

Midterm Review

Key Concepts from Lessons 1–9

Emile Latour

2026-02-11



Today's Agenda

- Quick overview of exam structure
- Key concepts review
 - Study design
 - Probability and Bayes' Theorem
 - Distributions (focus on R functions!)
 - Sampling distributions and CLT
 - Confidence intervals
 - Hypothesis testing
- Your questions

The midterm opens TODAY at 3:00 PM and closes Monday at 11:00 PM



Exam Logistics



Exam Details

Format:

- 8 parts, 120 points total
- Designed for 3-5 hours completion
- Mix of conceptual questions, R code, and interpretation

Resources allowed:

- Course materials (slides, homework, textbook)
- R documentation
- Your notes
- Other students
- AI assistants
- Online help forums

Submit both `.qmd` and `.html` files!



What's Covered

Part 1: Study design (10 pts)

Part 2: Descriptive stats & viz (15 pts)

Part 3: Probability (15 pts)

Part 4: Distributions (20 pts)

Part 5: Sampling distributions & CLT (15 pts)

Part 6: Confidence intervals (15 pts)

Part 7: Hypothesis testing (20 pts)

Part 8: Integration (10 pts)

Key datasets: `nhanes.samp` (you've used this in HW!)



General Tips

Before you start:

- Read all instructions carefully
- Set up your workspace (load packages, data)
- Check that code chunks run

Before submitting:

- Render one final time
- Check that all answers are complete
- Verify both files are being submitted

While working:

- Show your work and reasoning
- Provide interpretations in complete sentences
- Use comments in your R code
- Check that your document renders frequently
- **Save regularly**



Quick Concepts Review



Study Design: The Basics

Experiments vs. Observational Studies

Experiment:

- Researchers assign treatments
- Random assignment
- Can establish causation
- Example: Drug trial with treatment vs. placebo

Observational Study:

- Researchers observe without interfering
- No random assignment
- Can only show association
- Example: Reviewing medical records

Why does this matter?

Only randomized experiments can establish causal relationships!



Sampling Concepts

Key terms:

- **Population vs. Sample**
- **Simple random sample** (each individual has equal chance)
- **Convenience sample** (easily accessible - often biased)

Confounding variables:

- Associated with both explanatory and response variables
- Can make it look like there's a causal relationship when there isn't
- Example: Exercise and cardiovascular health might both be related to socioeconomic status



R Skills Review: Data Wrangling & Visualization



dplyr: The grammar of data manipulation

`dplyr` provides a consistent set of **verbs** for data manipulation:

Function	What it does
<code>filter()</code>	Keep rows that meet conditions
<code>select()</code>	Keep or drop columns
<code>mutate()</code>	Create or modify columns
<code>arrange()</code>	Sort rows
<code>group_by()</code>	Group data for summaries
<code>summarize()</code>	Calculate summary statistics

These verbs can be chained together with `%>%` for powerful data transformations.



ggplot2: The Basic Template

The ggplot2 pattern

```
1 library(ggplot2)
2
3 ggplot(data = dataset,
4         aes(x = variable, y = variable)) +
5   geom_() +                      # Choose your geometry
6   labs(title = "...",            # Add labels
7        x = "...",
8        y = "...")
```

Key geoms you need to know:

```
1 # Histogram (one continuous variable)
2 geom_histogram(bins = 20)
3
4 # Boxplot (continuous by categorical)
5 geom_boxplot()
6
7 # Scatterplot (two continuous variables)
8 geom_point()
```



ggplot2: Example

```
1 library(ggplot2)
2 library(oibiostat)
3 data("nhanes.samp")
4
5 # Histogram
6 ggplot(nhanes.samp, aes(x = Height)) +
7   geom_histogram(bins = 20) +
8   labs(title = "Distribution of Height",
9        x = "Height (cm)",
10       y = "Count")
11
12 # Boxplot by group
13 ggplot(nhanes.samp,
14         aes(x = Gender, y = Weight, fill = Gender)) +
15   geom_boxplot() +
16   labs(title = "Weight by Gender",
17        x = "Gender",
18        y = "Weight (kg)")
```

Remember: Start with `ggplot()`, then add layers with `+`



dplyr + rstatix: Summary Statistics

The pattern: `group_by()` then `summarize`

```
1 library(dplyr)
2 library(rstatix)
3
4 dataset %>%
5   group_by(grouping_variable) %>%
6   get_summary_stats(numeric_variable, type = "mean_sd")
```

Example:

```
1 # Summary stats by one group
2 nhanes.samp %>%
3   group_by(Gender) %>%
4   get_summary_stats(Height, type = "mean_sd")
5
6 # Summary stats by multiple groups
7 nhanes.samp %>%
8   group_by(Gender, SmokeNow) %>%
9   get_summary_stats(Weight, type = "mean_sd")
```



dplyr only: Summary Statistics

The pattern: `group_by()` then `summarize`

```
1 library(dplyr)
2
3 dataset %>%
4   group_by(grouping_variable) %>%
5   summarise(...)
```

