



### Wells drilled

Region or country	Wells forecast 2018	Wells drilled 2017	% diff.	Region or country	Wells forecast 2018	Wells drilled 2017	% diff.
North America	198	194	2.1	Congo	28	24	16.7
Canada	5	9	-44.4	Egypt	27	20	35.0
Cuba	0	0	***	Gabon	3	3	0.0
Mexico	44	38	15.8	Libya	6	5	20.0
U.S Alaska	12	11	9.1	Nigeria	35	28	25.0
U.S California	28	17	64.7	South Africa	3	0	
U.S Gulf of Mexico	109	119	-8.4	Tunisia	1	1	0.0
Others	0	0		Others	34	23	47.8
South America	89	82	8.5	Middle East	321	299	7.4
Argentina	1	0	•••	Iran	n.a.	n.a.	
Brazil	60	58	3.4	Neutral Zone	0	0	
Chile	0	0		Oman	1	2	-50.0
Colombia	2	3	-33.3	Qatar	67	61	9.8
Ecuador	0	0		Saudi Arabia	74	73	1.4
Peru	0	0	***	Turkey	1	0	
Trinidad & Tobago	18	16	12.5	UAE - Abu Dhabi	159	145	9.7
Venezuela	2	2	0.0	UAE - Dubai	8	8	0.0
Others	6	3	100.0	Others	11	10	10.0
Western Europe	337	315	7.0	Far East/South Asia	1,094	986	11.0
Denmark	5	4	25.0	Brunei	29	30	-3.3
France	0	0	***	China	280	230	21.7
Germany	3	1	200.0	India	101	96	5.2
Italy	3	1	200.0	Indonesia	48	46	4.3
Netherlands	14	9	55.6	Japan	1	1	0.0
Norway	210	205	2.4	Malavsia	57	49	16.3
United Kingdom	93	88	5.7	Myanmar	2	3	-33.3
Others	9	7	28.6	Pakistan	0	0	
Eastern Europe/FSU	98	90	8.9	Philippines	1	1	0.0
Croatia	2		#DIV/0!	Thailand	545	505	7.9
Former Soviet Unio	n 90	86	4.7	Vietnam	21	20	5.0
Russian Federatio	n n.a.	n.a.	***	Others	9	5	80.0
Others	90	86	4.7	South Pacific	31	19	63.2
Poland	1	1	0.0	Australia	27	16	68.8
Romania	5	3	66.7	East Timor	2	2	0.0
Others	0	0		New Zealand	1	0	
Africa	187	148	26.4	Papua New Guinea	1	1	0.0
Angola	50	44	13.6	World Total	2,355	2,133	10.4

<sup>\*</sup>Some countries are estimated.

n.a.---Not available.

### Presentation Outline

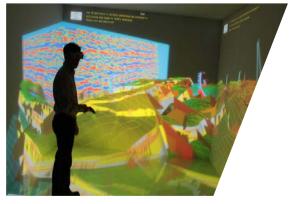
- Introduction
- ElasticDocs Workflow
- Machine Learning Metrics
- Experience with a Norwegian Dataset
- Future Developments

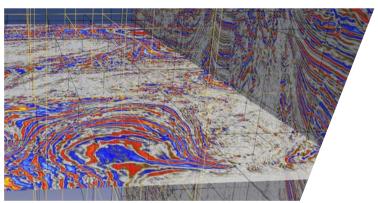
### Industry challenge

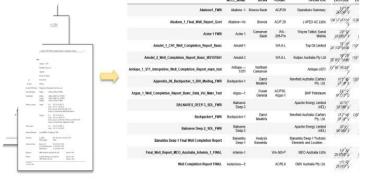
Highly advanced platforms for well and seismic data

