Hans van Lint, Yufei Yuan & **Friso Scholten**

A localized deterministic Ensemble Kalman Filter

LARGE-SCALE TRAFFIC STATE ESTIMATION

CONTENTS

INTRODUCTION

Dutch National Data Warehouse Traffic Information

- Network
  - √ 2500 km freeways
  - √ 3500 km prov/urban
  - √ 24,000 measurement sites
- Real-time Data
  - √ Dynamic: Flow, Speed, Occupancy, Travel time (lane / usr class specific), FCD
  - √ Status: roadworks, incidents, events
  - √ 150,000 measurements/min
- Historical database
  - √ 200 TB
  - √ Raw data

National Data Warehouse for Traffic Information

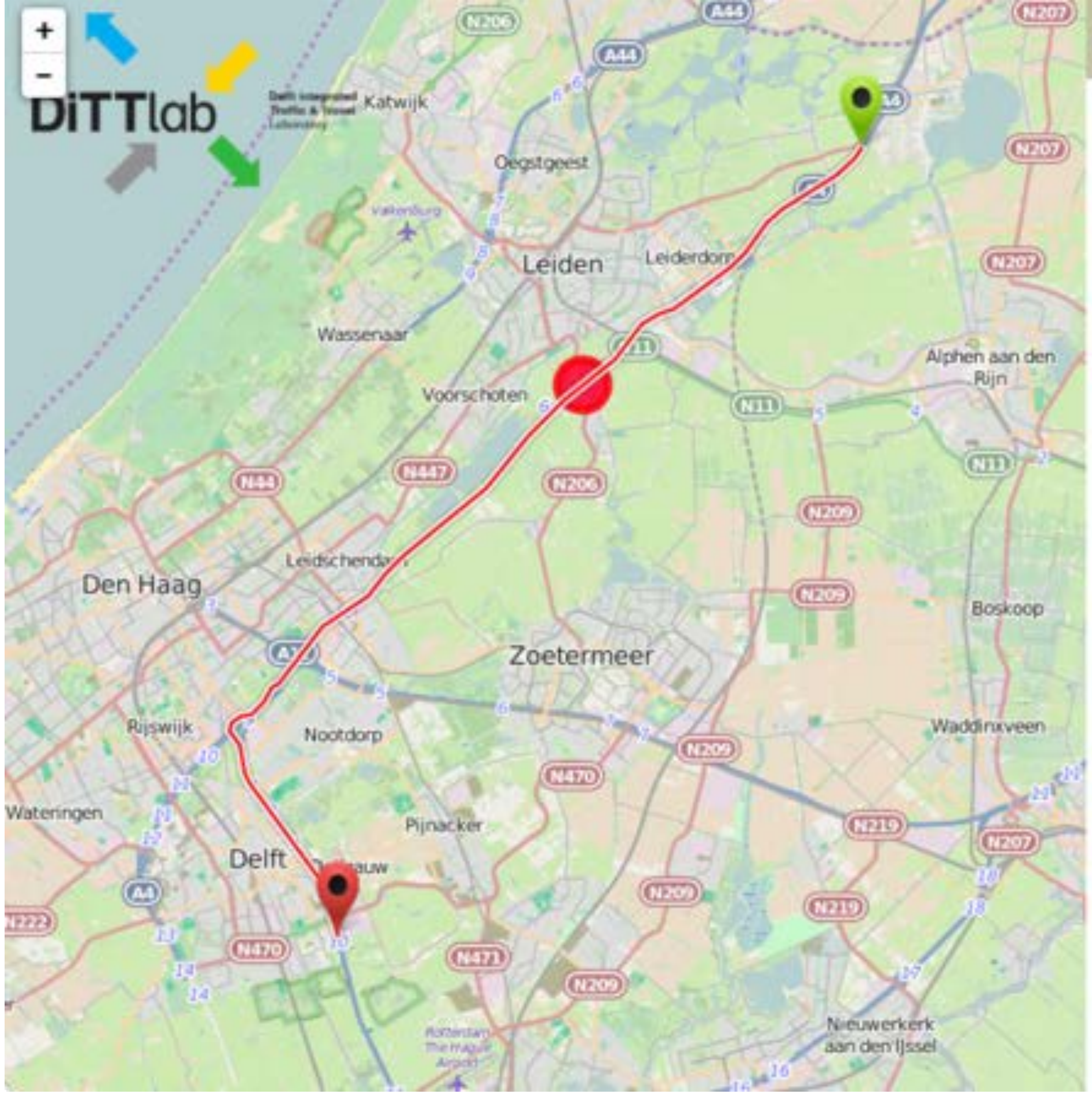
Introduction
KF Basics
EnKF
Simulations
Conclusions

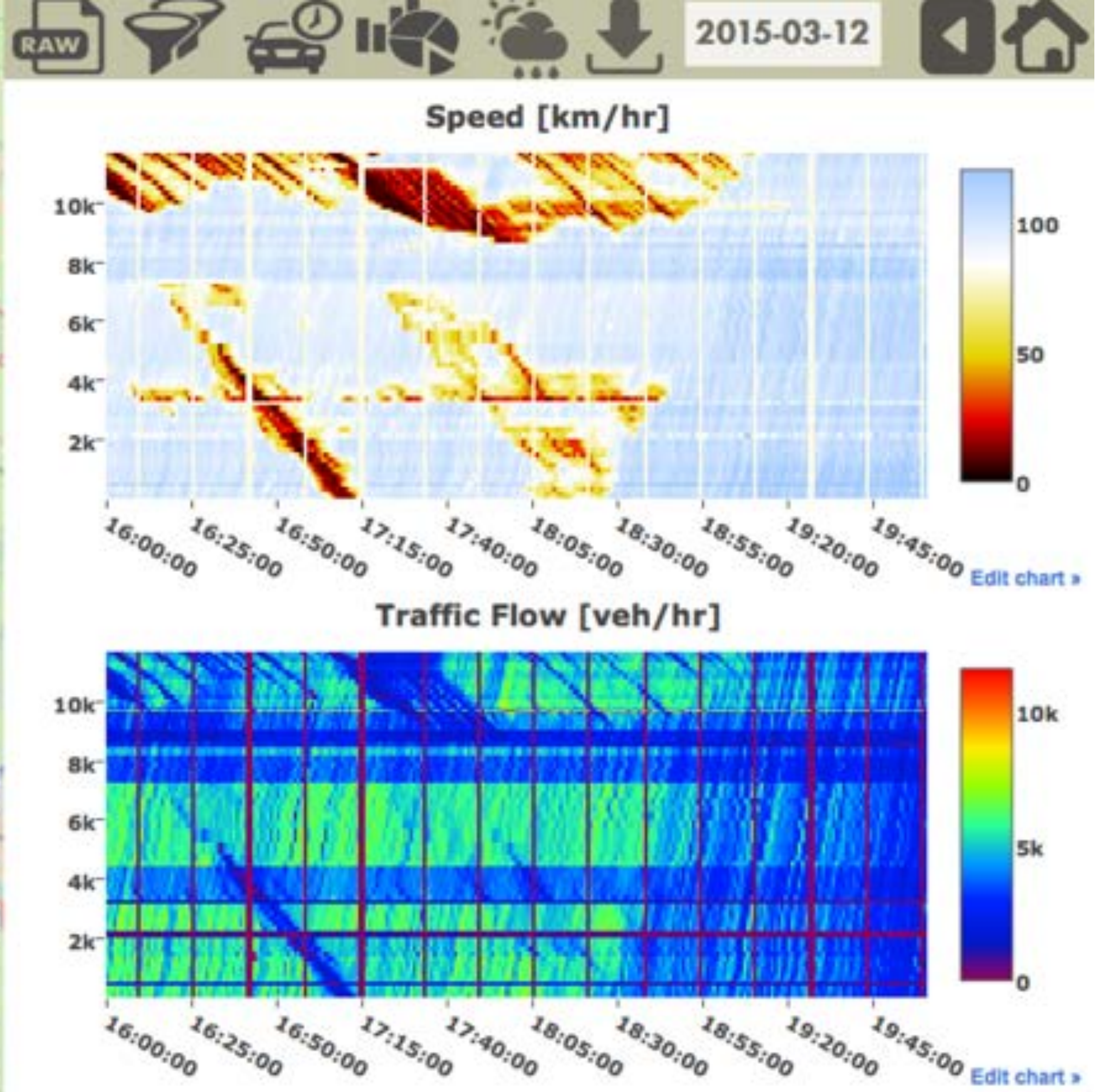
TUDelft

INTRODUCTION

Dutch National Data Warehouse Traffic Information

- Ambition
  - ✓ Build national traffic observatory (for RT and archived traffic info)
- From raw data to real information:
  - ✓ Intelligent database (search terms related to traffic patterns and explanatory factors)
  - ✓ Data-based routable network graphs
  - ✓ Densities, space mean speeds
  - ✓ Capacities, other FD params
  - ✓ MFDs and other agg state vars
  - ✓ Inflows, turns, OD flows
  - ✓ Opensource tools to dive into all this


DiTTlab
Katwijk
Oegstgeest
Leiden
Leiderdorp
Wassenaar
Voorschoten
Alphen aan den Rijn
Leidschendam
Den Haag
Zoetermeer
Boskoop
Rijswijk
Nootdorp
Waddinxveen
Wateringen
Pijnacker
Delft
Nieuwerkerk aan den IJssel


RAW
2015-03-12
Speed [km/hr]
10k
8k
6k
4k
2k
100
50
0
16:00:00
16:25:00
16:50:00
17:15:00
17:40:00
18:05:00
18:30:00
18:55:00
19:20:00
19:45:00
Edit chart »
Traffic Flow [veh/hr]
10k
5k
Edit chart »

