The Rules of Subsurface Analytics*

Jane McConnell¹ and Duncan Irving¹

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Abstract

Oil and Gas companies are increasingly embracing big data analytics and data driven approaches in the drive to optimize development and production costs, increase recovery factors, and ultimately better understand and quantify uncertainties in their workflows. Most companies now have a digitalization program in place and are taking steps towards this data-driven future. From the projects that Teradata has conducted in the Oil and Gas industry, we believe that implementing a successful analytics program in subsurface involves following a few key rules. Firstly, they require bringing together the right people. Ideally what we refer to as "T-shaped" people – people with deep knowledge in one or more areas, but wide (if shallow) knowledge of the whole process, and who are open to trying new approaches. Secondly, the right data platform. Subsurface data certainly meets the Big Data definition of volume, velocity, variety, and veracity. Performing analytics on deep and wide datasets requires thinking about parallelism and performance – while also thinking about storage costs. Ensuring that analytics projects provide measurable business value requires us to take an agile approach to project management, and to repeatedly check the business alignment to ensure that the analytical results we are delivering are in some way actionable. Companies do not make or save money by running analytics projects – that only happens when they can take the learnings from the analytics projects and put them to use. In analytics projects, a vast proportion of time is spent on locating and preparing data. The required data may be available only in application databases, only as original files, or spread around various systems. We take an approach we refer to as "good enough data management" when building an analytical data platform, where structure and quality are applied in a justin-time manner to meet the needs of the analytics. We will illustrate these key rules using case studies and anecdotes from past projects in Norway, UK, US, and South East Asia.

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THE RULES OF SUBSURFACE ANALYTICS

Jane McConnell, Teradata Duncan Irving, Teradata



Agenda

- Subsurface analytics is different
- The Rules
 - Rule 1: Right People
 - Rule 2: Right Platform
 - Rule 3: "Good Enough" Data Management
 - Rule 4: Agile Approach
 - Rule 5: Business Buy-in
- Recap



SUBSURFACE ANALYTICS IS DIFFERENT



Advancing the World of Petroleum Geosciences. When it all started for business analytics







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Figure 5. Leo Level set on business intelligence

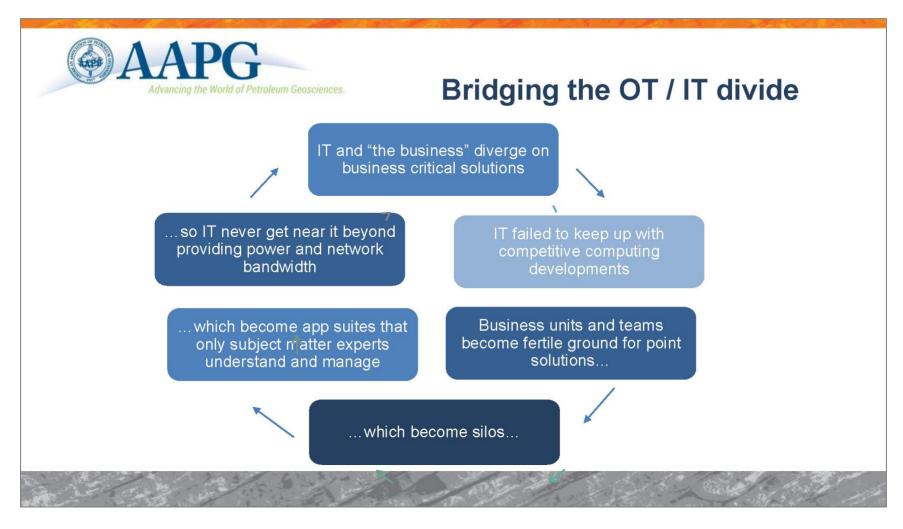


Figure 6. A lot has been written about the IT/OT divide over the last few years – mainly by Gartner... The normal examples given are SCADA systems, historians, PLCs – the technology of factories and of production operations. We have similar specialist technologies in subsurface too. Think about seismic processing, about interpretation suites like OpenWorks or Petrel.

