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Comment

J. Fan and J. S. Marron

1. GENERAL COMMENTS

We would like to thank the authors for a useful and informative article on the state of the art in nonparametric regression. Especially enjoyable were the novel and imaginative graphical methods that were developed to illustrate the points being made. These reveal more intuition behind the theoretical results of Stone (1977, 1982) and Fan (1992, 1993). It contains a nice summary of many points which have already been made and justified (theoretically and intuitively) by the recent papers of Chu and Marron (1991) and the discussions therein and of Fan (1992, 1993).

The main contribution of the paper is a very accessible introduction to a point which is becoming quite clear to insiders in the field of nonparametric regression: local (i.e., moving window) polynomial regression estimators have a number of compelling advantages over the more widely used and studied kernel estimators.

In view of the very large literature on kernel regression estimators, an interesting issue is why it took so long for the smoothing community at large to understand fully the benefits of local polynomials. We speculate that this was because of "equivalence results," the best known being Müller (1987) but see also Lejeune (1985), whose main intuitive message was for *equally*

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