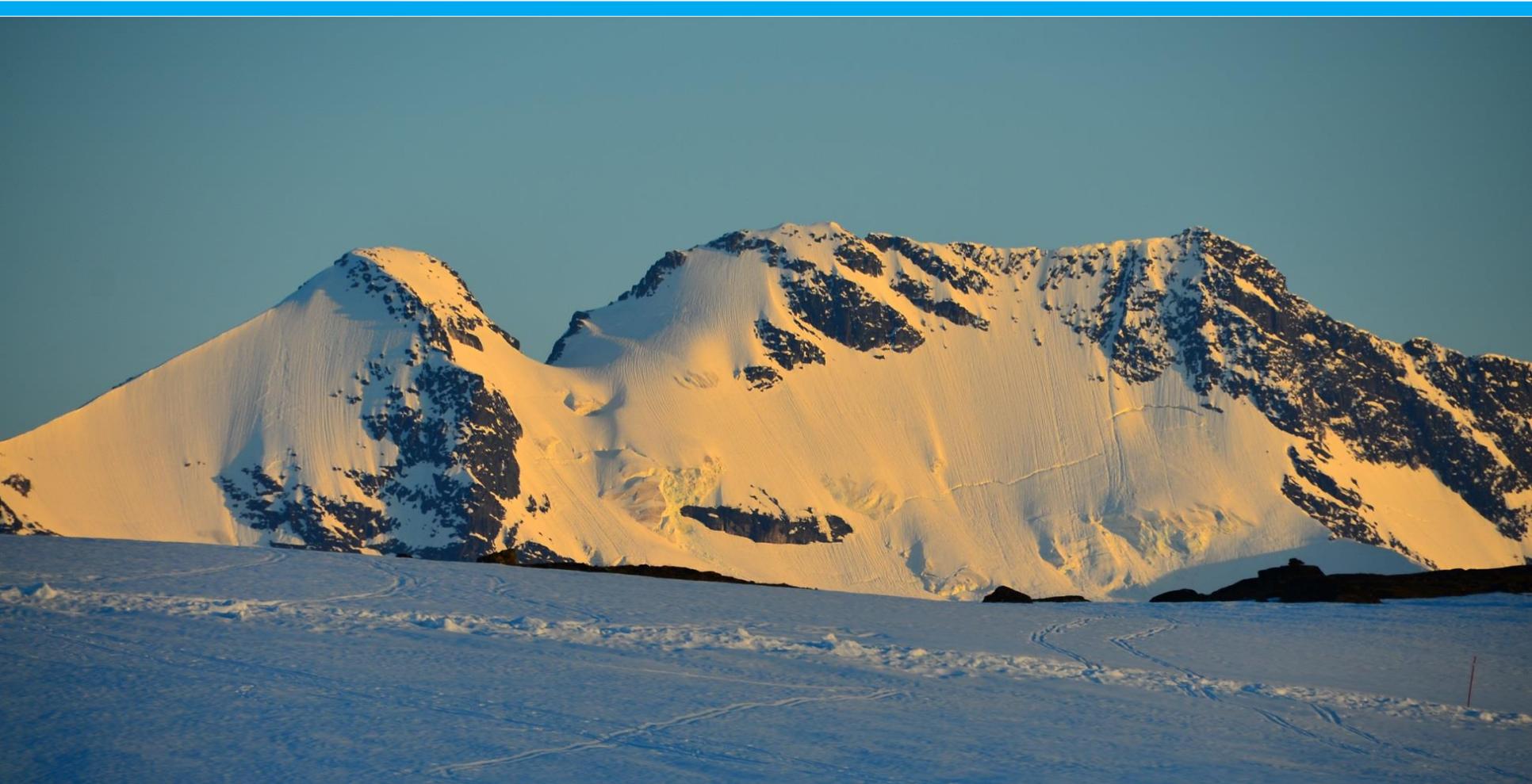


Stable and fast inversion with large data sets and non-diagonal R

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Outline

- › Analysis equation
- › Large data sets $m \gg N$
- › Measurements with correlated errors
- › Stable inversion of $C=HPH' + R$
- › Super-efficient subspace inversion

Analysis equation

- › Standard Kalman update equation

$$\Psi^a = \Psi^f + C_{\Psi\Psi} M^T \left(M C_{\Psi\Psi} M^T + C_{\epsilon\epsilon} \right)^{-1} (d - M \Psi^f)$$

Ensemble representation

› Ensemble matrix:
$$\mathbf{A} = (\boldsymbol{\Psi}_1, \boldsymbol{\Psi}_2, \dots, \boldsymbol{\Psi}_N)$$

› Ensemble perturbations:
$$\mathbf{A}' = \mathbf{A} - \overline{\mathbf{A}}$$

› Ensemble covariance:
$$\mathbf{C}_{\Psi\Psi}^e = \frac{\mathbf{A}' \mathbf{A}'^T}{N - 1}$$

Ensemble representation for measurements

- › Perturbed measurements: $\mathbf{d}_j = \mathbf{d} + \boldsymbol{\epsilon}_j$
- › Measurement matrix: $\mathbf{D} = (\mathbf{d}_1, \mathbf{d}_2, \dots, \mathbf{d}_N)$
- › Measurement perturbations: $\mathbf{E} = (\boldsymbol{\epsilon}_1, \boldsymbol{\epsilon}_2, \dots, \boldsymbol{\epsilon}_N)$
- › Measurement error cov: $\mathbf{C}_{\boldsymbol{\epsilon}\boldsymbol{\epsilon}}^e = \frac{\mathbf{E}\mathbf{E}^T}{N - 1}$

Analysis equation

- › Standard Kalman update equation

$$\Psi^a = \Psi^f + C_{\Psi\Psi} M^T \left(M C_{\Psi\Psi} M^T + C_{\epsilon\epsilon} \right)^{-1} (d - M \Psi^f)$$

- › Ensemble formulation

$$\mathbf{A}^a = \mathbf{A}^f + \mathbf{A}'^f (\mathbf{M} \mathbf{A}'^f)^T \left(\mathbf{M} \mathbf{A}'^f (\mathbf{M} \mathbf{A}'^f)^T + \mathbf{E} \mathbf{E}^T \right)^{-1} (\mathbf{D} - \mathbf{M} \mathbf{A}^f)$$

$$\mathbf{A}' = \mathbf{A} (\mathbf{I} - \mathbf{1}_N)$$

$$\mathbf{C} = \mathbf{S} \mathbf{S}^T + (N - 1) \mathbf{C}_{\epsilon\epsilon}$$

$$\mathbf{S} = \mathbf{M} \mathbf{A}'$$

$$\mathbf{D}' = \mathbf{D} - \mathbf{M} \mathbf{A}$$

Update equation

$$\begin{aligned}
 A^a &= A + A'S^T C^{-1} D' \\
 &= A + A(I - \mathbf{1}_N) S^T C^{-1} D' \\
 &= A(I + (I - \mathbf{1}_N) S^T C^{-1} D') & \mathbf{1}_N S^T &\equiv 0 \\
 &= A(I + S^T C^{-1} D') \\
 &= AX,
 \end{aligned}$$

- Solution searched for in the space spanned by prior realizations.
- Inversion of C with large $m \gg N$?

$$C = SS^T + (N - 1)C_{\epsilon\epsilon}$$

SQRT scheme

Update the mean and perturbations seperately

$$\bar{\boldsymbol{\psi}}^a = \bar{\boldsymbol{\psi}}^f + \mathbf{A}' \mathbf{S}^T \mathbf{C}^{-1} \left(\mathbf{d} - \mathbf{M} \bar{\boldsymbol{\psi}}^f \right)$$

$$\mathbf{A}^{a'} \mathbf{A}^{a'T} = \mathbf{A}' \left(\mathbf{I} - \mathbf{S}^T \mathbf{C}^{-1} \mathbf{S} \right) \mathbf{A}'^T$$

Still need to invert \mathbf{C}

Implementation issues

- › Need to invert

$$\mathbf{C} = \mathbf{S}\mathbf{S}^T + (N - 1)\mathbf{C}_{\epsilon\epsilon}.$$

- › May be singular or poorly conditioned.
- › Pseudo inversion:

$$\mathbf{C} = \mathbf{Z}\mathbf{\Lambda}\mathbf{Z}^T \Rightarrow \mathbf{C}^+ = \mathbf{Z}\mathbf{\Lambda}^+\mathbf{Z}^T$$

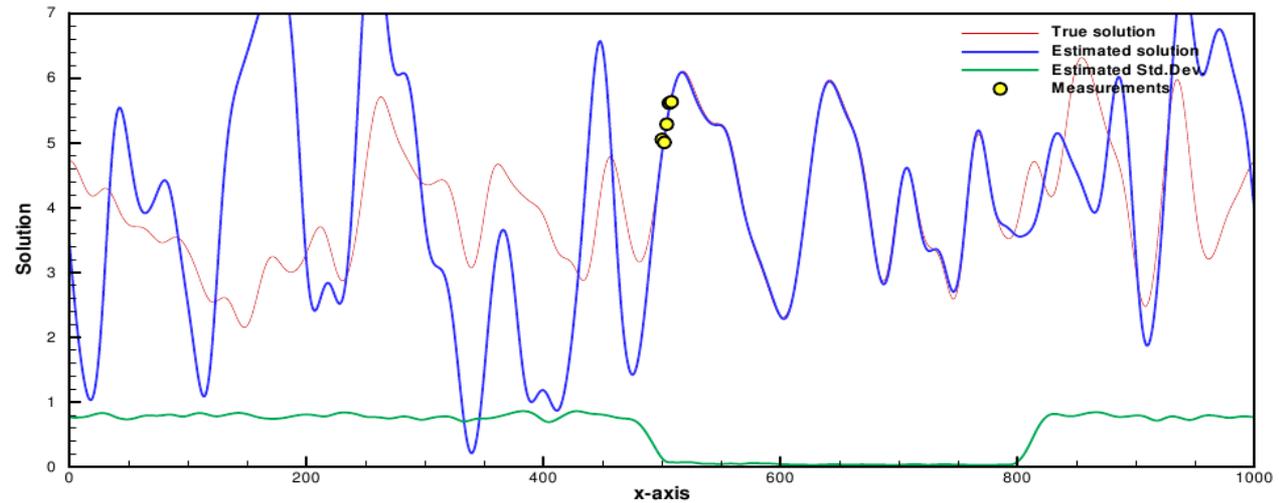
$$\text{diag}(\mathbf{\Lambda}^+) = (\lambda_1^{-1}, \dots, \lambda_p^{-1}, 0, \dots, 0).$$

$\mathcal{O}(m^3)$ operations.

