# CMPT 733 Data Preparation

Instructor Zhengjie Miao

Course website <a href="https://coursys.sfu.ca/2025sp-cmpt-733-g1/pages/">https://coursys.sfu.ca/2025sp-cmpt-733-g1/pages/</a>

Source based on slides by Jiannan Wang

## **Outline**

I. Data Preparation Overview

2. Data Preparation Tasks

Data Preparation Is **Still the Bottleneck!!!** 

2014

2020

The New Hork Times

#### For Big-Data Scientists, 'Janitor Work' Is Key Hurdle to Insights

Yet far too much handcrafted work — what data scientists call "data wrangling," "data munging" and "data janitor work" — is still required. Data scientists, according to interviews and expert estimates, spend from 50 percent to 80 percent of their time mired in this more mundane labor of collecting and preparing unruly digital data, before it can be explored for useful nuggets.



The State of Data Science 2020 Moving from hype toward maturity

We were disappointed, if not surprised, to see that data wrangling still takes the lion's share of time in a typical data professional's day. Our respondents reported that almost half of their time is spent on the combined tasks of data loading and cleansing. Data

## Trend: Data Prep about 38% of effort

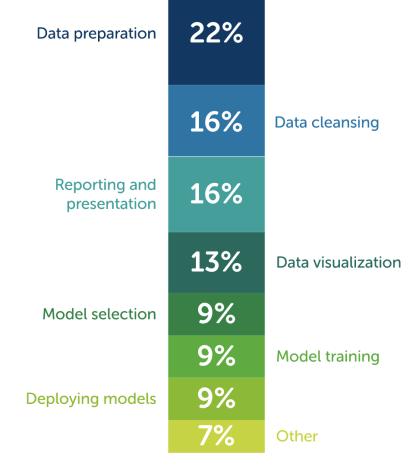
2022



## DATA PROFESSIONALS AT WORK

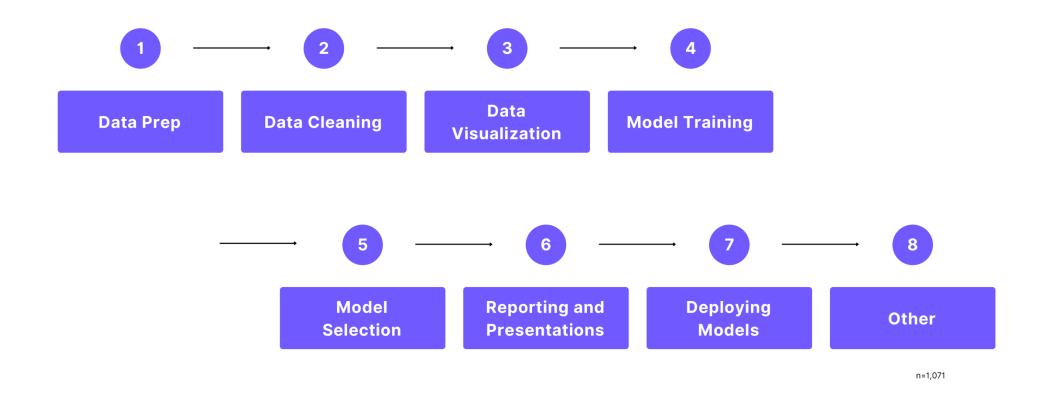
How do data scientists spend their time?

Data professionals spend their time on a variety of tasks that require diverse technical and non-technical skills. Respondents indicated they spend about 37.75% of their time on data preparation and cleansing. Beyond preparing and cleaning data, interpreting results remains critical. **Data visualization** (12.99%) and demonstrating data's value through reporting and presentation (16.20%) are essential steps toward making data actionable and providing answers to critical questions. Working with models through selection, training, and deployment takes about 26.44% of respondents' time (-8.56% YoY).



## Trend in 2023

Thinking about your current role, what tasks are most time consuming? (Responses ranked from most to least time consuming)

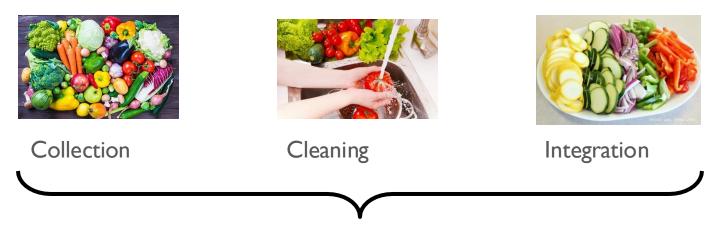


## Trend in 2023

Generative AI has been in the news for some time now, with the introduction of high-performing large language models (LLMs). In our data science practitioner track, 40% of respondents say their companies are working on internal generative AI tools, such as LLMs. While there are many conversations about the ethics and

The majority (63%) of data science practitioners say they're using generative AI the same amount or more this year compared to 2022. Respondents who report using these tools and techniques in their work most commonly use them for content creation (e.g., text or image generation) and data cleaning, visualization, and analysis. Less common use cases include automating tasks and writing and debugging code.

## Why Is Data Preparation Hard?



Analysis

How much time is spent on preparation?

- 1. Too many small problems (e.g., standardize date, dedup address, etc)
- 2. Humans have different levels of expertise (in data science and programming)
- 3. Domain specific (finance, social science, healthcare, economics, etc.)

## Data come from many sources and in a variety of formats

Source Data (Raw Text, HTML, Tweeter, Tiktok,...)



Structured	Semi-structured	Raw/Unstructured
CSV	JSON	Text
TSV	XML	Images
Excel	HTML	Audio
Dataframe	Python Pickle	Video
SQL	MongoDB	
• • •	•••	

