DS105W – Data for Data Science

Week 05

Summarising and Presenting Data

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Today's Goals

- **Learn:** Custom functions and the `.apply()` method
- **Discover:** Temporal grouping and summarisation
- **Apply:** Present summary tables with pandas Styler

Why this matters: These skills directly support your ✍️ Mini-Project 1 work.

1️⃣ From Loops to Functions

In the 💻 W04 Lab, you explored nested `np.where()` and boolean columns when classifying weather attributes like temperature and rainfall.

Today, we'll solve that same problem with a different (cleaner) approach: **custom functions** and the `.apply()` method.

The Problem We're Solving

The task was to classify weather based on temperature and rainfall into the following categories:

Category	Description
Hot & Dry	`temperature` > 25°C and `rainfall` < 1mm
Hot & Wet	`temperature` > 25°C and `rainfall` >= 1mm
Mild & Dry	`temperature` in 20-25°C and `rainfall` < 1mm
Mild & Wet	`temperature` in 20-25°C and `rainfall` >= 1mm
Cool	`temperature` < 20°C and `rainfall` any

With nested `np.where()`:

```
weather_type = np.where(
  temp >= 28,
  np.where(rain < 1, "Hot & Dry", "Hot & Wet"),
  np.where(
    temp >= 20,
    np.where(rain < 1, "Mild & Dry", "Mild & Wet"),
    "Cool"
  )
)
```

What if…

Instead of using nested `np.where()`, I could just more naturally say:

```
classify_weather(20, 1)
```

and get this as a response:

```
"Mild & Wet"
```

(a single normal string)

… so that I could apply this to every combination of temperature and rainfall I have in my dataset?

In the olden days…

Back in the days where we used `for` loops and separate lists/arrays, this would look like this:

```
weather_types = []

for i in range(len(temps)):
    weather_type = classify_weather(temps[i], rain[i])
    weather_types.append(weather_type)
```

But we don't do `for` loops anymore 🙃

In the age of pandas…

If we had such a way to classify weather, we could use **vectorised operations** in `pandas` to classify weather for every row in our dataset in a single line of code (instead of a `for` loop).

It would look like this:

```
df['weather'] = df.apply(classify_weather, axis=1)
```

Neat, wouldn't you say?

> I will explain the `axis=1` argument in more detail in a moment…

What is a function?

It's a reusable block of code that takes inputs and produces an output. You can **invoke** it by calling its name with the appropriate inputs.

How to define a function:

```python
def function_name(param1, param2, ...):
    """
    Docstring: What this function does
    """
    # Function body

    ...code that does something with the params...

    return output
```

Key components:

- `def`: defines a function
- Function name: **you choose** a descriptive and clear name
- Parameters: are the inputs to the function
- Docstring explains what it does
- `return` produces the output

Functions Make Logic Testable

You **always** test a function on single values first.

```python
# Test on single values first
print(f"30°C: {is_hot(30)}")    # True
print(f"20°C: {is_hot(20)}")    # False
print(f"25°C: {is_hot(25)}")    # True (boundary case)
```

Why test first? Easier to debug a function than nested `np.where()`!

From loops to functions

- The `.apply()` method in `pandas` allows you to apply a function to every element in a Series.
- It works kind of like a `for` loop, but cleaner and more efficient.
- It looks like this:

```
df['temperature'].apply(is_hot)
```

- The output is a new pandas Series with the same index as the original Series.

  That is, something like this:

```
is_hot    [True, False, False, True, ...]
dtype: object
```

Adding a new column to the DataFrame

- If you **assign** the output of the `.apply()` method to a new column in the DataFrame...
- using the `=` operator:

```
df['is_hot'] = df['temperature'].apply(is_hot)
```

- alternatively, you can use the `.assign()` method:

```
df = df.assign(is_hot=df['temperature'].apply(is_hot))
```

- Either way, you would get a new column in the DataFrame with the results:

date	temperature	is_hot
2024-08-15	28	True
2024-08-16	22	False
2024-08-17	26	True

Filtering data (recap)

- Last week, we talked about code that looked like this:

  ```
  df[df['temperature'] > 25]
  ```

  That is, you create a **boolean array** using a logical condition and then use it to filter the DataFrame.

- By the way, sometimes I find it clearner to split this into two steps:

  ```
  mask = df['temperature'] > 25
  df[mask]
  ```

  It makes it easier to read and debug.

Filtering data with `.apply()`

- You can also use `.apply()` to filter data.

  ```
  df[df['temperature'].apply(is_hot)]
  ```

  This is equivalent to the code we saw last week.

  ```
  mask = df['temperature'].apply(is_hot)
  df[mask]
  ```

When to use which?

> In this particular case, I think the first approach is easier to read and debug: `df[df['temperature'] > 25]`.
>
> This is because **greater than** (`>`) is a simple logical operation that is already vectorised and implemented in the `pandas` (and `numpy`) library.

- Make it a habit to **search through the pandas documentation** to see if the operation you want to perform is already vectorised.

The two types of `.apply()`

- When you do `df[column].apply(function)`, you are applying the function to **every element in the pandas Series**.
- But if you do `df.apply(function)`, you are applying the function to **each dimension (row or column) in the DataFrame**.

The two types of data in pandas

- Pandas has two major data types:
  - **Series**: one-dimensional (a single column or a single row).
    - It's essentially a `numpy` array with additional **metadata**: index and name.
  - **DataFrame**: two-dimensional (a table of rows and columns).
    - It's essentially a collection of pandas Series.

The two types of `.apply()` (continued)

- When you do `df[column].apply(function)`, you are applying the function to **every element in the pandas Series**.
- But if you do `df.apply(function)`, you are applying the function to **each dimension (row or column) in the DataFrame**.
  - You can specify an `axis` argument to control which dimension you want to apply the function to.
  - `axis=0` means “down the rows” (column-wise) and `axis=1` means “across columns” (row-wise).

One-liners with `lambda`

Sometimes you just want a quick, inline function for a one-liner. Use `lambda`.

```python
# Same as defining is_hot(), but inline
df['is_hot'] = df['temperature'].apply(lambda t: t >= 25)
```

You can also combine with `.assign()` for method chaining:

```python
df = (
    df
    .assign(
        year=lambda d: d['date'].dt.year,
        month=lambda d: d['date'].dt.month,
        is_hot=lambda d: d['temperature'] >= 25,
    )
)
```

When logic grows complex, prefer a named `def` function for readability and testing.

Comparing Approaches

Nested `np.where()` (W04 Lab):

```
weather = np.where(
    temp >= 28,
    np.where(rain < 1, "Hot & Dry", "Hot & Wet"),
    # ... unreadable nesting
)
```

Function + `.apply()` (Clean):

```
def classify_weather(row):
    temp = row['temperature']
    rain = row['rainfall']

    if temp >= 28 and rain < 1:
        return "Hot & Dry"
    # ... clear if-elif logic

df['weather'] = df.apply(classify_weather, axis=1)
```

💭 **Note**: I used `row` as the parameter rather than the individual columns.

When to Use Functions

Extract functions when:

- Logic is complex (multiple conditions)
- You need to test **edge cases** (lots of `if`-`elif`-`else` statements)
- You'll reuse the logic elsewhere
- Nested conditionals would become unreadable

Use built-in operations when:

- Logic is simple (one condition)
- Vectorised operations suffice
- Pandas/NumPy already has the operation

> 💡 Get used to searching the documentation. We can't possibly teach you all the operations that are available in `pandas` and `numpy`.

Connecting to Your Work

You might need to use custom functions (`def` statements) and `apply()` in your ✍️ Mini-Project 1 either to filter data based on complex logic or to create classification labels.

2️⃣ Temporal Data

To answer questions like the one you are working on in your Mini-Project 1, that is,

> *"Does London's air clean up on weekends?"*

You need to:

1. Work with `datetime` objects
2. Extract date components (year, month, day, day of week)
3. Aggregate data by date components to reveal patterns

DateTime Conversion

APIs typically return timestamps as Unix epoch (seconds since 1970):

```
1633046400  # What date is this?? 🤔
```

Convert to datetime:

```
df['date'] = pd.to_datetime(df['timestamp'], unit='s', utc=True)
```

Now you get readable dates:

```
2021-10-01 00:00:00+00:00
```

The `.dt` Accessor

Once you have datetime objects, you have superpowers!

