Multiscale Model Diagnostic

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NORCE

Model diagnostic of prior predictive distribution

$$x_e = g\left(m_e\right) + \epsilon_e; \quad e = 1, \ldots, E$$

g : forward model/simulator

m_e : prior parameter realization

ϵ_e : error realization

x_e : (perturbed) prior prediction

Model diagnostic of prior predictive distribution

...to reduce the risk of unsuccessful data assimilation

Assess if prior predictions are consistent with observed data, that is, if the observed data vector could be a credible realization from the prior predictive distribution

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Model diagnostic of prior predictive distribution

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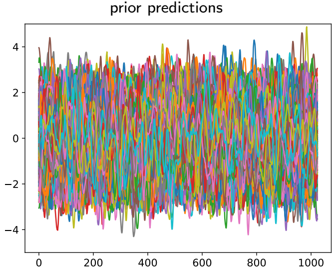
Assess if prior predictions are consistent with observed data, that is, if the observed data vector could be a credible realization from the prior predictive distribution

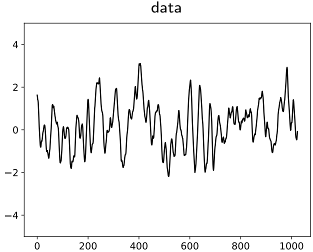
If not consistent, (part of) the modeling setup should be changed before data assimilation is performed

Coverage of individual observations by the ensemble of prior predictions is not sufficient for consistency, as coverage does not take into account trends and shapes

Model diagnostic of prior predictive distribution

The task





Could the black curve be a credible realization from the prior predictive distribution?

Multiscale model diagnostic of prior predictive distribution

Compare prior predictions and data on multiple scales of variation

Multiscale model diagnostic of prior predictive distribution

Compare prior predictions and data on multiple scales of variation

The method utilizes scalar products of prior predictions and data with certain multiscale vectors

$$
\begin{aligned}
\chi_{k,e} &= h_k^T x_e \\
\delta_k &= h_k^T d
\end{aligned}
$$

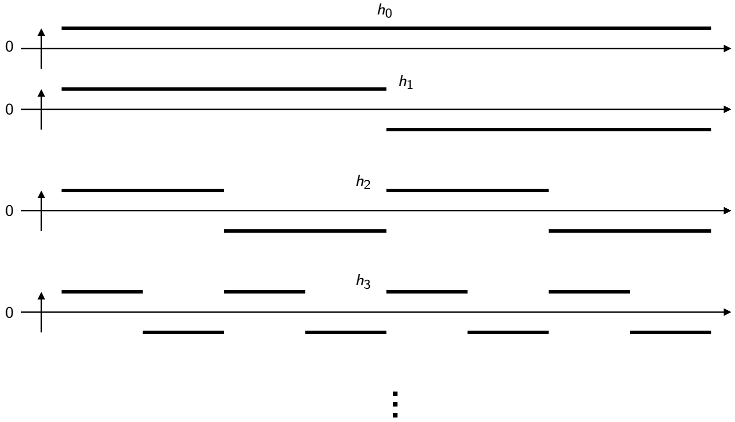
x_e : (recall) prior prediction

d : data

h_k : multiscale vector on scale k

Multiscale model diagnostic of prior predictive distribution

Multiscale vectors (the four vectors with the longest characteristic length)



Multiscale model diagnostic of prior predictive distribution

Application to real data

With real data, there is only a single data vector available

$$\delta_k = h_k^T d$$

Multiscale model diagnostic of prior predictive distribution

Application to real data and method assessment

With real data, there is only a single data vector available

$$\delta_k = h_k^T d$$

When assessing the method's applicability and robustness on toy problems, I will consider an ensemble of data realizations to avoid effects associated with a particular data vector

$$\delta_{k,e} = h_k^T d_e$$

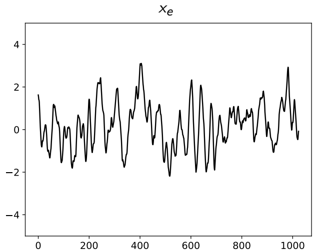
Empirical means, $M(\delta_k)$, and standard deviations, $S(\delta_k)$, will then be available for comparison with $M(\chi_k)$ and $S(\chi_k)$

Multiscale model diagnostic of prior predictive distribution

Method assessment on toy problems

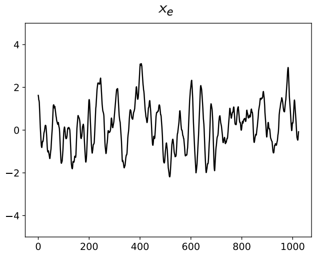
Method assessment on toy problems

Plot explanation

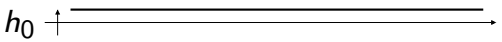


Method assessment on toy problems

Plot explanation



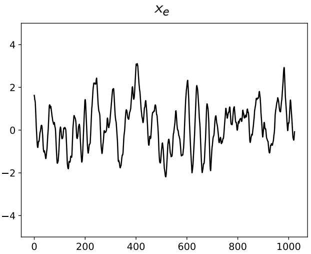
multiply x_e with



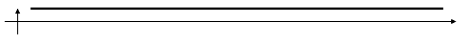
to obtain $\chi_{0,e}$

Method assessment on toy problems

Plot explanation



multiply x_e with

h_0 

to obtain $\chi_{0,e}$

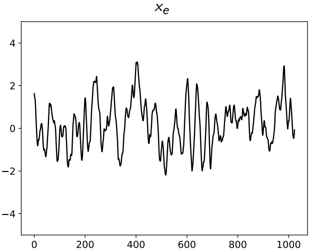
$\downarrow$

Repeat for all e and compute

$M(\chi_0)$ and $S(\chi_0)$

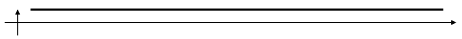
Method assessment on toy problems

Plot explanation



$\rightarrow$

multiply x_e with

h_0 

to obtain $\chi_{0,e}$

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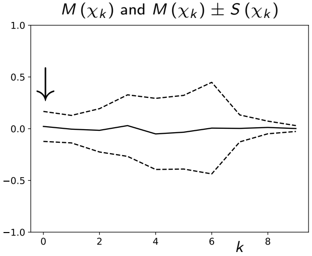
Repeat for all e and compute

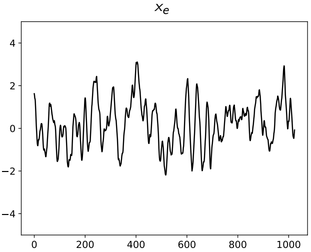
$M(\chi_0)$ and $S(\chi_0)$

$\leftarrow$



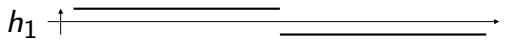
Method assessment on toy problems

Plot explanation



$\rightarrow$

multiply x_e with



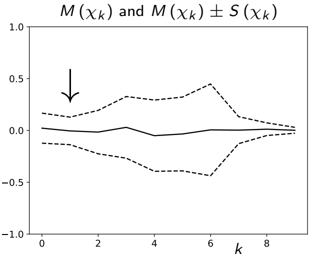
to obtain $\chi_{1,e}$

$\downarrow$

Repeat for all e and compute

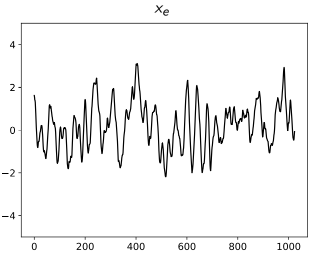
$M(\chi_1)$ and $S(\chi_1)$

$\leftarrow$



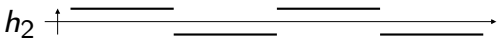
Method assessment on toy problems

Plot explanation



$\rightarrow$

multiply x_e with



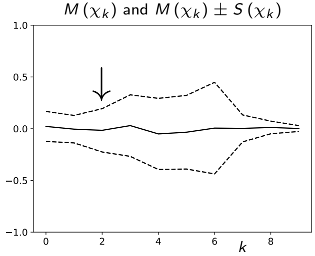
to obtain $\chi_{2,e}$

$\downarrow$

Repeat for all e and compute

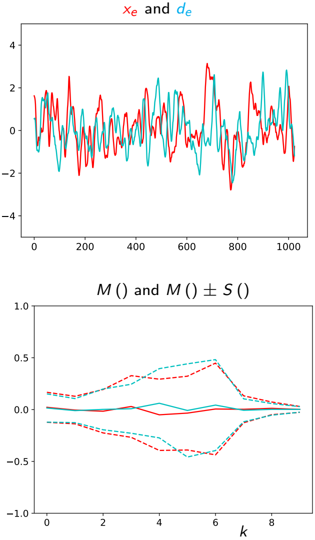
$M(\chi_2)$ and $S(\chi_2)$

$\leftarrow$



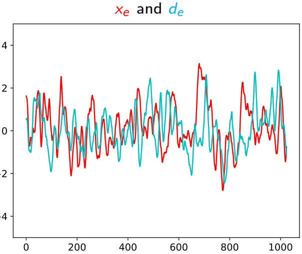
Method assessment on toy problems

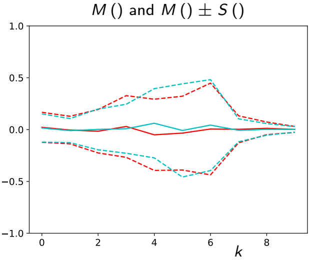
Plot explanation, use of colors: prior predictive, data



Method assessment on toy problems

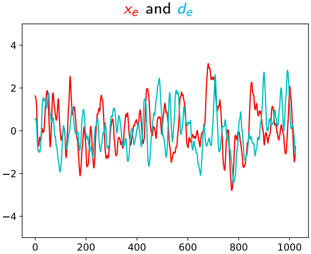
Example 1 - x_e and d_e from the same distribution

