

Variational data assimilation

Practicalities and Covariance Matrices

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7–10 March 2018, Univ. of Reading

Reminder of the cost function and an explicit formula for the analysis

The 4DVar cost function considered before

$$J(\mathbf{x}) = \frac{1}{2} (\mathbf{x}_0 - \mathbf{x}_0^b)^T \mathbf{B}_0^{-1}(\bullet) + \frac{1}{2} \sum_{i=0}^N (\mathbf{y}_i - \mathcal{H}_i(\mathbf{x}_i))^T \mathbf{R}_i^{-1}(\bullet)$$

... or more generically

$$J(\mathbf{x}) = \frac{1}{2} (\mathbf{x} - \mathbf{x}^b)^T \mathbf{B}^{-1}(\bullet) + \frac{1}{2} (\mathbf{y} - \mathcal{H}(\mathbf{x}))^T \mathbf{R}^{-1}(\bullet)$$

- The covariance matrices \mathbf{B} and \mathbf{R} influence the analysis profoundly.
- If $\mathcal{H}(\mathbf{x})$ is linear or weakly linear then $\mathcal{H}(\mathbf{x}^b + \delta\mathbf{x}) \approx \mathcal{H}(\mathbf{x}^b) + \mathbf{H}\delta\mathbf{x}$, and \mathbf{x}^a can be written explicitly:

$$\mathbf{x}^a = \mathbf{x}^b + \mathbf{B}\mathbf{H}^T (\mathbf{R} + \mathbf{H}\mathbf{B}\mathbf{H}^T)^{-1} (\mathbf{y} - \mathcal{H}(\mathbf{x}))$$

Example of non-linear model

Suppose we have the following \mathcal{M}

$$\mathbf{x} = \begin{pmatrix} \theta \\ \phi \end{pmatrix}$$

$$\frac{d\theta}{dt} = -\alpha(\theta - \phi)^2$$

$$\frac{d\phi}{dt} = g(\phi) + f(t)$$

Linearization (tangent linear model)

$$\begin{aligned}d\theta/dt &= -\alpha(\theta - \phi)^2 \\ \theta(t) &= \theta^R(t) + \delta\theta(t)\end{aligned}$$

$$\begin{aligned}d\phi/dt &= g(\phi) + f(t) \\ \phi(t) &= \phi^R(t) + \delta\phi(t)\end{aligned}$$

$$\begin{aligned}d\theta^R/dt &= -\alpha(\theta^R - \phi^R)^2 \\ d\delta\theta/dt &\approx -2\alpha(\theta^R - \phi^R)(\delta\theta - \delta\phi)\end{aligned}$$

$$\begin{aligned}d\phi^R/dt &= g(\phi^R) + f(t) \\ d\delta\phi/dt &\approx \left. \frac{dg}{d\phi} \right|_R \delta\phi + 0\end{aligned}$$

Euler scheme: $dx/dt \Rightarrow (x(t_{i+1}) - x(t_i)) / \Delta t$, let $F^R \equiv 2\alpha(\theta^R - \phi^R)$

$$\delta\theta(t_{i+1}) \approx \frac{\delta\theta(t_i) - \Delta t F^R (\delta\theta(t_i) - \delta\phi(t_i))}{\Delta t} \quad \delta\phi(t_{i+1}) \approx \frac{\delta\phi(t_i) + \Delta t (dg/d\phi) \delta\phi(t_i)}{\Delta t}$$

$$\begin{pmatrix} \delta\theta(t_{i+1}) \\ \delta\phi(t_{i+1}) \end{pmatrix} \approx \begin{pmatrix} 1 - \Delta t F^R & \Delta t F^R \\ 0 & 1 + \Delta t (dg/d\phi) \end{pmatrix} \begin{pmatrix} \delta\theta(t_i) \\ \delta\phi(t_i) \end{pmatrix}$$

