

# **Dirty Data in the Newsroom**

## Comparing Data Preparation in Journalism and Data Science

ACM CHI Conference on Human Factors in Computing Systems  
April 23-28, 2023, Hamburg, Germany



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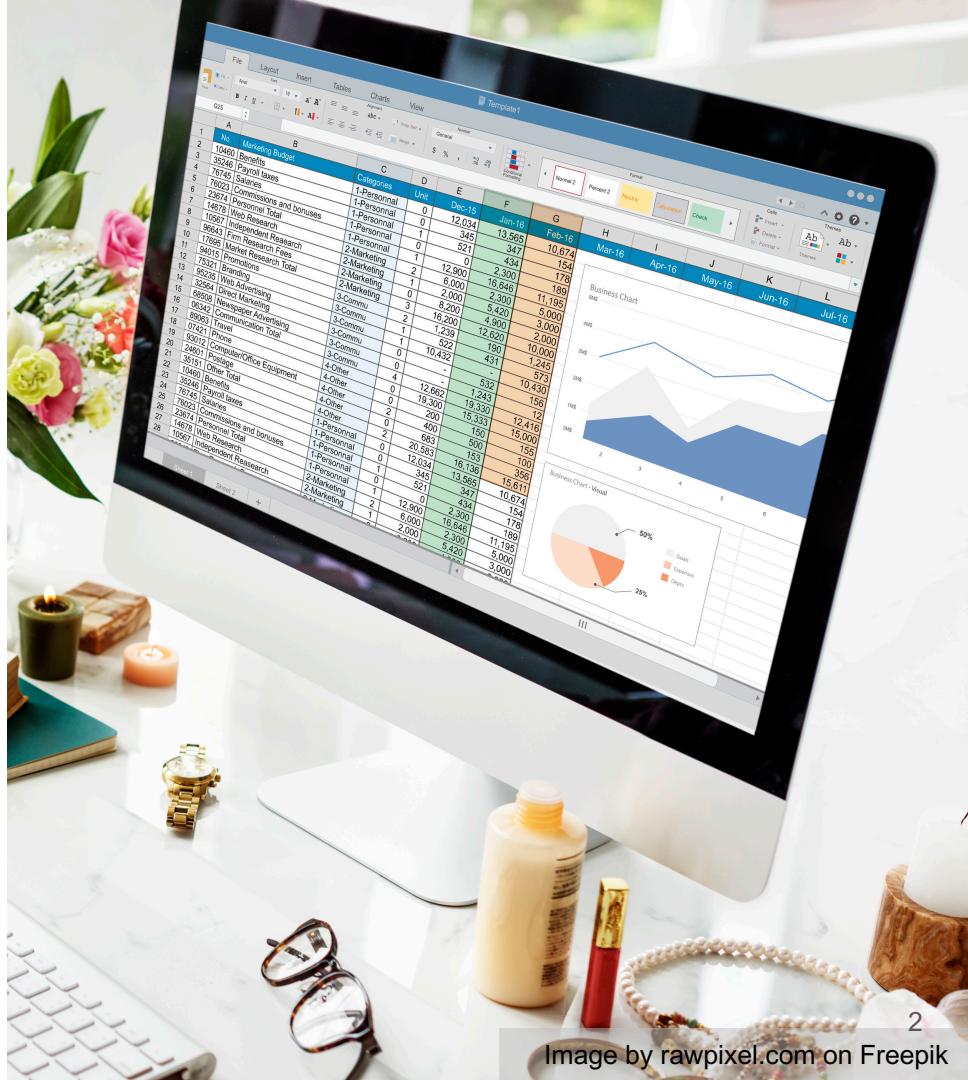


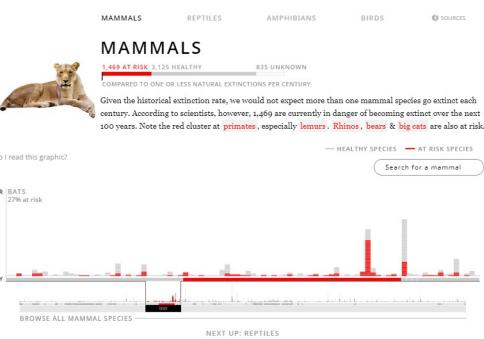
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# Data Preparation

- Getting data ready for analysis or visualization
  - Includes: wrangling, cleaning, munging, gathering, integrating, etc.
- Time-consuming process in data science
  - Up to 80% of someone's time

