

Ensemble Kalman Filter (EnKF)

This week you have been hearing about some techniques for combining data and model predictions to obtain an optimal estimate of the true state of a physical system. In particular we have been considering the following

Best estimate x^a

True Physics: $x_{k+1} = f(x_k) + w_k$ $x_k, w_k \in \mathbb{R}^n$ unknown physics

Model: $x_{k+1}^f = f(x_k^f)$ $x_k^f \in \mathbb{R}^n$

Measurements: $y_k = h(x_k) + z_k$ $y_k, z_k \in \mathbb{R}^m$ R

Here $f(x)$ drives the dynamics of our system and $h(x)$ is a function which takes our state space to our measurement space. Further w_k, z_k are assumed to be uncorrelated stationary zero-mean white noise (Gaussian) processes with covariance matrices given by Q_k and R_k respectively.

What is the best estimate?

$e = (x - x^f)$ $x^a = \min_x E[\text{Tr}(ee^T)]$ $\vec{x} = [x, y, z]$

$x^a = \min_x E[(x - x^f)^2 + (y - y^f)^2 + (z - z^f)^2]$

You have seen in the videos and worked out in the worksheets that when f and h are linear,

$f(x_k) = A_k x_k$ matrix

$h(x_k) = H_k x_k$ matrix

That the optimal estimate of the true state and the error at step k is given by:

$x_k^a = x_k^f + K(y_k^0 - H x_k^f)$ where $K_k = B_k^f H^T (H B_k^f H^T + R)^{-1}$

$B_k^a = B_k^f - K_k H B_k^f$

Here B_k^f is the error covariance we were minimizing the trace of!

$B_k^f = E[(x_k - x_k^f)(x_k - x_k^f)^T]$

$B_k^a = E[(x_k - x_k^a)(x_k - x_k^a)^T]$

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Prediction Step

$$x_{k+1}^f = A_k x_k^a$$

$$B_{k+1}^f = A_k B_k^f A_k^T + Q_k \text{ (Ricatti Equation)}$$

$$B_k^f = E[(x_k - x_k^f)(x_k - x_k^f)^T]$$

$$B_{xyk}^f = E[(x_k - x_k^f)(y_k - y_k^f)^T] = B_k^f H_k^T$$

$$B_{yyk}^f = E[(y_k - y_k^f)(y_k - y_k^f)^T] = H_k B_k^f (B_k^f)^T + R_k = E[(x_k - x_k^f)(x_k - x_k^f)^T] H_k^T H_k$$

Update Step

$$K_k = B_k^f H_k^T (H_k B_k^f H_k^T + R_k)^{-1}$$

$$x_k^a = x_k^f + K(y_k^0 - H x_k^f)$$

$$B_k^a = B_k^f - K_k H_k B_k^f$$

With these definitions we can rewrite the Kalman Gain Matrix as

$$K_k = B_{xyk}^f (B_{yyk}^f)^{-1}$$

This is all well and good provided our dynamics and operation operators are linear, what if they are not?

One very common approach is just to linearize them, for example the matrix A_k can just be taken to be the Jacobian of f at time step k , however if you have lots of variables, often the case for most real applications, this can be prohibitively computationally expensive. That linearization scheme is often referred to as the Extended Kalman Filter (EKF).

Another approach to dealing with nonlinear dynamics is through the Ensemble Kalman Filter (EnKF).

This approach is centered on approximating B_k^f , B_{xyk}^f , and B_{yyk}^f through a clever perturbation and averaging scheme. The basic scheme is outlined below.

1. From a series of perturbed forecasts $\{x_k^{fi}\}$ calculate the mean \bar{x}_k^f create the Error matrix:

$$E_k^f = [x_k^{f1} - \bar{x}_k^f, \dots, x_k^{fN} - \bar{x}_k^f]$$

2. Using the forecasts and that $y_k^f = h_k x_k^f$ create the observation error matrix

$$E_{yk}^f = [y_k^{f1} - \bar{y}_k^f, \dots, y_k^{fN} - \bar{y}_k^f]$$

3. Then estimate the needed covariance matrices as,

$$B_k^f \approx \hat{B}_k^f = \frac{1}{N-1} E_k^f (E_k^f)^T \quad B_{xyk}^f \approx \hat{B}_{xyk}^f = \frac{1}{N-1} E_{yk}^f (E_k^f)^T \quad B_{yyk}^f \approx \hat{B}_{yyk}^f = \frac{1}{N-1} E_{yk}^f (E_{yk}^f)^T$$

