Research Insights

Advancing Skill Development for Business Managers in Industry 4.0

Emerging Research and Opportunities

Sara Fazzin

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Advancing Skill Development for Business Managers in Industry 4.0:

Emerging Research and Opportunities

Sara Fazzin
H-Farm College, UK

A volume in the Advances in Logistics, Operations, and Management Science (ALOMS) Book Series

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701 East Chocolate Avenue, Hershey, PA 17033, USA
Tel: 717-533-8845 x100 • Fax: 717-533-8661
E-Mail: cust@igi-global.com • www.igi-global.com

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Preface

It was in 1993 when Duchessi, O'Keefe, and O'Leary were writing "In recent years, many companies have deployed Artificial Intelligence (AI), which has included neural networks, expert systems and voice-recognition systems. Yet managers and developers understand very little about how management and organisations affect or are affected by the technology" (Duchessi, O'Keefe, & O'Leary, 1993).

In our modern era, society seems more interested in technology and the way it affects people's lives and business. The flourishing of executive programmes in technology for business, computer science, big data, machine learning and artificial intelligence, among others, is an example of the new trend in Business schools and managerial practice around the world. Managers and professionals alike tend to believe it is paramount for their career to learn how to code, apply the latest models in artificial intelligence and machine learning, and so forth. In a word, the key concept should be fast-changing innovation. Buzz words like disruption, agile organisation, digital transformation, AI, big data, data science - just to mention a few - seem to be the answer to all the organisation's needs, to thrive and innovate. However, they are still words, and will remain the same if those leading the change do no fully understand the concept behind the buzzword, rather than the technicality of it. For this reason, this book has been designed to fill a gap in the modern skills-demand for managers, professionals and young graduates who want to update themselves in a fast-changing economy. While presenting hot topics in technology for business, we will try to deepen our knowledge of the Fourth Revolution, the Internet of Things and the modern jobs, to contextualise the rise of artificial intelligence, big data and machine learning in relation to the way markets and management behave.

Furthermore, we will embark on a journey to navigate the practical applications of technology in business, and how these disrupt several aspects of the organisation and the economy in general. For example, how Industry 4.0 affects the organisation? Which skills the new leader should have? What does disruption entitle? Answers to these questions are difficult to find, in particular if we consider most managers are not that tech savvy and are looking to learn the ropes to better understand transitions in their organisation.

By being able to understand the world we live in and the sociological, political and economical changes nations are experiencing, as well as becoming more literate about programming languages and AI and machine learning algorithms, systems and models, modern managers will achieve a set of skills that are paramount to the modern organisation. Design thinking approaches, IT-informed restructuring of departments, comprehensive knowledge of the digital process, are among those needed skills.

The book is presented in six chapters, each introducing a different topic related to the implication of technology in business. While the information provided tend not to be too technical, managers will find them interesting to the point they will be able to build on this basic knowledge to a more technical level.

Chapter 1, "The Fourth Industrial Revolution and the Internet of Things", introduces the state of art in terms of society and technological revolutions. History has always been a great indicator of past behaviour, as well as of future trends, and whilst disruption seems such a new concept nowadays, disruptive innovations have always been part of our history. Thus, the major industrial revolutions will be introduced, so to better understand the possible future paths.

Chapter 2, "The Power of Digital Transformation", presents the concept of digital transformation, and offers solutions on how to define it, the theories behind it and more specifically, the kind of skills required to successfully master a digital transformation project.

Chapter 3, "Computing, Data Science, and Other Skills for Managers", discusses the different skills and mindset, managers are required to have in order to be successful nowadays. Concepts related to data, such as data science and big data, have intrigued a huge number of people around the world, making traditional knowledge not viable anymore. Computing and data should then be learned in conjunction with other soft skills linked to emotional intelligence and leadership techniques, to allow modern employees and leaders to navigate the digital revolution.

Chapter 4, "AI and Other Technologies in Business", discusses the switch from the traditional business models, towards the modern one. In this economy, knowledge and data have an important role, that can be compared to that of technology itself, at a point where some organisations might be so proficient and knowledgeable that they risk not to see what is coming and prepare themselves for the disruption in their sector. The use of AI and other technologies in business will be then introduced, to better understand what is available to organisations and how to use such technologies efficiently.

Chapter 5, "Artificial Intelligence in Practice", presents machine learning techniques and artificial intelligence applications, their role in business as well as a practical application of it. A list of machine learning systems and models is offered, to highlight their importance in data-driven organisations, where the cost and or the advantages to implement such tools are far greater than having a human - or a team of humans - doing it.

Chapter 6, "The Future of Modern Jobs", tries to report what experts think our future will look like. Given the unprecedented disruption of the economy and our society, new job skills and performance measures will be introduced and discussed, to make an informed choice on the skills and knowledge managers and employees alike will need to invest into to make their job relevant.

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Chapter 1
The Fourth Industrial Revolution and the Internet of Things

ABSTRACT

History has always been a great indicator of past behaviour as well as of future trends. However, when you think of what future jobs may look like, you do not certainly expect to find a plausible response in the past. Technologies and scientific advancements in general make it almost impossible to predict what you will be required to know in order to get—or maintain—your job in the next six months, let alone in the next couple of years. Whilst disruption seems such a new concept nowadays, we will learn that disruptive innovations have always been part of our story. The authors look at the major industrial revolutions known to humans and discuss patterns to help us prepare for the forthcoming future.

THE ECONOMY DURING THE INDUSTRIAL REVOLUTIONS

According to the Merriam-Webster dictionary, an industrial revolution can be defined as "a rapid major change in an economy (as in England in the late 18th century) marked by the general introduction of power-driven machinery or by an important change in the prevailing types and methods of use of such machines" (see https://www.merriam-webster.com/dictionary/industrial%20revolution). Following this definition, we can say that we are

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now experiencing the so called Fourth Industrial Revolution, as a result of fundamental technological changes, which are derived from fast-paced ground-breaking scientific and technological advances. To use the concept of a technology adoption curve introduced by Bohlen, Beal and Rogers (1957; Rogers, 1962), we will see that new products or solutions usually follow a predictable trajectory which resembles a bell, with innovators as the earliest adopters, followed by the early adopters, the masses and finally the laggards. So, if we are in the middle of a fourth revolution, which ones have we already conquered?

From an historical perspective, our concept of economy started off with the agrarian revolution, which happened thousands of years ago, when humans moved from foraging to farming, through an extensive use of animals for production, communication and transportation. Although the first revolution lasted for a very long time, industrial revolutions appear to be much shorter. In fact, the first one only lasted for eighty years, from 1760 to 1840, while the following ones were on for less than sixty years.

As highlighted before, it was only in 1760 that the first industrial revolution arrived, bringing with it railroads and the invention of the steam engine as main innovation. If only you can get your head around the shock people have felt while looking at the first steam engine, and the wonder of getting on a train to reach far away destinations that could have meant days of unsafe and perilous travel for them, then you might be able to understand the astonishment such revolution brought with itself. Started in Britain, the First Industrial revolution spread throughout the Western Europe and to North America. What triggered it, was a successful agricultural production, which of course gave people more food to eat, and the opportunity to look for work and earn money. This meant that building new houses and methods of transportation for commuting became a priority. Industrial labor opportunities drew people to the cities from the countryside, in such an explosive way if we think that in 1750 only 15 percent of the population of Britain lived in towns. By 1850, over 50 percent of the entire population of Great Britain lived in either a town or a city, and by 1900 such percentage reached 85, with London having 4.5 million people, Glasgow 760 thousands, Liverpool 685 thousands, and Manchester and Birmingham 500 thousands inhabitants.

In this era, mechanisation of processes and production is a key factor to enable mass transportation of goods and people. The availability of better metals and richer fuel also contributed to industrialisation, through the invention of the steam engine, as we said earlier. Using coal and iron both as construction materials and fuel, the steam engine could power factories, locomotives and ships. Roads, canals and railways, which allowed goods to be sent over long distances, changed Britain dramatically. Visually, the revolution was clear in the new industrial towns, with the skyline dominated by smoking factories and overcrowded and dirty streets to match strict rules and punishments. The First Industrial Revolution saw also the mechanisation of the textile industry, thanks to new inventions, such as the spinning mule and the power loom. At the same time, Henry Bessemer helped developing an inexpensive process for mass producing steel, which was a fundamental innovation because iron and steel were key materials for constructing the tools and machinery, steam engines and ships needed for the industrial progress.

The Second Industrial Revolution appeared in the late nineteenth century, which saw the advent of mass production, electricity and assembly lines. A symbol of this second revolution is Henry Ford, who was a great car manufacturer; as well as the slaughterhouses in Cincinnati and Chicago, where the assembly line was first used on a large scale by the meat-packing industries during the 1870s. The Second Industrial Revolution is also known as the technological revolution, because it was very much underpinned by technological inventions and advancements. It happened primarily in Britain, Germany and United States, followed by France, Italy and Japan, where mass production grew exponentially, thanks to the invention of electricity and the exploitation of automation. It is interesting to highlight that with mass production, cars become far more affordable, even for the average family. Furthermore, during the Great Depression in 1892, Andrew Carnegie founded a steel company - Carnegie Steel Company, that covered and controlled every phase of business from raw materials to transportation, manufacturing and distribution of steel. This contributed to the railroad developments of seventy-five thousand miles of track in the US alone in the 1880s. The enormous expansion of rail and telegraph lines after 1870 allowed an unprecedented movement of people and ideas leading to what we could consider a wave of globalisation. Towards the end of this revolution, we can already consider the need for specialisation and customisation requested for different products and services. Faith and technological progress came into the general consciousness, and monuments like Gustav's Eiffel Tower still stand as a testament to this way of thinking. As we said earlier, railroads were expanding, cities were steadily growing and with them all a rapid increase in new innovations and technological advancements was brought on by increased competition by other nations. Furthermore, the Second Industrial Revolution saw the availability of Aspirin, thanks to the use of willow bark by a buyer chemist who went by the name of Felix Hoffman. On top of that, in this era, French and German inventors developed the airship. As an example, Ferdinand von Zeppelin patented his lighter-than-air ship in 1895, which used hydrogen. It made his first flight over Lake Constance in 1900, but it was hard to control and too big. Then, the Wright brothers came along and invented the three-axis control that allowed for a pilot to steer an aircraft and maintain equilibrium, finally solving what it was known as the flying problem. We had to wait until December 17th, 1903 for the Wright brothers to attempt the first successful flight with a lightweight gasoline engine powering twin propellers on the back of wings. At the same time, a great naval race was brewing between Germany and Britain, while governments from everywhere were looking into flight with great interest. Ammunition, chemicals and explosives were mass-produced as well, and by the time World War One started, France, Russia and Germany had more than 200 planes ready for use. Industrialised warfare was on its way, with the production of poison gas, tanks, machine guns and artillery. So, the end of the Second Industrial Revolution can be seen as the beginning of the modern era we all know. Although economic history books say it ended in the early twentieth century, data shows that 1.3 billion people, which are roughly 17% of humans in the world, have yet to experience this second industrial revolution.

For those lucky enough to have exploited its full benefits, the Third Industrial Revolution came about in the Sixties and brought with it marvellous things such as the development of semiconductors, which in turn led to mainframe computing and personal computing, and finally the internet. As it happens for the second one, the third industrial revolution is still unknown to four billion people. This era is about computerisation, and it goes beyond the static concept of automation - which is now at the basis of all manufacturing processes in plants and factories - to cover more about flexibility, adaptability, reliability and similar. At this stage, you will not need several people to accomplish the same amount of the work, and differently from the previous revolutions, no new skilled or unskilled workers' position is being created. The third revolution is also known as the digital revolution, because of the advancement of technology from analog, electronic and mechanical devices to digital technologies. The latter enable storage, retrieval, transmission, comparison, computation, connection, reliability and accuracy, so that there are plenty of opportunities to design and customise different types of tools and products. The digital revolution also marks the beginning of the information era. Information becomes a key player in the organisation, and it is at the core of the two major innovations, which are the programmable logic controller (or PLC) and the internet[1].

From 2010 onwards, researchers, practitioners and tech savvy alike have declared the start of the Fourth Industrial Revolution, also known with the term 'Industry 4.0' coined at the Hannover Fair in 2011, or as Brynjolfsson and McAfee called it in 2014, 'the second machine age'. The current industrial revolution is based on disruptive innovations such as the mobile internet, smaller and affordable sensors, machine learning and in general terms artificial intelligence. A culture of 'always on, always connected' have emerged in full force, thanks also to the advent of the iPhone in 2007 and the iPad in 2010, which revolutionised the way we interact daily with technology.

The Fourth Industrial Revolution or Industry 4.0

From this revolution, also known as Industry 4.0, the customer is the one that is gaining the most, considering that new products and services are offered at virtually no cost to improve our lives. At the same time, there is a huge mismatch and inequality, because for this new business model to be applied, there is a rising gap in wealth between investors-innovators-those who put the money versus employees. In other terms, technologies are now much more integrated (Manyika and Chui, 2014[2]).

While the previous three industrial revolutions have drastically changed the way people lived and created major societal changes, we can confidently say the fourth one is unique in terms of speed and pace of the new ideas. In particular, we are witnessing an incredible and disruptive change whose exponential velocity, breadth and depth (for the first time related also to change who we are), are transforming entire systems, across countries, industries, societies, governments and similar.

In what the revolution we are experiencing is so different? We might as well highlight now how the fourth revolution is creating profound shifts across industries, the society and governmental institutions. We will have the chance to discuss such disruption in greater detail throughout this book. At this stage, it is important to highlight that the main drivers of the Industry 4.0 are the information technology - now, thanks to the internet, we have much more data processing power; and the Internet of Things, which we will be discussing later on, and is driven by advancements in connectivity, decrease costs for hardware and physical sensors, as well as a great amount of data - or Big Data, and accessibility to everything from anywhere.

At the same time, one of the major points of differentiation is the fusion of technologies across three dimensions, which are physical, digital and biological. Companies that can combine such multiple dimensions are those who often disrupt the market they operate in.

In the physical realm, the Fourth Revolution can count on the creation of autonomous vehicles, whether these might be cars, trucks, drones, aircrafts, or boats; as well as 3D printing, which is said to be used to customise products, limiting costs related to the creation of rare or one of a kind produces and enabling access to perishable things, among other things. In recent years, while commercial 3D printing has yet to emerge, researchers are rumoured to be working already on a 4D printer prototype. Again, we can count on advancements in robotics, through the use and application of biomimicry, with the intent to mimic complex biological structures that resemble human ones; and finally, new materials are created, that are stronger, recyclable and adaptive, with a memory that enable them to return to their initial shape (Isaiah, 2015; Laslow, 2015)[3]. We will see later on an example of wearable tech on clothes.

With regard to the digital realm we were discussing earlier, an important term that comes to mind is the popular Internet of Things (or IoT), which can be defined as the relationship between things and people through the use of connected technologies - using virtual networks and sensors, to cite some - and platforms (Parker, van Alstyne & Choudary, 2016). Internet of Things is a very fashionable word to highlight the need of interaction between the physical and the digital, to create an effect of connected and augmented reality among us. Innovative examples brought by this Fourth Revolution can be summarised as follows. Firstly, we can mention the blockchain, which is a secure protocol where a network of computers check collectively a transaction before it is approved. The implications of the use of this technology in sectors such as finance, insurance and legal services, are already massive. For example, the modern investor can now also opt to invest in bitcoins, a digital currency that is an application of the blockchain. Lastly, we should mention the rise of the on-demand economy, which is led by new and unprecedented business models (see McKinsey, 2010, 2019; Investopedia, 2019) such as those of Uber. Thus, Uber capitalises on the use of a platform where supply and demand are matched in a low-cost way, and feedback among customers is provided to help building trust of the company, even though it might sound ridiculous to say Uber does not own a single car. Similar models, where physical assets are not owned, and social feedback is crucial to the success of the company, can be found in Alibaba and Facebook (among others, see Goodwin, 2015)[4].

The third and final realm is the so called biological, which can be seen in IBM's Watson supercomputer (see Cha, 2015)[5], capable in a couple of minutes of recommending personalised treatments for cancer patients; or in groundbreaking discoveries of creating genetically modified plants and animals. Researchers are now working on using 3D printing principles for the so-called bio-printing, whose main goal is the creation of living tissues.

Implications for Business

As we have seen, the Fourth Industrial Revolution has the potentiality to disrupt our society and the way we live in such profound ways we will never be able to predict (Haller, Karnouskos & Schroth, 2008). However, in relation to its impact on businesses, practitioners and managers alike agree on it creating four major impacts, regardless of industry. These can be summarised as follows.

The first and most important aspect to keep in mind, is the shift that has been recorded on customer expectation. Whether the business deals with B2B (Business to Business) or B2C (Business to Customer) operations, customers are always at the centre of each process, rather than transaction, and expect to be offered an enjoyable experience. Our modern economy is based more than ever on peer-to-peer sharing and user-generated content, which in turn make the customer experience crucial to the business survival. We also assist to a cultural shift from the need of ownership to a shared access to content, which can be explained through the rise of on-demand entertainment giants such as Netflix versus the declining business of DVDs. Although we do not own the digital content Netflix (or Disney Channel, Apple TV and similar, for that matter) allows us to watch, the monthly subscription is far cheaper than a single DVD and the amount of available movies, TV series and so on is far greater, which make it the perfect solution for the modern customer. All this available content, which is more and more digital, and the massive use of peer-to-peer feedback, bring with it also transparency for the customer, in particular when it comes down to prices. In this perspective, new digital business models are preferred to deal with the new expectations, which use purely digital platforms to sell digital products (think for example at how you buy ebooks now on Amazon's Kindle Store). At the same time, new business partnerships are formed, to foster collaborative innovation among multiple industries, with the aim to provide an integrated customer experience.

Another innovative product of the Fourth Revolution is the availability of data-enhanced products, which combine traditional physical objects (such as a tennis racquet) with sensors, to exploit the power of data to enhance performance, rather than be used to search for faults.

Among the changes we have seen, there are others that are just waiting to happen. In September 2015, the World Economic Report issued to the public presented 21 tipping points of technological shifts in the mainstream society[6]. These tipping points were part of a survey conducted by the World Economic Forum's Global Agenda Council on the Future of Software and Society, that involved 800 executives and experts who gave their professional opinions on the likelihood of new products going mainstream by 2025. Among them, it is interesting to consider the following ones, which are linked to wearable tech and augmented life through digital means. The report considers implantable technologies, such as implantable mobile phone, digital tattoos to unlock cars or phones, and similar. According to the experts involved in the study, implantable tech has the chance to be available to consumers before 2025 according to 82% of the interviewed. At the same time, experiments with the vision (meaning reading glasses connected to the Internet, such as in the case of Google Glass), will reach quote 10% by 2025 according to 86% the experts. Similarly, examples of wearable internet will be bought by 10% of humans globally, as agreed almost unanimously by the interviewed. Products like the Apple Watch or smart clothes, such as sport t-shirts from Ralph Lauren which can provide real-time workout data, are about to make their grand entrance, if they have not done already.

The opportunity to wear connected and augmented products goes hand in hand with the trend to cultivate our own personal digital presence, which should reach 80% of the population by 2025; and the use of artificial intelligence in decision making processes, where 45% of experts believe the first AI machine will be brought in on a corporate board of directors by 2025. Such deep shifts are made possible by the ambitious goals of reaching 90% of the population with regular access to the internet, giving birth to the so called ubiquitous computing paradigm, through the use of computers, smartphones or any other similar mean, to allow the presence of computing in its greater definition everywhere. Lastly, the use of sensors around the world will bounce the Internet of Things phenomenon and allow for the realisation of smart cities. According to the survey mentioned above, 89% of those interviewed think that 1 trillion sensors will be connected to the internet by 2025, which will be crucial to collect data and create an augmented reality around us, thus giving the basis for the first city with more than 50,000 inhabitants and no traffic lights to be built.

The Internet of Things

In this Chapter, we have discussed in several occasions about the importance of IoT, although we have yet to describe it as a concept. The name itself recalls a simple definition: it is about things connected to the internet. Which things then? Apparently any device, from fridges to cars, passing through TVs and mobile phones, can become highly intelligent - or smart - if connected securely to an autonomous network. According to Cisco Systems (2013), 1.5 trillion 'things' exist in the physical world, and it is expected that 99% of them will be connected at some point. Through the autonomous network, a huge amount of devices can connect securely to perform several closed-loop-type automation tasks, which can consist in collecting information, analysing it, predict future behaviours, applying logic and finally act. An example of this innovative process can be seen in the use of sensors (Gubbia et al., 2013) in smart cities and the agricultural business. When digitalised, farms are able to collect precious data in relation to humidity, rainfall activity and temperature, so that once everything has been collected, the appropriate amount of water can be sprayed at a determined time to maximise efficiency (Seneviratne, 2015). At the same time, street sensors in smart cities are able to collect data on empty parking spaces, which are in turn sent to autonomous cars which are then able to identify the best parking locations in the near vicinity[7]. Of course, being able to manage such a huge amount of data in this data supply chain, requires the ability of the IoT ecosystem to manage and process swiftly and reliably an ever increasing number of information. If we think for a moment that according to a recent study by IHS Markit[8] the number of IoT devices is expected to reach 125 billion in 2030, having grown from 27 billion in 2017, awareness of the Internet of Things phenomenon should grow exponentially as well. According to Google Trends data, a robust growth of the popularity of the search of the IoT term in internet by a user can be seen in the past five years.

In the following figures we can see 'IoT' picked the highest users' interest starting in 2016, and kept it at the highest levels since then.

If we break down this data according to region and cities, we have the most searching interest coming from China, South Korea, St. Helena, Taiwan and Singapore, with the United States of America at a surprising thirty place, and United Kingdom at thirty-two.

Figure 1. IoT Interest over time from Google Trends data (2019)

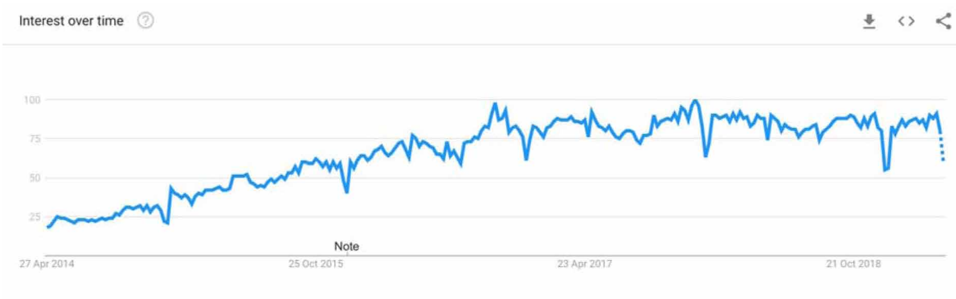
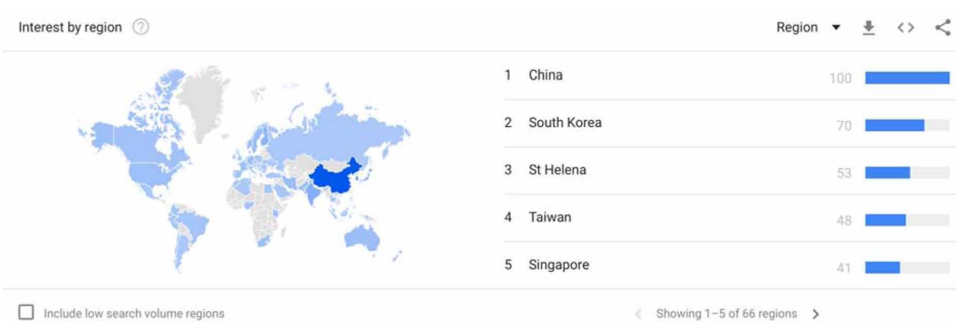


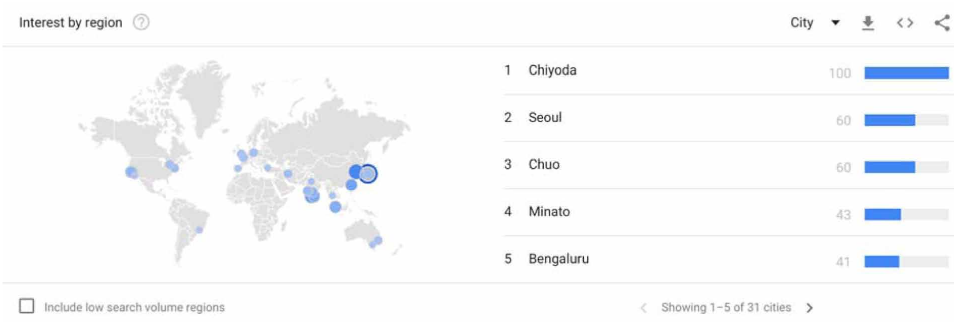
Figure 2. IoT Interest by region from Google Trends data (2019)



If we look into statistics for single cities, Chiyoda is in first place, followed by Seoul and Chuo, with San Francisco in thirteenth place and London only in twenty-second.

With these numbers in mind, it is not so difficult to believe the next step of the Fourth (or Fifth) Industrial Revolution will be the Internet of Everything, or IoE (ABI Research, 2014). How will the IoE differ from the IoT? There will be an inherent distinction between physical-first or digital-first products. If we think for a moment at hardcopies of a book, they fit in the physical-first category, while ebooks are digital-first ones. In this perspective, we can define physical-first objects as products and processes that do not generate and communicate data unless they are augmented or manipulated. On the other end, digital-first objects "are capable of generating data, and communicating it for further use, inherently and by design." (ABI Research, 2014). According to the experts in the field, in a decade any device could be able to interact with any other device without going directly to the Internet. Sensors from your car should be able to 'talk' with the sensors from your

Figure 3. IoT interest by city from Google Trends data (2019)



Imagine your home air conditioning system, to adjust the temperature when you are three miles away from your house. Things like this will be possible exploiting 125 billion devices interconnected with each other, changing once again the customer experience and their expectations. So the Internet of Everything will become the single space where physical and digital worlds are blended together.

According to the Boston Consulting Group report[9], it is expected that Internet of Things applications will be everywhere and affect all industries[10]. Examples of this can be found in several industry sectors. A good percentage of people is already wearing body sensors through what we call smart wearables, such as Fitbit and Apple watches, or the revolutionary Oura ring that celebrities are seen to sport, which are nothing less than smart watches, fitness trackers and similar, connected to each others, your smartphones and the cloud. A San Francisco-based company known as Adamant Technologies is currently developing a small processor that can digitalise smell and taste, thanks to roughly two thousands sensors that enable the processor to detect aromas and flavours (see for example https://slate.com/technology/2013/01/adamant-technologies-wants-to-give-your-smartphone-a-sense-of-smell.html).
Similarly, the IoT is changing the way we build our homes, using for example the AT&T Digital Life Smart Home products, such as smart thermostats (Lu et al., 2010), air sensors and kitchen, child monitoring and home security, that send data to the cloud through a M2X platform, available to millions of connected devices[11]. Another popular application of the Internet of Things is the self-driving - or autonomous - car (Brisbourne, 2014). We always look with interest at the latest model of Tesla or Waymo, the ex-Google car - or any other company joining in the race for the most secure self-driving car, for that matter. What we might not realise is that autonomous cars use sensors,

the same sensors normal cars have to assist us with parking for example. The main difference is that self-driving cars need a lot more sensors than what we currently have in commercial models, and the IoT will make it possible for such sensors to communicate among each others within the car, as well as with other sensors used in other vehicles, along the road and in general in smart cities. This approach is already successfully used in airline companies, which now are able to collect a huge amount of data. We are discussing 500 gigabytes of data per flight, using more than five thousands parameters from several sensors to check temperature, altitude and general performance data on the engines, which in turn have exponentially enhanced the reliability of such data. At the same time, we can see this approach also in oil rigs, where sensors can detect degradation and to provide visual recognition, which helps with preventive maintenance and inspection of equipment without the support of a human team. In more general terms, we can say that a vast network of sensors is a suitable solution to collect immediate feedback about changing conditions, whether these are related to temperature, climate, consumer behaviour or similar.

CONCLUSION

In this Chapter, we talked about the industrial revolutions that are part of our history, and discussed in particular the main characteristics of the Industry 4.0 and the Internet of Things. After highlighting the importance of connectivity, automation and augmentation of our physical reality in a digital one, we should take some time to start considering the challenges that businesses need to address. Data is one of the first that should come into mind. The authenticity, the truth or trustworthiness of the data that needs to be ascertained to be used, is paramount to the rise of artificial intelligence at its full. Managers, data scientists and any other interested in exploiting trends and parameters from data collected through connected sensors need to be ready to clean and filter it before they can use it efficiently. We will have the opportunity to see how this ‘cleaning’ mechanism works when we will approach artificial intelligence models from a practical perspective.

There is also customer’s expectation about the advancements in sensor technologies to take into account, especially in terms of lowering cost and further reduction in size, so that sensors can be embedded into various devices that are part of our daily life. New advancements in all industry sectors are expected to disrupt the way we live, we do business and we think about the future. While the wave of the Fourth Industrial Revolution is reaching its tipping point, managers and future businessmen alike are facing a challenge like never before.

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ENDNOTES

1 The PLC and the internet are the key technologies that drive the advancements in the Third Industrial Revolution. The PLC, or the programmable logic controller, is an industrial digital computer of a human interface and it is used to define control, diagnose, rectify problems in manufacturing processes. On the other end, the internet started as the ARPANET by the US Department of Defence back in 1969 to 1990.

2 According to Manyika and Chui, data shows an interesting trend related to automation in the industry. The Authors suggest to compare the three biggest companies in Detroit in 1990 with the three biggest companies in the Silicon Valley in 2014. This compering exercise will show that the latter had a higher market capitalisation, same revenues but ten times less employees (we are discussing 1.2 million employees versus 137,000). Manyika, J., & Chui, M. (2014). Digital Era Brings Hyperscale Challenges. *The Financial Times*, August 13.

3 An example of advanced nanomaterial can be the graphene, which is an excellent conductor of heath and electricity, as well as 200 hundred times

stronger than steel and thinner than a human hair by a million-times. It is almost impossible not to be impressed by such advancements, and the potentiality they bring with them. Now, the only downfall of it is the price, which is still far from competitive to be used commercially. You can read more about graphene in the following articles. Isaiah, D. (2015). Automotive Grade Graphene: the clock is ticking. *Automotive World*, August 26. Retrieved online at https://www.automotiveworld.com/articles/automotive-grade-graphene-clock-ticking/ Laslow, S. (2014). The Strongest, Most Expensive Material on Earth. *The Atlantic*, September 23. Retrieved online at https://www.theatlantic.com/technology/archive/2014/09/the-strongest-most-expensive-material-on-earth/380601/

4 According to Tom Goodwin, "Uber, the world's largest taxi company, owns no vehicles. Facebook, the world's most popular media owner, creates no content. Alibaba, the most valuable retailer, has no inventory. And Airbnb, the world's largest accommodation provider, owns no real estate." You can read more about Goodwin's take on the on-demand economy in his 2015 article. Goodwin, T. (2015). In the age of disintermediation the battle is all for the consumer interface. *TechCrunch*, March. See also Moazed, A. (2015). Five Things You Can Learn From One of Airbnb's Earliest Hustles. Inc. Retrieved online at https://www.inc.com/alex-moazed/cereal-obama-denver-the-recipe-these-airbnb-hustlers-used-to-launch-a-unicorn.html

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7 More information on AT&T projects on smart cities can be found online at https://www.business.att.com/solutions/Family/internet-of-things/smart-cities/.

