Hasso Plattner Institut

IT Systems Engineering | Universität Potsdam

Data Quality in Databases

OpEN.SC Symposium 8.5.2009

Felix Naumann
Hasso-Plattner-Institut
Fachgebiet Informationssysteme

The HPI – Hasso Plattner Institut

- Founded in 1998 as a Public Private Partnership
- Hasso Plattner, co-founder of SAP, endowed over 200 Mio. Euro.
- Adjoined with the University of Potsdam
  - Capital of Brandenburg, bordering Berlin
- 400 students – Bachelor, Master, and PhD

Information systems team

project **ViQTOR**

Paul **Führing**

Katrin **Heinrich**

DQ Annotation & Assessment

Prof. Felix **Naumann**

Information Integration

Information Quality

Jens **Bleiholder**

Data Fusion

project **HumMer**

project **fusem**

Christoph Böhm

Data Profiling & Cleaning

Armin **Roth**

project **System P**

Peer Data Management Systems

Service-Oriented Systems

Mohammed **AbuJarour**

Matching

Ontologies, Profiling

Frank **Kaufer**

Data Integration for Life Science Data Sources

project **Aladin**

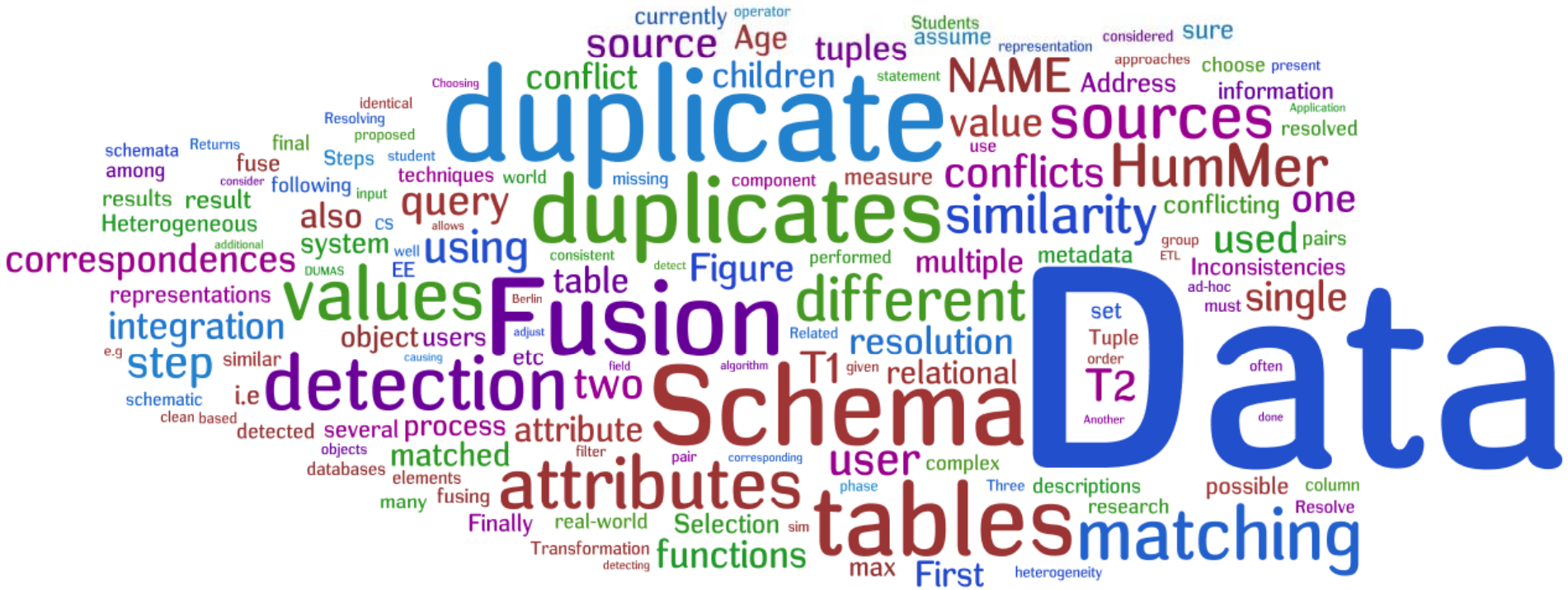
Jana **Bauckmann**

Alexander **Albrecht**

ETL Management

Data Profiling for Schema Management

“Data Fusion in Three Steps”
DE Bulletin, 2006



Wordle.net

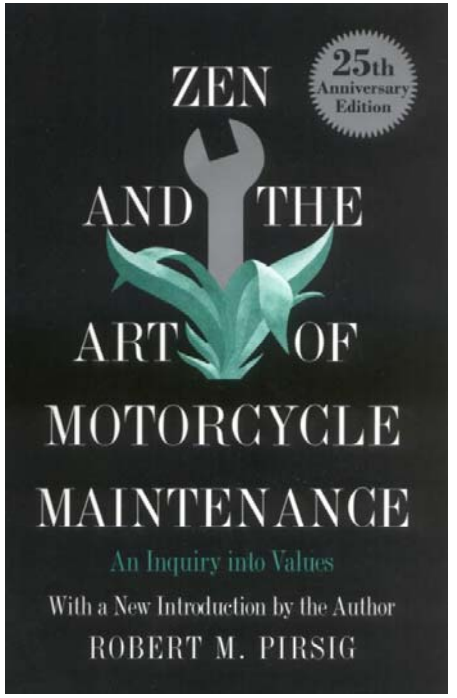
Overview

- Information Quality
- Step 1: Schema Matching
- Step 2: Duplicate detection
- Step 3: Data fusion
- Summary

Quality

"Even though quality cannot be defined, you know what it is."

Robert Pirsig



Zooming into Information Quality

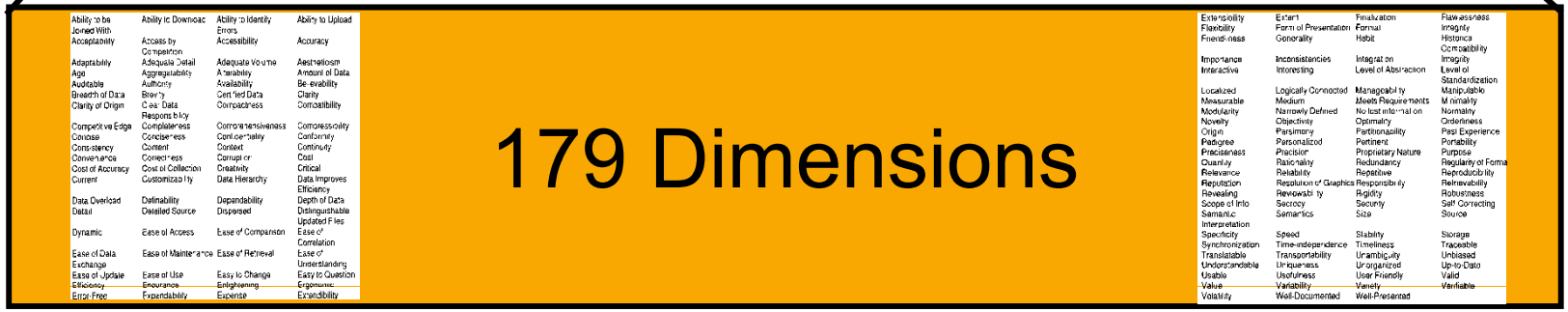
1

15

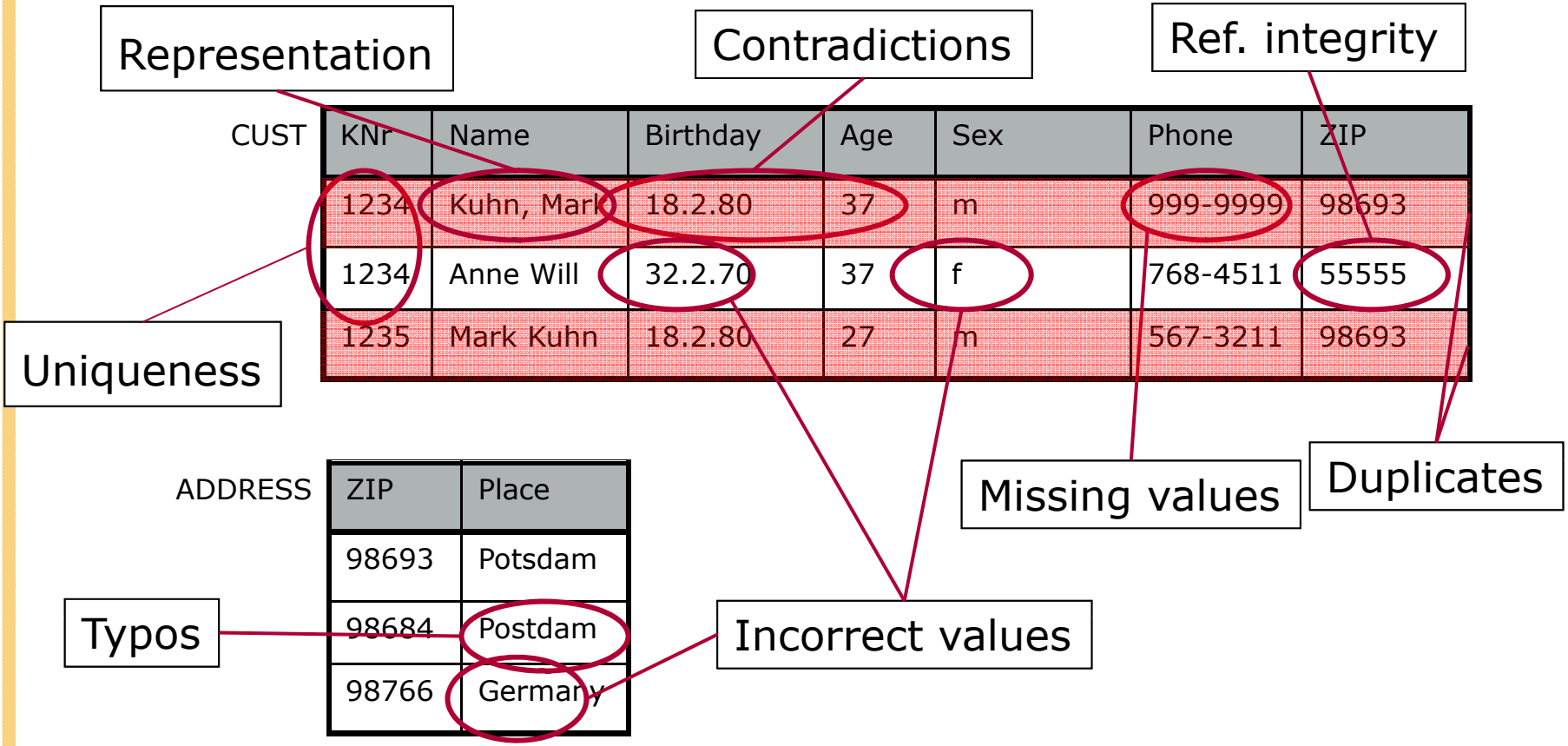
179

Fitness for use

Accuracy, Objectivity, Believability, Reputation, Accessibility, Security, Relevance, Value-Added, Timeliness, Completeness, Amount of Data, Interpretability, Understandability, Consistency, Concise Representation



Data Quality: Problems



DQ-Problems: Effects

- Fehlerhafte Warenpreise in Artikel-DB des US-Einzelhandels [English 1999]
  - Kosten für Konsumenten 2.5 Mrd $
  - 80% der Barcode-Scan-Fehler zulasten der Konsumenten
- US-Finanzbehörde 1992: knapp 100.000 Steuererstattungsbescheide unzustellbar [English 1999]
- 50-80% der Einträge im US-Vorstrafenregister ungenau, unvollständig oder fehlerhaft [Strong et al. 1997a]
- US-Post: von 100.000 Massen-Postsendungen bis zu 7.000 aufgrund von Adressfehlern unzustellbar [Pierce 2004]

IRS might be after you — to mail you a check

Incorrect addresses stall nearly 1,500 Tennessee refunds

By BONNA de la CRUZ
Staff Writer

Now that Tilcia L. Menifee knows that she'll be getting $500 in a tax refund from Uncle Sam, she can do some Christmas shopping, she said.

Death by Typo

‘Resurrected,’ but still wallowing in red tape

Government records incorrectly kill off thousands, and there’s no easy fix

By Alex Johnson and Nancy Amons
Reporters
MSNBC and NBC News
updated 6:21 p.m. ET Feb. 29, 2008

For a dead woman, Laura Todd is awfully articulate.

“I don’t think people realize how difficult it is to be dead when you’re not,” said Todd, who is very much alive and kicking in Nashville, Tenn., even though the federal government has said otherwise for many years.

Todd’s struggle started eight years ago with a typo in government records. The government has reassured her numerous times that it has cleared up the confusion, but the problems keep coming.

Story continues below ↓

Video

Launch

Does this woman look dead to you?
The government says Toni Anderson is dead, but she insists she is very much alive. David MacAnally of NBC affiliate WTHR reports from Muncie, Ind.
NBC News Channel

SPIEGEL ONLINE

28. Januar 2008, 11:27 Uhr

FRANKREICH

Telefonkundin erhält Rechnung über 63 Millionen Euro

Als eine Französin aus Lothringen unlängst ihre Telefonrechnung bekam, blieb ihr buchstäblich die Spucke weg: 63 Millionen Euro sollte sie begleichen. Dabei hatte sie ursprünglich nur um Korrektur einer Abrechnung in Höhe von 67 Euro gebeten.

Paris - "Da muss wohl ein Komma verrutscht sein", zitiert "Le Figaro" heute den Vizedirektor der französischen Telefongesellschaft Télé2, Olivier Anstett. Die Kundin aus dem Ort Herserange in der Nähe von Metz hatte sich zunächst über einen ihrer Meinung nach zu hohen Rechnungsbetrag von 67,69 Euro bei der Telefongesellschaft beschwert. Als eine Antwort ausblieb, schickte sie einen zweiten Brief. Daraufhin erhielt sie eine "korrigierte" Rechnung über die Summe 63.280.067,96 Euro.

