## Advanced Data Management (CSCI 640/490)

Data Integration

Dr. David Koop

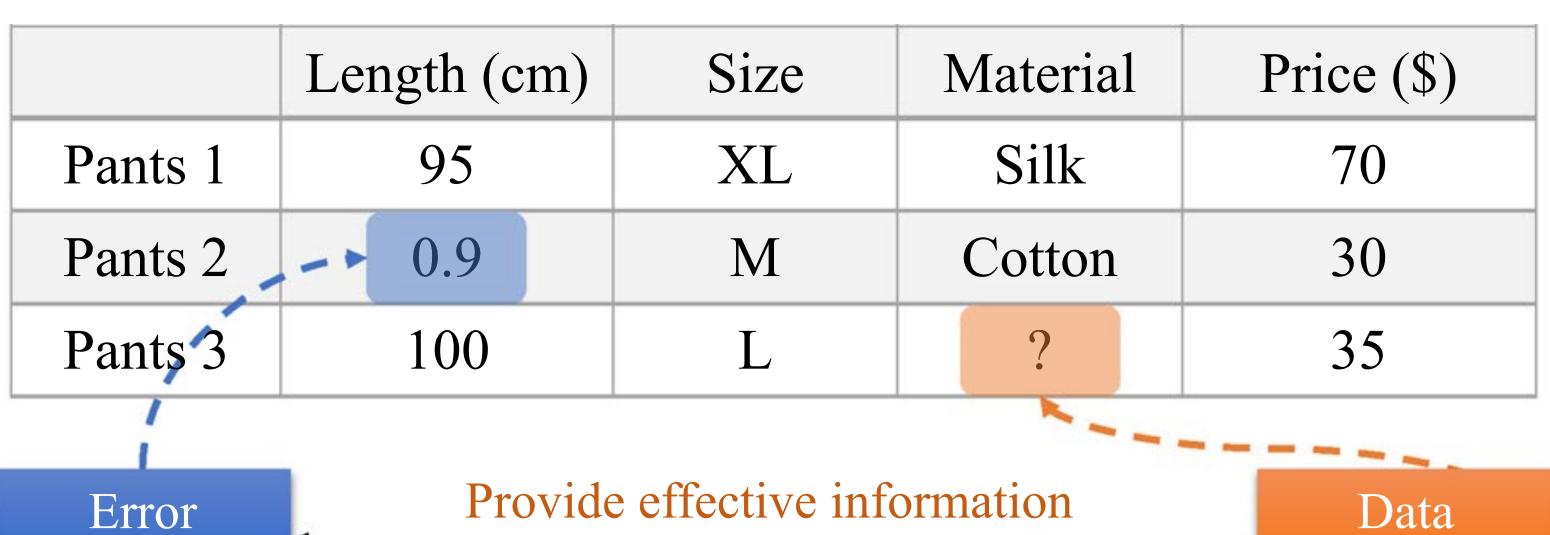


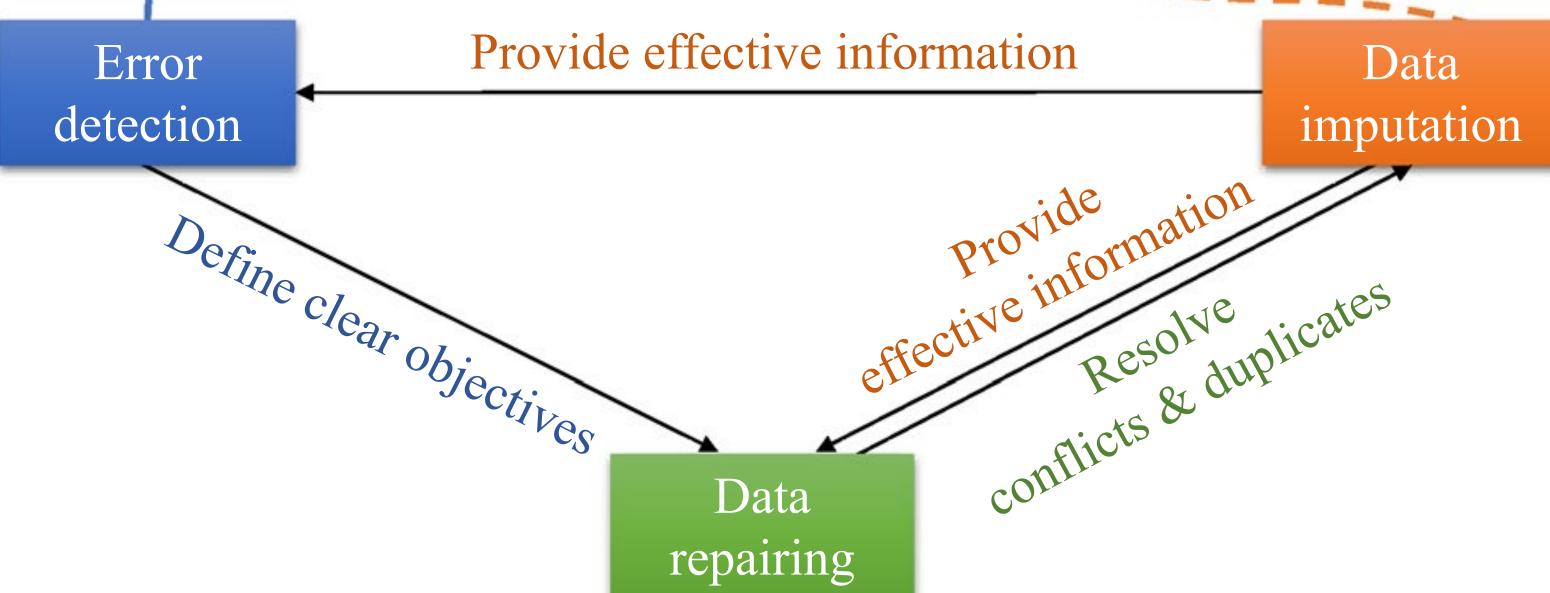
#### Data Cleaning Types

- How can statistical techniques improve efficiency or reliability of data cleaning? (Data Cleaning with Statistics)
  - Example: Wrangler, polars
- How how can we improve the reliability of statistical analytics with data cleaning? (Data Cleaning for Statistics)
  - Example: SampleClean

[D. Haas et al., 2016]

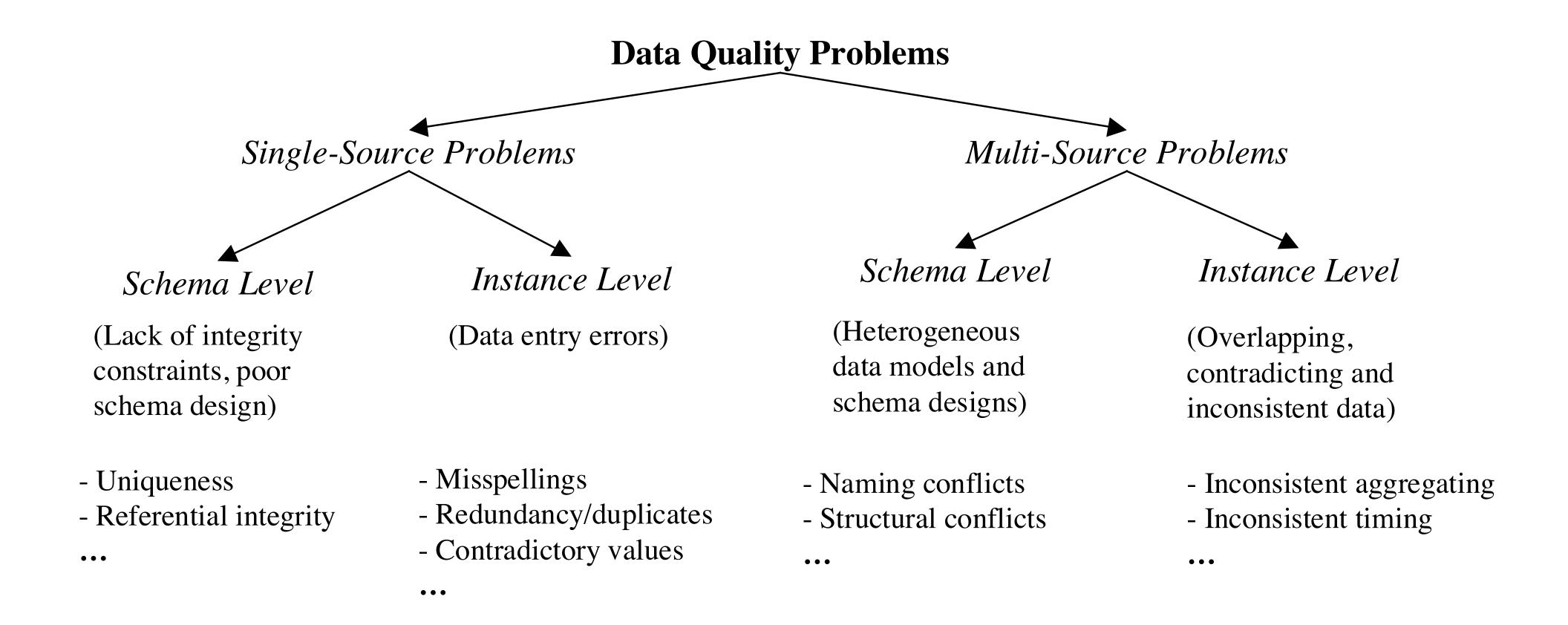
#### Data Cleaning Overview





[J. Zhu et al., 2024]