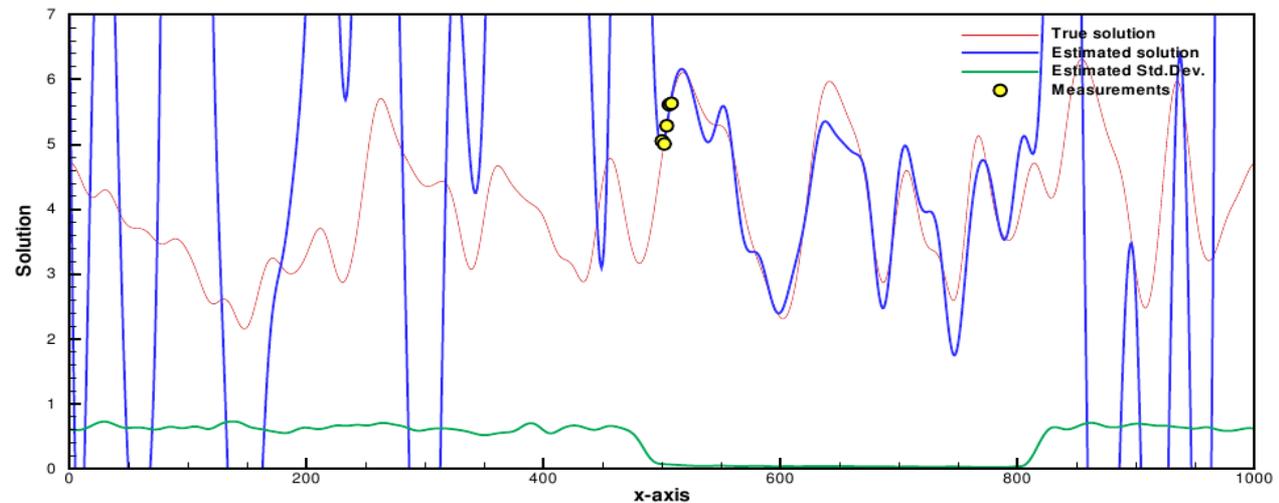
Example: EnKF with pseudo inversion of C

$\text{Eig}(1)/\text{eig}(5) = O(10^5)$

Truncation at 90% retains one eigenvalue out of five.



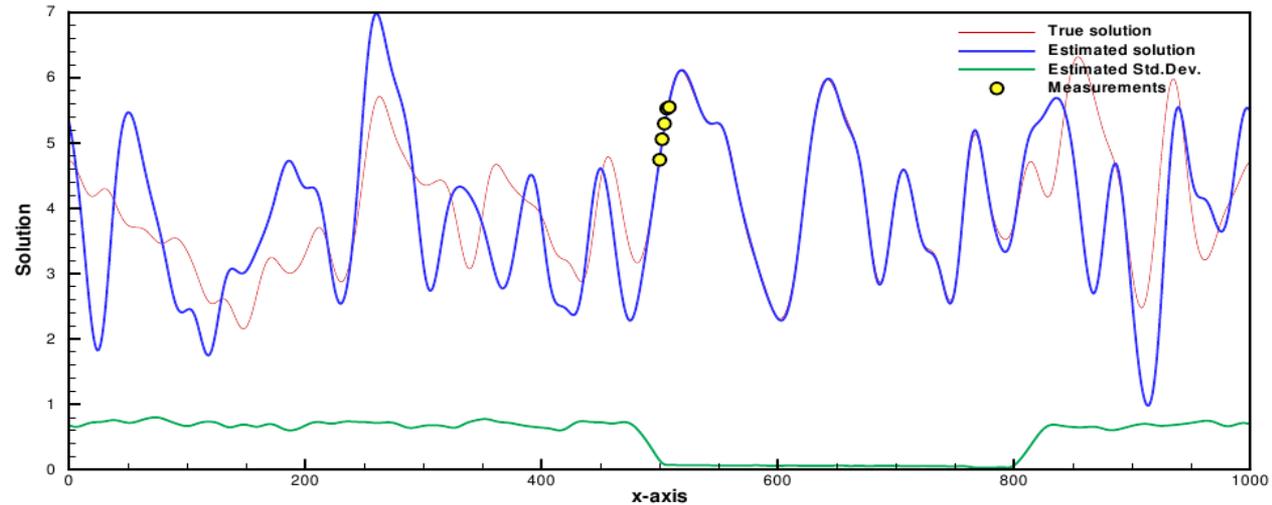
Truncation at 99.9% retains four eigenvalues out of five.



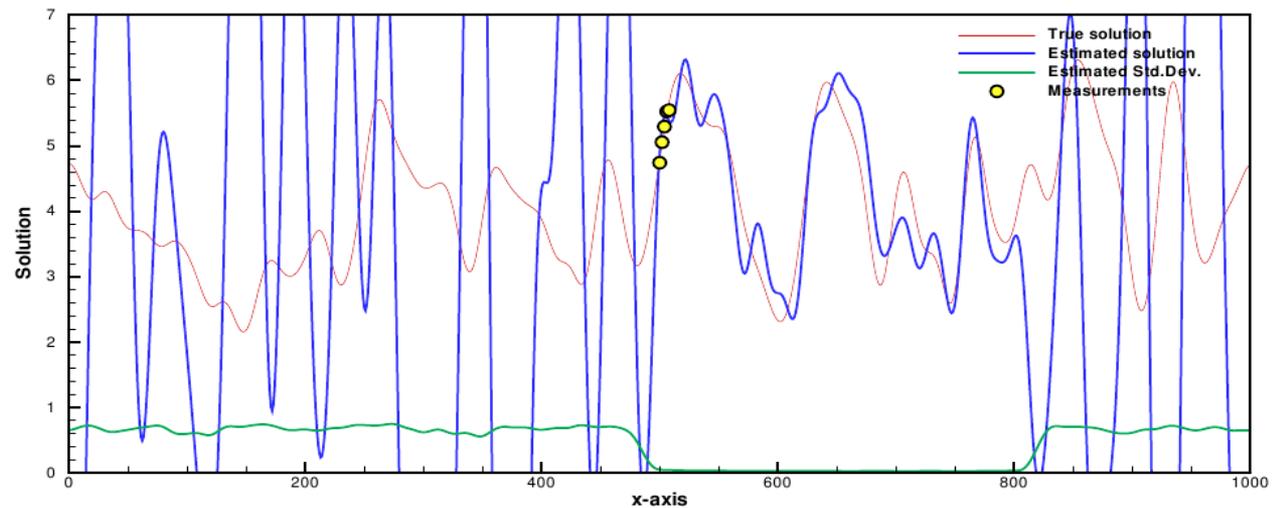
Example: EnSQR with pseudo inversion of C

