

Chapter 5

Regression

The Prediction Problem

How do we make predictions from data?

Every day, algorithms make predictions that affect your life:

- Spotify predicts which songs you'll like based on your listening history
- Insurance companies predict your risk based on demographics and behaviour
- Universities predict student success from high school grades
- Weather apps predict tomorrow's temperature from atmospheric data

Intended Learning Outcomes

By the end of this chapter, you will be able to:

- Understand the equation of a straight line
- Define the least squares regression line
- Calculate slope and intercept from summary statistics
- Make predictions and recognise when they are unreliable
- Interpret slope and intercept in context
- Calculate and interpret R^2
- Compute and analyse residuals
- Identify influential points
- Recognise lurking variables and ecological fallacy

PART 1

Review of Straight Lines

Quick Review: Straight Lines

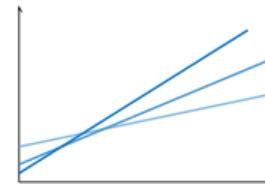
Straight Line

A **straight line** can be described by the equation

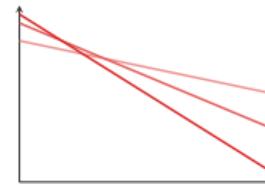
$$y = a + bx$$

where a is the **y -intercept** and b is the **slope**.

Positive Slopes ($a > 0$)



Negative Slopes ($a < 0$)

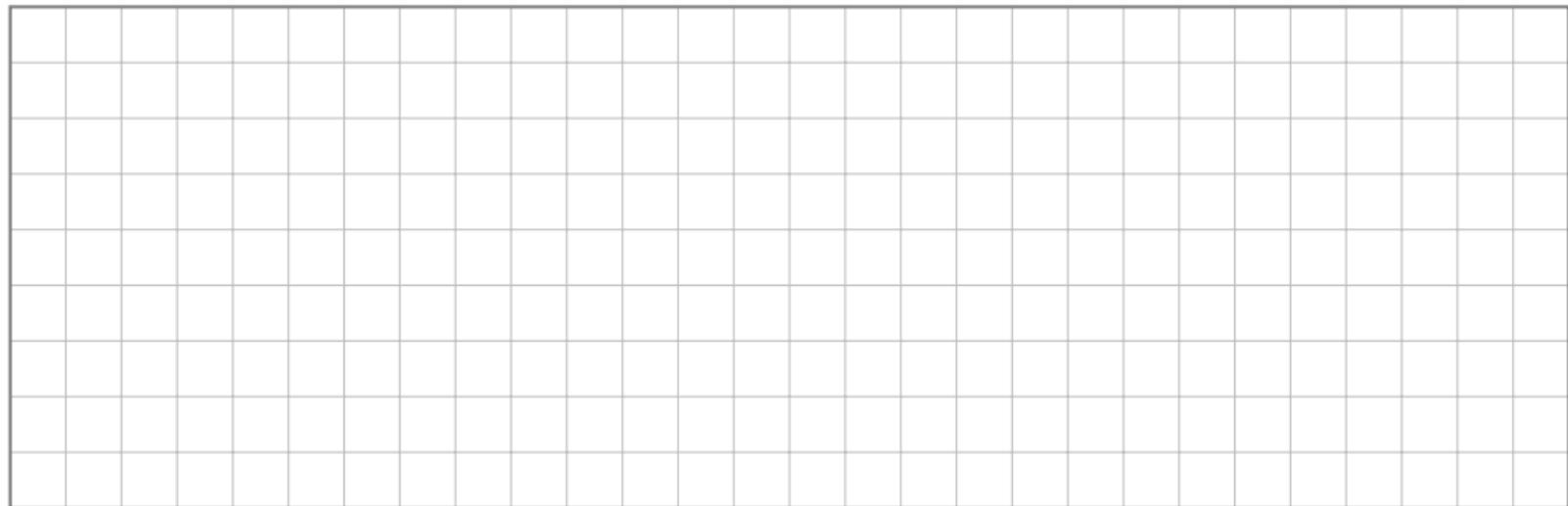


- The **slope** b tells you how much y changes when x increases by 1
- The **intercept** a is the value of y when $x = 0$

Example 5.1: Reviewing Lines

Given the points $(2, 5)$ and $(6, 13)$:

- Find the equation of the line passing through these points.
- What is the value of y when $x = 4$ on this line?



PART 2

Regression Lines

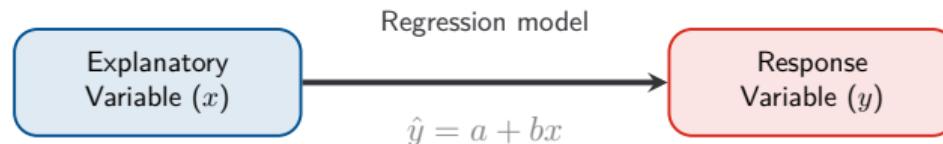
From Scatterplots to Prediction

Regression Line

A **regression line** is a straight line that describes how a response variable y changes as an explanatory variable x changes. It is used to **predict** the value of y based on the value of x .

New notation:

- \hat{y} = predicted value of y
- $\hat{y} = a + bx$ = the regression equation

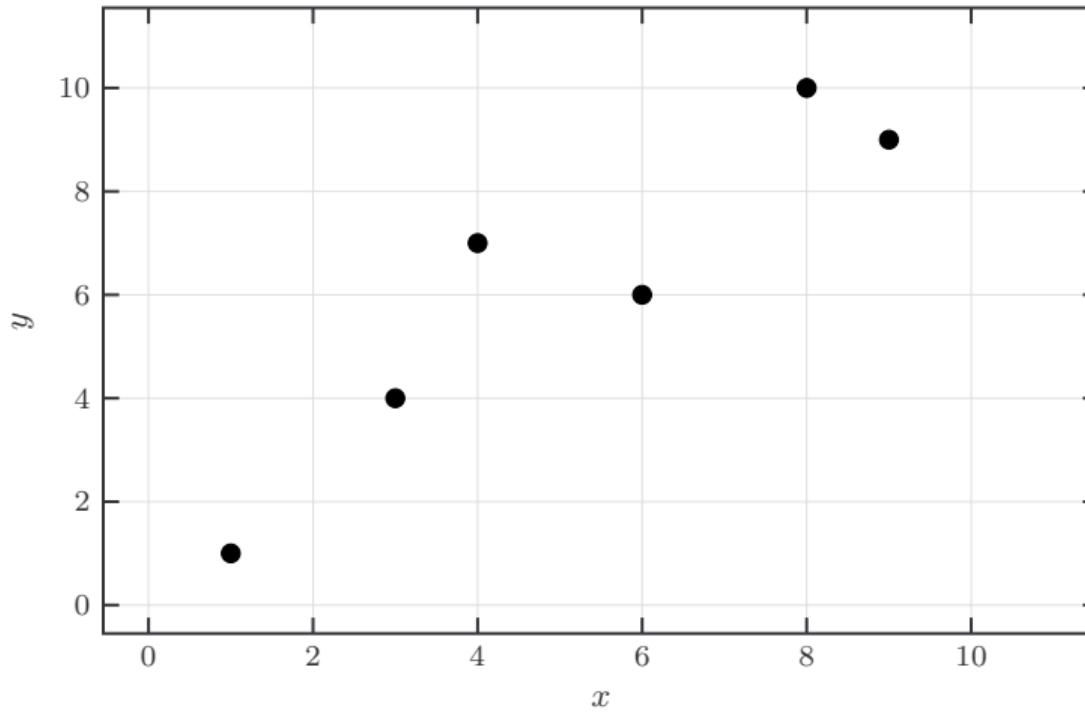


Notation Summary

We use \hat{y} ("y-hat") to denote predicted values from a regression line.

Symbol	Meaning
x	Explanatory variable (input)
y	Response variable (observed output)
\hat{y}	Predicted value of y from the regression line
\hat{y}_i	Predicted value for the i -th observation: $\hat{y}_i = a + bx_i$
a	y -intercept of the regression line
b	Slope of the regression line

What should our line be?



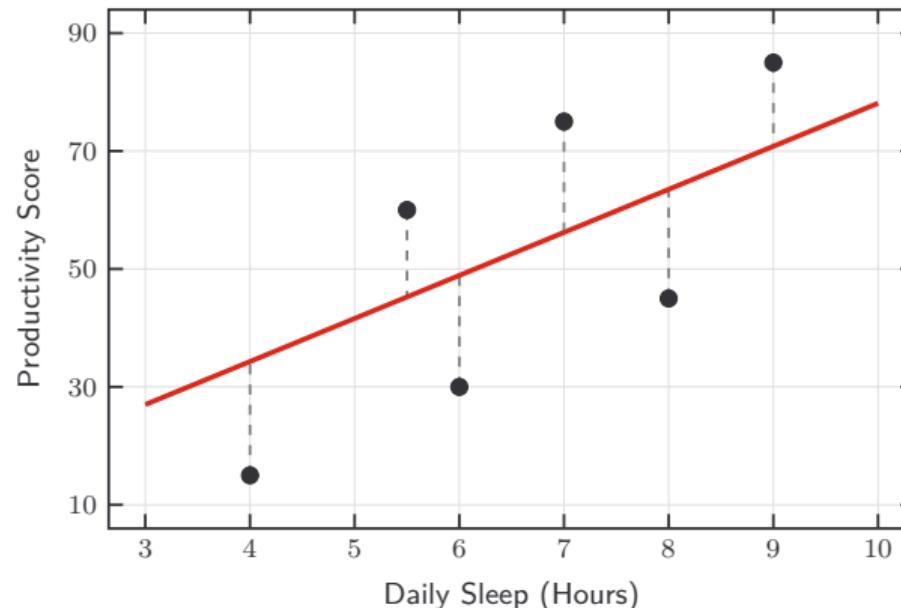
PART 3

The Least Squares Regression Line

Least Squares Regression Line

What is the least squares regression line?

The **least squares regression line** is the “best-fitting” straight line through a scatterplot.



The Least Squares Criterion

Least Squares Regression Line

The **least squares regression line** is the line that minimizes the sum of the **squared vertical distances** between observed values and predicted values:

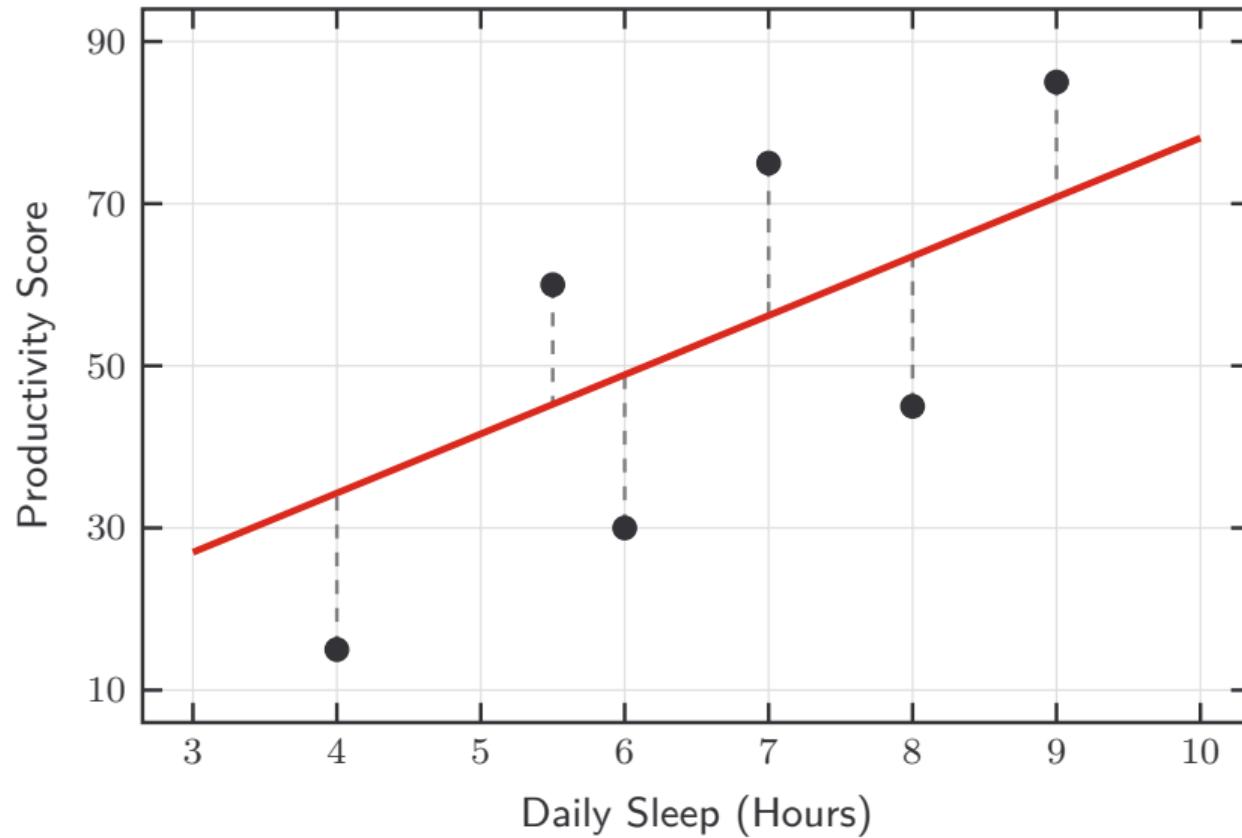
$$\text{Minimize } \sum_{i=1}^n (y_i - \hat{y}_i)^2$$



Why square the residuals?

- Treats positive and negative errors equally (no cancellation)
- Penalizes large errors more heavily than small ones
- Yields clean mathematical formulas

Visualising the Least Squares Idea



The Formulas for the Least Squares Line

The least squares regression line is given by

$$\hat{y} = a + bx,$$

where

$$b = r \cdot \frac{s_y}{s_x} \quad (\text{slope})$$

$$a = \bar{y} - b\bar{x} \quad (\text{intercept})$$

Example 5.2: Advertising and Daily Sales

Context: A small business tracks weekly ads and daily sales over 5 weeks. What is the least squares regression line of daily sales (y) on ads per week (x)?

Slope:

$b =$

Ads/week (x)	1	2	3	4	5
Sales (\$100s) (y)	1	5	11	9	9

Intercept:

$a =$

Summary statistics:

- $\bar{x} = 3$, $\bar{y} = 7$
- $s_x = 1.581$, $s_y = 4$

Equation:

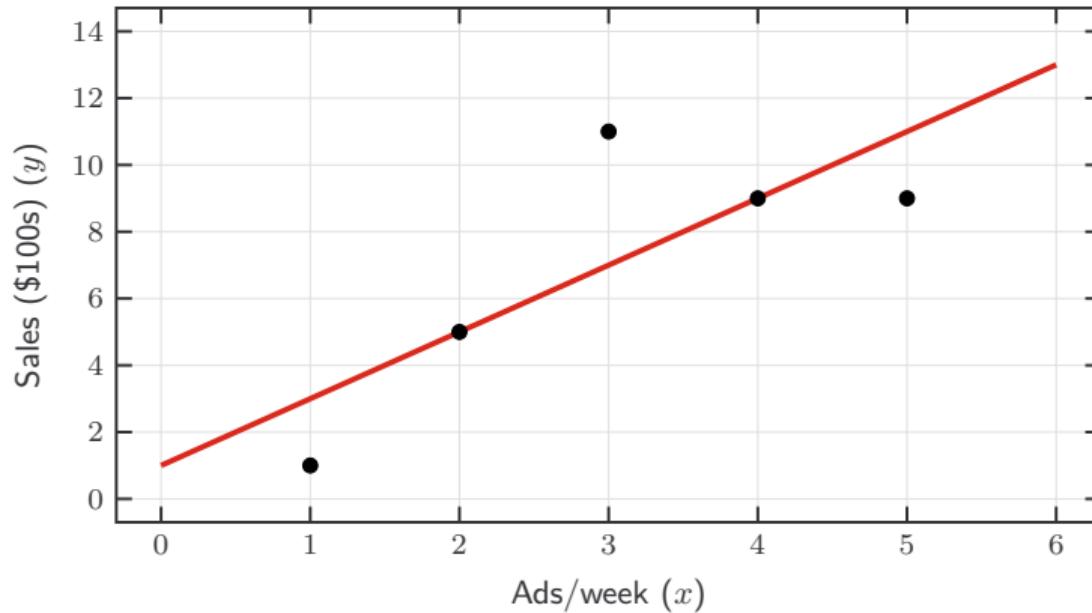
$\hat{y} =$

Phraseology

When we refer to the line predicting y from x , we can say any of the following:

- The regression of y on x
- The least squares regression line predicting y from x
- The least squares regression line with y as the response and x as the explanatory variable
- The line with y as the dependent variable and x as the independent variable
- The line modeling y as a function of x
- The line regressing y against x

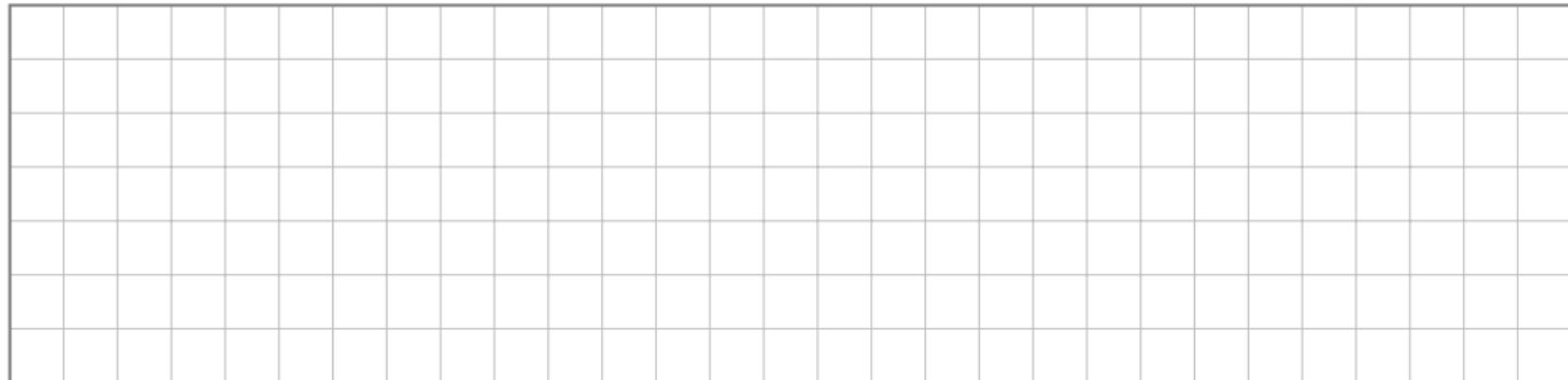
Advertising and Daily Sales: Visualization



Example 5.3: Spotify Playlist Data

Context: Data from 200 songs released in 2024. Find the regression line to predict total streams (millions) from the number of playlists (thousands) a song appears on. Summary statistics:

- $\bar{x} = 18.5$ thousand playlists
- $\bar{y} = 142.3$ million streams
- $s_x = 12.4$, $s_y = 98.7$
- $r = 0.78$



Understanding the Slope Formula

$$b = r \cdot \frac{s_y}{s_x}$$

What does this formula tell us?

- The **sign** of b matches the sign of r
 - Positive correlation \Rightarrow positive slope
 - Negative correlation \Rightarrow negative slope
- The **magnitude** depends on how spread out y is relative to x
 - If $s_y > s_x$: the slope is steeper than r
 - If $s_y < s_x$: the slope is flatter than r

Understanding the Intercept Formula

$$a = \bar{y} - b\bar{x}$$

What does this formula tell us?

- The regression line **always passes through** the point (\bar{x}, \bar{y})
 - This is the “balance point” of the data
 - Substituting $x = \bar{x}$ gives $\hat{y} = a + b\bar{x} = \bar{y}$
- The intercept a adjusts the line vertically to ensure it passes through (\bar{x}, \bar{y})

PART 4

Interpreting the Coefficients

Interpreting the Slope

Interpretation of Slope

The **slope** b represents the **predicted change** in y for a **one-unit increase** in x .

“For each additional [unit of x], the predicted [response variable] changes by b [units of y].”

Advertising example: For $\hat{y} = 1 + 2x$:

Spotify example: For $\hat{y} = 27.4 + 6.21x$:

Interpreting the Intercept

Interpretation of Intercept

The **intercept** a represents the predicted value of y when $x = 0$.

“When [explanatory variable] is zero, the predicted [response variable] is a [units].”

Spotify example: “A song on zero playlists would get 27.4 million streams.”

⚠ Caution: This interpretation is only meaningful if $x = 0$ makes sense in context.

Example 5.4: Interpreting a House Price Model

Context: A model predicts house prices (\$000s) from size (sq ft):

$$\hat{y} = 45 + 0.12x$$

Interpret the slope and intercept.

PART 5

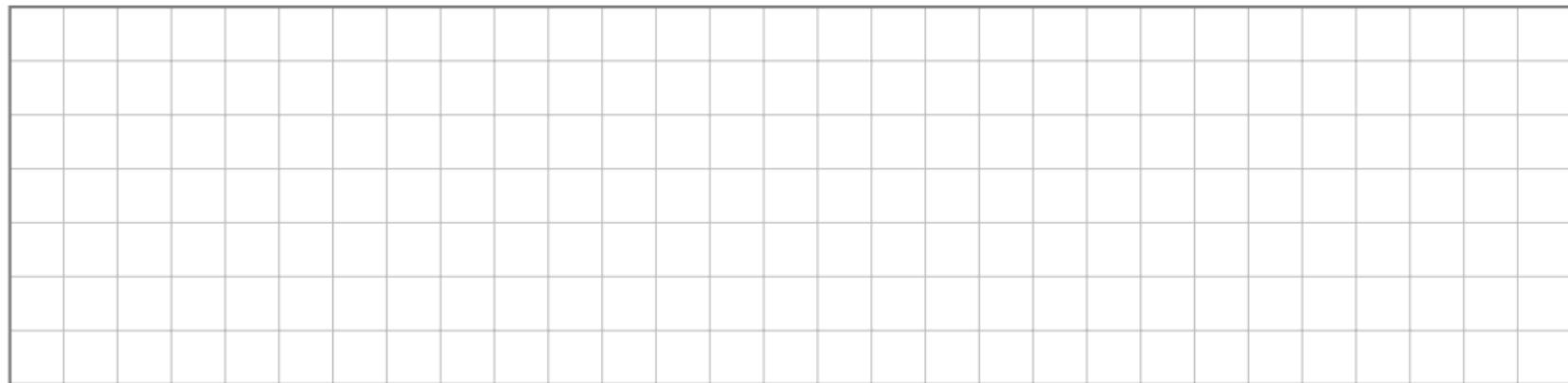
Predictions

How Do We Use the Regression Line?

To make predictions of the response variable y based on new values of the explanatory variable x .

Advertising example: $\hat{y} = 1 + 2x$

What is the expected daily sales if the business runs 7 ads per week?

A large, empty grid consisting of 20 columns and 10 rows of small squares, intended for students to work out the calculation of the expected daily sales.

