CHAPTER THREE

What Is Artificial Intelligence?

AS THE YEAR 2017 CAME to a close, the Big Four audit firms in the UK found themselves in hot water. Those whose assurance was supposed to be the pillar of trust upon which the financial markets' credibility and investor confidence reside were questioned and fined by the regulator. Something wasn't right. The audit quality was slipping. The process was failing. It appeared that audit firms were becoming better at winning business, but unable to deliver against the high standards set for the profession.

The concerns rose across a wide spectrum of stakeholders and the rendering of fines did not terminate the mounting trepidation. The actions of the regulators were followed by Parliament getting involved. A bill was proposed to break up the Big Four monopolies. In early 2019, the Business, Energy, and Industrial Strategy Committee of the UK Parliament held a session to question the representatives of "challenger" accountancy firms, including Grant Thornton, BDO, and Mazars (Parliament, 2019). The session was followed by questioning the Big Four – PwC, EY, Deloitte, and KPMG. The Committee raised concerns about the problems with the audit quality as well as lack of competition in the audit market. Pointing to the fact that 97% of the FTSE 350 market share is held by the Big Four audit firms, smaller firms pleaded that they needed to invest in technology and people in order to qualify for large clients (Competition and Markets Authority (CMA), 2019).

The growing rage from various elements of society demanded sincere introspection from the leading audit firms. They understood that the quality of audit needed to be improved, the reliability enhanced. As the Big Four reflected on

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what they could do, one of the major focus areas that emerged was the use of artificial intelligence (AI) to improve the audit effectiveness and efficiency.

While the example of the Big Four shows the adoption of AI to automate some parts of the audit process, consider the opportunity to strategically link these audit tasks in a series of interconnected and interdependent chunks to automate the entire audit process. Perhaps this is the reason why Osborn and Frey predicted, in their landmark paper, the likelihood of total audit automation as 94% (Frey and Osborne, 2017). Whether you are with the Big Four or not, clearly AI is the future of the audit and accounting profession.

The problems with audit quality, almost in every case, are human related and not procedural. In other words, the issues existed not because the audit methods failed or were not sufficient to perform a quality audit, but because of human error in judgment. AI does not eliminate human work as much as it eliminates human work errors, mistakes, and intentional misconduct.

A BRIEF HISTORY OF AI

The recent rise and the astounding novelty of AI belie the fact that the field has been around since the middle of the twentieth century. If you have seen the movie *The Imitation Game*, you will know that the movie is based upon a real story that depicts Alan Turing, the scientist who helped break the Nazi codes used in the Enigma machine and hence played a powerful role in helping the Allied forces win World War II against Nazi Germany. The same person also wrote an article published in 1950, titled “Computing Machinery and Intelligence,” which began by asking the question, “Can machines think?” Alan Turning’s article prompted others to think about the possibilities and nearly five years later three scientists sent out an invitation to several other scientists to hold a 6- to 8-week-long brainstorming session at Dartmouth in 1956. The proposal received wide acceptance and at the conclusion of that meeting, the field of AI was formally created.

The decades that followed turned out to be a rollercoaster for the field and the AI industry, as euphoric optimism was followed by states of hopeless despair. Periods known as the winters of AI happened in the 1960s, 1970s, and 1980s, when investment dried up and projects were folded. Overpromising and underdelivering led to credibility loss, and what was once considered possible turned into a despondent dream. Even though the failure was obvious, and the menacing overcast of negativity and pessimism could have shattered the research sanguinity, the AI research community continued to flounder through the wreckage left by the AI winters. Spirited and resilient in their pursuits, AI researchers produced some of the groundbreaking research in the 1970s and 1980s that would later create the foundation for a revolution to take shape.

LAUNCHPAD FACTORS

While the research breakthroughs were central to advancing the field, many of the critical elements needed for the launchpad were provided by the Internet and mobile phone revolutions. Specifically, five areas of capabilities sealed the powerful rise and the fate of the AI revolution:

1. **Data, Data, and More Data:** Smart phones and the Internet became the sources of immense amounts of data. From pictures to videos and documents to voice, we began piling up representations of our physical, cognitive, and time realities, capturing them in digital formats and loading them into the ocean of Internet. The digital content swelled, and so did our ability to tap into that data to gain new insights, develop new perspectives, discover new knowledge, and make better decisions. Algorithms that had been around since the 1960s, 1970s, and 1980s, and that were famished for data, suddenly found a new life. Like an animal species discovering a new and immense source of nourishment, the algorithms were deployed to voraciously gulp down the vast data sets. The age of AI had arrived. Among millions of other potential applications, images were used for recognition, videos for CGI, voice for security, IoT data for improving machine performance, and transactional data for making business decisions. A cycle was created where data generation increased the ability to find new patterns, to classify based upon predetermined criteria, and even to learn from the age-old reward-and-punishment model. All of that was made possible because of the data.
2. **Data Storage and Management:** The ability to produce data is one thing; being able to store it in a cost-effective way and organize it for fast retrieval is another. The work done by software and hardware engineers, as well as data managers, enabled us to store all the data being produced by us and our machines. The storage cost declined with technologies such as cloud, and the data management profession, and the data management body of knowledge, added to our ability to organize quality data and to make data more usable. Algorithms that have the propensity to devour

data entered a world where data was plentiful and data's variety, volume, and veracity were manageable.

3. **Processing Power:** The increase in processing power can be viewed in two ways: the graphic processing unit (GPU)-based power and the architectural power. The GPU power enhancement improved the ability of a machine to process data and the big data architectural improvement enabled multiple machines to work together in collaboration with each other to process major volumes of data. The combined effect of the two empowered the algorithms to achieve learning efficiency. How long it takes to process something is a major performance attribute of computational efficiency. Besides the nature and volume of data and the type of algorithm selected to solve a particular problem, what drives this performance attribute is processing power. Problems that used to take days or even weeks to solve, can now be solved in minutes and seconds. Great strides were made in improving processing power and that had a direct impact on greater use of machine learning.
4. **Global Network:** Unlike other fields, research sharing in the AI community comes with its own style and subtleties. This unique style is interesting enough to be described as "swag" by younger generations. First, the style element of that swag is that research sharing is done aggressively. The generous research sharing, at least up until the governments got involved, created an aura of global collaboration. Second, the time between authoring a research paper and its publication was kept to a minimum. This means that unlike social sciences where researchers have to wait, for what often seems like eternity, to get published, the research in AI is published quickly. Third, the large number of conferences allow ample opportunity for researchers to present research. With the Internet creating a globally networked community, the AI field experienced a sharp surge in research. Discovery accelerated and AI products and services found a new life.
5. **Algorithms and Approaches:** Even though the AI field experienced several winters, the optimism among the AI research community never faded. Committed as ever, they worked diligently to create new discoveries and solve problems. It may have been winter outside, but inside the research centers it was always spring. Many new approaches and algorithms were developed and presented. In many cases, algorithms that lay dormant because of a lack of processing power or data suddenly got a new life. The AI world was ready to leave behind its final winter.

Collectively, the work product of the last 50-plus years found its zenith when all the above forces lined up to support a spectacular resurgence in AI.

This time around, however, the only difference was that there was no going back. Just around 2011 or so, the winters were finally over and a permanent spring started.

DATA SCIENCE, MACHINE LEARNING, AI, AND EVERYTHING ELSE

The plethora of terminology that exists to describe the AI field can be overwhelming for those who are not exposed to it. It would be beneficial for the reader to get an understanding of these areas. First, let us clarify some of the misconceptions:

- **AI is IT:** As business professionals discover the remarkable potential of AI, they tend to reach out to their IT teams to seek help. Your general IT function may not have the capability to understand or serve your needs in AI. IT is not AI, and AI is not IT.
- **AI is machine learning:** The AI field is broader than just machine learning. Machine learning is one area in the broad AI field.
- **RPA is AI:** Robotic process automation (RPA) is sometimes confused with AI. While one can argue that a simple functional RPA bot can be viewed as a simple agent that performs as it is instructed to do, literally any software can be described that way. Hence, it is important to view RPA as a either a very rudimentary AI or not AI at all.
- **Data management is data science:** Some people also make the mistake of confusing data management with data science. Data management deals with organizing data while data science refers to using the data to build intelligent products and services.
- **Machine learning is the new AI and the old methods are not relevant anymore:** Significant recent developments in the AI field (for example, deep learning) may lead some to believe that the older models and approaches are not relevant anymore. This is not true. The new approaches are complementary to the older approaches. In fact. the older approaches are more suitable for certain types of problem classes. More recent developments when combined with the older methods give more robust and comprehensive solutions. For example, in many cases financial services providers need instantaneous decision-making on credit approvals and while neural networks (modern approach) can do the job, given the current state of the technology it is not possible to explain the reasoning behind the decision made by the neural network. For regulatory reasons, however, such decisions need to be explained. For example, a

judge in a court of law may want to know how a credit decision was made. For these types of situations, the search methods from classical AI would be far more useful. The key point is that machine learning is not the only AI branch that will be needed for audit transformation. We will need to include other types of AI also.

- **Machine learning is not AI:** Machine learning is based upon one branch of AI that is derived from statistical learning methods. The AI field is composed of many branches. In his book *The Master Algorithm*, Domingos calls them the tribes of AI (Domingos, 2015). In some cases, the tribalism is so prevalent that some hardcore adherents may describe machine learning as independent of AI. From their perspective AI is the rules-based approach enabled by search mechanisms while machine learning is statistical learning and hence is independent of the AI field. As explained before, machine learning is a branch of AI. Machine learning is not one method. There are several methods, ways of doing things, processes, problem areas, and approaches to machine learning. Many of those are described in the next two chapters.

From the perspective of this book, I prefer to view the AI field as composed of two main areas: the rule-based approach and the statistical learning approach. The first approach gave us the expert systems and RPA. The second approach (i.e., statistical learning) is what is driving the machine learning revolution. The Defense Advanced Research Projects Agency (DARPA) breaks down the two types into what DARPA calls the first and the second waves of AI (Launchbur, 2017).

DEFINITION OF AI

There are many definitions of AI. Several definitions cluster around building machines that can perform tasks that are typically performed by humans. For instance, IEEE defines artificial intelligence as:

> The combination of cognitive automation, machine learning, reasoning, hypothesis generation and analysis, natural language processing, and intentional algorithm mutation producing insights and analytics at or above human capability. (IEEE Corporate Advisory Group (CAG), 2017)

While I like most of those definitions, I define artificial intelligence as:

The technology with the ability to achieve goals in uncertain environments.

This definition establishes that we are conceptualizing an artifact that possesses artificial intelligence. This artifact dwells in or interacts with an environment. That environment can have many states. A single state environment has absolutely no change and will not require any intelligence to act upon. It will always be in the same state no matter what happens. It is not very interesting from our perspective.

A simple switch (on and off) has two states and can be viewed as an environment where, depending upon some condition, an AI entity can turn the switch on or off. This is an extremely limited use of intelligence – but at least now we have an environment that has some uncertainty (i.e., on or off).

As an environment becomes more complex, greater intelligence is needed to navigate through that. However, what do we mean by navigate through the uncertain environment? Why would an entity do that? The answer is that intelligent entity will not just wander through an uncertain situation purposelessly. It will always have a goal – even if the goal is to discover and explore (which may feel like purposeless wandering, but is not).

For example, performing a simple internal controls assessment based upon data provided is a process that has a large uncertainty. Even in a simple situation, there could be many possibilities. If you made a tree of how many on–off switches you would need for a complex problem like performing an internal controls audit, it can easily be composed of thousands or even millions of switches. To get to the right answers, your artifact will have to tread through that tree and make decisions along the way. But it will do that in accordance with some performance criteria and a goal. It will know when it has achieved its goal (i.e., completed its assessment).

An intelligent entity pursues and achieves goals in uncertain situations. Ideally, the intelligent entity will learn and constantly improve. It will accumulate experience and learn from mistakes. It will become better with each try.

In summary, artificial intelligence, or AI, is the technology (implying it is synthetic, engineered, and not natural or biological) that can pursue goals in uncertain environments.

TURING TEST

The Turing Test can be viewed as a measure of intelligence in an AI artifact. Another way to think about the Turing Test is to ask the question whether a computer can think like a human or not. It is named after Alan Turing (Turing, 1950). It can be viewed as a simple test where a human (Person B) and a computer (AI) interact with another person (Person A). The two humans and the computer are all located in separate rooms. The interaction is happening via computer terminals. Person A is talking to the computer (AI) and also to a human (Figure 3.1). Person A asks the questions and Person B and the computer (AI) answer the questions. During a sustained conversation, if Person A cannot tell the difference whether she is conversing with a computer or a human, the Turing Test is passed; else it failed.

Despite the advances in technology, it is safe to say that the Turing Test has not been fully passed. In certain cases, Turing can be passed if the environment is limited such that Person A can only ask specific or very limited questions. Even with the smartest computer, within a couple of minutes you will be able to tell if you are talking to a computer or a human. Humans have this great capacity to understand and tell stories, to understand and respond to humor, to talk about various subjects, to converse naturally, to use language creatively, and to understand the context in conversations. AI is still far away from having that.

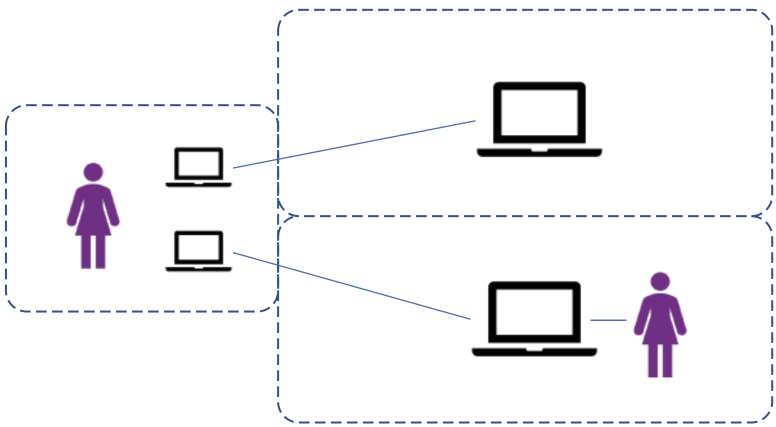

FIGURE 3.1 Turing Test

NARROW VERSUS GENERAL AI

Narrow AI

Narrow AI (also known as weak AI) is a system that can automate tasks that are typically performed by humans but do so in a specific narrow knowledge domain. The task could be descriptive, predictive, or prescriptive and the performance of the machine can be equal to or better than that of the human.

Artificial General Intelligence

Artificial general intelligence (AGI) is artificial intelligence that can perform human expert tasks in multiple domains. Their performance can be equal to or better than a human. AGI interacts with humans in a manner that humans cannot tell the difference whether they are acting with a machine or a human. In other words, they pass the Turing Test.

VIEW OF THE ENTERPRISE

For more than five decades, computers have played a powerful role in transforming our business and personal lives. The rise of computers in the business world can be described in four layers of recording transactions, analyzing or counting, optimizing, and predicting. These capabilities enabled us to design and develop descriptive, prescriptive, and predictive systems.

As shown in Figure 3.2, the left side displays the existing tech stack of a legacy firm. A legacy firm will generally have systems that transact, analyze, optimize, and predict. As shown in the middle, now we are adding learning capabilities. When we add the learning component, we get a three-layered architecture shown on the right (known as the CAT structure for Cognitive, Analytical, and Transactional). Our transactional systems reside in the bottom layer. Our analytical systems (e.g., Business Analytics) reside in the middle layer. And our Cognitive systems (e.g., RPA, Machine Learning) reside as the top layer.

In some ways we can assume that by adding the new learning layer, we are automating the four tasks of transacting, analyzing, optimizing, and predicting – and enhancing the machine's ability to autonomously perform the

