Correlation & Simple Regression

PSY 410: Data Science for Psychology

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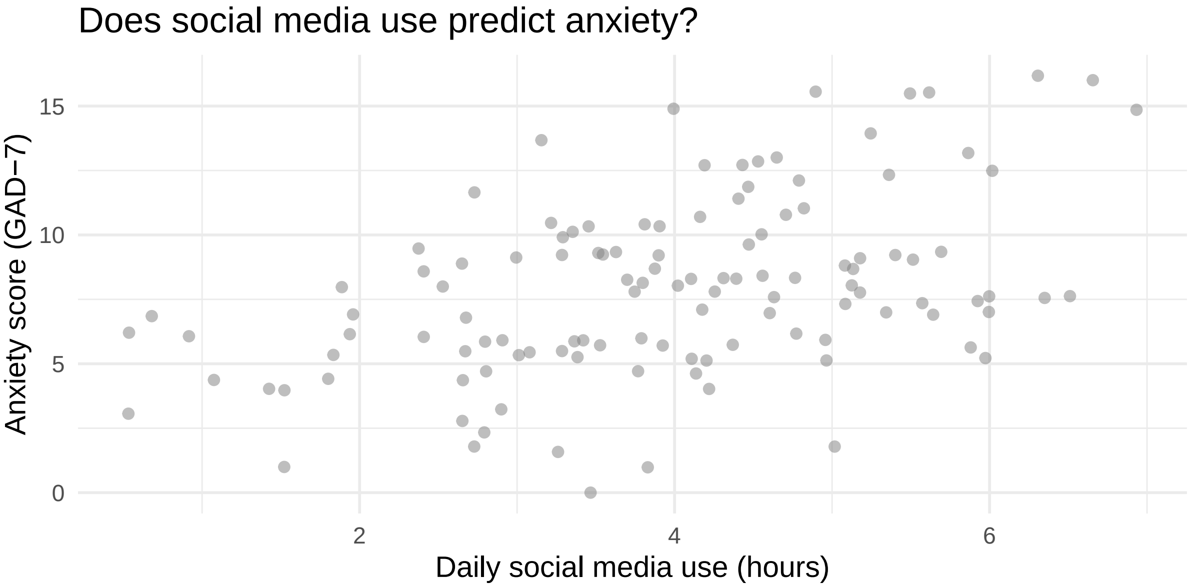
Setup

From patterns to numbers

You've been eyeballing patterns for 16 sessions



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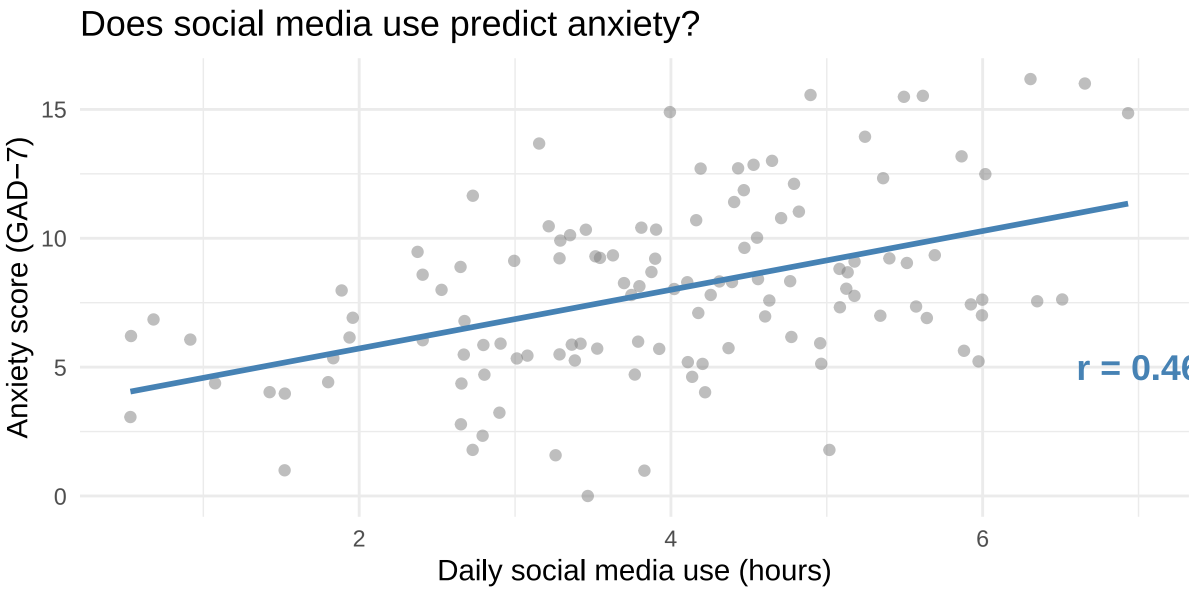
Today you learn to put a **number** on that pattern.

