Implementation of Machine Learning Systems to Enhance the Value of the CDA North Sea Data Set*

Philip Neri[1]

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Abstract

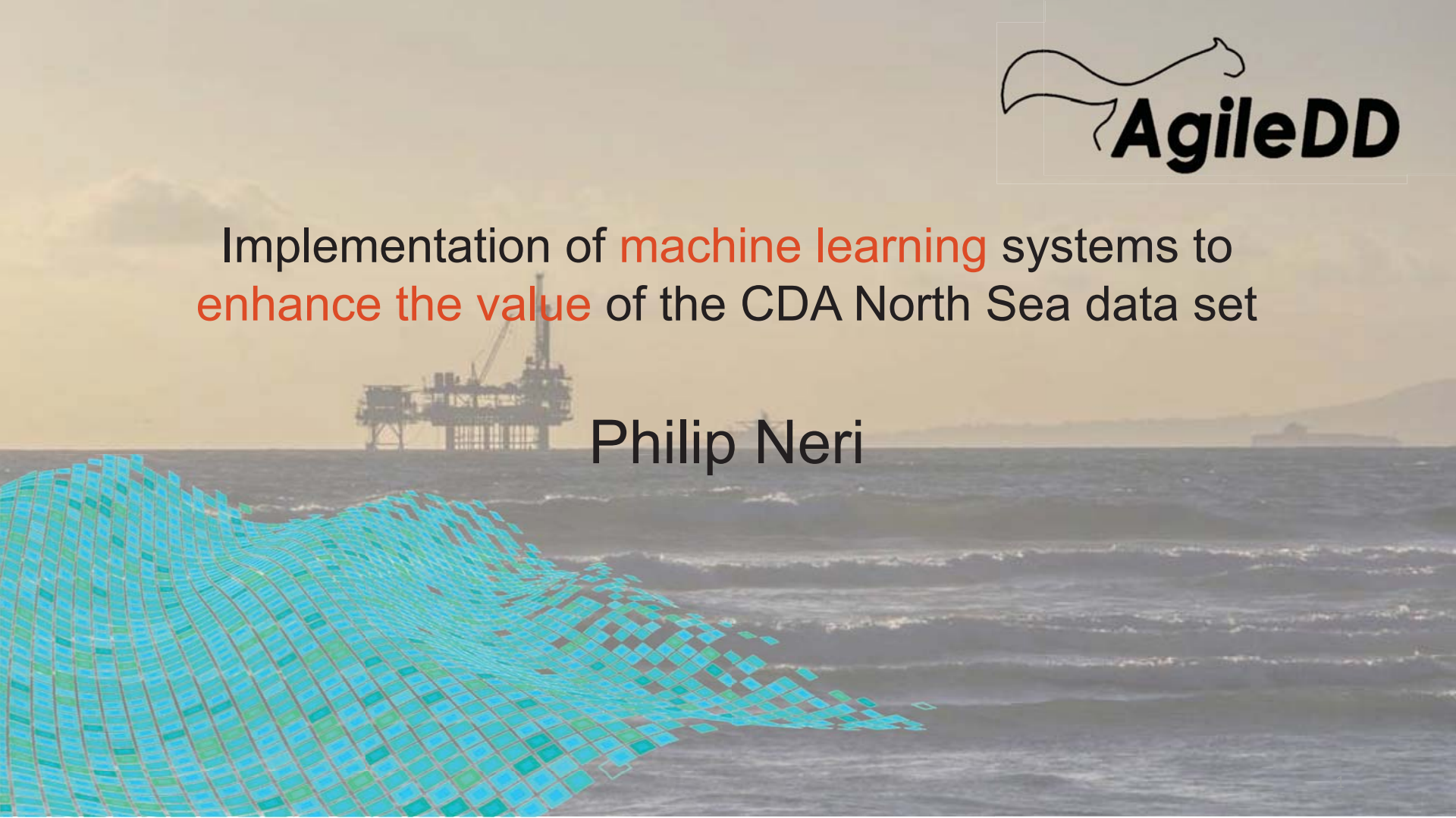
The CDA maintains a collection of well and seismic data submitted by the UKCS operators since the early days of the North Sea Exploration and Production in the 1960's. The collection of CDA well data has been made available to operators and authorities as a database of 11,500 well headers and as a set of 450,000 documents under various formats such as .pdf, .xls, .doc, .tiff, .jpg, .las, .dlis.

This collection of data is similar in its organization and content with legacy datasets that can be found in any industry: around 20% of the information is available in a structured form such as a relational database, and 80% in a semi-structured or unstructured form, typically grouped in folders containing various documents formatted as described above. Since most of the software and data management tools used in E&P can only access the structured information and in some cases some half-structured formats, it transpires that E&P decisions are based on a small part of the available stored information.

The low benchmark of 20% of available data is due to several factors, primarily the cost of indexing (classifying the documents per topic) and cataloguing the documents (extracting metadata from the document) which is currently a work-intensive process. But the cost is not the only limitation. The fixed nature of most of the subsurface data-models makes it almost impossible to catalog information which was not planned to be extracted in the initial stage of the data model design.

In 2016, the CDA launched a challenge to find new ways to extract value from its unstructured data assets. This article explores the application of newly developed Machine Learning Systems (MLS) to automate part of the indexing and cataloguing. MLS demonstrated a reduced time (and therefore cost) of access to information but also enriched the extracted information by qualifying its extraction confidence and source, and identifying replicates. They make it possible to perform data analysis of larger datasets in term of volume and variety.

The performance of Machine Learning Systems when applied to subsurface data management will be discussed, the limitation criteria listed, and some future possibilities to overcome the current limitations will be overviewed.



Implementation of machine learning systems to enhance the value of the CDA North Sea data set

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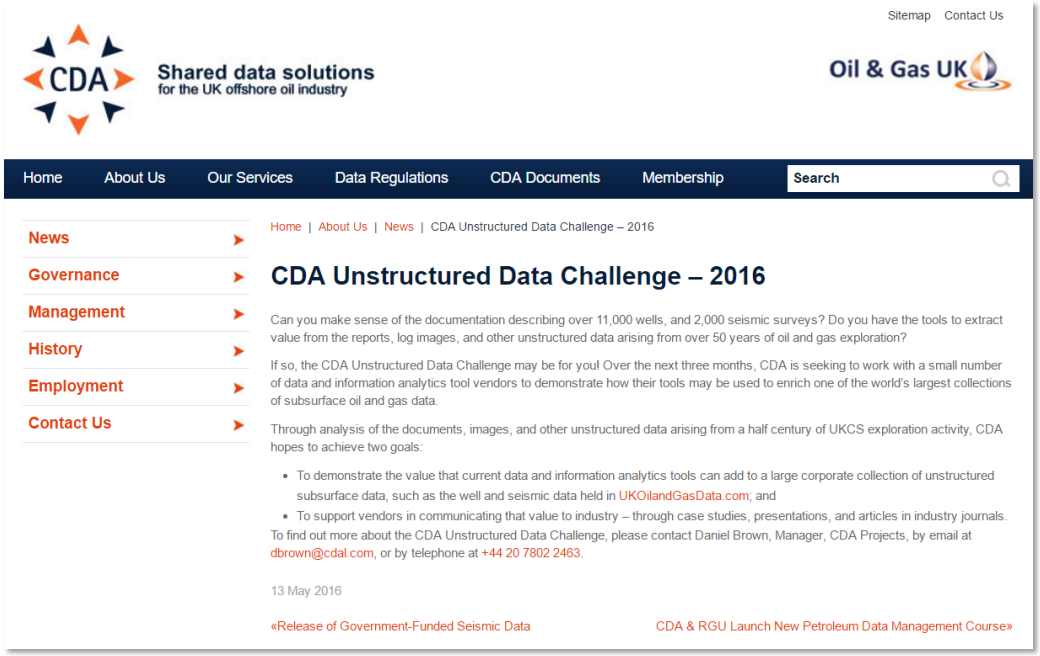
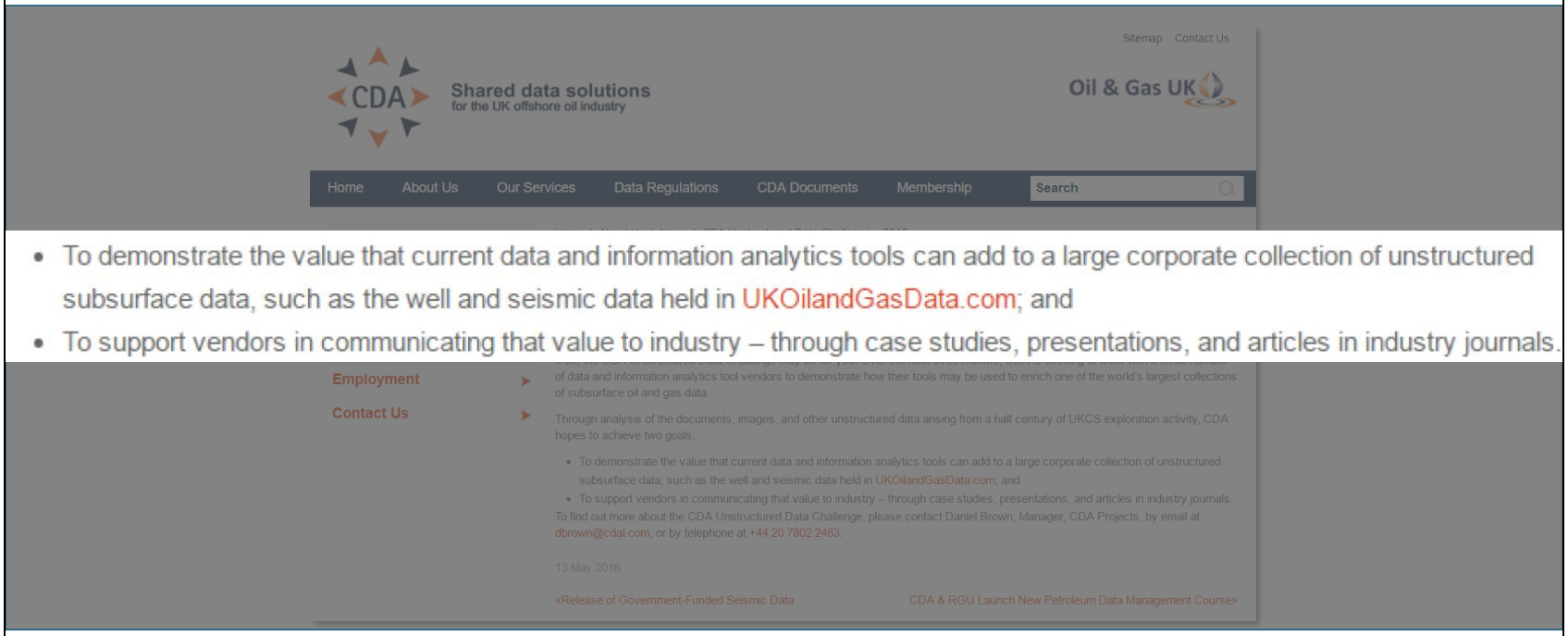
The CDA unstructured data challenge



