Exploratory Data Analysis: Covariation

PSY 410: Data Science for Psychology

Dr. Sara Weston

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Setup

From variation to covariation

Psychology is about relationships

Last time, you explored how individual variables behave — distributions, outliers, missing data.

. . .

But psychology is about *relationships*:

- Does **treatment** predict **depression**?
- Does **age** relate to **reaction time**?
- Does **anxiety** co-occur with **insomnia**?

. . .

Today we learn to **see** those relationships in data — before testing them statistically.

Categorical + Continuous

Example: Mental health by treatment group

```r
# Simulated therapy outcome data
therapy_data <- tibble(
  condition = rep(c("Control", "CBT", "Mindfulness"), each = 50),
  depression_post = c(
    rnorm(50, mean = 18, sd = 5),  # Control
    rnorm(50, mean = 12, sd = 5),  # CBT
    rnorm(50, mean = 14, sd = 5)   # Mindfulness
  )
)
```

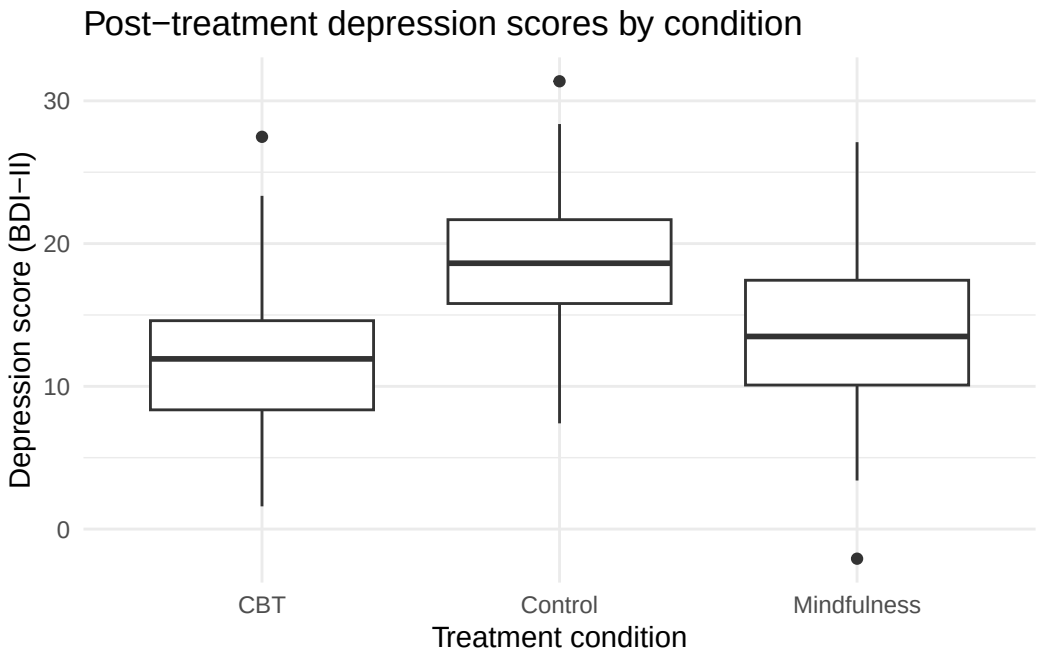
Example: Mental health by treatment group

```r
glimpse(therapy_data)
```

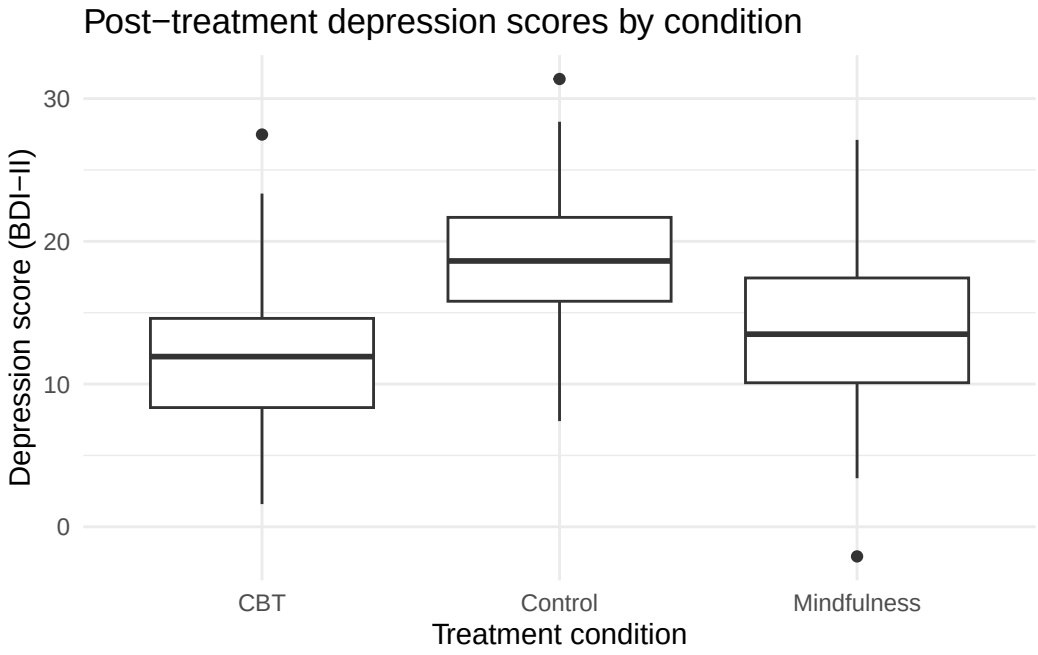
```
Rows: 150
Columns: 2
$ condition       <chr> "Control", "Control", "Control", "Control", "Control",~
$ depression_post <dbl> 20.92803, 21.47755, 31.37259, 15.71437, 13.53972, 19.4~
```

Boxplots: The classic choice

```r
ggplot(therapy_data, aes(x = condition, y = depression_post)) +
  geom_boxplot() +
  labs(
    title = "Post-treatment depression scores by condition",
    x = "Treatment condition",
    y = "Depression score (BDI-II)"
  ) +
  theme_minimal()
```



What boxplots show



- **Line in middle:** median
- **Box:** 25th to 75th percentile (IQR)

- **Whiskers:** extend to 1.5 × IQR
- **Dots:** outliers beyond whiskers

. . .

Great for comparing distributions, but they hide the actual data points.

The problem with boxplots

Boxplots summarize, but they hide important information:

- **The actual distribution shape** (is it bimodal? skewed?)
- **Individual data points** (how many observations are there?)
- **The raw data** (where do specific values fall?)

. . .

We can do better.

