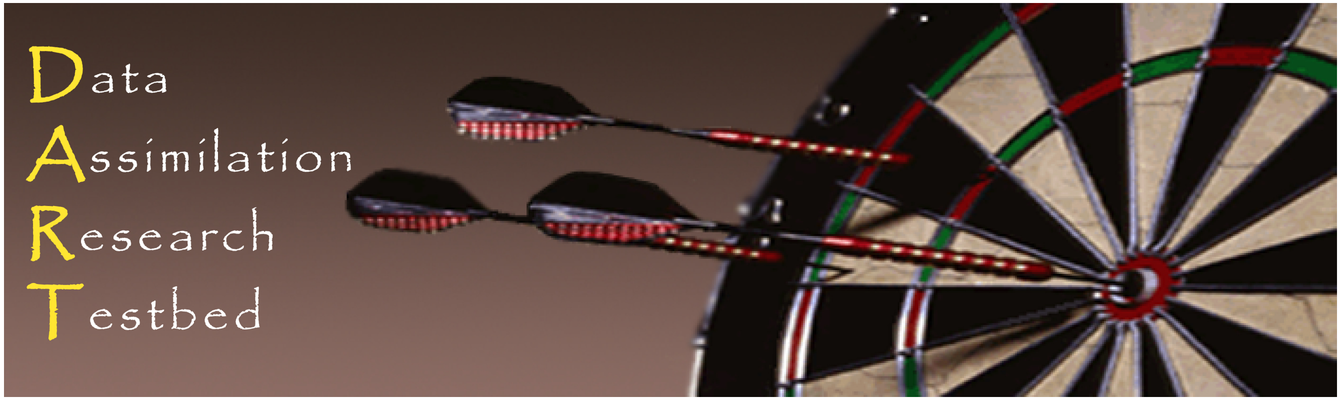
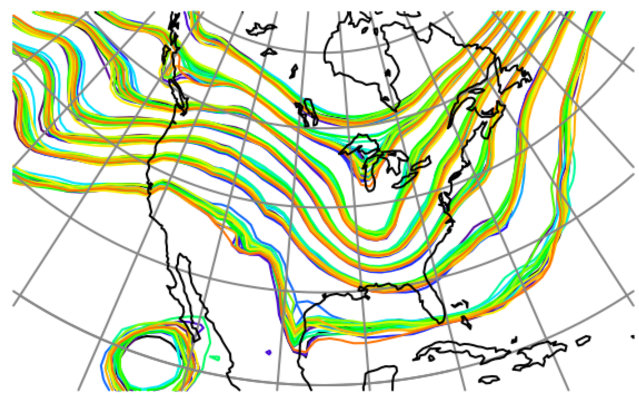


DART Tutorial Part II: How should observations impact an unobserved state variable? Multivariate assimilation.



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Single observed variable, single unobserved variable.

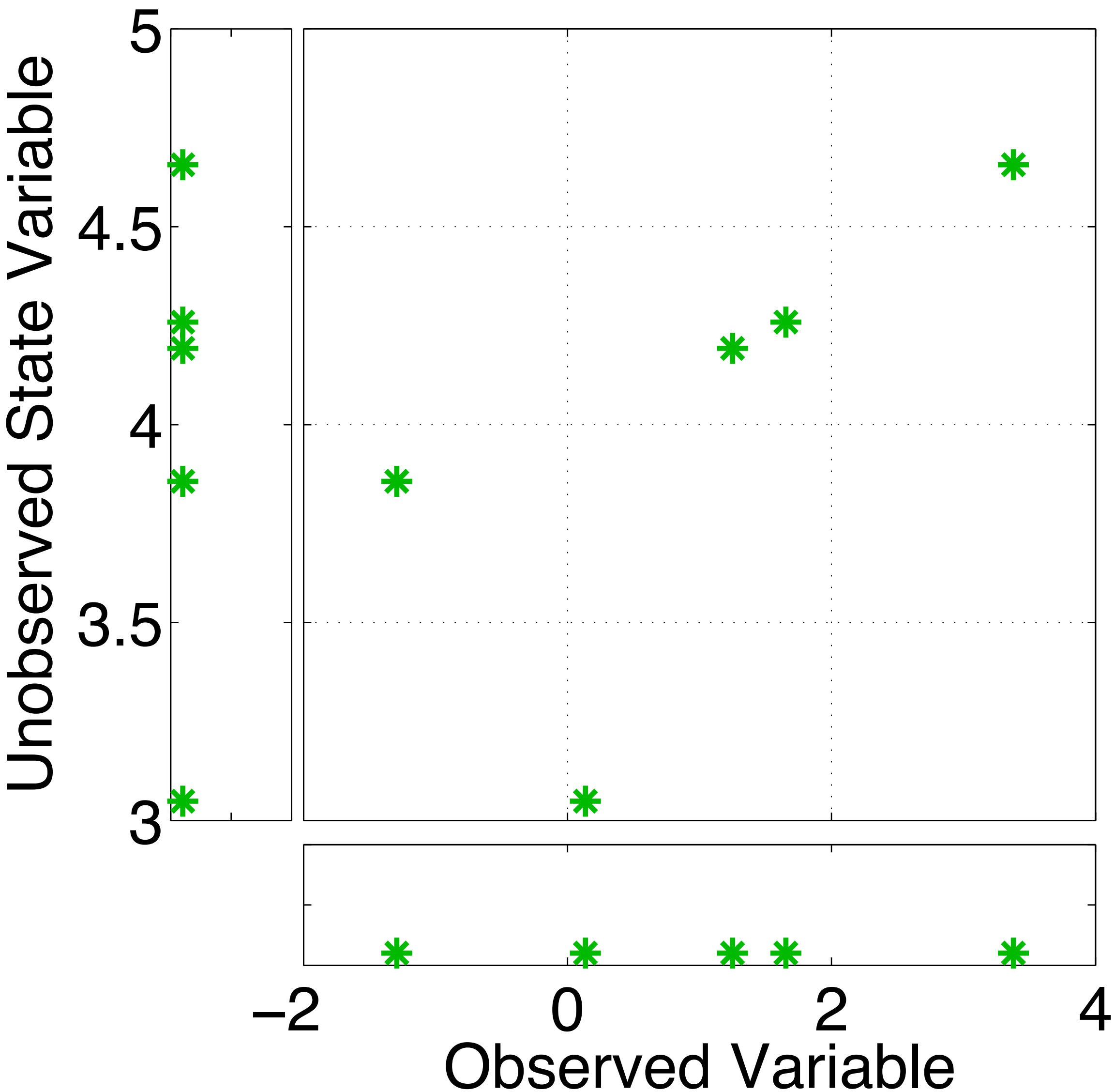
So far, have known observation likelihood for single variable.

Now, suppose prior has an additional variable.

Will examine how ensemble methods update additional variable.

Basic method generalizes to any number of additional variables.