Making Predictions with Regression

1. Compute the regression equation $\hat{y} = a + bx$ based on the data
2. Substitute the given x -value into the equation
3. Calculate \hat{y} (the predicted value)

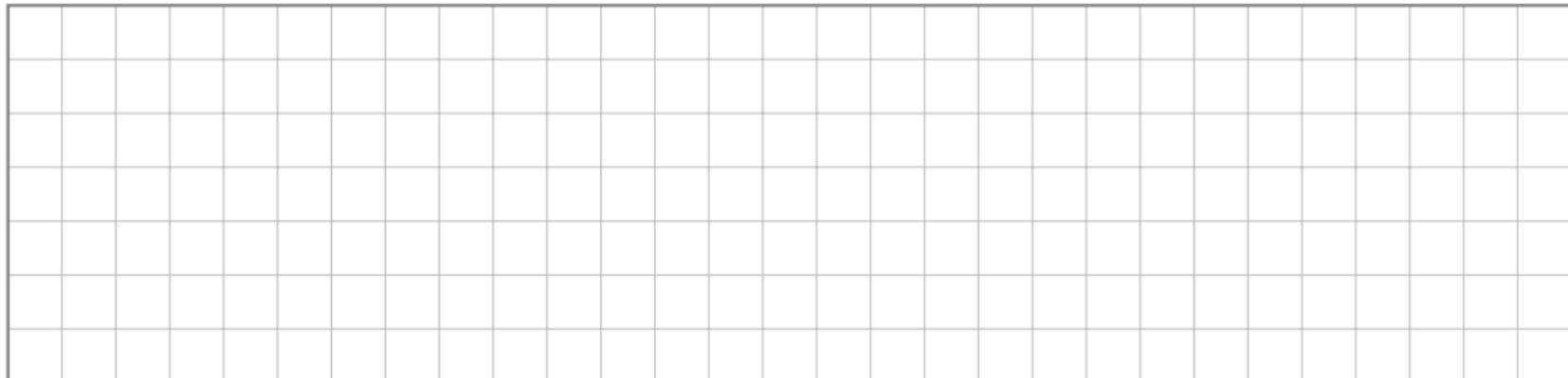
Example 5.3: Spotify Playlist Data (Continued)

Context: Data from 200 songs released in 2024. We want to predict total streams (millions) from the number of playlists (thousands) a song appears on.

Recall that the regression equation is:

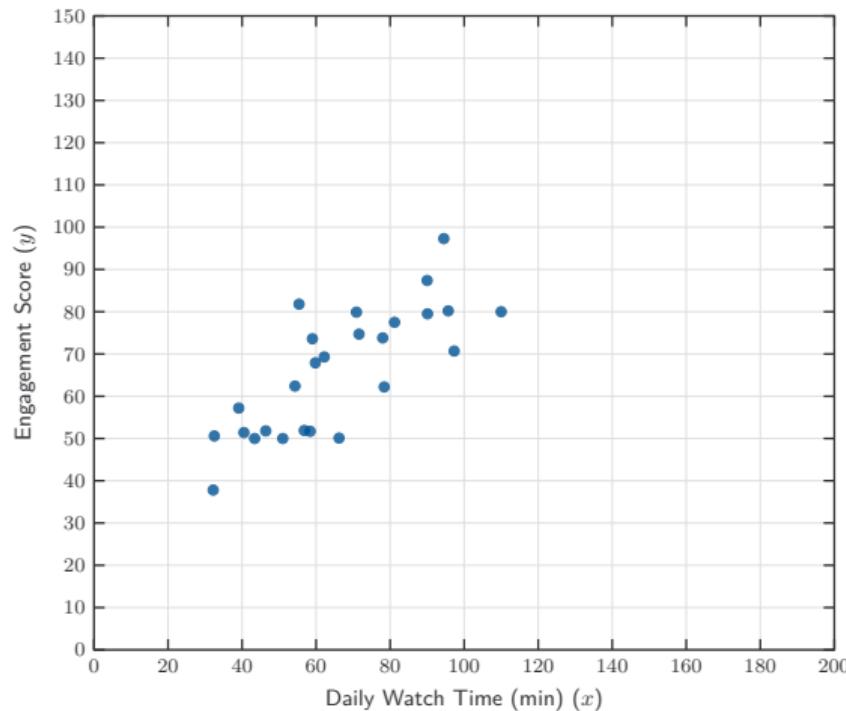
$$\hat{y} = 27.4 + 6.21x$$

- a) Find the predicted number of total streams for a song on 10,000 playlists.
- b) Find the predicted number of total streams for a song on 1,344 playlists.

A large, empty grid consisting of 20 columns and 15 rows of small squares, intended for students to use for working out calculations related to the example.

Example 5.5: Netflix Watch Time and Engagement

Context: Netflix analyzes subscriber data to predict monthly engagement score (0–100) from average daily watch time (minutes).

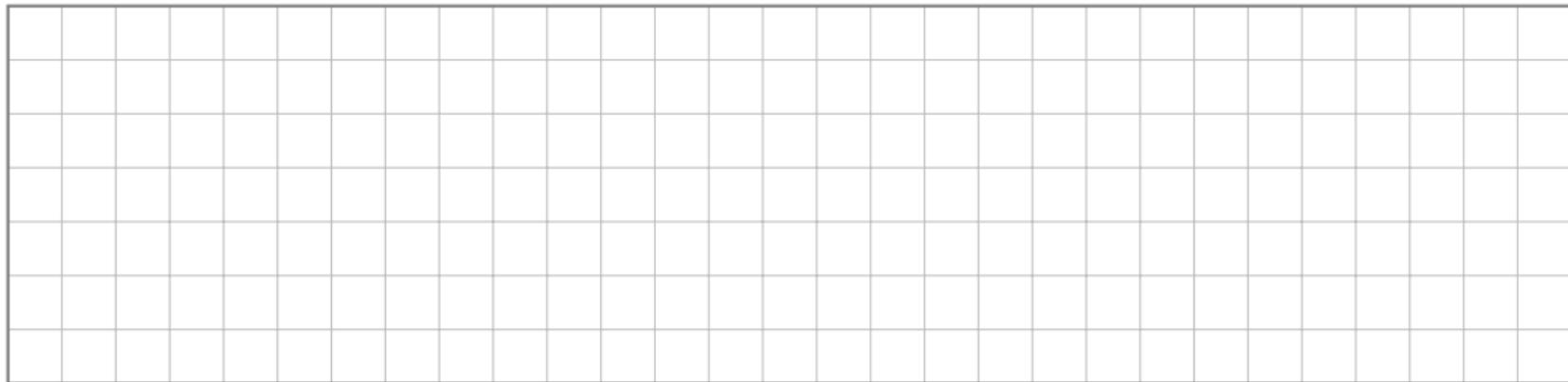


Example 5.5: Netflix Watch Time and Engagement (Continued)

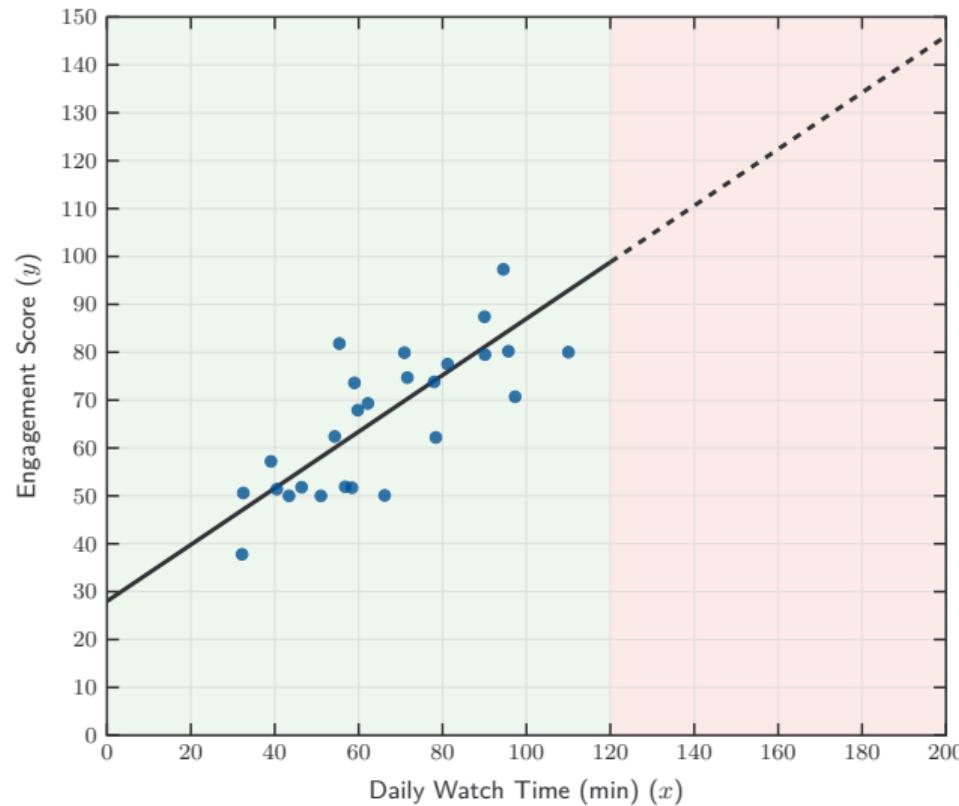
Context: Netflix analyzes subscriber data to predict monthly engagement score (0–100) from average daily watch time (minutes). Regression line: $\hat{y} = 28 + 0.59x$

Predict the engagement score for

- (a) a subscriber watching 60 min/day, and
- (b) a subscriber watching 180 min/day.

A large, empty grid consisting of 10 columns and 10 rows of small squares, intended for students to use for working out their calculations.

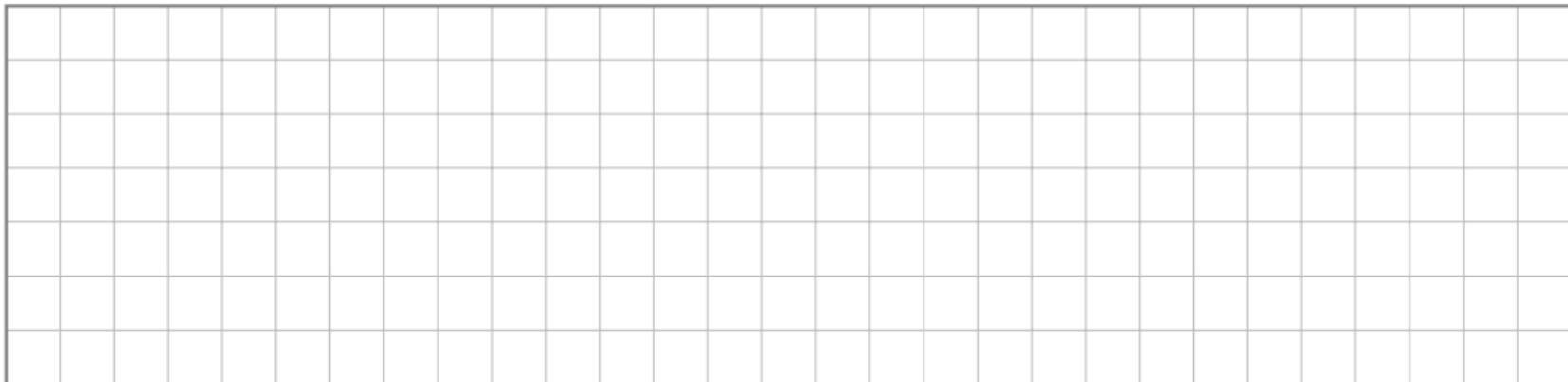
Example 5.5: Netflix Watch Time and Engagement



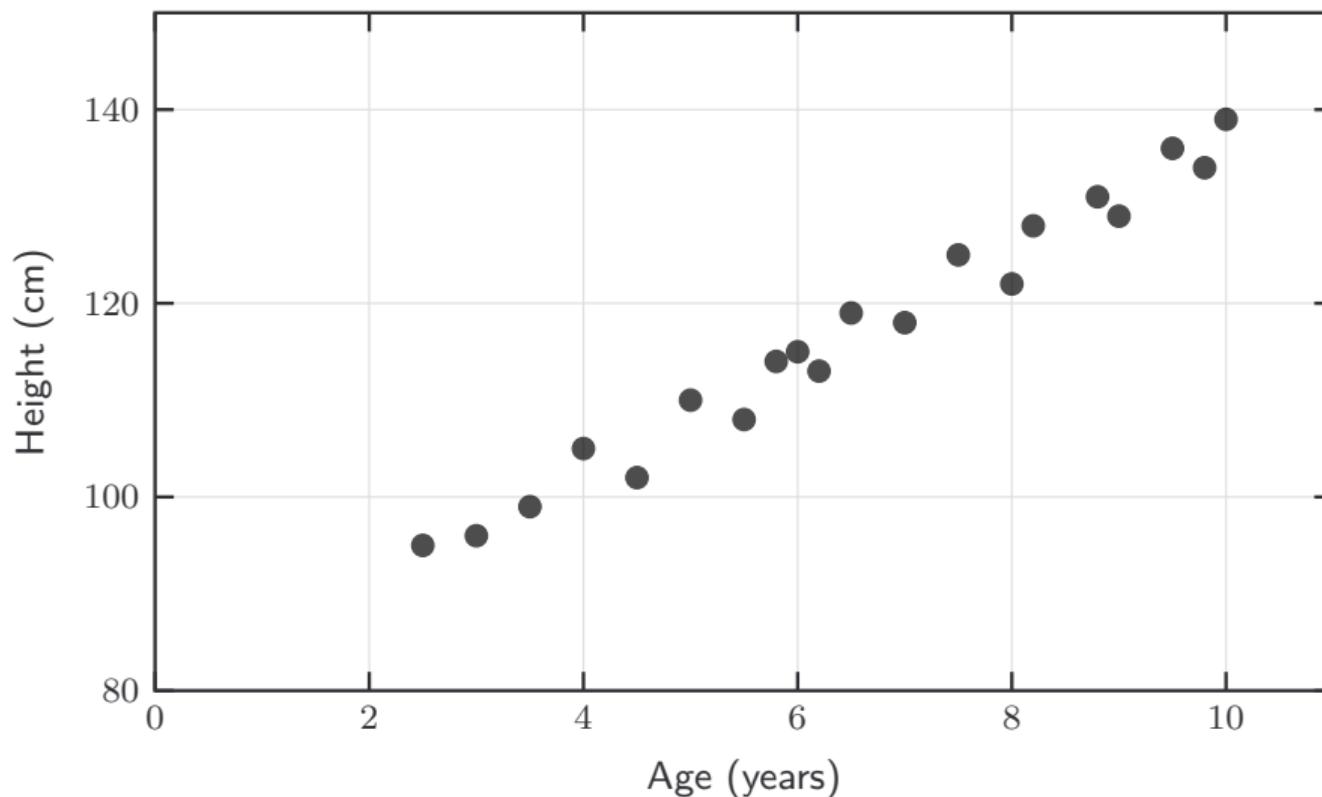
Example 5.6: Children's Height and Age

Context: A pediatrician models the relationship between children's height (cm) and age (years) for patients aged 2–10 years. Data from 180 children shows: $\bar{x} = 6.2$ years, $\bar{y} = 115.4$ cm, $s_x = 2.4$, $s_y = 14.8$, $r = 0.92$.

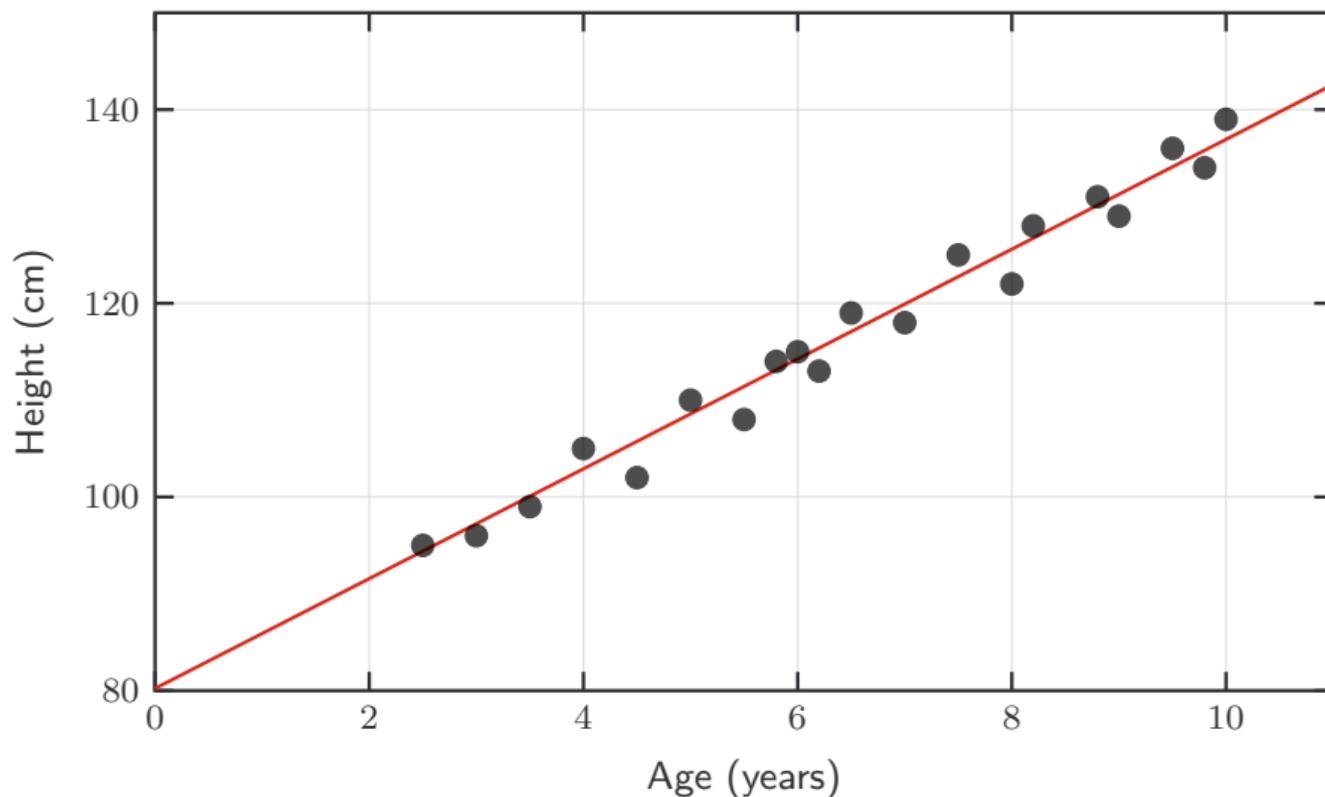
- (a) Predict the height of a 3-year-old.
- (b) Predict the height of a 7-year-old child.
- (c) Predict the height of a 33-year-old.



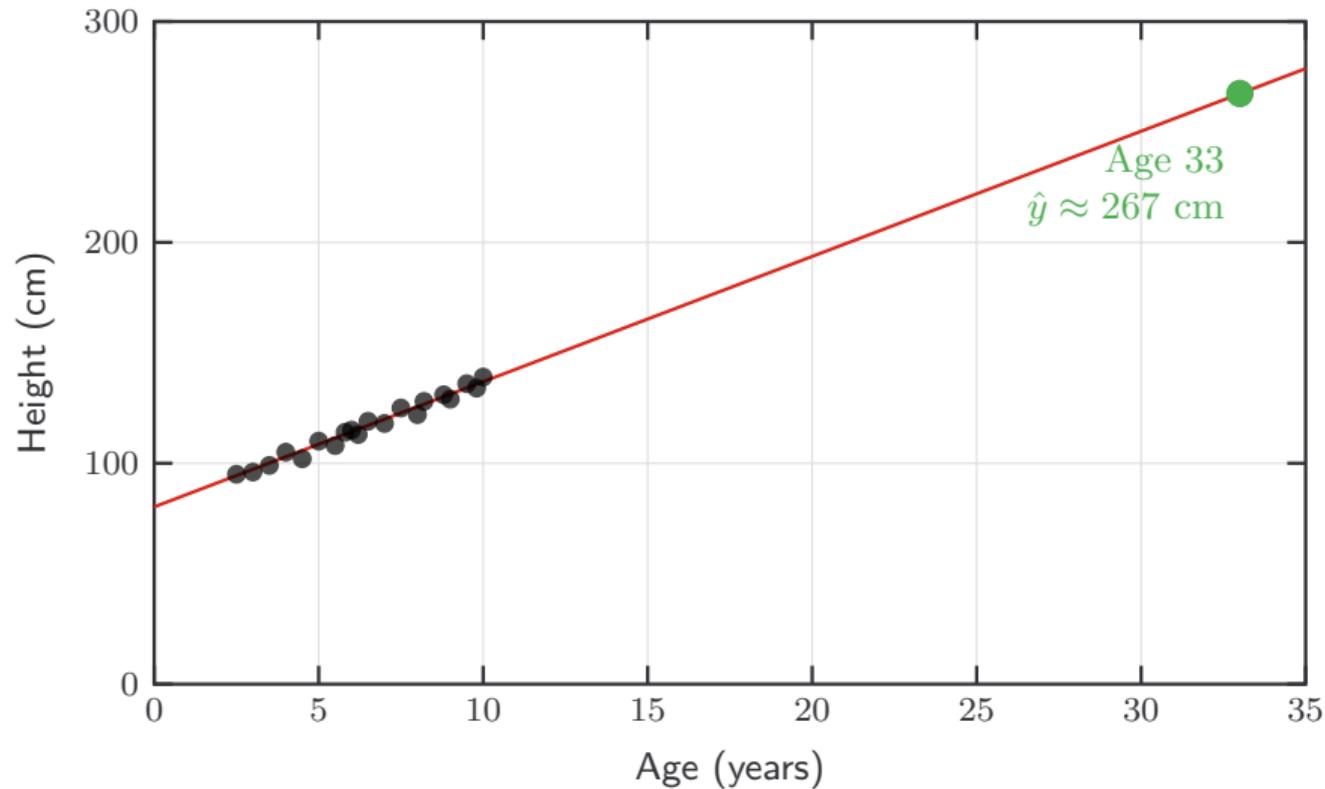
Example 5.6: Children's Height and Age



Example 5.6: Children's Height and Age



Example 5.6: Children's Height and Age



Limitations of Predictions

Predictions are not trustworthy if

- They are based on **extrapolation** (outside the data range)
- The predicted values are **inadmissible** in context (e.g., negative prices)

PART 6

Diagnostics

The Coefficient of Determination

Coefficient of Determination

The **coefficient of determination** R^2 is the **squared correlation** between x and y :

$$R^2 = r^2$$

The value R^2 always lies between 0 and 1.

The coefficient of determination R^2 represents the **proportion of variation** in the response variable y that is **explained** by the explanatory variable x using the regression line.

 **Key Point:** Higher R^2 means a better fit of the regression line to the data.

Example 5.7: Computing R^2

Advertising example: We found $r = 0.791$. What is R^2 ?

$$R^2 =$$

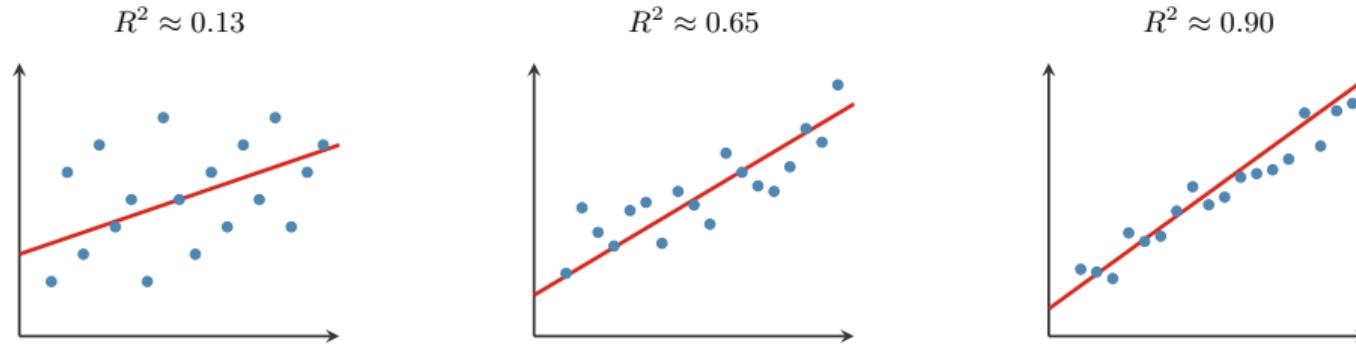
Interpretation:

Spotify example: We found $r = 0.78$. What is R^2 ?

$$R^2 =$$

Interpretation:

Visualising Different R^2 Values



Intuition: Higher R^2 means points cluster more tightly around the line.

Residual

A **residual** is the difference between an observed value and its predicted value from the regression line:

$$e_i = y_i - \hat{y}_i$$

Interpretation:

- **Positive residual:** Actual value is **above** the line (model **underestimates**)
- **Negative residual:** Actual value is **below** the line (model **overestimates**)
- **Zero residual:** Perfect prediction (point lies on line)

 **Key Point:** Residuals tell you how wrong each prediction is, and in which direction.

Example 5.8: Computing Residuals

Context: A bookstore tracks the number of hours open per day (x) and daily revenue in hundreds of dollars (y) over 5 days. The regression line is $\hat{y} = 2 + 3x$.

Hours (x)	Revenue (y)	Predicted (\hat{y})	Residual (e_i)
4	15		
6	19		
8	26		
10	31		
12	39		

Sum of Residuals is Zero



Note

The least squares method finds the line that minimizes $\sum(y_i - \hat{y}_i)^2$. Calculus shows that for this minimum, the sum of residuals must be zero:

$$\sum_{i=1}^n (y_i - \hat{y}_i) = 0$$

This means the average residual is also zero, which implies:

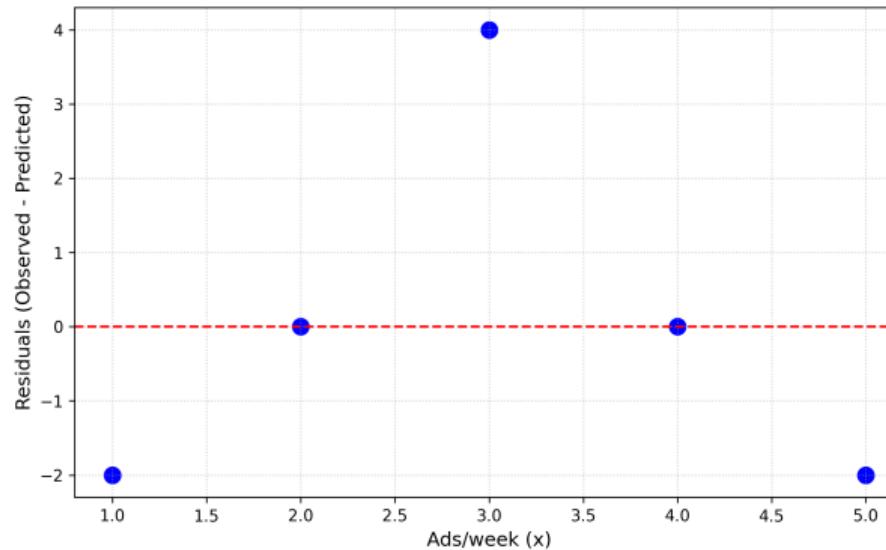
$$\bar{y} = \bar{\hat{y}} = a + b\bar{x}$$

 **Key Point:** This is why the regression line **always** passes through (\bar{x}, \bar{y}) .

Residual Plots: Checking Your Model

Residual Plot

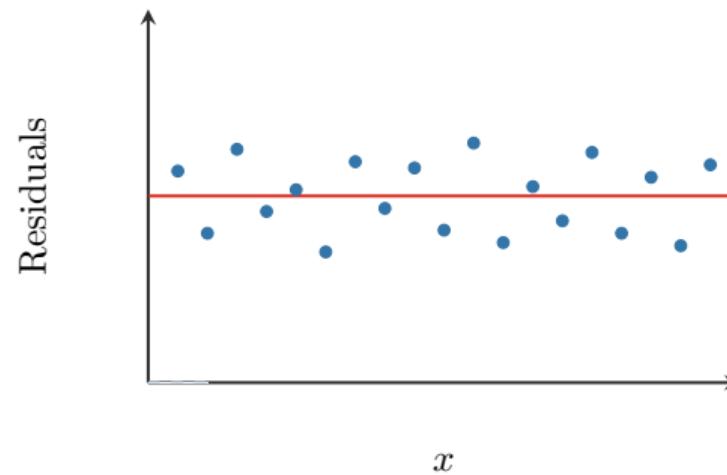
A **residual plot** shows residuals (y -axis) versus (fitted) predicted values or explanatory variable (x -axis).



Residual Plots

If the model is reasonable, then the residual plots would show:

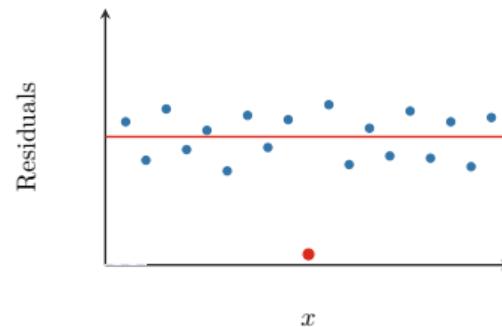
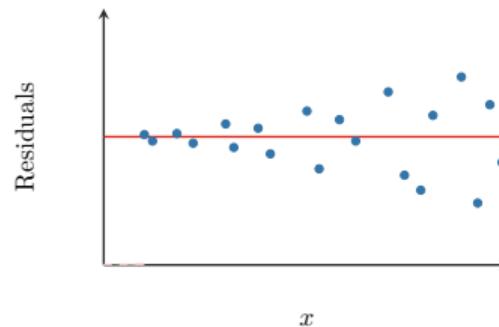
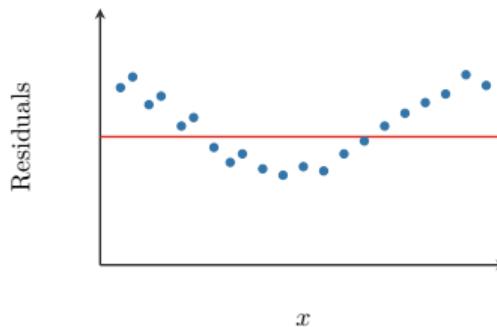
- No systematic pattern
- Points randomly distributed around zero
- Constant spread across all x values



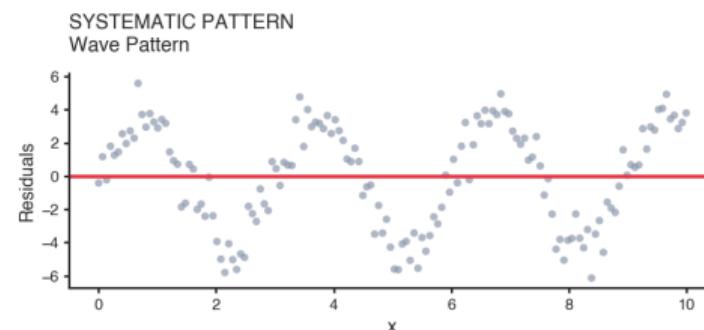
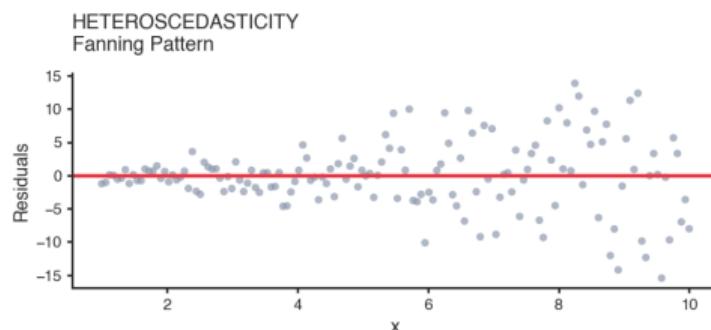
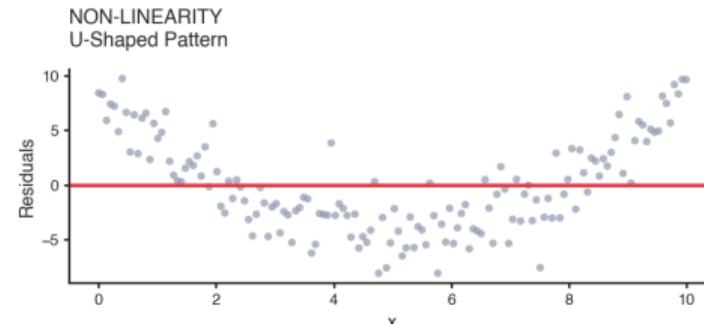
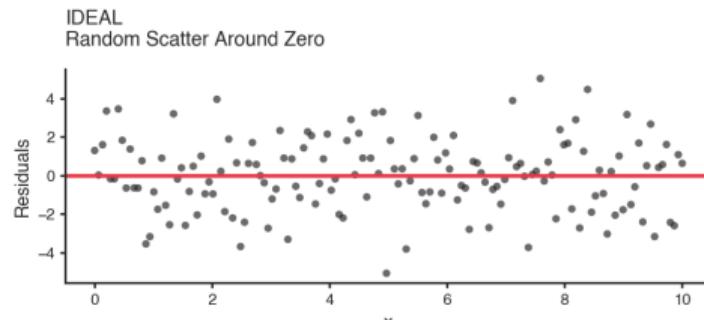
Residual Plots

Otherwise, we might see:

- Curved patterns (non-linearity)
- Funnel shapes (non-constant variance)
- Large residuals (potential outliers)



