

# Statistical Power and Bayesian Inference

# Today's objectives and plan

## Morning:

- Review the hypothesis testing and type I and type II errors; which error is more serious?
- Compute power; understand relationship and trade-offs against other factors (significance level, effect size, variance, sample size) that influence power
- Morning assignment: Compute power and sample size

## Afternoon:

- Review conditional probability
- Bayes' rule
- Bayesian inference
- Pair programming: Bayesian analysis, verification by simulation

Morning: Statistical Power

# Hypothesis Testing: Possible Outcomes

	$H_0$ is true	$H_0$ is false
Fail to reject $H_0$	Correct Decision ( $1 - \alpha$ )	Type II Error ( $\beta$ )
Reject $H_0$	Type I Error ( $\alpha$ )	Correct Decision ( $1 - \beta = \pi$ )

# Type I and Type II Errors

## Type I Error

$$= P(\text{Reject } H_0 \mid H_0 \text{ is true})$$

$$= \alpha \text{ (alpha, the significance level)}$$

## Type II Error

$$= P(\text{Fail to reject } H_0 \mid H_0 \text{ is false})$$

$$= \beta \text{ (beta)} = 1 - \pi \text{ (one minus power)}$$

Which Type of Errors is More Serious?

Example 1: You have been put on trial for murder

$H_0$ : You are innocent (presumption of innocence)

$H_A$ : You are guilty

The question for the jury is whether it finds enough evidence that you are guilty

# Example 1: You have been put on trial for murder (cont.)

	$H_0$ is true You are <b>truly</b> innocent	$H_0$ is false You are <b>truly</b> guilty
Fail to reject $H_0$ Did not found enough evidence that you are guilty: You are <b>declared</b> innocent	Correct	Type II Error You are guilty but set free
Reject $H_0$ Found enough evidence that you are guilty: You are <b>declared</b> guilty	Type I Error You are found guilty of a murder that you did not commit (and the murderer is still free...) <b>The American justice system puts a lot of emphasis on avoiding type I errors</b>	Correct



Example 2: You are being screened for a disease

$H_0$ : You don't have the disease

$H_A$ : You have the disease

The question for the test is whether it finds enough evidence (e.g., markers) that you have the disease

## Example 2: You are being screened for a disease (cont.)

	$H_0$ is true You <b>truly</b> are disease-free	$H_0$ is false You <b>truly</b> have the disease
Fail to reject $H_0$ Did not found enough evidence that you are sick: You are <b>declared</b> to be disease-free	Correct	Type II Error You'll have the incorrect assurance that you don't have the disease <b>As a result, you won't be treated for your disease</b>
Reject $H_0$ Found enough evidence that you are sick: You are <b>declared</b> to have the disease	Type I Error You'll be anxious for a while but this will lead to other testing procedures. Eventually, you'll discover that the initial test was incorrect	Correct

## Example 3: You are working on a new drug

$H_0$ : The new drug is not more effective than current drugs

$H_A$ : The new drug more effective than current drugs

Underpowered study:

With a type II error, you would fail to reject that the new drug is not more effective than current drugs while said drug being really more effective

# Minimizing the type II error ( $\beta$ )

Is equivalent to maximize  $\pi$

$$= 1 - \beta$$

$$= 1 - P(\text{Fail to reject } H_0 \mid H_0 \text{ is false})$$

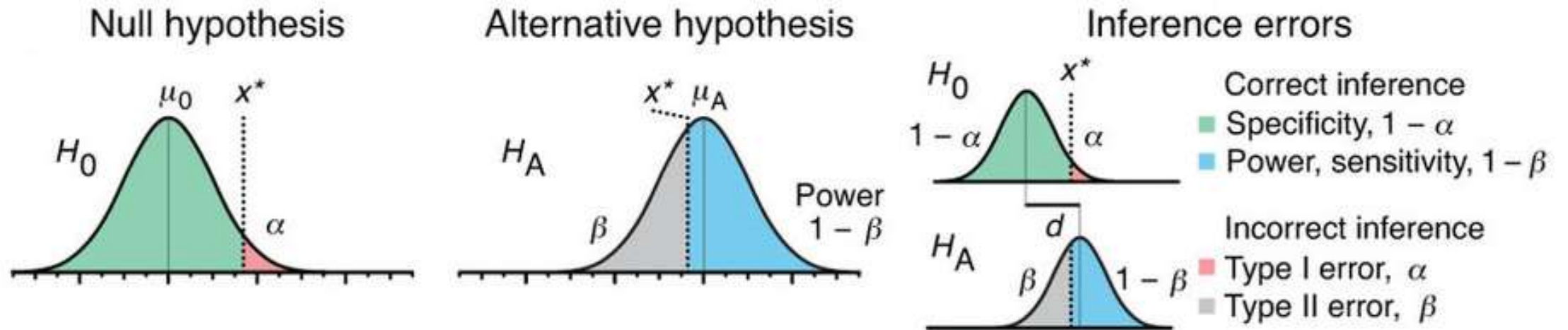
$$= P(\text{Reject } H_0 \mid H_0 \text{ is false})$$

