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Outline

1. Define likelihood
2. Interpretations of likelihoods
3. Likelihood plots
4. Maximum likelihood
5. Likelihood ratio benchmarks

Likelihood

- A common and fruitful approach to statistics is to assume that the data arises from a family of distributions indexed by a parameter that represents a useful summary of the distribution
- The **likelihood** of a collection of data is the joint density evaluated as a function of the parameters with the data fixed
- Likelihood analysis of data uses the likelihood to perform inference regarding the unknown parameter

Likelihood

Given a statistical probability mass function or density, say $f(x, \theta)$, where θ is an unknown parameter, the **likelihood** is f viewed as a function of θ for a fixed, observed value of x .

Interpretations of likelihoods

The likelihood has the following properties:

1. Ratios of likelihood values measure the relative **evidence** of one value of the unknown parameter to another.
2. Given a statistical model and observed data, all of the relevant information contained in the data regarding the unknown parameter is contained in the likelihood.
3. If $\{X_i\}$ are independent events, then their likelihoods multiply. That is, the likelihood of the parameters given all of the X_i is simply the produce of the individual likelihoods.

Example

- Suppose that we flip a coin with success probability θ
- Recall that the mass function for x

$$f(x, \theta) = \theta^x (1 - \theta)^{1-x} \quad \text{for } \theta \in [0, 1].$$

where x is either 0 (Tails) or 1 (Heads)

- Suppose that the result is a head
- The likelihood is

$$\mathcal{L}(\theta, 1) = \theta^1 (1 - \theta)^{1-1} = \theta \quad \text{for } \theta \in [0, 1].$$

- Therefore, $\mathcal{L}(.5, 1) / \mathcal{L}(.25, 1) = 2$,
- There is twice as much evidence supporting the hypothesis that $\theta = .5$ to the hypothesis that $\theta = .25$

Example cont'd

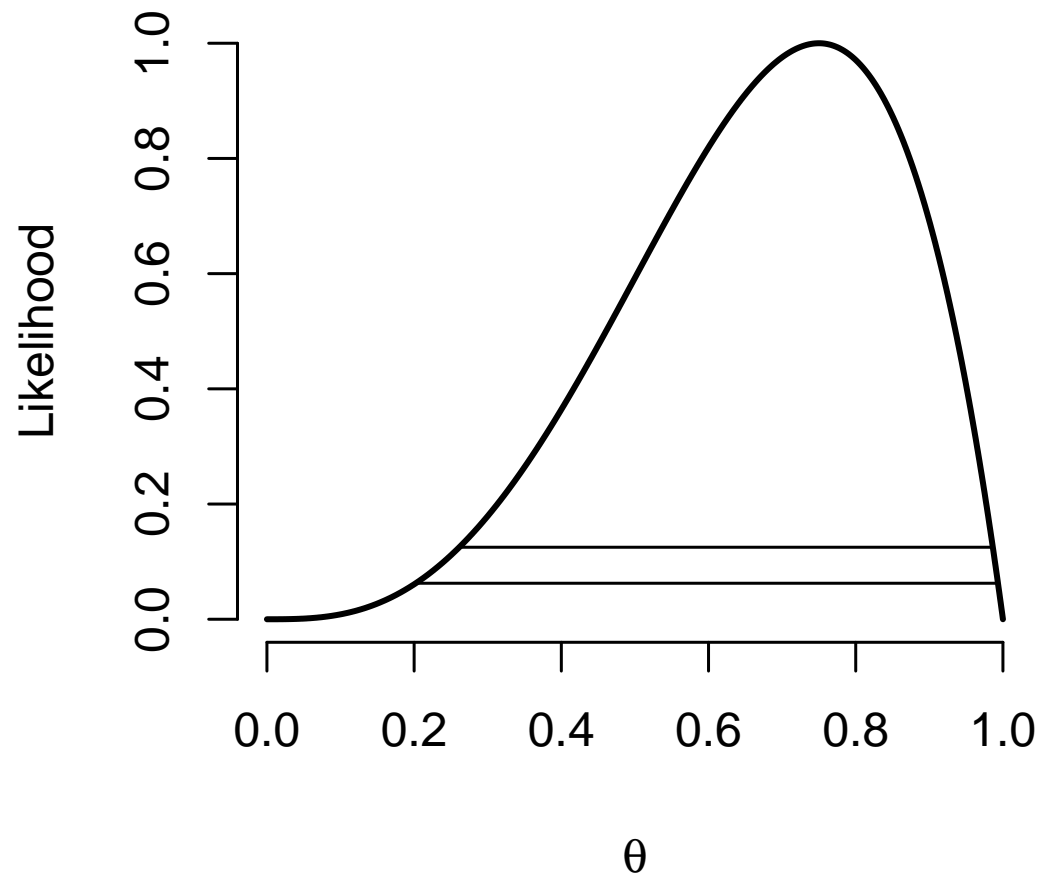
- Suppose now that we flip our coin from the previous example 4 times and get the sequence 1, 0, 1, 1
- The likelihood is:

$$\begin{aligned}\mathcal{L}(\theta, 1, 0, 1, 1) &= \theta^1(1 - \theta)^{1-1}\theta^0(1 - \theta)^{1-0}\theta^1(1 - \theta)^{1-1}\theta^1(1 - \theta)^{1-1} \\ &= \theta^3(1 - \theta)^1\end{aligned}$$

- This likelihood only depends on the total number of heads and the total number of tails; we might write $\mathcal{L}(\theta, 0, 3)$ for shorthand
- Now consider $\mathcal{L}(.5, 0, 3)/\mathcal{L}(.25, 0, 3) = 5.33$
- There is over five times as much evidence supporting the hypothesis that $\theta = .5$ over that $\theta = .25$

Plotting likelihoods

- Generally, we want to consider all the values of θ between 0 and 1
- A **likelihood plot** displays θ by $\mathcal{L}(\theta, x)$
- Usually, it is divided by its maximum value so that its height is 1
- Because the likelihood measures *relative evidence*, dividing the curve by its maximum value (or any other value for that matter) does not change its interpretation



Maximum likelihood

- The value of θ where the curve reaches its maximum has a special meaning
- It is the value of θ that is most well supported by the data
- This point is called the **maximum likelihood estimate** (or MLE) of θ

$$MLE = \operatorname{argmax}_{\theta} \mathcal{L}(\theta, x).$$

- Another interpretation of the MLE is that it is the value of θ that would make the data that we observed most probable

Maximum likelihood, coin example

- The maximum likelihood estimate for θ is always the proportion of heads
- Proof: Let x be the number of heads and n be the number of trials
- Recall

$$\mathcal{L}(\theta, x) = \theta^x (1 - \theta)^{n-x}$$

- It's easier to maximize the **log-likelihood**

$$l(\theta, x) = x \log(\theta) + (n - x) \log(1 - \theta)$$

Cont'd

- Taking the derivative we get

$$\frac{d}{d\theta}l(\theta, x) = \frac{x}{\theta} - \frac{n-x}{1-\theta}$$

- Setting equal to zero implies

$$\left(1 - \frac{x}{n}\right)\theta = (1 - \theta)\frac{x}{n}$$

- Which is clearly solved at $\theta = \frac{x}{n}$

- Notice that the second derivative

$$\frac{d^2}{d\theta^2}l(\theta, x) = -\frac{x}{\theta^2} - \frac{n-x}{(1-\theta)^2} < 0$$

provided that x is not 0 or n

What constitutes strong evidence?

- Again imagine an experiment where a person repeatedly flips a coin
- Consider the possibility that we are entertaining three hypotheses: $H_1 : \theta = 0$, $H_2 : \theta = .5$, and $H_3 : \theta = 1$

Outcome X	$P(X H_1)$	$P(X H_2)$	$P(X H_3)$	$\mathcal{L}(H_1)/\mathcal{L}(H_2)$	$\mathcal{L}(H_3)/\mathcal{L}(H_2)$
H	0	.5	1	0	2
T	1	.5	0	2	0
HH	0	.25	1	0	4
HT	0	.25	0	0	0
TH	0	.25	0	0	0
TT	1	.25	0	4	0
HHH	0	.125	1	8	0
HHT	0	.125	0	0	0
HTH	0	.125	0	0	0
THH	0	.125	0	0	0
HTT	0	.125	0	0	0
THT	0	.125	0	0	0
TTH	0	.125	0	0	0
TTT	1	.125	0	0	8

Benchmarks

- Using this example as a guide, researchers tend to think of a likelihood ratio
 - ▶ of 8 as being moderate evidence
 - ▶ of 16 as being moderately strong evidence
 - ▶ of 32 as being strong evidenceof one hypothesis over another
- Because of this, it is common to draw reference lines at these values on likelihood plots
- Parameter values above the $1/8$ reference line, for example, are such that no other point is more than 8 times better supported given the data