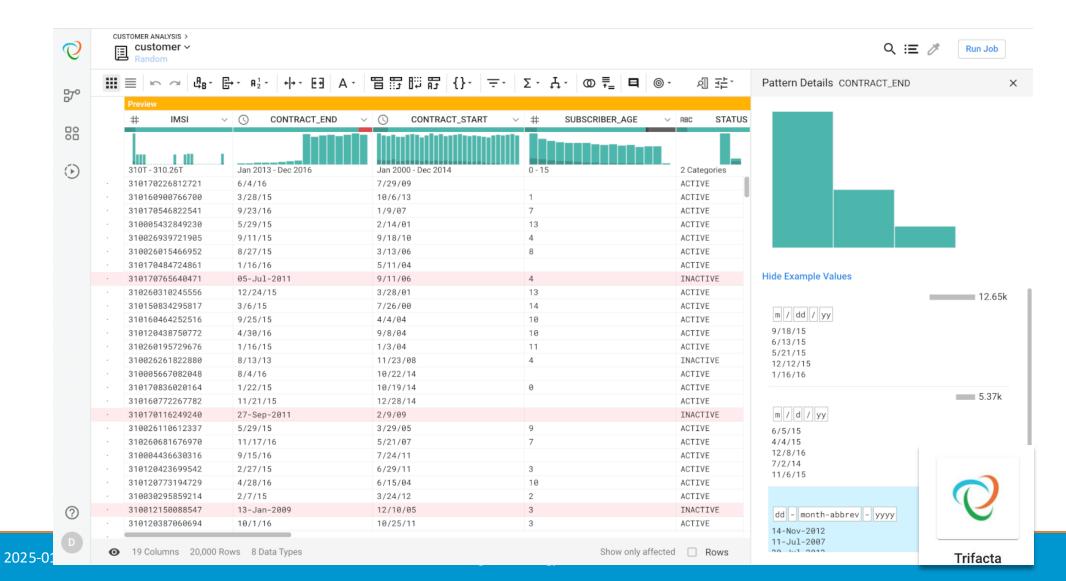
## Data are noisy

- Data entry errors
- Measurement errors
- Extraction errors
- Format conversion errors
- Non-uniform collection/sampling
- •

## **Human-in-the-loop Data Preparation**

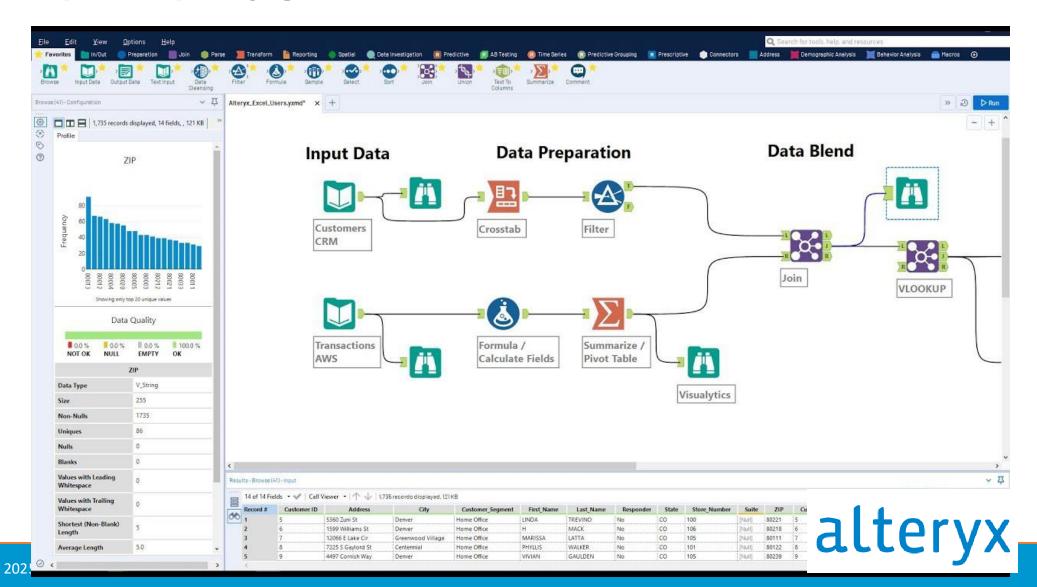
- Three Directions
- Spreadsheet GUI
- Workflow GUI
- Notebook GUI

## Spreadsheet GUI



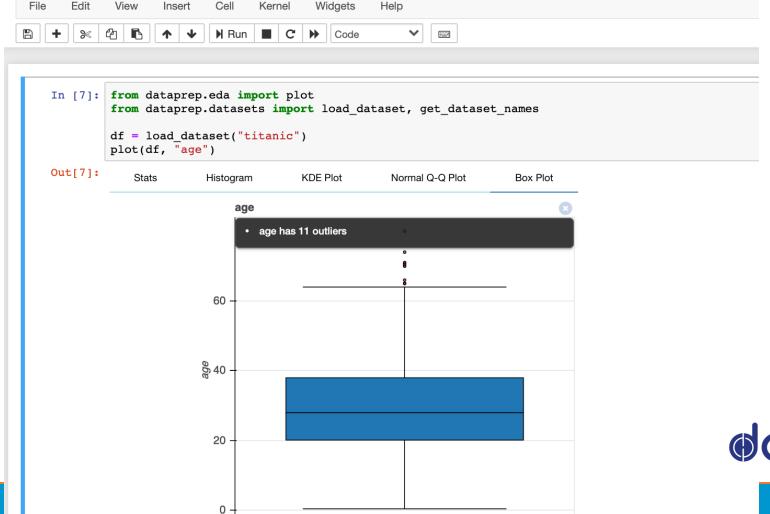
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## **Workflow GUI**



## **Notebook GUI**

Jupyter dataprep Last Checkpoint: 9 minutes ago (unsaved changes)



## Which Direction To Go?

Data Prep Market was valued at USD 4.02 Billion in 2024 and is projected to reach USD 16.12 Billion by 2031, growing at a CAGR of 19% from 2024 to 2031

Source: <a href="https://www.verifiedmarketresearch.com/product/data-prep-market/">https://www.verifiedmarketresearch.com/product/data-prep-market/</a>

#### Three Directions

- Spreadsheet GUI
- Workflow GUI
- Notebook GUI



Targeted at data scientists

## **Data Preparation Tasks**

#### Data Collection

- Where to collect
- How to collect

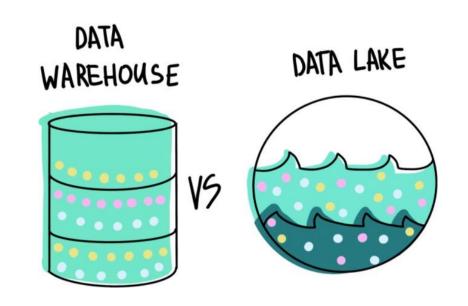
Data Cleaning

Data Integration

## Where to Collect?

#### Internal Data

- Data Warehouse (Tabular Data)
- System Logs (Text Files)
- Documents (Word, Excel, PDF)
- Multimedia Data (Video, Audio, Image)

