Introduction to relational plots and subplots

INTRODUCTION TO DATA VISUALIZATION WITH SEABORN

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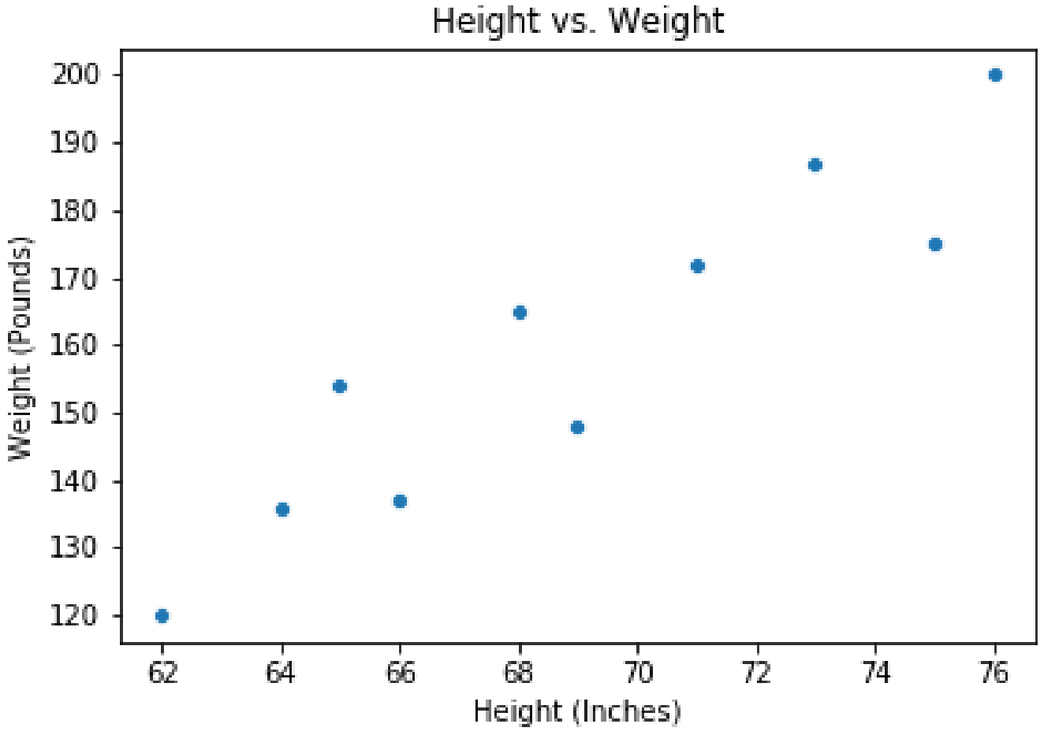
datacamp

Questions about quantitative variables

Relational plots

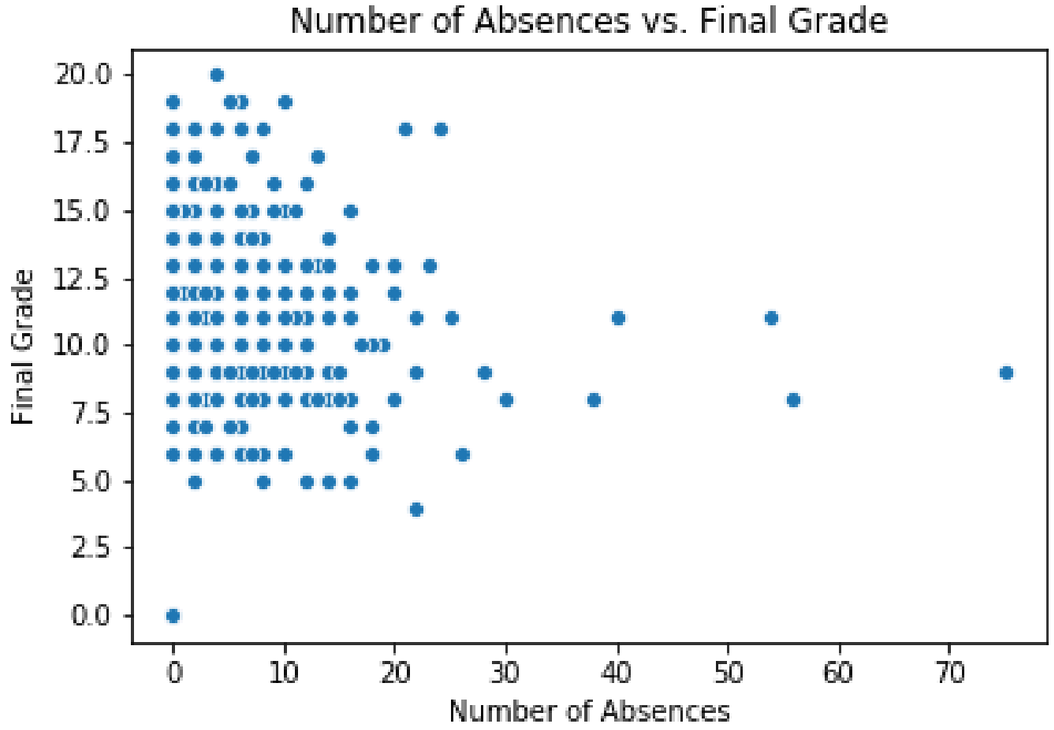
- Height vs. weight



Questions about quantitative variables

Relational plots

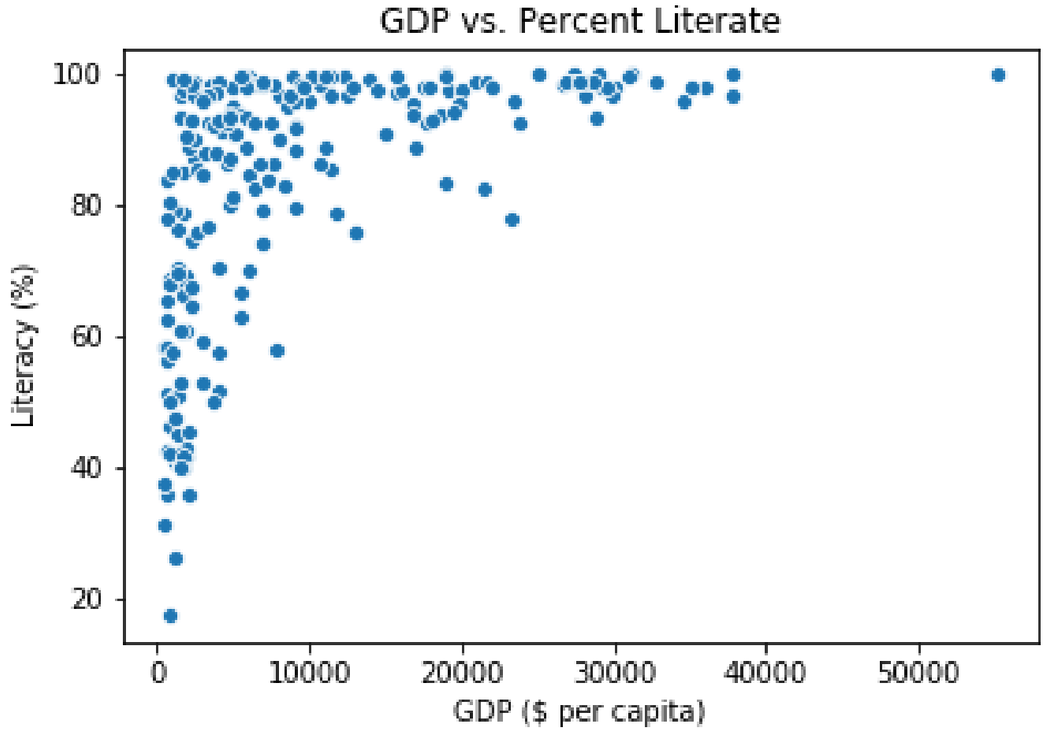
- Height vs. weight
- Number of school absences vs. final grade