Presenter's notes: In summer 2016 AgileDD, together with 7 other technology providers, was selected to participate in the first CDA unstructured data challenge. The idea was to illustrate how new technology could "enrich one of the world largest collections of subsurface O&G data.

This presentation will show you what we have achieved in a short period of 4 weeks in August 2016.

The CDA unstructured data challenge



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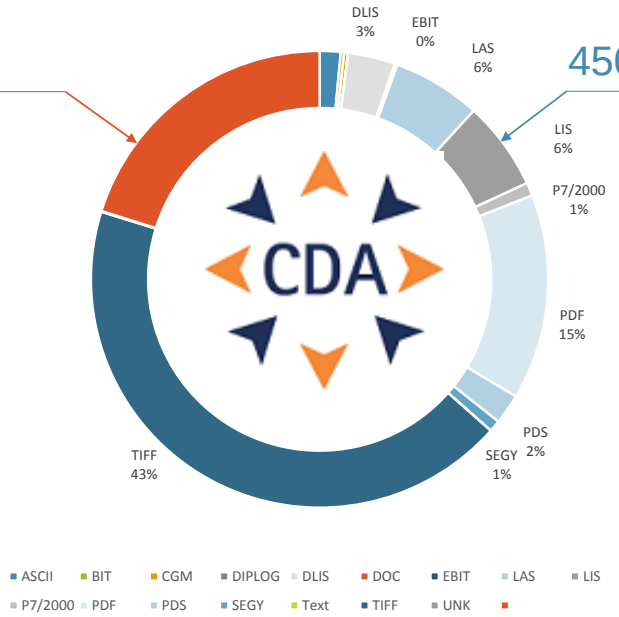
The CDA well data set

2 relational tables

- Well header
- CS8 file index



450,000 unstructured files

- End of well reports
- Wirelines, MWD
- Composites
- CCA and SCAL
- Geochemistry
- Fluid analysis
- Biostratigraphy
- Lithostratigraphy
- Cementation report
- Checkshots and VSP
- ...etc...

Presenter's notes: CDA is a significant and vitally important component of the private/public partnership that constitutes the NDR (National Data Repository) for the UKCS

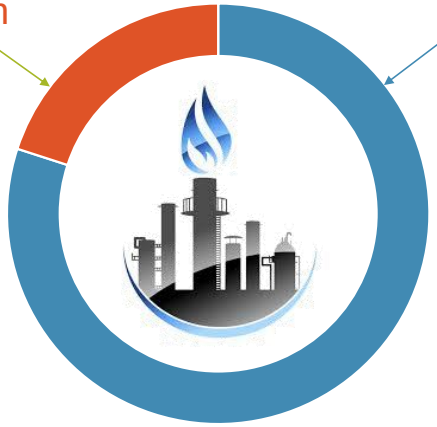
The CDA has collected information about 11,500+ offshore wells drilled over the last 60 years

This information is under the form of
450,000 unstructured files

The 80/20 ratio

20% structured information

- Easy to access
- Easy to query
- Easy to QC
- Easy to model and analyze



80% unstructured information

- Costly to index
- Costly to extract metadata
- Difficult to access and query
- Cannot feed analytical tools

Presenter's notes: The CDA data set is not so different from many others we can find in our industry and in some other industries. According to various sources (Merryl Lynch, EMC, Oracle ...) 80 % of the information is available in an unstructured format (PDF, TIFF ...)
This type of information is difficult to use, it cannot be used directly by the modeling of BI tools. Extracting metadata to create indexes and populate DBs is extremely costly and need SMEs that today are increasingly scarce in our industry.
This translates into the fact that only 20% of the information is available within structured database.

The big problem is that since this small part is easy to access and query, it trends to be the unique source of information to base decision

Your decision is at risk

20% structured information

- Easy to access
- Easy to query
- Easy to QC
- Easy to analyze

80% unstructured information

- Costly to index
- Costly to extract metadata
- Difficult to access and query
- Cannot feed analytical tools

Presenter's notes: And that makes your decision a very risky one.

What if we reverse the ratio ?

80% structured information

- Easy to access
- Easy to query
- Easy to QC
- Easy to analyze
- Easy to source
- With a known confidence level

20% unstructured information

- Automatic cataloging and indexing

Make your decision more reliable based on more structured data

Presenter's notes: Our ambition is to reverse the ratio. Using an automated process based on a machine learning system, we extract more information from your documents at a fraction of the cost and time, and this makes your decisions more reliable.

The advantages of automated cataloging

SAVE MONEY

Avoid populating databases manually

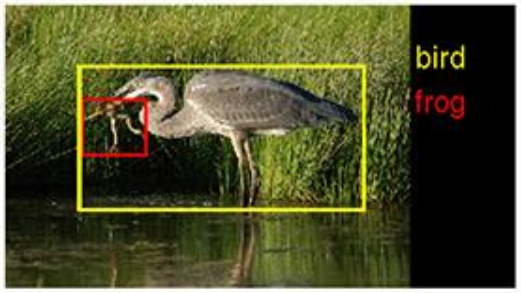
GO FASTER

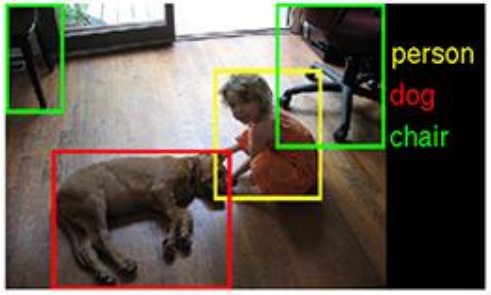
From data to decision

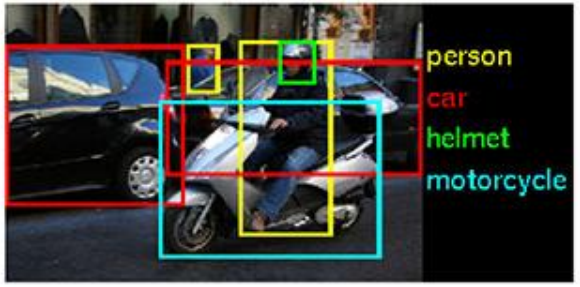
DE-RISK

Using more verified information

Why use a machine learning system?

