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# Artificial intelligence technology, capitalism, and the question of unemployment

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**Abstract:** Advancing artificial Intelligence draws most of its power from the artificial neural network, a software technique that has successfully replicated some information processing functions of the human brain and the unconscious mind. Jobs are at risk to disappear because even the tacit knowledge typically used by humans to perform complex tasks is now amenable to computerization. The paper discusses implications of this technology for capitalism and jobs, concluding that a very long run transition to a jobless economy should not be discarded. Rising business models and new collaborative schemes provide clues for how things may unfold. A scenario in which society is close enough to full unemployment is analyzed and strategic paths to tackle the challenges involved are discussed. The analysis follows an eclectic approach, based on the Marxist theory of historical materialism and the job task model created by mainstream economists.

**Keywords:** artificial intelligence; capitalism; technological unemployment; historical materialism.

**resumo:**
Avanços contemporâneos de inteligência artificial derivam principalmente da rede neural artificial, um algoritmo computacional que replica certas funções de processamento de informação do cérebro humano e da mente inconsciente. Empregos arriscam desaparecer porque mesmo o conhecimento tácito usado tipicamente por humanos em tarefas mais complexas tornou-se passível de ser computadorizado. O artigo discute implicações dessa tecnologia para o futuro do capitalismo e do mercado de trabalho, concluindo que uma transição a muito longo prazo para uma economia sem empregos não deve ser descartada. Novos modelos de negócios e novos esquemas colaborativos provêm pistas sobre como as transformações poderão ocorrer. Um cenário em que a sociedade chega perto o suficiente do pleno desemprego é analisado e caminhos estratégicos para se lidar com os desafios envolvidos são discutidos. A abordagem seguida é eclética, baseando-se na teoria marxista do materialismo histórico e no modelo de tarefas de trabalho criado por economistas do *mainstream*.

**palavras-chave**:

Inteligência artificial; capitalismo; desemprego tecnológico; materialismo histórico."

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## 1. Introduction

Since the Industrial Revolution, humanity has seen giant step advances in technology, but none which was able to put in check capitalism as a social production and distribution system. Hitherto, it seems that capitalism can always create new and more numerous jobs in response to technological change. For instance, this was the case during past technological revolutions, when the new jobs created by waves of innovation more than compensated the old jobs replaced with automated machines. But now, the rapidly advancing technology based on artificial intelligence (AI) threatens to place a more serious challenge: It is allowing for machines and algorithms endowed with AI capabilities that do many jobs more competently than skilled humans[1]. As a consequence, not only low-skilled, but also mid- and high-skilled workers have been replaced by intelligent devices, and it seems an upward trend.

Such scenery is unsettling because it points at a situation in which human labor becomes widely dispensable as input to the economic system. With a bit more of speculation, it may be a situation in which even entrepreneurial and firm management skills become dispensable. All of this may sound a too futurist perspective, notwithstanding many technology experts believe that AI is on the go to harshly change contemporary labor markets and capitalism (Bryjolfsson and McAfee 2013; Ford 2015). It can be measured also by a recent explosion of books, academic papers, news articles, sci−fi movies, documentary films, and many lectures and panel debates delivered on the subject[2]. Besides that, already in 2015, technology expert Martin Ford (2015) was showing evidence that, in the previous decade, GDP growth in the US had not been accompanied by an increase of labor working hours. Ford (2015) also made the point that AI is to promote disruptive technological changes that will displace highly skilled workers in areas such as medicine, health services, law, and finance, among many others. An earlier and much-cited study by Frey and Osborne (2013 and 2017), from Oxford University, reported estimates that 47% of jobs in the US would simply disappear within two decades to come as a consequence of computerization[3].

It seems like the contradiction between profit-oriented capitalism and the ultimate purpose of an economic system (which is to meet human society's needs) is going to burst. While advancing AI goes on to boost economic productivity in the next decades, the distribution of economic output is risking to collapse because of technological unemployment. To analyze this paradoxical trend with focus placed on capitalism and employment in the US, we chose Karl Marx and Frederic Engels' theory of historical materialism (HM) as a leading thread. Such theory provides a point from which to start a discussion on AI technology and the future of contemporary society[4]. Grounded in dialectics, HM theory predicts certain developments that result from economic contradictions. Its core message is that technological advances create new production possibilities that give birth to new relations of production. As the latter develop and spread across the existing economic system, a big pressure is placed over society to change the prevalent property relations and give way to a new economic system. We argue here that, more than any previous technological revolution, advancing AI is developing effective conditions to bring about a new, post−capitalist system. However, the latter need not be communism, as predicted in the original formulation of HM theory, but a new economic formation yet to be seen.

In addition to using HM theory, we divide our analysis into two branches. The first tries to understand how AI developments can create new conditions to organize social production in a way that is different from, but more advanced than, capitalism. For so, we develop an extreme and limiting case scenario for the future, comprised of a fully jobless society, and discuss the perspectives of alternative and more realistic scenarios that are close enough to it. The second branch tries to understand how non□capitalist relations of production that are under development now, and others which may develop in the future, can help produce a convergence towards the limiting case scenario of the first branch. We locate in the second branch the greatest challenges of analysis and the one most demanding of research efforts.

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[1] Future of Life Institute (n.d.).

[2] See the references' section of this paper.

[3] Frey and Osborne (2017) refer to computerization in a broad sense as job automation by means of computer-controlled equipment, which include non−AI and AI-based computer systems.

[4] This paper shall not be viewed as a Marxist text. The author only uses the HM theory to drive the analysis and to develop some future perspectives for capitalism and employment.

In our discussion, we are led to talk about artificial neural networks, a topic that seems misunderstood and underrated by scholars and people in general. We argue that the neural network technique replicates *typically human cognitive skills* that enable human workers to perform more complex, non–routine job tasks. The kind of tasks that traditional (non–intelligent) machines and software could not perform. From this fact, we draw different from usual interpretations of the human capital concept and of the role played by skilled human labor in the development of capitalism. We also conclude that human workers risk to be displaced from the economic system in a long run future. The reason is that, from now on, technology may be running to end the complementarity between physical capital and skilled human labor. Such complementarity has prevailed since the late $19^{th}$ century (Goldwin and Katz 2018), helping capitalism to persistently create new jobs in net terms. But, since the 1990s, it seems to be vanishing. We discuss these topics in detail.

In addition to this introduction, the paper is organized as follows. Section two describes, in brief, the historical materialism theory. Section three discusses the effects of past technological revolutions over jobs and employment. Section four develops on the recent AI advances. Section five introduces the concept of *typically human skills*, developed from the notions of cognitive abilities and tacit knowledge. Section seven describes the conditions that AI and technological advances are creating for the existence of a new, jobless mode of production. Section eight introduces the concept of *close enough* scenario and discusses strategic paths for a safe transition towards it. Section ten closes the paper with some final comments.

## 2. Historical Materialism

Along with Frederic Engels, Karl Marx developed the historical materialism (HM) theory in the first half of the $18^{th}$ century[5], much earlier than the studies for his major work *Capital*. As highlighted by Katz (1993), the study of HM theory is complicated by the fact that Marx himself never provided a systematic treatment of its central principles. The task of elaborating HM theory fell over Marx's interpreters, who tried to distill its tenets from Marx's historical writings. As a consequence, controversies among interpreters exist and different views of HM theory compete in the literature (Shimp 2009). In the sequel, we briefly outline our own interpretation, for it is the one we use in the remainder of the paper.

In order to exist, every society has to produce the goods and services that fulfill its material needs. The economic base of a society comprises not only the physical infrastructure used to produce those goods and services but also the set of social relations among society's members in the production process, which was called by Marx as "economic structure". Above the economic base, there is a complex system, called by Marx as "superstructure", which comprises social, legal, political, and ideological (self–consciousness) dimensions of society's organization. Under the materialistic view, it is the economic base that determines the superstructure, and not the contrary as presumed, for instance, in the idealistic view of Hegelian philosophers which was in vogue at the time of Marx and Engels.

Across history, the economic base takes different forms, namely modes of production. It is a central concept in HM theory. A mode of production is a historically determined stage of the economic base. It features a particular stage of development of the productive forces and, in connection with this stage, a particular set of relations of production. The productive forces are associated with the physical infrastructure and consist of labor power and skills plus the productive capacity of tools, machinery, facilities, lands, management practices, and knowledge. Relations of production, by their turn, are social relations the members of society establish among themselves in order to undertake social production. These relations are legally established as property relations: For instance, under the serfdom relation in feudalism, barons, who were the legal landlords, had legal rights to coerce the peasant serfs to work for them in their lands; also, under the capitalist relation in capitalism, burgeons or capitalists are the legal owners of the means of production and workers, yet legally free, are the non–owners of those means who have to work for the capitalists to survive.

[5] Karl Marx and Frederic Engels developed the HM theory early in *The German Ideology*, but this book was published only in 1932. Their early publications on the subject was *The Poverty of Philosophy*, written solely by Marx and published in 1847, and *The Communist Manifesto*, written by both authors and published in 1848. This theory is further presented in different parts of Marx's works. We follow here a famous passage in Marx's *Preface of The Contribution to the Critique of Political Economy*, published in 1859.