$$= P(\text{Reject } H_0 \mid H_A \text{ is true})$$

# Hypothesis Testing: Possible Outcomes

	$H_0$ is true	$H_0$ is false
Fail to reject $H_0$	Correct Decision ( $1 - \alpha$ )	Type II Error ( $\beta$ )
Reject $H_0$	Type I Error ( $\alpha$ )	Correct Decision ( $1 - \beta = \pi$ )

# Hypothesis Testing: Outcomes and Regions



# Compute Statistical Power of a Test

Example: One-sample Test of Mean

$H_0: \mu_1 - \mu_0 = 0$  (e.g., the test finds no evidence of the better effectiveness of the new drug)

$H_A: \mu_1 - \mu_0 > 0$  (e.g., the test finds evidence of the better effectiveness of the new drug)

# Compute Statistical Power of a Test (cont.)

First, we reject  $H_0$  when:

$$Z_\alpha \leq Z = \frac{X - \mu_0}{s/\sqrt{n}} \text{ or } \mu_0 + Z_\alpha \frac{s}{\sqrt{n}} = X^* \leq X$$

Then, we find the corresponding cut-off of this value under  $H_A$  is:

$$X^* = \mu_1 - Z_\beta \frac{s}{\sqrt{n}}$$

$$Z_\alpha + Z_\beta = \frac{\mu_1 - \mu_0}{s/\sqrt{n}}$$



# Statistical Power and its relationship with other Factors

$$Z_{\alpha} + Z_{\beta} = \frac{\mu_1 - \mu_0}{s / \sqrt{n}}$$

The equation above links the following variables:

- $\alpha$  (type I error; significance level)
- $\beta$  (type II error;  $\pi = 1 - \beta$ , the statistical power)
- $\mu_1 - \mu_0$  (effect size)
- $s$  (standard deviation)
- $n$  (sample size)

Define 4 of these variables and solve for the remaining one

# A. Type I Error and Type II Error Trade-Off

Assuming all other variables are fixed

$$Z_{\alpha} + Z_{\beta} = \frac{\mu_1 - \mu_0}{s / \sqrt{n}}$$

If  $\alpha \downarrow$  (Type I Error increases):  
?

# A. Type I Error and Type II Error Trade-Off (cont.)

Assuming all other variables are fixed

$$Z_{\alpha} + Z_{\beta} = \frac{\mu_1 - \mu_0}{s / \sqrt{n}}$$

If  $\alpha \downarrow$  (Type I Error increases):

- $Z_{\alpha} \uparrow, Z_{\beta} \downarrow$
- $\beta \uparrow$  (Type II error increases)
- $1 - \beta \downarrow$  (Power decreases)

## B. Power and Effect Size Trade-Off

Assuming all other variables are fixed

$$Z_{\alpha} + Z_{\beta} = \frac{\mu_1 - \mu_0}{s / \sqrt{n}}$$

If  $1 - \beta \uparrow$  (Power increases):  
?

## B. Power and Effect Size Trade-Off (cont.)

Assuming all other variables are fixed

$$Z_{\alpha} + Z_{\beta} = \frac{\mu_1 - \mu_0}{s / \sqrt{n}}$$

If  $1 - \beta \uparrow$  (Power increases):

- $\beta \downarrow$
- $Z_{\beta} \uparrow$
- $\mu_1 - \mu_0 \uparrow$  (Effect size increases)

## C. Power and Sample Size Trade-Off

Assuming all other variables are fixed

$$Z_{\alpha} + Z_{\beta} = \frac{\mu_1 - \mu_0}{s / \sqrt{n}}$$

If  $1 - \beta \uparrow$  (Power increases):  
?