You can extract components of the datetime object using the `.dt` accessor:

```
df['year'] = df['date'].dt.year
df['month'] = df['date'].dt.month
df['day'] = df['date'].dt.day
df['dayofweek'] = df['date'].dt.dayofweek  # Monday=0
```

Before:

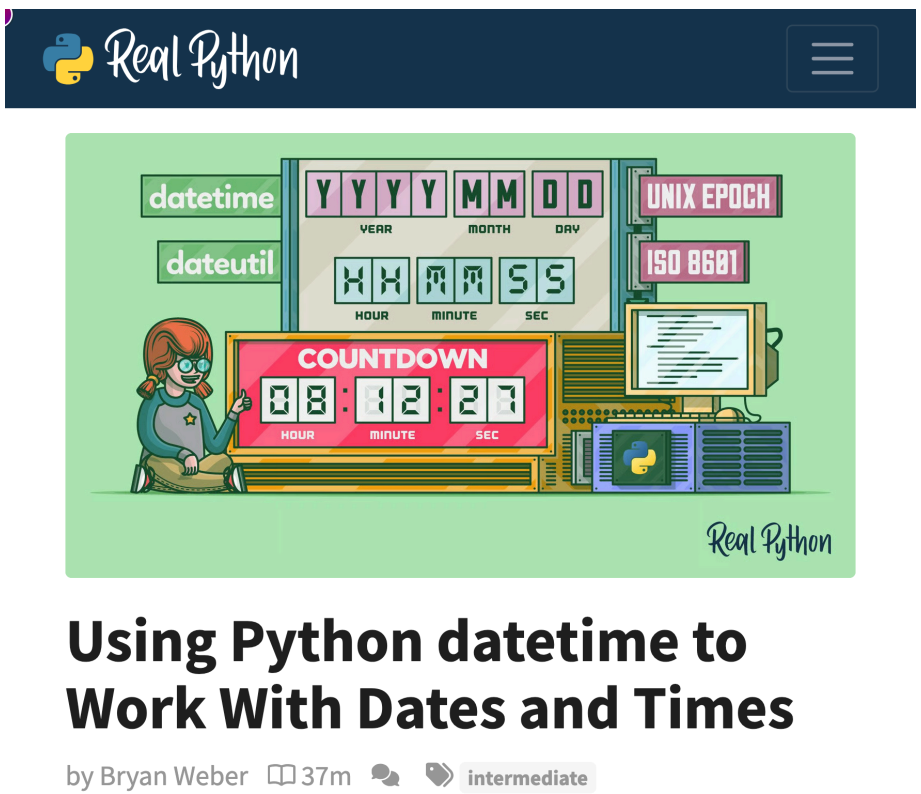
date
2024-08-15
2024-08-16
2024-08-17

After:

date	year	month	day	dayofweek
2024-08-15	2024	8	15	3 (Thursday)
2024-08-16	2024	8	16	4 (Friday)
2024-08-17	2024	8	17	5 (Saturday)

