Automation, per se, is not Job Elimination: How Artificial Intelligence Forwards Cooperative Human-Machine Coexistence

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***Abstract*—Recent advances in artificial intelligence (AI) and machine learning, combined with developments in neuromorphic hardware technologies and ubiquitous computing, promote machines to emulate human perceptual and cognitive abilities in a way that will continue the trend of automation for several upcoming decades. Despite the gloomy scenario of automation as a job eliminator, we argue humans and machines can cross-fertilise in a way that forwards a cooperative coexistence. We build our argument on three pillars: (i) the economic mechanism of automation, (ii) the dichotomy of 'experience' that separates the first-person perspective of humans from artificial learning algorithms, and (iii) the interdependent relationship between humans and machines. To realise this vision, policy makers have to implement alternative educational approaches that support lifelong training and flexible job transitions.**

***Keywords*-automation; robot density; artificial intelligence; phenomenology; human-machine coexistence**

I. Introduction

The rapid advances in artificial intelligence (AI) and machine learning, combined with recent developments in neuromorphic hardware technologies [1] and ubiquitous computing [2], promoted machines to emulate human-like perceptual and cognitive abilities [3] in a way that will continue the trend of automation (a.k.a computerization [4]) for several upcoming decades. Examples of areas in which automation has the potential to affect the future of humans include health care [5], transportation [6], education [7], justice [8], and economic inclusion [9].

As per the underlying mechanism, automation seems to be color-blind towards the occupational class of workers, *i.e.*, 'blue collar' vs. 'white collar' workers, as well as the type of work they are required to do, *i.e.*, 'manual' vs. 'cognitive' tasks. Experts widely agree on routine-based forms of work as the driving force, and, hence, the determinant of susceptibility to automation [4]. For example, the market of non-routine jobs has been expanding in the USA almost steadily in the years between 1983 and 2013. Routine jobs, on the other hand, did not experience much change in the same period of observation (Fig. 1). This requires rethinking the relation between human and machine, so as to enhance their collaboration over the feared view of having machines replace people.

Whereas debating about automation and its potential socioeconomic upshot for both individuals and human societies was a few years ago almost restricted to intellectuals and small groups of involved researchers, it is now increasingly becoming a major concern for policy makers and a topic of heated conversions among millions of working people [10]. A recent report by the Executive Office of the President in the US Administration looked at the impact of AI-driven automation on the US job market and found that investing in education in terms of high-quality early education as well as providing opportunities to lifelong learning would help prepare people to navigate job transitions successfully [11]. Similar concerns and conclusions were reported by other researchers and think-tanks [4], [12].

A common fear of the AI-driven automation is job loss. While there is the potential for wealth gains, based on increased productivity from AI, there is an emerging consensus that lower-paying jobs are more at risk and any efforts to educate or otherwise prepare new workers should be undertaken now. Predictions for jobs at risk range from a figure of 9% in the upcoming 1-2 decades to 47% [4]. It is worth saying that many jobs are likely to change but not disappear owing to the automation of associated tasks [13]. In addition, it appears wage inequality between high- and low-skilled jobs will exacerbate. For instance, in the U.S. AI would pressure 83% of jobs paying \$20 or less an hour in contrast to only 4% paying \$40 or more. If labor productivity increases but does not translate into wage increases, then economic gains could accrue to a select few, with an increasing divergence among cities in which there is occupational contraction and expansion [4]. Stephen Hawking expressed a similar concern in a December, 2016 editorial in which he warned that the rise of AI will likely extend job destruction from that which we have witnessed in traditional manufacturing to much deeper into the middle class [14].

