Module 2: Artificial Intelligence and Data Science

Video Transcripts

Module 2 Video Segment Break Down

Video 1: What is AI?

Artificial intelligence is a technology area often referred to as the general-purpose technology of the 21st century. This technology domain is assigned the same importance as the drivers of the first three industrial revolutions: the steam engine, electricity and the Internet.

There has been quite a buzz in the media about AI - not the least accelerated by a lot of Hollywood movies. On a positive note, more and more people are talking about AI. This is good because the more it’s talked about, the more people might get involved in this field. This will help us advance the capabilities of AI. But there is also a downside. As there is little understanding of what AI can or cannot actually do. Many people tend to fear AI, or only see the risks associated with this new technology. This can limit AI-induced human and economic growth.

First, let's look into what AI is and what AI isn't. For starters, there is no globally accepted definition of AI. First coined in 1956 by John McCarthy at the famous Dartmouth Conference, AI involves machines that can perform tasks that are characteristic of human intelligence.

Broadly speaking, AI enhances machines in four ability domains. The first domain is Reading & Writing. Examples include chatbots or virtual assistants. The second ability domain is Seeing & Recognizing. Examples include face recognition cameras, making use of Computer vision. Generating & navigating knowledge is the third ability domain. An example is analyzing text in legal documents. The fourth ability domain is Speaking & listening. Examples include Alexa and Siri that use Speech and audio analysis.

We can put AI into three categories, narrow, general and super-intelligent AI. Narrow AI is also sometimes described as "weak AI." It exhibits some facets of human intelligence and can do certain tasks extremely well, but is lacking skills in other areas. Right now, all AI technologies are working solely within Narrow AI, serving well-defined purposes.

General AI would have all of the characteristics of human intelligence. Super AI is what we see in Science Fiction movies. It refers to AI that is exceeding human intelligence in all areas. General and Super AI are sometimes described as "Strong AI."

Video 2: AI, ML, DL & Data Science

While AI is the umbrella term, it's often closely linked to other popular terms, like Machine Learning, Deep Learning and Data Science. Knowing what they are and the difference between them is crucial. It can help us understand the true utility of the technologies, and the difference between real value and hype.

Machine Learning, or ML, is a subset of AI. It refers to systems or algorithms that can learn by themselves. These are systems that get smarter and smarter over time, without or with much less human intervention than we used to. So, put differently: At its core, machine learning is simply a way of achieving AI.

Deep Learning, or DL, is a subset of Machine Learning that's inspired by the functionality of our brain cells called neurons. It's called "deep," because the neural networks have multiple layers that interconnect. Deep learning has been so far the most successful approach to many machine learning applications, because it can process bigger amounts of data and have more accurate results.

Companies have realized the value of using Machine Learning to treat big data, and in turn enable better business decisions. Therefore, data science is a crucial field nowadays. It involves statistics, mathematics and programming, and aims to attain meaning from data. But how is data science different from Artificial intelligence? Data science involves the processing, the analysis, prediction and visualization of data. But AI is the implementation of a model that's acted out by algorithms to predict future events. So, AI algorithms are the models that data science uses to make sense of data.

Data science is about extracting knowledge and insights from data. In order to do that, it borrows from statistics, computer science, information science and many other related fields. Thus, Data science is about understanding your data, dealing with databases, cleaning or manipulating data, and analysing it. Hence, data science is a rather broad field, with machine learning being a subset of it.

Video 3: Machine Learning and Deep Learning

The kind of AI algorithms used for learning, the basis for the "intelligence" in AI, is roughly based on three different models: Supervised, Unsupervised and Reinforcement Learning.

Supervised learning algorithms assume that we know what we are looking for. This means that the algorithm must be trained with data that has a label. In order for a machine to recognize photos of a dog, for example, it must be trained with sufficient photos that have a corresponding label: whether it's a dog or not. Use Supervised Learning when you know how to classify the input data, as well as the type of behavior you want to predict. Given new data, supervised learning algorithms can make the prediction.

Unsupervised Learning is a method by which machines recognize patterns and correlations in unordered data, or data without labels. For example, a machine can identify and group all songs that are similar to those you've been listening to. Use Unsupervised Learning when you don't know how to classify the data, but you want the algorithm to find patterns and classify the data for you.

Reinforcement Learning received a lot of attention from the public in connection with the victory of Google's DeepMind in the game Go. In this case, the machine receives "rewards" and "punishments" that tell it whether what it did was right or not. The algorithm is presented with data that has no labels, but is given a positive or negative result, which provides a feedback loop to the algorithm. For example, a machine can teach itself a game without lots of rules that need to be programmed beforehand. Reinforcement Learning has great potential for solving complex problems, in the field of autonomous driving for example. When should you use Reinforcement Learning? It's when you don't have a lot of training data, or you can't clearly define the ideal end state. Or the only way to learn about the environment is to interact with it.

The categories are somewhat overlapping and fuzzy, so a particular method can sometimes be hard to place in one category. For example, as the name suggests, so-called semi-supervised learning is partly supervised and partly unsupervised.

