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Fast stable restricted maximum likelihood and marginal likelihood estimation of semiparametric generalized linear models. (English) Zbl 1411.62089

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Summary: Recent work by *P. T. Reiss* and *R. T. Ogden* [J. R. Stat. Soc., Ser. B, Stat. Methodol. 71, No. 2, 505–523 (2009; Zbl 1248.62057)] provides a theoretical basis for sometimes preferring restricted maximum likelihood (REML) to generalized cross-validation (GCV) for smoothing parameter selection in semiparametric regression. However, existing REML or marginal likelihood (ML) based methods for semiparametric generalized linear models (GLMs) use iterative REML or ML estimation of the smoothing parameters of working linear approximations to the GLM. Such indirect schemes need not converge and fail to do so in a non-negligible proportion of practical analyses. By contrast, very reliable prediction error criteria smoothing parameter selection methods are available, based on direct optimization of GCV, or related criteria, for the GLM itself. Since such methods directly optimize properly defined functions of the smoothing parameters, they have much more reliable convergence properties. The paper develops the first such method for REML or ML estimation of smoothing parameters. A Laplace approximation is used to obtain an approximate REML or ML for any GLM, which is suitable for efficient direct optimization. This REML or ML criterion requires that Newton-Raphson iteration, rather than Fisher scoring, be used for GLM fitting, and a computationally stable approach to this is proposed. The REML or ML criterion itself is optimized by a Newton method, with the derivatives required obtained by a mixture of implicit differentiation and direct methods. The method will cope with numerical rank deficiency in the fitted model and in fact provides a slight improvement in numerical robustness on the earlier method of Wood for prediction error criteria based smoothness selection. Simulation results suggest that the new REML and ML methods offer some improvement in mean-square error performance relative to GCV or Akaike's information criterion in most cases, without the small number of severe undersmoothing failures to which Akaike's information criterion and GCV are prone. This is achieved at the same computational cost as GCV or Akaike's information criterion. The new approach also eliminates the convergence failures of previous REML- or ML-based approaches for penalized GLMs and usually has lower computational cost than these alternatives. Example applications are presented in adaptive smoothing, scalar on function regression and generalized additive model selection.

MSC:

62G05 Nonparametric estimation
62F15 Bayesian inference
62G08 Nonparametric regression and quantile regression

Keywords:

adaptive smoothing; generalized additive mixed model; generalized additive model; generalized cross-validation; marginal likelihood; model selection; penalized generalized linear model; penalized regression splines; restricted maximum likelihood; scalar on function regression; stable computation

Software:

LAPACK; BayesX; R

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