





Learn, Visualize, & Analyze

LAFOREST LAB R WORKSHOP

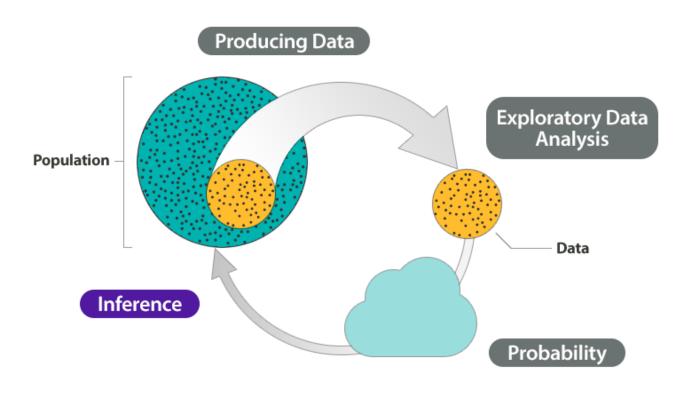
May 12-14th, 2025

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

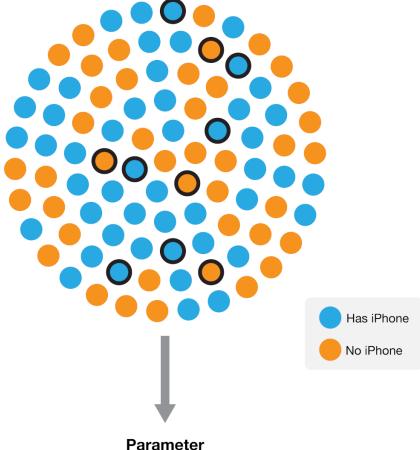




Statistical Inference

Population

All undergraduate students in North America

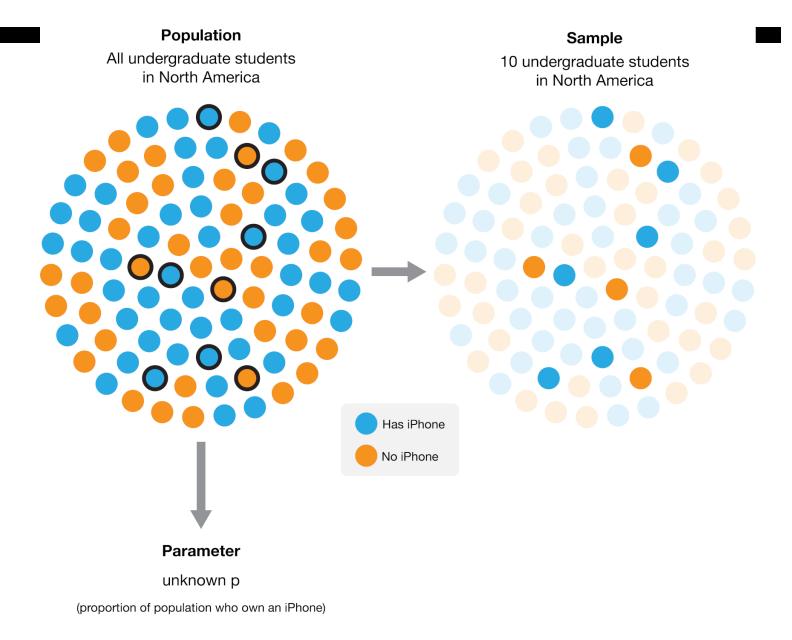


unknown p

(proportion of population who own an iPhone)

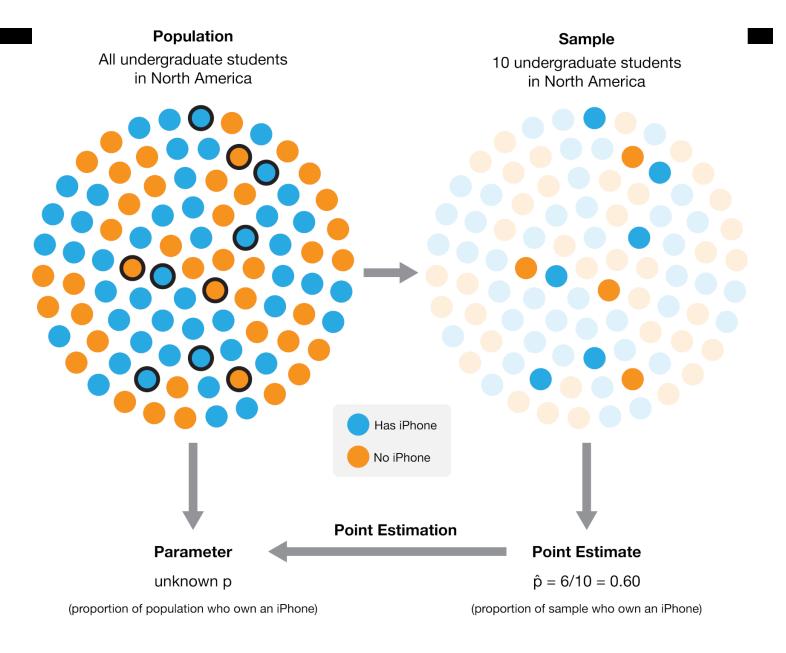


Statistical Inference





Statistical Inference





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.
- Strengths: Objective, widely used, standardized.
- **Limitations**: Ignores prior knowledge; misinterpreted p-values.



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3. Likelihood-Based Inference

- Core Idea: Focus on the likelihood function (support for hypotheses given data).
- 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	ce 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 $ ho$	



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

Non-Parametric

Parametric Test	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)



Let's code!