Variational data assimilation II

Background and methods

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Quiz

Consider the minimum point of the strong constraint cost function (the 'analysis')

What should we expect J_{min} to be?

$$\begin{aligned} J(\delta \mathrm{x}_0) &= \frac{1}{2}\left(\delta \mathrm{x}_0 - \delta \mathrm{x}_0^{\mathrm{b}}\right)^{\mathrm{T}} \mathrm{B}_0^{-1}\left(\bullet\right) + \\ &\quad \frac{1}{2}\sum_{i=0}^{T}\left(\mathrm{y}_i - \mathscr{H}_i(\mathrm{x}_i^{\mathrm{R}}) - \mathrm{H}_i \delta \mathrm{x}_i\right)^{\mathrm{T}} \mathrm{R}_i^{-1}\left(\bullet\right) \end{aligned}$$

- State vector size n, number of observations p.
- Assume B, R correct, $\mathscr{H}$, $\mathscr{M}$ perfect and linear, Gaussian error statistics.

1. $(n+p)/2$
2. $n/2$
3. $p/2$
4. No theoretical value

Hmmm ...

Some challenges ahead

- Methods assume that error cov. matrices are correctly known.
- Representing B_0.
  - Better models of B_0.
  - Flow dependency (e.g. Ensemble-Var or hybrid methods).
- Representing R_i.
  - Allowing for observation error covariances.
- Representing Q_i.
- Numerical conditioning of the problem.
- Application to more complicated systems (e.g. high-resolution models, coupled atmosphere-ocean DA, chemical DA).
- Variational bias correction.
- Moist processes, inc. clouds.
- Effective use on massively parallel computer architectures.

Making variational DA work – control variable transforms

- B_0 is an $n \times n$ matrix.
  - In operational problems B_0 is too large to store, let alone invert.
  - An unknowable matrix.
- Can model the essential features of B_0 with a change of variable, $\delta x = U\delta v$ (a control variable transform).
  - Hypothesise that the problem is much simpler when posed in terms of δv rather than δx.

Cost function in terms of δv	$\rightarrow$	Minimise w.r.t. δv (trivial B-matrix) $\nwarrow$ iterate $\swarrow$	$\rightarrow$	Convert back to δx

- Equivalent to solving original problem w.r.t. δx with $B_0 = UU^T$. See Bannister (2008).

CVTs in more detail

- Illustrate in simplest case: 3DVar with $x_0^R = x_0^b$ (and drop time index)

$$J^{3DVar}(\delta x) = \frac{1}{2}\delta x^T B^{-1}\delta x + \frac{1}{2}\left(y - \mathscr{H}(x^b) - H\delta x\right)^T R^{-1}(\bullet).$$

- Make a change of variable: $\delta x = U\delta v$ and assume B-matrix of errors in the δv representation is identity, I.

$$B = \left\langle \delta x \delta x^T \right\rangle_b = U\left\langle \delta v \delta v^T \right\rangle_b U^T = UIU^T = UU^T.$$

- Substitute into $J^{3DVar}(\delta x)$: gives a cost function w.r.t. δv

$$\begin{aligned}
J^{3DVar}(\delta v) &= \frac{1}{2}\delta v^T \delta v + \frac{1}{2}\left(y - \mathscr{H}(x^b) - HU\delta v\right)^T R^{-1}(\bullet) \\
\nabla_{\delta v} J^{3DVar} &= \delta v - U^T H^T \left(y - \mathscr{H}(x^b) - HU\delta v\right) \\
x^a &= x^b + U\left(\text{argmin}\left[J^{3DVar}(\delta v)\right]\right).
\end{aligned}$$

Estimating a B-matrix

$$\mathrm{x} = \begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{pmatrix} \qquad \mathrm{B} = \left\langle \left(\mathrm{x}^{\mathrm{b}} - \mathrm{x}^{\mathrm{t}}\right) \left(\mathrm{x}^{\mathrm{b}} - \mathrm{x}^{\mathrm{t}}\right)^{\mathrm{T}} \right\rangle_{\mathrm{b}}$$

$$= \begin{pmatrix} \left\langle (x_1^{\mathrm{b}} - x_1^{\mathrm{t}})^2 \right\rangle_{\mathrm{b}} & \cdots & \left\langle (x_1^{\mathrm{b}} - x_1^{\mathrm{t}})(x_n^{\mathrm{b}} - x_n^{\mathrm{t}}) \right\rangle_{\mathrm{b}} \\ \vdots & \ddots & \vdots \\ \left\langle (x_n^{\mathrm{b}} - x_n^{\mathrm{t}})(x_1^{\mathrm{b}} - x_1^{\mathrm{t}}) \right\rangle_{\mathrm{b}} & \cdots & \left\langle (x_n^{\mathrm{b}} - x_n^{\mathrm{t}})^2 \right\rangle_{\mathrm{b}} \end{pmatrix}$$

$\langle \bullet \rangle_{\mathrm{b}}$: average over population of possible backgrounds.

