MONASH University

# FIT1043 Introduction to Data Science

## Week 4

Ian K T Tan

School of Information Technology
Monash University Malaysia

*With materials from Wray Buntine, Mahsa Salehi*

# Learning Outcomes

Week 4

**By the end of this week you should be able to:**

- *Explain open data and linked open data*
- *Explain how to access to new data sources through APIs*
- *Identify how different APIs work*
- Inspect data quality problems in datasets and recommend solutions to fix them
- *Use data wrangling operations in Python*

# Data Wrangling

Manipulating data to make it directly usable for analysis

**Week 4**

- Common types of data that are at our disposal.
- Data wrangling and the goals of wrangling
- Data quality
- Data auditing
- Examples

# Data


MONASH University

# Databases

**Relational Databases**

- Oracle
- MySQL
- MariaDB
- MS-SQL

**Containing data for**

- Customer relationship management
- Mortgage, hire purchase, business loan system
- Salesforce automation
- Credit card system, ATM transactions, retail banking
- Human resource and payroll

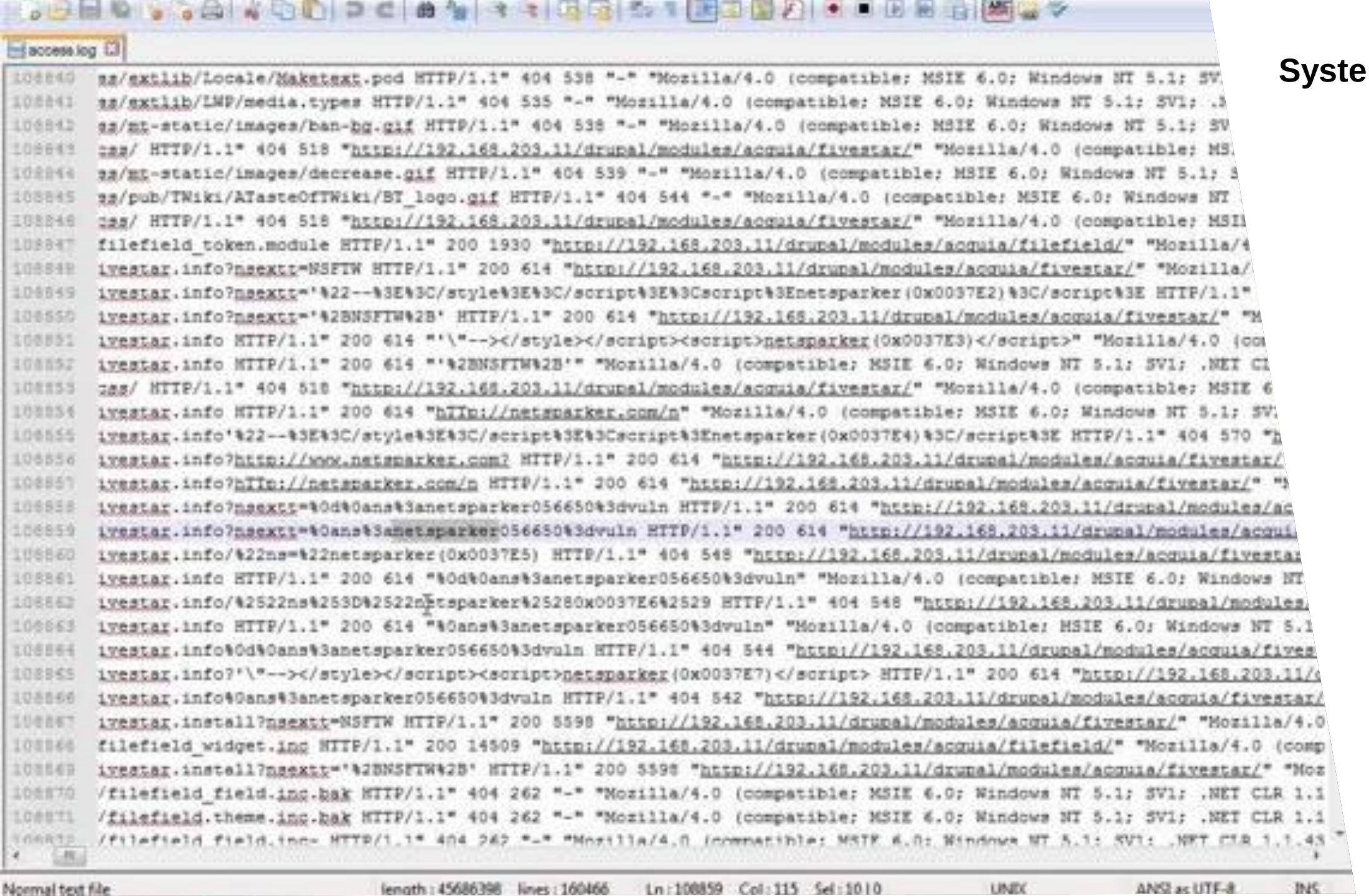
# Files

**Examples**

- ***System log files***
- Spreadsheets
- PDF files
- Image files
- Raw text files
- Formatted text files

MONASH University

# System Log Files




MONASH University

# Web & Crowd Sources

Open Data, REST API, Web Scrapping, etc.

