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Artificial Intelligence for Industrial Applications

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INTRODUCTION

After an extended period out of the limelight,* artificial intelligence, or AI, has returned to the public consciousness in a big way. AI's virtues and vices are now discussed daily in the popular press. While the societal implications of AI remain a topic of debate, it is broadly accepted that its business implications will be significant.

Among those who track such trends, AI is expected to be a large driver of enterprise competitiveness in the not-so-distant future. The views shared in a recent report by investment bank Goldman Sachs are representative of this sentiment. The paper states that "the ability to leverage AI technologies will become one of the major defining attributes of competitive advantage across all major industries in the coming years. While the strategy will differ by company size and industry, management teams that don't focus on leading in AI and benefiting from the resulting product innovation, labor efficiencies, and capital leverage risk being left behind."[1]

IT industry research firm Gartner anticipates this impact as well, and projects it to take root sooner than later. They foresee that "by 2018, more than half of large organizations around the globe will compete using advanced analytics and proprietary algorithms, causing disruption on a grand scale."[2]

The question for enterprises then is not when and if, but how. Unfortunately, answering even this basic question can be difficult today, because doing so requires a broad and clear understanding of the various ways that AI can impact the business. While much information on the topic exists, it tends to be very fragmented, poorly organized, and limited to only a small subset of use cases.

For better or worse, contemporary discussion of enterprise AI use cases has focused on applications in the digital domain. These are applications like getting people to click on ads, making recommendations, personalizing the customer experience, predicting customer churn, and detecting fraud of various sorts.

But what about those parts of an organization whose operations extend beyond the digital domain? Surely they need AI too?

* These quiet periods—and there have been several—are collectively known in the industry as "AI winters," calling to mind the term nuclear winter, representing the quiet—and destruction in terms of research budgets—after the flash.

The answer, we believe, is a resounding yes. In fact, AI presents a unique and compelling opportunity for those businesses whose operations span the virtual and physical worlds. To compete effectively, these firms must drive towards increased operational efficiency and asset utilization, and they must aspire to the same level of agility in the physical aspects of their business as they have sought in its virtual aspects.

It has become clear that some of the world's largest enterprises believe this as well. They are betting big on AI to create competitive advantage through increased situational awareness, greater efficiency, and higher quality. Consider a few examples:

- In the five years since Amazon's $775 million purchase of Kiva to form Amazon Robotics, the company has invested heavily in AI techniques, including sponsoring an annual RoboCup competition "to strengthen the ties between the industrial and academic robotic communities to promote shared and open solutions to some of the big problems in unstructured automation."[3]
- Supply chain services provider J.B. Hunt announced a five-year, $500 million effort to develop technology that will connect shippers and carriers by using real-time data and artificial intelligence to match freight with capacity.[4]
- Boeing has acquired Liquid Robotics, developer of autonomous maritime systems,[5] has established a joint Analytics lab with Carnegie Mellon University,[6] and has partnered with Microsoft,[7] to use its Azure cloud platform to improve the operational efficiency of aircraft.
- German manufacturer Bosch announced a €300 million investment in the new Bosch Center for Artificial Intelligence. According to Dr. Volkmar Denner, chairman of the board of management of Bosch, "Ten years from now, scarcely any Bosch product will be conceivable without artificial intelligence. It will either possess that intelligence itself, or AI will have played a key role in its development or manufacture."[8]

Our hope is that this paper will help illuminate where and how enterprises can apply AI to drive greater operational agility and performance across the set of use cases we call "industrial AI." We also discuss the challenges in and impediments to doing so, and offer some pointers for those organizations just getting started.

We begin by defining AI and Industrial AI.

What is Industrial AI?

To define industrial AI, we must first define AI itself. Although the field of artificial intelligence has existed for over half a century, it has no clear and all-encompassing definition. Further, the lines between AI and adjacent fields like machine learning, big data, predictive analytics, and IoT are often blurred, as are the lines between AI and subfields like deep neural networks and cognitive computing.

For our purposes, ***artificial intelligence*** refers to those computer science techniques and technologies that allow software to exhibit 'smarts'—in other words, to do things that seem human-like. This can include things like making decisions, recognizing objects, or understanding speech. It really is a very broad term.

Strictly speaking, ***machine learning*** (ML) is a subset of AI. ML refers to a set of techniques that allow us to create AI software by training that software with data) to display some desired intelligent behavior. This is as opposed to, for example, explicitly programming our software with a bunch of rules to generate our desired behavior—and it's a very powerful concept.

It is for this reason that, while machine learning is only one way to build an artificially intelligent system, for all practical purposes ML and AI are used interchangeably today. All the interesting activity in AI is in machine learning.[†]

What about ***cognitive computing***? It's a bit more esoteric a term, usually used to highlight capabilities akin to humans' higher level thinking and reasoning skills. An example would be the ability to determine the sentiment expressed in text or images, or what objects are present in pictures. But again, for all practical purposes, the term is most often used interchangeably with AI—in fact, it's the preferred term in some regions of the world—and the work in this field is based upon machine learning.

How does this relate to ***big data***? Well, data is used to train the machines, and the more you have of it the better (assuming it's high quality data).[9] And how about ***predictive analytics***? Well, machine learning can be a more powerful way to make predictions, and one that can learn from patterns in the data. But simple averages and other formulas can be used for predictions as well... these need not be based on ML/AI.