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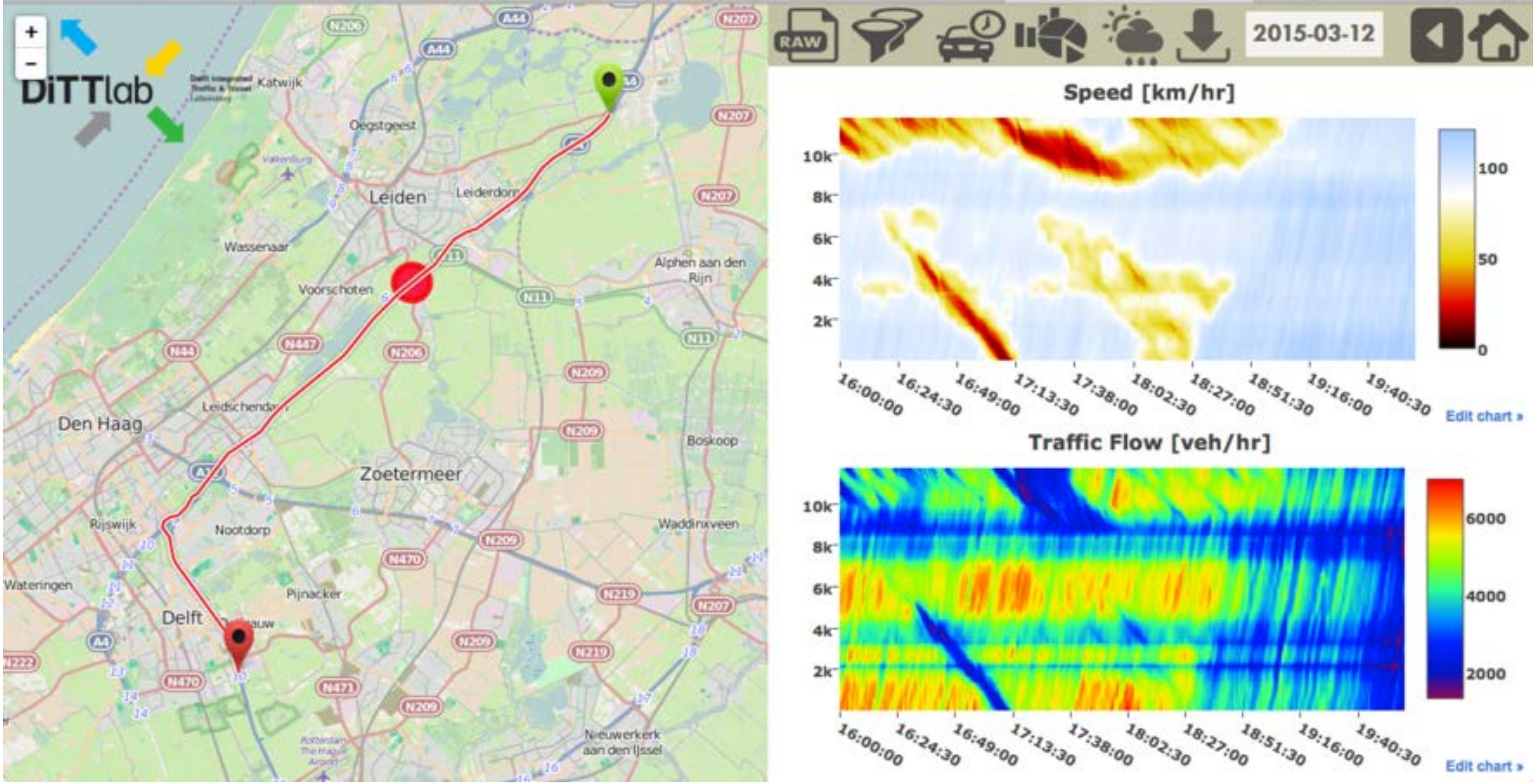
DiTTlab
2015-03-12
RAW
Speed [km/hr]
10k
8k
6k
4k
2k
100
50
0
16:00:00
16:24:30
16:49:00
17:13:30
17:38:00
18:02:30
18:27:00
18:51:30
19:16:00
19:40:30
Edit chart »
Traffic Flow [veh/hr]
6000
4000
2000
Katwijk
Oegstgeest
Leiden
Leiderdorp
Wassenaar
Voorschoten
Alphen aan den Rijn
Den Haag
Leidschendam
Zoetermeer
Boskoop
Rijswijk
Nootdorp
Waddinxveen
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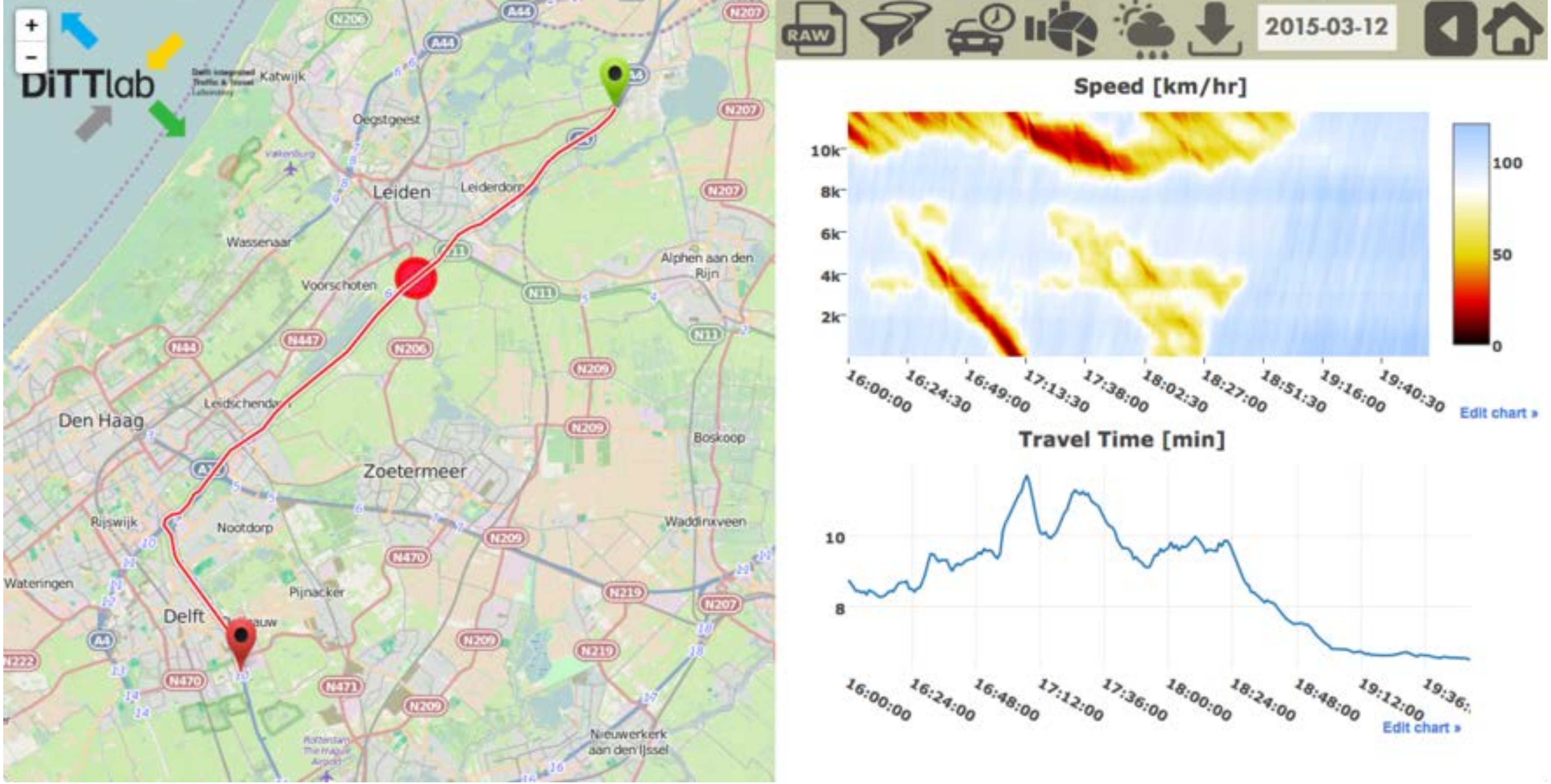
Nieuwerkerk aan den IJssel


DiTTlab
2015-03-12
Speed [km/hr]
10k
8k
6k
4k
2k
100
50
0
16:00:00
16:24:30
16:49:00
17:13:30
17:38:00
18:02:30
18:27:00
18:51:30
19:16:00
19:40:30
Edit chart »
Travel Time [min]
10
8
16:00:00
16:24:00
16:48:00
17:12:00
17:36:00
18:00:00
18:24:00
18:48:00
19:12:00
Edit chart »
Leiden
Den Haag
Zoetermeer
Delft

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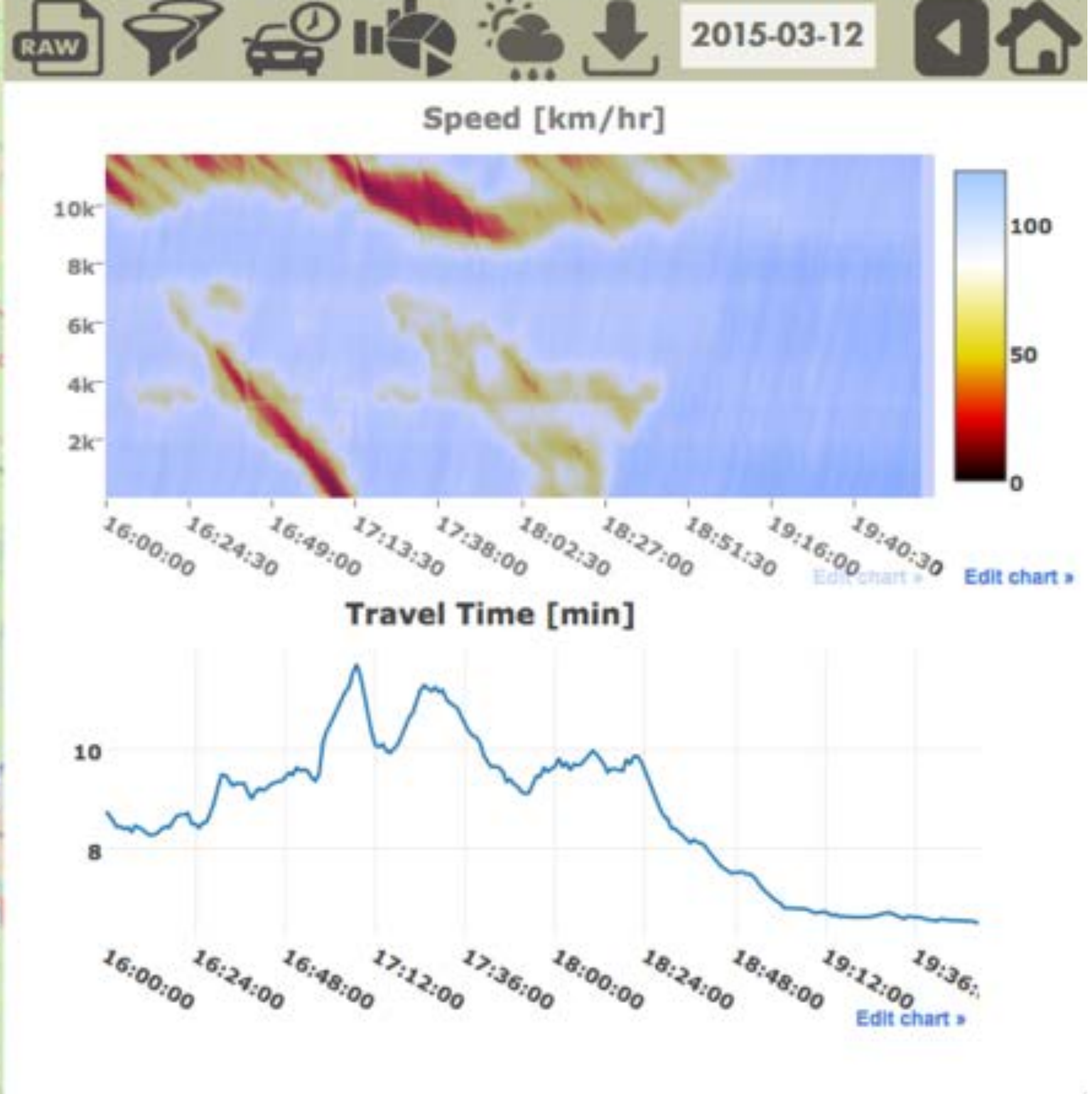
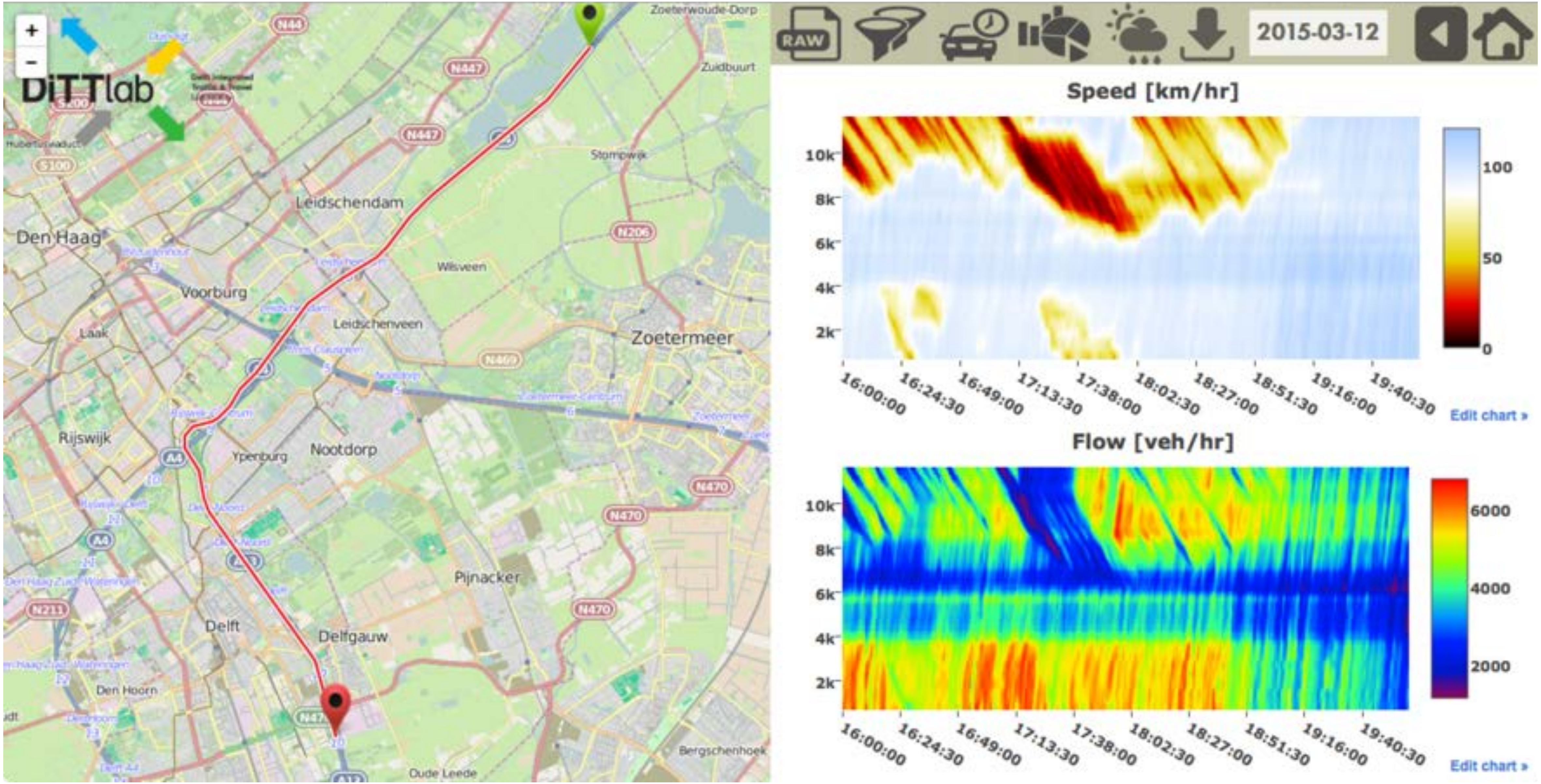
DiTTlab
eventtime : 2015-01-01 07:00:00, type : Road work,
subtype : RoadOrCarriagewayOrLaneManagement
Katwijk
Oegstgeest
Voorschoten
Alphen aan den Rijn
Leidschendam
Den Haag
Zoetermeer
Boskoop
Rijswijk
Nootdorp
Waddinxveen
Wateringen
Pijnacker
Delft
Nieuwerkerk aan den IJssel


RAW
2015-03-12
Speed [km/hr]
10k
8k
6k
4k
2k
16:00:00
16:24:30
16:49:00
17:13:30
17:38:00
18:02:30
18:27:00
18:51:30
19:16:00
19:40:30
100
50
0
Edit chart »
Travel Time [min]
10
8
16:00:00
16:24:00
16:48:00
17:12:00
17:36:00
18:00:00
18:24:00
18:48:00
19:12:00
Edit chart »

RAW 2015-03-12

```
TotFlowRoute = 26426.00 [veh]
AvgSpeedRoute = 69.05 [km/h]
PercMissingSpeedDetectors = 7.47 %
PercMissingFlowDetectors = 7.47 %
PercMissingSpeedCrossSections = 7.49 %
PercMissingFlowCrossSections = 7.47 %
TotalVehicleLossHours = 473.10 [veh-h]
TravelTimePercentile10 = 6.64 [min]
TravelTimePercentile25 = 7.24 [min]
TravelTimePercentile50 = 8.97 [min]
TravelTimePercentile75 = 9.70 [min]
TravelTimePercentile90 = 10.65 [min]
AvgTravelTime = 8.71 [min]
StdTravelTime = 1.45 [min]
```



Treiber, M. and D. Helbing, Reconstructing the Spatio-Temporal Traffic Dynamics from Stationary Detector Data. Cooper@tive Tr@nsport@tion Dyn@mics, 2002. 1: p. 3.1-3.24.
van Lint, J.W.C. and S.P. Hoogendoorn, A Robust and Efficient Method for Fusing Heterogeneous Data from Traffic Sensors on Freeways. CAICE, 2010. 25(8): p. 596-612.
Van Lint, J.W.C., Empirical Evaluation of New Robust Travel Time Estimation Algorithms. Transportation Research Record, 2010(2160): p. 50-59.