**Huge!**

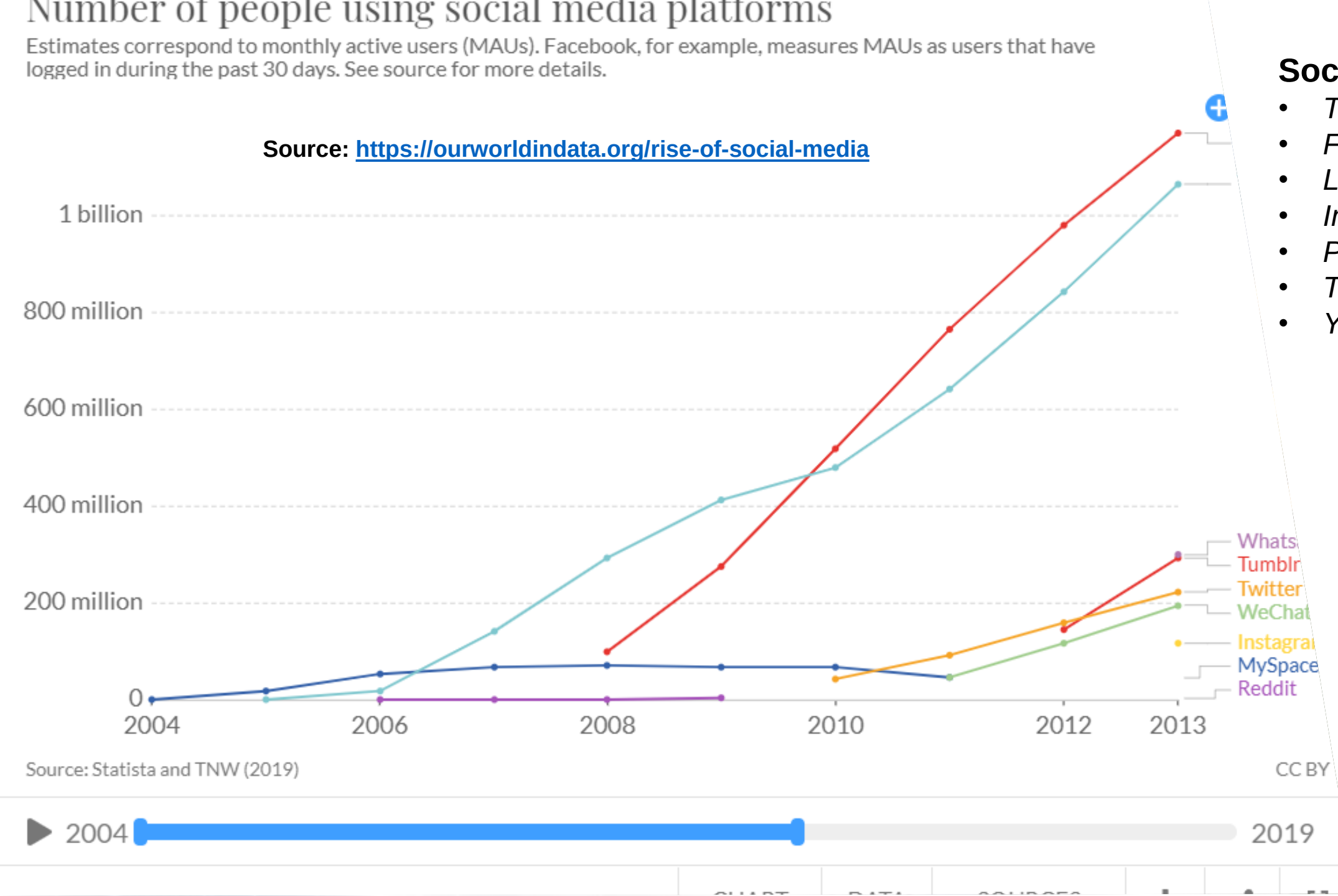
- What can we do with Web and other crowd sourced data?
- What type of web data?

**Data on the Web**

- News: Sports, Finance, World, Nation
- Blogs
- Corporates: Products & Services
- Government

# GDELT


MONASH University




**Source:** https://ourworldindata.org/rise-of-social-media

## Social Media

- *Twitter*
- *Facebook*
- *LinkedIn*
- *Instagram*
- *Pinterest*
- *TikTok*
- *YouTube*