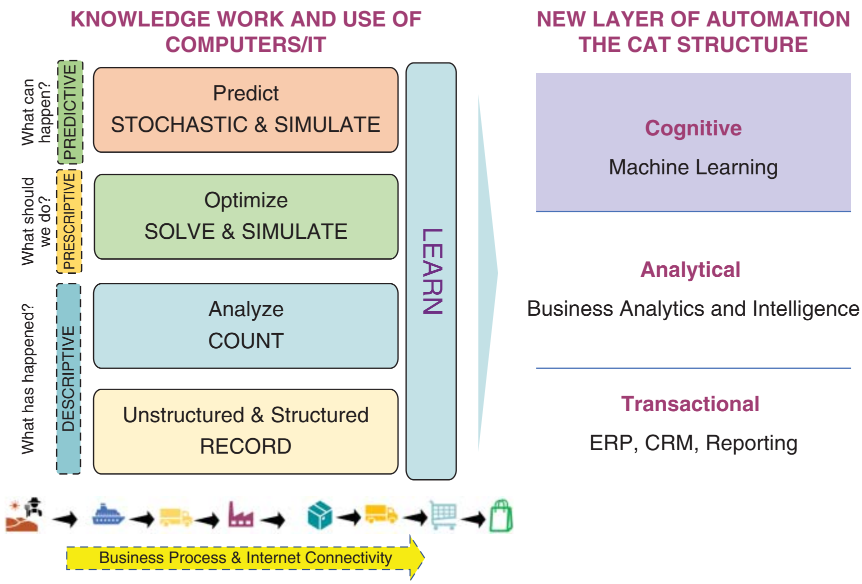

FIGURE 3.2 Enterprise Automation History

work of descriptive, prescriptive, and predictive analytics and with relevance and accuracy that is equal to or greater than a human's.

TOOLKIT FOR INTELLIGENT AUDIT AUTOMATION

As we envision and design the cognitive architecture, we recognize that we will need to use many different types of intelligent technologies. In addition to the IT infrastructure composed of regular software, analytics, business intelligence, data repositories, ETL, and other regularly used IT tools, IAA requires four specific technologies:

1. **Robotic Process Automation:** RPA is designed to replace repeatable human work where automation is done in an outside-in manner (van der Aalst et al., 2018). RPA is a software that (1) uses structured input (2) to process the input through rules (3) in order to generate some specific output. It is essentially a digital bot that is configured to automate simple, repeatable, low options tasks. RPA is also designed in a manner whereby it minimizes coding and is easy to use. While RPA vendors will claim that anyone can use it and that people with no knowledge or background

can easily automate functions from their desktops, RPA is a bit more complicated. RPA is now being used for audit automation (Zhang, 2019).

2. **Expert Systems:** Built mostly with if–then rules, expert systems are systems that emulate human expert decision-making. Expert knowledge is expressed as rules and decision-making is enabled by reasoning. Expert systems have been extensively used in audit. Significant literature exists on their use for audit purposes. However, recent analysis shows that their use has declined, and it appears that some of the more prominent expert systems are no longer being used (Gray et al., 2014).
3. **Process Mining:** Process mining refers to having automated ability to scan and extract knowledge from event logs. Such knowledge is used to identify and monitor processes. Our existing systems collect tons of meta-data about transactions and that meta-data can be used to understand the origins, steps, and ends of various processes. The discovered processes can be compared against some standards to determine compliance. They are also used to identify exceptions or anomalies. Process mining is now extensively used in audit (van der Aalst et al., 2010; Jans et al., 2013) and when combined with other systems can produce powerful results toward integrated IAA.
4. **Machine Learning:** Machine learning is a statistical learning method that uses data and algorithms to teach machines to perform tasks that are typically performed by humans. Machine learning is used in automating processes as well as automating both physical and cognitive work. We will cover machine learning in detail in the next two chapters.

Learning machines can be thought of as types of systems: (1) machines that are taught a specific function, and once they learn the task, they can continue to perform that task; and (2) machines that continue to learn and improve through experience. In both cases, some type of a performance measure is established, and the machine performs or improves in reference to the performance measure. It also implies that the machine is trying to perform a task in accordance with a goal.

The "doing" part of the task means that there is some input that comes from the machine's environment. The machine processes the input and then gives out something as output. The experience part is related to learning, that is, the machine's ability to learn.

A learning machine therefore can be viewed as intelligent. This machine operates in an environment and its environment can be simple or complex. The machine must have a way to receive the input. It should also have a way to use a learning method so it can learn.

Key Points

- AI is being viewed as a solution to several recent problems in audits.
- AI is not a new field. It has been around since the 1940s.
- AI has experienced several winters.
- Five factors have influenced the recent surge in AI: data, processing power, global research networks, algorithms, and data management.
- AI, data science, data management, and machine learning are different concepts. It is important to clarify them.
- The modern enterprise can now be viewed as three-layered architecture of cognitive, analytics, and transactional systems.
- The toolkit for IAA includes RPA, process mining, expert systems, and machine learning.

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