DS105W – Data for Data Science

Week 09

Exploratory Data Analysis & Data Visualisation

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Hour 1: 📊 Exploratory Data Analysis

Last week you learned **four tools** to reshape and merge your MP2 data.

This week: how to **understand** that data before drawing conclusions.

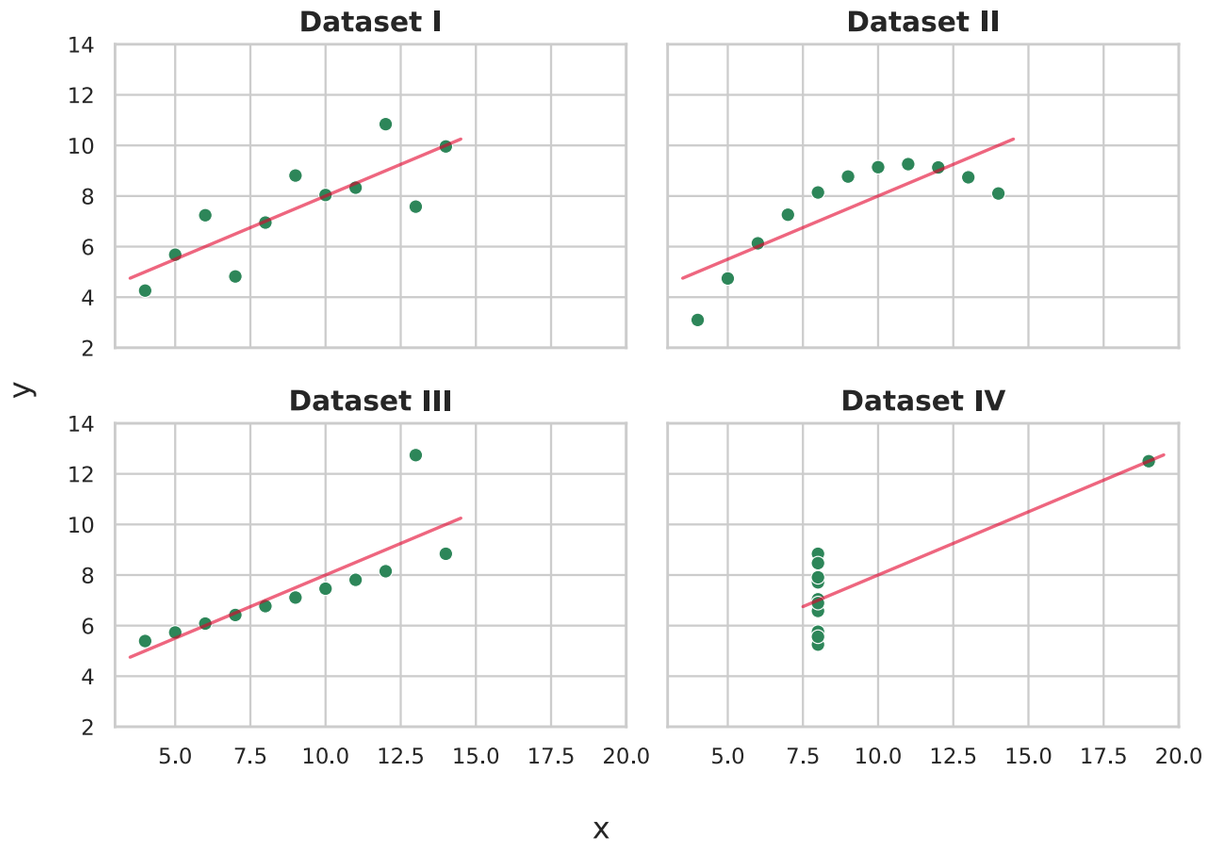
Why you can’t just look at the numbers

In 1973, statistician Francis Anscombe created four datasets that have **nearly identical** summary statistics:

Statistic	Dataset I	Dataset II	Dataset III	Dataset IV
Mean of x	9.0	9.0	9.0	9.0
Mean of y	7.50	7.50	7.50	7.50
Std dev of y	2.03	2.03	2.03	2.03
Correlation	0.816	0.816	0.816	0.816

All of these datasets have the same mean, same standard deviation, and same correlation. At this point, you would expect these datasets to look similar but they don’t.

Same mean, same std, same correlation — four very different datasets



Read more on Wikipedia: Anscombe’s quartet or the original paper:
Anscombe, F. J. “Graphs in Statistical Analysis.” The American Statistician 27, no. 1 (1973): 17-21.

The Datasaurus Dozen: same stats, very different shapes

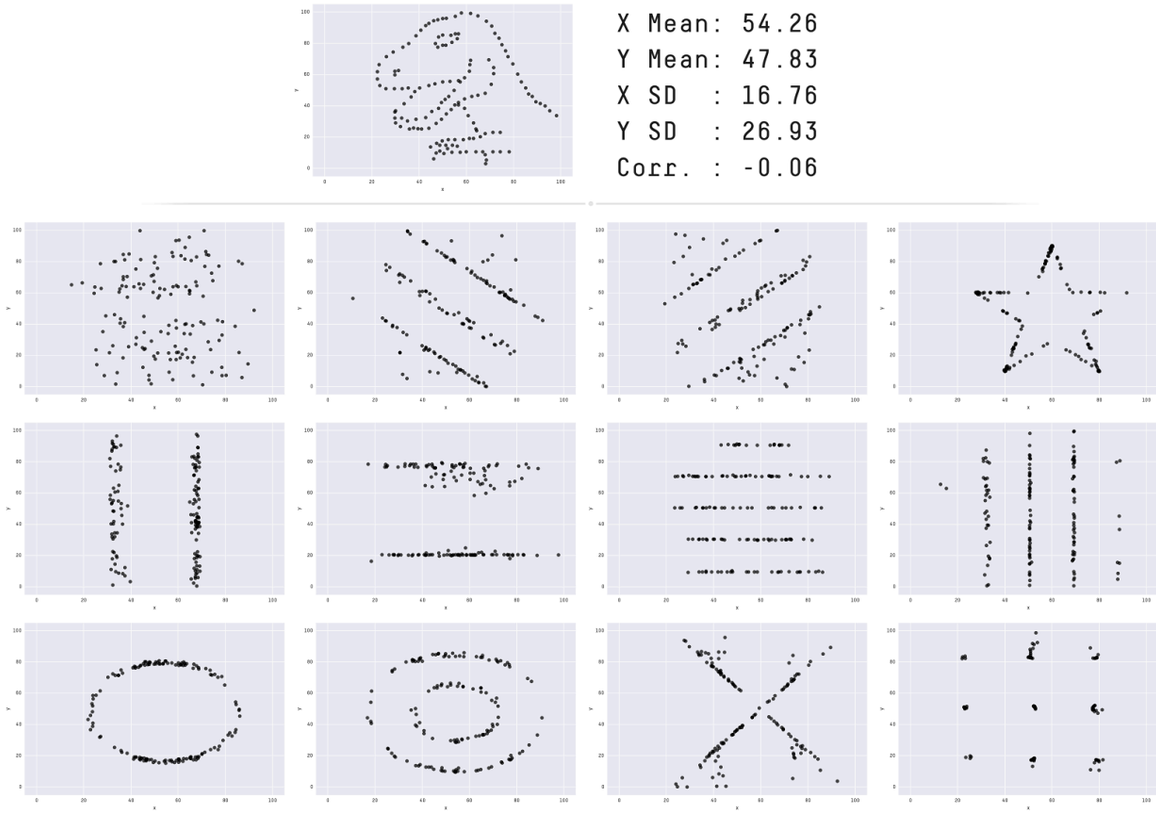
Matejka & Fitzmaurice (2017) pushed this idea to its extreme.

All 13 datasets have the same summary statistics to two decimal places:

- x mean = 54.26
- y mean = 47.83
- x SD = 16.76
- y SD = 26.93
- Pearson's R = −0.06

When you plot them, they look completely different.

Lesson: `.describe()` is where you **start**, not where you **stop**. Always visualise your data.



🔗 **LINK:** Same Stats, Different Graphs (Autodesk Research)

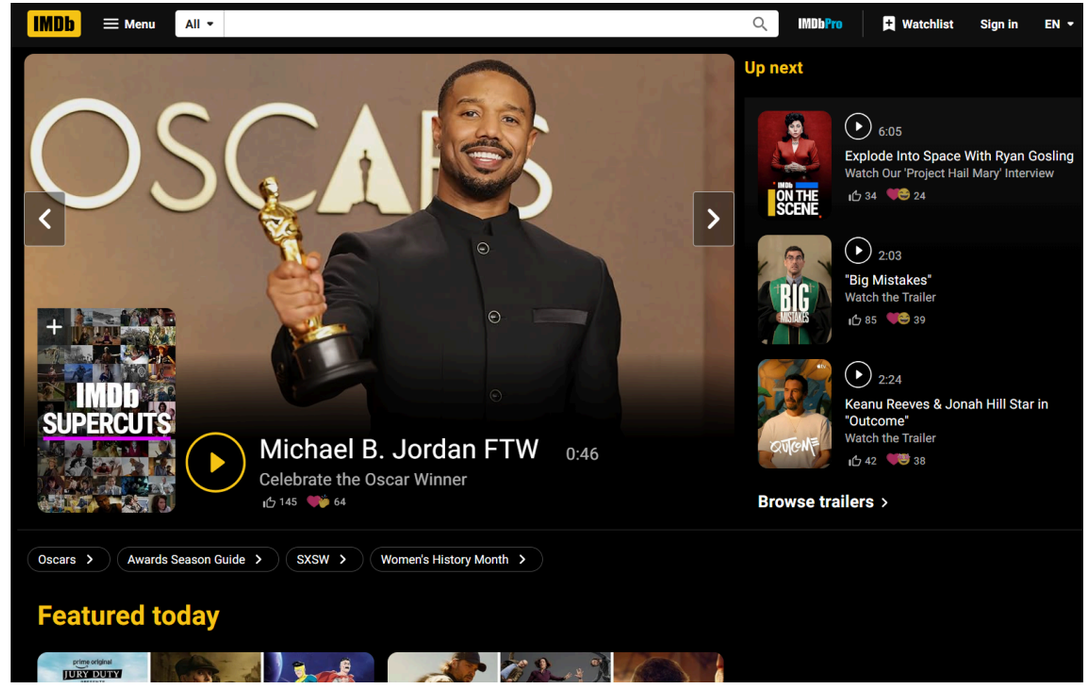
Today's EDA dataset: IMDb

Let me show you one particular dataset that could help me illustrate some of these concepts.

I will use data from the Internet Movie Database (IMDb), which is a popular online database of movies, TV shows, and the people involved in making them.

The data is spread across **multiple tables**, just like your MP2 data is spread across TfL journey files and the ONS Postcode Directory:

Table	What a row describes
`title_basics`	One title (movie, series, episode)
`title_ratings`	One title's average rating and vote count
`title_principals`	One person's role in one title
`name_basics`	One person (director, actor, etc.)



The IMDb homepage

How the IMDb tables connect

Tables are connected by **shared columns** (we also call them **keys**), the same principle as last week's `pd.merge()`.

`tconst` appears in both `title_basics` and `title_ratings`, just like postcodes appear in both your TfL data and the ONS directory.

```
# Same pattern as your MP2 merge!
df_movies = pd.merge(
    df_title_basics,
    df_title_ratings,
    on="tconst"    # shared key
)
```

title_basics:

tconst	primaryTitle	titleType
tt0111161	The Shawshank Redemption	movie
tt0068646	The Godfather	movie

title_ratings:

tconst	averageRating	numVotes
tt0111161	9.3	3120155
tt0068646	9.2	2175958

Connected by `tconst` → one merge gives you titles + ratings.

🔮 **Coming in 💻 W10 Lecture:** You'll learn how to do this same merge using the **SQL** language (`JOIN`) inside a database, rather than in pandas

1. Always check if your data is complete

```
# Quick and dirty way to check all columns at once
df_title_basics.notna().sum() / len(df_title_basics) * 100
```

Result:

```
tconst             100.000000
title_type         100.000000
primary_title       99.999809
original_title      99.999809
is_adult           100.000000
start_year          88.028503
end_year             1.238095
runtime_minutes     35.460020
genres              95.623222
dtype: float64
```

That is

- 100% of the lines have a `tconst`, `title_type`, and `is_adult`
- But only 1.24% has an `end_year`
- Weirdly, only 88% has a `start_year`?!

1.1 Investigate which rows are missing data

Run a follow-up check:

```
df_title_basics[df_title_basics['start_year'].isna()].head(n=10)
```

Then check which rows are missing data, and why.

- **Is this a data collection failure?** → try to fix it → document if unable to
- **Is it just how the data is structured?** → acknowledge how it might impact your analysis
- Don’t try to ‘impute’ missing data. It’s too advanced for this course.

1.2 Check if missingness is systematic

Sometimes missing data is the insight. Check whether missingness is systematic, meaning it appears more often for certain categories.

Table 1. How complete is table title_basics? (breakdown per field and title_type)

	start_year	end_year	runtime	genres	total
title_type					
tvPilot	100.00 %	0.00 %	0.00 %	0.00 %	1
tvShort	99.07 %	0.00 %	87.65 %	100.00 %	10,810
videoGame	97.43 %	0.00 %	1.06 %	85.28 %	45,838
tvSpecial	99.26 %	0.00 %	48.10 %	87.25 %	55,604
tvMiniSeries	93.26 %	57.00 %	35.06 %	95.24 %	66,293
tvMovie	97.20 %	0.00 %	68.70 %	91.24 %	152,979
tvSeries	91.65 %	38.40 %	37.36 %	92.06 %	290,570
video	99.42 %	0.00 %	68.01 %	97.35 %	318,364
movie	85.22 %	0.00 %	63.15 %	89.41 %	731,704
short	96.10 %	0.00 %	64.11 %	100.00 %	1,094,537
tvEpisode	86.48 %	0.00 %	28.22 %	95.82 %	9,296,511

Code recipe: completeness table

Step 1: Define a helper function that computes completeness percentages per group:

```
def count_completeness(group):
    total = len(group)
    return pd.Series({
        'total': total,
        'start_year': group['start_year'].notna().sum() / total * 100,
        'end_year': group['end_year'].notna().sum() / total * 100,
        'runtime': group['runtime_minutes'].notna().sum() / total * 100,
        'genres': group['genres'].notna().sum() / total * 100
    })
```

Step 2: Apply it to each `title_type` group and style with bars:

```
plot_df = (
    df_title_basics.groupby('title_type')
    .apply(count_completeness)[['start_year', 'end_year', 'runtime', 'genres', 'total']]
)

(plot_df.sort_values('total')
 .style
 .bar(vmin=0, vmax=100, height=100, width=100,
      props="border: 1px solid #212121;",
      subset=['start_year', 'end_year', 'runtime', 'genres'])
 .format('{:,.2f} %', subset=['start_year', 'end_year', 'runtime', 'genres'])
 .format('{:,.0f}', subset=['total'])
 .set_caption('Table 1. How complete is table title_basics?'))
```


What does this tell us?