#### Classifying Data Quality Problems

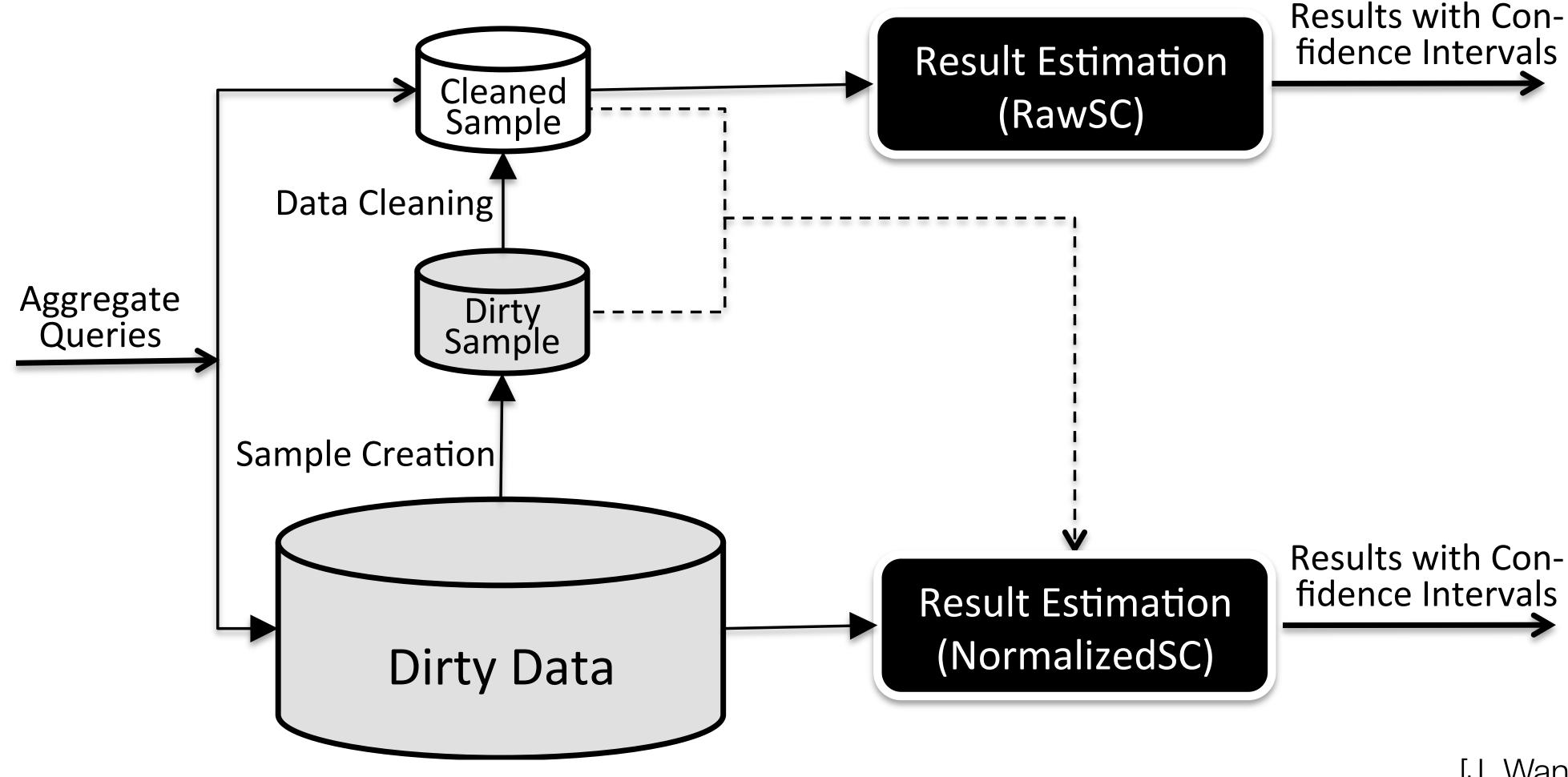


[E. Rahm & H. H. Do, 2000]

#### SampleClean (and Variants)

- Dirty Data?
  - Missing Values
  - Duplicate Values
  - Incorrect Values
  - Inconsistent Values
- Estimate query results using a sample of the data
- Two ideas:
  - Direct Estimate
  - Correction

### SampleClean Framework



[J. Wang et al., 2014]

#### HoloClean

- A holistic data cleaning framework that combines qualitative methods with quantitative methods:
  - Qualitative: use integrity constraints or external data sources
  - Quantitative: use statistics of the data
- Driven by probabilistic inference. Users only need to provide a dataset to be cleaned and describe high-level domain specific signals.
- Can scale to large real-world dirty datasets and perform automatic repairs with high accuracy

#### HoloClean

#### The HoloClean Framework Output Input **Proposed Cleaned Dataset** Dataset to be cleaned 1. Error detection **DBAName** Address City State Zip DBAName City State Address Zip 3465 S module John Chicago t1 60608 Morgan ST Veliotis Sr. 3465 S John Chicago 60608 Morgan ST 3465 S Veliotis Sr. Chicago t2 60608 Veliotis Sr. Morgan ST 3465 S John Chicago 60609 Morgan