Residual Plots



PART 7

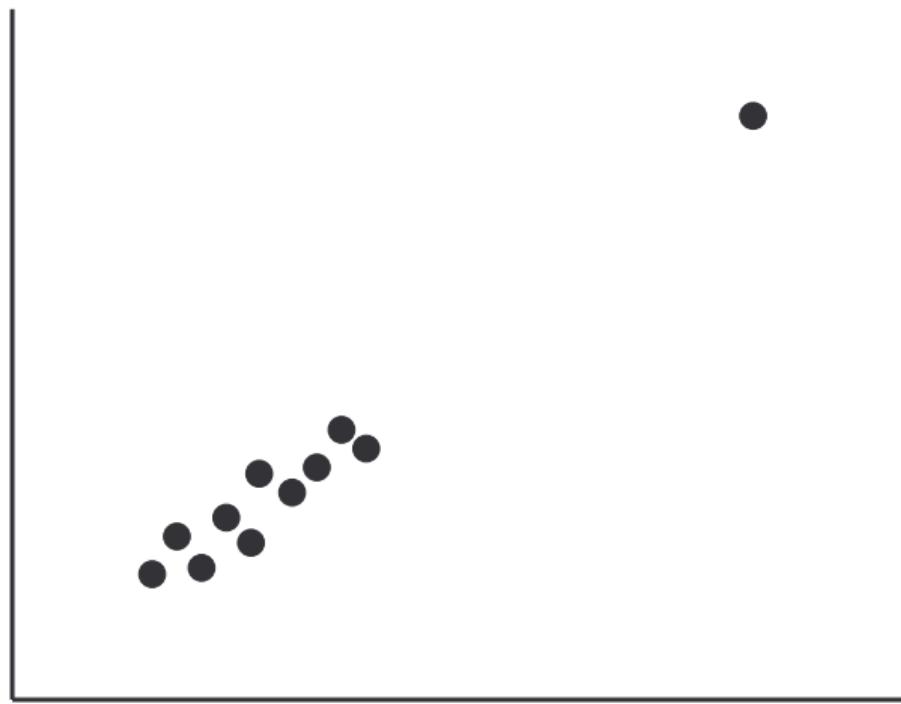
Outliers and Regression

Outliers and Regression

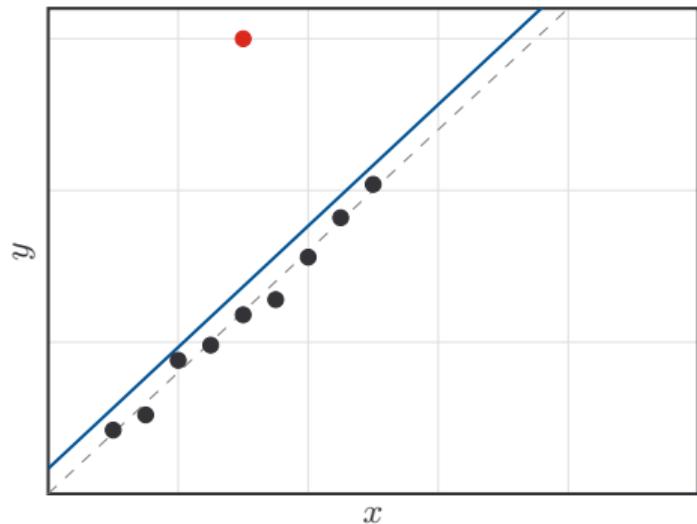
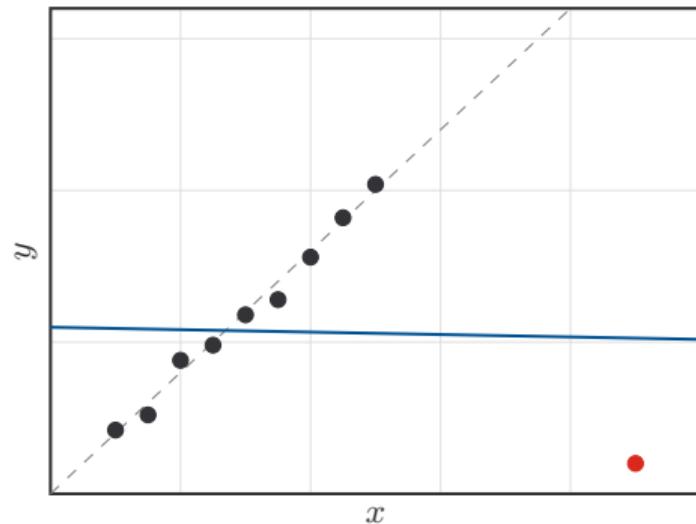
Certain types of outliers can substantially affect regression models in two ways:

- Position: They can pull the regression line toward themselves, changing both slope and intercept
- Strength: They can weaken the correlation (reduce R^2), making predictions less reliable

Impact on Regression Model



Types of Influential Points



What Makes an Outlier Influential?

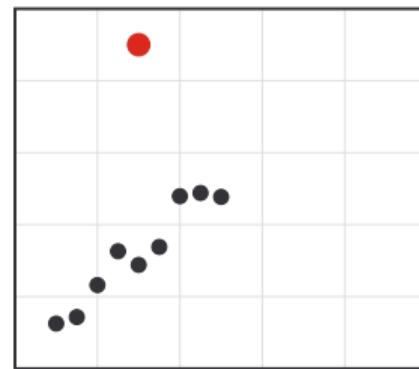
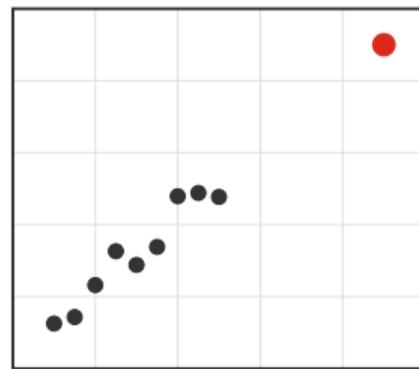
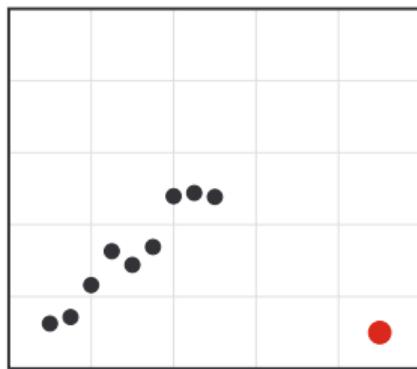
Influential Point

An **influential point** is an observation that, if removed, would substantially change the regression line (slope, intercept, or both).

Generally speaking, this is a point that has an extreme value of x with a value of y that deviates from the regression line.

Example 5.9: Identifying Influential Points

For each plot, indicate if the highlighted point is influential.



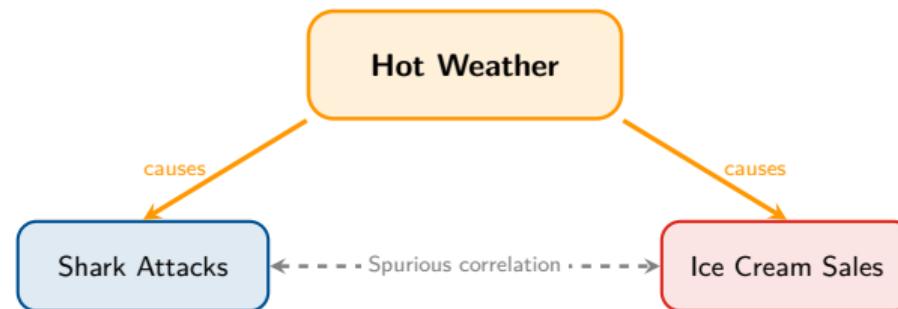
PART 8

Pitfalls

Lurking Variables

Lurking Variable

A **lurking variable** (or **confounding variable**) is an unobserved variable that influences **both** the explanatory and response variables, potentially creating a spurious association.



Correlation Does Not Imply Causation

⚠ Caution: A strong relationship between x and y does **not** mean that x causes y . There may be lurking variables creating a spurious association.

Famous examples of spurious correlations:

- Ice cream sales and drowning deaths (*lurking: summer weather*)
- Shoe size and reading ability in children (*lurking: age*)
- Number of firefighters and fire damage (*lurking: size of fire*)
- Nicolas Cage films and swimming pool drownings (*lurking: nothing, just coincidence!*)

The Ecological Fallacy

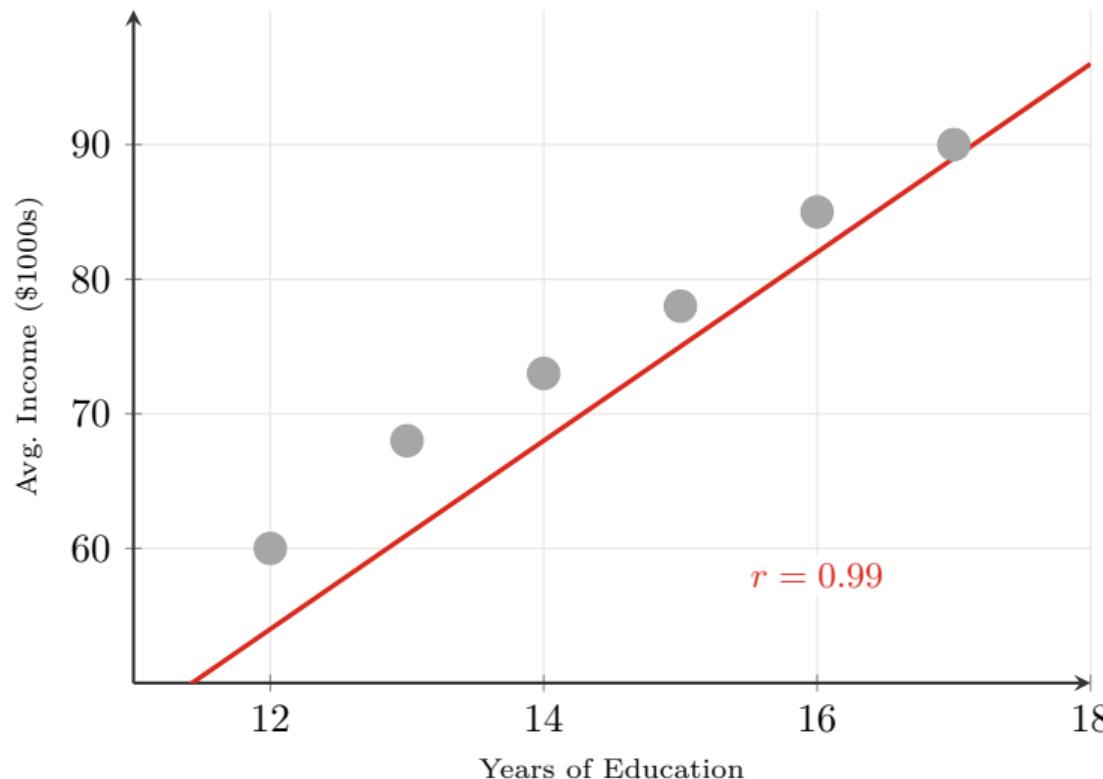
Ecological Fallacy

The **ecological fallacy** occurs when inferences about **individual** behaviour are incorrectly drawn from **aggregate** (group-level) data.

This is a special case of Simpson's paradox, which we will discuss in the next chapter.

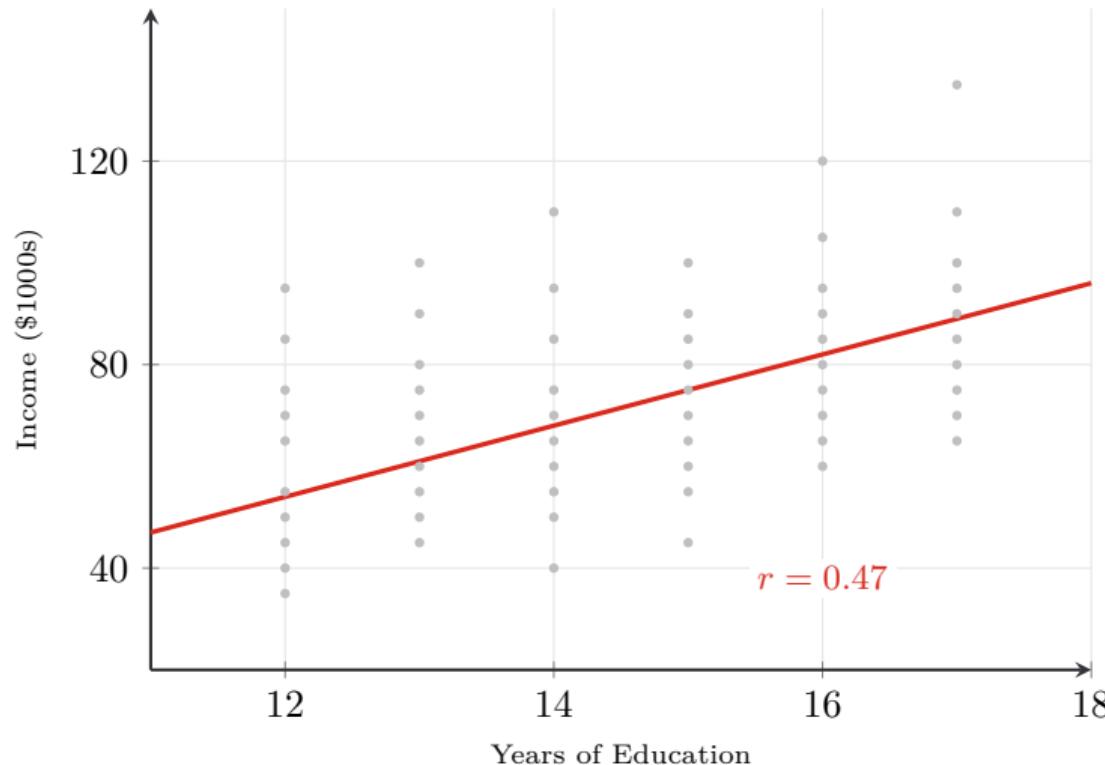
Example 5.10: Education and Income

Aggregate (group averages)



Example 5.10: Education and Income (Continued)

Individual level



Chapter Summary: Core Formulas

Least Squares Regression Line

$$\hat{y} = a + bx$$

where:

- **Slope:** $b = r \cdot \frac{s_y}{s_x}$
- **Intercept:** $a = \bar{y} - b\bar{x}$

Measuring Model Quality

- **Residual:** $e_i = y_i - \hat{y}_i$
- **Coefficient of determination:** $R^2 = r^2$

Chapter Summary: Interpretation

Understanding the Coefficients

Slope b : Change in predicted y for each one-unit increase in x

- “For each additional [unit of x], we predict y to change by b [units].”

