formly in λ. However, this approach may not succeed in controlling the asymptotic *level* of the confidence set. The problem is that the relevant asymptotic expansions may not converge uniformly over all λ, especially when λ is infinite dimensional.

An interesting strategy, proposed by Loh (1985) in a testing context, is to pick critical values so as to control the apparent level of the confidence set for θ over a confidence set for λ of level $1 - \varepsilon_n$, where ε_n is small. When feasible, this construction ensures that the level of the confidence set for θ is at least $1 - \alpha - \varepsilon_n$. One difficulty is finding a good confidence set for λ. If the latter is too large, then the induced confidence set for θ is likely to be inefficient. Perhaps the notion of controlling level of a confidence set for θ is too strong. On the other hand, controlling asymptotic coverage probability only pointwise in λ is clearly too weak.

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I found Professor Hall's unified treatment of bootstrap bounds and confidence intervals very valuable. I was particularly interested by his exploration of the relation between the accelerated bias correction bootstrap bounds and the Studentized bounds, a relationship which I also studied, but only in the parametric framework, in my discussion of Efron (1987). In my discussion I want to:

1. Argue at least heuristically that, in the nonparametric context, the second order equivalence of $\hat{\theta}_{\text{ABC}}$ and $\hat{\theta}_{\text{STUD}}$ holds quite generally for $\theta(F)$ a sufficiently smooth von Mises functional, provided that we Studentize properly. For example, it holds if the estimate $\hat{\theta} = \theta(\hat{F})$, where $\hat{F}$ is the empirical d.f., is an M estimate corresponding to a nice ψ function; see Huber [(1981), Chapter 2] for examples.
2. Suggest that quite generally in a parametric, nonparametric or semiparametric context, $\hat{\theta}_{\text{ABC}}$ and $\hat{\theta}_{\text{STUD}}$ are second order equivalent provided again that $\hat{\theta}$ is efficient and we Studentize properly, that is, by an efficient estimate of the asymptotic standard deviation of $\hat{\theta}$.