# ADMIN

- **Project Proposals (March 4)**
- **Lab 2 is out**
- **Lab 1 docker and M1**
- **Class ends at 3:40**

# 6.S080
# Data Cleaning

# EXAMPLE TASK


*How many people work in the US IT industry?*
*What is the avg revenue per employee in the tech industry?*

# EXAMPLE TASK

| Rank[1] | | Company | Fiscal Year Ending | Revenue ($B) USD | Employees | Headquarters |
|---|---|---|---|---|---|---|
| 1 | | Apple Inc. | 30 September 2017[2] | $229.2[1][3] | 123,000[3] | Cupertino, CA, US |
| 2 | | Samsung Electronics | 31 December 2017[4] | $211.9[1][5][6] | 320,670[7][8] | Suwon, South Korea |
| 3 | | Amazon | 31 December 2017[9][10] | $177.9[1][10] | 613,300[11] | Seattle, WA, US |
| 4 | | Foxconn | 31 December 2017[12][13] | $154.7–158[1][13][14] | 803,126[15] | New Taipei City, Taiwan |
| 5 | | Alphabet Inc. | 31 December 2017[16][17] | $110.8[1][17] | 80,110[18] | Mountain View, CA, US |
| 6 | | Microsoft | 30 June 2017[19] | $90.0[1] | 124,000[19] | Redmond, WA, US |
| 7 | | Huawei | 31 December 2017[20][21] | $89.3–92.5[1][21] | 180,000 | Shenzhen, China |
| 8 | | Hitachi | 31 March 2018[22] | $84.6[1] | 307,275 | Tokyo, Japan |
| 9 | | IBM | 31 December 2017[23][24] | $79.1[1] | 397,800 | Armonk, NY, US |
| 10 | | Dell Technologies | 31 January 2018[25][26] | $78.7[1][26] | 145,000[25] | Round Rock, TX, US |
| 11 | | Sony | 31 March 2018[27] | $77.1[1][28] | 117,300[27] | Tokyo, Japan |
| 12 | | Panasonic | 31 March 2018[29] | $72.0[1] | 274,143 | Osaka, Japan |
| 13 | | Intel | 31 December 2017[30] | $62.8[1] | 102,700 | Santa Clara, CA, US |
| 14 | | LG Electronics | 31 December 2017[31] | $54.3[1] | 74,000 | Seoul, South Korea |
| 15 | | JD.com | 31 December 2017[32] | $54.0[1] | 157,831 | Beijing, China |
| 16 | | HP Inc. | 31 October 2017[33] | $52.0[1] | 49,000 | Palo Alto, CA, US |

**Private and semipublic companies with the most employees in the world**

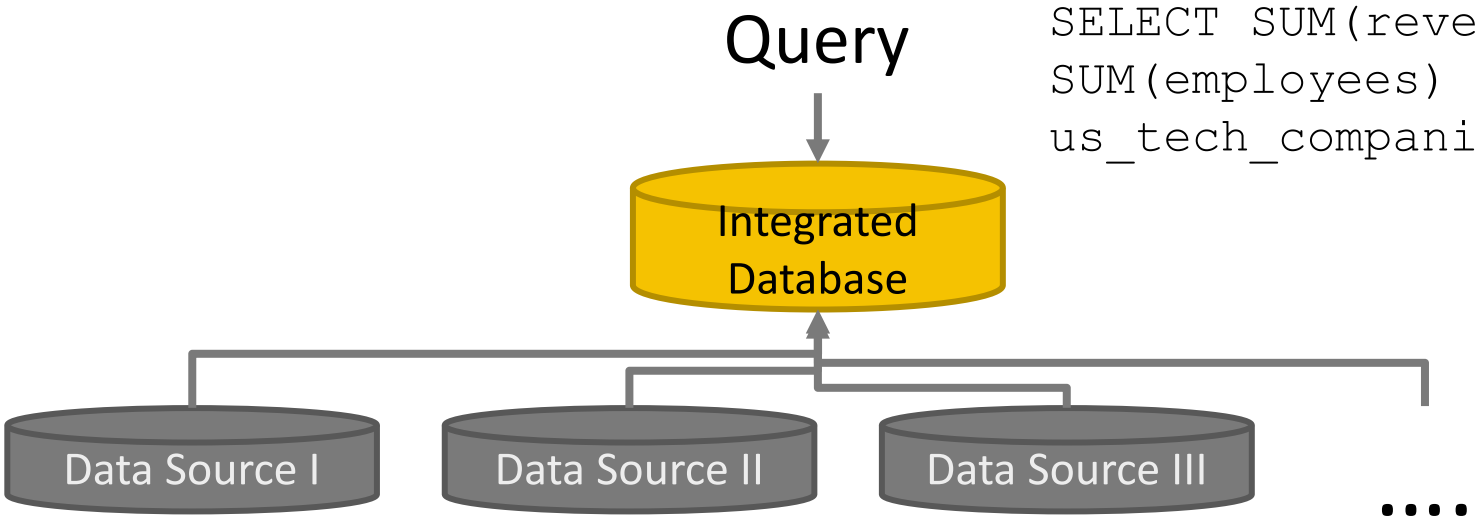
| Rank | Employer | Country | Employees |
|---|---|---|---|
| 1 | Walmart | United States | 2,200,000 |
| 2 | China National Petroleum | China | 1,382,401 |
| 3 | China Post Group | China | 935,191 |
| 4 | State Grid | China | 917,717 |
| 5 | Hon Hai Precision Industry (Foxconn) | Taiwan | 667,680 |
| 6 | Volkswagen | Germany | 664,496 |
| 7 | Amazon | United States | 647,500 |
| 8 | Sinopec Group | China | 619,151 |
| 9 | Compass Group | United Kingdom | 595,841 |
| 10 | United States Postal Service | United States | 565,802 |

**United States Largest Private Employers (as of 2017)[1][2][3][4]** [hide]

| Rank | Employer | Global number of Employees | Median annual pay |
|---|---|---|---|
| 1 | Walmart | 2,300,000 | $19,177 |
| 2 | Amazon | 469,690 | $36,969 |
| | Deutsche Post DHL | 499,018 | |
| 3 | United Parcel Service | 456,415 | $53,443 |
| 4 | Yum! Brands | 450,000 | $9,111 |
| 5 | Kroger | 449,000 | $21,075 |
| 6 | Home Depot | 413,000 | $20,095 |
| 7 | Berkshire Hathaway | 377,000 | $53,510 (BH directly employs c. 30 people. All the others are employed by the companies BH purchases.) |
| 8 | International Business Machines | 366,000 | $55,088 |
| 9 | FedEx | 357,000 | $50,017 |
| 10 | Target Corporation | 345,000 | $20,581 |
| 11 | General Electric | 313,000 | $57,211 |
| 12 | Walgreens Boots Alliance | 290,000 | $31,132 |
| 13 | Starbucks | 277,000 | $12,754 |
| 14 | Albertsons | 273,000 | |
| 15 | PepsiCo | 263,000 | $47,801 |
| 16 | Wells Fargo | 262,700 | $60,466 |
| 17 | Cognizant Technology Solutions | 260,000 | $31,998 |
| 18 | UnitedHealth Group | 260,000 | $58,378 |
| 19 | Lowe's | 240,000 | $23,905 |
| 20 | AT&T | 268,540 | $95,814 |

```
,name,domain,year founded,industry,size range,locality,country,linkedin url,current employee estimate,total employee estimate
5872184,ibm,ibm.com,1911,information technology and services,10001+,"new york, new york, united states",united states,linkedin.com/company/ibm,274047,716906
4425416,tata consultancy services,tcs.com,1968,information technology and services,10001+,"bombay, maharashtra, india",india,linkedin.com/company/tata-consultancy-services,190771,341369
21074,accenture,accenture.com,1989,information technology and services,10001+,"dublin, dublin, ireland",ireland,linkedin.com/company/accenture,190689,455768
2309813,us army,goarmy.com,1800,military,10001+,"alexandria, virginia, united states",united states,linkedin.com/company/us-army,162163,445958
1558607,ey,ey.com,1989,accounting,10001+,"london, greater london, united kingdom",united kingdom,linkedin.com/company/ernstandyoung,158363,428960
3844889,hewlett-packard,hpe.com,1939,information technology and services,10001+,"palo alto, california, united states",united states,linkedin.com/company/hewlett-packard-enterprise,127952,412952
2959148,cognizant technology solutions,cognizant.com,1994,information technology and services,10001+,"teaneck, new jersey, united states",united states,linkedin.com/company/cognizant,122031,210020
5944912,walmart,walmartcareers.com,1962,retail,10001+,"withee, wisconsin, united states",united states,linkedin.com/company/walmart,120753,272827
3727010,microsoft,microsoft.com,1975,computer software,10001+,"redmond, washington, united states",united states,linkedin.com/company/microsoft,116196,276983
3300741,at&t,att.com,1876,telecommunications,10001+,"dallas, texas, united states",united states,linkedin.com/company/at&t,115188,269659
5412257,united states air force,airforce.com,1947,defense & space,10001+,"randolph, texas, united states",united states,linkedin.com/company/united-states-air-force,113997,316549
2780814,pwc,pwc.com,1998,accounting,10001+,"new york, new york, united states",united states,linkedin.com/company/pwc,111372,379447
3972223,wells fargo,wellsfargo.com,,financial services,10001+,"san francisco, california, united states",united states,linkedin.com/company/wellsfargo,109532,264101
1454663,infosys,infosys.com,1981,information technology and services,10001+,"bangalore, karnataka, india",india,linkedin.com/company/infosys,104752,215718
3221953,deloitte,deloitte.com,1900,management consulting,10001+,"new york, new york, united states",united states,linkedin.com/company/deloitte,104112,329145
2994580,citi,citigroup.com,1812,financial services,10001+,"new york, new york, united states",united states,linkedin.com/company/citi,101482,298171
5372097,bank of america,bankofamerica.com,1968,banking,10001+,"charlotte, north carolina, united states",united
```

# EXAMPLE TASK




```
SELECT SUM(revenue)/
SUM(employees) FROM
us_tech_companies
```

On average what is the revenue per employee in the tech sector in the US?

# CLICKER: [HTTPS://CLICKER.MIT.EDU/6.S079/](https://clicker.mit.edu/6.S079/)

| Name | Address | #Employees | Revenue | Profit |
|---|---|---|---|---|
| Google | 1600 Amphitheatre Parkway, Mountain View, CA, 94043, USA | 60k | $89B | null |
| Apple | 1 Infinite Loop; Cupertino, CA 95014, USA | 66 | $215B | $45B |
| IBM | 1 New Orchard Rd; New York 10504, USA | 380k | $80B | $12B |
| International Business Machine | 10504; 1 New Orchard Rd | 380k | $-999B | $12B |
| Microsoft | Albuquerque, Mexico | 120k | $85B | $85B |
| Tableau | Seattle, Washington, United States | - | $0.9B | $1B |
| Tamr | 64 Church St, Cmabridge, MA 02138, United States | 20 | null | $-Y |

How many different **types** of errors can you find, which could influence our result (avg revenue per employee in the US )?

a) 1-2 error types
b) 3-4 error types
c) 5-6 error types

d) 7-8
e) over 8

# CLICKER: HTTPS://CLICKER.MIT.EDU/6.S079/

| Name | Address | #Employees | Revenue | Profit |
|---|---|---|---|---|
| Google | 1600 Amphitheatre Parkway, Mountain View, CA, 94043, USA | 60k | $89B | null |
| Apple | 1 Infinite Loop; Cupertino, CA 95014, USA | 66 | $215B | $45B |
| IBM | 1 New Orchard Rd; New York 10504, USA | 380k | $80B | $12B |
| International Business Machine | 10504; 1 New Orchard Rd | 380k | $-999B | $12B |
| Microsoft | Albuquerque, Mexico | 12[illegible]k | $85[illegible] | $85B |
| Tableau | Seattle, Washington, United States | - | $0.9B | $1B |
| Tamr | [illegible] United States | [illegible] | [illegible] | [illegible] |

Duplicate Entities
(Entity Resolution)

Pattern Violation

Outdated data / wrong data

Spelling mistakes / abbreviations

Encoding Error
(nb in thousands)

Rule Violations

Missing values
(known unknowns)

# MORE?

| Name | Address | #Employees | Revenue | Profit |
| --- | --- | --- | --- | --- |
| Google | 1600 Amphitheatre Parkway, Mountain View, CA, 94043, USA | 60k | $89B | null |
| Apple | 1 Infinite Loop; Cupertino, CA 95014, USA | 66 | $215B | $45B |
| IBM | 1 New Orchard Rd; New York 10504, USA | 380k | $80B | $12B |
| International Business Machine | 10504; 1 New Orchard Rd | 380k | $-999B | $12B |
| Microsoft | Albuquerque, Mexico | 120k | $85B | $85B |
| Tableau | Seattle, Washington, United States | - | $0.9B | $1B |
| Tamr | 64 Church St, Cmabridge, MA 02138, United States | 20 | null | $-Y |

Known Unknowns

# CLICKER: CLICKER.CSAIL.MIT.EDU/6.S080/

| Name | Address | #Employees | Revenue | Profit |
|---|---|---|---|---|
| Google | 1600 Amphitheatre Parkway, Mountain View, CA, 94043, USA | 60k | $89B | null |
| Apple | 1 Infinite Loop; Cupertino, CA 95014, USA | 66 | $215B | $45B |
| IBM | 1 New Orchard Rd; New York 10504, USA | 380k | $80B | $12B |
| International Business Machine | 10504; 1 New Orchard Rd | 380k | $-999B | $12B |
| Microsoft | Albuquerque, Mexico | 120k | $85B | $85B |
| Tableau | Seattle, Washington, United States | - | $0.9B | $1B |
| Tamr | 64 Church St, Cmabridge, MA 02138, United States | 20 | null | $-Y |
| **Amazon** | ?? | ?? | ?? | ?? |
| **Facebook** | ?? | ?? | ?? | ?? |
| ?? | ?? | ?? | ?? | ?? |
| ?? | ?? | ?? | ?? | ?? |

Unknown Unknowns

# OUTLINE

## Data Integration

- **Different schemas** →Schema matching
- **Duplicates** → Entity resolution
- **Contradicting data** → Data fusion

## Data Cleaning

- **Missing values** → Value imputation
- **Wrong data** → Outlier detection
- **Missing records** → Species estimation

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# WHY IS SCHEMA MATCHING HARD

SAP Community — Topics | Groups | Answers | Blogs | Events | Programs | Resources | What's New

Home › Community › Questions

Search Questions and Answers

Former Member
May 31, 2007 at 04:08

how many tal

3649 Views

hi experts,

pls tell no. of tables & t

Total tables in SAP

Add a Comment | Ale

0

Follow

RSS Feed

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2

Former Member
May 31, 2007 at 04:22 PM

in 4.6C version - 94,361 tables

Add a Comment | Alert Moderator | Share

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1

Former Member M
May 31, 2007 at 04:12 PM

<b>101,614</b> tables in SAP 46C...

You can look at DD02L for tables and TSTC for transaction codes...

Greetings,

Blag.

Add a Comment | Alert Moderator | Share

---

1

Former Member
May 31, 2007 at 04:14 PM

Hi

Very strange question...

In my system there're 105.382 tables DD02L and 60.263 transaction, but u can find out it by SE16 for table DD02L and TSTC.

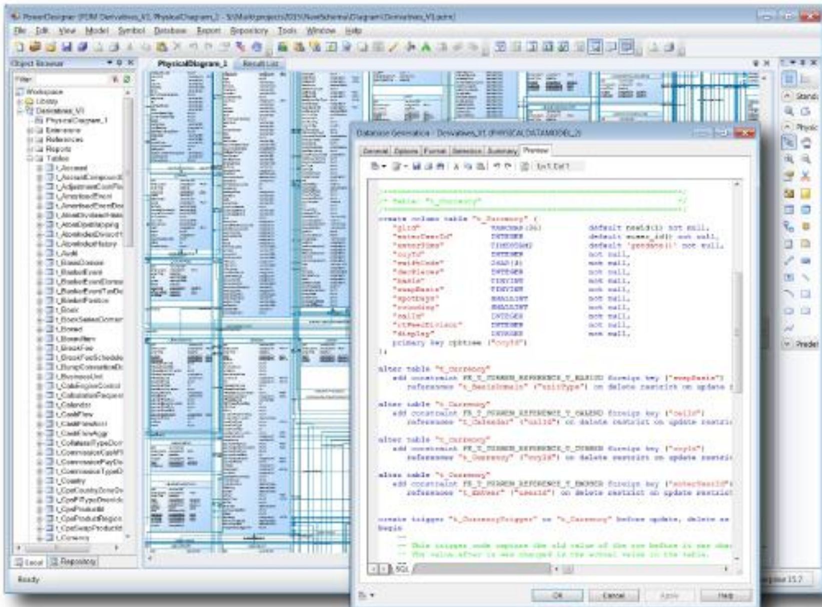
Every system'll have different number because there are different custom objects.

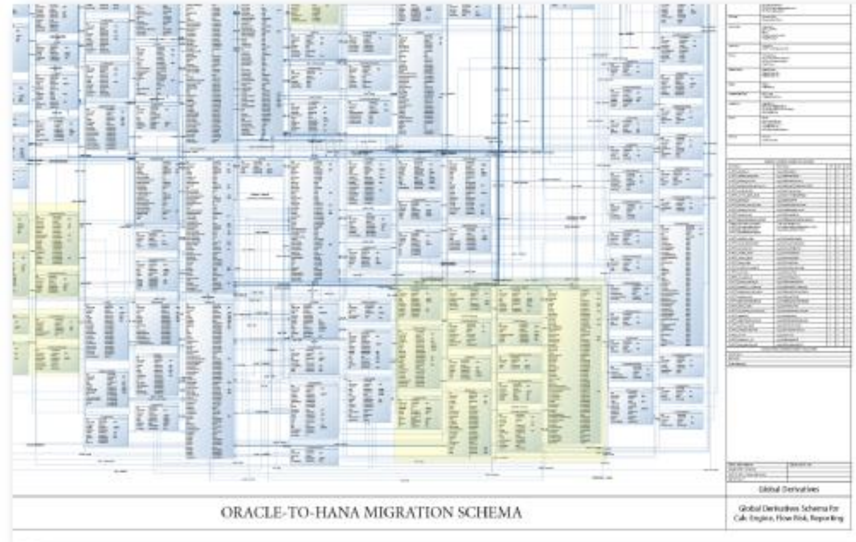
Max

Add a Comment | Alert Moderator | Share

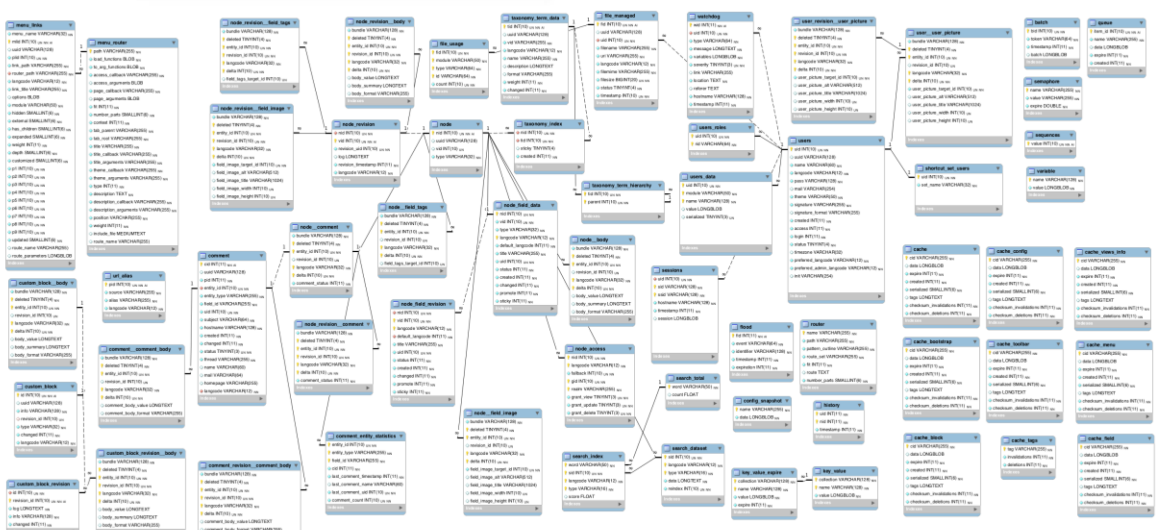
# SCHEMAS CAN BE REALLY COMPLICATED

SAP (very small fraction)






Drupal 8



# SCHEMA MATCHING

**Goal is to match columns from two tables, to produce a single table with the same schema**

**Complicated because people use different names for columns**

**Typical approach:  find columns with a similar name, the same data type, and high overlap in values**

**Measuring similarity and overlap are problems we will need to address in entity resolution as well …**

# DATA OFTEN HAS MANY CONSTRAINTS TOO

**Key, uniqueness, functional dependencies, foreign keys**

What do these terms mean?

