Why We Should All Be Bayesians

The Problem of Inferential Statistics in Organizational Science

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Test Results of Pregnancy Test in Maternity Clinic*

ACTUALLY ACTUALLY NOT PREGNANT

TEST SAYS PREGNANT 197 0

TEST SAYS NOT PREGNANT 1 2

TOTAL 198 2

A
1.0 different kind of being right

 $p(\theta \mid y)$

Probability of being right: .995 1.0

$$p(y | \theta)$$

Critical Insight #1:

What we care about as scientists is $p(\theta | y)$

... not $p(y | \theta)$

And, they are almost always NOT the same thing.

Test Results of Pregnancy Test in Maternity Clinic

	ACTUALLY PREGNANT	ACTUALLY NOT PREGNANT
TEST SAYS	197	0
TEST SAYS		2
TOTAL	198	(2)

Probability of being right: .995 1.0

Barnett: Problem is based on tests of 2 women who were not pregnant (i.e., small sample size).

The pharma collects more data...

	Actually Pregnant	Actually Not Pregnant		
Test Says Pregnant	197,000	0	1.0	Probability of Truth given the
Test Says Not Pregnant	1,000	2,000	.667	test results (observed data)
Total	198,000	2,000		

Probability of test being right given the Truth:

.995

1.0

Critical Insight #2:

Having more data does not solve the problem if you are answering the wrong question.

What Traditionalists do...

• **Assume** the population looks like θ , ask: What is the probability that the sample we observe looks like y (hypothesis testing)?

$$p(y | \theta)$$

This is **not an inference** – It is a mathematical deduction. Traditional statistics gives a great answer to the wrong question.

What Bayesians do is...

$$p(y | \theta) \Longrightarrow p(\theta | y)$$

$$p(\theta \mid y) = p(y \mid \theta)^{x} \frac{Bayesian}{Magic}$$

$$p(\theta \mid y) = p(y \mid \theta) \bullet \frac{p(\theta)}{p(y)}$$

Test Results of Pregnancy Test in Maternity Clinic

	ACTUALLY	ACTUALLY NOT PREGNANT
TEST SAYS		
PREGNANT	197	0
TEST SAYS		
NOT PREGNANT	1	2
TOTAL	198	2

$$p(y \mid \theta) = \frac{2}{2} = 1.0$$

$$p(\theta) = \frac{2}{200} = .01$$

$$p(y) = \frac{3}{200} = 0.015$$

$$p(\theta | y) = p(y | \theta) \bullet \frac{p(\theta)}{p(y)}$$
 $p(\theta | y) = 1.0 \bullet \frac{.01}{.015} = .667$

The General Framework in Science

Truth

	Actually Pregnant	Actually Not Pregnant
Test Says Pregnant	٠:	٠:
Test Says Not Pregnant	?	;

Data

Truth

	Actually Pregnant	Actually Not Pregnant	
Test Says Pregnant	5	?	198
Test Says Not Pregnant	?	Likelihood: 100% of "Not Pregnant" people will test negative.	3
	00.5%		200

Normalizing Constant (P(y)) = 3/200 = .015%

Conclusion: P(Not pregnant | test says "not pregnant")

- = Prior * Likelihood/Normalizing Constant
- = .005 * 1.0/.015 = .333

Data

College Campus

Truth

		Actually Pregnant	Actually Not Pregnant	
Data	Test Says Pregnant	?	0	9,900
	Test Says Not Pregnant	?	Likelihood: 100% of "Not Pregnant" people will test negative.	90,100

Normalizing Constant (P(y)) = 90100/100,000 = 90.1%

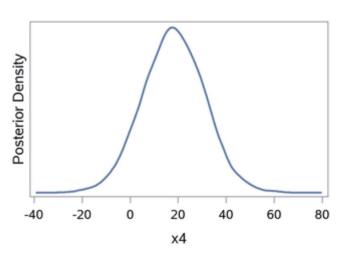
Conclusion: P(Not pregnant | test says "not pregnant") = Prior * Likelihood/Normalizing Constant = .9 * 1.0/.901 = .9989

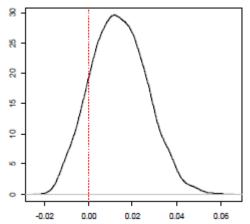
Critical Insight #3

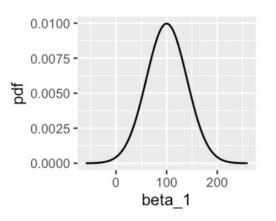
- Bayesians test their assumptions of their prior distributions by looking at how sensitive their results are to other alternative but reasonable priors.
 - They can use hyperparameters to describe and explore this sensitivity.
 - These hyperparameters can be used to look at meta analyses, also.

Critical Insight #4

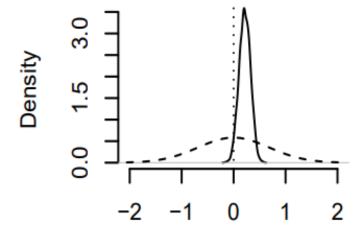
- Bayesians consider population parameters to be random variables, not fixed points. The key, then, is to describe the likelihood distribution of that population parameter.
 - This is often done graphically, not just with numbers.







 $P(\eta_2 > 0|data) = 0.98$



 η_2

Bayesian Analysis

- 1. Forces us to confront our assumptions about the population (although can resort to "uninformative priors" if have no idea).
- 2. Gives us the power to test the **sensitivity** of our results based on our assumptions.
- 3. Answers the right question: What can I infer about the population given the data I have?