DATA CLEANING & DATA MANIPULATION

PETRA ISENBERG

VISUAL ANALYTICS

With slides by Wesley Willett

WHAT IS “DIRTY DATA”?

BEFORE WE CAN TALK ABOUT CLEANING, WE NEED TO KNOW ABOUT TYPES OF ERROR AND WHERE THEY COME FROM

SOURCES OF ERROR

DATA ENTRY ERRORS

MEASUREMENT ERRORS

DISTILLATION ERRORS

DATA INTEGRATION ERRORS

[HELLERSTEIN 2008]

DATA ENTRY ERROR

LOTS OF DATA IS ENTERED BY HAND

TYPOGRAPHIC ERRORS

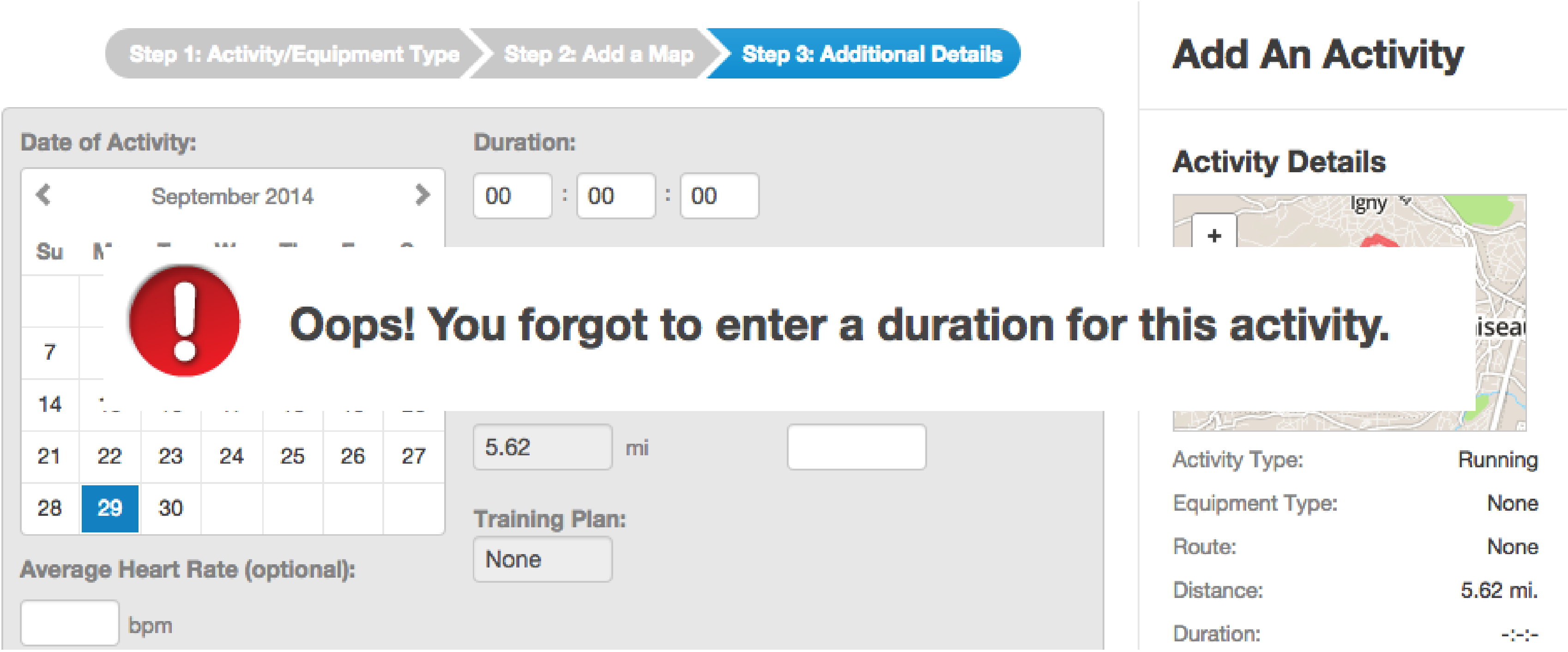
MISUNDERSTANDING DATA OR CONVENTIONS

“SPURIOUS INTEGRITY”

“SPURIOUS INTEGRITY”

ENTERING BAD DATA IN RESPONSE TO (OFTEN WELL-INTENTIONED) INTERFACE CONSTRAINTS

“SPURIOUS INTEGRITY”



Date of Activity:

September 2014

Su	M					
7						
14						
21	22	23	24	25	26	27
28	29	30				

Duration:

00 : 00 : 00

5.62 mi

Training Plan:

None

Average Heart Rate (optional):

bpm

Oops! You forgot to enter a duration for this activity.

Add An Activity

Activity Details

Activity Type:	Running
Equipment Type:	None
Route:	None
Distance:	5.62 mi.
Duration:	-:-:-

MEASUREMENT ERRORS

SENSOR ISSUES

MALFUNCTIONS

PLACEMENT

INTERFERENCE

MISCALIBRATION

DISTILLATION ERRORS

SOME DATA MAY BE LOST OR COMPRESSED
BEFORE IT ENTERS
THE DATABASE

0.345413 → 0.35

National Price Index → NPI

1985, $2, Apples
1985, $2, Oranges → 1985, $2, “Apples,Oranges,Cucumbers”
1985, $2, Cucumbers

DATA INTEGRATION ERRORS

DATA OFTEN COMES FROM MULTIPLE SOURCES

SCHEMAS CHANGE OVER TIME

DATA IS OFTEN COERCED FROM
ONE TYPE TO ANOTHER

CAN LEAD TO DATA LOSS,
DUPLICATION, AND OTHER

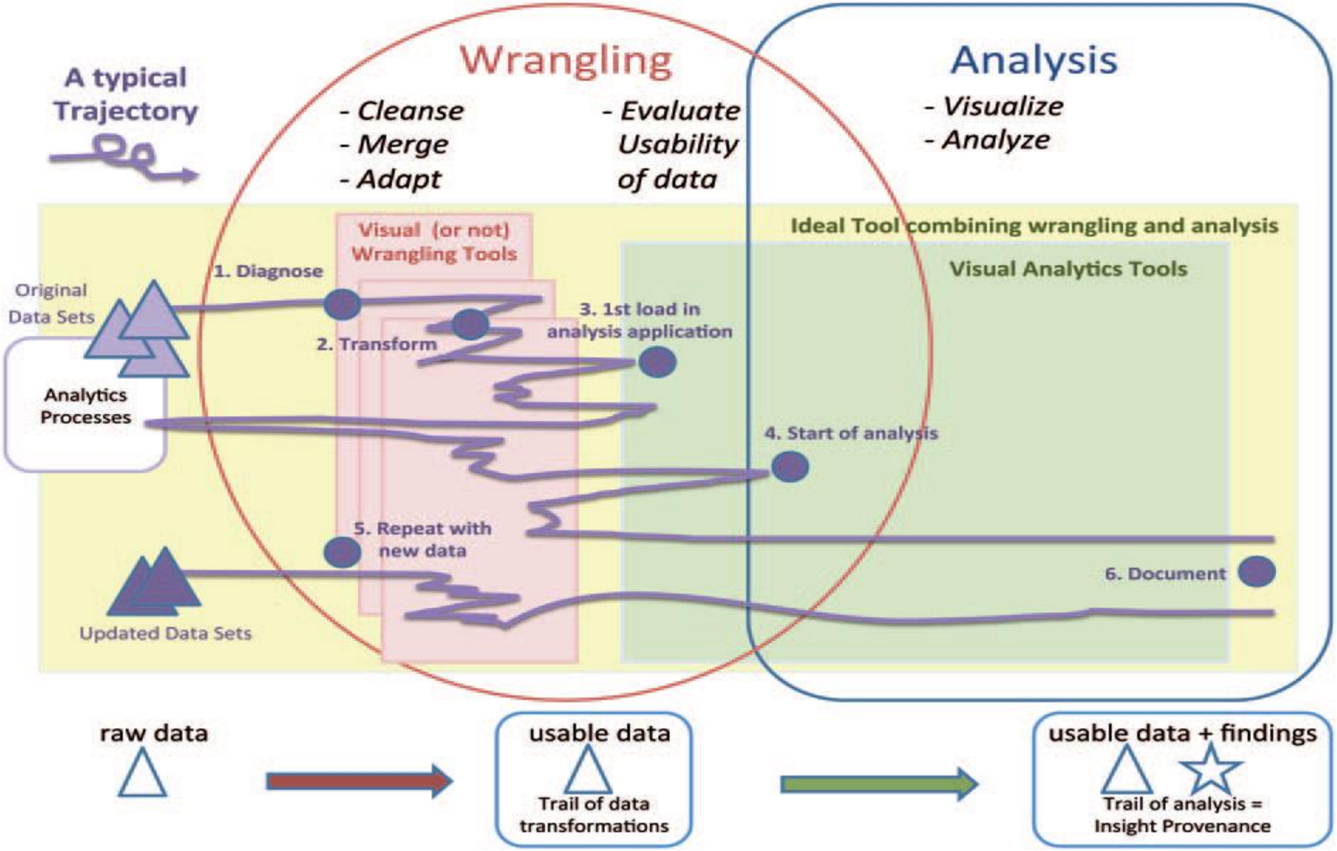
WHY IS THIS IMPORTANT?

MOST OF THE TIME IN THE DATA ANALYSIS PROCESS IS ACTUALLY SPENT HERE!

“I spend more than half my time integrating, cleansing, and transforming data without doing any actual analysis. Most of the time I’m lucky if I get to do any ‘analysis’ at all.”

[Kandel 2012]

ANALYSIS TRAJECTORIES



KANDEL ET AL. 2011

SOME DATA QUALITY ISSUES

MISSING DATA

MISSED MEASUREMENTS, REDACTED ITEMS, INCOMPLETE FORMS, ETC.

ERRONEOUS VALUES

MISSPELLINGS, OUTLIERS, “SPURIOUS INTEGRITY”, ETC.

ENTITY RESOLUTION

DIFFERENT VALUES, ABBREVS., 2+ ENTRIES FOR THE SAME THING?

TYPE CONVERSION

E.G., ZIP CODE OR PLACE NAME TO LAT-LON

DATA INTEGRATION

MISMATCHES AND INCONSISTENCIES WHEN COMBINING DATA

SOME APPROACHES FOR IMPROVING DATA QUALITY

TOOLS FOR MANIPULATING AND CLEANING DATA

SOME APPROACHES FOR IMPROVING DATA QUALITY

TOOLS FOR MANIPULATING AND CLEANING DATA

PREVENTING ERROR

CATCHING DIRTY DATA AT THE SOURCE

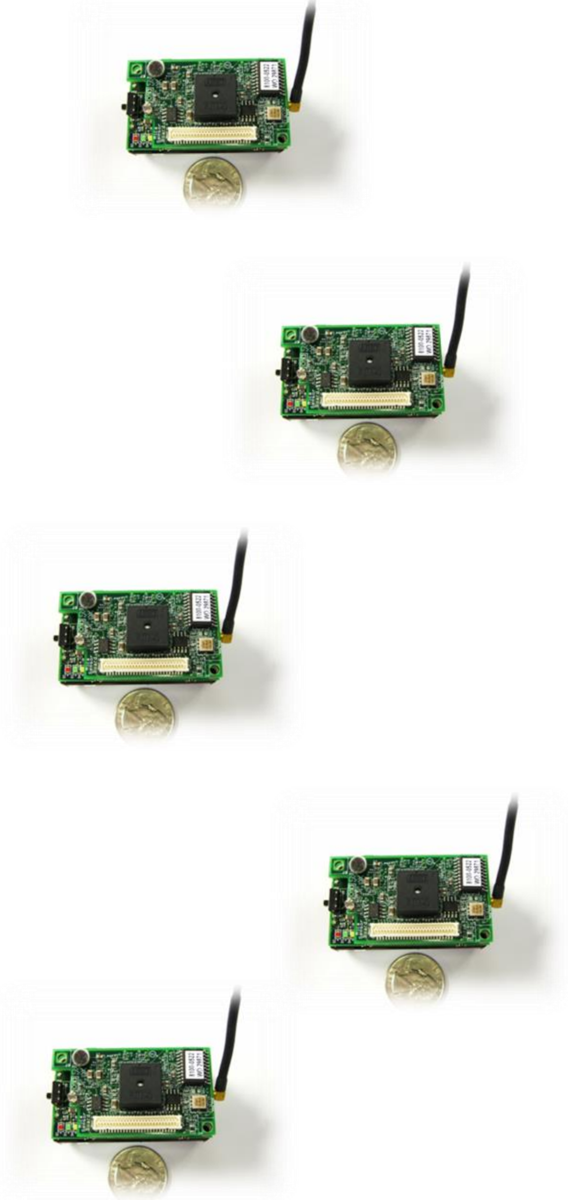
MINIMIZING SENSOR ERROR

CALIBRATE AND VERIFY SENSORS

CHECK SENSORS BEFORE DEPLOYMENT (AND PERIODICALLY REVALIDATE THEM)

USE REDUNDANT SENSORS

CHECK DATA AGAINST HISTORICAL LOGS OR COMPUTED MODELS



TRADE-OFFS BETWEEN **(RE)CALIBRATION** AND **REDUNDANCY**

REDUCING ERROR DURING DATA ENTRY

DOUBLE DATA ENTRY

PERFORM ALL DATA ENTRY TWICE

(IDEALLY BY SEPARATE PEOPLE)

IDENTIFY MISMATCHES AND DISCARD OR REPAIR

(VIA VOTING OR RE-ENTRY)

INTEGRITY CONSTRAINTS

This field is required.

TEMPERATURE xx °C

INTEGRITY CONSTRAINTS

Temperatures must be between -50ºC and 50ºC.

TEMPERATURE -60 ºC

INTEGRITY CONSTRAINTS

TEMPERATURE ________ °C

INTEGRITY CONSTRAINTS DO NOT PREVENT BAD DATA

ENFORCING CONSTRAINTS LEADS TO FRUSTRATION

FRICTION AND PREDICTION

USE DATA QUALITY MEASURES TO **PREDICT** HOW LIKELY A VALUE IS TO BE CORRECT.

ADJUST THE INTERFACE TO **ADD FRICTION** WHEN ENTERING UNLIKELY RESPONSES.

[HELLERSTEIN 2008]

FRICTION AND PREDICTION

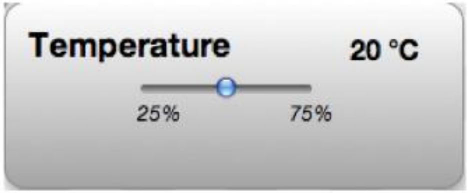
PRINCIPLE 1 DATA QUALITY SHOULD BE CONTROLLED VIA **FEEDBACK**, NOT **ENFORCEMENT**.

PRINCIPLE 2 FRICTION MERITS **EXPLANATION**.

PRINCIPLE 3 **ANNOTATION** SHOULD BE EASIER THAN OMISSION OR SUBVERSION.

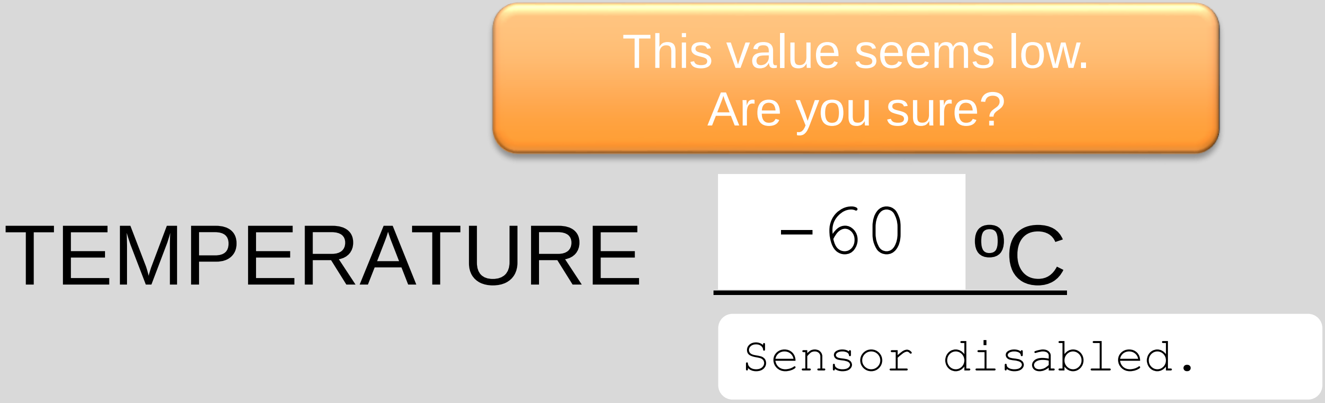
[HELLERSTEIN 2008]

FRICTION AND PREDICTION



[HELLERSTEIN 2008]

FRICTION AND PREDICTION



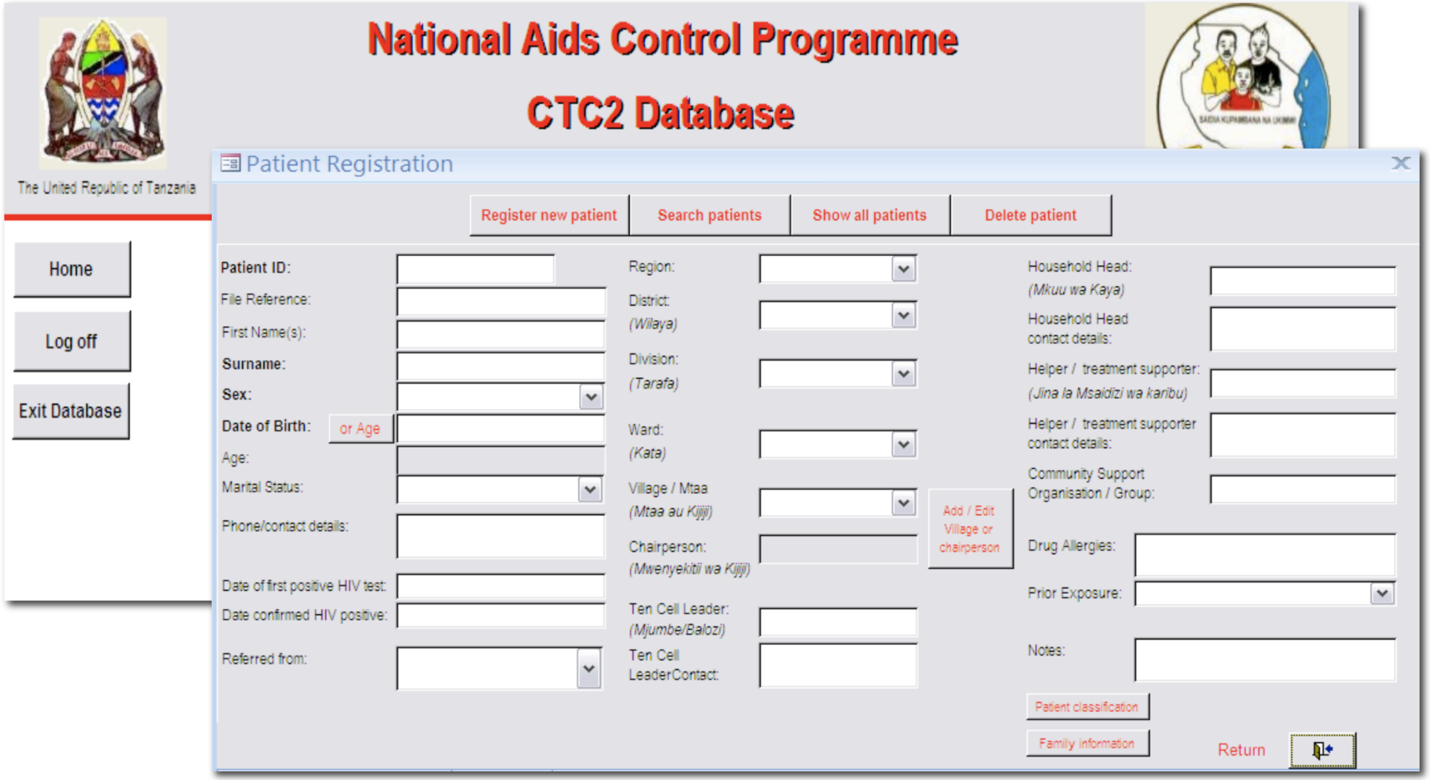
This value seems low.
Are you sure?

TEMPERATURE -60 ºC

Sensor disabled.

USHER

[Chen et al. 2010]



National Aids Control Programme

CTC2 Database

The United Republic of Tanzania

Home

Log off

Exit Database

Patient Registration

Register new patient | Search patients | Show all patients | Delete patient

Patient ID:

File Reference:

First Name(s):

Surname:

Sex:

Date of Birth: or Age

Age:

Marital Status:

Phone/contact details:

Date of first positive HIV test:

Date confirmed HIV positive:

Referred from:

Region:

District: *(Wilaya)*

Division: *(Tarafa)*

Ward: *(Kata)*

Village / Mtaa *(Mtaa au Kijiji)*

Add / Edit Village or chairperson

Chairperson: *(Mwenyekiti wa Kijiji)*

Ten Cell Leader: *(Mjumbe/Balozi)*

Ten Cell LeaderContact:

Household Head: *(Mkuu wa Kaya)*

Household Head contact details:

Helper / treatment supporter: *(Jina la Msaidizi wa karibu)*

Helper / treatment supporter contact details:

Community Support Organisation / Group:

Drug Allergies:

Prior Exposure:

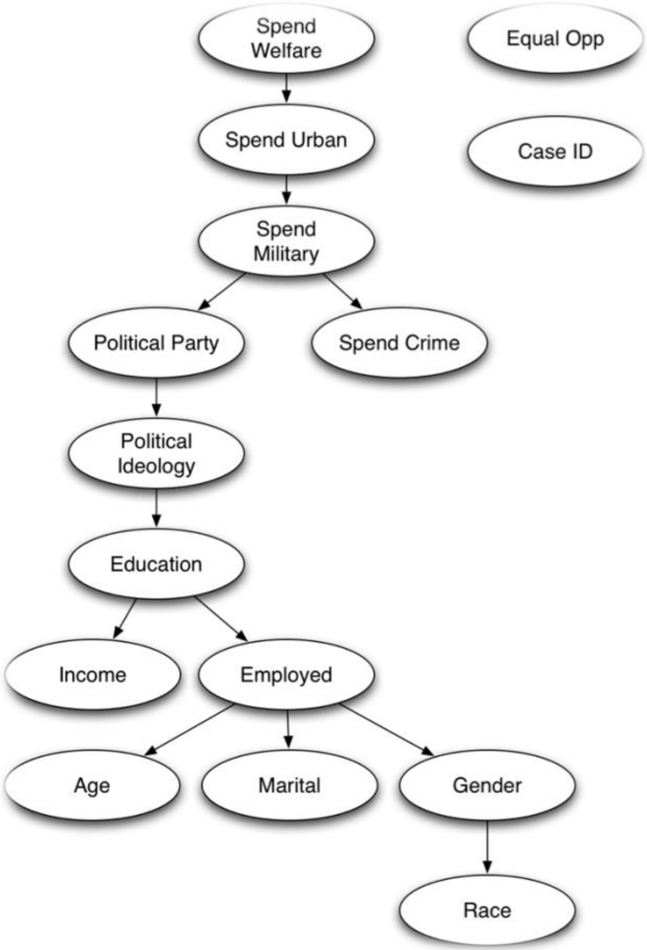
Notes:

Patient classification

Family information

Return

MS Access data entry forms for Tanzanian HIV/AIDS monitoring

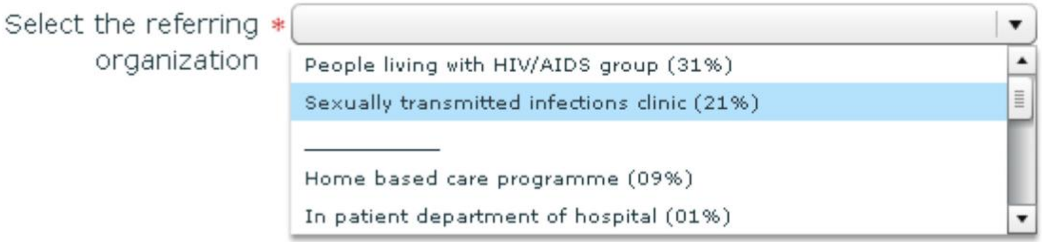


BUILD A MODEL to predict dependencies and relationships between questions.

[Chen et al. 2010]

DYNAMIC ORDERING

ALWAYS ASK THE MOST APPROPRIATE NEXT QUESTION



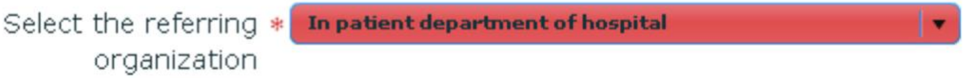
Select the referring organization *

People living with HIV/AIDS group (31%)

Sexually transmitted infections clinic (21%)

Home based care programme (09%)

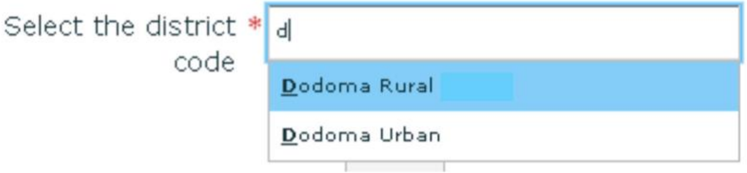
In patient department of hospital (01%)



Select the referring organization *

In patient department of hospital

SUGGEST THE MOST LIKELY ANSWERS

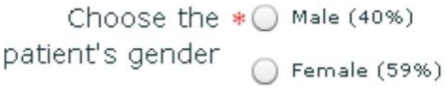


Select the district code *

d

Dodoma Rural

Dodoma Urban



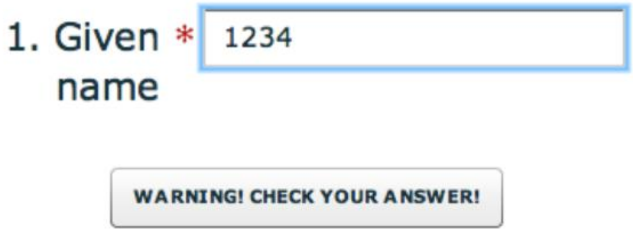
Choose the patient's gender *

○ Male (40%)

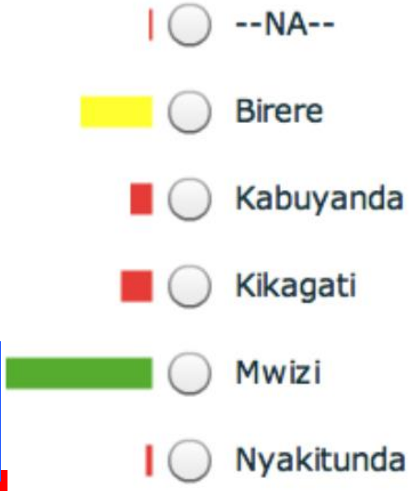
○ Female (59%)

[Chen et al. 2010]

SMART RE-ASKING AND SUGGESTIONS



1. Given name * 1234



- ○ --NA--
- ○ Birere
- ○ Kabuyanda
- ○ Kikagati
- ○ Mwizi
- ○ Nyakitunda

FRICTION

AUTOMATING ~~CONSTRAINTS~~

[Chen et al. 2010]

DETECTING ERRORS

LOOK FOR OUTLIERS / ANOMALIES

EXAMINE DATA TYPES

SCHEMA CHECKING

VALIDATE WITH OTHER DATA

OTHER HEURISTICS

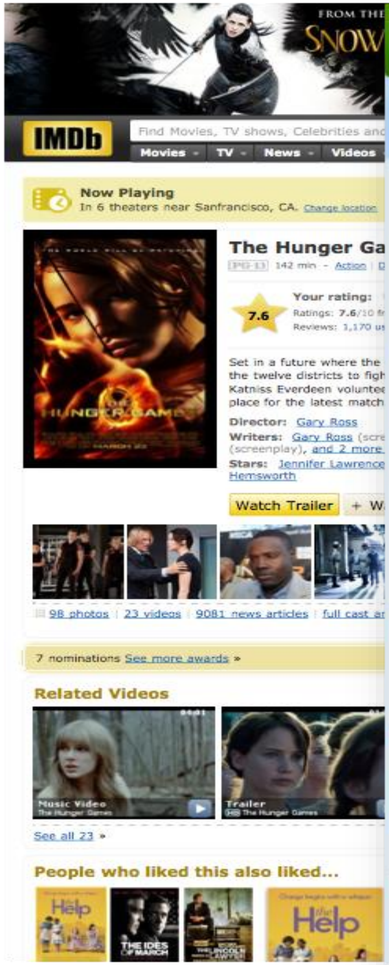
HISTORICALLY – MORE FOCUS ON AUTOMATED APPROACHES

“PROFILING” DATA

UNDERSTANDING WHAT ASSUMPTIONS YOU CAN MAKE ABOUT DATA

INTERACTIVELY IDENTIFYING DATA QUALITY ISSUES

AN EXAMPLE



IMDb

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Now Playing
In 6 theaters near Sanfrancisco, CA. Change location

The Hunger Ga

PG-13 142 min - Action | D

7.6 Your rating:
Ratings: 7.6/10 fr
Reviews: 1,170 us

Set in a future where the
the twelve districts to figh
Katniss Everdeen voluntee
place for the latest match

Director: Gary Ross
Writers: Gary Ross (scre
(screenplay), and 2 more
Stars: Jennifer Lawrence
Hemsworth

Watch Trailer + W

98 photos | 23 videos | 9081 news articles | full cast ar

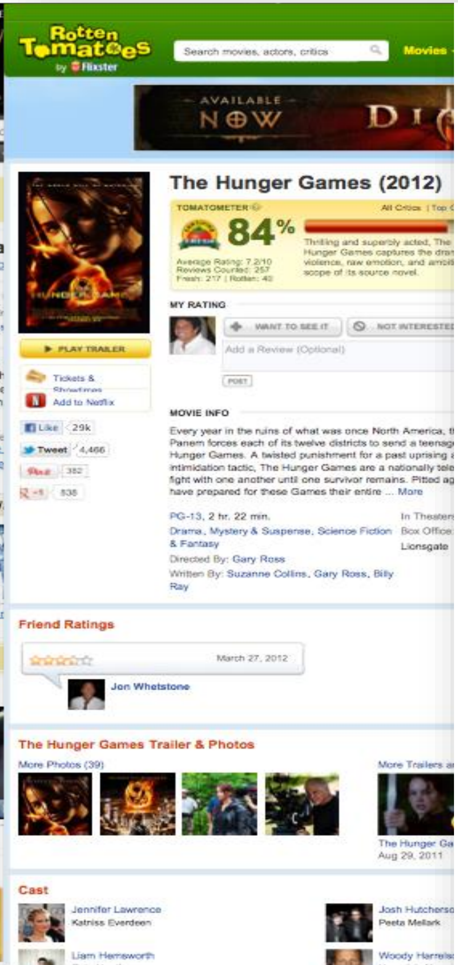
7 nominations See more awards »

Related Videos

Music Video The Hunger Games
Trailer The Hunger Games

See all 23 »

People who liked this also liked...



