

Brief Note on Symmetric Confidence Intervals

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Recall that a $(1 - \alpha)$ confidence interval for a parameter θ based on data X_1, \dots, X_n is a (random) interval $[\hat{\Theta}_n^-, \hat{\Theta}_n^+]$, where $\hat{\Theta}_n^- = g^-(X_1, \dots, X_n)$ and $\hat{\Theta}_n^+ = g^+(X_1, \dots, X_n)$ are some functions of the data satisfying

$$\mathbf{P}_\theta \left(\hat{\Theta}_n^- \leq \theta \leq \hat{\Theta}_n^+ \right) \geq 1 - \alpha.$$

Often, it is natural to construct a symmetric confidence interval $[\hat{\Theta}_n - \epsilon, \hat{\Theta}_n + \epsilon]$ around some estimator $\hat{\Theta}_n$. This reduces the problem to finding $\epsilon > 0$ such that

$$\mathbf{P}_\theta \left(|\hat{\Theta}_n - \theta| \geq \epsilon \right) \leq \alpha.$$

Example 1 (Confidence interval for mean of a bounded random variable). Suppose X_1, \dots, X_n are iid random variables in some bounded range $[a, b]$ with unknown mean μ . Then a confidence interval for μ using the sample average estimator $\hat{M}_n = \frac{1}{n} \sum_{i=1}^n X_i$ can be obtained using Hoeffding's inequality. In particular, taking $\epsilon = (b - a) \sqrt{\frac{1}{2n} \ln\left(\frac{2}{\alpha}\right)}$ yields a $(1 - \alpha)$ confidence interval $[\hat{M}_n - \epsilon, \hat{M}_n + \epsilon]$ for μ .

Example 2 (Confidence interval derived from an asymptotically normal estimator). Suppose X_1, \dots, X_n are iid random variables whose distribution is governed by some unknown parameter θ , and $\hat{\Theta}_n = g(X_1, \dots, X_n)$ is an asymptotically normal estimator of θ , i.e. that

$$\frac{\hat{\Theta}_n - \theta}{\sqrt{\mathbf{Var}_\theta(\hat{\Theta}_n)}} \xrightarrow{D} \mathcal{N}(0, 1).$$

Unless $\mathbf{Var}_\theta(\hat{\Theta}_n)$ is known, this does not directly yield a confidence interval for θ . However, if for some data-based estimator $\hat{V}_n = h(X_1, \dots, X_n)$ of $\mathbf{Var}_\theta(\hat{\Theta}_n)$ we have

$$\frac{\hat{\Theta}_n - \theta}{\sqrt{\hat{V}_n}} \xrightarrow{D} \mathcal{N}(0, 1),$$

then for large n , this can be used to obtain a normal-based (approximate) confidence interval for θ . In particular, taking $\epsilon = \sqrt{\hat{V}_n} \cdot z_{\alpha/2}$, where $z_{\alpha/2} = \Phi^{-1}(1 - \frac{\alpha}{2})$, yields a $(1 - \alpha)$ confidence interval $[\hat{\Theta}_n - \epsilon, \hat{\Theta}_n + \epsilon]$ for θ .

Example 3 (Confidence interval for mean of a normal random variable). Suppose X_1, \dots, X_n are iid normal random variables with unknown mean μ and unknown variance σ^2 , and let $\hat{M}_n = \frac{1}{n} \sum_{i=1}^n X_i$ and $\hat{S}_n^2 = \frac{1}{n-1} \sum_{i=1}^n (X_i - \hat{M}_n)^2$. Then

$$\frac{\hat{M}_n - \mu}{\frac{\hat{S}_n}{\sqrt{n}}} \sim t_{n-1},$$

where t_{n-1} denotes the t distribution with $n - 1$ degrees of freedom, and whose CDF Ψ_{n-1} is available in tables similarly to the standard normal CDF tables. In this case, one can obtain a t distribution based confidence interval for μ ; in particular, taking $\epsilon = \frac{\hat{S}_n}{\sqrt{n}} \cdot z'_{\alpha/2}$, where $z'_{\alpha/2} = \Psi_{n-1}^{-1}(1 - \frac{\alpha}{2})$, yields a $(1 - \alpha)$ confidence interval $[\hat{M}_n - \epsilon, \hat{M}_n + \epsilon]$ for μ . For large n , t_{n-1} is well-approximated by the standard normal $\mathcal{N}(0, 1)$, and so one can again fall back on a normal-based approximation, but for small n , the t_{n-1} -based confidence interval should be used.