8 Jenalea Howell quotes IHS Markit, saying that the number of connected IoT devices will surge to 125 billion by 2030. Howell, J. (2017). Number of Connected IoT Devices Will Surge to 125 Billion by 2030. *IHS Markit Press Release*, October 24. Retrieved online at https://technology.ihs.com/596542/number-of-connected-iot-devices-will-surge-to-125-billion-by-2030-ihs-markit-says IHS Markit (2017). *The Internet of Things: a movement, not a market.* Ebook. Retrieved online at https://cdn.ihs.com/www/pdf/IoT_ebook.pdf

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11 More information on AT&T home products can be found in the following links. AT&T Digital Life Home, retrieved online from https://my-digitallife.att.com/learn/home-security-and-automation AT&T M2X - How smart is your home, retrieved online at https://m2x.att.com/iot//industry-solutions/iot-data/smart-homes/

Chapter 2
The Power of Digital Transformation

ABSTRACT

In the previous chapter, the authors discussed the four industrial revolutions that are part of our economic history. Although each one of them had different innovations as driver, we can conclude that change—and the ability to sustain it—is what makes them successful. In this perspective, managers and leaders in general are required to embrace change and pursue it in the way they perceive strategy, goals, and innovative contribution. In this chapter, they discuss how to define digital transformation, the theories behind it, and more specifically, the kind of skills required to successfully master a digital transformation project. They also have the chance to interview a renowned professional in the field of digital transformation and see what experts suggest.

DIGITAL TRANSFORMATION: THE BASICS

According to IDC, digital transformation can be defined as "a continuous process by which enterprises adapt to or drive disruptive changes in their customers and markets (external ecosystem) by leveraging digital competencies to create new business models, products, and services"[1].

Therefore, we can say that digital transformation projects have at their core the enhancement of the customer experience, as well as lowering operational costs, through the integration of the physical and the digital realms of the

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business. New technologies are key enablers of this process, in particular the use of artificial intelligence to enhance business performance and efficiency, as well as prioritise customer experiences.

According to the experts (DeNisco Rayome, 2017), spending for digital transformation initiatives will hit $1.7 trillion globally by 2019, which will mean investments will rise up to 42% from 2017. This is in line with Gartner's position, who in 2015 surveyed CEOs and found they were expecting revenues coming from digital products, marketing and sales to double in 2017 the average 21% of 2014 (Raskino & Gartner, 2015).

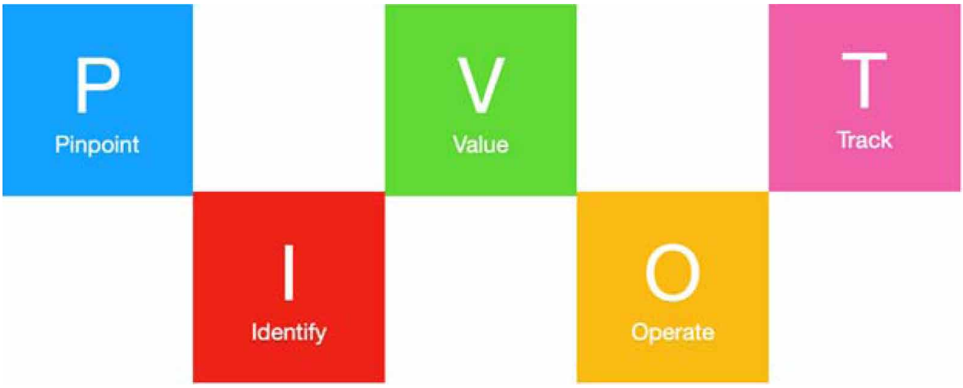
But how exactly does a digital transformation initiative work? The main objective here is to maximise the use of data, as created, collected and analysed in relation to customers and organisational operations in order to improve the processes. In order to achieve such goal, you must understand the business model you operate within, and avoid the perspective most use that digital transformation is only about using some technologies or develop an app[2]. The process is far more complex than this. Roger Liew perfectly summarised the feeling of confusion that pervades businessmen around the world when it comes to such topic. According to Liew, the modern environment "is brutally competitive. One of the challenges is that you don't know where the competitors are going to come from. In a fairly short span of time, Airbnb is on everybody's radar. The reason it's so competitive is because there's not a lot of switching costs for online customers. If you don't satisfy their demands today, it's fairly easy for them to switch to a competitor. That's what compels us to build something that is world class. If you stop focusing on that it puts you just a step behind" (as reported in Raskino & Gartner, 2015, p. 65). Similarly, Levy points out that "everyone is starting to worry about being 'Ubered'. It's the idea that you suddenly wake up to find your legacy business gone… clients have never been so confused or concerned about their brands or their business model" (Thompson, 2014).

Before going deeper into the practical aspects of the topic, it might be interesting to point out that digital disruption occurs at three level. First of all, there is a need for advancements in technology, without which most of the newest innovations will not be possible. The second level we need to take into account is culture, which we can here summarise as the people's ability to feel comfortable enough with the innovation to fully embrace it. Once people are ready for change, then the change needs to be implemented and go under regulation. We might as well provide an example to better understand these three levels, and as such we can mention the not so recent trend of buying clothes online. From a technological perspective, we needed Internet to make it work; then we needed women to feel comfortable enough to consider buying their clothes online, and finally we needed distance selling regulations to ensure the same consumer's rights as in traditional shopping methods, to make it convenient to switch from a brick-and-mortar shop to a digital one.

Thus, we can now conclude that digital transformation is linked to the concept of digital business[3], which simply refers to "the creation of new business designs by blurring the digital and physical worlds" (Raskino & Gartner, 2015). So first we needed the internet, that allowed businesses to have an online presence. Then businesses started to make their own electronic transactions (e-commerce), giving the way to different approaches to B2B (Business to Business) and B2C (Business to Customers). At this stage, digital marketing became the priority, with search engine advertising, social media, sharing and generally C2C (Customer to Customer) solutions. The digital business era is now complete thanks to the potentialities of the Internet of Things, and we will be moving towards autonomous business. How the advent of the IoT helped the digital business model? In 2012, Eric Babolat, CEO of the French tennis equipment company, invited the tennis world champion, Nadal, to test the company's 'Connect' racquet. The model was revolutionary because it captured data related to the player's forehands, backhands, smashes and serves, and sent this data to a tablet or smartphone. In order to achieve such amazing results, the racquet has been equipped with accelerometer and gyroscope sensors, a digital microprocessor, a battery and of course bluetooth wireless communication. Although it might seem impossible to believe, all of these materials do not change the way a player feels his racquet. The overall weight of the necessary equipment to collect the data is only 15 grams and are easily fit inside the handle. What is even more impressive, is that Babolat sells these racquets to everyone at a price that ranges from $300 to $400. But can they be legally used? The International Tennis Federation ruled in July 2013 that Babolat's racquets could be used during match play. This is a clear example of the successful blending of physical and digital realms to create innovation[4]. Another interesting example is Ford's experimental autonomous car that uses four LIDAR sensors to recreate a real-time 3D map of the car's surroundings[5].

How do these potentialities that modern technology brings affect digital transformation projects? Barry Libert and Meghan Beck, from AIMatters, have presented an interesting and integrated practical approach which should help organisations tackle digital transformation projects and AI-empowered changes in general (Libert, Beck & Wind, 2016). They suggest a five step model that can be used by any manager regardless of the sector and organisational position, to make sure a digital transformation project is completed and successful. In particular, the model, also known as PIVOT, consists of the following five steps. The first one is Pinpoint, which relies on the team's ability to find out and/or assess the starting business and mental models, both in relation to their company as well as the more general industry sector. In this phase, which can last typically from one day to a month, the team should gather information such as what the company sells, which market is targeting and how the business model can be compared with others in the same market. The next step considers Identify, which is none other than an exercise of taking a complete inventory of all company assets, meaning customers, partners, employees and of course all the data that relates to them. In this phase, it is important to remember that intangible assets (such as, for example, data related to sentiment or family links among customers and employees) are as valuable as majestic headquarters or any other physical asset. During the third step, managers should spend some time addressing Value, which is more of a planning phase to secure a technology platform where all the elements taken into account during the Identify step come to coexist and collaborate. Thus, at this stage, managers and their team should concentrate on envisioning the business as a digital network, where all aspects are interconnected through a digital platform, for a centralised experience. Once the team has conceptualised what they aim to achieve, it is time for step four, Operate. In this hands-on step, resources need to be invested in the new digital business model, in the form of time, talent and/or money, to prepare a pilot to test the concept in the digital world. Adjustments to the digital business model can then be made, and new ideas may arise during the test phase. Finally, managers are required to Track on the new model, adding KPIs to the standard financial performance, in order to measure interactions (whether these might be sales or other), employee engagement with the new platform and a sentiment analysis towards it; or things like how many products or services were created by customers, and how successful they are, in terms of creation of value and revenues.

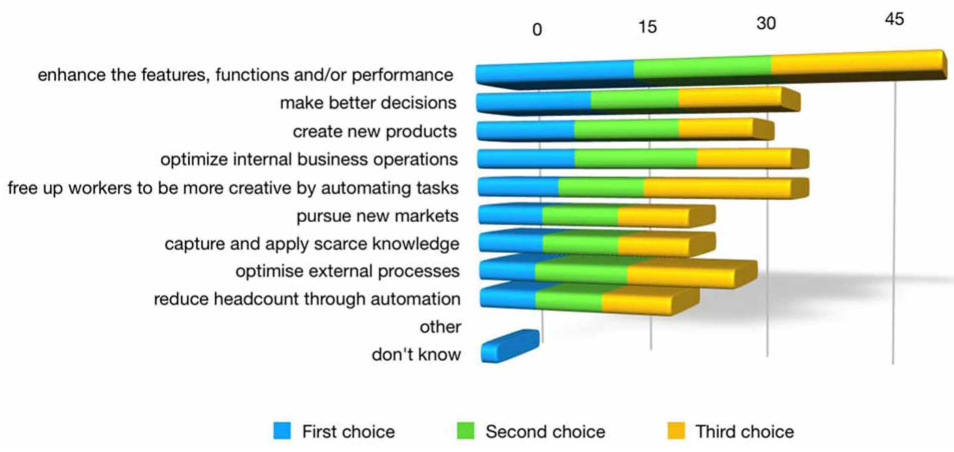
Figure 1. The PIVOT framework



The Digital Business Model

We have already highlighted how understanding the business model is paramount to define a successful digital transformation. As an example, we introduced the PIVOT framework, as a tool that can guide managers and leaders in delivering successful digital transformation projects. According to Deloitte (2017), managers are interested in AI-related projects - which can be inserted in a broader digital business model definition - for reasons different from what we may think. When we say business model, we refer to a set of activities for creating and capturing value, using resources to generate, deliver and bank on new products and services, offered to customers in new ways (among others, refer to Amit & Zott, 2001; Baden-Fuller & Morgan, 2010; Johnson, Christensen & Kagermann, 2008; Magretta, 2002; Massa, Tucci & Afuah,2017; Timmers, 1998; Teece, 2010; Zott & Amit, 2010). Now, Deloitte (2017) surveyed 250 “cognitive-aware” leaders within “cognitive-aware” companies, to better understand from these early adopters “what objectives they had for cognitive and AI technologies, how much they were spending on them, what benefits they have already achieved, and what challenges they have already encountered [. . .] their attitudes toward the technologies, and their feelings about the prospects of job loss from automation.” (p. 2). Looking at the survey results, we can appreciate that the three reasons indicated as first choice by managers for their use of AI-related business models are to “enhance the features, functions and/or performance of our products and services” (19%), to “make better decisions” (14%), and to “create new products” (12%).

Figure 2. Reasons to deploy AI-related business models
(Source: adapted from Deloitte's 2017 State of Cognitive Survey)



In this perspective, we can agree on the importance of network effects and multisided platforms[6] as core elements of a business model. This approach seems to be shared among companies such as Apple, Google, Uber, Airbnb, CNN, Alibaba, Microsoft, and Facebook[7], where the product or service offered become more valuable the more people use it (McIntyre & Srinivasan, 2017).

Before moving into deciding when a new product, service or technology is bound to be disruptive, we will need to define what is innovation. Peter Drucker (1985) states that "Innovation is the specific function of entrepreneurship. [. . .] It is the means by which the entrepreneur either creates new wealth-producing resources or endows existing resources with enhanced potential for creating wealth" (p. 20). Such concept can be then converted in something more practical, using the words of O'Sullivan and Dooley (2009), who see innovation as "the process of making changes, large and small, radical and incremental, to products, processes, and services that results in the introduction of something new for the organization that adds value to customers and contributes to the knowledge store of the organization." In such perspective, we can argue that innovating entitles transforming ideas into outputs, which are usually related to products, services and processes. In particular, these may be marketable products, whether these are physical objects, processes to make these products, services to deliver them or services for intangible products.

Businesses rarely come up with innovations in the true sense of the word, meaning a product, service or process that is novel and untried. More often, we come across extensions of an established product, which consist of proposing a different use for it; or a duplication of the same item, with a different creative touch that gives the company a chance to beat the competition. Finally, entrepreneurs might try the way of synthesising existing concepts into a new application.

Now we should have a better understanding of how new products should look like. Thus our next step would be looking into the reasons behind a new product, service or technology is regarded as to disrupt the market. Dr. Hwang refers to the theoretical background we discussed in the previous section, to present a model where technology (whether its existence, or its usage rate), regulation and culture are tipping points to assess whether a business is in the premature period (in which failure of a new innovation is probable) or in the mature period of success. It is not as easy as you might think to make an innovation take off. The fact that you have a great idea does not mean by default that it will also be successful. Think for example at Google's Glass augmented-reality eyewear, that was sold in 2013 and retired from the market in 2014 after the public complained about battery life, bugs and privacy. Google is a very well-known company, so why did its glasses not work out? We were simply not ready. This is also proved by the circumstance that, regardless of its failure, Google is still working on this project, in collaboration with Luxottica - whose Oakley brand sells augmented-reality ski goggles Airwave that are connected to smartphones. Another example related to the importance of culture is offered by the UK's GDS initiative (where GDS stands for Government Digital Service), lead by Mike Bracken under a political favour when people demanded for a better and quicker service in 2010, which was pushed on at the time after internet use had previously reached a tipping point in 2006.

Dr. Hwang did not theorised anything new. In fact, we can backdate the efforts of predicting when new products are likely to disrupt the market to 1986, when McKinsey's Dr. Richard Foster presented his work on S-Curves (Foster, 1986; Foster & Kaplan, 2001), even though we have to wait until 1991 to benefit from the more famous disruptive innovation model, as presented by Professor Clayton Christensen (1996, 1997). In the disruptive innovation model, we see incumbents presenting a new product in a mainstream market, which is where established products can be found. In order to be disruptive, the new product will need to present certain characteristics, which can be summarised as follows. The new product will need to cost less than established products serving the established market. It will also need to address a new market and perform worse than the established products, although its performance keeps improving. Strangely enough, according to Christensen, if the answer to all three questions is yes, then the new product is highly likely to be disruptive. At the same time, each company must understand if, after this exercise, the new product is bound to be disruptive only in the market, or it will be disruptive also for the company itself. In order to establish if the company's established products are susceptible to be replaced by disruptive innovations[8], there are specific characteristics managers should look for. In the first instance, the established product should have a performance that is higher than what the market expects, and for which customers are expected to pay a great deal of money. At the same time, when switching costs are found to be low, it is easier for the new product to substitute the established one.

Another interesting theoretical model is the so called Teece model, which gives managers the chance to analyse when a new innovation can disrupt the market, taking into account whether it can be easily imitated and at what extent, complimentary assets used to commercialised the invention are scarce and important. It might be not difficult to believe that in case an invention is easy to replicate and does not require important nor difficult to find complimentary assets, then it will not be able to make money out of it in the long term - or any at all, for that matter, considering that everybody will try to copy the idea. When the product is easy to imitate but complimentary assets are scarce and important, who owns such assets will make money.

The Digital Transformation Experience and Technology

One of the first questions managers should ask themselves before planning to implement a digital transformation initiative in their organisation, is the following: are we ready for it? It is not only about the cultural environment we are navigating, even though this is of the outmost importance. Sometimes managers forget to consider if their company is technology ready for the change. Without getting too technical, we can affirm that an organisation needs to transform its network and architecture in order to facilitate digital transformation, making sure its structure is capable of handling new digital processes and intensive workflows of data in a flexible and secure way.

Organisational locations can now connect to regional networks using fixed or wireless access, which will host local and regional data centres with network functions; while the core network will provide high-speed transport, and at the same time will host for large private and third-party clouds. If we are looking for a practical example, all datacenter solution providers (among others, Cisco, Aruba and HP) are powerful enough to use AI and related tools such as machine learning, to improve reliability of their services, while enhancing the proportion of cost and effectiveness. Companies that do not operate as datacenter can benefit from their services, to combine organisation-collected private data and network-collected data, which will give a clearer understanding of the trends within the organisation.

These solutions are possible thanks to the cloud and the virtualisation of physical tools (see for example Donovan & Prabhu, 2017), as well as the impressive developments in artificial intelligence and related technologies (among others, machine learning, deep learning, and chatbots), that allow us to easily collect and integrate a huge amount of data across several software components. One of the most recognisable and popular tool is the so called LAN network (which stands for Local Area Network), which is what creates the connectivity to end-users and/or the devices where data is created and consumed.

Once the organisational network structure is created and is fully functional, managers should concentrate on what they want to achieve with their digital transformation project. This passage will help them realise which tech tools might be better suited for the company, and which customer strategy can deliver the best results. In particular, we should consider how our customers are willing to interact and engage with the company, whether this can be achieved through the mobile, web, phone, or kiosks. Some organisations are far more advanced of others in their use of artificial intelligence technologies to gather customers' data related to, for example, how they give feedback (this may be linked to the keywords they use, the tone of their speech, or the sentiments they express). Interestingly, nowadays a large number of companies are switching from the customer care call centre we were all used to contact, to a chatbot service, which is nothing more than an automated system trained by experts to come up with very specific responses to customer complaints and issues. Chatbots should be able to formulate clear responses based on natural language questions, and can be embedded in mobile phone chats, Facebook messenger, website chats and so on - think for example at Telco chatbot, which is trained to check-in at a hotel, close a window in a car, provide information about train tables and much more. Because chatbots are meant to work alongside humans, not to steal their job, they are usually used to respond to customer's queries and if they are not trained to reply to a specific question, they will then pass along the query to a human.

Another great tool we can use to enhance the customer experience, is the voice interface. Each one of us has at least being part of a phone call where we were asked to press multiple number options, or reply via voice to be put in contact with the right department. Now, artificial intelligence tools are trained to understand the context and the intent behind our words and speech construction, as it happens at Verizon, where a system transcribes incoming calls, identifies the intent behind it and categorises accordingly the call in real time, to enhance the effectiveness of their customer centre. A more advanced use of AI functionalities allows us to reply to customers' queries using text-to-speech or speech synthesis technologies to speak with them. Furthermore, the customer experience is central to each business and its longevity. In this perspective, AI-trained systems are fundamental to analyse customers' emotions on the spot[9].

Whichever tech tool we might identify as the best one to answer our organisational needs, we have to recognise we live in a world that is over-connected. Modern disruptive technologies (you may think of mobile computing and virtual reality, to cite a few) are designed to create large-scale networks between people, computers and physical objects. This can be seen in the large use of virtual teams (Gilson, Maynard, Young, Vartiainen, & Hakonen, 2015), as well as smart working solutions[10]. In particular, employees can connect to their workplace using mobile devices and cloud services, which might be extremely convenient in terms of mobility (see for example Serban et al., 2015, in relation to leaders' new skills to cope with employees working from home or remotely) and knowledge sharing (Oldham & Da Silva, 2015; Pfeffer, 2013), but it deeply affects the work-life balance (Mazmanian, 2013). It appears evident technological advancements have changed the way we interact with customers, colleagues, and people in general, demonstrating the importance of new leadership skills and behaviours to accommodate different needs. While managers - or leaders - can count on augmented decision making capabilities thanks to AI-supported analysis of big data (Van Knippenberg, Dahlander, Haas, & George, 2015) rather than their own experience and intuition (McAfee & Brynjolfsson, 2012), humans will be assisted by technologies in performing their tasks (see, for example, Bresnahan, Brynjolfsson, & Hitt, 2000; Campion, Campion, Camion & Reider, 2016; Orlikowski & Robey, 1991; Shim, Warkentin, Courtney, Power, Sharda, & Carlsson, 2002). We have already seen how chatbots are used alongside human customer call centre operators, and we will discuss the future of jobs by the hand of artificial intelligence and new technologies at the end of this book[11]. In this perspective, we can say that companies try intensely to hire and retain talent, or they 'acqui-hire', which means they buy a company to acquire their talents as well as their products and customers.

The Innovator's Skills

Being an innovator is something the most acclaimed companies aspire to be, to imitate giants as Apple, Google, Samsung and Amazon, which have adopted an organisation-wide commitment towards corporate innovative strategy[12]. Well established organisations are finally realising how important it is to go back to their corporate strategy, now that they are intensively competing with start-ups. This means they are investing in development activities to encourage managers' innovative thinking (for example through corporate innovation training programs, such as that described in Kuratko, Covin, & Hornsby, 2014), as well as changing the work environment to better suit their modern needs.

Using this perspective, change management initiatives need to be taken into account, when they are a result of changing technologies rather than the use of different management styles. It is important here to highlight that there are several types of organisation, and several types of management as well. In the case of bottom-up management for example, we can cite kaizen and lean management styles. Kaizen (from the Japanese "change for the better") states that no actual status of processes or organisations is good enough to be kept as it is, which in turn requires continuous improvement of all organisational functions as well as all employees, from assembly line workers to top managers. On the other end, lean management is used in customer-oriented companies that value all stakeholders, from suppliers to customers, to employees. In this sense, using tools such as constant feedback and ownership, a lean organisation tries to balance the advances of batch-producing organisations (which consist of speed and low unit cost) with the benefits of a customer-oriented organisation (also known as quality, high flexibility and customisation). Although it is not the intent of this Chapter to review change management styles and models[13], it is important managers keep in mind the aftermath of change within the organisation.

When dealing with innovation, modern managers and leaders are required a great deal of skills. Among them, we can definitely count creativity and design thinking. While the word creativity[14] seems to be surrounded by a halo of scepticism when linked to important skills for managers to have, "Creativity occurs when a person, using the systems of a given domain such as music, engineering, business, or mathematics, has a new idea or sees a new pattern, and when this novelty is selected by the appropriate field for inclusion into the relevant domain." (Csikszentmihalyi, 1996). In this perspective, "a person isn't creative in general—you can't just say a person is "creative." You have to say a person is creative in X, whether it's writing, being a teacher, or running an organization. People are creative in something [...]. People who are creative are always thinking about the domains in which they work. They're always tinkering. They're always saying, "What makes sense here, what doesn't make sense?" And if it doesn't make sense, "Can I do something about it?" (Gardner, as quoted in Goleman, Kaufman & Ray, 1993, p. 26). Furthermore, it should appear more clear now that creativity does not entitle the ability to draw or paint like Michelangelo, nor it involves complicated arts and crafts projects. Being creative has more to do with the opportunity to think outside the box, to see processes and patterns that are not defined, is to believe that everything is possible and there might be more than one answer to even the most logical approach or theory. Using E. Paul Torrance's words, "creativity defies precise definition. This conclusion does not bother me at all. In fact, I am quite happy with it. Creativity is almost infinite. It involves every sense—sight, smell, hearing, feeling, taste, and even perhaps the extrasensory. Much of it is unseen, nonverbal, and unconscious. Therefore, even if we had a precise conception of creativity, I am certain we would have difficulty putting it into words. However, if we are to study it scientifically, we must have some approximate definition." (Torrance, 1998).

Creativity alone cannot form the modern manager. Someone once compared the melting pot of skills leaders need to cooking a stew[15]. Among them, design thinking is crucial. We should define design as the process that allows us to shape an idea into something real that others can understand and embrace, and which can be observed and manipulated (this might be a process, a product, a business model, or something different). As described in this way, design seems to be something magical, and once again too creative and out of reach for managers. However, this is not the case, or at least it shouldn't be. Design thinking enhances the individual's ability to accept that there are constraints to the way we live, think and act, as well as we design a product. Choices around the way we want it to look and feel, or the materials to use, or which features to introduce, are examples of the constraints designers - and managers - face everyday. Design thinking skills also rely on the logical process of determining which solution is the optimal one, while balancing it out with the creativity inspiration and the flexibility of the targeted market. Again, design thinkers have to cope well and embrace failure, as well as not get frustrated when the process needs several iteration steps, to finally reach the final product.

According to Nicola Rosa, a leading expert in extended reality from Accenture, "Digital transformation is an iterative innovation process, it's not a one-off event. I like to think about digital transformation like a form of art. Art is never finished, it's always evolving. Digital transformation is the art of innovating to create better processes and services, to increase the customer satisfaction, to reduce production cost, to increase employee's satisfaction which is extremely important as well, and to create new streams of business. Usually this kind of digital transformation is directly related to not only the iterative innovation that we were talking about before, but also to the creation of ecosystems from one or more points of the value chain. How can you create something that will enable customers to enter in any of those entry points? To expand your customer base, using the other elements of your ecosystem of services? This is what Apple has been doing in the past 15 years, differentiating their products, their offerings and creating an ecosystem. You have a service to download and stream music and movies, you have the iPhone which is a product, and you have the AppStore which is a software platform, and you have the MacBook which again is a hardware product, and you can use them more or less separately but at the end of the day they form an ecosystem. Whenever you are hooked with one of those products, for example you really like streaming from Apple Music or maybe you really like Macs laptops, once you are using any of those products you are hooked and gently pushed towards using the other products of this ecosystem. There are many companies right now going towards the same kind of approach, creating ecosystems of products and services rather than a single product or multiple parallel product offering."[16].

CONCLUSION

In this Chapter, we have discussed the basics of a digital transformation initiative, what managers need in order to be successful in their new digital business model, and which skills will be fundamental for the new manager. If there is something to remember about this Chapter, is probably the underlying principle according to which digital transformation is not about the use of a specific technology. On the contrary, it is more about an interconnected approach among employees, customers, suppliers and similar, through a digital platform that connects them and their data, in order to create an engaging and comprehensive customer experience. The role of AI and technology in general is changing the traditional business model (think for example at

Facebook and Uber), as well as the skills managers are required to master in order to lead successful digital projects.

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ENDNOTES

1 IDC is a research company that offers insights on the digital and technological landscape to businessmen. Their IDC MaturityScape: Digital Transformation (DX) tool, "provides a view of the breadth of business and IT management issues that encompass the challenge facing leaders who hope to transform how their enterprises leverage digital technologies for competitive advantage. According to the new report, IDC believes that enterprises will either become adept at digital transformation and thrive or fail to master the disciplines and struggle to survive. Moreover, IDC asserts that business leaders need to master not only the disciplines but also the alchemy of combining and managing their interactions to create digital gold". See more at https://www.idc.com/downloads/DX_UBER.pdf and https://www.idc.com/getdoc.jsp?containerId=US43220117.

2 An important aspect of a successful digital transformation has to do with businesses being equipped with a specific network architecture, where data and data-driven decision-making are at the core of the business processes and operations. Network functions that usually sit in the company's location are now virtualised, with only "white boxes" left in the physical place. These can be defined as commodity hardwares - also known as UCPEs, or Universal Customer Premises Equipment - used to host virtual applications, such as routers, firewalls, IoT gateways and AI functions.

3 Gartner defines digital as "signal transmission that conveys information through a series of coded pulses representing 1s and 0s (binary code)" (from https://www.gartner.com/it-glossary/digital), even though from a business perspective it is better a broader definition (see https://www.gartner.com/imagesrv/research/iot/pdf/iot-275309.pdf).

4 When discussing innovation, we are referring to a process, as well as an outcome based on change. Using Donald Marquis' words, "when an enterprise produces a good or service or uses a method or input that is new to it, it makes a technical change. The first enterprise to make a given technical change is an innovator. […] Another enterprise making the same technical change is presumably an imitator. […] Thus, an innovation can be thought of as the unit of technical change." See Marquis, D. (1972). Innovation. In E. Mansfield (Ed.), *Research and Innovation in the Modern Corporation*. New York, NY: Norton.

5 The LIDAR is a laser remote sensing system that scans the direct environment of the car up to sixty meters and from a 360° perspective. While scanning this portion of environment, it produces a 3D map of the surroundings, which in turn allows the car to be located, and the driver is made aware of road signs as well as obstacles along the route. This level of detailed data can be collected also through motion sensors integrated in the front and rear bumpers, so that information like the speed of cars behind or in front can be calculated to understand if the car needs to accelerate or slow down. On top of that, there is a camera placed by the interior rear-view mirror, to get data related to traffic lights, traffic signs and eventually, cyclists and pedestrians. To summarise, the LIDARs work in conjunction with the sensors and cameras to transmit data to a central system, which is independent. So, if you are wondering how an autonomous car works, the driver of a full autonomous one will just need to give a voice command to the car with a destination to reach, and enjoy the ride while the car assesses what to do and takes control of the car's steering wheel, accelerator and brakes. See for example Urmson, C. (2015). How a Driverless Car Sees the Road. *TED Talk*, June. Retrieved online at https://www.ted.com/talks/chris_urmson_how_a_driverless_car_sees_the_road?language=en [Accessed May 30, 2019].

6 A multisided platform is a technology, product or services that allows two or more groups of users with distinctive functions, to interact with each other. See McIntyre, D. P., & Srinivasan, A. (2017). Networks, platforms, and strategy: Emerging views and next steps. *Strategic Management Journal*, 38(1), 141–160. Parker, G. G., & Van Alstyne, M. W. (2005). Two-sided network effects: A theory of information product design. *Management Science*, 51(10), 1494–1504.

7 In 2018, data showed more than 60% of the world's most valuable companies were depending on network effects and/or multisided platforms to engage their customers.

8 There are several managerial and organisational approaches to innovation. Among them, an interesting one is the so called 'closed approach', whose aim is to generate new business breakthroughs using fully the people, knowledge, and technology the company has. In order to reach its objectives, the organisation is required to follow a simple list of rules, which entitle to hire the best and brightest people; be attentive of make discoveries in secret; go big on marketing, using the launch events as a platform to generate curiosity; be ready to invest great amounts in R&D, in order to ensure that your company generates the best ideas and stays

ahead of the competition; and finally, have a tight control of intellectual property. This and other approaches to innovation can be found in the following readings. Chesbrough, H. (2003). *Open Innovation: The New Imperative for Creating and Profiting from Technology*. Boston, MA: Harvard Business School Press. Laffley, A.G. & Charan, R. (2008). *The Game-Changer: How You Can Drive Revenue and Profit Growth with Innovation*. New York, NY: Crown Business. Sawyer, K. (2007). *Group Genius: The Creative Power of Collaboration*. New York, NY: Basic Books.

9 An example of this feature can be found in Watson Tone Analyser, a pre-trained service that can distinguish the tone used by a customer in their spoken or written language.

