

**Working with Likelihoods***(find and work with a partner)*

1. *Bernoulli Random Variable.* Say we flip a weighted coin  $n$  times, and each time the probability of heads (1) is  $p$ , so the probability of tails (0) is  $(1 - p)$ . Let  $y_i$  be the outcome of flip  $i$ . For example, if  $n = 10$ , we might observe these values:

$$\mathbf{y} = [0, 0, 1, 1, 0, 1, 0, 1, 0, 0]$$

In this case, the *likelihood* of  $p$  given this observed data is  $L(p) = p^4(1 - p)^6$ , since we observe four 1's and six 0's. In general, we can write the likelihood as

$$L(p) = \prod_{i=1}^n p^{y_i} (1 - p)^{1 - y_i},$$

so that for each  $y_i$ , only one of  $y_i$  and  $(1 - y_i)$  will be non-zero and contribute to the product. Note that  $L(p | \mathbf{y})$  is a more proper way of writing this (i.e. given the data), but we often omit this conditional part.

- (a) What is the *log likelihood*  $\ell(p)$  for this setup? Simplify as much as possible.

We will use the notation  $\bar{y} = \frac{1}{n} \sum_{i=1}^n y_i$  to denote the mean of  $\mathbf{y}$ .

$$\begin{aligned} \ell(p) &= \log L(p) = \sum_{i=1}^n [y_i \log(p) + (1 - y_i) \log(1 - p)] \\ &= \log(p) \sum_{i=1}^n y_i + \log(1 - p) \sum_{i=1}^n (1 - y_i) \\ &= n\bar{y} \log(p) + n(1 - \bar{y}) \log(1 - p) \end{aligned}$$

- (b) Our goal is to *maximize* the log likelihood. Take the derivative with respect to  $p$  and set it equal to 0. Solve for  $p$  – this becomes our MLE (maximum likelihood estimator),  $\hat{p}$ .

$$\begin{aligned} \ell'(p) &= \frac{n\bar{y}}{p} - \frac{n(1 - \bar{y})}{1 - p} = 0 && \# \text{ set equal to 0} \\ \Rightarrow p(1 - p) \frac{\bar{y}}{p} &= p(1 - p) \frac{(1 - \bar{y})}{1 - p} && \# \text{ divide through by } n \text{ and multiply by } p(1 - p) \\ \Rightarrow \bar{y} - \bar{y}p &= p(1 - \bar{y}) \\ \Rightarrow \boxed{\hat{p} = \bar{y}} \end{aligned}$$

- (c) For our concrete example above with  $n = 10$ , what is the MLE  $\hat{p}$ ? Does this match your intuition?

In our example, we take the mean of  $\mathbf{y}$ :

$$\hat{p} = \frac{0 \cdot 6 + 1 \cdot 4}{10} = \frac{2}{5} = 0.4$$

Although the sample size is small here, this should match our intuition – if we see slightly more tails than heads, then the coin is perhaps weighted slightly towards tails.