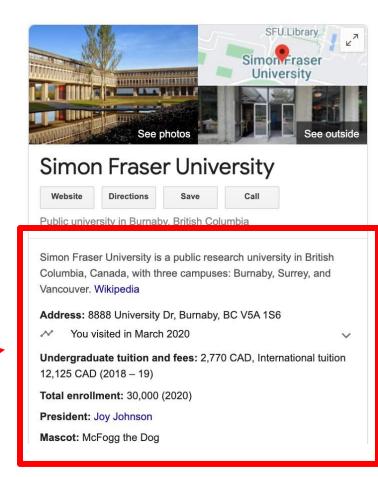


[Aside: AWS Data Lake on S3]

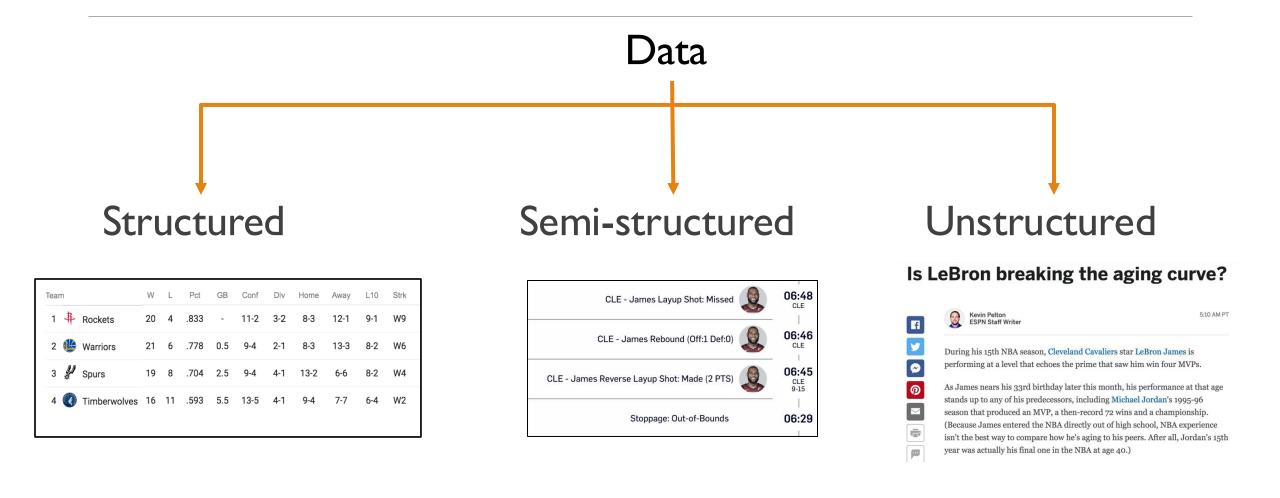
## Where to Collect?

#### External Data

- Web Pages
- Web APIs (<a href="https://github.com/public-apis/pub
- Open Data (<u>data.vancouver.ca</u>, <u>www.data.gov</u>)
- Knowledge Graph (Wikidata, Freebase)



## **Data Classification**



## Challenges

- Data Discovery
- How to find related data?

- Domain knowledge
- Information retrieval skills

- Data Privacy
- How to protect user privacy?

- Data masking
- Differential privacy

- Security
- How to avoid a data breach?

- Follow data access rules
- Encrypt highly confidential data

## **Getting Data**

- From CSV Files
- From JSON Files
- From the Web
- From HDFS
- From Databases
- From S3
- From Web APIs

## Load Data From CSV Files

CSV is a file format for storing tabular data

```
rankings.csv *

1 Team,Win,Loss,Win%

2 Houston Rockets,20,4,0.833

3 Golden State Warriors,21,6,0.778

4 San Antonio Spurs,19,8,0.704

5 Minnesota Timberwolves,16,11,0.593

6 Denver Nuggets,14,12,0.538

7 Portland Trail Blazers,13,12,0.52

8 New Orleans Pelicans,14,13,0.519

9 Utah Jazz,13,14,0.481
```

#### Reading CSV File (pandas library)

```
import pandas as pd

df = pd.read_csv('rankings.csv')
```

## Load Data From JSON Files

JSON is a file format for storing nested data (array, dict)

```
players.json x

1 {
2     "Kobe Bryant" :{
        "Born": "08/23/1978",
        "Number": ["8", "24"],
        "Team": ["Los Angeles Lakers"]
},

7     "Michael Jordan":{
        "Born": "02/17/1963",
        "Number": ["23"],
        "Team": ["Chicago Bulls", "Washington Wizards"]
}

11     }

12 }
```

#### Reading JSON File (pandas Libaray)

```
import pandas as pd
df=pd.read_json("players.json")
```

## Web Scraping

- Open web pages
- urllib2 (https://docs.python.org/2/library/urllib2.html)
- request (<u>http://docs.python-requests.org/en/master/</u>)
- Parse web pages
- Beautiful Soup (<a href="https://www.crummy.com/software/BeautifulSoup/">https://www.crummy.com/software/BeautifulSoup/</a>)
- lxml (<u>http://lxml.de/</u>)
- Putting everything together
- Scrapy (<u>https://scrapy.org/</u>)

## Before you scrape

Check to see if CSV, JSON, or XML version of an HTML page are available – better to use those

Check to see if there is a Python library that provides structured access (e.g., dataprep)

Check that you have permission to scrape

From "Deb Nolan. Web Scraping & XML/Xpath"

## If you do scrape

- Be careful to not to overburden the site with your requests
- Test code on small requests
- •Save the results of each request so you don't have to repeat the request unnecessarily
- CAPTCHA



From "Deb Nolan. Web Scraping & XML/Xpath"

## **Example Application Scenario: Experiential Hotel Search**



Hotel that is **less than \$300 per night**, has very clean room, and has a nice view of the city in Vancouver

Disclaimer: this is an imaginary application, not about how the real-world examples are built

## Where can we get those subjective

attributes?

Reviewed: January 16, 2024

9.0

Experience!

Clean rooms

Nice view

Good location

It was an exceptional stay. Highly recommended.

• It was so close to most attractions and everything is almost of walking distance. The room they gave us had an excellent view. Customer service was top-notch. We were checked in 3 hours prior to check-in time and after checking out they stored our luggages so we can still walk in the area without carrying our luggages around. Maintenance attended to our issue right away when something broke, cleaning staff was friendly.