When we want to start doing analytics on this data – we need to start bridging the divide - which means training IT on what we have been doing for the last decade or two, so that they can start helping us with what they know – business intelligence, analytics and machine learning, and the data platform.



How we manage our data

Custodian

- Controls access
- Avoids unknown data
- > Transfer data
- Avoids risk
- Hates change
- Acquires knowledge
- Creates walls

Curator

- Shares data
- Celebrates variety
- Enables access
- > Embraces risk
- > Owns change
- > Shares insights
- Teaches governance

Figure 7. A lot has been written about the IT/OT divide over the last few years – mainly by Gartner... The normal examples given are SCADA systems, historians, PLCs – the technology of factories and of production operations. We have similar specialist technologies in subsurface too. Think about seismic processing, about interpretation suites like OpenWorks or Petrel.

VS

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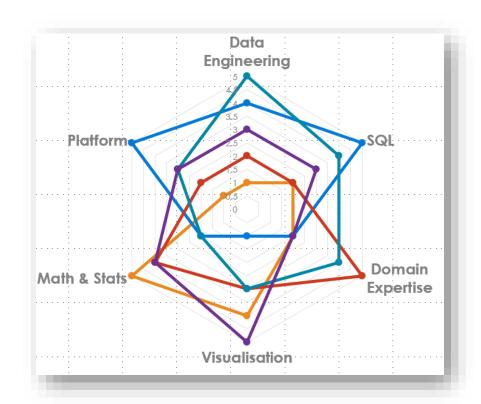


RULE 1: RIGHT PEOPLE



Right People, plural. And T-shaped.

- Too many disciplines for any one person to know it all
- "T-shaped people" who go wide across many disciplines but deep into their specific domain
- Need outstanding data management and data engineering skills (and culture)
- Need platform expertise for sustainability and deployment
- Need Subject Matter Expertise





Analytics / data science workflow





How we are working with a Norwegian operator

- Working as one team, hand-inhand with the customer
 - Subject matter expertise
 - Source system expertise
 - Data management skills
 - Data platform skills
 - Coding skills
 - Data science skills
 - Frontend/visualisation skills





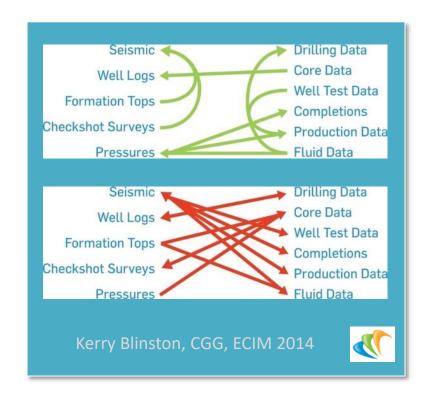
RULE 2: RIGHT PLATFORM



The problems with existing data stores

- "Knowledge development" applications come with import filters for specific file types and specific tasks
- Data is modelled logically for well-defined (and hence brittle) processes that may not reflect all (or even any!) use cases
- Only "perfect" data can be imported into applications or schemas

New data types, or new combinations, don't work very well in this old world





Build a new platform that all disciplines can use

- If we don't provide a platform for analytics, we will be in Desktop/Excel Hell.
- Build a platform that
 - Accepts data from any discipline
 - Makes it easy for data scientists to use their tools – R, Python etc
 - Provides the right level of governance and data quality
 - Provides parallelism and scale





Hidden Technical Debt in Machine Learning Systems

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Abstract

Machine learning offers a fantastically powerful toolkit for building useful complex prediction systems quickly. This paper argues it is dangerous to think of these quick wins as coming for free. Using the software engineering framework of technical debt, we find it is common to incur massive ongoing maintenance costs in real-world ML systems. We explore several ML-specific risk factors to account for in system design. These include boundary erosion, entanglement, hidden feedback loops, undeclared consumers, data dependencies, configuration



Figure 1: Only a small fraction of real-world ML systems is composed of the ML code, as shown by the small black box in the middle. The required surrounding infrastructure is vast and complex.

Static Analysis of Data Dependencies. In traditional code, compilers and build systems perform static analysis of dependency graphs. Tools for static analysis of data dependencies are far less common, but are essential for error checking, tracking down consumers, and enforcing migration and updates. One such tool is the automated feature management system described in [12], which enables data sources and features to be annotated. Automated checks can then be run to ensure that all dependencies have the appropriate annotations, and dependency trees can be fully resolved. This kind of tooling can make migration and deletion much safer in practice.



What a Machine Learning system

Hidden Technical Debt in Machine Learning Systems

really looks like



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RULE 3: "GOOD ENOUGH" DATA MANAGEMENT



"Good Enough" Data Management

- Curators mentor and support "citizen data management"
- Everyone cares about the data and its quality
- Everyone can do something about it when they find bad data
- Data governance is a function of data value

"Good Enough" means:

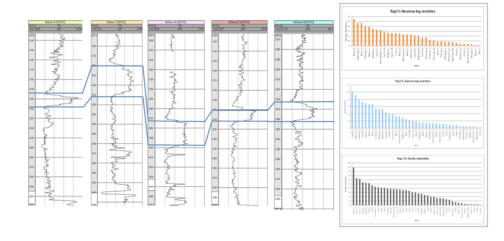
- Good: don't compromise on quality
- Enough: don't boil the ocean



"Difficult file formats" (Multi-structured data)

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- Historically, we've stripped all the context away from each measure and observation for the sake of more storage
- Parse out the measurement data
- Link it through time and space
- Relate using metadata and master data
- Pause until you know how you want to access it





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Text

- Language
- > Typos
- Consistency
- Quality

Use simple characterisation tools to understand what is in the data

Don't try to build a whole text input and cleansing framework, if you don't need it

Dealing with unstructured data

3203	recalibration	13
3204	receiver	8
6895	receiving	9
1273	recheck	7
6896	rechecked	9
6897	rechecks	8
6898	recleaning	10
3192	re-cleaning	11
6899	recomissioned	13
3206	recomissioning	14
3207	recommended	11
6900	recommission	12
3208	recommissioned	14
6901	recommissioning	15
6902	recorded	8
6903	recover	7
3210	recovery	8
227	rectification	13
3212	rectified	9
3213	rectify	7
6906	rectifying	10
3216	redivert	8
6907	reduce	6
3217	reduced	7
6910	reducer	7
3218	reducing	8
3219	reduction	9
3220	reenergise	10
3221	reenergised	11
3222	reestablished	13



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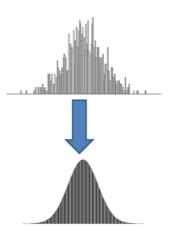
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	3204	receiver	8
	6895	receiving	9
	1273	recheck	7
	6896	rechecked	9
	6897	rechecks	8
	6898	recleaning	10
	3192	re-cleaning	11
	6899	recomissioned	13
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	6910	reducer	7
	3218	reducing	8
	3219	reduction	9
	3220	reenergise	10
	3221	reenergised	11
	3222	reestablished	13



Profiling data

- Storage is cheap
 - But still, sometimes we have a LOT of data with very low information density – eg passive seismic
- If the data is still to large to handle then profile and decimate (it's better than never using it!)

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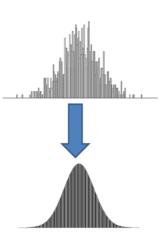


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967	4/3/2014	16:43:43	1478	1512	1507	1486	1501	1422	226	350	366	344	325	293	1588	13	90	0	30.4	2179	63	9.2	NA.	48	13.8	187	102.0	NA	137	5673	MS0.45.54	E010.04.71
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574	4/3/2014	16 49:25	1478	1505	1507	1406	1501	1428	329	350	368	344	328	293	1586	13	79	0	30.4	2178	43	10	NA.	40	13.8	187	152.2	NA -	137	5663	NSQ 44.04	E010.02.31
575	4/3/2014	10:49:31	1478	1505	1507	1456	1501	1426	329	350	355	344	328	293	1588	12	79	0	30.4	2178	63	9.0	NA.	46	138	187	102.2	NA .	137	5061	NS0 44.84	E010.02.31
576	4/3/2014	16:49:37	1478	1506	1507	1406	1501	1422	329	350	365	344	328	290	1582	13	85	0	30.6	2178	63	9.0	NA.	40	13.8	187	100.2	NA	137	5659	7450.44.60	E010.01.71
577	4/0/2014	16.49.43	1476	1505	1507	1406	1501	1422	329	350	358	344	328	292	1582	13	85	0	30.6	2170	63	10	NA.	40	138	167	102.2	NA.	537	5050	NS0 44.50	E010.01.71





RULE 4: AGILE APPROACH



Agile, Scrum, DevOps, AnalyticOps, Interactive Visualisation





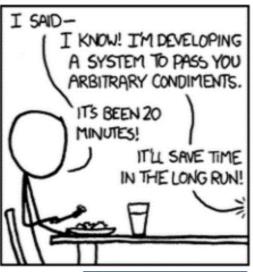
What not to do

Common resource-sinks:

- Point solutions
- Technology projects
- Waterfalls
- Brittle data modelling
- > ML/AI-driven project







© xkcd.com



Iterate.
One project at a time.
Deliver value often.

Review

Create concise business story
Highlight overall business impact
Include assumptions and sources
Follow up with business on the
actions

Prepare

Contextualise and plan
Form problem statement
Prioritise by impact
Communicate analysis plan and responsibilities

Execute

Build on prior work
Validate data
Recheck hypotheses
Drive insights and
recommendations

Assimilate

Store well-commented SQL Document in wiki Train BU in tool usage

Document

Post code to repository Stakeholder contacts Final presentations



Agility needs the right mindset



- > Working together
- Willing to take risks
- > Proactive
- Speed / Time-to-insight



RULE 5: BUSINESS BUY-IN



You Still Need a Business Question!

"We created an Analytics COE. We hired some data scientists. We installed Hadoop. We're ready to Machine Learn something now.

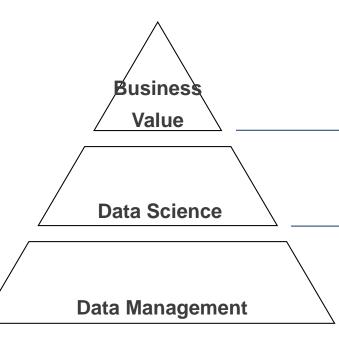
Do you have any use cases?"



https://imgs.xkcd.com/comics/machine_learning.png



Business-aligned data science



- What financial, operational or environmental impact are you delivering?
- What is the ACTION that you can take?
- What techniques, functions, workflows and skills are required?

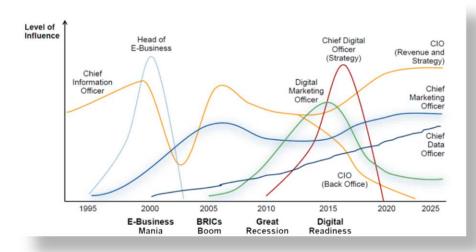
- What data is required and in what form?
- Do we even have the needed data?



Embed data ownership in the business units

- Engage with business leadership to plan, budget and deliver data-driven initiatives
- Define and drive data exploitation strategy
- Understand data value and leverage high value data for business impact

Business-focused data management



Source: Andrew White, Gartner 2017

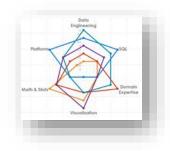
...do we need a **Chief Data Officer?**



IN SUMMARY

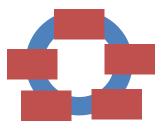


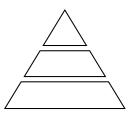
The Rules











Right People

Right Platform

Good Enough Data Management

Agile Approach

Business Buy-in



Data Management 2.0

Stop doing

- Brittle data management
- Silos
- Disposable data science
- Transfer and analysis in Excel

Keep doing

- Applying domain expertise
- High levels of governance
- Driving data quality
- Learning

Start doing

- Aligning with business
- Applying context
- Data profiling
- Enriching data
- Applying critical thinking



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