White Paper

The Emergence of Machine Learning in the Manufacturing Industry

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MANUFACTURING AT THE CUSP OF MASSIVE INFORMATION TRANSFORMATION

IDC Research estimates that the investment in digital technologies will generate $18.5 trillion in annual economic value add. This opportunity is causing CEOs across all industries to pivot their strategies around digital transformation. The manufacturing industry is one of the prime beneficiaries with the prospect of capturing nearly $8 trillion of the growth by delivering new customer experiences, driving new efficiencies, and vastly improving asset utilization.

Manufacturing is in the midst of a renaissance. Bolstered by governments -- well aware of both the job creation potential and the importance to economic security -- manufacturers are getting unprecedented support. The impact is already being felt, with indices of activity such as the Purchasing Manager's Index (PMI) at historic highs.

The renaissance isn't just about government support. Far from it. The number of emerging technologies is staggering. 3D printing and other additive technologies will widen the aperture on the number of products, or perhaps we should say experiences, that manufacturers can offer. Additive manufacturing is further bolstered by new materials that can be formulated at the molecular level. Rapid advances in robotics, both in the factory and the warehouse, are driving new levels of operational productivity. And the ability to put assets under surveillance with networked sensors promises to raise the effectiveness of those assets.

The technology that is most critical in pulling this advancement together is machine learning. The complexity of managing a vastly increased set products and services, the huge amounts of data from sensors to process, and the ability to adjust process automation quickly surpasses the ability of human-centric decision making. Machine learning models will become the central mechanism to tie it all together and realize the rewards of the digital economy.

Current State of Transformation

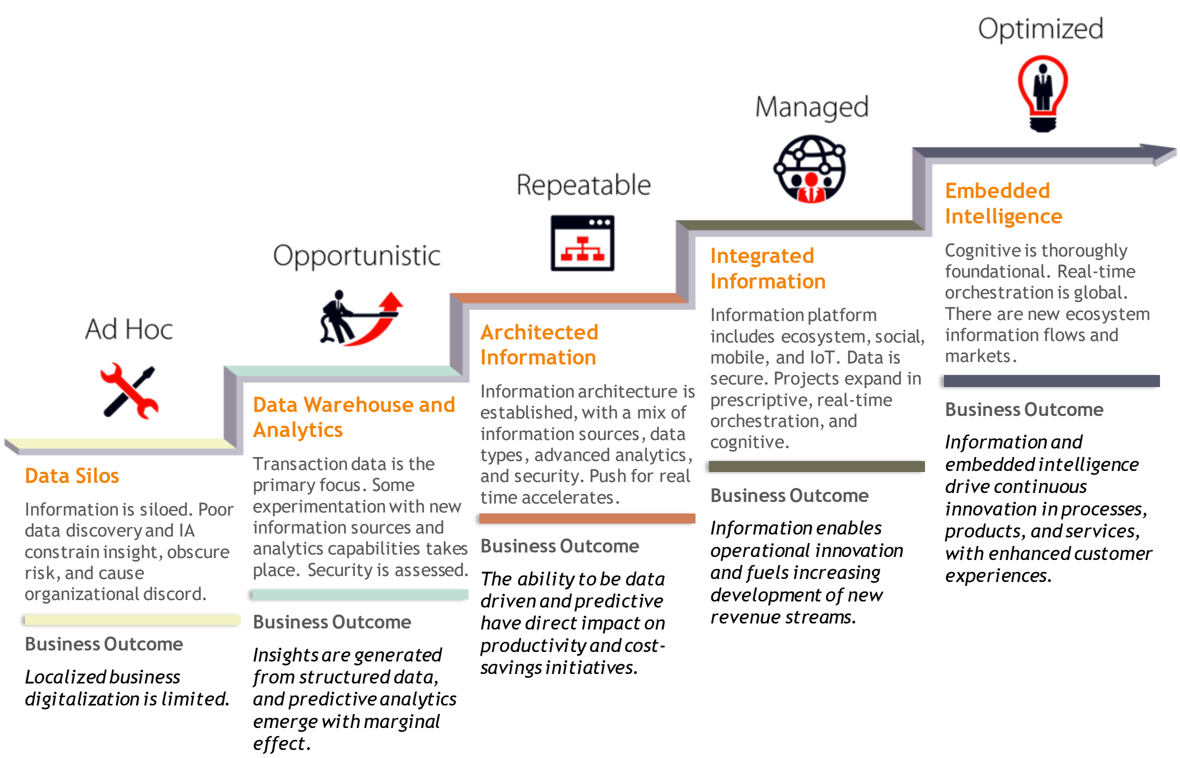
IDC developed a multi-tiered model to evaluate the relative maturity of companies in their digital transformation (see Figure 1). Benchmark surveys were first fielded in late 2015 with a subsequent update in the summer of 2017. What the overall results show is that, while there has been some progress, 59% of all companies remain stuck at either stage 2 or 3. These findings include over 1,600 responses across all industries and regions. The results for the manufacturing industry were very consistent with the overall analysis.