Look at the `end_year` column:

- Only `tvSeries` and `tvMiniSeries` have end years. All other types show 0%.
- The missingness is **structural**: only multi-episode content *have* an end year.

Now look at `runtime`:

- `tvEpisode` has only 28% runtime data. `videoGame` has only 1%.
- Video games don't have runtimes. This missingness is also systematic and not random.

For your ✍ Mini-Project 2: If, say, some routes or time bands have more missing journey legs than others, that might be the insight.

2. Check the distribution

I have this table of all directors listed on IMDb:

- In total I have **n = 266 466** directors
- Two numeric columns per director:
  - `total_movies`: how many movies they directed overall in their entire career
  - `top1000_movies`: how many of those fall in the top 1000 most popular and highly-rated movies

How could I make sense of the distribution of these two columns?

```
plot_df.head(10)
```

primary_name	total_movies	top1000_movies
Akira Kurosawa	31	13
Ingmar Bergman	41	10
Alfred Hitchcock	57	9
Martin Scorsese	53	9
Quentin Tarantino	15	9
Christopher Nolan	14	9
Stanley Kubrick	13	9
Ertem Egilmez	44	8
Steven Spielberg	37	8
Billy Wilder	26	8

2.1 How to get a sense of the distribution

You can use `describe()`:

```
plot_df['total_movies'].describe()
```

Which produces:

```
count    266466.000000
mean          2.662099
std           5.968662
min           1.000000
25%           1.000000
50%           1.000000
75%           2.000000
max         438.000000
Name: total_movies, dtype:
float64
```

How to read this output?

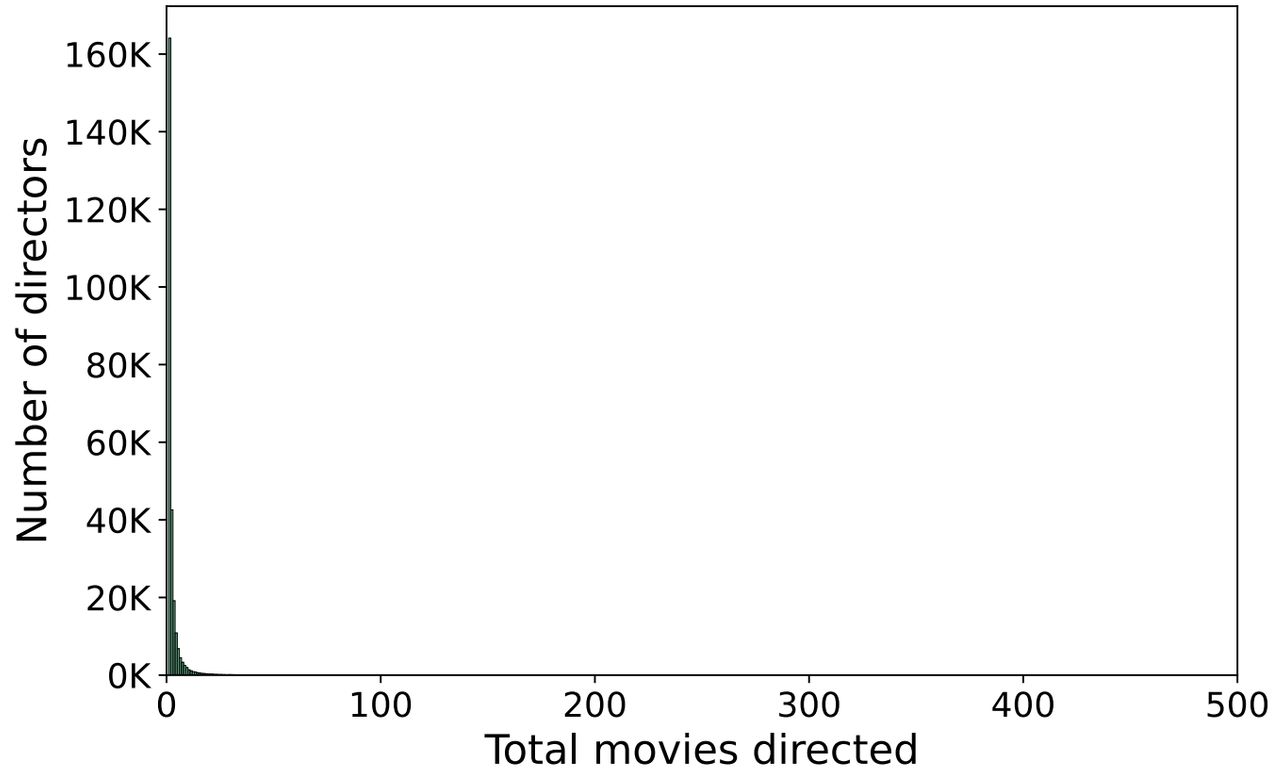
- `count` is the total number of directors
- `mean` is the statistical **mean** number of movies directed
- `std` is the standard deviation of the number of movies directed
- `min` is the minimum number of movies directed
- `25%` is the 25th percentile of the number of movies directed
- `50%` is the **median** number of movies directed
- `75%` is the 75th percentile of the number of movies directed
- `max` is the maximum number of movies directed

2.2 How to get a visual sense of the distribution

Histogram approach:

A histogram allows you to see the full distribution of the data.

In this case, the distribution is heavily **skewed**.



For NB03 exploratory plots, you don't need a polished title yet.

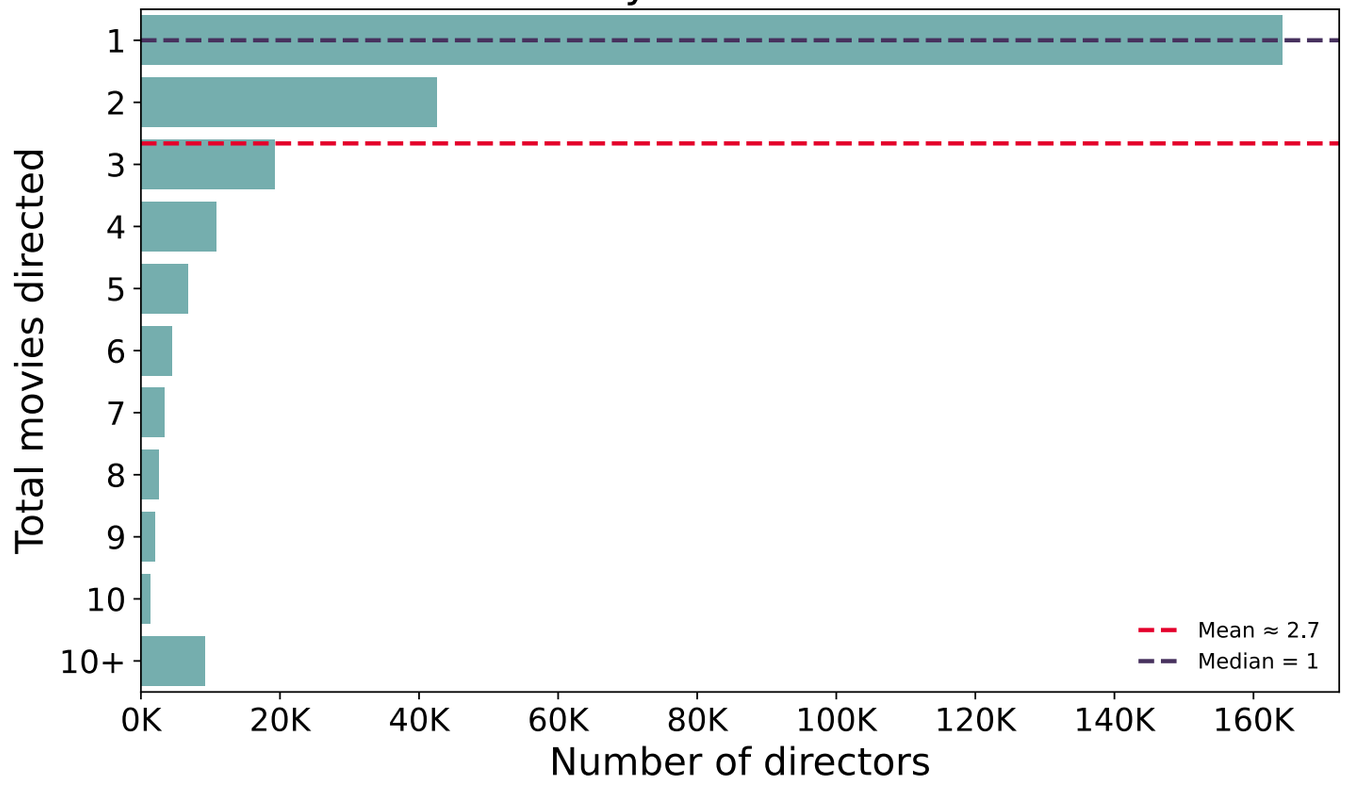
- When you are just exploring your data in your `NB03`, it's alright to just plot the histogram without a title for your own observations.
- 💡 If you think this is worth adding to your `REPORT.md`, then add a narrative title to your plot.

