Data Tidying and Cleaning

Preparing data
for knowledge extraction

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Data Tidying

Arranging data
in a meaningful manner

Tidy Data

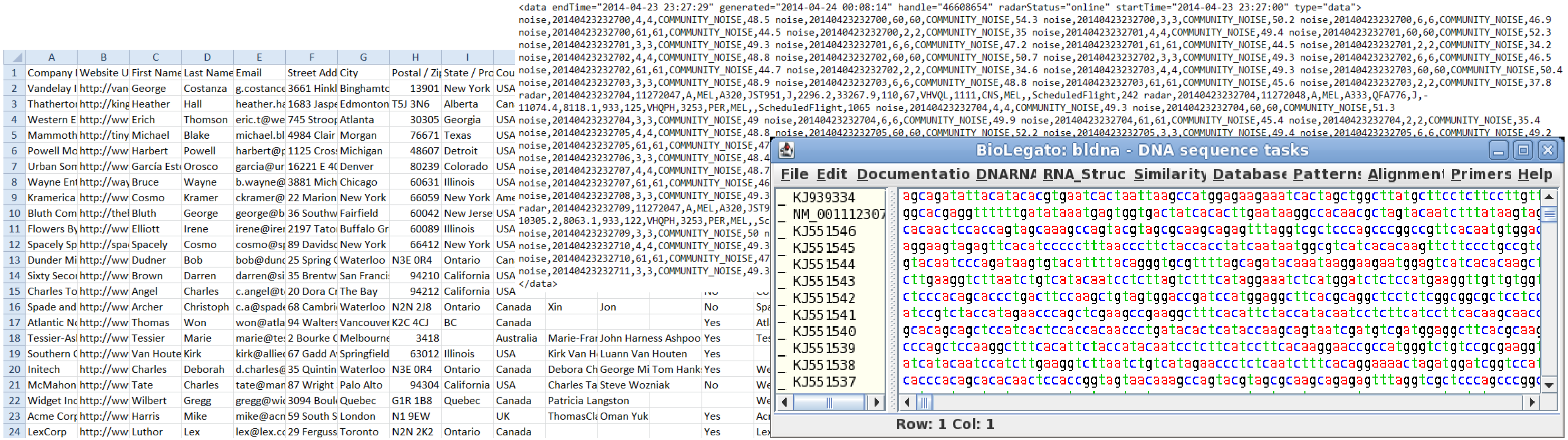
- Most important rules when creating (or using) datasets
  - Columns – attributes (features, variables)
  - Rows – observations
  - Cells – values (one observation of one feature)
  - All other data is called **messy data**
- Empirical rule for testing whether a dataset is tidy
  - Adding one more observation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

variables observations values

- 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	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

	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

Messy to Tidy Data

1. The table header contains values
   - Identify the variables and distribute (unpivot) the values
- Read the `data_tidying/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("data_tidying/pew.csv")
pew_tidy = pd.melt(pew,
    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 `data_tidying/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)

```
tb = pd.read_csv("data_tidying/tb.csv")
# Melt the values
tb = pd.melt(tb, id_vars = ["iso2","year"],
    value_name = "cases", var_name = "sex_and_age")

# Separate the columns and merge back
parts = tb["sex_and_age"].str.extract("(\D)(\d+)(\d{2})", expand = True)
parts.columns = ["sex", "age_lower", "age_upper"]
parts["age"] = parts["age_lower"] + "-" + parts["age_upper"]
print(parts.dropna().head())
tb = pd.concat([tb, parts], axis = 1)

# Remove missing values and sort them
tb = tb.drop(["sex_and_age", "age_lower", "age_upper"], axis = 1)
tb = tb.dropna()
tb = tb.sort_values(by = ["iso2", "year", "sex", "age", "cases"])

# The index is now wrong, reindex to make it better
tb = tb.reset_index()
del tb["index"]
```

Messy to Tidy Data (4)

3. Variables are stored in both rows and columns
   - Identify and split the variables
- Read the `data_tidying/weather.csv` dataset
  - Daily weather records in Mexico in 2010
  - d1, d2, etc. are the days of a month; also 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)

```
temp_data = pd.read_csv("data_tidying/weather.csv")

temp_data = pd.melt(temp_data,
    id_vars = ["id", "year", "month", "element"],
    var_name = "day")
temp_data["day"] = temp_data["day"].str.extract("(\d+)",
    expand = True).astype(np.int64)

# Remove missing days (e. g. 31st April) and dates with no records
temp_data = temp_data.dropna()
temp_data["date"] = pd.to_datetime(temp_data[["year", "month", "day"]])
temp_data = temp_data.drop(["year", "month", "day"], axis = 1)

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

# Pivoting returns a multi-indexed element, go back to a flat DataFrame
temp_data.reset_index(inplace = True)
temp_data.columns.name = ""
```