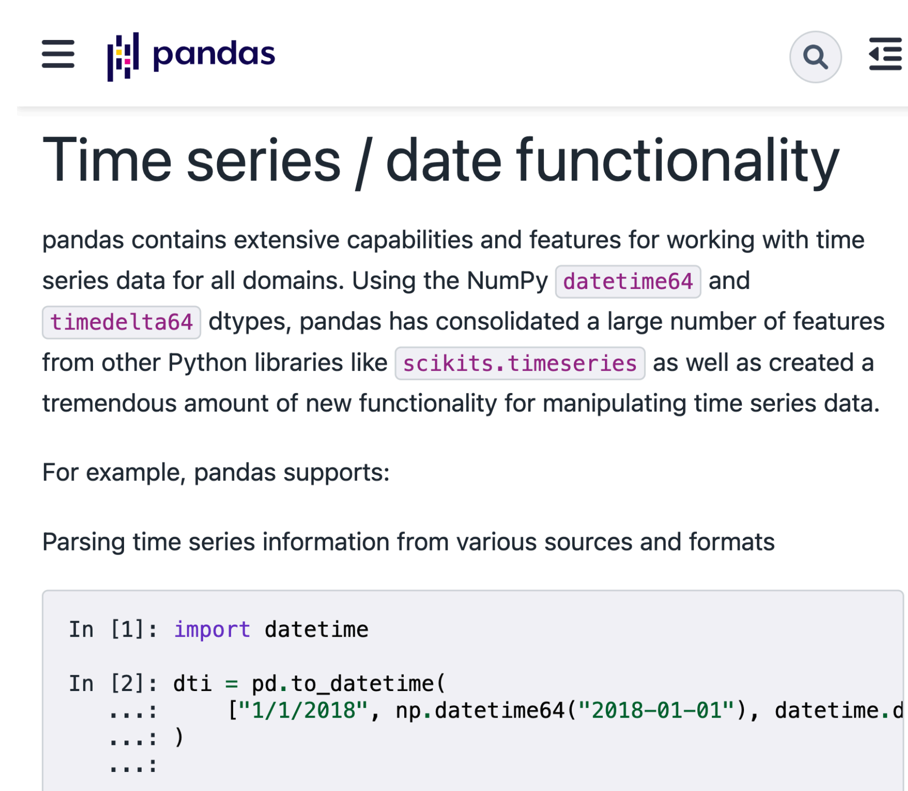
Recommended readings

I really like this **RealPython** tutorial Using Python datetime to Work With Dates and Times. Give it a read!



Most of the features that exist in the Python default `datetime` module are also available in the `pandas` library.

This pandas documentation page is also a good resource.



Time series / date functionality

pandas contains extensive capabilities and features for working with time series data for all domains. Using the NumPy `datetime64` and `timedelta64` dtypes, pandas has consolidated a large number of features from other Python libraries like `scikits.timeseries` as well as created a tremendous amount of new functionality for manipulating time series data.

For example, pandas supports:

Parsing time series information from various sources and formats

```
In [1]: import datetime

In [2]: dti = pd.to_datetime(
   ...:     ["1/1/2018", np.datetime64("2018-01-01"), datetime.d
   ...: )
   ...:
```

☕ Coffee Break

After the break:

- The `groupby()` method: split-apply-combine strategy
- pandas Styler for presenting your data

3️⃣ Split -> Apply -> Combine

Very often, we need to calculate summary statistics for groups of data instead of for the entire dataset.

For example, you might want to calculate the average temperature for each month in a year.

The `groupby()` method

The `pandas` library provides a method called `groupby()` to help you do precisely this:

```
df.groupby('year')['temperature'].mean()
```

Before (raw data):

date	year	temperature
2021-01-15	2021	5
2021-06-15	2021	22
2022-01-15	2022	6
2022-06-15	2022	24

What pandas will do:

- Separate the data into groups based on the `year` column.
- Calculate the `mean` for the entire `temperature` column for each year.
- Combine the results back together into a new DataFrame 👉

After:

year	temperature
2021	13.5
2022	15.0

GroupBy Fundamentals

Basic pattern:

```
df.groupby('grouping_column')['column_to_aggregate'].function()
```

Common aggregation functions:

- `.mean()` - average
- `.median()` - middle value
- `.sum()` - total
- `.max()` - maximum
- `.min()` - minimum
- `.count()` - number of items

Method Chaining for Readability

When chaining multiple operations, split them across lines:

```
plot_df = (
    df.groupby('year')['temperature']
     .mean()
     .reset_index()
)
```

Each operation is on its own line, making the transformation clear and debuggable. (R users might recognise this as similar to the `%>%` operator.)

Alternative (harder to read?):

```
plot_df = df.groupby('year')['temperature'].mean().reset_index()
```

Temporal Grouping Examples

```
# Average temperature by year (method chaining)
yearly_temps = (
    df
    .assign(year=df['date'].dt.year) # add a new column temporari
    .groupby('year')['temperature']
    .mean()
)
```

or, say:

```
# Count hot days by month (method chaining)
hot_days_per_month = (
    df.loc[df['is_hot']]
    .assign(month=df['date'].dt.month)
    .groupby('month')
    .size()
)
```

You can group by multiple columns

Here is an example of grouping by (year, month) combination:

```
# Average temperature by year and month (method chaining)
yearly_monthly_temps = (
    df
    .assign(year=df['date'].dt.year,
            month=df['date'].dt.month)
    .groupby(['year', 'month'])['temperature']
    .mean()
)
```

4️⃣ Presenting Your Data

You just learned to produce summary tables with `.groupby()`. Now let's make them **readable**.

