

Efficient big data assimilation through sparse representation: A case study in 4D seismic history matching

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The **National**
IOR Centre
of Norway



Outline

- Background
- Proposed framework
- Numerical examples
- Conclusion and future works

Background

What is history matching about ?



Who did this?



Effect – observed data



Cause – Petro-physical parameters (PERM, PORO)

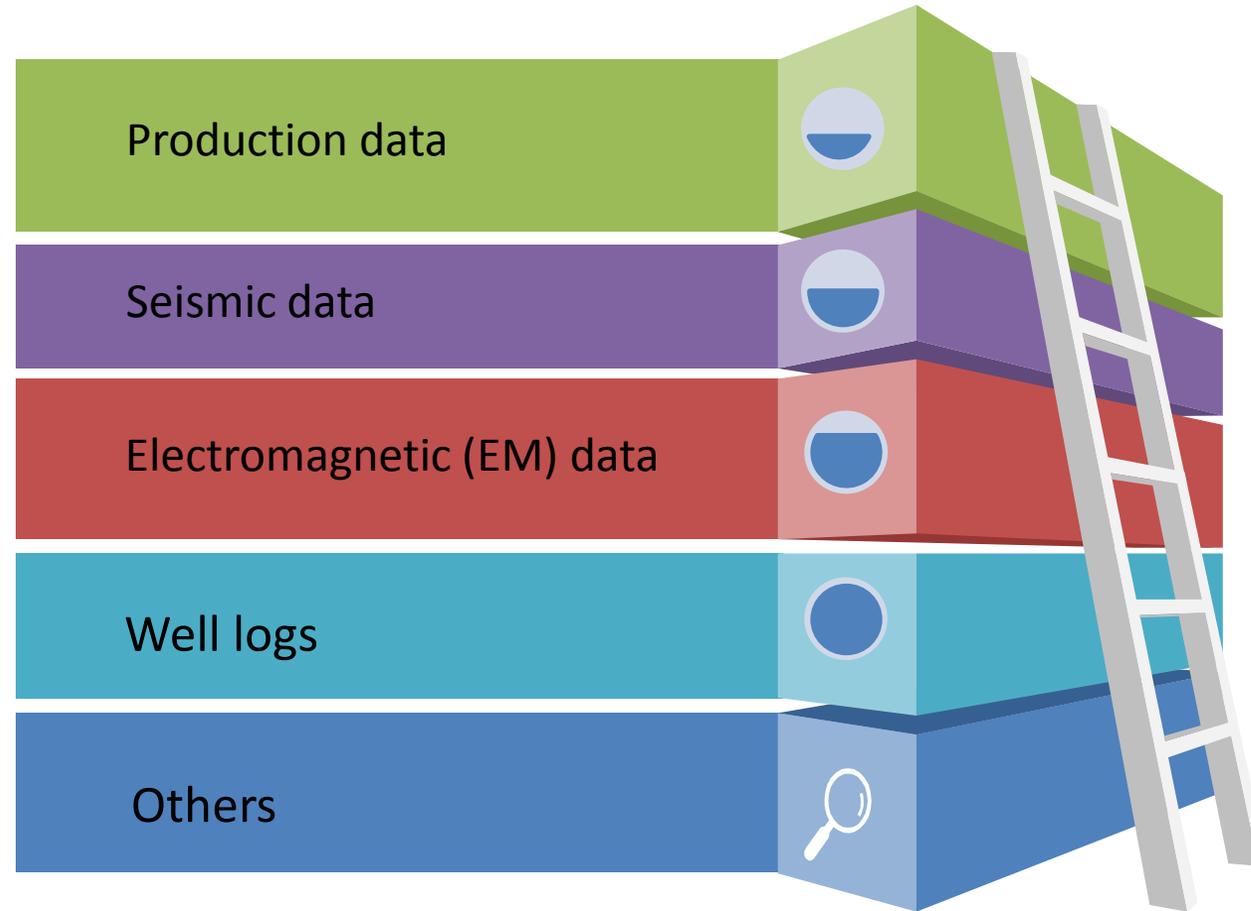


Detectives – history matching algorithms

History matching aims to find proper values of petro-physical parameters to explain observed data

Background

Data in history matching

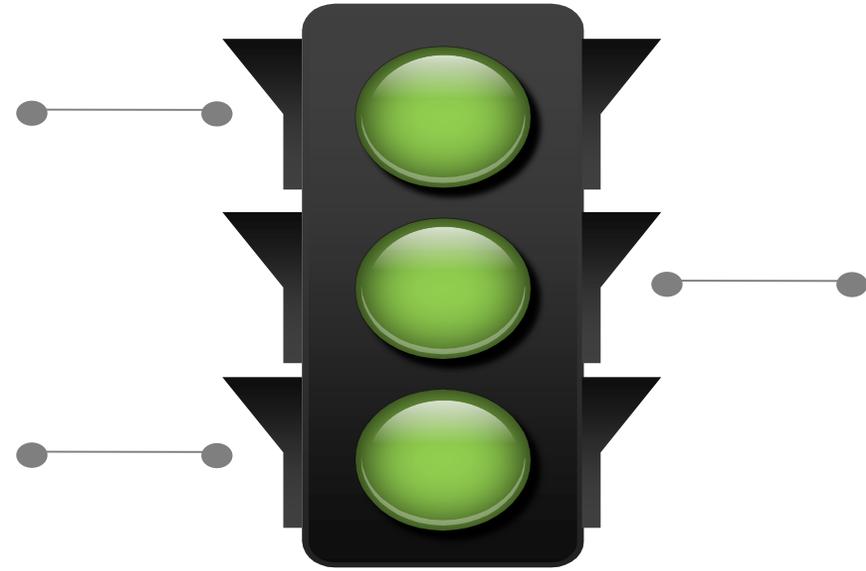


Background

Seismic data

- Amplitude versus angle (AVA);
- or raw seismic data

- Saturation and pressure maps



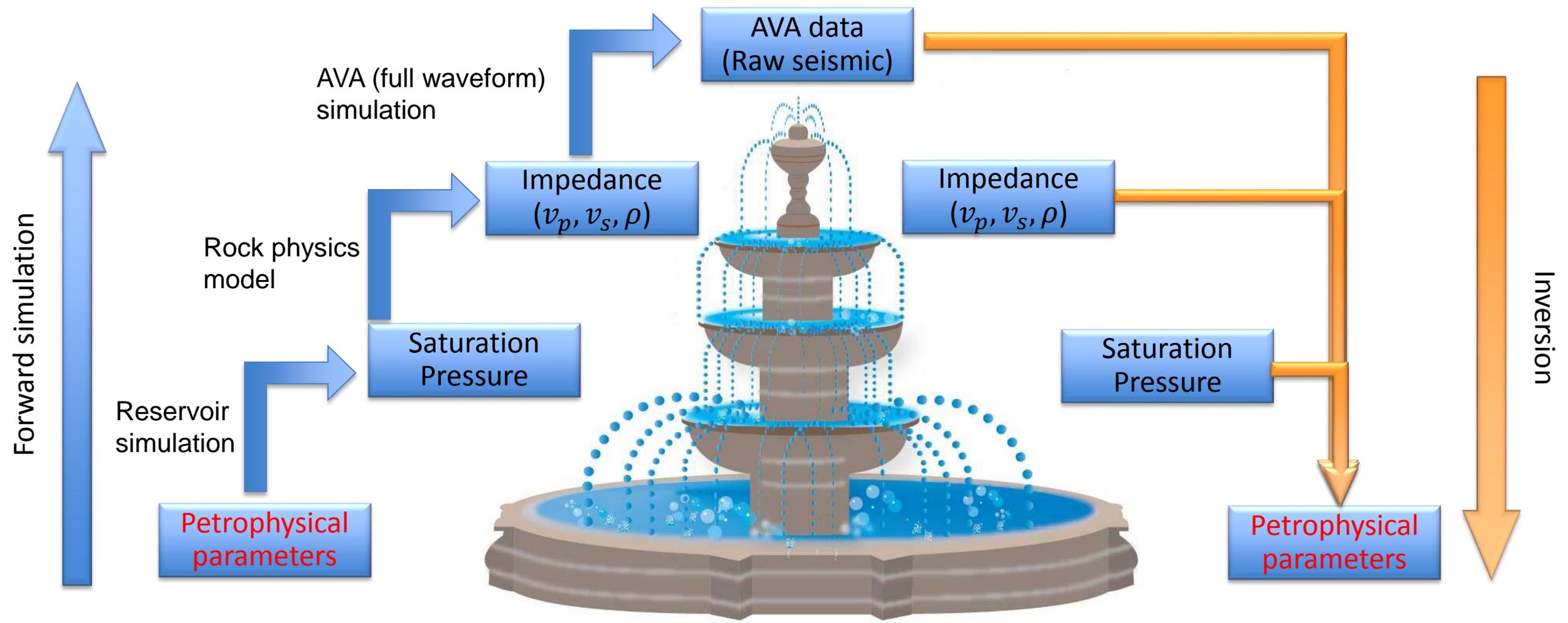
- Impedances (I_p, I_s);
- or velocities (v_p, v_s) and density

