

Bayes Workshop 1

Bayesian Probability and the Likelihood Function

Corson N. Areshenkoff

University of Victoria

March 9, 2016

The Problem

Find a coin on the sidewalk. How do we know if the coin is fair?
In other words, we want to know the probability p that a coin returns heads.

The Problem

How do we get p ?

- ▶ First, specify a probability model.
 - ▶ If a coin flip is random, what is its distribution?
 - ▶ If we flip the coin repeatedly, how many heads should we see?
- ▶ Then, collect data
 - ▶ Flip the coin many times and observe the proportion of heads.
 - ▶ The number of heads obtained in N independent flips of a coin is a *binomial* random variable.

Probability Mass Function

- ▶ The *probability mass function* (pmf) of a (discrete) random variable gives the probability of observing an outcome x .
- ▶ For N coin flips (with probability p of heads), the pmf gives the probability of observing k heads.

Probability Mass Function

How do we get the pmf?

Suppose we flip a fair coin 4 times ($N = 4, p = 0.5$). What is the probability that we get ONE head?

- ▶ The head happens with probability $\frac{1}{2}$
- ▶ Each tails happens with probability $\frac{1}{2}$, giving $\left(\frac{1}{2}\right)^3$
- ▶ ...but there are 4 places the head can appear.

So the probability is

$$P(1; N = 4, p = 0.5) = 4 \left(\frac{1}{2}\right) \left(\frac{1}{2}\right)^3$$

Probability Mass Function

In general, the binomial pmf is given by

$$P(k; N, p) = \underbrace{\binom{n}{k}}_{\# \text{ of ways}} \underbrace{p^k}_{k \text{ heads}} \underbrace{(1-p)^{n-k}}_{n-k \text{ tails}}$$

Likelihood

- ▶ When we flip a fair coin N times, we talk about the *probability* of observing k heads (N and p are fixed parameters; the *outcome* is unknown).
 - ▶ Probability mass function $P(k; N, p)$
- ▶ After performing the experiment and *observing* k heads, we can treat p as unknown and ask: what is the probability that a specific value of p would give us k heads? (what is the *likelihood* that p takes a specific value?)
 - ▶ Likelihood function $\mathcal{L}(p; N, k)$

Likelihood

A practical example:

- ▶ Flip a coin 4 times and observe 3 heads. Which value of p is most likely?
- ▶ For $p = 0$, the probability of observing 3 heads is zero, so so the likelihood that $p = 0$ is zero.
- ▶ For $p = 1/2$, the probability of observing 3 heads is 0.25, so so the likelihood that $p = 1/2$ is $1/4$.
- ▶ For $p = 3/4$, the probability of observing 3 heads is 0.43, so so the likelihood that $p = 3/4$ is 0.43.
 - ▶ This is the value of p with the *highest* likelihood. In other words, $p = 3/4$ maximizes the probability of obtaining our data.

The Likelihood Function

- ▶ Every statistical model (regression, distribution fitting, etc) produces a *likelihood function*, which gives the probability of obtaining a set of data for different values of the model parameters.
- ▶ If D are the data, and Θ are the parameters of the model (say, regression coefficients), then

$$\mathcal{L}(\Theta|D) = P(D|\Theta)$$

- ▶ Common practice is to choose the parameters values which maximize the likelihood function (i.e. which maximize the probability of obtaining the observed data).
 - ▶ This is *maximum likelihood estimation*, and the resulting parameter estimates are called the *maximum likelihood estimates* (MLE's)

The Likelihood Function

Some examples:

- ▶ The MLE for p in our coin flip example is the observed proportion of heads $\hat{p} = k/N$.
- ▶ The MLE's for the mean and variance of a normal distribution are

$$\hat{\mu} = \bar{X} = \frac{\sum_{i=1}^N x_i}{N}$$
$$\hat{\sigma}^2 = \frac{\sum_{i=1}^N (\bar{X} - x_i)^2}{N}$$

- ▶ The MLE's for a linear regression model are the usual least squares estimates.

The Likelihood Function

- ▶ The likelihood function is, arguably, the most important concept in statistical inference.
- ▶ **All of the information contained in the data about a model is contained in the likelihood function.**
- ▶ In practice, the natural logarithm of the likelihood function (the log-likelihood) is usually easier to work with.

Bayesian Estimation

Suppose that we pick up a newly minted coin and flip it $N = 4$ times, obtaining $k = 3$ heads. The MLE for the probability p is $k/N = 0.75$. Which is more plausible?

- ▶ The finely tuned machines used to mint the coin made a mistake, and somehow minted a highly unbalanced coin.
- ▶ The coin is fair, but just happened to return 3 heads.

The **data** block specifies the data that will be passed to Stan:

```
data {  
  int<lower=0> N; // Number of coin flips  
  int k;         // Number of heads  
}
```

The **parameters** block specifies the parameters of our model:

```
parameters {  
  real<lower=0, upper = 1> p;  
}
```

The **model** block specifies the likelihood/priors:

```
model {  
  h ~ binomial(N, p); // Likelihood  
  p ~ beta(1,1);      // Prior  
}
```

The complete .stan file is then:

```
data {  
  int<lower=0> N; // Number of coin flips  
  int k;         // Number of heads  
}  
  
parameters {  
  real<lower=0, upper = 1> p;  
}  
  
model {  
  h ~ binomial(N, p); // Likelihood  
  p ~ beta(1,1);      // Prior  
}
```