② · None

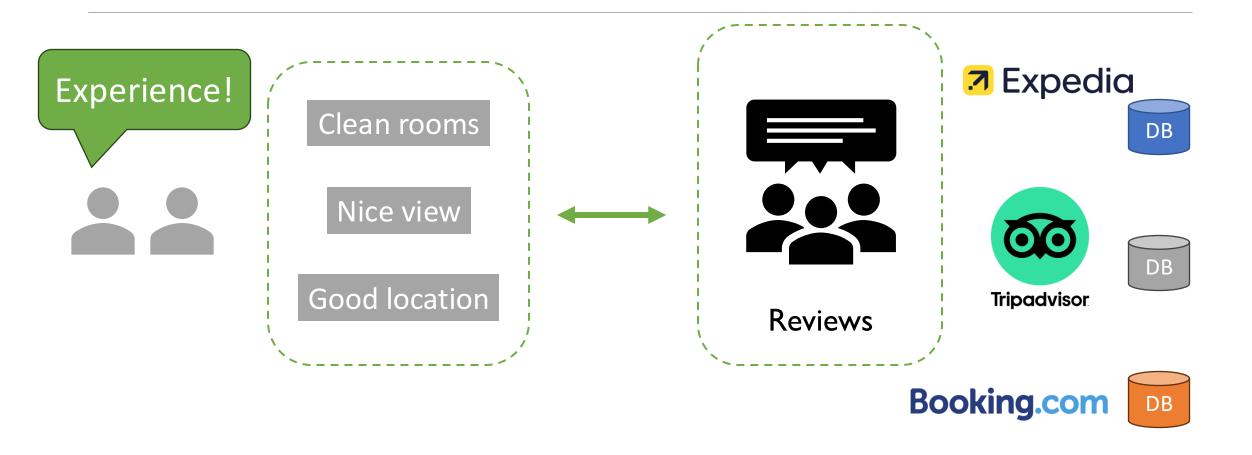
Not helpful

Reviewed: July 8, 2023

#### Very satisfied

• Upon arrival they had not given me the right room I had booked with booking.com. But they fixed it immediately once I brought it up.

## **Experiential Search**



## Preparing data for the search application

- Web scraping
- Information extraction (perhaps will cover in future lectures)
- Data cleaning
- Data integration
- Data annotation

## **Outline**

Data Collection

- Data Cleaning
- Dirty Data Problems
- Data Cleaning Tools
- Example: Outlier Detection
- Data Integration

## **Data Cleaning**

**NEWS** 

## Iowa City crime map shows 20 homicides in 2023. It's wrong.



**George Shillcock** 

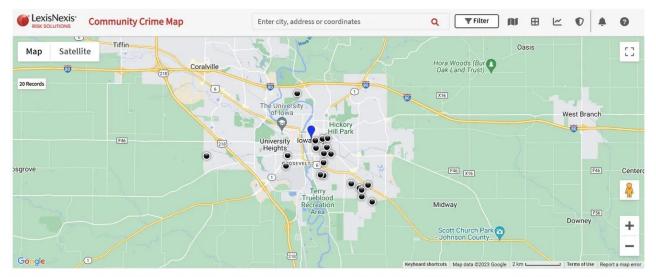
Iowa City Press-Citizen

Published 9:37 a.m. CT March 17, 2023









Because of a technical glitch, lowa City's community crime map is showing that 20 homicides occurred in the city between Jan. 1, 2023 and March 1, 2023. They didn't. *George Shillcock* 

He explained in an email that there had been a large-scale reclassification of National Incident-Based Reporting

System crime types in 2022. The city has an automated system that uses the crime types when it exports information about criminal activity from its records system to the LexisNexis site that manages the mapping.

Somewhere along the way, Hermiston said, the export process, relying on old codes, failed to capture the crime classifications properly. So suddenly the map reflected what looked like a brutal murder spree.

https://www.press-citizen.com/story/news/2023/03/17/iowa-city-crime-map-glitch-mistakenlhy-shows-20-homicides-in-2023/69959003007/

## **Dirty Data Problems**

- Parsing text into fields (separator issues)
- 2) Missing required field (e.g. no SIN)
- 3) Different representations (iphone 2 vs iphone 2<sup>nd</sup> generation)
- 4) Fields too long (get truncated)
- 5) Formatting issues especially dates
- 6) Primary key violation (two people with the same SIN)
- 7) Redundant Records (exact match or other)
- 8) Outliers (age = 120)
- Adapted from Stanford Data Integration Course

## Data Cleaning --- Error Detection

	Name	City	Star Rating	Minimum Price	Zip
t <sub>1</sub>	Sheraton Vancouver - Wall Centre	Burnaby	☆ ☆ ☆ ☆	\$260	V6Z 2R9
t <sub>2</sub>	TheBurrardHotel	Vancouver		\$200	V6Z 1Y7
t <sub>3</sub>	Element Metrotown	Burnaby	☆☆☆	\$3000	V5H 2A7
t <sub>4</sub>	Embarc Hotel	Vancouver	☆ ☆ ☆ ☆	\$180	V6Z 2R9

**Typos** 

**Duplicated values** 

Outliers

Missing values

**Constraint violation** 

## **Another Annoying Example**

Transactions
10 Dollars, credit
5Euros - debit
30 Pesos, credit
1 dollar, credit
7,00 euros, debit
credit 20 dollars
21 pesos
debit Fifty pesos and 10 euros

Amount	Currency	Mode
10	Dollars	credit
5	Euros	debit
30	Pesos	credit
1	Dollars	credit
7	Euros	debit
20	Dollars	credit
21	Pesos	?
50	Pesos	debit
10	Euros	debit

From Brandon Fain (Duke)

## **Data Cleaning Tools**

#### Python

- Missing Data (Pandas)
- <u>Deduplication</u> (Dedup)

#### **OpenRefine**

- Open-source Software (<u>http://openrefine.org</u>)
- OpenRefine as a Service (RefinePro)

#### Data Wrangler

- The Stanford/Berkeley Wrangler research project
- Commercialized (<u>Trifacta</u>)

### Not Many Tools.

That's why we are building DataPrep

(http://dataprep.ai)

```
import pandas as pd
from dataprep.clean import clean_country
df = pd.DataFrame({"country": ["USA", "country: Canada", " France ",
    "233", " tr "]})
clean_country(df, "country")
```

	country	country_clean
0	USA	United States
1	country: Canada	Canada
2	France	France
3	233	Estonia
4	tr	Turkey

## **Outlier Detection**

The ages of employees in a US company

Mean = 
$$\frac{1}{n} \sum_{i=1}^{n} x_i = 37$$

Stddev = 
$$\sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - mean)^2} = 16$$

$$[37 - 2 * 16, 37 + 2 * 16] = [4, 70]$$

### **Outlier Detection**

The ages of employees in a US company

1 20 21 21 22 26 33 35 36 37 39 42 45 47 54 57 61 62 400

Mean = 
$$\frac{1}{n} \sum_{i=1}^{n} x_i = 56$$

Stddev = 
$$\sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - mean)^2} = 83$$
 [56 - 2 \* 83, 56 + 2 \* 83] = [-109, 221]

