

Data Tidying and Cleaning

Preparing data
for knowledge extraction

Yordan Darakchiev

Technical Trainer

iordan93@gmail.com



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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)

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 `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
 - `m04`, `m514`, `m1524`, 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"]
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 [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", "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()
```

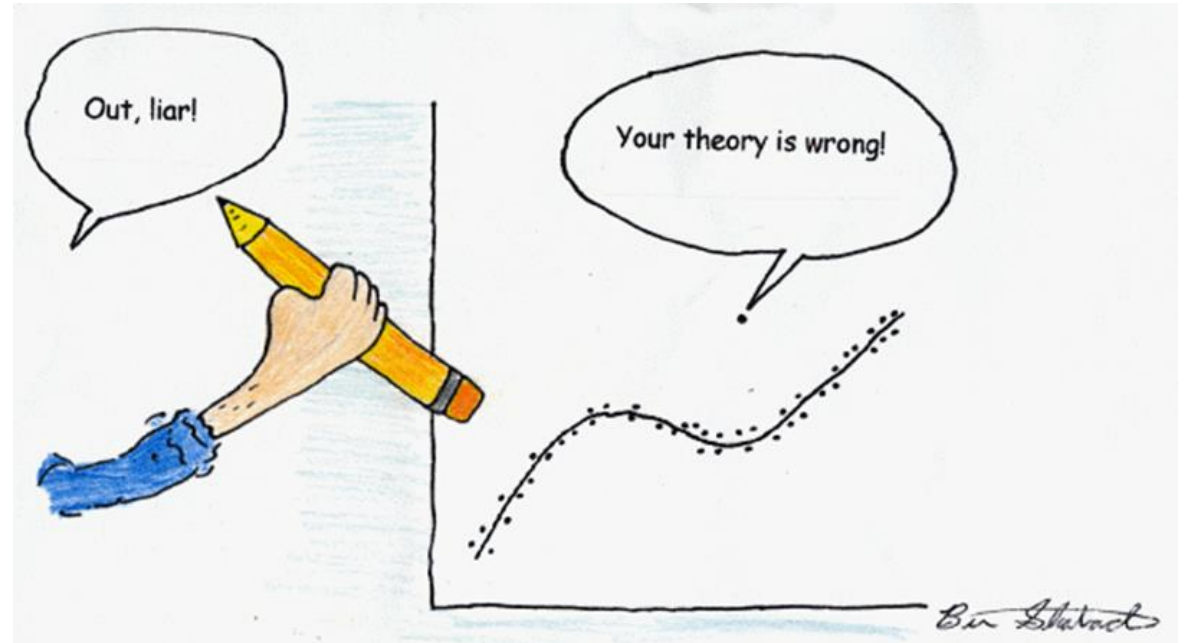
- Plot data – next time

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](https://scikit-learn.org/stable/modules/preprocessing.html))
 - 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

The image features a white background with two blue decorative bars. The top bar is a solid blue band at the very top. Below it is a thinner, darker blue band that curves slightly downwards from left to right. The bottom of the image is framed by a similar pattern of a thin dark blue band above a solid blue band, both curving upwards from left to right.

Questions?