

Jarad Niemi  
PhD Candidate  
Statistical Science  
Duke University



# Adaptive mixture filtering: an alternative to particle filtering?

Mike West  
Professor  
Statistical Science  
Duke University



## The Goal:

- Analytically approximate the filtering distributions of non-linear, non-Gaussian state space models

## The Procedure:

(all distributions conditioned on  $y_{1:t-1}$ )

- Assume filtered posterior

$$p(x_{t-1}) = \sum_{j=1}^J p_{t-1,j} f(\theta_{t-1,j})$$

- Approximate the joint

- by propagating posterior through the evolution equation

$$p(x_t, x_{t-1}) \approx \sum_{j=1}^J p_{t-1,j} p(x_t | \theta_{t-1,j}) f(\theta_{t-1,j})$$

- Extract and regenerate the prior

- component means are spread out
- component variances are small

$$p(x_t) \approx \sum_{j=1}^J p_{t-1,j} f(\theta_{t,j}')$$

- Approximate the joint, extract predictive

- by propagating prior through the observation equation

$$p(y_t, x_t) \approx \sum_{j=1}^J p_{t-1,j} p(y_t | \theta_{t,j}') f(\theta_{t,j}')$$

$$p(y_t) \approx \sum_{j=1}^J p_{t-1,j} g(\phi_{t,j})$$

- Approximate the posterior

- adjust component probabilities

$$p(x_t | y_t) \approx \sum_{j=1}^J p'_{t,j} f(\theta_{t,j}')$$

- Regenerate the posterior

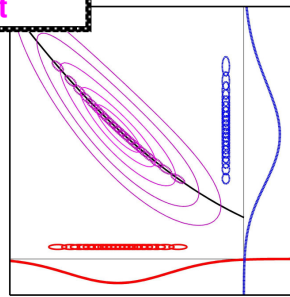
- component probabilities are equal
- component means are spread out
- component variances are small

$$p(x_t | y_t) \approx \sum_{j=1}^J p_{t,j} f(\theta_{t,j})$$

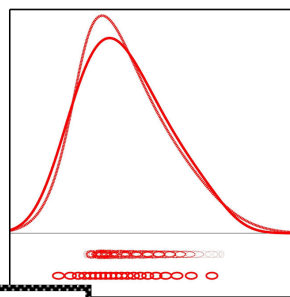
## A non-linear Gaussian example:

$$\begin{aligned} y_t &= f_t(x_t) + \nu_t & \nu_t &\sim N(0, V_t) \\ x_t &= g_t(x_{t-1}) + \omega_t & \omega_t &\sim N(0, W_t) \\ x_0 &= \sum_{j=1}^J p_{0,j} N(m_{0,j}, C_{0,j}) \end{aligned}$$

Approximate  
the joint

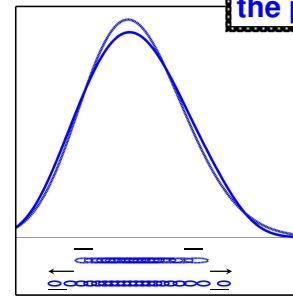


$$p(x_{t-1} | y_{1:t-1})$$

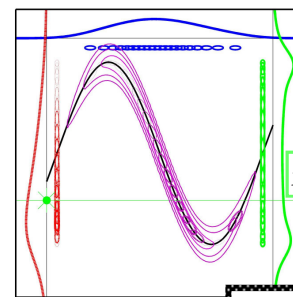


Regenerate  
the posterior

Regenerate  
the prior



$$p(x_t | y_{1:t-1})$$



Extract  
predictive

$$p(y_t | y_{1:t-1})$$

## vs particle filtering:

$$f_t(x) = x$$

$$g_t(x) = x$$

$$V = 0.1$$

$$W = 0.1$$

$$p(x_0) \sim N(0, 1)$$

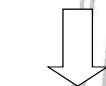
$$f_t(x) = x^2$$

$$g_t(x) = x - .2 \operatorname{atan}(x)$$

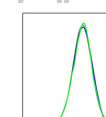
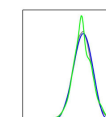
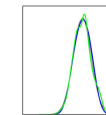
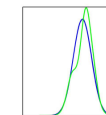
$$V = 0.1$$

$$W = 0.1$$

$$p(x_0) \sim N(0, 1)$$



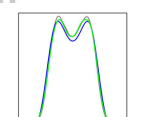
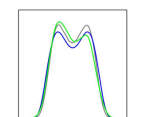
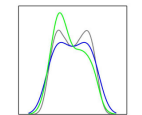
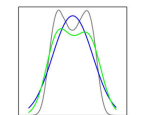
PF



increasing # of  
particles and  
components  
with equal  
computation  
times



PF (1e6 particles)



## References:

- Niemi, J.B. and West, Mike (2008) "Adaptive mixture modelling Metropolis methods for Bayesian analysis of non-linear state-space models." *Discussion Paper 08-21, Department of Statistical Science, Duke University*
- Harrison, P. and Stevens, C. (1971), "A Bayesian approach to short-term forecasting," *Operations Research Quarterly*, 22, 341-362.
- Alspach, D. L. and Sorenson, H. W. (1972), "Non-linear Bayesian estimation using Gaussian sum approximations," *IEEE Transactions on Automatic Control*, AC-17, 439-448.