Rotten Tomatoes by Flixster

Search movies, actors, critics Movies

The Hunger Games (2012)

TOMATOMETER All Critics | Top C

84%

Average Rating: 7.2/10
Reviews Counted: 257
Fresh: 217 | Rotten: 40

Thrilling and superbly acted, The Hunger Games captures the dra violence, raw emotion, and ambit scope of its source novel.

▶ PLAY TRAILER

Tickets & Showtimes
Add to Netflix

Like 29k
Tweet 4,466
Pin it 382
+1 838

MY RATING

WANT TO SEE IT | NOT INTERESTED

Add a Review (Optional)

POST

MOVIE INFO

Every year in the ruins of what was once North America, t Panem forces each of its twelve districts to send a teenag Hunger Games. A twisted punishment for a past uprising a intimidation tactic, The Hunger Games are a nationally tele fight with one another until one survivor remains. Pitted ag have prepared for these Games their entire ... More

PG-13, 2 hr. 22 min. In Theaters
Drama, Mystery & Suspense, Science Fiction & Fantasy Box Office
Lionsgate
Directed By: Gary Ross
Written By: Suzanne Collins, Gary Ross, Billy Ray

Friend Ratings

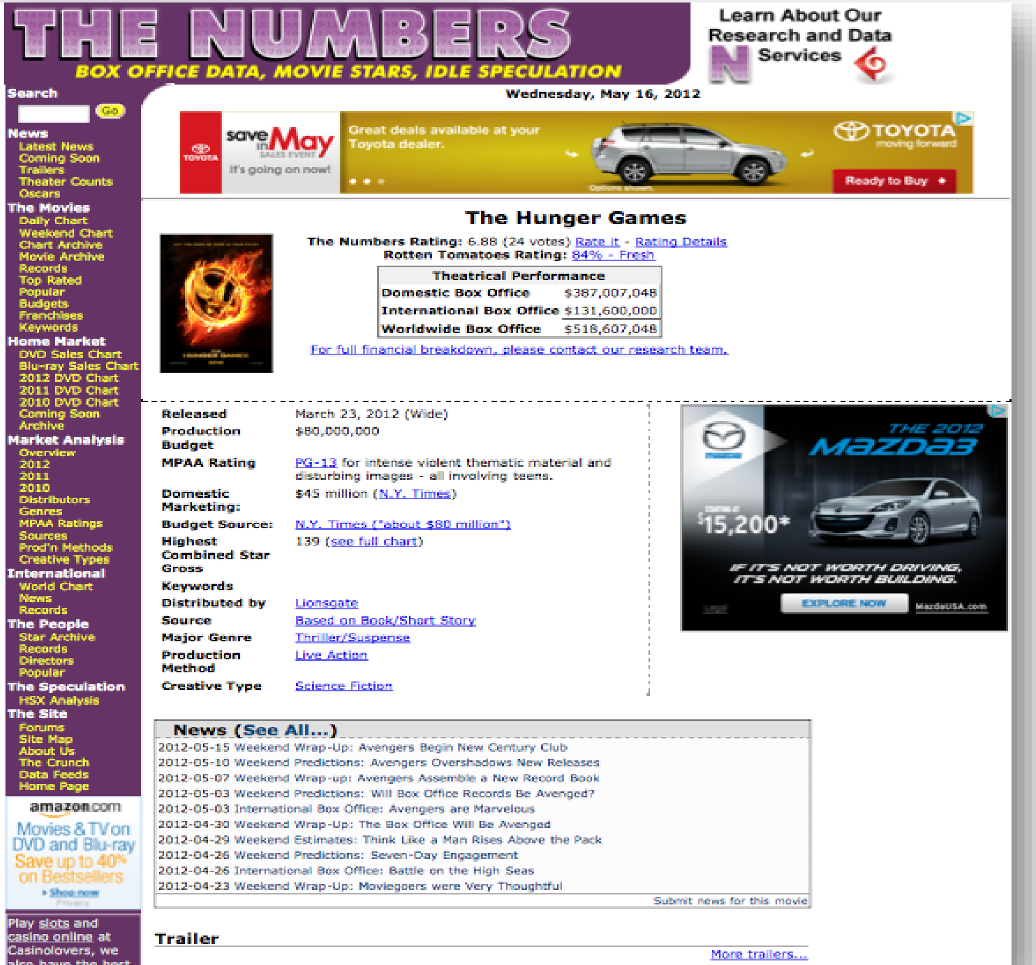
March 27, 2012
Jon Whetstone

The Hunger Games Trailer & Photos

More Photos (39) More Trailers
The Hunger Ga
Aug 29, 2011

Cast

Jennifer Lawrence Katniss Everdeen
Josh Hutcherson Peeta Mellark
Liam Hemsworth
Woody Harrelson



THE NUMBERS
BOX OFFICE DATA, MOVIE STARS, IDLE SPECULATION

Learn About Our Research and Data Services

Wednesday, May 16, 2012

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2012
2011
2010
Distributors
Genres
MPAA Ratings
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Star Archive
Records
Directors
Popular
The Speculation
HSX Analysis
The Site
Forums
Site Map
About Us
The Crunch
Data Feeds
Home Page

The Hunger Games

The Numbers Rating: 6.88 (24 votes) Rate it - Rating Details
Rotten Tomatoes Rating: 84% - Fresh

Theatrical Performance	
Domestic Box Office	$387,007,048
International Box Office	$131,600,000
Worldwide Box Office	$518,607,048

For full financial breakdown, please contact our research team.

Released	March 23, 2012 (Wide)
Production Budget	$80,000,000
MPAA Rating	PG-13 for intense violent thematic material and disturbing images - all involving teens.
Domestic Marketing:	$45 million (N.Y. Times)
Budget Source:	N.Y. Times ("about $80 million")
Highest Combined Star Gross	139 (see full chart)
Keywords	
Distributed by	Lionsgate
Source	Based on Book/Short Story
Major Genre	Thriller/Suspense
Production Method	Live Action
Creative Type	Science Fiction

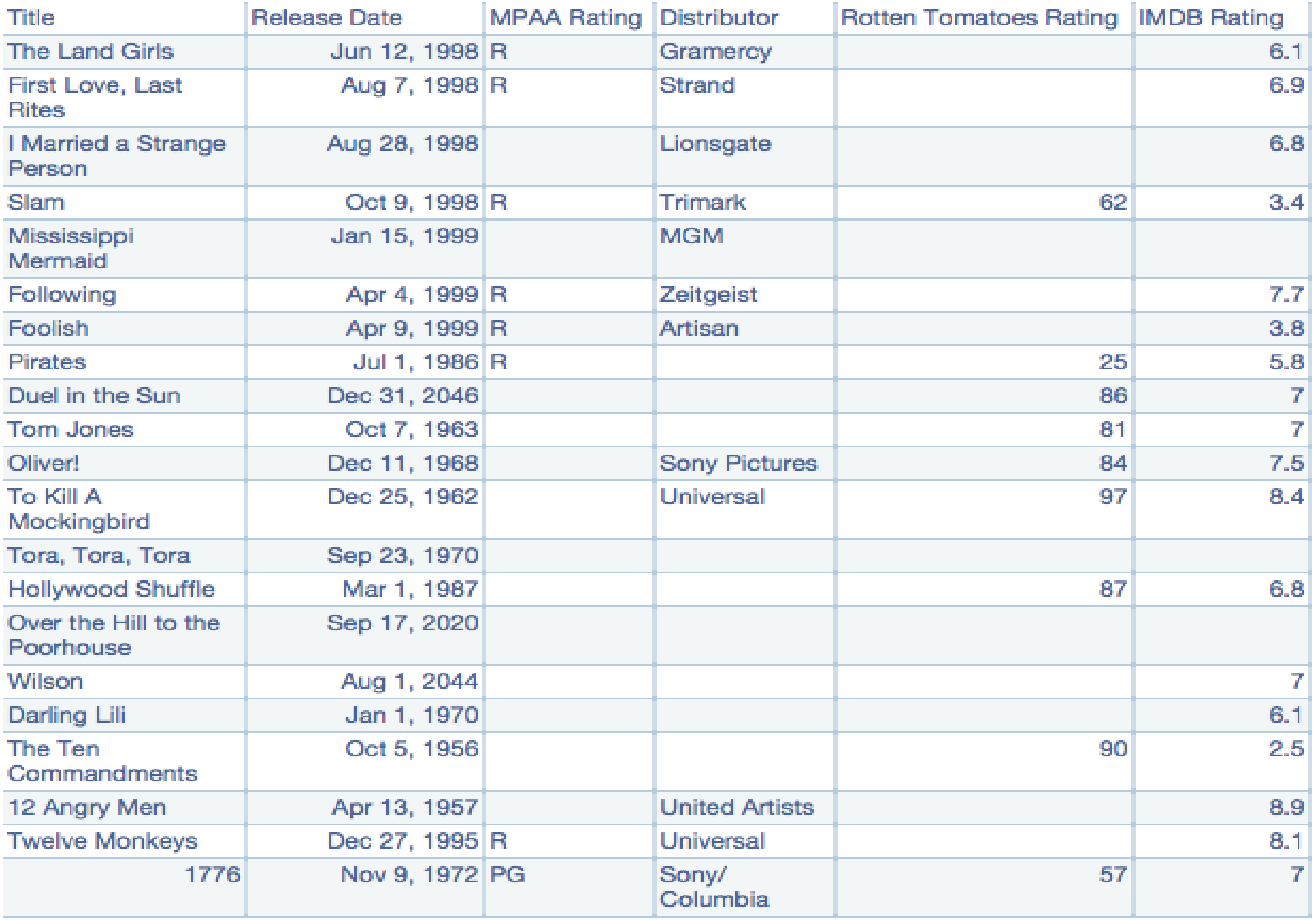
News (See All...)

2012-05-15 Weekend Wrap-Up: Avengers Begin New Century Club
2012-05-10 Weekend Predictions: Avengers Overshadows New Releases
2012-05-07 Weekend Wrap-up: Avengers Assemble a New Record Book
2012-05-03 Weekend Predictions: Will Box Office Records Be Avenged?
2012-05-03 International Box Office: Avengers are Marvelous
2012-04-30 Weekend Wrap-Up: The Box Office Will Be Avenged
2012-04-29 Weekend Estimates: Think Like a Man Rises Above the Pack
2012-04-26 Weekend Predictions: Seven-Day Engagement
2012-04-26 International Box Office: Battle on the High Seas
2012-04-23 Weekend Wrap-Up: Moviegoers were Very Thoughtful

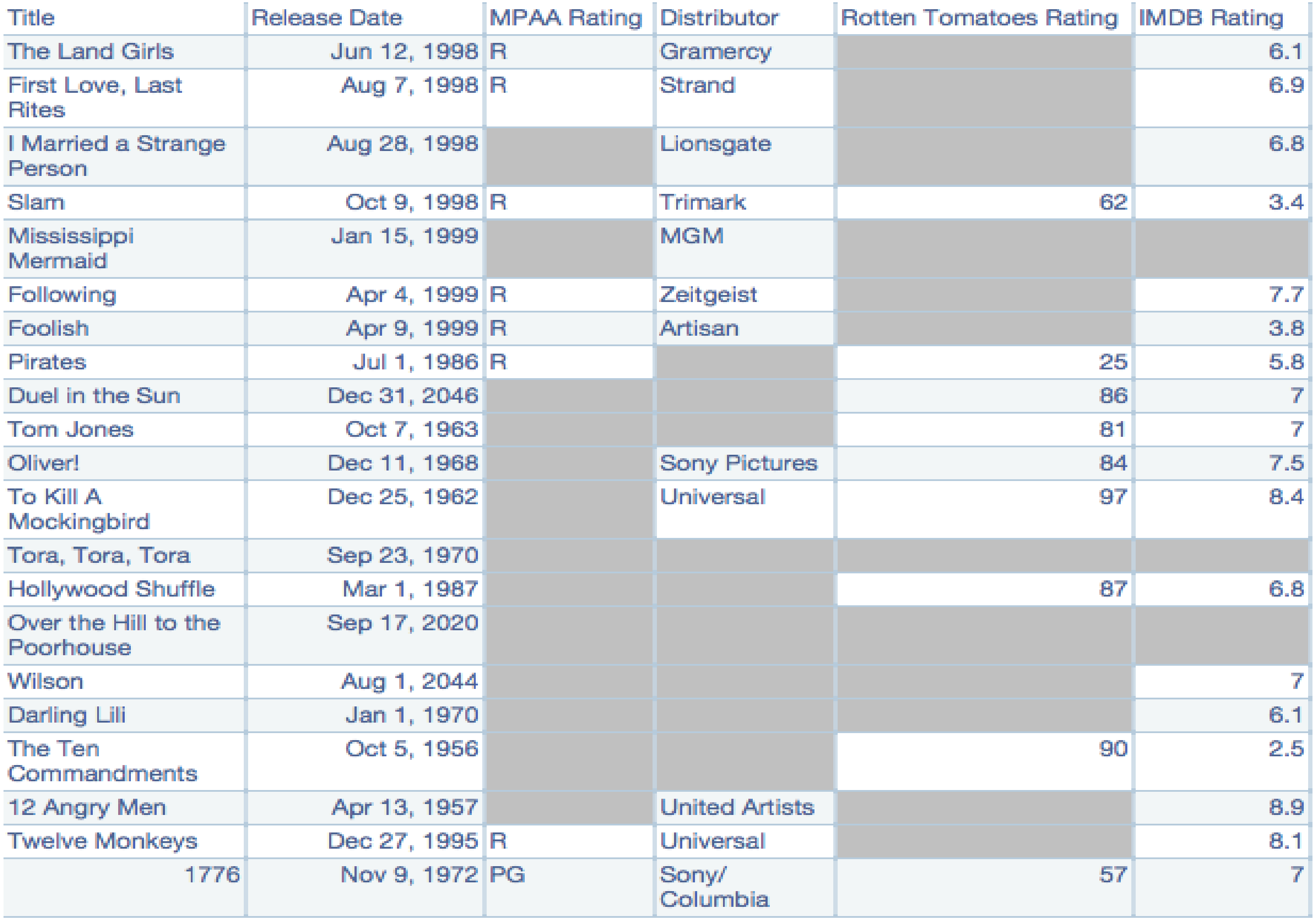
Submit news for this movie

Trailer

More trailers...



Title	Release Date	MPAA Rating	Distributor	Rotten Tomatoes Rating	IMDB Rating
The Land Girls	Jun 12, 1998	R	Gramercy		6.1
First Love, Last Rites	Aug 7, 1998	R	Strand		6.9
I Married a Strange Person	Aug 28, 1998		Lionsgate		6.8
Slam	Oct 9, 1998	R	Trimark	62	3.4
Mississippi Mermaid	Jan 15, 1999		MGM		
Following	Apr 4, 1999	R	Zeitgeist		7.7
Foolish	Apr 9, 1999	R	Artisan		3.8
Pirates	Jul 1, 1986	R		25	5.8
Duel in the Sun	Dec 31, 2046			86	7
Tom Jones	Oct 7, 1963			81	7
Oliver!	Dec 11, 1968		Sony Pictures	84	7.5
To Kill A Mockingbird	Dec 25, 1962		Universal	97	8.4
Tora, Tora, Tora	Sep 23, 1970				
Hollywood Shuffle	Mar 1, 1987			87	6.8
Over the Hill to the Poorhouse	Sep 17, 2020				
Wilson	Aug 1, 2044				7
Darling Lili	Jan 1, 1970				6.1
The Ten Commandments	Oct 5, 1956			90	2.5
12 Angry Men	Apr 13, 1957		United Artists		8.9
Twelve Monkeys	Dec 27, 1995	R	Universal		8.1
1776	Nov 9, 1972	PG	Sony/ Columbia	57	7



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Twelve Monkeys	Dec 27, 1995	R	Universal		8.1
1776	Nov 9, 1972	PG	Sony/ Columbia	57	7

Arnolds Park	Oct 19, 2007	PG-13	The Movie Partners
Sweet Sweetback's Baad Asssss Song	Jan 1, 1971		
And Then Came Love	Jun 1, 2007	Not Rated	Fox Meadow
Around the World in 80 Days	Oct 17, 1956	PG	United Artists
Barbarella	Oct 10, 1968		Paramount Pictures
Barry Lyndon	1975		Warner Bros.
Barbarians, The	March, 1987		
Babe	Aug 4, 1995	G	Universal
Boynton Beach Club	Mar 24, 2006	R	Wingate Distribution
Baby's Day Out	Jul 1, 1994	PG	20th Century

Bad Boys	Apr 7, 1995	6.6	53929
Body Double	Oct 26, 1984	6.4	9738
The Beast from 20,000 Fathoms	Jun 13, 1953		
Beastmaster 2: Through the Portal of Time	Aug 30, 1991	3.3	1327
The Beastmaster	Aug 20, 1982	5.7	5734
Ben-Hur	Dec 30, 2025	8.2	58510
Ben-Hur	Nov 18, 1959	8.2	58510
Benji	Nov 15, 1974	5.8	1801
Before Sunrise	Jan 27, 1995	8	39705

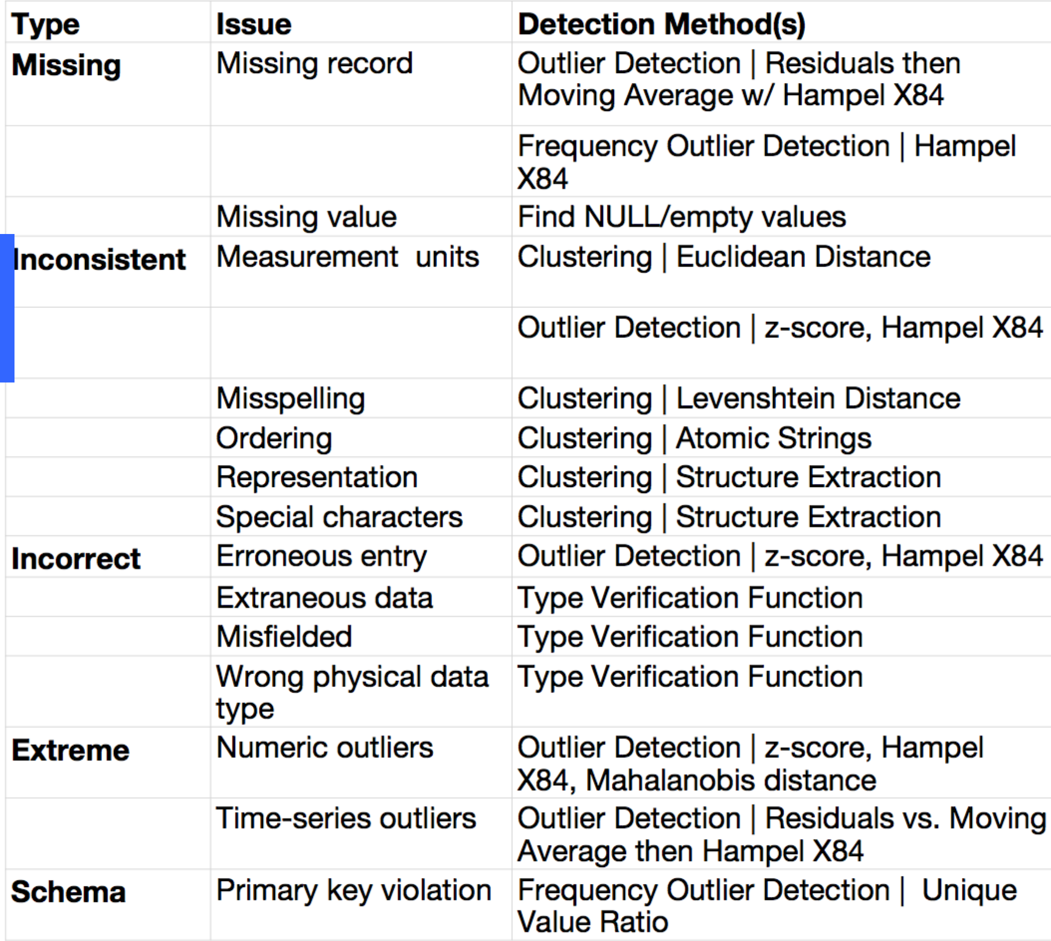
SOME DATA QUALITY ISSUES

MISSING DATA	MISSED MEASUREMENTS, REDACTED ITEMS, INCOMPLETE FORMS, ETC.
ERRONEOUS VALUES	MISSPELLINGS, OUTLIERS, “SPURIOUS INTEGRITY”, ETC.
ENTITY RESOLUTION	DIFFERENT VALUES, ABBREVS., 2+ ENTRIES FOR THE SAME THING?
TYPE CONVERSION	E.G., ZIP CODE OR PLACE NAME TO LAT-LON
DATA INTEGRATION	MISMATCHES AND INCONSISTENCIES WHEN COMBINING DATA

DETECTION METHODS

+ CAN IDENTIFY POTENTIAL ANOMALIES

- HARD TO KNOW IF THEY'RE REALLY ANOMALOUS OR HOW TO CORRECT THEM



Type	Issue	Detection Method(s)
Missing	Missing record	Outlier Detection | Residuals then Moving Average w/ Hampel X84
		Frequency Outlier Detection | Hampel X84
	Missing value	Find NULL/empty values
Inconsistent	Measurement units	Clustering | Euclidean Distance
		Outlier Detection | z-score, Hampel X84
	Misspelling	Clustering | Levenshtein Distance
	Ordering	Clustering | Atomic Strings
	Representation	Clustering | Structure Extraction
	Special characters	Clustering | Structure Extraction
Incorrect	Erroneous entry	Outlier Detection | z-score, Hampel X84
	Extraneous data	Type Verification Function
	Misfielded	Type Verification Function
	Wrong physical data type	Type Verification Function
Extreme	Numeric outliers	Outlier Detection | z-score, Hampel X84, Mahalanobis distance
	Time-series outliers	Outlier Detection | Residuals vs. Moving Average then Hampel X84
Schema	Primary key violation	Frequency Outlier Detection | Unique Value Ratio

MISSING AND IMPOSSIBLE VALUES

1. LOOK AT EMPTY/MISSING VALUES
2. LOOK AT IMPOSSIBLE VALUES

Gender = 3

Heart Rate = 0

Unlikely Dates (e.g. “01/01/0001”)

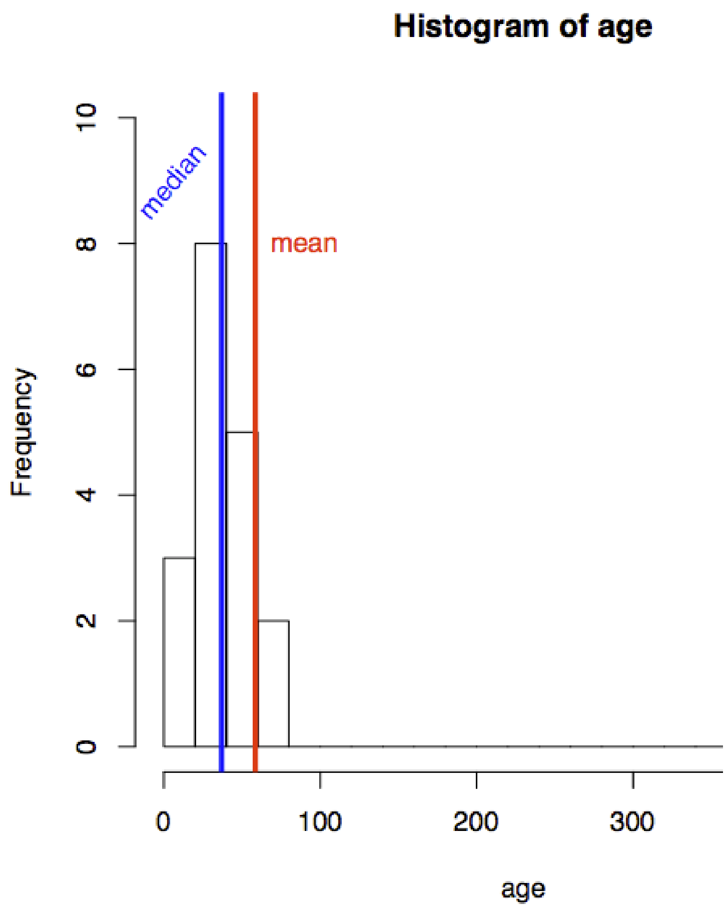
JUST SORTING THE DATA CAN HELP HIGHLIGHT ISSUES LIKE THESE

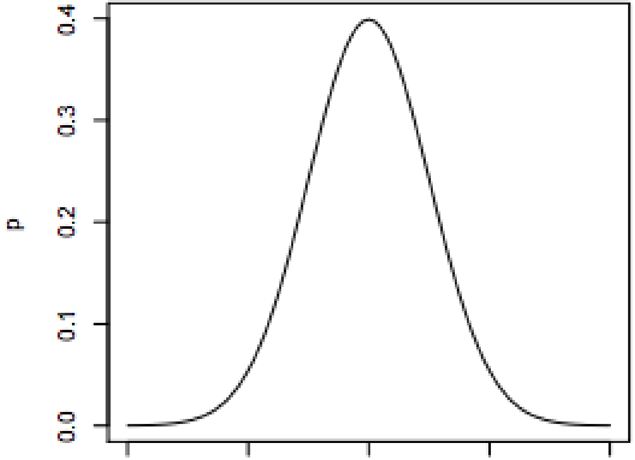
OUTLIER DETECTION

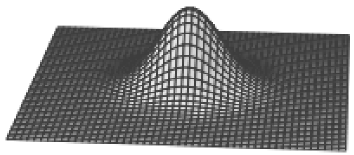
1. EXAMINE DISTRIBUTIONS
2. MODEL DATA AND LOOK FOR RESIDUALS
3. PARTITION DATA

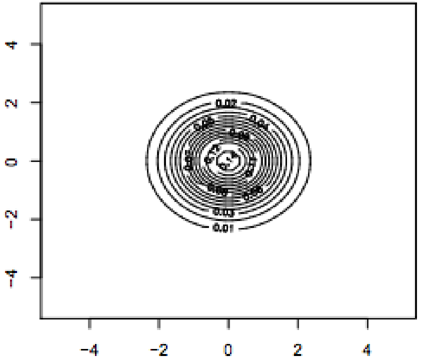
FOR ONE DATA DIMENSION OR MULTIPLE DIMENSIONS

EXAMINE DISTRIBUTIONS









DETECTING DUPLICATES

Title

Ben-Hur
Ben Hur
BEN-HUR
Ben-Hur (1959 film)

Name

Anand Vaskar
Anand Vaskkar
A. Vaskar
Vaskar, Anand

THESE *MIGHT* ALL BE THE SAME

SOME USEFUL DISTANCE METRICS

LEVENSHTEIN ("STRING-EDIT") DISTANCE

How many edits do I need to change one value into another?

Ben-Hur
Ben Hur

DISTANCE = 1

Anand Vaskar
Anand Vaskkar

DISTANCE = 1

SOME USEFUL DISTANCE METRICS

LEVENSHTEIN (“STRING-EDIT”) DISTANCE

How many edits do I need to change one value into another?

Ben-Hur
Ben-Hur (1959 film)

DISTANCE = 12

Anand Vaskar
Vaskar, Anand

DISTANCE = 12

SOME USEFUL DISTANCE METRICS

SOUNDEX / METAPHONE

How similar do they sound?