Seismic data at different "levels"

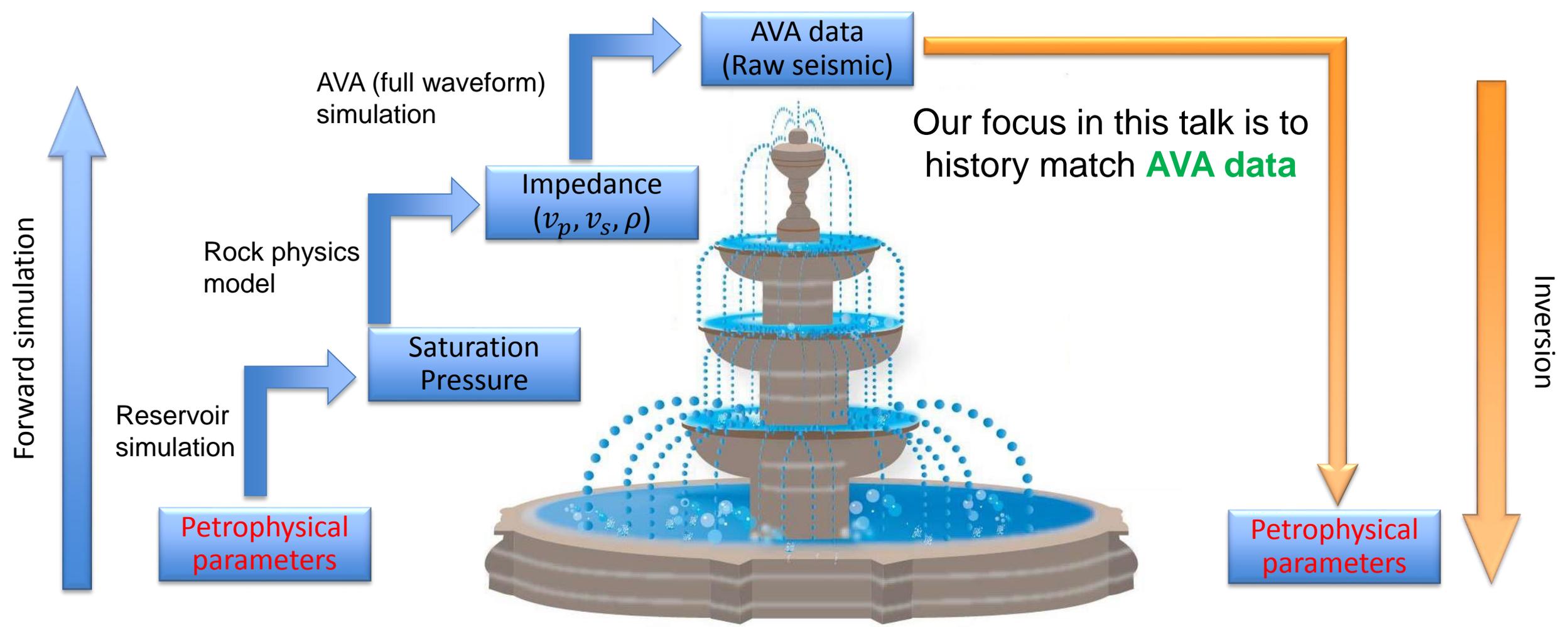
Background



Relation between reservoir petro-physical parameters and seismic data at different levels



Background



Background

Challenge in history-matching seismic data

HOW'S THE
BIG DATA PROJECT
COMING ALONG,
HOSKINS?



Conventional history
matching

- Small to moderate data
- Data size $<$ model size
- Moderate demand of computing power and memory

Seismic history
matching

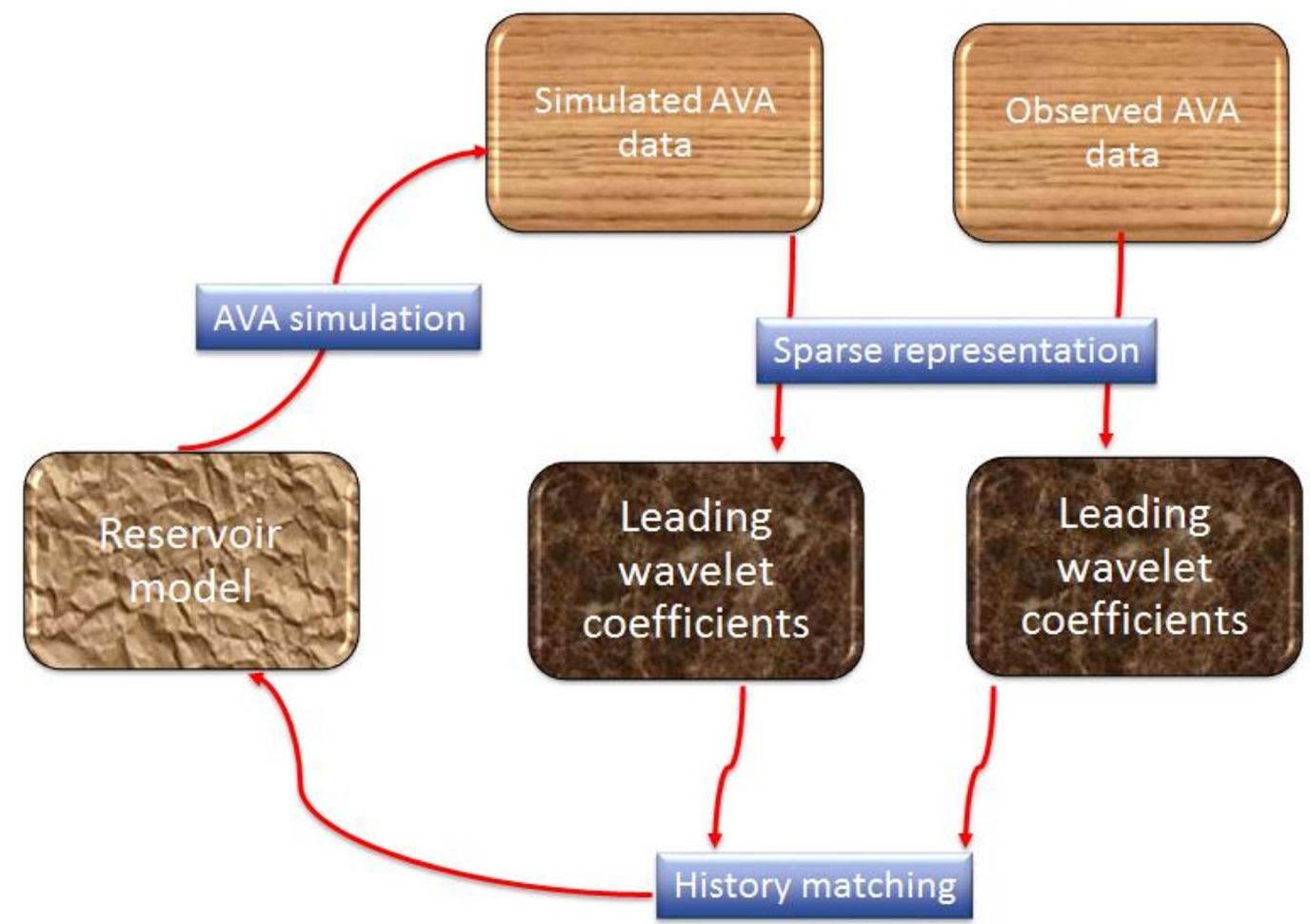
- Big data
- Data size \geq model size
- High demand of computing power and memory, if without an efficient method
- Extra computational issues