"Uns bleibt nur, uns bei der Kundin zu entschuldigen und dafür zu sorgen, dass so etwas nie wieder vorkommt", so der lapidare Kommentar des Vizechefs von Télé2.

Common Sense

Southwest

Published on Chanhassen Villager (http://www.chanvillager.com)

Property mistakenly valued at $189 million

By rcraw
Created 12/03/2007 - 4:46pm

Property mistakenly valued at $189 million results in tax adjustments in county

An $18,900 Waconia property that was mistakenly valued at $189 million is "throwing a wrench" into property tax statements and the Carver County budget. County officials issued a press release Monday detailing the problem that came to light last week.

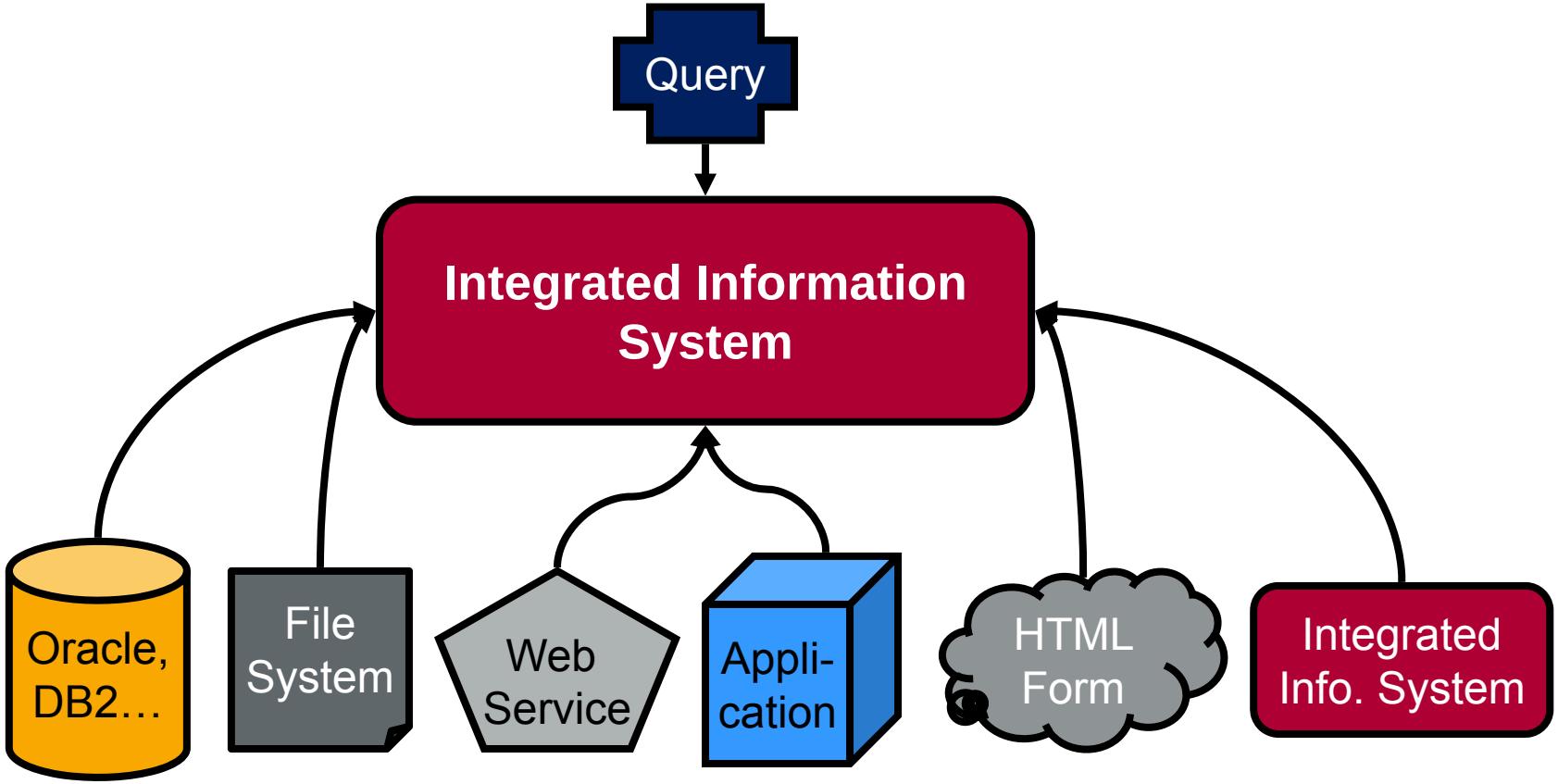
An error was identified in the estimated market valuations used to calculate Pay 2008 Proposed Property Taxes, according to the release. The County Assessor's Office placed an incorrect estimated market value on a parcel located in the city of Waconia, apparently resulting in extra zeroes being added to the value.

The mistake results in an imbalance in the amount of property taxes the county was expecting to collect. The mistake added about $900,000 in expected revenue, according to County Administrator David Hemze.

The county is planning to consider recommendations to cut the 2008 budget by $900,000 so that proposed property taxes will match tax notices sent to residents in November.

"It kind of threw a wrench into everything," said Hemze. "It's unfortunate. It's a mistake and we're concentrating on responding to the mistake and trying to ensure that it doesn't happen again." If the county does not cut the budget by $900,000, the county portion of property taxes would go up for all properties in the county. The effect would be greatest in Waconia, but Hemze said the average-valued home outside of Waconia would also experience a $29 increase on top of the number indicated on the November tax notices.

Integrated Information Systems



Overview

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- Step 1: Schema Matching
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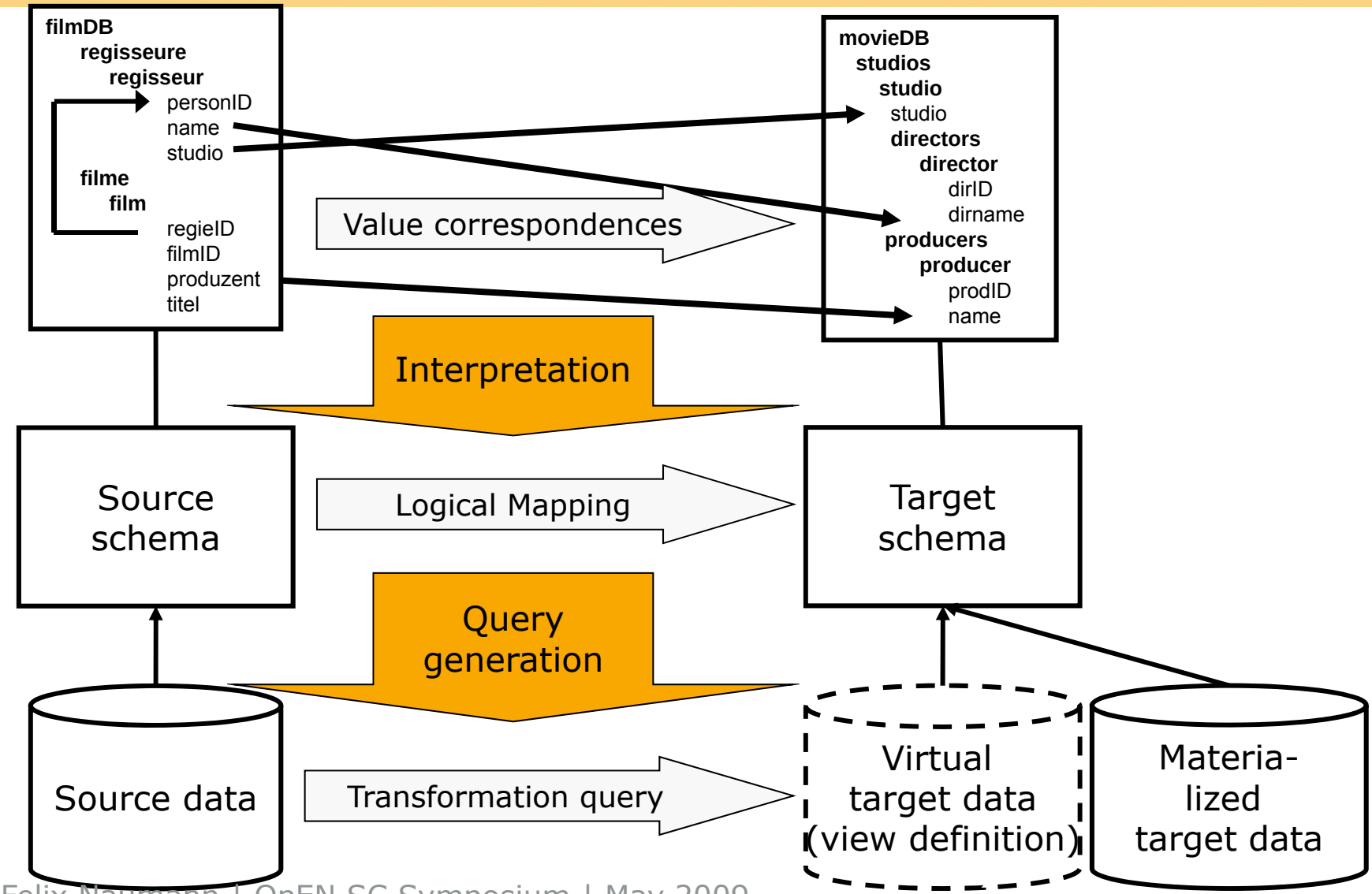
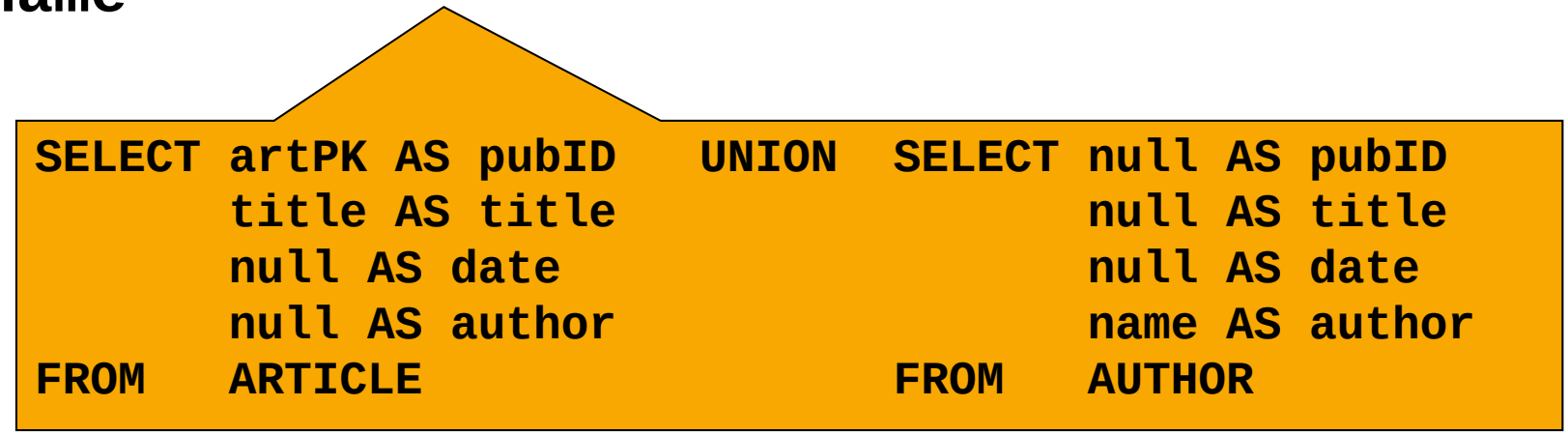
Schema Mapping in Context