$\text{Eig}(1)/\text{eig}(5) = O(10^5)$

Truncation at 90% retains one eigenvalue out of five.

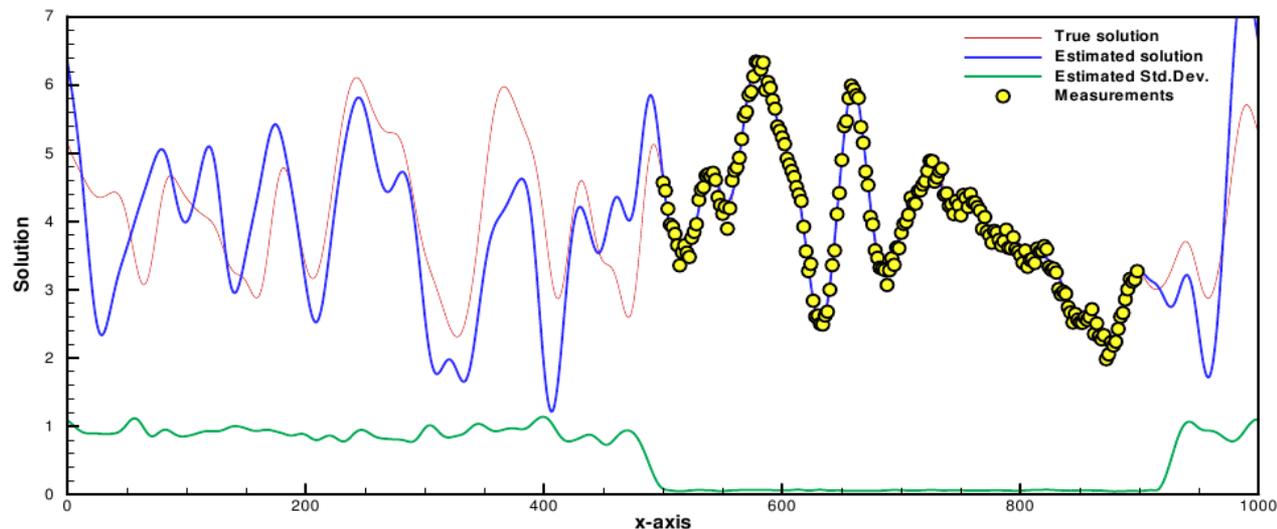


Truncation at 99.9% retains four eigenvalues out of five.

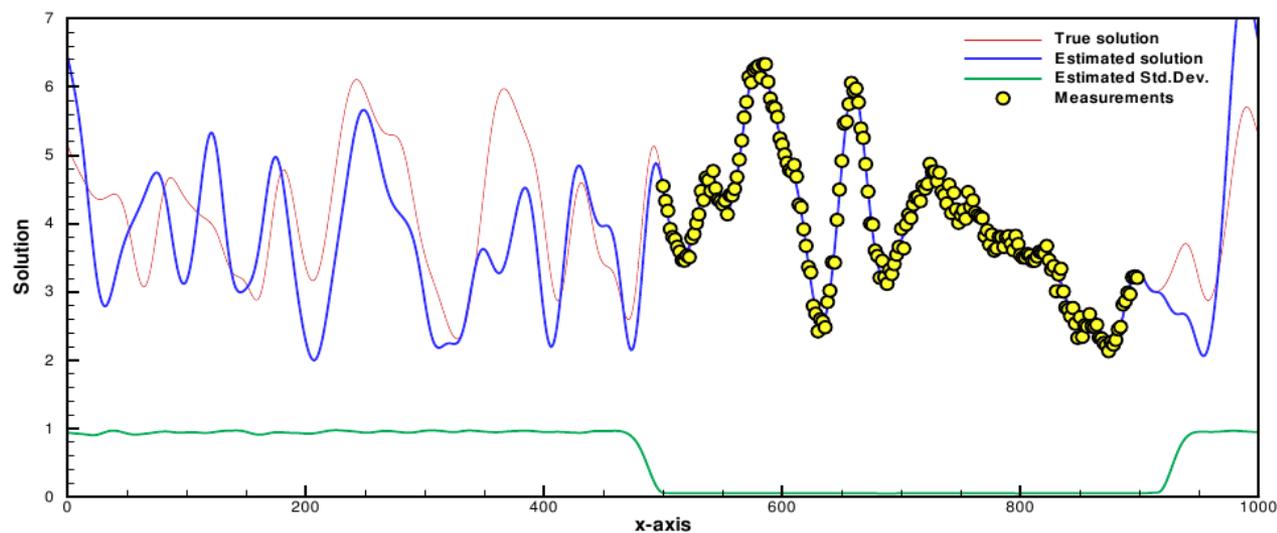


Example with 200 measurements

EnKF: Truncation at 99% retains about 40 eigenvalues.



