





Incorporating non-Gaussian observation errors into variational methods



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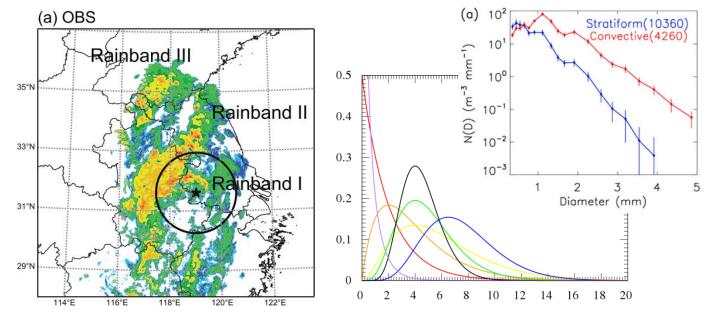


The observation errors can be quite non-Gaussian due to the errors in the observation operator

• Consider a perfect model state and a perfect observation:

$$y^{truth} \neq H(x^{truth})$$

- The errors in the observation operator *H* come from
 - e.g., inappropriate assumptions in *H*



Example: cloudy radiances

$$H = (RTM \circ M_{t_{initial} \to t_{obs}})$$

The error can be quite non-Gaussian when predicting clouds (e.g., due to the displacement error)

figures from Wang et al. (2020); Thomas et al. (2021)

How do we incorporate non-Gaussian errors into DA?

- Nonlinear DA methods, e.g., Particle Flow Filter Daum and Huang (2011); Liu and Wang (2016); Pulido and van Leeuwen (2019); Hu and van Leeuwen (2021)
- Variational methods
 - Derive the cost-function for the non-Gaussian pdf
 - Examples: varQC Anderson and Järvinen (1999), log-normal Fletcher and Zupanski (2006), Huber norm Huber (1972); Tavolato and Isaksen (2015)
- These methods require a prior assumption of the parametric form of the error distribution.

• **Motivation**: to propose a method that can incorporate non-Gaussian errors into the variational methods in a more general way

The "evolving-Gaussian" method for the variational methods

Key idea: approximate the cost-function iteratively using Gaussian errors.

 $J^{NG}(x)$ the cost-function from an arbitrary non-Gaussian pdf

$$J^{NG}(x_0) \xrightarrow{\text{find a Gaussian } G_0 \text{ s.t.}} J^{G_0}(x_0)$$
 the first-guess (background)
$$J^{NG}(x_1) \xrightarrow{\text{find } G_1 \text{ s.t.}} J^{G_1}(x_1)$$
 update the state
$$J^{NG}(x_1) \xrightarrow{\nabla J^{NG}(x_1) = \nabla J^{G_1}(x_1)} J^{G_1}(x_1)$$

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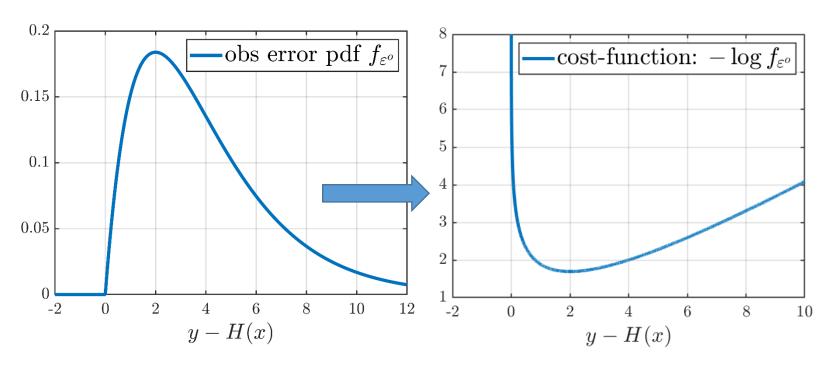
How do we find "the Gaussian(s)" in the evolving-Gaussian method?

- Assumptions:
 - Independent observation errors ⇒ the observation error pdf reduces to a 1-D pdf
 - We have access to the 1-D observation error pdf, denoted as $f_{\varepsilon^o}(y-H(x))$
- Consider the cost-function for one observation (at the *i* th iteration):

$$J^{NG}(x_i) = J_b(x_i) + J_o^{NG}(x_i)$$

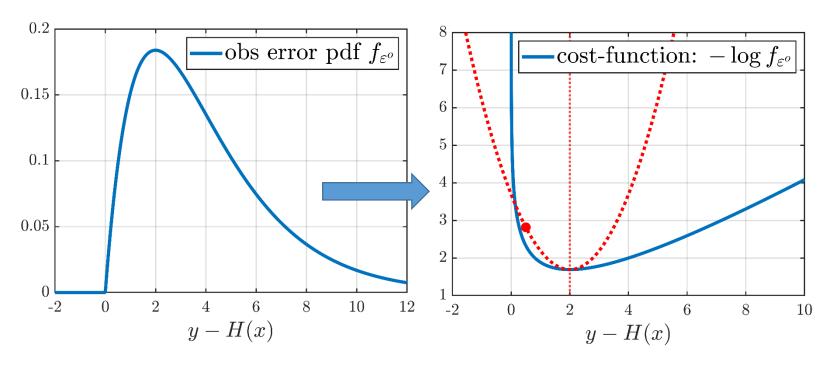
$$J_o^{NG}(x_i) = -\log f_{\varepsilon^o} \left(y - H(x_i) \right)$$

$$J_o^{G_i}(x_i) = \frac{1}{2} \left(\frac{H(x_i) - y + \mu_i}{\sigma_i} \right)^2 \quad \text{set } \mu_i = \text{the mode of } f_{\varepsilon^o}$$
 and solve σ_i by $\nabla J_o^{NG}(x_i) = \nabla J_o^{G_i}(x_i)$



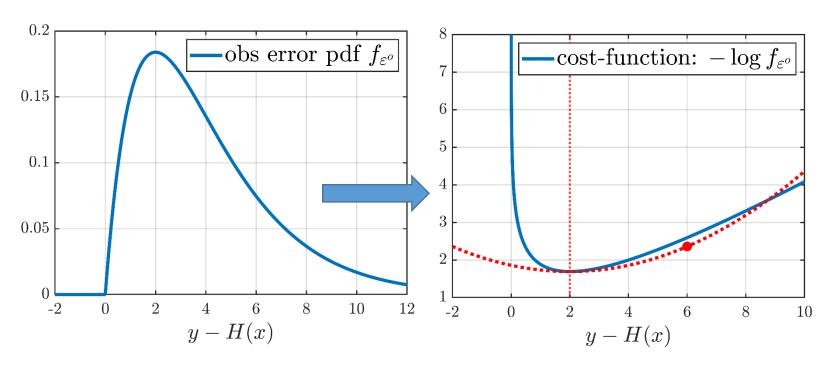
non-Gaussian obs error pdf $f_{\varepsilon^o}(y - H(x))$