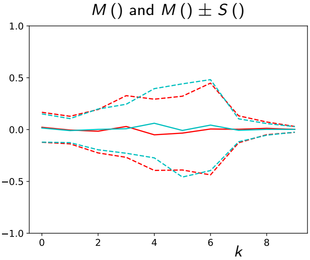


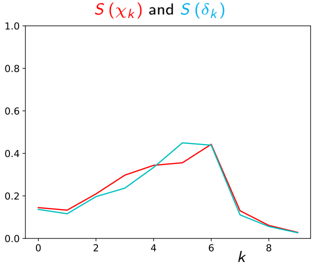


Method assessment on toy problems

Example 1 - x_e and d_e from the same distribution

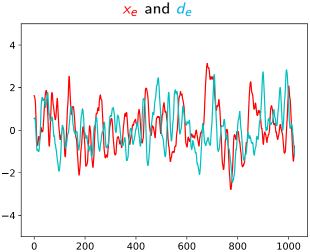


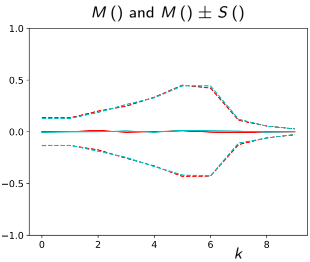


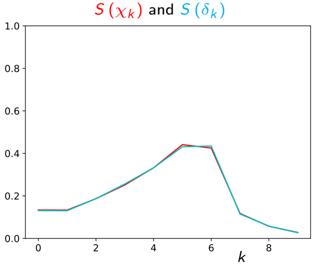


Method assessment on toy problems

Example 1 - x_e and d_e from the same distribution with ensemble size 1000

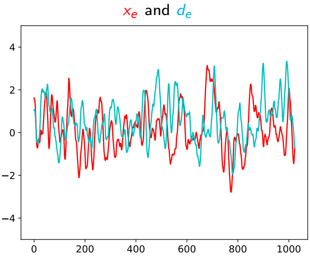


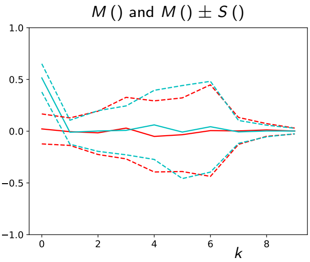




Method assessment on toy problems

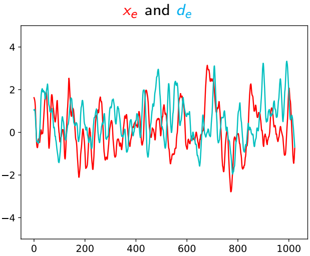
Example 2

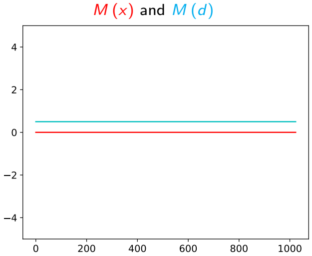


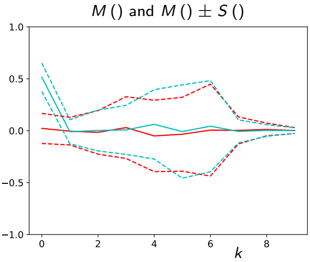


Method assessment on toy problems

Example 2 - different data means







Method assessment on toy problems

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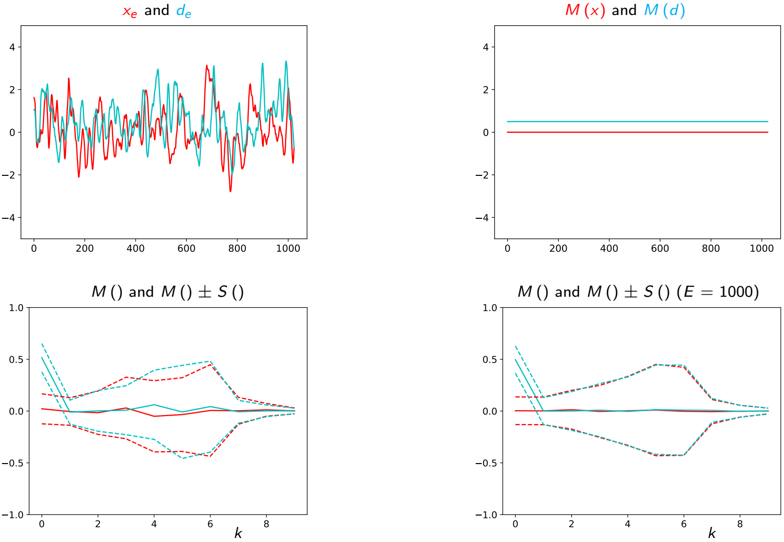
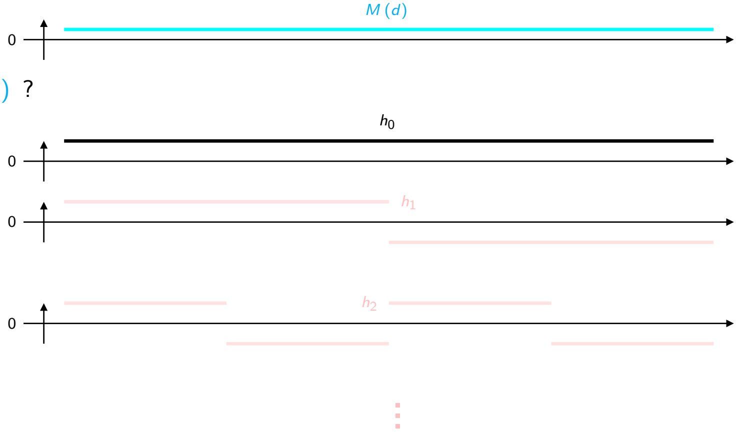


Method assessment on toy problems

Example 2 - simplified explanation of behaviour

$h_0^T M(d)$?



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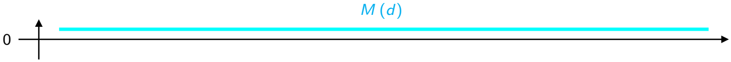
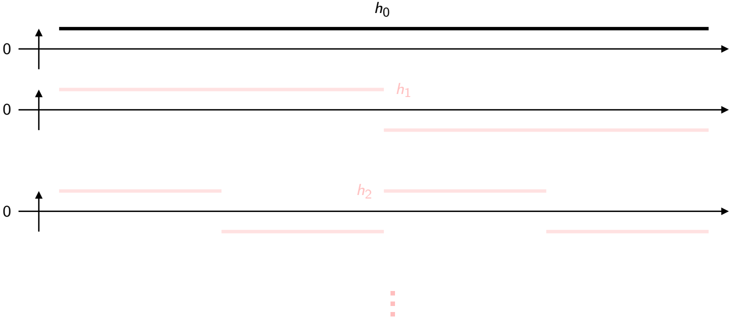


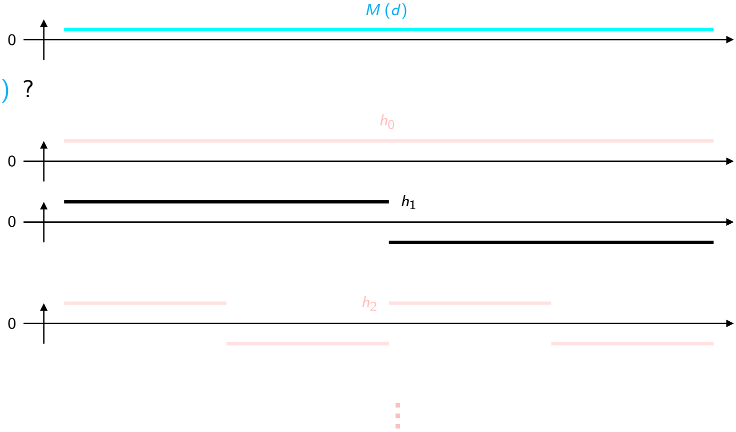
$$h_0^T M(d) > 0$$



Method assessment on toy problems

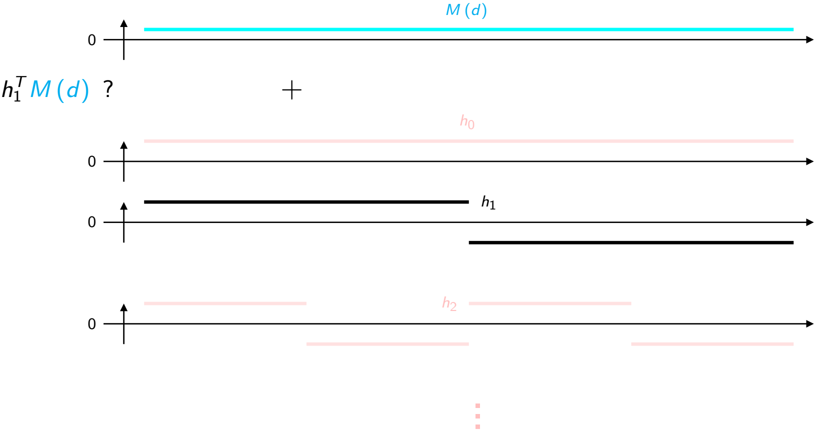
Example 2 - simplified explanation of behaviour

$h_1^T M(d)$?



