Assimilation Algorithms
Lecture 1: Basic Concepts

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Outline

Analysis

- Analysis: The process of approximating the true state of a (geo)physical system at a given time.
- For example:
  - Hand analysis of synoptic observations (1850 LeVerrier, Fitzroy).
  - Polynomial Interpolation (1950s Panofsky)
- An important step forward was made by Gilchrist and Cressman (1954), who introduced the idea of using a previous numerical forecast to provide a preliminary estimate of the analysis.
- This prior estimate was called the background.

Optimal interpolation

- Bergthorsson and Döös (1955) took the idea of using a background field a step further by casting the analysis problem in terms of increments which were added to the background.
- The increments were weighted linear combinations of nearby observation increments (observation minus background), with the weights determined statistically.
- This idea of statistical combination of background and synoptic observations led ultimately to Optimal Interpolation.
- The use of statistics to merge model fields with observations is fundamental to all current methods of analysis.

Data Assimilation

- An important change of emphasis happened in the early 1970s with the introduction of primitive-equation models.
- Primitive equation models support inertia-gravity waves. This makes them much more fussy about their initial conditions than the filtered models that had been used hitherto.
- The analysis procedure became much more intimately linked with the model. The analysis had to produce an initial state that respected the model's dynamical balances.
- Unbalanced increments from the analysis procedure would be rejected as a result of geostrophic adjustment.
- Initialization techniques (which suppress inertia-gravity waves) became important.

Data Assimilation

The idea that the analysis procedure must present observational information to the model in a way in which it can be absorbed (i.e. not rejected by geostrophic adjustment) led to the coining of the term data assimilation.

Google define:Assimilate

- To incorporate nutrients into the body after digestion
- To incorporate or absorb knowledge into the mind
- The social process of absorbing one cultural group into harmony with another
- The process by which the Borg integrate beings and cultures into their collective.
- The process of objectively adapting the model state to observations in a statistically optimal way taking into account model and observation errors

Data Assimilation

- A final impetus towards the modern concept of data assimilation came from the increasing availability of asynoptic observations from satellite instruments.
- It was no longer sufficient to think of the analysis purely in terms of spatial interpolation of contemporaneous observations.
- The time dimension became important, and the model dynamics assumed the role of propagating observational information in time to allow a synoptic view of the state of the system to be generated from asynoptic data.

Elementary Statistics

Suppose we want to estimate the temperature of this room, given:

- A prior estimate: T_b.
  - E.g., we measured the temperature an hour ago, and we have some idea (i.e. a model) of how the temperature varies as a function of time, the number of people in the room, whether the windows are open, etc.
- A thermometer: T_o.

Denote the true temperature of the room by T^*.

- The errors in T_b and T_o are:

$$\begin{aligned} \epsilon_b &= T_b - T^* \\ \epsilon_o &= T_o - T^* \end{aligned}$$

- We will assume that the error statistics of T_b and T_o are known, and that T_b and T_o have been adjusted (bias corrected) so that their mean errors are zero:

$$\overline{\epsilon_b} = \overline{\epsilon_o} = 0$$

Elementary Statistics

- We estimate the temperature of the room as a linear combination of T_b and T_o:

$$T_a = \alpha T_o + \beta T_b + \gamma$$

- Denote the error of our estimate as $\epsilon_a = T_a - T^*$.
- We want the estimate to be unbiased: $\overline{\epsilon_a} = 0$.
- We have:

$$T_a = T^* + \epsilon_a = \alpha\left(T^* + \epsilon_o\right) + \beta\left(T^* + \epsilon_b\right) + \gamma$$

- Taking the mean and rearranging gives:

$$\overline{\epsilon_a} = \left(\alpha + \beta - 1\right) T^* + \gamma$$

- Since this holds for any T^*, we must have
  - $\gamma = 0$, and
  - $\alpha + \beta - 1 = 0$.
- I.e. $T_a = \alpha T_o + (1 - \alpha) T_b$

Elementary Statistics

- The general Linear Unbiased Estimate is:

$$T_a = \alpha T_o + (1-\alpha) T_b$$

- Now consider the error of this estimate.
- Subtracting T^* from both sides of the equation gives

$$\epsilon_a = \alpha \epsilon_o + (1-\alpha)\epsilon_b$$

- The variance of the estimate is:

$$\overline{\epsilon_a^2} = \alpha^2 \overline{\epsilon_o^2} + 2\alpha(1-\alpha)\overline{\epsilon_o \epsilon_b} + (1-\alpha)^2 \overline{\epsilon_b^2}$$

- The quantity $\overline{\epsilon_o \epsilon_b}$ represents the covariance between the error of our prior estimate and the error of our thermometer measurement.
- There is no reason for these errors to be connected in any way.
- We will assume that $\overline{\epsilon_o \epsilon_b} = 0$.

