Data Tidying and Cleaning

Preparing data for knowledge extraction

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#DataScience

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Data Tidying

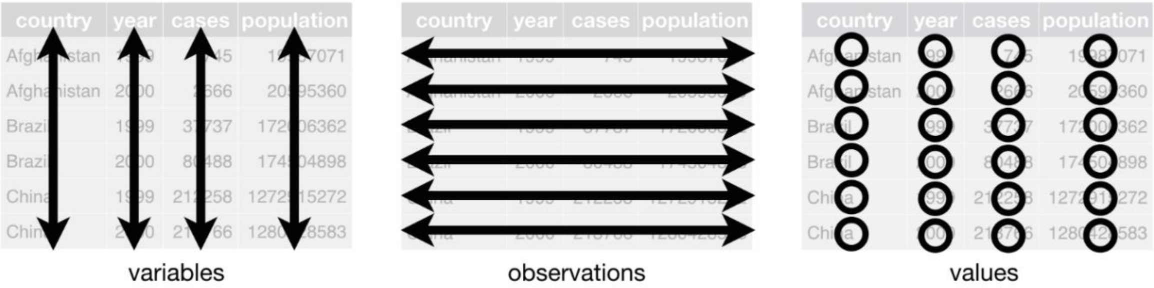
Arranging data
in a meaningful manner

Tidy Data

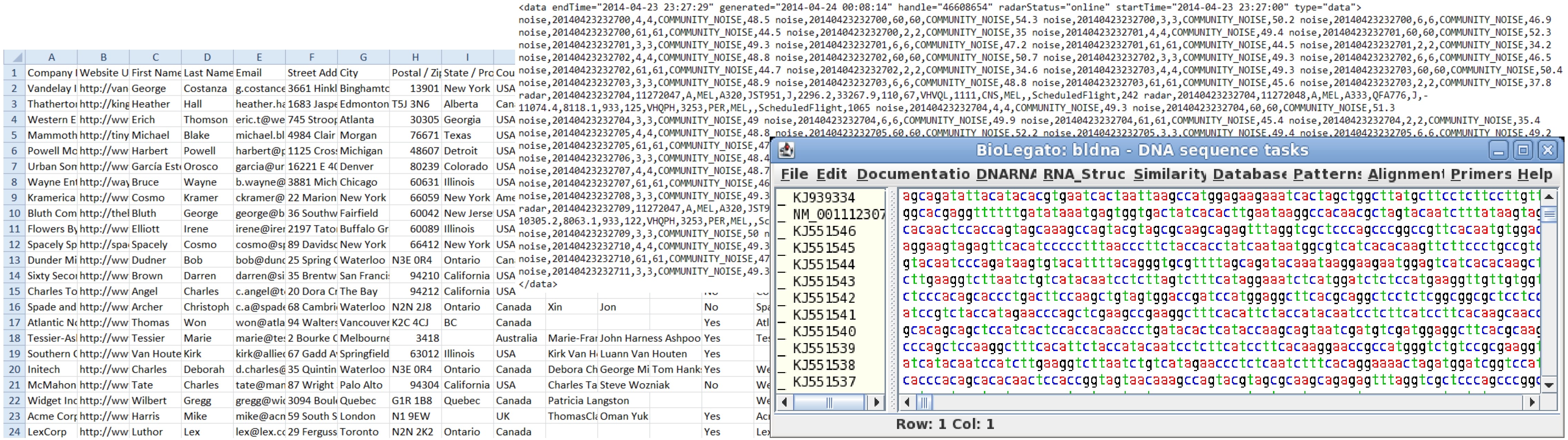
- Most important rules when creating (or using) datasets
  - Columns – attributes (features, variables)
  - Rows – observations
  - Cells – values (one observation of one feature)
  - All other data is called **messy data**
- Empirical rule for testing whether a dataset is tidy
  - Adding one more observation should create one new row
    - No new columns
    - No multiple rows
    - No partial rows, no changes to other rows
- pandas allows us to read, tidy up and transform datasets
  - Data modelling requires a tidy and clean dataset in order to work well (garbage in – garbage out)

Messy Data

- What we want



- What we get instead



Tidy and Messy Data

- A very good paper on tidy data
- Example: several datasets
  - Same information, different ease of use

	country	year	cases	population
1	Afghanistan	1999	745	19987071
2	Afghanistan	2000	2666	20595360
3	Brazil	1999	37737	172006362
4	Brazil	2000	80488	174504898
5	China	1999	212258	1272915272
6	China	2000	213766	1280428583

