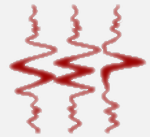
AVO Anomaly Detection using Principal Component Analysis

Stuart Farris

Stanford Exploration Project

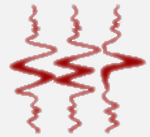
April 18, 2017

Motivation



Can we create a more robust approach for finding AVO anomalies while decreasing the analysis time
and increasing accuracy?

The Problem



- The Concept of AVO
  - Reflection coefficients are a function of impedance contrasts and angle of incidence.

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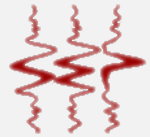

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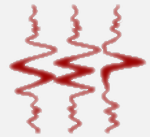

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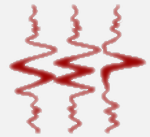

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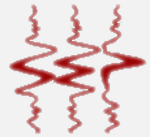

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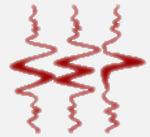

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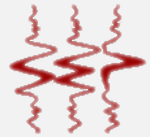
Time consuming!

Solution



- Reformulate AVO analysis as a dimensionality reduction problem.

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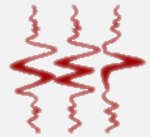
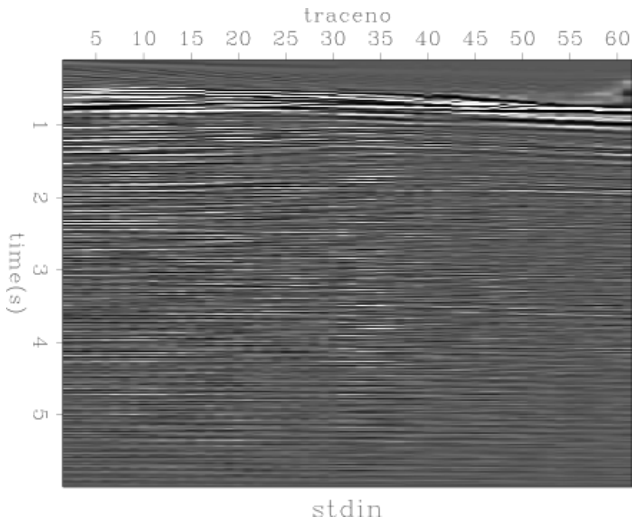


- Reformulate AVO analysis as a dimensionality reduction problem.
- Bougher and Herrmann (2016) showed principal component analysis (PCA) can identify AVO anomalies.

Method



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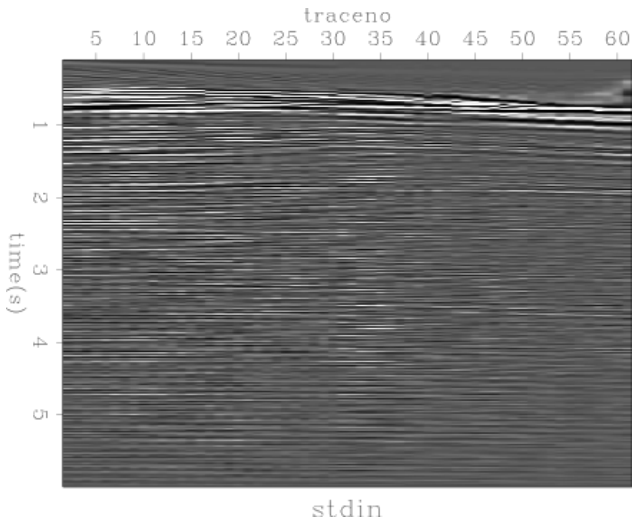

$$t_1 \downarrow \quad \begin{matrix} PC_1 \\ \begin{bmatrix} 0.15 \\ -0.1 \\ 0.12 \\ 0.6 \\ . \\ . \\ . \\ -1.0 \end{bmatrix} \end{matrix} + \begin{matrix} PC_2 \\ \begin{bmatrix} -0.4 \\ -1.2 \\ 0.3 \\ 0.21 \\ . \\ . \\ . \\ 0.5 \end{bmatrix} \end{matrix} + \ \ldots \ + \begin{matrix} PC_n \\ \begin{bmatrix} 0.04 \\ 0.01 \\ -0.15 \\ 0.67 \\ . \\ . \\ . \\ -0.01 \end{bmatrix} \end{matrix}$$

