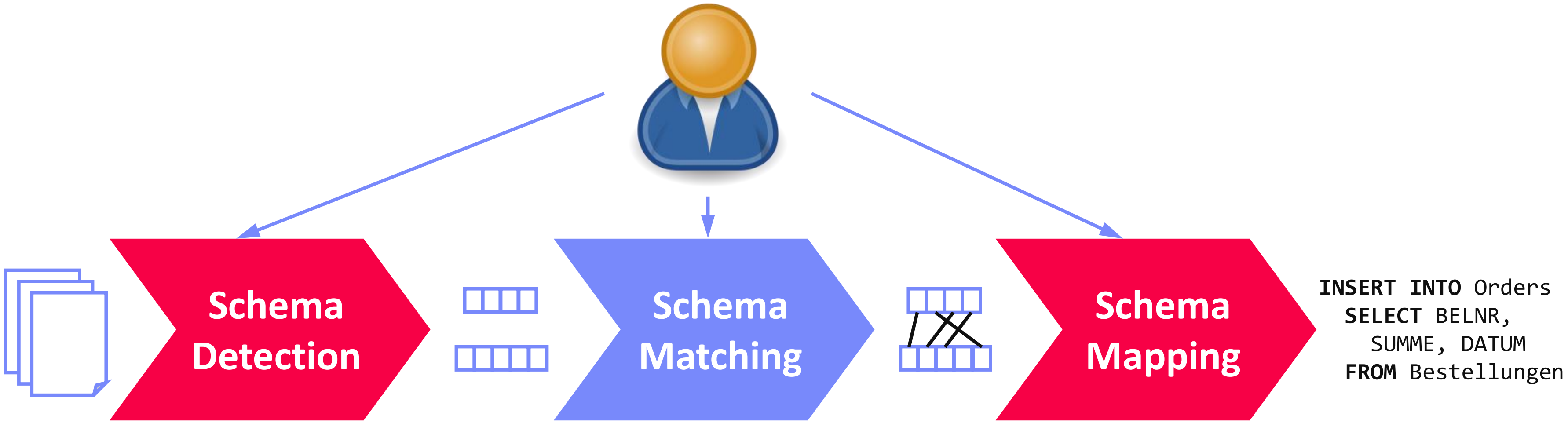
Schema Enforcement and Evolution

- **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)

