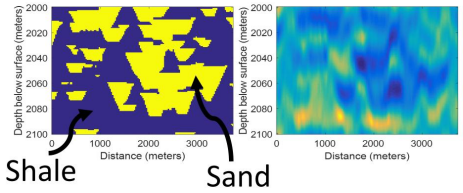
Semantic rock-type segmentation of seismic images

Anshuman Pradhan, *pradhan1@stanford.edu*

Segmenting seismic images into rock-types

Accurate decision-making in the petroleum industry is highly contingent on building a reliable model of the subsurface

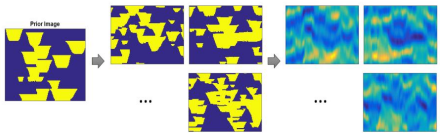
- **Target:** Subsurface rock types, **Data:** Seismic images acquired in an oil field
- **Challenge:** Seismic images lack high frequencies



Synthesis of data for training

Seismic data is normally collected once in an oil-field. So how can we generate data for training?

- **Solution:** Define prior distribution → Perform geo-statistical simulations for rock types → Simulate seismic by wave propagation physics



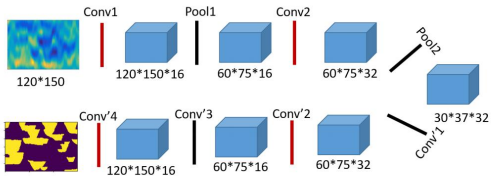
- Train/Dev/Test split: 25000/2500/2500

Efficacy of two semantic segmentation architectures were evaluated:

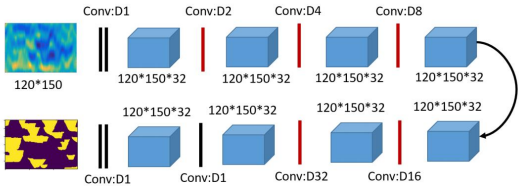
- Fully convolutional networks (FCNs) with encoder-decoder architectures. Spatial information lost due to pooling layers
- FCNs with dilated convolutional layers preserve spatial information by exponential expansion of receptive fields

Semantic segmentation architectures

- Fully convolutional network with encoder-decoder blocks:



- Dilated convolutional architecture:



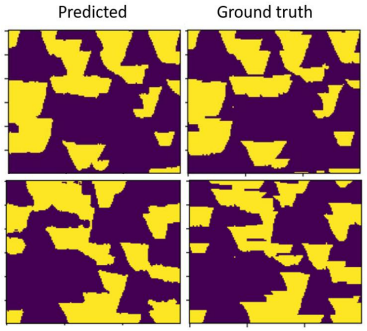
Train/dev/test set performance

Trained for 100 epochs. Metric: Mean pixel-wise accuracy

Architectures	Batch-norm	Training	Dev	Test
Enc-Dec shallow	No	0.871	0.873	0.873
Enc-Dec Deep	Yes	0.946	0.943	0.943
Dilated conv	Yes	0.954	0.949	0.949

Results

Two rock-type segmented seismic images with the dilated convolutional network from the test set are compared with the reference cases:



Discussion

The segmentation architectures demonstrate very good performance in segmenting the seismic images into rock types. Majority of misclassification seem to occur at the rock edges. This is probably beacuse seismic images lack very high frequencies, thus lacking enough resolution at these edges. This issue can be handled by designing a loss function with high penalization at these boundaries

Future work: Generate a more challenging training set derived from multiple prior images and containing multiple classes of rocks. Efficient handling of rock boundaries with advanced architectures

Reference: Long J, Shelhamer E, Darrell T. , 2015., Fisher Yu and Vladlen Koltun, 2016