

Decaying Average BMA

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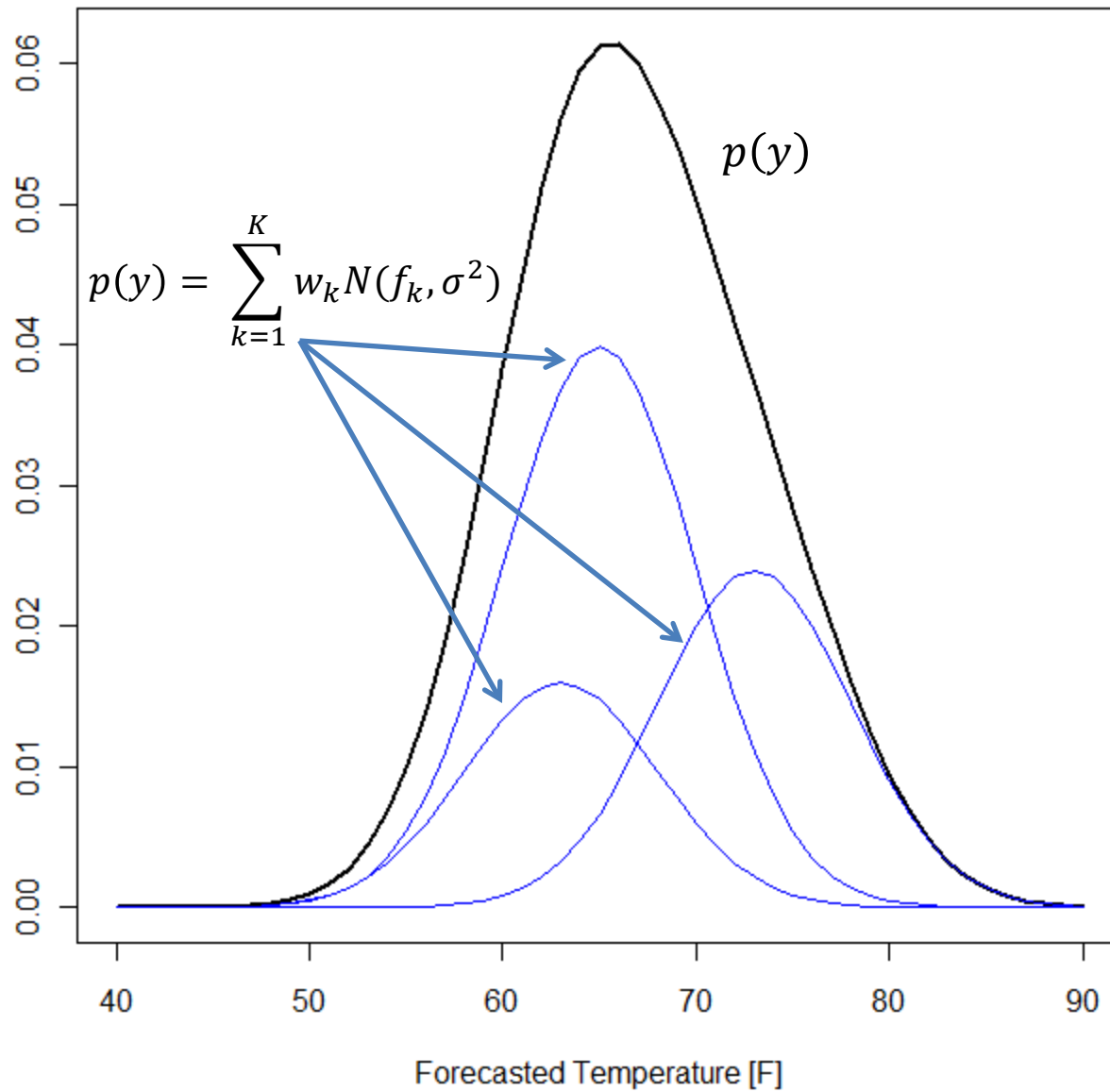
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Introduction

- Raftery et al. (2005) proposed applying Bayesian Model Averaging (BMA) to ensembles
- Basic Idea
 - Weight ensemble members based on past performance
 - Calibrate ensemble spread
 - Do this by fitting a Normal Mixture statistical model to ensemble member forecasts