ST Veliotis Sr. 3465 S t3 Chicago 60608 Morgan ST Veliotis Sr. 3465 S John 2. Automatic Chicago 60609 Veliotis Sr. Morgan ST 3465 S John Chicago 60608 dD compilation to a Veliotis Sr. Morgan ST 3465 S Cicago IL 60608 Johnnyo's Morgan ST probabilistic **Marginal Distribution** graphical model of Cell Assignments **Denial Constraints External Information** Possible Values | Probability Cell c1: DBAName → Zip Ext\_City Ext\_State Ext\_Address c2: Zip → City, State 60608 0.84 t2.Zip 3465 S Morgan ST c3: City, State, Address → Zip Chicago 60608 60609 0.16 3. Repair via Chicago 60610 0.95 Chicago **Matching Dependencies** statistical learning t4.City 0.05 Cicago Chicago 259 E Erie ST 60611 m1: $Zip = Ext_Zip \rightarrow City = Ext_City$ and infernece m2: Zip = Ext\_Zip → State = Ext\_State John Veliotis Sr. 0.99 60623 Chicago Cermak Rd t4.DBAName m3: City = Ext\_City \( \Lambda \) State = Ext\_State \( \Lambda \) Johnnyo's 0.01

T. Rekatsinas et al., 2017



 $\land$  Address = Ext\_Address  $\rightarrow$  Zip = Ext\_Zip

#### Data Cleaning and Al

- Traditional Methods are often efficient and interpretable
- Deep Learning is expensive and hard to understand but can be more effective
- Machine Learning provides a balance?

