

Study of the Algorithmic Complexity of the Ensemble Kalman Filter and its Efficient Implementations

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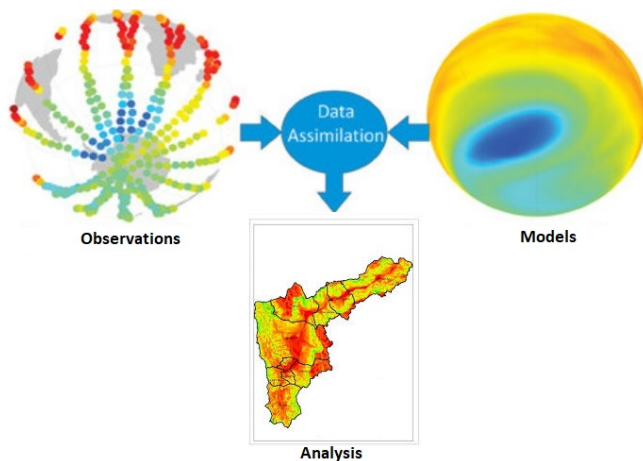
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 - Ensemble Kalman Filter (EnKF)
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Introduction



Gaussian

Ensemble Kalman Filter-EnKF

Variational Data Assimilation

Non-Gaussian

Particle Filters

Gaussian

Ensemble Kalman Filter-EnKF

Variational Data Assimilation

Non-Gaussian

Particle Filters

Current Work

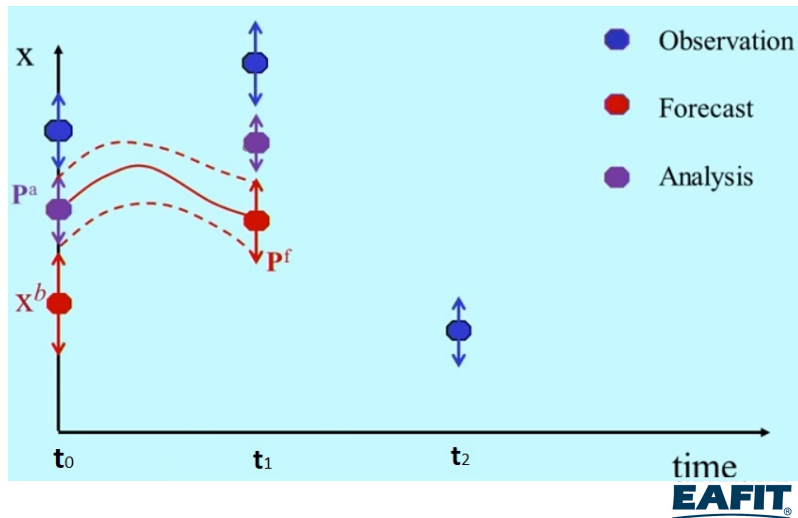
REnKF

En 4DVar

PF 4DVar

$$p(\mathbf{x}|\mathbf{y}) = \frac{p(\mathbf{y}|\mathbf{x}) \cdot p(\mathbf{x})}{p(\mathbf{y})}$$

Kalman Filter



Assume we seek to estimate the state $\mathbf{x} \in \mathbb{R}^n$

$$\mathbf{x}_{k+1} = \mathbf{M}(\mathbf{x}_k, t_k) + \mathbf{w}_k,$$

using the measurements $\mathbf{y} \in \mathbb{R}^m$

$$\mathbf{y}_k = \mathbf{H}_k \mathbf{x}_k + \mathbf{v}_k,$$

with

$$\mathbf{w}_k \sim \mathbf{N}(\mathbf{0}, \mathbf{Q}_k),$$

$$\mathbf{v}_k \sim \mathbf{N}(\mathbf{0}, \mathbf{R}_k),$$

$$\mathbf{Q}_k \in \mathbb{R}^{n \times n}, \mathbf{R}_k \in \mathbb{R}^{m \times m}.$$

$$\mathbf{M} : \mathbb{R}^n \rightarrow \mathbb{R}^n, \mathbf{H} : \mathbb{R}^n \rightarrow \mathbb{R}^m.$$

1. Forecast Step:

$$\mathbf{x}_{k+1}^f = \mathbf{M}_{k+1} \mathbf{x}_k^a,$$

$$\mathbf{P}_{k+1}^f = \mathbf{M}_{k+1} \mathbf{P}_k^a \mathbf{M}_{k+1}^T + \mathbf{Q}_{k+1}.$$

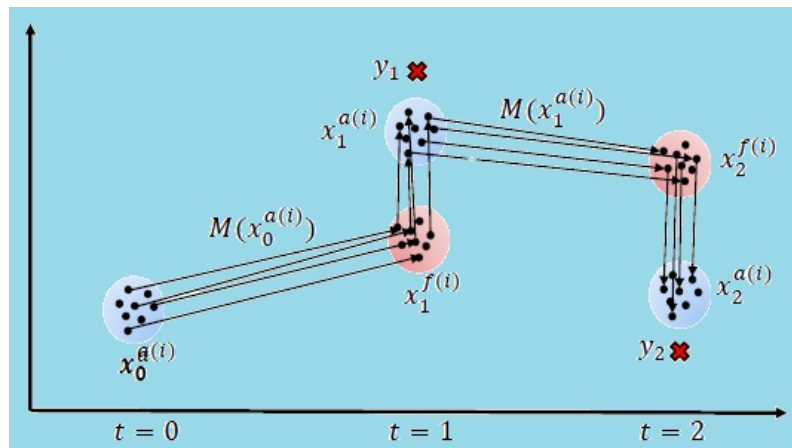
2. Analysis Step:

$$\mathbf{K}_{k+1} = \mathbf{P}_{k+1}^f \mathbf{H}^T \left(\mathbf{H} \mathbf{P}_{k+1}^f \mathbf{H}^T + \mathbf{R}_{k+1} \right)^{-1},$$

$$\mathbf{x}_{k+1}^a = \mathbf{x}_{k+1}^f + \mathbf{K}_{k+1} \left(\mathbf{y}_{k+1} - \mathbf{H} \mathbf{x}_{k+1}^f \right),$$

$$\mathbf{P}_{k+1}^a = \left(\mathbf{I} - \mathbf{K}_{k+1} \mathbf{H} \right) \mathbf{P}_{k+1}^f.$$

Ensemble Kalman Filter EnKF



Ensemble Kalman Filter EnKF

1. Forecast Step:

$$\mathbf{x}_{k+1}^f = \mathbf{M}_{k+1}(\mathbf{x}_k^a),$$

$$\mathbf{P}_{k+1}^f = \frac{1}{N-1} \sum_{i=1}^N (\mathbf{x}_i^f - \bar{\mathbf{x}}^f) (\mathbf{x}_i^f - \bar{\mathbf{x}}^f)^T,$$

with N , number of ensemble members and

$$\bar{\mathbf{x}}^f = \frac{1}{N} \sum_{i=1}^N \mathbf{x}_i^f.$$

2. Analysis Step:

$$\mathbf{K}_{k+1} = \mathbf{P}_{k+1}^f \mathbf{H}^T (\mathbf{H} \mathbf{P}_{k+1}^f \mathbf{H}^T + \mathbf{R}_{k+1})^{-1},$$

$$\mathbf{x}_{k+1}^a = \mathbf{x}_{k+1}^f + \mathbf{K}_{k+1} (\mathbf{y}_{k+1} - \mathbf{H} \mathbf{x}_{k+1}^f).$$



- **Advantage**

- ① To reduce the computational cost, in terms of the number of operations, of assimilating large data sets.
- ② The resulting algorithms scale linearly with respect to the number of observations.

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- ② The resulting algorithms scale linearly with respect to the number of observations.

- **Issues**

- ① The computational cost of the subsequent matrix operations can become expensive.
- ② The additional operations may contribute significantly to the total computational cost of the implementation.

SVD Implementation

```
1: procedure (SVD-EnKF)( $\mathbf{X}, \mathbf{X}', \mathbf{HX}', \mathbf{D}, \mathbf{E}$ )
2:    $[\Sigma, \mathbf{U}, \mathbf{V}] \leftarrow \text{SVD}(\mathbf{HX}' + \mathbf{E})$  ( $mN^2$ )
3:    $\Lambda \leftarrow \Sigma \Sigma^T$  ( $m$ )
4:    $s \leftarrow \sum_i \lambda_{i,i}$  ( $m$ )
5:    $p \leftarrow \max \{k \mid \sum_k \lambda_{k,k} |s| < 0.99\}$ 
6:    $\mathbf{X}_1 \leftarrow \Lambda^{-1} \mathbf{U}^T$  ( $mp$ )
7:    $\mathbf{X}_2 \leftarrow \mathbf{X}_1 \mathbf{D}$  ( $mnp$ )
8:    $\mathbf{X}_3 \leftarrow \mathbf{U} \mathbf{X}_2$  ( $mNp$ )
9:    $\mathbf{X}_4 \leftarrow (\mathbf{HX}')^T \mathbf{X}_3$  ( $mN^2$ )
10:   $\mathbf{X}^a \leftarrow \mathbf{X} + \mathbf{X}' \mathbf{X}_4$  ( $nN^2$ )
11:  return  $\mathbf{X}^a$ 
12: end procedure
```