Deep learning, in short, is Machine Learning through multiple layers to process more complex tasks. It's not unusual for humans to work towards a solution through multiple layers. For example, if you are a startup developing a product, you need to make complex decisions. You would probably conduct user journeys to understand the needs of your client, digging deeper and deeper about the users gain and pain points. Thus, you process information through multiple layers.

Deep learning works the same way. The network you see has an input and an output. In between, we see a number of so-called hidden layers of artificial "neuron" or nodes. Each layer processes information passed from the previous layer and transfers the results to the next.

So in the example, if the input is a picture of George Washington, the first layer identifies the edges, the second a combination of edges and so on. The more layers the system has, the more processing it takes, and the deeper the learning will be. So, deep learning is essentially about processing more data much more intensely.

Recent convolutional networks, like residual networks and highway networks, can even have more than a thousand layers. However, these networks are somewhat different from classical ones. Basically, every layer of a residual network learns what to add to its input, rather than completely transforms it.

Video 4: The Role of Data

In all approaches of machine learning and deep learning, data is the central input. Yet, while it's the key input, data is raw and pretty useless on its own. Data only becomes meaningful once we process, organize, interpret and derive action from it. Thus, data is different from information or insights.

An example would be to gather and analyze data about your sleep. One data point, for example the time you go to bed, is pretty useless by itself. Once you have, however, a collection of data points about when you go to bed and when you wake up, you can start to have meaningful information on the duration of your sleep.

Data insight is about drawing conclusions from data and information. For example, what is the effect of little sleep on my concentration? These are much more relevant questions to answer, versus how many hours I slept. So to be clear, data is raw and has noise, but once we analyze it, we can gather signals from it to create information, and then put this information into context to gain specific insight. And data insight is the ultimate goal of data analysis and the world of big data.

Hence, data is the starting point. As global data spheres are growing, so do the possibilities to generate previously impossible insights. Every minute, people send 16 million text messages, 156 million emails, weather channels are receiving 18 million requests, YouTube users watch 4.1 million videos, google delivers searches for 3.6 million searches. Worldwide data volume is expected to grow reaching a total data volume of 175 ZB in 2025. Just to put it into perspective, in 2017, the data volume reached 23 ZB meaning, 8 times less of what we are expecting in 2025.

Data can take many forms, from numerical data, to image data, to audio or text data. Data doesn't have to be real; it can also be synthetic, meaning that it's created by an algorithm. Synthetic data is used a lot to train autonomous vehicles. You might also know from headlines that an AI has composed a new song or produced a new piece of art.

Having more data for training and fitting of models is usually a good thing. But contrary to what terms like "Big Data" or "data is the new oil" suggest, large volumes of data are not a strict prerequisite for training AI. Increasingly, we are trying to distill insights from less data to avoid privacy issues, data pollution, and processing inefficiencies. In order to learn from small data volumes, AI must be prepared and have a specific objective. For example, a qualitative analysis can be performed to evaluate when crop failures are imminent based on the visual representation of grain. Then it can train algorithms to create agrotechnology solutions to recognize the best point for harvest.

Video 5: Current Capabilities of AI

If you are a regular news reader, you might hear about new breakthroughs, such as AI that has won in games against the best human players in the world. And we also all know the achievements of Amazon, Apple, Google and their Chinese counterparts. Yet, across the world, AI solves a wide range of economic and social issues that don't always make it into the mainstream news.

The American apparel company, Levi Strauss, used AI to run a promotion campaign that would drive up sales 5x higher than in 2019. In Germany, a startup from Munich called KONUX helps railway companies to continuously monitor and analyze the health of key switch components. It provides actionable recommendations to reduce maintenance costs and make trains more reliable. In India, the company Niramai has developed an AI powered solution that helps to detect breast cancer at a much earlier stage than traditional methods at a low cost, saving many lives. In Australia, image classification AI is used at Riverbend Pork Group to automatically scale and weigh pigs, making their production more profitable while decreasing the stress for the animals. And in Kenya, the company Tala allows anyone to apply for and instantly receive a loan even without an official track record.

To dissect the underlying capabilities, let's go back to the different kinds of Machine Learning and Deep Learning. The different types of machine learning and deep learning are being applied to recognize, predict and prescribe across an area of business functions. For example, different algorithms under the category of supervised learning can allow you to understand product sales drivers such as competition prices, distribution, and advertisement. They can also allow you to classify customers based on how likely they will repay a loan, or predict call volume in a call center for staffing decisions.

Under the category of unsupervised learning, we see a range of other capabilities and businesses cases. Recommendation engines for movies, songs or clothes fall into this category. Segmentation, for example of loyalty card users, also makes use of unsupervised learning. Reinforcement learning, on the other hand, is applied to train autonomous vehicles, or optimize the trading strategy for an options-trading portfolio.

In the area of deep learning, we can see convolutional neural networks applied to diagnose health diseases from medical scans. In addition, recurrent neural networks can provide language translation, or power chatbots that can address more nuanced customers' needs and inquiries.

However, let's not forget that AI is still very narrow. So far, AI can only take over narrowly defined tasks, not complete jobs or even projects. Thus, while AI is arguably better in identifying cancer than a human doctor, it can't replace the job of the doctor that entails not only diagnosis, but also context-sensitive treatment advice delivered to people with emotional sensitivity.

