EDA — Variation

PSY 410: Data Science for Psychology

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What is EDA?

Know your data before you test it

Before you run a single statistical test, you should know your data well enough to predict what the results will look like.

. . .

That's what EDA gives you — **no surprises**.

Exploratory vs. confirmatory

	Exploratory (EDA)	Confirmatory
Goal	Discover patterns	Test hypotheses
Attitude	Curiosity	Rigor
Questions	Open-ended	Pre-specified
Output	Visualizations, hunches	p-values, conclusions

EDA comes **first.** You can't test a hypothesis you didn't notice.

Good EDA means looking before you test

> “EDA is an attitude, not a technique.”
> — John Tukey

- Ask questions
- Answer them by visualizing data
- Use what you learn to ask new questions
- Repeat

There is no single “right” way to do EDA. The goal is **understanding.**

What we’re doing today

Exploring **variation** — what does a single variable look like?

- Distribution shape
- Center and spread
- Outliers and unusual values
- Missing data

Tomorrow: **covariation** — how do variables relate to each other?

Our dataset: Big Five Personality

```
glimpse(bfi)
```

```
Rows: 2,800
Columns: 28
$ A1        <int> 2, 2, 5, 4, 2, 6, 2, 4, 4, 2, 4, 2, 5, 5, 4, 4, 4, 5, 4, 4, ~
$ A2        <int> 4, 4, 4, 4, 3, 6, 5, 3, 3, 5, 4, 5, 5, 5, 5, 3, 6, 5, 4, 4, ~
$ A3        <int> 3, 5, 5, 6, 3, 5, 5, 1, 6, 6, 5, 5, 5, 5, 2, 6, 6, 5, 5, 6, ~
$ A4        <int> 4, 2, 4, 5, 4, 6, 3, 5, 3, 6, 6, 5, 6, 6, 2, 6, 2, 4, 4, 5, ~
$ A5        <int> 4, 5, 4, 5, 5, 5, 5, 1, 3, 5, 5, 5, 4, 6, 1, 3, 5, 5, 3, 5, ~
$ C1        <int> 2, 5, 4, 4, 4, 6, 5, 3, 6, 6, 4, 5, 5, 4, 5, 5, 4, 5, 5, 1, ~
$ C2        <int> 3, 4, 5, 4, 4, 6, 4, 2, 6, 5, 3, 4, 4, 4, 5, 5, 4, 5, 4, 1, ~
$ C3        <int> 3, 4, 4, 3, 5, 6, 4, 4, 3, 6, 5, 5, 3, 4, 5, 5, 4, 5, 5, 1, ~
$ C4        <int> 4, 3, 2, 5, 3, 1, 2, 2, 4, 2, 3, 4, 2, 2, 2, 3, 4, 4, 4, 5, ~
$ C5        <int> 4, 4, 5, 5, 2, 3, 3, 4, 5, 1, 2, 5, 2, 1, 2, 5, 4, 3, 6, 6, ~
$ E1        <int> 3, 1, 2, 5, 2, 2, 4, 3, 5, 2, 1, 3, 3, 2, 3, 1, 1, 2, 1, 1, ~
$ E2        <int> 3, 1, 4, 3, 2, 1, 3, 6, 3, 2, 3, 3, 3, 2, 4, 1, 2, 2, 2, 1, ~
$ E3        <int> 3, 6, 4, 4, 5, 6, 4, 4, NA, 4, 2, 4, 3, 4, 3, 6, 5, 4, 4, 4,~
$ E4        <int> 4, 4, 4, 4, 4, 5, 5, 2, 4, 5, 5, 5, 2, 6, 6, 6, 5, 6, 5, 5, ~
$ E5        <int> 4, 3, 5, 4, 5, 6, 5, 1, 3, 5, 4, 4, 4, 5, 5, 4, 5, 6, 5, 6, ~
$ N1        <int> 3, 3, 4, 2, 2, 3, 1, 6, 5, 5, 3, 4, 1, 1, 2, 4, 4, 6, 5, 5, ~
$ N2        <int> 4, 3, 5, 5, 3, 5, 2, 3, 5, 5, 3, 5, 2, 1, 4, 5, 4, 5, 6, 5, ~
$ N3        <int> 2, 3, 4, 2, 4, 2, 2, 2, 2, 5, 4, 3, 2, 1, 2, 4, 4, 5, 5, 5, ~
$ N4        <int> 2, 5, 2, 4, 4, 2, 1, 6, 3, 2, 2, 2, 2, 2, 2, 5, 4, 4, 5, 1, ~
$ N5        <int> 3, 5, 3, 1, 3, 3, 1, 4, 3, 4, 3, NA, 2, 1, 3, 5, 5, 4, 2, 1,~
$ O1        <int> 3, 4, 4, 3, 3, 4, 5, 3, 6, 5, 5, 4, 4, 5, 5, 6, 5, 5, 4, 4, ~
$ O2        <int> 6, 2, 2, 3, 3, 3, 2, 2, 6, 1, 3, 6, 2, 3, 2, 6, 1, 1, 2, 1, ~
$ O3        <int> 3, 4, 5, 4, 4, 5, 5, 4, 6, 5, 5, 4, 4, 4, 5, 6, 5, 4, 2, 5, ~
$ O4        <int> 4, 3, 5, 3, 3, 6, 6, 5, 6, 5, 6, 5, 5, 4, 5, 3, 6, 5, 4, 3, ~
$ O5        <int> 3, 3, 2, 5, 3, 1, 1, 3, 1, 2, 3, 4, 2, 4, 5, 2, 3, 4, 2, 2, ~
$ gender    <int> 1, 2, 2, 2, 1, 2, 1, 1, 1, 2, 1, 1, 2, 1, 1, 1, 2, 1, 2, 2, ~
$ education <int> NA, NA, NA, NA, NA, 3, NA, 2, 1, NA, 1, NA, NA, NA, 1, NA, N~
$ age       <int> 16, 18, 17, 17, 17, 21, 18, 19, 19, 17, 21, 16, 16, 16, 17, ~
```