2.3 Second attempt at visualising the distribution

If you further process the data carefully, you can get a more informative histogram 👉

- The **mean** number of movies (2.66) isn't a good measure of average when you have skewed distributions like this.
- The **median** number of movies (1) is a better measure of average in this case

Figure 1. The vast majority of directors in the database have only directed 1 movie!



2.4 Mean vs Median: why they disagree

The mean and median measure "center" in different ways:

- The **mean** minimises squared distances, so a value that's 10 away counts as **100×** worse than one that's 1 away. This is why outliers drag the mean: they get squared.
- The **median** only cares whether a value is above or below the middle, not how far. It's immune to extremes.

A concrete example:

```
journeys = [45, 48, 50, 52, 180]  # one disrupted trip
np.mean(journeys)   # → 75.0   (pulled by 180)
np.median(journeys) # → 50.0   (unaffected)
```

Replace `180` with `500` and the mean jumps to `139`, while the median stays at `50`.

	Mean	**Median**
Measures	Balance point (mass)	Middle position (rank)
Outlier sensitivity	One extreme value can wreck it	Barely moves
Best for	Symmetric data; totals & budgets	Skewed data; "typical" value
Partner statistic	Standard deviation	Interquartile range (IQR)

For example, The UK **Office for National Statistics** (ONS) reports **median** household income, not mean, because a few very high earners pull the mean above what any "typical" household actually experiences.

2.5 The gap between mean and median sometimes IS the insight

The size of the gap between these two measures can tell you something:

Mean vs Median	What it tells you
If mean ≈ median	→ distribution is roughly **symmetric**
If mean > median	→ distribution is **right-skewed** (long tail of high values)
If mean < median	→ distribution is **left-skewed** (long tail of low values)

In your ✍ Mini-Project 2: compute both. Report the gap. If they differ noticeably, that's evidence of skew, and the rubric rewards **justifying** your choice based on what your data looks like. Reporting only one without checking the other hides information. If you want to be more precise, read on kurtosis and consider using Pandas' `DataFrame.kurt()`

3. Check your distributions (another example)

Now, let's look at a distribution that is not skewed.

I selected only movies (`title_type = 'movie'`) that have more than 10,000 votes.

Here are the top 10 highest-rated popular movies of all time:

primary_title	year	average_rating	num_votes
The Shawshank Redemption	1994	9.30	3120155
The Godfather	1972	9.20	2175958
The Chaos Class	1975	9.20	45308
Attack on Titan the Movie: The Last Attack	2024	9.20	21568
Ramayana: The Legend of Prince Rama	1993	9.10	17401
The Dark Knight	2008	9.10	3095865
The Lord of the Rings: The Return of the King	2003	9.00	2119280
Schindler's List	1993	9.00	1555434
12 Angry Men	1957	9.00	956229
The Godfather Part II	1974	9.00	1462039

3.1 Boxplot as a visual summary of the distribution

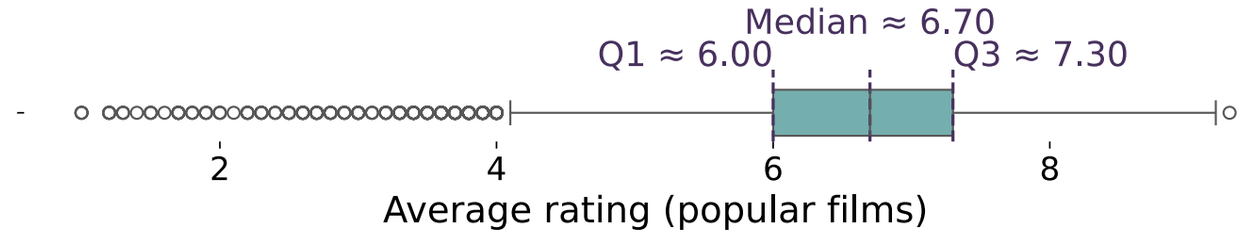
Once again, you can use `describe()`:

```
plot_df['average_rating'].describe()
```

Which produces:

```
count    12118.000000
mean         6.584832
std          1.016968
min          1.000000
25%          6.000000
50%          6.700000
75%          7.300000
max          9.300000
Name: average_rating, dtype:
float64
```

Alternatively, you can view this as a boxplot:



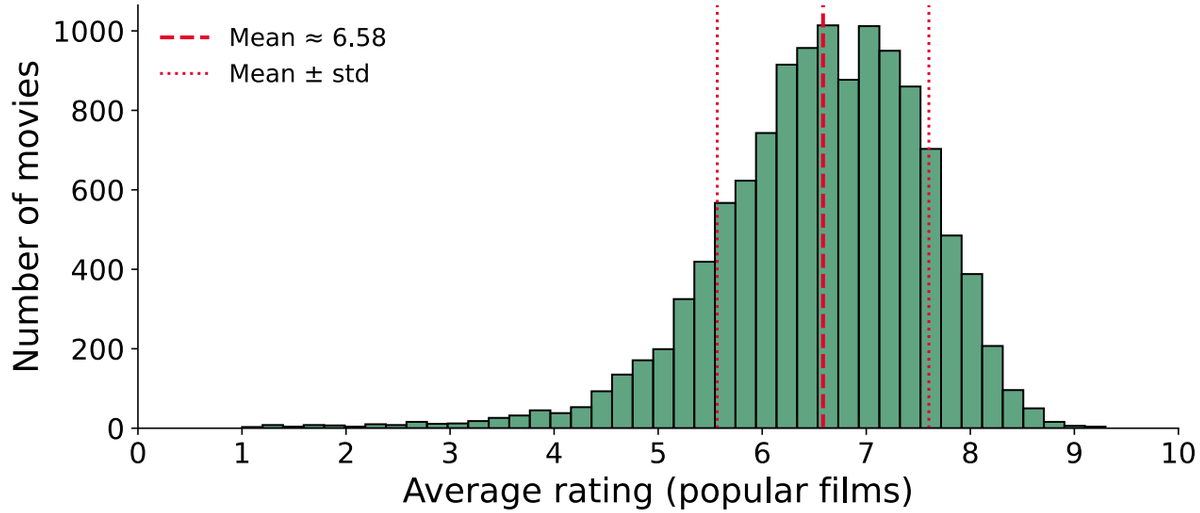
You can describe this as:

- *Typically*, popular movies have an average rating between 6.0 and 7.3.
- There are only a few movies with an exceptionally high rating (9.3)
- There is a small group (albeit a sizeable group) of movies with an average rating below 4.0

3.2 This time the histogram works

Because the distribution is not skewed, the distribution of the data is symmetric similar to a **normal distribution**.