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Proposed framework

Workflow



Proposed framework

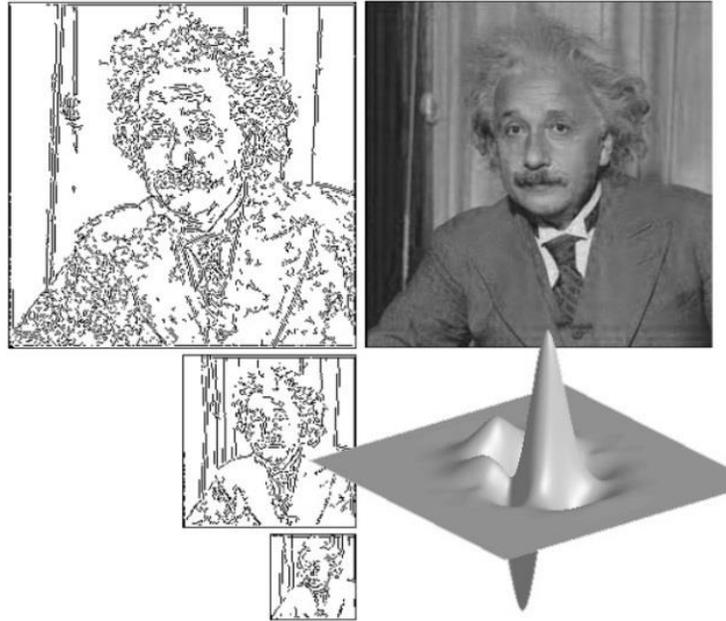
Motivation



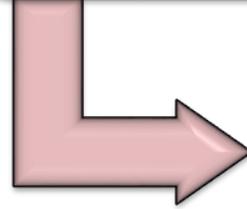
Use wavelet-based sparse representation to address the big data problem in seismic history matching.

Proposed framework

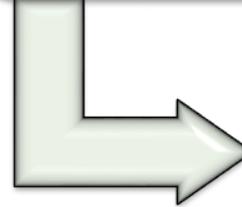
Wavelet-based sparse representation



- Discrete wavelet transform (DWT)



- Estimate noise of wavelet coefficients
- Apply thresholding to remove small wavelet coefficients



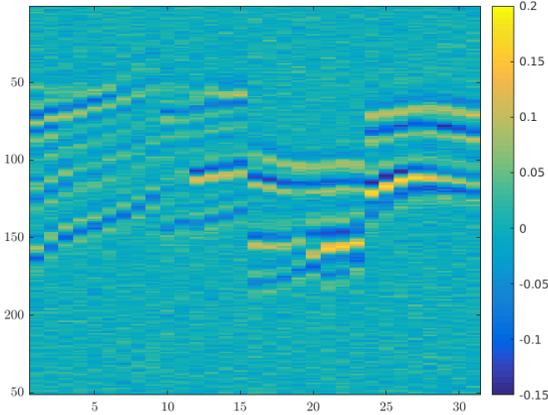
- Reduced data size
- Estimation of observation error covariance
- Applicability to various types of seismic data (AVA, impedance etc.)

Starck, Jean-Luc, Fionn Murtagh, and Jalal Fadili. Sparse Image and Signal Processing: Wavelets and Related Geometric Multiscale Analysis. Cambridge University Press, 2015

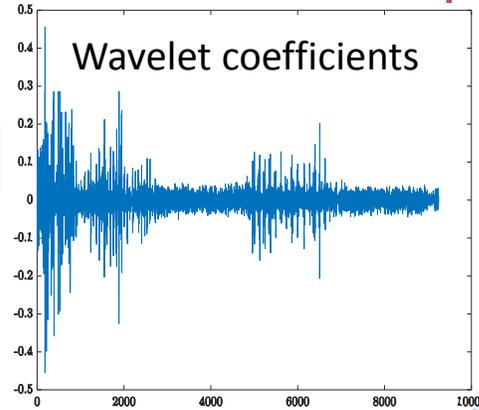
Proposed framework

Illustration: 2D data

Noisy AVA data (noise lv = 30%)



Wavelet transform

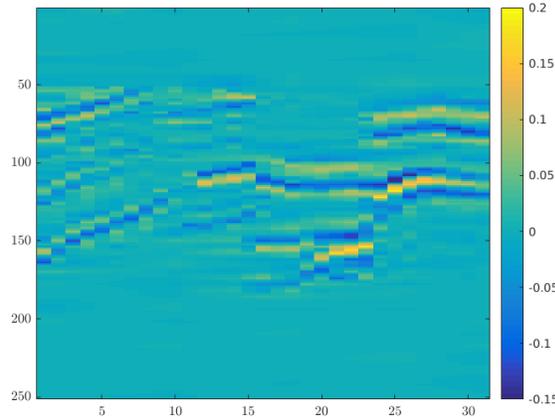
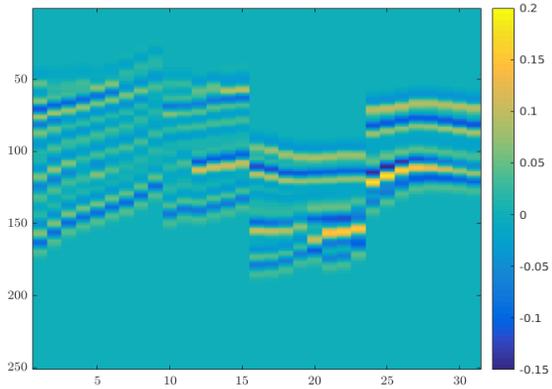


- Leading coefficients used in history matching
- Number of leading coefficients is about **6%** of the original

