

## Chapter 7: Estimating the CDF and Statistical Functionals

All of Statistics, Wasserman

**2.** Let  $X_1, \dots, X_n \sim \text{Bernoulli}(p)$ . Find the plug-in estimator and estimated standard error for  $p$ . Find an approximate 90 percent confidence interval for  $p$ . Let  $Y_1, \dots, Y_m \sim \text{Bernoulli}(q)$ . Find the plug-in estimator and estimated standard error for  $p - q$ . Find an approximate 90 percent confidence interval for  $p - q$ .

*Solution.* Let  $F$  be a Bernoulli( $p$ ) distribution. Then  $p = \int x dF(x)$  so the plug-in estimator is

$$\hat{p} = \int x d\hat{F}_n(x) = \sum_{i=1}^n X_i \cdot \frac{1}{n} = \bar{X}_n.$$

Calculating directly,

$$\text{se}(\hat{p}) = \text{se}_F(\hat{p}) = \sqrt{V_F(\bar{X}_n)} = \sqrt{\frac{V_F(X_1)}{n}} = \sqrt{\frac{p(1-p)}{n}}.$$

Therefore, the estimated standard error for  $p$  (equivalently, the plug-in estimator of  $T(F) = \text{se}_F(\hat{p})$ ) is

$$\widehat{\text{se}}(\hat{p}) = \sqrt{\frac{\hat{p}(1-\hat{p})}{n}}.$$

This coincides with the general plug-in formula for the standard error:  $\hat{\sigma}^2 = n^{-1} \sum_{i=1}^n (X_i - \bar{X}_n)^2$  (cf. Example 7.11) since for Bernoulli samples,  $\hat{p}(1-\hat{p})$  equals the sample variance. It's possible to avoid the general formula in this case since  $\text{se}(\hat{p})$  is a function  $p$ . By the CLT,  $\bar{X}_n \approx N(p, (\widehat{\text{se}}(\hat{p}))^2)$ . Therefore,

$$\bar{X}_n \pm z_{0.05} \sqrt{\frac{\hat{p}(1-\hat{p})}{n}}$$

is a (normal-based) 90 percent confidence interval. The following is cynically hand-wavy for multiple reasons<sup>1</sup> since Wasserman doesn't provide the tools for a rigorous solution. The plug-in estimator of  $p - q$  is (cf. Example 7.15)

$$\hat{p}_n - \hat{q}_m = \bar{X}_n - \bar{Y}_m.$$

Moreover,

$$\text{se}(\hat{p}_n - \hat{q}_m) = \sqrt{V(\bar{X}_n - \bar{Y}_m)} = \sqrt{V(\bar{X}_n) + V(\bar{Y}_m)} = \sqrt{(\text{se}(\hat{p}))^2 + (\text{se}(\hat{q}))^2}$$

Therefore,

$$\widehat{\text{se}}(\hat{p}_n - \hat{q}_m) = \sqrt{(\widehat{\text{se}}(\hat{p}))^2 + (\widehat{\text{se}}(\hat{q}))^2} = \sqrt{\frac{\hat{p}(1-\hat{p})}{n} + \frac{\hat{q}(1-\hat{q})}{m}}.$$

Assuming<sup>2</sup>  $\hat{p}_n - \hat{q}_m \approx N(p - q, (\widehat{\text{se}}(\hat{p}_n - \hat{q}_m))^2)$ ,

$$(\bar{X}_n - \bar{Y}_m) \pm z_{0.05} \sqrt{\frac{\hat{p}(1-\hat{p})}{n} + \frac{\hat{q}(1-\hat{q})}{m}}$$

is a (normal-based) 90 percent confidence interval. ◇

<sup>1</sup>(1) Is the plug-in estimator of a statistical functional of two distributions  $T(F, G)$  defined as  $T(\hat{F}_n, \hat{G}_m)$ ? (2) With respect to which distribution is  $V(\bar{X}_n - \bar{Y}_m)$  being calculated? (GPT's ans: It is taken with respect to the joint distribution  $(F^n \otimes G^m)$  of the two independent samples. Since the samples are independent, the cross-covariance term vanishes, yielding  $V(\bar{X}_n - \bar{Y}_m) = V(\bar{X}_n) + V(\bar{Y}_m)$ .)

<sup>2</sup>More hand-waving. Notice that the this would be a double limit:  $n, m \rightarrow \infty$ .

4. Let  $X_1, \dots, X_n \sim F$ . For a fixed  $x$ , use the CLT to find the limiting distribution of  $\hat{F}_n(x)$ .

*Solution.* Let  $x$  be fixed and let  $Y_i = I(X_i \leq x)$ . Note that  $Y_i \sim \text{Bernoulli}(F(x))$  are iid and  $\hat{F}_n(x) = \bar{Y}_n$ . Therefore, by the CLT

$$\hat{F}_n(x) = \bar{Y}_n \approx N\left(E(Y_1), \frac{V(Y_1)}{n}\right) = N\left(F(x), \frac{F(x)(1-F(x))}{n}\right).$$