When the data looks like a bell curve, the mean and the median are very similar and it makes sense to use mean and standard deviation to describe the distribution.



Using the mean and standard deviation as estimators, you can describe this as:

- *Most* popular movies have an average rating between 5.6 and 7.6, with an average rating of about 6.6.

4. Outliers are always worth investigating

Just who are these highly prolific directors?

```
df_top_directors[df_top_directors['total_movies'] > 400]
```

	nconst	primary_name	total_movies	top1000_movies
710	nm0644554	Kinya Ogawa	438	0
711	nm0183659	Gérard Courant	402	0

Do a bit of research to find out who these directors are and to confirm that this is not an error in your data collection process but rather a reflection of very unique individual careers.

What are these exceptionally highly rated movies?

```
df_top_movies[df_top_movies['average_rating'] > 9]
```

primary_title	year	avg_rating	num_votes
The Shawshank Redemption	1994	9.30	3120155
The Godfather	1972	9.20	2175958
The Chaos Class	1975	9.20	45308
Attack on Titan the Movie: The Last Attack	2024	9.20	21568

Whether this is an insight depends on your research question.

For your MP2: if some journeys take 3 hours when most take 45 minutes, is that a data error or a real phenomenon (e.g. disruptions)?

Coffee Break

Hour 2: 📊 Data Visualisation & Communication

You've checked your data quality and understand your distributions.

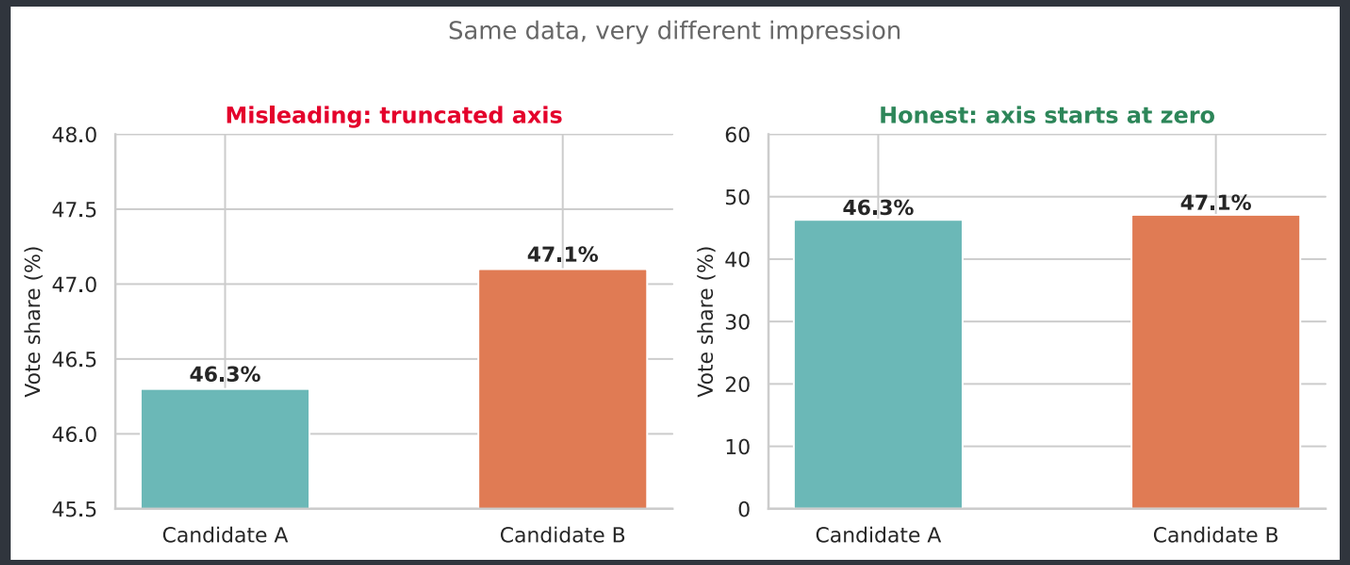
In Hour 2, you'll focus on how to **show** your findings honestly and avoid common mistakes.

The Seven Sins of Data Visualisation

(Or *some* sins, at least. There are many more.)

Sin	What goes wrong	How to fix it
Truncated axis	Y-axis doesn't start at zero, inflating differences	Start charts with countable or proportion at zero. Annotate if you MUST truncate
Pie chart overload	Too many slices and human eyes struggle with angle comparison	Use a bar chart instead or a maximum of 4-5 slices if you insist
3D for 2D data	Perspective distorts values, and back slices look smaller	Use 2D charts, because 3D adds no information
Rainbow colour maps	Perceptually uneven, with misleading yellow band	Use sequential or diverging palettes (viridis, coolwarm)
Overcrowding	Too many variables, labels, or data points in one chart	Simplify the chart, and use FacetGrid for multi-group comparison
Inconsistent scales	Different y-axes* or icon sizes distort comparison	Keep scales consistent across panels
Correlation as causation	Two trends may grow together and be unrelated	State associations, not causes (more on this later)

Sin #1: The truncated axis



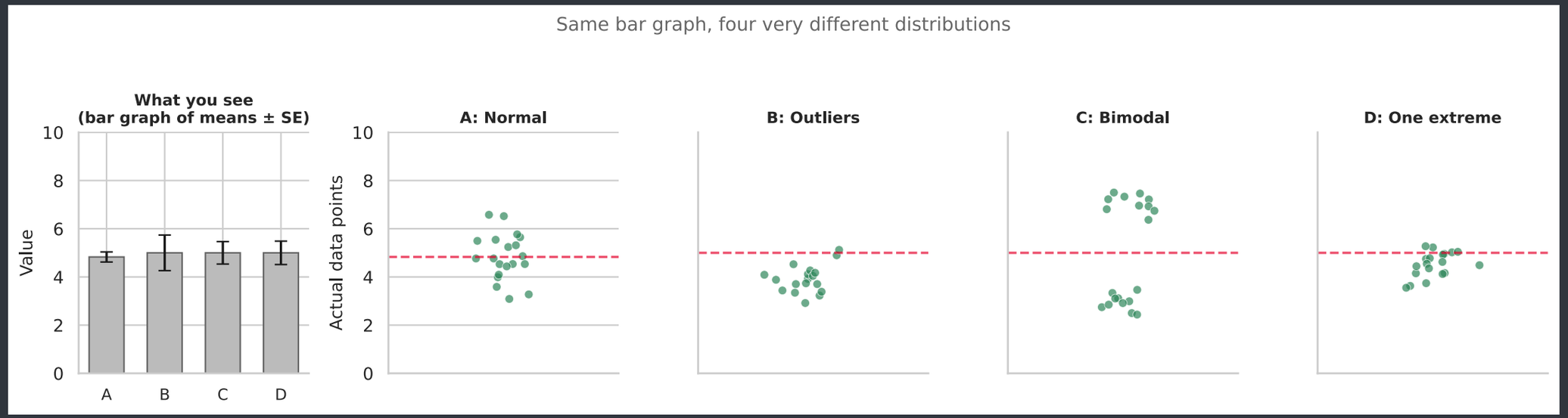
The **same data**, two very different impressions.

