Advances in Seismic Interpretation and Artificial Intelligence

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ScientiaGROUP
Oil & Gas Solution Services

ARTIFICIAL INTELLIGENCE

Artificial Intelligence

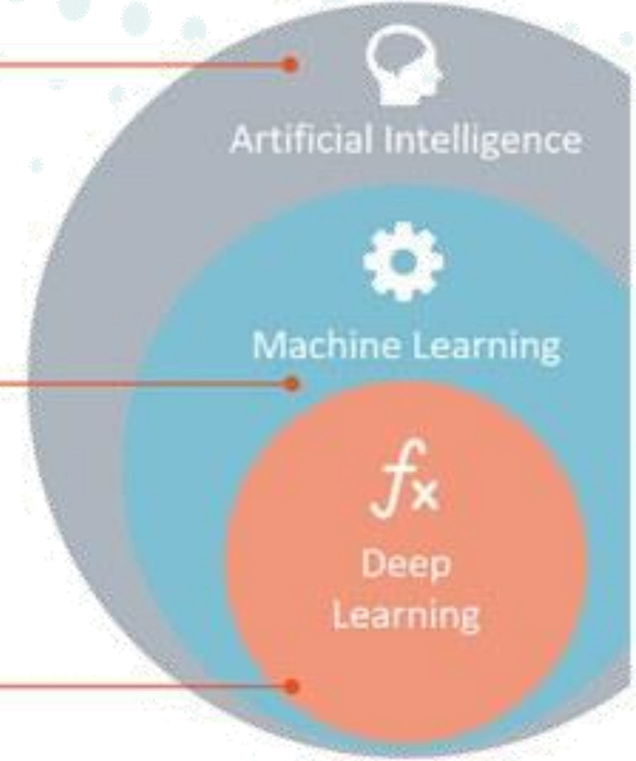
Any technique which enables computers to mimic human behavior.

Machine Learning

Subset of AI techniques which use statistical methods to enable machines to improve with experiences.

Deep Learning

Subset of ML which make the computation of multi-layer neural networks feasible.



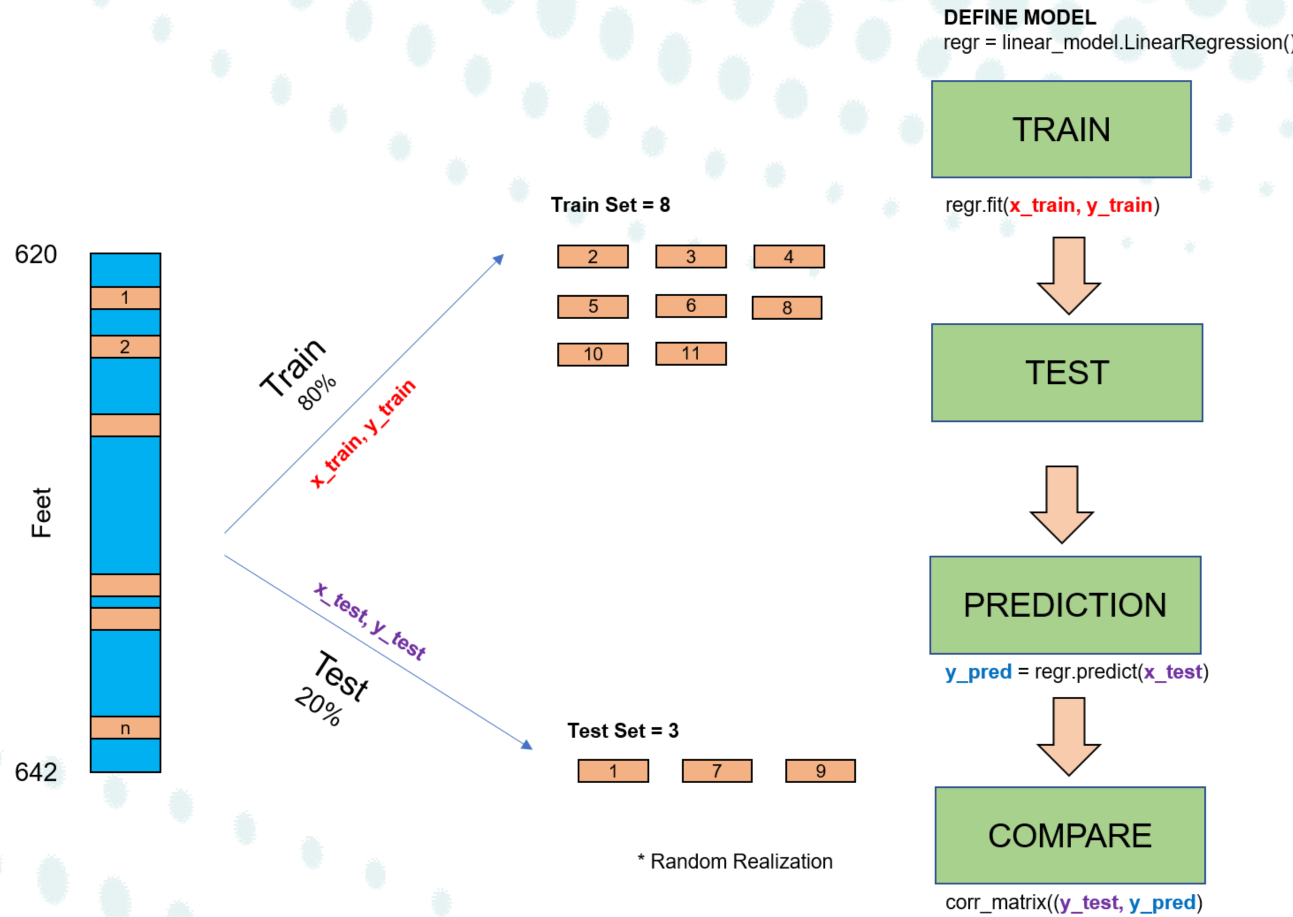
WORKFLOW

Poro – Perm Dataset

DATASET

	X	Y	
	Depth in m	plug porosity	kh in md
1	620	0.020	0.01
	622	0.020	0.02
	624	0.111	22
	626		
	628	0.095	10.5
	630	0.156	135.6
	632	0.150	120
	634	0.075	11
	636	0.105	15.3
	638	0.060	0.8
	640	0.179	350
11	642	0.156	130

Darling, 2005.



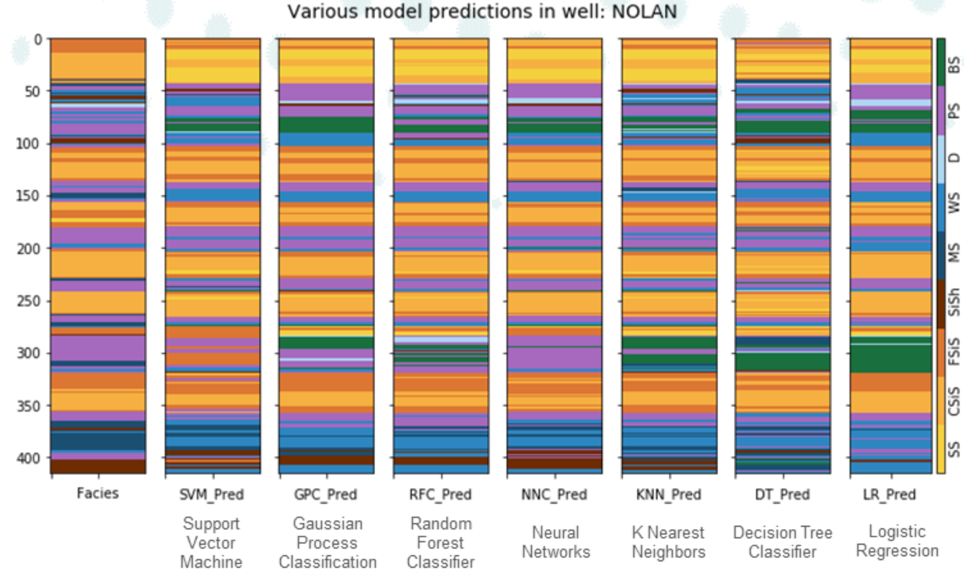
MACHINE LEARNING

Facies Classification

- **Data set**:
    - Field: Panoma (Kansas, United States)
    - Wells: 9
    - Well logs: 5
    - Hydrocarbon: Gas

- **Preliminary Conclusions**:
    - SVM, NNC and KNN showed better performance on the test data.
    - When it comes to examining models with new data (blind well), all model performance drops. This can be attributed to the scarcity of data.

To improve results, it is suggested:
- Introduce more data samples to the models.
- Optimize the model parameters in detail.

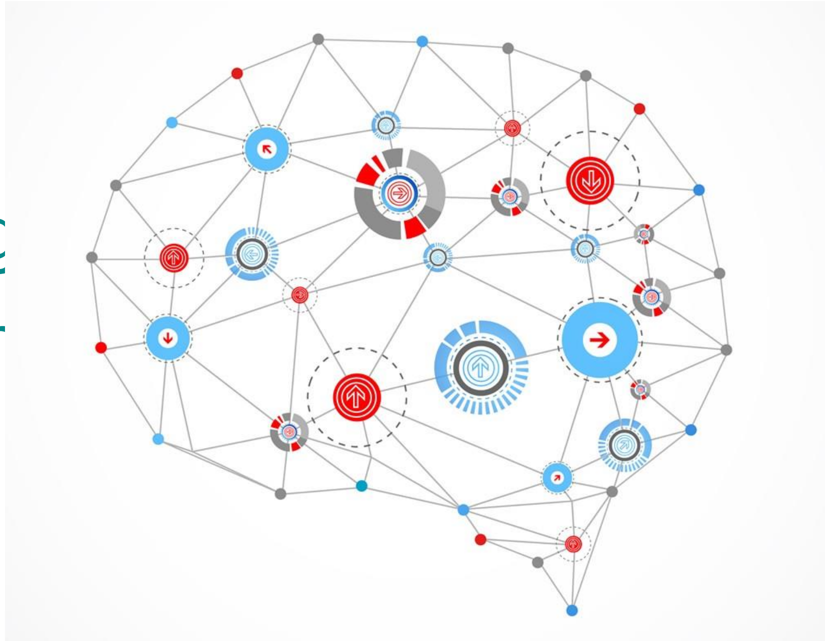


Reference:
- http://www.kgs.ku.edu/PRS/publication/2003/ofr2003-50.pdf
- https://www.sciencedirect.com/science/article/pii/S0098300406001956?via%3Dihub

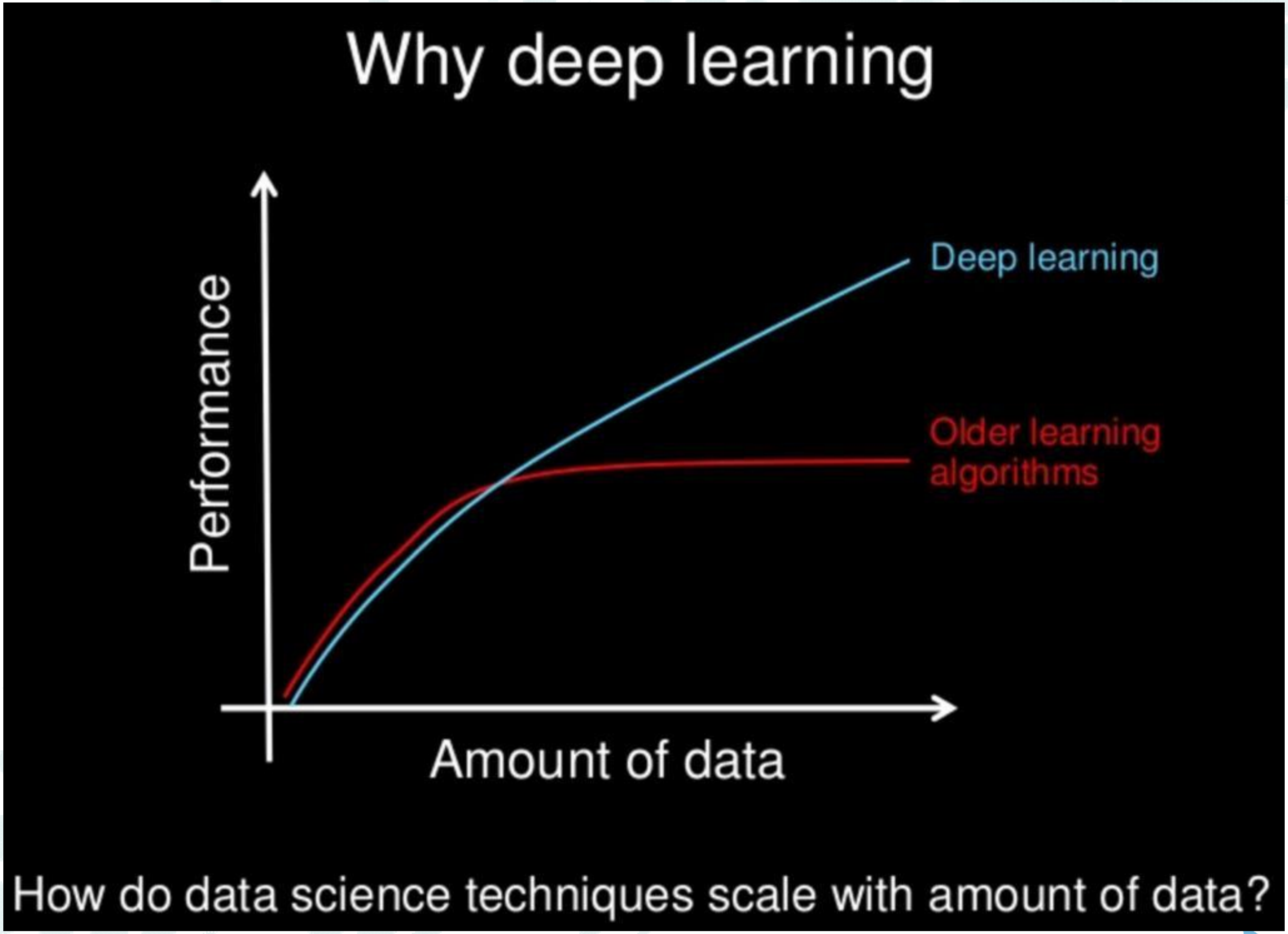
DEEP LEARNING

Deep learning is a subset of ML; in fact, it is simply a technique to perform machine learning.

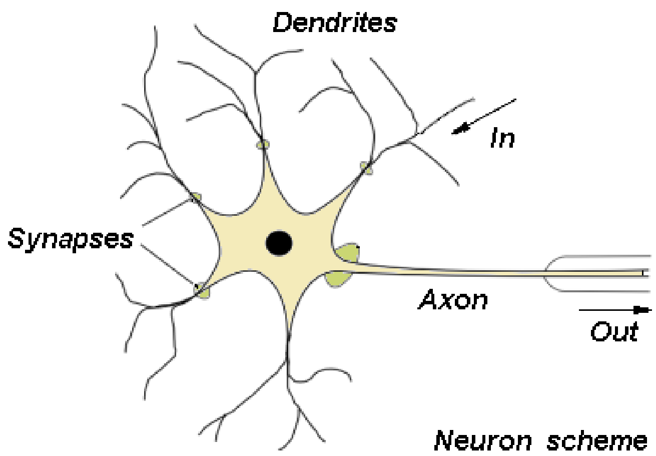
In other words, Deep Learninc is the next evolution of machir learning.

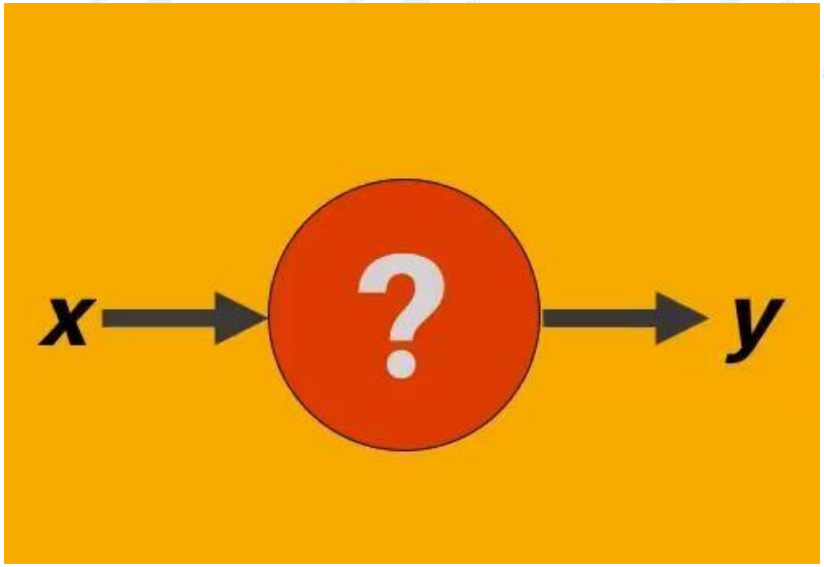


DEEP LEARNING



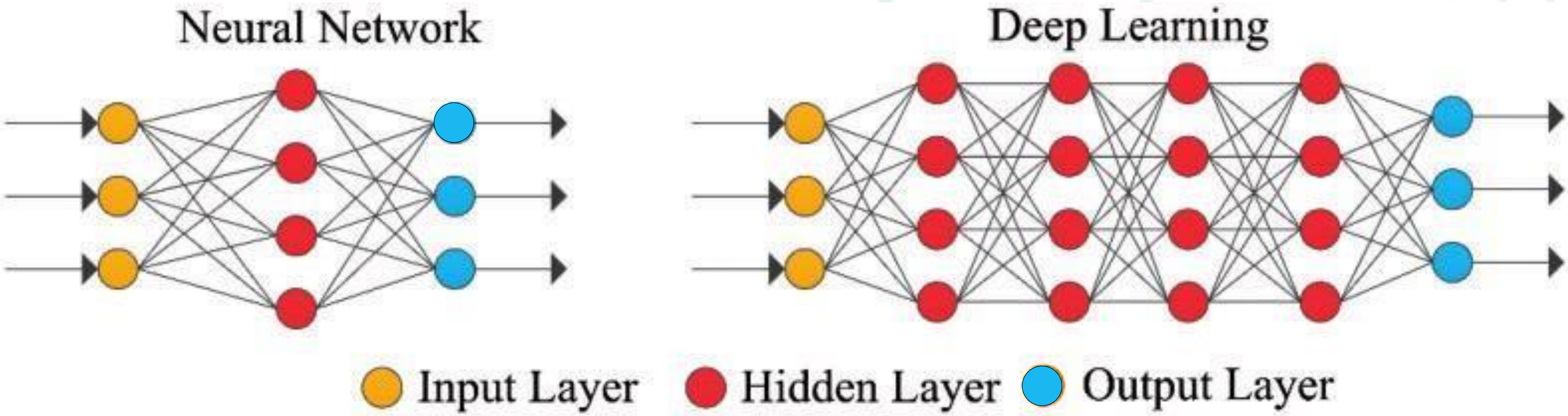
DEEP LEARNING
Neuron





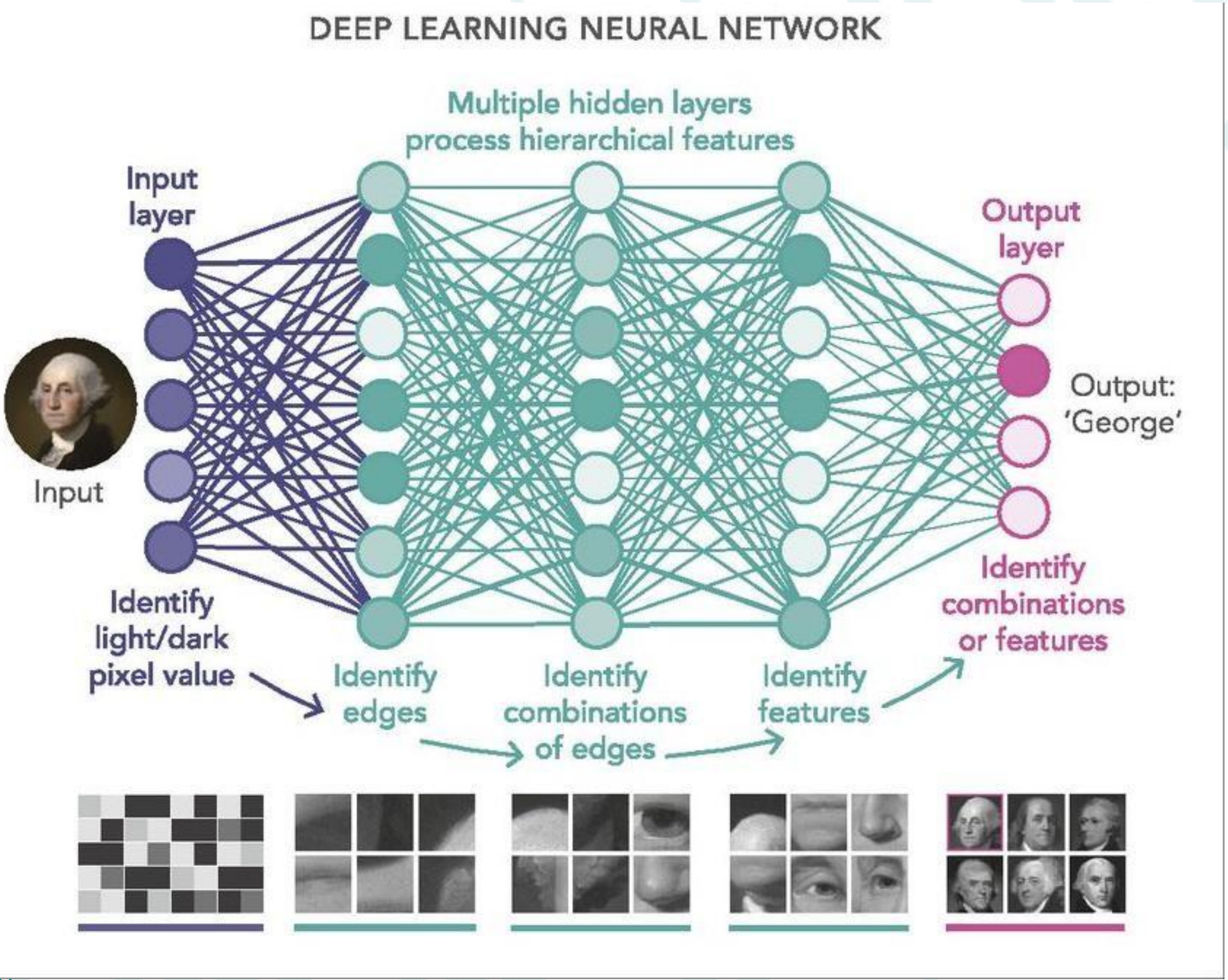
The element, or basic unit of any neural network is the "neuron"

DEEP LEARNING



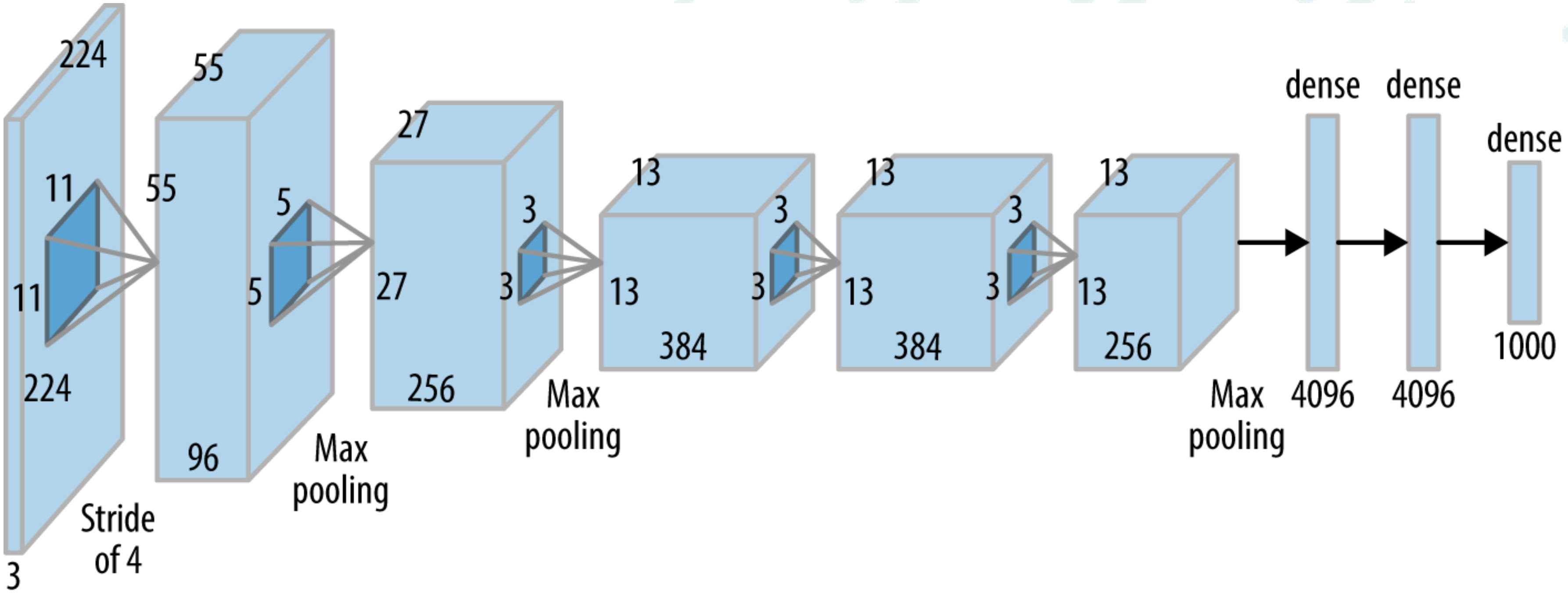
Where does the term "deep" come from?

DEEP LEARNING



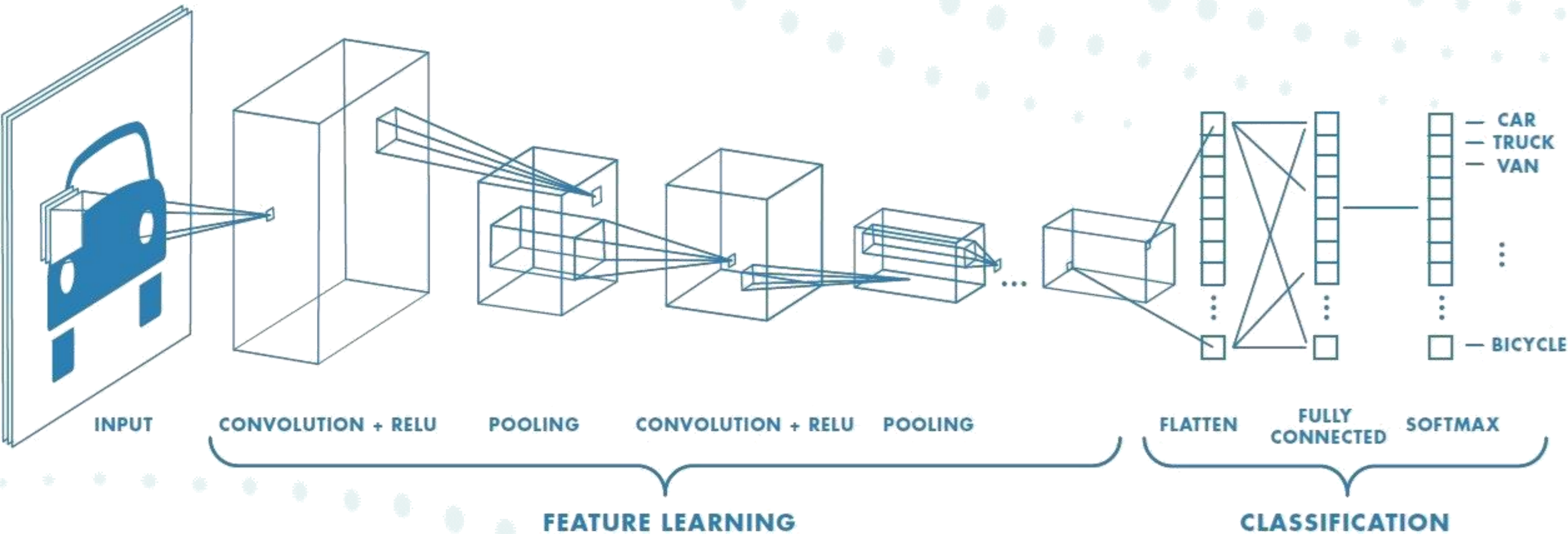
Just as we use our brains to identify patterns and classify various types of information, deep learning algorithms can be taught to perform the same tasks for machines.

Convolutional Neural Network CNN

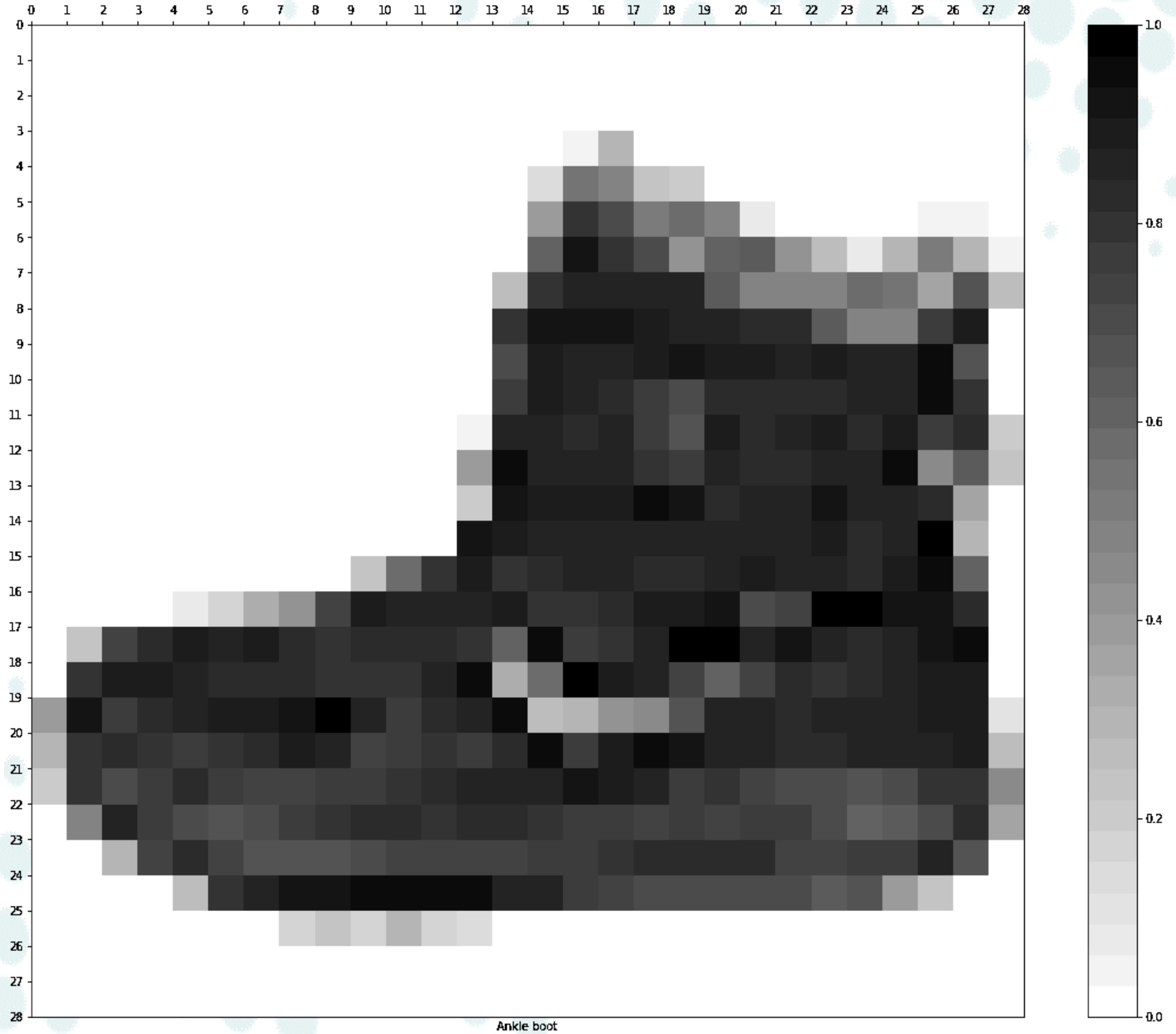


Neural**NETWORK**

Architecture



CNN
Image Pixel



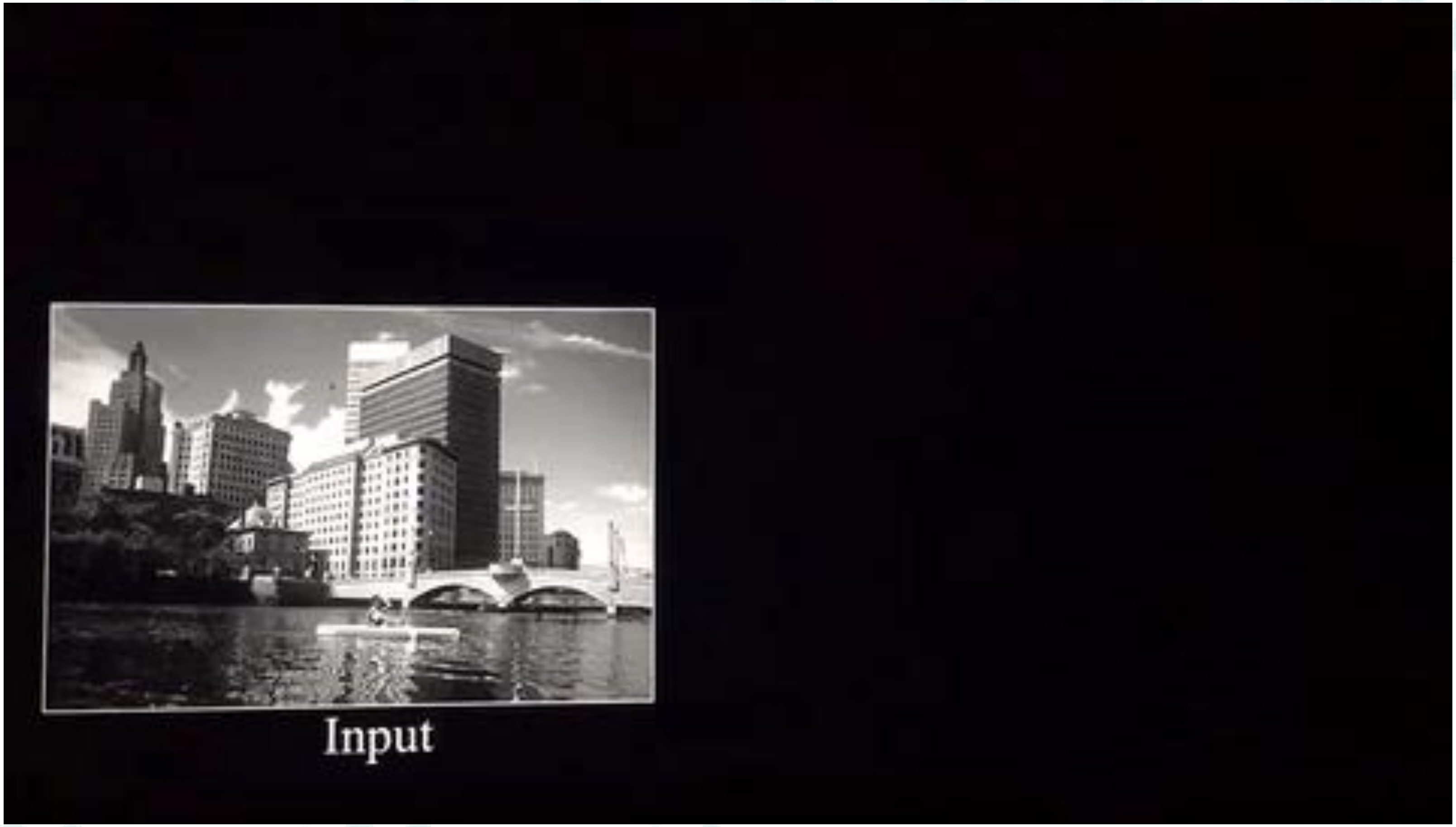
CNN
Image Pixel

Original Image

1	1	1	1	1	1
1	1	1	1	1	1
0	0	1	1	0	0
0	0	1	1	0	0
0	0	1	1	0	0
0	0	1	1	0	0

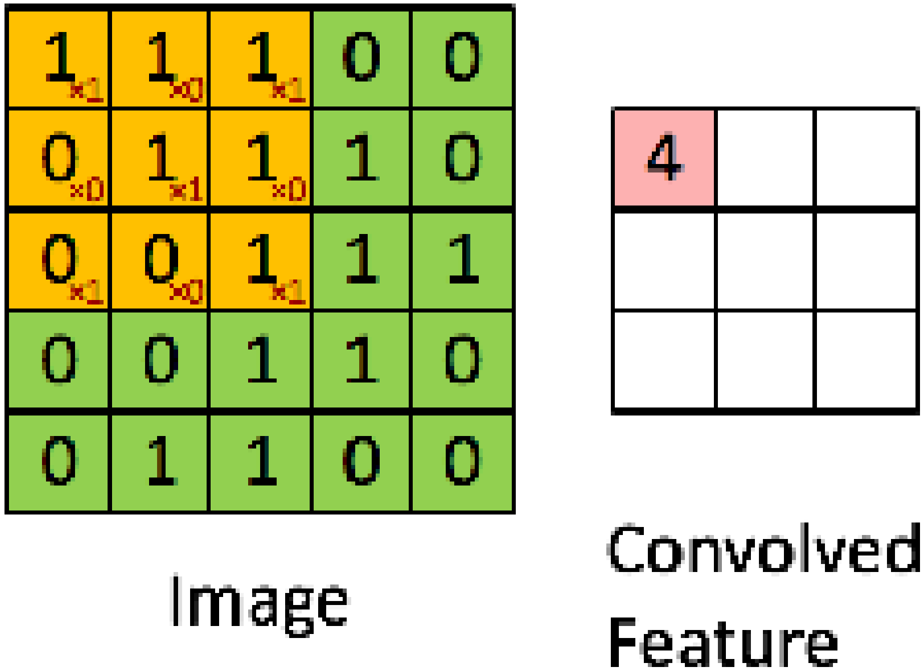
Feature Map

CNN
Feature Map



https://ujjwalkarn.me/2016/08/11/intuitive-explanation-convnets/

CNN - Downsizing Methods
Max Pooling



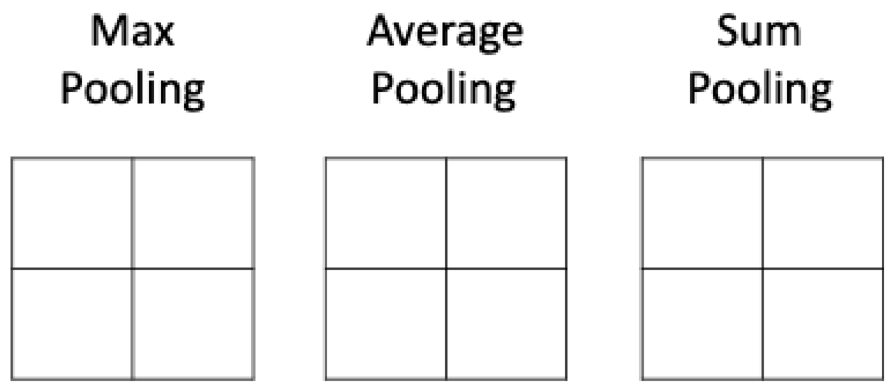
https://ujjwalkarn.me/2016/08/11/intuitive-explanation-convnets/

CNN - Downsizing Methods
Types of Pooling

Stride of 2 and a filter size of 2x2

Feature Map

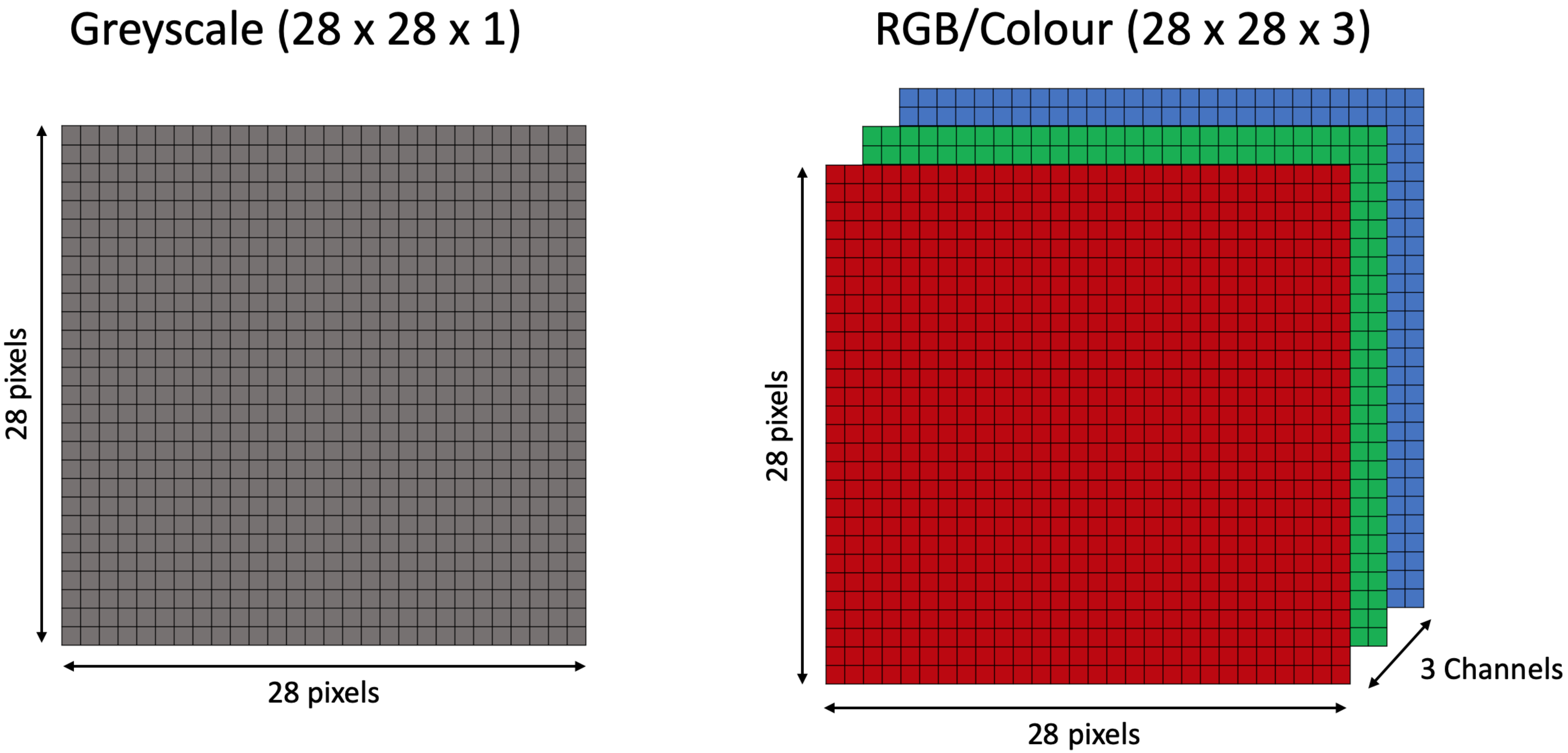
6	6	6	6
4	5	5	4
2	4	4	2
2	4	4	2



1. Max Pooling: Takes the maximum pixel value within the filter.
2. Average Pooling: Takes the average pixel value within the filter.
3. Sum Pooling: Sums the pixel values within the filter.

https://www.bouvet.no/bouvet-deler/understanding-convolutional-neural-networks-part-1

CNN
Image RGB



https://www.bouvet.no/bouvet-deler/understanding-convolutional-neural-networks-part-1

CNN
Max Pooling

0	0	0	0	0	0	...
0	156	155	156	158	158	...
0	153	154	157	159	159	...
0	149	151	155	158	159	...
0	146	146	149	153	158	...
0	145	143	143	148	158	...
...	...	...	...	...	...	...

Input Channel #1 (Red)

0	0	0	0	0	0	...
0	167	166	167	169	169	...
0	164	165	168	170	170	...
0	160	162	166	169	170	...
0	156	156	159	163	168	...
0	155	153	153	158	168	...
...	...	...	...	...	...	...

Input Channel #2 (Green)

0	0	0	0	0	0	...
0	163	162	163	165	165	...
0	160	161	164	166	166	...
0	156	158	162	165	166	...
0	155	155	158	162	167	...
0	154	152	152	157	167	...
...	...	...	...	...	...	...

Input Channel #3 (Blue)

-1	-1	1
0	1	-1
0	1	1

Kernel Channel #1

1	0	0
1	-1	-1
1	0	-1

Kernel Channel #2

0	1	1
0	1	0
1	-1	1

Kernel Channel #3

$$308 \quad + \quad -498 \quad + \quad 164 \quad + 1 = -25$$

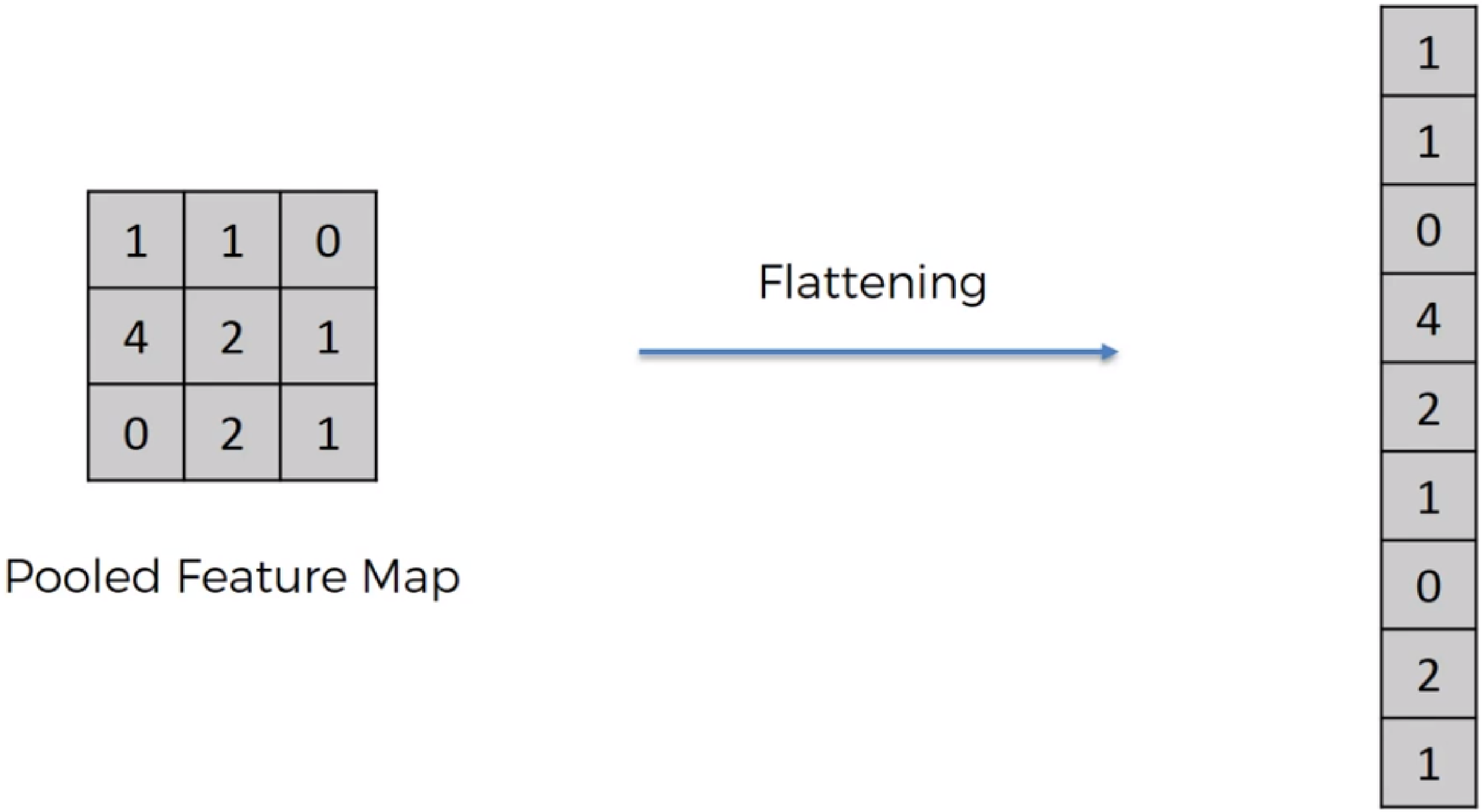
Bias = 1

Output

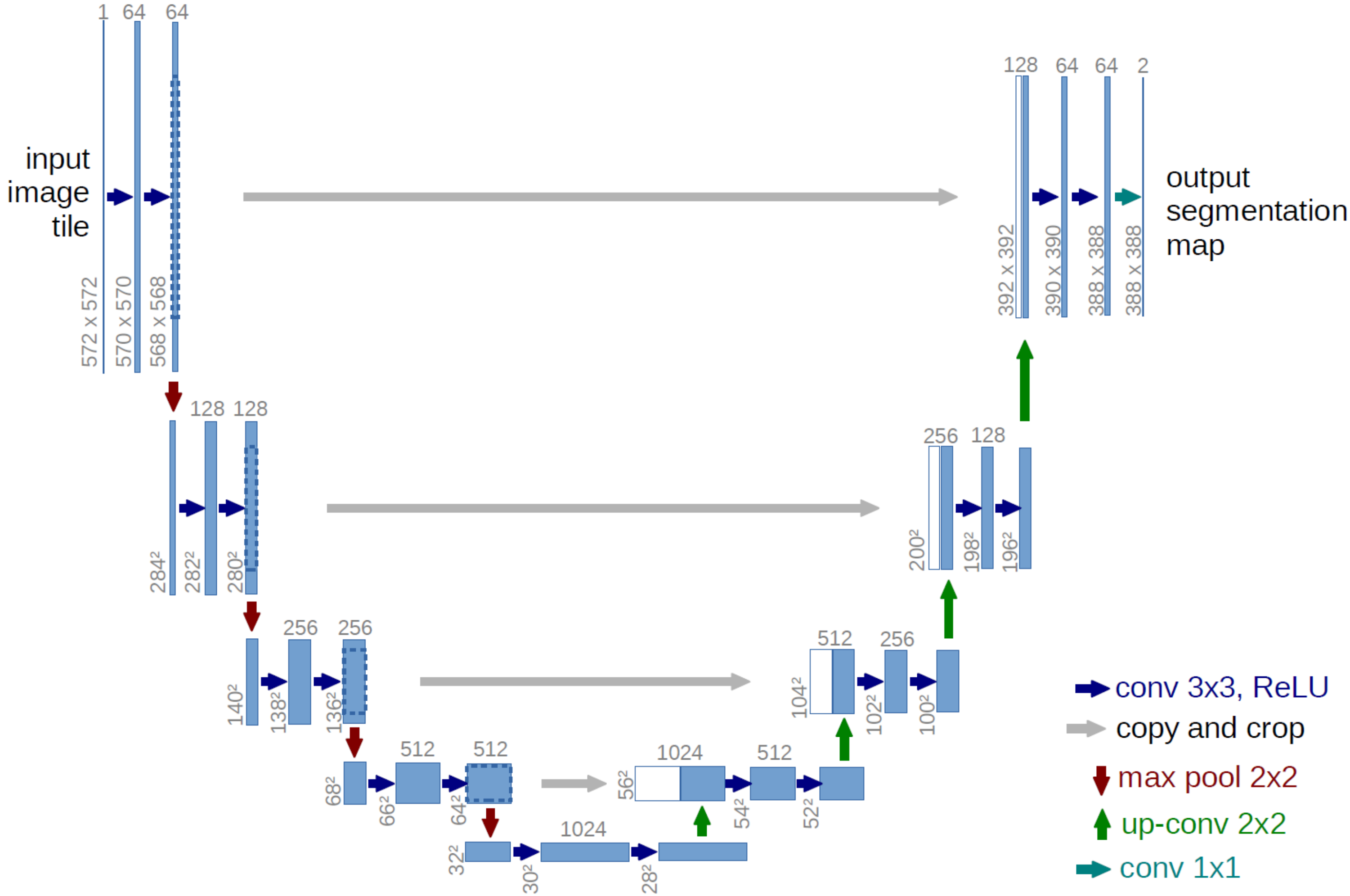
-25				...
				...
				...
				...
...	...	...	...	...

https://www.thelearningmachine.ai/cnn

CNN
Flatten Image



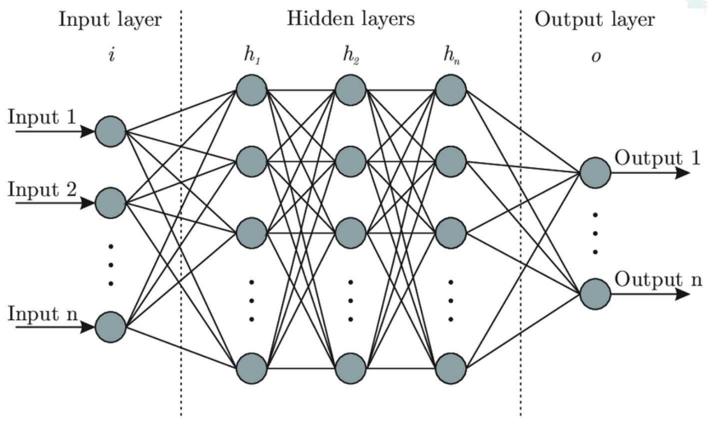
CNN
U-Net

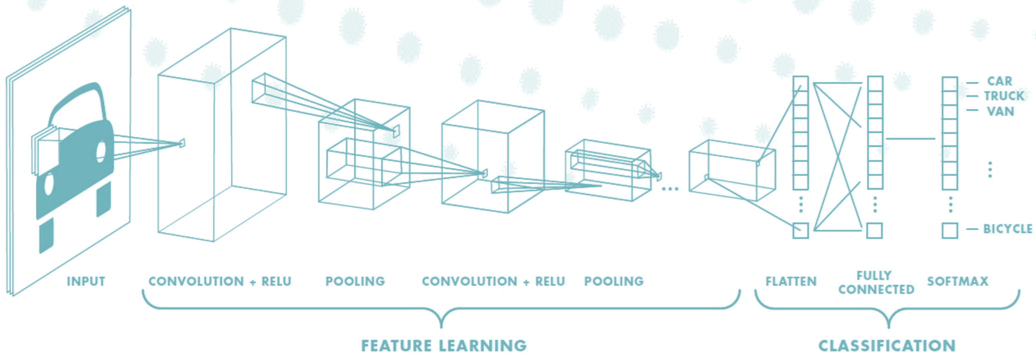


https://lmb.informatik.uni-freiburg.de/people/ronneber/u-net/

APPLICATIONS IN GEOSCIENCE

Convolutional Neural Networks (CNN)



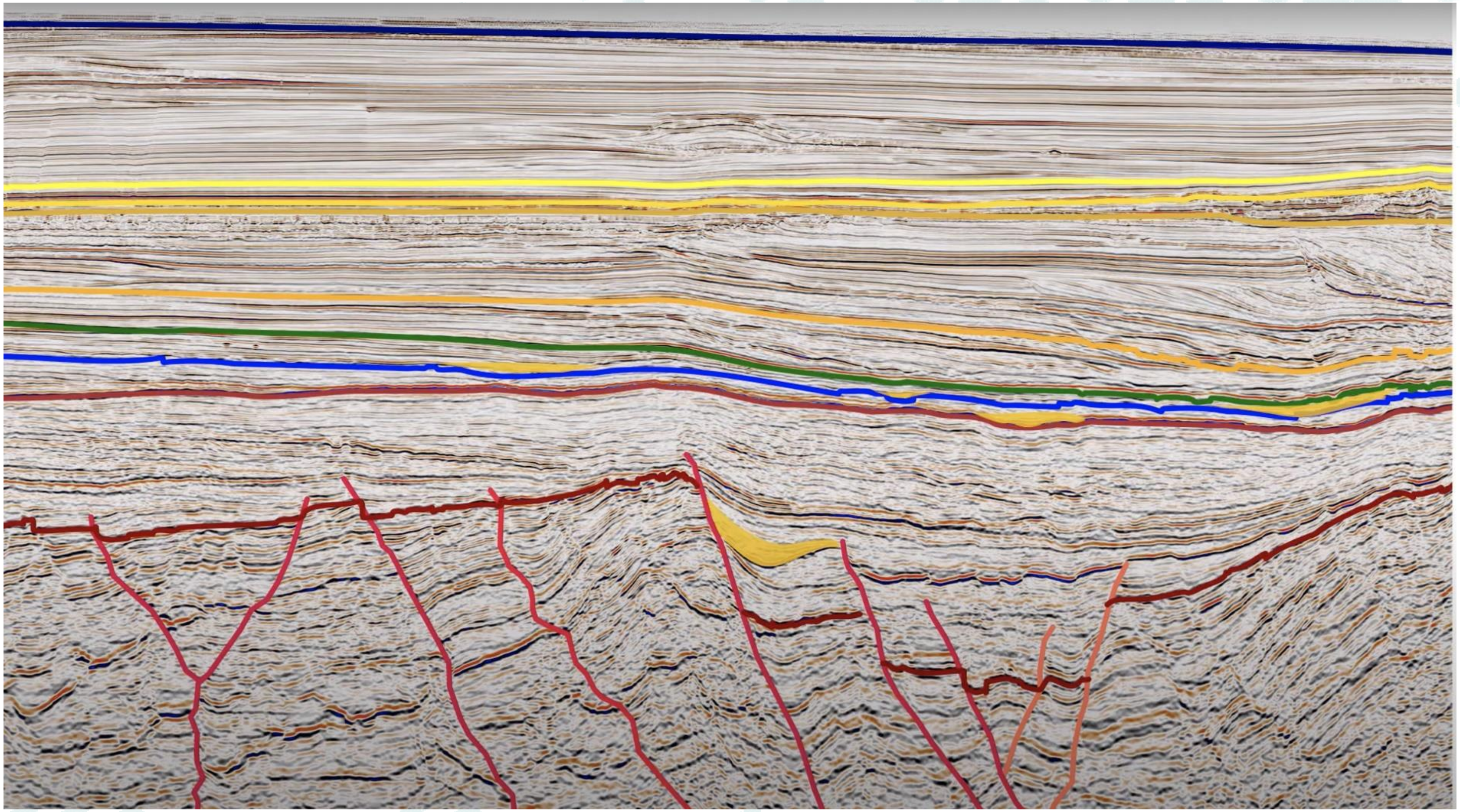


- Well log facies interpretation
- Well log missing log
- Well forecast
- AVO analysis

- Seismic interpretation
- Seismic automatic fault segmentation

APPLICATIONS IN GEOSCIENCE

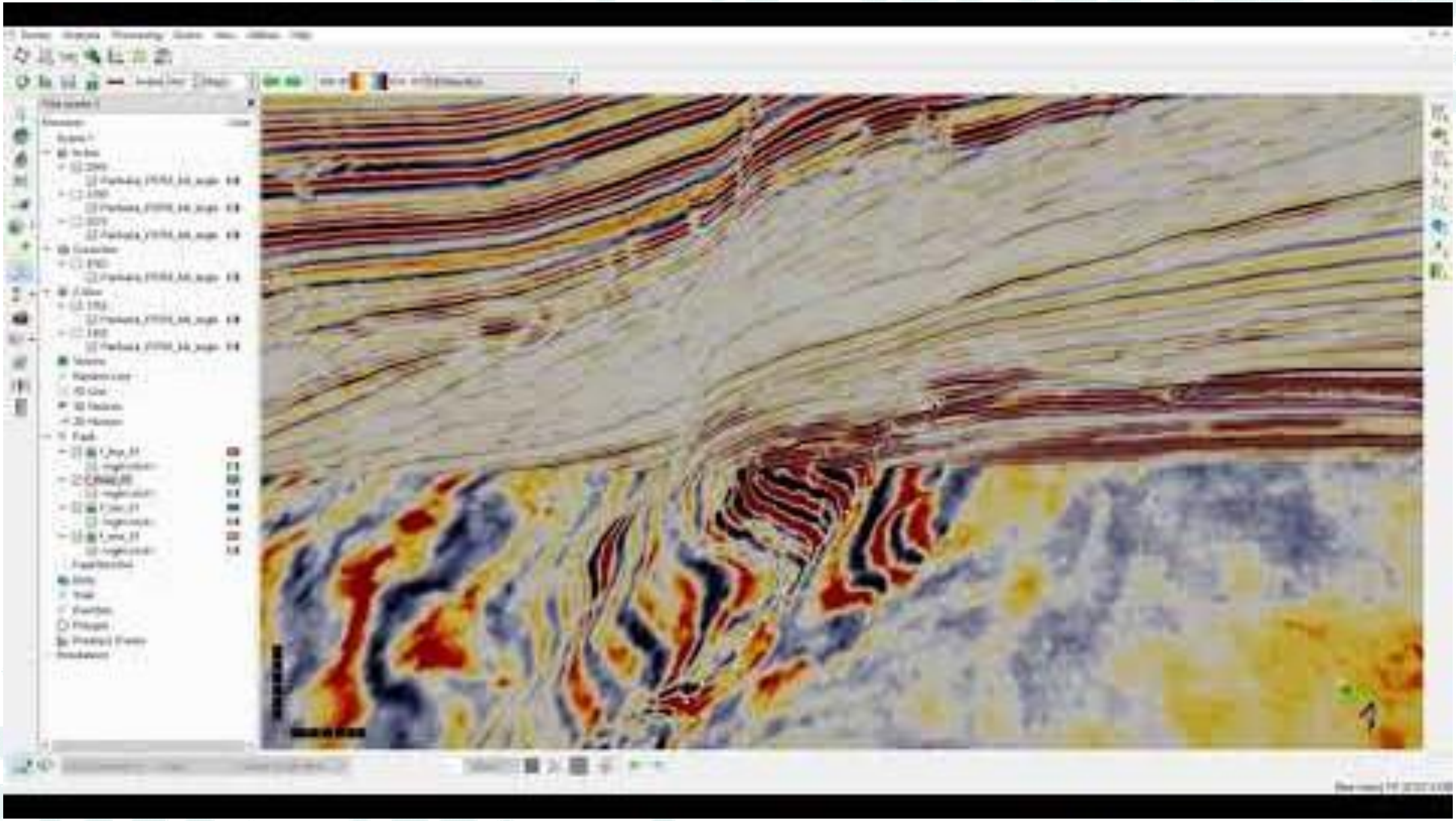
SEISMIC INTERPRETATION



Manual seismic data interpretation is time-consuming — taking weeks, months, or even longer. To accelerate processing, companies may require additional geoscientists which increases project costs.

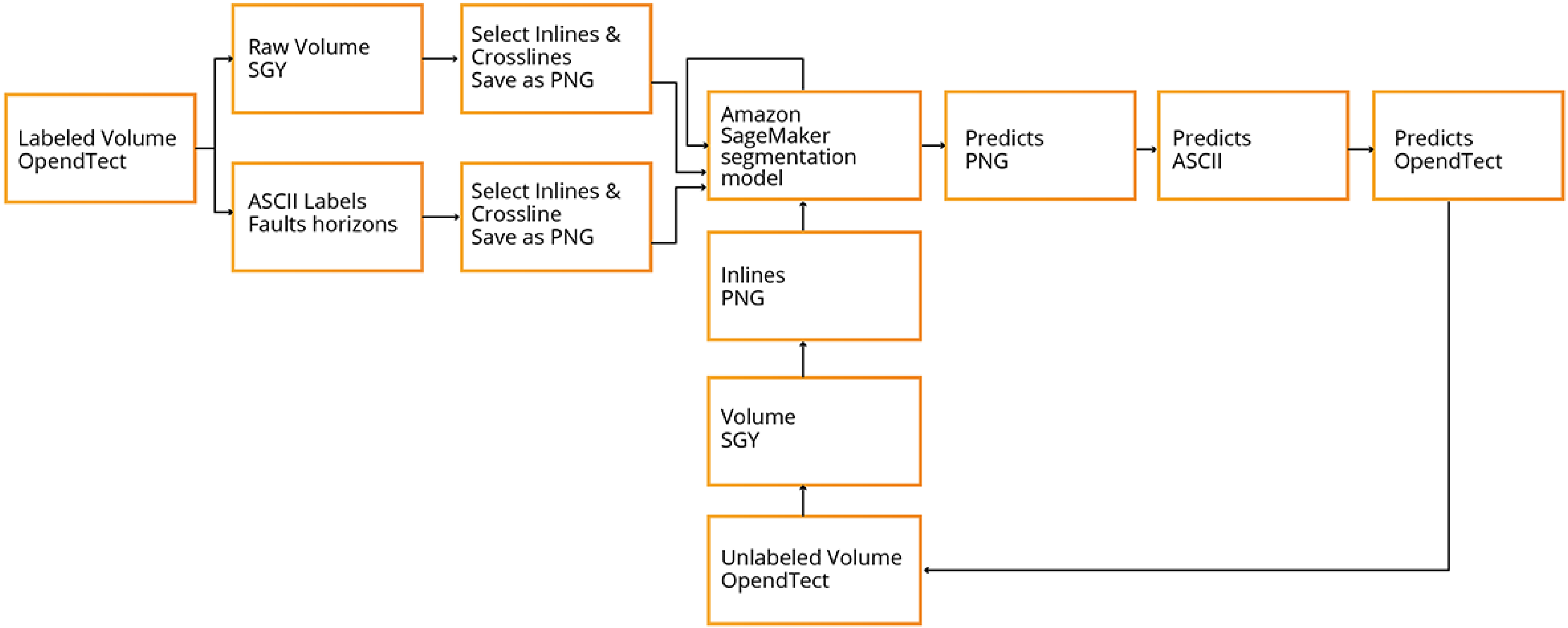
Reference: https://youtu.be/SU-hKHXCifU

SEISMIC INTERPRETATION



Reference: https://medium.com/whats-next-in/automating-horizons-detection-with-amazon-sagemaker-softserve-abaadc55efa2

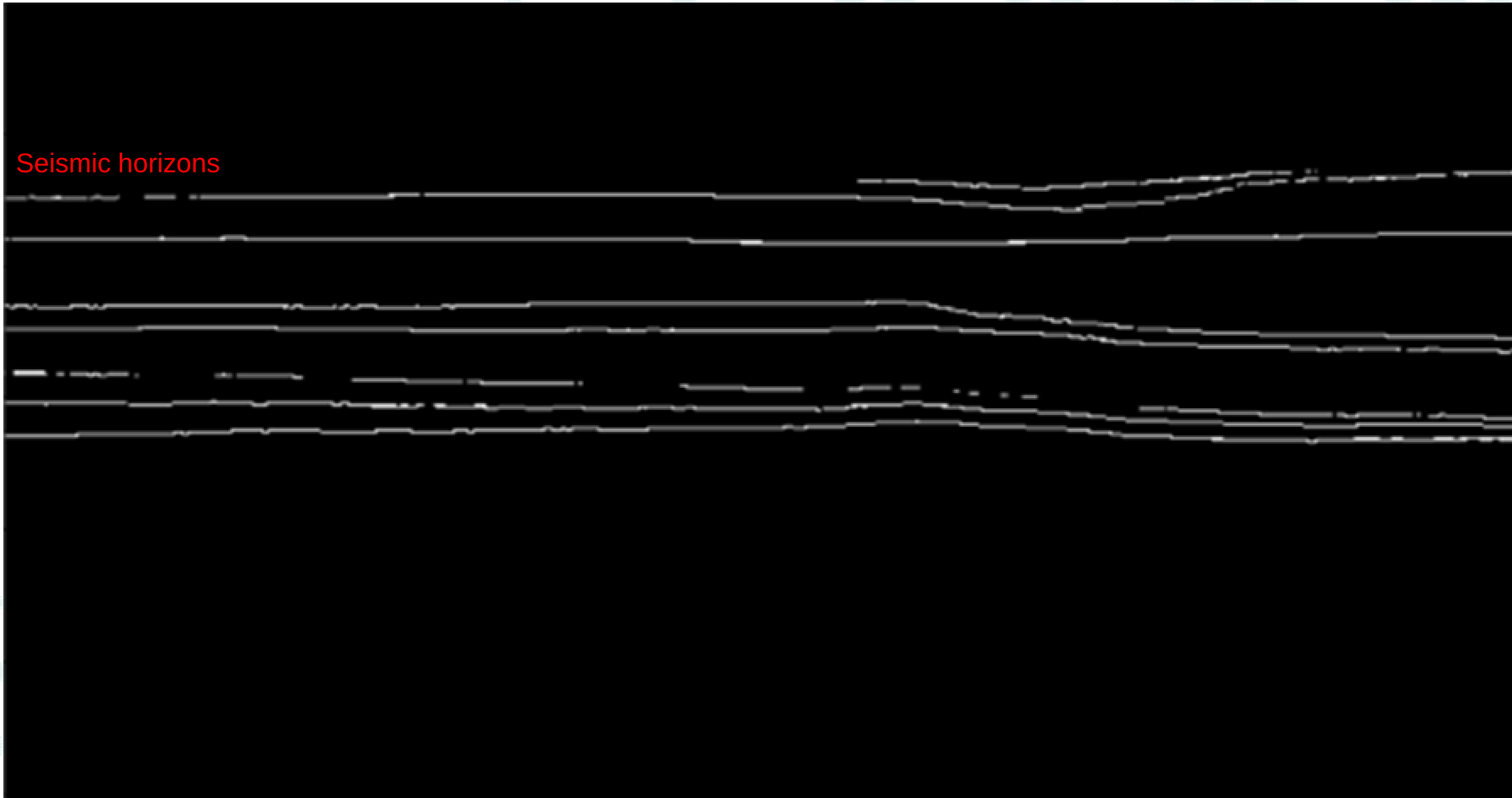
SEISMIC INTERPRETATION



Reference: https://medium.com/whats-next-in/automating-horizons-detection-with-amazon-sagemaker-softserve-abaadc55efa2

SEISMIC INTERPRETATION

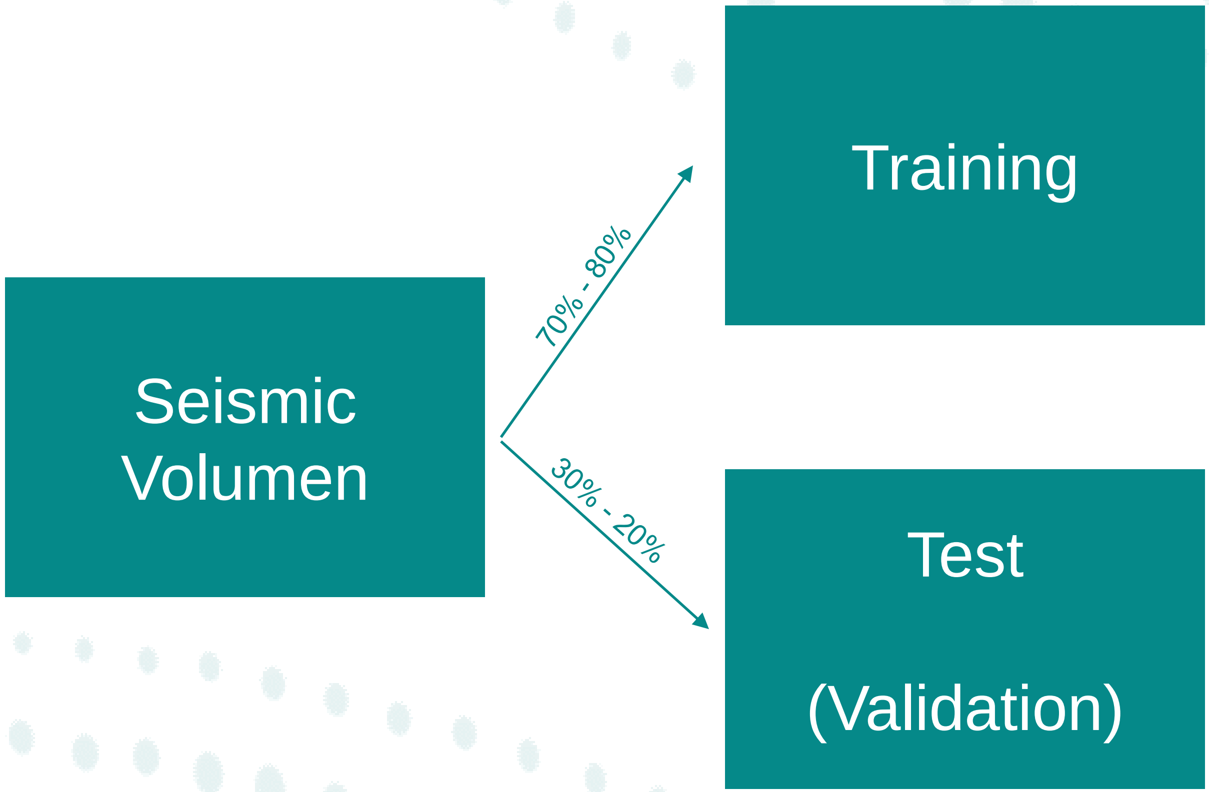
Poseidon volume



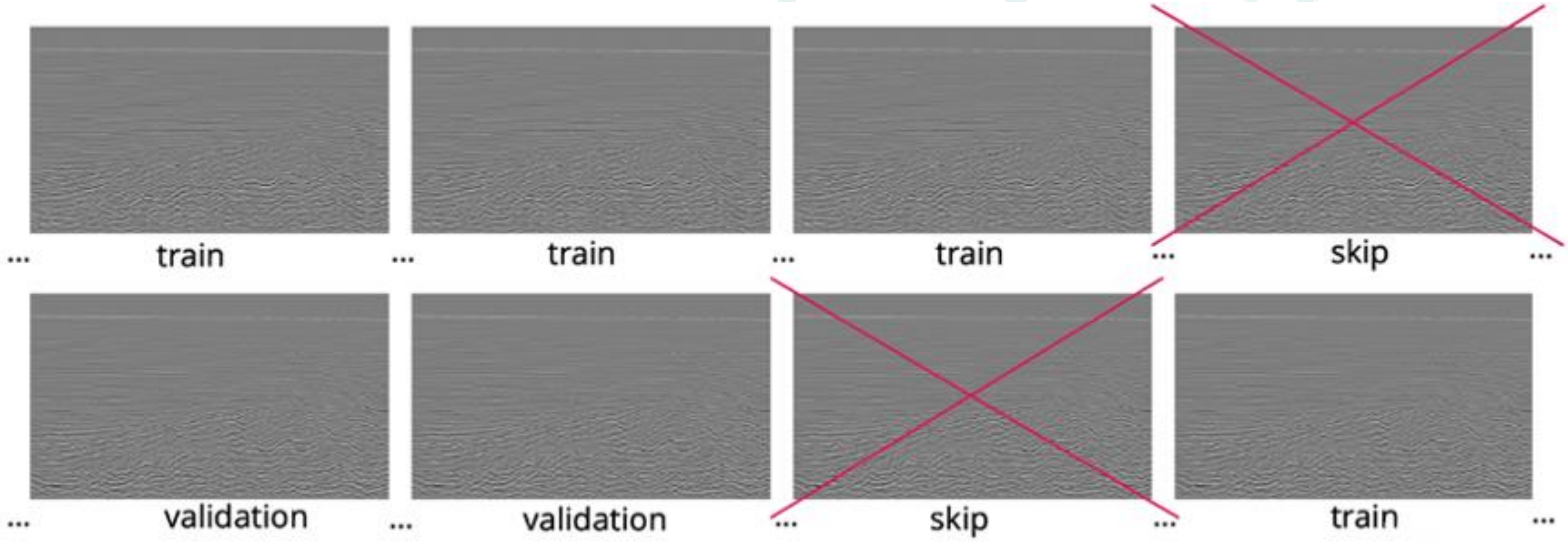
Mask: Seismic horizons interpreted by human seismic interpreter.

Reference: https://medium.com/whats-next-in/automating-horizons-detection-with-amazon-sagemaker-softserve-abaadc55efa2

SEISMIC INTERPRETATION



SEISMIC INTERPRETATION



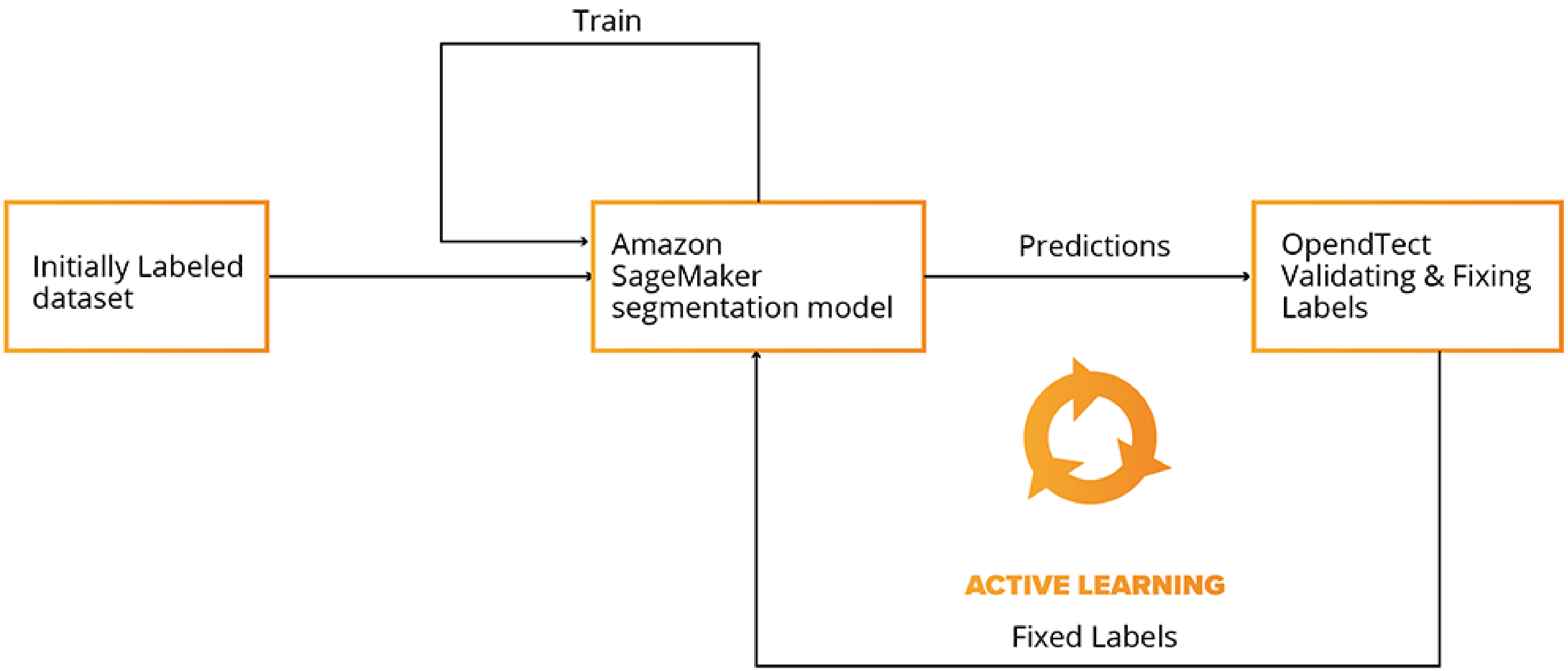
Reference: https://medium.com/whats-next-in/automating-horizons-detection-with-amazon-sagemaker-softserve-abaadc55efa2

Goal: minimize the correlation between sets and assure they both fully represent the volume.

SEISMIC INTERPRETATION

Reference: https://medium.com/whats-next-in/automating-horizons-detection-with-amazon-sagemaker-softserve-abaadc55efa2

SEISMIC INTERPRETATION

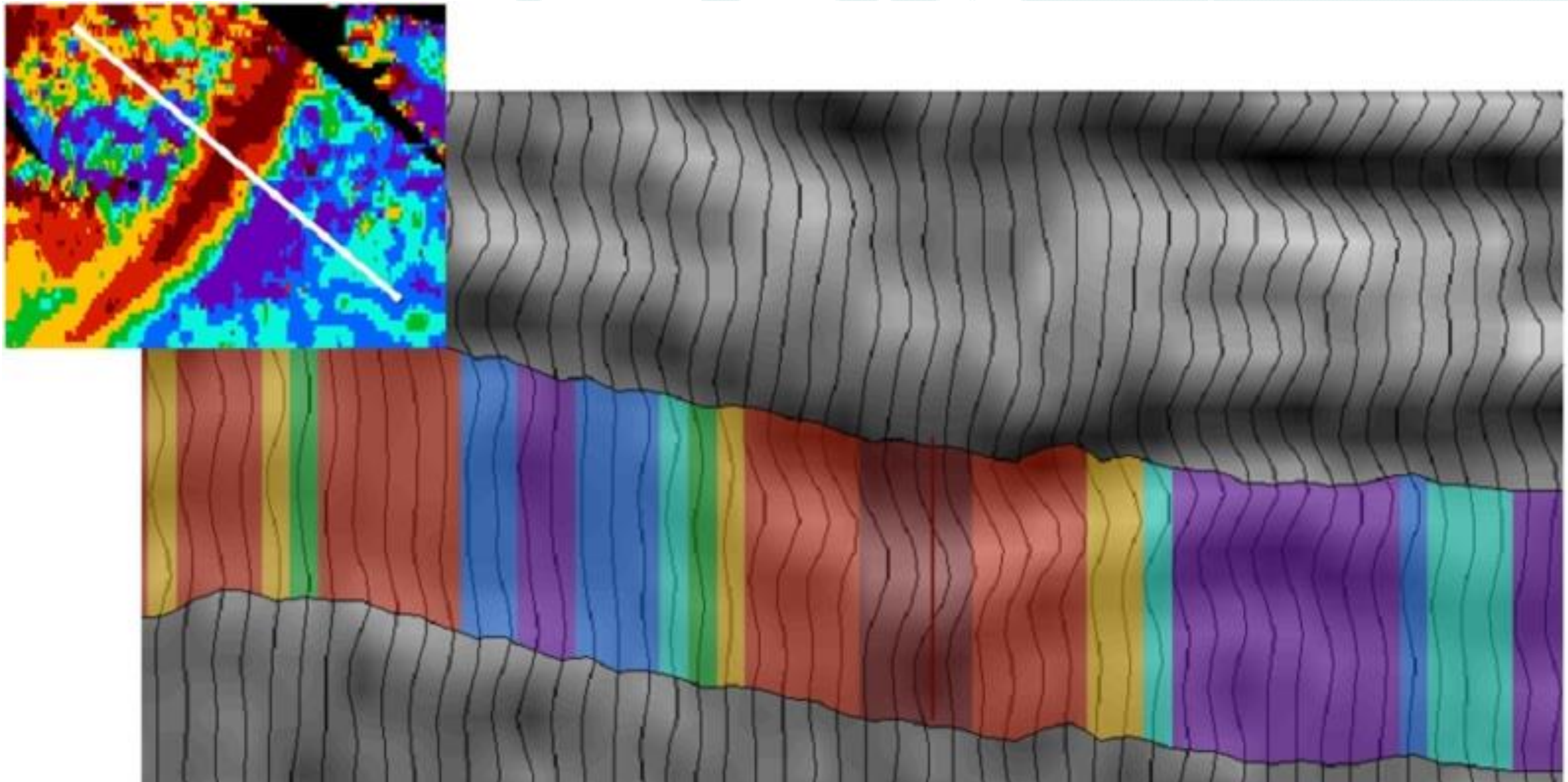


Reference: https://medium.com/whats-next-in/automating-horizons-detection-with-amazon-sagemaker-softserve-abaadc55efa2

Machine**LEARNING**

WellLog and Waveform **CLASSIFICACTION**

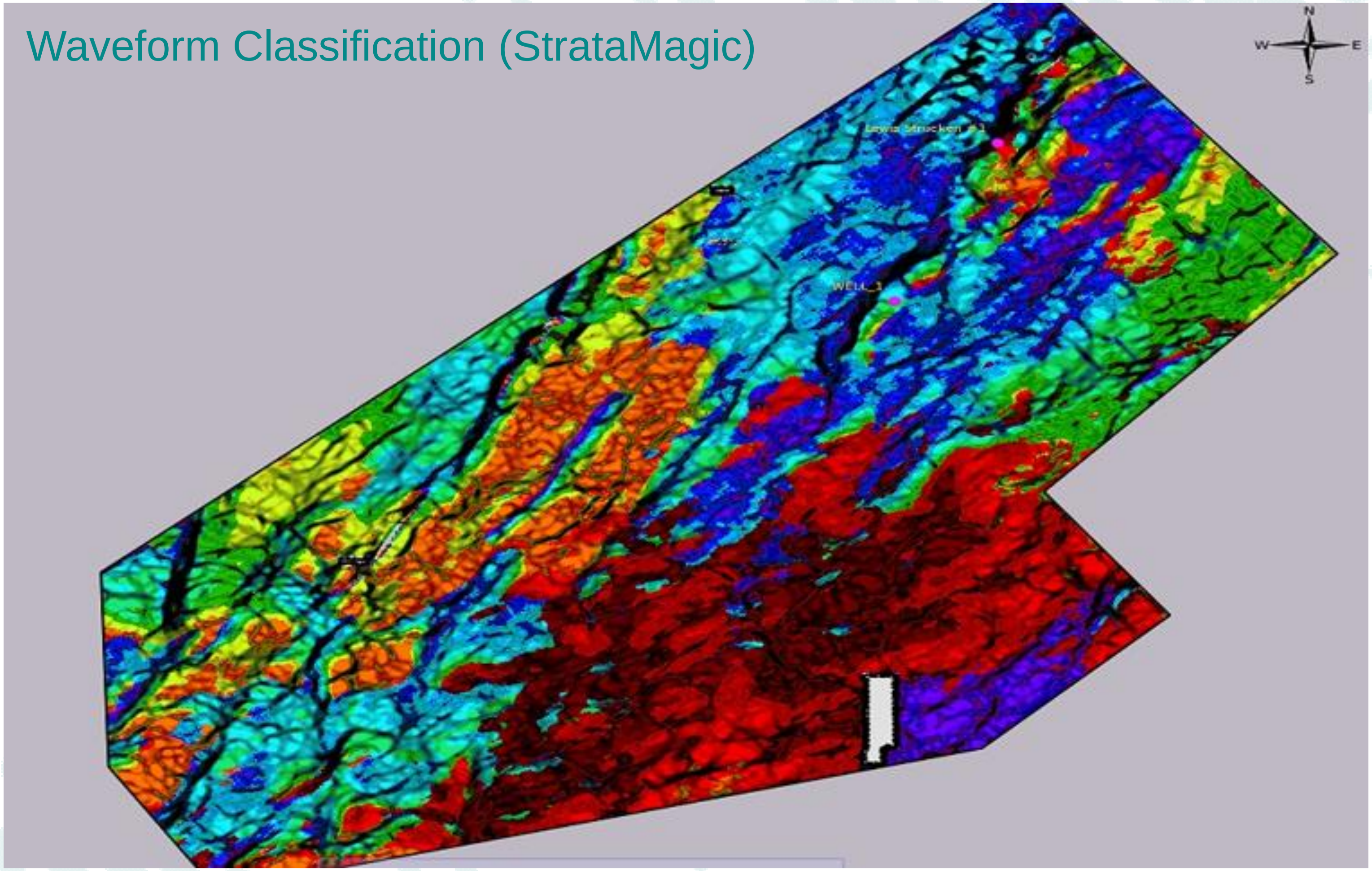
Machine Learninng Seismic Waveform



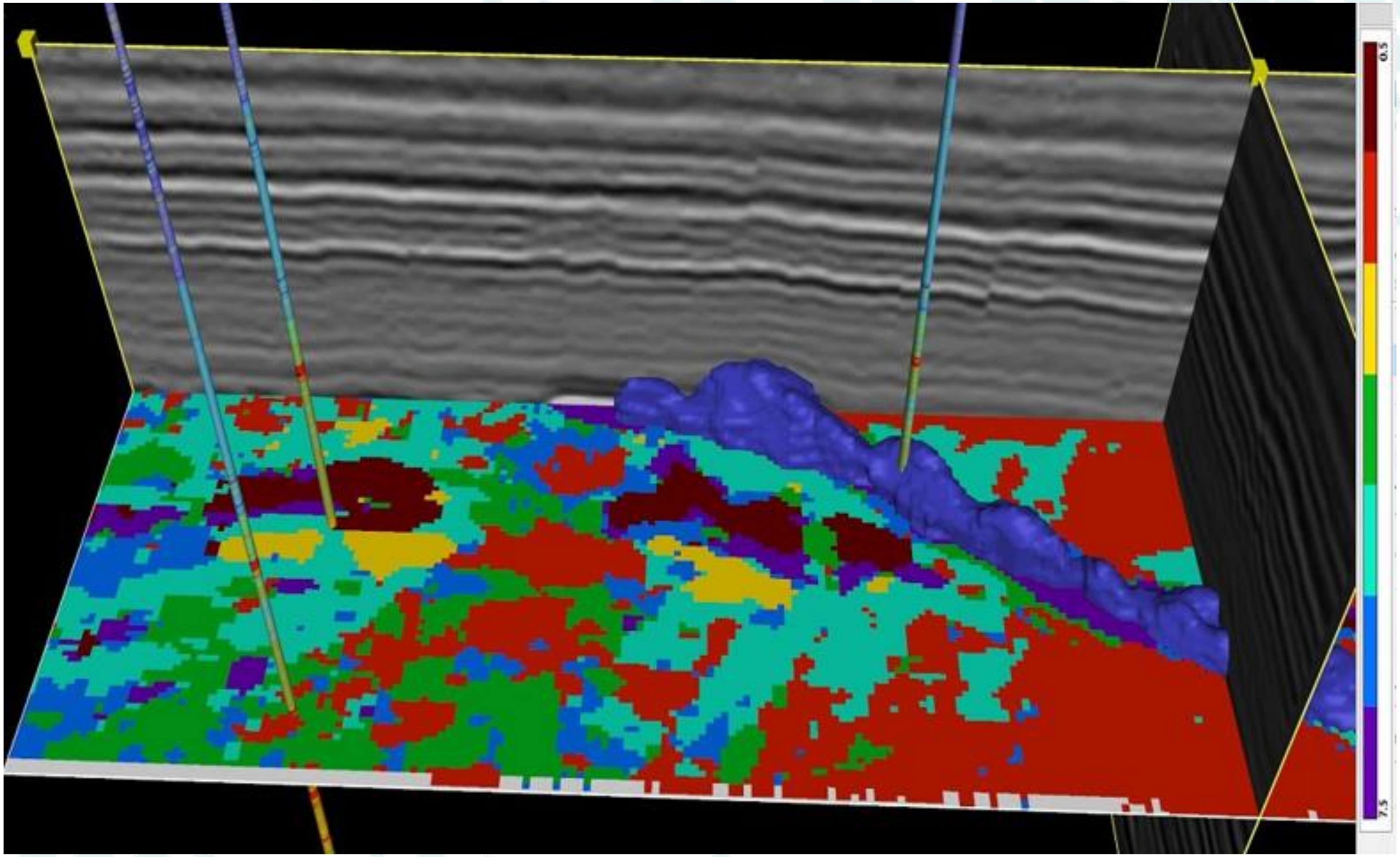
Waveform Classification (StrataMagic)

Machine Learninng Seismic Waveform

Waveform Classification (StrataMagic)

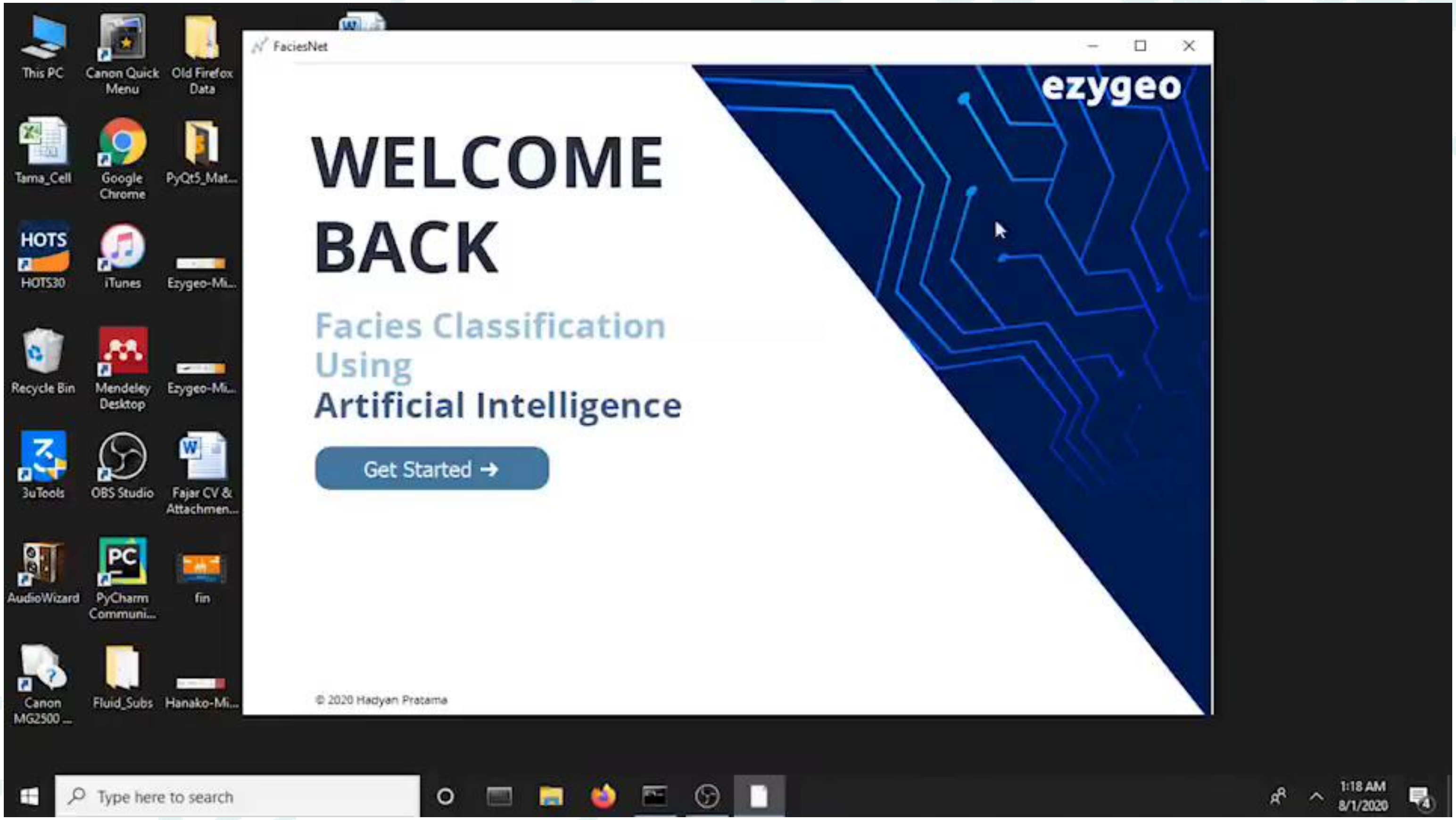


Machine Learninng Seismic Waveform



Waveform Classification (StrataMagic)

Machine Learninng in Well Log Classification



Reference: Hadyan Pratama

https://www.linkedin.com/feed/update/urn:li:activity:6695220090255880192/

https://www.researchgate.net/publication/332822872_Machine_Learning_Using_Optimized_KNN_K-Nearest_Neighbors_to_Predict_the_Facies_Classifications

Deep**LEARNING**

Fault**Detection**

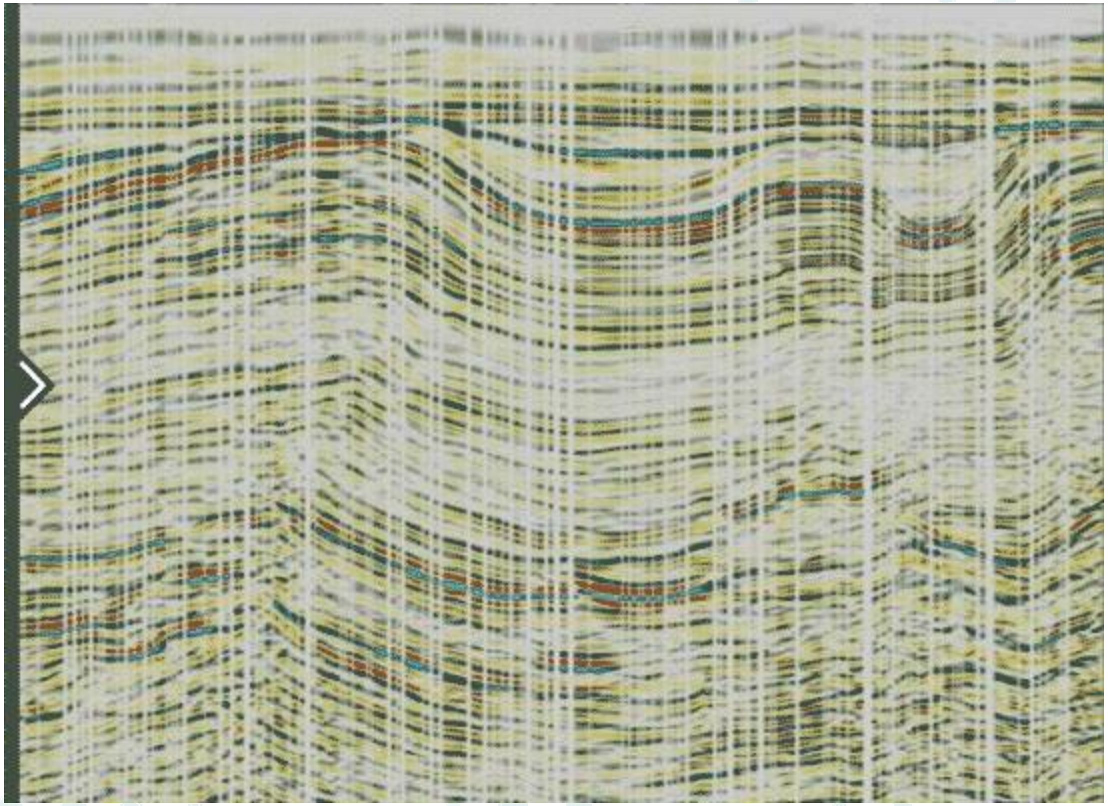
SG

Machine Learning in Well Log Classification

Reference: Hadyan Pratama

https://www.linkedin.com/feed/update/urn:li:activity:6687578099971969024/

U-Net Seismic Interpolation
dGB - OpendTect

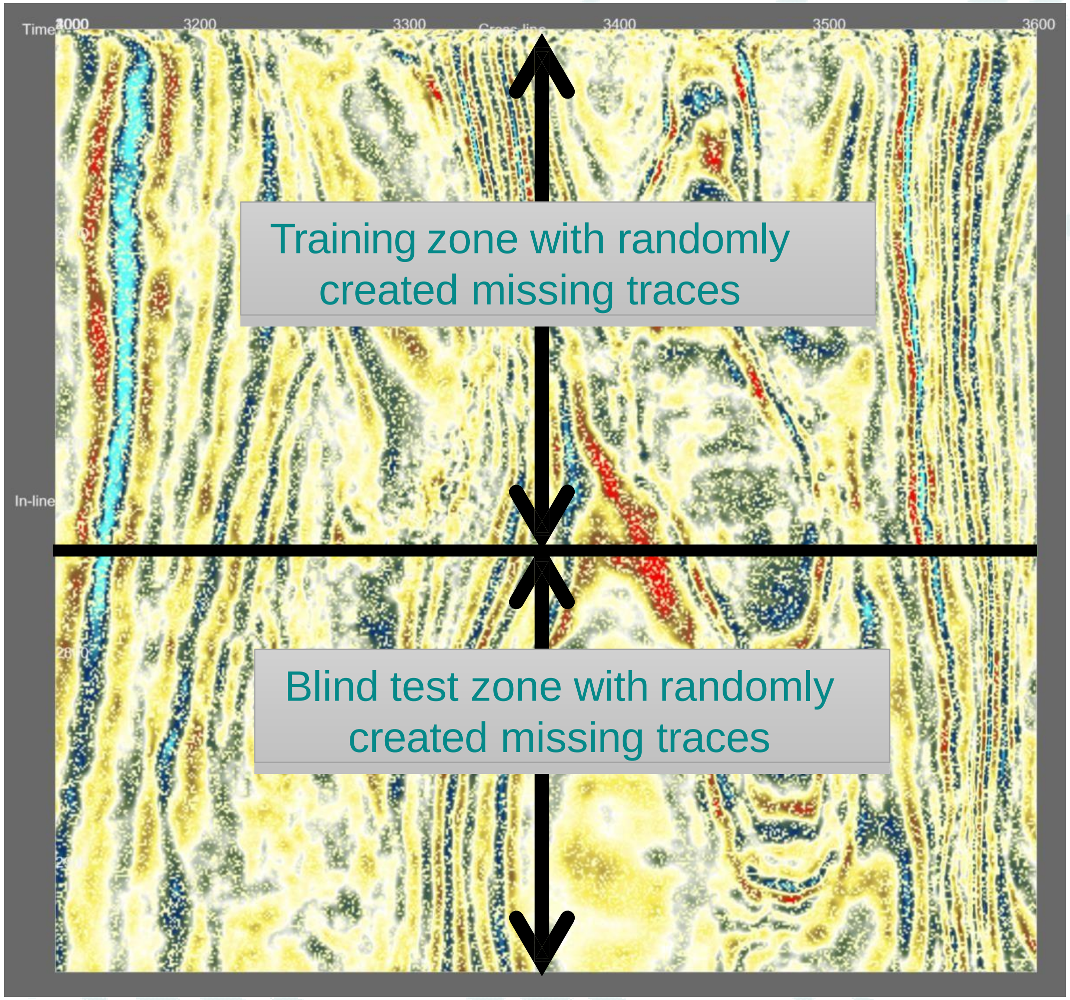


Reference: Marieke van Hout - de Groot

https://static.dgbes.com/images/PDF/U-Net_Interpolation.pdf

- A training set is created by randomly blanking approx. 16% of all traces in a 3D volume.
- U-Net was trained on 2D images of 128x128 samples.
- The depicted line is taken from a “blind test” area, i.e. an area from which no training examples were taken.
- The trained U-Net “AS IS” is applied to a nearby survey with many gaps in the upper section.
- Although the seismic character of the nearby survey is very different from the survey on which our U-Net was trained the interpolation worked remarkably well.

U-Net Seismic Interpolation
dGB - OpendTect



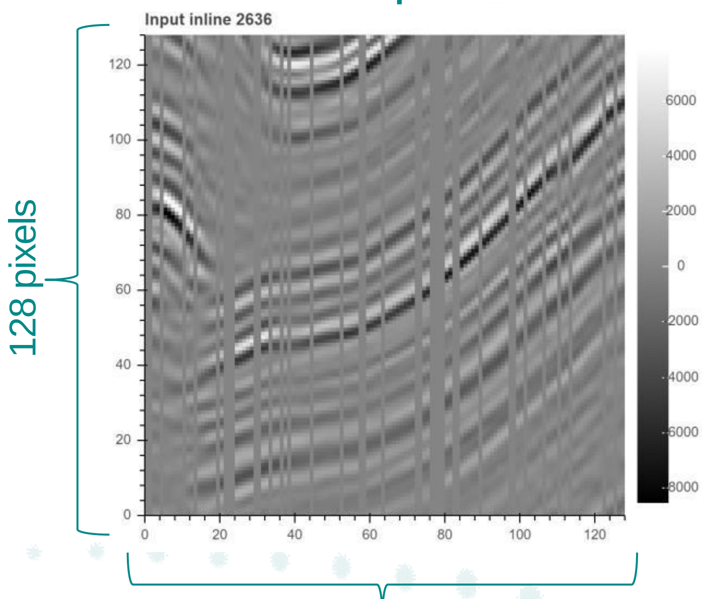
Example Data Set

- In the test were selected examples from one side of the volume for training the U-Net
- Trained U-Net was applied to the full volume, so that it is possible to validate the interpolation results in the blind test zone.

U-Net Seismic Interpolation
dGB - OpendTect

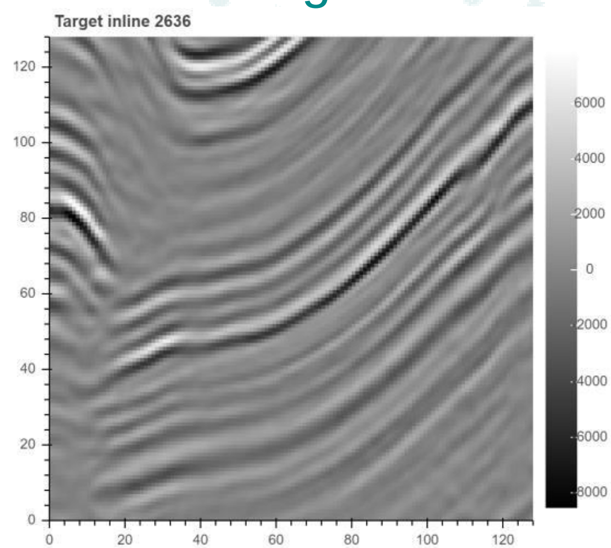
EXAMPLE FROM THE TRAINING SET

Input



128 pixels

Target



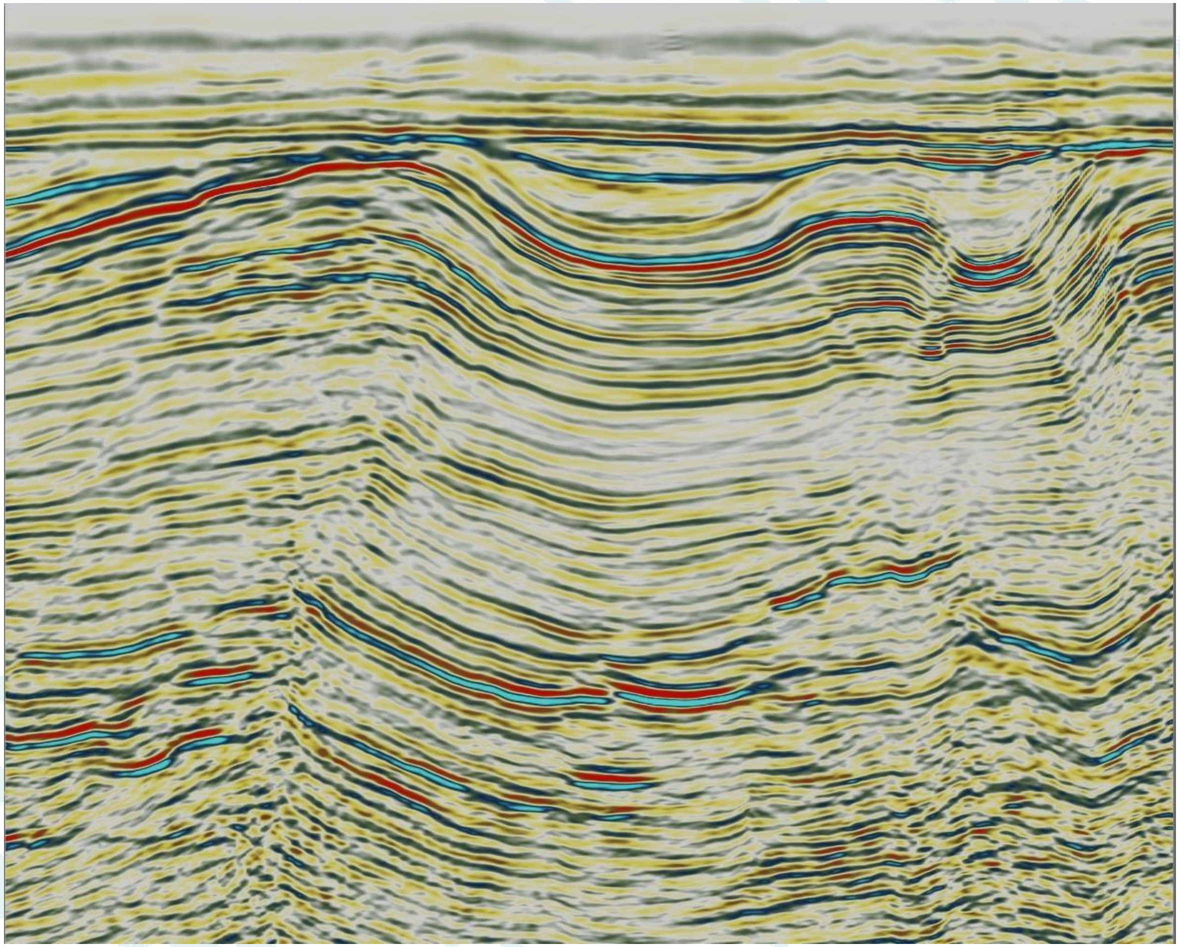
- Randomly blank +/- 16% of all traces.
- A training set was created for a U-Net that should transforms 2D images with blank traces to 2D images with complete coverage.
- Image dimensions are 128 x 128 samples extracted along inlines.