25 items measuring five personality factors (Agreeableness, Conscientiousness, Extraversion, Neuroticism, Openness) + demographics.

What's in here

Variable	Description
A1–A5	Agreeableness items (1–6 scale)
C1–C5	Conscientiousness items (1–6 scale)
E1–E5	Extraversion items (1–6 scale)
N1–N5	Neuroticism items (1–6 scale)
O1–O5	Openness items (1–6 scale)
gender	1 = male, 2 = female
education	1–5 (HS incomplete through graduate)
age	Age in years

Exploring distributions

Start simple: summary statistics

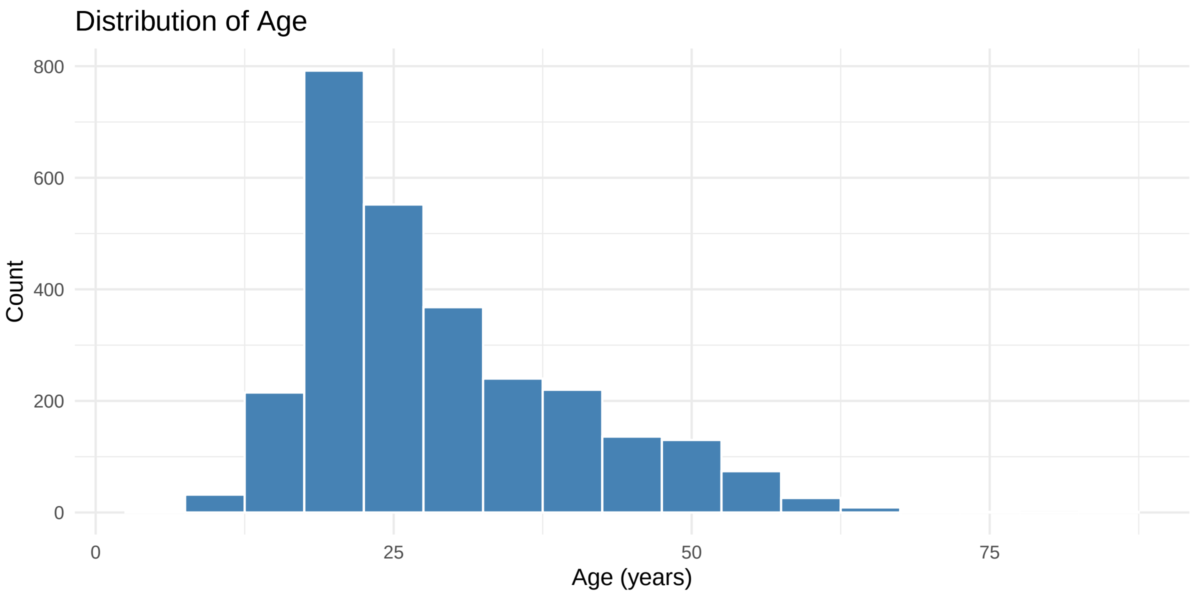
```
bfi |>
  select(age, gender, education) |>
  summary()
```

```
      age            gender        education
 Min.   : 3.00   Min.   :1.000   Min.   :1.00
 1st Qu.:20.00   1st Qu.:1.000   1st Qu.:3.00
 Median :26.00   Median :2.000   Median :3.00
 Mean   :28.78   Mean   :1.672   Mean   :3.19
 3rd Qu.:35.00   3rd Qu.:2.000   3rd Qu.:4.00
 Max.   :86.00   Max.   :2.000   Max.   :5.00
                                 NA's   :223
```

But summary stats can hide a lot. Always visualize.

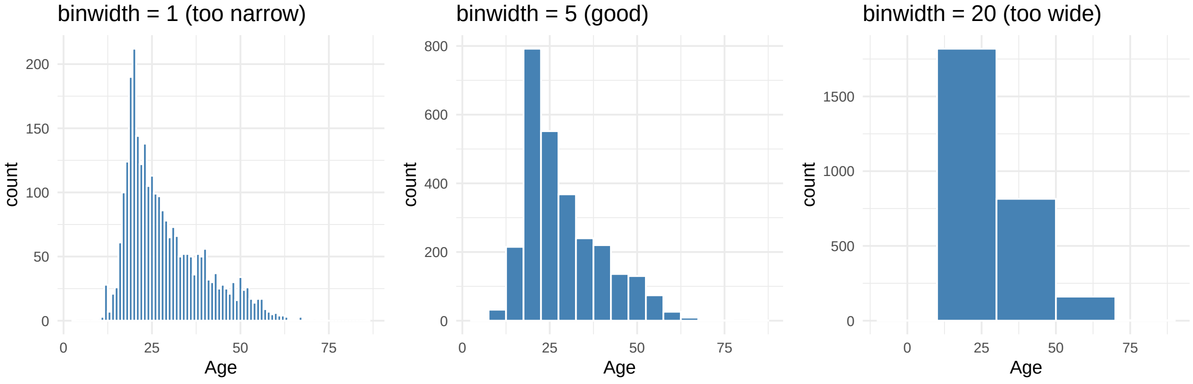
Histograms: the workhorse

```
bfi |>
  ggplot(aes(x = age)) +
  geom_histogram(binwidth = 5, fill = "steelblue", color = "white") +
  labs(
    title = "Distribution of Age",
    x = "Age (years)",
    y = "Count"
  ) +
  theme_minimal(base_size = 14)
```



Choosing binwidth

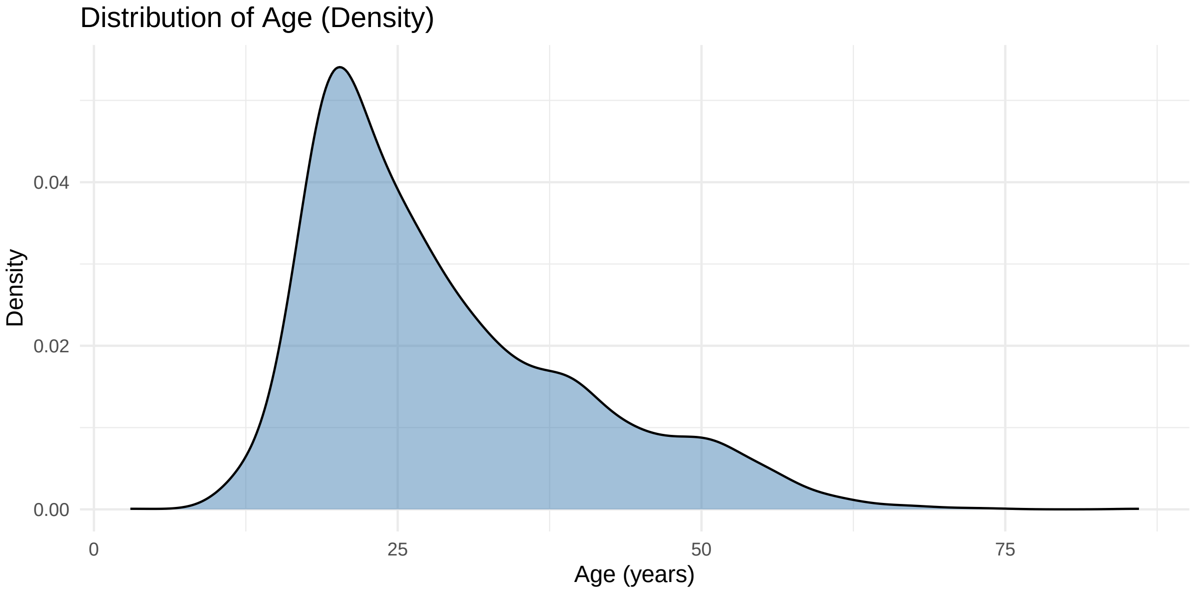
The binwidth matters a lot:



There's no "right" answer — try a few and pick the one that shows the shape clearly.