Example:

```
1 # Summary stats by one group
2 nhanes.samp %>%
3   group_by(Gender) %>%
4   summarise(n = sum(!is.na(Height)),
5             mean = mean(Height, na.rm = TRUE),
6             sd = sd(Height, na.rm = TRUE))
7
8 # Summary stats by multiple groups
9 nhanes.samp %>%
10  group_by(Gender, SmokeNow) %>%
11  summarise(n = sum(!is.na(Weight)),
12             mean = mean(Weight, na.rm = TRUE),
13             sd = sd(Weight, na.rm = TRUE))
```



Categorical Data: janitor::tabyl()

The pattern for frequency tables

```
1 library(janitor)
2
3 # One-way table
4 dataset %>%
5   tabyl(variable)
6
7 # Two-way table with row percentages
8 dataset %>%
9   tabyl(row_variable, column_variable) %>%
10  adorn_totals(where = "row") %>%
11  adorn_percentages("row") %>%
12  adorn_pct_formatting(digits = 1)
```

Example:

```
1 # Two-way table
2 nhanes.samp %>%
3   tabyl(Gender, SmokeNow) %>%
4   adorn_totals(where = "row") %>%
5   adorn_percentages("row") %>%
6   adorn_pct_formatting(digits = 1) %>%
7   adorn_ns()
```



Probability



Probability Notation Quick Reference

Basic probabilities:

- **Marginal:** $P(A)$ - probability of A alone
- **Joint:** $P(A \text{ and } B)$ - probability of both
- **Conditional:** $P(A | B)$ - probability of A given B

Key formula:

$$P(A | B) = \frac{P(\text{A and B})}{P(B)}$$

Independence:

Events A and B are independent if: $P(A \text{ and } B) = P(A) \times P(B)$



Probability Rules to Remember

General Addition Rule:

If A and B are any two events:

$$P(A \text{ or } B) = P(A) + P(B) - P(A \text{ and } B)$$

We subtract $P(A \text{ and } B)$ because those outcomes were counted twice.

General Multiplication Rule:

$$P(A \text{ and } B) = P(A | B) \times P(B)$$

This connects **joint** and **conditional** probabilities, and leads directly to Bayes' Theorem!

Special case: Independent events

If A and B are independent: $P(A \text{ and } B) = P(A) \times P(B)$



Bayes' Theorem: The Pattern

You'll almost always use it in this form:

$$\begin{aligned} P(A | B) &= \frac{P(B | A) \times P(A)}{P(B)} \\ &= \frac{P(B | A) \times P(A)}{P(B | A) \times P(A) + P(B | A^c) \times P(A^c)} \end{aligned}$$

In medical testing context:

$$P(\text{Disease} | \text{Test}+) = \frac{\text{sensitivity} \times \text{prevalence}}{\text{sensitivity} \times \text{prevalence} + (1 - \text{specificity}) \times (1 - \text{prevalence})}$$

Pro tip: Calculate numerator and denominator separately, then divide!



Bayes' Theorem: Step-by-Step

Given: Sensitivity = 0.90, Specificity = 0.85, Prevalence = 0.02

```
1 # Step 1: Set up
2 sensitivity <- 0.90      # P(Test + | Disease)
3 specificity <- 0.85      # P(Test - | No Disease)
4 prevalence <- 0.02       # P(Disease)
5
6 # Step 2: Calculate P(Test + | No Disease)
7 p_pos_given_healthy <- 1 - specificity
8 p_pos_given_healthy
```

```
[1] 0.15
```

```
1 # Step 3: Numerator (true positives)
2 numerator <- sensitivity * prevalence
3 numerator
```

```
[1] 0.018
```

```
1 # Step 4: Denominator (all positives)
2 denominator <- sensitivity * prevalence + p_pos_given_healthy * (1 - prevalence)
3 denominator
```

```
[1] 0.165
```

```
1 # Step 5: PPV
2 ppv <- numerator / denominator
3 ppv
```

```
[1] 0.1090909
```

Distributions: The R Functions



The Four Functions Pattern

Every distribution in R has 4 functions:

d-functions: `dbinom()`, `dnorm()`, `dpois()`

- “density” or “probability mass”
- **Exactly** x
- Returns: $P(X = x)$

q-functions: `qbinom()`, `qnorm()`, `qpois()`

- “quantile”
- What value gives this probability?
- Returns: value of x

p-functions: `pbinom()`, `pnorm()`, `ppois()`

- “cumulative probability”
- **At most** x (or **at least** with `lower.tail = FALSE`)
- Returns: $P(X \leq x)$ or $P(X > x)$

r-functions: `rbinom()`, `rnorm()`, `rpois()`

- “random”
- Generate random samples
- Returns: random values



Binomial Functions in R

The four binomial functions:

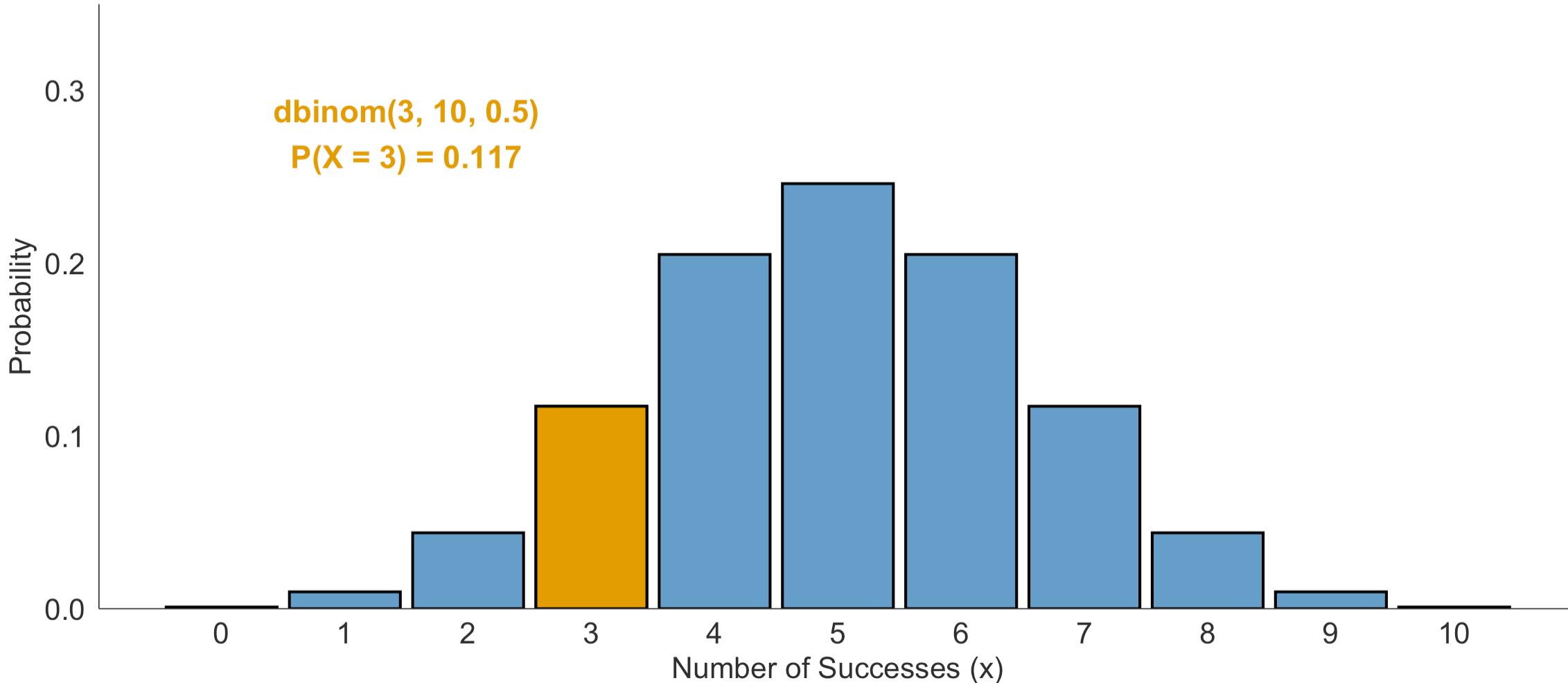
```
1 # d = probability of EXACTLY x successes
2 dbinom(x = 3, size = 10, prob = 0.5)
3 # "What's P(X = 3)?"
4
5 # p = cumulative probability (at most x OR at least x)
6 pbinom(q = 3, size = 10, prob = 0.5)
7 # "What's P(X ≤ 3)" (default)
8
9 pbinom(q = 3, size = 10, prob = 0.5, lower.tail = FALSE)
10 # "What's P(X > 3)?"
11
12 # q = quantile (what value gives this probability?)
13 qbinom(p = 0.25, size = 10, prob = 0.5)
14 # "What value has 25% of the distribution below it?"
15
16 # r = random samples
17 rbinom(n = 100, size = 10, prob = 0.5)
18 # "Give me 100 random draws"
```