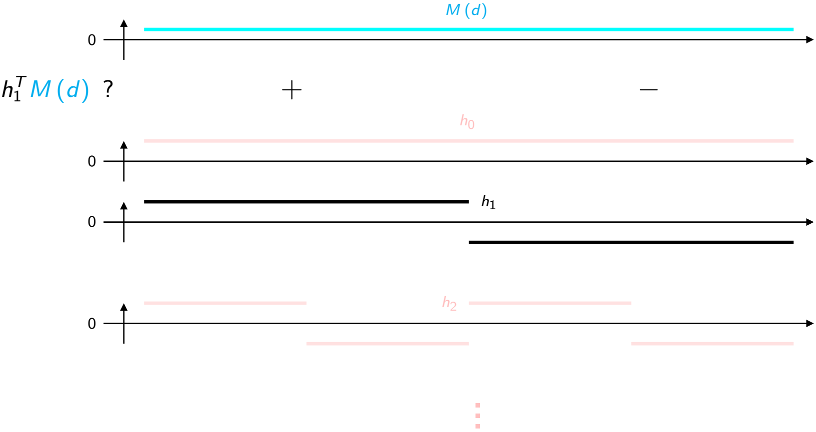
Method assessment on toy problems

Example 2 - simplified explanation of behaviour



Method assessment on toy problems

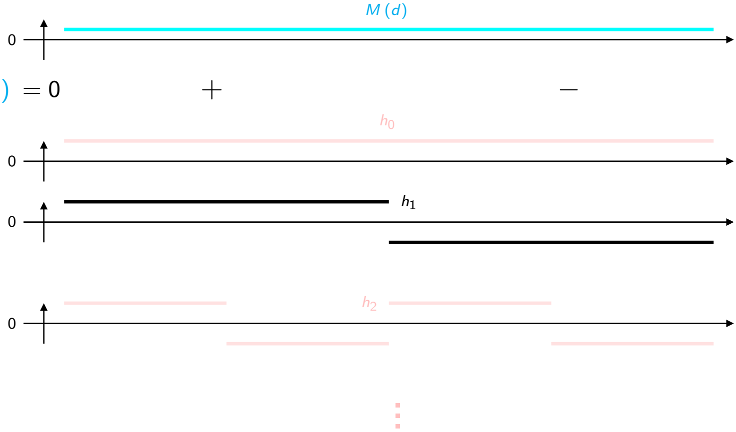
Example 2 - simplified explanation of behaviour



Method assessment on toy problems

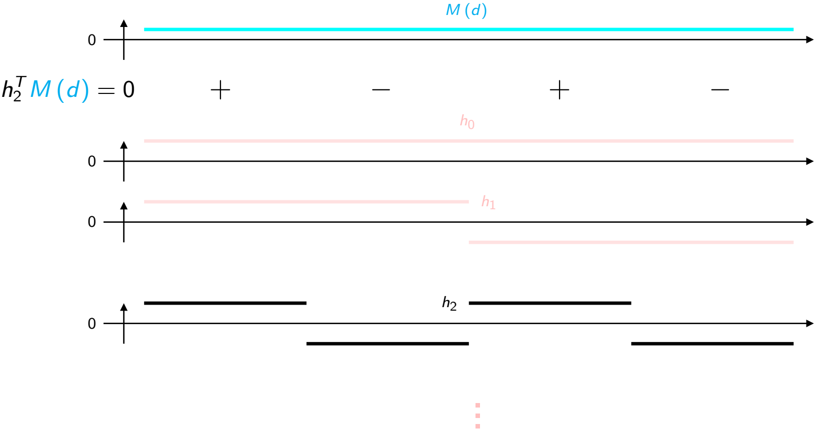
Example 2 - simplified explanation of behaviour

$$h_1^T M(d) = 0 \qquad + \qquad -$$



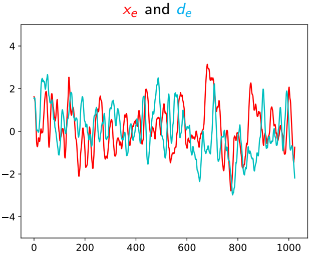
Method assessment on toy problems

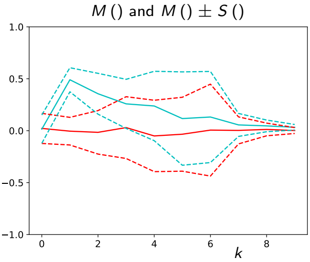
Example 2 - simplified explanation of behaviour

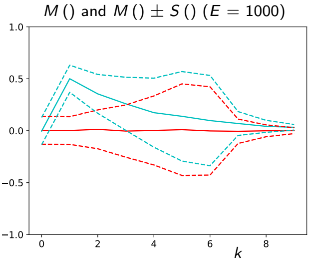


Method assessment on toy problems

Example 3

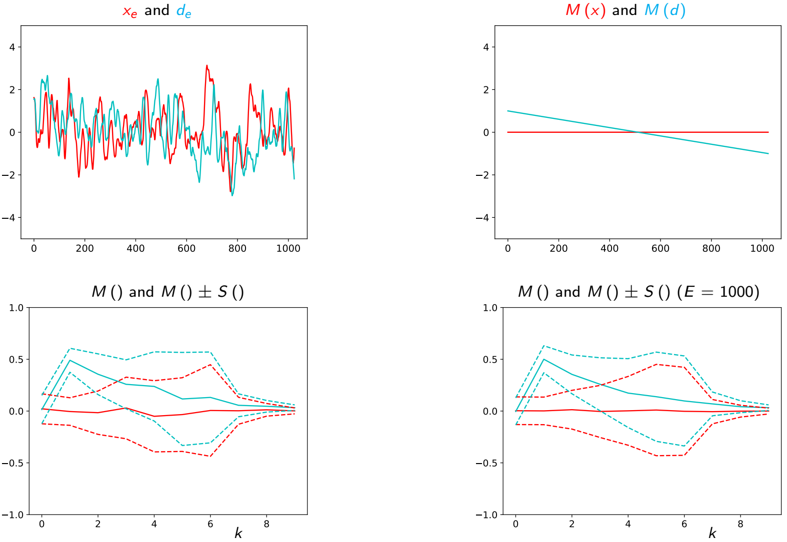






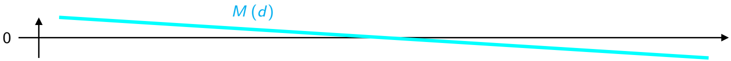
Method assessment on toy problems

Example 3 - decreasing data mean

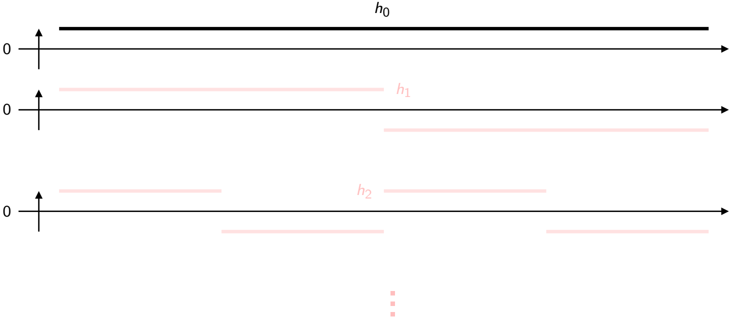


Method assessment on toy problems

Example 3 - simplified explanation of behaviour



$h_0^T M(d)$?



Method assessment on toy problems

Example 3 - simplified explanation of behaviour

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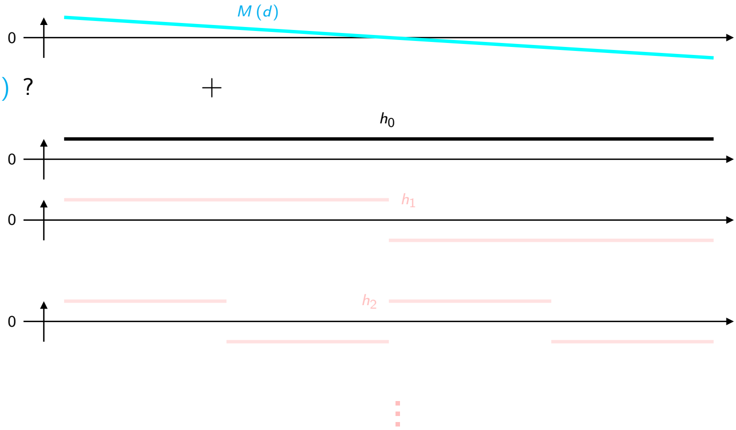

Method assessment on toy problems

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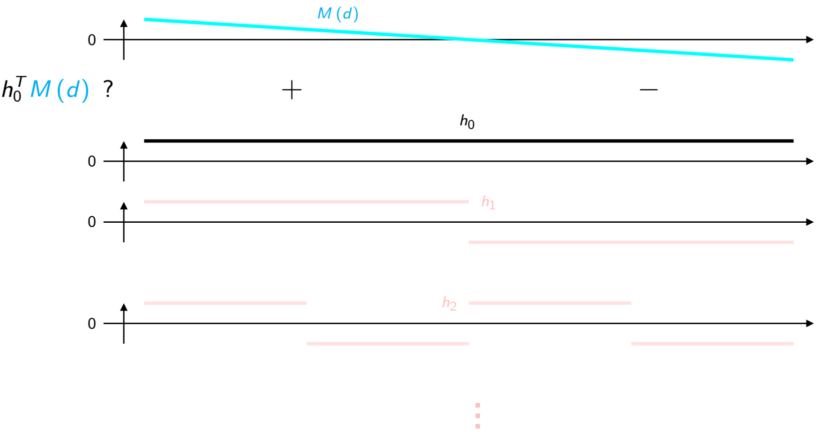