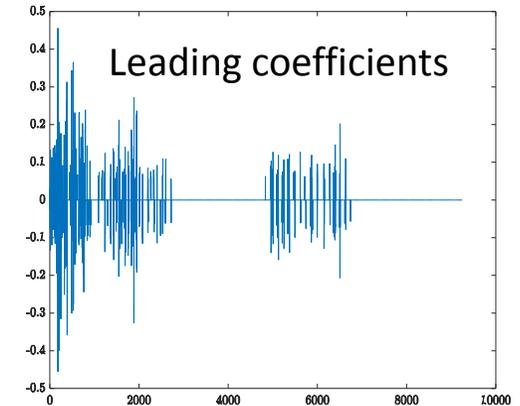
Thresholding

true noise STD = **0.0148**;
noise STD = **0.0141**

Reference AVA data



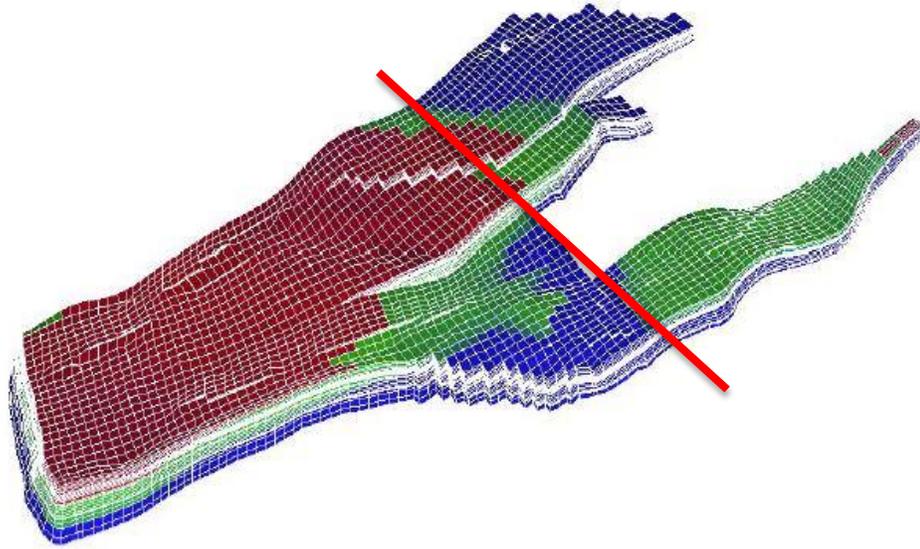
Inverse transform



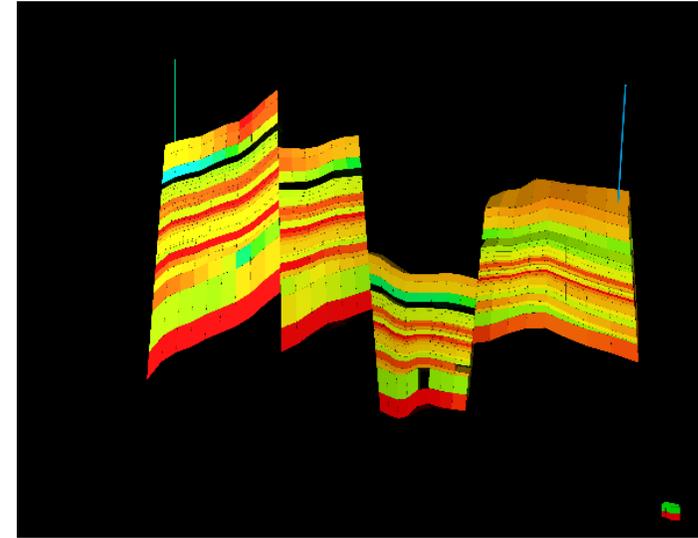
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Numerical example I: A 2D Norne field model



3D Norne field model



PERMX file of the 2D model

(The 2D model is kindly provided by **Dr. Mohsen Dadashpour**)

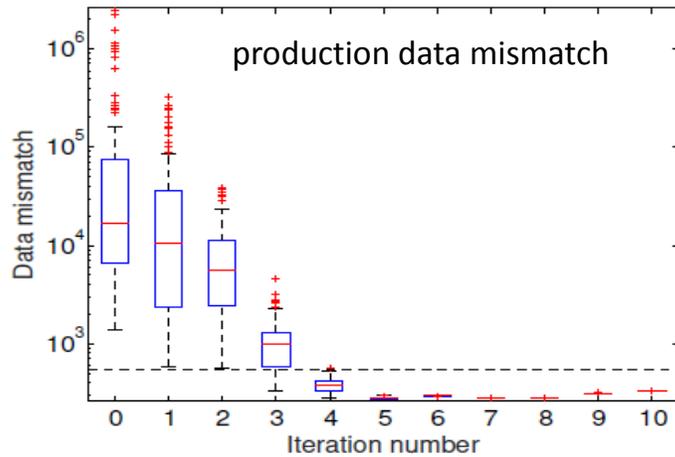
Experimental settings

Model size	39x1x26, with 739 out of 1014 being active gridcells
Parameters to estimate	PORO, PERMX. Total number is $2 \times 739 = 1478$
Production data (~10 yrs)	BHP, GOR, OPT, WCT. Total number is 135
4D seismic data (1 Base + 2 monitor surveys)	AVA intercept and gradient. Total number is 46686
Leading wavelet coefficients	Total number is 2746
History matching algorithm	Iterative ensemble smoother*

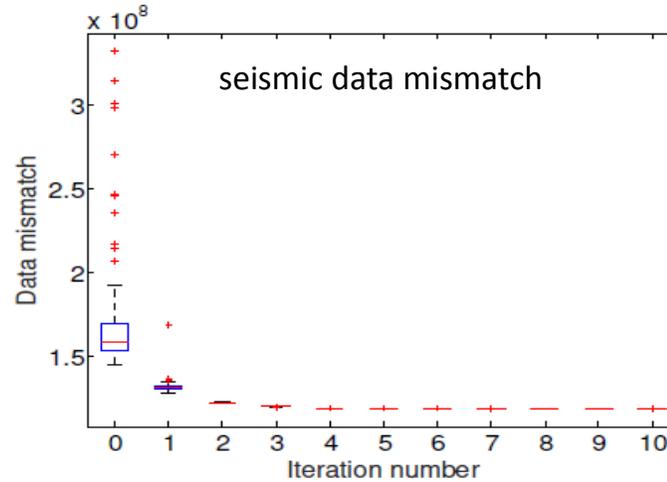
*Luo, X., et al. (2015). "Iterative ensemble smoother as an approximate solution to a regularized minimum-average-cost problem: theory and applications." SPE Journal, 20, 962 - 982, paper SPE-176023-PA.

Numerical example I: A 2D Norne field model

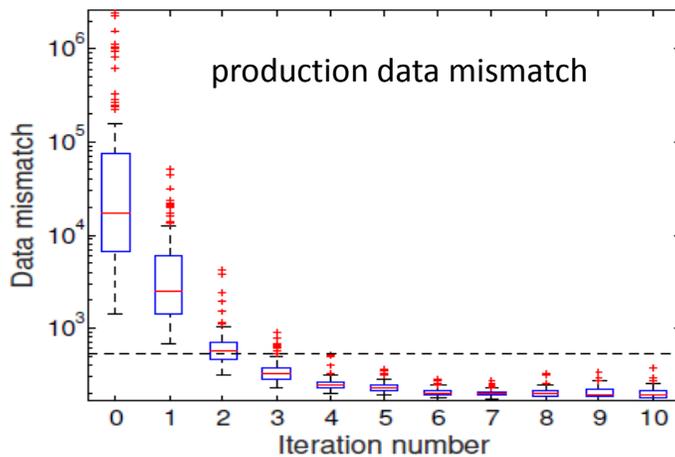
Results when both production and seismic data are used (more results in [SPE-180025-MS*](#))



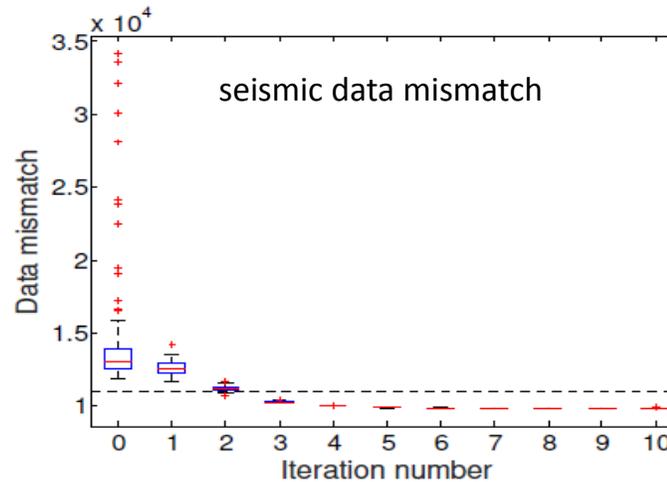
(a) Production data, full-data experiment



(b) Seismic data, full-data experiment



(c) Production data, sparse-data experiment



(d) Seismic data, sparse-data experiment

Production and seismic data mismatch

Results of history-matching original seismic data **without wavelet-base sparse representation**

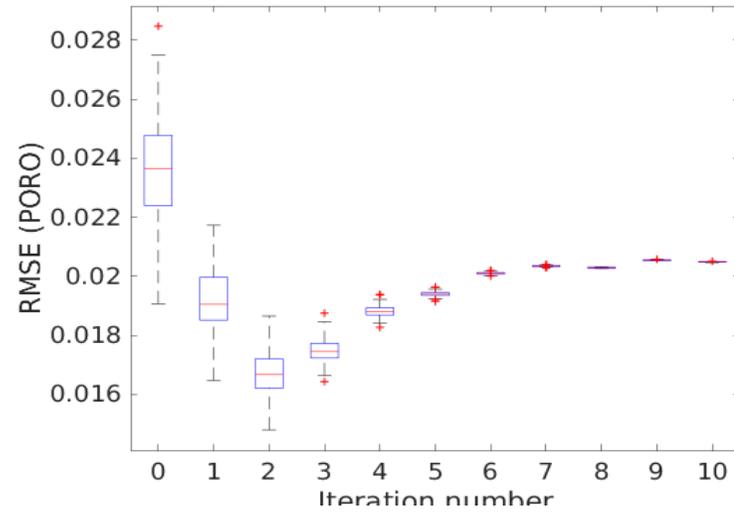
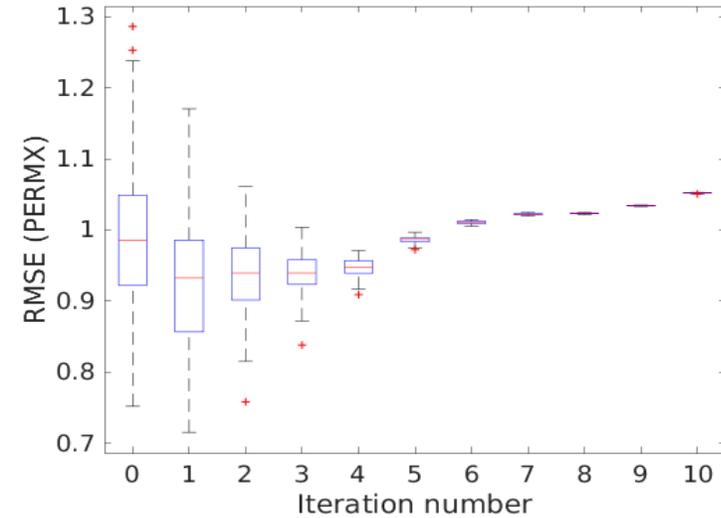
Production and seismic data mismatch