The same plot — with a number



Correlation measures the strength and direction. **Regression** draws the line.

Correlation

What correlation measures

Correlation (r) quantifies the **linear relationship** between two variables.

Value of r	Interpretation
r = 1.0	Perfect positive
r = 0.7	Strong positive
r = 0.3	Weak positive
r = 0.0	No linear relationship
r = -0.3	Weak negative
r = -0.7	Strong negative
r = -1.0	Perfect negative

. . .

Key: r tells you **direction** and **strength**, not causation.

cor() in R

```r
cor(study_data$hours_social_media, study_data$gad7_total)
```

```
[1] 0.4613455
```

. . .

That's it. One function, two variables, one number.

. . .

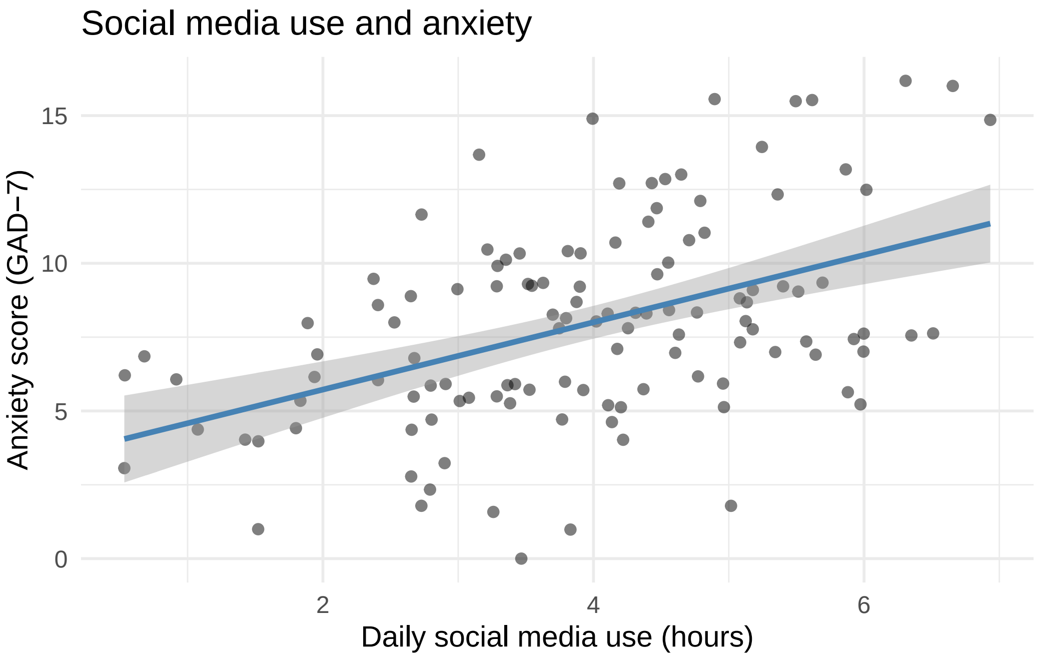
```r
# You can also use it inside a pipeline
study_data |>
  summarize(r = cor(hours_social_media, gad7_total))
```

```
# A tibble: 1 x 1
      r
  <dbl>
1 0.461
```

This is what geom_smooth() has been doing

Every time you wrote `geom_smooth(method = "lm")`, you were fitting a line through the data.

```r
ggplot(study_data, aes(x = hours_social_media, y = gad7_total)) +
  geom_point(alpha = 0.5) +
  geom_smooth(method = "lm", color = "steelblue") +
  labs(
    title = "Social media use and anxiety",
    x = "Daily social media use (hours)",
    y = "Anxiety score (GAD-7)"
  ) +
  theme_minimal()
```



cor.test() — is it statistically significant?

```
cor.test(study_data$hours_social_media, study_data$gad7_total)
```

```

	Pearson's product-moment correlation

data:  study_data$hours_social_media and study_data$gad7_total
t = 5.6485, df = 118, p-value = 1.138e-07
alternative hypothesis: true correlation is not equal to 0
95 percent confidence interval:
 0.3075349 0.5916611
sample estimates:
      cor 
0.4613455 
```

. . .

What to report: r, p-value, and 95% confidence interval.