Normal Mixture Model



Fitting the Statistical Model

- Challenge is to estimate statistical model parameters

$$p(\mathbf{y}) = \sum_{k=1}^K w_k N(\mathbf{f}_k, \sigma^2)$$

Where

w_k are weights $\rightarrow p(M_k | \mathbf{y}^T)$

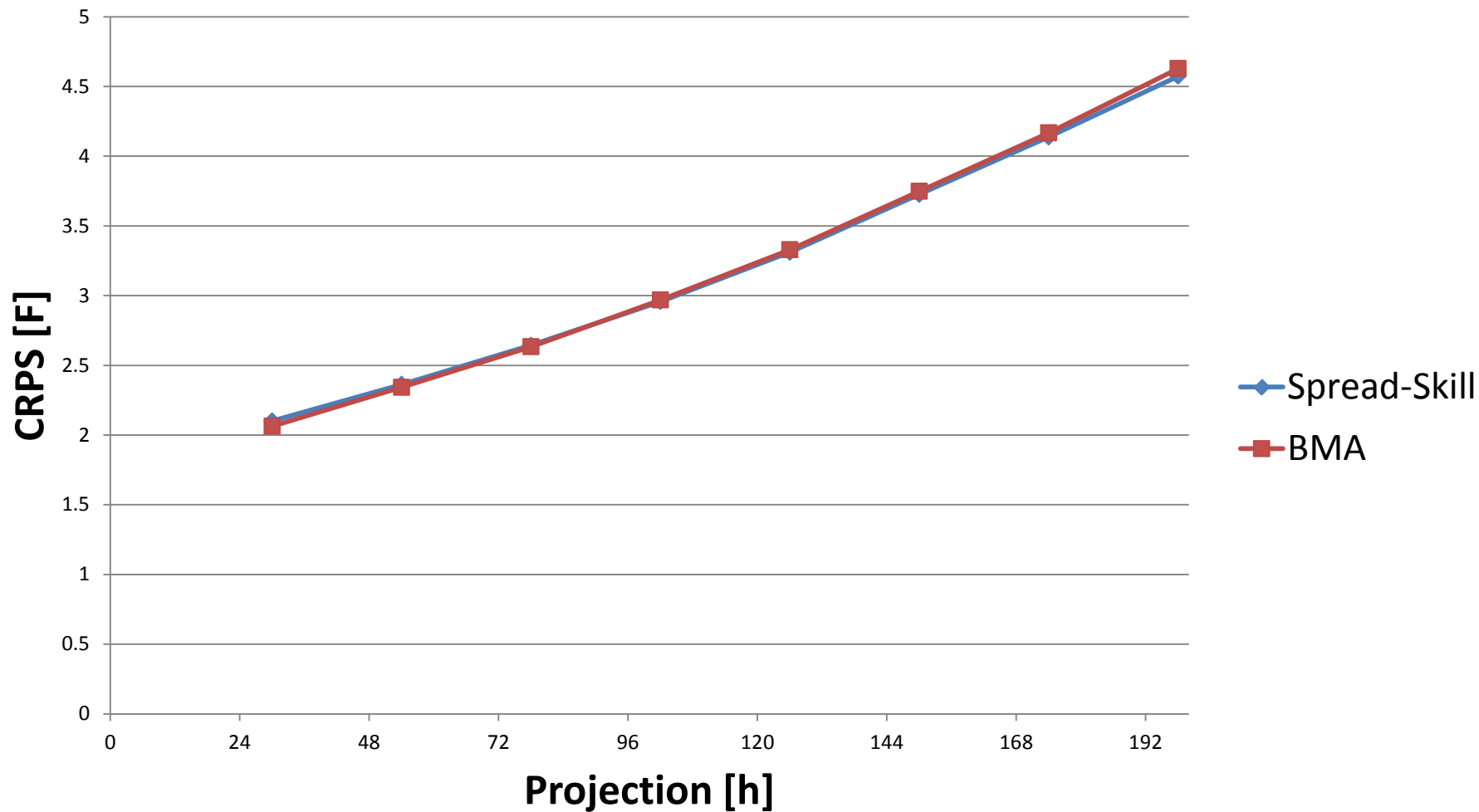
f_k is the ensemble-member forecast

σ is the predictive variance

- Raftery et al. (2005) estimated parameters with the Expectation Maximization Algorithm (Dempster et al., 1977).