**Students**

| ID# | Name | Phone | DOB |
|---|---|---|---|
| 500 | Matt | 555-4141 | 06/03/70 |
| 501 | Jenny | 867-5309 | 3/15/81 |
| 502 | Sean | 876-9123 | 10/31/82 |

| ID# | ClassID | Sem |
|---|---|---|
| 500 | 1001 | Fall02 |
| 501 | 1002 | Fall02 |
| 501 | 1002 | Spr03 |
| 502 | 1003 | S203 |

**Takes_Course**

| ClassID | Title | ClassNum |
|---|---|---|
| 1001 | Intro to Informatics | I101 |
| 1002 | Data Mining | I400 |
| 1003 | Internet and Society | I400 |

**Courses**

# DATA OFTEN HAS MANY CONSTRAINTS TOO

**value range, format, etc.**

Students

| ID# | Name | Phone | DOB |
| --- | --- | --- | --- |
| 500 | Matt | 555-4141 | 06/03/70 |
| 501 | Jenny | 867-5309 | 3/15/81 |
| 502 | Sean | 876-9123 | 10/31/82 |

| ID# | ClassID | Sem |
| --- | --- | --- |
| 500 | 1001 | Fall02 |
| 501 | 1002 | Fall02 |
| 501 | 1002 | Spr03 |
| 502 | 1003 | S203 |

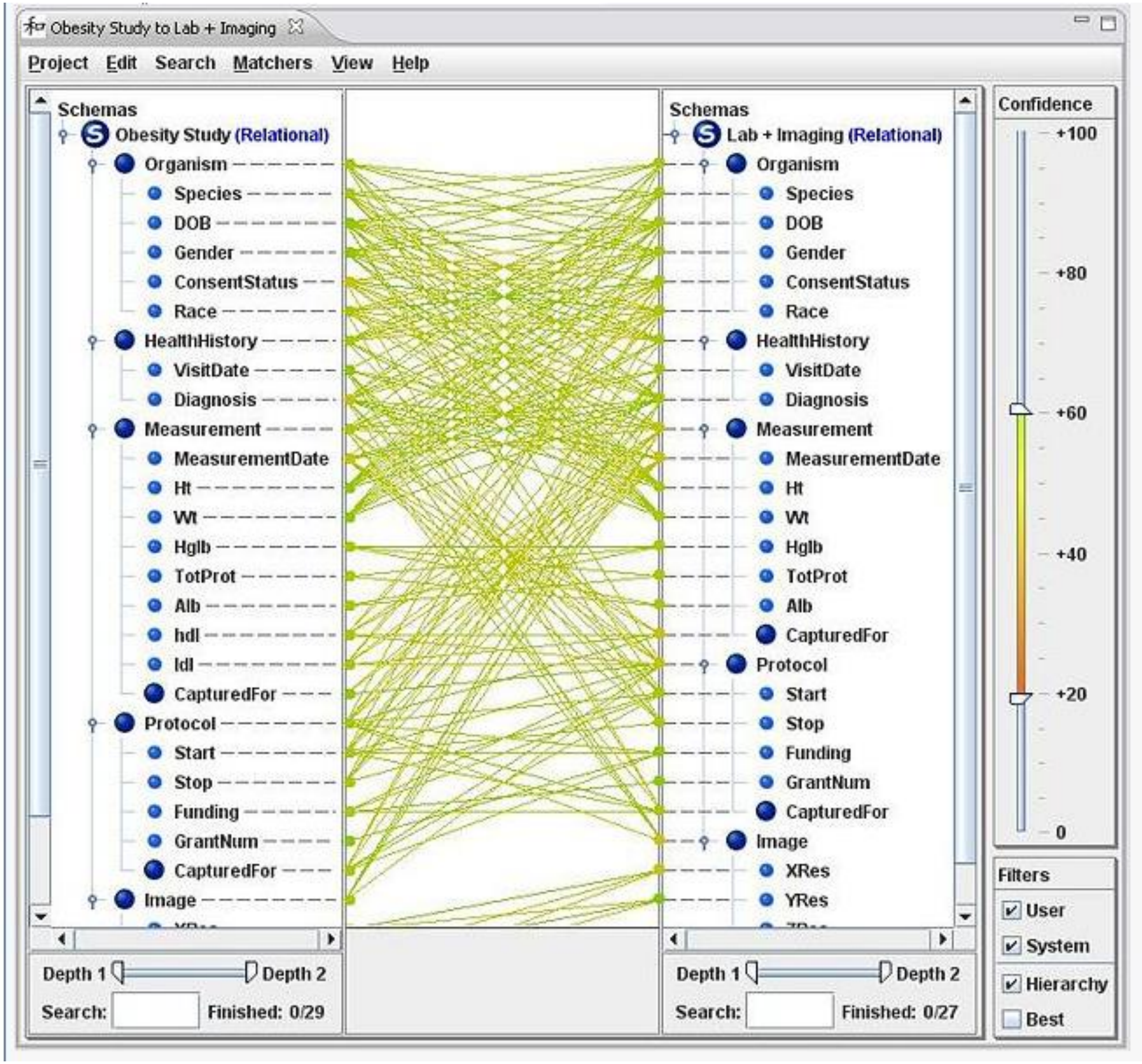
Takes_Course

| ClassID | Title | ClassNum |
| --- | --- | --- |
| 1001 | Intro to Informatics | I101 |
| 1002 | Data Mining | I400 |
| 1003 | Internet and Society | I400 |

Courses

http://openii.sourceforge.net/

# HARMONY

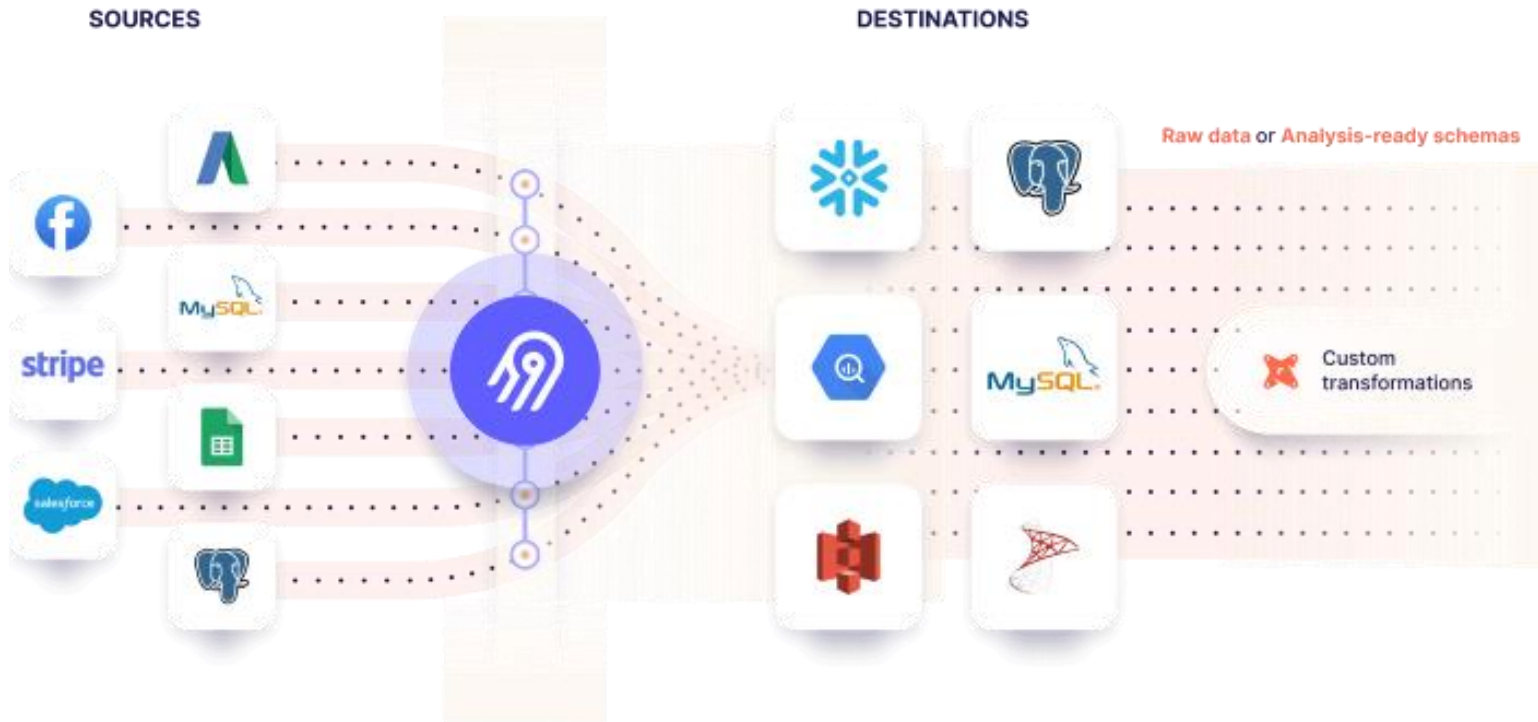


# EVERY COMPANY HAS TO DEAL WITH IT

salesforce
Google Ads
amazon advertising
cart.com
SAP
HubSpot
Marketo
okta
stripe
....

amazon REDSHIFT
snowflake
Google Big Query
Azure Synapse Analytics
....

# DATA INTEGRATION OPEN-SOURCE/STARTUPS




Airbyte

Fivetran

# OUTLINE

## Data Integration

- **Different schemas** →Schema matching
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## Data Cleaning

- **Missing values** → Value imputation
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# ENTITY RESOLUTION

"[The] problem of identifying and linking/grouping different manifestations of the same real world object."

**Challenges**

- Fundamental ambiguity
- Diversity in representations (format, truncation, ambiguity)
- Errors
- Missing data
- Records from different times
- Relationships in addition to equality

# TEXT SIMILARITY

## Customer

| Id | Name | Street | City | State | P-Code | Age |
|---|---|---|---|---|---|---|
| 1 | J Smith | 123 University Ave | Seattle | Washington | 98106 | 42 |
| 2 | Mary Jones | 245 3rd St | Redmond | WA | 98052-1234 | 30 |
| 3 | Bob Wilson | 345 Broadway | Seattle | Washington | 98101 | 19 |
| 4 | M Jones | 245 Third Street | Redmond | NULL | 98052 | 299 |
| 5 | Robert Wilson | 345 Broadway St | Seattle | WA | 98101 | 19 |
| 6 | James Smith | 123 Univ Ave | Seatle | WA | NULL | 41 |
| 7 | J Widom | 123 University Ave | Palo Alto | CA | 94305 | NULL |
| … | … | … | … | … | … | … |

# TEXTUAL SIMILARITY

**String Similarity function:**

- $Sim(string, string) \rightarrow numeric\ value$

**A “good” similarity function:**

- Strings representing the same concept ⇒ high similarity
- Strings representing different concepts ⇒ low similarity

# EDIT DISTANCE

**EditDistance(s1, s2):**

- Minimum number of edits to transform s1 to s2

**Edit:**

- Insert a character
- Delete a character
- Substitute a character

**Note: EditDistance(s1, s2) = EditDstance(s2, s1)**

# EDIT DISTANCE

**EditDistance ("Provdince", "Providence") = 2**

Provdince → Providence → Providence

**EditDistance("Seattle", "Redmond") = 6**

Seattle → Reattle → Redttle →

Redmtle → Redmole → Redmone →

→ Redmond

# EDIT DISTANCE PROBLEMS

**115$^{th}$ Waterman St., Providence, RI**

EditDistance = 1

**110$^{th}$ Waterman St., Providence, RI**

**Waterman Street, Providence, RI**

EditDistance = 4

**Waterman St, Providence, RI**

**Character Level vs. Word Level Similarity?**

# EDIT DISTANCE PROBLEMS

148th Ave NE, Redmond, WA

$\updownarrow$ EditDist = 0

148th Ave NE, Redmond, WA

148th Ave NE, Redmond, WA

$\updownarrow$ EditDist = 4

NE 148th Ave, Redmond, WA

Order sensitive Similarity?

# JACCARD SIMILARITY

- **Statistical measure**
- **Originally defined over sets**
- **String = set of words**

$$Jaccard(s1, s2) = \frac{|s1 \cap s2|}{|s1 \cup s2|}$$

- **Range of values = [0,1]**

# JACCARD SIMILARITY

148th Ave NE, Redmond, WA

$\updownarrow$

140th Ave NE, Redmond, WA

$$Jaccard = \frac{4}{4 + 2} \approx 0.66$$

# JACCARD SIMILARITY

148th Ave NE, Redmond, WA

NE 148th Ave, Redmond, WA

$$Jaccard = \frac{5}{5} = 1.0$$

# CLICKER

**What is the Jaccard Similarity between:**

iPad Two 16GB WiFi White

iPad 2nd generation 16GB Wifi White

(a) 3 / 8
(b) 4 / 11
(c) 4 / 7

# CLICKER:
# WHICH JACCARD SIMILARITY IS WRONG

A)

Microsoft Corporation

↕ Jaccard = 1/3

Microsoft Corp

B)

Microsoft Corporation

↕ Jaccard = 1/3

Oracle Corporation

C)

Waterman 115 St

↕ Jaccard = 1/4

115 Waterman Street

# WHAT CAN WE DO ABOUT?

Microsoft Corporation

↕

Microsoft Corp

Microsoft Corporation

↕

Oracle Corporation

# JACCARD SIMILARITY

$$Weight\ Function = \ wt: Elements \rightarrow \ \mathbb{R}^+$$

$$\boxed{WtJaccard(s1, s2) = \frac{wt(s1\ \cap s2)}{wt(s1\ \cup s2)}}$$

$$wt(s) = \sum_{e\ \in s} wt(e)$$

wt("Microsoft") > wt("Corporation")

Wt("Oracle") > wt("Corporation")

# IDF WEIGHTED

- IDF: Inverse Document Frequency

$$wt(word) = \log_e\left(\frac{size\ of\ corpus}{frequency(word)}\right)$$

- frequency(word) = defined using some “corpus”:
  - large table of records
  - Wikipedia?

# IDF WEIGHTED JACCARD

**Microsoft Corporation**

WtJaccard = 12.21 / ( 12.21 + 4.21 + 4.38)

= 12.21/20.8 = 0.59

**Microsoft Corp**

**Microsoft Corporation**

WtJaccard = 4.21/26.57 = 0.16

**Oracle Corporation**

$$\log_e\left(\frac{1{,}000{,}000}{5}\right)$$

| Word | Freq | IDF |
|---|---|---|
| Microsoft | 5 | 12.21 |
| Oracle | 39 | 10.15 |
| Corporation | 14782 | 4.21 |
| Corp | 12496 | 4.38 |

Corpus size = 1M records

# OTHER SIMILARITY FUNCTIONS

- Affine edit distance
- Cosine similarity
- Hamming distance
- Generalized edit distance
- Jaro distance
- Monge-Elkan distance
- Q-gram
- Smith-Warerman distance
- Soundex distance
- TF/IDF
- …many more

- No universally good similarity function
- Choice of similarity function depends on domains of interest, data instances, etc.