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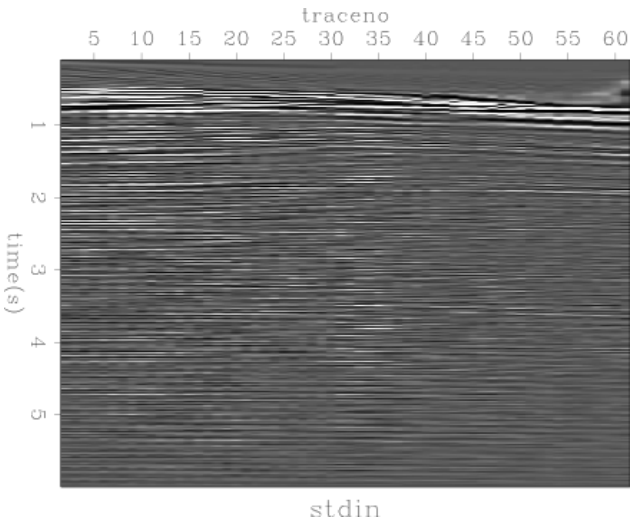

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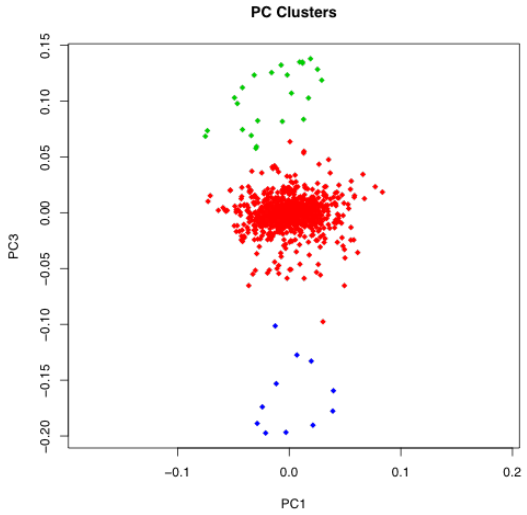

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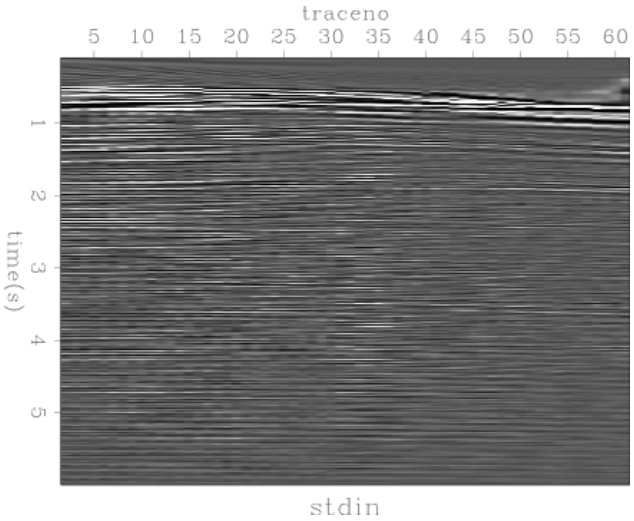