INTRODUCTION

Dutch National Data Warehouse Traffic Information

- Ambition
  - ✓ Build national traffic observatory (for RT and archived traffic info)
- Next step:
  - ✓ Scalable efficient <u>model-based</u> traffic state estimation: **densities** (inflows, turns)
- TRADE OFF
  - ✓ Estimation accuracy vs computational efficiency

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THE KALMAN FILTER

For any system cast in discrete state space form

- the KF is an efficient recursive solution for estimating state vector **x**;

$$\mathbf{x}_{k+1} = \mathbf{F}_k \mathbf{x}_k + \mathbf{G}_k \mathbf{u}_k + \mathbf{w}_k$$

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

- that is optimal in three ways
  - ➡Minimum error (co)variance
  - ➡Maximal posterior probability
  - ➡Conditional mean estimation

$$E(\mathbf{w}_k) = 0, \quad E(\mathbf{w}_k \mathbf{w}_l') = \begin{cases} \mathbf{Q}_k & k = l \\ 0 & k \neq l \end{cases}$$

$$E(\mathbf{v}_k) = 0, \quad E(\mathbf{v}_k \mathbf{v}_l') = \begin{cases} \mathbf{R}_k & k = l \\ 0 & k \neq l \end{cases}$$

- given a some (fairly strict) assumptions
  - ➡the validity of which strongly affect the quality of the result

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THE KALMAN FILTER

- Initial conditions (reasonable choices for **Q** and **R** must also be made)

$$\hat{\mathbf{x}}_{0|0} = \hat{\mathbf{x}}_0 , \mathbf{P}_{0|0} = \mathbf{P}_0$$

- Time-propagation (prediction):

$$\hat{\mathbf{x}}_{k|k-1} = \mathbf{F}_{k-1}\hat{\mathbf{x}}_{k-1|k-1} + \mathbf{G}_{k-1}\mathbf{u}_{k-1}$$

$$\mathbf{P}_{k|k-1} = \mathbf{F}_{k-1}\mathbf{P}_{k-1|k-1}\mathbf{F}_{k-1}^T + \mathbf{Q}_{k-1}$$

- Measurement adaptation (correction):

$$\mathbf{e}_k = \mathbf{y}_k - \mathbf{H}_k\hat{\mathbf{x}}_{k|k-1}$$

$$\mathbf{K}_k = \mathbf{P}_{k|k-1}\mathbf{H}_k \big/ \left(\mathbf{H}_k\mathbf{P}_{k|k-1}\mathbf{H}_k + \mathbf{R}_k\right)$$

$$\hat{\mathbf{x}}_{k|k} = \hat{\mathbf{x}}_{k|k-1} + \mathbf{K}_k\mathbf{e}_k$$

$$\mathbf{P}_{k|k} = \left[\mathbf{I} - \mathbf{K}_k\mathbf{H}_k\right]\mathbf{P}_{k|k-1}$$

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A CLOSER LOOK AT THE FILTER GAIN

sensitivity observation model
to changes in the state

$$\mathbf{K}_k = \frac{\mathbf{P}_{k|k-1}\mathbf{H}_k}{\mathbf{H}_k\mathbf{P}_{k|k-1}\mathbf{H}_k + \mathbf{R}_k}$$

error covariance of the innovations (i.e. uncertainty in
the new information we get from observations).

A CLOSER LOOK AT THE FILTER GAIN

$$\text{Kalman Gain} = \frac{\begin{array}{c}\text{uncertainty}\\ \text{in (process)}\\ \text{model}\end{array} \times \begin{array}{c}\text{Sensitivity}\\ \text{observation}\\ \text{model}\end{array}}{\begin{array}{c}\text{uncertainty in}\\ \text{observations}\end{array}}$$

So balance between uncertainty in process model and uncertainty in measurements / observation model!

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TRAFFIC FLOW SIMULATION MODELS

Are naturally cast in discrete state-space form

- Conservation of vehicles (+ possible additional pde for speed)

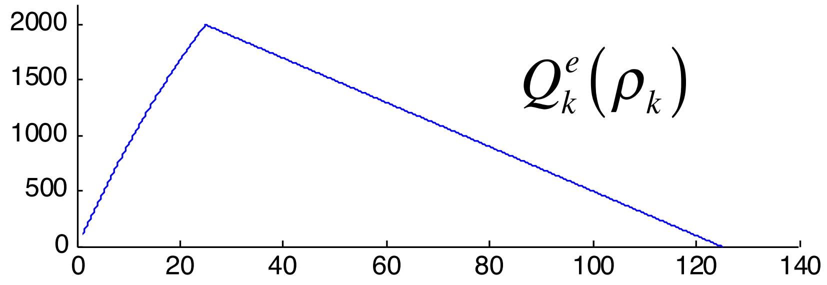
$$\mathbf{x}_{k+1} = f\left(\mathbf{x}_k, \mathbf{u}_k\right) + \mathbf{w}_k$$

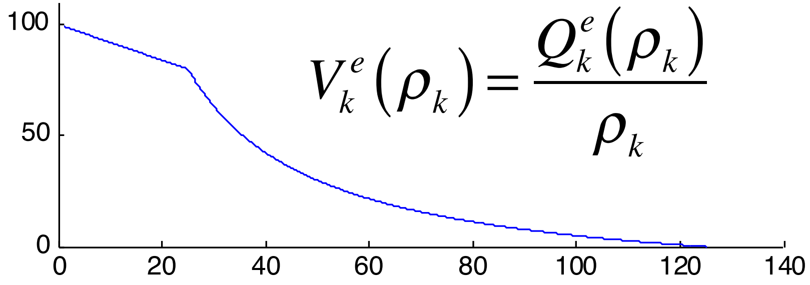
$$\text{typically } f : \rho_{k+1} = \rho_k + \frac{\Delta \mathbf{L}}{\Delta t}\left(\mathbf{q}_k^{in} - \mathbf{q}_k^{out} + \mathbf{r} - \mathbf{s}\right)$$

- Observation model typically fundamental diagram

$$\mathbf{y}_k = h_k\left(\mathbf{x}_k\right) + \mathbf{v}_k$$

$$\text{typically } h : \mathbf{q}_k = Q_k^e\left(\rho_k\right)$$





TRAFFIC STATE ESTIMATION

Extended Kalman filtering

- Nonlinear extension KF
- Assumptions
  - ➡ Process model can be approximated by 1st order Taylor expansion
  - ➡ Obs model can be approximated with 1st order Taylor expansion
  - ➡ All other KF assumptions (iid Gaussian WN, etc)

$$\mathbf{x}_{k+1} = f_k\left(\mathbf{x}_k\right) + \mathbf{w}_k$$

$$\mathbf{y}_k = h_k\left(\mathbf{x}_k\right) + \mathbf{v}_k$$

$$\mathbf{F}_k = \left.\frac{df_k\left(\mathbf{x}\right)}{d\mathbf{x}}\right|_{\mathbf{x}=\hat{\mathbf{x}}_k}$$

$$\mathbf{H}_k = \left.\frac{dh_k\left(\mathbf{x}\right)}{d\mathbf{x}}\right|_{\mathbf{x}=\hat{\mathbf{x}}_k}$$

EXTENDED KALMAN FILTER

- Many challenges
  - ➡ linearisation may cause adaptation in the wrong direction
  - ➡ Computing derivatives = pain in the @!$$ …
  - ➡ Scalability: matrix manipulations & inversions expensive
  - ➡(E)KF assumptions on violated all the time

$$\hat{\mathbf{x}}_{0|0} = \hat{\mathbf{x}}_0, \mathbf{P}_{0|0} = \mathbf{P}_0$$

$$\hat{\mathbf{x}}_{k|k-1} = f\left(\hat{\mathbf{x}}_{k-1|k-1}, \mathbf{u}_k\right)$$

$$\mathbf{P}_{k|k-1} = \mathbf{F}_{k-1}\mathbf{P}_{k-1|k-1}\mathbf{F}_{k-1}^T + \mathbf{Q}_{k-1}$$

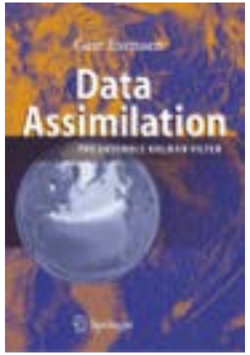
$$\mathbf{e}_k = \mathbf{y}_k - h\left(\hat{\mathbf{x}}_{k|k-1}\right)$$

$$\mathbf{K}_k = \mathbf{P}_{k|k-1}\mathbf{H}_k / \left(\mathbf{H}_k\mathbf{P}_{k|k-1}\mathbf{H}_k + \mathbf{R}_k\right)$$

$$\hat{\mathbf{x}}_{k|k} = \hat{\mathbf{x}}_{k|k-1} + \mathbf{K}_k\mathbf{e}_k$$

$$\mathbf{P}_{k|k} = \left[\mathbf{I} - \mathbf{K}_k\mathbf{H}_k\right]\mathbf{P}_{k|k-1}$$

ALTERNATIVE: ENSEMBLE KALMAN FILTER



- Use ensemble of *N* state vectors and noisy observation replications

$$\mathbf{X}_{0|0} = [\mathbf{x}_0^1, \ldots, \mathbf{x}_0^N],$$

$$\mathbf{X}_{k|k-1} = f\left(\mathbf{X}_{k-1|k-1}, \mathbf{U}_k\right)$$

- Predicting ensemble mean and variance is simple …

$$\mathbf{x}_{k|k-1} = E(\mathbf{X}_{k|k-1}) = \frac{1}{N}\sum_{i=1:N} \mathbf{x}_{k|k-1}^i$$

$$\mathbf{P}_{k|k-1} = \mathbf{A}_{k|k-1}\mathbf{A}_{k|k-1}^T / (N-1), \text{ with } \mathbf{A}_x = \mathbf{X}_x - E(\mathbf{X}_x)$$

- Update step similar to EKF
  ➡Still requires linearisation ?

$$\mathbf{D}_k = [\mathbf{d}_k^1, \ldots, \mathbf{d}_k^N], \text{with } \mathbf{d}_k^i = \mathbf{y}_k + \mathbf{e}_k^i$$

$$\mathbf{E}_k = \mathbf{D}_k - h\left(\mathbf{X}_{k|k-1}\right)$$

$$\mathbf{K}_k = \mathbf{P}_{k|k-1} / \left(\mathbf{H}_k \mathbf{P}_{k|k-1} \mathbf{H}_k + \mathbf{R}_k\right)$$

$$\mathbf{X}_{k|k} = \mathbf{X}_{k|k-1} + \mathbf{K}_k \mathbf{E}_k$$

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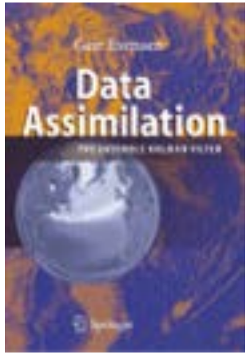
ALTERNATIVE: ENSEMBLE KALMAN FILTER



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

$$\mathbf{X}_{k|k} = \mathbf{X}_{k|k-1} + \mathbf{K}_k\mathbf{E}_k$$

$$\boxed{\begin{aligned} \mathbf{K}_k &= \tfrac{1}{N-1}\mathbf{A}_{k|k-1}(\mathbf{HA})^T / \mathbf{P}_{k|k}^*, \\ \text{with } \mathbf{P}_{k|k}^* &= \tfrac{1}{N-1}\mathbf{HA}(\mathbf{HA})^T + \mathbf{R}_k \\ \text{and } [HA^i] &= h(\mathbf{x}_{k|k-1}^i) - \frac{1}{N}\sum_{j=1:N} h(\mathbf{x}_{k|k-1}^j) \end{aligned}}$$

A CLOSER LOOK AT THIS FILTER GAIN

distance prior state to mean ensemble state

distance predicted observations to mean ensemble prediction

$$\mathbf{K}_k = \frac{\mathbf{A}_{k|k-1}\left(\mathbf{HA}\right)^T}{\mathbf{HA}\left(\mathbf{HA}\right)^T + \mathbf{R}_k}$$

total error variance (uncertainty) measurement equation

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A CLOSER LOOK AT THIS FILTER GAIN

$$\text{Kalman Gain} = \frac{\text{uncertainty in model predictions (sign?)}}{\text{uncertainty in observations}}$$

So again balance between uncertainty in model and uncertainty in measurements!

