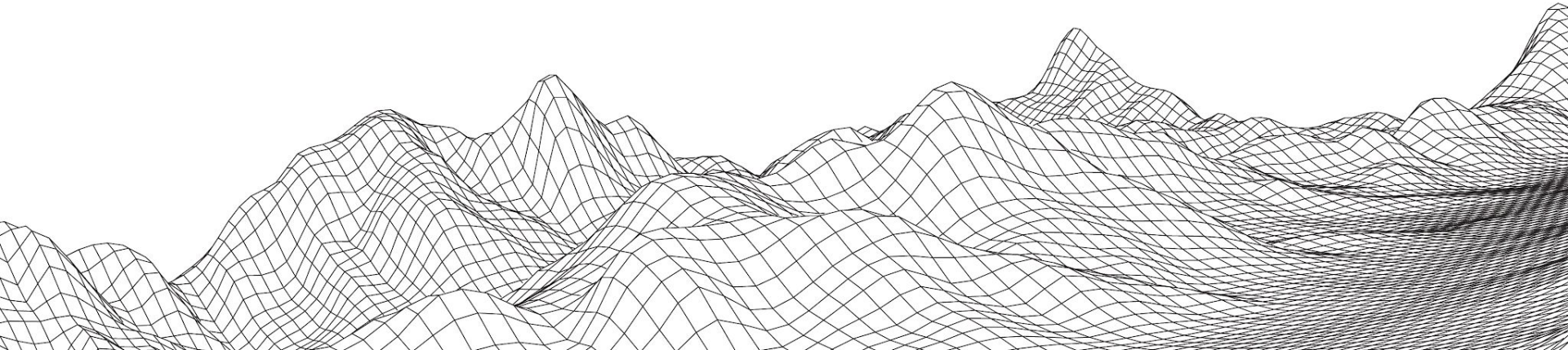


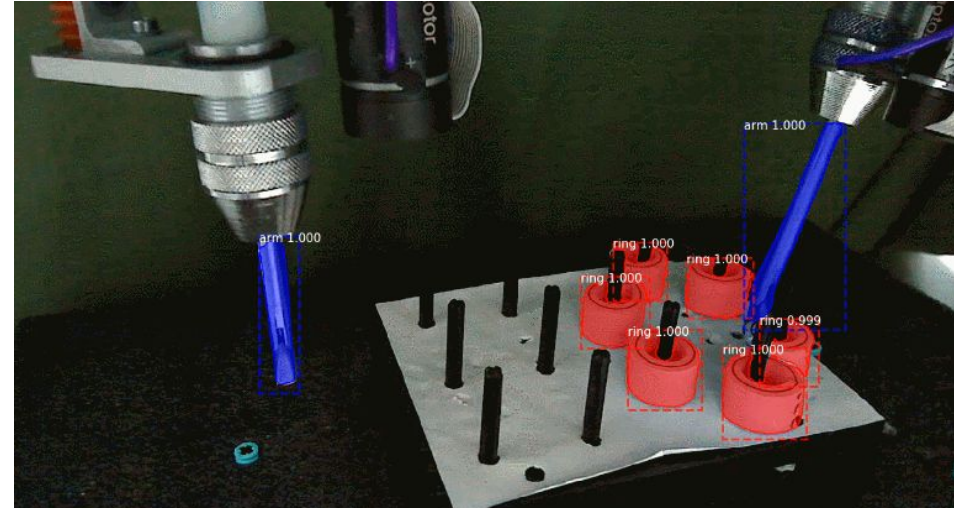
Machine learning assisted seismic interpretation

An integrated workflow for structural/stratigraphic interpretation, combined with reservoir characterisation

Behzad Alaei, Steve Purves, Eirik Larsen, and Dimitrios Oikonomou



Artificial Intelligence / Machine Learning

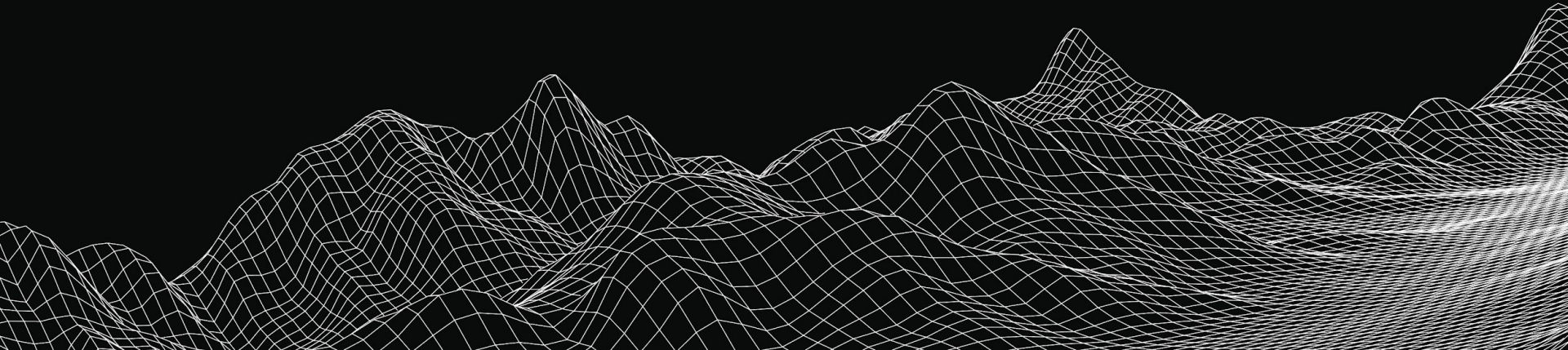


Computer Vision

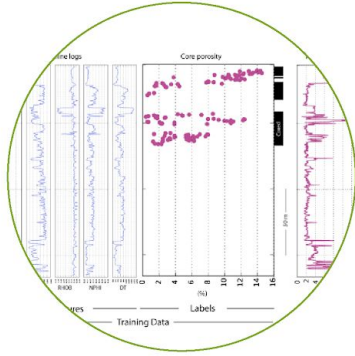
Mask R-CNN for object detection and instance segmentation on Keras and TensorFlow
https://github.com/matterport/Mask_RCNN



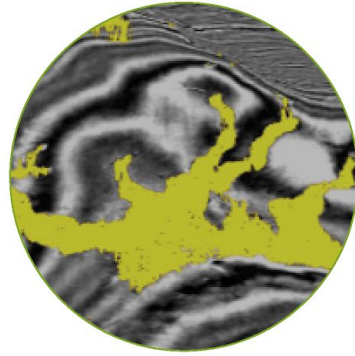
AI is Changing Geoscience Work



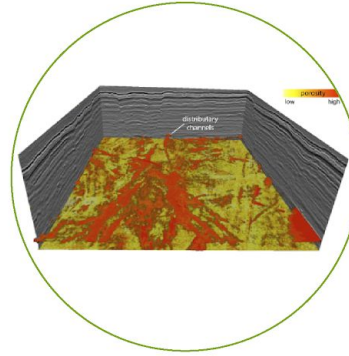
AI-assisted
well-data analysis



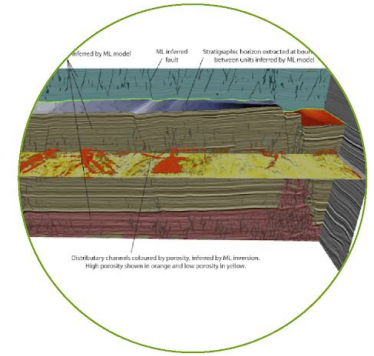
AI-assisted
seismic interpretation



AI-assisted
seismic inversion



AI-assisted
geomodelling



Enablers



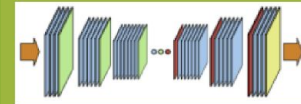
Democratization of
Sub-Surface Data



Open Source
Libraries



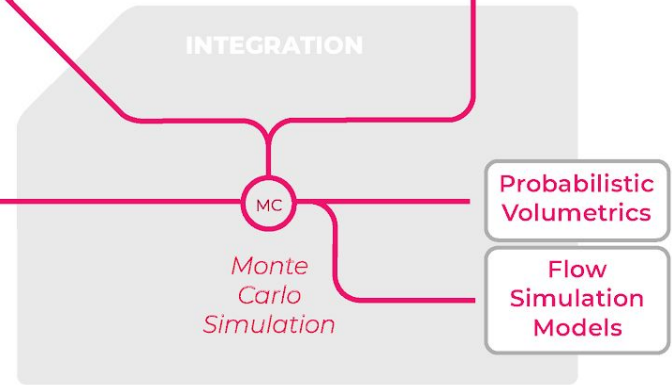
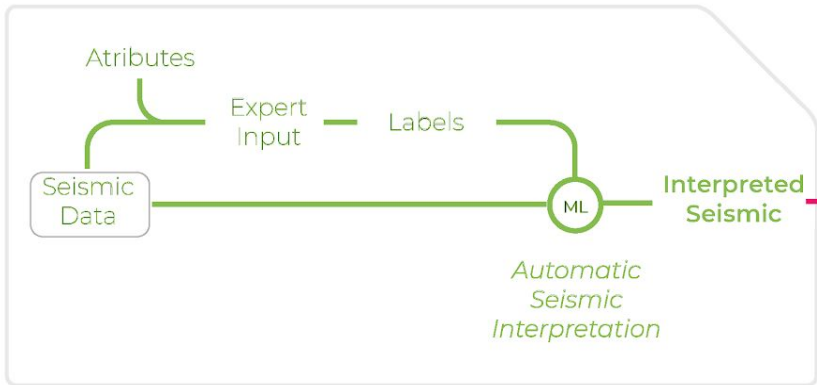
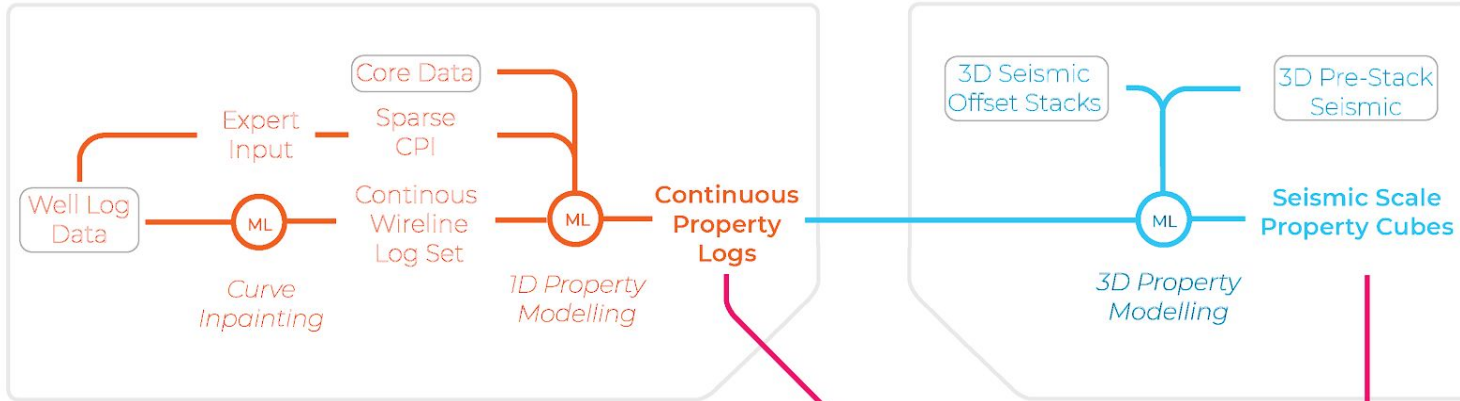
GPU Enabled High
Performance Computing



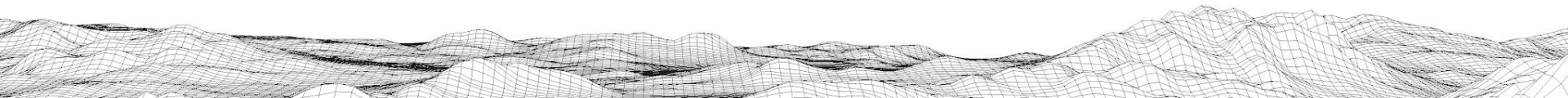
Algorithmic
Development

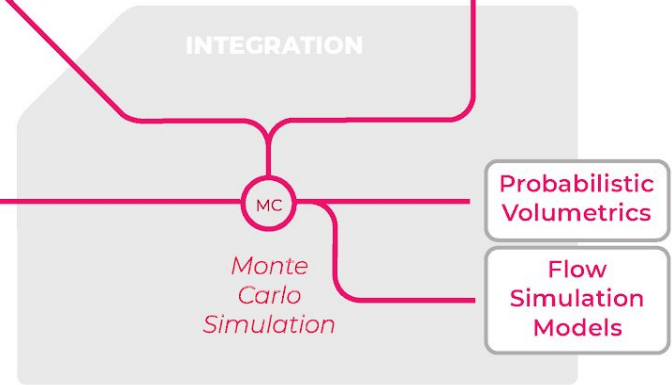
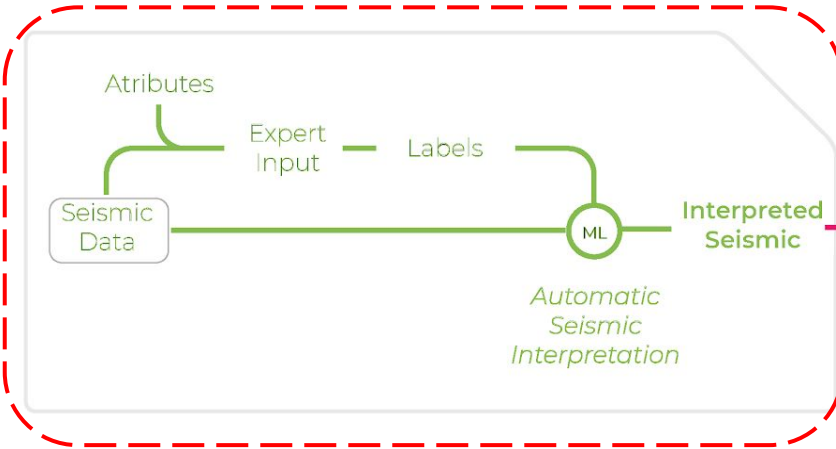
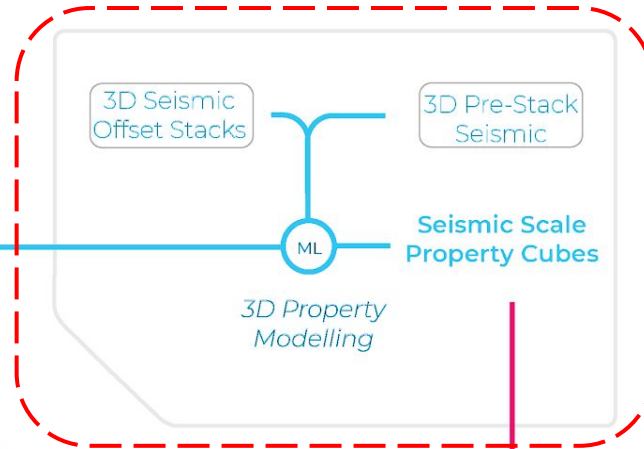
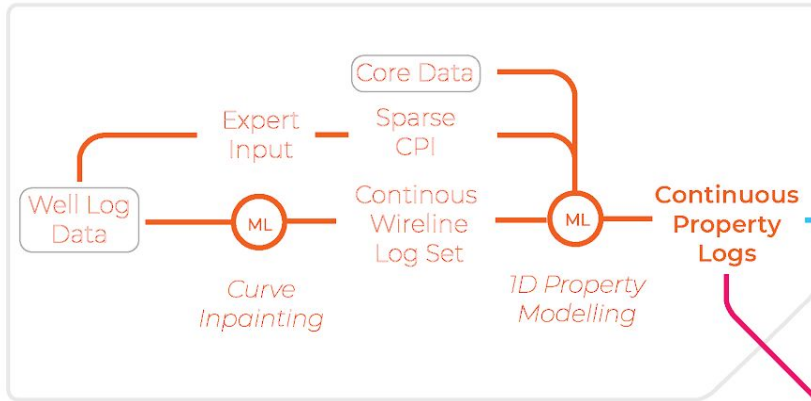


Data Analytics
Platforms

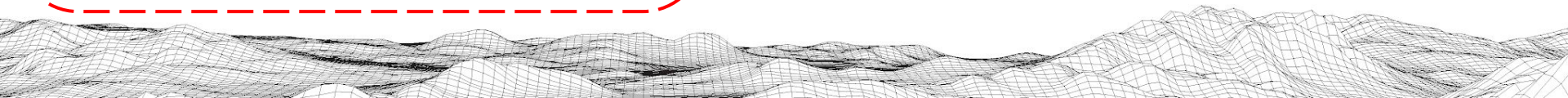


**DATA-DRIVEN
DECISIONS**





**DATA-DRIVEN
DECISIONS**



Outline

Seismic to well tie

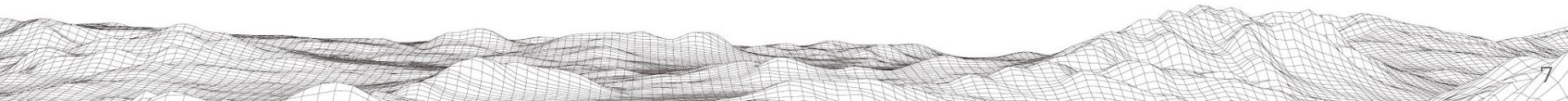
Automatic seismic interpretation: Horizon picking

Fault identification and extraction

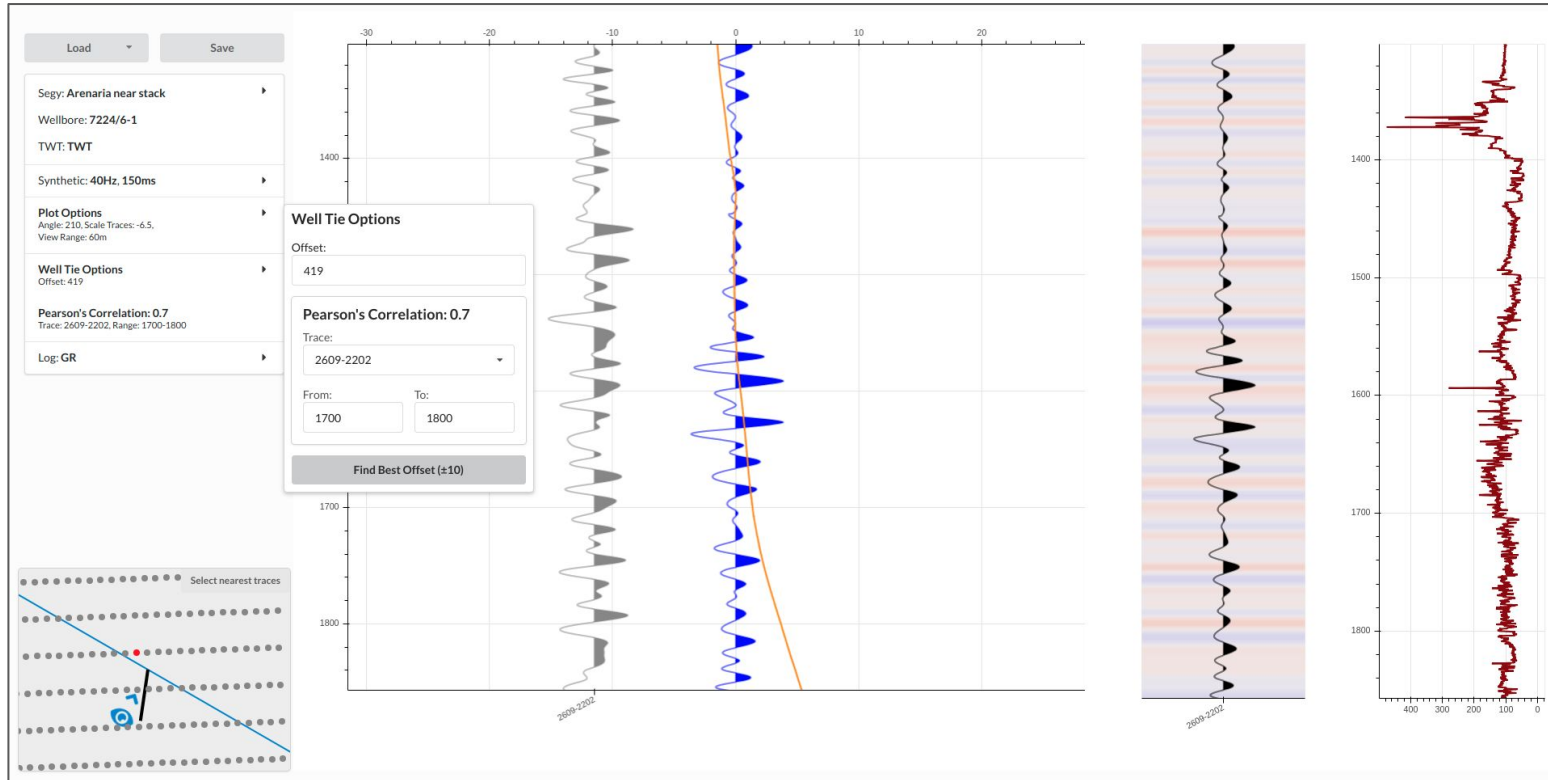
Geobody extraction

Property predictions

Uncertainty



Seismic to well tie



Automated Seismic Interpretation

Horizon picking

Workflow for lithostratigraphic picking:

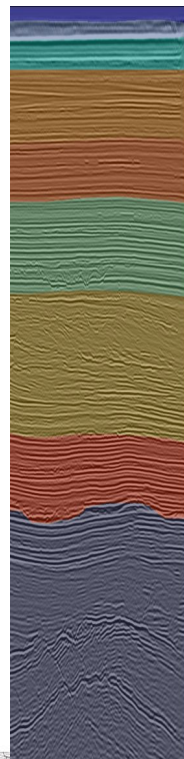
Labels: Geological intervals and

ML Algorithm: Volumetric classification of stratigraphic units using deep neural networks

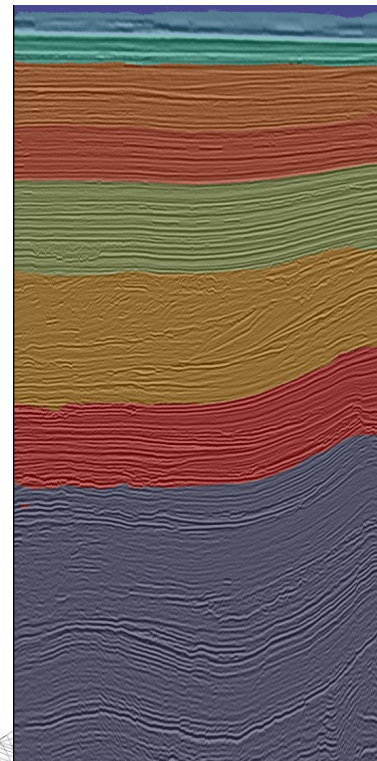
Output:

- Stratigraphic containers
- Extract surfaces as interfaces between units

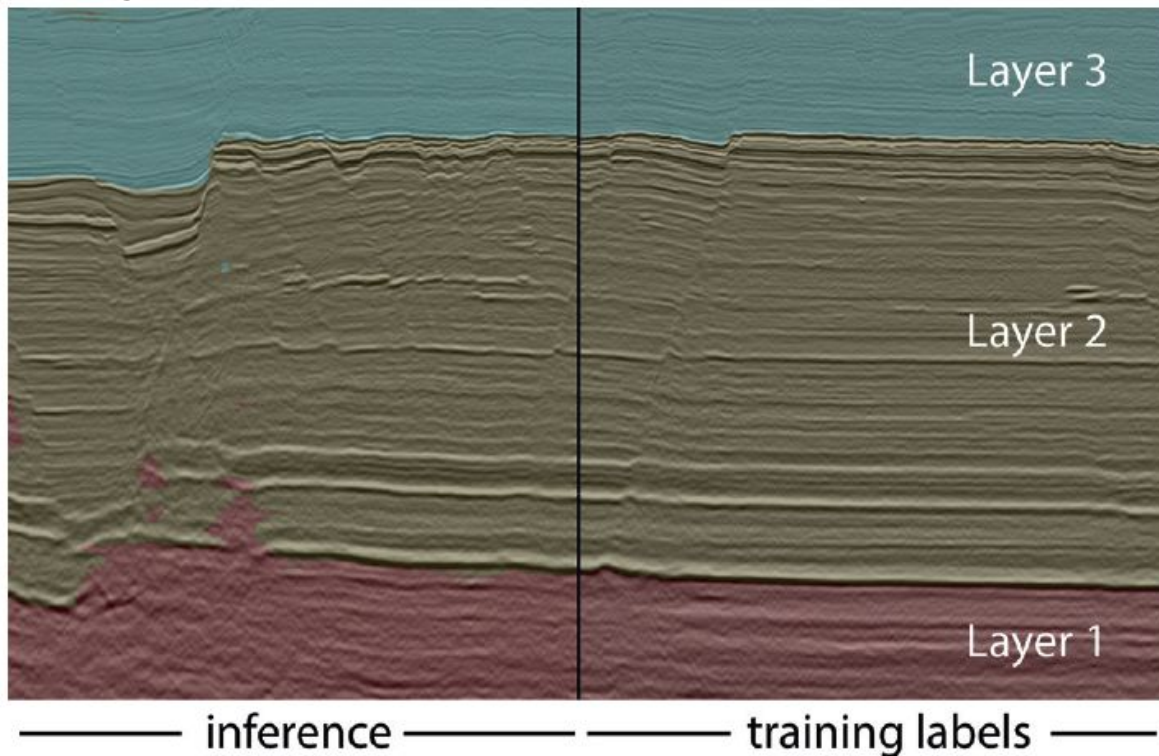
Example labels

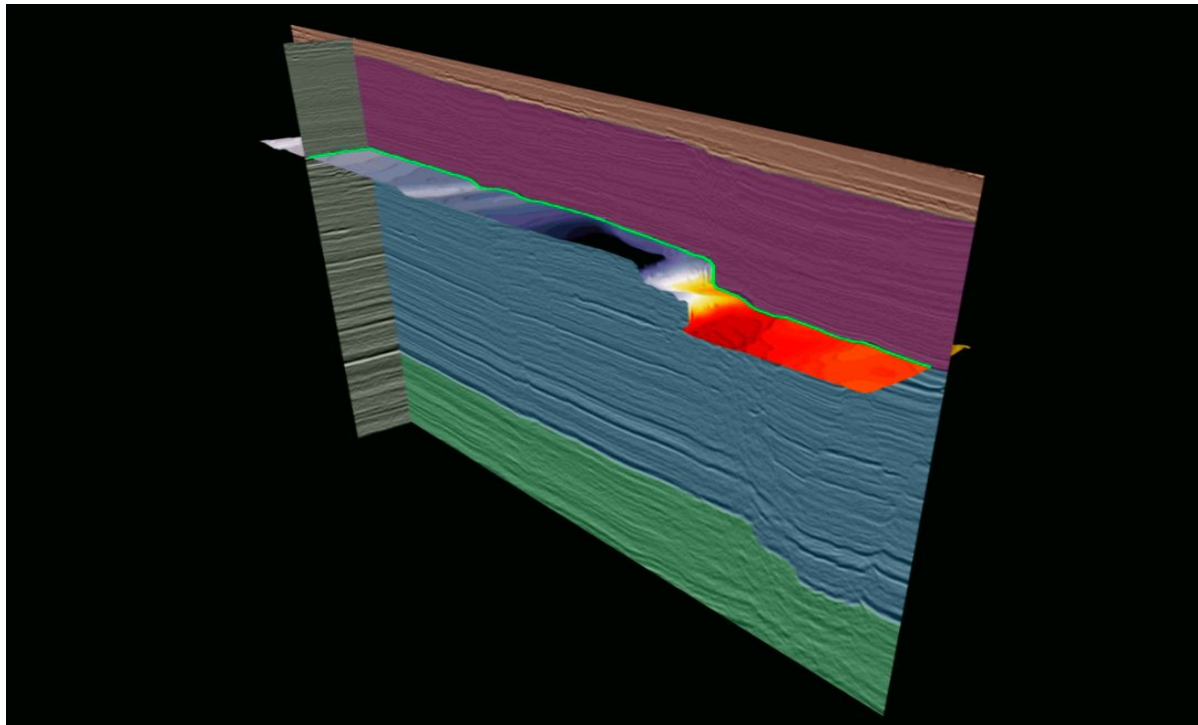


Inline Prediction



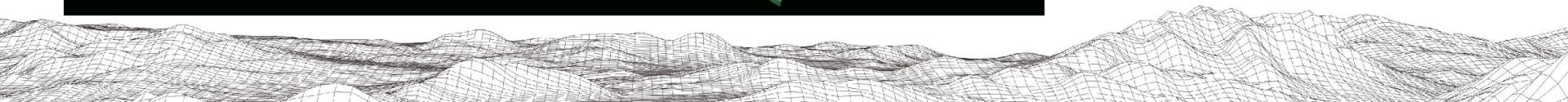
stratigraphic interpretation



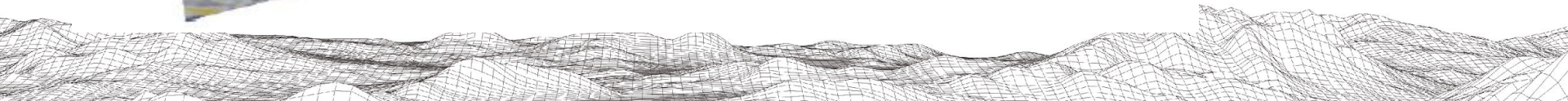
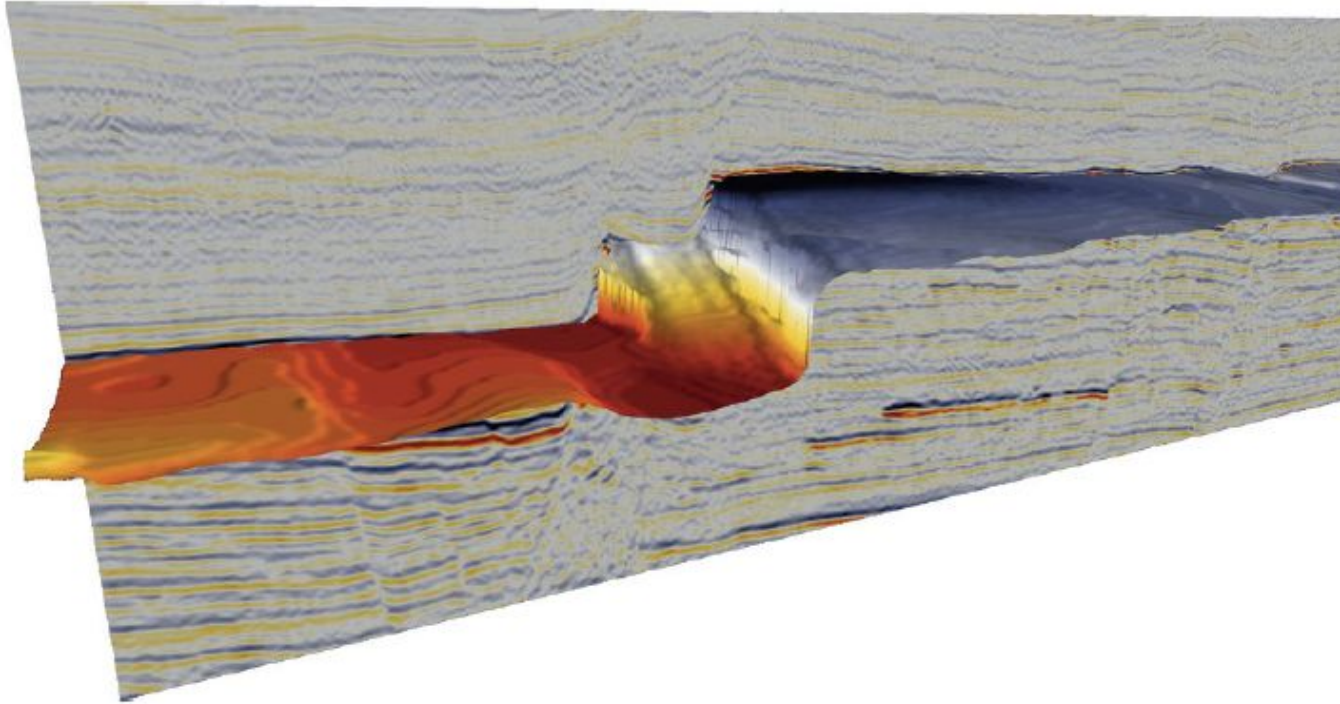


Stratigraphy:

- Stratigraphic intervals as volumetric containers
- Interface surface gridding to produce horizons



Automated Seismic Interpretation Norwegian Barents Sea



Structural interpretation-Fault imaging

Workflow for Fault Interpretation:

Labels:

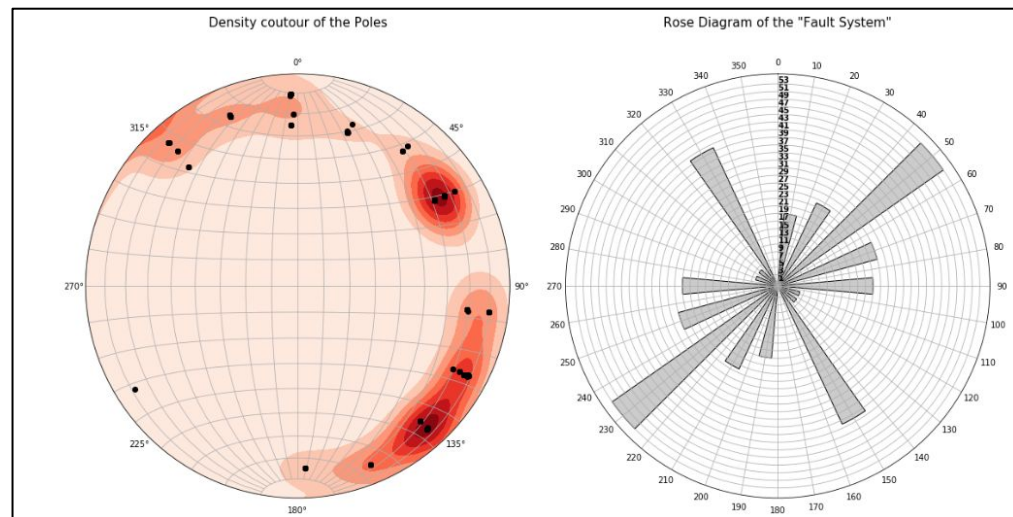
- Fault sticks
- Line drawings & images

ML Algorithm:

- Deep Fully Convolutional Networks

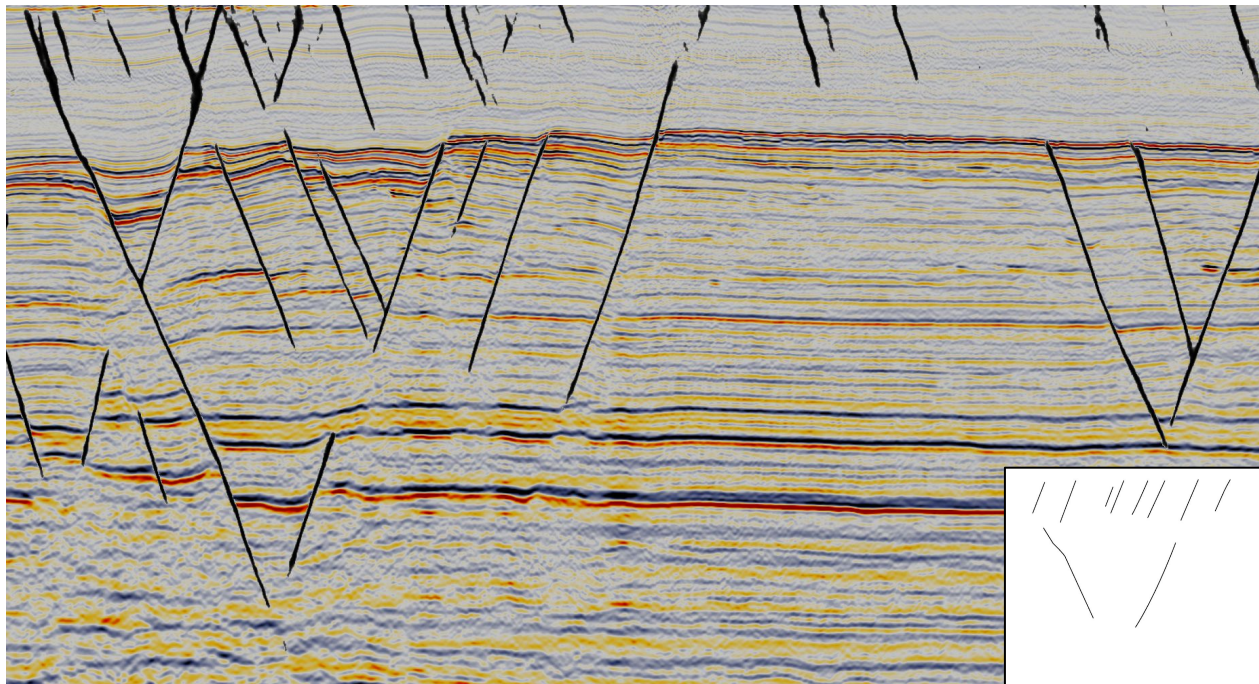
Output:

- Segmented Fault Volumes
- Fault Orientation Volumes



Automated Seismic Interpretation

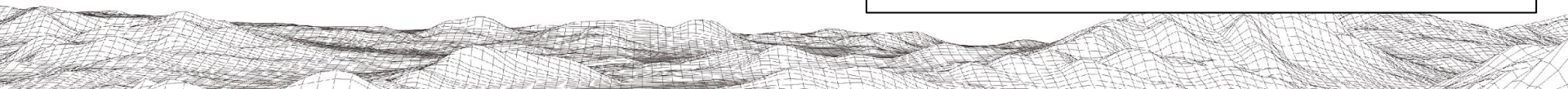
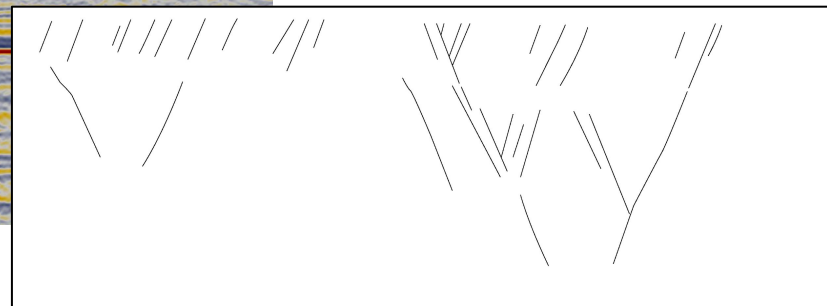
Fault interpretation



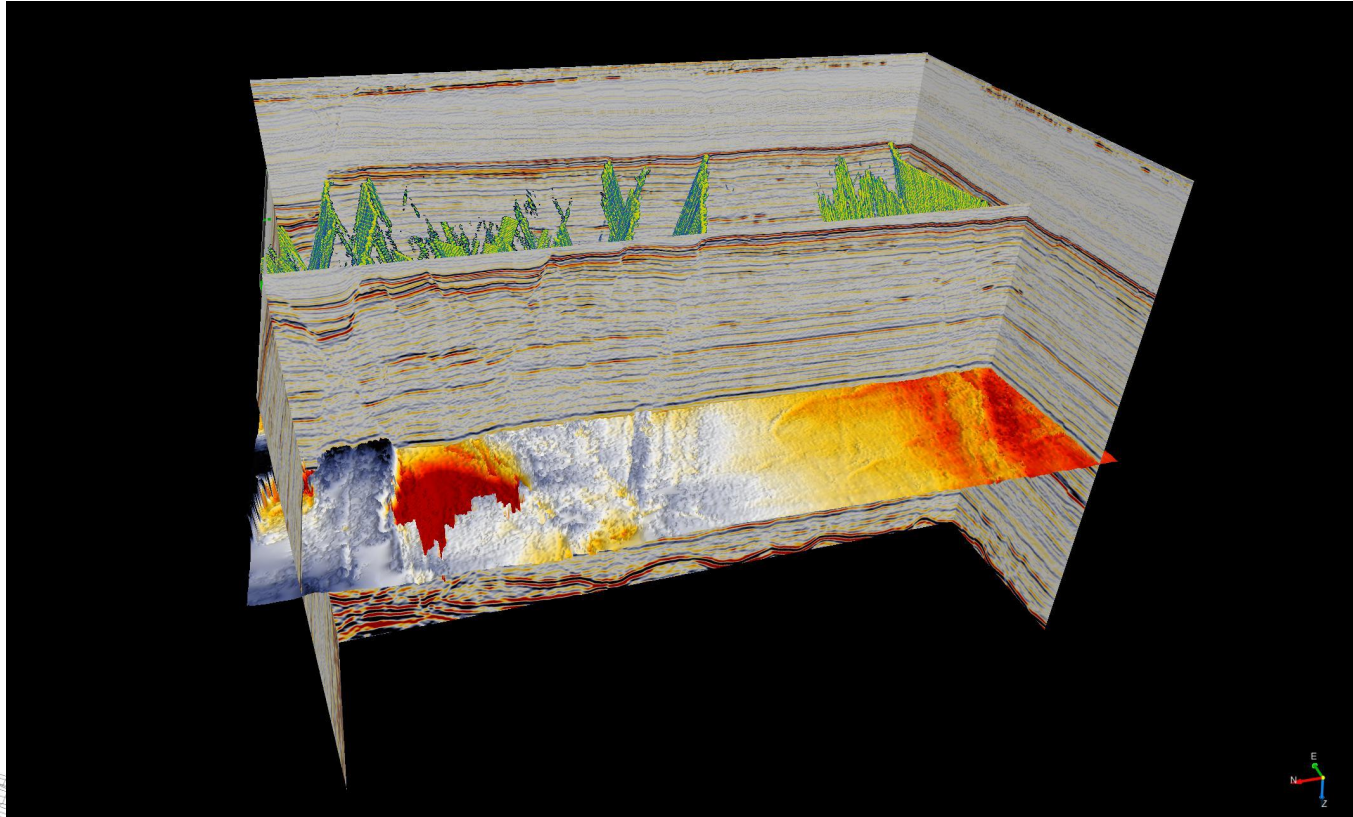
Deep Learning Model

trained on manual
fault picks on 15
inlines

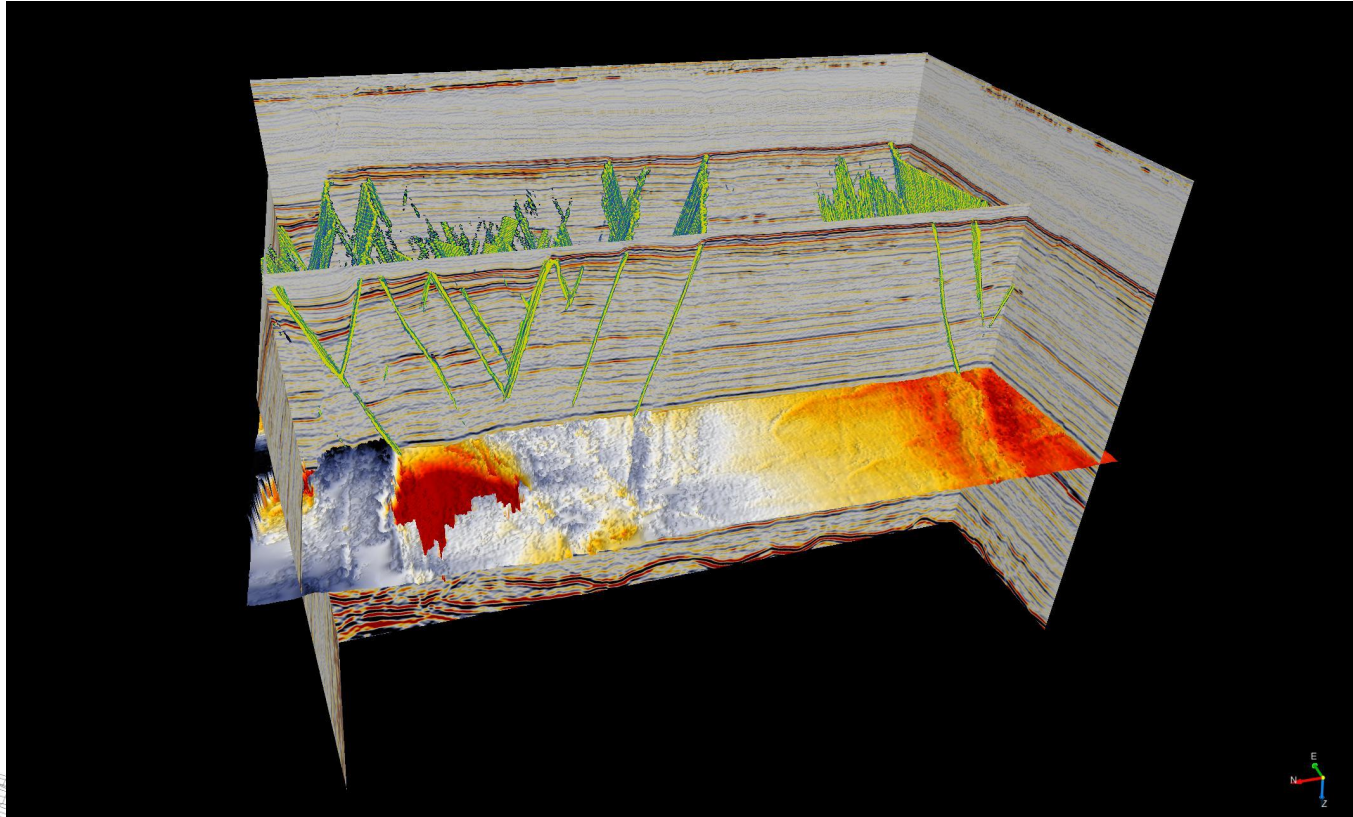
(below) representative
labels from a different
line



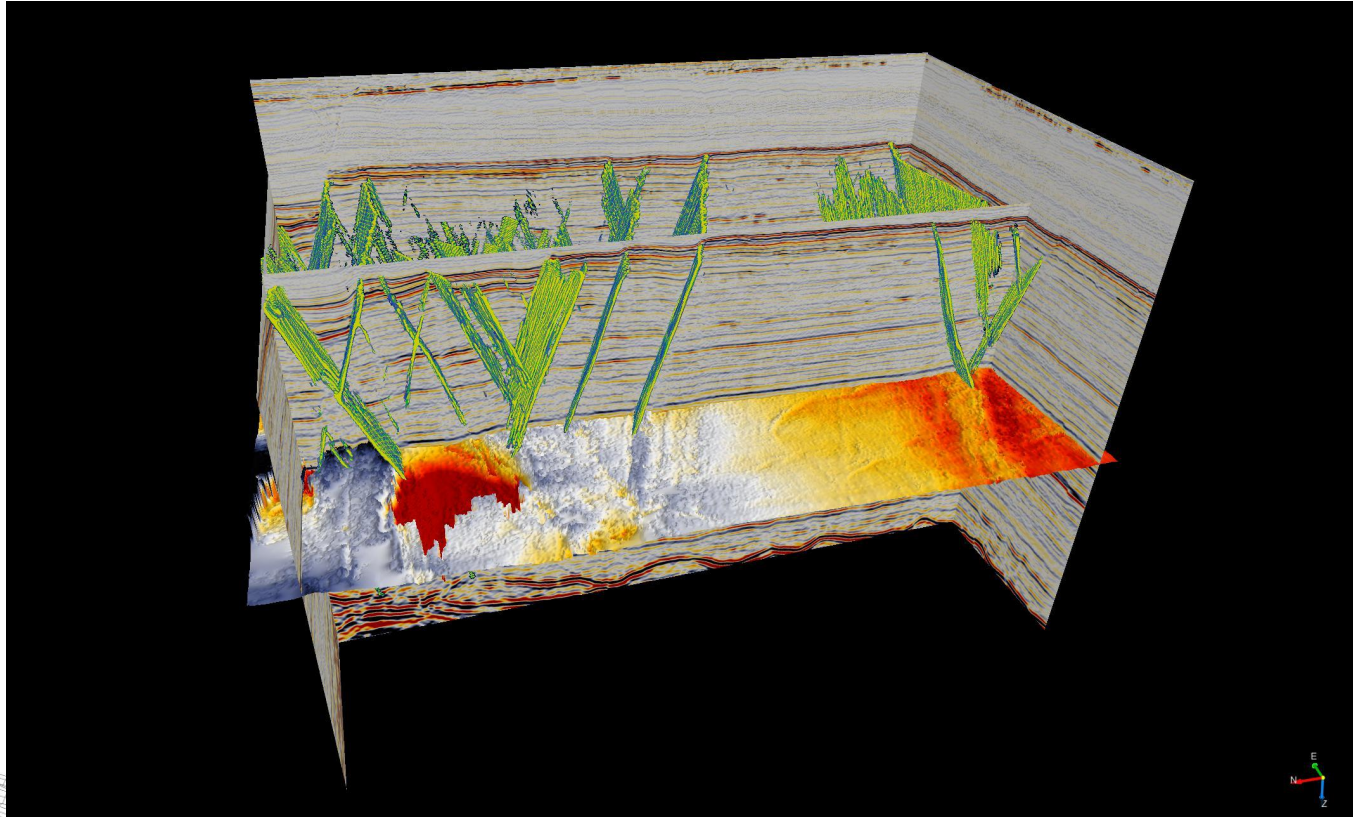
Fault interpretation Arenaria Barents Sea



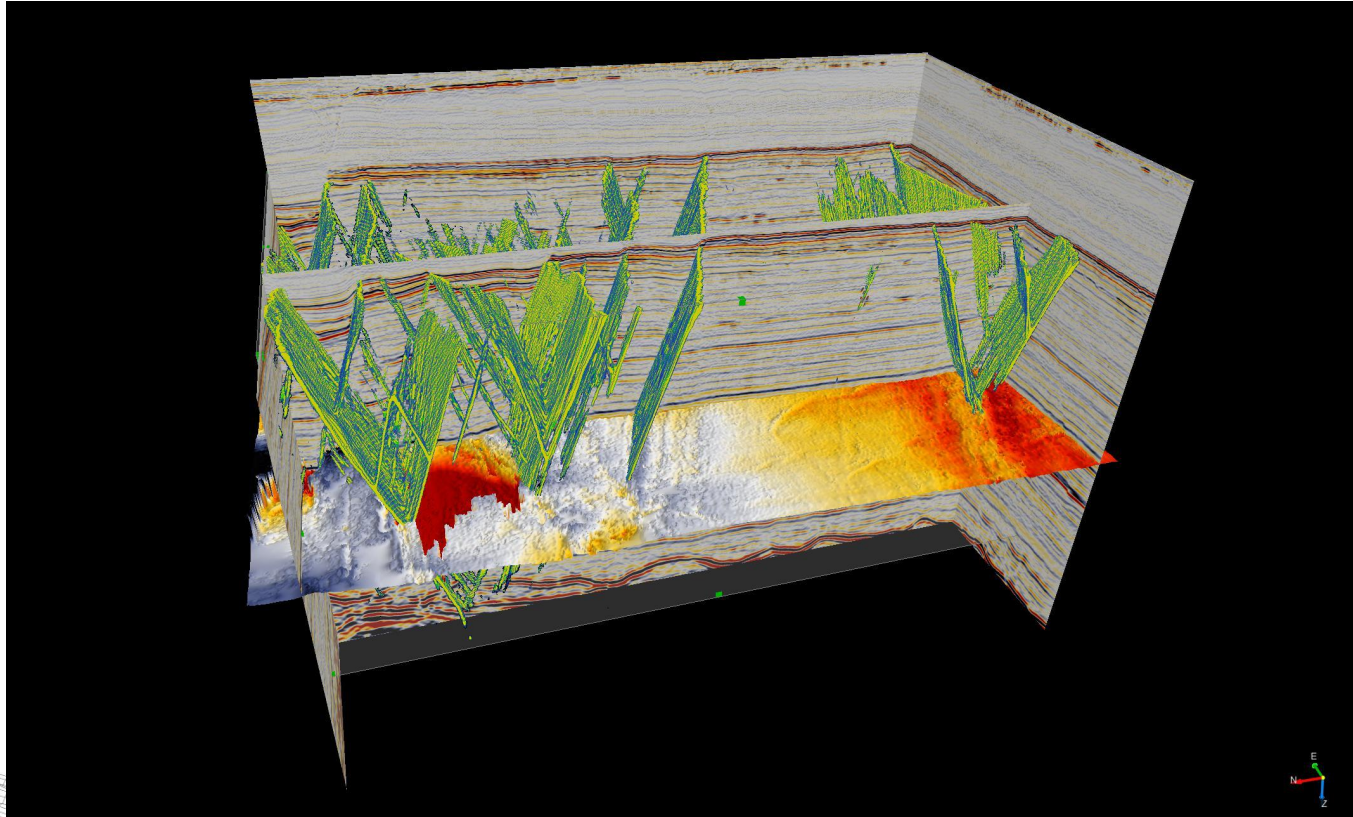
Fault interpretation Arenaria Barents Sea



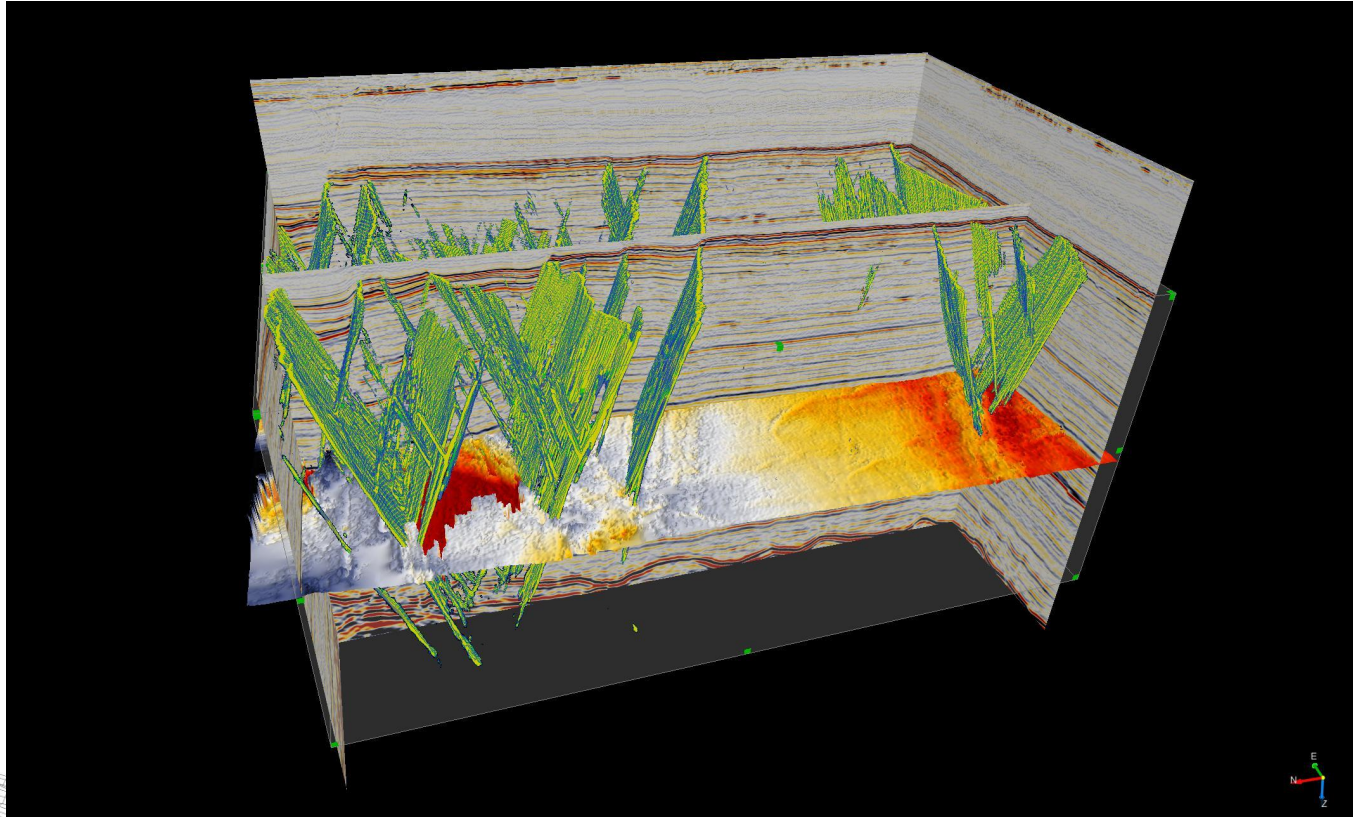
Fault interpretation Arenaria Barents Sea



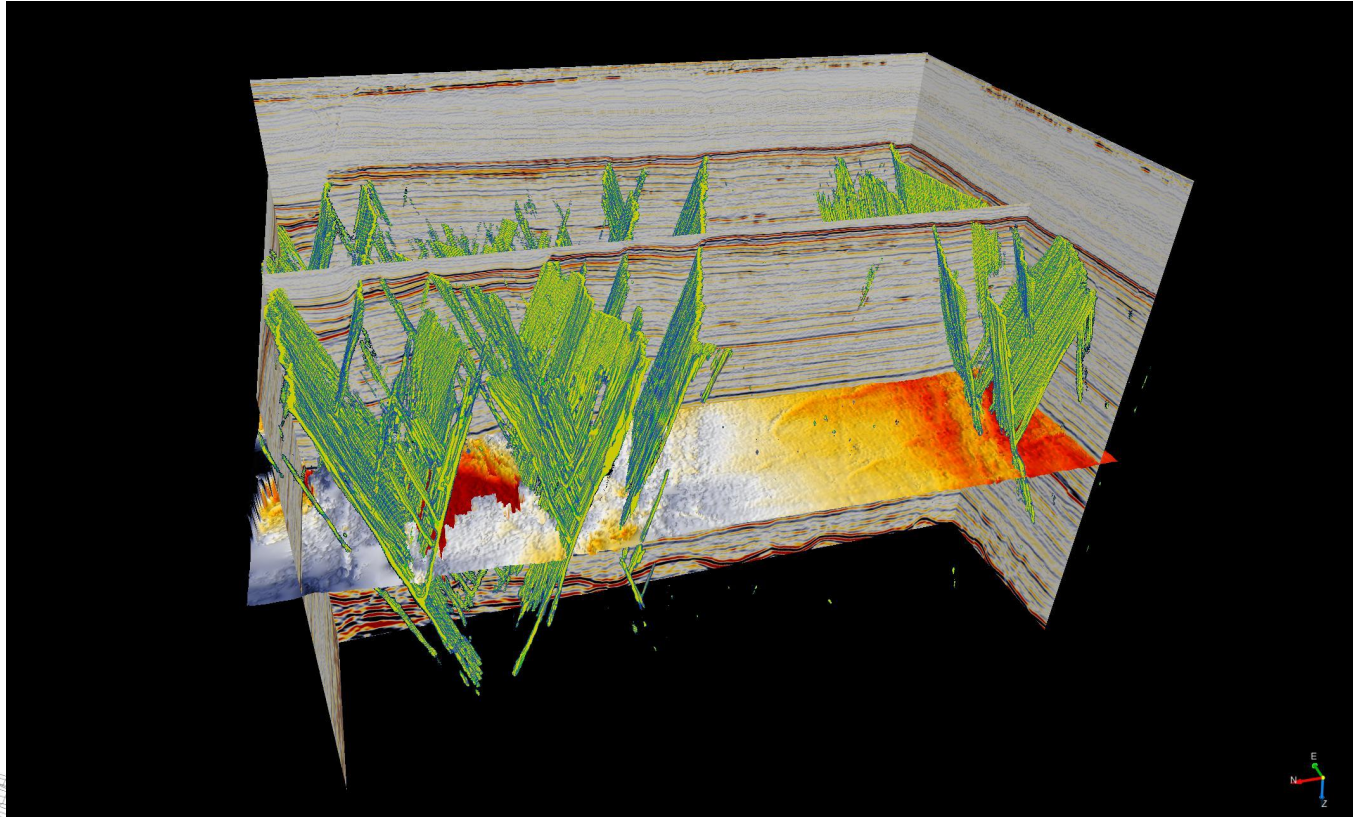
Fault interpretation Arenaria Barents Sea



Fault interpretation Arenaria Barents Sea



Fault interpretation Arenaria Barents Sea



ASI and geobody extraction

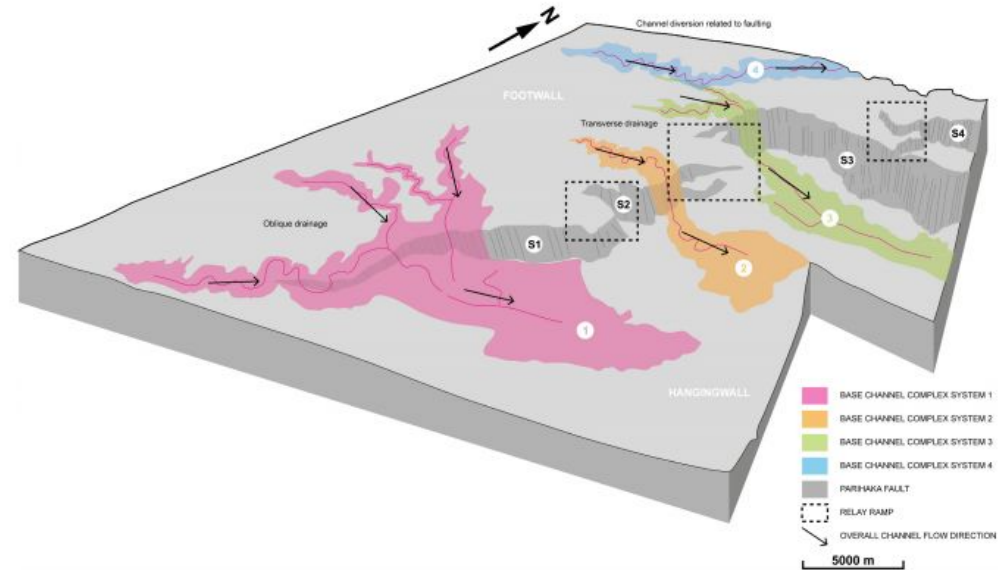
Gully Systems

Potential stratigraphic traps

Complex geomorphology

Varying infill response

Extensive and very difficult to pick



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

ASI and geobody extraction

Approach

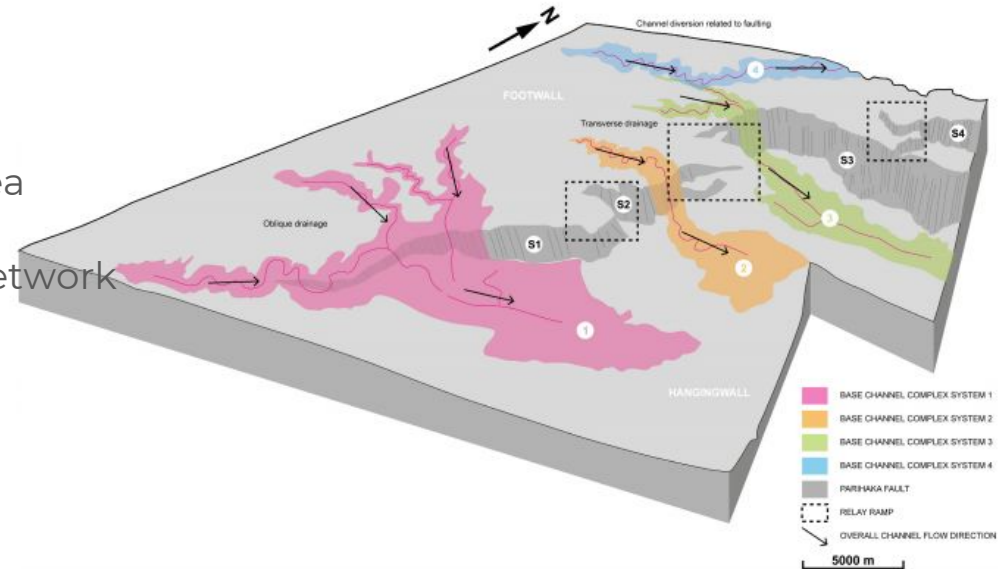
Labels:

- Polygons drawn on inline sections
- Order of 25 inlines over a cropped area

ML Algorithm: Deep Fully Convolutional Network with MonteCarlo Dropout

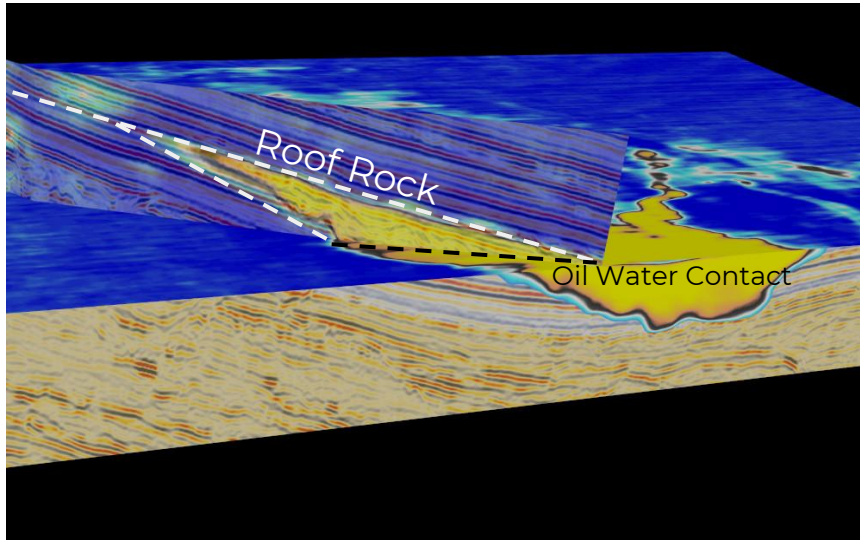
Output:

- Volumetric Geobodies
- Probabilistic Volumes Mean/Variance



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

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

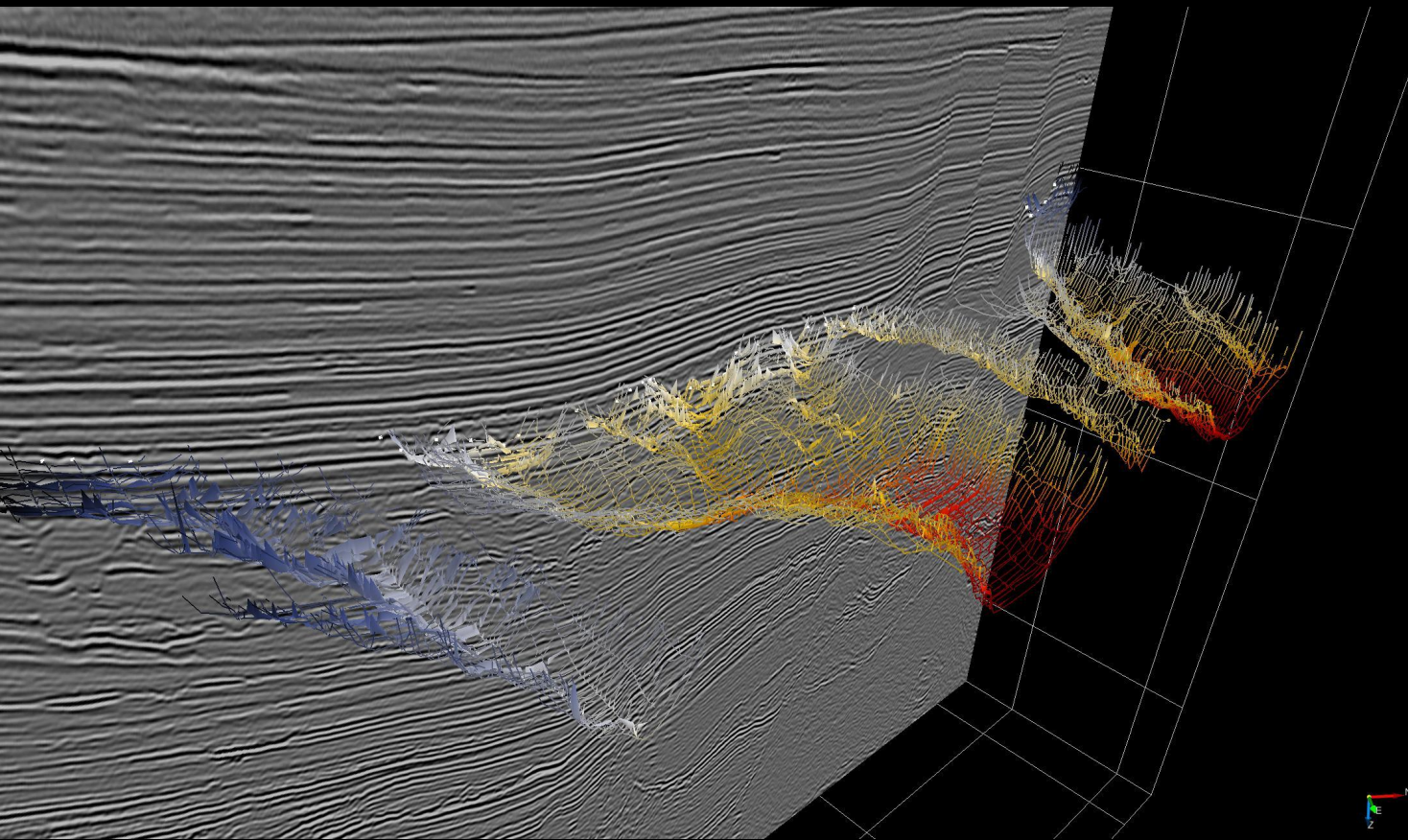
N/G = net / gross ratio

POR = porosity

S_{hc} = hydrocarbon saturation

FVF = formation volume factor

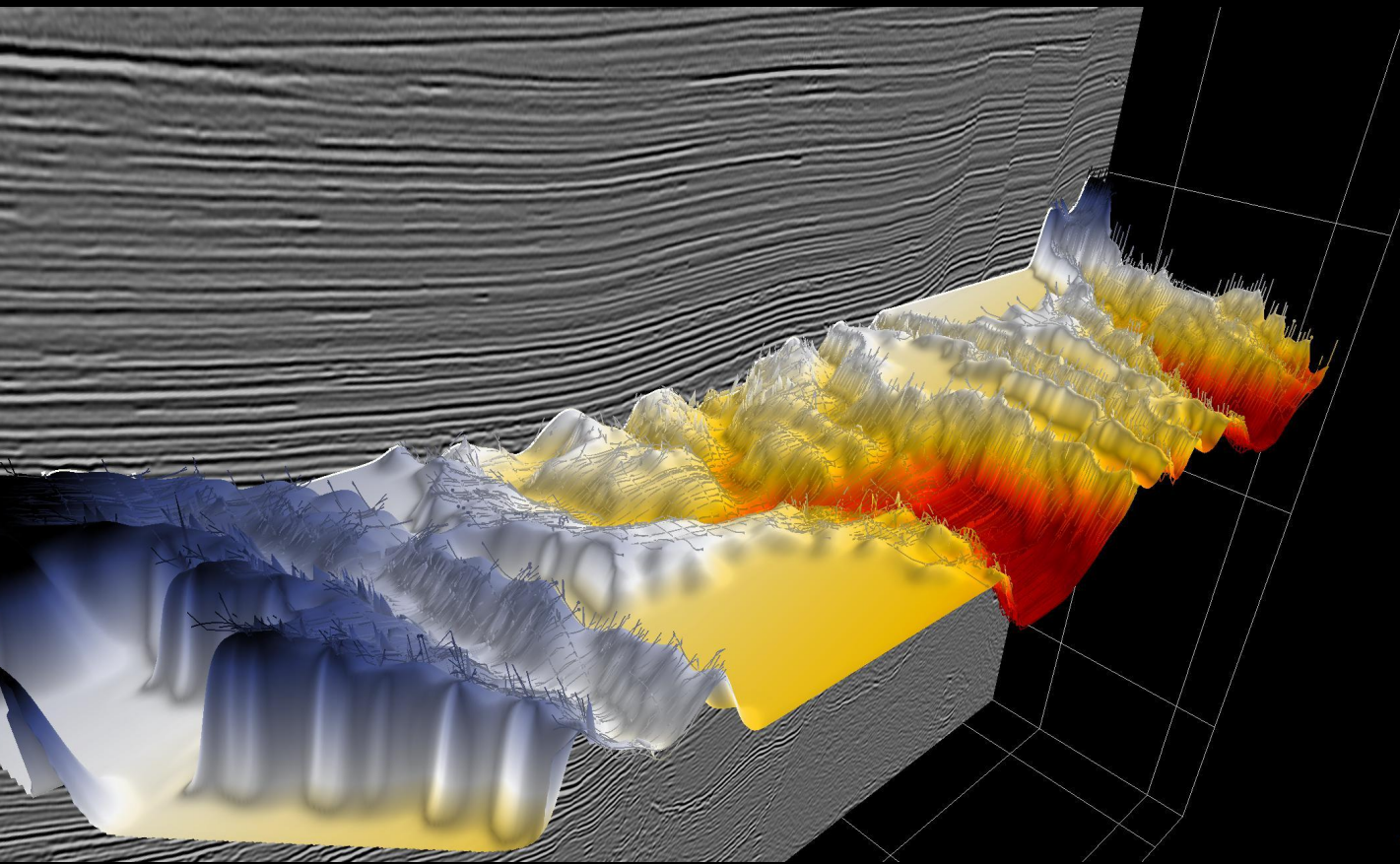
*of oil, solution gas, free gas, condensate and normal surface conditions



Interpretation of complex geobodies

hard-to-track basal surfaces

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



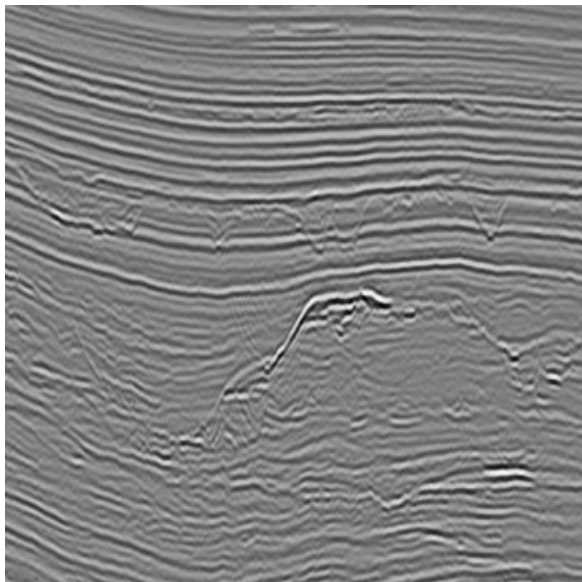
Interpretation of complex geobodies

hard-to-track basal surfaces

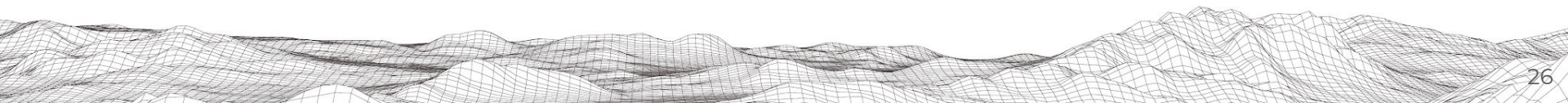
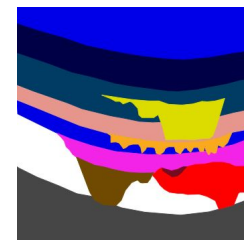
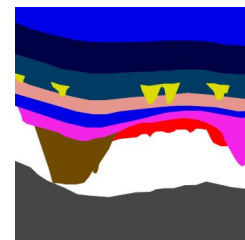
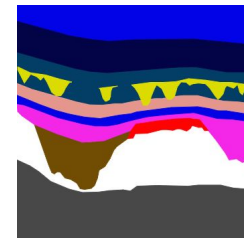
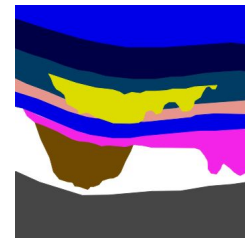
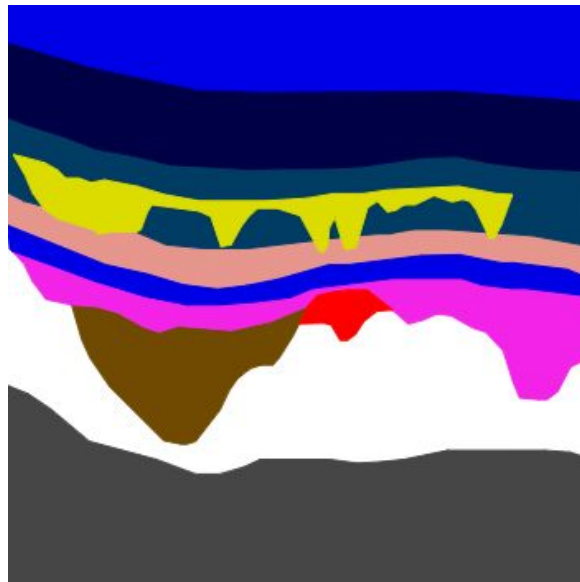
Manual (point) interpretation in traditional software takes time and is prone to errors

Gridding of manual (point) interpretation suffers from picking inconsistency

Gullies Labels



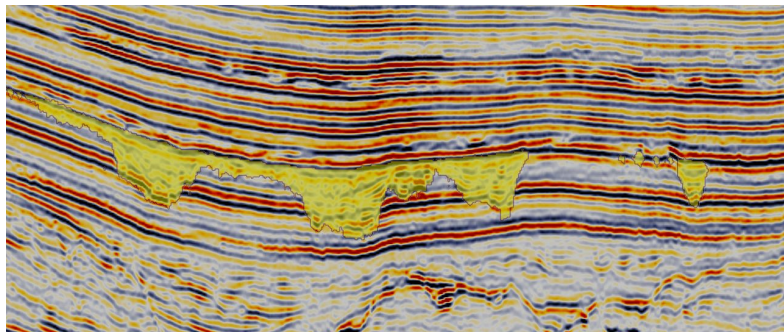
XI4910 - crop



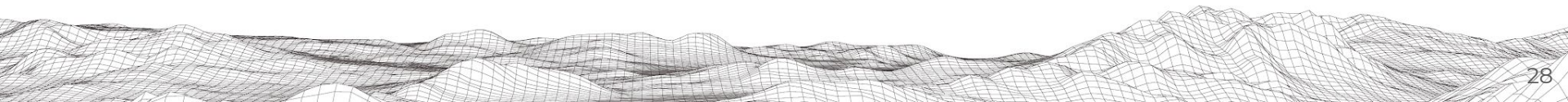
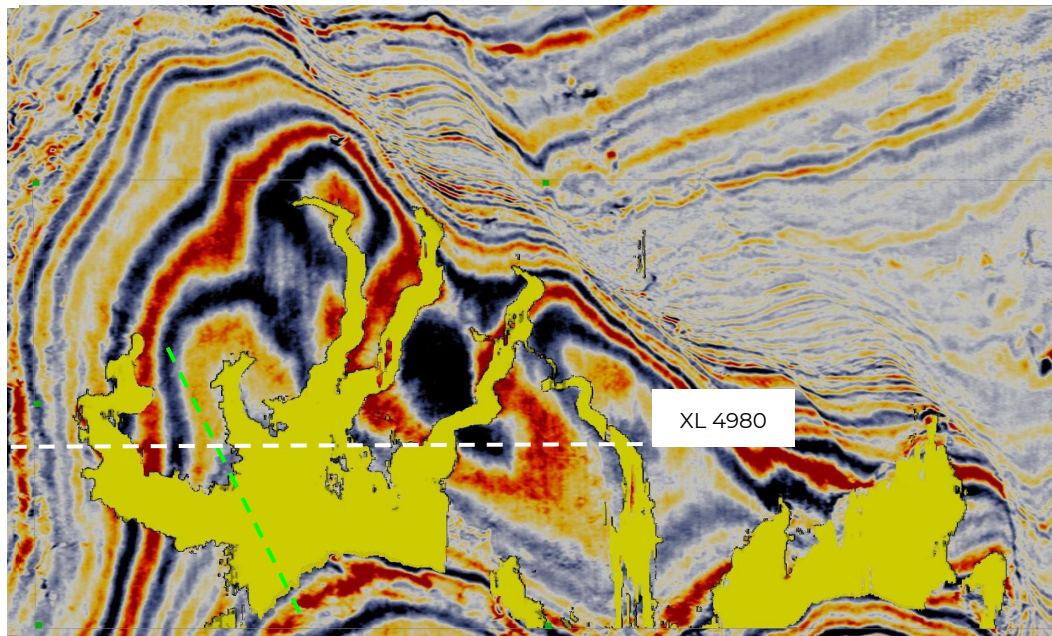
Gullies Labels & Predictions



Gullies Prediction

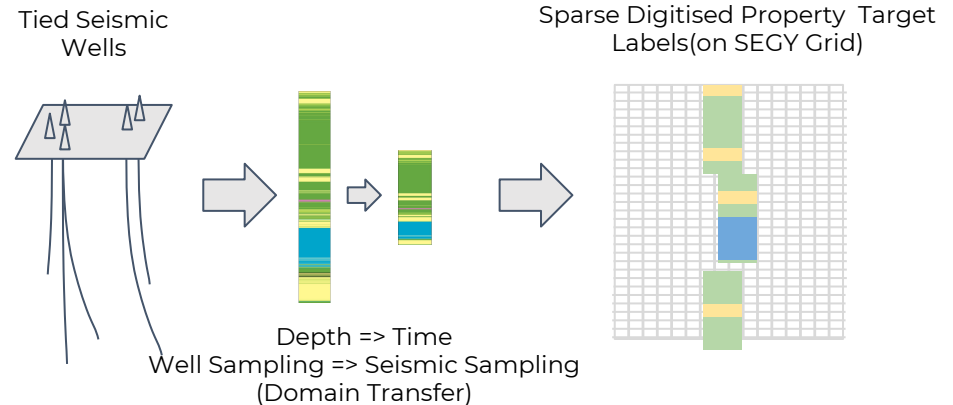


XL 4980

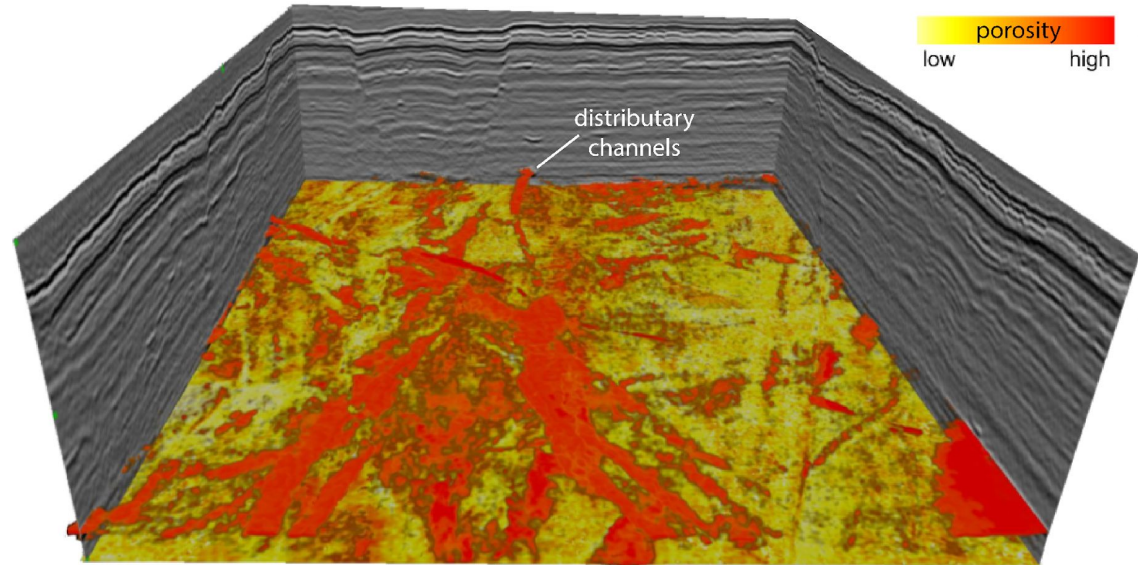
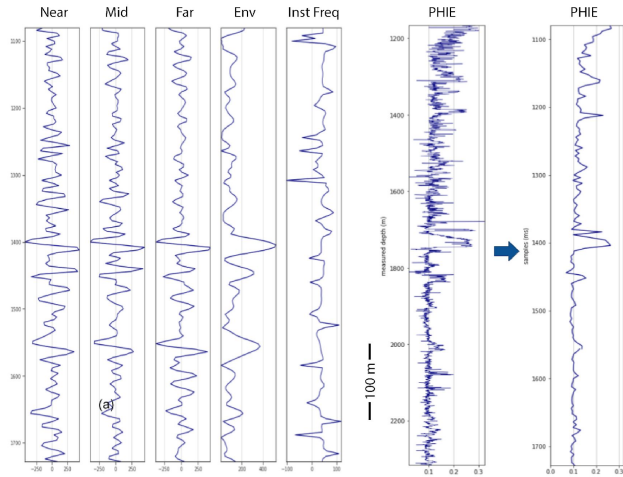


Quantitative interpretation

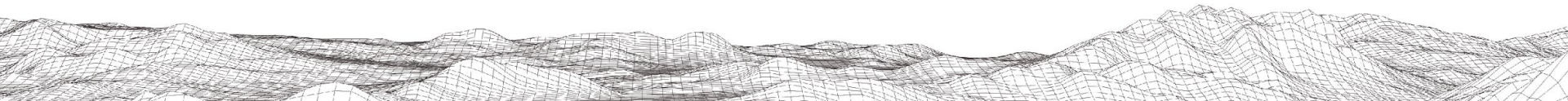
- Labels:
 - Continuous property logs (e.g. porosity, water saturation, and lithology) at wells
- Features:
 - Full and partial stacks
 - Interval velocity volumes
 - Attributes
- ML Algorithm
 - Deep fully convolutional neural network
- Output
 - 3D volumes of properties
 - 3D litho_fluid volumes



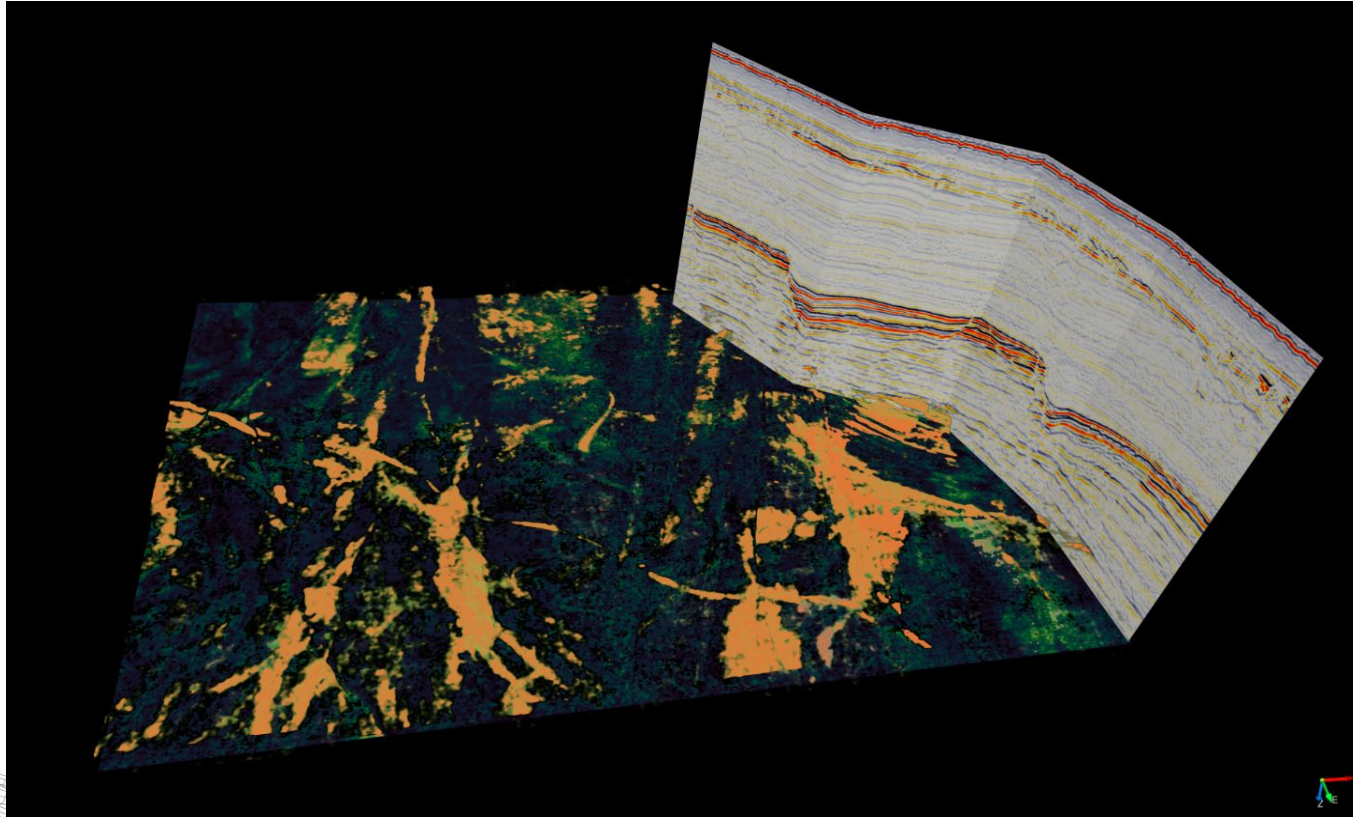
Predicting rock- and fluid-properties from 3D seismic



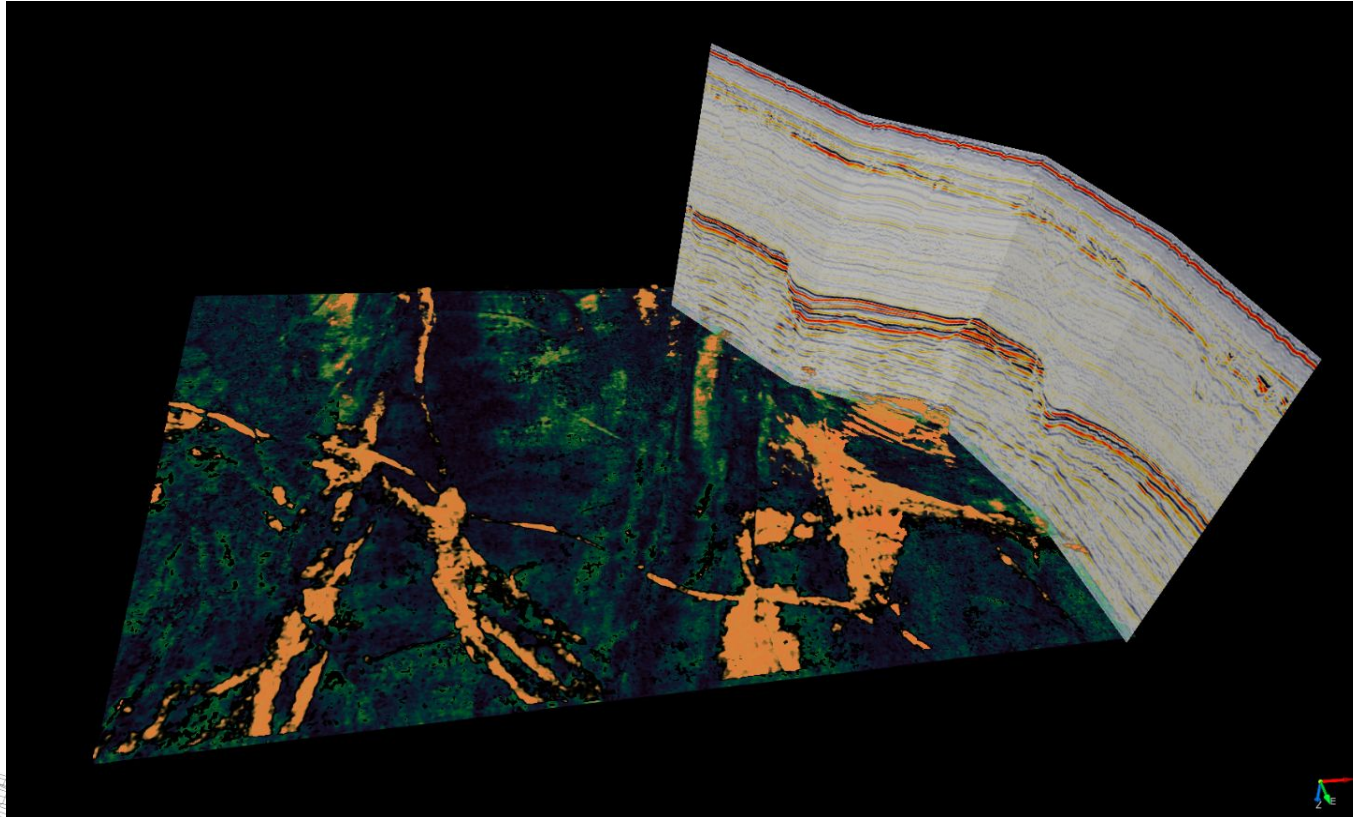
ML-derived 3D porosity model
inferred from seismic traces;
near, mid, far and seismic attributes



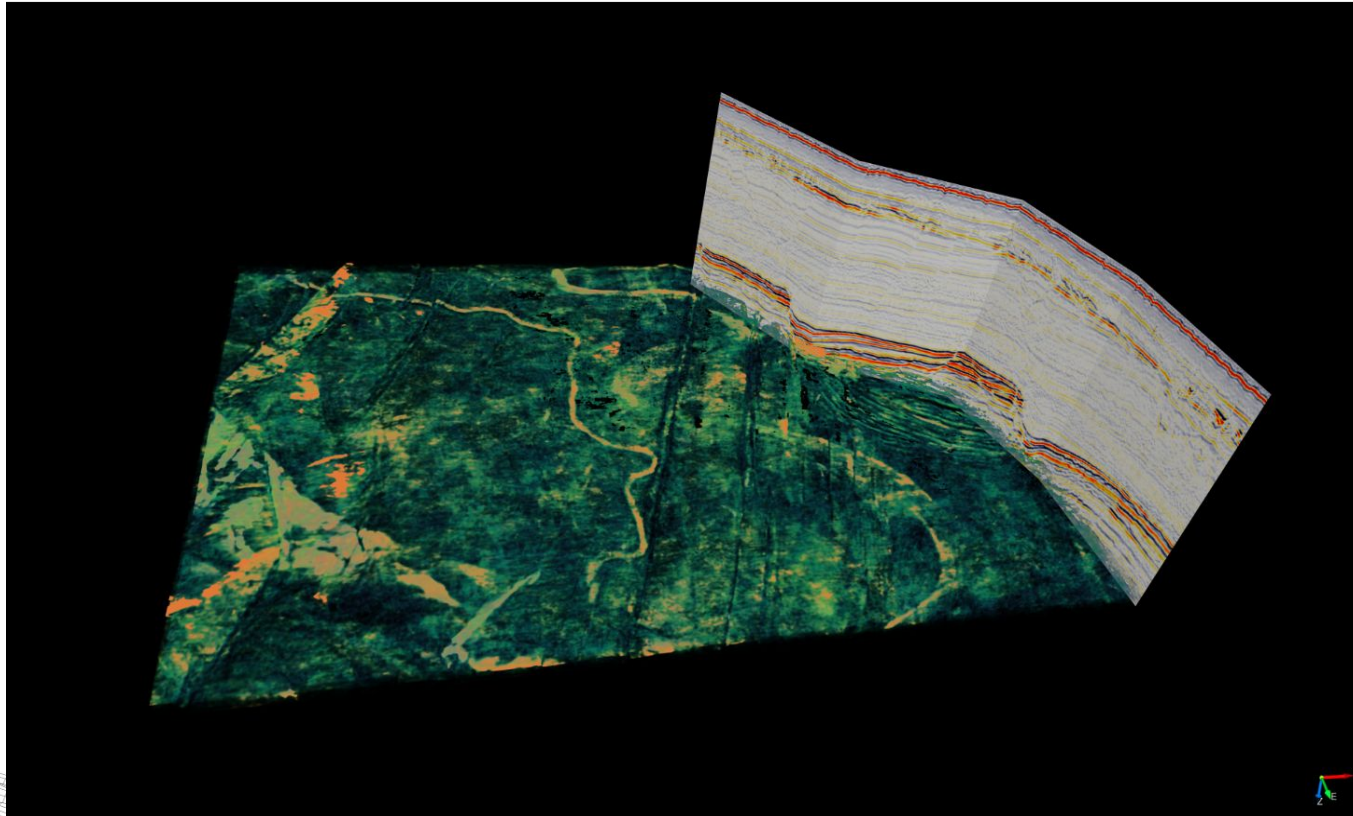
3D porosity volume Arenaria Barents Sea



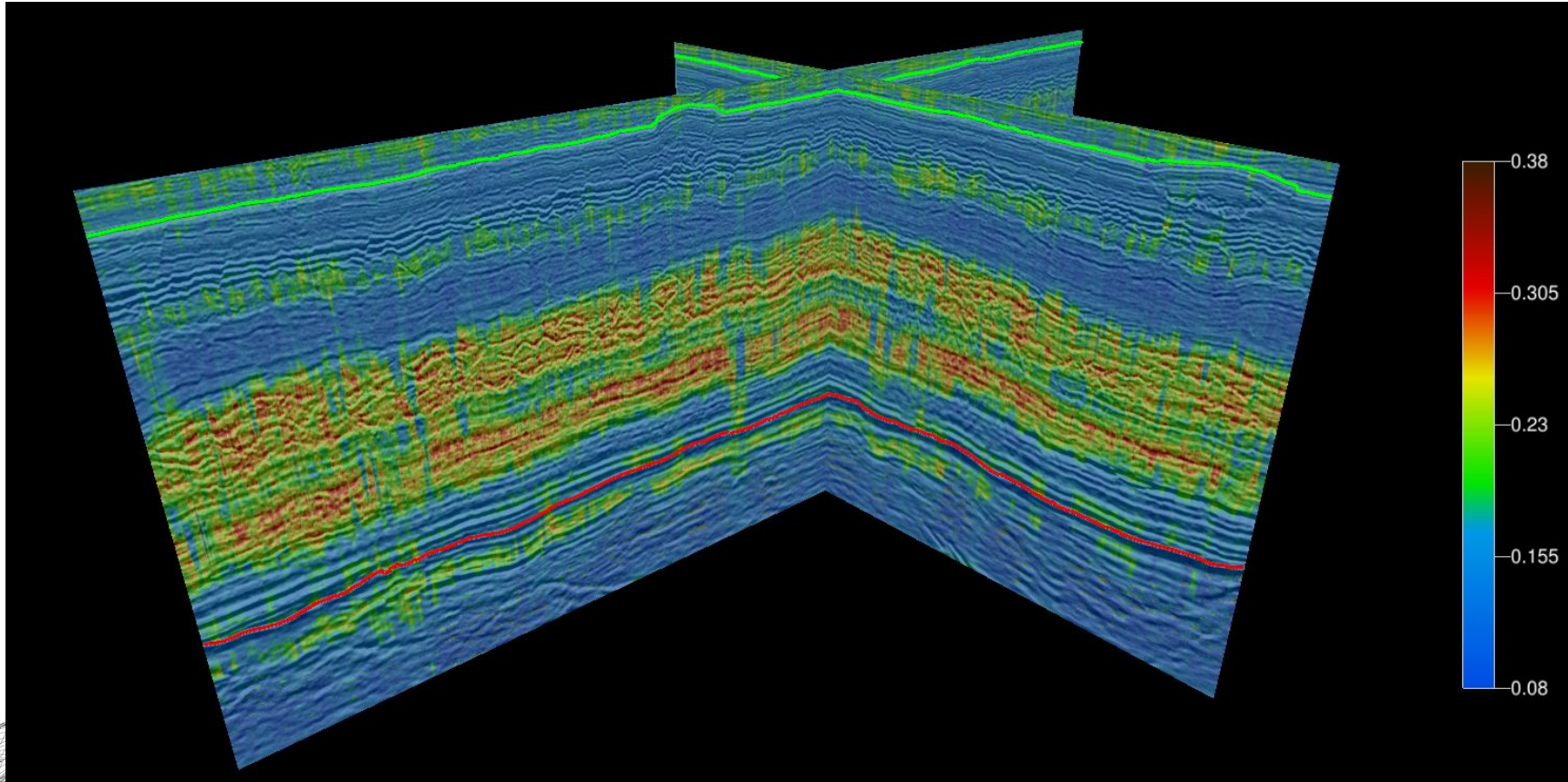
3D porosity volume Arenaria Barents Sea



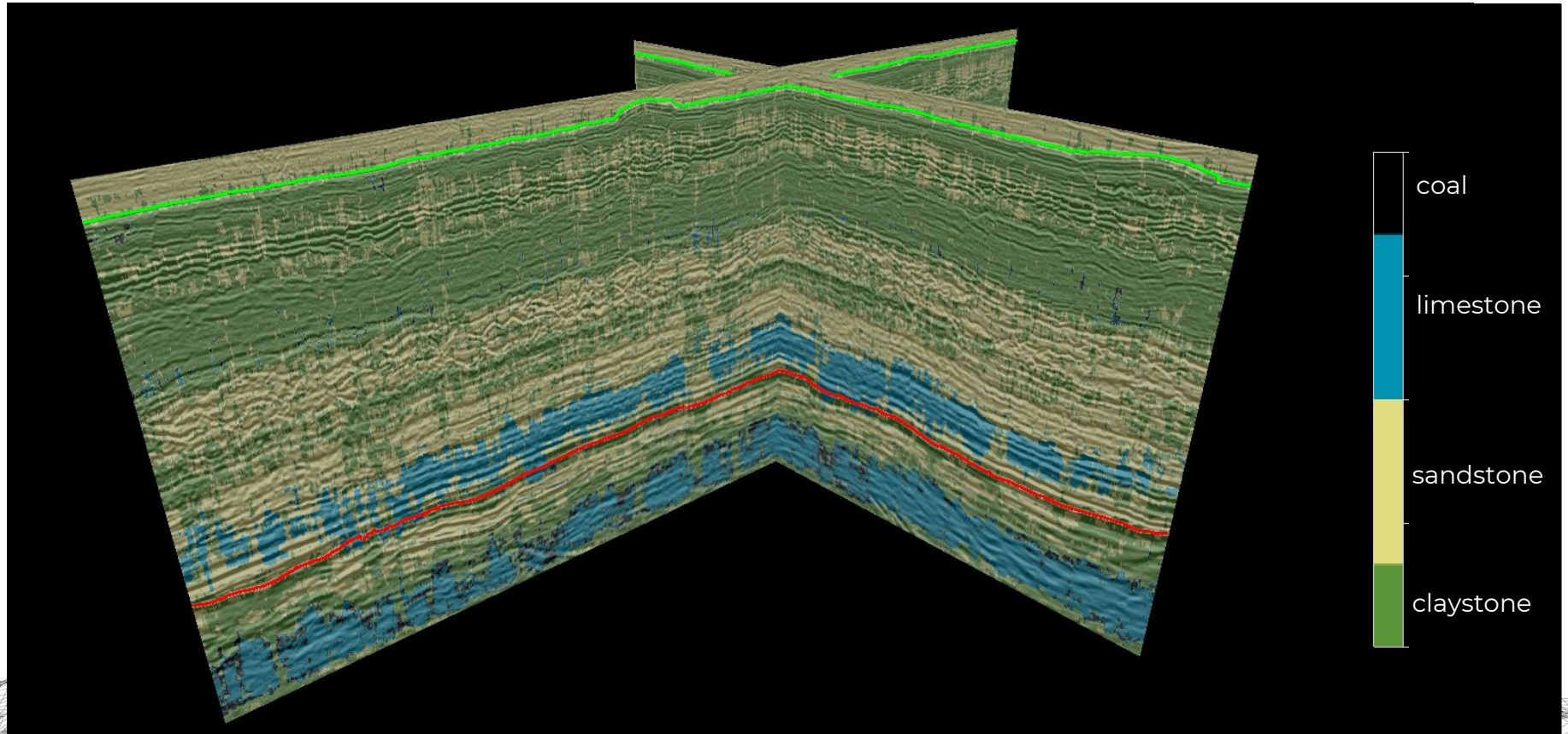
3D porosity volume Arenaria Barents Sea



3D porosity volume Sleipner Vest North Sea



3D multiclass lithology volume Sleipner Vest North Sea



Uncertainty

HCIP

=

GRV

*

N/G

*

POR

*

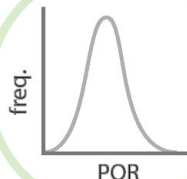
SHC

/

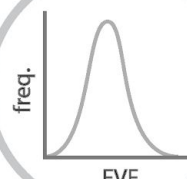
FVF



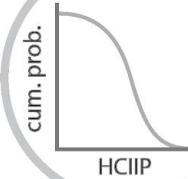
Deep Learning ASI with Uncertainty



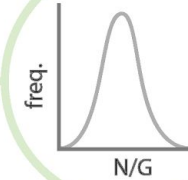
ML inversion and/or contextual queries on ML derived POR logs



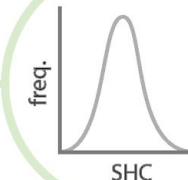
Contextual queries on analogous field data



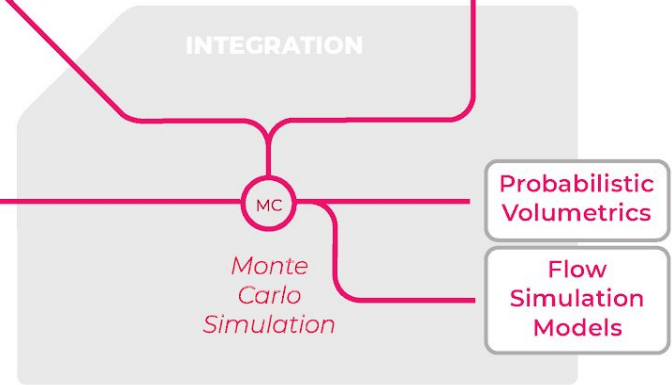
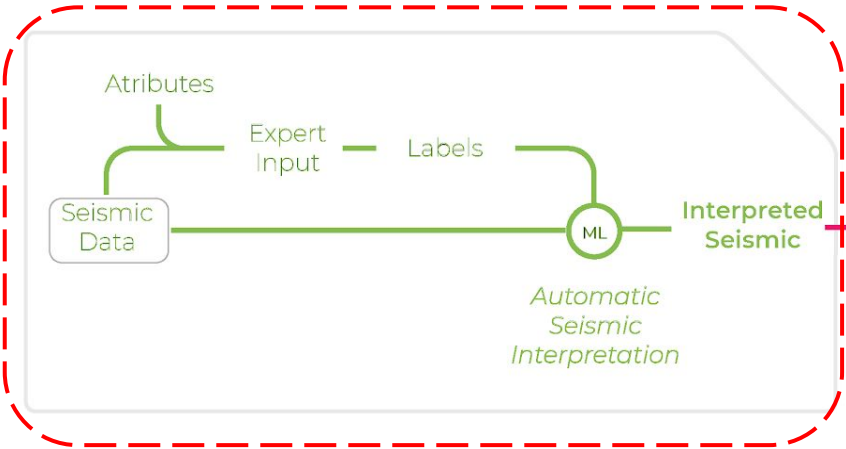
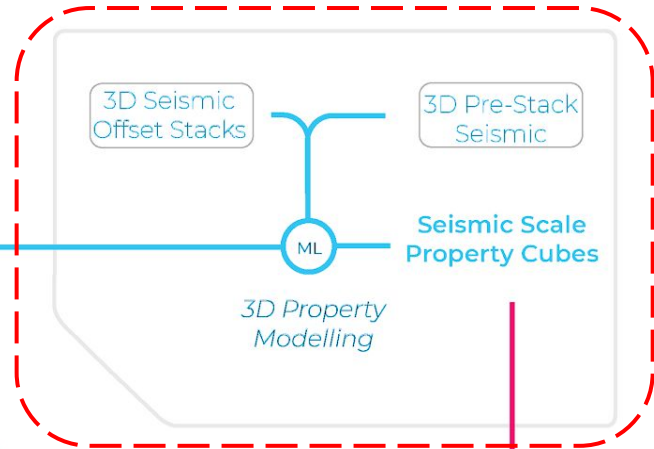
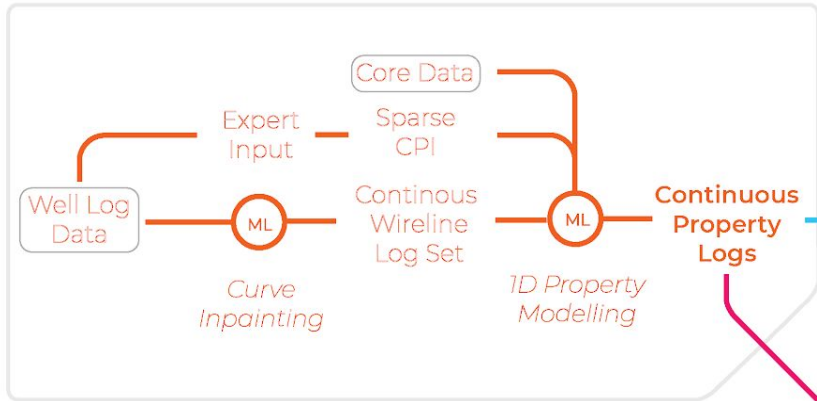
Monte Carlo simulation based on below distributions



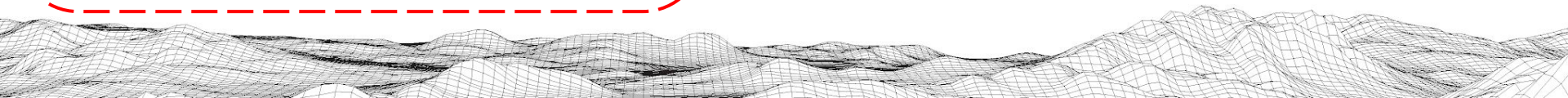
ML inversion and/or contextual queries on ML derived N/G logs



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



**DATA-DRIVEN
DECISIONS**





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