non-Gaussian cost-function
$$J_o^{NG} = -\log f_{\varepsilon^o}$$



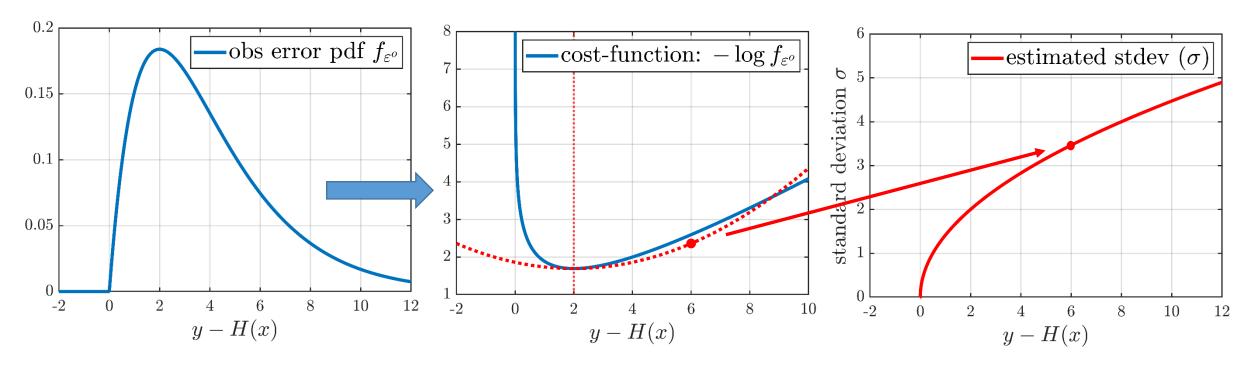
non-Gaussian obs error pdf $f_{\varepsilon^o}(y - H(x))$

(blue) non-Gaussian cost-function $J_o^{NG} = -\log f_{\varepsilon^o}$ (red) Gaussian cost-function $J_o^{G_i}$ when y - H(x) = 0.5



non-Gaussian obs error pdf $f_{\varepsilon^o}(y - H(x))$

(blue) non-Gaussian cost-function $J_o^{NG} = -\log f_{\varepsilon^o}$ (red) Gaussian cost-function $J_o^{G_i}$ when y - H(x) = 6.0



non-Gaussian obs error pdf $f_{\varepsilon^o}(y - H(x))$

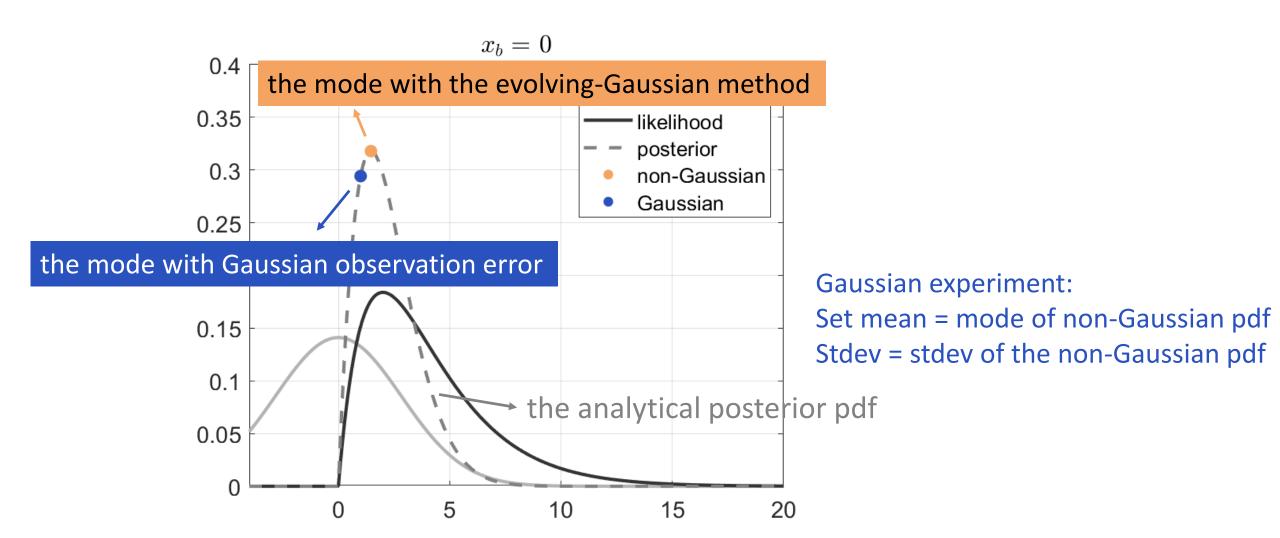
non-Gaussian cost-function $J_o^{NG} = -\log f_{\varepsilon^o}$

