CMPT 733
Data Preparation

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Data Preparation is the Bottleneck!

Doing data science is like cooking

Collection

Cleaning

Integration

Analysis

How much time will be spent on the preparation?

Outline

Data Collection

Data Cleaning

Data Integration

Outline

Data Collection

- Where to collect
- How to collect

Data Cleaning

Data Integration

Where to Collect?

Internal Data

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

Where to Collect?

External Data

- Web Pages
- Web Service (https://www.programmableweb.com/)
- Open Data (data.vancouver.ca, www.data.gov)
- Knowledge Base (Wikidata, Freebase)

Data Classification

Data

Structured

Team	W	L	Pct	GB	Conf	Div	Home	Away	L10	Strk
1 Rockets	20	4	.833	-	11-2	3-2	8-3	12-1	9-1	W9
2 Warriors	21	6	.778	0.5	9-4	2-1	8-3	13-3	8-2	W6
3 Spurs	19	8	.704	2.5	9-4	4-1	13-2	6-6	8-2	W4
4 Timberwolves	16	11	.593	5.5	13-5	4-1	9-4	7-7	6-4	W2

Semi-structured

CLE - James Layup Shot: Missed	06:48 CLE
CLE - James Rebound (Off:1 Def:0)	06:46 CLE
CLE - James Reverse Layup Shot: Made (2 PTS)	06:45 CLE 9-15
Stoppage: Out-of-Bounds	06:29

Unstructured

Is LeBron breaking the aging curve?

Kevin Pelton
ESPN Staff Writer

5:10 AM PT

During his 15th NBA season, Cleveland Cavaliers star LeBron James is performing at a level that echoes the prime that saw him win four MVPs.

As James nears his 33rd birthday later this month, his performance at that age stands up to any of his predecessors, including Michael Jordan's 1995-96 season that produced an MVP, a then-record 72 wins and a championship. (Because James entered the NBA directly out of high school, NBA experience isn't the best way to compare how he's aging to his peers. After all, Jordan's 15th year was actually his final one in the NBA at age 40.)

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
10
```

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

```
{
    "Kobe Bryant" :{
        "Born": "08/23/1978",
        "Number": ["8", "24"],
        "Team": ["Los Angeles Lakers"]
    },
    "Michael Jordan":{
        "Born": "02/17/1963",
        "Number": ["23"],
        "Team": ["Chicago Bulls", "Washington Wizards"]
    }
}
```

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 (http://docs.python-requests.org/en/master/)

Parse web pages

- Beautiful Soup (https://www.crummy.com/software/BeautifulSoup/)
- lxml (http://lxml.de/)

Putting everything together

- Scrapy (https://scrapy.org/)

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., tweetPy)

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"

Outline

Data Collection

Data Cleaning

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

Data Integration

Dirty Data Problems

From Stanford Data Integration Course:

1) Parsing text into fields (separator issues)
2) Missing required field (e.g. key field)
3) Different representations (iphone 2 vs iphone 2nd generation)
4) Fields too long (get truncated)
5) Formatting issues – especially dates
6) Outliers (age = 120)

Data Cleaning Tools

Python

- Missing Data (Pandas)
- Deduplication (Dedup)

OpenRefine

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

Data Wrangler

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

Not Many Tools.

That's why we are building Dataprep (http://dataprep.ai)

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

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

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

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

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

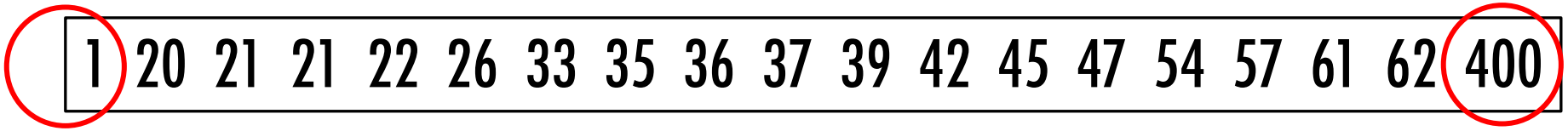
$$\text{Mean} = \frac{1}{n}\sum_{i=1}^{n} x_i = 56$$

$$[56 - 2 * 83, \quad 56 + 2 * 83] = \text{[-109, 221]}$$

$$\text{Stddev} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - \text{mean})^2} = 83$$

Outlier Detection

The ages of employees in a US company



Median = $\text{median}(x_i) = 37$

$[37 - 2 * 15,\ \ 37 + 2 * 15] = [7, 67]$

MAD = $\text{median}(|x_i - \text{median}(x_i)|) = 15$

Outline

Data Collection

Data Cleaning

Data Integration

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

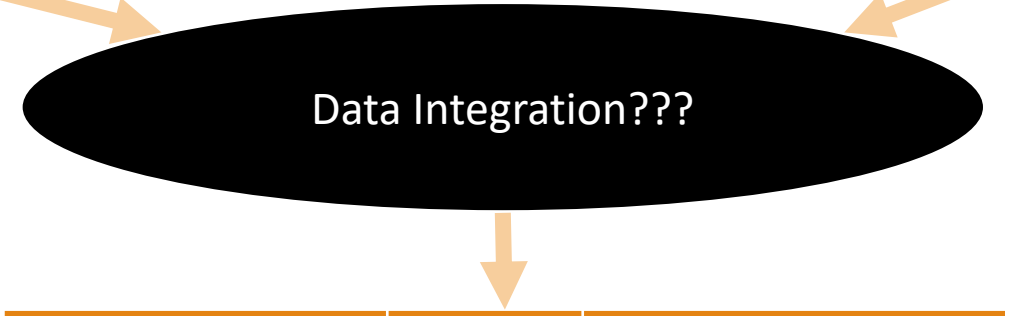
Data Integration Problem

Data Source 1 (from CourSys)

First Name	Last Name	Mark