The model itself is made up of five pillars including leadership, omni-experience, operating model, worksourcing, and information transformation. IDC has drilled deeper into this last topic as it relates to manufacturing as companies have identified this pillar as critical to breaking the deadlock and accelerating overall digital transformation progress.

Information transformation basically enables manufacturers to convert data into digital capital and use information as an asset. Essentially, manufacturers of all sizes and types must change how they apply information and analytics to their products, services, and processes. We can think of information transformation as the ability to "sense, analyze, and apply" information to help achieve key business objectives. Incorporating or "sensing" new data sources (IoT sensor data, weather and traffic feeds, customer sentiment) and "analyzing" that data with new types of analytics are important steps forward. "Applying" the data and analytics are also part of the journey for manufacturers as they move toward "integrated information" and "embedded intelligence" -- the most advanced stages of information transformation.

FIGURE 1

IDC Information Transformation in Manufacturing Maturity Model



Source: IDC, 2018

The two advanced stages can be summarized this way:

- Integrated Information: In this stage, manufacturers have brought together information sources with a concerted effort to include ecosystem, online, and IoT data to make the data more meaningful. They're also applying new types of analytics to enable better business decisions faster. Business decisions depend on access to and analysis of these essential data sources not just for executives in the C-suite but across many business roles; in design and engineering, in sales and marketing, in the supply chain, and even in the plant. Information and intelligence (analyzed information) enable more innovation in operations and the development of new revenue streams from products and data-enabled services.
- Embedded Intelligence: At this point, manufacturers are routinely applying information from many sources and in multiple forms, and basically, it's woven into their processes and products on a daily basis. Manufacturers that have advanced to this stage are also most likely using advanced visualization capabilities, machine learning, and predictive or prescriptive analytics routinely. They effectively increase the value of their data, whether through monetizing data or supporting business efficiency and generating opportunities throughout their ecosystems. Information and intelligence (analyzed information) enable innovation in operations and the development of new revenue streams from products and data-enabled services.

Learning to Innovate by Innovating through Learning

One of the most respected innovators from the manufacturing industry in the old economy was 3M Corporation. 3M was famous for making a distinction between invention and innovation. The company felt that invention was the big sudden idea — the epiphany, the proverbial light bulb going off over one's head. Innovation on the other hand was the result of learning — the ability to see the patterns in past activity and continuously improve. 3M asserts, quite correctly, that sustained success comes from innovation through learning.

Given the increased complexity that comes from offering a wider range of experiences, the availability of new vast stores of data, and the pressure to move ever faster, the learning required for innovation must be automated. Through the construction of analytic models like digital twins, manufacturers can establish sustained innovation. This situation is why there is tremendous interest in machine learning as the technical approach to achieve this goal.

What do you Mean by Machine Learning?

As with any popular technology trend, the vendors and trade press has convoluted the meaning of machine learning, artificial intelligence, cognitive, et al. Table 1 provides some definitional context for these terms from IDC efforts to establish a standard taxonomy.

