Rock Physics At-Scale, enabled by Big Data Analytics & Machine Learning

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Introduction

Today, technologies such as cloud computing, machine learning or big data are becoming mature and can now be applied on field such as rock physics to provide an end-to-end solution to integrate the voluminous information contained from various sources such as seismic, reports and well logs in an unprecedented scale.

The paper attempts to present the workflow applied to deliver an At-Scale Rock Physics Analytics hosted on the cloud providing a transversal platform for geophysicist, geologist and petrophysicist to collaborate on multi-basin scale. The workflow applied includes 1) Data mining of different sources and format 2) Machine-driven Petrophysics and Rock Physics 3) Visualisation on an interactive collaborative platform

Data Mining

Traditionally Rock Physics studies are conducted on a well-by-well basis and often on a per-block scale. Data mining allows to work on a far bigger scale with a lot more data, which are far more diverse. In this case, the numbers of wells were above 150 and the total number of files to be processed as seen on Figure 1 are on the magnitude of tens of thousands. There are 4,500 las and dlis files alone, which contained over 60,000 log curves, and geological reports with more than 200,000 pages of unstructured geoscience which are sources of relevant petrophysical parameters such as temperature, pressure, salinity, etc.

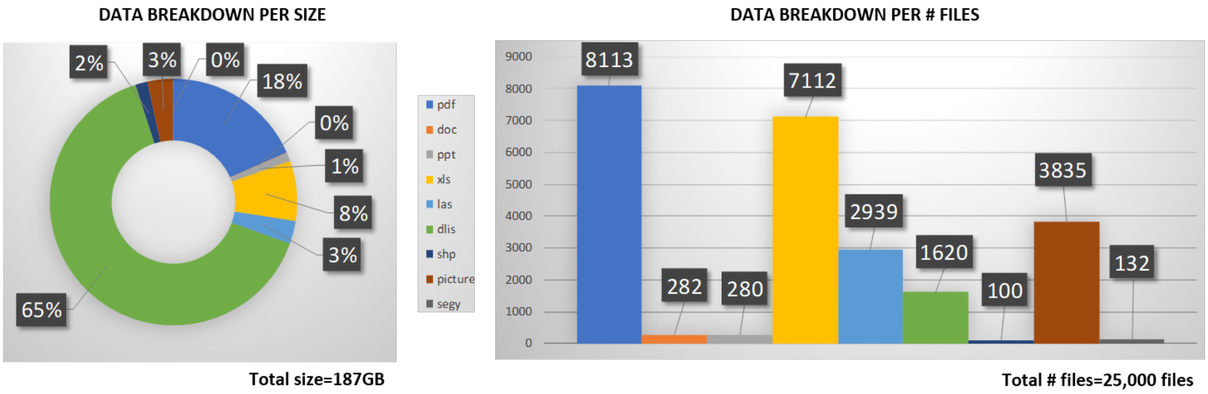

Figure 1 *Breakdown of total number files processed during rock physics data mining and the breakdown per file type. Multi-format input data includes over 4,500 las and dlis, over 60,000 log curves and more than 200,000 pages of unstructured data*

Machine Driven Petrophysics and Rock Physics

Once available on the datalake, given the amount of data to be processed, the different steps including data audit, editing of curves, splicing of logs and predicting of petrophysical properties (Por,Vsh,Sw) are assisted by machine to automate the repetitive tasks. Quality controls are performed at each individual steps using clustering techniques to spot similarities, and anomaly detection tools to identify potential outliers.

As soon as complete set of petrophysical properties are available, standard rock physics model are performed to describe the elastic behaviour of rocks in response to fluid and mineral changes. The access of information to be used for the rock physics model is highly facilitated through access of a dynamic search engine (ie. ElasticDocs) containing all well reports for the basin, allowing quick search over parameters to be inputted in the Rock Physics model.

Big Data Analytics and Visualization

With the ability to visualize huge amount of well data, we are able to formulate very early in the project, a top-down rock physics analysis strategy. This process includes defining wells in priority areas with the largest interval coverage, most complete set of data, and identifying various “type well” behaviours, both for prospective wells, dry wells, and wells with borehole problems. Very early on, it is possible to observe the elastic property behaviours across depths, and anticipate where impedance contrasts are likely to be expected.