Correlation matrix: multiple variables at once

```r
study_data |>
  select(hours_social_media, gad7_total, phq9_total, therapy_hours) |>
  cor(use = "complete.obs") |>
  round(2)
```

```
                   hours_social_media gad7_total phq9_total therapy_hours
hours_social_media               1.00       0.46       0.36          0.00
gad7_total                       0.46       1.00       0.22          0.09
phq9_total                       0.36       0.22       1.00          0.06
therapy_hours                    0.00       0.09       0.06          1.00
```

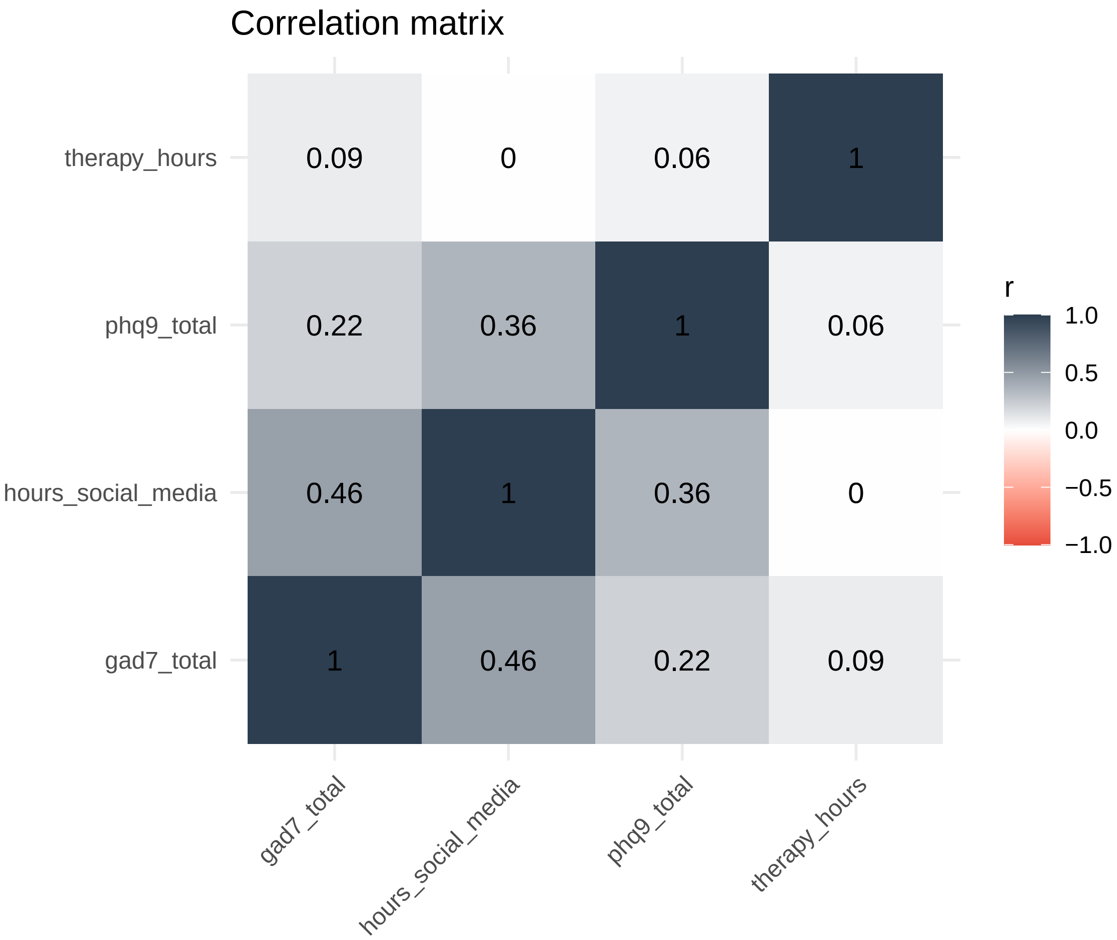
. . .

Each cell is the correlation between the row variable and the column variable. The diagonal is always 1 (a variable correlates perfectly with itself).

