COMP9321 Data Services Engineering

Term1, 2023

Week 2: Data Cleansing

Data Cleansing

- Datasets are messy, messy data can give wrong insights (Martin Goodson's story*)
- Cleansing/Cleaning data "find and remove or correct data that detracts from the quality, and thus the usability, of data. The goal of data cleansing is to achieve consistent, complete, accurate, and uniform data"**

*https://towardsdatascience.com/what-is-dirty-data-d96abbdf254e

** https://www.informatica.com/au/services-and-training/glossary-of-terms/data-cleansing-definition.html#fbid=eohTNIdjKaj

DB-hard Queries

Company_Name	Address	Market Cap
Google	Googleplex, Mtn. View, CA	$406Bn
Microsoft	Redmond, WA	$392Bn
Intl. Business Machines	Armonk, NY	$194Bn

```
SELECT Market_Cap
From Companies
Where Company_Name = “Apple”
```

Number of Rows: 0

Problem:
Missing Data

DB-hard Queries

Company_Name	Address	Market Cap
Google	Googleplex, Mtn. View, CA	$406Bn
Microsoft	Redmond, WA	$392Bn
Intl. Business Machines	Armonk, NY	$194Bn

```
SELECT Market_Cap
From Companies
Where Company_Name = "IBM"
```

Number of Rows: 0

Problem:
Entity Resolution

DB-hard Queries

Company_Name	Address	Market Cap
Google	Googleplex, Mtn. View, CA	$406
Microsoft	Redmond, WA	$392
Intl. Business Machines	Armonk, NY	$194
Hogwarts School of Witchcraft and Wizardry	Scotland, UK	$460

```
SELECT MAX(Market_Cap)
From Companies
```

Number of Rows: 1

Problem:
Unit Mismatch

Who's Calling Who'S Data Dirty?

Dirty Data

The Statistics View:

- There is a process that produces data
- We want to model ideal samples of that process, but in practice we have non-ideal samples:
  - **Distortion** – some samples are corrupted by a process
  - **Selection Bias** - likelihood of a sample depends on its value
  - **Left and right censorship** - users come and go from our scrutiny
  - **Dependence** – samples are supposed to be independent, but are not (e.g. social networks)
- You can add new models for each type of imperfection, but you can't model everything.
- What's the best trade-off between accuracy and simplicity?

Dirty Data

The Database View:

- I got my hands on this data set
- Some of the values are missing, corrupted, wrong, duplicated
- Results are absolute (relational model)
- You get a better answer by improving the quality of the values in your dataset

Dirty Data

The Domain Expert's View:

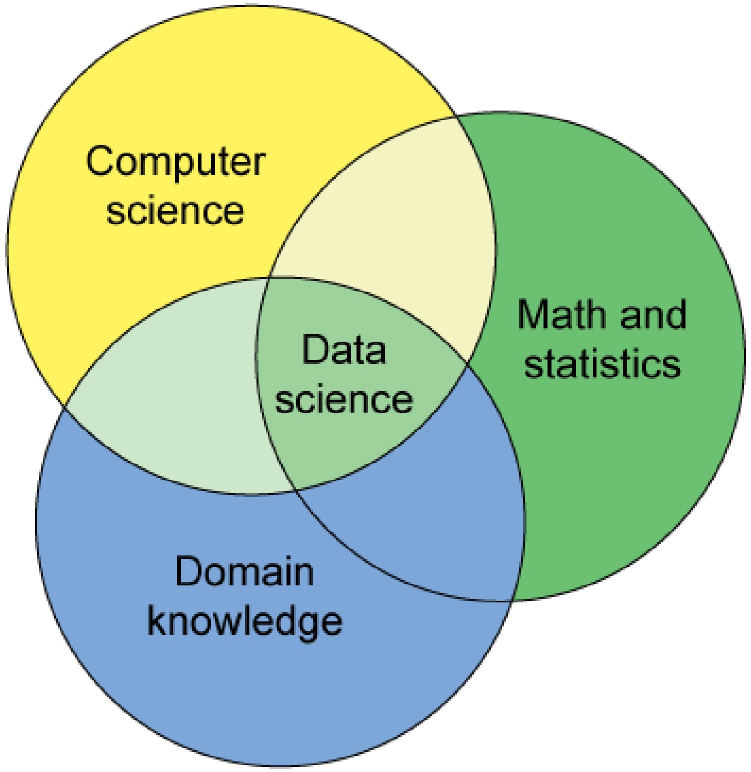
- This Data Doesn't look right
- This Answer Doesn't look right
- What happened?

Domain experts have an implicit model of the data that they can test against…

Dirty Data

The Data Scientist's View:

- Some Combination of all of the above



Example: Data Quality Problems

Representation

Contradictions

Ref. integrity

CUST

CNr	Name	Birthday	Age	Sex	Phone	ZIP
1234	Costa, Rui	18.2.80	37	m	999999999	1000
1234	Ana Costa	32.2.70	37	m	965432123	55555
1235	Rui Costa	18.2.80	27	m	963124568	1000

Uniqueness

Missing values

Duplicates

ADDRESS

ZIP	Place
1000	Lisboa
1000	Lsiboa
1024	Portugal

Typos

Incorrect values

Data Quality Problems

- (Source) Data is dirty on its own.
- Transformations corrupt the data (complexity of software pipelines).
- Data sets are clean but integration (i.e., combining them) mess them up.
- “Rare” errors can become frequent after transformation or integration.
- Data sets are clean but suffer “bit rot”
- Old data loses its value/accuracy over time
- Any combination of the above

Why Data Quality Problems Matter

Incorrect prices in inventory retail databases

- Costs for consumers 2.5 billion $
- 80% of barcode-scan-errors to the disadvantage of consumer

IRS 1992: almost 100,000 tax refunds not deliverable

- 50% to 80% of computerized criminal records in the U.S. were found to be inaccurate, incomplete, or ambiguous. [Strong et al. 1997a]

US-Postal Service: of 100,000 mass mailings up to 7,000 undeliverable due to incorrect addresses [Pierce 2004]

… …

How Data Quality Problems Happen

Incomplete data comes from:

 non available data value when collected

 different criteria between the time when the data was collected and when it is analyzed

 human/hardware/software problems

Noisy data comes from:

 data collection: faulty instruments

 data entry: human or computer errors

 data transmission

Inconsistent (and duplicate) data comes from:

 Different data sources, so non-uniform naming conventions/data codes

 Functional dependency and/or referential integrity violation

Application Scenarios

Integrate data from different sources

- E.g., populating data from different operational data stores or a mediator-based architecture

Eliminate errors and duplicates within a single source

- E.g., duplicates in a file of customers

Migrate data from a source schema into a different fixed target schema

- E.g., discontinued application packages

Convert poorly structured data into structured data

- E.g., processing data collected from the Web

Why Data Cleaning is Important

Activity of converting source data into target data without errors, duplicates, and inconsistencies, i.e., Cleaning and Transforming to get…

- **High-quality data!**

No quality data, no quality decisions!

 Quality decisions must be based on good quality data (e.g., duplicate or missing data may cause incorrect or even misleading statistics)

Data Quality Problems

Schema level data quality problems

- prevented with better schema design, schema translation and integration.

Instance level data quality problems

- errors and inconsistencies of data that are not prevented at schema level

Data Quality Problems

Schema level data quality problems

- Avoided by an RDBMS
  - Missing data – *product price not filled in*
  - Wrong data type – *“abc” in product price*
  - Wrong data value – *0.5 in product tax (iva)*
  - Dangling data – *category identifier of product does not exist*
  - Exact duplicate data – *different persons with same ssn*
  - Generic domain constraints – *incorrect invoice price*
- Not avoided by an RDBMS
  - Wrong categorical data – *countries and corresponding states*
  - Outdated temporal data – *just-in-time requirement*
  - Inconsistent spatial data – *coordinates and shapes*
  - Name conflicts – *person vs person or person vs client*
  - Structural Conflicts - *addresses*

