Crossing the frontier:

How to apply AI for impact

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Introduction

Unlocking AI value requires much more than algorithms

Analytics presents an enormous opportunity: an estimated global value of $9.5 trillion to $15.4 trillion, according to McKinsey research. About 40 percent of this value can be realized using the most advanced artificial intelligence (AI) techniques—those that fall under the umbrella of "deep learning," which utilize multiple layers of artificial neural networks. (For more on deep learning, including its major models and business use cases, see the appendix, "An executive's guide to AI.")

Some leading organizations, both digital natives and traditional companies, are moving fast to capitalize on the opportunities AI offers. However, large swaths of business leaders are still not exactly sure *where* they should apply AI to reap the biggest rewards, nor are they clear on *how* to embed AI across the business to ensure that the technology drives meaningful value, whether that be through powering better decision making or enhancing consumer-facing applications.

We've done extensive research and work with clients this year on both the "where" and the "how" of applying AI. To help answer the "where," we conducted an in-depth examination of more than 400 analytics use cases, from traditional methods to advanced AI, across 19 industries and nine business functions. To answer the "how," we surveyed executives at more than 1,000 companies globally to identify the most effective ways to scale AI and analytics beyond a few experimental use cases.

As for the "where," we found that the business areas that traditionally provide the most value to companies tend to be the areas where AI can have the biggest impact. In retail organizations, for example, marketing and sales has often provided significant value. Our research shows that using AI on customer data to personalize promotions, for example, can lead to a 1 to 2 percent increase in incremental sales for brick-and-mortar retailers alone. In advanced manufacturing, where operations often drive the most value, AI can enable forecasting based on underlying causal drivers of demand rather than prior outcomes, improving forecasting accuracy by 10 to 20 percent. This translates into a potential 5 percent reduction in inventory costs and revenue increases of 2 to 3 percent.

While applications of AI cover a full range of functional areas, it is in fact in these two cross-cutting ones—supply-chain management/manufacturing and marketing and sales—that we find AI can have the biggest impact, for now, in several industries. Combined, we estimate that these use cases make up more than two-thirds of the entire AI opportunity.

Another way business leaders can home in on where to apply AI is to simply look at the functions that are already taking advantage of traditional analytics techniques. We found that the greatest potential for AI to create value is in use cases where neural-network techniques could provide higher performance than that possible using established analytical techniques or where they could generate additional insights and applications. This is true for 69 percent of the AI use cases identified in our research.

When it comes to "how" to apply AI—arguably the more difficult question to answer and execute on—we identified several keys to successful implementation. In companies that have scaled analytics and AI, executives have a clear, shared vision. They've established a more robust talent model with clearly defined analytics roles and career paths. They've prioritized the top ten to 15 decision-making processes in their business in order to identify where applying AI might add the most value. They've adopted agile, collaborative environments. And they invest an outsized proportion of resources into the difficult "last mile," or integrating the output of AI models into frontline workflows, ranging from those of clinical-trial managers and sales-force managers to procurement officers. While these practices may seem obvious, we found that those successfully scaling AI and analytics were typically at least twice as likely to be engaging in these practices than those struggling to scale.

We don't want to come across as naive cheerleaders. We recognize the difficulty in shifting organizational cultures and practices. And we recognize the other tangible obstacles and limitations to implementing AI. Obtaining data sets that are sufficiently large and comprehensive enough to feed the voracious appetite that deep learning has for multiple forms of training data is a major challenge. So, too, is ensuring ethical AI, including providing data security and privacy protections and preventing human biases from creeping into AI algorithms. Making AI explainable can help in these efforts, although explainability is itself a challenge. However, it's one that *can* increasingly be overcome thanks to advances in the technologies themselves (and sometimes by simply sacrificing an inconsequential degree of model accuracy) and one that *must be* overcome for AI to gain a foothold in some industries such as healthcare and financial services to satisfy regulatory requirements and provide safe, premium care.

While businesses must prepare to be both vigilant and dogged as they deploy AI, the scale and beneficial impact of the technology on businesses, consumers, and society make it the responsibility of all organizations to explore the possible with AI.

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PART 1

The state of play

7 Artificial intelligence is getting ready for business, but are businesses ready for AI?

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Artificial intelligence is getting ready for business, but are businesses ready for AI?

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Companies new to the space can learn a great deal from early adopters who have invested billions in AI and are now beginning to reap a range of benefits.

Claims about the promise and peril of artificial intelligence (AI) are abundant—and growing. AI, which enables machines to exhibit humanlike cognition, can drive our cars or steal our privacy, stoke corporate productivity or empower corporate spies. It can relieve workers of repetitive or dangerous tasks or strip them of their livelihoods. Twice as many articles mentioned AI in 2016 as in 2015, and nearly four times as many as in 2014.[1] Expectations are high.

AI has been here before. Its history abounds with booms and busts, extravagant promises, and frustrating disappointments. Is it different this time? New analysis suggests yes: AI is finally

[1] Factiva.

starting to deliver real-life business benefits. The ingredients for a breakthrough are in place. Computer power is growing significantly, algorithms are becoming more sophisticated, and, perhaps most important of all, the world is generating vast quantities of the fuel that powers AI—data. Billions of gigabytes of it every day.

Companies at the digital frontier—online firms and digital natives such as Google and Baidu—are betting vast amounts of money on AI. We estimate between $20 billion and $30 billion in 2016, including significant M&A activity. Private investors are jumping in, too. We estimate that venture capitalists invested $4 billion to $5 billion in AI in 2016, and private equity firms invested $1 billion to $3 billion. That is more than three times as much as in 2013. An additional $1 billion of investment came from grants and seed funding.

For now, though, most of the news is coming from the suppliers of AI technologies. And many new uses are only in the experimental phase. Few products are on the market or are likely to arrive there soon to drive immediate and widespread adoption. As a result, analysts remain divided as to the potential of AI: some have formed a rosy consensus about AI's potential while others remain cautious about its true economic benefit. This lack of agreement is visible in the large variance of current market forecasts, which range from $644 million to $126 billion by 2025.[2] Given the size of investment being poured into AI, the low estimate would indicate that we are witnessing another phase in a boom-and-bust cycle.

Our business experience with AI suggests that this bust scenario is unlikely. In order to provide a more informed view, we decided to perform our own research into how users are adopting AI technologies. Our research offers a snapshot of the current state of the rapidly changing AI industry. To begin, we examine the investment landscape, including firms' internal investment in R&D and deployment, large corporate M&A, and funding from venture capital (VC) and private equity (PE) firms. We then combine use-case analyses and our AI adoption and use survey of C-level executives at more than 3,000 companies to understand how companies use AI technologies today.

AI generally refers to the ability of machines to exhibit humanlike intelligence—for example, solving a problem without the use of hand-coded software containing detailed instructions. There are several ways to categorize AI technologies, but it is difficult to draft a list that is mutually exclusive and collectively exhaustive, because people often mix and match several technologies to create solutions for individual problems. These creations sometimes are treated as independent technologies, sometimes as subgroups of other technologies, and sometimes as applications. Some frameworks group AI technologies by basic functionality, such as text, speech, or image recognition, and some group them by business applications such as commerce or cybersecurity.[3]

Trying to pin down the term more precisely is fraught for several reasons: AI covers a broad range of technologies and applications,

[2] Tractica; Transparency Market Research.

[3] Gil Press, "Top 10 hot artificial intelligence (AI) technologies," Forbes.com, January 23, 2017; "AI100: The artificial intelligence start-ups redefining industries," CBinsights.com, January 11, 2017.

some of which are merely extensions of earlier techniques and others that are wholly new. Also, there is no generally accepted theory of "intelligence," and the definition of machine "intelligence" changes as people become accustomed to previous advances.[4] Tesler's theorem, attributed to the computer scientist Larry Tesler, asserts that "AI is whatever hasn't been done yet."[5]

The AI technologies we consider in this paper are what is called "narrow" AI, which performs one narrow task, as opposed to artificial general intelligence, or AGI, which seeks to be able to perform any intellectual task that a human can do. We focus on narrow AI because it has near-term business potential, while AGI has yet to arrive.[6]

In this report, we focus on the set of AI technology systems that solve business problems. We have categorized these into five technology systems that are key areas of AI development: robotics and autonomous vehicles, computer vision, language, virtual agents, and machine learning, which is based on algorithms that learn from data without relying on rules-based programming in order to draw conclusions or direct an action. Some are related to processing information from the external world, such as computer vision and language (including natural-language processing, text analytics, speech recognition, and semantics technology); some are about learning from information, such as machine learning; and others are related to acting on information, such as robotics, autonomous vehicles, and virtual agents, which are computer programs that can converse with humans. Machine learning and a subfield called deep learning are at the heart of many recent advances in artificial intelligence applications and have attracted a lot of attention and a significant share of the financing that has been pouring into the AI universe—almost 60 percent of all investment from outside the industry in 2016.

Artificial intelligence's roller-coaster ride to today

Artificial intelligence, as an idea, first appeared soon after humans developed the electronic digital computing that makes it possible. And, like digital technology, artificial intelligence, or AI, has ridden waves of hype and gloom—with one exception: AI has not yet experienced wide-scale commercial deployment (see sidebar, "Fits and starts: A history of artificial intelligence").

That may be changing. Machines powered by AI can today perform many tasks—such as recognizing complex patterns, synthesizing information, drawing conclusions, and forecasting—that not long ago were assumed to require human cognition. And as AI's capabilities have dramatically expanded, so has its utility in a growing number of fields. At the same time, it is worth remembering that machine learning has limitations. For example,

4 Marvin Minsky, "Steps toward artificial intelligence," *Proceedings of the IRE*, volume 49, number 1, January 1961; Edward A. Feigenbaum, *The art of artificial intelligence: Themes and case studies of knowledge engineering*, Stanford University Computer Science Department report number STAN-CS-77–621, August 1977; Allen Newell, "Intellectual issues in the history of artificial intelligence," in *The Study of Information: Interdisciplinary messages*, Fritz Machlup and Una Mansfield, eds., John Wiley and Sons, 1983.

5 Douglas R. Hofstadter, *Gödel, Escher, Bach: An eternal golden braid*, Basic Books, 1979. Hofstadter writes that he gave the theorem its name after Tesler expressed the idea to him firsthand. However, Tesler writes in his online CV that he actually said, "Intelligence is whatever machines haven't done yet."

6 William Vorhies, "Artificial general intelligence—the Holy Grail of AI," DataScienceCentral.com, February 23, 2016.

because the systems are trained on specific data sets, they can be susceptible to bias; to avoid this, users must be sure to train them with comprehensive data sets. Nevertheless, we are seeing significant progress.

These advances have allowed machine learning to be scaled up since 2000 and used to drive deep learning algorithms, among other things. The advances have been facilitated by the availability of large and diverse data sets,

Fits and starts: A history of artificial intelligence

The idea of computer-based artificial intelligence dates to 1950, when Alan Turing proposed what has come to be called the Turing test: Can a computer communicate well enough to persuade a human that it, too, is human?[1] A few months later, Princeton students built the first artificial neural network, using 300 vacuum tubes and a war-surplus gyropilot.[2]

The term "artificial intelligence" was coined in 1955, to describe the first academic conference on the subject, at Dartmouth College. That same year, researchers at the Carnegie Institute of Technology (now Carnegie Mellon University) produced the first AI program, Logic Theorist.[3] Advances followed often through the 1950s: Marvin Lee Minsky founded the Artificial Intelligence Laboratory at MIT, while others worked on semantic networks for machine translation at Cambridge and self-learning software at IBM.[4]

Funding slumped in the 1970s as research backers, primarily the US government, tired of waiting for practical AI applications and cut appropriations for further work.[5] The field was fallow for the better part of a decade.

University researchers' development of "expert systems"—software programs that assess a set of facts using a database of expert knowledge and then offer solutions to problems—revived AI in the 1980s.[6] Around this time, the first computer-controlled autonomous vehicles began to appear.[7] But this burst of interest preceded another AI "winter."

Interest in AI boomed again in the 21st century as advances in fields such as deep learning, underpinned by faster computers and more data, convinced investors and researchers that it was practical—and profitable—to put AI to work.[8]

1 A. M. Turing, "Computing machinery and intelligence," *Mind*, volume 49, number 236, October 1950.

2 Jeremy Bernstein, "A.I.," *The New Yorker*, December 14, 1981.

3 Leo Gugerty, "Newell and Simon's Logic Theorist: Historical background and impact on cognitive modeling," *Proceedings of the Human Factors and Ergonomics Society Annual Meeting,* volume 50, issue 9, October 2006.

4 "The IBM 700 Series: Computing comes to business," IBM Icons of Progress, March 24, 2011.

5 Michael Negnevitsky, *Artificial intelligence: A guide to intelligent systems*, Addison-Wesley, 2002.

6 Edward A. Feigenbaum, "Expert systems in the 1980s," working paper, 1980.

7 Hans P. Moravec, "The Stanford Cart and the CMU Rover," *Proceedings of the IEEE*, volume 71, issue 7, July 1983; Tom Vanderbilt, "Autonomous cars through the ages," Wired.com, February 6, 2012.

8 Bruce G. Buchanan, "A (very) brief history of artificial intelligence," *AI Magazine*, volume 26, number 4, Winter 2005.

improved algorithms that find patterns in mountains of data, increased R&D financing, and powerful graphics processing units (GPUs), which have brought new levels of mathematical computing power. GPUs, which are specialized integrated circuits originally developed for video games, can process images 40 to 80 times faster than the fastest versions available in 2013. Advances in the speed of GPUs have enabled the training speed of deep learning systems to improve five- or sixfold in each of the last two years. More data—the world creates about 2.2 exabytes, or 2.2 billion gigabytes, of it every day—translates into more insights and higher accuracy because it exposes algorithms to more examples they can use to identify correct and reject incorrect answers. Machine learning systems enabled by these torrents of data have reduced computer error rates in some applications—for example, in image identification—to about the same as the rate for humans.

AI investment is growing rapidly, but commercial adoption is lagging

Tech giants and digital native companies such as Amazon, Apple, Baidu, and Google are investing billions of dollars in the various technologies known collectively as artificial intelligence. They see that the inputs needed to enable AI to finally live up to expectations—powerful computer hardware, increasingly sophisticated algorithmic models, and a vast and fast-growing inventory of data—are in place. Indeed, internal investment by large corporations dominates: we estimate that this amounted to $18 billion to $27 billion in 2016; external investment (from VCs, PE firms, M&A, grants, and seed funding) was around $8 billion to $12 billion (Exhibit 1).[7]

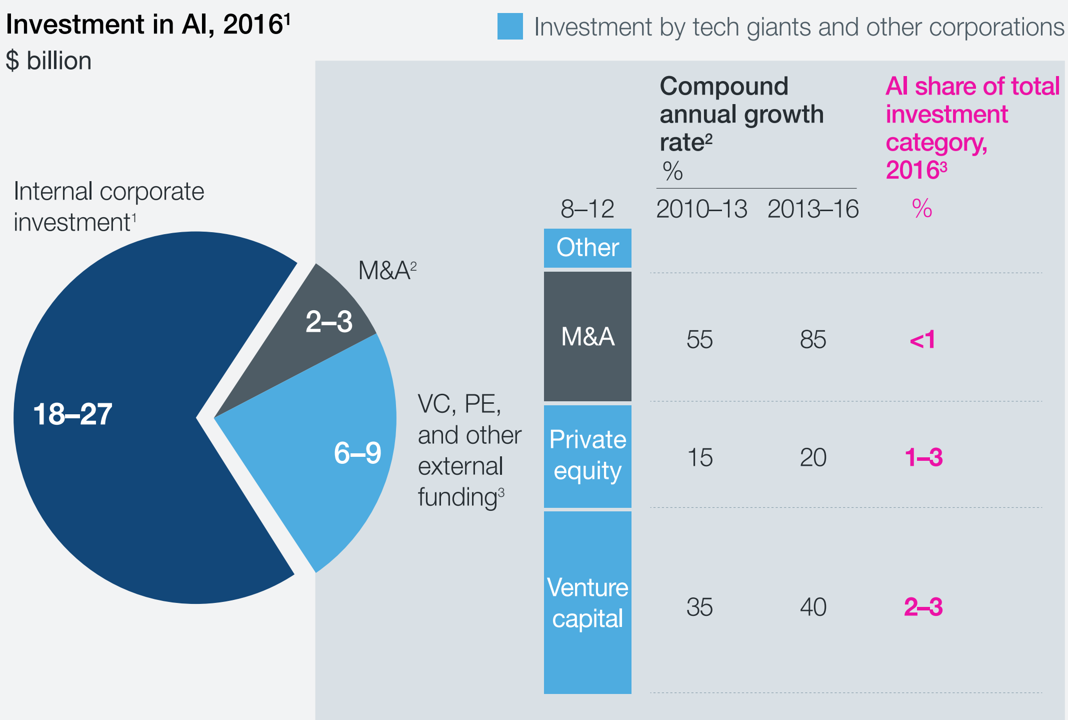
But for all the recent investment, the scope of AI deployment has been limited so far. That is partly due to the fact that one beneficiary of that investment, internal R&D, is largely focused on improving the firms' own performance. But it is also true that there is only tepid demand for artificial intelligence applications for businesses, partly due to the relatively slow pace of digital and analytics transformation of the economy. Our survey of more than 3,000 businesses around the world found that many business leaders are uncertain about what exactly AI can do for them, where to obtain AI-powered applications, how to integrate them into their companies, and how to assess the return on an investment in the technology.

Most of the investment in AI has consisted of internal spending—R&D and deployment—by large, cash-rich digital native companies. What is the large corporate investment in AI focused on? Bigger companies, such as Apple, Baidu, and Google, are working on suites of technologies internally but vary in the breadth and focus of their AI investment. Amazon is working on robotics and speech recognition, Salesforce on virtual agents and machine learning. BMW, Tesla, and Toyota are among the manufacturers making sizable commitments in robotics and machine learning for use in driverless cars. Toyota, for example, set aside $1 billion to establish a new research institute devoted to AI for robotics

[7] Internal investment includes research and development, talent acquisition, cooperation with scientific institutions, and joint ventures with other companies done by corporations. External investment includes mergers and acquisitions, private equity funding, venture capital financing, and seed funds and other early-stage investing. The estimates of external investment are based on data available in the Capital IQ, PitchBook, and Dealogic databases. Provided values are estimates of annual investment in AI, assuming that all registered deals were completed within the year of transaction. Internal investment is estimated based on the ratio of AI spend to revenue for the top 35 high-tech and advanced manufacturing companies focused on AI technologies.

Exhibit 1

Technology giants dominate investment in AI.



[1] Estimate of 2016 spend by corporations to develop and deploy AI-based products. Calculated for top 35 high-tech and advanced-manufacturing companies investing in AI. Estimate is based on the ratio of AI spend to total revenue calculated for a subset of the 35 companies.
[2] VC value is an estimate of VC investment in companies primarily focused on AI. PE value is an estimate of PE investment in AI-related companies. M&A value is an estimate of AI deals done by corporations. "Other" refers to grants and seed-fund investments. Includes only disclosed data available in databases and assumes that all registered deals were completed within the year of transaction. Compound annual growth rate values rounded.
[3] M&A and PE deals expressed by volume; VC deals expressed by value.

Source: Capital IQ; PitchBook; Dealogic; S&P; McKinsey Global Institute analysis

and driverless vehicles.[8] Industrial giants such as ABB, Bosch, GE, and Siemens also are investing internally, often in machine learning and robotics, seeking to develop specific technologies related to their core businesses. IBM has pledged to invest $3 billion to make its Watson cognitive computing service a force in the Internet of Things.[9] Baidu has invested

[8] Craig Trudell and Yuki Hagiwara, "Toyota starts $1 billion center to develop cars that don't crash," Bloomberg.com, November 6, 2015.

[9] "IBM invests to lead global Internet of Things market—shows accelerated client adoption," IBM press release, October 3, 2006.

$1.5 billion in AI research over the last two and a half years. This is in addition to $200 million it committed to a new in-house venture capital fund, Baidu Venture.[10]

At the same time, big tech companies have been actively buying AI start-ups, not just to acquire technology or clients but to secure qualified talent. The pool of true experts in the field is small, and Alibaba, Amazon, Facebook, Google, and other tech giants have hired many of them. Companies have adopted M&A as a way to sign up top talent, a practice known as "acqui-hiring," for sums that typically work out to $5 million to $10 million per person. The shortage of talent and cost of acquiring it are underlined by a recent report that companies are seeking to fill 10,000 AI-related jobs and have budgeted more than $650 million for salaries.[11]

Overall, corporate M&A is the fastest-growing external source of funding for AI companies, increasing in terms of value at a compound annual growth rate of over 80 percent from 2013 to 2016, based on our estimates. Leading high-tech companies and advanced manufacturers have closed more than 100 M&A deals since 2010. Google completed 24 transactions in that time, including eight in computer vision and seven in language processing. Apple, the second-most-active acquirer, has closed nine, split evenly among computer vision, machine learning, and language processing.

Companies are also expanding their search for talent abroad. Facebook, for instance, is opening an AI lab in Paris that will supplement similar facilities in New York and Silicon Valley—and make it easier for the company to recruit top researchers in Europe.[12] Google recently invested $4.5 million in the Montreal Institute for Learning Algorithms, a research lab at the University of Montreal; Intel donated $1.5 million to establish a machine learning and cybersecurity research center at Georgia Tech; and NVIDIA is working with the National Taiwan University to establish an AI laboratory in Taipei.[13]

The buzz over AI has grown loud enough to encourage venture capital and private equity firms to step up their investment in AI. Other external investors, such as angel funds and seed incubators, also are active. We estimate total annual external investment was $8 billion to $12 billion in 2016.[14]

Machine learning attracted almost 60 percent of that investment, most likely because it is an enabler for so many other technologies and applications, such as robotics and speech recognition (Exhibit 2). In addition, investors are

[10] Phoenix Kwong, "Baidu launches $200m venture capital unit focused on artificial intelligence," *South China Morning Post*, September 13, 2016.

[11] "U.S. companies raising $1 billion or more to fuel artificial intelligence (AI) development: Looking to staff 10,000+ openings, cites new Paysa research," Paysa press release, April 18, 2017.

[12] Cade Metz, "Facebook opens a Paris lab as AI research goes global," Wired.com, June 2, 2015.

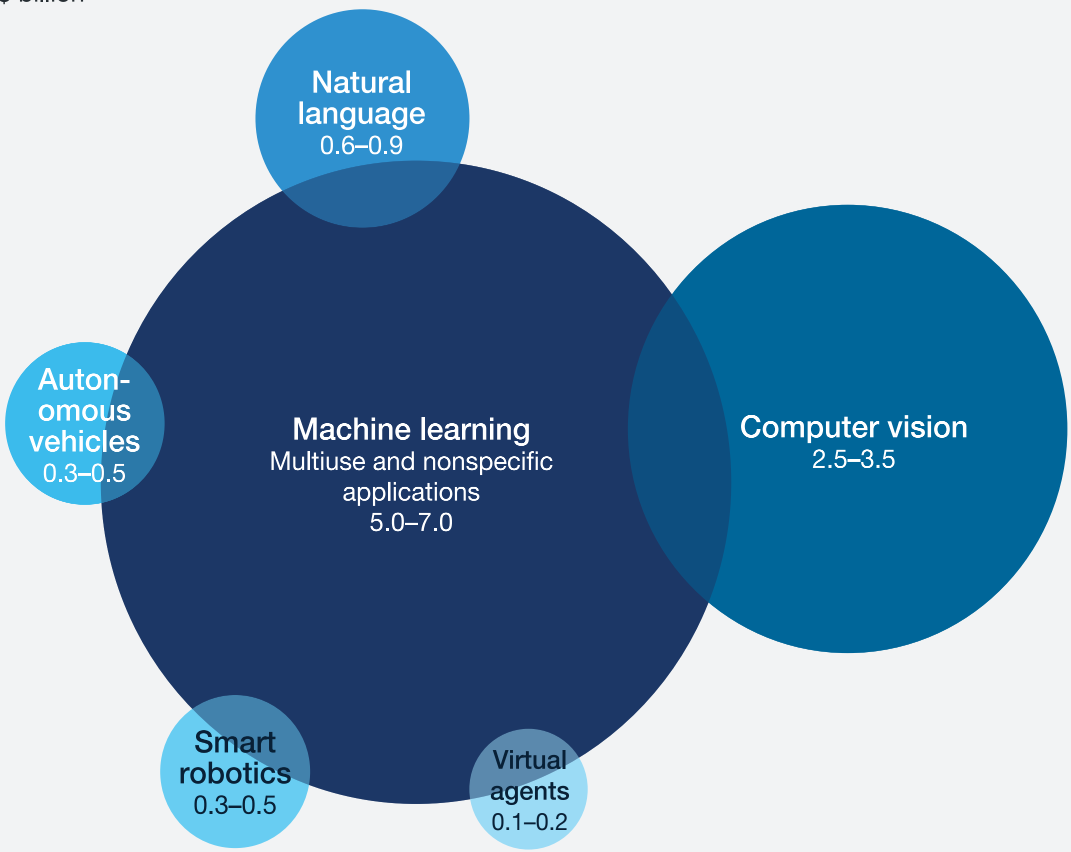
[13] Cade Metz, "Google opens Montreal AI lab to snag scarce global talent," Wired.com, November 12, 2015; "Georgia Tech launches new research on the security of machine-learning systems," Georgia Institute of Technology press release, October 31, 2016; "NVIDIA collaborates with Taipei Tech to establish Embedded GPU Joint Lab," National Taipei University of Technology press release, September 4, 2014.

[14] Estimates of external investment in AI vary widely because measurement standards vary. For example, Venture Scanner puts total funding of AI-related start-ups in 2016 at $2.5 billion, while Goldman Sachs estimates that the venture capital sector alone made $13.7 billion of AI-related investment that year.

Exhibit 2

Machine learning received the most investment, although boundaries between technologies are not clear-cut.

External investment in AI-focused companies by technology category, 2016[1]
$ billion



[1] Estimates consist of annual VC investment in AI-focused companies, PE investment in AI-related companies, and M&A by corporations. Includes only disclosed data available in databases and assumes that all registered deals were completed within the year of transaction.

Source: Capital IQ; PitchBook; Dealogic; McKinsey Global Institute analysis

drawn to machine learning because, as has long been the case, it is quicker and easier to install new code than to rebuild a robot or other machine that runs the software. Corporate M&A in this area is also growing fast, with a compound annual growth rate of around 80 percent from 2013 through 2016.

Investment in AI is still in the early stages and relatively small compared with the investment in the digital revolution. Artificial intelligence, for example, attracted 2 to 3 percent of all VC funding by value in 2016, while information technology in general soaked up 60 percent. AI also was a small fraction—1 to 3 percent—

of all investment by PE firms in 2016.[15] But AI investment is growing fast.

From 2013 through 2016, external investment in AI technologies had a compound annual growth rate of almost 40 percent. That compares with 30 percent from 2010 through 2013. Not only are deals getting bigger and more numerous, but they require fewer participants to complete the financing. This suggests that investors are growing more confident in the sector and may have a better understanding of the technology and its potential.

However, for the most part, investors are still waiting for their investments to pay off. Only 10 percent of start-up companies that consider machine learning to be a core business say they generate revenue, according to PitchBook. Of those, only half report more than $50 million in revenue. Moreover, external investment remains highly concentrated geographically, dominated by a few technology hubs in the United States and China, with Europe lagging far behind.

Firms and industries already on the digital frontier are adopting AI, but others are hesitant to act

Investors are pouring billions of dollars into AI companies based on the hope that a market of AI adopters will develop fairly quickly and will be willing to pay for AI infrastructure, platforms, and services. Clearly, Amazon, Google, and other digital natives are investing for their own applications, such as optimizing searches and personalizing marketing. But getting a sense of how much traditional companies in healthcare, retail, and telecom are spending on AI is not easy. For this reason, we conducted a survey to understand this situation in more depth.

In general, few companies have incorporated AI into their value chains at scale; a majority of companies that had some awareness of AI technologies are still in experimental or pilot phases. In fact, out of the 3,073 respondents, only 20 percent said they had adopted one or more AI-related technology at scale or in a core part of their business.[16] Ten percent reported adopting more than two technologies, and only 9 percent reported adopting machine learning.[17]

Even this may overstate the commercial demand for AI at this point. Our review of more than 160 global use cases across a variety of industries found that only 12 percent had progressed beyond the experimental stage. Commercial considerations can explain why some companies may be reluctant to act. In our survey, poor or uncertain returns were the primary reason for not adopting reported by firms, especially smaller firms. Regulatory concerns have also become much more important.