Visualizing a correlation matrix

```r
cor_matrix <- study_data |>
  select(hours_social_media, gad7_total, phq9_total, therapy_hours) |>
  cor(use = "complete.obs")

# Manual heatmap with ggplot
cor_matrix |>
  as.data.frame() |>
  rownames_to_column("var1") |>
  pivot_longer(-var1, names_to = "var2", values_to = "r") |>
  ggplot(aes(x = var1, y = var2, fill = r)) +
  geom_tile() +
  geom_text(aes(label = round(r, 2)), size = 4) +
  scale_fill_gradient2(low = "#e74c3c", mid = "white", high = "#2c3e50",
                       midpoint = 0, limits = c(-1, 1)) +
  labs(title = "Correlation matrix", x = NULL, y = NULL) +
  theme_minimal() +
  theme(axis.text.x = element_text(angle = 45, hjust = 1))
```



Correlation does NOT mean causation

Correlation	Why it's not causal
Ice cream sales & drowning deaths	Both increase in summer (confound: temperature)
Shoe size & reading ability	Both increase with age (confound: development)
Social media & anxiety	Anxious people may seek social media for comfort (reverse causation)

. . .

To establish causation, you need an experiment — random assignment, manipulation, control group. Correlation from observational data tells you variables are *related*, not that one *causes* the other.

Pair coding break

Your turn: Explore correlations

Using the `study_data` dataset (already loaded):

1. Compute the correlation between `therapy_hours` and `depression_post`
2. Is it positive or negative? What does that mean in plain language?
3. Create a scatterplot of this relationship with a trend line
4. Use `cor.test()` — is the correlation significant?

Time: 10 minutes

> 💡 Tip
>
> Negative correlation means as one variable goes up, the other goes down. Think about what that means for therapy and depression.

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.

Simple linear regression

From correlation to regression

Correlation tells you the relationship exists and how strong it is.

Regression goes further — it gives you an equation to **predict** one variable from another.

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The equation: **y = b0 + b1 * x**

- **b0** (intercept) = predicted y when x = 0
- **b1** (slope) = how much y changes for each 1-unit increase in x

lm() — fitting a model

```r
model <- lm(gad7_total ~ hours_social_media, data = study_data)
```

· · ·

Read this as: “Predict anxiety (`gad7_total`) from social media use (`hours_social_media`).”

The `~` means “predicted by.”

Reading the output

```r
summary(model)
```

```

Call:
lm(formula = gad7_total ~ hours_social_media, data = study_data)

Residuals:
    Min      1Q  Median      3Q     Max 
-7.3946 -2.0579 -0.2734  2.3845  6.9013 

Coefficients:
                   Estimate Std. Error t value Pr(>|t|)    
(Intercept)          3.4445     0.8437   4.083 8.13e-05 ***
hours_social_media   1.1395     0.2017   5.649 1.14e-07 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 3.074 on 118 degrees of freedom
Multiple R-squared:  0.2128,    Adjusted R-squared:  0.2062 
F-statistic: 31.91 on 1 and 118 DF,  p-value: 1.138e-07
```

What the numbers mean

Term	Estimate	p-value	In plain language
(Intercept)	3.445	0	Predicted anxiety when social media = 0 hours

Term	Estimate	p-value	In plain language
hours_social_media	1.139	0	For each additional hour of social media, anxiety increases by this much

. . .

In a sentence: For each additional hour of daily social media use, anxiety scores increase by about 1.1 points on the GAD-7.

R-squared: How much does the model explain?

```r
glance(model)$r.squared
```

```
[1] 0.2128397
```

. . .

R-squared tells you the proportion of variation in y explained by x.

- $R^2 = 0$ → the model explains nothing
- $R^2 = 1$ → the model explains everything
- $R^2 = 0.21$ → social media use explains about 21% of the variation in anxiety scores

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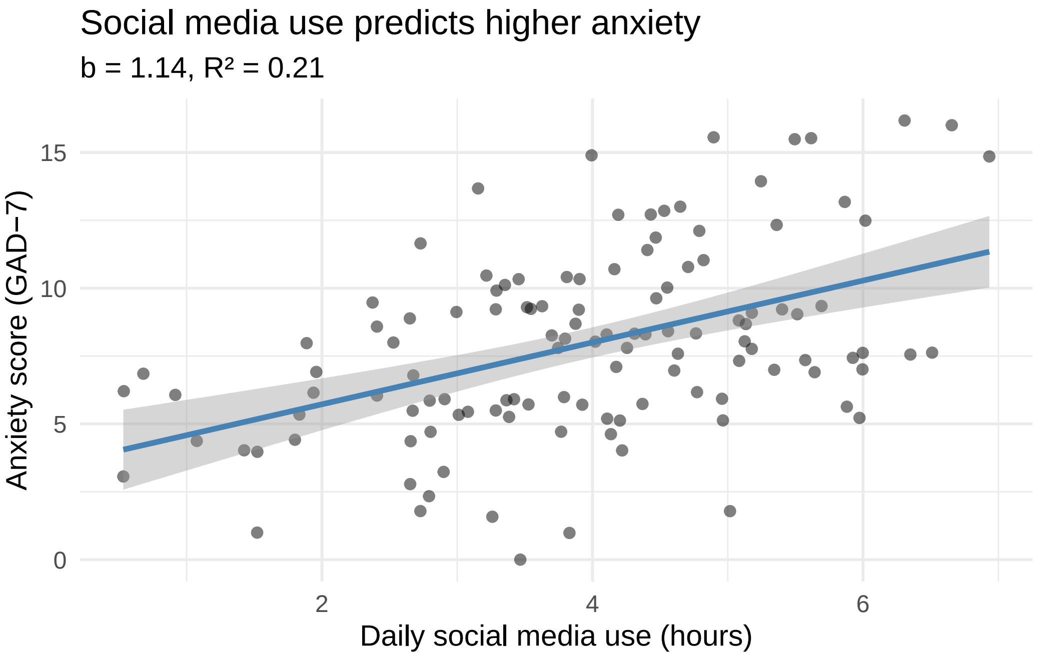
The other 79% is explained by other factors (genetics, life events, personality, etc.).