10 Technological innovations are bound to change the way we work. See, for example the followings. Barley, S. R. (2015). Why the internet makes buying a car less loathsome: How technologies change role relations. *Academy of Management Discoveries*, 1, 5-35. Colbert, A., Yee, N., & George, G. (2016). The digital workforce and the workplace of the Future. *Academy of Management Journal*, 59, 731-739. Haas, M. R., Criscuolo, P., & George, G. (2015). Which problems to solve? Online knowledge sharing and attention allocation in organizations. *Academy of Management Journal*, 58, 680-711. Parker, S. K., Wall, T. D., & Cordery, J. L. (2001). Future work design research and practice: Towards an elaborated model of work design. *Journal of Occupational and Organizational Psychology*, 74, 413-440.

11 We can pre-announce that a good majority of researchers and practitioners convened that middle-skilled jobs such as accountants and bank cashiers, would be the first ones to be automated (Autor, Katz, & Kearney, 2006; Bresnahan, 1999), together with white-collar workers (Frey & Osborne, 2017). On the other end, skilled employees will become more important (Brynjolfsson & Hitt, 2000), and this is linked to a series of new required competencies such as problem solving (Parker et al., 2001), social skills (see among others, Cascio & Montealegre, 2016; Frey & Osborne, 2017), quick decision making (Perlow, Okhuysen, & Repenning, 2002), creativity (Frenkel, Korczynski, Donoghue, & Shire, 1995), and an efficient use of large amounts of information (Van Knippenberg et al., 2015). For further references, see the following literature. Autor, D. H., Katz, H. L., & Kearney, M. S. (2006). The polarization of the U.S. labor market. *American Economic Review*, 95, 189-194. Bresnahan, T. F. (1999). Computerization and wage dispersion: An analytical

reinterpretation. *Economic Journal*, 109, 390-415. Brynjolfsson, E., & Hitt, L. (2000). Beyond computation: Information technology, organizational transformation and business performance. *Journal of Economic Perspectives*, 14, 23-48. Cascio, W. F., & Montealegre, R. (2016). How technology is changing work and organizations. *Annual Review of Organizational Psychology and Organizational Behavior*, 3, 349-375. Frenkel, S., Korczynski, M., Donoghue, L., & Shire, K. (1995). Re-constituting work: Trends towards knowledge work and info-normative control. *Work, Employment and Society*, 9, 773-796. Frey, C. B., & Osborne, M. A. (2017). The future of employment: How susceptible are jobs to computerization? T*echnological Forecasting and Social Change*, 114, 254-280. Parker, S. K., Wall, T. D., & Cordery, J. L. (2001). Future work design research and practice: Towards an elaborated model of work design. *Journal of Occupational and Organizational Psychology*, 74, 413-440. Perlow, L. A., Okhuysen, G. A., & Repenning, N. P. (2002). The speed trap: Exploring the relationship between decision making and temporal context. *Academy of Management Journal*, 45, 931-955. Van Knippenberg, D., Dahlander, L., Haas, M. R., & George, G. (2015). Information, attention, and decision making. *Academy of Management Journal*, 58, 649-657.

12 According to Ireland, Covin, and Kuratko, a corporate entrepreneurial (innovative) strategy is "a vision-directed, organization-wide reliance on entrepreneurial behavior that purposefully and continuously rejuvenates the organization and shapes the scope of its operations through the recognition and exploitation of entrepreneurial opportunity." See Ireland, R. D., Covin, J. G., & Kuratko, D. F. (2009). Conceptualizing corporate entrepreneurship strategy. *Entrepreneurship Theory and Practice*, 33(1), 19–46.

13 Among the noteworthy theories in change management, we can mention the three-stage model of change as proposed by Lewin, also known as the unfreezing-change- refreeze model which is based on the idea that prior learning needs to be rejected and replaced. Furthermore, we can mention Chin and Benne's "Effecting Changes in Human System" (1969) and Havelock (1973). These models either propose an empirical-rational approach, according to which if a proposed change is considered 'good' by the individual, it is likely to be implemented; or a power-coercive approach, which makes leverage on the power legislation and other actors may have (think for example at moral or political sanctions). A third approach, also known as the normative-re-educative approach,

is proposed, in which the individual is actively searching for ways to satisfy their own needs and interests, which in turn prompt a change. Another interesting theory is the one presented by Bullock and Batten, which uses the four phases of planned change as it occurs in project management. These phases are exploration, planning, action, and integration. Also, Beckhard and Harris propose the change formula, which is a mathematical representation of the change process. This states that, in order for change to occur, the dissatisfaction of the status quo (D), the desirability of the vision of change (V) as well as the practicality of it (F) need to outweigh the resistance (R) to the change itself. The basic notion is that, for change to occur, the costs of change must be outweighed by dissatisfaction with the status quo, the desirability of the proposed change, and the practicality of the change. In other words, $(D \times V \times F) > R$. It goes by itself that if any variable is zero or near zero, there is no chance to overcome the resistance to change. Finally, the 7-S Model proposed by McKinsey & Company's consultants in the late 1970s (Waterman Jr & Peters, 1980) is based on the belief managers have to address several variables that impact change all at the same time. For further readings, refer to the following literature. Beckhard, R., & Harris, R. T. (1987). *Organizational Transitions: Managing Complex Change: Understanding Complex Change.* Boston, MA: Addison-Wesley Series on Organization Development. Bennis, W. G., Benne, K. D., & Chin, R. (1969). *The Planning of Change* (2nd Edition). New York, NY: Holt, Rinehart and Winston. Havelock, R. G. (1973). *The Change Agent's Guide to Innovation in Education*. Educational Technology Publications. Waterman Jr, R. H., & Peters, T. (1980). *In Search Of Excellence: Lessons from America's Best-Run Companies.* New York, NY: Harper & Row.

14 Creativity is a not a state, it is a process that can be developed and improved, following four phases. During the first phase, there is a preparation period of investigation and information-gathering, also in fields different to the one directly involved. While the second phase - or incubation process - is more static and dictates to get away from the project for a while to allow the subconscious to do its part; the third phase revolves around the discovery of the idea. The last phase considers evaluation and implementation of the idea itself, through activities like prototyping and similar. See de Bono, E. (1992). *Serious Creativity: Using the Power of Creativity to Create New Ideas.* New York, NY: HarperBusiness.

15 According to Teresa Amabile, managers need to focus on domain skills, creative thinking skills and intrinsic motivation. In her own words, "the essential ingredient, something like vegetables or the meat in a stew, is expertise in a specific area: domain skills. These skills represent your basic mastery of a field . . . Creative thinking skills are like spices and herbs you use to bring out the flavor of the basic ingredients in a stew. They make the flavors unique, help the basic ingredients to blend and bring out something different . . . Finally, the element that really cooks the creative stew is passion. Creativity begins to cook when people are motivated by the pure enjoyment of what they are doing." (Amabile, as quoted in Goleman, Kaufman & Ray, 1993). In this perspective, we can define intrinsic motivation as being passionate about what you do, and who you do it with, among other things. Within the domain skills leaders have, divergent thinking might be the least explored in business, considering it is fundamentally linked to the ability of generating as many possible options, without being limited or biased from past experiences and/or prior knowledge. This approach does not entitle a flight of fancy, where managers are allowed big ideas and no constraints in making them become true. Disney is a good example of the discipline linked to one of these famous approaches - also known as blue sky thinking, which can be summarised in the following words. "Get a good idea, and stay with it. Dog it, and work at it until it's done, and done right." (Walt Disney, as quoted in Smith, 2001). Goleman, D., Kaufman, P., & Ray, M. (1993). *The Creative Spirit*. New York, NY: Plume. Smith, D. (2001). *The Quotable Walt Disney*. New York, NY: Disney.

16 Nicola "Nick" Rosa is Leading the Extended Reality team in Accenture Europe, as well as the Head for Immersive Learning for Accenture Global. Twitter: @nicolarosa LinkedIn: http://bit.ly/nicolarosa

Chapter 3
Computing, Data Science and Other Skills For Managers

ABSTRACT

Managers are required to have different skills and mindset in order to be successful nowadays. Business schools around the world contributed to the standardisation of knowledge and practices in the managerial environment, with MBA programmes being a must in every leader's curriculum. However, times are changing rapidly, and traditional knowledge around accounting or strategy models and tools need to be updated to consider the innovation brought in by technology. Concepts related to data, such as data science and big data, have intrigued a huge number of people around the world. Numbers are said to be an extensive source of knowledge, invaluable to those who want to improve processes, experiences, and efficiency in general. In this chapter, the authors discuss the new skills managers should learn to try have a better understanding of the subjects, fields, or abilities recruiters are looking for. Thus, we should still read this required expertise in conjunction with other soft skills linked to emotional intelligence and leadership techniques.

Computational Thinking or Being Logical

You might have heard of the phrase "computational thinking" in one of the fancy conventions for entrepreneurs and start-ups, maybe. Well, computational thinking defines the art of thinking computationally, or logically, in a way that each problem can be defined as a series of steps, with an input that generates

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an output through the use of algorithms for example[2]. When trying to figure out how computers work, we need to remind ourselves we are dealing with the binary system, rather than in scale 10. Computers understand 0 and 1 in a specific series. So for example, we have learned in school that we can separate numbers in units, tens, hundreds and so on, which means that we have 100 first (10 to the 2), then 10 (10 to the 1), and finally 1 (10 to the 0). Furthermore, if we use the binary system, we will have 4 (2 to the 2), then 2 (2 to the 1), and 1 (2 to the 0). If we wanted more numbers, we could move on after 4 to 8 (2 to the 3), 16 (2 to the 4), 32 (2 to the 5), and we could keep going. It seems easy enough, thus we will try to calculate how a computer would understand number 1. Using three digits, the number 1 will be written as 001 in the binary code, where the first 0 from the left equals to 4 times 0, the one in the middle is calculated as 2 times 0, and 1 is the result of 1 times 1. If that is correct, number 2 will be represented as 010 (4 times 0, plus 2 times 1, and 1 times 0). Number 3 will become 011 (again, 4 times 0, plus 2 times 1, plus 1 times 1). If we keep going on with this system and three digits, we can reach number 7 as a maximum, which will be represented as 111. How can we move on and write number 8? We will need to add another value, so that the computer reads 1000 (8 times 1, plus 4 times 0, plus 2 times 0, plus 1 times 0) and so on. Because the binary system implies the use of only two states (0 and 1), we can conventionally say that 0 corresponds to a switched off situation, while 1 represents a switched-on state. A very clear example of this concept can be found in lightbulbs or lamps, when our 0 will correspond to no light, and 1 to having light turned on in the room. Such switches are better known as transistors inside a computer's CPU (central processing unit).

Now that we should roughly understand how convert numbers using the binary code, what about letters? Surely we do use an absurd amount of letters everyday when we compute, whether it is with our laptop or through other means. So, what does the letter A corresponds to? Following the Unicode

Table 1. Example of numbers in binary code

			Binary				
		…	**16**	**8**	**4**	**2**	**1**
Example 1	**6**				1	1	0
Example 2	**12**			1	1	0	0
Example 3	**18**		1	0	0	1	0
Example 4	**25**		1	1	0	0	1

or ASCII - also known as the American Standard Code for Information Interchange - our letter A will correspond to the decimal number 65, which will then need to be converted in the binary 01000001. In other words, if I want to say “Hi Sara!”, my computer will need to receive the following binary string:

```
01001000 01101001 01010011 01100001 01110010 01100001 00100001
```

You should be aware that you can add as many zeros you want from the left, and the code will not be affected.

Ok, so that was for numbers and letters. What about images? When we log in our Facebook account, or we add a picture to an email, the computer needs to translate that image in a binary code it can understand. In this case, the range we can use goes between 0 and 255, which represent the amount of red, green and blue of each pixel in the image. The binary code will be able to describe up to 256 when using a trio of eight bits in different combinations of 0s and 1s. Therefore, in a graphic program, the number 85 can be represented as a medium amount of red, a medium amount of green and not too much blue, because 85 is way below half of 256, that will then result in a murky yellow.

Although these examples might be very interesting, we cannot expect everyone to start programming in binary code, and for so many basic things like each colour of an image, or a simple phrase. Computer scientists, programmers, engineers and the like do prepare this background information for those who are not skilled enough - or do not want to waste such a tremendous amount of time every time they encounter a basic function - in what is also known as library, which contains the most basic of instructions to reuse whenever we need them. Because computers, smartphones and similar have what we call RAM - their internal memory, which can nowadays consist of billions of bites - our device will contain tons of information and the way we can retrieve it is fascinating. If we think that our RAM gives us 4 gigabytes of space, we can easily assume that we have roughly four billions of bites at our disposal. Thus, how do we access them? If the information we want to retrieve is stored at byte number 1,002,345 rather than at number 76, would that mean that we have to add several steps the farther away we get from the first byte? Fortunately, this is not the case. Computing storage does not work in a linear way, so the position of the byte we are interesting in does not really count. We use what experts call a "load" function, where we ask the computer to load a specific byte or set of bytes from memory, and that will appear to us in a so called register, regardless of their numerical position.

Furthermore, we might want to investigate what happens when computers need to gather information from outside, let's say for example from the Internet. In this perspective, computers use protocols such as IP, DHC, DNS and so on, to intercommunicate with other computers or computer programmes, to get data from one place to another. Think for example at what happens when you log in to your Facebook account. You type www.facebook.com, which is your input, and you get your personal page on screen as output. But how did my computer know where to gather my data? My computer or smartphone will send a message to Facebook's servers via Internet once it is connected to a wi-fi or to the ethernet through a wired cable in the room, using a protocol known as DHCP - Dynamic Host Configuration Protocol. Once logged, you can type in what you want to search, and the computer will give you an IP address, which corresponds to a physical address in the computing world, in form of numbers dot numbers dot numbers dot numbers. You would not need to know the IP address of each website you want to visit, luckily your computer will automatically use a DNS protocol to transform what you type into the right numbers that are associated with the IP address you wanted. At that point, the IP address will communicate with the Internet my request, making sure that the data I am looking for gets from point A (my typing Facebook) to point B (accessing my Facebook personal page) using routers or gateways[3] to adopt a TCP protocol to send such data reliably, so to be sure they reach their destination[4]. At this point, we might appreciate that computers do have finite resources in relation to CPUs, RAMs and the likes. Nowadays, to surpass computers' physical constraints we revert to cloud solutions, offered by several tech companies like Amazon, Google and Microsoft. For example, you might be familiar with virtual servers, which are physical servers that you won't have in your office, because you will rent them and they will be stored at Microsoft's, or Google's, or any other provider you have chosen, which in turn will take care of your servers, in case of issues of power, cooling and malfunctioning hardwares, and provide you with backup services to avoid disruption in your business. At the same time, cloud computing services offer you the opportunity to auto scale, which relies on the automatic switch on or off of additional servers in case you need them. Upgrading to cloud solutions is of course optional, and it is linked basically to how much money you have to spend in your digital experience, and how prone you are to incur in risks related to service malfunction.

What Managers Need to Know When it Comes to IT

While we have discussed the binary code as the language computers understand, it might be useful now to deepen our knowledge of programming languages and web developments. These are definitely linked to the most common challenges managers will need to face in order to successful implement digital strategies within the organisation. In particular, there is no right and wrong programming language to choose, it all depends on the budget your company has, the type of server platform used, the programs needed, the prior knowledge in programming that your team has and so on.

Programming languages can be defined as a vocabulary and set of syntax rules used to instruct a computer to perform specific tasks, using variables and statements - which will tell the computer how to use the variables. They are important because without programming languages we cannot have computing, which can be intended here as the process of writing, testing, troubleshooting, and maintaining the source code of computer programs. There are several famous high-level programming languages, among which we can cite C, C++, and Pascal, that will need to be transformed - it can either be compiled or interpreted - into program language that the computer can understand. Compile a program means that the source code, written in a program language such as C++ or JAVA, is translated into a machine code through a compiler, so that the computer can perform tasks, which are output in form of a new file. Interpreting a program is slightly different, because a tool known as interpreter reads lines of source code one at the time, converts them into machine code and executes it. At this stage, we can say that there are three types of programming languages, that can be summarised as follows. Machine languages and assembly languages are so called low-level languages, because they are closer to the language understood by a computer. In fact, machine languages are made of binary digits that the computer reads and understand by itself, and it is almost impossible for humans to write. Similarly, assembly languages can be thought of as a string of executable instructions, which need to be translated by an assembler loaded into memory and executed. On the other hand, high-level languages (BASIC, C++, JAVA, Python and so forth) are more similar to what humans understand. So programmers will be able to use common words like “print”, “if”, “move”, which will need to be translated into machine language either using a compiler or an interpreter, as we saw earlier. For example, BASIC (or Beginner’s All-purpose Symbolic Instruction Code) was the first programming language to be developed, in 1950s, and it looks like this.

PRINT “Hello world!”

Later on, Microsoft implemented BASIC to develop what we know as Visual Basic, which provided a graphical environment, and looked slightly different from its predecessor (if we maintain the same example, Visual Basic looks more more like MsgBox “Hello, World!”).

Furthermore, C++ as developed at Bell Labs, is one of the most famous programming language for graphical applications both in Windows and Macintosh environments. It appears more structured, as you can appreciate in the example below.

```
#include <iostream>
 int main() {         std::cout << “Hello World!” <<
std::endl;         return 0; }
```

Interestingly, JAVA is a general purpose language which is predominantly used in the World Wide Web to build Android apps, desktop apps and games, that has specific syntax rules as follows:

```
/* * Outputs “Hello, World!” and then exits */
 public class HelloWorld {         public static void
main(String[] args) {                  System.out.
println(“Hello, World!”);         } }
```

If you are interested in learning how to code, probably Python is your first step when it comes to programming languages. Used to build desktop and web apps as well as data mining (if you think that Google, Instagram and Pinterest have been written with Python you might understand the potential of this language), it is very straightforward and looks like this:

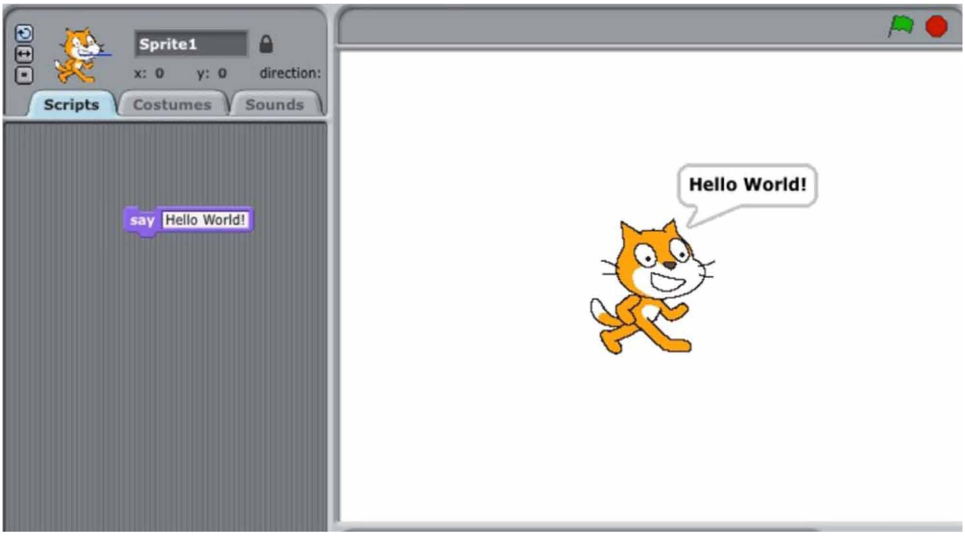
```
print(“Hello, World!”)
```

If you used Ruby, on the other end, you would have to write:

```
put ‘Hello, World!’
```

If you are still not convinced that you have what it takes to learn how to code, then you might start exploring the graphical world of Scratch. Developed by MIT researchers, Scratch is a graphical language available for free at https://scratch.mit.edu, which is usually used to develop kids’ coding and critical skills. The program revolves around Scratch, a sprite as programmers

Figure 1. Scratch



would call it[5], that we can make do things through simple commands which look like puzzle pieces[6]. It is very intuitive and applies concepts of logic[7], so if we wanted Scratch to say "Hello World!" as we looked at in the previous examples, we would see the following screen.

When thinking of the World Wide Web, you might not necessarily need a programming language. For example, HTML (HyperText Markup Language) is a mark-up language rather than a programming one, and it is used to write web pages. In particular, rather than loops, conditions, functions and so on, HTML has tags which tell a browser how to format and display information in the form of a web page, using as environment a web-based IDE (Integrated Development Environment), such as Cloud9 (see https://c9.io/login). Using HTML, our example will look like this:

```
<!DOCTYPE html>
<html>
        <head>
                <title>Example</title>
        </head>
        <body>
                <p>Hello, World!</p>
        </body>
</html>
```

In HTML, we can also embed pictures, which will be formatted as HelloWorld.jpg (this would look like the following: <img src="images/HelloWorld.jpg">), or weblink (such as: Hello, World!).

Programming languages and the rules that make them logical are fundamental to managers and leaders alike to understand if and how what they want to achieve is feasible. Non technical people might have a brilliant idea on how to improve the customer experience, or on how to make things look better, however it might not be as viable as they think. Being IT and coding literate, will help them realise beforehand what can and what cannot be achieved, and definitely improve communication among departments. In the same perspective, while managers are not required nor expected to be know-it-alls, other additional skills and knowledge can make the difference in the success of organisational projects. In the next sections, we will have the opportunity to reflect on the importance of data and data-driven approaches.

The Concept of Data

The Oxford Dictionary describes data as "facts and statistics collected together for reference or analysis" (see https://en.oxforddictionaries.com/definition/data). The given definition is limitless in these terms, and does not seem to provide a clear idea of what we should include. To prove the point, Inside Big Data (2017) provides an interesting calculation related to the size of the digital universe, which is doubling every two years. In particular, experts say that human-to-machine data is growing at 10x faster than business data, while machine-to-machine data at 50x. What does that mean? Such statistics surely indicates that data is a flourishing business, based on different sources and which can count on several types of data itself. While the amount of data available is now massive[8], it is important to understand how to properly collect, manage, store and interpret it. Businesses that control data control also technologies like AI tools. Before moving on to discuss big data, we might want to introduce the distinction between structured and unstructured data.

Structured data refers to data that is highly structured and can be organised in relational databases and spreadsheets, so that it is easily searchable. This happens, for example, with supply chains systems, credit card numbers, address or number of sales. On the other end, unstructured data refers to data that is difficult to collect, process and analyse, because being qualitative, it does not have a clear structure. Examples of this type of data can be found in text, videos, and social media activity. Thanks to the Internet of Things, unstructured data are predominant, and at the moment make up for 80% of the total data[9]. Unstructured data comes mostly from internet, which saw different phases that are linked to the collection of data itself. So for example, before the year 2000, content was mostly written and produced by companies and institutional stakeholders (i.e., news agencies), and the Internet user was expected to use it passively, in a sort of "encyclopaedia" way. That idea of Internet, also known as Web 1.0, changed dramatically after the 2000s when blogs appeared, starting a revolution of sharing content among users even without the interposition of official stakeholders. In this perspective, we can say that each one of us also has a digital identity, which is linked to all the things we do, say, look at, share and so on in the Internet. These consider both the information we - or a third party - provide voluntarily, as well as what we download, cookie preferences, websites we browse and so on. Once the Internet of Things is fully implemented, we will be able to collect even more data through connected devices and sensors, so that companies and Artificial Intelligence systems in particular can access data collections and repositories, to implement products and services in several sectors, such as health, transport and home automation. At this point, we might be able to realise how important is to have the right type and amount of data[10].

So what is the difference between data and big data? Big data can be defined as a large collection of data - or data sets - which are mainly unstructured[11] and difficult to manage with normal databases or statistical tools, because they are expected to grow exponentially and at a quick pace. This is a very practical definition of big data[12]. What are then the main characteristics of big data? Traditionally, experts have identify four or five characteristics that can help identifying which data falls under the definition of big data. These are also known as the four Vs, meaning Volume, Variety, Velocity, and Veracity, while the fifth one would be Value and it is linked to Smart Data.

Volume takes into account how much data is available to storage, filter, organise and finally analyse. If we consider that there are more than 4 billion Internet users right now (in 2014, for example, there were only 3 billion), connected through what has been estimated in 2018 as 18 billion devices (such as for example, computers, tablets, smartphones and video game platforms), information is digitalised in such a profound and massive way that billions of data are generated daily (Kemp, 2018; Knoll, 2018). These figures are expected to grow exponentially, in line with the number of connected devices - such as cameras, televisions, fridges and other devices used daily - so to reach more than 50,000 billion bytes of information per year. Of course, not all of this data will be valuable or pertinent to a specific company, so the phase of 'reducing' it, or carefully choosing which ones to consider, is fundamental. The second characteristic is the so called Variety, which refers to the use of several types of data. As we have said before, initially only highly structured data were used in decision-making databases, which could be designed according to different models[13]. The third V stands for velocity of data generated by users in the Internet, which companies need to process in real time, to enhance customers' engagement as well as their expectations. finally, veracity refers to the reliability and trustworthiness of the collected data, as well as its source, type and process used to optimise it. Without a reliable data set, results and insights will be biased and deviate the decision-making process for those who use it. This is linked to the potential fifth V, which represents value. Big Data allows companies to get information applicable to them, and able to inform their decision-making to enhance for example efficiency. This is possible when data from different sources, regardless of the model used to analyse and correlate them, become smart, meaning they are valuable to the company. Through business intelligence systems, data are treated to extract real value from them[14].

Data in Business: Business Intelligence and Other Tools

Now that we have somehow introduced the concept of data, we should have a look at what constitutes Business Intelligence, here intended as a technology-driven process and strategies to analyse data to make them of value to executives and managers alike. In particular, Business Intelligence (also known as BI) makes use of both computer tools and know-how to inform organisational decision-makers in a timely manner. When BI was first used in the late 1990s until early 2000s, data were still organised in terms of subject, whether this could be marketing, HR, finance, and so on[15]. The methodology used to achieve such result has been designed to link different rows in a table to other tables through a common attribute, also known as primary key, which is unique to a specific row or tuple (for example, driver's license number, national insurance number, and similar). As it might appear, relational databases are not meant to be use with data that are inconsistently formatted or unstructured. In this perspective, companies that do use relational databases will need to implement internally a strong data governance to keep data organised and in a normal form through specific processes, rules and systems. In particular, we can define data governance as "a system of decision rights and accountabilities for information-related processes, executed according to agreed-upon models which describe who can take what actions with what information, and when, under what circumstances, using what methods" (from The Data Governance Institute, http://www.datagovernance.com/adg_data_governance_definition/). A more complex version of relational database can be seen in the so called relational-object database, which merges a simpler object-oriented database with the relational structure.).

In this perspective, companies used to organise themselves around BI tools, so that they could get efficient reports. There was no possibility to adjust data in real time, or at least within the specific framework given by the customer's transaction. This is in line with the main goal of the early BI tools, which was to manage, monitor, classify and store data, without given information on future trends. After that, with more operational needs arising in the mid-2000s, new BI tools finally emerged, to allow the management and optimisation of the operational processes in real time. The new tools consist of BI platforms which integrate a consistent number of prediction functions, that can be accessed anytime and anywhere. We have already seen how much more data we have at our disposal since the advent of Internet and the Internet of Things, with so many connected devices. Thus, data to be integrated in BI tools and platforms are now massive and represent a real challenge in terms of data management, with unstructured and raw data produced on the Internet yet not well-implemented in such tools. To avoid this issue, Google launched Hadoop in 2004, which are platforms capable of processing huge volumes of data. We will discuss about them later on.

The process of gaining insights from data through the use of computing is also known as business analytics. This can be applied to several sectors, such as customer analytics, supply chain, fraud and risk analytics, and finally analytics in public domain[16]. However, several methods can be used in order to apply business analytics in a company. The first approach is usually related to the need of understanding what happened in the past, highlighting trends and patterns that can be helpful to better analyse the company in the present. This approach is also known as descriptive analytics, and uses several types of analysis such as data modelling, visualisation and regression, to try answering questions related to standard reporting and dashboards, ad hoc reporting and general query[17]. On the other end, we might want to understand what might happen in the future, and to achieve such result, we will need to revert to predictive analytics. As the name suggests, it has to do with the prediction of future probabilities and trends, while looking at relationships among data with a more mathematical approach[18]. Business performance is in this case the result of inherit relationship between data inputs and outputs, which take into account the past to make plausible prediction about the future. Predictive analytics can be used both in real time (think for example at the detection of suspicious transactions) as well as in batch, through the use of different categories of approaches[19]. A third approach, also known as prescriptive analytics, is concerned with identifying the best course of action to increase the chances of reaching the best outcome. Prescriptive analytics is more proactive, because it suggests new ways to operate and analyses business objectives to maximise the results, through the use of techniques such as simulation and optimisation - which aims to find out ways to achieve the best outcomes, even considering how to supersede uncertainty in data to better inform decision-making.

Again, we might want to consider other additional statistical approaches to use, such as data exploration, as presented by John Tukey (1977) as a reliable method to investigate anomalous data when we do not know precisely what we are looking for. Using specific tools, such as for example GGobi (http://ggobi.org), we can look at data to discover relationships not considered before. Furthermore, we might want to score data that we have - whether equations, documents, numbers, words, or Google searches - according to its importance. This is possible when using ranking techniques, which are different from text regression analysis that allows to transform qualitative data into quantitative ones after a period of training for the data set (see for example, Joshi, Das, & Smith, 2010). Finally, another interesting method to consider is the so called social graphing or networking, which produces visual graphs to show relationships within a network.

Whichever statistical analysis or approach your company decides to implement, data are fundamental to reach organisational goals, maximise efficiency and strategise every phase of the business. Some companies will have their own additional tools[20] to deal with massive amount of information, and consequently data, which are handled by a team of data analysts or scientists across departments. There are some open-source solutions that can actually be a good starting point for companies interested in exploiting data, such as Hadoop[21], a data-intensive software framework commercialised by Apache Foundation. Because it is open-source, several companies contribute to its development, like IBM and Facebook. In particular, Facebook's Hadoop cluster is believed to be the world's largest data farm (Yang, 2011).

While assessing which tool or statistical method is the most efficient to use, we always need to look at which data we have. These might be streaming or static, as we have seen when discussing the importance of real-time data in a specific analysis. Advancements in algorithms made it possible to require minimal intervention from humans, especially in the financial sector, where data related to trades of stocks, bonds, futures and other forms of investment need to be available to traders and brokers in real time. From this need, the so called algorithmic trading (Chan, 2013) came to life, to allow the understanding of movements in the market as they occur, while also taking into account static data about the past. From an opposite perspective, static data refer to information that we do not use immediately, rather we store it as a resource for a later analysis (think for example at archives of taxes or family photos, they are there and you might use them in the future if needed). We will have the opportunity to discuss algorithms and training data sets in the next Chapters, however for our purpose we might want to discuss further classifications of data, which are linked to specific types of analysis. For example, attribute data can be defined as data represented by identity or category, which we want to analyse in order to better understand how many units of the same attribute there are. Then again, ordinal data refer to numerical ratings (as it happens on Amazon for example), while continuous data are numbers on a scale with no jumps from one possible value to the next possible one.