As with every new wave of technology, we expect to see a pattern of early and late adopters among sectors and firms. We uncover six features of the early pattern of AI adoption, which is broadly in line with the ways companies have been adopting and using

[15] It is worth noting that VC funds were focusing on AI technology when choosing investments, while PE funds were investing in AI-related companies.

[16] Survey results throughout this discussion paper are weighted for firm size; “20 percent of firms” indicates firms representing 20 percent of the workforce.

[17] The eight technologies are natural-language processing, natural-language generation, speech recognition, machine learning, decision management, virtual agents, robotic process automation, and computer vision. The five technology systems are robotics and autonomous vehicles, computer vision, language, virtual agents, and machine learning.

the recent cohort of digital technologies. Not coincidentally, the same players who were leaders in that earlier wave of digitization are leading in AI—the next wave.

The first feature is that early AI adopters are from sectors already investing at scale in related technologies, such as cloud services and big data. Those sectors are also at the frontier of digital assets and usage.[18] This is a crucial finding, as it suggests that there is limited evidence of sectors and firms catching up when it comes to digitization, as each new generation of tech builds on the previous one.

Second, independently of sectors, large companies tend to invest in AI faster at scale. This again is typical of digital adoption, in which, for instance, small and midsized businesses have typically lagged behind in their decision to invest in new technologies.

Third, early adopters are not specializing in one type of technology. They go broader as they adopt multiple AI tools addressing a number of different use cases at the same time.

Fourth, companies investing at scale do it close to their core business.

Fifth, early adopters that adopt at scale tend to be motivated as much by the upside growth potential of AI as they are by cutting costs. AI is not only about process automation but is also used by companies as part of major product and service innovation. This has been the case for early adopters of digital technologies and suggests that AI-driven innovation will be a new source of productivity and may further expand the growing productivity and income gap between high-performing firms and those left behind.[19]

Finally, strong executive leadership goes hand in hand with stronger AI adoption. Respondents from firms that have successfully deployed an AI technology at scale tended to rate C-suite support nearly twice as high as those from companies that had not adopted any AI technology.

Early-adopting sectors are closer to the digital frontier

Sector-by-sector adoption of AI is highly uneven right now, reflecting many features of digital adoption more broadly. Our survey found that larger companies and industries that adopted digital technologies in the past are more likely to adopt AI. For them, AI is the next wave of digitization.

This pattern in the adoption of technology is not new—we saw similar behavior in firms adopting enterprise social technologies.[20] But this implies that, at least in the near future, AI deployment is likely to accelerate at the digital frontier, expanding the gap between adopters and laggards across companies, industries, and geographic regions.

[18] *Digital Europe: Pushing the frontier, capturing the benefits*, McKinsey Global Institute, June 2016; *Digital America: A tale of the haves and have-mores*, McKinsey Global Institute, December 2015.

[19] Rosina Moreno and Jordi Suriñach, “Innovation adoption and productivity growth: Evidence for Europe,” working paper, 2014; Jacques Bughin and Nicolas van Zeebroeck, “The right response to digital disruption,” *MIT Sloan Management Review*, April 2017.

[20] Jacques Bughin and James Manyika, “How businesses are using web 2.0: A McKinsey global survey,” *McKinsey Quarterly*, December 2007; Jacques Bughin and James Manyika, “Bubble or paradigm change? Assessing the global diffusion of enterprise 2.0,” in Alex Koohang, Johannes Britz, and Keith Harman, eds., *Knowledge Management: Research and Applications*, Informing Science, 2008.

The leading sectors include some that MGI's Industry Digitization Index found at the digital frontier, namely high tech and telecom and financial services.[21] These are industries with long histories of digital investment. They have been leaders in developing or adopting digital tools, both for their core product offerings and for optimizing their operations. However, even these sectors are far behind in AI adoption when compared with overall digitization (Exhibit 3).

Automotive and assembly is also highly ranked. It was one of the first sectors that implemented advanced robotics at scale for manufacturing and today is also using AI technologies to develop self-driving cars.

In the middle are less digitized industries, including resources and utilities, personal and professional services, and building materials and construction. A combination of factors may account for this. These sectors have been slow to employ digital tools generally, except for some parts of the professional services industry and large construction companies. They are also industries in which innovation and productivity growth has lagged, potentially in part due to their domestic focus. Some of these sectors have a particularly high number of small firms—an important predictor for AI adoption, as explored following.

Toward the bottom of the pack for now are traditionally less digital fields such as education and healthcare. Despite ample publicity about cutting-edge AI applications in these industries, the reality is that uptake appears to be low so far. Weaker adoption reflects the particular challenges faced in these sectors. In healthcare, for example, practitioners and administrators acknowledge the potential for AI to reduce costs but quickly add that they believe that regulatory concerns and customer acceptance will inhibit adoption.

When it comes to adopting AI, the bigger, the bolder

A stylized fact in IT literature is that large firms usually are early adopters of innovative technology, while smaller firms are more reluctant to be first movers.[22] We find the same digital divide when we look at AI: large firms have much higher rates of adoption and awareness. Across all sectors, larger firms—which we define as those with more than 500 employees—are at least 10 percent more likely than smaller firms to have adopted at least one AI technology at scale or in a core part of their business. In sectors with lower rates of AI uptake, the adoption rate of bigger companies was as much as 300 percent that of smaller companies.

Other digitization indicators reflect this fact, as highlighted in MGI's digitization work. Larger firms typically have access to more and better-structured data and are more likely to have employees with the technical skills needed to understand the business case for AI investment and to successfully engage suppliers. Bigger firms also have an advantage because the kind of fixed-cost investment required for AI tends to generate higher returns

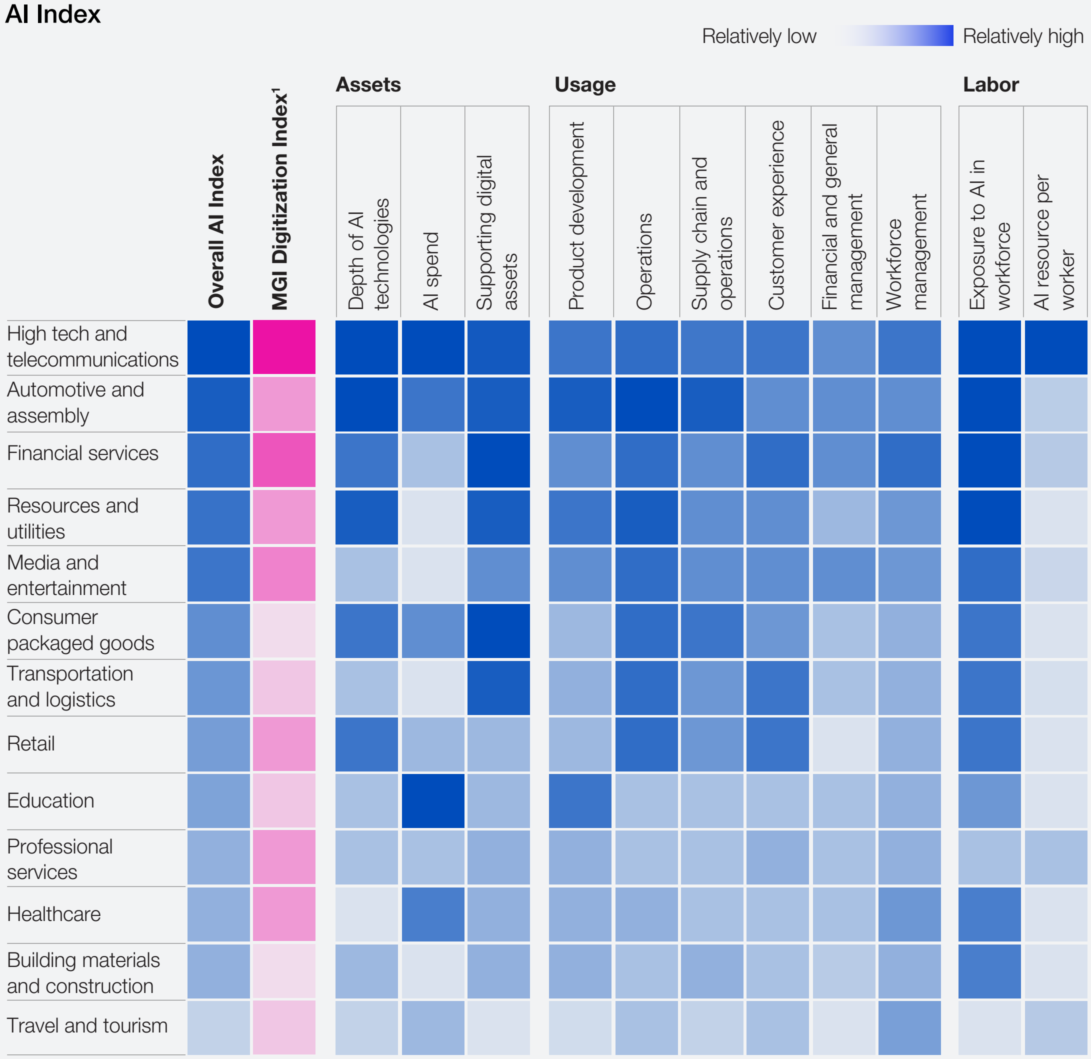
21 *Digital America: A tale of the haves and have-mores*, McKinsey Global Institute, December 2015.

22 Kevin Zhu, Kenneth L. Kraemer, and Sean Xu, "The process of innovation assimilation by firms in different countries: A technology diffusion perspective on e-business," *Management Science*, volume 52, number 10, October 2006; Chris Forman, Avi Goldfarb, and Shane Greenstein, "The geographic dispersion of commercial Internet use," in *Rethinking Rights and Regulations: Institutional Responses to New CommunicationTechnologies*, Lorrie Faith Cranor and Steven S. Wildman, eds., MIT Press, 2003.

Exhibit 3

Artificial intelligence (AI) adoption is occurring faster in more digitized sectors and across the value chain.

AI Index



[1] The MGI Digitization Index is GDP weighted average of Europe and United States.

Source: McKinsey Global Institute AI adoption and use survey; *Digital Europe: Pushing the frontier, capturing the benefits*, McKinsey Global Institute, June 2016; *Digital America: A tale of the haves and have-mores*, McKinsey Global Institute, December 2015; McKinsey Global Institute analysis when applied to a bigger base of costs and revenue.

Nonetheless, we find success stories among some smaller firms, too. Relative to larger companies, they can benefit from fewer issues with legacy IT systems and lower levels of organizational resistance to change. Smaller firms can also benefit from AI tools provided as a service.

Early AI adopters tend to become serial adopters

We looked at how firms deploy AI across eight different application areas and five technology systems.[23] Our results suggest that early-adopting firms are looking across multiple AI tools when they begin to adopt, rather than focusing on a particular technology. This is consistent with adoption patterns in other digital technologies.[24]

The phenomenon of multitechnology application is persistent at a sector level. Industries with high rates of adopting one technology have higher rates in adopting others. High tech and telecom, for example, report the highest rates of adoption across all five technology groups, while construction is among the lowest among all five.

However, there are anomalies. Education and healthcare are notable for being slow to adopt AI technology. In frontier sectors—those with a relatively high percentage of early adopters—two-thirds of firms that had already adopted one of the eight AI technologies had adopted at least two others as well. In healthcare, only one-third had, with language technologies the most likely to be deployed at scale or in a core part of the business.

Users are keeping artificial intelligence close to their core

Functionally, AI technologies are finding applications across the value chain, but with some parts of the value chain getting more attention than others. For example, customer service functions such as sales and marketing, as well as operations and product development, all tend to use the most commonly cited AI applications. General and financial management, by contrast, lag well behind. A similar pattern is found in big data. The literature shows that the most frequent big data applications originate in sales and marketing functions.[25]

In general, firms queried in our survey say they tend to adopt AI technologies affecting the part of their value chain closest to the core. Operations are an important area of adoption in the automotive and assembly and consumer packaged goods sectors, as well as utilities and resources. Operations and customer service are the most important areas for financial services. This is new. Previously, new digital technology tended to remain on the margins, away from the core of the business.

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[23] The eight technologies are natural-language processing, natural-language generation, speech recognition, machine learning, decision management, virtual agents, robotic process automation, and computer vision. The five technology systems are robotics and autonomous vehicles, computer vision, language, virtual agents, and machine learning.

[24] Sanjeev Dewan, Dale Ganley, and Kenneth L. Kraemer, "Complementarities in the diffusion of personal computers and the Internet: Implications for the global digital divide," *Information Systems Research*, volume 21, number 5, December 2010.

[25] Jacques Bughin, "Ten big lessons learned from big data analytics," *Applied Marketing Analytics*, volume 2, number 4, 2017.

However, in line with trends in technology, we also see sectors going deeper and broader as they increase their degree of AI adoption. Leading sectors are not only more extensively deploying AI in the core parts of their value chain, but they are also deploying it in more parts of their value chain.

Early adopters see AI increasing revenue, while companies experimenting with AI expect lower costs

As companies become more familiar with AI, their perceptions about its benefits change. The results of survey analysis show that early AI adopters are driven to employ AI technologies in order to grow revenue and market share, and the potential for cost reduction is a secondary idea. Firms that we consider more advanced AI adopters were 27 percent more likely to report using AI to grow their market than companies only experimenting with or partially adopting AI and 52 percent more likely to report using it to increase their market share. Experimenters, by contrast, were more focused on costs. They were 23 percent more likely than advanced AI adopters to point to labor cost reductions and 38 percent more likely to mention non-labor cost reductions.

In other words, the more companies use and become familiar with AI, the more potential for growth they see in it. Companies with less experience tend to focus more narrowly on reducing costs.

AI is not only about technical adoption but also about enterprise acceptance

To be successful, AI adoption requires buy-in by the executive suite to generate the momentum needed to overwhelm organizational inertia.

Successful AI adopters, according to our survey, have strong executive leadership support for the new technology. Representatives of firms that have successfully deployed an AI technology at scale tended to rate C-suite support nearly twice as high as those of companies that had not adopted any AI technology. They added that strong support came not only from the CEO and IT executives—that is, chief information officer, chief digital officer, and chief technology officer—but from all other C-level officers and the board of directors as well. Successful adopters also adjusted their firmwide strategy to become proactive toward AI.

AI's next challenge: Get users to adapt and adopt

IT industry analysts concur that the market size for AI technology will experience strong growth over the next three years. Most of the firms we surveyed expected to increase spending on AI in the coming three years, a finding echoed in other recent surveys. For example, 75 percent of the 203 executives queried in an Economist Intelligence Unit survey said AI would be "actively implemented" in their firms within three years (3 percent said it had already happened).

Expectations of how large this growth will be vary widely. Our survey documented relatively modest growth projections—only one-fifth of firms expected to increase expenditure by more than 10 percent. Industry analysts' forecasts of the compound annual growth rate ranged from just under 20 percent to nearly 63 percent, including both adoption by additional companies and increased spending within companies.[26] The actual growth rate may need to be toward the upper end of that range to meet the expectations of investors piling into the industry.

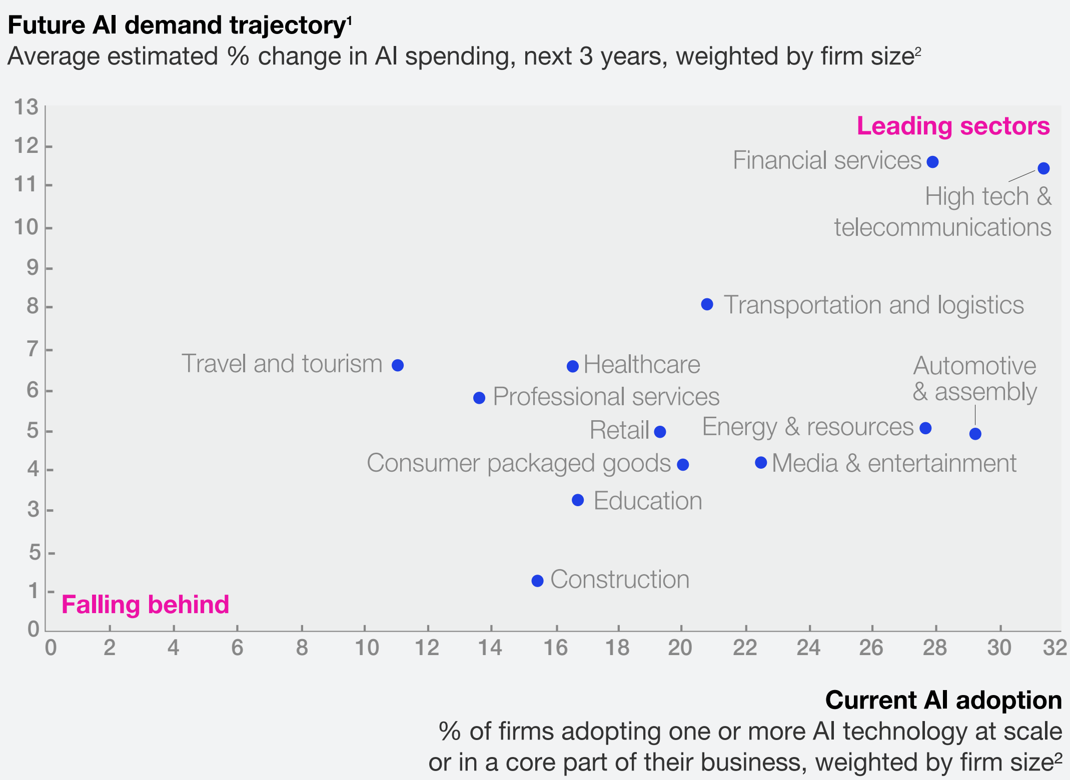
[26] The full range of forecasts: BCC Research, 19.7 percent; Transparency Market Research, 36.1 percent; Tractica, 57.6 percent; IDC, 58 percent; and Markets and Markets, 62.9 percent.

Growth will hinge on the ability of sectors and firms to overcome technical, commercial, and regulatory challenges. Our survey respondents and outside forecasters expect financial services, retail, healthcare, and advanced manufacturing to be in the AI vanguard. These are the industries where technical feasibility is relatively high (reflected in the case studies on the market today) and the business case for AI is most compelling. They are also the sectors with the highest degree of digital adoption to date—a key foundation for AI (Exhibit 4).

Technical challenges are an important differentiating factor between industries. While big tech and academia are pushing advances in the performance of the underlying technology, engineering solutions need to be worked out for specific use cases, requiring both data and talent. Industries such as

Exhibit 4

Sectors leading in AI adoption today also intend to grow their investment the most



[1] Based on the midpoint of the range selected by the survey respondent.
[2] Results are weighted by firm size.

Source: McKinsey Global Institute AI adoption and use survey; McKinsey Global Institute analysis financial services, high tech, and telecom have generated and stored large volumes of structured data, but others, including construction and travel, lag far behind.[27]

Commercial drivers also differ between sectors. Industries most likely to lead the adoption of AI technologies at scale are those with complex businesses in terms of both operations and geography and whose performance is driven by forecasting, fast and accurate decision making, or personalized customer connections. In financial services, there are clear benefits from improved accuracy and speed in AI-optimized fraud-detection systems, forecast to be a $3 billion market in 2020. In retail, there are compelling benefits from improved inventory forecasts, automated customer operations, and highly personalized marketing campaigns. Similarly, in healthcare, AI-powered diagnosis and treatment systems can both save costs and deliver better outcomes for patients.

Even where compelling commercial use cases have been engineered and are demanded by firms, regulatory and social barriers can raise the cost and slow the rate of adoption. Product liability is one such concern; it is especially troublesome for automakers and other manufacturers. Privacy considerations restrict access to data and often require it to be anonymized before it can be used in research. Ethical issues such as trained biases and algorithmic transparency remain unresolved. Preferences for a human relationship in settings such as healthcare and education will need to be navigated. Job security concerns could also limit market growth—there are already serious calls for taxes on robots.

These forces will help determine the industries that AI is likely to transform the most. However, if current trends hold, variation of adoption within industries will be even larger than between industries. We expect that large companies with the most digital experience will be the first movers because they can leverage their technical skills, digital expertise, and data resources to develop and smoothly integrate the most appropriate AI solutions.

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After decades of false starts, artificial intelligence is on the verge of a breakthrough, with the latest progress propelled by machine learning. Tech giants and digital natives are investing in and deploying the technology at scale, but widespread adoption among less digitally mature sectors and companies is lagging. However, the current mismatch between AI investment and adoption has not stopped people from imagining a future where AI transforms businesses and entire industries. ◆

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27 *A future that works: Automation, employment, and productivity*, McKinsey Global Institute, January 2017.

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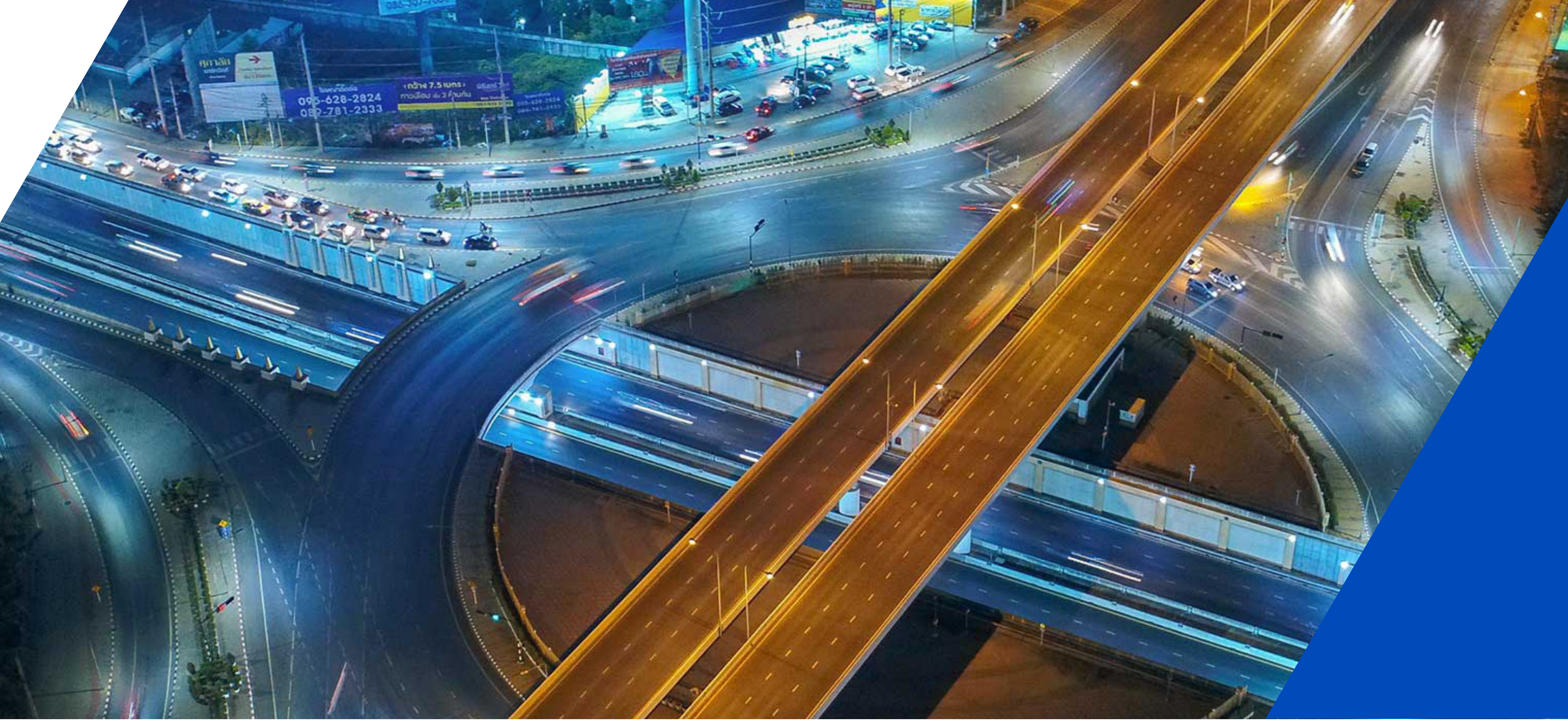
This article was excerpted from the McKinsey Global Institute discussion paper Artificial Intelligence: The Next Digital Frontier? *(2017).*



Notes from the AI frontier: Applications and value of deep learning

Michael Chui, Rita Chung, Nicolaus Henke, Sankalp Malhotra, James Manyika, Mehdi Miremadi, and Pieter Nel

An analysis of more than 400 use cases across 19 industries and nine business functions highlights the broad use and significant economic potential of advanced AI techniques.

Artificial intelligence (AI) stands out as a transformational technology of our digital age—and its practical application throughout the economy is growing apace. In our latest discussion paper, *Notes from the AI frontier: Insights from hundreds of use cases*, we mapped both traditional analytics and newer "deep learning" techniques and the problems they can solve to more than 400 specific use cases in companies and organizations.[1] Drawing on McKinsey Global Institute research and the applied experience with AI of McKinsey Analytics, we assess both the practical applications and the economic potential of advanced AI techniques across industries and business functions. Our findings highlight

[1] For the full McKinsey Global Institute discussion paper, see "Notes from the AI frontier: Applications and value of deep learning," April 2018, on McKinsey.com.

the substantial potential of applying deep-learning techniques to use cases across the economy, but we also see some continuing limitations and obstacles—along with future opportunities as the technologies continue their advance. Ultimately, the value of AI is not to be found in the models themselves, but in companies' abilities to harness them.

It is important to highlight that, even as we see economic potential in the use of AI techniques, the use of data must always take into account concerns including data security, privacy, and potential issues of bias.

Mapping AI techniques to problem types

As artificial intelligence technologies advance, so does the definition of which techniques constitute AI.[2] For the purposes of this article, we use AI as shorthand for deep-learning techniques that use artificial neural networks. We also examined other machine-learning techniques and traditional analytics techniques (Exhibit 1).

Neural networks are a subset of machine-learning techniques. Essentially, they are AI systems based on simulating connected "neural units," loosely modeling the way that neurons interact in the brain. Computational models inspired by neural connections have been studied since the 1940s and have returned to prominence as computer processing power has increased and large training data sets have been used to successfully analyze input data such as images, video, and speech. AI practitioners refer to these techniques as "deep learning," since neural networks have many ("deep") layers of simulated interconnected neurons.

We analyzed the applications and value of three neural network techniques:

- **Feed-forward neural networks:** The simplest type of artificial neural network. In this architecture, information moves in only one direction, forward, from the input layer, through the "hidden" layers, to the output layer. There are no loops in the network. The first single-neuron network was proposed already in 1958 by AI pioneer Frank Rosenblatt. While the idea is not new, advances in computing power, training algorithms, and available data led to higher levels of performance than previously possible.

- **Recurrent neural networks (RNNs):** Artificial neural networks whose connections between neurons include loops; RNNs are well suited for processing sequences of inputs. In November 2016, Oxford University researchers reported that a system based on recurrent neural networks (and convolutional neural networks) had achieved 95 percent accuracy in reading lips, outperforming experienced human lip readers, who tested at 52 percent accuracy.