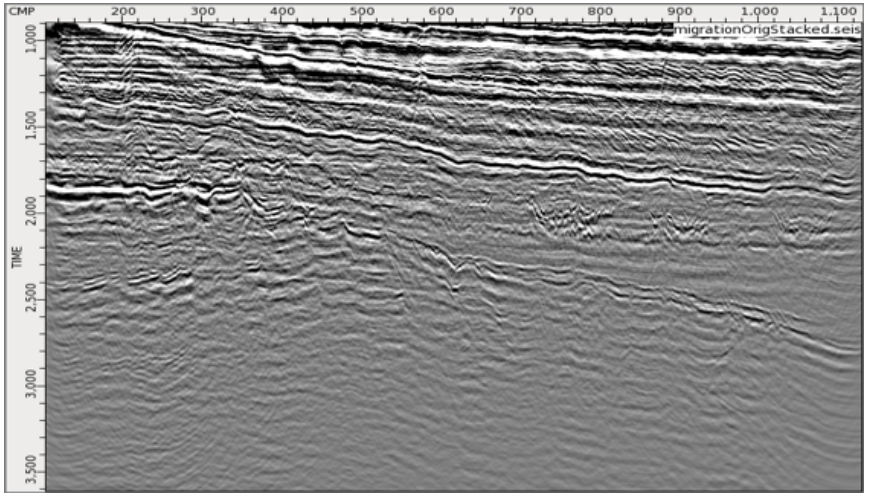

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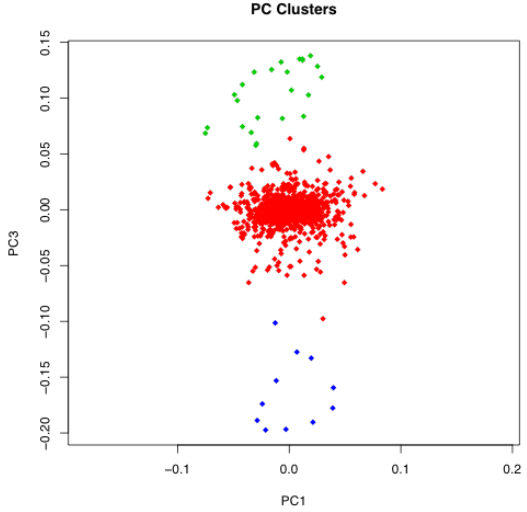

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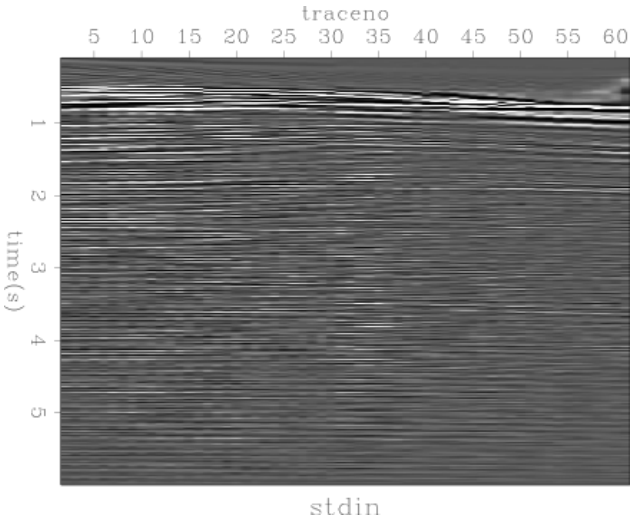

