DS105W – Data for Data Science

Week 08
🐼 Pandas Workshop: Reshaping, Pivoting, and Merging

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Hour 1: 🐼 Pandas Reshaping & Merging Workshop

Last week you collected TfL journey data and flattened nested JSON with `json_normalize()`.

This week you learn **four new tools** to reshape and combine that data for analysis.

Today's toolkit

	Tool	What it does	When you need it
1	`pd.concat()`	Stack DataFrames vertically	Combining route tables from separate files
2	`.melt()`	Reshape wide → long	Making summary tables plot-ready for seaborn
3	`.pivot_table()`	Reshape long → wide	Building route × time-band summary tables
4	`pd.merge()`	Connect DataFrames by a shared key	Adding ONS postcode context to your journey data

All four directly support your ✍ **Mini-Project 2** `NB02` (data transformation).

1️⃣ pd.concat(): Stacking DataFrames

You collected journey data for different routes and saved them as separate files in `data/raw/`. Now you need **one** DataFrame.

What `pd.concat()` does

```
df_all = pd.concat([df_barking, df_richmond], ignore_index=True)
```

BEFORE: two DataFrames

`df_barking`:

	destination	time_band	duration_min
0	Barking	peak	62
1	Barking	off-peak	48

`df_richmond`:

	destination	time_band	duration_min
0	Richmond	peak	44
1	Richmond	off-peak	35

AFTER `pd.concat()`

	destination	time_band	duration_min
0	Barking	peak	62
1	Barking	off-peak	48
2	Richmond	peak	44
3	Richmond	off-peak	35

NOTE: the parameter `ignore_index=True` is what resets the index to 0, 1, 2, 3, avoiding the situation leading to the confusion of having duplicate indices: 0, 1, 0, 1.

Making sense of the `axis` parameter (stacking rows)

When you set `axis=0` **(default)**, you stack rows:

```
pd.concat([df_a, df_b], axis=0)
```

	destination	time_band	duration_min
0	Barking	peak	62
1	Barking	off-peak	48
2	Richmond	peak	44
3	Richmond	off-peak	35

Use when: combining the same kind of data from different sources.

Making sense of the `axis` parameter (⚠ beware of this trap)

What if you set **`axis=1`** on the **same** DataFrames?

```
pd.concat([df_barking, df_richmond], axis=1)
```

	destination	duration_min	destination	duration_min
0	Barking	62	Richmond	44
1	Barking	48	Richmond	35

🚨 If you try `df["destination"]`, you get **two columns back**!! Future code you write might not work as you intend.

When `pd.concat(..., axis=1)` works

Attaching columns only make sense when each DataFrame holds *different* information about the *same* rows:

`df_journeys_slim`

origin	destination	duration_min
Stratford	Barking	62
Stratford	Richmond	44

`df_context`

borough	imd
Barking	3421
Richmond	29834

Because those dataframes share the same logical rows (the same destinations), you can `concat()` them side by side without creating duplicate columns.

```
df_combined = pd.concat([df_journeys_slim, df_context
                axis=1)
```

This same pattern applies to `pd.json_normalize()`: if the outer level is flat but one column still contains nested dicts, normalise that column separately and `concat(axis=1)` to stitch the pieces together.

2️⃣ melt(): Reshaping Wide → Long

Sometimes your summary table has many columns that represent the **same kind of measurement**. `melt()` unpivots those columns into rows so seaborn can use them.

The `melt()` cheatsheet

```python
df.melt(
    id_vars=["colA"],
    value_vars=["colB", "colC"],
    var_name="metric",
    value_name="value",
)
```

Parameter	What it does
`id_vars`	Columns to **keep** as identifiers (unchanged)
`value_vars`	Columns whose **headers become values** in a new column
`var_name`	Name for the new column holding the old headers
`value_name`	Name for the new column holding the old values

A simple `melt()`

Start small. Two metric columns → one `metric` column and one `value` column.

```
df.melt(id_vars="destination",
        value_vars=["duration_min", "walking_min"],
        var_name="metric", value_name="minutes")
```

BEFORE (wide)

destination	duration_min	walking_min
Barking	62	12
Richmond	44	8

AFTER (long)

destination	metric	minutes
Barking	duration_min	62
Richmond	duration_min	44
Barking	walking_min	12
Richmond	walking_min	8

The column **headers** moved into a new `metric` column. The **values** moved into a new `minutes` column.

Making sure your data is plot-ready

You used `groupby().agg()` from 💻 **W07 Lecture** and got this summary:

destination	peak_mean	offpeak_mean
Barking	61.6	48.4
Richmond	45.0	35.2
Croydon	52.8	40.2
Uxbridge	68.4	52.2

Good summary table for a report. But can you give this to `sns.barplot()` with a `hue` column? **No.** Seaborn needs a long format.

Melting the two columns

```
plot_df = summary.melt(id_vars="destination",
                       value_vars=["peak_mean", "offpeak_mean"],
                       var_name="time_band", value_name="mean_duration_min")
sns.barplot(data=plot_df,
            x="destination", y="mean_duration_min",
            hue="time_band")
```

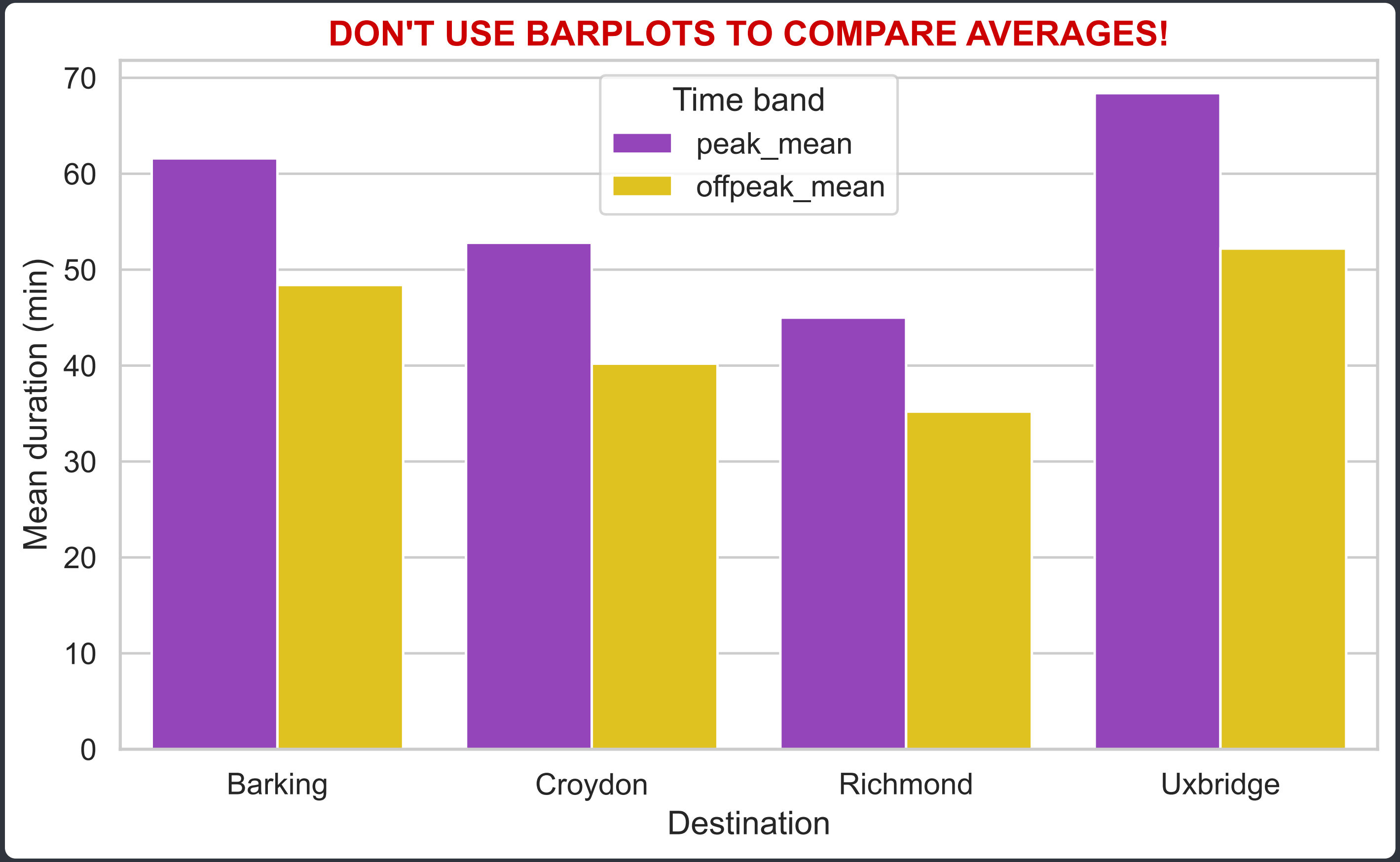
destination	time_band	mean_dur
Barking	peak_mean	61.6
Richmond	peak_mean	45.0
Croydon	peak_mean	52.8
Uxbridge	peak_mean	68.4
Barking	offpeak_mean	48.4
Richmond	offpeak_mean	35.2
Croydon	offpeak_mean	40.2
Uxbridge	offpeak_mean	52.2

Always create a `plot_df` that has the right data format before plotting.

1. Prepare the data shape first
2. Inspect it
3. Plot it

`melt()` bridges summary tables into that pattern so seaborn can use `time_band` as `hue`.

🚫 DO NOT USE: bar plots to compare means



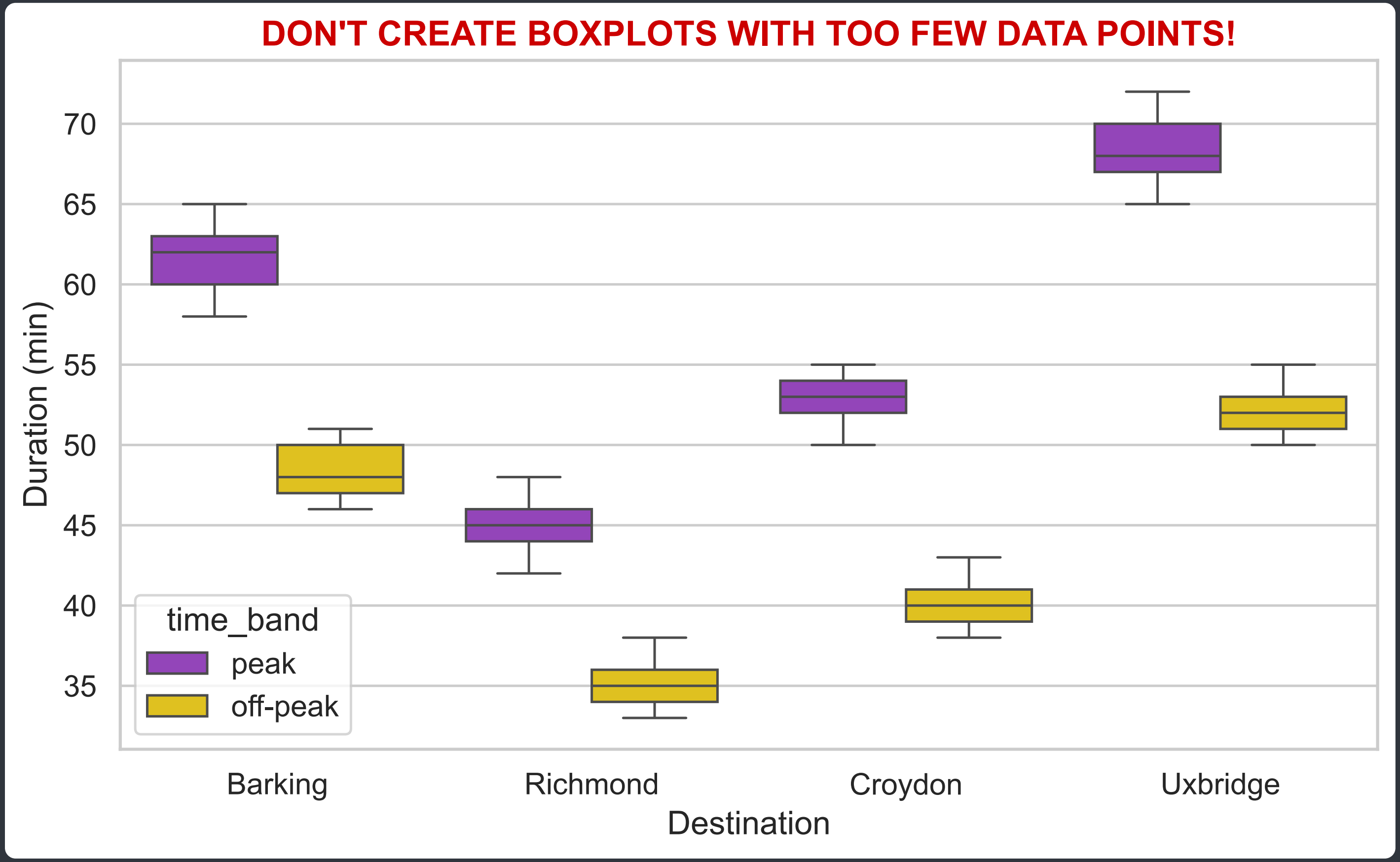
A bar plot of means hides the distribution. Two groups can have the same mean but wildly different spreads and you'd never know (Weissgerber et al., 2015).

```python
# NOT THE BEST VISUALISATION FOR THIS DATA
sns.barplot(data=plot_df, x="destination",
            y="mean_duration_min",
            hue="time_band")
```

Bars are better for comparing proportions and counts, not averages. You can't tell whether those 5 readings were tightly clustered or all over the place.

📖 **Friends Don't Let Friends Make Bad Graphs**: see rule #1

DO NOT USE: boxplots when n is small



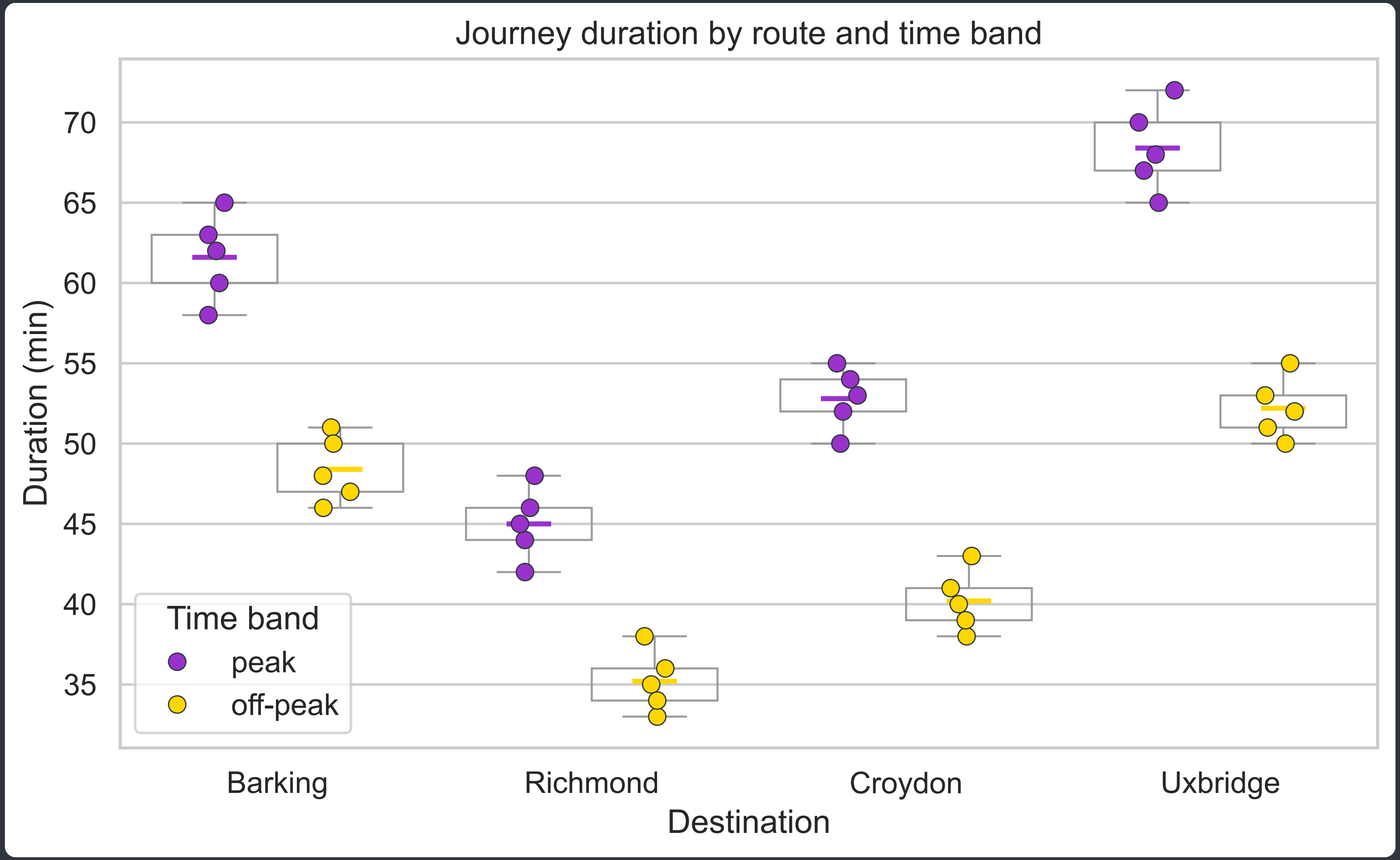
A boxplot shows median, quartiles, and whiskers — but quartiles only stabilise when n is large (roughly > 30–50). With n = 5 per group, the box is mostly noise.

```
sns.boxplot(data=df_all, x="destination",
            y="duration_min",
            hue="time_band")
```

Add or remove a single observation and the box, whiskers, and median line all shift dramatically. At this sample size the quartiles don't represent the population.

📖 **Friends Don't Let Friends Make Bad Graphs**: see rule #2

☑ Better: strip plot + summary overlay



Show every data point, overlay a transparent box for spread, and add a horizontal marker for the mean.

```
sns.stripplot(data=df_all, x="destination",
              y="duration_min", hue="time_band",
              dodge=True, size=7, jitter=0.12)

sns.boxplot(..., boxprops=dict(
    facecolor="none", edgecolor="#999"),
    showfliers=False)

sns.pointplot(..., markers="_",
    markersize=18, linestyle="none",
    estimator="mean")
```

Every observation is visible. The faint box hints at spread without claiming stable quartiles, and the horizontal marker shows the group mean.

Rule of thumb: if n < 30, show every data point. We'll dig deeper in 💻 **W09 Lecture**.

☕ Coffee Break

3 pivot() and pivot_table()

`melt()` goes wide → long.

What if you need to go **long** → **wide**? That's what `pivot()` and `pivot_table()` do.

The `pivot_table()` cheatsheet

```
df.pivot_table(
    index="colA",
    columns="colB",
    values="colC",
    aggfunc="mean",
)
```

Parameter	What it does
`index`	Column whose unique values become **row labels**
`columns`	Column whose unique values become **column headers**
`values`	Column to place in the cells
`aggfunc`	How to combine duplicates: `"mean"`, `"median"`, `"count"`, `lambda`, or a custom function

Simple `pivot()`: when each cell has exactly one value

If your data has no duplicate combinations of index + column, `pivot()` works directly:

```
df.pivot(index="destination", columns="time_band", values="duration_min")
```

BEFORE (long, no duplicates)

destination	time_band	duration_min
Barking	peak	62
Barking	off-peak	48
Richmond	peak	44
Richmond	off-peak	35

AFTER `pivot()`

destination	off-peak	peak
Barking	48	62
Richmond	35	44

Each `time_band` value became a column header. Each `destination` became a row.

What happens when there are duplicate values?

Your real data has **multiple** peak readings per route (you queried on different days). `pivot()` does not know which value to put in the cell.

```
df.pivot(index="destination", columns="time_band", values="duration_min")
# ValueError: Index contains duplicate entries, cannot reshape
```

destination	time _band	duration _min
Barking	peak	62
Barking	peak	58
Barking	peak	65
...	...	...

Three different peak readings for Barking. Which one goes in the cell?

destination	peak
Barking	62? 58? 65?

`pivot()` refuses because there's no single answer. This is where `pivot_table()` comes in ☞

`pivot_table()` handles duplicates with `aggfunc`

```
df.pivot_table(index="destination", columns="time_band",
               values="duration_min", aggfunc="mean")
```

BEFORE (long, with duplicates)

destination	time_band	duration_min
Barking	peak	62, 58, 65, 60, 63
Barking	off-peak	48, 51, 47, 50, 46
Richmond	peak	44, 48, 42, 46, 45
Richmond	off-peak	35, 38, 33, 36, 34

💡 I've simplified for the example, but imagine that in reality, we have 5 rows for each row above.

AFTER

`pivot_table(aggfunc="mean")`

destination	off-peak	peak
Barking	48.4	61.6
Richmond	35.2	45.0

`aggfunc="mean"` told pandas: "when there are multiple values per cell, take the mean."

Custom `aggfunc`: lambda and named functions

You're not limited to `"mean"` or `"median"`. You can pass your own function:

With a lambda:

```python
df.pivot_table(
    index="destination",
    columns="time_band",
    values="duration_min",
    aggfunc=lambda x: x.max() - x.min(),
)
```

Computes the **range** (max − min) per cell.

With a named function:

```python
def iqr(series):
    q75 = series.quantile(0.75)
    q25 = series.quantile(0.25)
    return q75 - q25

df.pivot_table(
    index="destination",
    columns="time_band",
    values="duration_min",
    aggfunc=iqr,
)
```

Any function that takes a Series and returns a single number works as `aggfunc`.

