Putting It All Together

PSY 410: Data Science for Psychology

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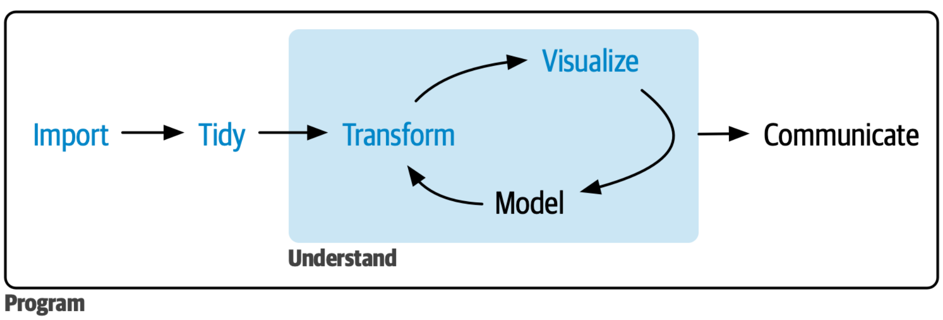
Setup

Looking back

The data science workflow



. . .

Ten weeks ago, you couldn't do any of this. Now you can do all of it.

Live demonstration

A real analysis: Start to finish

Let's analyze a complete psychology dataset together.

Research question: Does social media use predict anxiety in college students?

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I'll demonstrate the full workflow:

1. Import messy data
2. Clean and tidy
3. Explore with visualizations
4. Create publication-ready figures
5. Build a Quarto report

The dataset

```
# Simulated college student survey data
set.seed(2026)
social_media <- tibble(
  id = 1:200,
  age = sample(18:24, 200, replace = TRUE),
  gender = sample(c("Male", "Female", "Non-binary", "Prefer not to say"),
                  200, replace = TRUE),
  hours_social_media = rnorm(200, 4, 2),
  gad7_total = rnorm(200, 8, 5),  # Generalized Anxiety Disorder scale
  phq9_total = rnorm(200, 10, 6),  # Depression scale
  academic_year = sample(c("Freshman", "Sophomore", "Junior", "Senior"),
                         200, replace = TRUE)
) |>
  mutate(
    # Make anxiety correlate with social media use
    gad7_total = gad7_total + hours_social_media * 0.8,
    # Add some missing data
    hours_social_media = if_else(runif(200) < 0.05, NA_real_, hours_social_media),
    gad7_total = if_else(runif(200) < 0.08, NA_real_, gad7_total)
  )
```

Step 1: Explore the data

```
glimpse(social_media)
```

```
Rows: 200
Columns: 7
$ id                 <int> 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, ~
$ age                <int> 22, 18, 18, 23, 22, 24, 20, 21, 21, 22, 24, 21, 19,~
```

```
$ gender             <chr> "Non-binary", "Prefer not to say", "Female", "Prefe~
$ hours_social_media <dbl> 3.3448174, 3.2895680, 5.5618681, 5.2173403, 6.15235~
$ gad7_total         <dbl> NA, 11.577943, 12.102962, 17.555169, 18.276343, 15.~
$ phq9_total         <dbl> 8.50042866, 8.19341562, 1.00400734, 10.20523209, 4.~
$ academic_year      <chr> "Junior", "Freshman", "Sophomore", "Freshman", "Jun~
```

```
...
```

```
# Check for missing data
social_media |>
  summarize(across(everything(), ~sum(is.na(.x))))
```

```
# A tibble: 1 x 7
     id   age gender hours_social_media gad7_total phq9_total academic_year
  <int> <int>  <int>              <int>      <int>      <int>         <int>
1     0     0      0                  6         13          0             0
```

Step 2: Clean the data

```
social_media_clean <- social_media |>
  # Remove rows with missing outcome
  drop_na(gad7_total) |>
  # Create anxiety categories
  mutate(
    anxiety_category = case_when(
      gad7_total < 5 ~ "Minimal",
      gad7_total < 10 ~ "Mild",
      gad7_total < 15 ~ "Moderate",
      gad7_total >= 15 ~ "Severe"
    ),
    anxiety_category = factor(anxiety_category,
                              levels = c("Minimal", "Mild", "Moderate", "Severe")),
    # Reorder academic year
    academic_year = factor(academic_year,
                           levels = c("Freshman", "Sophomore", "Junior", "Senior"))
  )
```