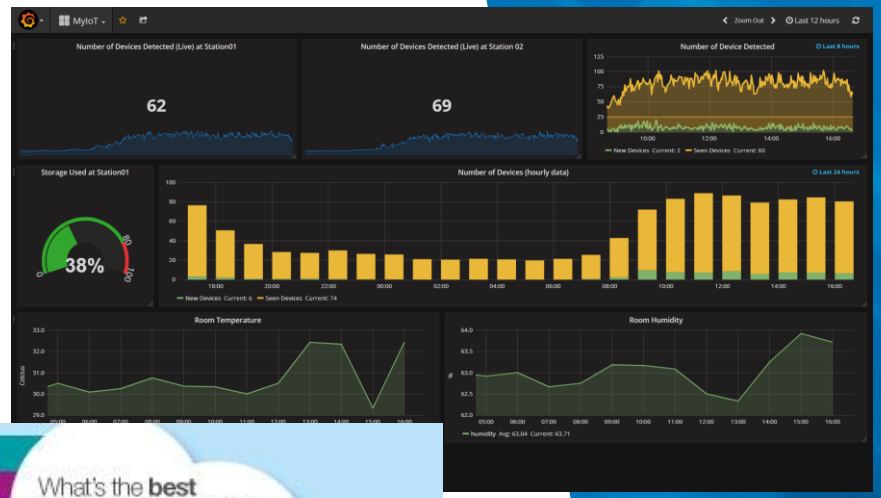
MONASH University

# Internet of Things (IoT)

The Future

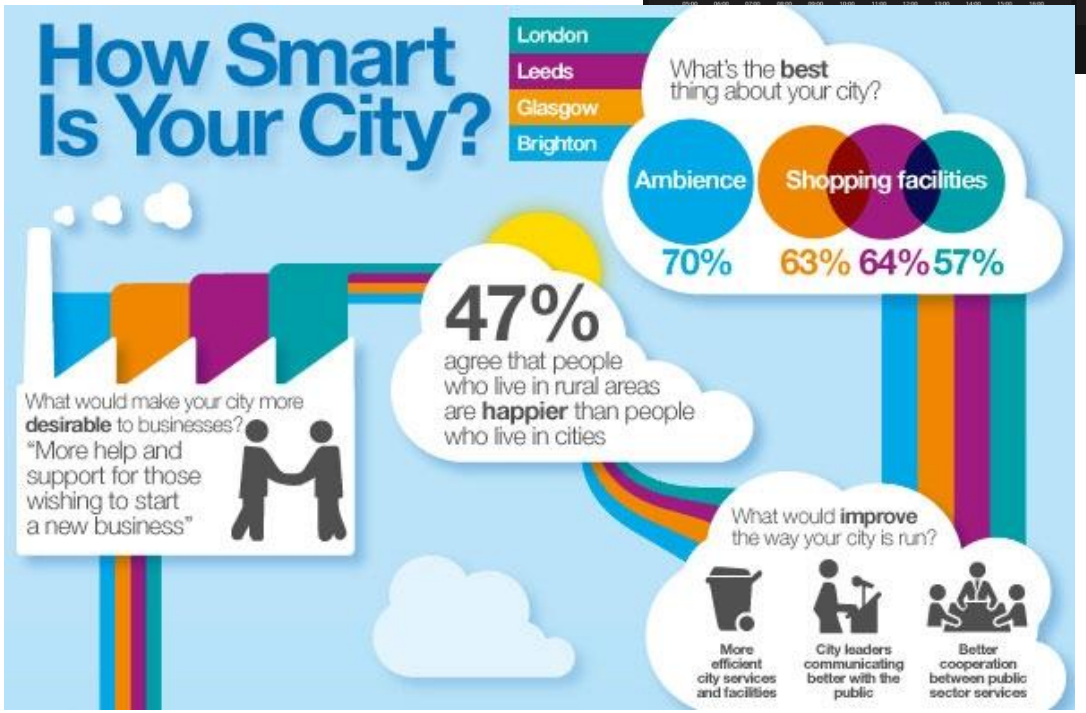
**Where?**

- Utilities – Water, Power, Street Lighting, Traffic Lights, Waste Disposal
- Vehicle to Vehicle, Autonomous Driving
- Monitoring Systems




**Mobile Phone Data**

- Location
- Browsing history
- Usage history
- Personal information




MONASH University

# Data Wrangling

MONASH University

**Ideal Data**

| | C | D | E | F | G | H | I | J | K | L |
|---|---|---|---|---|---|---|---|---|---|---|
| | 77516 | Bachelors | 13 | Never-married | Adm-clerical | Not-in-famil | White | Male | 2174 | |
| no | 83311 | Bachelors | 13 | Married-civ-spouse | Exec-managerial | Husband | White | Male | 0 | |
| | 215646 | HS-grad | 9 | Divorced | Handlers-cleaners | Not-in-famil | White | Male | 0 | 0 |
| | 234721 | 11th | 7 | Married-civ-spouse | Handlers-cleaners | Husband | Black | Male | 0 | 0 |
| | 338409 | Bachelors | 13 | Married-civ-spouse | Prof-specialty | Wife | Black | Female | 0 | 0 |
| | 284582 | Masters | 14 | Married-civ-spouse | Exec-managerial | Wife | White | Female | 0 | 0 |
| | 160187 | 9th | 5 | Married-spouse-abser | Other-service | Not-in-famil | Black | Female | 0 | 0 |
| no | 209642 | HS-grad | 9 | Married-civ-spouse | Exec-managerial | Husband | White | Male | 0 | 0 |
| | 45781 | Masters | 14 | Never-married | Prof-specialty | Not-in-famil | White | Female | 14084 | 0 |
| | 159449 | Bachelors | 13 | Married-civ-spouse | Exec-managerial | Husband | White | Male | 5178 | 0 |
| | 280464 | Some-colleg | 10 | Married-civ-spouse | Exec-managerial | Husband | Black | Male | 0 | 0 |
| | 141297 | Bachelors | 13 | Married-civ-spouse | Prof-specialty | Husband | Asian-Pac-Isl | Male | 0 | 0 |
| | 122272 | Bachelors | 13 | Never-married | Adm-clerical | Own-child | White | Female | 0 | 0 |
| | 205019 | Assoc-acdm | 12 | Never-married | Sales | Not-in-famil | Black | Male | 0 | 0 |
| | 121772 | Assoc-voc | 11 | Married-civ-spouse | Craft-repair | Husband | Asian-Pac-Isl | Male | 0 | 0 |
| | 245487 | 7th-8th | 4 | Married-civ-spouse | Transport-moving | Husband | Amer-Indian | Male | 0 | 0 |

MONASH University

CT Chest Hi Resolution 30/11/04 at 2156 CT-04-

REPORT:

Clinical note: transformed AML. Ongoing fevers.? Source. ? fungal infe

Report:

Axial 1.25 mm slices at 10 mm intervals taken in inspiration with selec
images in the prone position.

No mediastinal or hilar lymphadenopathy. Heart size is normal. Borderlir
enlargement of the main pulmonary outflow tract. There is smooth interlo
septal thickening throughout both lungs, which may be secondary to fluid
overload. There is a background of emphysematous changes , predominantly
the upper lobes. A 5 x 8 mm nodule is identified in the right upper lobe
(image 10). It is well-circumscribed with no evidence of surrounding
ground-glass opacity. No calcification or cavitation of this lesion. The
visualised portions of the liver and spleen appear normal, allowing for la
of intravenous contrast.

Conclusion:

Single nodule in right upper lobe has a non-specific appearance but given t
clinical history, this could represent a focus of fungal infection.