Method assessment on toy problems

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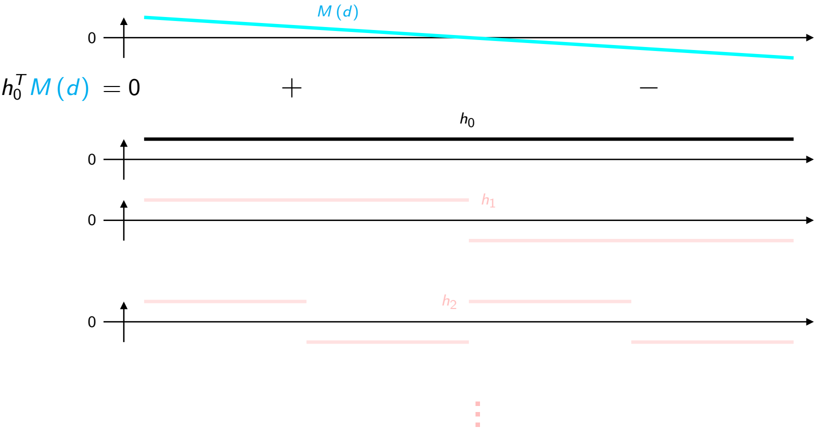
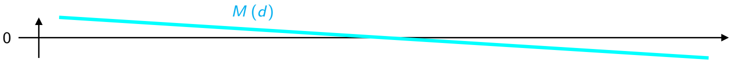
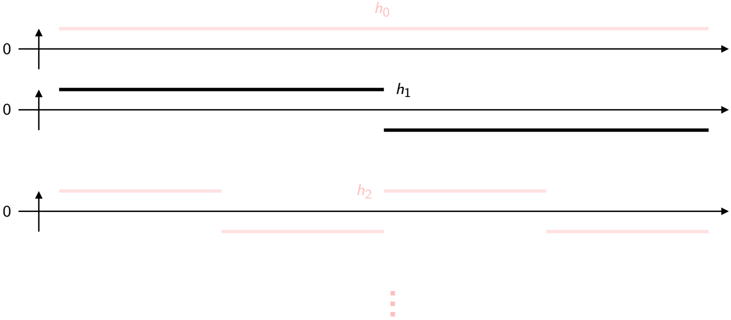


Method assessment on toy problems

Example 3 - simplified explanation of behaviour



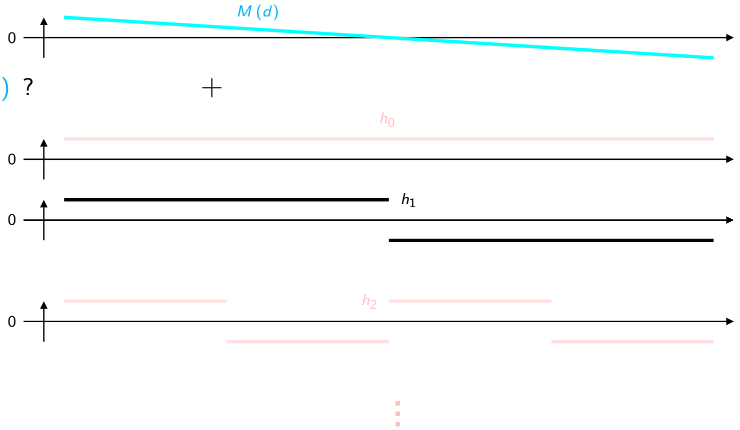
$h_1^T M(d)$?



Method assessment on toy problems

Example 3 - simplified explanation of behaviour

$h_1^T M(d)$?



Method assessment on toy problems

Example 3 - simplified explanation of behaviour

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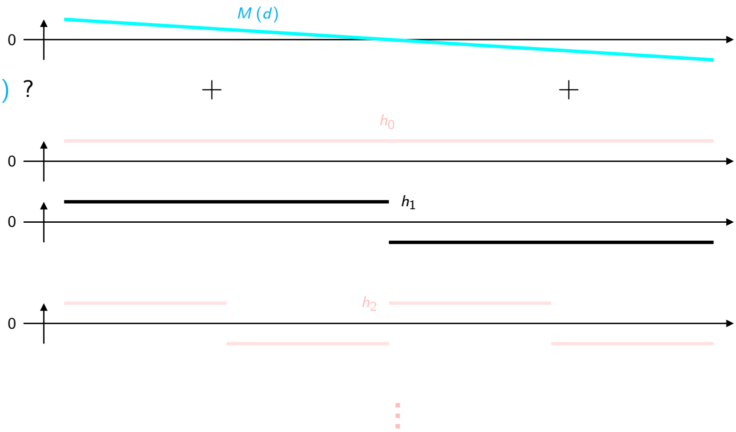
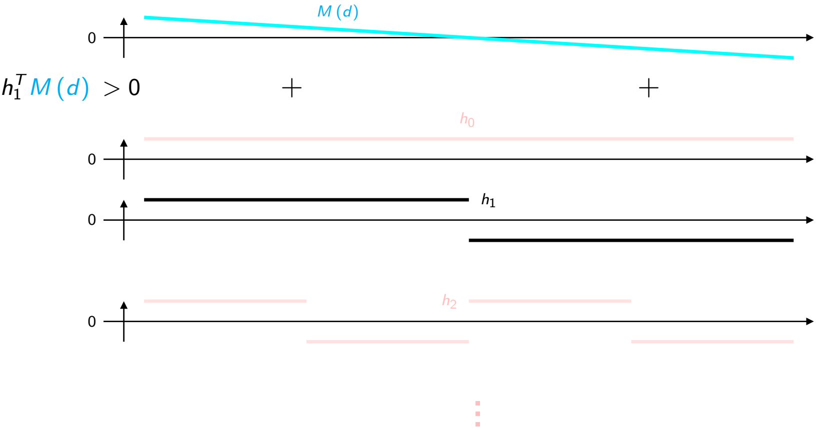


Method assessment on toy problems

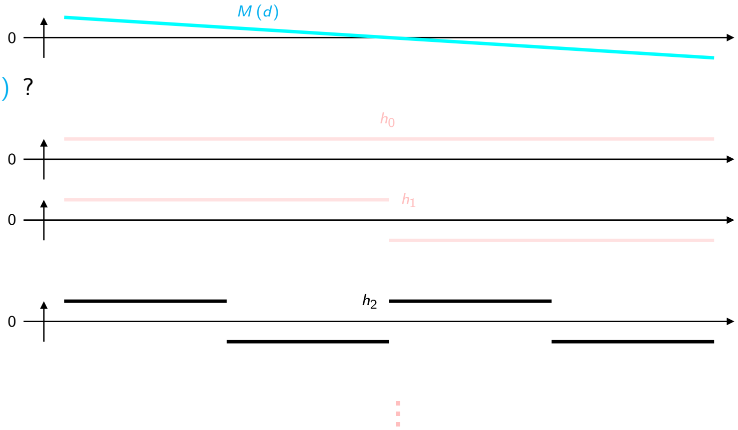
Example 3 - simplified explanation of behaviour



Method assessment on toy problems

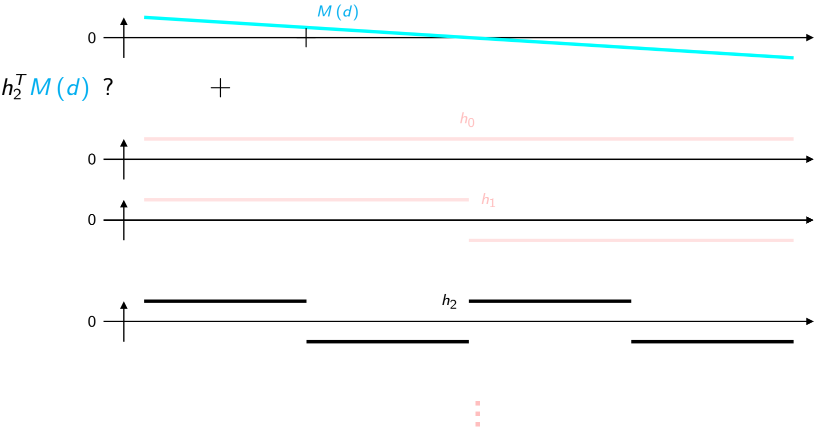
Example 3 - simplified explanation of behaviour

$h_2^T M(d)$?



Method assessment on toy problems

Example 3 - simplified explanation of behaviour



Method assessment on toy problems

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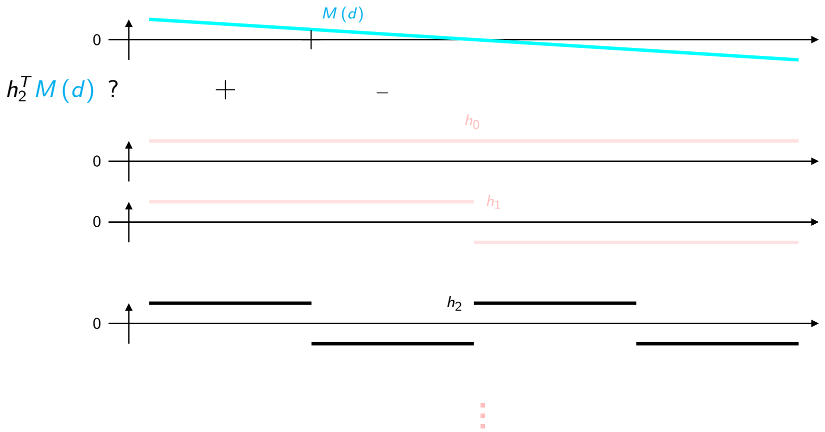
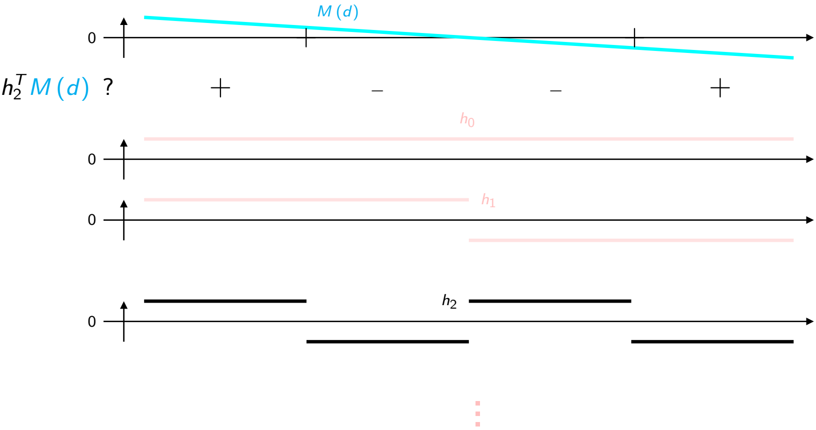