		Cost	Generalization	Interpretability	Efficiency	Effectiveness
	Traditional	¥			<i>P P P</i>	\$
AI $\left\{ \left[ \right] \right.$	ML	¥¥			5	\$\frac{1}{2}
	DL	¥¥¥			5	

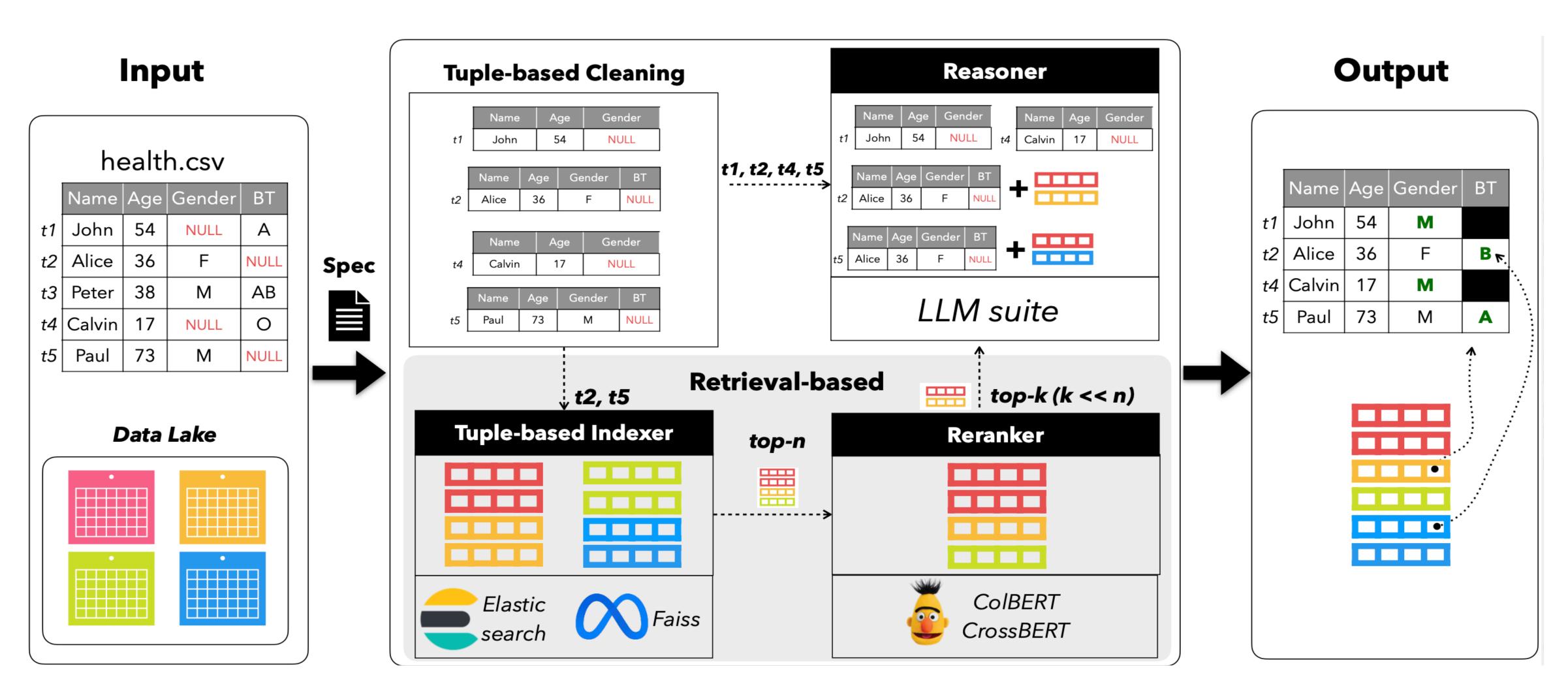
[J. Zhu et al., 2024]