# RECORD MATCHING PROBLEMS

## Customer

| Id | Name | Street | City | State | P-Code | Age |
|---|---|---|---|---|---|---|
| 1 | J Smith | 123 University Ave | Seattle | Washington | 98106 | 42 |
| 2 | Mary Jones | 245 3rd St | Redmond | WA | 98052-1234 | 30 |
| 3 | Bob Wilson | 345 Broadway | Seattle | Washington | 98101 | 19 |
| 4 | M Jones | 245 Third Street | Redmond | NULL | 98052 | 299 |
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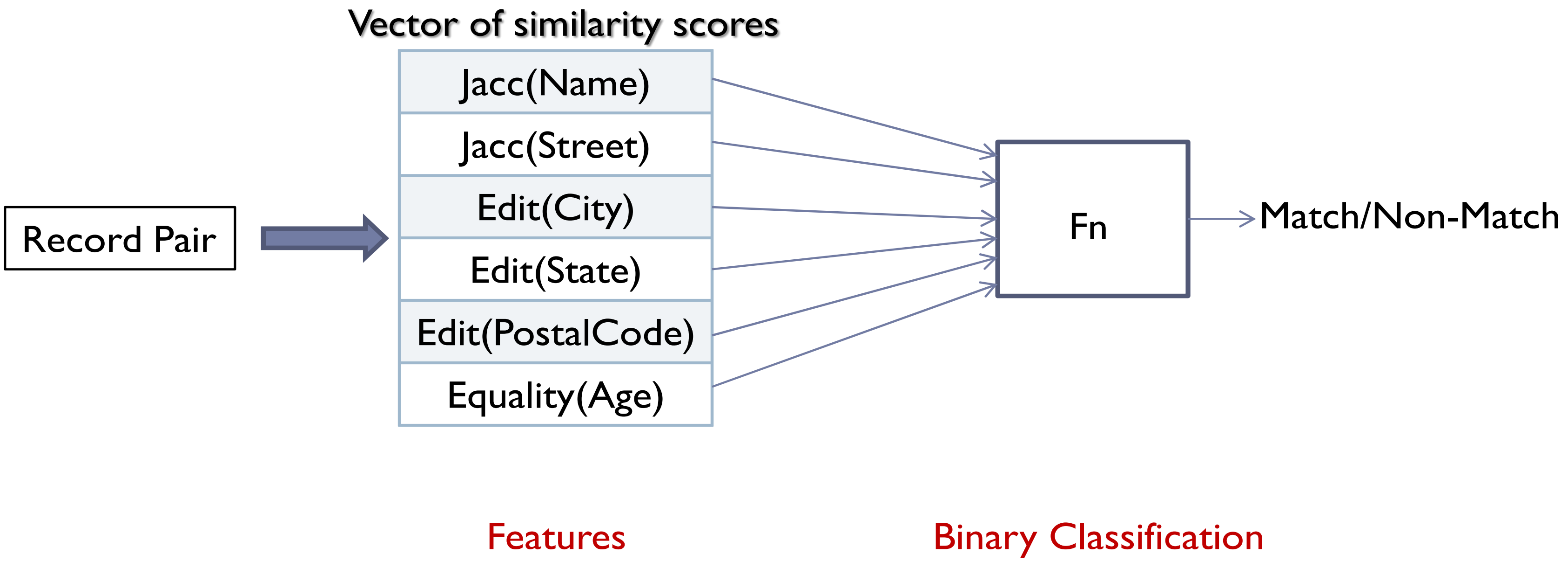
| 6 | James Smith | 123 Univ Ave | Seatle | WA | NULL | 41 |
| 7 | J Widom | 123 University Ave | Palo Alto | CA | 94305 | NULL |
| … | … | … | … | … | … | … |

*Wt c ca ∂l =r* 0.57 0.9l*a* 1.0 0.0 1.0 1.0

# COMBINING SIMILARITY FUNCTIONS



# LEARNING-BASED APPROACH

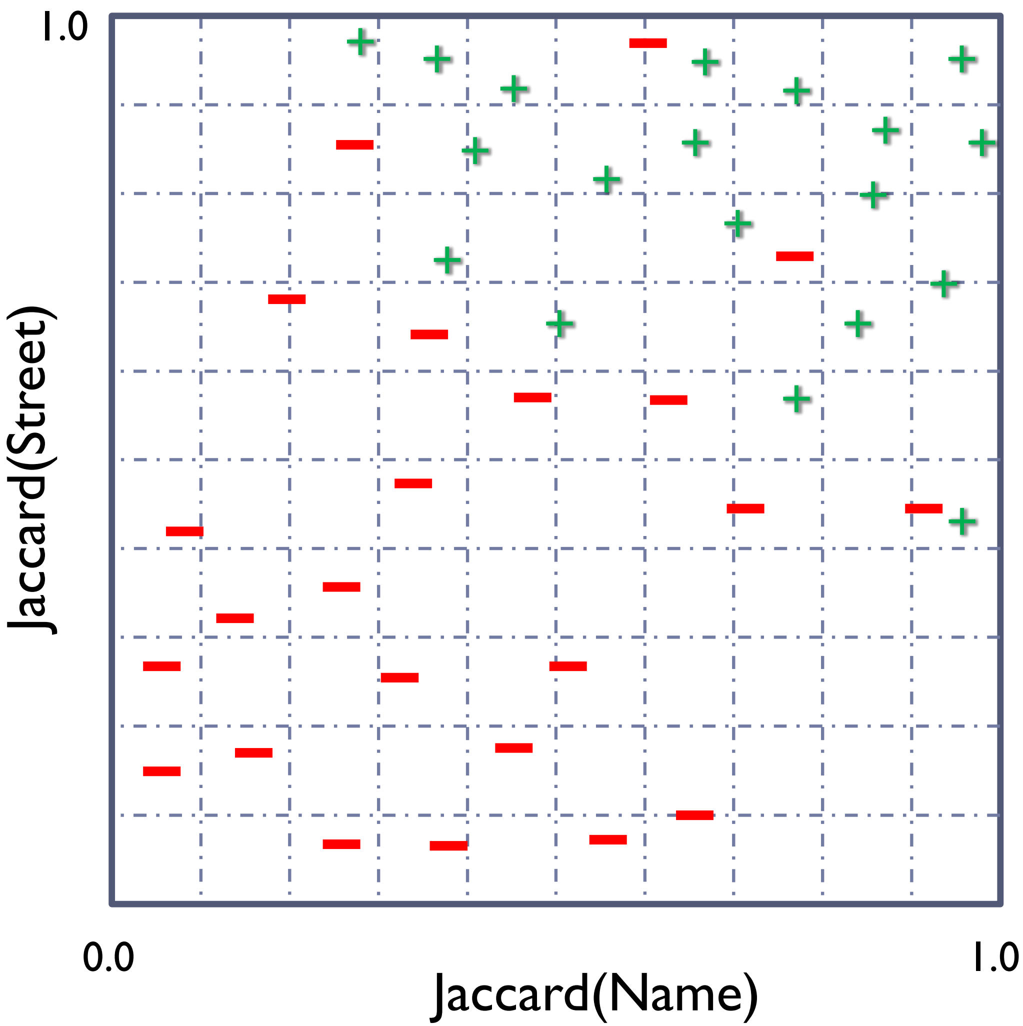
| | | | | | | |
|---|---|---|---|---|---|---|
| Bob Wilson | 345 Broadway | Seattle | Washington | 98101 | 19 | Match |
| Robert Wilson | 345 Broadway St | Seattle | WA | 98101 | 19 | |

| | | | | | | |
|---|---|---|---|---|---|---|
| B Wilson | 123 Broadway | Boise | Idaho | 83712 | 19 | Non-Match |
| Robert Wilson | 345 Broadway St | Seattle | WA | 98101 | 19 | |

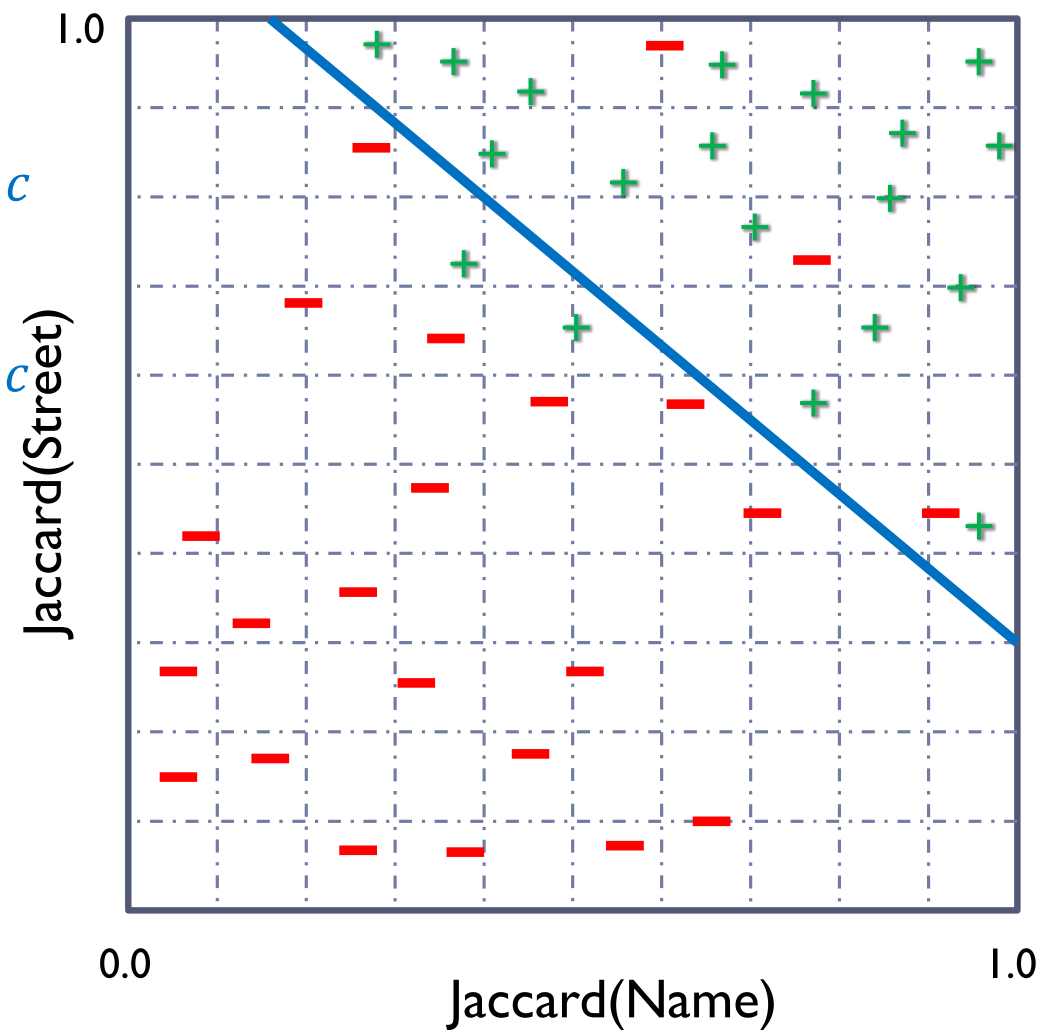
| | | | | | | |
|---|---|---|---|---|---|---|
| Mary Jones | 245 3rd St | Redmond | WA | 98052-1234 | 30 | Match |
| M Jones | 245 Third Street | Redmond | NULL | 98052 | 299 | |

| | | | | | | |
|---|---|---|---|---|---|---|
| Mary Jones | 245 3rd St | Redmond | WA | 98052-1234 | 30 | Non-Match |
| Robert Wilson | 345 Broadway St | Seattle | WA | 98101 | 19 | |

# LEARNING BASED APPROACH



# LEARNING BASED APPROACH




$0.73\ Ja\ (Name)$

$+$

$0.89\ Ja\ (Street) \geq 1$

# OUTLINE

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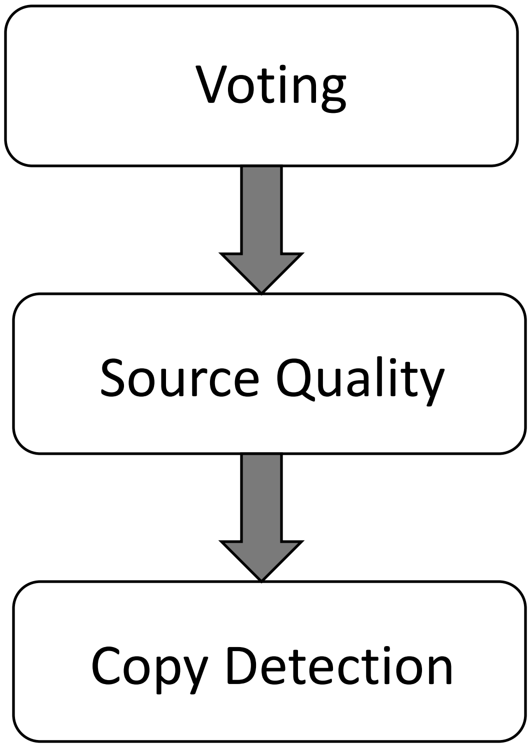
- **Missing records** → Species estimation

# DATA FUSION'S THREE COMPONENS

**Data fusion: voting + source quality + copy detection**

- Resolves inconsistency across diversity of sources




| | **S1** | **S2** | **S3** | **S4** | **S5** |
|---|---|---|---|---|---|
| Jagadish | UM | ATT | UM | UM | UI |
| Dewitt | MSR | MSR | UW | UW | UW |
| Bernstein | MSR | MSR | MSR | MSR | MSR |
| Carey | UCI | ATT | BEA | BEA | BEA |
| Franklin | UCB | UCB | UMD | UMD | UMD |

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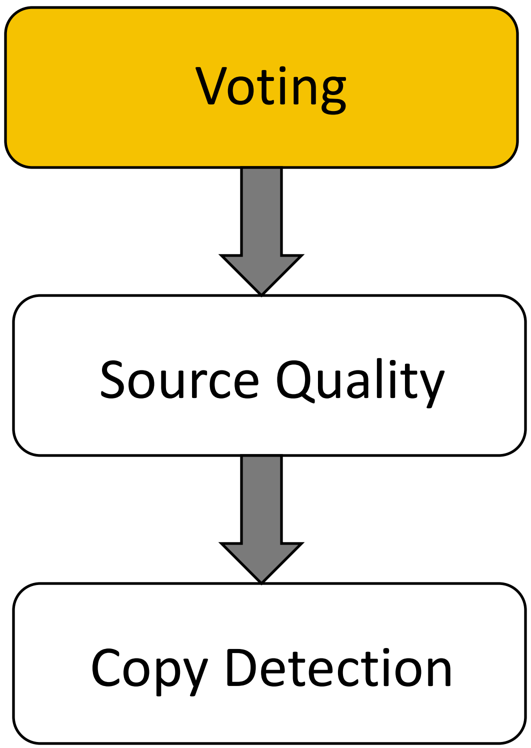


| | S1 | S2 | S3 |
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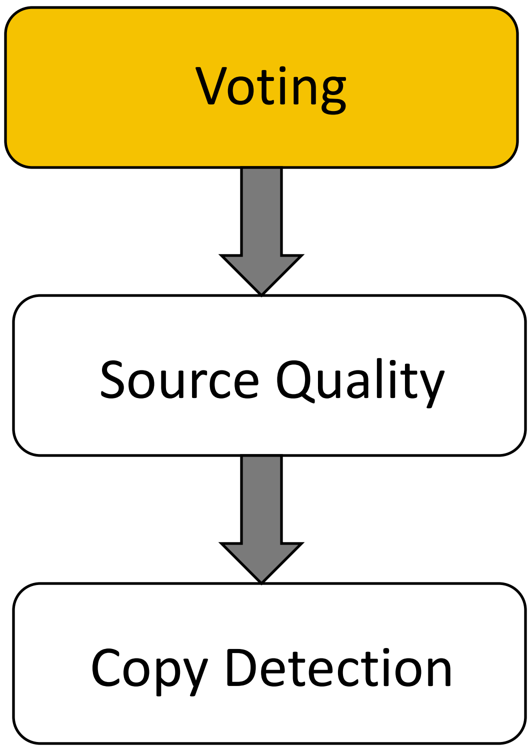
| Franklin | UCB | UCB | UMD |

# DATA FUSION'S THREE COMPONENS

**Data fusion: voting + source quality + copy detection**

- Supports difference of opinion

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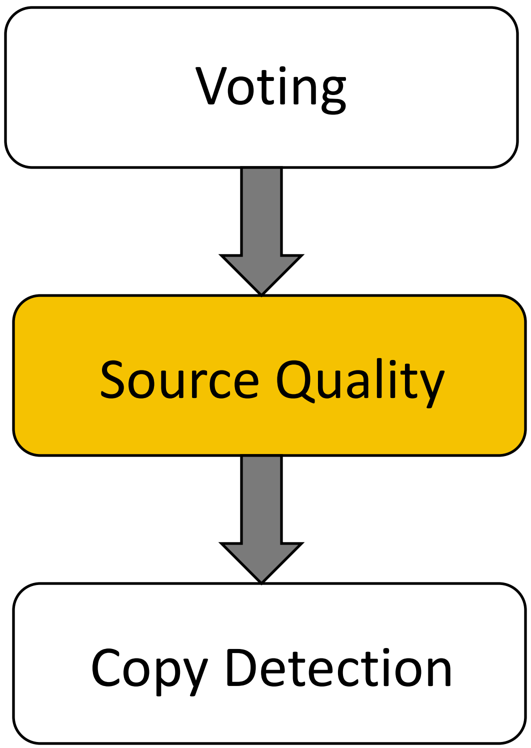
**Data fusion: voting + source quality + copy detection**

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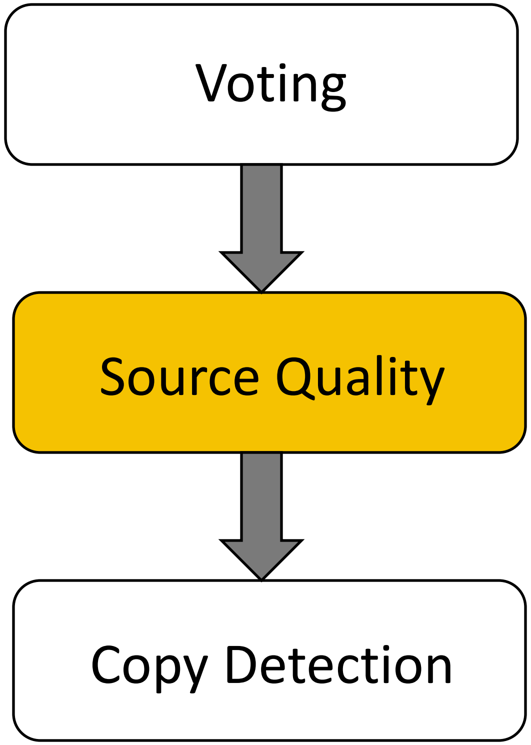
# DATA FUSION'S THREE COMPONENS

**Data fusion: voting + source quality + copy detection**

- Gives more weight to knowledgeable sources




| | S1 | S2 | S3 |
|---|---|---|---|
| Jagadish | UM | ATT | UM |
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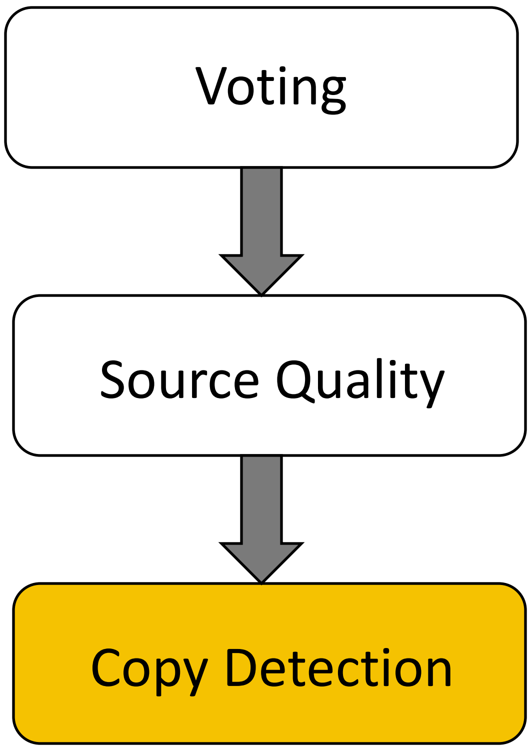
# DATA FUSION'S THREE COMPONENTS

**Data fusion: voting + source quality + copy detection**

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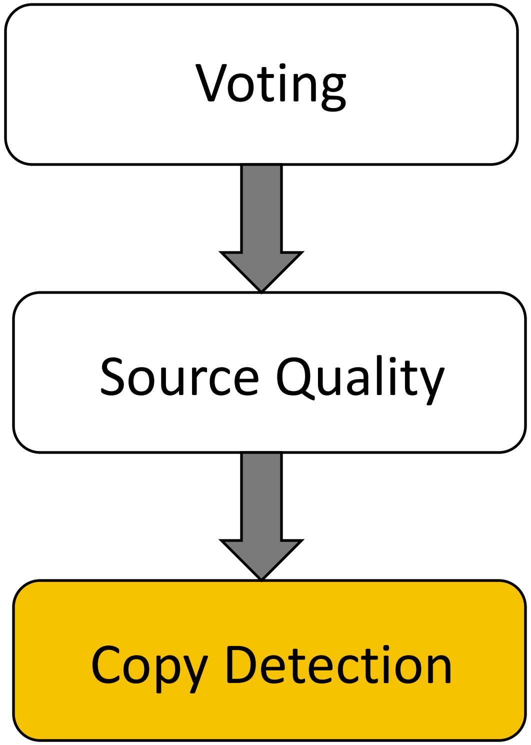
| Carey | UCI | ATT | BEA | BEA | BEA |
| Franklin | UCB | UCB | UMD | UMD | UMD |

# DATA FUSION'S THREE COMPONENTS

**Data fusion: voting + source quality + copy detection**

- Reduces weight of copier sources




| | S1 | S2 | S3 | ~~S4~~ | ~~S5~~ |
|---|---|---|---|---|---|
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| Dewitt | MSR | MSR | UW | ~~UW~~ | ~~UW~~ |
| Bernstein | MSR | MSR | MSR | ~~MSR~~ | ~~MSR~~ |
| Carey | UCI | ATT | BEA | ~~BEA~~ | ~~BEA~~ |
| Franklin | UCB | UCB | UMD | ~~UMD~~ | ~~UMD~~ |

# OUTLINE

## Data Integration

- **Different schemas** →Schema matching
- **Duplicates** → Entity resolution
- **Contradicting data** → data fusion

## Data Cleaning

- **Missing values** → Value imputation
- **Wrong data** → Outlier detection
- **Missing records** → Species estimation

# WHY ARE THE VALUES MISSING?

- **Missing Completely at Random (MCAR)**
  - Includes missing by design. For example: Survey randomly selects questions to reduce load

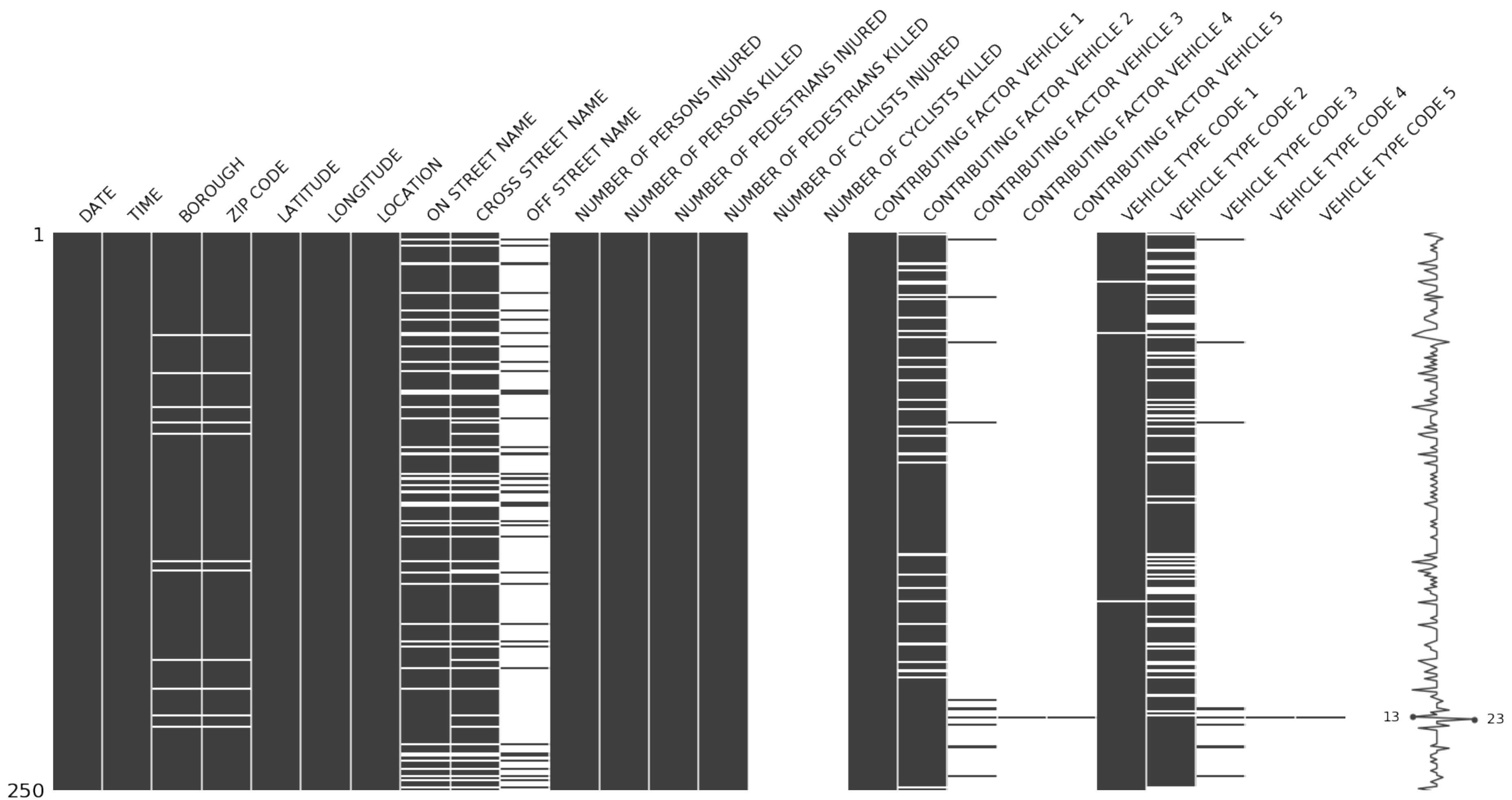
- **Missing at Random  (MAR)**
  - Better name:  Missing Conditionally at Random
  - Systematic relationship between the propensity of missing values and the *observed* data, but *not* the missing data.
    --> if we can control for this conditional variable, we can get a random subset.

- **Missing Not at Random, MNAR**
  - Relationship between the propensity of a value to be missing and its values.
  - Lowest education are missing on education or the sickest people are most likely to drop out of the study.
  - MNAR is called “non-ignorable” because the missing data mechanism itself has to be modeled as you deal with the missing data.

**Note:** null values are often encoded in various ways. Be aware of it!
Null, “null”, n/a, “”, 0, “empty”, 99999, 200.

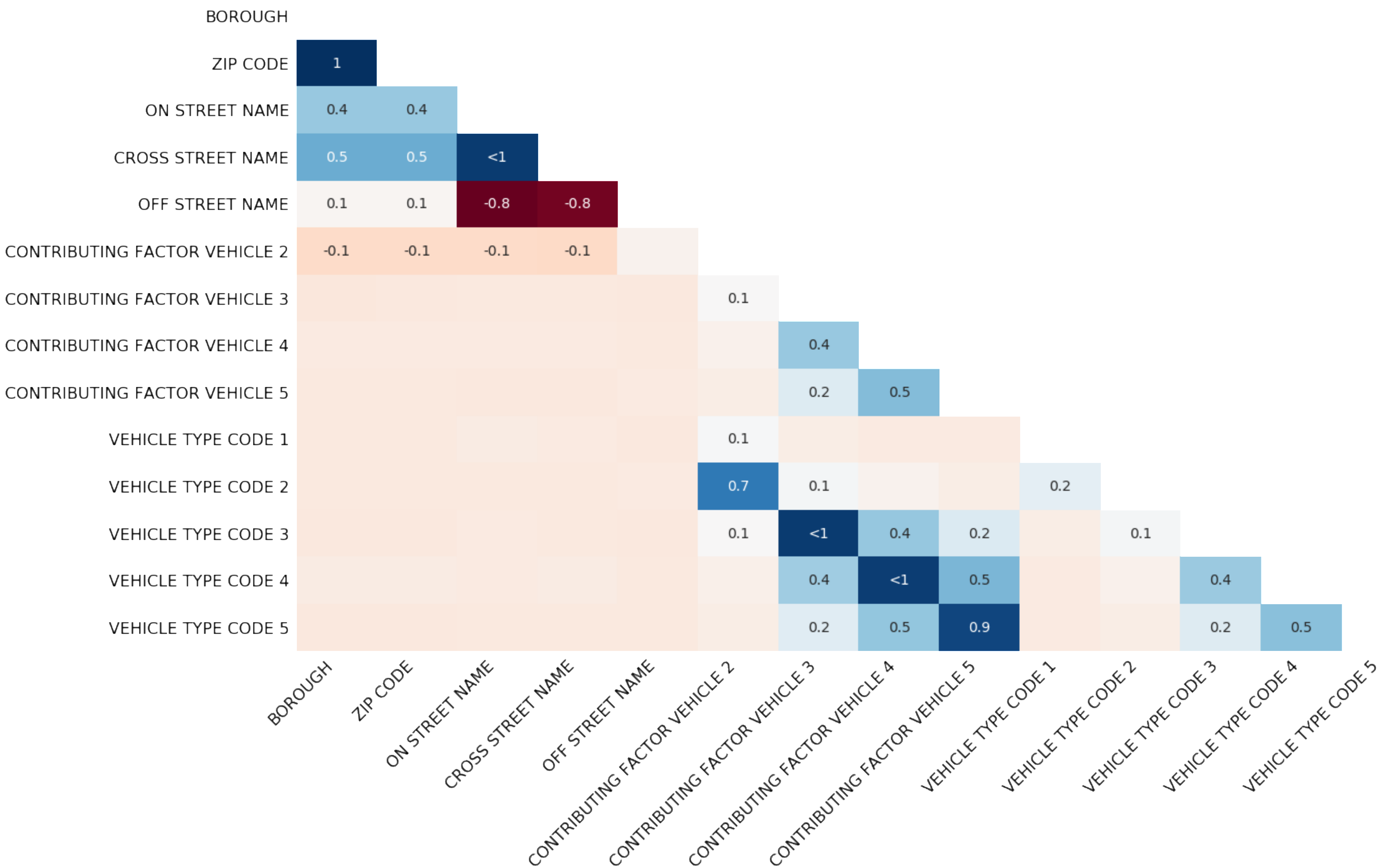
# HOW DO YOU START ADDRESSING MISSING VALUES?

# VISUALIZATIONS TO DETECT BIAS




A lot of tips here: https://github.com/ResidentMario/missingno

# VISUALIZATIONS TO DETECT BIAS

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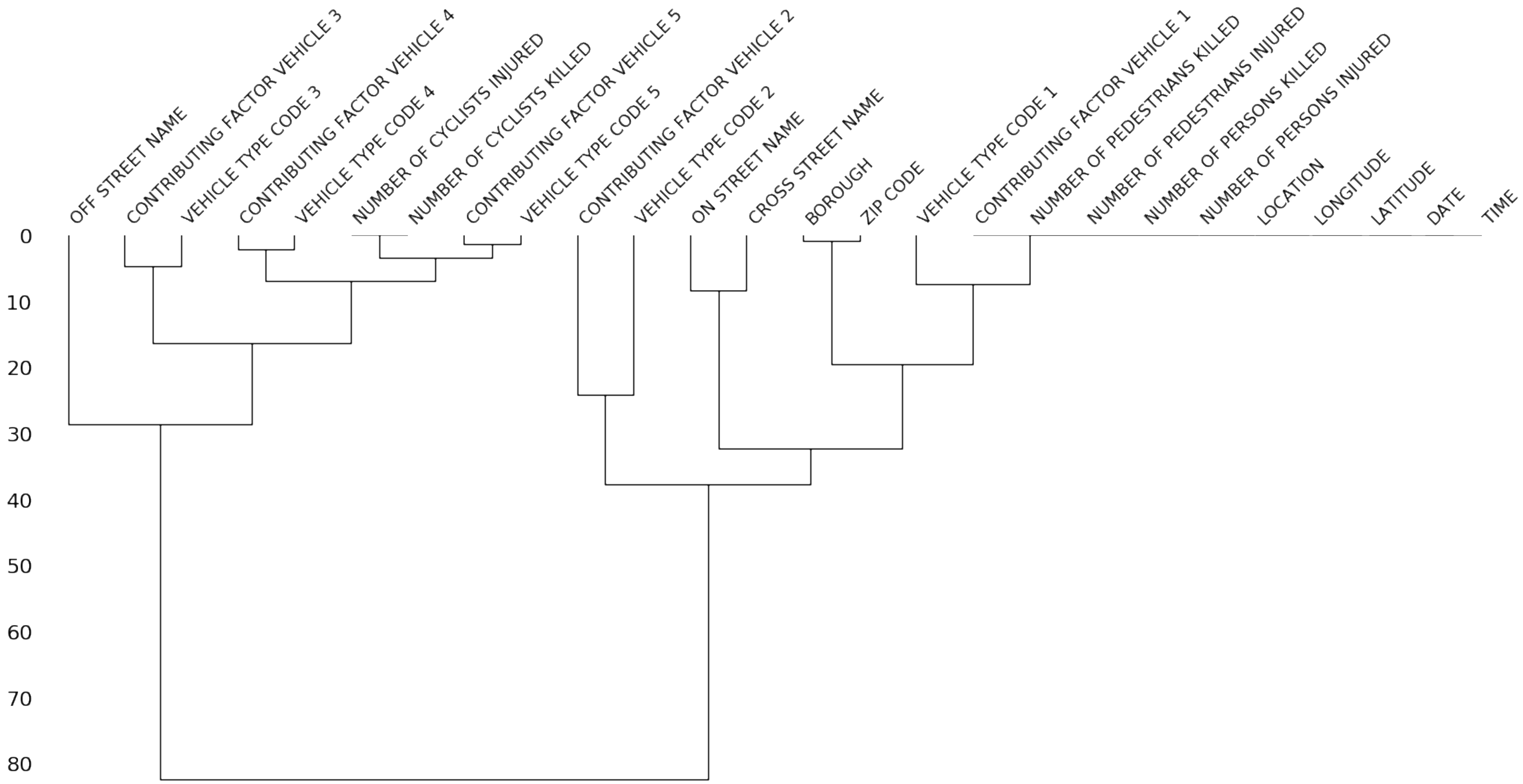
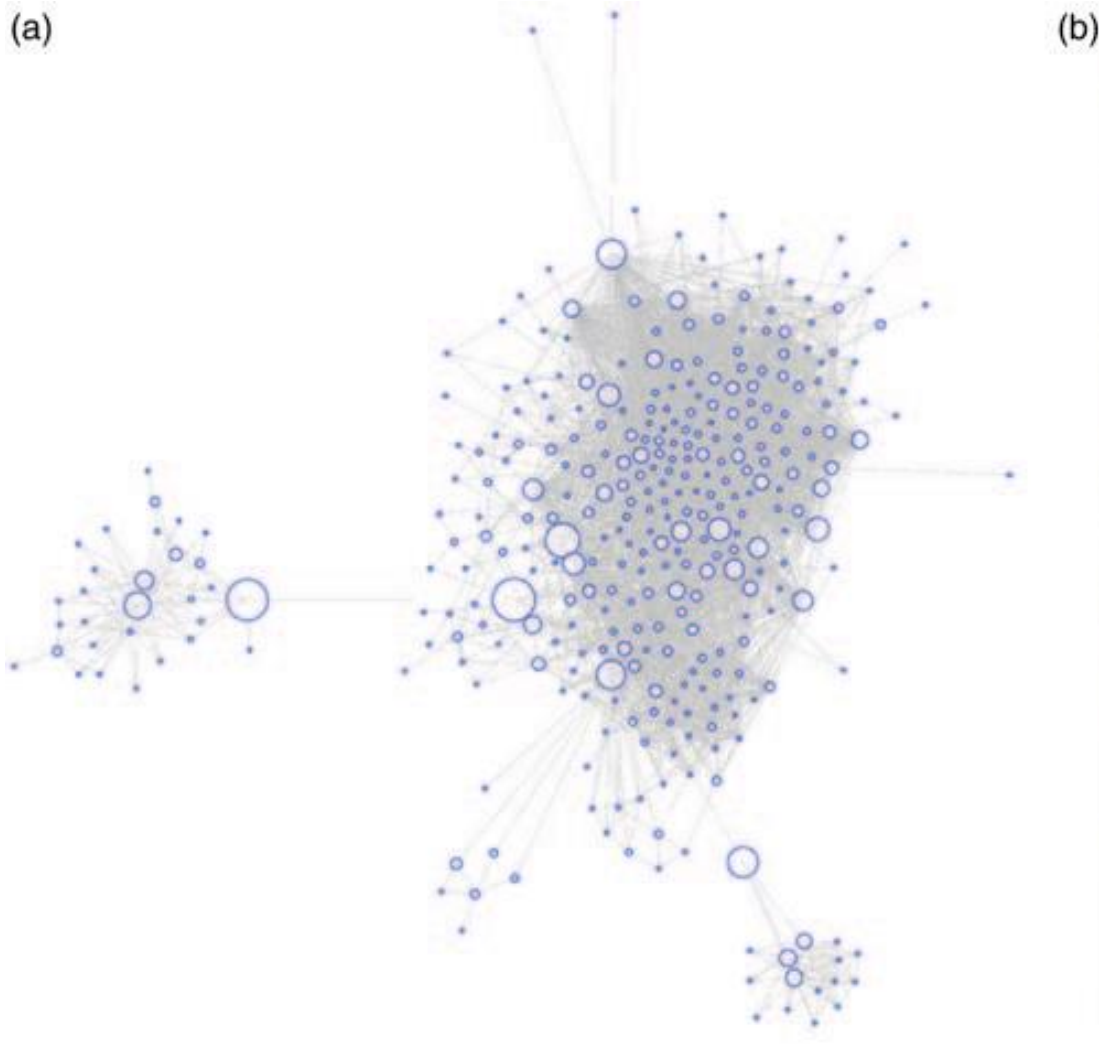
# VISUALIZATIONS TO DETECT BIAS