Computational cost: $O(nN^2 + mN^2 + mNp + mN + m)$

Cholesky Decomposition Implementation

```
1: procedure (CHOL-EnKF)( $\mathbf{X}, \mathbf{X}', \mathbf{HX}', \mathbf{D}, \mathbf{E}$ )
2:    $\mathbf{R} \leftarrow \frac{1}{N-1} \text{diag}(\mathbf{E}\mathbf{E}^T)$ 
3:    $\mathbf{Q} \leftarrow (N-1)\mathbf{I} + (\mathbf{HX}')^T \mathbf{R}^{-1} (\mathbf{HX}')$  ( $mN^2$ )
4:    $\mathbf{LL}^T \leftarrow \text{CHOLESKYM}(\mathbf{Q})$  ( $N^3$ )
5:    $\mathbf{Z} \leftarrow (\mathbf{HX}')^T \mathbf{R}^{-1} \mathbf{D}$  ( $mN^2$ )
6:    $\mathbf{W} \leftarrow \mathbf{Q}^{-1} \mathbf{Z}$  ( $N^3$ )
7:    $\mathbf{M} \leftarrow \mathbf{R}^{-1} [\mathbf{I} - (\mathbf{HX}'\mathbf{W})]$  ( $mN^2$ )
8:    $\mathbf{Z} \leftarrow (\mathbf{HX}')^T \mathbf{M}$  ( $mN^2$ )
9:    $\mathbf{X}^a \leftarrow \mathbf{X} + \frac{1}{N-1} \mathbf{X}'\mathbf{Z}$  ( $nN^2$ )
10:  return  $\mathbf{X}^a$ 
11: end procedure
```







Computational cost: $O(N^3 + nN^2 + mN^2)$

Sherman Morrison Implementation

```
1: procedure (MF-EnKF)( $\mathbf{X}, \mathbf{X}', \mathbf{HX}', \mathbf{D}, \mathbf{E}$ )
2:    $\mathbf{R} \leftarrow \text{diag}(\mathbf{E}\mathbf{E}^T)$ 
3:   call SM ( $\mathbf{R}, \mathbf{HX}', \mathbf{HX}', \mathbf{d}_1, \mathbf{z}_1$ ) ( $mN^2$ )
4:    $\mathbf{w} \leftarrow \mathbb{X}' (\mathbf{HX}')^T \mathbf{z}_1$  ( $nN$ )
5:    $\mathbf{x}_1^a \leftarrow \mathbf{x}_1 + \mathbf{w}$  ( $n$ )
6:   for do  $i \leftarrow 2, \dots, N$  do
7:     call SIMPLIFIED ( $\mathbf{R}, \mathbf{HX}', \mathbf{d}_i, \mathbf{z}_i$ ) ( $mN$ )
8:      $\mathbf{w} \leftarrow \mathbf{X}' (\mathbf{HX}')^T \mathbf{z}_i$  ( $nN$ )
9:      $\mathbf{x}_1^a \leftarrow \mathbf{x}_i + \mathbf{w}$  ( $n$ )
10:  end for
11:  return  $\mathbf{X}^a$ 
12: end procedure
```

Computational cost: $O(mN^2 + nN + mN + n)$

Thanks!

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Sherman-Morrison solver as described in Evensen 1994 y Maponi 2007.

```
1: procedure (SM)( $\mathbf{A}_0, \mathbf{U}, \mathbf{V}, \mathbf{b}, \mathbf{x}$ )
2:   Solve  $\mathbf{A}_0 \mathbf{x}_0 \leftarrow \mathbf{b}$ 
3:   Solve  $\mathbf{A}_0 \mathbf{y}_{0,k} \leftarrow \mathbf{u}_k$  for  $k \leftarrow 1, \dots, N$ 
4:   for do  $i \leftarrow 1 \dots, N - 1$ 
5:      $\mathbf{x}_i \leftarrow \mathbf{x}_{i-1} - \frac{\mathbf{v}_i^T \mathbf{x}_{i-1}}{1 + \mathbf{v}_i^T \mathbf{y}_{i-1,i}} \mathbf{y}_{i-1,i}$ 
6:     for do  $k \leftarrow i + 1, \dots, N$ 
7:        $y_{i,k} \leftarrow y_{i-1,k} - \frac{\mathbf{v}_i^T \mathbf{y}_{i-1,k}}{1 + \mathbf{v}_i^T \mathbf{y}_{i-1,i}} \mathbf{y}_{i-1,i}$ 
8:     end for
9:   end for
10:   $\mathbf{x}_N \leftarrow \mathbf{x}_{N-1} - \frac{\mathbf{v}_N^T \mathbf{x}_{N-1}}{1 + \mathbf{v}_N^T \mathbf{y}_{N-1,N}} \mathbf{y}_{i-1,i}$ 
11:  return  $\mathbf{x}$ 
12: end procedure
```

Simplified Sherman-Morrison Solver Subsequent Right-hand Sides

```
1: procedure (SIMPLIFIED)( $\mathbf{A}_0, \mathbf{V}, \mathbf{b}, \mathbf{x}$ )
2:   Solve  $\mathbf{A}_0 \mathbf{x}_0 \leftarrow \mathbf{b}$ 
3:   for do  $i \leftarrow 1, \dots, N$ 
4:      $\mathbf{x}_i \leftarrow \mathbf{x}_{i-1} - \frac{\mathbf{v}_i^T \mathbf{x}_{i-1}}{1 + \mathbf{v}_i^T \mathbf{y}_{i-1,i}} \mathbf{y}_{i-1,i}$ 
5:   end for
6:   return  $\mathbf{x}$ 
7: end procedure
```