

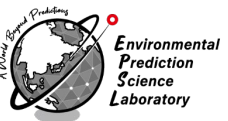
Data Assimilation - A12. EnVAR -

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Today's Goal

- ▶ **Lecture**

- ▶ what is the En-Var?
- ▶ what is the cost function of EnVAR?
- ▶ how to employ back propagation?

- ▶ **Training Course**

- ▶ to implement EnVAR

Review: 4DVAR

4DVAR Equation

Cost Function (scalar)

Tangent Linear Model $\mathbf{M}_{i|0} = \mathbf{M}_{i-1} \cdots \mathbf{M}_1 \mathbf{M}_0$

$$J(\delta \mathbf{x}_0) \approx \frac{1}{2} \delta \mathbf{x}_0^T \mathbf{B}_0^{-1} \delta \mathbf{x}_0 + \sum_{i=1}^k \frac{1}{2} (\mathbf{H}_i \mathbf{M}_{i|0} \delta \mathbf{x}_0 - \mathbf{d}_i^{o-b})^T \mathbf{R}_i^{-1} (H_i(M_{i|0}(\mathbf{x}_0)) - \mathbf{y}_i^o)$$

Jacobian ($\in \mathbb{R}^n$)

$$\frac{\partial J}{\partial (\delta \mathbf{x}_0)} \approx \mathbf{B}_0^{-1} (\delta \mathbf{x}_0) + \sum_{i=1}^k \underbrace{\mathbf{M}_0^T \cdots \mathbf{M}_{i-2}^T \mathbf{M}_{i-1}^T}_{\text{backpropagations}} \underbrace{\mathbf{H}_i^T}_{\text{obs operator}} \mathbf{R}_i^{-1} (H_i(M_{i|0}(\mathbf{x}_0)) - \mathbf{y}_i^o)$$

Hessian ($\in \mathbb{R}^{n \times n}$)

$$\frac{\partial^2 J}{\partial (\delta \mathbf{x}_0)^2} \approx \mathbf{B}_0^{-1} + \sum_{i=1}^k \mathbf{M}_0^T \cdots \mathbf{M}_{i-2}^T \mathbf{M}_{i-1}^T \mathbf{H}_i^T \mathbf{R}_i^{-1} \mathbf{H}_i \mathbf{M}_{i-1} \cdots \mathbf{M}_1 \mathbf{M}_0 = \mathbf{A}_0^{-1}$$

Problem to be solved

$$\delta \mathbf{x}_0^a = \operatorname{argmin} J(\delta \mathbf{x}_0) \quad \text{subject to} \quad \frac{\partial J}{\partial (\delta \mathbf{x}_0)} = 0$$

$$\mathbf{x}_0^a = \mathbf{x}_0^b + \delta \mathbf{x}_0^a$$

$$\mathbf{x}_i^a = M_{i|0}(\mathbf{x}_0^a)$$

Comparison

	4DVAR	4D EnVAR	EnKF
Solver	Iterative (OL & IL)	Iterative (IL only)	Deterministic
Ensemble FCST		<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>
TLM & ADJ of M	<input checked="" type="checkbox"/>		
TLM & ADJ of H	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	

Background Knowledge on Minimization

Minimization

Scalar Case

$$J = \frac{1}{2}px^2 + qx + r = \frac{1}{2}p\left(x + \frac{q}{p}\right)^2 + r'$$

$$J' = px + q \quad J'' = p$$

$$J' = 0 \Rightarrow x = -\frac{q}{p} = -(J'')^{-1}J'|_{x=0}$$

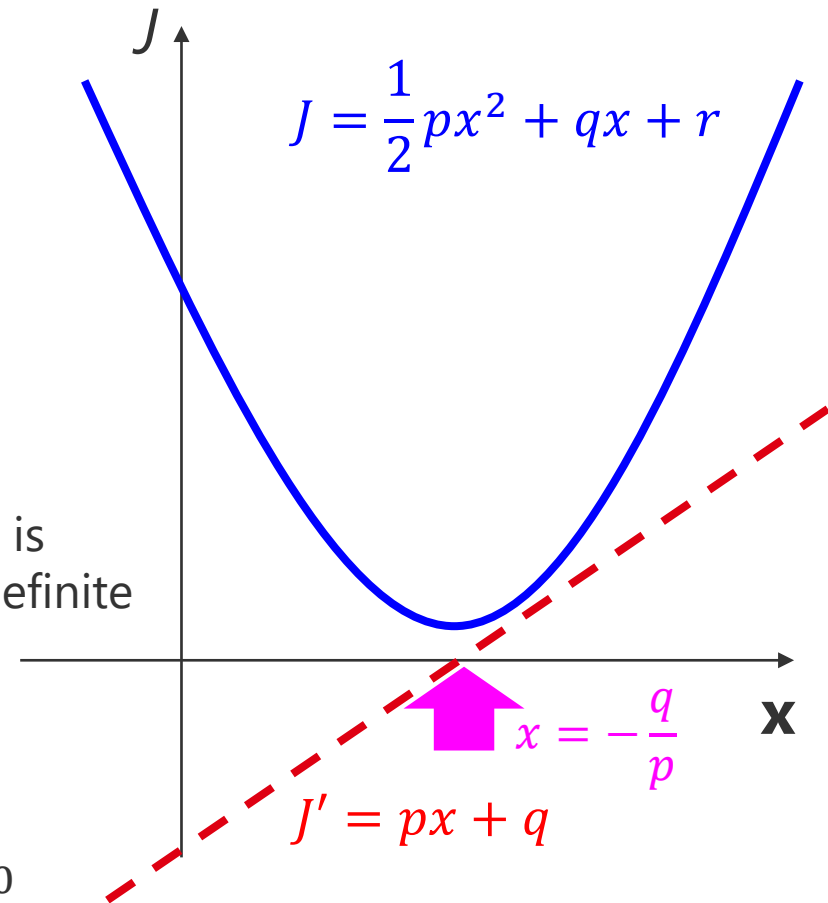
Multi-dimensional Case

$$J = \frac{1}{2}\mathbf{x}^T \mathbf{P}\mathbf{x} + \mathbf{q}^T \mathbf{x} + r$$

suppose \mathbf{P} is
 positive-semidefinite

$$J' = \mathbf{P}\mathbf{x} + \mathbf{q} \quad J'' = \mathbf{P}$$

$$J' = \mathbf{0} \Rightarrow \mathbf{x} = -\mathbf{P}^{-1}\mathbf{q} = -(J'')^{-1}J'|_{\mathbf{x}=\mathbf{0}}$$



Point 1: If inverse of Hessian $(J'')^{-1}$ is available

→ no iteration is necessary to find \mathbf{x} that minimizes the cost function

Point 2: But computing $(J'')^{-1}$ is expensive $\sim O(n^3)$ where n is the size of \mathbf{x}

→ For EnVAR, computing $(J'')^{-1}$ is affordable $\sim O(m^3)$

To see KF as minimization

Cost Function (scalar), Jacobian ($\in \mathbb{R}^n$), Hessian ($\in \mathbb{R}^{n \times n}$)

$$J(\delta \mathbf{x}) = \frac{1}{2} (\delta \mathbf{x})^T \mathbf{B}^{-1} (\delta \mathbf{x}) + \frac{1}{2} (\mathbf{H} \delta \mathbf{x} - \mathbf{d}_t^{o-b})^T \mathbf{R}^{-1} (\mathbf{H} \delta \mathbf{x} - \mathbf{d}_t^{o-b})$$

$$\begin{aligned} J'(\delta \mathbf{x}) &= \mathbf{B}^{-1} (\delta \mathbf{x}) + \mathbf{H}^T \mathbf{R}^{-1} (\mathbf{H} \delta \mathbf{x} - \mathbf{d}_t^{o-b}) \\ &= (\mathbf{B}^{-1} + \mathbf{H}^T \mathbf{R}^{-1} \mathbf{H}) \delta \mathbf{x} + \mathbf{H}^T \mathbf{R}^{-1} \mathbf{d}_t^{o-b} = \mathbf{A}^{-1} \delta \mathbf{x} - \mathbf{H}^T \mathbf{R}^{-1} \mathbf{d}_t^{o-b} \end{aligned}$$

$$J''(\delta \mathbf{x}) = \mathbf{B}^{-1} + \mathbf{H}^T \mathbf{R}^{-1} \mathbf{H}$$

