

# Advanced Data Management (CSCI 490/680)

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Data Fusion

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# Databases

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- Databases:
  - Have been around for years
  - Organize data by tables, allow powerful queries
  - Most support concurrency: allowing multiple users to work with the database at once
  - Provide many features to ensure data integrity, security
- Database Management Systems (DBMS): software that manages databases and facilitates adding, updating, and removing data as well as queries over the data
- Main language used to interact with databases:  
Structured Query Language (SQL)

# Football Game Data

- Have each game store the id of the home team and the id of the away team (one-to-one)
- Have each player store the id of the team he plays on (many-to-one)

## Player

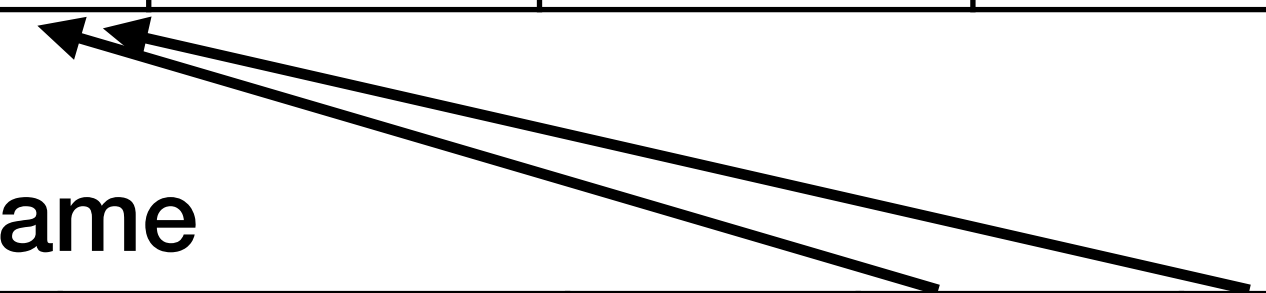
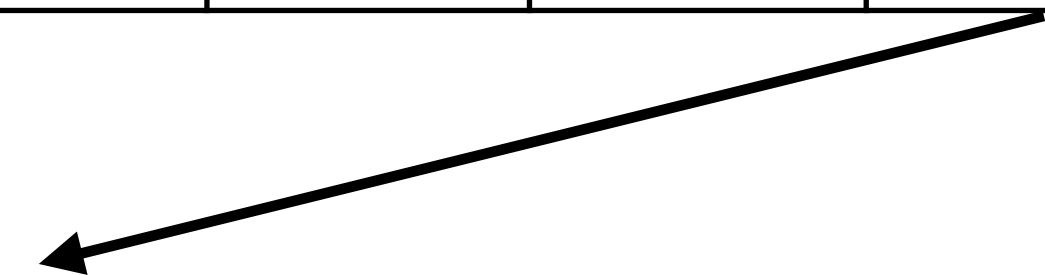
Id	Name	Height	Weight	TeamId
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## Team

Id	Name	Wins	Losses
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## Game

Id	Location	Date	Home	Away
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# Concatenation

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- Take two data frames with the same columns and add more rows
- `pd.concat([data-frame-1, data-frame-2, ...])`
- Default is to add rows (`axis=0`), but can also add columns (`axis=1`)
- Can also concatenate Series into a data frame.
- `concat` preserves the index so this can be confusing if you have two default indices (0,1,2,3...)—they will appear twice
  - Use `ignore_index=True` to get a 0,1,2...

# Merges (aka Joins)

- Want to join the two tables based on the location and date
- Location and date are the **keys** for the join
- Merges are **ordered**: there is a left and a right side

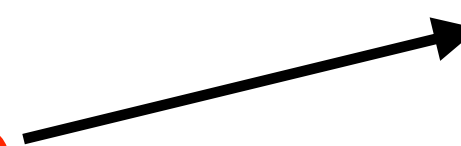
Game

Id	Location	Date	Home	Away
0	Boston	9/2	1	15
1	Boston	9/9	1	7
2	Cleveland	9/16	12	1
3	San Diego	9/23	21	1

Weather

wld	City	Date	Temp
0	Boston	9/2	72
1	Boston	9/3	68
...	...	...	...
7	Boston	9/9	75
...	...	...	...
21	Boston	9/23	54
...	...	...	...
36	Cleveland	9/16	81

No data for San Diego



# Types of Joins

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- Inner: intersection of keys (match on both sides)
- Outer: union of keys (if there is no match on other side, still include with NaN to indicate missing data)
- Left: always have rows from left table (no unmatched right data)
- Right: like left, but with no unmatched left data

# Data Merging in Pandas

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- `pd.merge(left, right, ...)`
- Default merge: join on matching column names
- Better: specify the column name(s) to join on via `on` kwarg
  - If column names differ, use `left_on` and `right_on`
  - Multiple keys: use a list
- `how` kwarg specifies type of join (`"inner"`, `"outer"`, `"left"`, `"right"`)
- Can add suffixes to column names when they appear in both tables, but are not being joined on
- Can also merge using the index by setting `left_index` or `right_index` to `True`

# Data Integration

```
select title, startTime
from Movie, Plays
where Movie.title=Plays.movie AND
        location="New York" AND
        director="Ava DuVernay"
```

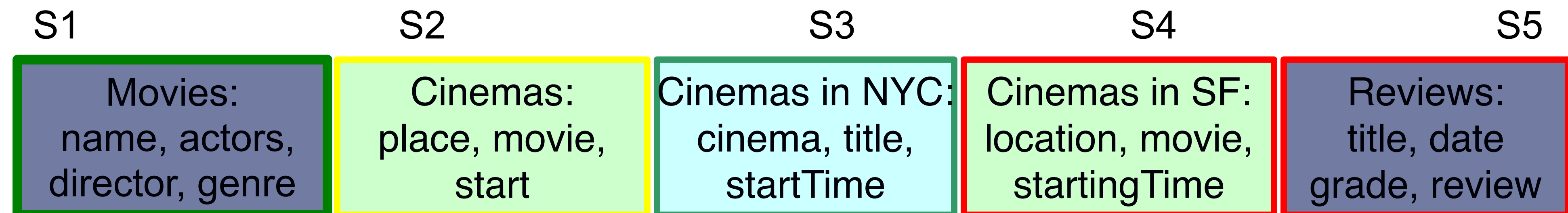
**Movie:** Title, director, year, genre

**Actors:** title, actor

**Plays:** movie, location, startTime

**Reviews:** title, rating, description

Sources S1 and S3 are relevant, sources S4 and S5 are irrelevant, and source S2 is relevant but possibly redundant.



