Deep learning for DAS-microseismic source estimation

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Problem Statement

- Different source mechanisms produce distinct DAS-seismic records.
- Can machine learning be used to learn these distinct features and characterize data based on source mechanics?
Convolutional Autoencoder (CAE) Architecture

GOAL: Minimize difference between input and reconstructed images

\[ J(W) = \| x_{in} - \hat{x} \|^2 \]
Convolutional Autoencoder (CAE) Architecture

**Input Image** $(x_{in})$

**Encoder**

**Decoder**

**Reconstructed Image** $(\hat{x})$

**GOAL:** Minimize difference between input and reconstructed images

$$J(W) = \|x_{in} - \hat{x}\|^2$$

**40 Epochs**
Convolutional Autoencoder (CAE) Architecture

Result: End-to-end feature extractor which maps an input image to its most salient features
Synthetic Test Dataset

- 10,000 microseismic images generated with analytic modeling tool.
  - 80% of images used to train CAE.
  - 20% of images used for validation.

- Random moment tensors constrained by being compensated linear vector dipole, tensile crack, or double couple dominate.
Pre-Processing for Moment Tensor Feature Extraction

- Raw data
- Pick apex, compute NMO, flatten
- Window and extract P-wave and S-wave
- Input for CAE
Goal: Select minimally complex feature space that leads to reasonable image reconstruction.
Generative adversarial networks are a two-player game

**Generator**: Given latent features - produce believable moment tensor for input feature representation.

**Discriminator**: Given a latent feature and label pair, discern physical labels from those generated by network $G$. 

![Diagram showing the flow of features and labels through the generator (G) and discriminator (D) networks.]
GAN Labeling of DAS-Microseismic Images
Full Moment Tensor Estimation

Error in $M_{xx}$

Error in $M_{xy}$

Error in $M_{xz}$

Error in $M_{yy}$

Error in $M_{yz}$

Error in $M_{zz}$
Field Data Reconstruction

Extracted P-wave

Extracted S-wave

Field Data

Reconstruction
Modeling and field data comparison

\[
M = \begin{bmatrix}
0.69 & 1.00 & -0.69 \\
1.00 & 0.35 & -0.22 \\
-0.69 & -0.22 & 0.69
\end{bmatrix}
\]

<table>
<thead>
<tr>
<th></th>
<th>Predicted</th>
<th>Field</th>
<th>Modeling</th>
</tr>
</thead>
<tbody>
<tr>
<td>u</td>
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<td>-0.2012</td>
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<tr>
<td>v</td>
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<td>0.3019</td>
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Field Data

Modeled Data
Conclusions and Future Work

Conclusions

• Convolutional autoencoder trained to compress input data to feature space representation.

• Processing of input data shown to be crucial.

• Two methods developed to use features for source mechanism information.
  • Clustering shown to group images by similar source mechanisms.
  • Generative adversarial network able to predict Hudson or full moment tensor.

• Extension to field data generated positive results.

Future Work

• Further study extension of methods to field data.

• Extend method for enhanced moment tensor information such as strike or dip.

• Use similar methods to launch other machine learning initiatives.
• CREWES Sponsors

• NSERC – CRDPJ 461179-13 and CRDPJ 543578-19

• CREWES Staff and Students

• Chevron Corporation
Estimating Seismic Source Mechanisms

- Source mechanisms estimated through moment tensor inversion (MTI)
- Allows for inferences about fracture mechanics.
  - Fracture orientations
  - Likely HC flow paths
  - Localized in situ stress state
  - Optimization of HF treatments
- MTI is an expensive and time-consuming process.
- Not readily transferable to new acquisition technologies like Distributed Acoustic Sensing (DAS).

\[
M = \begin{bmatrix}
M_{xx} & M_{xy} & M_{xz} \\
M_{yx} & M_{yy} & M_{yz} \\
M_{zx} & M_{zy} & M_{zz}
\end{bmatrix}
\]
Workflow

1. **Raw DAS-Microseismic Data**
2. **Process Data**
3. **Network Trained?**
   - No → **Train neural network**
   - Yes -> **Feature extractor**
4. **Feature space representation**
5. **Method 1**
   - Cluster images with similar source mechanics.
   - New data characterized based on cluster it belongs too.
6. **Method 2**
   - Train advanced network to learn moment tensor.
   - Estimate moment tensor of new datasets.
7. **Reduce Dimensionality** (PCA or TSNE)
   - **Clustered Images**
8. **Train Generative Adversarial Network**
   - **Prediction of Source Mechanism**
Method 1: *Clustering* in which we group points such that images with strong correlated features reside in the same group.

Method 2: *Generative adversarial network* that learns mapping from features for moment tensor estimate.
Dimensionality Reduction

- Dimensionality reduction techniques can help clustering algorithms find natural clusters.
- T-SNE is a nonlinear dimensionality reduction technique for visualizing high dimensional data.
- Separates natural clusters and eliminates crowding.

T-distributed stochastic neighbor embedding (T-SNE)
Clustering and Source Mechanism

- +CLVD Dominated
- TCO Dominated
- DC Dominated
- -CLVD Dominated
- TCC Dominated
- DC Dominated
- -CLVD/DC Mixed
- Noise
Method 1: *Clustering* in which we group points such that images with strong correlated features reside in the same group.

Method 2: *Generative adversarial network* that learns mapping from features for moment tensor estimate.
Reconstruction 10 Features

Wrong predicted moveout
Wrong node location
Incorrect polarity
Poor P-wave prediction
Wrong predicted moveout
Reconstruction 25 Features

Corrected moveout, but poor amplitude prediction

Poor p-wave prediction

Poor P-wave prediction

Corrected moveout, but poor amplitude prediction