## C. Power and Sample Size Trade-Off (cont.)

Assuming all other variables are fixed

$$Z_{\alpha} + Z_{\beta} = \frac{\mu_1 - \mu_0}{s / \sqrt{n}}$$

If  $1 - \beta \uparrow$  (Power increases):

- $\beta \downarrow$
- $Z_{\beta} \uparrow$
- $\frac{\mu_1 - \mu_0}{s / \sqrt{n}} \uparrow$
- $s / \sqrt{n} \downarrow$
- $n \uparrow$  (Sample size increases)

## D. Sample Size and Effect Size Trade-Off

Assuming all other variables are fixed

$$Z_{\alpha} + Z_{\beta} = \frac{\mu_1 - \mu_0}{s / \sqrt{n}}$$

If  $n \uparrow$  (Sample size increases):  
?



## D. Sample Size and Effect Size Trade-Off (cont.)

Assuming all other variables are fixed

$$Z_{\alpha} + Z_{\beta} = \frac{\mu_1 - \mu_0}{s / \sqrt{n}}$$

If  $n \uparrow$  (Sample size increases):

- $s / \sqrt{n} \downarrow$
- $\mu_1 - \mu_0 \uparrow$  (Effect size increases)

Power analysis allows you to determine the sample size needed to detect a particular effect

Morning assignment

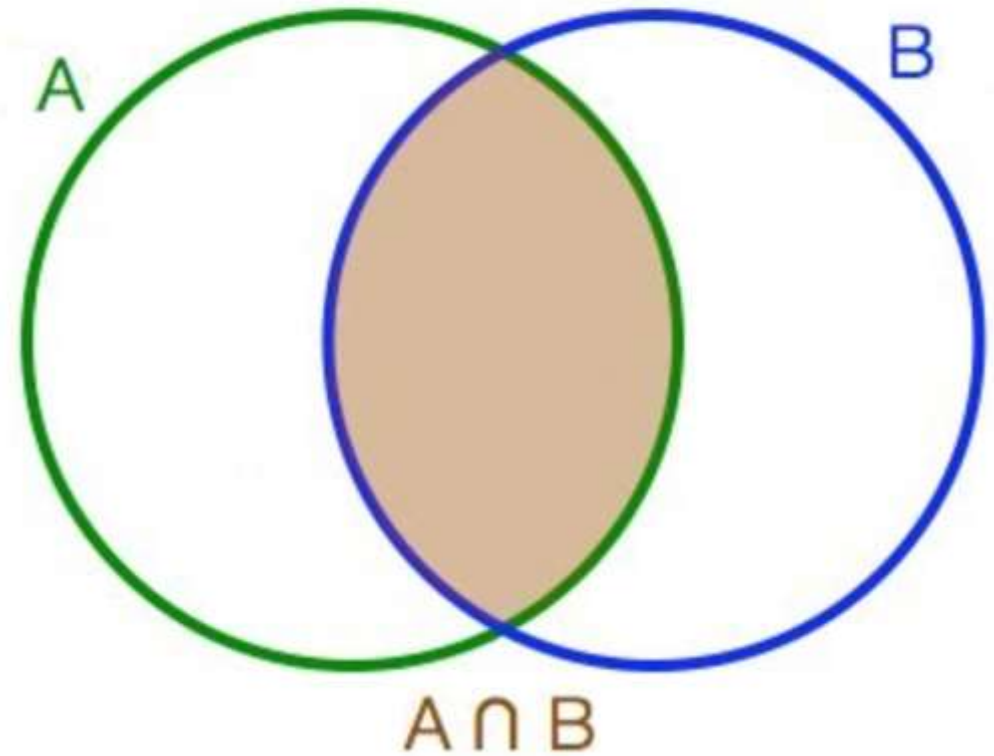
# Afternoon: Bayesian Inference

# Bayes' Rule: Motivation

- How to relate conditional probabilities between two events
- How to incorporate prior knowledge and belief into interpretation of data

