Deep learning for DAS-microseismic source estimation

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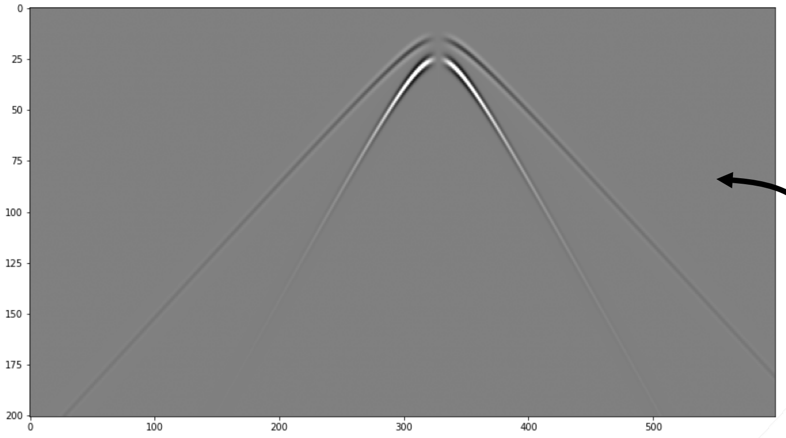
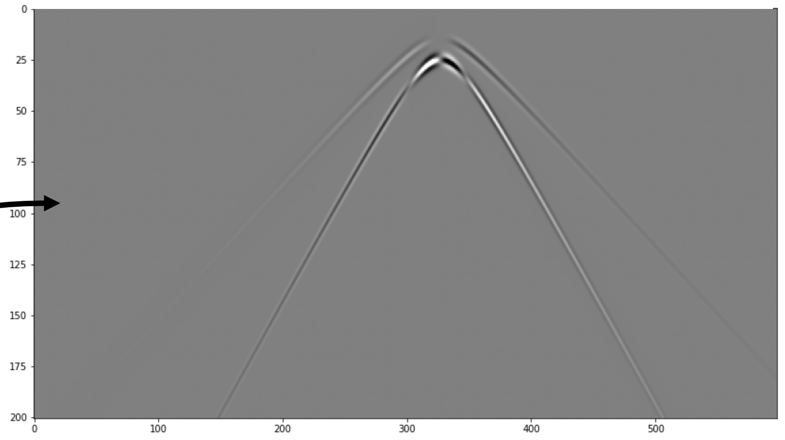
CREWES Annual Sponsors Meeting

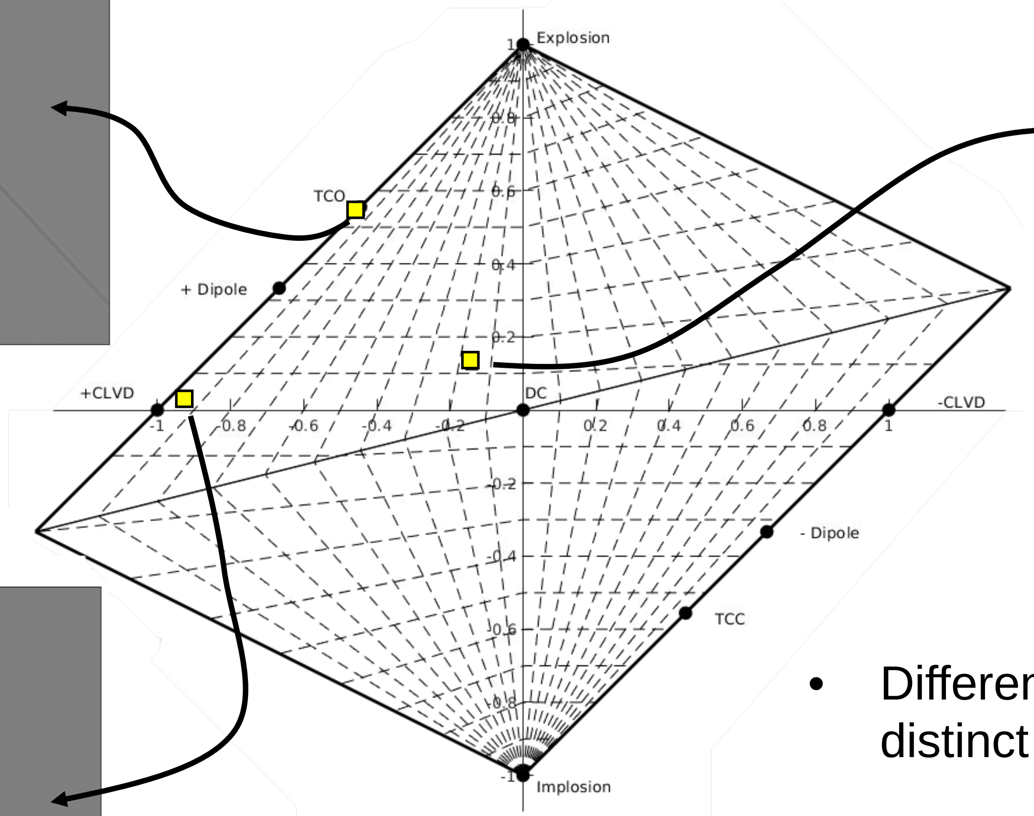
Problem Statement

Tensile Crack

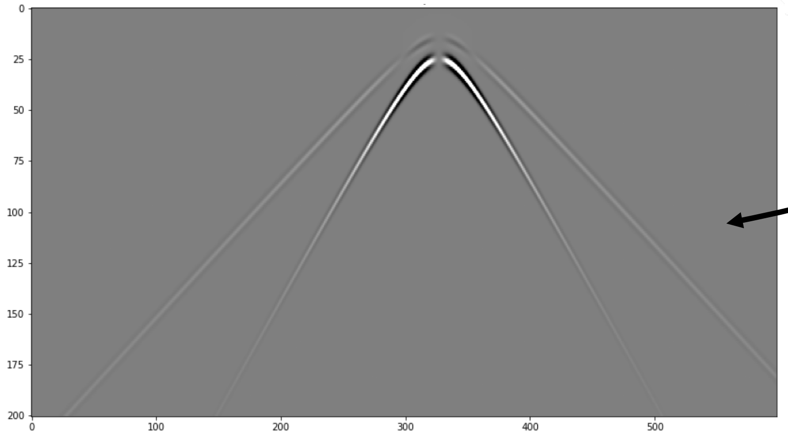


Double Couple



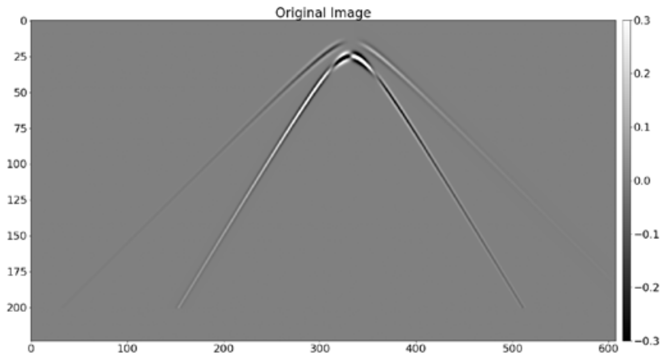


CLVD



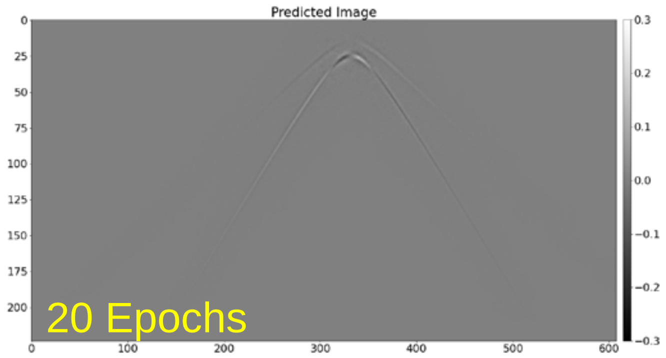
- Different source mechanisms produce distinct DAS-seismic records.
- **Can machine learning be used to learn these distinct features and characterize data based on source mechanics?**

Convolutional Autoencoder (CAE) Architecture



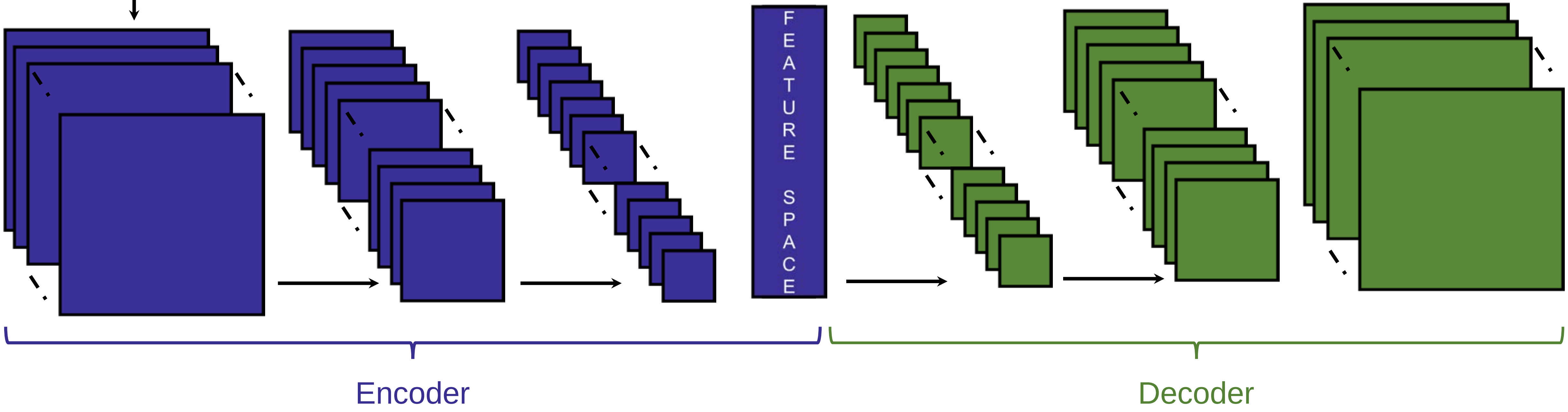
GOAL: Minimize difference between input and reconstructed images

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

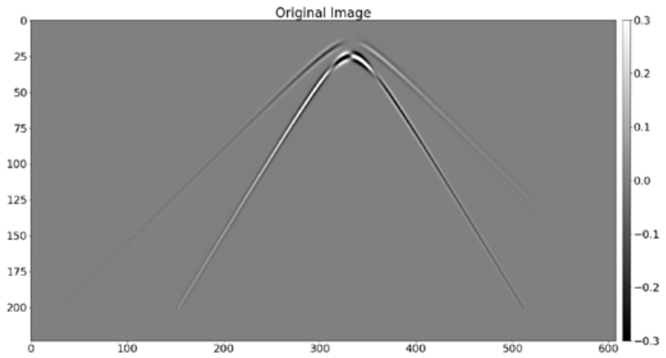


Input Image (x_{in})