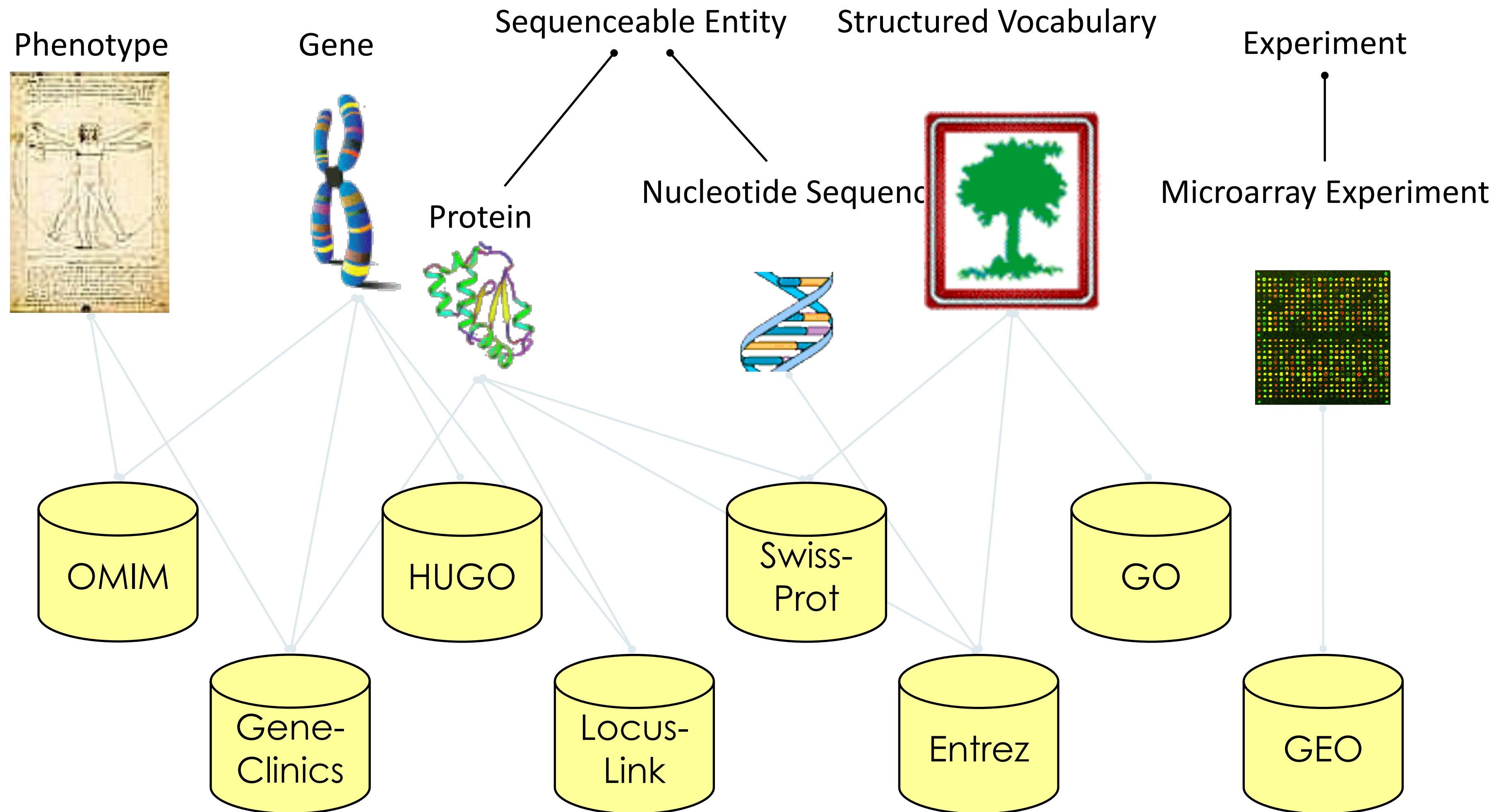
[AH Doan et al., 2012]

# Data Integration

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- Lots of data sources, how do we answer questions where we need to access data from more than one?
- Schema matching
- Problem of heterogeneity
- AI-Complete problem: difficulty is the same as making computers as intelligent as people
- Two techniques:
  - Mediation
  - Data Warehouses

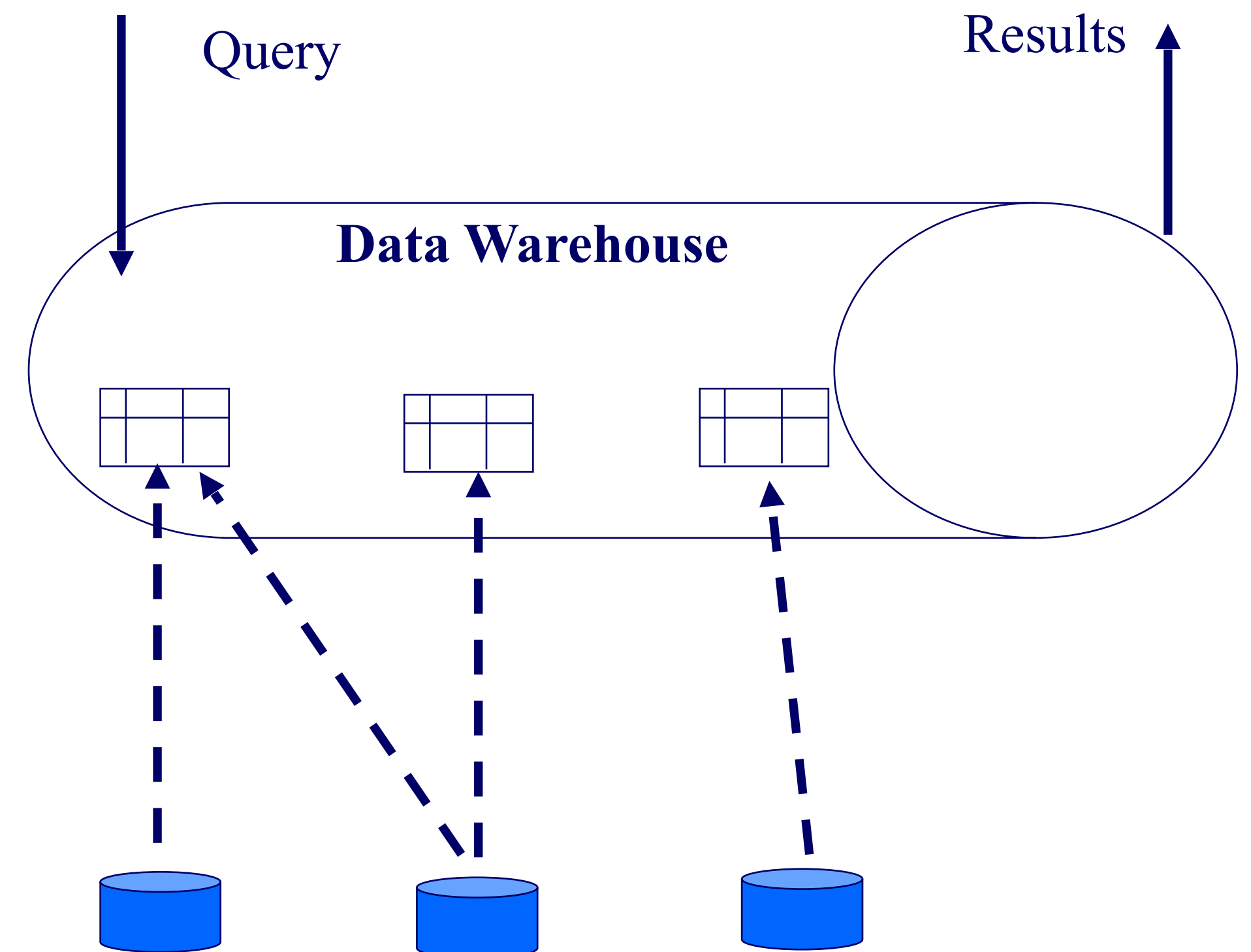
# Data Integration Application: Biomedical