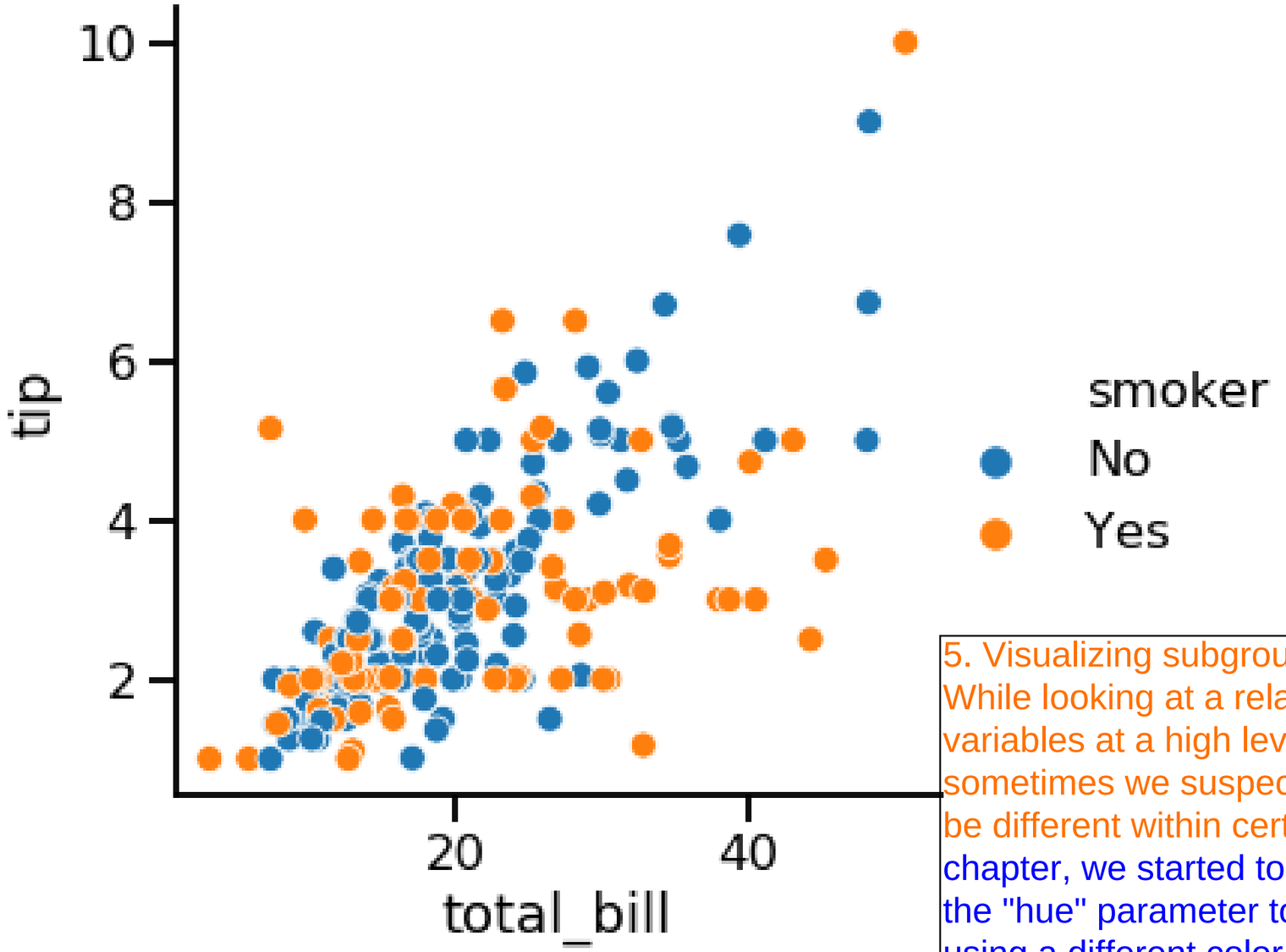


Questions about quantitative variables

Relational plots

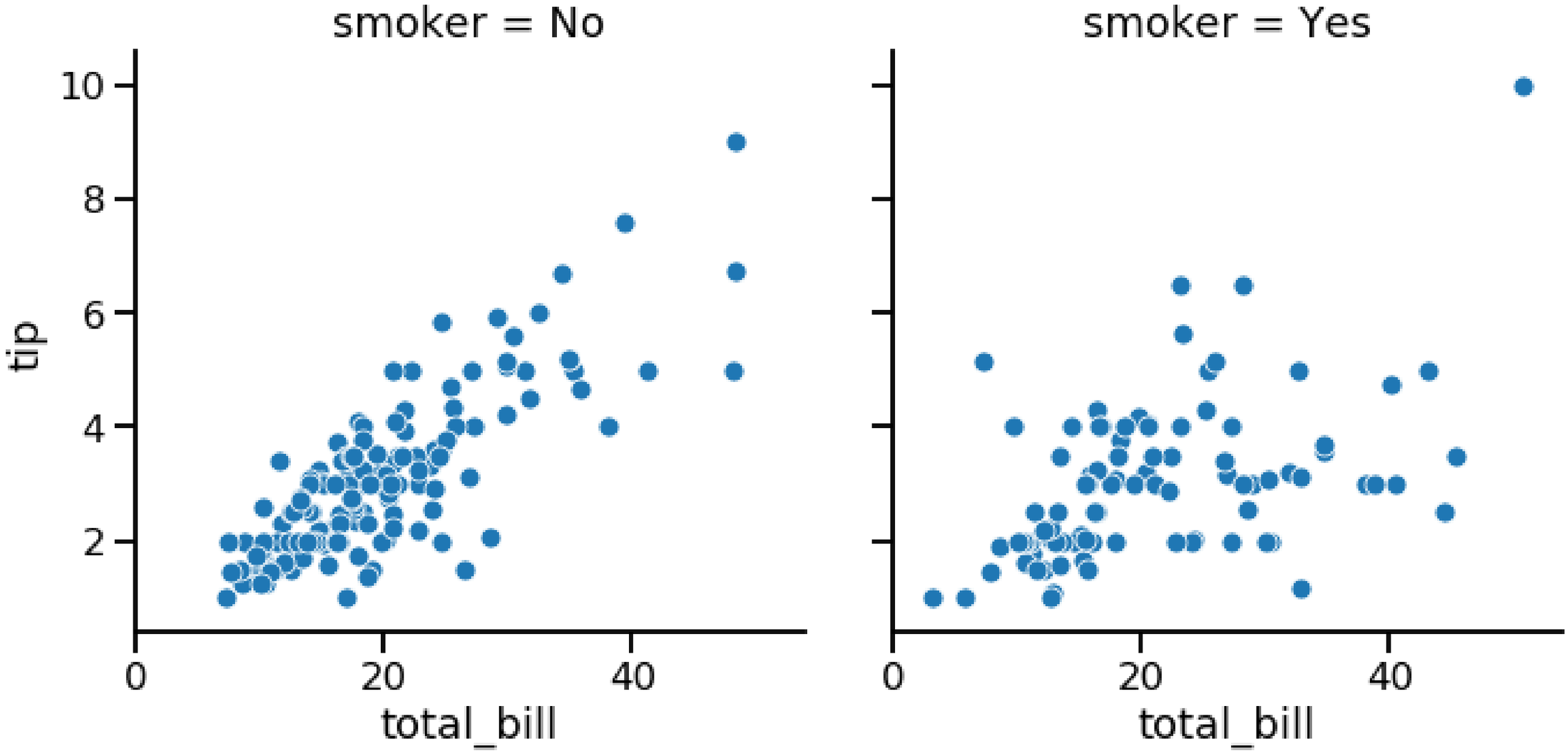
- Height vs. weight
- Number of school absences vs. final grade
- GDP vs. percent literate





5. Visualizing subgroups

While looking at a relationship between two variables at a high level is often informative, sometimes we suspect that the relationship may be different within certain subgroups. In the last chapter, we started to look at subgroups by using the "hue" parameter to visualize each subgroup using a different color on the same plot.


smoker = No
smoker = Yes
tip
10
8
6
4
2
0
20
40
total_bill
0
20
40
total_bill

Introducing relplot()

- Create "relational plots": scatter plots or line plots

Why use `relplot()` instead of `scatterplot()`?

- `relplot()` lets you create subplots in a single figure

7. Introducing relplot()
To do this, we're going to introduce a new Seaborn function: "relplot()". "relplot()" stands for "relational plot" and enables you to visualize the relationship between two quantitative variables using either scatter plots or line plots. You've already seen scatter plots, and you'll learn about line plots later in this chapter. Using "relplot()" gives us a big advantage: the ability to create subplots in a single figure. Because of this advantage, we'll be using "relplot()" instead of "scatterplot()" for the rest of the course.

scatterplot() vs. relplot()

Using `scatterplot()`

```
import seaborn as sns
import matplotlib.pyplot as plt

sns.scatterplot(x="total_bill",
                y="tip",
                data=tips)

plt.show()
```

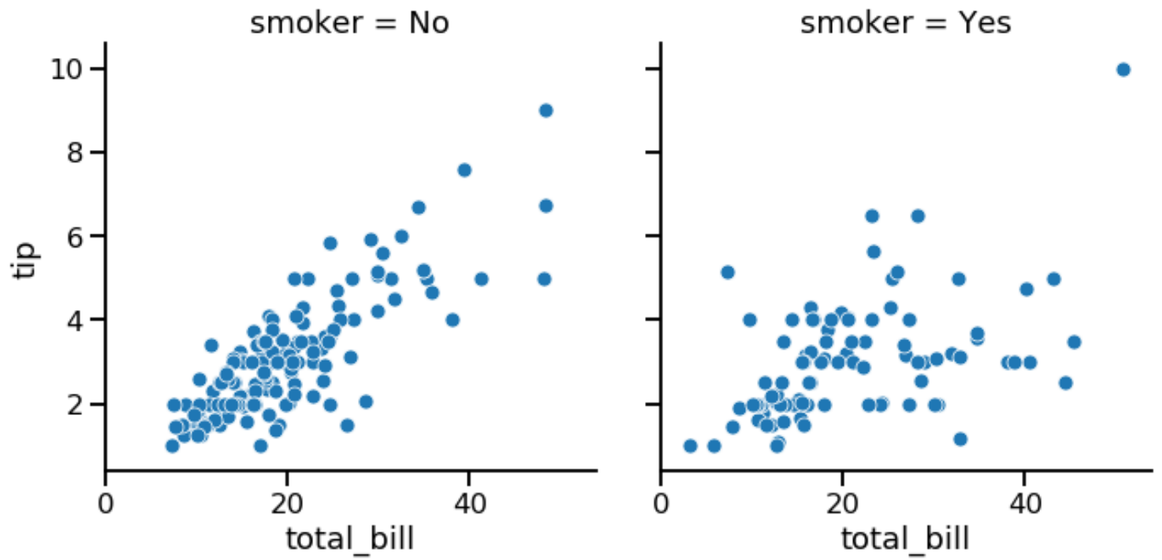
Using `relplot()`

```
import seaborn as sns
import matplotlib.pyplot as plt

sns.relplot(x="total_bill",
            y="tip",
            data=tips,
            kind="scatter")

plt.show()
```

8. scatterplot() vs. relplot()
Let's return to our scatter plot of total bill versus tip amount from the tips dataset. On the left, we see how to create a scatter plot with the "scatterplot" function. To make it with "relplot()" instead, we change the function name to "relplot()" and use the "kind" parameter to specify what kind of relational plot to use - scatter plot or line plot. In this case, we'll set kind equal to the word "scatter".

Subplots in columns

```
import seaborn as sns
import matplotlib.pyplot as plt

sns.relplot(x="total_bill",
            y="tip",
            data=tips,
            kind="scatter",
            col="smoker")
plt.show()
```

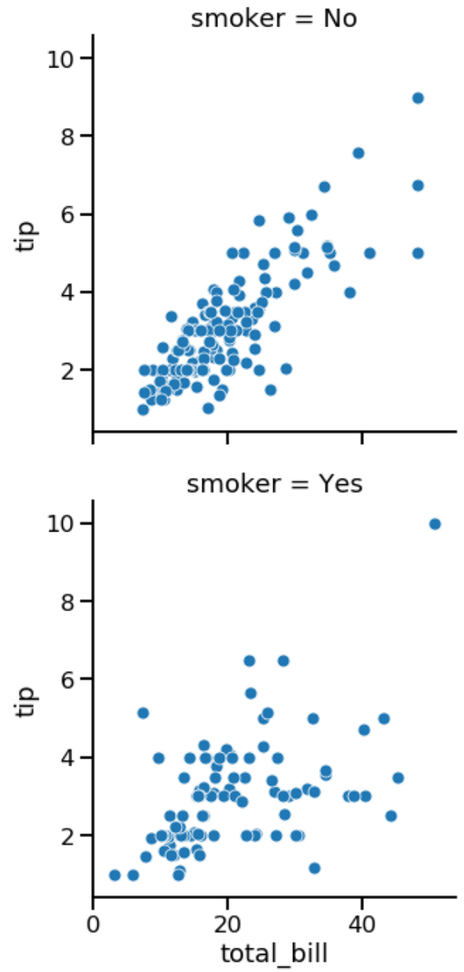


9. Subplots in columns
By setting "col" equal to "smoker", we get a separate scatter plot for smokers and non-smokers, **arranged horizontally in columns.**