Finally, for enterprises whose operations involve the physical world, the industrial ***internet of things*** (IoT/IIoT) is an increasingly important source of insight into the status, location and performance of enterprise assets (see Figure 1). Because IoT devices and sensors can number into the millions, and can report status with millisecond resolution, the resulting data volumes can quickly become voluminous, lending themselves to the application of machine learning techniques.

† Though, you can be sure, there are legions of academics who would dispute this point.

FIGURE 1. TRENDS DRIVING AI ADVANCEMENT

	All AI benefits from advances in:	Industrial AI further benefits from:
Data	Internet & social media data sources	Proliferation of networked sensors & connected devices
Hardware	Faster CPUs & GPUs; cloud	Intelligent devices & systems, robotics, autonomous vehicles
Software	ML/AI platforms, open source software, deep learning algorithms	Reinforcement & active learning, simulation, digital twins

The growing ubiquity of data, high-performance hardware and sophisticated software have all contributed to laying the groundwork for the current resurgence in artificial intelligence. A similar set of trends has created a rich opportunity in industrial AI.

Source: CloudPulse Strategies

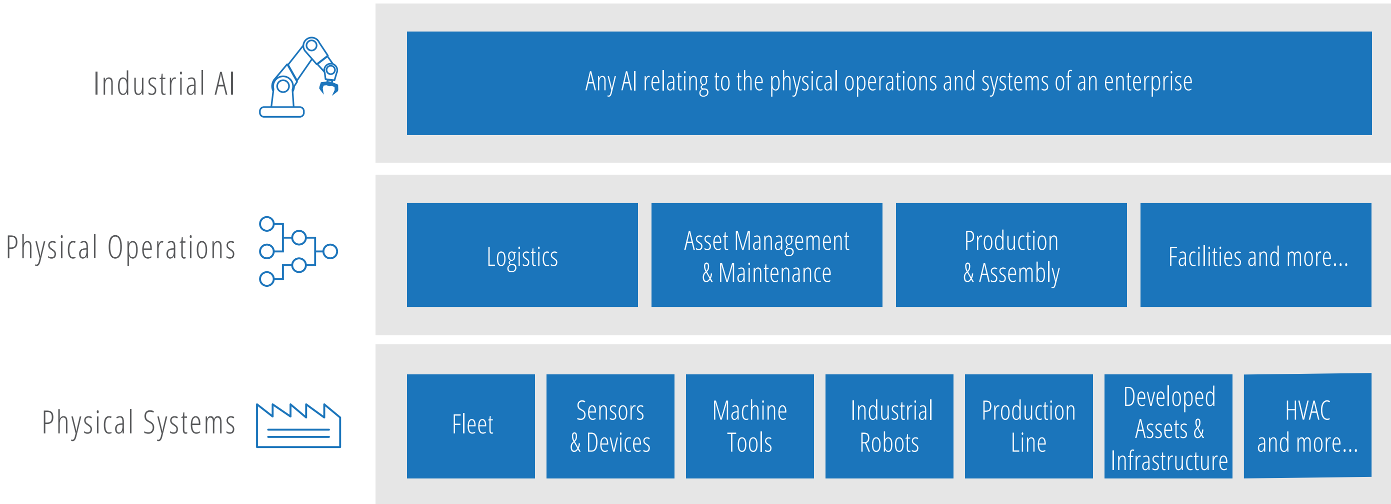
To what then does the term "industrial AI" refer? Well, certainly the word industrial has certain immediate connotations, primarily of manufacturing and heavy industry. But to limit our scope to just those industries would be to miss the less obvious connections between a broad set of related use cases, the environments they exist within, and the common challenges and requirements that they give rise to.

Rather than referring to a set of vertical industries, by industrial AI we're referring to a class of applications that can exist within any vertical:

> *We define industrial AI as any application of AI relating to the physical operations or systems of an enterprise. Industrial AI is focused on helping an enterprise monitor, optimize or control the behavior of these operations and systems to improve their efficiency and performance (see Figure 2).*

According to this definition, industrial AI includes, for example, applications relating to the manufacture of physical products, to supply chains and warehouses where physical items are stored and moved, to the operation of building HVAC systems, and much more (see Figure 3). Any company in any industry can have opportunities to apply industrial AI.

FIGURE 2. DEFINING INDUSTRIAL AI



Source: CloudPulse Strategies

Due to the physical nature of the systems and processes to which they relate, industrial AI systems share similar characteristics and constraints. For example, the fact that industrial AI ultimately relates to the physical systems of an enterprise tends to mean that access to training and test data is more difficult; the reliance on subject matter expertise is larger; the AI models themselves are harder to develop, train, and test; and the costs associated with their failure are greater. In other words, the stakes are higher. We elaborate on the significance of this in the next section.

How is Industrial AI Different?

A big part of what makes industrial AI different from consumer and other business applications of AI is the fact that the stakes are much higher. Exploring this notion further will help clarify these differences.

Consider one example: the case of a predictive maintenance system monitoring performance of an aircraft engine. In a recent Forbes article, Harel Kodesh, former vice president and CTO of GE Software notes that “if an analytical system on a plane determines an engine is faulty, specialist technicians and engineers must be dispatched to remove and repair the faulty part. Simultaneously, a loaner engine must be provided so the airline can keep up flight operations. The entire deal can easily surpass $200,000.”[10]

Clearly the cost of a "false positive" here is greater than the cost of Netflix showing the wrong movie recommendation, or Amazon upselling the wrong product. But the differences go further. This system is likely subject to any number of compliance requirements, and the system's recommended action might trigger a variety of reporting actions. The development of the predictive model is likely significantly more involved than building a recommender: a variety of live and simulated engine sensor data must be captured; the sensor data likely requires extensive cleaning before use; the model must be trained against the cleansed data; and it must be tested against a test dataset, in simulation, and in production. This process likely relies heavily on a variety of subject matter experts including systems engineers, maintenance and performance engineers, and more, not to mention the software engineering talent involved.

