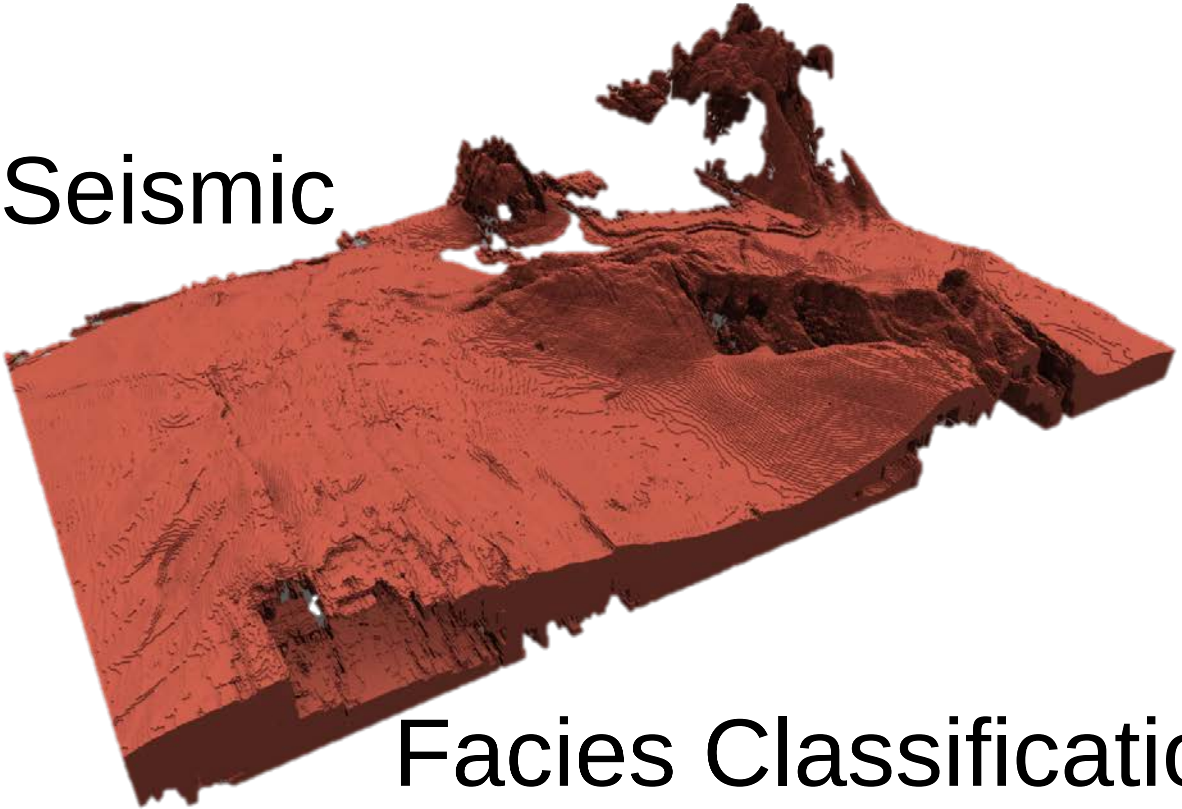
Imperial College London

Probabilistic Seismic

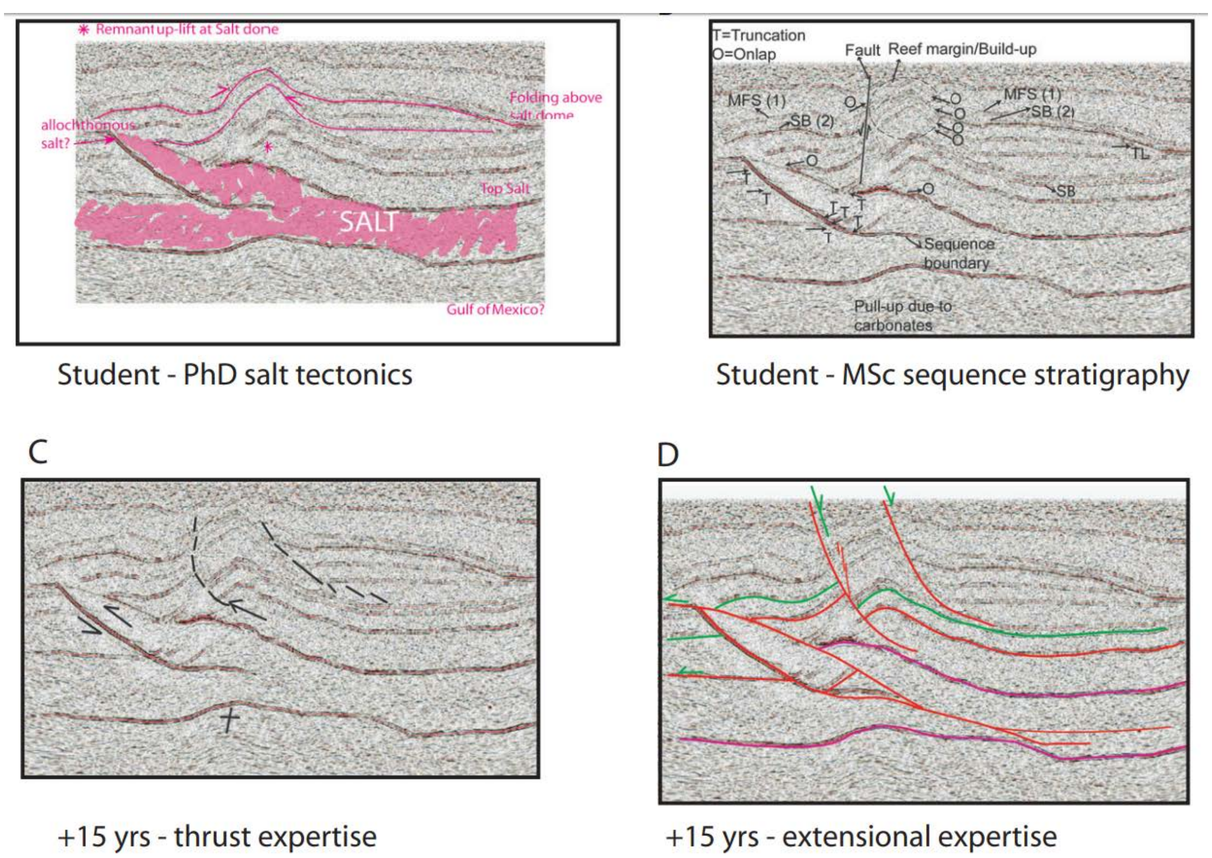


Facies Classification

Lukas Mosser, Michael Steventon, Rodolfo Oliveira

lukas.mosser15@imperial.ac.uk, michael.steventon13@imperial.ac.uk, rodolfo.oliveira15@imperial.ac.uk

A Bayesian View on Seismic Interpretation



Only 21% of G+G professionals got this correct

Bond et al (2007)

- Prior knowledge most important factor in the seismic interpretation
- Independent of data **prior** dominating term
- Machine Learning **can't** *interpret*
- But we can build models built on data and interpretations

Uncertainties in the seismic workflow

Data Acquisition

- Ambient Noise
- Acquisition Geometry
- Equipment Failure
- Tech Limitaitons

Data Processing

- Migration
- Time to Depth
- Noise Suppression
- Multiples
- Ghosting
- Down-sampling
- Etc…….