Reported by: D

PJL/PJL

A1.2f

Result type: CT Chest Hi Resolution
Result date: 11 January 2005 12:21
Result status: Auth (Verified)
Result title: CTCHEHI

**Data Reality**

MONASH University

# Why Wrangle?

**Working with Raw Data is challenging**

- Data comes in all shapes and sizes
- Different files have different formatting
- Mistakes in data entries

***We need techniques to cleanse and prepare the data!***

# Goals of Data Wrangling

**Transform Data into Usable Data**

Raw data ⇒ **Data Wrangling** ⇒ Tidy data ⇒ Data Analysis ⇒ Knowledge

*Data + Wrangling + Analysis = Data Product*

# What is Data Wrangling?

***Process of transforming "raw" data into data that can be analysed to generate valid actionable results and insights***

**Steps**

- Data pre-processing
- Data preparation
- Data cleansing
- Data transformation
- Etc.

# Data Quality


MONASH University

# Source of Data Quality Issues

**Causes**

- Interpretability issue
- Data format issue
- Inconsistent and faulty data
- Missing and incomplete data
- Outliers
- Duplicates

# Interpretability Issue

## Data quality problems

- Is there a proper documentation about the data?
  - Without proper documentation (i.e., a data dictionary), it is not possible for us to use the synthetic data.

- We might be able to guess the meaning of each column,
  - But in general,  we need a data dictionary to explain the fields

*Is this data interpretable?*

```
32,1,1,95,0,?,0,127,0,.7,1,?,?,1
34,1,4,115,0,?,?,154,0,.2,1,?,?,1
35,1,4,?,0,?,0,130,1,?,?,?,7,3
36,1,4,110,0,?,0,125,1,1,2,?,6,1
38,0,4,105,0,?,0,166,0,2.8,1,?,?,2
38,0,4,110,0,0,0,156,0,0,2,?,3,1
38,1,3,100,0,?,0,179,0,-1.1,1,?,?,0
38,1,3,115,0,0,0,128,1,0,2,?,7,1
38,1,4,135,0,?,0,150,0,0,?,?,3,2
38,1,4,150,0,?,0,120,1,?,?,?,3,1
40,1,4,95,0,?,1,144,0,0,1,?,?,2
```

MONASH University

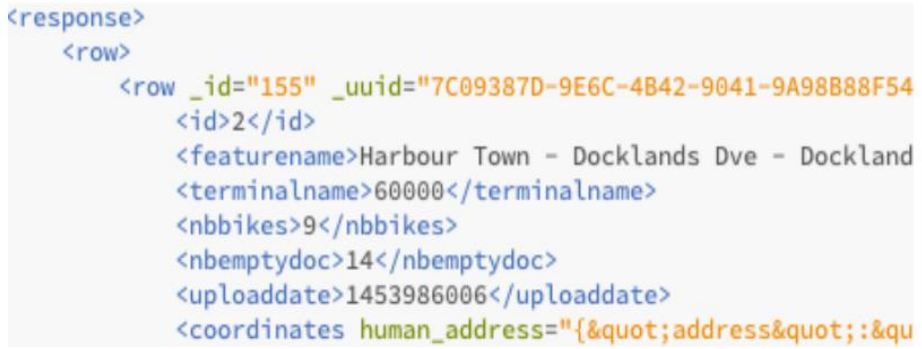
# Data format issue

## Data quality problems

- Data from different sources often have different data formats and are generated from different processes.
- It is challenging to integrate and manipulate data in different formats.

```
{
  "meta" : {
    "view" : {
      "id" : "tdvh-n9dv",
      "name" : "Melbourne bike share",
      "attribution" : "City of Melbourne, Australia",
      "averageRating" : 0,
      "category" : "Transport & Movement",
      "createdAt" : 1428898164,
      "description" : "Melbourne Bike Share is a joint RACV/Victoria
      "displayType" : "table",
```

JavaScript Object Notation (JSON)



```
<response>
    <row>
        <row _id="155" _uuid="7C09387D-9E6C-4B42-9041-9A98B88F54
            <id>2</id>
            <featurename>Harbour Town - Docklands Dve - Dockland
            <terminalname>60000</terminalname>
            <nbbikes>9</nbbikes>
            <nbemptydoc>14</nbemptydoc>
            <uploaddate>1453986006</uploaddate>
            <coordinates human_address="{&amp;quot;address&amp;quot;:&amp;qu
```

Extensible Mark-up Language (XML)

MONASH University

# Inconsistent and faulty data

## Data quality problems

- Mistyped data
- Inconsistent entry
- Extraneous data
- Etc.

*Mark Johnson, 31, 21/Aug/1985, 180, M, 0433010010, Melbourne VIC*

*Mr. Christian, Peter, 34, 21-09-1982, , M, 0433010118, Sydney NSW*

*Ethan Steedman, 32, 01/01/1982, 170, M, 0433210019, Sydney NSW*

MONASH University

# Missing values

## Data quality problems

- Data values that should be presented in a dataset but that are absent for many reasons.