CONCLUSION

Managers and entrepreneurs do not need to be programmers, engineers, statisticians, nor data scientists to understand the importance of IT skills, data and their analysis. The purpose of the Chapter was to briefly introduce you to the marvellous world of skills and knowledge managers are required to be aware of, such as programming languages, statistics and data analysis, in order for them to appreciate different ways of implementing the digital aspect of the business, as well as informing decision-making in the organisation. While there is a tremendous amount of programming languages and statistical softwares and tools that can be used in order to get the job done, we need to properly understand how to use them and for which purposes. Wanting to build an app, or a new website in JavaScript (just because it is the only name that stuck in our head) might be cool, but not necessarily what we are looking for to enhance the customer experience. At the same level, data, big data, data science are popular buzz words in the business community, and many managers have treated them as the solution to all their problems. Unfortunately, dealing with data does not necessarily guarantee an improvement in efficiency, or gaining more profits. Giants like Google[22], Facebook and

Amazon[23] rely on data in every aspect of their business, that is true. However, what makes them successful in their approach, is their knowledge of the data they need. Programming languages, as well as data per se are not all equal. Your company might recruit the best programmers in C++ and hold thousands of data, knowledge and information that it may seem impossible not to become the new Amazon. However, you might find out that you do not need C++ because everything else in your company speaks Java, and that all the data you collected are not relevant at all for what you need to achieve.

We have tried to highlight how data need to be classified, and be relevant to make a difference in data-driven companies. With the IoT and the advent of artificial intelligence programs, it will be paramount to be able to separate useful data from the remaining 'noise', as well as to find innovative ways to apply them to enhance customer expectations and experience. In the next Chapters, we will see why and how to use some of these data to apply artificial intelligence systems to your business.

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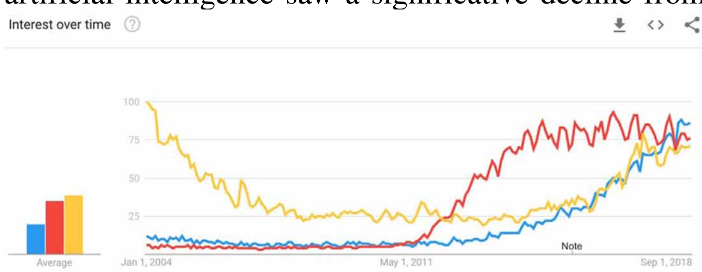
ENDNOTES

1 In the same years, searches for artificial intelligence were a lot than what we would expect them to be. Google Trends for the word searches "data science" (in blue), "big data" (in red) and "artificial intelligence" (in yellow) from 2004 show that interest in data science picked in 2016 and grew proportionally to reach its pick in early 2019, while big data is somewhat a hot topic since 2011. Interestingly, artificial intelligence saw a significative decline from 2005 to 2016.



(Source: Google Trends)

2 We should intend algorithms as step by step instructions on how to solve a problem, in which the instructions might be written in English, Java, C, C++, or any other programming language.

3 Routers have a specific function, which is basically to route data. They rely on multiple cables or have multiple virtual network/wireless connections to other routers as well, so that they make up an incredibly interconnected system. Historically, they tend to be named after the closest airport code to them.

4 Because routers can get very busy, it might happen that some data gets lost. The TCP protocol makes sure that lost data, independently from their type - it might be email services, chat services, web services on the server and so on - gets automatically resent. On the contrary, UDP is a

protocol that is trained not to resend data in case it is lost, for whatever reason, might this be malfunction, overloaded routers or technical problems.

5 A sprite is a sort of character capable of doing something within a program, such as for example move up or down, jump and talk.

6 In Scratch, there are different puzzle pieces that you might want to use. Some relate to motion, others to sound, and so forth. What you will probably find very interesting, is that pieces are somehow magnetically attracted to one another, and if the action I wanted Scratch or another sprite to perform sounds logical, then the two pieces will snap in place. You can also use logical constructs like "if then", "forever" and "repeat", as well as the opportunity to change a piece so that it asks for a Boolean question, to which we can reply with an action that reflects for example yes or no.

7 Whichever programming language you might end up choosing, there are always ground rules that resemble what we know as grammar. In particular, in AI projects programmers end up using production rules to represent knowledge. These can be represented using general forms, such as IF (Condition), THEN Action; or IF (Condition), THEN Fact. In line with this perspective, we can mention propositional logic, which is related to statements we assume to be true or false by deductive inference of a recognised truth of specific premises. If this seems complicated, we might want to go back to Socrates' deductive reasoning, according to which we say that Socrates is a man. If Socrates is a man, then Socrates is mortal. Therefore, Socrates is mortal. Propositional logic implies that we believe statement A (Socrates is a man) and statement B (If Socrates is a man, then Socrates is mortal) to be true, which in turn will make so that our deduction or statement C (Therefore, Socrates is mortal) is true. Unfortunately, it is not fundamental to make sure that the proposed line of reasoning makes sense. For our purposes, we only need to remember that propositional logic consists of a formal language and semantics which will give meaning to propositions, that can be either true or false. Every other atomic proposition is assigned a value T or F. In this perspective, we have a tautology if and only if the proposition is true in all possible worlds. Otherwise, if and only if it is false in all possible worlds, the proposition is known as contradiction. Through propositions, we can propose an argument, here intended as a set of propositions that can constitute the premises and the conclusion. The argument is sound if the premises are true and the conclusion is once again true, otherwise there

is a fallacy in our argument. At the same time, logical deduction is used also in artificial intelligence systems, when for example programmers try to solve puzzles like the following one: "There are two people named Charles and Luke. They each have one job, which are bank clerk and Spanish professor. Charles speaks only one language, while Luke holds a PhD in Spanish. Who holds which job?". Even though it might seem easy to reply, machines need to be properly written to understand such information in an automated reasoning program, which will still be missing common sense and knowledge.

8 Data are now collected everywhere, at any moment. To better understand the amount of data each of us produces, Fernando Iafrate offers an interesting recap of a fictional - not that much! - day. "Imagine what the typical day of an entrepreneur could look like in the not too distant future, where most of our everyday objects will be "smart" and connected... In the morning, I am woken up by my "smart bed", which calculated the ideal time (in my sleep cycle) to wake me up. My "smart bed" communicated with my "smart media hub" (Hi-Fi, video, Internet, etc.), which links me up to my favorite web radio station and also to my centralized controller, which controls my bathroom heating and water for a shower. After that, I put on my "smart glasses or lenses", and I am connected to the rest of the world. While I am having breakfast (suggested by my virtual sports coach via my smart glasses), I get a summary of what has happened in the world while I was asleep (I flick from content to content with a simple gesture of my eyes). I take a look at my diary for the day and simultaneously, my "smart fridge" asks me if I would like to place an order for certain products, and suggests some associated products and current promotions, which I validate with the blink of an eye. And then the day truly begins. I get in my smart car (which runs on renewable energy), and I confirm the autopilot to take me to my first meeting. In the meantime, I connect to a videoconference to take stock with my team, and finalize the preparations for this first meeting. I arrive at the location, my car parks itself in a power-charging space (charged by induction), my smart glasses guide me to my meeting (using augmented reality) and announce my imminent arrival to the person I am to meet with. All morning, we work on an urbanization file (I am an architect), with 3D projections of different prototypes, documents are exchanged via the "cloud", even my computer does not serve much purpose – I control all the actions via my "smart glasses" and/or a "smart table" (which serves as Human-Machine Interface). In the meantime, my virtual assistant

reminds me that she has to organize a certain number of appointments for the next two days, and asks me to validate them, which I do with a gesture on the "smart table" (though I could also have done it through my smart glasses). The meeting ends, and I video call a friend whom I see is available on the social network to organize a lunch with him. I suggest a restaurant and as we have access to the menu, we choose what we would like to eat while we talk, validate our reservation and the coordinates are sent to my smart car. The smart car takes me to the restaurant, where our table awaits, and the first dish is served within a few minutes of our arrival. The afternoon will be spent working on a joint project (in connected mode) with my collaborators (who are spread across multiple continents) and on the urbanization file for which we will validate a prototype so that we can materialize it on our 3D printer in order to present it the next day. The work day ends, I read over some messages that were pending, including an invitation (from my local sports club) to play an hour of tennis tonight (with a player I have never met but who has a similar level to me), which I accept. I then go to the tennis club via home, and my smart car chooses the optimal route. In the meantime, a drone has delivered my new racket that I ordered the day before. At the beginning of the evening, I arrive home for dinner with my family (it is now 8:30 pm), then I watch a sporting event (with a few connected friends, where everyone can see and review the action through their own smart glasses and from any angle they wish by connecting to one of the 50 cameras that broadcast the event). It is 11 pm and I receive a message from my smart bed suggesting a sleep duration of 6 h (having taken the next day's agenda into account). I decide to follow this advice and disconnect from the virtual world to enter a dream world." (Iafrate, 2018). Iafrate, F. (2018). *Artificial Intelligence and Big Data: The Birth of a New Intelligence*. Volume 8 – Advances in Information Systems SET. New York, NY: John Wiley & Sons.

9 This percentage is most definitely going to change, considering the huge amount of data that sensors and other smart tech are capable of collecting.

10 Research from IDC (2016) states as prediction no. 5, that companies with the right data will see an additional $430 billion in productivity gains by 2020. IDC (2016). *IDC FutureScape: Worldwide Big Data and Analytics 2016 Predictions*. Retrieved online at http://www.dbta.com/Readers/Subscriber.aspx?Redirect=http://www.dbta.com/DBTA-

Downloads/WhitePapers/IDC-FutureScape-Worldwide-Big-Data-and-Analytics-2016-Predictions-6492.pdf

[11] An IBM team has estimated that roughly 80% of data are unstructured and unused. As an example of the type of data they refer to, they have included social media feeds, web searches, research papers and other things with nothing or very few in common when it comes to formatting. On top of that, they also require greater computing power to be part of a data management system, in particular if we consider that unstructured data grow at 15 times the rate structured data do. In this perspective, unstructured data can be used to analyse useful insights for companies and sectors, using data that would have never been used otherwise because of its form. See among others, Eaton, C., DeRoos, D., Deutch, T., Lapis, G., & Zikopoulos, P. (2012). *Understanding Big Data: Analytics for Enterprise Class Hadoop and Streaming Data*. New York, NY: McGraw Hill.

[12] According to the McKinsey Global Institute (2011), "Big data refers to datasets whose size is beyond the ability of typical database software tools to capture, store, manage, and analyze. This definition is intentionally subjective and incorporates a moving definition of how big a dataset needs to be in order to be considered big data - i.e., we don't define big data in terms of being larger than a certain number of terabytes (thou- sands of gigabytes). We assume that, as technology advances over time, the size of datasets that qualify as big data will also increase. Also Endnote that the definition can vary by sector, depending on what type of software tools are commonly available and what sizes of datasets are common in a particular industry. With those caveats, big data in many sectors today will range from a few dozen terabytes to multiple petabytes (thousands of terabytes)." (Manyika, Chui, Brown, Bughin, Dobbs, Roxburgh, & Hung Byers, 2011). From a different perspective, IBM defines big data analysing its sources. So, "Every day, we create 2.5 quintillion bytes of data—so much that 90% of the data in the world today has been created in the last two years alone. This data comes from everywhere: sensors used to gather climate information, posts to social media sites, digital pictures and videos, purchase transaction records, and cell phone GPS signals to name a few. This data is big data.". Jacobson, R. (2013). 2.5 quintillion bytes of data created every day. How does CPG & Retail manage it? *IBM Industry Insights*, April 24. Retrieved online at https://www.ibm.com/blogs/insights-on-business/consumer-products/2-5-quintillion-bytes-of-data-created-every-day-how-does-cpg-retail-manage-it/; Manyika,

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[13] Furthermore, in the transactional data model, also known as standardised data model, the main goal is to minimise the duration of a transaction while maximising the numbers of actions that can be carried out simultaneously. If we think of Ebay for example, it is paramount to be able to support thousands of online customers that are browsing its catalogue and prices. This can be possible if the model does require only minimal - or not at all - access to historical data, which is avoidable when customers' data are divided into products, invoices and so on. In this perspective, there is no redundancy of data, however the way these are linked together needs to be handle properly by the internal solutions or applications of the system, which implies there is no possibility to apply analytics to this lot of data. Another type of model is the so called decision data model, which is used in particular to process a great amount of historical information. To reach this goal, stars models are used, where all information is stored in facts table - which will comprise data on customer, price, invoice, product and so on, and linked through analysis. Using this system, data will be redundant but less structured and unstructured data will have the chance to be integrated.

[14] Among others, in recent years there has been a growth in the use of data lake. A data lake is a different way of organising and storing data, where all kind of data is stored (whether raw or transformed), alloying analysts to see the source data without filters.

[15] Before moving on more technical approaches and tools, we should start from the easiest method to collect data, also known as flat file, which is a two-dimensional table arranged in a grid format. If this still seems strange to you, then we might as well referring to it as the common spreadsheet used to track data. Of course, when you think of an Excel spreadsheet you might have prepared with names, addresses, phone numbers and similar variables, you realise that this method will not work with large numbers of data, especially if we have to insert the majority of them manually. However, understanding a flat file is easy and immediate, and does not require the use of external tools. Flat files can be assembled to form a more complex database, which can be for example hierarchical (when there are series of parent/child relationships

like in an organisational chart, where the parent might have more than one child, but each child can only have one parent); or a network database, where there are pointers to other information in the database; or it might be relational, so that a large data file can be broken in smaller tables. Invented by Codd, it had the specific aim to protect "future users of large data banks from having to know how the data is organized in the machine (the internal representation)" (Codd, 1970). Codd, E. F. (1970). A Relational Model of Data for Large Shared Data Banks. *Commun. ACM* 13, 6 (June), 377-387. DOI=10.1145/362384.362685 http://doi.acm.org/10.1145/362384.362685.

16 Among the most common categories of business analytics, we can mention for example: 1. Customer analytics: this includes applications to marketing (customer profiling, segmentation, social network analysis, brand reputation analysis, marketing mix optimisation) and customer experience. Good examples of this category can be: SNAzzy (Social Network Analysis in Telecom) and VOCA (Voice-of-Customer Analytics); 2. Supply chain analytics: demand forecasting, optimisation of inventory, pricing, scheduling, transportation and storage, while mitigating and risk. Workforce Analytics - or Human Capital Analytics - applies to companies where human resources are the main means of production. 3. Fraud and risk analytics: assessment of several types of risk (market, operational, credit) especially for the financial sector; 4. Analytics in public domain: these are used by governments to track for example water leakages in distribution systems, develop smarter energy grids or traffic systems to improve public security.

17 In the standard reporting area, we try to answer to questions such as what happened, how the event compares to our planning and/or strategy, and what is happening now. Ad hoc reporting is more concerned with establishing the number, frequency and origin of specific events. Finally, general query tries to pin the exact origin and definition of the problem, as well as its causes.

18 To perform forecasting in the short-term when we have a substantial amount of data, we use predictive regression techniques, which rely heavily on maths to reduce error, particularly if adopted in the financial industry.

19 Six different categories of analysis can be used in the predictive approach. The first one is data mining, which is usually used to find correlation among data. When we need to have a clearer idea of deadlines or thresholds to correct a process or mend a piece of equipment, we should perform

a patter recognition and alert analysis. If we are concerned with what could happen, analysts might start a Monte-Carlo simulation, or a root cause analysis if the goal is to understand why a specific thing happened. Finally, forecasting models will give you an idea of what could happen in case the identified trends continue.

20 Interesting examples can be found in Google File System, which is presented as "a scalable distributed file system for large distributed data-intensive applications. It provides fault tolerance while running on inexpensive commodity hardware, and it delivers high aggregate performance to a large number of clients". Similarly, IBM proposes Apache MapReduce, "a programming paradigm that enables massive scalability across hundreds or thousands of servers in a Hadoop cluster". See https://ai.google/research/pubs/pub51; and https://www.ibm.com/analytics/hadoop/mapreduce.

21 Hadoop is a project based on two papers published by researchers at Google, which relate to Bigtable and MapReduce. According to the articles' abstract, "Bigtable is a distributed storage system for managing structured data that is designed to scale to a very large size: petabytes of data across thousands of commodity servers. Many projects at Google store data in Bigtable, including web indexing, Google Earth, and Google Finance. These applications place very different demands on Bigtable, both in terms of data size (from URLs to web pages to satellite imagery) and latency requirements (from backend bulk processing to real-time data serving). Despite these varied demands, Bigtable has successfully provided a flexible, high-performance solution for all of these Google products. In this article, we describe the simple data model provided by Bigtable, which gives clients dynamic control over data layout and format, and we describe the design and implementation of Bigtable". Furthermore, "MapReduce is a programming model and an associated implementation for processing and generating large datasets that is amenable to a broad variety of real-world tasks. Users specify the computation in terms of a map and a reduce function, and the underlying runtime system automatically parallelizes the computation across large-scale clusters of machines, handles machine failures, and schedules inter-machine communication to make efficient use of the network and disks. Programmers find the system easy to use: more than ten thousand distinct MapReduce programs have been implemented internally at Google over the past four years, and an average of one hundred thousand MapReduce jobs are executed on Google's clusters

every day, processing a total of more than twenty petabytes of data per day". Hadoop is considered the primary standard for distributed computing not only because it is free, also because it has both the power and the tools to deal with distributed nodes and clusters. In particular, Hadoop is based on MapReduce and Hadoop Distributed File System (HDFS), which are only a small example of interconnected projects related to Hadoop, such as Ambari, Cassandra, Chuwka, HBase, Mahout and ZooKeeper. For our purpose, we can say that Ambari is a web-based tool for provisioning, managing, and monitoring Apache Hadoop clusters (see https://ambari.apache.org); Cassandra is a scalable multi-master database (http://cassandra.apache.org); Chukwa can be defined as a data collection system for managing large distributed systems (http://chukwa.apache.org). On the other end, HBase is a scalable, distributed database that supports structured data storage for large tables (https://hbase.apache.org); Mahout represents a scalable machine learning and data mining library (http://mahout.apache.org); and finally, ZooKeeper has been developed as a high-performance coordination service for distributed applications (https://zookeeper.apache.org). Chang, F., Ghemawat, S., Hsieh, W. C., Wallach, D. A., Burrows, M., Chandra, T., Fikes, A., & Gruber, R. E. (2006-08). Bigtable: A distributed storage system for structured data. *ACM Trans. Comput. Syst.,* 26, 2, Article 4 (June). http://doi.acm.org/10.1145/1365815.1365816. Dean, J., & Ghemawat, S. (2004). MapReduce: Simplified data processing on large clusters. *Proceedings of the 6th conference on Symposium on Operating Systems Design & Implementation*, Volume 6. Retrieved online at https://static.googleusercontent.com/media/research.google.com/en//archive/mapreduce-osdi04.pdf

22 https://www.google.com/about/philosophy.html

23 https://ir.aboutamazon.com/corporate-governance

Chapter 4
AI and Other Technologies in Business

ABSTRACT

In the previous chapters, the authors discussed a switch from a traditional business model towards the modern digital business model, which seems to follow a specific pattern, as highlighted by strategist Tom Goodwin. In this economy, knowledge and data have an important role that can be compared to that of technology itself. Among other things, the authors discuss how companies need to overcome Polanyi's paradox as well as the so-called curse of knowledge—or status quo bias—according to which they might not understand how to innovate themselves because of it. In particular, some organisations might be so proficient and knowledgeable that they risk not seeing what is coming and preparing themselves for the disruption in their sector. The authors also discuss the use of AI and other technologies in business and how to use them efficiently.

AN INTRODUCTION TO THE ROLE OF KNOWLEDGE IN THE DIGITAL BUSINESS

Knowledge is a key component of an organisation. Whether we are discussing knowledge gathered from its employees, or the historical knowledge that is part of the organisation itself, knowledge has a fundamental role in the success of any business. Data represents one of the most concrete forms of knowledge we can find. We will see in the next Chapter which approaches to data can be used by managers.

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At this stage, we can affirm that the modern economy is based on three major trends. These can be seen as counterparts of the more traditional trilogy given by the human mind, products and the core. The first trend we should take into account is the circumstance that machines are more capable than ever. This is the case of AlphaGo, for example, which aims to replicate how the human brain works, adding speed, velocity and the ability to 'ingest' a great amount of data. The second trend that can be spotted relates to the use of platforms to sell products or physical goods that firms might not have. We have already mentioned how companies like Uber, Facebook, and Airbnb are offering products that they do not own, disrupting the traditional business model. At the same time, the crowd is involved in the designing process, to add expertise, needs and other information to the mix. So in the modern era, the so called core - meaning knowledge, processes and expertise that companies have internally - is substituted with external fonts of knowledge, as in the cases of GE and Indiegogo (Hurst, 2015; Shieber, 2015). Furthermore, Indiegogo can be described as an online crowdfunding community, where people provide financial support to ideas in exchange of rewards, not ownership of new products. In other terms, a reward can mean they will be the first to receive a product, that does not exist yet and might never exist.

To prove such point, according to Karim Lakhani for example, managers and in general businesses that want to innovate should not go to experts, they should go to externals. "In more than 700 challenges we have run on crowds for NASA, for the medical school, for companies - you name it - over the past five years, we've only had one failure [where] the crowd did not show up or did not work on the problem. In all other circumstances, we either met or vastly exceeded the internal solutions that existed" (as quoted in McAfee & Brynjolfsson, 2017, p. 255). If anyone is interested in involving the crowd, Topcoder, an online platform for computationally intensive problems, might be a useful tool to look at.

When previously discussing the abilities new machines have, we have mentioned AlphaGo. This is particular important in relation to the role of knowledge, and we will soon understand why. While trying to program an AI machine to play Go, researchers have to deal with Polanyi's Paradox - which basically states that we know more than we can tell - and in general terms, the fact that humans use tacit knowledge to deal with tasks. To avoid such paradox, a team at Google DeepMind built AlphaGo, which learnt to play studying millions of positions and simulate only the moves that it thought lead to victory. When the team thought AlphaGo was ready, it challenged the European Go Champion Fan Hui in 2015, winning 5 matches against 0. Critics were not that impressed, so the team challenged Lee Sedol, considered the best human Go player on the planet in 2016. Sedol thought it would be easy to win, however AlphaGo won the four matches in total, thus beating Sedol during the first three matches as well as the last one.

Such an accomplishment was already a great victory in itself, however it is important to highlight that it happened even though AI programs built for games do not learn very fast, because they require a huge amount of data to be trained. This is perfectly expressed by Kasparov, after he was beaten in 1997 by IBM's Deep Blue computer in a world-changing game of chess. Kasparov himself is recorded to have said "I had played a lot of computers but had never experienced anything like this. I could feel - I could smell - a new kind of intelligence across the table. While I played through the rest of the game as best I could, I was lost; it played beautiful, flawless chess the rest of the way and won easily" (Kasparov, 1996). What does this leave us with? After such a historical moment, now chess computers offer professional coaching to human amateurs.

In this perspective, experts concord that the Homo sapiens will be replaced by the Homo Digitalis (in part or totally digital), as part of the next evolutionary step. This evolution starts with co-learning, which is not the learning of a group, rather the learning of each individual of the group so that everyone in the group shares the same knowledge and becomes more intelligent. This way of learning uses computer code rather than traditional language and is already used by Apple (to improve speech-recognition software) and Tesla for autonomous driving projects.

Among other things, we should always consider that computers have an intrinsic advantage on us because they can change their own data and consequently change their behaviour to perform better. They also have more speed, memory capacity, power supply, they do not need sleep and rest, nor do they forget, and are not biased by emotions, which in turn makes them optimal and efficient decision-makers, that can share their knowledge without barriers. So, rather than trying to beat them or at least compete with them at a similar level, we should consider Michael Hammer and James Champy's approach (1993), according to which computers can handle the routines while humans should be empowered to use their judgement. However, there are opposite conclusions to such a view. In particular, we can quote Kahneman and Klein, who explained their position in the famous American Psychology article titled "Conditions for intuitive expertise: A failure to disagree" (2009).

Furthermore, they are firmly believers that "You should never trust your gut. You need to take your gut feeling as an important data point, but then you have to consciously and deliberately evaluate it, to see if it makes sense in the context." This attitude will also help to avoid bias in the algorithms as well, whether this was used to decide who to hire or to whom offer specific products with a discount[2].

A HISTORY OF AI AND OTHER TECHNOLOGIES

According to McAfee (in Walsh, 2017), "Anyone making confident predictions about anything having to do with the future of Artificial Intelligence is either kidding you or kidding themselves" (also quoted in Metz, 2017). Whether this affirmation will be proved to be correct or not, experts have predicted a Cambrian explosion[3] when it comes to AI and its implications.

Before diving into the history of Artificial Intelligence, it might be worth it to point out that the AI community split in two separated groups or philosophies. This will help to better understand how AI operates, and why certain applications of AI are more congenial than others. Now, the first group pursued the symbolic or rule-based artificial intelligence, which is the one that recalls the way adults learn a language. How is that? Adults tend to study the rules and grammar patterns first, and are more concerned with those rather than the ability to apprehend a subject through osmosis. On the other end, the second approach is based on statistical pattern recognition systems, that resemble the way children listen to others and then copy the recognised patterns. Whichever approach is used, we do seem to have reached such advancements thanks to neural networks. In particular, neural networks help because they can be trained using as much detailed historical data as possible, to the point that in 2016 a team from Microsoft Research stated one of the neural network they built had achieved human parity in conversational speech recognition.

Furthermore, experts tend to differentiate between weak AI and strong AI. While weak AI can be defined as the computer's ability to behave intelligently but not understanding, strong AI is somewhat close to human intelligence. According to Searle (1980), "the appropriately programmed computer really is a mind, in the sense that computers given the right programs can be literally said to understand and have other cognitive states". However, some of you may point out at this stage that human intelligence is created naturally and biologically, while artificial intelligence is not, and for that reason only they will never be the same[4]. To support such view, experts from several disciplines tend to reiterate the dominance that AI will always have over natural intelligence. For example, an artificially created intelligence will have more speed and require less 'down time' than natural intelligence. On the other end, machines are usually designed to handle few tasks, while humans are generally better at multitasking and be in charge of more complex activities. The same can be said about the machine's inability to perform complex movements, which is contrasted by its capability to avoid pre-conceived biases in decision-making, while being more precise and accurate in the tasks. Other two aspects can represent somehow a tie between computers and humans, in relation to their ability to adapt to changes in the environment (you might think humans should be naturally better at it, but machines are rapidly improving), and the cost linked to their intelligence[5].

Now that we have somehow listed similarities and differences between humans and machines, it might be worth it to further specify that AI is not equivalent to computational device - or computer. A computer is a computation machine that transforms '0s' and '1s' into manageable, smaller tasks. At this stage, we should all be familiar with the binary code, as introduced in Chapter 3, which is the numerical representation of the two states 'on' and 'off', converted into 0 and 1, to form text that a machine can convert[6]. So, for example, to say 'hello' in the binary code, we should write 01001000 01100101 01101100 01101100 01101111.

Of course, this has nothing to do with AI and what we are trying to achieve with it. Artificial Intelligence machines are designed to be more human-like, in the sense that an AI should be able to work around the 'on-off' situations, to come up with probabilistic decision-making and handle complex issues as well as humans can. In this perspective, we can say that a robot[7], an algorithm or a machine show AI when they can think and take decisions independently, whether the situation might be objective or subjective, with no help or guidance from humans.

The race towards proving that an AI solution can fool a human into thinking they are not dealing with a machine, started with Alan Turing and its Imitation Game[8]. At that point, interest in AI has risen among academics and scientists, who met in the summer of 1956 at the famous Dartmouth workshop also known as Dartmouth Summer Research Project on Artificial Intelligence, organised by John McCarthy, together with Marvin Minsky, Nathaniel Rochester and Claude Shannon (McCarthy, Minsky, Rochester, & Shannon, 1955).

In the 1960s, research developed in several areas, although we might just remember the attempt to develop chess and checkers-playing machines, even though we will need to wait several years before a machine will be able to beat a human. That would have been the case of Luigi Villa, who was beaten at backgammon by Hans Berliner's BKG 9.8 program in July 1979. At the same time, two important computer languages went on their quest to become popular, these being Fortran and LISP (for more info, see for example www.thocp.net/software/languages/fortran.htm and www.britannica.com/technology/LISP-computer-language), along with the study of the interaction between AI and human language - also known as natural language processing. At the same time, Unimation[9], the world's first robotics company, started supplying robotic arms to car manufacturers, in what is recalled as the beginning of the automation of tasks at scale. While the buzz around AI was intense and filled with big promises of rapid change ahead, a very negative report on machine translation signed by the Automatic Language Processing Advisory Committee in 1966, had the effect to completely stop research on natural language programming (Automatic Language Processing Advisory Committee, 1966). A similar sort happened to neural nets, thanks to the skepticism of Marvin Minsky and Seymour Papert (Minsky & Papert, 1972).

Moving on to the 1970s and 1980s[10], we can count on advancements in computing, thanks to the now less prohibited costs of machines, especially in terms of maintenance, and more powerful hardwares. Universities started to invest in computing programmes, retaining the talent to develop new and more interesting algorithms. At the same time, companies started realising they might be able to profit from such field, and invested lots of money in R&D (research and development) activities. Although this sounds really promising, advancements - if any - were still confined to research labs. Many historians remember this period as in between the first and second winter of AI, which happened around 1974–1980, and then from 1987 to 1993[11]. One of the main reasons behind the skepticism towards AI was linked to the timing of its developments. Spectacular breakthroughs were expected at any given moment, even though research required a huge amount of time and funds. Probably the most significant result achieved in those decades was the victory of IBM's Deep Blue against the chess world champion Gary Kasparov in 1996[12].

Once the new millennium came into view, AI had already found its way in business, which is in line with a general benevolent approach towards a massive digitalisation of services and products, that we have discussed in the previous Chapters. This new era was also linked to companies such as Google, Amazon and Netflix relying heavily on AI, thanks to some advancements in the hardware components. As an example, we can think of the use of the Graphic Processing Unit (GPU) instead of the Central Processing Unit, where each GPU represents a neuron. Using tons of structured and unstructured data from IoT applications, AI can now work on complicated algorithms in almost all sectors, such as medicine and health care, transport, home automation, gaming, personal assistants and consumer behaviour[13]. Applications of Artificial Intelligence can now spread at an incredible rate and innovate the business environment. Among them, we can certainly mention the blockchain. A technology recently invented by Satoshi Nakamoto (2008), it came to be as a response to avoid the involvement of banks, credit card companies and other financial intermediaries in online payments[14].

We will now discuss properties of AI and other topics related to it.

What AI is Exactly and its Links to Other Disciplines

For those who believe AI machines will take over a good amount of tasks that now only humans can do due to their need for natural intelligence, researchers agree that certain characteristics AI can achieve, differently from other technologies, could actually allow for such a view. (Zarkadakis, 2017). In particular, AI will have the so called 'prescience', which consists in the ability to predict and modify its behaviour according to the changes in the environment. At the same time, scientists are working on its ability to be autonomous, using sensory data to inform it of changes in its internal states and allowing it to take action independently. In this perspective, deep machine learning can give AI the opportunity to self-improve over time, at least at every occasion it comes in contact with a new set of data.

In order to reach the point of Artificial General Intelligence, which should imitate the human mind while exploiting the perks of being a sophisticated machine, AI projects are driven by four basic characteristics that we will list below. The machine will need to use complex algorithms to mimic the human decision-making process, using multiple inputs and optimisation variables, that can be either tangible or intangible factors. This is possible thanks to the huge amount of data that machines can collect from around the world - a phenomenon also known as Big Data. Then, of course, the AI machine need to be able to handle such algorithms and process the data, based on an advanced computing ability. It is well known that advancements in the field are linked to smaller and faster processors, for example. If the machine has these three things sorted, then the only problem it might encounter at this point is to find the right problem question to solve. So, scientists that develop AI solutions first need to define a problem that they have identified, and only then they can start building an AI which should be the right mix of complex algorithms, assessing and processing of data and finally, the required computing power in order to solve the problem.

