CrowdFlower

The Essential CIO Guide to AI

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Introduction

The topic of AI has reached such a fever pitch in the media with the coverage of driverless cars, conversational bots and even movies made by AI that it's only a matter of time before every CEO starts asking their CIO "What's our AI strategy." For many CIOs this will be a "deer in the headlights" moment since the topic of AI is so multi-faceted it's hard to know where to start. We put together this e-book as a primer for CIOs wanting to get to grips with the topic of AI.

In this e-book, we start by giving some insight and context into why your CEO is asking this question, why now, and why you. Then, we will give you a foundational framework to think about AI so you can give your CEO a thoughtful response. Finally, we will discuss how you as CIO, can engage the business on the topic of AI and important considerations when evaluating AI vendors.

CHAPTER 1

Why is AI trending now?

CIO: Why is my CEO asking me this?

So, why is the CEO asking you this now? CEOs are humans too and they react to their environment. Their environment is often dominated by other CEOs, their board, and the outside world. AI as a topic has risen to the boardroom and the popular press with even Vanity Fair recently publishing an article titled “Suddenly Everyone is Obsessed with AI.” So if your CEO hasn’t broached the AI topic yet, they soon will.

AI is a disruptive technology. According to Clayton Christensen, author of The Innovator's Dilemma, a disruptive technology "enables new markets to emerge" and disrupts an existing market.

Your CEO's success depends on how well they anticipate these technology disruptions, and use them to your company's advantage. At the end of the day, your company will either be part of the new economy that arises from the disruption, or part of the old order that fades into oblivion. And if AI is the next big technological disruption to hit companies, your CEO wants to be on the right side of this disruption.

A disruptive technology **"enables new markets to emerge"** and disrupts an existing market.

CLAYTON CHRISTENSEN
AUTHOR, THE INNOVATOR'S DILEMMA

Now that we have a brief idea as to why AI is suddenly becoming such a big deal, and why your CEO cares about it, let's look at the role of the CIO and how you're expected to deal with this new trend.

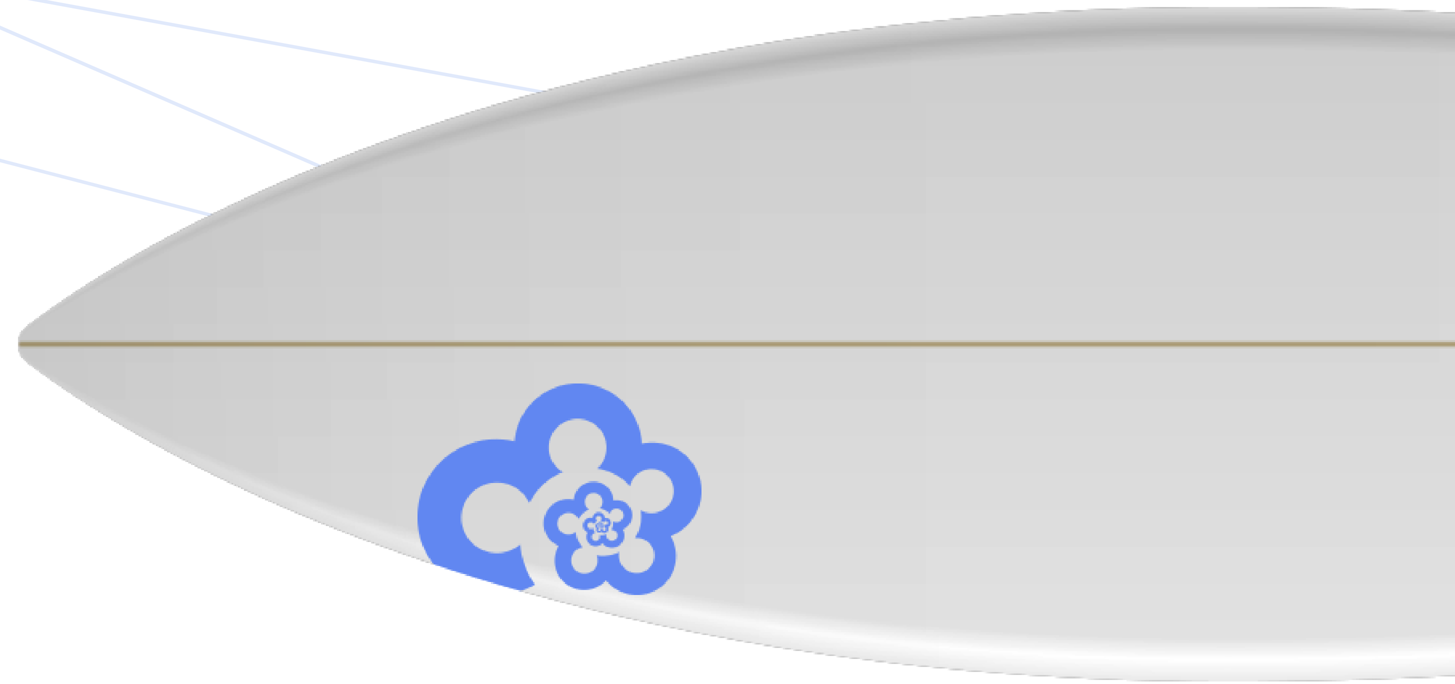
As CIO you may be thinking why is this question directed at me? Why isn't he asking the CFO, CTO, CMO, or COO? To answer that question we need to put AI in the historical context of the role of the CIO.