Video 6: Future Capabilities of AI

How might AI further develop in the future? What are under-explored aspects of AI? More human context-understanding is needed for AI to get to the next level. Therefore, we are currently also looking at a new phase of AI systems, namely the Contextual AI. This technology doesn't exist at this moment but is currently explored by being backed up with multibillion-dollar investments.

Contextualization and causality are drivers of human learning. When children drop a toy, they innately understand the cause and effect of that action: You let go of an object in mid-air, and the object will drop. While they're unfamiliar with the physical concept of gravity, they have an inherent ability to grasp the causality. Machines can't yet understand this concept. In reality, most AI is uniquely trained per task. Once trained in one pursuit, an AI system will need to be retrained and recalibrated to find and apply patterns in a new context, lacking versatility or generalization. Without logical reasoning, effective "few-shot" learning, long and short-term memory and abstract thinking, AI will remain narrow and limited in applications. At present, the field relies on statistics as the primary foundation for making computers act "smart," but building something better will require the introduction of new disciplines.

New approaches are needed to push today's narrow AI into new dimensions. These approaches might be based on so-called neuronal hardware, but regardless of the underlying technology, AI must move beyond models that augment correlation with probabilistic theory. And instead, we search for something that approximates humans' innate understanding of causation. The common concept of learning in humans and machines - reward and consequence - is seemingly coming to its limits. Instead, we need a model that grasps the ground truths of our world, a system that doesn't only predict based on experience, but at its core, understands why and how our bodies, thoughts and environment operate. Without such a technological leap, machine learning based on probabilistic models can only solve problems that we can define in a pre-ordained space.

This helps explain why autonomous driving is taking such a long time to realize. Although experts have developed vast capabilities for autonomous vehicles, a driverless car needs to adapt to and handle an endless number of scenarios, many of which are so-called "edge-cases," scenarios that don't happen frequently. But when they do, they are critical to human health and safety. Detecting a person on a street is easy. Detecting a person, pushing a shopping cart and shielding under an umbrella in the rain, is another story. If a car can only recognize a shopping cart and an umbrella, it must also understand that a person might be standing underneath, even if not visible. If a ball rolls into the street, the car has to understand that a young child might follow. Data scientists have tried to elevate AI into more sophisticated spheres from all sides, but they remain restricted to the mathematical realm of patterns of trial and error. Although current AI models don't have a good grasp of causality, context or emotions, new machine learning models are starting to push the boundaries of what had previously been impossible.

Video 7: Actors: Global Digital Platforms

AI is spreading in a variety of industries and social spheres. Technology companies, start-ups, scientific institutions and public institutions alike are actively investing in the further development of AI.

Before the boom of the digital economy, Silicon Valley operated in a world of tight engineering constraints. Engineers never had enough processing power, memory, storage or bandwidth, and had to make tradeoffs due to those constraints. As Roger McNamee, one of the first Facebook investors, mentor to Mark Zuckerberg and later a critic of the company, excellently analyses: "Internet platforms could not have happened in prior generations of technology. It needed processing power, memory and storage to transform from being limits to being turbochargers of growth, to allow a company like Facebook to flourish."

But Facebook and others not only managed to use the technological potential to their advantage, but also built business models that became known as platforms, with AI in the middle for processing user data.

A platform is a business model that creates value by facilitating exchanges between two or more interdependent groups, usually consumers and producers. A two-sided-marketplace business model is a platform for economic exchange. Two distinct user groups provide each other benefits based on the number of users in the network. A multi-sided platform is a business model that creates value for more than two user groups.

A digital platform's success is typically derived from a large user base that generates the volumes of user data needed to develop better services, which then attracts more users. It helps create network effects. There are two types of network effects: same-side network effects and cross-side network effects.

Same-side network effects are those where the strength of one side has an impact on its growth. It can be positive: Facebook, for example, is better with all of your friends on it, so you invite them. It can also be negative: Facebook is less attractive to advertisers when all of their competitors have already saturated the market.

Cross-side network effects are when the strength of one side has an impact on the growth of the other. They can be positive: the more readers a news website has, the more attractive it is to advertisers. And they can also be negative: the more advertisement a news website shows, the less attractive it is to potential readers.

The opening stages of a two-sided marketplace are challenging, because the service it offers isn't truly valuable until it has acquired a large enough base of loyal users on both sides. Value increases as the platform grows to match the demand on each side.

Like no other digital business model, platforms have shifted the balance of power in many markets. A steadily growing share of value creation is shifting from the producer of a product to the interaction manager between supply and demand. Since platforms have many competitive advantages over traditional companies, they are valued much higher on the stock exchanges. 7 of the 10 largest companies in the world by market capitalization are platform businesses in 2020.

Video 8: Actors: Startups

The wave of startups launched after 2003 was able to tap into a surplus of computer power and talent. Internet access to connect both was ubiquitous, decentralized and cheap. The new internet talent recognized that the penetration of broadband might enable them to build global consumer technology brands very quickly, so they opted for maximum scale. To grow as fast as possible, they did everything possible to eliminate frictions. Products were free, because successful business models evolved around free service for access to personal data, which then was used for target advertisement. This is the key revenue stream for many B2C platforms. In short, the time and attention span of users – measured in data – became a core commodity.