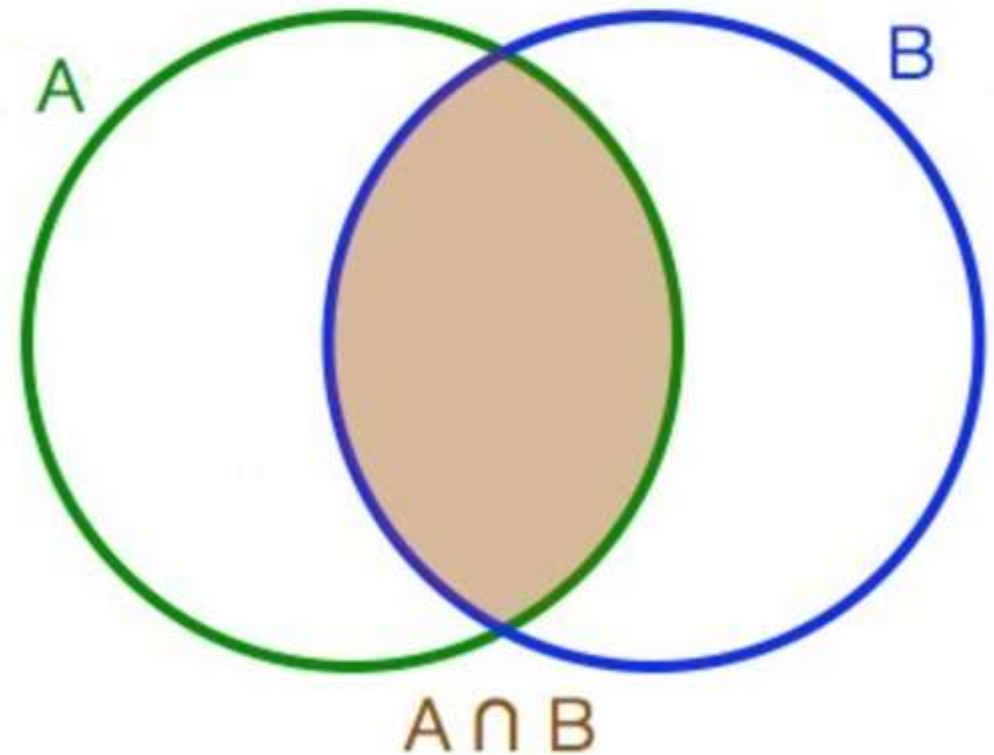
# Conditional Probability Review

$$P(B|A) = \frac{P(A \cap B)}{P(A)}$$



Poll: What's the probability of rolling a dice with a value less than 4 knowing that the value is odd