### **Outlier Detection**

The ages of employees in a US company

Median = 
$$median(X) = 37$$
 [37 - 2 \* 15, 37 + 2 \* 15] = [7, 67]

$$\mathsf{MAD} = \mathsf{median}\left(X - \mathsf{median}(X)\right) = 15$$

# **Data Preparation Tasks**

Data Collection

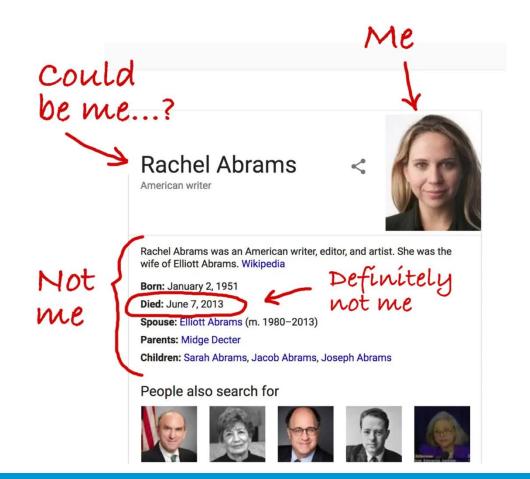
Data Cleaning

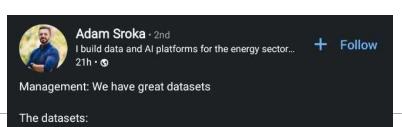
- Data Integration
- Data Integration Problem
- Three Steps (Schema Matching, Entity Resolution, Data Fusion)
- Example: Entity Resolution

#### The New Hork Times

### Google Thinks I'm Dead

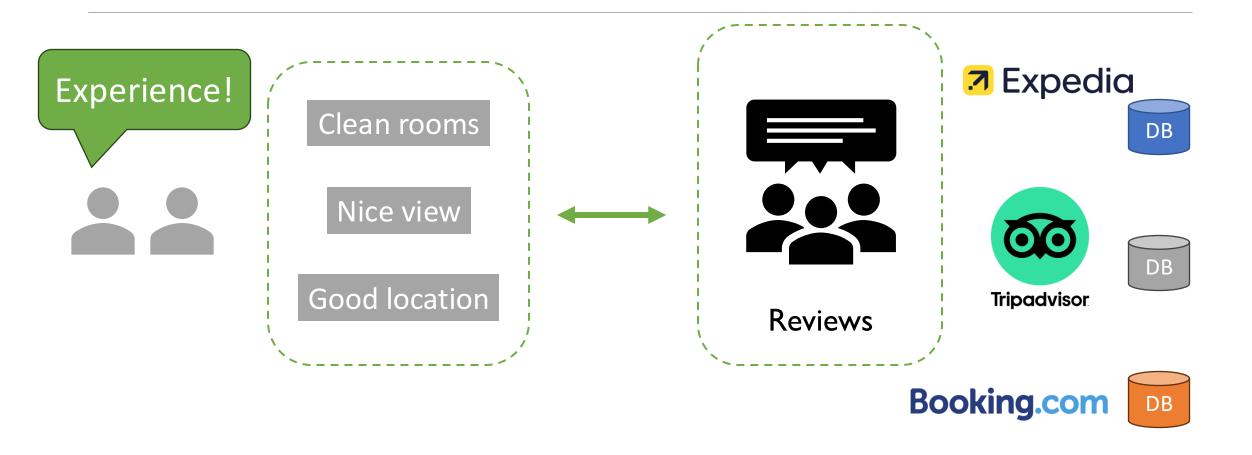
(I know otherwise.)





```
['St. Albans',
 'St.Albans',
 'St Albans',
 'St.Ablans',
 'St.albans',
 'St. Alans',
'S.Albans',
 'St..Albans',
 'S.Albnas',
 'St.Albnas',
 'St.Al bans',
 'St.Algans',
 'Sl.Albans',
 'St. Allbans',
 'St, Albans',
 'St. Alban',
 'St. Alban']
```

# **Experiential Search**



	Name	Address	Tel
A1	Sheraton Vancouver - Wall Centre	1000 Burrard Street , Vancouver	(604) 331-1000
A2 A3	The Burrard Hotel	1100 Burrard Street, Vancouver	(604) 681-2331
	Delta Hotels BCC	4331 Dominion Street, Burnaby	(604) 453-0750

	Zip	Hotel	Phone
B1	V4K 0B2	Delta Hotels by Marriott Vancouver Delta	+1 604-382-8222
B2	V6Z 1Y7	The Burrard	+1 800-663-0366
В3	V5G 1C7	Delta Hotels by Marriott Burnaby Conference Centre	+1 604-453-0750

Data Integration???

# Data Integration: Three Steps

#### Schema Mapping

- Creating a global schema
- Mapping local schemas to the global schema

#### **Entity Resolution**

You will learn this in detail later

#### Data Fusion

Resolving conflicts based on some confidence scores

#### Want to know more?

Anhai Doan, Alon Y. Halevy, Zachary Ives. <u>Principles of Data Integration</u>.
 Morgan Kaufmann Publishers, 2012.

# **Schema Mapping**

- Approaches:
  - View & logic-based: mapping between sources and the global schema
  - Learning to match:
    - Classify the semantic relation of attribute pairs
    - Cluster attributes
  - Universal schema
    - Fill in each cell by latent probabilities instead of one-to-one column mapping
    - Allow overlap, subset/superset, etc.
  - With the rise of LMs
    - Simply concatenating all values could work for certain tasks

