Cuillin

Cuttings Image Lithology Interpretation with Neural-Networks

David Wade *– Senior Developer, Software Inovation
Linn Arnesen – Project Leader, Petech research

Digital Subsurface

R&T strategic project in collaboration with DCoE

1. Digital safety, security & sustainability

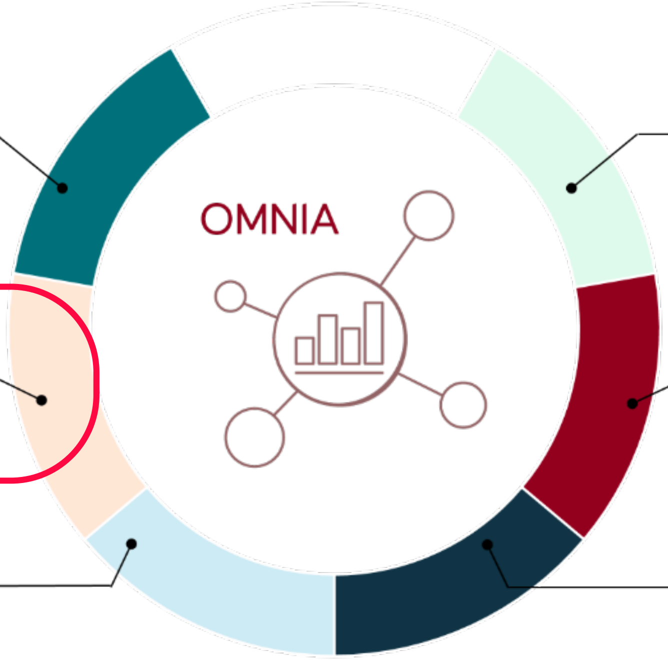
Cognitive safety for operational planning

2. Subsurface analytics

Subsurface data lake and experience platform

3. Next generation well delivery

Digital well planning and automated drilling control



6. Process digitalisation & commercial insight

Robotic process automation

5. Data driven operations

Integrated operation centres US and NCS

4. Field of the future

Digital twin

Digitalisation & innovation
Potential

Value creation producing fields[1]

Above **2** bn USD

Automated drilling – cost[2]
Around
-15 %

Field of the future – capex[3]
Around
-30 %

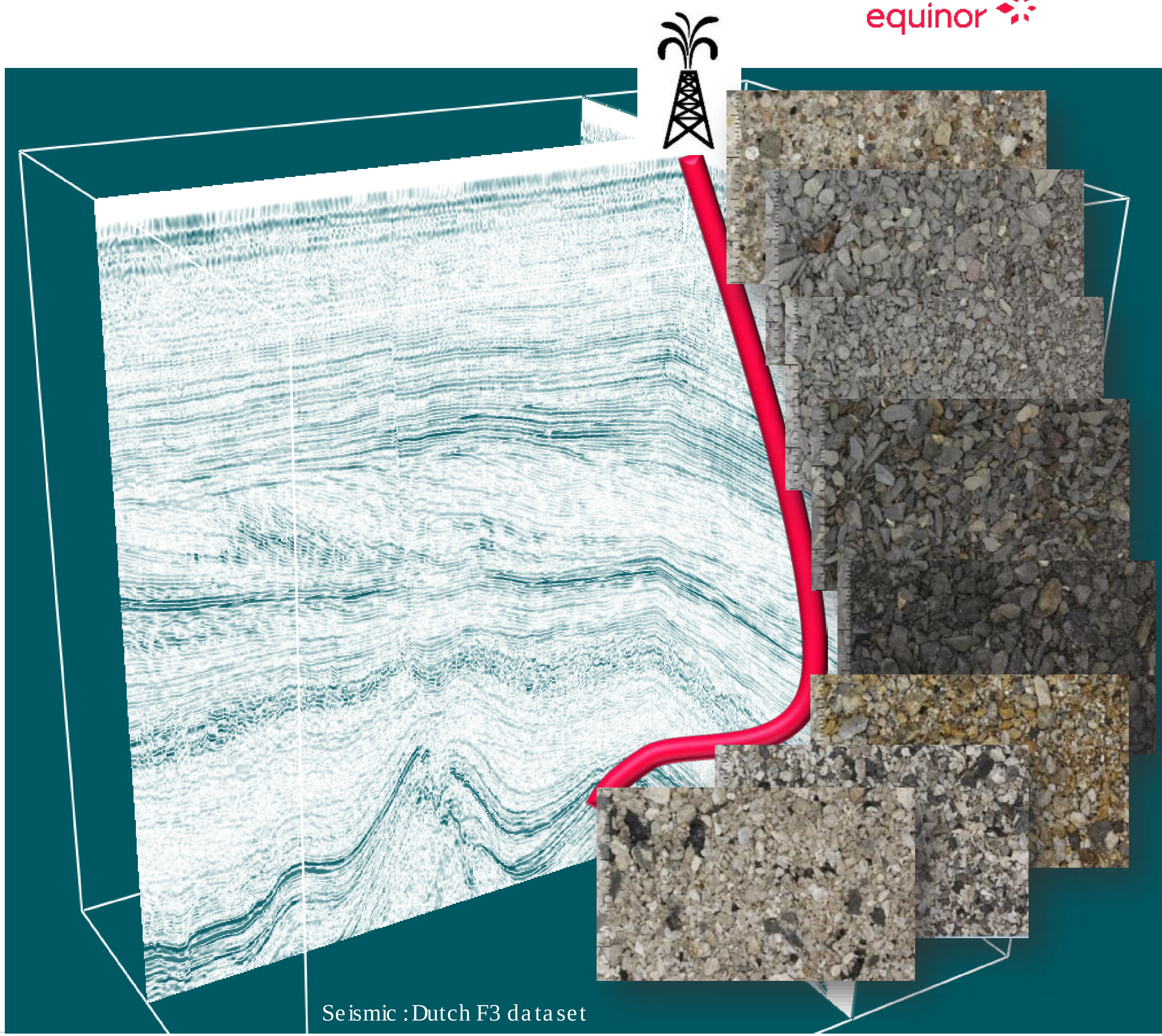
Integrated remote operations US Onshore

Around **500** million USD
Added value[4]

1. 3% increase in production – 2020 to 2025. Statoil share pre-tax.
2. Automated drilling compared to conventional.
3. New facility concept compared to conventional.
4. NPV increase based on the production and opex effects of the integrated control rooms.

Cuttings Images

- Usually the only person to see drill cuttings has been the Operations Geologist on the rig
- Textual descriptions are made and samples put into storage
- Photographing cuttings samples gives us access to a new data source
- With a photo every 3-10 m drilled, in each of our wells, this can quickly overwhelm human analysis capacity
- Can Deep Learning provide a way to focus the analysis?

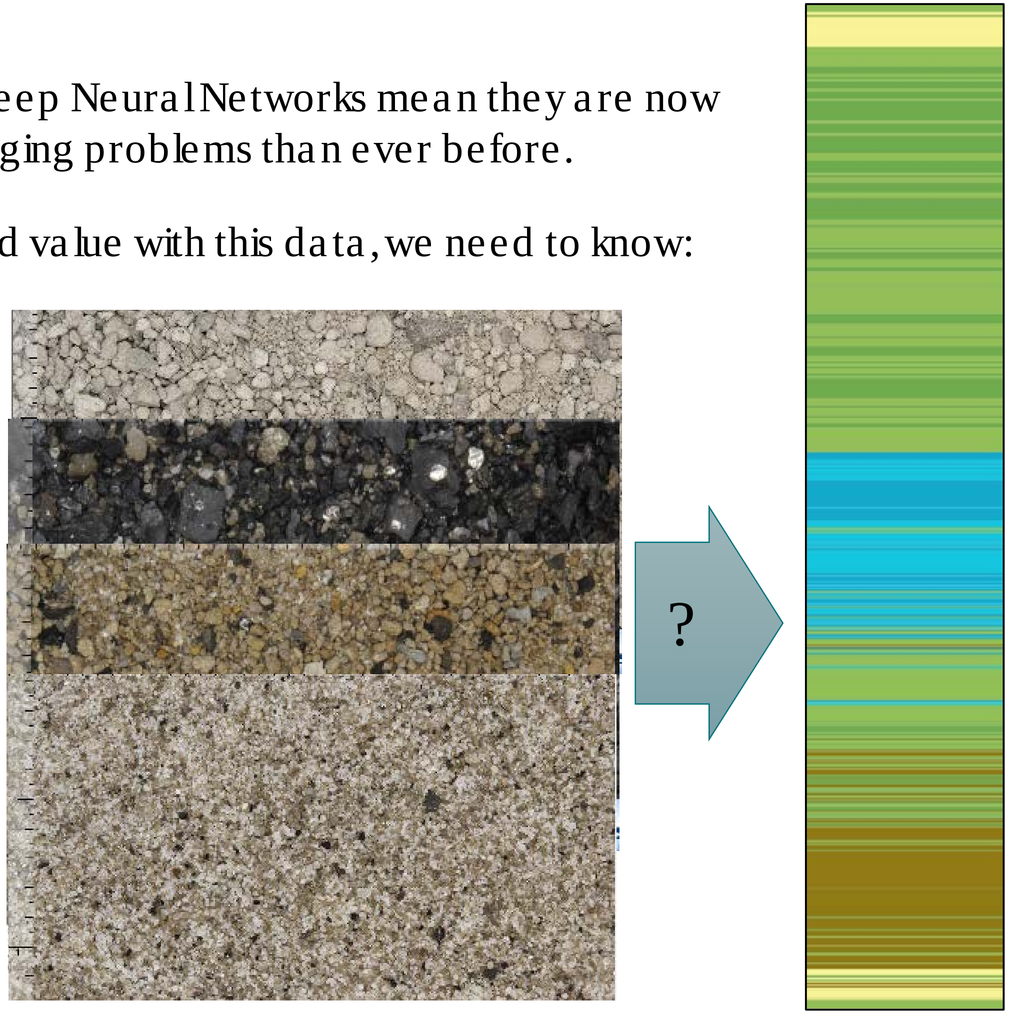


Deep Learning

Recent advances in the field of Deep Neural Networks mean they are now able to tackle much more challenging problems than ever before.

To understand whether it can add value with this data, we need to know:

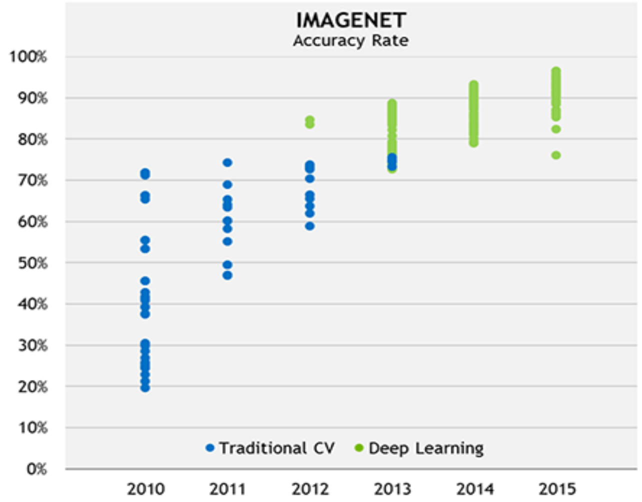
- What is Deep Learning?
- What can we do with it?
- What can't we do with it?
- What do we need to do it?



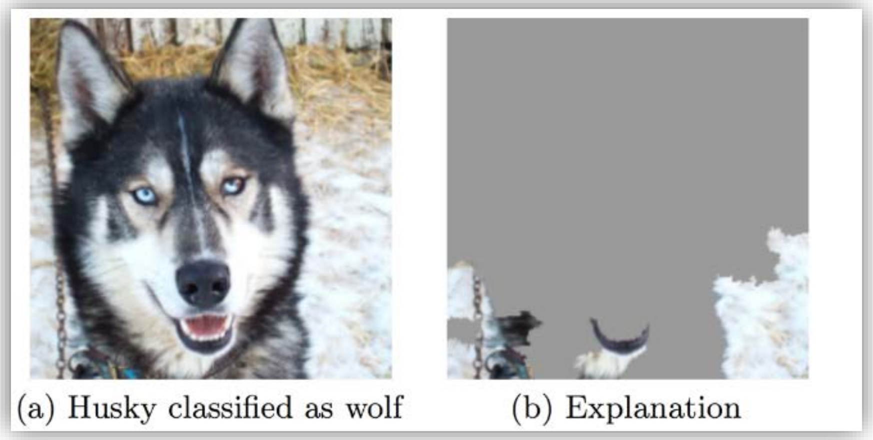
xkcd.com : 24/09/2014

Strengths & Weaknesses

- *Surprisingly* accurate at analysing data
- Takes care of feature engineering
- Faster to digest new data than humans
- Can use on almost any type of data

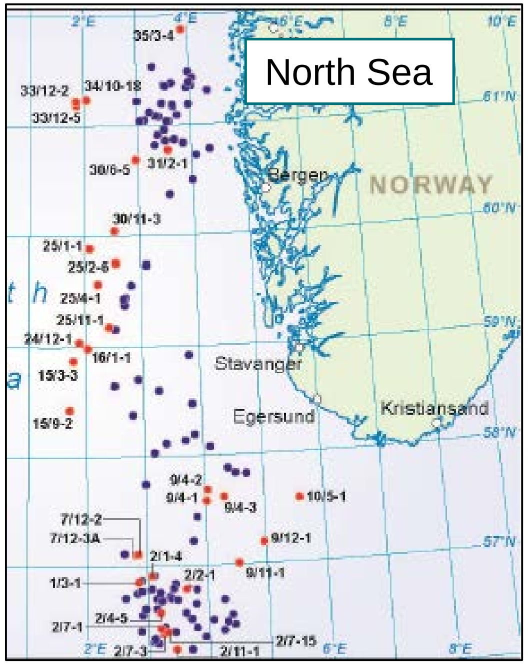


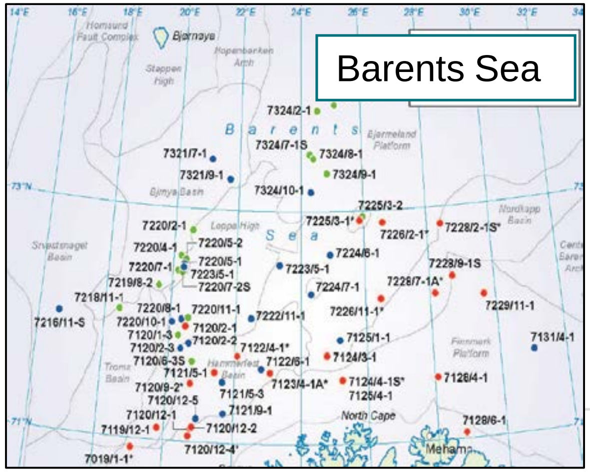
- Huge computational requirements
- Needs very large volumes of data, and easy to overfit
- Classifiers are *forced* to give an answer
- "Black-box" makes it hard to understand what's happening..situation improving

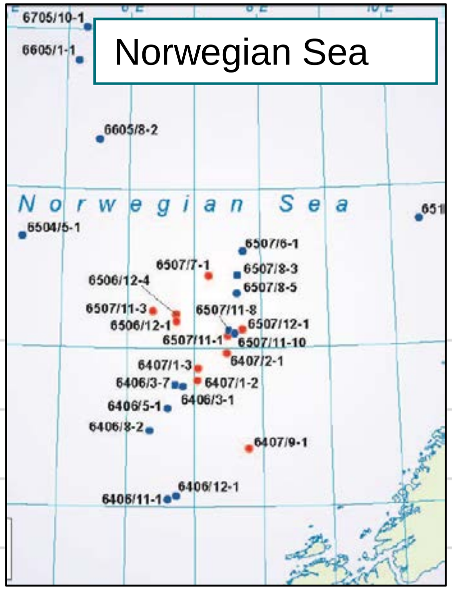


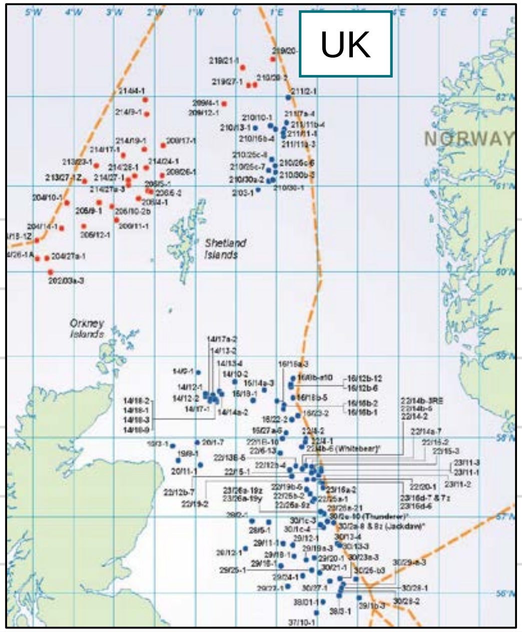
Ribeiro, M et. al, 2016
"Why Should I Trust You" Explaining the Predictions of Any Classifier

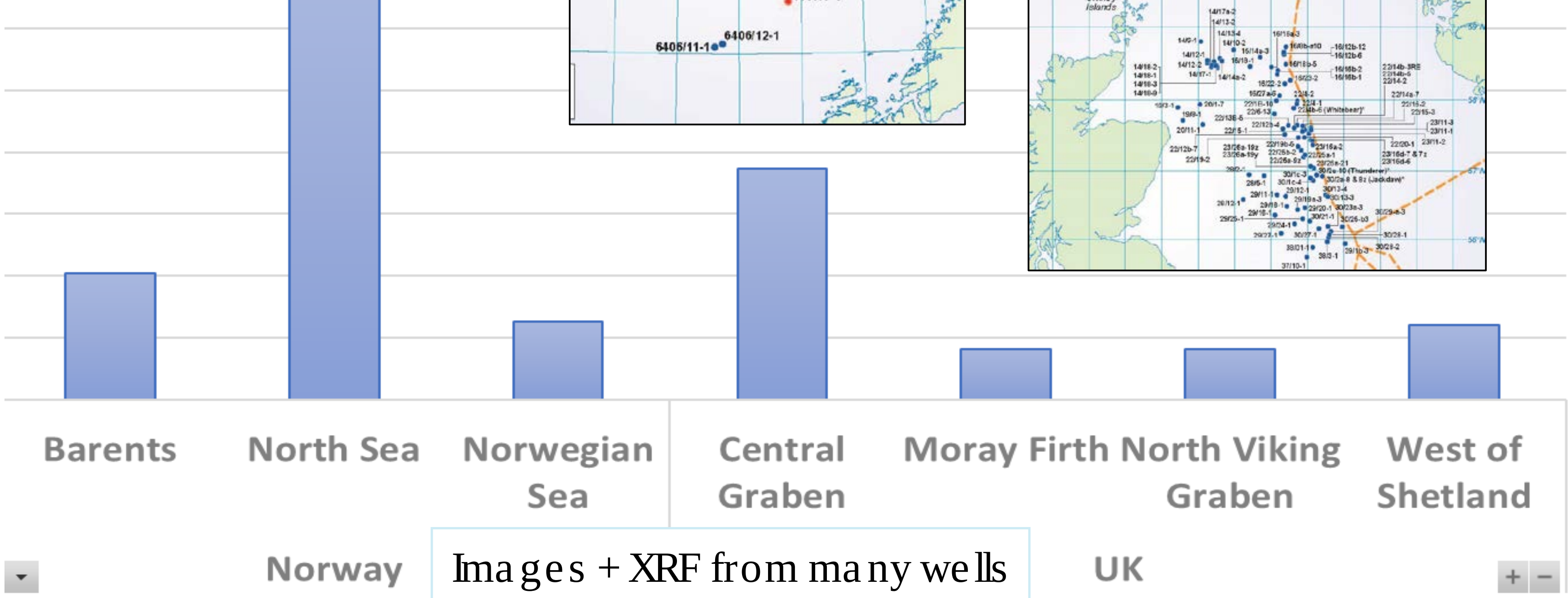
RockWash Data











Images + XRF from many wells

RockWash
Prep & Store Ltd

Google Cloud Platform

Can we just Google this?

The Google Cloud Plaform provides a 'Cloud Vision API'
https://cloud.google.com/vision/

- **Positive**
  - Easy to integrate & fairly cheap

- **Negative**
  - Doesn't really know geology

- **Deal breaker**
  - No way to teach it!

Web Entities

Gravel	0.82962
Pebble	0.58327
Limestone	0.57504

Web Entities

Gravel	0.84898
Soil	0.65864
Pebble	0.59017
Rock	0.5899
Igneous rock	0.57595

Neural Networks – in one slide!

- A Neural Network is the connection of:
    - Input data ➔ Artificial neurons ➔ Output data
  - Fully-connected layers:
    - Neurons perform operation on whole previous layer
  - Convolutional layers (in a CNN):
    - Neurons perform operation on selected areas of previous layer
- The operations of the neurons are defined by layer *weights*
- Good *weights* are discovered by a process of *training*
  - Training data is shown to a network
  - The difference between the network's guess and the actual answer is *backpropagated* through the network, and the *weights* incrementally update
- Once a network is trained, new examples can be given to it for *inferrence*

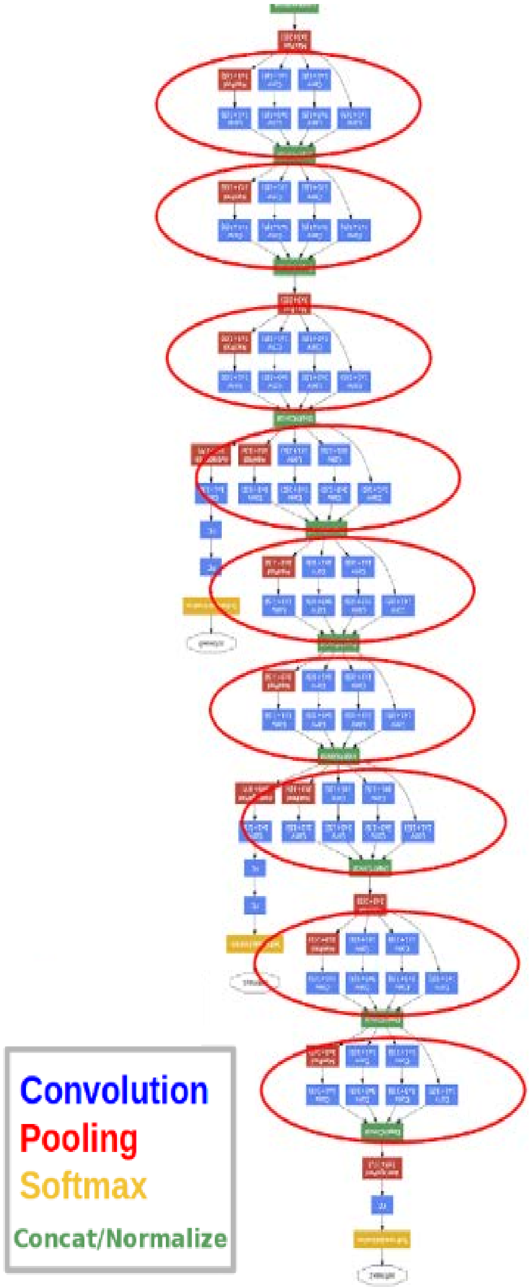
Interactive demo at: http://scs.ryerson.ca/~aharley/vis/conv/flat.html
Google for "aharley"

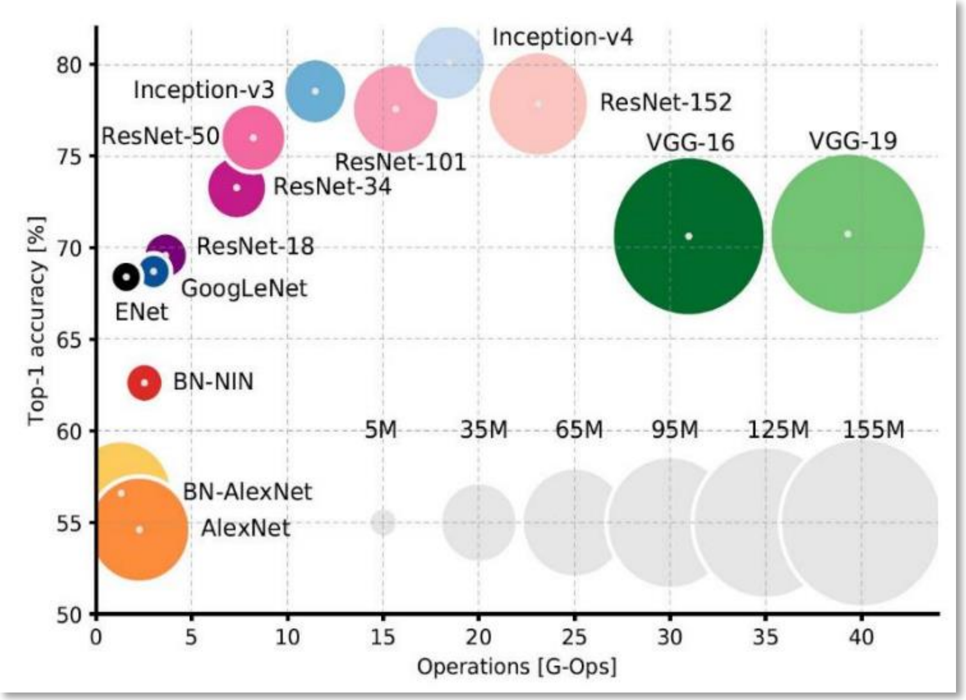
Selecting a DNN

- Larger and more complex DNNs have been developed since AlexNet's breakthrough in 2012

+ Their capabilities become more and more impressive in image classification
- Computational power required to train them (generally) increases

- Selected Inception-v3 as good compromise starting point
- Experimenting with others not hard





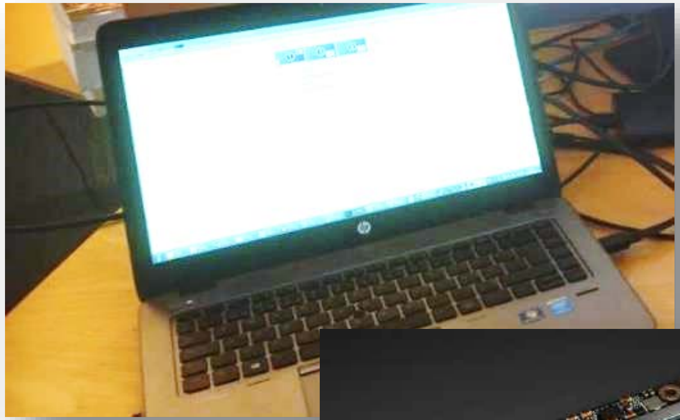
AN ANALYSIS OF DEEP NEURAL NETWORK MODELS FOR PRACTICAL APPLICATIONS
Canziani, Culurciello, Paszke

Compute power of a GPU

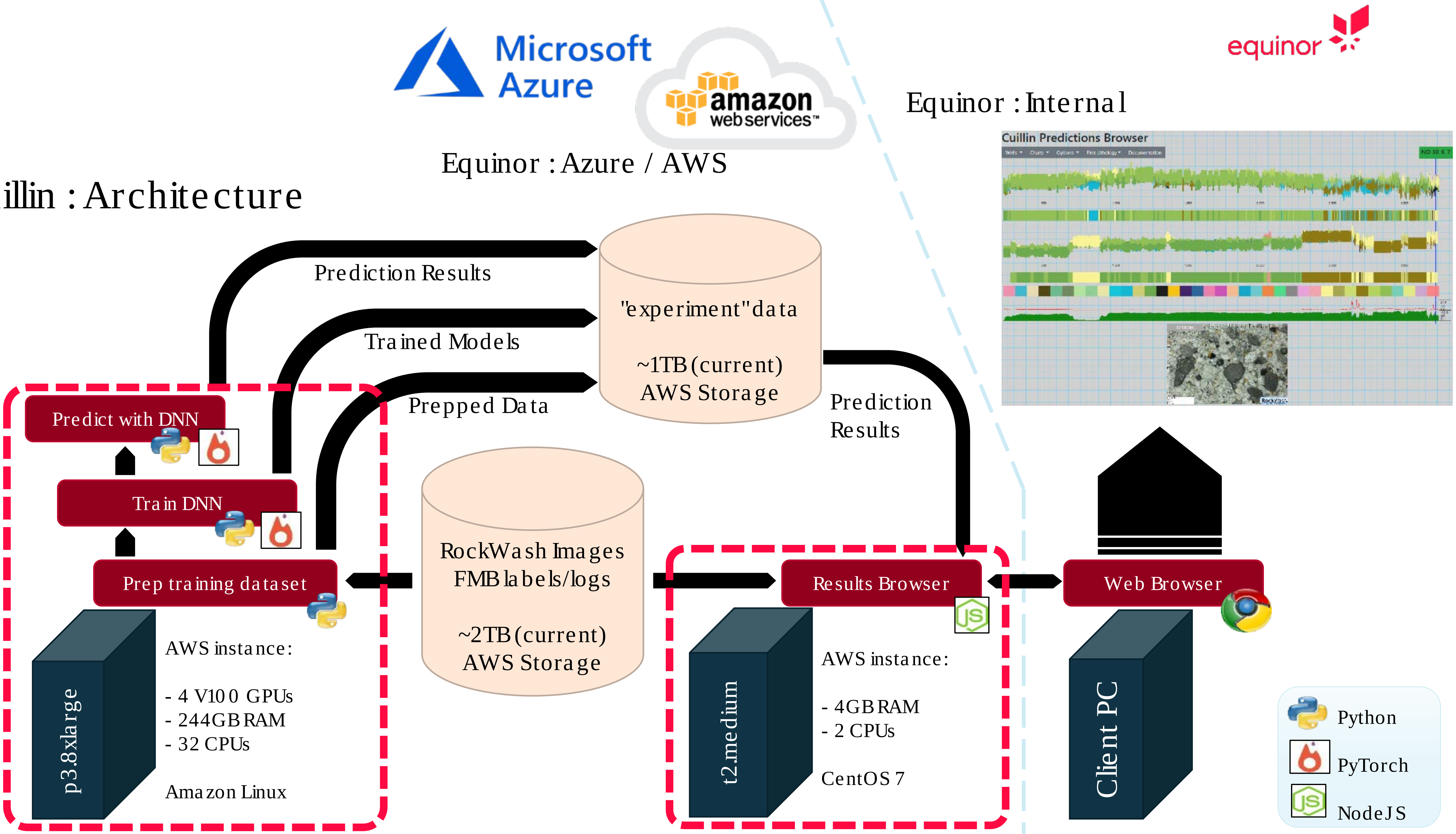
- Equinor standard laptop : Intel i5 5200u
    - o AVX2 (512-bit width FMA)
    - o 2 cores x 32SP ops/clock @ 2.2GHz
        - **140 Gflops**

- GPU : nVidia V100 :
    - o Streaming Multiprocessor : 64x FMA cores
    - o 80 SM cores x 128SP ops/clock @ 1.4GHz
        - **14000 Gflops = 14 Tflops**
        - **Tensor Operations = 125 Tflops**

- How to get hold of such power?



Cuillin : Architecture

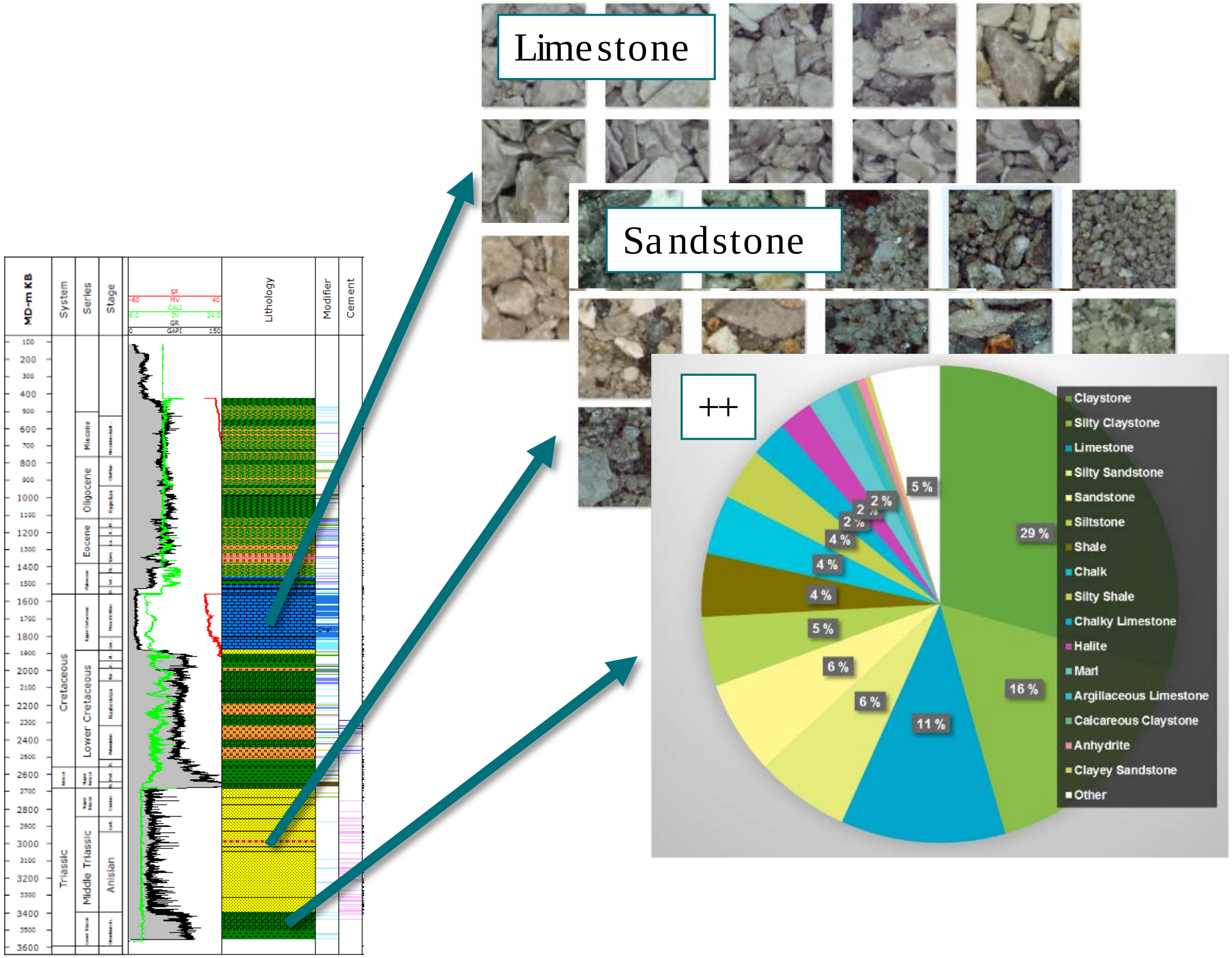


Cuillin : Training

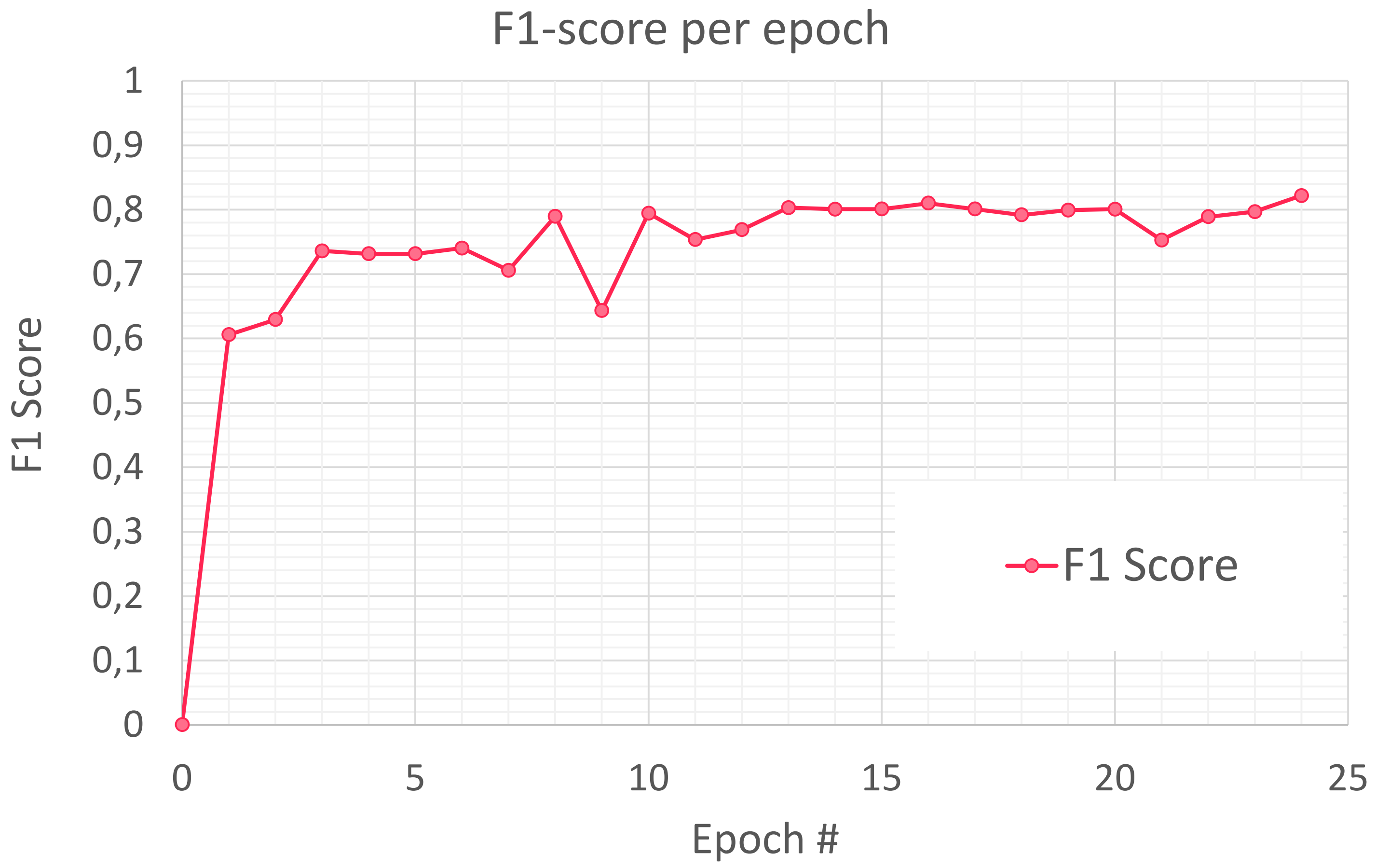
1. Split data into training and test set (at well-level)
2. Obtain Lithology labels for each image, discarding ambiguous images
3. Make 45 sub-crops per image
4. Use PyTorch framework to train a published DNN architecture to distinguish **10-15 lithology classes**
5. Additional tricks to improve generalization

Total data-prep & training time:

~7 hours on 4x V100 GPU AWS node



Cuillin : Training Accuracy



Predicted

Actual	SIEVE	CHALK	COAL	CHALKY LIMESTONE	SHALE	LIMESTONE	MARL	CLAYSTONE	SILTY CLAYSTONE	SILTSTONE	SILTY SANDSTONE	SAND GRAINS	MICACEOUS SAND	HALITE
	169	0	0	0	62	1	2	110	177	2	5	8	0	4
	0	1508	0	24	2	156	4	2	2	0	4	5	0	3
	0	0	684	0	58	1	2	10	5	3	16	64	12	0
	0	18	0	1451	1	97	0	4	2	0	0	0	0	2
	0	0	0	2	1806	2	9	383	76	5	1	87	0	14
	0	74	0	80	9	2427	19	69	22	33	5	6	0	1
	0	29	0	45	40	59	117	19	45	1	0	50	0	0
	0	47	0	3	192	108	14	2323	255	47	33	82	1	0
	0	7	0	1	9	2	3	116	286	16	3	6	0	1
	0	0	0	0	27	0	0	3	3	235	37	10	0	0
	0	3	0	0	0	1	0	0	0	7	93	76	0	0
	0	14	30	70	85	43	1	48	96	54	156	3288	25	5
	0	1	0	1	11	0	0	7	21	59	49	114	457	0
	0	2	0	0	9	23	0	4	0	3	3	7	0	1344

0.8 0.7 0.6 0.5 0.4 0.3 0.2 0.1 0.0

Cuillin : Inferrence

Datacentre :

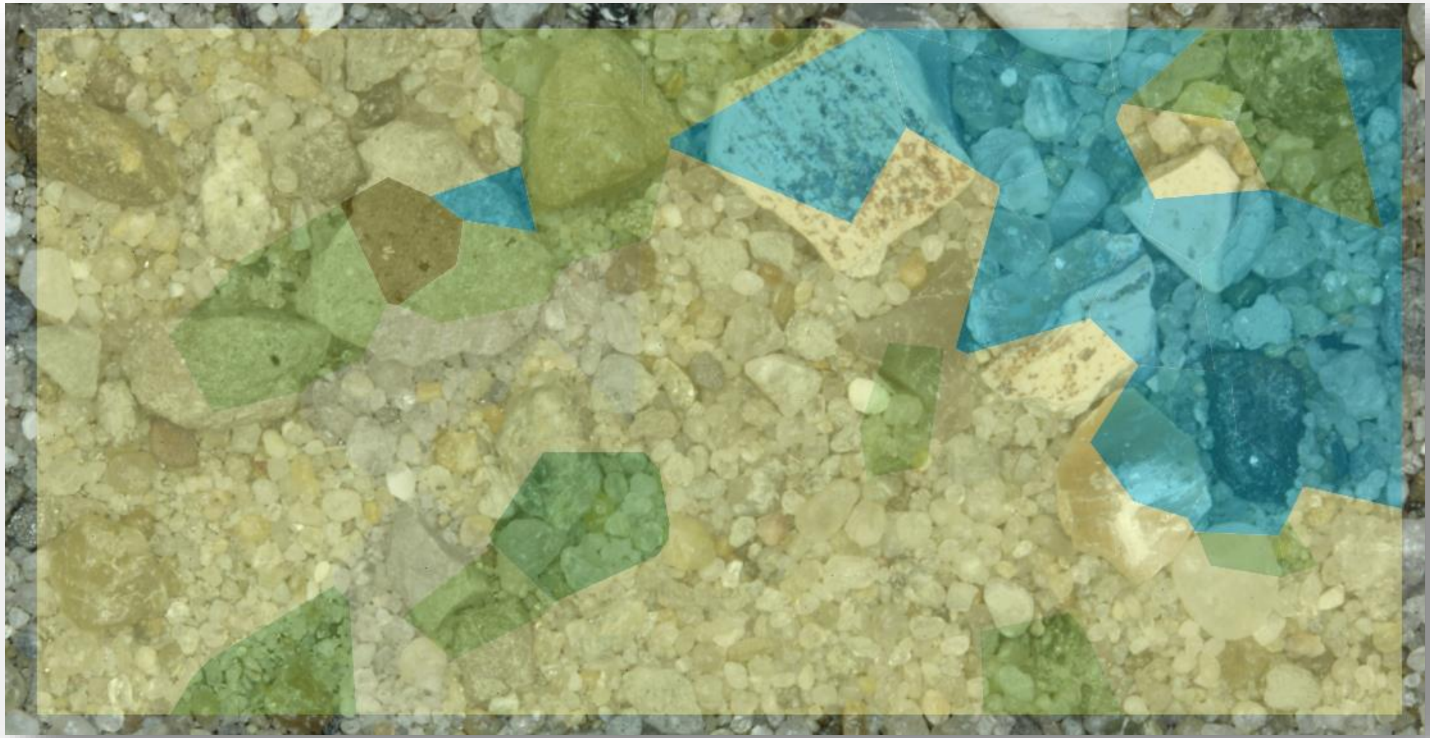
- Inferrencing speed is crucial to deploying Deep Learning models
- With 4x V100 GPUs **CUILLIN** can predict a lithology distribution for over 4 cuttings images / second
- For a typical well of 500-1000 images this takes 2-4 minutes

Edge Cases :

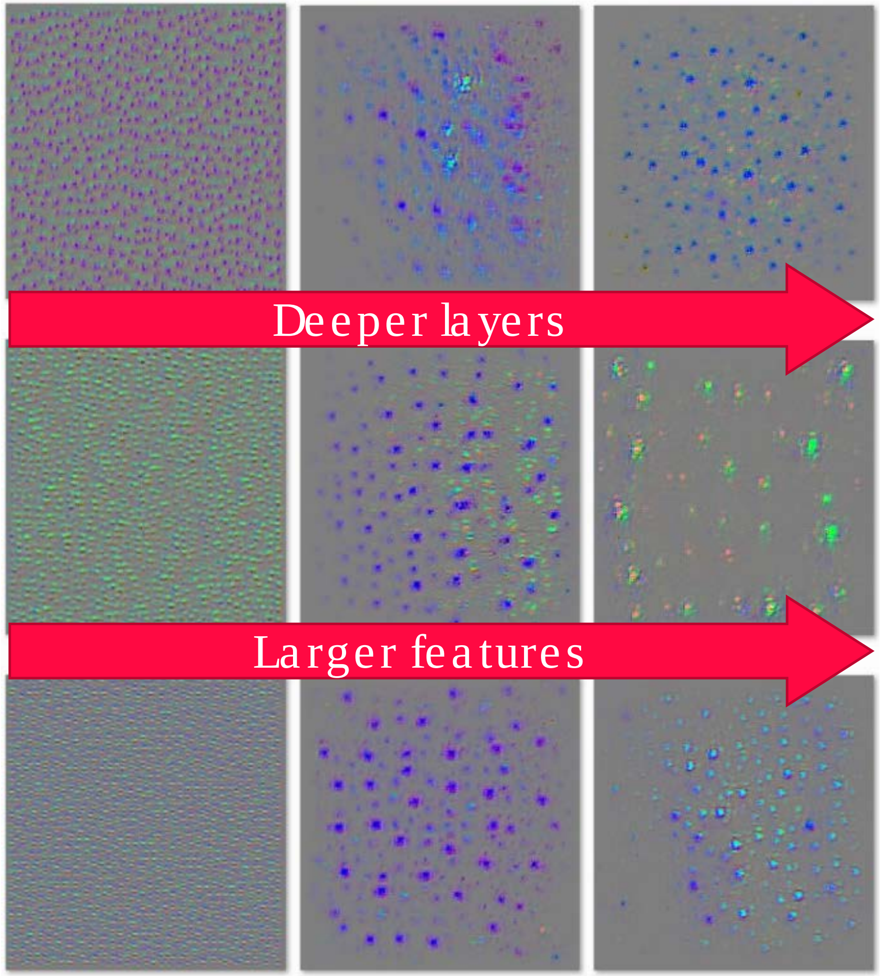
- While drilling on fixed installations we can assume a good data connection to shore – not so for exploration scenarios
- Trained Cuillin networks could be deployed in low-power embedded systems

Cuillin : Visualization

- Vizualizing what the networks "see" is challenging, but important:



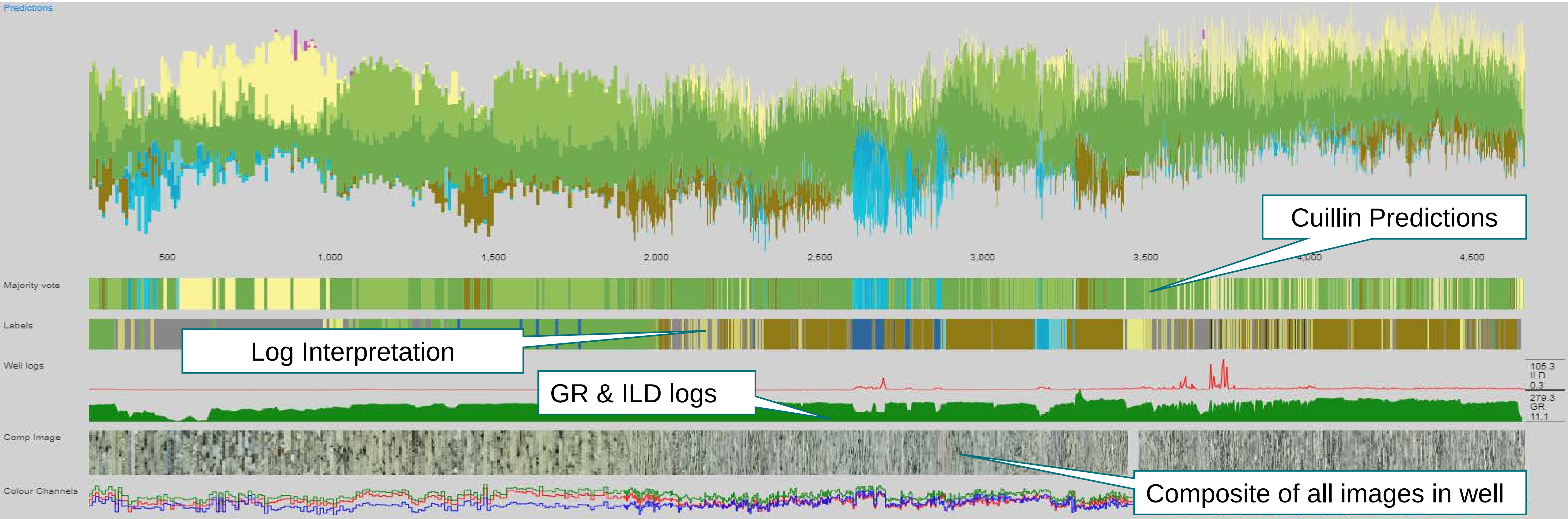
Predictions Voronoi diagram overlay to show spatial distribution of predictions across a cuttings image



Selected "Max-excitation" images for neurons in progressive network layers

Cuillin : Results Browser

With a rich set of additional data available alongside the image interpretation it's easy to gain confidence in Cuillin's interpretations, and identify potential new contributions to subsurface understanding



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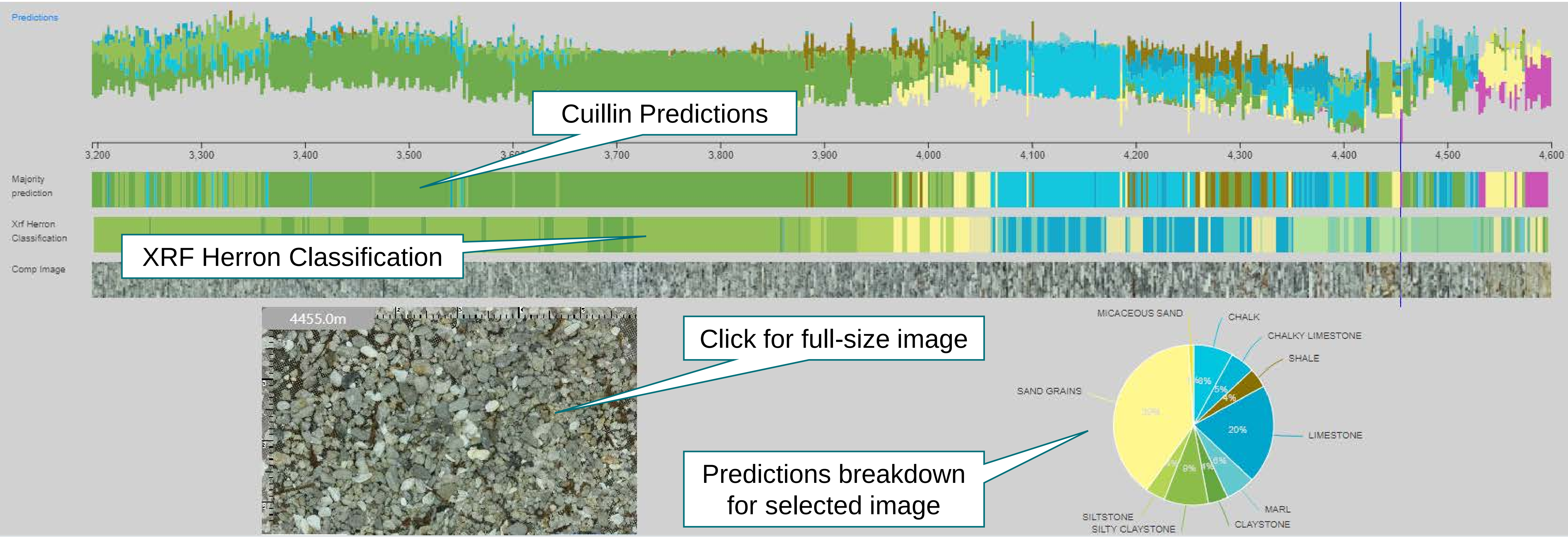

Cuillin – Cuttings Image Lithology Interpretation with Neural Neworks

David Wade * – Senior Developer, IT SI SIS
Data Science: Raymond Wiker, Xiaopeng Liao, Pier Lorenzo Paracchini,
Geoscience:: Linn Arnesen, Ole Finn Tjugen, Anne-Christin Ringdal, Ulrich Berner