where

$$L_2(x) = \int_{-\infty}^{\infty} 2\left(1 - \Phi(xu + \sqrt{n}\,c)\right)\phi(u)\,du.$$

Consider $\hat{\beta} \sim N_r(\beta, S^{-1})$, given S. Then we want to find an estimator $\tilde{\beta} = \tilde{\beta}(\hat{\beta}, S)$, given S, such that

$$E_\beta\left[L_2(\|\tilde{\beta} - \beta\|)|S\right] < E_\beta\left[L_2(\|\hat{\beta} - \beta\|)|S\right].$$

This again follows from Theorem 3.3.1 of Brown (1966). □

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1. Conditionality. A paradox is a self-contradictory statement, and a paradox in science demands resolution. The discovery of each new paradox creates an opportunity for a new growth and deeper understanding as we seek explanation.

Professor Brown's paradox is that conditionality is at odds with unconditional admissibility. While his concluding remarks do not resolve the paradox, he seems to take sides by insisting that we account for "the unconditional frequentist structure of the situation." I see it differently, and argue for being as conditional as possible in making statistical inferences.

It can happen, and did in Brown's example, that decision rules 1 and 2 with risks R_1 and R_2 obey $R_1 < R_2$ uniformly in the parameters when we average over an ancillary $\mathbf{V}$, but that the conditional risks, given $\mathbf{V}$, satisfy $R_1(\mathbf{V}) > R_2(\mathbf{V})$ for some parameters and some values of $\mathbf{V}$. If $\mathbf{V}$ occurs and is observed and it happens to be a value for which $R_1(\mathbf{V}) > R_2(\mathbf{V})$, then rule 2 is better for that $\mathbf{V}$. It matters not at all that for most $\mathbf{V}$, $R_1(\mathbf{V}) < R_2(\mathbf{V})$. Brown's example is less clear. We do not know for the observed $\mathbf{V}$ which $R(\mathbf{V})$ is smaller,

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