Summary of the Gaussian(s)
$$\sigma(y - H(x))$$

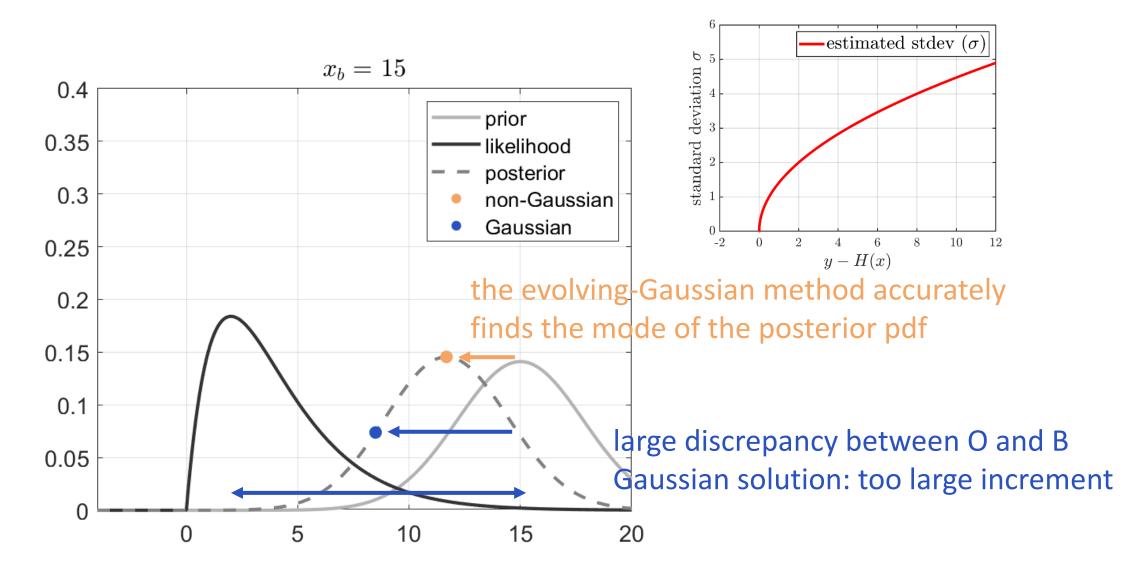
Remarks of the evolving-Gaussian method

- Easy: the cost-function remains the same, no need to change the cost-function at all.
- Efficient: all the work can be done offline, only need a lookup table $\sigma(y H(x))$
- In theory, we need to evolve the Gaussian for every inner and outer loops.
 - need to evaluate H for each inner loop
- What if we only evolve the Gaussian in the outer loop?
 - A similar idea to linearize H in each outer loop in the incremental (3)4D-Var
 - The cost-function remains quadratic in the inner loops

An idealized test for the evolving-Gaussian method in the outer loop



What can we learn from the idealized experiment?



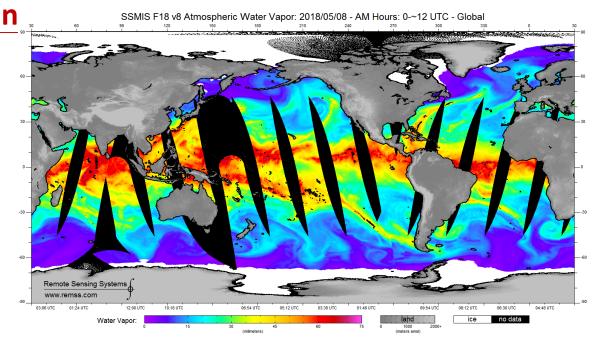
An implementation for the all-sky microwave radiance in IFS-ECMWF

- Selected SSMIS channels: ch12 (19H), ch13 (19V), ch14 (22V), ch16 (37V), ch17 (91V)
- The assumptions for the assimilation of the all-sky microwave radiances:
 - A "symmetric cloud"-dependent Gaussian observation error model