Intercept a : Predicted value of y when $x = 0$

- Only meaningful if $x = 0$ makes sense in context
- Often just a mathematical anchor for the line

Coefficient of determination R^2 : Proportion of variation in y explained by x

- “ $R^2 \times 100\%$ of the variation in [response] is explained by [explanatory variable].”

Chapter Summary: Making Predictions

How to Predict

1. Calculate regression equation $\hat{y} = a + bx$
2. Substitute the given value of x
3. Calculate \hat{y} (the predicted value)

When Predictions Fail

- **Extrapolation:** Predicting outside the range of observed x values
- **Inadmissible predictions:** Results that are impossible or nonsensical in context
 - Examples: negative prices, scores above 100%, heights of 300 cm

Chapter Summary: Model Diagnostics

Checking the Model

Residual plots should show:

- No systematic patterns
- Random scatter around zero
- Constant spread across all x values

Watch out for:

- Curved patterns (suggests non-linear relationship)
- Funnel shapes (non-constant variance)
- Large isolated residuals (potential outliers)

Influential points:

- extreme x values that deviate from the trend in y
- dramatically change slope and intercept

Chapter Summary: Common Pitfalls

Correlation \neq Causation

- A strong relationship between x and y does not mean x causes y
- **Lurking variables** can create spurious associations
- Example: Ice cream sales and drowning deaths (lurking: summer weather)

Ecological Fallacy

- Group-level patterns may not hold at the individual level
- Example: Countries with higher average education may have higher average income, but within countries the pattern could reverse

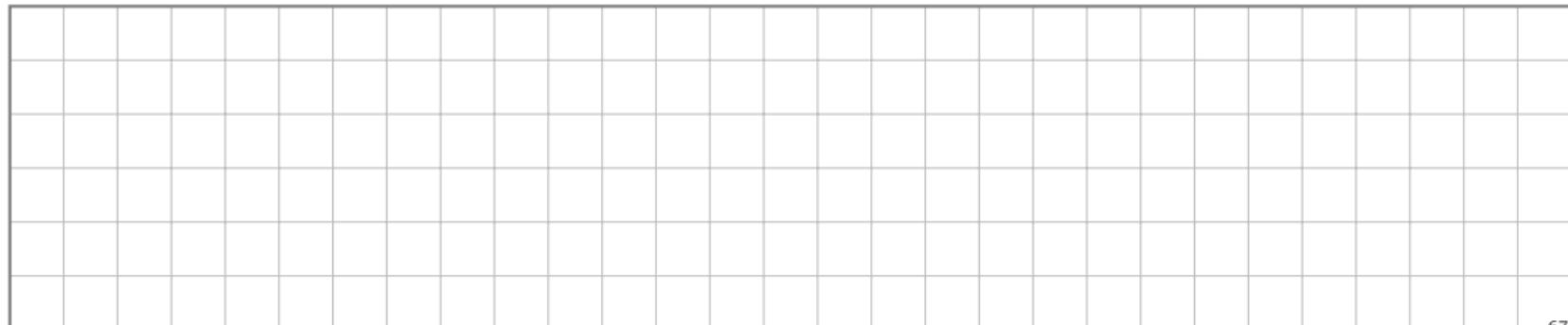
Additional Practice Problems

Example 5.11: Fast Food Spending

Context: A study of 50 college students examined the relationship between weekly fast food spending (\$) and GPA. Summary statistics:

- $\bar{x} = 15$ dollars, $\bar{y} = 3.2$ GPA
- $s_x = 8.5$, $s_y = 0.6$
- $r = -0.68$

- Calculate the slope and intercept of the regression line.
- Write the regression equation $\hat{y} = a + bx$.
- Interpret the slope in context.
- Predict the GPA of a student who spends \$25 per week on fast food.

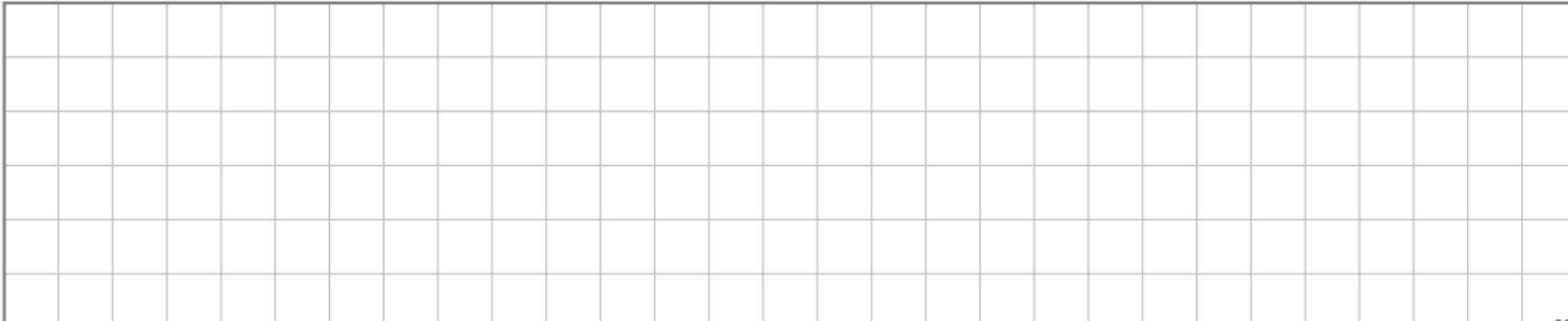


Example 5.12: Sleep and Test Performance

Context: A teacher tracks student sleep hours (night before exam) and exam scores (0–100) for 40 students. Summary statistics:

- $\bar{x} = 7$ hours, $\bar{y} = 72$ points
- $s_x = 1.8$, $s_y = 12.5$
- $r = 0.82$

- a) Find the regression equation.
- b) A student slept 9 hours. Predict their exam score.
- c) Calculate and interpret R^2 .
- d) Is this prediction reliable? Why or why not?



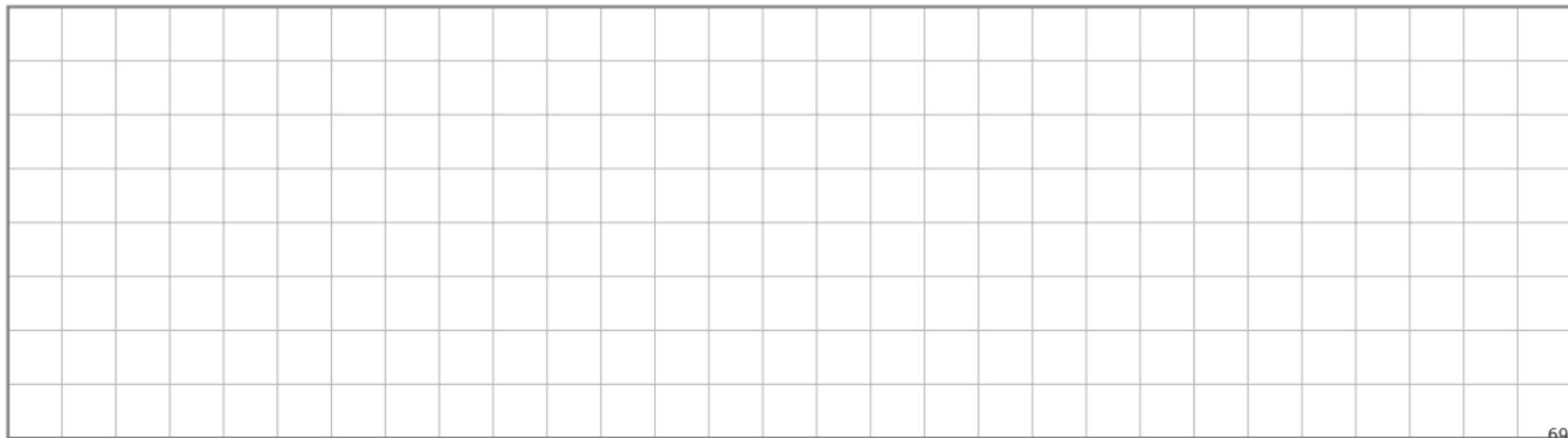
A large grid of 10 columns and 10 rows, intended for students to work out the regression equation on.

Example 5.13: Temperature and Coffee Sales

Context: A coffee shop records daily temperature ($^{\circ}\text{C}$) and coffee sales (cups sold) over 60 days. The regression line is:

$$\hat{y} = 280 - 8.5x$$

- a) Interpret the slope.
- b) Interpret the intercept. Does it make practical sense?
- c) Predict sales when it's 20°C .
- d) Predict sales when it's -5°C . Is this a reliable prediction? Why?



Example 5.14: Computing Residuals

Context: Using the fast food/GPA regression line $\hat{y} = 3.8 - 0.04x$, compute residuals for four students:

Student	Spending (x)	GPA (y)	Predicted (\hat{y})	Residual (e_i)
A	10	3.5		
B	20	3.0		
C	5	3.6		
D	30	2.8		

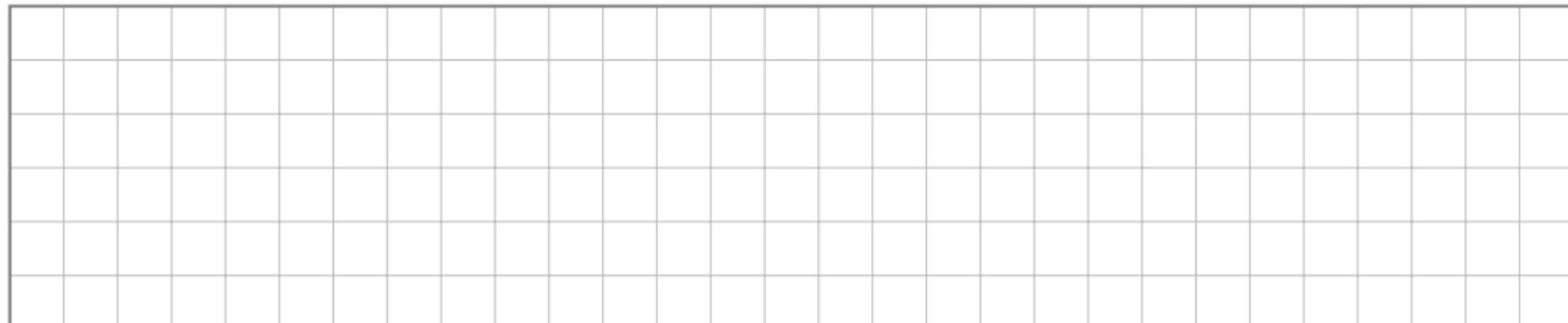
Which student's GPA does the model overestimate? Underestimate?