Example NAEFS Application

Max T, CRPS, Cool Season, 4 Years Cross Validated



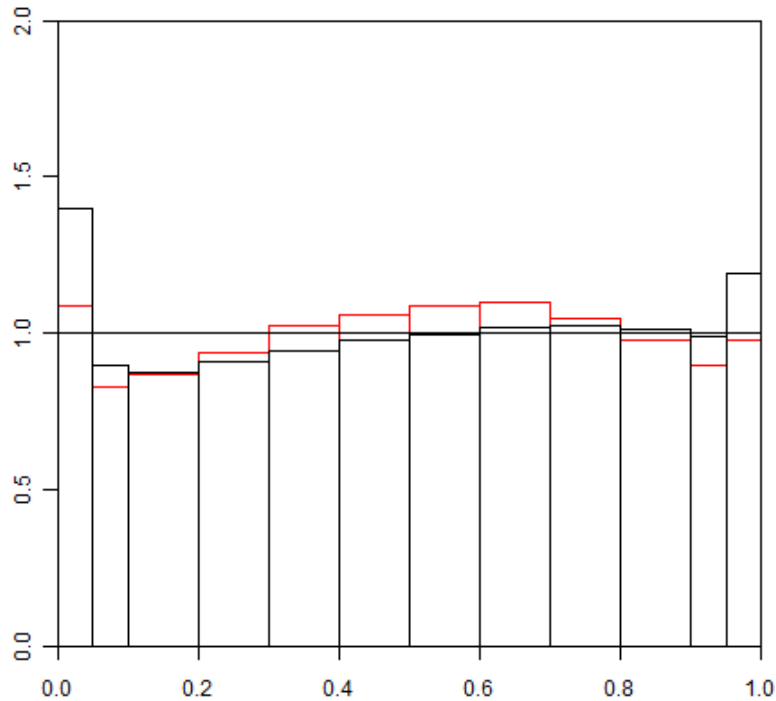
Example NAEFS Application

Spread-Skill

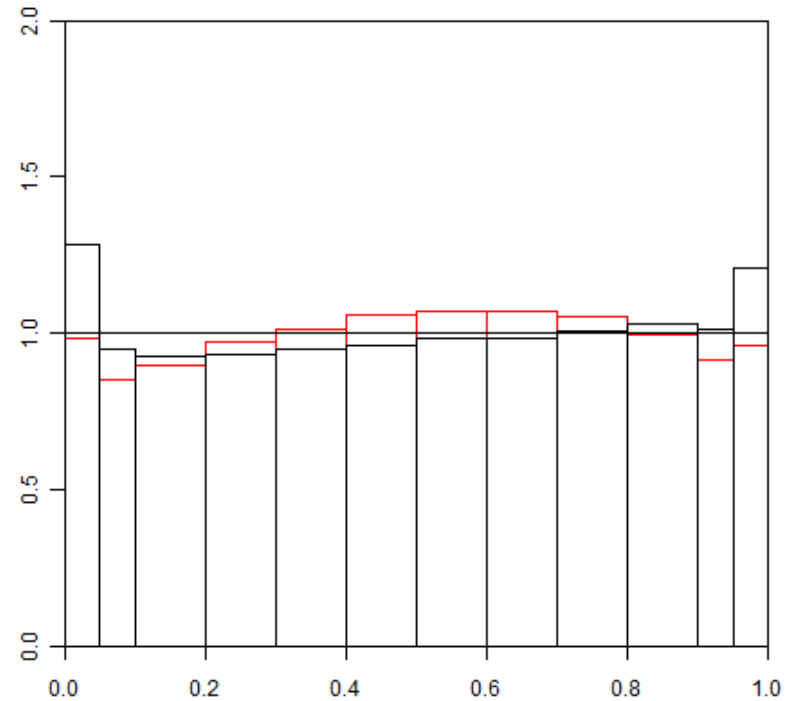
BMA

Max T, Cool Season, 4 Years,
Cross Validated

78-hr Projection Cool Season



126-hr Projection Cool Season





Fitting the Statistical Model

- EM Algorithm
 - Iterative
 - Must keep entire training sample on hand
 - Prone to overfitting with small samples (Hamill 2007)
- Propose Decaying Average BMA
 - Estimate parameters with decaying averages rather than EM algorithm
 - Stable estimates
 - Less data storage
 - Results comparable to EM algorithm
 - Similar to NCEP's bias correction

Decaying Average BMA

- Use similar formulation to Raftery et al. (2005)
- Continuously update estimate of weights and predictive standard deviation as past forecasts verify
- Update is via a decaying average

$$\text{New Estimate} = (0.95 \times \text{Old Estimate}) + (0.05 \times \text{Latest Estimate})$$

Decaying Average BMA

- Issue a forecasts
 - For example, the 42 hour 2-m temperature forecast
- Wait for forecast to verify
 - Different projections verify at different times
- Pair forecast with its verifying observation
- Begin update process

Decaying Average BMA

- Two-step procedure
 - First update weights
 - Then update predictive standard error
- Going to demonstrate procedure for updating weights
 - Update for predictive error is similar

For one case, take member forecasts and observation, and compute...

$$z_k^j = \frac{w_k^{j-1} g(y^j | f_k^j, \sigma^{j-1})}{\sum_{i=1}^K w_i^{j-1} g(y^j | f_i^j, \sigma^{j-1})}$$

w_k^{j-1} Previous weight estimate for member k

$g(y_t | f_{kt}, \sigma^{j-1})$ $N(f_k^j, \sigma^{j-1})$ evaluated at observation y_t .