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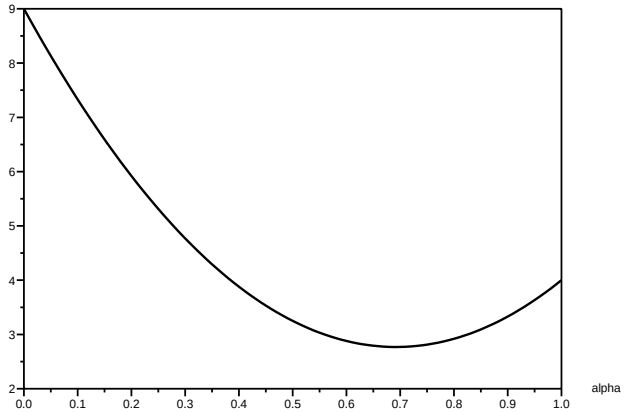
Elementary Statistics

$$\overline{\epsilon_a^2} = \alpha^2 \overline{\epsilon_o^2} + (1-\alpha)^2 \overline{\epsilon_b^2}$$

We can easily derive some properties of our estimate:

- $\frac{d\overline{\epsilon_a^2}}{d\alpha} = 2\alpha\overline{\epsilon_o^2} - 2(1-\alpha)\overline{\epsilon_b^2}$
- For $\alpha = 0$, $\overline{\epsilon_a^2} = \overline{\epsilon_b^2}$ and $\frac{d\overline{\epsilon_a^2}}{d\alpha} = -2\overline{\epsilon_b^2} < 0$
- For $\alpha = 1$, $\overline{\epsilon_a^2} = \overline{\epsilon_o^2}$ and $\frac{d\overline{\epsilon_a^2}}{d\alpha} = 2\overline{\epsilon_o^2} > 0$



From this we can deduce:

- For $0 \leq \alpha \leq 1$, $\overline{\epsilon_a^2} \leq \max(\overline{\epsilon_b^2}, \overline{\epsilon_o^2})$
- The minimum-variance estimate occurs for $\alpha \in (0,1)$.
- The minimum-variance estimate satisfies $\overline{\epsilon_a^2} < \min(\overline{\epsilon_b^2}, \overline{\epsilon_o^2})$

Elementary Statistics

The minimum-variance estimate occurs when

$$\frac{d\overline{\epsilon_a^2}}{d\alpha} = 2\alpha\overline{\epsilon_o^2} - 2(1-\alpha)\overline{\epsilon_b^2} = 0$$

$$\Rightarrow \quad \alpha = \frac{\overline{\epsilon_b^2}}{\overline{\epsilon_b^2} + \overline{\epsilon_o^2}}$$

It is not difficult to show that the error variance of this minimum-variance estimate is:

$$\overline{\epsilon_a^2} = \left(\frac{1}{\overline{\epsilon_b^2}} + \frac{1}{\overline{\epsilon_o^2}} \right)^{-1}$$

Extension to Multiple Dimensions

- Now, let's turn our attention to the multi-dimensional case.
- Instead of a scalar prior estimate T_b, we now consider a vector $\mathbf{x}_b$.
- We can think of $\mathbf{x}_b$ as representing the entire state of a numerical model at some time.
- The elements of $\mathbf{x}_b$ might be grid-point values, spherical harmonic coefficients, etc., and some elements may represent temperatures, others wind components, etc.
- We refer to $\mathbf{x}_b$ as the background
- Similarly, we generalize the observation to a vector $\mathbf{y}$.
- $\mathbf{y}$ can contain a disparate collection of observations at different locations, and of different variables.