Ensemble filters: Updating additional prior state variables

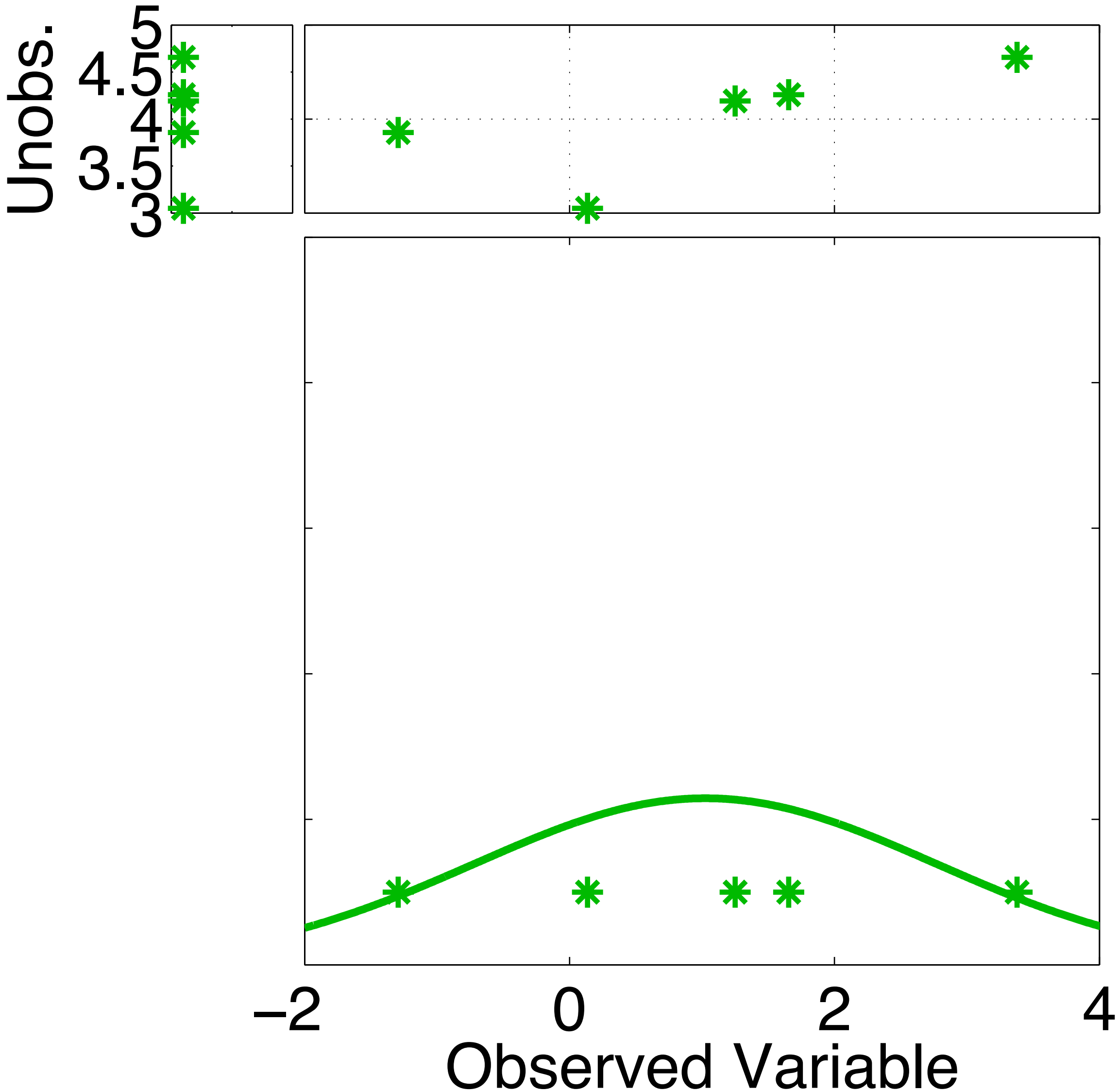


Assume that all we know is the prior joint distribution.

One variable is observed.

What should happen to the unobserved variable?

Ensemble filters: Updating additional prior state variables

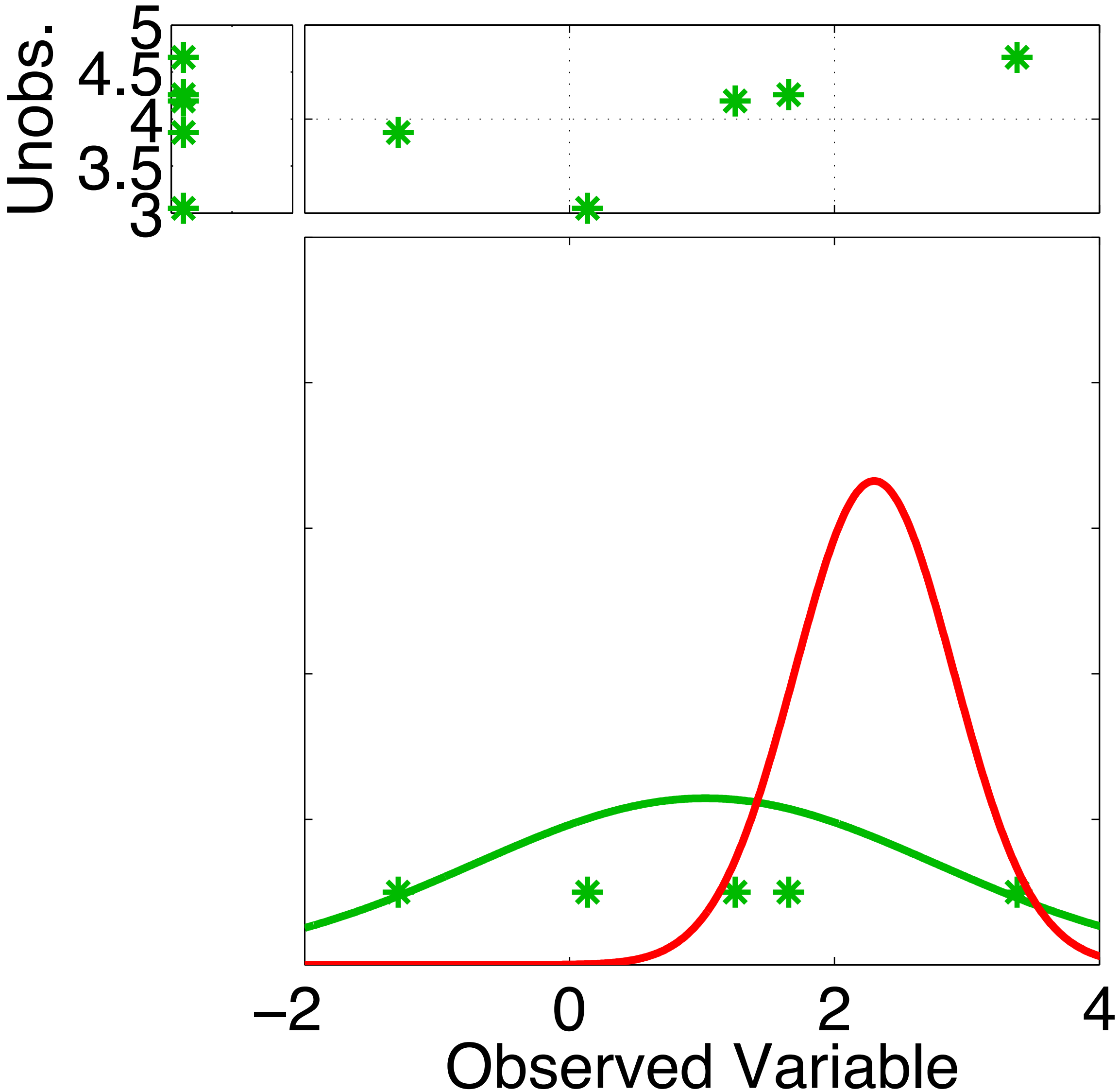


Assume that all we know is the prior joint distribution.

One variable is observed.

Update observed variable with one of the previous methods.

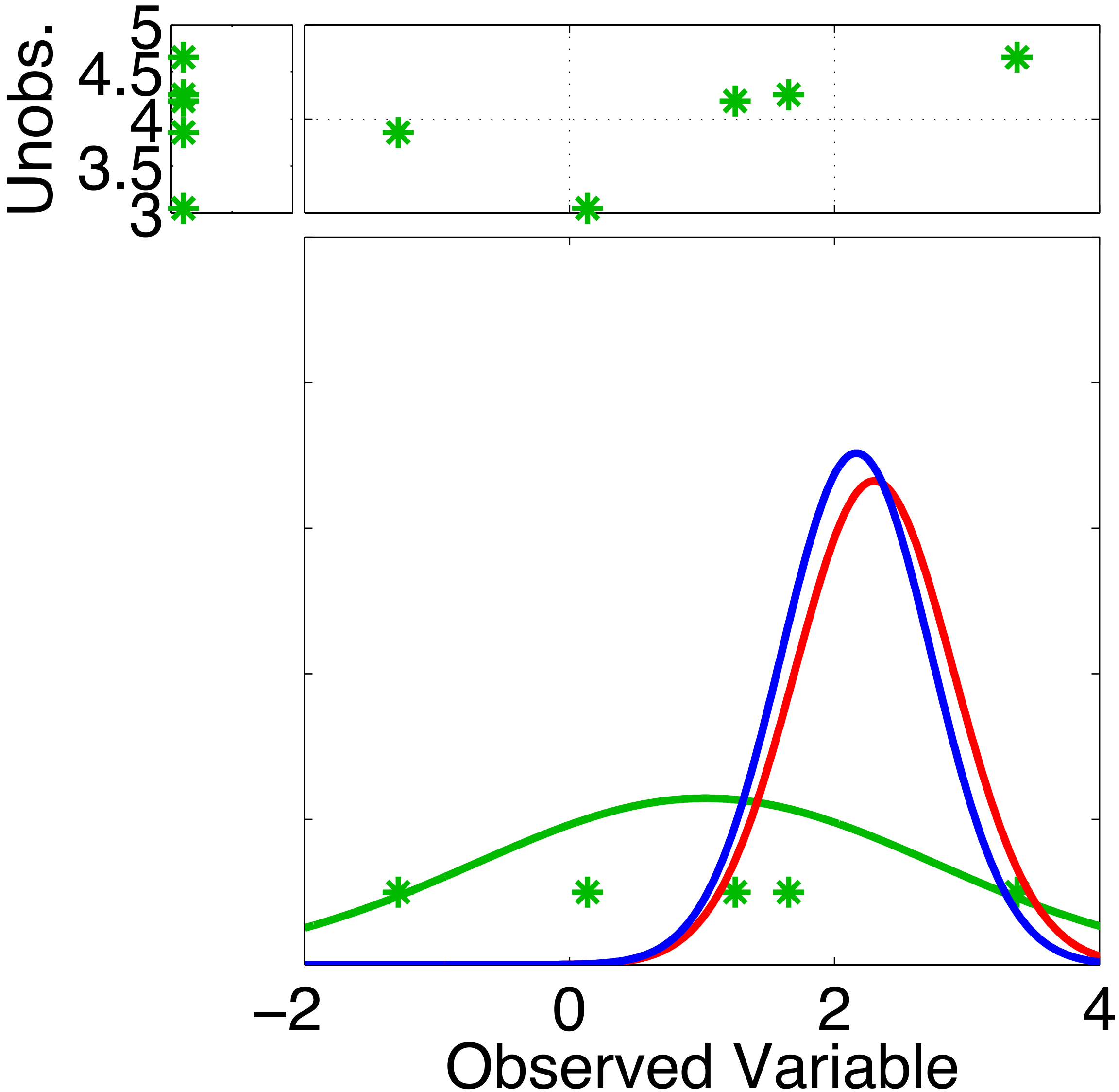
Ensemble filters: Updating additional prior state variables