Visual: dbinom() - EXACTLY

dbinom: Probability of EXACTLY x successes

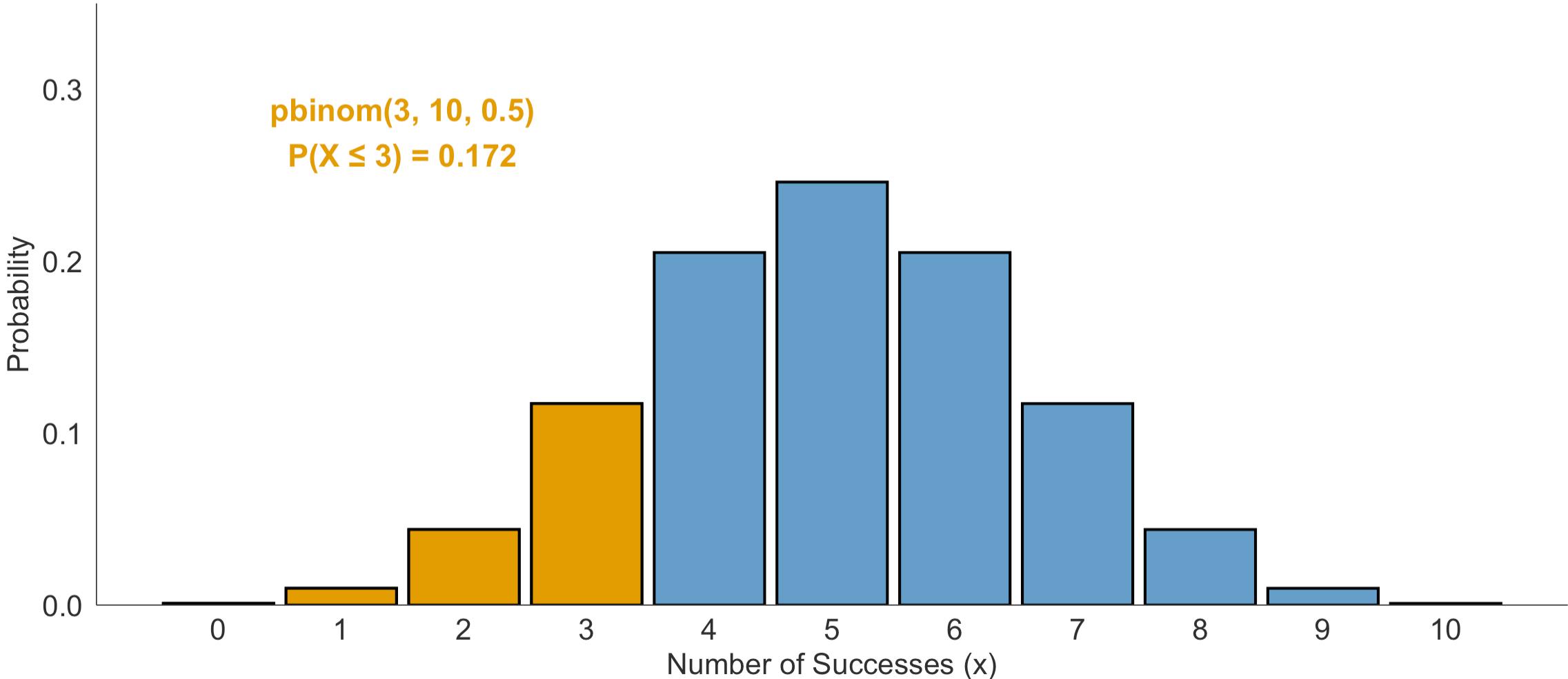
Binomial with n = 10, p = 0.5



Visual: `pbinom()` - AT MOST (default)