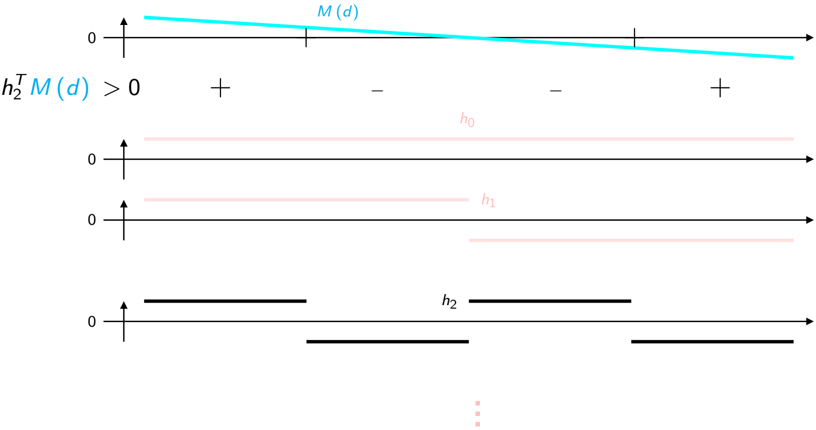
Method assessment on toy problems

Example 3 - simplified explanation of behaviour



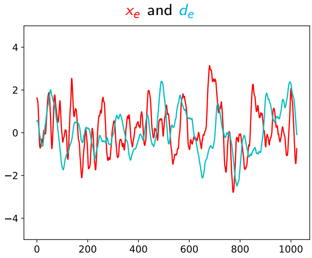
Method assessment on toy problems

Example 3 - simplified explanation of behaviour



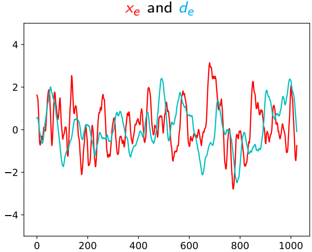
Method assessment on toy problems

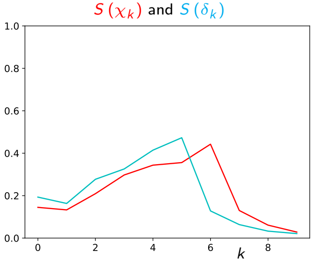
Example 4 - correlation lengths 25 (x) and 50 (d)



Method assessment on toy problems

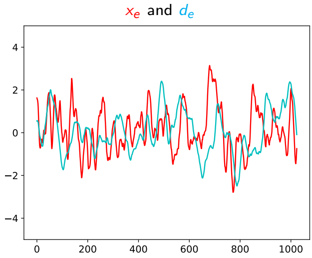
Example 4 - correlation lengths 25 (x) and 50 (d)

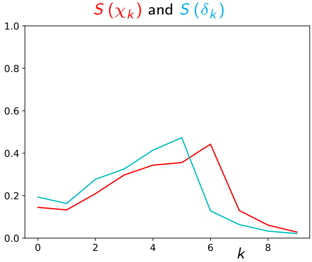


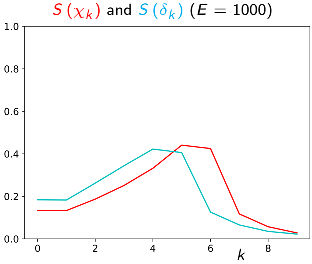


Method assessment on toy problems

Example 4 - correlation lengths 25 (x) and 50 (d)







Method assessment on toy problems

Example 4 - simplified explanation of behaviour

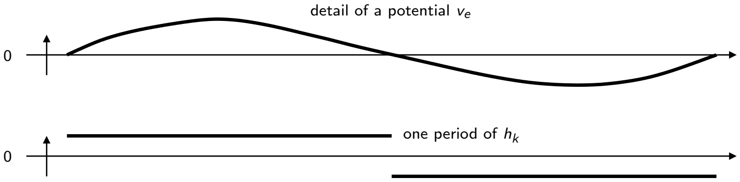
Let v denote either x or d

Method assessment on toy problems

Example 4 - simplified explanation of behaviour

Let v denote either x or d

$h_k^T v_e$?

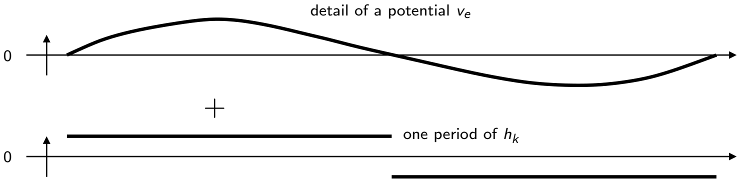


Method assessment on toy problems

Example 4 - simplified explanation of behaviour

Let v denote either x or d

$h_k^T v_e$?

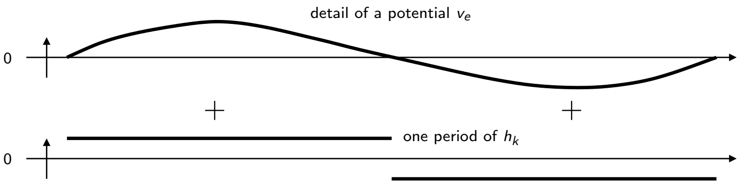


Method assessment on toy problems

Example 4 - simplified explanation of behaviour

Let v denote either x or d

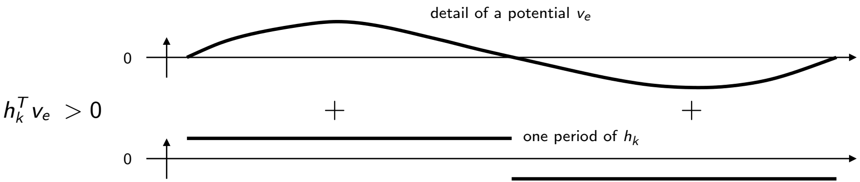
$h_k^T v_e$?



Method assessment on toy problems

Example 4 - simplified explanation of behaviour

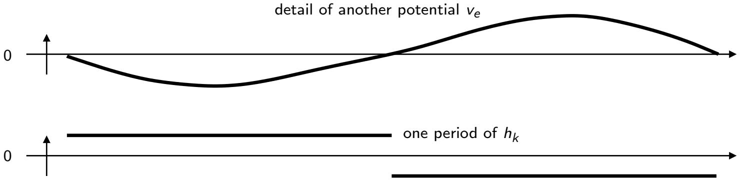
Let v denote either x or d



Method assessment on toy problems

Example 4 - simplified explanation of behaviour

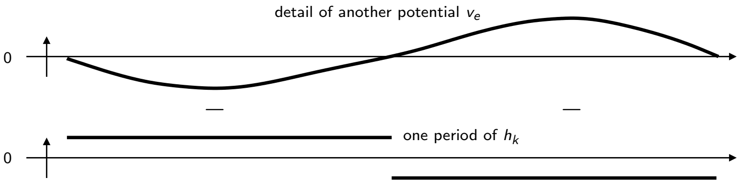
$h_k^T v_e$?



Method assessment on toy problems

Example 4 - simplified explanation of behaviour

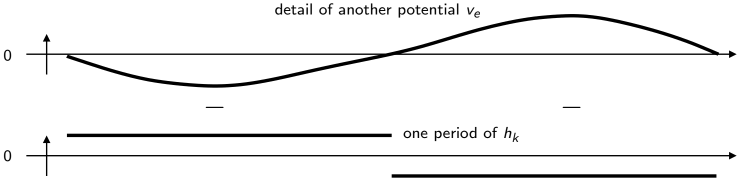
$h_k^T v_e < 0$



Method assessment on toy problems

Example 4 - simplified explanation of behaviour

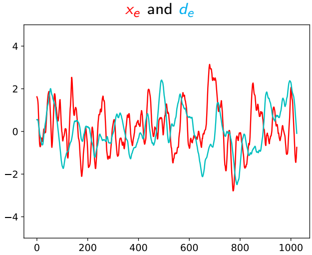
$h_k^T v_e < 0$

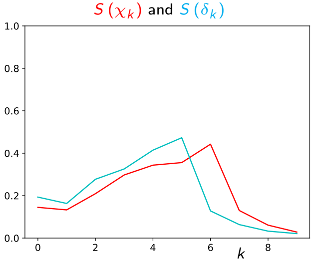


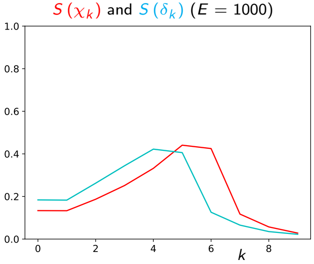
Large standard deviation of $h_k^T v_e$ when characteristic lengths of v_e and h_k are similar

Method assessment on toy problems

Example 4 - correlation lengths 25 (x) and 50 (d)

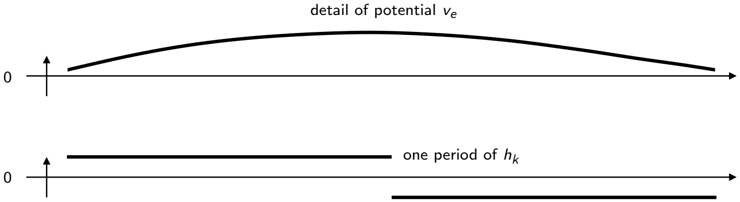






Method assessment on toy problems

Example 4 - simplified explanation of behaviour

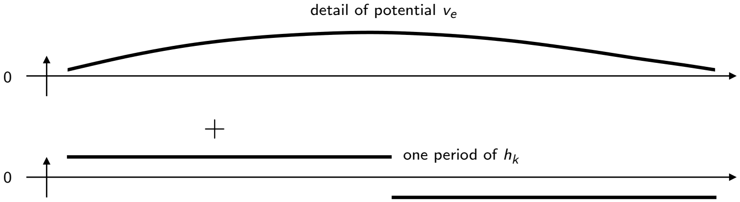


$h_k^T v_e$?

Method assessment on toy problems

Example 4 - simplified explanation of behaviour

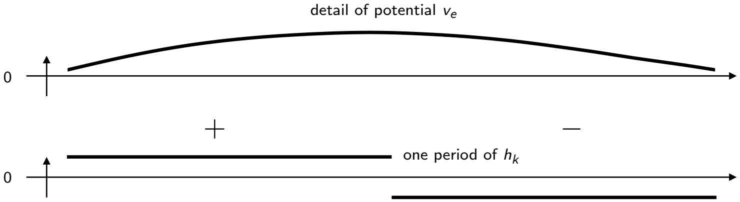
$h_k^T v_e$?



Method assessment on toy problems

Example 4 - simplified explanation of behaviour

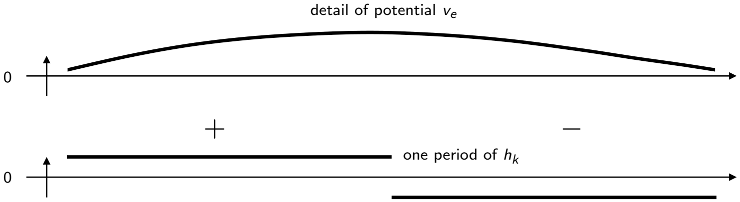
$h_k^T v_e$?



Method assessment on toy problems

Example 4 - simplified explanation of behaviour

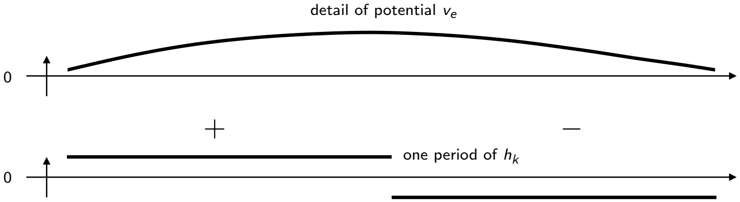
$h_k^T v_e \approx 0$



Method assessment on toy problems

Example 4 - simplified explanation of behaviour

$h_k^T v_e \approx 0$

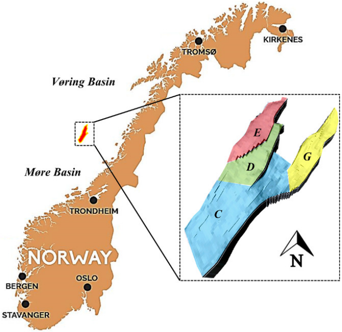


Small standard deviation when characteristic length of v_e is larger than that of h_k

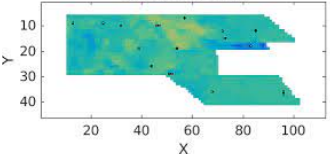
Application to real data

Application to real data

The Norne field

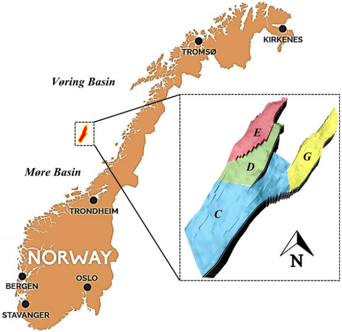


Simulation model geometry

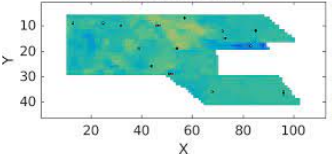


Application to real data

The Norne field



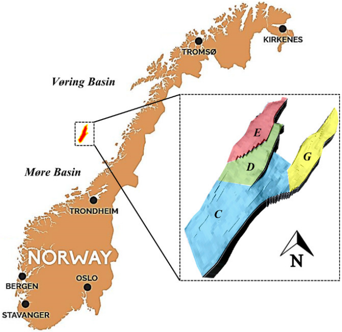
Simulation model geometry

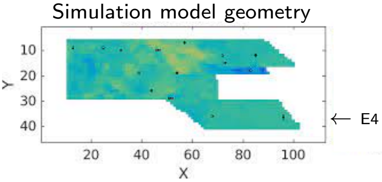


Data from G segment

Application to real data

The Norne field



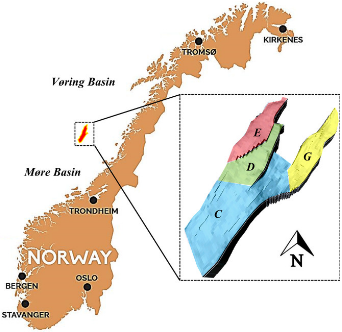


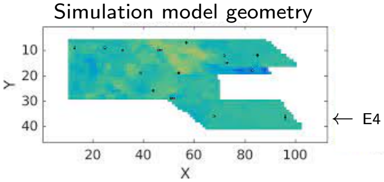
Data from G segment

- Production data from well E4 (wells: black dots on right figure)

Application to real data

The Norne field



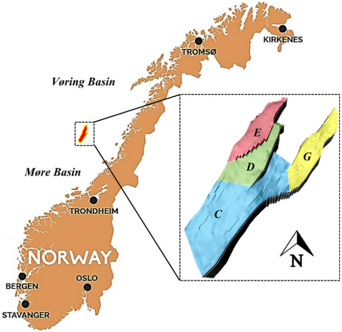


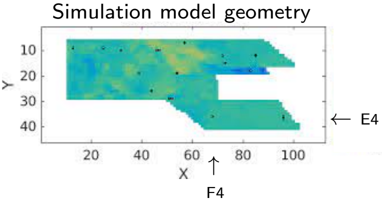
Data from G segment

- Production data from well E4 (wells: black dots on right figure)
- Time-lapse (4-D) impedance data from most of the segment

Application to real data

The Norne field





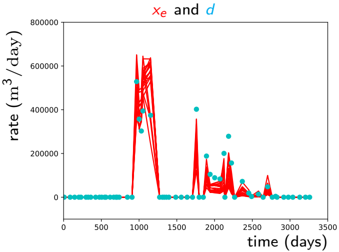
Data from G segment

- Production data from well E4 (wells: black dots on right figure)
- Time-lapse (4-D) impedance data from most of the segment
- RFT data from wells E4 and F4

Application to real data

Production data - results for well E4

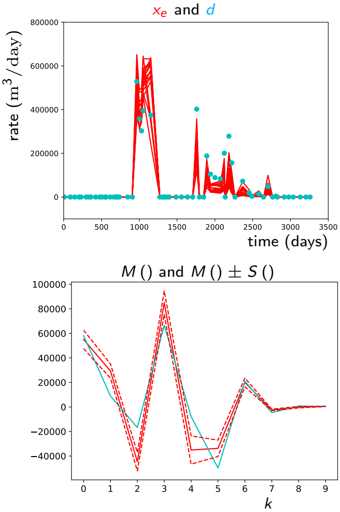
Gas



Application to real data

Production data - results for well E4

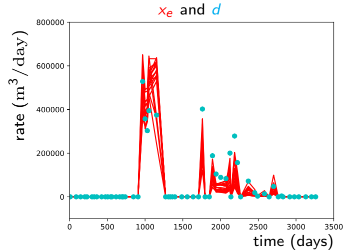
Gas

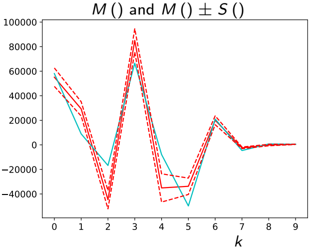


Application to real data

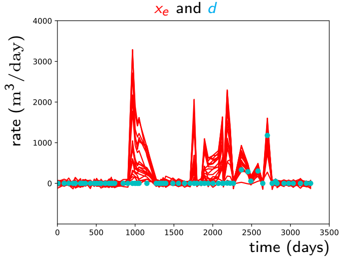
Production data - results for well E4

Gas





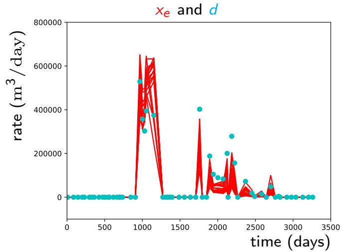
Water

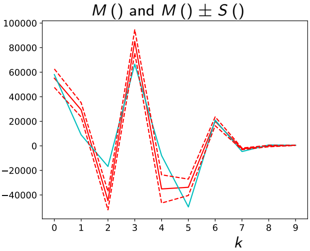


Application to real data

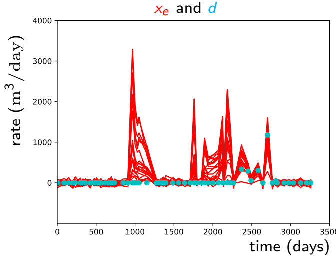
Production data - results for well E4

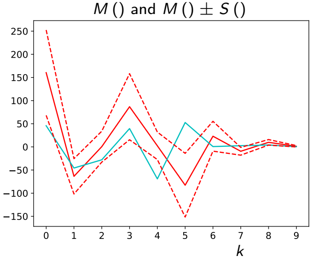
Gas





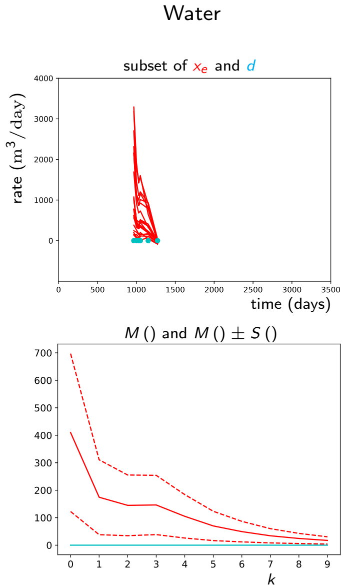
Water

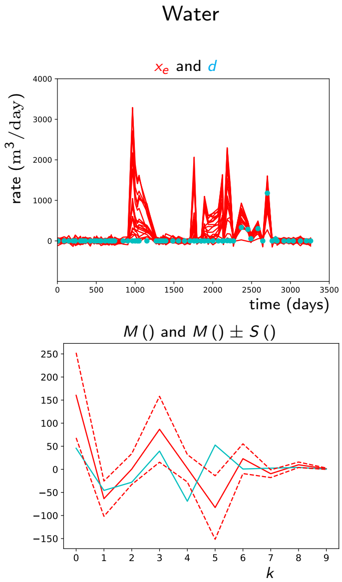




Application to real data

Production data - results for well E4





Application to real data

Time-lapse impedance data

Time-lapse data are obtained by subtracting data acquired from two surveys over the same study region at different times. The aim is to infer fluid movements and/or pressure changes in the subsurface over this time span, and also to infer flow-related rock properties, such as permeability (fluid conductivity)