	•	
-	• –	
	•	

	Name	Address	Tel
A1	Sheraton Vancouver - Wall Centre	1000 Burrard Street , Vancouver	(604) 331-1000
A2	The Burrard Hotel	1100 Burrard Street, Vancouver	(604) 681-2331
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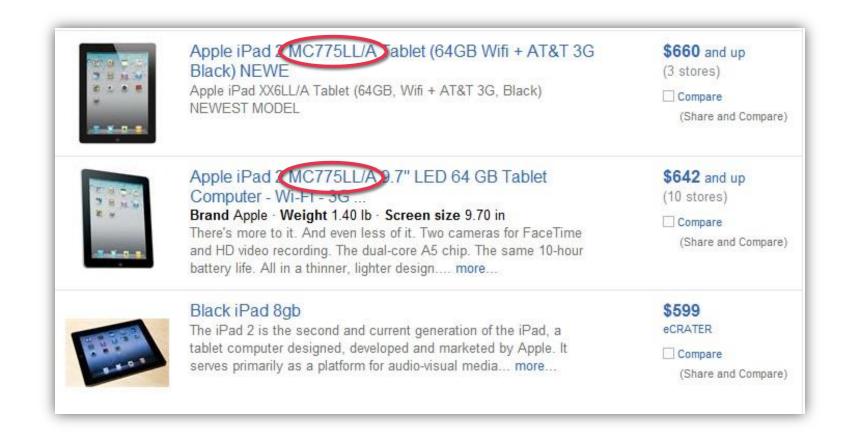
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В3	V5G 1C7	Delta Hotels by Marriott Burnaby Conference Centre	+1 604-453-0750

#### Integrated Data



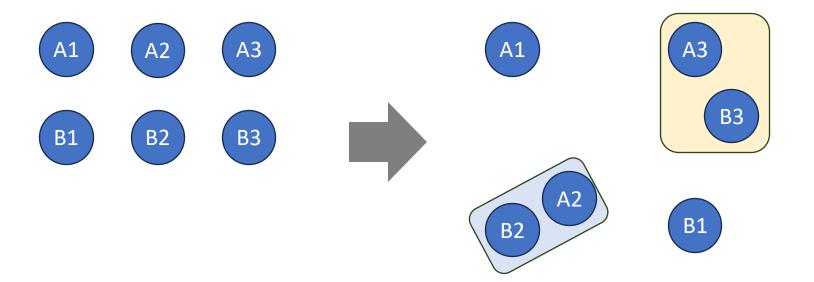
		Name	Address	Phone	Zip
H	H1	Sheraton Vancouver - Wall Centre	1000 Burrard Street , Vancouver	(604) 331-1000	
	H2	The Burrard Hotel	1100 Burrard Street, Vancouver	+1 800-663-0366	V6Z 1Y7
	Н3	Delta Hotels BCC	4331 Dominion Street, Burnaby	+1 604-453-0750	V5G 1C7
	H4	Delta Hotels by Marriott Vancouver Delta		+1 604-382-8222	V4K 0B2

# **Another Example of Entity Resolution**



### **Output of Entity Resolution**

- Also referred to as record linkage and entity matching
- Identify records in a (or more) dataset(s) representing the same entity



# **Entity Resolution Techniques**

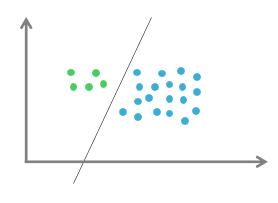
### Similarity-based

- Similarity Function Jaccard $(r,s) = \lfloor \frac{r \cap s}{r \cup s} \rfloor$
- Threshold (e.g., 0.8)

Jaccard(r1, r2) =  $0.9 \ge 0.8$  Matching Jaccard(r4, r8) = 0.1 < 0.8 Non-matching

### Learning-based

• Represent a pair of records as a feature vector



# **Similarity-based**

Suppose the similarity function is Jaccard.

Problem Definition

Given a table T and a threshold  $\theta$ , the problem aims to find all record pairs  $(r,s) \in T \times T$  such that  $Jaccard(r,s) \geq \theta$ 

The naïve solution needs  $n^2$  comparisons

# Filtering-and-Verification

### Step I. Filtering/blocking

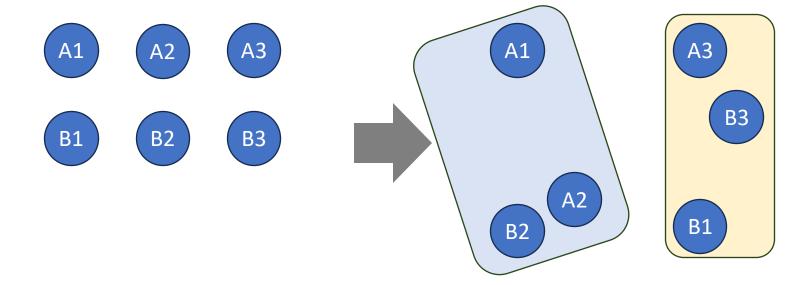
Removing obviously dissimilar pairs

### Step 2. Verification/pairwise matching

Computing Jaccard similarity only for the survived pairs

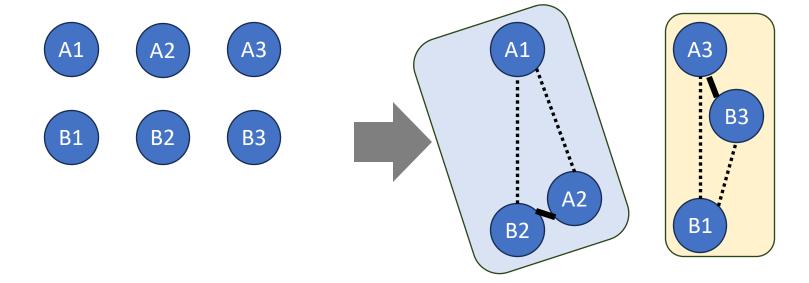
# Filtering/blocking

Removing obviously dissimilar pairs



### **Verification/Pairwise Matching**

Computing similarity only for the survived pairs



# **How Does Filtering Work?**

#### What are "obviously dissimilar pairs"?

- Two records are obviously dissimilar if they do not share any word.
- In this case, their Jaccard similarity is zero, thus they will not be returned as a result and can be safely filtered.

How can we efficiently return the record pairs that share at least one word?

 To help you understand the solution, let's first consider a simplified version of the problem, which assumes that each record only contains one word

# A simplified version

Suppose each record has only one word. Write an SQL query to do the filtering.

```
r<sub>1</sub> Apple
```

r<sub>2</sub> Apple

ra Banana

r<sub>4</sub> Orange

r<sub>5</sub> Banana

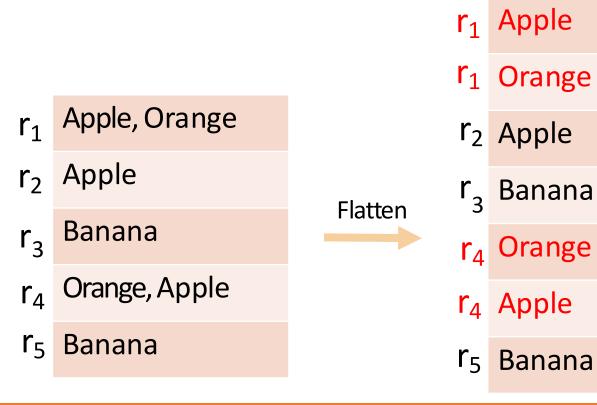
```
SELECT T1.id, T2.id
FROM Table T1, Table T2
WHERE T1.word = T2.word and T1.id < T2.id</pre>
```

Does it require  $n^2$  comparisons?

Output: (r1, r2), (r3, r5)

# A general case

Suppose each record can have multiple words.



- 1. This new table can be thought of as the <u>inverted index</u> of the old table.
- 2. Run the previous SQL on this new table and remove redundant pairs.

### Not satisfied with efficiency?

### Exploring stronger filter conditions

- Filter the record pairs that share zero token
- Filter the record pairs that share one token
- 0
- Filter the record pairs that share k tokens

### Challenges

 How to develop efficient filter algorithms for these stronger conditions?

Jiannan Wang, Guoliang Li, Jianhua Feng.

<u>Can We Beat The Prefix Filtering? An Adaptive Framework for Similarity Join and Search.</u> SIGMOD 2012:85-96.

# Not satisfied with result quality?

#### TF-IDF

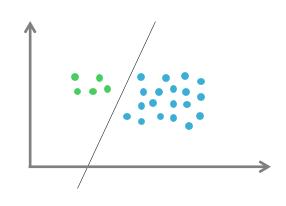
• Use weighted Jaccard: WJaccard $(r,s) = \frac{wt(r \cap s)}{wt(r \cup s)}$ 

### Crowdsourcing

 Ask human to decide whether two records are matching or not

### Learning-based

 Model entity resolution as a classification problem



# Human-in-the-loop: Crowdsourcing

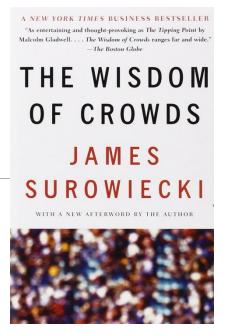
CMPT 884: Human-in-the-loop Data Management (SFU, Fall 2016)

https://sfu-db.github.io/cmpt884-fall16/

### **The Wisdom of Crowds**

What does it mean?

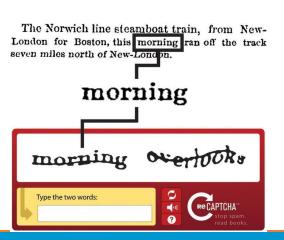
Two heads are better than one



### Some famous examples

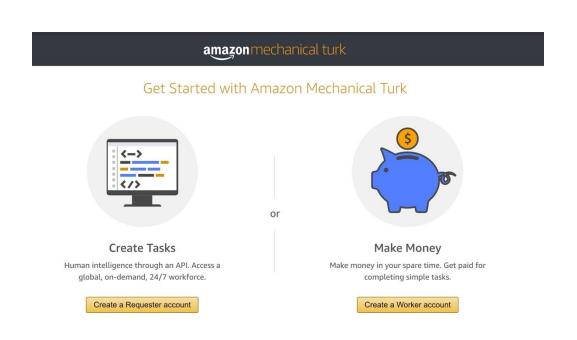


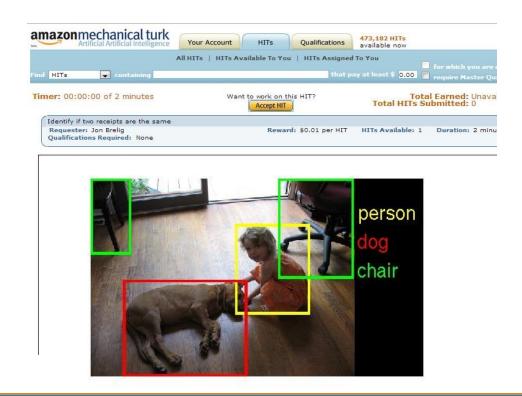




# **Amazon Mechanical Turk**

#### 500K+workers\*





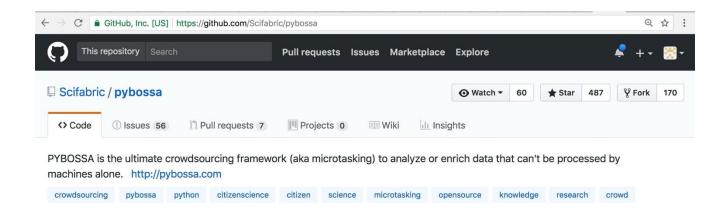
\* https://requester.mturk.com/tour

### Crowdsourcing may not work 🕾

### What if your data is confidential?

• E.g., Medical Data, Customer Data

### Internal Crowdsourcing Platform



# Crowdsourcing may not work <sup>(2)</sup>

What if your data is so big?