Reference: Marieke van Hout - de Groot

https://static.dgbes.com/images/PDF/U-Net_Interpolation.pdf

U-Net Seismic Interpolation
dGB - OpendTect

Original



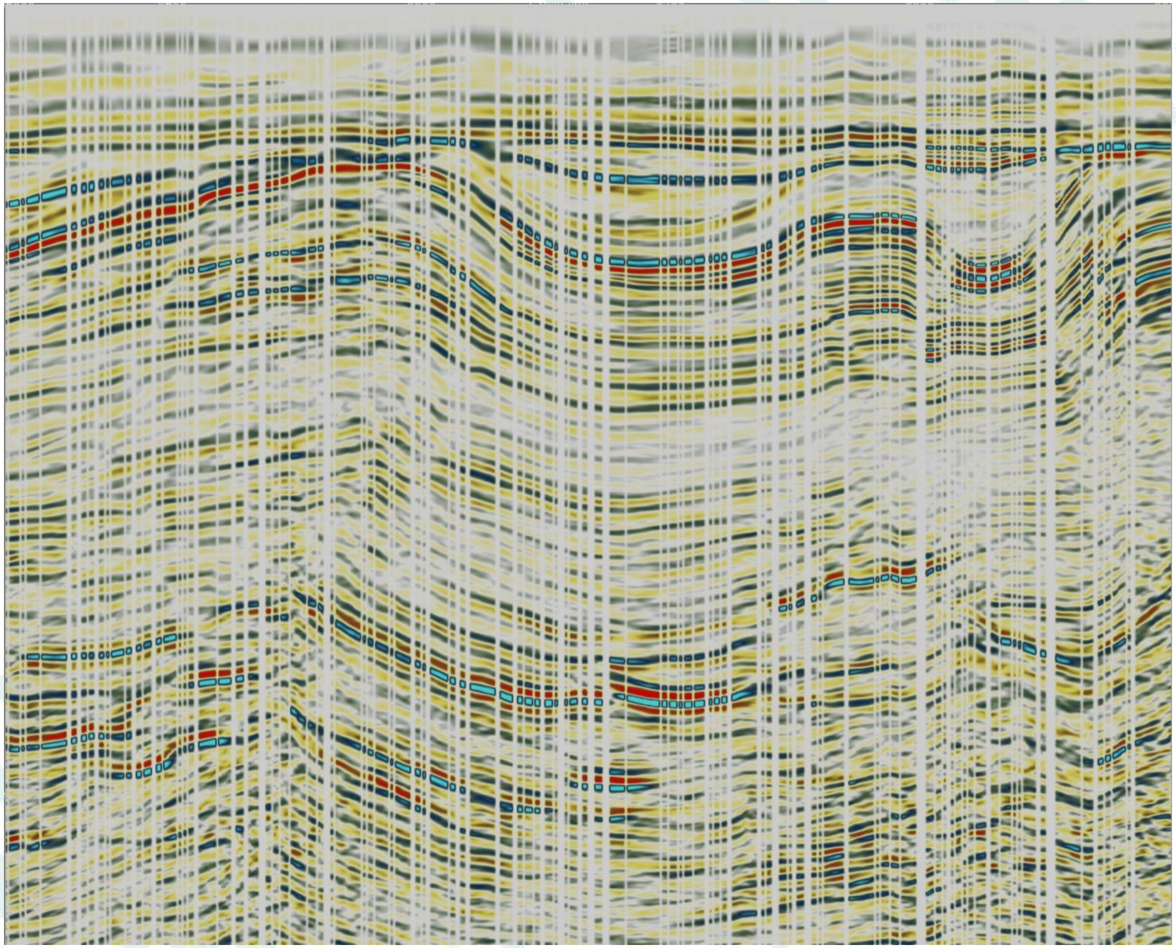
Inline 2900

Reference: Marieke van Hout - de Groot

https://static.dgbes.com/images/PDF/U-Net_Interpolation.pdf

U-Net Seismic Interpolation
dGB - OpendTect

Seismic with random holes



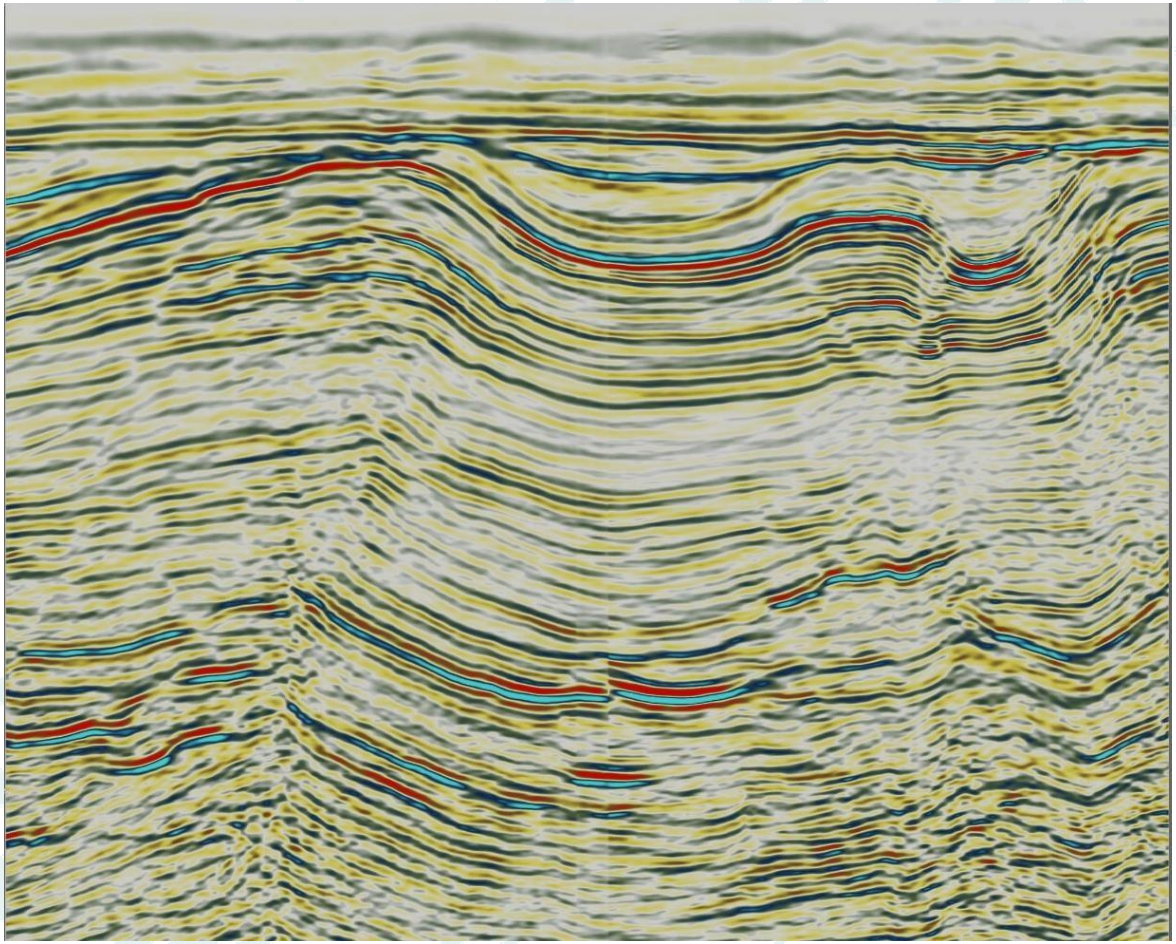
Inline 2900

Reference: Marieke van Hout - de Groot

https://static.dgbes.com/images/PDF/U-Net_Interpolation.pdf

U-Net Seismic Interpolation
dGB - OpendTect

Seismic with holes filled by U-Net



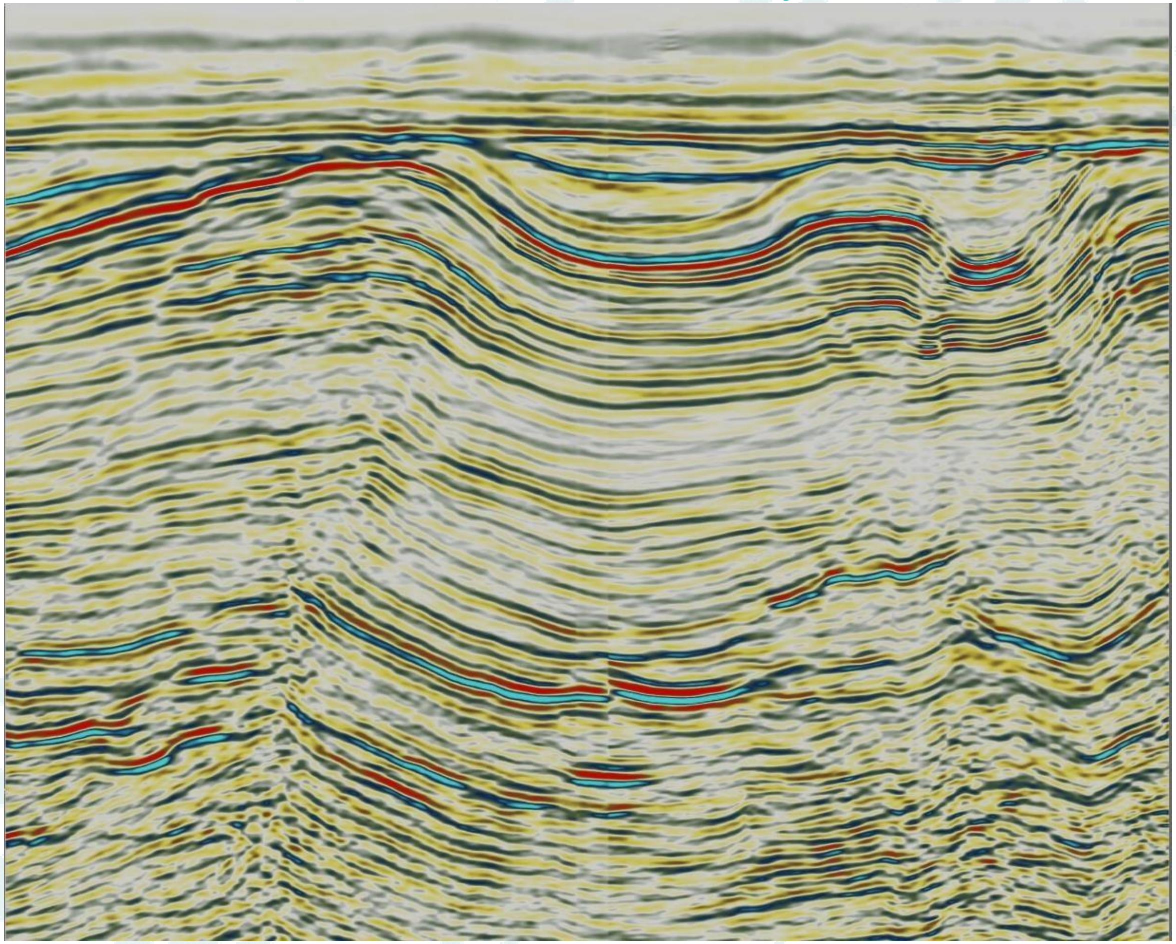
Inline 2900

Reference: Marieke van Hout - de Groot

https://static.dgbes.com/images/PDF/U-Net_Interpolation.pdf

U-Net Seismic Interpolation
dGB - OpendTect

Seismic with holes filled by U-Net



Inline 2900

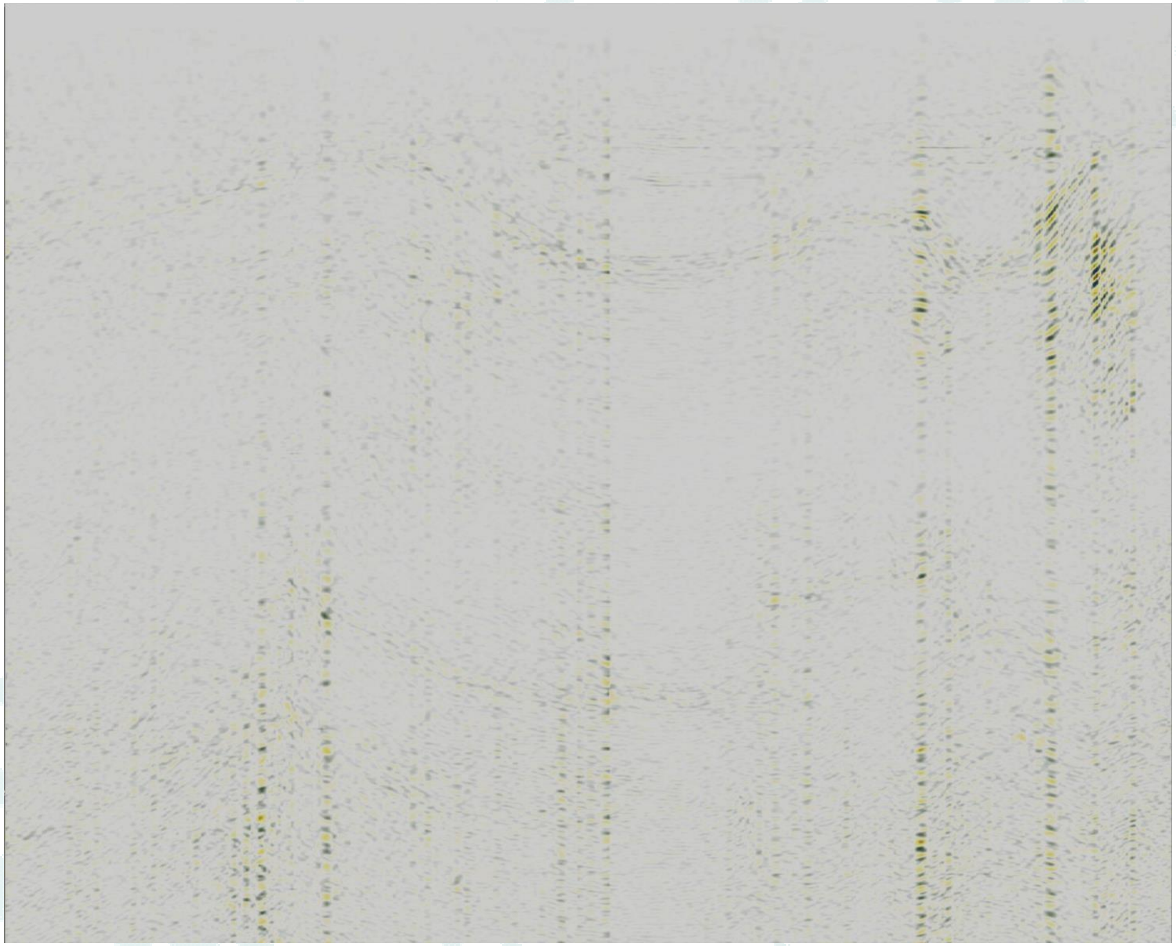
Reference: Marieke van Hout - de Groot

https://static.dgbes.com/images/PDF/U-Net_Interpolation.pdf

SG

U-Net Seismic Interpolation
dGB - OpendTect

Difference



Inline 2900

Applications:

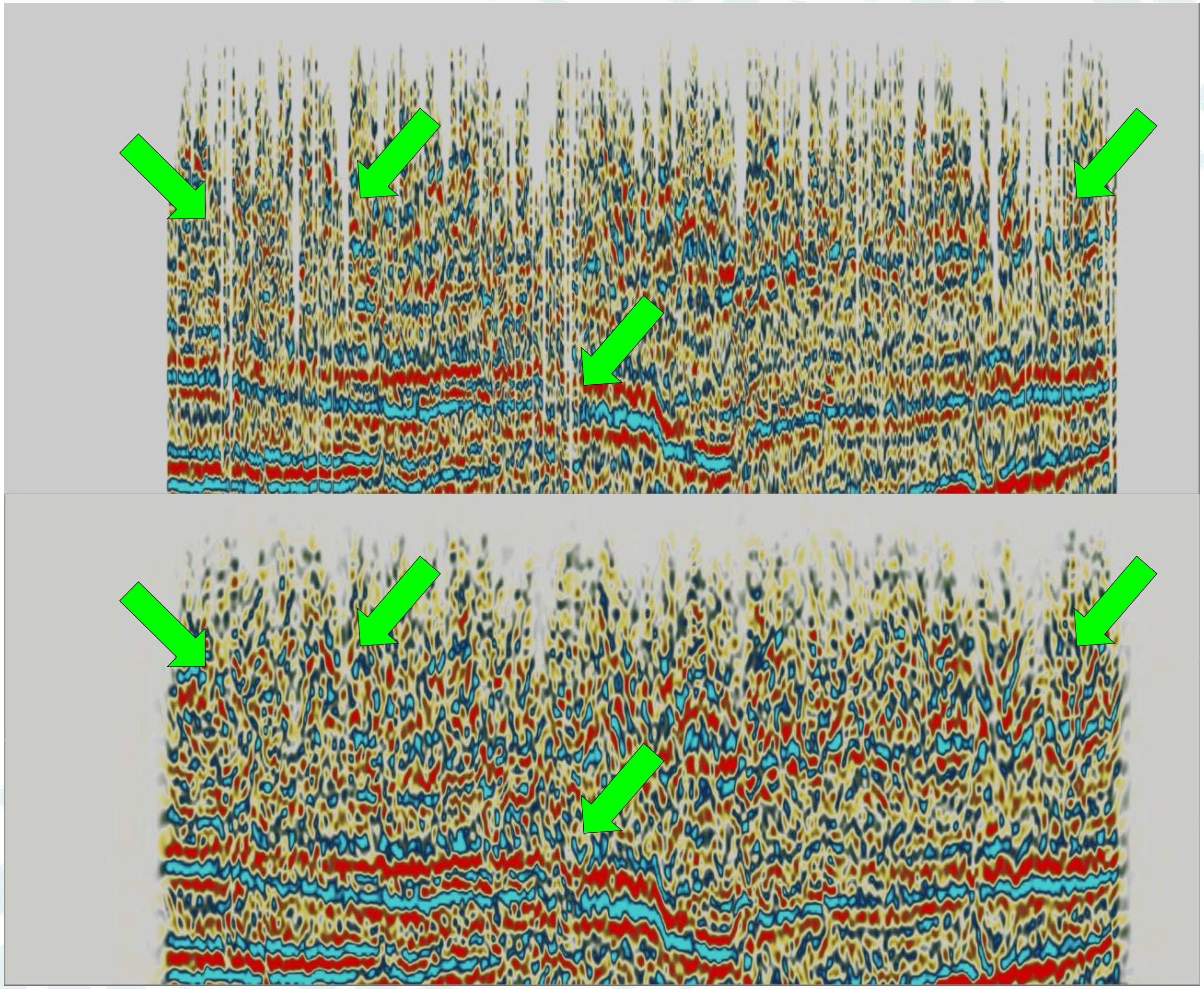
- Predict missing traces
- Create Super-sampled volumes (e.g. increase bin- size)

 Reference: Marieke van Hout - de Groot

https://static.dgbes.com/images/PDF/U-Net_Interpolation.pdf

U-Net Seismic Interpolation
dGB - OpendTect

Original Dataset



U-Net trained on Delft applied to Rotterdam

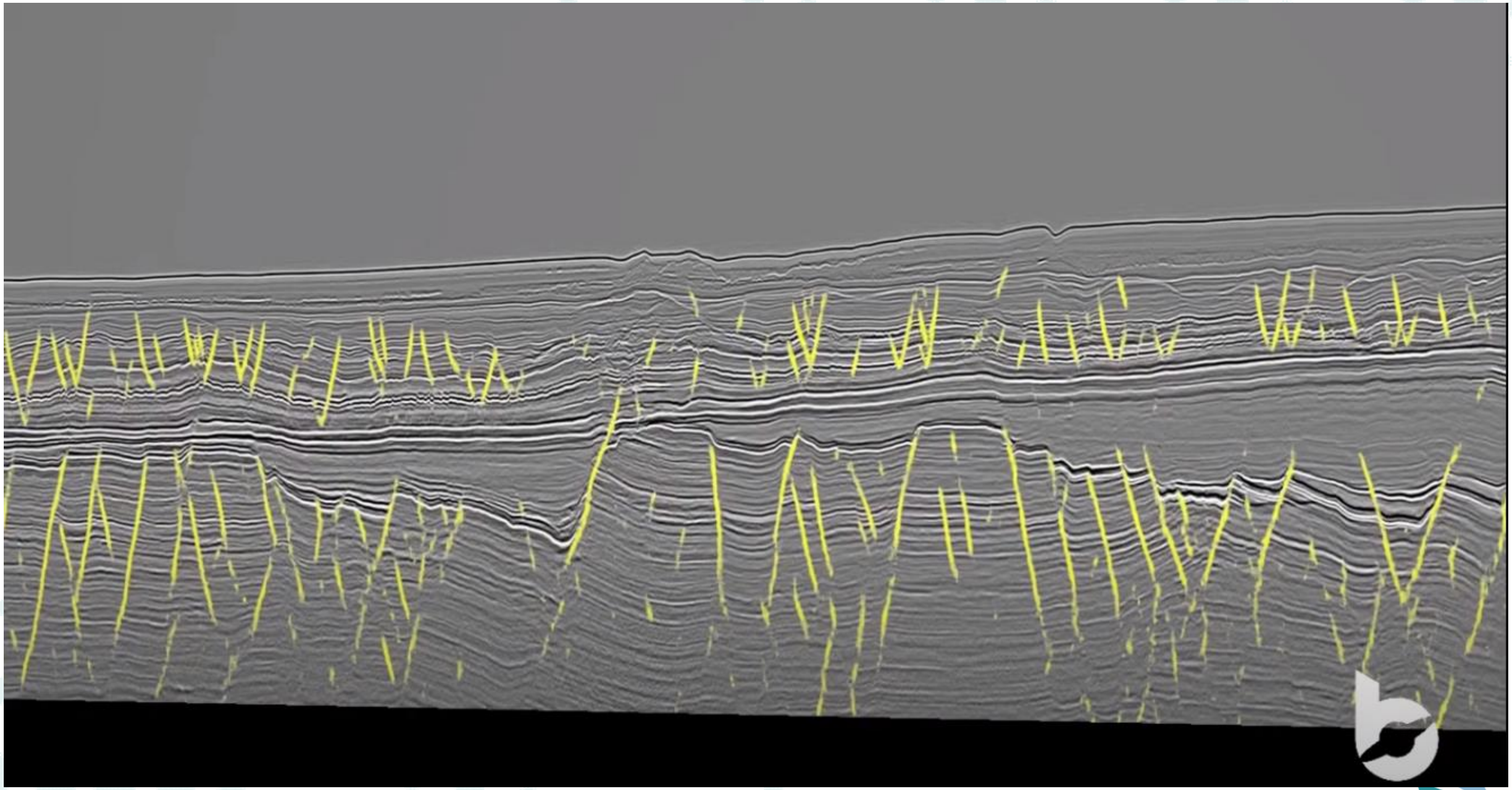
Shallow section of Rotterdam survey suffers from missing traces and undershoots

Reference: Marieke van Hout - de Groot

https://static.dgbes.com/images/PDF/U-Net_Interpolation.pdf

Deep**LEARNING**

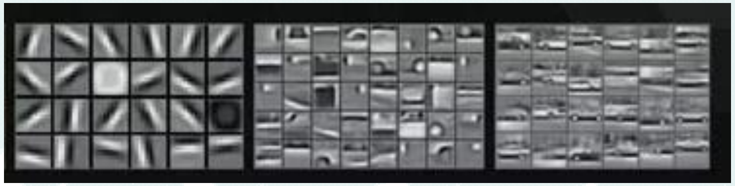
Fault Interpretation



https://www.youtube.com/watch?v=SEyBYHLP-YE

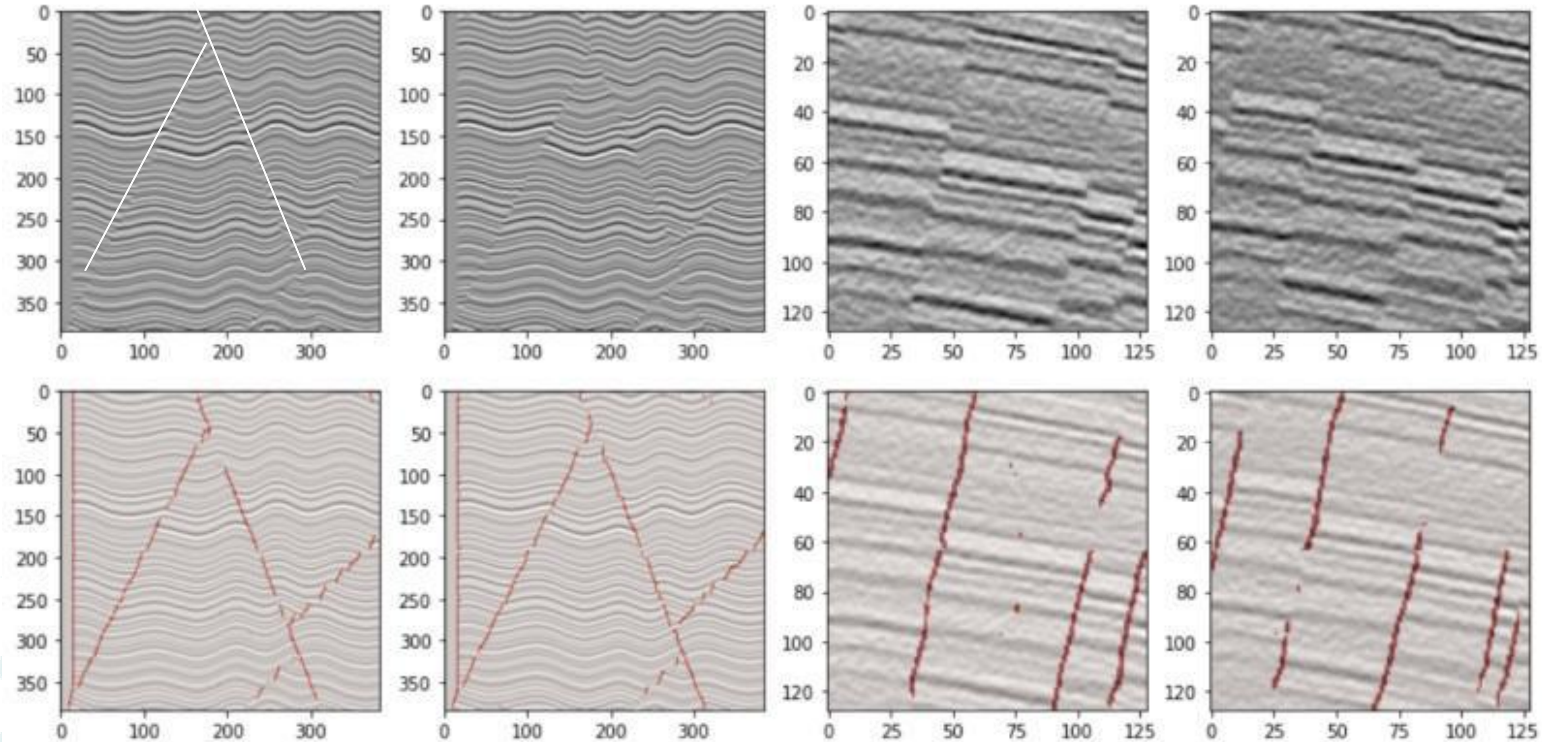
CNN

Fault Detection



1) DATOS SINTETICOS

2) DATOS SINTETICOS + RUIDOS



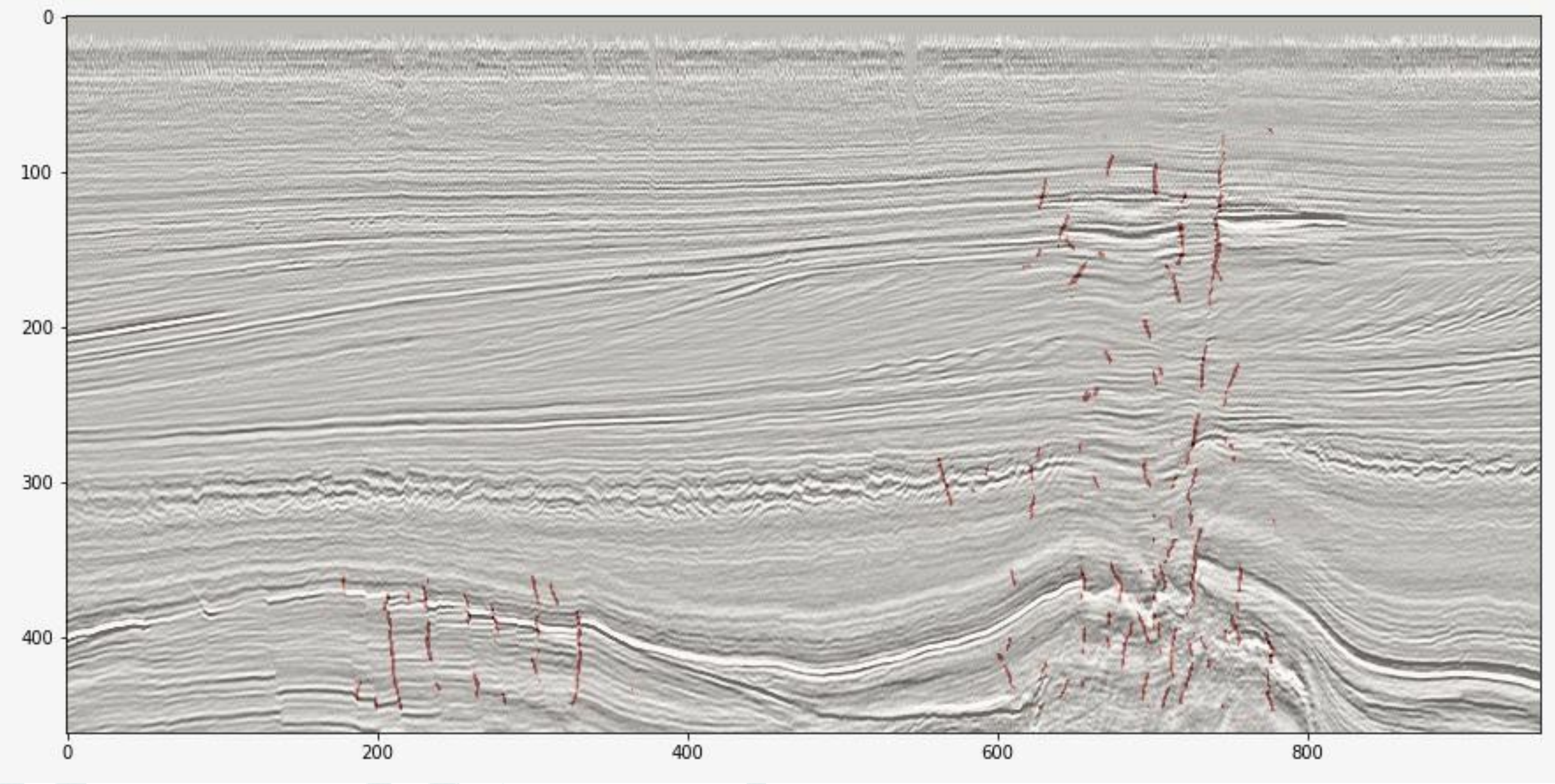
MILLONES DE LINEAS SISMICAS

80% Entrenamiento
20% Pruebas

Example from Ketut Toto Suryanhadinata

CNN

Fault Detection

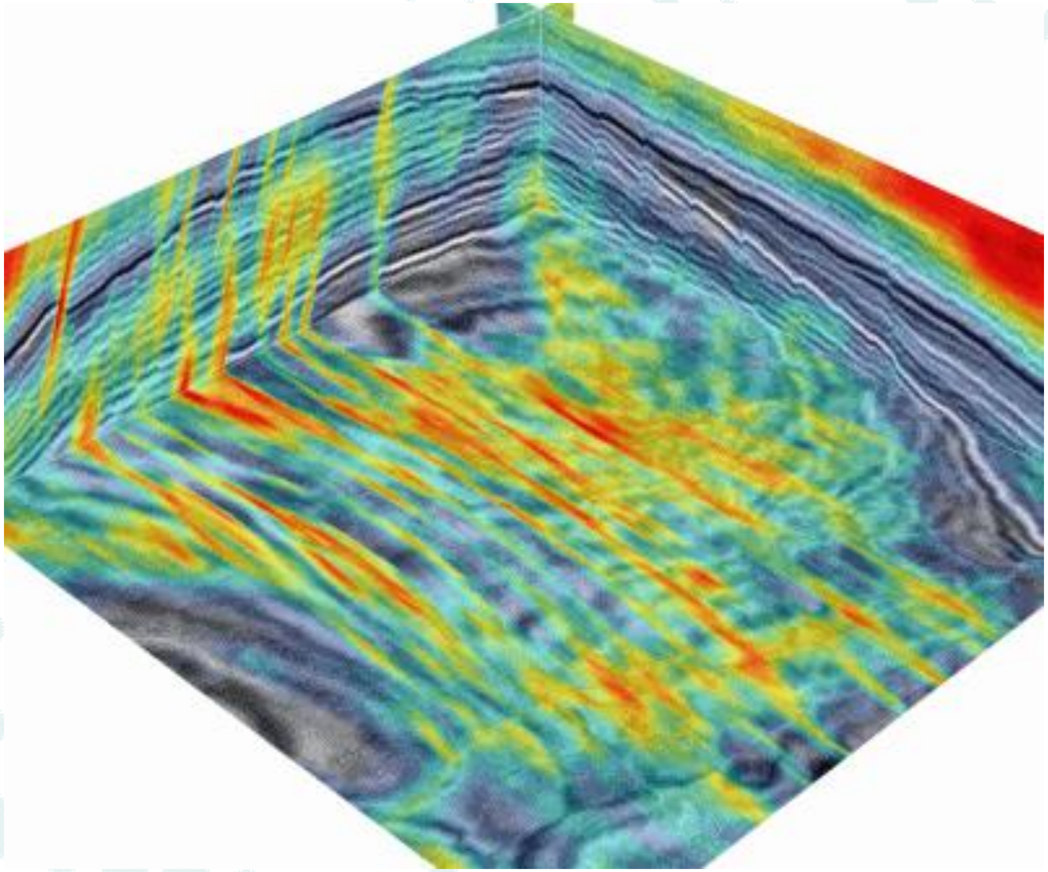


Final Result

Fault likelihood scanning

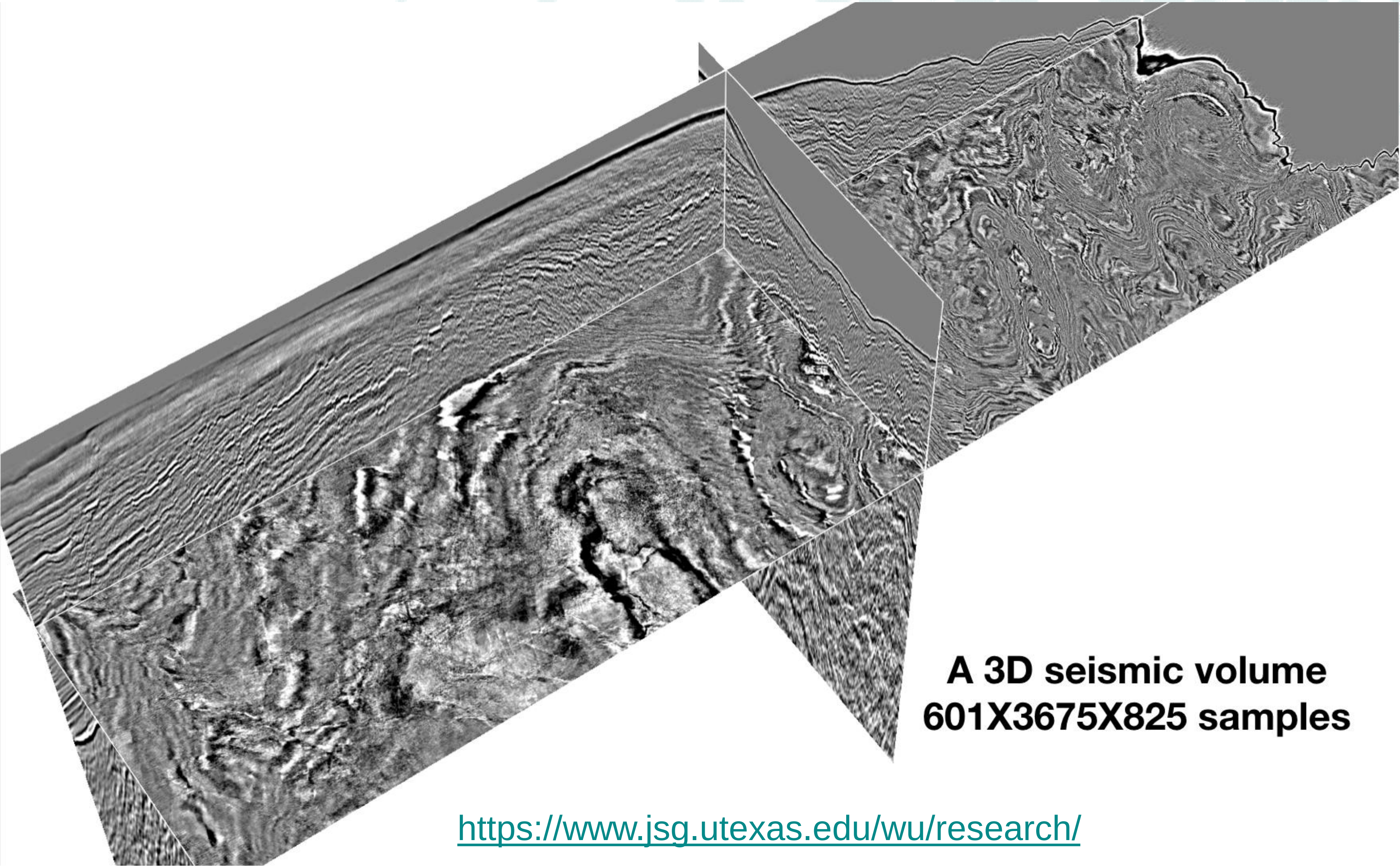
Hale, D., Methods to compute fault images, extract fault surfaces, and estimate fault throws from 3D seismic images, Geophysics, 78(2), O33-O43.

Wu, X. and D. Hale, 2016, 3D seismic image processing for faults. Geophysics, 81(2), IM1-IM11.



https://www.youtube.com/watch?v=wp6Vhv3BxBE

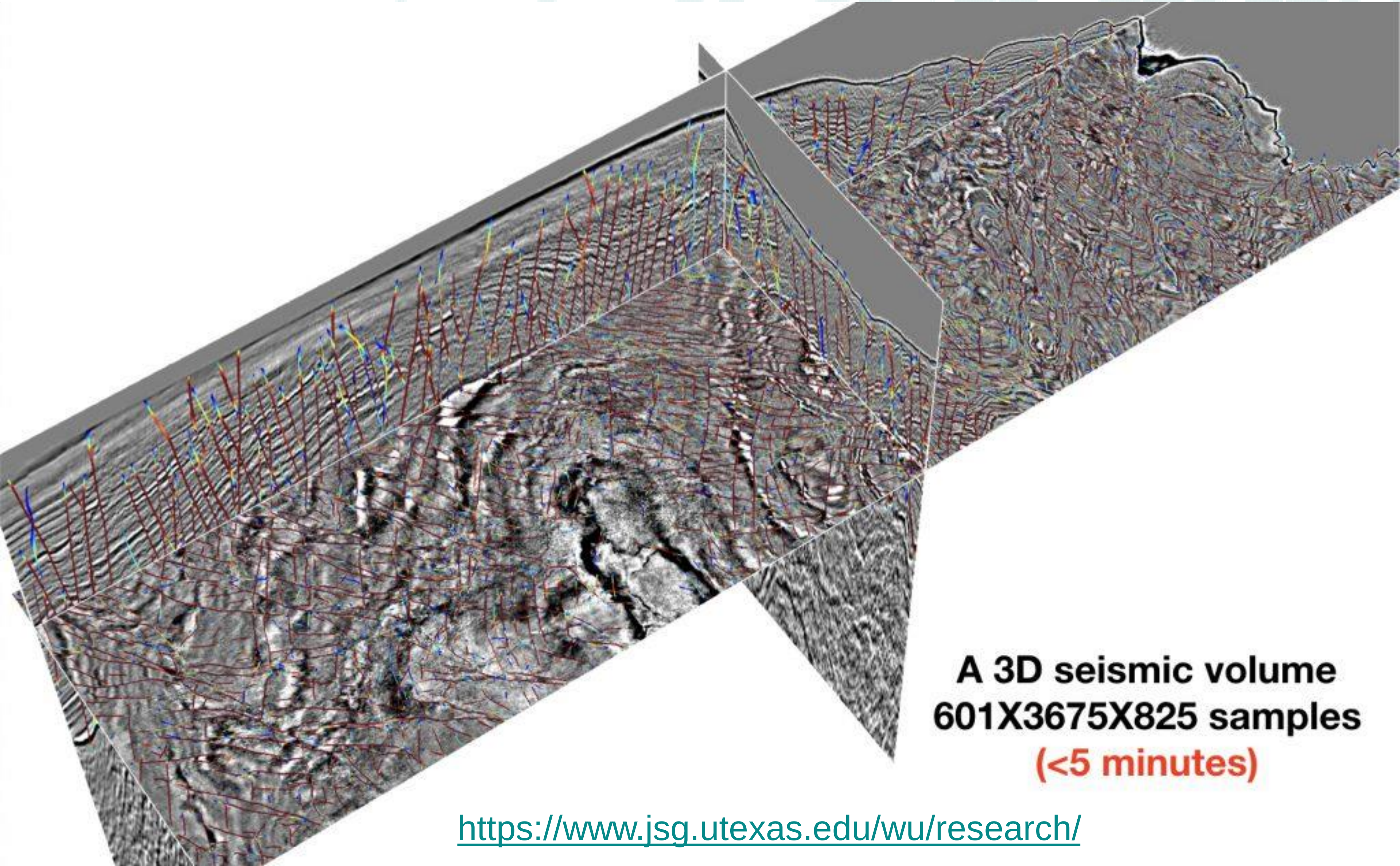
A better workflow for better fault detection



A 3D seismic volume
601X3675X825 samples

https://www.jsg.utexas.edu/wu/research/

A better workflow for better fault detection



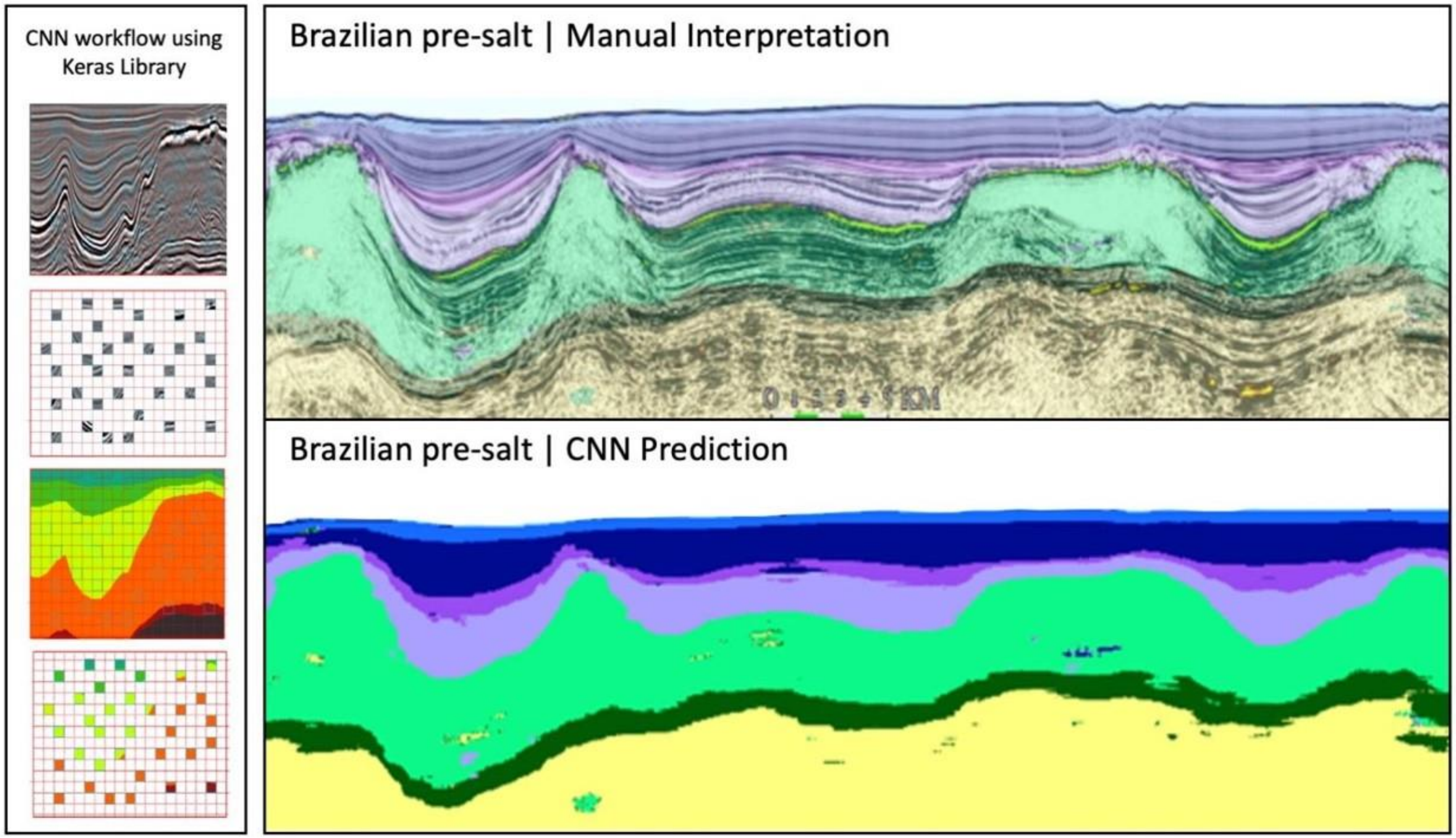
https://www.jsg.utexas.edu/wu/research/

Deep**LEARNING**

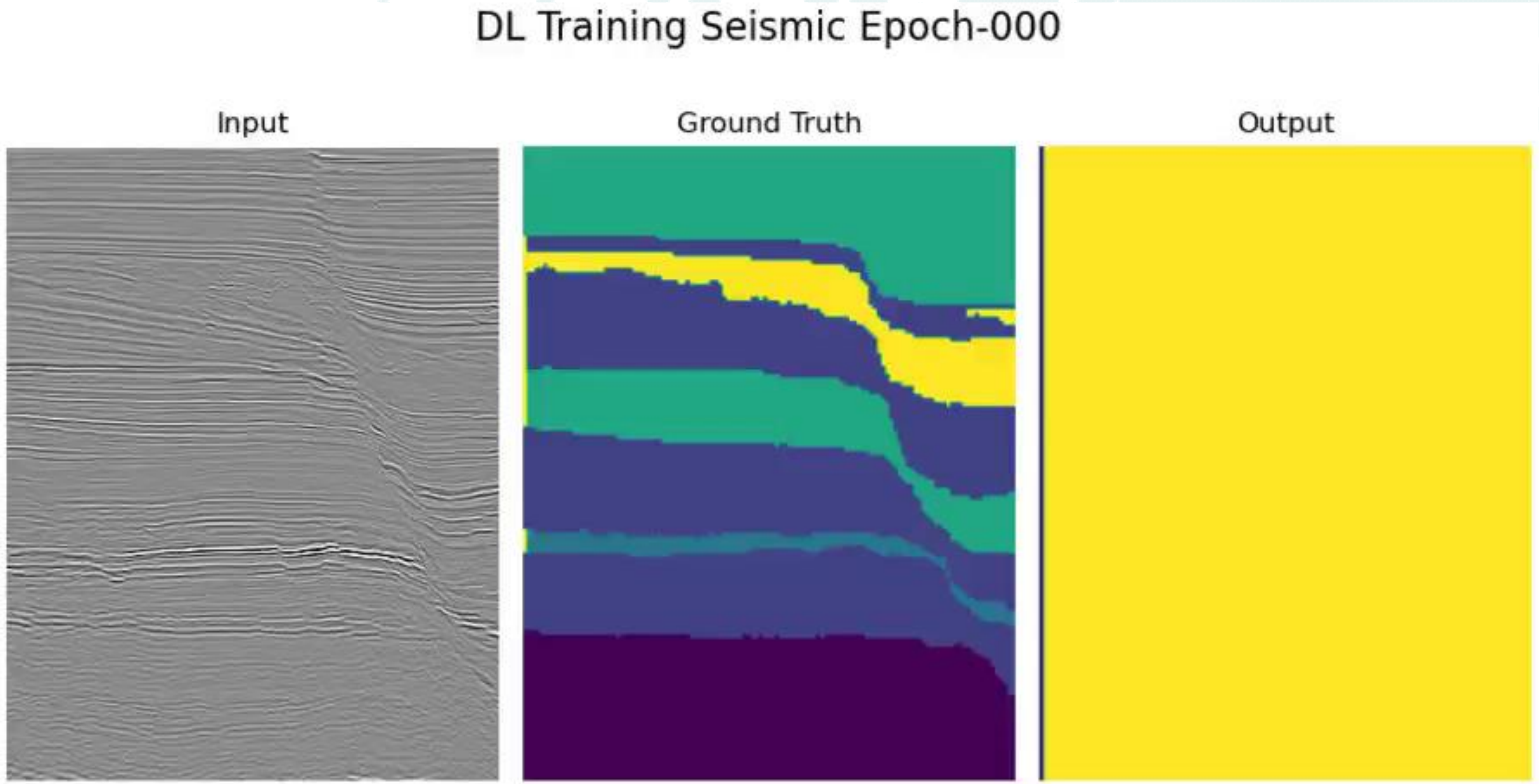
Seismic**INTERPRETATION**

CNN

Fault Detection

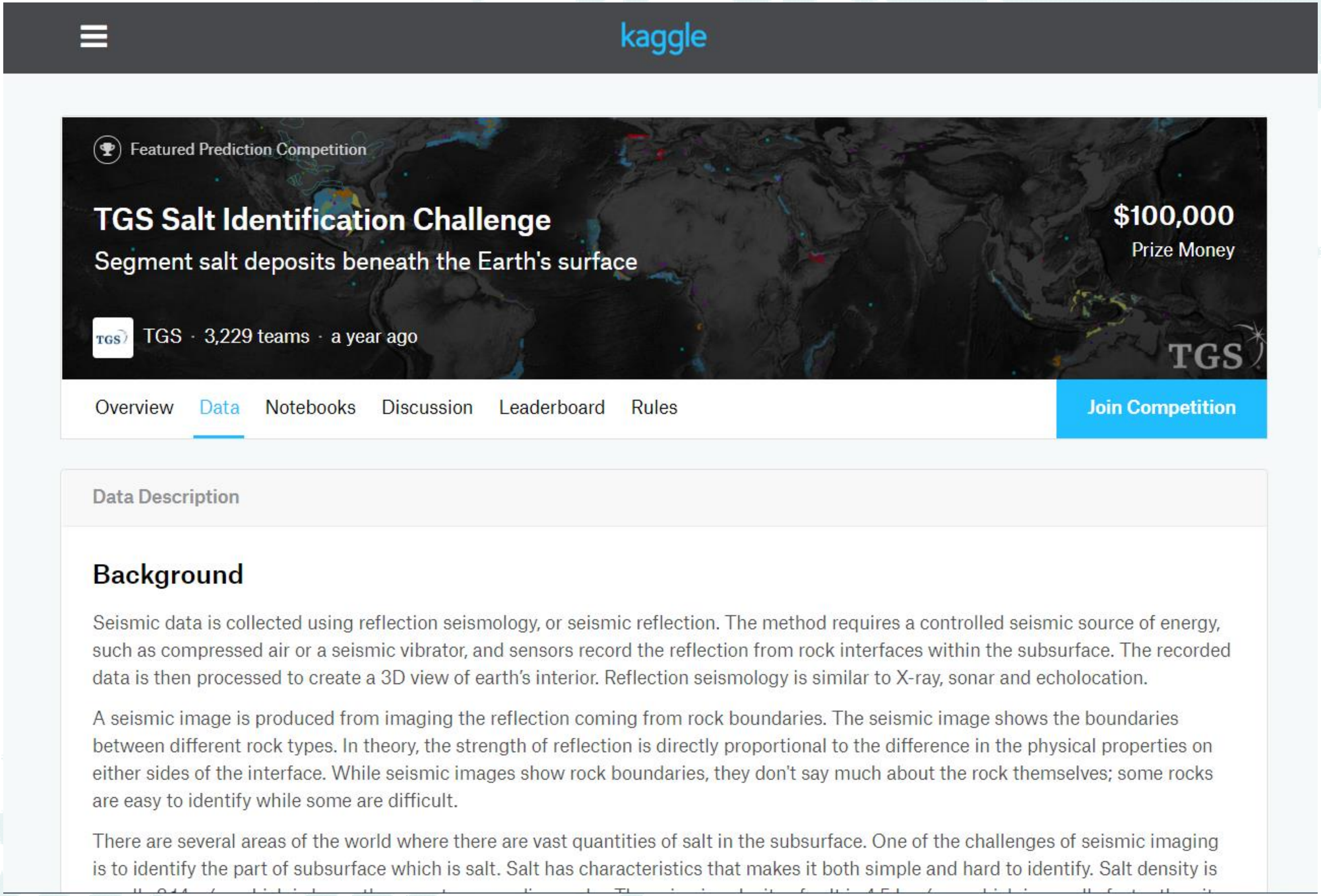


Convolutional Neural Networks



https://www.linkedin.com/posts/leo-c-0988727b_machinelearning-oilandgas-deeplearning-ugcPost-6697363832991567872-XwIC

SALT DETECTION


kaggle

Featured Prediction Competition

TGS Salt Identification Challenge

Segment salt deposits beneath the Earth's surface

TGS · 3,229 teams · a year ago

$100,000
Prize Money

TGS

Overview Data Notebooks Discussion Leaderboard Rules

Join Competition

Data Description

Background

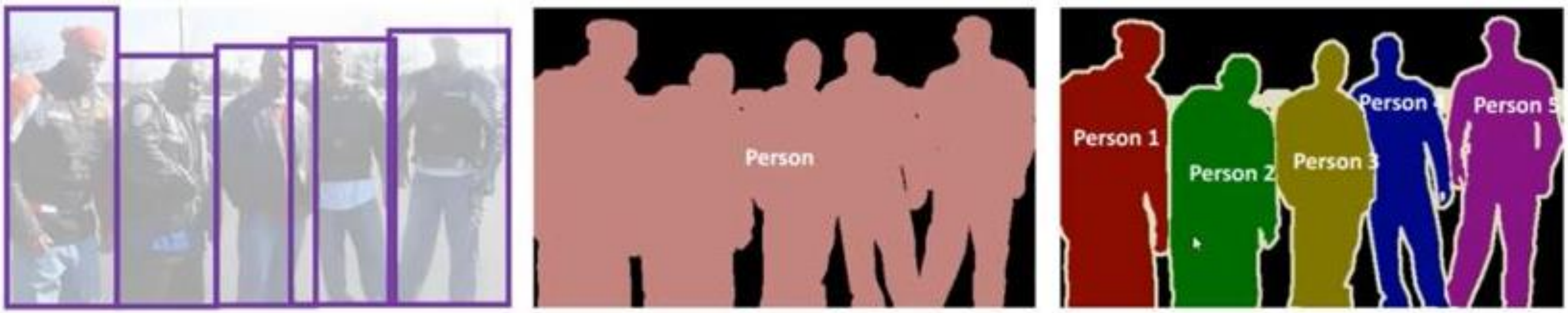
Seismic data is collected using reflection seismology, or seismic reflection. The method requires a controlled seismic source of energy, such as compressed air or a seismic vibrator, and sensors record the reflection from rock interfaces within the subsurface. The recorded data is then processed to create a 3D view of earth's interior. Reflection seismology is similar to X-ray, sonar and echolocation.

A seismic image is produced from imaging the reflection coming from rock boundaries. The seismic image shows the boundaries between different rock types. In theory, the strength of reflection is directly proportional to the difference in the physical properties on either sides of the interface. While seismic images show rock boundaries, they don't say much about the rock themselves; some rocks are easy to identify while some are difficult.

There are several areas of the world where there are vast quantities of salt in the subsurface. One of the challenges of seismic imaging is to identify the part of subsurface which is salt. Salt has characteristics that makes it both simple and hard to identify. Salt density is

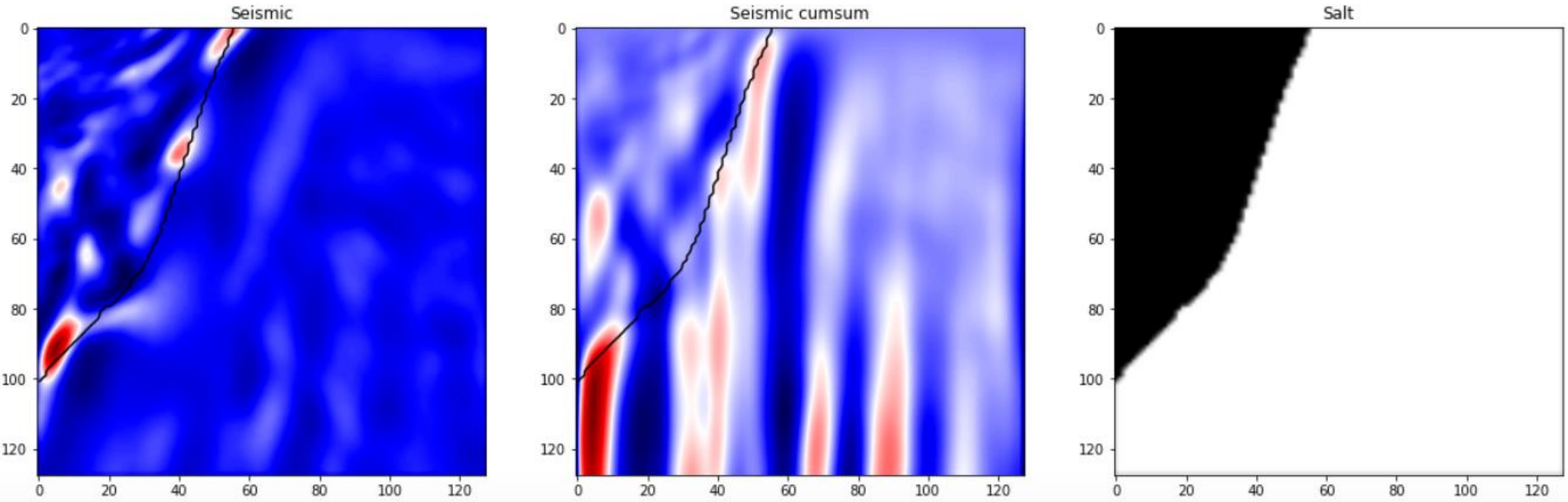
https://www.kaggle.com/c/tgs-salt-identification-challenge/data

SALT DETECTION
Problem

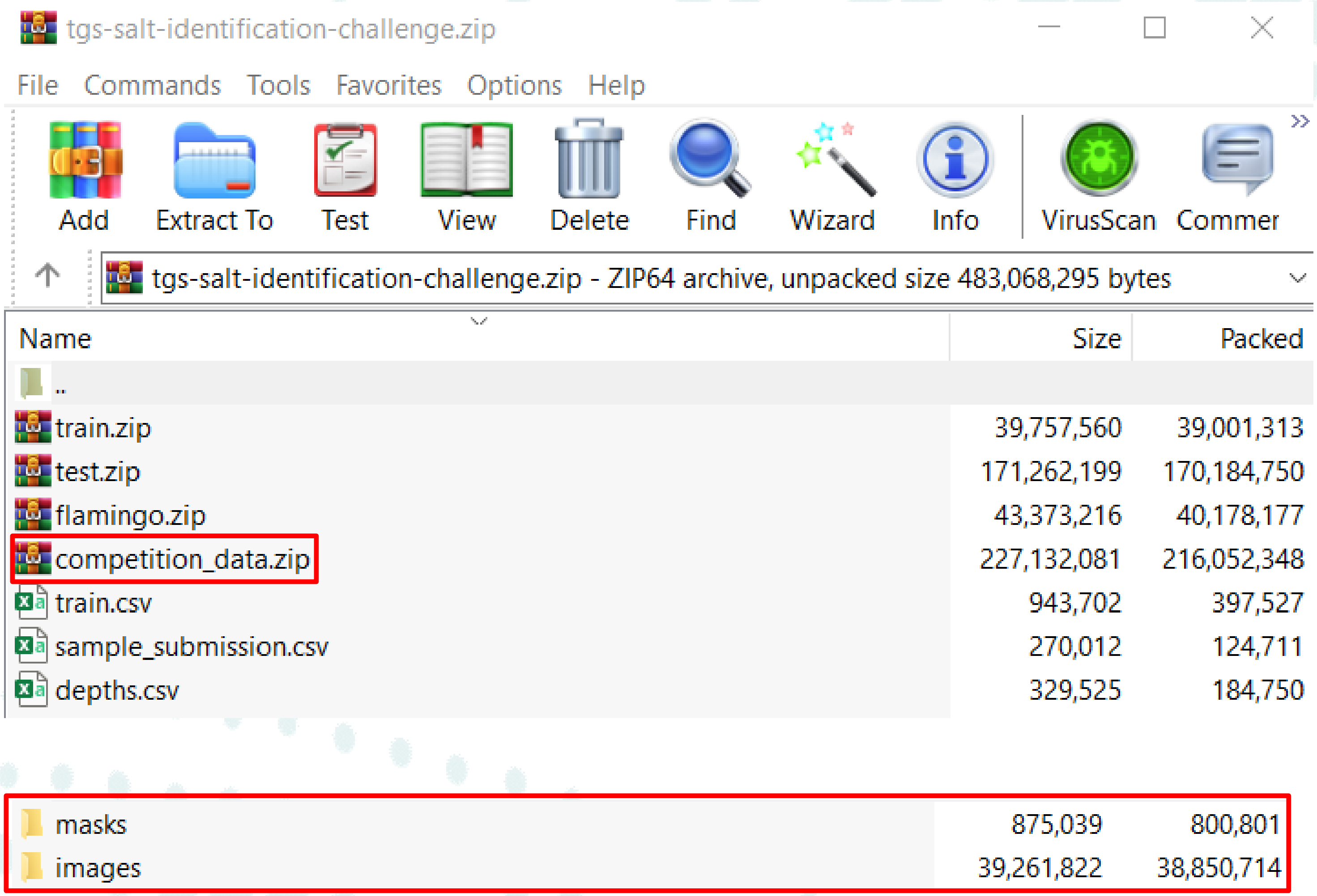


Object Detection | Semantic Segmentation | Instance Segmentation

SALT DETECTION
Problem

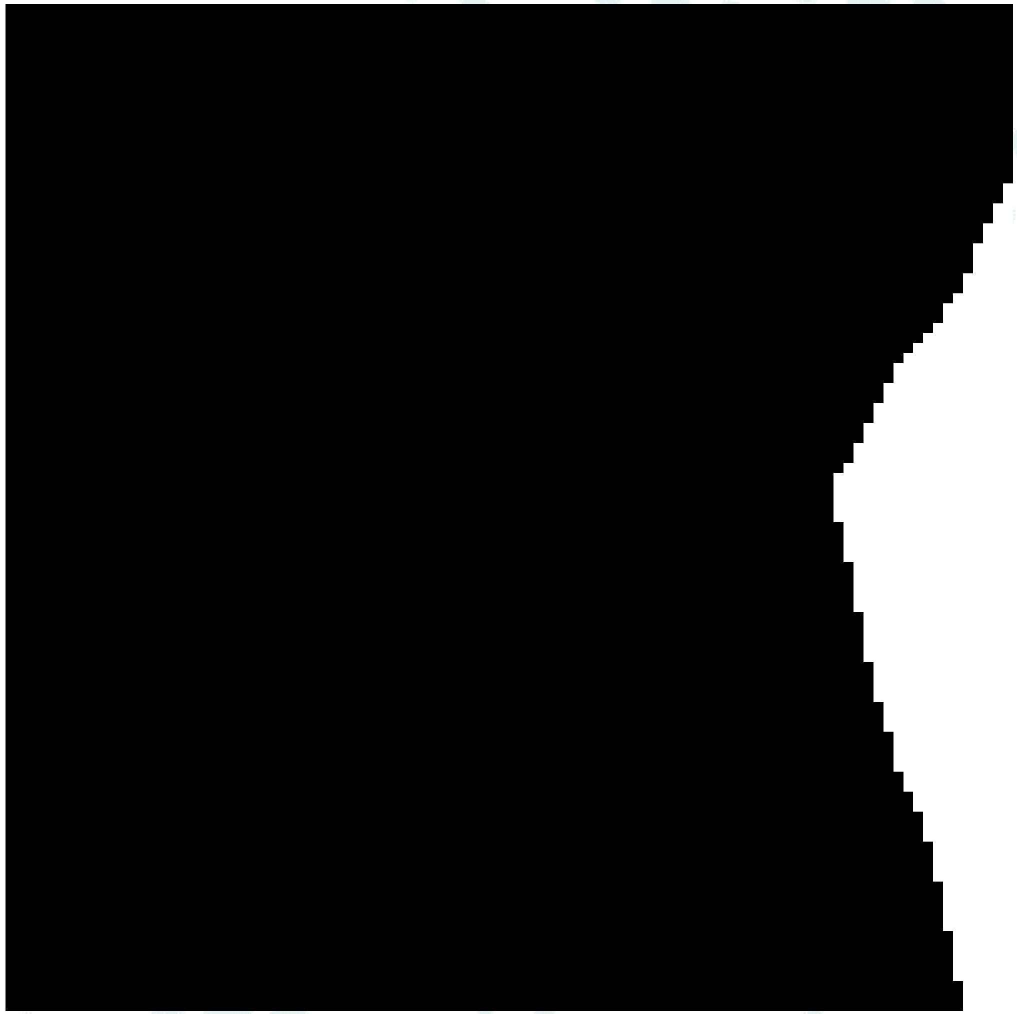


SALT DETECTION



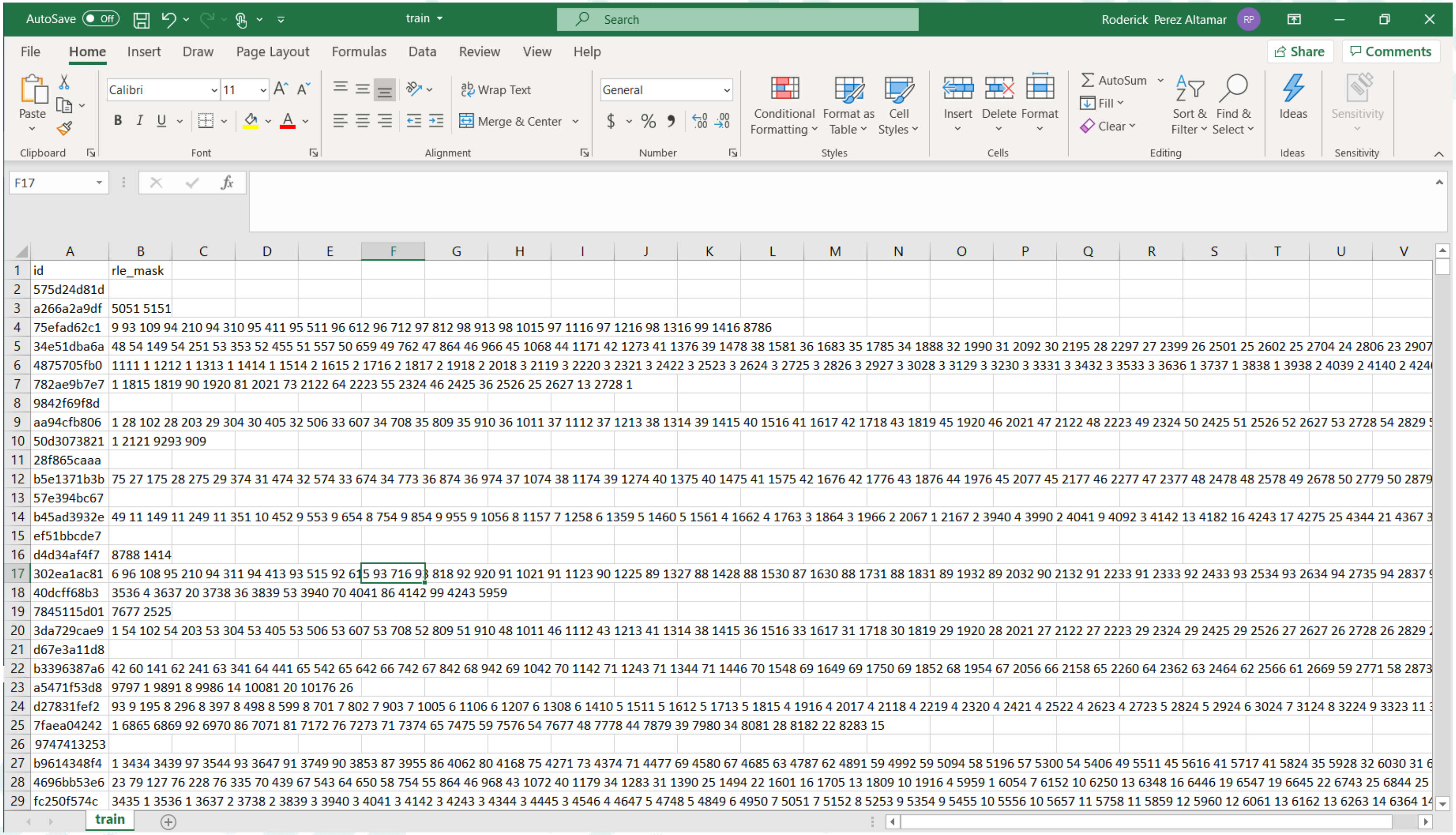
SALT DETECTION

train



SALT DETECTION

Train Data



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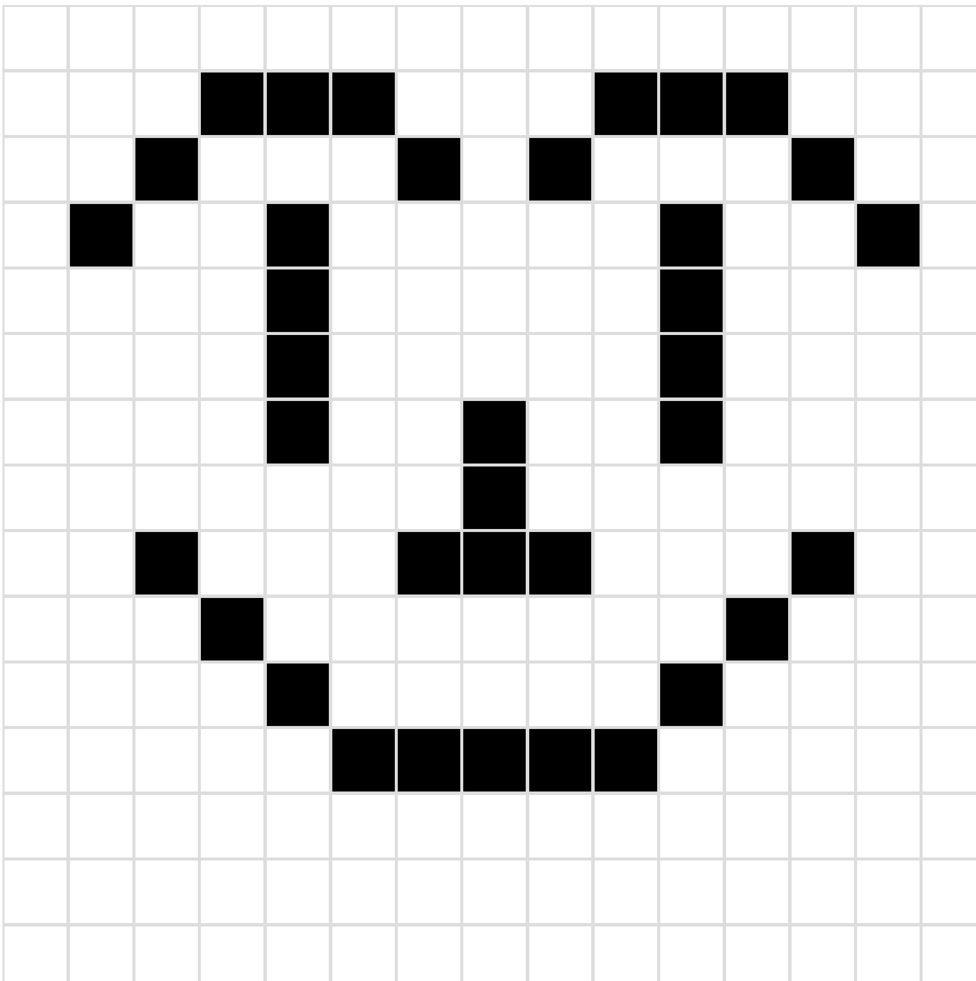
SALT DETECTION

Run Length Encoding

Bits for grid: 225



Bits for Run length encoding: 123

Edit

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5, 5, 5
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15
15

SALT DETECTION

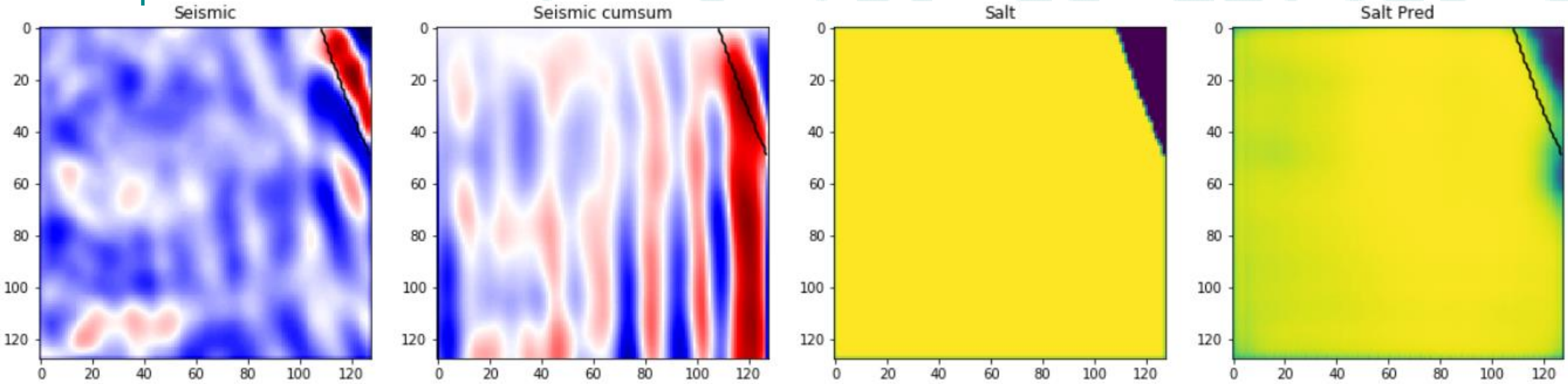
```
Epoch 1/50
213/213 [==============================] - ETA: 0s - loss: nan
Epoch 00001: val_loss did not improve from inf
213/213 [==============================] - 245s 1s/step - loss: nan - val_loss: nan
Epoch 2/50
213/213 [==============================] - ETA: 0s - loss: nan
Epoch 00002: val_loss did not improve from inf
213/213 [==============================] - 242s 1s/step - loss: nan - val_loss: nan
Epoch 3/50
213/213 [==============================] - ETA: 0s - loss: nan
Epoch 00003: ReduceLROnPlateau reducing learning rate to 0.00010000000474974513.

Epoch 00003: val_loss did not improve from inf
213/213 [==============================] - 245s 1s/step - loss: nan - val_loss: nan
Epoch 4/50
213/213 [==============================] - ETA: 0s - loss: nan
Epoch 00004: val_loss did not improve from inf
213/213 [==============================] - 242s 1s/step - loss: nan - val_loss: nan
Epoch 5/50
213/213 [==============================] - ETA: 0s - loss: nan
Epoch 00005: val_loss did not improve from inf
213/213 [==============================] - 242s 1s/step - loss: nan - val_loss: nan
Epoch 00005: early stopping
```

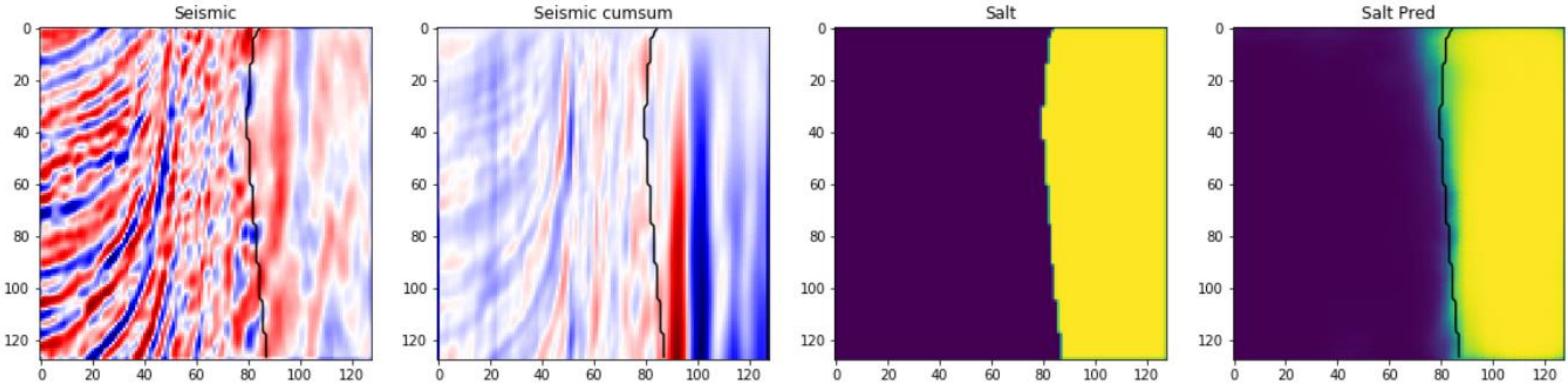
SALT DETECTION

Results

Example 1



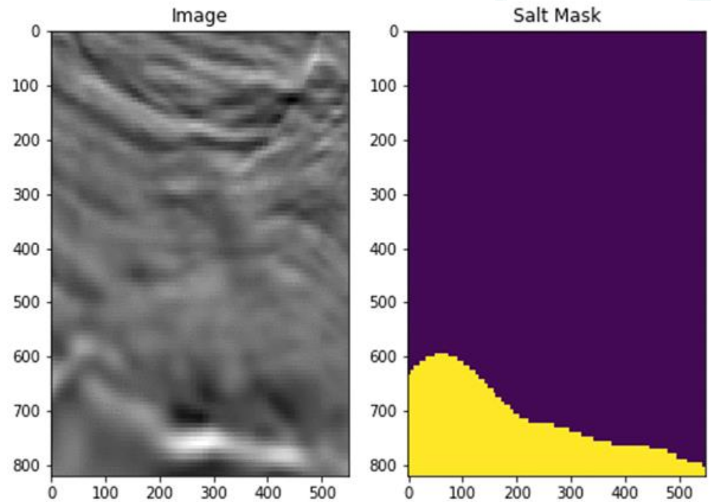
Example 2



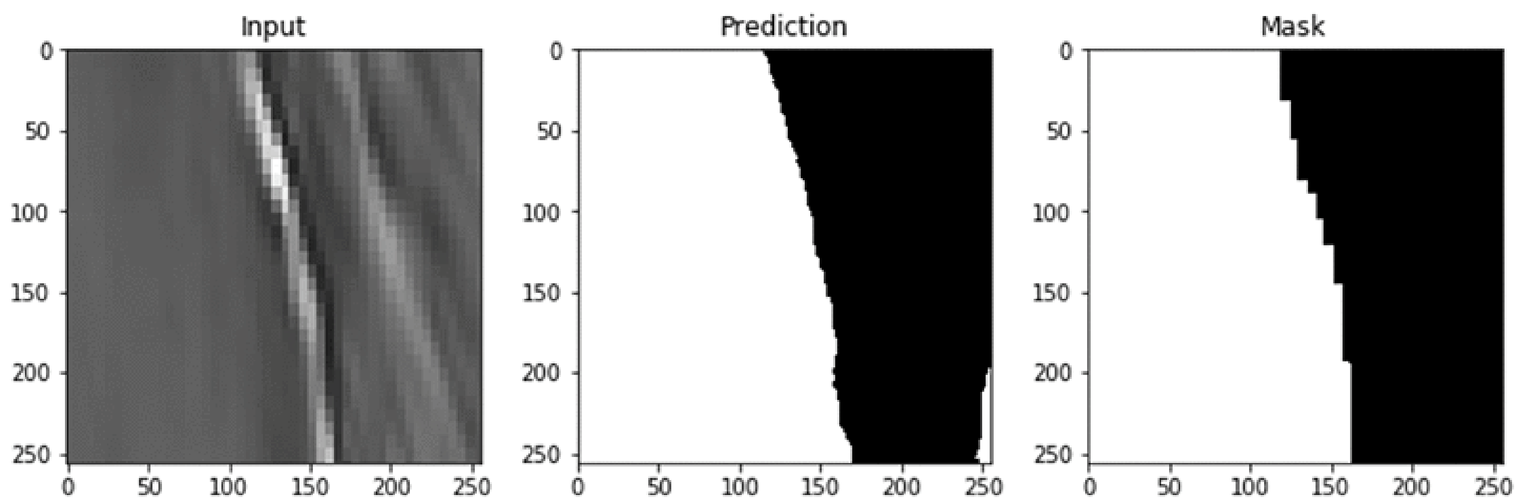
https://www.kaggle.com/bguberfain/unet-with-depth

INTERPRETING 3D SEISMIC DATA AUTOMATICALLY USING AMAZON SAGEMAKER

AWS



About this blog post	
Time to read	**15 minutes**
Time to complete	**~ 1 hour**
Cost to complete	**Under $60**
Learning level	**Intermediate (200)**
AWS services	**Amazon SageMaker, EC2, Amazon S3**

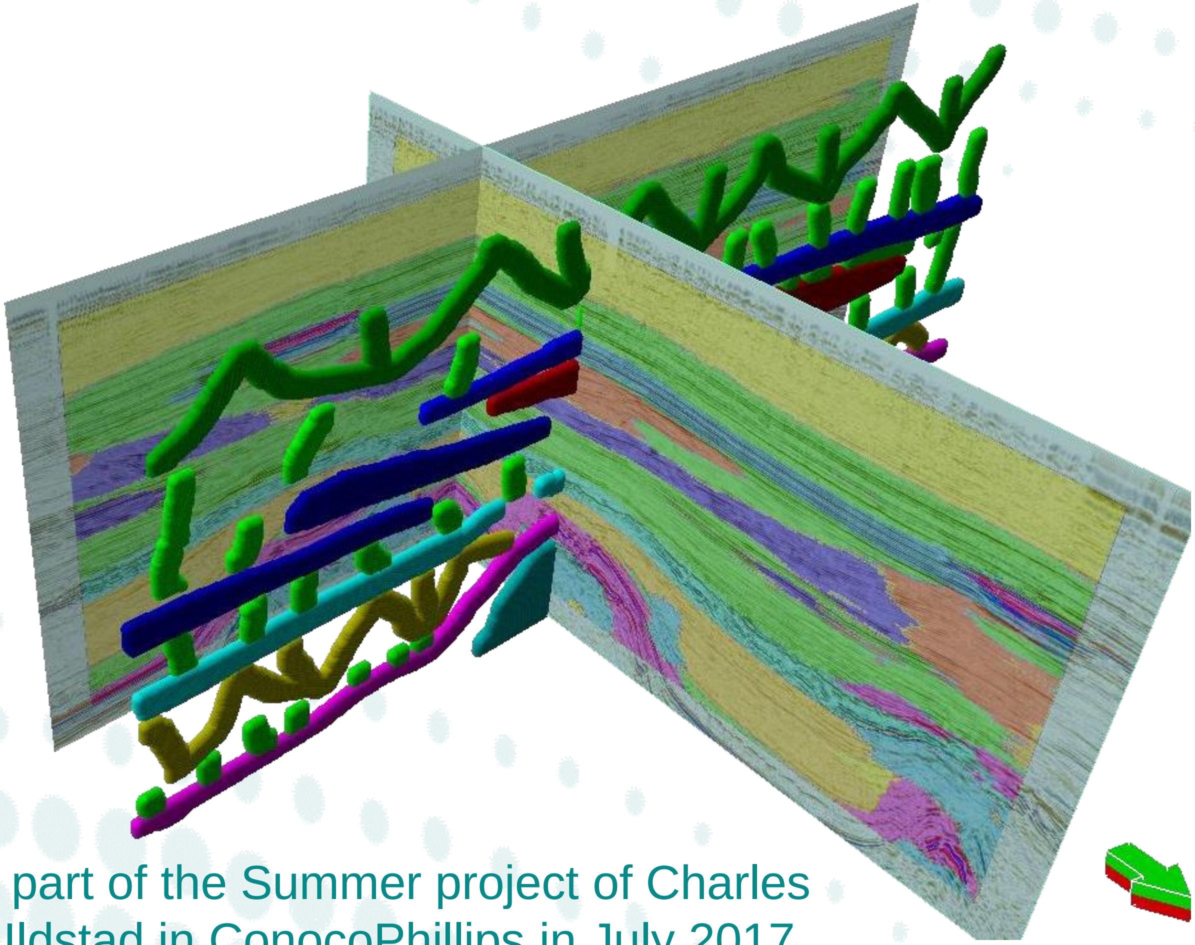


https://aws.amazon.com/blogs/machine-learning/interpreting-3d-seismic-data-automatically-using-amazon-sagemaker/

MULTILAYER FACIES CLASSIFICATION

MalenoV (MAchine LEarNing Of Voxels)

Auto-classified cube with 9 facies classes

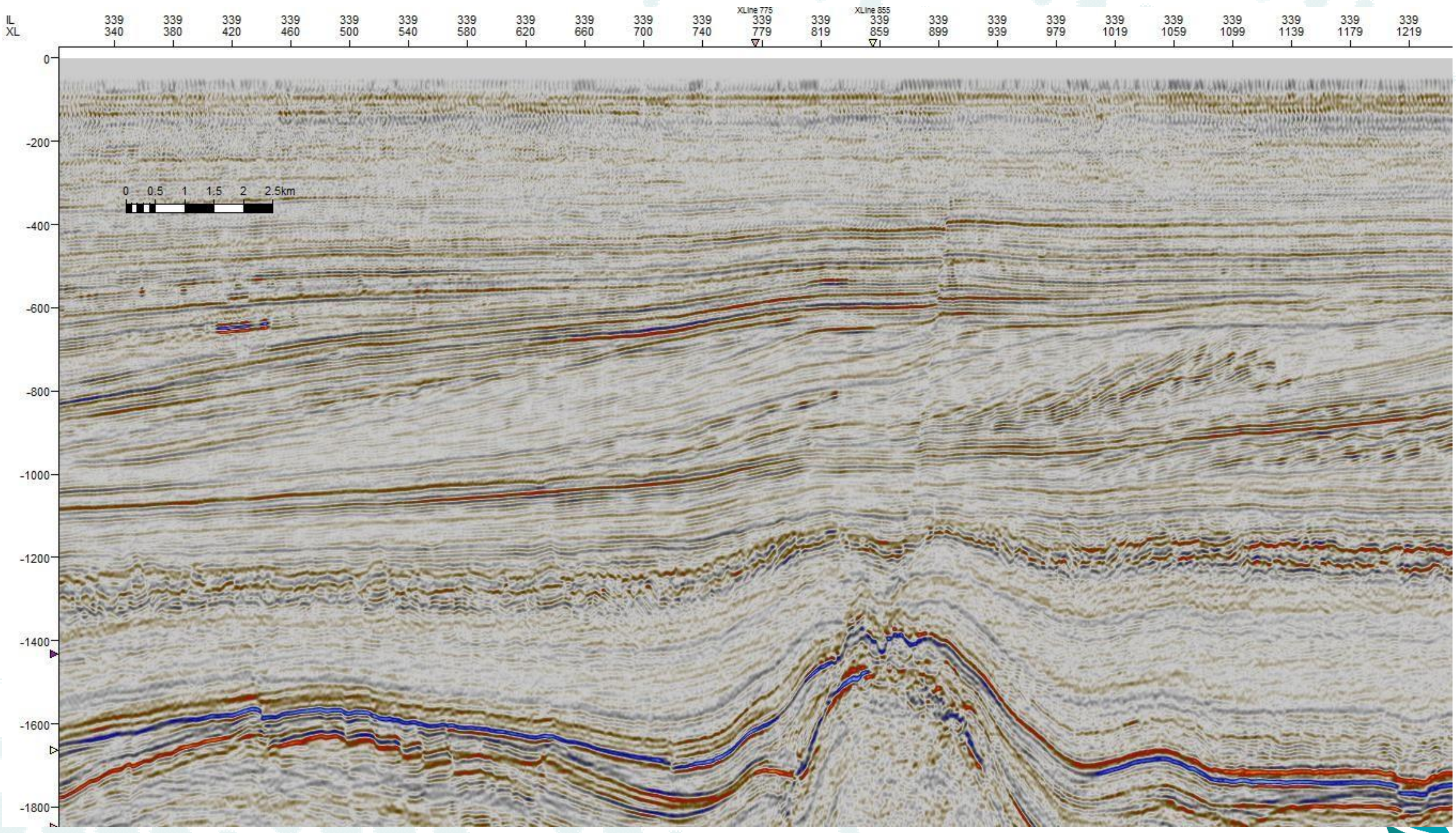


Created as part of the Summer project of Charles Rutherford Ildstad in ConocoPhillips in July 2017.

MULTILAYER FACIES CLASSIFICATION

MalenoV (MAchine LEarNing Of Voxels)

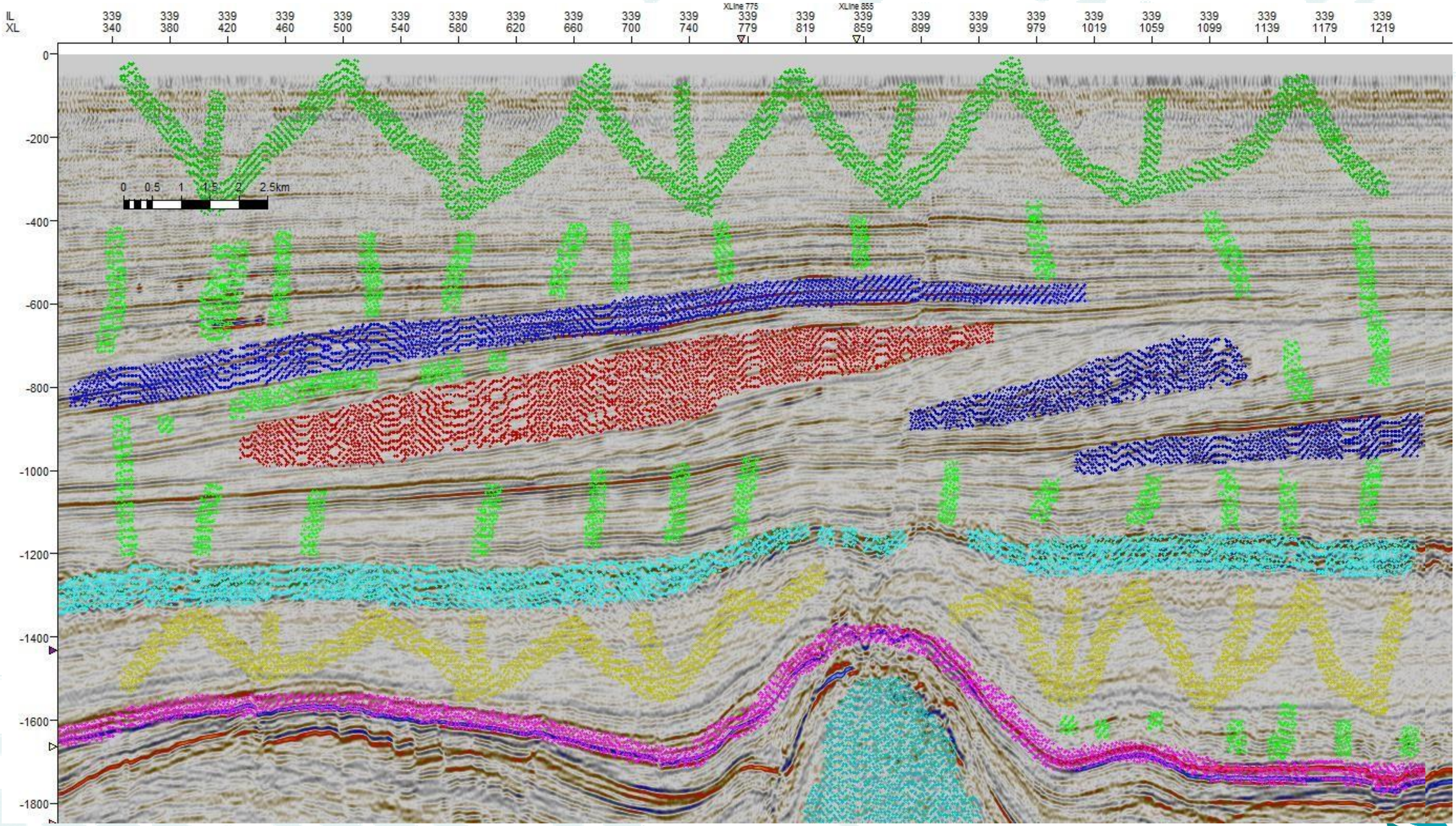
INPUT DATA



MULTILAYER FACIES CLASSIFICATION

MalenoV (MAchine LEarNing Of Voxels)

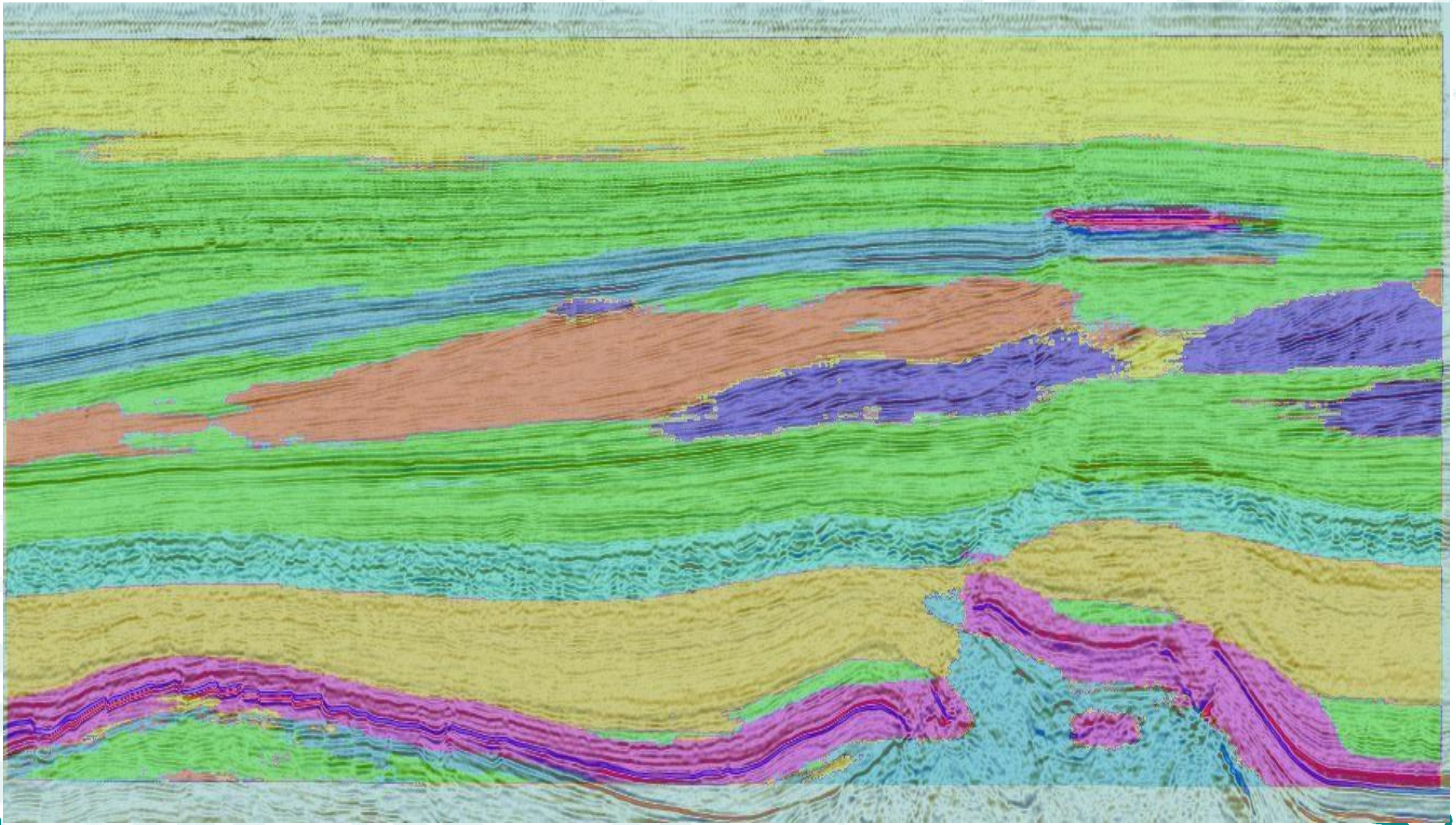
Annotation



MULTILAYER FACIES CLASSIFICATION

MalenoV (MAchine LEarNing Of Voxels)

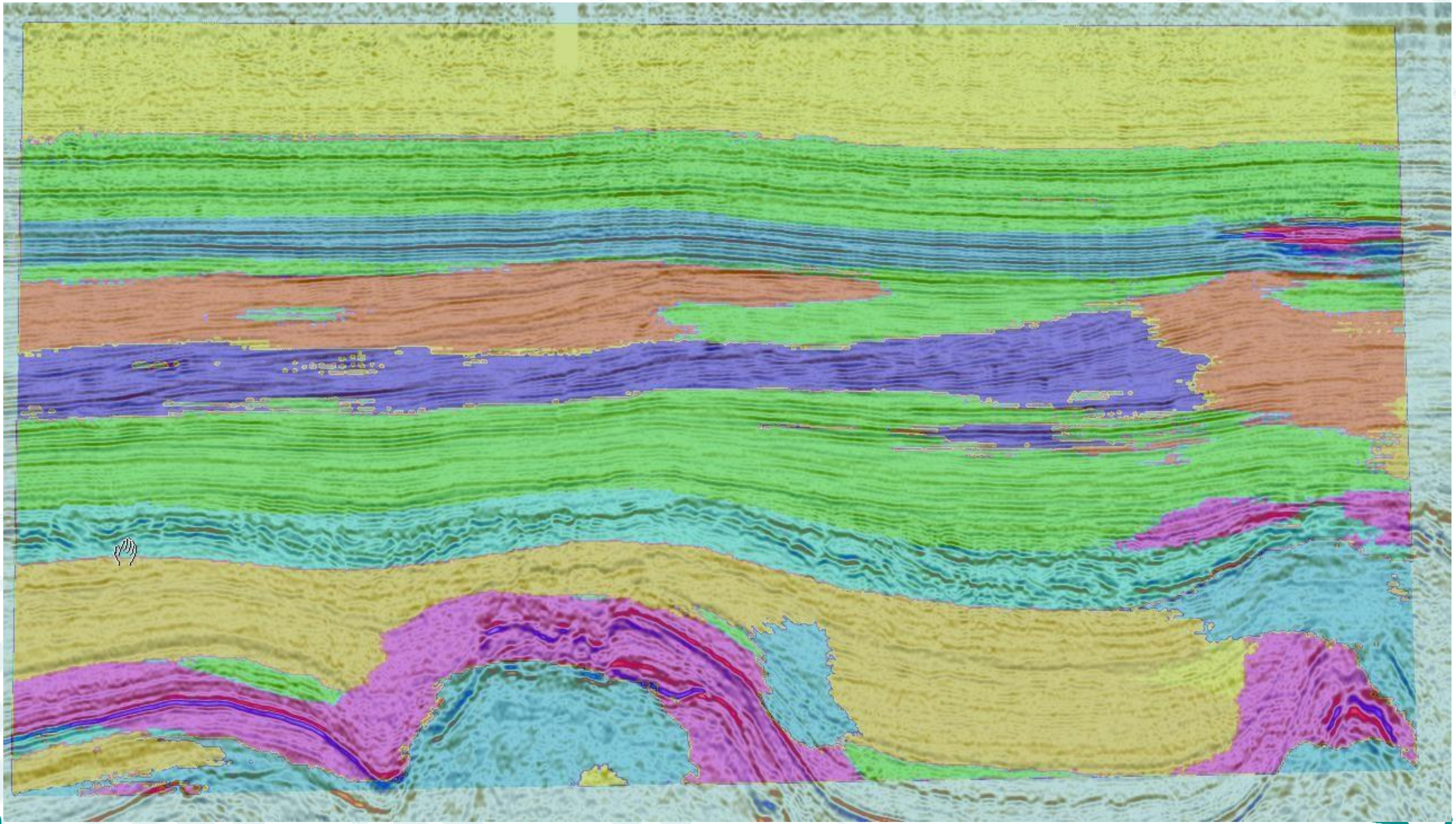
Multi facies classification (inline)



MULTILAYER FACIES CLASSIFICATION

MalenoV (MAchine LEarNing Of Voxels)

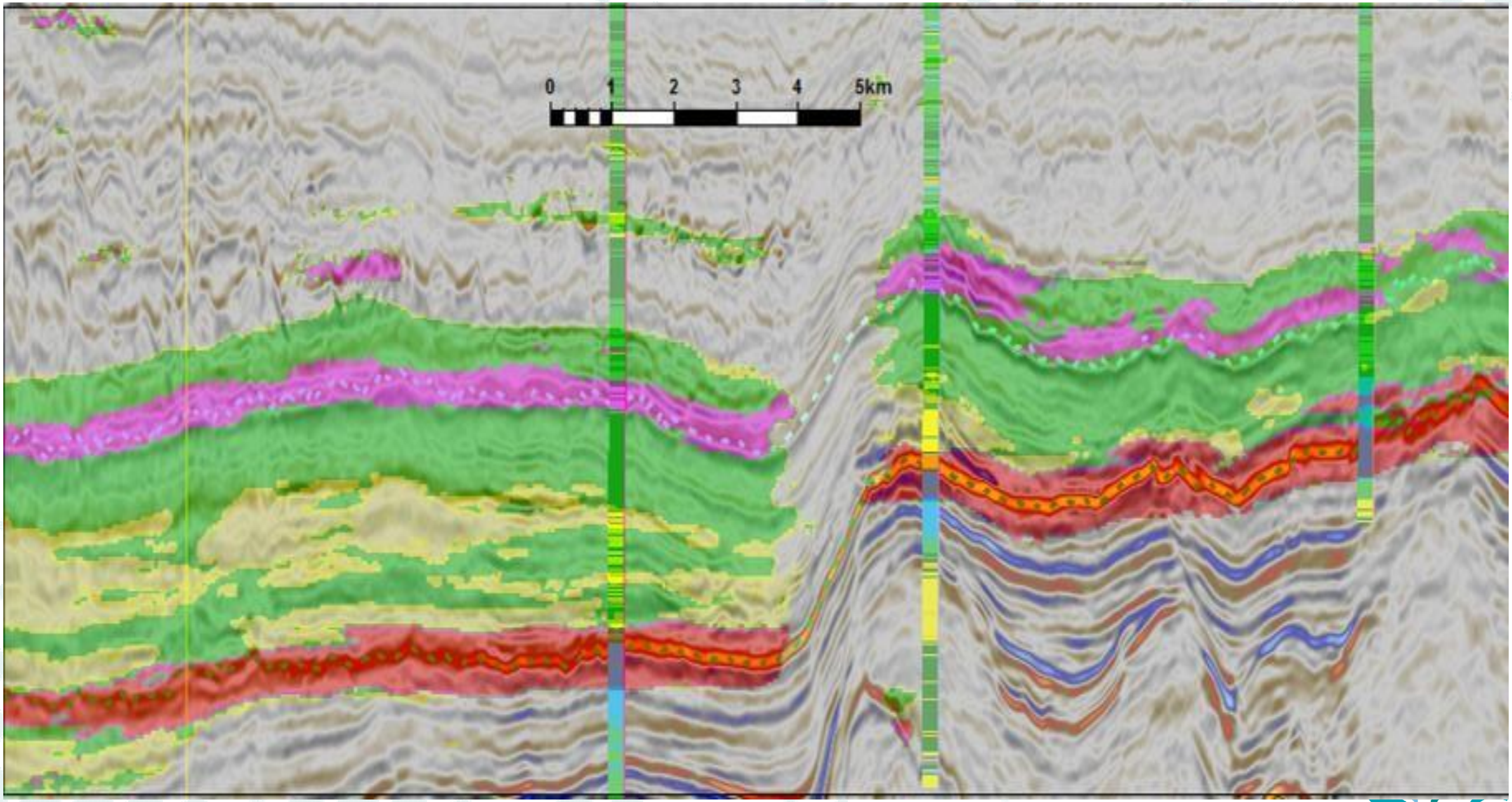
Multi facies classification (xline)



MULTILAYER FACIES CLASSIFICATION

MalenoV (MAchine LEarNing Of Voxels)

Sand / shale classification unnamed dataset



MULTILAYER FACIES CLASSIFICATION

References

- https://dramsch.net/assets/files/SEG_expanded_abstract_2018___Deep_learning_seismic_facies_on_state_of_the_art_CNN_architectures.pdf
- https://github.com/liveabstract/MalenoV
- https://www.researchgate.net/publication/320451332_Free_tool_Classifying_3D_seismic_facies_with_deep_neural_networks

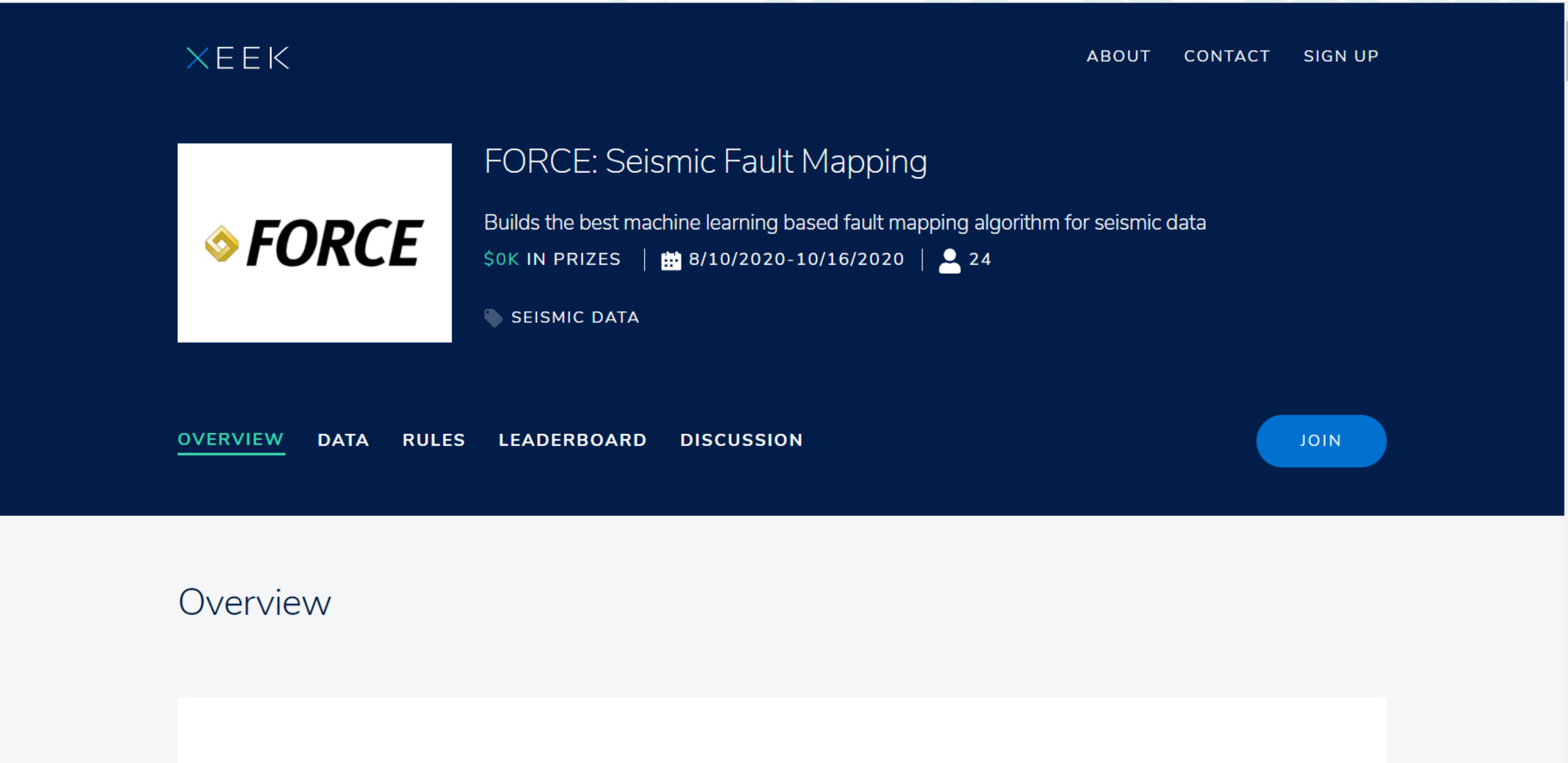
COMPETITIONS

- Parihaka data set.
- Cash prizes will be awarded totaling US$30,000.
- Link: https://www.aicrowd.com/challenges/seismic-facies-identification-challenge

COMPETITIONS

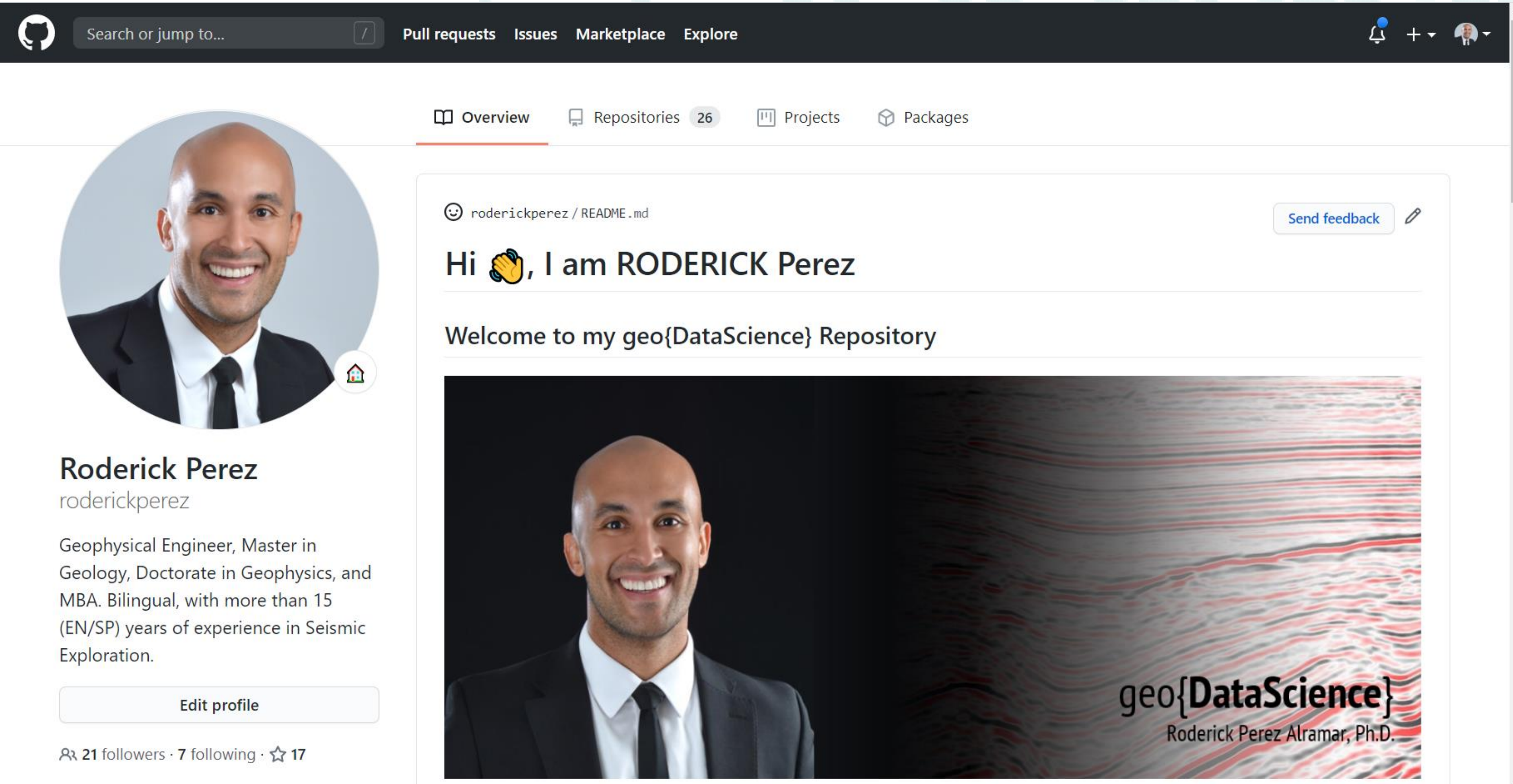
https://xeek.ai/challenges/force-well-logs/overview

COMPETITIONS



https://xeek.ai/challenges/force-seismic/overview

PYTHON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Welcome to my geo{DataScience} Repository
geo{DataScience}
Roderick Perez Alramar, Ph.D.
Roderick Perez
roderickperez
Geophysical Engineer, Master in Geology, Doctorate in Geophysics, and MBA. Bilingual, with more than 15 (EN/SP) years of experience in Seismic Exploration.
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COURSE

AAPG
Latin America & Caribbean Region

Course Description

Artificial Intelligence for Geoscience equips participants with the theoretical and practical knowledge to apply Machine Learning and Deep Learning concepts to the field of geosciences. Upon completion, course graduates will be able to use algorithms learned both to in their research and their professional careers.

Who should attend?

Geologists, Geophysicists, Petroleum Engineers, and Mineral Resources professionals and students interested in strengthening their knowledge of Python programming and learn about its applications in Artificial Intelligence (Machine Learning and Deep Learning).

Prerequisites

- Fluency in Spanish
- Basic to intermediate programming skills
- Medium to advanced knowledge of geology and geophysics

Dates

Saturdays: 7, 14, 21, 28 November

8:00 am – 5:00 pm*

**Times listed in Bogota time (GMT -5)*

Includes 40 academic hours (32 hours of lectures with instructor, 8 hours of exercises to be completed between classes)

Pricing

- $US 160 – AAPG LACR Professional Members
- $US 50 – AAPG LACR Student Members**

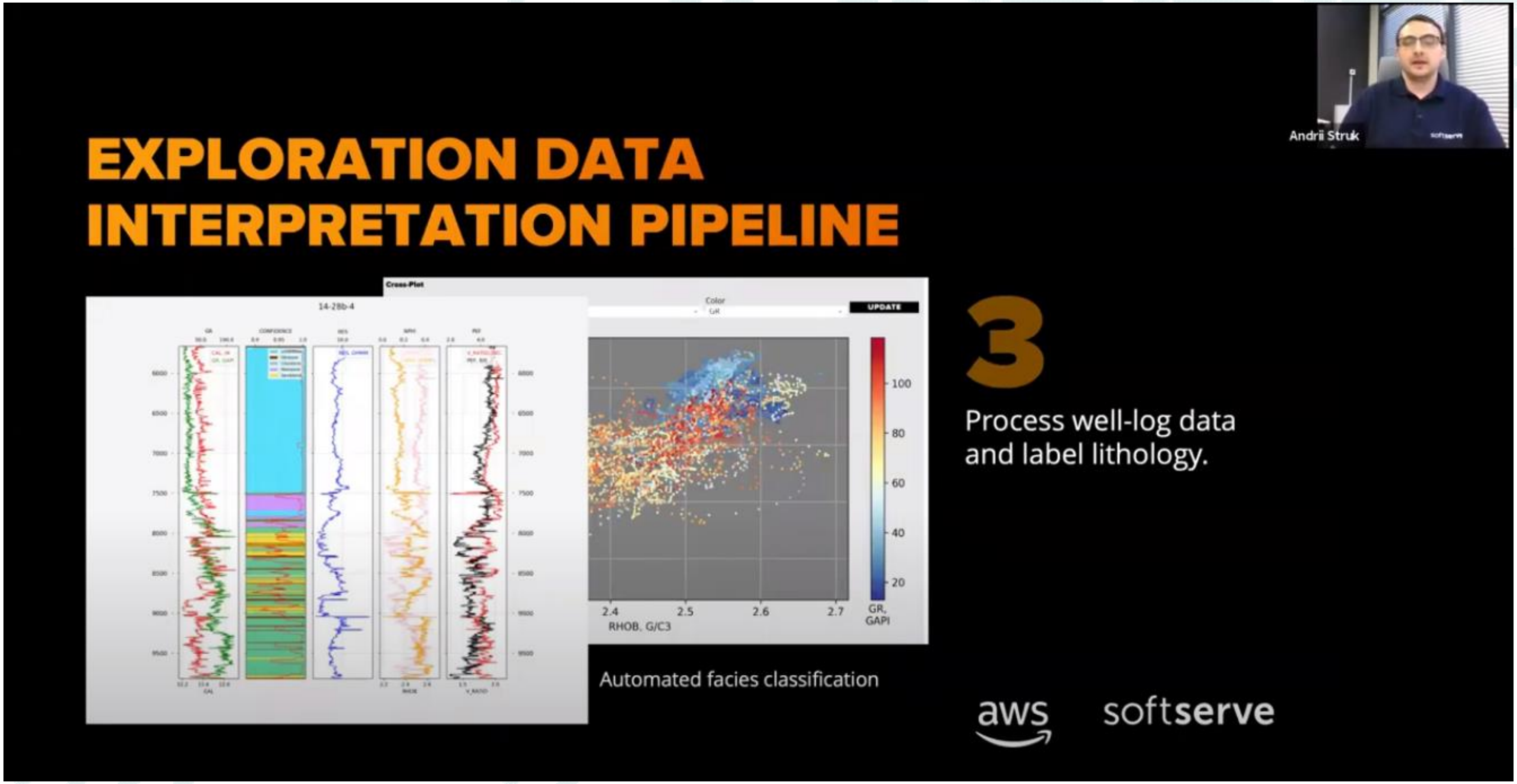
This course is open exclusively to members of the Latin America and Caribbean Region (LACR). Please check your membership status before registering. **Limited number of student registrations available by application only.

Instructor:
Roderick Perez, PhD.
ScientiaGROUP

Learn more at ***aapg.to/lacr2020machinelearning***

SG

EXTERNAL RESOURCES



ML for Exploration with Amazon SageMaker

Link: https://www.youtube.com/watch?v=LkyjGXGPS7I&feature=youtu.be

ScientiaGROUP

Oil & Gas Solution Services

SG