Reconstructed Image $(\hat{x})$



Convolutional Autoencoder (CAE) Architecture



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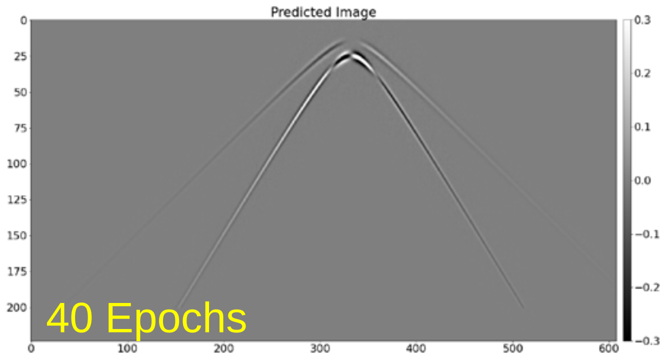

Input Image (x_{in})

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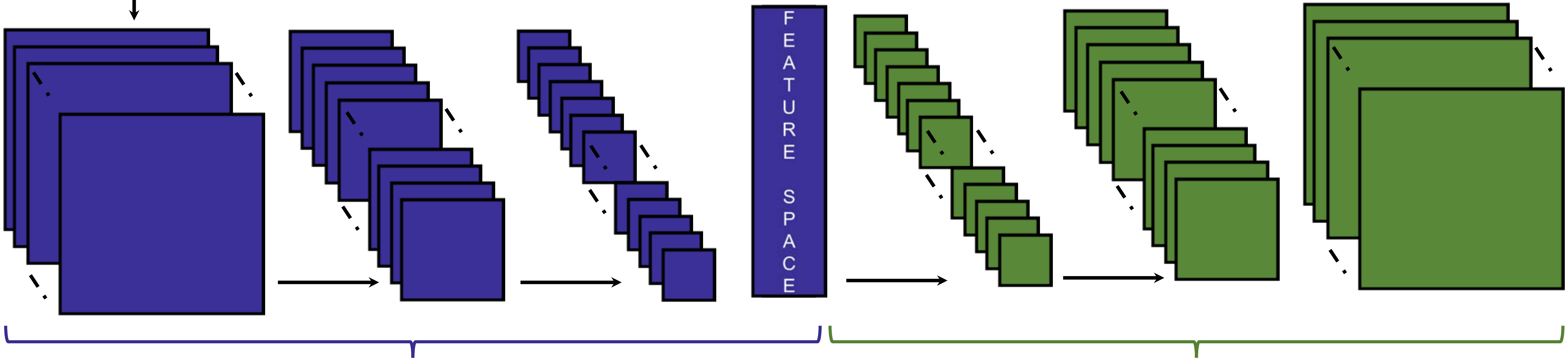
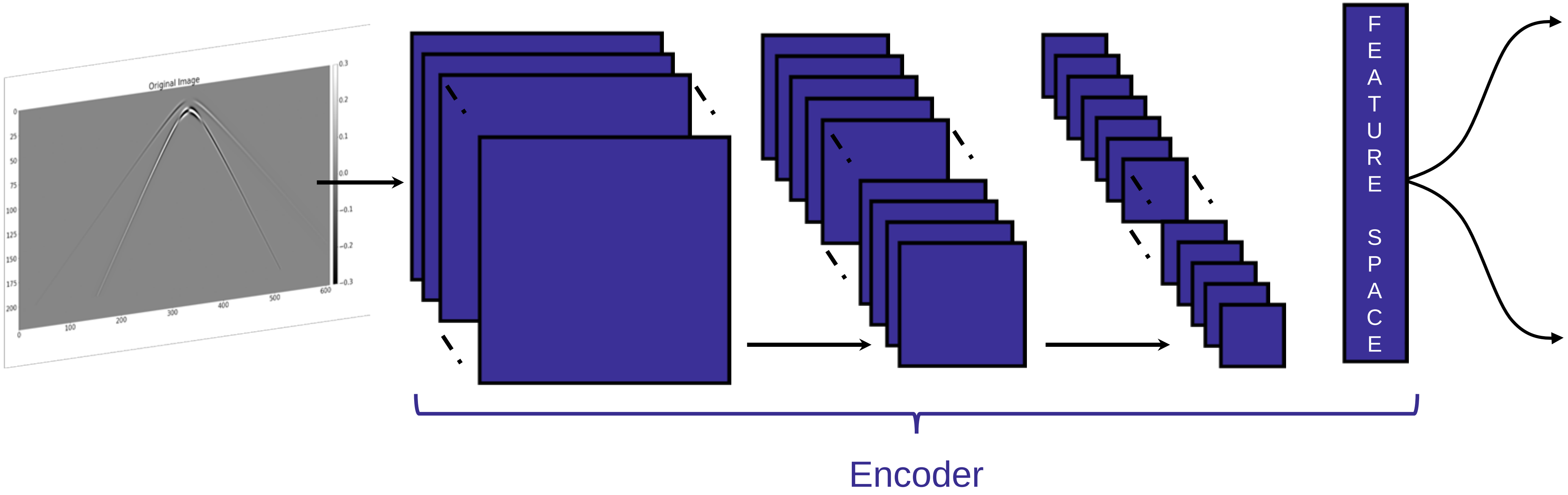


Encoder

Decoder

Convolutional Autoencoder (CAE) Architecture



Clustering

- K-means
- K-means++
- OPTICS
- **DBSCAN**

Estimate MT label

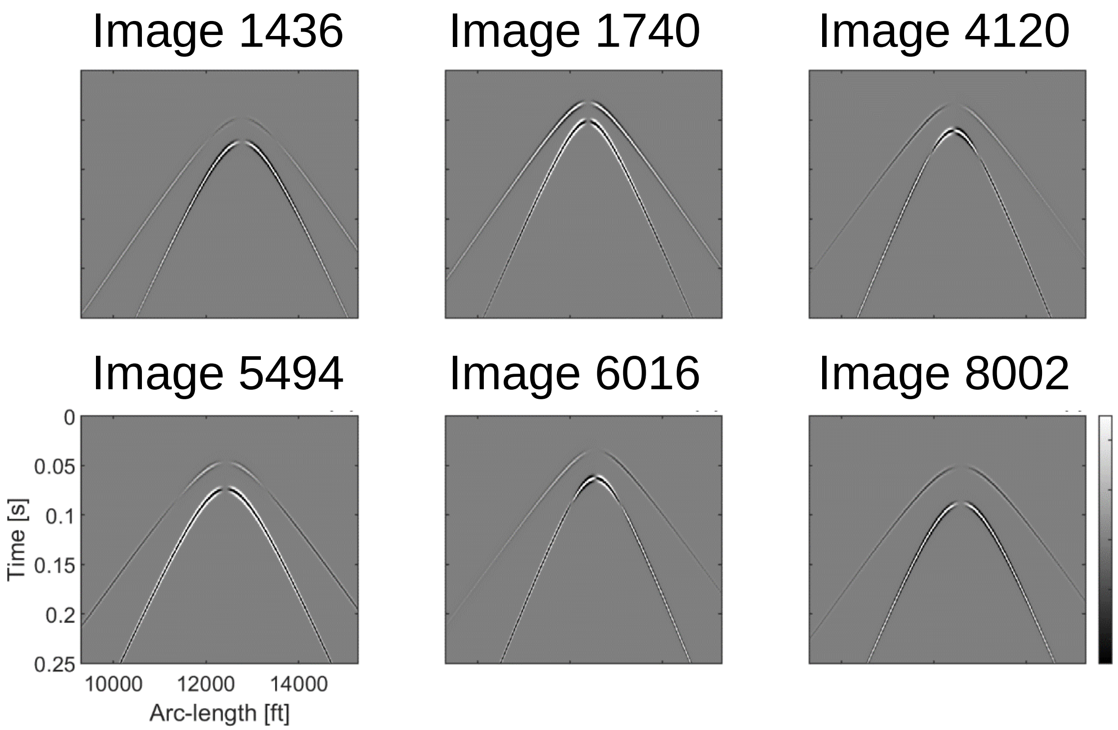
- Generative adversarial network

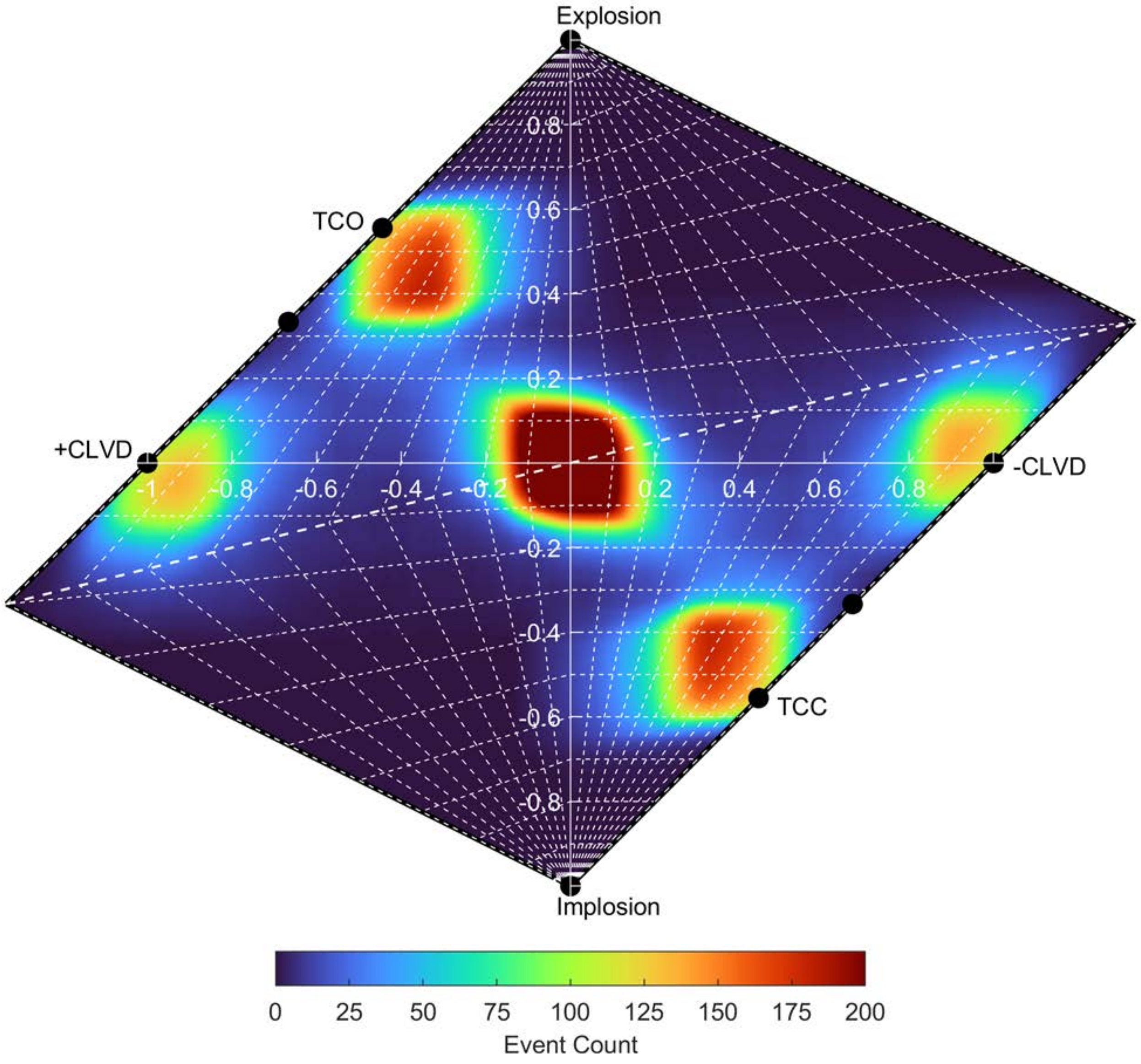
Result: End-to-end feature extractor which maps an input image to its most salient features