Adjoint formulation

$$\delta\theta(t_{i+1}) \approx \frac{\delta\theta(t_i) - \Delta t F^R(\delta\theta(t_i) - \delta\phi(t_i))}{\Delta t} \quad \delta\phi(t_{i+1}) \approx \frac{\delta\phi(t_i) + \Delta t (dg/d\phi)\delta\phi(t_i)}{\Delta t}$$

Recipe for adjoint

- $\delta\theta(t_i) := 0$
- $\delta\phi(t_i) := 0$
- $\delta\theta(t_i) := \delta\theta(t_i) + \delta\theta(t_{i+1})$
- $\delta\theta(t_i) := \delta\theta(t_i) - \Delta t F^R \delta\theta(t_{i+1})$
- $\delta\phi(t_i) := \delta\phi(t_i) + \Delta t (dg/d\phi) \delta\phi(t_{i+1})$
- $\delta\phi(t_i) := \delta\phi(t_i) + \Delta t F^R \delta\theta(t_{i+1})$

Exercise: write in matrix form and check transpose of linear model.

Remember: adjoint goes backwards!

Bug warning

- Correctness test (TLM coded correctly?)

$$\lim_{\gamma \rightarrow 0} \frac{\|\mathcal{M}(\mathbf{x}^R + \gamma \delta \mathbf{x}) - \mathcal{M}(\mathbf{x}^R) - \mathbf{M} \gamma \delta \mathbf{x}\|}{\|\mathbf{M} \gamma \delta \mathbf{x}\|} \stackrel{?}{\rightarrow} 0$$

- Validity test (TLM a good approximation?)

Does $\mathcal{M}(\mathbf{x}^R + \gamma \delta \mathbf{x}) - \mathcal{M}(\mathbf{x}^R)$ compare well to $\mathbf{M} \gamma \delta \mathbf{x}$?

- Adjoint test (TLM^T coded correctly?) – machine precision required!

$$(\mathbf{M} \delta \mathbf{x})^T (\mathbf{M} \delta \mathbf{x}) \stackrel{?}{=} \delta \mathbf{x}^T \mathbf{M}^T \mathbf{M} \delta \mathbf{x}$$

- Gradient test (tests many aspects of the DA)

$$\Phi \equiv \frac{J(\mathbf{x}^R + \gamma \hat{\mathbf{h}}) - J(\mathbf{x}^R)}{\gamma \hat{\mathbf{h}}^T \nabla J(\mathbf{x}^R)} \stackrel{?}{\rightarrow} 1 + \mathcal{O}(\alpha), \quad \hat{\mathbf{h}} = \frac{\nabla J(\mathbf{x}^R)}{\|\nabla J(\mathbf{x}^R)\|}$$

- Care must be taken with linearizing processes that are non-differentiable (e.g. switches), and with iterative processes.
- Adjoint coding techniques applies to observation operators, \mathbf{H} , as well as to time evolution models, \mathbf{M} .
- Tangent linear and adjoint code requires a reference state, \mathbf{x}^R , which needs to be stored or recalculated (can be difficult for large models).
- Automatic adjoint compilers exist (e.g. TAF, ODYSSEE, ADIFOR, Python modules).

- Coding a TLM and adjoint
 - W.C. Chao and L-P. Chang (1992), Development of a four-dimensional variational analysis system using the adjoint method at GLA. Part I: Dynamics. Mon. Wea. Rev., 120:1661-1673.
 - R. Giering and T. Kaminski (1998), Recipes for adjoint code construction. ACM Trans. On Math. Software, 24:437-474.
- Testing a TLM and adjoint:
 - Y. Li, I.M. Navon, W. Yang, X. Zou, J.R. Bates, S. Moorthi and R.W. Higgins (1994), Four-dimensional variational data assimilation experiments with a multilevel semi-Lagrangian semi-implicit general circulation model. Mon. Wea. Rev., 122:966-983.
 - A.S. Lawless, N.K. Nichols and S.P. Ballard (2003), A comparison of two methods for developing the linearization of a shallow-water model, Quart. J. Roy. Met. Soc., 129:1237-1254.