In closing I note that the bootstrap can be an inconsistent procedure when it is employed to correct potentially large biases of some nonparametric techniques. See Section 11.7 of Breiman et al. (1984).

REFERENCES

ATHREYA, K. B. (1987). Bootstrap of the mean in the infinite variance case. To appear in *Ann. Statist.*

BABU, G. J. and SINGH, K (1983). Inference on means using the bootstrap. *Ann. Statist.* **11** 999–1003.

BHATTACHARYA, R. N. and GHOSH, J. K. (1978). On the validity of the formal Edgeworth expansion. *Ann. Statist.* **6** 434–451.

BREIMAN, L., FRIEDMAN, J. H., OLSHEN, R. A. and STONE, C. J. (1984). *Classification and Regression Trees*. Wadsworth, Belmont, Calif.

EFRON, B. and TIBSHIRANI, R. (1986). Bootstrap methods for standard errors, confidence intervals, and other measures of statistical accuracy. *Statist. Sci.* **1** 54–75, 77.

GHOSH, M., PARR, W. C., SINGH, K. and BABU, G. J. (1984). A note on bootstrapping the sample median. *Ann. Statist.* **12** 1130–1135.

HARTIGAN, J. A. (1986). Comment on "Bootstrap methods for standard errors, confidence intervals, and other measures of statistical accuracy" by Efron and Tibshirani. *Statist. Sci.* **1** 75–77.

OLSHEN, R. A., GILPIN, E. A., HENNING, H., LEWINTER, M. L., COLLINS, D. and ROSS, J., JR. (1985). Twelve month prognosis following myocardial infarction: classification trees, logistic regression, and stepwise linear discrimination. In *Proceedings of the Berkeley Conference in Honor of Jerzy Neyman and Jack Kiefer* (L. M. Le Cam and R. A. Olshen, eds.) **1** 245–267. Wadsworth, Monterey, Calif.

STEIN, C. (1964). Inadmissibility of the usual estimator for the variance of a normal distribution with unknown mean. *Ann. Inst. Statist. Math.* **16** 155–160.

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1. General comments. This important paper is a major contribution to jackknife methodology. A major strength of the proposed weighted jackknife method is its ready extensibility to nonlinear situations, including the important generalized linear models with uncorrelated errors briefly discussed in Section 8.

In the case of a linear regression model with uncorrelated errors, the delete-1 jackknife variance estimator, $v_{J(1)}$, is shown to be exactly unbiased for $\mathrm{Var}(\hat{\beta})$ under $\mathrm{Var}(e) = \sigma^2 I$, and approximately unbiased (as $n \to \infty$) under $\mathrm{Var}(e) = \mathrm{diag}(\sigma_i^2)$. However, $v_{J(1)}$ seems to have no special advantage over the MINQUE (minimum norm quadratic unbiased estimator) of $\mathrm{Var}(\hat{\beta})$ (Rao (1973)) under the criterion of bias robustness since the latter estimator is exactly unbiased under $\mathrm{Var}(e) = \mathrm{diag}(\sigma_i^2)$ unlike $v_{J(1)}$. It may also be noted that the MINQUE of $\mathrm{Var}(\hat{\beta})$ seldom becomes negative definite even though the MINQUE of individual σ_i^2 may assume negative values. If $\theta = g(\beta)$, then the linearization technique can be used to get a MINQUE-based estimator of the variance of $\hat{\theta} = g(\hat{\beta})$. This variance estimator should be satisfactory since Wu's simulation study shows that