The Evolution of the CIO role

William Synnott, former Senior Vice President of the Bank of Boston, and William Gruber, former professor at the MIT Sloan School of Management, first formally defined the role of the CIO in 1981. They defined the CIO as the job title commonly given to the most senior executive in an enterprise responsible for the information technology and computer systems that support enterprise goals.

Up until about 2005 the CIO mandate was clear. Deploy the 6 or so key technologies to support the business: Accounting for Finance, Payroll & Benefits for HR, CRM for sales, Call centers for Support, Email and Security for all employees. The IT function collected the business requirements and then selected and delivered the application. It was very linear, typically took 12+ months and would only change every 5 years.

This new CIO role was not considered a glamorous or even mission-critical role initially. It was predominantly measured as a cost center and at one point the role was so unappreciated that the joke started circulating that CIO stood for "Career is Over."



Surfing the Waves

But like many executive roles, CIOs have had to evolve in response to their changing environment. For CIOs the biggest change in their environment was the nature of technology available to the enterprise. These changes would appear as waves to the IT function, starting from far away but gaining in power as they approached. Either CIOs had to learn to ride the wave, or be overpowered by the wave. Up until about 2005 there was just one wave, which was the transition from mainframes to client-server technology, but in the last 15 years the frequency and power of the waves has increased. A great CIO is like a great surfer. They can see the wave from far away and they can time how and when to ride it.

After 20+ years of calm, glassy sea the first big wave hit. Bigger and faster than anything a CIO had experienced previously. Drown or ride, those were your choices.

The Three Waves

On premise to
Cloud & Mobile & Social

Small Data to
Big Data

Unintelligent
applications to AI

The first wave:
On premise to Cloud & Mobile & Social

Salesforce was the first cloud vendor to reach $1B in revenue in 2009 and paved the way for the mainstream adoption of cloud applications in the enterprise. ServiceNow and Workday have since joined Salesforce in the "$1billion revenue" club for pure-play cloud applications companies.

The cloud wave was also amplified by the social and mobile technologies, which increased the volume of data shared across company boundaries. The launch of the iPhone, and the even more prolific Android mobile ecosystems began the mobile revolution. At the same time, social networking platforms like Facebook, Twitter, and LinkedIn were gaining mass adoption globally, connecting not just consumers, but professionals. This fundamentally changed the way enterprises function, and CIOs had to adapt accordingly.

This cloud wave profoundly changed the role of the CIO in two major ways. First, IT switched from being a capital cost to a variable operating cost where the premium was on speed and agility. This stressed the IT org that had been built for stability and governance. Rather than plan for periodic server hardware and legacy software upgrades, CIOs shifted to SaaS tools to support their business functions, and to public cloud vendors to rent servers and computing resources by the hour.

Second, the end user provisioning of cloud and BYOD mobile dynamic changed the balance of power. Previously, IT would tell employees what they would use. Now, employees choose what apps they want to use and bypass IT. Rather than deal with just 6-8 major business applications for the entire company, they now had to support at least a 10X increase in applications. As an example of the explosive growth just the Marketing function had 4,000 cloud applications available to them.

The CIO had to develop new policies and frameworks to co-opt rather than ignore this trend. Just as the CIOs were catching their breath, a second wave hit them.

The second wave:
Small Data to Big Data

The constant during the first wave was that IT's primary responsibility was still enabling business processes. This forced IT to focus almost exclusively on the applications running underneath those business processes. As the concept of the data itself being valuable and needing managing hit the mainstream in 2011 with the McKinsey Global Institute publication of "Big data: The next frontier for innovation, competition, and productivity," the role of the CIO changed once again.

CIO's had to become familiar with the 5Vs (Volume, Velocity, Variety, Variability, and Veracity) of big data. They had to understand new storage and compute approaches such as MapReduce, Hadoop, Spark, and Cassandra. They had to build analytics capabilities to present the data to business owners. The scope of their world dramatically expanded.

This wave is still in motion. It hasn't crashed on the shore yet. But on the horizon the beginnings of a third wave are emerging.

The third wave:
Unintelligent applications to AI

During the explosion of the number of cloud applications being used inside an organization, these applications were still unintelligent. Namely, the application itself didn't do anything unless a human took an action – responded to a support ticket, updated a sales opportunity – or maybe pre programmed a defined rule to follow – such as nurture a lead based on the lead activities. These applications were predominantly backward looking. They told you what had already happened. But with the collection of such big data sets from the previous wave, there was now a business imperative to glean more value from them. This meant one thing. Applications needed to become intelligent and predict what had not yet happened.

For AI to become possible we needed advances in 4 areas: data availability, processing power, machine learning talent, machine learning cloud offerings. All 4 advances have occurred in the last 24 months so AI for the enterprise is now possible.

AI requires structured data. While structured data refers to text files that are neatly labeled with rows and columns that can easily be ordered and processed by data mining tools, 80% of business relevant information is still unstructured. This includes texts, e-mails, digital images, audio, video, and social media posts. To make this unstructured data useful to the task at hand, you need humans to apply their intelligence in categorizing and labelling the data so it becomes structured and can be ingested by a machine learning model.

AI requires massive processing power. This processing power is now available, through advances in multi-core chip designs and the application of GPUs. A scientist working on an AI program at Google figured out that if you use GPUs instead of CPUs you can get computing tasks done a lot quicker with a lot less resources. It took just 64 GPUs to do the job originally designated for 2000 CPUs.

AI requires machine learning talent and machine learning platforms. According to LinkedIn, there are now at least 180,000 data scientists in North America and the big 5 technology players – Amazon, Google, IBM, Microsoft, and Salesforce – are actively targeting them with cloud machine learning offerings. Google's CEO has stated they are now an AI-first (rather than mobile-first) company and Microsoft's CEO has articulated 10 rules for AI.

The first examples of intelligence applications emerged in marketing and sales, with companies such as Quantcast doing predictive targeting and Everstring and Infer doing predictive lead scoring. But now we're seeing AI start to emerge in fields as diverse as automotive, healthcare, and retail.

So the waves are appearing on the horizon. It's only a matter of time before they hit the enterprise. Now that you know why the waves are appearing, what can you do to prepare? What's the equivalent of learning to surf when it comes to AI?

Next, we will give you a foundational framework to think about AI and how it relates to your business, so you can give your CEO a thoughtful response.

CHAPTER 2

A framework for understanding AI

In Chapter 1, we gave some insight and context into why your CEO is asking this question, why now, and why you. In Chapter 2, we will give you a foundational framework to think about AI so you can give your CEO a thoughtful response.

In the last chapter we introduced the metaphor of the CIO being able to ride the waves of technology disruption. To avoid being knocked off your board and swept out to sea, first you must develop a solid conceptual framework for understanding AI. Once you have that, you can engage with the business, and evaluate your options for working with vendors providing AI solutions.

Formulating a Framework for AI

Let's start off with some definitions of what AI is not. This is necessary because the media coverage of AI is not thoughtful but often hyperbolic.

MYTH #1

AI ≠ Machines > Humans

For the last 30 years the media has loved to portray AI as the replacement of humans by machines, whether it's Schwarzenegger in the Terminator or Alicia Vikander in Ex Machina. This is the wrong mental model for AI in the enterprise. The right framing is how can machines augment humans, not replace them. Even the recent the media coverage of Google's DeepMind/AlphaGo victory over Lee Sedol was simplistically portrayed as machine defeats human. The more accurate description would be machine plus many humans defeats single human.

Machines have advantages that humans do not: speed, cost, and consistency. Humans have advantages that machines do not: task complexity and breadth of task capability. The challenge is to find the right way to blend humans and machines, not replace humans with machines. As a reminder that machines aren't ready to take over from humans just yet, a number of robots in DARPA's robotics challenge last year struggled to open a door.

The more accurate description would be machine plus many humans defeats single human.

MYTH #2

AI ≠ Best Algorithm

For many people the terms AI and algorithm are synonymous. The best algorithm creates the best AI solution. Facebook has the best newsfeed algorithm, Netflix has the best movie recommendation algorithm, and Google has the best ad placement algorithm.

We think this is incomplete. AI and algorithm are not synonymous terms. Algorithms are a necessary component of AI, but not a defining one. Many leading experts such as Alexander Wissner-Gross now claim data – and not algorithms – are the key limiting factor to development of human-level artificial intelligence.

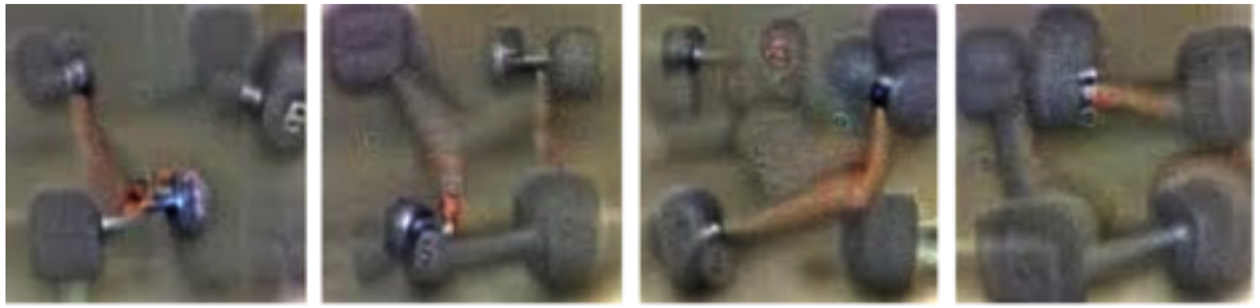
Year	Breakthoughs in AI	Datasets (First Available)	Algorithms (First Proposed)
1994	Human-level spontaneous speech recognition	Spoken Wall Street Journal articles and other texts (1991)	Hidden Markov Model (1984)
1997	IBM Deep Blue defeated Garry Kasparov	700,000 Grandmaster chess games, aka “The Extended Book” (1991)	Negascout planning algorithm (1983)
2005	Google’s Arabic and Chinese to English translation	1.8 trillion tokens from Google Web and News pages (collected in 2005)	Statistical machine translation algorithm (1988)
2011	IBM Watson became the world Jeopardy chanmpion!	8.6 million documents from Wikipedia, Wikitionary, Wikiquote and Project Gutenberg (updated in 2010)	Mixture-of-Experts algorithm (1991)
2014	Google’s GoogLeNet object classification at near-human performance	ImageNet corpus of 1.5 million labeled images and 1,000 object categories (2010)	Convolution neural network algorithm (1989)
2015	Google’s Deepmind achieved human parity in playing 29 Atari games by learning general control from video	Arcade Learning Environment dataset of over 50 Atari games (2013)	Q-learning algorithm (1992)
Average No. of Years to Breakthrough		3 years	18 years