- **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

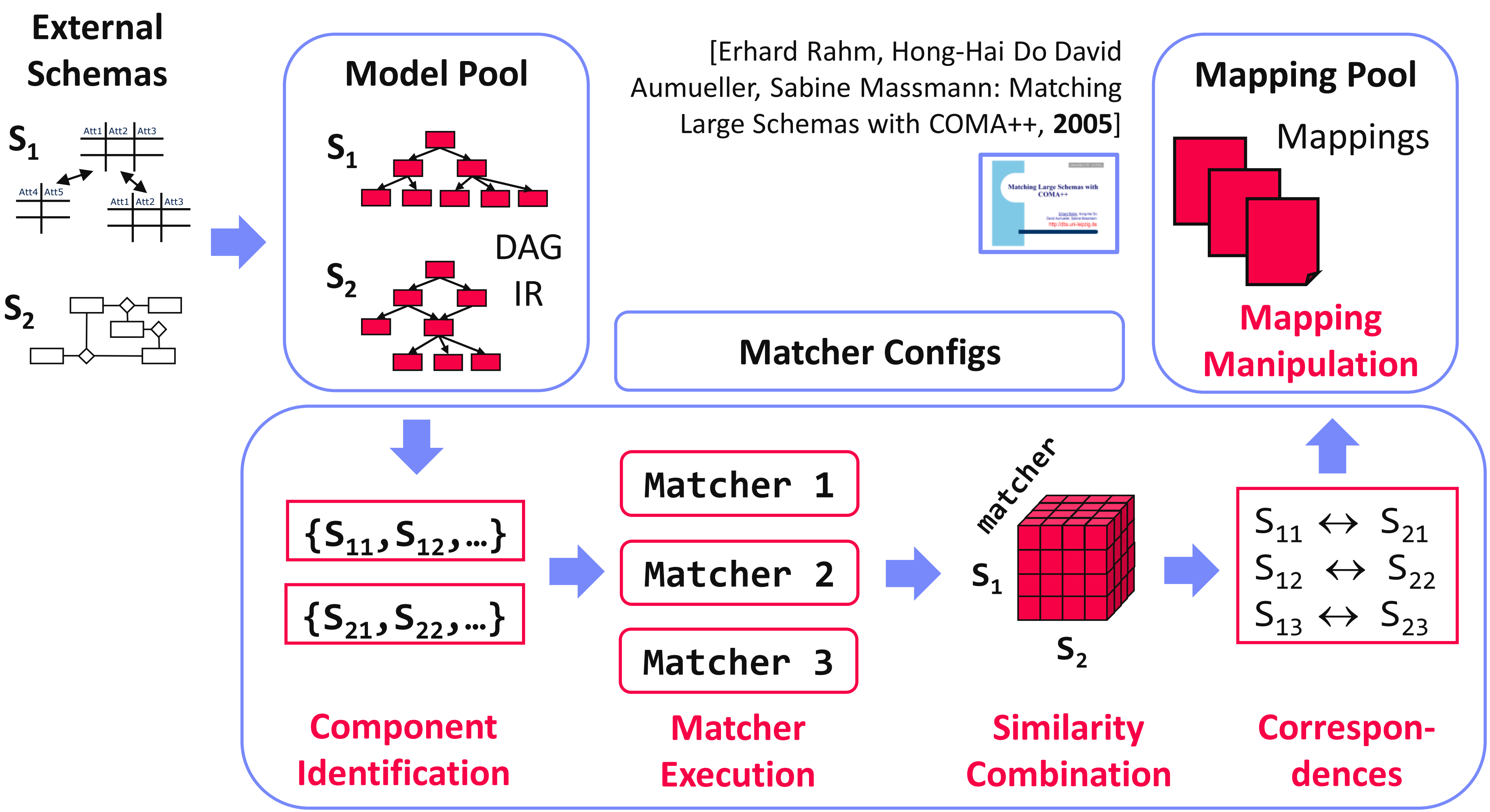
S2

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

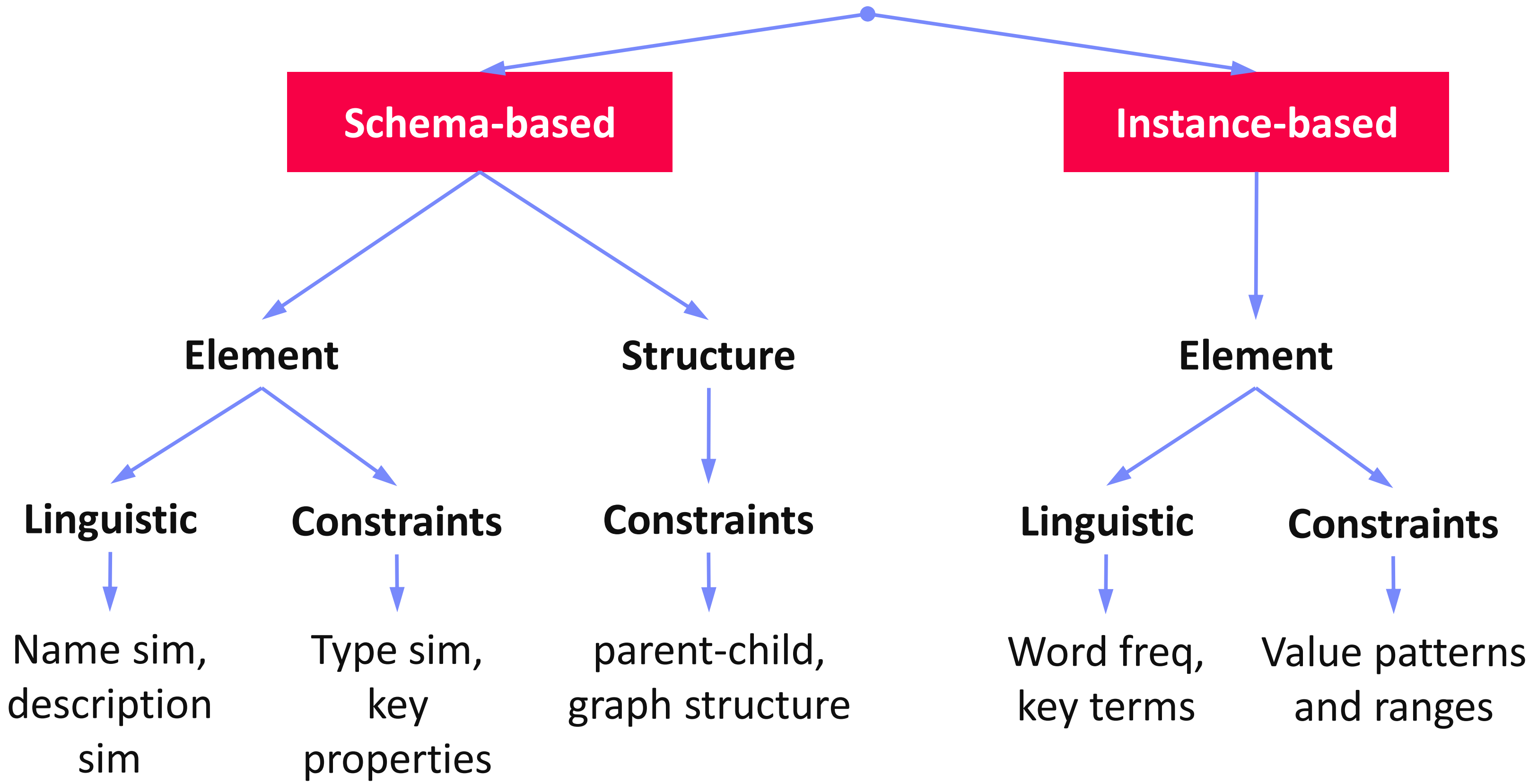
AuthorInfo	
AuthorID	**INT PK**
LastName	VARCHAR(32)
FirstName	VARCHAR(32)

System Architecture and Matching Process

[Erhard Rahm, Hong-Hai Do David Aumueller, Sabine Massmann: Matching Large Schemas with COMA++, **2005**]



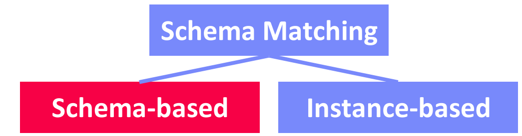
Classification of Matching Techniques



- **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

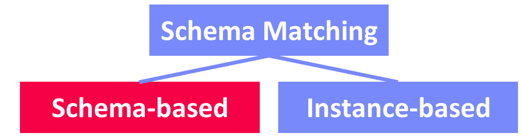
- **Example Trigram**

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

  - Similarity
    $= 2|S1 \cap S2| \;/\; (|S1|+|S2|)$
    $= 8/16 = 0.5$

(alignment irrelevant)

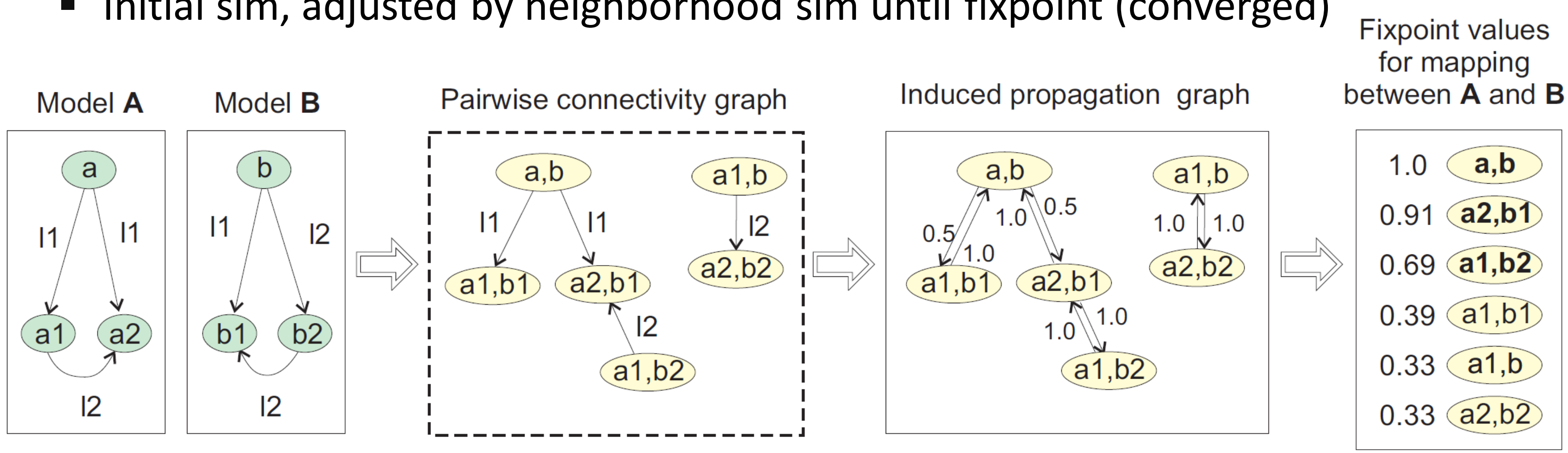
Selected Matchers, cont.



- **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 x B (PCG)
  - Propagation coefficients: 1/|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, cont.

Schema Matching
Schema-based | Instance-based

- **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

City
Munich, 80333
Dresden, 01199

5-letter numeric codes

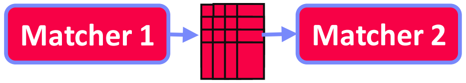
ZIP
01187
12437

Combination of Matchers

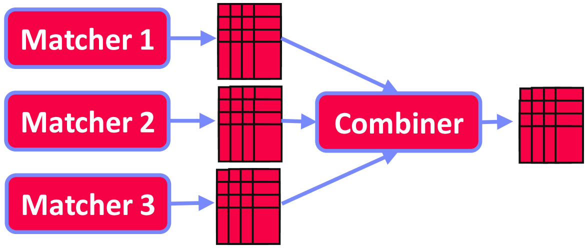
- **#1 Reuse**
  - Exploitation of transitive similarity
  - Fast and efficient matching, but potential for lost mappings (e.g., S3 misses attributes)

S1 ≅ S3 ∧ S3 ≅ S2
→ S1 ≅ S2

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



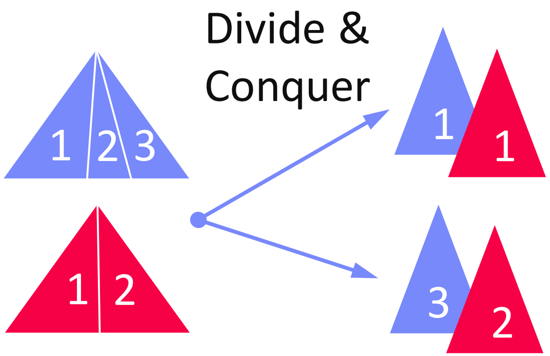
- **#3 Composite Matchers**
  - Select combination of complementary matchers in form of **ensemble**
  - **Aggregation** of similarity (e.g., trigram, synonym → avg/min/max)



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**]

Excursus: Stable Marriage Problem

Alternatively: **Maximal weight matching**

- **Problem Definition**
  - For common correspondences, global schema matching relates to the stable marriage (1:1) and hospitals/residence (1:N) problems

- **Example Stable Marriage**
  - **Stable matching:** there is no match (A, B), preferable for both A and B over their current matches
  - Input are bidirectional similarity (preference ranking)
  - **Deferred Acceptance Algorithm**

```
while(!converged)
  #1 unmatched As propose to
     highest-ranked, unasked Bs
  #2 Bs accept highest-ranked
     proposal (even if matched)
```

```
      A,     B,     C,     D
1: (3,6), (9,3), (0,9), (6,6)
2: (6,9), (0,0), (9,0), (3,9)
3: (3,0), (9,6), (6,3), (0,0)
4: (6,3), (0,9), (3,6), (9,3)
```

```
   Group A:        Group B:
1: B, D, A, C   A: 2, 1, 4, 3
2: C, A, D, B   B: 4, 3, 1, 2
3: B, C, A, D   C: 1, 4, 3, 2
4: D, A, C, B   D: 2, 1, 4, 3
```

Excursus: Stable Marriage Problem, cont.