In this perspective, we might find that the term Artificial Intelligence is yet too broad and generic. There are several different types of AI, which are specific for each problem you might need to solve. So, for example, you will look for a language-based AI whenever you need it to speak and recognise a set language. This particular type of AI is built to understand accents and vocabulary, to allow you to use them as customer service agents, telephone callers or even language teacher in some advanced digital course. At the same time, if you need someone capable of performing difficult, iterative and lengthy calculations, you will choose an AI trained with a special mathematical ability to do so.

Other AI projects focus on reasoning and problem solving, based on the cause and effect link, to make judgements and decisions based on given information. This type of reasoning is particularly helpful when you have multiple inputs and optimisation variables, and your goal is to find the most preferable solution. At the same time, researchers are also focusing on the ability of certain AIs to self-improve and learn from their own past experiences, which is at the basis of the reward technique used by programmers while developing a machine capable to beat human professionals at games like chess or Go. An interesting area of development is the one linked to the machine being able to show emotional intelligence, defined here as the ability of the AI to empathise with others and understand their feelings. Skepticism is the predominant feeling at the moment in this realm, with scientists trying to demonstrate that AI can actually read between the lines and grasp the meaning of the unsaid. On a similar note, AI has shown potential in dimensions linked to creativity. We might have read in the news of some pieces of art produced by AI and sold for a small fortune (see for example, http://www.bbc.com/culture/story/20181210-art-made-by-ai-is-selling-for-thousands-is-it-any-good; https://futurism.com/ai-now-produce-better-art-humans-heres-how/; https://www.iflscience.com/technology/ai-creates-rather-wonderful-art-that-fools-critics-its-not-humanmade/). What we might not be informed of, is the DeepDream experiment by Google, which proved AI can daydream similarly to children when asked what they actually see in a picture shown to them (see some results of the experiment at https://www.telegraph.co.uk/technology/google/11730050/deep-dream-best-images.html).

A productive area of development is related to systems that can reply to unstructured and generic questions which may not have been considered once the machine has been programmed. The best example of such advanced cognitive system is the world-famous Watson, developed by IBM's DeepQA project team lead by David Ferrucci. Watson was initially programmed to compete on the quiz show Jeopardy, that focuses on general knowledge. In 2011, the computer was able to defeat two former winners, Brad Rutter and Ken Jennings, thanks to its ability to access 200 million pages of structured and unstructured content in its 4 terabytes of disk storage. From this success, IBM decided to launch the first Watson's commercial application in February 2013, which revolved around a partnership with the health insurance company WellPoint and the Memorial Sloan Kettering Cancer Center in New York, to study lung cancer treatment.

Furthermore, a typical and accepted distinction among AI types is the one that differentiates between Narrow AI, which is an application that behaves intelligently in a well-defined area of expertise, and General AI, here intended as a system that can learn and act intelligently in different environments and problems in the same way a human does. We will see in the next Chapter how AI systems work in more detail, and deepen our understanding of machine learning and predictive analytics, as well as distinguishing between supervised, unsupervised and reinforcement learning. At this stage, it is important to understand that supervised learning happens when the machine deals with labeled data, and its training set has both observation and outcome data. Differently, in an unsupervised learning approach, the data set will not have outcome data. This means, for example, that we can use it to identify and group things based on similarities between them, but the machine will not be able to predict when a certain thing will be part of a group or not (you might know this process as clustering). Similarly to supervised learning, reinforcement learning is a process that adjusts itself based on outcome data. However, the machine is not fed with initial data - meaning no training set to train the model against, and the training is based on a reward approach, according to which the algorithm knows that if it behaves in a certain way, it will be rewarded something. This is particularly used to train programs for games, where the machine understands that the reward is victory (or any other intermediate passage), and adopts specific steps in order to win.

Machine learning, which can be here defined as the use of algorithms (or mathematical procedures) to analyse data, works through scorecards, decision trees and neural networks. Scorecards are simpler linear models, while decision trees are yet another form of predictive model, which represent a set of sequential and hierarchical decisions in a way that is easy to understand also for non-experts. Furthermore, we can say that deep neural networks are a complex net of tens of thousands of interconnected mathematical functions, which resemble the way neurons and their synapses look (Byrne, 2017). These are organised in successive layers (at the moment, these can reach to over 100 layers), where every single neuron processes information as taken from the previous layer, and proceeds to communicate the results to the next one, where information gets increasingly complex at each passage. This type of network works pretty well with classification, a technique that allows the network to learn from example through classification of a set of elements in a class (or category) which will then be put among several classes as per previous rules and instructions. So, for example, the network will be trained to learn which pictures have a cat in them, and it will know that any picture with a cat will be put under the class ‘cat’. The classification technique is not necessarily used to produce a ‘yes or not’ answer, such as belonging or not to the ‘cat’ class. It can be also used to determine the probability of belonging to a particular class. Once the training set is finalised, we can say that the machine has learned the classification - or structure - of the data automatically. This, in conjunction with the fact that you do not need a huge amount of specialised knowledge to collect and analyse the data, makes neural networks perfect to be applied in several sectors, like for example process management, robotics, image analysis and speech synthesis, requests for loans, and many more.

The potential disruption that Artificial Intelligence can cause in a variety of sectors is due to raise issues and concerns around hot topics[15], such as privacy, regulations and human rights. We have already discussed the fact that unfortunately, AI is not immune to bias. This happens because, whether we like it or not, AI machines use data collected by humans, and analyse them through algorithms and codes written and developed by humans. Us humans are not immune to biases, as we have demonstrated many times in many occasions. If we recall the inner biases found based on gender and race, for example, in loan-approval algorithms (Waddell, 2016) or predictive policing[16], or the potential problems that could be raised if AI profiled a specific population, then we might understand better the risks. So who will then be responsible if something goes wrong? Will it be the machines, or the developers, or the owners of the program? Would we be able to realise when the AI changed its own algorithms as a form of self-improvement, and if yes, can we how the changes might have affected the purpose of the AI machine itself? Thus, in 2017 Saudi Arabia was the first country to give citizenship to a robot, also known as Sophia (Hart, 2018). It might seem ironic that in a country where women have still to fight to conquer some fundamental rights, a robot seems to be allowed to do more than them. In this perspective, the Saudi Arabia's approach is in contrast with those who assume computers are somewhat less than humans, or are scared they will end us[17].

AI and its Applications in Business

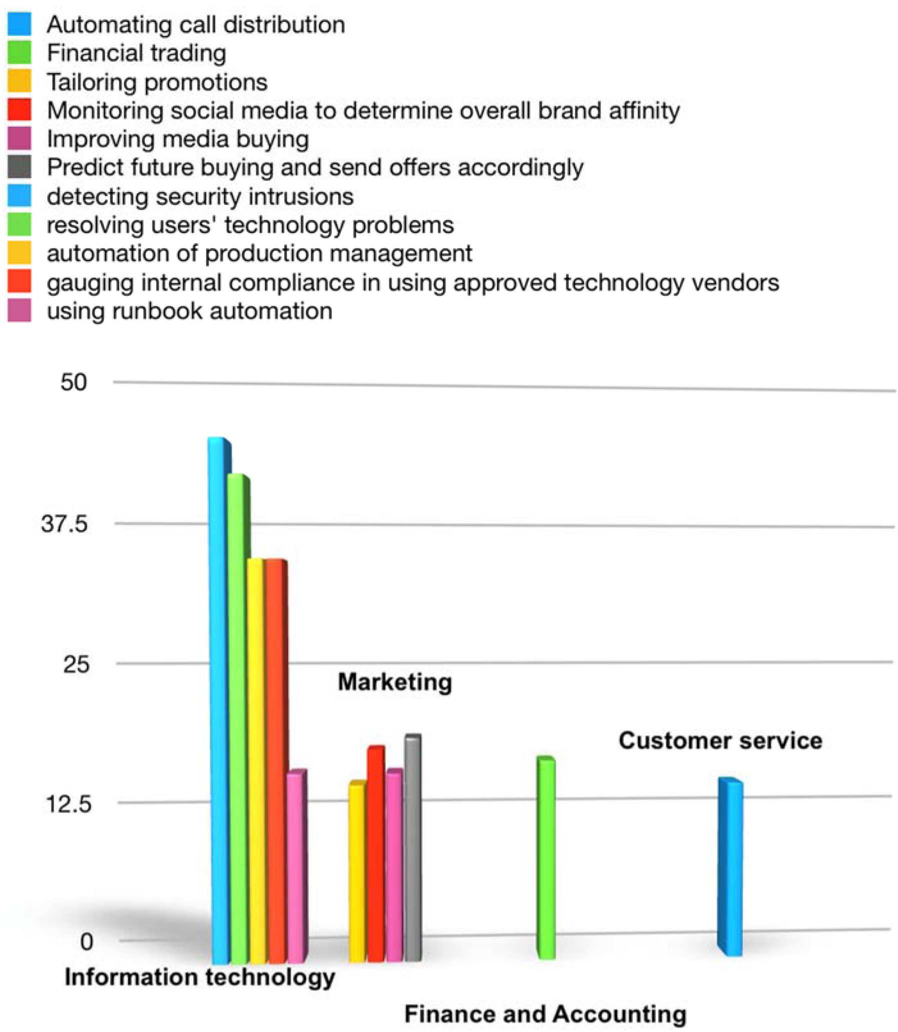
According to Bughin (Bughin, J. et al., 2017), Artificial Intelligence can build business value in four major P areas. First of all, we should think of 'Project', which relates to the way organisations can better forecast and source inventory and consumers' needs in general. Secondly, AI applications can enhance the way companies 'Produce' goods and services at lower cost and higher quality, while improving productivity and diminishing maintenance costs. We have cited before the revenue management approach, which is an effective way to 'Promote' products at the right price, conveying the right message to specific target customers, through the use of in-store analytics and insights, personalised engagement and promotional initiatives, thanks to a customer-driven experience. Finally, AI can 'Provide' an intensive and personalised user experience.

Experts usually agree on the importance of Artificial Intelligence applied to business, to the extent of saying AI applications are and will disrupt the market. So, of course, organisations are rushing to find a way to incorporate AI tools wherever they can, regardless of the company's sector and of the digital project they embark on. Giants like Google, Apple and Amazon do know how to properly use AI, and which type of AI to get the best results as well. Now, the issue lies ahead for smaller or less tech-savvy ones. Digital transformation consultants, AI experts and so on, all agree that companies new to AI should start with a small project with low-impact business value. We all would like to start big and achieve huge results, however this is not recommendable. Typically, managers would say on top of their head that the right approach to adopt AI within their organisation consists of the following steps. First, you should embark on a data ingestion, which is closely followed by data cleaning and transformation. At that point, you would start a phase of model training, followed by testing and validation, which could bring back to the previous phase in case of the need to a different model selection. Finally, once the model training proves to be reasonably working, we should see the final phase of deployment. Unfortunately, this process rarely works. According to Alyssa Sympson-Rochwerger, managers have a business problem that can be solved using AI if there are lots of unstructured and messy data, which can be for example photos, media, audio, social media text and so on. Her suggestions are pretty simple and practical, and require to start looking at the business value that can be achieved if the organisation breaks down into small and specific components the process we want to achieve. On top of that, the quality of production data should be significant and consistent so that the trained model is effective. In order to use unstructured data for example, managers need to be transparent in the way they use it, where it comes from and how the trained model that has been selected works. At the same time, managers that want to implement successful digital initiatives, need to learn through feedback loops that arise in the deployment of the trained model.

To summarise, we can say that a successful AI application should consist of five phases. Everything starts from the business problem we want to solve, and this can be done only interviewing those that claim to have such problem. In particular, we should identify priorities, value, stakeholders and resources that make up the business problem. The second phase consists of finding the right data, which will need to consider its availability and security, the cleaning of it, and similar. Once our data is cleaned and polished, we can move on to the next phase, which is model building, a process that will allow us to select the best one and benchmark our provisional results. Now it is time to deploy and measure the selected trained model, to then be able to learn actively from its tuning with a success monitoring phase.

This model should apply to every business sector. For example, agriculture technology helps increasing crop yield, efficiency and productivity, as well as reducing labour costs (Alltech, 2017; Sato, 2016). Companies in the agricultural field are using AI extensively. Resson deals with data-driven farming, and is able now to find out which grapes need pesticides and for which bugs. We can also mention OmniEarth Inc., that used IBM's Watson Virtual Recognition service to analyse massive amounts of satellite and aerial imagery, based on the idea they needed to evaluate and address the drought problem they had through a water usage approach on a parcel-by-parcel basis. In the education sector, companies want to scale quality of instruction and feedback, as well as reducing costs, and they apply AI to reach that goal (an example can be Blue Canoe and the revolutionary way it uses to learn new languages). Companies in the e-commerce sector want to improve search results and increase site conversion, which can be seen in Ebay and the opportunity it gives to its customers to take a picture of something they like, and then the app will perform a visual search in its billion products. Again, robotics and IoT are used to help the business automation, as in the case of Walmart, that went to Bossanova to put robots around its supermarket, to take pictures and identify products that are low in the shelves. These are all great examples of how AI is used to optimise the business processes and the

Figure 1. How Companies around the world are using AI solutions
(Source: Adapted from Oana, Cosmin, & Valentin, 2017)



customer experience, minimise the costs and maximise wherever possible the revenues.

CONCLUSION

In this Chapter, we introduced the concept of Artificial Intelligence and its ramifications in several aspects of our everyday life, such as privacy, ethics and of course, business. Looking at how AI systems were initially thought of, and the developments ever since, it is easier now to say that researchers' aim to build an artificial intelligence machine similar to how the human brain works is not such a far-fetched goal to reach. Although AI applications can have different forms and have invaded several different areas (from robotics to speech recognition, to self-driving cars and IoT devices), what makes AI possible is mainly a big chunk of reliable data to train AI algorithms with. If we look at the history of AI, its success came when researchers developed an algorithm complex enough to absorb a tremendous amount of structured and unstructured data, faster than a human could ever do, and from reliable sources to allow the machine to intelligently surpass or beat the human opponent. This was the case with AlphaGo, Watson and so on.

When it comes to business, AI can be used to improve efficiency and lower costs in areas such as finance and accounting, customer service, marketing and information technology. Artificial Intelligence is much more than automation, for example with its ability to credit consumer behaviour, tailor suggestions and marketing strategies (Johnson, 2015; Moorman, 2013), or support people on a daily basis through smart assistant. With the concept of blockchain and smart contracts, we wanted to point out one of the consequences of the Industry 4.0 and the Internet of Things, where experts are put somehow on the side and peer-to-peer advice is preferred. Reliability of feedback from private sources is an important part of what makes AI successful in a global environment, as well as advancements in complexity of algorithms, hardware and connection among devices to collect data.

In the next Chapter, we will learn more about the technical aspects of AI systems and will have the chance to see how AI can be implemented in a business-related context with practical examples.

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ENDNOTES

1 Tom Goodwin (2015) released a famous statement, affirming that "Uber, the world's largest taxi company, owns no vehicles. Facebook, the world's most popular media owner, creates no content. Alibaba, the most valuable retailer, has no inventory. And Airbnb, the world's largest accommodation provider, owns no real estate". Goodwin, T. (2015). The Battle Is For The Customer Interface. *TechCrunch.* Retrieved online at https://techcrunch.com/2015/03/03/in-the-age-of-disintermediation-the-battle-is-all-for-the-customer-interface/?guccounter=1&guce_referrer_us=aHR0cHM6Ly93d3cuZmFjZWJvb2suY29tLw&guce_referrer_cs=q8dATiGMQgSuTk5Wu4757Q [Accessed May 30, 2019].

2 An interesting example of the use of algorithms in decisions pertaining economics, comes from the so called Revenue Management, which is the approach of adjusting pricing on projected demand and supply (these could be flights and hotel rooms). In particular, it can be defined as a set of algorithms and technologies built to assist businesses that deal with finite capacity and perishable products. The ultimate goal is to sell as much products as possible to customers that are more willing to pay, and then sell the remaining ones to those further down the demand curve. See for example BBC (2014). Uber 'truly sorry' for price rise during Sydney siege. *BBC News*, December 24. Retrieved online at https://www.bbc.co.uk/news/technology-30595406 [Accessed May 30, 2019].

3 The Cambrian was a period of time which happened 500 million years ago, when in a brief period of time almost all forms of life on Earth appeared. Thus, the modern Cambrian era is said to happen in robotics - a term which includes robots, drones, autonomous cars and trucks. This era will possibly come to life thanks to major developments in five parallel, interdependent and overlapping areas, which can be included in the DANCE acronym (Data, Algorithms, Networks - whether in short and long distances, the Cloud, and Exponential improvements in digital hardware). Pratt, G. A. (2015). Is a Cambrian explosion coming for robotics? *Journal of Economic Perspectives*, 29, no. 3, 51-60. Retrieved online at https://www.aeaweb.org/articles?id=10.1257/jep.29.3.51 [Accessed May 30, 2019].

4 See, for example, the views expressed by Egor Dezhic, as accessible online at https://becominghuman.ai/artificial-vs-natural-intelligence-626b6c7addb2 [Accessed May 30, 2019].

5 This can be calculated for humans as the total cost of their life cycle, while in the case of machines, it entitles the overall cost of creating, operating and maintaining them.

6 AI initially was built on the foundation that it should copy the way neurons behave. McCulloh and Pitts (1943) proposed a definition of artificial neuron as a binary variable that is switched to either on or off. Donald Hebb (1949) added to this with his Hebbian learning for neural networks, while in 1951, Marvin Minsky and Dean Edmonds built the first neural network computer, known as SNARC. For further reference, see also http://cyberneticzoo.com/mazesolvers/1951-maze-solver-minsky-edmonds-american/. Hebb, D. (1949). *The Organization of Behavior*. New York, NY: John Wiley & Sons. McCulloch, W., & Pitts, W. (1943). A Logical Calculus of the Ideas Immanent in Nervous Activity. *Bulletin of Mathematical Biophysics*, Vol. 5, 115. https://doi.org/10.1007/BF02478259.

7 The word "robot" firstly appeared in a 1920 play, R.U.R. or Rossum's Universal Robots, by the Czech writer Karel Capek. In his native language, 'robota' meant serfdom. In the play, robots were synthetically produced, servile, flesh and blood creatures, who willingly agreed to follow humans' direction and take up on specific tasks, even though they could think for themselves. However, the term 'robotics' was coined in the 1940s by Isaac Asimov in his popular stories, like "Runaround", which introduced the concept of ethics applied to robots, through his Three Laws of robotics. Asimov, I. (1942). *Runaround*. New York, NY: Street & Smith Publications.

8 Turing wrote a paper in 1950 that was revolutionary, in the sense that he proposed a test to find out if a machine can exhibit intelligent behaviour which is indistinguishable from that of a human. His paper started off with a symbolic question, "I propose to consider the question, 'Can machines think?'". He used this probing approach to evaluate progress in the AI field. See Turing, A. M. (1950). Computing machinery and intelligence. *Mind*, 49, 433-60.

9 Founded in 1962 by Joseph F. Engelberger and George Devol, the company was located in Danbury, Connecticut. For more information, refer to www.botmag.com/the-rise-and-fall-of-unimation-inc-story-of-robotics-innovation-triumph-that-changed-the-world/.

10 Among the fundamental steps in AI history, we can count the followings. In 1955-1956, the first artificial intelligence program was developed by Allen Newell and Herbert Simon, also known as the Logic Theorist,

whose aim was to mimic the problem-solving skills of a human being. Scientists were able to see the program proving 38 of the first 52 theorems in Whitehead and Russell's Principia Mathematica (McCorduck, 2004). McCarthy presented the Advice Taker in 1958, a revolutionary program that was based on the distinction between knowledge - meaning the representation of the world - and the reasoning, which can be defined as the manipulation of the representation itself. From a different perspective, which was more oriented towards a means-end analysis based on how humans reach a goal while solving a problem, Newell and Simon developed a program also known as General Problem Solver (GPS), which was a program intended to work as a universal problem solver machine. Later on, researchers started to work using a different perspective, based on micro-worlds. Using McCarthy's approach according to which knowledge is represented by rules about a particular domain, while the reasoning becomes general-purpose algorithms able to manipulate the rules, Winston (1973), among others, programmed a robot capable of manipulating a set of blocks on a table, in several different ways. This approach is also known now as the block world. These early successes in AI were the reason behind an optimistic view on what AI would be able to achieve. Furthermore, different ways of dealing with complex research problems in AI emerged. Pearl (1988) and Neapolitan (1989) were the pioneers of the Bayesian networks; Holland (1975), Koza (1992) and Fogel (1994) dealt with evolutionary computation. At the same time, deep learning neural networks became popular to solve problems related to computer vision and speech recognition, while the field of Artificial General Intelligence (also known as AGI) emerged in 2007 to look for programs that can learn independently and make decisions in changing environments. An example of this can be seen in the work of Gerry Edelman, who was able to develop robot-like brain-based devices - or BBDs - able to interact with the environment. For further references, see the following literature. Goertzel, B., & Pennachin, C. (2007). *Artificial General Intelligence*. New York, NY: Springer. Goodfellow, I., Bengio, Y., & Courville, A. (2016). *Deep Learning*. Cambridge, MA: The MIT Press. McCarthy, J. (2007). From Here to Human-Level AI. *Artificial Intelligence*, Vol. 171, No. 18. Minsky, M. L., Singh, P., & Sloman, A. (2004). The St. Thomas Commonsense Symposium: Designing Architectures for Human-Level Intelligence. *AI Magazine*, Vol. 25, No. 2. Minsky, M. L. (2007). *The Emotion Machine: Commonsense Thinking, Artificial Intelligence and the Future of the*

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11 The first Winter of AI came about after the publication of Minsky and Papert's 'Perceptrons', the first systematic study of parallelism in computation. The second Winter was brought in by the diffusion of the desk computer, as commercialised by Apple and IBM, which in turn made the previous AI hardware somewhat obsolete. Experts do not all agree on the winter seasons of AI, so it might be interesting reading additional sources, such as https://www.technologyreview.com/s/603062/ai-winter-isnt-coming/. Minsky, M., & Papert, S. (1969). *Perceptrons: An Introduction to Computational Geometry.* Cambridge, MA: The MIT Press. Hernandez, D. (2015). How computers will think. *Fusion*, February 3. Retrieved online at https://splinternews.com/how-computers-will-think-1793844963 [Accessed May 30, 2019].

12 The public was amazed by the possibility that a machine could actually beat a human in what is considered one of the most cerebral games there are. In particular, we have TD-Gammon, an IBM computer backgammon program based on neural nets, capable to play backgammon at proficiency level. The time was right to put machines against humans in playing strategical games, and that was exactly what stopped somehow the critics towards AI and its allegedly slow progresses. Researchers have worked hard to duplicate the success of Deep Blue in other fields, like Go and Poker Texas Hold'Em. Thus, in 2016–17, we have AlphaGo, an AI Go player which played around 60 games with the top Go players around the world and won every single match; while in January 2017, Libratus demonstrated an AI program could bluff, winning at Texas Hold'Em at the expenses of top poker players. More information can be found online. Among others, you can refer to https://deepmind.com/research/alphago/ or https://www.ijcai.org/proceedings/2017/0772.pdf. Furthermore, with the new Millennium, the large diffusion of the World Wide Web and consequently related issues like big data, computational power and Cloud Computing, have allowed scientists to start exploring how the human brain-to-brain communication works. An interesting experiment conducted in 2013 by the Institute of Learning and Brain Studies at the

University of Washington, demonstrated how two people playing at the same video games in two different places could communicate their need for the other to shoot. In particular, through the use of an EEG machine with a transcranial magnetic stimulation coil positioned above the second person's head, researchers could prove that even without sound and visual stimulations, the first person could communicate their desire to shoot to the other. See Rao, R. P. N., Stocco, A., Bryan, M., Sarma, D., Youngquist, T. M., Wu, J., & Prat, C. S. (2014). A direct brain-to-brain interface in humans. *PloS one,* 9(11). Retrieved online at www.nbcnews.com/science/mind-meld-scientist-uses-his-brain-control-another-guys-finger-8C11015078 [Accessed May 30, 2019]. Silver, D., et al. (2016). Mastering the Game of Go with Deep Neural Networks and Search Trees. *Nature*, 529, 484-89. Retrieved online at https://www.nature.com/articles/nature16961 [Accessed May 30, 2019]. Ribeiro, J. (2016). AlphaGo's Unusual Moves Prove Its AI Prowess, Experts Say. *PC World*, March 14. Retrieved online at https://www.pcworld.com/article/3043668/alphagos-unusual-moves-prove-its-ai-prowess-experts-say.html [Accessed May 30, 2019].

13 Smart personal assistants have gained popularity since Siri, Alexa and Google Assistant became part of our lives. They are what we refer to as bots, capable of handling for us a small amount of daily tasks. In particular, the user can assign them a specific task to perform, and the bots have the ability to act and/or react with a certain degree of autonomy to the change of environment (for example, if they need to guide through the user in the processor changing an expired password). At the same time, personal assistants are required to be able to interact with other smart assistants and humans, as well as being able to learn from previous performances to improve. Interestingly, Google shocked everyone at an event in 2018, where Jeoffrey Grubb presented its Assistant making independently a phone call to a hairdresser and taking an appointment with no human intervention. The presentation was spectacular in so many ways, and the most amazing thing was the human-like voice that performed the call. Nobody could actually guess it was a bot. See for example, https://www.youtube.com/watch?v=D5VN56jQMWM or Welch, C. (2018). Google just gave a stunning demo of Assistant making an actual phone call. *The Verge*, May 8. Retrieved online at https://www.theverge.com/2018/5/8/17332070/google-assistant-makes-phone-call-demo-duplex-io-2018. Another interesting area of AI development is linked to the importance of consumer behaviour and experience, with regard to

for example revenue management or collaborative filtering techniques. Revenue management consists of rules to predict consumer demand, so that inventory and price availability are checked to maximise revenue growth. On the other end, collaborative filtering uses the opinions and feedback of a group to build recommendation systems to inform other consumers' choice. In this approach, consumers are offered products and services that should be of interest to them, based on complex data such as users' browsing data (this might consider the pages visited, the frequency of such visits, the content of your basket, for how long you visit a website and other people's vote). Experts usually refer to it as a system based on a "digital word of mouth". Similarly, AI can provide predictive models that help businesses predict the quality and pricing of specific products. See for example Ashenfelter, O. (2008). Predicting the quality and prices of Bordeaux wines. *Economic Journal*, 118, no. 529, F174-84.

[14] Nakamoto's solution was to create a new independent digital currency, also known as Bitcoin, while participants would use their digital signature to transfer the right amount of bitcoins in each transaction. Whenever a Bitcoin transaction happened, this would have been recorded in a ledger, that logged the amount of Bitcoins spent, and the identities of the seller and the buyer through their digital signatures. In particular, the system works as follows: 1) a transaction happens between buyer and seller, and it is broadcasted in real time throughout the system. 2) Specialised computers called nodes verify that the transactions were legitimate (for example, that the Bitcoins were not spent before somewhere else). 3) While checking the transaction, the nodes are in a competition between themselves to find a HASH, which is a short numeric summary of the current block. 4) The first node to find the right hash broadcasts it throughout the system, and as a reward can create and keep for itself a predetermined number of Bitcoins. 5) The other nodes verify the winning block (if they find something illegitimate or incorrect, they have other chances to get the reward). 6) If the block has been checked, then the nodes carry on with a new one and the process starts all over again. We can say that blockchain can be potentially used to record all kinds of transactions, not only Bitcoins, so Nick Szabo (1990s) advanced the idea of using it for digital smart contracts. In 2016, Ethereum was the most famous "decentralized platform that runs smart contracts: applications that run exactly as programmed without any possibility of downtime, censorship, fraud or third party interference". See Nakamoto, S. (2008).

Bitcoin: A Peer-to-Peer Electric Cash System. Retrieved online at https://bitcoin.org/bitcoin.pdf [Accessed May 30, 2019]. Szabo, N. (1996). Smart Contracts: Building Blocks for Digital Free Markets. *Extropy*, Issue n. 16. Retrieved online at http://www.fon.hum.uva.nl/rob/Courses/InformationInSpeech/CDROM/Literature/LOTwinterschool2006/szabo.best.vwh.net/smart_contracts_2.html [accessed May 30, 2019]. Reworked a year later as Szabo, N. (1997). Formalizing and securing relationships on public networks. *First Monday*, Vol. 2, No. 9. Retrieved online at https://ojphi.org/ojs/index.php/fm/article/view/548/469). Vigna, P., & Casey, M. J. (2015). *How Bitcoin and digital money are challenging the global economic order*. New York, NY: St. Martin's Press. McMillan, R. (2014). The inside story of Mt. Gox, Bitcoin's $460 Million disaster. *Wired*, March 3. Retrieved online at https://www.wired.com/2014/03/bitcoin-exchange/ [Accessed May 30, 2019]. Campbell, R. (2016). Holberton School begins tracking student academic credentials on the Bitcoin Blockchain. *Bitcoin Magazine*, May 18. Retrieved online at https://bitcoinmagazine.com/articles/holberton-school-begins-tracking-student-academic-credentials-on-the-bitcoin-blockchain-1463605176/ [Accessed May 30, 2019].

15 An interesting reading can be the Asilomar Principles on AI research, which discuss in form of open-ended questions the major aspects of AI research and development. These have now be signed by 1273 AI/Robotics researchers and an additional 2541 from other disciplines. According to the Future of Life Institute: "*Research Issues* 1) Research Goal: The goal of AI research should be to create not undirected intelligence, but beneficial intelligence. 2) Research Funding: Investments in AI should be accompanied by funding for research on ensuring its beneficial use including critical questions in computer science, economics, law, ethics, and social studies, such as: • How can we make future AI systems highly robust, so that they do what we want without malfunctioning or getting hacked? • How can we grow our prosperity through automation while maintaining people's resources and purpose? • How can we update our legal systems to be more fair and efficient, to keep pace with AI, and to manage the risks associated with AI? • What set of values should AI be aligned with, and what legal and ethical status should it have? 3) Science-Policy Link: There should be constructive and healthy exchange between AI researchers and policy makers. 4) Research Culture: A culture of cooperation, trust, and transparency should be fostered among researchers and developers of AI. 5) Race Avoidance: Teams

developing AI systems should actively cooperate to avoid corner-cutting on safety standards. Ethics and Values 6) Safety: AI systems should be safe and secure throughout their operational lifetime, and verifiably so where applicable and feasible. 7) Failure Transparency: If an AI system causes harm, it should be possible to ascertain why. 8) Judicial Transparency: Any involvement by an autonomous system in judicial decision-making should provide a satisfactory explanation auditable by a competent human authority. 9) Responsibility: Designers and builders of advanced AI systems are stakeholders in the moral implications of their use, misuse, and actions, with a responsibility and opportunity to shape those implications. 10) Value Alignment: Highly autonomous AI systems should be designed so that their goals and behaviors can be assured to align with human values throughout their operation. 11) Human Values: AI systems should be designed and operated so as to be compatible with ideals of human dignity, rights, freedoms, and cultural diversity. 12) Personal Privacy: People should have the right to access, manage and control the data they generate, given AI systems' power to analyze and utilize that data. 13) Liberty and Privacy: The application of AI to personal data must not unreasonably curtail people's real or perceived liberty. 14) Shared Benefit: AI technologies should benefit and empower as many people as possible. 15) Shared Prosperity: The economic prosperity created by AI should be shared broadly, to benefit all of humanity. 16) Human Control: Humans should choose how and whether to delegate decisions to AI systems, to accomplish human-chosen objectives. 17) Non-subversion: The power conferred by control of highly advanced AI systems should respect and improve, rather than subvert, the social and civic processes on which the health of society depends. 18) AI Arms Race: An arms race in lethal autonomous weapons should be avoided. Longer-term issues 19) Capability Caution: There being no consensus, we should avoid strong assumptions regarding upper limits on future AI capabilities. 20) Importance: Advanced AI could represent a profound change in the history of life on Earth, and should be planned for and managed with commensurate care and resources. 21) Risks: Risks posed by AI systems, especially catastrophic or existential risks, must be subject to planning and mitigation efforts commensurate with their expected impact. 22) Recursive Self-Improvement: AI systems designed to recursively self-improve or self-replicate in a manner that could lead to rapidly increasing quality or quantity must be subject to strict safety and control measures. 23) Common Good: Super-intelligence should only be developed in the service of widely shared ethical ideals, and for the benefit of all humanity rather than one state or organization." For more info, refer to https://futureoflife.org/ai-principles/?cn-reloaded=1.