## Data Repair using LLMs (RetClean)

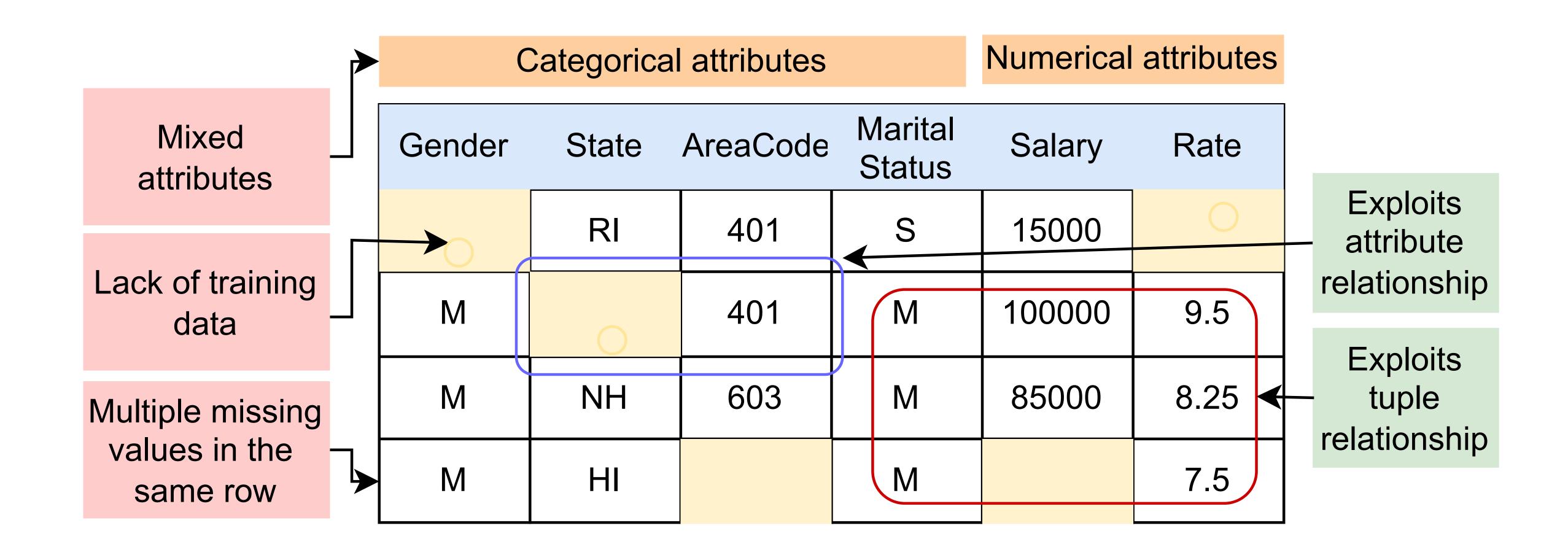
- Non-retrieval based: Send tuple to LLMs and identify tuple(s) and column(s) to be fixed
- Retrieval-based:
  - Indexer: Get top-k relevant tuples from a database/data lake
  - Reranker: Rank relevance using ColBERT/CrossBERT
  - Reasoner: Determine, using LLM, which tuple and value to use for fix
  - Reasoner keeps track of lineage

## Data Repair using LLMs (RetClean)



[Naeem et al., 2024]

### Data Imputation Challenges



[R. Cappuzzo et al., 2024]

#### CSAN Panel: Real Jobs in the Real World



- Tuesday, Oct. 7, 5:30–7:30pm
- Provides an insight into jobs from NIU alumni
- Food is Provided
- Sponsored by the Computer Science Alumni Network and the NIU Alumni Association

#### Test 1

- This Wednesday, October 8, 12:30-1:45pm in PM 103
- In-Class, paper/pen & pencil
- Covers material through this week
- Format:
  - Multiple Choice
  - Free Response
  - One extra 2-sided page for CSCI 640 Students
- Info will be on the course webpage

#### Assignment 3

- Clean the Ask a Manager Salary Survey Data
- Use polars to clean and transform data
- Will add a few more tasks or tasks using another tool

#### Outline

- Data Integration
- Data Matching (Entity Resolution)
- Data Fusion: Monday
- Data Fusion Techniques: Wednesday
  - Integrating Conflicting Data: The Role of Source Dependence, X. L. Dong et al., 2009
  - Quiz at the beginning of class on Wednesday, Oct. 15