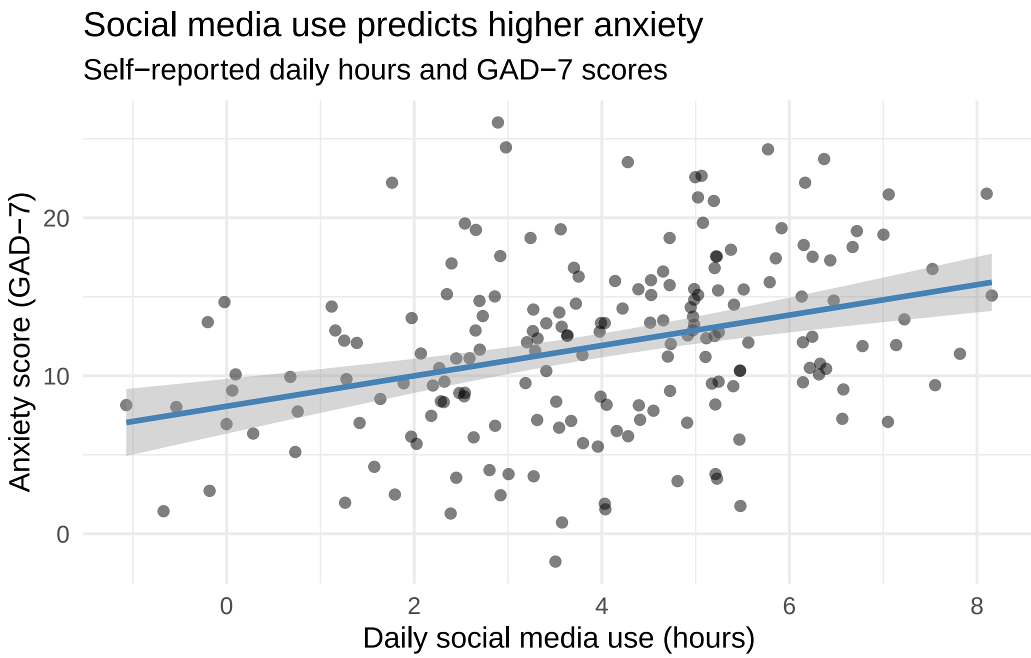
Step 3: Descriptive statistics

```
social_media_clean |>
  summarize(
    n = n(),
    mean_age = mean(age),
    mean_hours = mean(hours_social_media, na.rm = TRUE),
    sd_hours = sd(hours_social_media, na.rm = TRUE),
    mean_anxiety = mean(gad7_total),
    sd_anxiety = sd(gad7_total)
  )
```

```
# A tibble: 1 x 6
      n mean_age mean_hours sd_hours mean_anxiety sd_anxiety
  <int>    <dbl>      <dbl>    <dbl>        <dbl>      <dbl>
1   187     21.0       3.97     1.93         11.9       5.42
```

Step 4: Initial visualization

```
ggplot(social_media_clean, aes(x = hours_social_media, y = gad7_total)) +
  geom_point(alpha = 0.5) +
  geom_smooth(method = "lm", color = "steelblue") +
  labs(
    title = "Social media use predicts higher anxiety",
    subtitle = "Self-reported daily hours and GAD-7 scores",
    x = "Daily social media use (hours)",
    y = "Anxiety score (GAD-7)"
  ) +
  theme_minimal()
```



Step 5: Compute correlation

```
# Clean data for correlation (remove NAs)
correlation_data <- social_media_clean |>
  drop_na(hours_social_media, gad7_total)

cor_value <- cor(correlation_data$hours_social_media,
                 correlation_data$gad7_total)

cor_value
```