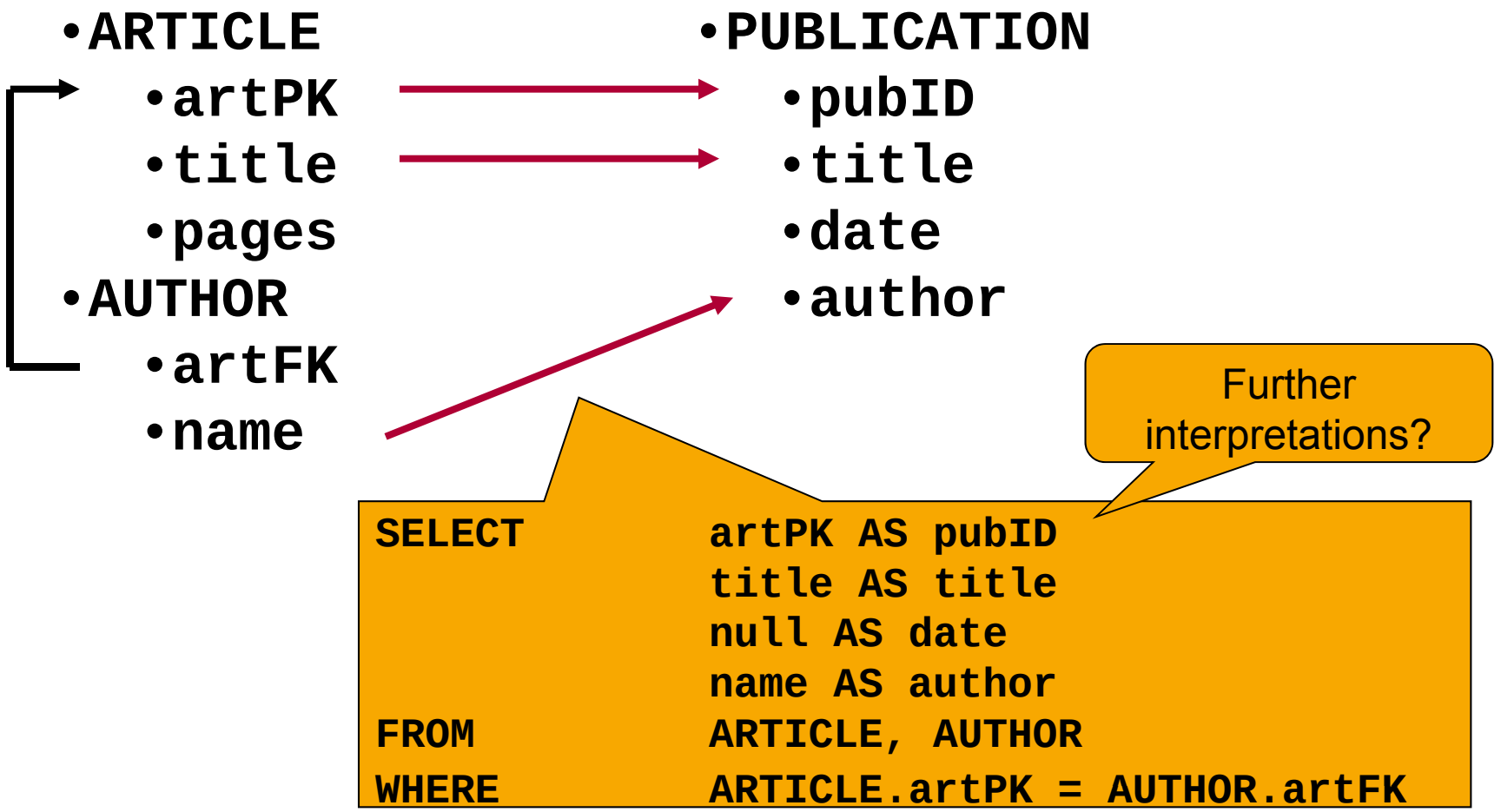
Schema Mapping Example

- **ARTICLE**
  - artPK
  - title
  - pages
- **AUTHOR**
  - artFK
  - name

- **PUBLICATION**
  - pubID
  - title
  - date
  - author



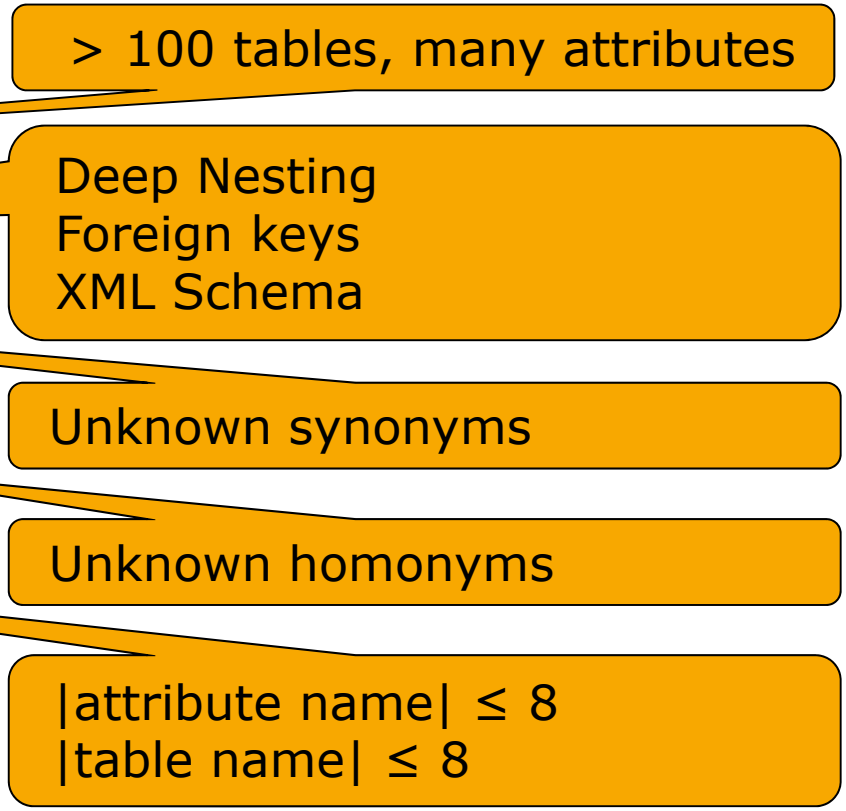
Schema Mapping Example

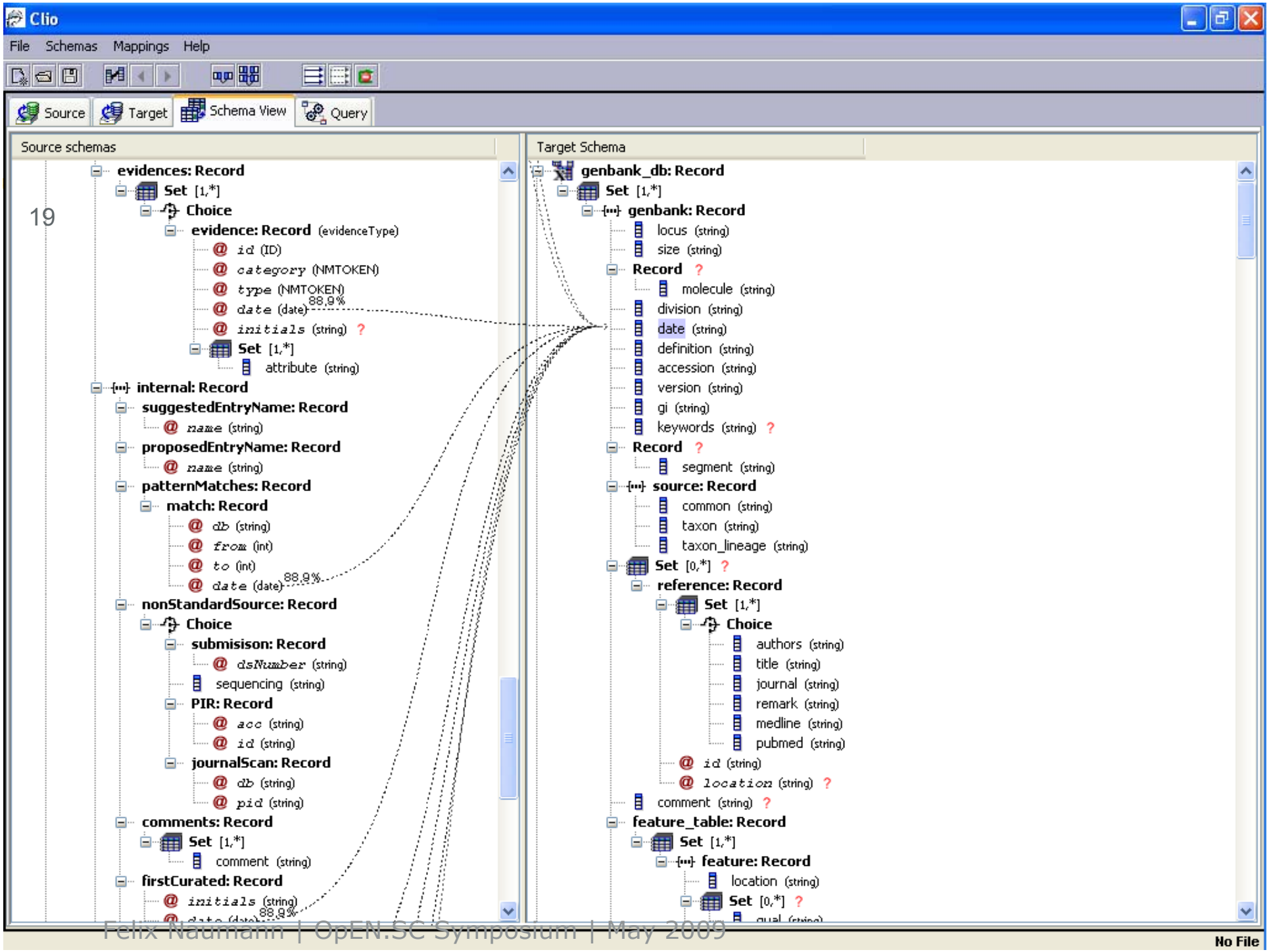


Schema Matching – Motivation

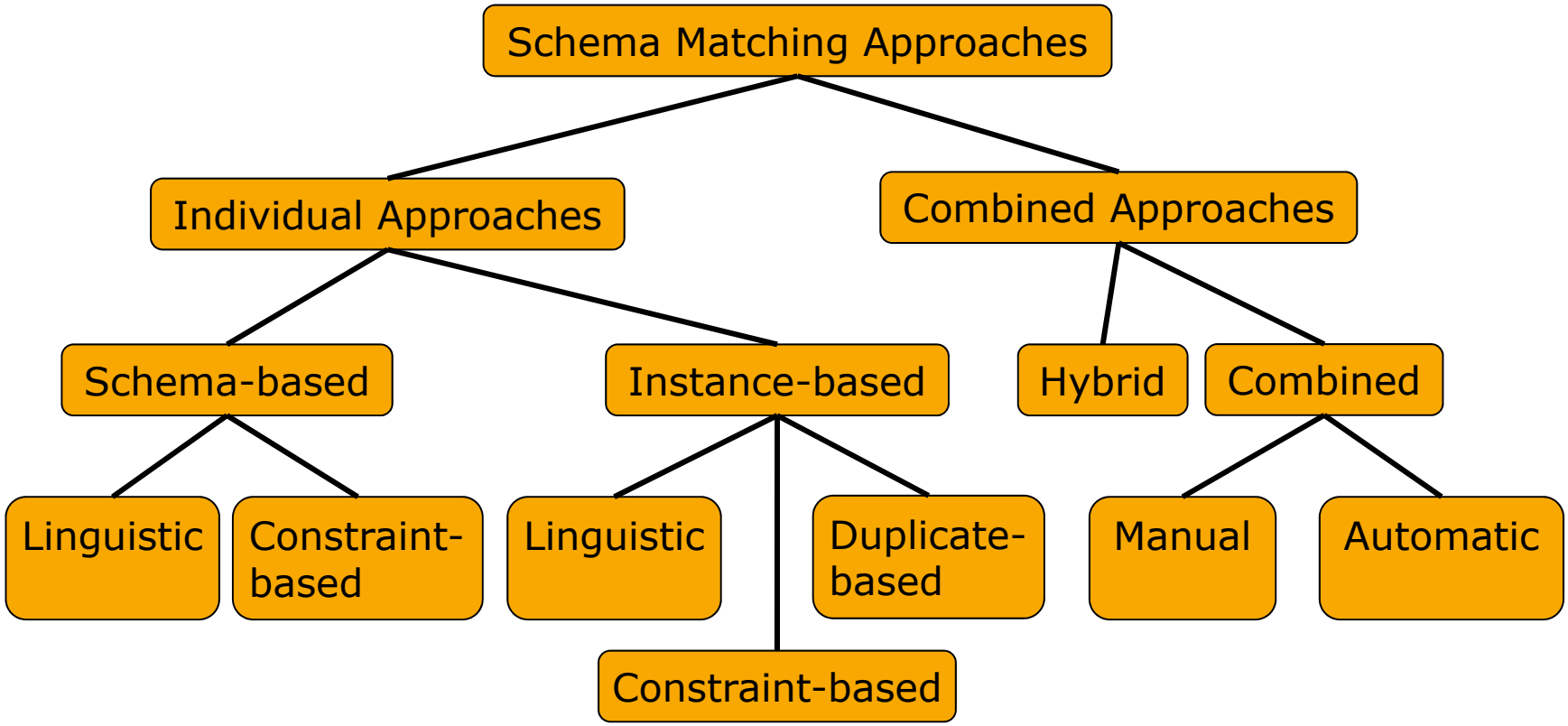
Schemata are

- large
- complex
- foreign
- confusing
- different language
- cryptic




Clio
File Schemas Mappings Help
Source Target Schema View Query
Source schemas
evidences: Record
Set [1,*]
Choice
evidence: Record (evidenceType)
id (ID)
category (NMTOKEN)
type (NMTOKEN)
date (date)
88,9%
initials (string) ?
Set [1,*]
attribute (string)
internal: Record
suggestedEntryName: Record
name (string)
proposedEntryName: Record
name (string)
patternMatches: Record
match: Record
db (string)
from (int)
to (int)
date (date)
88,9%
nonStandardSource: Record
Choice
submisison: Record
dsNumber (string)
sequencing (string)
PIR: Record
acc (string)
id (string)
journalScan: Record
db (string)
pid (string)
comments: Record
Set [1,*]
comment (string)
firstCurated: Record
initials (string)
88,9%
Target Schema
genbank_db: Record
Set [1,*]
genbank: Record
locus (string)
size (string)
Record ?
molecule (string)
division (string)
date (string)
definition (string)
accession (string)
version (string)
gi (string)
keywords (string) ?
Record ?
segment (string)
source: Record
common (string)
taxon (string)
taxon_lineage (string)
Set [0,*] ?
reference: Record
Set [1,*]
Choice
authors (string)
title (string)
journal (string)
remark (string)
medline (string)
pubmed (string)
id (string)
location (string) ?
comment (string) ?
feature_table: Record
Set [1,*]
feature: Record
location (string)
Set [0,*] ?
No File

Schema Matching Classification [RB01]