Minimization

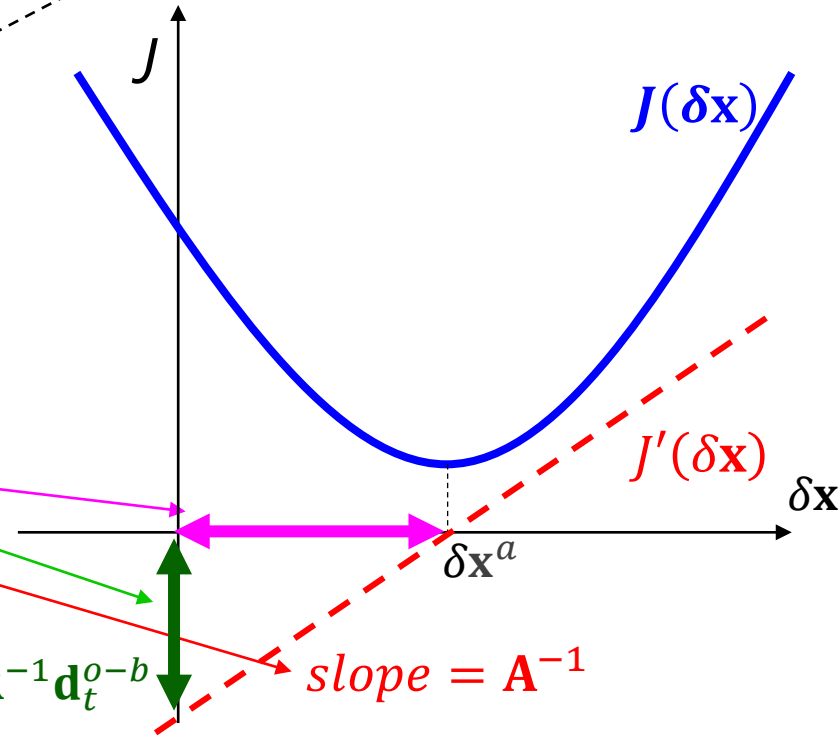
$$J'(\delta \mathbf{x}) = 0$$

$$\Rightarrow \delta \mathbf{x}^a = \mathbf{A} \mathbf{H}^T \mathbf{R}^{-1} \mathbf{d}_t^{o-b}$$

where $\mathbf{A} = (J'')^{-1}$

$$\mathbf{H}^T \mathbf{R}^{-1} \mathbf{d}_t^{o-b} = J' |_{\delta \mathbf{x}=0}$$

$$-\mathbf{H}^T \mathbf{R}^{-1} \mathbf{d}_t^{o-b} \quad \text{slope} = \mathbf{A}^{-1}$$



Pre-conditioning

Cost Function (scalar), Jacobian ($\in \mathbb{R}^n$), Hessian ($\in \mathbb{R}^{n \times n}$)

$$J(\delta \mathbf{x}) = \frac{1}{2} (\delta \mathbf{x})^T \mathbf{B}^{-1} (\delta \mathbf{x}) + \frac{1}{2} (\mathbf{H} \delta \mathbf{x} - \mathbf{d}_t^{o-b})^T \mathbf{R}^{-1} (\mathbf{H} \delta \mathbf{x} - \mathbf{d}_t^{o-b})$$

$$J'(\delta \mathbf{x}) = \mathbf{A}^{-1} \delta \mathbf{x} - \mathbf{H}^T \mathbf{R}^{-1} \mathbf{d}_t^{o-b}$$

$$J''(\delta \mathbf{x}) = \mathbf{A}^{-1}$$

variable conversion $\mathbf{z} = \mathbf{A}^{-1/2} \delta \mathbf{x}$

$$J(\mathbf{z}) = \frac{1}{2} (\mathbf{z})^T (\mathbf{z}) - (\mathbf{d}_t^{o-b})^T \mathbf{R}^{-1} \mathbf{H} \mathbf{A}^{1/2} \mathbf{z} + \frac{1}{2} (\mathbf{d}_t^{o-b})^T \mathbf{R}^{-1} \mathbf{d}_t^{o-b}$$