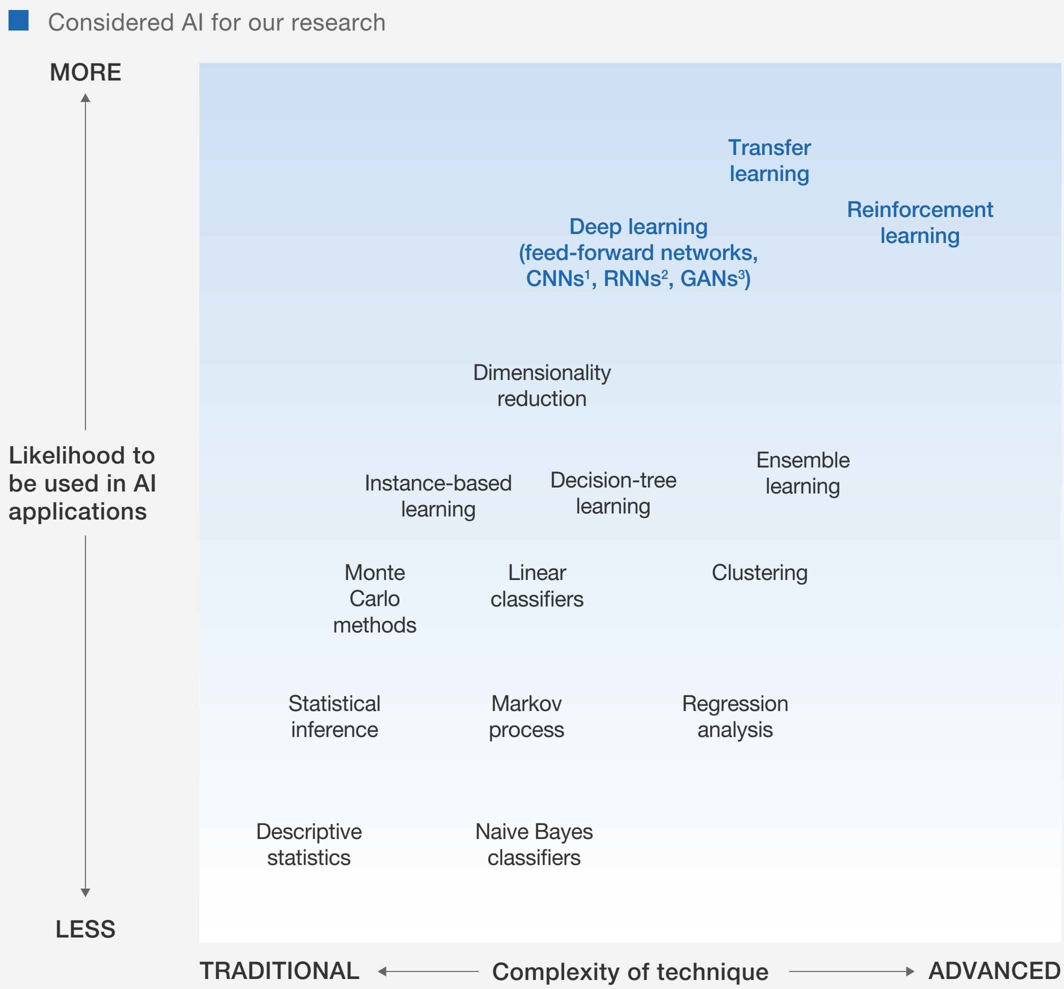
- **Convolutional neural networks (CNNs):** Artificial neural networks in which the connections between neural layers are inspired by the organization of the animal visual cortex, the portion of the brain that processes images; CNNs are well suited for perceptual tasks.

For our use cases, we also considered two other techniques—generative adversarial networks and reinforcement learning—but

[2] For more on AI techniques, including definitions and use cases, see "An executive's guide to AI" in the appendix.

Exhibit 1

We examined artificial intelligence (AI), machine learning, and other analytics techniques for our research.



[1] Convolutional neural networks.
[2] Recurrent neural networks.
[3] Generative adversarial networks.

Source: McKinsey Global Institute analysis

did not include them in our potential value assessment of AI, since they remain nascent techniques that are not yet widely applied.

- **Generative adversarial networks (GANs)** use two neural networks contesting one other in a zero-sum game framework (thus "adversarial"). GANs can learn to mimic various distributions of data (for example, text, speech, and images) and are therefore valuable in generating test data sets when these are not readily available.

- **Reinforcement learning** is a subfield of machine learning in which systems are trained by receiving virtual "rewards" or "punishments," essentially learning by trial and error. Google's DeepMind has used reinforcement learning to develop systems that can play games, including video games and board games such as Go, better than human champions.

In a business setting, these analytic techniques can be applied to solve real-life problems. The most prevalent problem types are classification, continuous estimation, and clustering. See sidebar, "Problem types and their definitions," for a list of problem types and their definitions.

Insights from use cases

We collated and analyzed more than 400 use cases across 19 industries and nine business functions. They provided insight into the areas within specific sectors where deep neural networks can potentially create the most value, the incremental lift that these neural networks can generate compared with traditional analytics (Exhibit 2), and the voracious data requirements—in terms of volume, variety, and velocity—that must be met for this potential to be realized. Our library of use cases, while extensive, is not exhaustive and may overstate or understate the potential for certain sectors. We will continue refining and adding to it.

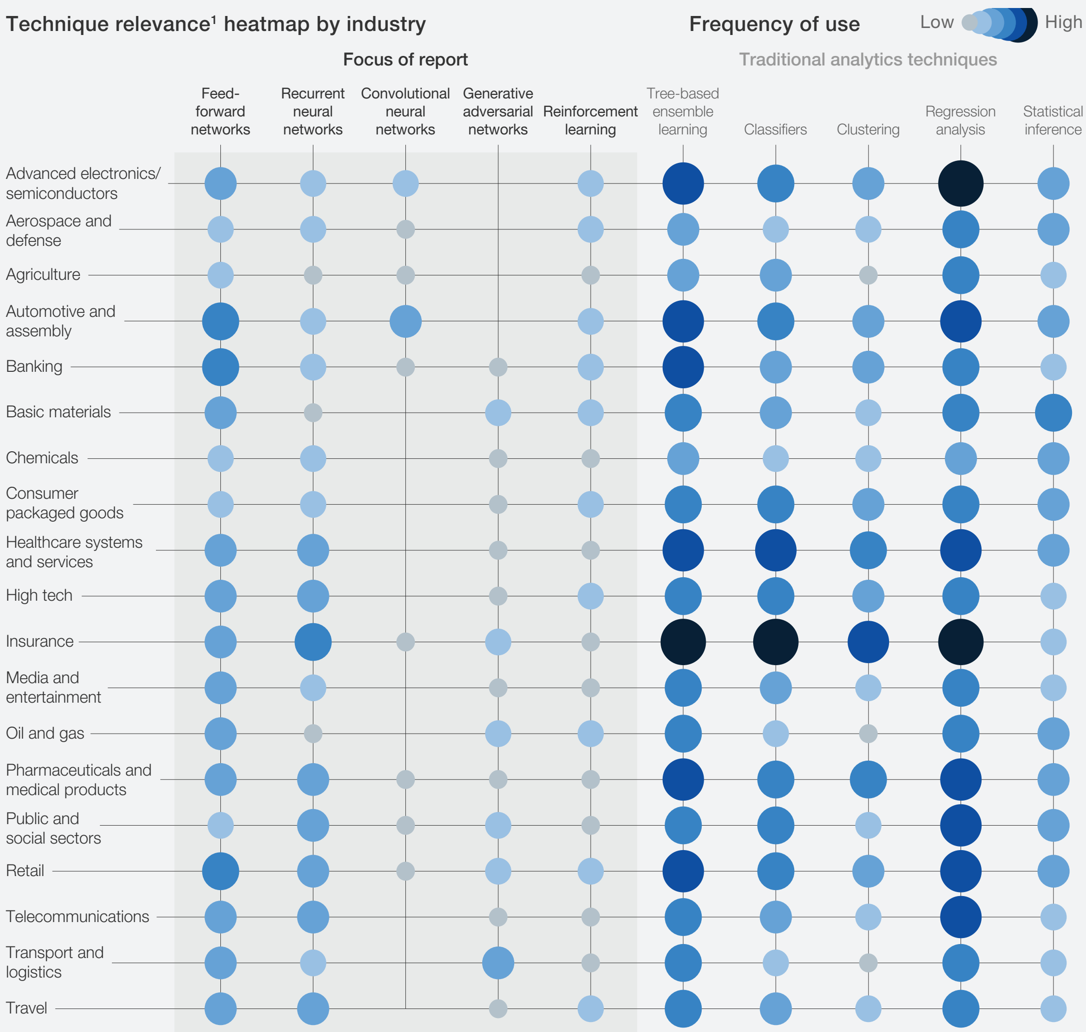
Following are examples of where AI can be used to improve the performance of existing use cases:

- **Predictive maintenance: The power of machine learning to detect anomalies.** Deep learning's capacity to analyze very large amounts of high-dimensional data can take existing preventive maintenance systems to a new level. Layering in additional data, such as audio and image data, from other sensors—including relatively cheap ones such as microphones and cameras—neural networks can enhance and possibly replace more traditional methods. AI's ability to predict failures and allow planned interventions can be used to reduce downtime and operating costs while improving production yield. For example, AI can extend the life of a cargo plane beyond what is possible using traditional analytics techniques by combining plane model data, maintenance history, and Internet of Things (IoT) sensor data such as anomaly detection on engine-vibration data, and images and video of engine condition.

- **AI-driven logistics optimization can reduce costs through real-time forecasts and behavioral coaching.** Application of AI techniques such as continuous estimation to logistics can add substantial value across sectors. AI can optimize routing of delivery traffic, thereby improving fuel efficiency and reducing delivery times. One European trucking company has reduced fuel costs by 15 percent, for example, by using sensors that monitor both vehicle performance and driver behavior; drivers receive real-time coaching, including when to speed up or slow down, optimizing fuel consumption and reducing maintenance costs.

Exhibit 2

Advanced deep-learning artificial intelligence techniques can be applied across industries, alongside more traditional analytics.



[1]Relevance refers to frequency of use in our use case library, with the most frequently found cases marked as high relevance and the least frequently found as low relevance. Absence of circles indicates no or statistically insignificant number of use cases.
Note: List of techniques is not exhaustive.

Source: McKinsey Global Institute analysis

Problem types and their definitions

Classification: Based on a set of training data, categorize new inputs as belonging to one of a set of categories. An example of classification is identifying whether an image contains a specific type of object, such as a cat or a dog, or a product of acceptable quality coming from a manufacturing line.

Continuous estimation: Based on a set of training data, estimate the next numeric value in a sequence. This type of problem is sometimes described as "prediction," particularly when it is applied to time-series data. One example of continuous estimation is forecasting the sales demand for a product, based on a set of input data such as previous sales figures, consumer sentiment, and weather.

Clustering: These problems require a system to create a set of categories, for which individual data instances have a set of common or similar characteristics. An example of clustering is creating a set of consumer segments, based on a set of data about individual consumers, including demographics, preferences, and buyer behavior.

All other optimization: These problems require a system to generate a set of outputs that optimize outcomes for a specific objective function (some of the other problem types can be considered types of optimization, so we describe these as "all other" optimization). Generating a route for a vehicle that creates the optimum combination of time and fuel utilization is an example of optimization.

Anomaly detection: Given a training set of data, determine whether specific inputs are out of the ordinary. For instance, a system could be trained on a set of historical vibration data associated with the performance of an operating piece of machinery, and then determine whether a new vibration reading suggests that the machine is not operating normally. Anomaly detection can be considered a subcategory of classification.

Ranking: Ranking algorithms are used most often in information-retrieval problems where the results of a query or request needs to be ordered by some criterion. Recommendation systems suggesting next product to buy use these types of algorithms as a final step, sorting suggestions by relevance, before presenting the results to the user.

Recommendations: These systems provide recommendations based on a set of training data. A common example of recommendations are systems that suggest "next product to buy" for an individual buyer, based on the buying patterns of similar individuals and the observed behavior of the specific person.

Data generation: These problems require a system to generate appropriately novel data based on training data. For instance, a music composition system might be used to generate new pieces of music in a particular style, after having been trained on pieces of music in that style.

- **AI can be a valuable tool for customer service management and personalization challenges.** Improved speech recognition in call center management and call routing as a result of the application of AI techniques allows a more seamless experience for customers—and more efficient processing. The capabilities go beyond words alone. For example, deep-learning analysis of audio allows systems to assess a customer's emotional tone; in the event a customer is responding badly to the system, the call can be rerouted automatically to human operators and managers. In other areas of marketing and sales, AI techniques can also have a significant impact. Combining customer demographic and past transaction data with social media monitoring can help generate individualized product recommendations. Next-product-to-buy recommendations that target individual customers—as companies such as Amazon and Netflix have successfully been doing—can lead to a twofold increase in the rate of sales conversions.

Two-thirds of the opportunities to use AI are in improving the performance of existing analytics use cases

In 69 percent of the use cases we studied, deep neural networks can be used to improve performance beyond that provided by other analytics techniques. Cases in which only neural networks can be used, which we refer to here as "greenfield" cases, constituted just 16 percent of the total. For the remaining 15 percent, artificial neural networks provided limited additional performance over other analytics techniques, because, among other reasons, of data limitations that made these cases unsuitable for deep learning (Exhibit 3).

Greenfield AI solutions are prevalent in business areas such as customer-service management, as well as among some industries where the data are rich and voluminous and at times integrate human reactions. Among industries, we found many greenfield use cases in healthcare, in particular. Some of these cases involve disease diagnosis and improved care and rely on rich data sets incorporating image and video inputs, including from MRIs.

On average, our use cases suggest that modern deep-learning AI techniques have the potential to provide a boost in additional value above and beyond traditional analytics techniques—ranging from 30 percent to 128 percent, depending on industry.

In many of our use cases, however, traditional analytics and machine-learning techniques continue to underpin a large percentage of the value-creation potential in industries including insurance, pharmaceuticals and medical products, and telecommunications, with the potential of AI limited in certain contexts. In part this is due to the way data are used by these industries and to regulatory issues.

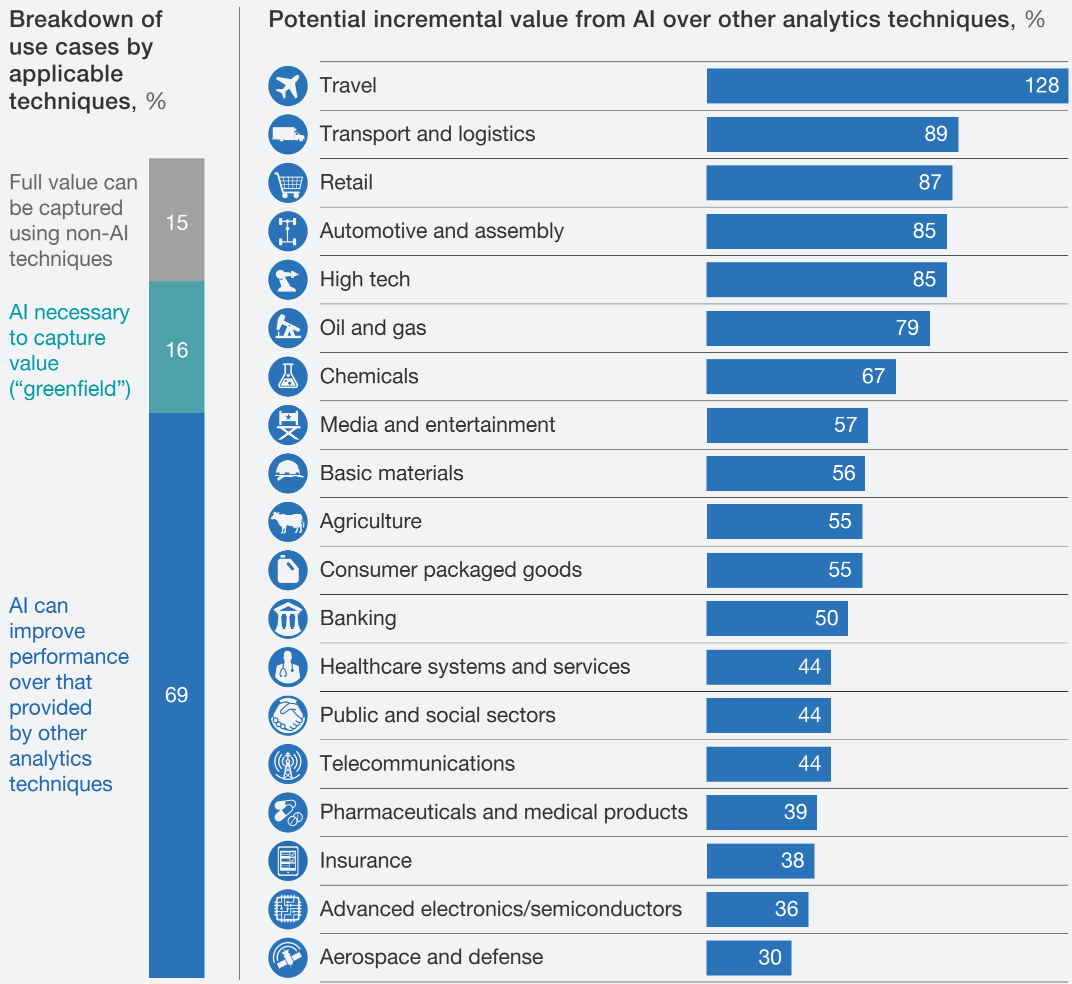
Data requirements for deep learning are substantially greater than for other analytics

Making effective use of neural networks in most applications requires large labeled training data sets alongside access to sufficient computing infrastructure. Furthermore, these deep-learning techniques are particularly powerful in extracting patterns from complex, multidimensional data types such as images, video, and audio or speech.

Deep-learning methods require thousands of data records for models to become relatively

Exhibit 3

In more than two-thirds of our use cases, artificial intelligence (AI) can improve performance beyond that provided by other analytics techniques.



Source: McKinsey Global Institute analysis

good at classification tasks and, in some cases, millions for them to perform at the level of humans. By one estimate, a supervised deep-learning algorithm will generally achieve acceptable performance with around 5,000 labeled examples per category and will match or exceed human-level performance when trained with a data set containing at least ten million labeled examples.[3] In some cases where advanced analytics are currently used,

[3] Ian Goodfellow, Yoshua Bengio, and Aaron Courville, *Deep Learning*, Cambridge, MA: MIT Press, 2016.

so much data are available—millions or even billions of rows per data set—that AI usage is the most appropriate technique. However, if a threshold of data volume is not reached, AI may not add value to traditional analytics techniques.

These massive data sets can be difficult to obtain or create for many business use cases, and labeling remains a challenge. Most current AI models are trained through “supervised learning,” which requires humans to label and categorize the underlying data. However, promising new techniques are emerging to overcome these data bottlenecks, such as reinforcement learning, generative adversarial networks, transfer learning, and “one-shot learning,” which allows a trained AI model to learn about a subject based on a small number of real-world demonstrations or examples—and sometimes just one.

Organizations will have to adopt and implement strategies that enable them to collect and integrate data at scale. Even with large data sets, they will have to guard against “overfitting,” where a model too tightly matches the “noisy” or random features of the training set, resulting in a corresponding lack of accuracy in future performance, and against “underfitting,” where the model fails to capture all of the relevant features. Linking data across customer segments and channels, rather than allowing the data to languish in silos, is especially important to create value.

Realizing AI’s full potential requires a diverse range of data types, including images, video, and audio

Neural AI techniques excel at analyzing image, video, and audio data types because of their complex, multidimensional nature, known by practitioners as “high dimensionality.” Neural networks are good at dealing with high dimensionality, as multiple layers in a network can learn to represent the many different features present in the data. Thus, for facial recognition, the first layer in the network could focus on raw pixels, the next on edges and lines, another on generic facial features, and the final layer might identify the face. Unlike previous generations of AI, which often required human expertise to do “feature engineering,” these neural network techniques are often able to learn to represent these features in their simulated neural networks as part of the training process.

Along with issues around the volume and variety of data, velocity is also a requirement: AI techniques require models to be retrained to match potential changing conditions, so the training data must be refreshed frequently. In one-third of the cases, the model needs to be refreshed at least monthly, and almost one in four cases requires a daily refresh; this is especially the case in marketing and sales and in supply-chain management and manufacturing.

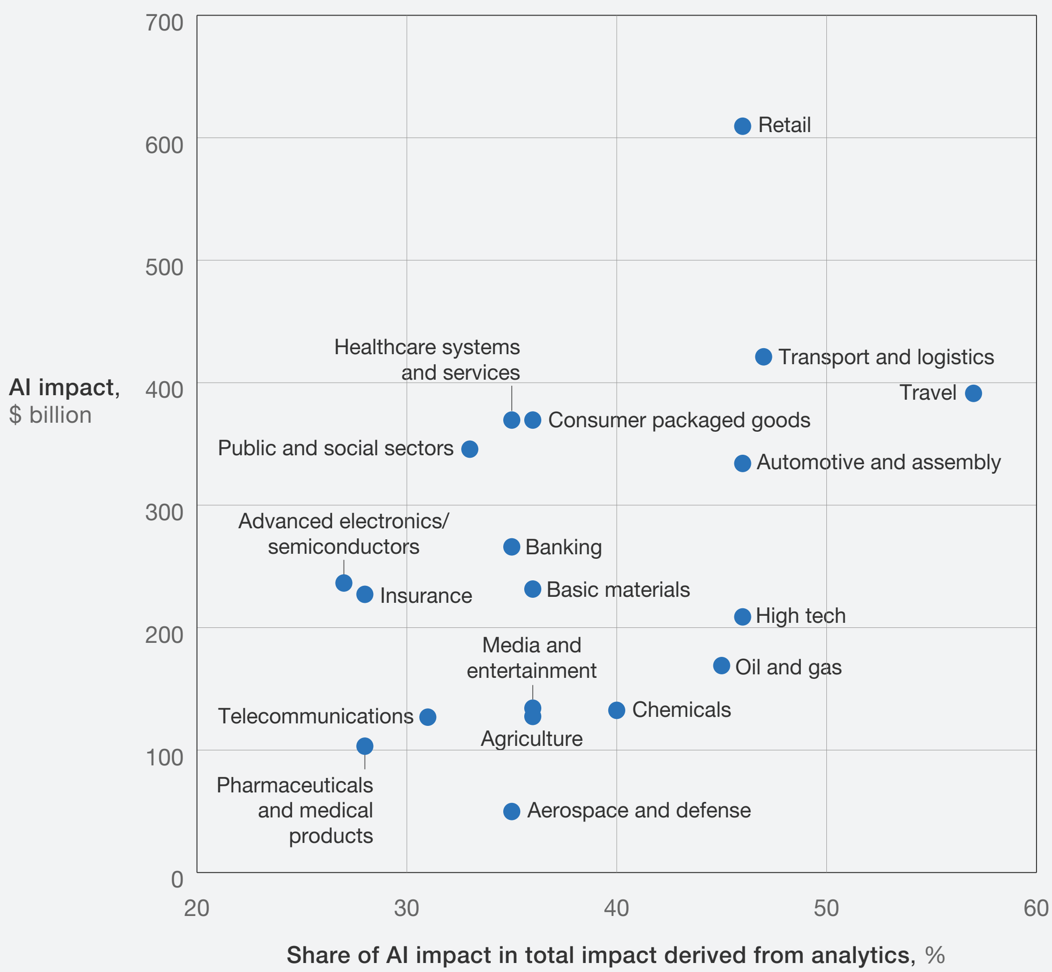
Sizing the potential value of AI

We estimate that the AI techniques we cite in the discussion paper together have the potential to create between $3.5 trillion and $5.8 trillion in value annually across nine business functions in 19 industries. This constitutes about 40 percent of the overall $9.5 trillion to $15.4 trillion annual impact that could potentially be enabled by all analytical techniques (Exhibit 4).

Per industry, we estimate that AI’s potential value amounts to between 1 and 9 percent of 2016 revenue. The value as measured by percentage of industry revenue varies significantly among industries, depending

Exhibit 4

Artificial intelligence (AI) has the potential to create value across sectors.



Source: McKinsey Global Institute analysis

on the specific applicable use cases, the availability of abundant and complex data, as well as regulatory and other constraints.

These figures are not forecasts for a particular period, but they are indicative of the considerable potential for the global economy that advanced analytics represents.

From the use cases we have examined, we find that the greatest potential value impact from using AI are both in top-line-oriented functions, such as marketing and sales, and bottom-line-oriented operational functions, including supply-chain management and manufacturing.

Consumer industries such as retail and high tech will tend to see more potential from marketing and sales AI applications because frequent and digital interactions between the business and customers generate larger data sets for AI techniques to tap into. E-commerce platforms, in particular, stand to benefit. This is because of the ease with which these platforms collect customer information such as click data or time spent on a web page. These platforms can then customize promotions, prices, and products for each customer dynamically and in real time.

Here is a snapshot of three sectors where we have seen AI's impact (Exhibit 5):

- In retail, marketing and sales is the area with the most significant potential value from AI, and within that function, pricing and promotion and customer-service management are the main value areas. Our use cases show that using customer data to personalize promotions, for example, including tailoring individual offers every day, can lead to a 1 to 2 percent increase in incremental sales for brick-and-mortar retailers alone.

- In consumer goods, supply-chain management is the key function that could benefit from AI deployment. Among the examples in our use cases, we see how forecasting based on underlying causal drivers of demand rather than prior outcomes can improve forecasting accuracy by 10 to 20 percent, which translates into a potential 5 percent reduction in inventory costs and revenue increases of 2 to 3 percent.

- In banking, particularly retail banking, AI has significant value potential in marketing and sales, much as it does in retail. However, because of the importance of assessing and managing risk in banking—for example, for loan underwriting and fraud detection—AI has much higher value potential to improve performance in risk in the banking sector than in many other industries.

The road to impact and value

Artificial intelligence is attracting growing amounts of corporate investment, and as the technologies develop, the potential value that can be unlocked is likely to grow. So far, however, only about 20 percent of AI-aware companies are currently using one or more of its technologies in a core business process or at scale.[4]

For all their promise, AI technologies have plenty of limitations that will need to be overcome. They include the onerous data requirements listed previously, but also five other limitations:

- First is the challenge of labeling training data, which often must be done manually and is necessary for supervised learning. Promising new techniques are emerging to address this challenge, such as reinforcement learning and in-stream supervision, in which data can be labeled in the course of natural usage.

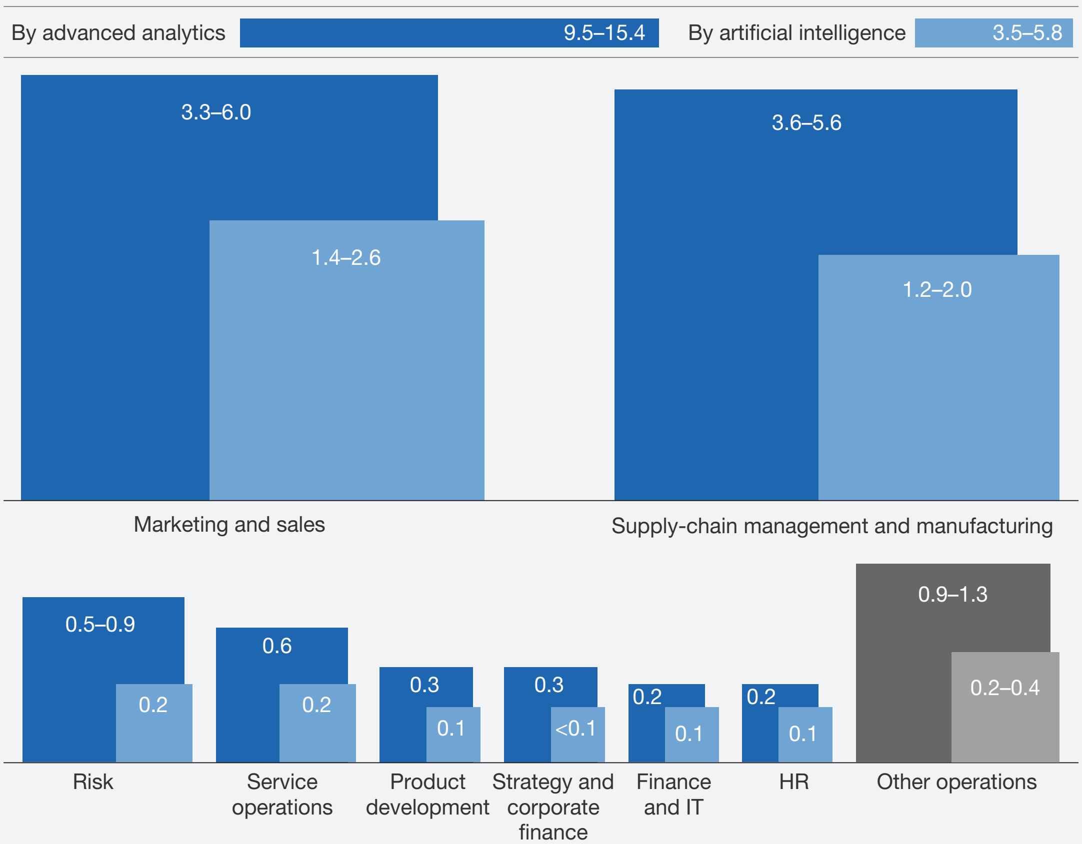
- Second is the difficulty of obtaining data sets that are sufficiently large and comprehensive to be used for training; for many business use cases, creating or obtaining such massive data sets can be difficult—for example, limited

[4] See "How artificial intelligence can deliver real value to companies," McKinsey Global Institute, June 2017, on McKinsey.com.

