Learn, Visualize, & Analyze

LAFOREST LAB R WORKSHOP

May 12-14th, 2025

DAY3: LEARNING GOALS

1. Understand Statistical Philosophies

- Compare **Frequentist**, **Bayesian**, and **Likelihood** approaches

2. Parametric vs. Non-Parametric Tests

- Choose tests based on data **distribution** and **type**
- Practice checks for normality (Shapiro-Wilk, Levene)

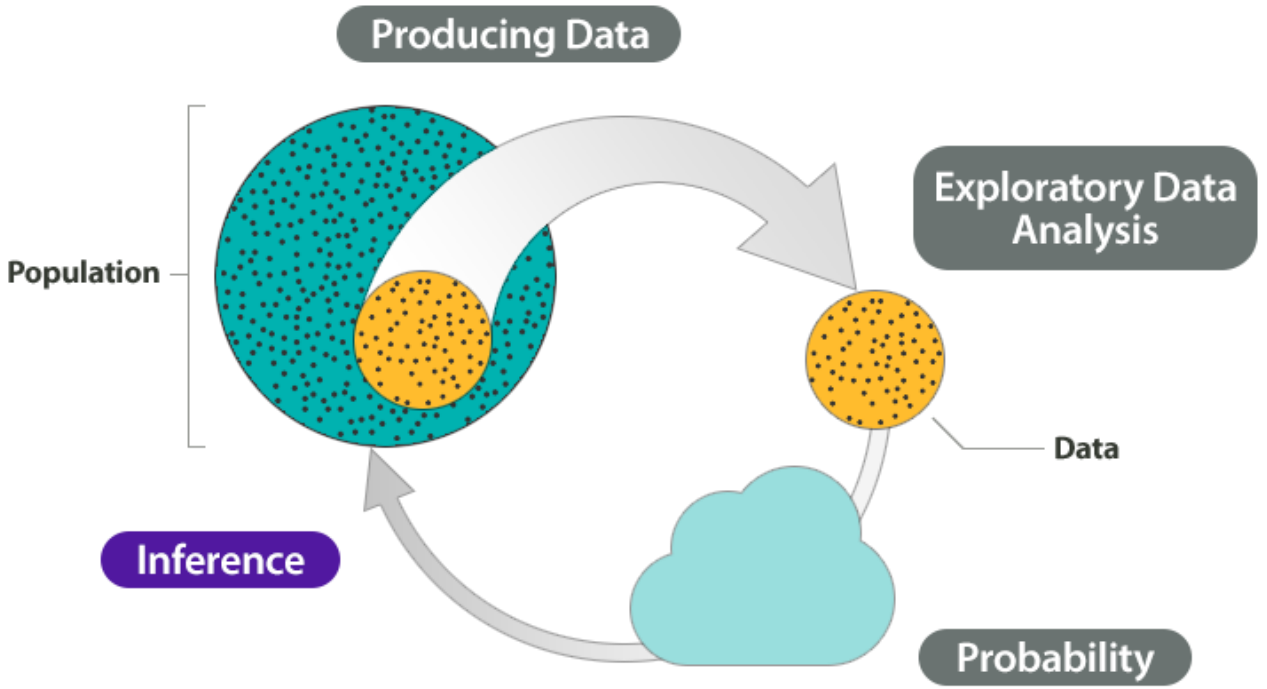
3. Perform Key Statistical Tests in R

- **t-tests**
- **ANOVA** (one-way, post-hoc tests)
- **Correlation** (Pearson, Spearman)

4. Build & Interpret Linear Models

- Simple/multiple **linear regression** (lm())
- **Linear mixed-effects models** (lmer() or nlme) for nested data
- Validate assumptions (residual plots)