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

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)

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

- Random `n` records

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

- Smallest / largest `n` records in a given column

```
temp_data.nsmallest(3, "column_name")
temp_data.nlargest(3, "column_name")
```

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

```
temp_data[temp_data.tmax > 30]
```

Subsetting Columns

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

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

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

```
temp_data[["tmin", "tmax"]]
```

- Combining filters

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

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

```
temp_data[(temp_data.date > "2010-08-01") & (temp_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:", temp_data.tmin.count()) # number of non-null values
print("Min:", temp_data.tmin.min())
print("Max:", temp_data.tmin.max())
print("Mean:", temp_data.tmin.mean())
print("Median:", temp_data.tmin.median())
print("Standard deviation:", temp_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
  - 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 have to rely on intuition and some common patterns
  - Tidy up the dataset
    - You have to 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 `apawlik@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_visibilty", "mean_visibility",
    "min_visibility", "max_wind", "mean_wind", "min_wind",
    "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
  - 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.index = weather.date
weather = weather.drop("date", axis = 1) # We don't need it twice,
# axis = 1 tells pandas to search for a column (axis = 0 -> row)

print(weather.loc[datetime(2012, 8, 19)]) # or weather.loc["2012-08-19"]
```

  - 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 each combination of `{cover, events}` occurred

```
for (cover, events), group_data in weather.groupby(["cloud_cover", "events"]):
    print ("Cover: {0}, Events: {1}, Count: {2}"
        .format(cover, events, len(group_data)))
# Or: weather.groupby(["cloud_cover", "events"]).count()
```

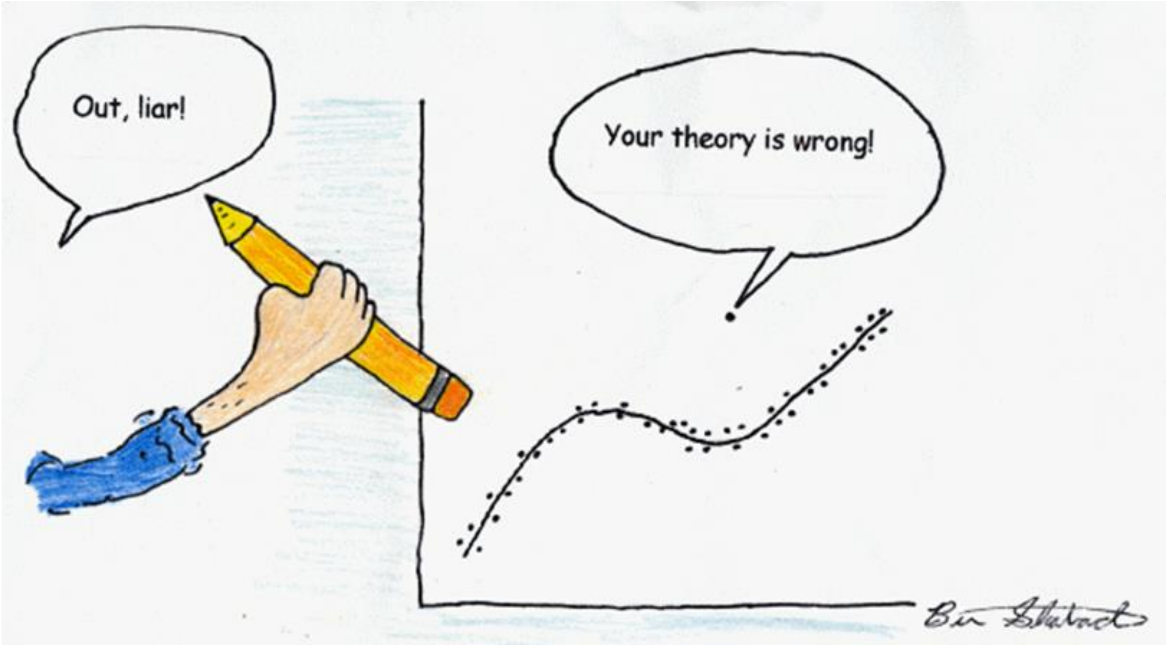
- Plot data – next time

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'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?