Data Wrangling with Python - Day 4

One should look for what is and not what he thinks should be. (Albert Einstein)

Warm up

Before we start, check out this article about some tricks using Pandas:
https://towardsdatascience.com/10-python-pandas-tricks-that-make-your-work-more-efficient-2e8e483808ba
In the chat, answer the following questions:

- Did you find any of the tips useful?
- Can you think of any tips or use cases for Pandas that you would like to share?

welcome back!

- In the last module you learned how to:
  - Work with Pandas series and dataframes
  - Read in a csv
- We will now load the same dataset from our data folder, clean it and apply functions to it

Module completion checklist

Objective	Complete
Load data into Python and inspect	
Summarize data using pandas	
Reshape data using pandas	

Import Pandas and os

- Let's import the `pandas` and `os` library
- Note: it is not required that you also import `numpy` in order to use `pandas`

```
import pandas as pd
import numpy as np
import os
```

Directory settings

- In order to maximize the efficiency of your workflow, you should encode your directory structure into `variables`
- Let the `main_dir` be the variable corresponding to your `skill-soft` folder

```
# Set `main_dir` to the location of your `skill-soft` folder (for Linux).
main_dir = "/home/[username]/Desktop/skill-soft"
```

```
# Set `main_dir` to the location of your `skill-soft` folder (for Mac).
main_dir = '/Users/[username]/Desktop/skill-soft'
```

```
# Set `main_dir` to the location of your `skill-soft` folder (for Windows).
main_dir = "C:\\Users\\[username]\\Desktop\\skill-soft"
```

```
# Make `data_dir` from the `main_dir` and
# remainder of the path to data directory.
data_dir = main_dir + "/data"
```

Setting working directory

- Set working directory to `data_dir`

```
# Set working directory.
os.chdir(data_dir)
```

```
# Check working directory.
print(os.getcwd())
```

```
/home/[user-name]/Desktop/skill-soft/data
```

Read data from csv file

- We are now going to use the function `read_csv` to read in our `household_poverty` dataset
- Let's load the entire dataset

```
household_poverty = pd.read_csv('household_poverty.csv')
print(household_poverty.head())
```

```
   male       hh_ID  rooms  ...  water_inside  years_of_schooling  Target
0     1  21eb7fcc1      3  ...             1                  10       4
1     1  0e5d7a658      4  ...             1                  12       4
2     0  2c7317ea8      8  ...             1                  11       4
3     1  2b58d945f      5  ...             1                   9       4
4     0  2b58d945f      5  ...             1                  11       4

[5 rows x 14 columns]
```

Inspect data

- What have we just created? **Let's inspect**

```
print(type(household_poverty))  #<- a pandas dataframe!
```

```
<class 'pandas.core.frame.DataFrame'>
```

```
print(len(household_poverty))   #<- returns the number of rows
```

```
1000
```

```
# You can also save the shape of the dataframe into 2 variables
# (since the returned is a tuple with 2 values).

nrows, ncols = household_poverty.shape
print(nrows)
```

```
1000
```

```
print(ncols)
```

```
14
```

Previewing data - using head method

- We've already used `.head()` command that shows the first few rows
- Let's inspect this data

```
print(household_poverty.head())  #<- pulls the first 5 rows (the default is 5)
```

```
   male       hh_ID  rooms  ...  water_inside  years_of_schooling  Target
0     1  21eb7fcc1      3  ...             1                  10       4
1     1  0e5d7a658      4  ...             1                  12       4
2     0  2c7317ea8      8  ...             1                  11       4
3     1  2b58d945f      5  ...             1                   9       4
4     0  2b58d945f      5  ...             1                  11       4

[5 rows x 14 columns]
```

- This is a great way to understand the data that we have without having to call the entire dataset

Previewing data - using head method

- We can specify the number of rows we want to see:

```
print(household_poverty.head(3)) #<- pulls the first 3 rows
```

```
   male       hh_ID  rooms  ...  water_inside  years_of_schooling  Target
0     1  21eb7fcc1      3  ...             1                  10       4
1     1  0e5d7a658      4  ...             1                  12       4
2     0  2c7317ea8      8  ...             1                  11       4

[3 rows x 14 columns]
```