Subplots in rows

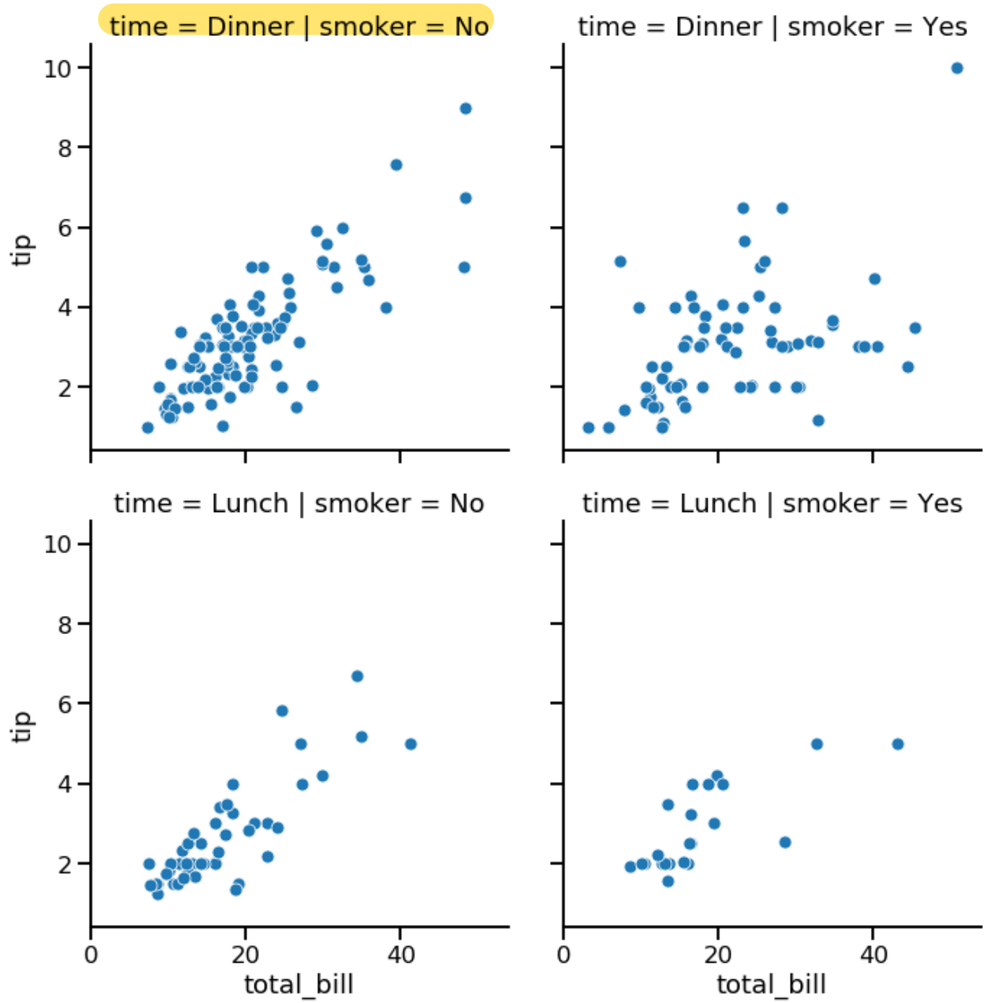
```
import seaborn as sns
import matplotlib.pyplot as plt

sns.relplot(x="total_bill",
            y="tip",
            data=tips,
            kind="scatter",
            row="smoker")
plt.show()
```

10. Subplots in rows
If you want to arrange these vertically in rows instead, you can use the "row" parameter instead of "col".



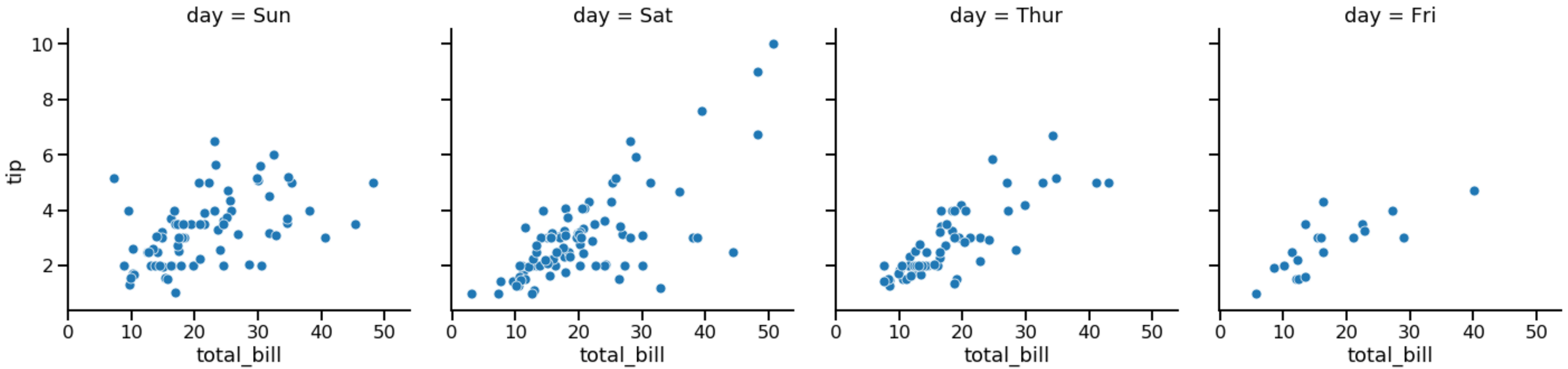
Subplots in rows and columns

```
import seaborn as sns
import matplotlib.pyplot as plt

sns.relplot(x="total_bill",
            y="tip",
            data=tips,
            kind="scatter",
            col="smoker",
            row="time")
plt.show()
```



11. Subplots in rows and columns
It is possible to use both "col" and "row" at the same time. Here, we set "col" equal to smoking status and "row" equal to the time of day (lunch or dinner). Now we have a subplot for each combination of these two categorical variables.

Subgroups for days of the week

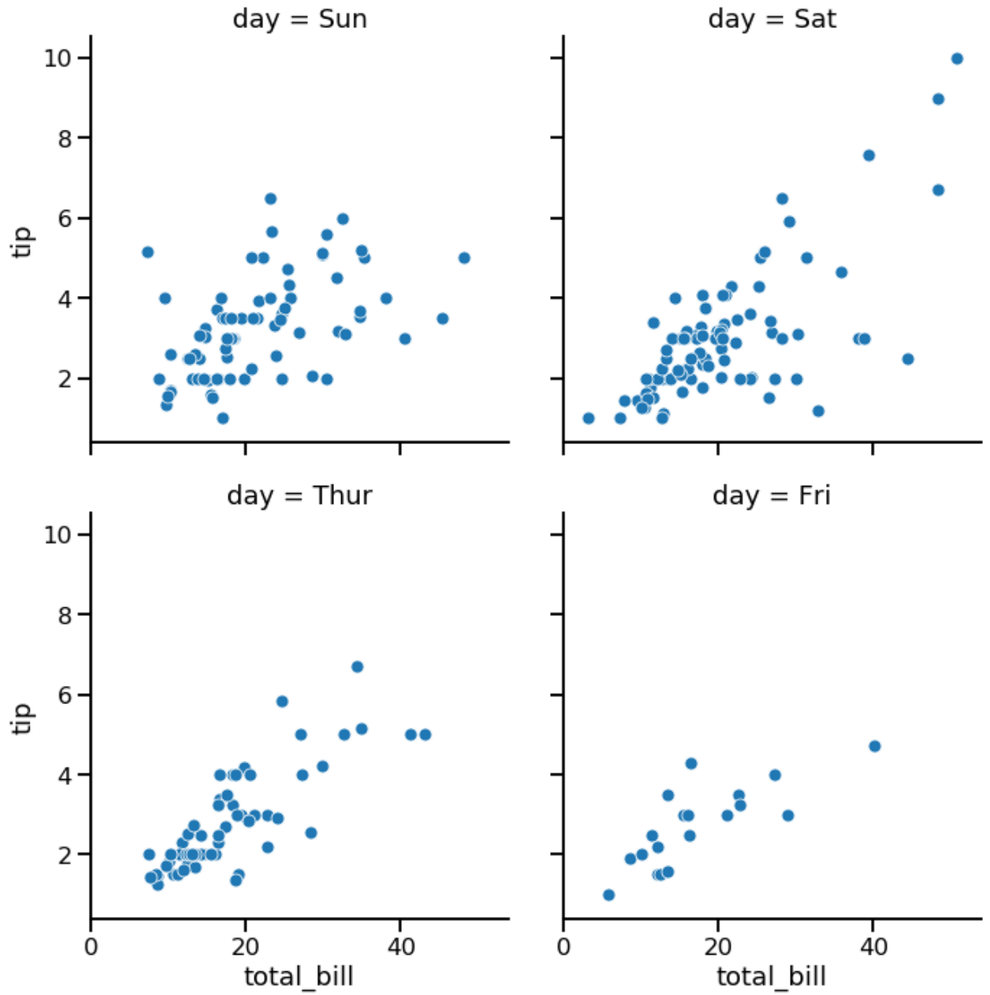


12. Subgroups for days of the week
As another example, let's look at subgroups based on day of the week. There are four subplots here, which can be a lot to show in a single row. To address this, you can use the "col_wrap" parameter to specify how many subplots you want per row.

Wrapping columns

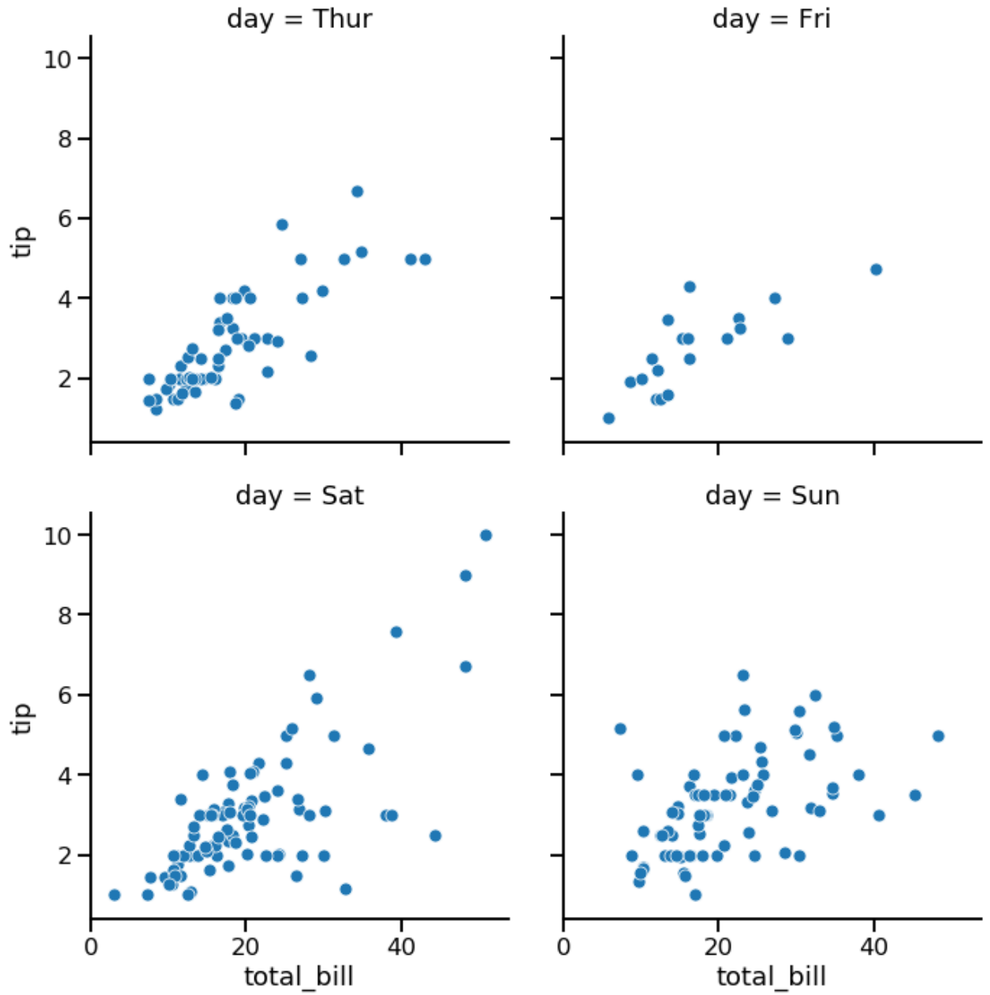
```
import seaborn as sns
import matplotlib.pyplot as plt

sns.relplot(x="total_bill",
            y="tip",
            data=tips,
            kind="scatter",
            col="day",
            col_wrap=2)
plt.show()
```