k Ensemble Member

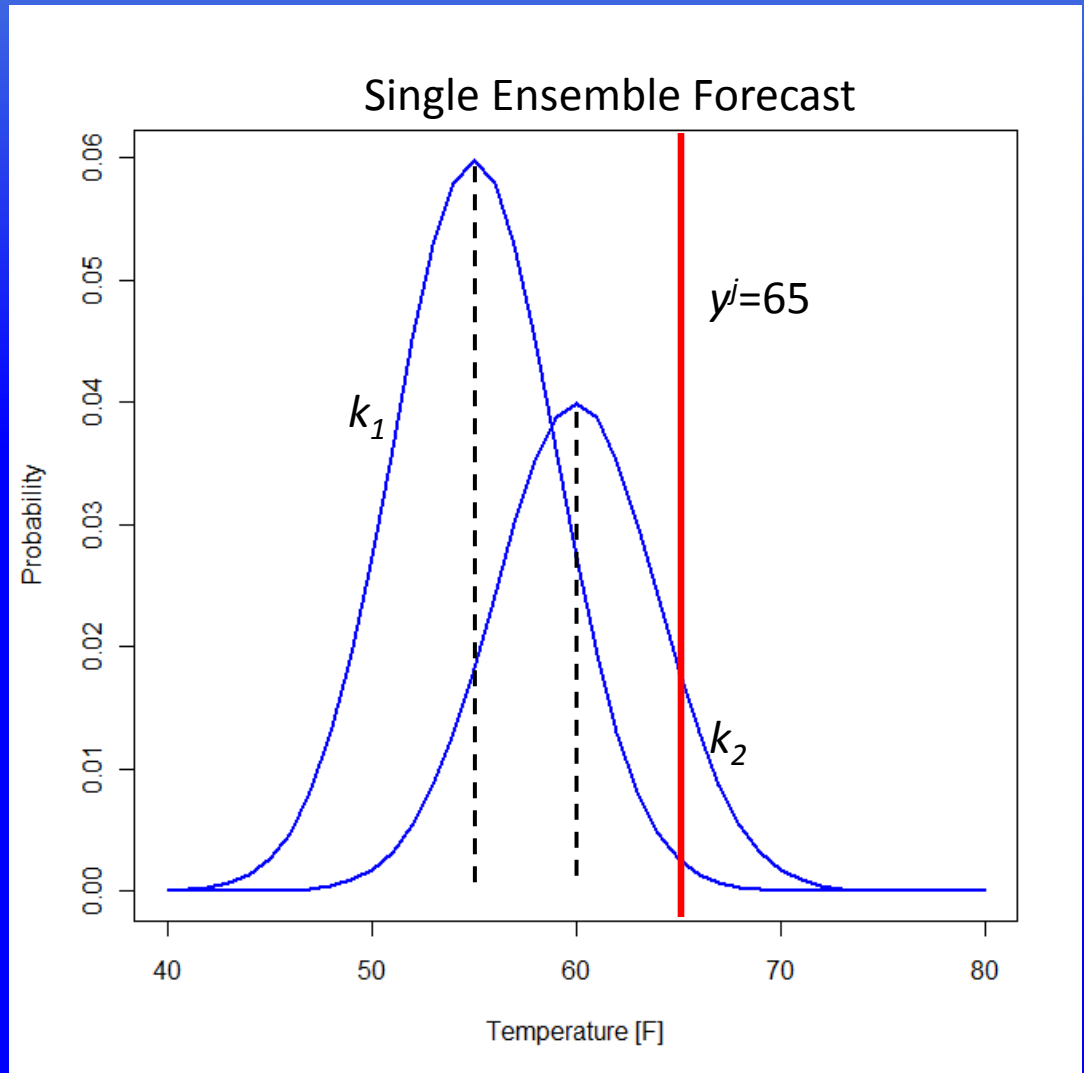
j Current day being verified

y_j Observation

Example Z calculation

$$z_k^j = \frac{w_k^{j-1} g(y^j | f_k^j, \sigma^{j-1})}{\sum_{i=1}^K w_i^{j-1} g(y^j | f_i^j, \sigma^{j-1})}$$