Extension to Multiple Dimensions

- The major difference between the simple scalar example and the multi-dimensional case is that there is no longer a one-to-one correspondence between the elements of the observation vector and those of the background vector.
- It is no longer trivial to compare observations and background.
- Observations are not necessarily located at model gridpoints
- The observed variables (e.g. radiances) may not correspond directly with any of the variables of the model.
- To overcome this problem, we must asume that our model is a more-or-less complete representation of reality, so that we can always determine "model equivalents" of the observations.

Extension to Multiple Dimensions

- We formalize this by assuming the existance of an observation operator, $\mathcal{H}$.
- Given a model-space vector, $\mathbf{x}$, the vector $\mathcal{H}(\mathbf{x})$ can be compared directly with $\mathbf{y}$, and represents the "model equivalent" of $\mathbf{y}$.
- For now, we will assume that $\mathcal{H}$ is perfect. I.e. it does not introduce any error, so that:

$$\mathcal{H}(\mathbf{x}^*) = \mathbf{y}^*$$

where $\mathbf{x}^*$ is the true state, and $\mathbf{y}^*$ contains the true values of the observed quantities.

Extension to Multiple Dimensions

- As we did in the scalar case, we will look for an analysis that is a linear combination of the available information:

$$\mathbf{x}_a = \mathbf{F}\mathbf{x}_b + \mathbf{G}\mathcal{H}(\mathbf{x}_b) + \mathbf{K}\mathbf{y} + \mathbf{c}$$

  where $\mathbf{F}$, $\mathbf{G}$ and $\mathbf{K}$ are matrices, and where $\mathbf{c}$ is a vector.
- If $\mathcal{H}$ is linear, we can proceed as in the scalar case and look for a linear unbiased estimate.
- In the more general case of nonlinear $\mathcal{H}$, we will require that error-free inputs ($\mathbf{x}_b = \mathbf{x}^*$ and $\mathbf{y} = \mathbf{y}^*$) produce an error-free analysis ($\mathbf{x}_a = \mathbf{x}^*$):

$$\mathbf{x}^* = \mathbf{F}\mathbf{x}^* + \mathbf{G}\mathcal{H}(\mathbf{x}^*) + \mathbf{K}\mathcal{H}(\mathbf{x}^*) + \mathbf{c}$$

- Since this applies for any $\mathbf{x}^*$, we must have $\mathbf{c} = 0$ and

$$\mathbf{F} + \mathbf{G}\mathcal{H}(\cdot) \equiv \mathbf{I} - \mathbf{K}\mathcal{H}(\cdot)$$

- Our analysis equation is thus:

$$\mathbf{x}_a = \mathbf{x}_b + \mathbf{K}\left(\mathbf{y} - \mathcal{H}(\mathbf{x}_b)\right)$$

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Extension to Multiple Dimensions

$$\mathbf{x}_a = \mathbf{x}_b + \mathbf{K}\left(\mathbf{y} - \mathcal{H}(\mathbf{x}_b)\right)$$

- Remember that in the scalar case, we had

$$\begin{aligned} T_a &= \alpha T_o + (1-\alpha) T_b \\ &= T_b + \alpha(T_o - T_b) \end{aligned}$$

- We see that the matrix $\mathbf{K}$ plays a role equivalent to that of the coefficient α.
- $\mathbf{K}$ is called the gain matrix.
- It determines the weight given to the observations
- It handles the transformation of information defined in "observation space" to the space of model variables.

Extension to Multiple Dimensions

- The next step in deriving the analysis equation is to describe the statistical properties of the analysis errors.
- We define

$$\begin{aligned} \epsilon_a &= \mathbf{x}_a - \mathbf{x}^* \\ \epsilon_b &= \mathbf{x}_b - \mathbf{x}^* \\ \epsilon_o &= \mathbf{y} - \mathbf{y}^* \end{aligned}$$

- We will assume that the errors are small, so that

$$\mathcal{H}(\mathbf{x}_b) = \mathcal{H}(\mathbf{x}^*) + \mathbf{H}\epsilon_b + O(\epsilon_b^2)$$

where $\mathbf{H}$ is the Jacobian of $\mathcal{H}$.

Extension to Multiple Dimensions

- Substituting the expressions for the errors into our analysis equation, and using $\mathcal{H}(\mathbf{x}^*) = \mathbf{y}^*$, gives (to first order):

$$\epsilon_a = \epsilon_b + \mathbf{K}\left(\epsilon_o - \mathbf{H}\epsilon_b\right)$$

- As in the scalar example, we will assume that the mean errors have been removed, so that $\overline{\epsilon_b} = \overline{\epsilon_o} = 0$. We see that this implies that $\overline{\epsilon_a} = 0$.
- In the scalar example, we derived the variance of the analysis error, and defined our optimal analysis to minimize this variance.
- In the multi-dimensional case, we must deal with covariances.

Covariance

- The covariance between two variables x_i and x_j is defined as

$$\mathrm{cov}(x_i, x_j) = \overline{(x_i - \overline{x_i})(x_j - \overline{x_j})}$$

- Given a vector $\mathbf{x} = (x_1, x_2, \cdots, x_N)^{\mathrm{T}}$, we can arrange the covariances into a covariance matrix, $\mathbf{C}$, such that $C_{ij} = \mathrm{cov}(x_i, x_j)$.
- Equivalently:

$$\mathbf{C} = \overline{(\mathbf{x} - \overline{\mathbf{x}})(\mathbf{x} - \overline{\mathbf{x}})^{\mathrm{T}}}$$

- Covariance matrices are symmetric and positive definite

Extension to Multiple Dimensions

- The analysis error is:

$$\begin{aligned}\epsilon_a &= \epsilon_b + \mathbf{K}(\epsilon_o - \mathbf{H}\epsilon_b) \\ &= (\mathbf{I} - \mathbf{KH})\epsilon_b + \mathbf{K}\epsilon_o\end{aligned}$$

- Forming the analysis error covariance matrix gives:

$$\begin{aligned}\overline{\epsilon_a\epsilon_a^{\mathrm{T}}} &= \overline{[(\mathbf{I} - \mathbf{KH})\epsilon_b + \mathbf{K}\epsilon_o]\,[(\mathbf{I} - \mathbf{KH})\epsilon_b + \mathbf{K}\epsilon_o]^{\mathrm{T}}} \\ &= (\mathbf{I} - \mathbf{KH})\overline{\epsilon_b\epsilon_b^{\mathrm{T}}}(\mathbf{I} - \mathbf{KH})^{\mathrm{T}} + (\mathbf{I} - \mathbf{KH})\overline{\epsilon_b\epsilon_o^{\mathrm{T}}}\mathbf{K}^{\mathrm{T}} \\ &\quad + \mathbf{K}\overline{\epsilon_o\epsilon_b^{\mathrm{T}}}(\mathbf{I} - \mathbf{KH})^{\mathrm{T}} + \mathbf{K}\overline{\epsilon_o\epsilon_o^{\mathrm{T}}}\mathbf{K}^{\mathrm{T}}\end{aligned}$$

- Assuming that the background and observation errors are uncorrelated (i.e. $\overline{\epsilon_o\epsilon_b^{\mathrm{T}}} = \overline{\epsilon_b\epsilon_o^{\mathrm{T}}} = 0$), we find:

$$\overline{\epsilon_a\epsilon_a^{\mathrm{T}}} = (\mathbf{I} - \mathbf{KH})\overline{\epsilon_b\epsilon_b^{\mathrm{T}}}(\mathbf{I} - \mathbf{KH})^{\mathrm{T}} + \mathbf{K}\overline{\epsilon_o\epsilon_o^{\mathrm{T}}}\mathbf{K}^{\mathrm{T}}$$

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Extension to Multiple Dimensions

$$\overline{\epsilon_a \epsilon_a^{\mathrm{T}}} = \quad (\mathbf{I}-\mathbf{K}\mathbf{H})\overline{\epsilon_b \epsilon_b^{\mathrm{T}}}(\mathbf{I}-\mathbf{K}\mathbf{H})^{\mathrm{T}} + \mathbf{K}\overline{\epsilon_o \epsilon_o^{\mathrm{T}}}\mathbf{K}^{\mathrm{T}}$$

- This expression is the equivalent of the expression we obtained for the error of the scalar analysis:

$$\overline{\epsilon_a^2} = (1-\alpha)^2\overline{\epsilon_b^2} + \alpha^2\overline{\epsilon_o^2}$$

- Again, we see that $\mathbf{K}$ plays essentially the same role in the multi-dimensional analysis as α plays in the scalar case.
- In the scalar case, we chose α to minimize the variance of the analysis error.
- What do we mean by the minimum-variance analysis in the multi-dimensional case?

Extension to Multiple Dimensions

- Note that the diagonal elements of a covariance matrix are variances $C_{ii} = \mathrm{cov}(x_i, x_i) = \overline{(x_i - \overline{x_i})^2}$.
- Hence, we can define the minimum-variance analysis as the analysis that minimizes the sum of the diagonal elements of the analysis error covariance matrix.
- The sum of the diagonal elements of a matrix is called the trace.
- In the scalar case, we found the minimum-variance analysis by setting $\frac{d\overline{\epsilon_a^2}}{d\alpha}$ to zero.
- In the multidimensional case, we are going to set

$$\frac{\partial \mathrm{trace}(\overline{\epsilon_a \epsilon_a^{\mathrm{T}}})}{\partial \mathbf{K}} = \mathbf{0}$$

- (Note: $\frac{\partial \mathrm{trace}(\overline{\epsilon_a \epsilon_a^{\mathrm{T}}})}{\partial \mathbf{K}}$ is the matrix whose ij^{th} element is $\frac{\partial \mathrm{trace}(\overline{\epsilon_a \epsilon_a^{\mathrm{T}}})}{\partial K_{ij}}$.)

Extension to Multiple Dimensions

- We have: $\overline{\epsilon_a \epsilon_a^{\mathrm{T}}} = (\mathbf{I}-\mathbf{KH})\overline{\epsilon_b \epsilon_b^{\mathrm{T}}}(\mathbf{I}-\mathbf{KH})^{\mathrm{T}} + \mathbf{K}\overline{\epsilon_o \epsilon_o^{\mathrm{T}}}\mathbf{K}^{\mathrm{T}}$.
- The following matrix identities come to our rescue:

$$\frac{\partial \mathrm{trace}(\mathbf{KAK}^{\mathrm{T}})}{\partial \mathbf{K}} = \mathbf{K}(\mathbf{A}+\mathbf{A}^{\mathrm{T}})$$

$$\frac{\partial \mathrm{trace}(\mathbf{KA})}{\partial \mathbf{K}} = \mathbf{A}^{\mathrm{T}} \qquad \frac{\partial \mathrm{trace}(\mathbf{AK}^{\mathrm{T}})}{\partial \mathbf{K}} = \mathbf{A}$$

- Applying these to $\partial \mathrm{trace}(\overline{\epsilon_a \epsilon_a^{\mathrm{T}}})/\partial \mathbf{K}$ gives:

$$\frac{\partial \mathrm{trace}(\overline{\epsilon_a \epsilon_a^{\mathrm{T}}})}{\partial \mathbf{K}} = 2\mathbf{K}\left[\mathbf{H}\overline{\epsilon_b \epsilon_b^{\mathrm{T}}}\mathbf{H}^{\mathrm{T}} + \overline{\epsilon_o \epsilon_o^{\mathrm{T}}}\right] - 2\overline{\epsilon_b \epsilon_b^{\mathrm{T}}}\mathbf{H}^{\mathrm{T}} = \mathbf{0}$$

- Hence: $\mathbf{K} = \overline{\epsilon_b \epsilon_b^{\mathrm{T}}}\mathbf{H}^{\mathrm{T}}\left[\mathbf{H}\overline{\epsilon_b \epsilon_b^{\mathrm{T}}}\mathbf{H}^{\mathrm{T}} + \overline{\epsilon_o \epsilon_o^{\mathrm{T}}}\right]^{-1}$.