Despite the gloomy scenarios that might cross the minds of many, we rather stand for an 'expectant' view, leaving room for a more optimistic picture where automation (if well-prepared to) could turn to a rosy future for humanity. We argue that even in the time of massive automation, humans

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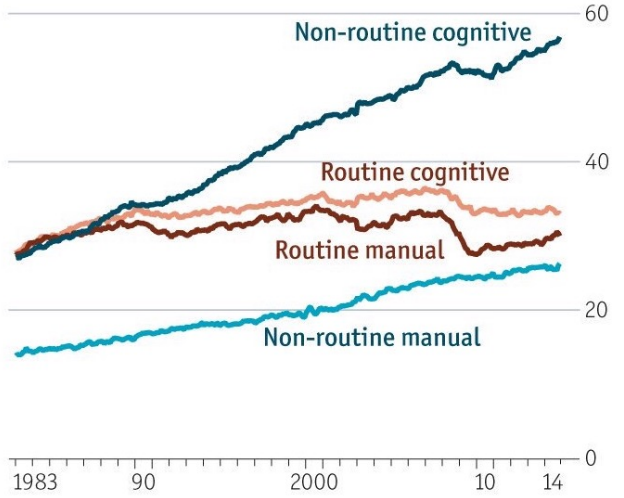

Fig. 1. Employment growth in millions of workers in routine and non-routine jobs (both manual and cognitive) as a function of time (source: US Population Survey, Federal Reserve Bank of St. Louis)

and machines can cross-fertilize in a way that forwards a cooperative coexistence. Our point of view stands on three pillars: (i) the economic mechanism of automation supported by observed patterns over the history of technology, (ii) the dichotomy of 'experience' that separates the first-person perspective of humans from the learning mechanisms in artificial systems, and (iii) the interdependent relationship between both protagonists, *i.e.*, humans and machines, in the narrative of automation.

The remainder of the paper is organised as follows. Section II introduces the present state of automation, providing examples of when it leads to more economic benefits. In Section III we list three arguments to justify our optimistic view of a cooperative human-machine coexistence as a consequence of automation. We finally conclude in Section IV with recommendations for lifelong education that should start immediately.

II. Automation at Present

A. Robot Density as a Measure for Automation

It is worth saying that automation is not a futuristic vision. Rather, it is a current reality that affects employment and transforms human life. To estimate the degree of automation within the international markets, experts use a measure called 'robot density' that compares the number of robotic units deployed in the labor market per $10,000$ human employees. The International Federation of Robotics (IFR) estimates that robot density will continue to increase during the coming years and that it will reach an average of approximately 13% in the years between 2015 and 2019 [15]. Figure 2 shows recent developments and future estimates. The big question in this development is whether an increased robot density leads to job substitution. Various studies show, rather, a positive impact of industrial robots on employment. For example, Graetz and Michaels analyzed data containing information on added value, labor and capital inputs and robot use for 238 country-industries in 17 countries. The analyzed data correspond to the years between 1993 and 2007. The authors found that industrial robots increased both labor and added value. Importantly, the deployment of industrial robots increased wages without having a significant effect on total hours worked despite the observation that hours of low-skilled and middle-skilled workers were reduced [16].

Another study by Barclays in the UK correlates investment in automation to the increase of employment [17]. The author of this study argues that an increase of $\pounds 1.24$bn in automation investment over the next 10 years could return $\pounds 60.5$bn more economic value over the same period, compared to the estimated 'usual' investment level. Moreover, this level of automation investment is expected to create 33,000 manufacturing jobs by 2020 and 73,500 jobs by 2025. In addition to the direct effects of increasing investment in automation and robotics, the study also points out to an indirect impact of such investments on the supply chain. It estimates that this leads to additional $\pounds 2.5$bn a year by 2020 and $\pounds 3.9$bn a year by 2025.

All these studies suggest that more jobs are expected to be created than eliminated by the current wave of automation.

B. When Automation Creates more Jobs than it Eliminates

Amazon is one example of a company in which an increase in automation created jobs. The retail giant added 15,000 robots in 2016 at 20 fulfillment centers for a total of 45,000 units, but instead of laying off 15,000 human employees, Amazon increased its workforce by approximately 46% [18]. Retailers are also more associated with a newer trend of employment change that involves e-commerce. In contrast to manufacturers, any job losses in the retail space are less hidden and involve the automation of rote processes such as picking and sorting, changes that show up clearly and are difficult to disguise.