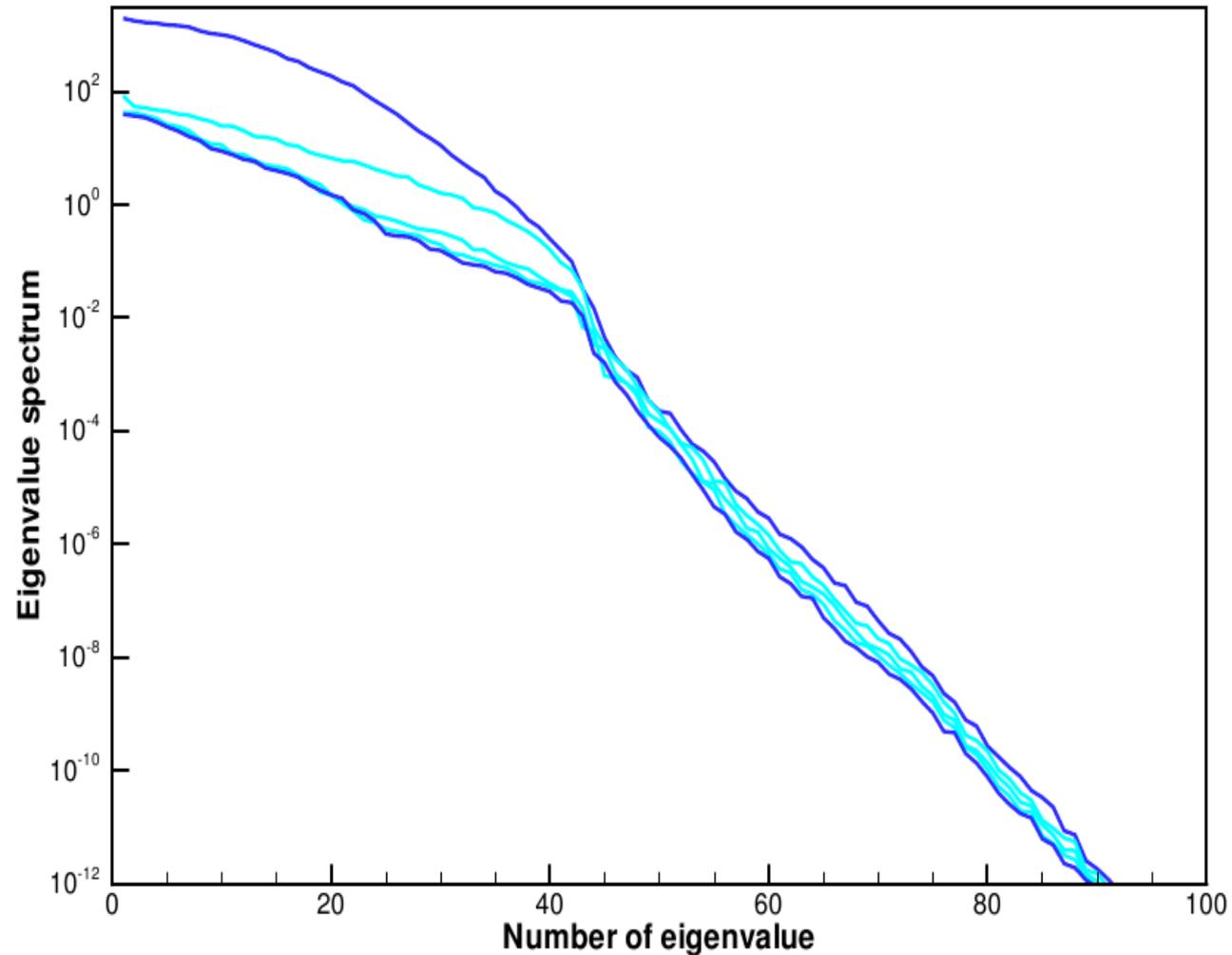
EnSQR: Truncation at 99% retains about 40 eigenvalues.



Example with 200 measurements

EnKF: Truncation at 99% retains about 40 eigenvalues.

EnSQR: Truncation at 99% retains about 40 eigenvalues.



Ensemble subspace inversion (1)

› Compute inversion in N -dim ensemble space rather than the m -dim meas. space.

› SVD of S

$$U_0 \Sigma_0 V_0^T = S$$

› Pseudo inverse of S

$$S^+ = V_0 \Sigma_0^+ U_0^T$$

$$\begin{aligned}
 C &= (U_0 \Sigma_0 \Sigma_0^T U_0^T + (N - 1) C_{\epsilon\epsilon}) \\
 &= U_0 (\Sigma_0 \Sigma_0^T + (N - 1) U_0^T C_{\epsilon\epsilon} U_0) U_0^T \\
 &\approx U_0 \Sigma_0 (I + (N - 1) \Sigma_0^+ U_0^T C_{\epsilon\epsilon} U_0 \Sigma_0^{+T}) \Sigma_0^T U_0^T \\
 &= S S^T + (N - 1) (S S^+) C_{\epsilon\epsilon} (S S^+)^T.
 \end{aligned}$$

Ensemble subspace inversion (2)

- › New expression for C

$$C \approx U_0 \Sigma_0 (I + X_0) \Sigma_0^T U_0^T$$

$$X_0 = (N - 1) \Sigma_0^+ U_0^T C_{\epsilon\epsilon} U_0 \Sigma_0^{+T}$$

- › Eigenvalue decomposition

$$Z_1 \Lambda_1 Z_1^T = X_0$$

- › C becomes

$$\begin{aligned} C &\approx U_0 \Sigma_0 (I + Z_1 \Lambda_1 Z_1^T) \Sigma_0^T U_0^T \\ &= U_0 \Sigma_0 Z_1 (I + \Lambda_1) Z_1^T \Sigma_0^T U_0^T \end{aligned}$$

Ensemble subspace inversion (3)

$$\begin{aligned}
 C &\approx U_0 \Sigma_0 (I + Z_1 \Lambda_1 Z_1^T) \Sigma_0^T U_0^T \\
 &= U_0 \Sigma_0 Z_1 (I + \Lambda_1) Z_1^T \Sigma_0^T U_0^T.
 \end{aligned}$$

› Pseudo inverse of C becomes

$$\begin{aligned}
 C^+ &\approx (U_0 \Sigma_0^{+T} Z_1) (I + \Lambda_1)^{-1} (U_0 \Sigma_0^{+T} Z_1)^T \\
 &= X_1 (I + \Lambda_1)^{-1} X_1^T,
 \end{aligned}$$

$$X_1 = U_0 \Sigma_0^{+T} Z_1.$$

$$m^2 N + m N^2$$

EnKF analysis by subspace pseudo inversion

$$A^a = A^f \left(I + S^T X_1 (I + \Lambda_1)^{-1} X_1^T (D - \mathcal{M}[A^f]) \right).$$

Low rank ensemble subspace inversion (1)

$$C_{\epsilon\epsilon}^e = \mathbf{E}\mathbf{E}^T / (N - 1) \quad \mathbf{C} = \mathbf{S}\mathbf{S}^T + \mathbf{E}\mathbf{E}^T$$

$$\begin{aligned} \mathbf{C} &\approx \mathbf{U}_0 \boldsymbol{\Sigma}_0 (\mathbf{I} + \boldsymbol{\Sigma}_0^+ \mathbf{U}_0^T \mathbf{E}\mathbf{E}^T \mathbf{U}_0 \boldsymbol{\Sigma}_0^{+\top}) \boldsymbol{\Sigma}_0^T \mathbf{U}_0^T \\ &= \mathbf{U}_0 \boldsymbol{\Sigma}_0 (\mathbf{I} + \mathbf{X}_0 \mathbf{X}_0^T) \boldsymbol{\Sigma}_0^T \mathbf{U}_0^T, \end{aligned}$$

$$\mathbf{X}_0 = \boldsymbol{\Sigma}_0^+ \mathbf{U}_0^T \mathbf{E}$$

$$\mathbf{U}_1 \boldsymbol{\Sigma}_1 \mathbf{V}_1^T = \mathbf{X}_0.$$

Low rank ensemble subspace inversion (2)

$$\begin{aligned}
 C &\approx U_0 \Sigma_0 (I + U_1 \Sigma_1^2 U_1^T) \Sigma_0^T U_0^T \\
 &= U_0 \Sigma_0 U_1 (I + \Sigma_1^2) U_1^T \Sigma_0^T U_0^T
 \end{aligned}$$

$$\begin{aligned}
 C^+ &\approx (U_0 \Sigma_0^{+T} U_1) (I + \Sigma_1^2)^{-1} (U_0 \Sigma_0^{+T} U_1)^T \\
 &= X_1 (I + \Sigma_1^2)^{-1} X_1^T,
 \end{aligned}$$

$$X_1 = U_0 \Sigma_0^{+T} U_1$$

 mN^2

EnKF subspace analysis with low-rank $C_{\epsilon\epsilon}$

$$A^a = A^f \left(I + S^T X_1 (I + \Sigma_1^2)^{-1} X_1^T (D - \mathcal{M}[A^f]) \right).$$

Summary of EnKF analyses implementations

Standard EnKF analysis

$$\mathbf{A}^a = \mathbf{A}^f \left(\mathbf{I} + \mathbf{S}^T \mathbf{C}^{-1} (\mathbf{D} - \mathcal{M}[\mathbf{A}^f]) \right),$$

$$\mathbf{C}^+ = \mathbf{Z} \mathbf{\Lambda}^+ \mathbf{Z}^T$$

$\mathcal{O}(m^3)$ operations.

EnKF analysis by subspace pseudo inversion

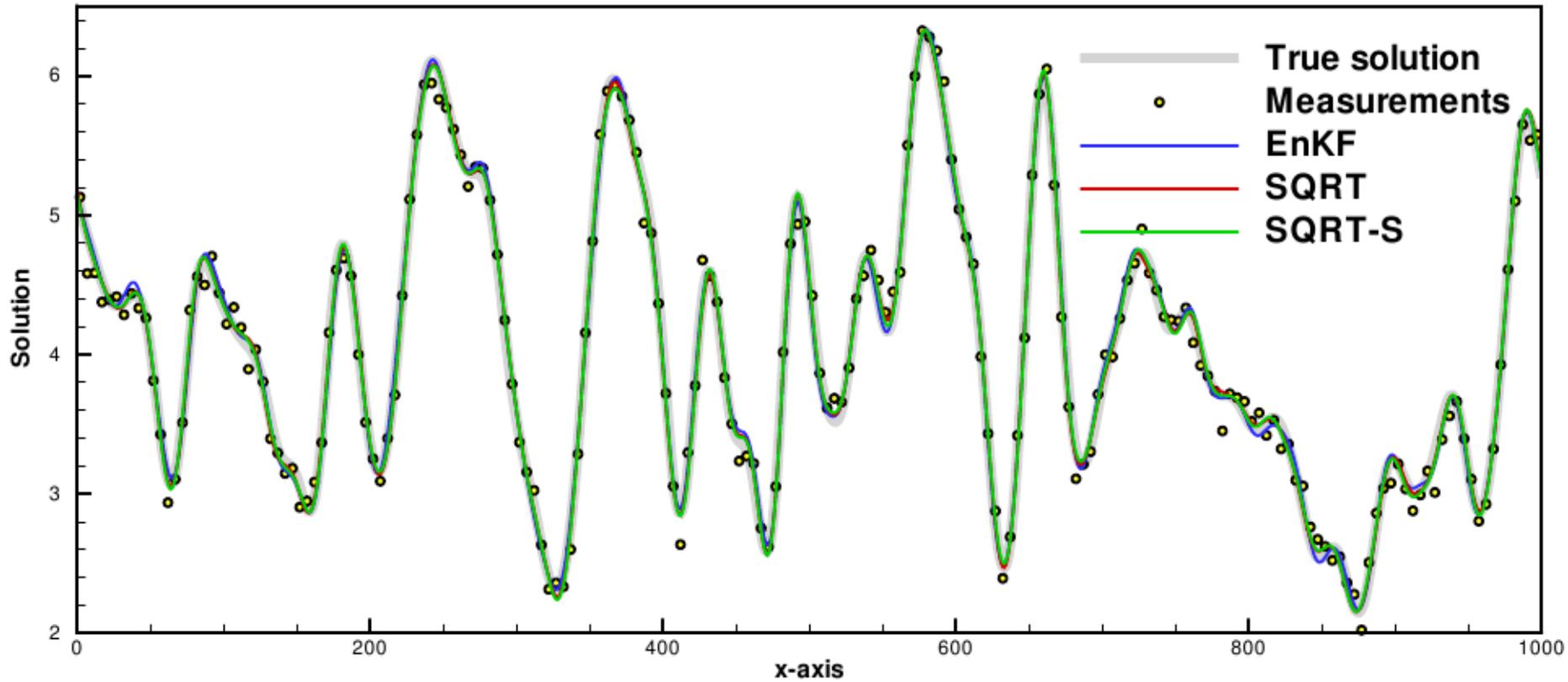
$$\mathbf{A}^a = \mathbf{A}^f \left(\mathbf{I} + \mathbf{S}^T \mathbf{X}_1 (\mathbf{I} + \mathbf{\Lambda}_1)^{-1} \mathbf{X}_1^T (\mathbf{D} - \mathcal{M}[\mathbf{A}^f]) \right).$$