$$P(B|A) = \frac{P(A \cap B)}{P(A)}$$

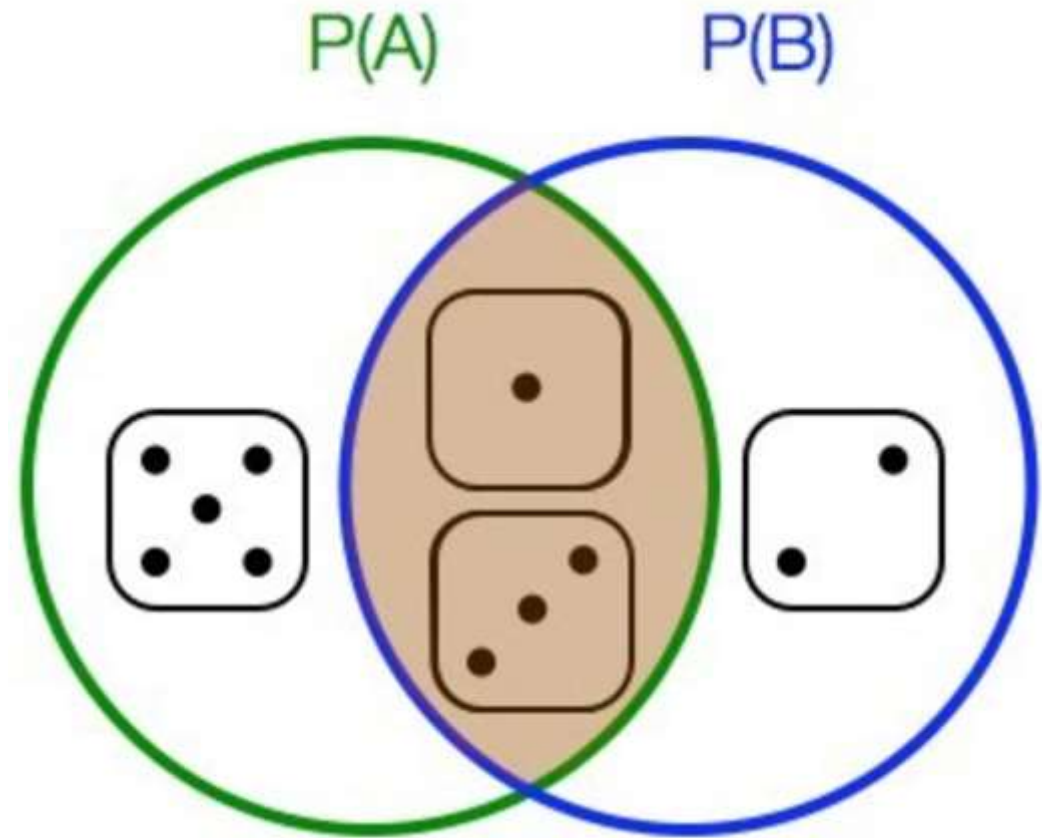


Poll: What's the probability of rolling a dice with a value less than 4 knowing that the value is odd