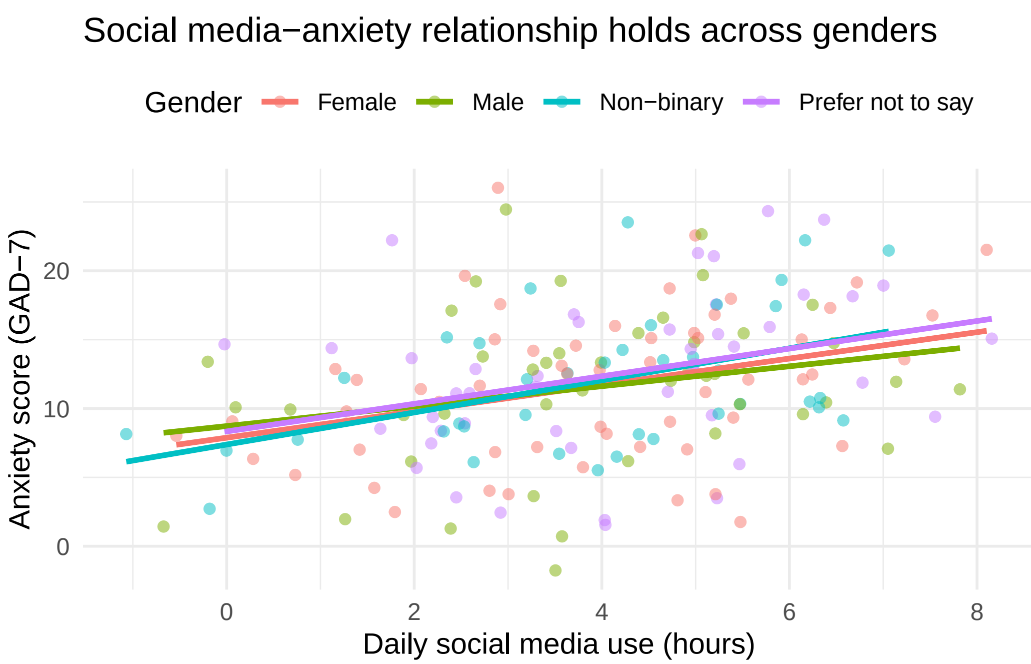
```
[1] 0.3388387
```

. . .

Finding: Moderate positive correlation (r = 0.34)

Step 6: Explore by gender

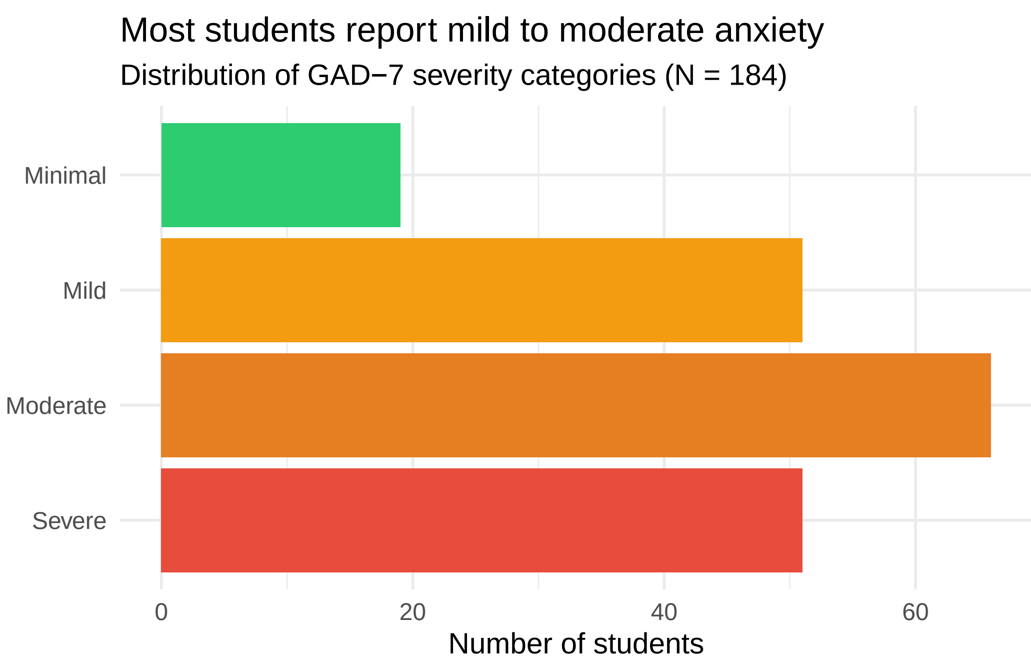
```r
ggplot(social_media_clean, aes(x = hours_social_media, y = gad7_total, color = gender)) +
  geom_point(alpha = 0.5) +
  geom_smooth(method = "lm", se = FALSE) +
  labs(
    title = "Social media-anxiety relationship holds across genders",
    x = "Daily social media use (hours)",
    y = "Anxiety score (GAD-7)",
    color = "Gender"
  ) +
  theme_minimal() +
  theme(legend.position = "top")
```



