Digital Oil and Gas

Volume III
Machine Learning

Run Simple

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Machine Learning

Commodity prices remain low and are not expected to dramatically increase

Oil and gas organizations must sustainably reduce cost structures

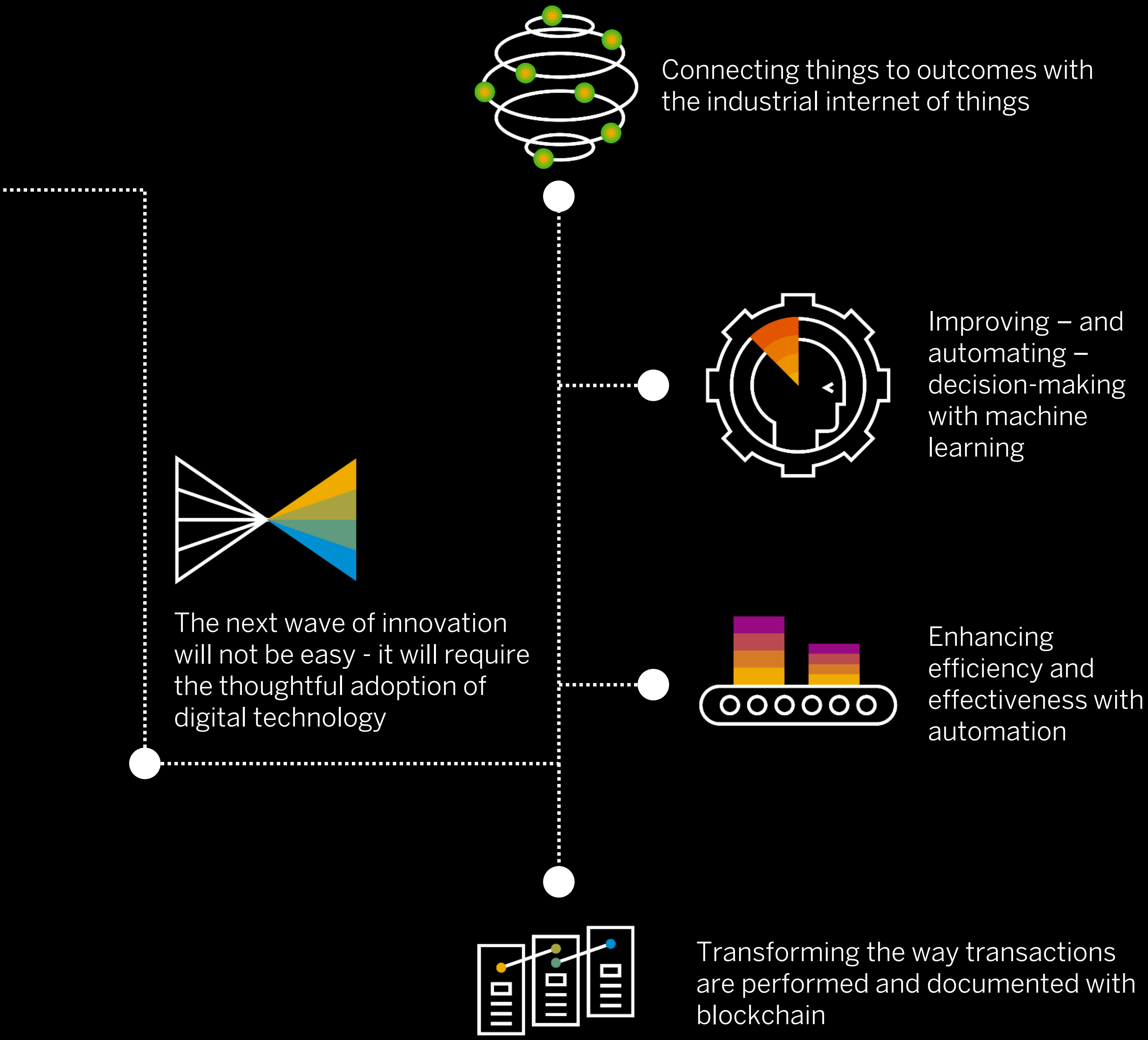
The industry is facing disruption from multiple sources – regulation, alternative energy, global demographics and more

