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I am grateful to be granted the opportunity to comment on this interesting paper. It represents a synthesis of several smoothing techniques under one characterisation, it proposes a useful way of carrying out multiple regression that lies somewhere between multiple linear regression and the general additive models that underline ACE, and it investigates the properties of a practicable algorithm for obtaining the fit of the models to a set of data. There is much to discuss in the paper but, apart from a few brief comments and questions near the end, I should like to concentrate my remarks on a particular aspect, namely, the concept of degrees of freedom associated with the fitted models and the relationship with the choice of smoothing parameter.

I shall lead into my specific points by observing that, at first sight, the structure under consideration offers a variety of immediately applicable smoothing techniques, as indicated early on in Figure 2. However, a closer reading reveals that, if one is confronted with a particular set of data, the situation is not quite so straightforward. The authors remark that all their generic, linear techniques are characterised, in some guise, by a smoothing parameter. If, however, the choice of smoothing parameter is to be data-driven, then the linearity is lost. They are quite correct, of course, but unfortunately one finds repeatedly, in the literature, that the choice of a good smoothing parameter is considered to be a rather sensitive issue and that automatic, data-driven