TABLE 1

Definitions of Advanced Analytics and Artificial Intelligence Terms

Term	Definition
Artificial Intelligence	The study and research of providing software and hardware that attempts to emulate a human being
Cognitive	Computing focused on reasoning and understanding that is inspired by human cognition. It is a subset of AI.
Machine Learning	The process of creating a statistical model from various types of data that perform various functions without having to be programmed by a human. Machine learning models are "trained" by various types of data (often, lots of data).
Conversational AI	A subset of cognitive/AI platforms that are specialized for the development of intelligent digital assistants and conversational chatbots.
Natural language processing	The ability to extract people, places, and things (also known as entities) as well as actions and relationships (also known as intents) from sentences and passages of unstructured text
Natural language generation	The ability to construct textual/conversational narratives from structured or semi structured data.

Source: IDC, 2018

General-purpose cognitive/AI software platforms are used to build intelligent applications that provide predictions, answers, or recommendations and are a platform for the development of cognitive applications. These applications automatically learn, adapt, and improve over time using information access processes combined with deep/machine learning.

It is also useful to think about the training of the models:

Supervised Learning Algorithms

Supervised learning algorithms consist of a target/outcome variable (or dependent variable) which is to be determined from a given set of predictors (independent variables). Using these set of variables, a function is generated that maps inputs to desired outputs. The training process continues until the model achieves a desired level of accuracy on the training data. Supervised learning algorithms are applied on prediction and classification problems. Predicting the price of the house using area of the house, number of bedrooms, and location of the house is a prediction problem since the price of the house is a numeric variable. Whereas in a classification problem we predict the class or category such yes/no or win/lose is a simple two class classification problem, will a customer buy a house or will the machine breakdown is a classification problem. Examples of Supervised learning algorithms include Regression, Decision Tree, Random Forest, XG Boost, KNN, Logistic Regression etc.

Unsupervised Learning Algorithms

Unsupervised learning algorithms do not have any target or outcome variable to predict/estimate. Clustering and dimension reduction algorithms come under unsupervised learning. Clustering algorithms are used to group population in different groups, which is widely used for segmenting customers in different groups for specific intervention. Examples of unsupervised learning include apriori algorithm, K-means, Factor Analysis, and Principal Component Analysis (PCA).

Reinforcement Learning

In reinforcement learning algorithms, the machine is trained to make specific decisions. It works this way: the machine is exposed to an environment where it trains itself continually using trial and error. This machine learns from past experience and tries to capture the best possible knowledge to make accurate business decisions. The Markov Decision Process is an example of reinforcement learning.

It is important to note that companies don't get particularly wrapped up in definitional constructs when investing, but they do often struggle to understand which approach is necessary to achieve the desired outcome. Investments are focused on creating a learning environment, an analytic model that can substantially improve the performance of line of business functions. These investments will propel greater maturity in information transformation and fundamentally transform the manufacturing industry.

THE EMERGENCE OF MACHINE LEARNING IN MANUFACTURING

In addition to the market factors already discussed, there are a number of technical advances that coincide with a surge in planned investment in machine learning. The principles of machine learning have been with us for more than 30 years. Seminal work in the 1980's established the groundwork for the theoretical basis, but it has taken some time to put that theory into practice.

Factors Converging to Enable Machine Learning

One of the barriers to realizing machine learning has been sheer compute power. Advances in compute capabilities have certainly made a steady march forward but the emergence of the cloud has been the most impactful in making machine learning economically feasible. The elasticity of the cloud is central to this impact as compute resources can be provisioned on demand, making it possible to run detailed analysis without substantial investment in the datacenter or expensive high performance computing services.

Another barrier has been the availability of data. Too much sparsity and the models can't adequately provide recommended actions. Investment in technologies like IoT as well as the increased availability of third party data economically provide the fuel that these machine learning engines need. As sources of vast amounts of data become available, the platforms we use for machine learning must come with strong semantic graphs to assure proper classification and management.

