# DATA CLEANING & DATA MANIPULATION

PETRA ISENBERG

VISUAL ANALYTICS

#### 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

### 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"

	9	tep 1:	: Activ	ity/Eq	uipme	ent Typ	e Step 2: Add a Map Step 3: Additional Details		Add An Acti	vity
Date	Date of Activity:						Duration:	Activity Details		
< Su						>	00 : 00 : 00	+ Igny \$		
7	Oops! You forgot to enter a duration for								this activity.	isea
21	22	23	24	25	26	27	5.62 mi		Activity Type:	Running
28	29	30					Training Plan:		Equipment Type:	None
Aver	Average Heart Rate (optional):							Route:	None	
Avoir	Average neart nate (optional).						Distance:	5.62 mi.		
	b	pm							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."

### 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

### **DETECTING ERRORS**

LOOK FOR OUTLIERS / ANOMALIES
EXAMINE DATA TYPES
SCHEMA CHECKING
VALIDATE WITH OTHER DATA
OTHER HEURISTICS

HISTORICALLY – MORE FOCUS ON AUTOMATED APPROACHES

### DETECTION METHODS

+ CAN IDENTIFY
POTENTIAL ANOMALIES

- HARD TO KNOW <u>IF</u> THEY'RE REALLY ANOMALOUS OR HOW TO CORRECT THEM

Туре	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")
```

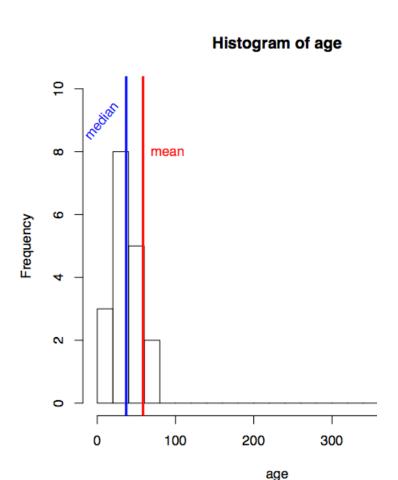
JUST <u>SORTING</u> THE DATA CAN HELP HIGHLIGHT ISSUES LIKE THESE

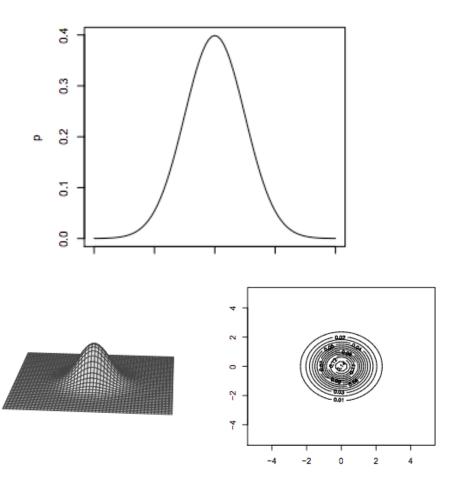
# OUTLIER DETECTION

- 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

#### LEVENSHTEIN ("STRING-EDIT") DISTANCE

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

Ben-Hur Ben Hur Anand Vaskar Anand Vaskkar

DISTANCE = 1

DISTANCE = 1

#### LEVENSHTEIN ("STRING-EDIT") DISTANCE

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

Ben-Hur

Ben-Hur (1959 film)

**Anand Vaskar** 

Vaskar, Anand

DISTANCE = 12

DISTANCE = 12

#### SOUNDEX / METAPHONE

How similar do they sound?

Ben-Hur

Ben-Hurr

Been Her

**Anand Vaskar** 

Anand Vaskkar

Ahnund Vachkar

#### "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

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—naking processes and efficiency optimizations, and in an increasing number of settings is the reason of letter of entire agencies or firms.