16 There are AI experiments on the assessment of the probability an individual is law-abiding versus criminal, using face recognition. In this perspective, San Francisco is the first US city to ban this type of technology. Among others, see Harwell, D. (2019). San Francisco becomes first city in U.S. to ban facial-recognition software. *The Washington Post*, May 14. Retrieved online at https://www.washingtonpost.com/gdpr-consent/?destination=%2ftechnology%2f2019%2f05%2f14%2fsan-francisco-becomes-first-city-us-ban-facial-recognition-software%2f%3f&utm_term=.3eea01735dfc [Accessed May 30, 2019]. Quach, K. (2016). AI can now tell if you're a criminal or not. *The Register*, November 18. Retrieved online at www.theregister.co.uk/2016/11/18/ai_can_tell_if_youre_a_criminal/ [Accessed May 30, 2019]. Sweeney, L. (2013). Discrimination in Online Ad Delivery. *Queue*, 11, no.3. Retrieved online at https://arxiv.org/pdf/1301.6822.pdf [Accessed May 30, 2019].

17 According to an article written by Christina Wong (2017), "Should artificially intelligent robots have the same rights as people? Yes, says one of Canada's top artificial intelligence (AI) entrepreneurs. Suzanne Gildert is co-founder and chief scientific officer of Kindred AI, a Vancouver startup whose backers include Google's venture capital arm. At the SingularityU conference in Toronto, Gildert made the case for extending human rights to artificially intelligent robots. "A subset of the artificial intelligence developed in the next few decades will be very human-like. I believe these entities should have the same rights as humans," said Gildert." Wong, C. (2017). Top Canadian researcher says AI robots deserve human rights. *IT Business*, October 11. Retrieved online at www.itbusiness.ca/news/top-canadian-researcher-says-ai-robots-deserve-human-rights/95730 [Accessed May 30, 2019].

Chapter 5
Artificial Intelligence in Practice

ABSTRACT

In this chapter, the authors discuss machine learning techniques and artificial intelligence applications, their role in business, and present a practical application of it. They try to highlight how important machine learning can be in data-driven organisations, where the cost and/or the advantages to implement such tools are far greater than having a human—or a team of humans—doing it.

MACHINES AND THEIR LEARNING

In the previous chapters, we have discussed about the importance of data and its proper use. We have also introduced artificial intelligence, and the marvellous achievements we could already celebrate. In this perspective, machine learning can be thought of as a set of mathematical rules - also known as algorithms - to analyse data. But how does machine learning work? There are several techniques that can be used to implement machine learning, according to the type of learning programmers have decided to use.

Thus, we can start with the most common technique in the field, also known as supervised learning, whose main objective is to train the machine into recognising one or more elements that have been previously identified, as contained in a digital data stream (which can be an image, a face, a sound, and so on). Ideally, supervised learning takes place when either we are trying

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to predict the class of an item, using what is known as classification models, or a number, in which case we are exploiting regression models. In both cases, we could use simple linear[1] and logistic regression[2] or more complex decision tree families[3]. Furthermore, this implies that we need to build a training set with thousands or millions of images, which will be supervised by analysts to make sure the right data are inserted, as well as to make sure the machine is actually learning and correct its errors, in case any have been detected. Once the first stage of the training process - also known as learning phase - has been completed, new images are introduced into the program, to see if the learning actually took place and it is sustained even with other tons of images added to the mix[4]. This process has benefitted from advancements in computational power and availability of data from the web and the Internet of Things, in particular when it comes to translation of text (Google Translate is a powerful AI tool that is able to find patterns and grammatical structures to translate words and more complex text), as well as facial recognition systems (see for example, Zakharov, Shysheya, Burkov & Lempitsky, 2019). Interestingly, supervised learning can be enhanced through a reward mechanism, according to which the model provides its margin of error, once it has understood the correlation between inputs and outputs and has been able to identify the probability of success in reaching specific objectives.

Although it might not seem so obvious, this trial and error process sounds fairly repetitive and automated for the machine, and still requires human intervention. Thus, we should look at another machine learning technique, which tries to imitate the way humans think and learn, through knowledge and experience. This technique is also known as unsupervised learning. As the name suggests, the machine is capable of autonomously evolving in its environment, through adaptation of its models. Here, humans will do not write a program or code to help the machine start its journey, in fact what is amazing about unsupervised learning is that no algorithm is written nor it contains prior knowledge. The machine independently starts clustering similar information, which means it groups together data that recognises as similar, with no idea of what to expect as output. This technique is based mainly on the use of neural networks (Rosenblatt, 1958; Rumelhart, Hinton & Williams, 1986), which imitate the way the human brain neurons work without having prior knowledge - or "pre-coding" - whatsoever, which are organised in successive layers that allow increasingly complex identification and filtering of data (images, text, and so on). We have already introduced examples of neural networks in the previous Chapter, while talking about victories of AlphaGo, as well as autonomous or self-driving cars. Thus, a neuron in machine learning is not a living thing, it is a simplistic representation of the way natural neurons behave, and are created using equations that provide computer code. To simplify the stages of such technique, the neuron has observation data as inputs, which are then multiplied by a weight (which can be either positive or negative) and added up to make up an initial score. At this stage, good practice tells us to transform the initial score in a score within the range 0-1, which will become our output. It is interesting to highlight that the inputs given to each neuron in the same layer are the same, however weights might differ, which will mean in contrast that each neuron produces a different score. At the same time, the outputs of the first layer become the inputs of the second one and so forth. Weights are usually assigned randomly (or value zero) by the training algorithm, and after an assessment on how accurate they are, they are adjusted to improve the predictive accuracy of the model, as many times as it is needed.

Deep learning is the latest and most accurate development in neural network models, and it puts achievements in AI a step closer to resemble humans[5]. Among deep learning models, we can cite back-propagation, a technique developed in 1986 by Rumelhart, Hinton, and Williams, which was based on neural networks being able to learn from every prediction. This is possible if we create nonlinear differentiable functions, where one is the original that will forward-propagate till the end of the network, and the other is the one we will use to compare against the 'label' or expected value. So when we have calculated the differences between first and second functions, these are back-propagated through the network to adjust its weights and biases using fractional differences (here intended as partial derivatives of the error with respect to each weight). This process allows to optimise the network through what we know as "gradient descent" (GD), which compares the error in the current result against the error in previous results, and pushes the function towards the direction of the descending gradient. Now, the problem is that deep networks have tons of weights and biases to check and adjust (we are looking at millions of data inputs), which makes it really difficult to achieve what we wanted to in a single gradient step. For this reason, it might be better to use a stochastic gradient descent (SGD) approach, which should look at a single sample from the input, try it in the network and adjust the gradient using the error in that single specific sample. In this perspective, the stochastic gradient descent keeps updating the weights after every single sample, while the gradient descent stops once it realises it cannot get any better or it has no more time to improve. Furthermore, we should point out that neural networks have evolved from their 'basic' form (dense networks that are used for example to solve particular tasks, such as identifying fraudulent transactions) into convolutional neural networks, made of specialised convolutional neurons, which are effectively used to process image data because they can learn to identify edges, ears, and other bits of a whole picture.).

We have already discussed in the previous Chapters how machine learning, as well as artificial intelligence systems, are determined by the data fed to the program itself. In particular, we have highlighted how raw data needs to be transformed into a format that can be understood by the program[6], which is usually known as "featurisation", a process that enables the transformation of incoming data into a specific format while extracting relevant data from irrelevant ones. Interestingly, if we already know what we are looking for in our data, we can label it, using numeric or categorical labels[7]. To explain it better using an example, we can say that if we are approaching an image recognition task, the features will be the pixels of each image, and our labels will be the main object in the picture (i.e., "cat"), taken from fixed labels that might be "cat", "dog", "house", "car" and so on.

Moving on from supervised learning, which presents a development data set that consists of observation and outcome data, machine learning experts cite unsupervised learning, which happens, as we saw earlier on, when we are looking for new knowledge, thus outcome data is not available. In other words, we might be in the condition of trying to understand if there are similarities or connections among a certain data set, but no prediction on how something or someone will behave is offered. In this perspective, clustering is the most used technique, and it allows to determine the proximity between data in terms of similarity, so clusters are identified in the development sample[8].

When no observation nor outcome data is available at the beginning of the procedure, reinforcement learning occurs. Reinforcement learning is similar to supervised learning in the perspective that they both run on neural network models, as well as they adjust themselves according to the outcomes of a given data set. However, reinforcement learning models do not learn from a prearranged data set, they do learn independently using a reward system, according to which the model gets something each time it is performing a task well. To better understand such differences, we might think of how such models go learning about chess, for example. Supervised learning models would use tons of moves from previous games as training set, and label the results of such moves to help the program understanding if the move was good or not. In reinforcement learning models, training data does not exist, so the program will make a move which is not the result of a training exercise, it is random. At every move, the program will then re-evaluate its paradigms and learn in a process of trial and error, which might make the learning too long and expensive.

Examples of Machine Learning Algorithms

In the previous Section, we have introduced some of the most common and fundamental machine learning techniques. For example, we have mentioned regression, whose main goal is to estimate or predict a response, while looking for factors that influence an output variable. Similarly to regression, logistic regression is a classifying technique mostly used by medical researchers, and those who have large but simple data sets. An example could be a medical study where researchers are interested in knowing the variables that influence mortality. Another type of regression is the so-called tree-based regression, in which a dataset is broken down into smaller subsets each time, to then mimic a tree with decision nodes and leaf nodes. Tree models are relatively easy to use, and simple to understand and interpret, especially considering that they can deal with large sets of data.

When talking about tree models, we can definitely cite gradient boosting algorithm, in which trees are trained one after another, using as training data those that have been identify as wrong in the previous tree. Similarly, random forest algorithms consist in the average of several decision trees. While each tree is trained using random sample of data, they are singularly weaker than the random forest one, which becomes better in the over-all performance thanks to the diversity each tree brings to it. At the same time, random forest algorithms are very easy to train and work well with machine learning.

Furthermore, we might be interested in using ensembling techniques when we are looking for the meaning of all predictions we have, to end up with a final one. This approach is particularly useful in case there are several predictors trying to predict the same thing, which will give a better result when using an ensemble algorithm. There are two types of ensemble algorithms, also known as boosting and bagging. Bagging is more successful when we apply model averaging techniques to a series of predictors or models we have built. On the other end, boosting is to be used when predictors are made sequentially, rather than independently. Gradient boosting is an example of this technique, which is easy to train yet difficult to understand and explain in its passages if changes - even minimal - are made to the training data set. Another interesting example of these models can be the so called adaptive boosting, which is a meta-algorithm we can use when the model's performance is not that great and we need to improve our models.

Among the algorithms that we have already cited, we also have K-means clustering, that can be defined as a simple method for estimating the mean (vectors) of a set of k-groups in an unsupervised setting, which means the algorithm itself should decide how to split in groups without human intervention. It is used in particular with a large number of variables, which in turn means there is a substantial number of groups to classify.

Furthermore, frequent pattern-growth is an algorithm used to find frequent patterns, which is mainly used in retail - think of Amazon, for example - where the market basket analysis is frequently used to find co-occurrence relationships. When we are interested in finding frequent individual items within a large database - for example, if we are interested in customer purchases - and expand them in larger item-sets following specific criteria, we might consider using priori algorithms. Such type of algorithms are great at finding association rules to generalise trends, which is at the core of the basket analysis, especially in case of big data.

An interesting one is the Naive Bayes approach, which classifies data items according to prior probabilities, likelihood and similar. The principal component analysis (or PCA) is mainly used in predictive modelling, and it is used to define a general structure among variables.

While we appreciate the idea behind big data and the Internet of Things, we also know how important is to decide which data to use. We have discussed the major algorithms which we might use to enhance performance, but what about unused or inappropriate data? In this case, dimensionality reduction algorithms are useful to remove data which is not appropriate for the analysis we are conducting, or it redundant. This is applicable in particular for data collected by sensors, which are extremely used in IoT and big data analysis.

Furthermore, we have discussed the use of neural networks and their more complex structure in the form of deep learning, which consists of several layers of neural networks that reproduce human-like processing, helpful to handle consistent amount of sophisticated data. Deep learning, as started by Andrew Ng[9] at Google, presents different architectures and models. Thus, we have deep learning architectures also known as generative, when we use unsupervised learning to learn a function able to approximate the model distribution to the true distribution, while generating new data points from the training set's true data distribution. Discriminative architectures can be defined as "intended to directly provide discriminative power for pattern classification, often by characterizing the posterior distributions of classes conditioned on the visible data" (Deng, 2012). Lastly, deep learning architectures can be hybrid, meaning present aspects of both discriminative and generative deep learning. Among these types of architecture, we can count different deep learning models, such as auto-encoder, deep belief network, restricted Boltzmann machines, and convolutional neural networks[10].

Artificial Intelligence Models and How to Implement Them

We have seen how data is crucial to machine learning, and consequently to implement artificial intelligence solutions. Data science informs the field, through a precise workflow with several steps to take to be successful. First of all, we need data. Data is acquired through several sources, although we have already anticipated the advent of the World Wide Web and Internet of Things, as well as the tremendous amount of users have changed the way we think about data. The acquired information or data is then used to develop a data set, after they undergo through a phase of preparation. As we discussed earlier, preparing the data means transform it in values that are understandable for the program, while at the same time initiate preprocessing and cleaning procedures to avoid flaws and misrepresentations. At this stage, data should be split to have a training set, and a validation set, to use after for testing the validity and performance of the model. The model will now need to be embedded for example in the decision-making process, or any other procedure we implemented it for. The process keeps iterating itself, using new data at each opportunity.

Machine learning and AI solutions have recently started to make an appearance, in a variety of forms and models. For example, those interested in starting a machine learning project, will need to look at AI software platforms available to them, which might be Amazon Machine Learning (see https://aws.amazon.com/machine-learning/), Microsoft Azure Learning Studio (https://studio.azureml.net), or IBM Watson (https://www.ibm.com/watson). An interesting fairly new one is Acumos (see https://www.acumos.org), described in its website as "a platform and open source framework that makes it easy to build, share, and deploy AI apps. Acumos standardizes the infrastructure stack and components required to run an out-of-the-box general AI environment". Platforms are not the only important type of tools you will need. In order to avoid repeating the same bits of coding, or instructions, software frameworks do rely on software libraries, which contain specific instruction sets that won't need to be programmed from scratch. Silicon vendors, such as Intel Math Kernel Library and Nvidia, follow the good practice of creating low-level libraries - which include assembly code, in the form of several mathematical and numerical kernels, that are then exposed to higher-level applications.

On top of that, big tech giants like Google, Microsoft and Facebook, tapping on their cloud services, have implemented several AI open-source software frameworks in the last years (an interesting list of available datasets can be found at http://deeplearning.net/datasets/). Thus, we are able to use one or more of the programming languages that we discussed in Chapter 3, such as Python and JavaScript, which can be easily integrated into machine and deep learning software frameworks, according to what we were dealing with (i.e., images, speech recognition, and so on). We will try to present here some of the most common software frameworks available in the market.

Probably the most common one, TensorFlow (https://www.tensorflow.org/) is an open source library, originally developed by researchers on the Google Brain Team, which is a deep learning artificial intelligence team that is exploring innovative ways to advance the start of art in AI and build intelligent machines. Because of its origin, TensorFlow is heavily used in several Google applications (i.e., YouTube), to work on image classification and recognition, recommendation, natural language understanding, as well as speech recognition. TensorFlow is implemented in Python (like Intel's Neon, available at https://www.intel.ai/neon-2-0-optimized-for-intel-architectures/#gs.gyivh3) and allows data flow graphs for numerical computation, as well as supporting deep learning and statistical machine learning algorithms. Data scientists, programmers and engineers that work on TensorFlow can use a suit of visualisation tools known as TensorBoard, to debug and optimise TensorFlow code when something is not quite right. Another software framework that works well with Python is Scikit-Learn (https://scikit-learn.org/stable/index.html), whose aim is to provide simple tools for data analytics tasks, which can be summarised as classification, regression, clustering, as well as dimensionality reduction, model selection and finally data preprocessing.

We have previously mentioned Apache Hadoop, which can be described as follows. "The Apache Hadoop software library is a framework that allows for the distributed processing of large data sets across clusters of computers using simple programming models. It is designed to scale up from single servers to thousands of machines, each offering local computation and storage. Rather than rely on hardware to deliver high-availability, the library itself is designed to detect and handle failures at the application layer, so delivering a highly-available service on top of a cluster of computers, each of which may be prone to failures" (from http://hadoop.apache.org). From Apache, we also have Apache Spark, which is "a unified analytics engine for large-scale data processing", used to process big data, and updated by a large community of developers. It offers a large selection of libraries, and it is easy to use because of its intuitiveness as well as the opportunity to interact with it from R, Python and other famous languages.

Another interesting example of software framework, as developed by Berkeley Artificial Intelligence Research team and community contributors, is the so called Caffe (see http://caffe.berkeleyvision.org/), which is written in C++, and presents a Python interface. Caffe is very well known in start-up environments and academic research projects, as well as industrial applications related to vision, speech, and multimedia in general. Similarly, H2O (https://www.h2o.ai/) has been developed for big data analytics for cloud computing, whose graphical user interface is compatible with the major internet browsers. It supports several statistical algorithms, such as K-means clustering, linear models, gradient boosting, distributed random forests, and much more.

Business Applications for Machine Learning Systems

Applications of Deep Learning in business are becoming incredibly huge, with the promise of exploiting data and analyse it in order for the organisation to enhance efficiency, as well as gaining competitive advantage. Thus, AI and machine learning techniques can be considered the way businesses are reverting to implement their processes successfully. The advantages are infinite, in particular if we consider in how many ways we can interpret the collected data. Let's say, for example, that our machine learning model analyses conversations to enhance customer engagement. Once that data is collected, the sales department should have a better understanding of the variables in language that seem to be linked to a sell, or at least predict plausible conditions for a sale to occur. At the same time, data could indicate to the marketing team which group of consumers to target, and what argument to use to attract potential buyers.

Among these types of applications, machine learning and AI can implement the so called recommendation systems, which are based on the classification of data according to three major categories, meaning items - or objects that are recommended, users and transactions between a user and the recommendation system itself. We might think about ratings, which might be numerical, ordinal or binary. We are all used to give ratings for a book, or a product, and we usually look through ratings before actually buying something, letting other customers' thoughts and experiences guide us in the process. In this perspective, businesses might be interested in predicting how much a user will like a specific item from a ranked list, or the likelihood they will like all the products that can be offered, regardless of their use and type. Similarly, you might have seen on famous websites, something that says "Who bought product X also bought this", or "Suggested movies" based on what you have watched in Netflix. Slightly less invasive are the suggestions offered by Amazon or eBay, in relation to products that might be interesting for them. Other recommendation systems might focus on providing a comprehensive sequence of products the user should like as a whole (this is more linked to playlist generation on Spotify). In any case, recommendation systems are based on ratings and feedback - which might include the user's feelings towards a specific product - given by other customers, which might be linked to the individual's attitude of sharing personal experiences (this might be the case in bad and good review on TripAdvisor or Just Eat) or promoting - at least influencing - a business.

Recommendation systems are based on different techniques, that can be summarised as follows:

- Content-Based recommendations, which are built on the believe users will more likely go for items similar to what they have already found interesting.
- Item representations, according to which items are 'judge' against a specific set of features (i.e., for movies, these may be actors, genres, language), whose value can be determined and analysed.
- User profiles can be used in machine learning techniques, where past behaviours towards items and products can be taken into account to predict interest (i.e., like or dislike functions in Facebook). This is particular true when we come across news recommendations, which are based on our reading history, and other variables such as access patterns to create our user profile and consequently recommend specific news. Furthermore, user's profile can be used also to be matched against characteristics of items we want to recommend.

- Finally, we have the so called collaborative recommendations, where in order to suggest items, we do not look for similarities between items previously bought by the user, but we look at similarities among users to suggest a specific item. In other words, it aggregates the ratings as indicated by users with similar rating patterns and comes out with a predicted rating for a given user.

Recommendations are not the only application of machine learning and AI algorithms in business. recently, a great deal of interest is surrounding natural language processing systems. When thinking about NLP, chatbots are the first thing that comes to mind. Whether we deal with chatbots answering general questions in help desks, waiting for them to redirect us to the most appropriate office or operator, or we came across a chatbot helpful enough to give us personalised shopping advice, it is all possible thanks to smart NPL-based search and machine learning algorithms. Good examples of the wonderful things chatbots can do, can be Apple's Siri and Amazon's Alexa, two very smart personal assistants capable of suggesting playlists, tell you about weather and call for you someone. At the same level, even text analytics is a huge interesting field for businesses to exploit, because it gives them useful information (i.e., places we have been, people we know) from text sources. These might be a summary of a long document, spam emails or translation from a different language. Based on text analysis, statistics and natural language processing, machine learning algorithms can also interpret the attitude, emotion, judgement or intent behind the words of a person into a positive, neutral or negative statement or a proper feeling, using what is known as sentiment analysis. This is particularly helpful to understand how consumers feel about your brand as well as your competitors, and at the same time predict customer trends, that can then be compared with what your organisation offers in terms of products, services and brand image. Sentiment analysis mainly uses reviews and social media to support marketing teams and customer service, as well as R&D projects with the testing of how a new product would be received from the market.

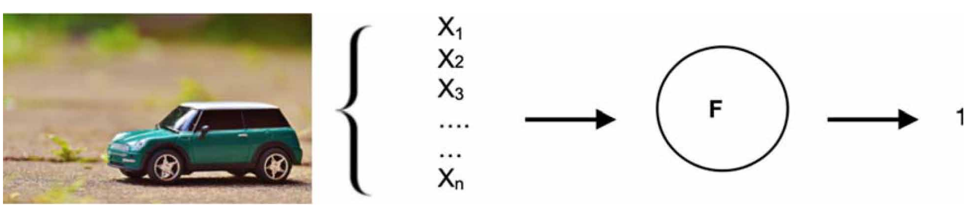
As we introduced NLP techniques, it might seem obvious now that their implementation costs are not so high and algorithms have become really precise, that these are heavily present in customer service, where a tremendous amount of data can be collected through speech recognition applications (to convert spoken language into text, which can then be structured and analysed as external data), question answering protocols (where the chatbots reply to questions posed by humans) and reputation monitoring. In this perspective, marketing and advertisement teams are willing to invest in machine learning and AI technologies to have a better understanding and accurate predictions on who to target, for example. Natural language processing systems can help them through keyword matching algorithms, and other applications that try to properly identify the contextual meaning of a word in a sentence. Similarly, NLP applications are used to understand the state of the industry, to better develop an effective strategy and gain some competitive advantage in the market.

A Practical Example of Machine Learning Algorithm

Managers do need to understand how AI and machine learning work in order to devise a sound strategy for innovation in their company. However, they are not required to be experts. We will offer here an example of different techniques we could use with the same goal in mind, taking into account experience and knowledge of teams, strategic aims, budget and so on.

Thus, we should remember that AI is the way to program computers to perform tasks that could have only been achieved by humans until now. How do we do that? First of all, we need to make sure that our AI program understand its tasks. During a first phase of training, we teach the program, so it can learn through examples (or training set), instead of step-by-step instructions. For example, if we want our AI program to learn how to drive a car, it will need to learn before hand how to recognise a car from a truck, or a pedestrian, a bus, and so on. Similarly to what we learned about the binary code, we will use labels for each item (i.e., pictures, media, text) of the training set, that conventionally will be "1" if the item is a car (or any other item we are trying to learn to recognise), or "0" if it is not a car. It might seem repetitive to point out again that our AI program will be accurate depending on how large the training set is, where having more data will make it more reliable.

Figure 1. Machine learning algorithm example



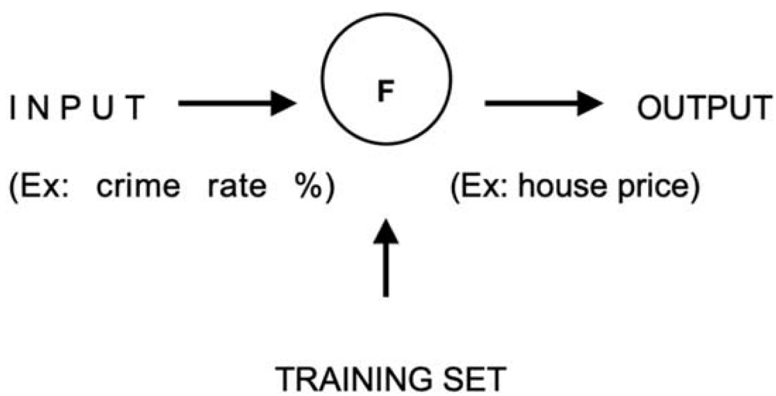
Thus, while having a huge amount of data might not be a problem anymore, thanks to the Internet, the IoT and social media, the labelling activity needs still human intervention, and because of this it is a costly and long procedure.

To simplify things, we should think of our AI system in terms of a function, where the input is the picture (of a car, truck, bus, train, etc.), and the output is a 0 or a 1. In order for the output to be decided, the algorithm will scan the picture in its entirety, looking through its variables or dimensions. These variables are taken into account with consideration of the number of pixels of each image. So, if our image is 100 pixels in height and 50 pixels width, the total number of pixels to check is 5000. Because each pixel requires 3 numbers to be allocated (one for the red colour, one for the green, and one for the blue), these 5000 pixels will translate into 15000 numbers - or variables - as input.

This is possible because, as we highlighted before, AI systems learn the function (F) from the training set, and only one input variable is inserted to then determine only one output number, using the following structure:

Now, if we think of something very practical, we might even be able to understand how this would work. So, let's say that we are into the real estate sector, and we want to predict the price of houses in a specific area. Thus, we already know that house prices are influenced by crime rates and/or proximity to good schools. We proceed to make a list of % in crime rates related to the numbers of residents in the area, which will become our training set. The houses we are looking at are in an area with a percentage of crime rate that is not yet calculated within our training set, let's say crime rate 23. Without using a machine learning function, we would probably approach the problem in this way: we would find out the two nearest crime rate percentages and

Figure 2. Simplified machine learning algorithm example



predict that the house price in the interested areas would be the average between the two nearest %. Hypothetically, we say that at crime rate % 22 corresponds a house price of 236, while at crime rate 24, house price goes down to 218. Following the human approach, the pricing of the houses we are looking at will probably sits at 227. However, using a machine learning function, we would use a k-nearest neighbours (KNN) algorithm to predict the house price in an area with 23% crime rate, which would look at the five nearest data points (not two), and the prediction would be 224, rather than 227. As we have anticipated in previous sections, the KNN technique is a fast and relatively simple way to train a machine learning algorithm to find a prediction, although the number of input variables needs to remain small.

What happens when we want to analyse complex behaviour then, such as in the case of e-commerce systems that recommend products to users? We will need to apply model-based machine learning, where a model is a function template with parameters that change the behaviour of the model. So, in case of f(x) = A + Bx, A and B are our parameters, and the model function will be a straight line. If we want to learn what happens in a more intuitive and engaging way, we are not looking for straight lines, we are trying to see what happens in a longer period - and our graphic would look like a curve - so we will add more parameters to the model function like this:

$$f(x) = A + Bx + Cx^2 + Dx^3$$

Going back to the previous example, when we argued that using the k-nearest neighbours algorithm, the house price in a 23% crime rate area would be 224, we can now use this model function to figure out the prediction error of our function, which will be the square difference between the prediction and the actual measured value:

$$\textit{Prediction error} = (f_{(23}) - 224)^2$$

This will allow us to compute the prediction error for any measured value in the training set, while initially randomly choose small numbers between 1 and 0 as initial values for the parameters. The goal of the procedure is for the machine learning algorithm to learn, reducing the prediction error by making small changes to all the coefficients of the model. If the change results in a smaller prediction error, we will keep the change, otherwise we discard it and keep iterating the process for thousands of times. Because we have to adjust the coefficients in our function, the prediction error - or cost function - model is good when we have a large numbers of variables, for which we allow a consistent amount of time for the learning to happen. We should remember that we will end up with a curve where data points are linked, whose learning rate started at 1 and then progressively reduced to a small number like 0.0000001.

What happens when we have like 50 million training data points? What would be the best approach to compute the prediction error of such a ginormous training set? Needless to say, the best way to tackle the task will be to compute the prediction errors of mini batches of roughly 10 thousands data points each. A mini batch can be defined as a random sample from which we can estimate the prediction error of the entire training set, through a stochastic learning procedure. This means that in the first iteration, we will compute the prediction error for the first mini batch; in the second iteration, we will compute the prediction error for the second mini batch, and so on, to speed up the process of completing the whole scan of the training set, also known as epoch.

Now that we have an idea of how stochastic learning happens, we can do more advanced operations using the gradient descent approach, which entitles the application of calculus to differentiate the prediction error with respect to the model parameters in each iteration, instead of randomly try to measure the parameters' value from a fixed number (1) down to 0.0000001. The use of the gradient descent (which implies calculus) and the stochastic learning (iterative computation in mini batches) can thus be combined into the stochastic gradient descent (or SGD).

Furthermore, we should be aware that computing the prediction error will involve performing mathematical operations in tons of data in the training set, which will then need to be collected in matrixes. A one dimension collection of data is also known as vector (i.e., [3 8 9 0 2]), while a two-dimension one is a matrix, that looks like this:

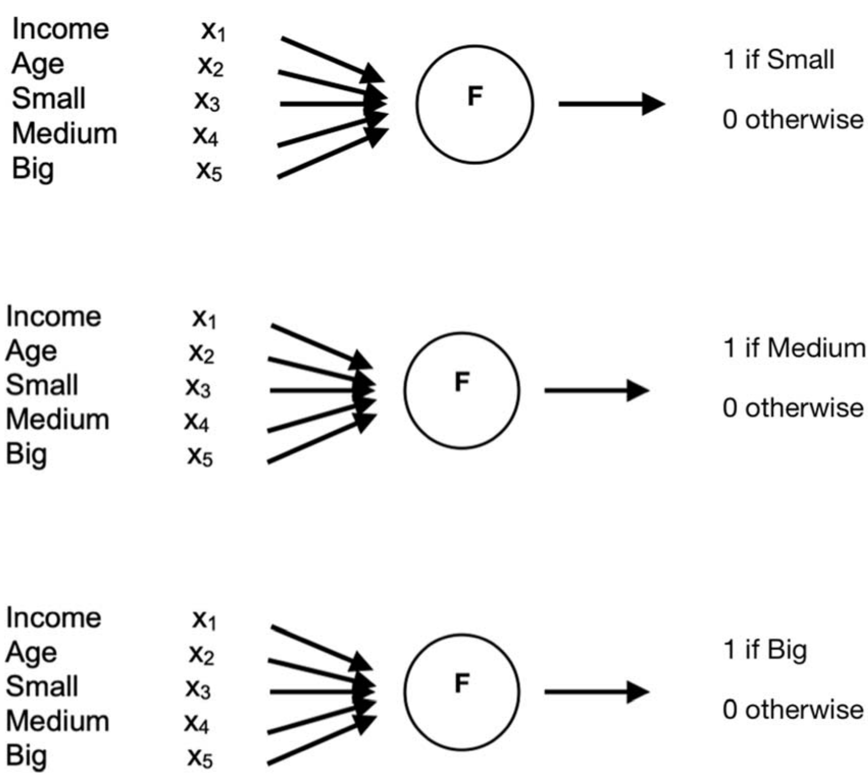
$$\begin{bmatrix} 5 & 7 & 9 & 4 & 6 \\ 2 & 3 & 5 & 8 & 6 \\ 4 & 8 & 9 & 2 & 1 \end{bmatrix}$$

A multi-dimension collection of data is also known as tensor, and it can be seen represented as a matrix of cubes, similar to a Rubik's cube. To support matrix and tensor operations, we usually use vectorisation programs, which are really fast because each data point is computed by different CPUs in parallel.

At this stage, we might be interested in more complex ways to solve our business problem. Let's imagine, for example, that we need to predict the type of car a buyer will choose among a huge selection. In the previous examples, we have seen how the output was a real number (that is the case in the example where we used regression), however in this case we will need to find out the brand of a car, which is a non-numerical output. To achieve this result, we will need to use a technique known as classification, where inputs are several different variables that might be, once again, non-numerical (i.e., type of previous car), to achieve an output that is either a 1 or a 0. To explain how this technique would work, we decide to use as input variables the followings: family income, age, and three models of cars of our invention (Big, Small, Medium). We will then use the one-hot encoding technique, which means that we will have only a 1 and 0s otherwise, as outputs. Figure 3 shows how it would look graphically.

Thus, what we are doing is training the model in three different ways, because we randomly decided we were going to consider 3 car models, meaning

Figure 3. Classification technique



that we would have 3 outputs (F will predict the type of car purchased), 15 inputs and 54 parameters.

Of course, we might not be as lucky as to only have 3 car models, which means we will need to find a way to train our model to understaffs where the output is a 0 or a 1. Without getting too much into detail, we can fairly affirm that each technique will be best served by a specific algorithm - or more. So, for example, classification models work well with sigmoid functions (where $F = 1/1 + e^{-z}$)[11], while models dealing with image recognition use convolution (a mathematical function of two functions - f and g - that produces a third function which represents how the shape of one function is modified by the other) and those related to spoken language prefer sequence models.

At this stage, we have already presented several models, whose level of difficulty vary according to what we want to achieve, and of course our (and our team's) knowledge of computing and algorithms. However, the only rule of thumb that we cannot forget at any time relates to the flexibility of the model we choose. What does that mean exactly? We should never choose a model that is not flexible enough, to avoid it being underfitting or producing a bias error. At the same time, models too flexible need to be avoided as well, because they will be overfitting, or producing a variance error. To simplify, your model will be underfitting when the error on both training set and new data are high; it will be overfitting when the error in the training set is low, but the error in the new data is high, while obviously, the model is just right when both errors are low. Thus, we start with a flexible model - we should remember our function $f(x)= A + Bx + Cx_2 + Dx_3 + Ex_4$ - and then we minimise the value of the parameters B, C, D and E. If we go back to our previous explanation, we were looking to find the prediction error, while the cost function will be the prediction error plus the absolute value of the parameters[12]. Once our learning procedure starts, its goal will be to minimise the prediction error as well as the parameters (B, C, D and E). Thus at this point, we will need to add a multiplier (m) of the parameters, to balance the minimising of both prediction error and parameters, as well as the flexibility of the model. This technique, also known as regularisation, allows the learning model to adapt in case of underfitting or overfitting results on new data.

To better understand Figure 4, we might need to introduce the training curve as well.

The point we indicated before as the moment where performance of new data becomes overfitting, is the same point we perform an early stop, which means we stop training at this point.

Figure 4. Regularisation technique

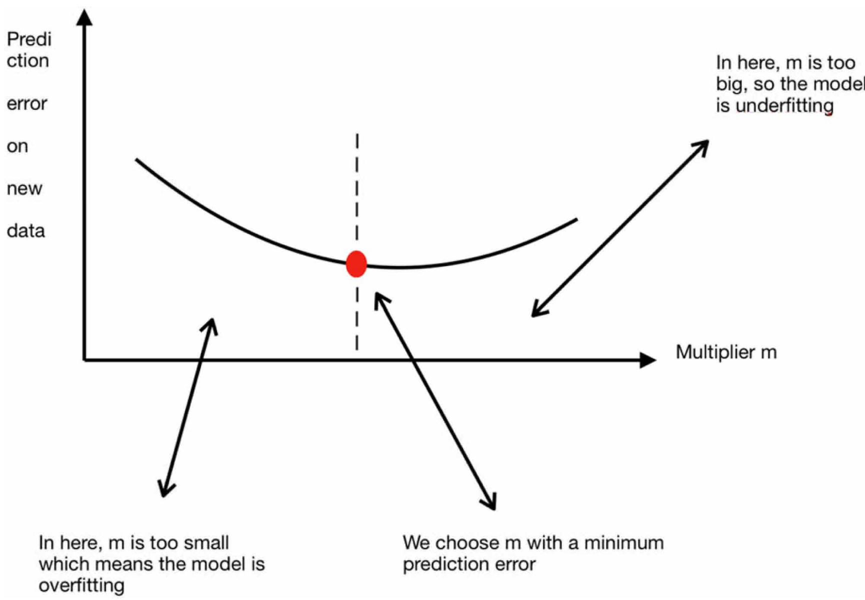
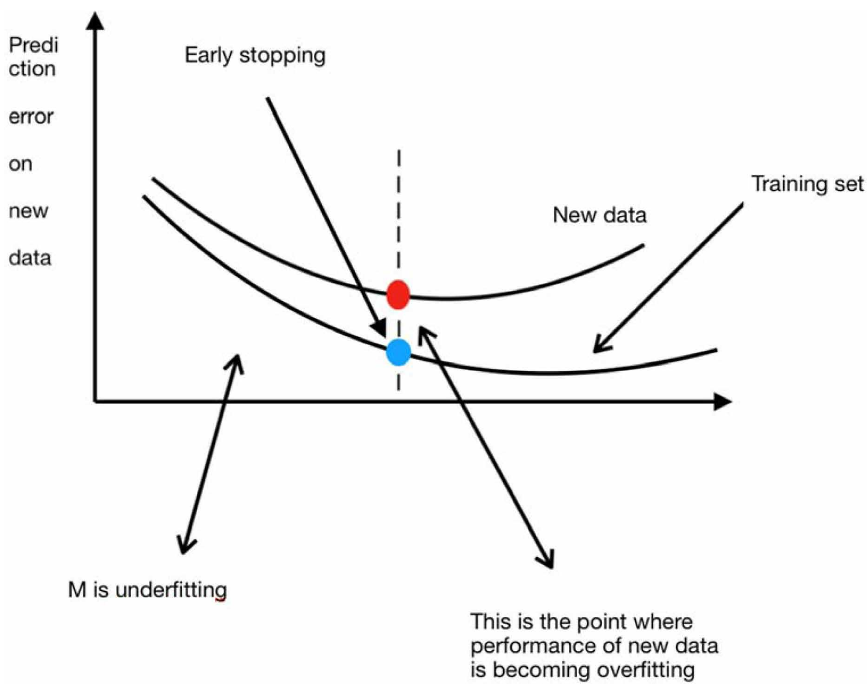


Figure 5. Regularisation technique with training curve



Now, it might be normal to be confused at this stage, thinking about how many models to choose from, how much training - and time - a model requires to see if it is working or not, which mathematical functions to use, and so on. Well, in terms of speeding up the process, we can use libraries[13] to see which models perform best in our specific example. This is possible because, while using libraries such as TensorFlow, Scikit-Learn or Theano, multiple models can be trained through the ensemble technique, which allows a combination of outputs from multiple models (through maybe the use of random forest to implement decision trees).

Whichever model we choose, the first thing we will need to ask ourselves is if what we want to achieve, discover or solve is a research problem, or it has already been solved. The major difference implies that you will need to invent a new AI technique in case of a research problem. However, the large majority will be solved problems, which means we can look at what others have used as solutions. Once this is established, we will need to ask ourselves if we need a very complicated deep learning solution with neural nets, or a simpler machine learning algorithm/model would do. Although playing with deep learning sounds fun and the best we could hope for, it is also true that our choice should be dictated by the size of the training set we have. Machine learning will be more accurate with a small set of training data, while deep learning neural networks will work better in case of large sets of training data. What constitutes large sets, and what is small? Below 100,000 dat, we can consider the training set as small. Over 1 million data, the training set will be large, and if yours is in between 100,000 and 1 million, you might want to gather additional data so to use deep learning. The last step in your quest for AI should involve the set up of the team. Is it better to buy or build in house your AI system? Once again, answer such question implies you critically understand your team, your budget and most importantly which question(s) you are trying to answer with AI.

CONCLUSION

Artificial Intelligence and machine learning have become core aspects of the way we think and plan business. With the advent of the Internet of Things and big data, we are compelled to use as many information as we can gather in order to solve complex problems and predictions. Managers are required to understand the possible solutions they might have at their disposal to innovate their business models, enhance customers' expectations or understand better the market they are in to gain competitive advantage. We have presented several types of machine learning algorithms that are available at the moment, and tried to give a basic introduction to the world behind deep learning models and solutions. Through a practical example, we aim to provide managers and no experts in the field a sound understanding of the reasoning and the process behind AI applications and their potential.

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ENDNOTES

1 A linear model is based on a simple formula to find the "best fit" line among data entries. For example, you want to know how long it will take to reach a specific destination, and you insert variables like traffic, train stations, and similar to get your answer. There are several linear methods, among which linear regression - or least squares regression - is the most standard form of linear model, to be used when we are looking for numerical variables. Because of their goal, which is once again to predict future numerical data, these techniques are used mainly to figure out future trends from historical data, for example in relation to sales, marketing returns and similar. However, they need to be interpreted in their context in order for the data to be truthful.

2 Logistic regression is the application of linear regression to classification problems, where we aim to find not a number, but rather a "yes or no" answer. As it happens with linear regression, also logistic regression techniques tend to overfit, in the sense that have difficulties in generalising new data into the training set, as well as not coping well with the prediction of complex behaviour.

3 When it comes to linear and logistic regression, scorecards are the type of models to use. Scorecards are mathematical models generally used to estimate the probability of a defined behaviour, such as for example in the case of customers requesting credit. Similarly, decision tree models are predictive and consist of a process that repeatedly splits

the development sample in smaller groups, which take into account information and characteristics from the previous nodes. Decision trees can be graphically represented in the form a tree, where the pointy bit is the starting point, each branch is a representation of the outcome of the test and le leaf nodes are representations of the classes. Every time that the test reaches a node, a pruning mechanism makes it so that conditions which do not improve the estimated accuracy of the rule are removed. For example, if we want to predict credit card fraud detection, we would look at the variables that best describes that risk, which could be the purchase amount. Following the variable "purchase amount", we could identify those who are likely to go for a large amount and split them from those who do not. We keep adding classes or categories of variables, using classification algorithms.

4 The process of training a model consists of taking an already existing machine learning algorithm and provide it with data to solve a specific problem. In case of supervised learning, where we do data and labels we are trying to predict, the process consists of an initial training set (which contains the data used to train the model), and a validation set, which comprises different data to check the validity of the system. In case more than one model has been used, to assess which one is performing better, a third round of checks takes place, also known as holdout. We will see in the practical example at the end of the Chapter, what happens with overfitting models, which are the ones that perform well with the training data but poorly with the validation set.

5 Deep learning can be defined as "a class of machine learning techniques that exploit many layers of non-linear information processing for supervised or unsupervised feature extraction and transformation, and for pattern analysis and classification" (Deng & Yu, 2013). Deng, L., & Yu, D. (2013). Deep Learning: Methods and Applications. *Foundations and Trends® in Signal Processing*, vol. 7, nos. 3-4, 197-387. Hanover, MA: Now Publishers Inc.

6 Converting data into something our program will understand is a fairly difficult process. In case of "categorical" data (i.e., colours or brands of cars), programmers and data scientists usually encode them as numbers, using the binary code. For example, they might decide to use the so called "one-hot encoding" method, according to which numbers are assigned to each category in form of a binary vector with only one "hot" enter. This can be summarised as follows. We randomly decide that "cat" is defined as [1, 0, 0], while "dog" equals to [0, 1, 0], and so

on. At the same time, when dealing with text, data scientists tend to use methods from natural language processing - or NLP. Among others, we can use "lemmisation", when words with the same root are converted to one label (i.e., 'stop', 'stops' and 'stopping' will be considered under 'stop'); or "stop-wording", that allows to not consider words like 'of', 'the' or 'and' into the data. Other interesting methods can be "feature engineering", which allows to reduce data to only specific components that are relevant to the task at hand; as well as "Term Frequency" (TF) and "Inverse Document Frequency" (IDF), that calculate the weight of specific words in a given text, or "words embeddings", when we want to group words contextually similar to find similar words.

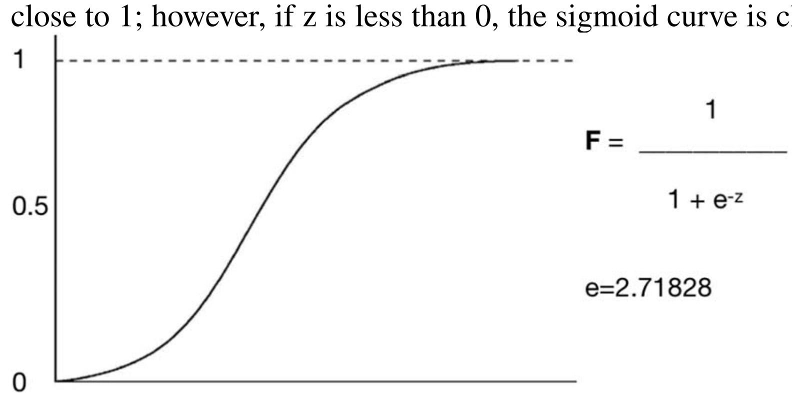
7 Numeric labels are normally used for regression problems, while categorical ones are used mainly for classification problems.

8 An example of this methods can be found in the k-nearest neighbour's algorithm, which allows to classify objects based on the predictions for its nearest neighbours. In practice, the method relies on the prediction value of an object, and because of the object's proximity to another one, it can predict also the value of its neighbour. The k-nearest neighbour algorithm is quite used in machine learning, although it doesn't appear to be very proactive in its role. As Akerkar (2019) describes it, "the training samples are described by n-dimensional numeric attributes. Each sample represents a point in an n-dimensional space; all the training samples are stored in an n-dimensional pattern space. When we have an unknown sample, the algorithm searches the pattern space for the k training samples that are closest to the unknown sample, the k training samples are the k "nearest neighbours" of the unknown sample.". To summarise, we might use this type of algorithm when there is a good amount of data to classify, which will make the classification process very long and time-consuming. A good example of this method can be represented by our goal to classify books. Variables to be taken into account might be word counts, sentence length, total number of pages, authorship, genre, date of publication, word frequencies and similar. Akerkar, R. (2019). *Artificial Intelligence for Business*. Cham, Switzerland: SpringerBriefs in Business.

9 Andrew Ng is a world-leading AI scientist, former head at Google Brain, as well as Silicon Valley entrepreneur, inventor and adjunct professor at Stanford. See Ng, A. (2019). *Machine Learning Yearning - Technical Strategy for AI Engineers, In the Era of Deep Learning*. Retrieved online at https://www.mlyearning.org [Accessed May 30, 2019].

10 Deep auto-encoder models are artificial neural networks which are able to learn different coding patterns, using a graphical configuration that resembles the following: an input layer, followed by one or more hidden layers, that feed into an output layer, which will have the same number of nodes as in the input layer. Deep Belief networks (also known as DBN) are "probabilistic generative models composed of multiple layers of stochastic, hidden variables" (Deng, 2012). Specifically, they work using multiple layers of variables that interconnect the layers themselves, and the hidden layers become the visible input layers of the network's adjacent layer, so that each layer is trained independently. Such structure is similar to a restricted Boltzmann machine (RBM), which is different from a Boltzmann machine (BM), that is composed by symmetrically connected neuron-like units which can decide whether to be on or off. Another interesting type of deep learning models is the so called convolutional neural network (CNN), that works in a way individual neurons are able to respond to overlapping regions in the visual field. CNNs can also be deep (DCNN), where the first layer trains to detect edges and consequently form templates for detecting edges. Subsequent layers will work on templates of different shapes and/or object positions or other relevant information. The output layers will then be able to form an image, as the result of all templates. Deng, L. (2012). *Three classes of deep learning architectures and their applications: a tutorial survey. APSIPA transactions on signal and information processing*. Retrieved online at https://pdfs.semanticscholar.org/5bd4/177440c17dad736f1e0d2227694d612f5a59.pdf [Accessed May 30, 2019].

11 A sigmoid function looks like an S-curve, whose shape differs according to the value of z. When z is more than 1, the sigmoid is close to 1; however, if z is less than 0, the sigmoid curve is close to 0.



12 There are two different types of regularisation that can be used. We introduced the first one, also known as L1 regularisation, where the cost function is calculated adding the absolute value of the parameters. *Cost function = prediction error + m (I B I + I C I + I D I + I E I)* L1 regularisation minimises the value of the parameters to 0, so that when it happens, it is a clear indicator that the parameters do not influence the output and by default, are not important for the machine learning. The process of eliminating non relevant variables is called dimensionality reduction, and the function will then look like this:

$$f(x) = Ax_1 + Bx_2 + Cx_3 + Dx_4 + Ex_5$$

$$\Big\downarrow \quad \textbf{When C = 0}$$

$$f(x) = Ax_1 + Bx_2 + Dx_4 + Ex_5$$

The second type of regularisation (L2) is given by the prediction error plus the sums of the squares of the parameters, as follows: *Cost function = prediction error + m* $(B^2 + C^2 + D^2 + E^2)$

13 Libraries usually support linear functions with no higher powers, that look like the following function: $f(x) = A + Bx_1 + Cx_2 + Dx_3 + Ex_4 + Fx_5$ To add squares and cubes, you will need to add expressions like $x_1 = u$; $x_2 = v$; $x_3 = u^2$; $x_4 = v^2$, $x_5 = uv$, that will transform the equation into the following: $f(x) = A + Bu + Cv + Du^2 + Ev^2 + Fuv$ Within a library, this is possible using built-in supports for non-linear machines (also known as support vector machines), that use the kernel trick to train the model to predict 0 or 1, given some values for x_1 and x_2. In particular, using multiple models at the same time, we will know the best one will be the model that is graphically equidistant from both 0 and 1, because it will be more likely to provide accurate predictions when new data will be used. To think of it, in a typical AI project, you will start off using a support vector machine and random forest algorithms. In case they both do not work well, the next phase involves multilayers neural networks, which is used in the case, for example, of product recommendations.

Chapter 6
The Future of Modern Jobs

ABSTRACT

Throughout this book, the authors have discussed the implications of the rise of artificial intelligence, Industry 4.0, the internet of things, and new business models that do not have any known precedents. While discussing the skills needed to survive in the modern economy, they have yet to address the issue of what will become of our jobs. Will our children dream of the same jobs we dreamed once before? Will they require the same studies we had to follow to reach our actual positions? Will our jobs still exist by the time we reach the pension, or will we need to reinvent everything that we know of? The authors do not have an answer to these questions; what they can do is only make educated guesses about what is about to come and be ready for it. In this last chapter, the authors see what experts think our future will look like and give their educated opinion in what to invest in our lifelong learning journey to be on top of this unprecedented disruption of the economy.

AN INTRODUCTION TO THE MODERN JOB ECONOMY

Advances in technology as those we have discussed in the previous Chapters, change the community in such profound ways that we have already experienced dramatic shifts to the way our economy and society work. For instance, we have evidence that the middle class no longer exists, and with that loss, we experience daily an inner conflict related to us as individuals, whether about who we are, or generally our sense of privacy and trust towards others or the system. From an ethical point of view, Michael Sandel affirms that

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"we seem to be increasingly willing to trade privacy for convenience with many of the devices that we routinely use" (Segran, 2015)[1]. Or we can use Sam Altman's words to say that "the best way AI can develop is if it's about individual empowerment and making humans better, and made freely available to everyone" (Levy, 2015)[2].

You will be able to find online several interesting articles and comic books related to a typical day in a student life - or manager, or simple person for what is worth. In what is supposed to be a funny and somehow shocking retelling of an absurd number of technologies used during a single day, experts warn about the continuous request to be social and digital. Data shows that 44% of teenagers never unplug from their smart devices, not even while playing sports or eating with people (see for example, Kuper, 2015; Turkle, 2015)[3]. In contrast, this new behavioural trend makes it possible for all of us to struggle with human connection, and that future generations are in serious need to learn such social and soft skills for their job (see for example Konrath et al., 2010)[4].

According to Klaus Schwab, we are already experiencing a great deal of deep change when it comes to our society and economy. "I believe that the combination of structural factors (over-indebtedness and ageing societies) and systemic ones (the introduction of the platform and on-demand economies, the increasing relevance of decreasing marginal costs, etc) will force us to rewrite our economic textbooks.", is what he pre-announces in his book 'The Fourth Industrial revolution' (p. 34). So, if that was true, we have to deal with some aftermath aspects we introduced in this book. For example, an important downfall of these changes is connected to the ethical aspects of technology. Initiatives such as that of the Future of Life Institute come into mind for their work on better understanding the social impact of technologies and which ways should be more effective in mitigating potential negative outcomes, whether related to artificial intelligence, nuclear technology, climate change or biotechnology. Being a Boston-based think tank which was founded by Skype co-founder Jaan Tallinn and physicist Anthony Aguirre, it counts hundreds of supporters and donors, such as Elon Musk, Morgan Freeman, Alan Alda and a distinguished community of academics on its scientific advisory board, like Nick Bostrom and Reik Brynjolfsson, and professor Stephen Hawking before his passing[5]. The Institute particularly looks at the existential risk coming from AI, biotechnology, nuclear technology, and climate change.

We have discussed the importance of ethics when dealing with new technologies and big data in the previous Chapters, and how this inform the way we interact in our jobs. However, it might be worth it to take into account that our modern world is characterised by ageing, which means that we assist to the fall of the working-age population, while the percentage of dependent elders increases[6]. In this perspective, we will encounter a paradigm shift in what we look for in employees, managers and leaders alike. When it comes to talent, Klaus Schwab predicts that "successful organisations will increasingly shift from hierarchical structures to more networked and collaborative models. Motivation will be increasingly intrinsic, driven by the collaborative desire of employees and management for mastery, independence and meaning. This suggests that businesses will become increasingly organised around distributed teams, remote workers and dynamic collectives, with a continuous exchange of data and insights about the things or tasks being worked on." (Schwab, 2017, p. 60). So what will be the skills and the jobs of the future? We will try to answer this question while being conscious of the so called productivity paradigm (The Conference Board, 2015). According to experts, we are experiencing a moment of distrust in technologies, in the sense that technological innovation is perceived to have failed in helping us achieving higher levels of productivity. On the other end, we are sensible and ready to take into account in our judgement that the modern economy has enhanced the number of free services available, a circumstance that in itself increases efficiency and consequently productivity. In other words, national statistics are unable to capture such unofficial greater value in our economical growth (DeLong, 2015).

THE FUTURE OF JOBS

Not many of us know that the first humanoid robot in the western world was designed and maybe also built by Leonardo da Vinci in 1495 (Rosheim, 2006). When we think of it in this way, our modern innovations do not seem so modern after all. However, our society is changing rapidly and at a pace that suggests a good attitude towards change is the most important skill we might need to learn.

The debate among practitioners and academics alike around the characteristics leaders and managers should have, now revolves around the contextual and sympathetic use of four different types of intelligence. According to Klaus Schwab, these can be summarised as follows. The first one is contextual, and of course represents the mind. The second one is the well-known emotional intelligence, which recounts self-awareness, empathy and other soft skills. This particular type of intelligence has risen to fame around the 1990s, thanks to the popularity given to it by David Goleman (1996, 1998, 2002). The third type of intelligence is the 'inspired' one, which comes from our soul, and taps into a sense of individual and shared purpose, for the greater common good. This should remind you of Otto Scharmer's Theory U[7]. The final one - the physical intelligence - closes the circle, and states that the body needs to stay active, young and in shape to cope under pressure. Stress management programs and intensive coaching - or yoga - sessions are an example of the health lifestyle modern businessman embrace.

If we couple this with the constant tension the rise of artificial intelligence brings in terms of uncertainty of jobs, it should be easier to understand the huge amount of data collected by supporters of against versus pro AI (World Economic Forum, 2016; 2018). For example, Carl Frey and Michael Osborne have presented a list of 702 jobs according to their likelihood of being automated (Frey & Osborne, 2013). The study affirms that about 47% of jobs in US are at risk within the next 1 or 2 decades, and the employment will increase only for high-income cognitive and creative jobs as well as low-income manual ones, while middle-income repetitive jobs will disappear. This should be in line with some trends recorded in the last decade. Crowdfunding platforms for consulting services have recently been developed, such as Open IDEO (where everyone can collaboratively solve design problems posted online), or Kaggle (clients give their data, ask a specific question and a network of statisticians from around the world compete to find the best solution). At the same time, in 2008 (Pew Research Center, 2008; 2013) for the first time in US people said that they were using more internet than the newspaper to see the news (40% vs 35%, while in 2013 it rises to 50%). Furthermore, according to Kristian Hammond, co-founder of Narrative Science, by mid-20s 90% of the news will be written by an algorithm that requires little to no help from humans.

The majority of experts and influencers from around the world usually agree on a soft position, according to which the future should see a collaboration between machines and humans[8], such that proposed by Erick Brynjolfsson and Andrew McAfee (2014), and experimented by Garry Kasparov and IBM with Watson. In this scenario, varied skills will be fundamental to survive in an environment where multi-disciplinarity is the norm and you are expected to have developed a great amount of general knowledge to apply in several contexts. The successful interaction between humans and machines can already be seen in specific sectors, such as healthcare. Nowadays there is huge interest in mobile health (or mHealth), that can be seen in the tremendous amount of apps, devices and systems that are built on existing mobile technology. As an example, more wearables such as Jawbone, Fitbit and MyFitnessPa, are sold everyday. These devices collect large volumes of our data related to pulse rate, sleep patterns, digestive behaviours, happiness levels and so on, to analyse them and create awareness. On top of that, Proteus Digital Health is developing a range of ingestibles, which are pill-shaped monitors that activate once in contact with the stomach acid, to check internally that everything is medically in order (Bilton, 2013).

If we look at more sophisticated forms of AI, Watson, the Artificial Intelligence computer from IBM, is used to support cancer diagnoses, recommend treatment plans (see for example Memorial Sloan Kettering Cancer Center, 2014) and help for people with PTSD (see Ravindranath, 2014). The healthcare sector is not the only one affected by massive innovations. If we take into account the education sector, several features and programs come into mind. For example, we can mention adaptive learning systems, such as Knewton, Reasoning Mind and DreamBox (see Newman, 2013). Practitioners are also using extensively social networks (i.e., Edmodo), media platforms (as an example, see Eddemic or ShareMyLesson) and platforms to share online content, such as TED talks, Khan Academy and YouTube EDU. Since a very young age, students are also exposed to platforms that certify the achievement of specific skills (like Accredible and Degreed) or offer general knowledge (one of the most famous one is definitely Wikipedia); as well as learning management systems or virtual learning environments, such as Moodle and BrightSpace; and enrol in MOOCs (Massive Open Online Courses), offered by providers such as Coursera and EdX, or Udacity where instructors are not necessarily academics refer to, as an example, Pennell, 2018; Rizvi, Donnelly & Barber, 2013).

The Role of Artificial Intelligence in Relation to Jobs

Artificial intelligence is said to be most disrupted innovation of this century. The jury is still out there in search for a verdict as to unanimously agree on the medium and long-term effects of AI on jobs. Positions on the matter vary in between the spectrum of an optimistic[9] or pessimistic view[10]. For those that like to point out that in the last sixty years AI did not live up to its promise[11], nothing relevant will come out of it at present. On the other end, for those who are very optimistic about the possibilities offered by AI, it is said to lead to more jobs. In this scenario, Artificial Intelligence is seen as one of the waves of the Fourth - or Fifth - Industrial Revolution, capable of creating an unprecedented technological shift.

In between these two radical positions, there are people believing that AI will be responsible for a significant number of job cuts in the next twenty years, in the region of 25 to 50%[12]. Now, if that was the case, things might go in two different directions. We might believe that such shift would create only cost savings that would benefit large corporations, leaving ordinary people worse off; or governments, either individually or collectively, will find a common solution to make sure such cost savings are put back to society. Possibly, a campaign like the one related to the UK's Brexit vote and the controversial election of Donald Trump as US President, could lead to some sort of result.

Others have expressed a different position, where a lower number of jobs will be lost - less than 10%, however there will be a clear concentration of impact effects on those jobs which require low skills. In this perspective, people from a poorer background will be impacted more, creating a domino effect of greater inequality within the society. However, there is still who thinks low and high skill jobs will be impacted in the same way, causing less societal issues and taking into account that high-skilled jobs require more investment in forms of salaries, education and learning in general.

Is AI fundamental to our jobs? "AI has an impact on organisations from several perspectives, which range from power shifts and reassignment of decision-making responsibilities at the top level, to departmental-levelled innovations to reduce costs, enhance services and improve personnel conditions. The role of management is crucial at this stage, and in order to facilitate AI implementation, leaders in each department are required to either act as a champion for AI systems in their area, or at least provide resources for its implementation." (Fazzin, 2019, p. 196).

Considering the huge amount of investments on AI-related mergers and acquisitions (an extraordinary $22 billions in 2017), it seems obvious the market is set on making true the predictions around the numbers of AI applications and their revenues expected to be generated in the next 20 years (they will allegedly reach $2.7 trillions). However, how AI is - or will be - used in the workplace? "First of all, Artificial Intelligence is part of the organisation through automation, which consists of creating a hardware or other mechanical means (for example, a robot) to do tasks that are highly repetitive or labour intensive. This happens in particular in manufacturing, however successful examples of automation can be seen also in other industry sectors, such as supply chains. Automation brings more efficiency and productivity in the company processes, while helping the access to data and ease the interaction between what data is available, how it can be applied and, more importantly, how it should be applied to help the business grow. Another interesting use of AI in the workplace, is the one more directly connected to people. Now, AI is already helping customer service teams to create a high-quality customer experience, for example through the use of chatbots. A more unusual use can be seen in the so called relationship bots, which are bots programmed virtually to predict things like the success of a human relationship, or the level of commitment of an employee, and in general terms, other group dynamics in the workplace that, as for now, we can only understand from personal experience. In this perspective, artificial intelligence is strictly linked to our concept of emotional intelligence and the fundamental role of emotion in the workplace, for different reasons, such as finding the right fit for your company." (Fazzin, 2019, p. 197).