Tidy dataset

	country	year	rate
1	Afghanistan	1999	745/19987071
2	Afghanistan	2000	2666/20595360
3	Brazil	1999	37737/172006362
4	Brazil	2000	80488/174504898
5	China	1999	212258/1272915272
6	China	2000	213766/1280428583

	country	year	key	value
1	Afghanistan	1999	cases	745
2	Afghanistan	1999	population	19987071
3	Afghanistan	2000	cases	2666
4	Afghanistan	2000	population	20595360
5	Brazil	1999	cases	37737
6	Brazil	1999	population	172006362
7	Brazil	2000	cases	80488
8	Brazil	2000	population	174504898
9	China	1999	cases	212258
10	China	1999	population	1272915272
11	China	2000	cases	213766
12	China	2000	population	1280428583

Messy to Tidy Data

1. The table header contains values
   - Identify the variables and distribute (unpivot) the values
- Read the `pew.csv` dataset
  - Distribution of income by religion
- Show the first 5 values (use the `head()` function)
  - Also see the number of variables and observations (`shape`)
  - This will also ensure that you've read the dataset correctly
  - Variables: religion, income, frequency
- Transform the dataset to make it tidy (docs)

```
pew = pd.read_csv("pew.csv")
pew_tidy = pew.melt(
    id_vars = ["religion"], # Identifier variables (all others are "unpivoted")
    var_name = "income", # Variable
    value_name = "frequency" # Value
)
```

Messy to Tidy Data (2)

2. Multiple variables stored in one column
   - Identify and split the variables into separate columns

- Read the `tb.csv` dataset
  - Tuberculosis cases
  - m**04**, m**514**, m**1524**, etc. contain two variables (gender and age)
    - male, 0-4 years old; male, 5-14 years old, etc.
    - There's also a problem with missing values (`NaN`)
- Tidying process
  - First, melt all columns (they are values and should not be)
  - Next, split the column names and extract the gender and age information
  - Add the new info to the dataset
  - Remove all missing values

Messy to Tidy Data (3)

```python
def process_age_group(age_group):
    ages = {"04": "0-4", "65": "65+", "u": "unknown"}
    if age_group in ages:
        return ages[age_group]
    else:
        # Put a dash before the last two digits
        return f"{age_group[:-2]}-{age_group[-2:]}"

tb = tb.melt(
    id_vars = ["iso2", "year"], var_name = "sex_and_age", value_name = "cases")

tb["sex"] = tb.sex_and_age.str.get(0)
tb["age_group"] = tb.sex_and_age.str.slice(1)
tb = tb.drop(columns = "sex_and_age")

tb.age_group = tb.age_group.apply(process_age_group)

# Tidy up the column and row order
tb = tb[["iso2", "year", "sex", "age_group", "cases"]]
tb = tb.sort_values(["iso2", "year"])
```

Messy to Tidy Data (4)

3. Variables are stored in both rows and columns
   - Identify and split the variables
- Read the `weather.csv` dataset
  - Daily weather records in Mexico in 2010
  - `d1`, `d2`, etc. are the days of a month;
    `tmin` and `tmax` should be columns
    - Make a new column with the date: `[date, tmin, tmax]`
- Tidying process
  - Melt all days
  - Create days based on date, month and year
  - Pivot the tmin and tmax columns

Messy to Tidy Data (5)

```
weather_data = weather_data.melt(
    id_vars = ["id", "year", "month", "element"], var_name = "day")
weather_data.day = weather_data.day.str.slice(1).astype(int)

# Remove missing / invalid days (e.g., 31st April) and dates with no records
weather_data = weather_data.dropna()
weather_data["date"] = pd.to_datetime(weather_data[["year", "month", "day"]])
weather_data = weather_data.drop(columns = ["year", "month", "day"])

# Pivot the elements back to their own columns
weather_data = weather_data.pivot_table(
    index = ["id", "date"], columns = "element", values = "value")

# Pivoting returns a multi-indexed element, go back to a flat DataFrame
weather_data = weather_data.reset_index()
weather_data.columns.name = ""
weather_data = weather_data[["id", "date", "tmin", "tmax"]]
```

Messy to Tidy Data (6)

4. One type in multiple tables
   - Merge the tables into one
     - Read all tables, add the new columns
     - Often the filename should be in its own column (if it's important)
     - Melt and tidy if necessary
5. Multiple types in one table
   - Split into more tables
     - If necessary, introduce relations (similar to a relational database)

- Each table should be responsible for one type of measurement
- * Read the `billboard.csv` dataset and apply those transformations

Operations on Datasets

Basic tools to get started working with messy data

Subsetting Rows

- Selecting only some rows (aka selection)
- First / last n records (observations)

```
weather_data.head(10)
weather_data.tail() # 5 by default
```

- Random n records

```
weather_data.sample(n = 10)
weather_data.sample() # 1 random record by default
```

- Smallest / largest n records in each column

```
weather_data.nsmallest(3, "tmax")
weather_data.nlargest(3, "tmax")
```

