Material Summary: Data Tidying and Cleaning

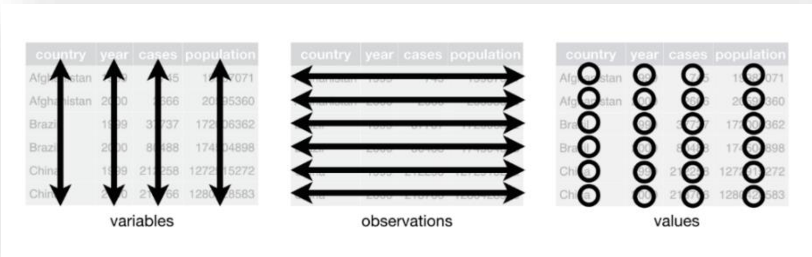
1. Data Tidying

1.1 Tidy Data

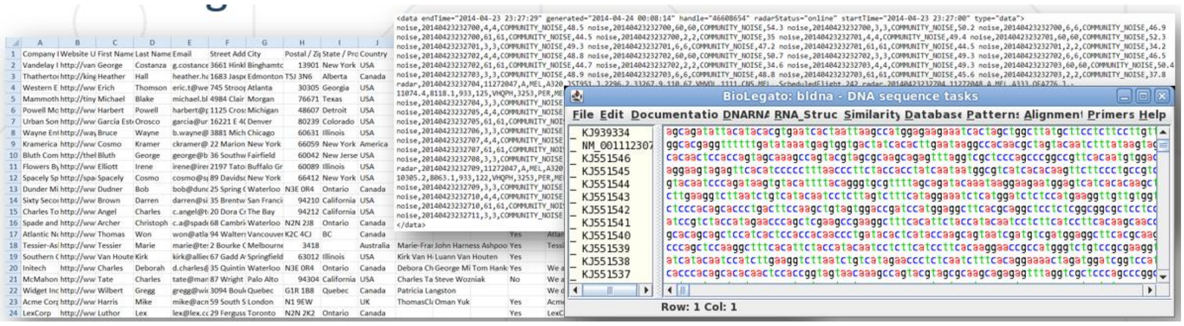
- Most important rules when creating (or using) datasets
    - Columns – attributes (features, variables)
    - Rows – observations
    - Cells – values (one observation of one feature)
    - All other data is called **messy data**
- Empirical rule for testing whether a dataset is tidy
    - Adding one 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)

1.2 Messy Data

- What we want



- What we get instead



1.3 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
```

1.4 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
)
```

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

```
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"])
```

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

```
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"]]
```

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

2. Operations on Datasets

2.1 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]
```

- 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")]
```

- 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()
```

3. Cleaning Data

3.1 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*

3.2 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
- 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
- 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
- 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

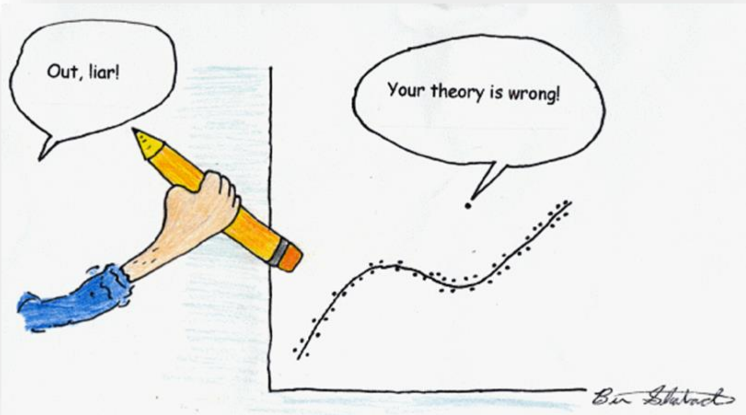
```
for (cover, events), group_data in weather.groupby(["cloud_cover", "events"]):
    print(f"Cover: {cover}, Events: {events}, Count: {len(group_data)}")
# Or: weather.groupby(["cloud_cover", "events"]).size()
```

- Plot data
    - Next time
- 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

3.3 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



3.4 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

3.5 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

SoftUni

Follow us: