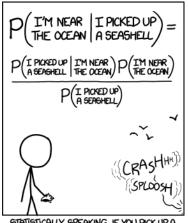
# Bayesian Updating: Discrete Priors: 18.05 Spring 2014 Jeremy Orloff and Jonathan Bloom



STATISTICALLY SPEAKING, IF YOU PICK UP A SEASHELL AND DON'T HOLD IT TO YOUR EAR, YOU CAN PROBABLY HEAR THE OCEAN.

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## Three 'phases'

- Data Collection:
   Informal Investigation / Observational Study / Formal Experiment
- Descriptive statistics
- Inferential statistics

To consult a statistician after an experiment is finished is often merely to ask him to conduct a post-mortem examination. He can perhaps say what the experiment died of.

R.A. Fisher

### What is a statistic?

**Definition**. A *statistic* is anything that can be computed from the collected data.

- Point statistic: a single value computed from data, e.g sample average  $\overline{x}_n$  or sample standard deviation  $s_n$ .
- Interval or range statistics: an interval [a,b] computed from the data. (Just a pair of point statistics.) Often written as  $\overline{x} \pm s$ .

#### Notation

Big letters X, Y,  $X_i$  are random variables.

Little letters x, y,  $x_i$  are data (values) generated by the random variables.

**Example.** Experiment: 10 flips of a coin:

 $X_i$  is the random variable for the  $i^{th}$  flip: either 0 or 1.

 $x_i$  is the actual result (data) from the  $i^{th}$  flip.

e.g.  $x_1, \ldots, x_{10} = 1, 1, 1, 0, 0, 0, 0, 0, 1, 0$ .

## Reminder of Bayes' theorem

Bayes's theorem is the key to our view of statistics. (Much more next week!)

$$P(H|D) = \frac{P(D|H)P(H)}{P(D)}.$$

$$P(\text{hypothesis}|\text{data}) = \frac{P(\text{data}|\text{hypothesis})P(\text{hypothesis})}{P(\text{data})}$$

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## Estimating a parameter

**Example.** Suppose we want to know the percentage p of people for whom cilantro tastes like soap.

Experiment: Ask n random people to taste cilantro.

Model:

 $X_i \sim \text{Bernoulli}(p)$  is whether the  $i^{\text{th}}$  person says it tastes like soap.

Data:  $x_1, \ldots, x_n$  are the results of the experiment

*Inference*: Estimate *p* from the data.

### Maximum likelihood estimate

The maximum likelihood estimate (MLE) is a way to estimate values of a *parameter of interest*.

**Example.** You ask 100 people to taste cilantro and 55 say it tastes like soap. Use this data to estimate p.

### Likelihood

For a given value of p the probability of getting 55 'successes' is the binomial probability

$$P(55 \text{ soap}|p) = \binom{100}{55} p^{55} (1-p)^{45}.$$

#### **Definition:**

The likelihood 
$$P(\text{data}|p) = \binom{100}{55} p^{55} (1-p)^{45}$$
.

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### MLE

The MLE is the value of p for which the observed data is most likely.

That is, the MLE is the value of p that maximizes the likelihood.

Calculus: To find the MLE, solve  $\frac{d}{dp}P(\text{data} \mid p) = 0$  for p.

**Note:** Sometimes the derivative is never 0 and the MLE is at an endpoint of the allowable range. We should also check that the critical point is a maximum.

$$\frac{dP(\text{data} \mid p)}{dp} = {100 \choose 55} (55p^{54}(1-p)^{45} - 45p^{55}(1-p)^{44}) = 0$$

$$\Rightarrow 55p^{54}(1-p)^{45} = 45p^{55}(1-p)^{44} \Rightarrow 55(1-p) = 45p \Rightarrow 55 = 100p$$

 $\Rightarrow$  the MLE  $\hat{p} = \frac{55}{100}$ .

# Log likelihood

Often convenient to use log likelihood.

$$\log \text{ likelihood} = \ln(\text{likelihood}) = \ln(P(\text{data} \mid p)).$$

### Example.

Likelihood 
$$P(\text{data}|p) = \binom{100}{55} p^{55} (1-p)^{45}$$
Log likelihood  $= \ln\left(\binom{100}{55}\right) + 55\ln(p) + 45\ln(1-p)$ .

(Note first term is just a constant.)

## **Board Question: Coins**

A coin is taken from a box containing three coins, which give heads with probability p=1/3, 1/2, and 2/3. The mystery coin is tossed 80 times, resulting in 49 heads and 31 tails.