Exhibit 5

Artificial intelligence's impact is likely to be most substantial in marketing and sales as well as supply-chain management and manufacturing, based on our use cases.

Value unlocked, $ trillion



Note: Figures may not sum to 100%, because of rounding.

Source: McKinsey Global Institute analysis

clinical-trial data to predict healthcare treatment outcomes more accurately.

- Third is the difficulty of explaining in human terms results from large and complex models: why was a certain decision reached? Product certifications in healthcare and in the automotive and aerospace industries, for example, can be an obstacle; among other constraints, regulators often want rules and choice criteria to be clearly explainable.

- Fourth is the generalizability of learning: AI models continue to have difficulties in carrying their experiences from one set of circumstances to another. That means that companies must commit resources to train new models even for use cases that are similar to previous ones. Transfer learning—in which an AI model is trained to accomplish a certain task and then quickly applies that learning to a similar but distinct activity—is one promising response to this challenge.

- The fifth limitation concerns the risk of bias in data and algorithms. This issue touches on concerns that are more social in nature and which could require broader steps to resolve, such as understanding how the processes used to collect training data can influence the behavior of the models they are used to train. For example, unintended biases can be introduced when training data is not representative of the larger population to which an AI model is applied. Thus, facial-recognition models trained on a population of faces corresponding to the demographics of AI developers could struggle when applied to populations with more diverse characteristics.[5] A recent report on the malicious use of AI highlights a range of security threats, from sophisticated automation of hacking to hyperpersonalized political disinformation campaigns.[6]

Organizational challenges around technology, processes, and people can slow or impede AI adoption

Organizations planning to adopt significant deep-learning efforts will need to consider a spectrum of options about how to do so. The range of options includes building a complete in-house AI capability, outsourcing these capabilities, or leveraging AI-as-a-service offerings.

Based on the use cases they plan to build, companies will need to create a data plan that produces results and predictions that can be fed either into designed interfaces for humans to act on or into transaction systems. Key data engineering challenges include data creation or acquisition, defining data ontology, and building appropriate data "pipes." Given the significant computational requirements of deep learning, some organizations will maintain their own data centers because of regulations or security concerns, but the capital expenditures could be considerable, particularly when using specialized hardware. Cloud vendors offer another option.

Process can also become an impediment to successful adoption unless organizations are digitally mature. On the technical side, organizations will have to develop robust data maintenance and governance processes and implement modern software disciplines such as Agile and DevOps. Even more challenging, in terms of scale, is overcoming the "last mile" problem of making sure the superior insights provided by AI are instantiated in the behavior of the people and processes of an enterprise.

On the people front, much of the construction and optimization of deep neural networks remains something of an art, requiring real experts to deliver step-change performance increases. Demand for these skills far outstrips supply at present; according to some estimates, fewer than 10,000 people have the

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[5] See Joy Buolamwini and Timnit Gebru, "Gender shades: Intersectional accuracy disparities in commercial gender classification," *Proceedings of Machine Learning Research*, 2018, Volume 81, pp. 1–15, proceedings.mlr.press.

[6] Peter Eckersley, "The malicious use of artificial intelligence: Forecasting, prevention, and mitigation," Electronic Frontier Foundation, February 20, 2018, eff.org.

skills necessary to tackle serious AI problems, and competition for them is fierce among the tech giants.[7]

AI can seem an elusive business case

Where AI techniques and data are available and the value is clearly proven, organizations can already pursue the opportunity. In some areas, the techniques today may be mature and the data available, but the cost and complexity of deploying AI may simply not be worthwhile, given the value that could be generated. For example, an airline could use facial recognition and other biometric scanning technology to streamline aircraft boarding, but the value of doing so may not justify the cost and issues around privacy and personal identification.

Similarly, we can see potential cases where the data and the techniques are maturing, but the value is not yet clear. The most unpredictable scenario is where either the data (both the types and volume) or the techniques are simply too new and untested to know how much value they could unlock. For example, in healthcare, if AI were able to build on the superhuman precision we are already starting to see with X-ray analysis and to broaden that to more accurate diagnoses and even automated medical procedures, the economic value could be very significant. At the same time, the complexities and costs of arriving at this frontier are also daunting. Among other issues, it would require flawless technical execution and resolving issues of malpractice insurance and other legal concerns.

Societal concerns and regulations can also constrain AI use. Regulatory constraints are especially prevalent in use cases related to personally identifiable information. This is particularly relevant at a time of growing public debate about the use and commercialization of individual data on some online platforms. Use and storage of personal information is especially sensitive in sectors such as banking, healthcare, and pharmaceuticals and medical products, as well as in the public and social sector. In addition to addressing these issues, businesses and other users of data for AI will need to continue to evolve business models related to data use in order to address societies' concerns. Furthermore, regulatory requirements and restrictions can differ from country to country, as well from sector to sector.

Implications for stakeholders

As we have seen, it is a company's ability to execute against AI models that creates value, rather than the models themselves. In this final section, we sketch out some of the high-level implications of our study of AI use cases for providers of AI technology, appliers of AI technology, and policy makers, who set the context for both.

- Many companies that develop or provide AI to others have considerable strength in the technology itself and the data scientists needed to make it work, but they can lack a deep understanding of end markets. Understanding the value potential of AI across sectors and functions can help shape the portfolios of these AI technology companies. That said, they shouldn't necessarily prioritize only the areas of highest potential value. Instead, they can combine that data with complementary analyses of the competitor landscape and their own existing strengths, sector or function knowledge, and customer relationships to shape their investment

[7] Cade Metz, "Tech giants are paying huge salaries for scarce AI talent, *New York Times*, October 22, 2017, nytimes.com.

portfolios. On the technical side, the mapping of problem types and techniques to sectors and functions of potential value can guide a company with specific areas of expertise on where to focus.

- Many companies seeking to adopt AI in their operations have started machine-learning and AI experiments across their business. Before launching more pilots or testing solutions, it is useful to step back and take a holistic approach to the issue, moving to create a prioritized portfolio of initiatives across the enterprise, including AI and the wider analytics and digital techniques available. For a business leader to create an appropriate portfolio, it is important to develop an understanding about which use cases and domains have the potential to drive the most value for a company, as well as which AI and other analytical techniques will need to be deployed to capture that value. This portfolio ought to be informed not only by where the theoretical value can be captured but also by the question of how the techniques can be deployed at scale across the enterprise. The question of how analytical techniques are scaling is driven less by the techniques themselves and more by a company's skills, capabilities, and data. Companies will need to consider efforts on the "first mile," that is, how to acquire and organize data and efforts, as well as on the "last mile," or how to integrate the output of AI models into frontline workflows, ranging from those of clincial-trial managers and sales-force managers to procurement officers. Previous McKinsey Global Institute research suggests that AI leaders invest heavily in these first- and last-mile efforts.

- Policy makers will need to strike a balance between supporting the development of AI technologies and managing any risks from bad actors. They have an interest in supporting broad adoption, since AI can lead to higher labor productivity, economic growth, and societal prosperity. Their tools include public investments in research and development as well as support for a variety of training programs, which can help nurture AI talent. On the issue of data, governments can spur the development of training data directly through open-data initiatives. Opening up public-sector data can spur private-sector innovation. Setting common data standards can also help. AI is also raising new questions for policy makers to grapple with, for which historical tools and frameworks may not be adequate. Therefore, some policy innovations will likely be needed to cope with these rapidly evolving technologies. But given the scale of the beneficial impact on business, the economy, and society, the goal should not be to constrain the adoption and application of AI but rather to encourage its beneficial and safe use. ◆

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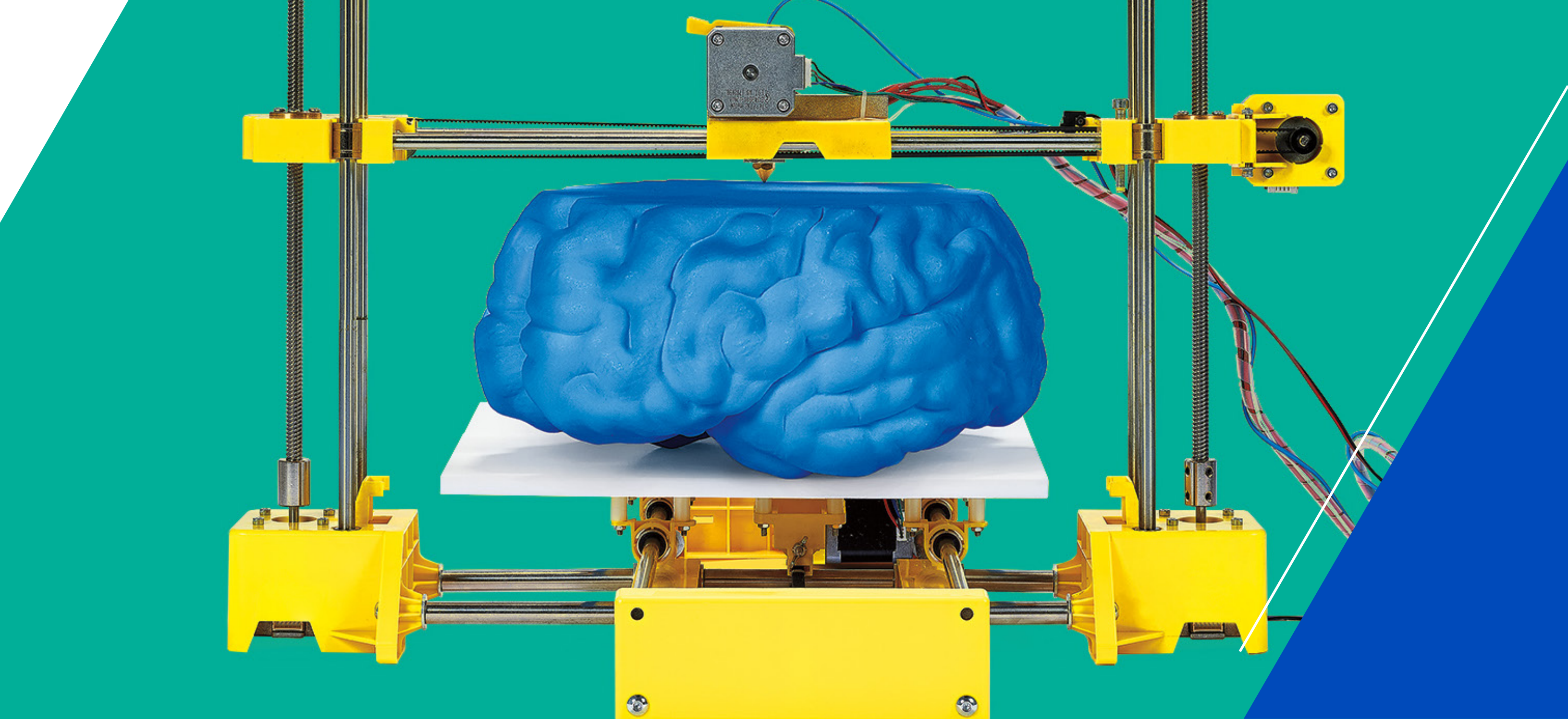


What AI can and can't do (yet) for your business

Michael Chui, James Manyika, and Mehdi Miremadi

Artificial intelligence is a moving target. Here's how to take better aim.

Artificial intelligence (AI) seems to be everywhere. We experience it at home and on our phones. Before we know it—if entrepreneurs and business innovators are to be believed—AI will be in just about every product and service we buy and use. In addition, its application to business problem solving is growing in leaps and bounds. And at the same time, concerns about AI's implications are rising: we worry about the impact of AI-enabled automation on the workplace, employment, and society.

A reality sometimes lost amid both the fears and the headline triumphs, such as Alexa, Siri, and AlphaGo, is that the AI technologies themselves—namely, machine learning and its subset, deep learning—have plenty of limitations that will still require considerable effort to overcome. This is an article about those limitations, aimed at helping executives better understand what may be holding back their AI efforts. Along the way, we will also highlight promising advances that are poised to address some of the limitations and create a new wave of opportunities.

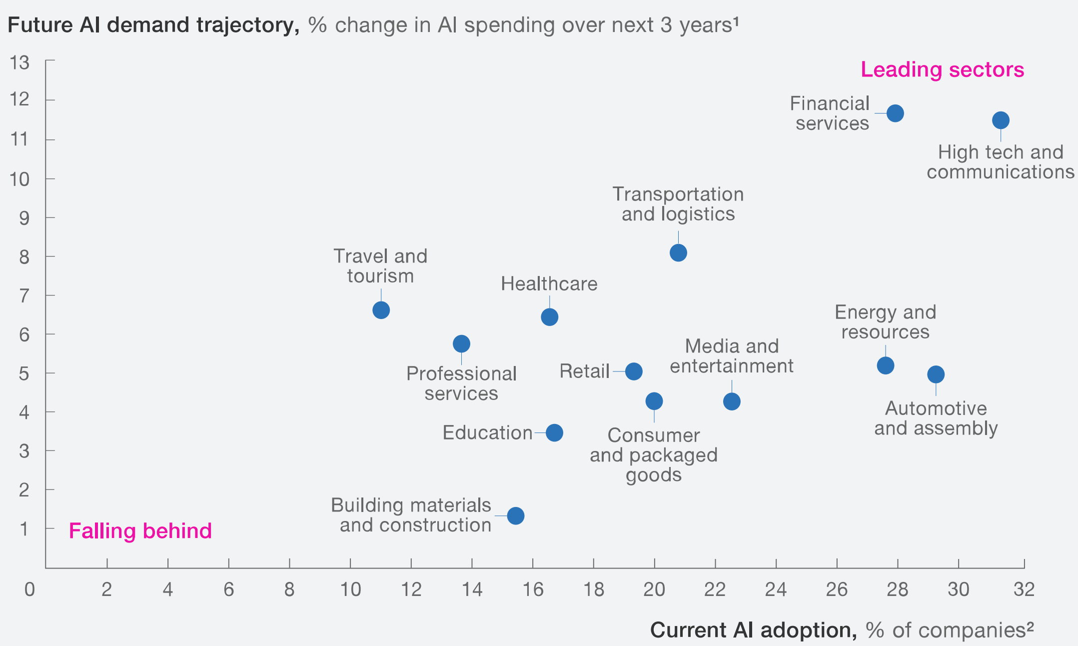
Our perspectives rest on a combination of work at the front lines—researching, analyzing, and assessing hundreds of real-world use cases—and our collaborations with some of the thought leaders, pioneering scientists, and engineers working at the frontiers of AI. We've sought to distill this experience to help executives who often, in our experience, are exposed only to their own initiatives and not well calibrated as to where the frontier is or what the pace setters are already doing with AI.

Simply put, AI's challenges and limitations are creating a "moving target" problem for leaders: it is hard to reach a leading edge that's always advancing. It is also disappointing when AI efforts run into real-world barriers, which can lessen the appetite for further investment or encourage a wait-and-see attitude, while others charge ahead. As recent McKinsey Global Institute research indicates, there's a yawning divide between leaders and laggards in the application of AI both across and within sectors (Exhibit 1).

Executives hoping to narrow the gap must be able to address AI in an informed way. In other words, they need to understand not just where AI can boost innovation, insight, and decision making; lead to revenue growth;

Exhibit 1

Leaders in the adoption of AI also intend to invest more in the near future compared with laggards.



[1] Estimated average, weighted by company size; demand trajectory based on midpoint of range selected by survey respondent.
[2] Adopting 1 or more AI technologies at scale or in business core; weighted by company size.

Source: McKinsey Global Institute AI adoption and use survey; McKinsey Global Institute analysis and capture of efficiencies—but also where AI can't yet provide value. What's more, they must appreciate the relationship and distinctions between technical constraints and organizational ones, such as cultural barriers; a dearth of personnel capable of building business-ready, AI-powered applications; and the "last mile" challenge of embedding AI in products and processes. If you want to become a leader who understands some of the critical technical challenges slowing AI's advance and is prepared to exploit promising developments that could overcome those limitations and potentially bend the trajectory of AI—read on.

Challenges, limitations, and opportunities

A useful starting point is to understand recent advances in deep-learning techniques. Arguably the most exciting developments in AI, these advances are delivering jumps in the accuracy of classification and prediction, and are doing so without the usual "feature engineering" associated with traditional supervised learning. Deep learning uses large-scale neural networks that can contain millions of simulated "neurons" structured in layers. The most common networks are called convolutional neural networks (CNNs) and recurrent neural networks (RNNs). These neural networks learn through the use of training data and backpropagation algorithms.

While much progress has been made, more still needs to be done.[1] A critical step is to fit the AI approach to the problem and the availability of data. Since these systems are "trained" rather than programmed, the various processes often require huge amounts of labeled data to perform complex tasks accurately. Obtaining large data sets can be difficult. In some domains, they may simply not be available, but even when available, the labeling efforts can require enormous human resources.

Further, it can be difficult to discern how a mathematical model trained by deep learning arrives at a particular prediction, recommendation, or decision. A black box, even one that does what it's supposed to, may have limited utility, especially where the predictions or decisions impact society and hold ramifications that can affect individual well-being. In such cases, users sometimes need to know the "whys" behind the workings, such as why an algorithm reached its recommendations—from making factual findings with legal repercussions to arriving at business decisions, such as lending, that have regulatory repercussions—and why certain factors (and not others) were so critical in a given instance.

Let's explore five interconnected ways in which these limitations, and the solutions emerging to address them, are starting to play out.

Limitation 1: Data labeling

Most current AI models are trained through "supervised learning." This means that humans must label and categorize the underlying data, which can be a sizable and error-prone chore. For example, companies developing self-driving-car technologies are hiring hundreds of people to manually annotate hours of video feeds from prototype vehicles to help train these systems. At the same time, promising new techniques are emerging, such as in-stream supervision (demonstrated by Eric Horvitz and his colleagues at Microsoft

[1] Stuart Russel et al., "Research priorities for robust and beneficial artificial intelligence," *AI Magazine*, winter 2015, AAAI.org.

Research), in which data can be labeled in the course of natural usage.[2] Unsupervised or semisupervised approaches reduce the need for large, labeled data sets. Two promising techniques are reinforcement learning and generative adversarial networks.

Reinforcement learning. This unsupervised technique allows algorithms to learn tasks simply by trial and error. The methodology hearkens to a "carrot and stick" approach: for every attempt an algorithm makes at performing a task, it receives a "reward" (such as a higher score) if the behavior is successful or a "punishment" if it isn't. With repetition, performance improves, in many cases surpassing human capabilities—so long as the learning environment is representative of the real world.

Reinforcement learning has famously been used in training computers to play games—most recently, in conjunction with deep-learning techniques. In May 2017, for example, it helped the AI system AlphaGo to defeat world champion Ke Jie in the game of Go. In another example, Microsoft has fielded decision services that draw on reinforcement learning and adapt to user preferences. The potential application of reinforcement learning cuts across many business arenas. Possibilities include an AI-driven trading portfolio that acquires or loses points for gains or losses in value, respectively; a product-recommendation engine that receives points for every recommendation-driven sale; and truck-routing software that receives a reward for on-time deliveries or reducing fuel consumption.

Reinforcement learning can also help AI transcend the natural and social limitations of human labeling by developing previously unimagined solutions and strategies that even seasoned practitioners might never have considered. Recently, for example, the system AlphaGo Zero, using a novel form of reinforcement learning, defeated its predecessor AlphaGo after learning to play Go from scratch. That meant starting with completely random play against itself rather than training on Go games played by and with humans.[3]

Generative adversarial networks (GANs). In this semisupervised learning method, two networks compete against each other to improve and refine their understanding of a concept. To recognize what birds look like, for example, one network attempts to distinguish between genuine and fake images of birds, and its opposing network attempts to trick it by producing what look very much like images of birds, but aren't. As the two networks square off, each model's representation of a bird becomes more accurate.

The ability of GANs to generate increasingly believable examples of data can significantly reduce the need for data sets labeled by humans. Training an algorithm to identify different types of tumors from medical images, for example, would typically require millions of human-labeled images with the type or stage of a given tumor. By using a GAN trained to generate increasingly realistic images of different types of tumors, researchers could train a tumor-detection algorithm that combines a much smaller human-labeled data set with the GAN's output.

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[2] Eric Horvitz, "Machine learning, reasoning, and intelligence in daily life: Directions and challenges," *Proceedings of Artificial Intelligence Techniques for Ambient Intelligence*, Hyderabad, India, January 2007.

[3] Demis Hassabis et al., *AlphaGo Zero: Learning from scratch*, deepmind.com.

While the application of GANs in precise disease diagnoses is still a way off, researchers have begun using GANs in increasingly sophisticated contexts. These include understanding and producing artwork in the style of a particular artist and using satellite imagery, along with an understanding of geographical features, to create up-to-date maps of rapidly developing areas.

Limitation 2: Obtaining massive training data sets

It has already been shown that simple AI techniques using linear models can, in some cases, approximate the power of experts in medicine and other fields.[4] The current wave of machine learning, however, requires training data sets that are not only labeled but also sufficiently large and comprehensive. Deep-learning methods call for thousands of data records for models to become relatively good at classification tasks and, in some cases, millions for them to perform at the level of humans.[5]

The complication is that massive data sets can be difficult to obtain or create for many business use cases (think: limited clinical-trial data to predict treatment outcomes more accurately). And each minor variation in an assigned task could require another large data set to conduct even more training. For example, teaching an autonomous vehicle to navigate a mining site where the weather continually changes will require a data set that encompasses the different environmental conditions the vehicle might encounter.

One-shot learning is a technique that could reduce the need for large data sets, allowing an AI model to learn about a subject when it's given a small number of real-world demonstrations or examples (even one, in some cases). AI's capabilities will move closer to those of humans, who can recognize multiple instances of a category relatively accurately after having been shown just a single sample—for example, of a pickup truck. In this still-developing methodology, data scientists would first pretrain a model in a simulated virtual environment that presents variants of a task or, in the case of image recognition, of what an object looks like. Then, after being shown just a few real-world variations that the AI model did not see in virtual training, the model would draw on its knowledge to reach the right solution.[6]

This sort of one-shot learning could eventually help power a system to scan texts for copyright violations or to identify a corporate logo in a video after being shown just one labeled example. Today, such applications are only in their early stages. But their utility and efficiency may well expand the use of AI quickly, across multiple industries.

Limitation 3: The explainability problem

Explainability is not a new issue for AI systems.[7] But it has grown along with the success and adoption of deep learning, which has given rise both to more diverse and advanced applications and to more opaqueness. Larger and more complex models make it hard to explain, in human terms, why a certain

[4] Robyn M. Dawes, "The robust beauty of improper linear models in decision making," *American Psychologist*, 1979, Volume 34, Number 7, pp. 571–82.

[5] Ian Goodfellow, Yoshua Bengio, and Aaron Courville, *Deep Learning*, Cambridge, MA: MIT Press, 2016.

[6] Yan Duan et al., *One-shot imitation learning*, December 2017, arxiv.org.

[7] Eric Horvitz et al., "The use of a heuristic problem-solving hierarchy to facilitate the explanation of hypothesis-directed reasoning," *Proceedings of Medinfo*, October 1986, pp. 27–31.

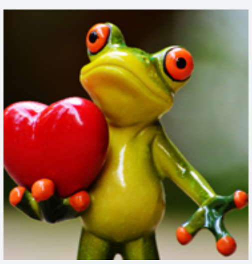
decision was reached (and even harder when it was reached in real time). This is one reason that adoption of some AI tools remains low in application areas where explainability is useful or indeed required. Furthermore, as the application of AI expands, regulatory requirements could also drive the need for more explainable AI models.[8]

Two nascent approaches that hold promise for increasing model transparency are local-interpretable-model-agnostic explanations (LIME) and attention techniques (Exhibit 2). LIME attempts to identify which parts of input data a trained model relies on most to make predictions in developing a proxy interpretable model. This technique considers certain

Exhibit 2

New techniques hold promise for making AI more transparent.

LIME[1] is a sensitivity analysis that reveals which parts of an input matter most to the eventual output.

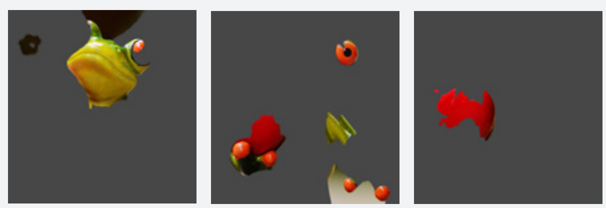


Turning off all but a few interpretable components of this image reveals the probability that the model will identify …

… a tree frog 54%

… billiard balls 7%

… a balloon 5%



Attention shines a spotlight on where the model is looking when it makes a particular decision.

Words relevant to food quality …

The fajita we tried was tasteless and burned and the mole sauce was way too sweet.

… or to service

They have one of the fastest delivery times in the city.

[1] LIME = local-interpretable-model-agnostic explanations.

Source: Carlos Guestrin, Marco Tulio Ribeiro, and Sameer Singh, “Introduction to local interpretable model-agnostic explanations (LIME),” August 12, 2016, O’Reilly, oreilly.com; Minlie Huang, Yequan Wang, Li Zhao, and Xiaoyan Zhu, *Attention-based LSTM for aspect-level sentiment classification*, Tsinghua University; Pixabay

[8] See, for example, the European Union’s proposed General Data Protection Regulation, which would introduce new requirements for the use of data.

segments of data at a time and observes the resulting changes in prediction to fine-tune the proxy model and develop a more refined interpretation (for example, by excluding eyes rather than, say, noses to test which are more important for facial recognition). Attention techniques visualize those pieces of input data that a model considers most as it makes a particular decision (such as focusing on a mouth to determine if an image depicts a human being).

Another technique that has been used for some time is the application of generalized additive models (GAMs). By using single-feature models, GAMs limit interactions between features, thereby making each one more easily interpretable by users.[9] Employing these techniques, among others, to demystify AI decisions is expected to go a long way toward increasing the adoption of AI.

Limitation 4: Generalizability of learning

Unlike the way humans learn, AI models have difficulty carrying their experiences from one set of circumstances to another. In effect, whatever a model has achieved for a given use case remains applicable to that use case only. As a result, companies must repeatedly commit resources to train yet another model, even when the use cases are very similar.

One promising response to this challenge is transfer learning.[10] In this approach, an AI model is trained to accomplish a certain task and then quickly applies that learning to a similar but distinct activity. DeepMind researchers have also shown promising results with transfer learning in experiments in which training done in simulation is then transferred to real robotic arms.[11]

As transfer learning and other generalized approaches mature, they could help organizations build new applications more quickly and imbue existing applications with more diverse functionality. In creating a virtual personal assistant, for example, transfer learning could generalize user preferences in one area (such as music) to others (books). And users are not restricted to digital natives. Transfer learning can enable an oil-and-gas producer, for instance, to expand its use of AI algorithms trained to provide predictive maintenance for wells to other equipment, such as pipelines and drilling platforms. Transfer learning even has the potential to revolutionize business intelligence: consider a data-analyzing AI tool that understands how to optimize airline revenues and can then adapt its model to changes in weather or local economics.

Another approach is the use of something approximating a generalized structure that can be applied in multiple problems. DeepMind's AlphaZero, for example, has made use of the same structure for three different games: it has been possible to train a new model with that generalized structure to learn chess in a single day, and it then soundly beat a world-champion chess program.[12]

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9 Yin Lou, Rich Caruana, and Johannes Gehrke, "Intelligible models for classification and regression," *Proceedings of the 18th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, New York: ACM, 2012, pp. 150–58.

10 For an earlier example application, see John Guttag, Eric Horvitz, and Jenna Wiens, "A study in transfer learning: Leveraging data from multiple hospitals to enhance hospital-specific predictions," *Journal of the American Medical Informatics Association*, 2014, Volume 21, Number 4, pp. 699–706.

11 Andrei A. Rusu et al., *Sim-to-real robot learning from pixels with progressive nets*, October 2016, arxiv.org.

12 David Silver et al., *Mastering chess and shogi by self-play with a general reinforcement learning algorithm*, December 2017, arxiv.org.

Finally, consider the possibilities in emerging meta-learning techniques that attempt to automate the design of machine-learning models. The Google Brain team, for example, uses AutoML to automate the design of neural networks for classifying images in large-scale data sets. These techniques now perform as well as those designed by humans.[13] That's a promising development, particularly as talent continues to be in short supply for many organizations. It's also possible that meta-learning approaches will surpass human capabilities and yield even better results. Importantly, however, these techniques are still in their early days.

