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The purpose of this study is to explore Bayesian model averaging in the propensity score context. Previous research on Bayesian propensity score analysis does not take into account model uncertainty. In this regard, an internally consistent Bayesian framework for model building and estimation must also account for model uncertainty. The significance of the current study is that it directly addresses the problem of uncertainty in propensity score models via the method of Bayesian model averaging (BMA). The usefulness of the proposed method is that it provides the investigator a way to incorporate prior knowledge regarding the relationship between the covariates and treatment selection (via the Kaplan and Chen, 2012 approach) while at the same time acknowledging model uncertainty via Bayesian model averaging. This paper provides a fully Bayesian MCMC methodology to obtain propensity score and treatment effect estimates, as well as R code to conduct such an analysis. Research design utilizes a combination of simulation studies and real data analysis. The simulation study examines the choice of parameter and model priors. The real data example examines a model relating full vs. part-day kindergarten attendance on achievement outcomes for first grade student using the ECLS-K. Preliminary findings suggest that the fully MCMC algorithm for Bayesian model averaging within the PSA framework provides accurate expected a posteriori estimates of the treatment effect. An appendix provides additional information on the two-step Bayesian PSA model, Bayesian model averaging, and computational considerations. Bayesian model averaging attempts to combine parameter estimation and model uncertainty in one coherent framework. The choice of prior is then critical. Within an explicit framework of ignorance we define a 'suitable' prior as one which leads to a continuous and suitable analog to the pretest estimator. The normal prior, used in standard Bayesian model averaging, is shown to be unsuitable. The Laplace (or lasso) prior is almost suitable. A suitable prior (the Subbotin prior) is proposed and its properties are investigated. Model uncertainty and model averaging in the estimation of benchmark dose. This paper considers model selection and model averaging in panel data models with a multifactor error structure. We investigate the limiting distribution of the common correlated effects estimator (Pesaran, 2006) in a local asymptotic framework and show that the trade-off between bias and variance remains in the asymptotic theory. We then propose a focused information criterion and a plug-in averaging estimator for large heterogeneous panels and examine their theoretical properties. The novel feature of the proposed method is that it aims to minimize the sample analog of the asymptotic mean squared error and can be applied to cases irrespective of whether the rank condition holds or not. Monte Carlo simulations show that both proposed selection and averaging methods generally achieve lower expected squared error than other methods. The proposed methods are applied to analyze the consumer response to gasoline taxes. This paper examines the problem of variable selection in linear regression models. Bayesian model averaging has become an important tool in empirical settings with large numbers of potential regressors and relatively limited numbers of observations. The paper analyzes the effect of a variety of prior assumptions on the inference concerning model size, posterior inclusion probabilities of regressors, and predictive performance. The analysis illustrates these issues in the context of cross-country growth regressions using three datasets with 41 to 67 potential drivers of growth and 72 to 93 observations. The results favor particular prior structures for use in this and related contexts. Abstract: A Bayes factor between two models can be greatly affected by the prior distributions on the model parameters. When prior information is weak, very dispersed proper prior distributions are often used. This is known to create a problem for the Bayes factor when competing models that differ in dimension, and it is of even greater concern when one of the models is of infinite dimension. Therefore, we propose an innovative criterion called the calibrated Bayes factor, which uses training samples to calibrate the prior distributions so that they achieve a reasonable level of "information". The calibrated Bayes factor is then computed as the Bayes factor over the remaining data. The level of "information" is tied to the concentration of training-updated prior distributions, which is carefully evaluated by monitoring the distribution of symmetrized Kullback-Leibler divergence between two likelihood functions drawn independently from the training-updated prior distribution. Monte Carlo Markov chain algorithms are widely used in this research to generate parameter draws from training-updated prior distributions. Subsampling is applied to reduce dependence among parameter draws. In high dimensional data analysis, we propose a sequential model averaging (SMA) method to make accurate and stable predictions. Specifically, we in- troduce a hybrid approach that combines a sequential screening process with a model averaging algorithm, where the weight of each model is determined by its Bayesian information (BIC) score (Schwarz, 1978; Chen and Chen, 2008). The sequential technique makes SMA computationally feasible with high dimensional data, because the averaging process assures the prediction's accuracy and sta- bility. Theoretical results show that SMA not only yields a good model, but also mitigates overfitting. In addition, we demonstrate that SMA provides con- sistent estimators for the regression coefficients and yields reliable predictions under mild conditions. Both simulations and empirical examples are presented to illustrate the usefulness of the proposed method. There is a rich history of work on model selection and averaging in the statistics literature. The Bayesian paradigm provides an approach to model selection which successfully overcomes the drawbacks for which frequentist hypothesis testing has been criticized. Most commonly, Bayesian model selection methods are based on the Bayes factor. Additionally, the Bayes factor has applications outside the realm of model selection, such as model averaging. In a formal sense, as a supplement to the prior odds, the Bayes factor produces the posterior odds for a pair of models. These posterior odds can be translated to posterior probabilities and yields a full posterior distribution that assigns a probability to each model as well as a distribution over the parameters for each model. Then the Bayesian model averaging provides better prediction by making inferences based on a weighted average over all of the models considered. This paper develops two-stage model averaging (2SMA), an extension of model averaging. 