*Missing values in the Switzerland heart disease data set are indicated by "?".*

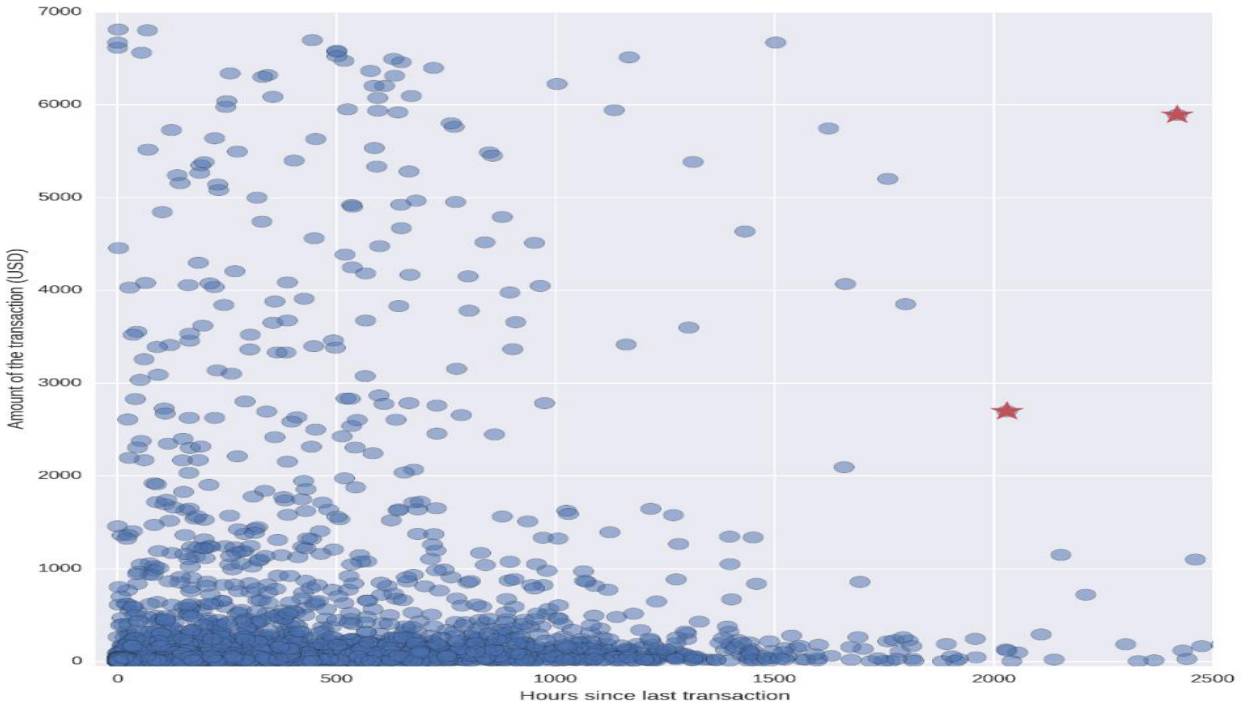
```
32,1,1,95,0,?,0,127,0,.7,1,?,?,1
34,1,4,115,0,?,?,154,0,.2,1,?,?,1
35,1,4,?,0,?,0,130,1,?,?,?,7,3
36,1,4,110,0,?,0,125,1,1,2,?,6,1
38,0,4,105,0,?,0,166,0,2.8,1,?,?,2
38,0,4,110,0,0,0,156,0,0,2,?,3,1
38,1,3,100,0,?,0,179,0,-1.1,1,?,?,0
38,1,3,115,0,0,0,128,1,0,2,?,7,1
38,1,4,135,0,?,0,150,0,0,?,?,3,2
38,1,4,150,0,?,0,120,1,?,?,?,3,1
40,1,4,95,0,?,1,144,0,0,1,?,?,2
```

MONASH University

# Outliers

Data quality problems

- An observation that lies in an abnormal distance from the majority of the other observations in the dataset.




MONASH University

# Duplicates

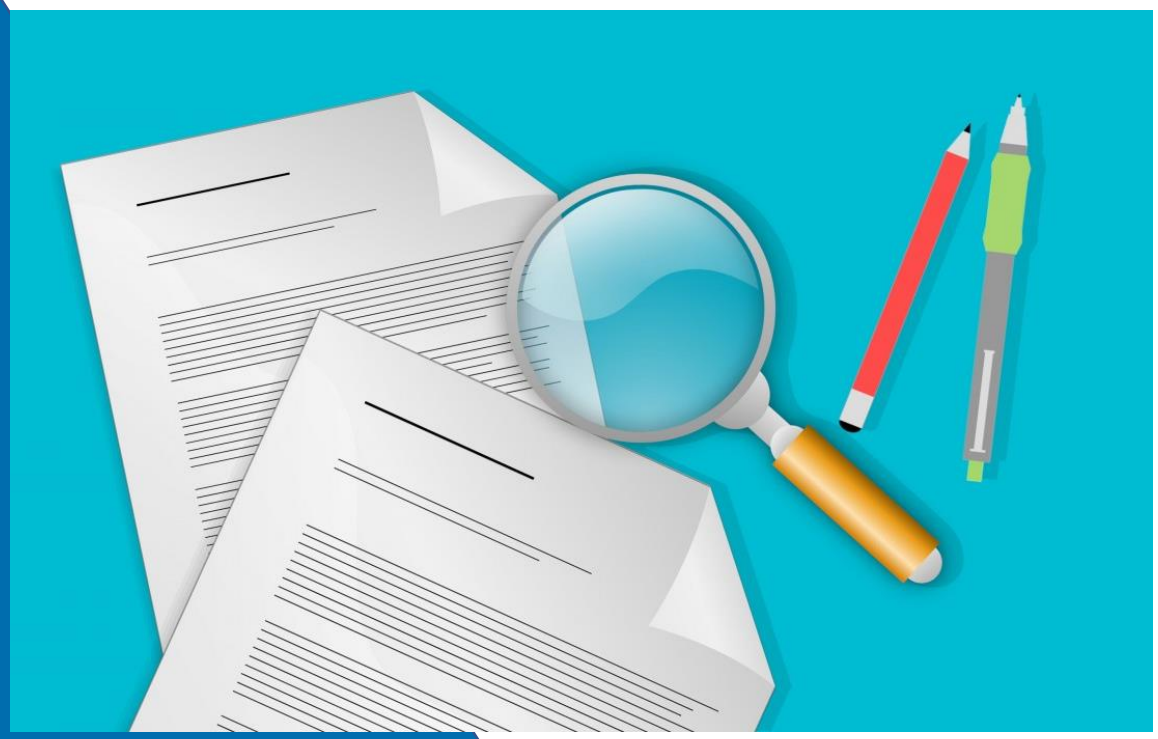
## Data quality problems

- Multiple data entries that correspond to the same piece of information

*Christoph Cleveland, 20, 10-10-1996, 50, M, 0433550210, Hobart TAS*

*Chris. Cleveland, 20, 10-10-1996, 176, M, 0433550210, Hobart TAS*

# Data Auditing



MONASH University

# Initial Data Auditing

Given a data set, what are the common initial auditing steps you would conduct?