Michael	Jordan	50
Kobe	Bryant	48

Data Source 2 (from survey)

Name	Background
Mike Jordan	C++, CS, 4 years
Kobe Bryant	Business, 2 years



Integrated Data

Name	Mark	Background
Michael Jordan	50	C++, CS, 4 years
Kobe Bryant	48	Business, 2 years

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

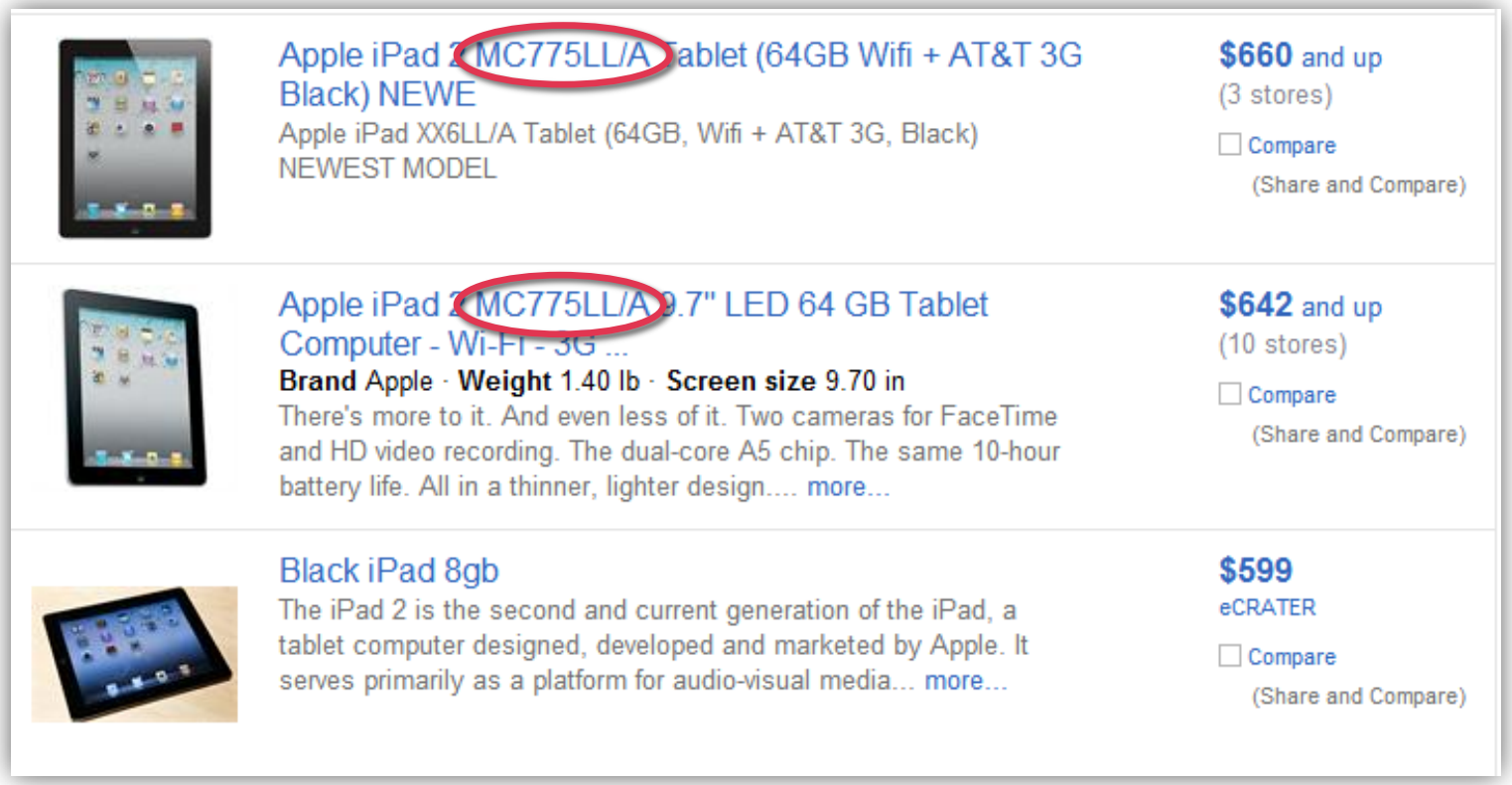
Data Fusion

- Resolving conflicts based on some confidence scores

Want to know more?

- Anhai Doan, Alon Y. Halevy, Zachary Ives. Principles of Data Integration. Morgan Kaufmann Publishers, 2012.

Entity Resolution



Output of Entity Resolution

ID	Product Name	Price
r_1	iPad Two 16GB WiFi White	$490
r_2	iPad 2nd generation 16GB WiFi White	$469
r_3	iPhone 4th generation White 16GB	$545
r_4	Apple iPhone 3rd generation Black 16GB	$375
r_5	Apple iPhone 4 16GB White	$520

(r_1, r_2) , (r_3, r_5)

Entity Resolution Techniques

Similarity-based

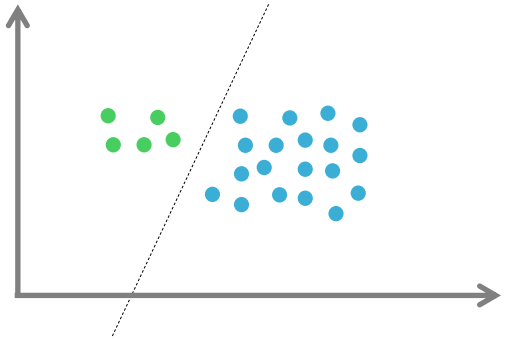
- Similarity Function (e.g., $\text{Jaccard}(r, s) = |\frac{r \cap s}{r \cup s}|$)
- Threshold (e.g., 0.8)

Jaccard(r1, r2) = 0.9 ≥ 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 θ, the problem aims to find all record pairs $(r, s) \in T \times T$ such that $\text{Jaccard}(r, s) \geq \theta$