- Subsetting by a Boolean expression (predicate)
  - Returns only rows where the expression returns `True`

```
weather_data[weather_data.tmax > 30]
```

Subsetting Columns

- Selecting only some columns (aka projection)
- Single column (returns a `Series` object)

```
weather_data["tmax"]
weather_data.tmax # Possible in most cases
```

- More than one column (returns a `DataFrame` object)

```
weather_data[["tmin", "tmax"]]
```

- Combining filters

```
weather_data[weather_data.date > "2010-08-01"][["date", "tmax"]]
weather_data.loc[weather_data.date > "2010-08-01", ["date", "tmax"]]
```

- A note on Boolean expressions
  - and, or, not are &, |, ~
  - **Always** put parentheses around the individual expressions

```
weather_data[
    (weather_data.date > "2010-08-01") & (weather_data.date < "2010-09-01")]
```

Summary Statistics and Grouping

- These methods work by columns
  - If multiple columns are passed, they are applied to each column individually

```
print("Count:", weather_data.tmin.count()) # number of non-null values
print("Min:", weather_data.tmin.min())
print("Max:", weather_data.tmin.max())
print("Mean:", weather_data.tmin.mean())
print("Median:", weather_data.tmin.median())
print("Standard deviation:", weather_data.tmin.std())
```

- Grouping
  - Splits the data into several groups based on the values of a column
  - We have to apply a method after grouping
    - Or iterate over the groups (using a `for`-loop)
  - Example: Average number of people for each income group

```
pew_tidy.groupby("income").mean()
```

Cleaning Data

You've got the data... now what?

Cleaning Data

- No common way of doing this
- We need to rely on intuition and some common patterns
  - Tidy up the dataset
    - You must know the dataset documentation first
  - Treat `nulls` / `NaNs`: either remove them or replace them
    - Replacing values might be **dangerous**
    - If done properly, it will affect the data in a positive way
  - Identify and fix errors (also **dangerous**)
  - Melt and pivot datasets
  - Merge (join) and separate datasets
  - Subset variables and / or observations
  - Summarize and group variables
  - Pandas Cheat Sheet

Example: Weather Data

- Since there's no common way of cleaning, we'll explore and clean a dataset, showing steps and examples as we go
- Dataset (weather data, courtesy of `synesthesiam@github`)
- Read the dataset (you don't need to download it)
  - See how many variables and observations are there
  - Display the first and last few rows to get a sense of the data
  - Check the data types (to see if something's wrong with the reading)
    - E.g., numbers recognized as strings
  - See a subset of the columns
  - Summarize (describe) the dataset

Example: Weather Data (2)

- The column names don't look good
  - Make them "pythonic" (lowercase_with_underscores)
    - This will make selecting them easier (`weather.mean_temp`)

```
weather.columns = ["date", "max_temp", "mean_temp", "min_temp", "max_dew",
    "mean_dew", "min_dew", "max_humidity", "mean_humidity",
    "min_humidity", "max_pressure", "mean_pressure",
    "min_pressure", "max_visibility", "mean_visibility",
    "min_visibility", "max_wind", "mean_wind", "max_gusts",
    "precipitation", "cloud_cover", "events", "wind_dir"]
```

- What are the ranges of data?
  - E. g. temperature, pressure, humidity
  - Use the `min()` and `max()` methods
- * Try to explore the data a bit
  - Plot a few histograms and / or boxplots to see the distributions

Example: Weather Data (3)

- Convert the dates to a `datetime` object
  - To make performing time-dependent analysis easier

```
weather.date = pd.to_datetime(weather.date)
```

  - If needed, use `apply()` to perform a function on every row

```
from datetime import datetime
def string_to_date(date_string):
    return datetime.strptime(date_string, "%Y-%m-%d")

weather.date = weather.date.apply(string_to_date)
```

    - It's even better to use dates as indices (when we need to subset date ranges or perform other time-dependent tasks)

```
weather = weather.set_index("date") # or use inplace = True

print(weather.loc[pd.to_datetime("2012-08-19")])
# or weather.loc["2012-08-19"], or any other formatting
```

  - Also see why precipitation is not a float and edit it

Example: Weather Data (4)

- Remove or replace missing values
  - In this case, replacing is better because removing takes away an entire row

```
weather_with_events = weather.dropna(subset = ["events"])
weather.events = weather.events.fillna("") # Better
```

- Try to see how variables interact – group the data
  - E.g., by cloud cover and events
  - Print the number of days when each combination of `{cover, events}` occurred

```
for (cover, events), group_data in weather.groupby(["cloud_cover", "events"]):
    print(f"Cover: {cover}, Events: {events}, Count: {len(group_data)}")
# Or: weather.groupby(["cloud_cover", "events"]).size()
```

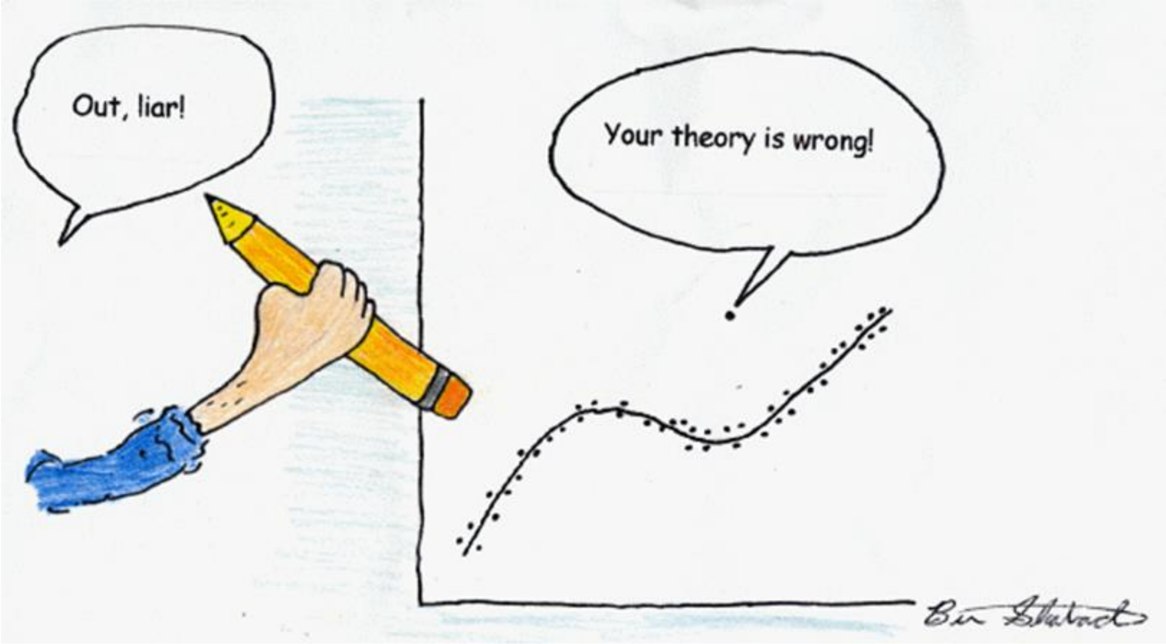
- Plot data
  - Next time

Example: Weather Data (5)

- If needed, perform transformations
  - Math operations: log, square root, addition, multiplication, etc.
    - Be careful as you'll get results in different dimensions
  - Normalizing scores (such as using Z-scores) is recommended in most cases
    - It's much better for ML algorithms to have data of similar scales
    - You can do that manually or use a library (such as sklearn.preprocessing)
  - By convention, calculated columns are added to the dataset
- **Describe all operations as you're doing them**
  - Describe what you're doing and why
    - Useful to check your work later (or allow others to do that)
  - If needed, save the resulting dataset into a file
    - Supply your data transformation log with it
    - Provide a dataset description

Outliers and Errors

- Outliers – values which are far from their expected range
  - Or having a very low probability of happening (assuming a model)
- Many possible cases
  - Wrong data entry (e.g. an adult weighing 5kg might be 50kg or something else)
  - Wrong assumptions (the data is correct, our view isn't)
- What to do?
  - Inspect the data point
  - Try to figure out what happened
    - If needed, remove the row or try to replace the value
  - Try a transformation
  - If possible, perform analysis with and without the outlier(s) and compare your results



Transformations on Features

- The quality of our results depends strongly on the features we use
  - "Garbage in – garbage out"
- Dimensionality reduction
  - Reducing the number of variables (features)
  - We can do this manually or use algorithms
  - Feature selection
    - Selecting only columns that are useful
  - Feature extraction
    - Transforming non-structured to structured data
      - Examples: images, audio, text
    - Getting meaningful features
- Feature engineering
  - Using our knowledge of the data to create meaningful features
    - Involves a lot of brainstorming and testing

Next Steps (Optional)

- Have a look at `scikit-learn`'s "Dataset Transformations" module
  - It describes the most common operations
    - Data cleaning
    - Dimensionality reduction
    - Feature extraction
- There are many algorithms based on
  - Data types (e.g., text or numerical data, labelled vs. not labelled)
  - Model types (how we want to present our data, e.g., linear model)
  - Algorithm types (e.g., finding similar news articles, recommending movies to users, classifying, etc.)
- No "hard and fast rule", use your intuition
  - Knowing more tools / models / algorithms -> better performance

Summary

- Messy and tidy data
  - Tidying up messy data
- Operations on datasets
- Cleaning data
  - Validation
  - Transformation
  - Error correction
  - Features
- Data tidying and cleaning as a process

Questions?