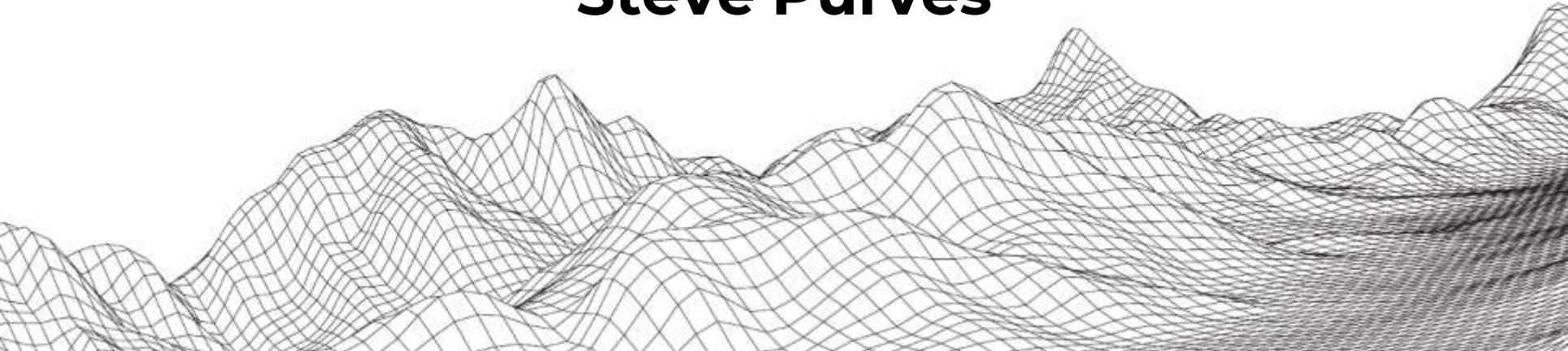


Incorporating Uncertainty in Automated Seismic Interpretation; Geobody Volumetrics

Steve Purves



Introduction

- **ML based seismic interpretation in an exploration context**
- **Uncertainty analysis in deep learning models**
- **Discuss how the additional information provided by machine learning can impact on volume estimates via examples on a well known dataset**

Subsurface Uncertainty

The subsurface is not uncertain.

What is uncertain is our measurements and models of the subsurface.

It is the uncertainty of these that we need to in turn model and work to quantify as well as understanding their accuracy.



Michael Pyrcz @GeostatsGuy · 1d

Embrace #uncertainty! It is not a property of the #subsurface, it's due to our ignorance! Result of sparse data + #heterogeneity! There is no objective uncertainty, it is a model that depends on scale & no matter what you do, don't even think about uncertainty in the uncertainty!

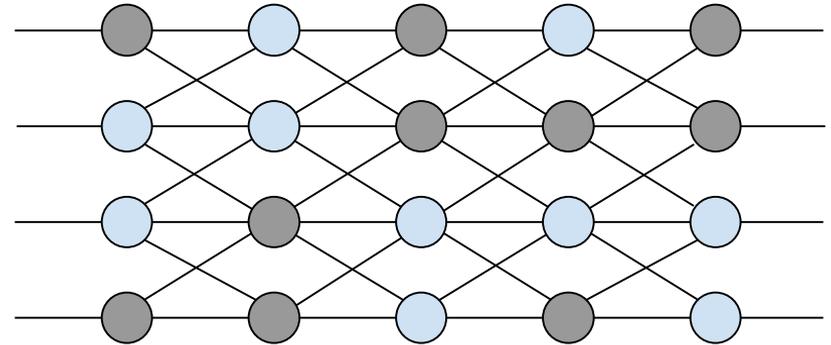


Uncertainty in Deep Learning

Dropout as a Bayesian Approximation:
Representing Model Uncertainty in Deep
Learning. Gal, Ghahramani. 2015 (rev.
2016) [<https://arxiv.org/abs/1506.02142>]

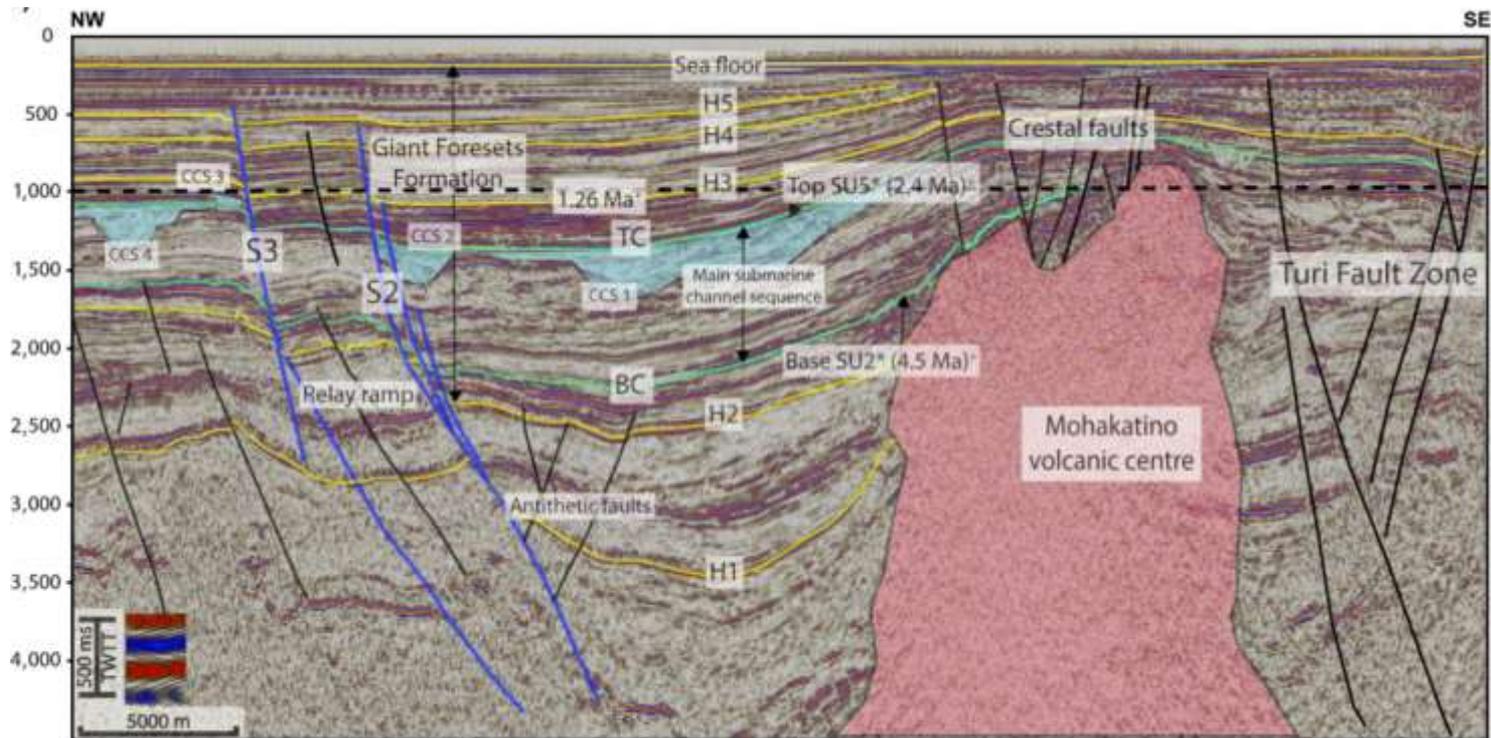
Probabilistic Seismic Facies
Classification. Mosser, Stevenson,
Oliveira. FORCE Seminar 2018
[<https://doi.org/10.5281/zenodo.1466917>]

Dropout randomly disables X% of units
in a network during training.



MC Dropout applies 50% dropout at training
and prediction time to approximate a
random process (Bernoulli Distribution)

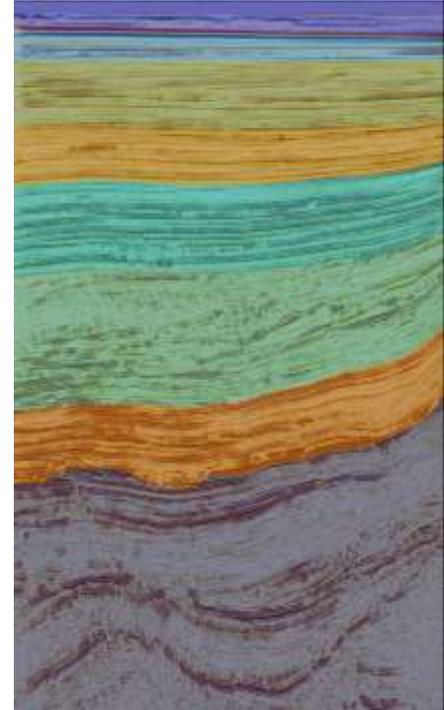
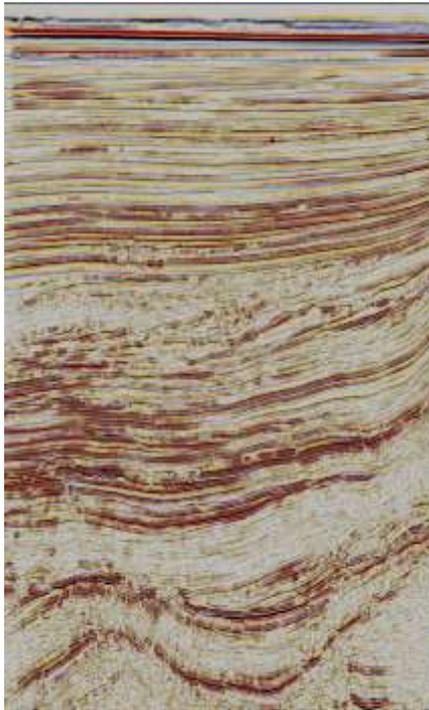
New Zealand - Taranaki Basin



Thanks to New Zealand GNS for providing the open seismic dataset

Reproduced from [Mattos, Alves & Scully 2018](#)

Lithostratigraphic Unit - Labelling



Lithostratigraphic Predictions

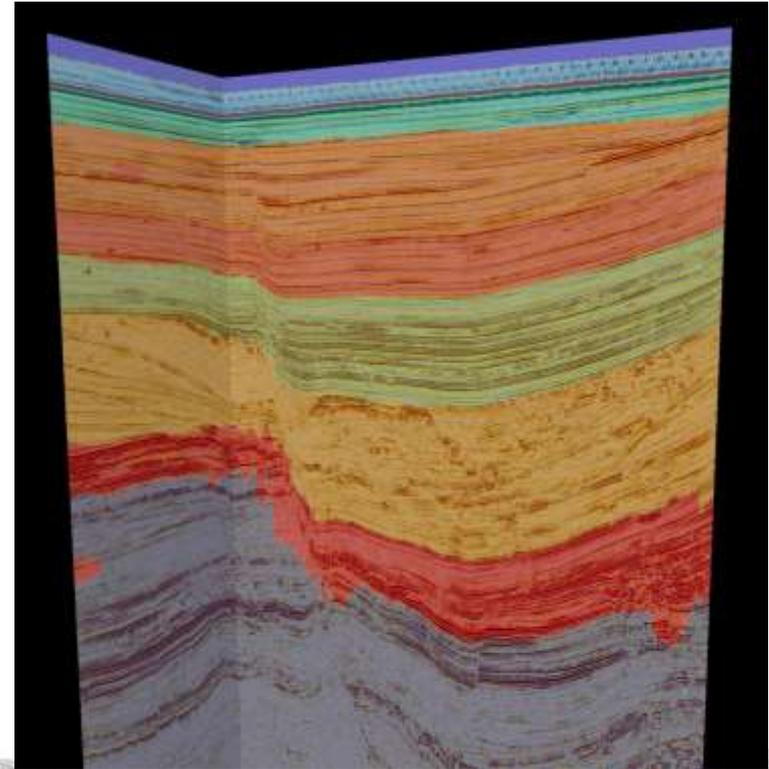
Example labels



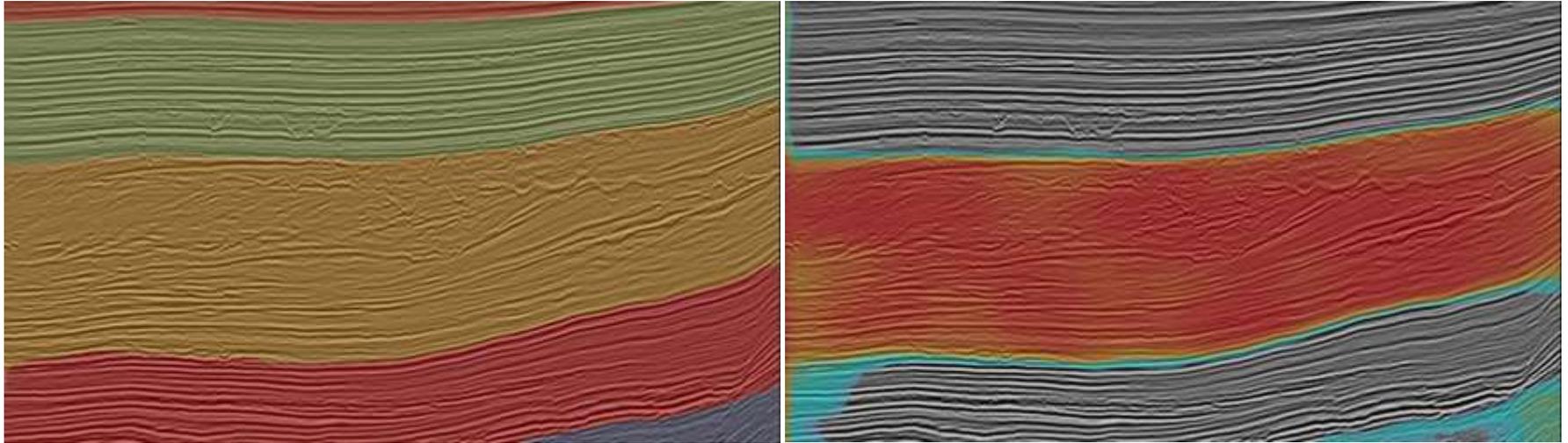
Inline Prediction



Crossline Prediction



200 Realisations - Lithostratigraphy



**Predicted lithostratigraphy classes
(orange) clinoform package**

**Frequency (occurrence, voxel-wise)
for clinoform package**

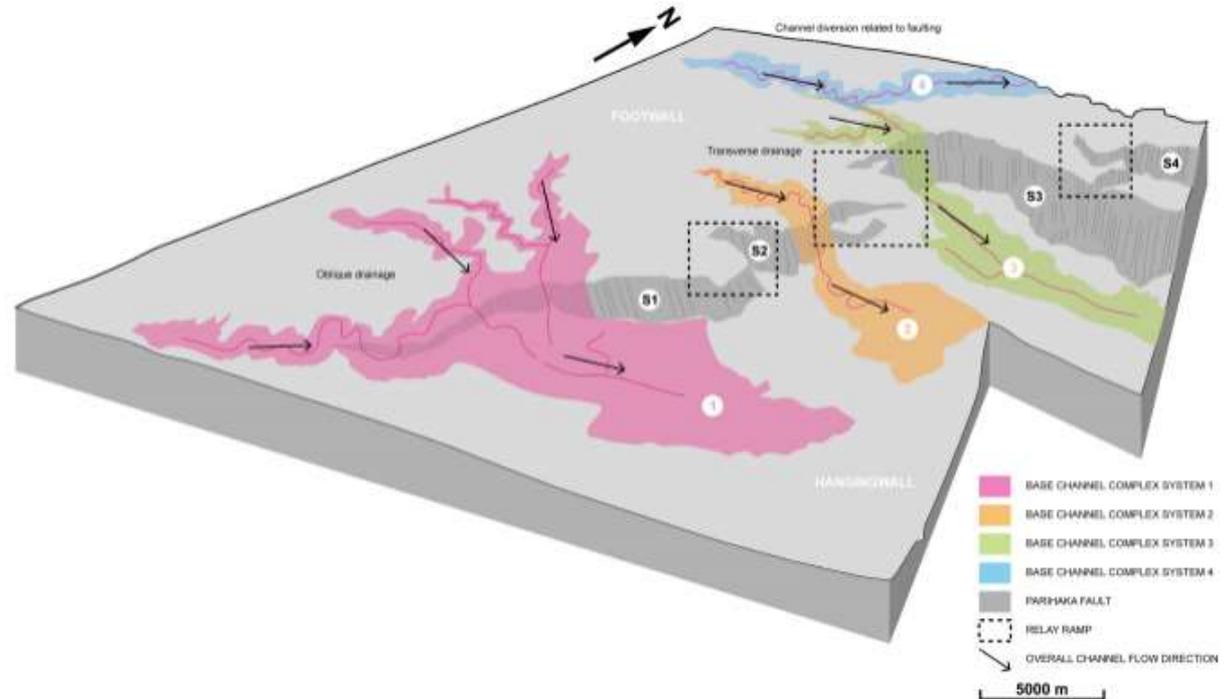
Gully Systems

Potential stratigraphic traps

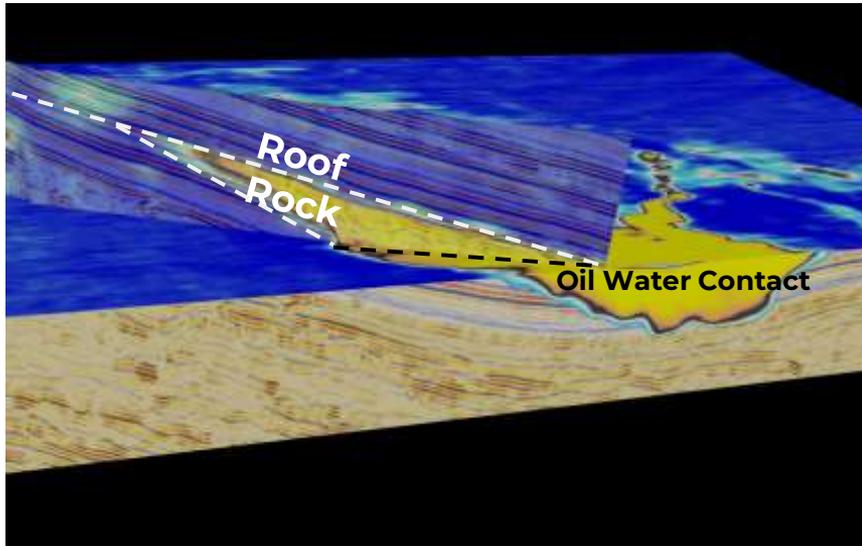
Complex geomorphology

Varying infill response

Extensive and difficult to pick



The Objective



$$\text{HCIIP} = \text{GRV} \times \text{N/G} \times \text{POR} \times S_{\text{hc}} / \text{FVF}$$

HCIIP = hydrocarbons in place*

GRV = gross rock volume

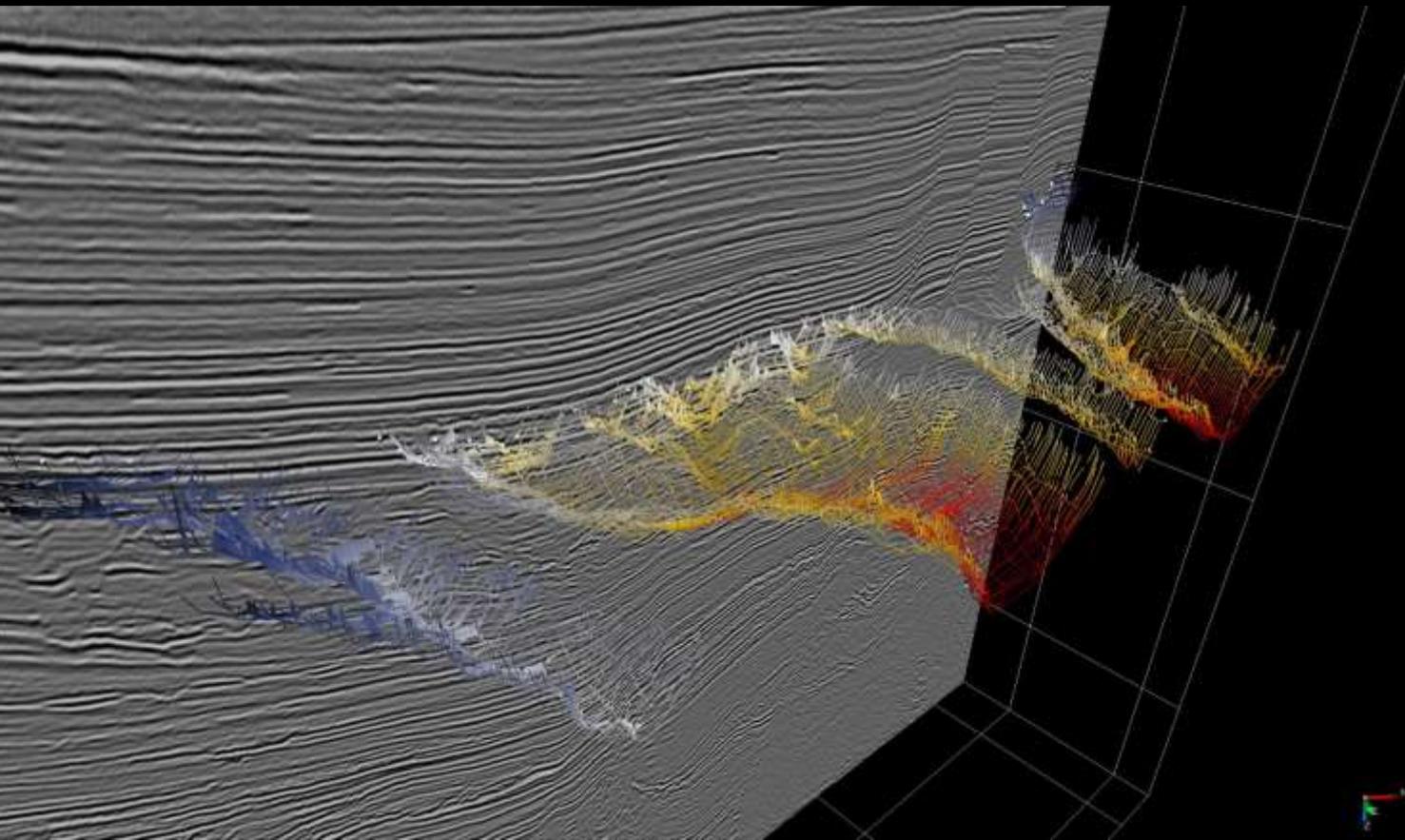
N/G = net / gross ratio

POR = porosity

S_{hc} = hydrocarbon saturation

FVF = formation volume factor

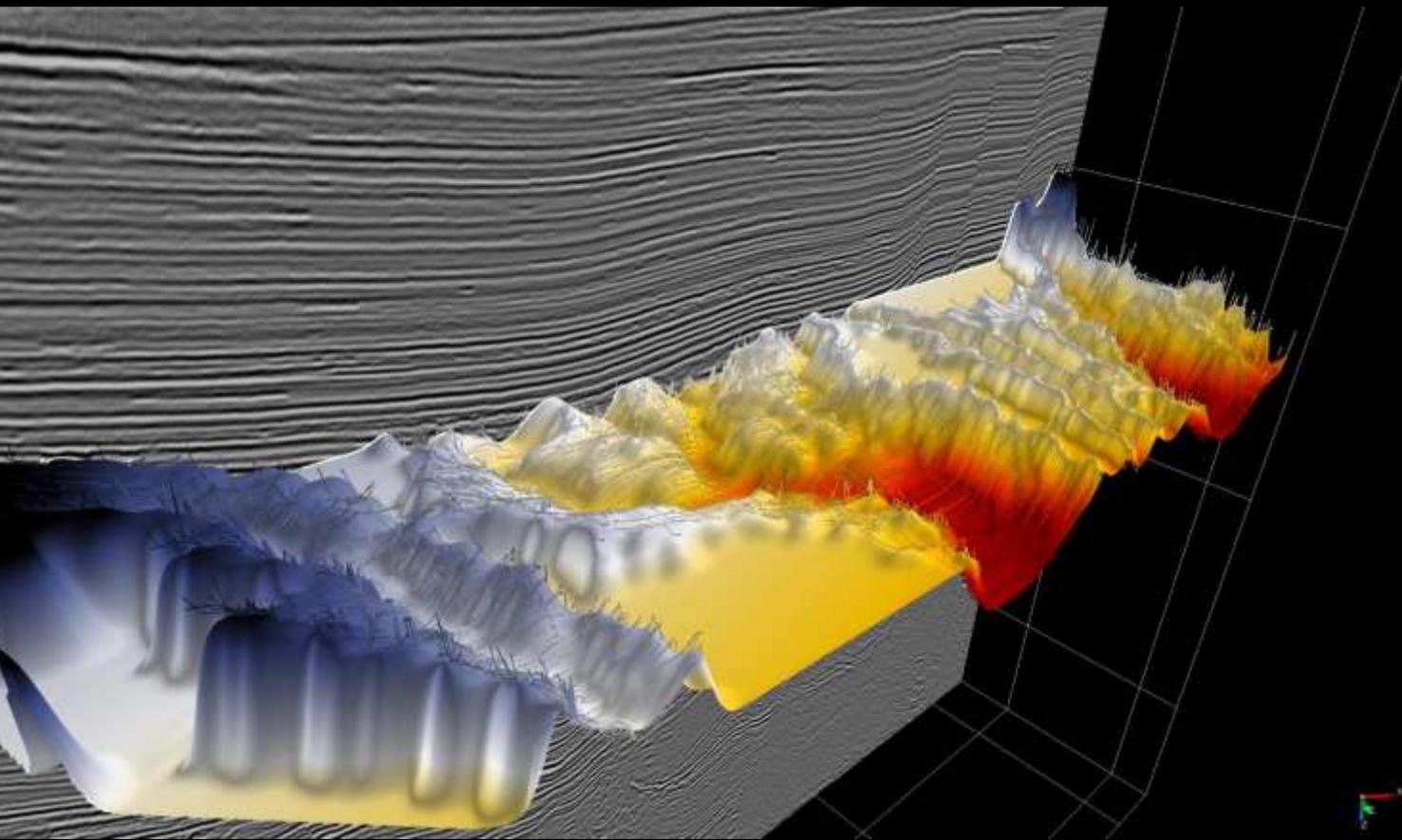
*of oil, solution gas, free gas, condensate and normal surface conditions



Interpretation of
complex geobodies

hard-to-track basal
surfaces

Manual (point)
interpretation in
traditional software
takes time and is
prone to errors



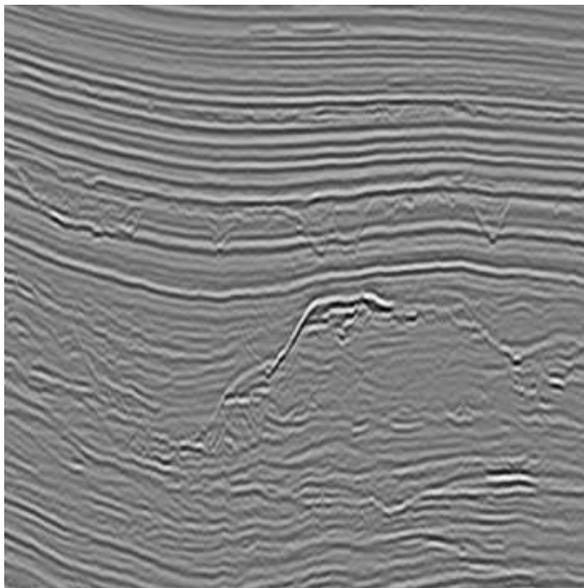
Interpretation of complex geobodies

hard-to-track basal surfaces

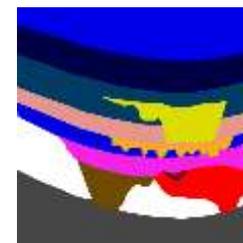
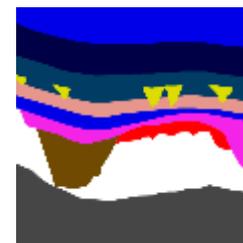
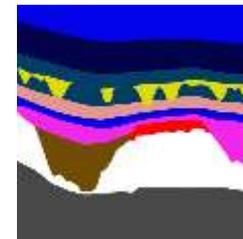
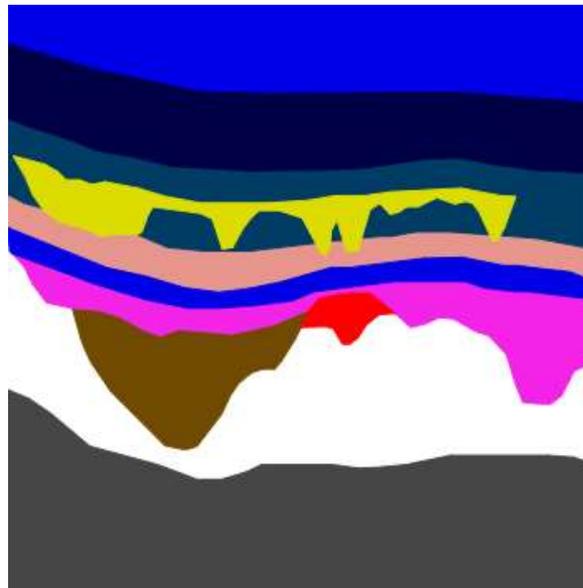
Manual (point) interpretation in traditional software takes time and is prone to errors

Gridding of manual (point) interpretation suffers from picking inconsistency

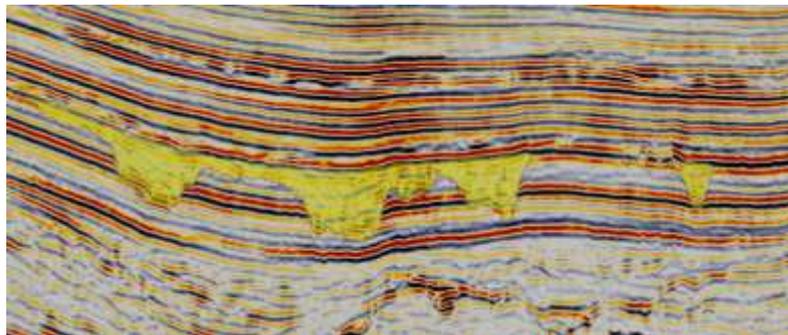
Gullies Labels



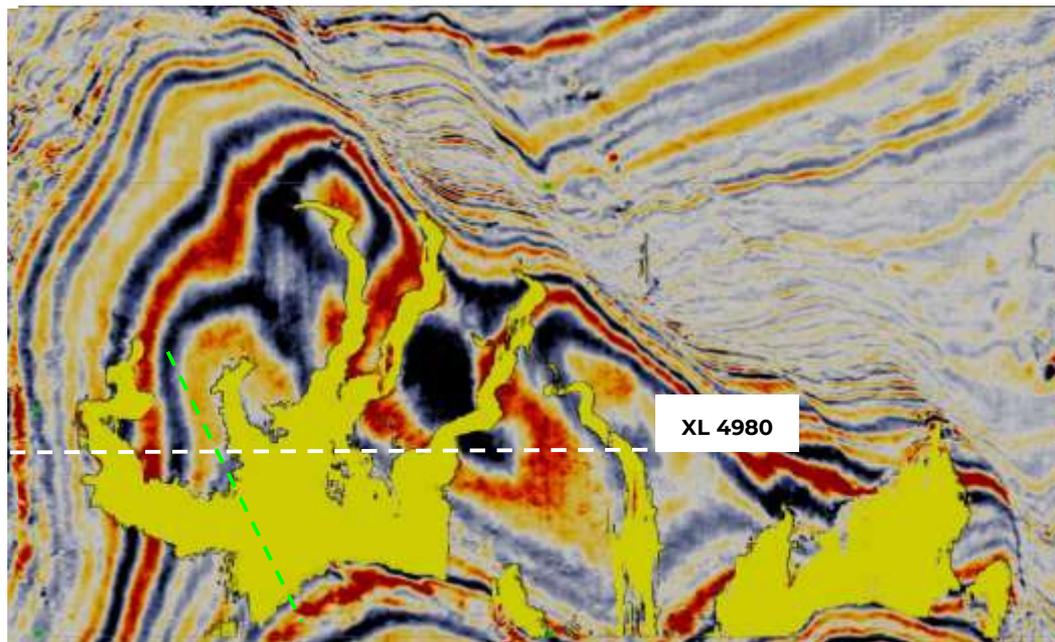
XI4910 - crop



Gullies Prediction

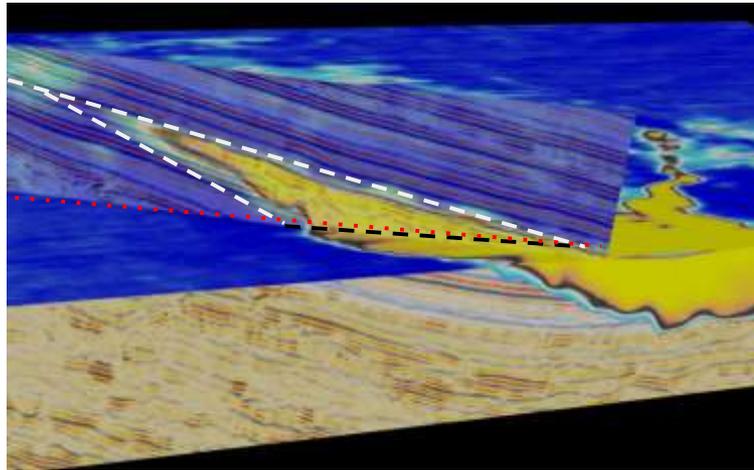


XL 4980



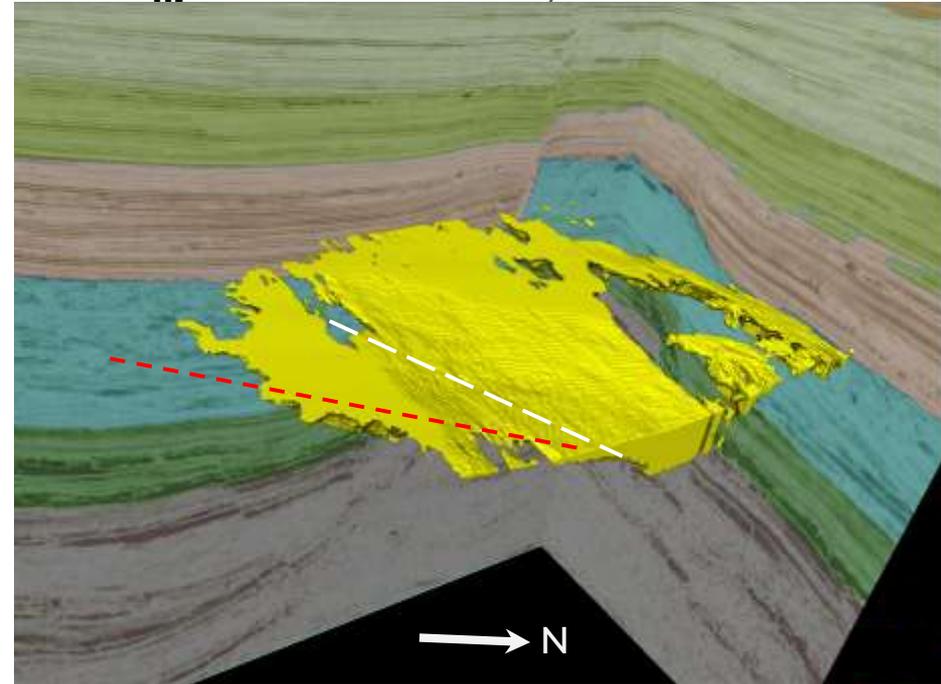
XL 4980

Isolating Potential Trap



(yellow) average across a number of realisations

Saddle point between N & S feeding

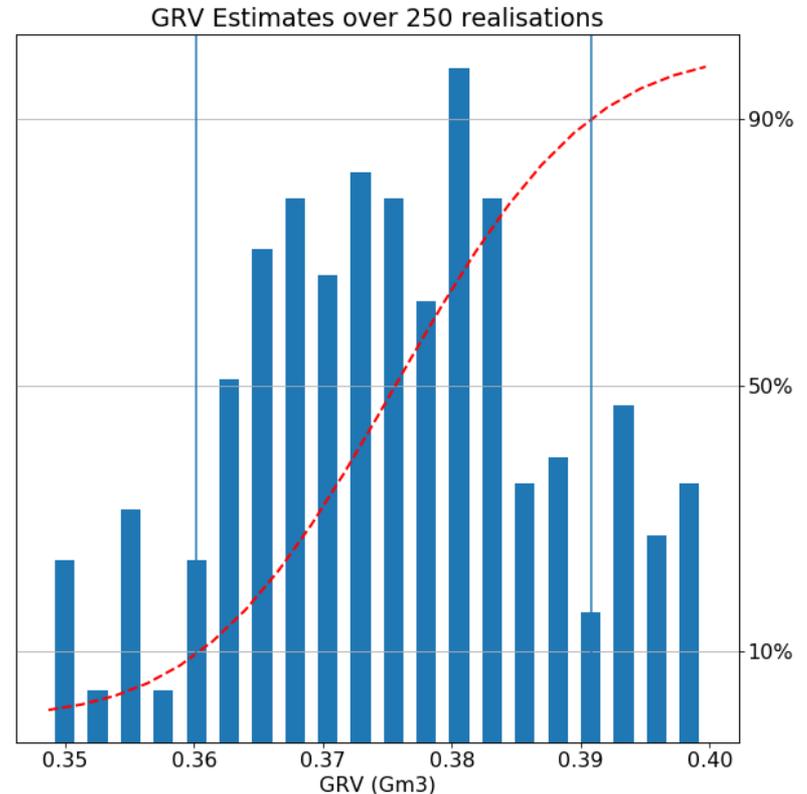


GRV Estimate for Gully

- 250 realisations using Monte Carlo Dropout
- Cropped at Oil/Water contact 1248ms
- Created stacked volume & examined the bounding geobody
- Created a bounding polygon & calculated GSV in this area for all realisations
- (p10=0.360, p90=0.391) Gm3

Training Time: 3 hours

Prediction: 1 min / realisation



HCIIP

=

GRV

*

N/G

*

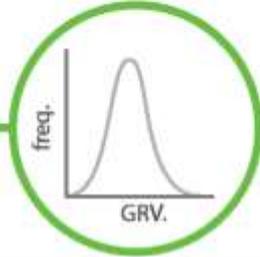
POR

*

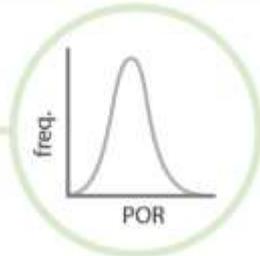
SHC

/

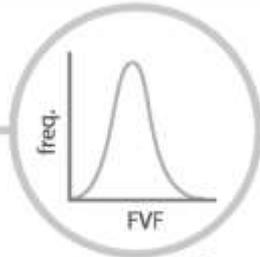
FVF



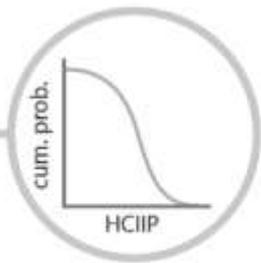
Deep Learning ASI with Uncertainty



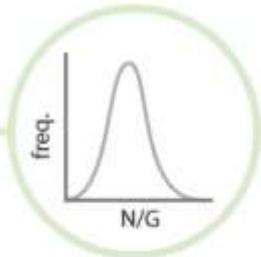
ML inversion and/or contextual queries on ML derived POR logs



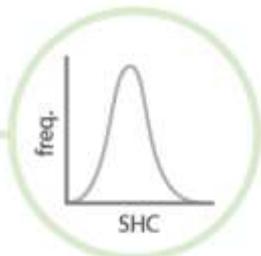
Contextual queries on analogous field data



Monte Carlo simulation based on below distributions



ML inversion and/or contextual queries on ML derived N/G logs



ML inversion and/or contextual queries on ML derived SHC logs



Conclusions

- Various approaches to introducing model uncertainty in ML methods (MC Dropout demonstrated here). These type of methods will be prevalent in approaches to ASI.
- This enable us to look a significantly more variation in static models than scenario analysis can achieve
- We will be generating interpretation data with quantification of uncertainty for probabilistic volumetrics
- Generate multiple realisations for flow simulation



**EARTH SCIENCE
ANALYTICS**