SOURCE: SPACE MACHINE

He reviewed the timing of the most publicized AI advances over the past 30 years, with the evidence suggesting many major AI breakthroughs have actually been constrained by the availability of high-quality training datasets.

To further illustrate this, let’s take a look at some of the research published by Google on artificial neural networks (ANN) that use learning algorithms. Google was training an artificial neural network – a computational model that draws inspiration from how brains work – in image classification. One of the tasks was identifying dumbbells. The ANN was trained by showing them many examples of what Google wanted them to learn, hoping they extract the essence of the matter at hand (e.g., a dumbbell needs a handle and 2 weights), and learn to ignore what doesn’t matter (a dumbbell can be different weights, sizes, colors, or orientation).

Unfortunately the ANN failed to completely distill the essence of a dumbbell.



Maybe it's never been shown a dumbbell without an arm holding it. These mistakes highlight that we need to be careful before completely removing humans from the process. A human can immediately see the mistake while a machine cannot. This element is called Human-in-the-loop (HITL).

So this brings us to a more complete working definition of AI for the enterprise.

AI = TD + ML + HITL

Training Data | Machine Learning | Human-in-the-loop

AI = TD + ML + HITL

We believe this is the essential equation that the CIO needs to understand if AI is to be a commercial success inside an enterprise. So, let's break it down and imagine a company is trying to create an AI solution that can categorize customer support tickets by severity level based on the unstructured text showing an exchange between a customer and a customer support rep discussing a particular topic or problem within the support ticket.

TD is Training Data. Training Data is a set of inputs with the correct outputs or examples with the correct labels that can be used to train the machine. In this example, the input is the unstructured text inside a support ticket. The output or answer is the label "severity level," which has been applied by humans according to definitions of severity levels specific to the company in question. An automotive manufacturer will want to define these severity levels differently from a retail banker or a wearable technology company.

ML is Machine Learning. The Machine Learning capability is the ability to convert Training Data into a predictive model that can be applied to new inputs – in this case new support tickets with unstructured text. You want the Machine Learning model to apply its predictive power to create new outputs – in this case the "severity level" label. One of the advantages of machines compared to humans is their ability to understand their own confidence level. Humans are notoriously overconfident at evaluating their own judgments. So you can accept or reject the prediction based on the Machine's own assessment of its confidence level. For example, if a support ticket has words and phrases, which haven't been seen in the training data, or seen very infrequently, then the machine will objectively assess its own confidence level as being low for that particular prediction.