[A. Doan et al., 2012]

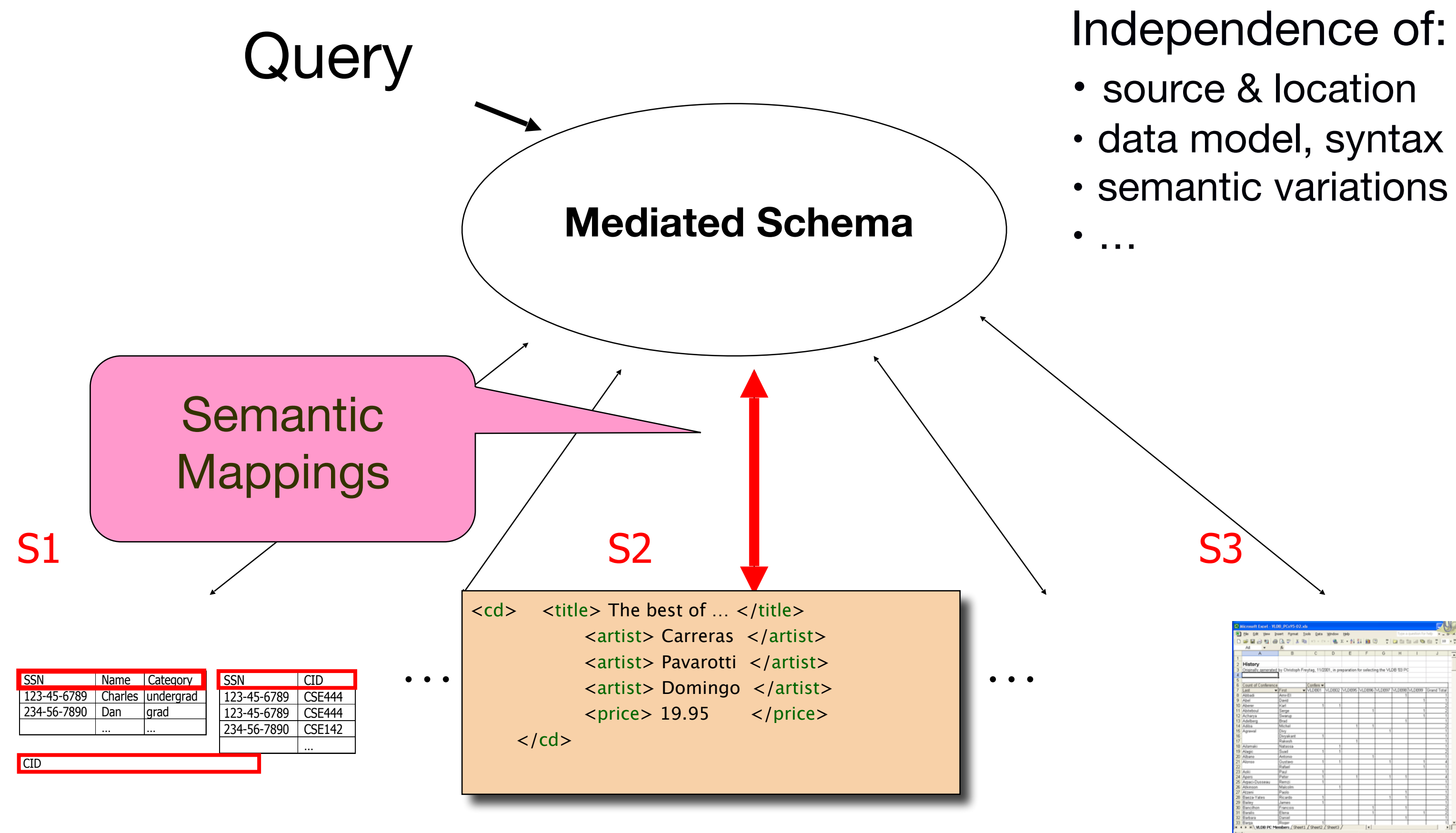
# Data Warehouses: Offline Replication

- Determine physical schema
- Define a database with this schema
- Define procedural mappings in an “ETL tool” to import the data and clean it.
- Periodically copy all of the data from the data sources
  - Note that the sources and the warehouse are basically independent at this point