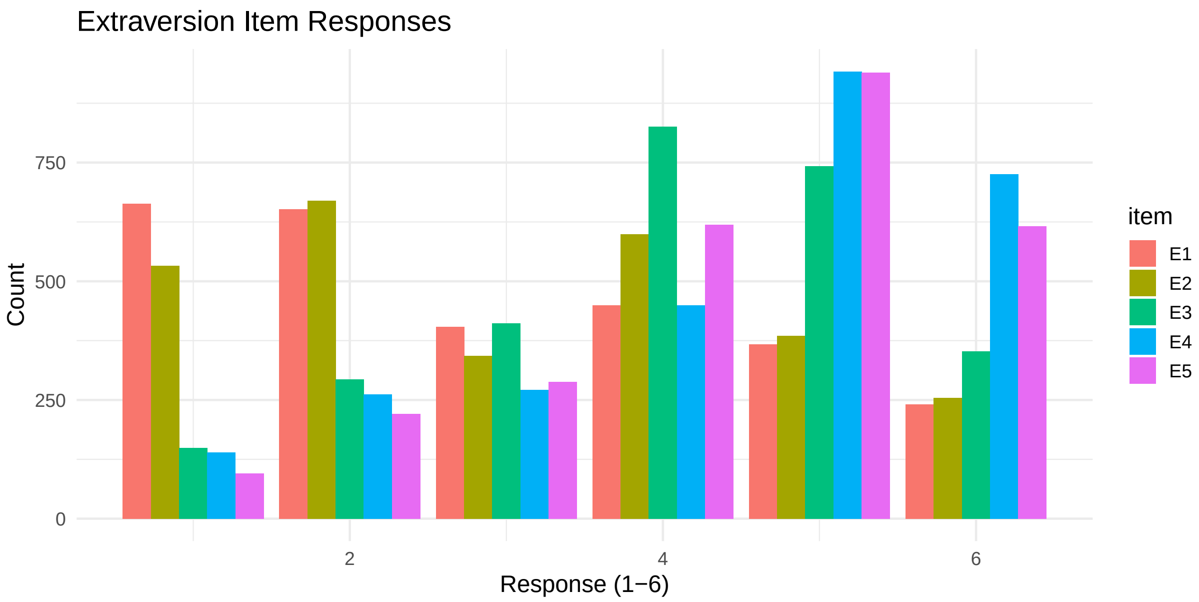
Density plots: smooth alternative

```
bfi |>
  ggplot(aes(x = age)) +
  geom_density(fill = "steelblue", alpha = 0.5) +
  labs(
    title = "Distribution of Age (Density)",
    x = "Age (years)",
    y = "Density"
  ) +
  theme_minimal(base_size = 14)
```



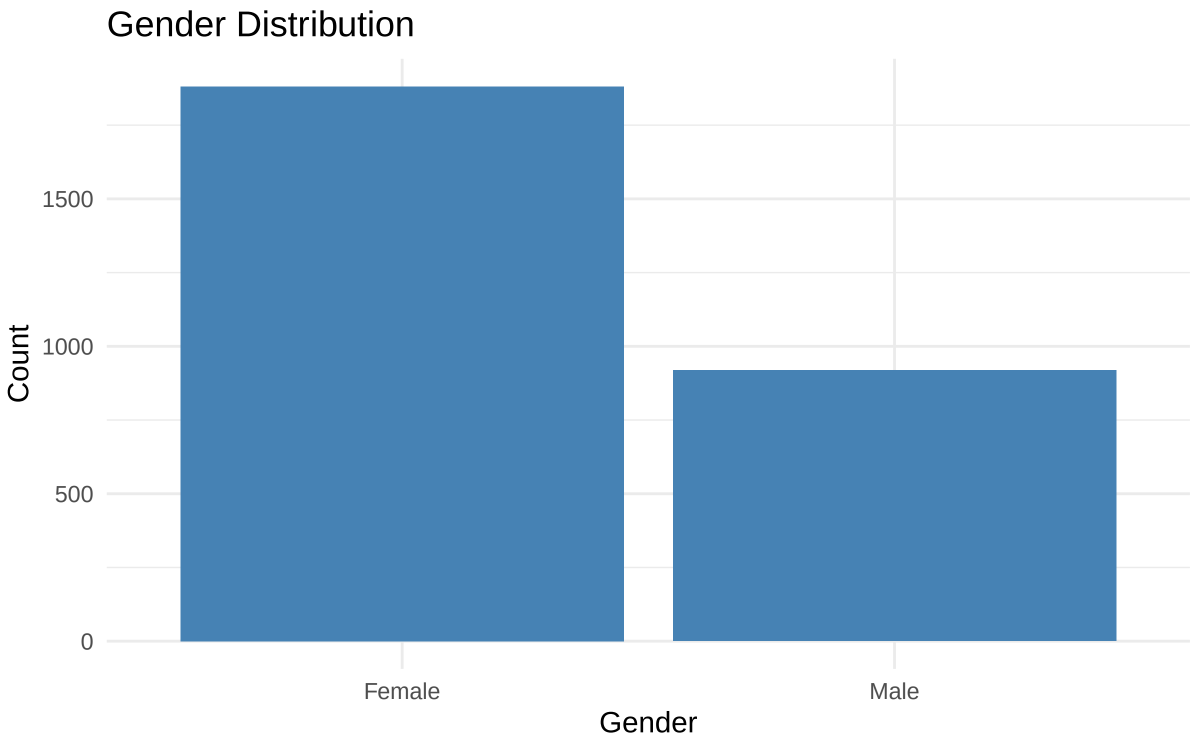
Exploring survey items

```
# All Extraversion items
bfi |>
  select(E1:E5) |>
  pivot_longer(everything(), names_to = "item", values_to = "response") |>
  ggplot(aes(x = response, fill = item)) +
  geom_bar(position = "dodge") +
  labs(
    title = "Extraversion Item Responses",
    x = "Response (1-6)",
    y = "Count"
  ) +
  theme_minimal(base_size = 14)
```



Categorical variables

```r
bfi |>
  mutate(gender = ifelse(gender == 1, "Male", "Female")) |>
  ggplot(aes(x = gender)) +
  geom_bar(fill = "steelblue") +
  labs(
    title = "Gender Distribution",
    x = "Gender",
    y = "Count"
  ) +
  theme_minimal(base_size = 14)
```



Counts and proportions

```
# Counts
bfi |>
  mutate(gender = ifelse(gender == 1, "Male", "Female")) |>
  count(gender)
```

```
# A tibble: 2 x 2
  gender     n
  <chr>  <int>
1 Female  1881
2 Male     919
```

Counts and proportions

```
# Proportions
bfi |>
```

```r
  mutate(gender = ifelse(gender == 1, "Male", "Female")) |>
  count(gender) |>
  mutate(proportion = round(n / sum(n), 3))
```

```
# A tibble: 2 x 3
  gender     n proportion
  <chr>  <int>      <dbl>
1 Female  1881      0.672
2 Male     919      0.328
```

Outliers

What are outliers?

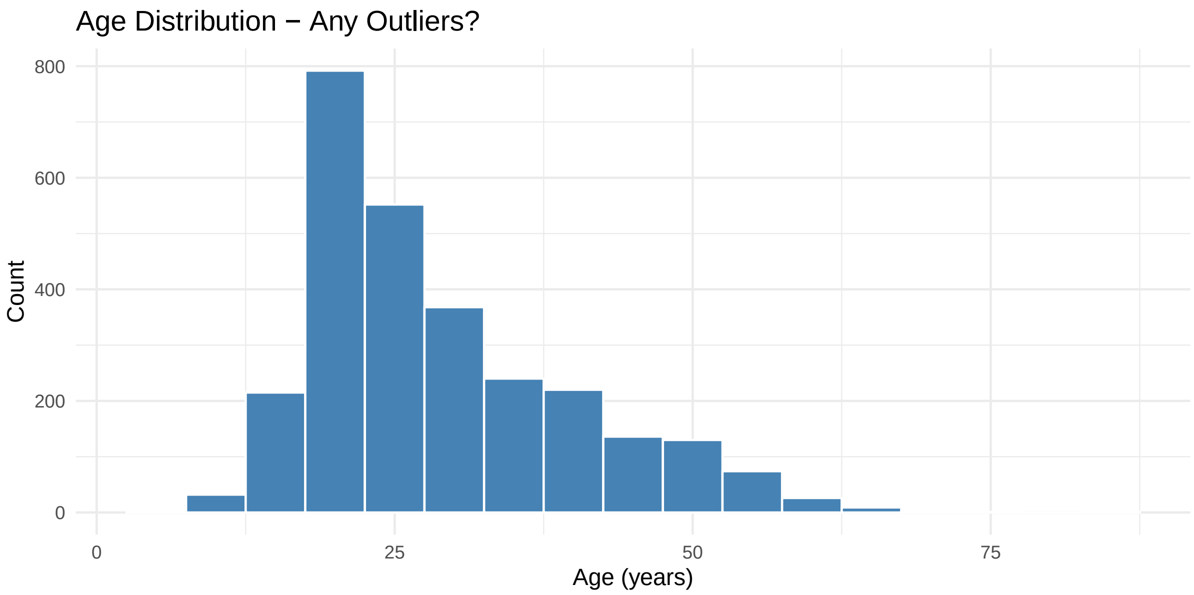
Values that are unusual compared to the rest of the data. They might be:

- **Real** — genuinely extreme values (a 95-year-old in a college study)
- **Errors** — data entry mistakes (age = 999)
- **Interesting** — worth investigating

Never delete an outlier without understanding it.

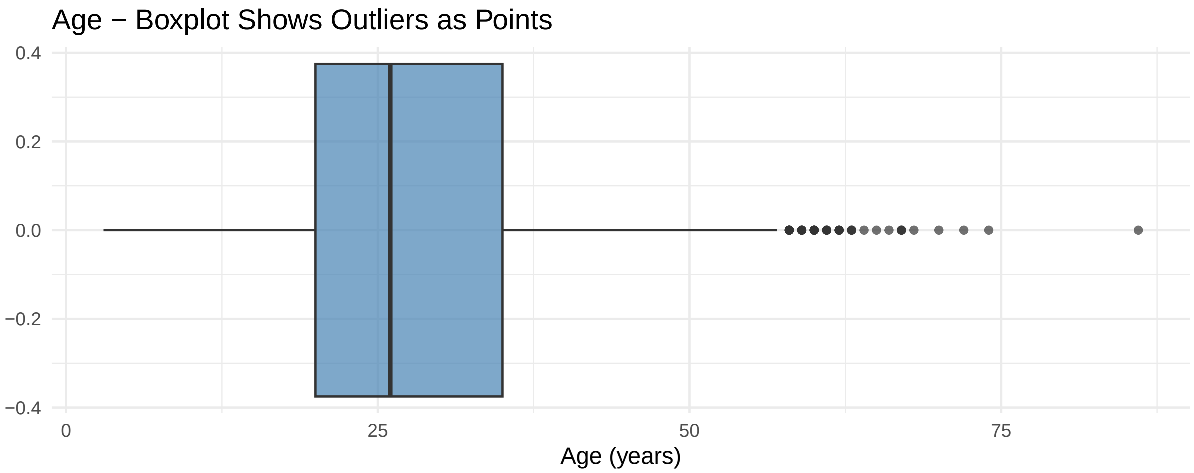
Spotting outliers visually

```r
bfi |>
  ggplot(aes(x = age)) +
  geom_histogram(binwidth = 5, fill = "steelblue", color = "white") +
  labs(
    title = "Age Distribution - Any Outliers?",
    x = "Age (years)",
    y = "Count"
  ) +
  theme_minimal(base_size = 14)
```



Spotting outliers with boxplots

```
bfi |>
  ggplot(aes(x = age)) +
  geom_boxplot(fill = "steelblue", alpha = 0.7) +
  labs(
    title = "Age - Boxplot Shows Outliers as Points",
    x = "Age (years)"
  ) +
  theme_minimal(base_size = 14)
```



Points beyond the whiskers are flagged as outliers by the 1.5×IQR rule.

Investigating outliers programmatically

```r
# Find unusually old or young participants
bfi |>
  filter(age > 60) |>
  select(age, gender, education)
```

```
# A tibble: 22 x 3
     age gender education
   <int>  <int>     <int>
 1    68      1         5
 2    64      2         5
 3    74      1         5
 4    63      2         3
 5    62      1         2
 6    86      2         2
 7    61      1         2
 8    67      1         5
 9    67      1         5
10    63      1         5
# i 12 more rows
```

What to do with outliers

Outlier type	What to do
Likely error (age = 999)	Fix or set to NA
Real but extreme	Note it, keep it, mention in write-up
Suspicious	Investigate further
Doesn't affect conclusions	Keep it, move on

Document your decisions. Future you will want to know.

Pair coding break

Your turn: 10 minutes

Using the `penguins` dataset (from the `palmerpenguins` package):

1. Plot the distribution of **flipper_length_mm** — what shape is it?
2. Check for **outliers** in flipper length. Are any values suspicious?

> Tip
>
> Try both a histogram and a boxplot. They show different things. Use `summary()` first to get oriented.

Before we move on

Upload your code to Canvas for participation credit. Paste what you have into today's in-class submission — it doesn't need to work perfectly.