MYTH

AI ≠ Machines > Humans

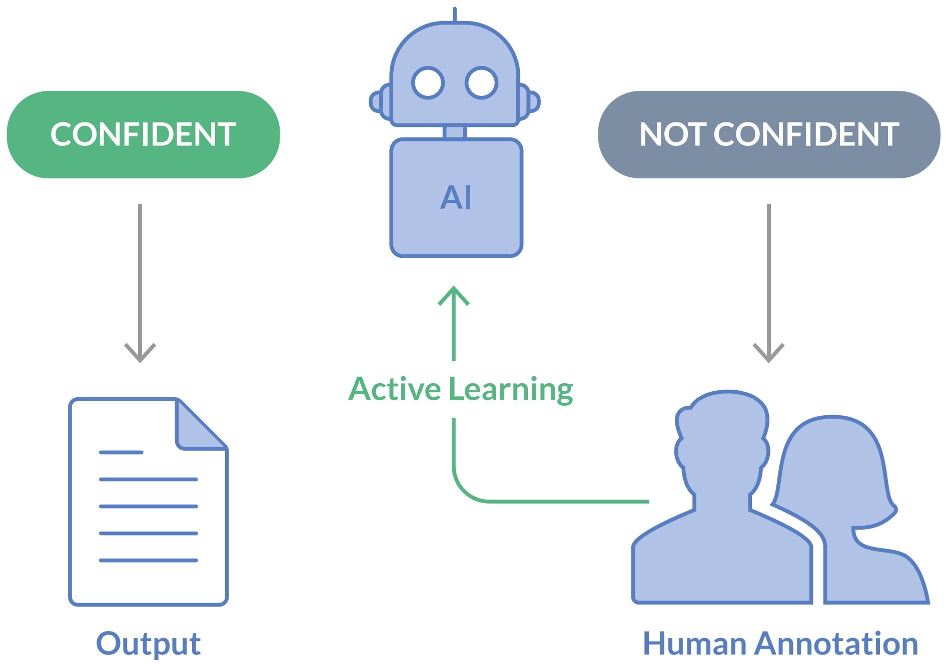
MYTH

AI ≠ Best Algorithm

TRUTH

AI = TD + ML + HITL

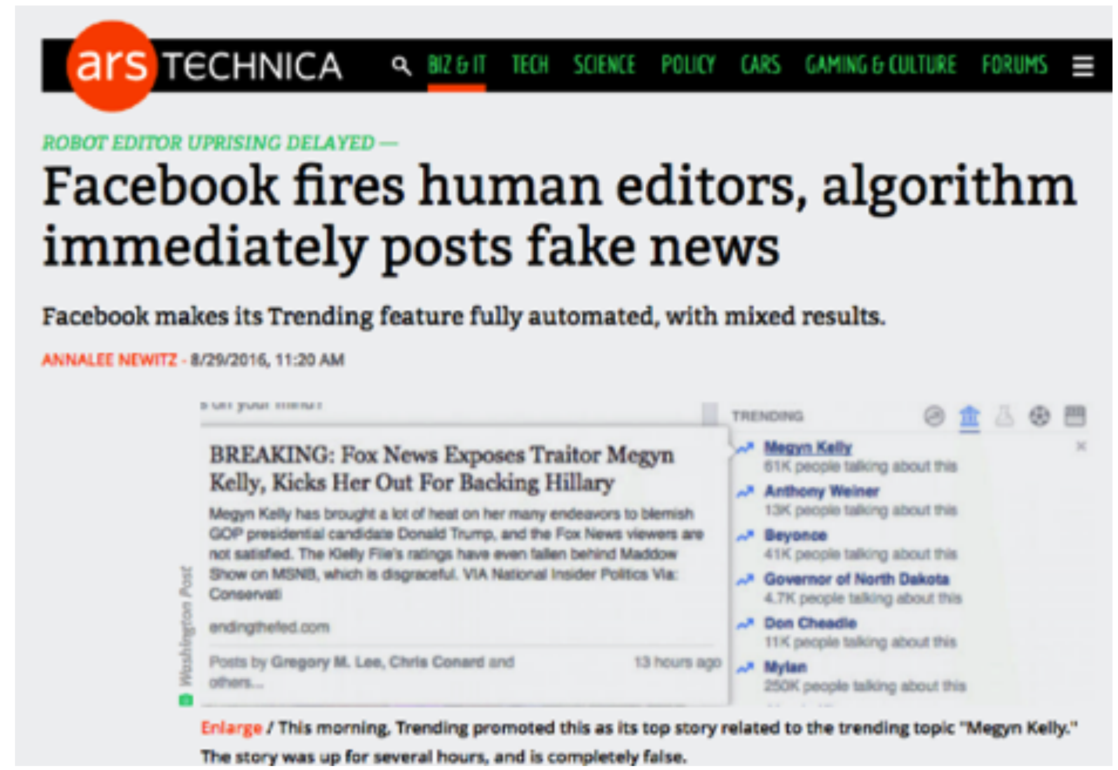
HITL is Human-in-the-loop. This is the critical third component of commercially viable AI. If the Machine Learning model is not confident in its prediction it can route it to humans to review and answer. In this blended model, you take advantage of the speed and scale of Machine Learning to address the less difficult tasks, while the humans handle the harder tasks. The result – an automated business process faster and more accurate than humans or machines alone. Humans and machines are better together.



Importance of Human-in-the-loop

Imagine a Data Scientist going to the VP Customer Support and saying “I have a machine learning model that is right 70% of the time. I think we should deploy it into production for classifying our support tickets and stop using humans.” The VP Customer Support will laugh at the Data Scientist and say, “I cannot afford to be wrong 30% of the time. So I can’t use your model.”

So how can companies move beyond this impasse? The solution is an approach called Human-in-the-loop where the model handles predictions where it’s confident but hands off predictions for human review where it’s not confident. If you deploy Machine Learning without Human-in-the-loop then you are saying you have 100% confidence in all the predictions from the model. If you do this, you will have avoidable bad outcomes.


ars TECHNICA BIZ & IT TECH SCIENCE POLICY CARS GAMING & CULTURE FORUMS

ROBOT EDITOR UPRISING DELAYED —

Facebook fires human editors, algorithm immediately posts fake news

Facebook makes its Trending feature fully automated, with mixed results.

ANNALEE NEWITZ - 8/29/2016, 11:20 AM

BREAKING: Fox News Exposes Traitor Megyn Kelly, Kicks Her Out For Backing Hillary

Megyn Kelly has brought a lot of heat on her many endeavors to blemish GOP presidential candidate Donald Trump, and the Fox News viewers are not satisfied. The Kelly File's ratings have even fallen behind Maddow Show on MSNB, which is disgraceful. VIA National Insider Politics Via: Conservati

endingthefed.com

Posts by Gregory M. Lee, Chris Conard and others... 13 hours ago

TRENDING

Megyn Kelly 61K people talking about this

Anthony Weiner 13K people talking about this

Beyonce 41K people talking about this

Governor of North Dakota 4.7K people talking about this

Don Cheadle 11K people talking about this

Mylan 250K people talking about this

Enlarge / This morning, Trending promoted this as its top story related to the trending topic "Megyn Kelly." The story was up for several hours, and is completely false.