Assume that all we know is the prior joint distribution. One variable is observed.

Update observed variable with one of the previous methods (here, the ensemble Kalman filter).

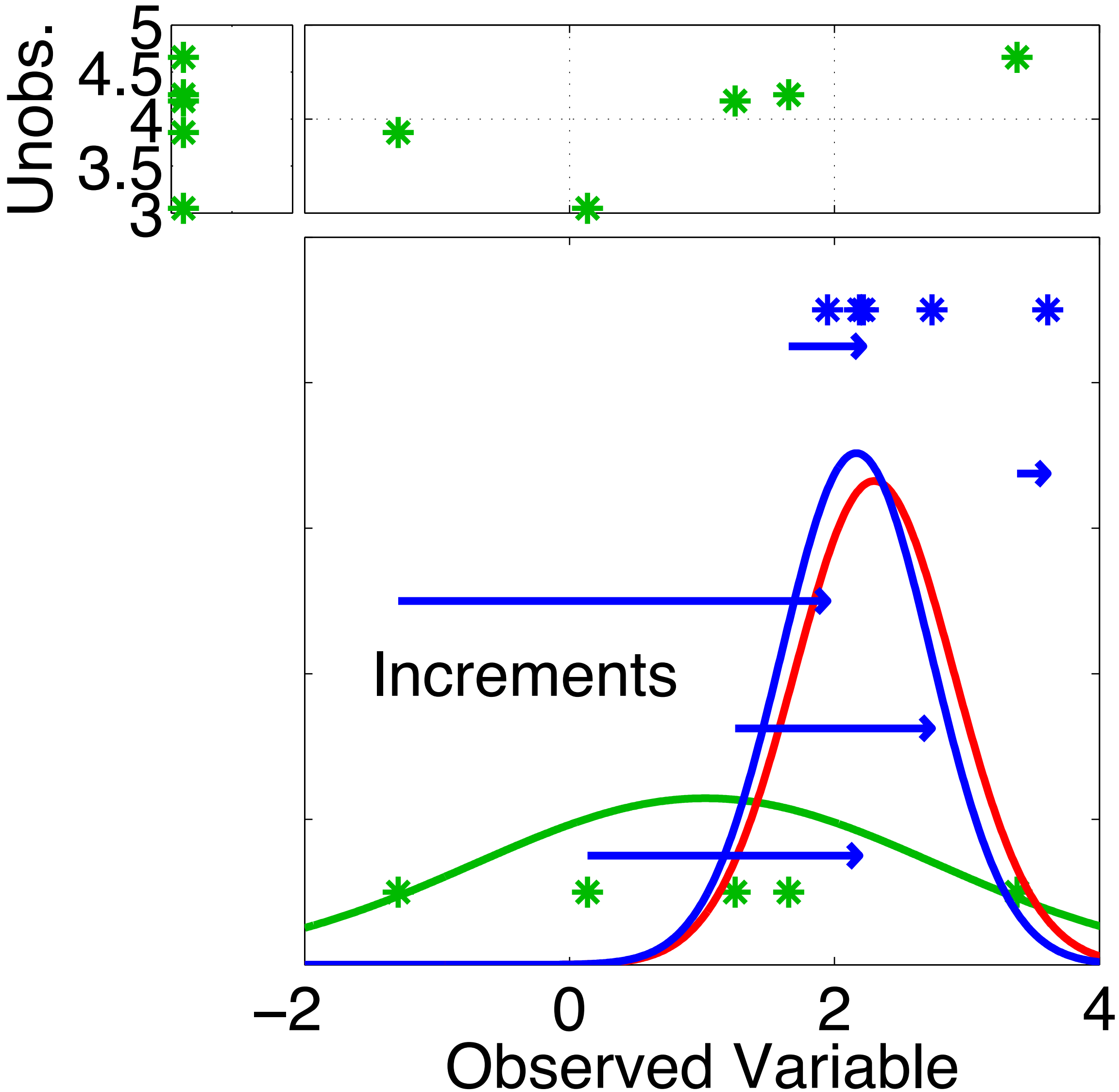
Ensemble filters: Updating additional prior state variables



Assume that all we know is the prior joint distribution. One variable is observed.

Update observed variable with one of the previous methods (here, the ensemble Kalman filter).

Ensemble filters: Updating additional prior state variables

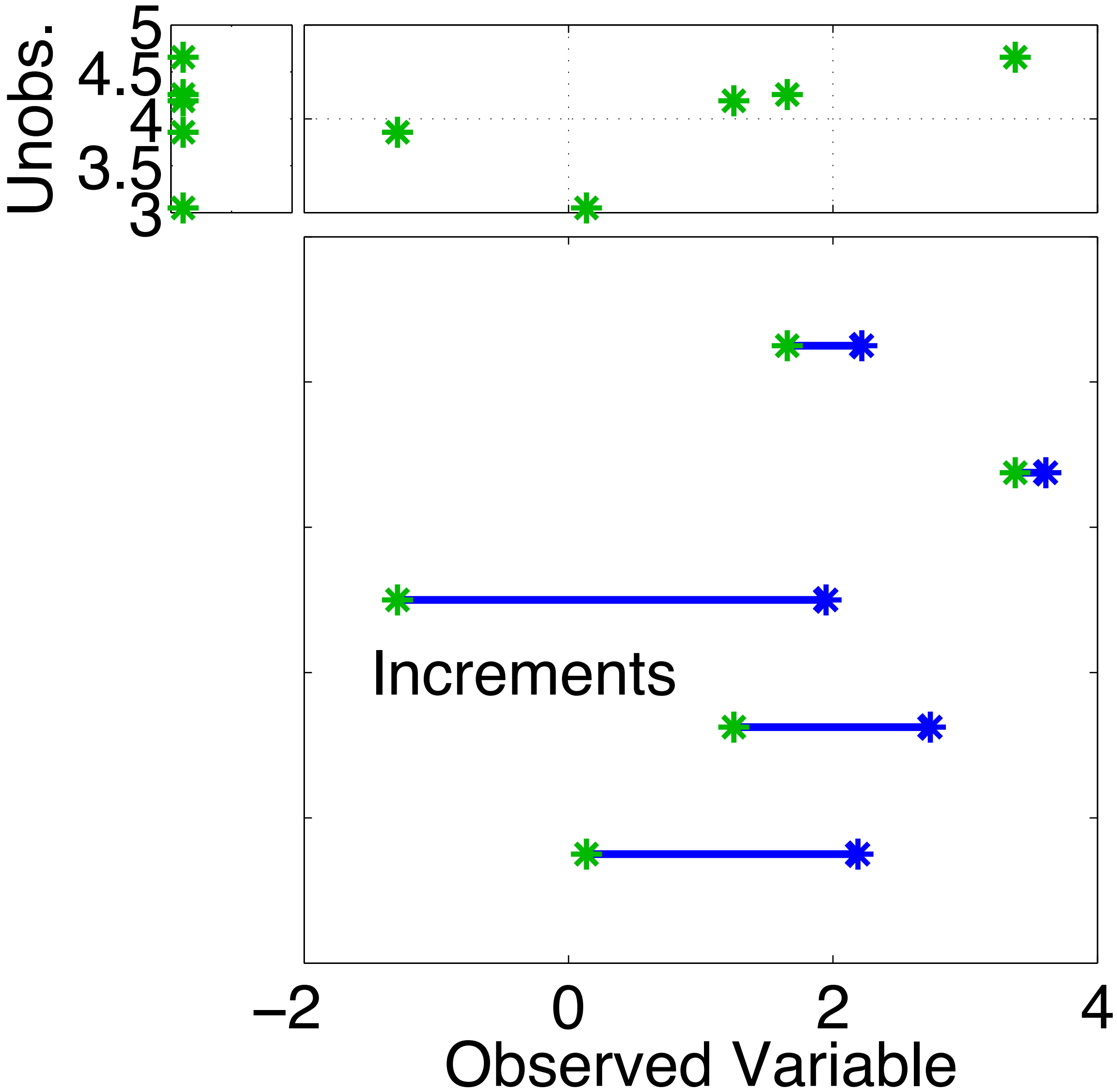


Assume that all we know is the prior joint distribution.

