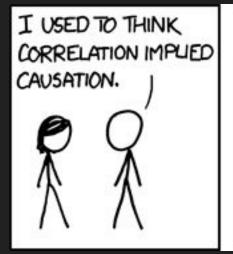
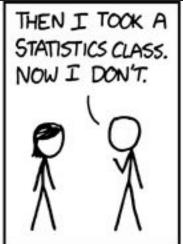
# Brief Introduction to Bayesian Inference

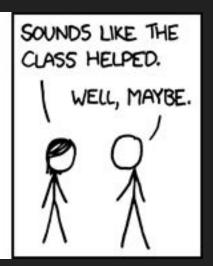
Byron J. Smith BMI 206 2020-11-19

Slides: https://bit.ly/36GJRrE

Code: https://bit.ly/36M3YVl







With help from XKCD

Byron J. Smith BMI 206 2020-11-19

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- Learn discrete facts about the world.
  - "COVID-19 is caused by SARS-CoV-2."
  - Karl Popper
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- Measure (continuous) parameters
  - "Wearing a mask decreases your risk of becoming infected with SARS-CoV-2 by 55.2%."
- ...But what about questions somewhere in between these two extremes?
  - "Does wearing a mask affect your risk of becoming infected?"

#### "Traditional": Null hypothesis statistical testing

"Does wearing a mask affect your risk of becoming infected?"

- Run an (e.g.) t-test
  - $\circ$  Implies a null hypothesis:  $H_0$  :  $\mu_{
    m mask} = \overline{\mu_{
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- Calculate p-value
- If p < 0.05 : we "reject the null hypothesis"</li>
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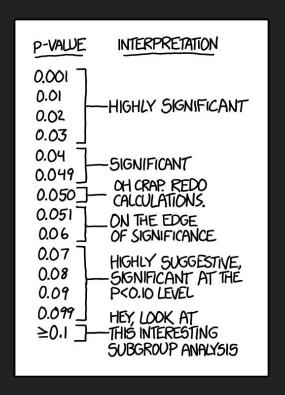
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#### **Shortcomings:**

- Misleading when:
  - Intuition/reality does not match test assumptions (E.g. small sample size)
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# Odds Are, It's Wrong

STATISTICS

# Measurement error and the replication crisis

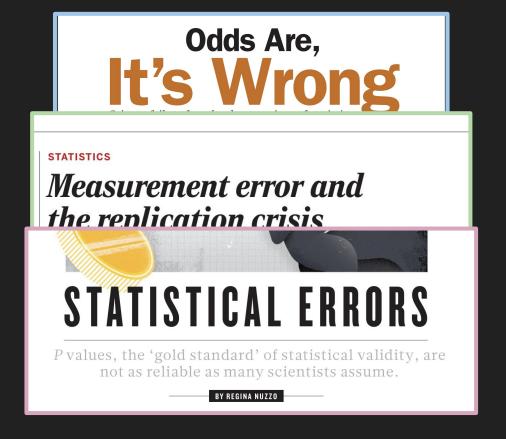
The assumption that measurement error always reduces effect sizes is false

By Eric Loken<sup>1</sup> and Andrew Gelman<sup>2</sup>

reliable measurement. In epidemiology, it

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#### What we would prefer:

"How does wearing a mask affect the risk of becoming infected?"

There is a 95% probability that wearing a mask decreases your risk of becoming infected by 50% or more

$$P(\theta|X) = \frac{P(X|\theta) P(\theta)}{P(X)}$$

#### **Parameters**

$$P(\theta|X) = \frac{P(X|\theta) P(\theta)}{P(X)}$$

Data 
$$P(\theta|X) = \frac{P(X|\theta) \, P(\theta)}{P(X)}$$

"Posterior"

$$P(\theta|X) = \frac{P(X|\theta) P(\theta)}{P(X)}$$

Have you seen this before?

$$P(\theta|X) = \frac{P(X|\theta)P(\theta)}{P(X)}$$

"Likelihood"

$$P(\theta|X) = \frac{\mathcal{L}(\theta|X)P(\theta)}{P(X)}$$

"Prior"

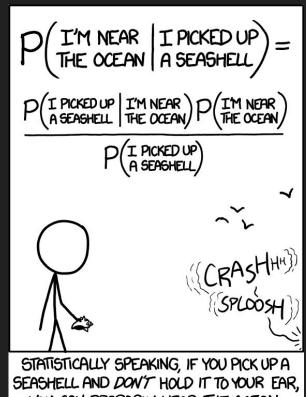
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"Normalizing Constant"

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YOU CAN PROBABLY HEAR THE OCEAN.

Rephrase: What is the relative risk to wearers vs. non-wearers?

heta Odds ratio of COVID-19 among wearers and non-wearers

$$P(X|\theta)$$

$$P(\theta)$$

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P( heta) - Prior probability of the given odds ratio

P(X)  $P(\theta|X) = \frac{P(X|\theta) P(\theta)}{P(X)}$ 

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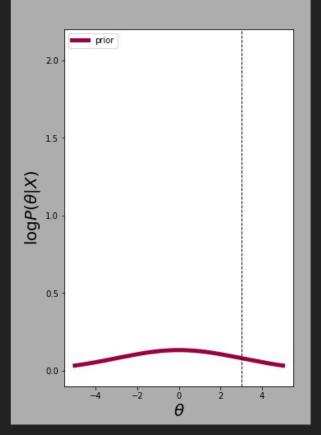
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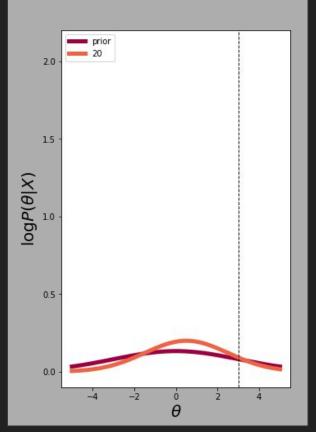
P(X| heta) Probability of the observed numbers, given the odds ratio

