Reservoir characterization in the presence of thin beds and elastically ambiguous facies

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Qeye

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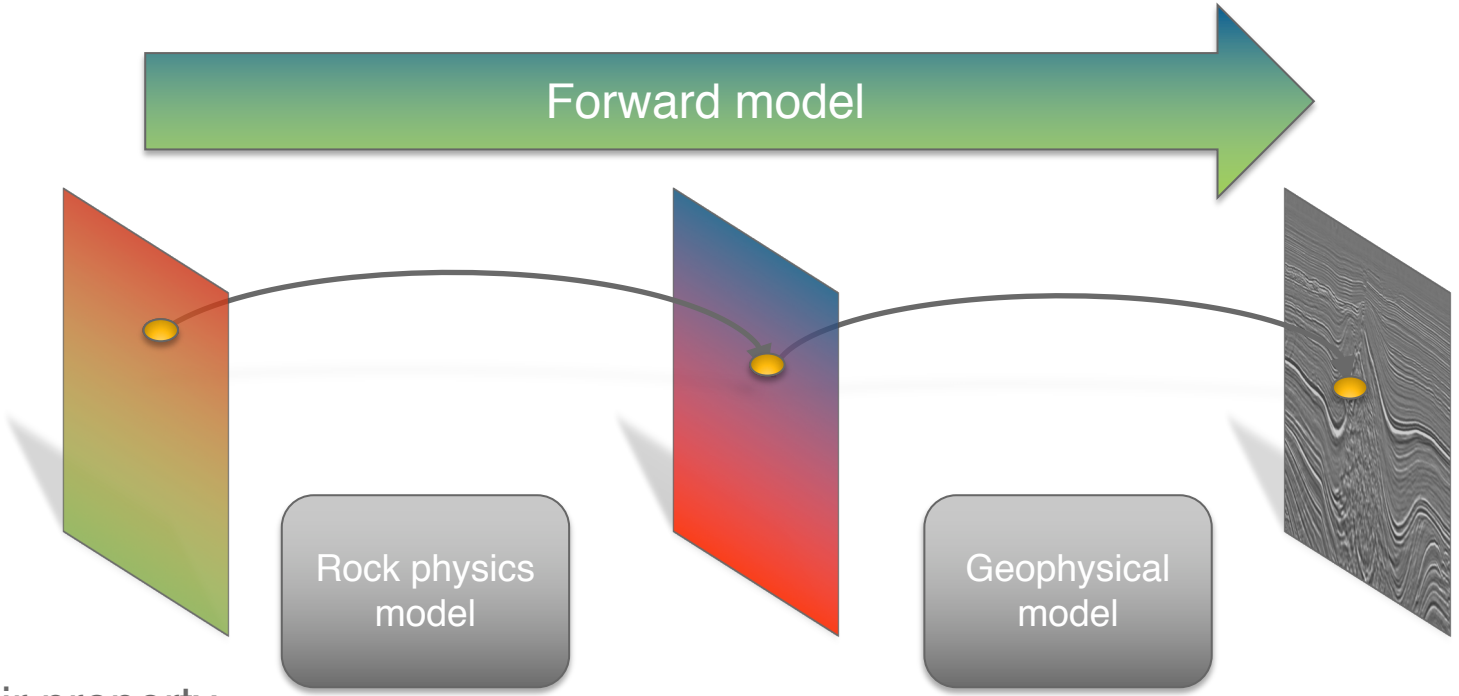