Data Quality Problems

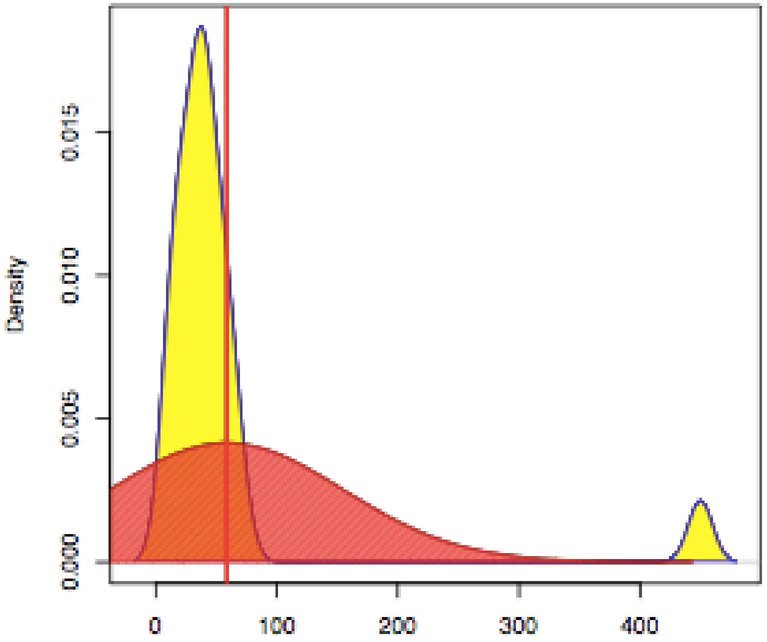
Instance level data quality problems

- Single record
  - Missing data in a *not null* field – *ssn:-9999999*
  - Erroneous data – *price:5 but real price:50*
  - Misspellings: *Morty Al-Banna vs Morty Al-Banana*
  - Embedded values: *dr. Morty Al-Banna*
  - Misfielded values: *city: Australia*
  - Ambiguous data: *M.Al-Banna,Sydney,Australia*
- Multiple records
  - Duplicate records: *Name:Morty Al-Banna, Birth:01/01/1980 and Name: Morty Al-Banna, Birth:01/01/1980*
  - Contradicting records: *Morty Al-Banna, Birth:01/01/1980 and Name: Morty Al-Banna, Birth:01/01/1982*
  - Non-standardized data: *Morty Al-Banna vs Al-Banna, Morty*

Numeric Outliers

12	13	14	21	22	26	33	35	36	37	39	42	45	47	54	57	61	68	450

ages of employees (US)



- median 37
- mean 58.52632
- variance 9252.041

Adapted from Joe Hellerstein's 2012 CS 194 Guest Lecture

Integration error

Data 1

…	Date(mm/dd/yyyy)	…
…	08/02/2019	…
…	09/02/2019	…

Data 2

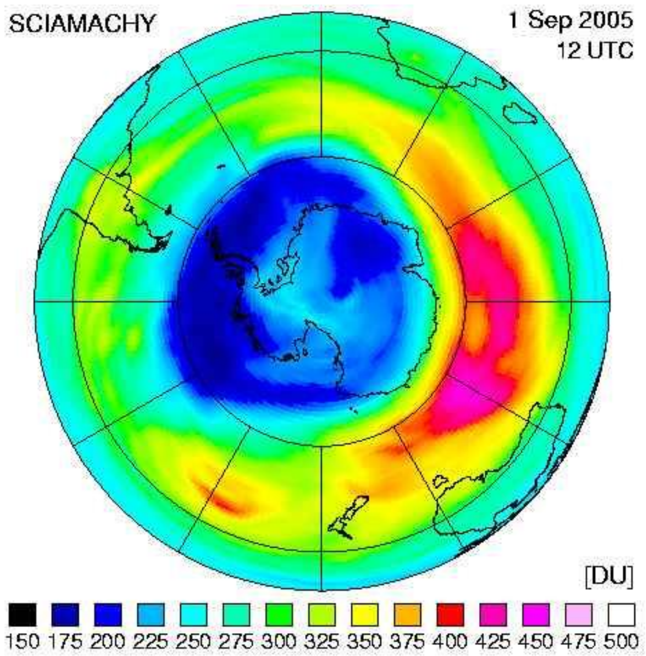
…	Date(dd/mm/yyyy)	…
…	08/08/2019	…
…	09/08/2019	…

…	Date(mm/dd/yyyy)	…
…	08/02/2019	…
…	09/02/2019	…
…	08/08/2019	…
…	09/08/2019	…

Data Cleaning Makes Everything Okay?