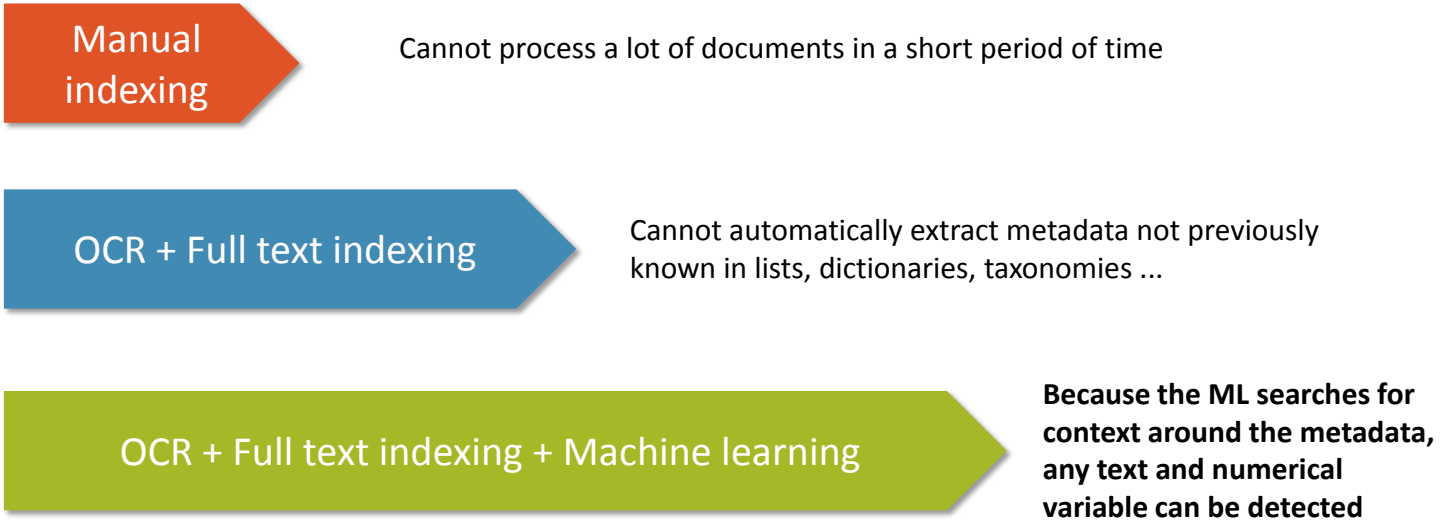






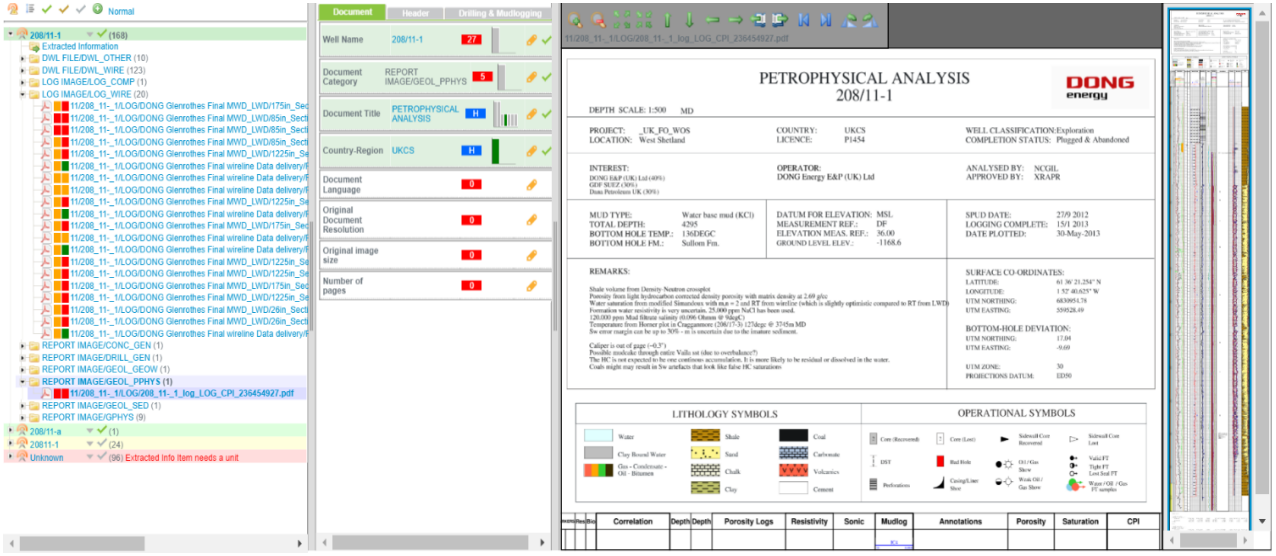
Presenter's notes: Supervised Machine Learning excels at recognizing a pattern in an unstructured context

ML exceeds manual and full text indexing



Presenter's notes: The capacity to detect the pattern around a target metadata item allows us to make a more efficient cataloging compared to a full text indexing. ML detects a numerical variable such as a coordinate, a depth, a temperature using the context of the value which is not possible even with the best Full text indexing

Example of indexing using the CS8 taxonomy and extraction of some well header metadata



Presenter's notes:

These few snapshots illustrate the capacity of our tools to:

- Detect the document category using the CS8 taxonomy used in the UK to describe each subsurface document. The CS8 taxonomy defines a document according to its "container" such as a report, log, digital document ... and its "contents" such as mud-logging, petrophysics, seismic, engineering ... Does the same automatically after training.
- Detect some well header metadata, text or numerical, using their context
- Associate a confidence factor to each extraction
- Display the variability of a particular metadata value for the same well

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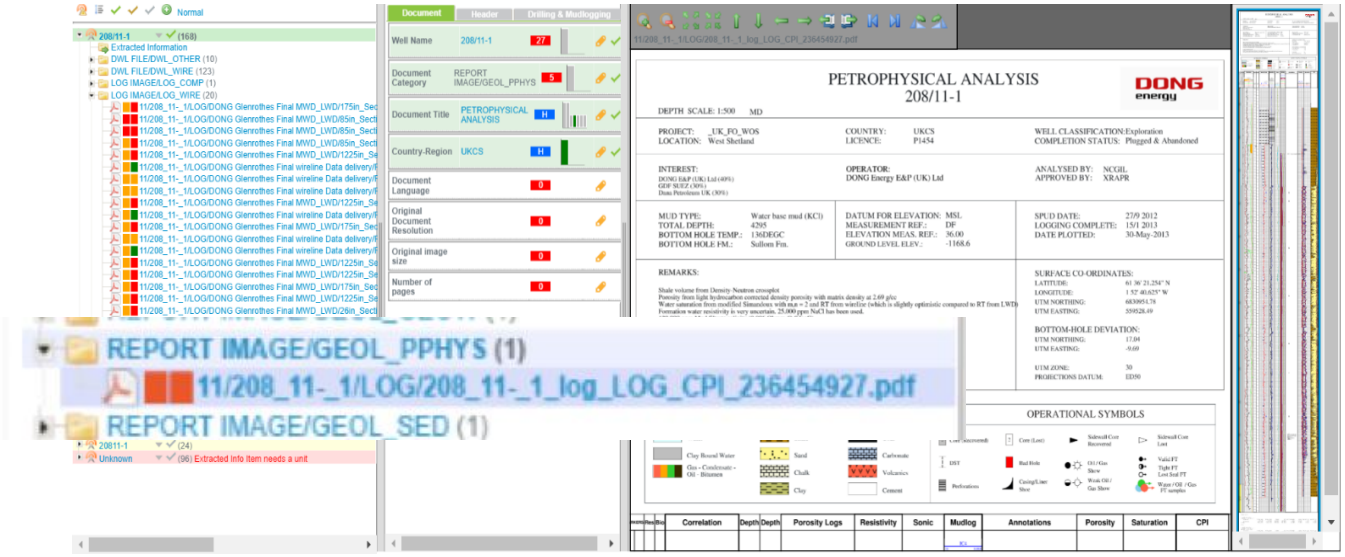

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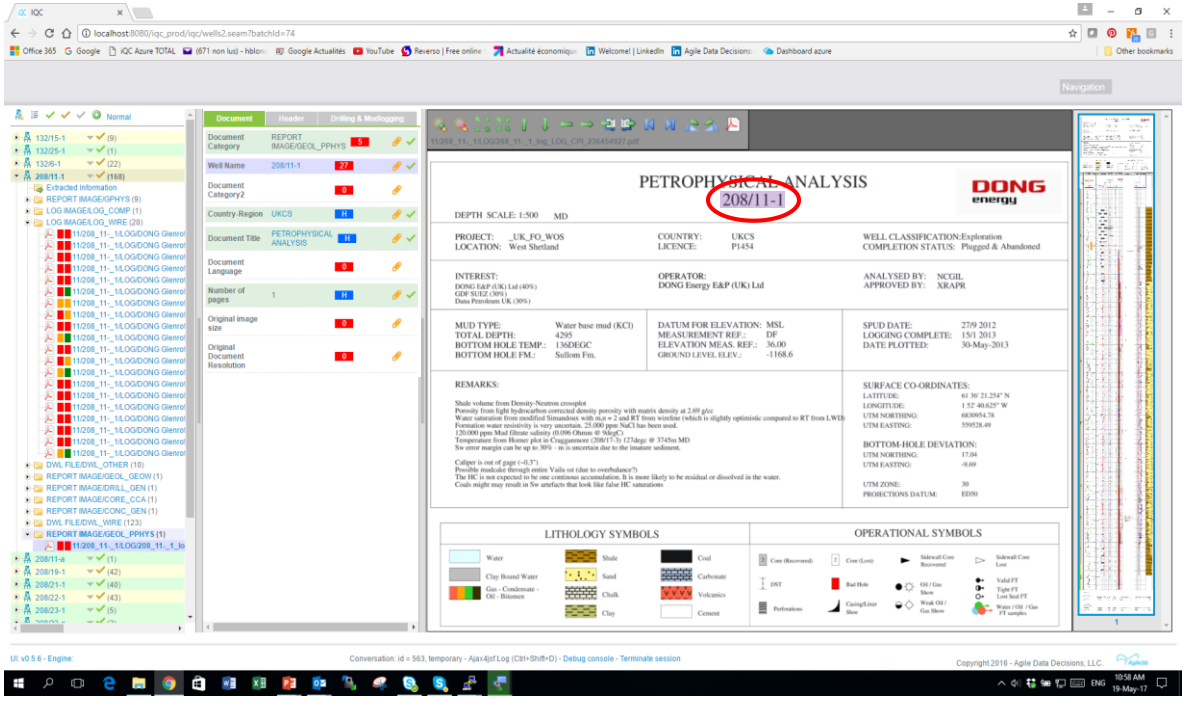

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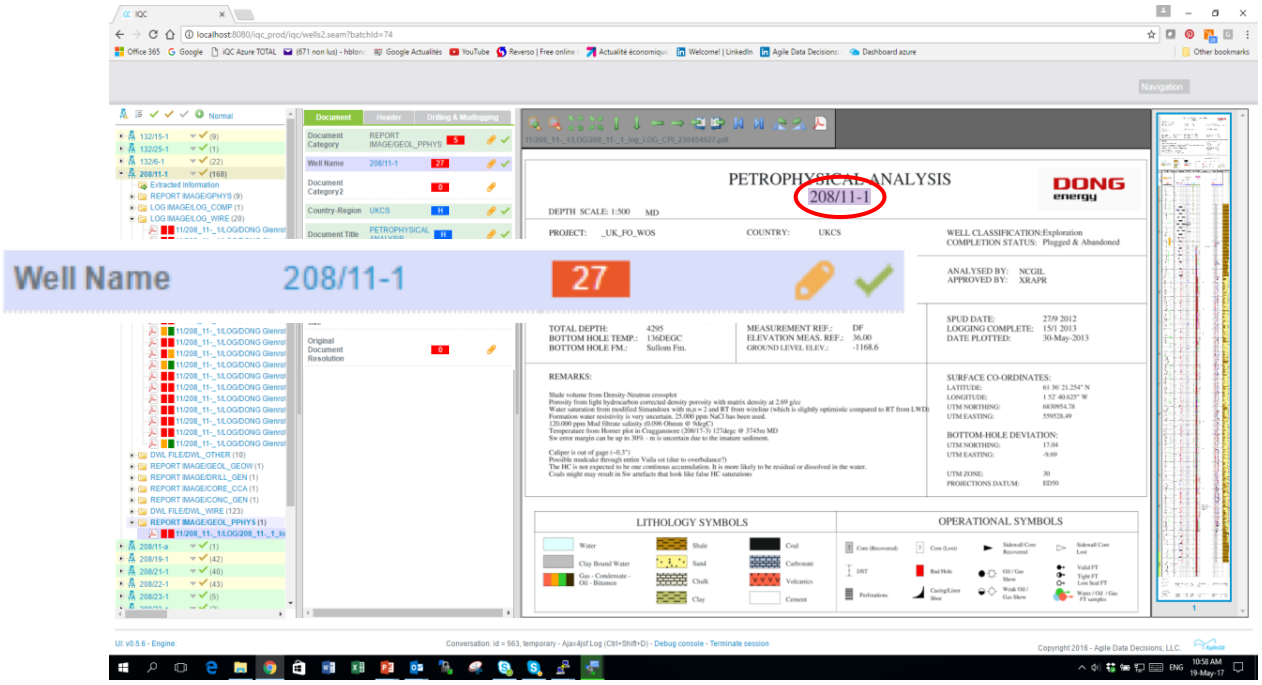

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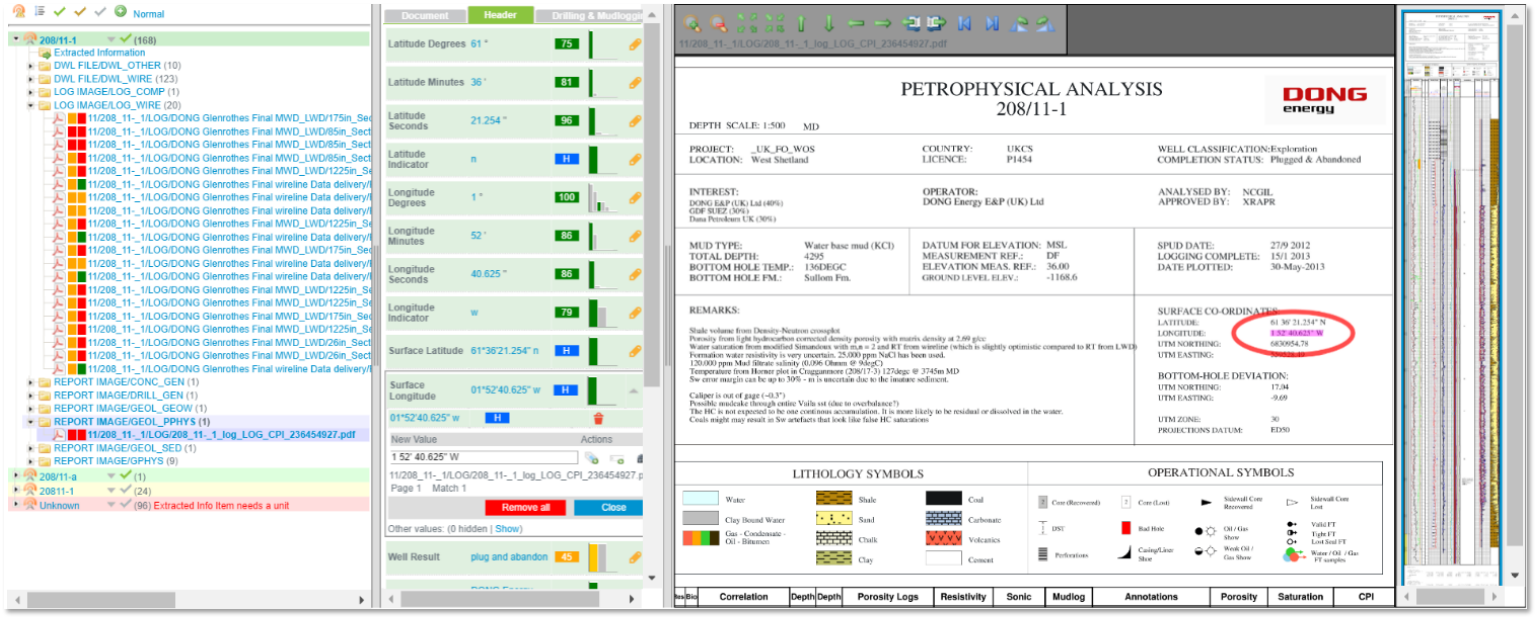

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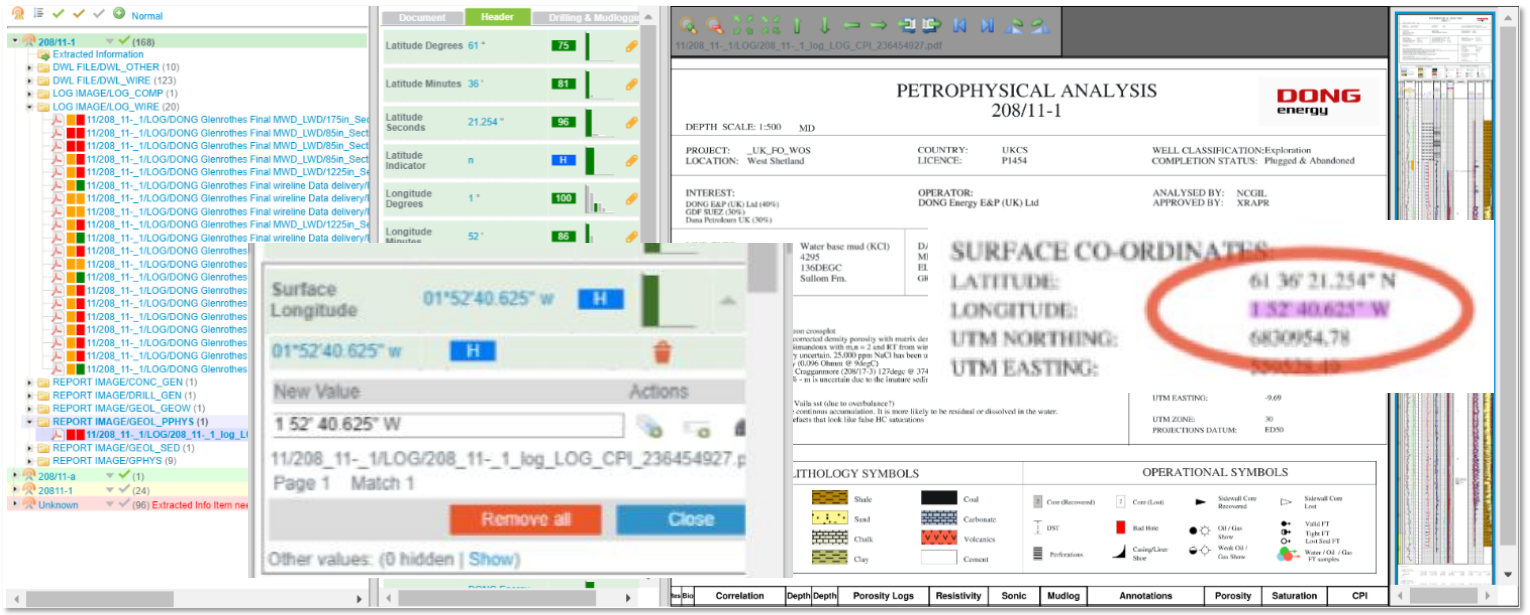

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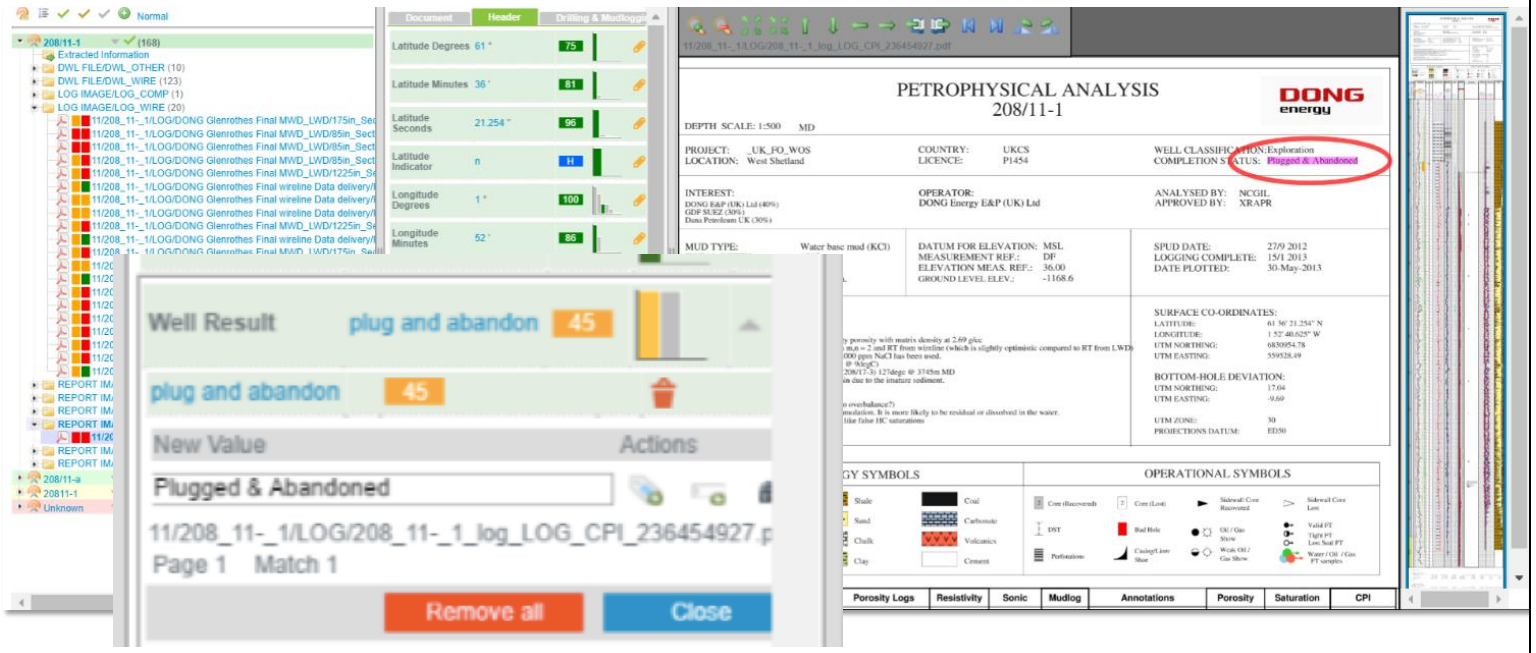

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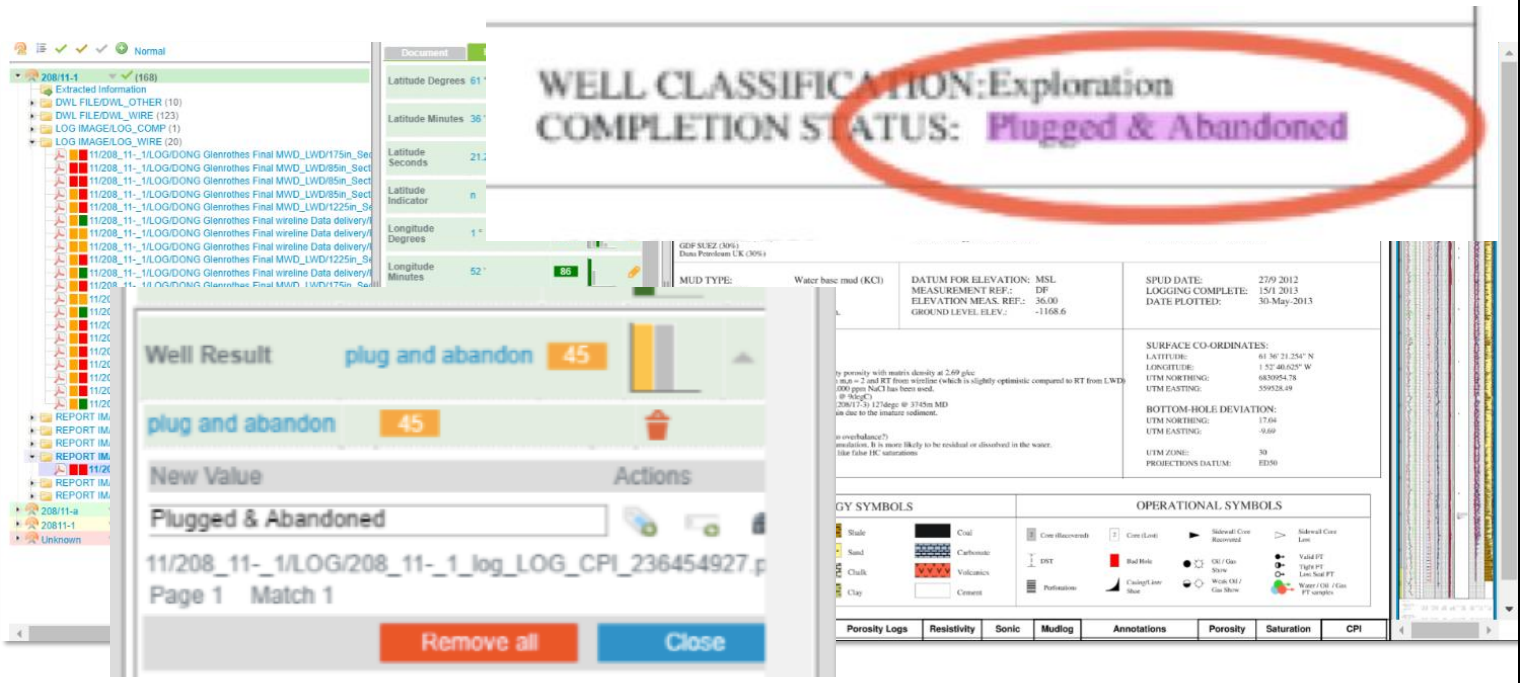

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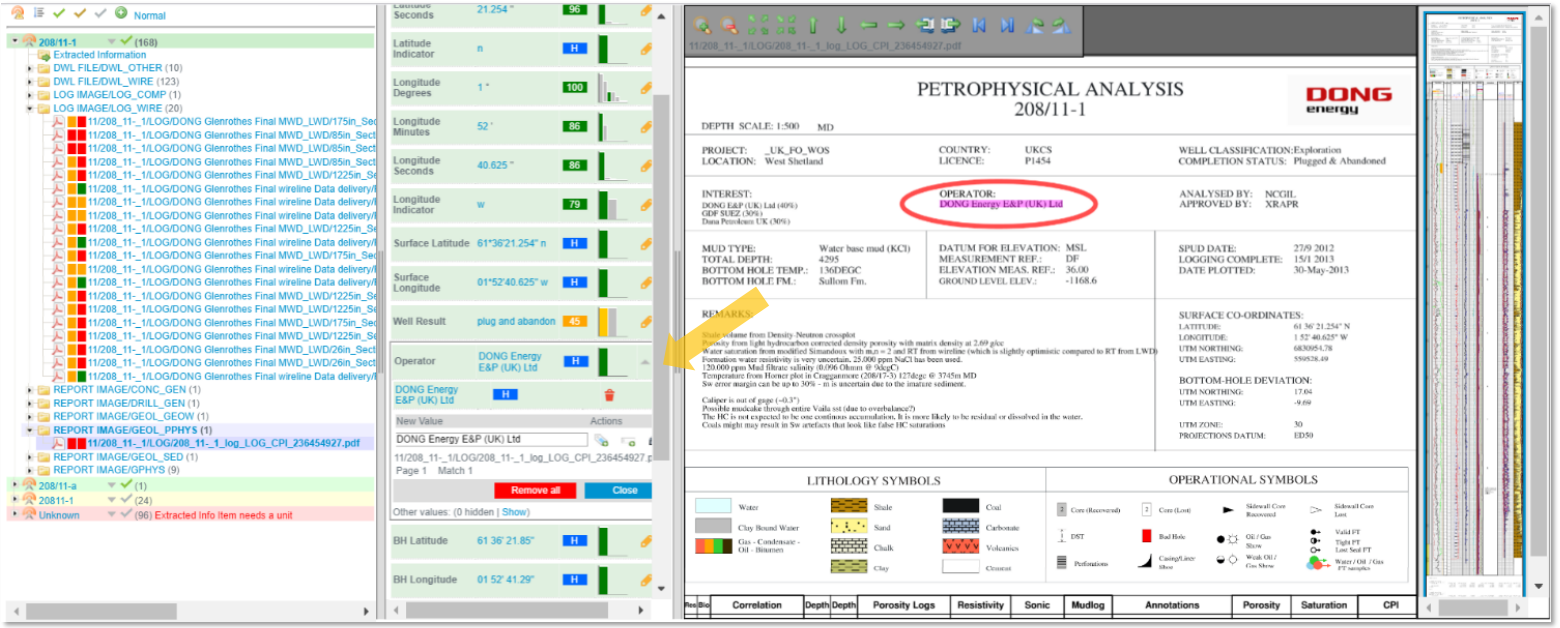

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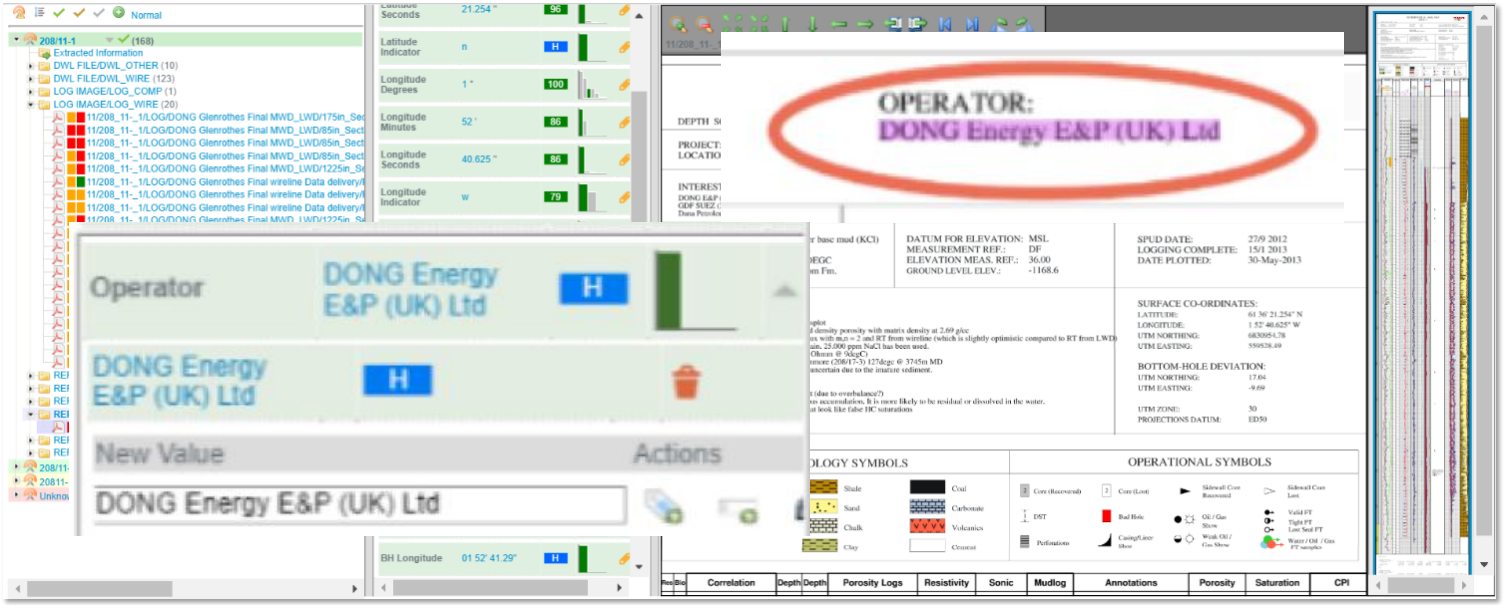

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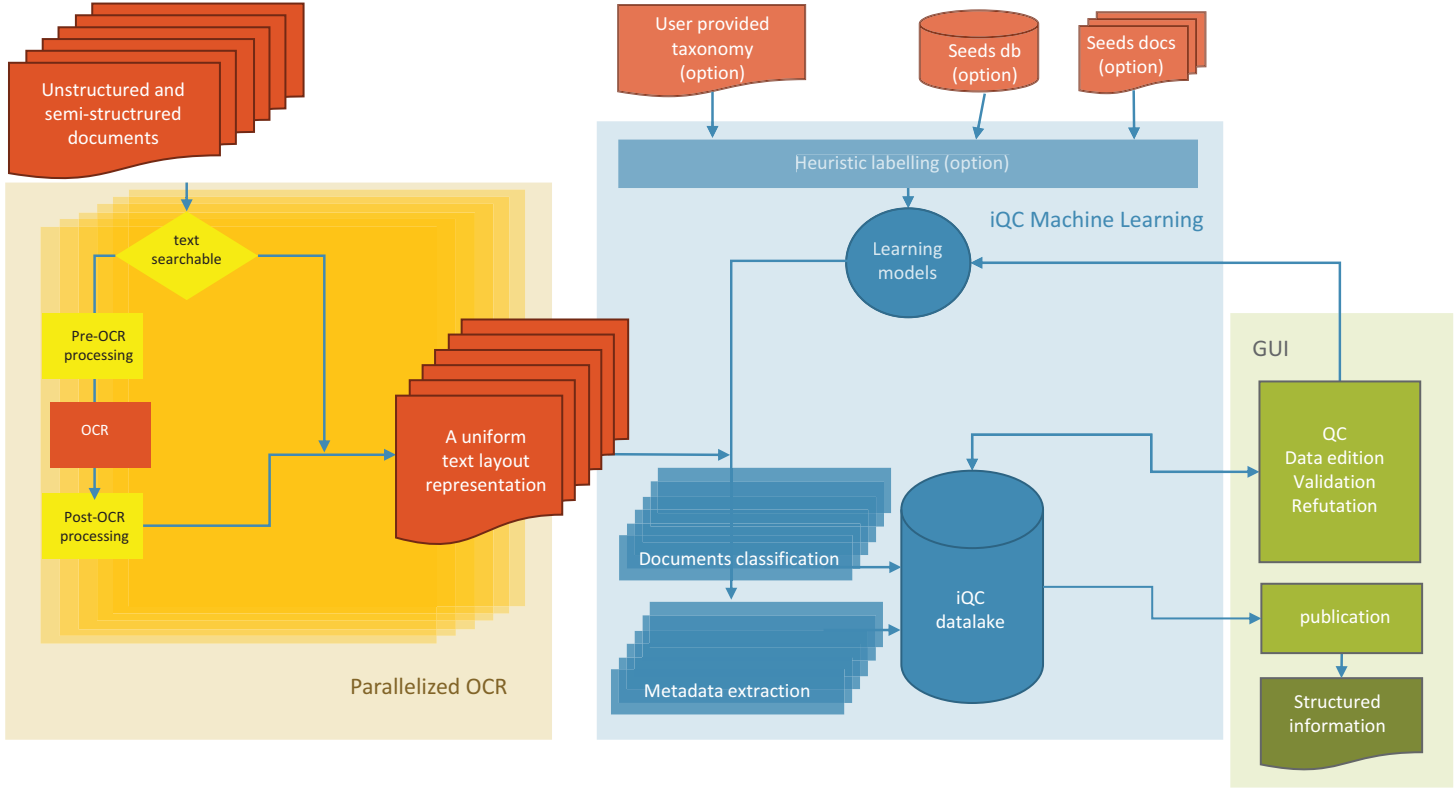
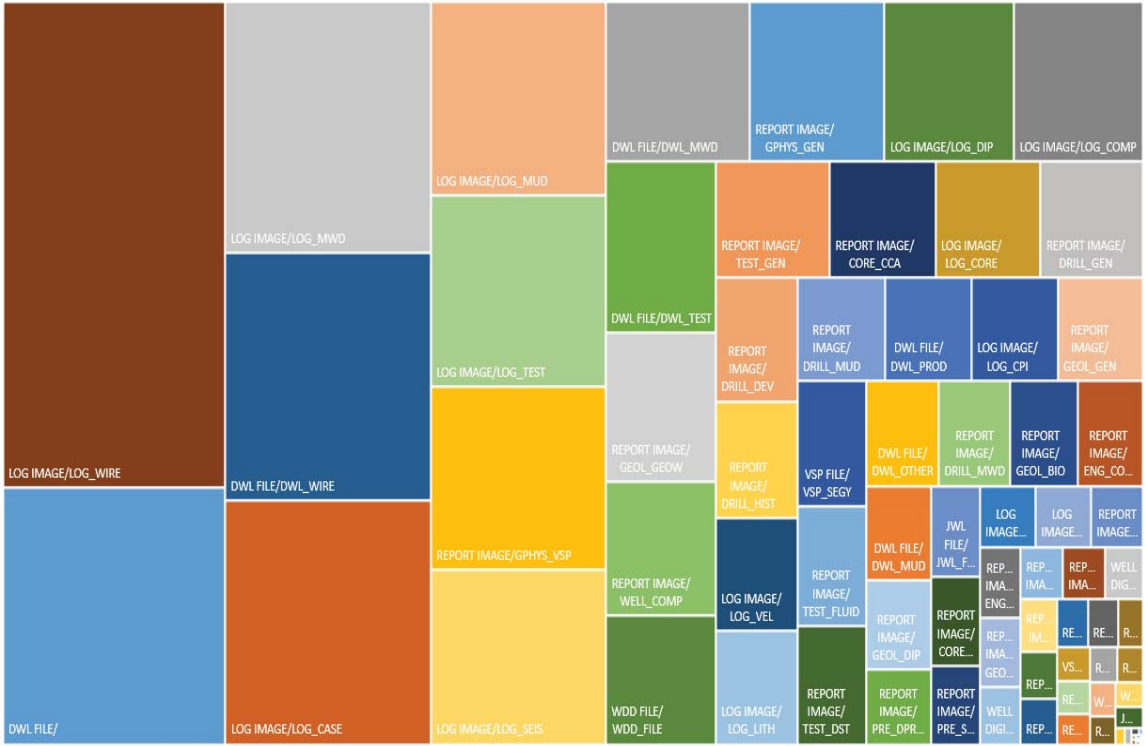
How does it work?



Document category

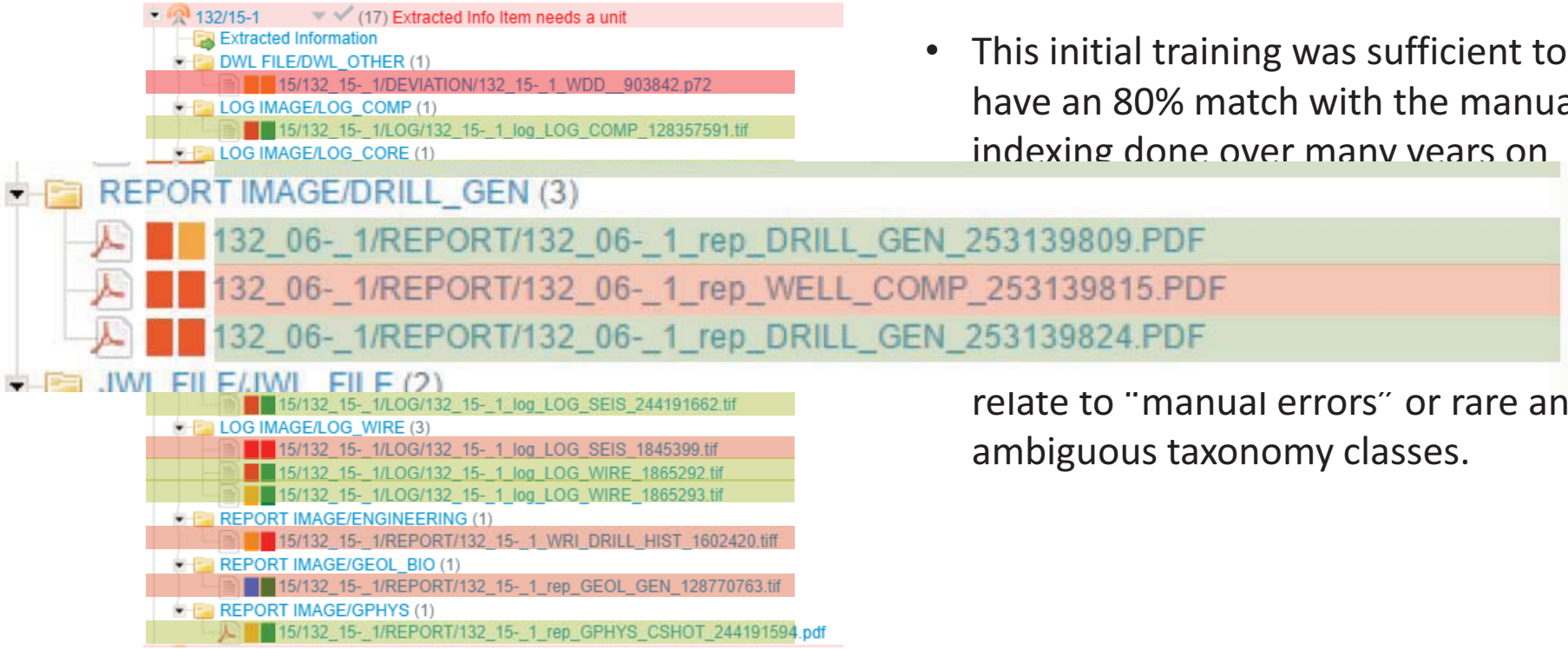


- In 2 days, iQC has been trained to use the CS8 taxonomy, using 2000 “seed” examples

Document category

- This initial training was sufficient to have an 80% match with the manual indexing done over many years on the 450,000 documents.
- The ratio moved up to 90% with a seed of 5,000 documents
- The 10% of remaining discrepancies relate to “manual errors” or rare and ambiguous taxonomy classes.

Document category



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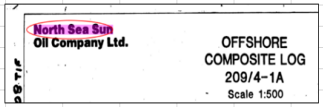
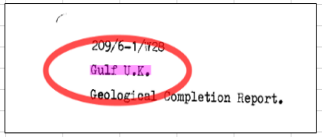
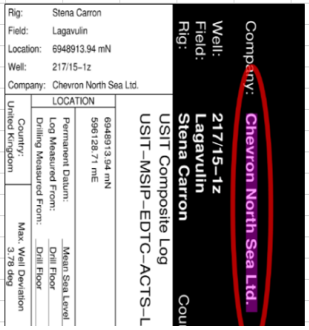
QC of the CDA tables according to the source documents

Wellbore	Attribute	Value	Confid	CDA wellbore	Original operator	
209/12-1	Operator	Marathon Oil U.K.. Ltd.	100	209/12- 1	MARATHON OIL (UK) LTD	
209/3-1a	Operator	MOBIL NORTH SEA LTD.	100	209/03- 1a	MOBIL NORTH SEA LIMITED	
209/4-1a	Operator	North Sea Sun Oil Company Ltd	100	209/04- 1a	AGIP (U.K.) LIMITED	Operator!J69
209/6-1	Operator	Gulf U.K.	100	209/06- 1	CHEVRON U.K. LIMITED	Operator!J75
213/23-1	Operator	MOBIL NORTH SEA LTD	100	213/23- 1	MOBIL NORTH SEA LIMITED	
213/26-1z	Operator	chevron	76	213/26- 1z	CHEVRON	
217/15-1z	Operator	Chevron North Sea Ltd.	100	217/15- 1z	0	Operator!J82
220/26-1	Operator	B.P. PETROLEUM DEVELOPMENT	100	220/26- 1	BP EXPLORATION OPERATING COMPANY LIMITED	
220/26-1st	Operator	B.P. PETROLEUM DEVELOPMENT	100	220/26- 1st	#N/A	
220/26-2	Operator	BP Petroleum Development Ltd	100	220/26- 2	BP EXPLORATION OPERATING COMPANY LIMITED	
74/1-1	Operator	Gas Council (Exploration) Ltd	100	74/01- 1	BG INTERNATIONAL LTD	
83/24-1	Operator	DEPARTMENT OF ENERGY	100	83/24- 1	HMG DEPARTMENT OF TRADE AND INDUSTRY	
86/17-1	Operator	Murphy Petroleum Limited	100	86/17- 1	MURPHY PETROLEUM LIMITED	
86/18-1	Operator	The British National Oil Corporation	100	86/18- 1	BP EXPLORATION OPERATING COMPANY LIMITED	
87/12-1a	Operator	BP Petroleum Development Ltd	100	87/12- 1a	BP EXPLORATION OPERATING COMPANY LIMITED	
87/14-1	Operator	Department of Energy, UK	100	87/14- 1	HMG DEPARTMENT OF TRADE AND INDUSTRY	
87/16-1	Operator	Department of Energy, U.K.	100	87/16- 1	HMG DEPARTMENT OF TRADE AND INDUSTRY	
88/2-1	Operator	Department of Energy, U.K	100	88/02- 1	HMG DEPARTMENT OF TRADE AND INDUSTRY	
8/15- 1	Operator	UNOCAL U.K. LIMITED	100	8/15- 1	UNOCAL NORTH SEA EXPLORATION LIMITED	
8/15-2a	Operator	Total Exploration and Production UK Ltd.	100	8/15- 2a	TOTAL	
8/20-1	Operator	Agip (UK) Ltd	100	8/20- 1	AGIP (U.K.) LIMITED	
8/25a-1	Operator	nautical petroleum	100	8/25a- 1	NAUTICAL	
8/30-1	Operator	Sovereign Oil & Gas Plc	100	8/30- 1	SANDS EXPLORATION LIMITED	Operator!J108
8/4-1	Operator	Chevron UK Ltd	100	8/04- 1	CHEVRON U.K. LIMITED	



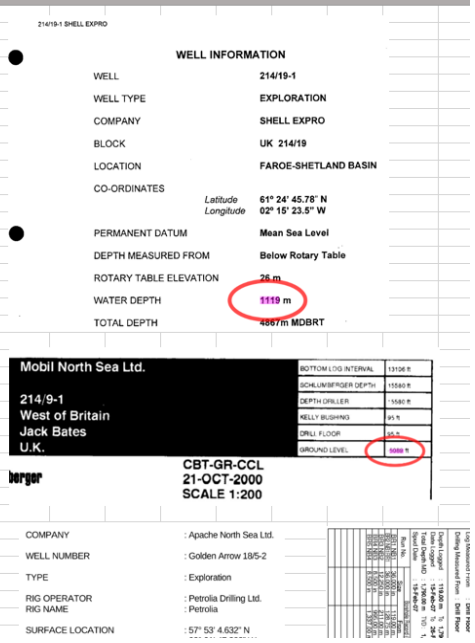




Presenter's notes: The automatic well header metadata extraction authorize to QC the CDA DB according to the source documents. This example shows the discrepancies on a text metadata (the well operator)

QC of the CDA tables according to the source documents

iQC wellbore	title	iQC val	unit	confidenceScore	CDA wellname	iQC value (m)	CDA Water Depth (m)	Delta	
214/17-1	Water Depth	3832	ft	80	214/17- 1	1167.99	1167.99	0.00	
214/19-1	Water Depth	1119	m	100	214/19- 1	1119.00	1000.05	118.95	Water Depth'IM3
214/4-1	Water Depth	5317	ft	60	214/04- 1	1620.62	1620.62	0.00	
214/9-1	Water Depth	5089	ft	60	214/09- 1	1551.13	1556	4.87	Water Depth'IM23
1/4-1	Water Depth	506	ft	100	1/04- 1	154.23	154.23	0.00	
1/4-2	Water Depth	479	ft	100	1/04- 2	146.00	146	0.00	
18/3-1	Water Depth	263	ft	100	18/03- 1	80.16	80.1624	0.00	
18/5-2	Water Depth	92.6	ft	100	18/05- 2	28.22	119	90.78	Water Depth'IM32
26/12-1	Water Depth	144	ft	100	26/12- 1	43.89	43.89	0.00	
26/14-1	Water Depth	225	ft	100	26/14- 1	68.58	68.58	0.00	
26/4-1	Water Depth	219	ft	100	26/04- 1	66.75	67.06	0.31	
26/7-1	Water Depth	64.9	m	100	26/07- 1	64.90	64.9	0.00	
26/8-1	Water Depth	186	ft	100	26/08- 1	56.69	56.69	0.00	
27/10-1	Water Depth	262	ft	100	27/10- 1	79.86	79.86	0.00	
27/3-1	Water Depth	246	ft	100	27/03- 1	74.98	74.98	0.00	
4/26-1A	Water Depth	351	ft	100	4/26- 1A	106.98	132.89	25.91	Water Depth'IM51
4/26-2	Water Depth	342	ft	100	4/26- 2	104.24	104.24	0.00	
7/16-1	Water Depth	417	ft	100	7/16- 1	127.10	127.1	0.00	
102/28-2	Water Depth	315	\N	100	102/28- 2	96.01	96.01	0.00	
103/1-1	Water Depth	316	ft	100	103/01- 1	96.32	96.32	0.00	
103/1-2	Water Depth	314	ft	100	103/01- 2	95.71	no value	no value	
103/18-1	Water Depth	232	\N	100	103/18- 1	70.71	70.71	0.00	
103/1a-2	Water Depth	314	ft	26	103/01a- 2	95.71	98.45	2.74	
103/2-1	Water Depth	375	ft	100	103/02- 1	114.30	114.3	0.00	
103/21-1	Water Depth	276	ft	100	103/21- 1	84.12	84.12	0.00	
106/18-1	Water Depth	299	ft	100	106/18- 1	91.14	91.14	0.00	
106/20-1	Water Depth	79.5	m	100	106/20- 1	79.50	79.5	0.00	
106/24-1	Water Depth	252	ft	100	106/24- 1	76.81	76.81	0.00	
106/24a-2B	Water Depth	241	ft	100	106/24a- 2B	73.46	73.46	0.00	
106/28-1	Water Depth	359	ft	100	106/28- 1	109.42	109.42	0.00	
107/1-1	Water Depth	237	ft	100	107/01- 1	72.24	72.24	0.00	
107/16-1	Water Depth	140	ft	100	107/16- 1	42.67	42.67	0.00	
107/21-1	Water Depth	176	ft	100	107/21- 1	53.64	53.64	0.00	
93/2-1	Water Depth	97.5	m	100	93/02- 1	97.50	97.54	0.04	
93/2-3	Water Depth	98.45	m	100	93/02- 3	98.45	98.15	0.30	
93/6-1	Water Depth	336	ft	100	93/06- 1	102.41	104.24	1.83	
99/12-1	Water Depth	53	ft	100	99/12- 1	16.15	16.46	0.31	



214/19-1 SHELL EXPRO

WELL INFORMATION

WELL	214/19-1
WELL TYPE	EXPLORATION
COMPANY	SHELL EXPRO
BLOCK	UK 214/19
LOCATION	FAROE-SHETLAND BASIN
CO-ORDINATES	
Latitude	61° 24' 45.78" N
Longitude	02° 15' 23.5" W
PERMANENT DATUM	Mean Sea Level
DEPTH MEASURED FROM	Below Rotary Table
ROTARY TABLE ELEVATION	26 m
WATER DEPTH	1119 m
TOTAL DEPTH	4867m MDBRT

Mobil North Sea Ltd.

214/9-1
West of Britain
Jack Bates
U.K.

BOTTOM LOG INTERVAL	13106 ft
SCHLUMBERGER DEPTH	13580 ft
DEPTH DRILLER	13580 ft
KELLY BUSHING	95 ft
DRILL FLOOR	95 ft
GROUND LEVEL	5089 ft

CBT-GR-CCL
21-OCT-2000
SCALE 1:200

COMPANY	: Apache North Sea Ltd.
WELL NUMBER	: Golden Arrow 18/5-2
TYPE	: Exploration
RIG OPERATOR	: Petrolia Drilling Ltd.
RIG NAME	: Petrolia
SURFACE LOCATION	: 57° 53' 4.632" N

Presenter's notes: Our capacity to extract numerical variables allowed us to QC the CDA DB according to the sources docs. It showed surprising "human errors" on some very easy to detect metadata. The main value is not only to alert on discrepancies but also to show immediately the documented source of information we have used to alert us, as well as our confidence in the automatic detection.

QC of the CDA tables according to the source documents

iQC wellbore	title	iQC val	unit	confidenceScore	CDA wellname	iQC value (m)	CDA Water Depth (m)	Delta	
214/17-1	Water Depth	3832	ft	80	214/17- 1	1167.99	1167.99	0.00	
214/19-1	Water Depth	1119	m	100	214/19- 1	1119.00	1000.05	118.95	Water Depth'!M3
214/4-1	Water Depth	5317	ft	60	214/04- 1	1620.62	1620.62	0.00	
26/12-1	Water Depth	144	ft	100	26/12- 1	43.89	43.89	0.00	
26/14-1	Water Depth	225	ft	100	26/14- 1	68.58	68.58	0.00	
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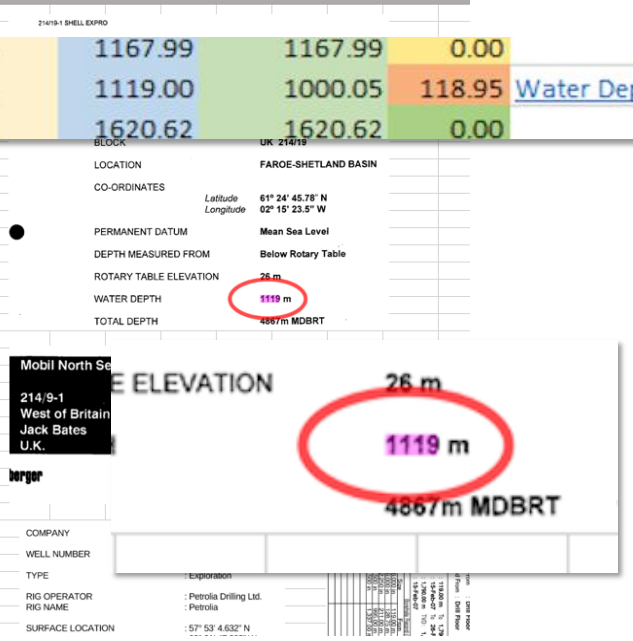

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Lessons learnt from the CDA challenge

- Machine learning detects metadata in unstructured documents that other methods cannot detect
- It supports the QC of a structured database using unstructured sources
- It makes it possible to easily extend the contents of the database “on demand”

- For us, the CDA challenge was also an opportunity to enrich our learning model and make it more stable

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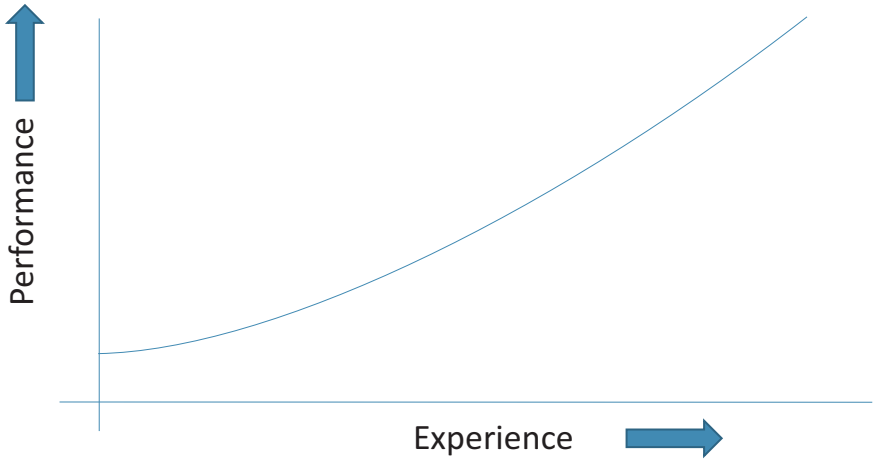
The (machine) learns with us!

Overview [edit]

Tom M. Mitchell provided a widely quoted, more formal definition: "A computer program is said to learn from experience *E* with respect to some class of tasks *T* and performance measure *P* if its performance at tasks in *T*, as measured by *P*, improves with experience *E*."[9] This definition is notable for its defining machine learning in fundamentally operational rather than cognitive terms, thus following Alan Turing's proposal in his paper "Computing Machinery and Intelligence" that the question "Can machines think?" be replaced with the question "Can machines do what we (as thinking entities) can do?"[10]



The (machine) learns with fresh data!

Looking ahead

- We are looking for documents to crunch
- We are engaging with early adopters
  - To perform pilot projects and feasibility studies system relative to their needs and objectives
  - To evaluate the performance of our machine learning

- We work in the cloud (Microsoft Azure®)
  - Our Learning models improve continuously
  - New users benefit from all accrued learning
  - An alternative configuration is to install our system locally

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