FIGURE 3. AI USE CASES WITHIN THE ENTERPRISE

	AI-Enabled Business Applications	Industrial AI
Primary domain:	Digital	Physical
Use cases:	• Marketing & sales • Customer service • HR • Productivity & collaboration • Analytics	• Predictive maintenance • Factory & warehouse automation • Supply chain management • Fleet logistics & routing • Quality control • Fault detection & isolation • HVAC automation
Data sources:	• Enterprise transactions • Business metrics • User interactions	• Enterprise data sources • SCADA systems • Industrial robots • IoT sensors
Delivery model:	Web, mobile, desktop	• Web, mobile, desktop • Industrial robots • Intelligent systems • Connected devices

While industrial AI use cases abound in manufacturing, it can benefit enterprises in a wide variety of industries, including retail & e-commerce, logistics, energy, utility, manufacturing, and more.

Source: CloudPulse Strategies

Industrial AI thus presents several challenges that differentiate it from consumer and business applications of AI, including:

Data acquisition and storage. Unlike “born digital” data captured, for example, from web interaction logs, industrial AI systems often rely on data captured from sensors that seek to represent the real world digitally. Unfortunately, this process can result in inherently noisy datasets. Sensor data can also be voluminous. Acquiring this data and storing it for analysis can be extremely complex. Furthermore, because of the cost of generating training data under a wide variety of conditions, simulation is often used. High-fidelity simulations, or “digital twins,” can be very effective, but can also be difficult to create and maintain, and computationally expensive to run.

Training challenges. Much of the recent fanfare around AI has been based on the success of “deep learning.” In most cases, these successes are based on supervised learning style problems in which deep neural networks are trained with labeled training data. While it can be difficult in any domain to collect the volume of labeled training data required to effectively train machine learning models, this can be particularly challenging in industrial scenarios in which few examples of the most interesting “black swan” events—such as part or product failures—occur. This increases the complexity of training and thus the overall cost of developing the machine learning system.

Testing costs and complexity. Testing AI systems on operating production lines, industrial equipment, warehouses and other industrial systems is both expensive and disruptive. Because of this, industrial AI systems are often trained and tested using simulation, the challenges of which have already been discussed.

High regulatory requirements. Industrial environments are often subject to compliance statutes that impact operations, including technical, legal and corporate requirements, and governmental regulations. Depending on the market and industry, compliance requirements span areas such as product safety, public/employee health and safety, environmental impact, and workplace safety, but they can also directly specify controls around automation systems, as does, for example, the European Machinery Directive.[11, 12] Regulatory controls, which often require that changes to industrial processes be extensively validated and verified, can be at odds with the goals of automation via AI, which encourage rapid adaptation of processes via closed-loop feedback.[13]

High cost of failure & change. As we saw in our aircraft engine example, it is common in industrial scenarios for the cost of failure to be extremely high. The cost of change is similarly high. When an enterprise has many millions of dollars invested in factories and warehouses, automation technology—AI or otherwise—must either work with those existing investments or demonstrate extremely compelling ROI.

Large state spaces. Modern industrial systems are extremely complex, often offering tens or hundreds of inputs over which machine learning algorithms may optimize. This can make for more complex development and training routines (both in terms of time and cost) and can require the use of sophisticated techniques to simplify the problem and ensure convergence to a solution.

Cost of talent. Data scientists, data engineers and data-savvy programmers and subject matter experts are the backbone of the team required to implement AI solutions. These skills are both rare and expensive in today's employment market, and firms must compete for top talent with internet leaders like Facebook and Google.

Why Industrial AI?

Given higher stakes, what's to motivate enterprises to do anything more than the status quo? In other words, why should enterprises care about industrial AI?

From a macroeconomic perspective, today's enterprises, particularly those with physical-domain operations, are under tremendous competitive pressure. They are competing not only with VC-funded internet companies with disruptive business models and the ability to operate at a loss for extended periods of time, but also with overseas competitors with fundamentally different economics and constraints.[14] This has lead enterprises to aggressively seek out opportunities to reduce costs, increase efficiencies, and innovate in their business models, the latter often under the banner of "digital transformation."

AI is an important tool for achieving all these things, and, for these reasons, has long been of interest to enterprises with industrial operations. Industrial AI use cases abounded in the 80s and early 90s, prior to the most recent "AI winter."[15] During this period, large firms including Boeing, JPL, Intel, and others, invested heavily in expert systems and other forms of AI to drive greater efficiencies.

In many ways, the industrial AI of the 80s and 90s and the industrial AI of today share common goals. With expert systems, enterprises of the former era sought to transfer knowledge from engineers and other subject matter experts (SMEs) to intelligent computer systems that could guide and assist humans in the performance of their work. Now, with both more sophisticated AI and more pervasive automation, we seek to transfer the knowledge to more intelligent, more powerful systems that can both assist humans and perform some of their tasks.

