Introduction to Statistics 18.05 Spring 2014

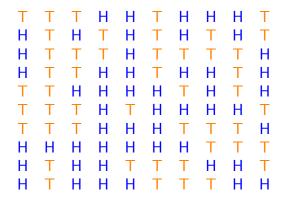
Three 'phases'

- Data Collection: Informal Investigation / Observational Study / Formal Experiment
- Descriptive statistics
- Inferential statistics (the focus in 18.05)

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.

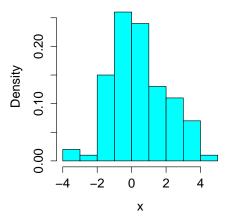
R.A. Fisher

Is it fair?



Is it normal?

Does it have $\mu = 0$? Is it normal? Is it standard normal?



Sample mean = 0.38; sample standard deviation = 1.59

What is a statistic?

Definition. A statistic is anything that can be computed from the collected data. That is, a statistic must be observable.

- 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 $\overline{x} \pm s$.
- **Important:** A statistic is itself a random variable since a new experiment will produce new data to compute it.

Concept question

You believe that the lifetimes of a certain type of lightbulb follow an exponential distribution with parameter λ . To test this hypothesis you measure the lifetime of 5 bulbs and get data $x_1, \ldots x_5$.

Which of the following are statistics?

- (a) The sample average $\overline{x} = \frac{x_1 + x_2 + x_3 + x_4 + x_5}{5}$.
- **(b)** The expected value of a sample, namely $1/\lambda$.
- (c) The difference between \overline{x} and $1/\lambda$.

 - 1. (a) 2. (b) 3. (c) 4. (a) and (b) 5. (a) and (c) 6. (b) and (c)
 - 7. all three 8. none of them

answer: 1. (a). λ is a parameter of the distribution it cannot be computed from the data. It can only be estimated.

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!)

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

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

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^{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.

Parameters of interest

Example. You ask 100 people to taste cilantro and 55 say it tastes like soap. Use this data to estimate p the fraction of all people for whom it tastes like soap.

So, p is the parameter of interest.

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

NOTICE: The likelihood takes the data as fixed and computes the probability of the data for a given *p*.

Maximum likelihood estimate (MLE)

The maximum likelihood estimate (MLE) is a way to estimate the value of a parameter of interest.

The MLE is the value of p that maximizes the likelihood.

Different problems call for different methods of finding the maximum.

Here are two -there are others:

- **1.** Calculus: To find the MLE, solve $\frac{d}{dp}P(\text{data} \mid p) = 0$ for p. (We should also check that the critical point is a maximum.)
- **2.** Sometimes the derivative is never 0 and the MLE is at an endpoint of the allowable range.

Cilantro tasting MLE

The MLE for the cilantro tasting experiment is found by calculus.

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

A sequence of algebraic steps gives:

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

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

Log likelihood

Because the log function turns multiplication into addition it is often convenient to use the log of the likelihood function

$$\log likelihood = ln(likelihood) = ln(P(data | p)).$$

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

<u>answer:</u> (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 $\hat{p} = 49/80$.

Continuous likelihood

Use the pdf instead of the pmf

Example. Light bulbs

Lifetime of each bulb $\sim \exp(\lambda)$.

Test 5 bulbs and find lifetimes of x_1, \ldots, x_5 .

- (i) Find the likelihood and log likelihood functions.
- (ii) Then find the maximum likelihood estimate (MLE) for λ .

answer: See next slide.

Solution

(i) Let $X_i \sim \exp(\lambda) = \text{the lifetime of the } i^{\text{th}} \text{ bulb.}$

Likelihood = joint pdf (assuming independence):

$$f(x_1, x_2, x_3, x_4, x_5 | \lambda) = \lambda^5 e^{-\lambda(x_1 + x_2 + x_3 + x_4 + x_5)}.$$

Log likelihood

$$\ln(f(x_1, x_2, x_3, x_4, x_5|\lambda)) = 5\ln(\lambda) - \lambda(x_1 + x_2 + x_3 + x_4 + x_5).$$

(ii) Using calculus to find the MLE:

$$\frac{d \ln(f(x_1, x_2, x_3, x_4, x_5 | \lambda))}{d \lambda} = \frac{5}{\lambda} - \sum x_i = 0 \implies \left[\hat{\lambda} = \frac{5}{\sum x_i}\right].$$

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Board Question

Suppose the 5 bulbs are tested and have lifetimes of 2, 3, 1, 3, 4 years respectively. What is the maximum likelihood estimate (MLE) for λ ?

Work from scratch. Do not simply use the formula just given.

Set the problem up carefully by defining random variables and densities.

Solution on next slide.

Solution

<u>answer:</u> We need to be careful with our notation. With five different values it is best to use subscripts. So, let X_j be the lifetime of the i^{th} bulb and let x_i be the value it takes. Then X_i has density $\lambda e^{-\lambda x_i}$. We assume each of the lifetimes is independent, so we get a joint density

$$f(x_1, x_2, x_3, x_4, x_5 | \lambda) = \lambda^5 e^{-\lambda(x_1 + x_2 + x_3 + x_4 + x_5)}.$$

Note, we write this as a conditional density, since it depends on λ . This density is our likelihood function. Our data had values

$$x_1 = 2$$
, $x_2 = 3$, $x_3 = 1$, $x_4 = 3$, $x_5 = 4$.

So our likelihood and log likelihood functions with this data are

$$f(2,3,1,3,4 \mid \lambda) = \lambda^5 e^{-13\lambda}, \qquad \ln(f(2,3,1,3,4 \mid \lambda)) = 5\ln(\lambda) - 13\lambda$$

Continued on next slide

Solution continued

Using calculus to find the MLE we take the derivative of the log likelihood

$$\frac{5}{\lambda} - 13 = 0 \implies \hat{\lambda} = \frac{5}{13}.$$

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