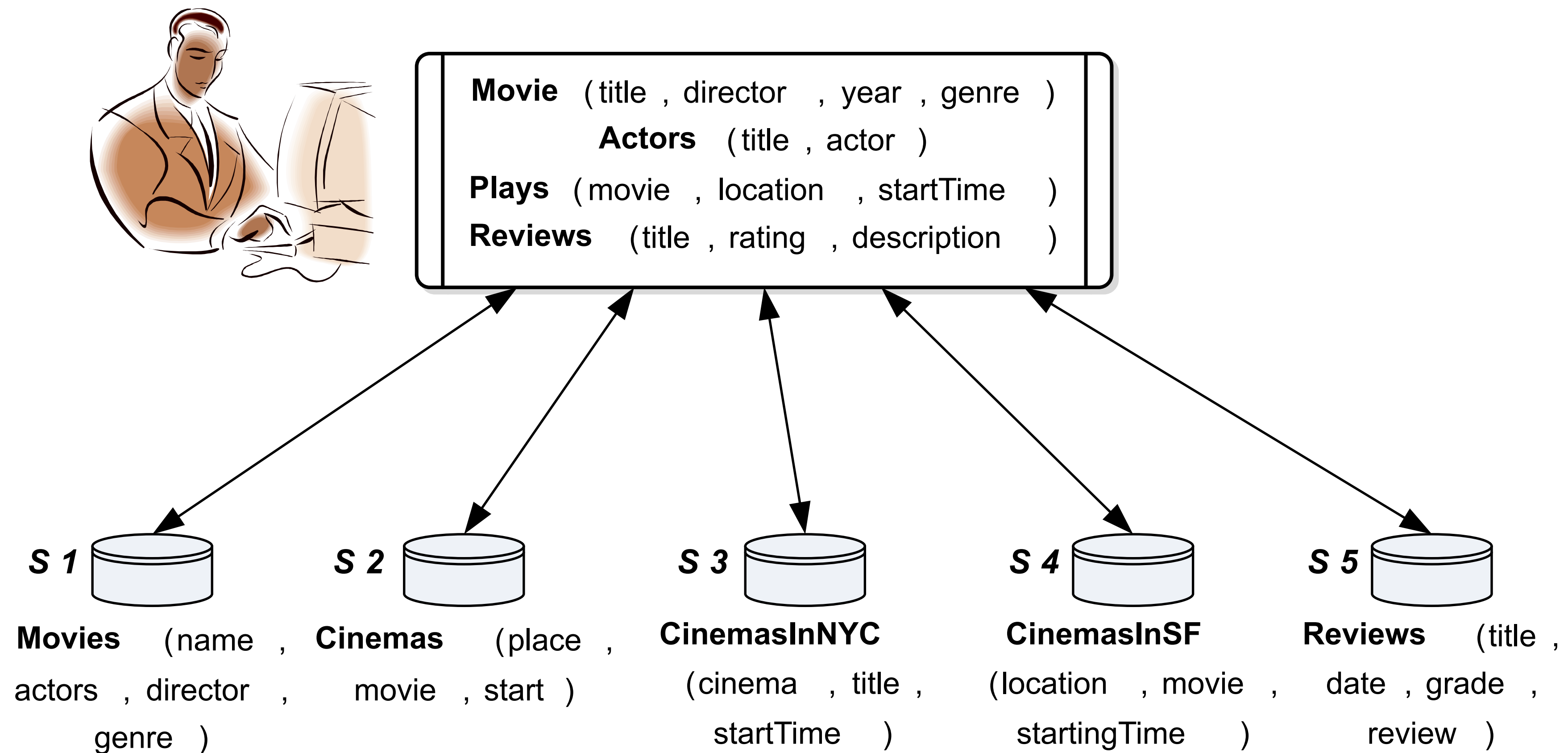
[A. Doan et al., 2012]

# Virtual Data Warehouses



[A. Doan et al., 2012]

# Integrated Schema Example



[A. Doan et al., 2012]

# Why is Data Integration Hard?

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- Systems-level reasons:
  - Managing different platforms
  - SQL across multiple systems is not so simple
  - Distributed query processing
- Logical reasons:
  - Schema (and data) heterogeneity
- ‘Social’ reasons:
  - Locating and capturing relevant data in the enterprise.
  - Convincing people to share (data fiefdoms)
    - Security, privacy and performance implications

[A. Doan et al., 2012]

# Assignment 3

- Same Info Wanted data
- Data wrangling with
  - Trifacta Wrangler
  - pandas
- For place, date extraction: 2 regexs, don't try to standardize anything, CS680 need to extract place details, date is EC
- Trifacta # of Rows Issue
- Due Wednesday, March 3

#	recid	#	order	#	date	ABC	place	state
1 - 41.23k		1 - 5		1 - 1.87k		5,431 Categories		44 Categories
	38575		1		null	MA, · BROOKLINE ·		MA
	34452		1		1857	NY, · NYC ·		NY
	34453		1		1857	NY, · NYC ·		NY
	34454		1		1857	NY, · NYC ·		NY
	35259		1		1855	OH, · CINCINNATI ·		OH
	37781		1		1864	MA, · ABINGTON ·		MA
	37781		2		05/67	MA, · BOSTON ·		MA
	37781		3		null	CA ·		CA
	39120		1		null	TX, · MILLICAN ·		TX
	34455		1		null	AUSTRALIA		null
	34776		1		null	IL, · CHICAGO		IL
	34881		1		64	NY, · BINGHAMPTON, · BROOME · CO. ·		NY
	35309		1		1860	IL ·		IL
	35537		1		1861	MA, · BOSTON ·		MA
	34757		1		null	TN, · NASHVILLE		TN
	38439		1		null	MA, · BOSTON		MA
	38439		2		null	CA, · SAN · FRANCISCO ·		CA
	41070		2		null	CINCINNATI		null
	33438		1		1862	MA, · BOSTON ·		MA
	33478		1		10/64	AL, · MOBILE ·		AL
	33478		2		null	IL, · ST. · TRELIA		IL
	33940		1		1857	NC ·		NC
	34331		1		02/65	MA, · BOSTON ·		MA
	33693		1		null	NY		NY
	33693		2		null	CANADAS		null
	34306		1		02/65	MA, · BOSTON ·		MA
	36900		1		null	PA, · PHILADELPHIA		PA
	37541		1		null	AUSTRALIA, · SIDNEY		null
	33485		1		1858	MA, · NEW · BEDFORD ·		MA

# Quiz

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- Login to Blackboard ([webcourses.niu.edu](https://webcourses.niu.edu))
- Quiz is under Tests & Quizzes
- Reading Quiz - 2021-02-24
- You have **five (5)** minutes to answer the **five (5)** multiple choice questions