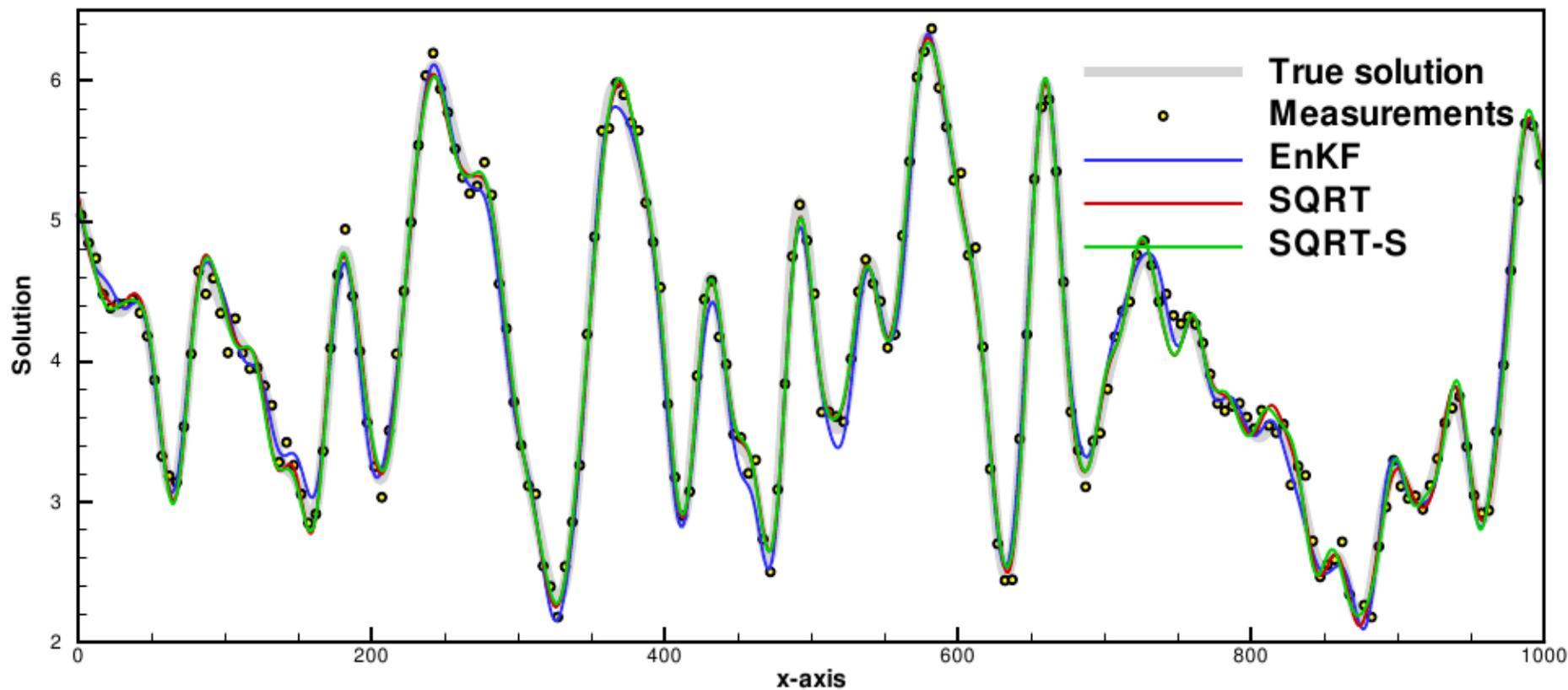
$$m^2 N + m N^2$$

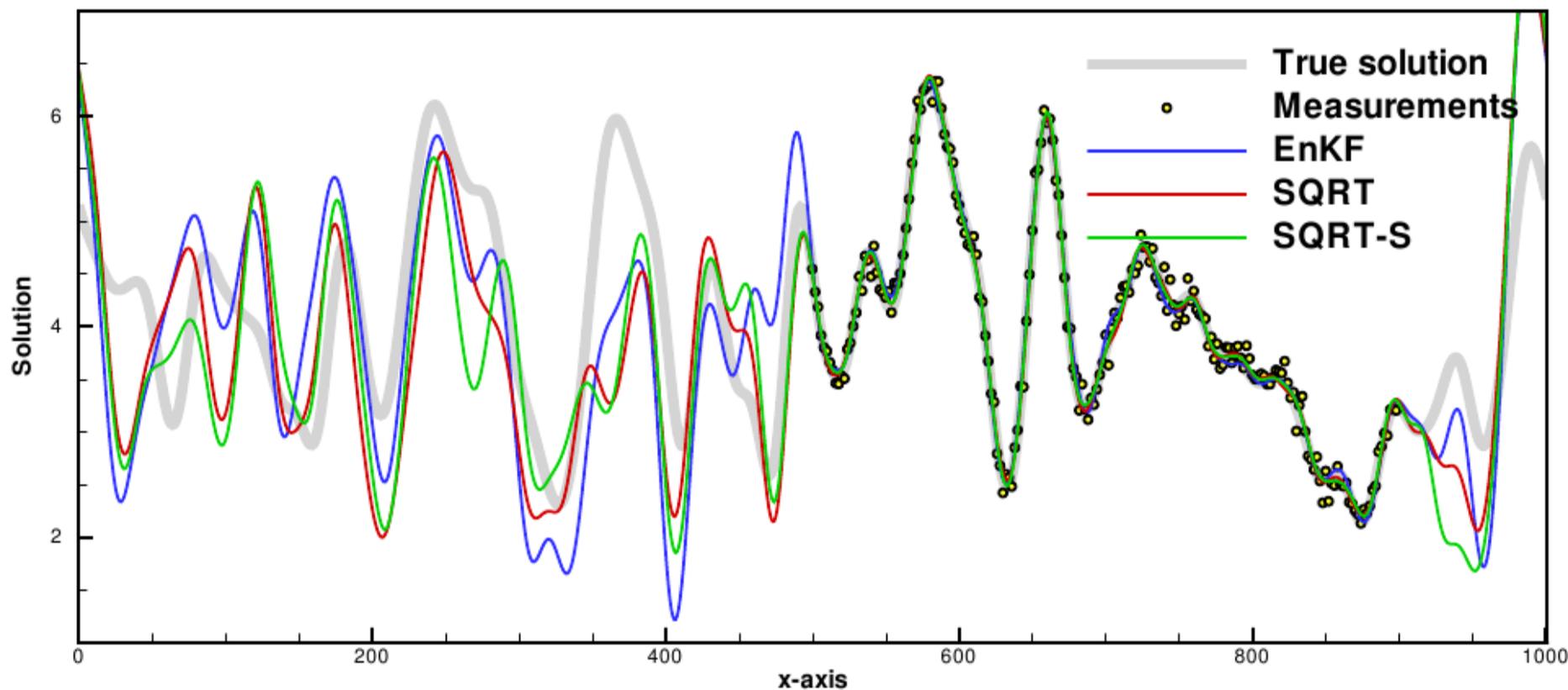
EnKF subspace analysis with low-rank $\mathbf{C}_{\epsilon\epsilon}$

$$\mathbf{A}^a = \mathbf{A}^f \left(\mathbf{I} + \mathbf{S}^T \mathbf{X}_1 (\mathbf{I} + \mathbf{\Sigma}_1^2)^{-1} \mathbf{X}_1^T (\mathbf{D} - \mathcal{M}[\mathbf{A}^f]) \right).$$

$$m N^2$$

Examples: Diagonal R 

Examples: Non-diagonal R 

Examples: Non-diagonal R and clustered data

Summary

- › Necessary to deal with the rank of C .
 - Pseudo inversion is key.
 - Adding a diagonal R may improve conditioning but does not add more “information.”

- › No need to restrict analysis to a diagonal R .
 - Analysis with full R as efficient.
 - No need to actually construct measurement error-covariance matrix.
 - Easier and faster to sample measurement perturbations in E .

- › Stable and efficient SQRT schemes that handle non-diagonal R are available.
 - Ensemble subspace pseudo inversion and representation of R using measurement perturbations.
 - Represent the measurement errors within the ensemble subspace!

- › Details in Evensen (2009), Chapter 14.