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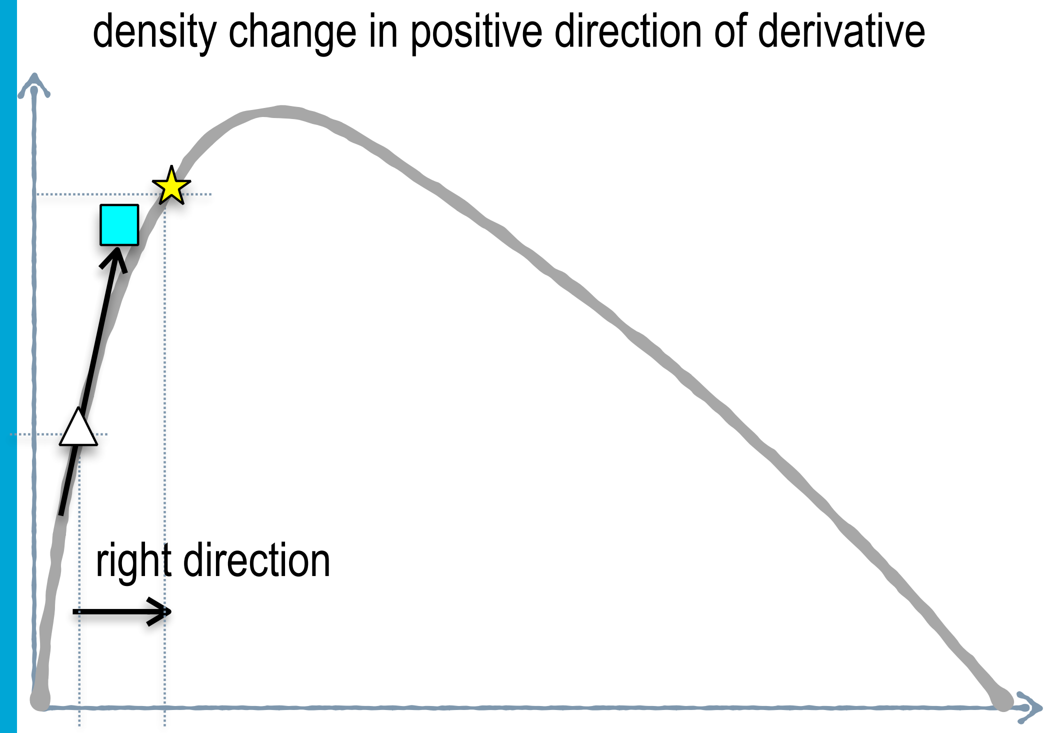
EKF VS ENKF

EnKF Improves upon the 'wrong sign' adaptation problem



☆Observation △Prior mean state ◇◆ Prior/posterior Ensemble ■ Posterior mean state

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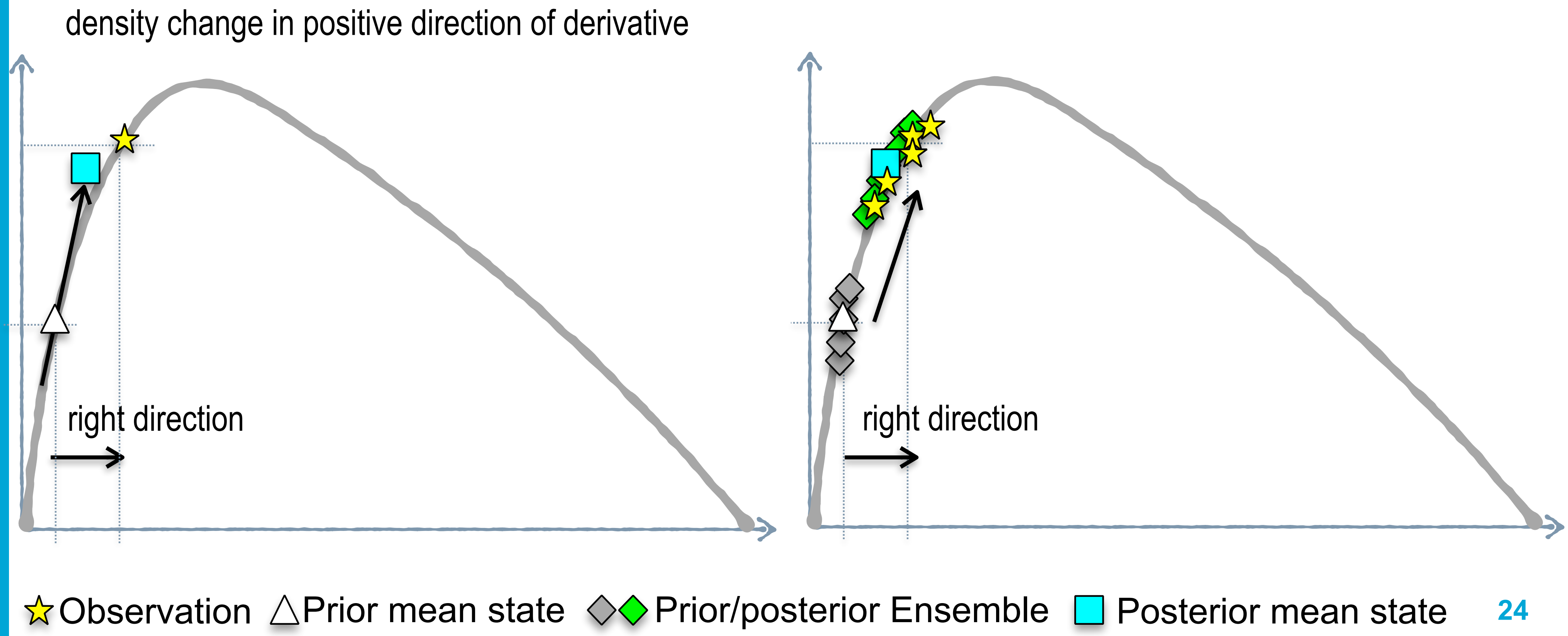
EKF VS ENKF

EnKF Improves upon the ‘wrong sign’ adaptation problem



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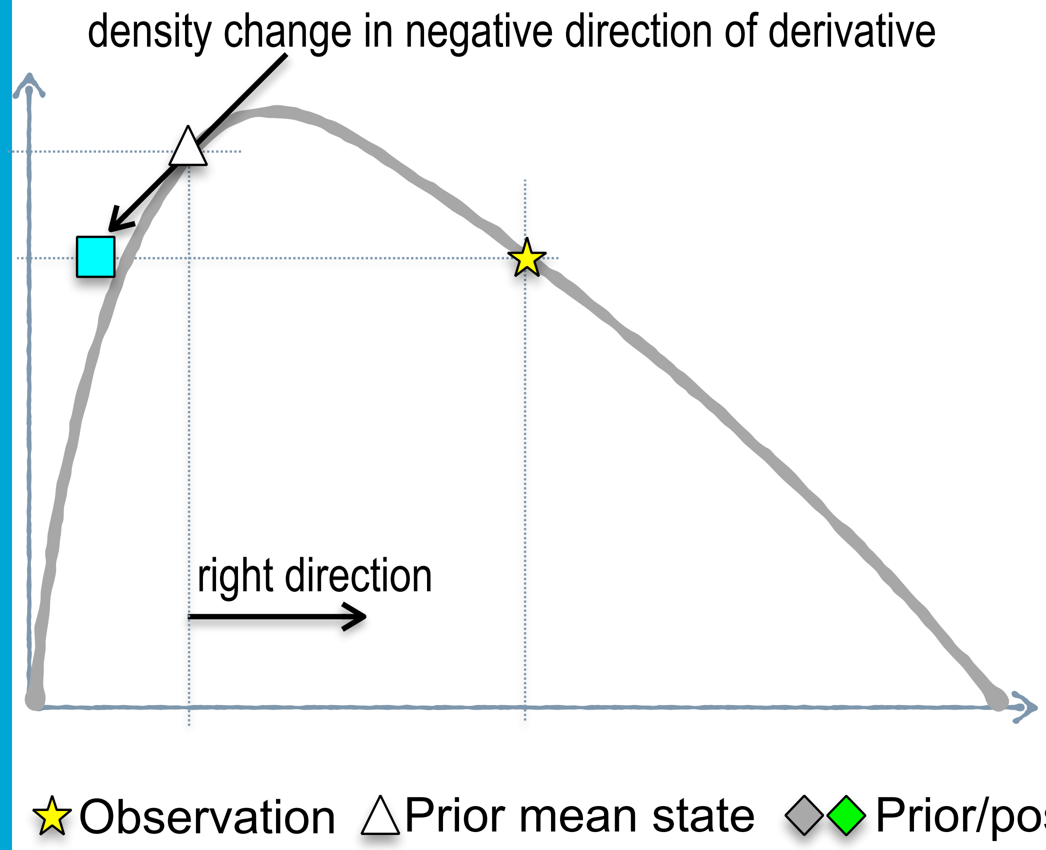

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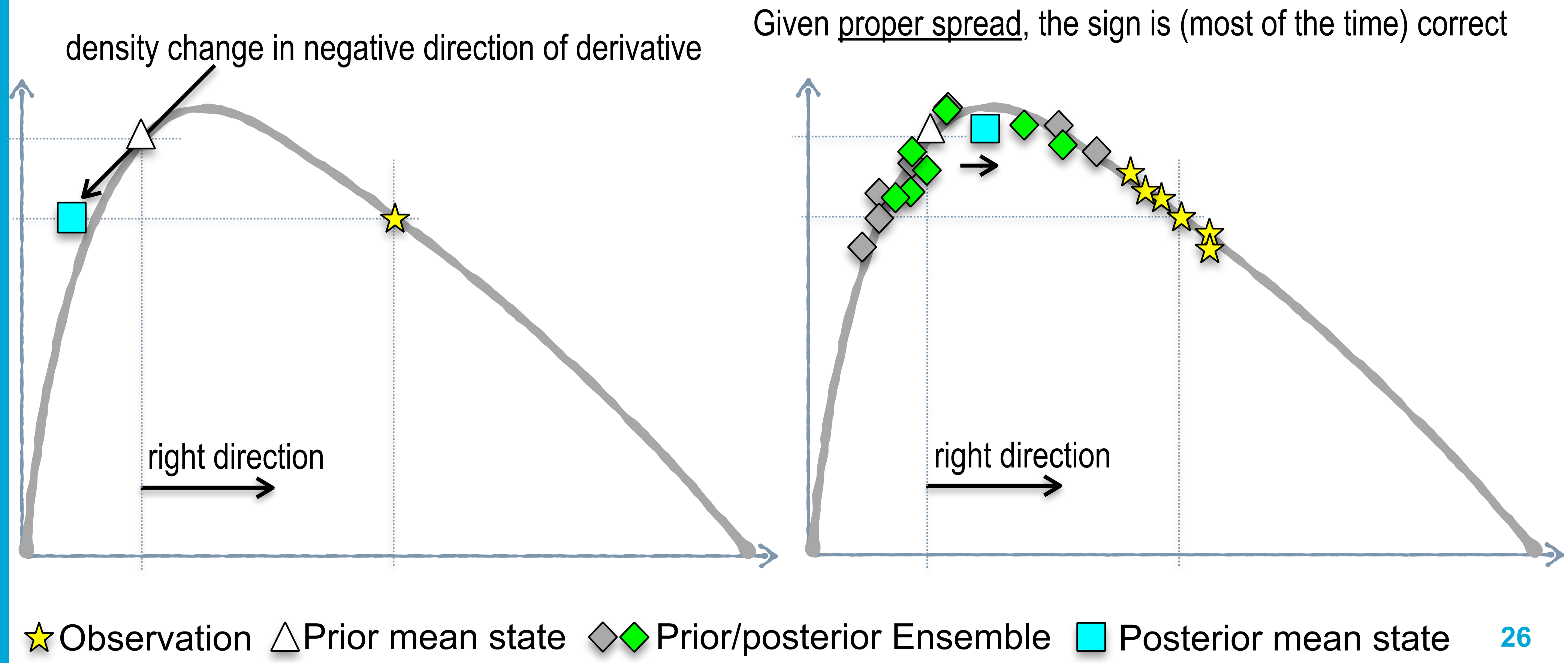