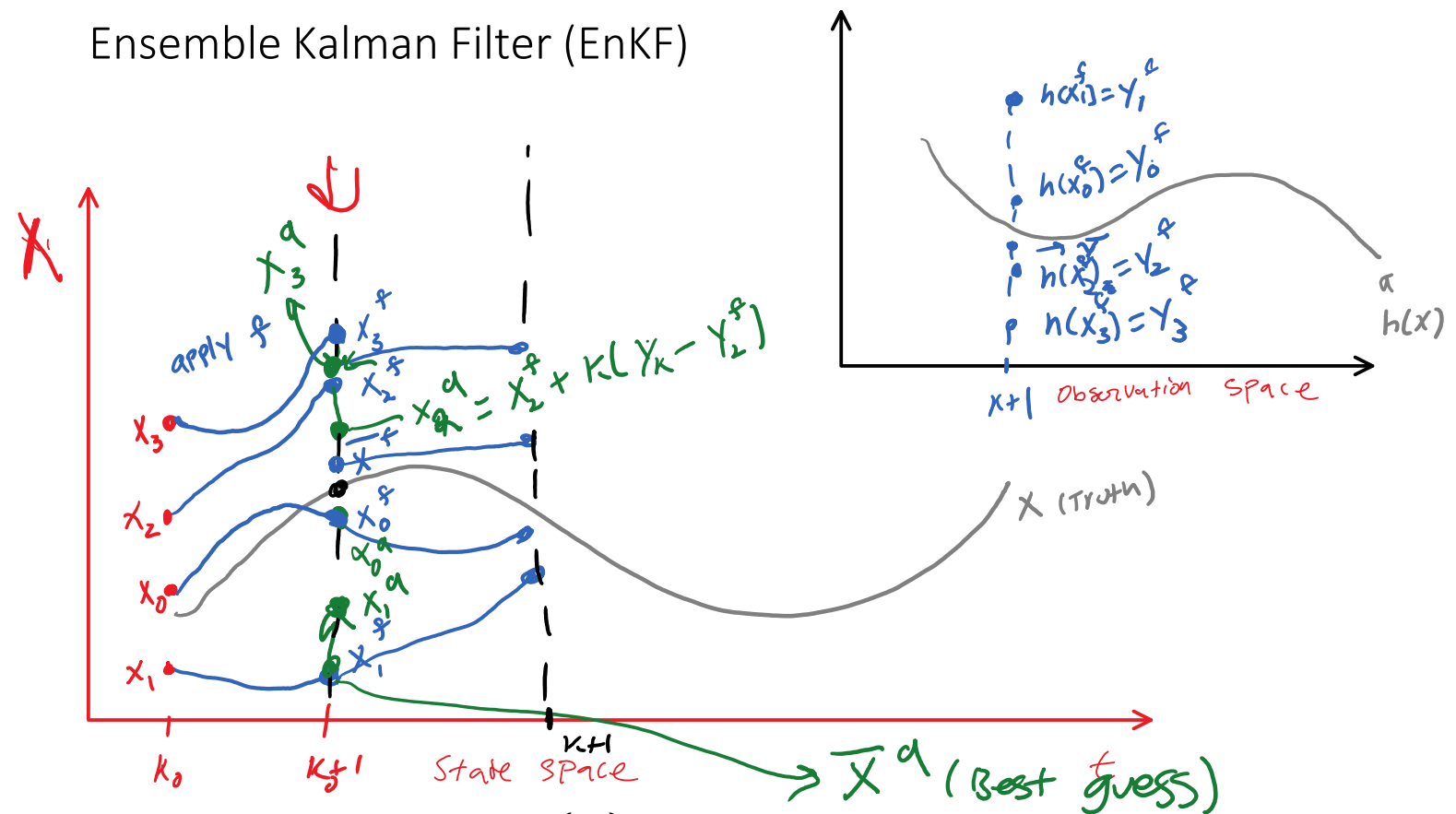
4. Next perform N parallel data assimilation steps on each member of the forecast ensemble.

$$x_k^{ai} = x_k^{fi} + \hat{K}_k (y_k^i - h(x_k^{fi})) \text{ where } \hat{K}_k = \hat{B}_{xyk}^f (\hat{B}_{yyk}^f)^{-1} \text{ and the observations perturbed as } y_k^i = y_k + z_k^i$$

5. Update the approximate error covariance as $\hat{B}_k^a = \frac{1}{N-1} E_k^a (E_k^a)^T$ where $E_k^a = [x_k^{a1} - \bar{x}_k^a, \dots, x_k^{aN} - \bar{x}_k^a]$