Previewing data - using sample method

- We can view some random rows in the dataframe by using the `.sample()` method

```
print(household_poverty.sample(n = 3))       #<- 3 random rows
```

```
     male       hh_ID  rooms  ...  water_inside  years_of_schooling  Target
472     1   8ac40302b      4  ...             1                   9       4
76      0   b2ceb3e5c      6  ...             1                  17       4
521     0   c865ef208      5  ...             1                   1       2

[3 rows x 14 columns]
```

Previewing data - using sample method

- We can specify to see a percentage rather than an actual exact number

```
print(household_poverty.sample(frac = .02)) #<- a random 2% of the rows
```

```
     male       hh_ID  rooms  ...  water_inside  years_of_schooling  Target
359     1   8e5f8c731      6  ...             1                   9       4
693     0   cd0157ab9      5  ...             1                   2       4
509     1   c64f7aa91      4  ...             1                   6       4
850     0   a6fa5d237      4  ...             1                   5       4
710     0   b03e62236      4  ...             1                  11       2
813     1   7b34d920f      5  ...             1                   8       1
559     0   e3a9c8aba      7  ...             1                  16       4
174     0   4b301d9b2      5  ...             1                   7       3
637     0   fd10905bc      4  ...             1                   5       2
111     0   c179fa326      5  ...             1                   7       4
918     1   f1a9eef39      4  ...             1                  11       2
72      1   a0a822586      6  ...             1                  15       4
127     0   52123171a      7  ...             1                  11       4
573     1   b8adfe034      4  ...             1                   8       4
30      1   f2fcf00fd      5  ...             1                   8       4
106     0   288b0f0fa      4  ...             1                  11       4
958     0   463d89601      5  ...             1                  14       4
658     1   f3f860f58      6  ...             1                   4       4
```

Reviewing household_poverty data

- We are now going to get to know our data better, using the following `pandas` techniques:
  - `.columns`
  - `.dtypes`
  - `.info()`
  - `.describe()`

```
print(household_poverty.columns)
```

```
Index(['male', 'hh_ID', 'rooms', 'males_tot',
'age', 'ppl_total', 'num_child',
       'bedrooms', 'dependency_rate',
'computer', 'disabled_ppl',
       'water_inside', 'years_of_schooling',
'Target'],
      dtype='object')
```

```
print(household_poverty.dtypes)
```

```
male                    int64
hh_ID                  object
rooms                   int64
males_tot               int64
age                     int64
ppl_total               int64
num_child               int64
bedrooms                int64
dependency_rate         int64
computer                int64
disabled_ppl            int64
water_inside            int64
years_of_schooling      int64
Target                  int64
dtype: object
```

Reviewing household_poverty data - info

```
print(household_poverty.info())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 14 columns):
 #   Column               Non-Null Count  Dtype
---  ------               --------------  -----
 0   male                 1000 non-null   int64
 1   hh_ID                1000 non-null   object
 2   rooms                1000 non-null   int64
 3   males_tot            1000 non-null   int64
 4   age                  1000 non-null   int64
 5   ppl_total            1000 non-null   int64
 6   num_child            1000 non-null   int64
 7   bedrooms             1000 non-null   int64
 8   dependency_rate      1000 non-null   int64
 9   computer             1000 non-null   int64
 10  disabled_ppl         1000 non-null   int64
 11  water_inside         1000 non-null   int64
 12  years_of_schooling   1000 non-null   int64
 13  Target               1000 non-null   int64
```

Reviewing household_poverty data - describe

```
print(household_poverty.describe())
```

```
                male         rooms  ...  years_of_schooling       Target
count  1000.000000  1000.000000  ...         1000.000000  1000.000000
mean      0.477000     5.244000  ...            8.055000     3.586000
std       0.499721     1.692728  ...            4.898568     0.833846
min       0.000000     1.000000  ...            0.000000     1.000000
25%       0.000000     4.000000  ...            5.000000     4.000000
50%       0.000000     5.000000  ...            8.000000     4.000000
75%       1.000000     6.000000  ...           11.000000     4.000000
max       1.000000    11.000000  ...           21.000000     4.000000

[8 rows x 13 columns]
```

Reviewing household_poverty data - index

- What is the index of this dataframe?

```
print(household_poverty.index)
```

```
RangeIndex(start=0, stop=1000, step=1)
```

- Remember, we can set the index as one of our columns
- What would make most sense with this dataset?

```
household_poverty = household_poverty.set_index('hh_ID')
print(household_poverty.index)
```

```
Index(['21eb7fcc1', '0e5d7a658', '2c7317ea8', '2b58d945f', '2b58d945f',
       '2b58d945f', '2b58d945f', 'd6dae86b7', 'd6dae86b7', 'd6dae86b7',
       ...
       'f54bc4b11', 'f54bc4b11', 'f54bc4b11', 'f54bc4b11', '34bab1f1f',
       '34bab1f1f', '34bab1f1f', '34bab1f1f', '52cf8fe9d'],
      dtype='object', name='hh_ID', length=1000)
```

- Now we can look up rows by the actual household IDs

Looking up by household ID

- Let's refresh looking up by index
- We can use `.loc` to look up by specific household ID

```
# Look up a specific row by index.
print(household_poverty.loc['21eb7fcc1'])
```

```
male                    1
rooms                   3
males_tot               1
age                    43
ppl_total               1
num_child               0
bedrooms                1
dependency_rate        30
computer                0
disabled_ppl            0
water_inside            1
years_of_schooling     10
Target                  4
Name: 21eb7fcc1, dtype: int64
```

- **When would something like this be useful in your data?**

Looking up by household ID

- We can use `.iloc` to look up by row number of the index

```
# Look up a specific row by index.
print(household_poverty.iloc[1])
```

```
male                    1
rooms                   4
males_tot               1
age                    67
ppl_total               1
num_child               0
bedrooms                1
dependency_rate        29
computer                0
disabled_ppl            0
water_inside            1
years_of_schooling     12
Target                  4
Name: 0e5d7a658, dtype: int64
```

Reset index

- And finally, we can reset our index back to the original index

```
household_poverty = household_poverty.reset_index()
```

- In the next part, you will load a dataset into your notebook and summarize data using pandas

Knowledge check 1

Exercise 1

Module completion checklist

Objective	Complete
Load data into Python and inspect	✔
Summarize data using pandas	
Reshape data using pandas	

Methods to summarize and group data in pandas

- What if we want more detailed summary metrics? Use `groupby()`!
- `groupby()` describes a process involving the following steps:
  - **splitting** the data into groups based on a specific criteria
  - **applying** a function to each group independently
- We'll be starting with the most straightforward part of `groupby()`, the split step

Splitting using groupby()

- A string passed to `groupby()` may refer to either a column or an index level
- We can either group by column or by index
- This fits into the **splitting** step, as we are splitting the data to be grouped by number of rooms
- We will group by the column `rooms` for now

```
grouped = household_poverty.groupby('rooms')
print(grouped.first())
```

```
            hh_ID  male  males_tot  ...  water_inside  years_of_schooling  Target
rooms                               ...
1       3e16fab89     1          2  ...             0                   6       4
2       d6dae86b7     0          1  ...             1                   0       4
3       21eb7fcc1     1          1  ...             1                  10       4
4       0e5d7a658     1          1  ...             1                  12       4
5       2b58d945f     1          2  ...             1                   9       4
6       65d20b573     0          2  ...             1                  14       4
7       bcc196e5a     0          1  ...             1                  13       4
8       2c7317ea8     0          0  ...             1                  11       4
9       6f1edad4e     1          3  ...             1                  13       4
10      bdd842cfd     1          2  ...             1                  11       4
11      b64f4194f     1          1  ...             1                   9       4

[11 rows x 13 columns]
```

Summarizing using groupby()

- All the summary functions can be applied to a group
- Here are the summary functions:

Function	Description
count	Number of non-null observations
sum	Number of non-null observations
max	Maximum of values
min	Minimum of values
mean	Mean of values
median	Arithmetic median of values
var	Variance of each object
std	Standard deviation of each object

Groupby() and summary functions

- We can now move to the second step of summarizing data, **applying** a function to the group
- Let's see the distribution of households by room

```
# We are counting the number of hh_IDs by number of rooms, and creating a dataframe.
hh_ID = grouped.count()[['hh_ID']]
print(hh_ID)
```

```
        hh_ID
rooms
1           8
2          19
3          90
4         227
5         291
6         156
7         112
8          59
9          14
10         17
11          7
```

```
# This syntax would do the same, but create a series.
print(grouped.count().hh_ID)
```

```
rooms
1           8
2          19
3          90
4         227
5         291
6         156
7         112
8          59
9          14
10         17
11          7
Name: hh_ID, dtype: int64
```

A little more about summarizing - sorting

- **Sorting**: ordering row(s) by value of column, either low to high (default) or high to low (`ascending = False`)

```
print(hh_ID.sort_values(by = ['hh_ID'], ascending = [False]))
```

```
        hh_ID
rooms
5         291
4         227
6         156
7         112
3          90
8          59
2          19
10         17
9          14
1           8
11          7
```

A little more about summarizing - filtering

- **Filtering**: using filter(s) to subset only certain aspects of your dataset

```
print(hh_ID.query('rooms < 5'))
```

```
        hh_ID
rooms
1           8
2          19
3          90
4         227
```

A little more about summarizing - new columns

- **Create new columns** by creating a series and adding it to a current `dataframe`

```
over100_hh = hh_ID['hh_ID'] > 100
# Add the new column.
hh_ID['over100_hh'] = over100_hh
print(hh_ID.head())
```

```
        hh_ID  over100_hh
rooms
1           8       False
2          19       False
3          90       False
4         227        True
5         291        True
```

Knowledge check 2

Exercise 2

Module completion checklist

Objective	Complete
Load data into Python and inspect	✔
Summarize data using pandas	✔
Reshape data using pandas	

Data wrangling and exploration

- Remember, a data scientist must be able to:
  - **Wrangle** the data (gather, clean, and sample data to get a suitable data set)
  - **Manage** the data for easy access by the organization
  - **Explore** the data to generate a hypothesis
- **The techniques we will learn in this course will help us achieve these goals!**

- **We will work with the entire Costa Rican dataset and see what we can discover. We will be:**
  - Cleaning the dataset
  - Wrangling the data for the purpose of visualizing the data and identifying patterns

Load the dataset

- Let's load the entire dataset
- For reshaping, we will be taking a specific subset
- We are now going to use the function `read_csv` to read in our `costa_rican_poverty` dataset

```
household_poverty = pd.read_csv("costa_rica_poverty.csv")
print(household_poverty.head())
```

```
  household_id         ind_id  rooms  ...  age  Target  monthly_rent
0     21eb7fcc1  ID_279628684      3  ...   43       4      190000.0
1     0e5d7a658  ID_f29eb3ddd      4  ...   67       4      135000.0
2     2c7317ea8  ID_68de51c94      8  ...   92       4            NaN
3     2b58d945f  ID_d671db89c      5  ...   17       4      180000.0
4     2b58d945f  ID_d56d6f5f5      5  ...   37       4      180000.0

[5 rows x 84 columns]
```

- The entire dataset consists of `9557` observations and `84` variables

Subsetting data

- We will explore a subset of this dataset, which includes the following variables:
  - **ppl_total**
  - **dependency_rate**
  - **num_adults**
  - **monthly rent**
  - **rooms**
  - **age**
  - *Target*
- We are choosing these variables because they illustrate the concepts best
- However, you should be able to work with (and visualize) all of your data

Subsetting data

- Let's subset our data so that we have the variables we need
- We are keeping `ppl_total`, `dependency_rate`, `num_adults`, `rooms`, `age`, `monthly_rent`, and `Target`
- Let's name this subset `costa_viz`

```
costa_viz = household_poverty[['ppl_total', 'dependency_rate',
                               'num_adults', 'rooms', 'age', 'monthly_rent',
                               'Target']]
print(costa_viz.head())
```

```
   ppl_total  dependency_rate  num_adults  rooms  age  monthly_rent  Target
0          1               37           1      3   43      190000.0       4
1          1               36           1      4   67      135000.0       4
2          1               36           1      8   92           NaN       4
3          4               38           2      5   17      180000.0       4
4          4               38           2      5   37      180000.0       4
```

Data prep: clean NAs

- Depending on **subject matter**, missing values might mean something
- Let's define the choices on **how we can handle NAs in our data:**
- drop columns that contain any `NA`s
- drop columns with a certain % of `NA`s
- impute missing values
- convert column with missing values to categorical
- Let's look at the count of NAs by column first:

```
print(costa_viz.isnull().sum())
```

```
ppl_total              0
dependency_rate        0
num_adults             0
rooms                  0
age                    0
monthly_rent        6860
Target                 0
dtype: int64
```

Data cleaning: NAs

- `monthly_rent` has many `NA` values!
- We could just drop this column, as the number is over 50%
- However, in this instance, we'll keep it, and **impute missing values** using the mean of the column
- There isn't a mathematical method for a precise percentage of NAs that we are OK with
- **That's why your subject matter expertise is so important!**

```
# Set the dataframe equal to the imputed dataset.
costa_viz = costa_viz.fillna(costa_viz.mean())
# Check how many values are null in monthly_rent.
print(costa_viz.isnull().sum())
```

```
ppl_total           0
dependency_rate     0
num_adults          0
rooms               0
age                 0
monthly_rent        0
Target              0
dtype: int64
```

Converting the target variable

- Let's convert poverty to a variable with two levels, which will help to balance it out
- The four original levels would also increase the complexity of the visualizations and the code
- For this reason, we will convert levels 1, 2 and 3 to `vulnerable` and 4 to `non_vulnerable`
- The levels translate to 1, 2 and 3 as being **vulnerable** households
- Level 4 is **non-vulnerable**

```
costa_viz['Target'] = np.where(costa_viz['Target'] <= 3, 'vulnerable', 'non_vulnerable')
```

```
print(costa_viz['Target'].head())
```

```
0    non_vulnerable
1    non_vulnerable
2    non_vulnerable
3    non_vulnerable
4    non_vulnerable
Name: Target, dtype: object
```

Data prep: target

- The next step of our data cleanup is to ensure the target variable is binary and has a label
- Let's look at the `dtype` of `Target`

```
print(costa_viz.Target.dtypes)
```

```
object
```

- We want to convert this to `bool` so that it is a binary class

```
costa_viz["Target"] = np.where(costa_viz["Target"] == "non_vulnerable", True, False)

# Check class again.
print(costa_viz.Target.dtypes)
```

```
bool
```

Data reshaping: wide vs long

- When we talk about data *reshaping*, what we usually mean is converting between what is called either **wide** or **long** data format
  - **Wide** data is much more visually digestible, which is why you're likely to come across it if you are using data from some type of report
  - **Long** data is much easier to work with in Pandas, and generally speaking in most data analysis and plotting tools

Data reshaping: wide vs long (cont'd)

- **Wide** data often appears when the values are some type of aggregate (we will use `mean` of groups)
- Let's make a dataframe with two rows and six columns that looks like this, it represents a typical **wide** dataframe

Target	ppl_total	dependency_rate	num_adults	rooms	age
`False`	4.358607	26.011233	2.388093	4.533839	31.314238
`True`	3.796531	25.425284	2.713809	5.205971	36.078886

Prepare data: group and summarize

- Now that we know how to group and summarize data, let's create a summary dataset that would include the following:
- Grouped data by `Target` variable
- Mean value computed on the grouped data that includes the following variables:
  - `ppl_total`
  - `dependency_rate`
  - `num_adults`
  - `rooms`
  - `age`