| | A | B | C | D | E | F | G | H | I | J | K | L | M | N | O | P |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | survived | pclass | sex | age | sibsp | parch | fare | embarked | class | who | adult_male | deck | embark_tow | alive | alone | name |
| 2 | 0 | 3 | male | 22 | 1 | 0 | 7.25 | S | Third | man | TRUE | | Southampto | no | FALSE | Braund, Mr. Owe |
| 3 | 1 | 1 | female | 38 | 1 | 0 | 71.2833 | C | First | woman | FALSE | C | Cherbourg | yes | FALSE | Cumings, Mrs. J |
| 4 | 1 | 3 | female | 26 | 0 | 0 | 7.925 | S | Third | woman | FALSE | | Southampto | yes | TRUE | Heikkinen, Miss |
| 5 | 1 | 1 | female | 35 | 1 | 0 | 53.1 | S | First | woman | FALSE | C | Southampto | yes | FALSE | Futrelle, Mrs. |
| 6 | 0 | 3 | male | 35 | 0 | 0 | 8.05 | S | Third | man | TRUE | | Southampto | no | TRUE | Allen, Mr. Will |
| 7 | 0 | 3 | male | | 0 | 0 | 8.4583 | Q | Third | man | TRUE | | Queenstown | no | TRUE | Moran, Mr. Jame |
| 8 | 0 | 1 | male | 54 | 0 | 0 | 51.8625 | S | First | man | TRUE | E | Southampto | no | TRUE | McCarthy, Mr. T |
| 9 | 0 | 3 | male | 2 | 3 | 1 | 21.075 | S | Third | child | FALSE | | Southampto | no | FALSE | Palsson, Master |
| 10 | 1 | 3 | female | 27 | 0 | 2 | 11.1333 | S | Third | woman | FALSE | | Southampto | yes | FALSE | Johnson, Mrs. O |
| 11 | 1 | 2 | female | 14 | 1 | 0 | 30.0708 | C | Second | child | FALSE | | Cherbourg | yes | FALSE | Nasser, Mrs. Ni |
| 12 | 1 | 3 | female | 4 | 1 | 1 | 16.7 | S | Third | child | FALSE | G | Southampto | yes | FALSE | Sandstrom, Miss |
| 13 | 1 | 1 | female | 58 | 0 | 0 | 26.55 | S | First | woman | FALSE | C | Southampto | yes | TRUE | Bonnell, Miss. |
| 14 | 0 | 3 | male | 20 | 0 | 0 | 8.05 | S | Third | man | TRUE | | Southampto | no | TRUE | Saundercock, Mr |
| 15 | 0 | 3 | male | 39 | 1 | 5 | 31.275 | S | Third | man | TRUE | | Southampto | no | FALSE | Andersson, Mr. |
| 16 | 0 | 3 | female | 14 | 0 | 0 | 7.8542 | S | Third | child | FALSE | | Southamtpo | no | TRUE | Vestrom, Miss. |
| 17 | 1 | 2 | female | 55 | 0 | 0 | 16 | S | Second | woman | FALSE | | Southampto | yes | TRUE | Hewlett, Mrs. ( |
| 18 | 0 | 3 | male | 2 | 4 | 1 | 29.125 | Q | Third | child | FALSE | | Queenstown | no | FALSE | Rice, Master. E |
| 19 | 1 | 2 | male | | 0 | 0 | 13 | S | Second | man | TRUE | | Southampto | yes | TRUE | Williams, Mr. C |
| 20 | 0 | 3 | female | 31 | 1 | 0 | 18 | S | Third | woman | FALSE | | Southampto | no | FALSE | Vander Planke, |
| 21 | 1 | 3 | female | | 0 | 0 | 7.225 | C | Third | woman | FALSE | | Cherbourge | yes | TRUE | Masselmani, Mrs |
| 22 | 0 | 2 | male | 35 | 0 | 0 | 26 | S | Second | man | TRUE | | Southampto | no | TRUE | Fynney, Mr. Joe |

MONASH University

# Data Auditing

Some general steps to perform data auditing (assuming you're given or have read the data into a DataFrame `df`)

- Dimension of the data: `df.shape()`
  - Number of rows
  - Number of columns

```
(8500, 10)
```

# Data Auditing

Head and tail rows: `df.head(); df.tail()`

| | survived | pclass | sex | age | sibsp | parch | fare | embarked | class | who | adult_male | deck | embark_town | alive | alone | name |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 0 | 3 | male | 22.0 | 1 | 0 | 7.2500 | S | Third | man | True | NaN | Southampton | no | False | Braund, Mr. Owen Harris |
| **1** | 1 | 1 | female | 38.0 | 1 | 0 | 71.2833 | C | First | woman | False | C | Cherbourg | yes | False | Cumings, Mrs. John Bradley (Florence Briggs Th... |
| **2** | 1 | 3 | female | 26.0 | 0 | 0 | 7.9250 | S | Third | woman | False | NaN | Southampton | yes | True | Heikkinen, Miss. Laina |
| **3** | 1 | 1 | female | 35.0 | 1 | 0 | 53.1000 | S | First | woman | False | C | Southampton | yes | False | Futrelle, Mrs. Jacques Heath (Lily May Peel) |
| **4** | 0 | 3 | male | 35.0 | 0 | 0 | 8.0500 | S | Third | man | True | NaN | Southampton | no | True | Allen, Mr. William Henry |

# Data Auditing

What are the numerical and categorical columns?