$$J'(\mathbf{z}) = \mathbf{z} - (\mathbf{d}_t^{o-b})^T \mathbf{R}^{-1} \mathbf{H} \mathbf{A}^{1/2}$$

$$J''(\mathbf{z}) = \mathbf{I}$$

with pre-conditioning, Hessian becomes to be the identity matrix

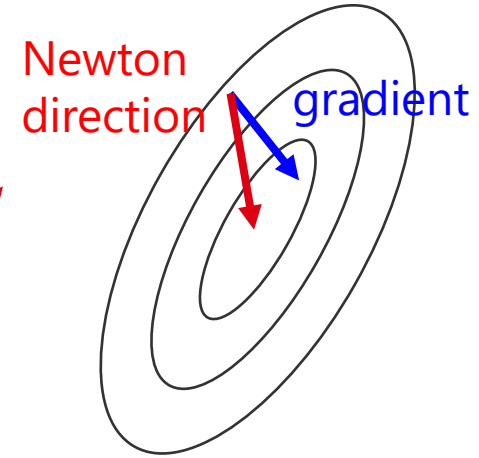
Comparison of minimizations

Gradient and Newton methods

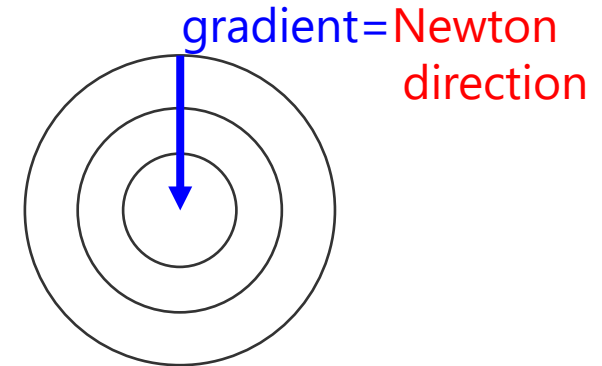
$$J' = \mathbf{B}^{-1}(\delta \mathbf{x}) + \mathbf{H}^T \mathbf{R}^{-1}(\mathbf{H} \delta \mathbf{x} - \mathbf{d}_t^{o-b})$$

$$\delta \mathbf{x} = -(\mathbf{J}''')^{-1} \mathbf{J}'$$

to change the gradient toward minima



pre-conditioning



with pre-conditioning, gradient gives the way toward minima because Hessian is the identity matrix

Computational Convergence

	Gradient	Newton
w/o pre-conditioning	slow	good
w/ pre-conditioning	good	/

EnVAR

(Ensemble Variational DA)

Cost Function of EnVAR

Cost Function of 4DVAR

$$H_i(M_{i|0}(\mathbf{x}_0)) - \mathbf{y}_i^o$$

$$J(\delta \mathbf{x}_0) \approx \frac{1}{2} \delta \mathbf{x}_0^T \mathbf{B}_0^{-1} \delta \mathbf{x}_0 + \sum_{i=1}^k \frac{1}{2} (H_i(M_{i|0}(\mathbf{x}_0)) - \mathbf{y}_i^o)^T \mathbf{R}_i^{-1} (H_i(M_{i|0}(\mathbf{x}_0)) - \mathbf{y}_i^o)$$

Cost Function (scalar)

ensemble

$$\mathbf{x}_0 = \bar{\mathbf{x}}_0^b + \delta \mathbf{x}_0 = \bar{\mathbf{x}}_0^b + \delta \mathbf{X}_0 \mathbf{w}$$

$$M_{i|0}(\mathbf{x}_0) = M_{i|0}(\bar{\mathbf{x}}_0^b + \delta \mathbf{X}_0 \mathbf{w})$$

$$J(\mathbf{w}) \approx \frac{1}{2} \mathbf{w}^T \mathbf{w} + \sum_{i=1}^k \frac{1}{2} (H_i(\bar{\mathbf{x}}_i^b + \delta \mathbf{X}_i \mathbf{w}) - \mathbf{y}_i^o)^T \mathbf{R}_i^{-1} (H_i(\bar{\mathbf{x}}_i^b + \delta \mathbf{X}_i \mathbf{w}) - \mathbf{y}_i^o)$$