Limitation 5: Bias in data and algorithms

So far, we've focused on limitations that could be overcome through technical solutions already in the works, some of which we have described. Bias is a different kind of challenge. Potentially devastating social repercussions can arise when human predilections (conscious or unaware) are brought to bear in choosing which data points to use and which to disregard. Furthermore, when the process and frequency of data collection itself are uneven across groups and observed behaviors, it's easy for problems to arise in how algorithms analyze that data, learn, and make predictions.[14] Negative consequences can include misinformed recruiting decisions, misrepresented scientific or medical prognoses, distorted financial models and criminal-justice decisions, and misapplied (virtual) fingers on legal scales.[15] In many cases, these biases go unrecognized or disregarded under the veil of "advanced data sciences," "proprietary data and algorithms," or "objective analysis."

As we deploy machine learning and AI algorithms in new areas, there probably will be more instances in which these issues of potential bias become baked into data sets and algorithms. Such biases have a tendency to stay embedded because recognizing them, and taking steps to address them, requires a deep mastery of data-science techniques, as well as a more meta-understanding of existing social forces, including data collection. In all, debiasing is proving to be among the most daunting obstacles, and certainly the most socially fraught, to date.

There are now multiple research efforts under way, as well as efforts to capture best practices, that address these issues in academic, nonprofit, and private-sector research. It's none too soon, because the challenge is likely to become even more critical, and more questions will arise. Consider, for example, the fact that many of these learning and statistically based predictive approaches implicitly assume that the future will be like the past. What should we do in sociocultural settings where efforts are under way to spur change—and where making decisions based on past behavior could inhibit progress (or, worse, build in resistance to change)? A wide variety of leaders, including business leaders, may soon be called upon to answer such questions.

[13] *Google Research Blog*, "AutoML for large scale image classification and object detection," blog entry by Barret Zoph, Vijay Vasudevan, Jonathon Shlens, and Quoc Le, November 2, 2017, research.googleblog.com.

[14] Jon Kleinberg, Sendhil Mullainathan, and Manish Raghavan, *Inherent trade-offs in the fair determination of risk scores*, November 2016, arxiv.org.

[15] See the work of Julia Angwin, Jeff Larson, Surya Mattu, Lauren Kirchner, and Terry Parris Jr. of ProPublica.

Hitting the moving target

Solutions to the limitations we have described, along with the widespread commercial implementation of many of the advances described here, could be years away. But the breathtaking range of possibilities from AI adoption suggests that the greatest constraint for AI may be imagination. Here are a few suggestions for leaders striving to stay ahead of—or at least not fall too far behind—the curve:

Do your homework, get calibrated, and keep up. While most executives won't need to know the difference between convolutional and recurrent neural networks, you should have a general familiarity with the capabilities of today's tools, a sense of where short-term advances are likely to occur, and a perspective on what's further beyond the horizon. Tap your data-science and machine-learning experts for their knowledge, talk to some AI pioneers to get calibrated, and attend an AI conference or two to help you get the real facts; news outlets can be helpful, but they can also be part of the hype machine. Ongoing tracking studies by knowledgeable practitioners, such as the AI Index (a project of the Stanford-based One Hundred Year Study on Artificial Intelligence), are another helpful way to keep up.[16]

Adopt a sophisticated data strategy. AI algorithms need assistance to unlock the valuable insights lurking in the data your systems generate. You can help by developing a comprehensive data strategy that focuses not only on the technology required to pool data from disparate systems but also on data availability and acquisition, data labeling, and data governance. Although newer techniques promise to reduce the amount of data required for training AI algorithms, data-hungry supervised learning remains the most prevalent technique today. And even techniques that aim to minimize the amount of data required still need some data. So a key part of this is fully knowing your own data points and how to leverage them.

Think laterally. Transfer-learning techniques remain in their infancy, but there are ways to leverage an AI solution in more than one area. If you solve a problem such as predictive maintenance for large warehouse equipment, can you also apply the same solution to consumer products? Can an effective next-product-to-buy solution be used in more than one distribution channel? Encourage business units to share knowledge that may reveal ways to use your best AI solutions and thinking in more than one area of the company.

Be a trailblazer. Keeping up with today's AI technologies and use cases is not enough to remain competitive for the long haul. Engage your data-science staff or partner with outside experts to solve a high-impact use case with nascent techniques, such as the ones discussed in this article, that are poised for a breakthrough. Further, stay informed about what's possible and what's available. Many machine-learning tools, data sets, and trained models for standard applications (including speech, vision, and emotion detection) are being made widely available. Sometimes they come in open source and in other cases through application programming interfaces (APIs) created by pioneering researchers and companies. Keep an eye on such possibilities to boost your odds of staking out a first-mover or early-adopter advantage.

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The promise of AI is immense, and the technologies, tools, and processes needed to fulfill that promise haven't fully arrived. If you

[16] See the AI Index (aiindex.org) and the One Hundred Year Study (ai100.stanford.edu).

think you can let the technology develop and then be a successful fast follower, think again. It's very difficult to leapfrog from a standing start, particularly when the target is moving so rapidly and you don't understand what AI tools can and can't do now. With researchers and AI pioneers poised to solve some of today's thorniest problems, it's time to start understanding what is happening at the AI frontier so you can position your organization to learn, exploit, and maybe even advance the new possibilities. ◆

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PART 2

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How to make AI work for your business

Jacques Bughin, Michael Chui, and Brian McCarthy

A survey of more than 3,000 executives sheds light on how businesses are using AI, offering lessons for CEOs, as we explain in this article for *Harvard Business Review*.

The buzz over artificial intelligence (AI) has grown loud enough to penetrate the C-suites of organizations around the world, and for good reason. Investment in AI is growing and is increasingly coming from organizations outside the tech space. And AI success stories are becoming more numerous and diverse, from Amazon reaping operational efficiencies using its AI-powered Kiva warehouse robots, to GE keeping its industrial equipment running by leveraging AI for predictive maintenance.

While it's clear that CEOs need to consider AI's business implications, the technology's nascence in business settings makes it less clear how to profitably employ it. Through a study of AI that included a survey of 3,073 executives and 160 case studies across 14 sectors and ten countries, and through a separate digital research program, we have identified ten key insights CEOs need to know to embark on a successful AI journey.

Don't believe the hype—not every business is using AI … yet.
While investment in AI is heating up, corporate adoption of AI technologies is still lagging. Total investment (internal and external) in AI reached somewhere in the range of $26 billion to $39 billion in 2016, with external investment tripling since 2013. Despite this level of investment, however, AI adoption is in its infancy, with just 20 percent of our survey respondents using one or more AI technologies at scale or in a core part of their business, and only half of those using three or more. (Our results are weighted to reflect the relative economic importance of firms of different sizes. We include five categories of AI technology systems: robotics and autonomous vehicles, computer vision, language, virtual agents, and machine learning.)

For the moment, this is good news for those companies still experimenting with or piloting AI (41 percent). Our results suggest there's still time to climb the learning curve and compete using AI.

However, we are likely at a key inflection point of AI adoption. AI technologies such as neural-based machine learning and natural-language processing are beginning to mature and prove their value, quickly becoming centerpieces of AI technology suites among adopters. And we expect at least a portion of current AI piloters to fully integrate AI in the near term. Finally, adoption appears poised to spread, albeit at different rates, across sectors and domains. Telecom and financial services are poised to lead the way, with respondents in these sectors planning to increase their AI tech spend by more than 15 percent a year—seven percentage points higher than the cross-industry average—in the next three years.

Believe the hype that AI can potentially boost your top and bottom line.
Thirty percent of early AI adopters in our survey—those using AI at scale or in core processes—say they've achieved revenue increases, leveraging AI in efforts to gain market share or expand their products and services. Furthermore, early AI adopters are 3.5 times more likely than others to say they expect to grow their profit margin by up to five points more than industry peers. While the question of correlation versus causation can be legitimately raised, a separate analysis uncovered some evidence that AI is already directly improving profits, with return on AI investment in the same range as that for associated digital technologies such as big data and advanced analytics.

Without support from leadership, your AI transformation might not succeed.
Successful AI adopters have strong executive-leadership support for the new technology. Survey respondents from firms that have successfully deployed an AI technology at scale tend to rate C-suite support as being nearly twice as high as that at those companies that have not adopted any AI technology. They add that strong support comes not only from the CEO and IT executives but also from all other C-level officers and the board of directors.

You don't have to go it alone on AI—partner for capability and capacity.
With the AI field recently picking up its pace of innovation after the decades-long "AI winter," technical expertise and capabilities are in short supply. Even large digital natives such as Amazon and Google have turned to companies and talent outside their confines to beef up their AI skills. Consider, for example, Google's

acquisition of DeepMind, which is using its machine-learning chops to help the tech giant improve even core businesses such as search optimization. Our survey, in fact, showed that early AI adopters have primarily *bought* the right fit-for-purpose technology solutions, with only a minority of respondents both developing and implementing all AI solutions in-house.

Resist the temptation to put technology teams solely in charge of AI initiatives.

Compartmentalizing accountability for AI with functional leaders in IT, digital, or innovation can result in a hammer-in-search-of-a-nail outcome: technologies being launched without compelling use cases. To ensure a focus on the most valuable use cases, AI initiatives should be assessed and co-led by both business and technical leaders, an approach that has proved successful in the adoption of other digital technologies.

Take a portfolio approach to accelerate your AI journey.

AI tools today vary along a spectrum ranging from tools that have been proven to solve business problems (for example, pattern detection for predictive maintenance) to those with low awareness and currently limited but high-potential utility (for example, application of AI to develop a competitive strategy). This distribution suggests that organizations could consider a portfolio-based approach to AI adoption across three time horizons:

Short-term: Focus on use cases where there are proven technology solutions today, and scale them across the organization to drive meaningful bottom-line value.

Medium-term: Experiment with technology that's emerging but still relatively immature (deep-learning video recognition) to prove its value in key business use cases before scaling.

Long-term: Work with academia or a third party to solve a high-impact use case (augmented human decision making in a key knowledge-worker role, for example) with bleeding-edge AI technology to potentially capture a sizable first-mover advantage.

Machine learning is a powerful tool, but it's not right for everything.

Machine learning and its most prominent subfield, deep learning, have attracted a lot of media attention and received a significant share of the financing that has been pouring into the AI universe, garnering nearly 60 percent of all investments from outside the industry in 2016.

But while machine learning has many applications, it is just one of many AI-related technologies capable of solving business problems. There's no one-size-fits-all AI solution. For example, the AI techniques implemented to improve customer-call-center performance could be very different from the technology used to identify credit-card-payments fraud. It's critical to look for the right tool to solve each value-creating business problem at a particular stage in an organization's digital and AI journey.

Digital capabilities come before AI.

We found that industries leading in AI adoption—such as high tech, telecom, and automotive—are also the ones that are the most digitized. Likewise, within any industry, the companies that are early adopters of AI have already invested in digital capabilities, including cloud infrastructure and big data. In fact, it appears that companies can't easily leapfrog to AI without digital-transformation experience. Using a battery of statistics, we found that the odds of generating profit from using AI are 50 percent higher for companies that have strong experience in digitization.

Be bold.
In a separate study on digital disruption, we found that adopting an offensive digital strategy was the most important factor in enabling incumbent companies to reverse the curse of digital disruption. An organization with an offensive strategy radically adapts its portfolio of businesses, developing new business models to build a growth path that is *more robust* than *before* digitization. So far, the same seems to hold true for AI: early AI adopters with a very proactive, strictly offensive strategy report a much better profit outlook than those without one.

The biggest challenges are people and processes.
In many cases, the change-management challenges of incorporating AI into employee processes and decision making far outweigh technical AI implementation challenges.

As leaders determine the tasks that machines should handle, versus those that humans perform, both new and traditional, it will be critical to implement programs that allow for constant reskilling of the workforce. And as AI continues to converge with advanced visualization, collaboration, and design thinking, businesses will need to shift from a primary focus on process efficiency to a focus on decision-management effectiveness, which will further require leaders to create a culture of continuous improvement and learning.

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Make no mistake: the next digital frontier is here, and it's AI. While some firms are still reeling from previous digital disruptions, a new one is taking shape. But it's early days. There's still time to make AI a competitive advantage. ◆

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Ten red flags signaling your analytics program will fail

Oliver Fleming, Tim Fountaine, Nicolaus Henke, and Tamim Saleh

Struggling to become analytics-driven? One or more of these issues is likely what's holding your organization back.

How confident are you that your analytics initiative is delivering the value it's supposed to?

These days, it's the rare CEO who doesn't know that businesses must become analytics-driven. Many business leaders have, to their credit, been charging ahead with bold investments in analytics resources and artificial intelligence (AI). Many CEOs have dedicated a lot of their own time to implementing analytics programs, appointed chief analytics officers (CAOs) or chief data officers (CDOs), and hired all sorts of data specialists.

However, too many executives have assumed that because they've made such big moves, the main challenges to becoming analytics-driven are behind them. But frustrations are beginning to surface; it's starting to dawn on company executives that they've failed to convert their analytics pilots into scalable solutions. (A recent McKinsey survey found that only 8 percent of 1,000 respondents with analytics initiatives engaged in effective scaling practices.) More boards and shareholders are pressing for answers about the scant returns on many early and expensive analytics programs. Overall, McKinsey has observed that only a small fraction of the value that could be unlocked by advanced-analytics approaches has been unlocked—as little as 10 percent in some sectors.[1] And McKinsey's AI Index reveals that the gap between leaders and laggards in successful AI and analytics adoption, within as well as among industry sectors, is growing.

That said, there's one upside to the growing list of misfires and shortfalls in companies' big bets on analytics and AI. Collectively, they begin to reveal the failure patterns across organizations of all types, industries, and sizes. We've detected what we consider to be the ten red flags that signal an analytics program is in danger of failure. In our experience, business leaders who act on these alerts will dramatically improve their companies' chances of success in as little as two or three years.

1. The executive team doesn't have a clear vision for its advanced-analytics programs.

In our experience, this often stems from executives lacking a solid understanding of the difference between traditional analytics (that is, business intelligence and reporting) and advanced analytics (powerful predictive and prescriptive tools such as machine learning).

To illustrate, one organization had built a centralized capability in advanced analytics, with heavy investment in data scientists, data engineers, and other key digital roles. The CEO regularly mentioned that the company was using AI techniques, but never with any specificity.

In practice, the company ran a lot of pilot AI programs, but not a single one was adopted by the business at scale. The fundamental reason? Top management didn't really grasp the concept of advanced analytics. They struggled to define valuable problems for the analytics team to solve, and they failed to invest in building the right skills. As a result, they failed to get traction with their AI pilots. The analytics team they had assembled wasn't working on the right problems and wasn't able to use the latest tools and techniques. The company halted the initiative after a year as skepticism grew.

First response: The CEO, CAO, or CDO—or whoever is tasked with leading the company's analytics initiatives—should set up a series of workshops for the executive team to coach its members in the key tenets of advanced analytics and to undo any lingering misconceptions. These workshops can form the foundation of in-house "academies" that can continually teach key analytics concepts to a broader management audience.

2. No one has determined the value that the initial use cases can deliver in the first year.

Too often, the enthusiastic inclination is to apply analytics tools and methods like wallpaper—as something that hopefully will benefit every corner of the organization to which it is applied. But such imprecision leads only to large-scale waste, slower results (if any), and less confidence, from shareholders and employees alike, that analytics initiatives can add value.

That was the story at a large conglomerate. The company identified a handful of use cases and began to put analytics resources against them. But the company did not precisely assess the feasibility or calculate the business value that these use cases could generate, and, lo and behold, the ones it chose produced little value.

[1] See "The age of analytics: Competing in a data-driven world," McKinsey Global Institute, December 2016, on McKinsey.com

First response: Companies in the early stages of scaling analytics use cases must think through, in detail, the top three to five feasible use cases that can create the greatest value quickly—ideally within the first year. This will generate momentum and encourage buy-in for future analytics investments. These decisions should take into account impact, first and foremost. A helpful way to do this is to analyze the entire value chain of the business, from supplier to purchase to after-sales service, to pinpoint the highest-value use cases (Exhibit 1).

To consider feasibility, think through the following:

- Is the data needed for the use case accessible and of sufficient quality and time horizon?
- What specific process steps would need to change for a particular use case?
- Would the team involved in that process have to change?
- What could be changed with minimal disruption, and what would require parallel processes until the new analytics approach was proven?

Exhibit 1

Analytics use cases should be prioritized based on feasibility and impact.

Step 1: Create a list of use cases.

Sample list for consumer-packaged-goods company

Sales/customer relationship management (CRM)

1. Overall brand management
2. Overall campaign management
3. 360° view of shopper
4. Targeted acquisition campaigns
5. Real-time image advertising (awareness)
6. Retargeting campaign

Marketing

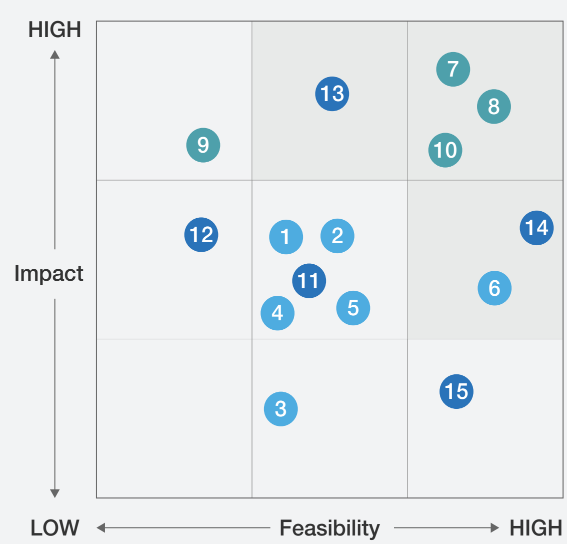
7. Optimization of spend across media
8. Optimization of spend within digital media
9. Digital attribution modeling
10. Performance advertising (sales)

Innovation

11. Consumer insights (social listening/sentiment analysis)
12. New product success (predictive behavior model)
13. Product customization at scale
14. Open innovation on promotion mechanisms
15. New digital sales models

Step 2: Prioritize them.

Sample impact vs feasibility matrix



3. There's no analytics strategy beyond a few use cases.

In one example, the senior executives of a large manufacturer were excited about advanced analytics; they had identified several potential cases where they were sure the technology could add value. However, there was no strategy for how to generate value with analytics beyond those specific situations.

Meanwhile, a competitor began using advanced analytics to build a digital platform, partnering with other manufacturers in a broad ecosystem that enabled entirely new product and service categories. By tackling the company's analytics opportunities in an unstructured way, the CEO achieved some returns but missed a chance to capitalize on this much bigger opportunity. Worse yet, the missed opportunity will now make it much more difficult to energize the company's workforce to imagine what transformational opportunities lie ahead.

As with any major business initiative, analytics should have its own strategic direction.

First response: There are three crucial questions the CDO or CAO must ask the company's business leaders:

- What threats do technologies such as AI and advanced analytics pose for the company?
- What are the opportunities to use such technologies to improve existing businesses?
- How can we use data and analytics to create new opportunities?

4. Analytics roles—present and future—are poorly defined.

Few executives can describe in detail what analytics talent their organizations have, let alone where that talent is located, how it's organized, and whether they have the right skills and titles.

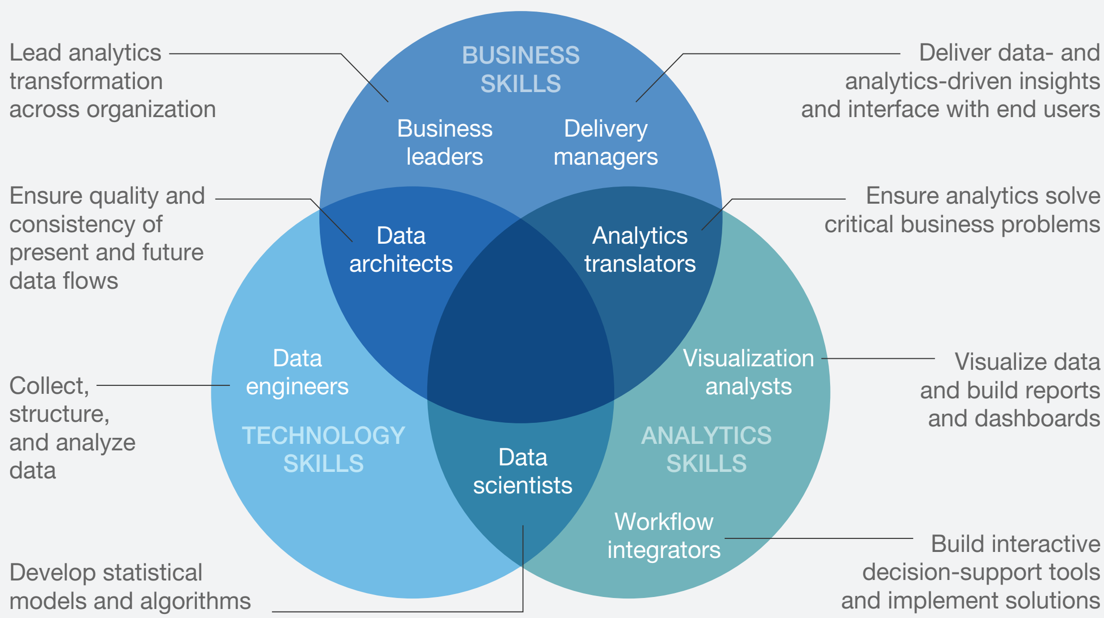
In one large financial-services firm, the CEO was an enthusiastic supporter of advanced analytics. He was especially proud that his firm had hired 1,000 data scientists, each at an average loaded cost of $250,000 a year. Later, after it became apparent that the new hires were not delivering what was expected, it was discovered that they were not, by strict definition, data scientists at all. In practice, 100 true data scientists, properly assigned in the right roles in the appropriate organization, would have sufficed. Neither the CEO nor the firm's human-resources group had a clear understanding of the data-scientist role—nor of other data-centric roles, for that matter.

First response: The right way to approach the talent issue is to think about analytics talent as a tapestry of skill sets and roles (Exhibit 2). Naturally, many of these capabilities and roles overlap—some regularly, others depending on the project. Each thread of that tapestry must have its own carefully crafted definition, from detailed job descriptions to organizational interactions. The CDO and chief human resources officer (CHRO) should lead an effort to detail job descriptions for all the analytics roles needed in the years ahead. An immediate next step is to inventory all of those currently with the organization who could meet those job specifications. And then the next step is to fill the remaining roles by hiring externally.

Exhibit 2

Organizations need a variety of analytics talent with well-defined roles.

Analytics roles and responsibilities



5. The organization lacks analytics translators.

If there's one analytics role that can do the most to start unlocking value, it is the analytics translator. This sometimes overlooked but critical role is best filled by someone on the business side who can help leaders identify high-impact analytics use cases and then "translate" the business needs to data scientists, data engineers, and other tech experts so they can build an actionable analytics solution. Translators are also expected to be actively involved in scaling the solution across the organization and generating buy-in with business users. They possess a unique skill set to help them succeed in their role—a mix of business knowledge, general technical fluency, and project-management excellence.

First response: Hire or train translators right away. Hiring externally might seem like the quickest fix. However, new hires lack the most important quality of a successful translator: deep company knowledge. The right internal candidates have extensive company knowledge and business acumen and also the education to understand mathematical models and to work with data scientists to bring out valuable insights. As this unique combination of skills is hard to find, many companies have created their own translator academies to train these candidates. One global steel company, for example, is training 300 translators in a one-year learning program. At McKinsey, we've created our own academy, training 1,000 translators in the past few years.

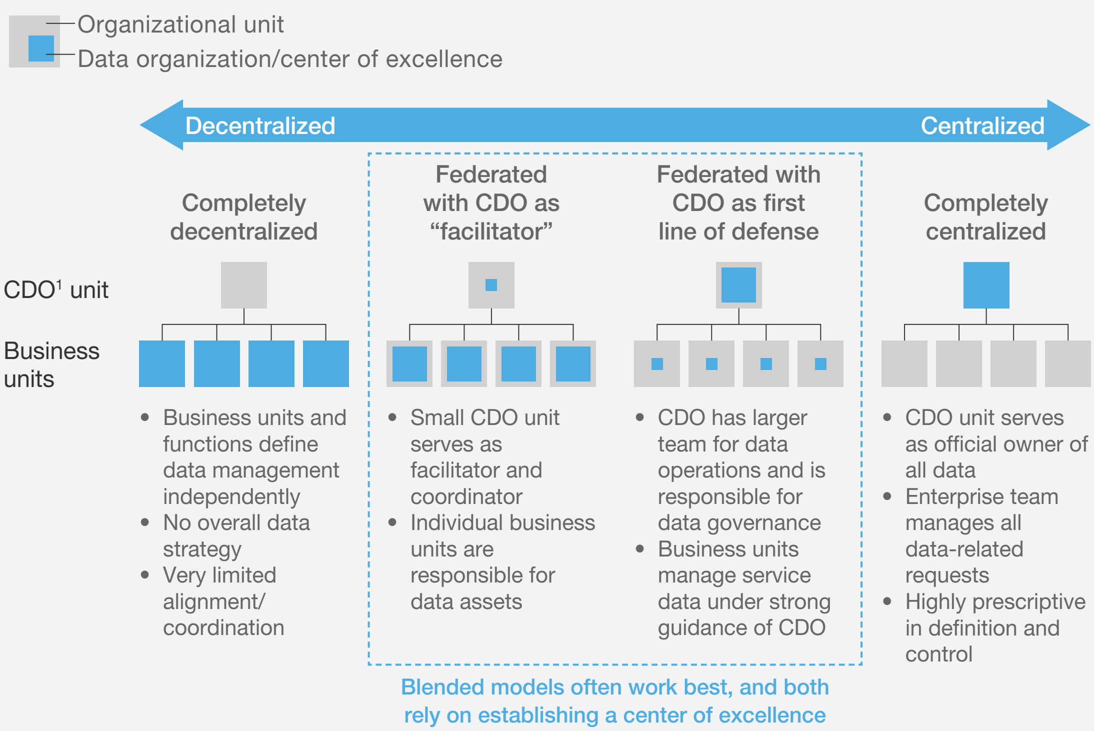
6. Analytics capabilities are isolated from the business, resulting in an ineffective analytics organization structure.
We have observed that organizations with successful analytics initiatives embed analytics capabilities into their core businesses. Those organizations struggling to create value through analytics tend to develop analytics capabilities in isolation, either centralized and far removed from the business or in sporadic pockets of poorly coordinated silos. Neither organizational model is effective. Overcentralization creates bottlenecks and leads to a lack of business buy-in. And decentralization brings with it the risk of different data models that don't connect (Exhibit 3).

A definite red flag that the current organizational model is not working is the complaint from a data scientist that his or her work has little or no impact and that the business keeps doing what it has been doing. Executives must keep an ear to the ground for those kinds of complaints.

Exhibit 3

Hybrid organizational models often work best for broadscale analytics initiatives.

Organizational types



[1]Chief data officer.

First response: The C-suite should consider a hybrid organizational model in which agile teams combine talented professionals from both the business side and the analytics side. A hybrid model will retain some centralized capability and decision rights (particularly around data governance and other standards), but the analytics teams are still embedded in the business and accountable for delivering impact.

For many companies, the degree of centralization may change over time. Early in a company's analytics journey, it might make sense to work more centrally, since it's easier to build and run a central team and ensure the quality of the team's outputs. But over time, as the business becomes more proficient, it may be possible for the center to step back to more of a facilitation role, allowing the businesses more autonomy.

7. Costly data-cleansing efforts are started en masse.

There's a tendency for business leaders to think that all available data should be scrubbed clean before analytics initiatives can begin in earnest. Not so.

McKinsey estimates that companies may be squandering as much as 70 percent of their data-cleansing efforts. Not long ago, a large organization spent hundreds of millions of dollars and more than two years on a company-wide data-cleansing and data-lake-development initiative. The objective was to have one data meta-model—essentially one source of truth and a common place for data management. The effort was a waste. The firm did not track the data properly and had little sense of which data might work best for which use cases. And even when it had cleansed the data, there were myriad other issues, such as the inability to fully track the data or understand their context.