One variable is observed.

Compute *increments* for prior ensemble members of observed variable.

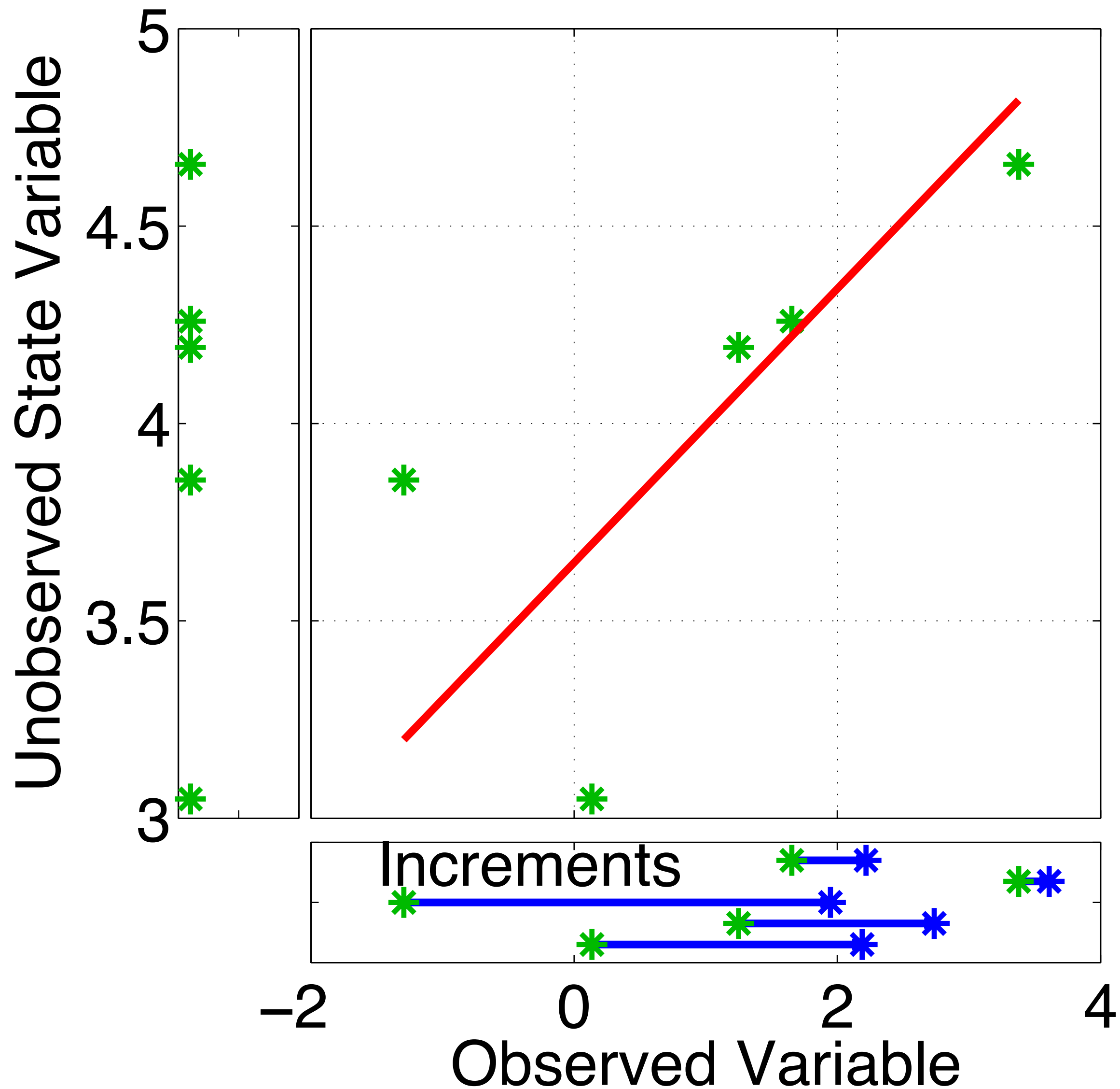
Ensemble filters: Updating additional prior state variables



As we'll see, by computing the increments, we guarantee that if the observation doesn't impact the observed variable, the unobserved variable is unchanged.

This is highly desirable!

Ensemble filters: Updating additional prior state variables



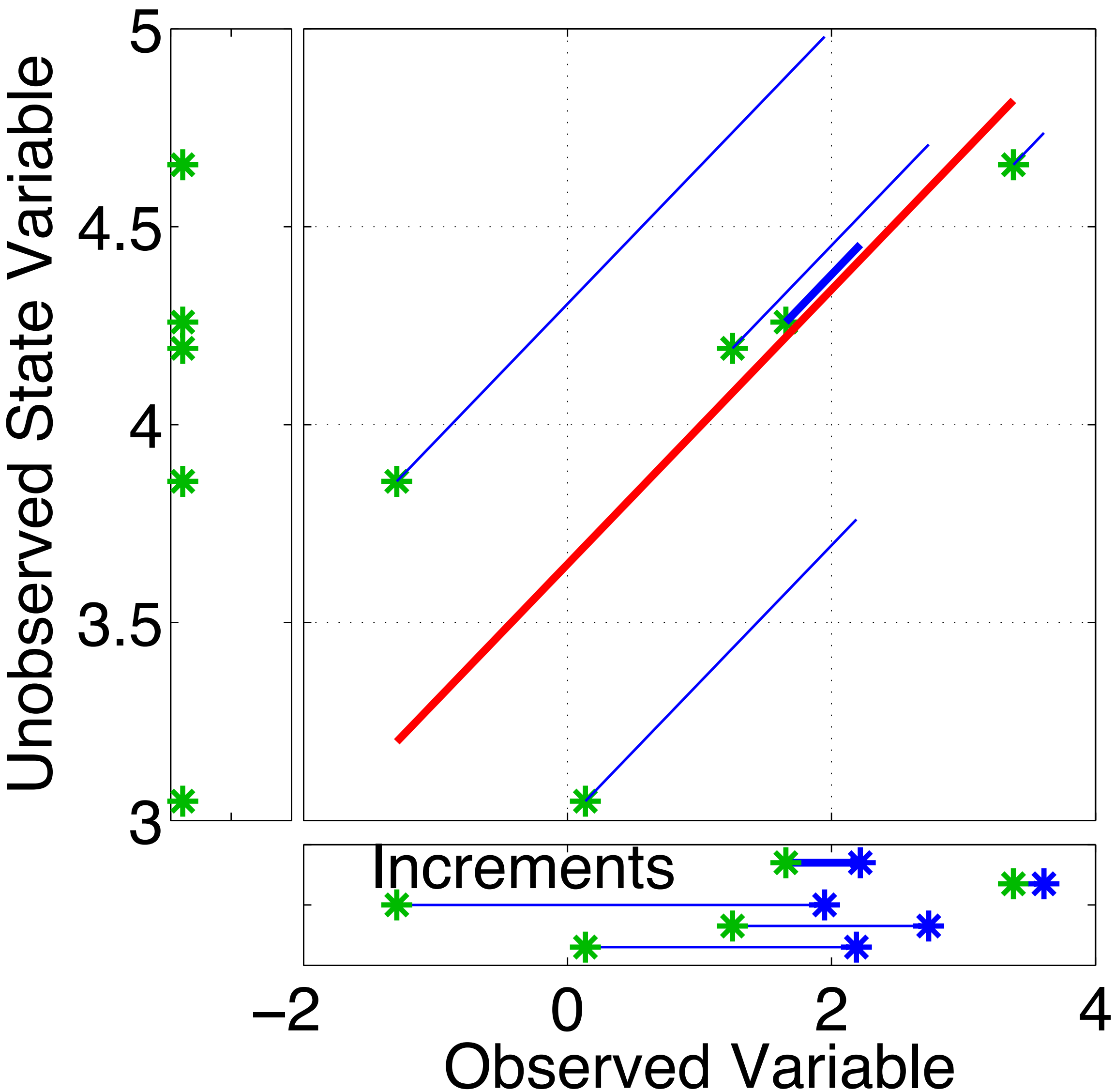
Have joint prior distribution of two variables.

How should the unobserved variable be impacted?

1st choice: least squares

Begin by finding least squares fit.

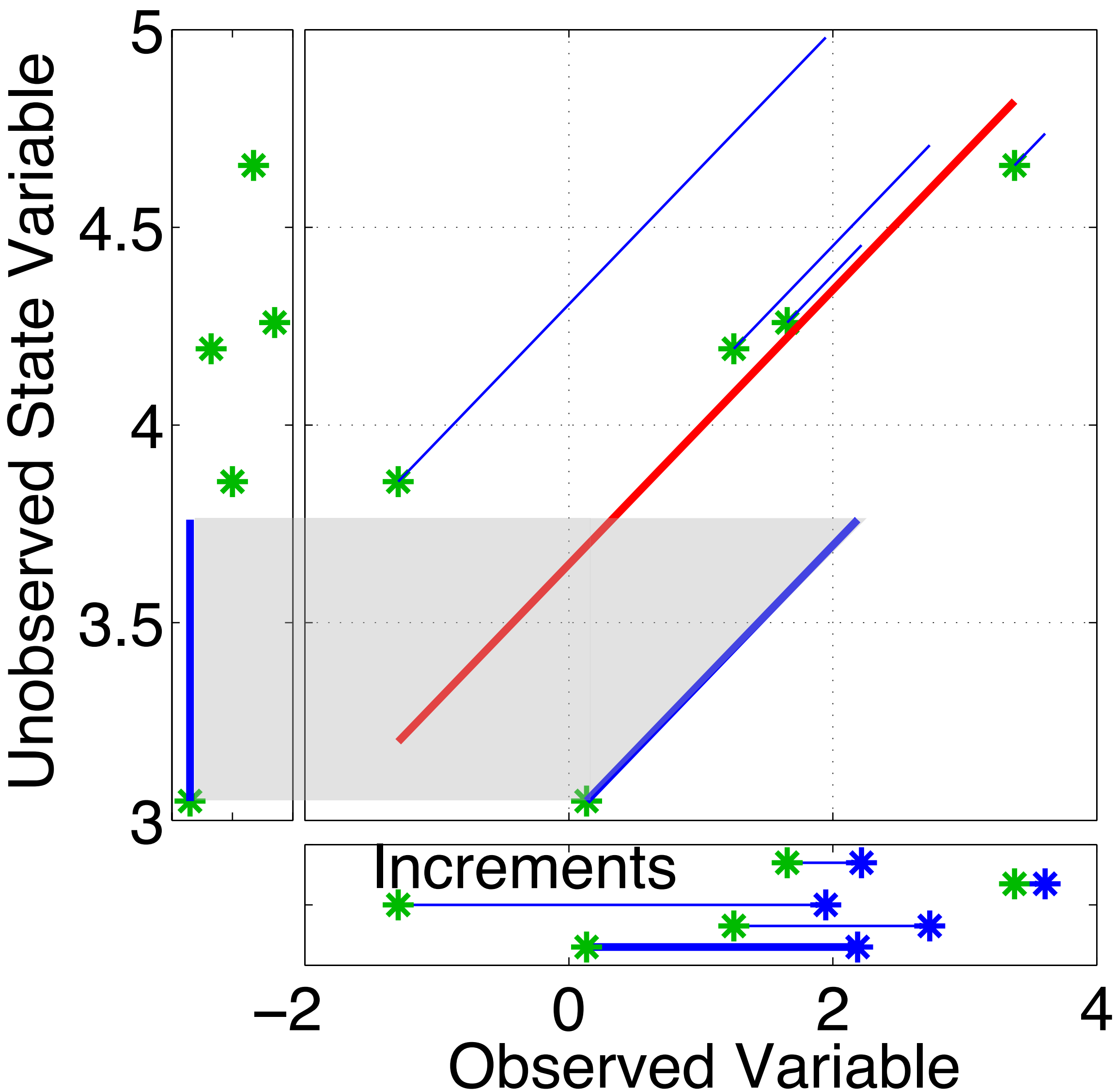
Ensemble filters: Updating additional prior state variables



Have joint prior distribution of two variables.

Next, regress the observed variable increments onto increments for the unobserved variable.

Ensemble filters: Updating additional prior state variables

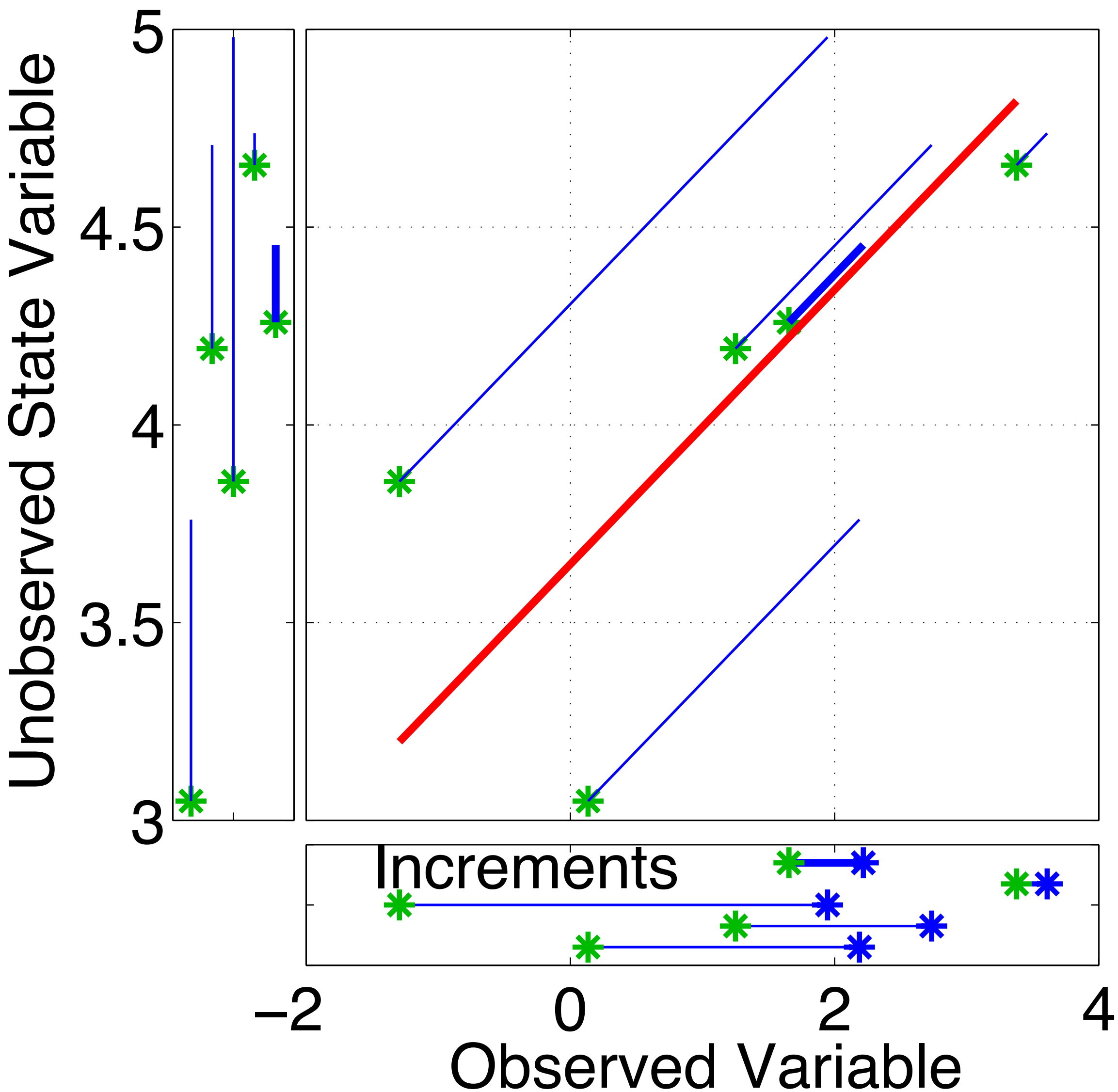


Have joint prior distribution of two variables.

Regression: Equivalent to first finding image of increment in joint space.

Then projecting from joint space onto unobserved priors.

Ensemble filters: Updating additional prior state variables

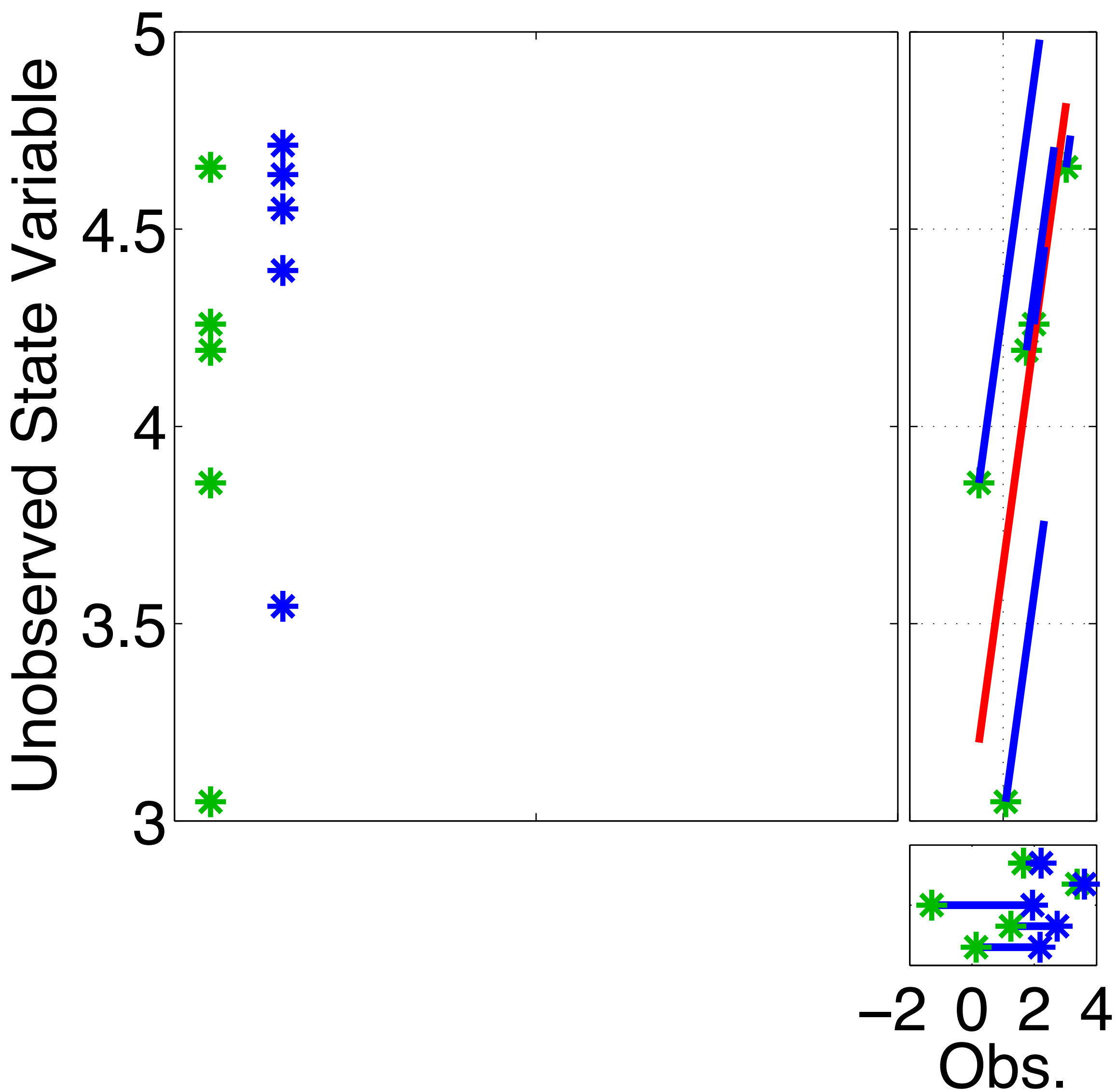


Have joint prior distribution of two variables.

Regression: Equivalent to first finding image of increment in joint space.

Then projecting from joint space onto unobserved priors.

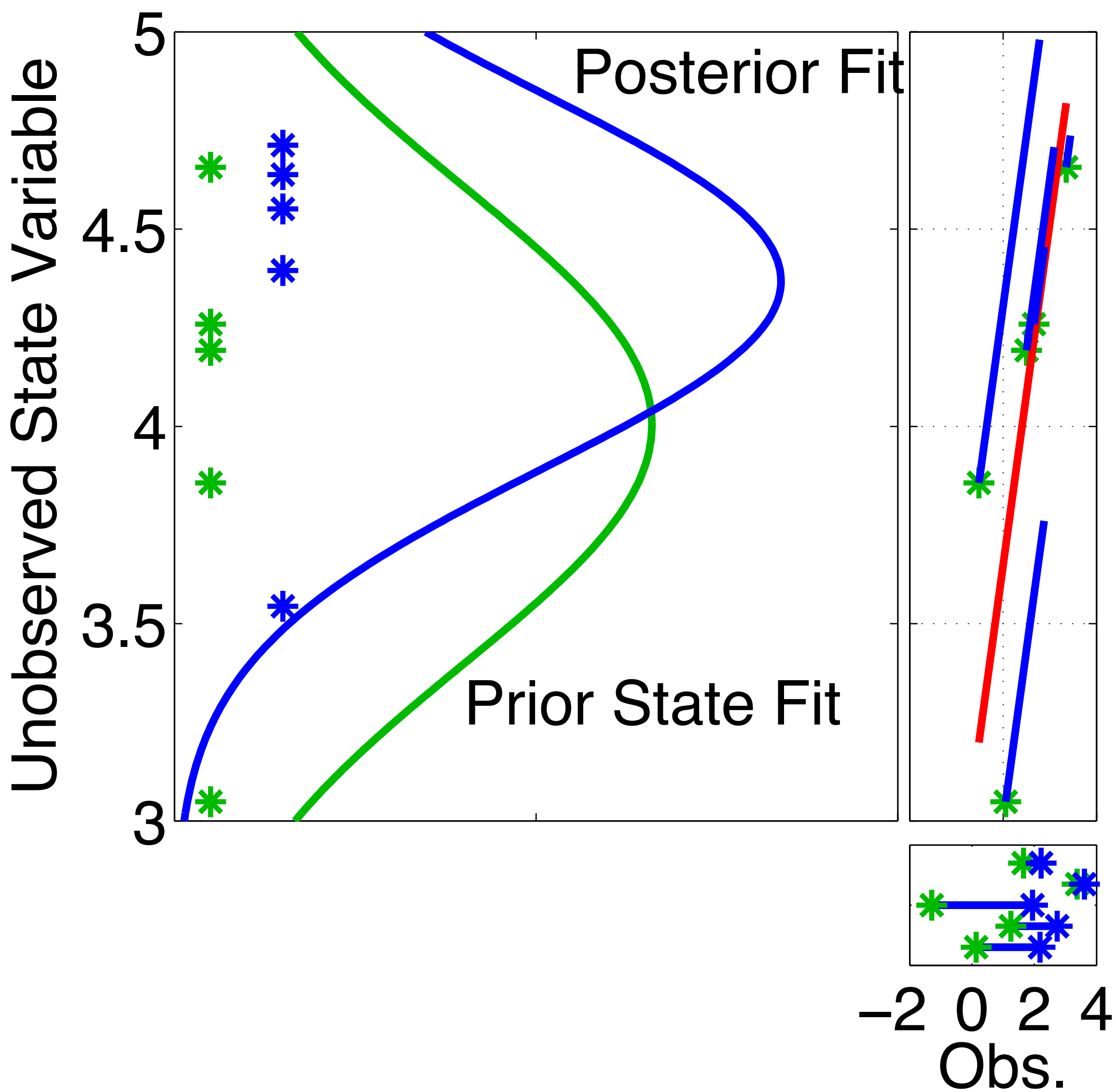
Ensemble filters: Updating additional prior state variables



Now have an updated (posterior) ensemble for the unobserved variable.

Note: the stars at left are not aligned with the ends of the blue lines at upper right. This is because an extra step has been taken in this example to account for sampling error (more in the next lecture).