and is no increasing number of settings in the reason d'avec of extire agencies or firms. Despite the importance of data officient and analysis, that goaling remains a persuave and theory produce in almost every large organization. The presence of increave or inconsistent and can singularize distort the results of analyses, often penging the portant's hearifus of information-driven approaches. As a result, there has been a sarriey of research over the last many contractive and the same of the contractive driven approaches. As a result, there has been a sarriey of research over the last many contractive driven approaches. As a result, there has been a sarriey of research over the last many contractive driven approaches. As a result, there has been a sarriey of research over the last many contractive driven approaches and the contractive driven are driven and the contractive driven and the contractive driven and the contractive driven are driven and the contractive driven are driven and the contractive driven and the contractive driven are driven and th

In this sport, we curve date cleaning nethods that flows the error in quantitative stringth of lands, the slight way for the cleaning methods for side types of attributes. The discussion is targeted at computer penetitioners who massage inguity datasets of gastlands, and disquires obviously data start paid satisfies of quantitative information, and designes obviously data start paid satisfies of quantitative information of designes overly data analysis not produce the institute of the contractive of th

#### 1.1 Sources of Error in Data

Before a data item cords up in a datablese, it typically passes through a number of separitoristic methods human interaction and computation. But across on covery in at every sport the precess from initial data expedition to archival storage. An understanding of the sources of data expension to archival storage. An understanding of the sources of the survey on the united boots in designing data collection and custion techniques that mitigate which is the survey we utilize tasks outside a survey as the United Nations Economic Commission for Europe (UNICE), which holds the experige on this sension.

## 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: <u>KEEP</u>, <u>REMOVE</u>, OR <u>REPAIR</u>?

BADLY-STORED DATES, ADDRESSES, OR KEYS MAY NEED TO BE <u>PARSED MANUALLY</u>

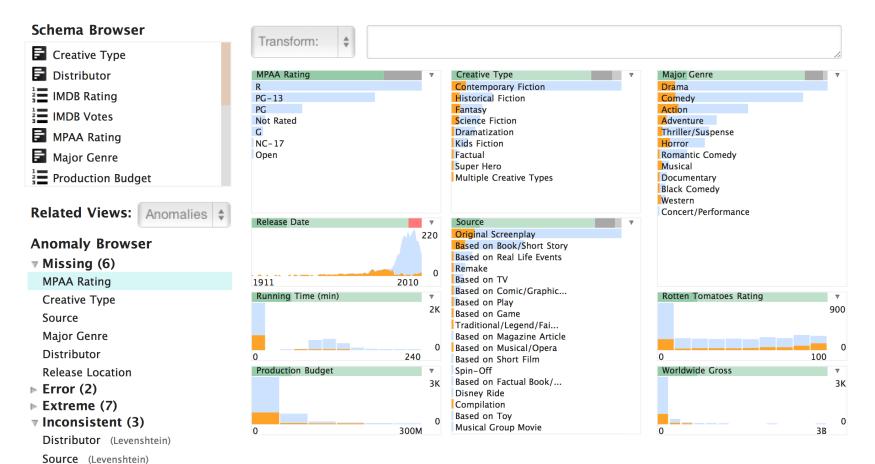
## DECIDING HOW TO FIX PROBLEMS

FUZZY MATCHING SYSTEMS

MACHINE LEARNING TO DETECT/RESOLVE FRRORS

USUALLY REQUIRES HUMAN JUDGMENT (ESPECIALLY FOR NEW DATA)

#### INTERACTIVE PROFILING

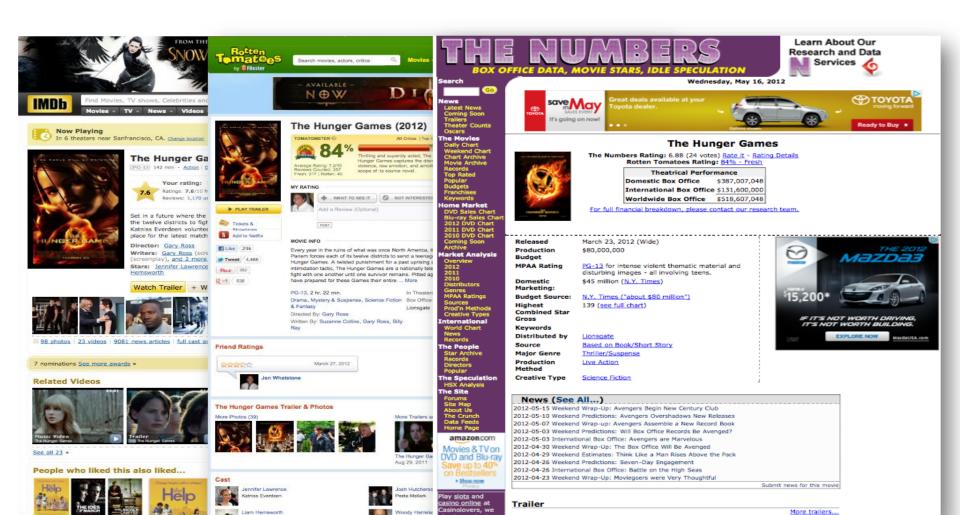


#### "PROFILING" DATA

<u>UNDERSTANDING</u> WHAT ASSUMPTIONS YOU CAN MAKE ABOUT DATA

INTERACTIVELY IDENTIFYING DATA QUALITY ISSUES

#### AN EXAMPLE



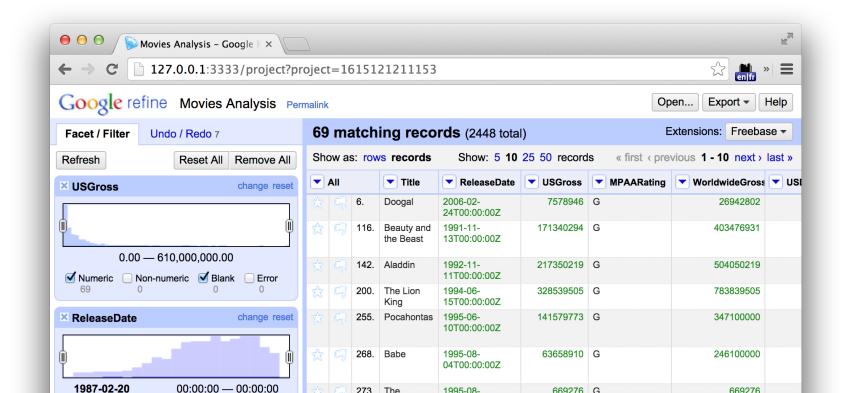
Title	Release Date	MPAA Rating	Distributor	Rotten Tomatoes Rating	IMDB Rating
The Land Girls	Jun 12, 1998	R	Gramercy		6.1
First Love, Last Rites	Aug 7, 1998	R	Strand		6.9
l Married a Strange Person	Aug 28, 1998		Lionsgate		6.8
Slam	Oct 9, 1998	R	Trimark	62	3.4
Mississippi Mermaid	Jan 15, 1999		MGM		
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

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
l 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

Arnolds Park	Oct 19, 2007	PG-13	The Movie Partners
Sweet Sweetback's Baad Assss 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

# PROFILING IN OPEN REFINE



## INTERACTIVE DATA CLEANING



Trifacta Wrangler

https://www.trifacta.com/



Wrangler (Stanford HCI Group)

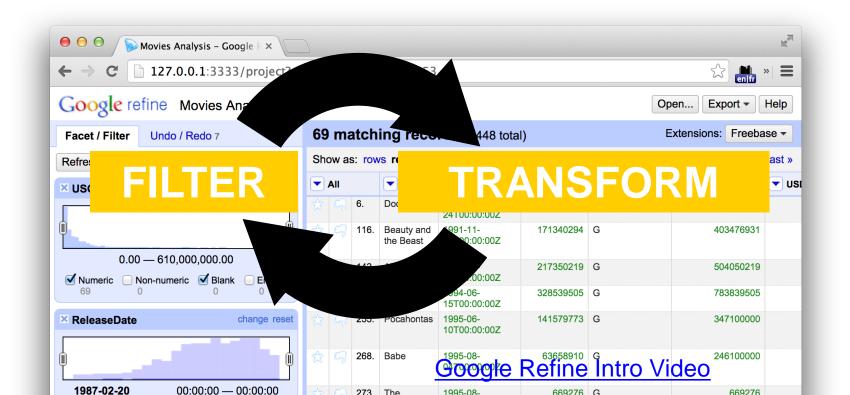
http://vis.stanford.edu/wrangler/



**OpenRefine** (formerly Google Refine)

http://openrefine.org/

# DATA CLEANING IN GOOGLE REFINE



#### 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

,

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

#### **CSVKIT**

☆ csvkit

1.03

Search docs

Tutorial

Reference

Tips and Troubleshooting

Contributing to csvkit

Release process

License

Changelog



Make and receive SMS messages in your applications with just a few lines of code.

Docs » csvkit 1.0.3

C Edit on GitHub

#### **csvkit 1.0.3**

#### **About**

```
build passing FIXME Migrate to GitLab coverage 87% pypi v1.0.3 license MIT
```

python 2.7 | 3.3 | 3.4 | 3.5 | 3.6

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:

Repository: https://github.com/wireservice/csvkit