First response: Contrary to what might be seen as the CDO's core remit, he or she must not think or act "data first" when evaluating data-cleansing initiatives. In conjunction with the company's line-of-business leads and its IT executives, the CDO should orchestrate data cleansing on the data that fuel the most valuable use cases. In parallel, he or she should work to create an enterprise data ontology and master data model as use cases become fully operational.

8. Analytics platforms aren't built to purpose.

Some companies know they need a modern architecture as a foundation for their digital transformations. A common mistake is thinking that legacy IT systems have to be integrated first. Another mistake is building a data lake before figuring out the best ways to fill it and structure it; often, companies design the data lake as one entity, not understanding that it should be partitioned to address different types of use cases.

In many instances, the costs for such investments can be enormous, often millions of dollars, and they may produce meager benefits, in the single-digit millions. We have found that more than half of all data lakes are not fit for purpose. Significant design changes are often needed. In the worst cases, the data-lake initiatives must be abandoned.

That was the case with one large financial-services firm. The company tried to integrate its legacy data warehouses and simplify its legacy IT landscape without a clear business case for the analytics the data would fuel. After two years, the business began to push back as costs escalated, with no signs of value being delivered. After much debate, and after about 80 percent of the investment budget had been spent, the program screeched to a halt.

First response: In practice, a new data platform can exist in parallel with legacy systems. With appropriate input from the chief information officer (CIO), the CDO must ensure that, use case by use case, data ingestion can happen from multiple sources and that data cleansing can be performed and analytics conducted on the platform—all while the legacy IT systems continue to service the organization's transactional data needs.

9. Nobody knows the quantitative impact that analytics is providing.

It is surprising how many companies are spending millions of dollars on advanced analytics and other digital investments but are unable to attribute any bottom-line impact to these investments.

The companies that have learned how to do this typically create a performance-management framework for their analytics initiatives. At a minimum, this calls for carefully developed metrics that track most directly to the initiatives. These might be second-order metrics instead of high-level profitability metrics. For example, analytics applied to an inventory-management system could uncover the drivers of overstock for a quarter. To determine the impact of analytics in this instance, the metric to apply would be the percentage by which overstock was reduced once the problem with the identified driver was corrected.

Precisely aligning metrics in this manner gives companies the ability to alter course if required, moving resources from unsuccessful use cases to others that are delivering value.

First response: The business leads, in conjunction with translators, must be the first responders; it's their job to identify specific use cases that can deliver value. Then they should commit to measuring the financial impact of those use cases, perhaps every fiscal quarter. Finance may help develop appropriate metrics; the function also acts as the independent arbiter of the performance of the use cases. Beyond that, some leading companies are moving toward automated systems for monitoring use-case performance, including ongoing model validation and upgrades.

10. No one is hyperfocused on identifying potential ethical, social, and regulatory implications of analytics initiatives.

It is important to be able to anticipate how digital use cases will acquire and consume data and to understand whether there are any compromises to the regulatory requirements or any ethical issues.

One large industrial manufacturer ran afoul of regulators when it developed an algorithm to predict absenteeism. The company meant well; it sought to understand the correlation between job conditions and absenteeism so it could rethink the work processes that were apt to lead to injuries or illnesses. Unfortunately, the algorithms were able to cluster employees based on their ethnicity, region, and gender, even though such data fields were switched off, and it flagged correlations between race and absenteeism.

Luckily, the company was able to pinpoint and preempt the problem before it affected employee relations and led to a significant regulatory fine. The takeaway: working with data, particularly personnel data, introduces a host of risks from algorithmic bias. Significant supervision, risk management, and mitigation efforts are required to apply the appropriate human judgment to the analytics realm.

First response: As part of a well-run broader risk-management program, the CDO should take the lead, working with the CHRO and the company's business-ethics experts and legal counsel to set up resiliency testing services that can quickly expose and interpret the secondary effects of the company's analytics programs. Translators will also be crucial to this effort.

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There is no time to waste. It is imperative that businesses get analytics right. The upside is too significant for it to be discretionary. Many companies, caught up in the hype, have rushed headlong into initiatives that have cost vast amounts of money and time and returned very little.

By identifying and addressing the ten red flags presented here, these companies have a second chance to get on track. ◆

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Breaking away: The secrets to scaling analytics

Peter Bisson, Bryce Hall, Brian McCarthy, and Khaled Rifai

A handful of the world's companies have cracked the code on embedding analytics into every layer of their organizations.

The time for simple experimentation with analytics is over—and most companies know it. Across industries, we see organizations investing heavily to integrate analytics throughout their entire business in an effort to capture a portion of the $9.5 trillion to $15.4 trillion of value that the McKinsey Global Institute estimates advanced analytics can enable across industries globally.[1]

Despite this investment, senior executives tell us that their companies are struggling to capture real value. The reason: while they're eking out small gains from a few use cases, they're failing to embed analytics into all areas of the organization.

However, in a recent McKinsey Analytics survey of 1,000 companies with more than $1 billion in revenue and spanning 13 sectors and 12 geographies, we identified an elite group of companies that is achieving the elusive goal of analytics at scale.

What does analytics at scale look like? One major US retailer responded to

[1] See "Notes from the AI frontier: Applications and value of deep learning," McKinsey Global Institute, April 2018, on McKinsey.com.

fast-changing consumer behaviors and fierce online competition by reshaping its entire business around analytics. A state-of-the-art analytics capability would span all eight of its business units, all six of its major operational functions, and all 60 million of its customers.

The results have been impressive. The new capability aggregates all customer interactions and extensive customer information across brands and channels, enabling the company's analytics teams to target offers to customers at a microsegment level. And the impact truly spans the organization. In marketing, for example, the company can deliver personalized content through its website, emails, and digital ads. In strategic planning, the capability pinpoints neighborhoods where people make the most online and catalog purchases in order to identify the most promising future store locations.

However, getting to that point wasn't easy. The company had to overcome many challenges, including the toughest of all—bridging the "last mile," or delivering the right insights to the right people at the right time in a way that informs their decision making to drive better business outcomes.

How the best break away from the rest

To achieve similar success in scaling analytics, organizations can look to the practices of the 8 percent of companies in our survey that are breaking away from the pack. Based on our research, there are nine critical drivers of these breakaway companies' relative success at scaling analytics (Exhibit 1). (See sidebar,

Exhibit 1

Breakaway companies scale analytics by significantly outperforming in 9 critical areas across 3 categories.

Aligning on strategy	Building the right foundations of data, technologies, and people	Conquering the last mile by embedding analytics into decision making and processes
1. Obtaining a strong, unified commitment from all levels of management 2. Increasing analytics investments, with a focus on the last mile	3. Developing a clear data strategy with strong data governance 4. Using sophisticated analytics methodologies 5. Possessing deep analytics expertise enabled by a tailored talent strategy 6. Creating cross-functional, collaborative agile teams	7. Prioritizing top decision-making processes 8. Establishing clear decision-making rights and accountability 9. Empowering the front lines to make analytics-driven decisions

"About the research," for more on the study methodology.) These drivers fall into three main categories: strategy, foundational capabilities, and activities geared toward the last mile of embedding analytics into the fabric of the organization.

What surprised us was not necessarily the small size of this breakaway group or even their practices but how wide the divide was between them and the rest of the pack.

Aligning on strategy

To get the most from their analytics investments, organizations need to plug analytics into the critical strategic areas of the company, which are typically those that cut across business functions, such as customer experience.

One large US company did not learn this lesson until three years into its analytics journey. It had hired large numbers of data scientists and launched more than 50 pilot projects to test new capabilities. While the company had success in some areas, not one of those pilots was successfully scaled across the company. Its analytics team was working on an island, with no connection to cross-functional business strategy, and, as a result, produced limited impact.

About the research

For this primary research, we conducted 1,000 phone-based survey interviews with C-suite executives from companies with more than $1 billion in revenues across geographies and sectors. Companies were sampled globally, including from Australia, Brazil, China, France, Germany, India, Japan, New Zealand, the Nordic countries, Singapore and Southeast Asia, Spain, the United Kingdom, and the United States.

Organizations covered all major sectors, including automotive, banking, consumer, energy (including oil and gas), healthcare, high tech, insurance, pharmaceuticals, resources (including mining and utilities), retail, telecommunications, and transportation and travel.

The survey included 36 questions focused on analytics strategy, organization, data, models and tools, and value assurance, with an emphasis on diagnosing the challenge of last-mile delivery of analytics at scale. The questions were adapted from McKinsey's Analytics Quotient, which is an objective and comprehensive assessment of a company's analytics maturity along key dimensions that drive financial performance.

To analyze the data, we identified five indicators as proxies for successful analytics programs at scale. These included analytics spend as a percentage of IT spending; satisfaction with return on investment (ROI) on analytics; level of impact aspired to; length of analytics journey; and spend on embedding as a percentage of analytics spend. We supplemented this with financial data—for example, three-year and five-year averages of total returns to shareholders (TRS)—from a third of the companies. We created a composite score for each company from these metrics, which showed a positive correlation with average TRS, adjusted for industry effects. We then performed a k-means clustering across the full data set for all questions. These analyses revealed a breakaway "best-performing" cluster of companies, which demonstrated superior performance in the majority of the remaining variables.

Adopting analytics across all lines of business and functions requires a clear, coordinated strategy and focused investment.

Driver #1: Obtaining a strong, unified commitment from all levels of management

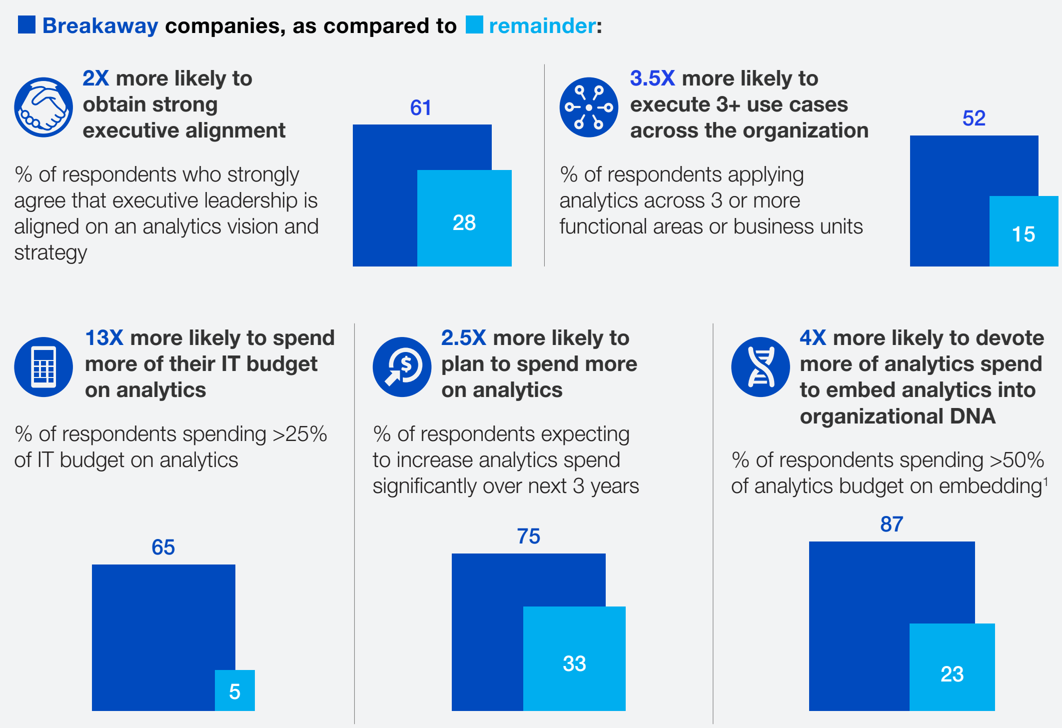
Companies in the breakaway group are twice as likely as their peers to report that their leadership team is completely aligned on an analytics vision and strategy (Exhibit 2). Within these companies, senior leadership has set the clear goal of integrating analytics not just into certain business units and functions but across all operations. As a result, breakaway companies are 3.5 times more likely than their peers to be applying analytics to three or more functional areas.

This level of commitment starts at the top, but it must also reach deep into the organizational structure. One major US bank cultivates this type of focus by making analytics expertise a requirement for business leadership positions—not just the C-suite but the entire management team, a group that includes hundreds of executives.

Breakaway companies also understand the importance of securing buy-in even further

Exhibit 2

Breakaway companies set a sound strategy for scaling analytics.



[1]For example, integrating analytics into workflows.

Source: McKinsey analysis

down the corporate ladder. Fifty-seven percent of the breakaway group report that their middle management fully believes becoming an analytics-driven organization is imperative to staying relevant and competitive, a figure nearly twice that of other respondents.

Driver #2: Increasing analytics investments, with a focus on the last mile

Breakaway companies spend more than other organizations on analytics, and they plan to increase these investments further. Two-thirds of breakaway companies (versus only 5 percent of other respondents) already spend more than 25 percent of their IT budgets on analytics, a category that can include a long list of analytics-related expenditures such as data, technology, analytics talent, and embedding analytics into business-process workflows. And the breakaway group intends to double down by increasing that funding significantly in the future, with 75 percent reporting plans to boost their analytics spending, compared with only 33 percent of other respondents planning to do so.

Most important, breakaway companies target much of this spending toward the biggest challenge companies face in extracting value from analytics—the last mile, or embedding analytics into the core of all workflows and decision-making processes (more on this later). Nearly 90 percent of breakaway organizations devote more than half of their analytics budgets to this effort, versus only 23 percent of all other organizations that do so.

Building the right foundations

Breakaway companies outperform other respondents in establishing the building blocks of effective analytics, including data, processes, technologies, and people.

Driver #3: Developing a clear data strategy with strong data governance

Breakaway organizations are 2.5 times more likely than their peers to report having a clear data strategy and twice as likely to report strong data-governance practices that allow them to identify and prioritize data (Exhibit 3).

We find that the most successful data strategies include four key elements:

- A clear data ontology based on both current and projected use cases.

- A corresponding master data model across key domains (for example, customer, product, location, employees), with established business ownership for how they are addressed.

- Governance plans that clearly establish who is accountable for the quality and maintenance of each data set and that segment the data sets into hierarchical categories, understanding that not all data receive “first-class” treatment. For example, the mission-critical data, such as personal health records for healthcare payors and providers, are stored in the highest-quality and most easily accessible system. The next level of data (for example, those highly applicable to specific functions such as marketing) includes highly curated data sets for analytics and does not have the same level of rigorous governance. Everything else is stored in the cheapest possible manner to minimize overall costs.

- A complete understanding of and plan for the technical requirements of the data environments (for example, use cases might require a dynamic environment in which data are automatically and continually updated), including systems capable of moving data

Exhibit 3

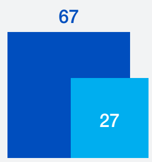
Strong foundational capabilities in data, analytics practices, and people enable breakaway companies to scale.

Breakaway companies, as compared to remainder:

Data

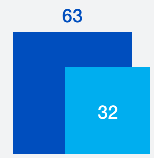
2.5X more likely to have sound data strategy

% of respondents who strongly agree that they have a clear data strategy to support their analytics strategy



2X more likely to have strong data governance

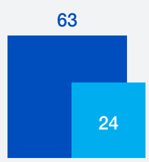
% of respondents who strongly agree that their data-governance practices allow them to identify and prioritize their most important data



Analytics methodologies

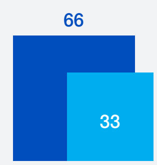
2.5X more likely to have clear methodology

% of respondents who strongly agree that they have a clear methodology for development of models, interpretation of insights, and deployment of new capabilities



2X more likely to use challenge and test system

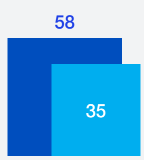
% of respondents who strongly agree that they have a system to continually challenge and test quality and performance of analytics models



Talent and organization

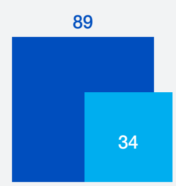
1.5X more likely to have deep data and analytics expertise

% of respondents who strongly agree that their company has deep functional data and analytics expertise



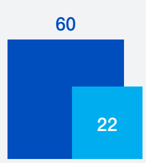
2.5X more likely to employ more data and analytics talent

% of respondents with more than 25 data and analytics professionals per 1,000 FTEs[1]



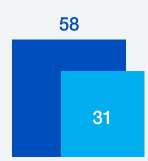
3X more likely to have well-defined analytics roles and career paths

% of respondents who strongly agree that they have a clear center of gravity for analytics talent, with well-defined roles and career-development paths



2X more likely to use cross-functional, agile teams

% of respondents who strongly agree that their analytics operating model revolves around cross-functional teams



[1]Full-time equivalents.

Source: McKinsey analysis

from one classification to another as their relative importance fluctuates over time. For example, for an insurer, data on catastrophe modeling might not always be mission critical but would likely rise to that level in the face of an oncoming storm or wildfire.

Driver #4: Using sophisticated analytics methodologies

Breakaway companies are 2.5 times more likely than other respondents to have a clear methodology for developing analytics models, interpreting insights, and deploying the new capabilities that they build.

We find that companies with leading analytics programs not only focus on model development through their methodologies but also work to continuously maintain and upgrade models as part of a sophisticated model-management function. Many breakaway companies constantly test and upgrade the quality and performance of analytics models using a challenge and test approach that pits existing data sources and algorithms against new and potentially better alternatives. Breakaway companies are twice as likely as others to employ this approach.

Breakaway companies are also more likely to use sophisticated analytics techniques, such as reinforcement learning and deep learning, which can provide a substantial lift in value over using more traditional analytics approaches. McKinsey Global Institute research shows, for example, that using more sophisticated deep-learning techniques for next-product-to-buy recommendations can potentially double the value they provide.[2]

Driver #5: Possessing deep analytics expertise enabled by a tailored talent strategy

Breakaway companies are 1.5 times more likely than their peers to have deep functional expertise in the areas of data science, data engineering, data architecture, and analytics transformation. In purely numeric terms, they are 2.5 times more likely than other companies to employ more than 25 analytics professionals per 1,000 full-time equivalents (FTEs). This difference is even more dramatic among respondents in certain industries. For example, breakaway retail companies are seven times more likely to have 50 or more analytics professionals per 1,000 FTEs (the industry average is closer to 20 per 1,000 FTEs) than the rest of retail respondents.

Breakaway companies obtain this expertise with strategies to attract and retain the best analytics professionals that go far beyond compensation. Companies in the breakaway group, for example, are three times more likely than their peers to establish a clear core center of gravity of analytics talent in their organizations. With a leader who has a seat at the executive table, such as a chief analytics officer, and a surrounding group of like-minded peers, analytics professionals are more likely to feel that they are integral to the company's organizational goals—and they will also be best positioned to help the organization achieve them.

Breakaway companies also source and keep scarce talent by creating well-defined roles and career paths that are specifically designed for analytics professionals, as opposed to being retrofitted from other roles in the organization. Some companies have created dual career tracks (for example, technical and managerial) and rotational programs that cycle analytics talent through both business and technical roles.

Many companies successfully scaling analytics have focused on developing integrated analytics talent strategies that span their businesses. They have created analytics innovation centers near research and

[2] See "Visualizing the uses and potential impact of AI and other analytics," McKinsey Global Institute, April 2018, on McKinsey.com.

entrepreneurship talent markets, recruited tech and analytics executives in key management roles, developed analytics career paths, and assigned analytics talent to projects that excite them most. Senior executives have enlisted managers from across their companies to integrate analytics and analytics professionals into key areas of their businesses.

Driver #6: Creating cross-functional, collaborative agile teams

Breakaway companies create collaborative cultures that foster innovation and propel analytics initiatives throughout the organization.

Nearly 60 percent of breakaway organizations use cross-functional teams, versus less than a third of the remaining respondents that do so. These teams are made up of highly committed business representatives, analytics translators, user-experience design experts, data engineers, and data scientists who are often encouraged to work together in agile teams. And the diversity of their membership helps mitigate the risk of creating another isolated silo (such as design, digital) as the company builds its analytics capabilities. The result: high-impact, end-to-end analytics use cases.

Conquering the last mile by embedding analytics into decision-making processes

The biggest challenge in any organization's analytics journey is turning insights into outcomes—what we call the last mile, which is where the value of analytics is ultimately extracted.

Embedding is the key to conquering the last mile. It's a two-step process: first, organizations must make analytics extremely user-friendly and customized for each group making priority decisions (for example, store managers, clinical laboratory specialists). This requires a combination of the right technical tools (for example, API-enabled middleware) and support tools such as intuitive dashboards, recommendation engines, and mobile apps. It also often requires obtaining design talent and capabilities not typically found in analytics departments or elsewhere in the company. Second, and often more challenging, companies must embed analytics-based decision making into the corporate culture, creating an environment in which workers embrace analytics as an essential tool that challenges established thinking and augments their judgment.

Without completing the last mile, analytics investments can go to waste. For example, a large US financial-services company made a significant commitment to analytics for fraud detection. It had been working on its analytics capability for several years, made sizable investments, and deployed some 1,500 analytics professionals in a center of excellence. The analytics were performing well, picking up several telltale signs of fraud in online forms, including the speed at which product applications were filled out, the time of day the applications were submitted, and even the lack of capitalization of names. However, the company was not seeing significant changes in outcomes initially. The reason: even though it had world-class fraud-detection algorithms, it had not created the processes to integrate these insights into the day-to-day work and decisions of its employees on the front line (for example, customer service representatives or credit underwriters) in order to prevent fraud.

Although breakaway companies have not entirely mastered embedding, they are well ahead of the field due to their success in the following areas.

Driver #7: Prioritizing top decision-making processes

In every organization, thousands of decisions affect business outcomes every day. Any and all of these could be informed by data insights. To achieve meaningful impact with analytics, breakaway companies prioritize and then map the decisions that will drive the most value by being addressed with “right-time” data insights. This endeavor is not unlike the business-process-reengineering wave that swept the corporate world in the 1980s and 1990s. We’re essentially seeing an evolution of the science of decision making.

To some extent, it’s not the process these companies use to prioritize decisions that’s important—it’s the fact that they are prioritizing decisions at all. While prioritization might seem like job one, breakaway companies are almost twice as likely to have identified and prioritized the top ten to 15 decision-making processes in which to embed analytics (Exhibit 4).

One global cruise company provided precisely this type of strategic direction by deciding that its analytics initiative would be anchored in the customer experience. By prioritizing and embedding analytics into critical decisions affecting the customer experience across its multiple brands, the company could deliver data-informed travel packages to customers, personalize guest experiences based on documented customer preferences, optimize pricing across its fleet of ships, and even enhance the scheduling of its routes based on consumer buying patterns.

Driver #8: Establishing clear decision-making rights and accountability

Another part of completing the last mile is making clear who in the organization is

Exhibit 4

Breakaway organizations are closer to completing the last mile.

Breakaway companies, as compared to remainder:

2X more likely to prioritize top decision-making processes

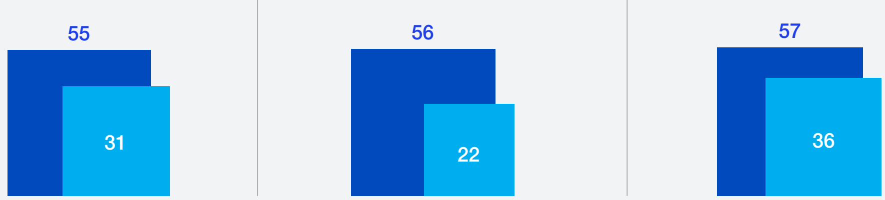
% of respondents who strongly agree that they have clearly prioritized the top 10–15 key decision-making processes in which to embed analytics insights

2.5X more likely to establish decision-making rights and accountability

% of respondents who agree that their organization has established clear accountability and decision rights by role and a clear process for escalation in the organization

1.5X more likely to achieve quick, continually refined decision making

% of respondents who strongly agree that their organization makes decisions quickly and continually refines its approach as it learns more



Source: McKinsey analysis

empowered to make particular analytics-based decisions on a day-to-day basis—as well as holding business-unit leaders accountable for making sure that their team members have the tools they need to do so. Breakaway organizations are more than twice as likely as other companies to agree with the statement, "Our organization has clear accountability and decision rights by role, with most decisions made at the working-team level, and a clear process for escalation in the organization."

One consumer-goods company provides a good example of how a lack of accountability can sabotage success with analytics. Its regional business heads derailed an expensive and well-designed analytics program funded by corporate by simply ignoring it.

We find that the analytics vision set out by the C-suite, and the CEO in particular, must be not only clear but also motivational in order to spur buy-in from business heads and others further down the corporate ladder—particularly the ever-critical middle management.

One visionary leader motivated management at an oil and gas company by providing a level of autonomy to members of the group. A new technology and analytics team of 30 people was established and tasked with simply using analytics to improve business performance—the team could select the first use cases. The managers chose two oil-platform quality and safety use cases. In just one year, the team built a data platform and machine-learning capability that helped decrease accidents. Excited by the improvements, dozens of additional employees became part of the team that would enable the next set of analytics use cases.

Driver #9: Empowering the front lines to make analytics-driven decisions

Getting management on board is only part of the battle—to turn analytics insights into outcomes, organizations must ultimately enable frontline employees to easily leverage analytics to make decisions. Breakaway companies are about 1.5 times more likely than other respondents to report that their organizations have achieved quick, continually refined decision making through analytics, one of the keys to the last mile.

Here is one example of what this allows companies to achieve: a major retailer saw a significant increase in sales by delivering demographic data on customers to store managers on a daily basis and empowering them to act on the insights the data provided (for example, penetration and shopping frequency by demographic segment in the trade area of the store).

Companies of all industries and sizes can upgrade the scope and impact of their analytics by applying the lessons from our breakaway companies in each of these nine areas. However, the most important takeaway from this research might be found in the one area in which even some breakaway companies are still falling short: bridging the last mile.

Most companies start their analytics journey with data; they determine what they have and figure out where it can be applied. Almost by definition, that approach will limit analytics' impact. To achieve analytics at scale, companies should work in the opposite direction. They should start by identifying the decision-making processes they could improve to generate additional value in the context of the company's business strategy and then work backward to determine what type of data insights are required to influence these decisions and how the company can supply them. In other words, the last mile should be the starting point of the analytics journey. ◆

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The authors wish to thank Nila Bhattacharyya, Laura DeLallo, Clarice Lee, and John Saunders for their contributions to this article.

Photo credit: Getty Images

Analytics translator: The new must-have role

Nicolaus Henke, Jordan Levine, and Paul McInerney

The search for vital analytics talent has often focused on data scientists. In this article for *Harvard Business Review*, we describe the overlooked analytics role that's even more critical to fill.

It's no secret that organizations have been increasingly turning to advanced analytics and artificial intelligence (AI) to improve decision making across business processes—from research and design to supply chain and risk management.

Along the way, there's been plenty of literature and executive hand-wringing over hiring and deploying ever-scarce data scientists to make this happen. Certainly, data scientists are required to build the analytics models—largely machine learning and, increasingly, deep learning—capable of turning vast amounts of data into insights.

More recently, however, companies have widened their aperture, recognizing that success with AI and analytics requires not just data scientists but also entire cross-functional, agile teams that include data engineers, data architects, data-visualization experts, and—perhaps most important—translators.

Why are translators so important? They help ensure that organizations achieve real impact from their analytics initiatives (which has the added benefit of keeping data scientists fulfilled and more likely to stay on, easing executives' stress over sourcing that talent).

What exactly is an analytics translator?

To understand more about what translators are, it's important to first understand what they aren't. Translators are neither data architects nor data engineers. They're not even necessarily dedicated analytics professionals, and they don't possess deep technical expertise in programming or modeling.

Instead, translators play a critical role in bridging the technical expertise of data engineers and data scientists with the operational expertise of marketing, supply chain, manufacturing, risk, and other frontline managers. In their role, translators help ensure that the deep insights generated through sophisticated analytics translate into impact at scale in an organization. By 2026, the McKinsey Global Institute estimates that demand for translators in the United States alone may reach two to four million.

What does a translator do?

At the outset of an analytics initiative, translators draw on their domain knowledge to help business leaders identify and prioritize their business problems, based on which will create the highest value when solved. These may be opportunities within a single line of business (e.g., improving product quality in manufacturing) or cross-organizational initiatives (e.g., reducing product delivery time). Translators then tap into their working knowledge of AI and analytics to convey these business goals to the data professionals who will create the models and solutions. Finally, translators ensure that the solution produces insights that the business can interpret and execute on, and, ultimately, communicates the benefits of these insights to business users to drive adoption.