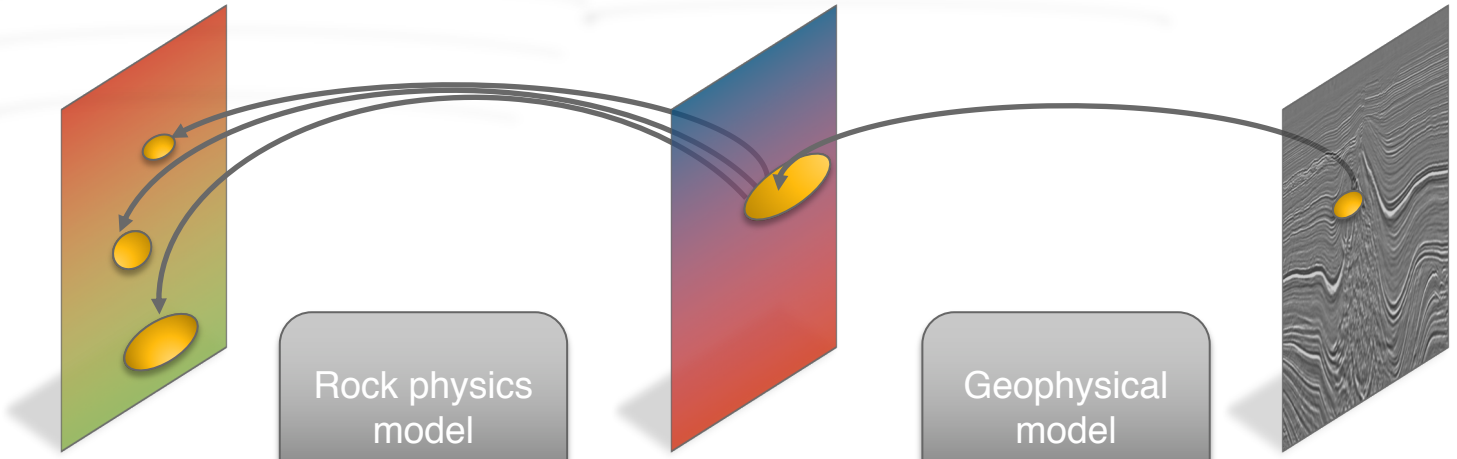

Reservoir property domain

Elastic domain

Seismic amplitude observation

Inverse problem

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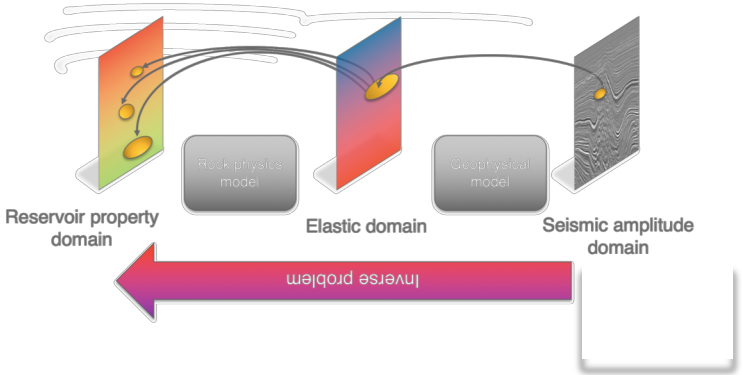
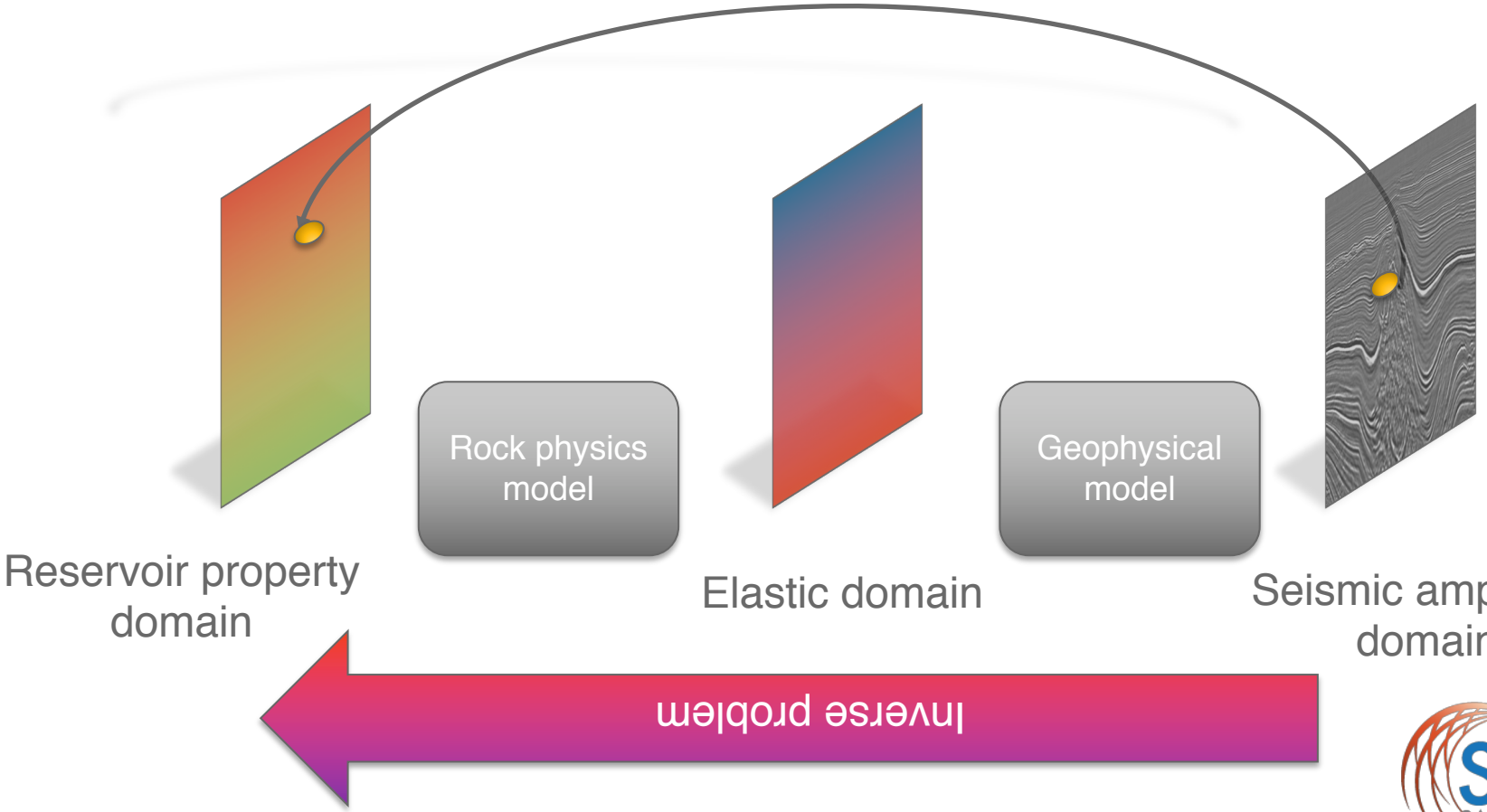
Reversing is much harder..

- The inverse problem is non-unique
- By the time we reach the property domain it can be highly non-unique
  - Several petrophysically discrete facies can have the same elastic properties
  - Interbedded facies can have the same response as a single package of their average properties
  - Noise in the seismic data make the problem worse
  - Accounting for the lack of seismic low frequencies bias the results – not always in the right way



Reversing is much harder..

- But it helps if you know what you are looking for!
- Traditionally, we are using
  - depth trends
  - 3D spatial low frequency volumes
- But there are additional sources of information we have not been using

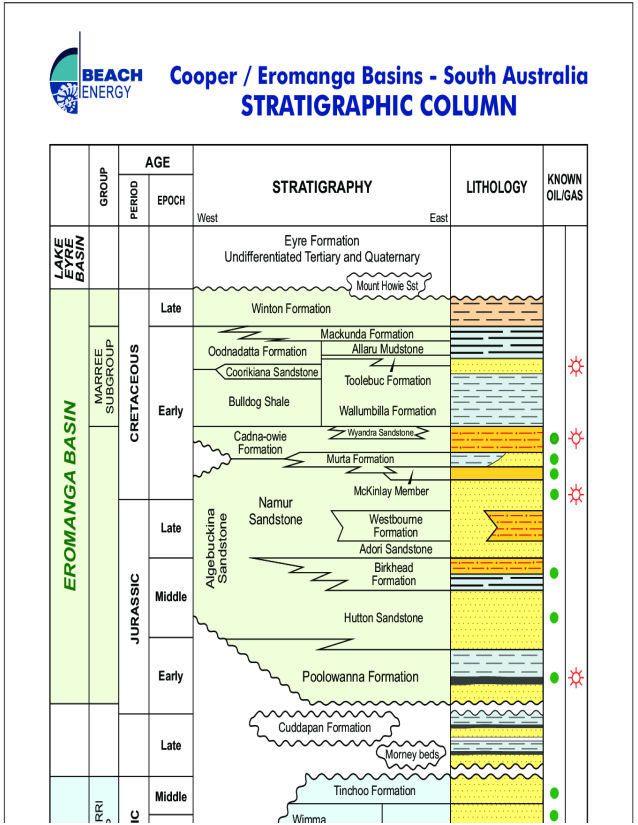

Rock physics model
Geophysical model
Reservoir property domain
Elastic domain
Seismic amplitude domain
Inverse problem

Probabilistic inversion challenges

- The problem is analytically intractable
- Numerical methods are exact in theory…
- …but computationally expensive…
- … and open questions about convergence, number of statistical independent realizations etc.

- Some model assumptions and/or approximations are needed!
- Need to work at scale – many terabytes of data across multiple angle-stacks

The facies constellation



- Any information that
  - lists the facies expected to be present
  - describes the probability of one facies appearing above another
  - in this case a facies is any discrete unit
  - each facies my have many sub-facies with different mineralogies, saturations and/or porosities
  - ensure that the facies constellation is broad yet plausible

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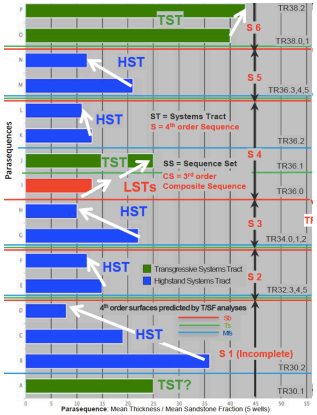
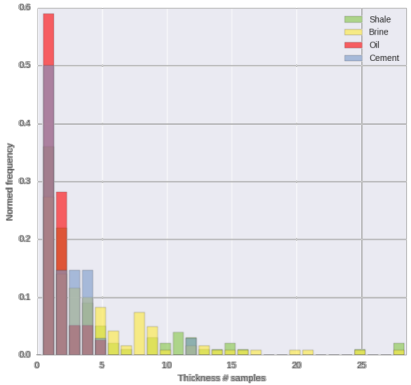
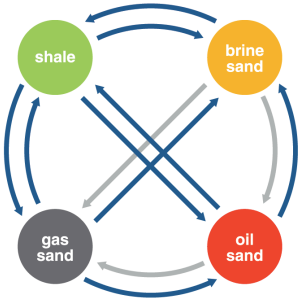
The facies constellation







- Combined with any information that:
  - describes the probability distribution of the facies thicknesses
  - fit this information to a model that is broad yet plausible
- Allows you model the earth as a Markov process that describes the transitions between facies as you move up or down a trace

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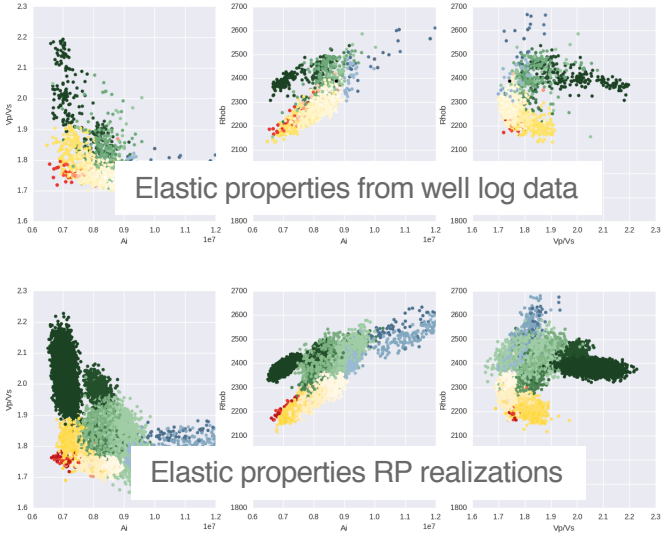
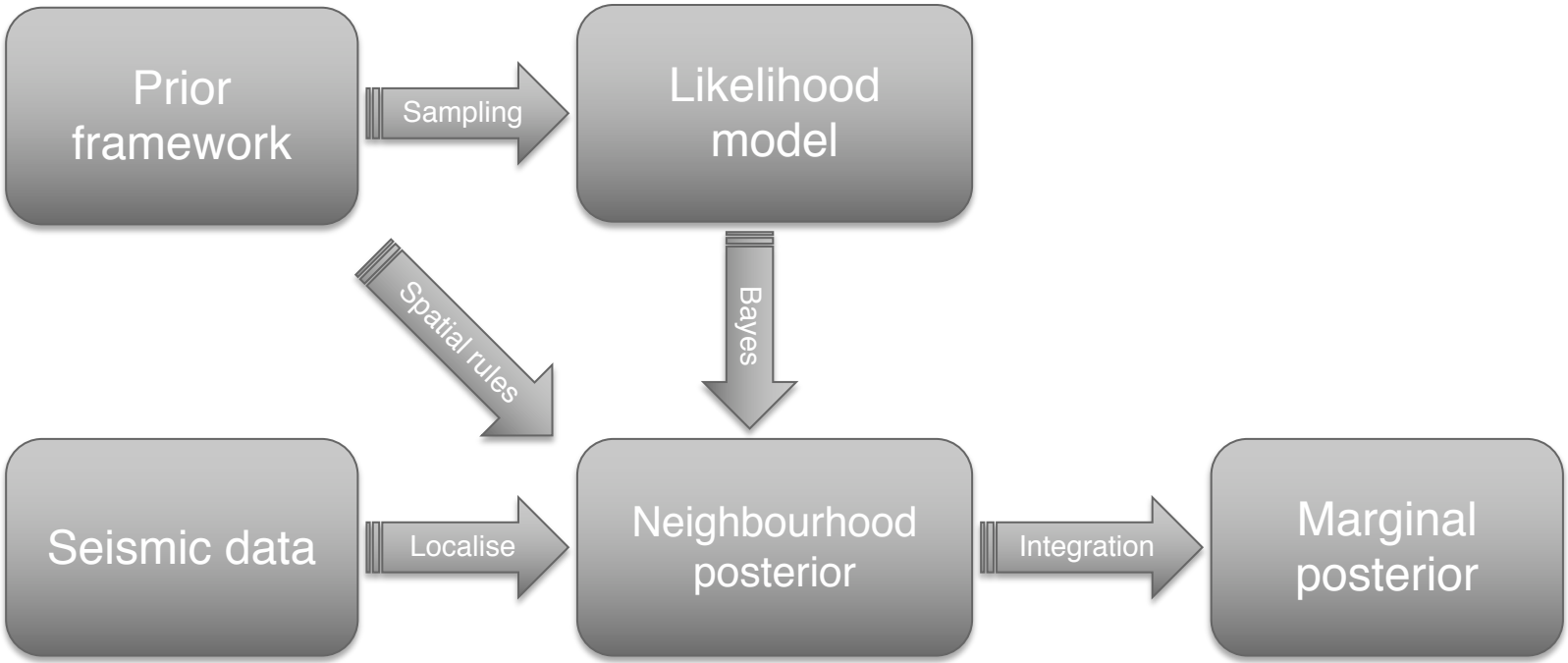
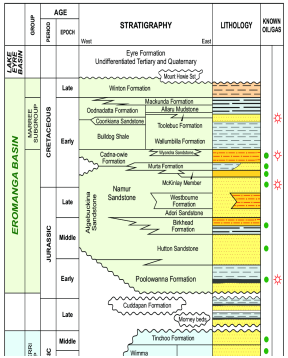
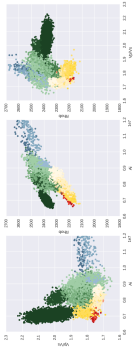
The statistical rock physics model