The specific benefits of such artificial intelligence systems in industrial environments are many. At a high level, they include:

Enhanced, and predictive, situational awareness. By allowing enterprises to model complex industrial systems, industrial AI allows enterprises to increase quality, reduce downtime, avoid stock-outs, reduce risk, and more.

Better planning and decision-making. By helping enterprises assess the effectiveness of different policies in dynamic, unpredictable environments, industrial AI helps enterprises increase process efficiency, improve asset utilization, increase yields, and optimize the design and management of complex systems.

Greater efficiency & productivity. Industrial AI lets enterprises enhance the results they achieve through automation, resulting in increased production, increased product quality, lower labor costs, reduced errors and rework, lower material consumption and less waste.

These benefits correspond directly to the three broad opportunities for applying industrial AI that we introduced in its definition and expand on in the following section. Together, they enable enterprises to improve operational and business performance, while simultaneously increasing agility and innovation.

Industrial AI Use Case Examples

A framework for thinking about different types of industrial AI scenarios is helpful in identifying the areas of a business in which to apply it. We categorize industrial AI applications as ***monitoring***, ***optimization***, or ***control*** based on the degree of automation that they seek to provide. This model applies to both digital-domain and physical-domain use cases (see Figure 4).

In this section, we explore these categories and present representative use cases for each. The list of use cases provided herein is not intended to be exhaustive; rather they are presented to illustrate a few of the many opportunities available to apply industrial AI.

Monitoring

In industrial scenarios, there is a continual need to monitor the performance of systems and processes to identify or predict faults or other situations likely to produce undesirable results. Using machine learning, models can be trained on available data to learn the internal, opaque state of complex systems. These models can then be queried to predict those system's future state, given a set of input data.

There are many examples of monitoring applications that benefit from an AI-based approach:

Quality control. A common manufacturing use case for AI is for machines to visually inspect items on a production line. Using AI allows quality control to be automated, and ensures that all final product is inspected, allowing fewer defects to reach customers compared to traditional statistical sampling methods. In addition to ensuring that products are free of imperfections, AI-based visual inspection systems can validate many product attributes including geometry and tolerances, surface finish, product classification, packaging, color & texture.[16]

Fault detection & isolation. In regulated manufacturing environments, ensuring process compliance can be expensive and time consuming. In many such scenarios, lives are at stake—as can be the case in the food, chemical and energy industries. By monitoring a variety of system operational factors, AI can be used in the detection, prediction and diagnosis of undesirable operating conditions in industrial systems. By accelerating or replacing unreliable and time-consuming human analysis, automated process surveillance helps prevent or minimize system downtime and the persistence of hazardous conditions.

FIGURE 4. ENTERPRISE AI APPLICATIONS LANDSCAPE

	AI-Enabled Business Applications	Industrial AI
Monitoring	• Business incident response • Brand sentiment monitoring • Fraud detection	• Quality control • Productive maintenance • Supply chain risk management
Optimization	•Campaign planning • Personalization & recommendations • Demand forecasting & planning	• Process planning • Job shop scheduling • Fleet management
Control	• Process automation • Camaign automation • Automated trading	• Factory automation • Autonomous vehicles • Smart grids

Source: CloudPulse Strategies

Predictive maintenance. Predictive maintenance is a rapidly growing subset of fault detection and isolation, focused on predicting the failure of deployed systems before they result in downtime. Aircraft engines provide an oft-cited example: GE's GEnx engine is embedded with 5,000 sensors producing 5-10 TB of performance, health and efficiency data each day of flight. This data allows GE systems to predict failures before they happen and proactively schedule repairs and order replacement parts.[17]

Inventory monitoring. AI powers a wide variety of inventory management and supply chain use cases, allowing enterprises to avoid costly stock-outs. Hardware retailer Lowe's is currently testing the LoweBot, an autonomous mobile robot operating in stores in the San Francisco Bay Area. In addition to its customer service tasks, the LoweBot uses an on-board computer vision system to detect misplaced and out-of-stock inventory on store shelves.[18] Similar systems are being deployed in warehouses, with several startups experimenting with drone-based approaches.

Supply chain risk management. Effective management of a complex, global supply chain demands the ability to identify and mitigate potential disruptions before they cause delays or shortages. AI can be used to predict supply disturbances before they happen, providing early warning for enterprise supply chains based on potential disruptors sourced from global news, event and weather feeds.

Optimization

AI-based planning and decision support systems go a step beyond monitoring and allow users to determine a path, or plan, for getting to a desired system state in a way that optimizes a target set of business metrics. Note that in classical academic artificial intelligence circles, "planning" refers to a specific category of problem, often formulated with unrealistic constraints, such as offline agents operating in static, deterministic environments.[19] Here we use the term in the broader business sense. Optimization activities that can benefit from the application of ML & AI include:

Process planning. Many industrial scenarios involve complex sequences of work whose ordering can significantly impact factors such as cost, time, quality, labor input, materials input, tool life and waste. A simple and well-studied example is the sequence of operations required to create a machined part or die using Computer Numeric Control (CNC) machines. A given part is made up of a sequence of operations such as cuts. Each cut is made using a specific tool, of which there are many, but only a few can be loaded on the machine at the same time. A variety of different optimization problems arise from this scenario, including set-up planning, operation selection and sequencing, machine and tool selection, and tool path sequencing. Each of these has been solved with a variety of machine learning techniques including genetic algorithms and neural networks.[20, 21]