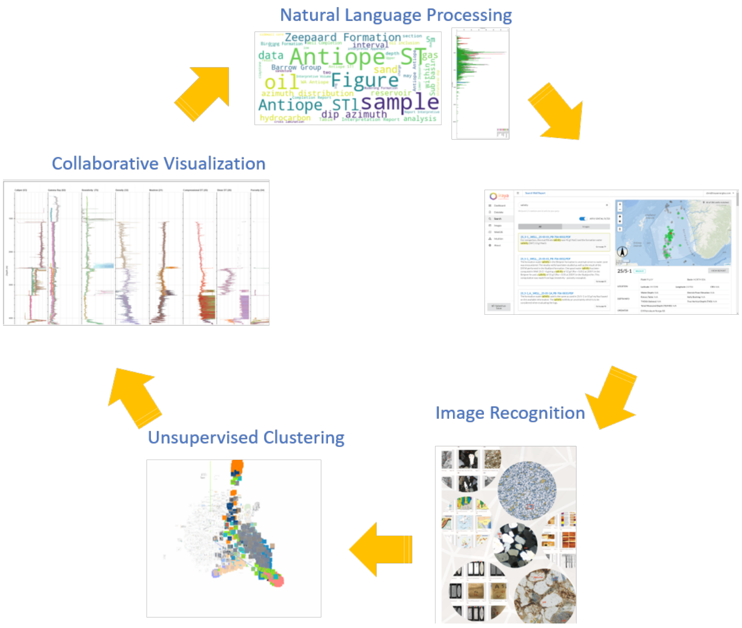

Figure 2 *Multi-format unstructured data supporting Rock Physics analysis at-scale*

Another benefit of this At-Scale Rock Physics processing is that it enables higher level of confidence on parameter selection. Clay volume cut-offs, end member definitions, and depth trends for rock physics model building are more easily picked and validated by the huge volume of data available.

All input and processed data are available in an interactive knowledge platform, to allow user to seamslessly interact with the data, and experiment some what-if scenarios.

Conclusion

As a conclusion, working on an At-Scale Rock Physics over multi-basins is ambitious but has many benefits. Primarily, it allows for a geologically-constrained Rock Physics models that are supported by huge amount of data, as opposed to a limited block-by-block approach where data is sparse. The efficiency in implementation of this workflow is made possible by injecting automation and machine learning techniques throughout the process. In addition, having a collaborative ecosystem and platform that is accessible by multiple users in the organization allows for knowledge to be captured by the organization, and reused as new data for new processes in the E&P workflow.

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Why people matter in a successful digitalisation strategy

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Introduction

In this paper we investigate the factors that drive success in digitalization, and why this strategy is primarily driven by people, for people.

Aside of the perceived technological benefits brought about by developments in Artificial Intelligence, Big Data, or Cloud Computing, organizations face new challenges when implementing digitalization efforts. Different stakeholders evaluate digitalization thru multi-colored lenses – executives look at costs and results, senior domain experts look for reliability, middle management look at resource availability, and young professionals look at novelty.

To be successful, it is necessary for the digitalization effort to look across and meet the various business, technical, and cultural needs of the stakeholders within the organization. To identify digitalization projects that bring the most value, we should ask three main questions: 1) the desirability: what do people want, and need? 2) the feasibility: what can the people do? 3) the viability: how can people succeed?

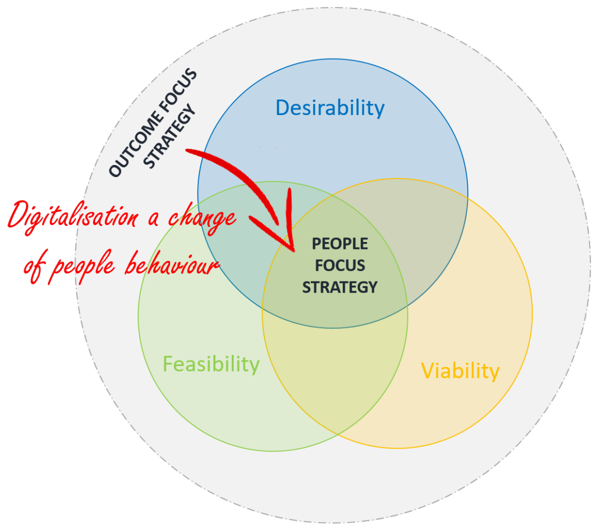

Figure 1 *A people-focused strategy intersecting desirability, feasibility and viability of digitalization projects within the organization*

Methodology

The technical possibilities for digitalization in oil & gas industry are clearly exciting, the technical options are almost endless, hence, it becomes important to look at the organization's hierarchy of needs with regards to new technology adoption.

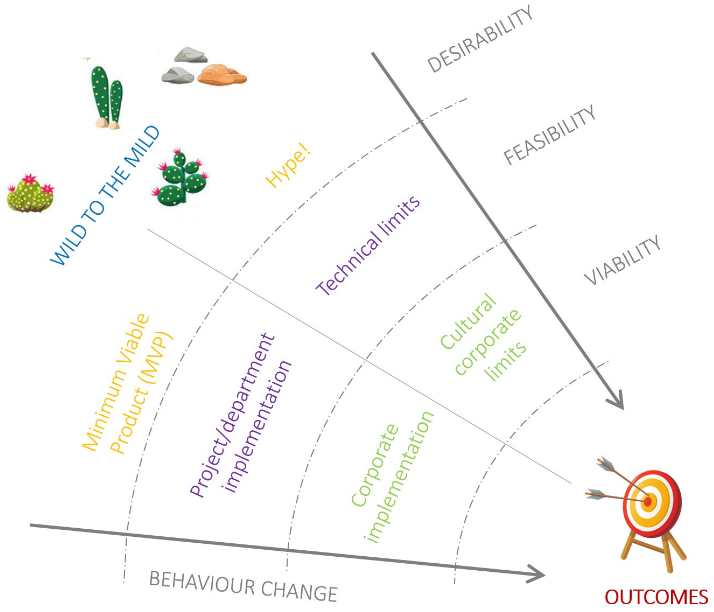

Figure 2 *Road map for a successful digital implementation. Timelines from ideation to tangible outcomes vary based on technical and cultural factors.*

A natural start place to start is with brainstorming digitalization ideas, from the “wild to the mild”, where anything is possible. This Stage 1 is typically very informal. They may be facilitated or observed through hackathons. Even a simple team discussion can be a design thinking exercise.

From brainstorming, there are typically ‘proof-of-concepts” labs, where experimentations are highly frequent, and necessary. The goal in this stage 2, is to go beyond the hype of the technology, test desireability and functionality with the main users. Then, Minimum Viable Products (MVPs) are assessed, to see if they address the desire of the stakeholders. Multiple pivots are done if needed. Experiments are performed either on individual level or the team level. From the peak of inflated expectations that is typical in Stage 1, in Stage 2 we experience the so-called *Trough of Disillusionment* and then quite fortunately, start to move towards that coveted road towards technology enlightenment.

Once successful, the MVP moves onto a project, or department-based implemementation, allowing the technical limits to be fully-tested, particularly with regards to scaleability and production-readiness of the solution. Here, in Stage 3, domain-expertise and engineering go hand-in-hand in identifying the best configurations for the technology for further corporate implementation.

At the corporation level, it is recognized that technology implementation often goes with seismic cultural shifts, since traditional paradigms of domain expertise ownership, data access, and organizational silos are most likely going to be disrupted by big data connectivity, which are inherent in these digitalization efforts.

Results

In this paper, we share our observations, pitfalls, and lessons learned based on our experiences on the first three stages of digitalization process.

Problem Forming vs Problem Solving

As geoscientists faced with subsurface problems, we are easily tempted to roll our sleeves and attack the problems with the best algorithms available, and get to work. In our digitalization exercise, we find that that properly forming or framing the problem from the onset, is even more critical than solving the problem *pronto*. During this problem forming step, we take a moment to ask– i.e is this problem a pain point across my subsurface team (s)? Do we have the right data, does the solution already exists thru standard softwares? How much incremental value do I expect? Based on the answers to these questions, we are able to sift thru between disruptive innovation ideas, and incremental innovation. This allows us to rank digitalization opportunities, and allocate valueable human and compute resources to those ideas which truly bring disruptive value, and at the same time, harvest early from low-hanging digital fruits.

Safe-to-Fail vs Fail-Safe Environment

The oil and gas industry for strong reason, is a very risk-adverse industry. As such, reliability of technical results is ensured by implementing strict stage-gate processes. This works very well when desired outcomes and processes behind it are are already clearly established.

In a new digitalization efforts, however, proposed technologies are very new. In perspective, Tensorflow is just over three years old, more open-source algorithms are becoming released daily, and yes, some of them, can be buggy. As such, standards do not necessarily exist, and sequential stage-gate processes do not necessarily work.

What many organizations find is that it is necessary to introduce a digitalization lab within operational team, where significant flexibility and experimentation is allowed into digitalization process, within a constrained, safe-to-fail/ fail-fast environment, while at the same time, the right technological tools are provided to achieve desired moonshot results.

A purely experimental team, however, can be costly for an organization to maintain and may not necessarily be aligned for operational implementation. The digitalization objective therefore, includes research, development, *AND* production. As such it is also important that team is of the right bite-size, right composition, with the right timelines to evaluate technical results and empowered to pivot and reposition for success.

Sustained vs Dilettante Transformation

We all heard about the story of a powerful AI team who forgot to call the domain expert (geoscientist), and six months or one year down the line, unable to deploy because there was no proper mode of distribution or visualization for the individual Jupyter notebooks.

Transformative ideas must be transformed into codes, and codes must be fed with data, data must be cleaned, cleaned data must have databases, databases must have interfaces, transformed into deployable sotwares, and deployable softwares must be maintained.

Rather than a one-day exercise, a successful digitalization strategy requires sustained efforts to go through across this full pipeline, and commitment from the organization to allocate of human and technology resources to achieve successful corporate-wide adoption.

The Digital Geoscientist

While there has been much debate over technology taking over human functions, we believe that technology should be enabling humans make better, evidenced-based decisions from the extremely Big Data that our industry grapples with. Undoubtably, machines can deal with repetitive tasks, complex data, identify trends, cluster anomalies, but the cognitive responsibility of creating hypotheses, explaining the "why's" and the "why nots" remain with geoscientists who create and utilize these technologies.

In the process of testing and implementing ElasticDocs, the AI-enabled tool as use-case for our unstructured subsurface data analysis, our goal was not simply to utilize automated blackboxes but to have available explainable machine learning models and transparent visualization platform that the digital geoscientist is comfortable to use, to break and to push to its limits- a clear case of the domain experts taking control in driving and pushing technology forward for its own benefits, within an operational environment.

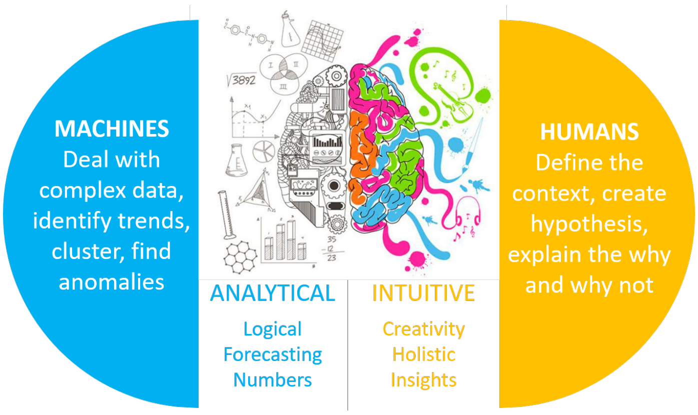

Figure 3 *Combining complementary strength of machines (analytics) and humans (cognitive) in digitalization*

Conclusion

As a conclusion, digital transformation is a complex process that requires rigorous technical analysis combined with organizations' culture of flexibility and openess to innovation. By focusing on the human drivers within the context of desirability, feasibility and viability, it is possible to accelerate digital adoption and achieve tangible outcomes aligned to the needs of the organization.

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