13. Wrapping columns
Here, we set "col_wrap" equal to two plots per row.



Ordering columns

```
import seaborn as sns
import matplotlib.pyplot as plt

sns.relplot(x="total_bill",
            y="tip",
            data=tips,
            kind="scatter",
            col="day",
            col_wrap=2,
            col_order=["Thur",
                       "Fri",
                       "Sat",
                       "Sun"])

plt.show()
```



14. Ordering columns

We can also change the order of the subplots by using the "col_order" and "row_order" parameters and giving it a list of ordered values.

Let's practice!

INTRODUCTION TO DATA VISUALIZATION WITH SEABORN

Customizing scatter plots

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Scatter plot overview

Show relationship between two quantitative variables

We've seen:

- Subplots (`col` and `row`)
- Subgroups with color (`hue`)

New Customizations:

- Subgroups with point size and style
- Changing point transparency

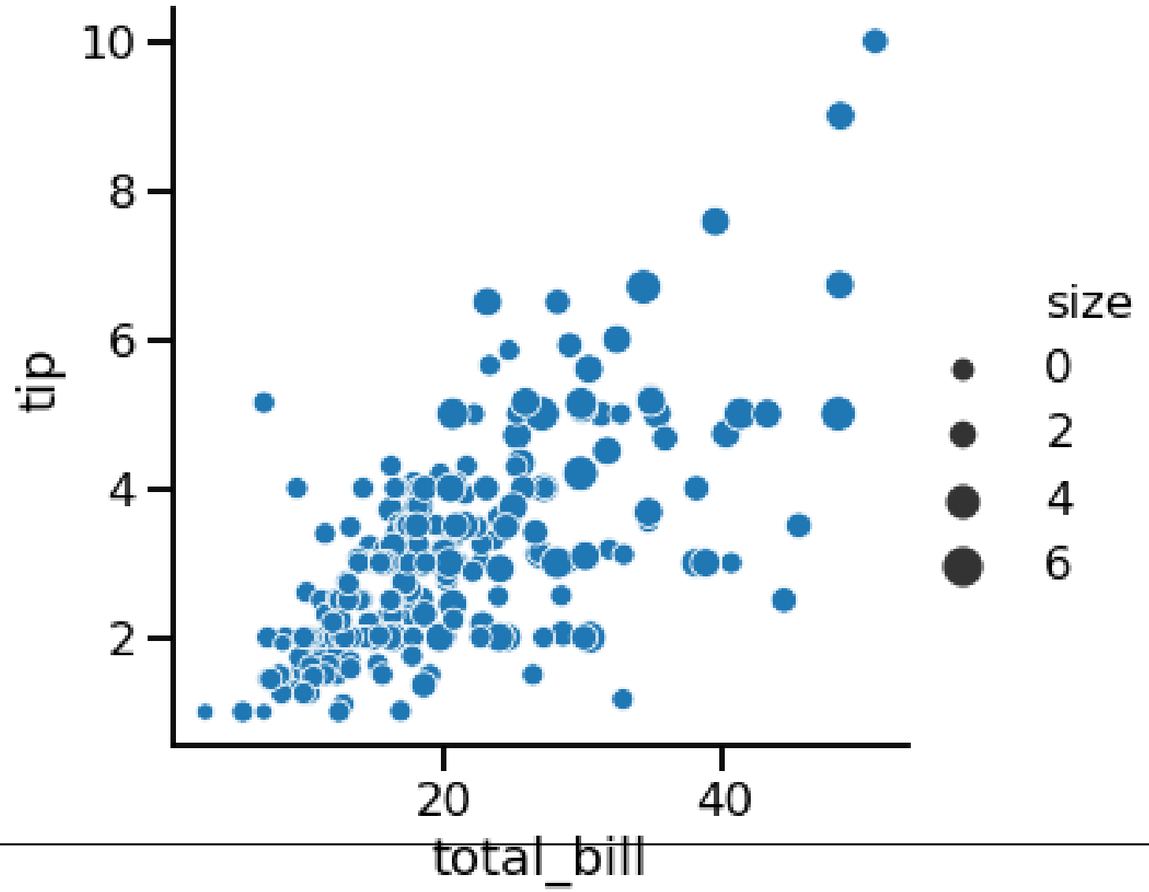
Use with both `scatterplot()` and `relplot()`

All of these options can be used in both the "scatterplot()" and "relplot()" functions, but we'll continue to use "relplot()" for the rest of the course since it's more flexible and allows us to create subplots. For the rest of this lesson, we'll use the tips dataset to learn how to use each customization and cover best practices for deciding which customizations to use.

Subgroups with point size

```
import seaborn as sns
import matplotlib.pyplot as plt

sns.relplot(x="total_bill",
            y="tip",
            data=tips,
            kind="scatter",
            size="size")
plt.show()
```



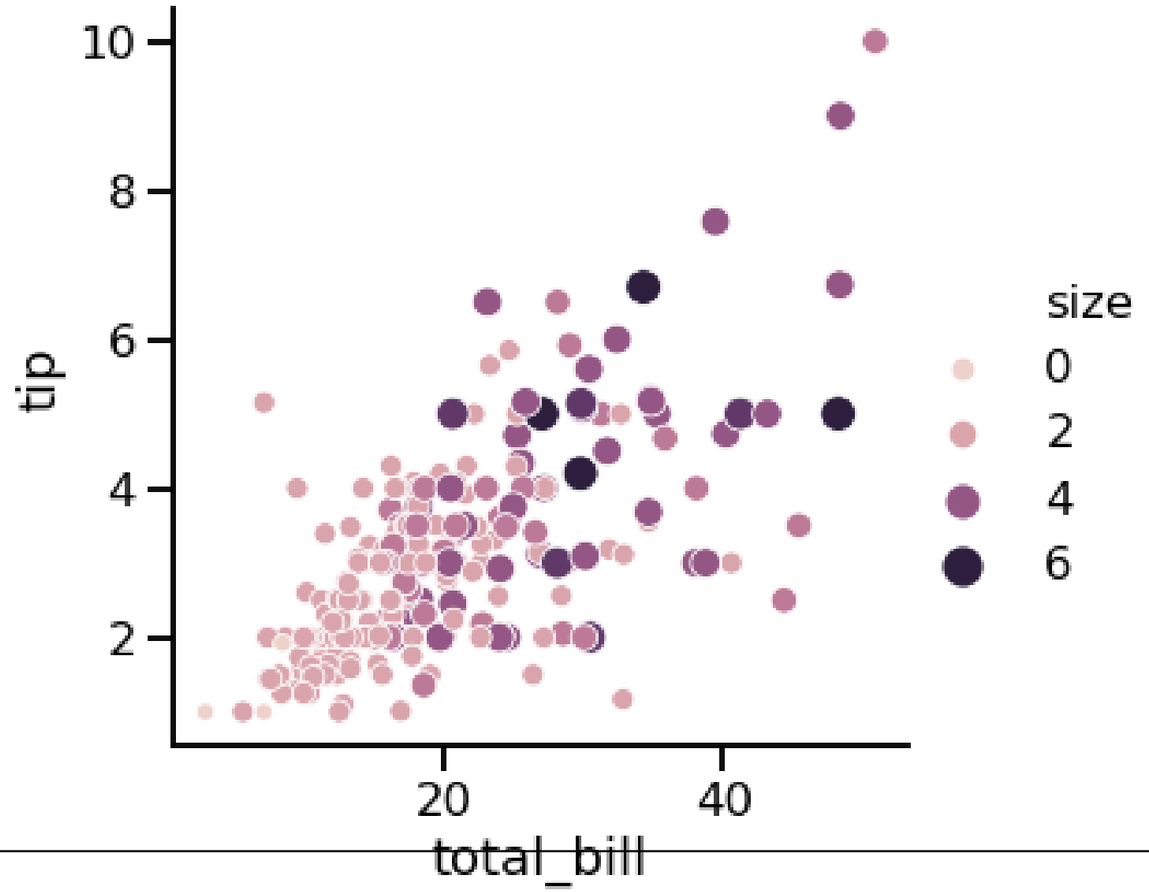
3. Subgroups with point size

We want each point on the scatter plot to be sized based on the number of people in the group, with larger groups having bigger points on the plot. To do this, we'll set the "size" parameter equal to the variable name "size" from our dataset. As this example demonstrates, varying point size is best used if the variable is either a quantitative variable or a categorical variable that represents different levels of something, like "small", "medium", and "large". **This plot is a bit hard to read because all of the points are of the same color.**

Point size and hue

```
import seaborn as sns
import matplotlib.pyplot as plt

sns.relplot(x="total_bill",
            y="tip",
            data=tips,
            kind="scatter",
            size="size",
            hue="size")
plt.show()
```