Results of history-matching leading wavelet coefficients

*Luo, X., et al. (2016). An Ensemble 4D Seismic History Matching Framework with Sparse Representation Based on Wavelet Multiresolution Analysis. SPE Bergen One Day Seminar, Bergen, Norway, 20 April, 2016. Paper SPE-180025-MS.

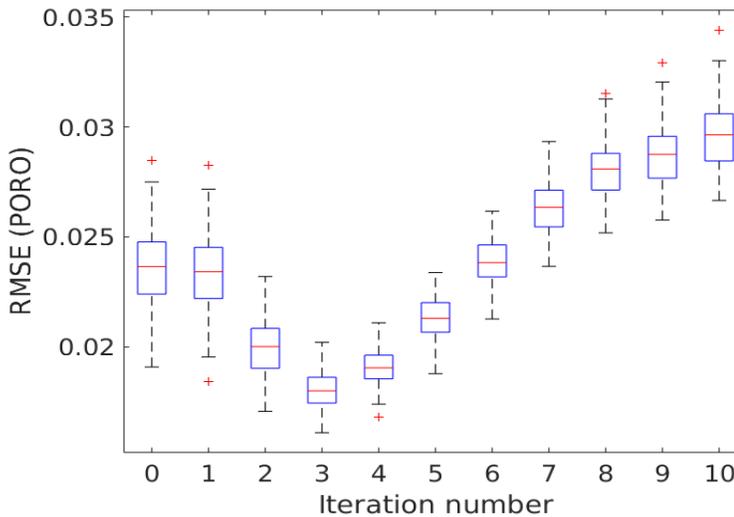
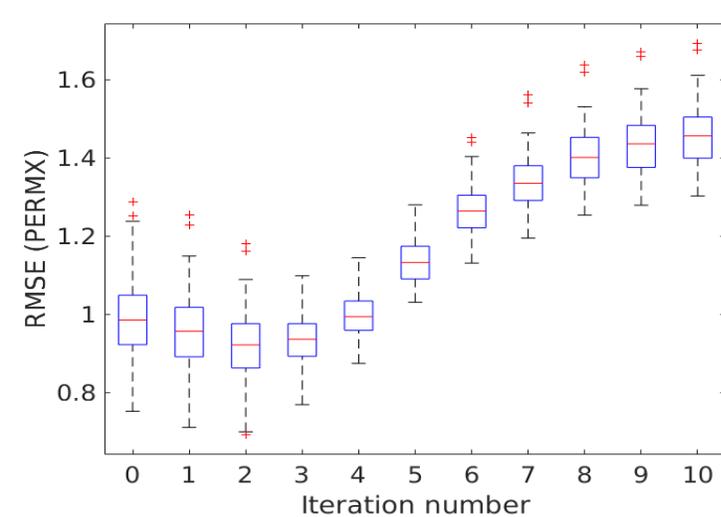
Numerical example I: A 2D Norne field model

Results when both production and seismic data are used (more results in [SPE-180025-MS*](#))



RMSE of PERMX (left) and PORO (right)

Results of history-matching original seismic data **without wavelet-base sparse representation**



RMSE of PERMX (left) and PORO (right)

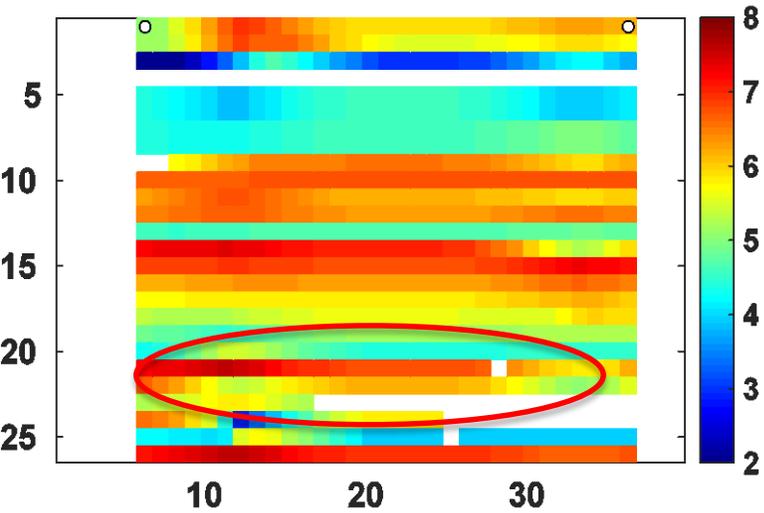
Results of history-matching leading wavelet coefficients

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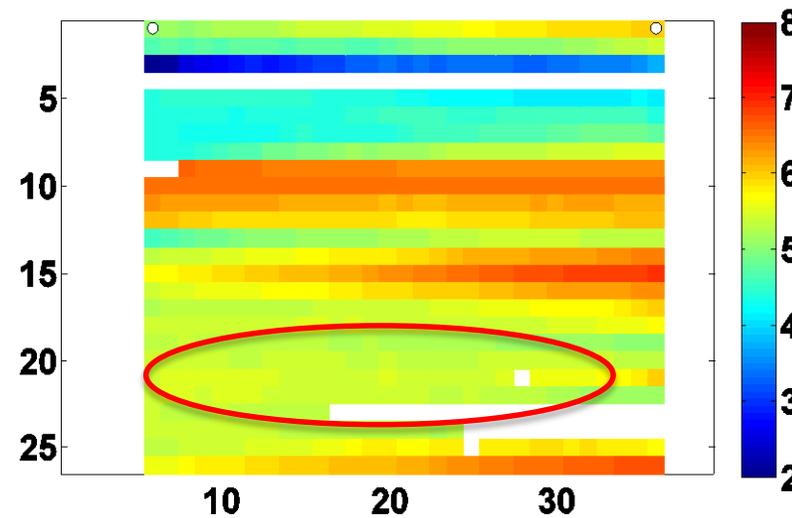
Numerical example I: A 2D Norne field model

Results when both production and seismic data are used (more results in SPE-180025-MS*)

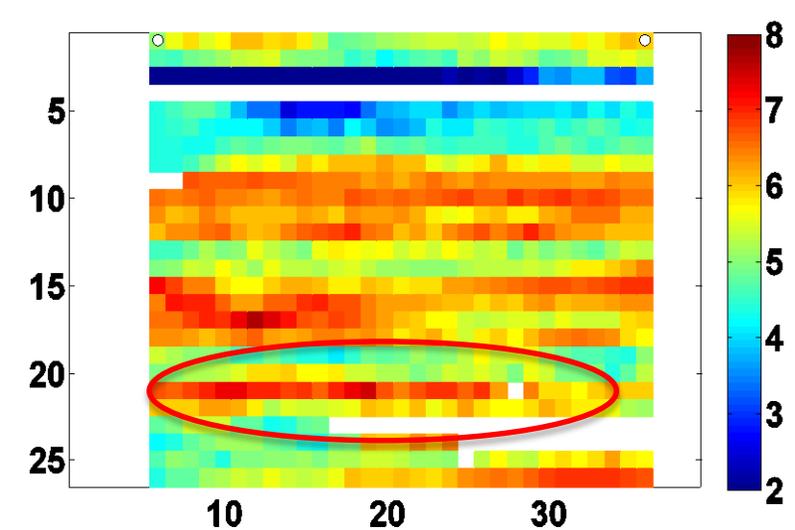
Reference log PERMX



Mean log PERMX of initial guess



Mean log PERMX after history matching



*Luo, X., et al. (2016). An Ensemble 4D Seismic History Matching Framework with Sparse Representation Based on Wavelet Multiresolution Analysis. SPE Bergen One Day Seminar, Bergen, Norway, 20 April, 2016. Paper SPE-180025-MS.