Check basic information about the dataframe

- Number of records,
- Whether there are null values,
- Etc

datatype: `df.info()`

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 892 entries, 0 to 891
Data columns (total 16 columns):
survived       892 non-null int64
pclass         892 non-null int64
sex            892 non-null object
age            715 non-null float64
sibsp          892 non-null int64
parch          892 non-null int64
fare           892 non-null float64
embarked       890 non-null object
class          892 non-null object
who            892 non-null object
adult_male     892 non-null bool
deck           204 non-null object
embark_town    890 non-null object
alive          892 non-null object
alone          892 non-null bool
name           892 non-null object
dtypes: bool(2), float64(2), int64(4), object(8)
memory usage: 99.4+ KB
```

# Data Auditing

Check some basic statistics about columns:

- Numerical columns: `df.describe()`
- Object columns: `df.describe(include=[np.object])`

*https://pandas.pydata.org/pandas-docs/stable/reference/api/pandas.DataFrame.describe.html*

| | survived | pclass | age | sibsp | parch | fare |
|---|---|---|---|---|---|---|
| **count** | 892.000000 | 892.000000 | 715.000000 | 892.000000 | 892.000000 | 892.000000 |
| **mean** | 0.384529 | 2.307175 | 29.720517 | 0.522422 | 0.381166 | 32.201737 |
| **std** | 0.486757 | 0.836750 | 14.490914 | 1.102264 | 0.805706 | 49.665589 |
| **min** | 0.000000 | 1.000000 | 0.420000 | 0.000000 | 0.000000 | 0.000000 |
| **25%** | 0.000000 | 2.000000 | NaN | 0.000000 | 0.000000 | 7.917700 |
| **50%** | 0.000000 | 3.000000 | NaN | 0. | | |
| **75%** | 1.000000 | 3.000000 | NaN | 1. | | |
| **max** | 1.000000 | 3.000000 | 80.000000 | 8. | | |

| | sex | embarked | class | who | deck | embark_town | alive | name |
|---|---|---|---|---|---|---|---|---|
| **count** | 892 | 890 | 892 | 892 | 204 | 890 | 892 | 892 |
| **unique** | 4 | 3 | 3 | 3 | 7 | 7 | 2 | 891 |
| **top** | male | S | Third | man | C | Southampton | no | Behr, Mr. Karl Howell |
| **freq** | 574 | 644 | 491 | 538 | 60 | 643 | 550 | 2 |

MONASH University

# Data Auditing

Check correlation amongst variables: `df.corr()`

| | survived | pclass | age | sibsp | parch | fare | adult_male | alone |
|---|---|---|---|---|---|---|---|---|
| **survived** | 1.000000 | -0.339932 | -0.079229 | -0.035960 | 0.080874 | 0.257012 | -0.555222 | -0.204758 |
| **pclass** | -0.339932 | 1.000000 | -0.367110 | 0.083789 | 0.019245 | -0.548667 | 0.092448 | 0.137065 |
| **age** | -0.079229 | -0.367110 | 1.000000 | -0.301632 | -0.185857 | 0.096148 | 0.278219 | 0.196753 |
| **sibsp** | -0.035960 | 0.083789 | -0.301632 | 1.000000 | 0.414985 | 0.159654 | -0.253892 | -0.583247 |
| **parch** | 0.080874 | 0.019245 | -0.185857 | 0.414985 | 1.000000 | 0.216221 | -0.350200 | -0.582176 |
| **fare** | 0.257012 | -0.548667 | 0.096148 | 0.159654 | 0.216221 | 1.000000 | -0.181997 | -0.271540 |
| **adult_male** | -0.555222 | 0.092448 | 0.278219 | -0.253892 | -0.350200 | -0.181997 | 1.000000 | 0.403131 |
| **alone** | -0.204758 | 0.137065 | 0.196753 | -0.583247 | -0.582176 | -0.271540 | 0.403131 | 1.000000 |

# Examples



MONASH University

# [1] Misspelling and Inconsistency

| ..... | **Suburbs** |
|---|---|
| ..... | burwood. |
| ..... | springvale |
| .... | Burwood |
| .... | Springvae |
| .... | East Melbourne |
| ..... | E. Melbourne |
| ..... | ..... |

- *What are the problems?*
- *How can you detect these data problems?*
- *How can you resolve them?*

# [1] Misspelling and Inconsistency

- Inconsistency
  - common cases:
    - upper vs. lower case
    - inconsistency in domain value representation, e.g., 0 vs. No, 1 vs. Yes
  - detecting and fixing
    - investigate unique domain values (`unique()`)
    - make the representation consistent, e.g., replace
- Misspelling
  - investigate unique domain values (`unique()`)
  - string matching
    - calculate domain value frequencies (`value_counts()`)
    - for all values, find matches for the infrequent values
    - replace infrequent values with the best match (if it exists) from the more frequent values.

# [2] Irregularities

| ..... | **Entry Time** |
|---|---|
| ..... | 12/13/2010 |
| ..... | 1/1/2014 |
| .... | 45/2/2010 |
| .... | 20/3/2011 |
| .... | 2/14/2014 |
| ..... | 25/12/2014 |
| ..... | ..... |