On the left, the y-axis starts at 44%, making a 1-percentage-point difference look enormous. On the right, the y-axis starts at 0, showing the true proportion.

Rule of thumb: bar charts should always start at zero. Line charts sometimes have legitimate reasons to zoom in, but you should annotate why.

📖 Flourish: Common Mistakes in Data Visualization

Sin #2: Bar plots hide distributions



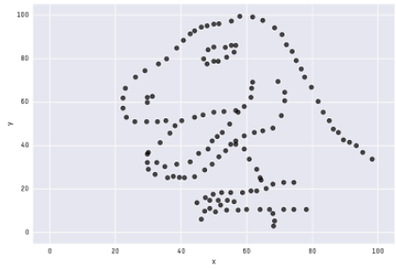
All four distributions produce **the same bar graph** (same mean, same error bar). But look at the actual data:

- One is normally distributed ☑️
- One has two outliers pulling the mean ⚠️
- One is bimodal (two distinct groups!) 🚨
- One has a single extreme outlier 🚨

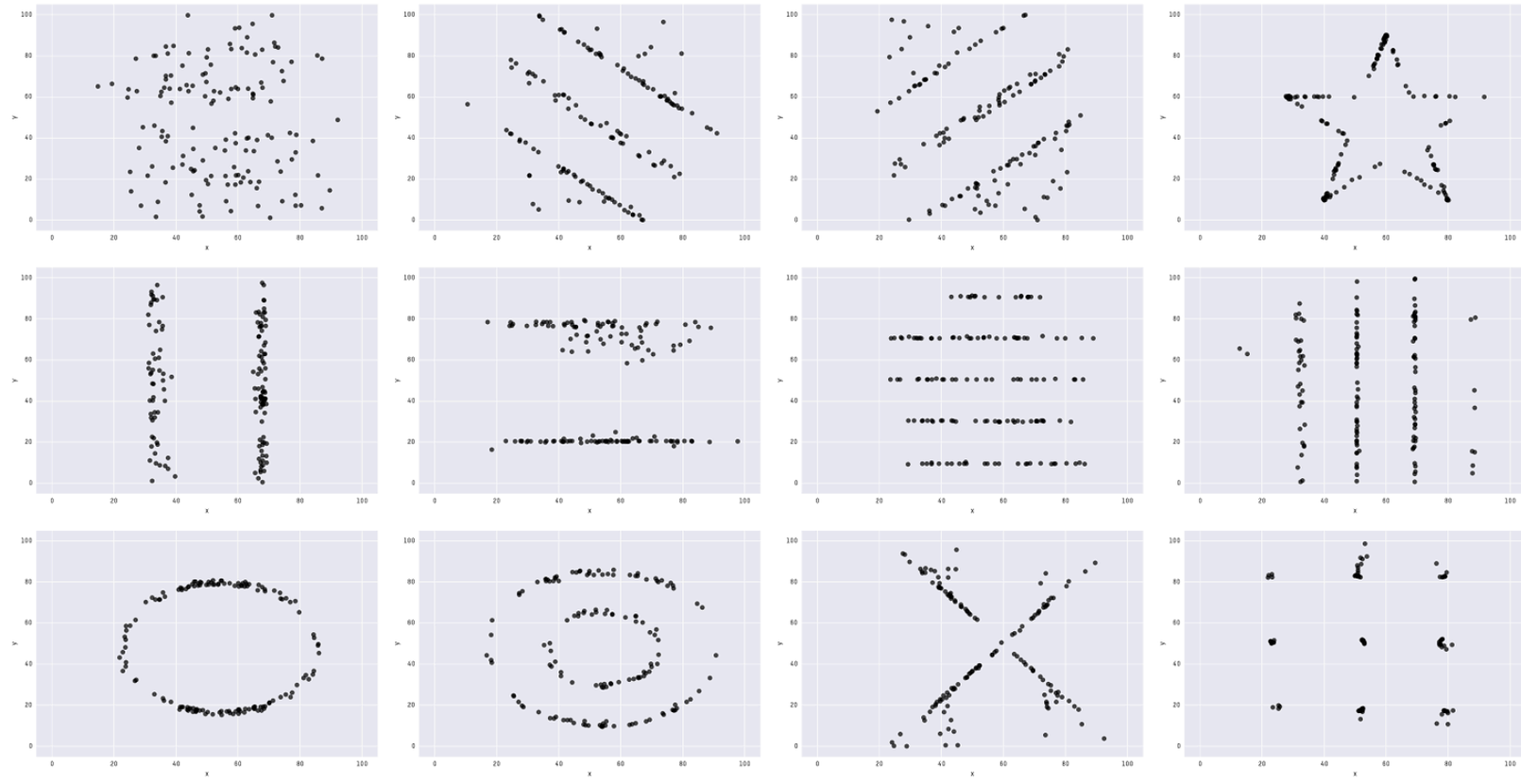
You saw this principle in 💻 **W08 Lecture** with the strip+box+mean plot. This is the research paper behind it.

📖 Weissgerber et al. (2015), open access

The same lesson as the Datasaurus



```
X Mean: 54.26
Y Mean: 47.83
X SD  : 16.76
Y SD  : 26.93
Corr. : -0.06
```



What good data visualisation looks like

Good visualisations make your message clear and help your audience interpret complex information.

Here's one I really love 👇

🔗 **LINK:** We compared eight AI search engines. They're all bad at citing news. (Columbia Journalism Review)

Why this visualisation works

1. **Progressive disclosure**: Guides the reader step-by-step
2. **Clear annotations**: Explains what you're seeing
3. **Thoughtful colour use**: Consistent meaning throughout
4. **Hierarchy of information**: Most important insights are emphasised
5. **Multiple views**: Shows the same data in different ways for deeper understanding

More examples I love

- 🔗 **LINK:** Ali Wong's Stand-Up Routine (The Pudding)
  (how they made it)
- 🔗 **LINK:** Why do cats and dogs...
  (design process)
- 🔗 **LINK:** EURO 2024 Final Scrollytelling Analysis, Grand Prize winner of the **Closeread Prize 2025**
  (all 40 submissions on the Posit Forum)
- 🔗 **LINK:** If the Moon Were Only 1 Pixel (Josh Worth), scroll through the solar system at scale

Across these examples, the author guides interpretation with a clear narrative rather than leaving the viewer with an unlabeled chart.

🏆 Hall of Fame / 🗑️ Hall of Shame

Now it's your turn. Open the `#social` channel on Slack and find two threads:

🏆 **Hall of Fame:** Share a link or screenshot of a data visualisation you think is **excellent**. Explain in one sentence what makes it work.

🗑️ **Hall of Shame:** Share a link or screenshot of a data visualisation that is **misleading, confusing, or ugly**. Identify which sin it commits.

Take 5 minutes now. We'll look at a few submissions together.

Let's look at what you found

For each example, ask:

- **What story** is the visualisation trying to tell?
- **Does the chart type** fit the data? (categorical → bar; time → line; distribution → histogram/box)
- **Could it mislead?** Truncated axis? Missing context? Pie chart with 15 slices?
- **What would you change** to make it clearer?

These are the same questions you should ask about your own plots before putting them in `REPORT.md` of your ✍️ **Mini Project 2**.

Static Insights vs Interactive Dashboards

Static insights
(what your REPORT.md should do)

- Guide the reader through **YOUR** analytical conclusions
- Present findings in a structured narrative
- Make specific claims supported by evidence
- Even “there is no noticeable pattern” is a valid conclusion
- The author (you) is making the argument

Interactive dashboards
(complementary only)

- Allow readers to explore data themselves
- No pre-determined narrative or conclusions
- Enable filtering, selection, custom views
- The reader makes their own discoveries
- Better suited for the **Group Project** (and even then, only AFTER you’ve told the story)

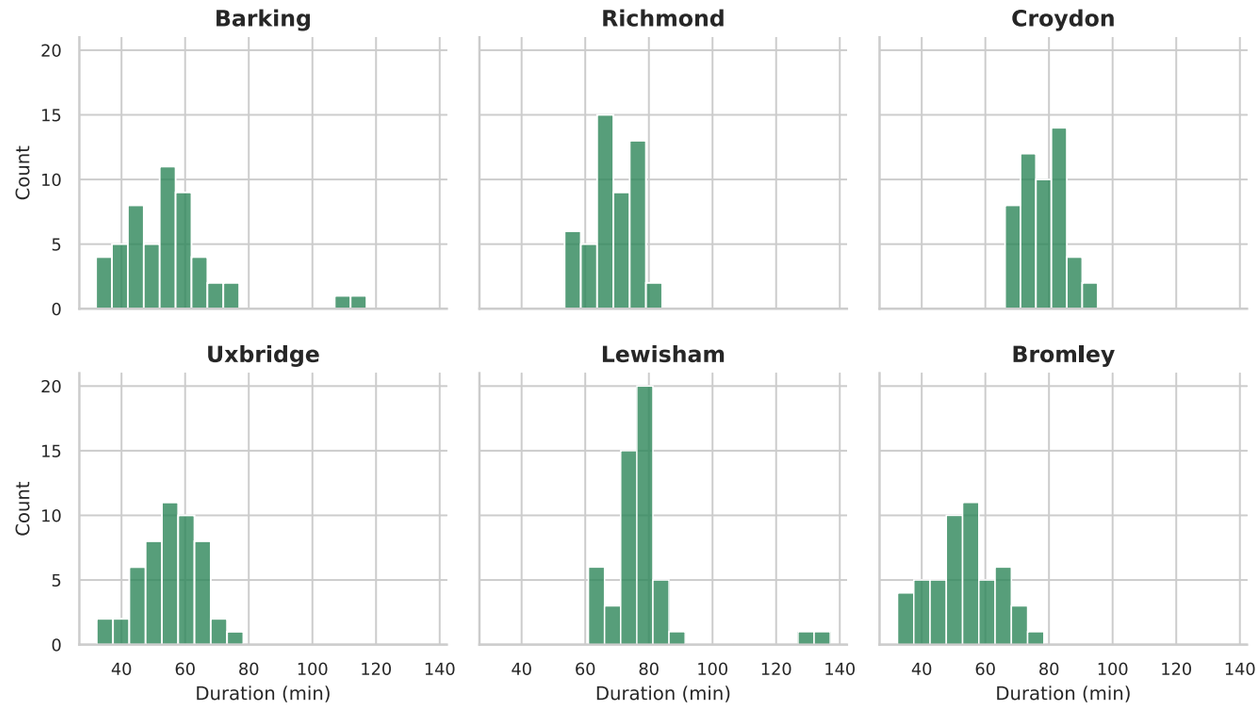
For your Mini-Project 2 REPORT.md: Present clear findings and arguments. Your two insights should state what you found and why it matters, with evidence beyond the chart itself.

FacetGrid: comparing groups systematically

When you have multiple groups (destinations, time bands, boroughs), plotting them all on one axis gets crowded.

`sns.FacetGrid` creates a **grid of subplots**, one per group, with consistent axes so comparisons are fair.

```
g = sns.FacetGrid(
    df_all,
    col="destination",
    col_wrap=3,
    height=3
)
g.map_dataframe(
    sns.histplot,
    x="duration_min",
    binwidth=5
)
```

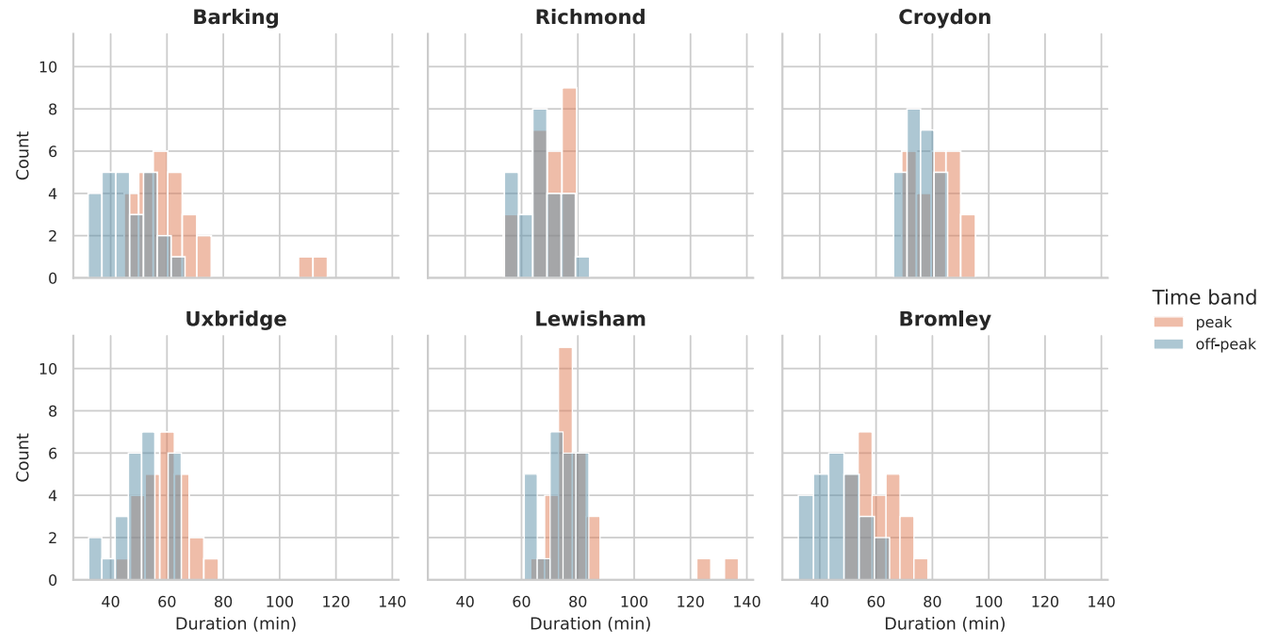


Each panel shows the distribution for one destination. Same x-axis, same y-axis, so you can compare shapes at a glance.