Synthetic Test Dataset

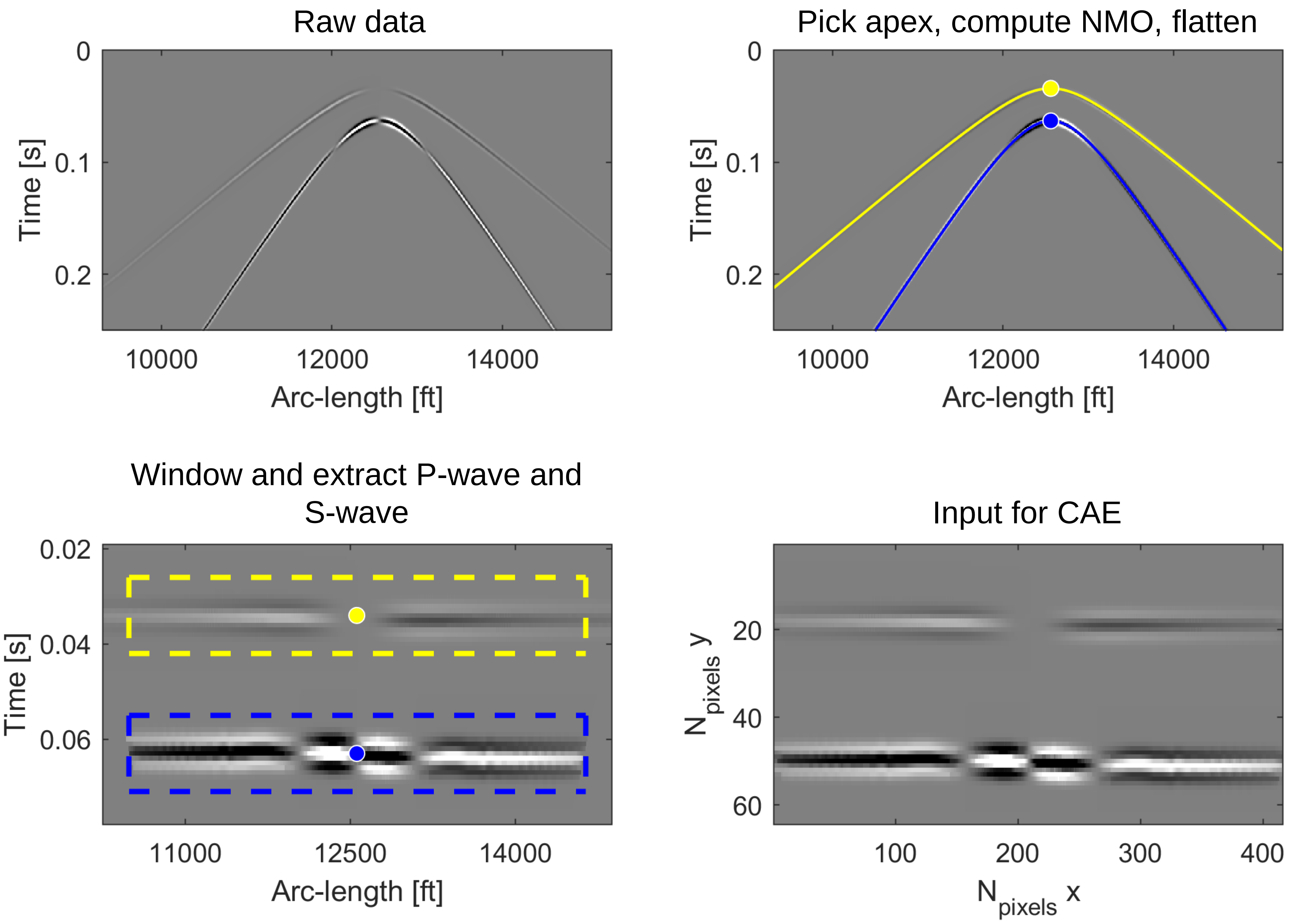
- 10,000 microseismic images generated with analytic modeling tool.
  - 80% of images used to train CAE.
  - 20% of images used for validation.

- Random moment tensors constrained by being compensated linear vector dipole, tensile crack, or double couple dominate.

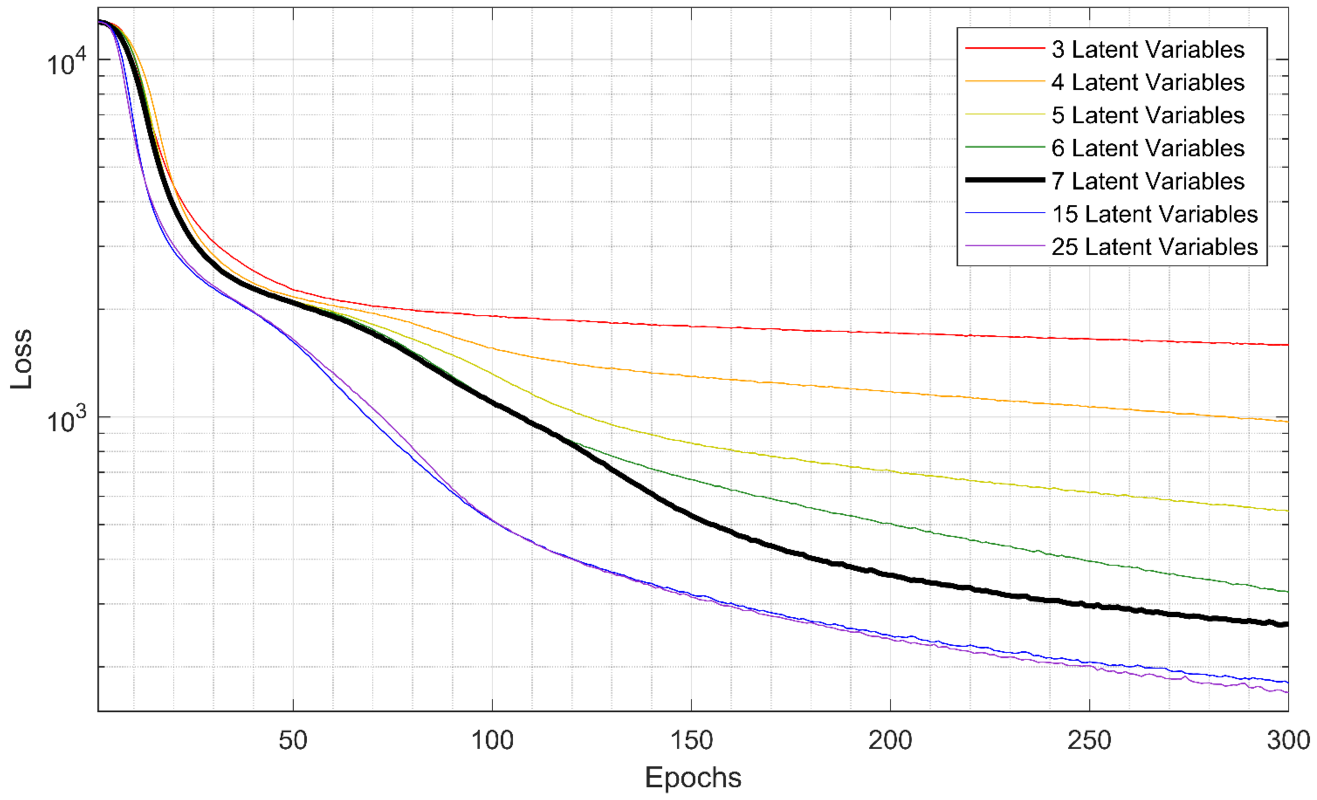


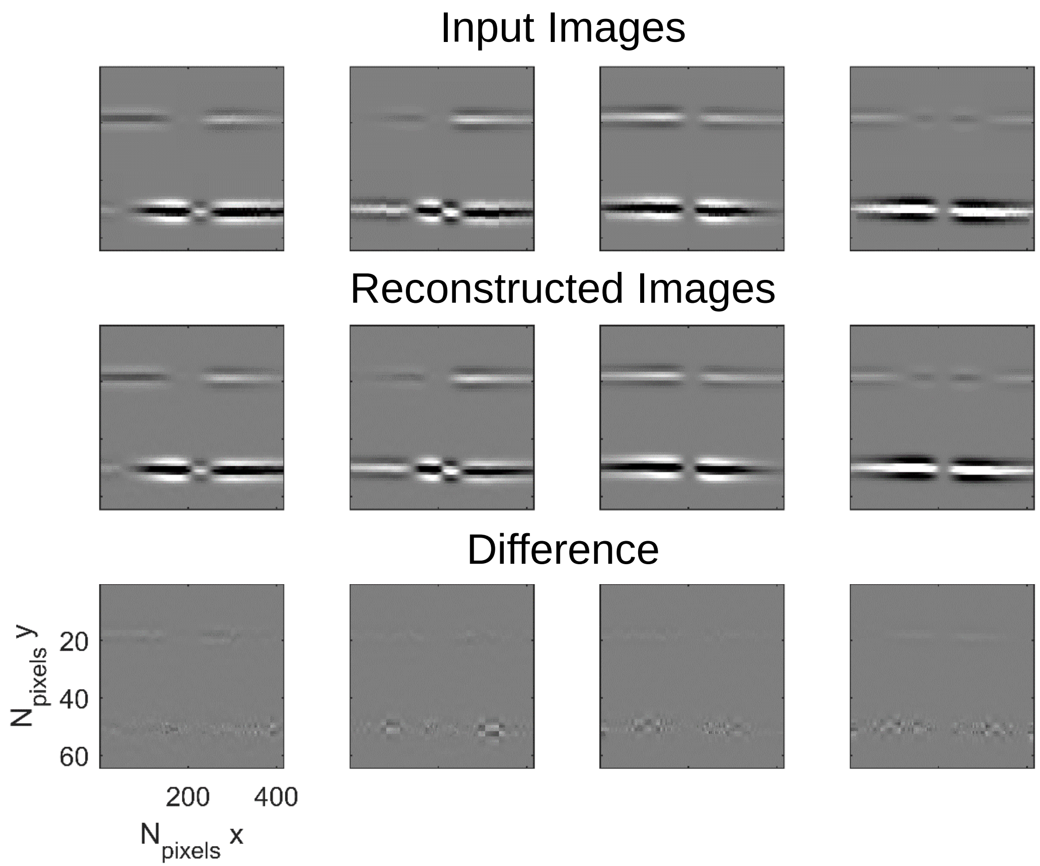


Pre-Processing for Moment Tensor Feature Extraction



Goal: Select minimally complex feature space that leads to reasonable image reconstruction.