Application to real data

Time-lapse impedance data

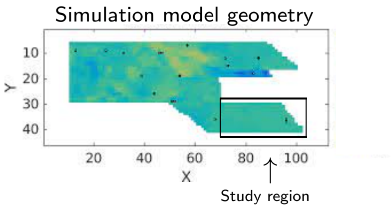
Time-lapse data are obtained by subtracting data acquired from two surveys over the same study region at different times. The aim is to infer fluid movements and/or pressure changes in the subsurface over this time span, and also to infer flow-related rock properties, such as permeability (fluid conductivity)

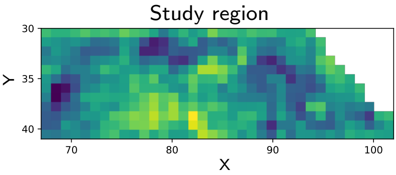
Impedance (density $\times$ velocity) data for a subsurface region are obtained by inverting seismic data observed in the sea water or at the sea floor. Hence, they are not really data, but it is common to split the assimilation of time-lapse seismic data into flow-related rock properties this way

Application to real data

Time-lapse impedance data - study region

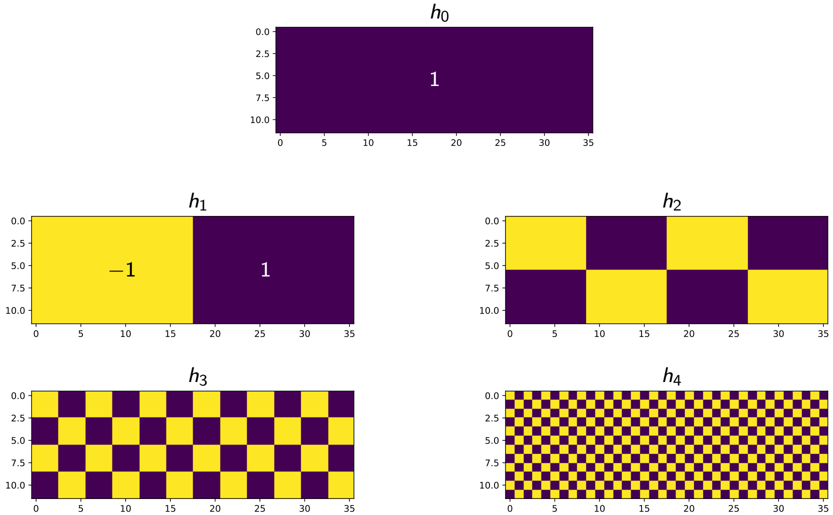
The major part of the Norne G segment constitutes the study region





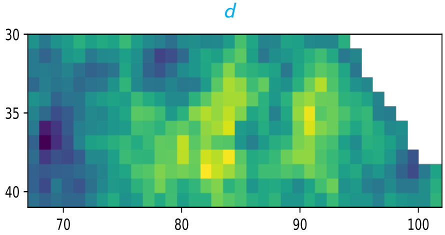
Application to real data

Time-lapse impedance data - multiscale vectors



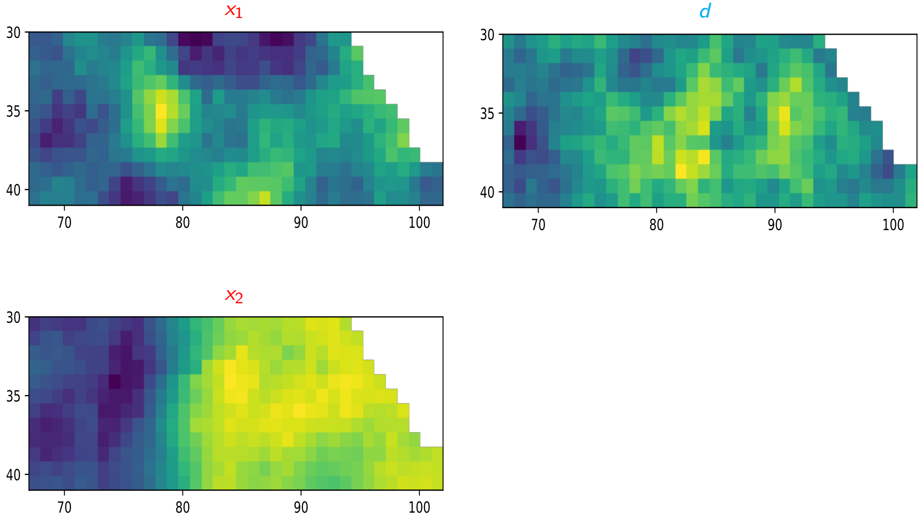
Application to real data

Time-lapse impedance data - time span 2001-2003



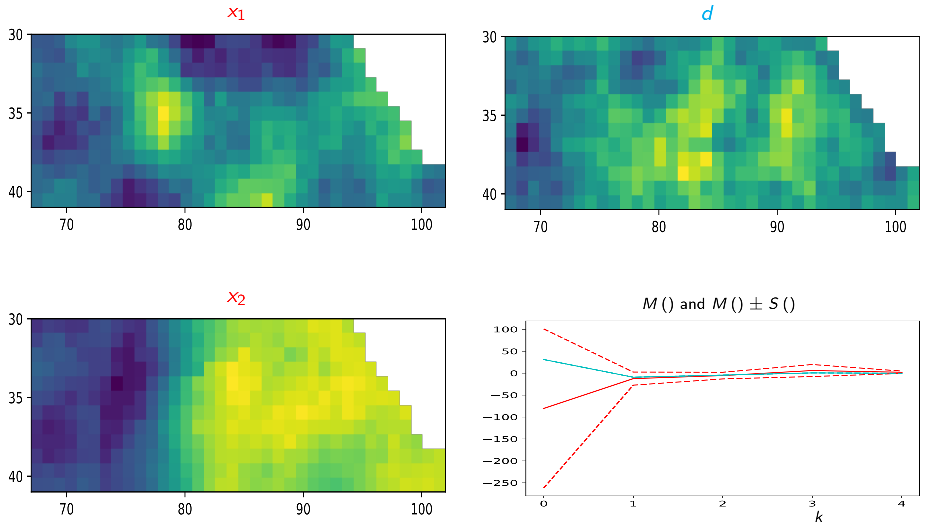
Application to real data

Time-lapse impedance data - time span 2001-2003



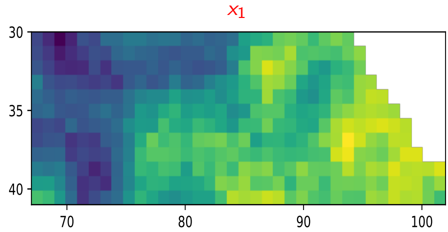
Application to real data

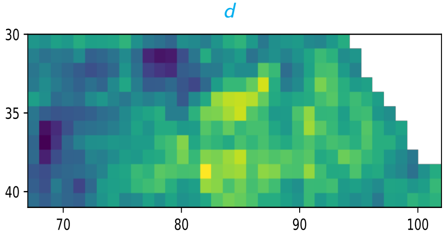
Time-lapse impedance data - time span 2001-2003 - results