Ben-Hur
Ben-Hurr
Been Her

Anand Vaskar
Anand Vaskkar
Ahnund Vachkar

SOME USEFUL DISTANCE METRICS

“FINGERPRINTING” METHODS

Strip away unimportant details.

(e.g., remove punctuation, capitals, and sort)

Anand Vaskar → anand vaskar

Vaskar, Anand → anand vaskar

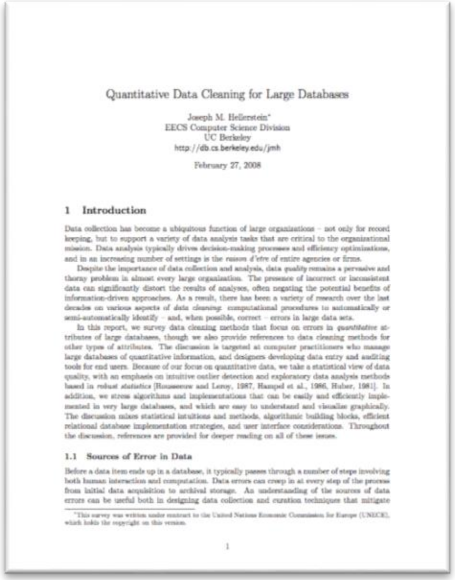
AND MANY MORE

STRING/KEY COMPARISONS

DISTANCE METRICS FOR NUMERIC DATA

e.g., HAMPEL X84 (UNIVARIATE), MAHALANOBIS (MULTIVARIATE)

“Quantitative Data Cleaning for Large Databases”
Hellerstein (2008)



Quantitative Data Cleaning for Large Databases

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UC Berkeley
http://db.cs.berkeley.edu/jmh

February 27, 2008

1 **Introduction**

Data collection has become a ubiquitous function of large organizations – not only for record keeping, but to support a variety of data analysis tasks that are critical to the organizational mission. Data analysis typically drives decision-making processes and efficiency optimizations, and in an increasing number of settings is the *raison d'etre* of entire agencies or firms.

Despite the importance of data collection and analysis, data *quality* remains a pervasive and thorny problem in almost every large organization. The presence of incorrect or inconsistent data can significantly distort the results of analyses, often negating the potential benefits of information-driven approaches. As a result, there has been a variety of research over the last decades on various aspects of *data cleaning*: computational procedures to automatically or semi-automatically identify – and, when possible, correct – errors in large data sets.

In this report, we survey data cleaning methods that focus on errors in *quantitative* attributes of large databases, though we also provide references to data cleaning methods for other types of attributes. The discussion is targeted at computer practitioners who manage large databases of quantitative information, and designers developing data entry and auditing tools for end users. Because of our focus on quantitative data, we take a statistical view of data quality, with an emphasis on intuitive outlier detection and exploratory data analysis methods based in *robust statistics* [Rousseeuw and Leroy, 1987, Hampel et al., 1986, Huber, 1981]. In addition, we stress algorithms and implementations that can be easily and efficiently implemented in very large databases, and which are easy to understand and visualize graphically. The discussion mixes statistical intuitions and methods, algorithmic building blocks, efficient relational database implementation strategies, and user interface considerations. Throughout the discussion, references are provided for deeper reading on all of these issues.

1.1 **Sources of Error in Data**

Before a data item ends up in a database, it typically passes through a number of steps involving both human interaction and computation. Data errors can creep in at every step of the process from initial data acquisition to archival storage. An understanding of the sources of data errors can be useful both in designing data collection and curation techniques that mitigate

[*] This survey was written under contract to the United Nations Economic Commission for Europe (UNECE), which holds the copyright on this version.

1

DECIDING HOW TO FIX PROBLEMS

YOU CAN DO ALMOST ALL OF
THIS IN **SQL …** BUT IT'S A LOT OF WORK

DECIDING HOW TO FIX PROBLEMS

WHICH DUPLICATE TO KEEP?

OUTLIERS: KEEP, REMOVE, OR REPAIR?

BADLY-STORED DATES, ADDRESSES, OR KEYS MAY NEED TO BE PARSED MANUALLY

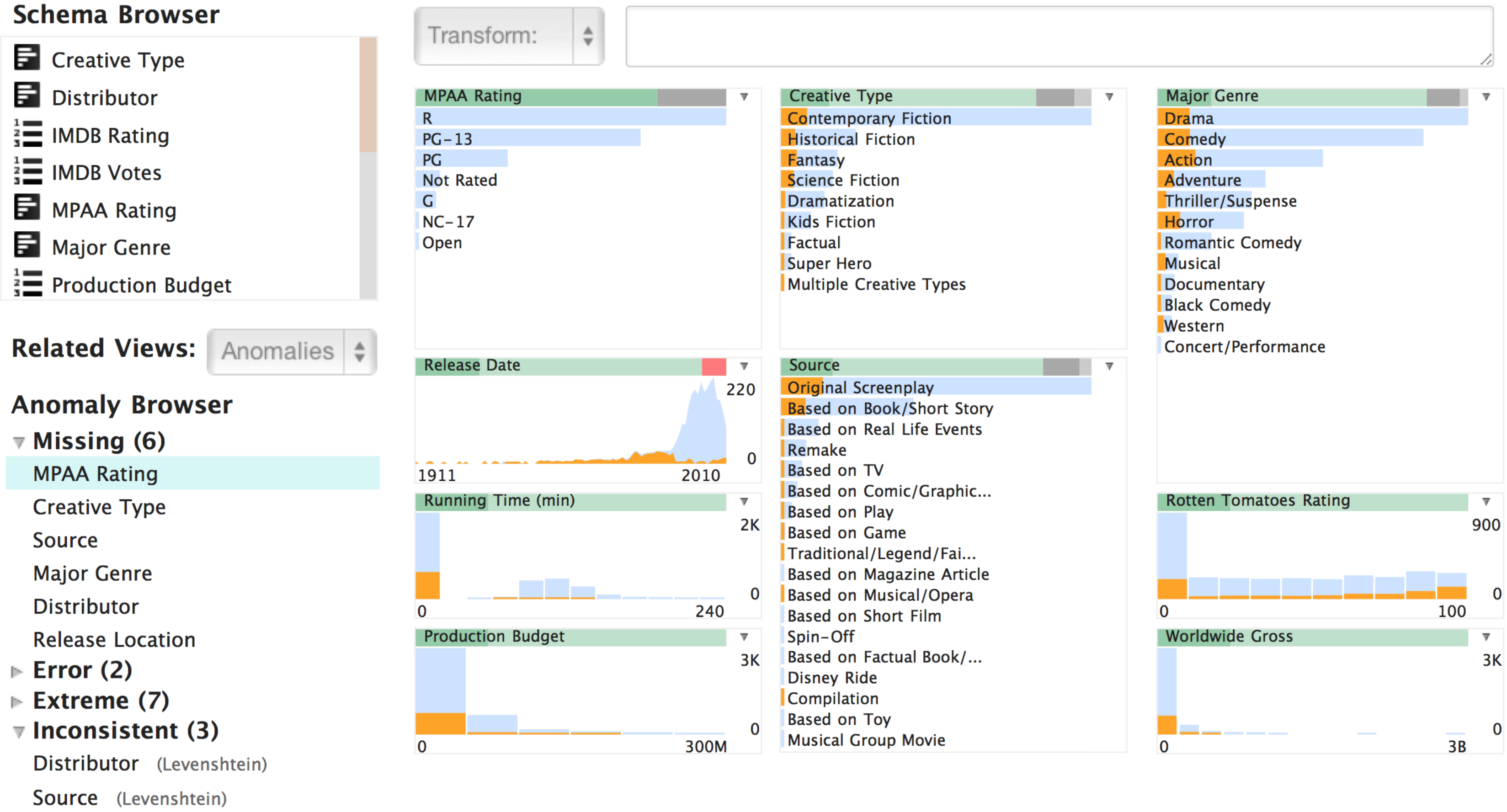
DECIDING HOW TO FIX PROBLEMS

FUZZY MATCHING SYSTEMS

MACHINE LEARNING TO DETECT/RESOLVE ERRORS

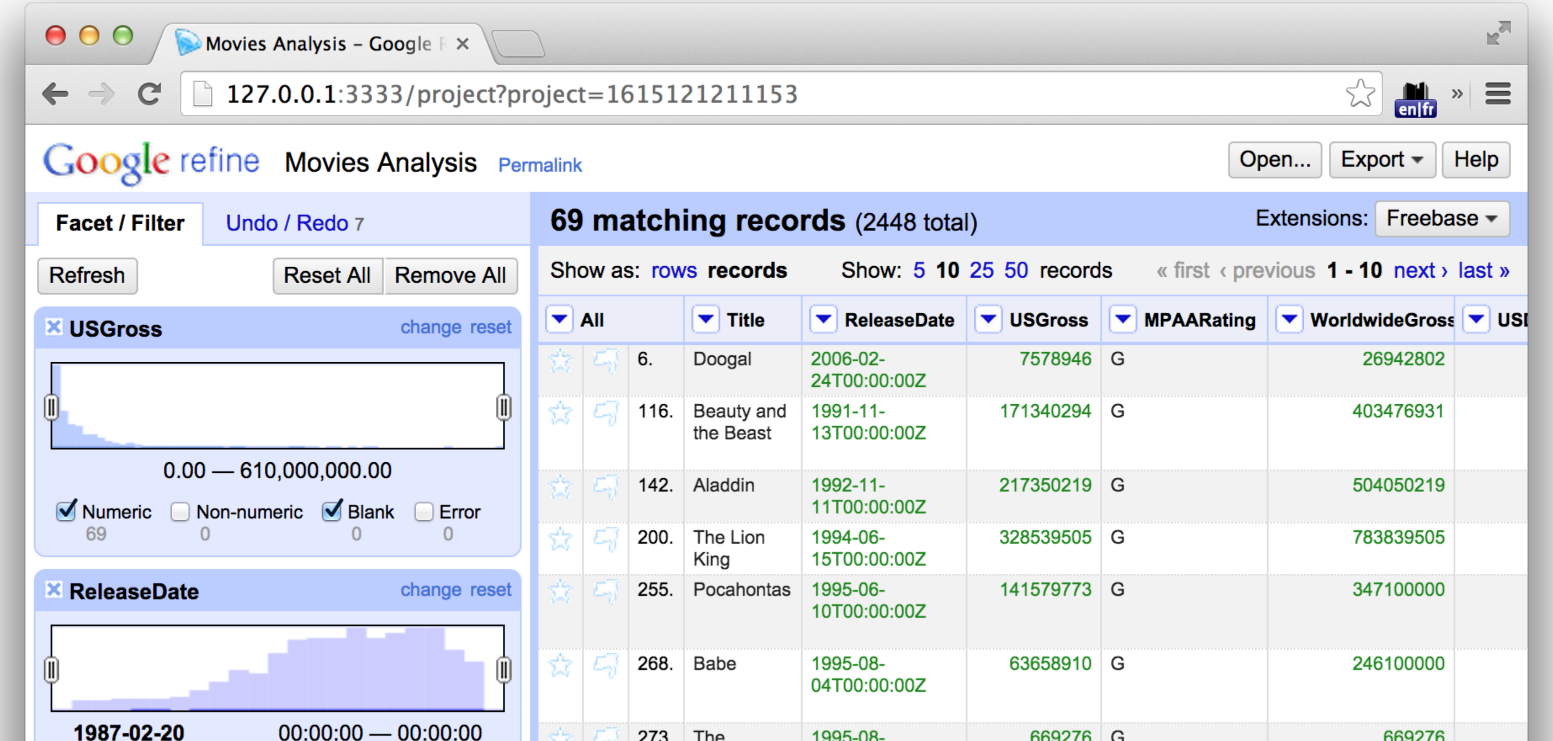
USUALLY REQUIRES HUMAN JUDGMENT
(ESPECIALLY FOR NEW DATA)

INTERACTIVE PROFILING



PROFILER [KANDEL ET AL. 2012]

PROFILING IN OPEN REFINE



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Open... Export Help

Facet / Filter Undo / Redo 7

Refresh Reset All Remove All

USGross change reset

0.00 — 610,000,000.00

☑ Numeric 69 ☐ Non-numeric 0 ☑ Blank 0 ☐ Error 0

ReleaseDate change reset

1987-02-20 00:00:00 — 00:00:00

69 matching records (2448 total)

Extensions: Freebase

Show as: rows **records** Show: 5 **10** 25 50 records « first ‹ previous **1 - 10** next › last »

All			Title	ReleaseDate	USGross	MPAARating	WorldwideGross	USI
☆		6.	Doogal	2006-02-24T00:00:00Z	7578946	G	26942802	
☆		116.	Beauty and the Beast	1991-11-13T00:00:00Z	171340294	G	403476931	
☆		142.	Aladdin	1992-11-11T00:00:00Z	217350219	G	504050219	
☆		200.	The Lion King	1994-06-15T00:00:00Z	328539505	G	783839505	
☆		255.	Pocahontas	1995-06-10T00:00:00Z	141579773	G	347100000	
☆		268.	Babe	1995-08-04T00:00:00Z	63658910	G	246100000	
☆		273.	The	1995-08-	669276	G	669276	

SOME APPROACHES FOR IMPROVING DATA QUALITY

TOOLS FOR MANIPULATING AND CLEANING DATA

“WRANGLING” DATA

CLEANING AND TRANSFORMING DATASETS TO MAKE IT <u>POSSIBLE</u> TO ANALYZE AND VISUALIZE THEM

COMMON OPERATIONS

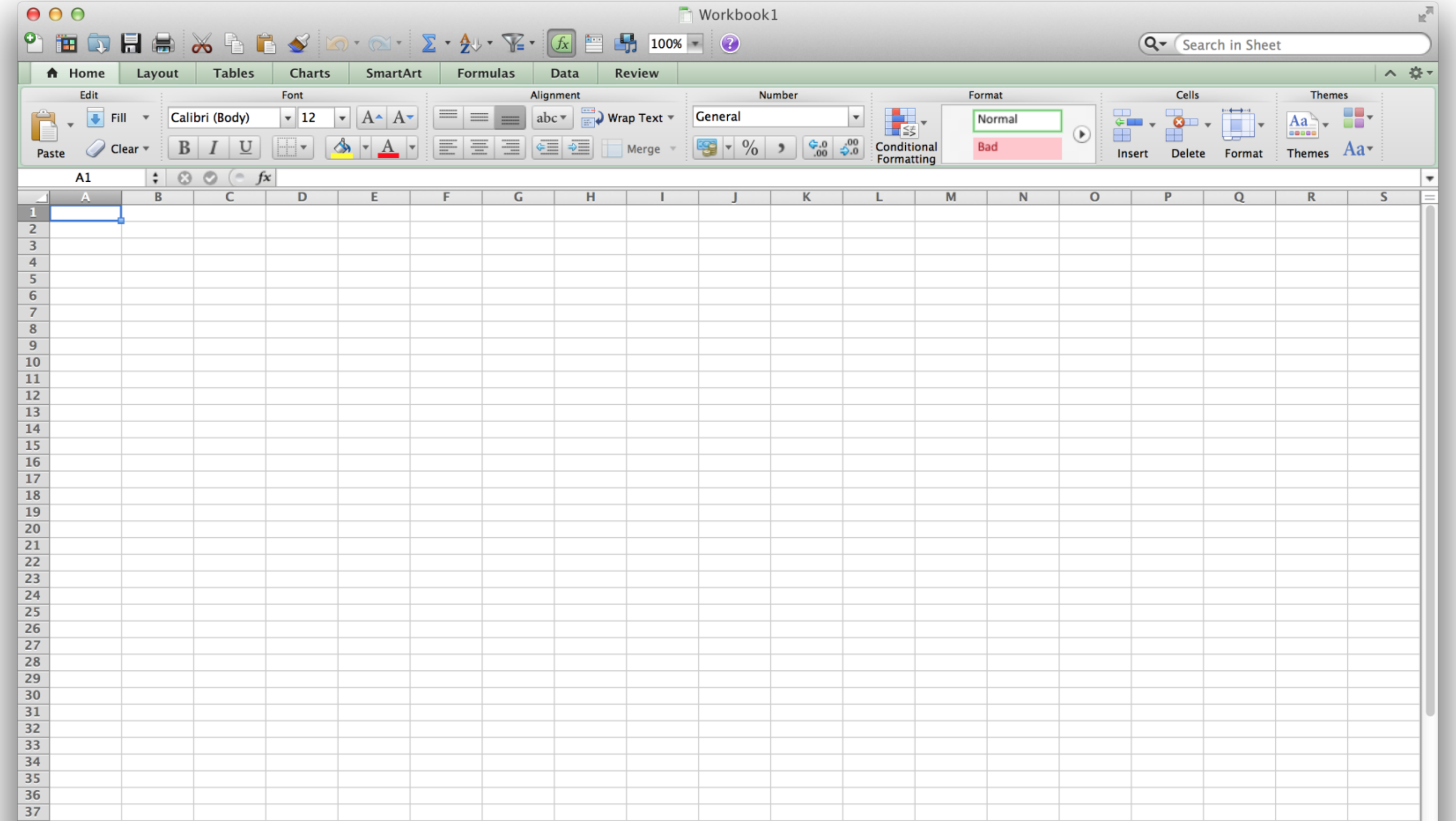
CORRECTING AND REMOVING ERRORS

CHANGING FORMATS

REMOVING FORMATTING

CONNECTING AND RESOLVING DATA

SPREADSHEETS

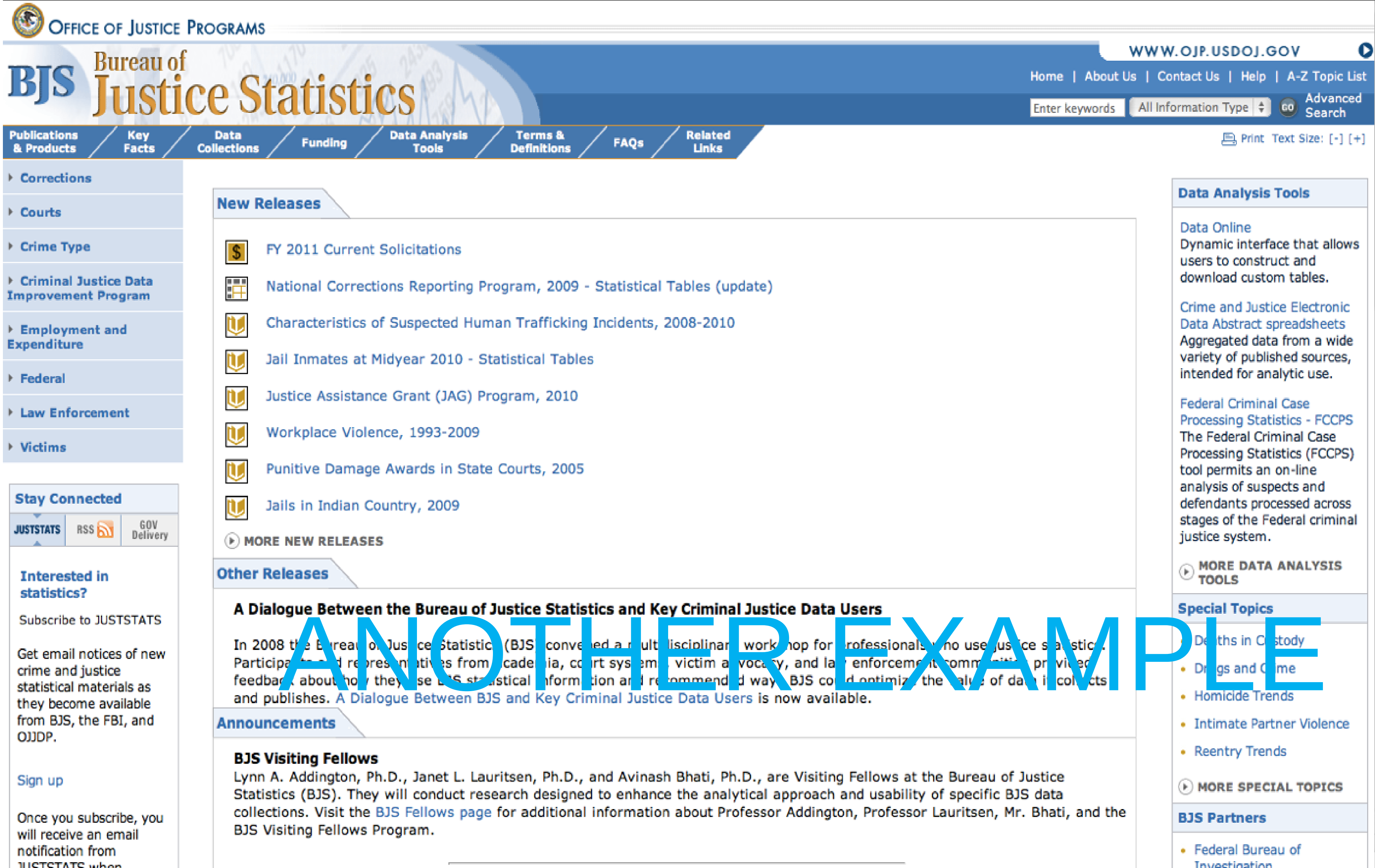


TRANSFORMATIONS ARE TIME-CONSUMING

“I spend more than half my time integrating, cleansing, and transforming data without doing any actual analysis. Most of the time I’m lucky if I get to do any ‘analysis’ at all.”

“Most of the time once you transform the data, the insights can be scarily obvious.”

[Kandel 2012]



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- FY 2011 Current Solicitations
- National Corrections Reporting Program, 2009 - Statistical Tables (update)
- Characteristics of Suspected Human Trafficking Incidents, 2008-2010
- Jail Inmates at Midyear 2010 - Statistical Tables
- Justice Assistance Grant (JAG) Program, 2010
- Workplace Violence, 1993-2009
- Punitive Damage Awards in State Courts, 2005
- Jails in Indian Country, 2009

MORE NEW RELEASES

Other Releases

A Dialogue Between the Bureau of Justice Statistics and Key Criminal Justice Data Users

In 2008 the Bureau of Justice Statistics (BJS) convened a multidisciplinary workshop for professionals who use justice statistics. Participants and representatives from academia, court systems, victim advocacy, and law enforcement communities provided feedback about how they use BJS statistical information and recommended ways BJS could optimize the value of data it collects and publishes. A Dialogue Between BJS and Key Criminal Justice Data Users is now available.

Announcements

BJS Visiting Fellows

Lynn A. Addington, Ph.D., Janet L. Lauritsen, Ph.D., and Avinash Bhati, Ph.D., are Visiting Fellows at the Bureau of Justice Statistics (BJS). They will conduct research designed to enhance the analytical approach and usability of specific BJS data collections. Visit the BJS Fellows page for additional information about Professor Addington, Professor Lauritsen, Mr. Bhati, and the BJS Visiting Fellows Program.

Data Analysis Tools

Data Online
Dynamic interface that allows users to construct and download custom tables.

Crime and Justice Electronic Data Abstract spreadsheets
Aggregated data from a wide variety of published sources, intended for analytic use.

Federal Criminal Case Processing Statistics - FCCPS
The Federal Criminal Case Processing Statistics (FCCPS) tool permits an on-line analysis of suspects and defendants processed across stages of the Federal criminal justice system.

MORE DATA ANALYSIS TOOLS

Special Topics

- Deaths in Custody
- Drugs and Crime
- Homicide Trends
- Intimate Partner Violence
- Reentry Trends

MORE SPECIAL TOPICS

BJS Partners

- Federal Bureau of Investigation

ANOTHER EXAMPLE

State	2004	2005	2006	2007	2008			
Alabama	4029.3	3900	3937	3974.9	4081.9			
Alaska	3370.9	3615	3582	3373.9	2928.3			
Arizona	5073.3	4827	4741.6	4502.6	4087.3			
Arkansas	4033.1	4068	4021.6	3945.5	3843.7			
California	3423.9	3321	3175.2	3032.6	2940.3			
Colorado	3918.5	4041	3441.8	2991.3	2856.7			
Connecticut	2684.9	2579	2575	2470.6	2490.8			
Delaware	3283.6	3118	3474.5	3427.1	3594.7			
District of Columbia	4852.8	4490	4653.9	4916.3	5104.6			
Florida	4182.5	4013	3986.2	4088.8	4140.6			
Georgia	4223.5	4145	3928.8	3893.1	3996.6			
Hawaii	4795.5	4800	4219.9	4119.3	3566.5			
Idaho	2781	2697	2386.9	2264.2	2116.5			
Illinois	3174.1	3092	3019.6	2935.8	2932.6			
Indiana	3403.6	3460	3464.3	3386.5	3339.6			
Iowa	2904.8	2845	2870.3	2648.6	2440.5			
Kansas	4015.5	3806	3858.5	3693.8	3397			
Kentucky	2540.2	2531	2621.9	2524.6	2677.1			
Louisiana	4419.1	3696	4088.5	4196.1	3880.2			
Maine	2413.7	2419	2546.1	2448.3	2463.7			
Maryland	3640.7	3551	3481.2	3431.5	3516			
Massachusetts	2468.2	2358	2396	2399.2	2402			
Michigan	3066.1	3098	3226	3057.8	2945.7			
Minnesota	3041.6	3088	3088.8	3045	2858.1			
Mississippi	3481.1	3274	3213	3137.8	2941.7			
Missouri	3900.1	3929	3828.4	3828.2	3663.6			
Montana	2936.1	3146	2863.4	2863.6	2720.9			
Nebraska	3519.6	3432	3364.9	3142.8	2878.3			
Nevada	4210	4246	4099.6	3785.1	3456.4			

Year	Property Crime Rate				
Reported crime in Alabama					
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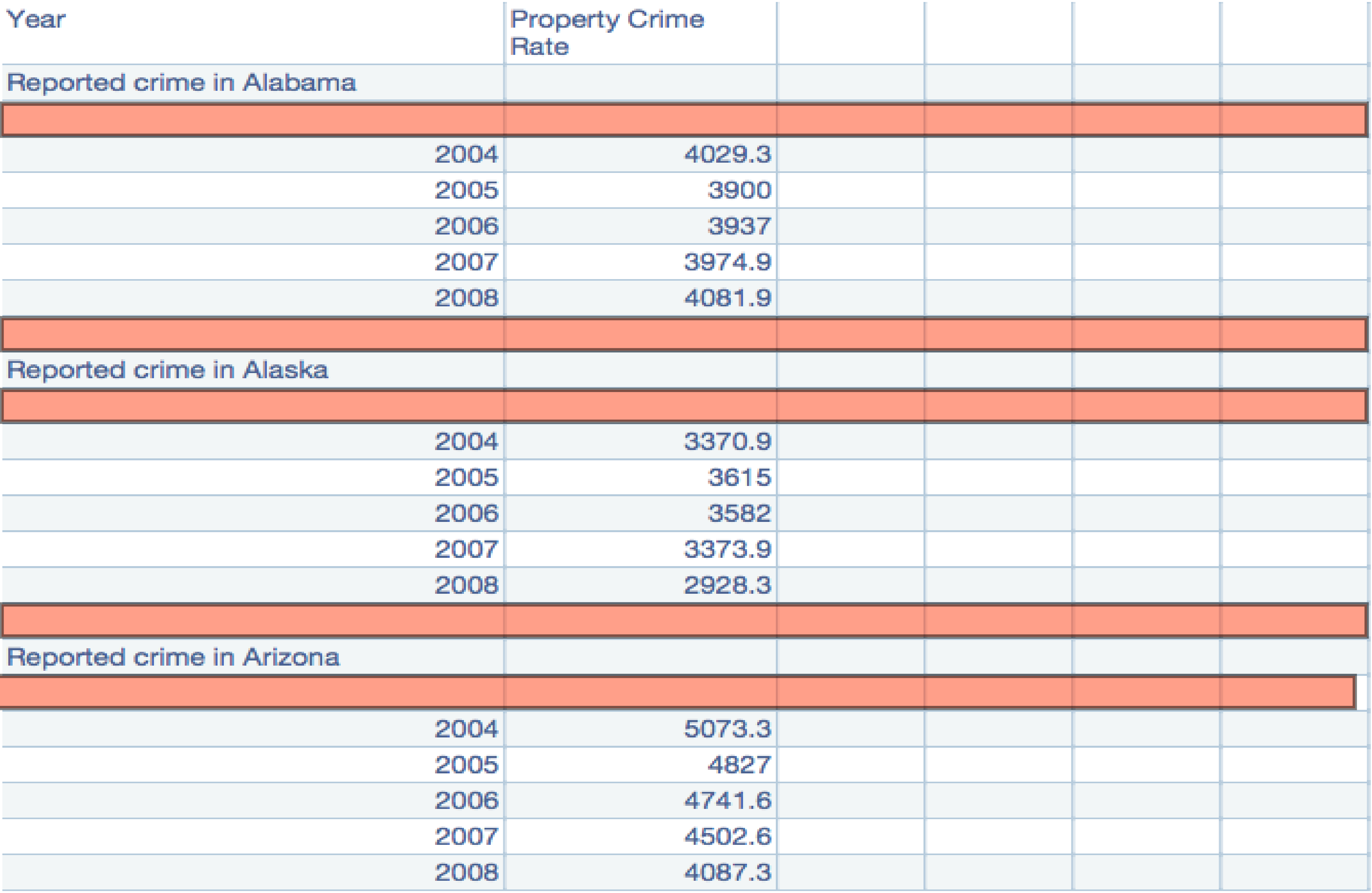
2008	4087.3				