Numerical example I: A 2D Norne field model

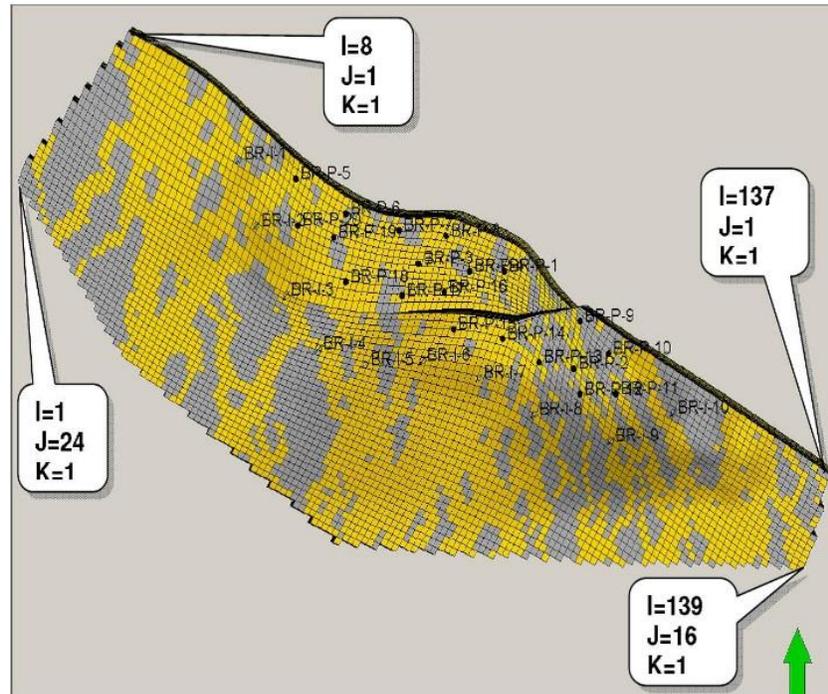
Our finding in this particular case
(for more information see SPE-180025-MS)



Through sparse representation,
better history matching results
are obtained in comparison to
the case of using the original
AVA attribute data

Numerical example II: 3D Brugge field model

Experimental settings



Grid geometry of Brugge field

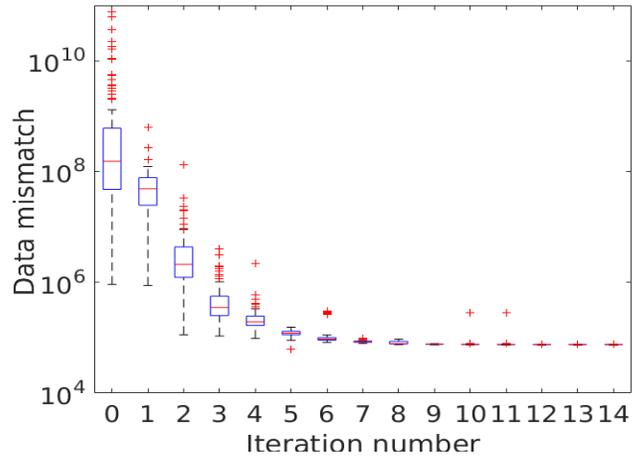
Model size	139x48x9, with 44550 out of 60048 being active gridcells
Parameters to estimate	PORO, PERMX, PERMY, PERMZ. Total number is $4 \times 44550 = 178,200$
Production data (~10 yrs)	BHP, OPR, WCT. Total number is 1400
4D seismic data (1 Base + 2 monitor surveys)	Near and far-offset AVA data. Total number is $\sim 7 \times 10^6$ (needing too much computer memory to be used directly)
Leading wavelet coefficients	Two cases: 1. Total number is $178,332$ ($\sim 2.5\%$); 100K case 2. Total number is 1665 ($\sim 0.02\%$). 1K case
History matching algorithm	Iterative ensemble smoother*

*Luo, X., et al. (2015). "Iterative ensemble smoother as an approximate solution to a regularized minimum-average-cost problem: theory and applications." SPE Journal, 20, 962 - 982, paper SPE-176023-PA.

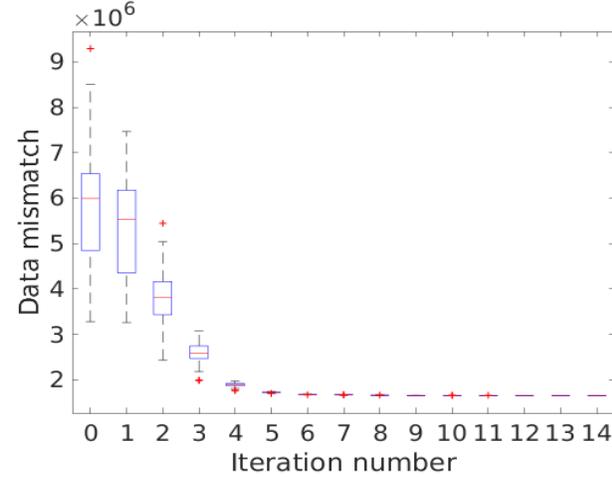
Numerical example II: 3D Brugge field model

Results when both production and seismic data are used (more results to be presented in **ECMOR***)

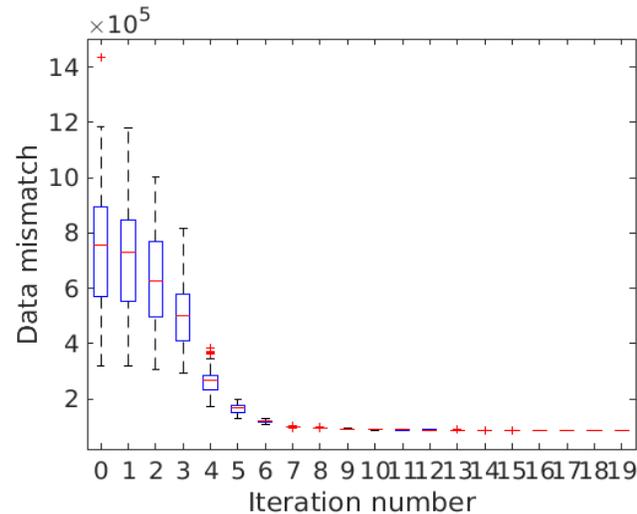
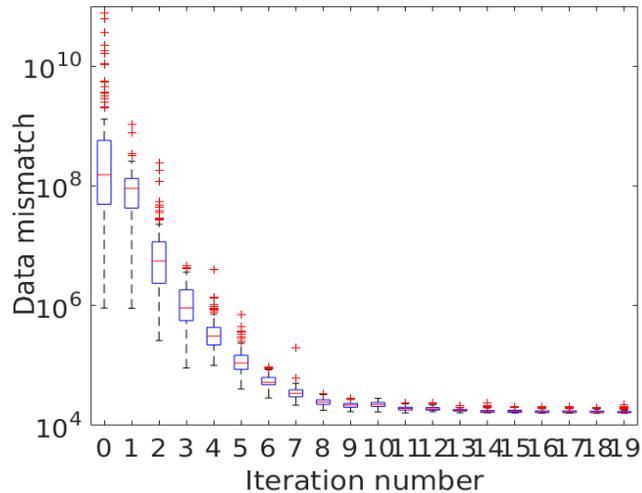
Production data mismatch



Seismic data mismatch



**Production and seismic data mismatch in
100K case**



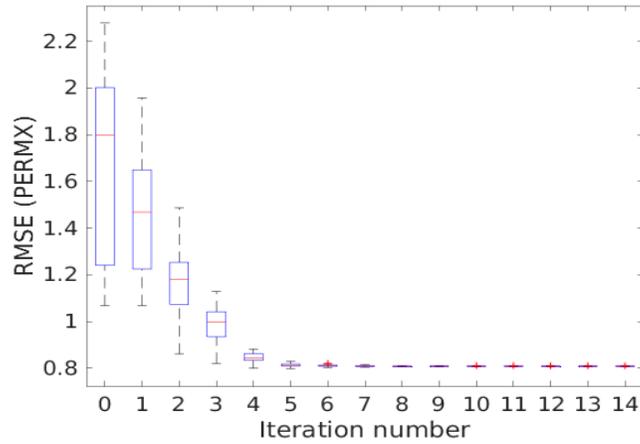
**Production and seismic data mismatch in
1K case**

*Luo, X., et al. (2016). An Ensemble 4D Seismic History Matching Framework with Sparse Representation and Noise Estimation: A 3D Benchmark Case Study. 15th European Conference on the Mathematics of Oil Recovery (ECMOR), Amsterdam, Netherlands, 29 August - 01 September, 2016.