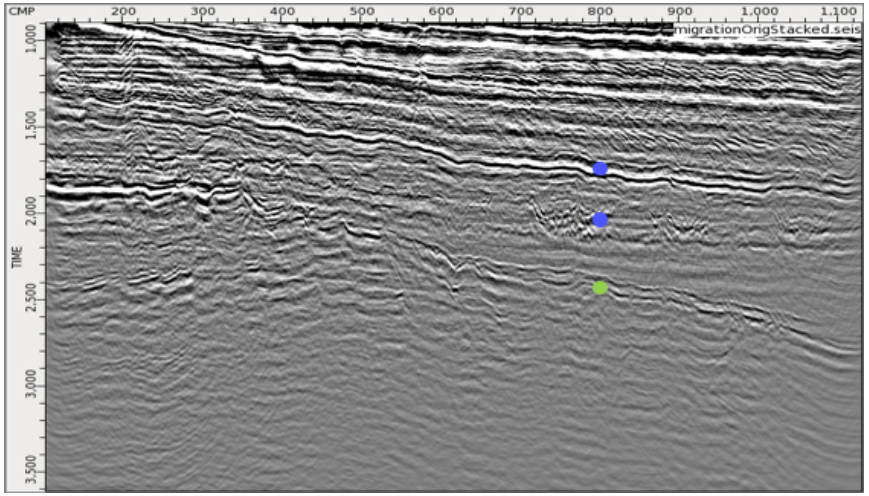

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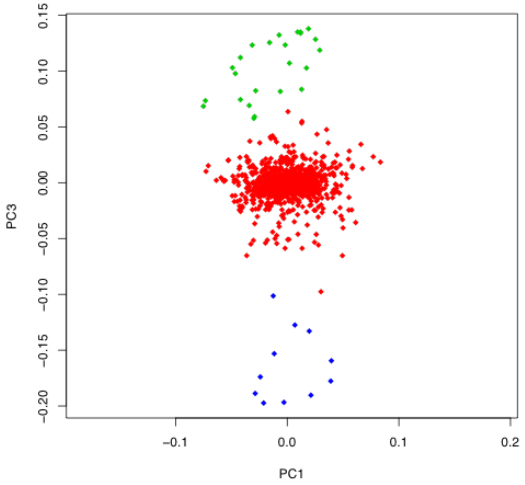

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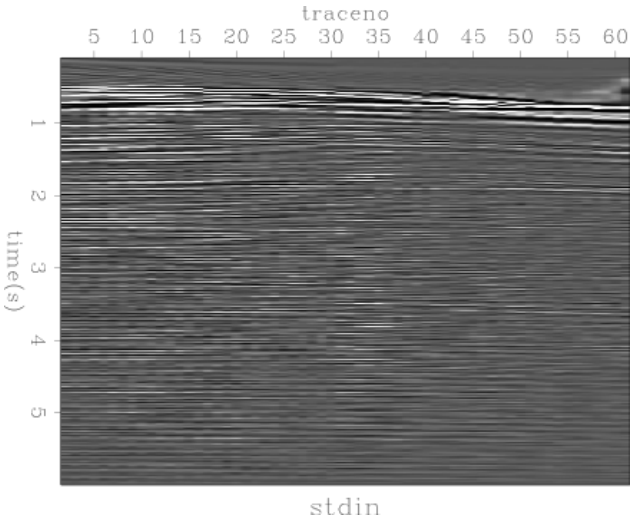