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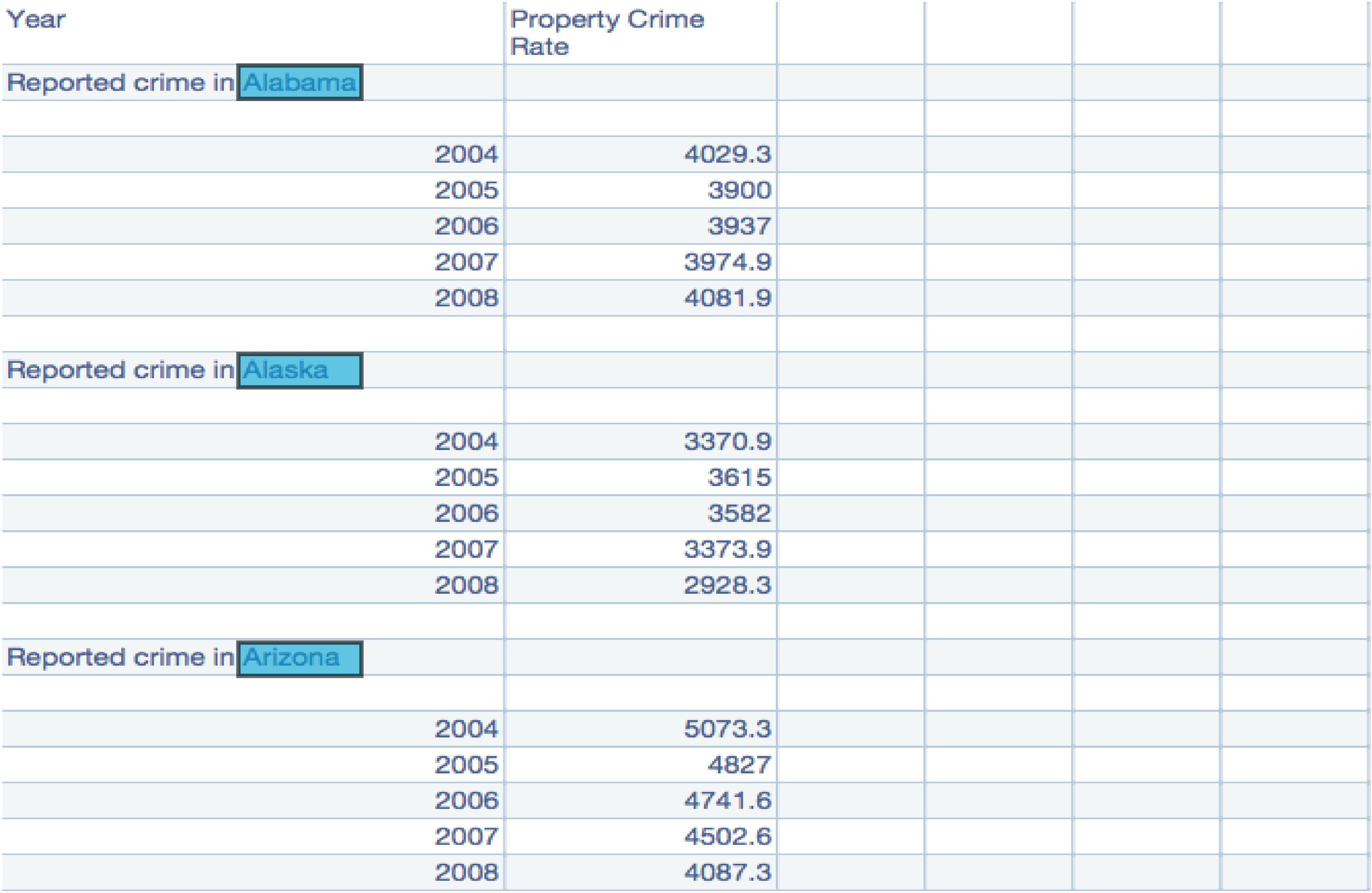

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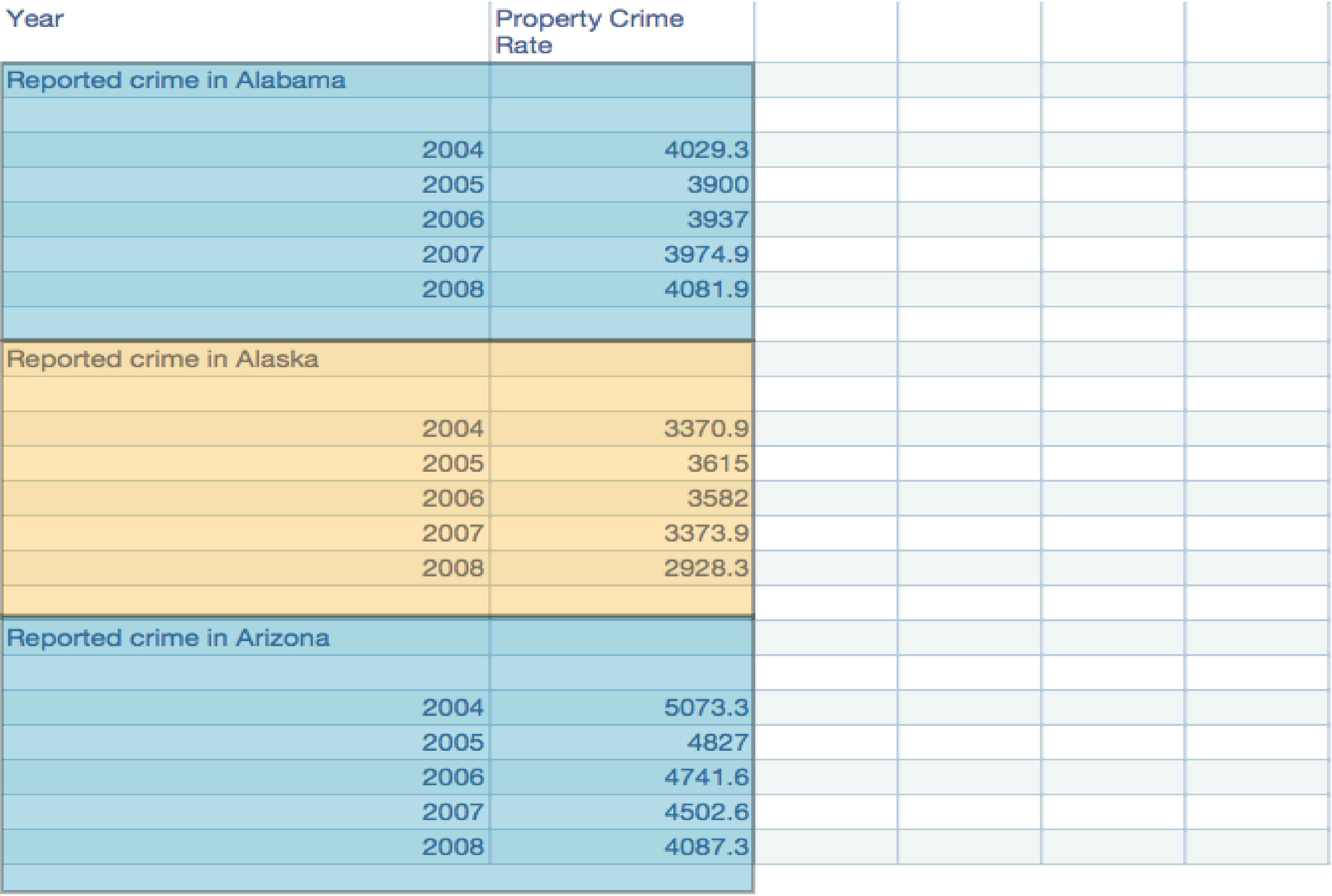

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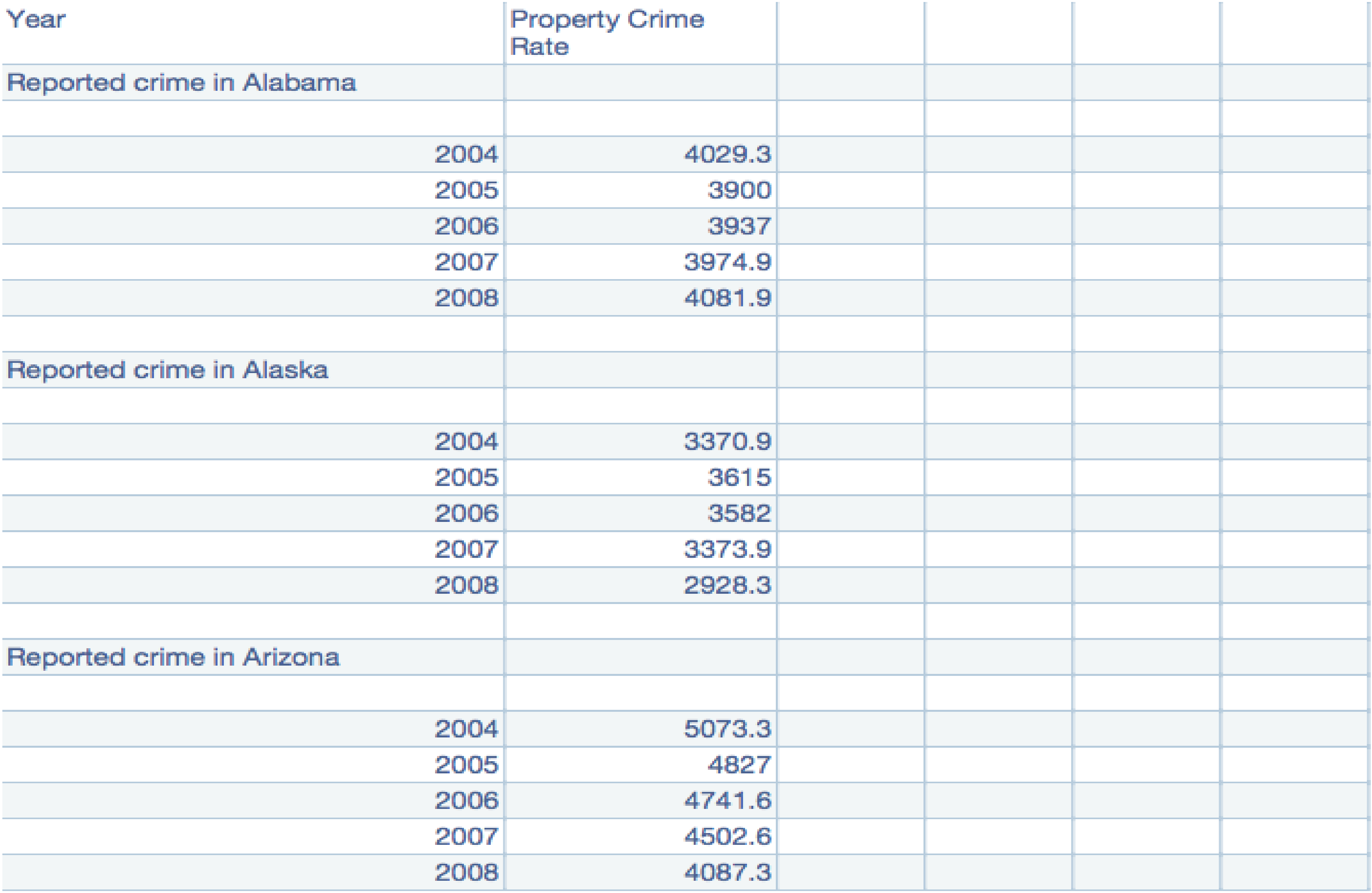

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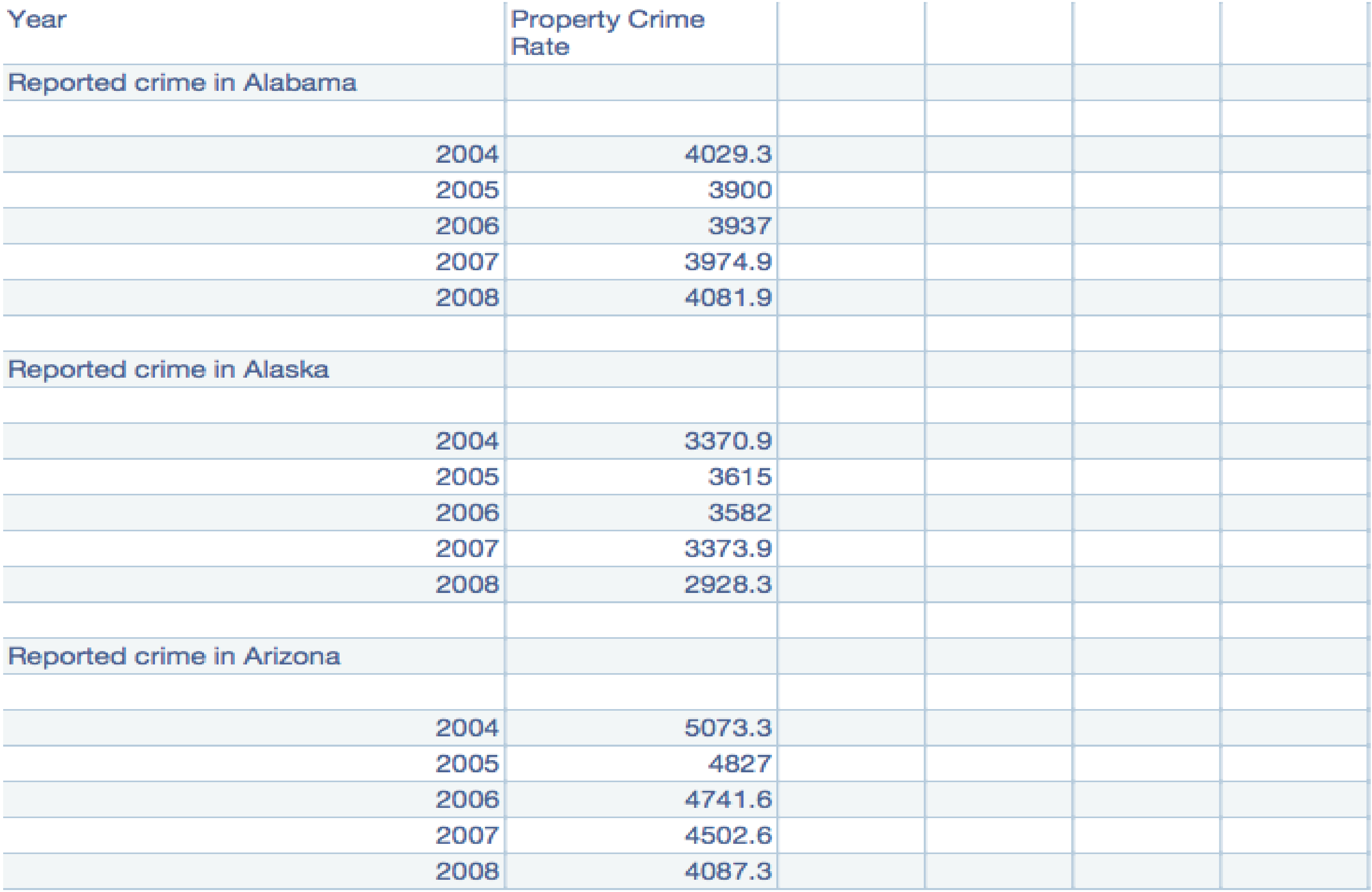

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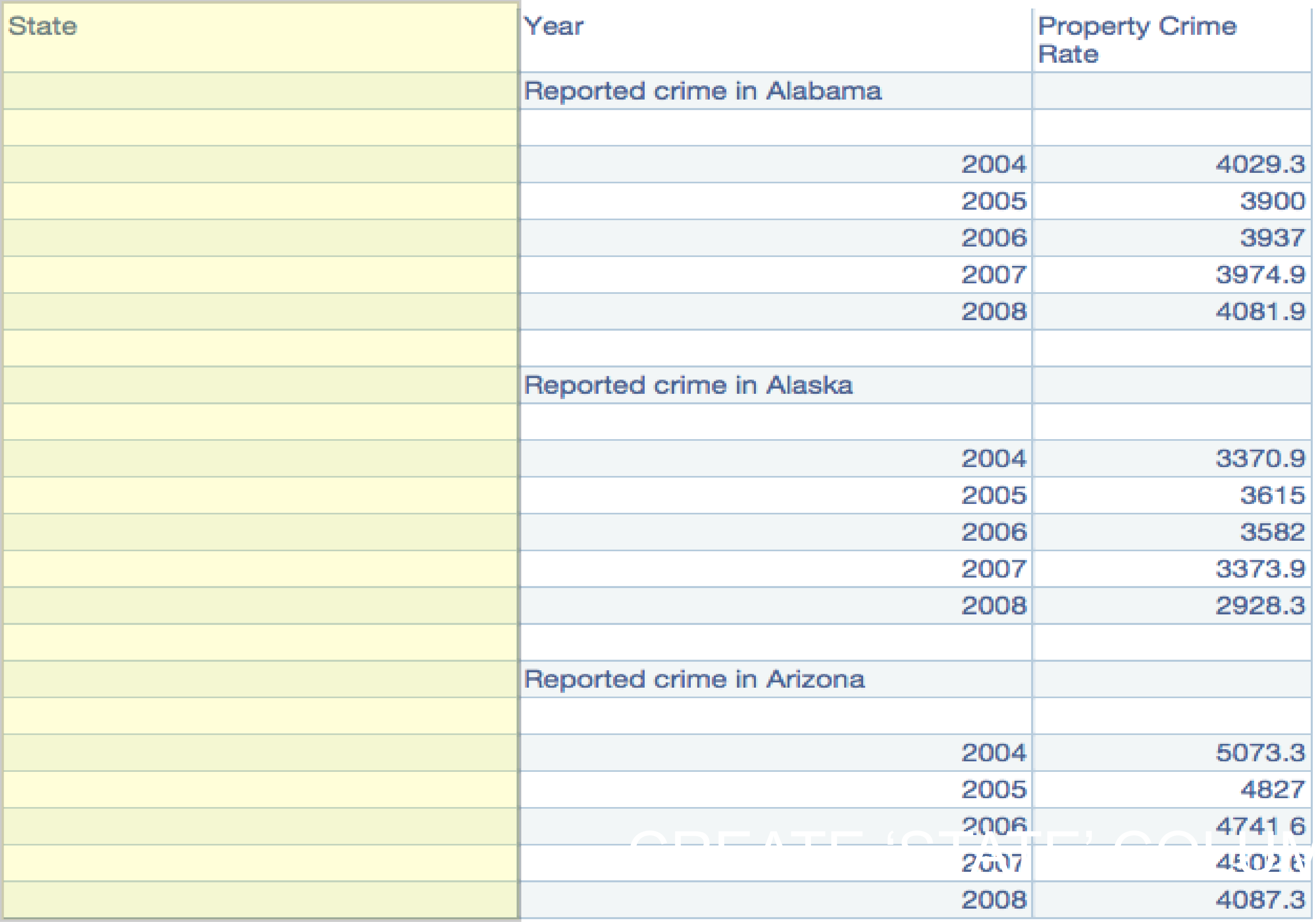

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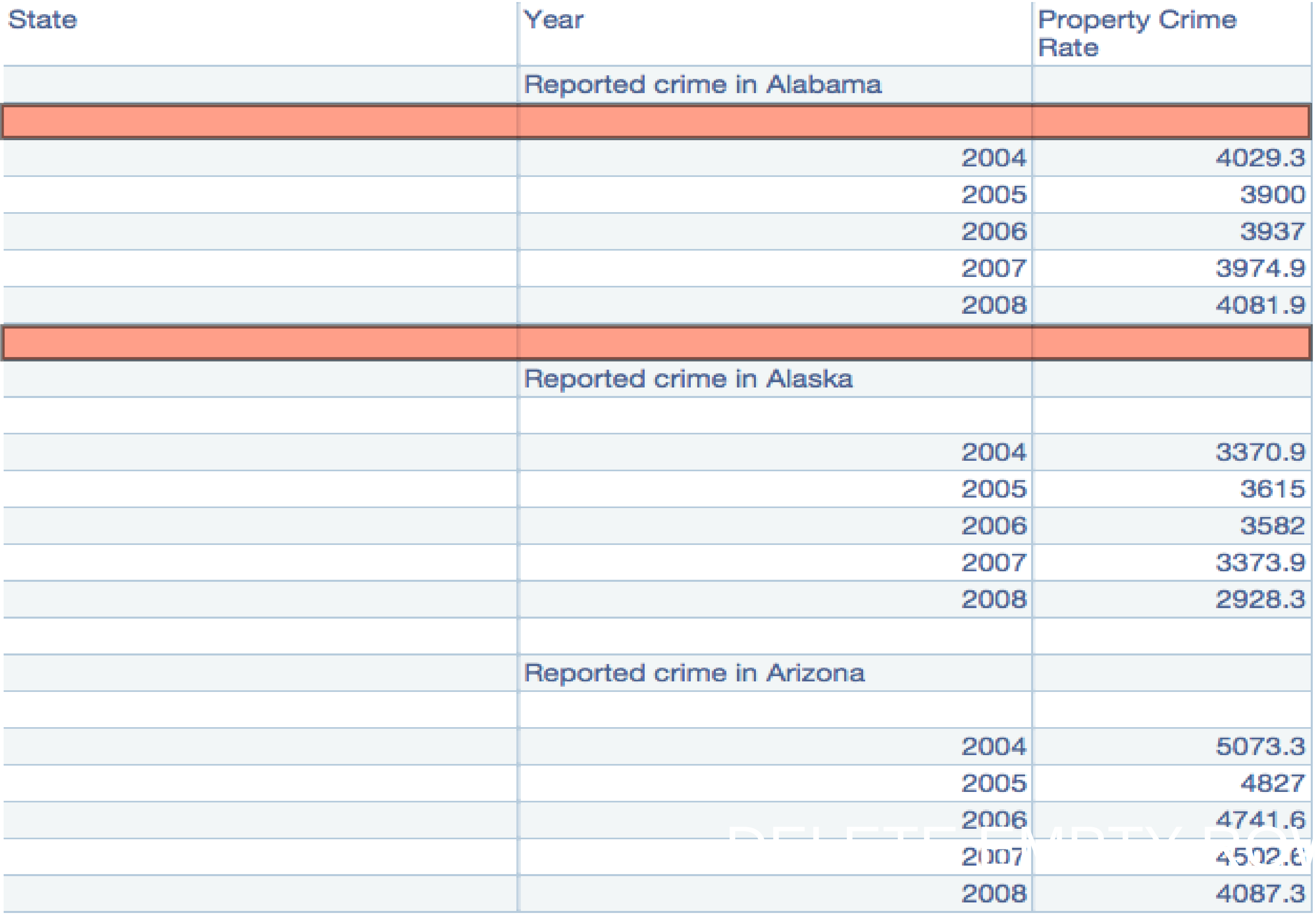
	2008	4087.3

CREATE ‘STATE’ COLUM



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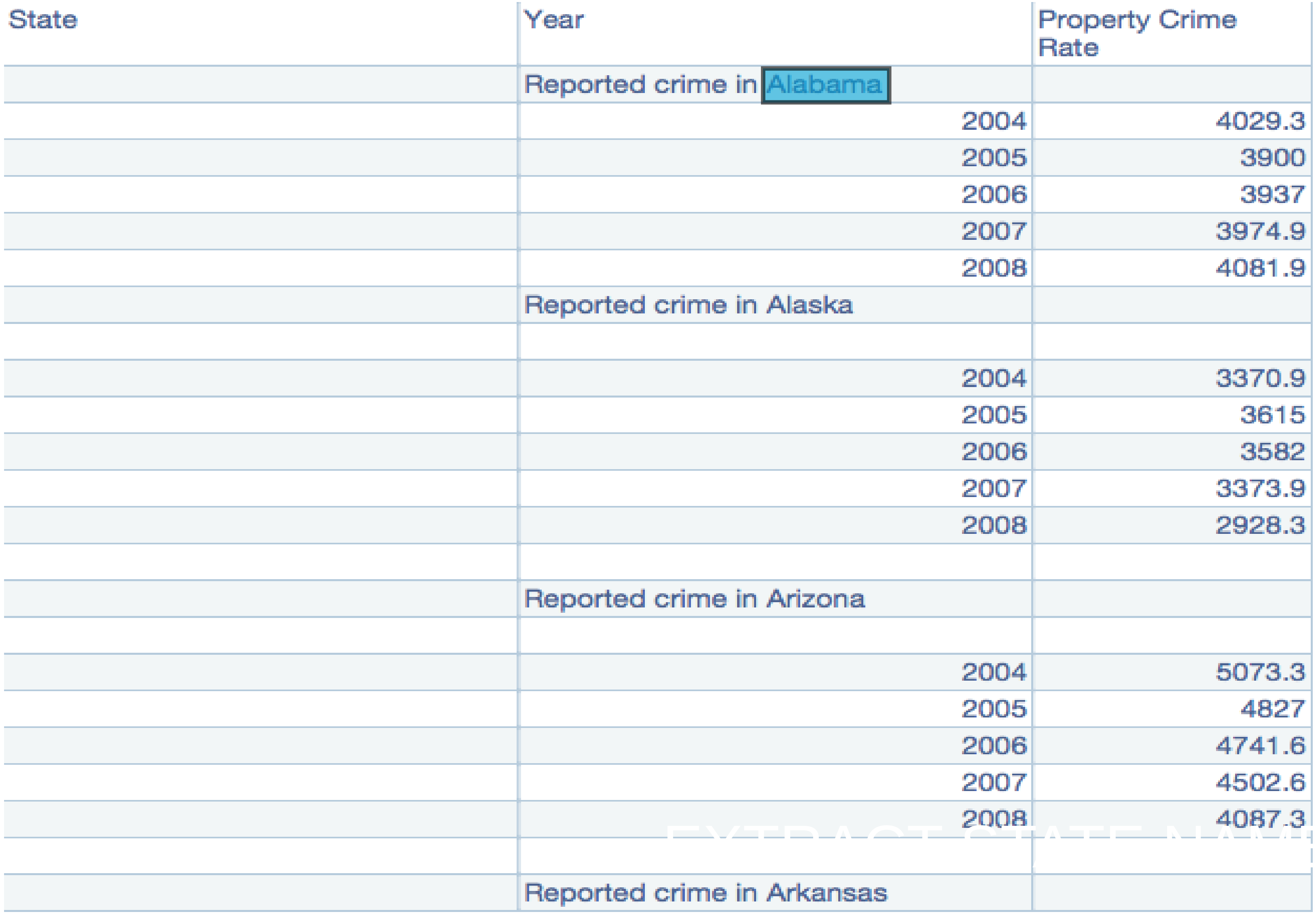
DELETE EMPTY ROW



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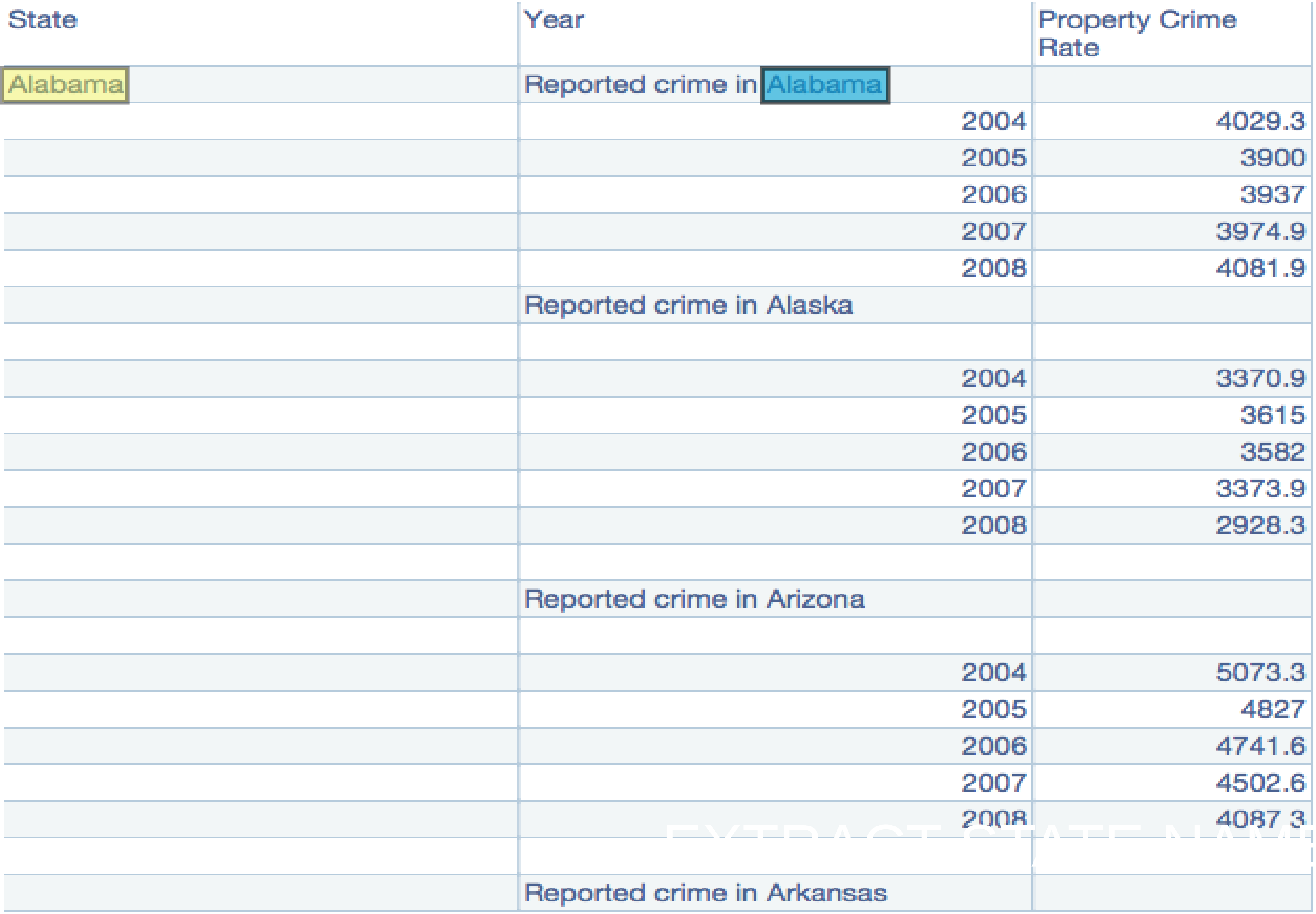
	Reported crime in Arkansas	