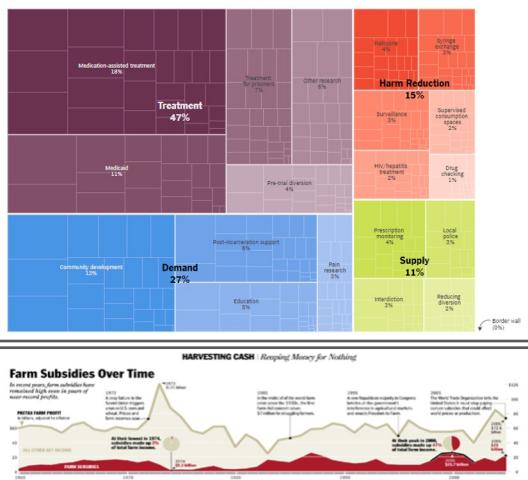




The Upshot

## *How a Police Chief, a Governor and a Sociologist Would Spend \$100 Billion to Solve the Opioid Crisis*

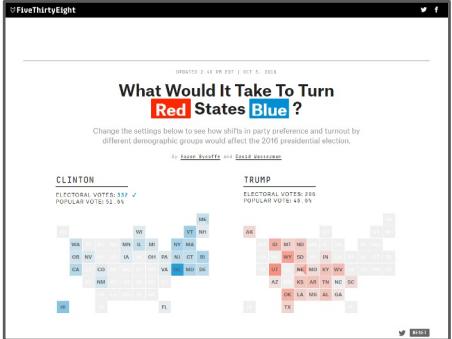
By 105M KATZ FEB. 14, 2010



# The New York Times

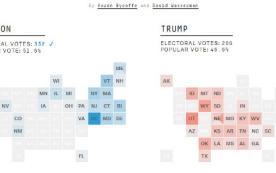
NEW YORK WEDNESDAY, APRIL 8, 2020

### **Late Edition**



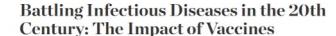
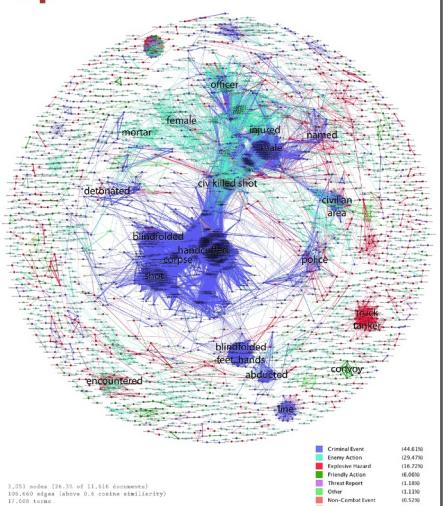
## What Would It Take To Turn Red States Blue?

Change the settings below to see how shifts in party preference and turnout by different demographic groups would affect the 2016 presidential election.



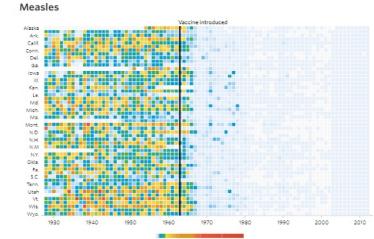
A

Wikileaks Iraq SIGACTS (redacted) - Dec 2006



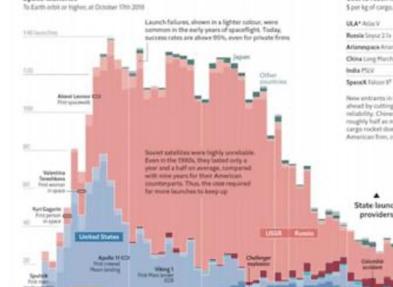
By Tynan DeBold and Dov Friedman  
Published Feb. 11, 2015 at 3:45 a.m. ET

The number of infected people, measured over 70-some years and across all 50 states and the District of Columbia, generally declined after vaccines were introduced.