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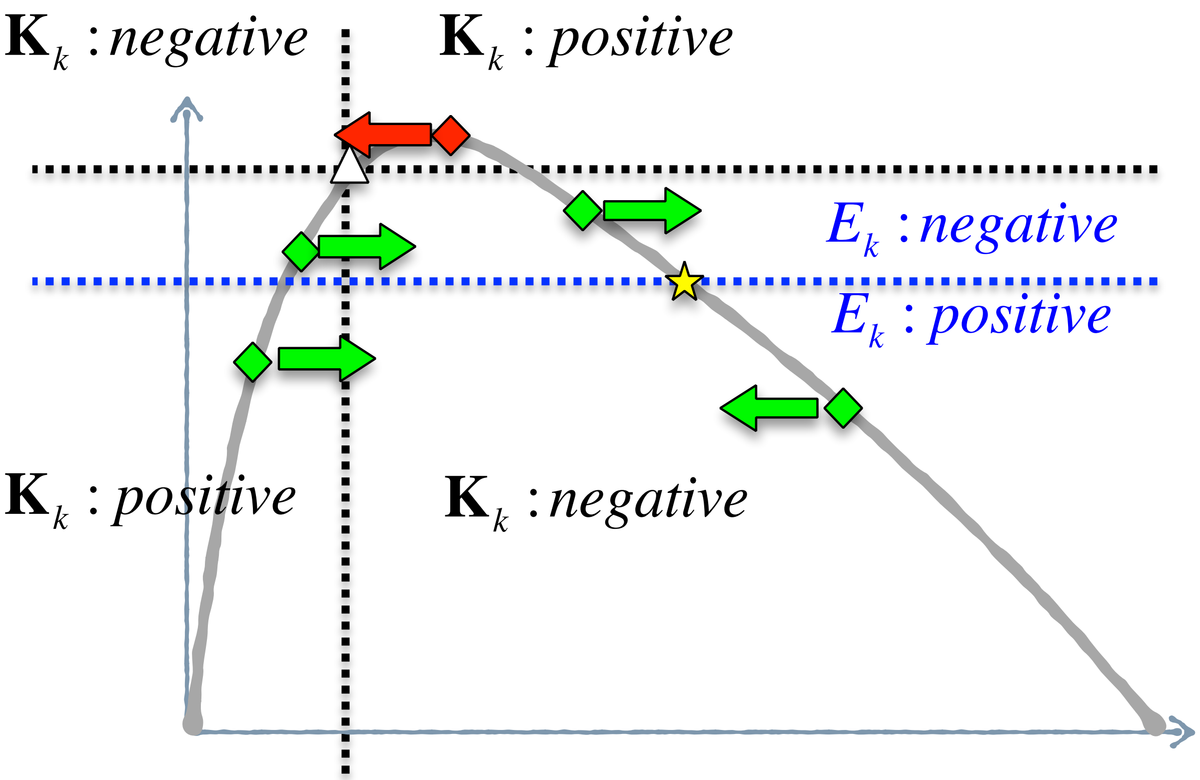
EKF VS ENKF

EnKF Improves upon the 'wrong sign' adaptation problem

$$\mathbf{X}_{k|k} = \mathbf{X}_{k|k-1} + \mathbf{K}_k \mathbf{E}_k$$

In this case most ensemble members move in the correct direction: so does the ensemble mean



$$\mathbf{K}_k = \frac{1}{N-1}\mathbf{A}_{k|k-1}(\mathbf{HA})^T / \mathbf{P}^*_{k|k},$$

$$\text{with } \mathbf{P}^*_{k|k} = \frac{1}{N-1}\mathbf{HA}(\mathbf{HA})^T + \mathbf{R}_k$$

$$\text{and } [HA^i] = h(\mathbf{x}^i_{k|k-1}) - \frac{1}{N}\sum_{j=1:N} h(\mathbf{x}^j_{k|k-1})$$

ENKF FOR LARGE-SCALE ESTIMATION

Three further adaptations

- Getting rid of expensive matrix inversion
- Deterministic instead of stochastic resampling of **D**
- Localisation of the filter

ENKF FOR LARGE-SCALE ESTIMATION

Three further adaptations

- Getting rid of expensive matrix inversion
  - ➡Computational cost traditional EnKF: **O(m³ + m²N +mN² + nN²)**
    - cubic in nr measurements: (2 as much ⇒8 times more cost)
    - quadratic in state variables and ensemble members
  - ➡Computational cost SMW alternative: **O(N³+mN²+nN²)**
    - linear in measurements and state size
    - quadratic in ensemble members: 8

Sherman-Morrison-Woodbury (SMW) formula, e.g. W.Hager, SIAM Rev., 31(2), 221–239

$$\mathbf{K}_k = \frac{1}{N-1}\mathbf{A}_{k|k-1}(\mathbf{HA})^T \underbrace{\left(\frac{1}{N-1}\mathbf{HA}(\mathbf{HA})^T + \mathbf{R}_k\right)^{-1}}_{\Downarrow}$$

$$\mathbf{R}^{-1}\left[\mathbf{I} - \frac{1}{N-1}(\mathbf{HA})\left(\mathbf{I} + (\mathbf{HA})^T\mathbf{R}^{-1}\frac{1}{N-1}(\mathbf{HA})\right)^{-1}(\mathbf{HA})^T\mathbf{R}^{-1}\right]$$

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ENKF FOR LARGE-SCALE ESTIMATION

Three further adaptations

- Getting rid of expensive matrix inversion
- Deterministic instead of stochastic resampling of **D**
  - ➡Correct: ensemble spans about the same (model) subspace as the forecasting errors (else: filter divergence looms …)
  - ➡Stochastic resampling may lead to clustering ensemble

$$\mathbf{D}_k = [\mathbf{d}_k^1, \ldots, \mathbf{d}_k^N], \text{with } \mathbf{d}_k^i = \mathbf{y}_k + \mathbf{e}_k^i \qquad \mathbf{x}_{k|k} = \mathbf{x}_{k|k-1} + \mathbf{K}_k\left(\mathbf{d}_k - h\left(\mathbf{x}_{k|k-1}\right)\right)$$

$$\mathbf{X}_{k|k} = \mathbf{X}_{k|k-1} + \mathbf{K}_k\left(\mathbf{D}_k - h\left(\mathbf{X}_{k|k-1}\right)\right) \longrightarrow \mathbf{A}_{k|k} = \mathbf{A}_{k|k-1} + \mathbf{K}_k^A\left(\mathbf{D}_k - \mathbf{AH}_k\right)$$

- ➡Deterministic approach manipulates $\mathbf{K}_k^A$ so that innovation / residuals **AH** ALWAYS spread entire measurement space (with cov **R**)

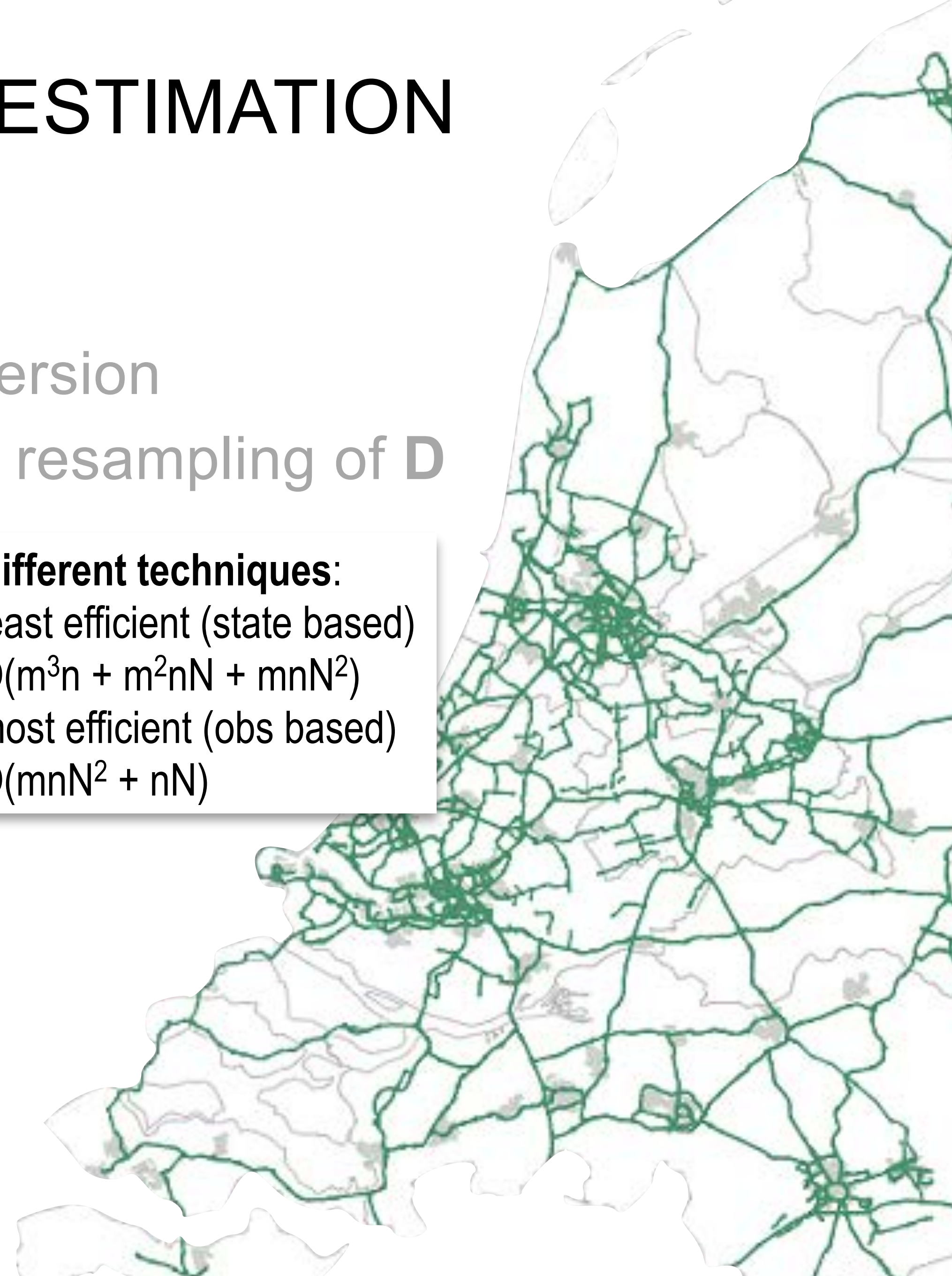
Sakov, P., & Oke, P. R. (2008). A deterministic formulation of the ensemble kalman filter: an alternative to ensemble square root filters. Tellus A, 60 (2), 361-371.

ENKF FOR LARGE-SCALE ESTIMATION

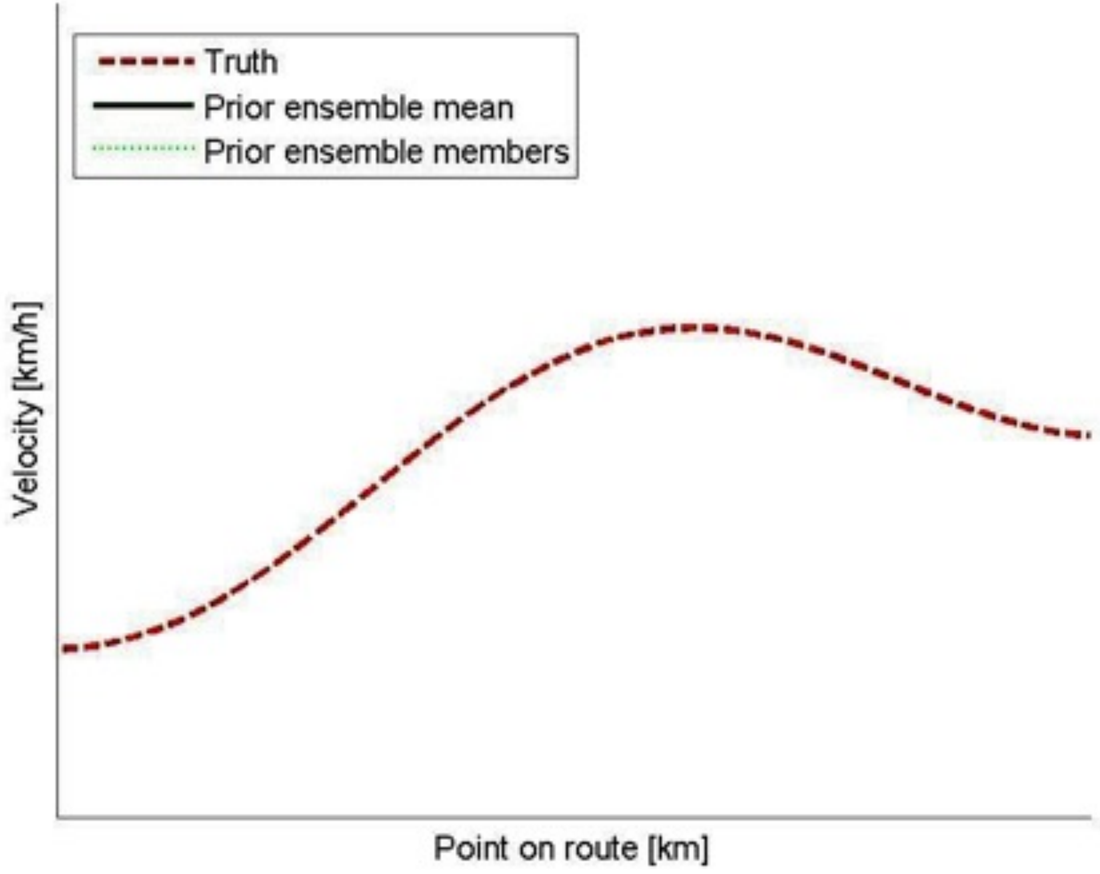
Three further adaptations

- Getting rid of expensive matrix inversion
- Deterministic instead of stochastic resampling of **D**
- Localisation of the filter
  - ➡ Further reduces computational costs (chops up Cov matrix => update equations in small bits)
  - ➡ Avoids spurious correlations
  - ➡ Increases effective ensemble size (and spread!)
  - ➡ *Note: localisation does minimise effect SMW formulation*