The naïve solution needs n^2 comparisons

Filtering-and-Verification

Step 1. Filtering

- Removing obviously dissimilar pairs

Step 2. Verification

- Computing Jaccard 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_1	Apple
r_2	Apple
r_3	Banana
r_4	Orange
r_5	Banana

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

Does it require n^2 **comparisons ?**

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

A general case

Suppose each record can have multiple words.

r_1	Apple, Orange
r_2	Apple
r_3	Banana
r_4	Orange, Apple
r_5	Banana

Flatten

r_1	Apple
r_1	Orange
r_2	Apple
r_3	Banana
r_4	Orange
r_4	Apple
r_5	Banana

1. This new table can be thought of as the **inverted index** 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
- ....
- 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.
Can We Beat The Prefix Filtering? An Adaptive Framework for Similarity Join and Search.
SIGMOD 2012:85-96.

Not satisfied with result quality?

TF-IDF

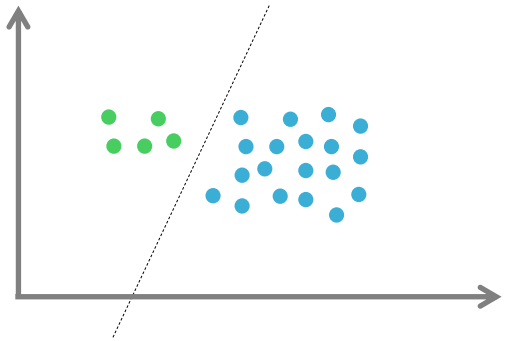
- Use weighted Jaccard: $\mathbf{WJaccard}(r, s) = \frac{wt(r \cap s)}{wt(r \cup s)}$

Crowdsourcing