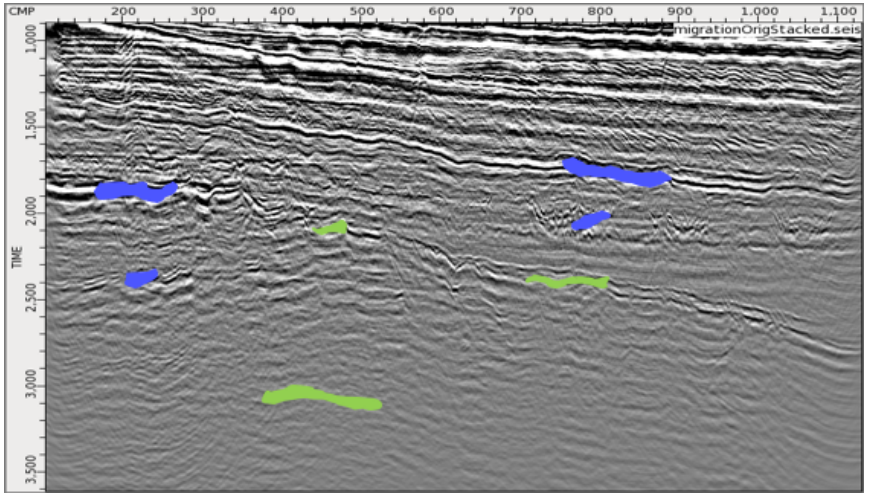

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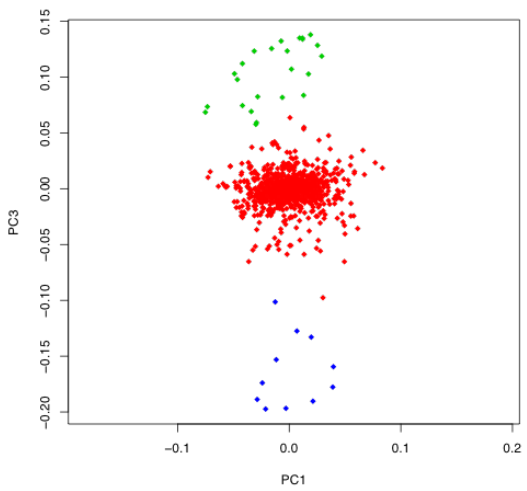
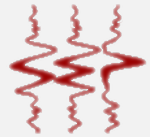


Our Method Adaptations

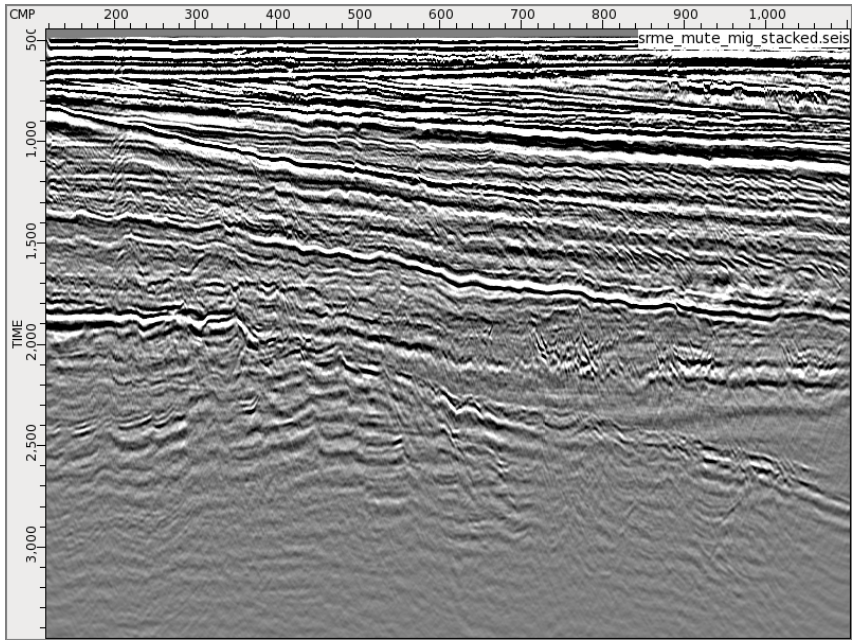


We expand on the PCA technique by:

1. Using field data.
2. Evaluating higher principal components.
3. Using synthetic model to evaluate what affects principal components.