Job shop scheduling. The job shop scheduling problem, a specific type of process planning problem, models the allocation of jobs of varying processing times to a set of machines with varying processing power. Job shop scheduling provides a well-studied, if idealized, model for many common industrial scenarios. Many different types of problems can be modeled using the general job shop scheduling approach and AI, including the famous "traveling salesperson problem," which seeks to optimize the routing of a salesperson traveling to a list of cities given the distances between each city pair. These problems have been historically solved using operations research methods such as combinatorial optimization, but lend themselves to learning approaches that can more easily adapt to changes in their environment.[22, 23, 24]

Yield management. In manufacturing, the yield of a given processes can mean the difference between profitable and unprofitable products. For example, in semiconductor manufacturing, in the face of increasingly complex manufacturing processes, with many hundreds of process parameters coming into play in the production of a single wafer, traditional techniques for estimating and optimizing yields have become untenable. Machine learning allows manufacturers to fully utilize available data to continually improve process quality and increase yields.[25]

Anticipatory logistics & supply chain management. Supply chain management is traditionally a two-step process. First statistical tools are used to produce a demand forecast. The forecast is then used as input to an optimization process that evaluates the cost of stock-outs against the delivery times, holding costs and other factors associated with the supply chain. Supply chain managers can then use tools to produce a plan for what to order and when. Using machine learning, it is now possible to implement a single-step process that learns the relationship between all available input data, including traditional supply chain data such as inventory levels, product orders, and competitive data, as well as external data like weather, social media signals and more, to produce better operational performance.[26]

Product design. As digital and physical products grow in complexity, AI can be applied to accelerate the design process and facilitate product engineering and manufacture. With generative design, designers can specify a product by its constraints, and allow a machine learning algorithm to produce design alternatives that optimize qualities such as weight or performance.[27] Airbus and Autodesk have used this process to create an airplane cabin partition whose design mimics cellular and skeletal structure and is 45% lighter and stronger than current designs[28]. Machine learning can also be used to supplement the intuition of product designers to ensure that designed products are actually manufacturable,[29] and can be used in conjunction with product testing data to identify product deficiencies and suggest alternative designs.

Facilities location. Machine learning systems can be used to direct the placement of a wide variety of physical facilities within an environment. At the microscopic level, this includes the placement of circuits and components within a semiconductor such as an FPGA,[30] but it also includes the placement of roads and power substations within residential areas, the location of conference rooms and other facilities within an office building,[31] and the positioning of wireless and other sensors within a factory.

Control

Control systems ultimately form the heart of any modern industrial operation, and are required by organizations that seek to reap the full benefits of automation. Within the realm of control, there are many examples of applications that benefit from artificial intelligence and machine learning. These include:

Robotics. Robots are used in a wide variety of industrial scenarios, for diverse applications such as pick and place, sorting, assembly, painting, welding, storage and retrieval, Machine tending, in which robots load or operate other machines such as CNC, is another popular application.[32] Traditionally, robots are explicitly programmed by directing them to move through series of points in two-or three dimensional space and perform specific actions at these points. Newer approaches, such as collaborative robots ("co-robots"), simplify programming by allowing these points to be captured by physically positioning the robot.

The problem with both approaches is that, independent of how the points are captured, the robot is intolerant to changes in the environment or variations in the position of the items it is manipulating. AI, coupled with computer vision technologies, allows robots to avoid potential interference by humans or other robots and to accommodate randomly positioned or mispositioned items without operator intervention.

Autonomous vehicles. Autonomous mobile robots are deployed in large number in warehouses and factories, to support material transport and pick-and-pack applications. In addition, autonomous robots and flying drones are being put into service to support inventory management applications in warehouses. Artificial intelligence coupled with computer vision techniques allows autonomous robots to complete these tasks more effectively, to better understand, map and navigate their environments, and to be used more safely around humans.

Factory automation. Industry 4.0, smart factories, and lights-out manufacturing all refer to a vision of the plant or warehouse that is data-driven, intelligent and highly automated. This vision relies heavily on robots and autonomous vehicles to move materials and assemble goods, on AI-based computer vision to detect faults and defects, and on smart systems to coordinate and optimize the flow of work around the factory.

HVAC automation. In addition to being costly to operate, HVAC systems are often poorly behaved, noisy, and unpredictable under real-world circumstances. 33 This is especially true as equipment ages and older equipment is replaced, sometimes with units that are mismatched or out of spec with the original system design. In these situations, control strategies derived by HVAC engineers assuming ideal conditions fail to operate in an optimal manner. Machine learning can help building owners maximize comfort, reduce energy costs, eliminate system faults, and extend the life of HVAC equipment. Google has successfully used an AI system based on neural networks to control about 120 data center variables, such as fans, cooling systems, and windows, resulting in a 40% cut in electricity used for cooling and a 15% reduction in overall data center power consumption.[34]

Smart grids. Smart grids enhance traditional power distribution systems with data and connectivity to and from devices like smart meters, storage and charging systems, and distributed generation infrastructure. AI allows the smart grid to predict demand and faults in the power network, and promptly respond to changing conditions, improving power quality and consistency.[35]

Monitoring, Optimization & Control as an AI Maturity Model

Monitoring, optimization & control are related in that each successive degree of automation depends on, or assumes, the previous. In addition, each requires increasing degrees of trust on the part of the user. As a result, these three often form a progression, or maturity model, with companies first deploying monitoring systems to help them understand the current state of their operations and predict faults; then, as trust grows, they employ AI-based planning and decision support systems to tell them what to do given a current state of the world; finally, and with the requisite controls in place, they allow AI-based control systems to automatically take the actions needed to achieve a desired end-state through robotics or other technologies (see Figure 5).