Given the diversity of potential use cases, translators may be part of the corporate strategy team, a functional center of excellence, or even a business unit assigned to execute analytics use cases.

What skills do translators need?

The wide range of responsibilities—leader, communicator, project manager, industry expert—inherent in the translator role makes the following skills essential.

Domain knowledge

Domain knowledge is by far the most important skill for any translator. Translators must be experts in both their industry and their company to effectively identify the value of AI and analytics in the business context. They must understand the key operational metrics of the business and their impact on profit and loss, revenue, customer retention, and so on. Additionally, knowledge of common use cases (e.g., predictive maintenance, supply-chain management, inventory management, personalized marketing, churn prediction, etc.) in their domain is important.

General technical fluency

In addition to their domain knowledge, translators must possess strong acumen in quantitative analytics and structured problem solving. They often have a formal STEM (science, technology, engineering, and mathematics) background or self-taught

The analytics translator role

At each step of the analytics initiative, the translator has an important role to play.

Step 1: Identifying and prioritizing business use cases
Translator role: Works with business-unit leaders to identify and prioritize problems that analytics is suited to solve.

Step 2: Collecting and preparing data
Translator role: Helps identify the business data needed to produce the most useful insights.

Step 3: Building the analytics engine
Translator role: Ensures the solution solves the business problem in the most efficient and interpretable form for business users.

Step 4: Validating and deriving business implications
Translator role: Synthesizes complex analytics-derived insights into easy-to-understand, actionable recommendations that business users can easily extract and execute on.

Step 5: Implementing the solution and executing on insights
Translator role: Drives adoption among business users.

knowledge in a STEM field. And while they don't necessarily need to be able to build quantitative models, they do need to know what types of models are available (e.g., deep learning versus logistic regression) and to what business problems they can be applied. Translators must also be able to interpret model results and identify potential model errors, such as overfitting.

Project-management skills

A mastery of process-management skills is a must. Translators should be able to direct an analytics initiative from ideation through production and adoption and have an understanding of the life cycle of an analytics initiative and the common pitfalls.

An entrepreneurial spirit

In addition to these "teachable" skill sets, translators also should have an entrepreneurial mind-set. They need the enthusiasm, commitment, and business savvy to navigate the many technical, political, and organizational roadblocks that can emerge. This is often less teachable—or at least less straightforwardly so—and the availability of entrepreneurial individuals can depend in part on the organization's culture.

Where can organizations find translators?

Given the urgent need for translators, hiring externally might seem like the quickest fix. However, new hires lack the most important quality of a successful translator: deep company knowledge. As a result, training existing employees often proves to be the best option for filling the translator void.

Of course, this route presents its own challenges, considering there are currently no certifications or degrees for translators. In response, many companies have created their own translator academies. One global steel company, for example, is training 300 managers in a one-year learning program. At McKinsey, we've even created an academy in our own firm, training 1,000 translators in the past year.

Academy curricula frequently range from exploring the art of the possible to studying specific AI techniques and methods. Formats include both courses and immersion.

Some organizations train translators through apprenticeships in multifunctional, agile teams on real AI and analytics transformation projects. These companies often combine apprenticeship programs with an academy, designing deliberate learning journeys, typically a year in length, for each individual.

Who is currently responsible in your organization for connecting AI and analytics with business goals? In many organizations, data professionals and business leaders often struggle to articulate their needs in a language that the other can execute on.

Translators bring a unique skill set to help businesses increase the return on investment for their analytics initiatives. They're instrumental in identifying, from the myriad possible opportunities, which are the *right* opportunities to pursue, and they can help ensure that all participants, from data professionals to business executives, work in harmony to realize the promise these technologies offer. ◆

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This article first ran in *Harvard Business Review*.

Photo credit: Getty Images

The economics of artificial intelligence

Rotman School of Management professor Ajay Agrawal explains how AI changes the cost of prediction and what this means for business.

With so many perspectives on the impact of artificial intelligence (AI) flooding the business press, it's becoming increasingly rare to find one that's truly original. So when strategy professor Ajay Agrawal shared his brilliantly simple view on AI, we stood up and took notice. Agrawal, who teaches at the University of Toronto's Rotman School of Management and works with AI start-ups at the Creative Destruction Lab (which he founded), posits that AI serves a single, but potentially transformative, economic purpose: it significantly lowers the cost of prediction.

In his new book, *Prediction Machines: The Simple Economics of Artificial Intelligence*, coauthored with professors Joshua Gans and Avi Goldfarb, Agrawal explains how business leaders can use this premise to figure out the most valuable ways to apply AI in their organization. The commentary here, which is adapted from a recent interview with McKinsey's Rik Kirkland, summarizes Agrawal's thesis. Consider it a CEO guide to parsing and prioritizing AI opportunities.

The ripple effects of falling costs

When looking at artificial intelligence from the perspective of economics, we ask the same, single question that we ask with any technology: What does it reduce the cost of? Economists are good at taking the fun and wizardry out of technology and leaving us with this dry but illuminating question. The answer reveals why AI is so important relative to many other exciting technologies. AI can be recast as causing a drop in the cost of a first-order input into many activities in business and our lives—prediction.

We can look at the example of another technology, semiconductors, to understand the profound changes that occur when technology drops the cost of a useful input. Semiconductors reduced the cost of arithmetic, and as they did this, three things happened.

First, we started using more arithmetic for applications that already leveraged arithmetic as an input. In the '60s, these were largely government and military applications. Later, we started doing more calculations for functions such as demand forecasting because these calculations were now easier and cheaper.

Second, we started using this cheaper arithmetic to solve problems that hadn't traditionally been framed as arithmetic problems. For example, we used to solve for the creation of photographic images by employing chemistry (film-based photography). Then, as arithmetic became cheaper, we began using arithmetic-based solutions in the design of cameras and image reproduction (digital cameras).

The third thing that happened as the cost of arithmetic fell was that it changed the value of other things—the value of arithmetic's complements went up and the value of its substitutes went down. So, in the case of photography, the complements were the software and hardware used in digital cameras. The value of these increased because we used more of them, while the value of substitutes, the components of film-based cameras, went down because we started using less and less of them.

Expanding our powers of prediction

As the cost of prediction continues to drop, we'll use more of it for traditional prediction problems such as inventory management because we can predict faster, cheaper, and better. At the same time, we'll start using prediction to solve problems that we haven't historically thought of as prediction problems.

For example, we never thought of autonomous driving as a prediction problem. Traditionally, engineers programmed an autonomous vehicle to move around in a controlled environment, such as a factory or warehouse, by telling it what to do in certain situations—*if* a human walks in front of the vehicle (*then* stop) or *if* a shelf is empty (*then* move to the next shelf). But we could never put those vehicles on a city street because there are too many *ifs*—*if* it's dark, *if* it's rainy, *if* a child runs into the street, *if* an oncoming vehicle has its blinker on. No matter how many lines of code we write, we couldn't cover all the potential *ifs*.

Today we can reframe autonomous driving as a prediction problem. Then an AI simply needs to predict the answer to one question: What would a good human driver do? There are a limited set of actions we can take when driving ("*thens*"). We can turn right or left, brake or accelerate—that's it. So, to teach an AI to drive, we put a human in a vehicle and tell the human to drive while the AI is figuratively sitting beside the human watching. Since the AI doesn't have eyes and ears like we do, we give it cameras, radar, and light detection and ranging (LIDAR). The AI takes the input data as it comes in through its "eyes" and looks over to the human and tries to predict, "What will the human do next?"

The AI makes a lot of mistakes at first. But it learns from its mistakes and updates its model every time it incorrectly predicts an action the human will take. Its predictions start getting better and better until it becomes so good at predicting what a human would do that we don't need the human to do it anymore. The AI can perform the action itself.

The growing importance of data, judgment, and action

As in the case of arithmetic, when the price of prediction drops, the value of its substitutes will go down and the value of its complements will go up. The main substitute for machine prediction is human prediction. As humans, we make all kinds of predictions in our business and daily lives. However, we're pretty noisy thinkers, and we have all kinds of well-documented cognitive biases, so we're quite poor at prediction. AI will become a much better predictor than humans are, and as the quality of AI prediction goes up, the value of human prediction will fall.

But, at the same time, the value of prediction's complements will go up. The complement that's been covered in the press most is data, with people using phrases such as "data is the new oil." That's absolutely true—data is an important complement to prediction, so as the cost of prediction falls, the value of a company's data goes up.

But there are other complements to prediction that have been discussed a lot less frequently. One is human judgment. We use both prediction and judgment to make decisions. We've never really unbundled those aspects of decision making before—we usually think of human decision making as a single step. Now we're unbundling decision making. The machine's doing the prediction, making the distinct role of judgment in decision making clearer. So as the value of human prediction falls, the value of human judgment goes up because AI doesn't do judgment—it can only make predictions and then hand them off to a human to use his or her judgment to determine what to do with those predictions.

Another complement to prediction is action. Predictions are valuable only in the context of some action that they lead to. So, for example, one of the start-ups we work with at the Creative Destruction Lab built a very good demand-forecasting AI for perishable food such as yogurt. Despite its accuracy, this prediction machine is worth zero in the absence of a grocery retailer deciding how much yogurt to buy. So, besides owning data as an asset, many incumbents also own the action.

A thought experiment for the top team

One approach to pinpoint ways to use AI in business is to review organizational workflows—the processes of turning inputs into outputs—and break them down into tasks. Then, look for the tasks that have a significant prediction component that would benefit from a prediction machine. Next, determine the return on investment for building a prediction machine to do each task, and simply rank those tasks in order from top to bottom.

Many of the AIs created out of this exercise will be efficiency-enhancing tools that will give the company some kind of a lift—possibly a 1 percent to 10 percent increase in EBITDA or some other measure of productivity.

However, to anticipate which AI tools will go beyond increasing efficiency and instead lead to transformation, we employ an exercise called "science fictioning." We take each AI tool and imagine it as a radio volume knob, and as you turn the knob, rather than turning up the volume, you are instead turning up the prediction accuracy of the AI.

To see how this works, imagine applying the exercise to Amazon's recommendation engine. We've found its tool to be about 5 percent accurate, meaning that out of every 20 things it recommends, we buy one of them and not the other 19. That accuracy sounds lousy, but when you consider that the tool pulls 20 items from Amazon's catalog of millions of items and out of those 20 we buy one, it's not that bad.

Every day people in Amazon's machine-learning group are working to crank up that prediction-accuracy knob. You can imagine that knob is currently at about two out of ten. If they crank it to a four or a five, we'll now buy five or seven out of 20 things. There's some number at which Amazon might think, "We are now sufficiently good at predicting what you want to buy. Why are we waiting for you to shop at all? We'll just ship it." By doing this, Amazon could increase its share of wallet for two reasons. The first is that it preempts you from buying those goods from its competitors, either online or offline. The second is that, if you were wavering on buying something, now that it's on your porch you might think, "Well, I might as well just keep it."

This demonstrates that by doing only one thing—turning up the prediction-accuracy knob—the change made by AI goes from one that's incremental (offering recommendations on the website) to one that's transformational: the whole business model flips from shopping and then shipping to shipping and then shopping.

Five imperatives for harnessing the power of low-cost prediction

There are several things leaders can do to position their organizations to maximize the benefits of prediction machines.

1. Develop a thesis on time to AI impact

The single most important question executives in every industry need to ask themselves is: How fast do I think the knob will turn for a particularly valuable AI application in my sector? If you think it will take 20 years to turn that knob to the transformational point, then you'll make a very different set of investments today than if you think it will take three years.

Looking at the investments various companies are already making can give you an idea of their thesis on how soon the knob will hit the transformation point. For example, Google acquired DeepMind for over half a billion dollars at a time when the company was generating almost no revenue. It was a start-up that was training an AI to play Atari games. Google clearly had a thesis on how fast the knob would turn.

So if I were a CEO in any industry right now, my number-one job would be to work with my leadership team to develop a thesis for each of the key areas in my organization on how fast the dial will turn.

2. Recognize that AI progress will likely be exponential

As executives develop their thesis on timing, it's important to recognize that the progress in AI will in many cases be exponential rather than linear. Already the progress in a wide range of applications (e.g., vision, natural language, motion control) over the last 12 months was faster than in the 12 months prior. The level of investment is increasing rapidly. The quality-adjusted cost of sensors is falling exponentially. And the amount of data being generated is increasing exponentially.

3. Trust the machines

In most cases, when AIs are properly designed and deployed, they're better predictors than humans are. And yet we're often still reluctant to hand over the reins of prediction to machines. For example, there have been studies comparing human recruiters to AI-powered recruiters that predict which candidates will perform best in a job. When performance was measured 12, 18, and 24 months later, the recruits selected by the AI outperformed those selected by the human recruiters, on average. Despite this evidence, human recruiters still often override the recommendations provided by AIs when making real hiring decisions.

Where AIs have demonstrated superior performance in prediction, companies must carefully consider the conditions under which to empower humans to exercise their discretion to override the AI.

4. Know what you want to predict

I work at a business school, so, using my domain as an example, if you read business-school brochures, they're usually quite vague in terms of what they're looking for in prospective students. They might say, "We want the best students." Well, what does "best" mean? Does it mean best in academic performance? Social skills? Potential for social impact? Something else?

The organizations that will benefit most from AI will be the ones that are able to most clearly and accurately specify their objectives. We're going to see a lot of the currently fuzzy mission statements become much clearer. The companies that are able to sharpen their visions the most will reap the most benefits from AI. Due to the methods used to train AIs, AI effectiveness is directly tied to goal-specification clarity.

5. Manage the learning loop

What makes AI so powerful is its ability to learn. Normally we think of labor as being learners and of capital as being fixed. Now, with AI, we have capital that learns. Companies need to ensure that information flows into decisions, they follow decisions to an outcome, and then they learn from the outcome and feed that learning back into the system. Managing the learning loop will be more valuable than ever before.

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In response to a surge of advances in AI by other countries, particularly China, Robert Work, a former deputy secretary of defense, was recently quoted in a *New York Times* article as saying, "This is a Sputnik moment." He was, of course, referencing America's catch-up reaction to the Soviet Union's launching of Sputnik I, the world's first earth-orbiting satellite, in 1957. This initiated the space race, led to the creation of NASA, and resulted in the Americans landing on the moon in 1969.

This sentiment for defense applies broadly today. Organizations in every industry will soon face their own Sputnik moment. The best leaders, be they visionary or operationally oriented, will seize this moment to lead their organizations through the most disruptive period they will experience in their professional lives. They will recognize the magnitude of the opportunity, and they will transform their organizations and industries. And as long as proper care is exercised, we'll be better off for it. ◆

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Photo credit: Getty Images

AI advice from around the industry

Experts on artificial intelligence share their thoughts on where AI is headed and how companies can prepare.

Artificial intelligence (AI) is on most every executive's mind and agenda, and no industry will be untouched by the changes and disruption these technologies bring. Here, AI experts share their insights on the trajectory of AI, how companies will need to adapt, and how the technology can be harnessed to transform organizations.

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Andrew Ng

Cofounder of Coursera, AI Fund, and Landing.AI

On what it means to become an AI-enabled company

I think AI will bring about a transformation of a lot of companies and even the rise of new types of companies. Today, we have things called Internet companies. The fundamental thing that defines an Internet company is not whether you operate a website. It's whether you have architected your whole company to leverage the new capabilities the Internet gives you.

With the rise of AI, we're still figuring out how to architect our companies to leverage AI capabilities. Just as building a website doesn't make you an Internet company, sprinkling on a little bit of machine learning doesn't make you an AI company.

On how to find and develop AI talent

Today, AI talent is scarce, and you just can't find enough AI talent and engineers. Another thing that may be even more scarce is the skill to take the AI technology and figure out how to take it to market. For a lot of the companies, the best hope might be to try to hire one strong AI leader and then build a centralized AI organization that you can then matrix into your various business units.

One other thing I've seen that's really effective at a few organizations is to have executives send a very clear message that employee development is valued.

Thanks to the rise of online education, I think that AI talent is disseminating very rapidly. There are tons of resources on the Internet, but to use resources like that to level up your whole employee base, that would make your whole organization more effective at maybe working with your centralized AI organization.

On how AI companies think about data strategy and competition

I think that true AI organizations are much more sophisticated, much more strategic in data acquisition. So, for example, I've done things like launch a product in one geography to acquire data to then take to the next geography. But then we don't monetize any of this.

If you can just have enough data to launch a product that's good enough, that allows you to enter a positive feedback loop in which your users help you generate more data. More data makes the product even better, so you have more users. And that positive feedback loop allows you to accumulate data, so that maybe after a few years you could have a pretty defensible business.

For example, today the large web-search engines have an incredibly valuable data asset of what web pages people click on when they search on certain things. That data asset is incredibly valuable for building a good web-search engine.

We can take all this data and monetize it somewhere totally different. The sophisticated AI organizations are definitely playing these multiyear chess games, doing multiyear strategic planning in order to play out data acquisition.

On whether companies with less data can compete on AI

There's so much data in the world that I don't think any one company today has a reasonable strategy for acquiring the majority of valuable data. And in fact, data tends to be most valuable in the vertical in which you collected it or are applying it.

There's actually plenty of opportunities, both for moderately-sized teams and larger corporations, as well as for even small start-ups, to use AI to attack new verticals.

Andrew McAfee

Principal research scientist at the Massachusetts Institute of Technology (MIT)

On whether AI disruption is overstated or underappreciated

There are billions of people walking around with a supercomputer, by the standards of a generation ago, in their pocket. Those devices are connected to each other and to this thing that we call the Internet. And then, just within the past five or six years at most, all the promises made by the artificial intelligence community have started to be delivered on.

So we really are living in this era of machine learning, which is the dominant AI technology, and probably will be for some time to come. Executives who I talk to today are a lot more aware of previous waves of disruption, and they're more keenly aware of the possibility that it's going to happen again. They've internalized Andy Grove's advice that only the paranoid survive.

However, even though they see a lot of disruption coming, I still think that many really smart, well-managed companies are underestimating the scale, scope, and speed of disruption this time around.

On how AI will change the way executives do their jobs

There are some things about running an organization that I don't think are going to change, even in the face of these crazy, powerful technologies: articulating a compelling vision that will attract talent, customers, and stakeholders; being true to that vision; and managing the culture that you've created to go tackle those visions. Those are deeply human skills, and leaders who are good at them are going to become even more valuable.

A lot of executives who I talk to think that a big part of their job is making the tough calls; relying on the experience, industry knowledge, and judgment that they've built up; and having a clearer crystal ball of things that are going to happen in the industry or in the future than other competitors have.

While I value those things, I value them a lot less than I used to, because of two fundamental changes that are occurring. Number one, over and over again we're seeing that technology is better at human-judgment tasks than humans. To me, it's the most unsettling by-product of the machine-learning revolution.

And number two, I was just on a panel with a set of machine-learning all-star geeks, and when talking about the future of the technology, one of them said, "Well, as far as we can see into the future. I'm talking three to five years." And I'm thinking, "Hold on. What? Only three to five years?" We used to think about business generations being a lot more on the timescale of human generations—a decade or two. He said, "Why even think about what might be happening 36 months from now, because so much is going to change between now and then."

Both of these developments are pretty profoundly upsetting to the kind of Industrial Age. I don't mean that disparagingly, but these are both really, really deep threats to the model of running an organization that we've built up over a couple of centuries.

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Bill Ready

Chief operating officer for PayPal

On how the cloud has leveled the AI playing field

Now that AI and machine learning are available via cloud platforms, which is democratizing access to them, it feels a lot like mobile was in 2010 or 2011. It sounds a bit outlandish to many to say, "We think that many people can engage in these capabilities." However, it is in fact the case that you now have great platforms making this technology available.

The winner in AI, up until this point, has been whomever had the best computer-science PhDs. But now that you have platforms democratizing access to these capabilities, I think there will be a shift. Now the winner is going to be whomever comes up with the best practical applications of these technologies.

On where to apply AI in your organization

The fundamental concept of machine learning is taking a big data set and applying it in a way that you can have a machine learning from positive and negative outcomes to figure out how to correlate the two. And if you talk to somebody who knows their business, it's not really about the computer-science aspect as much as it is about asking, "Where are the natural feedback loops in the business? Where are there opportunities for catalogued positive and negative outcomes to be stored in a repository and fed into these systems?" And every business has feedback loops.

For people that don't necessarily understand the technology, they should think about how their organization learns and realize that every place where the organization learns and every place where there's a feedback loop likely presents opportunities to apply AI and machine-learning technologies. And there are now foundational platforms available that can allow them to do that.

Jana Eggers

CEO of Nara Logics

On how to get started with AI

Most people get stuck on the data part, and they think that their data aren't clean enough, or they don't have enough, so they think they need to first go get data.

You have enough data. I'm not the only one who says this. Jeff Dean from Google was asked at a conference recently, "Will mere mortal companies ever have enough data, because they're never going to have the levels that Google or Facebook have?" And he said, "Yes, absolutely." And I completely agree with that. And I tell companies to start with their own data because they know it best.

There will be times that you do want to go and get some augmenting data, but your first project should be with your own data. And I'm very much an advocate of it being customer-facing data rather than data on internal process. I think that with internal process, we get a little bit caught up in incrementalism. We're a bit more used to being bold with our customers.

There's a lot of opportunity there with AI to really think differently about interacting with your customers, and you've done that some already with the Internet and with mobile. So I would focus on the external-facing customers. And that doesn't mean that they have to be consumers. It can be B2B as well.

On the need to become a learning organization to leverage AI

I don't think you can do AI well and be successful at it without becoming a learning organization. Do I think you can do a pilot project? Absolutely. There's a lot of people who have done those. However, I do not fundamentally believe you actually could go into production in a true-scale AI situation without checking some of the boxes of being a learning organization.

And my learnings over the last seven months or so have been that AI can actually help you become a learning organization. It helps in that you're bringing data out of the silos and intermixing data in ways that you really weren't before. Most organizations have marketing data over here, production data over there, etc. AI can bring those streams together, which is part of systems thinking, part of being a learning organization.

AI uses a lot of data, so you can't easily explain the data. You can't go in and simply categorize things, because it's too big. So you have to start building frameworks and conceptualizations, which is another piece of being a learning organization.

So there are a lot of different aspects of a learning organization that AI just requires you to do. I do think that AI is going to force us into that, but I also think that if you know that, you can actually highlight it and go faster yourself. ◆

Andrew Ng was interviewed by **Michael Chui**, a partner of the McKinsey Global Institute, who is based in McKinsey's San Francisco office; **Andrew McAfee** and **Bill Ready** were interviewed by **Rik Kirkland**, the senior managing editor of McKinsey Publishing, who is based in the New York office; **Jana Eggers** was interviewed by **Laura DeLallo**, the senior editor of McKinsey Analytics, who is based in the Stamford office.

Photo credit: Getty Images

Controlling algorithmic bias

Tobias Baer and Vishnu Kamalnath

Myths aside, artificial intelligence is as prone to bias as the human kind. The good news is that the biases in algorithms can also be diagnosed and treated.

Companies are moving quickly to apply machine learning to business decision making. New programs are constantly being launched, setting complex algorithms to work on large, frequently refreshed data sets. The speed at which this is taking place attests to the attractiveness of the technology, but the lack of experience creates real risks. Algorithmic bias is one of the biggest risks because it compromises the very purpose of machine learning. This often-overlooked defect can trigger costly errors and, left unchecked, can pull projects and organizations in entirely wrong directions. Effective efforts to confront this problem at the outset will repay handsomely, allowing the true potential of machine learning to be realized most efficiently.

Machine learning has been in scientific use for more than half a century as a term describing programmable pattern recognition. The concept is even older, having been expressed by pioneering mathematicians in the early 19th century. It has come into its own in the past two decades, with the advent of powerful computers, the Internet, and mass-scale digitization of information. In the domain of artificial intelligence, machine learning increasingly refers to computer-aided decision making based on statistical algorithms generating data-driven insights.

Among its most visible uses is in predictive modeling. This has wide and familiar business applications, from automated customer recommendations to credit-approval processes. Machine learning magnifies the power of predictive models through great computational force. To create a functioning statistical algorithm by means of a logistic regression, for example, missing variables must be replaced by assumed numeric values (a process called imputation). Machine-learning algorithms are often constructed to interpret "missing" as a possible value and then proceed to develop the best prediction for cases where the value is missing. Machine learning is able to manage vast amounts of data and detect many more complex patterns within them, often attaining superior predictive power.

In credit scoring, for example, customers with a long history of maintaining loans without delinquency are generally determined to be of low risk. But what if the mortgages these customers have been maintaining were for years supported by substantial tax benefits that are set to expire? A spike in defaults may be in the offing, unaccounted for in the statistical risk model of the lending institution. With access to the right data and guidance by subject-matter experts, predictive machine-learning models could find the hidden patterns in the data and correct for such spikes.

The persistence of bias

In automated business processes, machine-learning algorithms make decisions faster than human decision makers and at a fraction of the cost. Machine learning also promises to improve decision quality, due to the purported absence of human biases. Human decision makers might, for example, be prone to giving extra weight to their personal experiences. This is a form of bias known as anchoring, one of many that can affect business decisions. Availability bias is another. This is a mental shortcut (heuristic) by which people make familiar assumptions when faced with decisions. The assumptions will have served adequately in the past but could be unmerited in new situations. Confirmation bias is the tendency to select evidence that supports preconceived beliefs, while loss-aversion bias imposes undue conservatism on decision-making processes.

Machine learning is being used in many decisions with business implications, such as loan approvals in banking, and with personal implications, such as diagnostic decisions in hospital emergency rooms. The benefits of removing harmful biases from such decisions are obvious and highly desirable, whether they come in financial, medical, or some other form.

Some machine learning is designed to emulate the mechanics of the human brain, such as deep learning, with its artificial neural networks. If biases affect human intelligence, then what about artificial intelligence? Are the machines biased? The answer, of course, is yes, for some basic reasons. First, machine-learning algorithms are prone to incorporating the biases of their human creators. Algorithms can formalize biased parameters created by sales forces or loan officers, for example. Where machine learning predicts behavioral outcomes, the necessary reliance on historical criteria will reinforce past biases, including stability bias. This is the tendency to discount the possibility of significant change—for example, through substitution effects created by innovation. The severity of this bias can be magnified by machine-learning algorithms that must assume things will more or less continue as before in order to operate. Another basic bias-generating factor is incomplete data. Every machine-learning algorithm operates wholly within the world defined by the data that were used to calibrate it. Limitations in the data set will bias outcomes, sometimes severely.

Predicting behavior: 'Winner takes all'

Machine learning can perpetuate and even amplify behavioral biases. By design, a social-media site filtering news based on user preferences reinforces natural confirmation bias in readers. The site may even be systematically preventing perspectives from being challenged with contradictory evidence. The self-fulfilling prophecy is a related by-product of algorithms. Financially sound companies can run afoul of banks' scoring algorithms and find themselves without access to working capital. If they are unable to sway credit officers with factual logic, a liquidity crunch could wipe out an entire class of businesses. These examples reveal a certain "winner takes all" outcome that affects those machine-learning algorithms designed to replicate human decision making.

Data limitations

Machine learning can reveal valuable insights in complex data sets, but data anomalies and errors can lead algorithms astray. Just as a traumatic childhood accident can cause lasting behavioral distortion in adults, so can unrepresentative events cause machine-learning algorithms to go off course. Should a series of extraordinary weather events or fraudulent actions trigger spikes in default rates, for example, credit scorecards could brand a region as "high risk" despite the absence of a permanent structural cause. In such cases, inadequate algorithms will perpetuate bias unless corrective action is taken.

Companies seeking to overcome biases with statistical decision-making processes may find that the data scientists supervising their machine-learning algorithms are subject to these same biases. Stability biases, for example, may cause data scientists to prefer the same data that human decision makers have been using to predict outcomes. Cost and time pressures, meanwhile, could deter them from collecting other types of data that harbor the true drivers of the outcomes to be predicted.

The problem of stability bias

Stability bias—the tendency toward inertia in an uncertain environment—is actually a significant problem for machine-learning algorithms. Predictive models operate on patterns detected in historical data. If the same patterns cease to exist, then the model would be akin to an old railroad timetable—valuable for historians but not useful for traveling in the here and now. It is frustratingly difficult to shape machine-learning algorithms to recognize a pattern that is not present in the data, even one that human analysts know is likely to manifest at some point. To bridge the gap between available evidence and self-evident reality, synthetic data points can be created. Since machine-learning algorithms try to capture patterns at a very detailed level, however, every attribute of each synthetic data point would have to be crafted with utmost care.

