Say Yes to the Guess: Tailoring Elegant Ensembles on a Tight (Data) Budget

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Ensemble Bayesian Model Averaging (EBMA)

EBMA is principled way of combining a number of different prediction models to increase out-of-sample predictive power

- Component models are weighted based on predictive performance in calibration period
- The EBMA prediction is then a finite mixture model of the different component models
- The predictive pdf for the EBMA model can be written as: $p(y|f_1^{t^*}, \ldots, f_K^{t^*}) = \sum_{k=1}^{K} w_k g_k(y|f_k^{t^*})$, where w_k are the weights associated with each model

Ensemble Bayesian Model Averaging (EBMA)

- Model weights are estimated using an expectation-maximization (EM) algorithm
- More accurate models in the calibration period receive higher weights
- Models making more unique predictions are favored

Adjusting EBMA to Forecasting in the Social Sciences

Forecasting efforts in the social sciences are often hampered by data problems

- Often observations are missing
- Rarely are missing observations truly random
- Numerous forecasting models, but few true data observations to calibrate

Adjusting EBMA to Forecasting in the Social Sciences

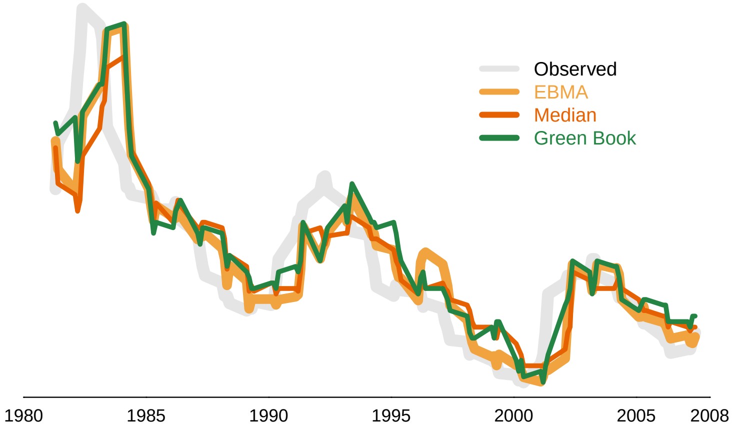
- To incorporate models with missing data we adjust the EM algorithm following Fraley, Raftery and Gneiting (2010)
- To make small sample adjustments we introduce a "wisdom of the crowds" parameter $c \in [0, 1]$
- Thus when estimating model weights, for each model there is a minimum $\frac{c}{k}$ probability that the observation is best represented by this model

Applying EBMA to Predict Quarterly Unemployment in the US

- Predictions from the Survey of Professional Forecasters (SPF) from the Philadelphia Federal Reserve Bank
- Green Book of the Fed
- Predictions four quarters into the future
- Rolling calibration window of ten quarters
- Minimum of five forecasts in the calibration period for model inclusion

Applying EBMA to Predict Quarterly Unemployment in the US

Figure: Observed and forecasted U.S. unemployment (1981-2007)



Applying EBMA to Predict Quarterly Unemployment in the US

	MAE	RMSE	MAD	RMSLE	MAPE	MEAPE	MRAE	PW
EBMA (c=0)	0.54	0.74	0.37	0.093	8.37	6.49	**0.73**	**27.36**
EBMA (c=0.05)	**0.54**	0.74	**0.37**	**0.093**	**8.33**	**6.30**	0.75	**27.36**
EBMA (c=0.1)	0.54	0.74	0.35	0.093	8.40	6.44	0.76	28.30
EBMA (c=1)	0.61	0.80	0.46	0.102	9.72	8.92	0.95	46.23
Green Book	0.57	**0.73**	0.43	0.093	9.37	8.81	1.00	45.28
Forecast Median	0.62	0.81	0.47	0.103	9.83	8.87	0.98	47.17
Forecast Mean	0.61	0.80	0.46	0.102	9.71	9.06	0.93	46.23

Predicting the Incumbent Voteshare in the 2012 Presidential Election

Table: Pre-election forecasts of the percent of the two-party vote going to the incumbent party in U.S. Presidential elections

	F	A	C	H	LBRT	L	Hol	EW	Cuz
1992	55.7	46.3	49.7	48.9	47.3				
1996	49.5	57.0	55.5	53.5	53.3		57.2	55.6	
2000	50.8	53.2	52.8	54.8	55.4	60.3	60.3	55.2	
2004	57.5	53.7	52.8	53.2	49.9	57.6	55.8	52.9	51.1
2008	48.1	45.7	52.7	48.5	43.4	41.8	44.3	47.8	48.1

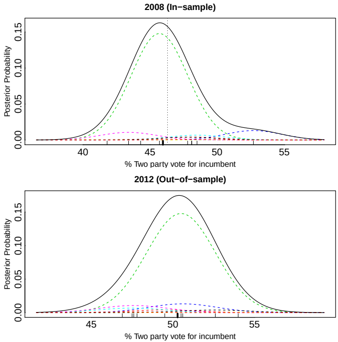
Predicting the Incumbent Voteshare in the 2012 Presidential Election

Table: Model weights and in-sample fit statistics for EBMA model of U.S. Presidential Elections (1992-2008)

	EBMA Weight	RMSE	MAE
EBMA		1.92	1.56
Fair	0.02	5.53	4.58
Abramowitz	0.78	2.02	1.72
Campbell	0.07	3.46	2.88
Hibbs	0.04	2.68	2.44
Lewis-Beck, Rice, and Tien	0.06	2.78	2.28
Lockerbie	0.00	7.33	6.97
Holbrook	0.01	5.73	4.77
Erikson and Wlezien	0.02	2.74	2.25
Cuzàn	0.00	1.27	0.95

Predicting the Incumbent Voteshare in the 2012 Presidential Election

Figure: Predictive ensemble PDFs of incumbent-part vote share in U.S. Presidential Elections



Conclusion

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