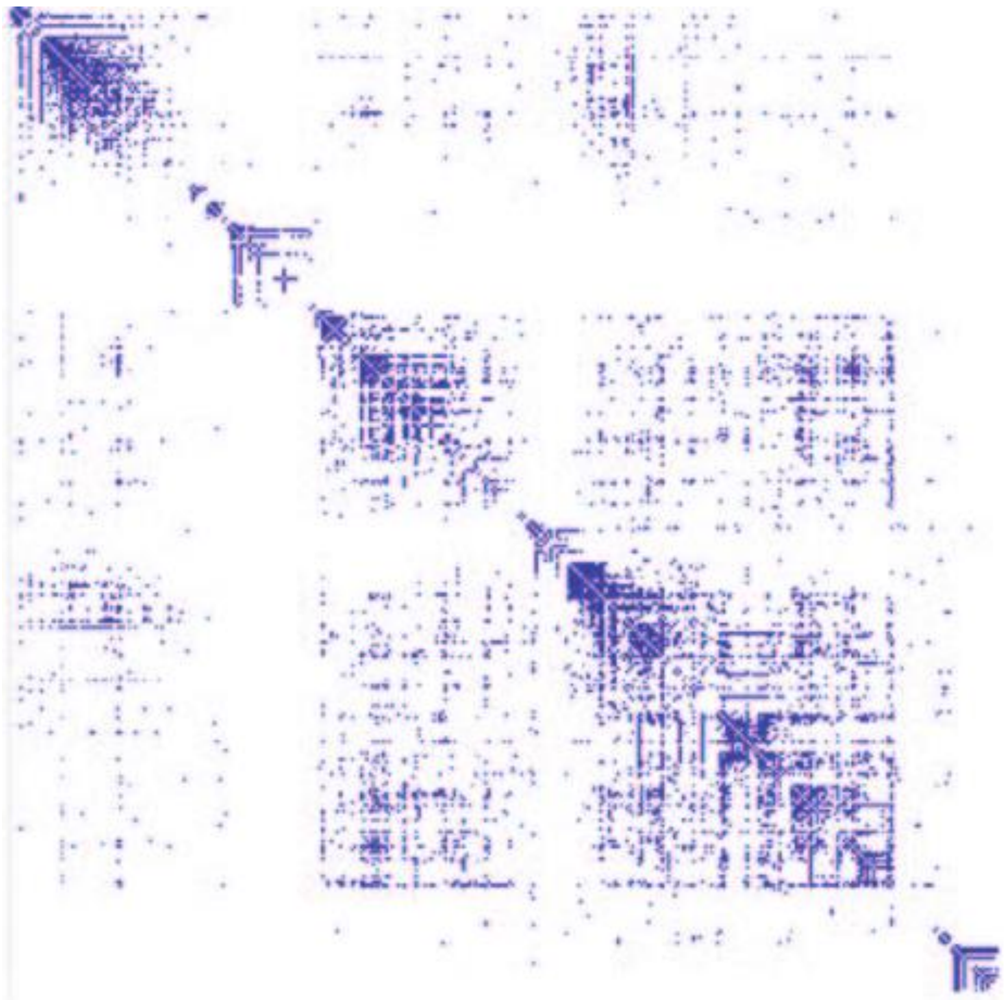

Alternative: Frequent pattern mining

# FACEBOOK SOCIAL GRAPH: VISUALIZATION THE NODE-LINK DIAGRAM



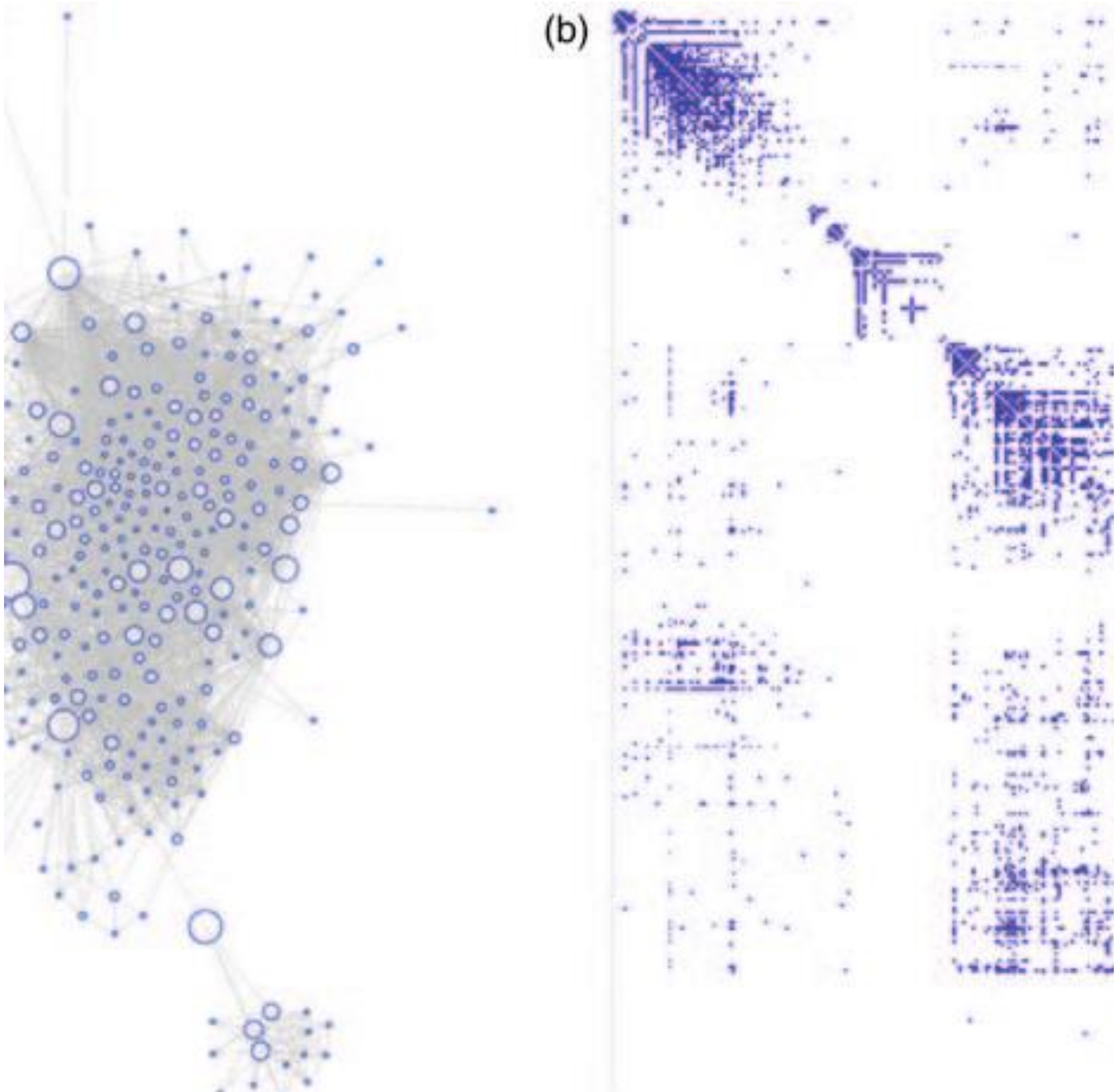

[Sean Kandel et al: Research directions in data wrangling: Visualizations and transformations for usable and credible data, Information Visualization, 2011]

# FACEBOOK SOCIAL GRAPH: VISUALIZATION THE NODE-LINK DIAGRAM



[Sean Kandel et al: Research directions in data wrangling: Visualizations and transformations for usable and credible data, Information Visualization, 2011]

# FACEBOOK SOCIAL GRAPH: SORTING BY RAW DATA




[Sean Kandel et al: Research directions in data wrangling: Visualizations and transformations for usable and credible data, Information Visualization, 2011]

**CLASS TASK:**

COME UP WITH AT LEAST 5 TECHNIQUES TO DEAL WITH MISSING VALUES

# TECHNIQUES TO DEAL WITH MISSING VALUES (ONLY FOR MCAR / MAR)

- Pairwise (rarely used)
- Listwise deletion (better)
- Mean Substitution
- Dummy variable adjustment
- Maximum Likelihood Estimation
- Random sample from existing values/ reasonable distribution
- Multiple Imputation

Special cases:

- Last Observation
- Techniques for categorical values

# PAIRWISE AND LISTWISE DELETION

```
SELECT SUM(revenue)/
SUM(employees) FROM
us_tech_companies
```

## Pairwise Deletion

| Name | Address | #Employees | Revenue | Profit |
|---|---|---|---|---|
| Google | 1600 Amphitheatre Parkway, Mountain View, CA, 94043, USA | 60k | $89B | |
| Apple | 1 Infinite Loop; Cupertino, CA 95014, USA | 66 | $215B | $45B |
| IBM | 1 New Orchard Rd; 10504, USA | 380k | $80B | $12B |
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| ~~Tableau~~ | ~~Seattle, Washington, United States~~ | | ~~$5M~~ | ~~$8M~~ |
| ~~Tamr~~ | ~~64 Church St, Cambridge, MA 02138, USA~~ | ~~20~~ | ~~$-X~~ | ~~$-Y~~ |