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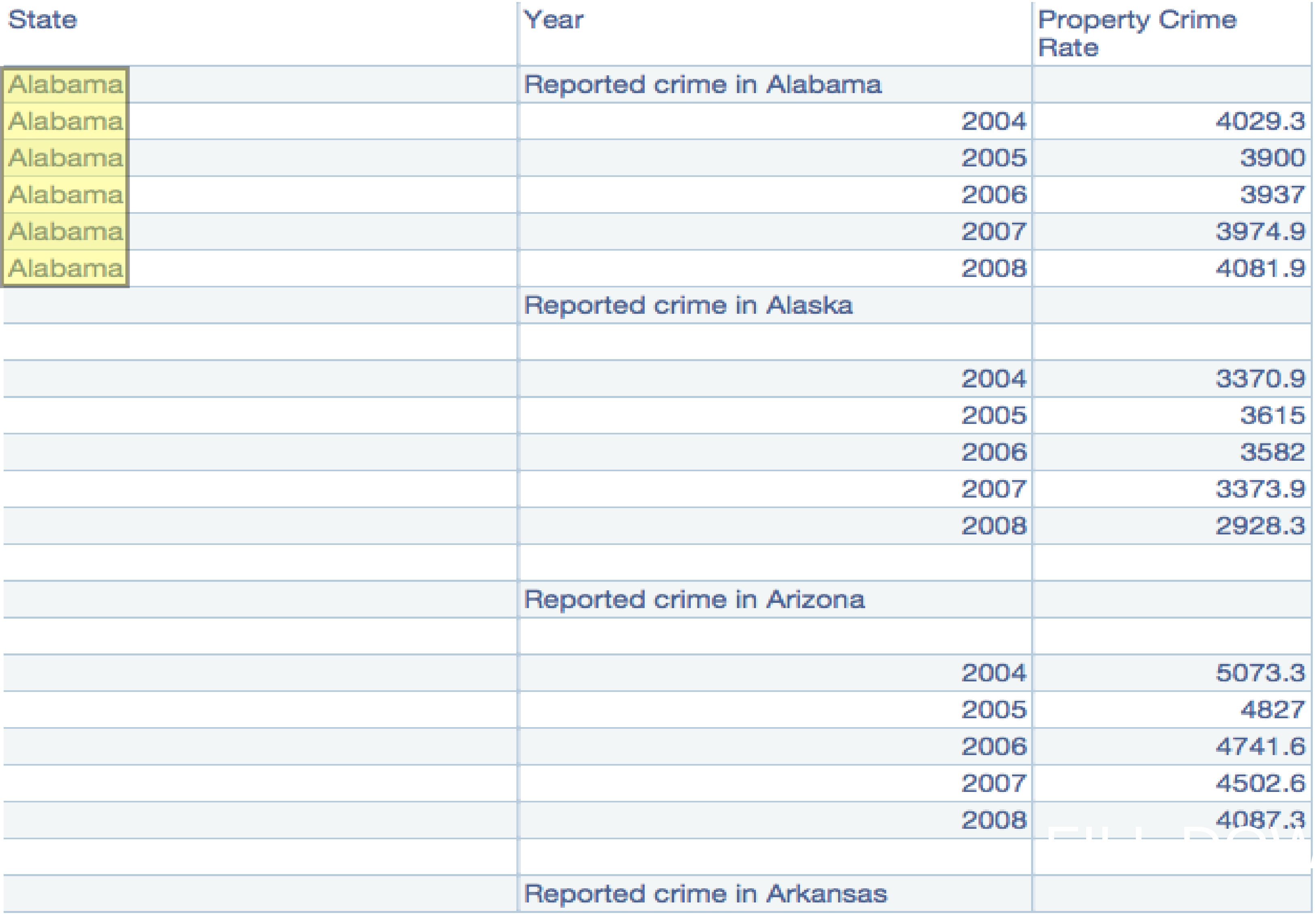

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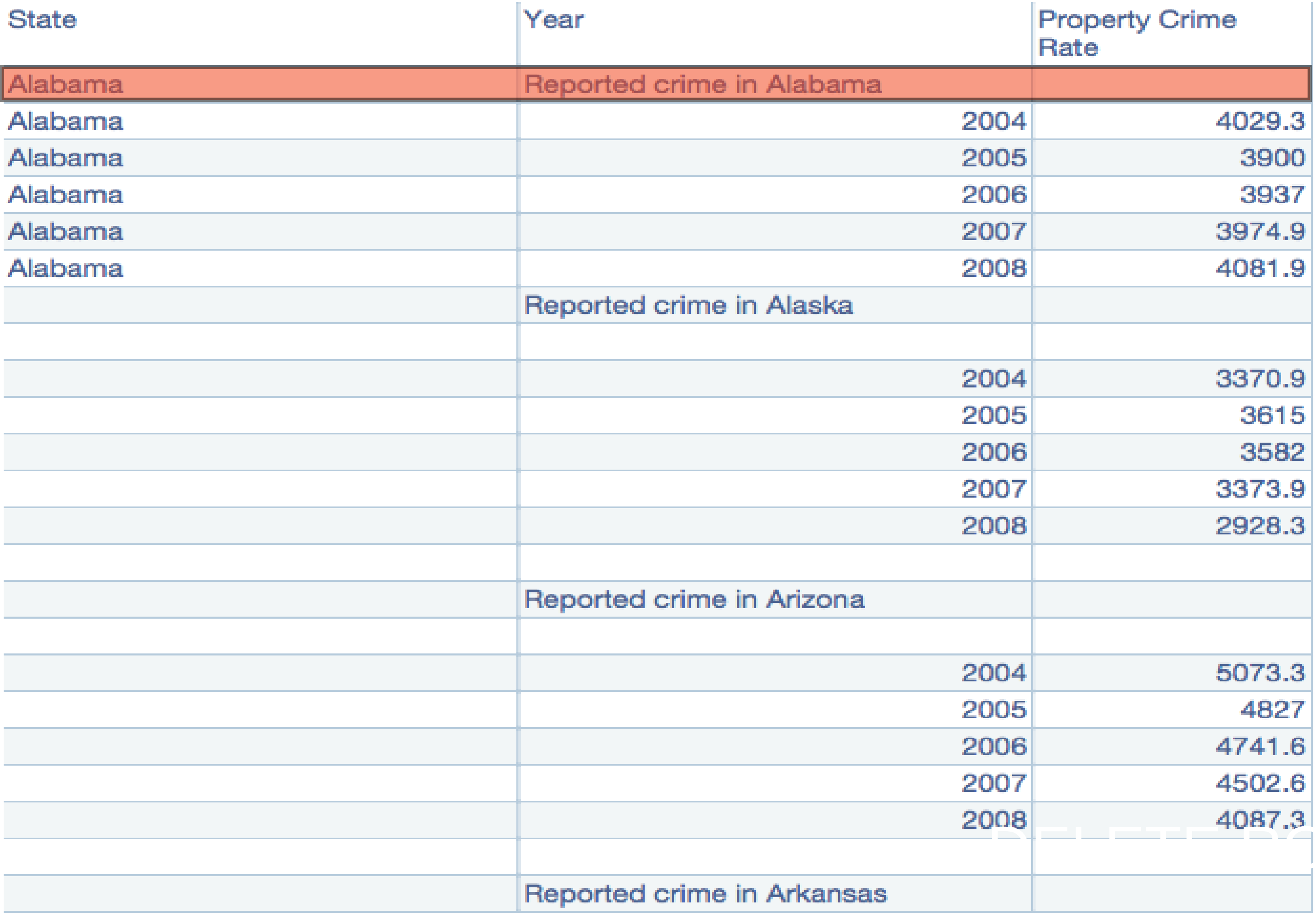

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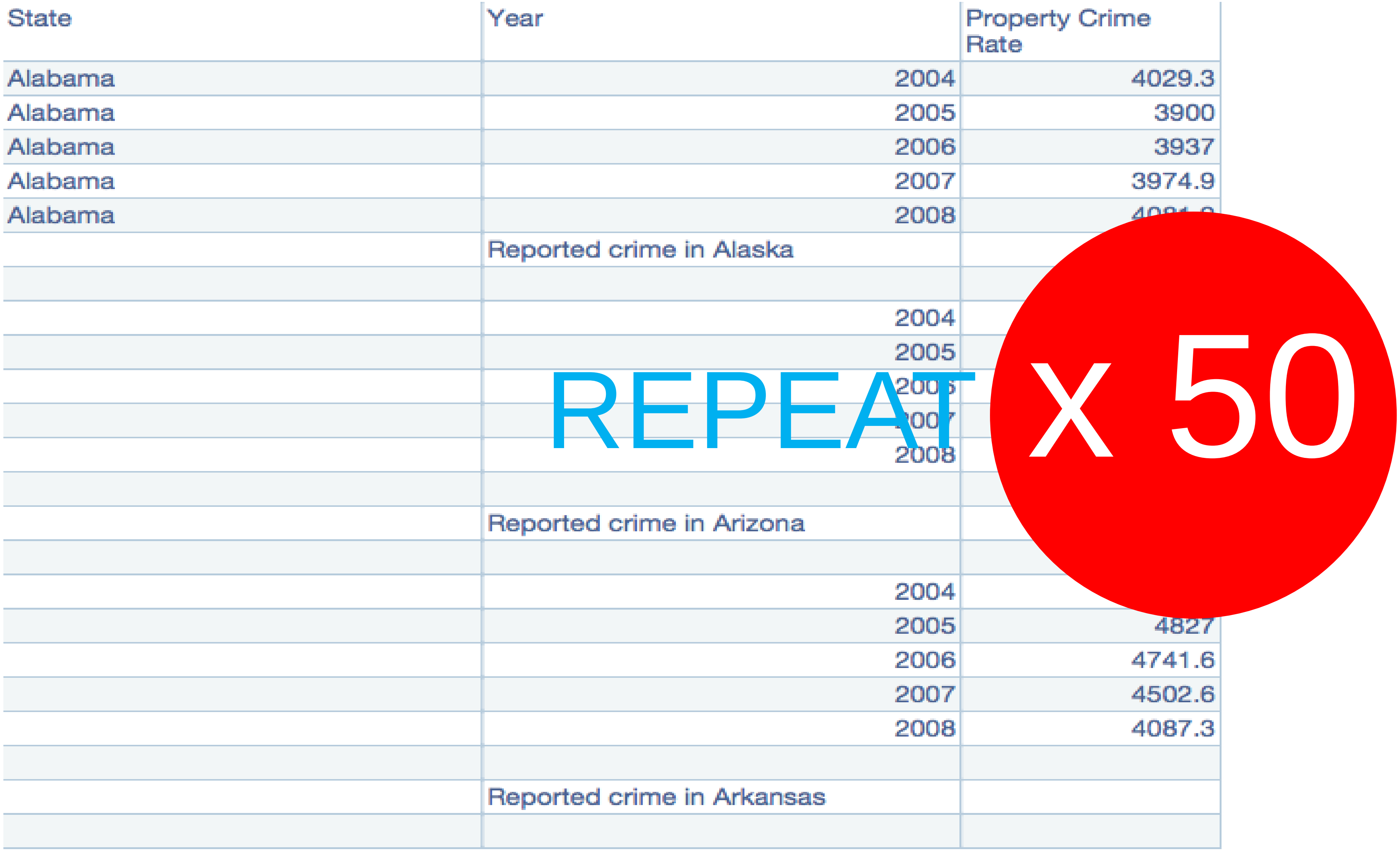

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Alabama	2005	3900
Alabama	2006	3937
Alabama	2007	3974.9
Alabama	2008	[illegible]
	Reported crime in Alaska	
	2004	[illegible]
	2005	[illegible]
	2006	[illegible]
	2007	[illegible]
	2008	[illegible]
	Reported crime in Arizona	
	2004	[illegible]
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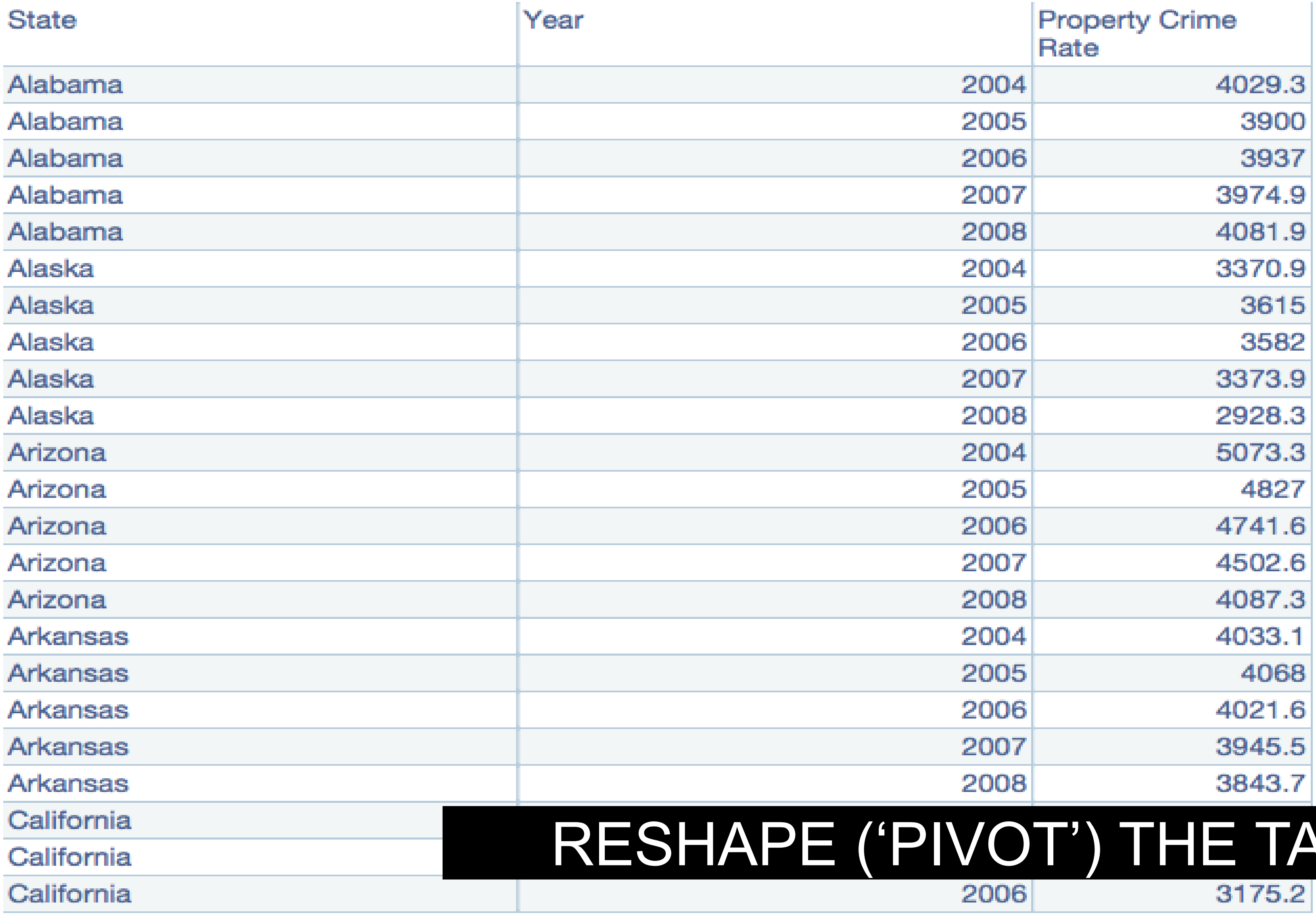
	2008	4087.3
	Reported crime in Arkansas	

REPEAT x 50



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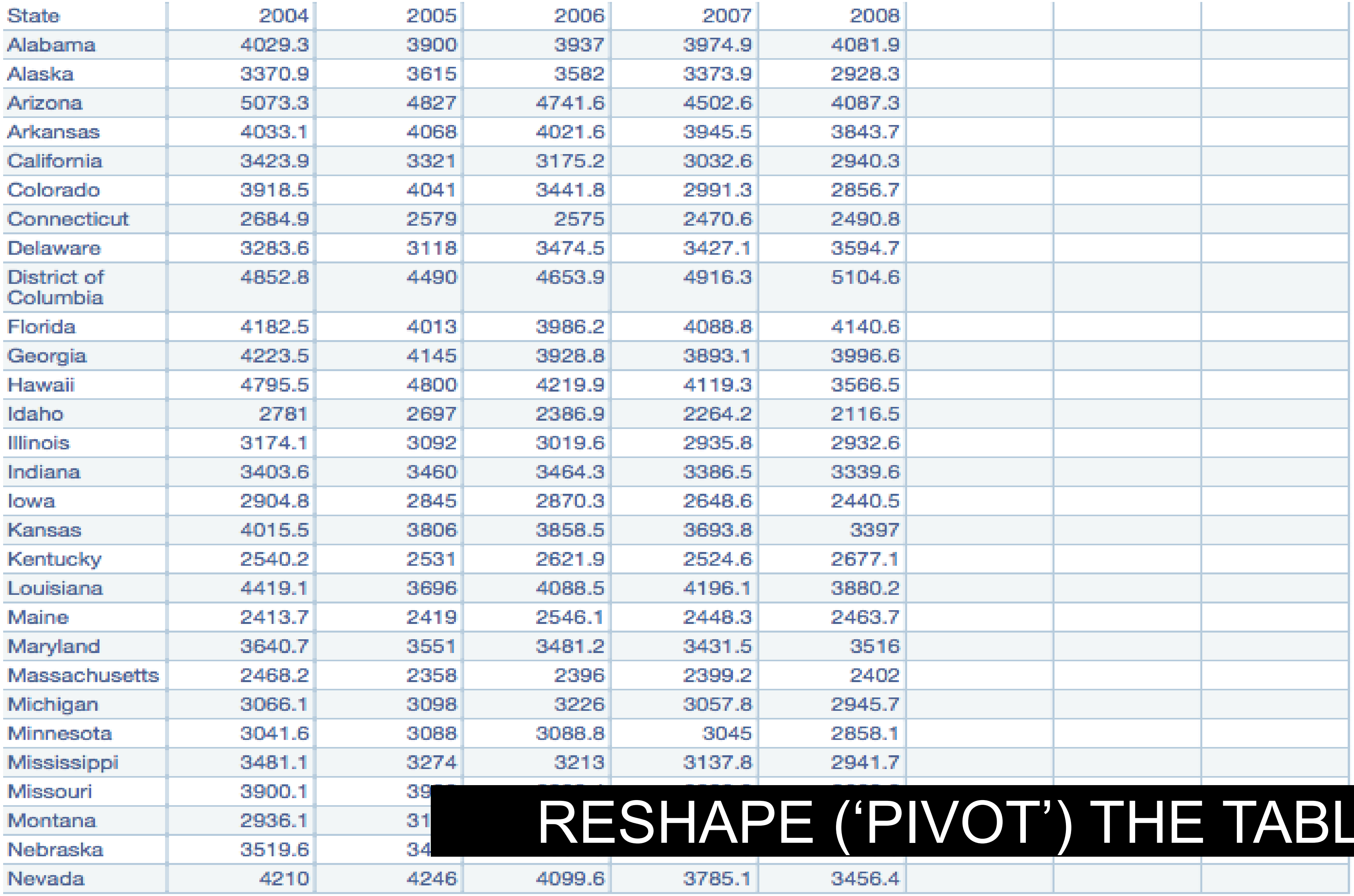
Alaska	2008	2928.3
Arizona	2004	5073.3
Arizona	2005	4827
Arizona	2006	4741.6
Arizona	2007	4502.6
Arizona	2008	4087.3
Arkansas	2004	4033.1
Arkansas	2005	4068
Arkansas	2006	4021.6
Arkansas	2007	3945.5
Arkansas	2008	3843.7
California	[illegible]	[illegible]
California	[illegible]	[illegible]
California	2006	3175.2

RESHAPE (‘PIVOT’) THE TABLE



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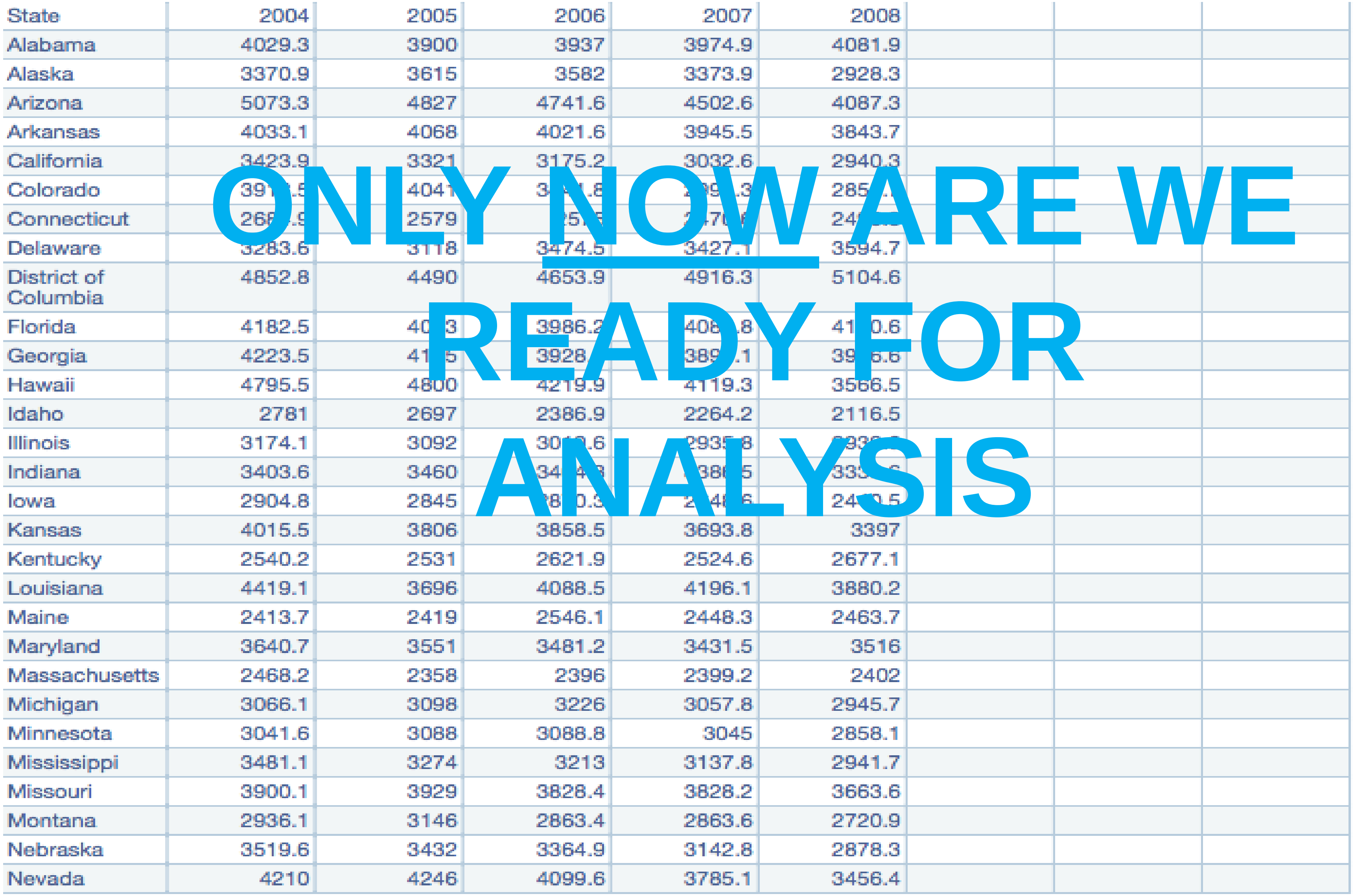
Arizona	5073.3	4827	4741.6	4502.6	4087.3			
Arkansas	4033.1	4068	4021.6	3945.5	3843.7			
California	3423.9	3321	3175.2	3032.6	2940.3			
Colorado	3918.5	4041	3441.8	2991.3	2856.7			
Connecticut	2684.9	2579	2575	2470.6	2490.8			
Delaware	3283.6	3118	3474.5	3427.1	3594.7			
District of Columbia	4852.8	4490	4653.9	4916.3	5104.6			
Florida	4182.5	4013	3986.2	4088.8	4140.6			
Georgia	4223.5	4145	3928.8	3893.1	3996.6			
Hawaii	4795.5	4800	4219.9	4119.3	3566.5			
Idaho	2781	2697	2386.9	2264.2	2116.5			
Illinois	3174.1	3092	3019.6	2935.8	2932.6			
Indiana	3403.6	3460	3464.3	3386.5	3339.6			
Iowa	2904.8	2845	2870.3	2648.6	2440.5			
Kansas	4015.5	3806	3858.5	3693.8	3397			
Kentucky	2540.2	2531	2621.9	2524.6	2677.1			
Louisiana	4419.1	3696	4088.5	4196.1	3880.2			
Maine	2413.7	2419	2546.1	2448.3	2463.7			
Maryland	3640.7	3551	3481.2	3431.5	3516			
Massachusetts	2468.2	2358	2396	2399.2	2402			
Michigan	3066.1	3098	3226	3057.8	2945.7			
Minnesota	3041.6	3088	3088.8	3045	2858.1			
Mississippi	3481.1	3274	3213	3137.8	2941.7			
Missouri	3900.1	[illegible]	[illegible]	[illegible]	[illegible]			
Montana	2936.1	[illegible]	[illegible]	[illegible]	[illegible]			
Nebraska	3519.6	[illegible]	[illegible]	[illegible]	[illegible]			
Nevada	4210	4246	4099.6	3785.1	3456.4			

RESHAPE (‘PIVOT’) THE TABLE

ONLY NOW ARE WE READY FOR ANALYSIS



State	2004	2005	2006	2007	2008			
Alabama	4029.3	3900	3937	3974.9	4081.9			
Alaska	3370.9	3615	3582	3373.9	2928.3			
Arizona	5073.3	4827	4741.6	4502.6	4087.3			
Arkansas	4033.1	4068	4021.6	3945.5	3843.7			
California	3423.9	3321	3175.2	3032.6	2940.3			
Colorado	[illegible]	4041	[illegible]	[illegible]	[illegible]			
Connecticut	[illegible]	2579	[illegible]	[illegible]	[illegible]			
Delaware	3283.6	3118	3474.5	3427.1	3594.7			
District of Columbia	4852.8	4490	4653.9	4916.3	5104.6			
Florida	4182.5	[illegible]	3986.2	[illegible]	[illegible]			
Georgia	4223.5	[illegible]	[illegible]	[illegible]	[illegible]			
Hawaii	4795.5	4800	4219.9	4119.3	3566.5			
Idaho	2781	2697	2386.9	2264.2	2116.5			
Illinois	3174.1	3092	[illegible]	[illegible]	[illegible]			
Indiana	3403.6	3460	[illegible]	[illegible]	[illegible]			
Iowa	2904.8	2845	[illegible]	[illegible]	[illegible]			
Kansas	4015.5	3806	3858.5	3693.8	3397			
Kentucky	2540.2	2531	2621.9	2524.6	2677.1			
Louisiana	4419.1	3696	4088.5	4196.1	3880.2			
Maine	2413.7	2419	2546.1	2448.3	2463.7			
Maryland	3640.7	3551	3481.2	3431.5	3516			
Massachusetts	2468.2	2358	2396	2399.2	2402			
Michigan	3066.1	3098	3226	3057.8	2945.7			
Minnesota	3041.6	3088	3088.8	3045	2858.1			
Mississippi	3481.1	3274	3213	3137.8	2941.7			
Missouri	3900.1	3929	3828.4	3828.2	3663.6			
Montana	2936.1	3146	2863.4	2863.6	2720.9			
Nebraska	3519.6	3432	3364.9	3142.8	2878.3			
Nevada	4210	4246	4099.6	3785.1	3456.4			