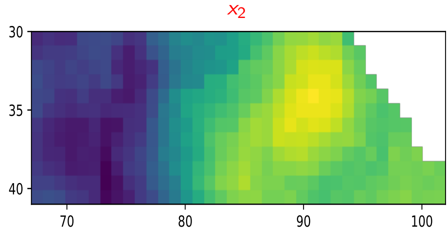


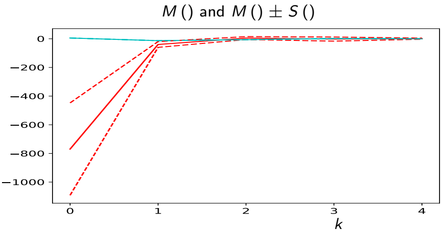
Application to real data

Time-lapse impedance data - time span 2001-2004 - results



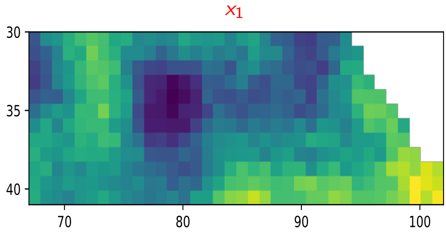


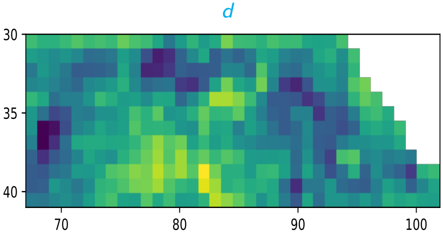


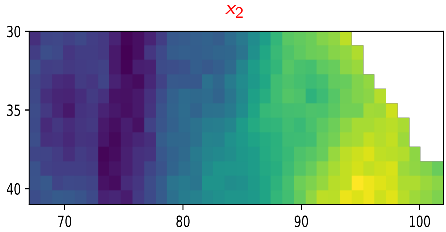


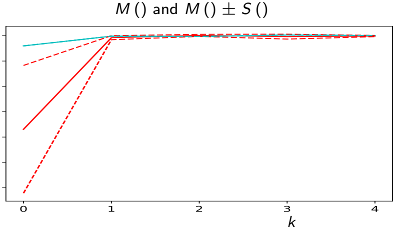
Application to real data

Time-lapse impedance data - time span 2001-2006 - results





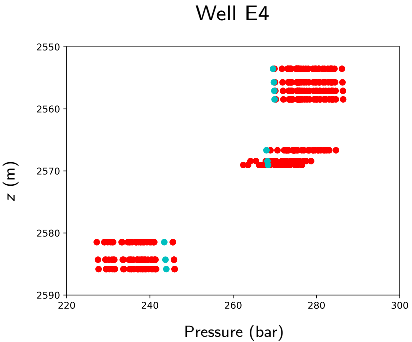




Application to real data

RFT data

RFT (Repeat Formation Tester) data consist of pressure values along the wellbore



Application to real data
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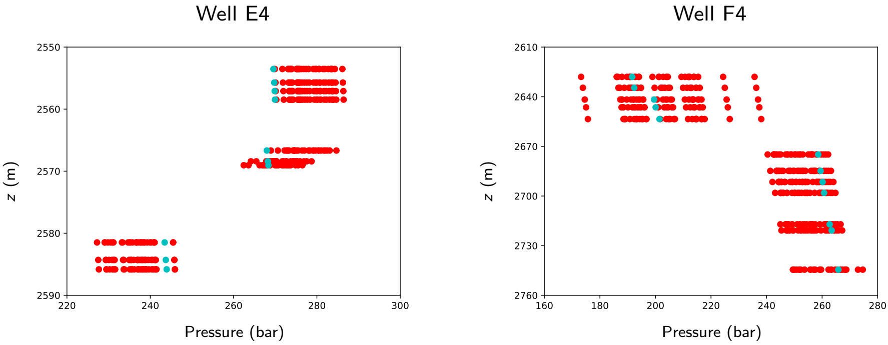
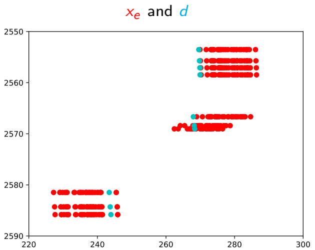
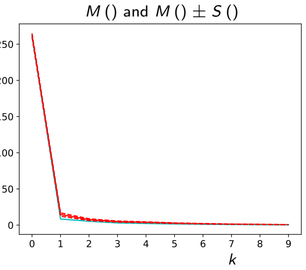


Application to real data

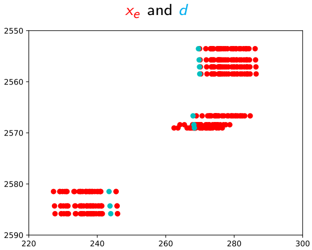
RFT data - results for well E4

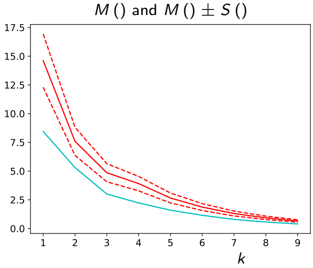




Application to real data

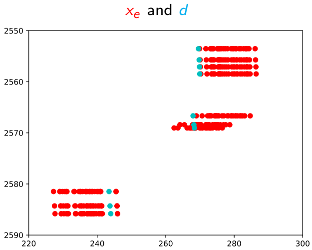
RFT data - results for well E4

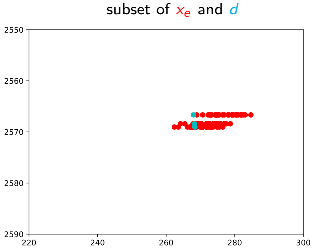


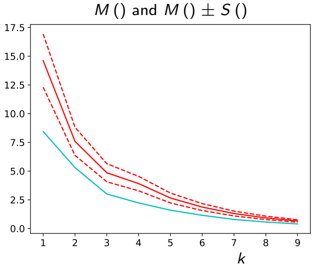


Application to real data

RFT data - results for well E4

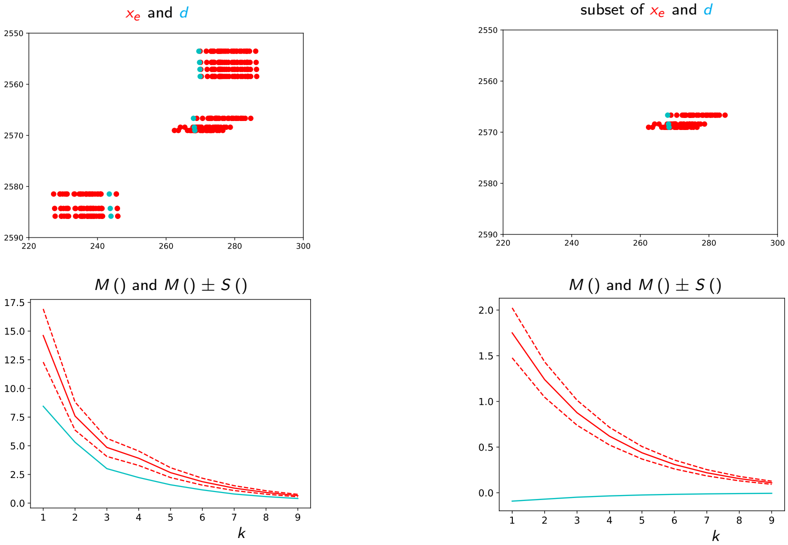






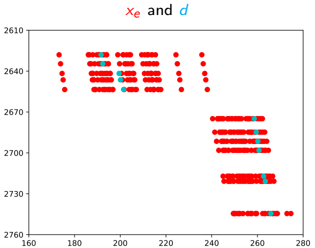
Application to real data

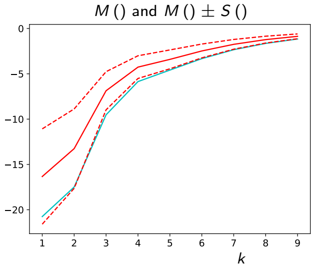
RFT data - results for well E4



Application to real data

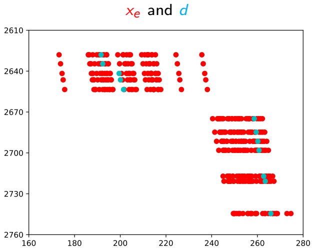
RFT data - results for well F4

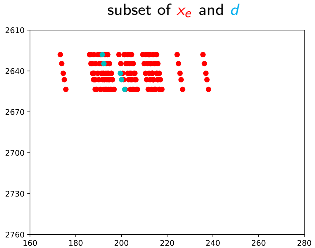


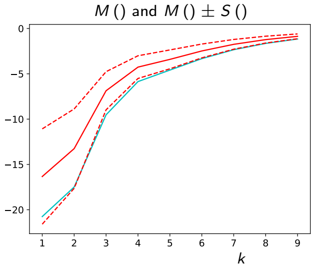


Application to real data

RFT data - results for well F4







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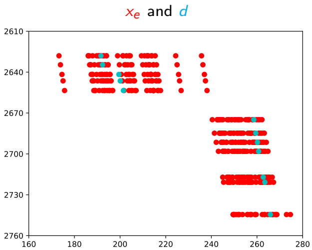

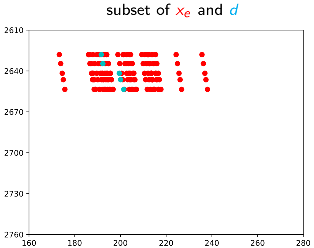

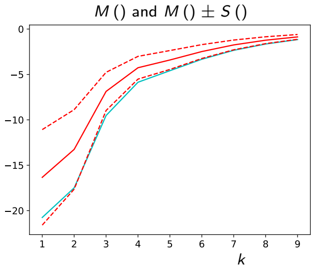

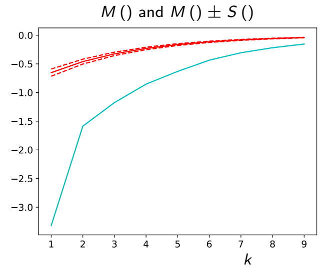

Summary

Multiscale model diagnostic (MMD) discriminates well between realizations from different distributions

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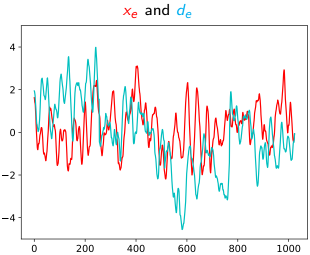
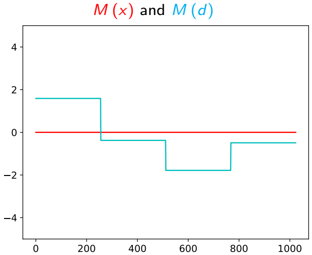
MMD is straightforward and computationally inexpensive

In simplistic situations, MMD gives guidance regarding what changes that are desireable for the prior predictive distribution

Method assessment on toy problems

Example 5 - blockwise varying data mean





Method assessment on toy problems

Example 5 - blockwise varying data mean