Thanks to the diffusion of innovation know-how, and low-cost ubiquitous internet access and compute power, the global startup ecosystems are prospering. They are entering and disrupting every industry, ranging from healthcare to finance, from education to manufacturing, from food & agriculture to retail and warehousing.

Venture Capital into AI Startups has increased from $4.25 billion in 2014 to $26.58 billion in 2019, reaching that increase of $22.33 billion within a mere 5 years. Not only has the volume picked up, but also the numbers of deals. For example, in the United States, the number of AI investment deals increased from 308 in 2014, to 695 in 2019.

While most AI Startups are coming from the U.S., China is catching up rapidly. But any company innovation strategy focusing only on those two power houses would be short-sighted. Pockets of disruptive AI innovators are equally popping up all over the world. For example, think about Cyber Security in Israel, or FinTech in the UK, or health and manufacturing AI in Germany, or Smart City AI in Singapore. Let's also not forget that in terms of population size, India will take over China by 2027, providing the preconditions for making the country the world's largest digital market.

But be careful! The control over key assets of the current wave of advanced digitalization, such as cutting edge talent or compute power and data, reside in the hands of a small set of platform companies. It is therefore critical to also work with early stage companies as part of your innovation management, for example through Corporate Venture Capital or other open innovation mechanisms. This can allow you to secure access to potentially disruptive products or services, before they get gobbled up by larger platforms.

Video 9: Actors: Research Organizations

For companies to remain competitive in the dawning cognitive economy and the AI space, it's critical to secure a steady pipeline of Fluid Phase projects, as well as a smaller number of Transition Phase projects, in order to be ready to overlay another S-curve of a new technology when the previous one matures.
As a result, nearly every AI platform company has created its own R&D Center. Prominent ones include Google Brain, Facebook AI Research, Baidu Research, and Alibaba DAMO, all aimed at creating innovation from within and attracting top-tier machine learning researchers from the outside. The strategy is working: Resulting products have now become essential building blocks to these companies' product pipelines, and to the global machine learning industry itself. Some examples include Google's TensorFlow library, Amazon's Inferential chip and IBM Q System One.

Companies such as Google and Alibaba recognize and embrace the prospering global innovation ecosystems. They are providing a blueprint for research outreach strategies, working with R&D centres that are spread across the globe.

Next to company AI research labs, universities and public research programs are targeting the next breakthroughs in the AI realm. Governments also recognize AI capabilities as a strategic asset, given a growing number of national AI strategies since 2016.

American universities such as Stanford, MIT, and UC Berkeley are some of the best academic institutions in the world to produce talent and research advancements. But they are by far not the only ones anymore. Tsinghua and Peking University in China, Oxford and Cambridge Universities in UK or ETH and EPFL in Switzerland equally belong to the most recognized universities in terms of AI research in the world.

Beyond just institutions, we see a number of countries with particular high AI research density. Countries like Singapore, and Switzerland, closely followed by Israel, boast even higher or similar ratios of AI researchers / population than the US. And depending on economic clusters, you will find excellent AI researchers also in countries you would not expect. In Sweden, for example, researchers have advanced AI to predict conflicts across the world, which could provide relevant information for your supply chain management. And in Bangladesh, we've been seeing research output on the application of AI to detect faults in textile. Thus, when conceiving your R&D strategies, think beyond the AI hubs that come immediately to mind!

<u>Video 10: Colliding Trends: Eroding Trust in the Digital Economy</u>

B2C platforms, such as Google and Facebook, have significantly advanced digitization of an increasing number of social and economic spheres. However, they have also become a liability, as they tend to over-collect or overuse the data they hold. Individuals and businesses have little recourse to address their concerns, because the large platforms have evolved into oligopolistic market structures thanks to reinforcing network effects. In most cases, only established platform companies have access to such significant user volumes, which give them an edge over competitors in collecting data and designing attractive products. This limits new players from entering and serving markets, and it gives these platforms nearly unfettered control over the marketplaces, developers, merchants, and consumers that rely on them. Yet, it also tends to isolate data in ways that lead to one-dimensional use cases and limited value. This affects not only economic growth, but societal growth as well, with mistrust in the global digital economy at an all-time high.

Let me quickly underline this with some numbers: 76% of users in the U.S. are increasingly concerned about privacy due to internet companies. 45% of internet users are more worried about their privacy than a year ago. Only 31% Americans aged 19-28 believe that tech companies are doing enough to protect their personal data.

Some of the highest profile cases are the Facebook-Cambridge Analytica data sharing scandal, Microsoft's partnership with the U.S. Immigration and Customs Enforcement agency, and controversies around Amazon's Face Recognition Software. It's likely that this is only the beginning of an increasing number of AI-related scandals. High-profile cases of fraud and ethical violations are not caused solely by technology companies. Their expanding use of and reliance on AI exacerbates the risk, and broadens the types of potential ethical violations.