The availability of open source algorithms also provides a catalyst for investment. In particular, the Apache stack, TensorFlow, Spark, Storm have democratized the mathematical models needed to implement machine learning. These efforts enable companies to move quickly and focus on the semantic graphs and knowledge bases that create the value for the user.

There has been a lot of hand wringing over the shortage of data scientists. While this is certainly true and a barrier, there has been a significant effort in creating educational programs and the overall level of expertise is growing quickly. Also, the traditional IT service firms have made significant investments and provide access to the necessary expertise when needed.

As these obstacles continue to be mitigated, investment in machine learning will increase dramatically in the manufacturing industry. However, this is not a traditional IT project in that it is not the implementation of an application, but the building and continuous tuning of a model. Traditional providers of technology and services may not be keeping up and manufacturers must not expect incumbents to be ready. Consequently, manufacturers must open up to a wider range of potential partners.

Machine Learning is Everywhere in the Stack

Traditional views of system architecture look at three major levels — data, logic and interface. As manufacturers weave machine learning into what they do, it has transformative impact at each of the tiers.

At the data and content level, deep learning approaches can better organize and understand both structured and unstructured data. A manufacturer and retailer of fine crystal figurines has used deep learning to organize and index images from its catalogs that go back more than 100 years. Using this repository, the manufacturer is able to match broken pieces to the original product to offer repair. Using machine learning to organize data can be a key step in enabling further machine learning. These techniques can also be very useful in training reference bases for visual inspection systems in the factory.

At the logic level, the ability of machine learning to see patterns and suggest actions creates the ability to establish self-healing processes. A large white goods manufacturer has a goal to eliminate 3 to 5 levels of management by rapidly moving away from spreadsheet based-decision making and toward more autonomy and augmentation. A large part of this effort involves the investment in machine learning models across all corporate functions.

The growing availability and deployment of intelligent assistants for consumers has companies thinking about how they might use natural language processing as a primary interface for employees, partners, and customers. A large food company has built a natural language interface around its repository of recipes that allows the customer to prepare the meal while interacting with the site. The ability to query models through voice will become increasingly common.

One note of caution. These examples represent the application of machine learning in a narrow context — data, logic and interface. This is evidence of early adoption, but largescale transformation will come when all these approaches are integrated into building all-encompassing decision models across the functional areas of a manufacturing company.

The Role of the Line of Business

A consistent trend over the last several years has been the shift in technology investment away from the traditional IT organization and toward the functional line of business leadership. This activity is certainly seen in the manufacturing industry. It is important to note in the context of machine learning because the line of business will be at the center of funding, building, and using machine learning models.

As one manufacturer told us, IT implements systems and the line of business builds models. This assertion makes perfect sense as the key to realizing value from machine learning is the ability to provide the semantic graph, the contextual understanding that will enable the model to learn. This graph will come from the line of business experts. The semantic graph provides definition to the data, articulates the relationships that guide the logic, and creates the vocabulary for language processing.

IT still has a role. IT department needs to govern the platform to provide the necessary scale and staff should be providing guidelines on which algorithms to deploy and how to manage them. IT will also be able to assure that information and logic moves freely across the models to prevent them from becoming silos and to minimize integration costs.

UNDERSTANDING THE BENEFIT OF MACHINE LEARNING INVESTMENT

The impetus for using machine learning to move toward the goal of embedded intelligence is rooted in the wide horizon of opportunities to increase revenue, improve productivity, and raise asset utilization. Gaining executive support for comprehensive investment in machine learning depends heavily on articulating the impact.

New and Enhanced Revenue Opportunities

New growth in the markets that manufacturers participate in is underpinned by creating embedded intelligence in the products and surrounding services. Highly engineered products such as vehicles, equipment, and machinery are increasingly connected and provide a platform for new revenue models. Consumer goods manufacturers are increasingly interested in understanding the buying context to drive higher net promoter scores. And materials companies are innovating at the molecular level and want to use machine learning to tailor compounds to a customer's applications.

Engineering intensive industry segments are leveraging the connected nature of products to grow revenue. Consumption based sales models put the onus on the manufacturer to optimize performance and this requires the use of machine learning tools to use historic data to better recognize patterns. Additionally, there is further opportunity to offer content (applications, data) that enhance the experience much like a game console on a mobile phone. IDC estimates that overall markets in engineering intensive segments will grow by 20 to 25 percent over the next five years and machine learning will be integral to capturing this opportunity.

Consumer goods companies are moving toward more of a direct sales model with consumers. Machine learning techniques help them understand the purchase journey in the context of the specific customer's need. For example, McCormick & Company, the market leading company in spices, has built a site called FlavorPrint that uses input from consumers on their tastes to recommend spice combinations to use in their recipes. Efforts like this will raise net promoter scores (NPS) and academic research as shown that higher NPS scores correlate to superior market share gains.

A recent special feature in the Economist magazine declared that we are in the "golden age of materials" as advances in materials science create new opportunities to innovate. Chemical, metal, textile, and pulp/paper producers are now able to understand their products at a molecular level. Building the bridge between customer requirements and those molecular models requires advanced machine learning. Market share gains in these segments will depend on the ability to achieve these innovations and margins for custom compounds are, on average, one third higher.

Productivity Gains for Operations and Knowledge Workers

Transformation of the operating model is a popular topic in manufacturing – from Europe, Industrie 4.0, China 2025, or the US with Industrial IoT or Smart Manufacturing. At the heart of this active discussion is a tremendous opportunity to improve productivity. And this opportunity is as large as the initial mechanization of the industry or the benefits derived from continuous improvement disciplines like Lean or Six Sigma.

Machine learning can actually incorporate improvement methodologies in software and enable self-healing automation in factories, supply chains, and other processes. Manufacturers want to use machine learning to evolve from simple automation to new levels of autonomy. IDC estimates that the effectiveness of operational processes can be improved by 15 to 45% depending on the industry.

While there is excitement about the possibilities of higher levels of autonomy in operational processes, there may be an even greater opportunity in automating decision making. The white goods manufacturer discussed earlier has a goal of eliminating 3 to 5 levels of management through the use of advanced analytic models and machine learning techniques. IDC recommends that companies use a planning assumption of doubling the productivity of their knowledge workers when planning machine learning investments.

Asset Utilization can also be Substantially Improved

Manufacturing companies are generally asset intensive. The ability to meet financial goals is usually heavily dependent on keeping high value operating assets in service. The opportunity entails more than just availability and should take into account the throughput of the equipment and the quality of the output.

Machine learning models that can tune run rates, predict failures, and recommend corrective actions to adverse quality can improve all three elements of effectiveness. Manufacturers can expect improvements in overall effectiveness up to 25%.

Pulling the Pieces Together to Build the Business Case

Pierre du Pont was the chief financial officer under Alfred Sloan at General Motors during a period in which the company became the most valuable enterprise in the world. Du Pont may be best known for creating a framework for evaluating financial performance by tracking all the components of return on investment – revenue, costs, and asset levels.

A key part of moving to the embedded intelligence level of maturity discussed previously is the recognition that taking a holistic view of the machine learning opportunity across all the dimensions of revenue, productivity, and asset utilization is far superior to one-off use cases implemented separately. IDC recommends that companies take a center of excellence approach and invest in a platform that will allow them to exercise all their options more efficiently.

RECOMMENDATIONS: TAKE STEPS TO AUTOMATE ORGANIZATIONAL LEARNING

Justifying investment in machine learning models can draw on many elements we have just discussed. Getting the right process and technology in place to achieve success can be more difficult. IDC offers a four-step approach to follow: understand models; unify governance; build on a common platform; and choose the right services provider

Understand the Models

Just as there are different approaches to training, there are also different models to keep in mind when building organizational competence in machine learning (see figure 2).

FIGURE 2

Types of Machine Learning Models

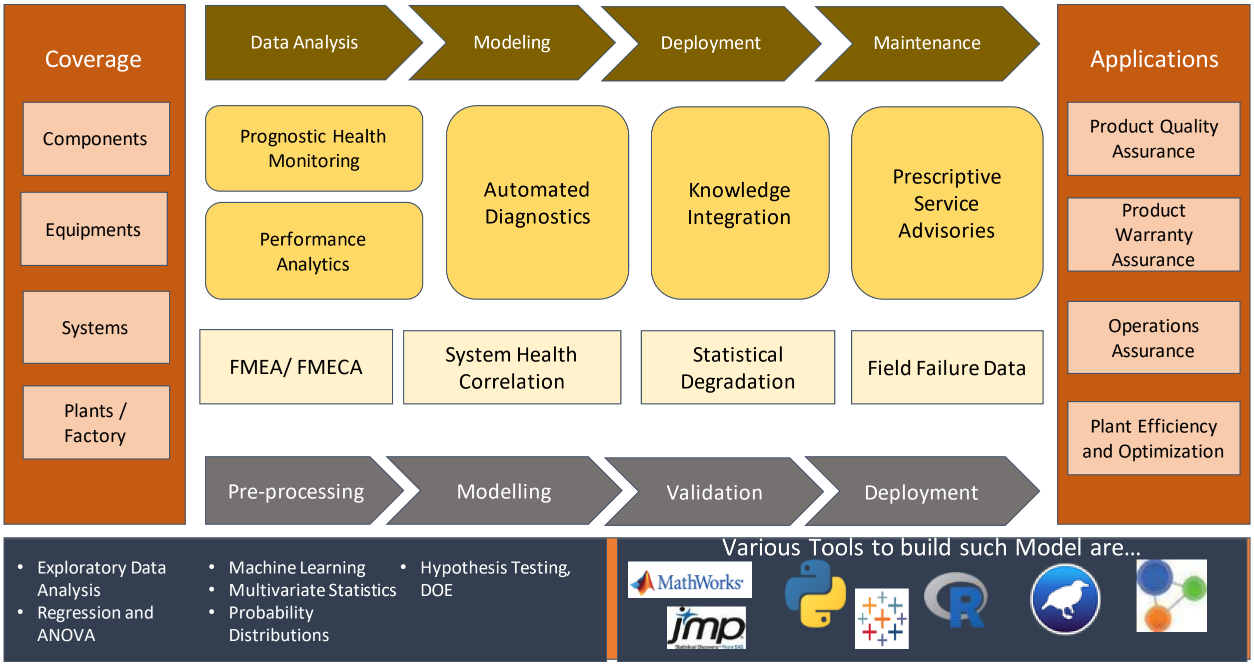
PLACE "DIGITAL TWIN"	PROCESS "CONTROL ROOM"	PERSON "JOURNEY MAP"
▪ Basis of model is science ▪ Math is well known ▪ Omni-system ▪ Focus for product and asset management	▪ Queueing theory ▪ Impacted by variability ▪ Omni-dimensional ▪ Focus for operations processes	▪ Basis of model is behavior ▪ Math is difficult to establish ▪ Omni-channel ▪ Focus for customer engagement

Source: IDC, 2018

The first type of model is a digital representation of something physical (machine, manufacturing plant, etc.) or a digital twin. The mathematical basis of the model is science – physics, chemistry, biology, et al., so the math is well known and proven. In the past, manufacturers built reference models of each individual system and then evaluated performance in a multi-system approach. Machine learning allows manufacturers to better simulate and understand how the systems perform together, an "omni-system" approach. Manufacturers can also create an individual digital twin for every product sold rather than just have a reference model. These models, thanks to the math, can be trained and are commonly used for product and asset management. Figure 3 provides an architectural reference for a digital twin.

FIGURE 3

Example of a Digital Twin Architecture for Engineering



Source: Tech Mahindra, 2018

Process models create control rooms or control towers that in turn lead to the ability to create visibility into the status of process with the additional ability to apply machine learning to improve the process. These models are based on queueing theory or stochastic models. The math is well established but the process itself is tremendously impacted by variability. Historically, manufacturing companies have looked at processes in a multi-dimensional (inventory optimization, on time delivery, or cost for example) fashion, but using advanced analytic tools can take a omni-dimensional approach - the ability to evaluate and optimize a number at dimensions at once.

These models are best suited for untrained learning. Consider the discipline of Lean Sigma. Anomalies are detected and a process is kicked off (DMAIC in Six Sigma terms: define, measure, analyze, improve, control) to identify a root cause and implement corrective action to remove the variability. Imagine this Black Belt expertise captured in a machine learning algorithm that continuously invokes this process at tremendous scale. These models are best applied to operational processes including the factory and supply chain of course, but also engineering and shared service processes as well.

The third model looks at behavior. People are much less reliable than science or statistics so the variability of results is high and the ability to control the variability is low. Think of these models as journey maps – how a customer, employee, or partner interacts with our systems. We have traditionally tried to manage these journeys by channel – web, in person, mobile device, or phone for example, but now the goal is to provide a consistent experience across all channels – an omni-channel experience.

These models are prime candidates for reinforcement learning. It is common practice in e-commerce to do A/B testing. A/B testing tries two (or more) different approaches to an interaction, evaluates the effectiveness of the approaches, and then makes the more successful approach the standard. This continuous experimentation and refinement of the experience is enhanced by machine learning.

IDC recommends that manufacturing companies identify and document the different types of models they would like to build. Then articulate the capabilities and information already in place as well as the gaps. Creating this meta-model repository will unify understanding within the organization of the digital twins, control rooms, and journey maps that need to be deployed.

Unify Governance of Machine Learning Investment

The models described in the previous section shouldn't be implemented in isolation. Line of business functional leadership will want to incorporate all of the models to improve their outcomes. Further, giving the organization the ability to see across functions creates feedback mechanisms to improve overall performance.

IDC recommends that companies create a center of excellence for machine learning and advanced analytics. This organization should be staffed by domain experts from the functional leadership, data scientists, and IT deployment experts. The center of excellence should be the primary job of the personnel involved and not a part-time working group activity. This group should be charged with building the business justification, identifying the models/use cases, and establishing and executing on a road map. Generally, the roadmap should look across three horizons of investment — establishing a foundation, creating the decision environments, and, third, accelerating learning.

Build on a Common Platform

From a technology perspective, companies should try to avoid multiple point applications. Although this approach might enable a faster time to benefit in a narrow problem space, the ability to magnify benefits within the functional domain and across domains will be diminished. Also, the cost to maintain multiple independent implementations will become increasingly higher.

IDC recommends that companies look to establish a common set of tools to implement all functional decision models. Selection shouldn't necessarily focus on the training algorithms. These programs have been established for many years and the differences from one technology vendor to the next is nominal and, in fact, there are many viable open source options.

Rather, heavy weighting should be given to the ability to manage and understand the data and information being used in the models. One area is data management itself. Prioritize vendors that can manage the data flow from end-to-end — from acquisition to organization to quality control. Second, look for vendors that can bring semantic graphs or maps that are critical to the models ability to make inferences. These semantic maps should be industry and function specific. Without these tools, companies will quickly turn their data lake into a data swamp.

Choose the Right Services Partner

Companies can't expect a software provider to be comprehensive in its semantic maps; a real understanding will likely come from service providers that bring a deep knowledge of manufacturing, specifically the engineering, supply chain, and factory functions.

Service providers will also be an important source of data science expertise. Not only are data science skills in high demand, the resource needs of most companies are uneven. IDC recommends that companies staff to a base level when it comes to data scientists and engage service providers to satisfy spikes in demand and to bring industry knowledge.

Choosing the technology platform and selecting a services partner are the two most important decisions an organization will make on the path of implementing machine learning. Service providers should have demonstrated capabilities not just in machine learning, but in machine learning within the manufacturing industry. Bringing the right partner in early can clear the way for more rapid implementation and benefit realization.

The opportunity for competitive benefit is clear and present. Establishing innovation through automated learning will be the most important critical success factor for manufacturers in the digital economy.

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