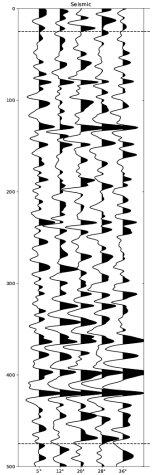


- For every (sub-facies) construct a statistical rock physics model
  - Capture the observed distributions of elastic properties in each facies
  - Include correlation lengths
  - Include any observed elastic property cross correlations
  - Extend these distributions to ensure that they are broad and yet plausible

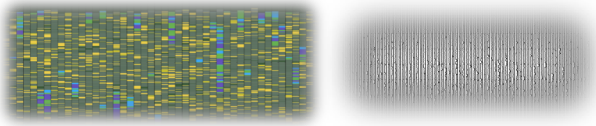








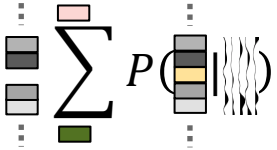
Sampling



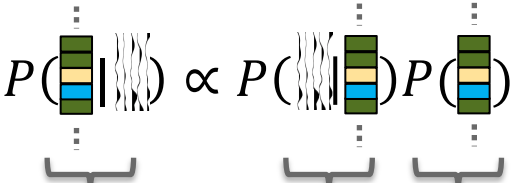
Spatial rules

$$P(A|B) = \frac{P(B|A)P(A)}{P(B)}$$

Bayes



Localise

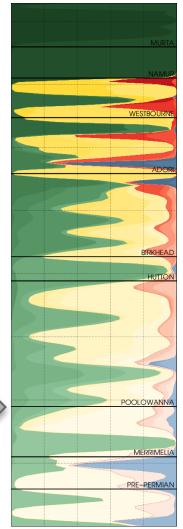


neighbourhood posterior

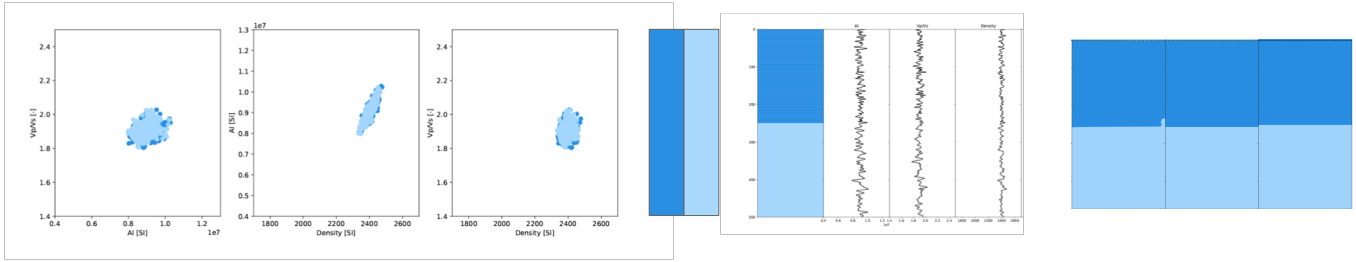
likelihood

prior

Integration



Extreme synthetics – elastic ambiguity



Two facies:

- identical mean elastic properties
- identical distributions for each property
- identical cross correlations between properties

The only difference between them is the spatial correlation length (dark varies faster then light)

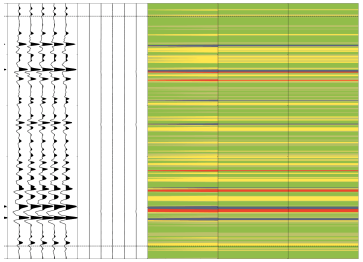
Current methods would fail – 50:50 chance

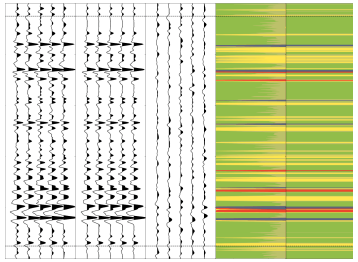
In the no noise synthetic:

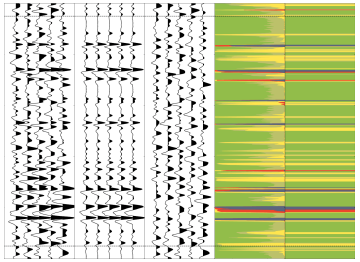
- equivalent or better results for facies variations
  - in mean
  - skew
  - distribution

Algorithm matches numerically exact HM-MCMC
Algorithm outperforms HM by several OoM

Extreme synthetics – thin beds







Thin interbedded facies synthetic:

- olive and green facies highly ambiguous
- multiple stacked beds below tuning thickness
- Gradually increase noise levels

Current methods would fail

- beds too thin to be correctly classified
- interbedded facies ≡ mean package response
- pointwise ⇒ characterization power degrades rapidly with noise

Perfect reconstruction in the no noise case
Elastic ambiguity challenged by noise
Thin bed performance is extremely robust