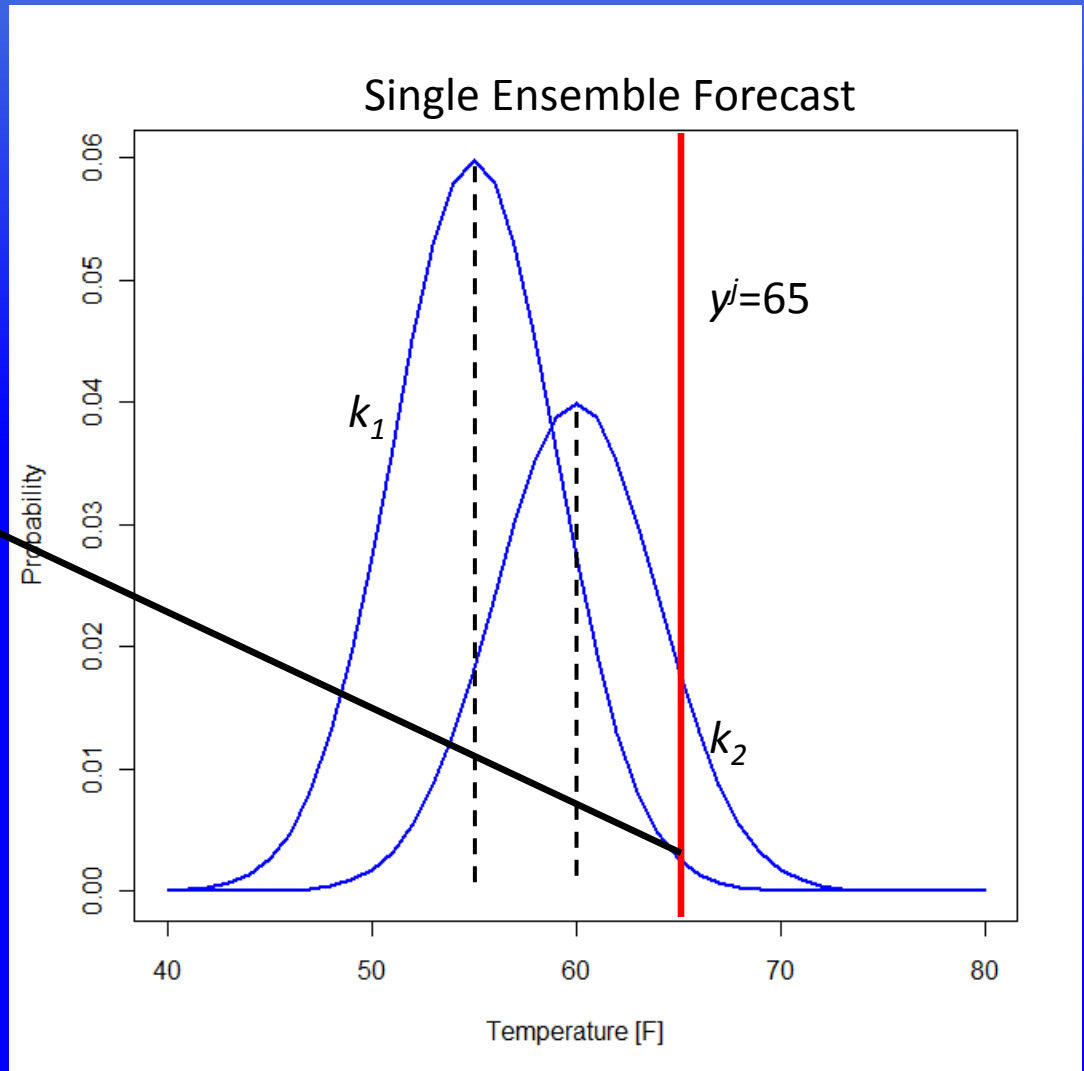
$$z_1^j = \frac{0.005}{0.005 + 0.020}$$



Example Z calculation

$$z_k^j = \frac{w_k^{j-1} g(y^j | f_k^j, \sigma^{j-1})}{\sum_{i=1}^K w_i^{j-1} g(y^j | f_i^j, \sigma^{j-1})}$$