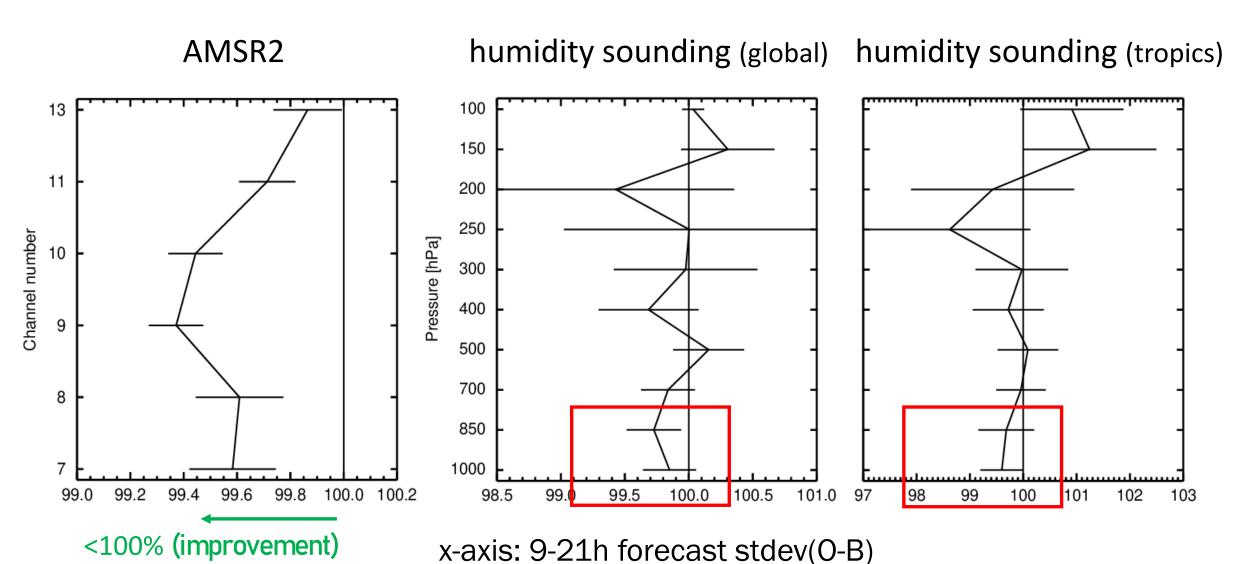
$$\overline{C_{37}} = \frac{C_{37}^o + C_{37}^b}{2}$$

Geer and Bauer (2011)

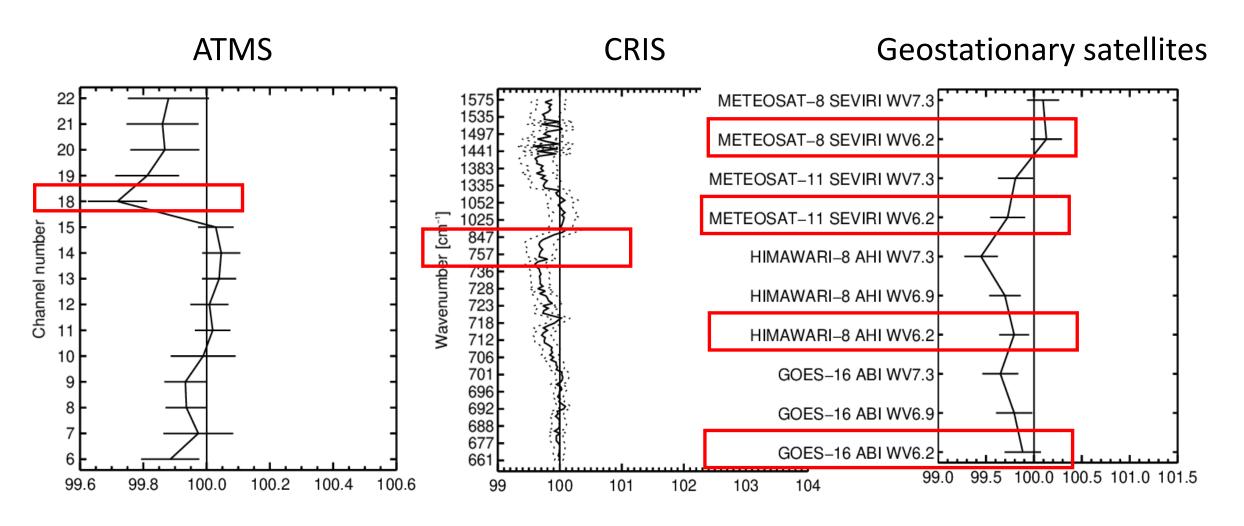
 The O-B (innovation) pdf is assumed to be the observation error pdf*
(*subtracting the background error from O-B does not improve the results)