Visualizing the regression line

```r
ggplot(study_data, 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 = paste0("b = ", round(tidy(model)$estimate[2], 2),
                      ", R² = ", round(glance(model)$r.squared, 2)),
    x = "Daily social media use (hours)",
    y = "Anxiety score (GAD-7)"
  ) +
  theme_minimal()
```



From EDA to modeling

broom::tidy() — clean coefficient tables

The raw `summary()` output is hard to work with. `broom::tidy()` gives you a tidy data frame:

```
tidy(model)
```

```
# A tibble: 2 x 5
  term              estimate std.error statistic     p.value
  <chr>                <dbl>     <dbl>     <dbl>       <dbl>
1 (Intercept)           3.44     0.844      4.08 0.0000813
2 hours_social_media    1.14     0.202      5.65 0.000000114
```

. . .

Now you can use `knitr::kable()` to make a nice table:

```r
tidy(model) |>
  knitr::kable(digits = 3)
```

term	estimate	std.error	statistic	p.value
(Intercept)	3.445	0.844	4.083	0
hours_social_media	1.139	0.202	5.649	0

broom::glance() — model-level statistics

```r
glance(model) |>
  select(r.squared, adj.r.squared, sigma, p.value) |>
  knitr::kable(digits = 3)
```

r.squared	adj.r.squared	sigma	p.value
0.213	0.206	3.074	0

. . .

- **r.squared:** proportion of variance explained
- **adj.r.squared:** adjusted for number of predictors
- **sigma:** residual standard error (typical prediction error)
- **p.value:** is the overall model significant?

The pattern: see it, then quantify it

The workflow you now know:

1. **Explore** — scatterplot to see the relationship
2. **Correlate** — `cor()` to measure strength and direction
3. **Model** — `lm()` to get the equation and test significance
4. **Report** — `broom::tidy()` + `knitr::kable()` for clean tables

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This is what researchers do. You now have the tools.

What’s next

This is just the beginning

Today you learned **simple** regression — one predictor, one outcome.

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Real research often uses:

- **Multiple regression** — several predictors at once (`lm(y ~ x1 + x2 + x3)`)
- **ANOVA** — comparing group means (`aov(y ~ group)`)
- **Mixed models** — handling repeated measures and nested data
- **Mediation/moderation** — testing how and when effects occur

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All of these build on `lm()`. The syntax is nearly identical.

You have the R skills for all of this

The hard part — learning R, wrangling data, making visualizations — is done.

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Adding statistics is now just learning **new functions** in a language you already speak.

```
# Multiple regression - same lm(), just add predictors
lm(gad7_total ~ hours_social_media + age + gender, data = study_data)

# ANOVA - same idea
aov(gad7_total ~ condition, data = study_data)
```

Get a head start

End-of-deck exercise

Using the `study_data` dataset:

1. Run a regression predicting `phq9_total` (depression) from `hours_social_media`
2. What is the slope? Interpret it in a sentence.
3. What is R^2? Is social media use a good predictor of depression?
4. Create a scatterplot with the regression line and report the key statistics in the subtitle
5. **Bonus:** Use `broom::tidy()` to create a clean results table

Wrapping up

Before next class

No new reading — focus on your final project!

Do:

- Submit Assignment 8 (due today)
- Finish your final project (due Wednesday)
- Consider: could a correlation or regression strengthen your project?

The one thing to remember

The pattern you see in a scatterplot and the numbers from `lm()` are telling you the same story — one with your eyes, one with math.