Statistical Inference



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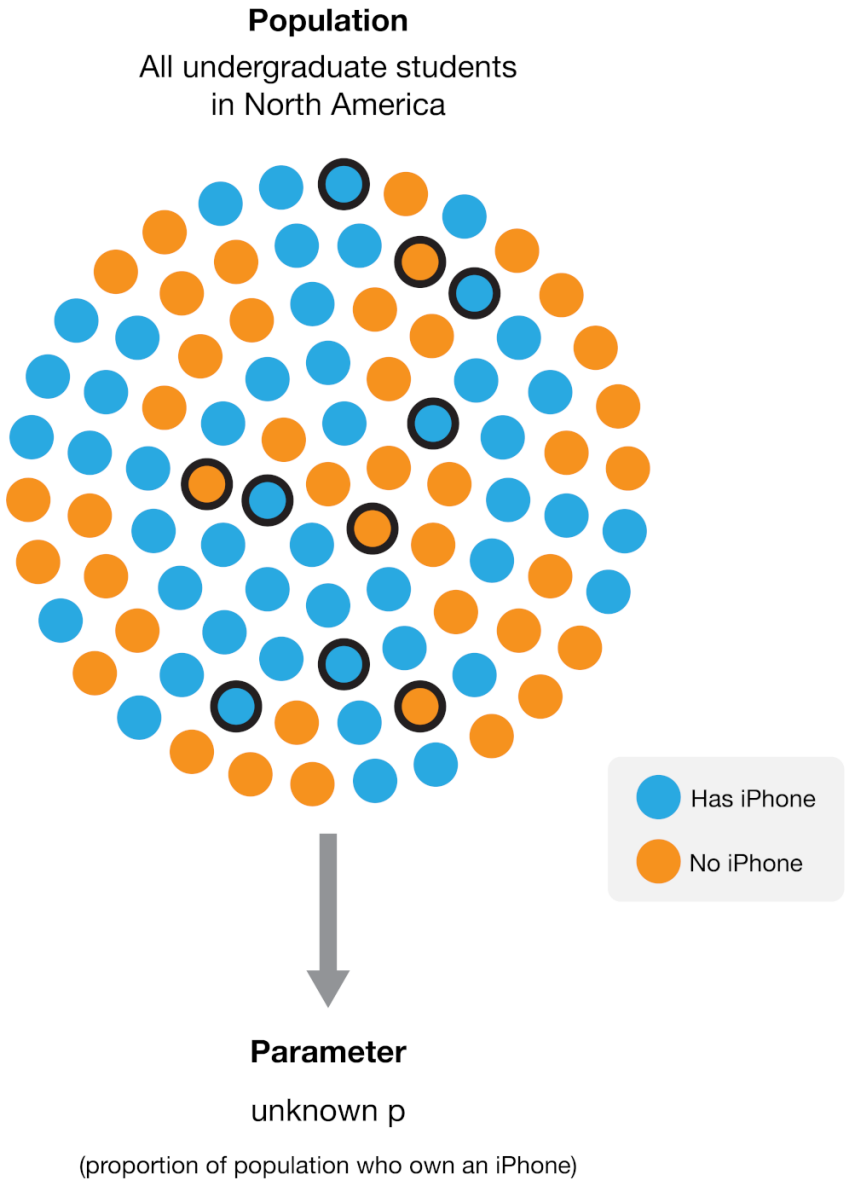

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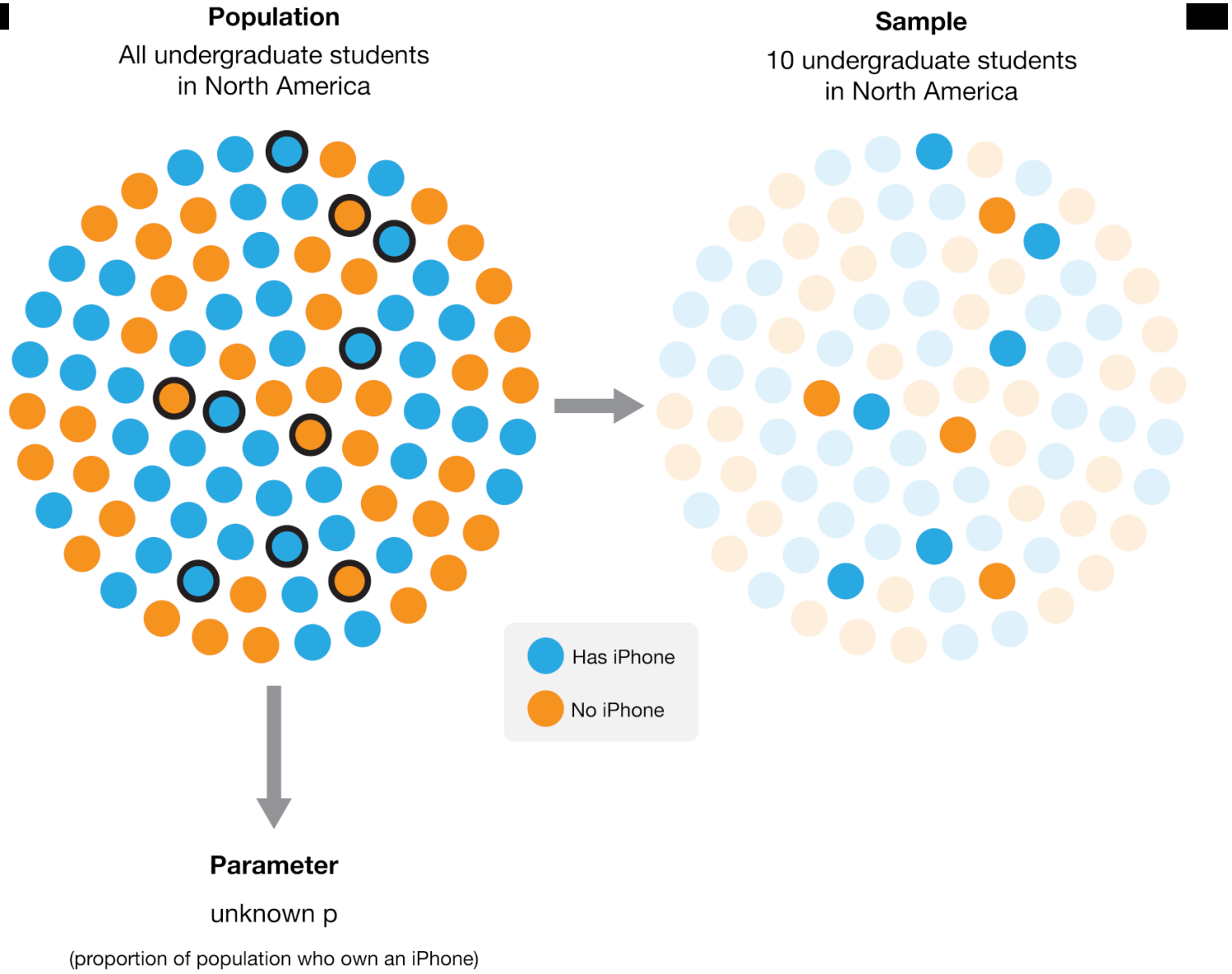