B = dice with a value less than 4

A = dice with an odd number

$$P(B|A) = \frac{P(A \cap B)}{P(A)} = \frac{2}{3}$$



# Bayes' Rule

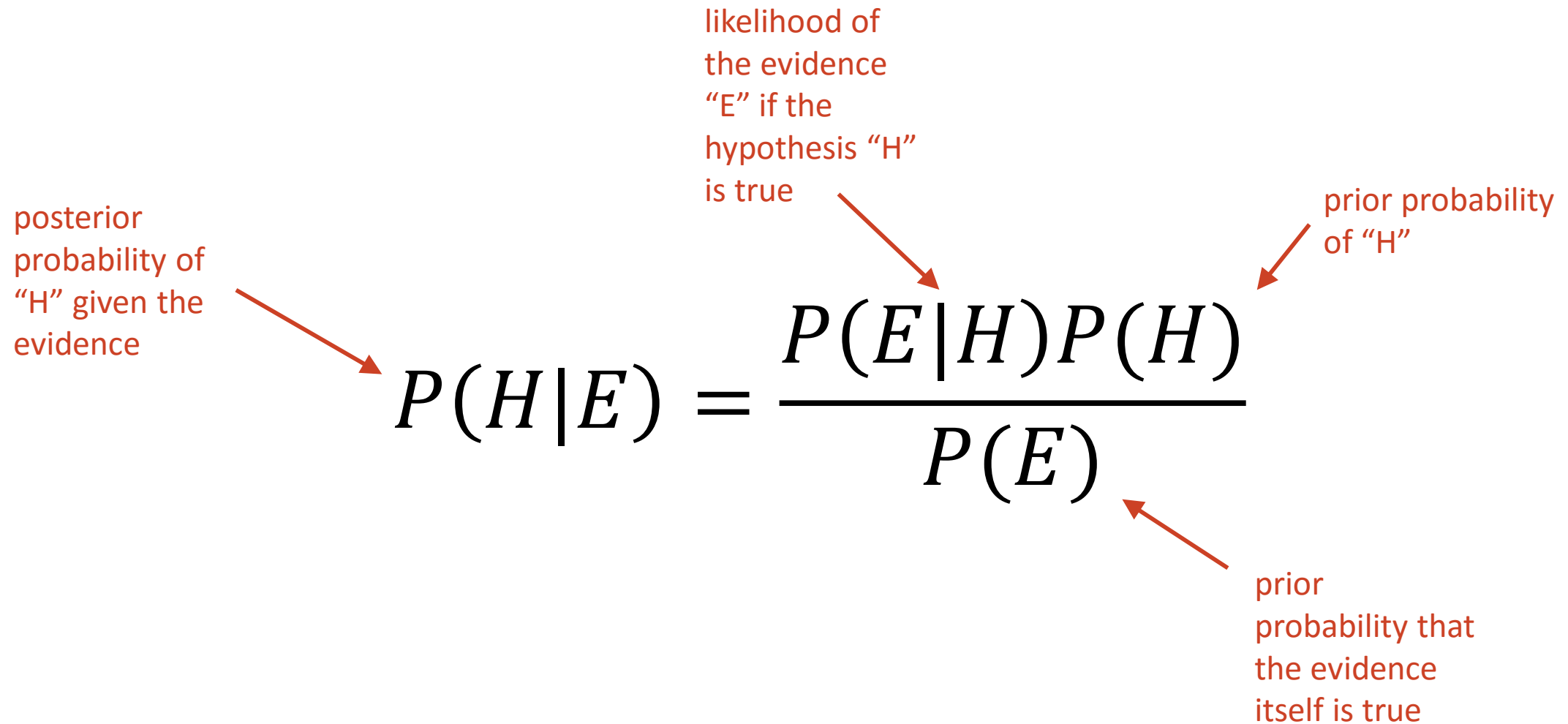


Diagram illustrating Bayes' Rule with explanatory labels and arrows:

- posterior probability of "H" given the evidence** (points to  $P(H|E)$ )
- likelihood of the evidence "E" if the hypothesis "H" is true** (points to  $P(E|H)$ )
- prior probability of "H"** (points to  $P(H)$ )
- prior probability that the evidence itself is true** (points to  $P(E)$ )

$$P(H|E) = \frac{P(E|H)P(H)}{P(E)}$$



Bayes' Rule (cont.)

$$P(H|E) = \frac{P(E|H)P(H)}{P(E|H)P(H) + P(E|H^c)P(H^c)}$$

# Poll: You are planning a picnic today

You are planning a picnic today, but the morning is cloudy. What is the chance that it will rain during the day knowing that:

- 50% of all rainy days start off cloudy
- Cloudy mornings are common (40% of days start cloudy)
- This month is usually a dry month (only 3 of 30 days tend to be rainy)

Poll: You are planning a picnic today

$P(\text{rainy day} \mid \text{cloudy morning}) =$

$$\frac{P(\text{cloudy morning} \mid \text{rainy day})P(\text{rainy day})}{P(\text{cloudy morning})} =$$

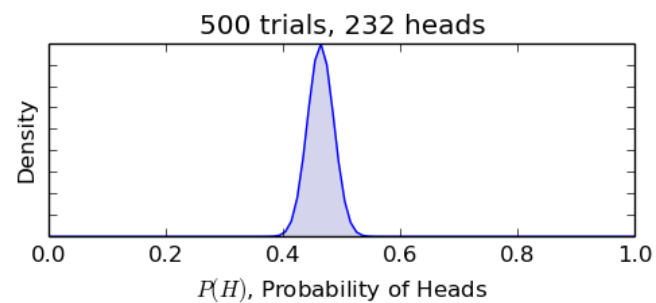
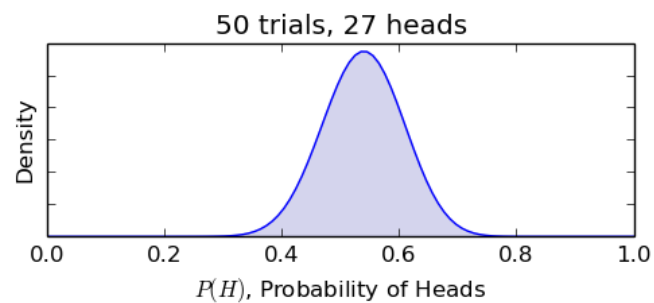
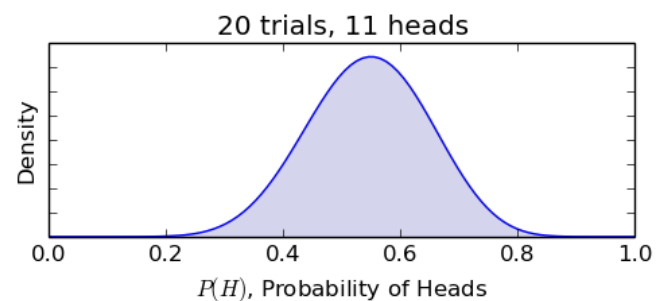
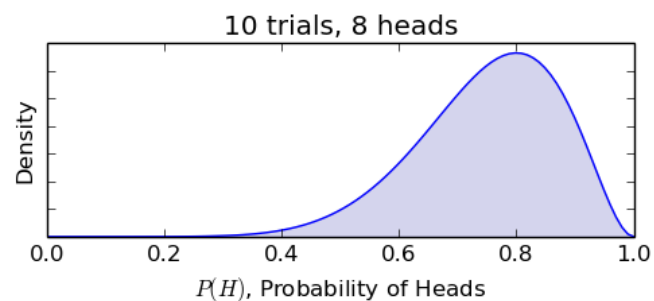
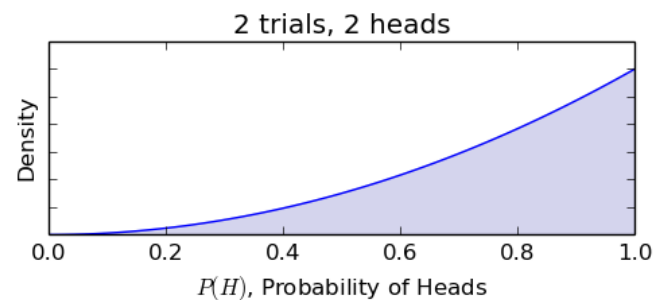
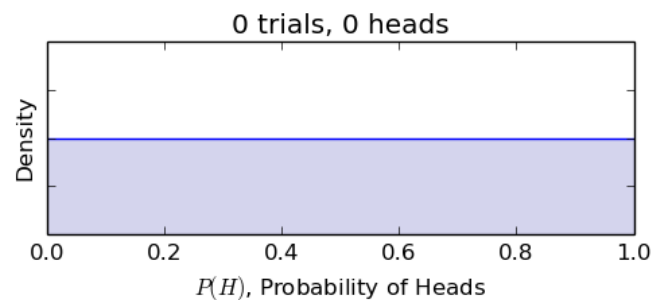
$$\frac{.5 * 3/30}{.4} = .125$$