MACHINE LEARNING WITHOUT HUMAN-IN-THE-LOOP LEADS TO BAD OUTCOMES

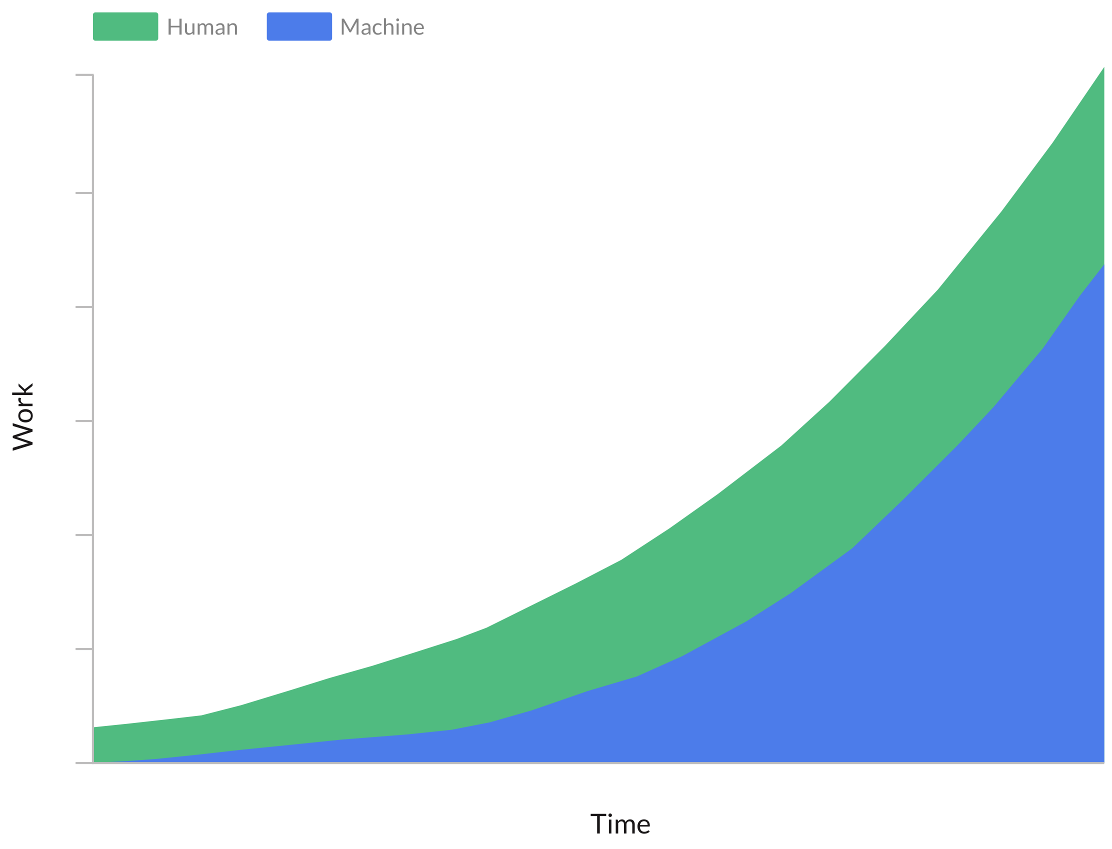
Earlier this year, Facebook faced criticisms that its Trending feature was surfacing news stories biased against conservatives. In response to this criticism the company fired all the human editors for Trending, replacing them with an algorithm that promotes stories based entirely on what Facebook users are talking about.

Within 72 hours, according to the Washington Post, the top story on Trending was a fake story about how Fox News icon Megyn Kelly was a pro-Clinton "traitor" who had been fired. A Human-in-the-loop approach would have prevented this obviously flawed outcome.

If you apply Human-in-the-loop then you have started to automate a business process. Initially that business process – say classifying support tickets – is 100% human. Then the Machine Learning model handles the high confident cases, which is maybe 10-20% of the volume, but humans still handle the vast majority because the model is not yet confident enough. Over time the model continues to ingest new training data – the human output – and becomes more accurate and more confident, so the percentage of work done by the model increases. Additionally, the volume of work that can be handled by this semi-automated process dramatically increases.

Machine → High Confidence Predictions

Human → Low Confidence Predictions



AI is machines augmenting humans, not replacing humans. In the third and final chapter, we will talk about how to engage the business and think through important considerations for evaluating vendors.

CHAPTER 3

Applying AI to your business

In the first chapter, we gave some insight and context into why your CEO is asking this question, why now, and why you the CIO. In the second chapter, we gave you a foundational framework to think about AI so you could give your CEO a thoughtful response. In this chapter we will discuss how you can engage the business on the topic of AI and consider important criteria when evaluating AI vendors.

Engaging the Business

So now you have the AI = TD + ML + HITL conceptual model to apply to your business, it's time to start engaging with your executive counterparts in marketing, product, sales, and customer support.