Missing data — a first look

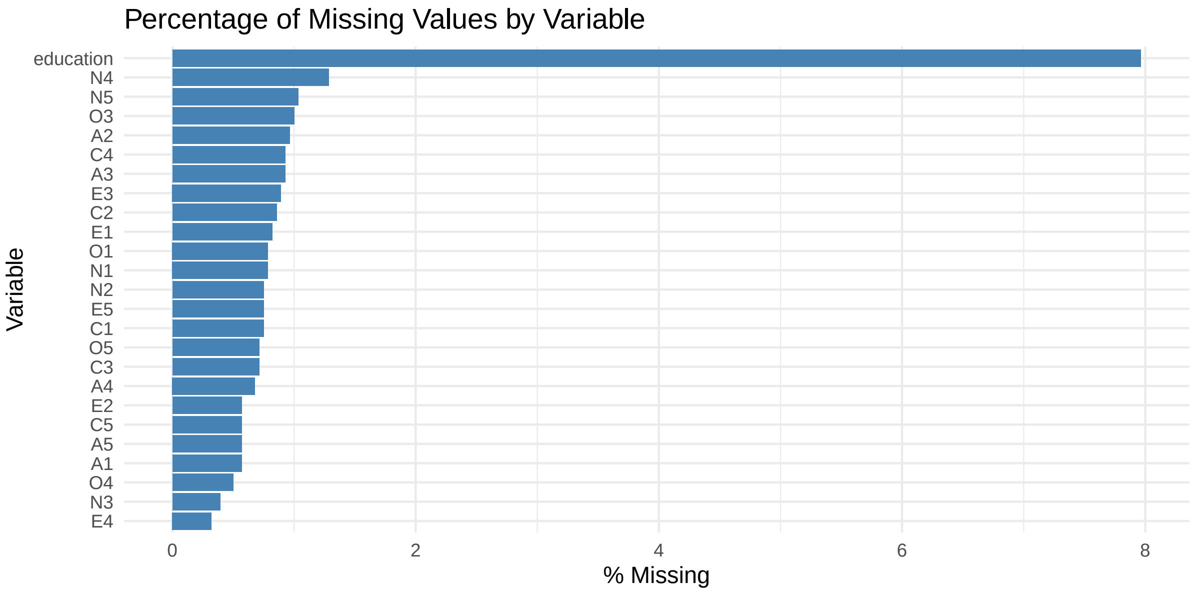
Missing data is everywhere

```r
# How much missing data do we have?
bfi |>
  summarize(across(everything(), ~ sum(is.na(.)))) |>
  pivot_longer(everything(), names_to = "variable", values_to = "n_missing") |>
  arrange(desc(n_missing))
```

```
# A tibble: 28 x 2
   variable  n_missing
   <chr>         <int>
 1 education       223
 2 N4               36
 3 N5               29
 4 O3               28
 5 A2                27
 6 A3                26
 7 C4                26
 8 E3                25
 9 C2                24
10 E1                23
# i 18 more rows
```

Visualizing missingness

```
bfi |>
  summarize(across(everything(), ~ mean(is.na(.)))) |>
  pivot_longer(everything(), names_to = "variable", values_to = "pct_missing") |>
  mutate(pct_missing = pct_missing * 100) |>
  filter(pct_missing > 0) |>
  arrange(desc(pct_missing)) |>
  ggplot(aes(x = reorder(variable, pct_missing), y = pct_missing)) +
  geom_col(fill = "steelblue") +
  coord_flip() +
  labs(
    title = "Percentage of Missing Values by Variable",
    x = "Variable",
    y = "% Missing"
  ) +
  theme_minimal(base_size = 14)
```



Why it matters for EDA

Missing data can bias your exploration:

- If missingness is related to the variables you're studying, your distributions are wrong
- If certain groups are more likely to have missing data, you might miss important patterns

We'll cover this in depth in Session 14. For now: **always check for missing data before exploring.**