In response, regulators across the globe have pushed back. The DoJ's lawsuit against Google in October 2020 hailed the largest since the Microsoft lawsuit. The EU attempted to design platform regulation with the European Digital Service Act, rewriting liability rules for digital service companies.

Yet, platforms are here to stay at least for the moment. The mistrust in the digital economy increases with new AI applications such as DeepFakes, where realistic images are being distorted through the deep learning technology of AI. These images look extremely real and convincing for the audience. We have seen deep fakes that have tricked banker CFO's in making wire transfers to wrong recipients, or video clips that faked messages of real political figures.

This leads to "Responsible Tech," "Human-Centric Tech" and "AI For Good." Responsible tech becomes a market differentiator not only key for tech companies, but also non-digital native companies. One of my former clients, a cleaning machine producer from Europe, saw a competitive advantage in positioning the new products as privacy respecting, when a competitor's autonomous vacuum cleaner was reported to be able to create a map of the user's home, but could later share the data with Amazon, Apple or Google.

Video 11: Colliding Trends: De-Siloing and Leveraging Data

99.5% of data we produce is locked in organizational, application, or industry silos. The lack of access to data, especially for non-digital platforms and smaller actors, limits their ability to participate in digital value creation. Because data silos limit economic and societal growth, an array of innovators, governments, and civil society actors have started to prioritize efforts to open them up. Even established businesses and entrepreneurs have joined the call for broader access, identifying a growing number of institutional solutions to make data more accessible across industries or organizations.

One such idea is data marketplaces. These are online businesses or platforms where users can purchase data sets or gain access to real time data streams. Data marketplaces would tap into a massive revenue opportunity: The global data economy is estimated to be worth USD 3 trillion.

Despite some early attempts by Microsoft, Amazon, and a growing number of startups, no one has yet found a solution to effectively price data. To date, marketplace developers continue to struggle with thorny issues for both themselves and their potential users, including regulatory compliance risks, competitive concerns, and the tenuous balance between the loss of privacy and the potential economic benefits of sharing one's data.

Besides data marketplaces, open data approaches have also received attention from several governments, non-profits, and commercial organizations alike. Open data is free, easily accessible, and open for sharing, providing a partial counterbalance to the ocean of siloed and controlled data sets. These shared pools can yield immense returns from global innovation initiatives that researchers, startups, and NGOs seek to tackle. For example, FoodTrade Menu used the shared European Data Portal to help restaurants and caterers create menus with the most up-to-date allergen information. Yet, companies should be careful when relying on open data, since their quality and maintenance is not always secured. While new means of data-sharing have emerged in recent years, many suffer from asymmetric incentives and security issues, driven primarily by worries over data privacy and security.

Hence, research has started to focus on reducing the volume of data that machines need in order to learn. One promising result of this effort is Federated learning. Federated learning processes offer an alternative, allowing users to essentially "share" a machine learning algorithm without sharing their data. While most AI systems require a centralized dataset for training, this model trains an algorithm across multiple edge devices, each of which holds their data samples instead of exchanging them.

Federated learning systems are being explored to improve health information systems' predictive capabilities, while maintaining the information privacy of users and hospitals. Such improvements to privacy-preserving systems can facilitate a new generation of AI-assisted services that satisfy regulatory and legal concerns and empower citizens to own and gain from their data.

Video 12: Colliding Trends: Talent Scarcity

The surge of Computer Science programs resulted in talent volume that eventually helped ignite and drive the technological transformation of the recent years. However, the demand is currently outstripping the talent supply.

As per an assessment of McKinsey, in Germany alone, 700,000 additional tech specialists are needed by 2023 to meet the economy's demand for them. For Agile skills, demand will be four times greater than supply, and for big data talent, 50 to 60 percent greater. Globally, 3.5 million cybersecurity positions are projected to be unfilled in 2021. Linked to the scarcity of AI talent is the cost factor of talent. Top-notch talent remains very expensive, often only affordable for cash-rich technology platforms. For example, a top researcher with a Ph.D. in Artificial Intelligence can make up to $ 1.6 million/year.

One role in particular, the data scientist, has been especially difficult for leaders to fill, as competition for its elusive knowledge increased. In 2019, employment-related search engine Indeed.com reported that job postings on its site for data scientists had more than tripled since December 2013.

According to another McKinsey study, incumbent companies found it especially hard to compete with start-ups and tech giants such as Google to attract or retain the best practicing data scientists. One multinational retail conglomerate, for example, put in place a highly attractive package last year, with education perks and salaries up to 20 percent higher than market rates, in order to attract the 30-plus data scientists needed to support its strategic AI road map.

An analysis of national AI Strategies revealed that all major economies in the world are pursuing the promotion of talent as a strategic top priority. However, it will unlikely be sufficient to tap into the full potential of AI for the following reasons. The first reason is Mobility. 53% of all the top-tier AI researchers are immigrants or foreign nationals currently working in a different country from where they received their undergraduate degrees. The second reason is Breadth. While the availability of AI and data scientists is critical for any country to benefit from the AI, it's worth mentioning that operationalizing AI requires developers and engineers, as well as AI savvy business experts and product developers. These are likely to come less from academic programs, and more from skills based training courses.