Extension to Multiple Dimensions

$$\mathbf{K} = \overline{\epsilon_b \epsilon_b^{\mathrm{T}}} \mathbf{H}^{\mathrm{T}} \left[\mathbf{H} \overline{\epsilon_b \epsilon_b^{\mathrm{T}}} \mathbf{H}^{\mathrm{T}} + \overline{\epsilon_o \epsilon_o^{\mathrm{T}}} \right]^{-1}$$

- This optimal gain matrix is called the Kalman Gain Matrix.
- Note the similarity with the optimal gain we derived for the scalar analysis: $\alpha = \overline{\epsilon_b^2}/(\overline{\epsilon_b^2} + \overline{\epsilon_o^2})$.
- The variance of analysis error for the optimal scalar problem was:

$$\overline{\epsilon_a^2} = \left(\frac{1}{\overline{\epsilon_b^2}} + \frac{1}{\overline{\epsilon_o^2}} \right)^{-1}$$

- The equivalent expression for the multi-dimensional case is:

$$\overline{\epsilon_a \epsilon_a^{\mathrm{T}}} = \left[\left(\overline{\epsilon_b \epsilon_b^{\mathrm{T}}} \right)^{-1} + \mathbf{H}^{\mathrm{T}} \left(\overline{\epsilon_o \epsilon_o^{\mathrm{T}}} \right)^{-1} \mathbf{H} \right]^{-1}$$

Notation

- The notation we have used for covariance matrices can get a bit cumbersome.
- The standard notation is:

$$\begin{aligned} \mathbf{P}^a &\equiv \overline{\epsilon_a \epsilon_a^{\mathrm{T}}} \\ \mathbf{P}^b &\equiv \overline{\epsilon_b \epsilon_b^{\mathrm{T}}} \\ \mathbf{R} &\equiv \overline{\epsilon_o \epsilon_o^{\mathrm{T}}} \end{aligned}$$

- In many analysis schemes, the true covariance matrix of background error, $\mathbf{P}^b$, is not known, or is too large to be used.
- In this case, we use an approximate background error covariance matrix. This approximate matrix is denoted by $\mathbf{B}$.

Alternative Expression for the Kalman Gain

Finally, we derive an alternative expression for the Kalman gain:

$$\mathbf{K} = \mathbf{P}^b\mathbf{H}^{\mathrm{T}}\left[\mathbf{H}\mathbf{P}^b\mathbf{H}^{\mathrm{T}} + \mathbf{R}\right]^{-1}$$

Multiplying both sides by $\left[(\mathbf{P}^b)^{-1} + \mathbf{H}^{\mathrm{T}}\mathbf{R}^{-1}\mathbf{H}\right]$ gives:

$$\begin{aligned}\left[(\mathbf{P}^b)^{-1} + \mathbf{H}^{\mathrm{T}}\mathbf{R}^{-1}\mathbf{H}\right]\mathbf{K} &= \left[\mathbf{H}^{\mathrm{T}} + \mathbf{H}^{\mathrm{T}}\mathbf{R}^{-1}\mathbf{H}\mathbf{P}^b\mathbf{H}^{\mathrm{T}}\right]\left[\mathbf{H}\mathbf{P}^b\mathbf{H}^{\mathrm{T}} + \mathbf{R}\right]^{-1} \\ &= \mathbf{H}^{\mathrm{T}}\mathbf{R}^{-1}\left[\mathbf{R} + \mathbf{H}\mathbf{P}^b\mathbf{H}^{\mathrm{T}}\right]\left[\mathbf{H}\mathbf{P}^b\mathbf{H}^{\mathrm{T}} + \mathbf{R}\right]^{-1} \\ &= \mathbf{H}^{\mathrm{T}}\mathbf{R}^{-1}\end{aligned}$$

Hence:

$$\mathbf{K} = \left[(\mathbf{P}^b)^{-1} + \mathbf{H}^{\mathrm{T}}\mathbf{R}^{-1}\mathbf{H}\right]^{-1}\mathbf{H}^{\mathrm{T}}\mathbf{R}^{-1}$$

Optimal Interpolation

- Optimal Interpolation is a statistical data assimilation method based on the multi-dimensional analysis equations we have just derived.
- The method was used operationally at ECMWF from 1979 until 1996, when it was replaced by 3D-Var.
- The basic idea is to split the global analysis into a number of boxes which can be analysed independently:

$$\mathbf{x}_a^{(i)} = \mathbf{x}_b^{(i)} + \mathbf{K}^{(i)} \left(\mathbf{y}^{(i)} - \mathcal{H}^{(i)}(\mathbf{x}_b) \right)$$

