

(1)

Recall our first maximum likelihood example:

- 16 babies shared a video of a character trying to go up a hill.
- Each baby chose to play with either the helpful toy or the unhelpful toy.
- ~~14~~¹⁴ babies chose the helpful toy
- Our model was

$$X \sim \text{Binomial}(16, \hat{p})$$

↑ a random variable: # of babies choosing the helpful toy in a hypothetical replication of this experiment.

Could be different if:

- different babies included in study
- different babies in a different mood
- etc.

$$\hat{p}^{\text{MLE}}$$

- Maximum likelihood estimate is ~~\hat{p}^{MLE}~~ = $\frac{14}{16}$
- estimate of p based on this specific sample
- Maximum likelihood estimator is $\hat{p}^{\text{MLE}} = \frac{X}{n}$
- a random variable: if we ~~replicate the~~ replicate the experiment we may observe a different value of X and in turn get a different estimate.

Def.: Suppose $\hat{\theta}$ is an estimator of a parameter θ .
The probability distribution of the random variable $\hat{\theta}$ is referred to as its sampling distribution

(2)

Recall that for a discrete random variable Y ,
 the distribution is given by its p.m.f., : $f_Y(y) = P(Y=y)$.

For our Binomial example, the possible values of the estimator $\hat{\theta}^{\text{MLE}}$ are $\frac{0}{16}, \frac{1}{16}, \frac{2}{16}, \dots, \frac{16}{16}$

Also, $P(\hat{\theta}^{\text{MLE}} = \frac{14}{16}) = P(X=14) = \binom{16}{14} \theta^{14} (1-\theta)^{16-14}$

the only way the estimator would be $\frac{14}{16}$ is if we observe $x=14$

A table to summarize the distribution of $\hat{\theta}^{\text{MLE}}$:

$\hat{\theta}^{\text{MLE}}$	0/16	1/16	2/16	...	16/16
$P(\hat{\theta}^{\text{MLE}} = \hat{\theta}^{\text{MLE}} \theta)$	$\binom{16}{0} \theta^0 (1-\theta)^{16}$	$\binom{16}{1} \theta^1 (1-\theta)^{16-1}$	$\binom{16}{2} \theta^2 (1-\theta)^{16-2}$...	$\binom{16}{16} \theta^{16} (1-\theta)^{16-16}$

Questions we might ask about the sampling distribution:

1) Is $E[\hat{\theta}] = \theta$? (On average across all samples, will we recover the correct value of θ ?)

Def: If $E[\hat{\theta}] = \theta$, $\hat{\theta}$ is said to be an unbiased estimator of θ .

Def: The bias of $\hat{\theta}$ as an estimator of θ is

$$\text{Bias}(\hat{\theta}) = E(\hat{\theta}) - \theta, \text{ we want bias close to 0}$$

$$E(\hat{\theta}) = E\left(\frac{X}{n}\right) = \frac{1}{n} \cdot E(X) = \frac{1}{n} \cdot n\theta = \theta. \text{ For binomial model, } \hat{\theta}^{\text{MLE}} \text{ is unbiased.}$$

(3)

2) What is $\text{Var}(\hat{\theta})$?

Describes variability in estimates of θ across different samples.

→ higher variance means estimates may be very different across different samples.

In general we want variance close to 0.

$$\text{Var}(\hat{\theta}_{MLE}) = \text{Var}\left(\frac{X}{n}\right) = \frac{1}{n^2} \cdot \text{Var}(X) = \frac{1}{n^2} n \cdot p \cdot (1-p) = \frac{\theta(1-\theta)}{n}$$

Def: The standard error of an estimator is its standard deviation.

3) What is the average squared difference between $\hat{\theta}$ and θ ?

$$\begin{aligned} \text{MSE}(\hat{\theta}) &= E[(\hat{\theta} - \theta)^2] \\ &= E[\cancel{\hat{\theta}^2} - 2\hat{\theta}\theta + \cancel{\theta^2}] E[(\hat{\theta} - E(\hat{\theta})) + E(\hat{\theta}) - \theta]^2 \\ &= E[\{\hat{\theta} - E(\hat{\theta})\}^2 + 2(\hat{\theta} - E(\hat{\theta}))(E(\hat{\theta}) - \theta) + (E(\hat{\theta}) - \theta)^2] \\ &\quad \text{nothing random} \\ &= E[\{\hat{\theta} - E(\hat{\theta})\}^2] + 2(E(\hat{\theta}) - \theta) \cdot E[\hat{\theta} - E(\hat{\theta})] \\ &\quad \text{not random} \\ &\quad + E[\{E(\hat{\theta}) - \theta\}^2] \\ &\quad \text{nothing random} \\ &= E[\{\hat{\theta} - E(\hat{\theta})\}^2] + 2\{E(\hat{\theta}) - \theta\} \cdot \cancel{\{E(\hat{\theta}) - E(\hat{\theta})\}} \\ &\quad + \{E(\hat{\theta}) - \theta\}^2 \end{aligned}$$

$$= \text{Var}(\hat{\theta}) + \{\text{Bias}(\hat{\theta})\}^2$$

We would like $\text{MSE}(\hat{\theta})$ to be small.

$$\begin{aligned} \text{Ex: } \text{MSE}(\hat{\theta}) &= \text{Var}(\hat{\theta}) + \{\text{Bias}(\hat{\theta})\}^2 \\ &= \frac{\theta(1-\theta)}{n} + \theta^2 = \frac{\theta(1-\theta)}{n} \end{aligned}$$