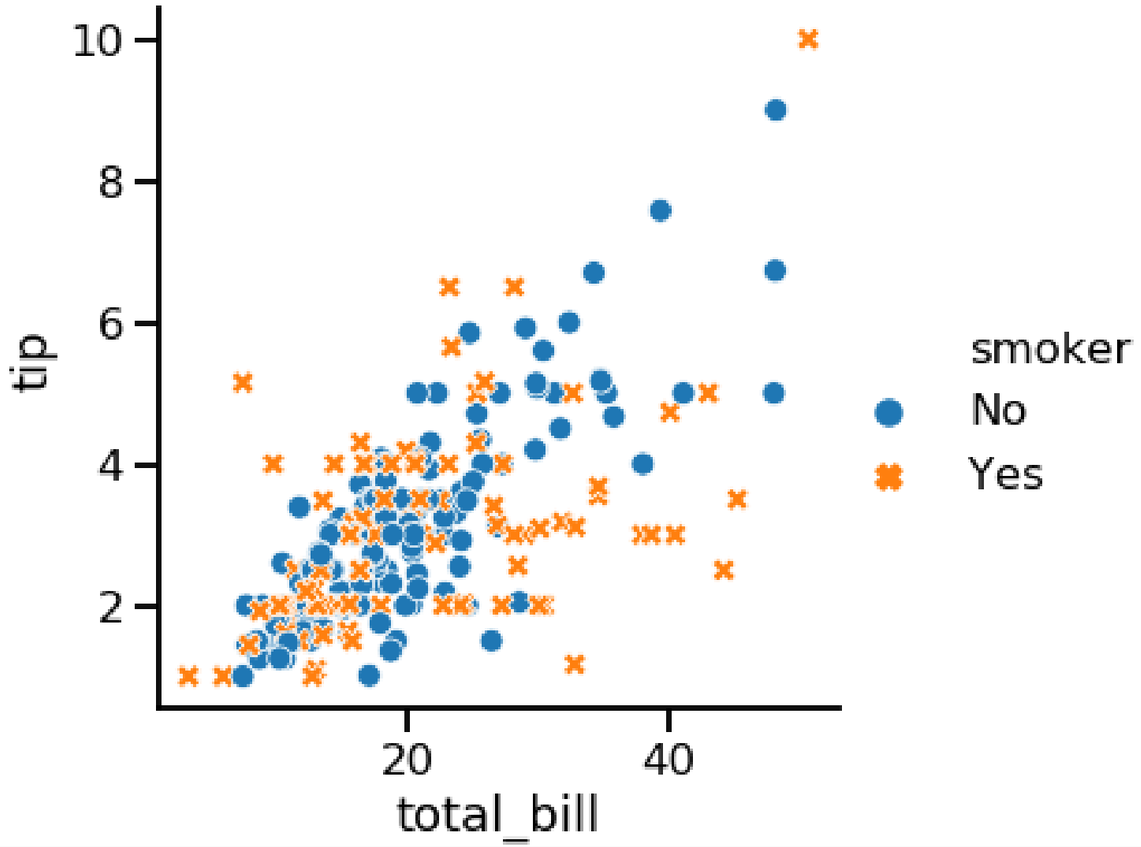
4. Point size and hue

We can make it easier by using the "size" parameter in combination with the "hue" parameter. To do this, set "hue" equal to the variable name "size". Notice that because "size" is a quantitative variable, Seaborn will automatically color the points different shades of the same color instead of different colors per category value like we saw in previous plots. Now larger groups have both larger and darker points, which provides better contrast and makes the plot easier to read.

Subgroups with point style

```
import seaborn as sns
import matplotlib.pyplot as plt

sns.relplot(x="total_bill",
            y="tip",
            data=tips,
            kind="scatter",
            hue="smoker",
            style="smoker")
plt.show()
```

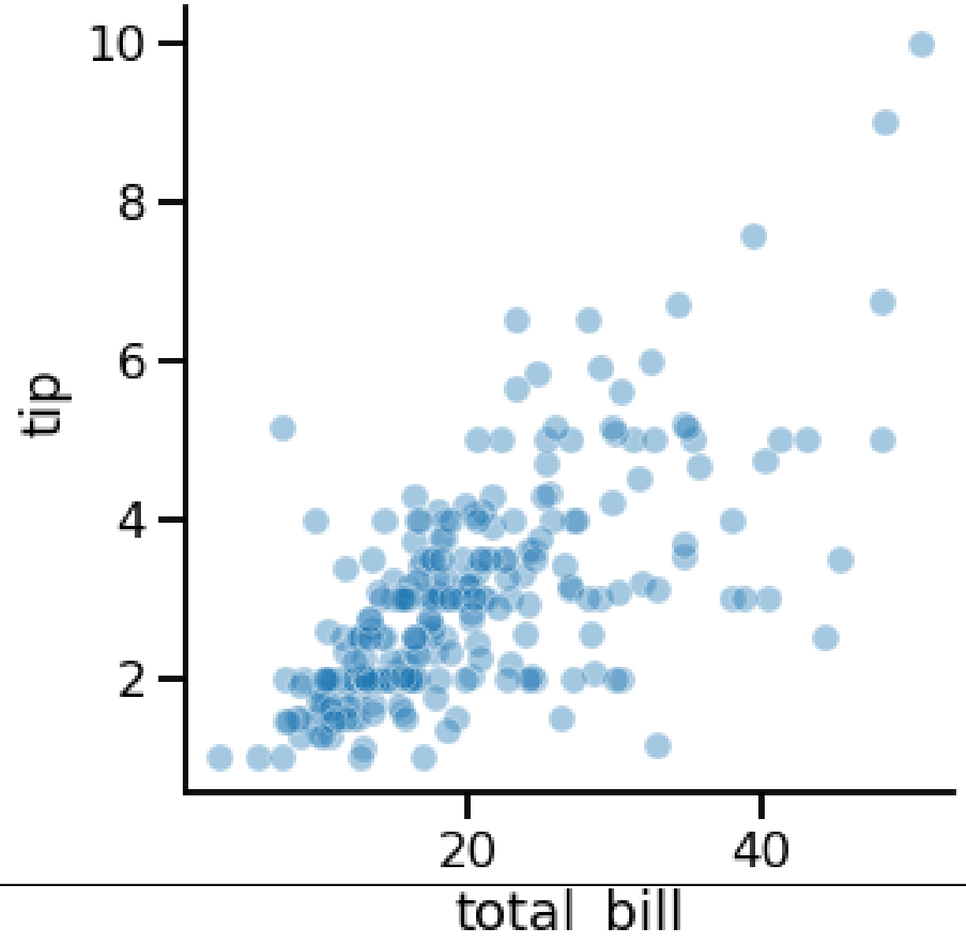


5. Subgroups with point style
The next customization we'll look at is the point style. Setting the "style" parameter to a variable name will use different point styles for each value of the variable. Here's a scatter plot we've seen before, where we use "hue" to create different colored points based on smoking status. Setting "style" equal to "smoker" allows us to better distinguish these subgroups by plotting smokers with a different point style in addition to a different color.

Changing point transparency

```
import seaborn as sns
import matplotlib.pyplot as plt

# Set alpha to be between 0 and 1
sns.relplot(x="total_bill",
            y="tip",
            data=tips,
            kind="scatter",
            alpha=0.4)
plt.show()
```



6. Changing point transparency
The last customization we'll look at is point transparency. Setting the "alpha" parameter to a value between 0 and 1 will vary the transparency of the points in the plot, with 0 being completely transparent and 1 being completely non-transparent. Here, we've set "alpha" equal to 0.4. This customization can be useful when you have many overlapping points on the scatter plot, so you can see which areas of the plot have more or less observations.

Let's practice!

INTRODUCTION TO DATA VISUALIZATION WITH SEABORN

Introduction to line plots

INTRODUCTION TO DATA VISUALIZATION WITH SEABORN

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What are line plots?

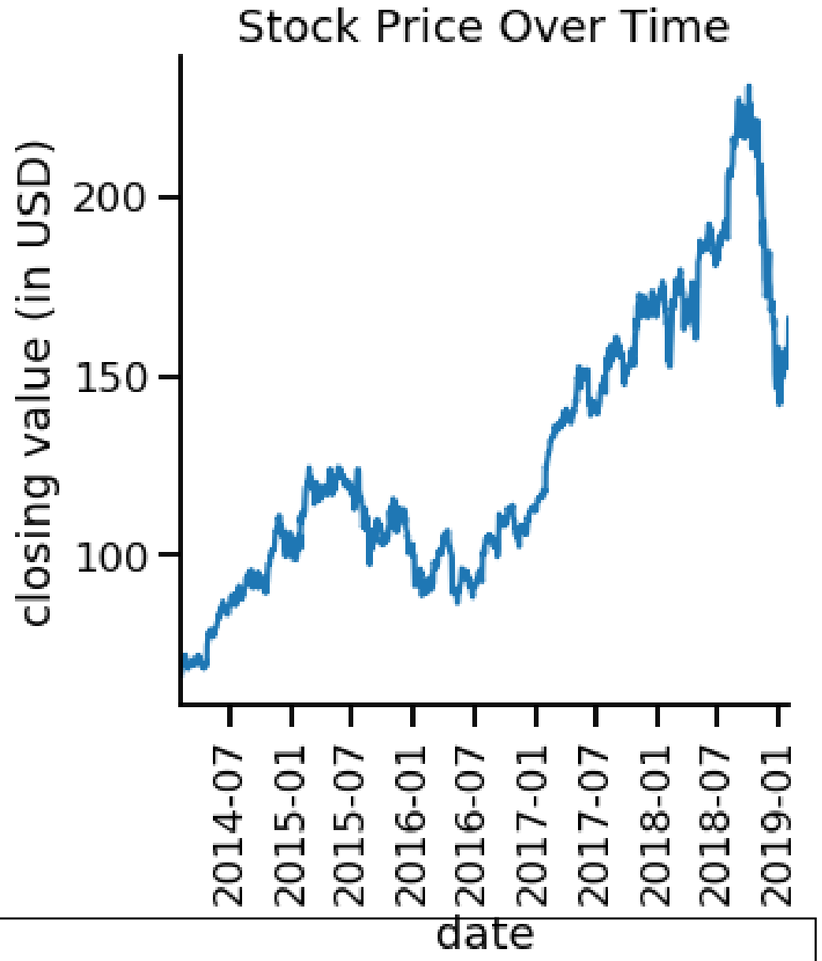
Two types of relational plots: scatter plots and line plots

Scatter plots

- Each plot point is an independent observation

Line plots

- Each plot point represents the same "thing", typically tracked over time



2. What are line plots?
In Seaborn, we have two types of relational plots: scatter plots and line plots. While each point in a scatter plot is assumed to be an independent observation, line plots are the visualization of choice when we need to track the same thing over time. A common example is tracking the value of a company's stock over time, as shown here.

Air pollution data

- Collection stations throughout city
- Air samples of nitrogen dioxide levels

3. Air pollution data
In this video, we'll be using data on the levels of air pollution in a city. There are many air collection stations around the city, each measuring the nitrogen dioxide level every hour for a single day. Long-term exposure to high levels of nitrogen dioxide can cause chronic lung diseases. Let's begin with the simple case where we have one data point per x-value. Here we have one row per hour over the course of the day with the average nitrogen dioxide level across all the stations in a column called "NO_2_mean".