# PAIRWISE AND LISTWISE DELETION

```
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## Listwise Deletion

| Name | Address | #Employees | Revenue | Profit |
|---|---|---|---|---|
| ~~Google~~ | ~~1600 Amphitheatre Parkway, Mountain View, CA, 94043, USA~~ | ~~60k~~ | ~~$89B~~ | |
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# PAIRWISE AND LISTWISE DELETION

**Pairwise Deletion**

- Only cases relating to each pair of variables with missing data involved in an analysis are deleted.
- Advantage: keeps as many cases as possible for each analysis, uses all information possible with each analysis
- Disadvantage: cannot compare analyses because sample is different each time, sample size vary for each parameter estimation, can obtain nonsense results

**Listwise Deletion**

- Only analyze cases with available data on each variable
- Advantage: simplicity and comparability across analyses
- Disadvantage: reduces statistical power (reduced sample size), not use all information, estimates may be biased if data not MCAR

# FIRST INITIAL CLEANING

**Look for fields with very high percentage of missing fields**

- It may be necessary to exclude field and use an alternative

**Look for records with a high percentage of missing fields**

- Consider excluding the case
- For example, someone who has started inputting a survey and given up after two questions!

**Document that you did delete them. Very risky to forget it**

# UNIVARIATE SINGLE IMPUTATION

## MEAN SUBSTITUTION

**Mean Substitution**

- Replace missing value with the sample mean or mode. Then, run analyses as if all complete cases

# UNIVARIATE SINGLE IMPUTATION
## MEAN SUBSTITUTION

**Mean Substitution (do not use)**

- Replace missing value with the sample mean or mode. Then, run analyses as if all complete cases
- Advantage: We can use complete case analyses
- Disadvantage: Reduces variability, weakens the correlation estimates because it ignores the relationship between variables, it creates artificial band
- Unless the proportion of missing data is low, do not use this method.
- Inappropriate for categorical variables.

**Dummy variable adjustment**

- Create an indicator variable for missing value (1 for missing, 0 for observed), impute missing value to a constant (such as mean)

https://scikit-learn.org/stable/modules/impute.html

# MULTIVARIATE SINGLE IMPUTATION

**Regression imputation**

- Replace missing values with predicted score from regression equation. Use complete cases to regress the variable with incomplete data on the other complete variables.

https://scikit-learn.org/stable/modules/impute.html

# MULTIVARIATE IMPUTATION

**Regression imputation**

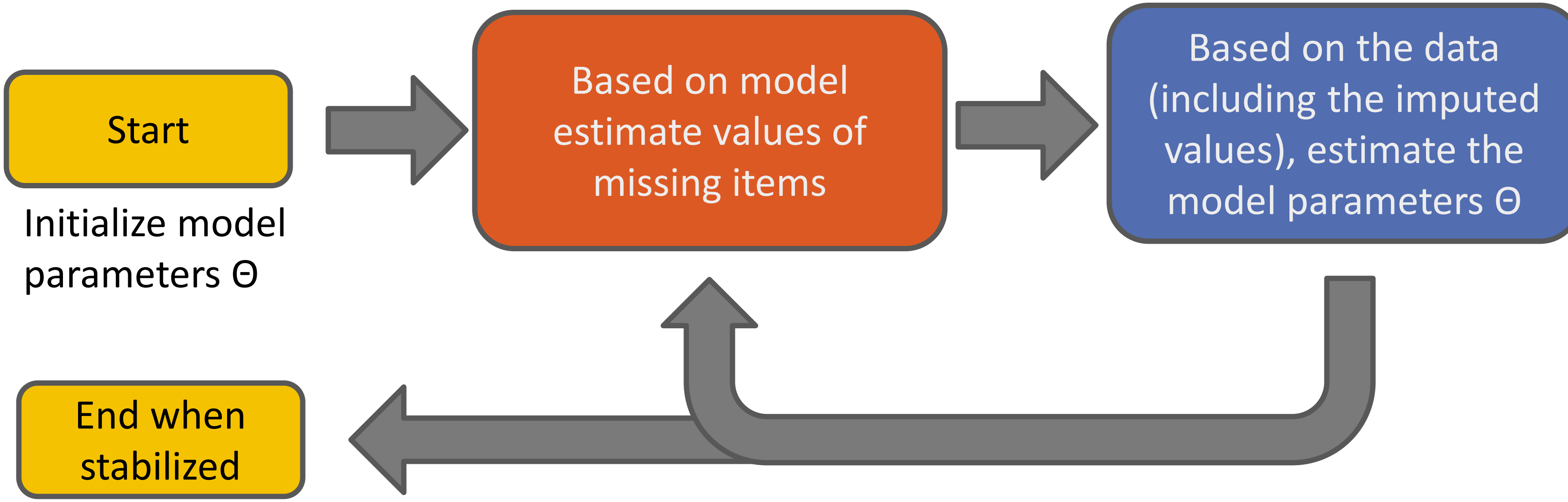
- Replace missing values with predicted score from regression equation. Use complete cases to regress the variable with incomplete data on the other complete variables.
- Advantage: Uses information from the observed data, gives better results than previous ones
- Disadvantage: over-estimates model fit and correlation estimates, weakens variance

**Maximum Likelihood Estimation (MICE)**

- Identifies the set of parameter values that produces the highest log-likelihood.
- ML estimate: value that is most likely to have resulted in the observed data

https://scikit-learn.org/stable/modules/impute.html

# EM ALGORITHM



# EM IMPUTATION METHODS

According to the key result of Dempster, Laird and Rubin (1977), $\theta^{(t+1)}$ is better estimate than $\theta^{(t)}$, because the change from $\theta^{(t)}$ to $\theta^{(t+1)}$ in each iteration increases the log likelihood,

$$l\left(\theta^{(t+1)} \middle| Y_{obs}\right) \geq l\left(\theta^{(t)} \middle| Y_{obs}\right).$$

Therefore, iteration of EM algorithm can be considered in two steps: **Expectation Step** and **Maximization Step**.

**E-Step:** In this step, the function $Q\left(\theta \middle| \theta^{(t)}\right)$ is calculated as the conditional expectation of complete data log likelihood over the conditional predictive distribution, $f\left(Y_{mis} \middle| Y_{obs}, \theta^{(t)}\right)$, of $Y_{mis}$ given $Y_{obs}$ and a current estimate of $\theta$, say $\theta^{(t)}$.

**M-Step:** In this step, estimation of $\theta^{(t+1)}$ is carried out as if there were no missing data which is achieved by maximizing $Q\left(\theta \middle| \theta^{(t)}\right)$ from E-step.

In order to define convergency of iterations, differences of parameter estimations derived in the each iteration are considered. If the difference of consecutive estimates less than selected threshold value, then iterations are stopped. Estimations from the last iteration are used as parameter estimations.

We will cover this algorithm in more depth later

# MULTIVARIATE SINGLE IMPUTATION

**Nearest neighbors imputation**

- KNN defines for each sample or individual a set of K-nearest neighbors and then replaces the missing data for a given variable by averaging (non-missing) values of its neighbors
- Advantage: Simple, uses information from the observed data, experimentally shows good performance
- Disadvantage: not statistically grounded, might over-estimates model fit and correlation

**Fuzzy K-means Clustering**

**Bayesian Principal Component Analysis**

**Deep Learning-based approaches**

….

https://scikit-learn.org/stable/modules/impute.html

# SIMPLE STOCHASTIC IMPUTATION

**Random sample from existing values:**

- Randomly generate an integer from 1 to $n\text{-}n_{missing}$, then replace the missing value with the corresponding observation that you chose randomly

| Name | Address | #Employees | Revenue | Profit |
|---|---|---|---|---|
| Google | 1600 Amphitheatre Parkway, Mountain View, CA, 94043, USA | 60k | $89B | $10B |
| Apple | 1 Infinite Loop; Cupertino, CA 95014, USA | 66k | $215B | $45B |
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| Microsoft | Albuquerque, New Mexico | 120k | $85B | $85B |
| Tableau | Seattle, Washington, United States | | $5M | $8M |

# SIMPLE STOCHASTIC IMPUTATION

**Random sample from existing values:**

- Randomly generate an integer from 1 to max($n_{missing}$) then replace the missing value with the corresponding observation that you chose randomly

| Name | Address | #Employees | Revenue | Profit |
|---|---|---|---|---|
| Google | 1600 Amphitheatre Parkway, Mountain View, CA, 94043, USA | 60k | $89B | $10B |
| Apple | 1 Infinite Loop; Cupertino, CA 95014, USA | 66k | $215B | $45B |
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- Randomly generate number between 1 and 4: Say 2 → Replace $Y_{3,5}$ by $Y_{2,3}$= 66k

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- Randomly generate number between 1 and 4: Say 2 → Replace $Y_{3,5}$ by $Y_{2,3}$= 66k

- Disadvantage: It may change the distribution of data
- **Hot-deck approach:** draws are made from units with complete data that are 'similar' to the one with missing values (donors).

# SIMPLE STOCHASTIC IMPUTATION

**Random sample from existing values:**

- Randomly generate an integer from 1 to n-$n_{missing}$, then replace the missing value with the corresponding observation that you chose randomly

| Name | Address | #Employees | Revenue | Profit |
|---|---|---|---|---|
| Google | 1600 Amphitheatre Parkway, Mountain View, CA, 94043, USA | 60k | $89B | $10B |
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- Randomly generate number between 1 and 4: Say 2 → Replace $Y_{3,5}$ by $Y_{2,3}$= 66k
- Disadvantage: It may change the distribution of data
- **Hot-deck approach:** draws are made from units with complete data that are 'similar' to the one with missing values (donors).

**Randomly sample from a reasonable distribution**

- Very similar, just based on samples from a distribution.
- For example, if gender is missing and you have the information that there re about the sample number of females and males in the population.  Gender ~Ber(p=0.5) or estimate p from the observed sample
- Disadvantage: distributional assumption may not be reliable (or correct), even the assumption is correct, its representativeness is doubtful

# MULTIPLE IMPUTATION (MI)

Multiple imputation (MI) one of the most attractive methods for general-purpose handling of missing data in multivariate analysis.

1. Impute missing values using an appropriate model that incorporates random variation.
2. Do this M times producing M “complete” data sets.
3. Perform the desired analysis on each data set using standard complete-data methods.
4. Average the values of the parameter estimates across the M samples to produce a single point estimate.
5. Calculate the standard errors by (a) averaging the squared standard errors of the M estimates (b) calculating the variance of the M parameter estimates across samples, and (c) combining the two quantities using a simple formula

# LAST OBSERVATION CARRIED FORWARD

- This method is specific to time or longitudinal data problems.
- For each individual, NAs are replaced by the last observed value of that variable. Then, analyze data as if data were fully observed.
- Disadvantage: The covariance structure and distribution change seriously

| Cases | 1 | 2 | 3 | 4 | 5 | 6 |
|---|---|---|---|---|---|---|
| 1 | 3.8 | 3.1 | 2.0 | 2.0 | 2.0 | 2.0 |
| 2 | 4.1 | 3.5 | 2.8 | 2.4 | 2.8 | 3.0 |
| 3 | 2.7 | 2.4 | 2.9 | 3.5 | 3.5 | 3.5 |

# CATEGORICAL VALUES

**Extra category**

- This is bad practice
- In many statistical analysis the impact of this strategy depends on how missing values are divided among the real categories, and how the probability of a value being missing depends on other variables;
- very dissimilar classes can be lumped into one group;
- severe bias can arise, in any direction, and when used to stratify for adjustment (or correct for confounding) the completed categorical variable will not do its job properly.

**Better techniques:**

- Maximum Likelihood Estimation
- KNN
- Stochastic variants

# CLICKER

| Name | Address | #Employees | Revenue | Profit |
|---|---|---|---|---|
| Google | 1600 Amphitheatre Parkway, Mountain View, CA | 50000 | $100000M | $40000M |
| Apple | 1 Infinite Loop; Cupertino, CA 95014, USA | 70000 | $200000M | $50000M |
| IBM | 1 New Orchard Rd; 10504 | 400000 | $100000M | null |
| Microsoft | Albuquerque, New Mexico | 130000 | $125000M | $40000M |
| Tableau | Seattle, Washington, United States | 4000 | $1000M | null |
| Tamr | 64 Church St, Cambridge, MA 02138, USA | 30 | $10M | $1M |
| Einblick Analytics | null | 8 | $0.01M | $0M |
| Determined AI | California | 15 | null | $0.01M |

Calculate the result for `SELECT SUM(revenue)/SUM(employees) FROM s_tech_companies`
With listwise deletion, mean and linear regression substitution

For this example, which technique to deal with null values leads to the lowest revenue per employee value:

a) Listwise deletion
b) Mean substitution
c) Regression imputation

# CLICKER

| Name | Address | #Employees | Revenue | Profit |
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| Microsoft | Albuquerque, New Mexico | 130000 | $125000M | $40000M |
| ~~Tableau~~ | ~~Seattle, Washington, United States~~ | ~~4000~~ | ~~$1000M~~ | ~~null~~ |
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| ~~Einblick Analytics~~ | ~~null~~ | ~~8~~ | ~~$0.01M~~ | ~~$0M~~ |
| ~~Determined AI~~ | ~~California~~ | ~~15~~ | ~~null~~ | ~~$0.01M~~ |

Calculate the result for `SELECT SUM(revenue)/SUM(employees) FROM s_tech_companies` with

a) Listwise deletion: $425B / $250k = $1.7M per employee

b) Mean substitution:

c) Regression imputation

# CLICKER

| Name | Address | #Employees | Revenue (M) | Profit (M) |
|---|---|---|---|---|
| Google | 1600 Amphitheatre Parkway, Mountain View, CA | 50000 | $100000M | $40000M |
| Apple | 1 Infinite Loop; Cupertino, CA 95014, USA | 70000 | $200000M | $50000M |
| IBM | 1 New Orchard Rd; 10504 | 400000 | $100000M | null |
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| Tableau | Seattle, Washington, United States | 4000 | $1000M | null |
| Tamr | 64 Church St, Cambridge, MA 02138, USA | 30 | $10M | $1M |
| Einblick Analytics | null | 8 | $0.01M | $0M |
| Determined AI | California | 15 | $75000M | $0.01M |

Calculate the result for `SELECT SUM(revenue)/SUM(employees) FROM s_tech_companies` with

a) Listwise deletion: $425B / $250k = $1.7M per employee
b) Mean substitution: $600B / 654k = $0.92M per employee
c) Regression imputation

# CLICKER

| Name | Address | #Employees | Revenue (M) | Profit (M) |
|---|---|---|---|---|
| Google | 1600 Amphitheatre Parkway, Mountain View, CA | 50000 | $100000M | $40000M |
| Apple | 1 Infinite Loop; Cupertino, CA 95014, USA | 70000 | $200000M | $50000M |
| IBM | 1 New Orchard Rd; 10504 | 400000 | $100000M | null |
| Microsoft | Albuquerque, New Mexico | 130000 | $125000M | $40000M |
| Tableau | Seattle, Washington, United States | 4000 | $1000M | null |
| Tamr | 64 Church St, Cambridge, MA 02138, USA | 30 | $10M | $1M |
| Einblick Analytics | null | 8 | $0.01M | $0M |
| Determined AI | California | 15 | $55000M | $0.01M |

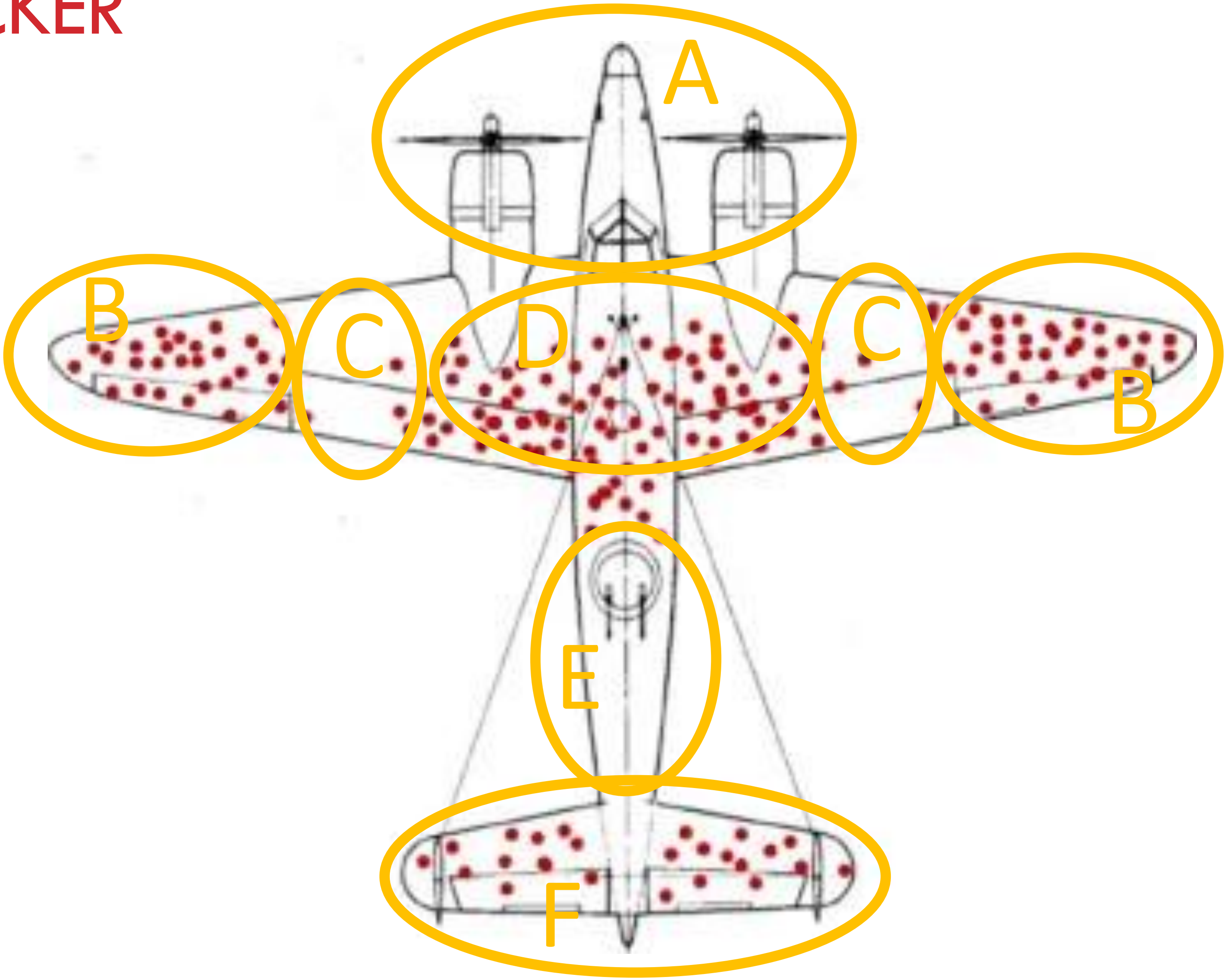
Calculate the result for `SELECT SUM(revenue)/SUM(employees) FROM s_tech_companies` with

a) Listwise deletion: $425B / $250k = $1.7M per employee
b) Mean substitution: $600B / 654k = $0.92M per employee
c) Regression imputation: $580B /654k = $0.89M per employee

Rev = 55346 + 0.212 * emp

I

# CLICKER

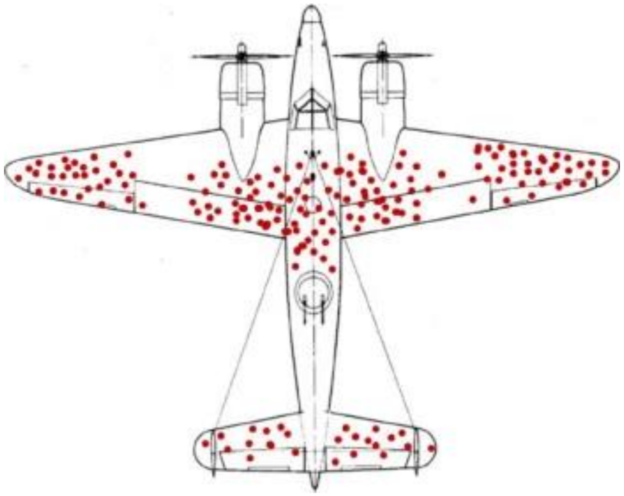



Where would you enforce the plane?

# UNKNOWN UNKOWNS

| Name | Address | #Employees | Revenue | Profit |
|---|---|---|---|---|
| Google | 1600 Amphitheatre Parkway, Mountain View, CA, 94043, USA | 60k | $89B | null |
| Apple | 1 Infinite Loop; Cupertino, CA 95014, USA | 66 | $215B | $45B |
| IBM | 1 New Orchard Rd; New York 10504, USA | 380k | $80B | $12B |
| International Business Machine | 1 New Orchard Rd; 10504 | 380k | $-999B | $12B |
| Microsoft | Albuquerque, Mexico | 120k | $85B | $85B |
| Tableau | Seattle, Washington, United States | - | $0.9B | $1B |
| Tamr | 64 Church St, Cmabridge, MA 02138, United States | 20 | null | $-Y |
| **Amazon** | ?? | ?? | ?? | ?? |
| **Facebook** | ?? | ?? | ?? | ?? |
| ?? | ?? | ?? | ?? | ?? |
| ?? | ?? | ?? | ?? | ?? |

# IF YOU CAN ESTIMATE THEM DEPENDS ON THE SAMPLING SCENARIO



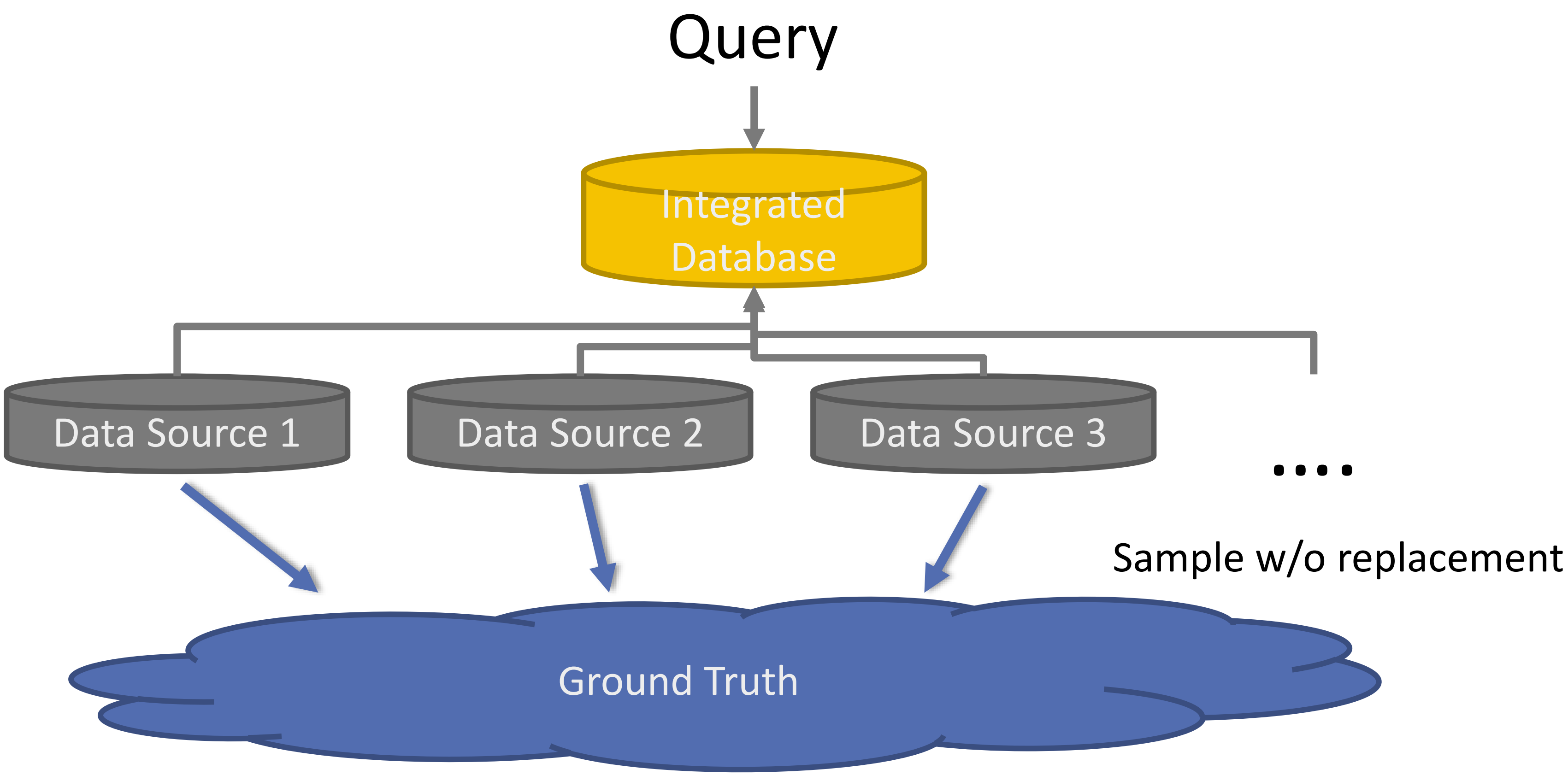
VS

| Name | Address | #Employees | Revenue | Profit |
|---|---|---|---|---|
| Google | 1600 Amphitheatre Parkway, Mountain View, CA, 94043, USA | 60k | $89B | null |
| Apple | 1 Infinite Loop; Cupertino, CA 95014, USA | 66 | $215B | $45B |
| IBM | 1 New Orchard Rd; New York 10504, USA | 380k | $80B | $12B |
| International Business Machine | 1 New Orchard Rd; 10504 | 380k | $-999B | $12B |
| Microsoft | Albuquerque, Mexico | 120k | $85B | $85B |
| Tableau | Seattle, Washington, United States | - | $0.9B | $1B |
| Tamr | 64 Church St, Cmabridge, MA 02138, United States | 20 | null | $-Y |
| **Amazon** | ?? | ?? | ?? | ?? |
| **Facebook** | ?? | ?? | ?? | ?? |
| ?? | ?? | ?? | ?? | ?? |
| ?? | ?? | ?? | ?? | ?? |

# THE IMPACT OF THE **UNKNOWN UNKNOWNS** ON QUERY RESULTS

*How many people work in the US IT industry*

```
SELECT SUM(employees)
FROM us_tech_companies
```




Assumption: Enough data sources , Data sources are (semi-) independent

# Sampling - Statistic

$$\sum$$

| Name | Address | #Employees | Revenue | Profit | Frequency |
|---|---|---|---|---|---|
| Google | Address I | 60k | $89B | $10B | 5 |
| Apple | Address II | 66k | $215B | $45B | 4 |
| IBM | Address II | 380k | $80B | $12B | 4 |
| Microsoft | Address | 120k | $85B | $85B | 5 |
| Tableau | Address | 3.2k | $500 | $8M | 2 |
| Tamr | Address | 20 | $-X | $-Y | 1 |

**Fingerprint (i.e., f-statistic):**

$f_1$: 1 → **Singletons** (items which were exactly observed once)

$f_2$: 1

$f_4$: 2

$f_5$: 2

# MANY WAYS TO ESTIMATE THE NUMBER OF MISSING ITEMS

- Good-Turing Estimate / Chao84
- Chao92
- Pattern Maximum Likelihood
- Linear programming-based solutions (see Valiant brothers)
- …

# ESTIMATING THE NUMBER OF DISTINCT BUTTERFLY SPECIES

17500 **species** known in the world

# GOOD-TURING / CHAO84 ESTIMATE

Unique Items

$$\hat{N} = \frac{\boxed{c}}{\left(1 - \boxed{{f_1}/{n}}\right)}$$

Missing mass

Number of Unknown Unknowns:

$$M = \hat{N} - c$$

*Note, we usually prefer* ***Chao92****: A. Chao and S. Lee, “****Estimating the Number of Classes via Sample Coverage****,” Journal of the American Statistical Association, vol. 87, no. 417, pp. 210–217, 1992*
*over* ***Chao84****: A. Chao, “****Nonparametric Estimation of the Number of Classes in a Population****,” SJS, vol. 11, no. 4, 1984*

# A NAÏVE ESTIMATOR FOR THE IMPACT OF THE UNKNOWN UNKNOWNS

```
SELECT SUM(employees)
FROM us_tech_companies
```

$$\sum employees\ ,\ \Delta(employees, fingerprint)$$

$$\Delta_{Naive} = M \cdot \phi$$

Estimate of Unknown Unknowns Count

Average Value of Knowns
(aka mean substitution)

# A NAÏVE ESTIMATOR FOR THE IMPACT OF THE UNKNOWN UNKNOWNS

Number of unique records i.e., count(*)

Value sum over all unique items

$$\Delta_{Naive} = \boxed{\frac{c}{\left(1 - {}^{f_1}/_{n}\right)}} \cdot \boxed{\frac{\boxed{\sum_{\{c\}} v}}{c}}$$

Estimated number of missing records

Mean value

# EXAMPLE

MIT Fan DB

| FanID | Name | Address | Email | FanOf | Genre |
|---|---|---|---|---|---|
| 2 | Tim | 46 Pumpkin St | timk | Nickelback, Creed, Limp Bizkit | Terrible |
| 3 | Matt | Vassar Str | Mattp | Nickelback | Terrible |

MIT CSAIL DB

| ID | Name |
|---|---|
| 10 | Tim |
| 14 | Matt |

MIT Department DB

| ID | Name |
|---|---|
| 10 | Tim |
| 14 | Joana |

| FanID | Name | Address | Email | FanOf | Genre | Frequency |
|---|---|---|---|---|---|---|
| 2 | Tim | 46 Pumpkin St | timk | Nickelback, Creed, Limp Bizkit | Terrible | 3 |
| 3 | Matt | Vassar Str | Mattp | Nickelback | Terrible | 2 |
| 4 | Joana | | | | | 1 |

$$\#\text{Missing} = \frac{c}{\left(1-{}^{f_1}/_{n}\right)} = \frac{3}{(1-{}^{1}/_{6})} = 3.6$$

Note estimator shouldn't be used if sample coverage is below 80% (1 − f1/n) and such a small number of data sources (independent samples)

# EXAMPLE

$$\#\text{Missing} = \frac{c}{\left(1 - {}^{f_1}/_{n}\right)} = \frac{3}{(1 - {}^{1}/_{6})} = 3.6$$

| FanID | Name | Address | Email | FanOf | Genre | Frequency |
|---|---|---|---|---|---|---|
| 2 | Tim | 46 Pumpkin St | timk | Nickelback, Creed, Limp Bizkit | Terrible | 3 |
| 3 | Matt | Vassar Str | Mattp | Nickelback | Terrible | 2 |
| 4 | Joana | | | Cold Play | OK | 1 |

# EXAMPLE

$$\#\text{Missing} = \frac{c}{\left(1-{}^{f_1}/_{n}\right)} = \frac{3}{\left(1-{}^{1}/_{6}\right)} = 3.6$$

| FanID | Name | Address | Email | FanOf | Genre | Frequency |
|---|---|---|---|---|---|---|
| 2 | Tim | 46 Pumpkin St | timk | Nickelback, Creed, Limp Bizkit | Terrible | 3 |
| 3 | Matt | Vassar Str | Mattp | Nickelback | Terrible | 2 |
| 4 | Joana | | | Cold Play | OK | 1 |
| …. | … | .. | … | … | … | … |
| 5 | Sam | Christmas St | Samm | Celine Dion | As cheesy as deep-fried camembert [1] | |


[1] https://www.telegraph.co.uk/music/concerts/cheesy-deep-fried-camembert-celine-dion-o2-arena-review/

# WRONG DATA: RULE-BASED APPROACHES

| Name | Address | #Employees | Revenue | Profit |
|---|---|---|---|---|
| Google | 1600 Amphitheatre Parkway, Mountain View, CA, 94043, USA | 60k | $89B | null |
| Apple | 1 Infinite Loop; Cupertino, CA 95014, USA | 66 | $215B | $45B |
| IBM | 1 New Orchard Rd; New York 10504, USA | 380k | $80B | $12B |
| International Business Machine | 10504; 1 New Orchard Rd | 380k | $-999B | $12B |
| Microsoft | Albuquerque, Mexico | 120k | $85B | $85B |
| Tableau | Seattle, Washington, United States | - | $0.9B | $1B |
| Tamr | [illegible] United States | 20 | null | [illegible] |

Encoding Error
(nb in thousands)

Rule Violations

Outdated data / wrong data

Spelling mistakes / abbreviations

# TWO COMPONENTS

1. **Detection**
2. **Repair**
   - Detection techniques can be used for repair
   - Missing value techniques

# ERROR DETECTION

FD: [country] -> [capital]

CFD: [country = China] -> [capital = Beijing]

**emp**

| | name | country | capital | city | salary | tax |
|---|---|---|---|---|---|---|
| r1 | Nan | China | Beijing | Beijing | 50000 | 1000 |
| r2 | Yin | China | Shanghai | Hongkong | 40000 | 1200 |
| r3 | Si | Netherlands | Den Hagg | Utrecht | 60000 | 1400 |
| r4 | Lei | Netherlands | Amsterdam | Amsterdam | 35000 | 800 |

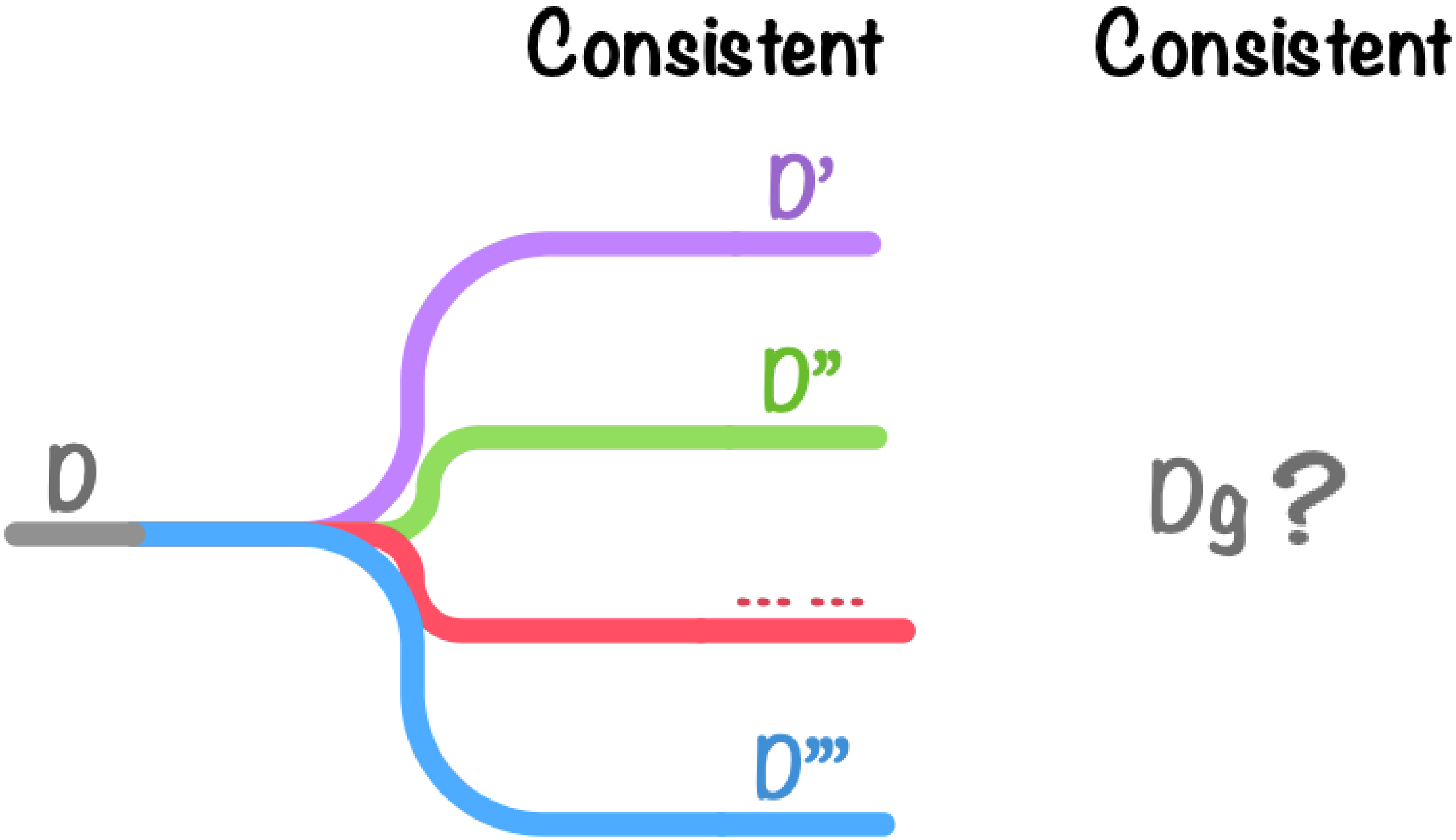
**cap**

| | country | capital |
|---|---|---|
| **s1** | China | Beijing |
| **s2** | Canada | Ottawa |
| **s3** | … | … |

CD: ]t1, t2 (t1.salary > t2.salary and t1.tax < t2.tax)

MD: (emp[country] = cap[country]) -> (emp[capital] <=> cap[capital])

# COMPUTING A CONSISTENT DATABASE




find a D' such that dist(D,D') is minimum

# COMPUTING A CONSISTENT DATABASE

FD1: [nationality] -> [capital]

FD2: [areacode] -> [capital]

| | name | nationality | capital | areacode | bornAt | salary | tax |
|---|---|---|---|---|---|---|---|
| r1 | Nan | China | Beijing | 10 | Shenyang | 50000 | 1000 |
| r2 | Yan | China | Shanghai<br>Beijing | 10 | Hangzhou | 40000 | 900 |
| r3 | Si | China | Beijing | 10 | Changsha | 60000 | 1400 |
| r4 | Miura | China | Tokyo<br>Beijing | 3 | Kyoto | 35000 | 800 |

Equivalence class

Vertex cover

SAT solver

… …

# CONFIDENCE VALUES INTERACTION

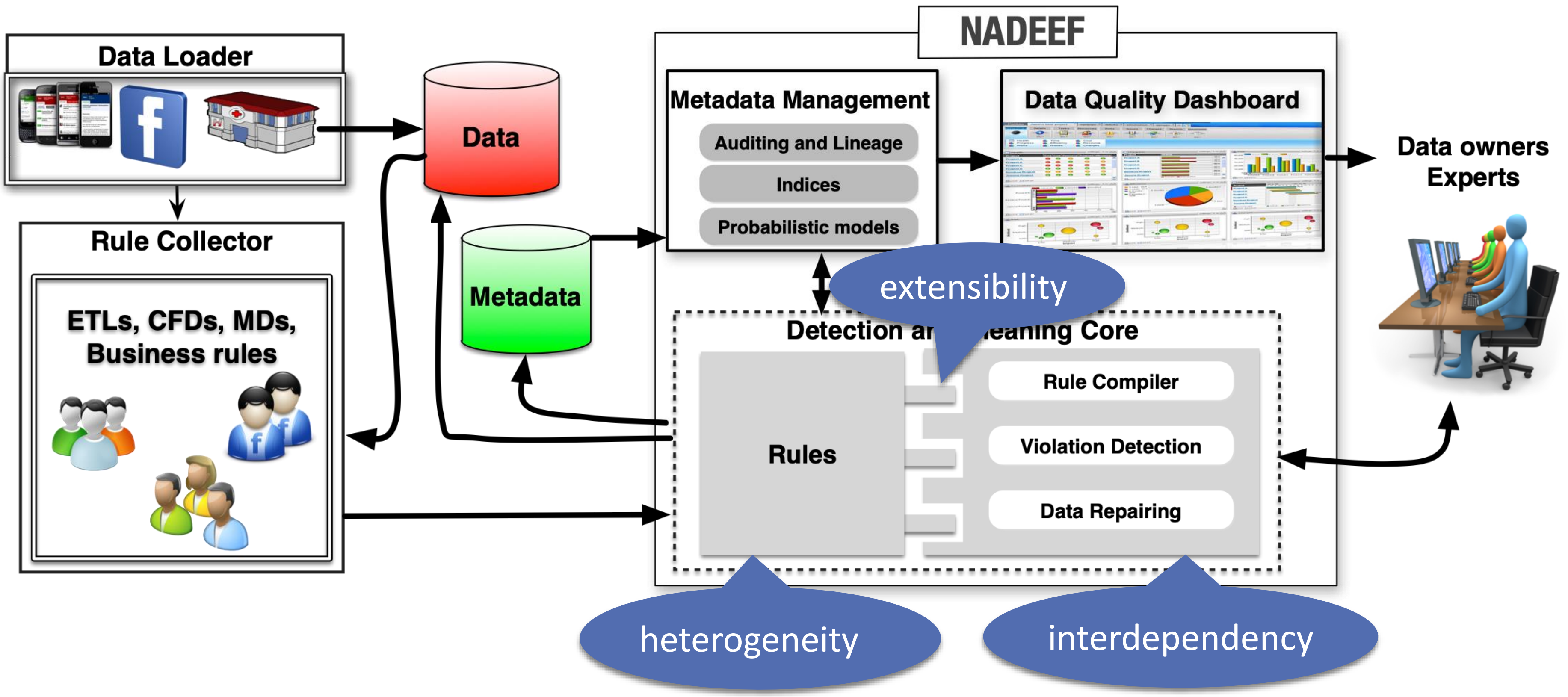
FD: [nationality] -> [capital]

MD: ((nationality, country) -> (capital, capital))

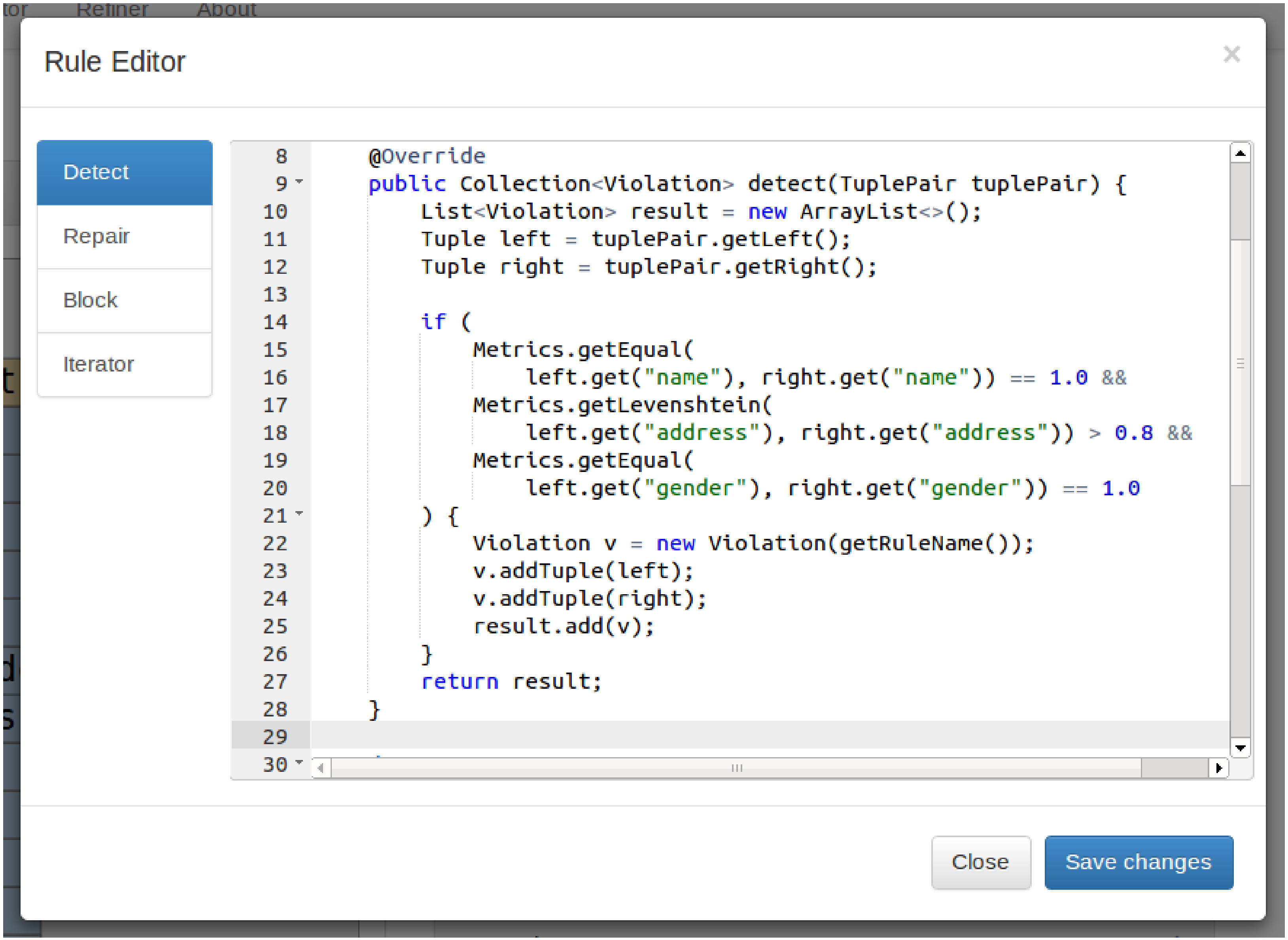
| | name | nationality | capital | bornAt |
|---|---|---|---|---|
| r1 | Nan (0.9) | China (1.0) | Beijing (1.0) | Shenyang (0.9) |
| r2 | Yan (0.8) | China (1.0) | Beijing (0.5) | Hangzhou (0.9) |
| r3 | Si (0.9) | Canada (1.0) | Ottawa (1.0) | Changsha (0.8) |
| r4 | Miura (0.9) | Canada (0.9) | Vancuver (0.5) | Kyoto (1.0) |

| | country | capital |
|---|---|---|
| s1 | China (1.0) | Beijing (1.0) |
| s2 | Canada (1.0) | Ottawa (1.0) |
| s3 | Japan (1.0) | Tokyo (1.0) |

# NADEEF


Data Loader
Rule Collector
ETLs, CFDs, MDs, Business rules
Data
Metadata
NADEEF
Metadata Management
Auditing and Lineage
Indices
Probabilistic models
Data Quality Dashboard
Data owners Experts
extensibility
Detection and Cleaning Core
Rules
Rule Compiler
Violation Detection
Data Repairing
heterogeneity
interdependency

# NADEEF



Refiner
About
Rule Editor
Detect
Repair
Block
Iterator
@Override
public Collection<Violation> detect(TuplePair tuplePair) {
List<Violation> result = new ArrayList<>();
Tuple left = tuplePair.getLeft();
Tuple right = tuplePair.getRight();
if (
Metrics.getEqual(
left.get("name"), right.get("name")) == 1.0 &&
Metrics.getLevenshtein(
left.get("address"), right.get("address")) > 0.8 &&
Metrics.getEqual(
left.get("gender"), right.get("gender")) == 1.0
) {
Violation v = new Violation(getRuleName());
v.addTuple(left);
v.addTuple(right);
result.add(v);
}
return result;
}
Close
Save changes

# OUTLIER DETECTION

# ANOMALY/OUTLIER DETECTION

**What are anomalies/outliers?**

- The set of data points that are considerably different than the remainder of the data

**Variants of Anomaly/Outlier Detection Problems**

- Given a database D, find all the data points $\mathbf{x} \in D$ with anomaly scores greater than some threshold t
- Given a database D, find all the data points $\mathbf{x} \in D$ having the top-n largest anomaly scores $f(\mathbf{x})$
- Given a database D, containing mostly normal (but unlabeled) data points, and a test point **x**, compute the anomaly score of **x** with respect to D

**Applications:**

- Credit card fraud detection, telecommunication fraud detection, network intrusion detection, fault detection

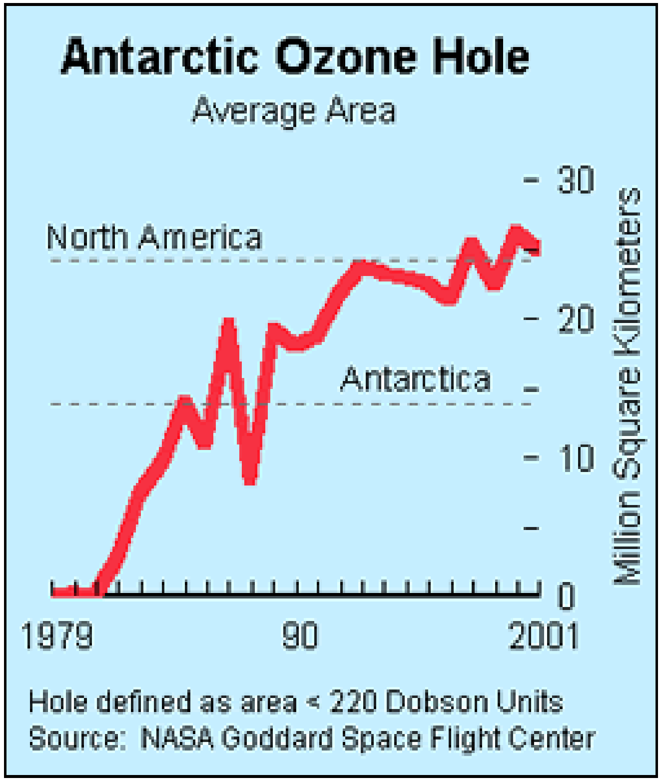
# IMPORTANCE OF ANOMALY DETECTION

## Ozone Depletion History

In 1985 three researchers (Farman, Gardinar and Shanklin) were puzzled by data gathered by the British Antarctic Survey showing that ozone levels for Antarctica had dropped 10% below normal levels

Why did the Nimbus 7 satellite, which had instruments aboard for recording ozone levels, not record similarly low ozone concentrations?

The ozone concentrations recorded by the satellite were so low they were being treated as outliers by a computer program and discarded!




Sources:
http://exploringdata.cqu.edu.au/ozone.html
http://www.epa.gov/ozone/science/hole/size.html

# ANOMALY DETECTION

**Challenges**

- How many outliers are there in the data?
- Method is unsupervised
  - Validation can be quite challenging (just like for clustering)
- Finding needle in a haystack

**Working assumption:**

- There are considerably more "normal" observations than "abnormal" observations (outliers/anomalies) in the data

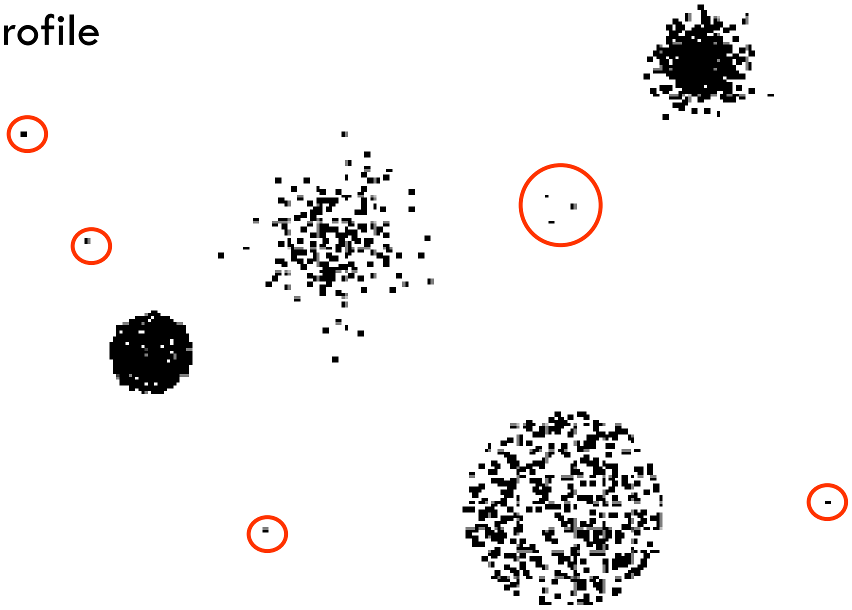
# ANOMALY DETECTION SCHEMES

## General Steps

- Build a profile of the "normal" behavior
  - Profile can be patterns or summary statistics for the overall population
- Use the "normal" profile to detect anomalies
  - Anomalies are observations whose characteristics differ significantly from the normal profile

## Types of anomaly detection schemes

- Graphical
- Model-based
- Distance-based
- Clustering-based

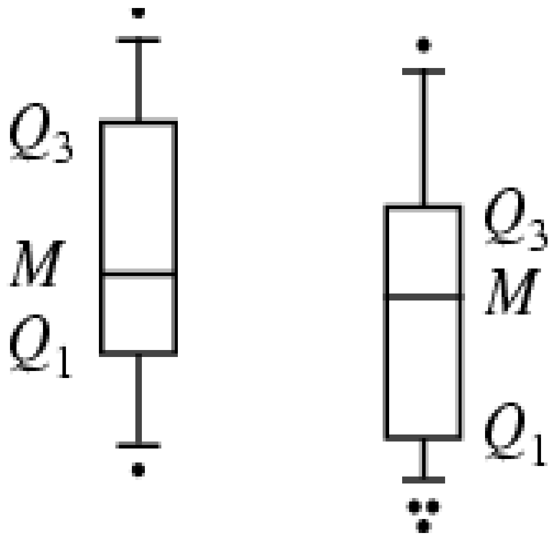


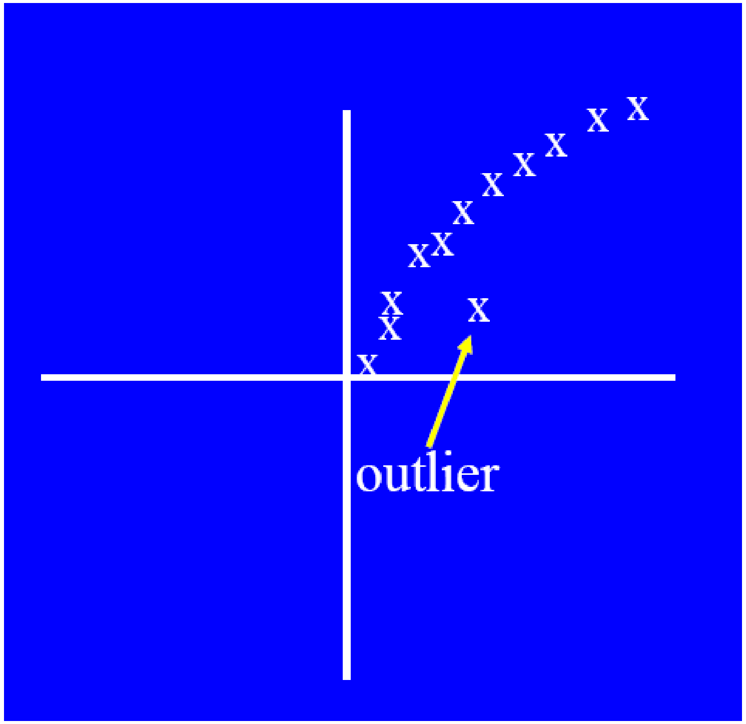
# GRAPHICAL APPROACHES

**Boxplot (1-D), Scatter plot (2-D), Spin plot (3-D)**

**Limitations**

- Time consuming
- Subjective



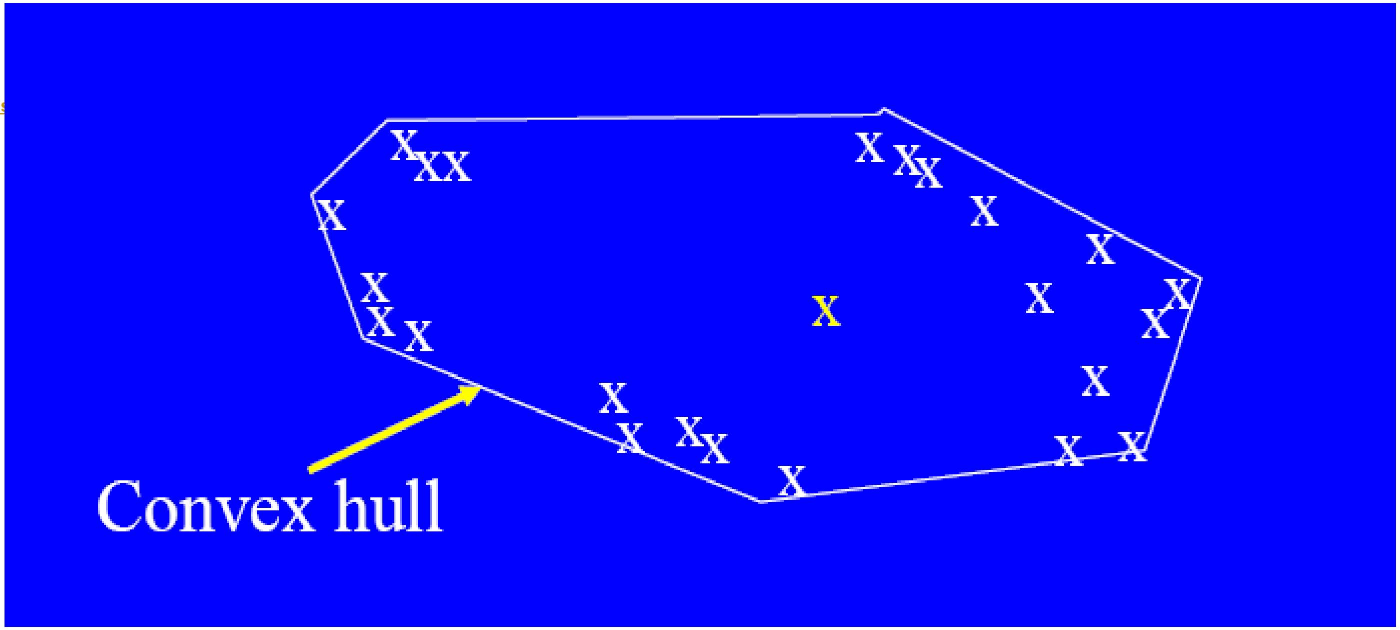



# CONVEX HULL METHOD

**Extreme points are assumed to be outliers**

**Use convex hull method to detect extreme values**

http://cgm.cs

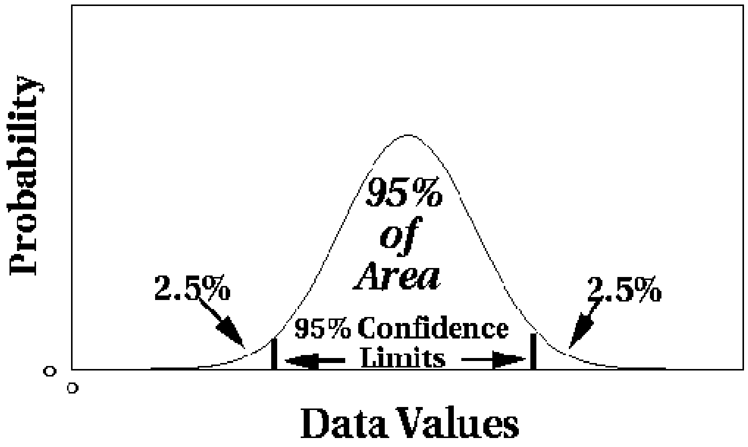


# STATISTICAL APPROACHES---MODEL-BASED

**Assume a parametric model describing the distribution of the data (e.g., normal distribution)**

**Apply a statistical test that depends on**

- Data distribution
- Parameter of distribution (e.g., mean, variance)
- Number of expected outliers (confidence limit)



# GRUBBS' TEST

**Detect outliers in univariate data**

**Assume data comes from normal distribution**

**Detects one outlier at a time, remove the outlier, and repeat**

- $H_0$: There is no outlier in data
- $H_A$: There is at least one outlier

**Grubbs' test statistic:**

**Reject $H_0$ if:**

$$G = \frac{\max \left| X - \overline{X} \right|}{s}$$

$$G > \frac{(N-1)}{\sqrt{N}} \sqrt{\frac{t^2_{(\alpha/N, N-2)}}{N - 2 + t^2_{(\alpha/N, N-2)}}}$$

# STATISTICAL-BASED – LIKELIHOOD APPROACH

**Assume the data set D contains samples from a mixture of two probability distributions:**

- M (majority distribution)
- A (anomalous distribution)

**General Approach:**

- Initially, assume all the data points belong to M
- Let $L_t(D)$ be the log likelihood of D at time t
- For each point $x_t$ that belongs to M, move it to A
  - Let $L_{t+1}$ (D) be the new log likelihood.
  - Compute the difference, $\Delta = L_t(D) – L_{t+1}$ (D)
  - If $\Delta > c$ (some threshold), then $x_t$ is declared as an anomaly and moved permanently from M to A

# LIMITATIONS OF STATISTICAL APPROACHES

**Most of the tests are for a single attribute**

**In many cases, data distribution/model may not be known**

**For high dimensional data, it may be difficult to estimate the true distribution**

# DISTANCE-BASED APPROACHES

**Data is represented as a vector of features**

**Three major approaches**

- Nearest-neighbor based
- Density based
- Clustering based

# NEAREST-NEIGHBOR BASED APPROACH

**Approach:**

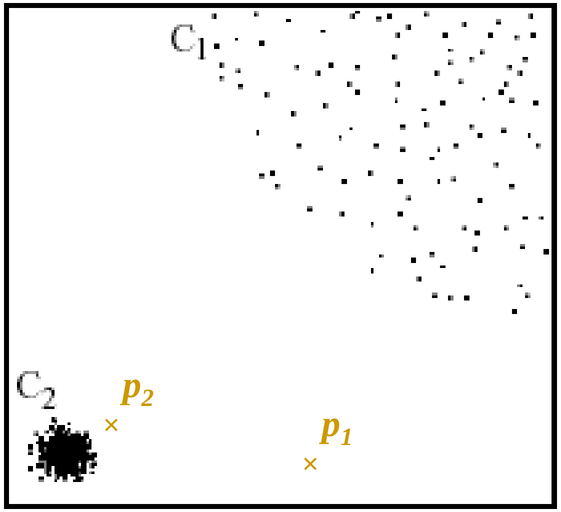
- Compute the distance between every pair of data points
- There are various ways to define outliers:
  - Data points for which there are fewer than *p* neighboring points within a distance *D*
  - The top n data points whose distance to the kth nearest neighbor is greatest
  - The top n data points whose average distance to the k nearest neighbors is greatest

# DENSITY-BASED: LOF APPROACH

**For each point, compute the density of its local neighborhood; e.g. use DBSCAN's approach**

**Compute local outlier factor (LOF) of a sample *p* as the average of the ratios of the density of sample *p* and the density of its nearest neighbors**

**Outliers are points with largest LOF value**




In the NN approach, $p_2$ is not considered as outlier, while LOF approach find both $p_1$ and $p_2$ as outliers

**Alternative approach: directly use density function; e.g. DENCLUE's density function**

# CLUSTERING-BASED

**Idea: Use a clustering algorithm that has some notion of outliers!**

**Problem what parameters should I choose for the algorithm; e.g. DBSCAN?**

**Rule of Thumb: Less than x% of the data should be outliers (with x typically chosen between 0.1 and 10); x might be determined with other methods; e.g. statistical tests.**

| | FN | LN | St | city | CC | country | tel | gd |
|---|---|---|---|---|---|---|---|---|
| $t_1$: | David | Jordan | 12 Holywell Street | Oxford | 44 | UK | 66700543 | Male |
| $t_2$: | Paul | Simon | 5 Ratcliffe Terrace | Oxford | 44 | UK | 44944631 | Male |

(a) $D_1$: An instance of schema bank

| | FN | LN | str | city | CC | country | phn | when | where |
|---|---|---|---|---|---|---|---|---|---|
| $r_1$: | David | Jordan | 12 Holywell Street | Oxford | 44 | UK | 66700543 | 1pm 6/05/2012 | Netherlands |
| $r_2$: | Paul | Simon | 5 Ratcliffe Terrace | Oxford | 44 | UK | 44944631 | 11am 2/12/2011 | Netherlands |
| $r_3$: | David | Jordan | 12 Holywell Street | Oxford | 44 | Netherlands | 66700541 | 6am 6/05/2012 | US |
| $r_4$: | Peter | Austin | 7 Market Street | Amsterdam | 31 | UK | 55384922 | 9am 6/02/2012 | Netherlands |

(b) Database $D_2$: An instance of schema tran

r1: (on table tran) if a customer's CC is 31, but his/her country is neither Netherlands nor Holland, update the country to Netherlands;

r2: (on tables bank and tran) if the same person from different tables has different phones, the phone number from table bank is more reliable;

r3: (on table tran) a country code (CC) uniquely determines a country;

r4: (on table tran) if two purchases of the same person happened in the Netherlands and the US (East Coast) within 1 hour (assuming 6 hours' time difference between these two countries), these two purchases are either a fraud or were erroneously recorded.

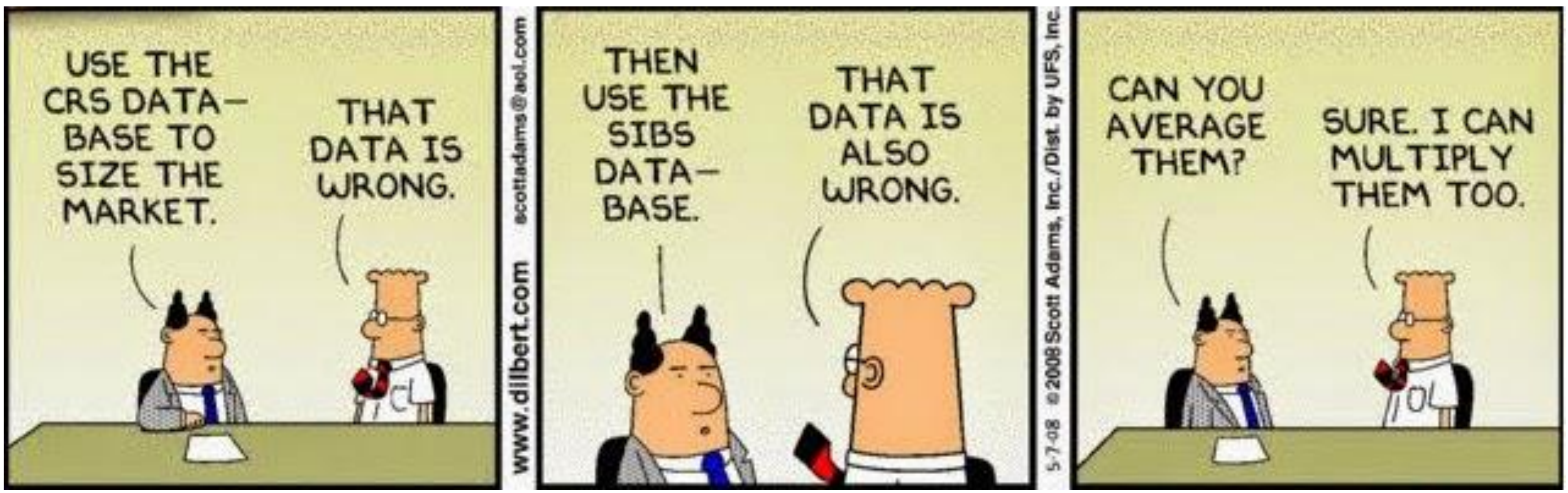
```
Class Rule1 {                                                  /* for φ1 */
  set⟨cell⟩ vio(Tuple s1) {                                /*s1 in table tran */
    if (s1[CC]=31 ∧ (s1[country] ≠Netherlands ∨ s1[country] ≠Holland))
      return { s1[CC, country]; }
    return ∅;
  }
  set⟨Expression⟩ fix (set⟨cell⟩ V) {
    return { V.s[country] ← Netherlands; }
  } } /* end of class definition */