6. Evolve the ensemble of analysis vectors forward perturbed as $x_{k+1}^{fi} = f(x_k^{ai}) + w_k^i$ and then repeat!

Ensemble Kalman Filter (EnKF)



1. From a series of perturbed forecasts $\{x_k^{f,i}\}$ calculate the mean \bar{x}_k^f create the Error matrix :

$$E_k^f = [x_k^{f,1} - \bar{x}_k^f, \dots, x_k^{f,N} - \bar{x}_k^f]$$

2. Using the forecasts and that $y_k^f = h_k x_k^f$ create the observation error matrix

$$E_{y_k}^f = [y_k^{f,1} - \bar{y}_k^f, \dots, y_k^{f,N} - \bar{y}_k^f]$$

3. Then estimate the needed covariance matrices as,

$$B_k^f \approx \hat{B}_k^f = \frac{1}{N-1} E_k^f (E_k^f)^T \quad B_{yy_k}^f \approx \hat{B}_{yy_k}^f = \frac{1}{N-1} E_{y_k}^f (E_{y_k}^f)^T \quad B_{xy_k}^f \approx \hat{B}_{xy_k}^f = \frac{1}{N-1} E_k^f (E_{y_k}^f)^T$$

Next perform N parallel data assimilation steps on each member of the forecast ensemble.

$$x_k^{a,i} = x_k^{f,i} + \hat{K}_k (y_k^i - h(x_k^{f,i})) \text{ where } \hat{K}_k = \hat{B}_{xy_k}^f (\hat{B}_{yy_k}^f)^{-1} \text{ and the observations perturbed as } y_k^i = y_k + z_k^i$$

4. Update the approximate error covariance as,

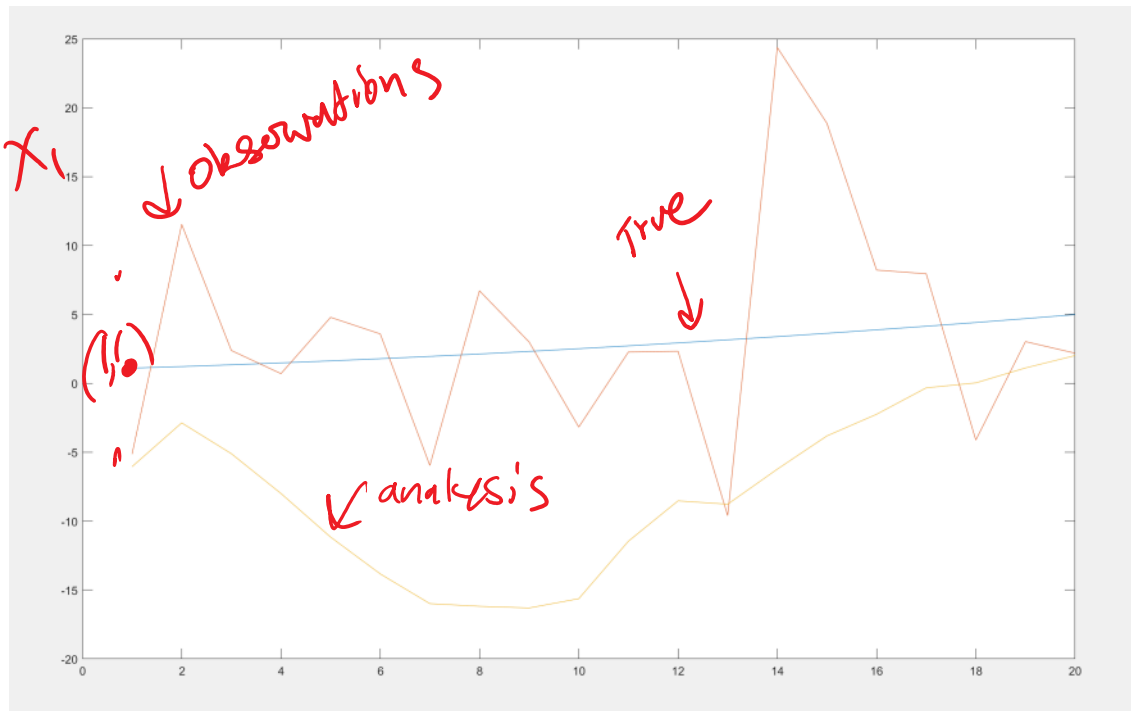
$$\hat{B}_k^a = \frac{1}{N-1} E_k^a (E_k^a)^T \text{ where } E_k^a = [x_k^{a,1} - \bar{x}_k^a, \dots, x_k^{a,N} - \bar{x}_k^a]$$

5. Evolve the ensemble of analysis vectors forward perturbed as

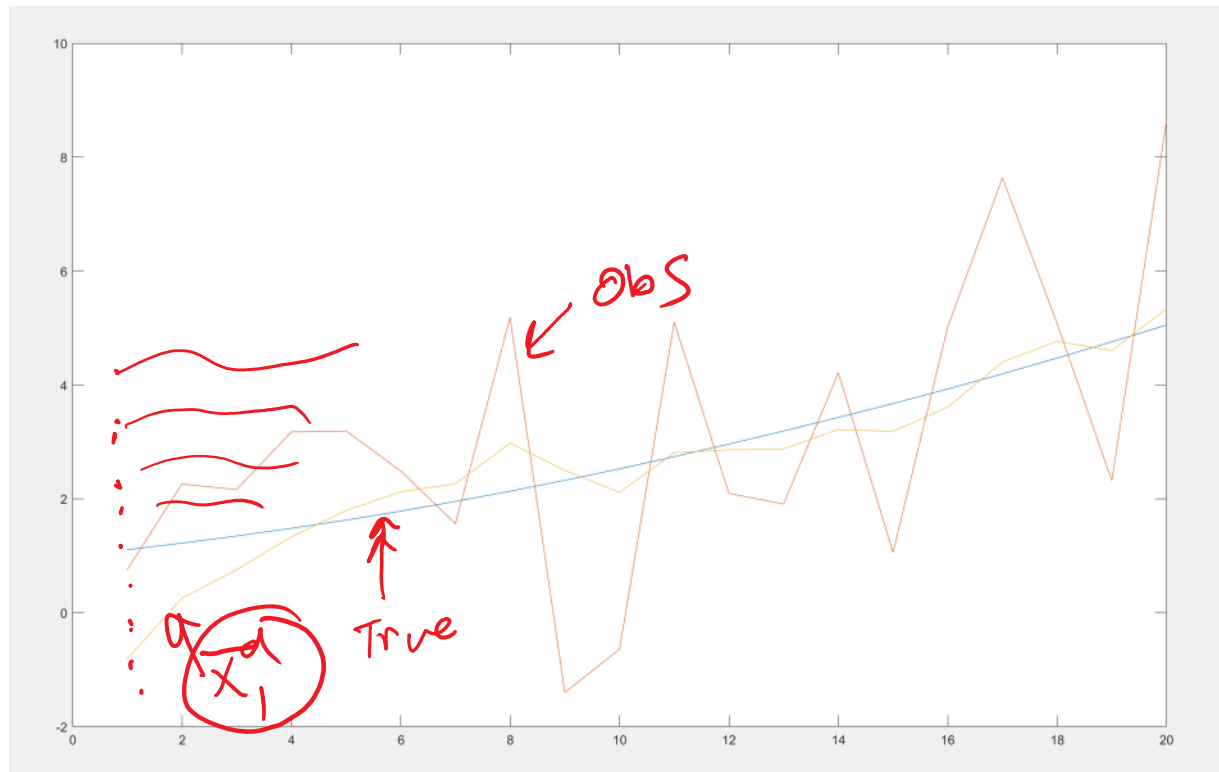
$$x_{k+1}^{f,i} = f(x_k^{a,i}) + w_k^i$$

and then repeat!

Ensemble Kalman Filter (EnKF)