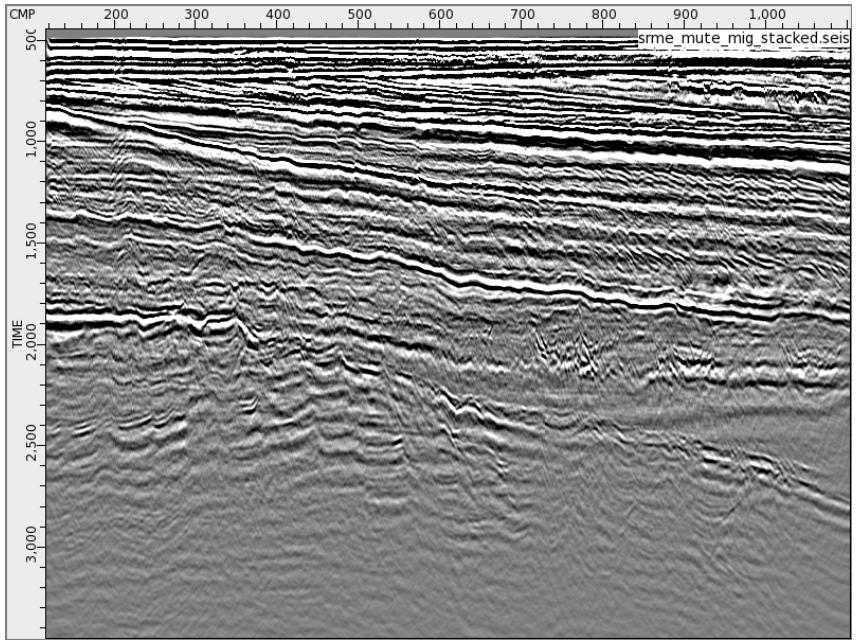
Data

- Mobil Viking Graben 2D data.

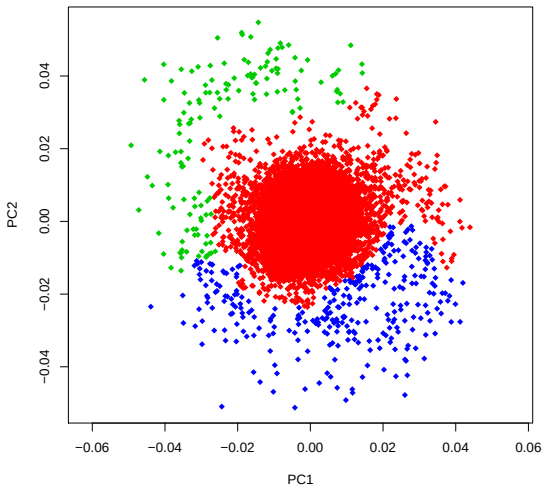


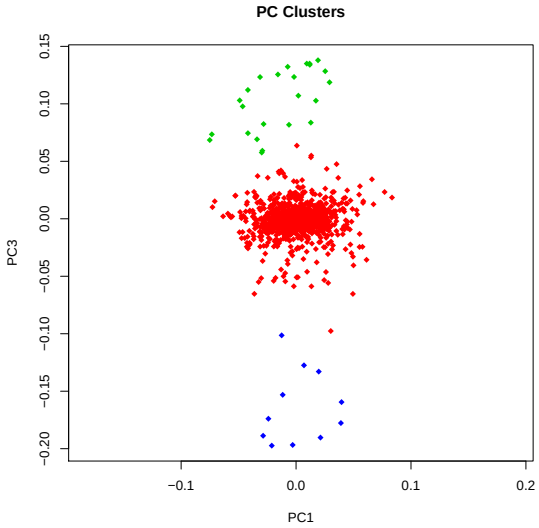
Data

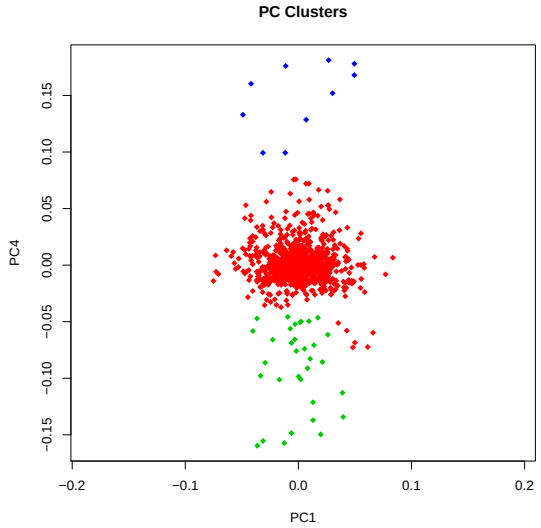
- Mobil Viking Graben 2D data.
- Preprocessing
  - Amplitude balancing.
  - Surface related multiple elimination.
  - Prestack Kirchhoff migration.