HM theory was developed from the study of how previous forms of organizing society's economic base, each form corresponding to a particular mode of production, changed in time. An essential message of HM theory is that, whenever the economic base changes, or, more precisely, whenever a mode of production transits to another mode, the superstructure follows behind and changes also. Marx listed a historical sequence of four modes of production: Asiatic, ancient, feudalism, and modern bourgeois (capitalism). In spite of controversies, HM theory is well accepted by many Marxists to explain the transition from feudalism to capitalism (Hilton 1976). However, it was stated by Marx as a universal law that can explain the transition from any mode of production to the next in the historical sequence. Thus, in principle, it might apply also to the case of capitalism and its transition to a new mode of production. Marx called this new mode 'communism', but in what follows we think of it, instead, as simply the post-capitalist mode[6].

Each mode of production corresponds to a particular stage in the development of productive forces. Such a stage, by its turn, is suited to particular forms displayed by the relations of production. In other words, the stage of development of productive forces intertwines with the prevalent relations of production and conditions the particular features displayed by each mode of production. However, the productive forces are always developing, either by their own or motivated by the prevalent relations of production. For instance, in feudalism, the relations between barons and serfs in the rural areas, and between masters and apprentices in the urban guilds promoted the technical advances of productive forces but at a slow pace. By contrast, in capitalism, the relations between capitalists and workers and among capitalists themselves via competition provide strong incentives for the permanent improvement of productive forces. In such a way that it has no match as compared with previous modes of production.

Within HM theory, it is through the development of productive forces that important things happen. Such process creates new possibilities of production that at some moment give rise to new (different) relations of production. As long as these new relations show to be more productive than the old ones, they start to undermine the prevalent mode of production. It happens because, while old and new relations co-exist for some time, they compete with each other. The new relations pressure by spreading across the economic system, while the old ones react by using the superstructure dimensions and other devices to refrain the advancement of the new[7]. At a certain stage, the tension between the two gets so high that a period of social revolution begins and unfolds toward establishing new property relations and a whole new superstructure. This completes the transition from the old to the new mode of production.

In sum, we might list the following stages of transition within HM theory:

1. *Development of productive forces:* during the prevalence of a particular mode of production, the productive forces are always developing;
2. *New relations of production:* the development of productive forces can happen more or less fast but at some moment gives birth to new relations of production;
3. *Conflict development:* while the new relations of production co-exist with the old ones (typical of the prevalent mode of production), a conflict between them develops;
4. *Social revolution:* as the conflict strain between new and old relations gets high enough, a period of social revolution starts in order to establish new property relations, transform the whole superstructure, and complete the installation of the new mode of production.

The HM theory sketched above highlights two central elements: *relations of production* and *development of productive forces*. In the remainder of this text, we'll discuss both in more detail, placing focus on the transition from capitalism to a new mode of production and the effects over employment. With regard to relations of production, a major question concerns *what* are the new relations of production under development now and *whether* they will be able to overthrow the capitalist ones. With regard to the development of productive forces, a central topic regards the *conditions* that new AI advances are

[6] HM theory received many critics for stating that capitalism will be followed by communism. We follow here the view of Shimp (2009), in a defense that it does not invalidate HM theory: "… a model is measured upon its ability to explain and predict. Historical materialism can be used to explain the past. It can also be used to predict, just maybe not to the extent that Marx used it. Historical materialism can *predict that capitalism will be replaced, but what exactly will replace the current mode of production cannot be predicted with any degree of certainty*." (Shimp 2009, 50; italics are ours).

[7] For instance, the medieval guilds used to make pressures over the British parliament against the introduction of machines in factories. The famous Luddites protested at the point of physically destroying machines (Frey and Osborne 2013).

producing so that at some point in the future a more advanced mode of production will be able to exist in place of capitalism. We start by examining the latter issue. Hence, in the next sections, we present some history of technological developments and jobs during capitalism, with a particular emphasis on AI's history, and then a discussion on the perspectives being produced by AI developments for the future of work.

## 3. Technology and Jobs

The technological developments brought about since the inception of capitalism have had important effects on the kinds of job opportunities and the composition of employment. According to Frey and Osborne (2013), during the first industrial revolution (IR1), the introduction and widespread of factories produced a job "deskilling" process. Previously, industrial production was mainly undertaken by artisans. These were relatively skilled workers whose set of manual skills was acquired through many years of training. As opposed to the artisan shop, the factory workplace featured a larger space and a different layout that favored an increased division, simplification, and specialization of labor tasks. These specialized tasks demanded little skills and a small degree of education from workers but enabled the production of the same output with fewer man–hours than the artisan shop. With this higher productivity of factories, the artisan shop almost disappeared. In a later stage of the IR1, the generalized introduction of machines pushed further the deskilling process by allowing the automation of many repetitive and routine tasks which were already performed by unskilled workers[8]. As a consequence, workers were relegated to execute ever simpler tasks which depended on ever simpler skills. Notwithstanding, as the demand for labor at that time was intensive because of a fast–growing industrial production, wages kept increasing. Frey and Osborne (2013) highlight that, in the end, the deskilling process favored the unskilled worker in detriment of the relatively skilled artisan.

The labor deskilling produced by technological developments was prevalent in the early history of capitalism and the 19th century. In a superb book, Goldin and Katz (2008) argue that things changed in the 2nd Industrial Revolution (IR2) era and the 20th century, when technological developments went hand–in–hand with the demand for educated workers as a result of *capital–skill complementarity*[9]. At the turn of the 20th century, with the increasing presence of the US leading the world economy and progressively surpassing Great Britain, the advent of electricity and the improvements in factory systems allowed production in large scale. However, it had the effect of bringing about complex management problems to the factory workplace that fostered the demand for more skilled labor. Skilled, blue-collar workers were demanded to operate and maintain the machines, while highly educated, white-collar ones were demanded to manage the factories. Also, the expansion of office workplaces in urban centers and cities called the clerk worker to enter the scene. Many skilled and highly educated workers, like secretaries, cashiers, file clerks, bookkeepers, accountants, managers, lawyers, and engineers saw a boom in the demand for their services. In the US, as a result of earlier developments in education and particularly in the higher education system with the Morrill Acts of 1862 and 1890, the supply of clerk workers was able to respond fast to the increase in demand, at the point of making the wage differentials between clerks and production workers to narrow[10].

[8] Such a process of replacing unskilled workers by machines in industrial production was extensively analyzed by Marx (1867) in *Capital*. It was also considered by classical economists, such as Adam Smith, Ricardo, and Babbage. For details, see the study of Bruger and Gherke (2017).

[9] To avoid confusion, we shall state that *capital–skill complementarity* is an expression used by mainstream economists. As such, the term "capital" here refers to the factor of production. In a Marxist context, the expression might be read as *technical relations of complementarity between constant (physical) capital and skilled human labor*.

[10] The Morrill Land–Grant Act was a bill passed by the American Congress in 1862 that conceded generous pieces of land to American states. The purpose was to induce states to create colleges and universities in the fields of agriculture and mechanical sciences. This was the start of the contemporary complex of American state universities and at that time was important to boost the American higher education system. It was later extended by the Morrill Act of 1890, which conceded cash instead of land and targeted at the former Confederate States from the American Civil War of 1861–1865. The Acts are noteworthy because the American higher education system had been developing prior to the boom in labor demand for highly educated workers of the IR2 era. Also, the High School movement was in fast development at the end of the 19th century and achieved near universalization of access by the

The 3rd Industrial Revolution (IR3) era, which started after WW2, witnessed the rise of the digital computer and the growing incorporation of information technology (IT) in economic activities. In industrial production, IT was overwhelmingly important in the adoption of computer–controlled machinery/equipment and eventually of robots. The first robot was introduced in factory production by General Motors in 1961. The automation of job tasks usually performed by production workers was massive within this process, at the point of inducing President Lindon Johnson to create a commission in 1964 to study and recommend solutions to the problem (Author 2015b). However, the incorporation of IT produced its most disruptive effects over job tasks in clerical activities. There have been mainly two kinds of effects: automation of clerical activities and enhanced computer–skill complementarity. In the 1970s and 1980s, computer development was fast, starting from large mainframe computers and then moving to desktop and notebook personal microcomputers. Stemming from computer's falling prices and escalating processing power (Nordhaus, 2007), such a process made a large number of clerical activities to vanish or almost disappear: telephone operators, bank tellers, file clerks, and secretaries were the most affected. On another hand, the destruction of such activities gave way to system's analysts, computer programmers, and other computer–skilled workers that were able to operate office software like word processors, spreadsheet calculators, and database managers. Therefore, instead of simply finishing other clerical activities (like in the case of automation), this complementarity between computers and human skills gave birth to new kinds of jobs.

In addition, a sandglass effect over the composition of employment has developed, with the increase in the shares of unskilled and highly skilled workers and the decrease in the share of skilled, blue-collar workers (Author 2015a and 2015b). This sandglass effect is usually referred to in the literature as "job polarization". As labor markets have kept expanding in the last three decades of the 20th century, jointly with job polarization an increasing demand for highly educated workers has accompanied the increasing use of IT (see the green line in graph 1).

Author, Levy, and Murname (2003) developed an interesting study on the causes of this empirically verified correlation between IT and demand for highly educated labor. They were concerned with the question: What computers do and what people do with computers that translate into demand for more human–skills in jobs?[11] In the search for an answer, they worked out a simple model based on two criteria for classifying human labor tasks. The first criterion sets down that a task can be *manual* or *cognitive*, with the latter meaning a task that involves analytic problem–solving and/or complex human interaction. The second criterion sets down that a task can be *routine*, in the sense that explicit rules regarding how to perform the task are known, or *non-routine*, in the sense that the rules involved in undertaking the task are unknown or known only tacitly[12].

They concluded that computers can substitute for workers with advantages in those tasks that are routine, either manual or cognitive. With regard to tasks that are non-routine, computers are *very limited* to substitute for human workers in the case of manual tasks but have *strong complementarities* in the case of cognitive tasks. These conclusions are illustrated in chart 1, which reproduces with some modifications table 1 of Author, Levy, and Murnane (2003). With computer prices falling precipitously from 1970 to 2002 (Frey and Osborne, 2019; Nordaus, 2007), they concluded that industries whose labor input was intensive in routine tasks content invested much in computer technology to *substitute for* workers, while industries intensive in non-routine task content also invested in computer technology but to *complement* human labor. Thus, the strong complementarity was likely the major factor behind the increased demand, empirically observed, for highly educated labor. Note that, along with the limited substitution of computers for human labor in non–routine manual tasks, their approach can also explain the phenomenon of job polarization.

1930s (Goldin and Katz 2008, 12). Thus, American developments in education, which were not matched by European countries at that time, were very important in allowing the supply of educated workers, both blue and white collars, to keep pace with the fast development of capitalism in the US at the turn of the 19th to the 20th century.

[11] Author, Levy, and Murnane (2003, p. ??)

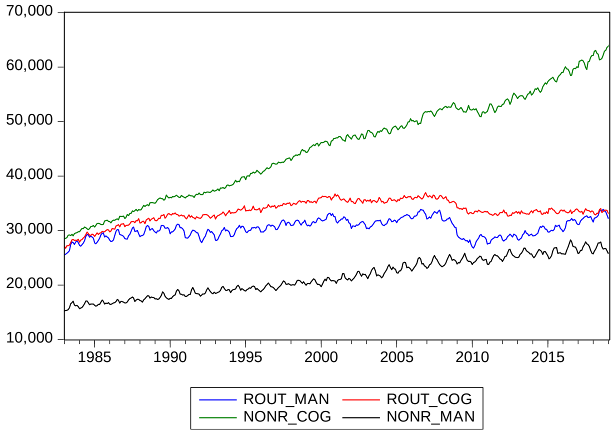
[12] Author, Levy, and Murnane (2003) set down this definition of a non–routine task based on the Polanyi's paradox, which states that "We can know more than we can tell" (Polanyi 1966; see also Author 2015; and section 5 of this paper). Many labor tasks fall into this category, for instance: driving a car, cooking meals, and writing an article.

Chart 1: Computer versus human skill in labor tasks

| *Type of Task* | *Routine* | *Non–routine* |
|---|---|---|
| *Manual* | Substantial substitution | Limited substitution or complementarity |
| *Cognitive** | Substantial substitution | Strong complementarities |

Source: Adapted from Author, Levy, and Murname (2003), Table 1. * Regards problem–solving (or analytic) and complex communication (interactive) tasks.

Graph 1 displays four employment time series in US along the last four decades. The series are grouped according to the four task kinds of table 1 and run from January 1983 to March 2019. The series of non-manual cognitive tasks (green line) trends upward and fluctuates above the other series, showing it embraces the largest part of employed people. It corresponds to those activities that demand high skilled (college level) workers, also growing faster than the other ones. It is somehow accompanied by the series of non-routine manual tasks (dark line), which displays a steadier behavior, both for its ascending trend and its seasonal pattern. It corresponds to tasks which demand unskilled and skilled workers (up to high-school level), but are difficult to automate because the rules for their execution are not explicitly known or known only tacitly. Note it is the series which fluctuates bellow the other ones all the time, showing it embraces the minor part of employed people. The blue and red lines correspond to routine tasks: manual (blue) and cognitive (red). They stay between the dark and the green lines and contrast with these two because they don't display an upward trend, fluctuating instead around a somewhat stable level all the time. A reason for this stable behavior is the fact that routine tasks, either manual or cognitive, have been automated along the last four decades.




Graph 1. United States: Employment by task kind 1983-2019

Source: For January 1983 to December 2015, FRED (2016); for January 2016 to February 2019, updates by Ferreira Netto (2019). Notes: *rout_man* is routine-manual tasks; *rout_cog* is routine-cognitive tasks; *nonr_cog* is non-routine cognitive tasks; *nonr_man* is non-routine manual tasks.

Author, Levy, and Murname (2003) identified the presence or absence of explicit rules within tasks (what defines them as routine or non-routine) as the key component to understanding how computer technology had produced a skill–bias content in labor demand. The authors concluded that IT would keep substituting for skilled workers on manual and cognitive tasks that are routine because the availability of explicit rules allows to computer code these kinds of tasks. In the case of non-routine tasks, and they cited in particular as examples the activities of truck driving and handwriting cuff, IT would hardly substitute for human labor. However, Frey and Osborne (2013), just ten years later, observe that AI developments applied to IT were successful in creating a driverless car and in developing computer programs able to read handwriting cuff. Therefore, the recent AI developments have allowed that IT invades the group of non–routine tasks[13]. In their study, Frey and Osborne (2013) also developed a statistical model to compute the chance that, in the next two decades, each occupation in a set with 702 occupations will be computerized in the US[14]. They obtained a figure of 47% for the share of job occupations that are to disappear. In order to understand why the recent IT developments threaten to substitute for highly educated labor *even in the case of non–routine tasks*, we have to place focus on some particularities of advancing AI technology.

## 4. AI Developments

As a formal field of scientific inquiry, AI research started in the 1950s and has since worked to expand the frontiers of information technology by trying to replicate human intelligence in computers. Up to the 1990s, it had developed two major branches of research: expert systems and machine learning. Expert systems are based on programming rules in computers so that computers can solve problems based on these rules[15]. Along the way, expert systems showed to be limited to tackle large-scale problems because of the hard–programming efforts needed to input a large number of rules into computers. On the other hand, the branch of machine learning has shown fruitful and promising developments.

Early computers were highly powerful to perform complex, large-scale numerical computations and to organize, store, and query relational databases filled with structured data. However, they were very limited to perform pattern recognition tasks that are typically easy for humans, like identifying persons and objects in photos or recognizing handwriting cuff. Machine learning is based on replicating human-like processing of information in computers, so as to endow these machines with those typically human skills of pattern recognition. Up to the turn of the century, machine learning research had achieved remarkable progress thanks to its major technique, a software device known as artificial neural network (NN). A NN mimics the human brain intelligence in computers using mathematical models that represent information processing functions of the human neural system. A major property of NNs is that they enable computers to develop intelligence through a learning process, just as humans do, what gave the AI branch the name ‘machine learning’. This learning capability is put into action by training, a process in which a dataset is repeatedly presented to a NN. This process of training/learning is quite important for making the programming effort needed to develop a NN considerably smaller than in the case of an expert system. Instead of imputing rules into a computer, one just lets a NN recognize patterns in the data and learn by itself implicit rules. However, this data–dependency for training NNs put AI research nearly dormant for many years since the mid-1990s.

Until recently, data shortage along with limitations of memory size and computer speed had prevented more broadly, large-scale applications of NNs. However, things changed in response to a couple of trends that have developed since the beginning of the new century. The first trend has been what technology experts call Moore's Law, the fact that computer capabilities increase exponentially by doubling every 18 to 24 months. Indeed, as a result of Moore's Law, computers today are many times more powerful than they were at the turn of the century. Among the many outcomes of such a process, a major one has been the development and widespread use of cloud computing, notably via the Internet. The so-called Internet Cloud is a large scale data processing environment provided by large corporations of the information services industry. The Internet Cloud is physically located in data centers scattered around the world and which are equipped with collections of powerful computer servers. The advantages to users accruing from sharing computing resources on the Internet Cloud consist of reduced costs, storage availability, and increased processing speed. Such advantages have made people and organizations move in a massive fashion their domestic data processing to the Internet Cloud, turning it the largest data processing environment used in the Digital Age.

[13] See also Ford (2015) for a number of examples of non–routine tasks that advancing AI technology is getting able to computerize.

[14] BBC News developed a website in which any person can use Frey and Osborne’s model to compute the chances that a robot takes her job. The site address is http://www.bbc.com/news/technology-34066941.

[15] An example of an expert system is a wizard that assists users to install programs in computers.

The second trend has been the development of a phenomenon called Big−Data. As computers' capabilities expanded, a colossal amount of data has been recorded at the Internet Cloud and is permanently increasing. Part of these data consists of information on Internet users' behaviors, such as transactions, searches, and website accesses. Another part consists of data captured by sensors present in physical devices connected to the Internet of Things' networks. Such large amount of data naturally carries with it many new business opportunities. However, the sheer big sizes of the new databases, of the order of zettabytes (trillion terabytes), along with their unstructured nature prevented the use of traditional tools for data management and analysis for some time.

Together, these two trends set the background for a big push to machine learning applications and a recovery of AI research. The plenty availability of data has provided developers with improved conditions for training NN based systems, including the possibility of using new kinds of NNs enhanced with a new technique known as Deep Learning (large scale NNs with many hidden layers of neurons which are capable of reproducing abstract reasoning). Indeed, recent experimentations made by startup firms and corporations gave rise to disruptive technological applications of NNs. In 2010, IBM accomplished a breakthrough with IBM Watson ("Smartest Machine on Earth" 2011), a supercomputer system which displays two important features: the capacity to search information in different datasets filled with structured or unstructured data; and the ability to process natural language. IBM Watson was originally developed to compete at the famous CBS' TV Game *Jeopardy!*, a quiz show involving general knowledge in which only humans had participated in until then. At the contest, IBM Watson was installed in a large collection of computer servers. It was not connected to the Internet but stored a large dataset filled with structured and unstructured data, including the full text of Wikipedia (Wikipedia 2018b). IBM Watson could search fast this huge dataset to provide the answers, but its remarkable capacity to recognize natural language was crucial in the end. In *Jeopardy*!, the questions are presented to contestants in the form of answers for which they have to develop proper questions. Even with this inverted answer−question system, IBM Watson could communicate and respond accordingly, at the point of beating the other contestants.

A similar kind of application of sophisticated NN software was developed by DeepMind, a British startup firm created in 2010 (Silver *et al* 2017). It was later acquired by Google in 2014 and turned into Google Deepmind (GD) division. A GD team created AlphaGo ("AlphaGo" 2017), a super-intelligent program developed to play the ancient Chinese board game Go[16]. In 2016, AlphaGo was able to win Lee−Sedol, a 9−dan (highest degree) Go player from South−Korea who had won 18 international titles. AlphaGo became the first computer system to beat a game−player champion using a trained, instead of a programmed, system[17]. AlphaGo caught the attention of the AI community because of its ability to learn by itself a highly complex system. But, it showed yet another important feature: it was able to develop game strategies completely unknown to Lee−Sedol and to many experienced Go players who watched the contest. In other words, it showed some *creativity*. Such experiment highlights a remarkable potential for machine learning techniques, notably NNs, as it points out not only to the possibility that AI devices can find solutions to complex problems, but also that they can do it creatively and in ways unattainable by humans. In addition, AlphaGo's developers claim they started an era of "General Purpose AI" because super intelligent programs such as AlphaGo are able to learn many different things (not only games) and thus have great potential to be applied in a wide range of society's complex problems ("AlphaGo" 2017).

[16] The Chinese Go played by AlphaGo resembles the game of checkers, as it consists of a 19x19 board game playable by two persons using homogeneous pieces colored white and black. However, it is a game much more complex than Chess because the number of possible legal moves has as lower bound $2x10^{120}$ in the case of Chess and $2x10^{170}$ in the case of Go (Wikipedia 2018a). Therefore, Go is around $10^{50}$ times more complex than Chess.

[17] Previously, other supercomputers had already been able to beat game−player champions, like the famous case of IBM's Deep Blue supercomputer which beat the world's best Chess player Garry Kasparov in 1997. However, Deep Blue did not use a machine learning software, but a kind of an expert system which used "brute force" to calculate several steps ahead of the game before a particular move (Korf, 1997). The experiment with the AlphaGo program was different in two respects: First, the Go game has a level of complexity remarkably superior to Chess ($10^{50}$ times more); second, AlphaGo used a system based on deep NNs to learn from scratch how to play the game Go and developed, with human help that provided selected training data, sufficient skills to beat a 9−dan degree human champion. A 2017 paper by DeepMind's developers of Alphago (Silver et al, 2017) announced that a new version, AlphaGo−0 (also based on deep NN), was able to develop from scratch and by playing only with itself sufficient skills to win 100 times the previous version of AlphaGo.

Other large corporations of the information technology business, like Apple, Facebook, Microsoft, and Amazon, have come along with IBM and Google making large-scale investments in AI systems. What has motivated these large corporations to develop such systems is, ultimately, the purpose to gain competitive advantages in the information services industry. Indeed, they have put available those super intelligent systems on a commercial basis[18] to private firms and other institutions that are using them with many purposes, ranging from business planning and marketing strategies to support of scientific studies in many research areas.

What has also been crucial for making all of this possible are new tools of data analysis that benefit from the machine learning developments embodied in those systems. Labeled under the umbrella of Big–Data Analytics or Data Science, these new tools enable to extract meaningful knowledge from Big–Data and thereby provide highly improved support to decision making. As a major outcome, these novel data processing resources have opened up new perspectives for disruptive technological solutions to rise up in practically all problem domains of society in the next decades. Actually, such a process is already ongoing. Schwab (2016) argue we are now (early 21st century) in transit to a Fourth Industrial Revolution (IR4), a new period of disruptive technological changes in which the physical, digital, and biological dimensions go on to integrate into cyber–physical systems highly digitized. It results from ongoing technological advances in many fields, notably robotics, AI, nanotechnology, quantum computing, biotechnology, and also from particular developments in large-scale communications such as the Internet Cloud and the Internet of Things. Nonetheless, as a highly important side effect, such disruptive developments are also placing a serious menace to human jobs, even to those dependent on highly skilled workers. More precisely, they menace to end the complementarity between fixed capital and human labor that has prevailed since the end of the 19th century.

## 5. The End of Capital–Skill Complementarity

The study by Author, Levy, and Murname (2003) that we mentioned earlier[19] calls our attention to peculiar skills of human workers. It regards those skills that enable them to perform *non-routine* job tasks, either manual or cognitive. Non–routine manual tasks are highly dependent on human dexterity to be performed (Padir 2017). Examples are tasks of housekeeping and product wrapping services. AI developments are already having a great role in robotics because robots controlled by an artificial neural network can be efficiently trained to perform manual tasks (Knight 2018). However, robots lag behind in dexterity skills. Current research on mobile robotics faces as its major challenge to develop mechanical robots with a dexterity level at least equivalent to human workers'. On another hand, important progresses have been made in recent years (Ibelle 2018). Robots such as Baxter, developed by RethinkRobotics in 2011, can learn using computer vision how to execute a manual task which is being performed by a human person, such as making coffee and folding shirt. Others, such as the humanoid series Atlas developed with military purposes by Boston Dynamics, can parkour and even perform backflips (Simon 2018). Notwithstanding, it seems that some years are still ahead before robots' dexterity revolutionizes at the point of triggering new waves of automation.

For both non–routine kinds of tasks, manual and cognitive, but mostly in the case of the later, cognitive skills are necessary. Acquiring such skills involves the use of human cognitive abilities to develop knowledge. Many scholars see knowledge as featured with two basic dimensions: explicit and tacit. *Explicit knowledge* consists of rules that humans know regarding how to perform routine tasks and which can be easily transferred to other humans using verbal language, visual symbols, or another kind of code. *Tacit knowledge* consists of those things someone knows but which he/she cannot easily and directly transfer to others. Usually, tacit knowledge manifests itself when someone is acting or doing something. Examples are playing a musical instrument or riding a bicycle. Learning how to perform such activities cannot be fully undertaken without practice and experience.

*Tacit knowledge* is the source of the so-called *Polanyi's paradox* epitomized in the statement "we can know more than we can tell" (Polanyi 1966). Philosopher Michael Polanyi introduced the concept of

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[18] For instance, at the site IBM Cloud (https://www.ibm.com/cloud/) IBM provides many IT services based on IBM Watson.

[19] See also the studies by Author (2015 and 2015b).

tacit knowledge in mid–1950s and devoted a book to discuss its importance and implications, mostly within epistemology (Polanyi 1966). Since then, tacit knowledge as a concept has spurred a large body of literature that includes controversial clashes among many interpreters (Yu 2003). Eventually, it became widely accepted and used in various areas, such as philosophy, cognitive psychology, organization theory, knowledge management, and AI, just to mention a few. According to Polanyi (1966), tacit knowledge is more important than explicit knowledge. The former comprises the most part of the knowledge a person possesses and grounds the use and development of explicit knowledge. As such, tacit knowledge resembles what is called in cognitive psychology as *unconscious knowledge*, say, the knowledge a human person has developed and stored in its unconscious mind (Augusto, 2010).

Psychologists generally consent that thought processes are driven by two different compartments of the human mind: conscious and unconscious. With regard to information processing, the conscious mind (CM) deals with language and a limited amount of memory. It also functions continuously for only a limited period of time, after which it needs some rest or attention diverted to other subjects. The unconscious mind (UM), by its turn, can deal with a large amount of information in a highly associative manner and has a huge capacity of memory storage. It is also able to process information continuously, even when we are asleep. This is why, for instance, that after hours consciously trying to solve a difficult problem without success, a solution suddenly pops up in our mind as an insight. It results from the remarkable capacity of our UM, regarded by cognitive psychologists as vastly superior to our CM for information processing (Dijksterhuis and Nordgren 2006).

The UM is also able to deal with different kinds of information, either structured or unstructured. It has a large capacity for making complex associations of ideas and to develop and store cognitive schemes. Altogether, such features of the UM indicate that most of our personal knowledge is embedded within it. We are unconscious of this knowledge but it shows itself up whenever we take some action while performing some task. Some cognitive psychologists associate this unconscious knowledge with the concept of tacit knowledge (Augusto, 2010). Furthermore, in physical terms, it is well known from neuroscience studies that the human brain processes information by means of a biological neural network featured with nearly a hundred billion cells called neurons. Therefore, a close connection exists among the concepts of UM, tacit knowledge, and NN (Sæbø, 2015).

By succeeding to develop a mathematical model of a human NN, it seems that AI scientists have replicated the powerful information processing capabilities of the UM. However, it is still early to say that they have replicated only a part of such capabilities or that they have actually accomplished more. Cognitive scientists are still far from learning the limits of artificial NNs, and it is probably the reason why technology experts have so high expectations with advancing AI. Even in the case that artificial NNs comes to replicate only a part of the information processing potentials of the UM, advancing computer capacity may compensate such disadvantage in the future and allow that AI surpasses human intelligence anyway. In the field of knowledge management, it is accepted that tacit knowledge (at least part of it) can be articulated or turned into explicit (Nonaka and Takeuchi 1995). Hence, experts in this field usually recommend that organizations convert as much as possible the tacit knowledge of their workers into explicit. The more from tacit to explicit that knowledge can be converted, the more job tasks can be automated. But, the difficulty in automating non-routine tasks lies precisely on the tacit knowledge needed to perform them. Tacit knowledge cannot be easily codified within a mechanical device (like a machine) nor within a computer program. In humans, it develops by practice and experience, but can remarkably improve by instruction and education. According to psychological studies, cognitive *innate* abilities and the use of language allow humans to develop intelligence in a far superior fashion than animals (Dennet 1994). It is such *cognitive abilities* that allow humans to develop and improve tacit knowledge, creating thereby *cognitive skills*[20]. Such skills are germane to the human brain's processing and storage of information, the mechanics of which is understood (yet only partly) thanks to developments in psychology, neuroscience, and the AI branch of machine learning. Hereafter, we call as *typically human skills* (THS) those *cognitive* skills that allow humans to perform non–routine tasks.

[20] We shall make clear our distinction between the expressions "cognitive abilities" and "cognitive skills". Cognitive abilities regard innate capacity of humans to learn and thereby develop knowledge, either explicit or tacit. Cognitive skills are cognitive abilities developed. It regards the capacity to manage explicit knowledge but is particularly important for using the tacit knowledge to perform non–routine tasks.

The capacity to develop the THS is determinant for the existence of human capital (HC). In economics and the social sciences, the notion of HC was described with different but similar connotations since Adam Smith. Nowadays, it is widely understood as all the knowledge, skills, and health that humans develop from practice, training, and education so that ultimately increase their productivity (Goldwin 2016). Note that it is quite close to our notion of THS added with health conditions. For the sake of this paper, we might think that HC can be described symbolically by such a sum: HC = THS + Health.

There seems to be a wide consensus among economists and social scientists that HC was, and still is, the major force behind technology, innovation, and economic growth. More than fixed capital and labor, HC is seen as responsible for the remarkable increase in total factor productivity (TFP) displayed by capitalist economies during the 20th century (Goldin and Katz 2008). In the 1950s, economist Moses Abramovitz (1956) discovered that the increase of US output along 1870 to 1950 had been faster than the increases in fixed capital and labor. Later, as many economists attributed this phenomenon to HC, the concept gained prominence in the scholarly literature and the society at large. Whilst economists have always recognized that HC resulted from cognitive abilities and skills, it seems they have ascribed secondary importance to these[21]. We argue that the core component of HC is comprised by the THS because these are responsible to endow HC with its capacity to be developed and improved. Hereafter, we'll prefer using the expression THS whenever we need to refer to HC.

Hitherto, the THS have provided human workers with great advantages over machines and software to perform non–routine tasks. As mentioned before, by the early 20th century, despite persistent efforts of capitalist firms to substitute fixed capital for human labor (automation), the deskilling process crashed into the complexities of producing goods and services to mass consumption and the expansion of cities. To deal with such challenges of the IR2, fixed capital and technology were important but far from sufficient. What made the difference was not exactly HC, the supply of which was rapidly increasing because of the American pioneering efforts in education. Our present-day knowledge about the human brain's processing of information allows that we risk a different interpretation: The THS were in a sense the most sophisticated "technology" available at the time. Yet a natural and biological one, the THS empowered humans to perform non–routine tasks involved in machine operation and maintenance, factory management, and a wide range of clerical work activities. In other words, the THS fitted uniquely to the non-routine job tasks demanded by the IR2 and thereby were pivotal to allowing capitalism's development from that stage on[22].

What is so important with regard to THS? Under a contemporary perspective, THS mean human capabilities of sensing, gathering, and processing information from a variety of sources to deal with uncertainties present in ill-structured problems of decision making. Central to these capabilities is human intelligence, defined loosely as human capacity to learn in and adapt to uncertain and changing environments within which non–routine tasks are performed. As such, the THS were a *marvel* that the scientific knowledge available at that time was very far from automating. This is why fixed capital technology and skilled labor were but complementary, not substitute, to each other. We might even say that it was not technology that permitted skilled human workers to be more productive, but the THS which created technology and allowed its potentials to be fully unleashed. Moreover, the education system in the US, already massified at the early 20th century, permitted to unleash such THS from most of the American people. Thereby, the THS add as another major factor, if not the most important, behind the rising to prominence of American capitalism. Of course, the plentiful availability of natural resources scattered across a large geographical area to be exploited, technological revolutions, and money capital to finance private and public investments were crucial. Notwithstanding, it was the 'technology' embodied in the THS that managed all of this to turn into a reality the remarkable expansion of capitalism in US and, with some delay, in Europe and the rest of the world as well[23].

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[21] Labor economists have also considered non–cognitive skills. According to Heckman and Rubinstein (2001), these comprise "… motivation, tenacity, trustworthiness, and perseverance …". We don't deny the importance of such non–cognitive skills, but they seem as secondary to the cognitive ones when the complexities we refer to here are taken into account.

[22] Goldwin and Katz (2008) make this point but referring to HC instead of THS.

[23] Europe and the rest of the world lagged far behind the US in education development during the whole IR2. For details, see Goldwin (2016).

Now, let's turn to a point we made at the beginning of this paper, that capitalism has always been able to create new jobs even when it was undergoing the technological revolutions of the past. Many technology experts (e.g. Bryjholfson and McAfee 2014; Ford 2015) believe that, with the AI revolution, things will be different this time. Why? Our answer is that advancing AI technology is threatening to *substitute for the THS*. Precisely the kind of human skills that hitherto has allowed skilled and highly skilled human labor to be complementary to fixed capital and technology. Even more, the kind of human skills that, since the early days of capitalism in 18th century Britain, scientific knowledge has been unable to automate. However, advancing AI jointly with developments in mobile robotics are now turning fixed capital and skilled labor from complementary into substitute factors of production. While human labor has always been an object of replacement, the THS have also always made the difference in social production. But now, not only AI threatens to make those THS obsolete at the point of making them not typically human anymore: It also threatens to bring back a deskilling process, similar to the one that prevailed in the (late) 18th and 19th centuries[24].

## 7. Conditions for a New Mode of Production

In this section, we discuss some conditions that AI developments are bringing for the installation of a new mode of production. In order to discuss this and other topics regarding the effects of AI over capitalism and employment, in this section we use a strategy of considering a limiting case scenario. We explicitly assume that, somewhere in a very long–run future[25], advancing AI technology *fully displaces human skills in jobs*. We are aware that such assumption is extreme, but it provides two advantages: First, it is well known that exploring an idealized situation grounded in explicit assumptions can provide relevant insights about a more complex reality. We also took care of making the assumptions as general as possible. Second, we think it is unimportant whether such extreme scenario will be possible or not. It suffices that society approaches it to some degree for its major consequences to realize.

Advancing AI has been pervasive in many domain-specific fields and, as in the case of IT, is evolving to be a general purpose technology. It has been applied directly to innovations in IT proper or indirectly as a tool for technological developments in other research fields. These include leading domain-specific fields such as mobile robotics, precision mechanics, molecular biology, and nanotechnology. Furthermore, technological advances in these and other fields have fostered innovations in medicine, health services, pharmaceuticals, other chemical products, and industrial processes. Altogether, such developments are progressively morphing the way social production is undertaken. In a very long–run future, as AI becomes widely pervasive in society, it is possible that human labor becomes obsolete for social production. If it comes true, social production will be undertaken under conditions completely different from todays'. Our point in this section is that such conditions will be strong enough to allow the existence of a new mode production which is different from capitalism (but which do not necessarily imply socialism or communism). Mostly, these conditions will be the result of particular features already displayed by advancing AI technology. In the following paragraphs, we explore some of these AI features and the implications of those conditions.

We start by depicting the most immediate product of AI: an intelligent machine or algorithm (IMA). Basically, an IMA can be classified into one of the following cases:

a) Physical robot equipped with and controlled by an intelligent computer;
b) Physical robot remotely controlled by an intelligent computer; and
c) Intelligent virtual or algorithmic robot.

[24] In a sense, such a conclusion calls for some reinstatement of Marx's theory of the working class proletarianization in capitalism.

[25] It is important to observe that the effects we consider to be produced over society by advancing AI technology depend on how far in the future goes our scope of analysis. In a near future, there is little sense to assume AI fully displaces humans in jobs. On the contrary, it is likely that advancing AI technology comes to create many waves of new kinds of jobs. But, we are working here under the assumption that any new jobs still dependent on human skills to be created in the short– and long–runs by advancing AI technology will eventually vanish in a very long–run future.

An IMA can operate individually or in a network connection with other IMAs. We list in the sequel three features of IMAs that are noteworthy:

- *Productivity*: As in the case of traditional (non–intelligent) MAs, IMAs can perform tasks much faster than humans and on a continuous basis, say, without the need to stop for resting, feeding, sleeping, socially interacting, etc. Essentially, this is what makes IMAs more productive than humans;
- *Non–compensation*: IMAs do not demand *wages* or any kind of *compensation*. They work for free for their owners. It means that IMAs operate, or perform tasks, for only two simple reasons: they have goals and are plugged into electrical outlets (the goals are usually set up in their programming by the IMAs' owners[26], which can be a private or a state organization);
- *Technical efficiency*: Human workers only produce efficiently when strongly motivated, for instance by earning a good salary or by getting at risk to be fired. They achieve their maximum productivity rate, or do their best, only when they receive strong incentives, whether positive or negative. They follow the rules of the capitalist game. In contrast to human workers, IMAs do not depend on particular motivations or incentives. They always work at their maximum productivity rates (which are higher than humans'). They follow only the physical laws. As technical devices, IMAs' only *motivation* to function, or to 'work', is their energy inlay. In this sense, they will stop working only if they were unplugged from electrical outlets. Also, IMAs operate with the same stamina whatever the goals and tasks posed to them: whether the goal is maximum profit or minimum price, or whether the task is recognizing a face or understanding a question. Goals and tasks can vary in complexity, but IMAs always operate with the same devotion. They don't prefer a task to another. They simply 'work' and always do their best. No more, no less;

These productivity, non-compensation, and technical efficiency features have particular importance for the issues we are discussing. These features are shared by traditional MAs, but they loom in importance and perspective under our assumption that, in the future, IMAs will reach the capacity of replacing human labor even in firm management tasks. In such a setting, society would be able to have firms supplying goods and services *efficiently without profits motivation*.

The last statement needs more explanation. A capitalist firm, as we know it today, is a production unit of the economy devoted to providing some good or service. However, it pursues that goal primarily by generating profits. Say, a production unit in capitalism has as primary goal generating profits for the firm's owners (human capitalists) and only as a secondary goal the provision of goods and services to society. If there were no possibility of profits, the good or the service would not be produced or supplied by the firm. Motivated by the perspective of obtaining profits, the human owners of the capitalist firm decide that it purchases inputs and hire human workers. The basic motivation of the latter to work for the capitalist firm is that they need wages to access social output. However, after being hired, workers develop additional motivations resulting from the fear to be fired and get unemployed for an uncertain period of time. Workers' motivations do not end here, as many of them also expect to improve their living conditions. For so, they endeavor to upgrade to better-paying positions within the firm or move to better-paying firms. These human motivations, either of capitalist owners or of workers, are behind the relations of production in capitalism.

Such (humanly motivated) capitalist mode of providing goods and services to society is known, and often hailed, to be the most "efficient" in history. Indeed, it has shown in practice to be efficient with regard to quantity and quality of the goods and services produced, minimum production costs incurred, and incentives provided for technological developments[27]. But, it is a result of how the capitalist system

[26] AI experts believe that in the future IMAs will be able to reprogram themselves and thereby will develop their own goals, what is bringing much anxiety to those concerned with the issue of singularity.

[27] In standard economic theory, capitalism is also hailed to display a particular kind of efficiency known as Pareto efficiency. It is achieved by free markets under perfect competition in all economic industries and corresponds to an equilibrium state in which one individual can improve only by worsening the situation of other individuals. It is a particular and quite theoretically concept of efficiency that is difficult to be measured and observed in practice.

manages human motivations and all its efficiency is fundamentally dependent on these motivations. Because such capitalist efficiency is produced by *human motivations* to earn profits and work, we call it here as *behavioral efficiency*.

Now, let us consider IMAs operating the capitalist firm in place of a team of human workers. When IMAs perform tasks, they are optimizing an objective function. Their goal is to attain the extremum (maximum or minimum) of the objective function. According to the non–compensation feature, this goal is set up by the IMA owner and can be different things. For instance, IMAs may alike pursue profit generation and maximization for the firms' owners. Because of the productive and technical efficiency features, a team of IMAs will be able, in a very long–run future, to do it more efficiently than a team of human workers. However, IMAs can also be programmed or trained to have *different goals*, say, different than pursuing profits or compensations. For instance, IMAs can be programmed/trained to optimize the provision of the good or the service so as to fulfill a set of society´s needs, including the needs for environmental and health protection, and technological development. And again, because of the productivity, non–compensation, and technical efficiency features, IMAs can do it efficiently and in this case much better than a team of human workers who depend on those typically human motivations to do their best. Because of the technical efficiency feature, it is not the case that IMAs would work harder motivated for getting a better position in the firm (targeting a higher wage) or because of a fear to be fired. IMAs would simply work and do their best better than humans. And trying to replicate those human motivations in IMAs, through a different programming/training, would make no sense.

Let us try yet a simpler example. Suppose that somewhere in the future we have a firm operated only by IMAs and dedicated to providing a single good in the market. There is no human worker in this firm. All tasks associated with production and firm management are performed by IMAs (thus, robots and virtual algorithms). Now, suppose IMAs were programmed/trained to manage the firm with the goal to provide this good at the least possible price to consumers, under a restriction of zero–profit, or of just a small amount of profit only to preserve financial balance. Note we are not saying "maximum profit" but "minimum price", so that it is a nonprofit-oriented firm. Because of productivity, non-compensation, and technical efficiency features, IMAs will be able to manage the firm *efficiently* (given its minimum price goal) and the consequence would be lower price and more plenty provision of the good to consumers than if the IMAs had operated the firm with the goal of profits maximization. The efficiency of IMAs' work within this firm is not altered by having a different goal. They work under *technical efficiency*, not under *behavioral efficiency* as do human workers (or economic agents).

These considerations lead us to the following conclusion. The productivity, non-compensation, and technical efficiency features plus the assumption that IMAs will replace all human workers in the future comprise conditions for a new, post–capitalist mode of production to exist. *A mode that may be efficient without depending on agents searching for profits*. Advancing AI technology is leading us to such a limiting case future. A future in which human society as a whole will not need to work and the 'IMA workers' (or better, IMA based systems) will be able to provide with abundance the needs of all society's members. It would be a heavenly world, except for the fact that property relations in society would have to be different from todays'. For non-employable human members of society be able to consume and live, they will need somehow to have rights to access IMA based social output. If not, the heavenly future would turn into a distribution collapse.

Whether it is possible or not that advancing AI technology will take us at a limiting case, jobless future is not relevant. What matters is that by getting close enough to it, we'd be already exposed to its hazardous consequences. Can advancing AI technology take us so far? We do not have a well-defined probability distribution for the degree of closeness to such a future. Nevertheless, up to this point, our reflections have led us to the conclusion that *close enough* is not an unlikely event. By a *close enough scenario* (CES), we mean a situation in which the consequences would be essentially the same as those of the pure limiting case (fully jobless society). If IMAs are not to replace 100% of human workers in jobs, it suffices to be a high figure, like, for instance, 47% (as predicted by Frey and Osborne 2013, for the next two decades) or something more. It would also create a distribution collapse, almost certainly.

We see just two possibilities in which AI might not be a threat. The first is a scenario in which advancing AI technology eventually *fails* to replace much of the THS. In this case, AI would simply be a

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However, free markets based capitalism can be ascribed to displaying those more practical efficiency concepts discussed here.

frustrated promise. The second is a *transhumanist* scenario in which advancing AI and other technologies can physically improve the THS by transforming the human body. Since a few years ago, technology expert Ray Kurzweil has expressed his belief that nanotechnology will be able in the future to allow the human brain connect directly to computers and the Internet[28] (Miles 2015). In September 2017, biomedical engineers at Wits University, from Johannesburg, South Africa, connected for the first time a human brain to the Internet using a (non–nano) technology based on small chips (Medical Express 2017). This second scenario thus involves the improvement of THS by the technological improvement of the human body, turning human workers each time more productive. It can be further enhanced by technological advances in other areas such as medicine and molecular biology.

The fact is that both scenarios ('frustrated promise' and 'transhumanist") would keep human labor still complementary to fixed capital. As yet, we can only assume that AI threatens to, not that AI will, replace in full the THS in the future. While technology remains dependent on the THS, human labor will not be replaced in full. The second, transhumanist scenario seems more effective in saving human jobs from disappearing and thereby keeping the capitalist system, once more, able to create new jobs for humans.

There seem to be two trends here: The first, that AI technology *succeeds* to replace human labor and thereby ends the complementarity of fixed capital with human labor (eventually creating a jobless society); the second, that AI *fails* to replace human labor ('frustrated promise' or 'transhumanist' scenarios) and thereby keeps the latter still complementary to fixed capital. We illustrate both trends in figure 3. Exactly which trend will prevail in the long run, it is early to say. But we shall bear in mind that, as long as capitalist firms keep seeing the replacement of human labor and its THS as an advantageous business strategy, the trend towards a jobless future is to prevail.

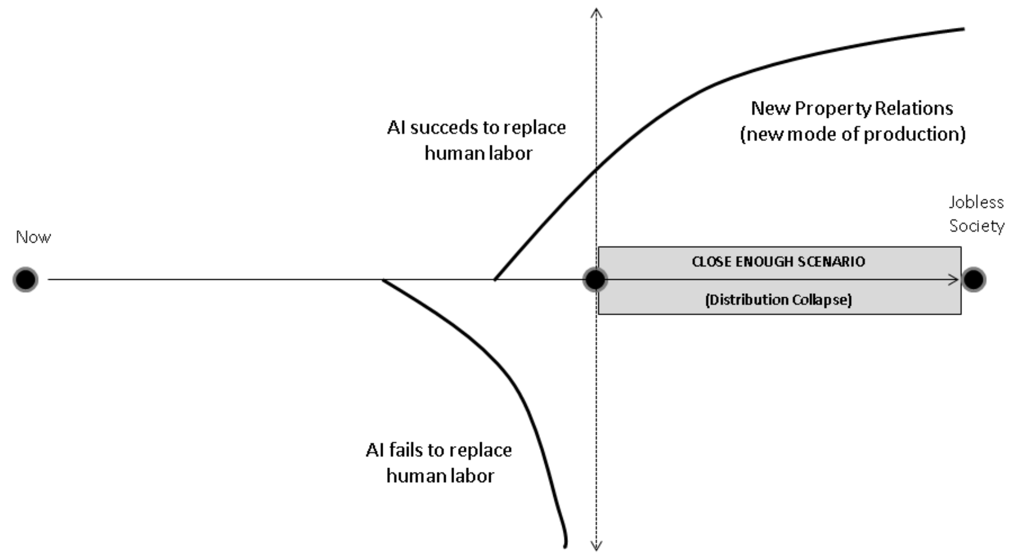


Figure 1. Scenarios on the run towards a jobless society.

If AI is leading us towards the jobless society and we cross the middle point, then we will be in the CES (gray region). It is a dangerous area where society undergoes a distribution collapse. In case AI *succeeds* to replace human labor, we enter the CES. But we might avoid the distribution collapse if new property relations warranting social output is accessible to the whole society were implemented (dark curve growing). Another way to avoid the distribution collapse is by not entering the CES, which might be possible in case AI *fails* to replace human labor (dark curve dropping; in this case, fixed capital and human labor remain complementarians and capitalism stands still).

[28] The sci-fi movie industry has recently explored such possibility in the film Anon, by director Andrew Niccol. The script, however, is more ambitious and features a world in which people's brains connect directly to the Internet Cloud without the need of computers, mobiles or tablets.

## 8. Relations of Production

We have just concluded it is not unlikely that advancing AI technology is leading us to be *close enough* to a fully jobless society in the future. However, it is not clear how we'll arrive at such a CES. We also have to make some considerations regarding the transition from now to such a future. We've learned that property relations will have to be different[29] to escape the distribution collapse. Now, the basic questions are: What can we do to arrive safely at such a CES? What are the present opportunities to help us fight this challenge? Will the new (non–capitalist) relations of production developing now converge to a jobless mode of production and *naturally* avoid the distribution collapse? It is here that futurist efforts can be important and HM theory particularly useful. We consider in this section some possible paths toward the CES.

A first path is society developing conscious and strategic movements. Some important efforts are ongoing. For instance, expert's alerts of the potential AI threats to employment have sensitized institutions, political leaderships, and elite groups. A measure of society's concerns are the many discussions undertaken recently in international forums. For instance, the WEF Annual Meetings held in the last three years delivered many discussion panels and experts' interviews on subjects such as advancing AI (WEF 2017a), technological unemployment (WEF 2017b), fourth industrial revolution (WEF 2017c), and universal basic income (WEF 2017d). Some consensus has emerged on two major courses of actions: retraining workers to the new, upcoming environment and redesigning safety nets, maybe including the adoption of universal basic income. We have short room here to dive deeper into such issues, but it matters to say that such conscious efforts are undoubtedly the best avenue for a safe transition towards the CES. It is society itself trying to work out solutions in a negotiated and peaceful way.

A second path links to one of HM theory's predicted developments. As we described in section 3, HM theory's last stage of transition between modes of production is a period of social revolution. A very undesirable outcome because of its potentially violent implications, it can happen even before new, more advanced relations of production develop. It can result from generalized distress of the population with a lack of responses by part of society's elites in the event that technological unemployment grows out of control. We must not disregard it as a possible scenario. It can happen, for instance, due to a lack of agreement among elite groups over policy responses. A major risk for society here was pointed out by Brynjolfsson (WEF 2017d), who argued that AI-based technology develops faster than society's institutions can change to adapt to the new environment.

Another possible path associated with HM theory regards its transition stages before the last one. In this case, the development of AI and other technologies is to enter into conflict with the capitalist relations of production. As we saw in section 3, it means that new relations of production were to spring up from the new production possibilities. The challenge here is to properly identify these new relations of production. For so, we have to answer questions such as: What are the relations of production under development now that are different from the capitalist relations? Which ones are the most likely, in the sense of more advanced, to displace the capitalist relations? There are no easy answers to these questions. What seems clear is that the issues most demanding of research efforts stay here.

For instance, the rapid changes are at every time introducing new possibilities of production, mostly for private businesses but also for collaborative schemes. The new possibilities for private businesses may not imply new relations of production, just different business models. The new possibilities for collaborative schemes may be new relations of production, but not advanced enough to overthrow capitalist relations. In fact, a clue to identify new relations of production is to look into the alternative schemes developing at the margins of the capitalist economy. For instance, there are workers' owned cooperatives producing particular goods for the market. Some are profit–oriented, some are not. The work is developed in a cooperative fashion based on the common interests of all participants (Worth 2013). Other examples are the Free Software Movement (Wikipedia 2018c) and the collaborative, nonprofit wiki–based scheme of the Wikimedia Foundation (2018) used to produce Wikipedia: The Free Encyclopedia. These alternative schemes have been able to compete and even displace some

[29] If they have to be different, it means we'll have a new mode of production that is different from nowadays' capitalism. HM theory predicts that the drive towards a new mode of production after capitalism is new relations of production.

profit–oriented firms in their industries (Pati 2012). However, it is still difficult to imagine them spreading throughout the economy displacing most of profit-oriented, capitalist firms.

At the moment, most collaborative schemes are based on IT and the Internet, but they may also reach some tangible industries in the future. A relevant example is 3D printing. It is an new technology which producing disruptive innovations not only for industrial production but also for the business of tangible goods. A 3D printer runs a process in which a molten plastic or metal, or other feedstock, is transformed into very thin and superposed layers of material thereby forming a printed object. The process is software driven and the object form is determined by digital blueprints which are to be widely available on the Internet. With costs of 3D printers and feedstocks declining, in the future most consumer products might be produced at home. In principle, consumers would print their desired objects by purchasing digital blueprints sold in specialized, profit–oriented sites on the Internet. However, an important fact about 3D printing is that, since its inception, its creators have been concerned that the software used to printing is open source and free (Rifkin 2014), which has allowed space for digital blueprints to be also available for free under collaborative schemes. Hence, the world market of digital blueprints might be divided between collaborative and profit–oriented segments. It means that industrial production of tangible goods in the future might be, at least in a significant part, supplied for free or almost free. The collaborative segment might expand with the help of (fast) advancing AI technology. Also, important, such a process implies an evolving and natural transformation of property relations because people might have access to a good part of social output for free.

## 9. Final Comments

We have examined in this paper some challenges that advancing AI technology is placing to capitalism and employment. We chose to place focus on these specific topics because we see in the prospective developments of AI and technology in general good opportunities for solving recurrent problems of capitalism, like its propensity for high and increasing inequality and its limited effectiveness to end poverty. AI evolving up to the point of almost fully displacing labor as an input to the economic system is but one possibility for the future. Although we cannot evaluate the chances for this possibility, we concluded that it is not unlikely and this was the motivation to study it here. Our analysis looked into the extreme case of a fully jobless society and also a similar, but more realistic case of a CES. Both scenarios presume that a distribution collapse will turn up along the way. The extreme scenario is to happen in a very long run, but the CES not too far away in the future, and this is the real motive of concern. We cannot precise the best alternative path that society should follow to avoid the distribution collapse. We only bet that negotiated efforts are the better strategy to work out a safe and peaceful transition.

In the case of the CES, HM theory provide some clues about the ongoing developments. We shall pay attention to the new business models surging from the rapid advancing technology because they can bear the embryo of new and winning relations of production. Also, advances in collaborative schemes are of obvious importance because these already embrace alternative relations of production. These seem to be the issues most demanding of research efforts and monitoring schemes. We finish by stressing Brynjolfsson's remark: AI technology advances faster than society's institutions can change. It is maybe the hardest challenge brought about by the present context. In order to properly address all the issues involved, many efforts are needed. In addition to the ongoing discussions coming about in the media, universities, international forums, and social nets, society must use all the available resources to develop good policy responses, including advancing AI technology.

## References


Abramovitz, M. 1956. "Resource and output trends in the United States since 1870." American Economic Review 46(2): 5–23.

*Alphago*. 2017. Netflix website. Directed by Greg Kohs. Los Gatos: Netflix.

Augusto, L. M. 2010. "Unconscious knowledge: a survey." *Advances in Cognitive Psychology*, 6: 116–141.

Author, D. H. 2015a. "Why are there still so many jobs? The history and future of workplace automation." *Journal of Economic Perspectives* 29 (3): 3–30.

_________. 2015b. "Polanyi's Paradox and the shape of employment growth." In *Economic Policy Proceedings: Reevaluating Labor Market Dynamics*. Saint Louis: Federal Reserve Bank of St. Louis, 129–177.

Author, D. H., Levy, F. and R. J. Murname. 2003. "The skill content of recent technological change: an empirical exploration." *The Quarterly Journal of Economics* 118 (4):1279–1333.

Bostrom, N. 2014. *Superintelligence: Paths, Dangers, Strategies*. Oxford, UK: Oxford University Press.

Braverman, H. 1998. *Labor and monopoly capital: the degradation of work in the twentieth century*. 25th Anniversary Edition. Monthly Review Press: New York.

Brugger, F. and C. Gherke. 2017. "Skilling and deskilling technological change in classical economic theory and its empirical evidence." Working Paper 2017–02, Karl–Franzens–University Graz, Faculty of Social and Economic Sciences.

Cellan–Jones, R. 2017. "Google Deepmind: AI becomes more alien." *BBC News*. October 18, 2017. http://www.bbc.com/news/technology-41668701.

Dennett, D. C. 1994. "The Role of Language in Intelligence." in *What is Intelligence? The Darwin College Lectures*, ed. Jean Khalfa. Cambridge: Cambridge University Press. https://ase.tufts.edu/cogstud/dennett/papers/rolelang.htm.

Dijksterhuis, A., and L. F. Nordgren. 2006. "A theory of unconscious thought." *Perspectives on Psychological Science* 1: 95-109.

Ferreira Netto, M. de L. 2019. Inteligência Artificial e o comportamento dos empregos nos EUA. Monografia de Final de Curso. Faculdade de Economia. Universidade Federal de Juiz de Fora: Juiz de Fora..

Freeman, C. 1995. The "'National System of Innovation' in historical perspective." *Cambridge Journal of Economics* 19: 5-24.

Ford, M. 2016. *Rise of the Robots: Technology and the Threat of a Jobless Future*. Basic Books: New York.

FRED. 2016. "Job Polarization". Federal Reserve Economic Database's Blog. https//fredblog.stlouisfed.ofg/2016/04/job-polarization.

Frey, C. B. and M. A. Osborne. 2013. "The future of employment: how susceptible are jobs to computerization?" Oxford Martin School. Manuscript. Accessed November 9, 2017. https://www.oxfordmartin.ox.ac.uk/downloads/academic/The_Future_of_Employment.pdf .

Frey, C. B. and M. A. Osborne. 2017. "The future of employment: how susceptible are jobs to computerization?" *Technological Forecasting and Social Change* 114: 254–280.

Future of Life Institute. n.d. "Benefits & risks of artificial intelligence." Accessed May 5, 2017. https://futureoflife.org/background/benefits-risks-of-artificial-intelligence/.

Goldwin, C. 2016. "Human Capital." In *Handbook of Cliometrics*, edited by C. Diebolt and M. Haupert, 55–86. Berlin: Springer.

Goldin, C., and Lawrence F. K. 2008. *The Race between Education and Technology*. Cambridge: Harvard University Press.

Hailesilassie, T. 2016. "Rule Extraction algorithm for deep neural networks: a review." *International Journal of Computer Science and Information Security* 14 (7): 377–381.

Heckman, J. and Y. Rubinstein. 2001. "The importance of noncognitive skills: lessons from the GED Testing Program." *The American Economic Review* 91(2): 145–149.

Hilton, R.(ed.). 1976. *The Transition from Feudalism to Capitalism*. London: New Left Books.

Ibelle, R. 2018. "Robot dexterity will be the next big breakthrough in smart machines." *Nanowerk*. January 24, 2018. https://www.nanowerk.com/news2/robotics.

Knight, W. 2018. "Robots get closer to human–like dexterity." *MIT Technology Review*. March 26, 2018. https://www.technologyreview.com/s/610587/robots-get-closer-to-human-like-dexterity.

Korf, R. "Did Deep-Blue use AI?" AAAI Technical Report WS-97-04. https://www.aaai.org/Papers/Workshops/1997/WS-97-04/WS97-04-001.pdf

Marx, K. 1859. *A Contribution to the Critique of Political Economy*. Translated by S.W. Ryazanskaya. Moscow: Progress Publishers, 1977. Marxists Internet Archive.

https://www.marxists.org/archive/marx/works/1859/critique-pol-economy/preface.htm.

________. 1887. *Capital.* Volume I. First Edition in English. Translated by Samuel Moore and Edward Aveling. Moscow: Progress Publishers.

https://www.marxists.org/archive/marx/works/download/pdf/Capital-Volume-I.pdf.

Mason, P. 2015. *Postcapitalism: A Guide to Our Future*. New York: Allen Lane.

Medical Express. 2017. "Biomedical engineers connecting a human brain to the internet in real time." Accessed May 29, 2018. https://medicalxpress.com/news/2017-09-biomedical-human-brain-internet-real.html.

Miles, K. 2017. "Ray Kurzweil: In the 2030s, nanobots in our brains will make us 'Godlike'." *Hungtinton Post*. October 10, 2015. Updated: October 26, 2017. https://www.huffingtonpost.com/entry/ray-kurzweil-nanobots-brain-godlike_us_560555a0e4b0af3706dbe1e2.

Nonaka, I. and H. Takeuchi. 1995. *The Knowledge-Creating Company*. New York: Oxford

University Press.

Nodhaus, W. D. 2007. Two centuries of productivity growth in computing. *Journal of Economic History* 67 (1): 128-159

Padir, T. 2017. "Making robots that can work with their hands." *The Conversation*. April 24, 2017. https://theconversation.com/making-robots-that-can-work-with-their-hands-73831.

Pati, A. 2012. "Co-operatives: outperforming the competition." *The Guardian*, June 28, 2012.

https://www.theguardian.com/social-enterprise-network/2012/jun/28/co-operatives-outperforming-competition.

Polanyi, M. 1966. *The Tacit Dimension*. University of Chicago Press: Chicago.

Rifkin, J. 1995. *The End of Work*. New York: Putnam's Sons.

Rifkin. J. 2015. *The Zero Marginal Cost Society: The Internet of Things, the Collaborative Commons, and the Eclipse of Capitalism*. New York: Palgrave McMillan.

Rosenblatt, F. 1958. "The Perceptron: A probabilistic model for information storage and organization in the brain." Psychological Review 65: 386–408.

Sæbø, S. 2015. "Polanyi and the neural networks." *Metacognition*. November 11, 2018. http://blogg.nmbu.no/solvesabo/2015/11/polyani-and-the-neural-networks/.

Schmidhuber, J. 2014. "Deep Learning in Neural Networks: An Overview." Technical Report IDSIA-03-14 / arXiv:1404.7828 v4 [cs.NE].

Schmidhuber, J. 2015. "Deep Learning." *Scholarpedia*, 10(11):32832. Accessed 5/6/2018 from http://www.scholarpedia.org/article/Deep_Learning#References.

Schumpeter, J. A. 1942. *Capitalism, Socialism and Democracy*. 5th Edition, 1976. New York: Routledge.

Shimp, K. 2009. "The Validity of Karl Marx's Theory of Historical Materialism." *Major Themes in Economics* 11: 35-56.

Silver, D., J. Schrittwieser, K. Simonyan*, I. Antonoglou, A. Huang, A. Guez, T. Hubert, L. Baker, M. Lai, A. Bolton, Y. Chen, and T. Lillicrap, F. Hui, L. Sifre, G. van den Driessche, T. Graepel, D. Hassabis. 2017. "Mastering the game of Go without human knowledge." *Deepmind*. Accessed May 1, 2018. https://deepmind.com/documents/119/agz_unformatted_nature.pdf.

Simon, M. "Watch Boston Dynamics' humanoid robot do parkour." *Wired*. October 11, 2018. https://www.wired.com/story/watch-boston-dynamics-humanoid-robot-do-parkour/.

"Smartest Machine on Earth." 2011. DVD. Directed by Michael Bicks. Arlington: Public Broadcasting Service.

Ticktin, H. The Permanent crisis, decline and transition of capitalism. *Critique: Journal of Socialist Theory*, 45(3). 359-386. 2017.

The Economist. 2016. "The return of the machinery question." Special Report/Artificial Intelligence. The Economist, June 25, 2016.

Williams, R. n.d. Processing information with unconscious mind. Journal Psyche. Accessed September 13, 2018. http://journalpsyche.org/processing-information-with-nonconscious-mind

Wikimedia Foundation. 2018. "Wikimedia Foundation." Accessed December 1, 2018.

https://wikimediafoundation.org/.

Wikipedia. 2018a. "Go (game)". Last edited December 20, 2017. Wikipedia Foundation. Accessed January 15, 2018. https://en.wikipedia.org/wiki/Go_(game).

Wikipedia. 2018b. "Watson (computer)". Last edited December 23, 2017. Wikipedia Foundation. Accessed January 15, 2018. https://en.wikipedia.org/wiki/Watson_(computer).

Wikipedia. 2018c. "Open Source Initiative." Last edited September 6, 2018. Wikipedia Foundation. Accessed December 1, 2018.

https://en.wikipedia.org/wiki/Open_Source_Initiative.

World Economic Forum. 2017a. "A basic income for all: dream or delusion?" Panel Session with speakers: Michael Sandel, Amitabh Kant, Neelie Kroes, Tamzin Booth, Guy Standing. Video 52:02.

https://www.weforum.org/events/world-economic-forum-annual-meeting-2017/sessions/a-basic-income-for-all-dream-or-delusion.

__________. 2017b. "An insight, an idea with Guy Standing." Interview by Zanny Minton Beddoes. Video, 37:16.

https://www.weforum.org/events/world-economic-forum-annual-meeting-2017/sessions/an-insight-an-idea-with-guy-standing.

__________. 2017c. "Artificial Intelligence." Panel Session, with speakers: Ron Gutman, Robert F. Smith, Ginni Rometty, Satya Nadella, Joichi Ito. Video, 56:31.

https://www.weforum.org/events/world-economic-forum-annual-meeting-2017/sessions/the-real-impact-of-artificial-intelligence.

__________. 2017d. "Issue Briefing: Jobs and the Fourth Industrial Revolution." Panel Session, with speakers: Erik Brynjolfsson, Suzanne Fortier, Saadia Zahidi. Video 31:52.

https://www.weforum.org/events/world-economic-forum-annual-meeting-2017/sessions/jobs-and-the-fourth-industrial-revolution.

Worth, T. 2013. "Can co-ops redefine sustainable business?" *The Guardian*. November 21, 2013. https://www.theguardian.com/sustainable-business/cooperatives-sustainable-business-structures.

Yu, Z. 2003. "Tacit knowledge/knowing and the problem of articulation." *Tradition and Discovery* 30, 1, 11–22.