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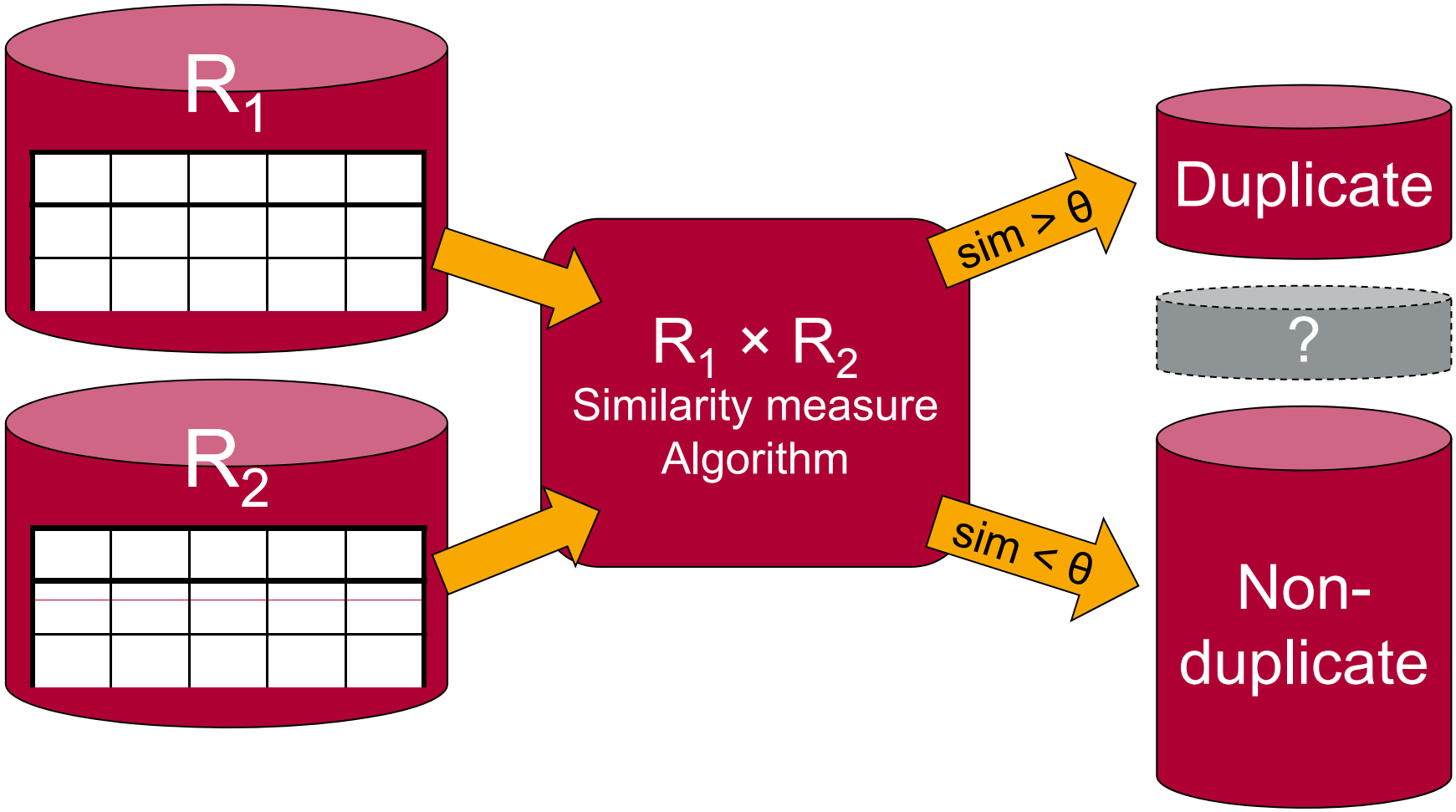
Duplicate Detection

Duplicate detection is the discovery of multiple representations of the same real-world object.

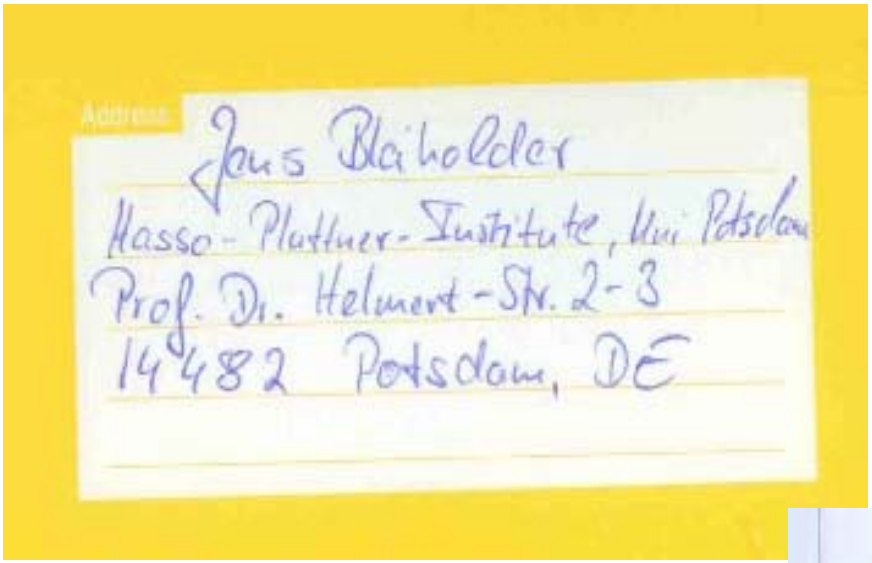
- Problem 1: Representations are not identical.
  - *Fuzzy duplicates*
- Solution: Similarity measures
  - Value- and record-comparisons
  - Domain-dependent or domain-independent

- Problem 2: Data sets are large.
  - Quadratic complexity: Comparison of every pair of records.
- Solution: Algorithms
  - E.g., avoid comparisons by partitioning.

Duplicate Detection



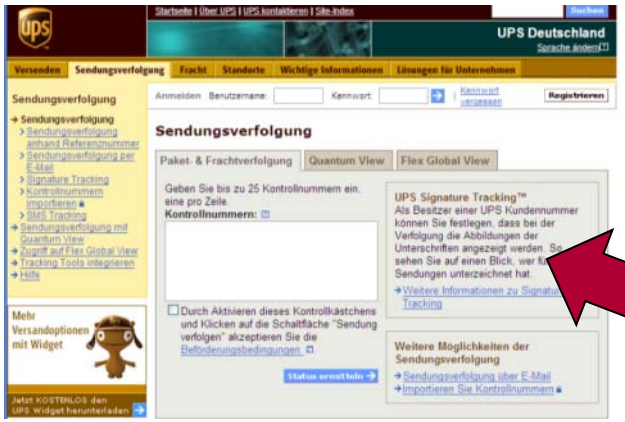
Origins of duplicates



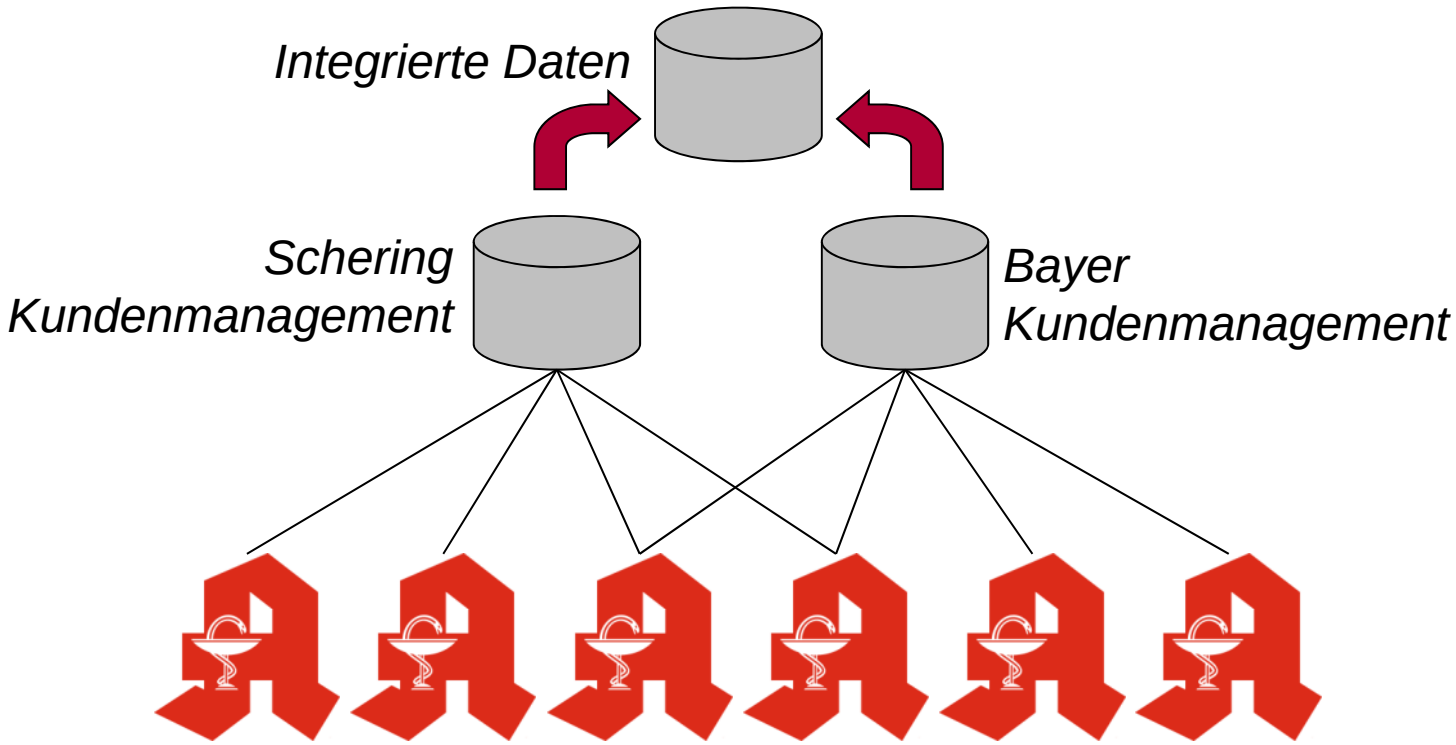
Original

Scanned

Origins of duplicates



Origins of duplicates



German names

Difficult names

488941 britney spears	29 britent spears	9 brinttany spears	5 brney spears	3 britiy sp
40134 brittany spears	29 brittnany spears	9 britanay spears	5 broitney spears	3 britmeny
36315 brittney spears	29 britttany spears	9 britinany spears	5 brotny spears	3 britneeey
24342 britany spears	29 btiney spears	9 britn spears	5 bruteny spears	3 britnehy
7331 britny spears	26 birttney spears	9 britnew spears	5 btiyney spears	3 britnely
6633 briteny spears	26 breitney spears	9 britneyn spears	5 btrittney spears	3 britnesy
2696 britteny spears	26 brinity spears	9 britrney spears	5 gritney spears	3 britnetty
1807 briney spears	26 britenay spears	9 brtiny spears	5 spritney spears	3 britnex s
1635 brittny spears	26 britneyt spears	9 brtittney spears	4 bittny spears	3 britneyxx
1479 brintey spears	26 brittan spears	9 brtny spears	4 bnritney spears	3 britnity
1479 britanny spears	26 brittne spears	9 brytny spears	4 brandy spears	3 britntey
1338 britiny spears	26 btittany spears	9 rbitney spears	4 brbritney spears	3 britnyey
1211 britnet spears	24 beitney spears	8 birtiny spears	4 breatiny spears	3 britterny
1096 britiney spears	24 birteny spears	8 bithney spears	4 breetney spears	3 brittneey
991 britaney spears	24 brightney spears	8 brattany spears	4 bretiney spears	3 brittnney
991 britnay spears	24 brintiny spears	8 breitny spears	4 brfitney spears	3 brittnyey
811 brithney spears	24 britanty spears	8 breteny spears	4 briattany spears	3 brityen s
811 brtiney spears	24 britenny spears	8 brightny spears	4 brieteny spears	3 briytney
664 birtney spears	24 britini spears	8 brintay spears	4 briety spears	3 brltney s
664 brintney spears	24 britnwy spears	8 brinttey spears	4 briitny spears	3 broteny s
664 briteney spears	24 brittni spears	8 briotney spears	4 briittany spears	3 brtaney s
601 bitney spears	24 brittnie spears	8 britanys spears	4 brinie spears	3 brtiiany
601 brinty spears	21 biritney spears	8 britley spears	4 brinteney spears	3 brtinay s
544 brittaney spears	21 birtany spears	8 britneyb spears	4 brintne spears	3 brtinney
544 brittnay spears	21 biteny spears	8 britnrey spears	4 britaby spears	3 brtitany
364 britey spears	21 bratney spears	8 britnty spears	4 britaey spears	3 brtiteny
364 brittiny spears	21 britani spears	8 brittner spears	4 britainey spears	3 brtnet sp
329 brtney spears	21 britanie spears	8 brottany spears	4 britinie spears	3 brytiny s
269 bretney spears	21 briteany spears	7 baritney spears	4 britinney spears	3 btney spe
269 britneys spears	21 brittay spears	7 birntey spears	4 britmney spears	3 drittney
244 britne spears	21 brittinay spears	7 biteney spears	4 britnear spears	3 pretney s
244 brytney spears	21 brtany spears	7 bitiny spears	4 britnel spears	3 rbritney
220 breatney spears	21 brtiany spears	7 breateny spears	4 britneuy spears	2 barittany
220 britiany spears	19 birney spears	7 brianty spears	4 britnewy spears	2 bbbritney
199 britnney spears	19 brirtney spears	7 brintye spears	4 britnmey spears	2 bbitney s
163 britnry spears	19 britnaey spears	7 britianny spears	4 brittaby spears	2 bbritny s

False Duplicates

Melanie Weis

List of publications from the DBLP Bibliography Server - FAQ

Coauthor Index - Ask others: ACM DL - ACM Guide - CiteSeer - CSB - Google

		2006
7	EE	Sven Puhlmann, Melanie Weis, Felix Naumann: XML Duplicate Detection Using Sorted Neighborhoods. EDBT 2006: 77
6	EE	Melanie Weis, Felix Naumann: Detecting Duplicates in Complex XML Data. ICDE 2006: 109
5	EE	Jan Hegewald, Felix Naumann, Melanie Weis: XStruct: Efficient Schema Extraction from Multiple and Large XML Docum
		2005
4	EE	Melanie Weis, Felix Naumann: DogmatiX Tracks down Duplicates in XML. SIGMOD Conference 2005: 431-442
3	EE	Alexander Bilke, Jens Bleiholder, Christoph Böhm, Karsten Draba, Felix Naumann, Melanie Weis: Automatic Data Fusion
2	EE	Melanie Weis, S. Müller, Claus-E. Liedtke, Martin Pahl: A framework for GIS and imagery data fusion in support of carto
		2004
1		Melanie Weis, Felix Naumann: Detecting Duplicate Objects in XML Documents. IQIS 2004: 10-19

Company duplicates

Add a position

It appears as though **Hasso Plattner Institute** is not in your profile. Would you like to add it now?