# Record Linkage Motivation

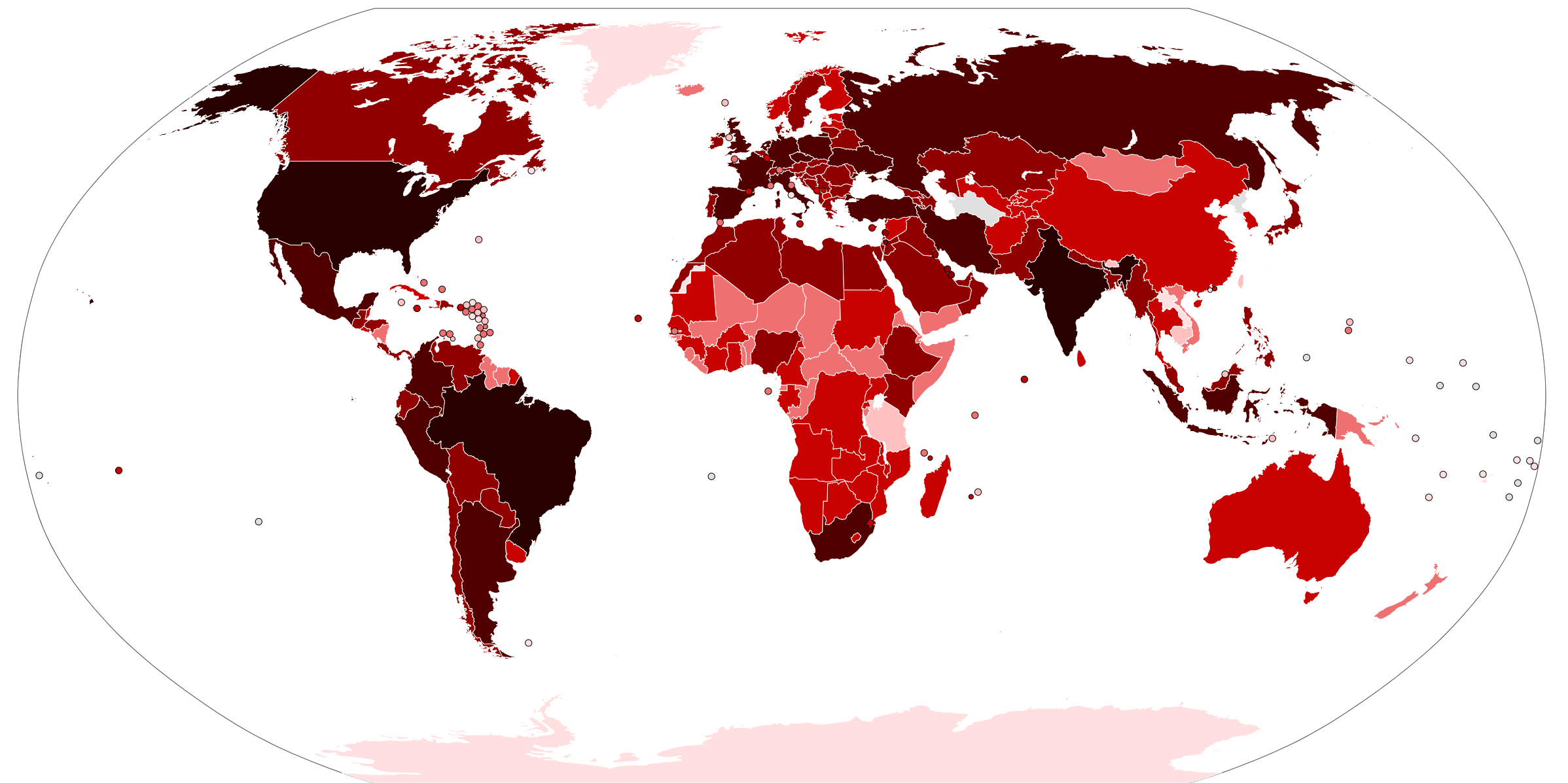
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- Often data from different sources need to be integrated and linked
  - To allow data analyses that are impossible on individual databases
  - To improve data quality
  - To enrich data with additional information
- **Lack of unique entity identifiers** means that linking is often based on personal information
- When databases are linked across organisations, maintaining privacy and confidentiality is vital
- The linking of databases is challenged by **data quality**, **database size**, and **privacy concerns**

[P. Christen , 2019]

# Motivating Example

- Preventing the outbreak of epidemics requires monitoring of occurrences of unusual patterns of symptoms, ideally in real time
- Data from many different sources will need to be collected (including travel and immigration records; doctors, emergency and hospital admissions; drug purchases; social network and location data; and possibly even animal health data)



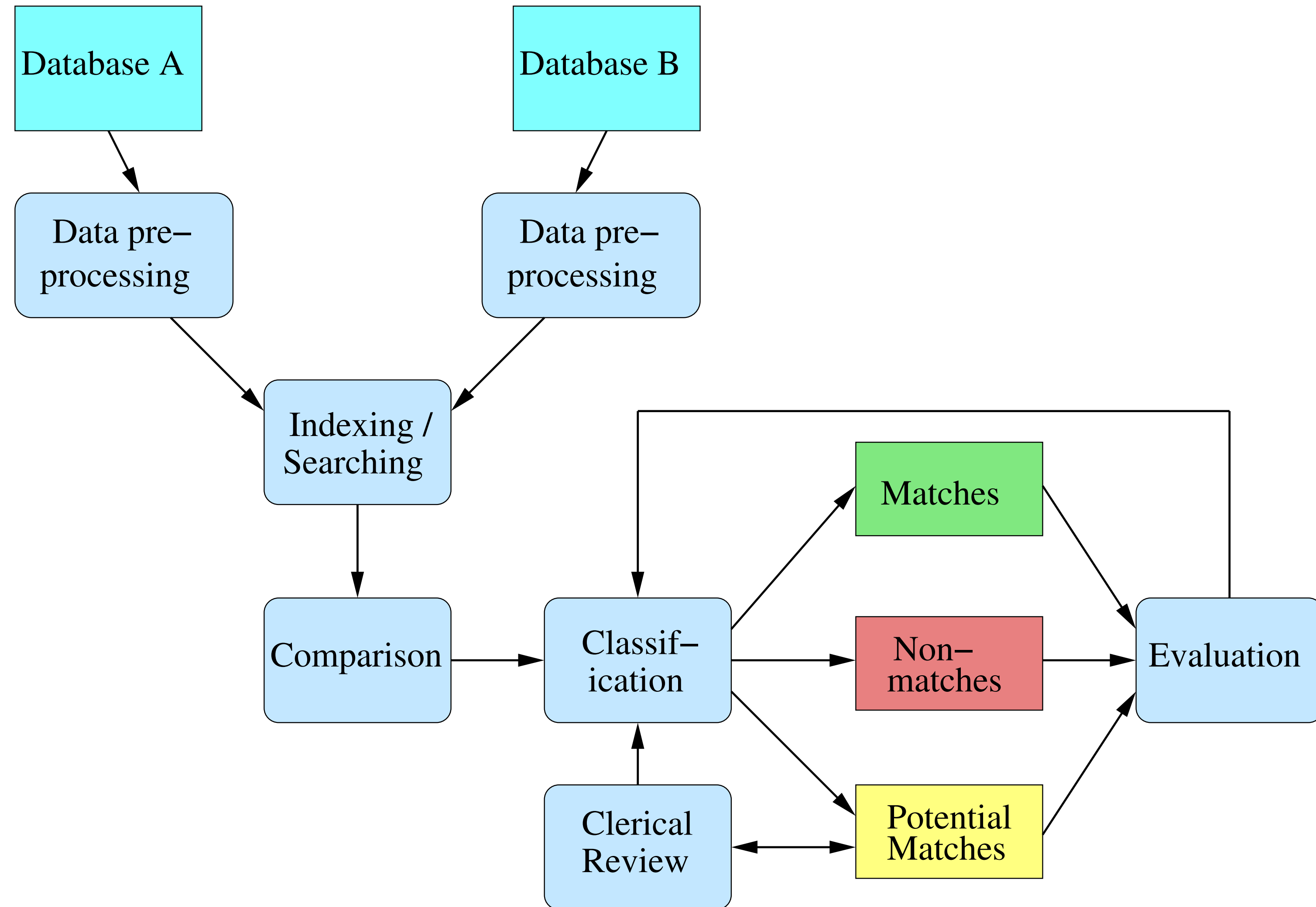
[P. Christen , 2019], image: [Pharexia, [Wikipedia](#)]

# Record Linkage

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P. Christen

# Record Linkage Process



[P. Christen , 2019]

# Record Linkage Techniques

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- Deterministic matching
  - Rule-based matching (complex to build and maintain)
- Probabilistic record linkage [Fellegi and Sunter, 1969]
  - Use available attributes for linking (often personal information, like names, addresses, dates of birth, etc.)
  - Calculate match weights for attributes
- “Computer science” approaches
  - Based on machine learning, data mining, database, or information retrieval techniques
  - Supervised classification: Requires training data (true matches)
  - Unsupervised: Clustering, collective, and graph based

[P. Christen , 2019]

# Data Matching & Data Fusion

- Google Thinks I'm Dead  
(I know otherwise.) [R. Abrams, NYTimes, 2017]
- Not only Google, but also Alexa:
  - "Alexa replies that Rachel Abrams is a sprinter from the Northern Mariana Islands (which is true of someone else)."
  - "He asks if Rachel Abrams is deceased, and Alexa responds yes, citing information in the Knowledge Graph panel."

*Me* ↓

*could be me...?* →

**Rachel Abrams**  
American writer

Rachel Abrams was an American writer, editor, and artist. She was the wife of Elliott Abrams. [Wikipedia](#)

**Born:** January 2, 1951

**Died:** June 7, 2013

**Spouse:** Elliott Abrams (m. 1980–2013)


**Parents:** Midge Decter

**Children:** Sarah Abrams, Jacob Abrams, Joseph Abrams

*Not me* {

*Definitely not me* ←

People also search for



# Data Integration and Data Fusion

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- Data Integration: focus on integrating data from different sources
- When sources are orthogonal, no problems
- What happens when two sources provide the same type of information and they **conflict**?
- Data Fusion: create a single object while resolving conflicting values

# Data Fusion— Resolving Data Conflicts in Integration

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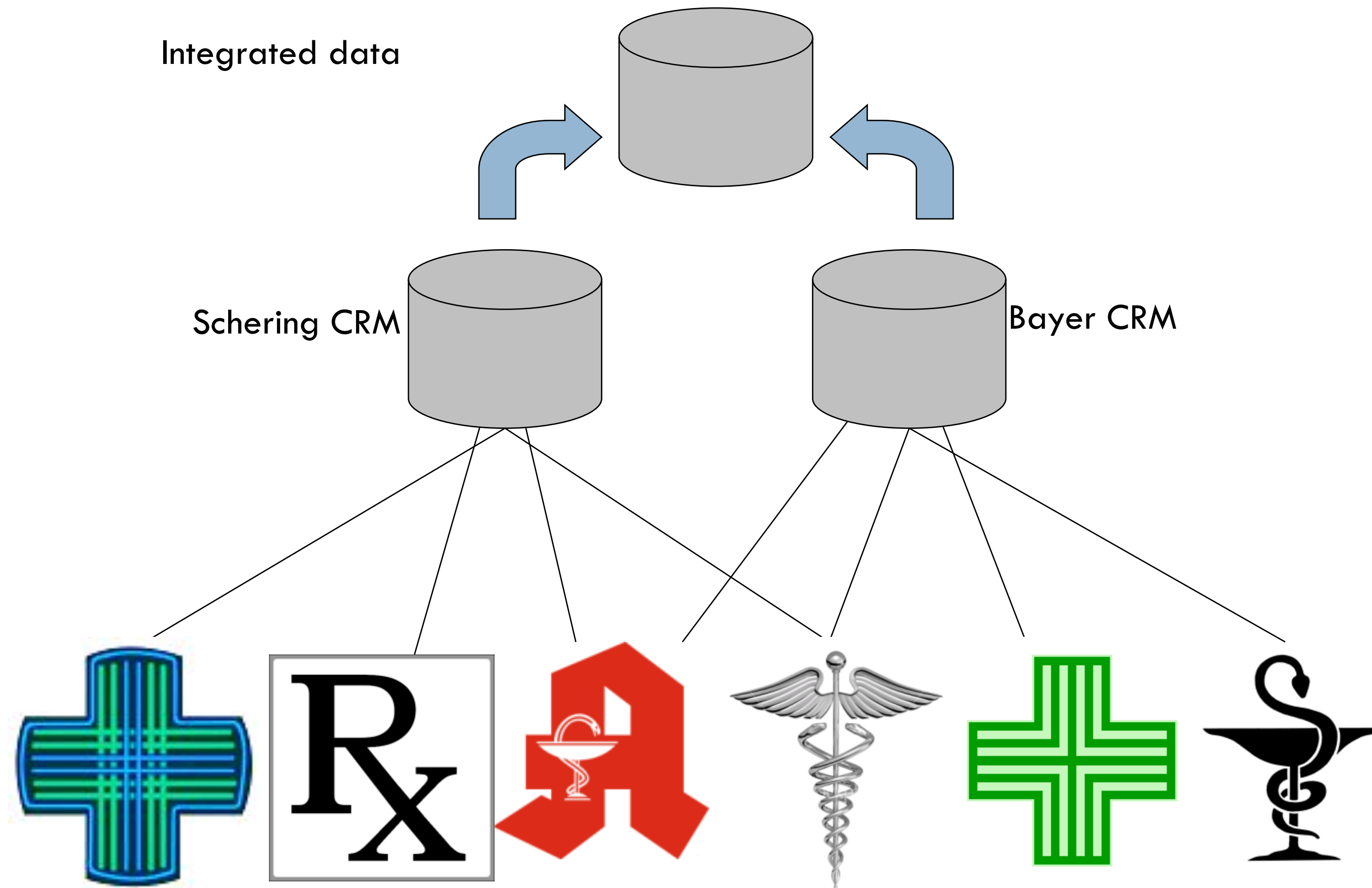
X. L. Dong and F. Naumann