In opposition to the simplistic notion that automation equals job loss, more involvement in technology in general and robotic automation in particular often means more growth in the workforce. Amazon will open a new plant in Houston, Texas in the Summer of 2017 (Fig. 3). Hiring expectations were originally 1,000 jobs with benefits, then increased to 2,000, and finally reached 2,500 [19]. This hiring comes despite the prevalence of robots that began with the acquisition of Kiva Systems, a Boston robotics company, in March 2012. In this case, increase in customer demand caused increased automation and more hiring of humans. In addition, Amazon provides training to employees who work with robots so that the skills they learn are transferable [20].

III. Why Automation Does not Imply Job Elimination

A. The Economic Mechanism of Automation

While there are plenty of historical examples showing how job displacement from technology resulted in the availability of new jobs, such as an increase in retail banking as

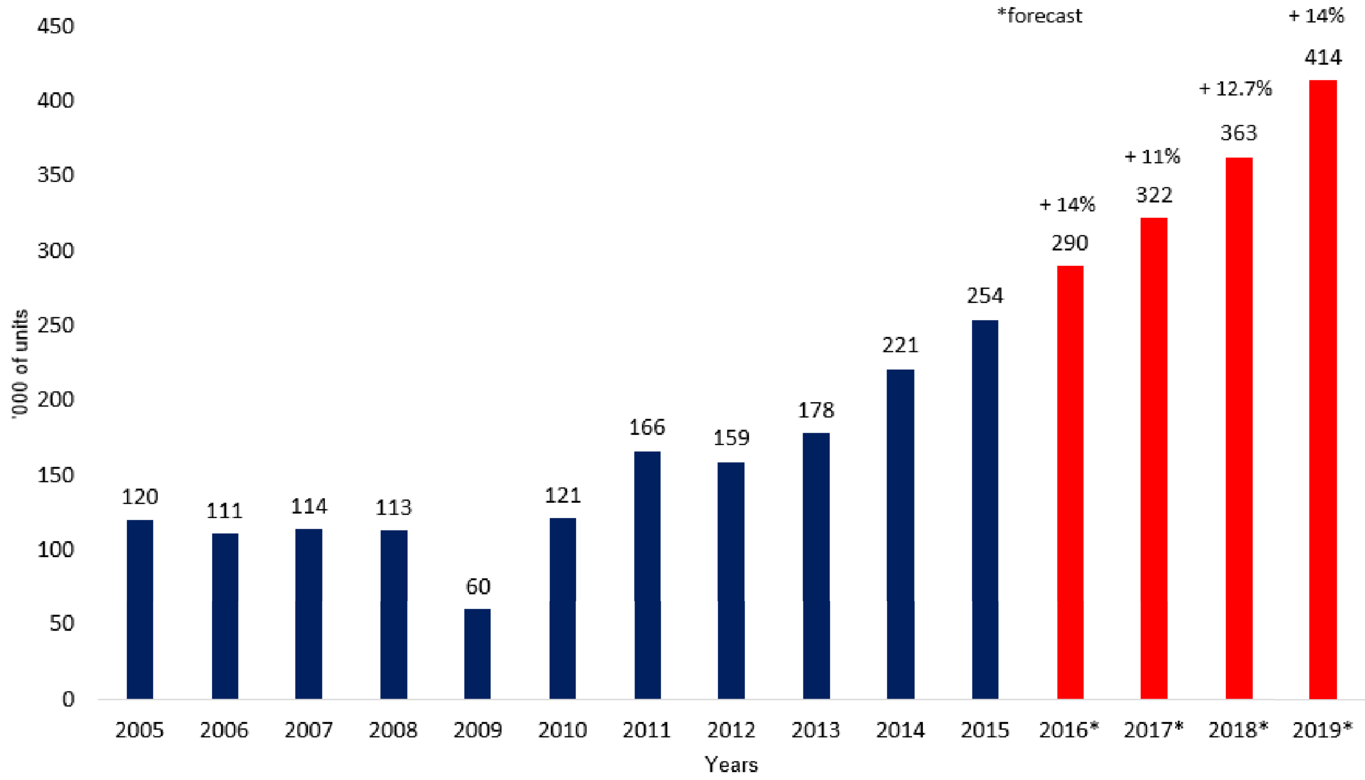

Fig. 2. World wide annual supply of industrial robots 2005 - 2019* (source: International Federation of Robotics)

banks opened additional branches following the introduction of ATMs, current job displacement presents particular issues. For example, automated vehicles will eventually lead to a shortage of truck drivers. However, with an increase in demand from online shopping, fewer persons want to become truck drivers, which does not fit the simplistic narrative of increasingly greater job loss.