12.5%; not too bad compared with 50%..., let's have a picnic!

# Bayesian Inference

- Bayesian updates his or her beliefs after seeing evidence
  - John Maynard Keynes, a great economist and thinker, said “When the facts change, I change my mind. What do you do, sir?”
- Probability is seen as a measure of believability in events

# Bayesian Updates



# Relating Prior Knowledge/Belief to Data

You have a drawer of 100 coins, 10 of which are biased

$$P(\text{head} \mid \text{fair}) = .5$$

$$P(\text{head} \mid \text{biased}) = .25$$

You randomly choose a coin and flip it once. It comes up heads

1. What is  $P(\text{fair} \mid \text{head})$ ?
2. What if you flip it a second time and it comes up heads again?

# Relating Prior Knowledge/Belief to Data

After the first coin flip,  $E = [\text{head}]$

- H = fair coin

$$P(\text{fair} \mid \text{head}) =$$

$$\frac{P(\text{head} \mid \text{fair})P(\text{fair})}{P(\text{head} \mid \text{fair})P(\text{fair}) + P(\text{head} \mid \text{biased})P(\text{biased})} = \frac{.5 \times .9}{.5 \times .9 + .25 \times .1} = .947$$

- H = biased coin

$$P(\text{biased} \mid \text{head}) =$$

$$\frac{P(\text{head} \mid \text{biased})P(\text{biased})}{P(\text{head} \mid \text{fair})P(\text{fair}) + P(\text{head} \mid \text{biased})P(\text{biased})} = \frac{.25 \times .1}{.5 \times .9 + .25 \times .1} = .053$$

# Relating Prior Knowledge/Belief to Data

After the second coin flip,  $E = [\text{head}, \text{head}]$

- $H = \text{fair coin}$

$$P(\text{fair} \mid \text{head}) =$$

$$\frac{P(\text{head} \mid \text{fair})P(\text{fair})}{P(\text{head} \mid \text{fair})P(\text{fair}) + P(\text{head} \mid \text{biased})P(\text{biased})} = \frac{.5 \times .947}{.5 \times .947 + .25 \times .053} = .973$$

- $H = \text{biased coin}$

$$P(\text{biased} \mid \text{head}) =$$

$$\frac{P(\text{head} \mid \text{biased})P(\text{biased})}{P(\text{head} \mid \text{fair})P(\text{fair}) + P(\text{head} \mid \text{biased})P(\text{biased})} = \frac{.25 \times .947}{.5 \times .947 + .25 \times .053} = .027$$



Afternoon pairing