In business, the explosive growth of complex and time-sensitive data enables decisions that can give you a competitive advantage, but these decisions depend on analyzing at a speed, volume, and complexity that is too great for humans. AI is filling this gap as it becomes ingrained in the analytics technology infrastructure in industries like healthcare, financial services, and travel.

To successfully apply AI to your business the first place to look is wherever data is being analyzed. Whenever data needs to be analyzed, AI is the perfect vehicle to achieve this. With companies collecting masses of information thanks mostly to social media, making sense of this information and finding value is perfect for AI.

Sales is a common function of any enterprise and Salesforce predicts that nearly 60% of business' sales teams will increase their use of sales analytics this year. For example, companies can now use analytics to decide which sales representatives should get which leads, what time of day to contact a customer, and whether they should e-mail them, text them, or call them.

Marketing is another function of the enterprise that could be greatly enhanced by the use of AI. AI is driving huge change in the way enterprises can target audiences for marketing and advertising - even for smaller companies. This means that businesses are able to target their spend, increase ROI and allow advertising to do what it should - give people adverts they want to see. For example, in programmatic ad buying on the Web, computers decide which ads should run in which publishers' locations.

Massive volumes of digital ads and a never-ending flow of clickstream data depend on machine learning, not people, to decide which web ads to place where. Firms like DataXu use machine learning to generate up to 5,000 different models a week, making decisions in under 15 milliseconds, so that they can more accurately place ads that customers are more likely to click on.

Customer support is also ripe for an AI makeover, as many of the repetitive aspects of customer services could be handled by an artificial intelligence. Whether consumers will be happy to speak to a machine is another matter entirely, as automated switchboards continue to be a major pressure point for consumers when contacting businesses and organizations.

Focus on Outcomes not Technologies

Avoid the trap of taking the conversation with your executive counterparts in Marketing, Product, Sales and Customer Support too quickly into techno speak. Focus the initial conversation on the outcomes that matter to them. A good way to focus the conversation is to start with 2 questions:

1. What are you already doing that you want to do faster/cheaper/better?

2. What are you not currently doing that you want to start doing?

For example, you may have the SVP of Customer Support say that s/he is not happy with the quality and consistency of how they classify the severity level of support tickets since it's the individual customer support reps doing the classifying and the incentives are misaligned. Or you might have the VP Product say they need to start collecting relevance data for search queries and results to understand how well they are meeting customer demand. Or you might have the CMO say they need to start collecting sentiment data from Twitter to establish a baseline for how customers view their brand and products so they are not flying blind when they embark on expensive campaigns.

Explaining AI

Once you've established the outcomes that matter to your executive counterparts, you can then introduce the concept of AI. Don't lead with it. The goal is not AI for the sake of AI, but AI that helps the business meet its business objectives. With the clarity of the business outcomes you want to help deliver against, you can now introduce the conceptual framework with the AI = TD + ML + HITL equation. Step through the equation and translate what each concept mean in terms they understand to them.

For example, if the CMO wants to start doing sentiment analysis at scale then walk through the following:

- **Training Data:** Download the tweets from Twitter based on the #hashtags and @mentions that matter. Define the questions and sentiment scale you want to use. Find humans to apply the classification.

- **Machine Learning:** Create a model that can predict sentiment based on the Training Data. Apply the predictive model to new tweets. Model assigns a confidence level to each individual level sentiment prediction.

- **Human-in-the-loop:** Use humans to override the model predictions with low confidence. Add the new human labeled data to continue to train and improve the model.

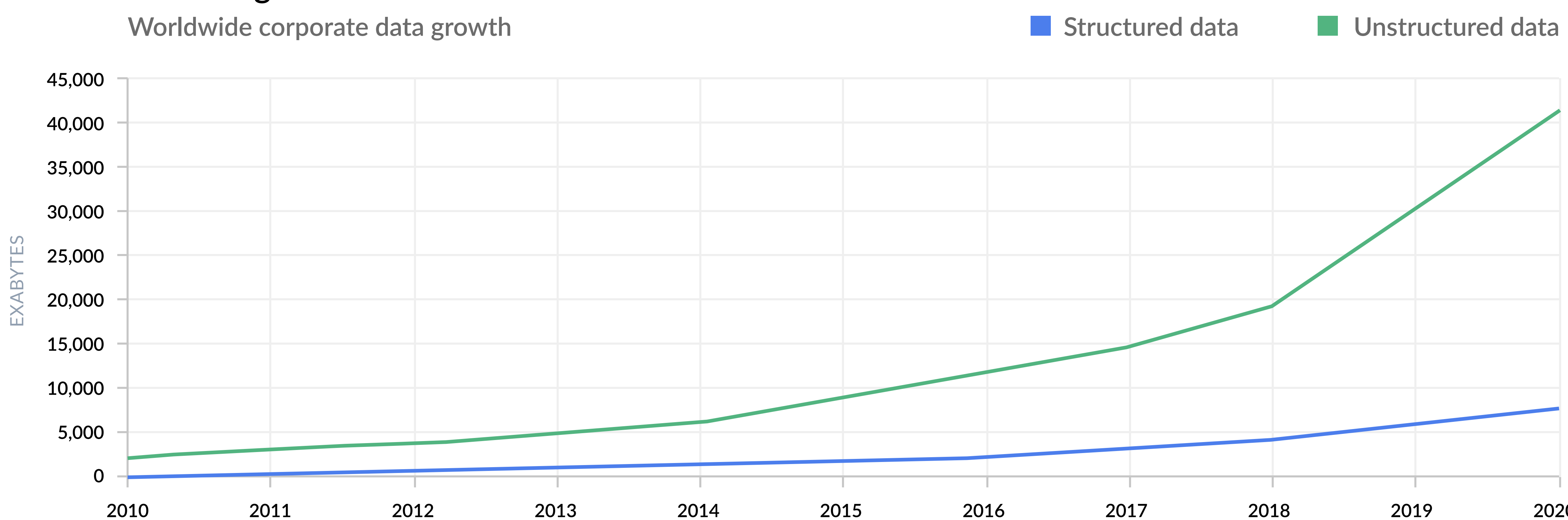
Systems of Record with Unstructured Data

Once your executive counterparts in Marketing, Product, Sales and Customer Support have a solid foundational understanding of how AI could apply to their business priorities, then you can move on to taking stock of the nature of the data in the mission-critical customer and product systems of record. Specifically, you want to understand what are the sources of unstructured data (text, images, audio, video) that if structured could be the initial training data.

If you're like the typical enterprise then probably your unstructured data volume is 4X your structured data volume.

Massive growth in Unstructured Data

Worldwide corporate data growth



SOURCE: IDC THE DIGITAL UNIVERSE, DEC 2012

Examples of unstructured data could include:

- Tweets from customers discussing your products or brand
- Customer attributes written into a sales opportunity in Salesforce Sales Cloud or Microsoft Dynamics CRM
- Product descriptions and images in your product catalogue system of record
- Relevance labels in your search algorithm
- Email conversations between customers and support reps in support tickets in your Salesforce Service Cloud, Microsoft Dynamics CRM or Zendesk

Once you have understood how and where your business is collecting unstructured data, and the path to turn that into structured training data, then machine learning is a possibility.

Evaluating your Vendors

The third and final part of how to respond to your CEO's question "What is our AI strategy?" after formulating a framework and engaging the business, is evaluating your vendors. Managing vendor risk has been part of the CIO's mandate since the role emerged. Developing this competence has been more important as the number of vendors exploded with the emergence of the cloud wave.

Rather than rehash all the typical considerations when evaluating vendors, let's call out three factors worthy of extra focus specifically for vendors claiming to deliver AI solutions.

Single Domain vs. General Purpose

Some vendors such as Wise.io have chosen a single domain (customer support) while others such as CrowdFlower and Sentient have chosen to build a general purpose platform that can fulfill many machine learning use cases for text, images, audio, and video data.

While one approach is not inherently better than the other, there is a long-term trend and desire for CIOs to rationalize the number of vendors they manage so there is a slight bias towards a general purpose platform, if (and it's a big if) that general purpose platform can meet the business needs of the different functions.

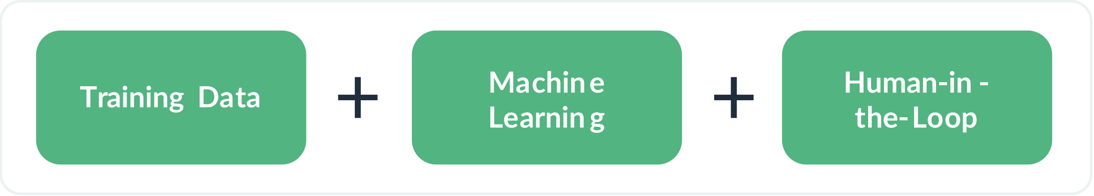
Black Box vs. White Box

With the emergence of 180,000 data scientists in North America over the past 5 years, the organizational model of where they fit is still developing. Some more mature organizations have a Chief Data Officer with a centralized data science function, but the more common model seems to be a decentralized model with data scientists sprinkled across an organization inside different functions.

In the decentralized scenario there will inevitably be a broad spectrum in the skill set of the data scientists within a single company. Some will have advanced machine learning backgrounds, while some will have progressed to the data science role from being a software engineer or a data analyst. Those with the advance machine learning chops probably won't be satisfied with a black box approach where it's not transparent how an algorithm works and they can't fine tune the parameter weightings. Bear this in mind when considering solutions that are black box only.

Point Solution vs. Integrated Platform

Many vendors claim to be AI solutions, but as you now know they are conflating AI with Machine Learning. Commercially viable AI needs the 3 critical components of Training Data, Machine Learning and Human-in-the-loop to be integrated together. So you have a choice. Either select 2 or 3 different vendors for Training Data, Machine Learning and Human-in-the-loop or integrate them yourself. Even with well-defined RESTful APIs there is still a cost to do that. Or look for a solution that has Training Data, Machine Learning and Human-in-the-loop integrated into a single platform.



Conclusion

Now that you're armed with an approach for how to engage your business on the topic of AI, why wait for your CEO to ask, "What's our AI strategy?" Instead be proactive and tell your CEO "Here's our AI strategy." The days of CIO meaning "career is over" are long gone. It's time for the best CIOs to seize the initiative and ride the AI wave.

For more information, visit ai.crowdflower.com

CrowdFlower