Raincloud plots

The modern psych visualization

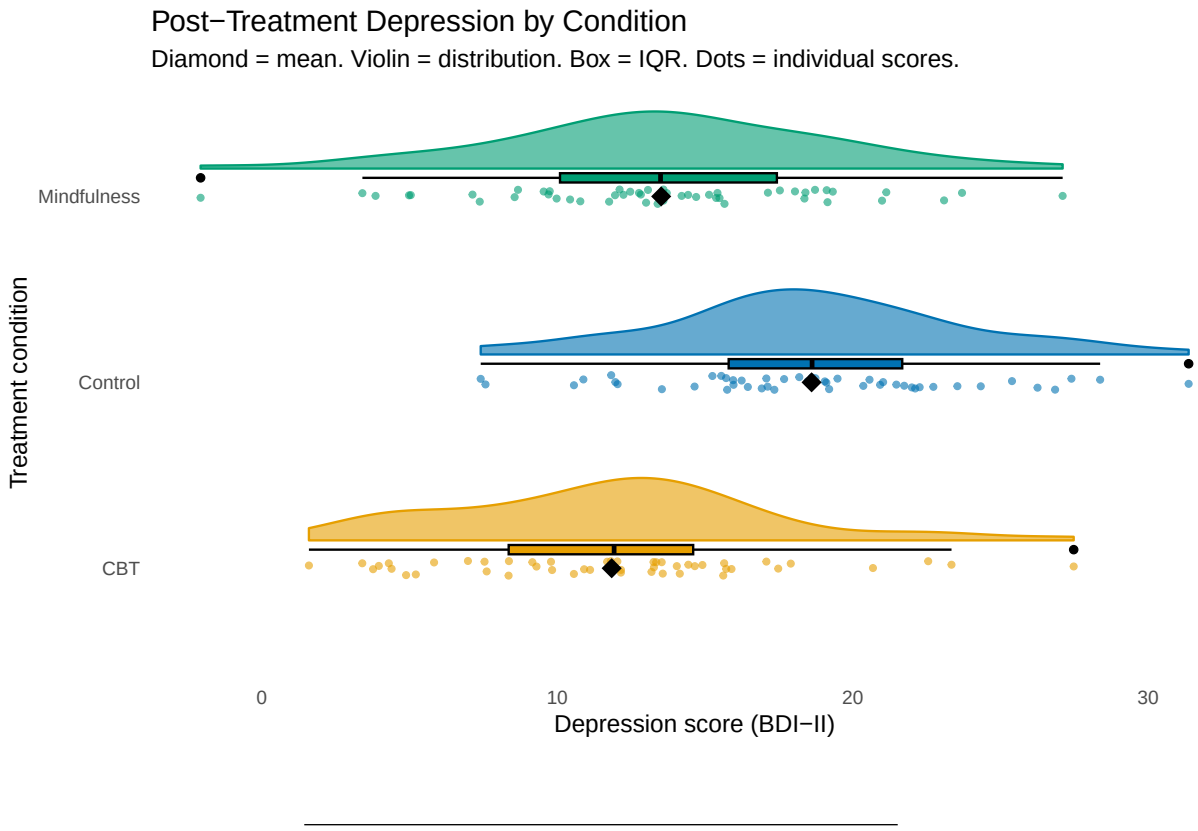
Raincloud plots combine three elements:

1. **Violin** (distribution shape)
2. **Boxplot** (summary stats)
3. **Jittered points** (individual data)

They're increasingly popular in psychology publications because they show **everything**.

Use the `ggrain` package. (More details here.)

Building a raincloud

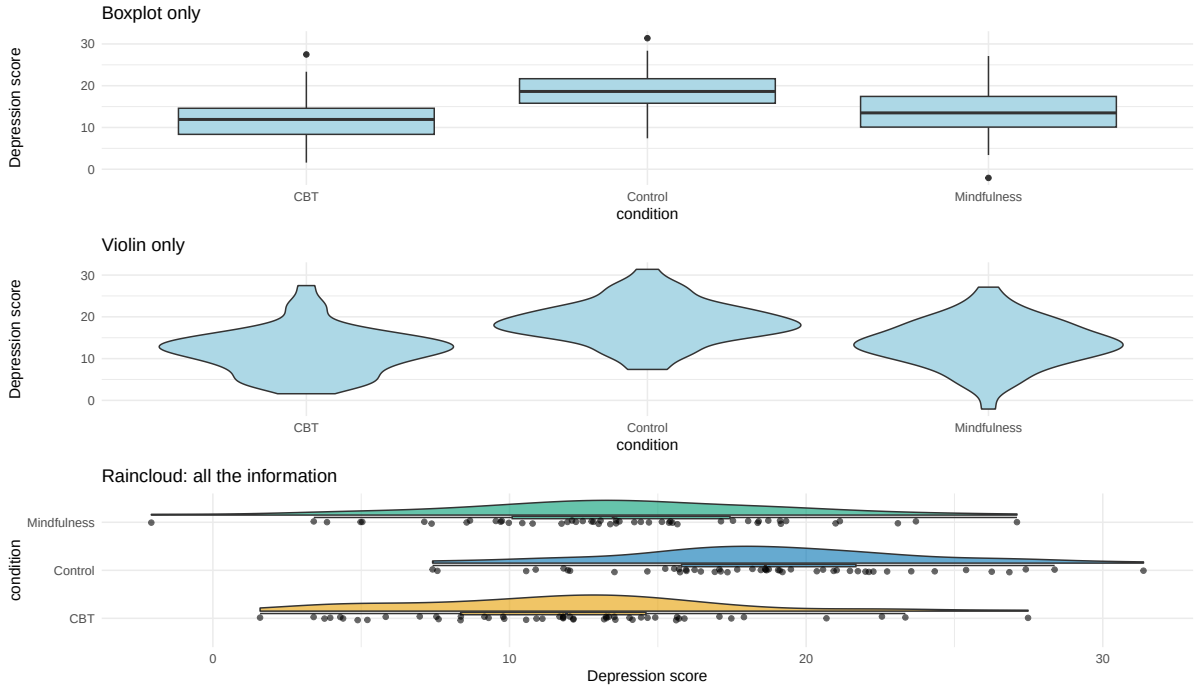



```
library(ggrain)
therapy_data |>
  ggplot(aes(
    x = condition,
    y = depression_post,
    fill = condition,
    color = condition)) +
  # geom_rain creates all parts of your raincloud
  geom_rain(
    alpha = .6,
    # change just the boxplot part
    boxplot.args = list(color = "black")) +
  # The mean
  stat_summary(fun = mean, geom = "point", shape = 18, size = 5, color = "black") +
  scale_fill_manual(
    values = c("Control" = "#0072B2", "CBT" = "#E69F00", "Mindfulness" = "#009E73")) +
```

```
  scale_color_manual(
    values = c("Control" = "#0072B2", "CBT" = "#E69F00", "Mindfulness" = "#009E73")) +
  labs(
    title = "Post-Treatment Depression by Condition",
    subtitle = "Diamond = mean. Violin = distribution. Box = IQR. Dots = individual scores."
    x = "Treatment condition",
    y = "Depression score (BDI-II)"
  ) +
  coord_flip() +
  theme_minimal(base_size = 14) +
  theme(
    legend.position = "none",
    panel.grid = element_blank())
```

Why raincloud s are great

Compare these three views of the **same data**:



When to use which

Plot type	Shows	Best for
Boxplot	Median, IQR, outliers	Quick comparison, large datasets
Raincloud	Distribution + summary + raw data	Psychology papers, presentations, publications
Violin + jitter	Distribution + raw data	Alternative to raincloud, simpler to code

Pair coding break

Your turn: Compare by gender

Using the therapy data, explore whether depression scores differ by gender:

1. Add a `gender` variable to the data (use `sample()` to randomly assign "Male", "Female", "Non-binary")
2. Create a visualization showing depression scores by gender
3. Try at least two different geom types
4. Add appropriate labels

Time: 10 minutes

Categorical + Categorical

Example: Diagnosis by gender

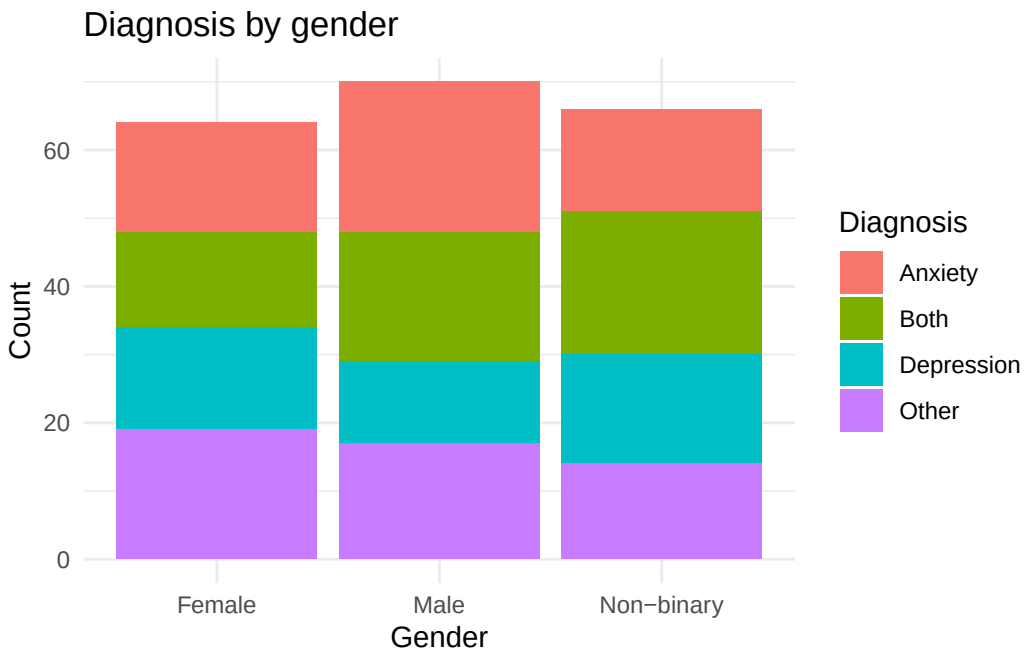
```
# Simulated diagnostic data
diagnosis_data <- tibble(
  gender = sample(c("Male", "Female", "Non-binary"), 200, replace = TRUE),
  diagnosis = sample(c("Depression", "Anxiety", "Both", "Other"),
                     200, replace = TRUE)
)

head(diagnosis_data)
```

```
# A tibble: 6 x 2
  gender     diagnosis
  <chr>      <chr>
```

```
1 Female     Depression
2 Non-binary Other
3 Non-binary Other
4 Non-binary Other
5 Male       Both
6 Female     Depression
```

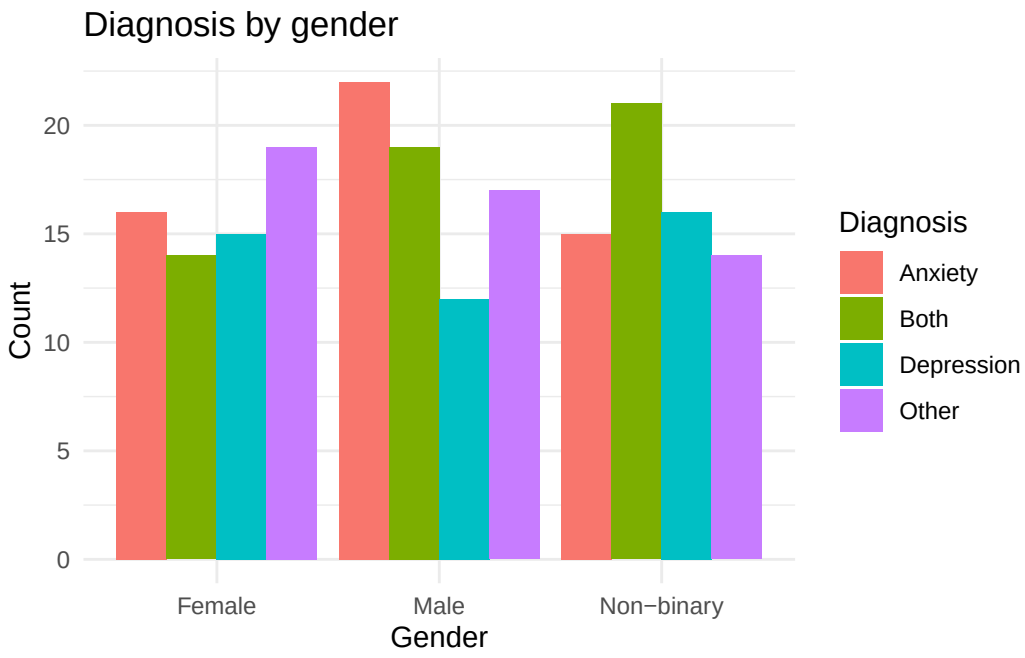
Option 1: Stacked bar chart

```r
ggplot(diagnosis_data, aes(x = gender, fill = diagnosis)) +
  geom_bar() +
  labs(
    title = "Diagnosis by gender",
    x = "Gender",
    y = "Count",
    fill = "Diagnosis"
  ) +
  theme_minimal()
```



Option 2: Side-by-side bars

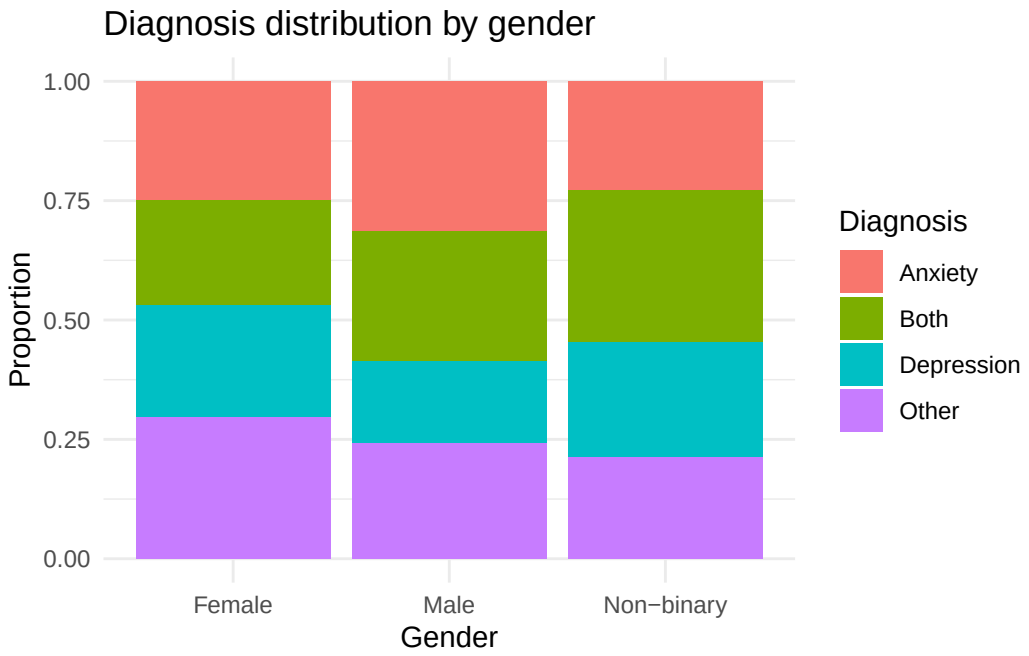
```
ggplot(diagnosis_data, aes(x = gender, fill = diagnosis)) +
  geom_bar(position = "dodge") +
  labs(
    title = "Diagnosis by gender",
    x = "Gender",
    y = "Count",
    fill = "Diagnosis"
  ) +
  theme_minimal()
```



Option 3: Proportions

```
ggplot(diagnosis_data, aes(x = gender, fill = diagnosis)) +
  geom_bar(position = "fill") +
  labs(
    title = "Diagnosis distribution by gender",
    x = "Gender",
    y = "Proportion",
    fill = "Diagnosis"
```

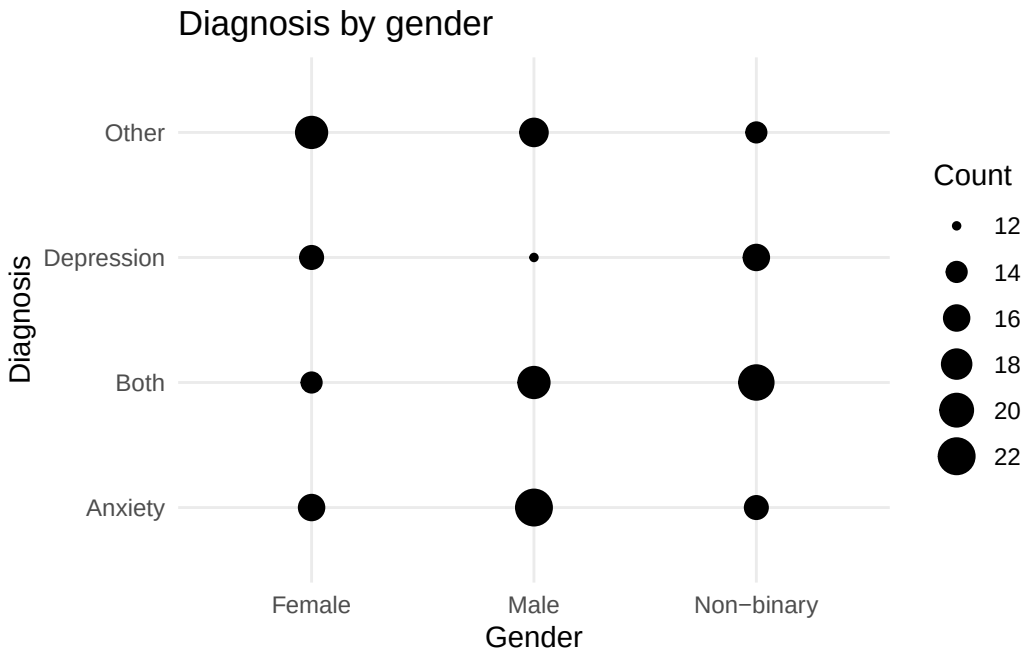
```
  ) +
  theme_minimal()
```



Option 4: geom_count()

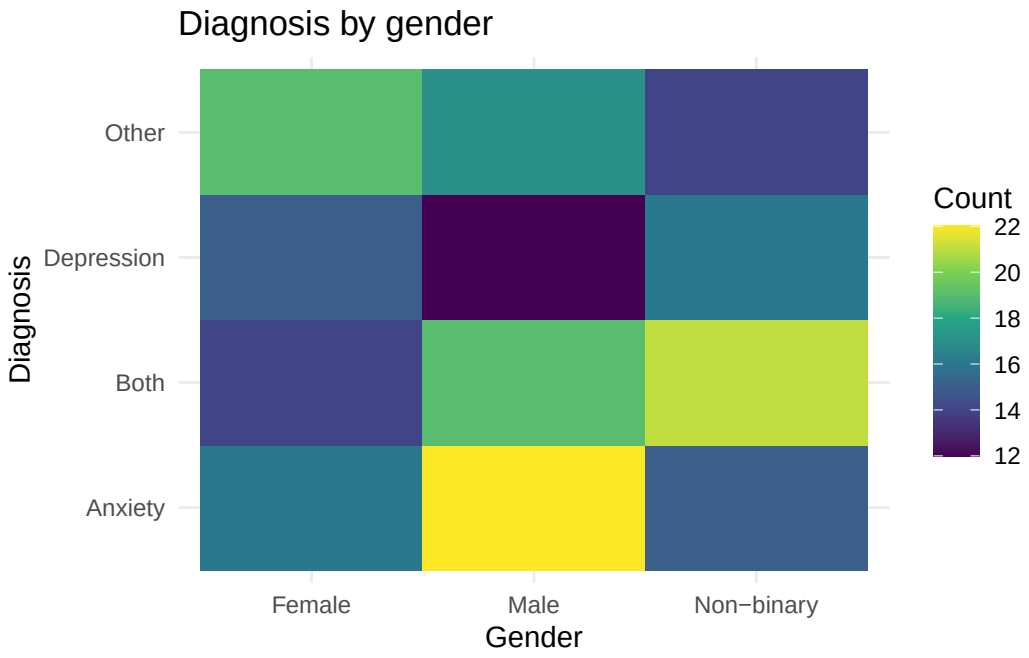
Shows the *size* of overlaps:

```
ggplot(diagnosis_data, aes(x = gender, y = diagnosis)) +
  geom_count() +
  labs(
    title = "Diagnosis by gender",
    x = "Gender",
    y = "Diagnosis",
    size = "Count"
  ) +
  theme_minimal()
```



Option 5: Tile with counts

```
diagnosis_counts <- diagnosis_data |>
  count(gender, diagnosis)

ggplot(diagnosis_counts, aes(x = gender, y = diagnosis, fill = n)) +
  geom_tile() +
  scale_fill_viridis_c() +
  labs(
    title = "Diagnosis by gender",
    x = "Gender",
    y = "Diagnosis",
    fill = "Count"
  ) +
  theme_minimal()
```



Continuous + Continuous

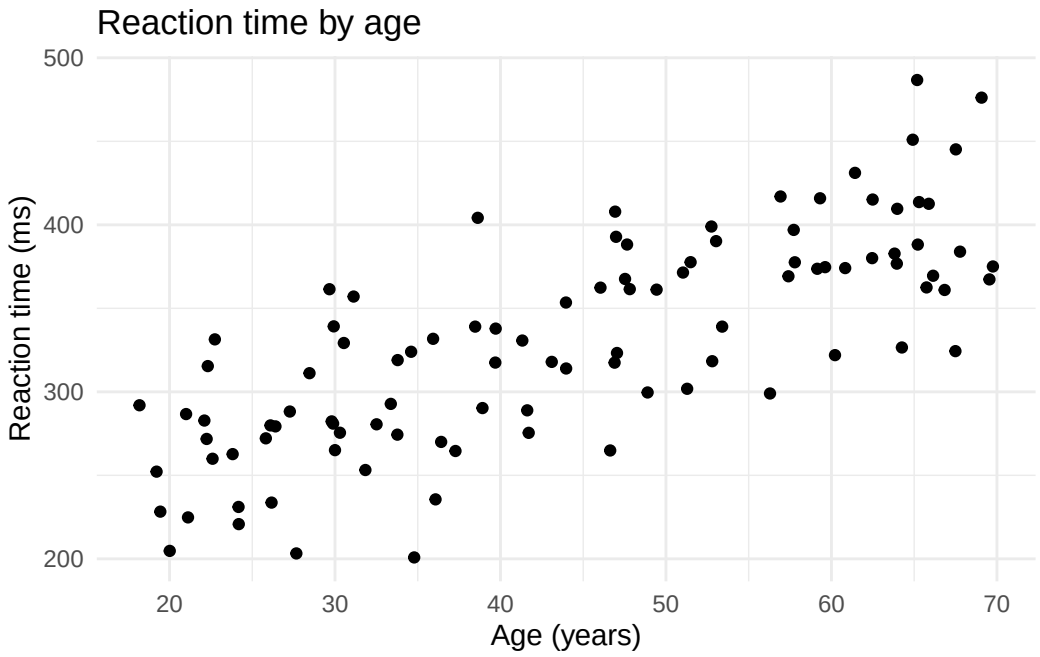
The classic: Scatterplots

```
# Simulated reaction time data
rt_data <- tibble(
  age = runif(100, 18, 70),
  reaction_time = 200 + age * 3 + rnorm(100, 0, 40)
)

glimpse(rt_data)
```

```
Rows: 100
Columns: 2
$ age           <dbl> 24.17121, 20.01237, 69.54667, 60.83108, 56.28694, 65.179~
$ reaction_time <dbl> 231.0764, 204.7547, 367.3308, 374.0941, 299.0114, 486.71~
```

Basic scatterplot

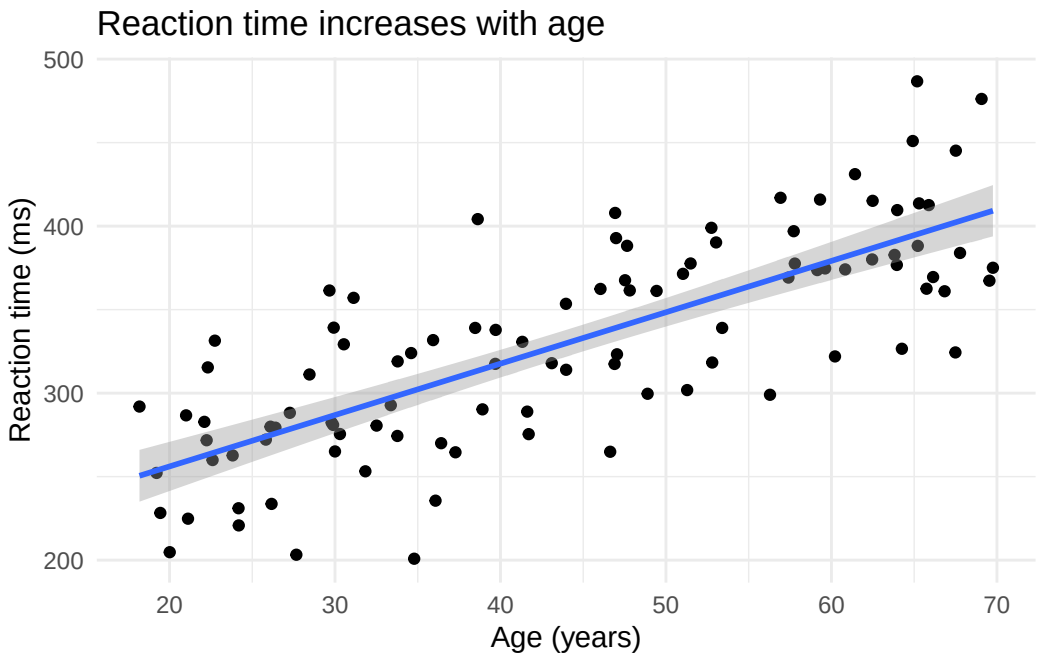
```
ggplot(rt_data, aes(x = age, y = reaction_time)) +
  geom_point() +
  labs(
    title = "Reaction time by age",
    x = "Age (years)",
    y = "Reaction time (ms)"
  ) +
  theme_minimal()
```



Add a trend line

```
ggplot(rt_data, aes(x = age, y = reaction_time)) +
  geom_point() +
  geom_smooth(method = "lm", se = TRUE) +
  labs(
    title = "Reaction time increases with age",
    x = "Age (years)",
    y = "Reaction time (ms)"
```

```
  ) +
  theme_minimal()
```