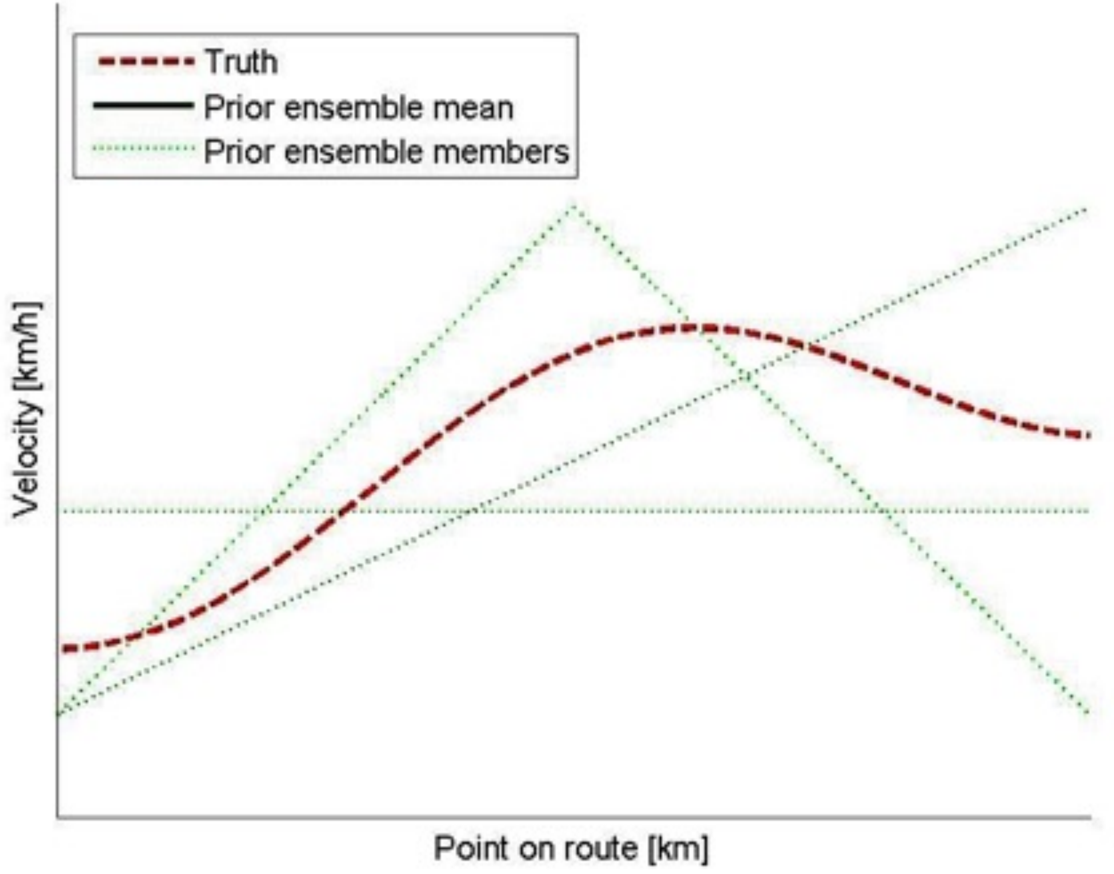
Different techniques:
least efficient (state based)
$O(m^3n + m^2nN + mnN^2)$
most efficient (obs based)
$O(mnN^2 + nN)$



LOCALISATION INCREASES EFFECTIVE ENSEMBLE SIZE



LOCALISATION INCREASES EFFECTIVE ENSEMBLE SIZE



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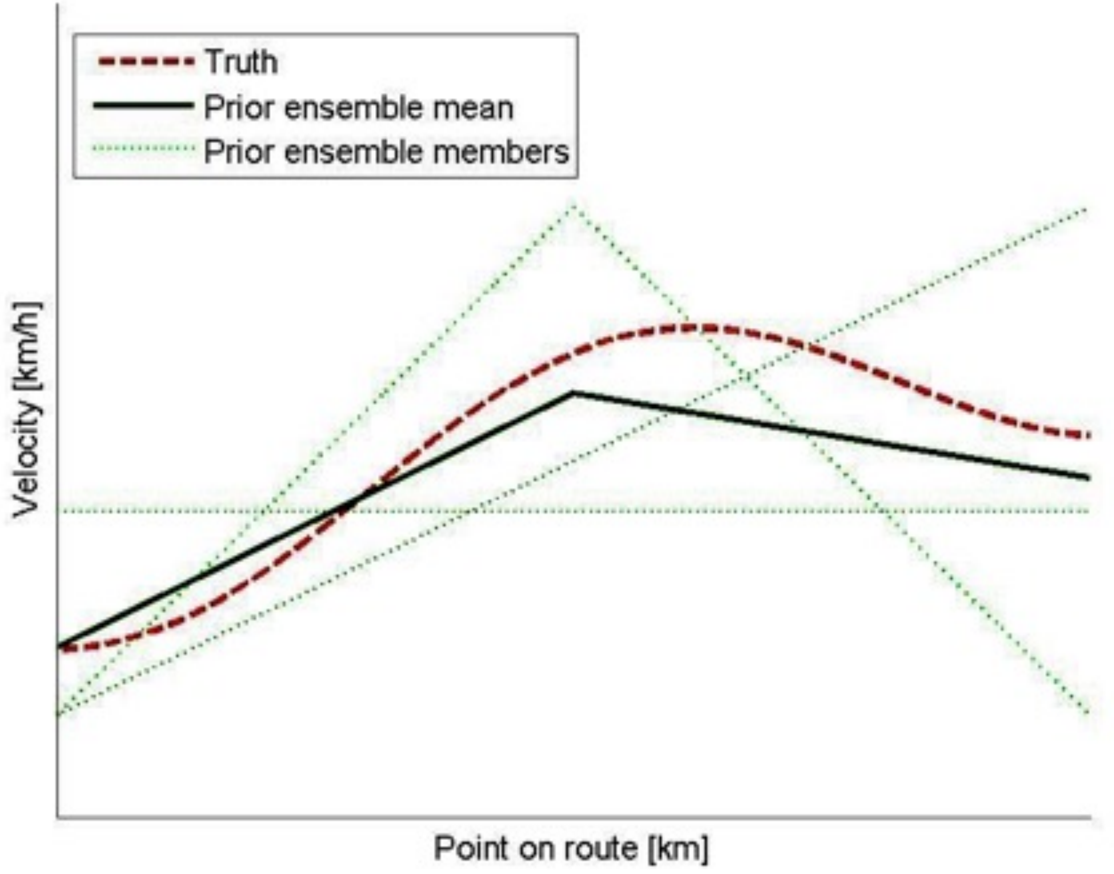
LOCALISATION INCREASES EFFECTIVE ENSEMBLE SIZE



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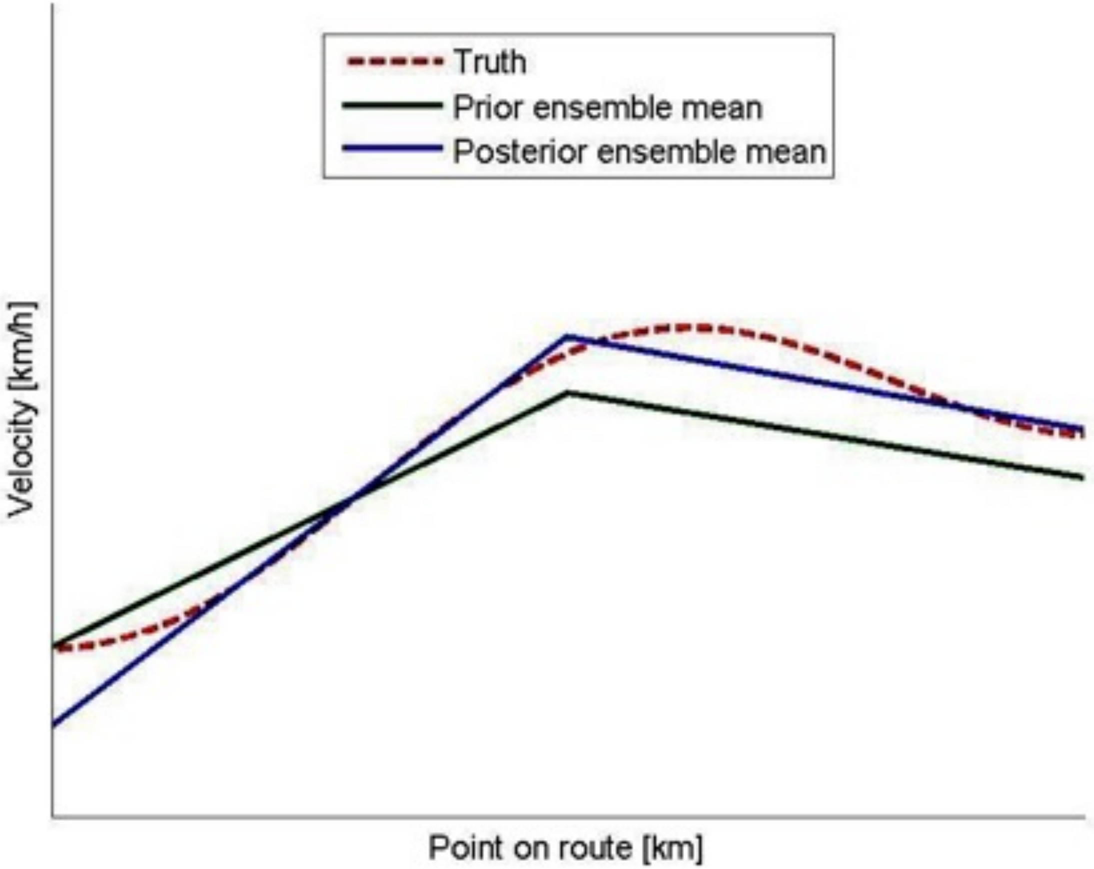
LOCALISATION INCREASES EFFECTIVE ENSEMBLE SIZE



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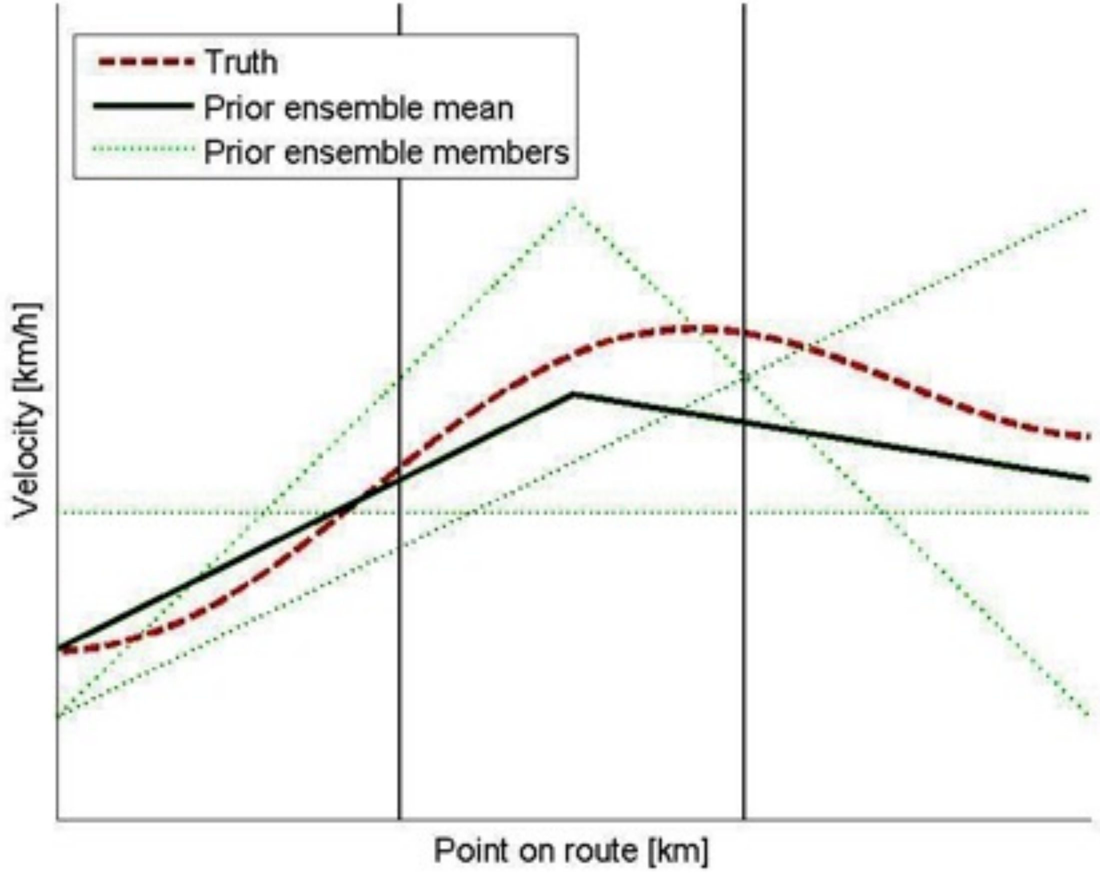
LOCALISATION INCREASES EFFECTIVE ENSEMBLE SIZE