Prepare data: group and summarize (cont'd)

```
# Group data by `Target` variable.
grouped = costa_viz.groupby('Target')
```

```
# Compute mean on the listed variables using the grouped data.
costa_grouped_mean = grouped.mean()[['ppl_total','dependency_rate','num_adults','rooms','age']]
print(costa_grouped_mean)
```

```
        ppl_total  dependency_rate  num_adults     rooms         age
Target
False    4.358607        26.011233    2.388093  4.533839  31.314238
True     3.796531        25.425284    2.713809  5.205971  36.078886
```

Prepare data: group and summarize (cont'd)

```
# Reset index of the dataset.
costa_grouped_mean = costa_grouped_mean.reset_index()
print(costa_grouped_mean)
```

```
   Target  ppl_total  dependency_rate  num_adults     rooms        age
0   False   4.358607        26.011233    2.388093  4.533839  31.314238
1    True   3.796531        25.425284    2.713809  5.205971  36.078886
```

- The reason we call this dataframe **wide** is because each variable has its own column (i.e. `ppl_total`, `age`, etc.)
- It makes the table easier to present, but is inconvenient to run analyses on or visualize

Why long?

- Now let's convert this **wide** data to the **long** format
- The `metric` variable, which was previously presented in 5 columns (i.e. `ppl_total`, `age`, etc), should be put into a single column
- The `mean` variable was the values in the columns corresponding to those variables
- That's the format we expect to get when we convert our **wide** dataframe to **long**
- This format is very convenient to work with when we run analysis and plot data

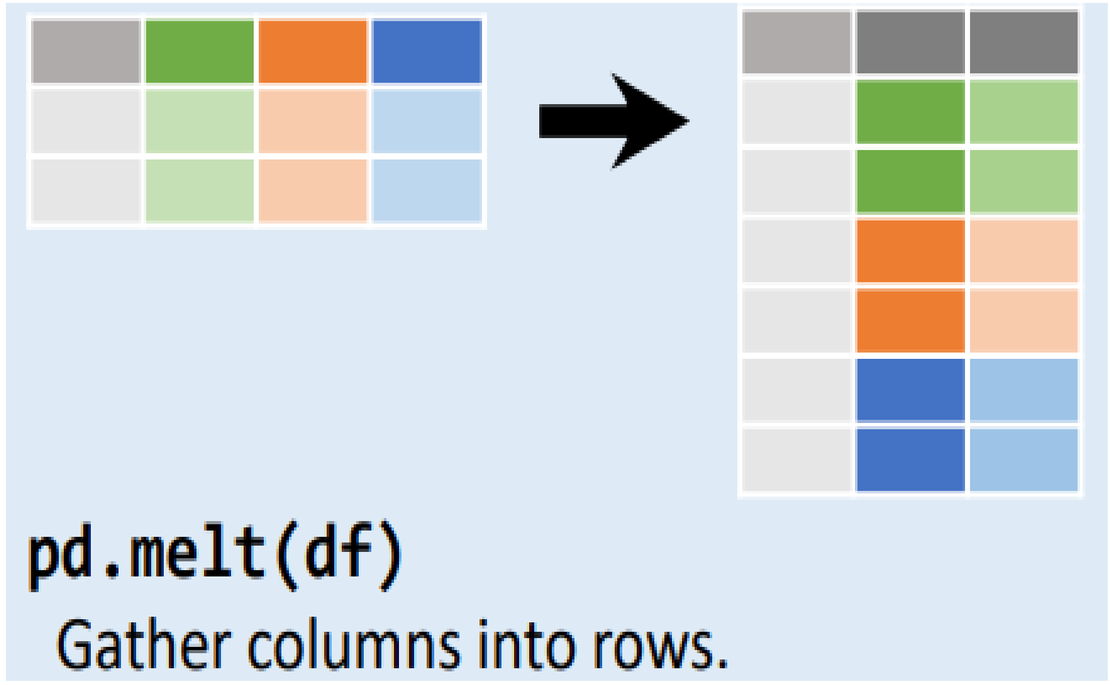
mrc_class	metric	mean
False	ppl_total	4.358607
True	ppl_total	3.796531
False	dependency_rate	26.011233
True	dependency_rate	25.425284
False	num_adults	2.388093
True	num_adults	2.713809
False	rooms	4.533839
True	rooms	5.205971
False	age	31.314238
True	age	36.078886