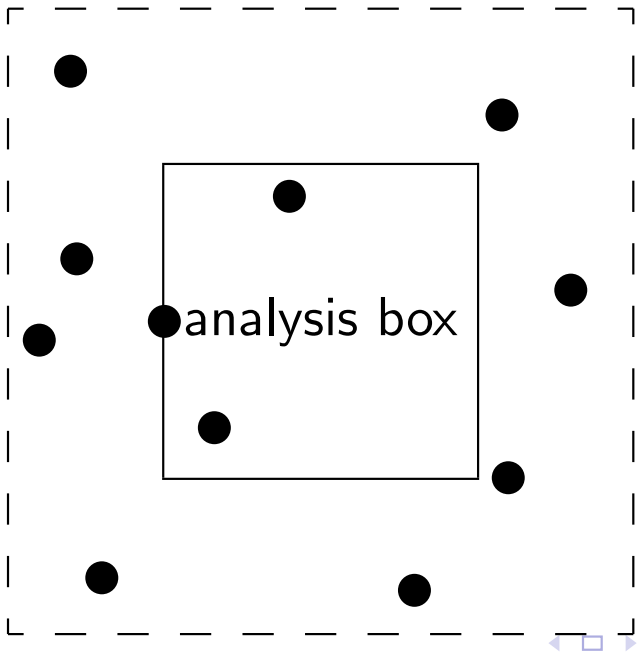
where

$$\mathbf{x}_a = \begin{pmatrix} \mathbf{x}_a^{(1)} \\ \mathbf{x}_a^{(2)} \\ \vdots \\ \mathbf{x}_a^{(M)} \end{pmatrix} \qquad \mathbf{x}_b = \begin{pmatrix} \mathbf{x}_b^{(1)} \\ \mathbf{x}_b^{(2)} \\ \vdots \\ \mathbf{x}_b^{(M)} \end{pmatrix} \qquad \mathbf{K} = \begin{pmatrix} \mathbf{K}^{(1)} \\ \mathbf{K}^{(2)} \\ \vdots \\ \mathbf{K}^{(M)} \end{pmatrix}$$

Optimal Interpolation

$$\mathbf{x}_a^{(i)} = \mathbf{x}_b^{(i)} + \mathbf{K}^{(i)} \left(\mathbf{y}^{(i)} - \mathcal{H}^{(i)}(\mathbf{x}_b) \right)$$

- In principle, we should use *all* available observations to calculate the anaysis for each box. However, this is too expensive.
- To produce a computationally-feasible algorithm, Optimal Interpolation (OI) restricts the observations used for each box to those observations which lie in a surrounding selection area:



Optimal Interpolation

- The gain matrix used for each box is:

$$\mathbf{K}^{(i)} = \left(\mathbf{P}^b\mathbf{H}^{\mathrm{T}}\right)^{(i)} \left[\left(\mathbf{H}\mathbf{P}^b\mathbf{H}^{\mathrm{T}}\right)^{(i)} + \mathbf{R}^{(i)}\right]^{-1}$$

- Now, the dimension of the matrix $\left[\left(\mathbf{H}\mathbf{P}^b\mathbf{H}^{\mathrm{T}}\right)^{(i)} + \mathbf{R}^{(i)}\right]$ is equal to the number of observtions in the selection box.
- Selecting observations reduces the size of this matrix, making it feasible to use direct solution methods to invert it.
- Note that to implement Optimal Interpolation, we have to specify $\left(\mathbf{P}^b\mathbf{H}^{\mathrm{T}}\right)^{(i)}$ and $\left(\mathbf{H}\mathbf{P}^b\mathbf{H}^{\mathrm{T}}\right)^{(i)}$. This effectively limits us to very simple observation operators, corresponding to simple interpolations.
- This, together with the artifacts introduced by observation selection, was one of the main reasons for abandoning Optimal Interpolation in favour of 3D-Var.

Summary

- We derived the linear analysis equation for a simple scalar example.
- We showed that a particular choice of the weight α given to the observation resulted in an optimal minimum-variance analysis.
- We repeated the derivation for the multi-dimensional case. This required the introduction of the observation operator.
- The derivation for the multi-dimensional case closely parallelled the scalar derivation.
- The expressions for the gain matrix and analysis error covariance matrix were recognisably similar to the corresponding scalar expressions.
- Finally, we considered the practical implementation of the analysis equation, in an Optimal Interpolation data assimilation scheme.