- Ask human to decide whether two records are matching or not

Learning-based

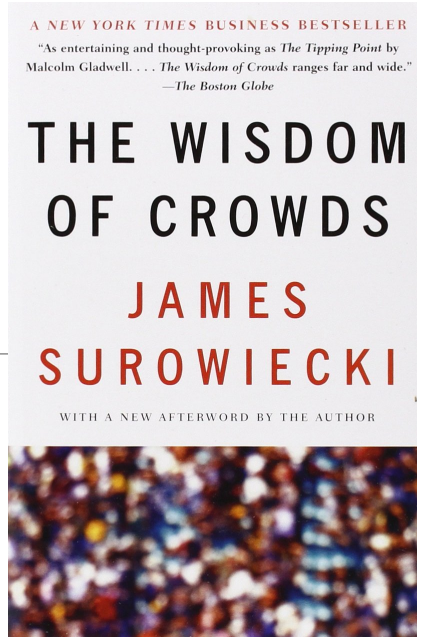
- Model entity resolution as a classification problem



Crowdsourcing

CMPT 884: Human-in-the-loop Data Management (SFU, Fall 2016)
https://sfu-db.github.io/cmpt884-fall16/

The Wisdom of Crowds

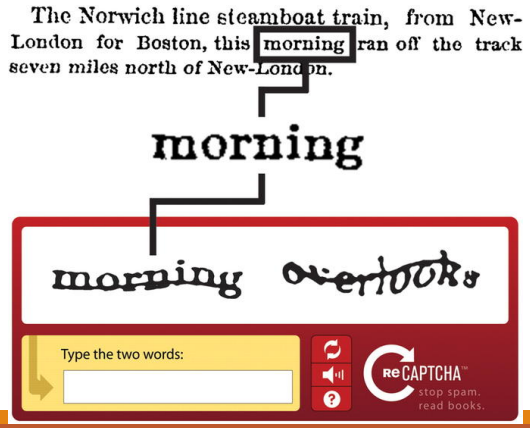


What does it mean?

- Two heads are better than one

Some famous examples

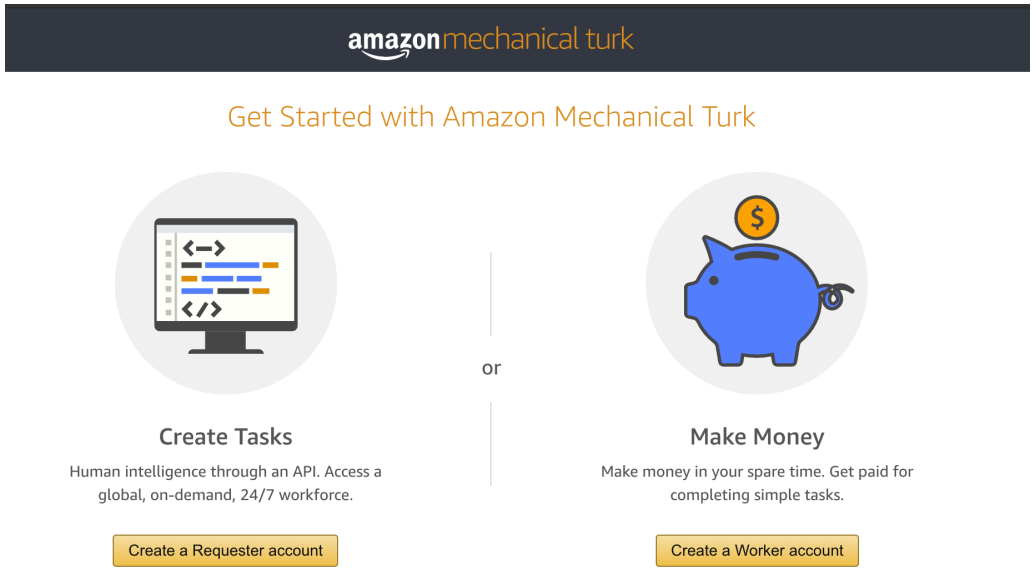
WIKIPEDIA



Crowdsourcing Platforms

Amazon Mechanical Turk

500K+ workers*



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

Industrial Survey

Company	Team	Persona
Amazon	Product classification	Largely single-case user
Captricity	Focus of large part of company	Largely single-case user
Dropbox	Single person consulting several teams	Multi-case user / Internal provider
Facebook	Entities team	Multi-case user
Flipora	Startup CTO	Multi-case user
GoDaddy	Small business data extraction	Multi-case user
Groupon	Merchant data team	Multi-case user
Google	Internal crowdsourcing team	Internal provider
Google	Web knowledge discovery team	Multi-case user
LinkedIn	Single person consulting several teams	Multi-case user / Internal provider