Algorithm matches numerically exact HM-MCMC
Algorithm outperforms HM by several OoM

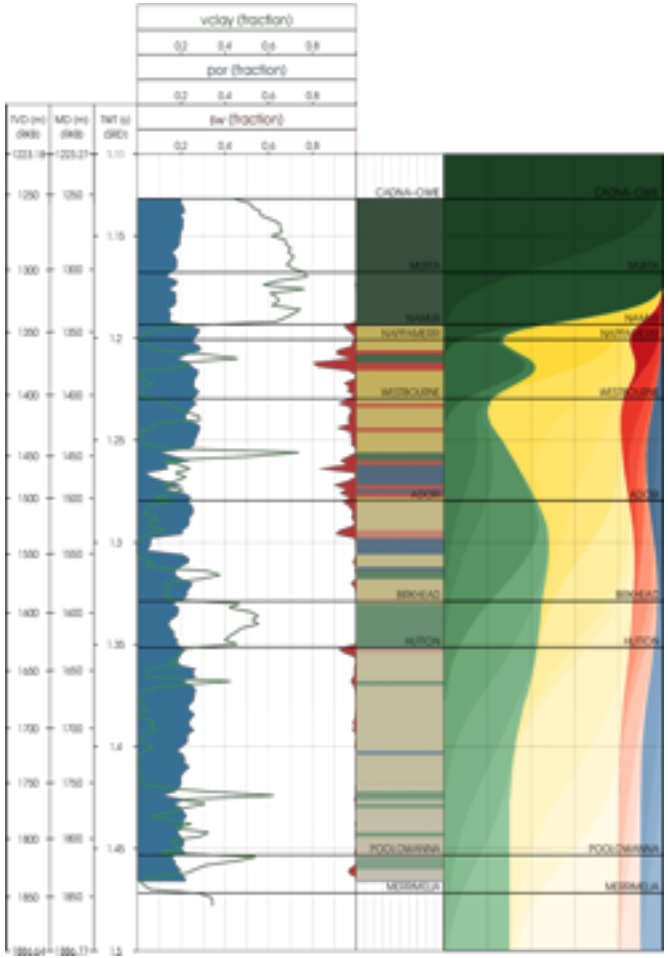
Real data example

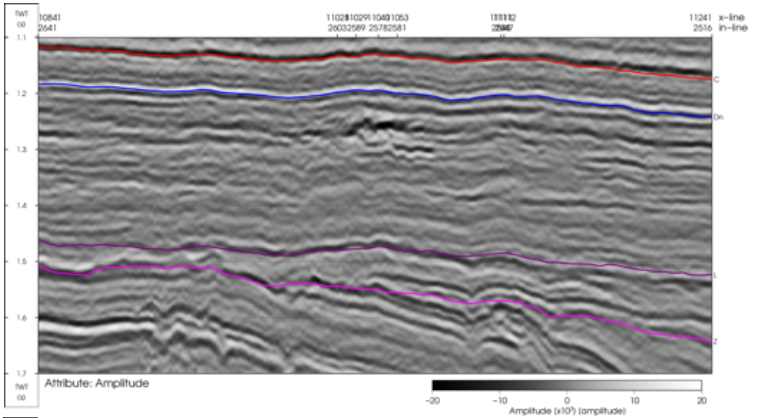
From well logs and stratigraphic column construct prior framework

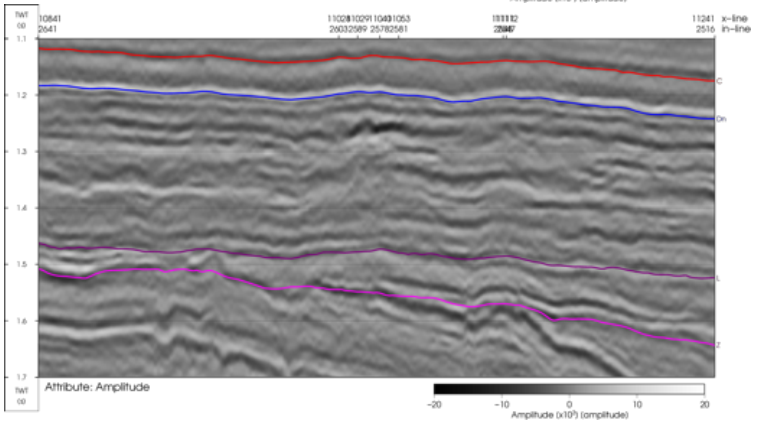
- spatially uninformed
- extremely broad…
- …yet plausible

Expose some noisy land seismic to the prior framework

- Cooper basin – Australia
- seismic known to be challenging
- traditional inversion results poor