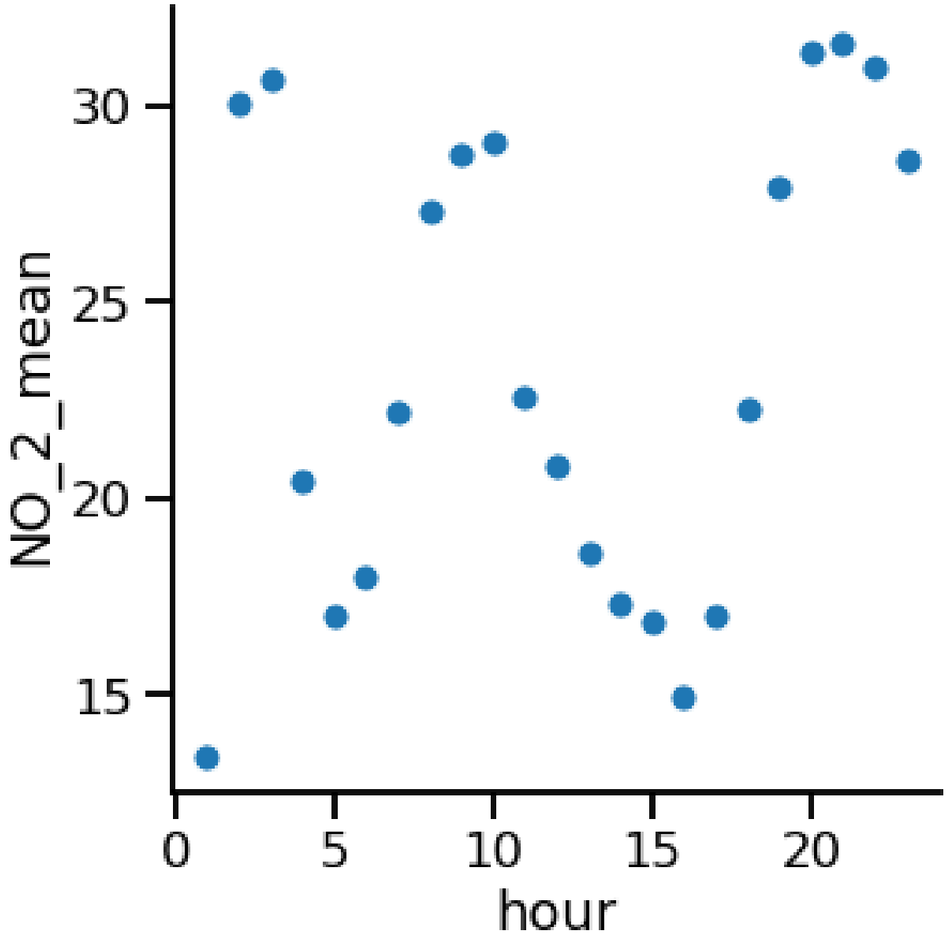
	hour	NO_2_mean
0	1	13.375000
1	2	30.041667
2	3	30.666667
3	4	20.416667
4	5	16.958333

Scatter plot

```
import matplotlib.pyplot as plt
import seaborn as sns

sns.relplot(x="hour", y="NO_2_mean",
            data=air_df_mean,
            kind="scatter")

plt.show()
```



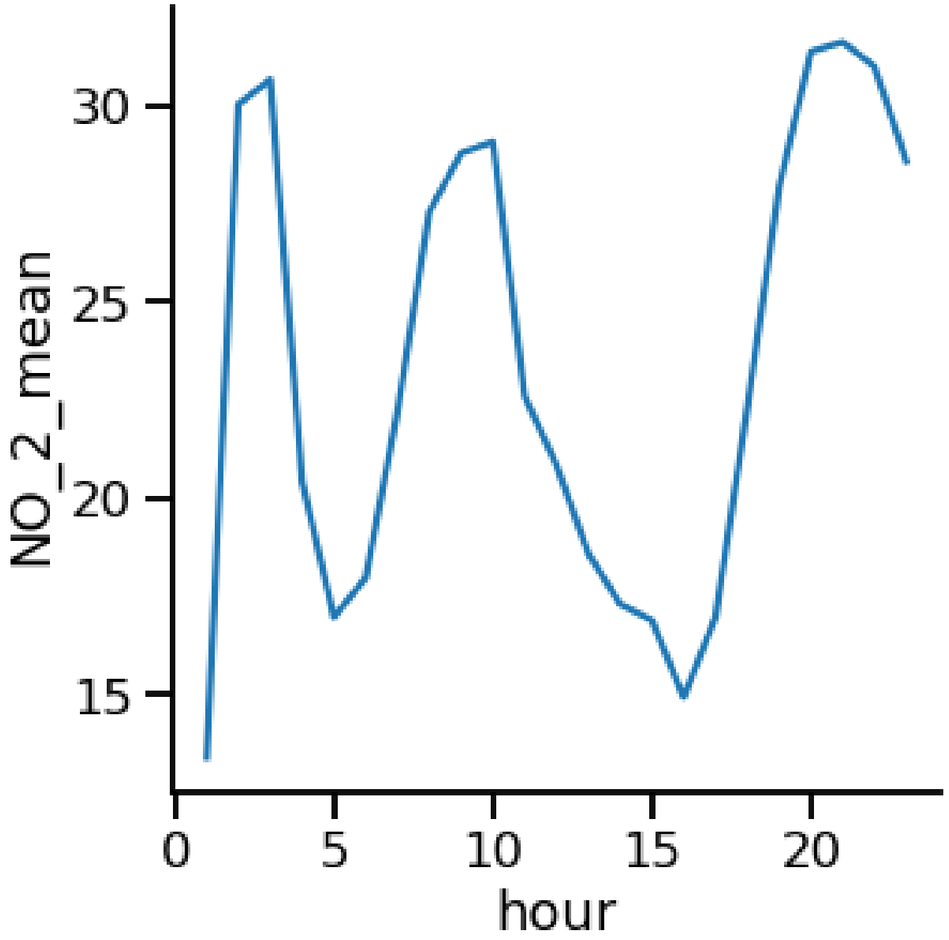
4. Scatter plot
This is a scatter plot with the average nitrogen dioxide level on the y-axis and the hour of the day on the x-axis. We're tracking the same thing over time, so a line plot would be a better choice.

Line plot

```
import matplotlib.pyplot as plt
import seaborn as sns

sns.relplot(x="hour", y="NO_2_mean",
            data=air_df_mean,
            kind="line")

plt.show()
```



5. Line plot
By specifying "kind" equals "line", we can create a line plot and more easily see how the average nitrogen dioxide level fluctuates throughout the day.

Subgroups by location

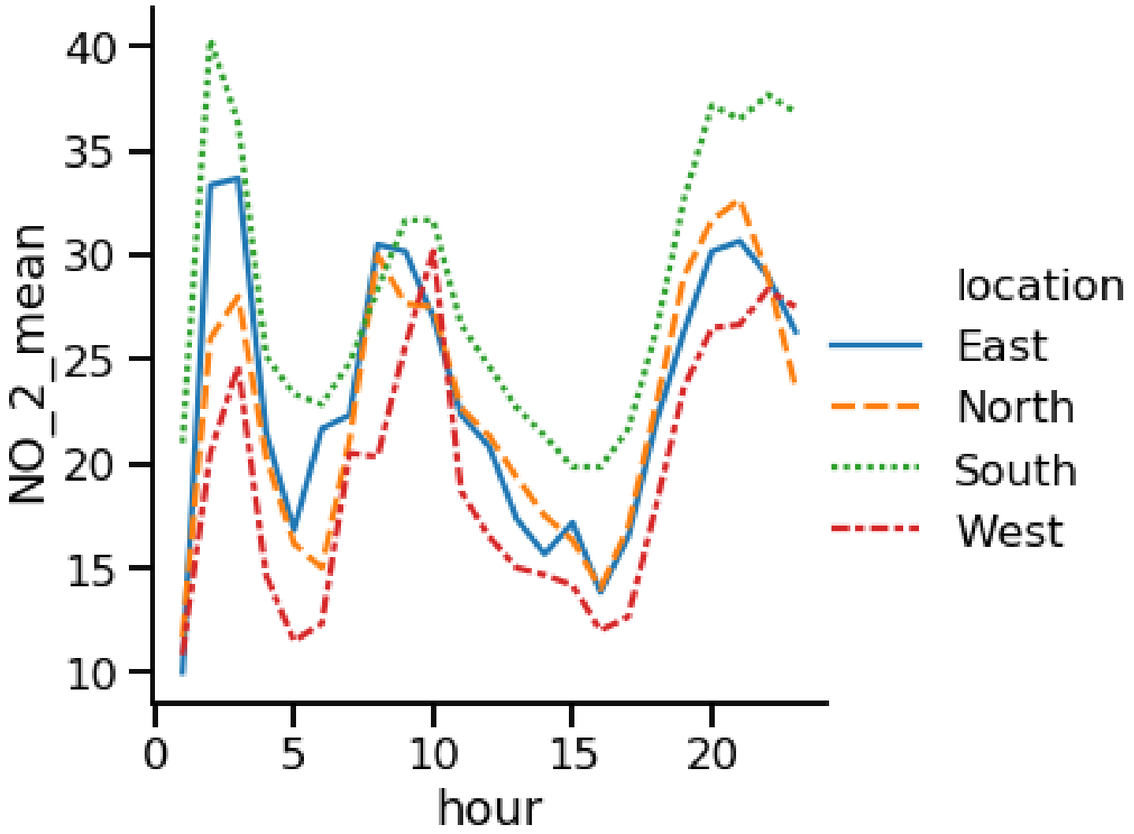
	hour	location	NO_2_mean
0	1	East	10.000000
1	1	North	11.666667
2	1	South	21.000000
3	1	West	10.833333
4	2	East	33.333333

6. Subgroups by location
We can also track subgroups over time with line plots. Here we have the average nitrogen dioxide level for each region (North, South, East, and West) for each hour in the day.

Subgroups by location

```
import matplotlib.pyplot as plt
import seaborn as sns

sns.relplot(x="hour", y="NO_2_mean",
            data=air_df_loc_mean,
            kind="line",
            style="location",
            hue="location")
plt.show()
```