E.g., Label 10 million images

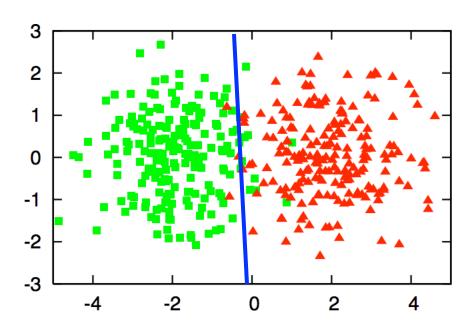
# Crowdsourcing may not work ©

What if your data is so big?
• E.g., Label 10 million images

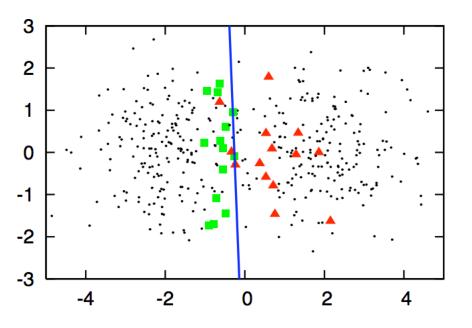
# Human-in-the-loop: Active Learning

# **Active Learning**

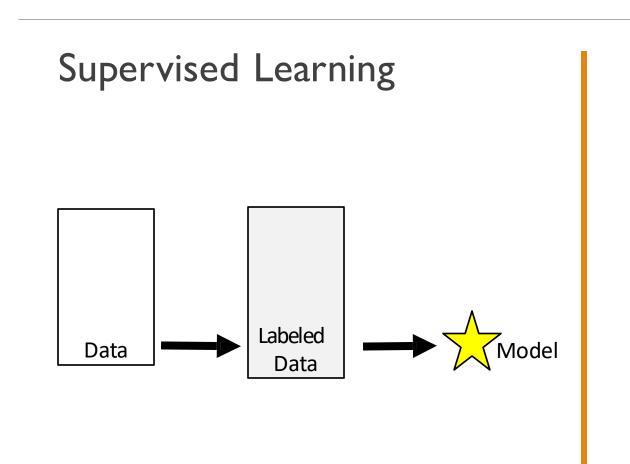
### Supervised Learning

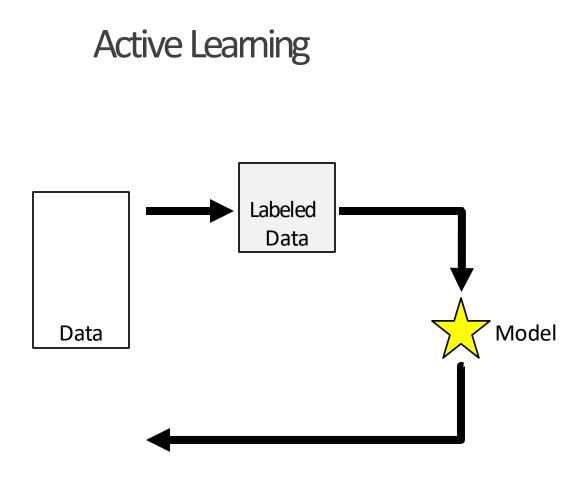


### **Active Learning**



### Workflow



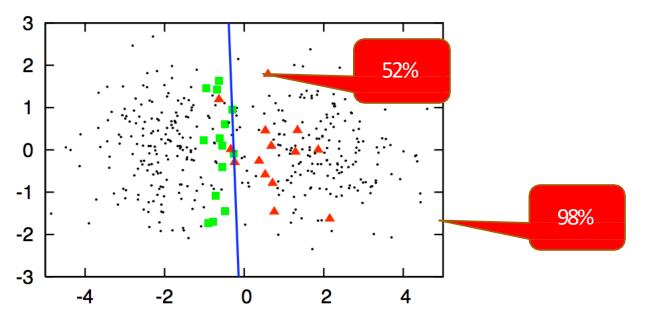


# **Query Strategy**

- Which data points should be labeled?
- Uncertain Sampling
- Query-By-Committee
- Expected Error Reduction
- Expected Model Change
- Variance Reduction
- Density-Weighted Methods
  - Settles, Burr. "Active learning literature survey." University of Wisconsin, Madison 52.55-66 (2010): 11.

# **Uncertain Sampling**

Pick up most uncertain datapoints to label



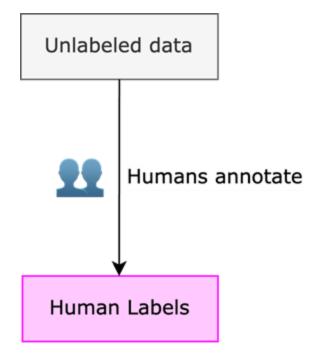
Logistic Regressionpredict\_proba(X)

# Crowdsourcing may not work ©

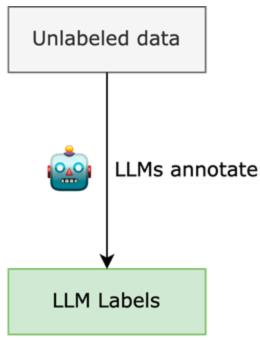
What if your data is so big?
• E.g., Label 10 million images

Human-in-the-loop: fully automated with LLM?

### Perhaps not there yet

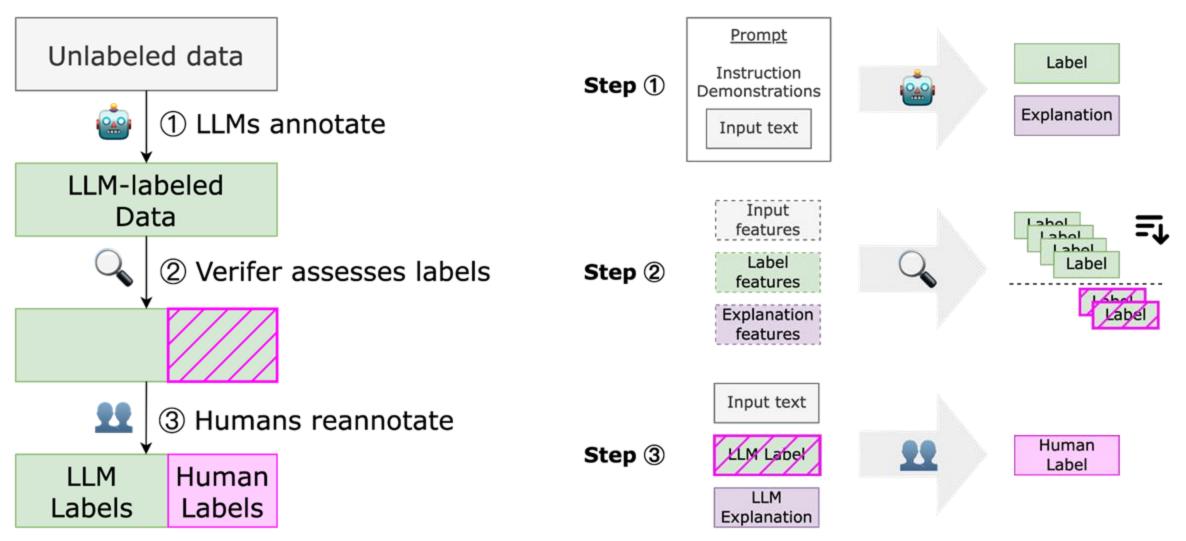


- X time consuming
- X not scalable
- **X** costly



- √good zero-shot and few-shot learners for many NLP tasks
- ✓ much cheaper
- performance varies across tasks, labels, and instances

### **Human-LLM Collaborative Annotation Framework**



Wang et al. "Human-LLM collaborative annotation through effective verification of LLM labels." CHI 2024



#### Preppin' Data

A weekly challenge to help you learn to prepare data and use Tableau Prep

https://preppindata.blogspot.com/

#### **Data Collection**

Where to collect, How to Collect

### Data Cleaning

Dirty Data Problems, Data-cleaning tools

### Data Integration

Schema Mapping, Entity Resolution, Data Fusion

### **Entity Resolution**

Similarity-based, Crowdsourcing, Active Learning, LLM