Jacobian ($\in \mathbb{R}^m$)

$$\frac{\partial J}{\partial(\mathbf{w})} \approx \mathbf{w} + \sum_{i=1}^k \delta \mathbf{Y}_i^T \mathbf{R}_i^{-1} (H_i(\bar{\mathbf{x}}_i^b + \delta \mathbf{X}_i \mathbf{w}) - \mathbf{y}_i^o)$$

Hessian ($\in \mathbb{R}^{m \times m}$)

$$\frac{\partial^2 J}{\partial(\mathbf{w})^2} \approx \mathbf{I} + \sum_{i=1}^k \delta \mathbf{Y}_i^T \mathbf{R}_i^{-1} \delta \mathbf{Y}_i = \tilde{\mathbf{A}}_0^{-1}$$

analysis error covariance in ensemble subspace

Point 1:

$\delta \mathbf{X}$ is not changed
over iterations (one ens. fcst)

Point 2:

nonlinearity of obs ope. H should
be considered for every iteration.

Otherwise, EnVAR yields the
same analysis of ETKF.

Importance of non-linearity

Cost Function (scalar) and Jacobian ($\in \mathbb{R}^m$) w/ nonlinearity

$$J(\mathbf{w}) \approx \frac{1}{2} \mathbf{w}^T \mathbf{w} + \sum_{i=1}^k \frac{1}{2} (H_i(\bar{\mathbf{x}}_i^b + \delta \mathbf{X}_i \mathbf{w}) - \mathbf{y}_i^o)^T \mathbf{R}_i^{-1} (H_i(\bar{\mathbf{x}}_i^b + \delta \mathbf{X}_i \mathbf{w}) - \mathbf{y}_i^o)$$

$$\frac{\partial J}{\partial(\mathbf{w})} \approx \mathbf{w} + \sum_{i=1}^k \delta \mathbf{Y}_i^T \mathbf{R}_i^{-1} (H_i(\bar{\mathbf{x}}_i^b + \delta \mathbf{X}_i \mathbf{w}) - \mathbf{y}_i^o)$$

$$H_i(\bar{\mathbf{x}}_i^b + \delta \mathbf{X}_i \mathbf{w}) - \mathbf{y}_i^o \approx \mathbf{H} \delta \mathbf{X}_i \mathbf{w} - \mathbf{d}_i^o \equiv \delta \mathbf{Y}_i \mathbf{w} - \mathbf{d}_i^o$$

Cost Function (scalar) and Jacobian ($\in \mathbb{R}^m$) w/o nonlinearity

$$J(\mathbf{w}) \approx \frac{1}{2} \mathbf{w}^T \mathbf{w} + \sum_{i=1}^k \frac{1}{2} (\delta \mathbf{Y}_i \mathbf{w} - \mathbf{d}_i^o)^T \mathbf{R}_i^{-1} (\delta \mathbf{Y}_i \mathbf{w} - \mathbf{d}_i^o)$$

$$\frac{\partial J}{\partial(\mathbf{w})} \approx \mathbf{w} + \sum_{i=1}^k \delta \mathbf{Y}_i^T \mathbf{R}_i^{-1} (\delta \mathbf{Y}_i \mathbf{w} - \mathbf{d}_i^o) \quad \frac{\partial^2 J}{\partial(\mathbf{w})^2} \approx \mathbf{I} + \sum_{i=1}^k \delta \mathbf{Y}_i^T \mathbf{R}_i^{-1} \delta \mathbf{Y}_i = \tilde{\mathbf{A}}_0^{-1}$$

$$\frac{\partial J}{\partial(\mathbf{w})} = 0 \Rightarrow \mathbf{w} + \sum_{i=1}^k \delta \mathbf{Y}_i^T \mathbf{R}_i^{-1} (\delta \mathbf{Y}_i \mathbf{w} - \mathbf{d}_i^o) = 0$$

Point 1: the weight can be determined deterministically (no iteration is needed).

Point 2: the analysis is equivalent to 4D-LETKF (\rightarrow no reason to use iterative solver)

Thank you for your attention!

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Further information is available at
<https://kotsuki-lab.com/>