◇

5. Let  $x$  and  $y$  be two distinct points. Find  $\text{Cov}(\hat{F}_n(x), \hat{F}_n(y))$ .

*Solution.* Calculating directly,

$$\begin{aligned} \text{Cov}(\hat{F}_n(x), \hat{F}_n(y)) &= \text{Cov}\left(\frac{1}{n} \sum_{i=1}^n I(X_i \leq x), \frac{1}{n} \sum_{j=1}^n I(X_j \leq y)\right) \\ &= \frac{1}{n^2} \sum_{i=1}^n \sum_{j=1}^n \text{Cov}(I(X_i \leq x), I(X_j \leq y)) \\ &= \frac{1}{n^2} \sum_{i=1}^n \text{Cov}(I(X_i \leq x), I(X_i \leq y)) \end{aligned}$$

where the last equality is because  $X_i \perp X_j$  for  $i \neq j$ . Moreover,

$$\begin{aligned} \text{Cov}(I(X_i \leq x), I(X_i \leq y)) &= E(I(X_i \leq x) \cdot I(X_i \leq y)) - E(I(X_i \leq x)) \cdot E(I(X_i \leq y)) \\ &= F(\min\{x, y\}) - F(x)F(y) \end{aligned}$$

since

$$I(X_i \leq x) \cdot I(X_i \leq y) = \begin{cases} 1 & \text{if } X_i \leq \min\{x, y\}, \\ 0 & \text{otherwise.} \end{cases}$$

Therefore,

$$\text{Cov}(\hat{F}_n(x), \hat{F}_n(y)) = \frac{1}{n} (F(\min\{x, y\}) - F(x)F(y)).$$

◇

6. Let  $X_1, \dots, X_n \sim F$ . Let  $a < b$  be fixed numbers and define  $\theta = T(F) = F(b) - F(a)$ . Let  $\hat{\theta} = T(\hat{F}_n)$ . Find the estimated standard error of  $\hat{\theta}$ . Find an expression for an approximate  $1 - \alpha$  confidence interval for  $\theta$ .

*Solution.* Calculating directly,

$$\begin{aligned} (\text{se}(\hat{\theta}))^2 &= V(\hat{F}_n(b) - \hat{F}_n(a)) \\ &= V(\hat{F}_n(a)) + V(\hat{F}_n(b)) - 2\text{Cov}(\hat{F}_n(a), \hat{F}_n(b)) \\ &= \frac{1}{n} (F(a)(1-F(a)) + F(b)(1-F(b)) - 2(F(a) - F(a)F(b))) \\ &= \frac{\theta(1-\theta)}{n}. \end{aligned}$$

Therefore, the estimated standard error of  $\hat{\theta}$  is

$$\widehat{\text{se}}(\hat{\theta}) = \sqrt{\frac{\hat{\theta}(1-\hat{\theta})}{n}}$$

and  $\hat{\theta} \pm z_{\alpha/2} \cdot \sqrt{\frac{\hat{\theta}(1-\hat{\theta})}{n}}$  is an approximate  $1 - \alpha$  CI for  $\theta$ . Alternatively, let  $W_i = I(a < X_i \leq b)$  for  $i = 1, \dots, n$ . Then  $P(W_i = 1) = P(a < X_i \leq b) = F(b) - F(a) = \theta$  and  $\bar{W}_n = \hat{F}_n(b) - \hat{F}_n(a) = \hat{\theta}$ . In words,  $\hat{\theta}$  is the sample mean of iid Bernoulli( $\theta$ ) variables. The desired results follow immediately. ◇

**9.** 100 people are given a standard antibiotic to treat an infection and another 100 are given a new antibiotic. In the first group, 90 people recover; in the second group, 85 people recover. Let  $p_1$  be the probability of recovery under the standard treatment and let  $p_2$  be the probability of recovery under the new treatment. We are interested in estimating  $\theta = p_1 - p_2$ . Provide an estimate, standard error, an 80 percent confidence interval, and a 95 percent confidence interval for  $\theta$ .

*Solution.* Notice this is a particular case of Exercise 2<sup>3</sup>. The plug-in estimate of  $\theta$  is

$$\hat{\theta} = \hat{p}_1 - \hat{p}_2 = 0.9 - 0.85 = 0.05.$$

The estimated standard error is

$$\widehat{\text{se}} = \sqrt{\frac{\hat{p}_1(1 - \hat{p}_1)}{n_1} + \frac{\hat{p}_2(1 - \hat{p}_2)}{n_2}} = \sqrt{\frac{0.9(1 - 0.9)}{100} + \frac{0.85(1 - 0.85)}{100}} = 0.0466.$$

A  $1 - \alpha$  confidence interval for  $\theta$  is<sup>4</sup>

$$0.05 \pm z_{\alpha/2} \cdot 0.0466.$$

◇

---

<sup>3</sup>We are implicitly assuming two independent iid samples:  $X_1, \dots, X_{100} \sim \text{Bernoulli}(p_1)$  and  $Y_1, \dots, Y_{100} \sim \text{Bernoulli}(p_2)$ .

<sup>4</sup>GPT says normal approximation is fine here since  $n_k \hat{p}_k$  and  $n_k(1 - \hat{p}_k)$  are all  $\geq 10$ .