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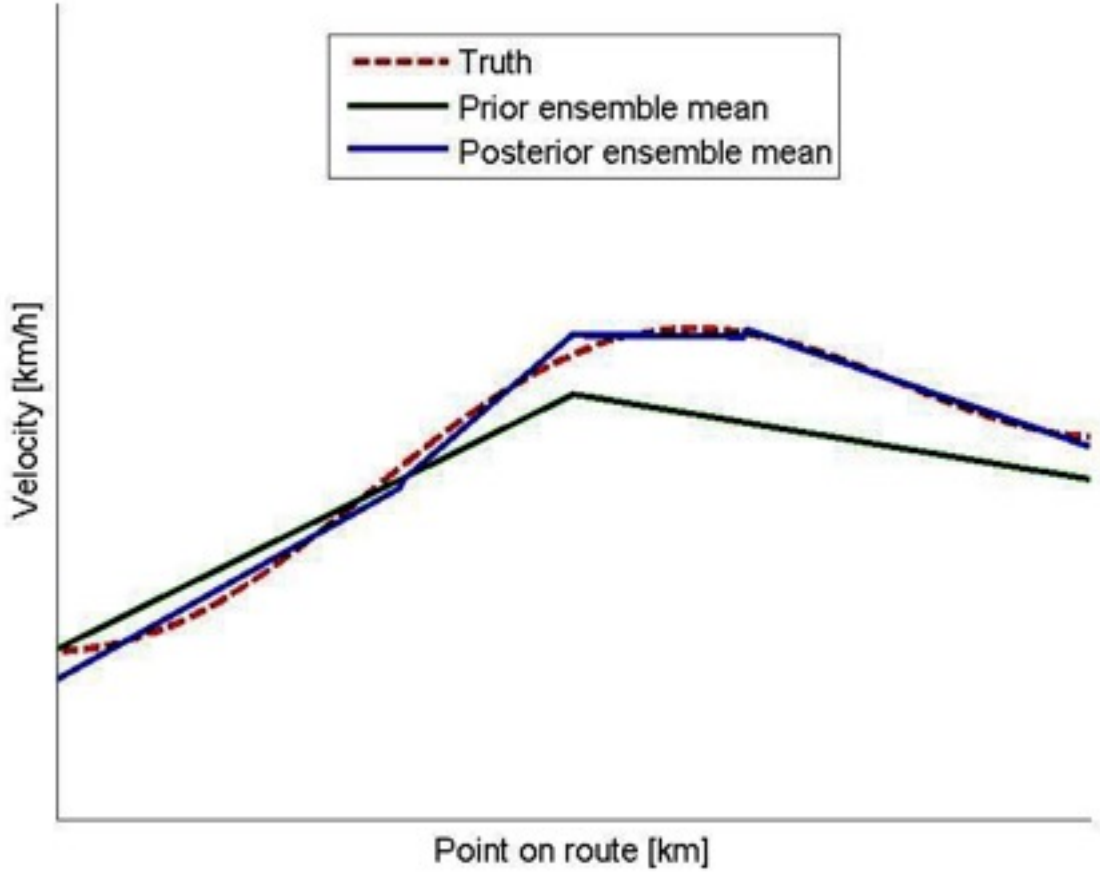
LOCALISATION INCREASES EFFECTIVE ENSEMBLE SIZE



Note: Localisation may induce "jumps" in the state, which may not be realistic

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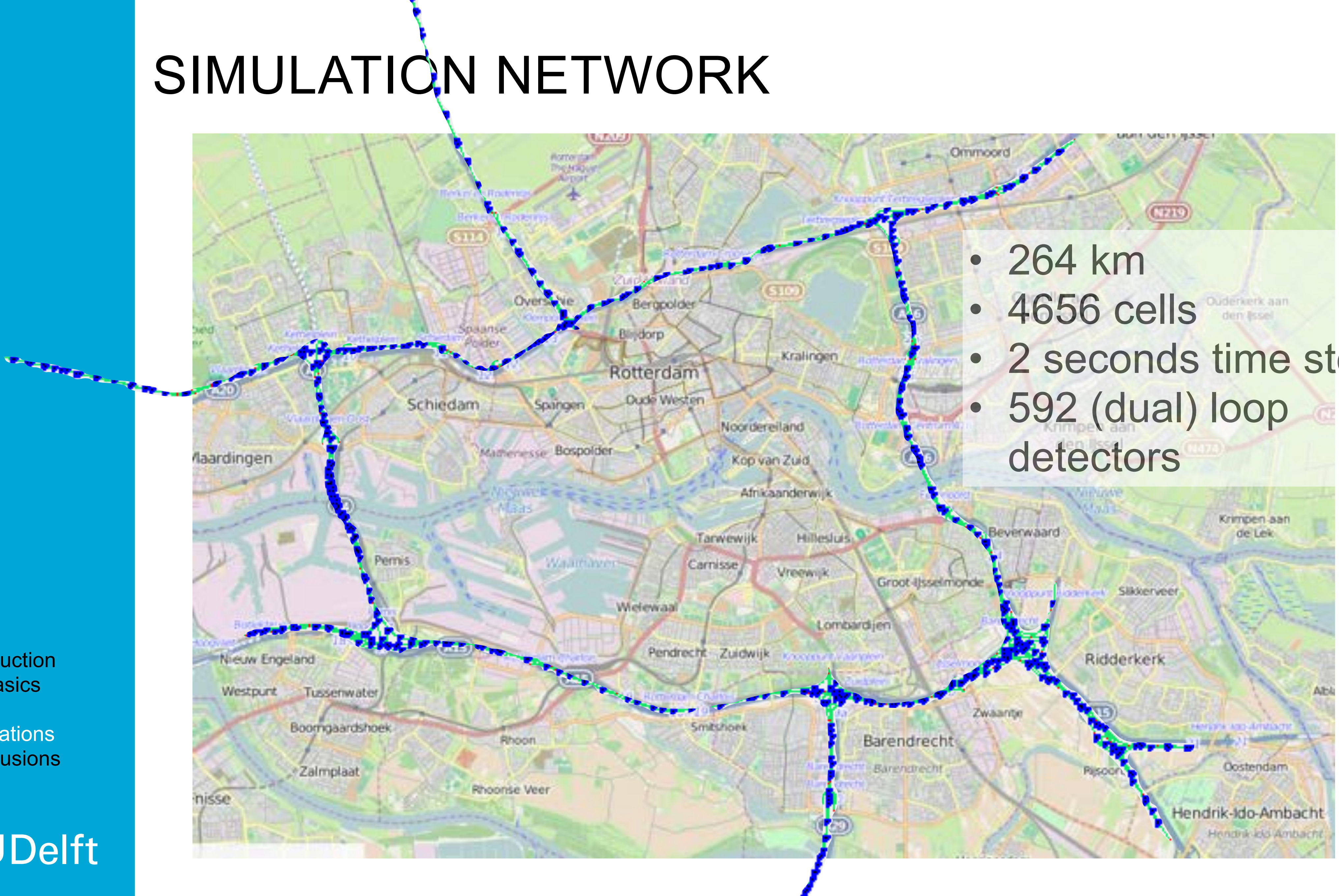
SIMULATION NETWORK



- 264 km
- 4656 cells
- 2 seconds time step
- 592 (dual) loop detectors

Introduction
KF Basics
EnKF
Simulations
Conclusions

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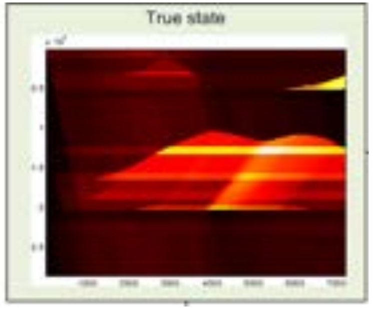
EXPERIMENTAL SETUP



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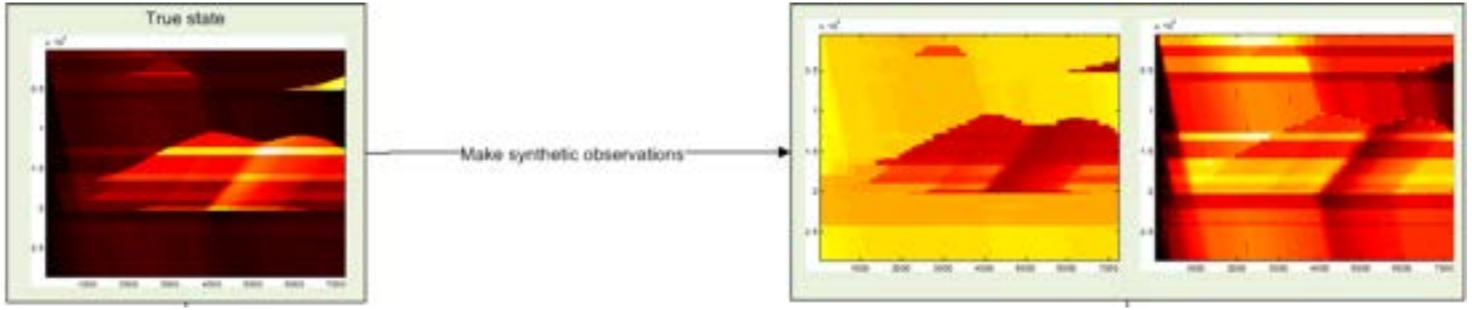
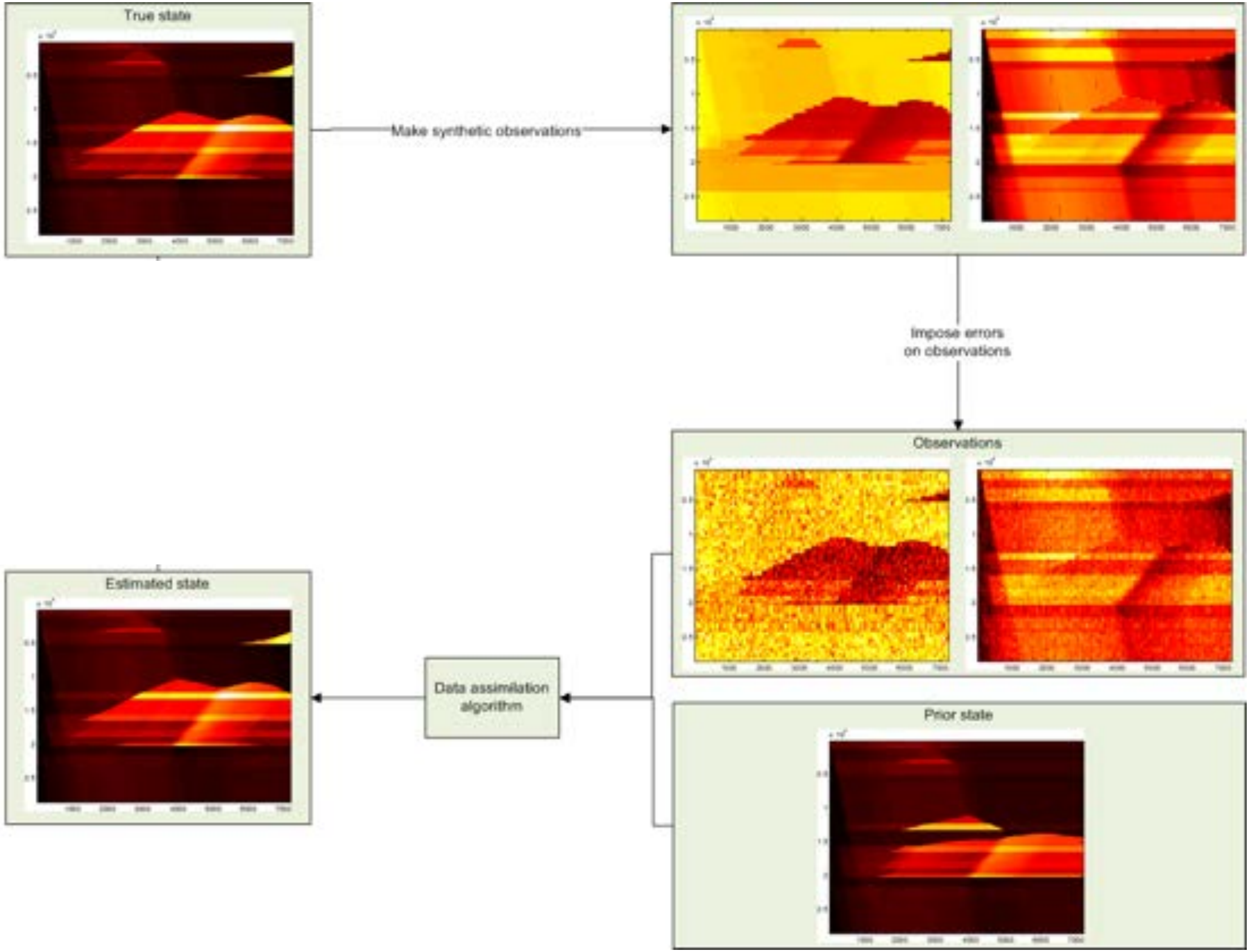
EXPERIMENTAL SETUP



