

Innovation Statistics

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Desroziers et al. 2005

A set of diagnostics in observation space.

$$\text{Recall } \vec{d}^{o-b} = \vec{y}^o - \vec{h}(\bar{x}^b) \quad (1)$$

Define another two differences:

$$\vec{d}^{o-a} = \vec{y}^o - \vec{h}(\bar{x}^a) \quad (2)$$

$$\vec{d}^{a-b} = \vec{h}(\bar{x}^a) - \vec{h}(\bar{x}^b) \quad (3)$$

Note that $\bar{h}(\bar{x})$ is used instead of $h(\bar{x})$ for some cases.

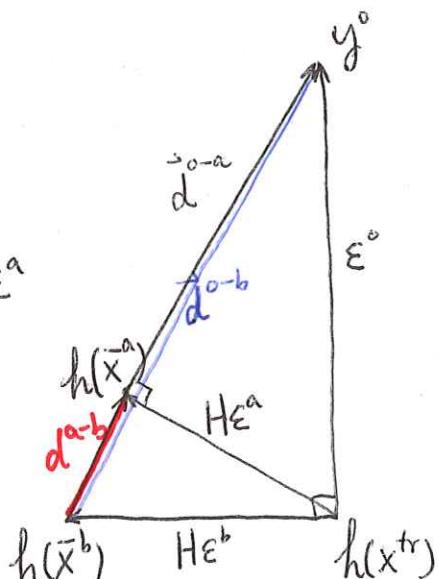
$$\vec{y}^o = \vec{h}(x^{tr}) + \vec{\varepsilon}^o$$

$$\bar{x}^b = x^{tr} + \varepsilon^b$$

$$h(\bar{x}^b) = h(x^{tr}) + H\varepsilon^b$$

$$\text{similarly, } h(\bar{x}^a) = h(x^{tr}) + H\varepsilon^a$$

→ Geometric representation of relation between \vec{d}^{o-b} , \vec{d}^{a-b} and \vec{d}^{o-a}



→ $\vec{\varepsilon}^o$ is orthogonal to $H\varepsilon^b$, because observation errors are not correlated with background errors:

$$\mathbb{E}(\varepsilon^o \varepsilon^{bT}) = 0$$

$$\begin{aligned} \vec{d}^{o-b} &= h(x^{tr}) + \varepsilon^o - h(x^{tr}) - H\varepsilon^b \\ &= \varepsilon^o - H\varepsilon^b \end{aligned} \quad (4)$$

$$\begin{aligned} \mathbb{E}(d^{o-b}(d^{o-b})^T) &= \mathbb{E}(\varepsilon^o \varepsilon^{o^T}) + H \mathbb{E}(\varepsilon^b \varepsilon^{b^T}) H^T \\ &= R + H P^b H^T \end{aligned} \quad (5)$$

- This relation should hold if filter is performing as expected: P^b is correctly characterizing background error ε^b .
- If P^b is too small compared to actual $\mathbb{E}(\varepsilon^b \varepsilon^{b^T})$, which means filter is too confident about the background, after assimilation, $P^a = (I - KH)P^b$ is reduced even more. Over time, when P^b is always too small, less and less weight will be given to observation, eventually ignoring observations

$$x^a = (I - KH)x^b + K y^o$$

$K \rightarrow 0, x^a \rightarrow x^b$

This is called "catastrophic filter divergence"

→ filter solution diverge from truth, yet P^b keeps decreasing.

→ One way to diagnose for this situation is

calculating the "consistency ratio":

$$CR = \frac{\text{tr}[H P^b H^T + R]}{\text{tr}[\mathbb{E}(d^{o-b}(d^{o-b})^T)]}$$

actual spread

expected spread

If $CR = 1$: filter performance is well characterized by P^b → good spread skill.

If $CR < 1$: ensemble is under-dispersive
→ susceptible to filter divergence

If $CR > 1$: ensemble is over-dispersive.

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Several other equalities:

$$d^{a-b} \cong H(\bar{x}^a - \bar{x}^b) = HK d^{a-b}$$

$$\begin{aligned} E[d^{a-b}(d^{a-b})^T] &= HK E[d^{a-b}(d^{a-b})^T] \\ &= HP^b H^T (HP^b H^T + R)^{-1} (HP^b H^T + R) \\ &= HP^b H^T \end{aligned}$$

$$\begin{aligned} d^{a-a} &= y^a - h(\bar{x}^b) + h(\bar{x}^b) - h(\bar{x}^a) \\ &\cong d^{a-b} - H(\bar{x}^a - \bar{x}^b) = (I - HK)d^{a-b} \end{aligned}$$

$$\begin{aligned} E[d^{a-a}(d^{a-b})^T] &= (I - HK)E[d^{a-b}(d^{a-b})^T] \\ &= R(HP^b H^T + R)^{-1} (HP^b H^T + R) \\ &= R \end{aligned}$$

$$\begin{aligned} E[d^{a-b}(d^{a-a})^T] &= HK E[d^{a-b}(d^{a-b})^T] (I - HK)^T \\ &= HP^b H^T (HP^b H^T + R)^{-1} R = H(I - KH)P^b H^T \\ &= HP^a H^T \end{aligned}$$

In summary:

$$E[d^{a-b}(d^{a-b})^T] = HP^b H^T + R$$

$$E[d^{a-b}(d^{a-b})^T] = HP^b H^T$$

$$E[d^{a-a}(d^{a-b})^T] = R$$

$$E[d^{a-b}(d^{a-a})^T] = HP^a H^T$$

Hint: use the triangle to remember these.