Preliminary results suggest lower tropospheric water vapor, cloud and precipitation are improved, especially in the tropics.

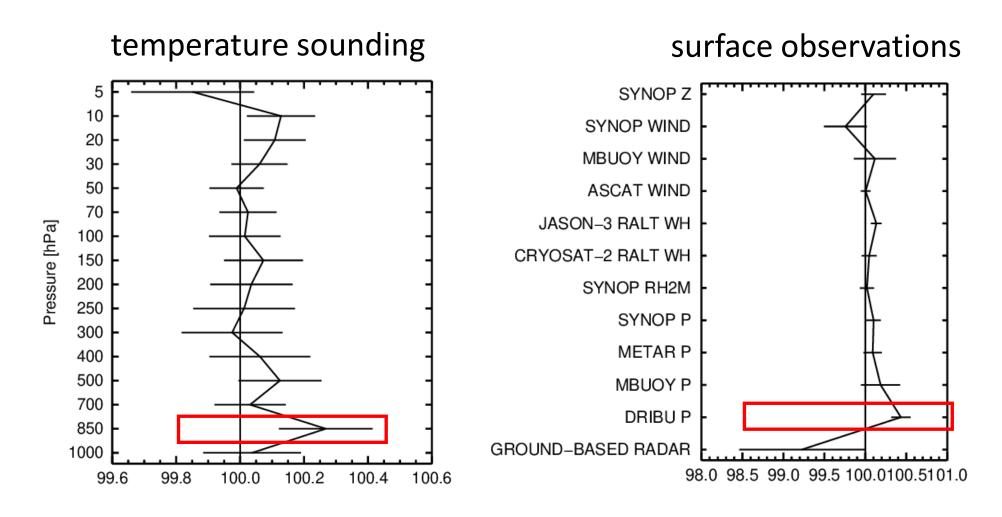


Preliminary results suggest lower tropospheric water vapor, cloud and precipitation are improved, especially in the tropics.



x-axis: 9-21h forecast stdev(O-B)

There are degradations in temperature and surface pressure



x-axis: 9-21h forecast stdev(O-B)

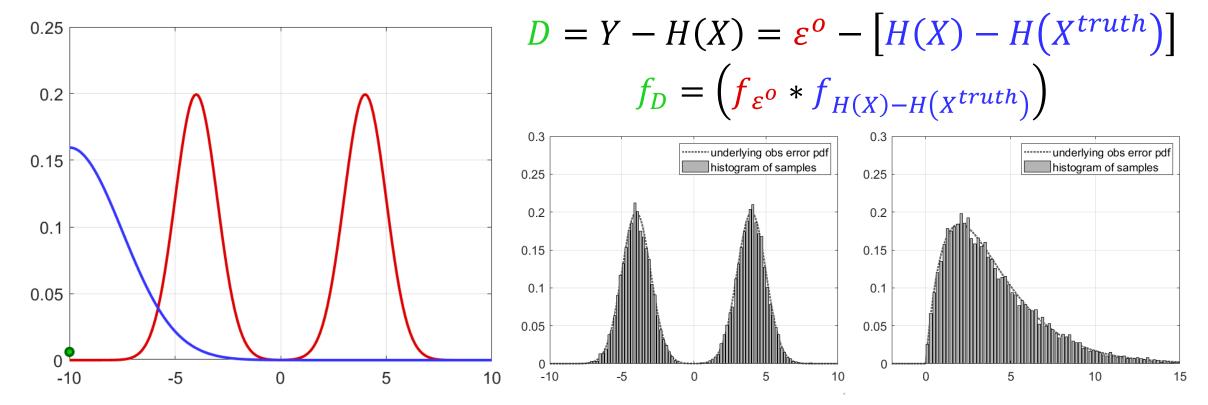
Deconvolution-based Observation Error Estimation (DOEE)