Step 7: Anxiety categories

```r
social_media_clean |>
  count(anxiety_category) |>
  mutate(anxiety_category = fct_rev(anxiety_category)) |>
  ggplot(aes(x = n, y = anxiety_category, fill = anxiety_category)) +
  geom_col() +
  scale_fill_manual(values = c(
```

```r
    "Minimal" = "#2ecc71",
    "Mild" = "#f39c12",
    "Moderate" = "#e67e22",
    "Severe" = "#e74c3c"
  )) +
  labs(
    title = "Most students report mild to moderate anxiety",
    subtitle = "Distribution of GAD-7 severity categories (N = 184)",
    x = "Number of students",
    y = NULL
  ) +
  theme_minimal() +
  theme(legend.position = "none")
```



Step 8: Create summary table

```r
summary_table <- social_media_clean |>
  group_by(anxiety_category) |>
  summarize(
    N = n(),
    Mean_Hours = mean(hours_social_media, na.rm = TRUE),
```

```r
    SD_Hours = sd(hours_social_media, na.rm = TRUE),
    Mean_Age = mean(age),
    .groups = "drop"
  )

knitr::kable(summary_table, digits = 1,
             col.names = c("Anxiety Category", "N", "M Hours", "SD Hours", "M Age"))
```

Anxiety Category	N	M Hours	SD Hours	M Age
Minimal	19	3.0	1.7	21.2
Mild	51	3.2	2.0	20.9
Moderate	66	4.1	1.8	20.7
Severe	51	5.0	1.5	21.2

Step 9: Write it up in Quarto

````
## Results

We analyzed data from 187 college students
(M age = 21 years).
Students reported using social media an average of
4
hours per day (SD = 1.9).

Social media use was positively correlated with anxiety scores
(r = 0.34, p < .001), such that students who
used social media more reported higher anxiety levels.

```{r}
#| echo: false
#| fig-cap: "Relationship between social media use and anxiety"
# [Insert scatterplot code]
```
````

What this demonstrates

Complete workflow — import to interpretation **Data cleaning** — handling missing data, creating factors **Multiple visualizations** — exploring from different angles **Summary**

statistics — both numerical and tabular **Inline reporting** — no hard-coded numbers
Clear narrative — telling the story

When things break

The 6 errors you'll see most often

Error	What it means	Fix
`object 'x' not found`	Typo, wrong capitalization, or object not created yet	Check spelling; run the code that creates it
`could not find function`	Typo in function name or package not loaded	Check spelling; run `library()`
`unexpected symbol`	Missing `|>`, `+`, comma, or parenthesis	Check the line *before* the error
`non-numeric argument`	Math on text — variable is character, not numeric	Check type with `class()` or `glimpse()`
`did you mean '=='?`	Used `=` (assignment) instead of `==` (comparison) in `filter()`	Change `=` to `==`
ggplot `+` error	Missing `+` between ggplot layers	Every line except the last needs `+`

A 5-step debugging strategy

1. **Read the error message** — actually read it. It tells you *where* and *what*.

. . .

2. **Check the basics** — package loaded? Object created? Spelling correct?

. . .

3. **Run line by line** — pipe chains: run from the top, adding one line at a time. Which line breaks?

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4. **Simplify** — make a tiny test dataset (`tibble(x = 1:3)`) and try the same operation.

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5. **Google it** — include "R", the package name, and the exact error message.

When you ask for help: make a reprex

Reprex = **repr**oducible **ex**ample — the smallest code that recreates your error.

. . .

Bad: "My code doesn't work. Help!"

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Good:

> "I'm trying to filter my data but getting 'object not found':
>
> ```
> library(tidyverse)
> data <- tibble(x = 1:3, y = c("a", "b", "c"))
> filter(data, x > 1)
> # Error: object 'data' not found
> ```
>
> I expected rows where x > 1."

. . .

Tip: Use `dput()` to share a small slice of your real data so others can recreate it exactly.

Where to get help after this course

- Stack Overflow — searchable Q&A (look for green checkmark)
- Posit Community — friendly R forum
- R4DS Slack — real-time chat
- R-Ladies — supportive community with local chapters

. . .

Before posting: search first, be specific, show what you tried, and include a reprex.