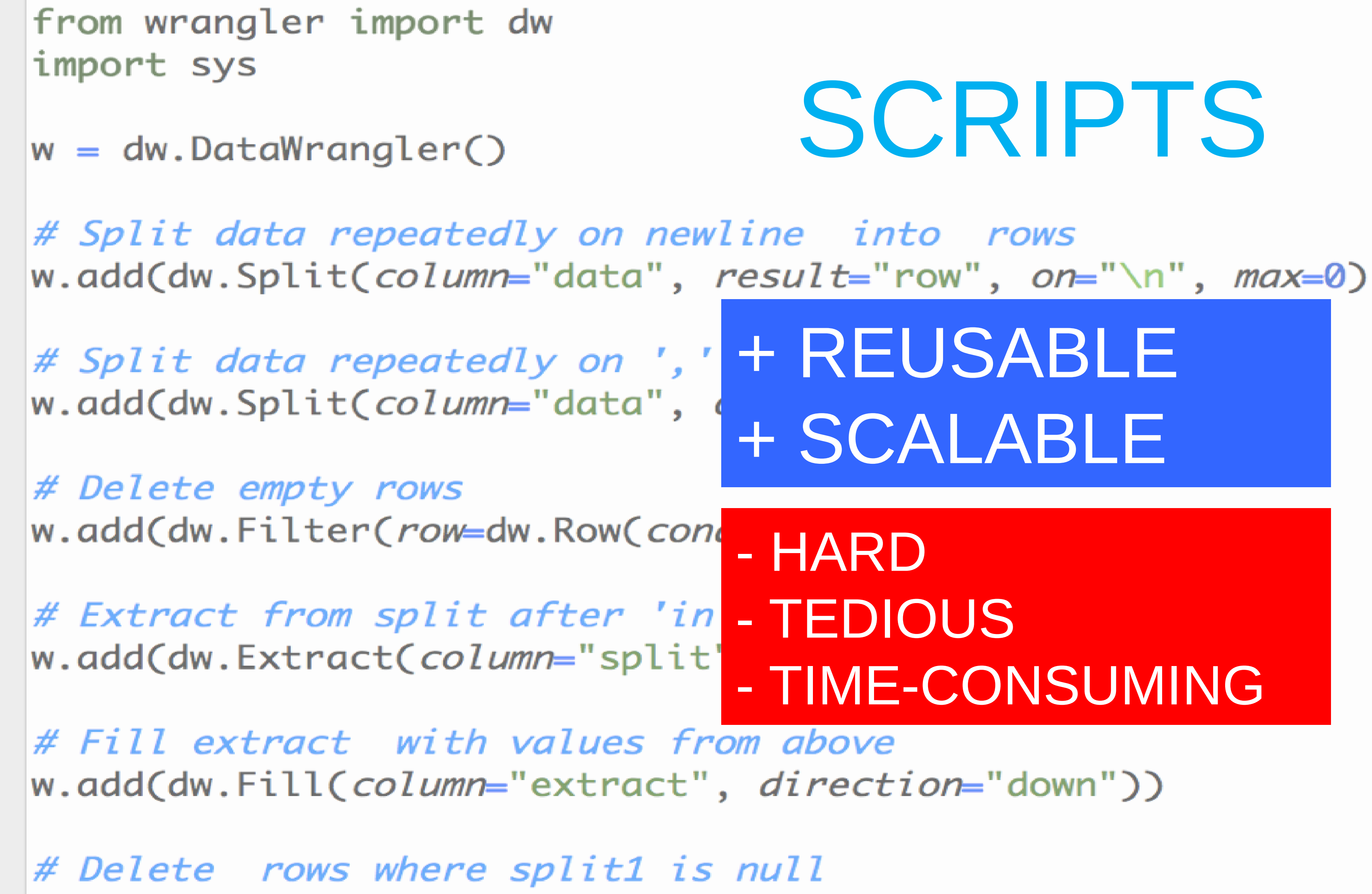
SPREADSHEETS

+ FAMILIAR
+ VISUAL

- TEDIOUS
- TIME-CONSUMING
- REPETITIVE

State	2004	2005	2006	2007	2008
Alabama	4029.3	3900	3937	3974.9	4081.9
Alaska	3370.9	3615	3582	3373.9	2928.3
Arizona	5073.3	4827	4741.6	4502.6	4087.3
Arkansas	4033.1	4068	4021.6	3945.5	[illegible]
California	3423.9	3321	3175.2	3032.6	2940.3
Colorado	3918.5	4041	3441.8	2991.3	2856.7
Connecticut	2684.9	2579	[illegible]	[illegible]	[illegible]
Delaware	3283.6	3118	[illegible]	[illegible]	[illegible]
District of Columbia	4852.8	4490	[illegible]	[illegible]	[illegible]
Florida	4182.5	4013	[illegible]	[illegible]	[illegible]
Georgia	4223.5	4145	[illegible]	[illegible]	[illegible]
Hawaii	4795.5	4800	[illegible]	[illegible]	[illegible]
Idaho	2781	2697	[illegible]	[illegible]	[illegible]
Illinois	3174.1	3092	[illegible]	[illegible]	[illegible]
Indiana	3403.6	3460	[illegible]	[illegible]	[illegible]
Iowa	2904.8	2845	[illegible]	[illegible]	[illegible]
Kansas	4015.5	3806	[illegible]	[illegible]	[illegible]
Kentucky	2540.2	2531	2621.9	2524.6	2677.1
Louisiana	4419.1	3696	4088.5	4196.1	3880.2
Maine	2413.7	2419	2546.1	2448.3	2463.7
Maryland	3640.7	3551	3481.2	3431.5	3516
Massachusetts	2468.2	2358	2396	2399.2	2402

SCRIPTS

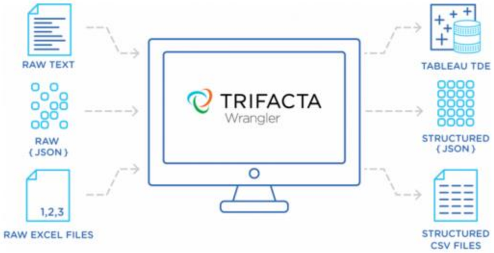


```
from wrangler import dw
import sys

w = dw.DataWrangler()

# Split data repeatedly on newline  into  rows
w.add(dw.Split(column="data", result="row", on="\n", max=0)

# Split data repeatedly on ','
w.add(dw.Split(column="data", c

# Delete empty rows
w.add(dw.Filter(row=dw.Row(conc

# Extract from split after 'in
w.add(dw.Extract(column="split'

# Fill extract  with values from above
w.add(dw.Fill(column="extract", direction="down"))

# Delete  rows where split1 is null
```

+ REUSABLE
+ SCALABLE

- HARD
- TEDIOUS
- TIME-CONSUMING

INTERACTIVE DATA CLEANING



Trifacta Wrangler
https://www.trifacta.com/

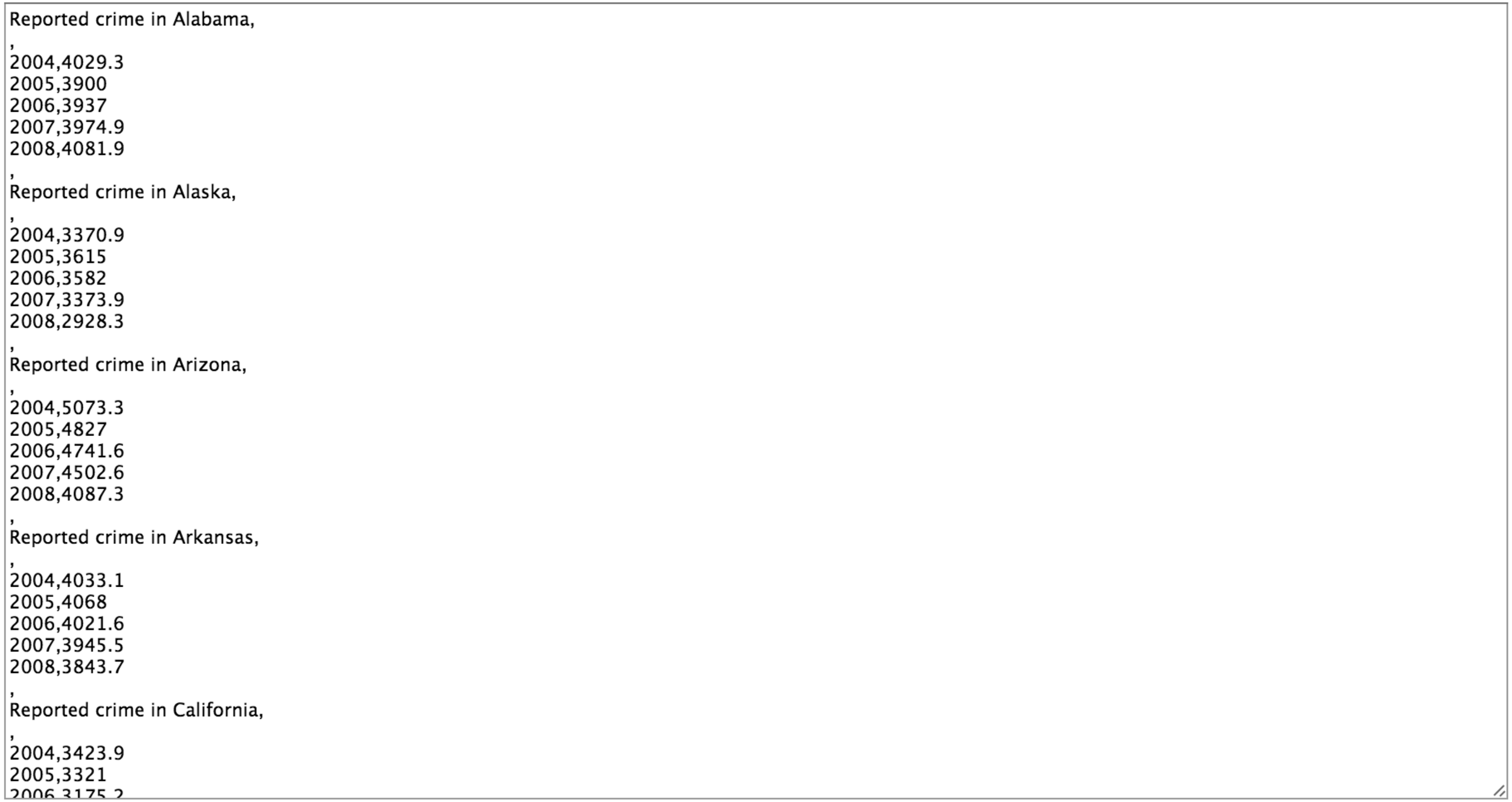
Wrangler
vis.stanford.edu/wrangler

Wrangler (Stanford HCI Group)
http://vis.stanford.edu/wrangler/

OPEN Refine

OpenRefine (formerly Google Refine)
http://openrefine.org/

INTERACTIVE DATA CLEANING BY EXAMPLE

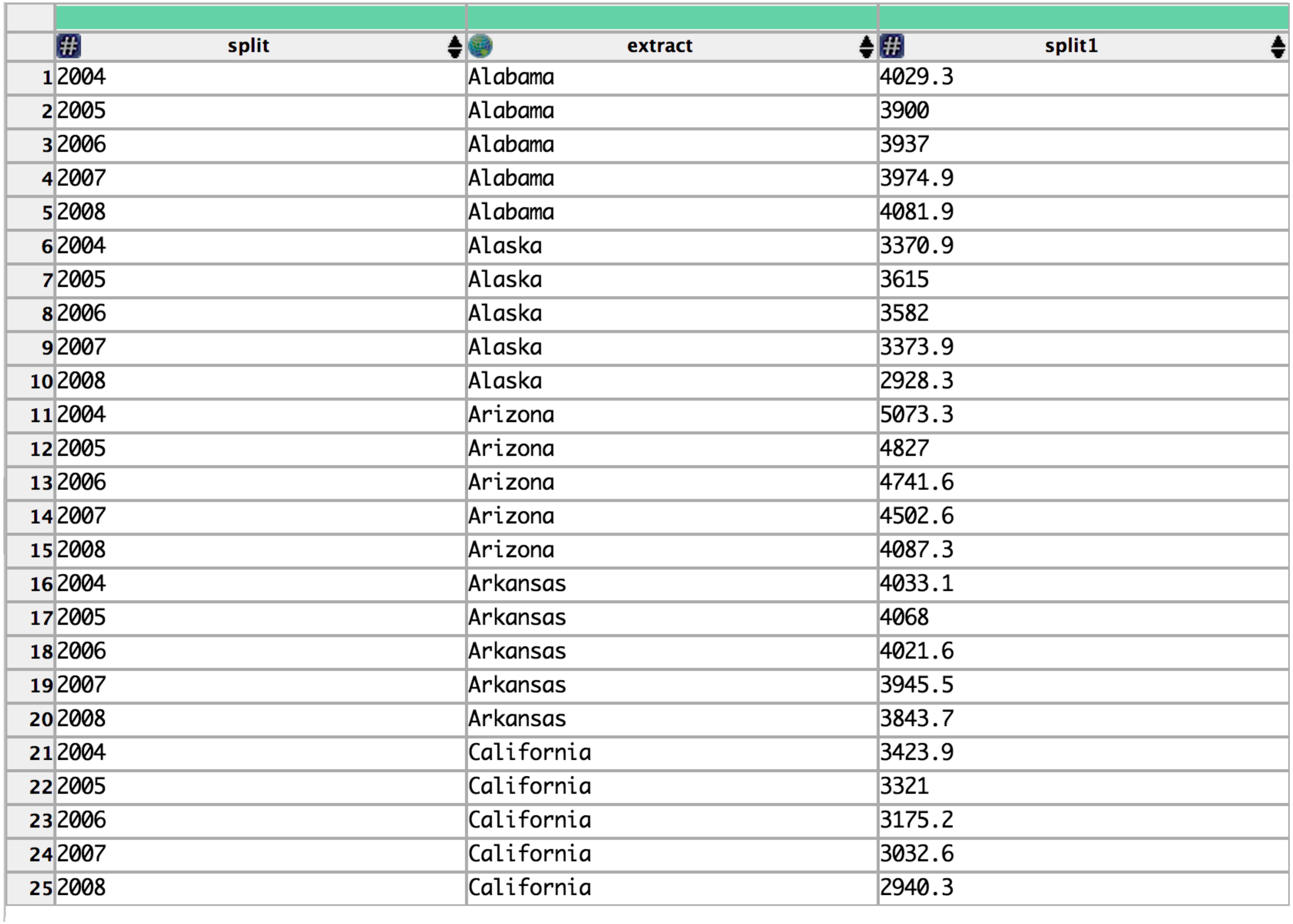


```
Reported crime in Alabama,
,
2004,4029.3
2005,3900
2006,3937
2007,3974.9
2008,4081.9
,
Reported crime in Alaska,
,
2004,3370.9
2005,3615
2006,3582
2007,3373.9
2008,2928.3
,
Reported crime in Arizona,
,
2004,5073.3
2005,4827
2006,4741.6
2007,4502.6
2008,4087.3
,
Reported crime in Arkansas,
,
2004,4033.1
2005,4068
2006,4021.6
2007,3945.5
2008,3843.7
,
Reported crime in California,
,
2004,3423.9
2005,3321
2006,3175.2
```

(http://vimeo.com/19185801)

WRANGLER [KANDEL ET AL. 2011]

[redacted]



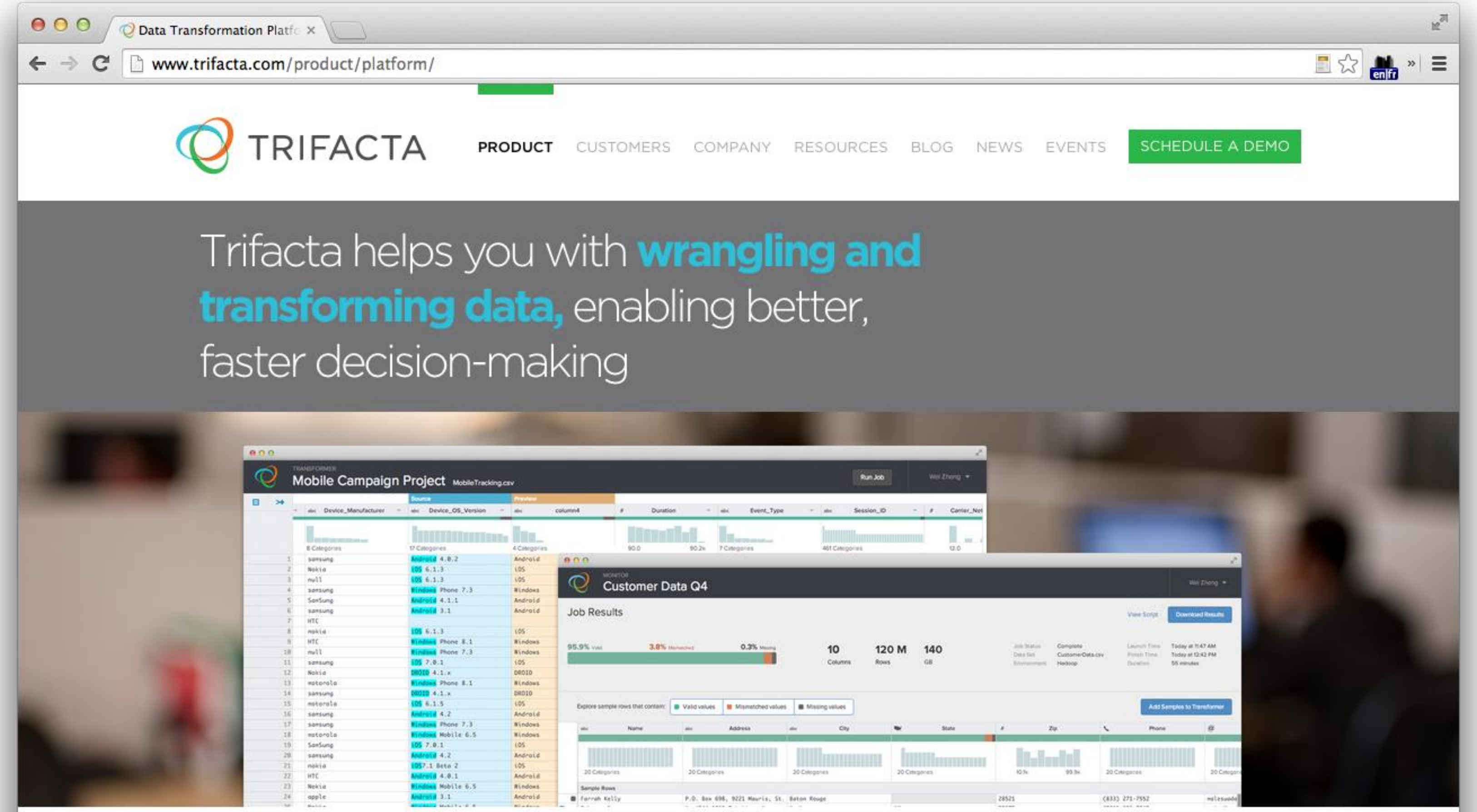
	split	extract	split1
1	2004	Alabama	4029.3
2	2005	Alabama	3900
3	2006	Alabama	3937
4	2007	Alabama	3974.9
5	2008	Alabama	4081.9
6	2004	Alaska	3370.9
7	2005	Alaska	3615
8	2006	Alaska	3582
9	2007	Alaska	3373.9
10	2008	Alaska	2928.3
11	2004	Arizona	5073.3
12	2005	Arizona	4827
13	2006	Arizona	4741.6
14	2007	Arizona	4502.6
15	2008	Arizona	4087.3
16	2004	Arkansas	4033.1
17	2005	Arkansas	4068
18	2006	Arkansas	4021.6
19	2007	Arkansas	3945.5
20	2008	Arkansas	3843.7
21	2004	California	3423.9
22	2005	California	3321
23	2006	California	3175.2
24	2007	California	3032.6
25	2008	California	2940.3

WRANGLER [KANDEL ET AL. 2011]

```
from wrangler import dw
import sys

if(len(sys.argv) < 3):
        sys.exit('Error: Please include an input and output file.  Example python script.py
input.csv output.csv')

w = dw.DataWrangler()

# Split data repeatedly on newline  into  rows
w.add(dw.Split(column=["data"],
             table=0,
             status="active",
             drop=True,
             result="row",
             update=False,
             insert_position="right",
             row=None,
             on="\n",
             before=None,
             after=None,
             ignore_between=None,
             which=1,
             max=0,
             positions=None,
             quote_character=None))
```

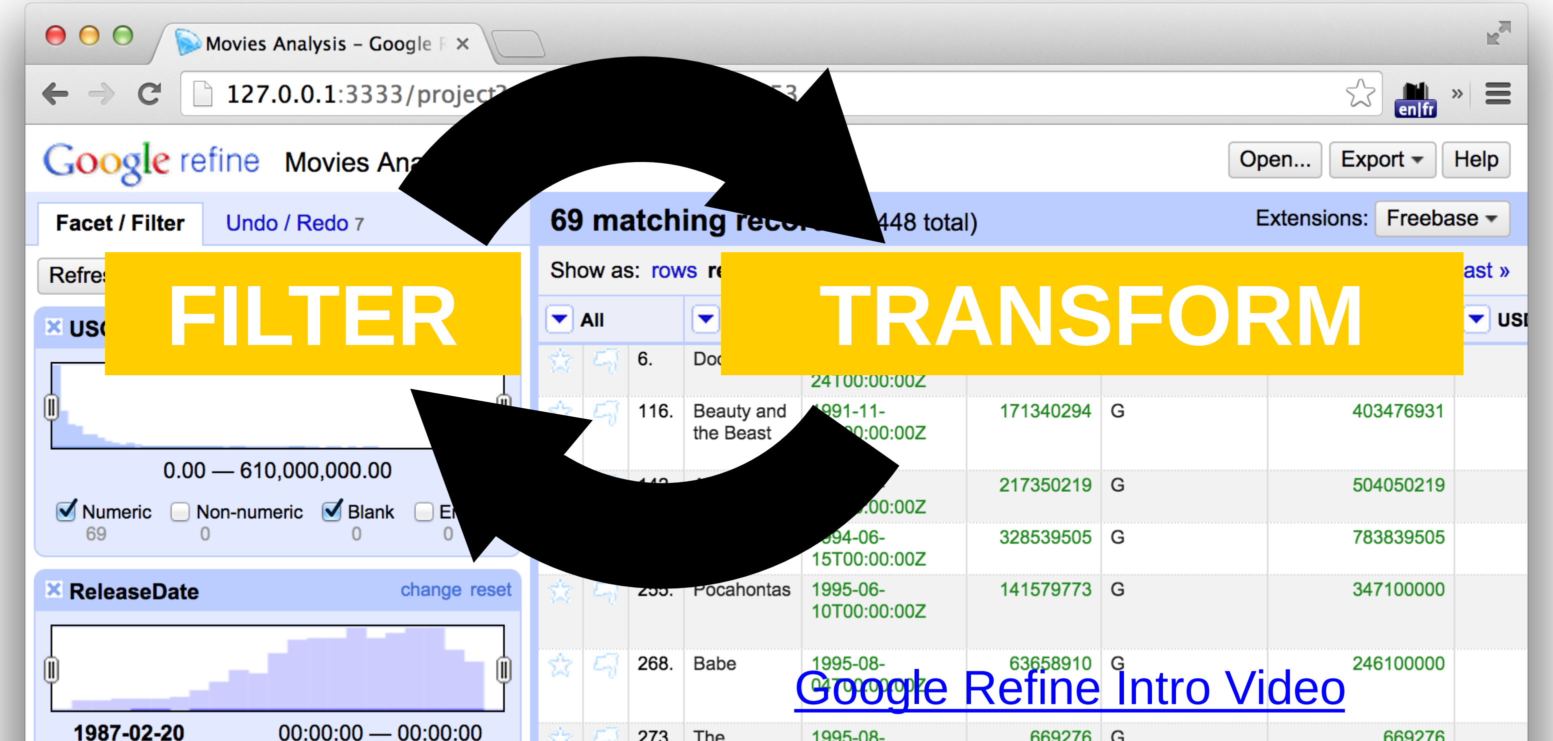
WRANGLER [KANDEL ET AL. 2011]

RESEARCH → PRODUCTS



Trifacta helps you with **wrangling and transforming data,** enabling better, faster decision-making

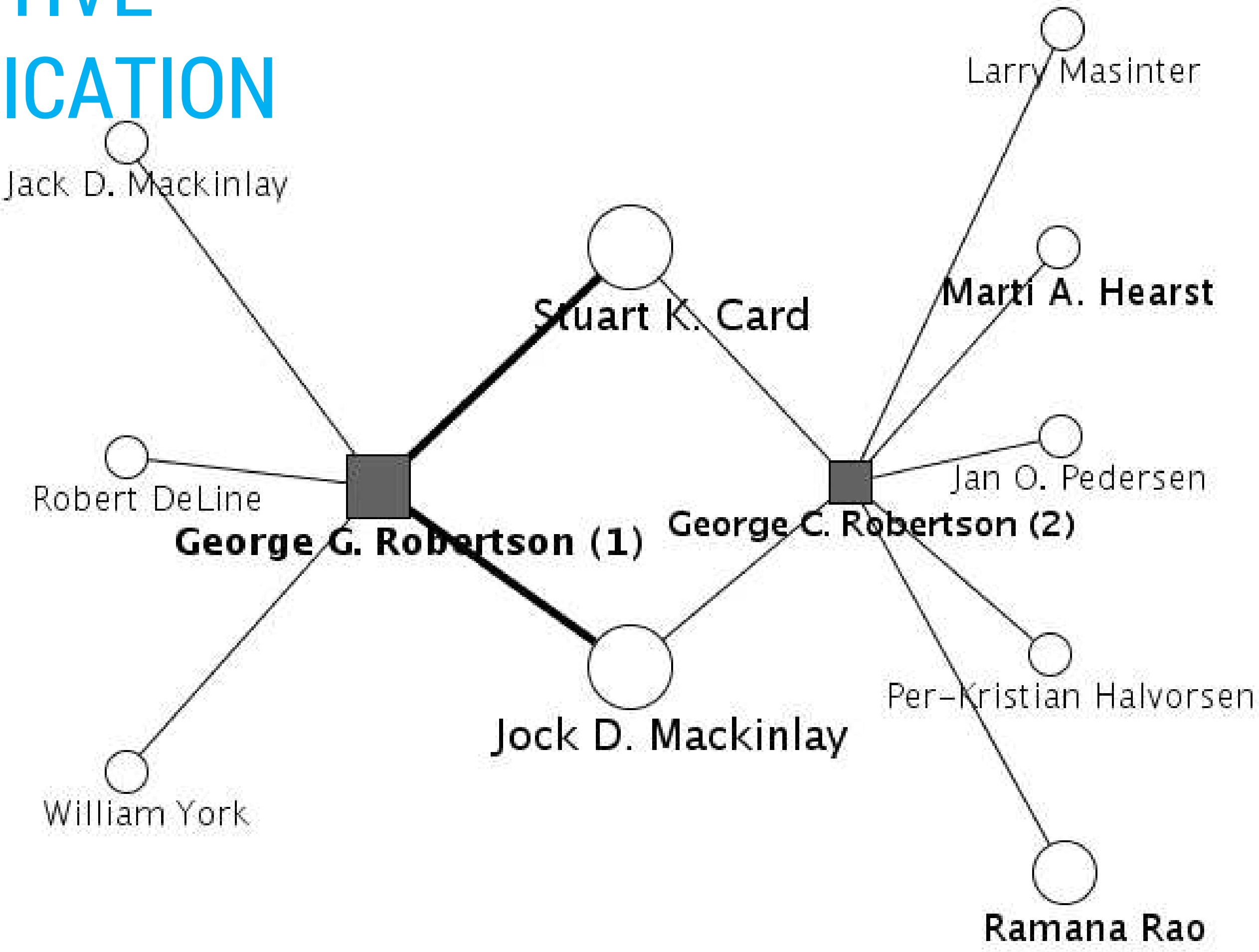
DATA CLEANING IN GOOGLE REFINE


FILTER
TRANSFORM
Movies Analysis – Google R
127.0.0.1:3333/project
Google refine Movies Ana
Open...
Export
Help
Facet / Filter
Undo / Redo 7
69 matching rec 448 total)
Extensions: Freebase
Show as: rows
ast »
All
USD
0.00 — 610,000,000.00
☑ Numeric 69
□ Non-numeric 0
☑ Blank 0
□ Er 0
ReleaseDate change reset
1987-02-20
00:00:00 — 00:00:00
116. Beauty and the Beast 1991-11- 00:00:00Z 171340294 G 403476931
00:00Z 217350219 G 504050219
994-06-15T00:00:00Z 328539505 G 783839505
255. Pocahontas 1995-06-10T00:00:00Z 141579773 G 347100000
268. Babe 1995-08-04T00:00:00Z 63658910 G 246100000
273. The 1995-08- 669276 G 669276