Job Title:

Company: Hasso Plattner Institute

Years: to Still in this position

Add this position or Skip this

Positions already in your profile:

- Hasso-Plattner-Institut
- Humboldt-Universität
- IBM Almaden Research Center
- IBM Almaden
- Humboldt-Universität

Motivation

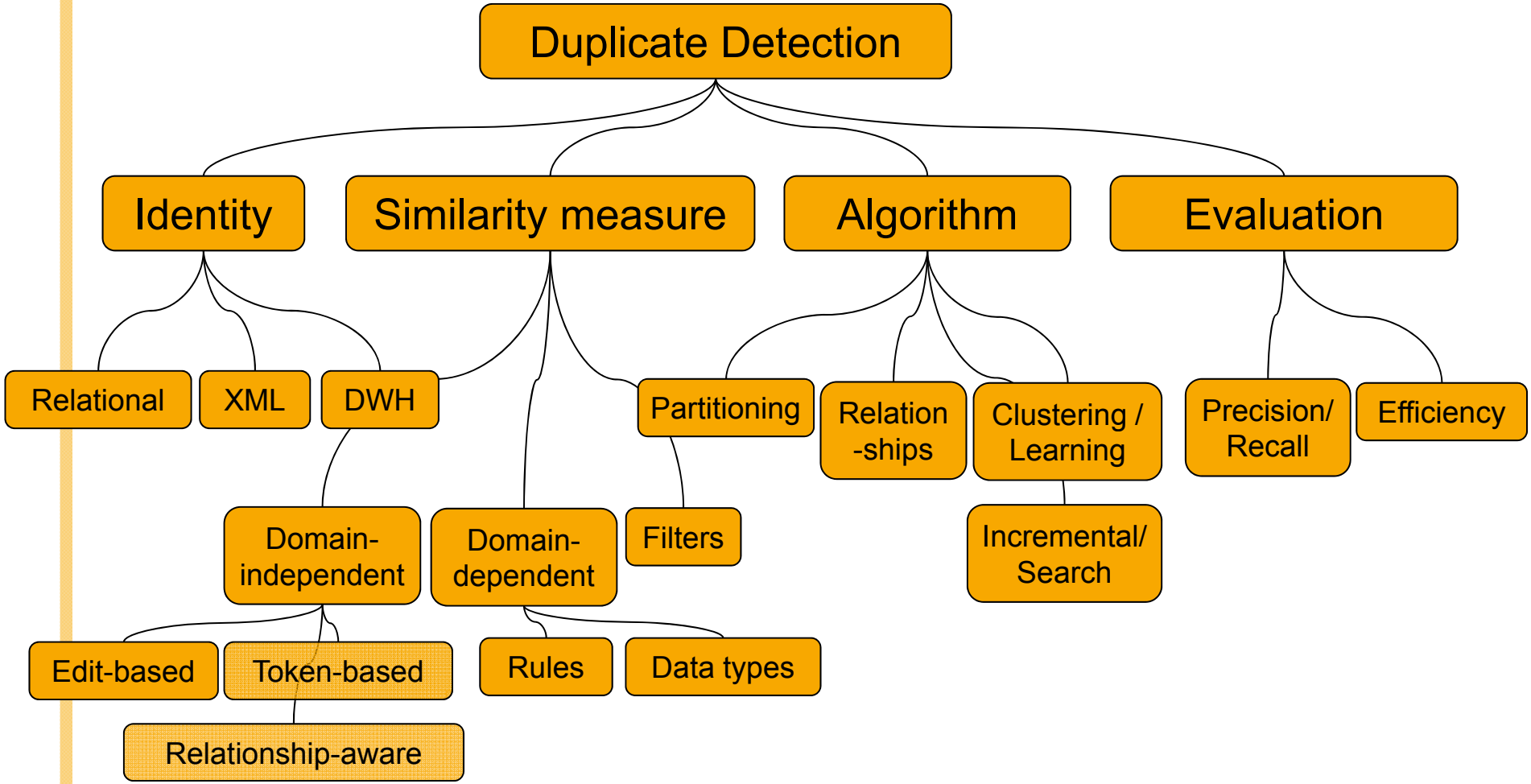
- Possible effects
  - Example: Portfolio Management Offers
  - Credit maximum not detected
  - Too low inventory levels
  - No quantity discount for multiple orders
  - Total revenue of preferred customers unknown
  - Multiple mailings of same catalog to same household
- General problems
  - Additional, unnecessary IT expenses
  - Low customer satisfaction
  - Potentials and dangers not detected
  - Poor quality financial data

Customer	Revenue
BMW	20.000
BaMoWe	5.000.000
Bayerische Motorenwerke	300.000
…	…

Ironically, “Duplicate Detection” has many Duplicates

- Household matching
- Doubles
- Duplicate detection
- Mixed and split citation problem
- Record linkage
- Object identification
- Match
- Deduplication
- Fuzzy match
- Object consolidation
- Entity resolution
- Entity clustering
- Approximate match
- Identity uncertainty
- Reference reconciliation
- Merge/purge
- Hardening soft databases
- Householding
- Reference matching

Duplicate Detection – Research



Token-based Similarity Measures

- Tokens
  - Words / Terms
  - n-grams
- Jaccard
  - |{common tokens}| / |{all tokens}|
- TFIDF [Cohen et al. 2003]
  - Term frequency: *tf*
  - Inverse document frequency: *idf*
  - TFIDF: log (*tf*+1) x log (*idf*)
  - Common words have low weight
  - Similarity measure: Cosine similarity of term vectors weighted by TFID
- And many more
  [Koudas Srivastavasa 2005]

Edit-based Similarity Measures

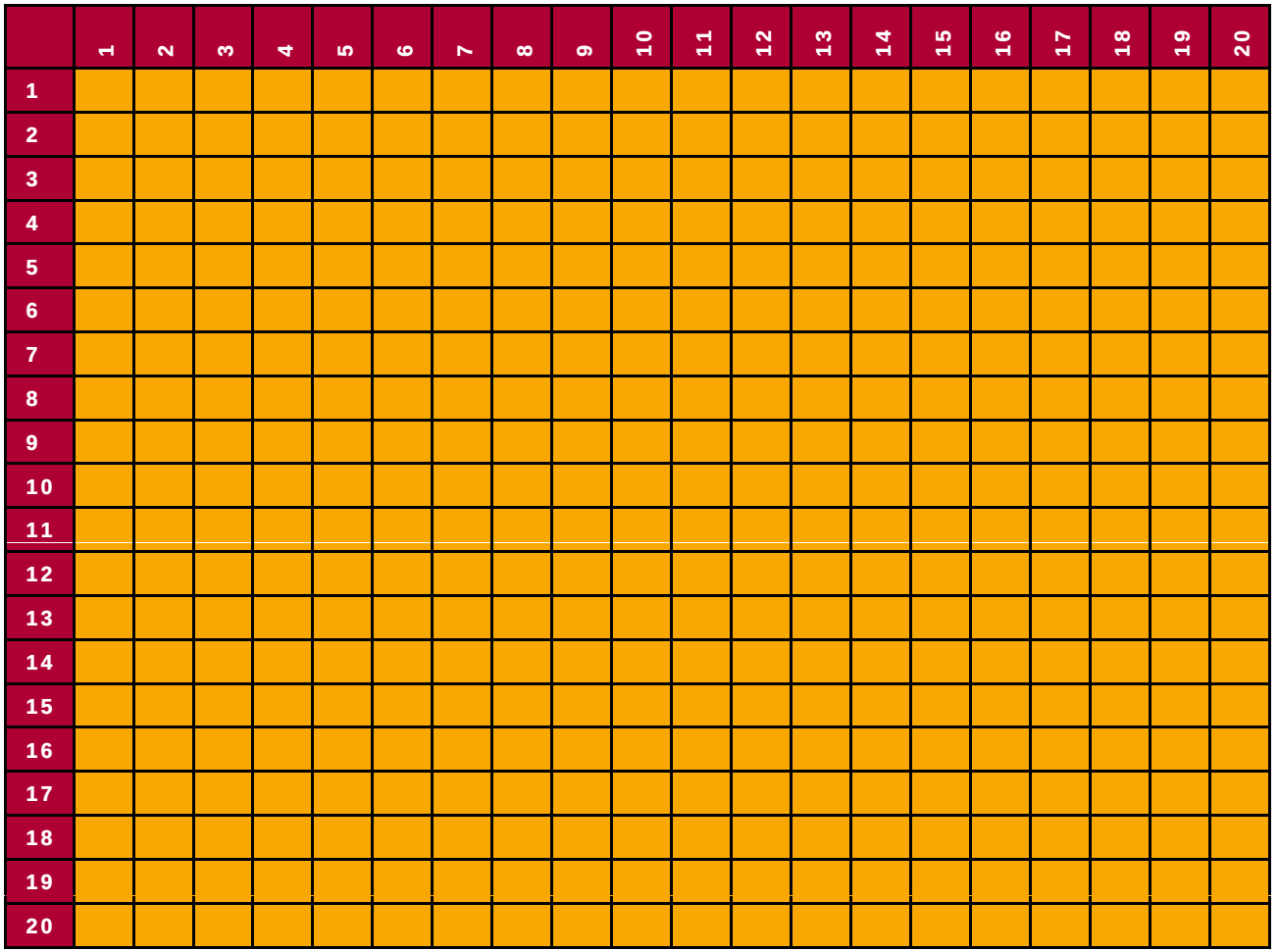
- Jaro [Jaro 1989] / Jaro-Winkler [Winkler 1999]
  - Common letters within ½ string length
  - Transposed letters
- Edit-distance / Levenshtein-distance [Levenshtein 1965]
  - Minimum number of edits from one word to the other
  - Domain-specific costing
  - Dynamic Programming
- Soundex
  - 4-letter code for each word
  - SOUNDEX('Farwick ') = F620
- …

Frass, Fricke, Fahruschi, Feuerhake

Record Pairs as Matrix

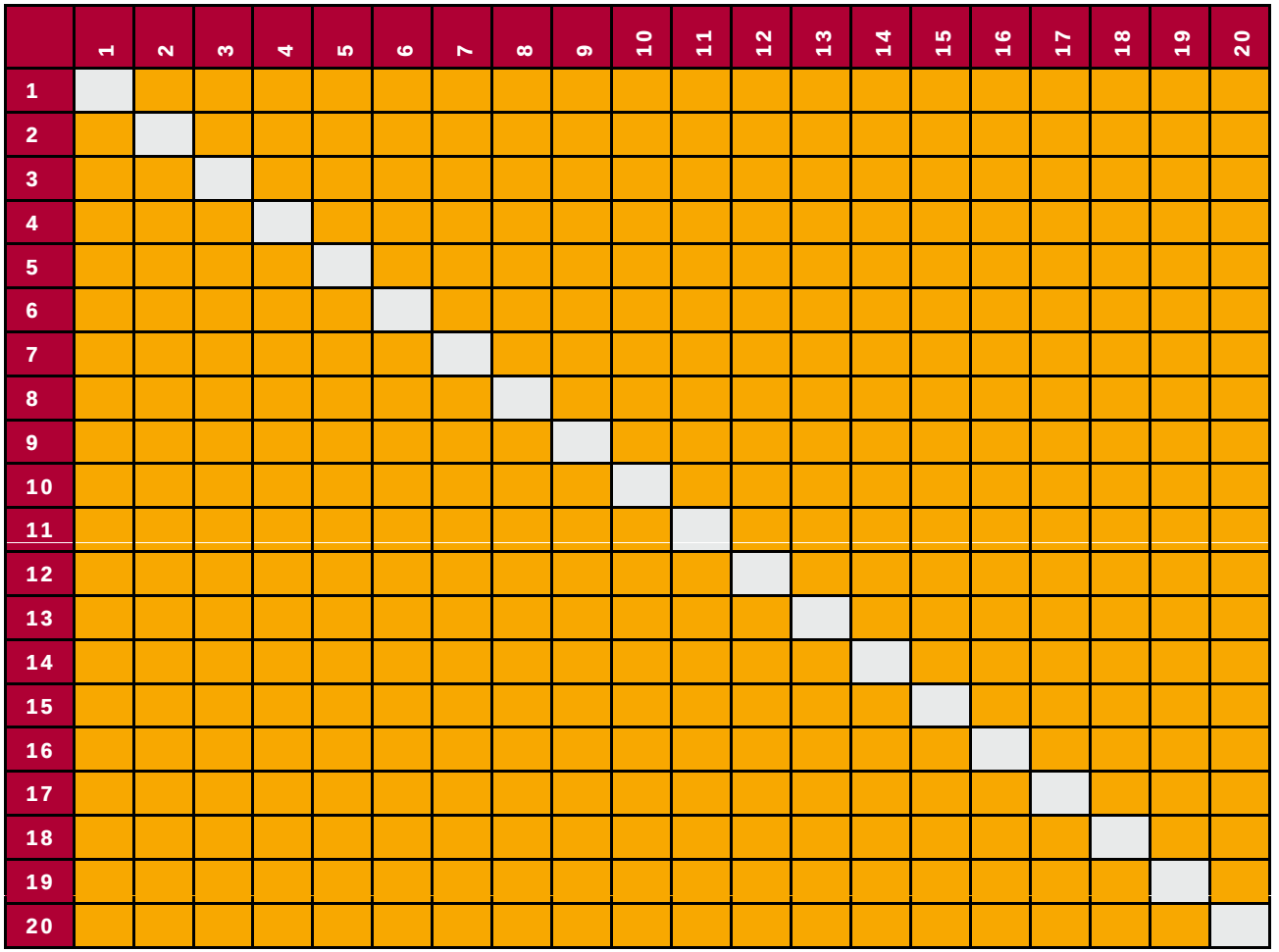
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1																				
2																				
3																				
4																				
5																				
6																				
7																				
8																				
9																				
10																				
11																				
12																				
13																				
14																				
15																				
16																				
17																				
18																				
19																				
20																				