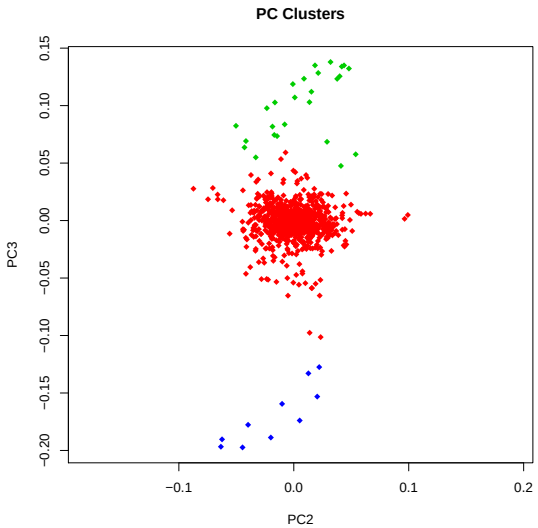


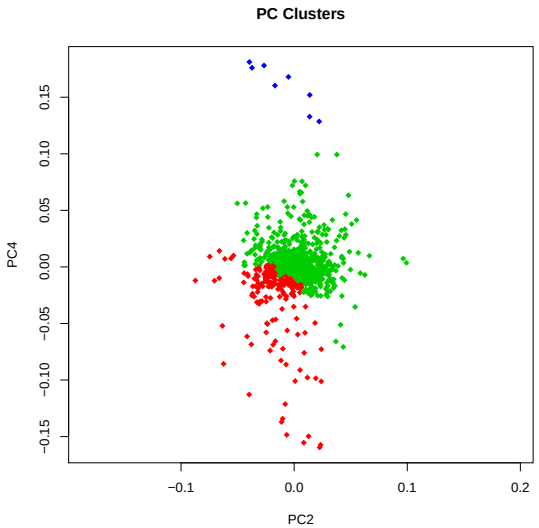
Preliminary Results

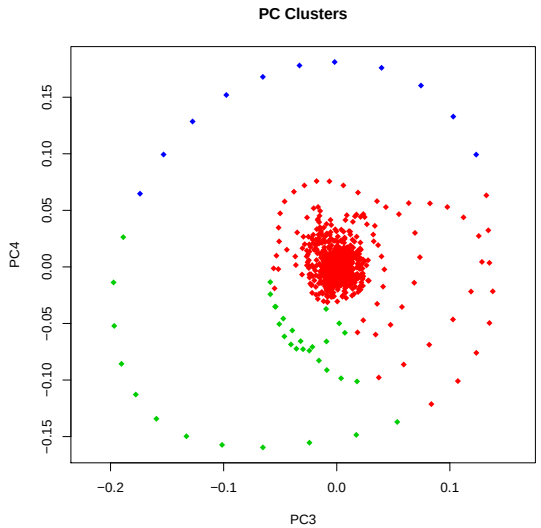




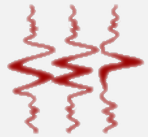








Towards a Better Understanding



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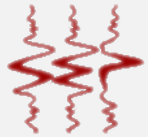

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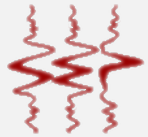

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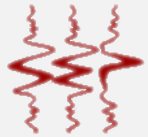

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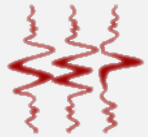

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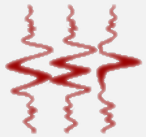
- How can we bridge the gap between PCA and rock physics?
- Link PCA anomalies to known physical anomalies.
  - Create synthetic earth models.
  - Insert various anomalies (gas, oil, anisotropy, attentuation).
  - Observe effects on principal components.

Moving Forward



- Map to image space

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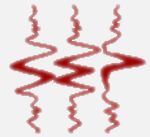

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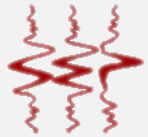

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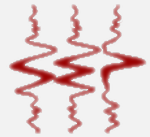

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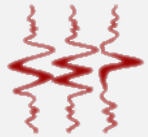
- Forward modeling to link to physics

Thanks for listening



Questions?