`pbinom` with `lower.tail = TRUE` (default): AT MOST x successes

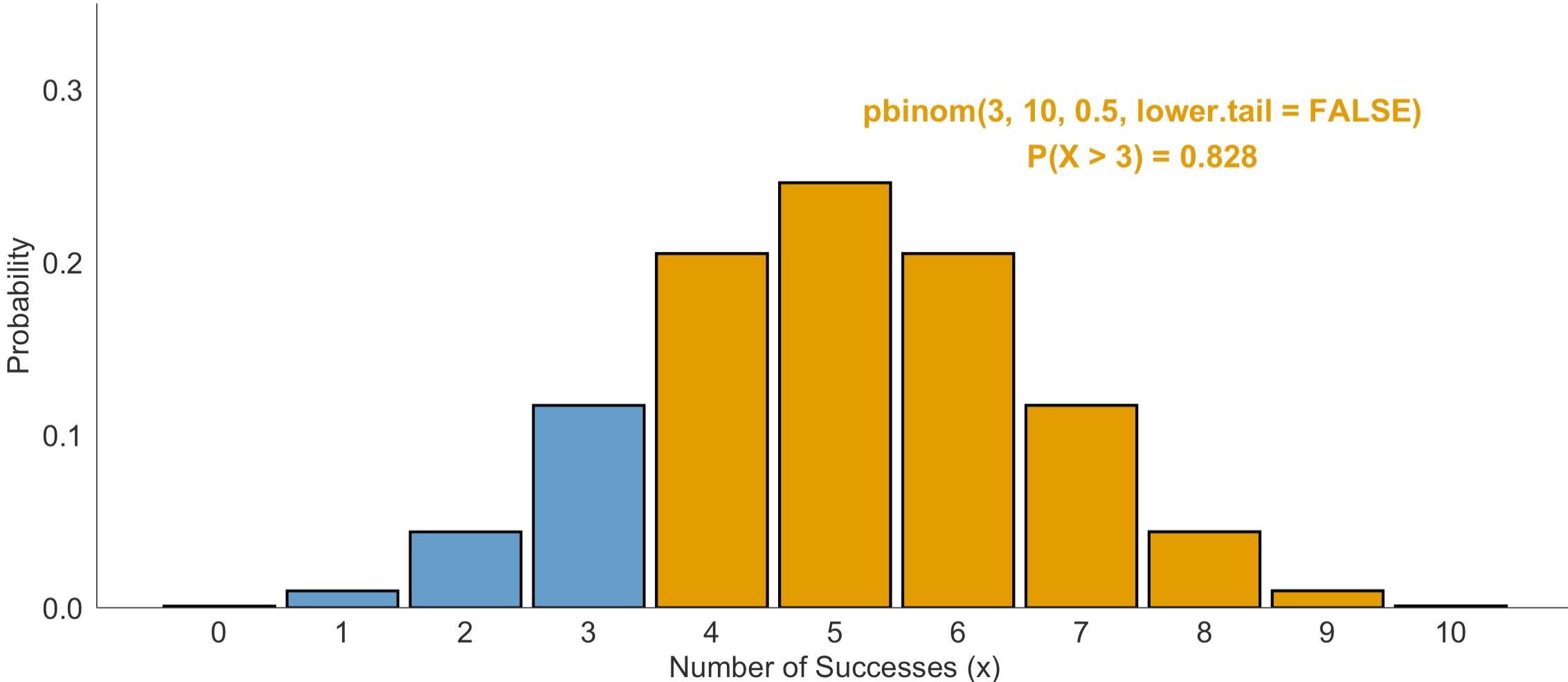
Binomial with $n = 10$, $p = 0.5$



Visual: `pbinom(..., lower.tail = FALSE) - MORE THAN`

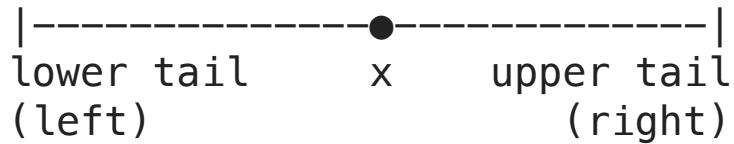
`pbinom` with `lower.tail = FALSE`: MORE THAN x successes

Binomial with $n = 10$, $p = 0.5$



The `lower.tail = TRUE/FALSE` Concept

Visual Guide



`lower.tail = TRUE` → gives you $P(X \leq x)$ — everything to the **LEFT** of (and including) x

`lower.tail = FALSE` → gives you $P(X > x)$ — everything to the **RIGHT** of x

Quick decision rule:

- Question has “**less than**” or “**at most**” → `lower.tail = TRUE` (default)
- Question has “**greater than**” or “**at least**” → `lower.tail = FALSE`



Common Confusion: "At least 5" (Discrete Distributions)

Question: What is $P(X \geq 5)$ for a binomial distribution?

Step 1: Translate to something the computer understands

- "At least 5" = "5 or more" = "greater than 4"
- So: $P(X \geq 5) = P(X > 4)$

Step 2: Code it

```
1 # Correct!
2 pbinom(q = 4, size = 10, prob = 0.5, lower.tail = FALSE)
3
4 # Also correct (but slightly more work)
5 1 - pbinom(q = 4, size = 10, prob = 0.5)
```

Key Point

For discrete distributions: " $X \geq 5$ " is the same as " $X > 4$ " because we can't have 4.5 successes!

This slide applies to **binomial and Poisson** (discrete). For Normal (continuous), $P(X \geq 5) = P(X > 5)$ - no adjustment needed!



Practice: Binomial Questions

A vaccine is 75% effective. You vaccinate 20 people.

Which R function do you use?

Question 1: What's the probability that *exactly* 15 are protected?

```
1 # Your answer:
```

Question 2: What's the probability that *at most* 12 are protected?

```
1 # Your answer:
```

Question 3: What's the probability that *at least* 18 are protected?

```
1 # Your answer:
```

Question 4: What's the expected number protected?

```
1 # Your answer:
```



Practice: Binomial Answers (1/2)

A vaccine is 75% effective. You vaccinate 20 people.

Question 1: What's the probability that *exactly* 15 are protected?

```
1 # Question 1: Exactly 15
2 dbinom(x = 15, size = 20, prob = 0.75)
[1] 0.2023312
```

Question 2: What's the probability that *at most* 12 are protected?

```
1 # Question 2: At most 12
2 pbinom(q = 12, size = 20, prob = 0.75)
[1] 0.1018119

1 # OR: pbinom(q = 12, size = 20, prob = 0.75, lower.tail = TRUE)
```



Practice: Binomial Answers (2/2)

Question 3: What's the probability that *at least* 18 are protected?

```
1 # Question 3: At least 18 (same as > 17)
2 pbinom(q = 17, size = 20, prob = 0.75, lower.tail = FALSE)
```

```
[1] 0.09126043
```

```
1 # OR: 1 - pbinom(q = 17, size = 20, prob = 0.75)
```

Question 4: What's the expected number protected?

```
1 # Question 4: Expected value
2 n <- 20
3 p <- 0.75
4 expected <- n * p
5 expected
```

```
[1] 15
```

```
1 # Bonus: standard deviation
2 variance <- n * p * (1 - p)
3 st_dev <- sqrt(variance)
4 st_dev
```

```
[1] 1.936492
```