The industry has already extracted as much value as possible from three main areas of cost

1 Reducing organizational headcount

2 Increasing pressure on supplier pricing

3 Redesigning processes for incremental efficiencies


Connecting things to outcomes with the industrial internet of things
Improving – and automating – decision-making with machine learning
The next wave of innovation will not be easy - it will require the thoughtful adoption of digital technology
Enhancing efficiency and effectiveness with automation
Transforming the way transactions are performed and documented with blockchain

Machine learning is blurring the line between computer programming and human decision-making

Machine learning is a field of study that gives computers the ability to improve their own performance on a task without being explicitly told how to do so by a human. This allows a machine to mimic complex decision-making using mathematical functions. Machine learning is sub-field of artificial intelligence, and refers to the use of algorithms to achieve human-like behaviours[1].

In traditional programs, a developer provides specific instructions and rules for a computer to carry out on a provided set of data. In machine learning programs, the developer creates a model and provides it with historical data. The model uses the historical data to predict future outcomes, assesses the accuracy of its predictions, and adjusts its calculations accordingly without human intervention. In addition, machine learning can consume data in unstructured formats such as pictures or conversational sentences. It does not require data to be neatly structured into tables.

There are two kinds of machine learning:

1. **Supervised learning** is when data provided to the model includes both inputs and outputs. The model must identify the relationship between them. For example, a model could identify the relationship between the temperature, pressure and volume of steam injected into a SAGD well and that well's production levels
2. **Unsupervised learning** is when the data provided to the model is a set of inputs, and the machine identifies different 'clusters' or classifications within that data. For example, a model could be given a set of well characteristics and classify them itself according to potential for production

Advancements in several areas of technology make this complex process feasible today:

- Modern technology generates significantly more structured and unstructured data
- The increased volume of data can be stored and accessed by powerful real-time databases
- Data can be interpreted more effectively by the increased processing power of graphical processing units and advancements in algorithms in deep neural networks

Traditional Programming	Machine Learning
• Based on rules specified by a human programmer • Requires exact parameters for all conditions • Consumes only structured data • Performance on a given task is standard • No training set of data required • Focused on analysis of past data	• Based on functions originally written by a human programmer • Uses fuzzy logic to approximate decision-making • Consumes structured and unstructured data • Performance on a given task improves over time • Training set of data required • Focused on making predictions with new data

Figure 1 – Comparing Traditional Programming and Machine Learning

Machine learning will automate knowledge work similar to how robotics is automating manual work

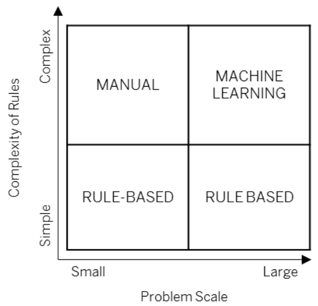


Figure 2 – Identifying Appropriate Machine Learning Problems[1]

Not all problems can or should be solved by machine learning. Instead, organizations will be best served by identifying large-scale problems with complex rules that historically have required humans to address them. The value of machine learning is in finding ways to automate knowledge work that cannot be addressed by traditional computer programming. Knowledge work is typically complex - it requires an understanding of multiple factors under different conditions, all which can influence decision-making depending on their interactions. This type of work is typically more expensive and error-prone, as it requires significant human resources to interpret information and make decisions. Using machine learning, decision-making rules can be codified, executed, evaluated and improved in a repeatable manner. It combines the complex decision-making that humans bring to unique scenarios with the tireless rigour of computer-driven analysis.

The key outcome of effectively applying machine learning to oil and gas business challenges is an overall improvement in profitability. Machine learning will be a critical factor in tying the data collected via the Industrial Internet of Things (IIoT) into automation, so that individual decision points can be automatically addressed by algorithms, instead of human agents. Similar to how automation removes or reduces the human element from action, machine learning removes the human element from decision-making. This will help move from things to outcomes in a more seamless, accurate and cost-effective manner.

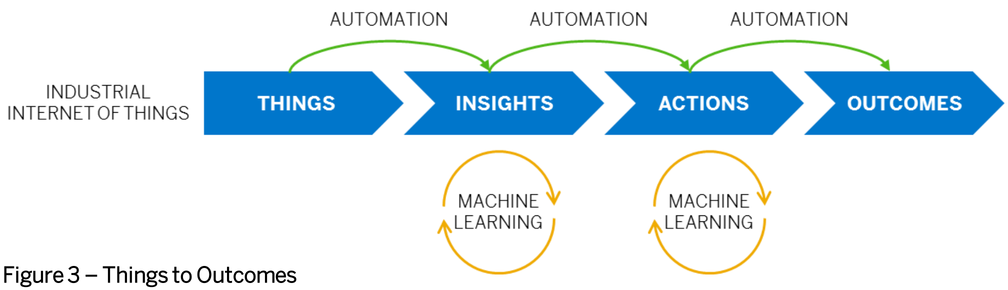


Figure 3 – Things to Outcomes

Machine learning will support lower cost structures across the oil and gas value chain

With benchmark oil prices under pressure and a relatively flat forward curve (as of March 2017[2]), every organization in the industry is compelled to find ways to sustainably reduce their cost structures. Every day, the oil and gas industry makes complex operational decisions related to where to explore and produce hydrocarbons, how to operate assets efficiently, and how to take refined products to the market in a profitable manner. A multitude of factors must be considered at each stage of the hydrocarbon value chain, and historically this complexity could only be managed by humans consuming information and making decisions based on a combination of data and intuition. Now, with the advent of machine learning, it is possible to automate that decision-making process to increase accuracy and decrease associated costs.

Here are seven challenges across the hydrocarbon value chain where machine learning will have an impact:

1. Determining where to drill and what method to use to optimize time, cost and production
2. Optimizing in situ and mining production in oil sands to maximize production and minimize downtime
3. Monitoring and predicting potential safety risks
4. Forecasting pipeline capacity to optimize operations and revenue
5. Monitoring and predicting failure of pipeline integrity
6. Optimizing refinery operations to maximize throughput and minimize downturn
7. Demand modelling for retail centres to optimize distribution and revenue

Applying machine learning will improve organizational profitability and safety

Machine learning will deliver better, faster decision-making across the enterprise, which ultimately enhances revenue and decreases operational costs while enhancing safety and security

BETTER, FASTER DECISION-MAKING

INCREASED REVENUE	DECREASED COSTS	ENHANCED SAFETY & SECURITY
Optimizing exploration, production and refining output • Recommend exploration locations based on historical data • Recommend adjustments to production and refine equipment settings to finer detail and with greater accuracy Reduced downtime • Monitor and predict equipment failure and recommend maintenance/replacement strategies Optimized revenue generation • Recognize patterns in supply and demand for pipeline utilization or retail centres • Provide recommendations for optimal distribution	Reduced number of errors • Reduce human error in operations tasks using accurate, self-improving modelling Reduced human involvement • Require fewer resources to monitor and complete tasks	Reduced human exposure to unfavourable environments • Teach automated vehicles to monitor remote or dangerous locations using computer vision Enhanced site security • Use computer vision to predict potential security threats Increased equipment safety • Improve consistency, coverage and accuracy of equipment integrity monitoring

Figure 4 – The Value of Machine Learning

Machine learning can help organizations determine where and how to drill and develop wells

OPTIMIZING FIELD DEVELOPMENT EXECUTION FOR UNCONVENTIONAL ASSETS

BUSINESS CHALLENGE

Exploration and production (E&P) organizations develop wells based on incomplete data and intuitive decisions; the number of factors to consider makes algorithmic decision-making seem impossible

It can take more than six months to connect feedback from production data to well design, leading to lost production, lost time and additional costs from continuing suboptimal development execution

SOLUTION DESCRIPTION

- An E&P organization develops an initial model for well productivity and decline curve
- The organization gathers information from the exploratory wells drilled in the area to provide inputs (location, drilling program, completion design) and outputs (well production, decline curve) for the formation's training set data
- Training set data is captured during drilling, completion and initial production of exploratory wells with the help of sensors
- Training set data is used by the model to test and improve its predictions and calculations for future production and decline curves for development wells
- The model recommends adjustments to location, drilling program and completion design for the next cycle

POTENTIAL VALUE

- Reduced cost of exploration
- Increased agility of production decisions

Machine learning can optimize injection and minimize steam breakthrough for in-situ production

REAL-TIME IN-SITU STEAM OPTIMIZATION

BUSINESS CHALLENGE

In-situ production of Canadian oil sands requires the efficient operation of paired wells

Engineers must closely monitor critical metrics (such as the steam-to-oil ratio surfacing) to optimize steam usage and oil production to ensure that steam from the injector does not reach the producing line

SOLUTION DESCRIPTION

- A machine learning model is created to monitor formation characteristics, steam injection rates and production statistics
- Inputs and results from prior wells and historical trends within the well pair are used as the training set to solidify the accuracy of the model's prediction
- During production the algorithm receives measurements of the steam-to-oil ratio and compares that output to known inputs for injection rate, formation characteristics, and other key measures
- Results are fed back into the model to improve calculations and make recommendations for optimal inputs
- Steam-to-oil ratio outputs are also used to predict likely steam breakthrough; these predictions will be fed back into the algorithm to improve calculations for optimal inputs

POTENTIAL VALUE

- Optimized production output
- Optimized cost of steam injection
- Minimized steam breakthrough

Machine learning can maximize the utilization and uptime of midstream assets

FORECASTING PIPELINE UTILIZATION

BUSINESS CHALLENGE

Pipeline organizations must balance a vast array of factors when forecasting oil and gas supply and demand throughout their networks[3]

To operate profitably, organizations must optimize infrastructure usage, making sure they are serving customers effectively while managing capital expenditures[4]

SOLUTION DESCRIPTION

- A machine learning model consumes known variables (e.g. production and consumption) across the network, along with unknown variables (e.g. market conditions, potential economic changes, potential throughput, required maintenance and asset age)
- Using past data, machine learning models predict where and when there could be surges in supply or demand, enabling pipeline organizations to adjust inputs and outputs in response
- Machine learning models predict where specific assets are most likely to fail, supporting predictive maintenance, thus minimizing unnecessary maintenance and the associated costs
- Better utilization of the existing infrastructure informs decisions to build or acquire new components, further optimizing the cost structure of pipeline organizations

POTENTIAL VALUE

- Optimized throughput and revenue generation
- Optimized cost of fuel transport and capital expenditures
- Increased predictability of uptime and downtime

Machine learning can be paired with automation to monitor equipment conditions

REMOTE EQUIPMENT MONITORING

BUSINESS CHALLENGE

E&P companies own and operate a significant number of heavy assets, which are typically distributed across geographies or located in remote or unfavourable conditions

Monitoring these assets is accomplished through some control systems, but also requires physical inspections by human agents

SOLUTION DESCRIPTION

- A machine learning model processes unstructured information in the form of videos of assets
- The model is fed data about features associated with healthy, underperforming, or dangerous assets
- The model is paired with a remote vehicle, such as a drone, which can inspect the asset continuously and provide input information
- The model classifies the inputs according to identified features, and consistently improves accuracy as more inspections are complete
- Results are provided to another automated machine or to a human agent for action

POTENTIAL VALUE

- Increased safety
- Increased efficiency and production

Executing machine learning requires a strong foundation along with some specific requirements

To take advantage of machine learning, organizations must have a strong foundation of standardized tools, processes and data, supported by the right competencies, platform and database structures. They also need a clear and effective governance model for each.

MASTER DATA MANAGEMENT	ENTERPRISE DIGITAL CORE	REAL TIME TRANSACTION PLATFORM	REAL TIME ANALYTICAL PLATFORM
Simplified, standardized, complete, and cleansed data; master data governance structure	Single source of enterprise truth for all transactions related to finance, supply chain, logistics, maintenance, and projects	Transactional platform must have the computational power to allow for real time posting and analytics (no batch jobs)	Analytical platform must have the computational power to allow for real time replication of relevant data, with appropriate data tiering
WORKFORCE MANAGEMENT PLATFORM	**STANDARD PROCESSES AND TOOLS**	**ENTERPRISE CLOUD STRATEGY**	**ENTERPRISE INTEGRATION STRATEGY**
Single platform to capture hire to retire processes for both employees and contractors	Standardization across business units allows for scalability of technology solutions, simplifying deployment and maximizing value	A clearly defined cloud strategy helps make deployment decisions easier, avoiding the distraction of having to discuss it for each selected technology	A clear approach to integration can simplify

In addition to the strong foundation, machine learning will require the following[1]:

- A large amount of data that can be used for training set information, complemented by sensors and connected networks that gather new data inputs in real time
- An agile platform that can handle large data volumes and integrate data sources on which to build machine learning models
- Machine learning APIs to support business applications that can access the outputs of the machine learning models
- Business and technical services to support enterprise applications and build on new models

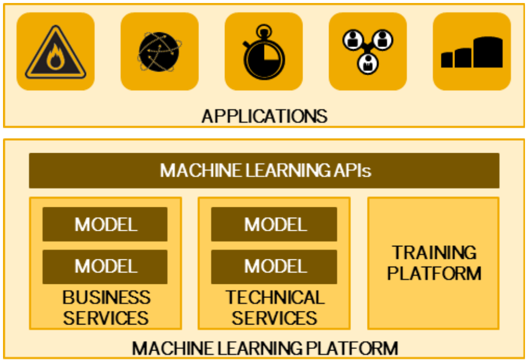


Figure 5 – Enterprise Machine Learning Architecture

WHAT YOU CAN DO NOW

Oil and gas companies can take immediate steps to begin taking advantage of machine learning

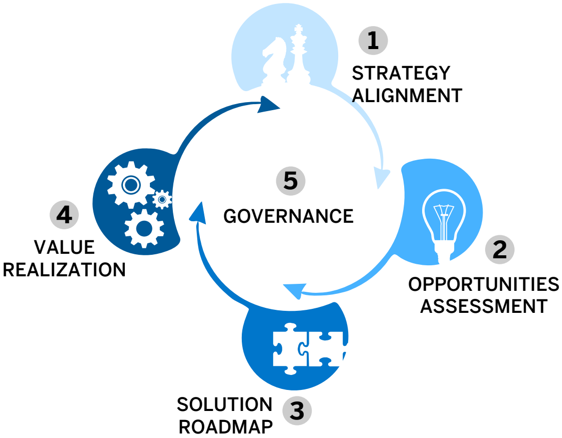


Figure 6 – Technology Transformation Methodology

1. **Strategy Alignment:** Translate corporate priorities and initiatives into technology priorities
2. **Opportunities Assessment:** Explore opportunities based on strategic initiatives and prioritize based on value
3. **Solution Roadmap:** Document end-state solution, qualitative and quantitative benefits, and strategic roadmap
4. **Value Realization:** Measure value delivered through transformation
5. **Governance:** Maximize and accelerate value from investments with governance based on executive engagement, value delivery and continuous innovation

Here's how to get started with machine learning:

1. Challenge assumptions about what can be done by a computer instead of a knowledge worker. The first step is shifting perspective on what is possible
2. Hire the required skill set. Demand for data scientists is increasing across industries, so attracting and retaining the appropriate talent must be a priority[5]
3. Set up a robust, powerful cloud platform. This will allow faster prototyping and testing
4. Ensure data is being captured and stored in an efficient and accessible manner. A significant volume of clean, standardized data is a pre-requisite for a machine learning model
5. Identify the right problems to solve. To warrant investment, a machine learning problem should be large and complex, with patterns that are generally understood but cannot be written down as rules. The right problem will serve as a proof of concept and stepping stone towards enterprise-level machine learning

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Kristen Cornell – Financial Services, Finance, Risk and Compliance

Cathy Tough – Utilities

Ryley Kornelsen – Oil and Gas, Digital HR

Sam Masri
National Vice President
Head of SAP Canada Industry Value Engineering
sam.masri@sap.com

Matthew Smith
Senior Principal, Industry Value Engineering, SAP Canada Inc.
Matt is an experienced advisory professional, focused on helping organizations understand and map out how to leverage technology-enabled business transformation to realize their strategic objectives.

Ryley Kornelsen
Senior Consultant, Industry Value Engineering, SAP Canada Inc.
Ryley is a professional problem solver. She works with organizations to understand and articulate their challenges, and then identify means of addressing them through technology and innovation.