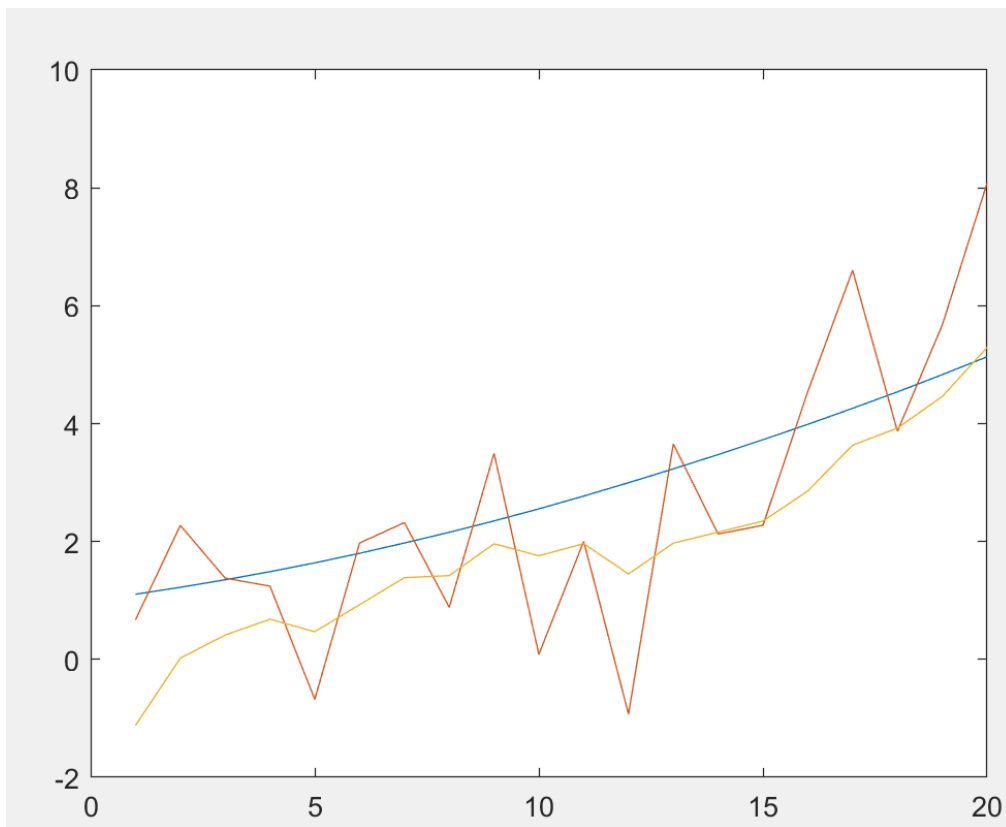


2 members
Initial condition STD 10

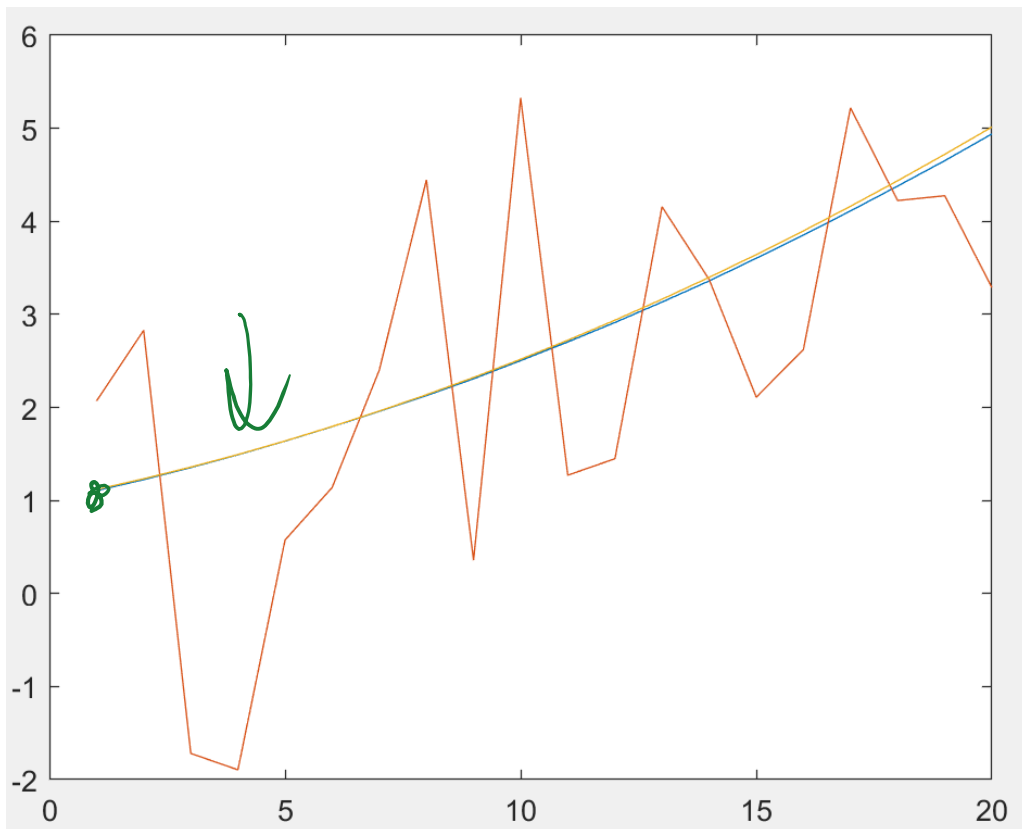


20 members initial
Condition STD 10

Ensemble Kalman Filter (EnKF)



50 members
Initial condition std 10



50 members
Initial condition std 0.1

