Proposal Status | MAIN

Organization: Washington University

Review #4

Proposal Number:	1152472
NSF Program:	Political Science
Principal Investigator:	Montgomery, Jacob
Proposal Title:	Collaborative Research on Ensemble Methods for the Prediction of Political Outcomes
Rating:	Good

REVIEW:

What is the intellectual merit of the proposed activity?

Accounting for model uncertainty by calculating posterior model probabilities is an important innovation in data analysis in general and, as the proposers convincingly show in their proposal, highly effective in improving accuracy of forecast. However, the idea of incorporating model uncertainty has been considered as a Bayesian formula for a long time and hence social scientists who received no training in Bayesian camp tend to consider it as a distant practice in their data analysis. In that regard, the proposed project can contribute to broaden the implementation of this idea in social science data analysis.

Having said that, I also have several questions about specifics of the project, which I will list in the following.

Methodological Advancements from the Project

First, the most important and clearly stated methodological goal of this project is to develop EBMA method in binary (and discrete in general) data context. My guess is that the proposers will use Vrugt, Diks and Clark (2008)'s DiffeRential Evolution Adaptive Metropolis (DREAM) MCMC method. It is not clear how the proposers will implement data augmentation methods using the DREAM MCMC method in EBMA context. This methodological advancement is crucial in this project because there is already a well-known R package called ensembleBMA that implements most of EBMA methods using EM algorithm. To repeat, in order for software contribution of this project to be meaningful, the proposers should be able to develop new EBMA methods for discrete data using the DREAM MCMC method.

The DREAM MCMC method is a computationally expensive algorithm that uses N different Markov chains in parallel in order to investigate highly complex surface of model space. The cost of computation increases as ensemble sizes increase and in nonlinear contexts. Also, the well-known data augmentation method for binary data (Albert and Chib's method) suffers from a high correlation between latent parameters and model parameters. There are not one but many data augmentation methods in Bayesian statistics and the proposers should choose them with care given the high cost of computation. There is no discussion of whether the proposers have knowledge and programming skills in coding the DREAM MCMC method in discrete data contexts using low-level computer languages, which is essential information to predict the probability of project success. The proposers may find it helpful an R package for the DREAM MCMC method in R-Forge (https://r-forge.r-project.org/R/?group_id=545).

Second, the proposers mentioned that they will develop alternative model weights 'to incorporate the entire predictive PDFs of component forecasts so that model weights reflect not only components'accuracy, but also their precision' using both Bayesian and bootstrap methods. This would be a huge methodological contribution to the literature because EBMA and BMA have been criticized to use arbitrary ways to approximate posterior model probabilities.

I could be wrong on this but I personally do not think that even the most sophisticated state-of-art method in statistics and computational sciences cannot 'incorporate the entire predictive PDFs of component forecasts' from a variety of complex models (including subjective experts opinion models) with varying parameter spaces in linear and nonlinear model contexts. The proposers need to restate this goal in a more practical form or should indicate how Bayesian and bootstrap methods can be applied to achieving this goal.

Last, I think the proposers should think harder about how to convince general audience about the necessity of accounting for model uncertainty in social sciences.
BMA weights each single model prediction by the corresponding posterior model probability. As the proposers are well aware, some quantitative social scientists are reluctant to accept the idea of accounting for model uncertainty and prefer to find 'the best predictions' (project summary). This is not because they are ignorant about the method but they think weights on multiple models to be unnecessary or even useless. This proposal sells the method based on its predictive accuracy: EBMA is 'usually more accurate than any individual component model' and 'less likely to make dramatically incorrect predictions'(2). However, there is no free lunch in finding good statistical estimators: we gain one (e.g. efficiency) by compromising the other (e.g. bias). I wonder whether the proposers can provide convincing logics and examples to show why the compromise suggested by EBMA is a way to go in forecasting and how EBMA can improve theory-driven (as opposed to data-driven) forecasting models in social sciences.

What are the broader impacts of the proposed activity?

The contributions of this project will have the largest impact on the forecasting literature in international politics that one of the investigators has an expertise on. However, through the contribution of free software package and the publication of an introductory article, the project may have larger impacts on political science as a whole and social sciences in general.

Summary Statement

The proposed project intends to introduce Ensemble Bayesian model averaging (EBMA) technique as an improved forecasting tool for social scientists. Three goals of the project are the extension of EBMA to binary data, software contribution as an R package, and publication of an introductory article of EBMA. Overall, I think these three goals will be important contributions to empirical social scientists who want to learn and use sophisticated forecasting tools in their analysis.

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