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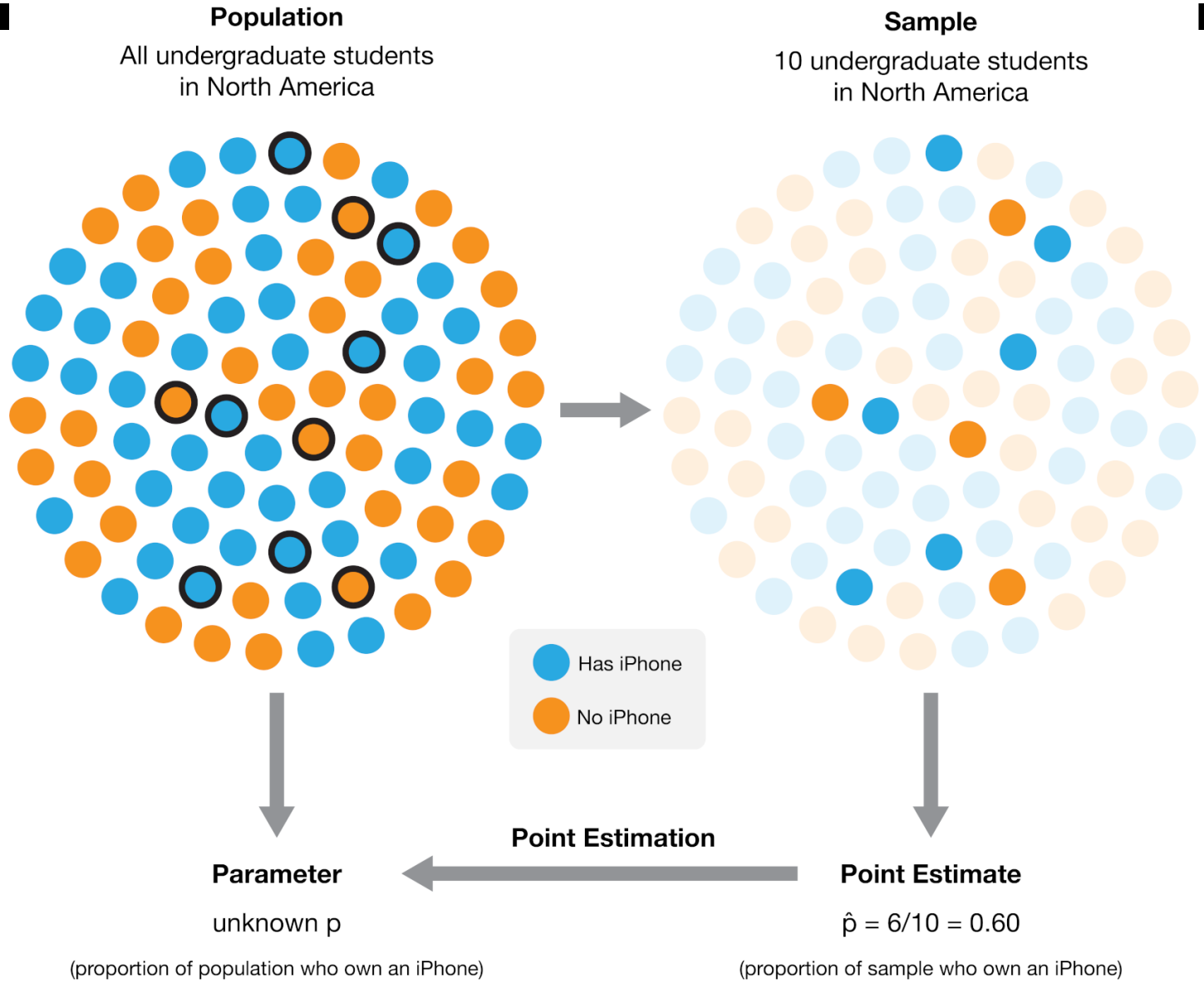