Ensemble filters: Updating additional prior state variables

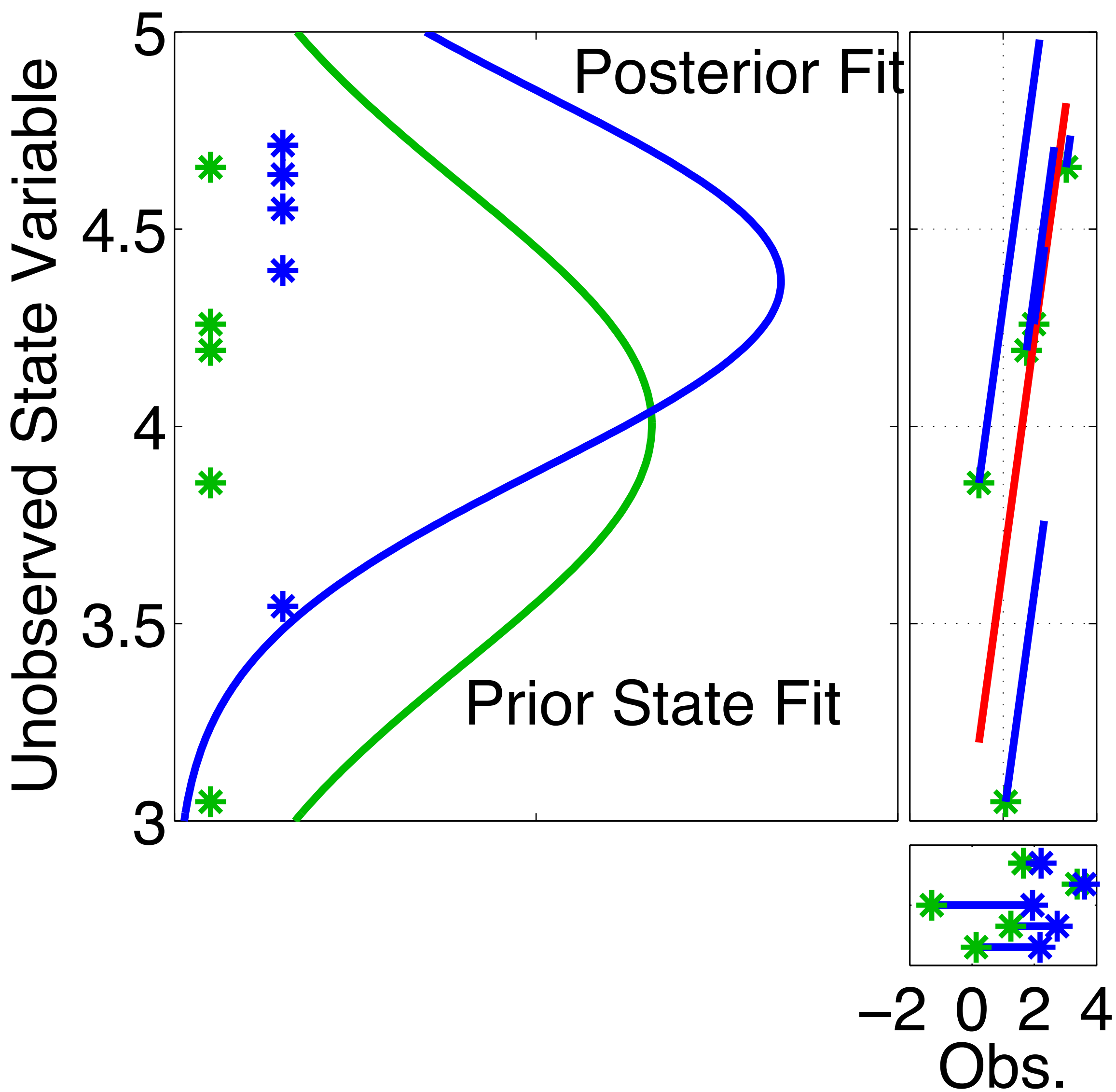


Now have an updated (posterior) ensemble for the unobserved variable.

Fitting Gaussians shows that mean and variance have changed.

Other features of the prior distribution may also have changed.

Ensemble filters: Updating additional prior state variables



CRITICAL POINT:

Since impact on unobserved variable is simply a linear regression, can do this INDEPENDENTLY for any number of unobserved variables!

Could also do many at once using matrix algebra as in traditional Kalman Filter.

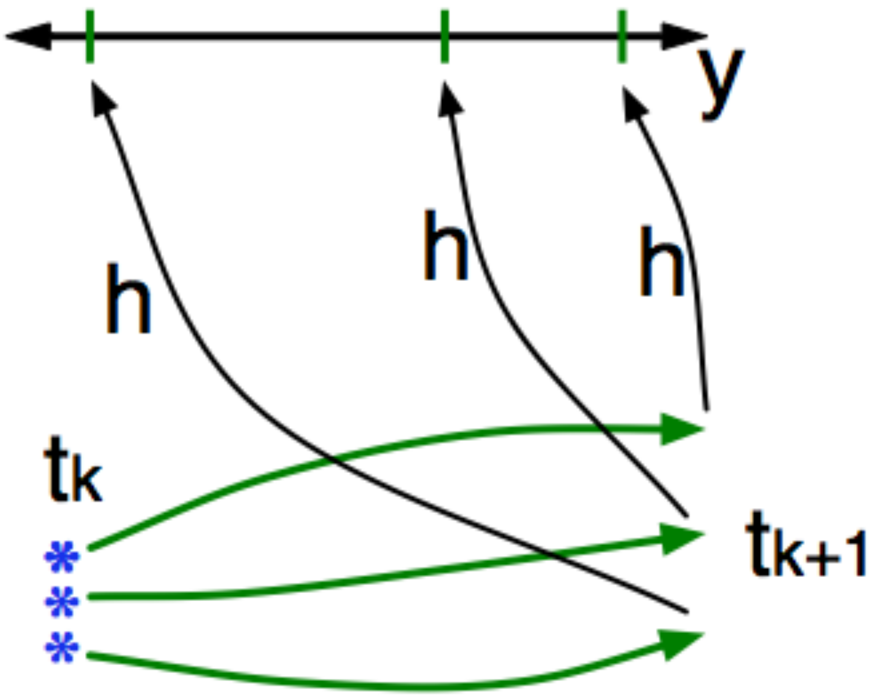
How an Ensemble Filter Works for Geophysical Data Assimilation

1. Use model to advance ensemble (3 members here) to time at which next observation becomes available.

Ensemble state estimate after using previous observation (analysis)

Ensemble state at time of next observation (prior)

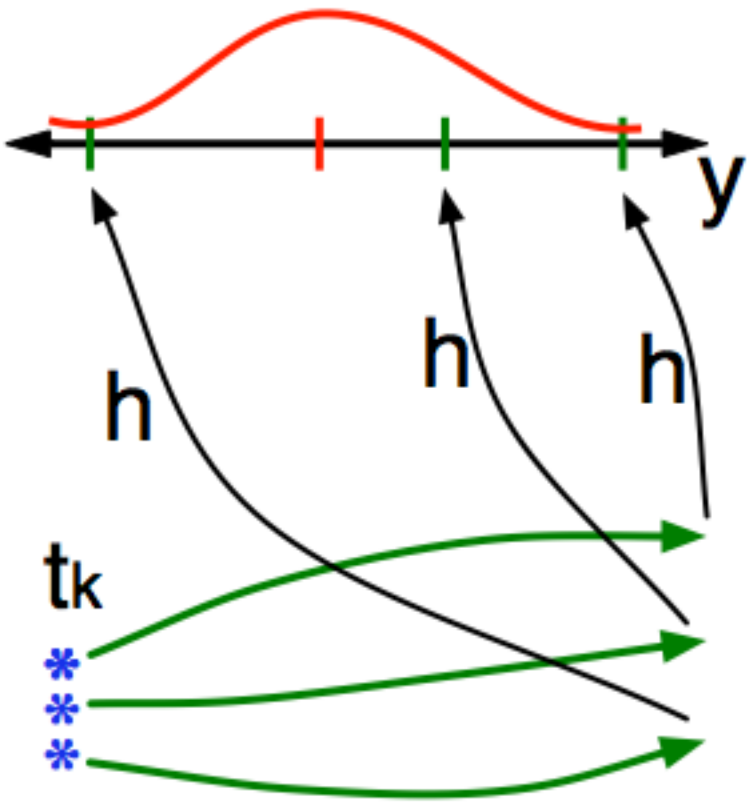
2. Get prior ensemble sample of observation, $y = h(x)$, by applying forward operator **h** to each ensemble member.