Example 5.15: Putting It Together

Context: A researcher studying 100 athletes measures training hours per week (x) and performance score (0–100) (y). Results:

- Regression equation: $\hat{y} = 40 + 2.1x$
- $R^2 = 0.71$
- Data range: 5–25 training hours
- Three athletes have residuals of -8 , $+5$, and $+12$

- a) Interpret $R^2 = 0.71$ in context.
- b) Which athlete's performance does the model most severely overestimate?
- c) Predict the score for an athlete training 15 hours/week.
- d) Predict the score for an athlete training 40 hours/week.

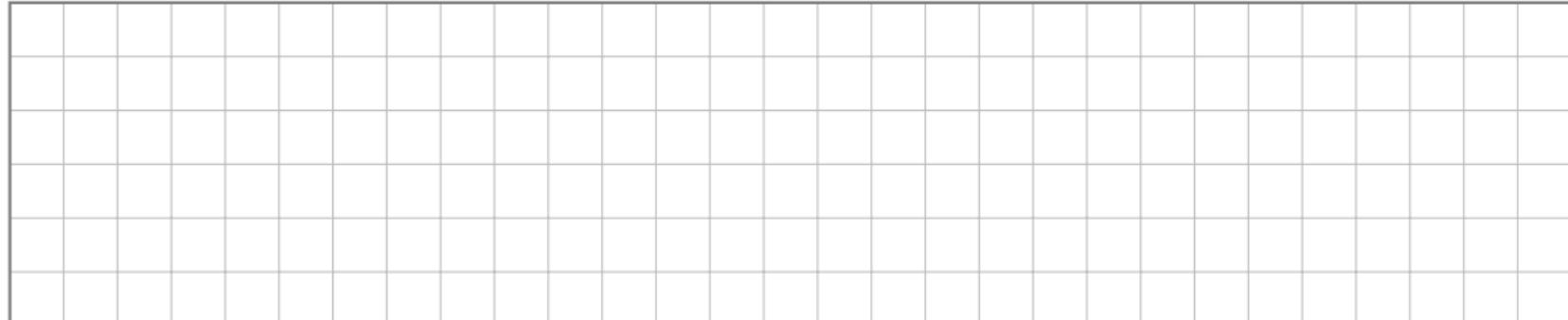


Example 5.16: Fitness App Data

Context: A fitness app tracked 50 users over 12 weeks to understand the relationship between weekly workout sessions and weight loss (kg).

	Sessions/week	Weight loss (kg)
Mean	$\bar{x} = 3.50$	$\bar{y} = 4.20$
Standard deviation	$s_x = 1.41$	$s_y = 1.68$

The regression equation is $\hat{y} = 0.63 + 1.02x$. Find R^2 for this linear model.

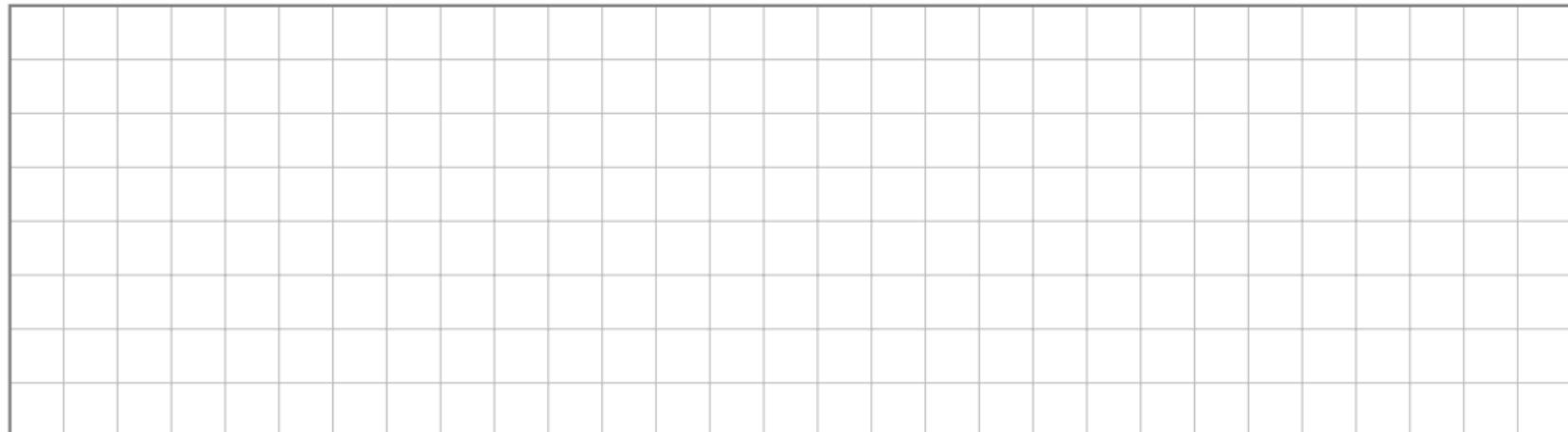


Example 5.17: Height and Shoe Size (Part 1)

Context: A researcher studies the relationship between height (in inches) and shoe size (US men's sizing) among college students. After collecting data, they obtain the following least squares regression line:

$$\text{Height} = 50 + 2.5 \times (\text{Shoe Size})$$

(a) Suppose the residual for a particular observation is 1 inch and the observed height is 74 inches. What is the shoe size of this student? Show your work.

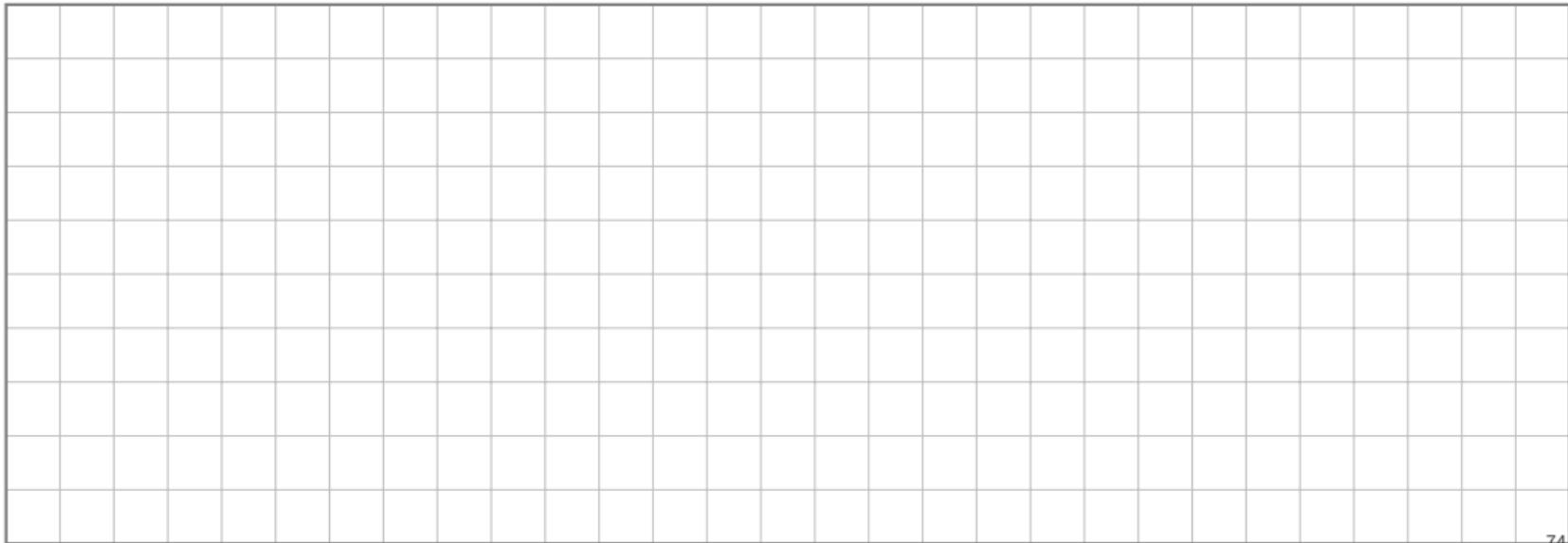
A large, empty grid consisting of 10 columns and 10 rows of small squares, intended for students to show their work for the problem.

Example 5.17: Height and Shoe Size (Part 2)

Context: Continuing with the regression line:

$$\text{Height} = 50 + 2.5 \times (\text{Shoe Size})$$

(b) If the mean height of the sampled students is 66.67 inches, what is the mean shoe size? Show your work.

A large, empty grid for working out the problem. It consists of 10 columns and 10 rows of small squares, providing a space for calculations and drawing.

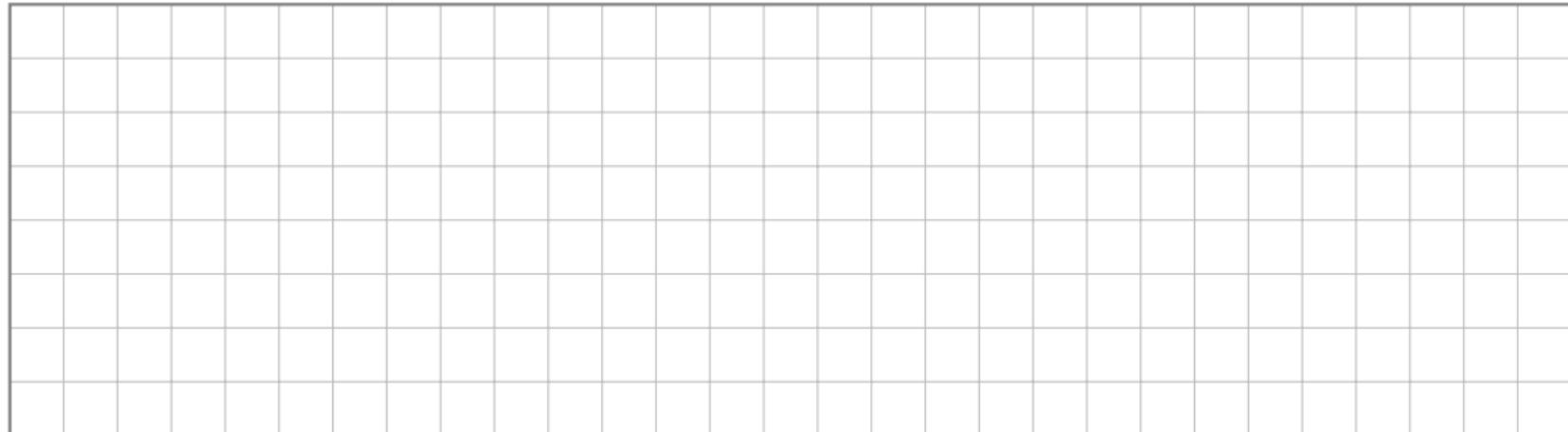
Example 5.17: Height and Shoe Size (Part 3)

Context: Using the same data, the researchers found that the least squares regression line for predicting shoe size from height is:

$$\text{Shoe Size} = -3.2 + 0.16 \times (\text{Height})$$

(c) Calculate the correlation coefficient (r) between height and shoe size. Show your work.

Hint: Consider the relationship between the two slopes and the correlation coefficient.



Example 5.17: Height and Shoe Size (Part 4)

(d) If we measure height in centimeters instead of inches (where 1 inch = 2.54 cm), would the correlation coefficient change? Would the slope of the regression line change? Explain.

Consider both:

- How does a linear transformation affect correlation?
- How does a linear transformation affect the slope?