FacetGrid with hue

Add `hue` to compare subgroups within each panel:

```
g = sns.FacetGrid(
    df_all,
    col="destination",
    hue="time_band",
    col_wrap=3,
    height=3,
)
g.map_dataframe(
    sns.histplot,
    x="duration_min",
    binwidth=5,
    alpha=0.5,
)
g.add_legend()
```

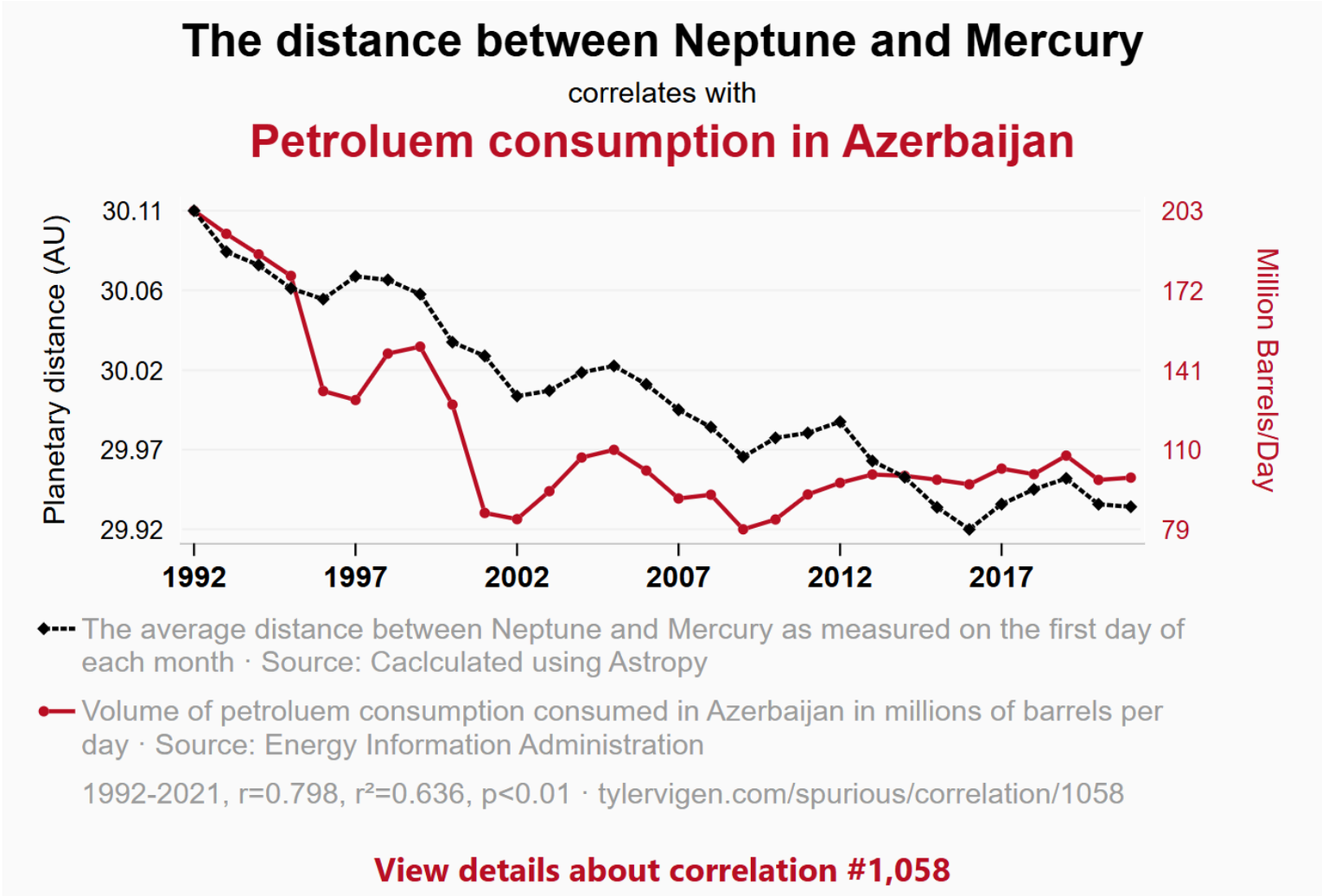


Now you can see whether peak vs off-peak distributions differ *within* each destination and *across* destinations. **But the key takeaway might not be super obvious, you need to guide your reader if you produce more complex visualisations like these.**

📖 seaborn FacetGrid documentation: `col_wrap`, `sharex`, `sharey` are your friends.

5. Correlation is not causation

Key rule: **“correlation does not imply causation.”**



Two trends can move together because:

1. **Coincidence:** the variables correlate in this time period
2. **Confounding variable:** a third factor drives both
3. **Reverse causation:** the direction is the opposite of what you assumed
4. **Actual causation:** rare, and requires much more evidence than a chart

📖 Tyler Vigen’s Spurious Correlations: hilarious examples of correlation without causation.

What this means for your MP2

If you merged your TfL journey data with the ONS Postcode Directory, you might find:

> "Boroughs with higher deprivation scores (lower IMD rank) tend to have longer peak journey times."

That's a **correlation**. It is NOT evidence that deprivation *causes* worse transport. Many confounding factors could explain this:

- More deprived boroughs may be further from central London (geography, not deprivation)
- They may have fewer transport connections (infrastructure investment, not deprivation itself)
- Your sample of postcodes may not be representative

In your REPORT.md: State what you observe. Use language like "is associated with" or "tends to co-occur with" rather than "causes" or "leads to."

Closeread: an optional upgrade for your REPORT.md

Closeread is a Quarto extension for **scrollytelling**, where text narrates alongside highlighted visuals as the reader scrolls.

Many of the examples from earlier use scrollytelling.

If you use closeread for your MP2:

- It **fully replaces** REPORT.md (you don't submit both)
- It's one route to higher Communication marks if used well
- But a solid REPORT.md with clear narrative titles and well-chosen visuals is **enough**

☞ If going for that route, you would have to go through the Quarto documentation yourself!

Getting started:

```
quarto add qmd-lab/closeread
```

```
---
title: "My MP2 Report"
format:
  closeread-html: default
---
```

🔗 closeread.dev: documentation and examples

🔗 Closeread Prize Winners (Posit): see what's possible

What's Next?

- **In the 💻 W09 Lab tomorrow:** NB03 working session (apply today's EDA to your MP2 data) + **form your groups** for the 📦 Group Project (3-4 people, ideally from the same lab section).
- **Week 10 Lecture:** Using Git as a team: `git fetch`, `git pull`, merge conflicts. Essential for your group project.
- **Monday W11:** Formative group pitch presentations (not graded, but you'll get feedback from Jon and the TAs that will help your project). The 📦 Group Project is worth **40%** of your final grade, assessed on the final submission in May.

The EDA checklist for your NB03

Before you write your REPORT.md, make sure you've done this in NB03:

Step	What to check	Tools
1	**Completeness**: what percentage of each column has data?	`.notna().sum() / len(df)`
2	**Systematic missingness**: does missingness vary by group?	`.groupby().apply()` with a completeness function
3	**Distribution shape**: is it skewed or symmetric?	`sns.histplot()`, `.describe()`
4	**Central tendency**: is mean or median more appropriate?	Compare both; justify your choice
5	**Outliers**: are extreme values errors or real phenomena?	Filter and investigate; domain reasoning
6	**Relationships**: do variables co-vary? (association, not causation)	Grouped comparisons, FacetGrid
7	**Visualisation**: does your plot show the data honestly?	Strip+box+mean for small n; narrative titles

Then pick your two best insights for REPORT.md. Each insight needs a narrative title that states your finding.

Appendix

Post-Lecture Actions

- Start applying the EDA checklist to your MP2 NB03
- Compute both mean and median for your journey times: do they differ?
- Try at least one FacetGrid with your MP2 data
- Come to tomorrow's lab ready to form your group project team

Key References

- 📖 Weissgerber et al. (2015): Beyond bar and line graphs
- 📖 Same Stats, Different Graphs (Autodesk): Datasaurus Dozen
- 📖 Friends Don't Let Friends Make Bad Graphs
- 📖 Tyler Vigen's Spurious Correlations
- 📖 Closeread documentation
- 📖 seaborn FacetGrid docs

Looking Ahead

- **Tomorrow (W09 Friday)**: NB03 working session + group formation
- **W10 Lecture (Thursday)**: Git collaboration for teams
- **Wednesday 1 April, 8pm**: ✍️ Mini-Project 2 deadline
- **Monday W11**: Formative group pitches (optional but recommended)
- **May 2026**: 📦 Group Project final submission (40% of grade)