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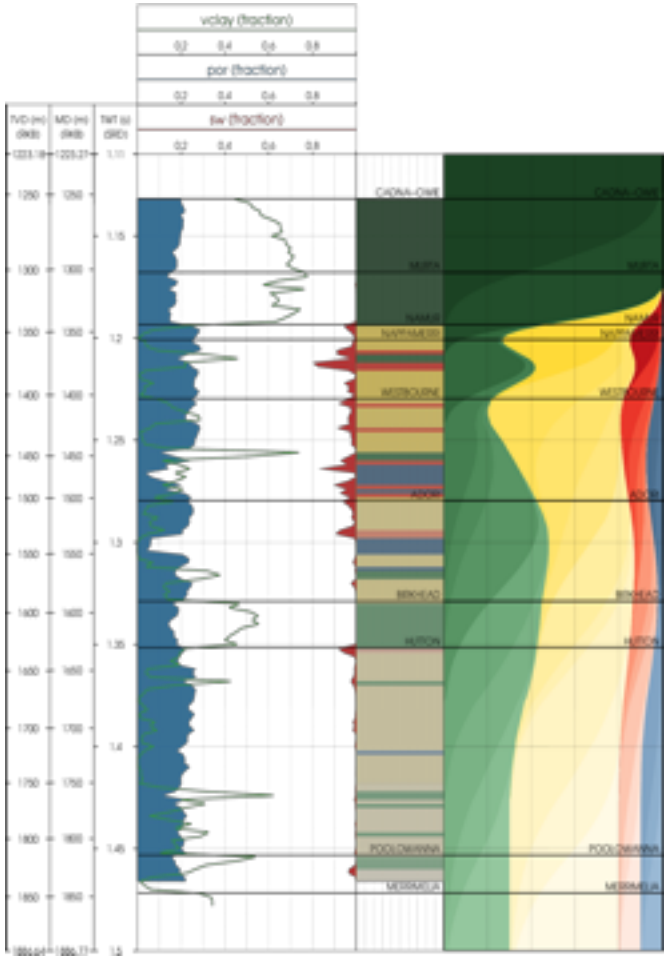
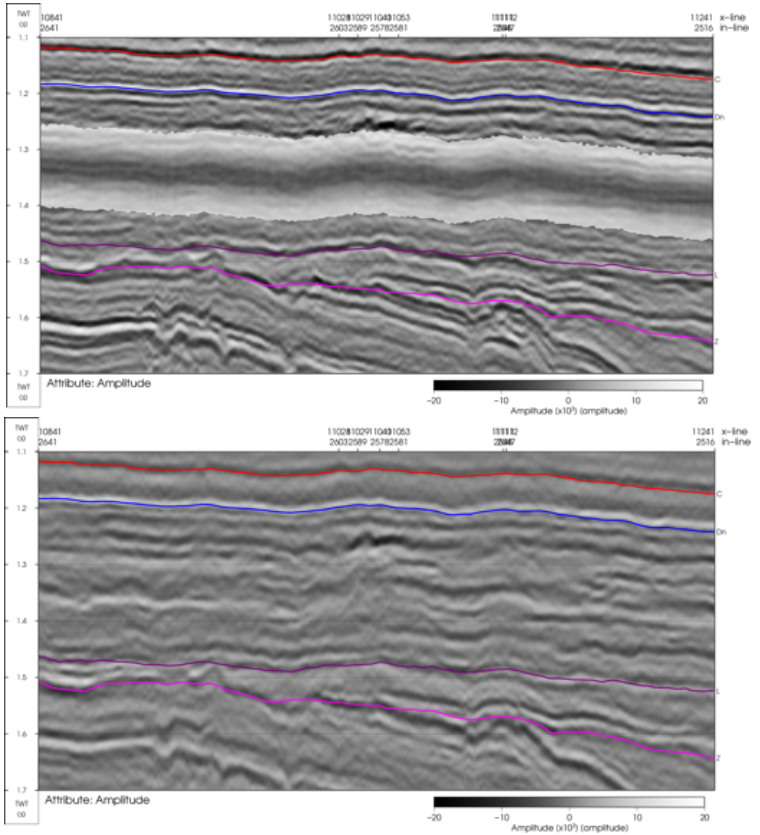
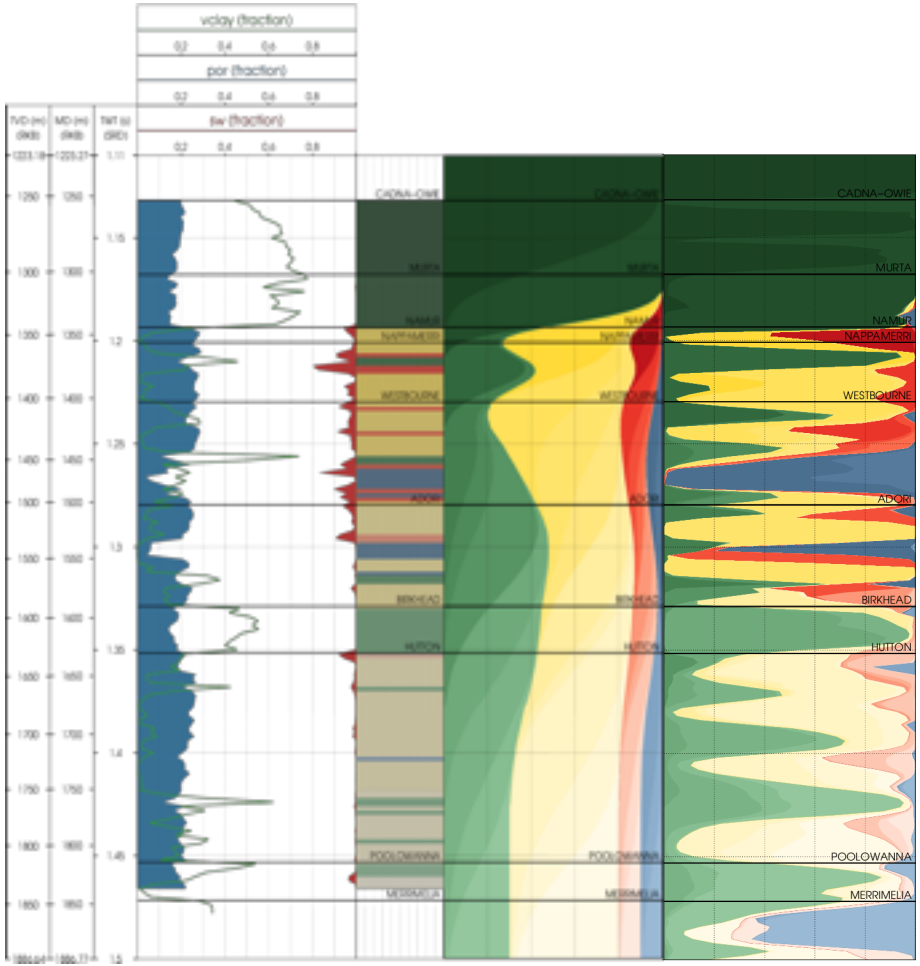
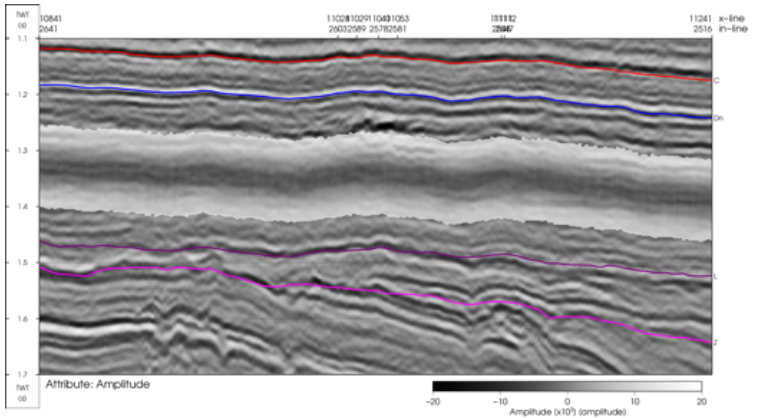
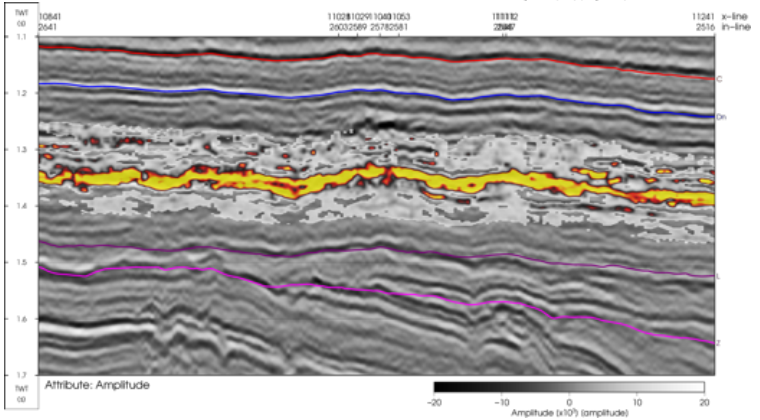