- (a) What is the likelihood of this data for each type on coin? Which coin gives the maximum likelihood?
- (b) Now suppose that we have a single coin with unknown probability p of landing heads. Find the likelihood and log likelihood functions given the same data. What is the maximum likelihood estimate for p?

See next slide.

#### Solution

**answer:** (a) The data D is 49 heads in 80 tosses.

We have three hypotheses: the coin has probability  $p=1/3,\ p=1/2,\ p=2/3.$  So the likelihood function P(D|p) takes 3 values:

$$P(D|p = 1/3) = {80 \choose 49} \left(\frac{1}{3}\right)^{49} \left(\frac{2}{3}\right)^{31} = 6.24 \cdot 10^{-7}$$

$$P(D|p = 1/2) = {80 \choose 49} \left(\frac{1}{2}\right)^{49} \left(\frac{1}{2}\right)^{31} = 0.024$$

$$P(D|p = 2/3) = {80 \choose 49} \left(\frac{2}{3}\right)^{49} \left(\frac{1}{3}\right)^{31} = 0.082$$

The maximum likelihood is when p = 2/3 so this our maximum likelihood estimate is that p = 2/3.

Answer to part (b) is on the next slide

# Solution to part (b)

(b) Our hypotheses now allow p to be any value between 0 and 1. So our likelihood function is

$$P(D|p) = \binom{80}{49} p^{49} (1-p)^{31}$$

To compute the maximum likelihood over all p, we set the derivative of the log likelihood to 0 and solve for p:

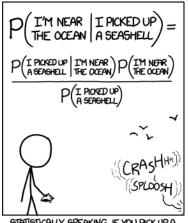
$$\frac{d}{dp}\ln(P(D|p)) = \frac{d}{dp}\left(\ln\left(\binom{80}{49}\right) + 49\ln(p) + 31\ln(1-p)\right) = 0$$

$$\Rightarrow \frac{49}{p} - \frac{31}{1-p} = 0$$

$$\Rightarrow p = \frac{49}{80}$$

So our MLE is  $\hat{p} = 49/80$ .

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## Board Question: Dice

Five dice: 4-sided, 6-sided, 8-sided, 12-sided, 20-sided.

Jon picks one at random and, without showing it to you, rolls it and reports a 13.

- 1. Make a table and compute the posterior probabilities that the chosen die is each of the five dice.
- 2. Same question if he rolls a 5.
- 3. Same question if he rolls a 9.

(Keep the tables for 5 and 9 handy! Do not erase!)



## Tabular solution

 $\mathcal{D}=$  'rolled a 13'

			unnormalized	
hypothesis	prior	likelihood	posterior	posterior
$\mathcal{H}$	$P(\mathcal{H})$	$P(\mathcal{D} \mathcal{H})$	$P(\mathcal{D} \mathcal{H})P(\mathcal{H})$	$P(\mathcal{H} \mathcal{D})$
$\mathcal{H}_4$	1/5	0	0	0
$\mathcal{H}_6$	1/5	0	0	0
$\mathcal{H}_8$	1/5	0	0	0
$\mathcal{H}_{12}$	1/5	0	0	0
$\mathcal{H}_{20}$	1/5	1/20	1/100	1
total	1		1/100	1

## Tabular solution

 $\mathcal{D} = \text{`rolled a 5'}$ 

			unnormalized	
hypothesis	prior	likelihood	posterior	posterior
$\mathcal{H}$	$P(\mathcal{H})$	$P(\mathcal{D} \mathcal{H})$	$P(\mathcal{D} \mathcal{H})P(\mathcal{H})$	$P(\mathcal{H} \mathcal{D})$
$\mathcal{H}_4$	1/5	0	0	0
$\mathcal{H}_6$	1/5	1/6	1/30	0.392
$\mathcal{H}_8$	1/5	1/8	1/40	0.294
$\mathcal{H}_{12}$	1/5	1/12	1/60	0.196
$\mathcal{H}_{20}$	1/5	1/20	1/100	0.118
total	1		.085	1

## Tabular solution

 $\mathcal{D} = \text{`rolled a 9'}$ 

			unnormalized	
hypothesis	prior	likelihood	posterior	posterior
$\mathcal{H}$	$P(\mathcal{H})$	$P(\mathcal{D} \mathcal{H})$	$P(\mathcal{D} \mathcal{H})P(\mathcal{H})$	$P(\mathcal{H} \mathcal{D})$
$\mathcal{H}_4$	1/5	0	0	0
$\mathcal{H}_6$	1/5	0	0	0
$\mathcal{H}_8$	1/5	0	0	0
$\mathcal{H}_{12}$	1/5	1/12	1/60	0.625
$\mathcal{H}_{20}$	1/5	1/20	1/100	0.375
total	1		.0267	1