# Data Fusion Summary

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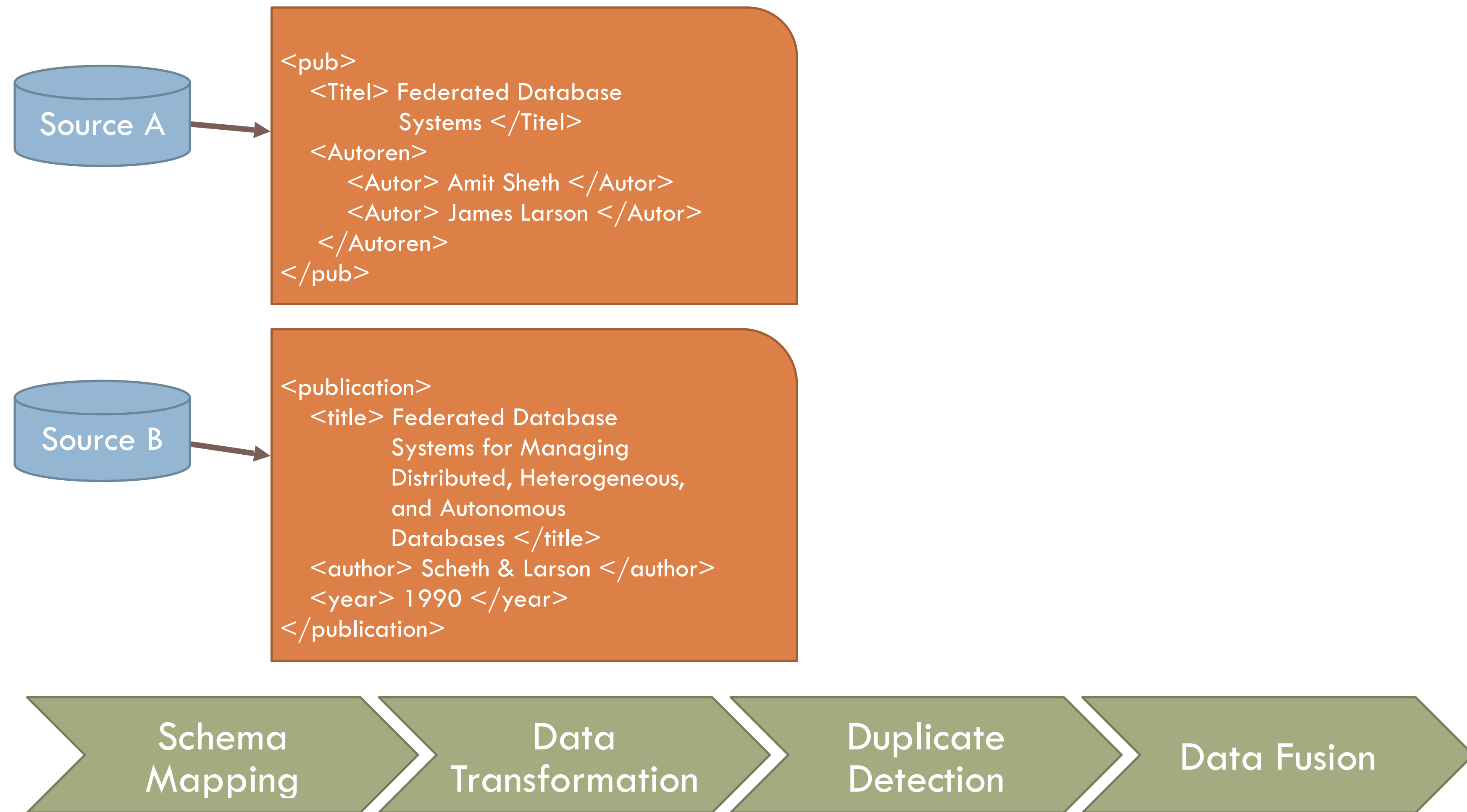
- Conflict resolution strategies
- "Truth-discovery" techniques
  - Accuracy
  - Freshness
  - Dependence
- Fusion Issues
  - Accuracy
  - Efficiency
  - Usability
  - How fusion fits with the rest of data integration?

# Data Conflicts



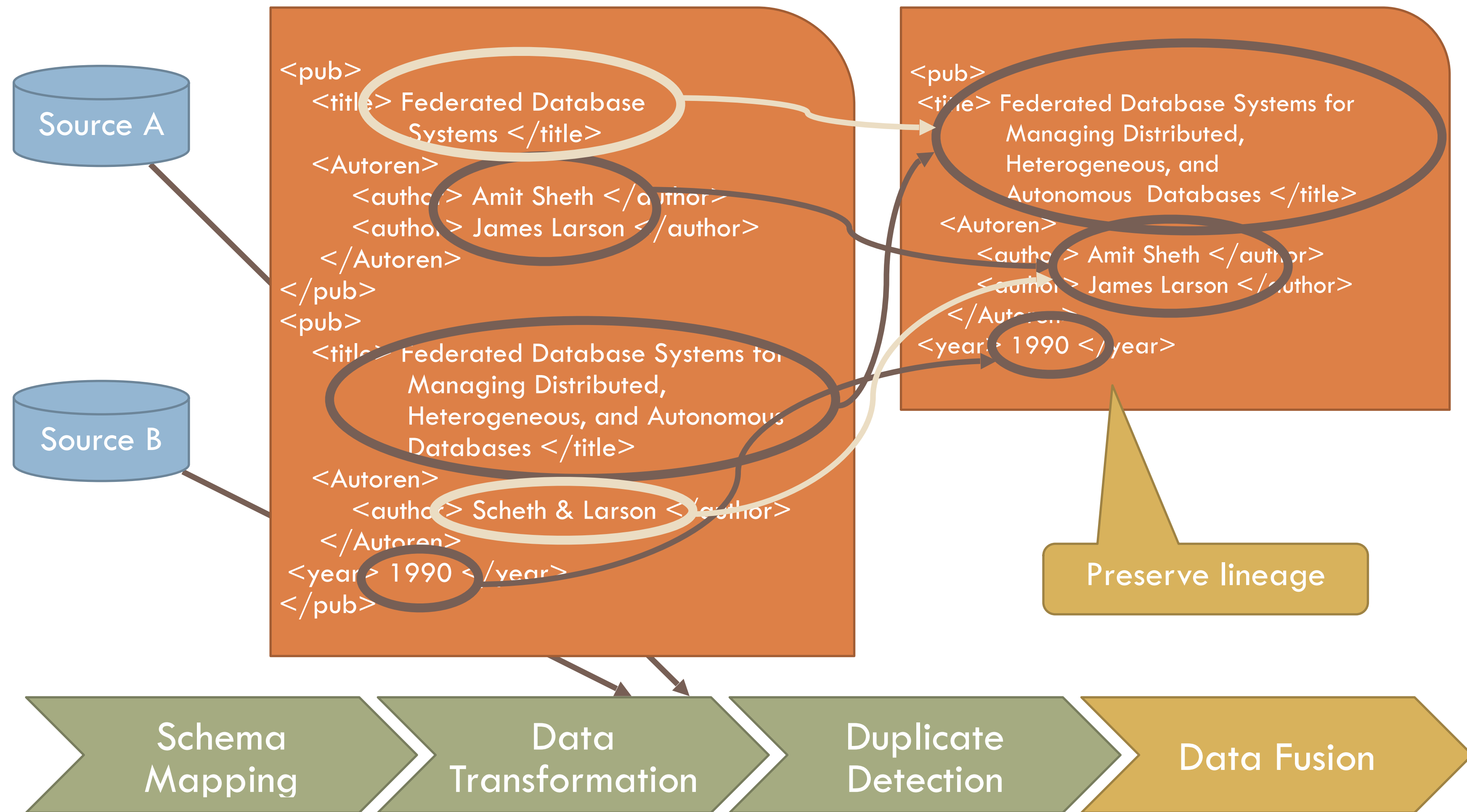
[L. Dong and F. Naumann, 2009]