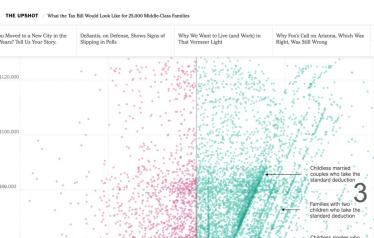
### Graphic detail

Scans



## What the Tax Bill Would Look Like for 25,000 Middle-Class Families

By GREGORY ANDREW COOPERMAN, MD, FAAP



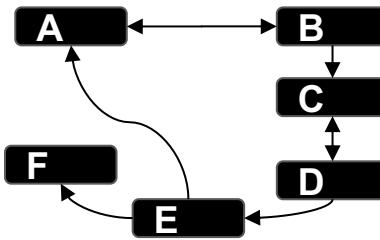


4  
Illustration by Barry Blitt, *Vanity Fair*



**How closely does research  
on data scientists apply to data journalists,  
with regards to data preparation?**

## Phase 1



Data science process papers (16)

Issues

11

15

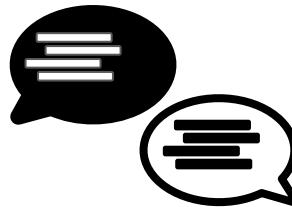
Activities

30

13

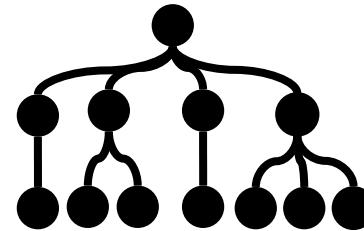
Augmented model of preparation activities

## Phase 2



Data journalist interviews (36)

## Phase 3

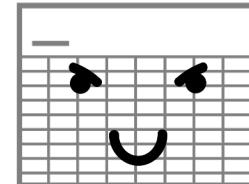


Dirty data Taxonomies (16)

Data issues (60)

Model-discrepancy taxonomy of dirty data

## Phase 4



Data preparation nightmares (63)

Four challenges in multi-table data integration



From data science



From data journalism



From database research



Our contributions

# Contributions



1

Augmented model  
of preparation  
activities



2

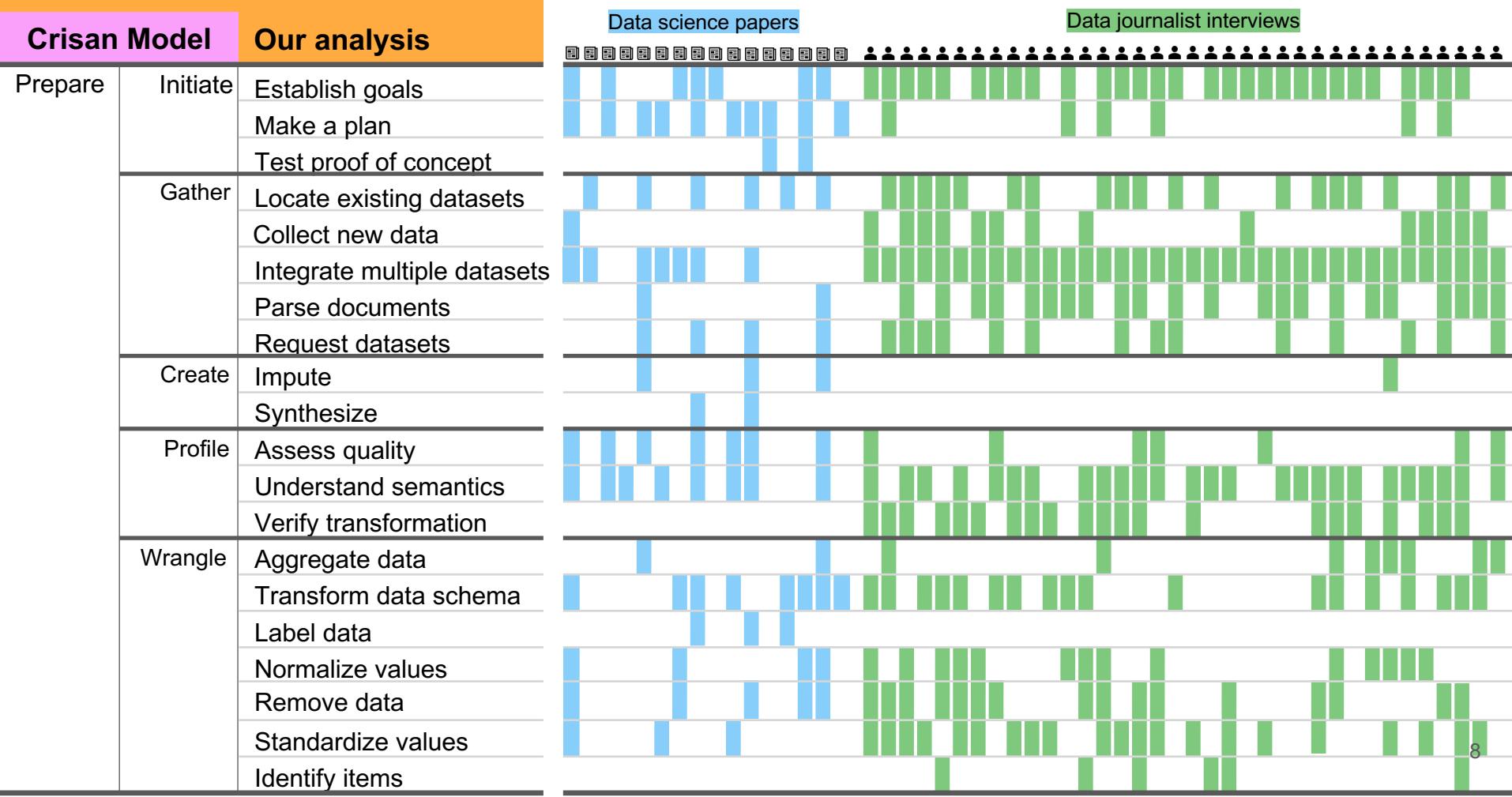
Model-discrepancy  
taxonomy of  
dirty data