That AI-driven automation is on the verge of completely and permanently replacing a large percentage of the workforce is an overly simplistic narrative of eventual machine domination. While automation typically takes away some of the tasks found in white-collar and middle-skill jobs, the jobs themselves require a combination of creativity and problem solving [21]. AI is the electronic equivalent of a Swiss army knife; in other words, machines are not intelligent in the same way as humans [22]. Furthermore, we need to examine automation in the context of economic trends and cycles for a complete understanding on employment.

Observations of technology professionals exemplify the view that fear of mass replacement is unwarranted. White-collar workers should welcome their electronic colleagues, according to Rachel Grimes, the president of the International Federation of Accountants. Because bookkeeping software and online tax returns are taking care of administrative chores, accountants no longer have to do routine work. [23]. Again, labor and automation complement one another. Journalists and even experts overemphasize machine substitution and ignore subsequent productivity, increased earnings, and augmented demand for labor [23]. Neil Kinson, at London-based automation and robotics firm Redwood Software, when referring to Siri and Alexa stated "*as much as I love and adopt those technologies, it is a leap to say, whether I'm a bank or a utility, that I would entrust the management of my customers to that kind of artificial intelligence*" [emphasis added] [23].

There is a growing consensus that a far more substantial concern is the retraining of workers. A survey of adult skills in information processing by the OECD (2016) revealed older workers in 33 countries were much more likely to lack problem solving skills and computer training. For instance, a third of those aged 55 or over had no computer experience compared to under 10% of those aged 25-34. In this context even the World Bank is discussing Swiss, Finnish, and French debates on a universal basic income, though in a blog it promotes public works programs for both social inclusion and societal stability in order to accommodate those who will become displaced. Elderly care is one instance in which increased automatisation results in real contributions to pubic life and "work may replace work" [24].

In general, proponents of a positive impact of automation on job market argue that saving money by reducing labor through automation leaves a factory with two options: it either (i) lowers prices or (ii) generates more profit and/or pays higher wages. In the former case, increased demand through selling more products is likely to lead to the need of more workers. In the latter case, investment and/or consumption are expected to increase, which can lead to more production, and thus, more

Fig. 3. Amazon's fulfillment centers include robots that quickly fetch inventory for warehouse workers who pack and ship (source: [19])

employment.

B. Human Experience vs. Learning in Artificial Systems

The second aspect that speaks for humans and machines coexisting on the job market as opposed to the alternative of machines eliminating jobs is the different categories of consciousness that might be assigned to them. While the first-person perspective of experience is fundamental to humans, there is only a third-person frame of reference when it comes to describing learning mechanisms in artificial systems. Unlike in the category of AI, phenomenology provides a methodology to study experience.

Phenomenology explicates the essence or form of human experience via dialogue [25]. Persons, objects, and events are experienced in the world, in me, or in the space between myself and someone I am talking with. Although providing a description of the experience of 'experience' is often difficult [26], phenomenology aims to contact pure phenomena independent of and prior to any reflective interpretation as we actually live and experience them. According to Husserl, phenomenology allows us to grasp the world of everyday experience as given in direct and immediate experience [27]. The corresponding careful study of existence implies that being is always actually being-in-the-world, such that removing either "a person" or "the world" is meaningless [28]. In this sense, human workers are still productive in a way that would complement the type of productivity achieved by artificial systems. As a consequence, human workers within the coming decades are more likely to be displaced rather than replaced by machines. This shifts the debate from its current state of fearing job elimination to a more realistic position, where strategies of how to prepare for reassigning roles of human and machine on the job market should be implemented urgently.

Looking at the concept of 'experience' as machines deploy it when learning to perform tasks suggests they cannot prosper without having humans exist side by side with them. This is because algorithms, which are the instructing tools of machines, learn (at least as much as this concerns human cognitive abilities) by distilling no less than *human experiences*. Despite its central position in 'learning theory' ([29] and [30]) and in face of numerous neuroscience related accounts ([31]) and information theoretic approaches for encoding it [32], the question of how experience can be generalized, *i.e.*, transferred, from a context where it was acquired into a new one where it achieves optimal performance within considerably shorter time [33], remains open [34]. Hence, for machines to perform well in their task domains, they should have as many examples of experiences, definitely *probed* by humans, as it takes to acquire the underlying ability that is required for solving the given task. Decreasing the number of human workers will decrease the number of examples of human performance, which will degrade the performance of machines. Thus, for machines to thrive, they need continual feeding with data that reflect human experiences.

Furthermore, observing recent technological, theoretical, and empirical developments in AI, Eliasmith predicted that within the coming 50 years, technology, in its quest to emulate the human-mind, will result in what was referred to as *convincing* examples of 'artificial minds' [35]. Without trying to construe what an 'artificial mind' might be, Eliasmith suggested that realizing this vision can be achieved by merely relying on the sophisticated but poorly understood classification methods that are typical in machine learning and other fields of AI. While we do not aim to refute the vision of 'artificial minds', we argue that until they become part of our daily lives, humans with their *experiential* characteristics and machines with their computational prowess can complement each other on the job market. In the aftermath, we will need to grapple with the fuller capacity and practical impact of the predicted artificial minds.

C. The Interdependent Human-Machine Relationship

Chess has always been used as an example for discrepancies and analogies between human cognitive abilities and the computational capabilities as well as the limitations of machines. It was not until 1997 when the world's chess champion, then Gary Kasprov, was beaten by IBM's Deep Blue that people imagined this could happen. The argument had always been that machine intelligence playing chess against a human Grand Master was merely a combination of computational prowess and probabilistic search algorithms. Kasparov suggested extending the game through what was called 'advanced chess', a version in which human players play against each other while being assisted by computer software. Each of the games lasted for 60 minutes, which meant that a human player had to cut the search algorithm when it took longer than it should have in order not to lose technically. The surprising result was that a tournament organized in 1998 was won by a team of amateurs who were skilled at integrating machine assistance [36]. Smart amateurs could even beat Hydra, a supercomputer better than Deep Blue, by using analytic skill sets. It was the *combination* of strategic guidance with tactical acuity that gave victory. The clear conclusion to draw was neither humans nor computers were smarter at chess. Rather, working together resulted in the best performance [37].

Another case of the cooperative combination of big data and human judgment is baseball. Moneyball [38] documents the use of deep data analysis to find undervalued players without the inefficiency and biases that often plague decision making in sports, business, and other domains. Filtering out emotional responses to and biases in the assessment of player performance resulted in an impressive, immediate improvement of the Oakland Athletics in 2002. It was remarkable that the team's payroll was only a quarter of that of the New York Yankees, perhaps a contributing factor to go against conventional wisdom and embrace statistical analysis. The army of scouts that went around to evaluate players was using small sample sizes, author Michael Lewis claimed. Instead of assessing professional potential that deep data analysis can do better, it would be more helpful for the scouts to act as journalists to find out who the players are. Specifically, 5 useful factors to determine were: whether they are hiding an injury, if they listen to their coaches, how they handle living away from home, if they have a drug problem, and whether they have unusual issues or strange problems with teammates. The key is to know what people do well and what the algorithm does well [38].