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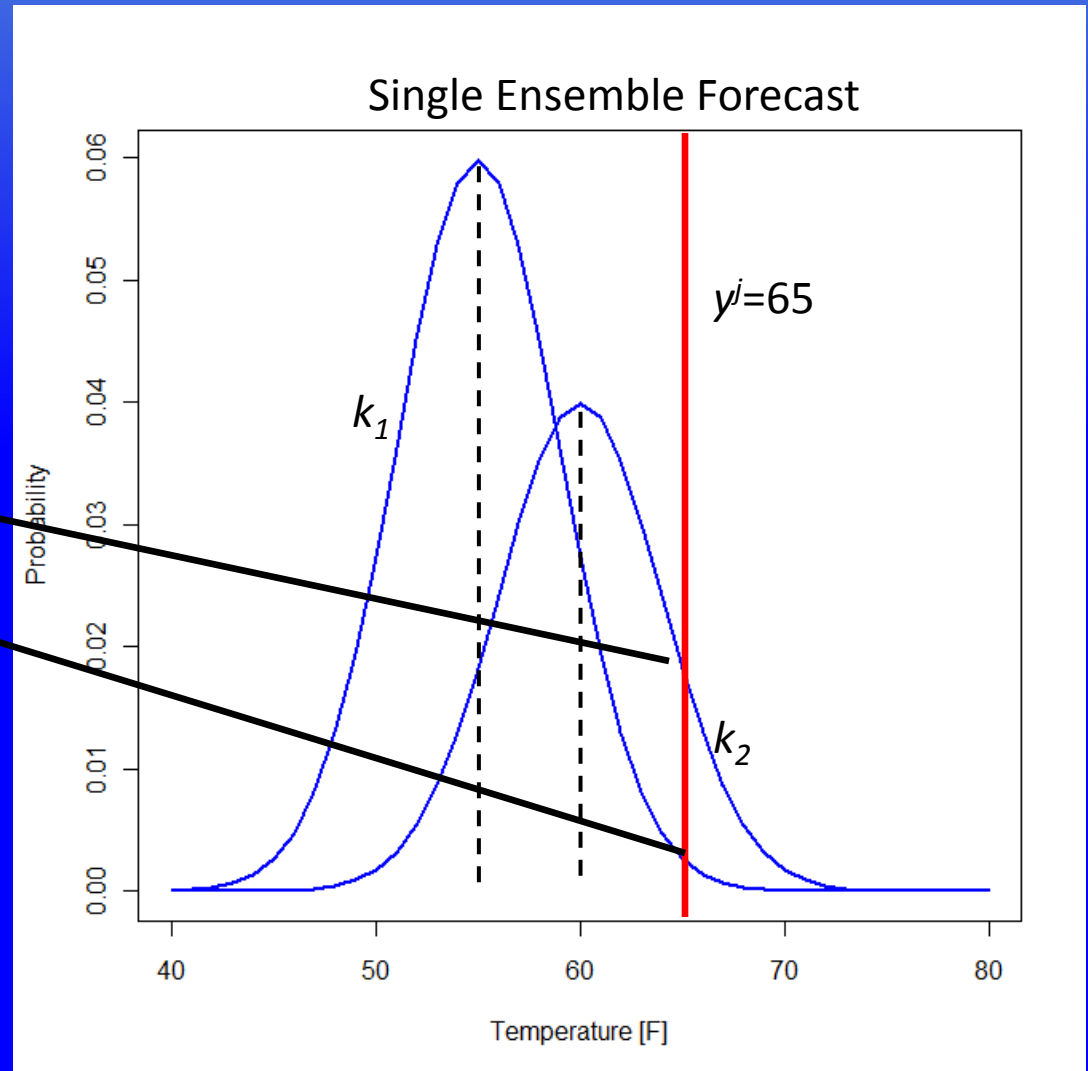


Example Z calculation

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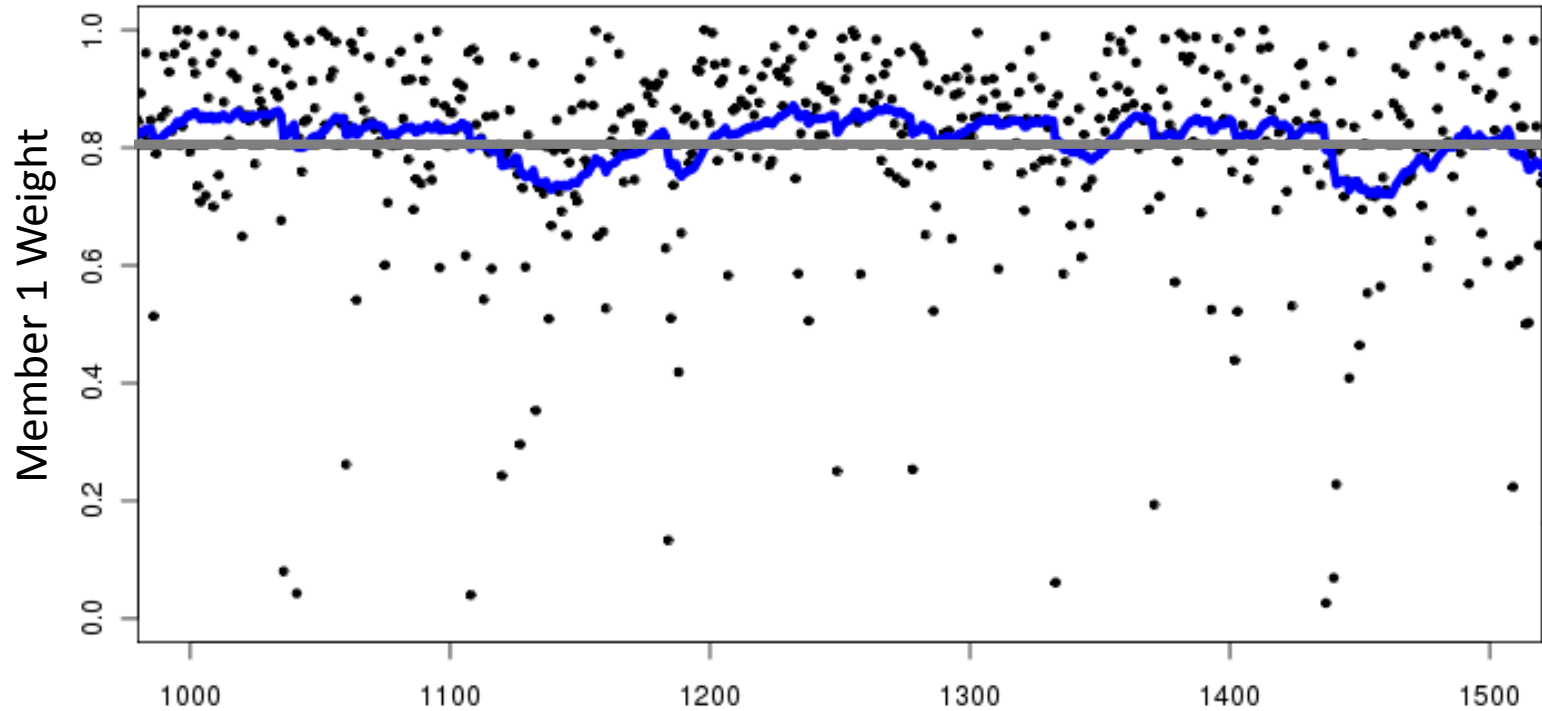
$$z_1^j = \frac{0.005}{0.005 + 0.020}$$