EXPERIMENTAL SETUP



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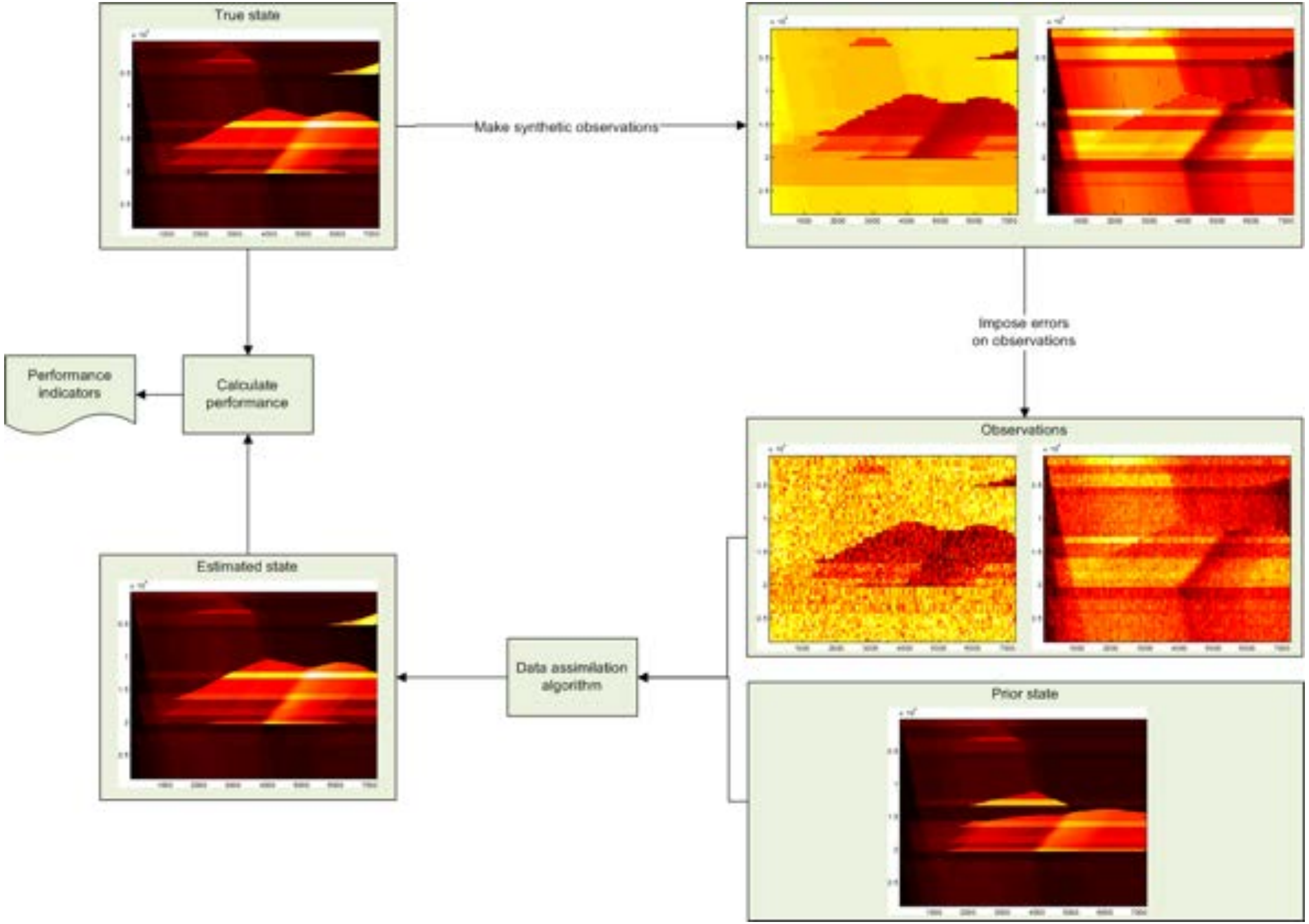
EXPERIMENTAL SETUP



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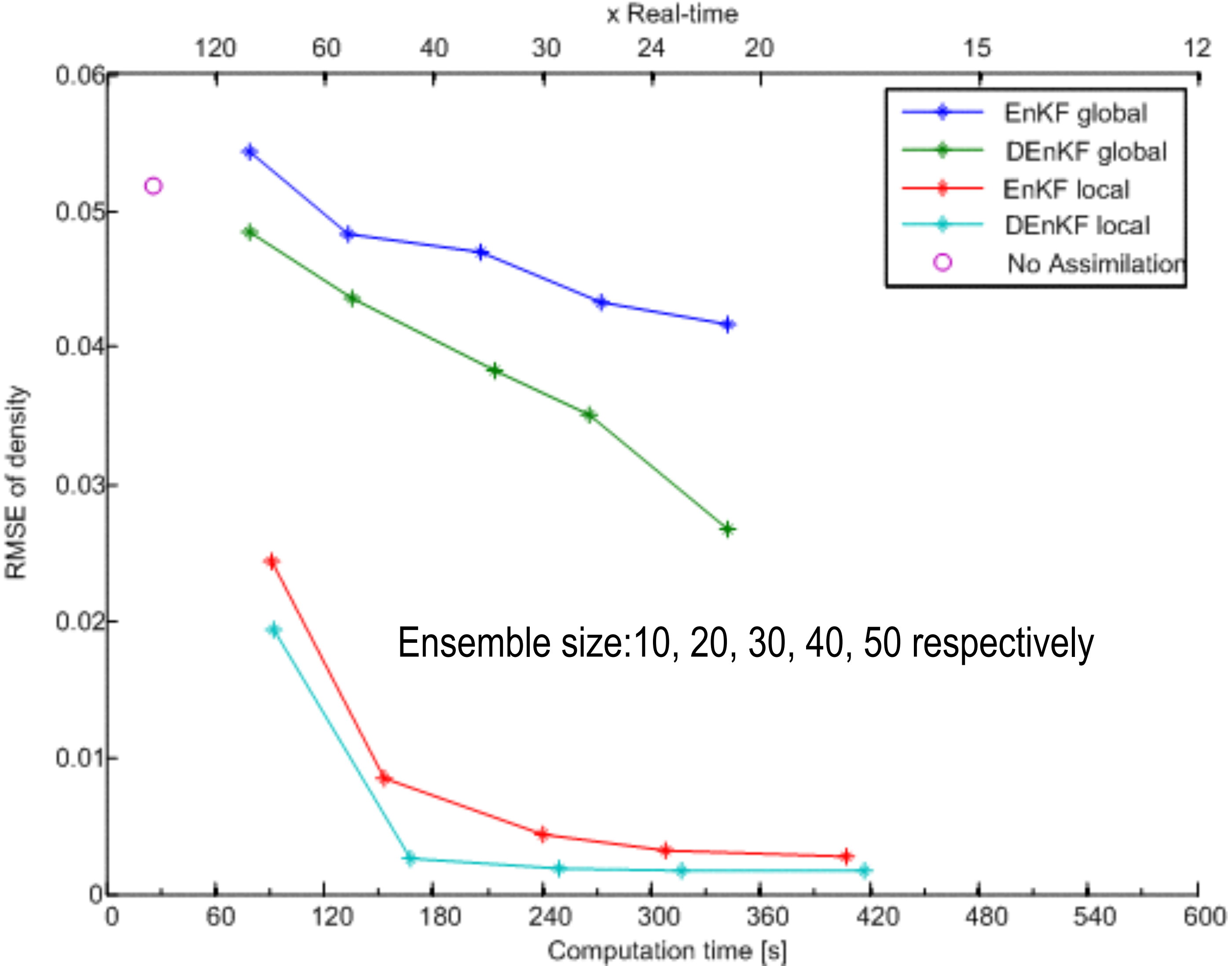
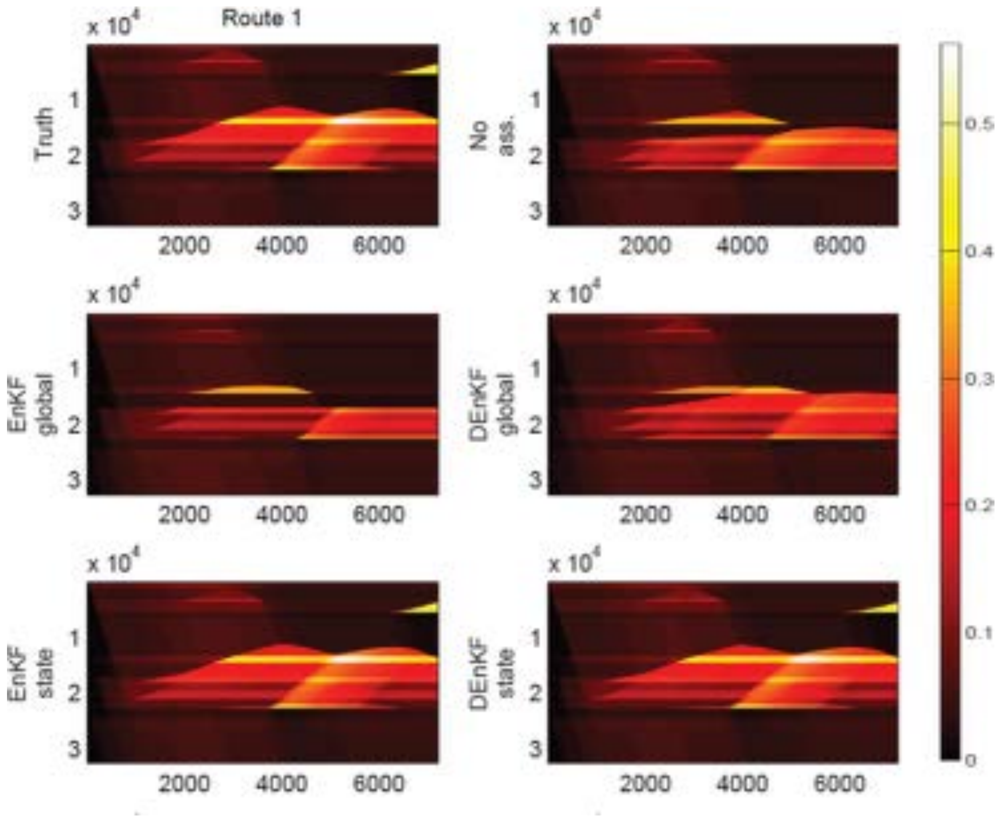
RESULTS



x Real-time
120
60
40
30
24
20
15
12
0.06
0.05
0.04
0.03
0.02
0.01
0
RMSE of density
0
60
120
180
240
300
360
420
480
540
600
Computation time [s]
EnKF global
DEnKF global
EnKF local
DEnKF local
No Assimilation
Ensemble size:10, 20, 30, 40, 50 respectively



Route 1
Truth
No ass.
EnKF global
DEnKF global
EnKF state
DEnKF state
2000
4000
6000

RESULTS

	Localized EKF	Localized (D)EnKF
Reference	Van Hinsbergen et al. (2012)	*This research*
Hardware	3.0 GHz dual-core, 2 GB RAM	2.6 GHz quad-core i5-3230M, 8 GB RAM
Length network	272 km	264 km
Model time step	5 s	2 s
Number of cells	1911	4656
Number of detectors in network	531	592
Number of used measurements	398	1184
Computational speed	$\approx 20\times$ real-time	$\approx 40\times$ real-time

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CONCLUSIONS

- Localized DEnKF overall winner in this study …
  - ➡Faster than Localised EKF on similar case
  - ➡More accurate and faster than all other EnKF alternatives
  - ➡No need (on the contrary) for SWM reformulation
- Localization of EnKF is absolutely crucial:
  - ➡Higher estimation accuracy (larger effective ensemble)
  - ➡Lower computational burden
- Deterministic sampling beneficial
  - ➡outperforms stochastic slightly
  - ➡more robust wrt smaller ensemble sizes

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NEXT STEPS

Dutch National Data Warehouse Traffic Information

- In the coming few years we are going to work on implementing and further developing these ideas on real-data
- Many additional puzzles:
  - ➡Network graph updating
  - ➡Parameter estimation (dual filtering?)
  - ➡Inflows / turns / ODs / Paths
  - ➡Urban / provincial (different data, different state variables)

National Data Warehouse
for Traffic Information

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