The Skills You Need to Learn

When asked about the skills of the future, those related to computing are the easiest to guess. Collaboration and leadership make the top skills list, and if we look at the Institute for The Future's Future Work Skills 2020 report, a list of ten essential skills have been highlighted to match the foreseen six or seven drivers of change. In this interesting list, first place is given to sense-making, which is here intended as our ability to make sense out of the surrounding situations, using a sensible and rational approach to find out suitable solutions. In second place we can find social intelligence, as the individual's ability to reach out to the right audience. Then we should consider novel and adaptive thinking, as the capability to apply different perspectives to explore ideas; as well as cross-cultural competency, which is the attitude of understanding and operate in different cultural settings. Computational thinking, as the ability to understand data-based reasoning and transform them into abstract concepts, and new media literacy are skills well linked to the Industry 4.0 and the advancement of technology. As highlighted in the previous Chapters, managers and people alike are required to use a trans-disciplinary approach to things, and members of teams are expected to have a good understanding of different disciplines. This is also linked to the need of businesses for employees with a design mindset, which will allow them to represent and develop tasks for a specific outcome. Finally, the report indicates cognitive load management (as the ability to prioritise and filter information in accordance with our needs) and virtual collaboration as a much needed skill for the future jobs.

These are amazing skills to have and to learn, however they require practice, training, mindfulness and a lifelong learning and reflective perspective. Furthermore, what would more practical or vocational skills to have to be competitive in the job market of the future?

Nowadays, experts and practitioners all agree the necessary knowledge - or understanding - is very technical and might comprise software, IT, electronic, mechatronics, sensors, embedded systems, mechanical, thermal, or chemical process engineering. And the required capabilities comprise programming skills, interpretation of failure notifications of machines, quality control tasks, and maintenance. Such technical knowledge then needs to be applied using a variety of soft skills. We have seen them earlier, and we might see in our own experience how much we rely on reflectiveness, intercultural perspective, resilience, problem solving and a critical thinking approach.

Interestingly, according to Edward Ward, UK manager at Le Wagon, "Demand for people with digital skills massively outweighs supply, and that gap is increasing. There are currently 220,000 vacancies for digital roles in the UK. By 2023 this figure is expected to be 900,000. That is how rapidly it's growing, and clearly shows the need to educate your own employees in coding or at least bring in young talent to grow with your business."[13].

From a recent study, it appears that the UK is already facing a skills gap in computing literacy, which has been determined to cost 63 billions of pounds a year in lost income. The circumstance that the UK is one of the few nations to have introduced coding in the national curriculum since 2014, appears to have no direct consequence on such data. The importance of computers and digital technologies in general is well known and widely accepted. As we have mentioned earlier on, young children are exposed to coding, robotics and different uses of digital platforms and tools, such as Prezi and Scratch. They are also encouraged to see such skills as something dynamic and with great potential, where logic and creative problem solving are core keys to unlock the potential of innovation[14].

Another interesting sector where new skills are required, is linked to innovation in augmented and virtual reality products. With the term virtual reality we mean a "high-end user–computer interface that involves real-time simulation and interactions through multiple sensorial channels" (Burdea & Coiffet, 2017), which can encompass all five senses (meaning eyesight, hearing, tact, smell and taste - see Foxlin, 2002). The virtual reality business is fairly new, considering that the first patent of the sector was issued in the US in 1962 to Morton Heilig. His invention, known as Sensorama Simulator, is believed to be the first virtual reality video arcade, which simulated a motorcycle ride through New York. Those who tried the game could experience the effect of the wind in their faces through the use of fans, the aftermaths of potholes in New York City thanks to a vibrating chair, and the smell of food when the program showed shops. However, we had to wait until 1987 for the first virtual reality product to be sold in the shops, courtesy of Jaron Lanier's VPL Inc. and its DataGlove, the first sensing glove that allowed for gesture interaction with computers through fibre-optic sensors. Unfortunately, the DataGlove was not a success, due to its high price, and was almost immediately substituted by Nintendo's PowerGlove. In UK, Division Ltd. introduced in 1991 the first integrated commercial VR workstation, which you might know under the name of Vision, and right after the more powerful Provision 100 (Grimsdale, 1992).

Creative industries such as gaming and film production, have intensively used virtual reality in the last forty decades, and rely heavily on creative designers, engineers, scientists and researchers to keep progressing in this sector. The Internet of Things will open the doors to new innovations, thanks to the massive use of sensors everywhere and its goal to interconnect them to create an augmented reality for everyone to enjoy. In this perspective, design thinking principles, perseverance, creativity and complex problem solving logic are among the soft skills required from everyone regardless of their position.

Furthermore, we have seen how technologies impact on jobs and the new demands in terms of skills. A sector that could potentially be revolutionised is human resources. Even though HR practitioners have expressed mixed feelings[15] about the potential of AI to overcome modern challenges in personnel management, emerging Artificial Intelligence solutions have been tested in the last decade. As an example, start-up company Interviewed promises an algorithm capable to recognise soft skills[16] through the candidate speech patterns. Its cofounder Chris Bakke says that "an algorithm's ability to recognize empathy is evidence of a new hiring technique—one in which machines assess, but humans make the final call." (Captain, 2016).

Why would we use algorithms or AI in general to support our decisions in hiring[17]? There are several possible answers, and all of them have somehow to take into account the so called human factor, meaning the knowledge, skills, sentiment and biases of the individuals that are part of the hiring process[18]. So, if the use of AI applications in HR could improve processes and enhance overall business performance, why its adoption seems to be so slow? Practitioners have highlighted several issues that are to blame, such as financial barriers (costs related to AI tools are still high for the majority of organisations, and find employees skilled enough to know how to use them might prove to be difficult and expensive) and technical, considering that privacy is a big issue[19]. An interesting study conducted by HR.com in 2017, found out that only 8% of the respondents to the survey strongly agreed to be knowledgeable in the area of artificial intelligence applied to HR, and only another 27% even moderately agreed, with the majority of participants considering themselves knowledgeable (HR.com, 2017). From the same survey, other interesting data emerge in relation to the practical use of AI in companies. Although these figures are expected to rise in the future, only 7% of interviewed affirm that the organisation they work for make an extensive use of AI at present, while 39% believe their company would do so in five years.

It might be worth it to highlight that good managers should not jump on the AI train and try at any cost to ’modernise’ their organisation throwing here and there some cool tech-related words. As we have seen in Chapter 2, in order to have a successful digital transformation, you need to have a clear vision of what you want to achieve and which tools are better suited for your needs. Not all AI tools will do, nor they will solve the issues you want to solve. Whether you have identified a potential area for improvement in the HR department or another stop of the supply chain, artificial intelligence products require an adaptive environment and a team of specialists that suggest the right solutions. There is a huge difference between cloud solutions, which are supposed to enable a pre-trained model with storage for deployment, testing, improvement and quality assurance; or a language and natural language processing software, whose goal is to solve contextual and narrative issues through a standardised programming language and related tools. Other products a company may require are digital assistance tools (something like Alexa or Google Assistant), which should be able to support personal queries across multiple devices; bots, that are useful to automate back-office and enterprise operations using a plug-in; automated machine learning tools to support problem-solving through the use of quality data and advanced algorithms; and more.

In this perspective, modern jobs will require a comprehensive understanding of the digital process in an organisation, and require technical knowledge to a certain extent, while work environments will be organised in team, where diversified knowledge and skills are fundamental to thrive.

CONCLUSION

Whatever the future might bring, Artificial Intelligence is here to stay, together with the other technologies the future will make available to us. Although we cannot be fairly sure of what jobs might look like, we can all agree they will change at a rapid pace. The ability to adapt and reinvent ourselves, combined with empathy and a general good emotional intelligence, are core aspects of the skills educators and practitioners should pass on. While technical knowledge would need to be varied for the benefit of the team, and to better accommodate the attitude towards multi-disciplinarity, soft skills will be the hardest to gain. Even though we might lose jobs against more precise, more intelligent and definitely faster machines, new jobs will arise to compensate the machines' inability - at least for now - to feel and sympathise with other humans. The position in the middle, which seeks a close relationship between humans and machines, seems to be the better solution moving forward. In this perspective, we recognise and exploit the machines' strengths and play them to the advantage of the society, through cooperation and team-work with a digital world that we might have some difficulties to imagine now.

Whichever the profession you want to go for, a lifelong learning attitude and the self-awareness that we all need to have at least a basic understanding of several disciplines to converse with our colleagues, will be one of the skills great managers of the future will need to have, together with adaptability to change in a fast pacing environment that does know no barriers or limitations.

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1 The quote comes from Segran, E. (2015). The Ethical Quandaries You Should Think About the Next Time You Look at Your Phone. *Fast Company*, October 5. Retrieved online at https://www.fastcompany.

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4 Practitioners and experts alike have always considered making eye contact, talking, and the appropriate use of body language as key communication skills of humans. In an age where most of the interactions are digital and we tend to be always connected, such skills fail to be learnt. The field of Emotional Intelligence is probably one of the most famous in relation to its goal of sharing awareness among leaders about the importance of human emotions and connections. See for example Konrath, S., O'Brien, E., & Hsing, C. (2010). Changes in dispositional empathy in American College students over time: A meta-analysis. *Personality and Social Psychology Review*, 15(2), 180-198. DOI: 10.1177/1088868310377395 Goleman, D. (1996). *Emotional Intelligence*. London: Bloomsbury.

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5 AI and its impact on our future is one of the hottest topics of the past decade. Experts, academics, leaders and in general anyone with a voice is either an enthusiastic supporter or worried about advising people to avoid AI progress at any cost. Initiatives like the Future of Life Institute pop out to campaign for either one or the other part. According to Max Tegmark, President of the Future of Life Institute, "Everything we love about civilization is a product of intelligence, so amplifying our human intelligence with artificial intelligence has the potential of helping civilization flourish like never before – as long as we manage to keep the technology beneficial". At the same time we have influencing people like Warren Buffet expressing their opinions on the matter, such as https://www.linkedin.com/pulse/warren-buffett-predicts-significantly-less-employment-chip-cutter/. Tegmark, M. (2019). *Benefits & risks of artificial intelligence.* Retrieved online at https://futureoflife.org/background/benefits-risks-of-artificial-intelligence/ [Accessed May 3, 2019].

6 Governments tend to reply to this issue in a similar way, which is usually by increasing drastically retirement ages, causing other side effects such as discontentment and insecurity in those who are planning retirement.

7 Otto Scharmer, senior lecturer at MIT, developed "Theory U as a social field theory that not only looks at the what and the how but that really makes visible the source dimension that we're operating from as individuals, as teams, as organizations, as larger systems, and the impact it has depending on which source we're operating from." (from Scharmer's "Leading Change in Time of Disruption" lab). Furthermore, Scharmer points out the importance of "differentiating between three inner places or three capacities that we need to cultivate as change makers, innovators, and leaders. The first one is the open mind, by which we mean the capacity to suspend our old habits of judgment, basically, to see with fresh eyes. The second one is the open heart, by which we mean the capacity to empathize to redirect our attention, to look at a problem not just from ones own angle, but also from the angle of the other stakeholders that are involved in the situation. Then number three, to cultivate the open will, which is essentially the capacity to let go and let come, let go of the old and let come of the emerging new possibilities. These two insights basically summarize the two foundation stones of the U theory and the U process. So it's a process on the one hand. But

it's this inner cultivation, work related to the opening of the mind, the opening of the heart, and the opening of the will, on the other hand, that in our view really makes all the difference." While trying to answer the question on how to transform what he just said in something practical, Scharmer came up with Theory U, which "really is these two things. It's on the one hand a framework, on the other hand, it's a method which is a set of tools and practices that actually allows you to move from one state of the social field that's operating, say, in a very reactive way, to another state of the social field that's more generative and more co-creative.". In other words, Theory U sets out to help us better understand how social actions come to be, and how to quickly react and change in order to adapt to the future. How can we do that? Apparently through a shift in consciousness from ego-system to eco-system awareness, which not only looks at our collective - hence, social capabilities, it also succumbs to what Scharmer calls the blind spot. This would be the inner place, or source from which leaders do what they do. This need for a better leadership is at the base of Theory U, which consists of five steps. The first one, also known as "co-initiating", involves the individual taking the time to better understand the world around them, and listening to others. Then follows the second step, or "co-sensing", which needs us to observe, observe and then again observe, with our mind and heart open. At the bottom of our U, we are required to let go of our old self and embrace our future self, the best we can be. This is step three, "presencing". At this moment, our old self and our future best self connect together and resonate with one another to enter a deeper source of knowing, where we do realise what we do not need anymore. Once you have worked on yourself, letting your future best self prevail, than you are open to new possibilities ("co-creating"), which arise when trying new practices, behaviours and similar. The last step, or "co-evolving", implies that your personal journey influences the way you look at the social environment you live in, and lead the change in an eco-system approach rather than only in yourself. To summarise, then "By moving through the "U" process we learn to connect to our essential self in the realm of presencing - a term coined by Scharmer that combines the present with sensing. Here we are able to see our own blind spot and pay attention in a way that allows us to experience the opening of our minds, our hearts, and our wills. This wholistic opening constitutes a shift in awareness that allows us to learn from the future as it emerges, and to realize that future in the world.". [Extract from Fazzin, S. (2019). *Emotion-Based Approaches to Personnel*

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8 Elon Musk is a famous entrepreneur and CEO of Tesla and SpaceX, as well as cofounder with Sam Altman of OpenAI, a non-profit company whose goal is to find solutions for safer AI. On top of it, Musk is a high-profile investor in Vicarious, a start-up company with the ambitious goal to build a computer that can think like a person, through the use of a neural network trained to replicate the part of the brain that controls vision, body movement and language. According to Elon Musk, humans need to learn how to cooperate with machines, to avoid becoming redundant. Although we cannot compete against machines, we will need to embrace change and close the bridge between human and digital intelligence. In this perspective, he is constantly warning people about the threat posed by deep AI, which is different from the use of 'normal' algorithms applied to business needs and similar. Musk also suggests to regulate AI at national and international level, to avoid that researchers build something too dangerous for humankind without even realising it. At the same time, AI's immediate threat is related to the loss of jobs, which he predicts will reach 15% of the global workforce affected by it, first of all thanks to self-driving cars. Dowd, M. (2017). Elon Musk's billion-dollar crusade to stop the A.I. *Vanity Fair*, April. Retrieved online at www.vanityfair.com/news/2017/03/elon-musk-billion-dollar-crusade-to-stop-ai-space-x [Accessed May 3, 2019]. Finlay, S. (2017). We should be as scared of artificial intelligence as Elon Musk is. *Fortune*, August 18. Retrieved online at http://fortune.com/2017/08/18/elon-musk-artificial-intelligence-risk/ [Accessed May 3, 2019]. Hull, D. (2017). Elon Musk's Neuralink gets $27 million to build brain computers. *Bloomberg Technology*, August 25. Retrieved online at www.bloomberg.com/news/articles/2017-08-25/elon-musk-s-neuralink-gets-27-million-to-build-brain-computers [Accessed May 3, 2019]. Umoh, R. (2017). Why Elon Musk might be right about his

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9 It is interesting to highlight how, among others, computer scientist and futurist Ray Kurzweil is very optimistic about AI and its impact on our lives. According to him, there will be a time when computers will become better than humans, and this can be seen as a repetitive cycle in our history, considering that a good amount of jobs have been lost several times before. In an interview appeared in Fortune, Kurzweil affirms that "We have already eliminated all jobs several times in human history. How many jobs circa 1900 exist today? If I were a prescient futurist in 1900, I would say, "Okay, 38% of you work on farms; 25% of you work in factories. That's two-thirds of the population. I predict that by the year 2015, that will be 2% on farms and 9% in factories." And everybody would go, "Oh, my God, we're going to be out of work." I would say, "Well, don't worry, for every job we eliminate, we're going to create more jobs at the top of the skill ladder." And people would say, "What new jobs?" And I'd say, "Well, I don't know. We haven't invented them yet.". Similarly, Peter H. Diamandis, Chairman of the X Prize Foundation and the co-author of "Abundance: The Future Is Better Than You Think", affirms that "Artificial Intelligence (AI) is a massive opportunity for humanity, not a threat. AI will level the global playing field. In the future, AI will democratize the ability for everyone to have equal access to services ranging from healthcare to finance advice. And likely it will do all of these things for free, or nearly for free, independent of who you are or where you live. Ultimately, AIs will dematerialize, demonetize and democratize all of these services, dramatically improving the quality of life for 8 billion people, pushing us closer towards a world of abundance. Why I Don't Fear AI (At Least, Not For Now). First of all, we (humans) consistently overreact to new technologies. Our default, evolutionary response to new things that we don't understand is to fear the worst. Nowadays, the fear is promulgated by a flood of dystopian Hollywood movies and negative news that keeps us in fear of the future. In the 1980s, when DNA restriction enzymes were discovered, making

genetic engineering possible, the fear mongers warned the world of devastating killer engineered viruses and mutated life forms. What we got was miracle drugs, and extraordinary increases in food production. The Benefits Outweigh the Risks. AI will be an incredibly powerful tool that we can use to expand our capabilities and access to resources. In short, humanity will ultimately collaborate and co-evolve with AI. When we talk about all of the problems we have on Earth, and the need to solve them, it is only through such AI-human collaboration that we will gain the ability to solve our grandest challenges and truly create a world of abundance". For more information and other interesting posts, see www.diamandis.com. Mark Zuckerberg, co-founder and CEO of Facebook, has a similar view. "One reason I'm so optimistic about AI is that improvements in basic research improve systems across so many different fields—from diagnosing diseases to keep us healthy, to improving self-driving cars to keep us safe, and from showing you better content in News Feed to delivering you more relevant search results. … Every time we improve our AI methods, all of these systems get better. I'm excited about all the progress here and its potential to make the world better. […] I think people who are naysayers and try to drum up these doomsday scenarios—I just, I don't understand it. It's really negative and in some ways I actually think it is pretty irresponsible." Diamandis, P. H., & Kotler, S. (2012). *Abundance: The Future Is better Than You Think*. New York, NY: Free Press. Lev-Ram, M. (2017). Why futurist Ray Kurzweil isn't worried about technology stealing your job. *Fortune*, September 24. Retrieved online at http://fortune.com/2017/09/24/futurist-ray-kurzweil-job-automation-loss/ [Accessed May 3, 2019].

10 On the pessimistic side of AI, we can definitely find Nick Bostrom, the University of Oxford philosophy professor who is famous for warning us about the dangers of super-intelligence, which can easily become unfriendly and prevent humans from changing its preferences or even worst, replacing it. As director of the University of Oxford's Future of Humanity Institute, Bostrom argues that because of its increased use, AI could turn dark at any moment and quickly dispose of humans, who are still too focused on gnawing at the "economic miracles and technological awesomeness" generated by it, to realise that we will no longer exist to benefit from such marvellous things, like a "Disneyland without children" (see Cardinali, 2016). Stephen Hawking, renowned physicist and popular author, focused his attention on the increasing importance of robot machines in our society, and how this could lead to potential

disaster for humankind. According to him, AI will be "either the best, or the worst thing, to ever happen to humanity". Hawking's position was somewhat balanced between the potential good AI brings with it, and the danger in case humans are not able to control eventual downfalls. On the same perspective, Bill Gates, Co-Founder of Microsoft and Co-Chairman of Bill & Melinda Gates Foundation, is concerned about the existential threat from superintelligent machines at the point that he believes them more dangerous than a nuclear catastrophe. In his view, machines will start being useful to humans, doing lots of jobs that are repetitive and taking some stress out of employees. However, once they become more advanced, we will have on our hands a great challenge to handle machines so progressed. This will mean a consistent risk of job losses, which can only be stopped if robots or their owners/makers are forced to pay the same amount of taxes a human worker should pay. Furthermore, Gates observes that technology has the potential to accentuate the disparity between the rich and poor, also pointing out that poorer people have less possibility to be exposed to technology in schools, which will in turn accentuate the gap. These types of barriers will slow down the pace of innovation and automation, allowing governments, markets and the public to gain more time to better handle the transition without succumbing to the machines. On the opposite end, according to Satya Nadella, Chief Executive Officer at Microsoft, AI could be a vital driver of growth, instead of creating wealth disparity. In particular, "It's not like we actually have economic growth today. So we actually need technological breakthrough, we need AI. We should do our very best to train people for the jobs of the future. […] Our responsibility is to have the AI augment the human ingenuity and augment the human opportunity. I think that's the opportunity in front of us and that's what we have got to go to work on". Cardinali, F. (2016). A Disneyland without Children? *LACE Project*, Aug. 22. Retrieved online at http://www.laceproject.eu/blog/disneyland-without-children/ [Accessed May 3, 2019]. Clinch, M. (2017). Microsoft CEO Nadella: We have no global growth, we need AI. *CNBC*, January 17. Retrieved online at www.cnbc.com/2017/01/17/microsoft-ceo-nadella-we-have-no-global-growth-we-need-ai.html [Accessed May 3, 2019]. Delaney, K. J. (2017). The robot that takes your job should pay taxes, says Bill Gates. *Quartz*, February. Retrieved online at https://qz.com/911968/bill-gates-the-robot-that-takes-your-job-should-pay-taxes/ [Accessed May 3, 2019]. Gamble, H., & Clinch, M- (2017). Bill Gates says technology could 'accentuate' the gap between the rich and poor. *CNBC*, November 15. Retrieved online at www.cnbc.com/2017/11/14/bill-gates-defends-the-rise-of-the-robots.html [Accessed May 3, 2019]. Holley, P. (2015). Bill Gates on dangers of artificial intelligence: 'I don't understand why some people are not concerned'. *Washington Post*, January 29. Retrieved online at www.washingtonpost.com/news/the-switch/wp/2015/01/28/bill-gates-on-dangers-of-artificial-intelligence-dont-understand-why-some-people-are-not-concerned/ [Accessed May 3, 2019]. Morris, D. Z. (2017). Bill Gates says robots should be taxed like workers. *Fortune*, February 18. Retrieved online at http://fortune.com/2017/02/18/bill-gates-robot-taxes-automation/ [Accessed may 3, 2019]. Among articles that discuss Stephen Hawking's views on the dangers of AI, see for example Griffin, A. (2015). Stephen Hawking: Artificial Intelligence Could Wipe Out Humanity When It Gets Too Clever As Humans Will Be Like Ants. *The Independent*, October 8. Retrieved online at https://www.independent.co.uk/life-style/gadgets-and-tech/news/stephen-hawking-artificial-intelligence-could-wipe-out-humanity-when-it-gets-too-clever-as-humans-a6686496.html [Accessed May 3, 2019].

11 An initial phase of great interest in AII has been followed by what experts call a long AI winter, which is nothing else that a moment in history when AI was not seen favourably among scientists and researchers, nor media and organisations.

12 According to a survey administered by HR.com in 2017, the majority of participants (53%) thought that employees will increasingly take orders from Artificial Intelligence machines, while only 13% of them were convinced this scenario would not play out. At the same time, it is interesting to see how participants to the survey saw the relationship between AI-related technologies and the loss of jobs. The majority of them believe there is no actual correlation between such technologies and a significative gain or loss of jobs, however those that say there will be a net loss of jobs are twice as many as those who are convinced there will be a net gain. See HR.com (2017). *The State of Artificial Intelligence in HR - Getting up to speed on AI in order to gain maximum advantage for the HR function.* Retrieved online at https://harbinger-systems.com/wp-content/uploads/2017/12/WP_StateofArtificialIntelligenceinHR_HarbingerSystems_112717.pdf [Accessed May 3, 2019].

13 Le Wagon is an entrepreneurs' coding bootcamp. More information can be found at https://www.lewagon.com. See also https://www.director.co.uk/coding-the-skill-you-need-to-learn-22003-2/.

[14] An interesting application of this perspective can be seen in what experts call affective computing. In 1997, Rosalind Picard made "a call for a change in computing, a declaration that we have left a key term out of the computer intelligence equation… computers that recognise and express affect" (Sarangi & Sharma, 2019, p. 250). What is exactly affective computing and why it could be so important? Using deep machine learning techniques and a large database of emotions to use for training purposes, affective computing aims to build systems capable of detecting users' emotions and express its own, using a variety of sensors to do the job. Furthermore, the system is trained to recognise emotions through body language, facial expressions, posture, blinking patterns, and the electrical activity in the brain. Sarangi, S., & Sharma, P. (2019). *Artificial Intelligence: Evolution, Ethics and Public Policy*. Abingdon, Oxon: Routledge.

[15] According to a study conducted by the Human Resources Professionals Association (HRPA) in 2017, only 6% of HRPA survey respondents believed AI solutions in HR could help with promotions, and 5.6% thought it could improve retention. This data shows that organisations are likely to not invest enough to embark in a digital transformation project of their own, nor to retain top talent. See HRPA (2017). A New Age of Opportunities: What Does Artificial Intelligence Mean for HR Professionals?. *HRPA Publications.* Retrieved online at https://www.hrpa.ca/Documents/Public/Thought-Leadership/HRPA-Report-Artificial-Intelligence-20171031.PDF [Accessed May 3, 2019].

[16] According to start-up company Interviewed, its algorithm is trained to recognise the presence of soft skills, such as empathy. See more at Captain, S. (2016). How AI is Changing Human Resources. *Fast Company*. September 12. Retrieved online at https://www.fastcompany.com/3062995/how-ai-is-changing-human-resources [Accessed May 3, 2019].

[17] A good example of AI tool for HR is the HR cloud solution SuccessFactors, which is known to be able to efficiently handle tasks usually completed manually by managers, employees and the HR department. These tasks can be repetitive, such as the viewing and updating of employee information and any other low-value task that can be easily automated, or dynamic and engaging like team training programs and aspects of the hiring process. SuccessFactors can count on conversational AI capabilities with conversational through the integration of Recast.AI, SAP Leonardo ML Foundation, IBM Watson, ServiceNow and Microsoft Azure/Skype.

18 To prove this point, we can refer to the use of a psychological tool also known as the Implicit Association Test (IAT), which has been used to demonstrate how people's subconscious word associations indicate bias. Once we realise that we carry biases, whether we like it or not, we should be more inclined in recognising that such biases have found their way into job descriptions, as well as resume selections. Through the use of AI, employers can adopt algorithms capable of detecting such biases in the way we communicate and write, so that our language can help improving the hiring process and welcome diverse applicants. See more at Hutson, M. (2017). Even artificial intelligence can acquire biases against race and gender. *Science*, April 13. Retrieved online at http://www.sciencemag.org/news/2017/04/even-artificial-intelligence-can-acquire-biases-against-race-and-gender [Accessed May 3, 2019].

19 Barriers to a wide adoption of AI tools in HR can be related to internal costs for softwares and skilled personnel, as well as ongoing maintenance costs. To be effective and actual, AI tools need to be constantly revised and updated to fit the organisational changes. Other issues are related to the need for privacy, where confidential HR data must by law be accessed securely and available only to those authorised to see them. In general terms, experts interviewed on this topic seem to believe that AI tools for HR purposes are great on paper, but yet to be proved efficient in practice. On the other end, such tools should reduce the amount of time HR professionals should spend on administrative and automatic tasks, as well as offering support in routine queries, retention rates and recruiting practices. AI tools can revolutionise the way the HR sector is structured in key areas, which can be defined as compensation and payroll, talent acquisition and retainment, learning and development, as well as analytics and metrics. In particular, experts predict that AI supports HR practitioners in recruiting in eight different ways. First of all, screening the candidate is easier if there is a chance for them to learn more about the organisation they are applying for or joining. This can be achieved through the adoption of chat boxes that respond to questions about the company and request feedback as well as thoughtful information about the candidate himself. An interesting use of AI can be already seen in websites offering jobs, such as Indeed or LinkedIn Jobs. The use of technology in these cases allows applicants to avoid reverting back to the original job site, while being kept informed about the application's progress using automated e-mails and/or messaging systems. Candidates seem to be more engaged, and the company is

reassured to get a quicker response from them, whether they are offered the position or not. Surely you have come across a company that requires to create an account, which allows you to apply for other positions within the company without having to register again, update your records and so on. AI tools can also be used to facilitate the post-offer acceptance process for example, while functioning as a bridge between the company and the hired person during the weeks before the starting date of their contract. After that, the AI tool offers an invaluable support during the induction of new hires, when company policies, procedures, good practice and culture. Instead of relying heavily on colleagues we do not know yet, we can find information and resources in our computer. While social interaction among peers is always important, people might have a series of questions related to benefits, holidays, pension schemes and so on, which may require little to substantial HR intervention. Artificial Intelligence tools can once again be helpful when answers are provided through chat box, email forms or other digital solutions. Similarly, once our position in the company is secure enough, HR-developed training programs can be shared through the company's learning environment, to support career development and easily share achievement and career-related option with line managers and peers. Furthermore, more mundane tasks such as scheduling a call or booking a place for a meeting, can be achieved by AI tools with no need for employees to worry about such things.

Related Readings

To continue IGI Global's long-standing tradition of advancing innovation through emerging research, please find below a compiled list of recommended IGI Global book chapters and journal articles in the areas of business leadership, entrepreneurship, and business management. These related readings will provide additional information and guidance to further enrich your knowledge and assist you with your own research.

Abalkhail, J. M. (2018). Arab Gulf Women and the Labyrinth of Leadership. In E. Al-A'ali, M. Al-Shammari, & H. Masri (Eds.), *Arab Women and Their Evolving Roles in the Global Business Landscape* (pp. 26–50). Hershey, PA: IGI Global. doi:10.4018/978-1-5225-3710-6.ch002

Abe, E. N., & Abe, I. I. (2019). Integrating Multiculturalism in the Design and Implementation of Work-Life Balance Strategies. In S. Atiku (Ed.), *Contemporary Multicultural Orientations and Practices for Global Leadership* (pp. 100–120). Hershey, PA: IGI Global. doi:10.4018/978-1-5225-6286-3.ch006

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About the Author

Sara Fazzin is what she calls a pastor of skills in the fields of education, innovation, creativity and strategic management. In 2013 Sara was awarded the Doctorate of Management and Business Administration by “G. D’Annunzio” Department of Business Studies, Chieti, Italy. On October 2016, she completed the PG CHEP Programme at Essex University, UK, where she worked since 2013. During some formative experiences as practitioner, mainly as CEO and Head of HR in different Italian firms, Sara continued her academic research in a multi-disciplinary approach, with publications in the areas of organisational theory, knowledge management, artificial intelligence and emotion in the workplace. A proud Fellow of the Higher Education Academy in UK (FHEA) and an editorial member of the international journal IJKM, Sara leads undergraduate and postgraduate programmes in management and innovation in London. Dedicated to technology, innovation and creativity in the workplace, Sara enjoys to spend time with her students, debate about the latest tech breakthrough and engage peers and colleagues from everywhere in the future of higher education.

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