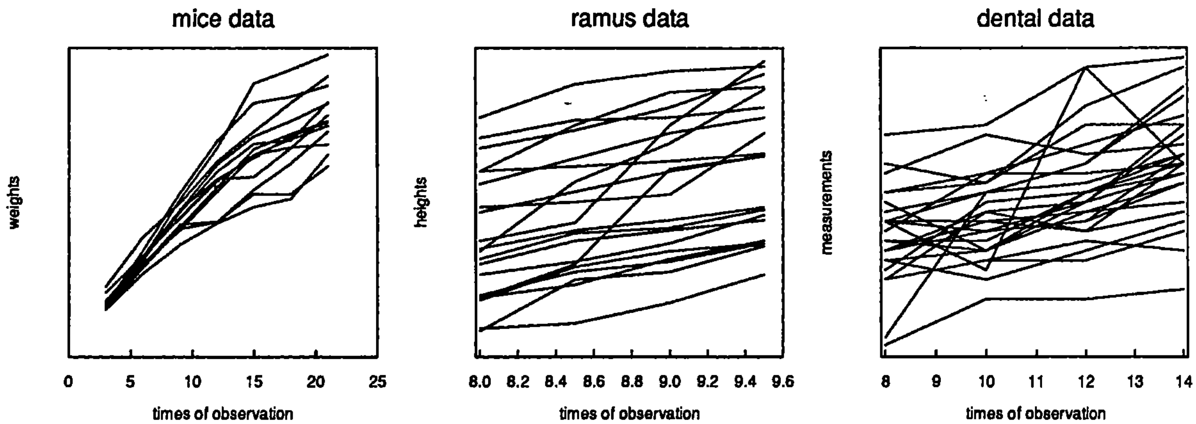

FIG. 2. *Plots of example data.*

where

$$g^* = \left[\frac{(n+1)(s-k)}{(n+1)(s-k)+2}\right]\left[\frac{n-k-2}{n}\right].$$

In conclusion, we agree with Professor Rao that his empirical Bayes predictor of future observations in growth curve models performs better than its least squares counterpart. We have also described several other empirical Bayes prediction methods. With the three example data sets, we have found our calibrated empirical Bayes predictor to yield smaller CVAE and to be more stable than its calibrated least squares counterpart.

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Comment: On Exchangeability Judgments in Predictive Modeling and the Role of Data in Statistical Research

David Draper

Professor Rao has shared with us some thought-provoking ideas on prediction in growth curve modeling. The paper has four basic attributes, two of which seem positive and two negative. On the positive side,

- the basic problem is predictive in nature, thereby emphasizing inference on observable quantities (future values of outcome variables of interest) rather than on unobservable quantities (parameters); and

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