Microsoft	Internal crowdsouricng team	Internal provider
Microsoft	Search relevance team	Multi-case user
Youtube	Crowdsourcing team	Largely single-case user

Use Cases

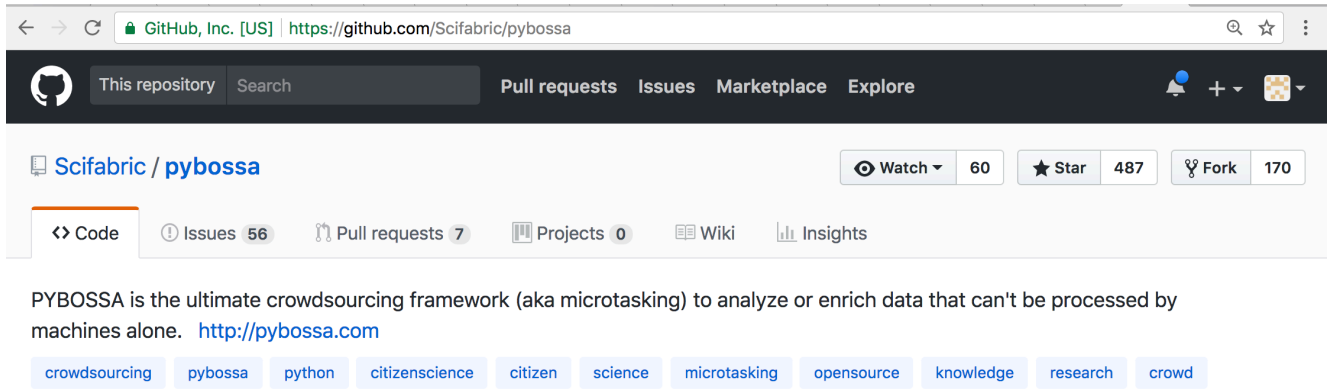
Use Cases	# Participants
Classification	12
Entity resolution	6
Data cleaning	5
Ranking	5
Spam detection	5
Data extraction	5
Text generation	5

Crowdsourcing may not work ☹

What if your data is confidential?

- E.g., Medical Data, Customer Data

Internal Crowdsourcing Platform



Crowdsourcing may not work ☹

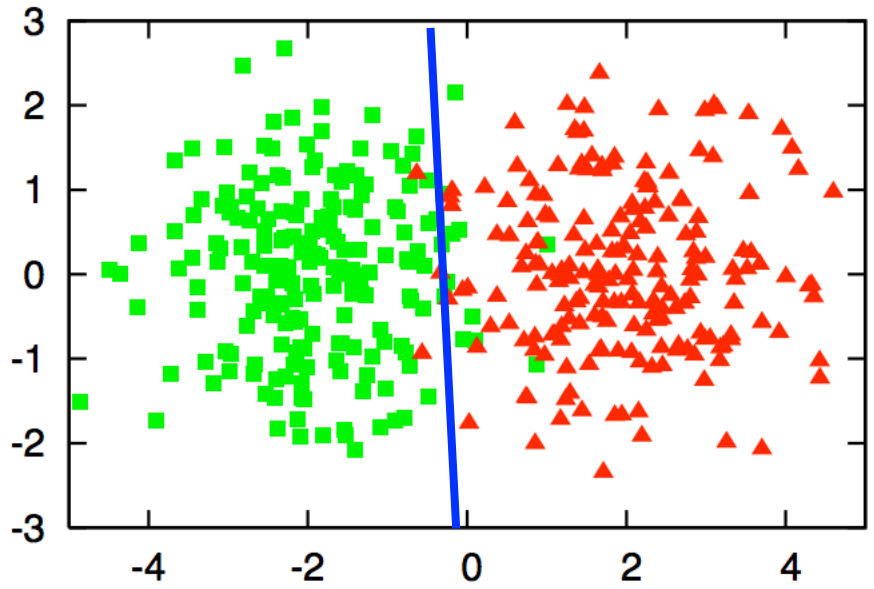
What if your data is so big?

- E.g., Label 10 million images

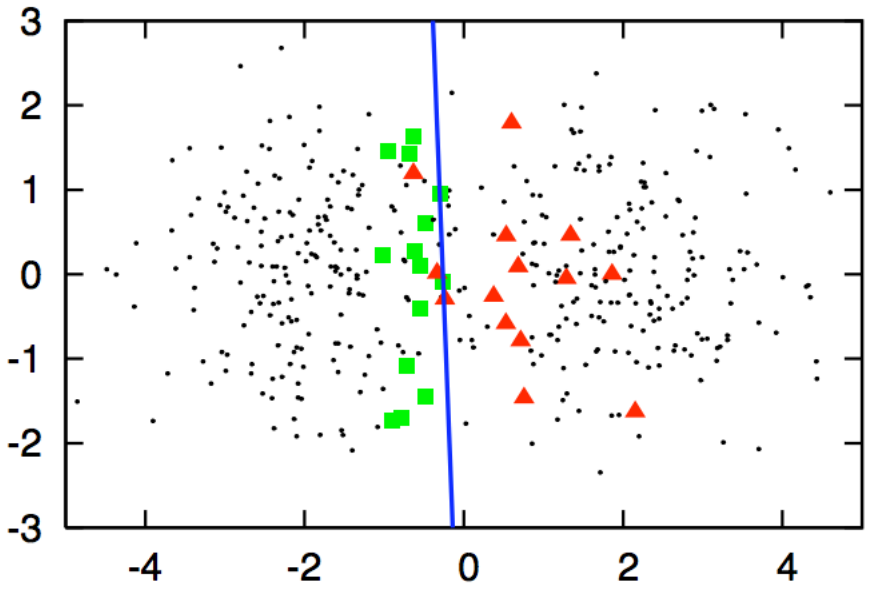
Active Learning

Active Learning

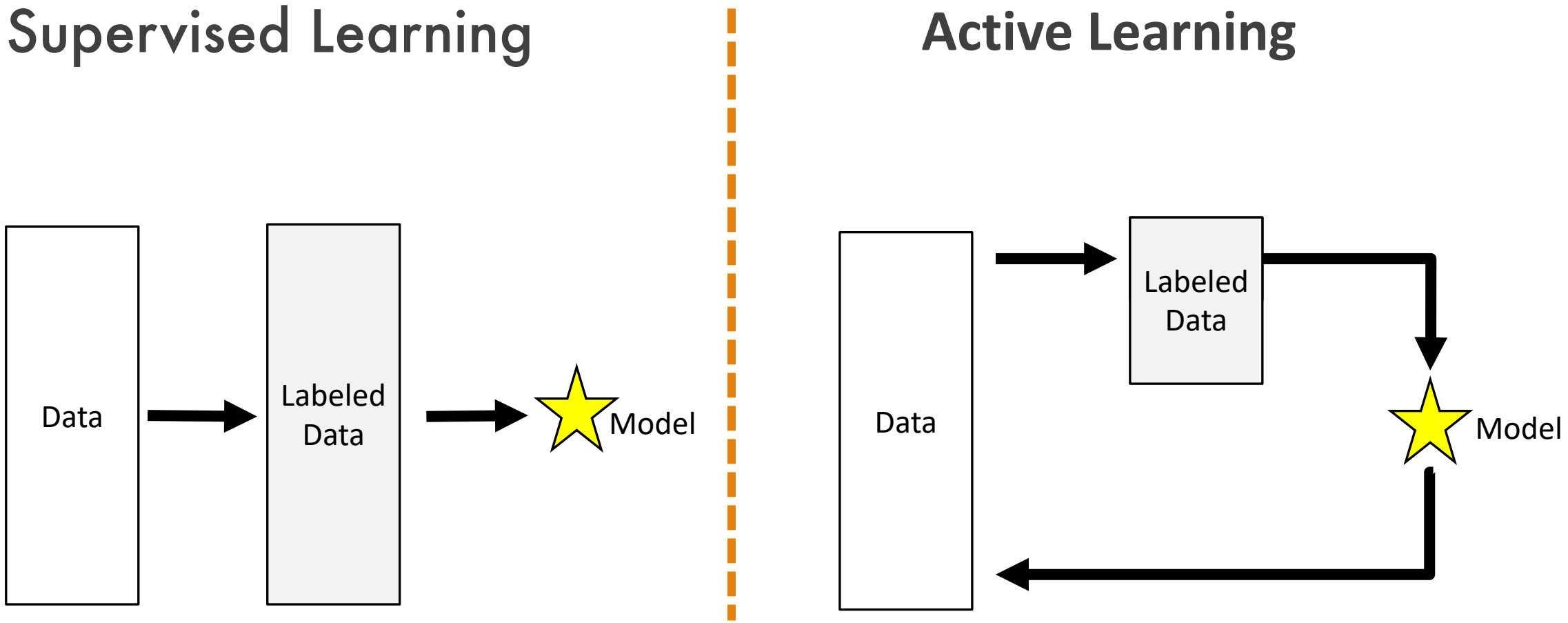
Supervised Learning



Active Learning



Workflow


Supervised Learning
Data
Labeled Data
Model
Active Learning
Data
Labeled Data
Model

Query Strategy

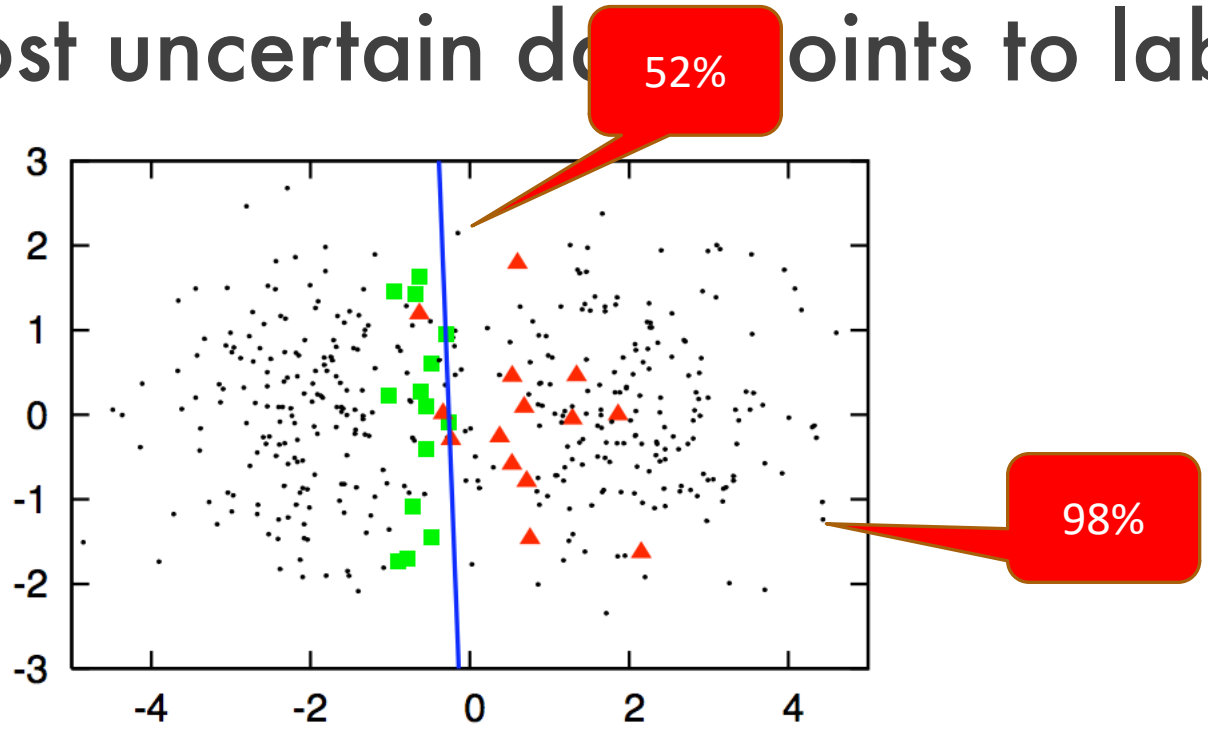
Which data points should be labeled?

- 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 data points to label



Logistic Regression

- predict_proba(X)

Summary

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