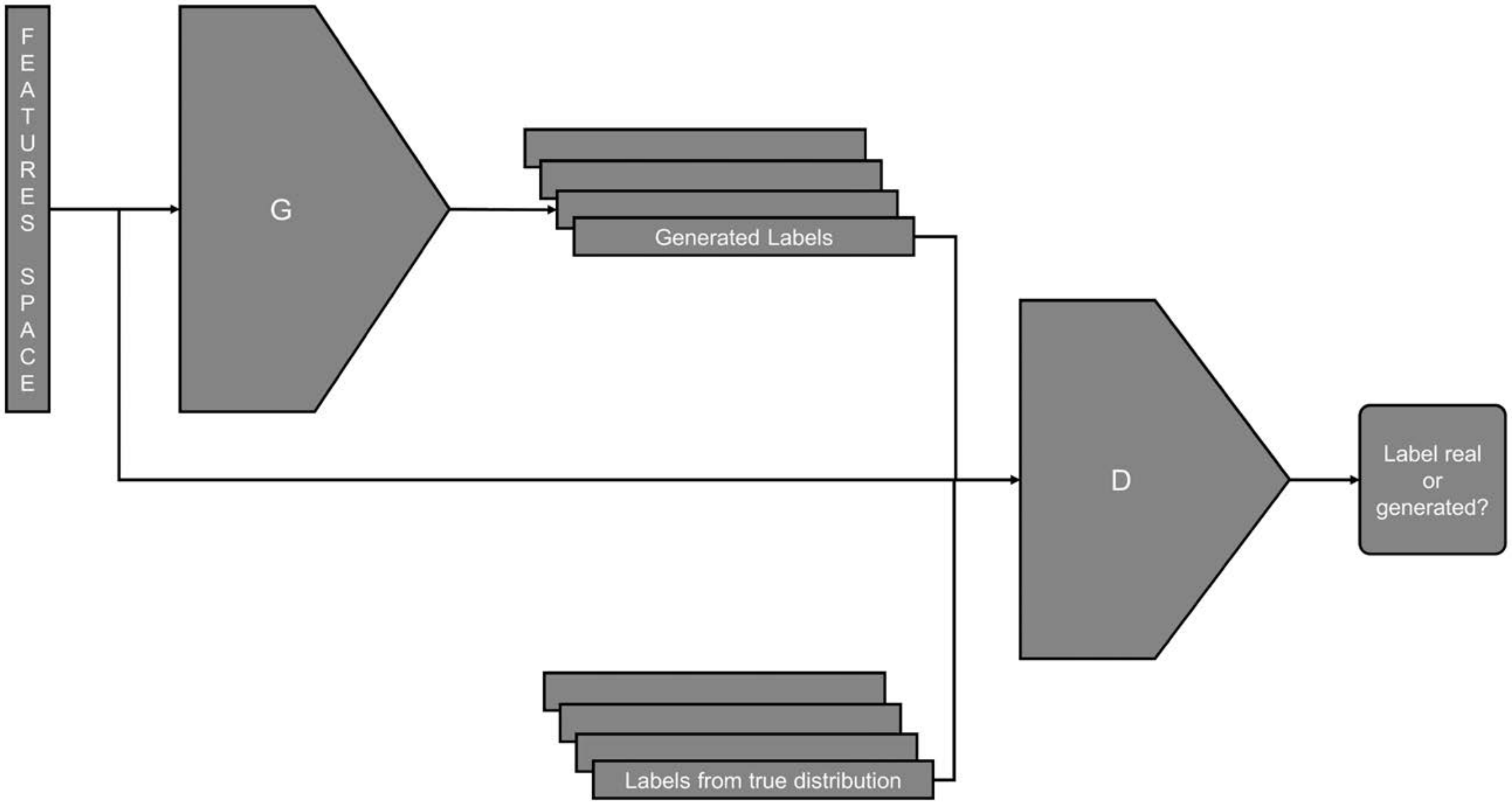


Generative Adversarial Network for Labelling

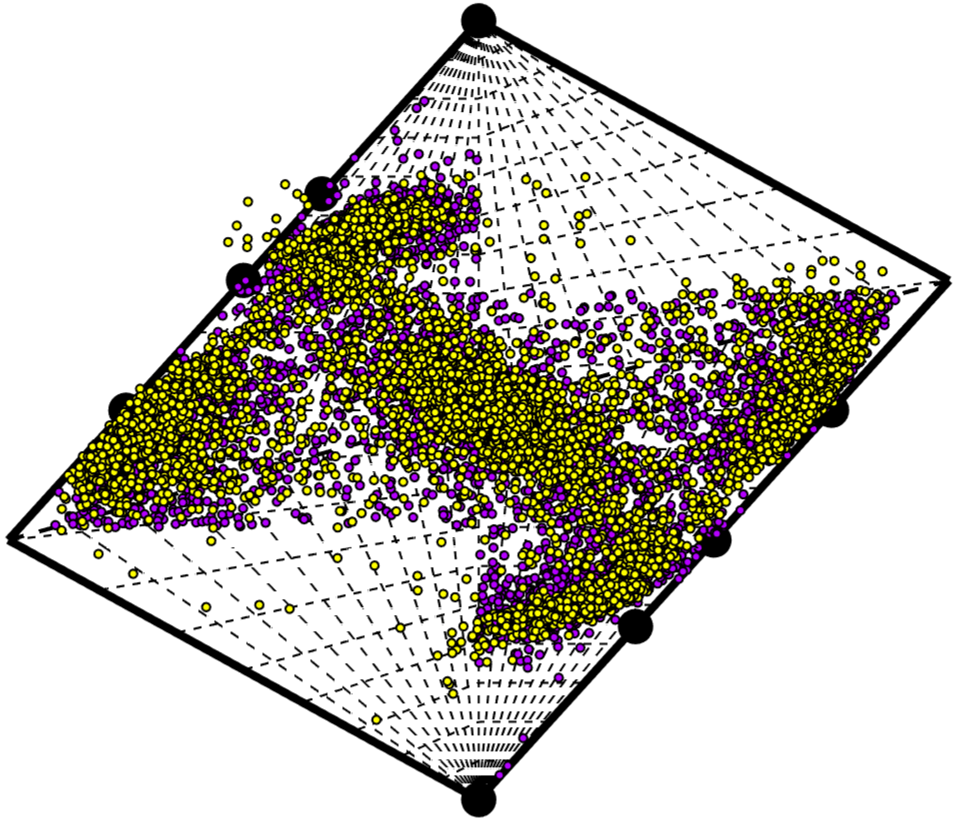
Generative adversarial networks are a two-player game

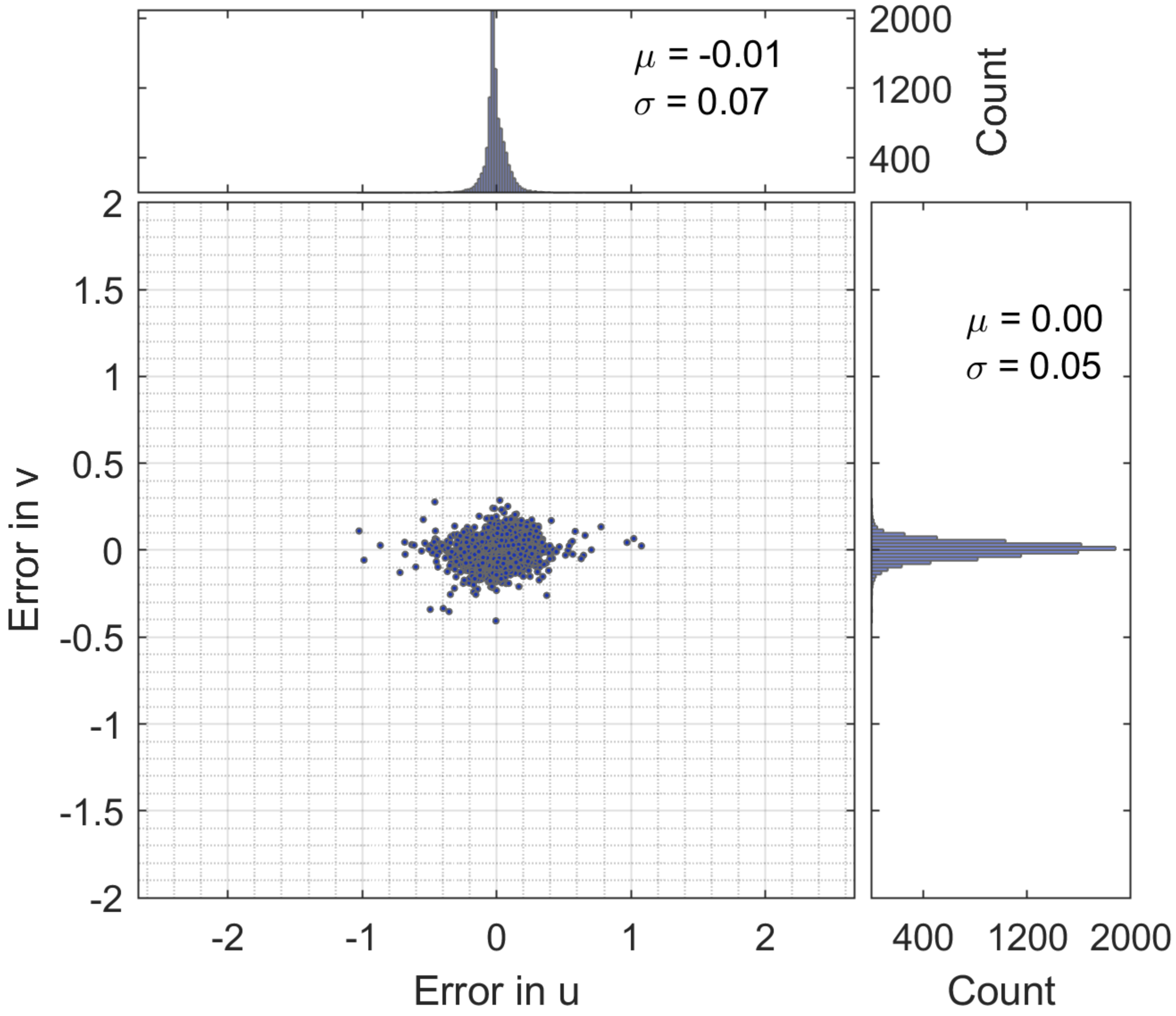
Generator: Given latent features - produce believable moment tensor for input feature representation.

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

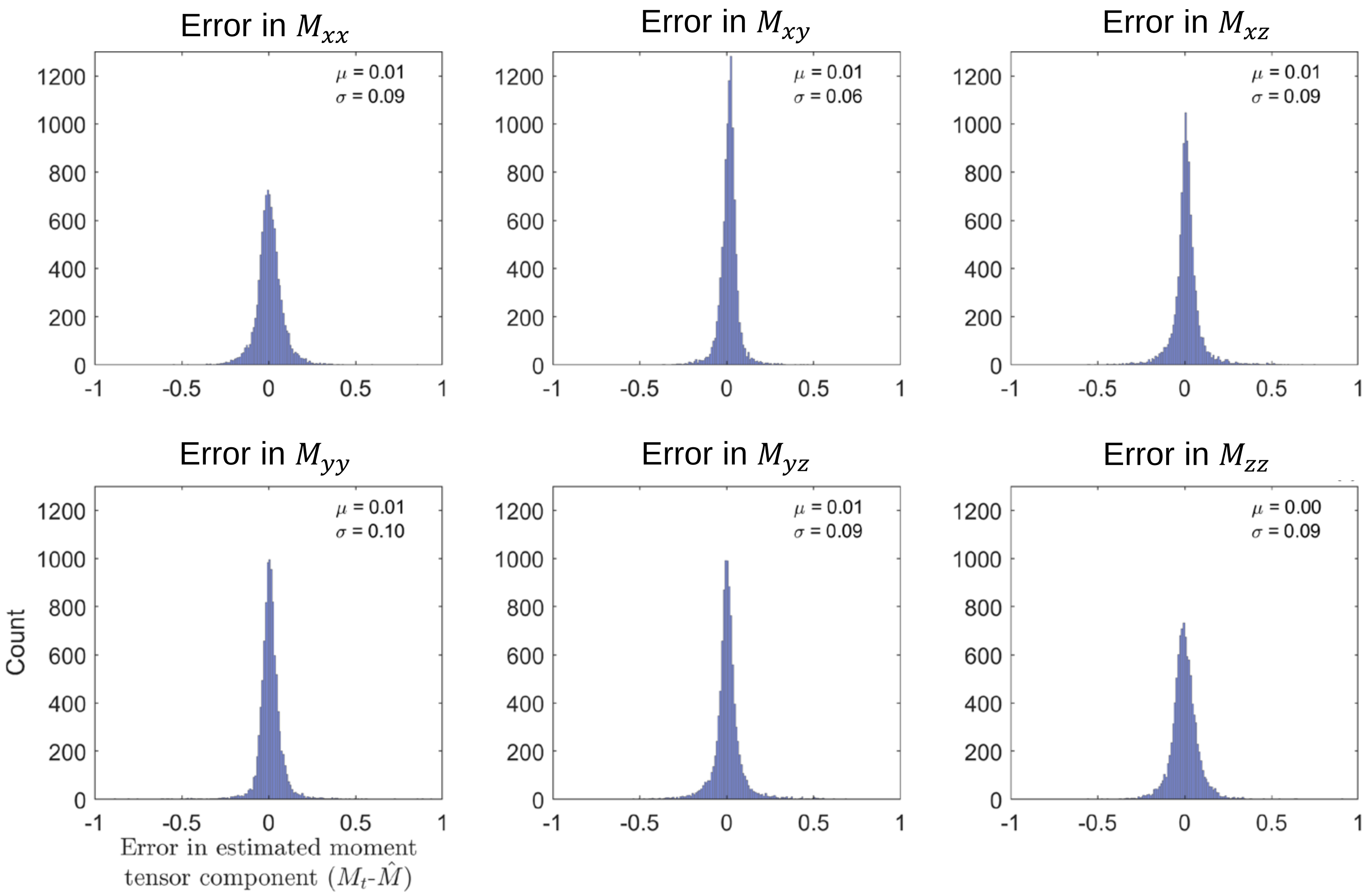


GAN Labeling of DAS-Microseismic Images

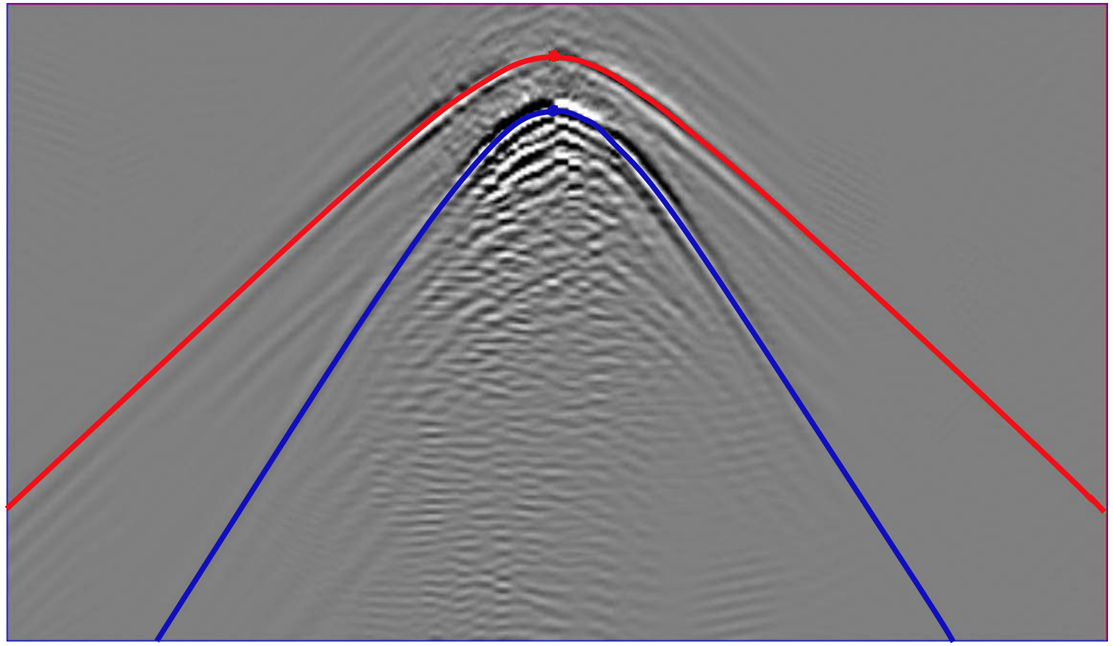


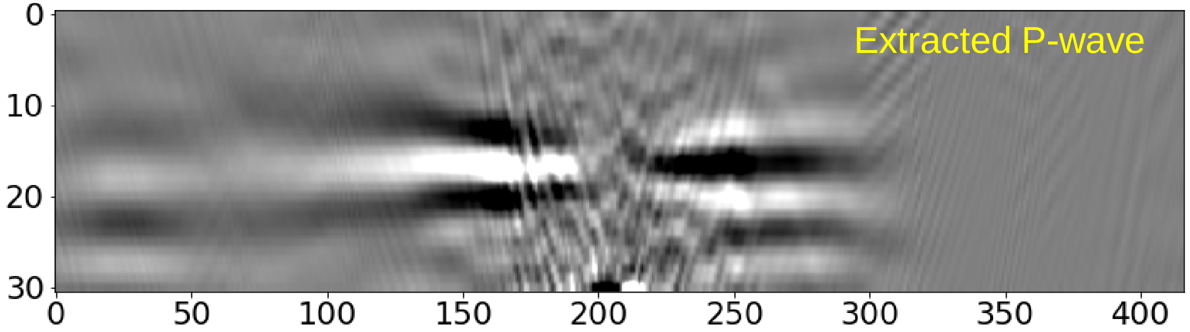


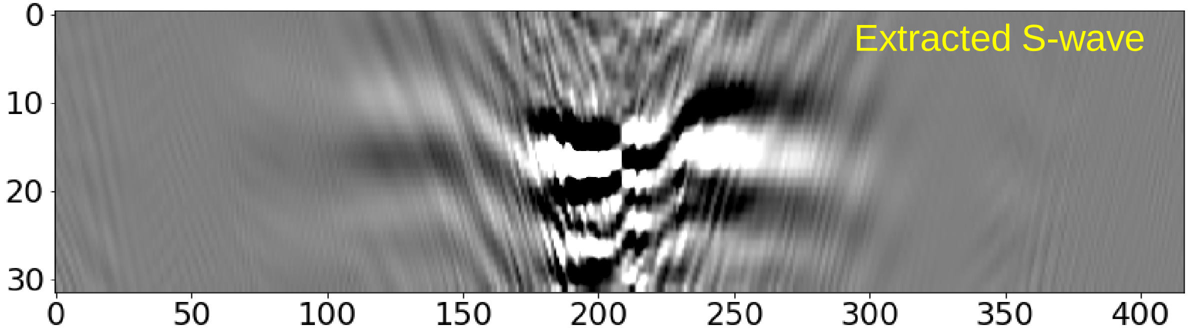
Full Moment Tensor Estimation

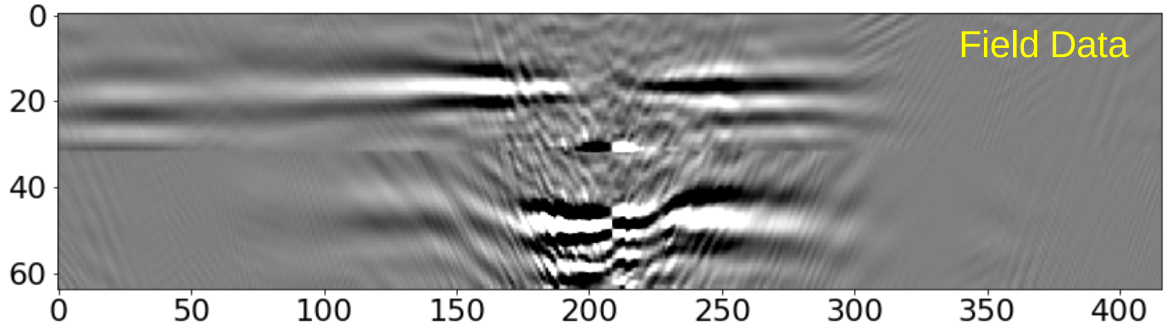


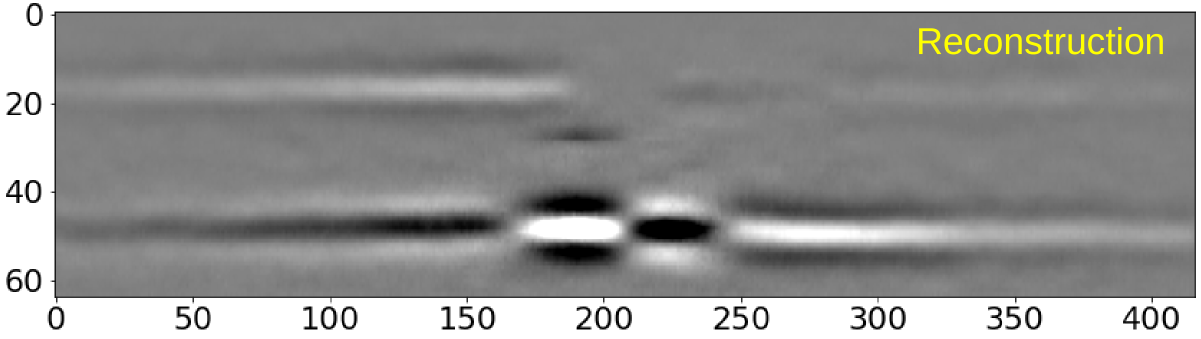
Field Data Reconstruction







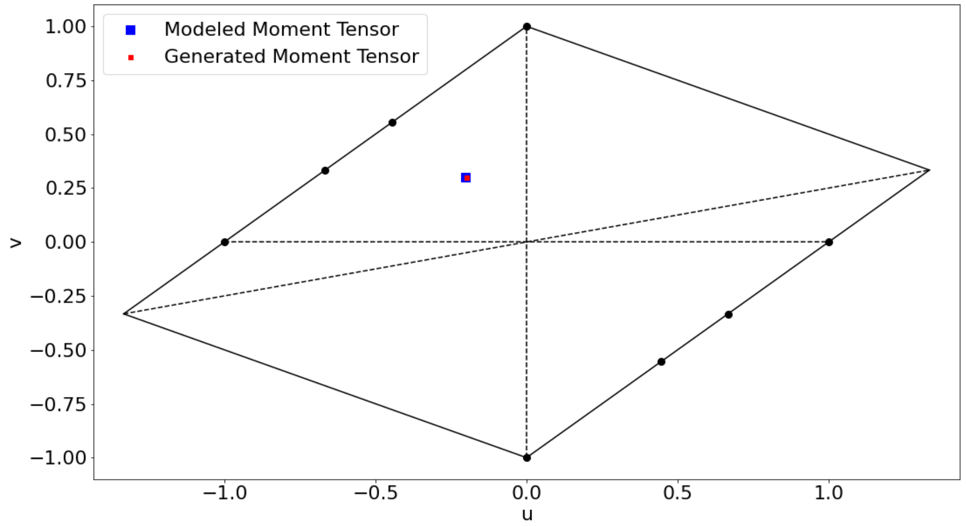


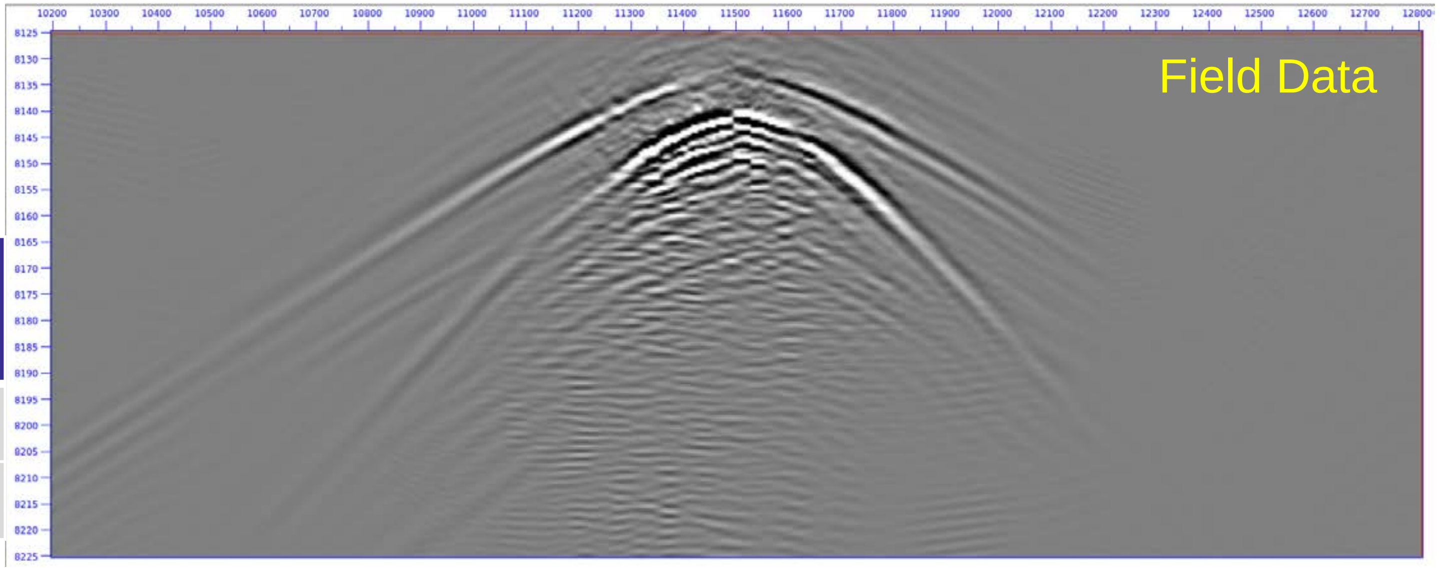


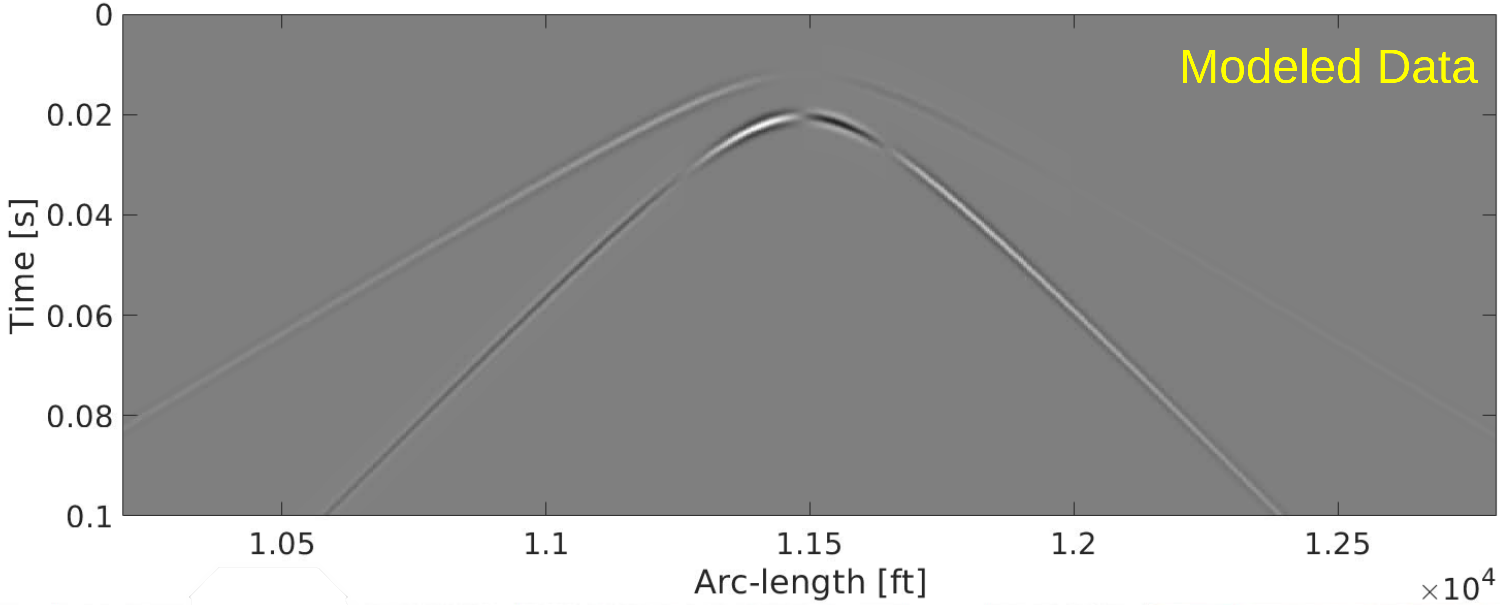
Modeling and field data comparison

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

	Predicted Field	Modeling
u	-0.1994	-0.2012
v	0.3006	0.3019







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.

Acknowledgements

- CREWES Sponsors
- NSERC – CRDPJ 461179-13 and CRDPJ 543578-19
- CREWES Staff and Students
- Chevron Corporation

Estimating Seismic Source Mechanisms

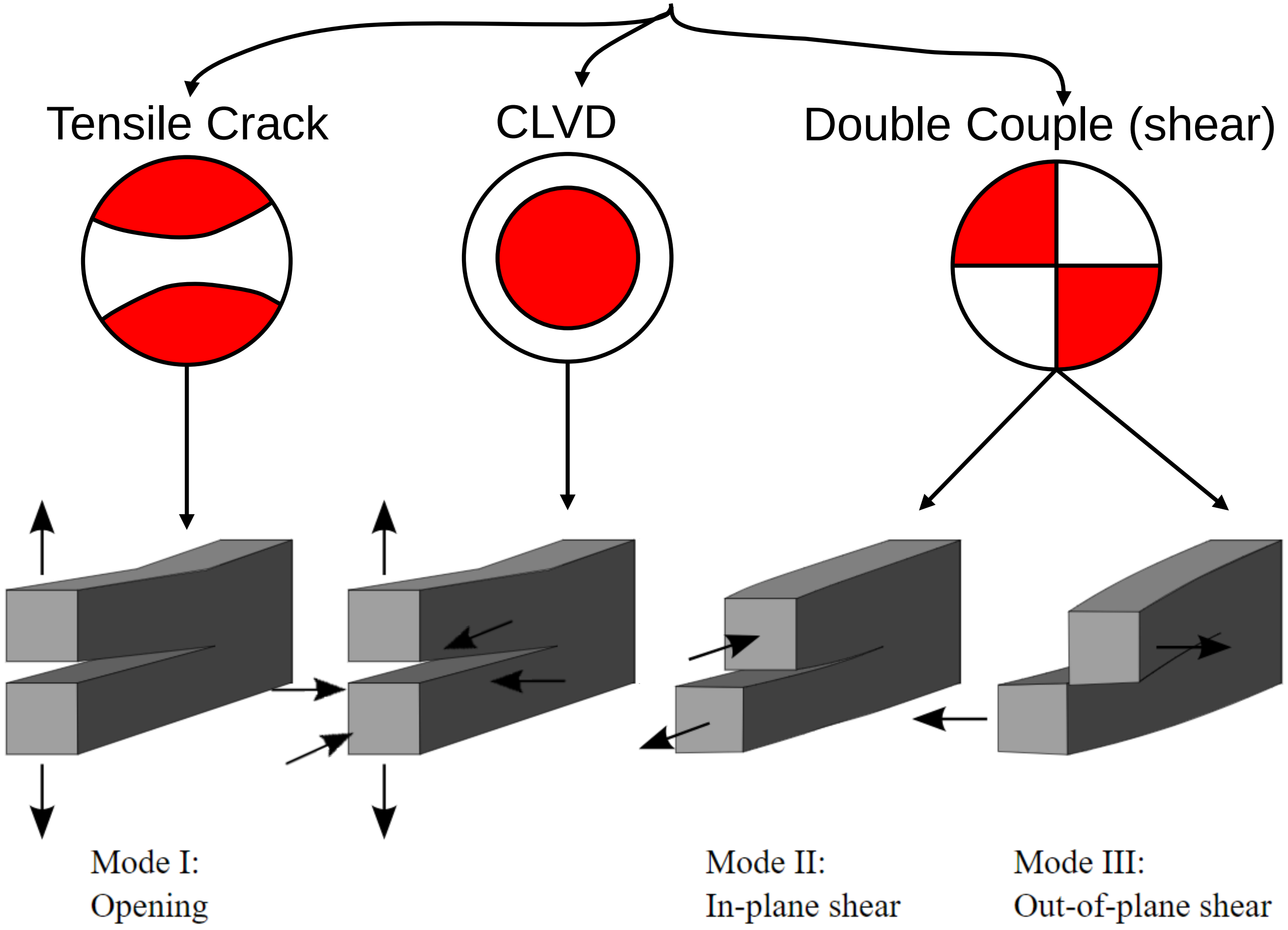
- Source mechanisms estimated through moment tensor inversion (MTI)

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

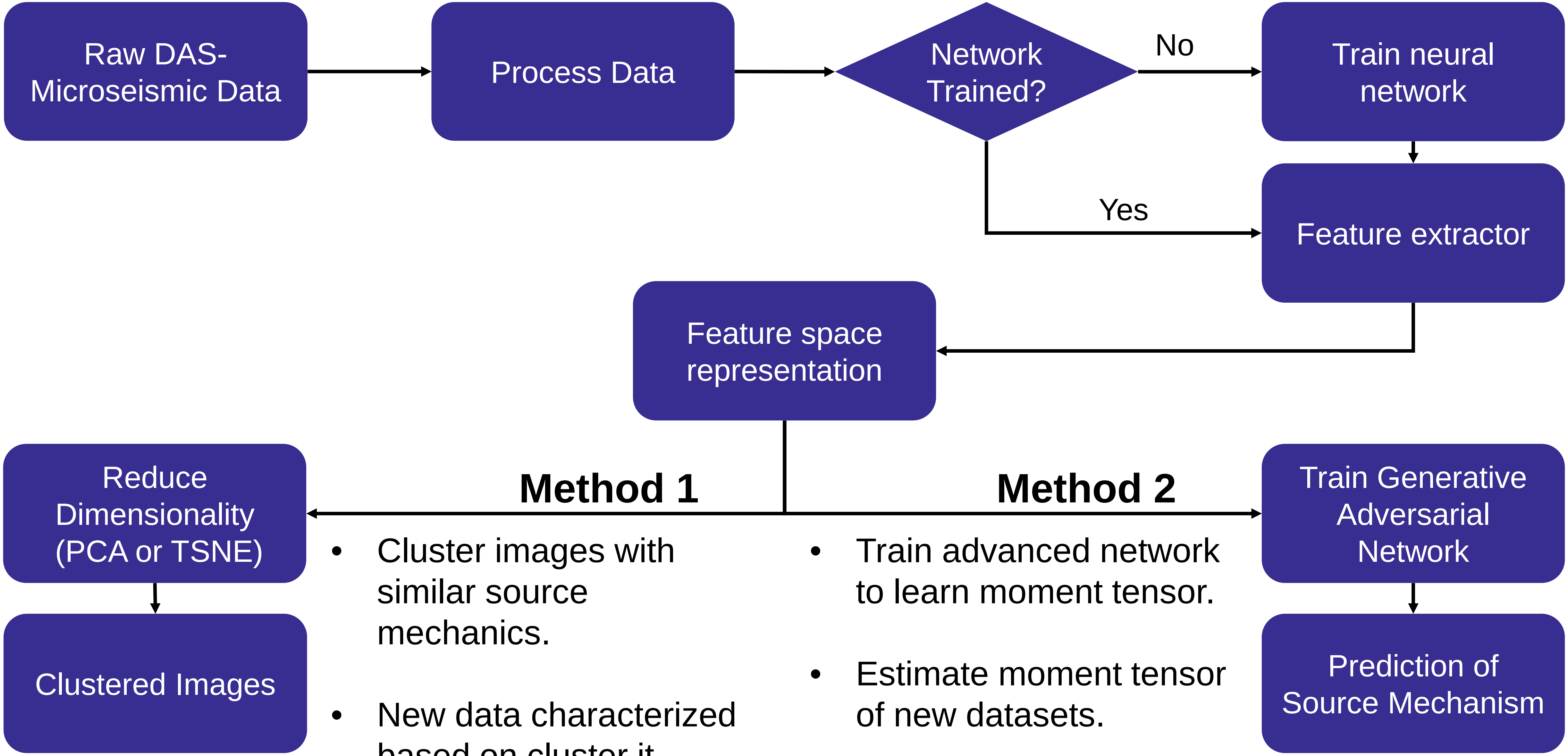
- Allows for inferences about fracture mechanics.
  - Fracture orientations
  - Likely HC flow paths
  - Localized in situ stress state
  - Optimization of HF treatments

- MTI is an expensive and time-consuming process.

- Not readily transferable to new acquisition technologies like Distributed Acoustic Sensing (DAS).



Workflow



Method 1

- Cluster images with similar source mechanics.
- New data characterized based on cluster it belongs too.

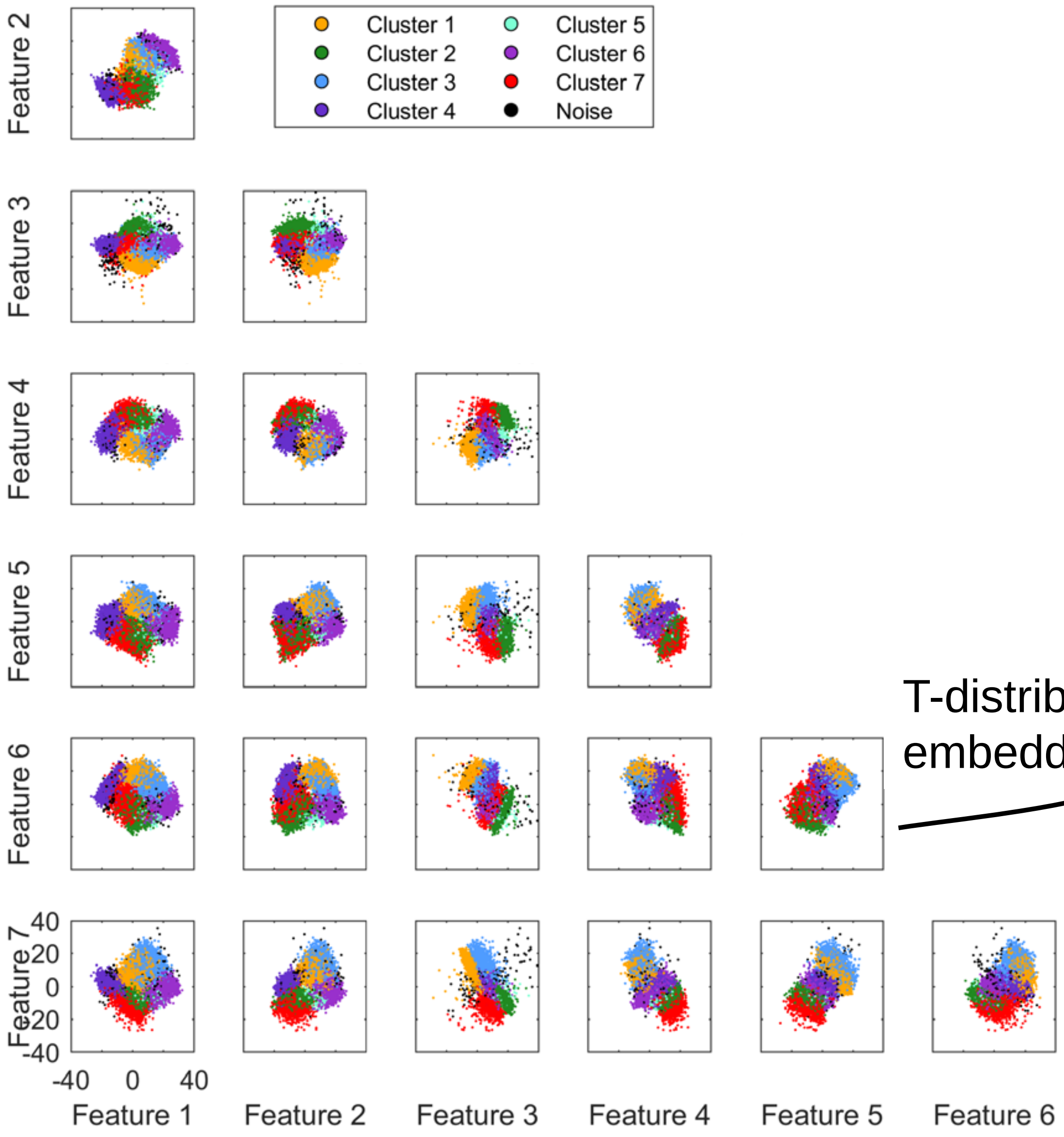
Method 2

- Train advanced network to learn moment tensor.
- Estimate moment tensor of new datasets.

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

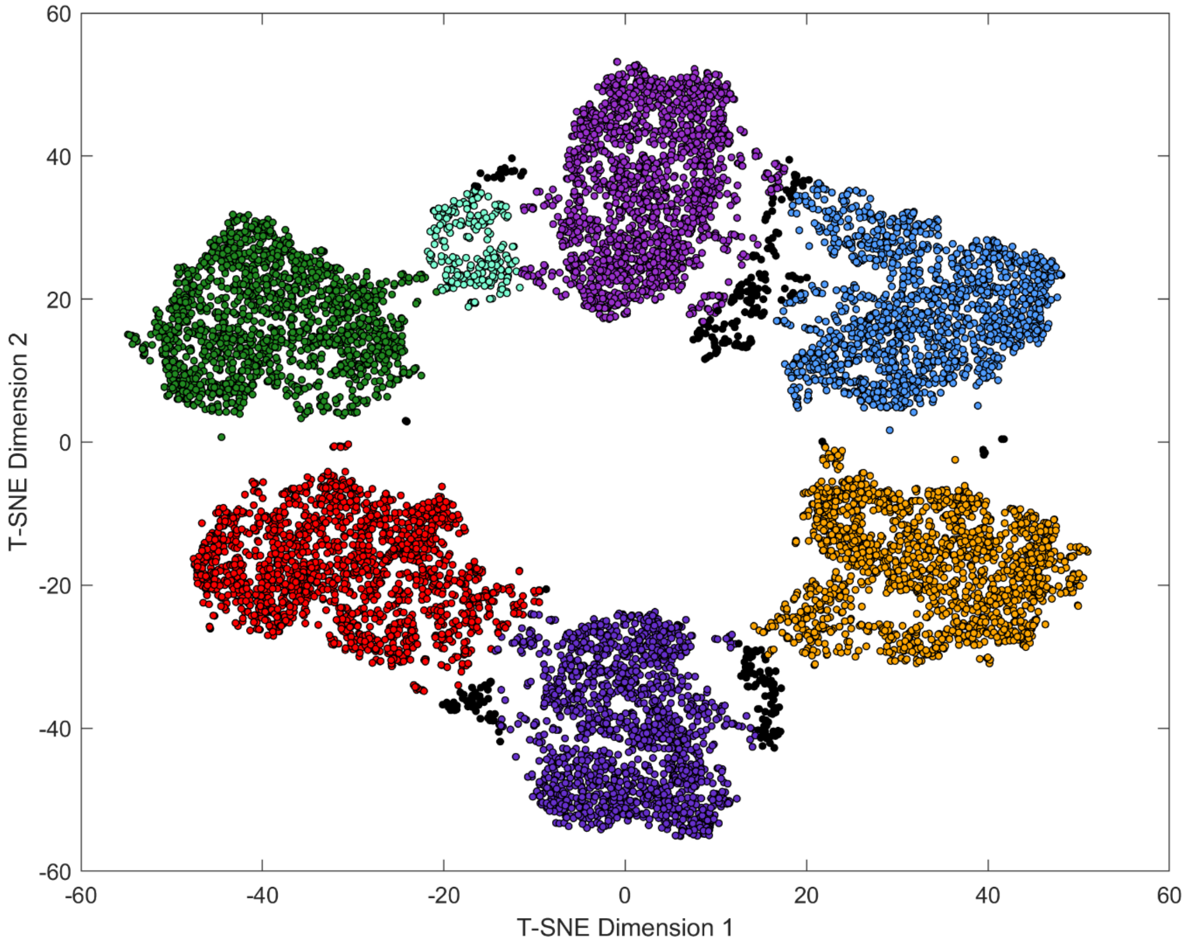


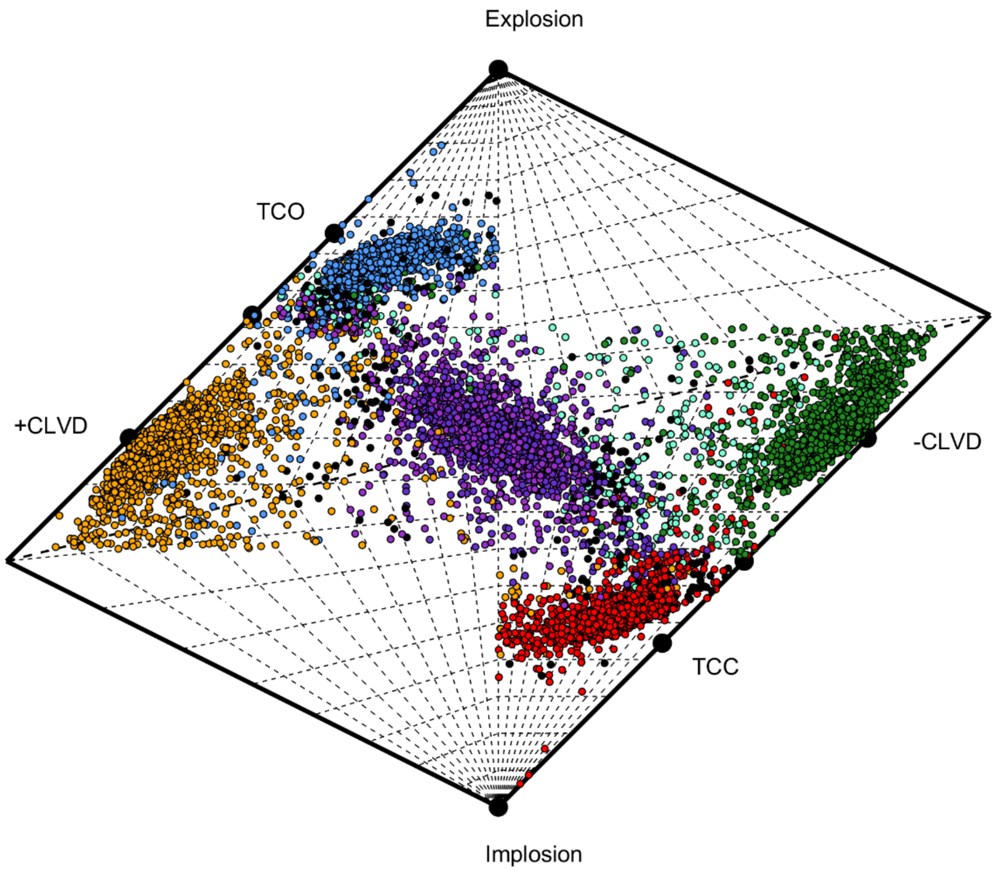
T-distributed stochastic neighbor embedding (T-SNE)

- 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.

Clustering and Source Mechanism

+CLVD Dominated | -CLVD Dominated | -CLVD/DC Mixed
TCO Dominated | TCC Dominated | Noise
DC Dominated | DC Dominated



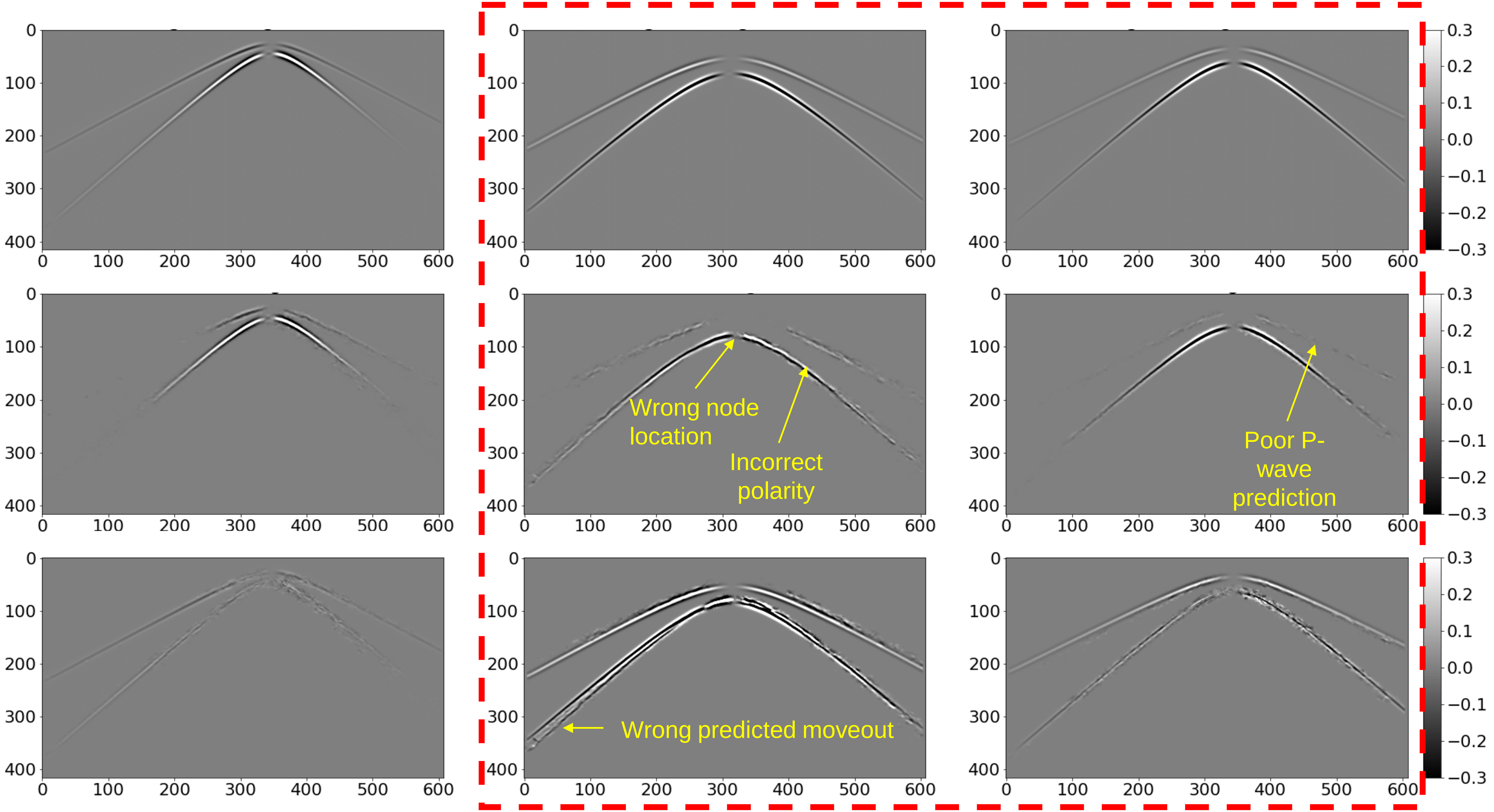


Analyzing Feature Space

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



Reconstruction 25 Features