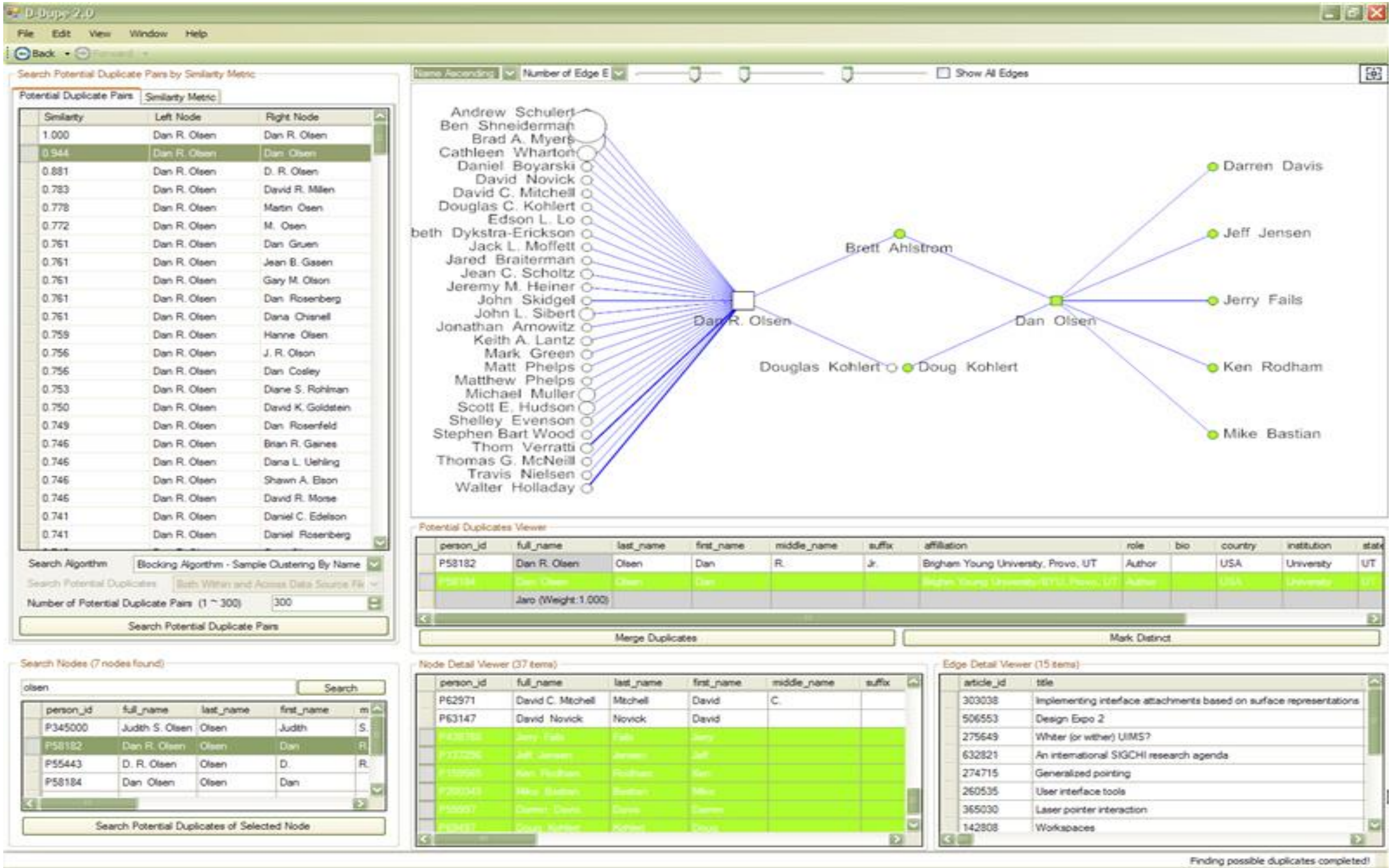
Google Refine Intro Video

THERE ARE LOTS OF OTHER SPECIALIZED TOOLS

INTERACTIVE DE-DUPLICATION



D-DUPE [BILGIC ET AL. 2008]



Search Potential Duplicate Pairs by Similarity Metric

Potential Duplicate Pairs | Similarity Metric

Similarity	Left Node	Right Node
1.000	Dan R. Olsen	Dan R. Olsen
0.944	Dan R. Olsen	Dan Olsen
0.881	Dan R. Olsen	D. R. Olsen
0.783	Dan R. Olsen	David R. Millen
0.778	Dan R. Olsen	Martin Olsen
0.772	Dan R. Olsen	M. Olsen
0.761	Dan R. Olsen	Dan Gruen
0.761	Dan R. Olsen	Jean B. Gasen
0.761	Dan R. Olsen	Gary M. Olson
0.761	Dan R. Olsen	Dan Rosenberg
0.761	Dan R. Olsen	Dana Chisnell
0.759	Dan R. Olsen	Hanne Olsen
0.756	Dan R. Olsen	J. R. Olson
0.756	Dan R. Olsen	Dan Cosley
0.753	Dan R. Olsen	Diane S. Rohlman
0.750	Dan R. Olsen	David K. Goldstein
0.749	Dan R. Olsen	Dan Rosenfeld
0.746	Dan R. Olsen	Brian R. Gaines
0.746	Dan R. Olsen	Dana L. Uehling
0.746	Dan R. Olsen	Shawn A. Elson
0.746	Dan R. Olsen	David R. Morse
0.741	Dan R. Olsen	Daniel C. Edelson
0.741	Dan R. Olsen	Daniel Rosenberg

Search Algorithm: Blocking Algorithm - Sample Clustering By Name

Search Potential Duplicates: Both Within and Across Data Source Fil

Number of Potential Duplicate Pairs (1 ~ 300): 300

Search Potential Duplicate Pairs

Potential Duplicates Viewer

person_id	full_name	last_name	first_name	middle_name	suffix	affiliation	role	bio	country	institution	state
P58182	Dan R. Olsen	Olsen	Dan	R.	Jr.	Brigham Young University, Provo, UT	Author		USA	University	UT
P58184	Dan Olsen	Olsen	Dan			Brigham Young University/BYU, Provo, UT	Author		USA	University	UT
	Jaro (Weight:1.000)										

Merge Duplicates | Mark Distinct

Search Nodes (7 nodes found)

olsen | Search

person_id	full_name	last_name	first_name	m
P345000	Judith S. Olsen	Olsen	Judith	S.
P58182	Dan R. Olsen	Olsen	Dan	R.
P55443	D. R. Olsen	Olsen	D.	R.
P58184	Dan Olsen	Olsen	Dan	

Search Potential Duplicates of Selected Node

Node Detail Viewer (37 items)

person_id	full_name	last_name	first_name	middle_name	suffix
P62971	David C. Mitchell	Mitchell	David	C.	
P63147	David Novick	Novick	David		
[illegible]	Jerry Fails	Fails	Jerry		
[illegible]	Jeff Jensen	Jensen	Jeff		
[illegible]	Ken Rodham	Rodham	Ken		
[illegible]	Mike Bastian	Bastian	Mike		
[illegible]	Darren Davis	Davis	Darren		
[illegible]	Doug Kohlert	Kohlert	Doug		

Edge Detail Viewer (15 items)

article_id	title
303038	Implementing interface attachments based on surface representations
506553	Design Expo 2
275649	Whiter (or wither) UIMS?
632821	An international SIGCHI research agenda
274715	Generalized pointing
260535	User interface tools
365030	Laser pointer interaction
142808	Workspaces

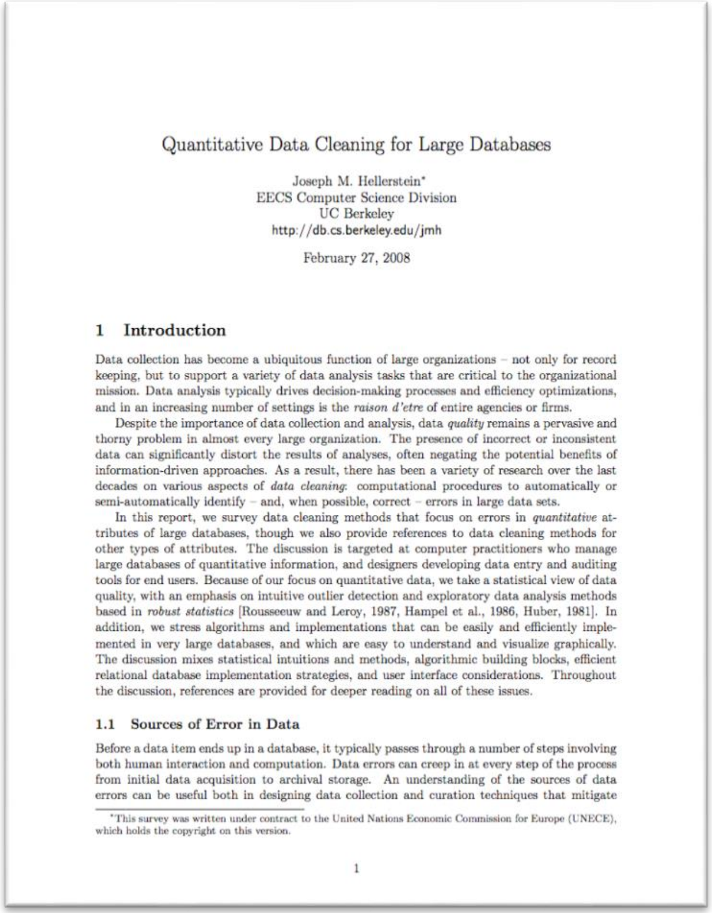
Finding possible duplicates completed!

D-DUPE [BILGIC ET AL. 2008]

REFERENCES

“Quantitative Data Cleaning for Large Databases”

Hellerstein (2008)



Quantitative Data Cleaning for Large Databases

Joseph M. Hellerstein*
EECS Computer Science Division
UC Berkeley
http://db.cs.berkeley.edu/jmh

February 27, 2008

1 Introduction

Data collection has become a ubiquitous function of large organizations – not only for record keeping, but to support a variety of data analysis tasks that are critical to the organizational mission. Data analysis typically drives decision-making processes and efficiency optimizations, and in an increasing number of settings is the *raison d'etre* of entire agencies or firms.

Despite the importance of data collection and analysis, data *quality* remains a pervasive and thorny problem in almost every large organization. The presence of incorrect or inconsistent data can significantly distort the results of analyses, often negating the potential benefits of information-driven approaches. As a result, there has been a variety of research over the last decades on various aspects of *data cleaning*: computational procedures to automatically or semi-automatically identify – and, when possible, correct – errors in large data sets.

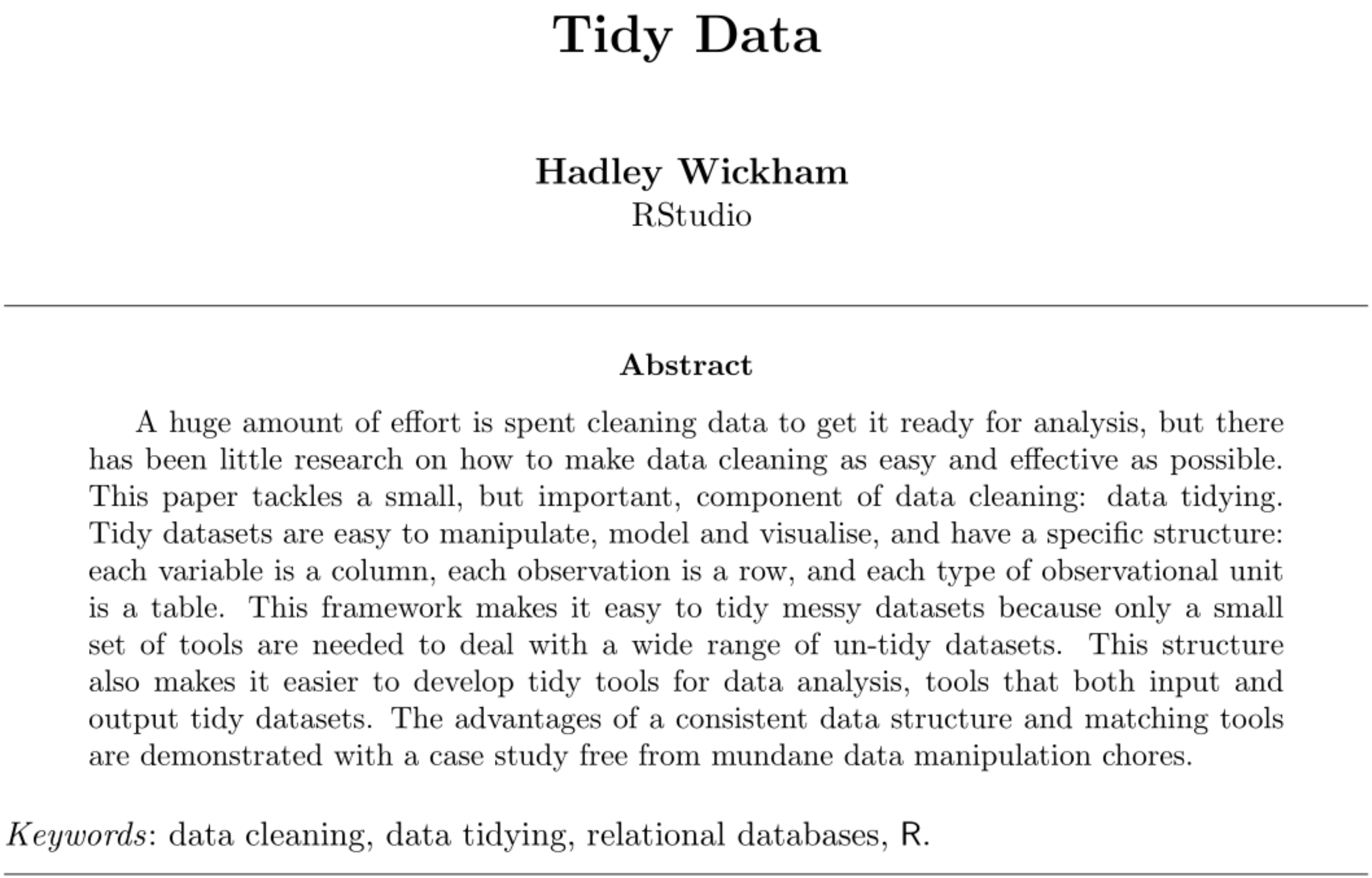
In this report, we survey data cleaning methods that focus on errors in *quantitative* attributes of large databases, though we also provide references to data cleaning methods for other types of attributes. The discussion is targeted at computer practitioners who manage large databases of quantitative information, and designers developing data entry and auditing tools for end users. Because of our focus on quantitative data, we take a statistical view of data quality, with an emphasis on intuitive outlier detection and exploratory data analysis methods based in *robust statistics* [Rousseeuw and Leroy, 1987, Hampel et al., 1986, Huber, 1981]. In addition, we stress algorithms and implementations that can be easily and efficiently implemented in very large databases, and which are easy to understand and visualize graphically. The discussion mixes statistical intuitions and methods, algorithmic building blocks, efficient relational database implementation strategies, and user interface considerations. Throughout the discussion, references are provided for deeper reading on all of these issues.

1.1 Sources of Error in Data

Before a data item ends up in a database, it typically passes through a number of steps involving both human interaction and computation. Data errors can creep in at every step of the process from initial data acquisition to archival storage. An understanding of the sources of data errors can be useful both in designing data collection and curation techniques that mitigate

*This survey was written under contract to the United Nations Economic Commission for Europe (UNECE), which holds the copyright on this version.

TIDY DATA PRINCIPLES



Tidy Data

Hadley Wickham
RStudio

Abstract

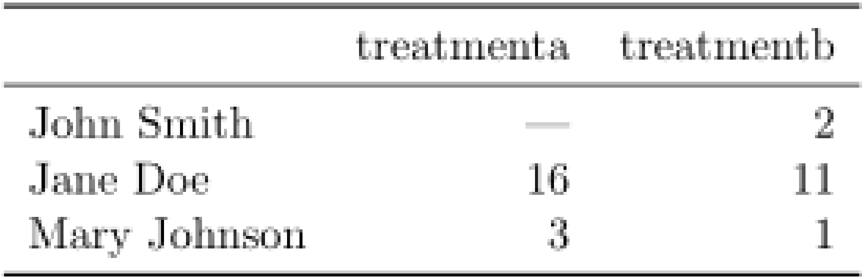
A huge amount of effort is spent cleaning data to get it ready for analysis, but there has been little research on how to make data cleaning as easy and effective as possible. This paper tackles a small, but important, component of data cleaning: data tidying. Tidy datasets are easy to manipulate, model and visualise, and have a specific structure: each variable is a column, each observation is a row, and each type of observational unit is a table. This framework makes it easy to tidy messy datasets because only a small set of tools are needed to deal with a wide range of un-tidy datasets. This structure also makes it easier to develop tidy tools for data analysis, tools that both input and output tidy datasets. The advantages of a consistent data structure and matching tools are demonstrated with a case study free from mundane data manipulation chores.

Keywords: data cleaning, data tidying, relational databases, R.

TIDY DATA

= data structured to facilitate analysis

labelled columns



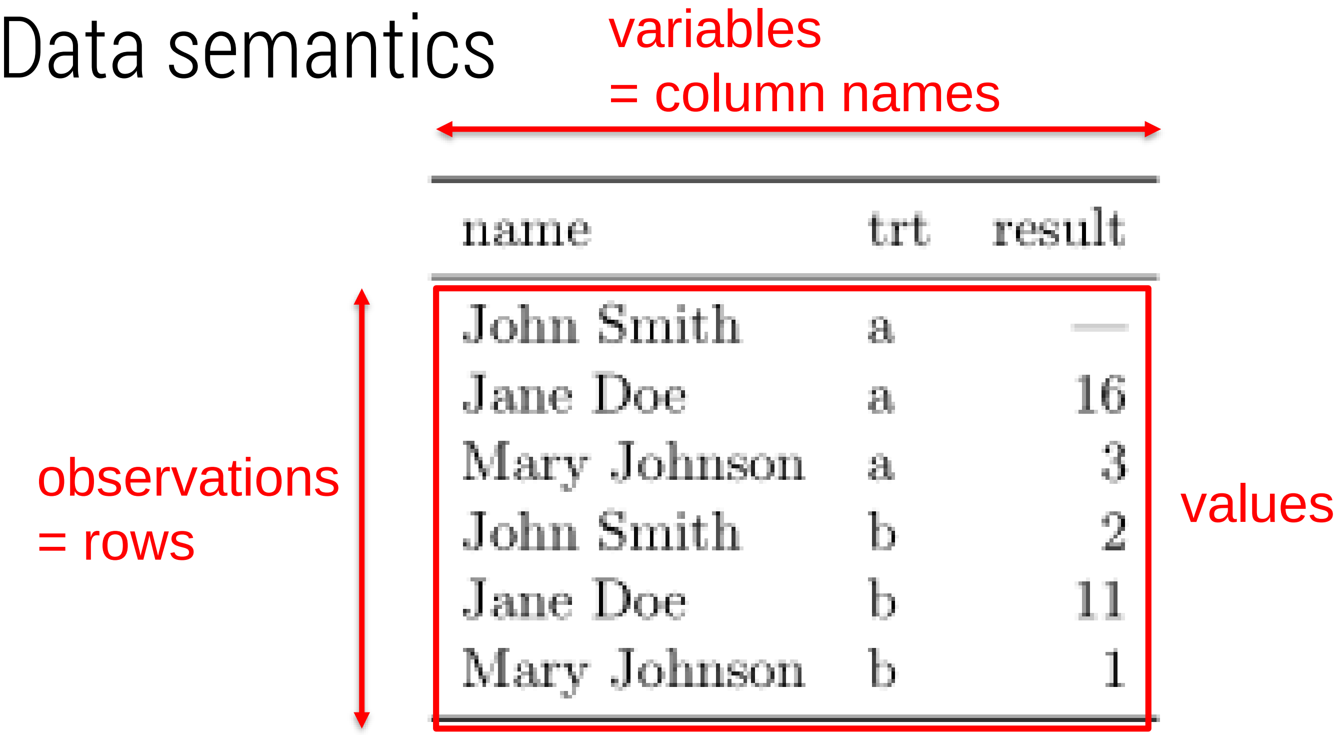
	treatmenta	treatmentb
John Smith	—	2
Jane Doe	16	11
Mary Johnson	3	1

labelled rows

= data structure

TIDY DATA

Data semantics



variables
= column names

name	trt	result
John Smith	a	—
Jane Doe	a	16
Mary Johnson	a	3
John Smith	b	2
Jane Doe	b	11
Mary Johnson	b	1

observations
= rows

values

TIDY DATA

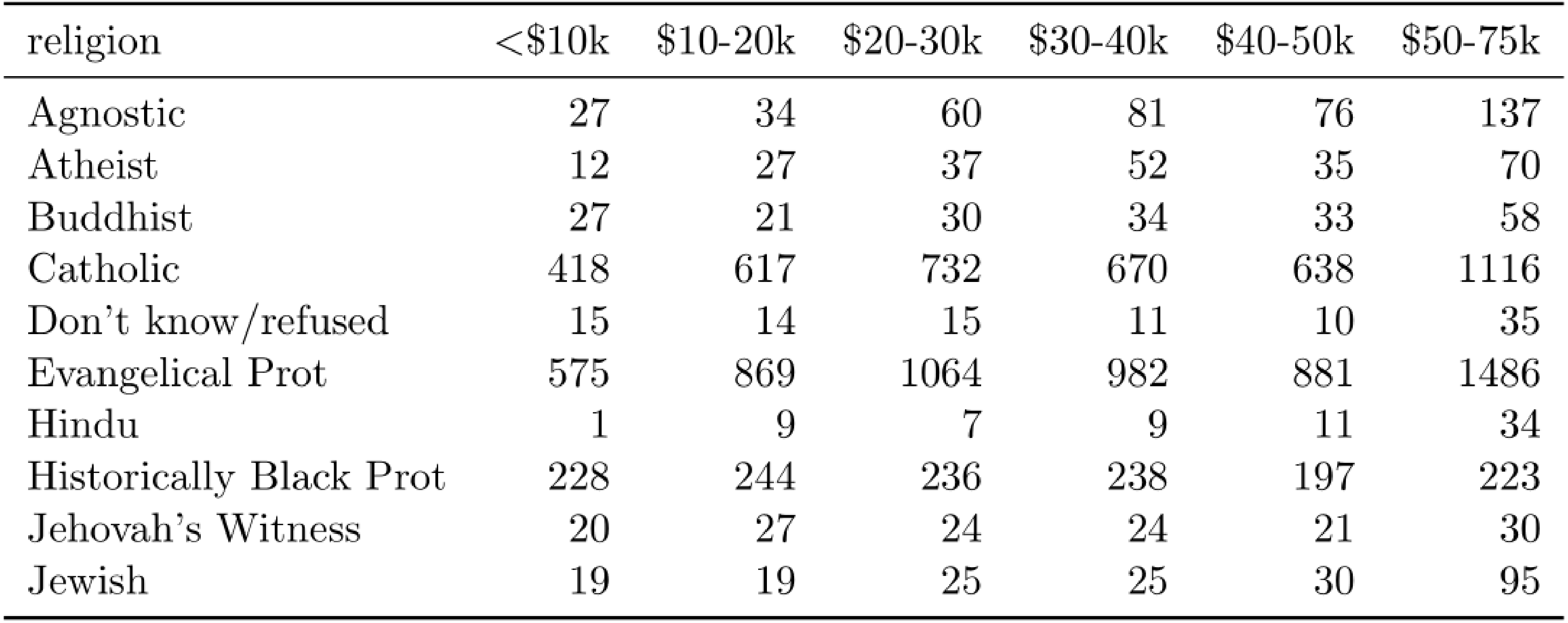
- Variables are columns
- Observations are rows
- Each observational unit in one table

In addition: put fixed variables first and then measured variables last

If you order, do so by the first variable

MESSY DATA - EXAMPLES

Column headers = values, not variables

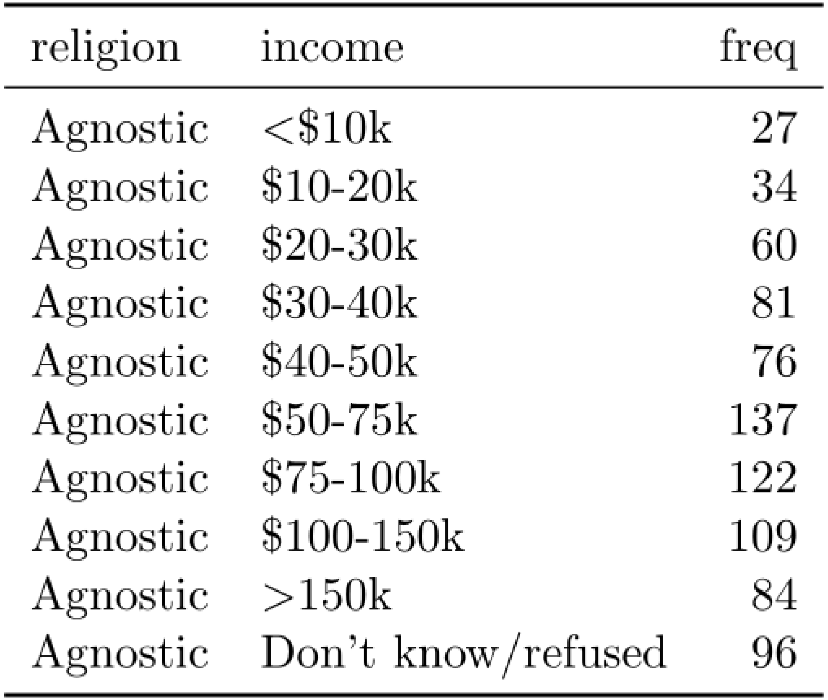


religion	<$10k	$10-20k	$20-30k	$30-40k	$40-50k	$50-75k
Agnostic	27	34	60	81	76	137
Atheist	12	27	37	52	35	70
Buddhist	27	21	30	34	33	58
Catholic	418	617	732	670	638	1116
Don't know/refused	15	14	15	11	10	35
Evangelical Prot	575	869	1064	982	881	1486
Hindu	1	9	7	9	11	34
Historically Black Prot	228	244	236	238	197	223
Jehovah's Witness	20	27	24	24	21	30
Jewish	19	19	25	25	30	95

MESSY DATA - EXAMPLES

Better (most of the time)

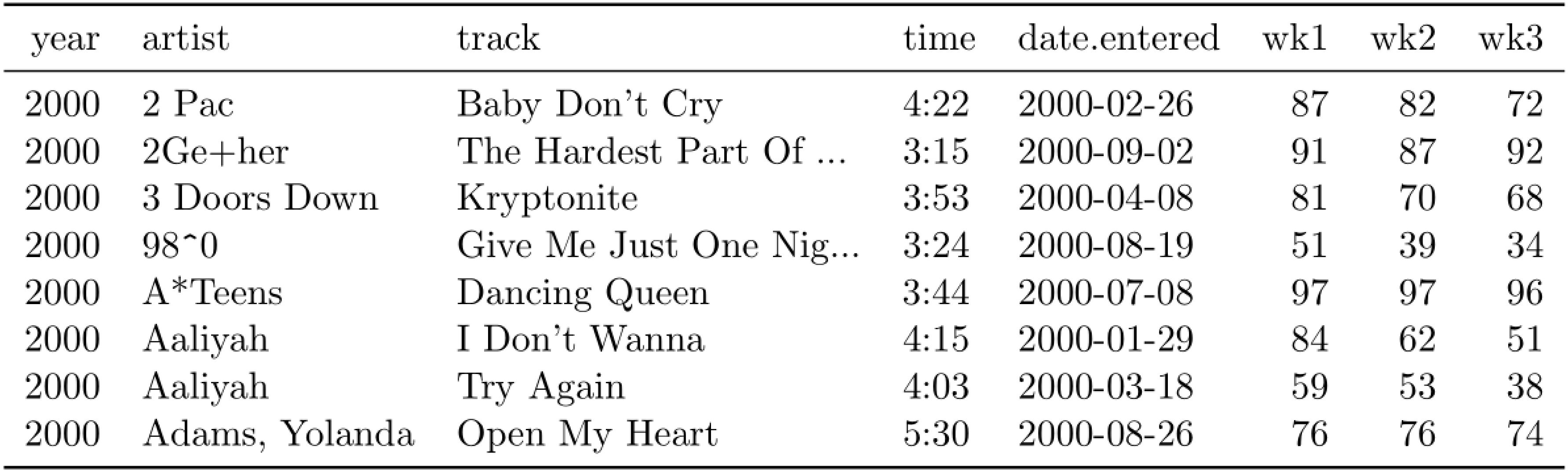
Process to produce this
= melting



religion	income	freq
Agnostic	<$10k	27
Agnostic	$10-20k	34
Agnostic	$20-30k	60
Agnostic	$30-40k	81
Agnostic	$40-50k	76
Agnostic	$50-75k	137
Agnostic	$75-100k	122
Agnostic	$100-150k	109
Agnostic	>150k	84
Agnostic	Don't know/refused	96

YOU!

This table is good for data entry but not analysis. How do we tidy it up?