Class Rule2 {                                                  /* for φ2 */
  set⟨cell⟩ vio (Tuple s1, Tuple s2) {            /*s1 in bank, s2 in tran */
    if (s1[LN, St, city]=s2[LN, str, city] ∧ s1[FN] ≈ s2[FN] ∧ s1[tel] ≠ s2[phn])
      return { s1[FN, LN, St, city, tel], s2[FN, LN, str, city, phn]; }
    return ∅;
  }
  set⟨Expression⟩ fix (set⟨cell⟩ V) {
    return { V.s2[phn] ← V.s1[tel]; }
  } } /* end of class definition */

Class Rule3 {                                                  /* for φ3 */
  set⟨cell⟩ vio (Tuple s1, Tuple t2) {             /* s1, s2 in table tran */
    if (s1[CC] = s2[CC] ∧ s1[country] ≠ s2[country])
      return { s1[CC, country], s2[CC, country]; }
    return ∅;
  }
  set⟨Expression⟩ fix (set⟨cell⟩ V) {
    set⟨Expression⟩ fixes;
    fixes.insert(V.s1[country] ←V.s2[country]);
    fixes.insert(V.s2[country] ←V.s1[country]);
    return fixes;
  } } /* end of class definition */

Class Rule4 {                                                  /* for φ4 */
  set⟨cell⟩ vio (Tuple s1, Tuple s2) {              /*s1, s2 in table tran */
    if (s1[LN, city, CC, tel] = s2[LN, city, CC, tel]
      ∧s1[where] = Netherlands ∧ s2[where] = US ∧ s1[FN] ≈ s2[FN]
      ∧(s1[when] − s2[when] ≥ 5) ∧ (s1[when] − s2[when] ≤ 7)
      return { s1[FN, LN, city, CC, tel, when, where],
        s2[FN, LN, city, CC, tel, when, where]; }
    return ∅;
  } } /* end of class definition */
```

**Figure 3: Sample rules**


USE THE CRS DATA-BASE TO SIZE THE MARKET.
THAT DATA IS WRONG.
scottadams@aol.com
www.dilbert.com
THEN USE THE SIBS DATA-BASE.
THAT DATA IS ALSO WRONG.
5-7-08 © 2008 Scott Adams, Inc./Dist. by UFS, Inc.
CAN YOU AVERAGE THEM?
SURE. I CAN MULTIPLY THEM TOO.

# WHY IS FINDING VIOLATIONS EXPENSIVE?