The appearance of a hole in the earth's ozone layer over Antarctica, first detected in 1976, was so unexpected that scientists didn't pay attention to what their instruments were telling them;

they thought their instruments were malfunctioning.



In fact, the data were rejected as unreasonable by data quality control algorithms

Conventional Definition of Data Quality

Accuracy

- The data was recorded correctly.

Completeness

- All relevant data was recorded.

Uniqueness

- Entities are recorded once.

Timeliness

- The data is kept up to date.
  - Special problems in federated data: time consistency.

Consistency

- The data agrees with itself.

Accuracy

Closeness between a value v and a value v'

considered as the correct representation of the realworld phenomenon that v aims to represent.

- Ex: for a person name “John”, v’=John is correct, v’=Jhn is incorrect

Syntatic accuracy

closeness of a value v to the elements of the corresponding definition domain D

- Ex: if v=Jack, even if v’=John , v is considered syntactically correct because it is an admissible value in the domain of people names.
- Measured by means of comparison functions (e.g., edit distance) that returns a score

Accuracy

Semantic accuracy

closeness of the value v to the true value v’

- Measured with a <yes, no> or <correct, not correct> domain
- Coincides with correctness
- The corresponding true value has to be known
- e.g., Donald Trump vs The Donald

Ganularity of accuracy definition

Accuracy may refer to:

- a single value of a relation attribute
- an attribute or column
- a relation
- the whole database

Completeness

"The extent to which data are of sufficient breadth, depth, and scope for the task in hand."

Three types:

- **Schema completeness**: degree to which concepts and their properties are not missing from the schema
- **Column completeness**: evaluates the missing values for a specific property or column in a table.
- **Population completeness**: evaluates missing values with respect to a reference population

Completeness of relational data

The **completeness of a table** characterizes the extent to which the table represents the real world.

- **The presence/absence and meaning of null values**

Example: Person(name, surname, birthdate, email), if email is null may indicate the person has no mail (no incompleteness), email exists but is not known (incompletenss), it is not known whether Person has an email (incompleteness may not be the case)

Completeness of relational data

- **Validity of open world assumption (OWA) or closed world assumption (CWA)**
  - OWA: cannot state neither the truth or falsity of facts not represented in the tuples of a relation
  - CWA: only the values actually present in a relational table and no other values represent facts of the real world.

Example

```
Statement: "Mary" "is a citizen of" "France"
```

```
Question: Is Paul a citizen of France?
```

```
"Closed world" (for example SQL) answer: No.
"Open world" answer: Unknown.
```

Time-related Dimensions

Currency:

concerns how promptly data are updated

- Example:
  - if the residential address of a person is updated (it corresponds to the address where the person lives) then the currency is high

Volatility:

characterizes the frequency with which data vary in time

- Example:
  - Birth dates (volatility zero) vs stock quotes (high degree of volatility)

Time-related Dimensions

Timeliness

- expresses how current data are for the task in hand

- Example:
  - The timetable for university courses can be current by containing the most recent data, but it cannot be timely if it is available only after the start of the classes.

Consistency

Captures the violation of semantic rules defined over a set of data items, where data items can be tuples of relational tables or records in a file

- Integrity constraints in relational data
  - Domain constraints, Key, inclusion and functional dependencies
- Data edits: semantic rules in statistics

Others

- Interpretability: concerns the documentation and metadata that are available to correctly interpret the meaning and properties of data sources
- Synchronization between different time series: concerns proper integration of data having different time stamps.
- Accessibility: measures the ability of the user to access the data from his/her own culture, physical status/functions, and technologies available.

Problems …

Unmeasurable

- Accuracy and completeness are extremely difficult, perhaps impossible to measure.

Context independent

- No accounting for what is important. E.g., if you are computing aggregates, you can tolerate a lot of inaccuracy.

Vague

- The conventional definitions provide no guidance towards practical improvements of the data.

Useful Read

- Python for Data Analysis, Wes McKinney
- https://www.altexsoft.com/blog/datascience/preparing-your-dataset-for-machine-learning-8-basic-techniques-that-make-your-data-better/
- https://pandas.pydata.org/pandas-docs/stable/tutorials.html
- https://realpython.com/python-data-cleaning-numpy-pandas/
- https://www.dataquest.io/blog/machine-learning-preparing-data/