vclay (fraction)
por (fraction)
sw (fraction)
TVD (m)
MD (m)
TWT (s)
CADNA-OWE
MURTA
NAAMA
WITTEGURNE
ADAM
BEKHEAD
HUTTON
POOLTAWANNA
MESSAMBA


x-line
in-line
Attribute: Amplitude
Amplitude (x10³) (amplitude)







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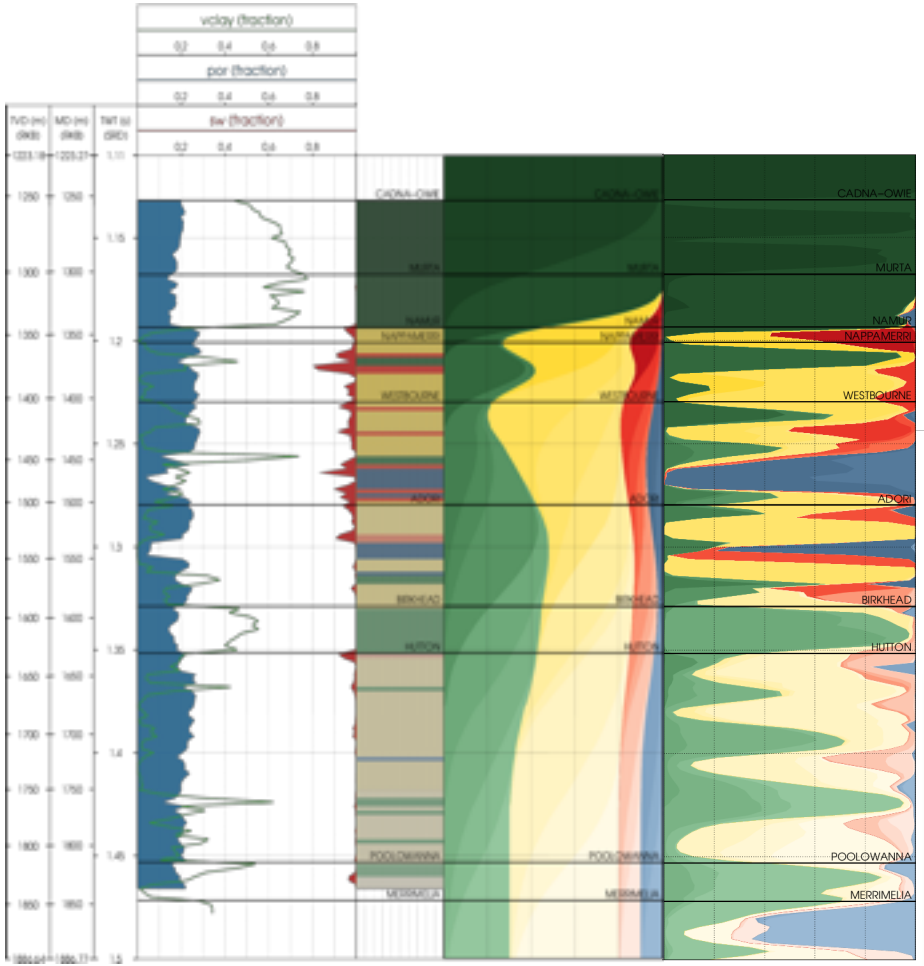