Problem

The 'truth', x^{t}, that appears in the definition of error, $\varepsilon = \mathrm{x}^{\mathrm{b}} - \mathrm{x}^{\mathrm{t}}$, is unknowable, so need a proxy for this quantity.

Approaches to estimating a B-matrix (1)

"Canadian quick" method

$$\mathrm{x}^{\mathrm{b}} - \mathrm{x}^{\mathrm{t}} \sim \left(\mathrm{x}^{\mathrm{b}}(t+T) - \mathrm{x}^{\mathrm{b}}(T)\right)/\sqrt{2}.$$

Take population from one long time run, Polavarapu et al. (2005).

Approaches to estimating a B-matrix (2)

Analysis of innovations

Choose a pair of direct/independent obs locations separated by Δr:

$$\begin{aligned} & \left[y_r - x_r^{\mathrm{b}}\right]\left[y_{r+\Delta r} - x_{r+\Delta r}^{\mathrm{b}}\right] = \\ \left[\left\{y_r - x_r^{\mathrm{t}}\right\} - \left\{x_r^{\mathrm{b}} - x_r^{\mathrm{t}}\right\}\right] & \left[\left\{y_{r+\Delta r} - x_{r+\Delta r}^{\mathrm{t}}\right\} - \left\{x_{r+\Delta r}^{\mathrm{b}} - x_{r+\Delta r}^{\mathrm{t}}\right\}\right] = \\ & \left[\varepsilon_r^y - \varepsilon_r^{\mathrm{b}}\right]\left[\varepsilon_{r+\Delta r}^y - \varepsilon_{r+\Delta r}^{\mathrm{b}}\right]. \end{aligned}$$

Take the expectation:

$$\begin{aligned} \left\langle \left[\varepsilon_r^y - \varepsilon_r^{\mathrm{b}}\right]\left[\varepsilon_{r+\Delta r}^y - \varepsilon_{r+\Delta r}^{\mathrm{b}}\right]\right\rangle &= \left\langle \varepsilon_r^y \varepsilon_{r+\Delta r}^y \right\rangle + \left\langle \varepsilon_r^{\mathrm{b}} \varepsilon_{r+\Delta r}^{\mathrm{b}} \right\rangle \\ &= \sigma_{\mathrm{o}}^2 \delta_{\Delta r,0} + \sigma_{\mathrm{b}}^2 \mathrm{cor}_{\mathrm{b}}(\Delta r). \end{aligned}$$

Above assumes obs and bg errors, as are errors between obs at different locations. Take population from many pairs with same Δr. Rutherford (1972), Hollingsworth and Lönnberg (1986), Järvinen (2001).

Approaches to estimating a B-matrix (3)

National Meteorological Center (NMC) method

Choose pairs of lagged forecasts valid at the same time, e.g.:

$$\mathrm{x}^{\mathrm{b}} - \mathrm{x}^{\mathrm{t}} \sim \left(\mathrm{x}_{48}^{\mathrm{b}}(t) - \mathrm{x}_{24}^{\mathrm{b}}(t)\right) / \sqrt{2}.$$

Take population from difference at many times. Parrish and Derber (1992), Berre et al. (2006).

Approaches to estimating a B-matrix (4)

Ensemble method

If you have an ensemble that is correctly spread:

$$\mathrm{x}^{\mathrm{b}} - \mathrm{x}^{\mathrm{t}} \quad \sim \quad \mathrm{x}^{\mathrm{b}}_{(i)} - \langle \mathrm{x}^{\mathrm{b}} \rangle$$

or

$$\mathrm{x}^{\mathrm{b}} - \mathrm{x}^{\mathrm{t}} \quad \sim \quad \left(\mathrm{x}^{\mathrm{b}}_{(i)} - \mathrm{x}^{\mathrm{b}}_{(j)} \right) / \sqrt{2}.$$

Take population from ensemble members and over many times. Houtekamer et al. (1996), Buehner (2005), Bonavita et al. (2015).

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