On inferring noise in probabilistic seismic AVO inversion using Hierarchical Bayes

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Seismic noise

• What is the uncertainty on seismic data?
Seismic noise

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• Simple example:
Seismic noise
Seismic noise
Seismic noise
Seismic noise
Seismic noise

• What is seismic noise (uncertainty)?
  – Multiples
  – Background noise
  – Measurement errors
  – Artifacts from processing
  – Etc.

• Noise is important, yet difficult to describe
Probabilistic inverse problem

• Correct evaluation of the likelihood is essential
  – Requires a good model for the measurement and theory uncertainties
  – Assume some noise model (inferring from nearby wells?)
Inferring noise in probabilistic inversion

• Alternative approach
  – Estimate the noise as part of the inversion
  – Proposed to infer variance of noise using hierarchical Bayes inference scheme as part of the inversion\textsuperscript{1,3,4,5,6,7}
Seismic noise

• Setup a simple synthetic case study to test this approach
  – Eliminate unknowns (if possible?)
  – Same forward model, same prior, etc.
  – Know the true solution (reference model)
  – Well-known (well-described) familiar test scenario

• Adapt Gaussian prior and linear seismic AVO forward model formulated from Buland & Omre (2003)²
Reference data
Stochastic model
Stochastic model

μ

C_M

m

d_{obs}

C_D

h
Sampling algorithm

- Sampling algorithm adapted from Malinverno & Briggs (2004)\textsuperscript{5}
Test case 1

A common practice for inferring noise is to assume an uncorrelated noise model:

- Highest possible entropy (Unpredictability)

\[ h = h_1 = \sigma_d \]

\[ h_1 \sim \text{Uniform}(0.00001, 1) \]
Test cases
Results case 1

Case 1: $p(h_1|d_{obs})$
Test case 2

• Use the correct shape (same covariance) as used to generate noise

\[ h = [h_1, h_2] = [\sigma_d, \sigma_T] \]

\[ h_1, h_2 \sim \text{Uniform}(0.00001, 1) \]
Results case 2

Case 2: $p(h_1|d_{obs})$

Case 2: $p(h_2|d_{obs})$

Run 1  Run 2  $\sigma_d$  $\sigma_T$  $\sigma_{d+T}$
Summary

1. The hierarchical Bayes approach was in all cases able to accurately estimate the variance of the uncorrelated noise on the data.
2. Case 1 shows noise being fitted as data when assuming uncorrelated noise in a scenario with correlated noise.
3. Case 2 shows that it is possible to infer the variance of the noise if the correct shape is known.
4. Case 3 shows that some improvements can be gained by assuming some correlation of error. Still see biased results!
References


Test case 3

• Use the estimated shape
  – wavelet with correlation between angles

\[ h = [h_1, h_2] = [\sigma_d, \sigma_W] \]

\[ h_1, h_2 \sim \text{Uniform}(0.00001, 1) \]
Results case 3

Case 3: $p(h_1|d_{obs})$

Case 3: $p(h_2|d_{obs})$

Run 1  Run 2  $\sigma_d$  $\sigma_T$  $\sigma_{d+T}$
Log-likelihood + Cross Correlation

**Case 1**

**Case 2**
Log-likelihood + Cross Correlation

Case 3

![Graphs showing log-likelihood and cross correlation](image)
Comparison with non-hierarchical inversion

Non-hierarchical Bayesian linear AVO inversion for comparison:
Comparison with non-hierarchical inversion

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Non-hierarchical Bayesian linear AVO inversion for comparison: