Exponentially Available Intelligence:

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EXPONENTIALLY AVAILABLE INTELLIGENCE: AI, DATA AND THE DRAMATIC DIGITIZATION OF TRADITIONAL INDUSTRY

INTELIGENCIA DISPONIBLE EXPONENCIALMENTE: INTELIGENCIA ARTIFICIAL, DATOS Y LA DIGITALIZACIÓN DE LA INDUSTRIA TRADICIONAL

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SUMMARY

This paper is concerned with Artificial Intelligence (AI) and its effect on business and society. The aims of the paper are as follow. First, to define and illustrate AI. Secondly, to connect AI to other developments in digital technology and more broadly to other innovations. Thirdly, to introduce the implications for business. Fourthly, to establish key questions for society in general.

Kew words: Artificial intelligence, Big Data, digitalization, transformation, machine learning.

RESUMEN

Este artículo estudia la Inteligencia Artificial (IA) y sus efectos en el ámbito empresarial y en la sociedad. Los objetivos del artículo son los siguientes. Primero, definir y explicar la IA. En segundo lugar, conectar la IA con otros desarrollos en tecnología digital y en términos más generales. Tercero, presentar las implicaciones en el ámbito empresarial. Por último, se determinan las cuestiones clave que se derivan para la sociedad en general.

Palabras clave: Inteligencia artificial, Big Data, digitalización, transformación, aprendizaje de máquinas.

Introduction

This paper is concerned with the development of Artificial Intelligence (AI) and its value to business. AI is understood as constituting a family of components that add to existing components in the functionality of digital firms (Figures 1 and 2). A conceptual table is presented (Figure 3) that depicts AI as the fulcrum of a connected network of digital innovations. Ultimately, in application, AI is not separate from these other innovations in data and hardware but will become the most obvious manifestation of the combined effect of these innovations when they are deployed together. Business will buy and provide intelligence, and that intelligence will increasingly be gained from software. Overall, we will have more intelligence available to society, what Nordhaus (2015) has called "exponentially available intelligence." It follows that after defining and illustrating AI, we consider it as a General Purpose Technology, providing the focal point of the digitization phenomenon. The paper then considers the implications of digitization for business. The focus given is upon traditional industry, those sectors that are not usually demarcated as being part of the 'Information Technology' or 'Digital' sector, but which are nevertheless profoundly affected or occupied by it. Although we note that the digitization of traditional industry is likely to expand across many sectors, we choose to provide examples from three; automotive, finance and universities. Finally, the paper seeks to chart the major implications for society more widely, seeking to establish key questions that will be confronted through the digitization of traditional industry.

The aims of the paper are thus;

1. to define and illustrate AI.
2. to connect AI to other developments in digital technology and more broadly.
3. to introduce the implications for business.
4. to establish key questions for society more broadly.

The sections in the paper that follow from this introduction are, first, 'Artificial Intelligence – What is it?' After this, there follows the section 'How Does AI Relate to Other Innovations?' The third section is then concerned with 'The Digitization of Traditional Industry.' The final section is 'Implications.'

Artificial Intelligence – What is it?

AI has a long history. Arguably its roots stretch to the earliest work on logical reasoning in different societies across the globe. Later, in the 13th Century, the Majorcan philosopher Ramon Llull developed logical reasoning machines (Artau & Joaquín, 1939), work which had influence on many including Gotfried Leibniz and Thomas Hobbes in the 17th Century. Hobbes proposed that "Reasoning is nothing but reckoning"

(Hobbes, 1651), but it was not until the development of electronic computation in the 20th Century that AI entered widespread research. Some of the most significant early work took place in Manchester, UK, where the development of the Baby and Ferranti Mark One were very significant achievements in early computation (Croarken, 1993). In this context, Alan Turing proposed his famous 'Turing Test' for the achievement of AI (Turing, 1956). His work continues to attract increasing public regard. From the 1950s onwards, however, the USA began to dominate in the development of Computer Science and the growth of the IT Industry. As the influence of these industries continued to develop, the idea of an AI that could masquerade as human (the essence of the Turing Test), became more likely and attracted more public debate. The term 'the singularity' is most associated with the academic and author Vinge (2007) who proposed that a point will come where the "human era" ends, and plentiful and powerful AI creates an augmented species and a world beyond human comprehension. Famously, Kurzweil (2014), proposed that "the singularity is near", language which echoed that of biblical prophecy (Harari 2016). Kurzweil identified 2045 as the likeliest date for the achievement of the singularity, and his work gained additional credence by his subsequent appointment to Google. As the 21st Century passed into its second decade, AI has become evermore topical mainly as a result of the public achievements of the IBM Watson project and Google's Brain project. The informed public is becoming used to hearing that current AI can defeat human contestants at General Knowledge, that AI can outperform doctors in medical diagnoses, that it can provide legal expertise, that it can drive a car more safely than a human, and that it is becoming capable of recognising visual objects without human supervision (IBM, 2016; Wired, 2012). There is a present debate in society. Will AI be good for our species or bad? Notable figures such as Hawkins, Gates and Musk have raised and contributed to this debate (e.g. BBC, 2016a).

Technological Drivers

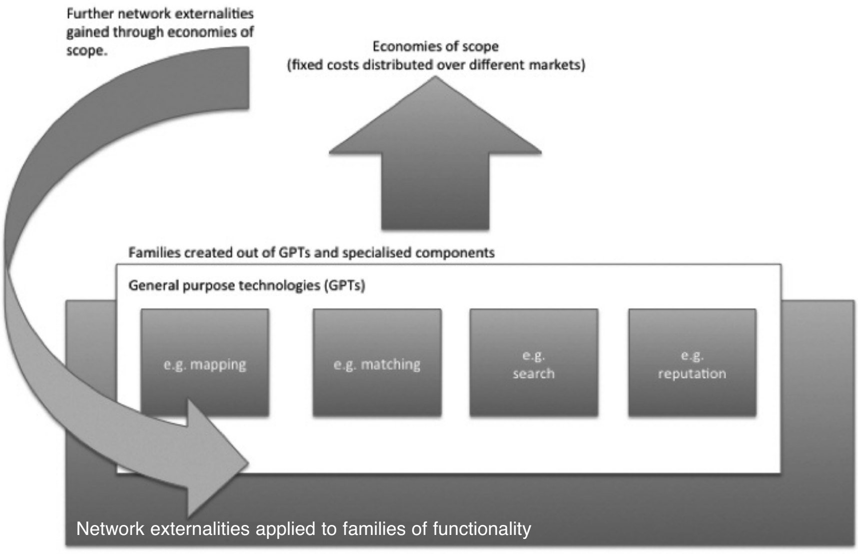
General Purpose Technologies (GPT) can be defined as 'technology that initially has much scope for improvement and eventually comes to be widely used, to have many uses, and to have many Hicksian and technological complementarities' (Lipsey et al., 1998). Electricity, steam and information and communications technologies (ICT) are generally regarded as being among the most important examples (Crafts, 2004).

Example GPTs include mapping algorithms, matching algorithms (e.g. job markets, dating markets), search engines, reputation systems (e.g. driver and passenger evaluation on taxi networks, traveller and host evaluation on travel systems), and recommendation systems (e.g. personalised marketing). Successful digital firms have clusters of such GPTs together with other, distinct components in order to maximise perceived customer value and positive network externalities. These clusters are known as 'families.' The creation of a successful family permits economies of scope; a key feature in digital business and a trademark of major firms such as Amazon, Apple and Google. In these industries, variable costs are sometimes close to zero, meaning that economies of scale are often not as significant as they are in traditional industry, although there are still key aspects of many digital firms where scale economies apply (e.g. order warehousing, manufacture of hardware.)

Figure 1 gives a schema to describe the digital firm. It represents a family of GPTs together with other components that are deployed to create positive network externalities, introduced below, through and creating economies of scope. Successful firms of this type will potentially exhibit Levin's characteristics of fast innovation, scalability and customization. Moreover, at the industry level, there will be potentially new job market structures and greater centralization (Brynjolfsson & McAfee, 2014).

Figure 1

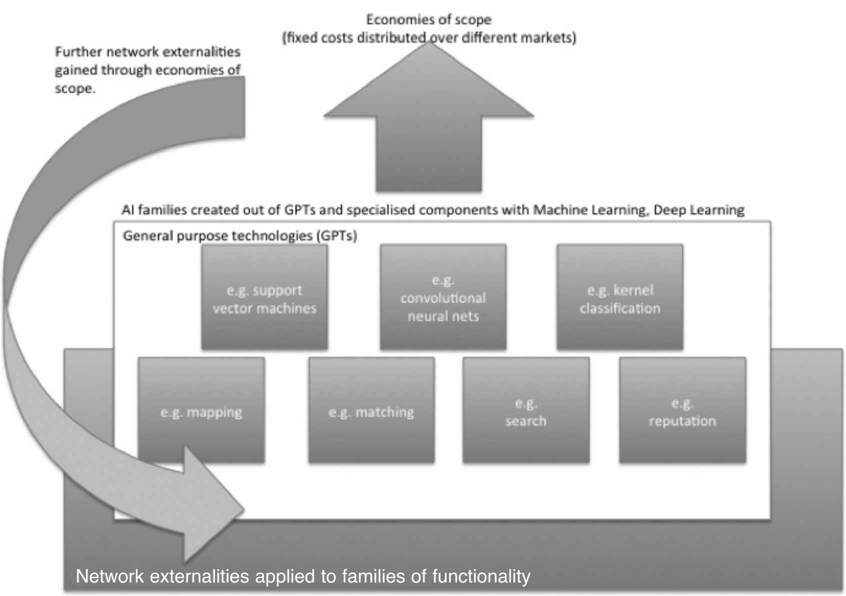
Schema to depict digital components and network externalities



At Figure 2 the schema is altered to include AI components. Based on the principles of machine learning and deep learning, described below, AI has come into prospect through a combination of innovations. Key amongst these are Natural Language Processing, the ability to interpret natural sentence forms, speech recognition and image recognition. These feature in different projects including IBM's Watson project and the Google Brain project. They enable many innovations including, for example, image recognition, speech recognition and a QA basis for computing. This latter term refers to 'Question Answer', and identifies algorithms that are able to provide a precise and accurate answer to a question expressed by human. This precision is different to conventional search whereby a large range of ranked responses are provided in response to keywords in a statement or question. Figure 2 selects ML techniques (support vector machines, convolutional neural nets, kernel classification) that act as GPTs and are amenable to positive network externalities. One implication is that learning dynamics are further emphasised as greater AI proficiency implies further progress on a learning curve.

Figure 2

Schema to depict digital components including AI and network externalities



Statistics and Machine Learning

AI is the application of modern non-parametric statistical techniques through software combined with large data sets to deal with bias-variance trade-off. Non-parametric statistical techniques include random forest, neural nets, support vector machines, kernel classification techniques, kernel estimation, spline regression, regularisation techniques (such as Lasso), and re-enforcement learning rules. Understood as statistics, AI does not represent more than this. Breiman's work on "Two cultures" makes this point plainly (Breiman, 2001). The software industry represents AI as new because it is developing systems that exploit these statistical approaches at new scale and in new combinations with other components, but the discipline of AI inherits from existing work in statistics (e.g. Efron and Tibshirani, 1994; Silverman, 1986), and makes this work more amenable to application by virtue of greater scale.

Typically, programmers refer to the concept of Machine Learning (ML) as core to the progress of modern AI. Unlike conventional programming where a program is set to solve a problem based on pre-specified rules, ML relies on the assumption that for many real-world problems, there are no specific rules to follow. This is best illustrated through an example. Take for example the problem of writing a programme that can recognise if there is a tree in an image. What rules follow? To begin with, it is possible to start by specifying the features that are distinctive in a tree. Trees have branches, they have leaves and the leaves are normally green so on and so forth. The problem with this approach is threefold. Firstly, the large variation in types of a tree constrains the programmer in setting generalisable rules about trees. Secondly, even if the programmer is able to find generalisable rules, it will still be very complex to program them. Thirdly, even if it is possible to accomplish the first two tasks, there are still variations in the way trees can be presented in an image (e.g. the image is taken on a sunny/cloudy day, there is a person standing in front of a tree or the images are taken from different angle). ML can overcome the aforementioned difficulties by virtue of a concept called feature representation. Rather than trying to find, design and code the generalised roles manually, ML uses data to learn the features. This is possible through the use of statistical techniques such as artificial neural networks (e.g. Geman et al., 1992; Rosenblatt, 1958). Human supervision of these ML processes is common, but algorithms can also be developed to work without supervision to identify distinct objects. This relies on even higher computational power approach, as the algorithms will break a sequence of data such as an image into particles (or tiles) and seek associations between them.

How Does AI Relate To Other Innovations?

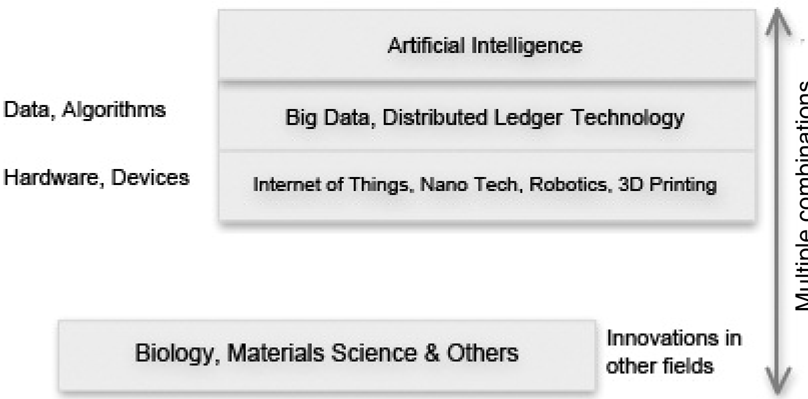
Concepts such as "the singularity" perhaps distract attention from the reality of AI as we know it now. Rather than envisaging a great step to be taken at some point in the future, we should recognise that greater and greater intelligence is coming by increments into the market already. It has been for some time and will continue as ML is combined with more data. Thus, as software systems mature, as new software is released into phones, and as new functionality is taken on into products like cars, there is a growth and extension of available intelligence. One manifestation of this is that software becomes better at prediction. This is fundamental. If one considers the very wide range of areas in which prediction is important to business, through sales, supply-chain, markets and so forth, one gathers insight into the minimum likely provenance of AI. Prediction is at the heart of the environmental strategy of business, and is necessarily accompanied by adaptability and then, from that, resilience (Beer, 1979).

Rather than understanding AI as a separate step yet to be taken, we describe it as a gradient that digitization is already ascending. It follows that it is important not to define AI too discretely but rather to see it as a constant evolution and deepening of the capabilities of software systems of all types. Existing software systems act intelligently (e.g. a spreadsheet is good at calculus) and to the business world AI will present as a constant enrichment and extension of capabilities already established. This process is likely to be rapid. There is evidence that the technology is outstripping the best predictions of a little more than a decade ago (Levy and Murnane, 2004). Systems are becoming increasingly intelligent, and in practice, we encounter AI in conjunction with other innovations in digitization and with innovations from other disciplines entirely. Our table below (Figure 3) depicts this. The table is not exhaustive, but highlights key topics known today.

Amongst those innovations depicted in Figure 3, there is greatest conceptual overlap between AI and 'Big Data.' Today, the progress of AI depends upon huge data sets and these huge data sets cannot be marshalled without advances in AI. There is a case for treating them highly related concepts[1]. This is a point made by Athey (2016a), for example in relation to Google PageRank. This technology allows "massive, decentralised, iterative innovation," as new code is brought in and tested amongst sub-samples of users. Around 10,000 randomised control trials are run in a year, thereby allowing the service to get better every day as a kind of constant learning cycle. Such systems of constant learning are also associated with other Machine Learning applications hosted in the cloud. The implication is that there is a kind of democratisation of innovation as open platforms allow new innovators to build upon the successes of previous Machine Learning applications. Hence, the level of intelligence potentially rises exponentially.

Figure 3

The Intelligence Available to Society (example innovations)



The Digitization of Traditional Industry

Network Externalities

Levin (2013) writes of a Digital Economy that is markedly different to the traditional economy. Information goods are characterized by large scale, increased customization and rapid innovation. Levin notes that the

[1] Note also fields where smaller data sets are applicable, and that there is research to improve the reliability of learning drawn from small data sets, for example in neuroscience Ferguson et al. (2014).

Internet has lowered a range of economic costs, thereby underpinning new firm characteristics, boundaries and supply-relationships. It can be argued that the same effects will apply to some extent wherever software networks are introduced. The Internet has diminished the cost of creating and distributing many types of products and services, the cost of acquiring information about these goods, and the cost of gathering and utilizing data on consumer preferences and behaviour. As AI advances, the prospect increases of two further developments. The first is that digital firms become more proficient at attaining and maintaining these characteristics of large scale, increased customization and rapid innovation. The second is that these characteristics increasingly affect traditional industry; that as traditional industry becomes more dependent on increasingly intelligent software, so it also becomes more like a digital industry.

The pivotal concept in understanding this is that of the 'network externality' or 'network effect' (Katz & Shapiro, 1985). The terms are synonymous. Network externalities are said to exist when the benefit a consumer derives from owning a product or service escalates as the number of other consumers of the product or service increases. There are many examples. A telephone system increases its value as new users join the system. An online game increases its value as new players enter into it, as there are more opponents with whom competitions can be constructed. An operating system on a mobile device increases its value as new consumers adopt it, as there are greater incentives for application developers to create further functionality for the operating system.

We describe industries that are characterised by the impact of network externalities as 'network industries'. There are some key nuances such as the difference between direct and indirect network externalities, and the difference between positive and negative network externalities. Briefly, the concepts of direct and indirect network effects discriminate between those that bring benefit directly, such as new users on a telephone system, and those that encourage additional market activity and supply, such as incentives for developers to create applications for an operating system. The concepts of positive and negative externalities describe the distinction between agreeable outcomes of network externalities (e.g. more people that you can call with your mobile phone) and disagreeable consequences (e.g. congestion of the telephone network.)

As AI and data both deepen and extend the dependency of different industries upon software, so it becomes likely that these traditional industries will take on some of the characteristics of network industries. Levin's account of large scale, increased customization and rapid innovation will become increasingly applicable across different industries and we are likely to see industrial structures become more like that of the digital sector where large platforms (Rochet & Tirole, 2006) dominate, including household names such as Amazon, Facebook, Google, Microsoft and Taobao.

The Automotive Sector

In September 2016, BMW announced the concept of an AI enabled motorcycle. Named the Motorrad Vision Next 100, the motorcycle will be able to maintain itself upright at all times, both whilst in motion and whilst parked. With such safe technology, BMW speculates that the rider would be freed of the need for protective clothing and a helmet. With this announcement, BMW brought to motorcycles some of the AI technology that we have already seen in motor cars, especially through Tesla, Google, Uber/Ford and Volvo (BMW, 2016; McKinsey, 2015; Shapiro, 2016).

The autonomous car has progressed towards the market through two paths of development. The first of these has been the extensive and widely publicised trials of prototype technology under the direct control of the innovating firm. Google has been the most prominent company carrying out these machine learning trials, mostly on public roads in California. As of September 2016 Google has achieved 2,102,047 miles whilst achieving a markedly lower accident rate than human drivers (Google, 2016). Google reports that it is working on advanced driving problems with its fleet of cars, writing "After 2 million miles of testing, our cars are more prepared to handle rare and unusual situations that human drivers may come across only once in a lifetime. In the last few months, we've seen everything from a horseback rider in the middle of the road, to a man wielding a chainsaw in the street (don't worry, he was trimming trees!), to a couple riding unicycles side-by-side" (Google, 2016). The implication here is that the centralised architecture of machine learning, allows all cars to benefit from common learning experiences whereas human drivers benefit only from the learning of their own experiences behind the wheel. An accompanying publicity drive by Google anticipates that the autonomous car will enable mobility amongst underserved consumer groups, such as the disabled, the elderly and children, thus bringing into prospect of an enlarged market for car journeys, and thus ever greater network externalities. Whilst these trials have taken place, a second path of development has arisen through the extension of functionality in existing cars available on the market. The most prominent example is that of Tesla's 'Autopilot' system. In 2014, Tesla announced a restricted self-driving mode for its Model S car. This allows drivers to select a hands-free mode where the car steers itself and maintains distance from surrounding traffic, even changing lanes without the driver taking the steering wheel. Tesla collects data from all cars whether or not they are operating under this mode and uses it to further enhance the intelligence of the system. This is a process of machine learning, through which Tesla has acquired data relating to more than 780,000,000 miles of road use by May 2016, and over 100,000,000 miles of road use utilizing Autopilot (MIT Technology Review, 2016). This very rapid rate of data acquisition supports Tesla's target of a fully autonomous car in 2018. Through this machine learning programme, Tesla has been able to teach its Autopilot system to tackle even difficult road sections by training it with data gained from Tesla cars on those same sections of road but in normal driving mode. Tesla cars routinely report on how their autonomous pilot would have dealt with a road situation versus how the driver actually dealt with it, hence the company claim that each car becomes more intelligent with every mile travelled by it or another Tesla car (MIT Technology Review, 2016).

The mapping systems used in car satellite navigation give another clear example of network externalities. Again, we see intelligence growing as systems become trained by data gained from traffic conditions on defined sections of road. The more users, the better the data and the more accurate the predictions (e.g. repeat congestion patterns in Bilbao during Athletic Bilbao games in the evening, variances due to weather patterns in the city during the game.) The main systems in the market are Google, TomTom NV and HERE. Given their importance to the car market now and likely increased importance in the future, especially as autonomous driving becomes more normal, it makes sense that a consortium of German manufacturers acquired the HERE mapping business from Nokia (The Guardian, 2015).

The Financial Sector

The Financial Sector has traditionally been a leading adopter of IT and digital systems. The modernisation of banking, for example, relied upon new IT infrastructure and a range of consumer applications such as ATMs and internet-based apps. Stock markets also came to rely upon software and today trading platforms automate purchase and sale decisions according to parameters supplied to them. Given the centrality of prediction to this process, it is inevitable that more and more intelligence will be deployed to provide greater and greater anticipation of the market. Rather than merely reacting to price, AI will enable trading platforms that analyse history, identify patterns and make predictions. Notable new companies such as Aidyia, Sentient and Rebellion Research utilize AI to predict market trends, to isolate particular trends and to improve the AI models themselves.

Today, FinTech, or innovative digital technology oriented towards financial markets, has become a major topic of research and investment for large financial companies across the globe. Perhaps just as tellingly, it has become a major interest of startup investors. New startup companies address many parts of the finance industry including credit scoring, insurance and fraud detection where there are immediate potential for AI. Aire is a credit-scoring algorithm that uses predictive analytics. Brolly is a new venture in insurance. Ravelin Technology utilizes AI in fraud prevention. There are also startup ventures in consumer banking, bond markets, financial planning, banking for the unbanked and other areas.

Ever since Fairbank and Morris of Capital One recognised that the credit card market is primarily a market for information, it has become obvious how the whole of the banking industry is subject to innovation in information. The task of banking is to remedy or manage transaction costs through its functions such as information management, risk diversification and liquidity transformation: all of these are suited to the deployment of AI. In a BBC report, Antony Jenkins, former CEO of Barclays Bank, gave the opinion "I believe that in twenty years time, we may not need banks at all" (BBC, 2016b). This opinion derives from analysis of three technologies. The first is peer-to-peer lending, which is a form of matching market and likely to continue to improve with the development of increasingly intelligent computing. Funding Circle, Lending Club and Zopa are examples. The second is online (sometimes foreign) exchange which is a form of disintermediating ledger. Again, the technology will develop through increasing network externalities and the acquisition of greater data will drive greater intelligence. The third technology is distributed public ledger technology (DLT), that enables secure and transparent transactions of many types (e.g. financial, legal) without the involvement of a third-party. This is not an AI application but commentators have speculated on the potential of DLT, smart contracting through systems like Ethereum (a DLT development) and AI in combination. The result might be firms that can be created or closed very quickly (e.g. within a day), or even firms that can create themselves in response to intelligent detection of a market opportunity (Guerrini, 2015, Pilkington, 2016)

Athey (2016b) acknowledges some practical and immediate impact of DLT on the financial sector. Identifying that the flow of funds and information becomes instantaneous and simultaneous, she reports that this will allow smaller banks to carry out the functions of larger banks, as the level of capitalisation will be less. Many transactions will proceed without intermediaries, costs will come down, and countries in the global economy where it is difficult to secure reliable and rapid banking services, will be supported by the new systems. She describes the effect of the changes as "essentially like removing a global tax on commerce and payments" (Athey, 2016b, also Shin, 2014).

The University Sector

Online education has been growing and gaining interest over several decades. Most recently, much attention has been given to the rise of open, large-scale courses known as Massive Open Online Courses (MOOCS). Deming et al. (2016) provide a good summary of the state of the market, reporting that millions of students have enrolled in MOOCs delivered by major research universities such as Harvard, MIT, Princeton and Stanford (Ho et al. 2014, McPherson and Bacow 2015, Waldrop 2014). Amongst these MOOCs are edX, a partnership of Harvard University and MIT, Coursera which was established by Daphne Koller and Andrew Ng, both professors of AI, and Udacity, a Stanford spin-out pioneered by Sebastian Thrun who was associated with the Google autonomous car project. In 2014, one third of college students in degree-granting U.S. institutions took at least one course online (Allen and Seaman, 2015). This rise of online courses and degrees has led to predictions that competition from MOOCs and other online course offerings will lead to "disruptive innovation" in higher education (e.g. Christensen and Eyring 2011; Cowen and Tabarrok 2014). Current evidence establishes that as a result of online programmes, greater competitive pressures and productivity enhancement are evident amongst the least selective institutions but also that these benefits are currently restricted to these institutions (Deming et al., 2016).

Online education incorporates GPTs like matching algorithms, reputation systems and recommender systems. They are subject to network externalities and will grow in value as they grow in use. As AI is deployed within them, utility will accelerate more quickly, potentially having pedagogical benefits e.g. AI that is able to personalize material to learning styles of students, speech-based interaction with students. Economies of scope might be developed providing, for example, matching markets with employment opportunities, retraining support and commerce through purchase of support materials, related travel and social events.

Implications

MIT researchers Brynjolfsson and McAfee have developed a series of studies of the economic impacts of the advance of increasingly capable software and machines. These studies include two books (Brynjolfsson & McAfee, 2012, 2014). Their work is part of an increasingly significant set of economic analyses that address the likely implications of the development of AI, data and the impact of digitization across the economy.

Similar to previous technological shifts in society, the key data will describe the rates of destruction/creation of jobs, the costs of capital and the capital intensity of firms. In common commentary there is often a reflex argument that technological renewal has historically been associated with a pattern of destruction of some industries but greater job creation overall. Brynjolfsson and McAfee (2012, 2014) warn against such confidence reporting that the data we have to date shows growing wealth differentials, a "hollowing-out" of the economy (middle class job losses), and a breakdown of the traditional compact that growing economic productivity tends to lift wealth for all economic participants in society. Clearly, governmental policy needs to consider and address such trends.

Athey (2016a) also recognises these macro-economic policy implications, additionally highlighting the challenge of transition costs for governments. Like Brynjolfsson and McAfee, she also highlights likely benefits of the increased use of AI in society. She identifies that learning about the effects of policies implemented by governments might become more systematic and quicker, as data is drawn quickly about impacts on society. She reports potential benefits in public arenas such as fairer and better sentencing and probation decisions in the legal system, better predictions and inspections for government enforcement (fire services, police searches, trading standards) and open data for citizen innovation and learning.

We conclude that the benefits and implications of AI are of serious debate, and that it is inevitable that serious advances will be made. Traditional industry is becoming digitized and with the process come new opportunities for the development of AI. The ultimate structure and pace of the change remains uncertain but, prosaically, it seems wise for business and governments to invest now. Beyond this, there are potential clues to the structure and pace of AI given by the concepts of Moravec's Paradox and a "growth singularity." These are summarised below.

Moravec's Paradox

One clue identified by Brynjolfsson and McAfee (2012, 2014) is that of Moravec's Paradox. This might provide insight into economic restructuring in society, although it is a research topic rather than a finding. Moravec's Paradox is intuitively appealing and is well-encapsulated by Pinker (1995): "The main lesson of thirty-five years of AI research is that the hard problems are easy and the easy problems are hard. The mental abilities of a four-year-old that we take for granted – recognizing a face, lifting a pencil, walking across a room, answering a question – in fact solve some of the hardest engineering problems ever conceived... As the new generation of intelligent devices appears, it will be the stock analysts and petrochemical engineers and parole board members who are in danger of being replaced by machines. The gardeners, receptionists, and cooks are secure in their jobs for decades to come."

The suggestion is that the limitations of AI will provide an opening for increased human activity, in sentient, sensory and empathetic tasks: caring, designing, creating, craft and improvising. Sociologically, one can construct a thesis – for example that the development of services around eating and drinking, boutique hotels, spas, beauticians, and so forth, is indicative of a movement in society - but satisfactory data is not available and, as Brynjolfsson and McAfee note, the capabilities of AI continue to develop and "make inroads" into Moravec's Paradox. For now, the demarcation between human tasks and the tasks of AI remains an open question, and we might even ask whether a demarcation will survive at all.

"An ever-increasing pace of improvements cascade through the economy"

Nordhaus (2015), asked us to consider the idea that "that rapid growth in computation and artificial intelligence will cross some boundary" leading to a situation where "economic growth will accelerate sharply as an ever-increasing pace of improvements cascade through the economy." Though unproven, and "not near", this idea is now subject to serious scrutiny.

Nordhaus's paper was prepared for the Cowles Foundation for Research in Economics at Yale University. In it he acknowledges the more common debate about the prospect of prolonged stagnation in the economy. This prospect draws in many different arguments and questions. Will economic growth slow and perhaps even reverse under the weight of resource depletion? Will overpopulation and diminishing returns lower living standards? Will unchecked carbon dioxide emissions lead to catastrophic changes in climate and ecosystems? What will be the effect of ageing populations? Will innovativeness be restricted?

Nordhaus sets these arguments aside in order to analyse an alternative scenario based upon the possibility of technologically driven growth of a scale and consequence that societies have rarely or never encountered. This prospect directly references many computer scientists, prominent amongst whom is Kurzweil (2014). Accepting that to some the thesis will "read like science fiction", Nordhaus classifies this technological thesis as "accelerationist": an ever-accumulating pace of change will characterise technological developments and thence growth in the economy.

Nordhaus sets a number of tests for the accelerationist thesis, based on the idea of a "growth Singularity" that is signified by growth rates greater than 20% per annum. One of the tests given applies to demand and six apply to supply. The available data shows that only two of the tests are on course to be met and even then, not quickly (circa 100 years). The summary of Nordhaus's work then, is that more normal growth patterns apply for the knowable future. Nonetheless, an alternative scenario of "an ever-increasing pace of improvements cascade through the economy" is now taken seriously, and Nordhaus's tests can be reapplied in the future to evaluate whether there is any change in likelihood or timescales.

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