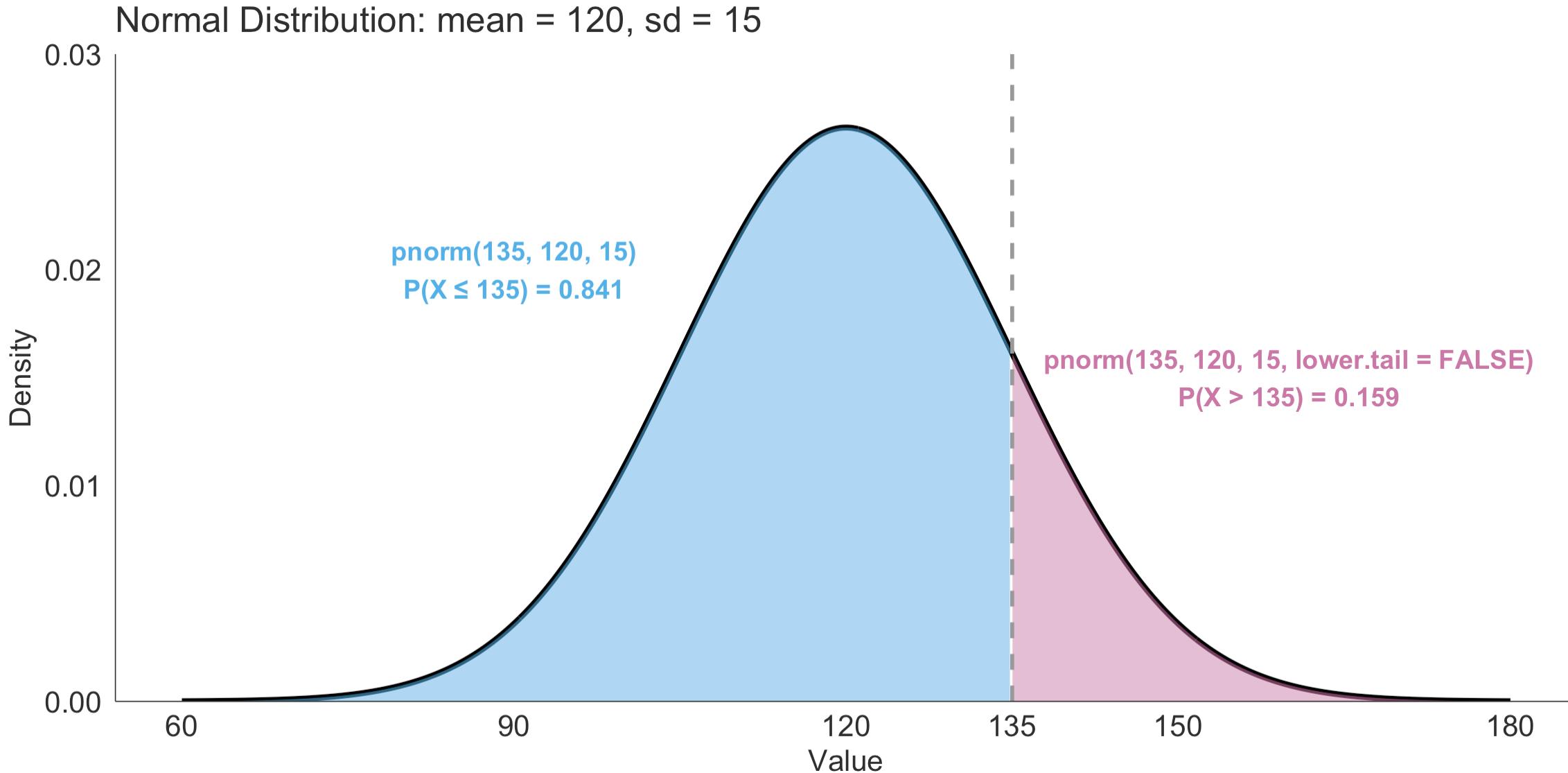
Normal Distribution Functions

The same pattern applies!

```
1 # d = density (height of curve at x)
2 dnorm(x = 120, mean = 100, sd = 15)
3 # Rarely used in practice
4
5 # p = cumulative probability
6 pnorm(q = 120, mean = 100, sd = 15)
7 # "What proportion have values ≤ 120?"
8
9 pnorm(q = 120, mean = 100, sd = 15, lower.tail = FALSE)
10 # "What proportion have values > 120?"
11
12 # q = quantile (most common!)
13 qnorm(p = 0.95, mean = 100, sd = 15)
14 # "What value has 95% below it?" (95th percentile)
15
16 # r = random samples
17 rnorm(n = 100, mean = 100, sd = 15)
18 # "Give me 100 random values from this distribution"
```



Visual: Normal Distribution



Practice: Normal Distribution

Blood pressure is Normal with mean = 120 mmHg, sd = 15 mmHg.

Which R function?

Question 1: What proportion have BP above 135?

1 # Your answer:

Question 3: What BP value is the 90th percentile?

1 # Your answer:

Question 2: What proportion have BP between 110 and 130?

1 # Your answer:

Question 4: If we want the middle 95%, what are the cutoffs?

1 # Your answer:



Practice: Normal Answers (1/2)

```
1 mu <- 120
2 sigma <- 15
3
4 # Question 1: Above 135
5 pnorm(135, mean = mu, sd = sigma, lower.tail = FALSE)
```

```
[1] 0.1586553
```

```
1 # OR
2 1 - pnorm(135, mean = mu, sd = sigma, lower.tail = TRUE)
```

```
[1] 0.1586553
```

```
1 # Question 2: Between 110 and 130
2 pnorm(130, mean = mu, sd = sigma) - pnorm(110, mean = mu, sd = sigma)
```

```
[1] 0.4950149
```



Practice: Normal Answers (2/2)

```
1 # Question 3: 90th percentile  
2 qnorm(0.90, mean = mu, sd = sigma)
```

```
[1] 139.2233
```

```
1 # Question 4: Middle 95% (2.5th to 97.5th percentiles)  
2 qnorm(0.025, mean = mu, sd = sigma) # Lower
```

```
[1] 90.60054
```

```
1 qnorm(0.975, mean = mu, sd = sigma) # Upper
```

```
[1] 149.3995
```



Sampling Distributions & CLT



Central Limit Theorem: What You Need to Know

The CLT in plain language

For a random sample of size n from ANY population with mean μ and SD σ :

The sampling distribution of \bar{X} is approximately normal when n is large (≥ 30)

With:

- Mean = μ
- Standard Error = σ / \sqrt{n}

Why this matters:

1. We can use normal distribution tools even if data aren't normal
2. Larger samples → smaller standard error → more precise estimates
3. This is the foundation for confidence intervals and hypothesis tests!



Standard Error vs. Standard Deviation

Don't confuse these!

Standard Deviation (s or σ):

- Measures spread of *individual observations*
- Describes variability in the data
- Formula: $s = \sqrt{\frac{\sum(x_i - \bar{x})^2}{n-1}}$

Standard Error (SE):

- Measures uncertainty of the *sample mean*
- Describes variability of \bar{x} across (theoretical) samples
- Formula: $SE = \frac{s}{\sqrt{n}}$

Key insight: SE gets smaller as n increases, but s stays roughly the same!



Example: CLT in Action

Population: Mean = 5.1 hours, SD = 1.9 hours, right-skewed

Sample: n = 40

What's the sampling distribution of \bar{X} ?

```
1 # Parameters
2 mu <- 5.1
3 sigma <- 1.9
4 n <- 40
5
6 # Sampling distribution
7 mean_xbar <- mu
8 se_xbar <- sigma / sqrt(n)
9
10 mean_xbar
```

[1] 5.1

```
1 se_xbar
```

[1] 0.3004164

```
1 # Example probability about the sample mean, P(Xbar > 5.6)
2 pnorm(5.6, mean = mean_xbar, sd = se_xbar, lower.tail = FALSE)
```

[1] 0.04802059

Sampling distribution: approximately $\text{Normal}(\text{mean} = \mu, \text{sd} = \frac{s}{\sqrt{n}})$. Even though the original data are right-skewed!



Confidence Intervals



Confidence Interval Formula

General form

point estimate \pm critical value $\times SE$

For a mean:

$$\bar{x} \pm t^* \times \frac{s}{\sqrt{n}}$$

Where:

- \bar{x} = sample mean
- t^* = critical value from t-distribution with $df = n - 1$
- s = sample standard deviation
- n = sample size



Calculating a 95% CI in R (1/2)

```
1 # Sample data
2 n <- 25
3 xbar <- 14.2
4 s <- 1.8
5 confidence_level <- 0.95
6
7 # Step 1: Find critical value
8 t_star <- qt((1 + confidence_level) / 2, df = n - 1)
9 # OR: qt(0.975, df = 24)
10 t_star
```

```
[1] 2.063899
```

```
1 # Step 2: Calculate standard error
2 SE <- s / sqrt(n)
3 SE
```

```
[1] 0.36
```



Calculating a 95% CI in R (2/2)

```
1 # Step 3: Calculate margin of error  
2 margin_error <- t_star * SE  
3 margin_error
```

```
[1] 0.7430035
```

```
1 # Step 4: Build the interval  
2 lower <- xbar - margin_error  
3 upper <- xbar + margin_error  
4  
5 c(lower, upper)
```

```
[1] 13.457 14.943
```



Interpreting Confidence Intervals

Correct interpretation

"We are 95% confident that the population mean is between 13.5 and 14.9."

What this means:

- If we repeated this process many times (new samples, new CIs)
- About 95% of those intervals would contain the true μ
- We don't know if *this specific interval* contains μ , but we're using a reliable method

Common mistakes - DON'T SAY:

- **✗** "There's a 95% probability that μ is in this interval"
- **✗** "95% of the data are in this interval"
- **✗** "We're 95% sure the sample mean is in this interval"



What Affects CI Width?

$$\text{Margin of error} = t^* \times \frac{s}{\sqrt{n}}$$

To get a narrower CI:

1. **Increase sample size** ($n \uparrow \rightarrow SE \downarrow \rightarrow$ narrower CI)
2. **Decrease confidence level** (95% \rightarrow 90% \rightarrow smaller t^* \rightarrow narrower CI)
 - But this means less confidence!
3. **Reduce variability** ($s \downarrow \rightarrow SE \downarrow \rightarrow$ narrower CI)
 - Often not under our control

Trade-off: Precision vs. Confidence



Hypothesis Testing



The Hypothesis Testing Framework

Six steps:

1. **State hypotheses:** H_0 and H_A
2. **Set significance level:** Usually $\alpha = 0.05$
3. **Check assumptions:** Independence, normality/large sample
4. **Calculate test statistic:** $t = \frac{\bar{x} - \mu_0}{s/\sqrt{n}}$
5. **Find p-value:** Probability of seeing data this extreme if H_0 true
6. **Make conclusion:** Reject H_0 if p-value < α



Writing Hypotheses

Template

$H_0 : \mu = \mu_0$ (null value)

$H_A : \mu \neq \mu_0$ (two-sided) OR $\mu > \mu_0$ OR $\mu < \mu_0$ (one-sided)

Example: Is mean body temperature different from 98.6°F?

- $H_0 : \mu = 98.6$
- $H_A : \mu \neq 98.6$

In words:

- H_0 : The population mean body temperature is 98.6°F
- H_A : The population mean body temperature is not 98.6°F



P-values: What They Mean

Definition

The p-value is the probability of observing data as extreme as (or more extreme than) what we observed, **assuming H_0 is true**.

Interpretation guide:

- $p\text{-value} < 0.05 \rightarrow$ Strong evidence against $H_0 \rightarrow$ Reject H_0
- $p\text{-value} \geq 0.05 \rightarrow$ Insufficient evidence \rightarrow Fail to reject H_0

What p-values are NOT

- \times NOT the probability that H_0 is true
- \times NOT the probability of making an error
- \times NOT a measure of effect size or importance



One-Sample t-test in R

```
1 # Using raw data
2 t.test(data$variable,
3         mu = null_value,
4         alternative = "two.sided") # or "less" or "greater"
```

Example:

```
1 # Test if mean pulse rate is different from 72 bpm
2 data("nhanes.samp")
3
4 t.test(nhanes.samp$Pulse,
5        mu = 72,
6        alternative = "two.sided")
```



Understanding t.test() Output

One Sample t-test

```
data: nhanes.samp$Pulse
t = 2.1383, df = 170, p-value = 0.03392
alternative hypothesis: true mean is not equal to 72
95 percent confidence interval:
 72.15999 76.00376
sample estimates:
mean of x
74.08187
```

What to report:

- **t-statistic:** How many SEs away from null value
- **p-value:** Evidence against H_0
- **95% CI:** Range of plausible values for μ
- **Sample mean:** Our point estimate



Connection: CIs and Hypothesis Tests

Key relationship

For a two-sided test at $\alpha = 0.05$:

If the 95% CI does NOT contain μ_0 , then we reject $H_0 : \mu = \mu_0$

If the 95% CI DOES contain μ_0 , then we fail to reject H_0

Both methods use the same math - just different framing!

- CI: "What values are plausible for μ ?"
- Hypothesis test: "Is this specific value plausible?"



Final Reminders



Statistical Significance vs. Practical Significance

Don't confuse these!

Statistical significance ($p < 0.05$):

- Evidence that there's a real effect
- Doesn't tell you if the effect matters

Practical/Clinical significance:

- Effect is large enough to matter in real-world terms
- You must judge this based on context

Example: A drug lowers blood pressure by 0.5 mmHg ($p = 0.001$)

- Statistically significant? Yes
- Clinically meaningful? No (too small to affect patient outcomes)



Common Mistakes to Avoid

1. **Forgetting to check assumptions** before running tests
2. **Confusing standard deviation and standard error**
3. **Using `lower.tail = TRUE` when you need `FALSE`** (or vice versa)
4. **Misinterpreting p-values and confidence intervals**
5. **Forgetting to include `na.rm = TRUE`** when there are missing values
6. **Not rendering your document before submitting**

Pro tip: When using `pbinom()` or `ppois()`, sketch a quick picture to check if you want the left or right tail!



Exam Strategy

Time management:

- Don't get stuck on one question
- Move on and come back if needed
- Leave buffer time for rendering and checking

Interpretation questions:

- Write in complete sentences
- Reference numbers from your calculations
- Connect to context (not just abstract statistics)

Coding questions:

- Show your work (don't just give answers)
- Use comments to explain your logic
- Check that your code actually runs!



Resources

During the exam:

- Lecture slides (especially the summary slides)
- Homework solutions (you've seen similar questions!)
- R help: [?t.test](#), [?pnorm](#), etc.

After you submit:

- The exam will close Monday at 11 PM
- Solutions will be available after
- We'll get feedback to you within a week
- Remember: This is a learning experience!



Questions?



Your Turn!

What questions do you have?

- Concepts that are still unclear?
- R functions you're unsure about?
- Specific exam questions you want to discuss?

Remember:

- Exam opens today at 3 PM
- You have until Monday at 11 PM
- You've got this! 💪



Good luck!

You're well prepared:

- You've done the homework
- You've come to class
- You've practiced with R
- You know where to find help

Trust your preparation and think carefully about each question.