2SMA allows researchers to incorporate economic theory or prior economic information into their forecasts. By using prior economic information, 2SMA leverages models known to perform well while diversifying across peripheral forecasts. 2SMA is an easy-to-implement, general framework that can be easily combined with other model averaging techniques. In an application, we develop two-stage Bayesian model averaging (2SBMA) and two-stage equal-weighted averaging (2SEWA). 2SBMA and 2SEWA are the two-stage model averaging extensions of dynamic Bayesian model averaging and equal-weighted averaging. Using these techniques, we forecast stock returns. Our results indicate that the 2SBMA and the 2SEWA forecasts statistically outperform the benchmark random-walk plus drift over the sample period. The 2SBMA and 2SEWA forecasts also both beat their traditional model averaging counterparts. The authors consider the following scenario: Two agents construct models of an endogenous price process. One agent thinks the data are stationary, the other thinks the data are nonstationary. A policymaker combines forecasts from the two models using a recursive Bayesian model averaging procedure. The actual (but unknown) price process depends on the policymakerâ€TMs forecasts. The authors find that if the policymaker has complete faith in the stationary model, then beliefs and outcomes converge to the stationary rational expectations equilibrium. However, even a grain of doubt about stationarity will cause beliefs to settle on the nonstationary model, where prices experience large self-confirming deviations away from the stationary equilibrium. The authors show that it would take centuries of data before agents were able to detect their model misspecifications. Hjort and Claeskens (HC) argue that statistical inference conditional on a single selected model underestimates uncertainty, and that model averaging is the way to remedy this; we strongly agree. They point out that Bayesian model averaging (BMA) has been the dominant approach to this, but argue that its performance has been inadequately studied, and propose an alternative, Frequentist Model Averaging (FMA). We point out, however, that there is a substantial literature on the performance of BMA, consisting of three main threads: general theoretical results, simulation studies, and evaluation of out-of-sample performance. The theoretical results are scattered, and we summarize them. The results have been quite consistent: BMA has tended to outperform competing methods for model selection and taking account of model uncertainty. The theoretical results depend on the assumption that the "practical distribution" over which the performance of methods is assessed is the same as the prior distribution used, and we investigate sensitivity of results to this assumption in a simple normal example; they turn out not to be unduly sensitive. Given a data set, you can fit thousands of models at the push of a button, but how do you choose the best? With so many candidate models, overfitting is a real danger. Is the monkey who typed Hamlet actually a good writer? Choosing a model is central to all statistical work with data. We have seen rapid advances in model fitting and in the theoretical understanding of model selection, yet this book is the first to synthesize research and practice from this active field. Model choice criteria are explained, discussed and compared, including the AIC, BIC, DIC and FIC. The uncertainties involved with model selection are tackled, with discussions of frequentist and Bayesian methods; model averaging schemes are presented. Real-data examples are complemented by derivations providing deeper insight into the methodology, and instructive exercises build familiarity with the methods. The companion website features Data sets and R code. This paper considers forecast combination in a predictive regression. We construct the point forecast by combining predictions from all possible linear regression models given a set of potentially relevant predictors. We propose a frequentist model averaging criterion, an asymptotically unbiased estimator of the mean squared forecast error (MSFE), to select forecast weights. In contrast to the existing literature, we derive the MSFE in a local asymptotic framework without the i.i.d. normal assumption. This result allows us to decompose the MSFE into the bias and variance components and also to account for the correlations between candidate models. Monte Carlo simulations show that our averaging estimator has much lower MSFE than alternative methods such as weighted AIC, weighted BIC, Mallows model averaging, and jackknife model averaging. We apply the proposed method to stock return predictions. Default prior choices fixing Zellner's g are predominant in the Bayesian Model Averaging literature, but tend to concentrate posterior mass on a tiny set of models. The paper demonstrates this supermodel effect and proposes to address it by a hyper-g prior, whose data-dependent shrinkage adapts posterior model distributions to data quality. Analytically, existing work on the hyper-g-prior is complemented by posterior expressions essential to fully Bayesian analysis and to sound numerical implementation. A simulation experiment illustrates the implications for posterior inference. Furthermore, an application to determinants of economic growth identifies several covariates whose robustness differs considerably from previous results. Bayesian Model Averaging (BMA) provides a coherent mechanism to address the problem of model uncertainty. In this paper we extend the BMA framework to panel data models where the lagged dependent variable as well as endogenous variables appear as regressors. We propose a Limited Information Bayesian Model Averaging (LIBMA) methodology and then test it using simulated data. Simulation results suggest that asymptotically our methodology performs well both in Bayesian model selection and averaging. In particular, LIBMA recovers the data generating process very well, with high posterior inclusion probabilities for all the relevant regressors, and parameter estimates very close to the true values. These findings suggest that our methodology is well suited for inference in dynamic panel