FIGURE 5. TRENDS DRIVING AI ADVANCEMENT

	Monitoring	Optimization	Control
Provides	Situational & Predictive Awareness	Planning & decision support	Automated response to environmental changes
Offers	• Increased quality • Reduced downtime • Decreased stock-outs • Reduced risk	• Greater efficiency • Improved utilization • Increased yields • More effective designs	• Increased production & productivity • Lower labor costs • Reduced waste
Requires	• Data sources, e.g. networked sensors	• Effective monitoring • More sophisticated analytics	• Effective optimization systems • Integration with physical systems, e.g. robotics and tools

Source: CloudPulse Strategies

Applying Industrial AI

As enterprises embark on the path towards industrial AI, they will find a variety of approaches, products and services that aim to facilitate the journey. In this section, we explore some minimal requirements for industrial AI solutions, and look at the broad landscape of offerings available in the market.

Industrial AI Requirements

Effective industrial AI offerings must help enterprises overcome the challenges and impediments previously discussed. To do so, offerings must exhibit a variety of attributes, such as:

Trainability on limited examples. To help overcome the training challenges of industrial AI problems, tools must use sophisticated techniques to allow training to be performed and models to be developed using few examples of the most interesting behaviors, such as defects, faults, or failure conditions. Care must be taken during training to preserve the statistical distribution of faults to avoid creating biased AI systems.

Simulation-based training. Effective tools for industrial AI must work seamlessly with simulation environments to help enterprises address the limited training example problem, and the need to train models without taking industrial systems out of service.

Explainability. One of the biggest barriers to AI's acceptance is trust. Until trust is established—and beyond—it is important for its users to be able to understand the "reasoning" behind machine-made decisions. This is an important consideration for AI tools because different machine learning approaches have differing degrees of explainability. Systems based on neural networks are notoriously opaque, but techniques exist to make deep learning models explainable.

Provable safety. Related to explainability is the fact that in regulated industries, and in situations where humans could get hurt, the burden is on users and vendors to prove the ultimate safety of their systems. Likewise, systems that control significant company assets must also be demonstrably impervious to catastrophic or costly failure. AI systems in these environments must build-in multiple levels of safeguards to ensure proper behavior.

Ability to leverage subject matter expertise. Effective training and operation of industrial AI systems requires that they incorporate institutional knowledge from existing people and processes. This knowledge provides critical constraints to AI models, while remaining easier to implement and maintain than rule-based systems. Industrial AI systems should facilitate the capture of subject matter expertise, and the incorporation of this knowledge into generated models.

Ease and speed of use. Tools for creating industrial AI systems must be useable and understandable by both enterprise developers and SMEs, such as classically trained process engineers. To promote innovation, the tools used by implementation teams must empower them to rapidly experiment and iterate quickly. Tools that operate at a "just right" level of abstraction will enhance productivity and understandability, while still providing the flexibility to tackle real world problems.

Deployment flexibility. While some industrial systems exist in highly controlled environments, others are exposed to the elements and other demanding conditions. Still others are highly distributed or mobile. For this reason, industrial AI solutions must support a variety of deployment options, including cloud computing, on-premises deployment, and embedded or ruggedized systems.

AI Solutions Landscape

Enterprises have a variety of technology options at their disposal to aid them in the creation of industrial AI solutions. Ultimately, the only way to know the best technology for a given situation is to understand the options and their trade-offs, and compare them to the general requirements presented above, and the specific requirements of a given use case. While a detailed discussion of specific tools, products or services is beyond the scope of this report, understanding the different types of offerings makes it easier to evaluate them.

There are five general classes of technology that you might consider for your industrial AI projects (see Figure 6):

Point solutions. Point solutions are software, hardware, or combinations of the two, that add intelligence to specific industrial systems, tools or processes. An example might be a smart CNC machine, that uses AI to perform its job better, or a co-robot, that uses AI to allow users to train it more easily. This feature-specific AI is typically limited in scope, and if it meets the needs of a limited use case, can allow the enterprise to solve that specific problem quickly.

FIGURE 6. AI SOLUTIONS LANDSCAPE

	Point Solutions	Pre-Trained Models & API Services	Development Platforms	Development Libraries	Statistical Toolkits & Packages
Example	Baxter robot's built in collaborative feature, OKUMA CNC control, Falkonry's pattern recognition software	AWS AI Services, Clarifai, Google AI APIs, IBM Watson, Microsoft Cognitive Services	Amazon ML, Azure ML, BigML, Bonsai, GE Predix, Google Cloud ML Engine, H2O	Keras, Caffe, Chainer, Keras, OpenCV, scikit-learn, TensorFlow, Theano, Torch	R, SAS, SPSS
Pros	• Self-contained • Easy to get started • Pre-trained models • Single-vendor support • Will become increasingly ubiquitous as more and more robots, tools and software come with AI built-in	• Easily accessible • Easy-to-integrate APIs • Pre-trained models • On-demand pricing • Eliminate deployment complexity	• Attempt to provide power & ease of use • Flexible & customizable • Train own models with own data • Easily tailored to unique needs • Higher level of abstraction can accelerate application development • Support for full application development lifecycle	• Low levels of abstraction offer greatest flexibility • Often available as open source software • Choose & train own models with own data • Easily tailored to unique needs • Can be integrated into application development lifecycle	• Statisticians most familiar with these tools • Most flexibility in terms of available models & training methods • Allows creation of highly unique and differentiating models
Cons	• May still require some configuration, integration and/or training • Harder to tailor to specific domain or business needs • Not as differentiating as custom-built solutions • All-or-none deployment	• Works best with cloud-resident data • Limited or no ability to train on your own data • Available APIs cover only most common aspects of most common use cases • Limited deployment options	• Not plug and play • Vendor "opinions" can become constraints • Significant application development & SME resources/investment needed to get value • Requires stronger technical skills than point solutions & APIs	• Longer time-to-value than off-the-shelf, cloud solutions • Requires stronger technical skills than off-the-shelf, cloud solutions	• Hardest to use • Requires sophisticated statistical skills • May require disparate tools to support full complement of model/ solution types • Limited-to-no support for full lifecycle of AI applications

