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References

Bradley: Robustness? **Bradley-1978**

James V. Bradley. "Robustness?" In: *British Journal of Mathematical and Statistical Psychology* 31.2 (Nov. 1978), pp. 144–152. DOI: 10.1111/j.2044-8317.1978.tb00581.x.

Abstract: The actual behaviour of the probability of a Type I error under assumption violation is quite complex, depending upon a wide variety of interacting factors. Yet allegations of robustness tend to ignore its highly particularistic nature and neglect to mention important qualifying conditions. The result is often a vast overgeneralization which nevertheless is difficult to refute since a standard quantitative definition of what constitutes robustness does not exist. Yet under any halfway reasonable quantitative definition, many of the most prevalent claims of robustness would be demonstrably false. Therefore robustness is a highly questionable concept.

Efron: Bootstrap methods: Another look at the jackknife **Efron-1979a**

Bradley Efron. "Bootstrap methods: Another look at the jackknife". In: *The Annals of Statistics* 7.1 (Jan. 1979). DOI: 10.1214/aos/1176344552.

Abstract: We discuss the following problem: given a random sample $\boldsymbol{X} = (X_1, X_2, \dots, X_n)$ from an unknown probability distribution F, estimate the sampling distribution of some prespecified random variable $R(\boldsymbol{X}, F)$, on the basis of the observed data $\boldsymbol{x}$. (Standard jackknife theory gives an approximate mean and variance in the case $R(\boldsymbol{X}, F) = \theta\left(\hat{F}\right) - \theta(F)$, θ some parameter of interest.) A general method, called the "bootstrap" is introduced, and shown to work satisfactorily on a variety of estimation problems. The jackknife is shown to be a linear approximation method

for the bootstrap. The exposition proceeds by a series of examples: variance of the sample median, error rates in a linear discriminant analysis, ratio estimation, estimating regression parameters, etc.

Efron: Computers and the theory of statistics: Thinking the unthinkable — Efron-1979b

Bradley Efron. "Computers and the theory of statistics: Thinking the unthinkable". In: *SIAM Review* 21.4 (Oct. 1979), pp. 460–480. DOI: 10.1137/1021092.

Abstract: This is a survey article concerning recent advances in certain areas of statistical theory, written for a mathematical audience with no background in statistics. The topics are chosen to illustrate a special point: how the advent of the high-speed computer has affected the development of statistical theory. The topics discussed include nonparametric methods, the jackknife, the bootstrap, cross-validation, error-rate estimation in discriminant analysis, robust estimation, the influence function, censored data, the EM algorithm, and Cox's likelihood function. The exposition is mainly by example, with only a little offered in the way of theoretical development.

Hinkley: Jackknifing in unbalanced situations — Hinkley-1977

David V. Hinkley. "Jackknifing in unbalanced situations". In: *Technometrics* 19.3 (Aug. 1977), pp. 285–292. DOI: 10.1080/00401706.1977.10489550.

Abstract: Both the standard jackknife and a weighted jackknife are investigated in the general linear model situation. Properties of bias reduction and standard error estimation are derived and the weighted jackknife shown to be superior for unbalanced data. There is a preliminary discussion of robust regression fitting using jackknife pseudo-values.

S. D. Horn et al.: Estimating heteroscedastic variances in linear models

Horn-Horn-Duncan-1975

Susan D. Horn, Roger A. Horn, and David B. Duncan. "Estimating heteroscedastic variances in linear models". In: *Journal of the American Statistical Association* 70.350 (June 1975), pp. 380–385. DOI: 10.1080/01621459.1975.10479877.

Rubin: Inference and missing data **Rubin-1976**

Donald B. Rubin. "Inference and missing data". In: *Biometrika* 63.3 (1976), pp. 581–592. DOI: 10.1093/biomet/63.3.581.

Abstract: When making sampling distribution inferences about the parameter of the data, θ, it is appropriate to ignore the process that causes missing data if the missing data are 'missing at random' and the observed data are 'observed at random', but these inferences are generally conditional on the observed pattern of missing data. When making direct-likelihood or Bayesian inferences about θ, it is appropriate to ignore the process that causes missing data if the missing data are missing at random and the parameter of the missing data process is 'distinct' from θ. These conditions are the weakest general conditions under which ignoring the process that causes missing data always leads to correct inferences.