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Thin plate regression splines. (English) [Zbl 1063.62059]

Summary: I discuss the production of low rank smoothers for $d \geq 1$ dimensional data, which can be fitted by regression or penalized regression methods. The smoothers are constructed by a simple transformation and truncation of the basis that arises from the solution of the thin plate spline smoothing problem and are optimal in the sense that the truncation is designed to result in the minimum possible perturbation of the thin plate spline smoothing problem given the dimension of the basis used to construct the smoother. By making use of Lanczos iteration the basis change and truncation are computationally efficient.

The smoothers allow the use of approximate thin plate spline models with large data sets, avoid the problems that are associated with 'knot placement' that usually complicate modelling with regression splines or penalized regression splines, provide a sensible way of modelling interaction terms in generalized additive models, provide low rank approximations to generalized smoothing spline models, appropriate for use with large data sets, provide a means for incorporating smooth functions of more than one variable into nonlinear models and improve the computational efficiency of penalized likelihood models incorporating thin plate splines. Given that the approach produces spline-like models with a sparse basis, it also provides a natural way of incorporating unpenalized spline-like terms in linear and generalized linear models, and these can be treated just like any other model terms from the point of view of model selection, inference and diagnostics.

MSC:

62G08	Nonparametric regression and quantile regression
62J12	Generalized linear models (logistic models)

Cited in **93** Documents

Keywords:

generalized additive model; thin plate spline

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gss

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