- **Example DIA WS19/20 Project**
  - #4 **Stable Marriage Algorithms in Linear Algebra**, Thomas Wedenig

```
  while(sum(S) > 0) {
    Stripped_preferences = S %*% P
    Mask_matrix = matrix(0.0, rows=n, cols=n)

    parfor(i in 1:n) {
      max_proposal = as.scalar(Stripped_preferences[i, as.scalar(proposer_pointers[i])])
      if(max_proposal != 0) {
        proposer_pointers[i] = as.scalar(proposer_pointers[i]) + 1
        Mask_matrix[max_proposal, i] = 1
      }
    }

    # Hadamard Product
    Propose_round_results = Mask_matrix * A
    best_proposers_vector = rowIndexMax(Propose_round_results)
    prev_best_proposers = rowIndexMax(Result_matrix)
```

- **Others:**
  - **Hospitals and Residents Problem** (aka Collage Admission Problem)

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	*relational*	√	-	-	-	-	√
schemas	*XML*	√	-	-	-	(√)	√
	ontologies	√	√	√	√	√	√
compreh. GUI		√	(√)	?	?	√	√
Matchers	*linguistic*	√	√	√	√	√	√
	structure	√	√	√	√	√	√
	Instance	√	-	√	√	√	-
use of ext.dictionaries		√	?	√	√	√	√

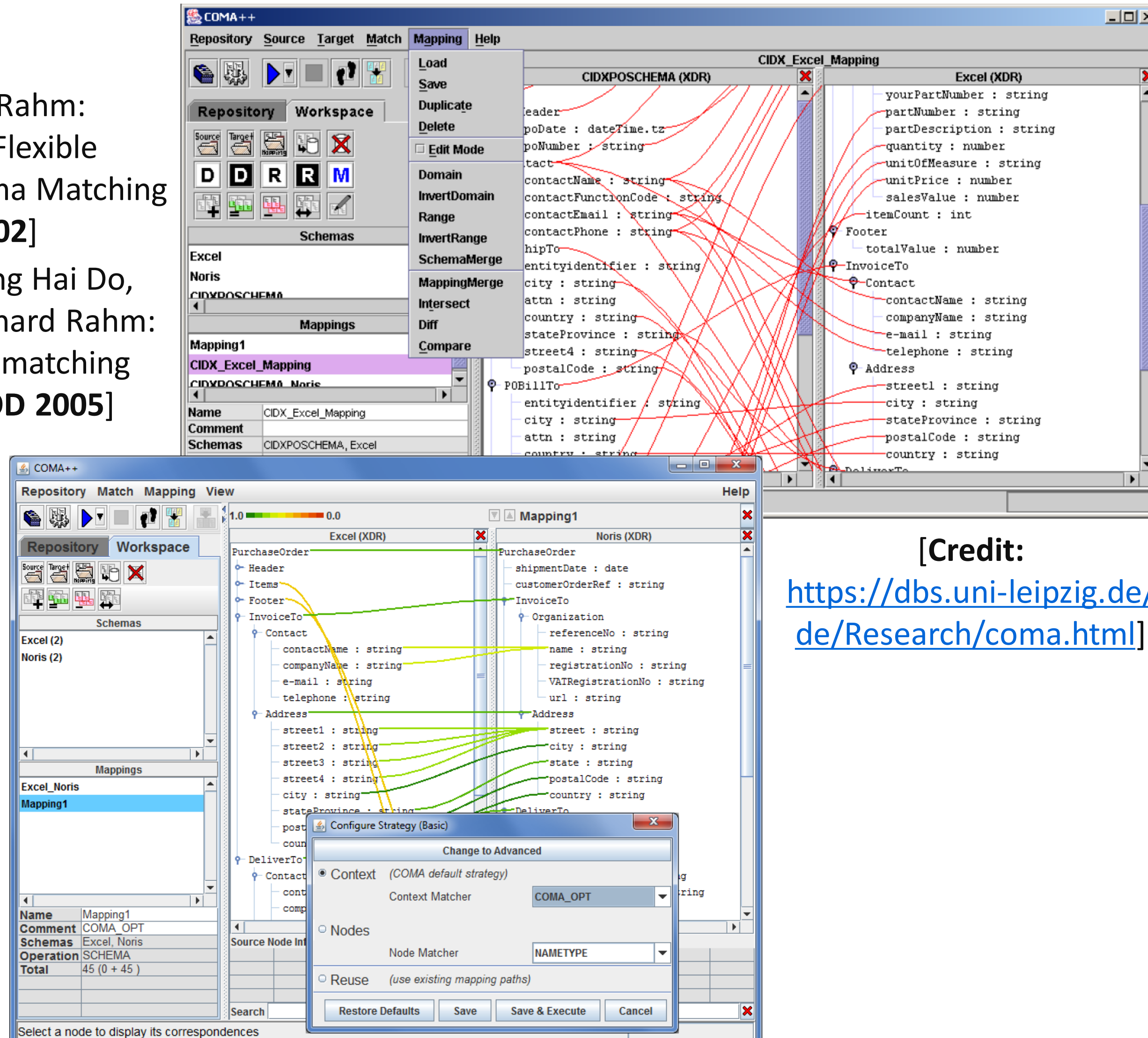
Schema Matching Tools, cont.

COMA system for **com**bining **ma**tch algorithms in a flexible way)

- **COMA ++**

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

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

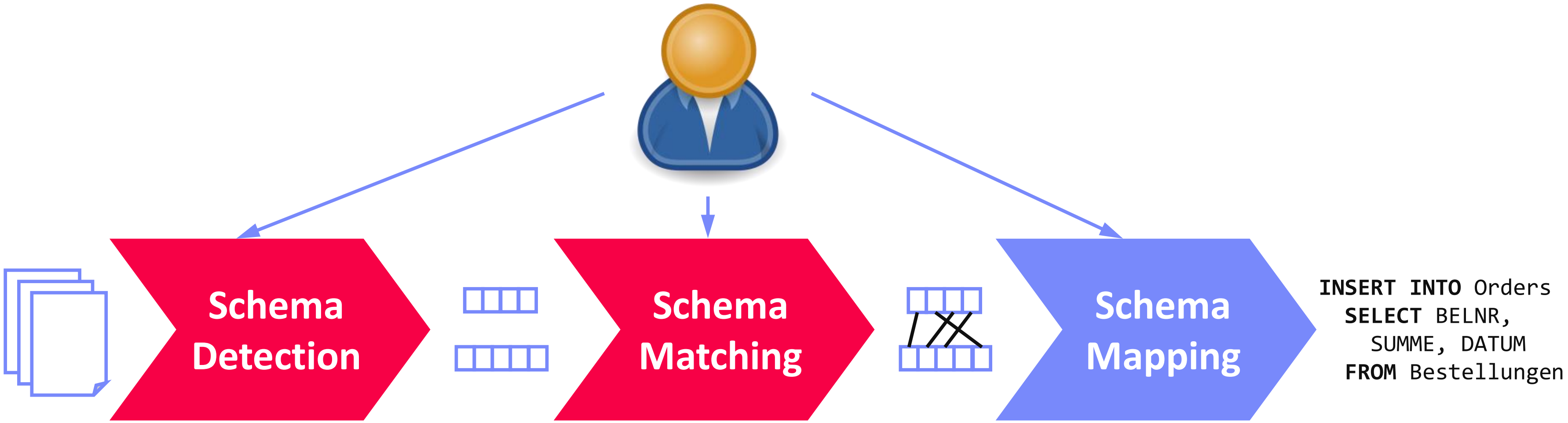


- **COMA 3.0**
  - 2011/2012
  - Ontology Merging
  - Workflow Management

[**Credit:** https://dbs.uni-leipzig.de/de/Research/coma.html]

[Felix Naumann: Informationsintegration –
Schema Mapping, HPI Lecture, 2012]

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**

Article
artPK
title

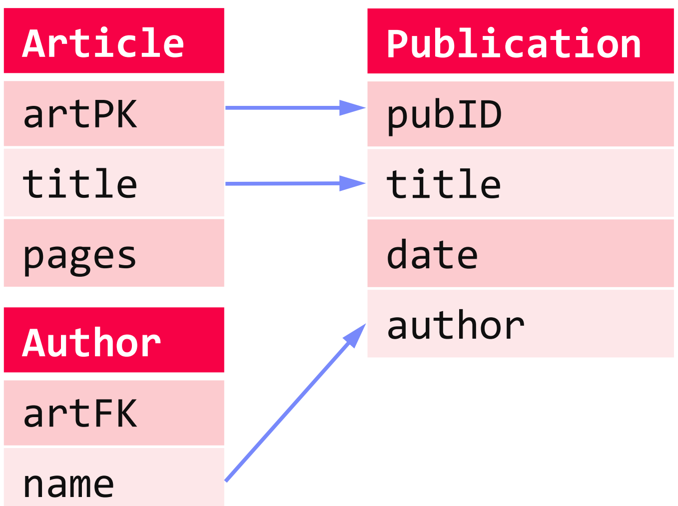
Publication
pubID
title
date

Transformation Query:

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

Mapping Interpretations

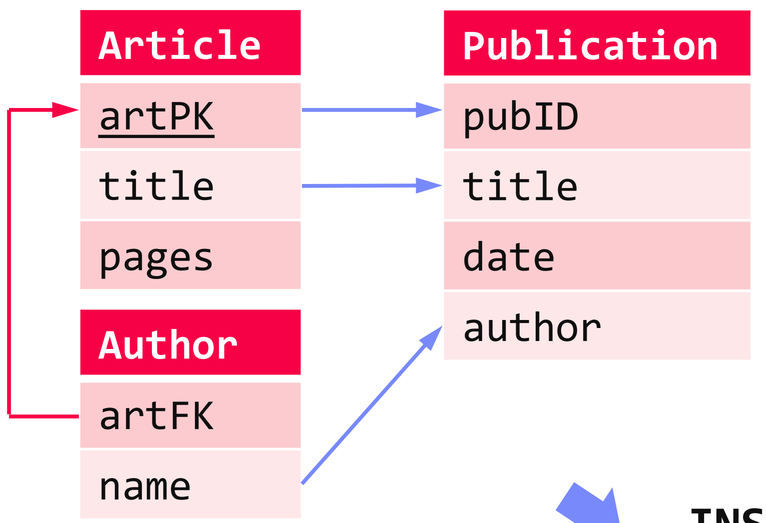
- **Without Intra-Schema Correspondences**




```sql
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**



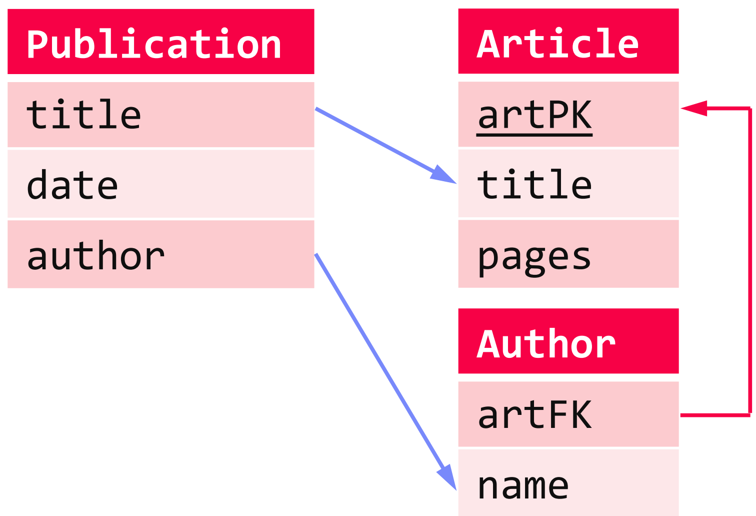