- *What are the problems?*
- *How can you detect these data problems?*
- *How can you resolve them?*

# [2] Irregularities

- Common cases:
  - invalid dates
  - domain dependent value, value not valid for a specific domain, e.g., negative value for number of passengers
- Detecting
  - investigate unique domain values (`unique()`)
  - investigate value ranges for the column
  - type casting, e.g., parse date string to datetime object, catch exceptions when it is not a valid date format
- Fixing
  - refer to documentation if it exists, to see whether these values have special meaning
  - replace
  - remove

# [3] Integrity Constraint Violation

| …. | year_built | time_settled |
|---|---|---|
| ….. | 2010 | 12/13/2010 |
| ….. | 2010 | 1/1/2014 |
| …. | 2010 | 45/2/2002 |
| …. | 2010 | 20/3/2011 |
| …. | 2021 | 2/14/2014 |
| ….. | ….. | ….. |

- *What are the problems?*
- *How can you detect these data problems?*
- *How can you resolve them?*

# [3] Integrity Constraint Violation

- Common case:
  - highly dependent on context, e.g.,
    - sold date vs. advertised date,
    - one field is the sum of the other two,
    - land size must be larger than building size, etc.
- Detecting
  - highly dependent on the domain and problems
- Fixing
  - swap
  - remove, etc.

# [4] Duplicates

| Index | Name | Gender | D.O.B | Mobile | Address | ..... |
|---|---|---|---|---|---|---|
| 10 | John | N/A | 7/9/1985 | 0412685210 | N/A | ..... |
| 145 | John Walter | M | 7/9/1985 | 0412685210 | 2 Yale st., burwood | ..... |
| 200 | John Walter | Male | 7/9/1985 | 0412685210 | 2 Yale street, burwood | .... |
| 268 | Walter, John | Male | 7/9/1985 | 0412685210 | 2 Yale street, burwood | .... |
| 450 | John Walter | - | 1985 | - | 2 Yale street, burwood | ..... |
| ..... | ..... | | ..... | | | ..... |

- *What are the duplications in the example and how to detect and resolve these data duplications?*

# [4] Duplicates

- Common cases:
    - complete duplication
    - duplicate due to field missing
        - different record have different piece of info
- Detecting
    - identifying keys to check duplicates
        - fixing other quality issues
        - try different keys
- Fixing
    - combine information/merge
    - remove duplicates

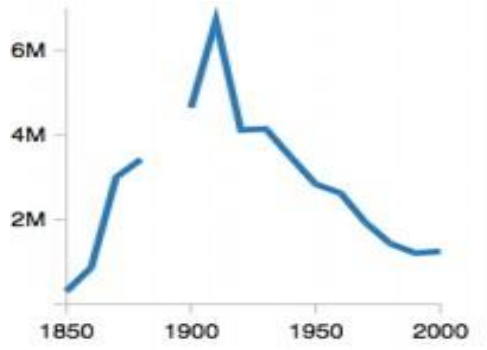
# [5] Missing Values

| Adv. Price | Bedrooms | Land (sqm) | Condition | Suburb | Source |
|---|---|---|---|---|---|
| 800000 | 2 | - | Old | CBD | realestate |
| 80 | 2 | 250 | * | CBD | domain |
| 1100000 | - | - | Fair | Burwood | realestate |
| * | 3 | 800 | * | Dandenong | domain |
| Contact Agent | - | 500 | Fair | Burwood | realestate |
| ….. | | ….. | | ….. | ….. |

- *How to detect these missing value records and how to fix them?*

# [5] Missing Values

- Detecting
  - investigate unique domain values (`unique()`)
  - investigate value range, cautious about extremely small and large values
  - domain analysis
- Fixing
  - imputation
    - mean and mode
    - regression (find variables that are closely related (e.g., `df.corr()`)
    - dummy value
  - removal
  - all depends on the situation and needs justification

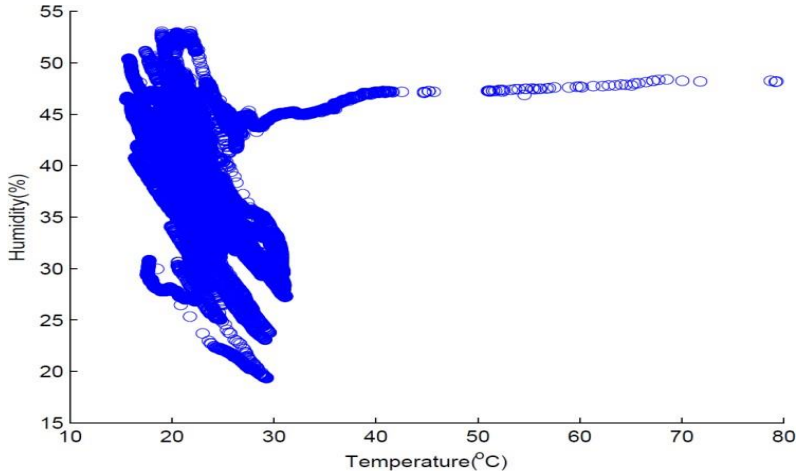


# [6] Outliers

| Adv. Price | Bedrooms | Land (sqm) | Condition | Suburb | Source |
|---|---|---|---|---|---|
| 800000 | 2 | - | Old | CBD | realestate |
| 80 | 2 | 250 | Fair | CBD | domain |
| 1100000 | - | 550 | Fair | Burwood | realestate |
| 500000 | 8 | 800 | New | Dandenong | domain |
| 500000 | - | 500 | Fair | Burwood | realestate |
| ….. | | ….. | | ….. | ….. |

- *How to detect these outliers? Can we directly remove outliers once found from tools, e.g., boxplot?*

# [6] Outliers




- Common cases: numerical field
- Challenge:
  - not easy to find
- Detecting
  - range of values `df.describe()`
  - Graphical tools, e.g., boxplot (default using a IQR rule)
  - 3σ edit rule
  - Good to do some comparison between results found by different identifiers
- Fixing
  - Similar to handling missing values

# Recap: Learning Outcomes

Week 4

**By the end of this week you should be able to:**

- Explain open data and linked open data
- Explain how to access to new data sources through APIs
- Identify how different APIs work
- Inspect data quality problems in datasets and recommend solutions to fix them
- *Use data wrangling operations in Python (in Tutorials)*