In 2007, an economist with an inkling that credit-card defaults and home prices were linked would have been unable to build a predictive model showing this relationship, since it had not yet appeared in the data. The relationship was revealed, precipitously, only when the financial crisis hit and housing prices began to fall. If certain data limitations are permitted to govern modeling choices, seriously flawed algorithms can result. Models will be unable to recognize obviously real but unexpected changes. Some US mortgage models designed before the financial crisis could not mathematically accept negative changes in home prices. Until negative interest rates appeared in the real world, they were statistically unrecognized and no machine-learning algorithm in the world could have predicted their appearance.

Addressing bias in machine-learning algorithms

As described in a previous article in *McKinsey on Risk*,[1] companies can take measures to eliminate bias or protect against its damaging effects in human decision making. Similar countermeasures can protect against algorithmic bias. Three filters are of prime importance.

First, users of machine-learning algorithms need to understand an algorithm's shortcomings and refrain from asking questions whose answers will be invalidated by algorithmic bias. Using a machine-learning model is more like driving a car than riding an elevator. To get from point A to point B, users cannot simply push a button; they must first learn operating procedures, rules of the road, and safety practices.

Second, data scientists developing the algorithms must shape data samples in such a way that biases are minimized. This step is a vital and complex part of the process and worthy of much deeper consideration than can be provided in this short article. For the moment, let us remark that available historical data are often inadequate for this purpose, and fresh, unbiased data must be generated through a controlled experiment.

Finally, executives should know when to use and when not to use machine-learning algorithms. They must understand the true values involved in the trade-off: algorithms offer speed and convenience, while manually crafted models, such as decision trees or logistic regression—or for that matter even human decision making—are approaches that have more flexibility and transparency.

What's in your black box?

From a user's standpoint, machine-learning algorithms are black boxes. They offer quick and easy solutions to those who know little or nothing of their inner workings. They should be applied with discretion, but knowing enough to exercise discretion takes effort. Business users seeking to avoid harmful applications of algorithms are a little like consumers seeking to eat healthy food. Health-conscious consumers must study literature on nutrition and read labels in order to avoid excess calories, harmful additives, or dangerous allergens. Executives and practitioners will likewise have to study the algorithms at the core of their business and the problems they are designed to resolve. They will then be able to understand monitoring reports on the algorithms, ask the right questions, and challenge assumptions.

In credit scoring, for example, built-in stability bias prevents machine-learning algorithms from accounting for certain rapid behavioral shifts in applicants. These can occur if applicants recognize the patterns that are being punished by models. Salespeople have been known to observe the decision patterns embedded in algorithms and then coach applicants by reverse-engineering the behaviors that will maximize the odds of approval.

[1] Tobias Baer, Sven Heiligtag, and Hamid Samandari, "The business logic in debiasing," May 2017, McKinsey.com.

A subject that frequently arises as a predictor of risk in this context is loan tenor. Riskier customers generally prefer longer loan tenors, in recognition of potential difficulties in repayment. Many low-risk customers, by contrast, aim to minimize interest expense by choosing shorter tenors. A machine-learning algorithm would jump on such a pattern, penalizing applications for longer tenors with a higher risk estimate. Soon salespeople would nudge risky applicants into the approval range of the credit score by advising them to choose the shortest possible tenor. Burdened by an exceptionally high monthly installment (due to the short tenor), many of these applicants will ultimately default, causing a spike in credit losses.

Astute observers can thus extract from the black box the variables with the greatest influence on an algorithm's predictions. Business users should recognize that in this case loan tenor was an influential predictor. They can either remove the variable from the algorithm or put in place a safeguard to prevent a behavioral shift. Should business users fail to recognize these shifts, banks might be able to identify them indirectly, by monitoring the distribution of monthly applications by loan tenor. The challenge here is to establish whether a marked shift is due to a deliberate change in behavior by applicants or to other factors, such as changes in economic conditions or a bank's promotional strategy. In one way or the other, sound business judgment therefore is indispensable.

Squeezing bias out of the development sample

Tests can ensure that unwanted biases of past human decision makers, such as gender biases, for example, have not been inadvertently baked into machine-learning algorithms. Here a challenge lies in adjusting the data such that the biases disappear.

One of the most dangerous myths about machine learning is that it needs no ongoing human intervention. Business users would do better to view the application of machine-learning algorithms like the creation and tending of a garden. Much human oversight is needed. Experts with deep machine-learning knowledge and good business judgment are like experienced gardeners, carefully nurturing the plants to encourage their organic growth. The data scientist knows that in machine learning the answers can be useful only if we ask the right questions.

In countering harmful biases, data scientists seek to strengthen machine-learning algorithms where it most matters. Training a machine-learning algorithm is a bit like building muscle mass. Fitness trainers take great pains in teaching their clients the proper form of each exercise so that only targeted muscles are worked. If the hips are engaged in a motion designed to build up biceps, for example, the effectiveness of the exercise will be much reduced. By using stratified sampling and optimized observation weights, data scientists ensure that the algorithm is most powerful for those decisions in which the business impact of a prediction error is the greatest. This cannot be done automatically, even by advanced machine-learning algorithms such as boosting (an algorithm designed to reduce algorithmic bias). Advanced algorithms can correct for a statistically defined concept of error, but they cannot distinguish errors with high business impact from those of negligible importance.

Another example of the many statistical techniques data scientists can deploy to protect algorithms from biases is the careful analysis of missing values. By determining whether the values are missing systematically, data scientists are introducing “hindsight bias.” This use of bias to fight bias allows the algorithm to peek beyond its data-determined limitations to the correct answer. The data scientists can then decide whether and how to address the missing values or whether the sample structure needs to be adjusted.

Deciding when to use machine-learning algorithms

An organization considering using an algorithm on a business problem should be making an explicit choice based on the cost-benefit trade-off. A machine-learning algorithm will be fast and convenient, but more familiar, traditional decision-making processes will be easier to build for a particular purpose and will also be more transparent. Traditional approaches include human decision making or handcrafted models such as decision trees or logistic-regression models—the analytic workhorses used for decades in business and the public sector to assign probabilities to outcomes. The best data scientists can even use machine-learning algorithms to enhance the power of hand-crafted models. They have been able to build advanced logistic-regression models with predictive power approaching that of a machine-learning algorithm.

Three questions can be considered when deciding to use machine-learning algorithms:

- **How soon do we need the solution?** The time factor is often of prime importance in solving business problems. The optimal statistical model may be obsolete by the time it is completed. When the business environment is changing fast, a machine-learning algorithm developed overnight could far outperform a superior traditional model that is months in the making. For this reason, machine-learning algorithms are preferred for combating fraud. Defrauders typically act quickly to circumvent the latest detection mechanisms they encounter. To defeat fraud, organizations need to deploy algorithms that adjust instantaneously, the moment the defrauders change their tactics.

- **What insights do we have?** The superiority of the handcrafted model depends on the business insights embedded in it by the data scientist. If an organization possesses no insights, then the problem solving will have to be guided by the data. At this point, a machine-learning algorithm might be preferred for its speed and convenience. However, rather than blindly trusting an algorithm, an organization in this situation could decide that it is better to bring in a consultant to help develop value-adding business insights.

- **Which problems are worth solving?** One of the promises of machine learning is that it can address problems that were once unrecognized or thought to be too costly to solve with a handcrafted model. Decision making on these problems has been heretofore random or unconscious. When reconsidering such problems, organizations should identify those with significant bottom-line business impact and then assign their best data scientists to work on them.

In addition to these considerations, companies implementing large-scale machine-learning programs should make appropriate organizational and cultural changes to support them. Everyone within the scope of the programs should understand and trust the machine-learning models—only then will maximum impact be achieved.

Implementation: Standards, validation, knowledge

How would a business go about implementing these recommendations? The practical application and debiasing of machine-learning algorithms should be governed by a conscious and eventually systematic process throughout the organization. While not as stringent and formal, the approach is related to mature model development and validation processes by which large institutions are gaining strategic control of model proliferation and risk. Three building blocks are critically important for implementation:

- **Business-based standards for machine-learning approvals.** A template should be developed for model documentation, standardizing the process for the intake of modeling requests. It should include the business context and prompt requesters with specific questions on business impact, data, and cost-benefit trade-offs. The process should require active user participation in the drive to find the most suitable solution to the business problem (note that passive checklists or guidelines, by comparison, tend to be ignored). The model's key parameters should be defined, including a standard set of analyses to be run on the raw data inputs, the processed sample, and the modeling outputs. The model should be challenged in a discussion with business users.

- **Professional validation of machine-learning algorithms.** An explicit process is needed for validating and approving machine-learning algorithms. Depending on the industry and business context—especially the economic implication of errors—it may not have to be as stringent as the formal validation of banks' risk models by internal validation teams and regulators. However, the process should establish validation standards and an ongoing monitoring program for the new model. The standards should account for the characteristics of machine-learning models, such as automatic updates of the algorithm whenever fresh data are captured. This is an area where most banks still need to develop appropriate validation and monitoring standards. If algorithms are updated weekly, for example, validation routines must be completed in hours and days rather than weeks and months. Yet it is also extremely important to put in place controls that alert users to potential sudden or creeping bias in fresh data.

- **A culture for continuous knowledge development.** Institutions should invest in developing and disseminating knowledge on data science and business applications. Machine-learning applications should be continuously monitored for new insights and best practices, in order to create a culture of knowledge enhancement and to keep people informed of both the difficulties and successes that come with using such applications.

Creating a conscious, standards-based system for developing machine-learning algorithms will involve leaders in many judgment-based decisions. For this reason, debiasing techniques should be deployed to maximize outcomes. An effective technique in this context is a "premortem" exercise designed to pinpoint the limitations of a proposed model and help executives judge the business risks involved in a new algorithm.

Sometimes lost in the hype surrounding machine learning is the fact that artificial intelligence is as prone to bias as the real thing it emulates. The good news is that biases can be understood and managed—if we are honest about them. We cannot afford to believe in the myth of machine-perfected intelligence. Very real limitations to machine learning must be constantly addressed by humans. For businesses, this means the creation of incremental, insights-based value with the aid of well-monitored machines. That is a realistic algorithm for achieving machine-learning impact. ◆

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Will artificial intelligence make you a better leader?

Sam Bourton, Johanne Lavoie, and Tiffany Vogel

Agile leadership and AI both depend on learning to let go.

Consider this real-life scene: Reflecting on the difficult moments of his week, the new CEO of a UK manufacturer felt angry. His attention kept going back to the tension in several executive-team meetings. He had an urge to shake the team and push several of its members, who were riven by old conflicts, to stop fighting and start collaborating to solve the company's real problems. He also sensed, though, that a brute-force approach was unlikely to get very far, or to yield the creative insights that the company desperately needed to keep up with its fast-changing competitive environment. Instead, he calmed himself, stopped blaming his team, and asked himself whether he could break the logjam by pursuing truly new approaches to the company's problems. It was then that his mind turned to, of all things, artificial intelligence.

Like many leaders, the CEO was struggling to cope with the stress induced by uncertainty, rising complexity, and rapid change. All of these are part and parcel of today's business environment, which is different enough from the one many of us grew up with to challenge our well-grooved leadership approaches. In a recent article, we described five practices that can help you step back from the tried and true and become more inwardly agile (see "Leading with inner agility," on McKinsey.com). Here, we want to describe the relationship between some of those ideas and a technology that at first glance seems to add complexity but in fact can be a healing balm: artificial intelligence (AI), which we take to span the next generation of advanced data and analytics applications. Inner agility and AI may sound like strange bedfellows, but when you consider crucial facts about the latter, you can see its potential to help you lead with clarity, specificity, and creativity.

The first crucial fact about AI is that you don't know ahead of time what the data will reveal. By its very nature, AI is a leap of faith, just as embracing your ignorance and radical reframing are. And like learning to let go, listening to AI can help you find genuinely novel, disruptive insights in surprising and unexpected places.

A second fact about AI is that it creates space and time to think by filtering the signal from the noise. You let the algorithms loose on a vast landscape of data, and they report back only what you need to know and when you need to know it.

Let's return to the CEO above to see an example of these dynamics in action. The CEO knew that his company's key product would have to be developed more efficiently to compete with hard-charging rivals from emerging markets. He urgently needed to take both cost and time out of the product-development process. The standard approach would have been to cut head count or invest in automation, but he wasn't sure either was right for his company, which was exhausted from other recent cost-cutting measures.

All this was on the CEO's mind as he mused about the problematic executive dynamics he'd been observing—which, frankly, made several of his leaders unreliable sources of information. It was the need for objective, creative insight that stoked the CEO's interest in AI-fueled advanced data analytics. A few days later, he began asking a team of data-analytics experts a couple broad and open-ended questions: What are the causes of inefficiencies in our product design and development workflow? What and where are the opportunities to improve performance?

The AI team trained their algorithms on a vast variety of data sources covering such things as project life-cycle management, fine-grained design and manufacturing documents, financial and HR data, suppliers and subcontractors, and communications data. Hidden patterns in the communication networks led to a detailed analysis of the interactions between two key departments: design and engineering. Using aggregated data that didn't identify individual communications, the team looked at the number of emails sent after meetings or to other departments, the use of enterprise chat groups and length of chats, texting volume, and response rates to calendar invites. The algorithms surfaced an important, alarming discovery: the two departments were barely collaborating at all. In reality, the process was static: designers created a model, engineers evaluated and commented, designers remodeled, and so on. Each cared solely about its domain. The data-analytics team handed the CEO one other critical fact: by going back five years and cross-referencing communications data and product releases, they provided clear evidence that poor collaboration slowed time to market and increased costs.

By liberating the AI team to follow a direction and not a destination, the CEO's original question of how to improve productivity became a much more human question:

"How are we working as a team, and why?" Based on this new empirical foundation, he enlisted the engineering and design leaders to form a cross-disciplinary team to reimagine collaboration. Working with the data scientists, the team was able to identify and target a 10 percent reduction in time to market for new-product development and an 11 percent reduction in costs. But the CEO didn't stop there. He also used the experience to ask his executive team to develop a new agility. The previously fractured team worked hard to build a foundation of trust and true listening. Regular check-ins helped them pause, formulate new questions, invite healthy opposition, and ask themselves, "What are we really solving for?" The team was growing more complex to address the company's increasingly complex challenges.

In our experience, AI can be a huge help to the leader who's trying to become more inwardly agile and foster creative approaches to transformation. When a CEO puts AI to work on the toughest and most complex strategic challenges, he or she must rely on the same set of practices that build personal inner agility. Sending AI out into the mass of complexity, without knowing in advance what it will come back with, the CEO is embracing the discovery of original, unexpected, and breakthrough ideas. This is a way to test and finally move on from long-held beliefs and prejudices about the organization and to radically reframe the questions in order to find entirely new kinds of solutions. And the best thing about AI solutions is that they can be tested. AI creates its own empirical feedback loop that allows you to think of your company as an experimental science lab for transformation and performance improvement. In other words, the hard science of AI can be just what you need to ask the kind of broad questions that lay the foundation for meaningful progress. ◆

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Appendix

An executive's guide to AI

Staying ahead in the accelerating artificial intelligence (AI) race requires executives to make nimble, informed decisions about where and how to employ AI in their business. One way to prepare to act quickly: know the AI essentials presented in this guide. (For an interactive version of the AI guide, including a detailed timeline of the convergence of advancements that have propelled AI from hype to reality, see "An executive's guide to AI," on McKinsey.com.)

Artificial intelligence: A definition

AI is typically defined as the ability of a machine to perform cognitive functions we associate with human minds, such as perceiving, reasoning, learning, and problem solving. Examples of technologies that enable AI to solve business problems are robotics and autonomous vehicles, computer vision, language, virtual agents, and machine learning.

Machine learning: A definition

Most recent advances in AI have been achieved by applying machine learning to very large data sets. Machine-learning algorithms detect patterns and learn how to make predictions and recommendations by processing data and experiences, rather than by receiving explicit programming instruction. The algorithms also adapt in response to new data and experiences to improve efficacy over time.

Machine learning provides predictions and prescriptions

Types of analytics (in order of increasing complexity)

Descriptive | Predictive | Prescriptive

Descriptive
- Describe **what happened**
- Employed heavily across all industries

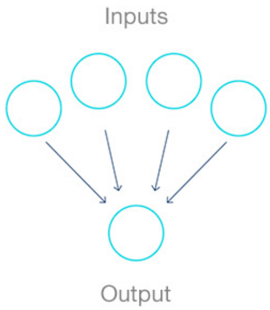
Predictive
- Anticipate **what will happen** (inherently probabilistic)
- Employed in data-driven organizations as a key source of insight

Prescriptive
- Provide recommendations on **what to do** to achieve goals
- Employed heavily by leading data and Internet companies

Focus of machine learning

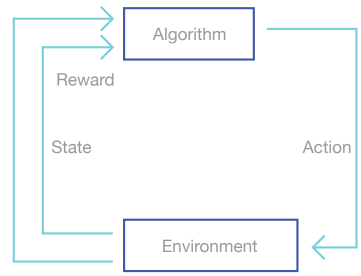
Understanding the major types of machine learning

Supervised learning



Unsupervised learning

Reinforcement learning



What it is

Supervised learning: An algorithm uses training data and feedback from humans to learn the relationship of given inputs to a given output (eg, how the inputs "time of year" and "interest rates" predict housing prices)

Unsupervised learning: An algorithm explores input data without being given an explicit output variable (eg, explores customer demographic data to identify patterns)

Reinforcement learning: An algorithm learns to perform a task simply by trying to maximize rewards it receives for its actions (eg, maximizes points it receives for increasing returns of an investment portfolio)

When to use it

Supervised learning: You know how to classify the input data and the type of behavior you want to predict, but you need the algorithm to calculate it for you on new data

Unsupervised learning: You do not know how to classify the data, and you want the algorithm to find patterns and classify the data for you

Reinforcement learning: You don't have a lot of training data; you cannot clearly define the ideal end state; or the only way to learn about the environment is to interact with it

How it works

Supervised learning:

1. A human labels every element of the input data (eg, in the case of predicting housing prices, labels the input data as "time of year," "interest rates," etc) and defines the output variable (eg, housing prices)
2. The algorithm is trained on the data to find the connection between the input variables and the output
3. Once training is complete—typically when the algorithm is sufficiently accurate—the algorithm is applied to new data

Unsupervised learning:

1. The algorithm receives unlabeled data (eg, a set of data describing customer journeys on a website)
2. It infers a structure from the data
3. The algorithm identifies groups of data that exhibit similar behavior (eg, forms clusters of customers that exhibit similar buying behaviors)

Reinforcement learning:

1. The algorithm takes an action on the environment (eg, makes a trade in a financial portfolio)
2. It receives a reward if the action brings the machine a step closer to maximizing the total rewards available (eg, the highest total return on the portfolio)
3. The algorithm optimizes for the best series of actions by correcting itself over time

Supervised learning: Algorithms and sample business use cases[1]

Algorithms	Sample business use cases
Linear regression Highly interpretable, standard method for modeling the past relationship between independent input variables and dependent output variables (which can have an infinite number of values) to help predict future values of the output variables	▪ Understand product-sales drivers such as competition prices, distribution, advertisement, etc ▪ Optimize price points and estimate product-price elasticities
Logistic regression Extension of linear regression that's used for classifation tasks, meaning the output variable is binary (eg, only black or white) rather than continuous (eg, an infinite list of potential colors)	▪ Classify customers based on how likely they are to repay a loan ▪ Predict if a skin lesion is benign or malignant based on its characteristics (size, shape, color, etc)
Linear/quadratic discriminant analysis Upgrades a logistic regression to deal with nonlinear problems—those in which changes to the value of input variables do not result in proportional changes to the output variables.	▪ Predict client churn ▪ Predict a sales lead's likelihood of closing
Decision tree Highly interpretable classification or regression model that splits data-feature values into branches at decision nodes (eg, if a feature is a color, each possible color becomes a new branch) until a final decision output is made	▪ Provide a decision framework for hiring new employees ▪ Understand product attributes that make a product most likely to be purchased
Naive Bayes Classification technique that applies Bayes theorem, which allows the probability of an event to be calculated based on knowledge of factors that might affect that event (eg, if an email contains the word "money," then the probability of it being spam is high)	▪ Analyze sentiment to assess product perception in the market ▪ Create classifiers to filter spam emails

[1] We've listed some of the most commonly used algorithms today—this list is not intended to be exhaustive. Additionally, a number of different models can often solve the same business problem. Conversely, the nature of an available data set often precludes using a model typically employed to solve a particular problem. For these reasons, the sample business use cases are meant only to be illustrative of the types of problems these models can solve.

Supervised learning: Algorithms and sample business use cases (continued)

Algorithms	Sample business use cases
Support vector machine A technique that's typically used for classification but can be transformed to perform regression. It draws an optimal division between classes (as wide as possible). It also can be quickly generalized to solve nonlinear problems	▪ Predict how many patients a hospital will need to serve in a time period ▪ Predict how likely someone is to click on an online ad
Random forest Classification or regression model that improves the accuracy of a simple decision tree by generating multiple decision trees and taking a majority vote of them to predict the output, which is a continuous variable (eg, age) for a regression problem and a discrete variable (eg, either black, white, or red) for classification	▪ Predict call volume in call centers for staffing decisions ▪ Predict power usage in an electrical-distribution grid
AdaBoost Classification or regression technique that uses a multitude of models to come up with a decision but weighs them based on their accuracy in predicting the outcome	▪ Detect fraudulent activity in credit-card transactions. Achieves lower accuracy than deep learning ▪ Simple, low-cost way to classify images (eg, recognize land usage from satellite images for climate-change models). Achieves lower accuracy than deep learning
Gradient-boosting trees Classification or regression technique that generates decision trees sequentially, where each tree focuses on correcting the errors coming from the previous tree model. The final output is a combination of the results from all trees	▪ Forecast product demand and inventory levels ▪ Predict the price of cars based on their characteristics (eg, age and mileage)
Simple neural network Model in which artificial neurons (software-based calculators) make up three layers (an input layer, a hidden layer where calculations take place, and an output layer) that can be used to classify data or find the relationship between variables in regression problems	▪ Predict the probability that a patient joins a healthcare program ▪ Predict whether registered users will be willing or not to pay a particular price for a product

Unsupervised learning: Algorithms and sample business use cases[2]

Algorithms	Sample business use cases
K-means clustering Puts data into a number of groups (k) that each contain data with similar characteristics (as determined by the model, not in advance by humans)	■ Segment customers into groups by distinct charateristics (eg, age group)—for instance, to better assign marketing campaigns or prevent churn
Gaussian mixture model A generalization of k-means clustering that provides more flexibility in the size and shape of groups (clusters)	■ Segment customers to better assign marketing campaigns using less-distinct customer characteristics (eg, product preferences) ■ Segment employees based on likelihood of attrition
Hierarchical clustering Splits or aggregates clusters along a hierarchical tree to form a classification system	■ Cluster loyalty-card customers into progressively more microsegmented groups ■ Inform product usage/development by grouping customers mentioning keywords in social-media data
Recommender system Often uses cluster behavior prediction to identify the important data necessary for making a recommendation	■ Recommend what movies consumers should view based on preferences of other customers with similar attributes ■ Recommend news articles a reader might want to read based on the article she or he is reading

[2] We've listed some of the most commonly used algorithms today—this list is not intended to be exhaustive. Additionally, a number of different models can often solve the same business problem. Conversely, the nature of an available data set often precludes using a model typically employed to solve a particular problem. For these reasons, the sample business use cases are meant only to be illustrative of the types of problems these models can solve.

Reinforcement learning: Sample business use cases[3]

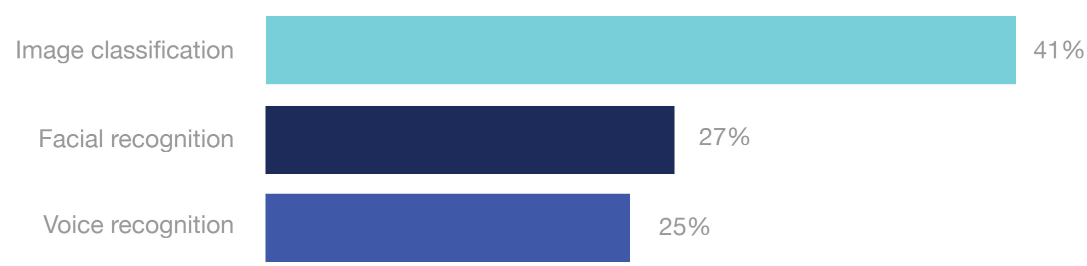
- Optimize the trading strategy for an options-trading portfolio
- Balance the load of electricity grids in varying demand cycles
- Stock and pick inventory using robots
- Optimize the driving behavior of self-driving cars
- Optimize pricing in real time for an online auction of a product with limited supply

Deep learning: A definition

Deep learning is a type of machine learning that can process a wider range of data resources, requires less data preprocessing by humans, and can often produce more accurate results than traditional machine-learning approaches. In deep learning, interconnected layers of software-based calculators known as "neurons" form a neural network. The network can ingest vast amounts of input data and process them through multiple layers that learn increasingly complex features of the data at each layer. The network can then make a determination about the data, learn if its determination is correct, and use what it has learned to make determinations about new data. For example, once it learns what an object looks like, it can recognize the object in a new image.

Deep learning can often outperform traditional methods

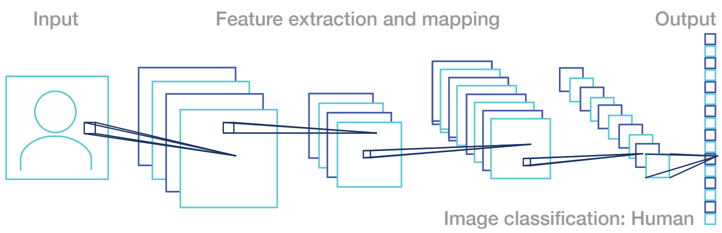
% reduction in error rate achieved by deep learning vs traditional methods



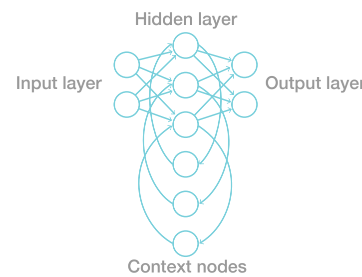
[3] The sample business use cases are meant only to be illustrative of the types of problems these models can solve.

Understanding the major deep learning models and their business use cases[4]

Convolutional neural network



Recurrent neural network



	Convolutional neural network	Recurrent neural network
What it is	A multilayered neural network with a special architecture designed to extract increasingly complex features of the data at each layer to determine the output	A multilayered neural network that can store information in context nodes, allowing it to learn data sequences and output a number or another sequence
When to use it	When you have an unstructured data set (eg, images) and you need to infer information from it	When you are working with time-series data or sequences (eg, audio recordings or text)

[4] The sample business use cases are meant only to be illustrative of the types of problems these models can solve.

	Convolutional neural network	Recurrent neural network
How it works	**Processing an image** 1. The convolutional neural network (CNN) receives an image—for example, of the letter “A”—that it processes as a collection of pixels 2. In the hidden, inner layers of the model, it identifies unique features, for example, the individual lines that make up “A” 3. The CNN can now classify a different image as the letter “A” if it finds in it the unique features previously identified as making up the letter	**Predicting the next word in the sentence “Are you free ______?”** 1. A recurrent neural network (RNN) neuron receives a command that indicates the start of a sentence 2. The neuron receives the word “Are” and then outputs a vector of numbers that feeds back into the neuron to help it “remember” that it received “Are” (and that it received it first). The same process occurs when it receives “you” and “free,” with the state of the neuron updating upon receiving each word 3. After receiving “free,” the neuron assigns a probability to every word in the English vocabulary that could complete the sentence. If trained well, the RNN will assign the word “tomorrow” one of the highest probabilities and will choose it to complete the sentence
Business use cases	■ Diagnose health diseases from medical scans ■ Detect a company logo in social media to better understand joint marketing opportunities (eg, pairing of brands in one product) ■ Understand customer brand perception and usage through images ■ Detect defective products on a production line through images	■ Generate analyst reports for securities traders ■ Provide language translation ■ Track visual changes to an area after a disaster to assess potential damage claims (in conjunction with CNNs) ■ Assess the likelihood that a credit-card transaction is fraudulent ■ Generate captions for images ■ Power chatbots that can address more nuanced customer needs and inquiries

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