FluSight Network Ensemble

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Overview

The FluSight Network (FSN) ensemble model is a multimodel ensemble; a convex combination of component predictive densities. The predictive density of the multimodel ensemble is given by

$$f(z_{t,r,w}) = \sum_{c=1}^{C} \pi_{c,t,r} f_c(z_{t,r,w})$$

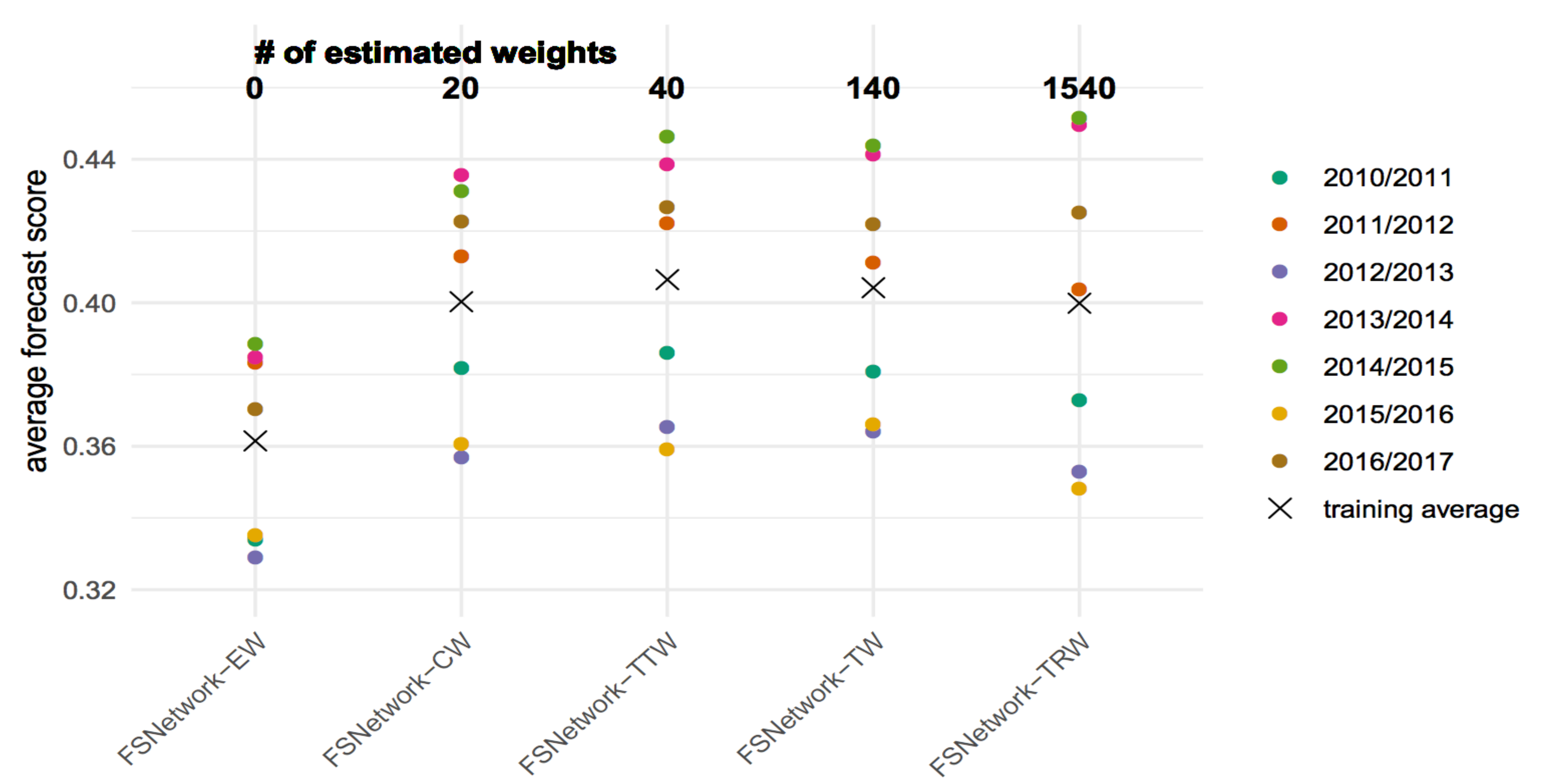
where $z_{t,r,w}$ denotes the ILI value at target t, at week w, in region r, C denotes the number of ensemble components, and $\pi_{c,t,r}$ is the component model weight. Five FluSight ensembles assign weights at different spatial scales and for different targets

Model	Weight Type
FSNetwork-CW	Constant weights
FSNetwork-EW	Equal weights
FSNetwork-TRW	Target-region-based weight
FSNetwork-TW	Target-based weights
FSNetwork-TTW	Target-type-based weight

EM Algorithm for Weighted Density Ensembles

- The FSN model assumes ILI values are generated from a mixture of C component models, and chooses weights that optimize a loglikelihood via an Expectation Maximization (EM) algorithm.
- The "E step" computes the number of times each component model was chosen to generate an ILI value. The "M step" calculates the fraction of times each method was chosen divided by the total number of epidemic weeks in the training set

Performance



Reich, Nicholas G., et al. "A collaborative multiyear, multimodel assessment of seasonal influenza forecasting in the United States." *Proceedings of the National Academy of Sciences* 116.8 (2019): 3146-3154.

Adaptive Ensemble

The adaptive ensemble is a multimodel ensemble, but unlike the FSN ensemble, recomputes component model weights every week.

A Bayesian approach requires a pre-specified prior distribution over ensemble weights.

$$p(\pi|Z,\mathcal{D}) \propto p(\pi) \times p(\mathcal{D}, Z|\pi),$$

Our adaptive ensemble chose a uniform time-dependent Dirichlet distributed prior.

$$\pi_t \sim \text{Dir}\left[\alpha(t)\right]$$

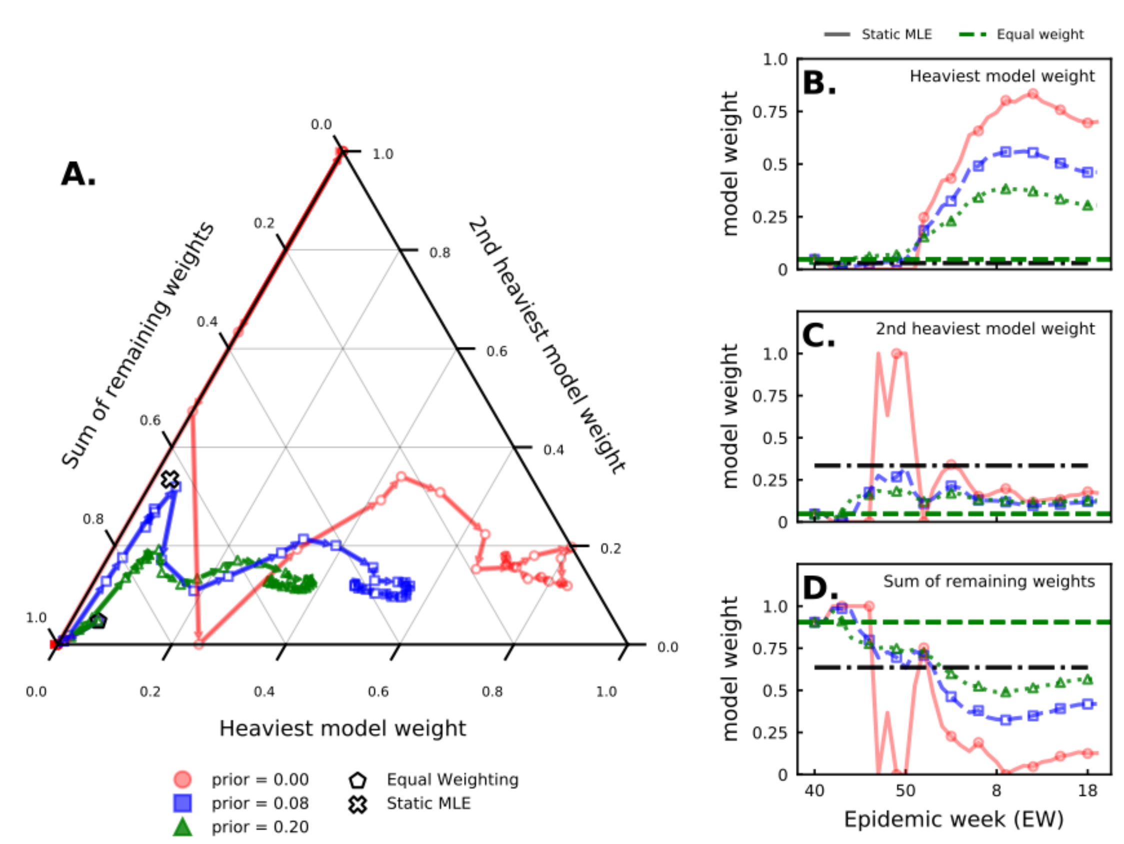
$$p[\pi_t|\alpha(t)] = \frac{\Gamma\left[\sum \alpha(t)\right]}{\prod \Gamma\left[\alpha(t)\right]} \prod_{m=1}^{M} \pi_m^{\alpha(t)-1}$$

$$\alpha(t) = \rho \frac{N(t)}{M}$$

where N is the number of epidemic weeks, M the number of models and ρ the prior strength.

Variational Inference Algorithm

Weights are optimized via a Variational inference algorithm, similar in spirit to the FSN's EM algorithm.



The 2017/2018 season shows adaptive ensemble weights (i) only near equal weighting in the beginning of the season and (ii) different than the FSN (static) ensemble weights. The adaptive ensemble shows better performance than an equally-weighted ensemble and similar performance to the FSN (static) ensemble.