Source: CloudPulse Strategies

Point solutions fail, however, to provide a platform for industrial AI that is applicable across multiple use cases. Customizing point solutions to meet the needs of a given enterprise's real-world use cases can be challenging, and the effort to do so can eliminate their time-to-market advantage.

Pre-trained AI models and services. The major cloud computing providers are all heavily invested in providing pre-trained machine learning services that run in their clouds. These APIs can eliminate much of the complexity of standing up computing environments, and training and deploying machine learning models. They are often limited in the breadth of models they support, the ability to train using enterprise data, and in their supported deployment options.

Development platforms. While AI depends on an understanding of data science and statistics, building enterprise-ready AI systems is as much a software engineering exercise as it is a data science one. AI-centric software development platforms can help teams deliver scalable, production-ready AI systems quickly, by providing tightly integrated support for the entire lifecycle of an AI system, including training models, deploying them, integrating them with downstream applications and systems, and monitoring their performance over time. Implementing industrial AI using development platforms requires stronger technical skills than point or pre-trained offerings, but can be more accessible than developer toolkits or statistical packages.

Developer libraries. Recent years have seen an explosion in the number of AI toolkits and libraries available to developers, especially as open source software. The various toolkits differ primarily in the platforms and languages they support, the level of abstraction they provide for the developer, and the assumptions they make (i.e. their "opinions"). For example, Python's scikit-learn and Google's TensorFlow are low level libraries, while the Keras library provides a higher-level API (that can run on TensorFlow) specifically for deep learning tasks.

Statistical packages. A variety of statistical toolkits and packages are available, primarily targeting statisticians and data scientists with statistical leanings. These low-level tools have strong support for the modeling phase of developing machine learning applications, but often provide little support for production deployment. As a result, models developed using these tools are often re-implemented prior to use.

It's worth noting that the delineation between these categories isn't perfect, and some tools span multiple categories.

Getting Started

We've seen that the challenges facing those adopting industrial AI can be steep. As a result, knowing exactly where and how to get started can be intimidating. We've found the following points to be important for enterprise business and technology leaders to keep in mind.

1. Establish the team

As with any other enterprise initiative, making progress with industrial AI requires ensuring that the right team is in place. The following roles should be represented on an organization's initial AI teams:

Executive champion. For most enterprises, adopting industrial AI will require a certain amount of retooling, including new equipment and software, new people and skills, and new processes. Along with this retooling comes a level of change that requires great energy and sometimes breeds resistance. For this reason, it is important to have adequate executive support for an enterprise's first AI efforts. Tying your industrial AI effort to broader corporate digitalization or transformation initiatives, or industry efforts such as Industry 4.0, can also be effective.

Domain experts. Subject-matter experts are a critical element of any AI initiative. These team members understand the business, its goals and its processes, and already use analytics to help them manage it. They may have little knowledge of machine learning, but they should understand the power of data, and be excited about the opportunity to apply it, and AI, to the business' industrial challenges.

Data scientists. The backbone of any AI effort, data scientists have a deep understanding of the application of mathematics and statistics to building machine learning and AI. Unfortunately, the market for them is very competitive. The good news is that most businesses don't need to hire an army of PhDs to implement industrial AI; you likely already have the talent you need, though you might need to supplement existing statistical, data management or software development skills with training in modern machine learning practices.

Software developers. While many data scientists can program, finding expert-level statistical and software engineering skills in a single individual can be daunting. Rather, it's helpful to include both data scientists and software developers on your industrial AI project teams. This allows individuals in each of these roles to innovate more rapidly in their respective areas.

As you get your industrial AI effort off the ground, you'll need to scale it. Enterprises have the usual options for closing any skills gaps required to support industrial AI projects:

Hire. Hiring allows your organization to build long-term capability and institutional knowledge, but can take longer and doesn't scale (up or down) as easily.

Engage generalist consultants. The large consulting firms are all building practices around machine learning and AI. They can be useful partners in helping you craft and implement your industrial AI vision, but they do so at great expense.

Work with specialists. Boutique data science firms specialize in helping enterprises implement machine learning and AI solutions. They offer the agility and scalability of using outside resources, without the overhead of larger generalist firms.

Leverage vendor talent. The previous section provided a high-level overview of some of the technology choices available to support your industrial AI projects. Taking advantage of the expert talent vendors can offer can be a cost-effective option, especially for integration-oriented tasks, but only the largest vendors are set up to support long-term engagements.