A practical application for current employees, in this case writers, is turning machine-readable datasets into written texts for humans to read. Automated writing leaves human writers with more time to focus on more important projects that need more elaboration than repetition of numbers. Companies Narrative Science and Automated Insights boast they help solve the problem of data overload. They take data from a particular field and transform it into coherent narratives, allowing for customization of style, form, and format to match the language and context of a specific industry. Examples include a financial website that reports overnight changes in price or supply of commodities, trade reports, and basic statistics from common sporting events that do not require extensive analysis or flair. In a competition in America between a machine from Automated Insights and a reporter from National Public Radio, the machine generated a generic story faster, but one from the journalist was more clever (2 minutes versus 7 minutes) [39]. Lowering the price for more tedious writing means freeing capacity for writers, such as when the Associated Press increased the number of articles on companies' quarterly earnings reports from 300 to 3000 using the technology [40].

A more recent example for potential cooperative human-machine coexistence can be seen in Radiology. This is one of the fields in medicine that is susceptible to eminent massive automation. In their role as medical doctors, radiologists strive to treat diseases in that they first conduct relevant diagnoses. In practice, this translates to interpreting medical images such as x-ray, CT, and MRI images (a. k. a. radiographs). Interpreting such radiographs is an expert-based task that involves pattern recognition. Recently, a computer successfully found fractures in radiographs and highlighted these fractures by applying a deep learning search on a database that contained both categories of radiographs, i.e., radiographs with and without fractures. It is worth stating that some analyses cannot be automated [41]. Identifying those that can be automated by AI, however, means that radiologists have more time to concentrate on other tasks such as screening populations for lung and breast cancer.

IV. Final Discussion and Conclusions

There have been a series of reports indicating an increased level of automation with subsequent job loss. Beginning with the Oxford Martin school [4], which was initially published in 2013, a figure of 47% was reported as the degree of entire occupations subject to elimination. In contrast, an OECD report [13] stated a considerably lower figure of 9% when taking into account specific tasks within jobs that would become automated. The World Economic Forum released a report in January 2016 claiming that we will lose a net 5 million jobs by 2020 [42]. This is an estimation based on a subtraction of 7 million jobs but an addition of 2 million. A pair of reports from McKinsey in 2016 and 2017 added to the literature [43], [44]. The earlier one claimed up to 60% of all professions will be affected, with manufacturing and food service at the greatest risk. The more recent one listed the potential for automation by country, from South Africa at 41% to Japan at 55.7%, representing percentages of work activities subject to automation from the adaptation of current technology. There is an examination of several particular and universal factors including education and training of workers, advanced & developing economies, and young vs. aging populations. One prediction from Price Waterhouse Coopers is that up to 30% of jobs in the UK, 35% in Germany, and 38% in America could be lost to automation by the early 2030s [45]. Automation, however, is not a zero-sum game for the labor market because AI-related technology will result in job gains elsewhere in the economy.

Two other reports are notable for their claims. The International Federation of Robotics [15] reported automation has led to an overall increase in demand, which in turn leads to new jobs, and has had a positive impact on wages. It increases productivity and competitiveness, but important for this paper is the acknowledgement that robots complement and augment labor. The Economic Policy Institute went farther to say there is no evidence automation leads to joblessness or even inequality [46].

The idea of having humans and machines collaborate rather than merely interacting is, on one hand, a positive and a straightforward step towards humanizing automation. On the other hand, however, certain issues should be addressed to make this possible. For example, further research is needed to answer questions about age and gender categories, financial status, and other contextual factors that would affect humans' readiness to collaborate with machines in times of massive automation. A recent study on humans' attitudes towards ubiquitous systems (such as the wearable Google Glass) found that, besides privacy, people have other concerns such as cost and risk with their willingness to use such technologies. Surprisingly, the youngest (16-25 years old) among the participants of this study were the most concerned about privacy issues [47].

Furthermore, the ongoing digital revolution and the underlying technological developments in computing and communication systems marks the advent of a new era that, by and by, tends to put the traditional model of education into perspective. Rather than relying on time limited education, people need to access educational opportunities more than once during their lifetimes in response to evolving career obligations and changing socioeconomic requirements.

ACKNOWLEDGEMENT

The authors would like to thank the anonymous reviewers for their valuable time and helpful comments.

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