Thus, for leaders, one tricky question is: Where do I find the right people to do all the work of upgrading businesses and processes for AI?

Video 13: Strategic Considerations: Ensuring Organizational AI Readiness

As we have learned, Artificial Intelligence technologies simulate human cognitive and physical processes with increasing impact in every sector. Thus, it's imperative for companies to evaluate how well their organization is prepared to leverage AI development, adoption and scaling. Companies should also recognize potential harmful missteps, and prioritize areas for action and investment.

Thus, assessing the "AI readiness" of a company is critical. "AI Readiness" refers to the current state of a company's preparedness to responsibly explore, develop, implement, market and scale AI applications. Companies need to become AI ready both for its own commercial growth and for societal progress, all while mitigating related ethical risks for itself and its stakeholders. To that end, it captures the company's economic performance and holistic advancement of AI across multiple dimensions.

For an AI maturity assessment, we need to consult at least these five dimensions: (1) Implications for a company's strategy, (2) R&D and operational capabilities for developing AI, (3) Accessing data and enabling data-driven decisions, (4) Ethics and governance, (5) Building the right talent base.

Before we take a closer look at those dimensions individually, I would like to recommend that you look for a Company AI Readiness Assessment Tool. We have developed one called CAIR, but there are also others. We have realized how important it is for companies to self-assess their AI capabilities to enable strategic discussions. Now, let's dive right into the different dimensions.

Video 14: Strategic Considerations: Cognitive Tech Strategy – Not a Stepchild

AI requires explicit linkages to company's strategies. Experiments will only be meaningful if the learnings of their successes or failures are tied into the organization's goals. A strategy needs to include sensing changes in the external business environment, and leveraging an organization's internal capabilities and resources. A strategy can then link them, and proactively position the company in more advantageous ways in the business arena.

Because AI allows organizations to explore new markets and optimize processes for faster growth and greater efficiency, organizations that are not digitally native also need to identify and leverage their competitive advantages, and develop hybrid physical-digital positions. Top-level strategy and leadership are also essential, because AI-powered products and services impact processes or business models, and thus require preconditions that often span multiple areas across an organization.

A narrow AI strategy might not be enough. More often than not, it makes sense to consider broader technology strategies that embrace not just AI by itself, but AI and Data Science in conjunction with a broader Digital Strategy that addresses the Internet of Everything, Compute Power or Virtual Reality. This is even more important, because cognitive tech almost always enhances essentially all parts of the value chain for a company's existing products and services.

In "Business Models, Talent, Culture and Organization Enhancement", deep tech enhances employees, management, partners, and vendor engagement through the Enterprise Social Network to create knowledge sharing and a collaborative culture. It also enables Enterprise Mobility to capture untapped talent by enabling remote working capabilities. Next, deep tech can allow not only Process Digitization for improving customer, employee and partner service delivery, but also Worker Enablement for better productivity. It helps with Performance Management, making it easier to track KPIs and manage employees, especially remote workers.

In "Operational Improvement", deep tech improves efficiency and effectiveness by leveraging DevOps for faster enterprise application development. In addition, Big Data can be used for data-driven decisions, demand forecasting, inventory control, and supplier management. Deep tech can also leverage Connectivity, IoT & Machine Learning, and Hybrid Cloud. Connectivity enables connected fleets for monitoring inbound logistics and tracking assets. IoT & Machine

Learning allows Condition Monitoring, Predictive Maintenance, cost analysis, waste and downtime reduction. And Hybrid Cloud enables the connection between suppliers and partners.

In “Customer experience improvement”, deep tech improves customer experience and engagement by leveraging Analytics, Big Data, and IoT to provide contextualized in-store experience. It also leverages Machine Learning for Predictive Marketing, and increases customer touchpoints by integrating with mobile, social, web and ecommerce services. Deep tech enables IoE to connect all customer devices, and provide location-based, contextual services and products. It can also create a delivery model that’s reframed toward an interactive and engaging customer experience.

Video 15: Strategic Considerations: R&D and Operational Capabilities - Build or Buy AI (Part A)

Companies don’t have to develop all AI in-house. They now can tap into an ever-growing number of AI solutions providers, which in most instances are better, more cost-effective, or enable a quicker start. However, the value creation of both digital and physical products is increasingly generated through AI components. As such, company-owned Intellectual Property related to AI increasingly serves as a differentiator. Thus, companies are faced with the question of when to build AI internally, and when to buy it from vendors and third-party providers.

Boston Consulting Group provides a great framework to answer this question. Executives should view these options in light of two questions: How valuable is the process or offering to your future success? How strong is your ownership, control, or access to high-quality, unique data, relative to the AI vendor?

Based on the two dimensions, there are four options to the Build-or-Buy Choice. Let’s take a look at each one of them.

The first option is called Commodities. This area is the closest to an off-the-shelf solution. It’s a great entry portal into AI for companies. They can share data with vendors without the fear of losing competitive differentiation, since the processes in this quadrant are offering little strategic value to the company. If they manage their relationship with vendors properly, they can lower costs, and improve the performance of such areas as HR, finance, IT infrastructure, and maintenance. It is the proverbial low-hanging fruit of AI.

The second option is called Hidden Opportunities. Sometimes companies have access to data sources in areas that are not critical to competitive advantage. These data sources provide an opportunity for companies to tap into the technological expertise of AI suppliers, and generate quick wins and insights. Woodside Energy, for example, worked with IBM Watson to make 30 years of expert knowledge gained from oil platform operations accessible to all employees in the company. These approaches can pay dividends in several ways. Often companies can uncover a hidden treasure in massive collections of data, and gain skill and experience in training AI algorithms.

Video 16: Strategic Considerations: R&D and Operational Capabilities - Build or Buy AI (Part B)

The third option is called Danger Zones. Danger zones pose both perils and opportunities. The perils arise because vendors have better access to data than the companies themselves in strategically critical areas. When companies are in a danger zone, they should limit their dependency on the vendor, and minimize the possible loss of competitive differentiation. But if companies can manage the relationship well and develop their own competitive sources of data, danger zones can morph into gold mines, and become areas of strong competitive importance and data differentiation.

For health care providers, machine diagnosis of radiological images is a danger zone. By working with hospitals, research organizations and others, a vendor could conceivably create a comprehensive, high-quality database of images that would trump the capability of any single provider. Companies in a similar situation should have data-acquisition strategies that will support their AI activities. They need to find ways to acquire differentiated data, create a novel data mashup from multiple sources, or even acquire suppliers of data in areas critical to their competitive advantage. Without a distinct collection of data to feed into their AI engines, they will be stuck in a bad place.

The fourth option is called Gold Mines. Companies need to do AI themselves when they have a gold mine. Vendors and experts can be brought in to accelerate development, but only in supportive roles. Many of the most promising gold mines will necessarily involve managing complex “frenemy” relationships with suppliers. In the self-driving vehicle market, for example, all manufacturers deal with the leading AI vendors for various services. In such an environment, companies must have a sharp sense of what they should manage in-house, when they must look externally for data or expertise, and how to protect their competitive position.

While the decision of when to buy or make is critical, don’t forget that AI changes how jobs and tasks are done. Hence, processes and structures are required for not only the development, but also the adoption of AI products. For example, it’s critical to train users or employees to work on the interface with the machine. Afterall, introducing new ways to work is always a change management process.

Video 17: Strategic Considerations: Enabling Data-Driven Decisions (Part A)

Data is not the same as information or insights, but without data, there’s no way to generate information or insight. Yet, data remains in organizational and industry silos. Thus, encouraging a data driven culture within your organization is as critical as having high-quality data sourcing strategies in place.

According to Roopesh Varier, a Vice President at Data & Analytics at Personal Capital, a data driven culture goes through several maturity stages. The first stage is intuition based decisions. Here, data is not a priority in the company or partnership. The second maturity stage is subject matter expert based decisions. Here, data value is talked about but not used. The third maturity stage is historical study based decisions. At this stage, data is used as a valuation tool, but not integrated as part of core roadmap. The fourth maturity stage is fact and metrics based decisions. At this stage, data is considered to be the core IP of a company or partnership. When moving the company towards embracing data and AI, it's not hard to imagine that the transition from the third to the fourth stage is the most important but also challenging.

To encourage such a data driven decision culture, change needs to be induced from the top. Executive buy-in is key for a company or partnership to have a data-driven culture, and data should be leveraged to drive key value propositions. But adoption has to be from grass roots to build competitive advantage. To that end, leaders must help their people understand the Why behind the actionable data strategy.

Building a data driven decision culture also requires finding a data champion in different groups, hiring the right talent, as well as experimenting in well-defined “sandboxes” to show results and drive adoption. Once experiments are successful and value has been established, data access rights can be assigned and potentially democratized and diffused across the whole organization. Regular data cleaning routines safeguard high value data for actionable decisions. Keep humans in the loop by encouraging employees to ask “what if” questions. This will be helpful to keep up the curiosity and longevity in a business.

Video 18: Strategic Considerations: Enabling Data-Driven Decisions (Part B)

Data driven culture is the precondition for developing and scaling AI across business units. But we also need to have practical strategies in place to access and harvest data for specific actionable use cases. For this, it’s good to break down the data value creation chain:

First, you have to identify your data needs. Derived from your use cases, you need to define what kind of data is required. AI-driven products must teach their underlying machine learning model to recognize patterns and correlations in data. These data are called training data, and can be collections of images, videos, text, audio and more. You don't always need large data batches; you might want to keep an eye on the trend of “Small Data.”

Second, you have to source your data. Once you’ve identified the type of training data you need, you need to figure out how and where to get it. This could mean using an existing dataset from open data platforms, collecting your own data, creating it synthetically, or a combination of the three. Make sure that whatever you decide, you have permission to use this data and the infrastructure to keep it safe.

Third, the data needs to be cleaned and split into test and training data. For supervised learning, having accurate data labels is crucial for achieving relevant ML output. Labels can be added through automated processes, or by people called raters.

Fourth, data needs to be processed. This is where the actual AI comes into play. Once your model has been trained with your training data, you need to evaluate the output to assess whether it’s addressing your target user needs based on the success metrics you defined in the first stage. If not, you’ll need to tune it accordingly. This is the stage where algorithms are applied often more than once to identify the best performing one.

Video 19: Strategic Considerations: Safeguarding Data and AI – Distilling Value Responsibly and Ethically

In order to use and process data responsively, the entire value chain needs to be covered by safeguards, compliance and governance frameworks. This starts with so-called data checks. Even diverse datasets might have inherent biases and flaws, based on things like curation rationale or demographics of data providers and collectors. Data statements about the sourcing and labelling of the data can help users understand how AI might overgeneralize. With regard to governing AI algorithms, we can increase the fairness, explainability and transparency of AI by conducting algorithm audits. Even a well-developed AI system might cause harm due to unintended consequences. This is because AI obfuscates and modularizes processes to the point where a single human can no longer see the full picture. Organizations need to use system mapping to assess second- and third-order effects of these systems. To ensure that people, business units and firms adhere to ethics standards, companies need to have transparent and adaptive operational governance systems in place.

Here are some efforts to translate principles into practices. First, use technical tools. For example, the AI Fairness 360 Toolkit is a toolkit of metrics to check for unwanted bias in datasets and machine-learning models, as well as algorithms to mitigate such bias.

Second, have oversight boards and committees. For example, Microsoft AETHER Committee is composed of seven working groups within Microsoft. It proactively formulate internal policies to tackle specific AI-related issues in a responsible way.

Third, use frameworks and best practices. For example, the Assessment List of the Ethics Guidelines for Trustworthy AI is a resource developed by the European Commission's High-Level Expert Group on Artificial Intelligence. It operationalizes key requirements for ethical AI and offers guidance on practical implementation.

Fourth, create standards and certifications. For example, The Institute of Electrical and Electronics Engineers, or IEEE, created the Ethics Certification Program for Autonomous and Intelligent Systems. It develops metrics and processes toward the implementation of a certification methodology addressing transparency, accountability, and algorithmic bias.

Last but not least, have regulations in place, such as California's Restrictions and legal liability for the use of 'deepfakes.'

Within companies, we also need to make use of a whole spectrum of governance instruments, including incentives systems, standards, audit systems, ethic training and games as well as oversight committees. To be sure, there's an increased attention not only on AI product development and governance, but also on the market entry and customer education. We call that "Last Mile Support" or "Symbio-Intelligence" - that is, the best possible interaction between people and machines.

Video 20: Strategic Considerations: Building the Right Talent Base

Companies face talent scarcity, and there are strategic implications for a company's HR department. To secure top talent, companies need to use a set of strategies in hiring, reskilling, upskilling, reallocating, and sourcing.

The first step in closing the skills gap is a rigorous discipline in identifying specific talent needs. In a McKinsey survey, nearly twice as many respondents who report successful transformations, compared with those who don't, said that their companies set hiring goals based on specific skills needs.

McKinsey recommends the following hiring practices as the most effective.

First, favor quality over quantity. Given the scale of the need, organizations tend to focus on quantity. However, they should favor quality even more. A single expert or highly skilled engineer is as productive as eight novices. Finding these anchor hires and giving them a high compensation package is more cost-effective in the long run, and greatly helps in recruiting additional people who want to work with the very best.

Another effective practice is finding adaptable learners. Tech talent has always been accustomed to lifelong learning, as their fields change and new ones emerge rapidly. Technology skills evolve so quickly, so focusing solely on credentials and specific skills when hiring is not enough. In addition to specialized talent, the best companies look for “strong talent,” who have the ability to learn and adapt.

The next hiring practice is “Techies for techies” recruiting. The reality is that techies want to talk to techies rather than to HR people with limited tech knowledge. Acquiring top talent also requires the use of a broad set of recruiting channels, such as developer conferences and hackathons. Keep an open mind about educational qualifications, and be aware that 85 percent of developers are at least partially self-taught. It’s also crucial to move quickly. Applicants often have multiple offers and are used to rapid recruiting processes.

Keep in mind that reskilling is cheaper than hiring. New hires are two to three times more likely to leave than existing employees. Large tech players understand this, and often opt to invest more significantly in reskilling their workforce. Effective reskilling and upskilling, however, don’t require large outlays. By using existing training budgets more strategically, companies can move away from broad learning programs, and create targeted learning journeys that focus on top-priority areas for the business. Courses can also be shorter and easier to fit into work schedules than traditional curriculum.

McKinsey therefore proposes learning journeys, a set of connected learning experiences that drive sustained performance improvements. Learning journeys have been highly effective in closing skills gaps, as they blend a variety of different training formats, such as digital, cohort-based, or on-the job learning.

While talent scarcity, attracting new talent and upskilling existing workforce will be critical for the years to come, here’s one emerging technology that should be closely observed by today’s leaders. Automated Machine Learning, or AutoML, automates the process of applying machine learning to real-world problems. In essence, it allows non-experts to use machine learning models and techniques to solve problems. As AutoML automates tasks across data preparation, modeling, and tuning steps, it will begin to replace some of the original data science tasks that required highly skilled domain expertise. Watch this space closely. Determine when to invest in it, and when to focus on and upskill your Machine Learning talent.