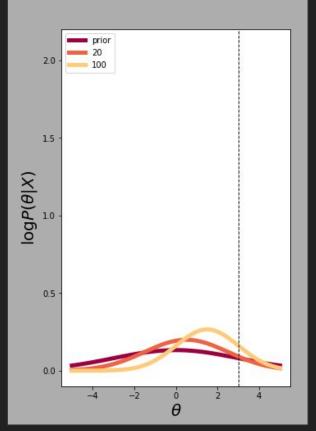
P( heta) Prior probability of the given odds ratio

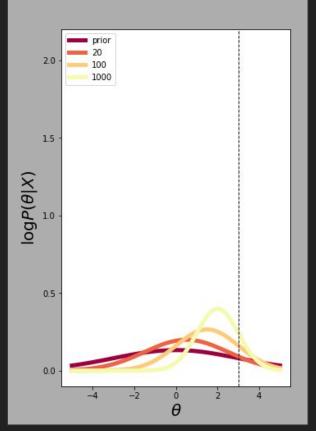
(X) Marginal probability of this observation

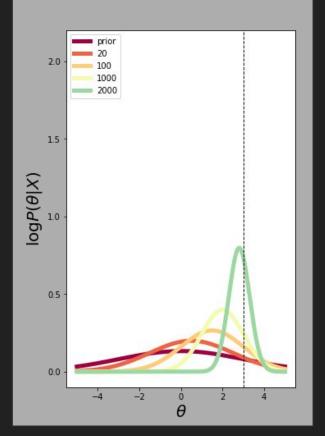
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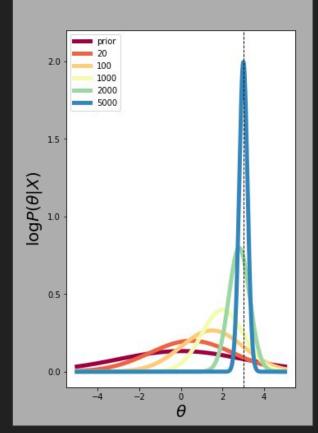












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Hard

$$P(\theta|X) = \frac{P(X|\theta) P(\theta)}{\int_{\Theta} P(X|\theta') P(\theta') d\theta'}$$

- Hard
- Easier: Sampling from the posterior

$$P(\theta|X) = \frac{P(X|\theta) P(\theta)}{\int_{\Theta} P(X|\theta') P(\theta') d\theta'} \propto P(X|\theta) P(\theta)$$

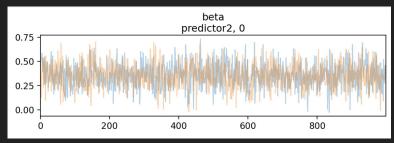
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- Markov-Chain Monte Carlo (Metropolis-Hastings algorithm)

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# Sampling heta from the posterior

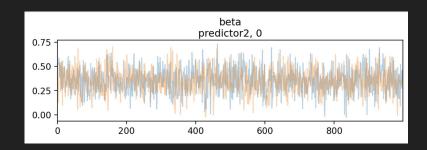
Markov-Chain Monte Carlo (Metropolis-Hastings algorithm)

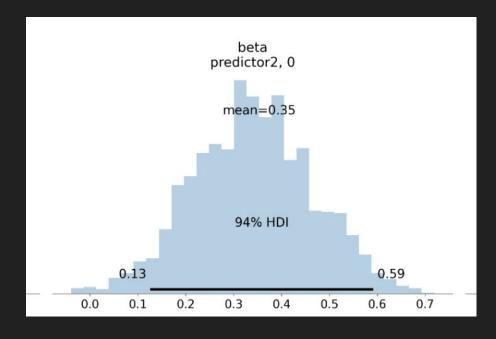
$$\theta_1, \theta_2, \theta_3, ..., \theta_n$$



# Sampling heta from the posterior

- Markov-Chain Monte Carlo (Metropolis-Hastings algorithm)
- Use samples from the posterior to calculate
  - Expectations
  - Credible intervals





### Why doesn't everyone do it this way?

### Computation

- Scales unfavorably with number of parameters, size of data
- May require many samples due to "poor mixing"

#### The Prior

- "Introduces bias"
- Subject to criticism

### Alternatives

Maximum likelihood

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Maximum likelihood

### Computation

- Huge progress in last 20 years.
- HMC, Variational Inference

#### The Prior

- Useful for incorporating expert knowledge, constraints, intuition.
- Makes assumptions explicit

### Alternatives

Challenging to assess
 uncertainty from point estimates

## Logistic Regression

$$y_i \sim \text{Bernoulli}(p_i)$$
  
 $\log \text{it}(p_i) = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \dots + \beta_K x_{iK}$   
 $\beta_k \sim \text{Normal}(0, 1)$ 

## Try it out!

https://bit.ly/36M3YVl

## Logistic Regression

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### Logistic Regression

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 $\beta_k \sim \text{Laplace}(1)$ 

### Democratized statistical modeling

- Emphasizes parameter estimates and uncertainty over p-values
- "Inference Button": flexible, well built software to sample from and interpret models
  - STAN, PyMC3, Pyro, Turing.jl
- Only scratched the surface in this session

Every Statistics XKCD (44 and counting): https://bit.ly/32YH4Jc