3

Challenges in  
multi-table  
data integration

# Augmented model of prep. activities



# Contributions



1

Augmented model  
of preparation  
activities



2

Model-discrepancy  
taxonomy of  
dirty data



3

Challenges in  
multi-table  
data integration

# Model-discrepancy taxonomy of dirty data

- Consider data as a design artifact
  - Dirty data = discrepancy in mental models
- Extend issue analysis to incorporate database literature
  - Analyze 16 taxonomies on dirty data: cluster 330 issues → 45 DB issues
- Combine into synthesis set of 60 issues
- Categorize into new model-discrepancy taxonomy
  - Data qualities axis
    - Existing qualities: completeness, accuracy
    - New qualities: form, granularity, relation, semantics
  - Data objects axis: table, attribute, item, value
- More details in the paper

# Contributions



1

Augmented model  
of preparation  
activities



2

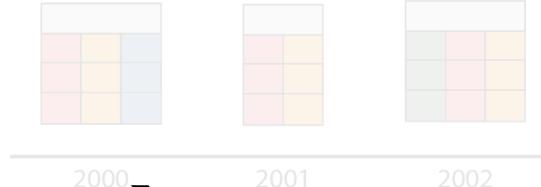
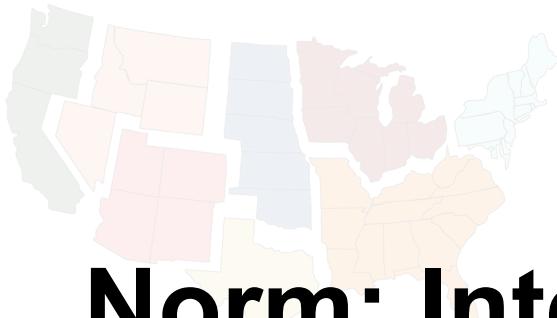
Model-discrepancy  
taxonomy of  
dirty data