```
INSERT INTO Publication
  SELECT artPK, title,
         NULL, name
  FROM Article, Author
  WHERE artPK = artFK
```

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**

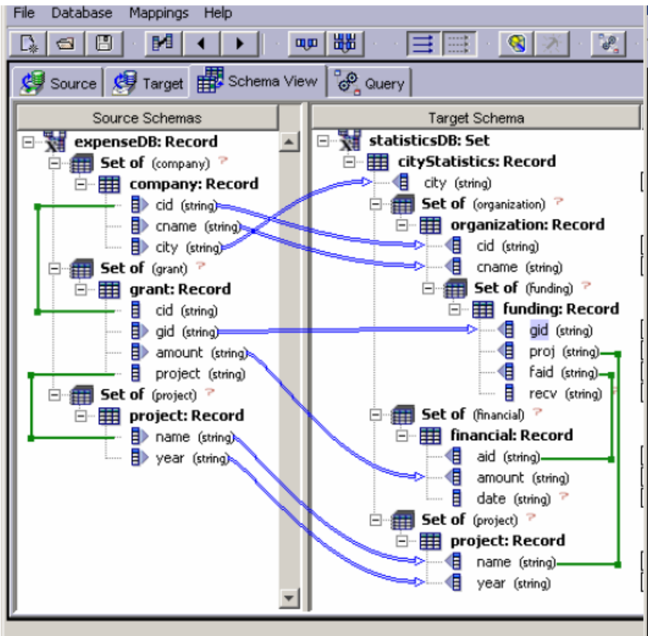


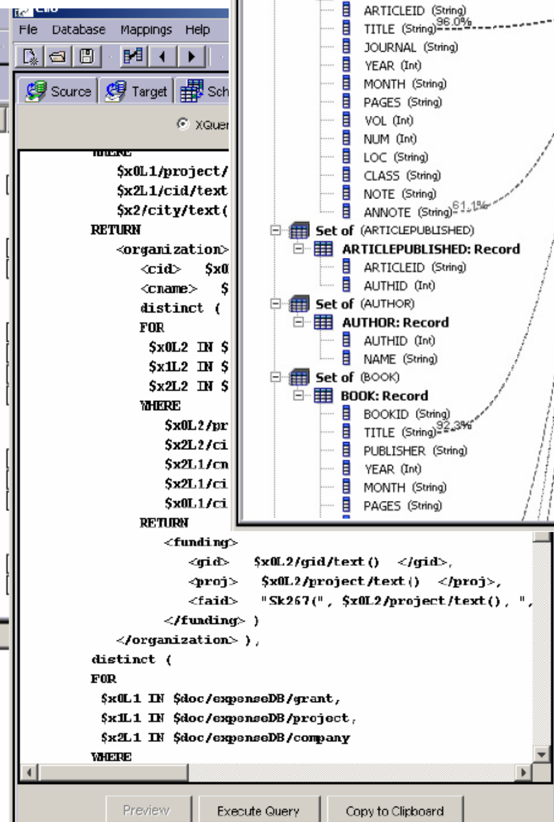

```sql
INSERT INTO Article
  SELECT DISTINCT
    SK(title), title, NULL
    FROM Publication

INSERT INTO Author
  SELECT SK(title), author
    FROM Publication
```

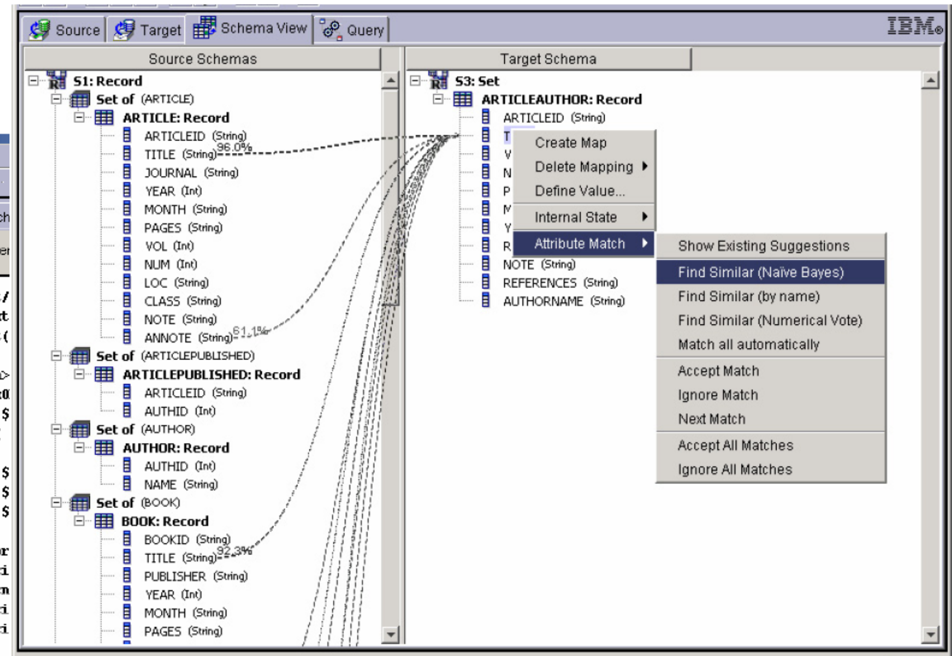
- **Skolem Function (SK):** unique key generation from tuple values t[X] of an attribute set X

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

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

- **Schema Detection**
- **Schema Matching**
- **Schema Mapping**

"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 (Data Integration Architectures)**
  - **05 Entity Linking and Deduplication** [Nov 03]
  - **06 Data Cleaning and Data Fusion** [Nov 10]