Pair coding break

Your turn: Debug this code

This code has several errors. Find and fix them all:

```r
library(tidyverse)

# Load data
Study_data <- tibble(
  id = 1:5,
  Score = c(10, 15, 12, 18, 14),
  Group = c("A", "B", "A", "B", "A")
)

# Analyze
study_data |>
  filter(Group = "A") |>
  summarize(
    mean_score = mean(score)
    sd_score = sd(score)
  )
```

Time: 10 minutes

> Tip
>
> There are at least 4 bugs. Read each line carefully and check: names, operators, punctuation.

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.

Where to go from here

You have the foundation

This course covered **data wrangling and visualization** — the foundation of data science.

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What's next?

- **Statistics in R** — inference, hypothesis testing
- **Advanced R programming** — functions, iteration
- **Version control** — Git and GitHub
- **Interactive tools** — Shiny dashboards
- **Machine learning** — tidymodels framework

Statistics in R

You can now learn inferential statistics:

```
# t-test
t.test(gad7_total ~ gender, data = social_media_clean)

# ANOVA
aov(gad7_total ~ academic_year, data = social_media_clean)

# Regression
lm(gad7_total ~ hours_social_media + age, data = social_media_clean)
```

. . .

Courses to consider:

- PSY 420: Advanced Statistics
- STAT 510: Applied Regression
- Online: Learning Statistics with R

Writing functions

Automate repetitive tasks:

```r
# Instead of copying this code multiple times...
compute_scale_score <- function(data, items) {
  data |>
    rowwise() |>
    mutate(score = mean(c_across(all_of(items)), na.rm = TRUE)) |>
    ungroup()
}

# Use it anywhere
phq9_scored <- compute_scale_score(my_data, c("phq1", "phq2", "phq3"))
```

Version control with Git

Track changes to your code over time:

- **Never lose work** — full history of changes
- **Collaborate easily** — merge changes from multiple people
- **Professional standard** — expected in industry and academia

. . .

Resources:

- Happy Git with R
- GitHub Learning Lab

Interactive visualizations with Shiny

Create web apps for your data:

```r
library(shiny)

ui <- fluidPage(
  selectInput("condition", "Choose condition:", choices = c("CBT", "Control")),
  plotOutput("plot")
)

server <- function(input, output) {
  output$plot <- renderPlot({
    data |> filter(condition == input$condition) |> ggplot(...)
  })
}
```

```r
shinyApp(ui, server)
```

Machine learning with tidymodels

Predictive modeling with tidy syntax:

```r
library(tidymodels)

# Split data
data_split <- initial_split(social_media_clean)
train_data <- training(data_split)
test_data <- testing(data_split)

# Fit model
lm_fit <- linear_reg() |>
  fit(gad7_total ~ hours_social_media + age, data = train_data)

# Make predictions
predict(lm_fit, test_data)
```

Learning resources

Free online resources

Books:

- R for Data Science (2e) — your textbook
- Learning Statistics with R
- Advanced R
- ggplot2: Elegant Graphics for Data Analysis

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Interactive learning:

- Posit Primers
- R-Bootcamp
- swirl — learn R in R

Community resources

Weekly challenges:

- #TidyTuesday — practice data viz
- Advent of Code — programming puzzles

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Communities:

- R-Ladies — inclusive R community
- R for Data Science Slack
- Posit Community
- Local R user groups (search Meetup.com)

Keep practicing

The only way to maintain skills: use them

. . .

Ideas:

- Analyze data from your own research
- Replicate figures from published papers
- Join #TidyTuesday
- Help friends/labmates with their data
- Create a personal website with Quarto
- Build a data visualization portfolio

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> Tip
>
> Aim for 1 hour per week — consistency matters more than intensity

Final reflections

What makes a good data scientist?

It's not about knowing every function or memorizing syntax.

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Good data scientists:

1. **Ask good questions** — what story is the data telling?
2. **Stay curious** — always learning new tools and techniques
3. **Communicate clearly** — make complex findings accessible
4. **Work reproducibly** — others can verify and build on your work
5. **Think critically** — question assumptions, check for bias
6. **Persist through errors** — debugging is part of the job

. . .

You've developed all of these skills this quarter.

The growth mindset

Ten weeks ago, many of you had never written a line of code.

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Now you can:

- Import and clean messy data
- Create publication-quality visualizations
- Wrangle complex datasets with joins and pivots
- Handle missing data appropriately
- Build reproducible reports

. . .