Data Interpretation

- Noise
- Artefacts
- Resolution
- Visual Representation

An interpreters, prior knowledge or lack of, bias, conceptual uncertainty can be an important source of error in the seismic workflow.

Types of Uncertainty

Aleatoric Uncertainty

- Inherent “Noise” in Data
- Not explained with more data
- E.g. physical limits of data

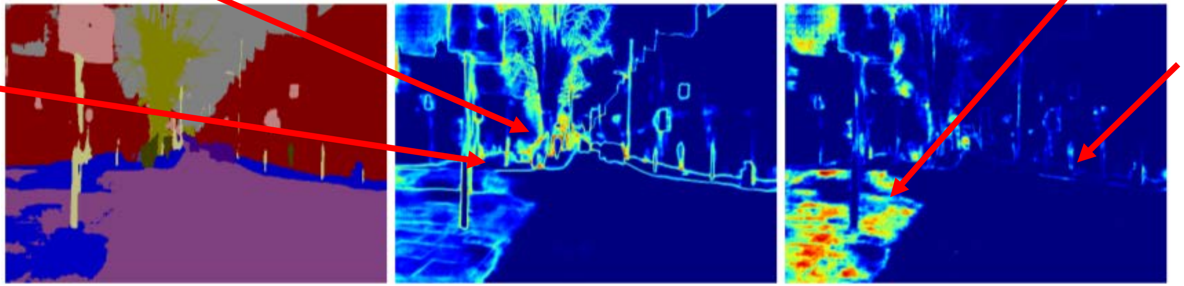
Epistemic Uncertainty

- Model Errors
- Can be explained with more data
- Seismic – often small data
  Getting more data often not an option

Distant Objects may be occluded

Textural Uncertainty

Boundary Detection



No Boundary issues

Distant Objects can’t be explained with more data

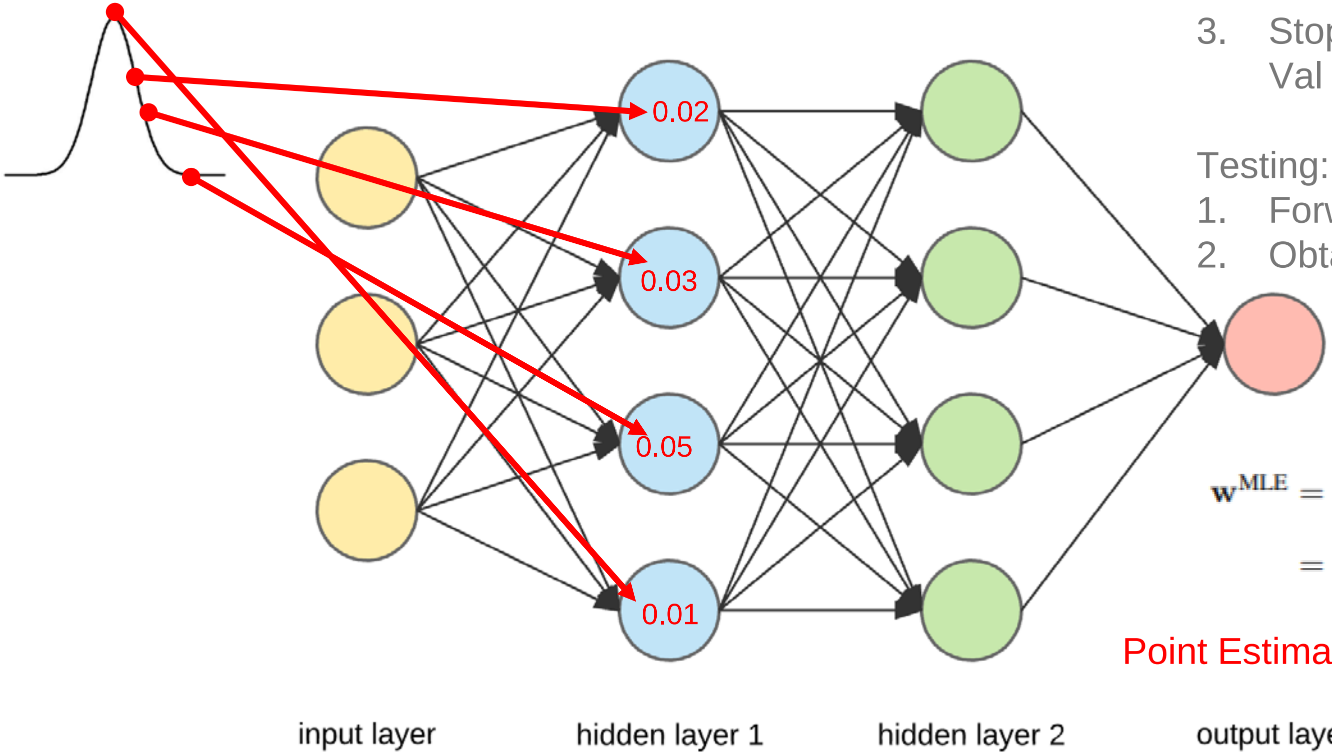
(c) Semantic Segmentation
(d) Aleatoric Uncertainty
(e) Epistemic Uncertainty

From Deterministic to Bayesian Neural Networks

Training:
1. Initialize Weights
2. Gradient Descent
3. Stop when (Accuracy):
   Val Measure < Train Measure

Testing:
1. Forward pass test sample
2. Obtain prediction

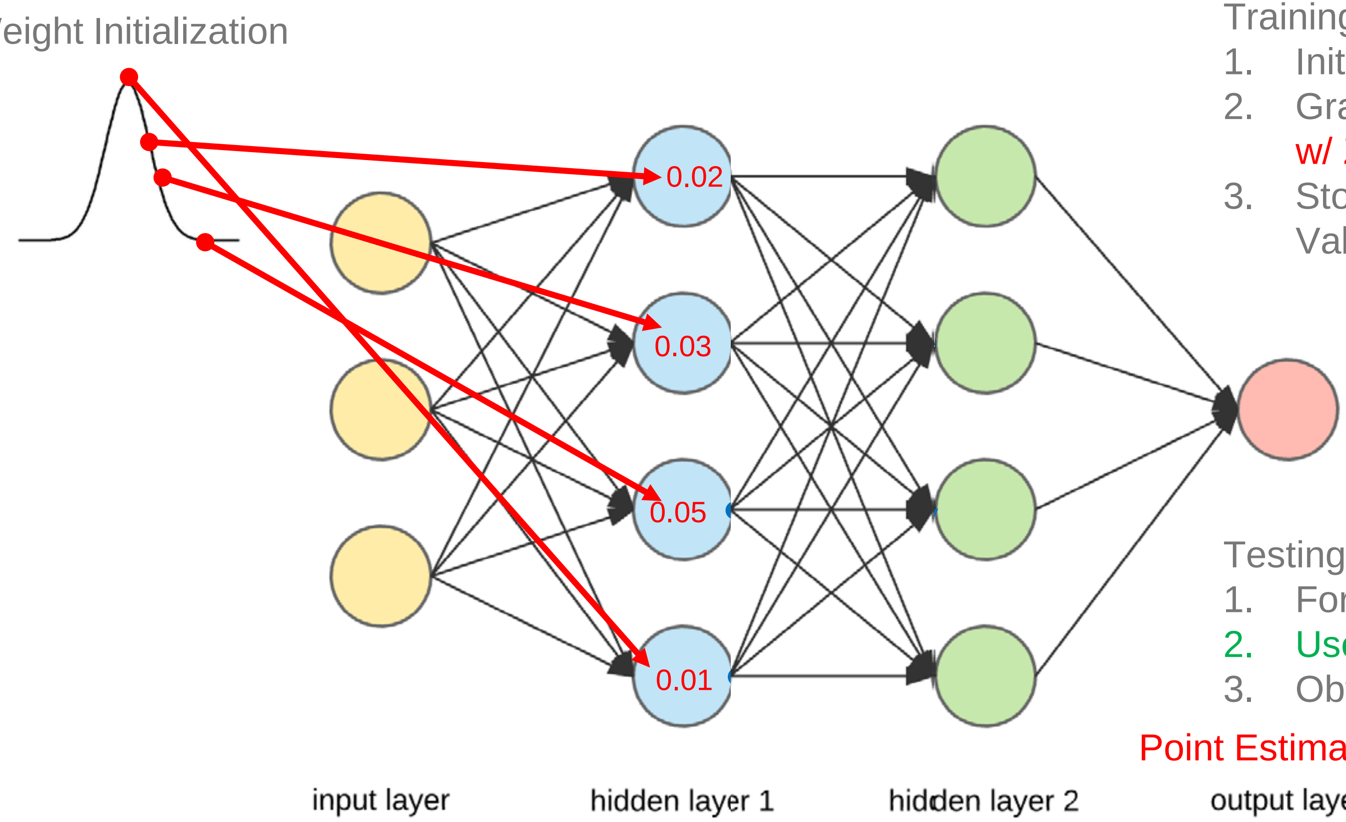
Weight Initialization



$$\mathbf{w}^{\text{MLE}} = \arg\max_{\mathbf{w}} \log P(\mathcal{D}|\mathbf{w})$$
$$= \arg\max_{\mathbf{w}} \sum_i \log P(\mathbf{y}_i|\mathbf{x}_i, \mathbf{w}).$$

Point Estimates, no weight uncertainty

Deterministic Neural Networks with Dropout



Training:

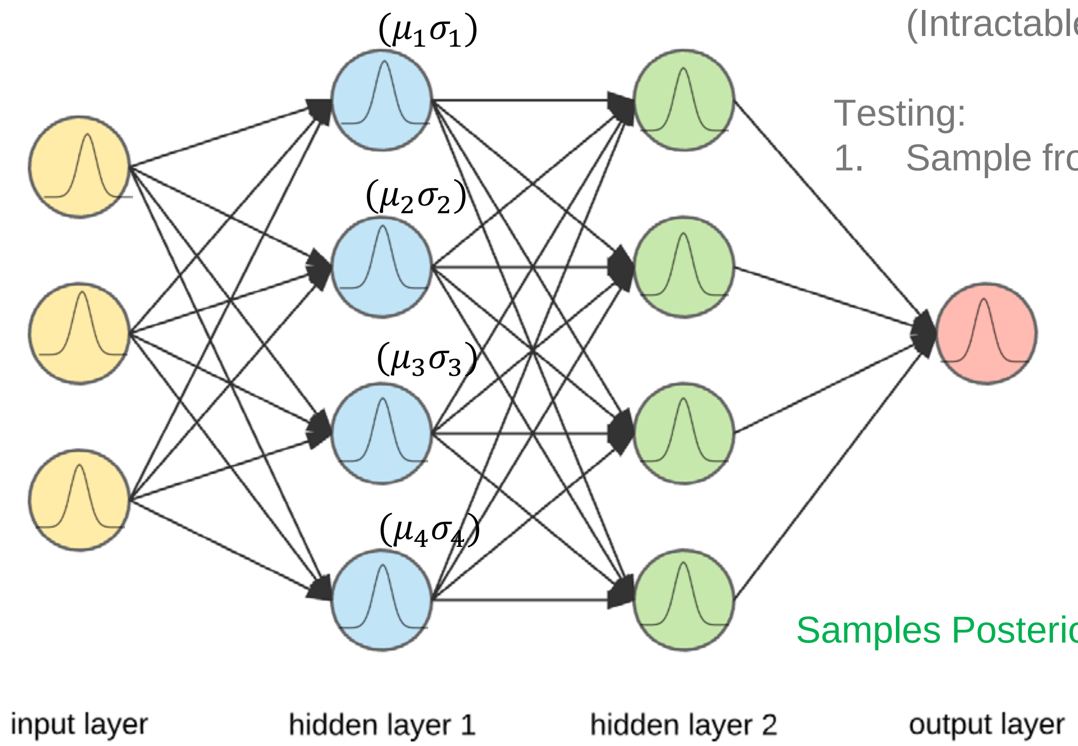
1. Initialize Weights
2. Gradient Descent
   w/ Zero weights at random
3. Stop when (Accuracy):
   Val Measure < Train Measure

Testing:

1. Forward pass test sample
2. Use all weights (no dropout)
3. Obtain prediction

Point Estimates, no weight uncertainty

Bayesian Neural Networks

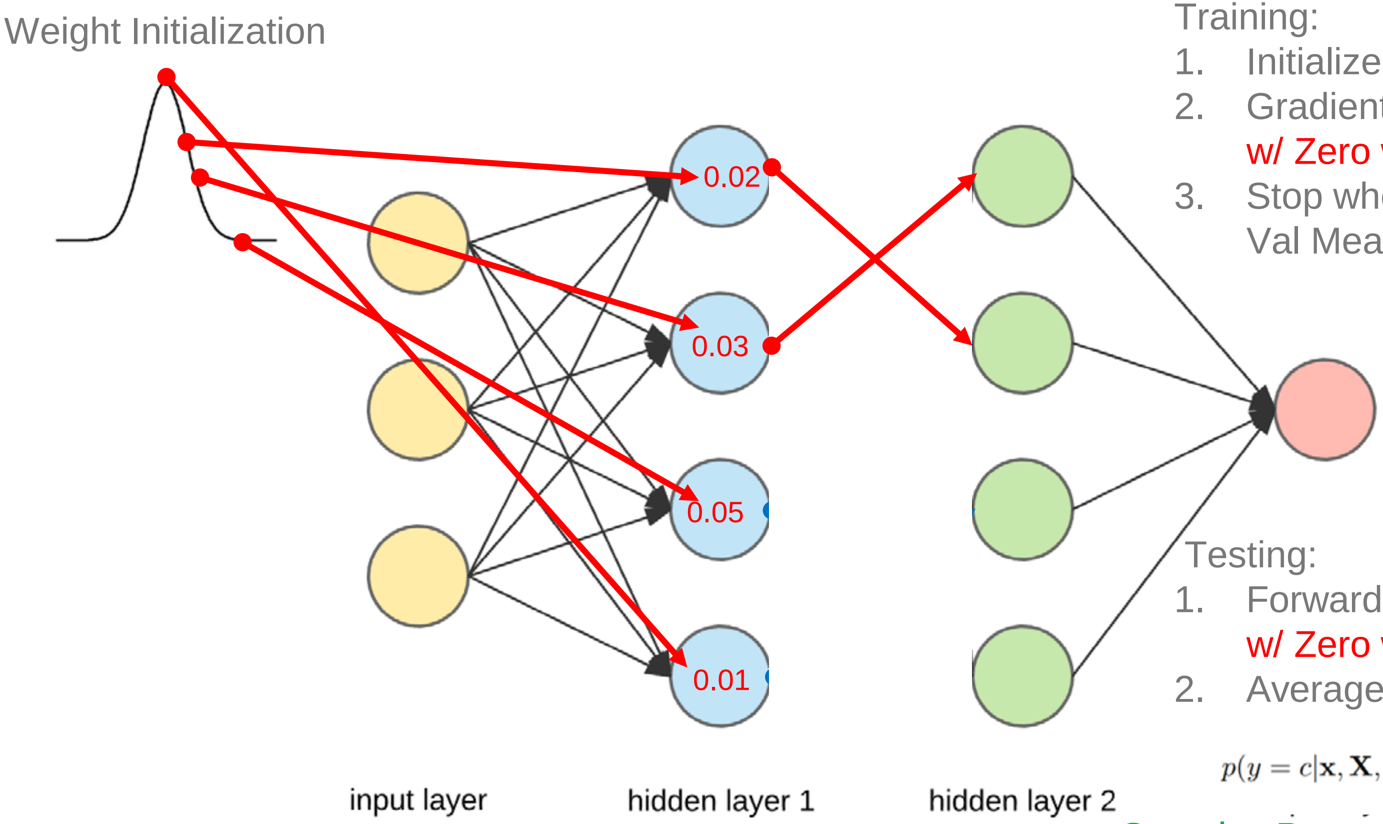


Training:
1. Select a distribution over weights
2. Posterior Inference of weight distributions
   (Intractable in neural nets)

Testing:
1. Sample from posterior predictions

Samples Posterior Distribution of Weights

Approximate Posterior Inference by Dropout



Training:

1. Initialize Weights
2. Gradient Descent
   w/ Zero weights at random
3. Stop when (Accuracy):
   Val Measure < Train Measure

Testing:

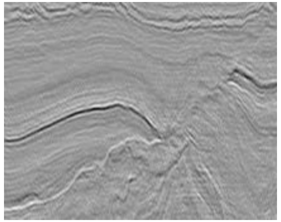
1. Forward pass test sample N times
   w/ Zero weights at random
2. Average N Predictions

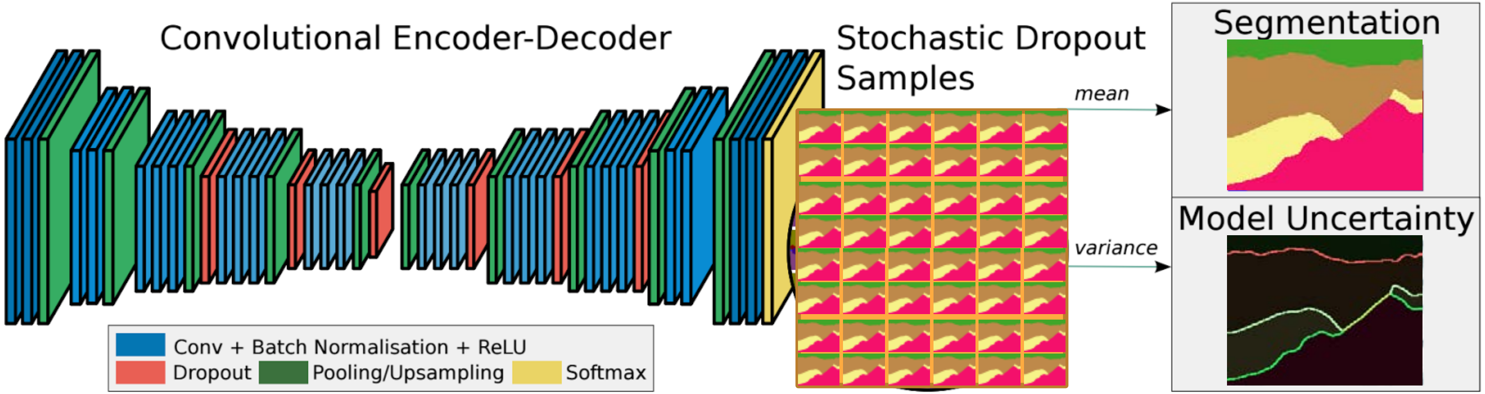
$$p(y = c|\mathbf{x}, \mathbf{X}, \mathbf{Y}) \approx \frac{1}{T}\sum_{t=1}^{T} \text{Softmax}(\mathbf{f}^{\widehat{\mathbf{W}}_t}(\mathbf{x}))$$

~ Samples Posterior Distribution of Weights

Model Architecture – Bayesian ConvNet: Segnet

Input Single Patch





Dropout after every convolution operation!

1. Apply dropout at training time
2. Apply dropout at val/test time

Sample N Forward Predictions!

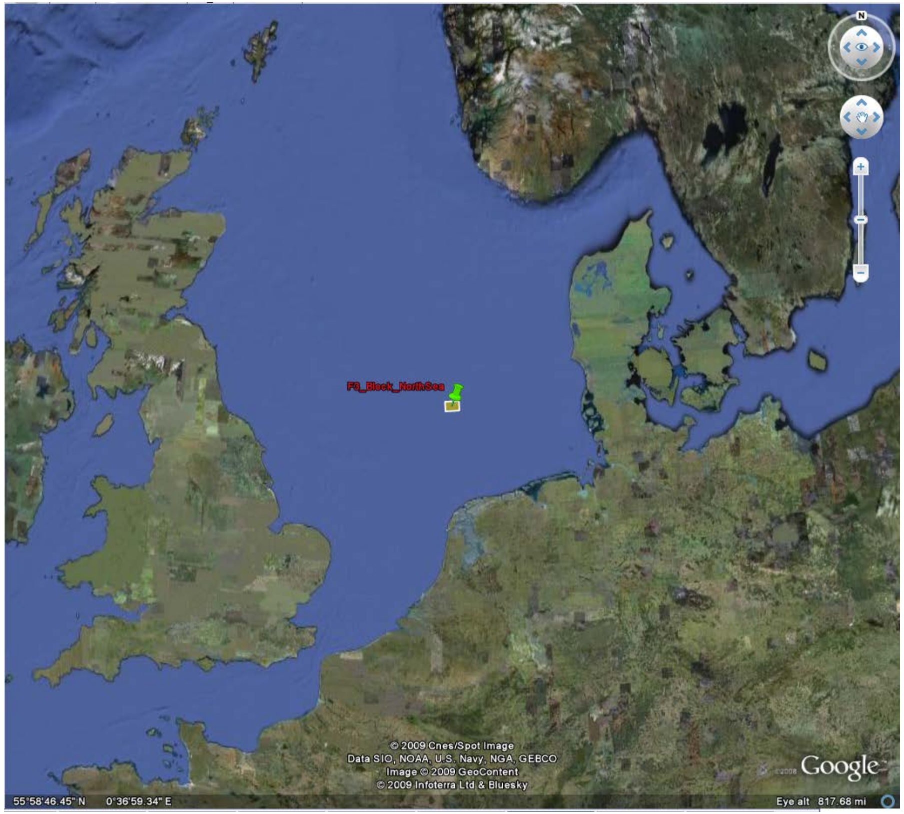
For each Patch in Inline/Xline

1. Average N Predictions
2. Compute Classwise Prediction Variance
   -> Model Unvertainty -> Epistemic

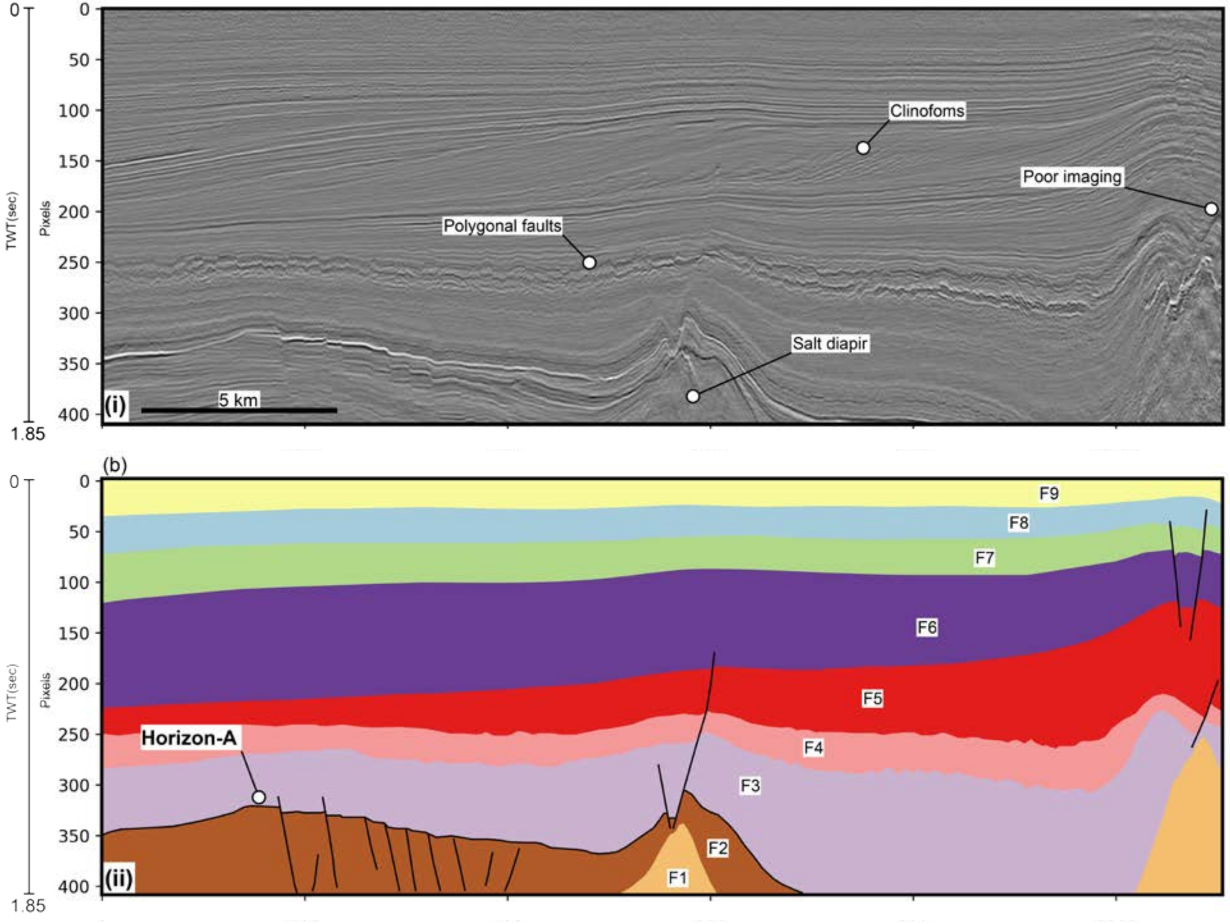
Reassemble patches to obtain Inline/Xline

Dataset

F3 Dataset – **OPEN ACCESS** – Dutch NLOG Database https://opendtect.org/osr/Main/NetherlandsOffshoreF3BlockComplete4GB	
Basin	Southern North Sea
Processing	Pre-Stack Time Migration
Area (km^2)	380
Bin Size (m)	25 × 25
Sampling Interval (ms)	4
Inline Range	100 - 750
Crossline Range	300 - 1250
Z Range (ms)	0 - 1850
Data Size	~1.0 GB
# of Training/Val Inlines	5 Training / 4 Validation



Seismic Facies Classificaiton



Facies	Seismic-based interpretation (no wells)
F10	*Biogenic Gas*
F9	*Acquisition footprint*
F8	*Bedded Sediments*
F7	*Bedded sediments*
F6	*Clinofroms (Deltaic)*
F5	*Bedded sediments*
F4	*Polygonal faulted sediments*
F3	*Bedded sediments*
F2	*Bedded sediments*
F1	*Salt tectonics*

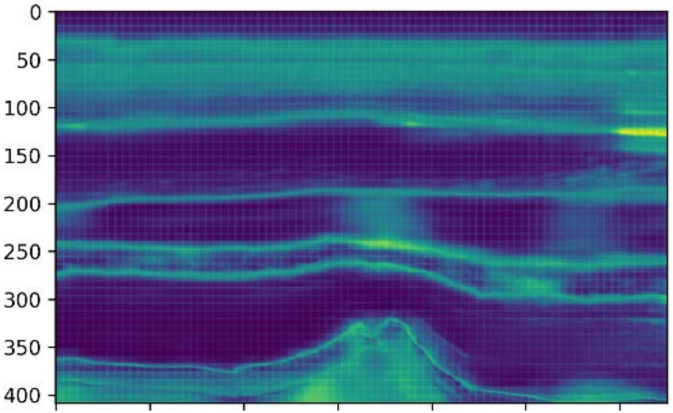
Validation Inline 4xx

*Gold Standard Annotation

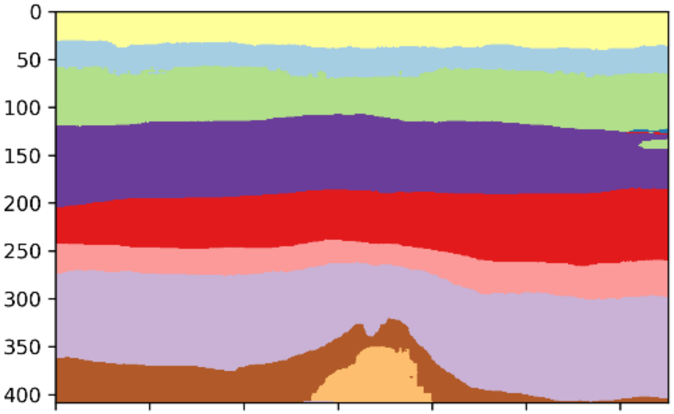
Amplitude

Ground Truth*

Prediction Variance



Prediction

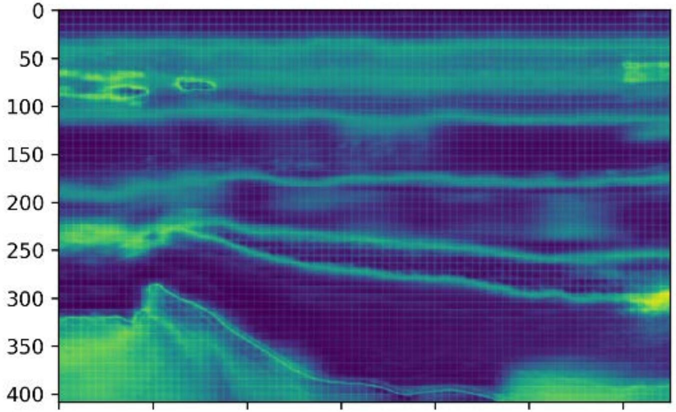


Validation Inline 6xx

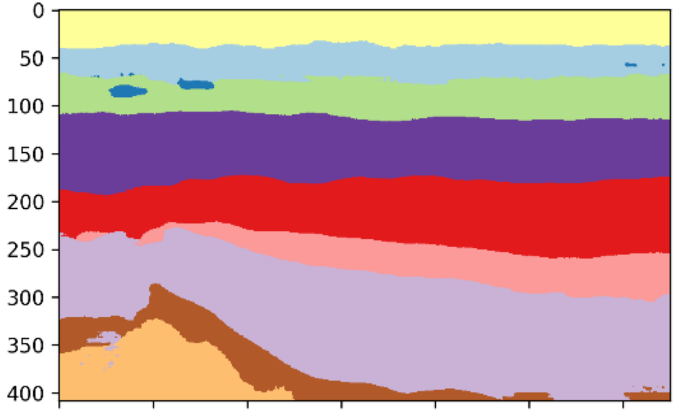
Amplitude

Ground Truth*

Prediction Variance



Prediction

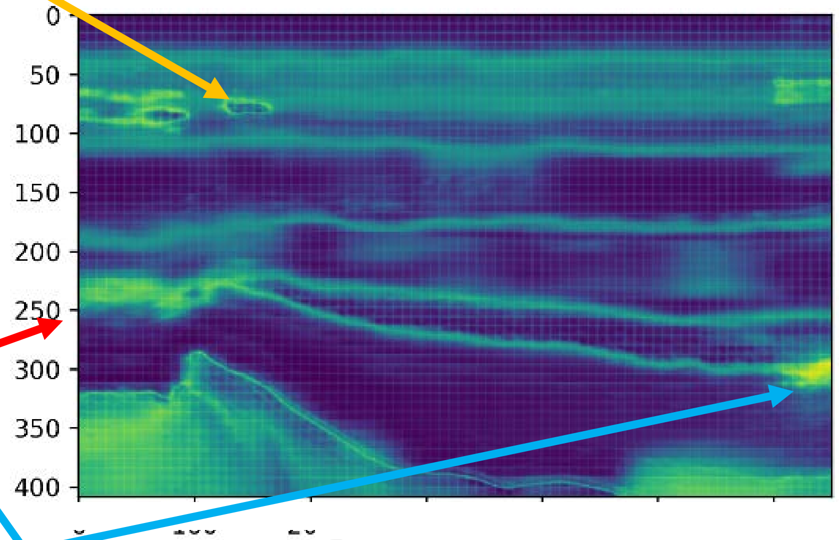


Uncertainty Features and Metrics

Bright Spot Delineation

Amplitude

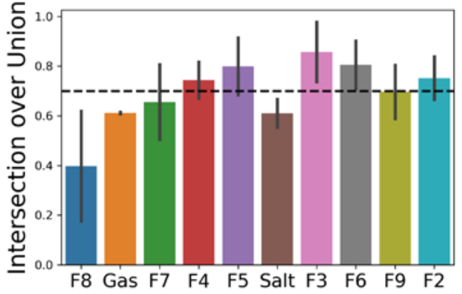
Prediction Variance



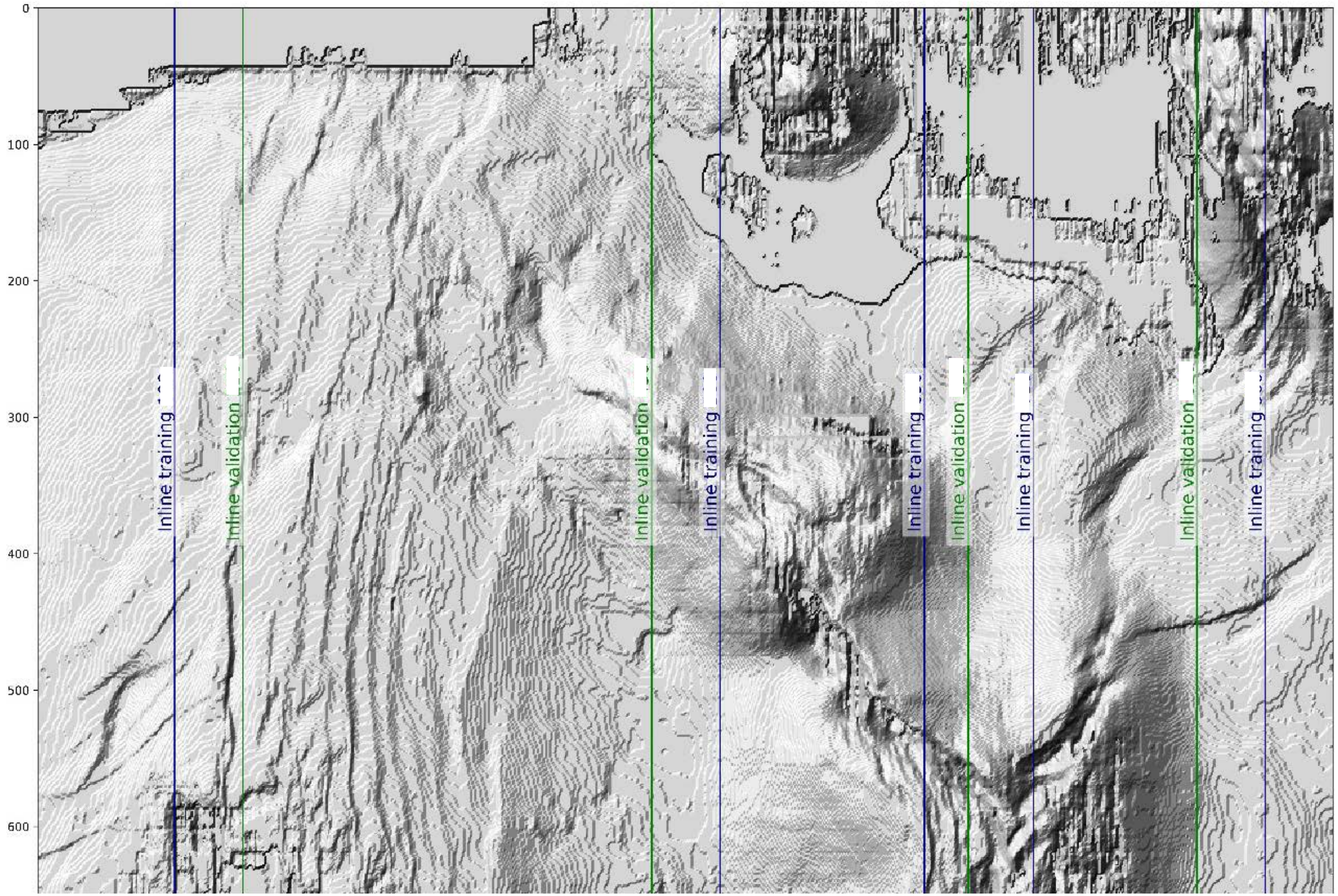
Faulted Layer Pinchout?

Low Data Quality

IoU Salt: 0.79 +/- 0.13
IoU Gas: 0.61 +/- 0.01
IoU Polygonal: 0.74 +/- 0.08

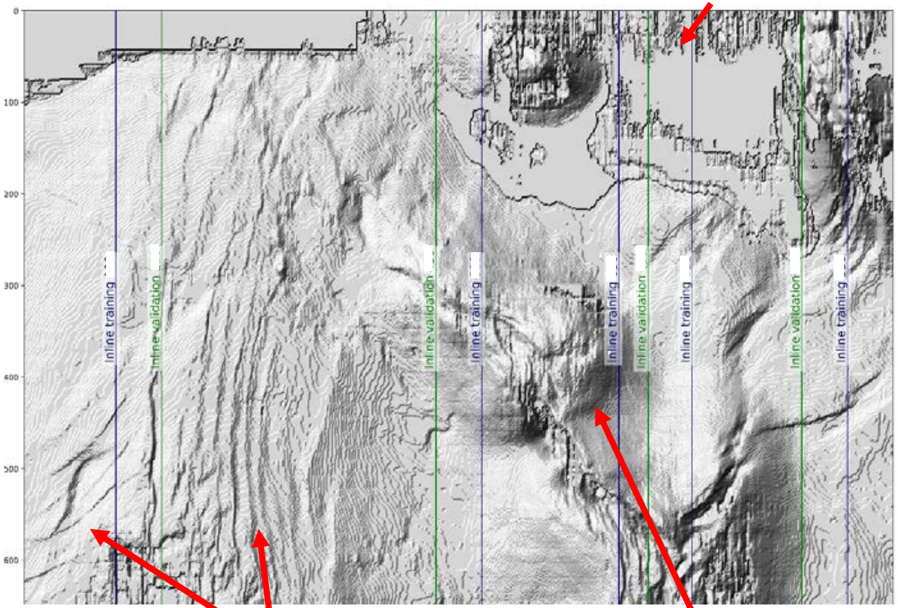


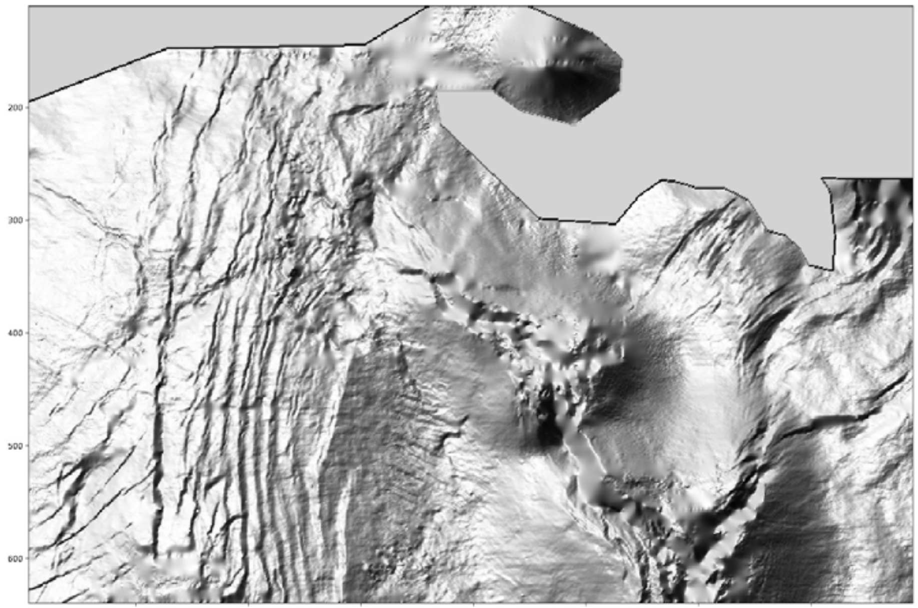
Top Salt Horizon



Top Salt: Bayesian CNN vs Human Interpreter

Data Quality issues lead to higher uncertainty



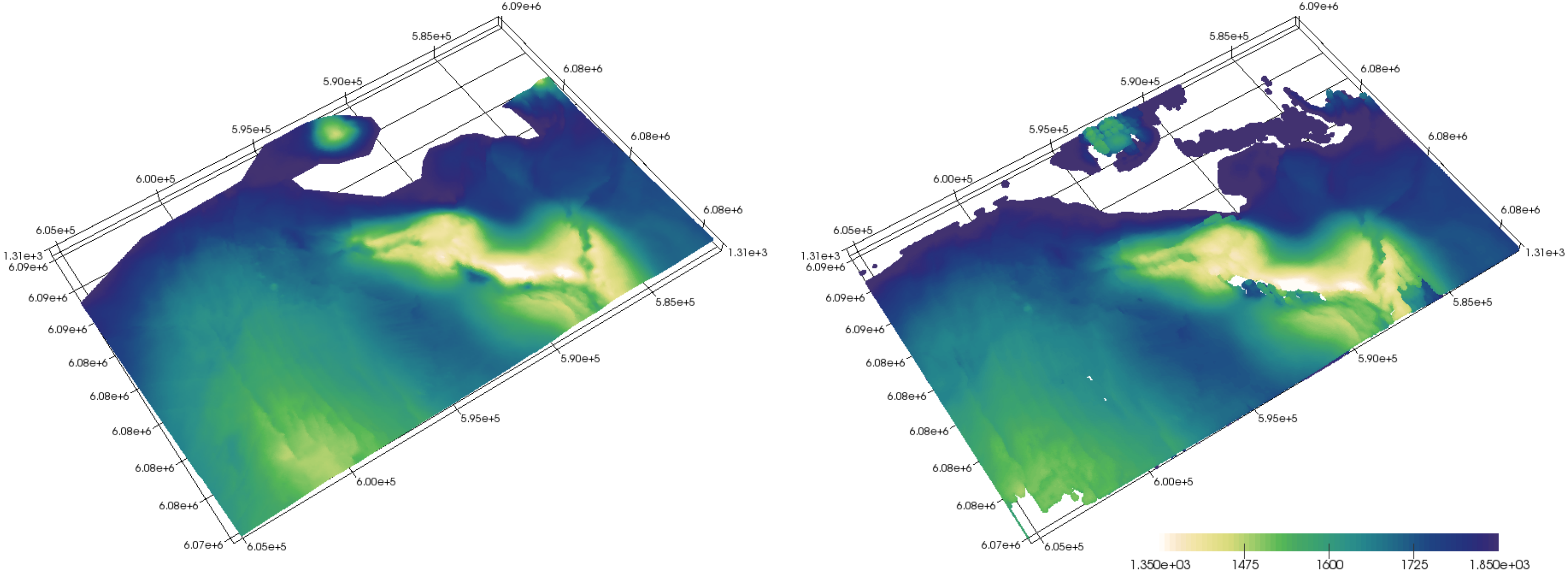


Good Fault Zone Detection

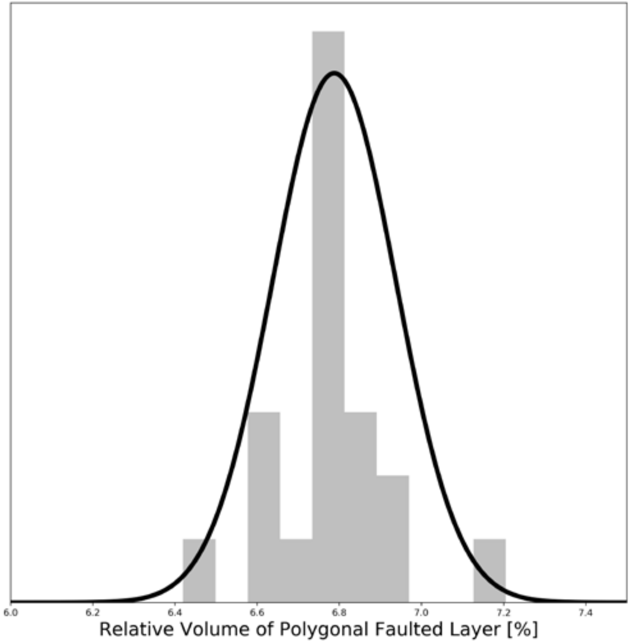
Salt Structure

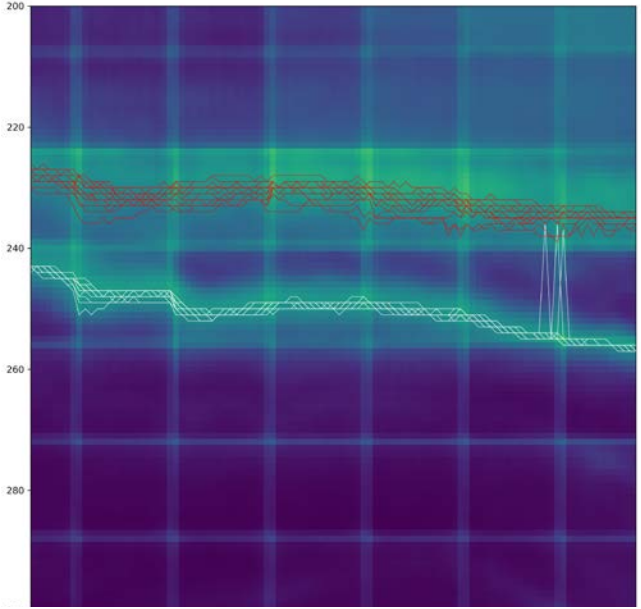
Same Interpreter as for Training Data (i.e. Mike)

Extracted Top Salt Surface Comparison



Polygonal Fault Volume Probabilistic Estimate





What did and what did not work? Open Challenges

- What did work?
  - Patch-based training better for small datasets, not enough data for full x/inline
  - Monte-Carlo Dropout *can* be applied to any neural network
  - Segnet provides good results
- What did not work?
  - U-Net not clear how big impact of skip connections is on uncertainty
  - MalenoV dataset too limited.
- Open Challenges:
  - Baseline dataset: Possibly this one?
  - How to deal with multiple interpretations?

Conclusions

- Two Types of Uncertainty: Epistemic and Aleatoric
- Traditional Neural Networks Provide no measure of model uncertainty (UQ on weights)

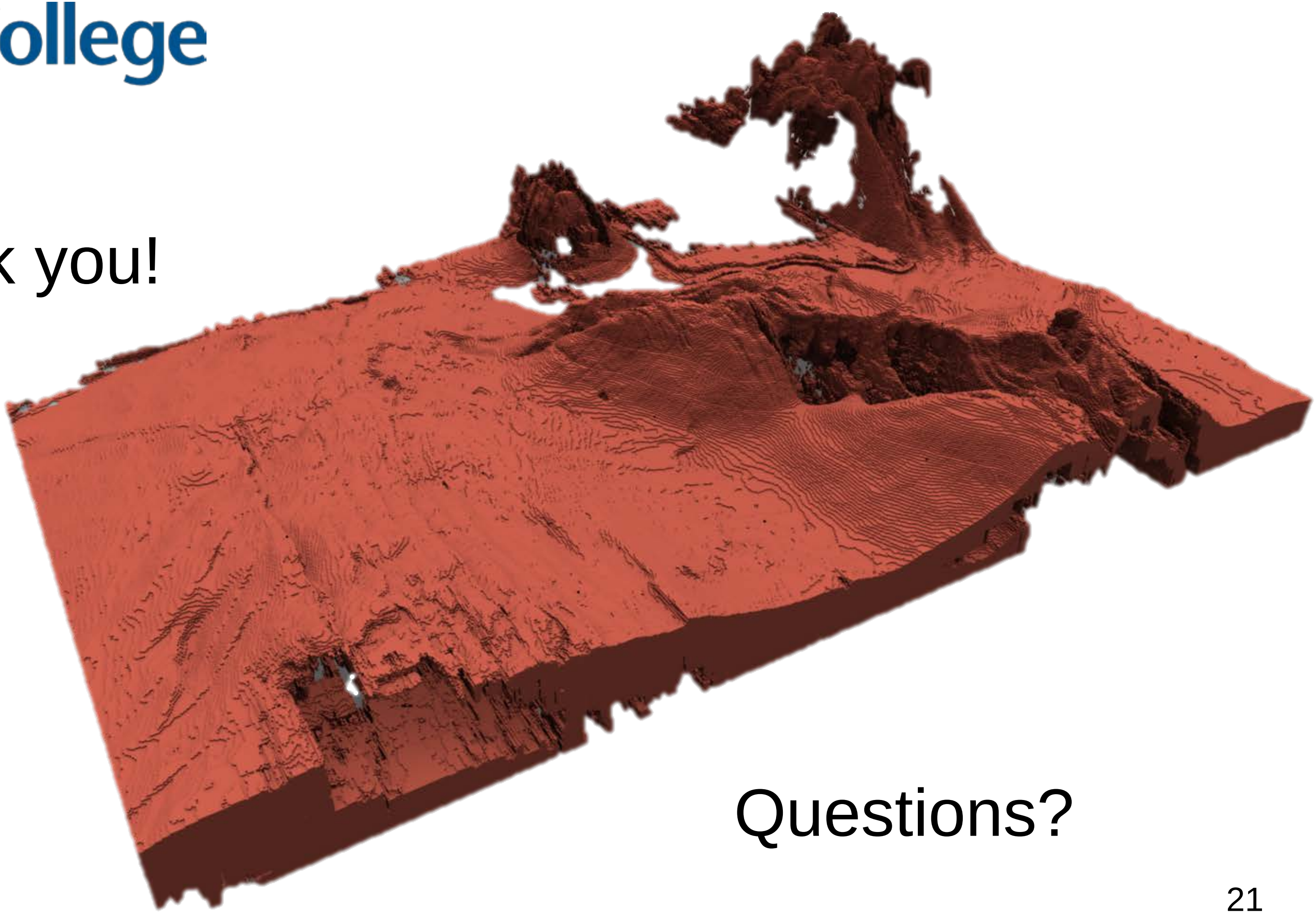
- Bayesian Neural Networks allow estimation of model uncertainty
- Dropout applied at test time can approximate posterior inference

- Bayesian Neural Networks allow good prediction on small datasets

- Allows Variance in predictions to be incorporated into
    - Decision making process
    - Data Acquisition Strategy

Imperial College London

Thank you!



Questions?

Imperial College London

Backup Slides