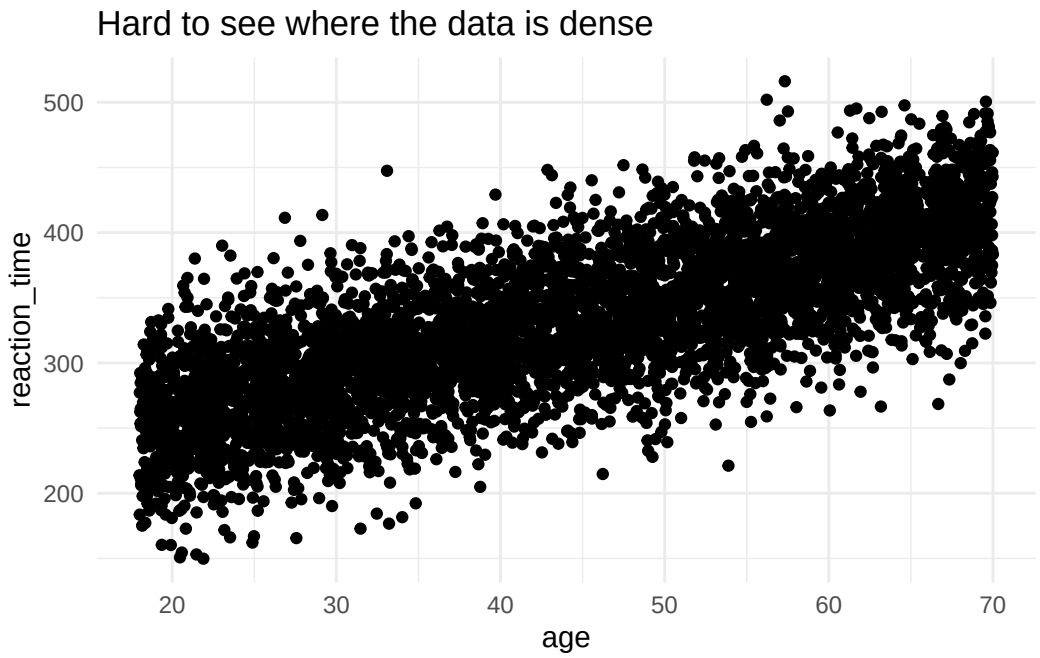
The problem: Overplotting

With lots of data, points overlap and hide the true density:

```
# Lots of data
big_rt_data <- tibble(
  age = runif(5000, 18, 70),
  reaction_time = 200 + age * 3 + rnorm(5000, 0, 40)
)
```

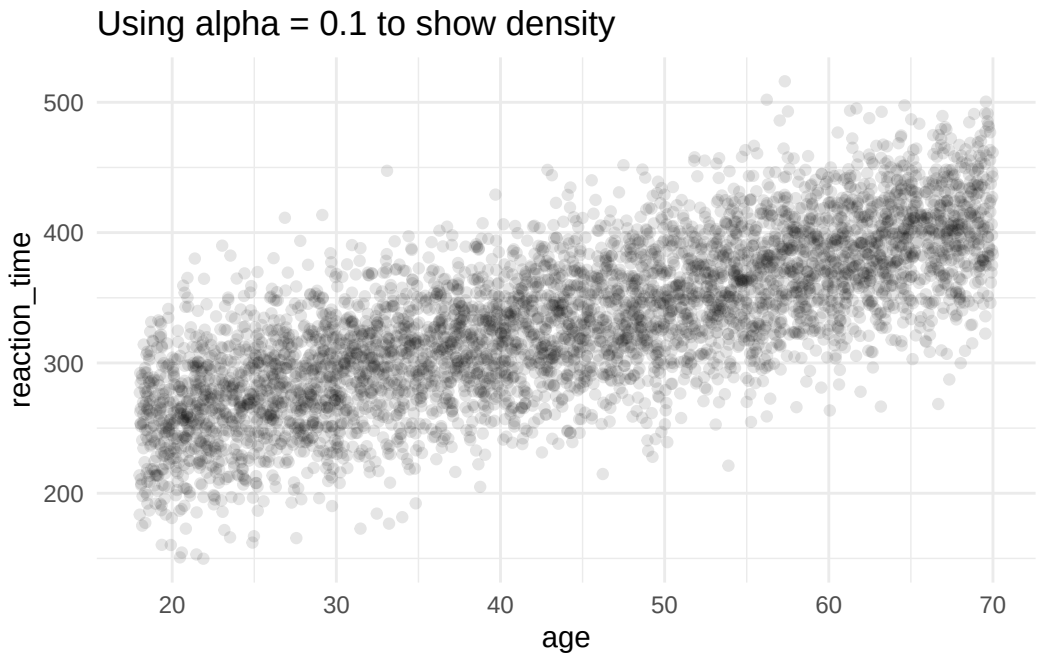
Overplotting problem demonstrated

```
ggplot(big_rt_data, aes(x = age, y = reaction_time)) +
  geom_point() +
  labs(title = "Hard to see where the data is dense") +
  theme_minimal()
```



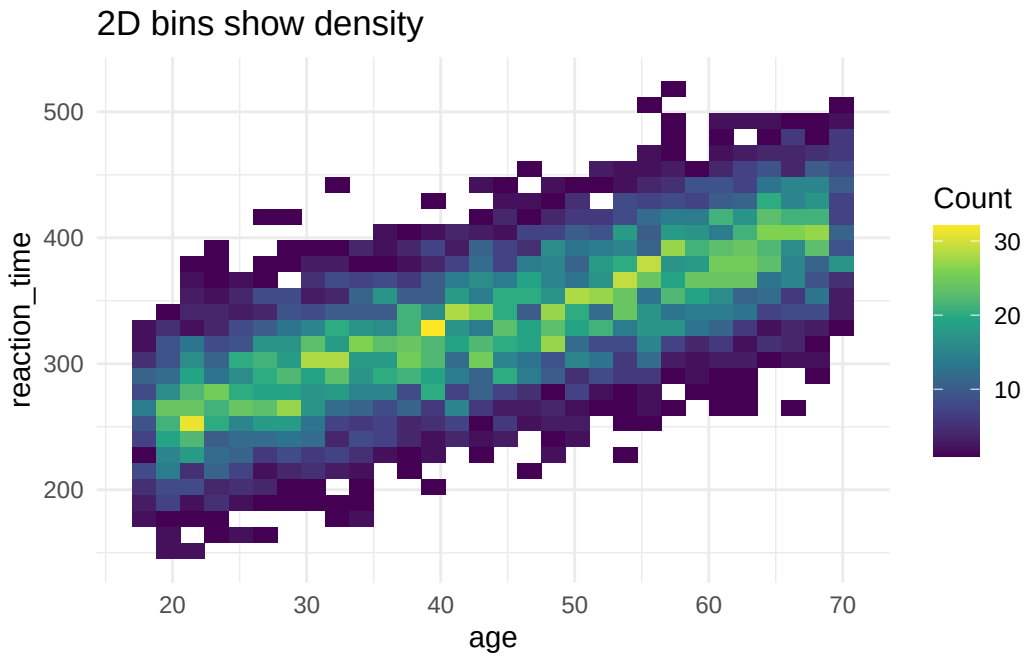
Solution 1: Transparency (alpha)

```
ggplot(big_rt_data, aes(x = age, y = reaction_time)) +
  geom_point(alpha = 0.1) +
  labs(title = "Using alpha = 0.1 to show density") +
  theme_minimal()
```



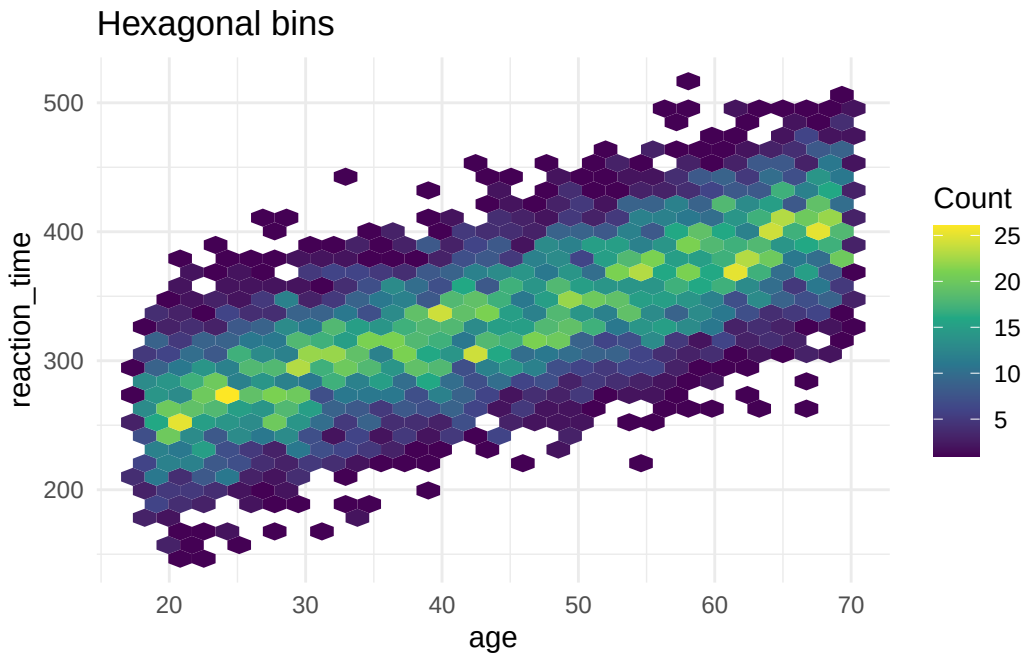
Solution 2: geom_bin2d()

```
ggplot(big_rt_data, aes(x = age, y = reaction_time)) +
  geom_bin2d() +
  scale_fill_viridis_c() +
  labs(
    title = "2D bins show density",
    fill = "Count"
  ) +
  theme_minimal()
```



Solution 3: geom_hex()

```
ggplot(big_rt_data, aes(x = age, y = reaction_time)) +
  geom_hex() +
  scale_fill_viridis_c() +
  labs(
    title = "Hexagonal bins",
    fill = "Count"
  ) +
  theme_minimal()
```



Correlation coefficient

A single number summary of the linear relationship:

```
cor(rt_data$age, rt_data$reaction_time)
```

```
[1] 0.769784
```

. . .

> **Note**
>
> - **r = 1:** perfect positive relationship
> - **r = 0:** no linear relationship
> - **r = -1:** perfect negative relationship

. . .

But always plot your data first! (See: Anscombe's Quartet)

Patterns and models

What patterns tell us

When you see covariation, ask:

1. **Could it be coincidence?** (Maybe, especially with small samples)
2. **What's the mechanism?** (How are these variables related?)
3. **Is there a confound?** (Could a third variable explain both?)

. . .

> ⚠ Warning
>
> **Correlation Causation**
> Covariation suggests a relationship, but doesn't prove one variable *causes* the other.

Real data example

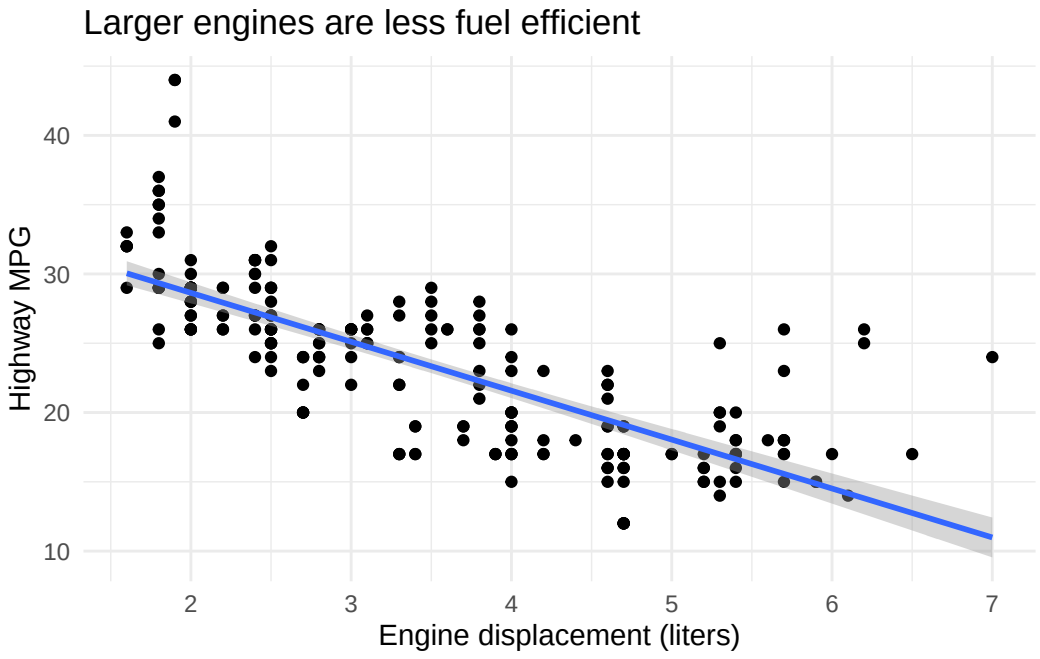
Let's explore a real dataset: `mpg` (fuel economy data)

```
glimpse(mpg)
```

```
Rows: 234
Columns: 11
$ manufacturer <chr> "audi", "audi", "audi", "audi", "audi", "audi", "audi", "~
$ model        <chr> "a4", "a4", "a4", "a4", "a4", "a4", "a4", "a4 quattro", "~
$ displ        <dbl> 1.8, 1.8, 2.0, 2.0, 2.8, 2.8, 3.1, 1.8, 1.8, 2.0, 2.0, 2.~
$ year         <int> 1999, 1999, 2008, 2008, 1999, 1999, 2008, 1999, 1999, 200~
$ cyl          <int> 4, 4, 4, 4, 6, 6, 6, 4, 4, 4, 4, 6, 6, 6, 6, 6, 6, 8, 8, ~
$ trans        <chr> "auto(l5)", "manual(m5)", "manual(m6)", "auto(av)", "auto~
$ drv          <chr> "f", "f", "f", "f", "f", "f", "f", "4", "4", "4", "4", "4~
$ cty          <int> 18, 21, 20, 21, 16, 18, 18, 18, 16, 20, 19, 15, 17, 17, 1~
$ hwy          <int> 29, 29, 31, 30, 26, 26, 27, 26, 25, 28, 27, 25, 25, 25, 2~
$ fl           <chr> "p", "p", "p", "p", "p", "p", "p", "p", "p", "p", "p", "p~
$ class        <chr> "compact", "compact", "compact", "compact", "compact", "c~
```

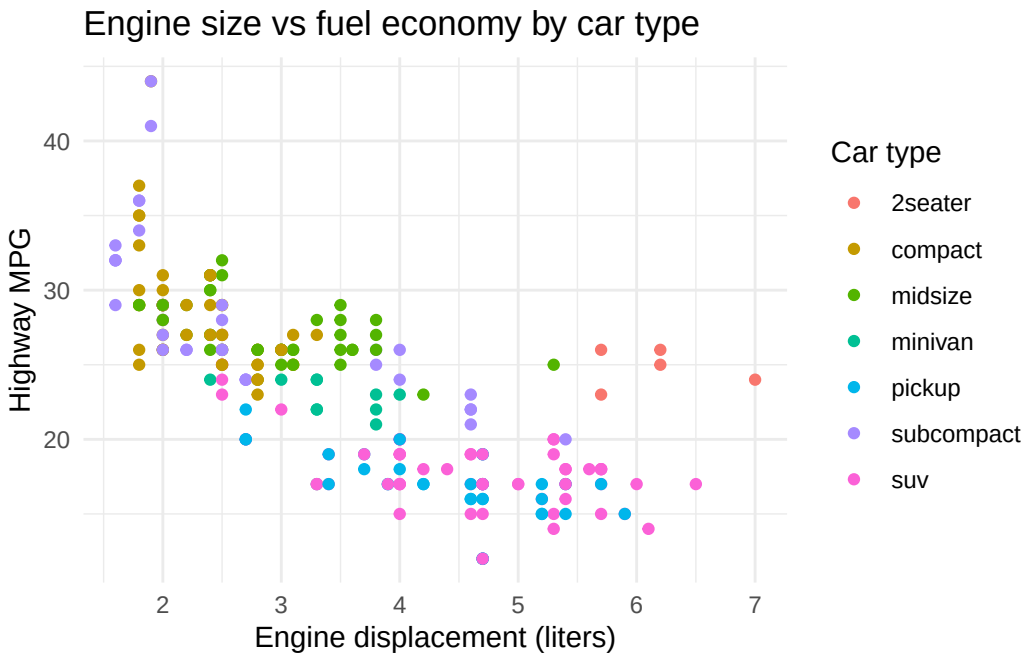
Question 1: Does engine size affect fuel economy?

```r
ggplot(mpg, aes(x = displ, y = hwy)) +
  geom_point() +
  geom_smooth(method = "lm") +
  labs(
    title = "Larger engines are less fuel efficient",
    x = "Engine displacement (liters)",
    y = "Highway MPG"
  ) +
  theme_minimal()
```



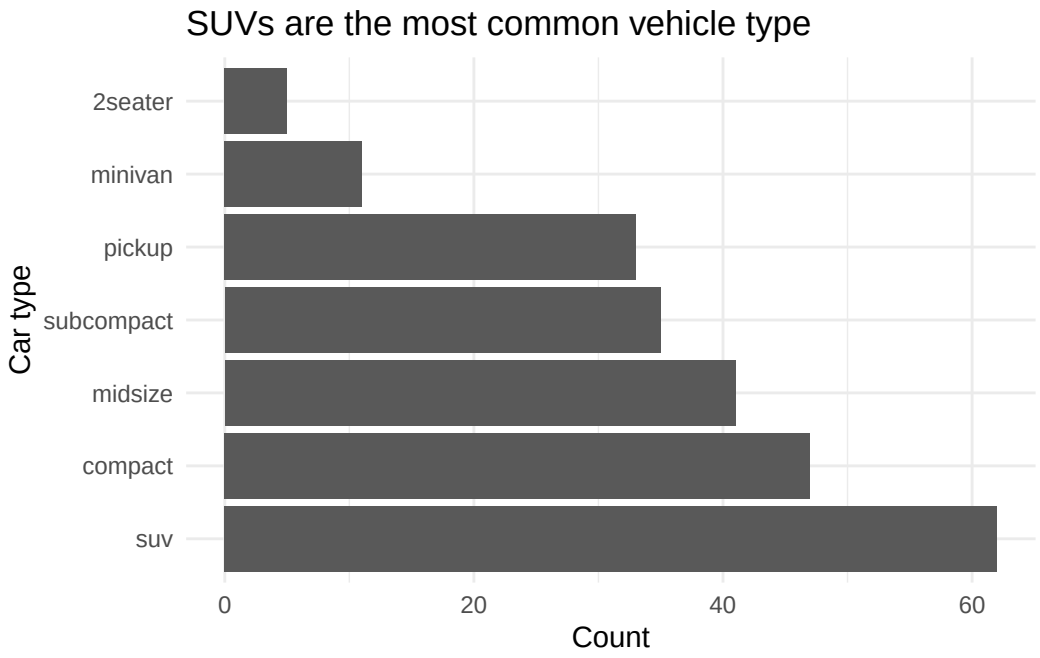
Question 2: Does this vary by car type?

```r
ggplot(mpg, aes(x = displ, y = hwy, color = class)) +
  geom_point() +
  labs(
    title = "Engine size vs fuel economy by car type",
    x = "Engine displacement (liters)",
    y = "Highway MPG",
    color = "Car type"
  ) +
  theme_minimal()
```



Question 3: Which car types are most common?

```
ggplot(mpg, aes(y = fct_infreq(class))) +
  geom_bar() +
  labs(
    title = "SUVs are the most common vehicle type",
    x = "Count",
    y = "Car type"
  ) +
  theme_minimal()
```



End-of-deck exercise

Your final project proposal

For your final project, you'll need to:

1. Choose a dataset with at least 2-3 variables of interest
2. Formulate 2-3 research questions about relationships in the data
3. Plan visualizations to explore those relationships

Exercise: Start exploring potential datasets. Find one that interests you and create 2-3 exploratory visualizations showing different types of covariation (categorical + continuous, continuous + continuous, etc.).

This will form the basis of your proposal, **due today!**

Wrapping up

Key takeaways

1. **Covariation = relationships** between variables
2. **Different plot types** for different variable combinations:

    - Categorical + continuous: boxplot, raincloud plots
    - Categorical + categorical: bar charts, tiles, geom_count()
    - Continuous + continuous: scatterplot, 2D bins, hex
3. **Raincloud plots** are the gold standard for psychology — they show distribution, summary stats, and raw data
4. **Watch for overplotting** — use alpha, jitter, or binning
5. **Always visualize first** before computing correlations
6. **Patterns suggest but don't prove** causation

Before next class

Read:

- R4DS Ch 12: Logical vectors
- R4DS Ch 13: Numbers

Do:

- Submit Assignment 5
- Submit your Final Project Proposal (due today!)
- Start thinking about how you'll compute scale scores (next session)

The one thing to remember

Relationships hide in data. Your job is to make them visible — carefully, honestly.

See you Monday for data types and scale scoring!