Melt ↔ Pivot: two directions of the same reshape

Wide format (good for summary tables)

destination	off-peak	peak
Barking	48.4	61.6
Richmond	35.2	45.0

Long format (good for seaborn plots)

destination	time_band	duration
Barking	off-peak	48.4
Barking	peak	61.6
Richmond	off-peak	35.2
Richmond	peak	45.0

Wide → `.melt()` → Long → `.pivot_table()` → Wide

Choose the shape that fits your next step: wide for readable tables, long for seaborn `hue` arguments.

4️⃣ pd.merge(): Connecting DataFrames on a Key

Your TfL data has postcodes. The ONS Postcode Directory has borough names, IMD ranks, and LSOA codes. `merge()` connects the two by matching on a shared column.

The `merge()` cheatsheet

```
pd.merge(
    df_left,
    df_right,
    left_on="colA",
    right_on="colX",
    how="left",
)
```

Use `on="col"` instead if both DataFrames share the same column name.

Parameter	What it does
`left_on`	Key column in the **left** DataFrame
`right_on`	Key column in the **right** DataFrame
`how`	`"inner"` keeps only matches; `"left"` keeps all left rows (fills NaN if no match)

Matching on a shared key

```python
df_enriched = pd.merge(df_journeys, df_ons[["pcds", "oslaua", "imd"]],
                        left_on="destination_postcode", right_on="pcds",
                        how="left")
```

LEFT: `df_journeys`

destination	dest _postcode	duration _min
Barking	IG11 7QJ	62
Richmond	TW9 1DN	44
Croydon	CR0 1NX	52

RIGHT: `df_ons`

pcds	oslaua	imd
IG11 7QJ	E09000002	3421
TW9 1DN	E09000027	29834
CR0 1NX	E09000008	8734

AFTER `pd.merge(..., how="left")`

destination	dest _postcode	duration _min	oslaua	imd
Barking	IG11 7QJ	62	E09000002	3421
Richmond	TW9 1DN	44	E09000027	29834
Croydon	CR0 1NX	52	E09000008	8734

The blue postcode was the matching key. The green columns came from the right DataFrame.

`how="inner"` vs `how="left"`

What happens when a postcode in your journey data doesn't exist in the ONS file?

`how="inner"`
(only matches survive)

destination	dest_postcode	oslaua
Barking	IG11 7QJ	E09000002
Richmond	TW9 1DN	E09000027

⚠ Croydon's postcode wasn't in the ONS file, so the row **disappeared**.

`how="left"`
(all left rows survive)

destination	dest_postcode	oslaua
Barking	IG11 7QJ	E09000002
Richmond	TW9 1DN	E09000027
Croydon	CR0 1NX	NaN

The row survived but the ONS columns are NaN because there was no match.

Recommendation for MP2: Use `how="left"` so you can see which postcodes failed to match. Then investigate why.

⚠ When keys don’t match: the silent merge failure

Postcodes can look different in your TfL data vs the ONS file:

Your TfL data	ONS file	Will they match?
`IG11 7QJ`	`IG11 7QJ`	✅ Yes
`ig11 7qj`	`IG11 7QJ`	❌ No (case mismatch)
`IG117QJ`	`IG11 7QJ`	❌ No (missing space)
`CR0 1NX`	`CR0 1NX`	❌ No (leading/trailing spaces)

Fix both sides before merging:

```
df_journeys["dest_clean"] = (df_journeys["destination_postcode"]
                             .str.strip().str.upper().str.replace(" ", ""))
df_ons["pcds_clean"] = df_ons["pcds"].str.strip().str.upper().str.replace(" ", "")
```

Don’t go just by what AI is telling you: learn about string methods in the Pandas documentation.

Always verify after merging:

```
print(f"Rows before: {len(df_journeys)}, Rows after: {len(df_enriched)}")
print(f"Unmatched postcodes: {df_enriched['oslaua'].isna().sum()}")
```

What's Next?

- **In the 💻 W08 Lab tomorrow**, your class teacher will walk you through merging your own TfL data with the real ONS Postcode Directory, something that will help you build your ✍️ **Mini-Project 2** `NB02`.
- **By the end of lab**, you should have a working merge pipeline: `data/raw/` → reshape → merge with ONS → save to `data/processed/`.
- **Week 09:** EDA quality checks, mean vs median, correlation vs causation, `plot_df` refinement, and an introduction to something called closeread.
- **Week 10:** ✍️ **Mini-Project 2** deadline: Monday 23 March, 8 pm.