From GroupBy to Presentation

Here is the `yearly_stats` table we produced earlier:

```
yearly_stats = (
    weather_df
    .groupby('year')['temp']
    .agg(['mean', 'max', 'min', 'std'])
    .reset_index()
)
```

year	mean	max	min	std
2005	14.349041	29.8	0.5	6.341563
2006	14.675342	31.5	0.8	6.764682
2007	14.390685	26.4	1.6	5.042399

It’s fine but it would be better if all the decimal places were aligned.

pandas Styler basics

The `.style` method returns a **Styler** object you can customise:

```
yearly_stats.style.format("{:.1f}")
```

year	mean	max	min	std
2005	14.3	29.8	0.5	6.3
2006	14.7	31.5	0.8	6.8

Documentation tips:

- Read all about the `.style` method in the pandas documentation.

`.format()` for number control

You can format different columns differently. For example, you can format the `mean` column to show 1 decimal place and the `std` column to show 2 decimal places:

```
yearly_stats.style.format({
    "mean": "{:.1f}°C",
    "max":  "{:.1f}°C",
    "min":  "{:.1f}°C",
    "std":  "{:.2f}"
})
```

This doesn't change the underlying data but just how it is displayed.

👉 Train your documentation skills by reading about these `{:1f}` strings in the official Python documentation.

`.background_gradient()` for visual patterns

```
yearly_stats.style.background_gradient(subset=['mean'], cmap='YlOrRd')
```

The gradient highlights the column values using colour. Hotter years get warmer colours.

Can you see the warming trend now? The colour does the work.

> 💡 `cmap` stands for “colour map”. `'YlOrRd'` goes from yellow (low) to red (high). Other useful maps: `'Blues'`, `'RdYlGn'`, `'coolwarm'`.

👉 Train your documentation skills by reading about the `cmap` parameter in the matplotlib documentation.

`.bar()` for inline comparison

```
yearly_stats.style.format(precision=2).bar(subset=['max'], co
```

Inline bars within cells give immediate visual comparison of magnitude. You can see which years had the highest maximum temperatures at a glance.

Combining Styler methods

Chain methods together to build a complete presentation:

```
(
    yearly_stats.style
    .format({"mean": "{:.1f}°C", "max": "{:.1f}°C",
             "min": "{:.1f}°C", "std": "{:.2f}"})
    .background_gradient(subset=['mean'], cmap='YlOrRd')
    .bar(subset=['max'], color='#ED9255')
    .set_caption("London's average temperature has risen [this much]")
)
```

`.set_caption()` is where your **narrative title** goes. The caption tells the reader what the table means, not what it contains.

A note on AI and styling

Formatting tables is the kind of task that I really don't mind if you delegate to an AI chatbot. The Styler API has dozens of options and memorising them is not a good use of your time.

What I'd recommend:

1. Do the DataFrame transformation yourself (the `.groupby()`, the filtering, the `.reset_index()`). That's where your analytical thinking lives.
2. Once you have the table you want to present, ask an AI chatbot to produce the Styler code. Something like: *"Style this DataFrame so the mean column has a yellow-to-red gradient and all temperatures show one decimal place."*
3. **Then check the output.** Does the colour scale make sense for your data range? Are the column names what you expected? Does `.set_caption()` say what you actually found?

Compare what the chatbot gives you against the pandas Styler documentation. AI chatbots sometimes hallucinate method names or use deprecated parameters. The docs are the ground truth.

> 💡 The skill here is knowing what table you want and being able to verify the result. The syntax is just plumbing.

Styler for your Mini-Project 1

Your NB03 requires **two insights**. You can present them as:

- 2 styled DataFrames
- 1 styled DataFrame + 1 seaborn visualisation
- 2 seaborn visualisations

You now have everything you need to produce styled DataFrame insights and tomorrow's lab will give you the essentials of seaborn if you choose to use visualisations in your Mini-Project 1.

Looking Ahead

- **Tomorrow's lab:** the essentials of seaborn (in case you want to use visualisations in your Mini-Project 1)
- You now have the tools to start NB02 and NB03 using styled DataFrames
- Seaborn is optional for MP1 but gives you more presentation options

Resources:

- 📓 Lecture notebook (downloadable)
- 💻 W05 Lab tomorrow
- 💬 Post questions in `#help` on Slack
- 📅 Attend drop-in sessions

Looking ahead: Week 06 (Reading Week) is focus time for Mini-Project 1 completion.