# Information Integration



[L. Dong and F. Naumann, 2009]

# Information Integration



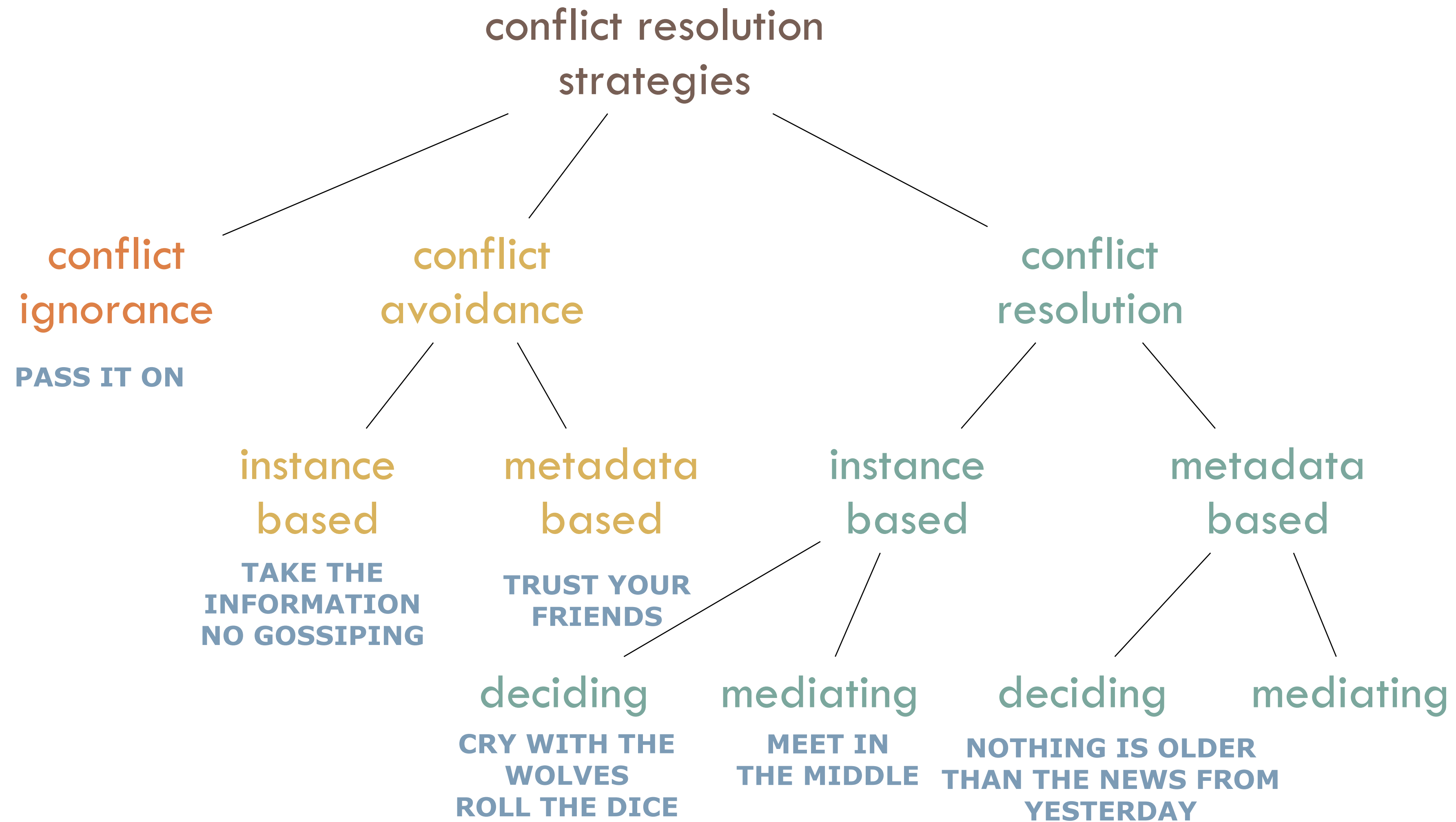
[L. Dong and F. Naumann, 2009]

# Data Fusion

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- Problem: Given a duplicate, create a single object representation while resolving conflicting data values.
- Difficulties:
  - Null values: Subsumption and complementation
  - Contradictions in data values
  - Uncertainty & truth: Discover the true value and model uncertainty in this process
  - Metadata: Preferences, recency, correctness
  - Lineage: Keep original values and their origin
  - Implementation in DBMS: SQL, extended SQL, UDFs, etc.

# Conflict Resolution Strategies



[L. Dong and F. Naumann, 2009]

# Integrating Conflicting Data: The Role of Source Dependence

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X. L. Dong, L. Berti-Equille, and D. Srivastava