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Scientific methodology

Perform literature review

State hypothesis

Establish study design

Acquire data

Analyze data

Reach conclusion

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6. **Enhances Reproducibility**
    - Transparent protocols enable peer validation and replication.

Study design: what does your instinct tell you?

Aspect	Good Design	Bad Design
Research Question	Clear, focused, and testable hypothesis.	Vague or overly broad question.
Bias Control	Minimized via randomization, blinding, controls.	Susceptible to selection, measurement, or confounding bias.
Sample Size	Powered statistically to detect effects (e.g., pre-hoc power analysis).	Too small (Type II error) or unnecessarily large (wasted resources).
Variables	Key variables defined (independent/dependent/confounders).	Poorly defined or unmeasured confounders.
Data Collection	Standardized protocols (replicable).	Ad-hoc methods (prone to inconsistency/error).
Statistical Plan	Pre-specified primary analysis (avoids p-hacking).	Post-hoc "fishing" for significant results.
Reproducibility	Detailed methods (others can replicate).	Missing critical details.
Outcome	Valid, reliable, and actionable conclusions.	Misleading or uninterpretable results.

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Statistical Inference: 3 Key Approaches

1. Frequentist Statistics

- **Core Idea**: Probability = long-run frequency of events.
- **Focus**: *P(data | hypothesis)* (e.g., p-values, confidence intervals).
- **Tools**: Hypothesis tests (t-tests, ANOVA), Null Hypothesis Significance Testing.

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- **Focus**: Compare models via likelihood ratios (no priors).
- **Tools**: MLE, AIC/BIC, profile likelihoods.

- **Strengths**: Flexible; bridges Frequentist and Bayesian ideas.
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Parametric vs. non-parametric tests

Feature	Parametric Tests	Non-Parametric Tests
Assumptions	Normality, equal variance, independence	Fewer assumptions (ordinal/any distribution)
Data Types	Continuous, normally distributed	Ordinal, skewed, or small samples
Power	Higher power (when assumptions met)	Robust but less powerful
Examples	t-tests, ANOVA, Pearson's r	Wilcoxon, Kruskal-Wallis, Spearman's ρ

Basic parametric tests

Test	Predictor (X)	Outcome (Y)	Answer	R Function
t-test	2 groups	Continuous	"Are means different?"	t.test(y ~ group, data)
ANOVA	3+ groups	Continuous	"Which groups differ?"	aov(y ~ group, data)
Correlation	Continuous	Continuous	"How strong is the linear link?"	cor.test(data$x, data$y)
Regression	1+ continuous/cat.	Continuous	"How does X affect Y?"	cor.test(data$x, data$y)

Basic non-parametric tests

Parametric Test	Non-Parametric Alternative	When to Use It	R Function
Independent t-test	**Mann-Whitney U test**	Compare 2 independent groups (ordinal/skewed)	wilcox.test(y ~ group)
Paired t-test	**Wilcoxon signed-rank test**	Compare paired measurements (non-normal)	wilcox.test(y1, y2, paired=TRUE)
One-way ANOVA	**Kruskal-Wallis test**	Compare 3+ independent groups	kruskal.test(y ~ group)
Pearson correlation	**Spearman's rank correlation**	Assess monotonic relationships	cor.test(x, y, method="spearman")
Repeated-measures ANOVA	**Friedman test**	Compare 3+ paired groups	friedman.test(y ~ group | subject)

Excel, csv, txt...

How to get your data in a good format?

Let’s code!