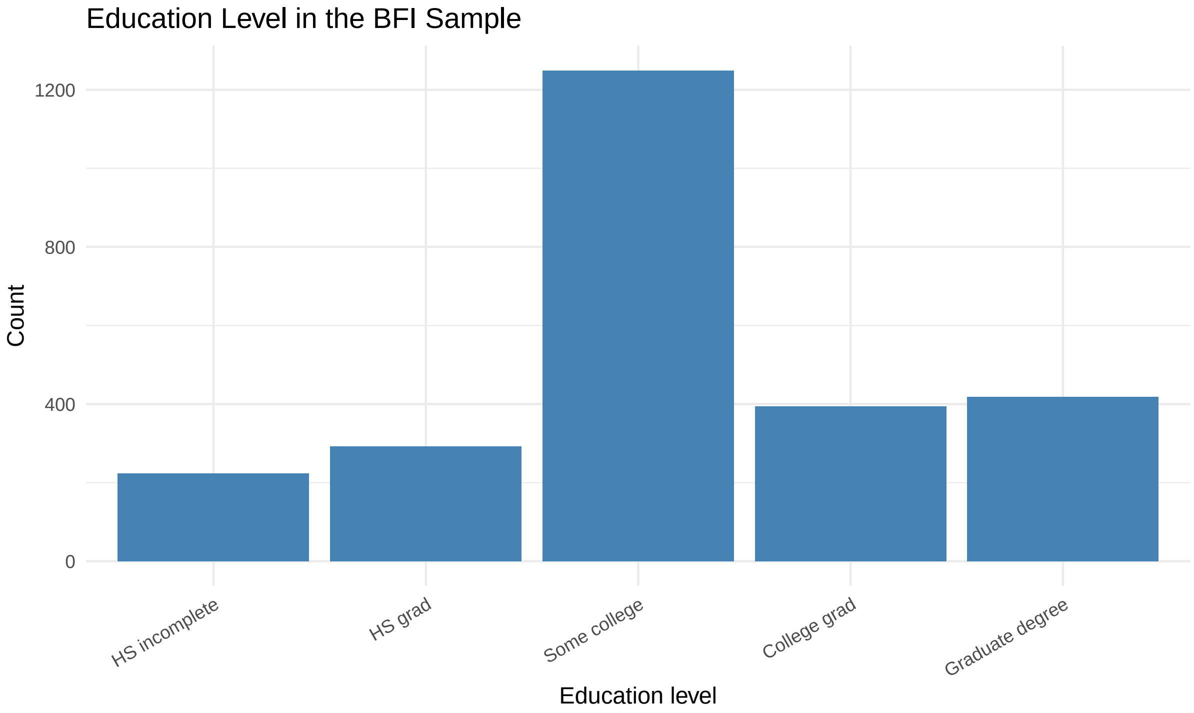
The EDA workflow

A systematic approach

1. **Look at the structure** — `glimpse()`, `summary()`
2. **Check for missing data** — how much? Which variables?
3. **Explore each variable** — histograms, bar charts, summaries
4. **Look for outliers** — boxplots, programmatic checks
5. **Ask questions** — what surprised you? What do you want to know more about?
6. **Repeat** — EDA is iterative

Putting it together: a mini-EDA

```r
# Education distribution - what does it look like?
bfi |>
  filter(!is.na(education)) |>
  mutate(education = factor(education, labels = c(
    "HS incomplete", "HS grad", "Some college",
    "College grad", "Graduate degree"
  ))) |>
  ggplot(aes(x = education)) +
  geom_bar(fill = "steelblue") +
  labs(
    title = "Education Level in the BFI Sample",
    x = "Education level",
    y = "Count"
  ) +
  theme_minimal(base_size = 14) +
  theme(axis.text.x = element_text(angle = 30, hjust = 1))
```



Get a head start

Assignment 5 preview

Assignment 5 will have you do a full EDA on a psychology dataset. Start now:

1. Load `bfi` and run `glimpse()` and `summary()`
2. Pick **3 variables** and create distributions for each
3. For each one: What shape is it? Any outliers? Any missing data?
4. Write down **one question** each distribution makes you want to ask

That's the core of EDA — noticing things and getting curious.

Wrapping up

EDA toolkit so far

Tool	When to use
`glimpse()`	First look at structure
`summary()`	Quick numeric summaries
`geom_histogram()`	Continuous distributions
`geom_density()`	Smooth distribution shape
`geom_bar()`	Categorical distributions
`geom_boxplot()`	Outlier detection
`count()`	Frequency tables
`is.na()` / `sum(is.na())`	Missing data check

Before next class

Read:

- R4DS Ch 10: Exploratory data analysis (sections 10.5–10.6)

Practice:

- Explore at least 3 variables in `bfi`
- Look for outliers and missing data
- Start generating questions

Key takeaways

1. **EDA is an attitude** — curiosity, not confirmation
2. **Always visualize** — summary stats hide patterns
3. **Outliers are information** — investigate, don’t delete
4. **Check missing data first** — it affects everything
5. **Ask questions, then answer them** — that’s the loop

The one thing to remember

EDA isn’t a step you finish. It’s the habit of looking at your data before you believe anything about it.

Next time: EDA — Covariation