Unstructured documents are difficult to access

Decades-worth of geological insights **LOST** 















### Value Proposition

#### **ElasticDocs Container & Workflow**

Information geolocation & density



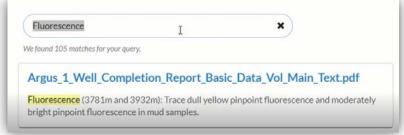
Metadata extraction

Abstract\_FWR Abstract\_FWR Abstract\_Encore Basis ACR729 Opensis Abstract\_FineI\_Well\_Report\_Govt Abstract\_Encore Basis ACR729 Opensis Abstract\_FineI\_Well\_Report\_Govt Abstract\_Encore Basis ACR729 JAP Acres FWR Acres FWR

Autoimage clustering & classification



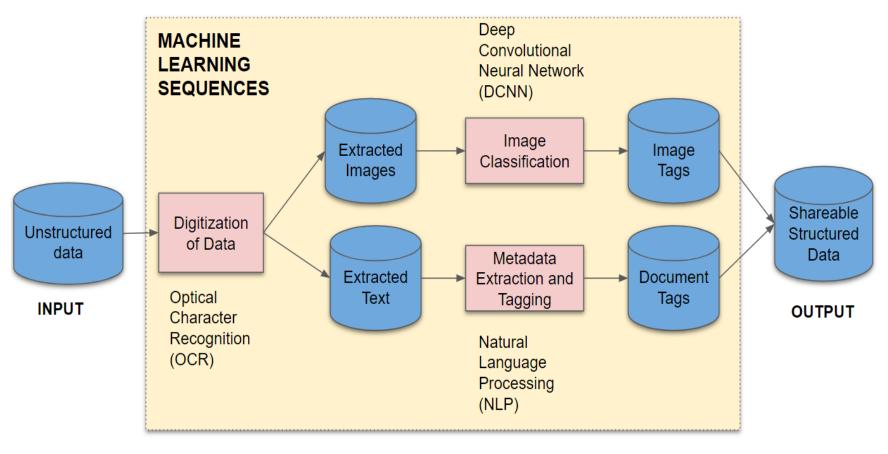
Global elastic search in corpus





### ElasticDocs<sup>TM</sup> Workflow

#### **IMAGE ANALYSIS**



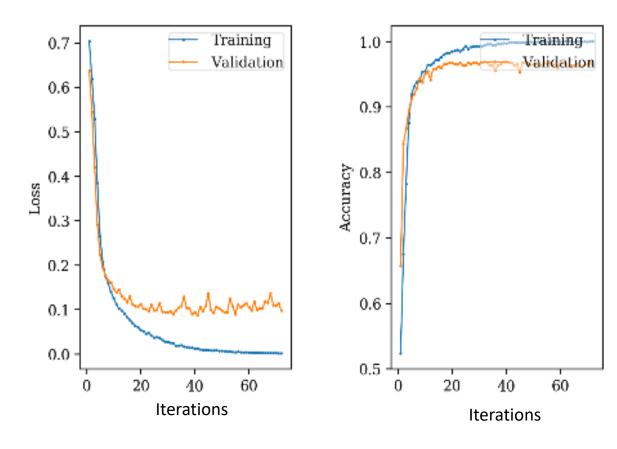
**TEXT ANALYSIS** 

### Classification metrics

Machine learning	Tasks	KPI	Time
application			
Optical character	Text Extraction and Image Extraction	4,542 pages, 6.31 GB, 25 Final Well Reports	10 hours
recognition	Text Extraction only, excluding Image Classification	150,000 pages	3 hours
Deep convolutional neural network	Image Classification	2,598 tagged images input, 16% Tables, 6% Figures, 19% Map, 24% Charts, 33% Noise	20-30 mins during training
Natural language	Lithology / Geology Indicator Frequency Analysis (i.e Carbonates, Sandstone, etc )		4 hours
processing	Well Cataloging	1,500+ input las files, 515 curves identified, 5,681 top log curves (cali, gr, neu, por)	2,5 hours

## Metrics: speed and accuracy

### **Training Loss**



### Automated image classification

#### Supervised image clustering

	Precision	Recall	F1-score
Chart	0.89	0.95	0.92
Core	0.98	1.00	0.99
Figure	0.94	0.72	0.82
Мар	0.90	0.98	0.94
SEM	1.00	0.92	0.96
Stratigraphy	0.97	0.85	0.91
Table	0.95	0.96	0.95
Average/total	0.94	0.94	0.94

#### **Precision and Recall**

- 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

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

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



#### Input:

- o 400 pdf files
- 12,000 lines of tagged for hydrocarbon keywords :
  - Flour
  - Fluorescence
  - Fluor
  - Good show
  - No show odor
  - Stain
  - Streaming

#### Experiment:

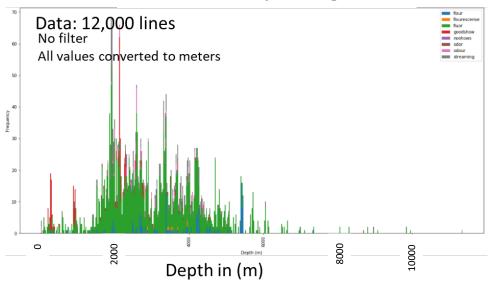
 Used Named Entity Recognition to identify depths from the tagged items. Vintage docs require denoising filters







#### Named entity recognition





### Norwegian dataset

Some of the errors in depth values are observed Original PDF investigated

#### Reasons:

Unknown unit of measurements

```
'_ _!n~-~ Fluor fair to good. Cut poor. Gas 300 to 600 units. ' Detected: [ 300,600 ]
```

Error caused by spacing

```
'yel wh res Fluor no vis res. 3 959 as 3958m 3 960 Sst: ' Detected: [959,3958,960]
```

Error caused by OCR

'milky white cut fluor. no cut colour. 332lm - Sandstone: It. gry very fine ' Detected: [332]

Error caused by OCR mode
 Difference in modes for "paragraph" vs "table" format

#### "paragraph"

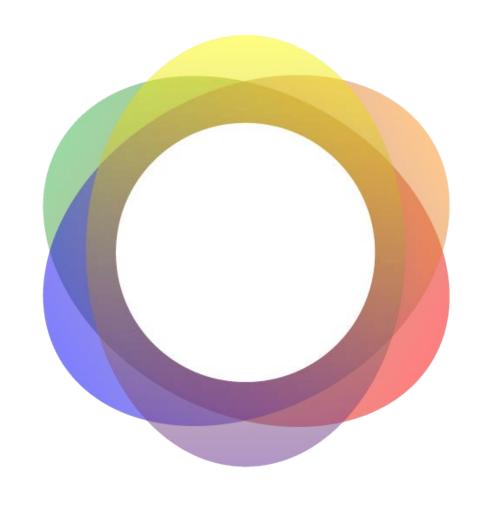
Skagerrak Formation - Undifferentiated Triassic 3173.5 to 3225m (T.D.) (-3071.4 to -3122.5m) Thickness; 51.1 m + Sandatone likology continued down isto the upper part of the Skagerrak Formation with only miner initial colour changes in cuttings or core, but the higher clay content was apparent on the gamma ray log (increase 55 to 80 API).

Lithology comprised sandstone, olive grey and light brown grey, becoming increasingly greenish grey with depth, soluriests to milig and containally present inged and locally orange iron stained, proforminantly very fine to fine, subsequalty to subrounded, and well sorted quarte grains, well comented, with a dolomitic and locally (accontentations of mins in lumine were developed, pythe was also present, as nodular and crystallite accrosion. Carbonacoous materia, including plant remains (sometimes pyritisted) was concentrated mainly in the upper part of the interval. Claystone internations swarfed in color from darke grey and blush grey, and were firm to moderately hand, colomine, intercooks, with distorest edit and sand are fairs.



### Exciting stuff to add...

- Editable image tags to source documents
- Deeper level of auto-image classifications, i.e.
  - ➤ Tables to formation tops
  - > Thin sections to mineralogies
- Hydrocarbon show extraction
- Filter by geolocation
- Image search, i.e "google vision"
- Semantic segmentation



# Thank you!

Questions?

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