Number of comparisons: All pairs



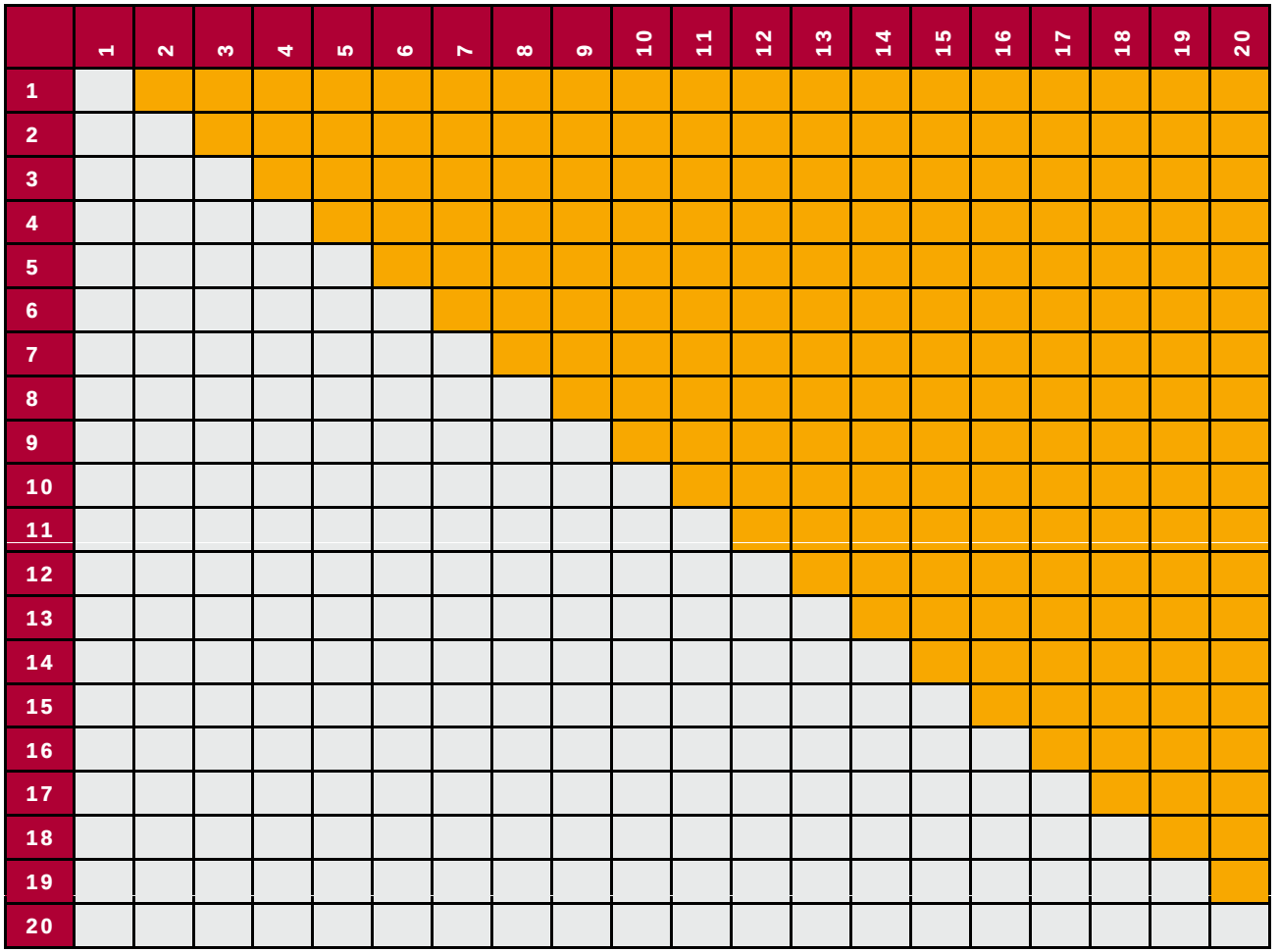
400 comparisons

Reflexivity of Similarity



380 comparisons

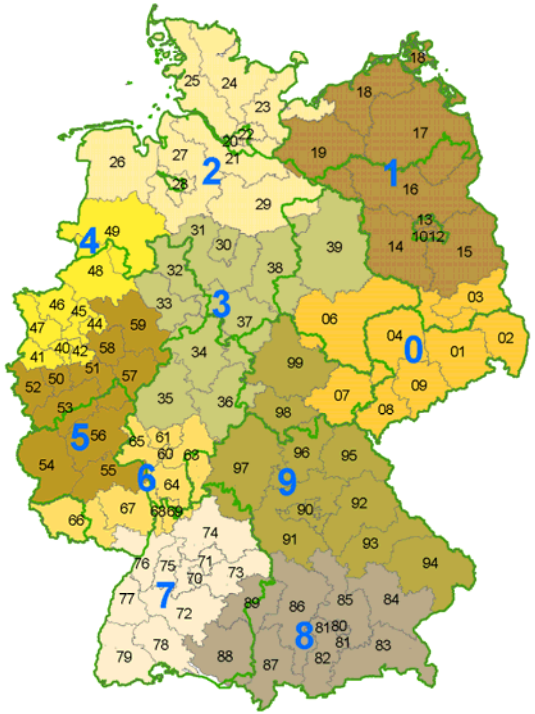
Symmetry of Similarity



190 comparisons

Partitioning / Blocking

- Partition the records (horizontally) and compare pairs of records only within a partition.
  - Partitioning by first two zip-digits
    - Ca. 100 partitions in Germany
    - Ca. 100 customers per partition
    - => 495.000 comparisons
  - Partition by first letter of surname
  - …



Source: wikipedia.de

- Idea: Partition multiple times by different criteria.
  - Then apply transitive closure on discovered duplicates.

Complexity

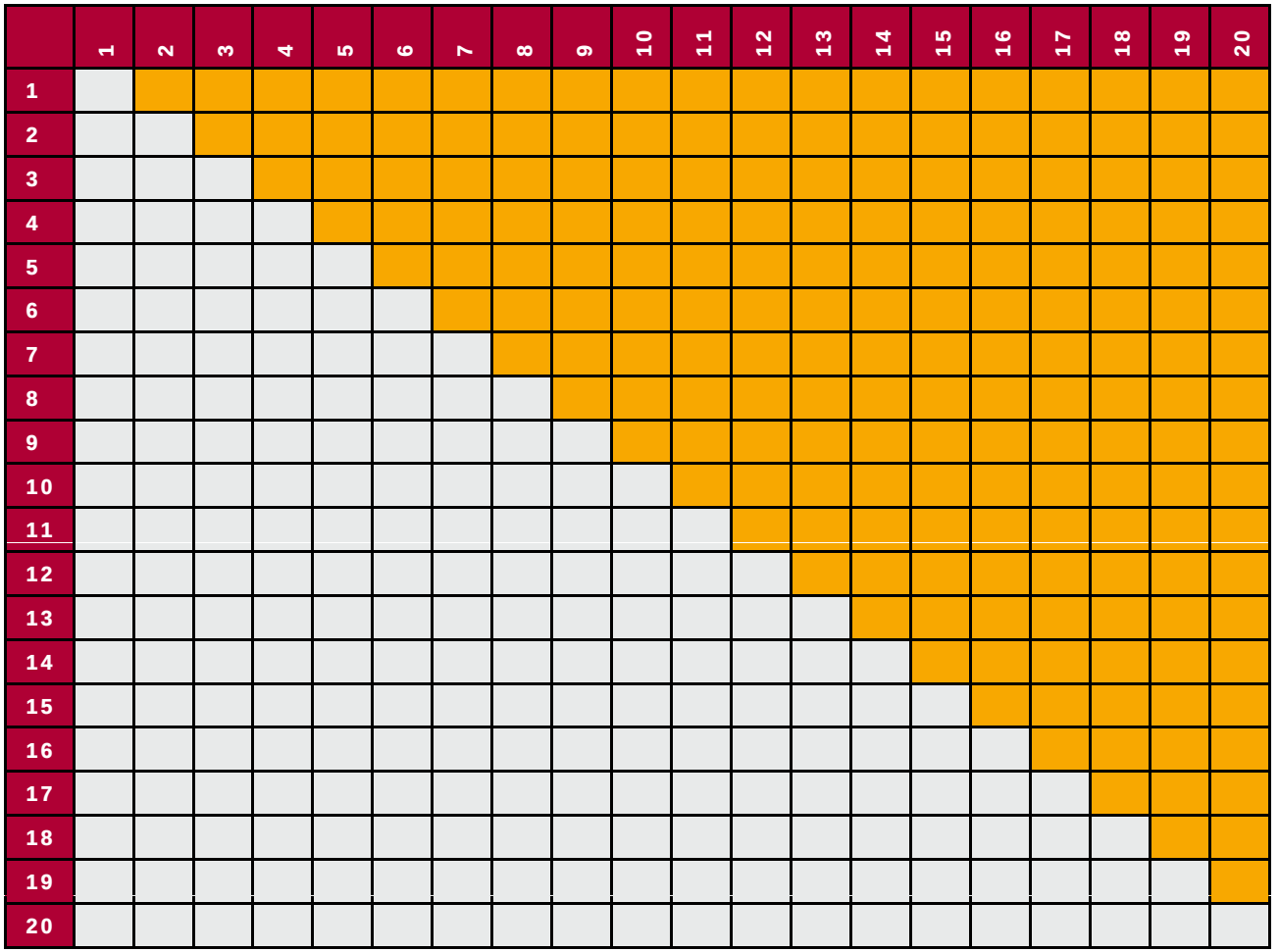
Still: Too many comparisons

- 10.000 customers => 49.995.000 comparisons
  - $(n^2 - n) / 2$
  - Each comparison is expensive (complex similarity measures).

Idea: Avoid comparisons by heuristics

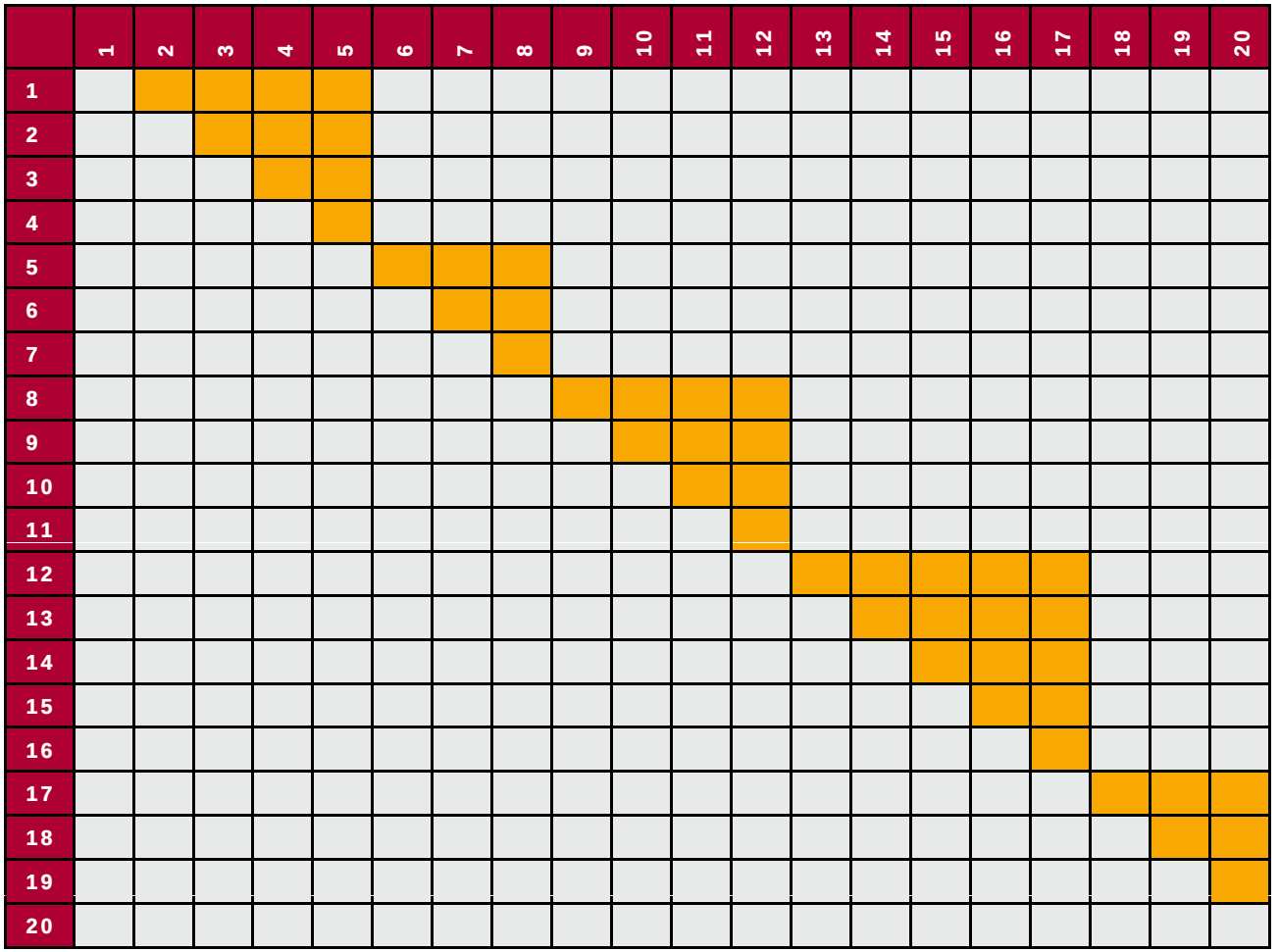
- Filtering of records
- Partitionierung

Records sorted by ZIP



190 comparisons

Blocking by ZIP



47 comparisons

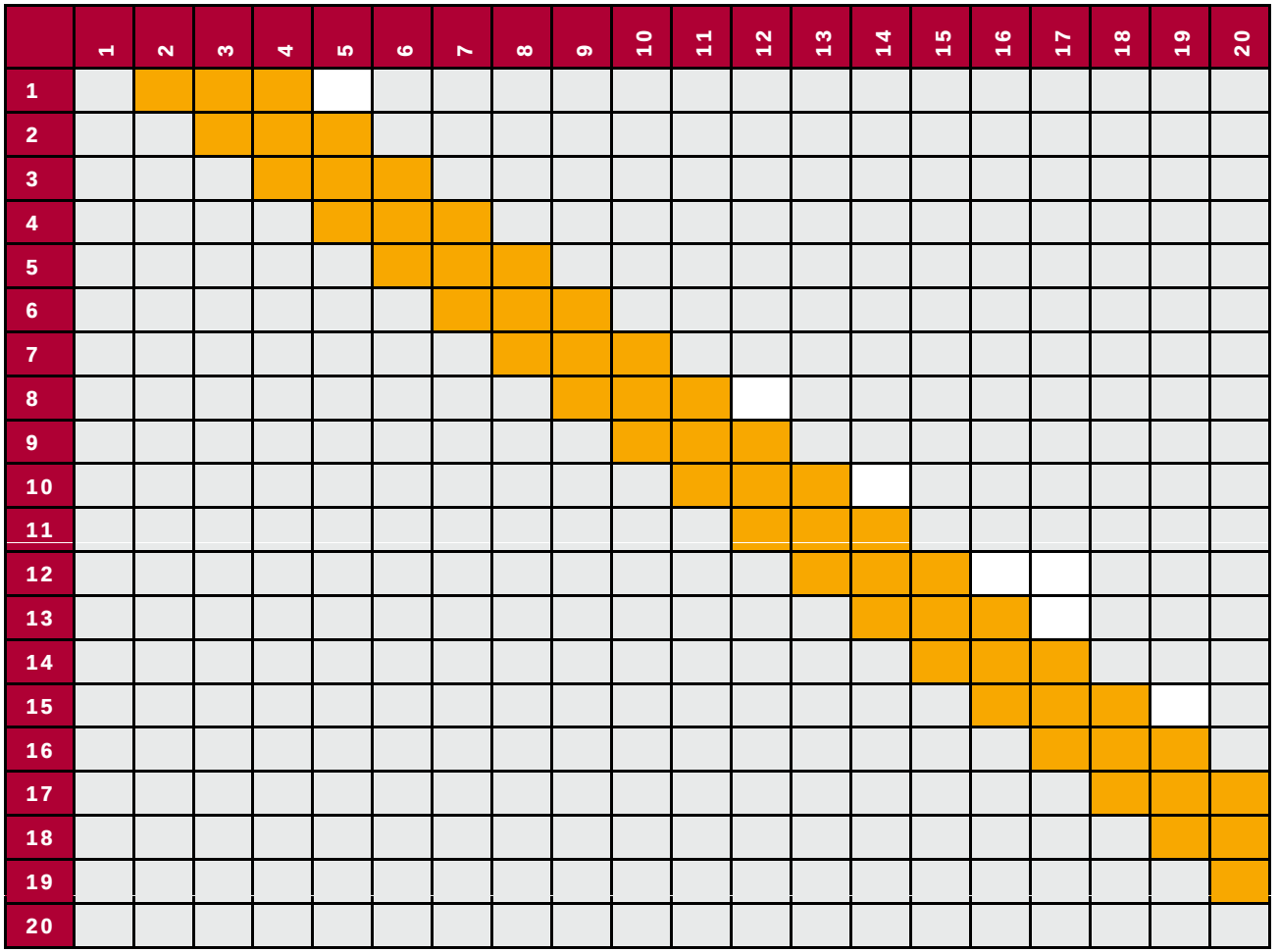
Sorted Neighborhood
[Hernandez Stolfo 1998]

- Idea
  - Sort tuples so that similar tuples are close to each other.
  - Only compare tuples within a small neighborhood (window).

1. Generate key
   - E.g.: SSN+"first 3 letters of name" + ...
2. Sort by key
   - Similar tuples end up close to each other.
3. Slide window over sorted tuples
   - Compare all pairs of tuples within window.

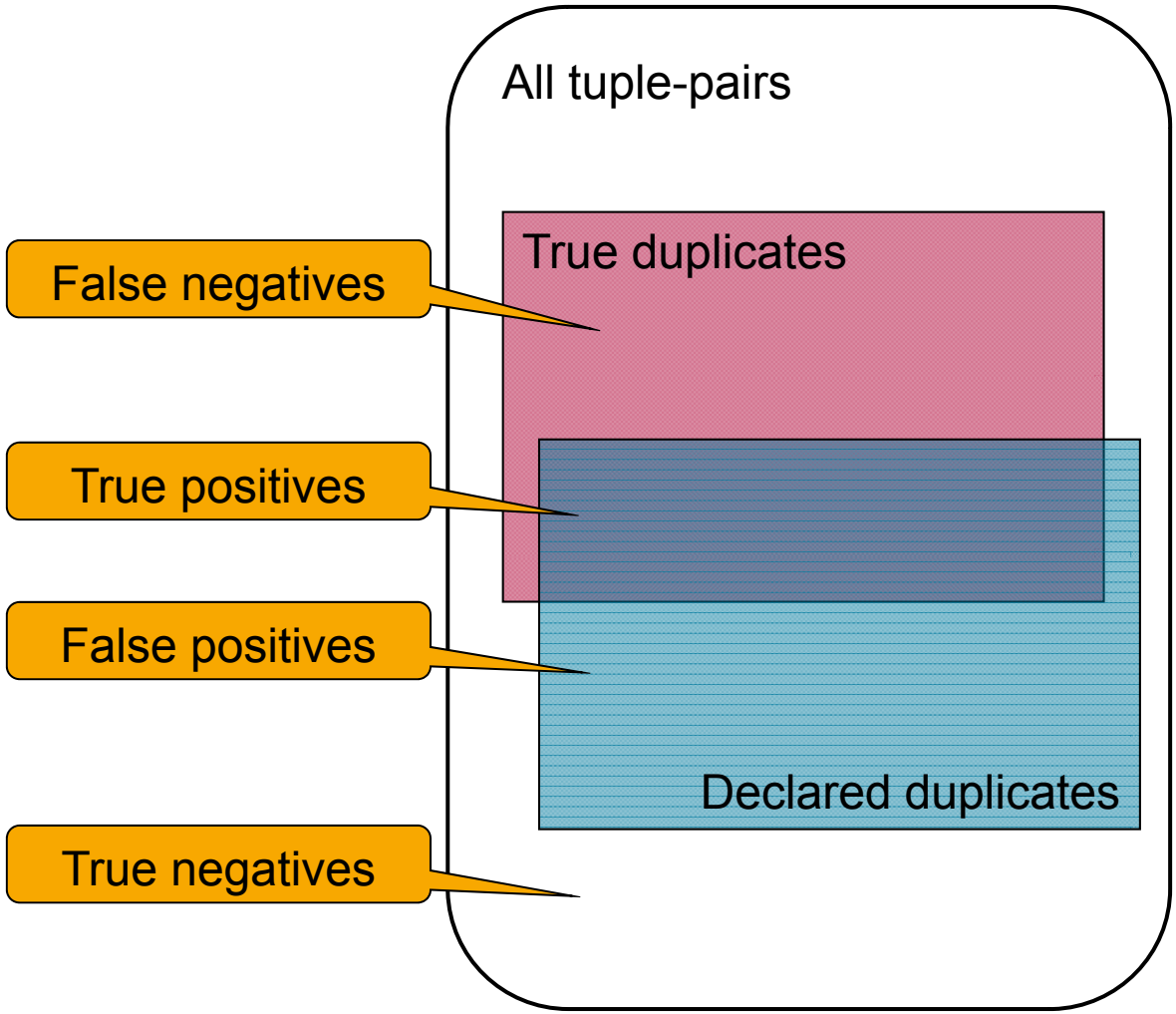
- Problems
  - Choice of key
  - Choice of window size
- Complexity: At least 3 passes over data
  - Sorting!

SNM by ZIP (window size 4)



54 comparisons

Precision & Recall
(≈ correctness and completeness)

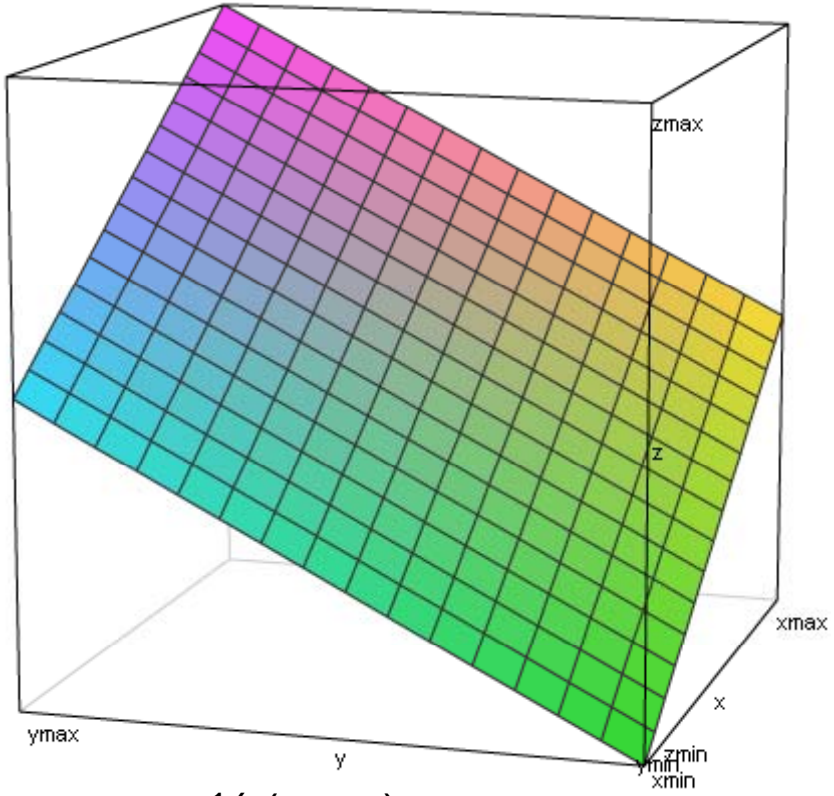


Precision = True positives / Declared duplicates

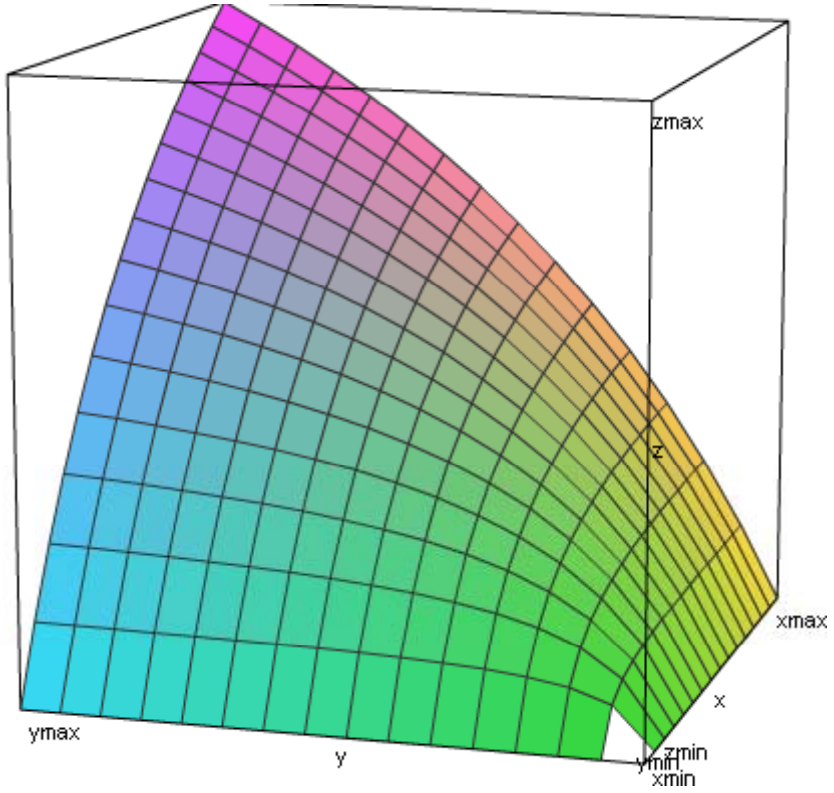
Recall = True positives / True duplicates

F-Measure = 2 · Precision · Recall / Precision + Recall

Arithmetic mean („Average“) vs. Harmonic mean („F-Measure“)

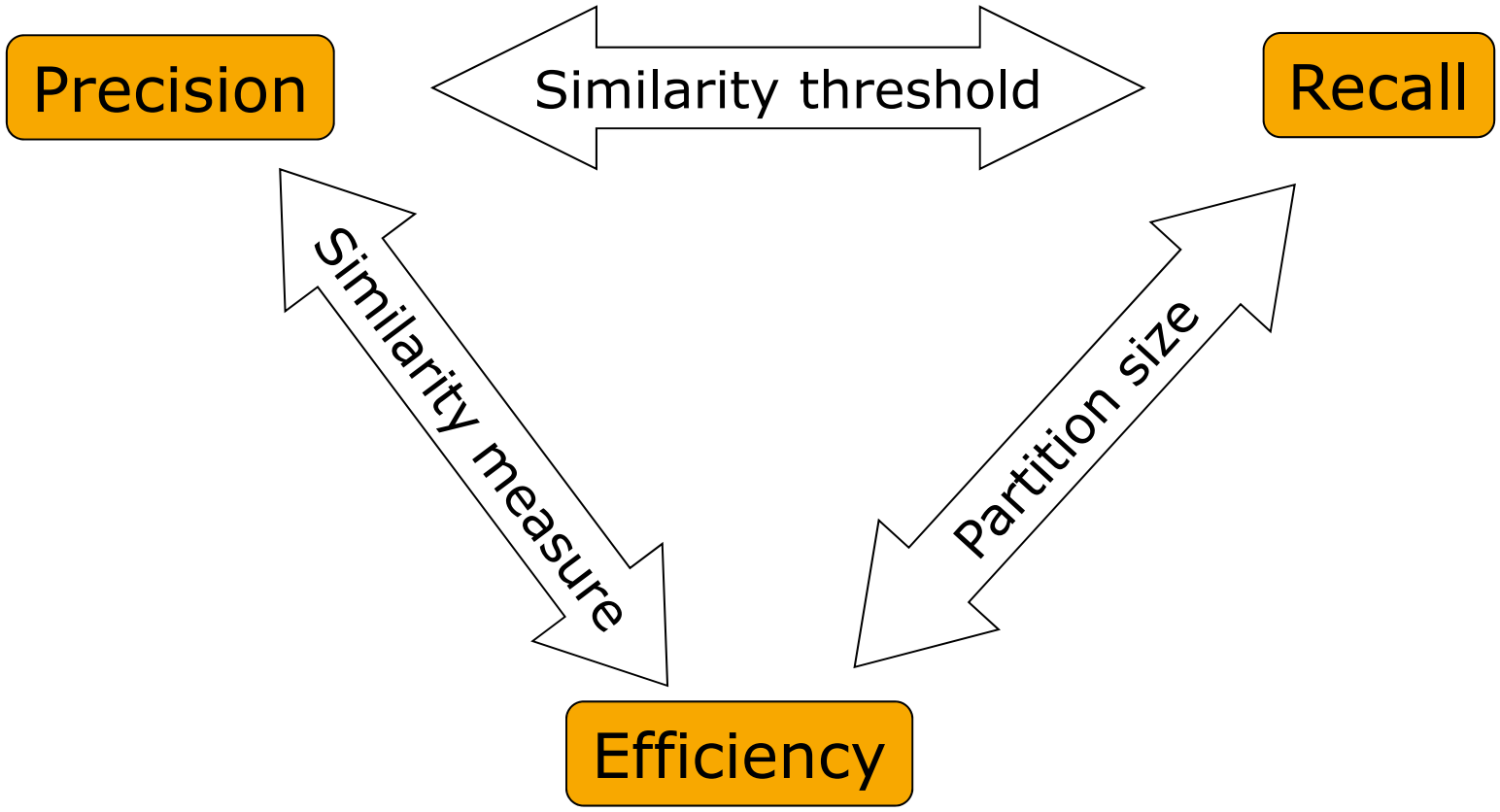


$z = ½ (x + y)$



$z = 2 (x \cdot y) / (x + y)$

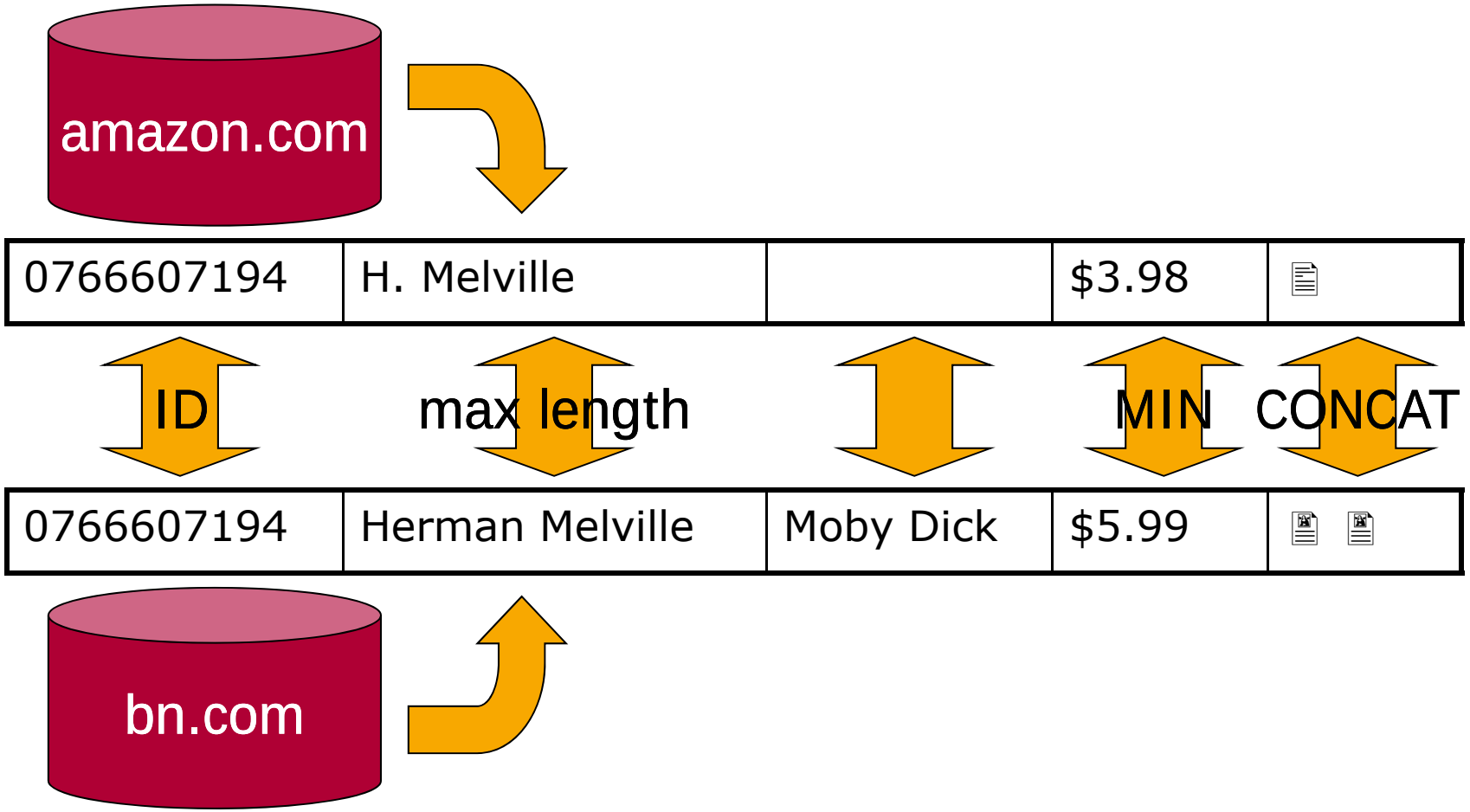
Duplikaterkennung – Zielkonflikte



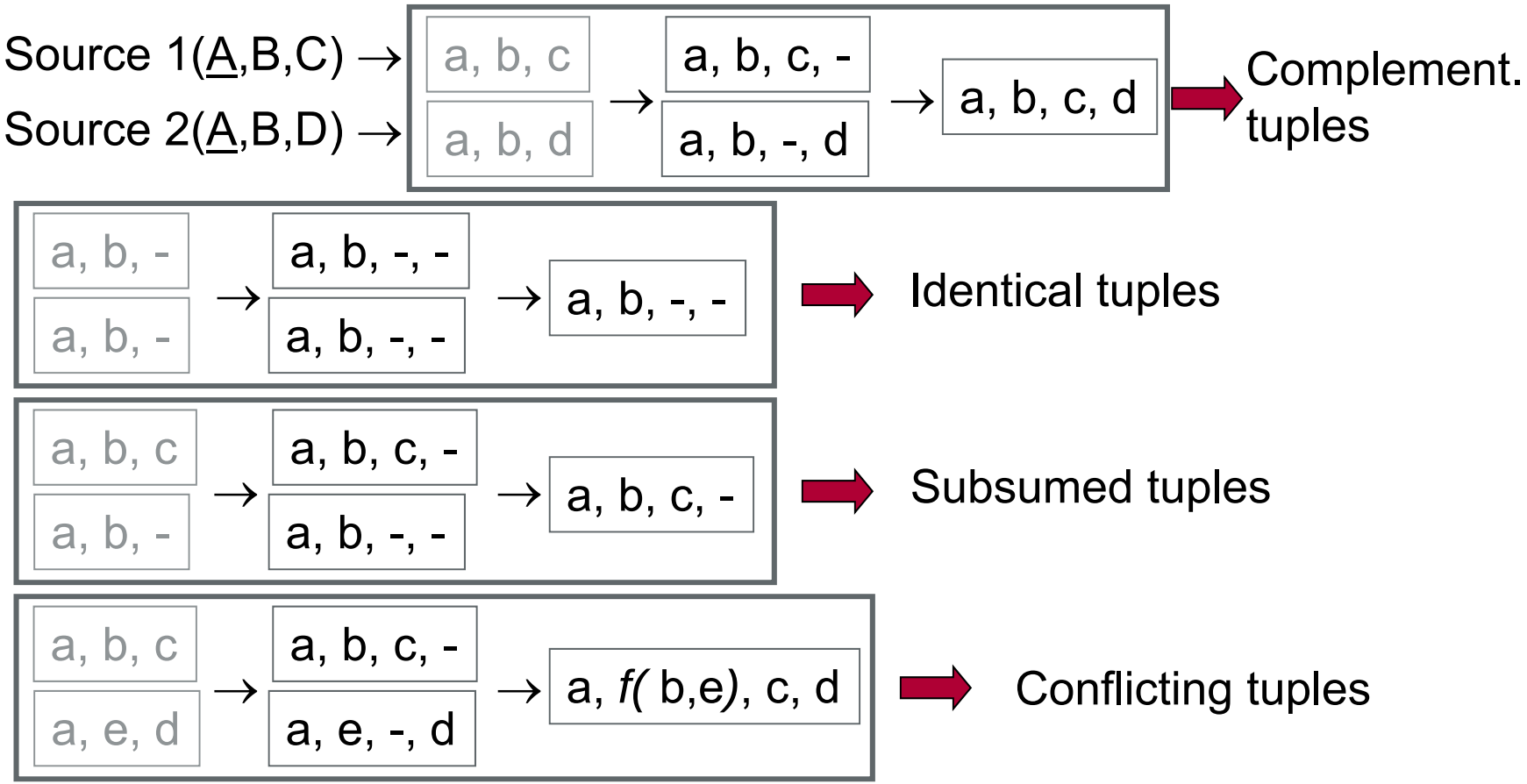
Overview

- Information Quality
- Step 1: Schema Matching
- Step 2: Duplicate detection
- Step 3: Data fusion
- Summary

Data Fusion


amazon.com
0766607194
H. Melville
$3.98
ID
max length
MIN
CONCAT
0766607194
Herman Melville
Moby Dick
$5.99
bn.com

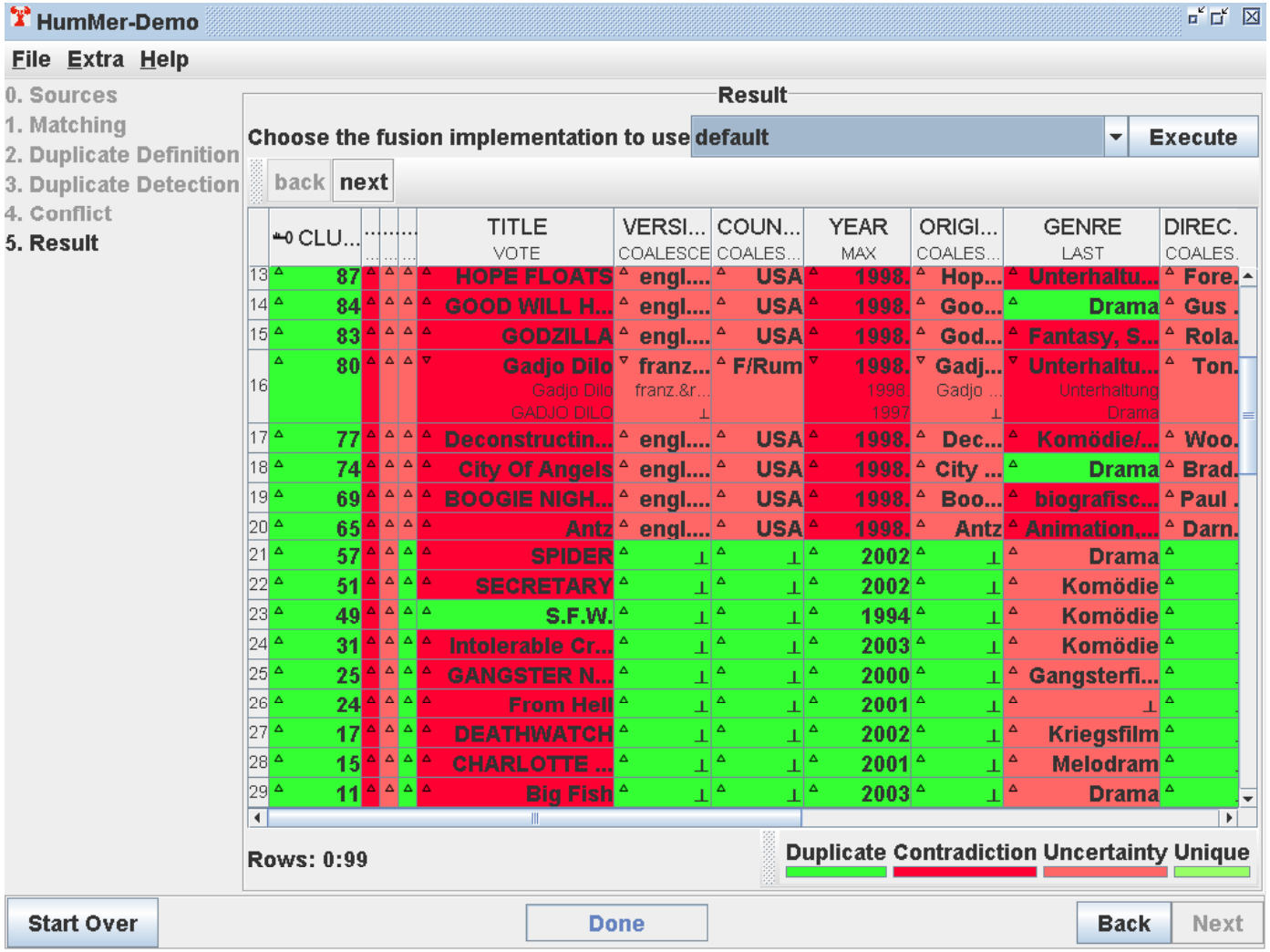
“Proper” Data Fusion



Conflict Resolution Functions

Min, Max, Sum, Count, Avg, StdDev	Standard aggregation
Random	Random choice
First, Last	Choose first/last value; depends on order
Longest, Shortest	Choose longest/shortest value
Choose(*source*)	Choose value froma particular source
ChooseDepending(*col*, *val*)	Choose depending on *val* in other column *col*
Vote	Majority decision
Coalesce	Choose first non-null value
Group, Concat	Group or concatenate all values
MostRecent	Choose most recent (up-to-date) value
MostAbstract, MostSpecific	Use a taxonomy / ontology
….	….

Visualization of Integrated Data



Overview

- Information Quality
- Step 1: Schema Matching
- Step 2: Duplicate detection
- Step 3: Data fusion
- Summary

Summary

- Data Quality
- Step 1: Schema Matching
  - Similarity Measure
  - Combination of methods
- Step 2: Duplicate Detection
  - Similarity Measure
  - Algorithm
  - Data Model
- Step 3: Data Fusion
  - Relational Operators
  - Conflict Resolution
  - Visualization of Semantics and Overlap