data models with short time periods in the presence of endogenous regressors under model uncertainty. Along with many practical applications, Bayesian Model Selection and Statistical Modeling presents an array of Bayesian inference and model selection procedures. It thoroughly explains the concepts, illustrates the derivations of various Bayesian model selection criteria through examples, and provides R code for implementation. The author shows how to implement a variety of Bayesian inference using R and sampling methods, such as Markov chain Monte Carlo. He covers the different types of simulation-based Bayesian model selection criteria, including the numerical calculation of Bayes factors, the Bayesian predictive information criterion, and the deviance information criterion. He also provides a theoretical basis for the analysis of these criteria. In addition, the author discusses how Bayesian model averaging can simultaneously treat both model and parameter uncertainties. Selecting and constructing the appropriate statistical model significantly affect the quality of results in decision making, forecasting, stochastic structure explorations, and other problems. Helping you choose the right Bayesian model, this book focuses on the framework for Bayesian model selection and includes practical examples of model selection criteria. "Recent empirical work has considered the prediction of inflation by combining the information in a large number of time series. One such method that has been found to give consistently good results consists of simple equal weighted averaging of the forecasts over a large number of different models, each of which is a linear regression model that relates inflation to a single predictor and a lagged dependent variable. In this paper, I consider using Bayesian Model Averaging for pseudo out-of-sample prediction of US inflation, and find that it gives more accurate forecasts than simple equal weighted averaging. This superior performance is consistent across subsamples and inflation measures. Meanwhile, both methods substantially outperform a naive time series benchmark of predicting inflation by an autoregression"--Federal Reserve Board web site. This book provides a concise and accessible overview of model averaging, with a focus on applications. Model averaging is a common means of allowing for model uncertainty when analysing data, and has been used in a wide range of application areas, such as ecology, econometrics, meteorology and pharmacology. The book presents an overview of the methods developed in this area, illustrating many of them with examples from the life sciences involving real-world data. It also includes an extensive list of references and suggestions for further research. Further, it clearly demonstrates the links between the methods developed in statistics, econometrics and machine learning, as well as the connection between the Bayesian and frequentist approaches to model averaging. The book appeals to statisticians and scientists interested in what methods are available, how they differ and what is known about their properties. It is assumed that readers are familiar with the basic concepts of statistical theory and modelling, including probability, likelihood and generalized linear models. This paper extends the Bayesian Model Averaging framework to panel data models where the lagged dependent variable as well as endogenous variables appear as regressors. We propose a Limited Information Bayesian Model Averaging (LIBMA) methodology and then test it using simulated data. Simulation results suggest that asymptotically our methodology performs well both in Bayesian model averaging and selection. In particular, LIBMA recovers the data generating process well, with high posterior inclusion probabilities for all the relevant regressors, and parameter estimates very close to their true values. These findings suggest that our methodology is well suited for inference in short dynamic panel data models with endogenous regressors in the context of model uncertainty. We illustrate the use of LIBMA in an application to the estimation of a dynamic gravity model for bilateral trade. This paper considers the problem of inference for nested least squares averaging estimators. We study the asymptotic behavior of the Mallows model averaging estimator (MMA; Hansen, 2007) and the jackknife model averaging estimator (JMA; Hansen and Racine, 2012) under the standard asymptotics with fixed parameters setup. We find that both MMA and JMA estimators asymptotically assign zero weight to the under-fitted models, and MMA and JMA weights of just-fitted and over-fitted models are asymptotically random. Building on the asymptotic behavior of model weights, we derive the asymptotic distributions of MMA and JMA estimators and propose a simulation-based confidence interval for the least squares averaging estimator. Monte Carlo simulations show that the coverage probabilities of proposed confidence intervals achieve the nominal level. Bayesian variable selection has experienced substantial developments over the past 30 years with the proliferation of large data sets. Identifying relevant variables to include in a model allows simpler interpretation, avoids overfitting and multicollinearity, and can provide insights into the mechanisms underlying an observed phenomenon. Variable selection is especially important when the number of potential predictors is substantially larger than the sample size and sparsity can reasonably be assumed. The Handbook of Bayesian Variable Selection provides a comprehensive review of theoretical, methodological and computational aspects of Bayesian methods for variable selection. The topics covered include spike-and-slab priors, continuous shrinkage priors, Bayes factors, Bayesian model averaging, partitioning methods, as well as variable selection in decision trees and edge selection in graphical models. The handbook targets graduate students and established researchers who seek to understand the latest developments in the field. It also provides a valuable reference for all interested in applying existing methods and/or pursuing methodological extensions. Features: • Provides a comprehensive review of methods and applications of Bayesian variable selection. • Divided into four parts: Spike-and-Slab Priors; Continuous Shrinkage Priors; Extensions to various Modeling; Other Approaches to Bayesian Variable Selection. • Covers theoretical and methodological aspects, as well as worked out examples with R code provided in the online supplement. • Includes contributions by experts in the field.