3

Challenges in  
multi-table  
data integration

## Four integration challenges



**Norm: Integrate → clean**

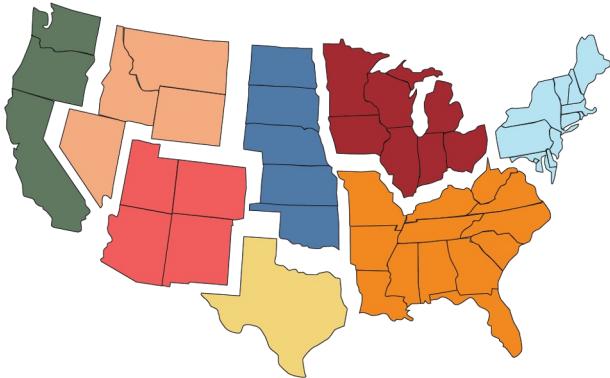
Regional

Diachronic

**Findings: Clean → integrate**

Fragmented

Disparate



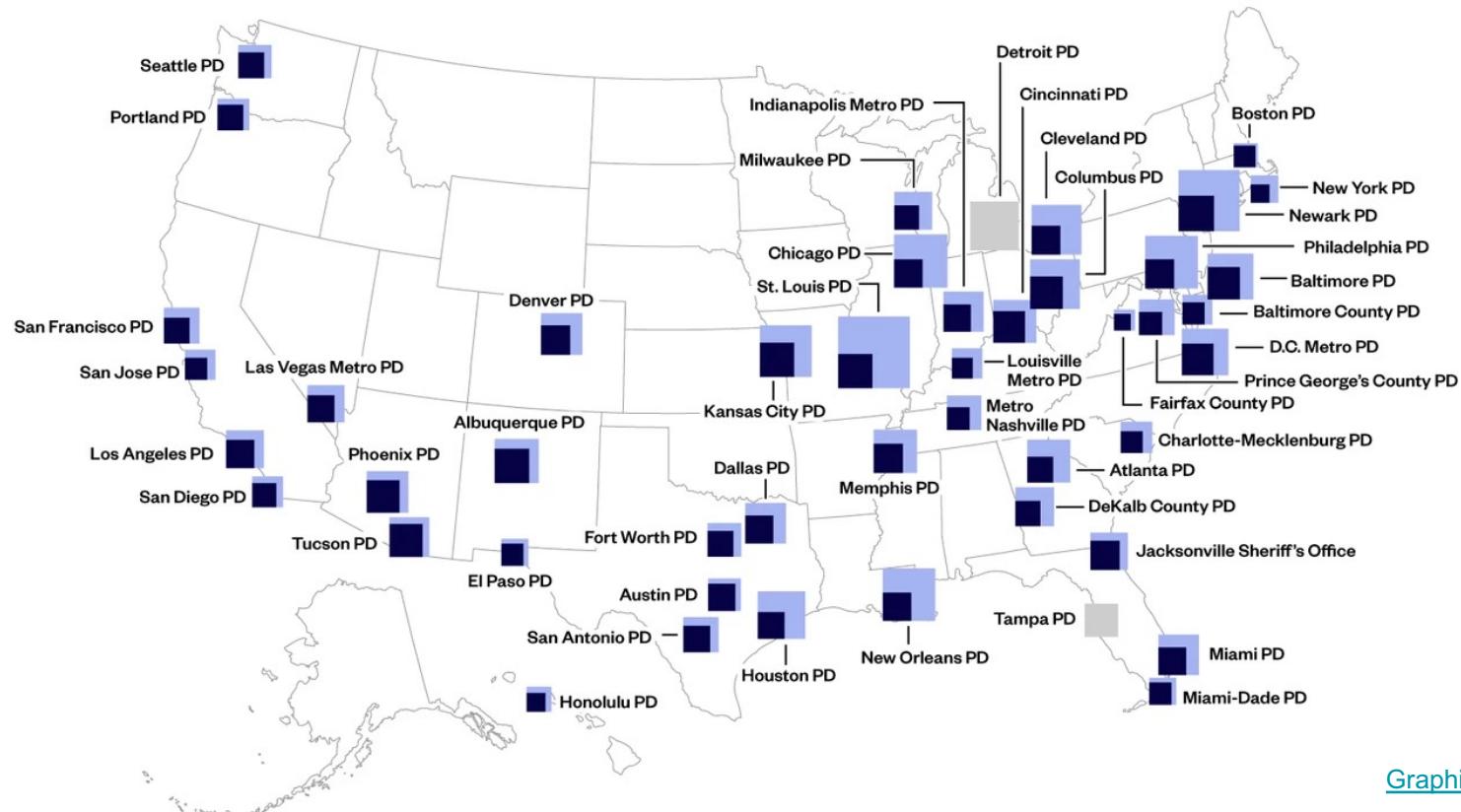
## Regional datasets

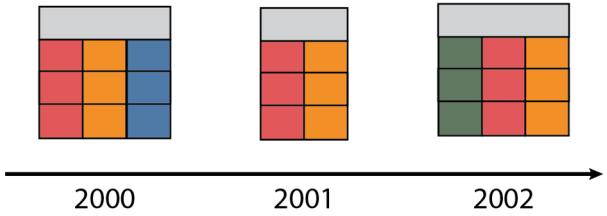
Tables with inconsistencies due to  
independent, spatially dispersed data sources