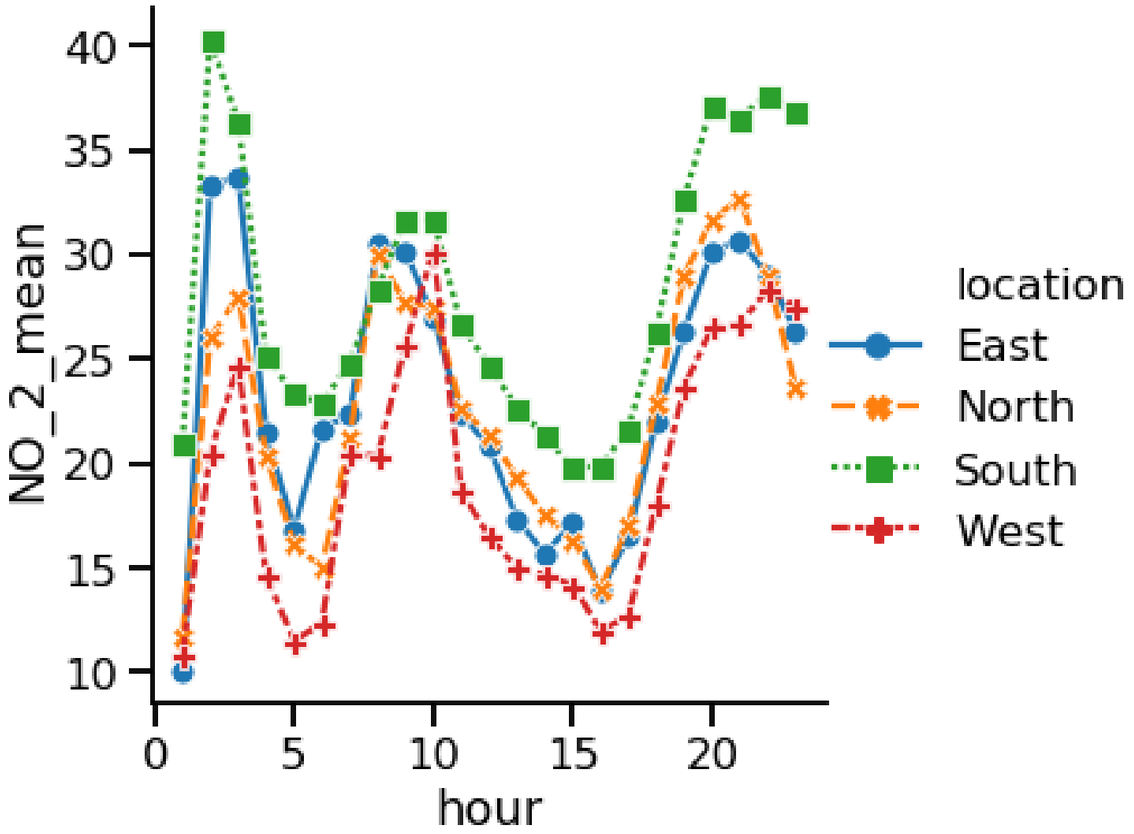


7. Subgroups by location
Setting the "style" and "hue" parameters equal to the variable name "location" creates different lines for each region that vary in both line style and color. Here, we can see that the South region tends to have slightly higher average nitrogen dioxide levels compared to the other regions.

Adding markers

```
import matplotlib.pyplot as plt
import seaborn as sns

sns.relplot(x="hour", y="NO_2_mean",
            data=air_df_loc_mean,
            kind="line",
            style="location",
            hue="location",
            markers=True)
plt.show()
```

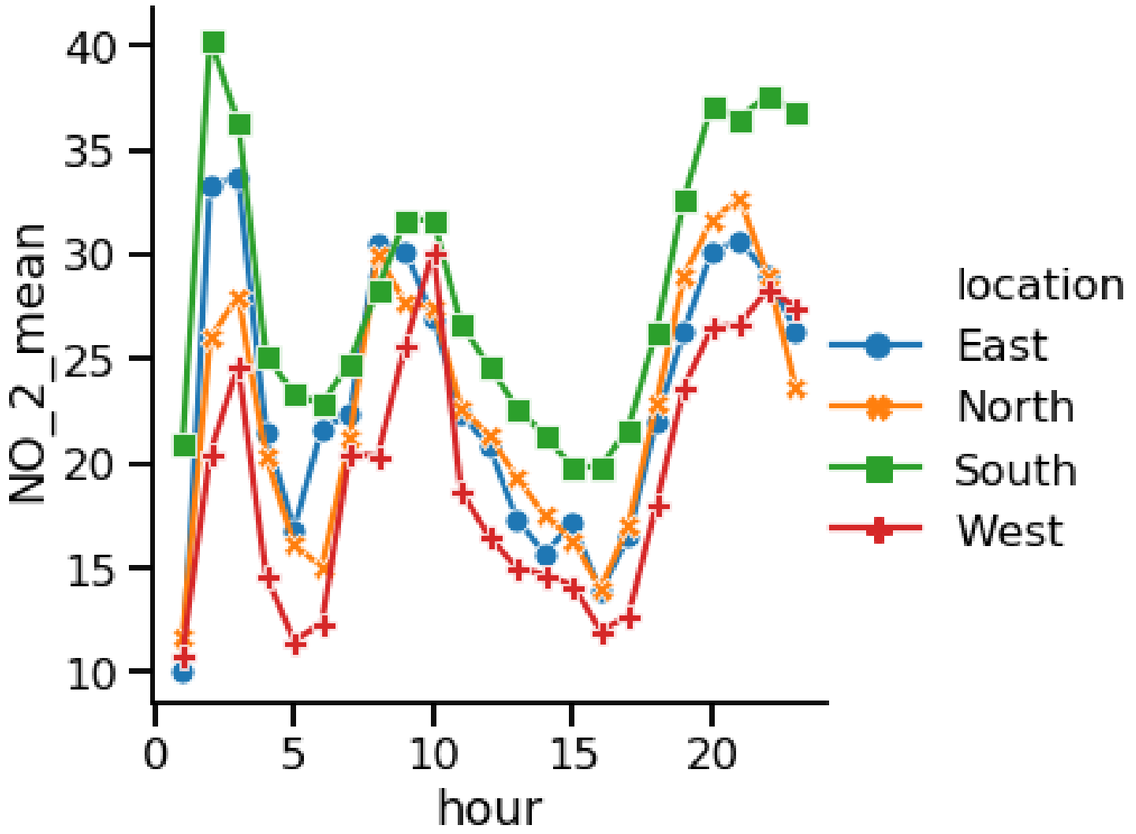


8. Adding markers
Setting the "markers" parameter equal to "True" will display a marker for each data point. The marker will vary based on the subgroup you've set using the "style" parameter.

Turning off line style

```
import matplotlib.pyplot as plt
import seaborn as sns

sns.relplot(x="hour", y="NO_2_mean",
            data=air_df_loc_mean,
            kind="line",
            style="location",
            hue="location",
            markers=True,
            dashes=False)
plt.show()
```



9. Turning off line style

If you don't want the line styles to vary by subgroup, set the "dashes" parameter equal to "False".

Multiple observations per x-value

	hour	NO_2	station	location
0	1	15.0	28079004	South
1	1	33.0	28079008	South
2	1	11.0	28079011	South
3	1	12.0	28079016	South
4	1	23.0	28079017	South

10. Multiple observations per x-value
Line plots can also be used when you have more than one observation per x-value. This dataset has a row for each station that is taking a measurement every hour.

Multiple observations per x-value

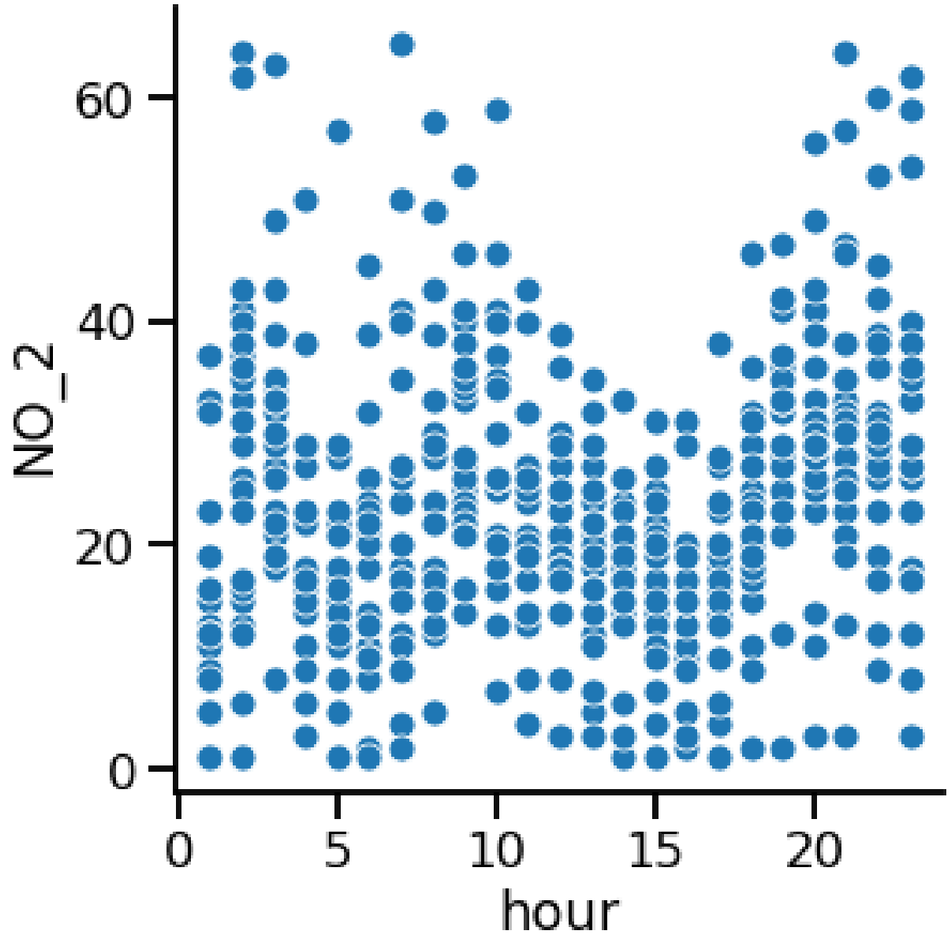
Scatter plot

```
import matplotlib.pyplot as plt
import seaborn as sns

sns.relplot(x="hour", y="NO_2",
            data=air_df,
            kind="scatter")

plt.show()
```

11. Multiple observations per x-value
This is the scatter plot, displaying one point per observation.



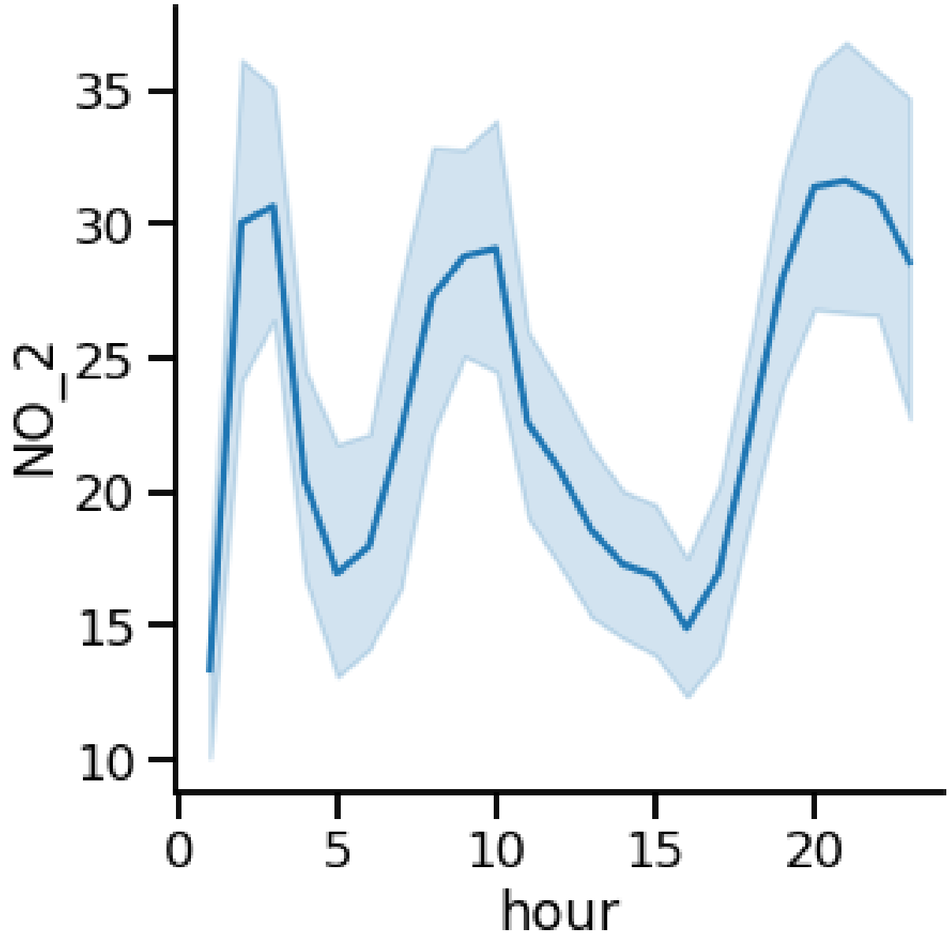
Multiple observations per x-value

Line plot

```
import matplotlib.pyplot as plt
import seaborn as sns

sns.relplot(x="hour", y="NO_2",
            data=air_df,
            kind="line")

plt.show()
```