## Introduction to Data Integration

A. Doan, A. Halevy, and Z. Ives



#### Data Integration

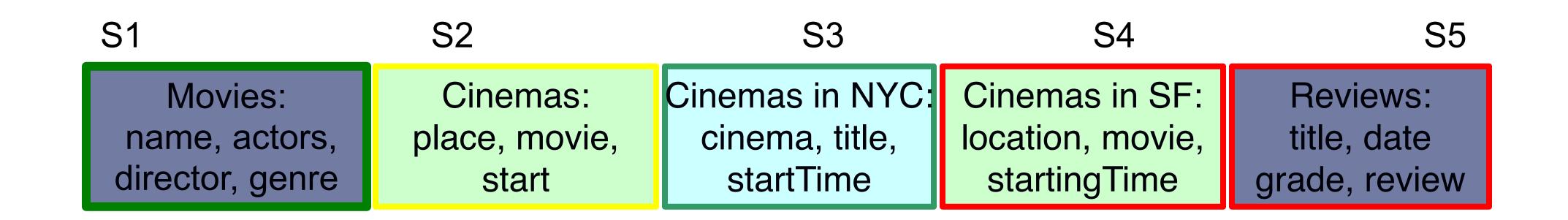
Movie: Title, director, year, genre

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 & Data Matching

- Data Integration: focus on integrating data from different sources
- Data Matching (aka Entity Resolution aka Record Linkage):
  want to know that two entities (often in different sources) are the same "real" entity

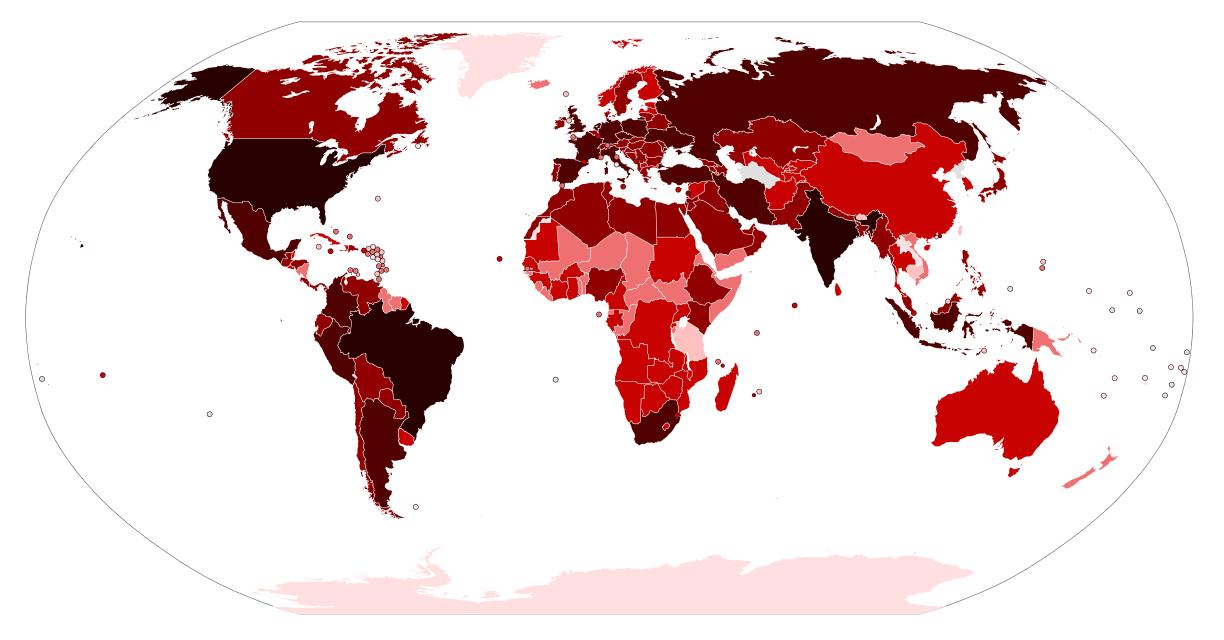
#### Record Linkage Motivation

- 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

P. Christen