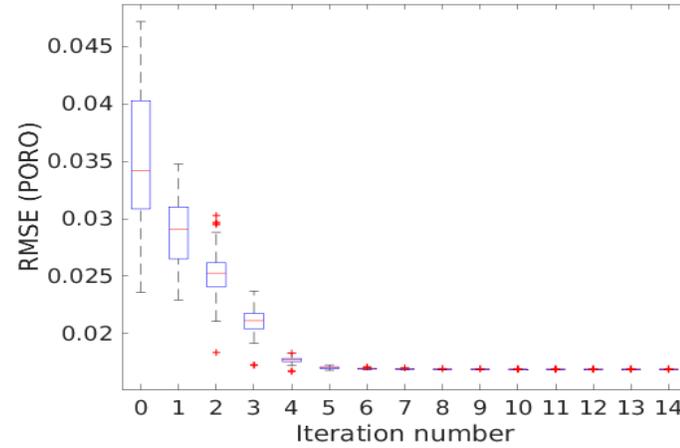
Numerical example II: 3D Brugge field model

Results when both production and seismic data are used (more results to be presented in **ECMOR***)

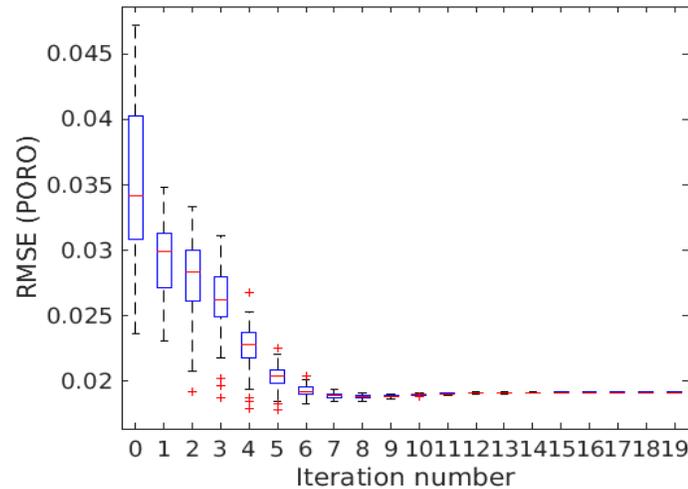
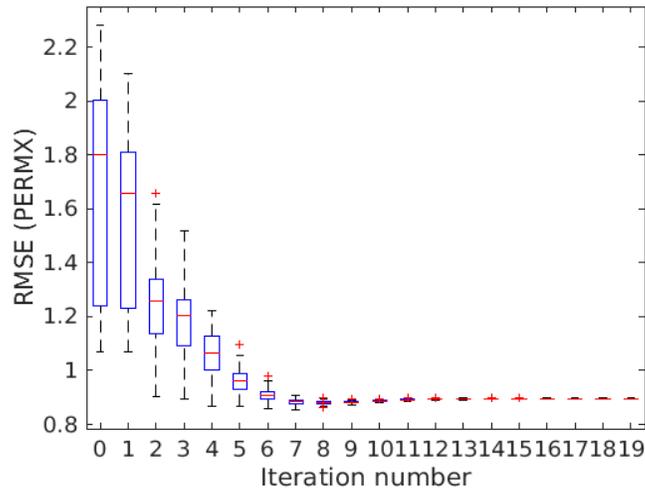
RMSE of PERMX



RMSE of PORO



**RMSE of PERMX (left) and PORO (right) in
100K case**



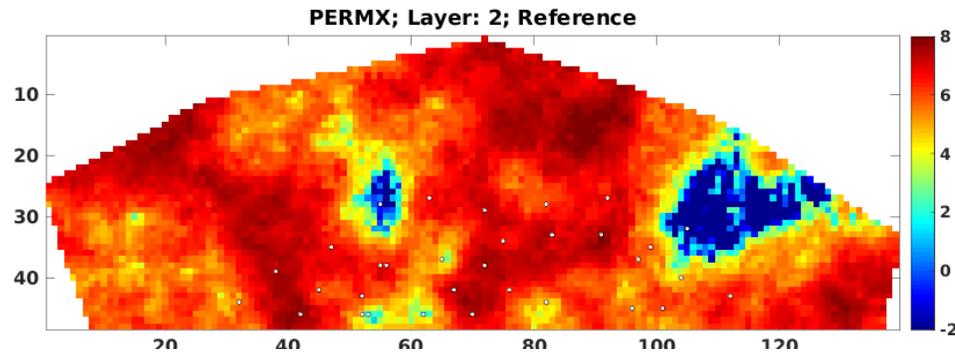
**RMSE of PERMX (left) and PORO (right) in
1K case**

*Luo, X., et al. (2016). An Ensemble 4D Seismic History Matching Framework with Sparse Representation and Noise Estimation: A 3D Benchmark Case Study. 15th European Conference on the Mathematics of Oil Recovery (ECMOR), Amsterdam, Netherlands, 29 August - 01 September, 2016.

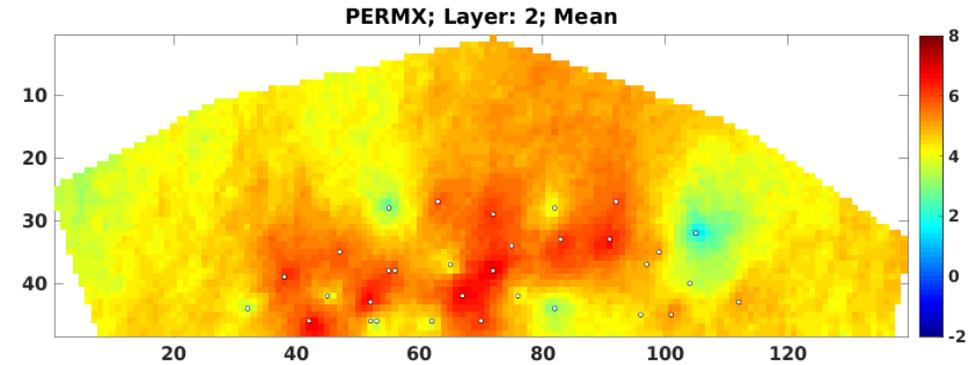
Numerical example II: 3D Brugge field model

Results when both production and seismic data are used (more results to be presented in **ECMOR***)

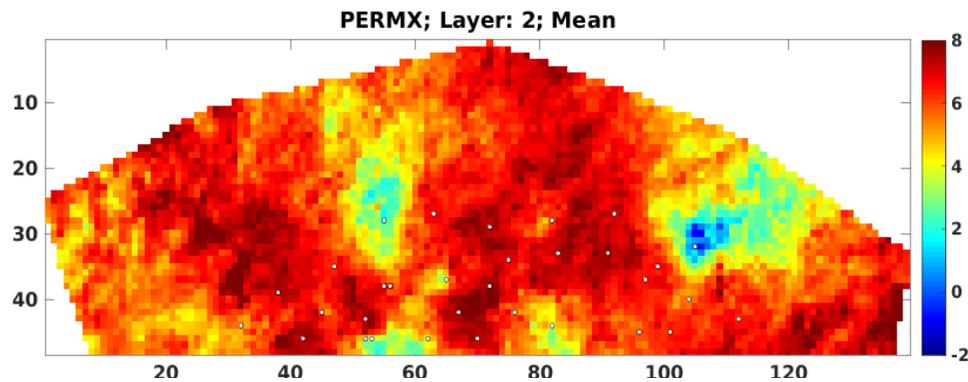
Reference log PERMX (at layer 2)