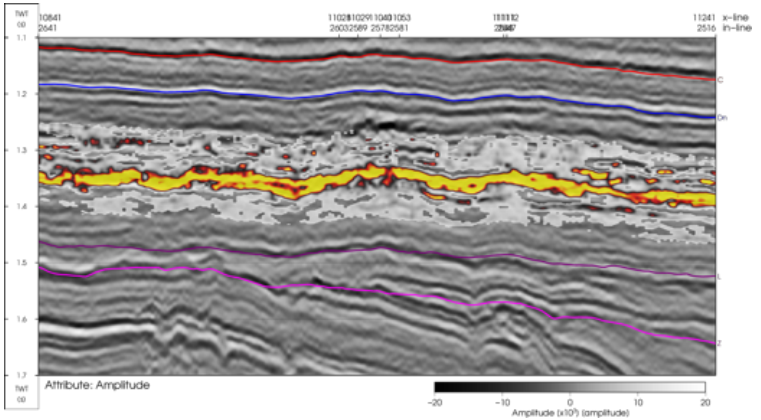

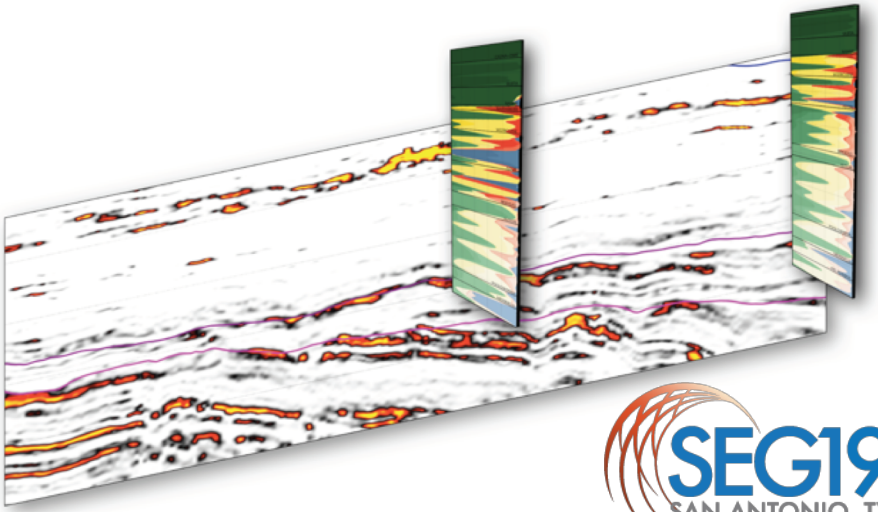

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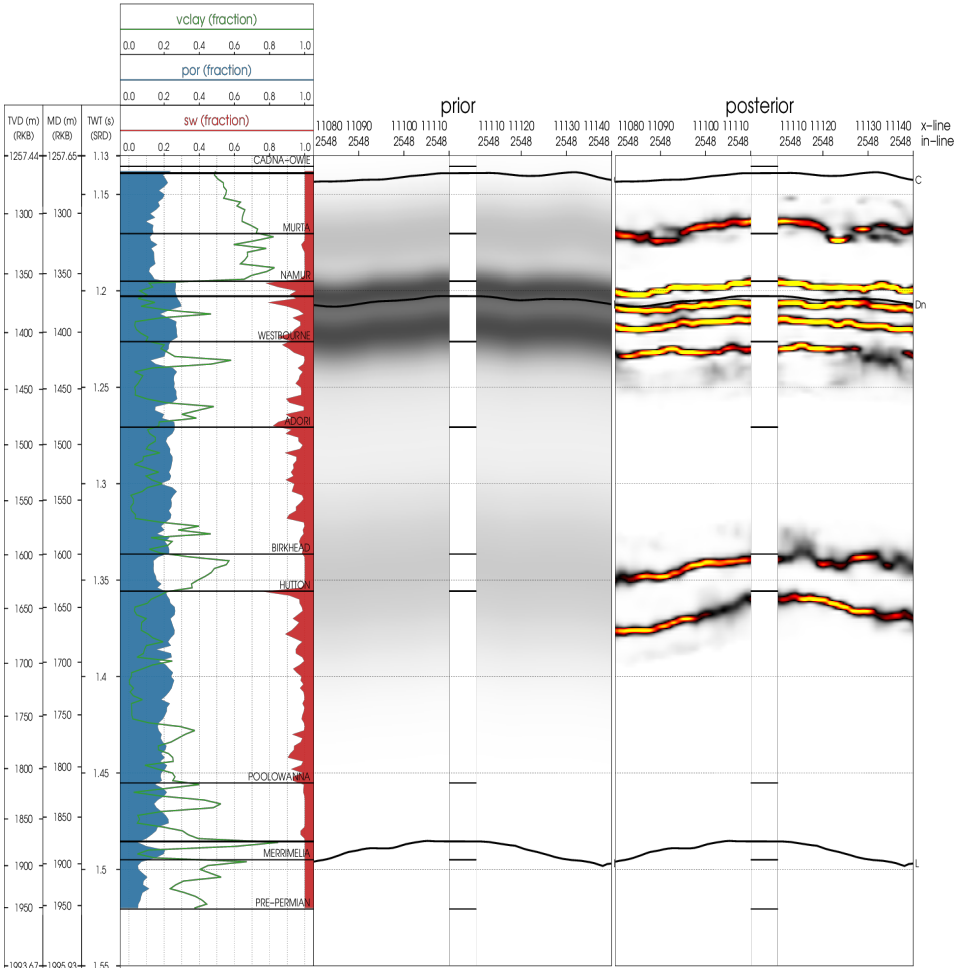

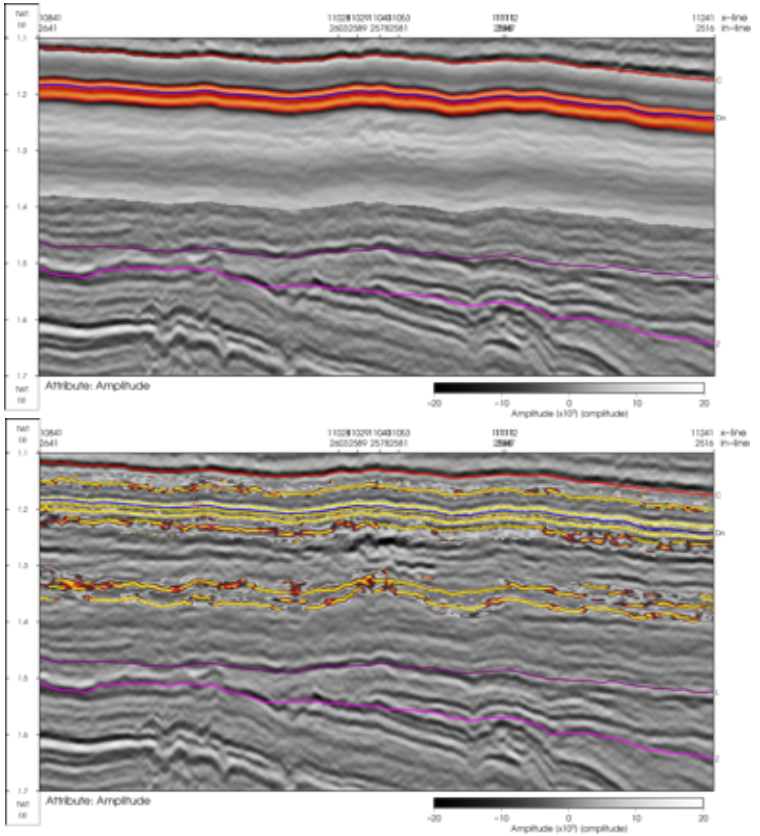

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Conclusions

- Direct Probabilistic Inversion allow for solving the seismic AVO inverse problem as a Bayesian inference problem
  - A rigorous quantitative propagation of uncertainties
  - Flexible integration of information from diverse sources
  - Allows to estimate key surfaces with uncertainty
  - Possible to resolve below tuning thickness
  - Possible to characterise facies that are extremely similar

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