Wide to long format: melt

To convert from **wide** to **long** format, we use the Pandas `melt` function with the following arguments:

1. Wide dataframe
2. Variable(s) that will be preserved as the `ids` of the data (i.e. like `Target` with values `True` and `False` in our case)
3. Name of the variable that will now contain the column names from the wide data we want to melt together
4. Name of the column that will contain respective values corresponding to the melted columns

```
pd.melt(df,                              #<- 1
        id_vars = ['id_col'],    #<- 2
        var_name = 'some_var',   #<- 3
        value_name = 'some_val') #<- 4
```



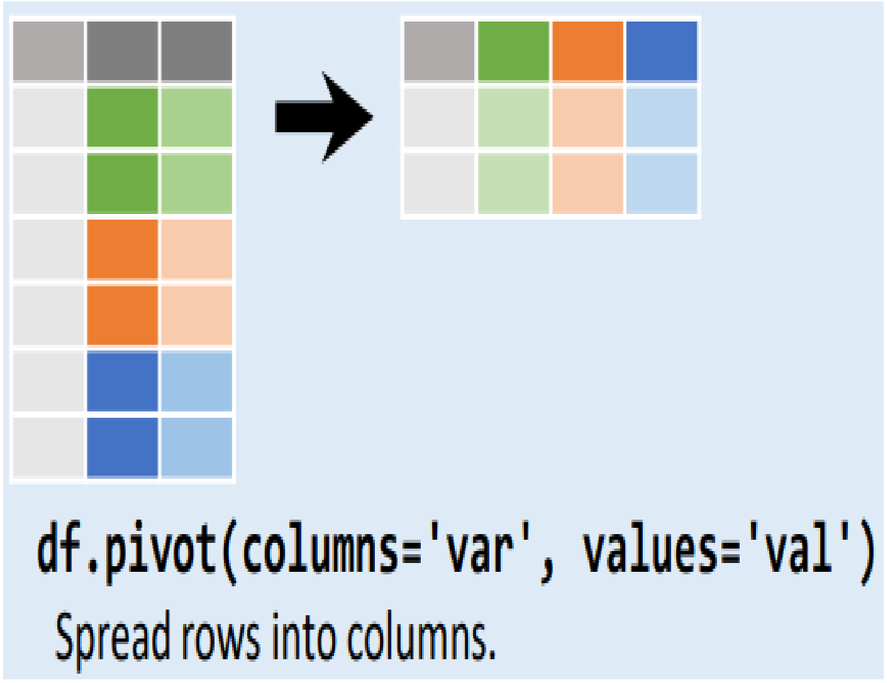
Wide to long format: melt (cont'd)

```
# Melt the wide data into long.
costa_grouped_mean_long = pd.melt(costa_grouped_mean,        #<- wide dataset
                                  id_vars = ['Target'],      #<- identifying variable
                                  var_name = 'metric',       #<- contains col names of wide data
                                  value_name = 'mean')       #<- contains values from above columns
print(costa_grouped_mean_long)
```

```
   Target            metric        mean
0   False         ppl_total    4.358607
1    True         ppl_total    3.796531
2   False  dependency_rate   26.011233
3    True  dependency_rate   25.425284
4   False       num_adults    2.388093
5    True       num_adults    2.713809
6   False            rooms    4.533839
7    True            rooms    5.205971
8   False              age   31.314238
9    True              age   36.078886
```

Long to wide format: pivot

```
df.pivot(index = ['id_col'],     #<- 1
         columns = 'some_var',   #<- 2
         values = 'some_val')    #<- 3
```



We can convert the **long** data back to **wide** format with the `.pivot()` method

1. The `index` argument refers to what values *will become* the `ids` in the new dataframe
2. The `columns` argument refers to the values of which column will be converted to column names
3. Lastly, we supply the `values` argument, which is the field to use to fill in the values of the wide data