That's incredible growth.

Errors are part of the process

Remember:

- Everyone gets errors — even experienced programmers
- Errors mean you're learning
- Each error you solve makes you better
- The frustration is temporary; the skills are permanent

. . .

> ❗ Important
>
> If you take one thing from this course: **You can learn hard things.**

Thank you

Thank you for:

- Showing up and participating
- Helping each other
- Asking questions
- Persisting through challenges
- Trusting the process

. . .

You've been a great class. I'm excited to see what you do with these skills.

Final project presentations

Presentation guidelines

Format: 5 minutes per person

What to include:

1. Research question (1 min)
2. Dataset description (1 min)
3. Key finding with visualization (2 min)
4. Implications/what you learned (1 min)

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Tips:

- Show 1-2 of your best figures
- Focus on the story, not technical details
- Practice timing!

Presentation order

We'll go alphabetically by last name.

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Remember:

- This is a supportive environment
- Everyone is nervous — that's normal
- We want to hear about your work
- Questions are signs of interest, not criticism

Course evaluations

Please fill out course evaluations

Your feedback helps me improve the course for future students.

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What's helpful:

- Specific examples (this assignment, that lecture)
- Constructive suggestions
- What worked well (so I keep doing it)
- What didn't work (so I can change it)

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I read every evaluation carefully.

Final words

Keep learning

The field of data science is constantly evolving:

- New packages are released every day
- Best practices change
- Tools improve

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Stay curious. Stay connected. Keep coding.

You're now a data scientist

You have the skills to:

- Answer questions with data
- Create compelling visualizations
- Conduct reproducible research
- Teach yourself new tools

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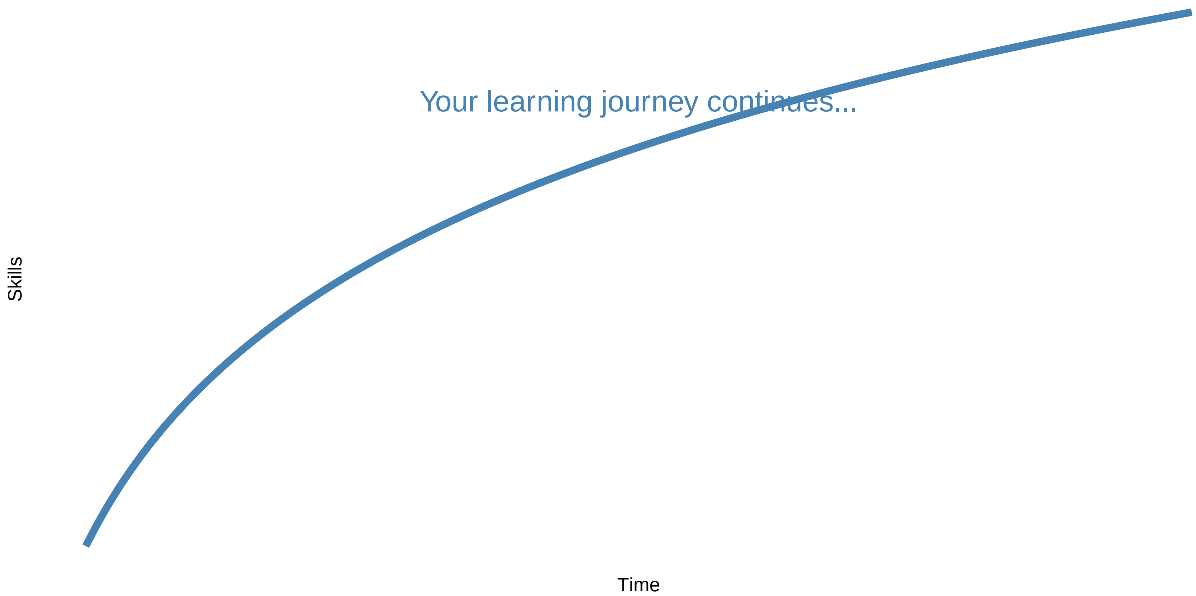
Use them.

Make psychology more reproducible, transparent, and data-driven.

Final final words



Thank you!

Good luck with your final projects and future data science adventures!

Stay in touch:

- **?var:instructor.email**
- Office hours (through finals week)

. . .

Now let's see your final projects!