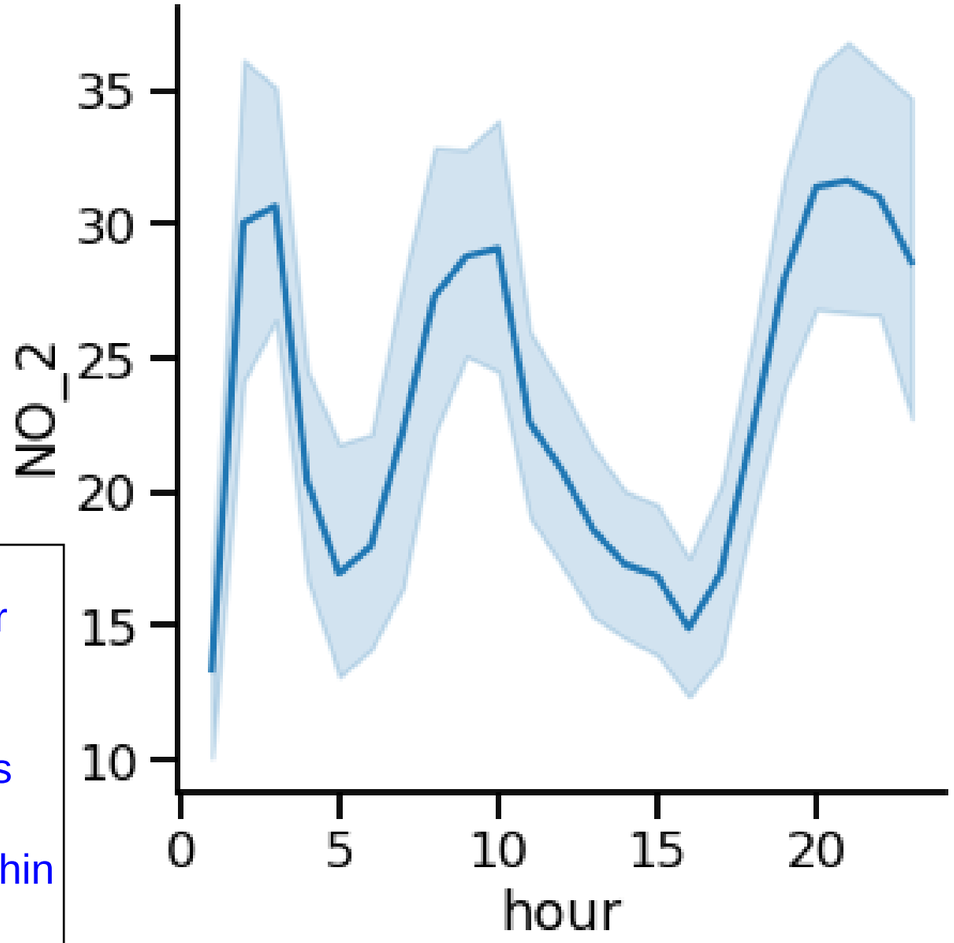


12. Multiple observations per x-value
This is the line plot. If a line plot is given multiple observations per x-value, it will aggregate them into a single summary measure. By default, it will display the mean.

Multiple observations per x-value

Shaded region is the confidence interval

- Assumes dataset is a random sample
- 95% confident that the mean is within this interval
- Indicates uncertainty in our estimate

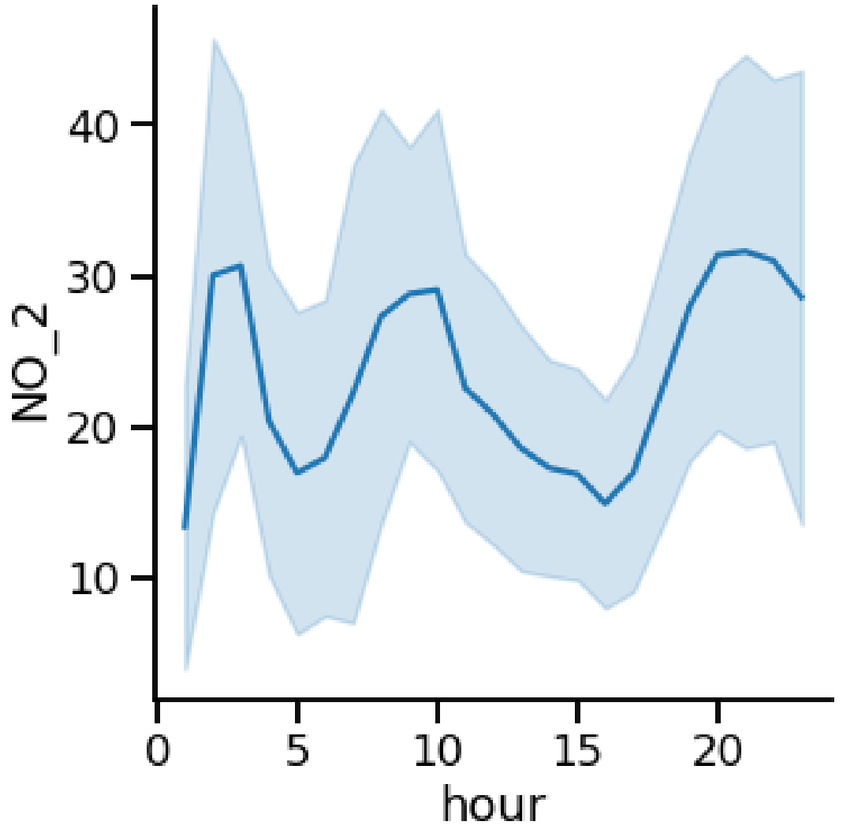


13. Multiple observations per x-value
Notice that Seaborn will automatically calculate a confidence interval for the mean, displayed by the shaded region. Assuming the air collection stations were randomly placed throughout the city, this dataset is a random sample of the nitrogen dioxide levels across the whole city. This confidence interval tells us that based on our sample, we can be 95% confident that the average nitrogen dioxide level for the whole city is within this range. Confidence intervals indicate the uncertainty we have about what the true mean is for the whole city.

Replacing confidence interval with standard deviation

```
import matplotlib.pyplot as plt
import seaborn as sns

sns.relplot(x="hour", y="NO_2",
            data=air_df,
            kind="line",
            ci="sd")
plt.show()
```

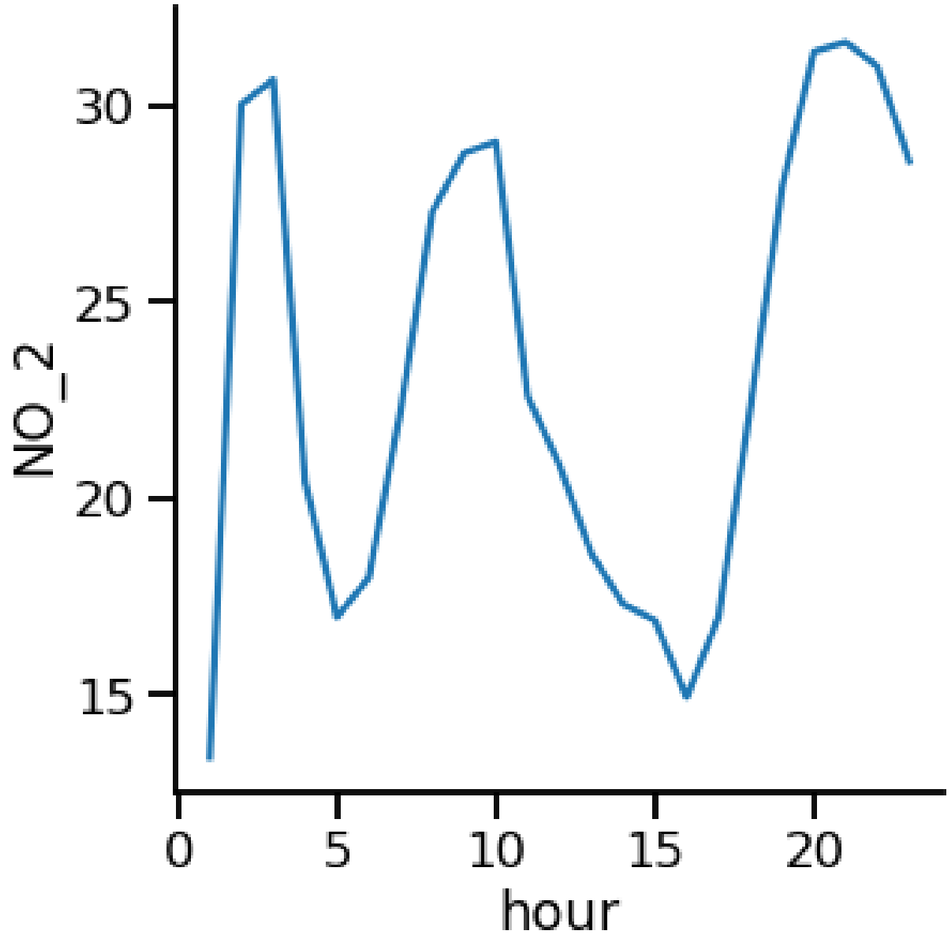


14. Replacing confidence interval with standard deviation
Instead of visualizing a confidence interval, we may want to see how varied the measurements of nitrogen dioxide are across the different collection stations at a given point in time. To visualize this, set the "ci" parameter equal to the string "sd" to make the shaded area represent the standard deviation, which shows the spread of the distribution of observations at each x value.

Turning off confidence interval

```
import matplotlib.pyplot as plt
import seaborn as sns

sns.relplot(x="hour", y="NO_2",
            data=air_df,
            kind="line",
            ci=None)
plt.show()
```



15. Turning off confidence interval
We can also turn off the confidence interval by setting the "ci" parameter equal to "None".

Let's practice!

INTRODUCTION TO DATA VISUALIZATION WITH SEABORN