Hu, van Leeuwen and Geer (under review)

• Currently, the innovation pdf is assumed to be the observation error pdf (for the all-sky microwave radiances).

How do we identify the pdf of an arbitrary non-Gaussian observation error?

DOEE can be used to find a non-parametric observation error pdf:



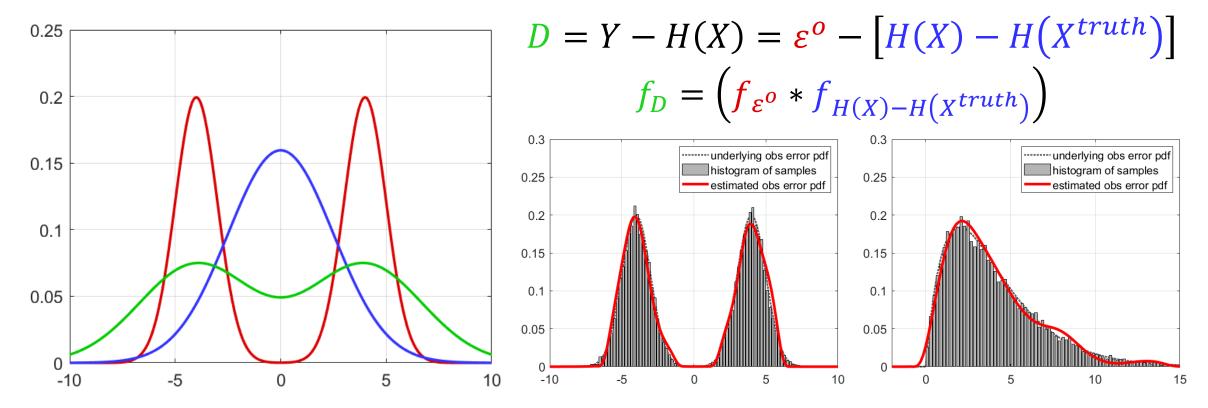
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Future work and possible applications

- Incorporate non-Gaussian observation error for more observation types.
- The evolving-Gaussian method for the inner-loop using approximated H(x)

Possible applications:

- ML based observation operator ("surrogate observation operator")
- The errors from the ML observation operator can be difficult to estimate
- DOEE can be used to estimate the errors from the ML observation operator
- DOEE + evolving-Gaussian method can be applied in 4D-Var.

Conclusions

- We propose a new way, the evolving-Gaussian method, to incorporate general non-parametric observation error pdfs into the variational methods.
- The evolving-Gaussian method does not require revising the cost-function, and therefore it is easy to implement in a full-scale weather prediction system without adding much computational cost.
- We have implemented the evolving-Gaussian method for the all-sky microwave radiances in IFS-ECMWF, resulting in improved short-term forecasts of the lower-tropospheric cloud, water vapor and precipitations, especially in the tropics.
- The evolving-Gaussian method, together with the non-Gaussian observation error estimation technique DOEE, can potentially address the issues regarding the complicated errors in the observation operators.

Contact Info

 Feel free to send me an email for any questions, comments or more info about DOEE/the evolving-Gaussian method!

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