# Regional: Police shootings in the United States

■ FATAL SHOOTINGS  
■ ALL SHOOTINGS  
■ UNKNOWN

1 5  
RATE PER 100K

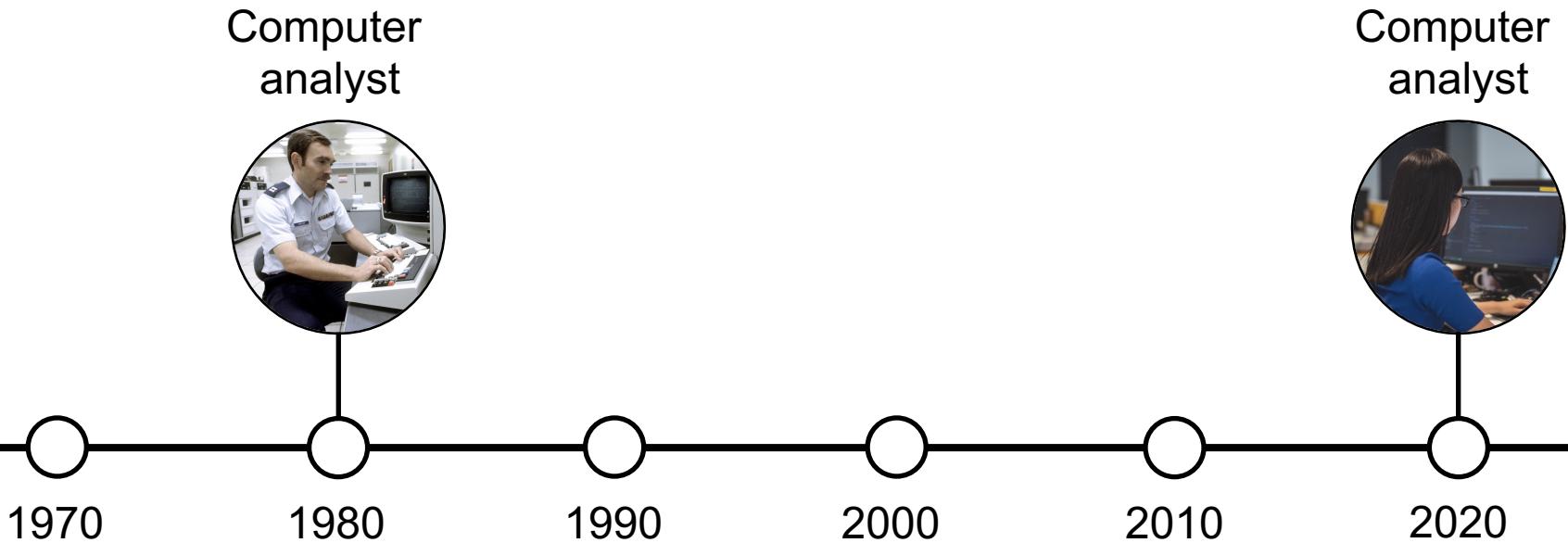


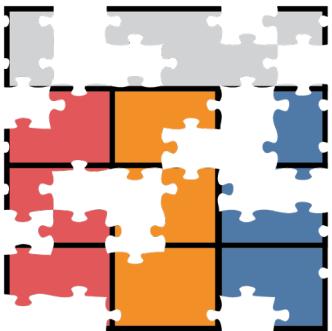


## Diachronic datasets

Tables on the same phenomena that evolve over time

# Diachronic: Economic data from Bureau of Labor Statistics

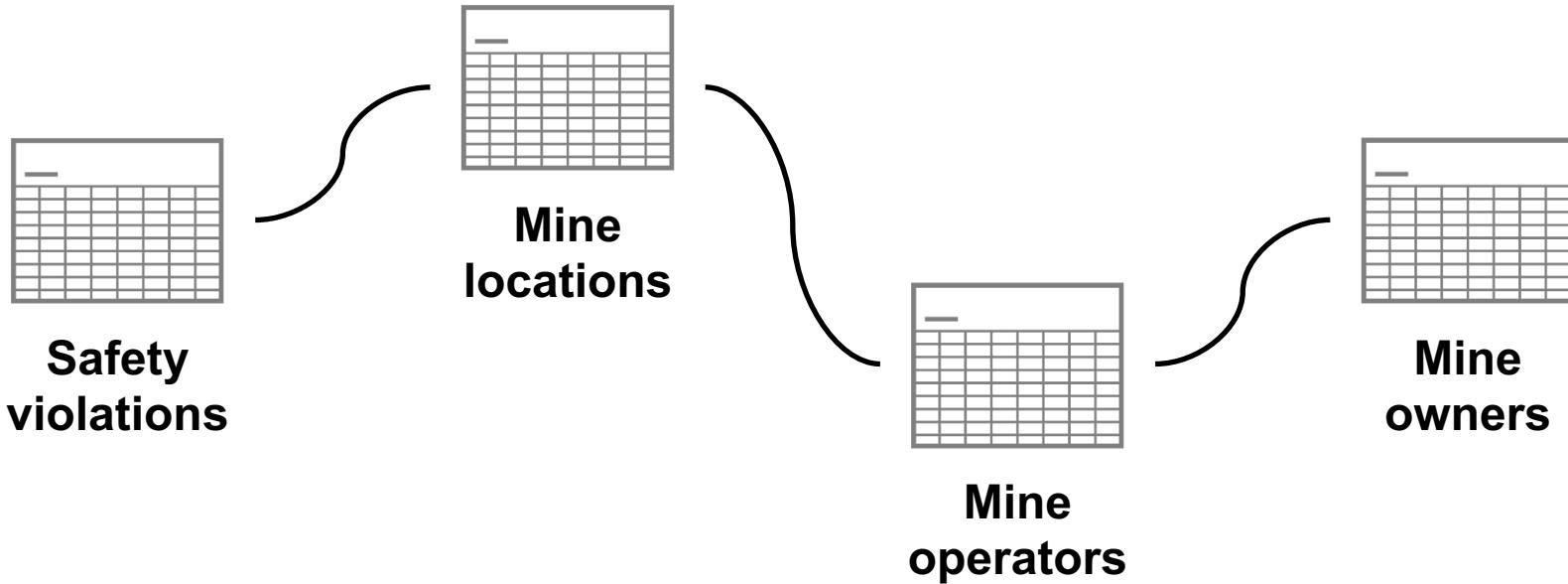


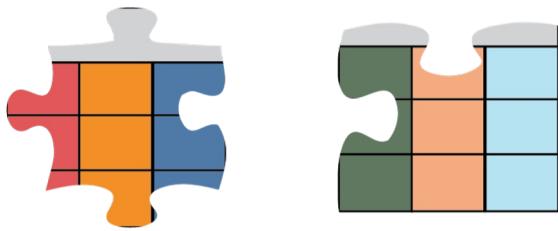


## Fragmented datasets

Tables on a similar topic that contain different yet related items.

# Fragmented: Unpaid mine safety violations



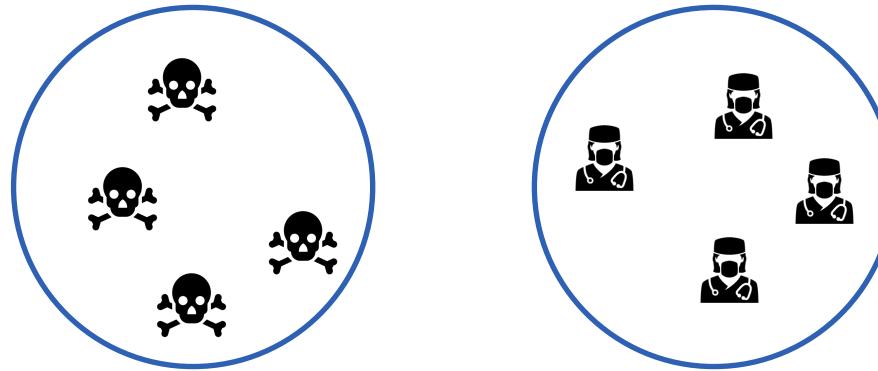


## Disparate datasets

Tables that are topically dissimilar and seemingly unrelated.

# Disparate: Opioid overdoses

Healthcare workers  
from opioid overdoses



# THE SPOKESMAN-REVIEW

Spokane, Washington Est. May 19, 1883

Washington Idaho

NEWS > SPOKANE

**Washington nurses, health care workers are dying of opioid overdoses**

Sun., Feb. 4, 2018

Icons by  
[Minh Do](#) and  
[Sascha Elmendorf](#),  
Noun Project

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@tamaramunzner 

## Contributions:

- Augmented model of preparation activities
- New model-discrepancy taxonomy of dirty data
- Four challenges in multi-table data integration

