

Statistical Foundations for Biomedical Research

Statistical Mindset

Beyond the P-value



Statistics vs. Math

Math is about certainty; Statistics is about **quantifying uncertainty**.

The Workflow: Population → Sample → Inference.

Why it matters in BioMed: Biological variation is huge. We need to distinguish "signal" (the treatment effect) from "noise" (natural variation).

Descriptive Stats – The "First Look"

Don't Trust the Mean!

Central Tendency: Mean vs. Median.

•*Tip:* Use Median for skewed data (e.g., length of hospital stay).

Dispersion: Standard Deviation (SD) vs. Interquartile Range (IQR).

The Visual Check: Always plot your data (Histograms, Boxplots) before running tests. Anscombe's Quartet shows that different data patterns can have the same mean.

Where to Start? The 4-Step "Health Check"

Before you analyze, "Listen" to your Data



1. The Shape & Types (The Skeleton)

- How many patients (N) vs. how many variables?
- Are the variables correctly typed? (e.g., Is "Gender" a category or a number? Is "Date" actually a date or just text?)
- Check if your variables are correctly recognized (Numeric, Categorical, Date). Ensure your Sample Size (N) matches your expectations.

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2. Missingness (The Gaps)

- Where are the holes? Is data missing at random, or is there a pattern? (e.g., Are older patients skipping the weight question?)

Rule: If a variable has >30-40% missing values, it might be unusable.

- Identify missing values. Are they random or biased? *Tip:* Variables with >30% missing values may compromise your study.

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3. The "Sense" Test (Outliers & Sanity)

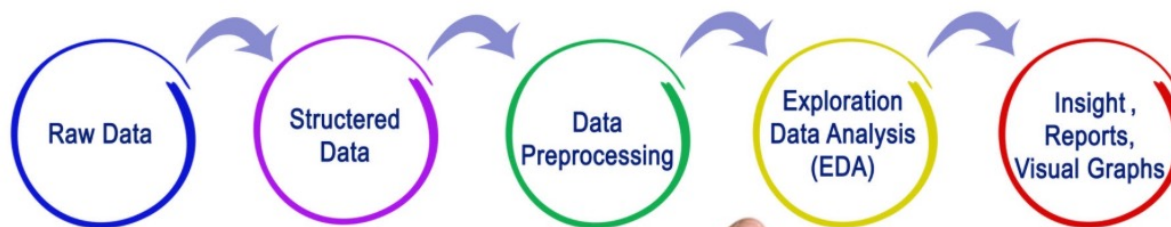
- Look for impossible values: A heart rate of 0 or a BMI of 150.
"Are these typos or extreme clinical cases?"

Decide how to handle them **before** you start.

4. Distribution & Balance (The Heartbeat)

- Is your outcome variable balanced? (e.g., In a rare disease study, do you have 100 cases vs. 1,000,000 controls?)
- Is the data normally distributed? This dictates if you use a T-test or a Non-parametric test.

Exploration Data Analysis



Hypothesis Testing (The Logic)

Guilty until proven Innocent

- ❑ **Null Hypothesis (H0):** No effect, no difference.
- ❑ **Alternative Hypothesis (H1):** There is an effect.
- ❑ **The P-value:** The probability of seeing your results (or more extreme) **if the null hypothesis is true.**



Warning! A p-value < 0.05 is not a "seal of truth"; it's just a threshold of surprise.

Choosing the Right Test

Data Type	Comparison	Test Example
Continuous (Normal)	2 Groups	T-test
Continuous (Non-normal)	2 Groups	Mann-Whitney U
Categorical	Frequencies	Chi-square / Fisher's Exact
Continuous	Relationship	Pearson/Spearman Correlation

Clinical vs. Statistical Significance

Do large samples reveal everything?

The Sample Size Trap: With 1,000,000 patients, even a 0.1 mmHg drop in blood pressure becomes "statistically significant" ($p < 0.001$), but it's **clinically irrelevant**.

Effect Size: Tell us *how much* it matters (e.g., Cohen's d, Odds Ratio).

Confidence Intervals (CI): as much useful as p-values. They show the range of the likely true effect.

Ok, it is statistically significant, but is it clinical relevant?

Correlation vs. Causation

The Data Scientist's Golden Rule

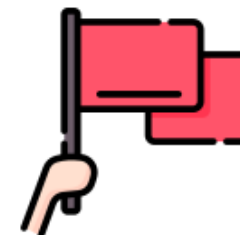
The Data Scientist's Golden Rule

- **Correlation:** Two variables move together.
- **Causation:** One variable *causes* the other to move.
- **Confounding Factors:** The "Hidden Variable" (e.g., Ice cream sales and drowning deaths both increase in summer; the cause is the Heat, not the ice cream).

Avoid Data Dredging: do not torture your data.

The "Bullshit Detector" – Top 3 Statistical Red Flags

Don't be Fooled by Numbers



P-Hacking (The "Fishing Expedition")

1

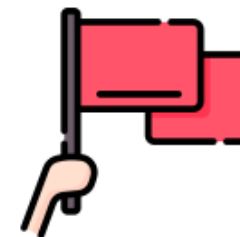
The Trap: Testing 50 different variables until one finally hits $p < 0.05$ by pure chance.

The Red Flag: A study that reports a significant result for a very specific sub-group that wasn't the original focus.

The Fix: Always define your hypothesis *before* looking at the data.

The "Bullshit Detector" – Top 3 Statistical Red Flags

Don't be Fooled by Numbers



Missing Confidence Intervals (CI)

2

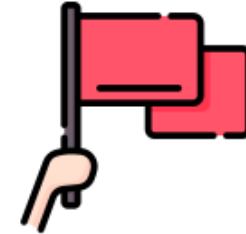
The Trap: Reporting only the p-value ($p=0.04$) to claim success.

The Red Flag: A "significant" result where the Confidence Interval is huge (e.g., an Odds Ratio of 1.5 but with a CI of [1.01 to 25.0]).

The Fix: If the CI is too wide, the estimate is imprecise. The "p" tells you it's there; the "CI" tells you if it's reliable.

The "Bullshit Detector" – Top 3 Statistical Red Flags

Don't be Fooled by Numbers



Hidden Axes & Relative Risk Bias

The Trap: Saying "Treatment X reduces risk by 50%"

3

The Red Flag: If the absolute risk drops from 2% to 1%, it is a 50% relative reduction, but only a **1% absolute difference**.

The Fix: Always look at the **Absolute Risk Reduction (ARR)**. Don't let the Y-axis of a graph start at 40% to make a small difference look like a mountain.



Comments & Questions



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Feitos
de outra
—**materia**