Long to wide format: pivot (cont'd)

```
# Melt the long data into wide.
costa_grouped_mean_wide = costa_grouped_mean_long.pivot(
                                                    index = 'Target',   #<- identifying variable
                                                    columns = 'metric', #<- col names of wide data
                                                    values = 'mean')    #<- values from above

columns
print(costa_grouped_mean_wide)
```

```
metric         age  dependency_rate  num_adults  ppl_total     rooms
Target
False    31.314238        26.011233    2.388093   4.358607  4.533839
True     36.078886        25.425284    2.713809   3.796531  5.205971
```

Knowledge check 3

Exercise 3

Module completion checklist

Objective	Complete
Load data into Python and inspect	✔
Summarize data using pandas	✔
Reshape data using pandas	✔

Summary

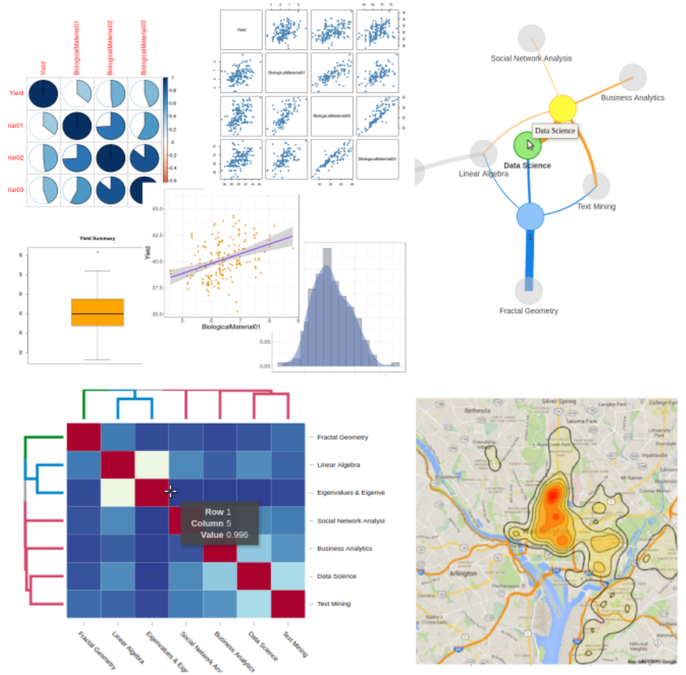
- We have covered the following throughout this course:

Objective	Complete
Data science life cycle and use cases	✔
Working with Numpy arrays	✔
Applying operations on Pandas series and dataframe	✔
Working with a dataset and reshaping variables	✔

What next?

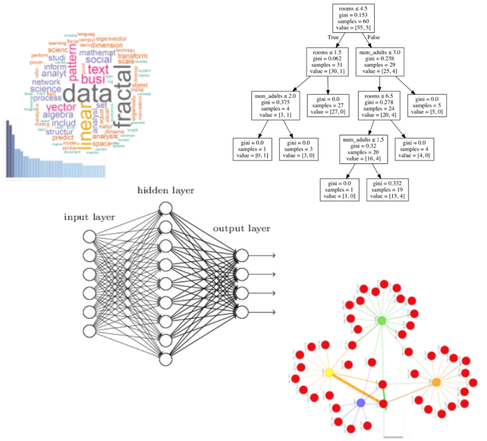
The next steps after cleaning the data is to try out:

- **Exploratory data analysis** using visualizations
  - EDA is commonly the first step taken after we encounter a dataset
  - It's important to perform EDA as it gives us an idea on how to deal with the data and gain insights from it



What next?

- **Data modeling**
  - Supervised machine learning is the task or predicting or classifying an output based on predictors, or input variables
  - Below are some examples of how you would apply these algorithms in business scenarios



Question to answer	Real world example
What is the value based on predictors?	Predicting the number of bikes rented based on the weather
What category is this in?	Anticipating if your customer is pregnant, remodeling, just got married, etc.
What is the probability that something is in a given category?	Determining the probability that a piece of equipment will fail, or that someone will buy your product

This completes our module

Congratulations!