2. Start with a business problem

While we generally advise against the pursuit of technology for technology's sake, we believe the impact of AI to be so dramatic that it is important to prioritize exploratory AI investments. However, even when the initial investment decision is driven by a desire to build AI competency, as soon as a commitment to invest has been made, it becomes critical to shift focus to business problems.

The use cases presented herein represent only a few of the many available opportunities to gain increased efficiencies and competitive advantage through industrial AI. Any of these use cases could be the starting place for your industrial AI effort, but others should be considered as well. The industrial AI team should identify and prioritize these opportunities based on risk/reward tradeoffs.

Note that there are two ways to approach risk/reward for AI projects. Some enterprises choose to swing for the fences, focusing their limited human and financial resources on those opportunities with the biggest payoff. Others choose to get their feet wet with well-defined, incremental projects that have a high likelihood of success. Either of these approaches can be effective; in fact, even larger efforts should be broken down into smaller efforts to make them easier to manage.

3. Know your "good enough"

AI uses data to train a statistical model to identify trends, make predictions or plans, or take actions. This training process is inherently one where you start with low accuracy and continue to push forward until you've achieved acceptable accuracy. Read that again. The goal is not perfection, it is acceptable accuracy. As in many other endeavors, training an AI system to achieve 90% accuracy from nothing can be much easier than getting the next 5% accuracy out of the system.

For this reason, it is important to know when you've achieved "good enough" for a given project. In speech recognition, 90% accuracy is mostly useless, whereas a system that identifies 90% of the defects missed by human inspectors can be of great value to the business.

In some cases, you might determine that the standard for good enough is so high that AI isn't up to the task. Other times, this might prompt you to redefine your problem so that the goal is more achievable. Don't forget to set a stretch goal as well, to drive your team to think creatively about the problem at hand.

4. Keep it simple

Albert Einstein famously said, "everything should be made as simple as possible, but not simpler." That's certainly the case with industrial AI. If business goals are truly driving your AI projects, your team's excitement about various AI techniques and technologies should inform, but not drive, their ultimate technology direction.

There are many amazing new machine learning approaches and technologies coming online, and it can be tempting for teams to gravitate towards the latest techniques getting all the press. But the adage "if all you have is a hammer, everything looks like a nail" applies here.

Look for the simplest way to achieve your project objectives. It often turns out that 80% of the value of applying machine learning can be easily extracted using basic, well-understood, highly-explainable machine learning techniques.

5. Think hybrid intelligence

Reading the press, you'd get the impression that AI is about to put humans out of work. In fact, the reality is that today's AI is largely dependent on human intelligence to function. To ensure the success of your industrial AI projects, it's critical to incorporate the knowledge of your employees and other humans in designing and training the systems, establishing best practices, and, once deployed, in managing, overseeing and correcting them.

Silicon Valley won't tell you this, but some of the most successful AI systems in production are hybrid AI systems. Hybrid AI seeks not to replace human labor, but to eliminate the most boring and repetitive aspects of it, allowing humans to spend more time on complex requests. Even looking to the future, a realistic scenario for many AI systems still anticipates significant human involvement, with humans handling perhaps the most complex 10% of requests.[36]

6. Connect with the broader industrial AI community

Despite its long history, enterprise AI is a nascent and fast moving field. Even for those who work in it every day, it can be challenging to keep up with all the latest advances in technology and approaches. For this reason, we recommend that those in the field make special efforts to stay connected to the broader AI community, including peers in industry and academia.

A wide variety of applied and industry-specific AI conferences exist—in every region of the world—to facilitate these connections. A list of industry conferences and events is maintained, along with other industrial AI resources, on the CloudPulse Strategies website at www.cloudpulsestrat.com/IndustrialAI.

Podcasts can also be a useful source of information. The author hosts a popular one called This Week in Machine Learning (TWiML) & AI that aims to expose listeners to new ideas and experts in the field each week. The podcast can be found at www.twimlai.com.

Conclusion: Building the Future with AI

Industrial AI lets enterprises better monitor, optimize, and control their physical operations and systems. Doing so leads to greater visibility and situational awareness, improved planning and decision-making, and increased efficiency and productivity.

The implications for companies are significant: AI's rapidly growing capability and maturity, combined with the high levels of automation found in modern industrial environments, has created a window of opportunity for forward-looking companies to leap ahead of the competition.

Now is the time for those that hope to take advantage of this opportunity to begin the process of building competency in industrial AI. We hope this paper has been a valuable resource in helping you to get started.

FOR MORE INFORMATION

For more information about Industrial AI and to keep up to date with our latest research in this area, visit www.cloudpulsestrat.com/IndustrialAI. For a series of podcasts on Industrial AI that accompanies this research, visit www.twimlai.com/IndustrialAI.

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In 2016, Sam launched This Week in Machine Learning & AI, a podcast that exposes listeners to top thinkers and cutting edge ideas in ML & AI research and practice. The show has quickly become a popular resource for data scientists and machine learning engineers, CTOs and company founders, IT & product leaders, as well as tech-savvy business leaders.

Prior to founding CloudPulse six years ago, Sam spent 15 years bringing technology products to market in roles spanning executive management, marketing, sales, business development and technology delivery. Most recently, Sam was vice president of product management and marketing for St. Louis-based Appistry, an award-winning provider of “data cloud” software for enterprises including FedEx and State Street Bank.

Sam holds BS and MS degrees in electrical engineering from Rensselaer Polytechnic Institute and Northwestern University, respectively.

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