Theory: observations from instruments with uncorrelated errors can be done sequentially.

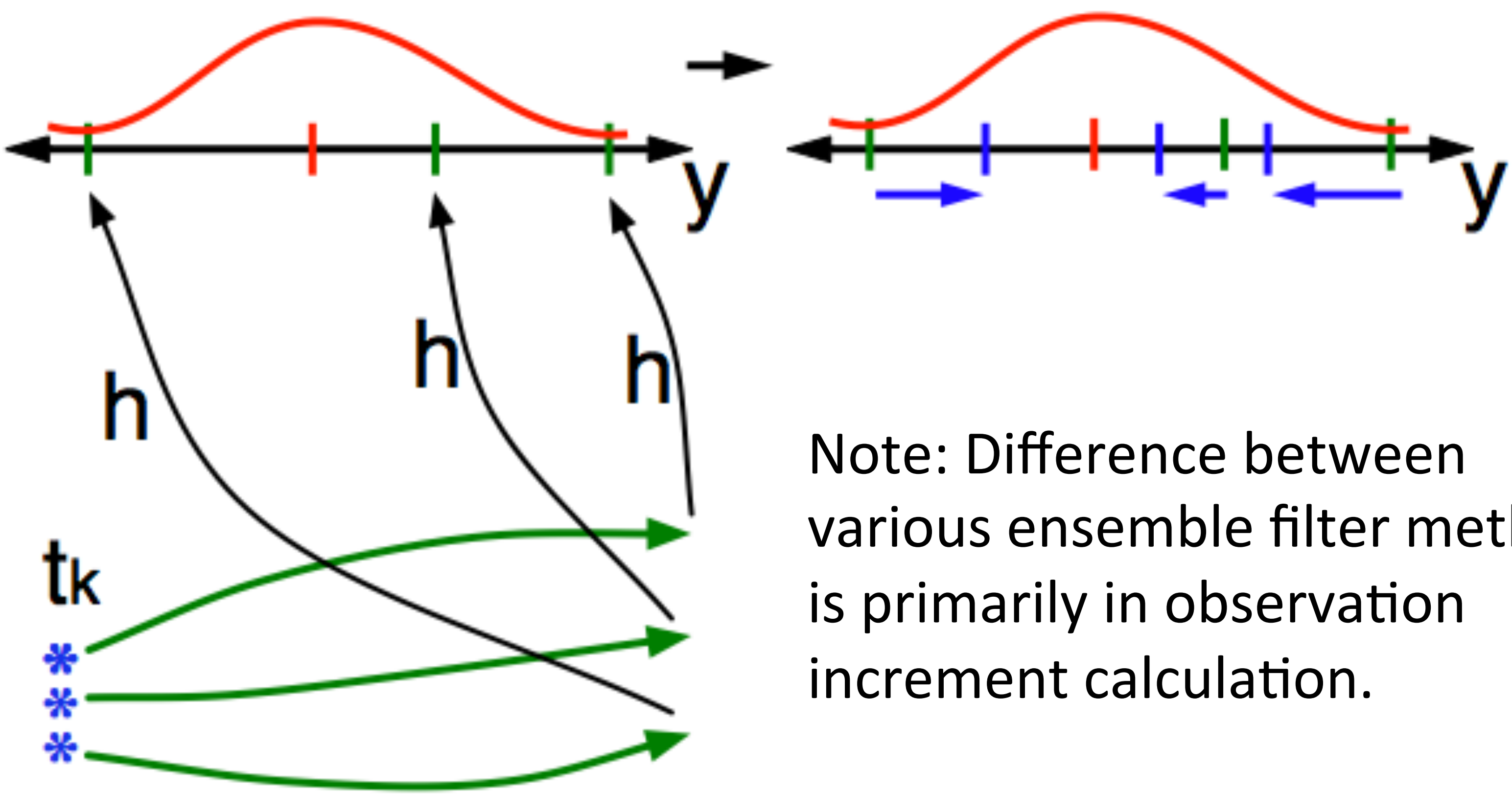
How an Ensemble Filter Works for Geophysical Data Assimilation

3. Get observed value and observational error distribution from observing system.



How an Ensemble Filter Works for Geophysical Data Assimilation

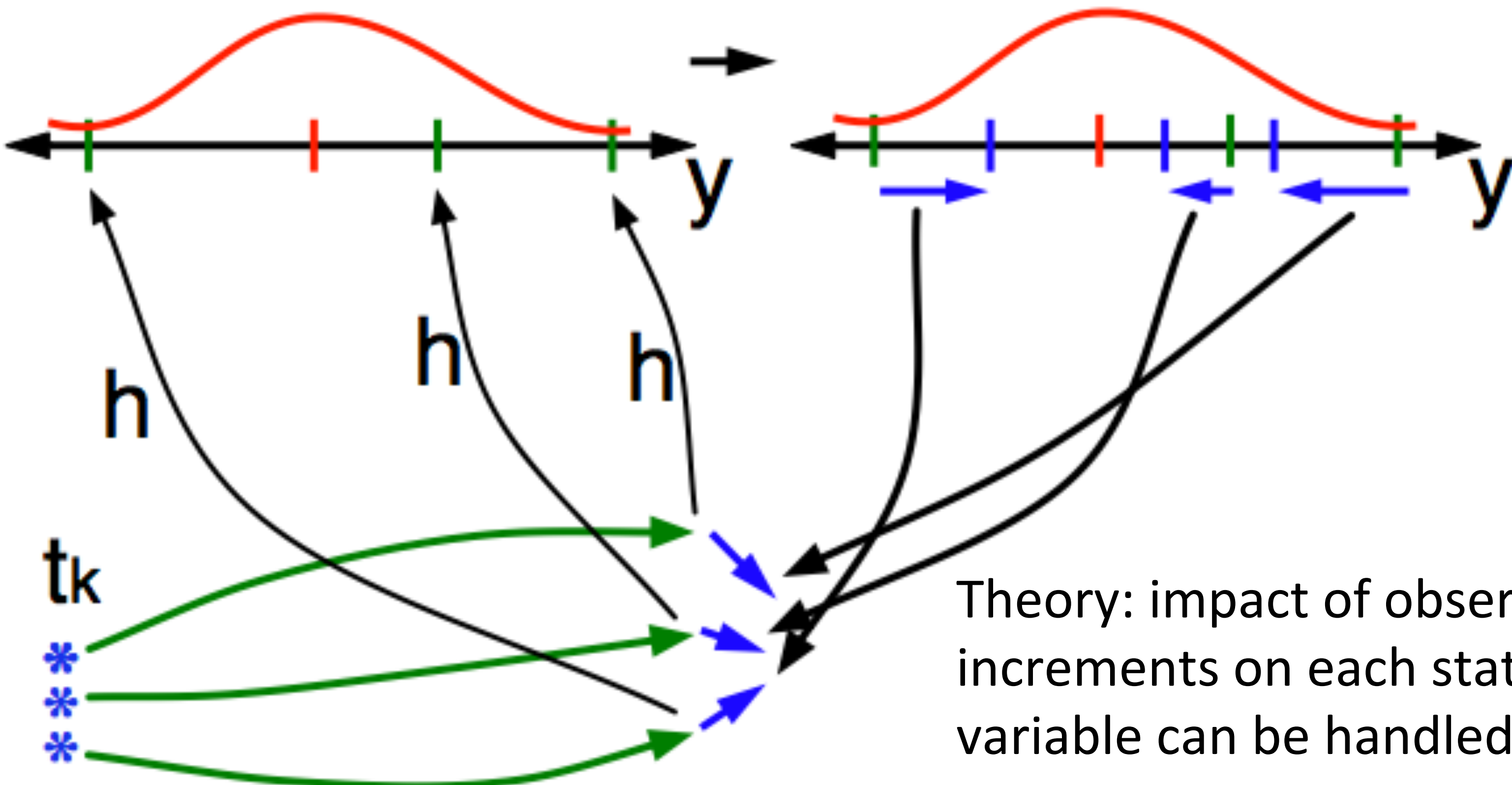
4. Find the increments for the prior observation ensemble (this is a scalar problem for uncorrelated observation errors).



Note: Difference between various ensemble filter methods is primarily in observation increment calculation.

How an Ensemble Filter Works for Geophysical Data Assimilation

5. Use ensemble samples of y and each state variable to linearly regress observation increments onto state variable increments.



Theory: impact of observation increments on each state variable can be handled independently!

How an Ensemble Filter Works for Geophysical Data Assimilation

6. When all ensemble members for each state variable are updated, there is a new analysis. Integrate to time of next observation …