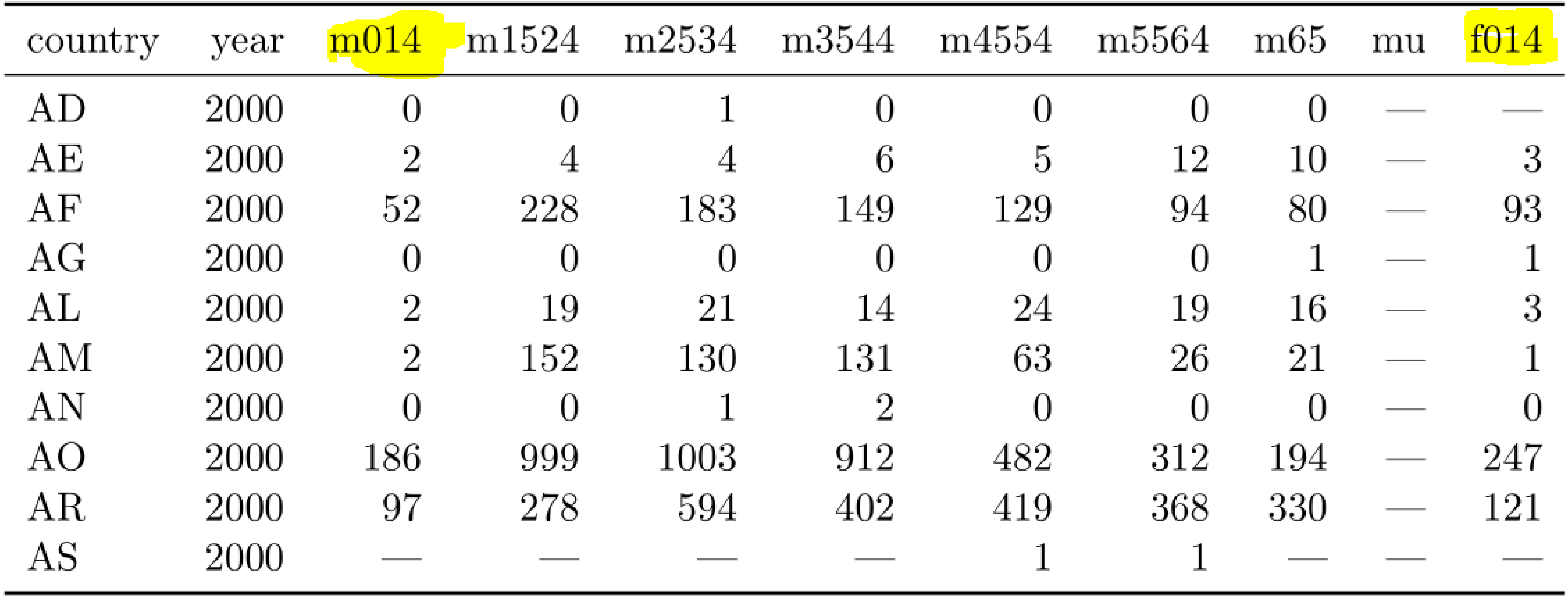


year	artist	track	time	date.entered	wk1	wk2	wk3
2000	2 Pac	Baby Don't Cry	4:22	2000-02-26	87	82	72
2000	2Ge+her	The Hardest Part Of ...	3:15	2000-09-02	91	87	92
2000	3 Doors Down	Kryptonite	3:53	2000-04-08	81	70	68
2000	98^0	Give Me Just One Nig...	3:24	2000-08-19	51	39	34
2000	A*Teens	Dancing Queen	3:44	2000-07-08	97	97	96
2000	Aaliyah	I Don't Wanna	4:15	2000-01-29	84	62	51
2000	Aaliyah	Try Again	4:03	2000-03-18	59	53	38
2000	Adams, Yolanda	Open My Heart	5:30	2000-08-26	76	76	74

year	artist	time	track	date	week	rank
2000	2 Pac	4:22	Baby Don't Cry	2000-02-26	1	87
2000	2 Pac	4:22	Baby Don't Cry	2000-03-04	2	82
2000	2 Pac	4:22	Baby Don't Cry	2000-03-11	3	72
2000	2 Pac	4:22	Baby Don't Cry	2000-03-18	4	77
2000	2 Pac	4:22	Baby Don't Cry	2000-03-25	5	87
2000	2 Pac	4:22	Baby Don't Cry	2000-04-01	6	94
2000	2 Pac	4:22	Baby Don't Cry	2000-04-08	7	99
2000	2Ge+her	3:15	The Hardest Part Of ...	2000-09-02	1	91
2000	2Ge+her	3:15	The Hardest Part Of ...	2000-09-09	2	87
2000	2Ge+her	3:15	The Hardest Part Of ...	2000-09-16	3	92
2000	3 Doors Down	3:53	Kryptonite	2000-04-08	1	81
2000	3 Doors Down	3:53	Kryptonite	2000-04-15	2	70
2000	3 Doors Down	3:53	Kryptonite	2000-04-22	3	68
2000	3 Doors Down	3:53	Kryptonite	2000-04-29	4	67
2000	3 Doors Down	3:53	Kryptonite	2000-05-06	5	66

MESSY DATA - EXAMPLES

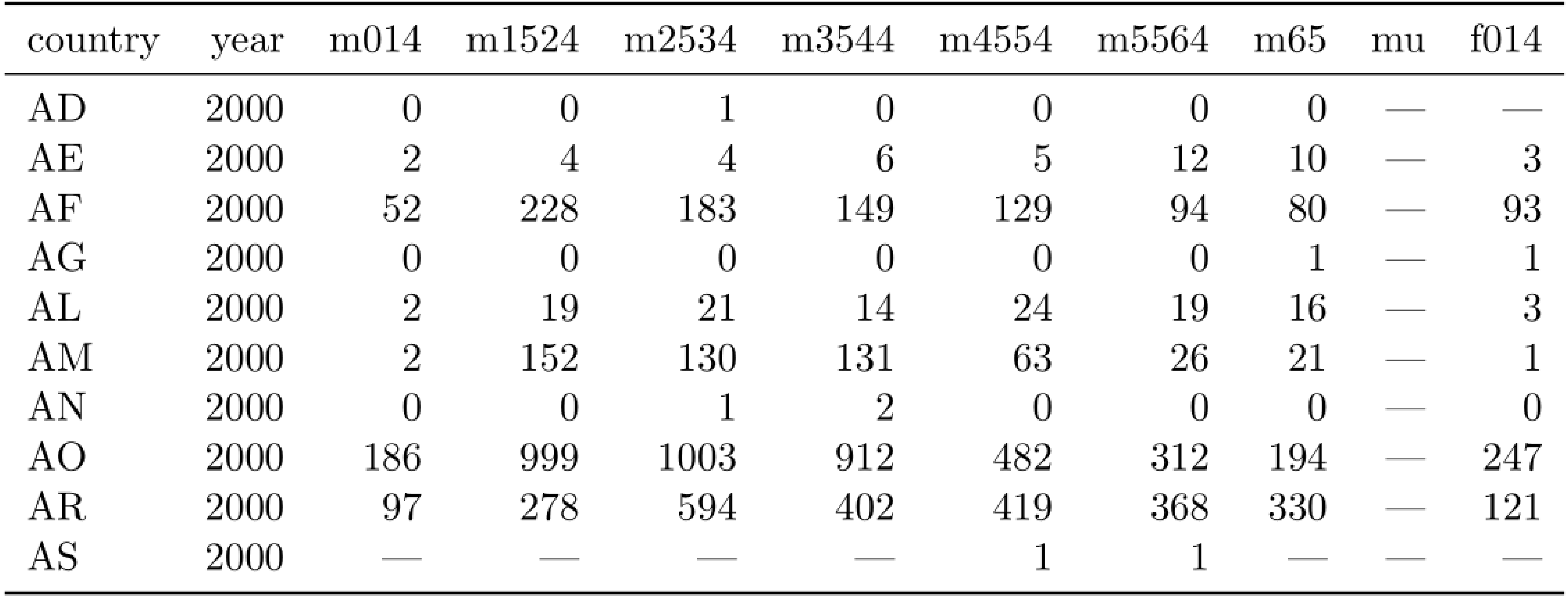
Multiple variables in one column



country	year	m014	m1524	m2534	m3544	m4554	m5564	m65	mu	f014
AD	2000	0	0	1	0	0	0	0	—	—
AE	2000	2	4	4	6	5	12	10	—	3
AF	2000	52	228	183	149	129	94	80	—	93
AG	2000	0	0	0	0	0	0	1	—	1
AL	2000	2	19	21	14	24	19	16	—	3
AM	2000	2	152	130	131	63	26	21	—	1
AN	2000	0	0	1	2	0	0	0	—	0
AO	2000	186	999	1003	912	482	312	194	—	247
AR	2000	97	278	594	402	419	368	330	—	121
AS	2000	—	—	—	—	1	1	—	—	—

FIRST WE MELT

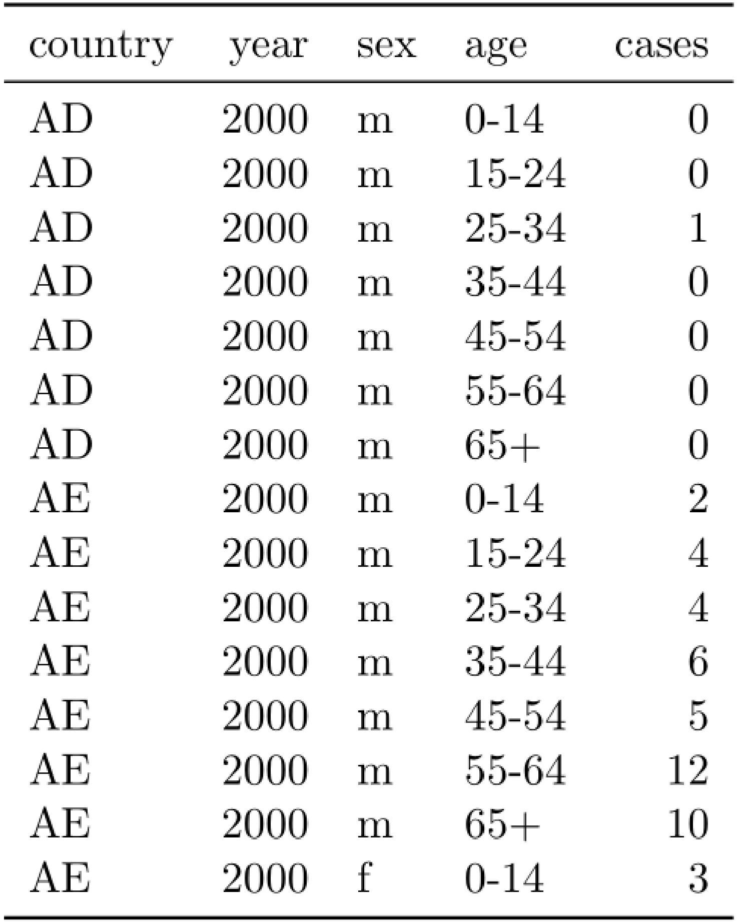
How do we do this…?



country	year	m014	m1524	m2534	m3544	m4554	m5564	m65	mu	f014
AD	2000	0	0	1	0	0	0	0	—	—
AE	2000	2	4	4	6	5	12	10	—	3
AF	2000	52	228	183	149	129	94	80	—	93
AG	2000	0	0	0	0	0	0	1	—	1
AL	2000	2	19	21	14	24	19	16	—	3
AM	2000	2	152	130	131	63	26	21	—	1
AN	2000	0	0	1	2	0	0	0	—	0
AO	2000	186	999	1003	912	482	312	194	—	247
AR	2000	97	278	594	402	419	368	330	—	121
AS	2000	—	—	—	—	1	1	—	—	—

country	year	column	cases
AD	2000	m014	0
AD	2000	m1524	0
AD	2000	m2534	1
AD	2000	m3544	0
AD	2000	m4554	0
AD	2000	m5564	0
AD	2000	m65	0
AE	2000	m014	2
AE	2000	m1524	4
AE	2000	m2534	4
AE	2000	m3544	6
AE	2000	m4554	5
AE	2000	m5564	12
AE	2000	m65	10
AE	2000	f014	3

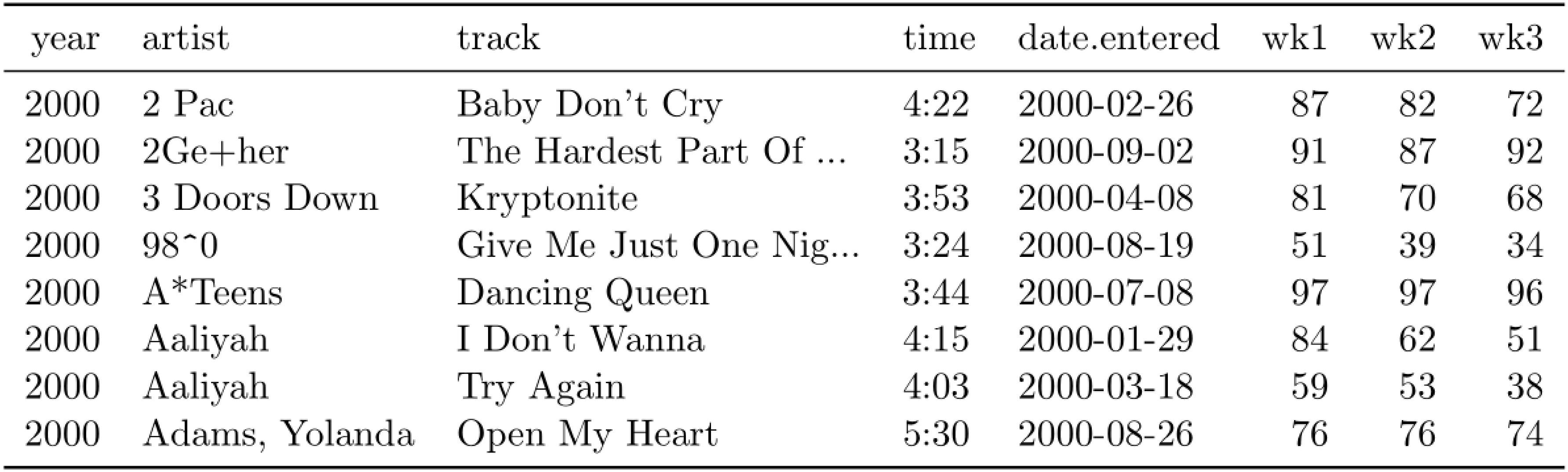
NEXT: SPLIT COLUMNS



country	year	sex	age	cases
AD	2000	m	0-14	0
AD	2000	m	15-24	0
AD	2000	m	25-34	1
AD	2000	m	35-44	0
AD	2000	m	45-54	0
AD	2000	m	55-64	0
AD	2000	m	65+	0
AE	2000	m	0-14	2
AE	2000	m	15-24	4
AE	2000	m	25-34	4
AE	2000	m	35-44	6
AE	2000	m	45-54	5
AE	2000	m	55-64	12
AE	2000	m	65+	10
AE	2000	f	0-14	3

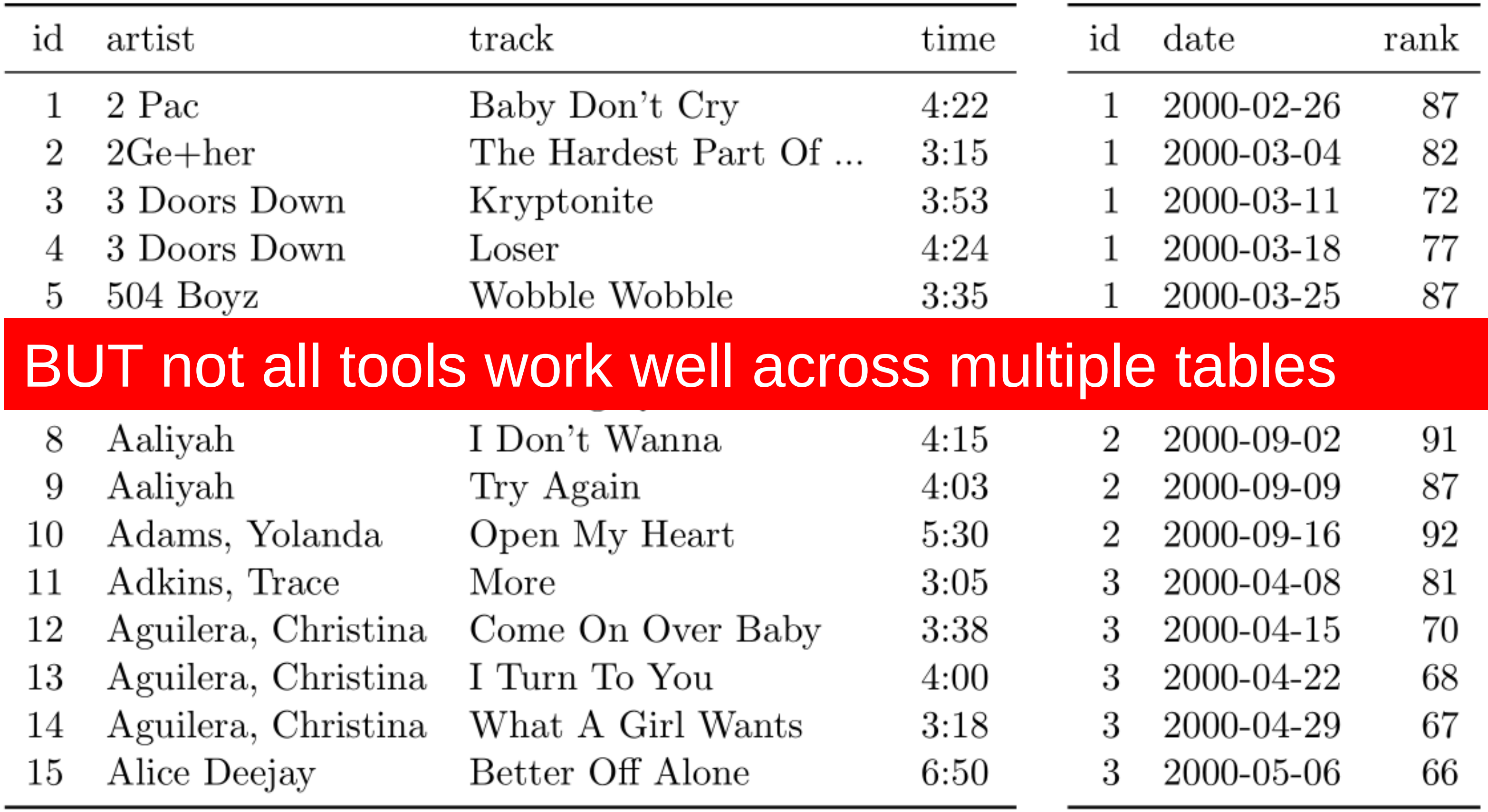
MESSY DATA - EXAMPLES

Multi observational units in the same table



year	artist	track	time	date.entered	wk1	wk2	wk3
2000	2 Pac	Baby Don't Cry	4:22	2000-02-26	87	82	72
2000	2Ge+her	The Hardest Part Of ...	3:15	2000-09-02	91	87	92
2000	3 Doors Down	Kryptonite	3:53	2000-04-08	81	70	68
2000	98ˆ0	Give Me Just One Nig...	3:24	2000-08-19	51	39	34
2000	A*Teens	Dancing Queen	3:44	2000-07-08	97	97	96
2000	Aaliyah	I Don't Wanna	4:15	2000-01-29	84	62	51
2000	Aaliyah	Try Again	4:03	2000-03-18	59	53	38
2000	Adams, Yolanda	Open My Heart	5:30	2000-08-26	76	76	74

TIDYER & MORE SPACE EFFICIENT

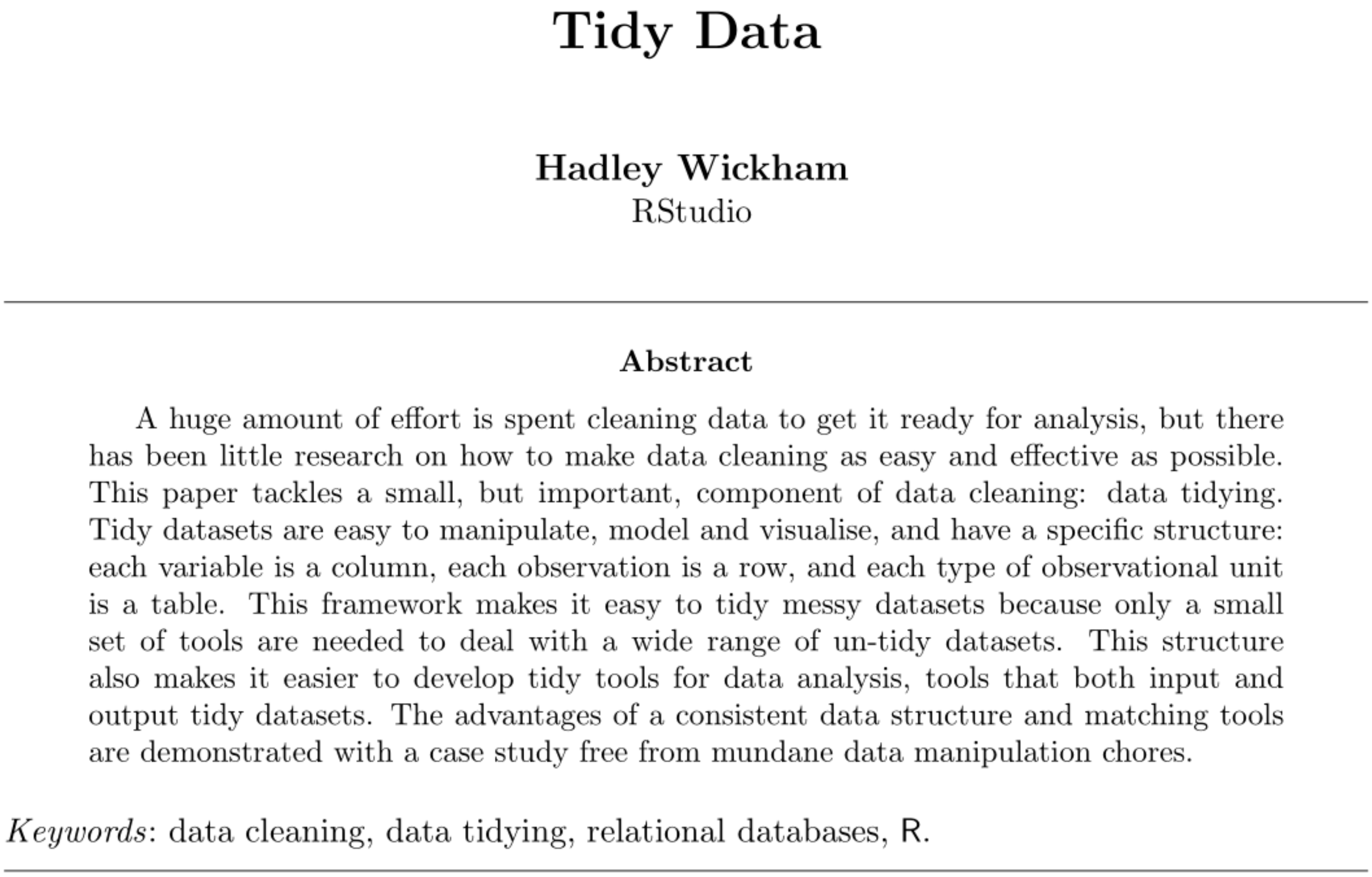


id	artist	track	time
1	2 Pac	Baby Don't Cry	4:22
2	2Ge+her	The Hardest Part Of ...	3:15
3	3 Doors Down	Kryptonite	3:53
4	3 Doors Down	Loser	4:24
5	504 Boyz	Wobble Wobble	3:35
8	Aaliyah	I Don't Wanna	4:15
9	Aaliyah	Try Again	4:03
10	Adams, Yolanda	Open My Heart	5:30
11	Adkins, Trace	More	3:05
12	Aguilera, Christina	Come On Over Baby	3:38
13	Aguilera, Christina	I Turn To You	4:00
14	Aguilera, Christina	What A Girl Wants	3:18
15	Alice Deejay	Better Off Alone	6:50

id	date	rank
1	2000-02-26	87
1	2000-03-04	82
1	2000-03-11	72
1	2000-03-18	77
1	2000-03-25	87
2	2000-09-02	91
2	2000-09-09	87
2	2000-09-16	92
3	2000-04-08	81
3	2000-04-15	70
3	2000-04-22	68
3	2000-04-29	67
3	2000-05-06	66

BUT not all tools work well across multiple tables

MORE EXAMPLES HERE



Tidy Data

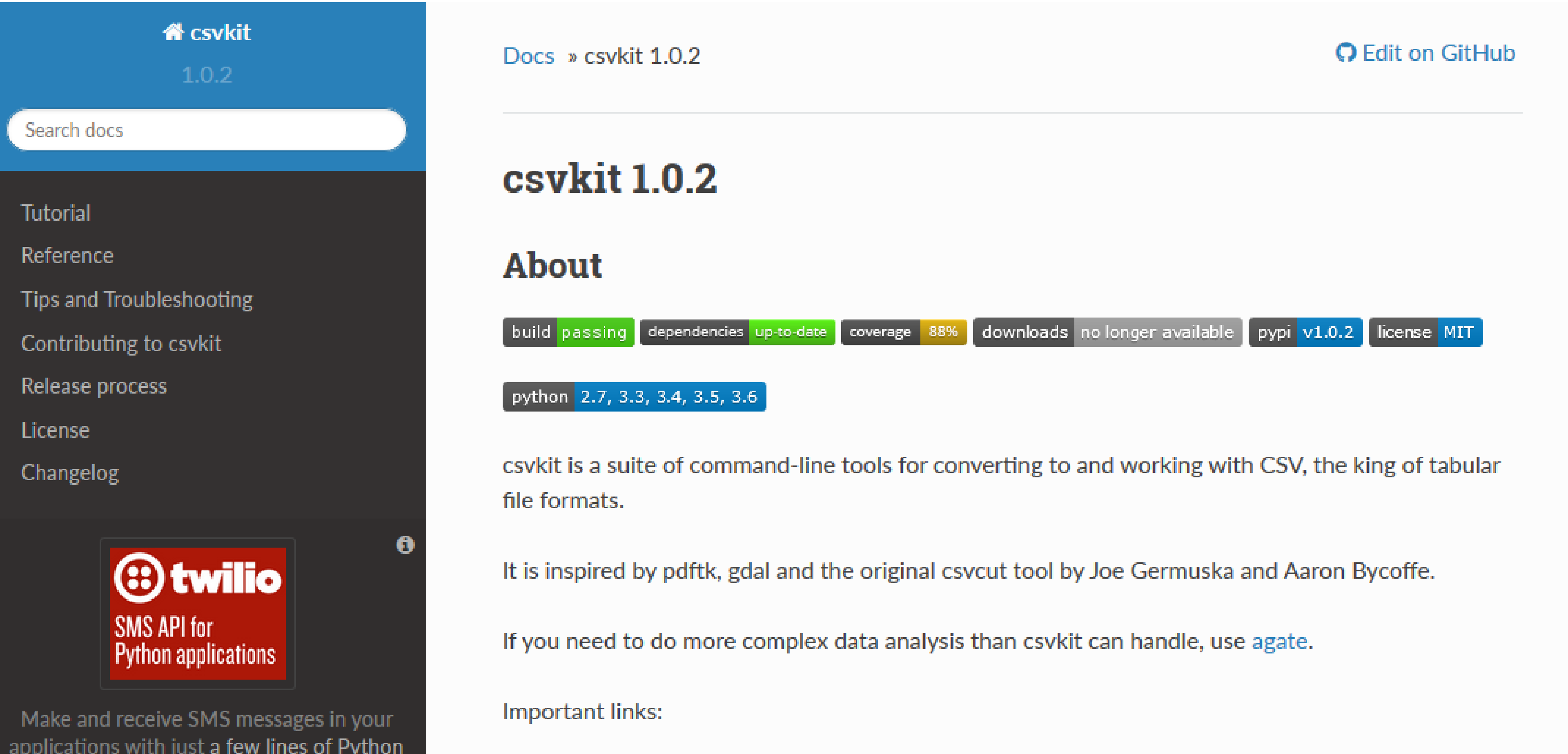
Hadley Wickham
RStudio

Abstract

A huge amount of effort is spent cleaning data to get it ready for analysis, but there has been little research on how to make data cleaning as easy and effective as possible. This paper tackles a small, but important, component of data cleaning: data tidying. Tidy datasets are easy to manipulate, model and visualise, and have a specific structure: each variable is a column, each observation is a row, and each type of observational unit is a table. This framework makes it easy to tidy messy datasets because only a small set of tools are needed to deal with a wide range of un-tidy datasets. This structure also makes it easier to develop tidy tools for data analysis, tools that both input and output tidy datasets. The advantages of a consistent data structure and matching tools are demonstrated with a case study free from mundane data manipulation chores.

Keywords: data cleaning, data tidying, relational databases, R.

CSVKIT



csvkit 1.0.2

About

csvkit is a suite of command-line tools for converting to and working with CSV, the king of tabular file formats.

It is inspired by pdftk, gdal and the original csvcut tool by Joe Germuska and Aaron Bycoffe.

If you need to do more complex data analysis than csvkit can handle, use agate.

Important links: