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EAGE Conference on Reservoir Geoscience

3-5 DECEMBER 2018 • KUALA LUMPUR, MALAYSIA

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Elastic Docs As An Automated Information Retrieval Platform For Unstructured Reservoir Data Utilizing a Sequence of Smart Machine Learning Algorithms within a Hybrid Cloud Container

N.M. Hernandez, P.J. Lucanas, I. Panganiban, C. Mamador, C.Yu *Iraya Energies*

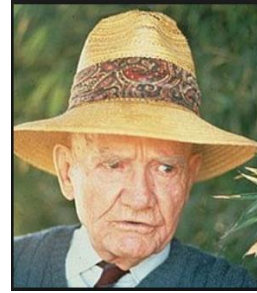
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Outline of Presentation

- Problem Statement
 - *Dealing with Unstructured Reservoir Data*
- Methodology
 - *Machine Learning*
 - *Database & Infrastructure*
- Results
 - *Supervised and Unsupervised*
 - *NLP & Reservoir Image Processing*
 - *Metrics*
 - *API Demonstration*
- Conclusion





“Where oil is first found is in the minds of men”

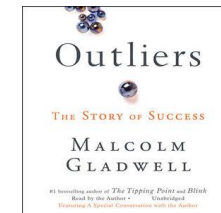
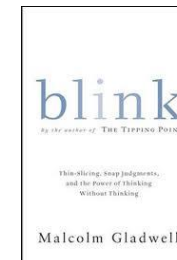
-Wallace E. Pratt

Pioneer Petroleum Geologist (1959)

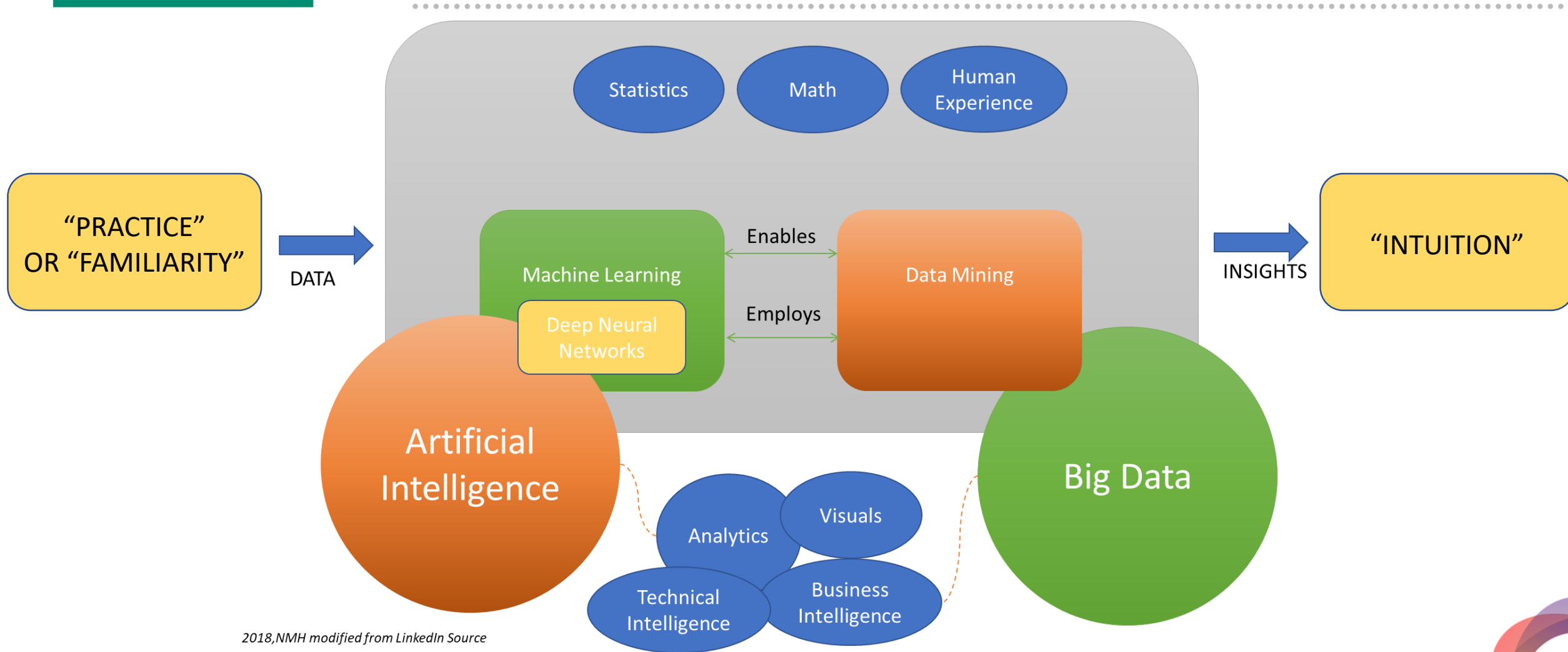
“Good intuition requires years of practice”

-Malcolm Gladwell

Author, Blink

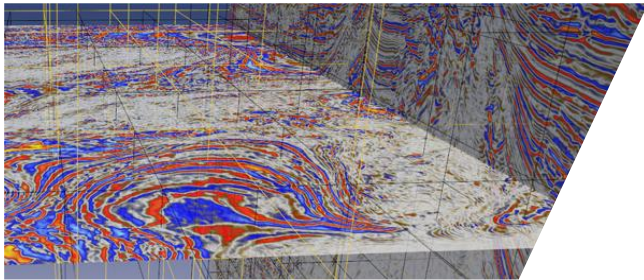
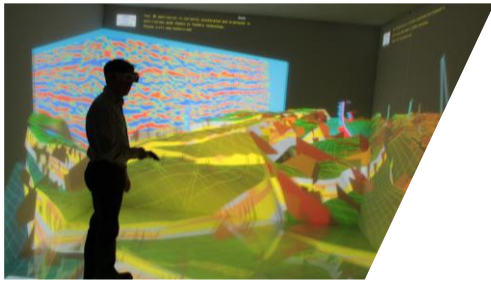


Symbiosis between ML and Data Mining



Problem Statement: ElasticDocs

Highly advanced platforms for well and seismic data



Unstructured documents are inaccessible



Technical Memory is Lost



Reservoir Properties

Geological Interpretations



Problem Statement

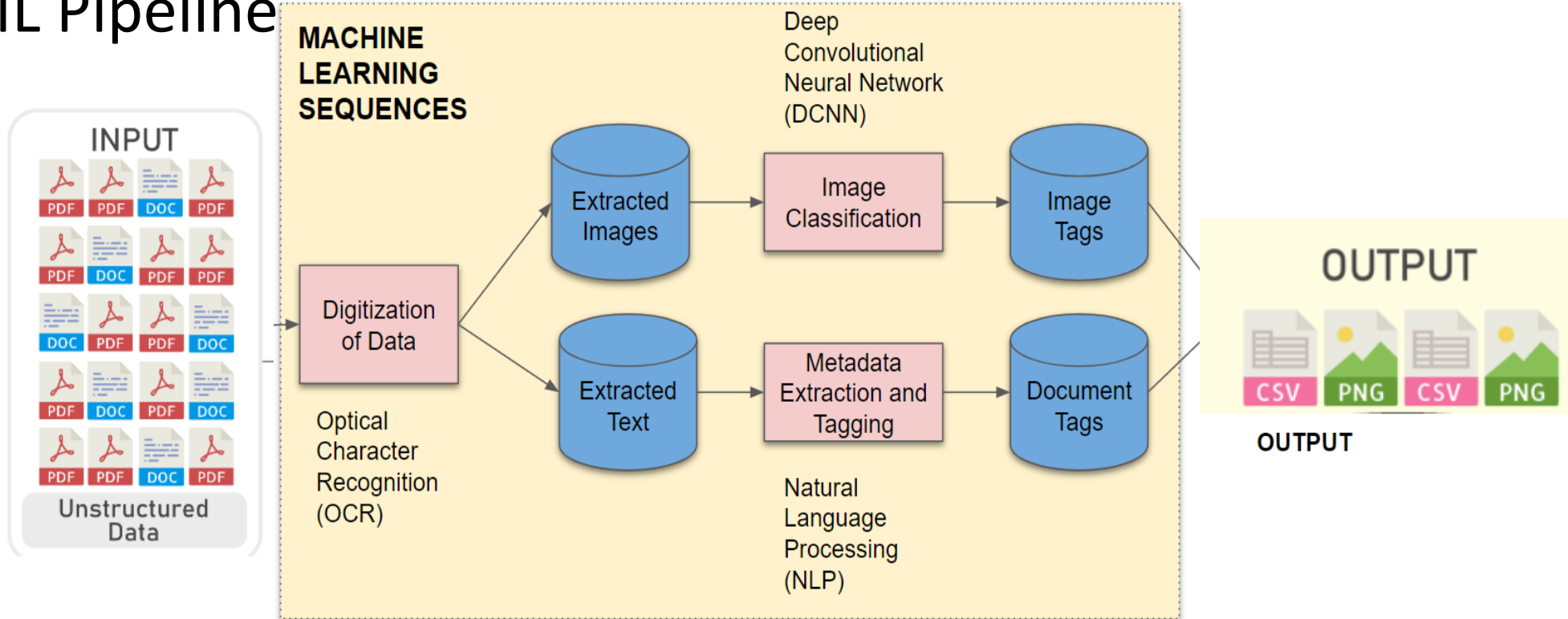
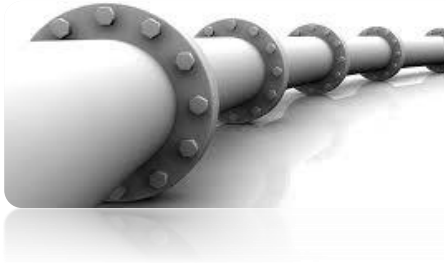
Using the latest advances in Machine Learning:

- How to gain reservoir experience leveraging from existing data
- How to maintain or recover corporate memory



Methodology

ElasticDocs ML Pipeline



TEXT ANALYSIS

Methodology

IT Infrastructure

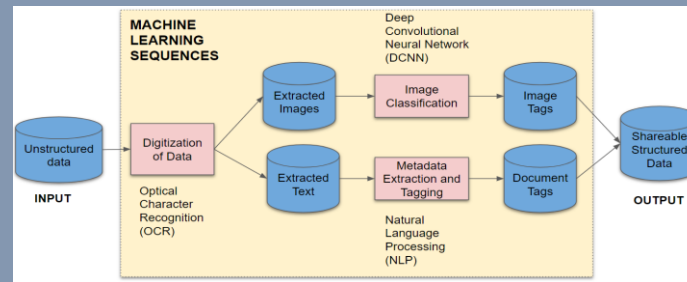
GPU
CPU

Cloud-Based
Or Hybrid
Infrastructure

Database
SQL
NoSQL

Microservices

ML Core



User-Facing API

Web Layer

GIS Layers

CURATED, OPEN SOURCE LIBRARIES

Python, Tensorflow, Leaflet, Elasticsearch, etc

Named Entity Recognition

Geology Identification

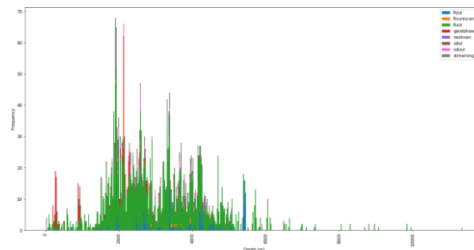
("the glauconitic claystone sample is barren of foraminifera. no definitive environment interpretation is possible.",{'entities':[(4,25,'GEOL')]}),

("massive claystone interbedded with silty claystone and thin argillaceous siltstone",{'entities':[(8,17,'GEOL'),(35,50,'GEOL'),(60,82,'GEOL')]}),

("chevron australia pty ltd acme 1",{'entities':[]}), *(example of no geological entity to be detected)*

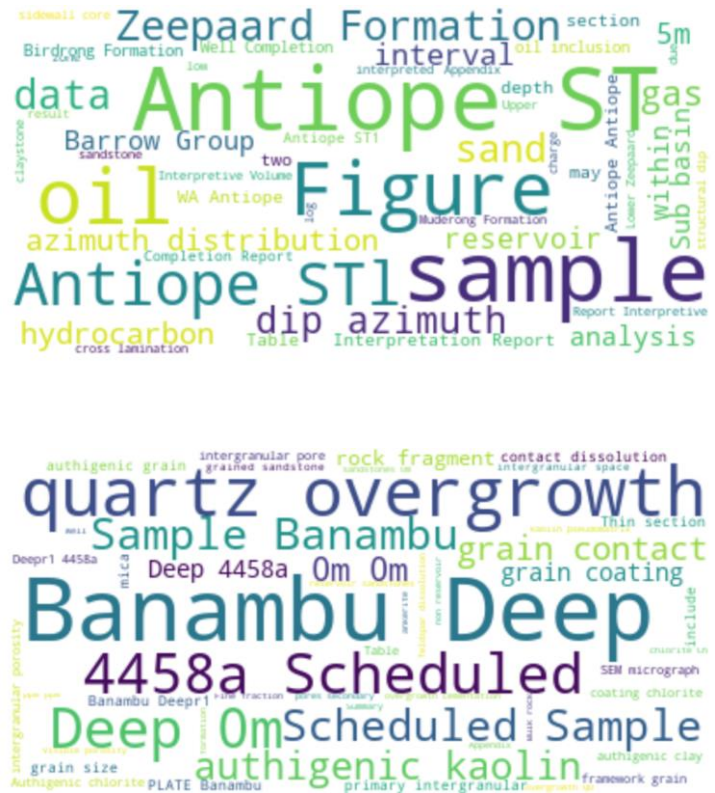
Hydrocarbon show Identification

("STAIN N~D FLUORESCENCE 3699-3709m This interval constitutes the upper part of the ",{'entities':[(23,27,'DEPTH'),(28,32,'DEPTH')]}),



Natural Language Processing

Word Clouds



Unsupervised Clustering with Topic Models

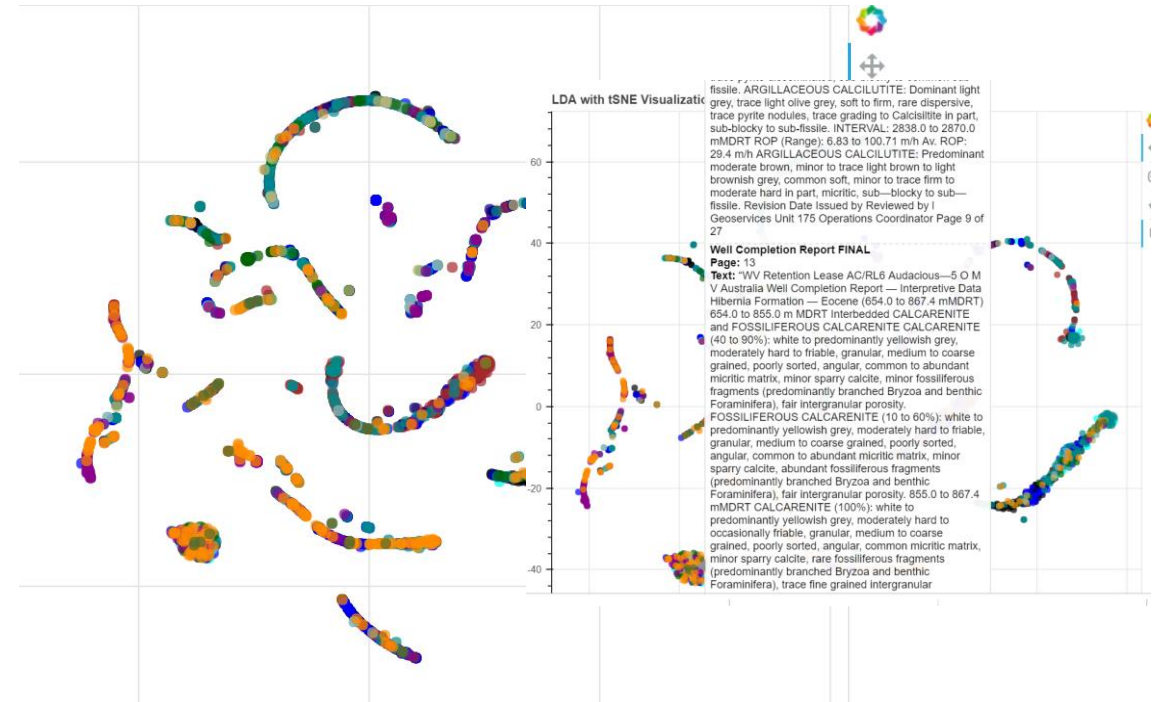
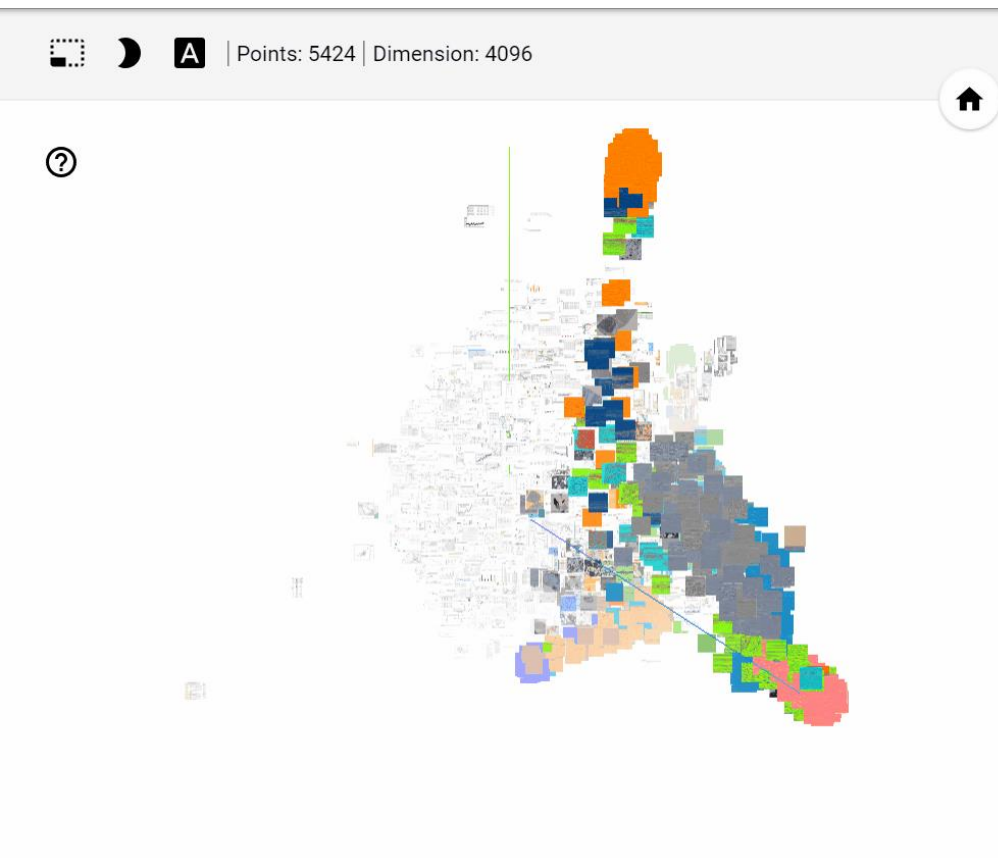


Image Recognition

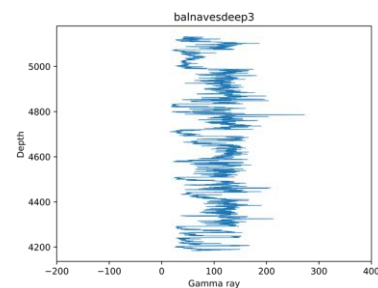
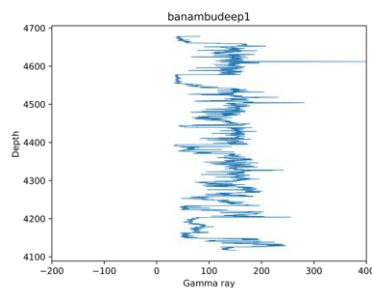
Multi-Format Images

	Precision	Recall	F1-score
Map	0.83	0.96	0.89
Seismic	1.00	0.95	0.97
Core	0.89	0.98	0.94
SEM	0.95	0.93	0.94
Others	0.91	0.73	0.81

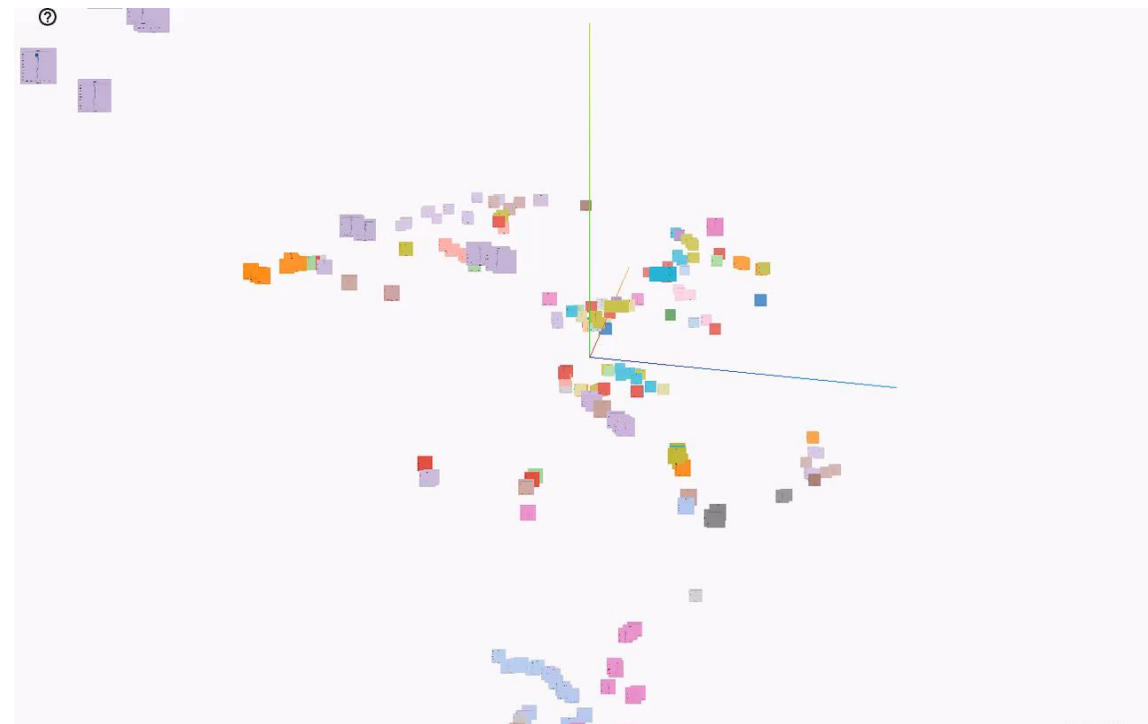
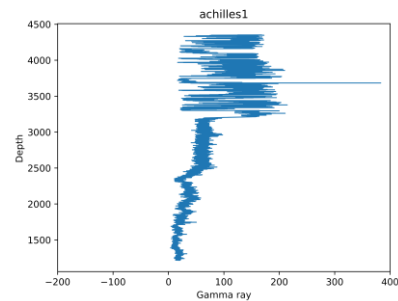
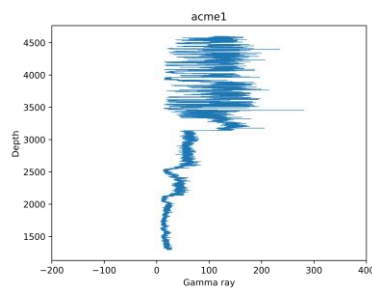


Well Twinning

Twin Set A



Twin Set B

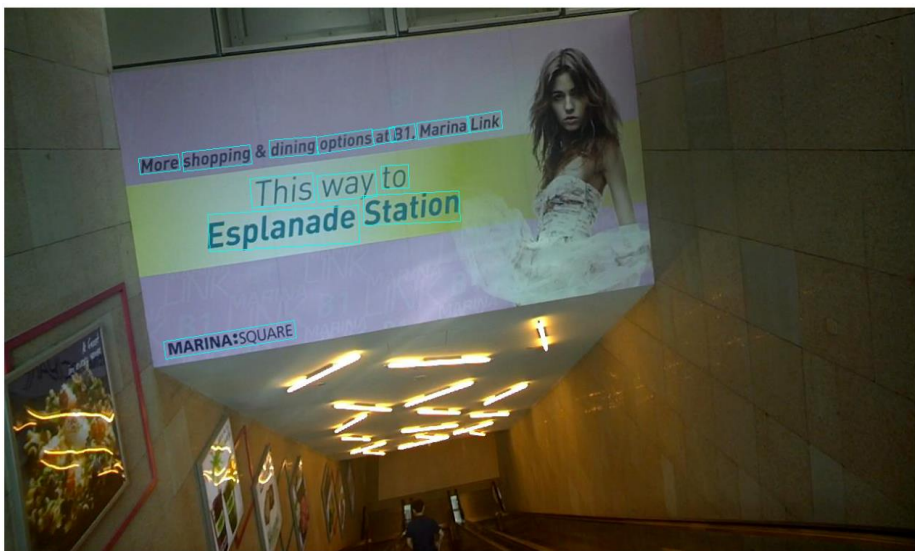


Applications in:

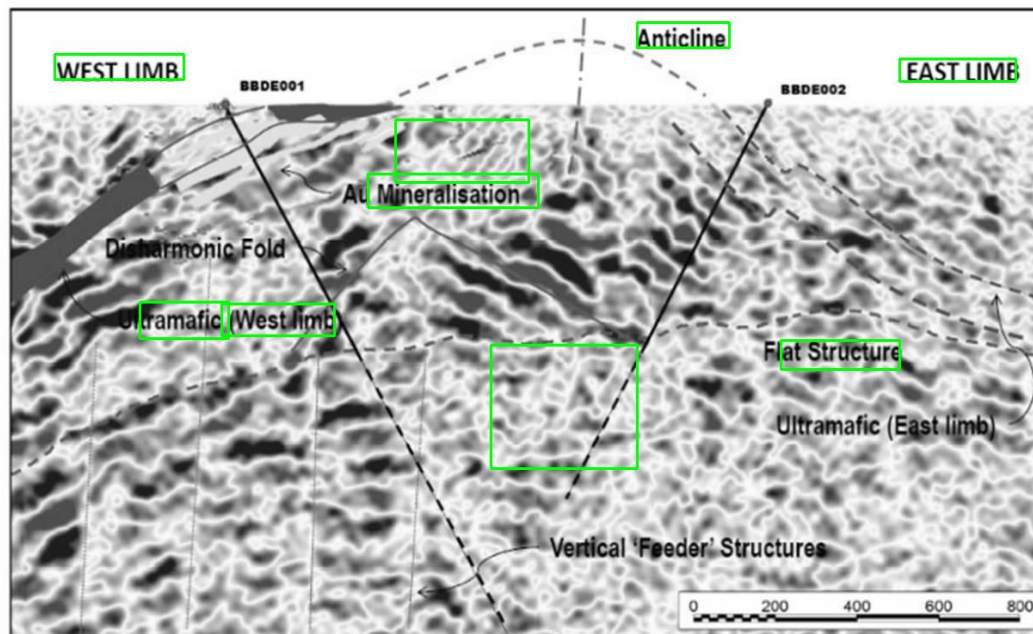
- Analog Search
- Anomaly detection
- Quality control

Scene Detection

Train Station Signage

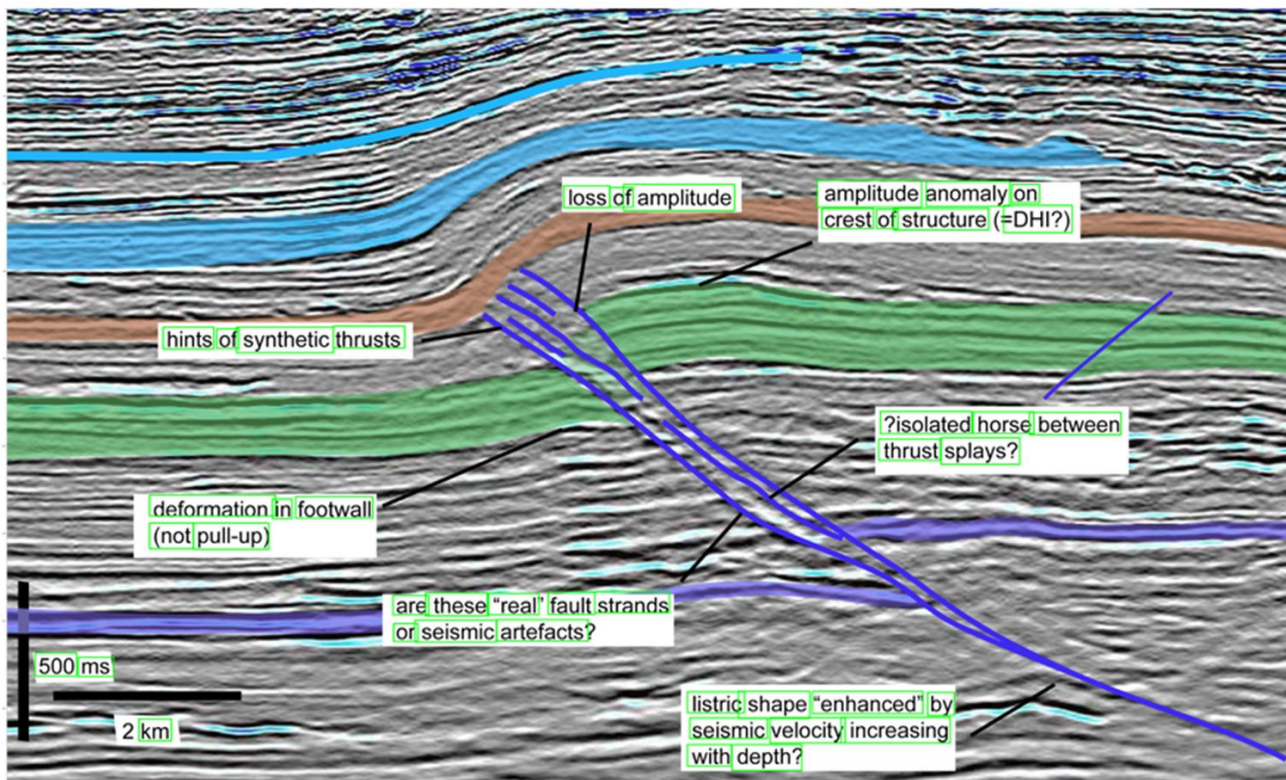


Seismic Signage



Cross-section on Seismic Line Showing Planned Drill Holes

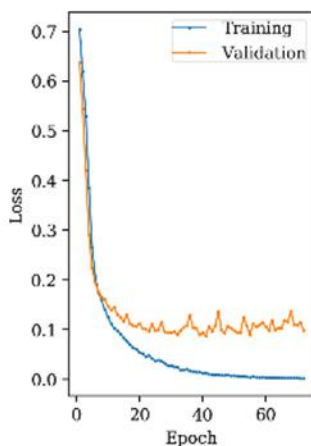
Scene Detection



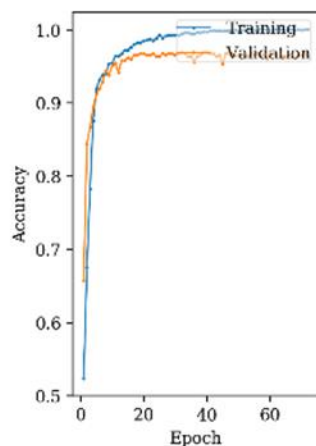
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 in
 of
 'synthetic
 =DHI?)

Speed



Training Loss



Accuracy



- Precision: proportion of positive identification is correct

$$Precision = \frac{T.P.}{T.P. + F.P.}$$

- Recall: proportion of actual positives is correct

$$Recall = \frac{T.P.}{T.P. + F.N.}$$

- F1 score: harmonic mean of precision and recall

$$F1\ score = \frac{2(\text{precision} * \text{recall})}{\text{precision} + \text{recall}}$$

		Predicted	
		0	1
Actual	0	T.N.	F.P.
	1	F.N.	T.P.

Precision and Recall

Metrics

ML Application	Task	Speed
OCR	Text Extraction only, excluding Image Classification	150,000 pages 13 hrs
	Text Extraction and Image Extraction	4,542 pages 6.31 GB 25 Final Well Reports 10 hrs
NLP	Lithology / Geology Indicator Frequency Analysis (i.e Carbonates, Sandstone, etc)	4 hours
	Well Cataloguing	1,500+ input las files 66, 515 curves identified 5,681 top log curves (cali, gr, neu, por..) 2 hrs 33.66 min
DCNN	Imag Classification	2,598 tagged images input 16% Tables 6% Figures 19% Map 24% Charts 33% Noise 20-30 mins during training <s after training Currently includes 8 classes: thin section SEM, seismic, stratigraphic chart, cores, map and general classes such as chart, figure, table

Tying it all together with an API

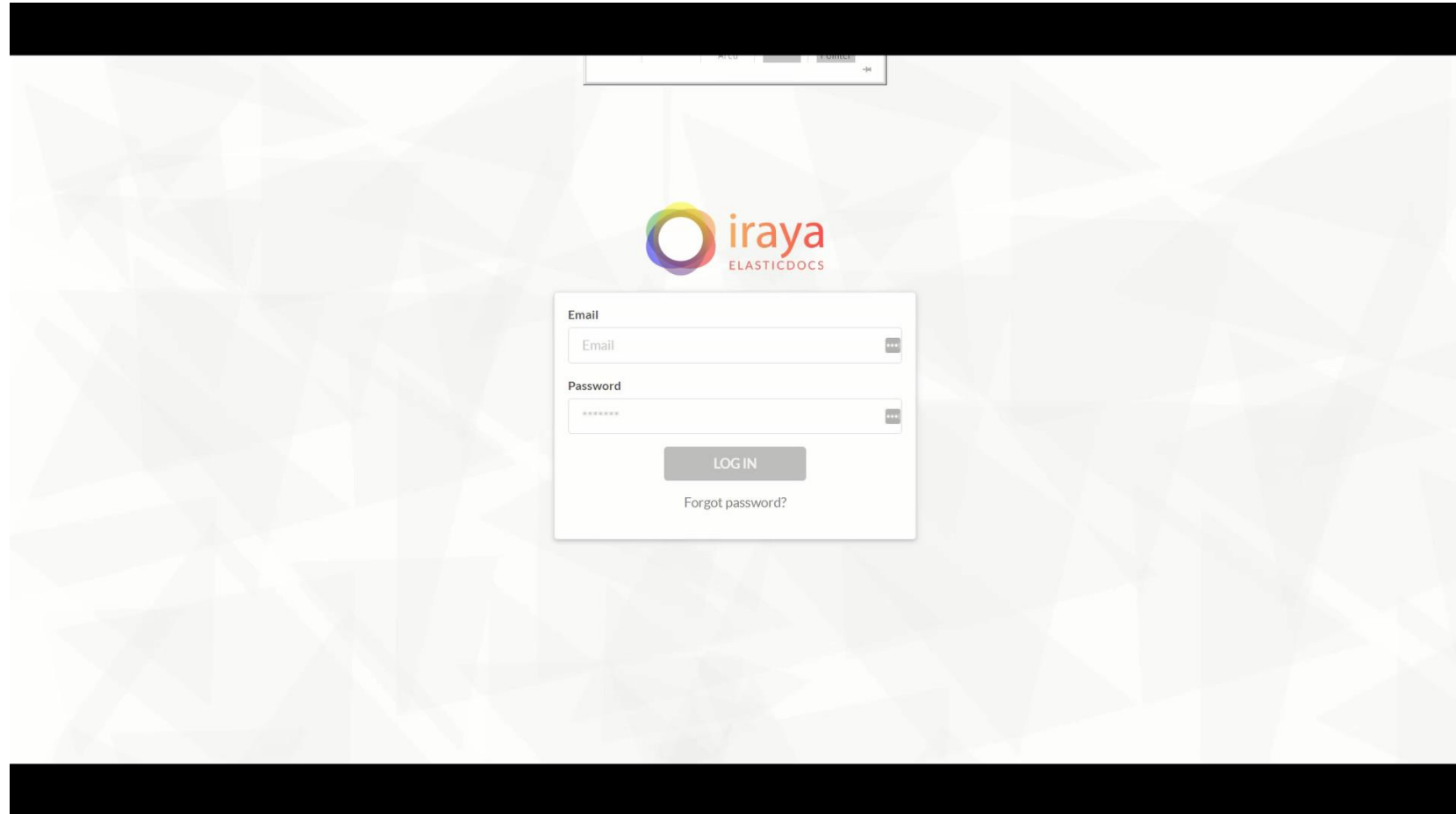
ElasticDocs

- ElasticSearch
- Geolocation
- Metadata extraction
- AutoImage Recognition

Supports geoscientists'

- Knowledge
- Intuition
- Experience

through accessible,
verifiable big data



Conclusion

Dealing with **huge amount** of unstructured reservoir dataset is made **more effective in ElasticDocs** by:

- Curation and thorough investigation of appropriate machine learning algorithms
- Creating both structured and non-structured database to host and properly standardize reservoir data as input to machine learning algorithm
- Apply appropriate compute infrastructure, leveraging on availability of compute resources, either with on-prem or cloud
- Design a **user-friendly API** that all geoscientists can access and analyze their own data

There is **huge potential** in application of machine learning, and we are barely scratching the surface

- complex networks
 - Increasing granularity in object identification
- 