$$z_1^j = 0.2$$



Decaying Average BMA Example

Hypothetical 2 member ensemble



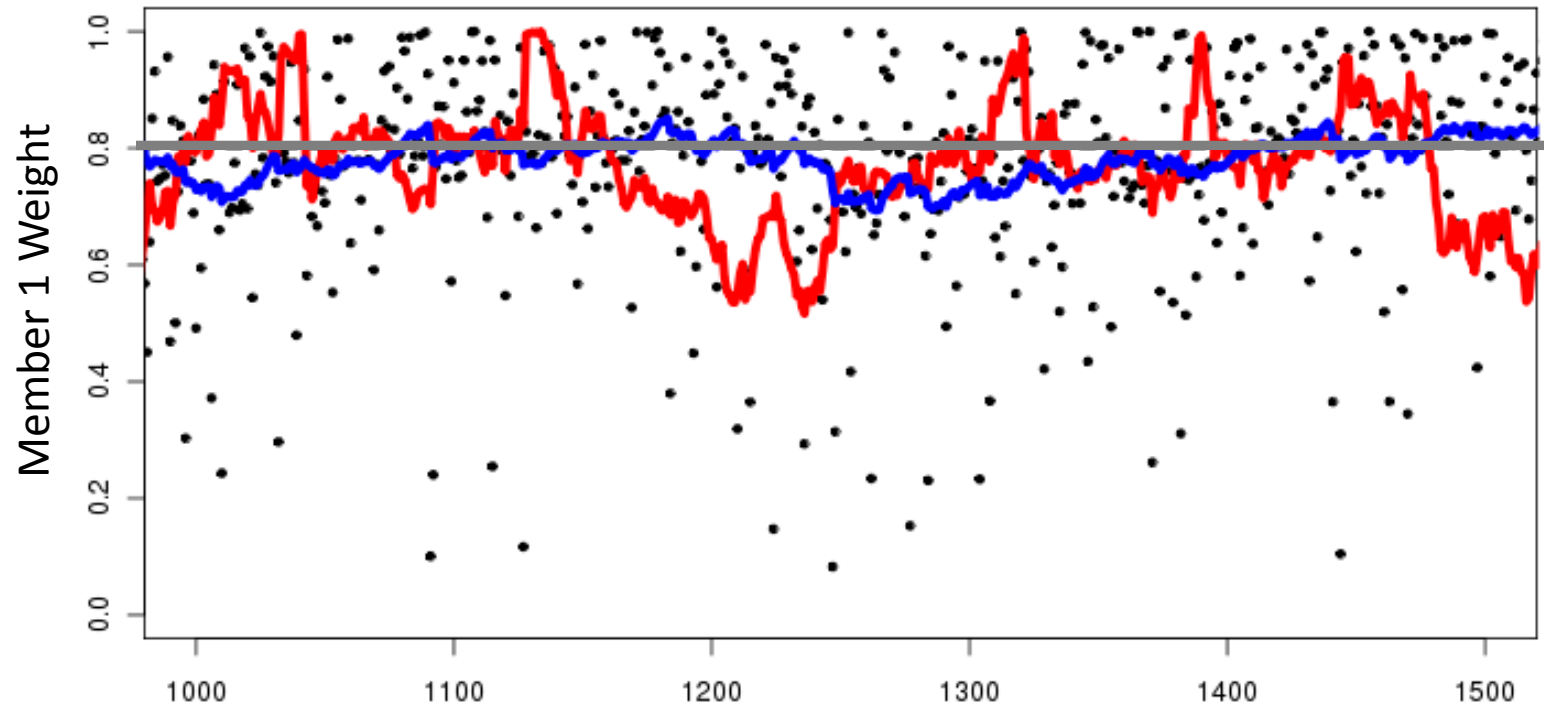
• Single z Value

Day in Sample

— Decaying Average ($\alpha = 0.05$)