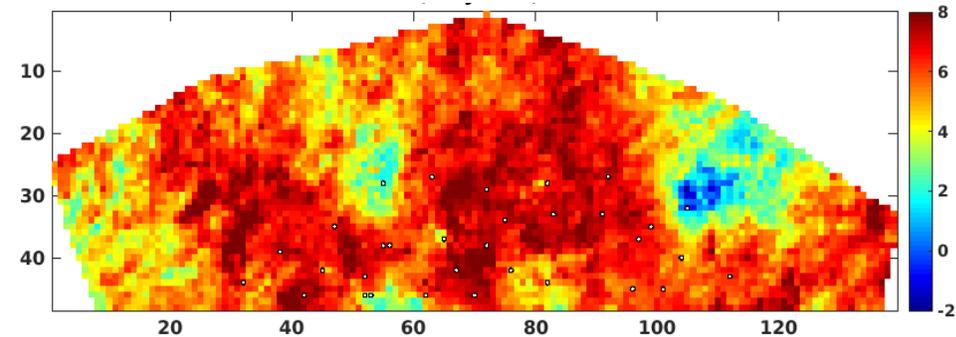
Mean log PERMX (at layer 2) of initial guess



Mean log PERMX (at layer 2) after history matching (100K)



Mean log PERMX (at layer 2) after history matching (1K)

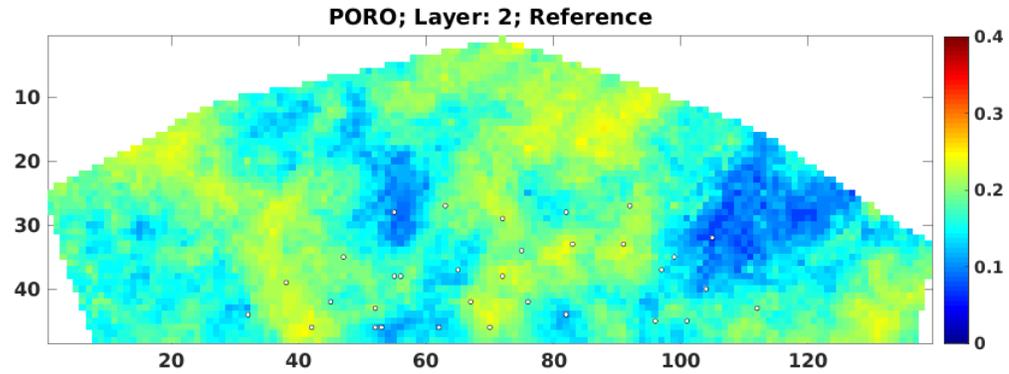


*Luo, X., et al. (2016). An Ensemble 4D Seismic History Matching Framework with Sparse Representation and Noise Estimation: A 3D Benchmark Case Study. 15th European Conference on the Mathematics of Oil Recovery (ECMOR), Amsterdam, Netherlands, 29 August - 01 September, 2016.

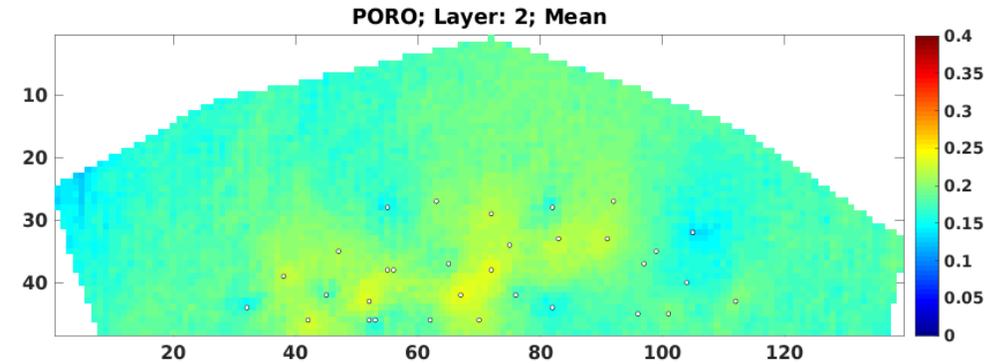
Numerical example II: 3D Brugge field model

Results when both production and seismic data are used (more results to be presented in **ECMOR***)

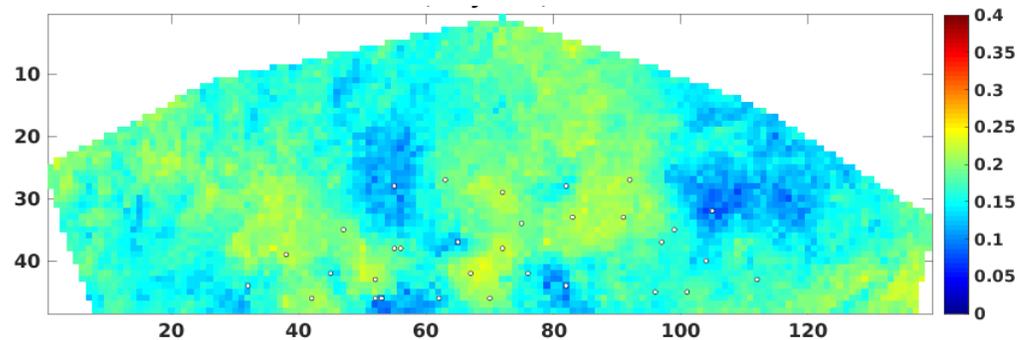
Reference PORO (at layer 2)



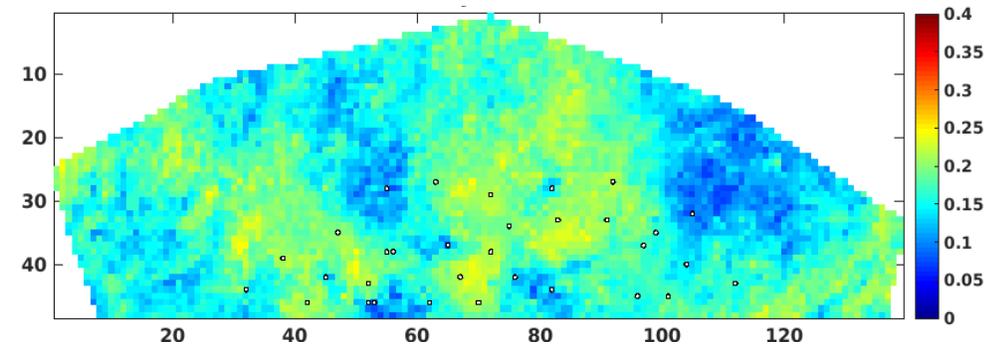
Mean PORO (at layer 2) of initial guess



Mean PORO (at layer 2) after history matching (**100K**)



Mean PORO (at layer 2) after history matching (**1K**)



*Luo, X., et al. (2016). An Ensemble 4D Seismic History Matching Framework with Sparse Representation and Noise Estimation: A 3D Benchmark Case Study. 15th European Conference on the Mathematics of Oil Recovery (ECMOR), Amsterdam, Netherlands, 29 August - 01 September, 2016.

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Conclusion and future works

Advantages in using wavelet-base sparse representation
In seismic history matching

Efficient reduction of data size

Intrinsic noise estimation in the data

Applicability to various types of data (AVA,
impedance, saturation map etc.)

Conclusion and future works

Possible future investigations

Field case studies

Various types of seismic data

Covariance localization/local analysis

Acknowledgements / Questions

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All authors acknowledge the Research Council of Norway and the industry partners – ConocoPhillips Skandinavia AS, BP Norge AS, Det Norske Oljeselskap AS, Eni Norge AS, Maersk Oil Norway AS, DONG Energy A/S, Denmark, Statoil Petroleum AS, ENGIE E&P NORGE AS, Lundin Norway AS, Halliburton AS, Schlumberger Norge AS, Wintershall Norge AS – of The National IOR Centre of Norway for financial supports