McAndrew, Thomas, and Nicholas G. Reich. "Adaptively stacking ensembles for influenza forecasting with incomplete data." *arXiv preprint arXiv:1908.01675* (2019).

Ensemble Calibration

The Beta-transformed linear pool (BLP), proposed by Ranjan and Gneiting (2010), models an ensemble transformed by a Beta distribution.

$$\text{BLP(ILI)} = \mathcal{B}_{\alpha,\beta}\left(\sum_{m=1}^{M} \pi_m F_m(\text{ILI})\right)$$

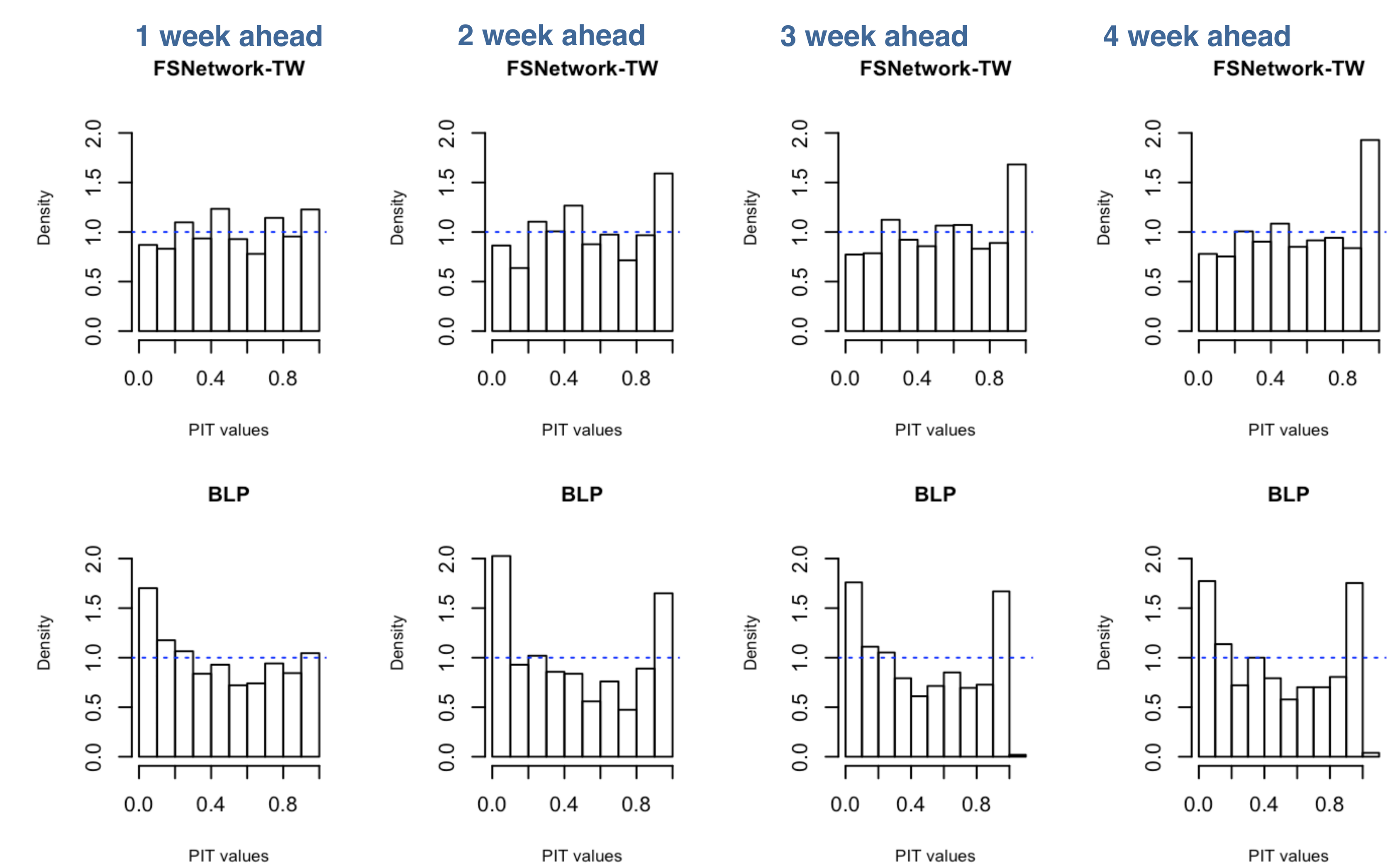
where BLP is the final cumulative distribution, $\mathcal{B}$ a cumulative beta distribution, and F a component model's cumulative density

The additional beta transform is meant to correct the traditional ensemble's tendency to be overdispersed and miscalibrated.

We are now building a novel BLP model that first corrects component model distributions via their own beta transformation, computes a convex combination of these better calibrated component models, and final beta transforms the weighted ensemble.

Probability integral transform (PIT) histograms by target 2017/2018 season

FSNetwork-TW and BLP ensembles trained on the 2010/2011 season to 2016/2017 season.



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