Comparison with Raftery's BMA

Hypothetical 2 member ensemble



- Single z Value
- Decaying Average ($\alpha = 0.05$)
- EM Algorithm (50 days)

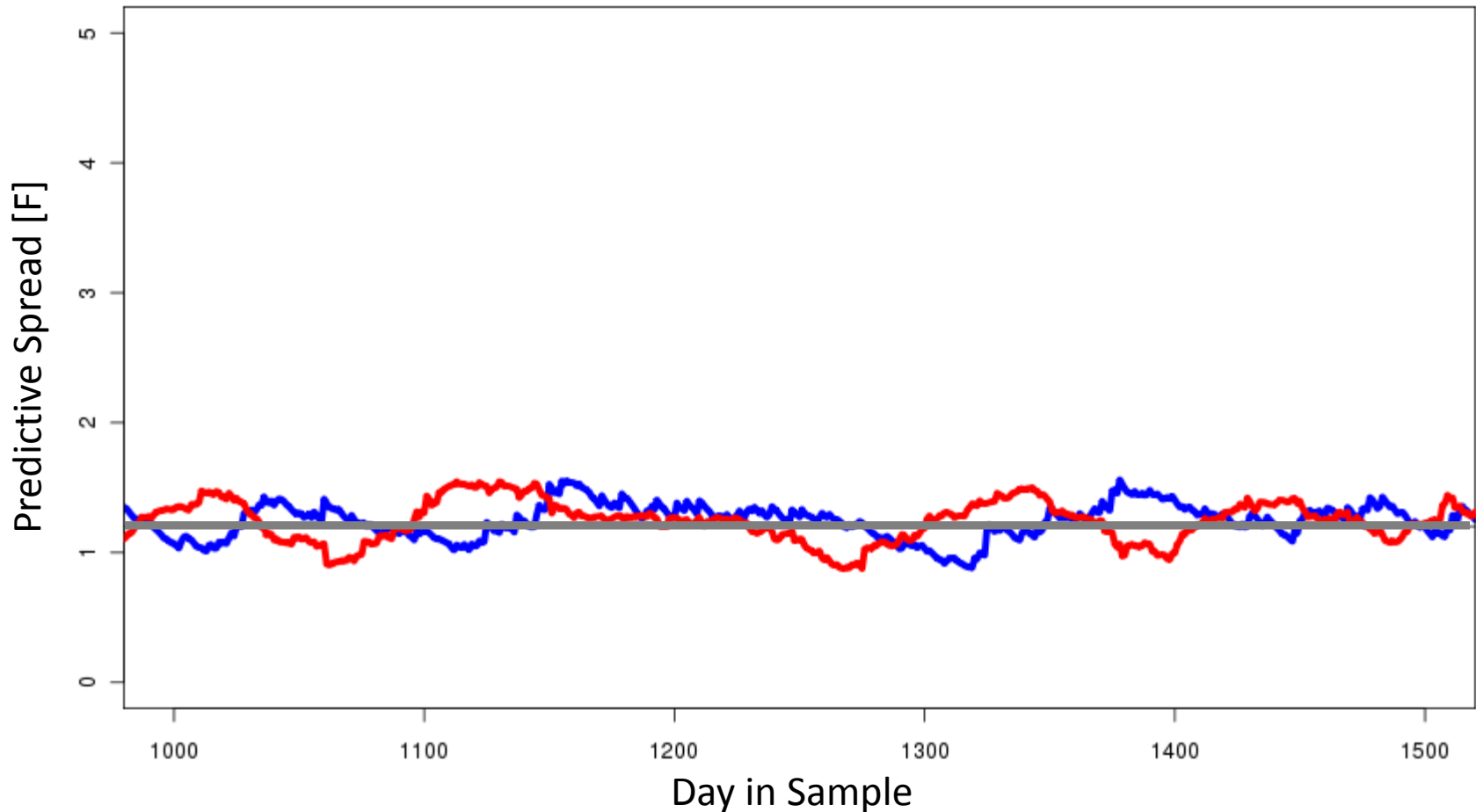
Decaying Average BMA Spread

- With today's z_k^j values compute

$$s^{2(j)} = \sum_{k=1}^K z_k^j (y^i - f_k^j)^2$$

k	Ensemble Member
j	Current day being verified
y_j	Observation
f_j	Ensemble Member Forecast k

Comparison with Raftery's BMA



- Decaying Average ($\alpha = 0.05$)
- EM Algorithm (50 days)

Conclusions

- Propose to use Decaying Average BMA
 - Stable parameter estimates
 - Less data storage (~3 days)
 - Avoids iterative algorithm
 - Results asymptotically similar to EM algorithm
- SREF
 - 21 members – 3 distinct models
 - 7 member sub-ensembles -> 3 weights, 1 standard deviation