ARTIFICIAL INTELLIGENCE (AI), AUTOMATION AND EMPLOYMENT

Joël Christoph[1]
B.Sc Economics with a Year Abroad
Final year
University College London

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Introduction

Around the world, technological unemployment has re-emerged as a primary concern. The December 2018 G20 Leaders' declaration chooses to focus on "the future of work", amid concerns that breakthroughs in Artificial Intelligence may fundamentally alter human societies (G20 Leaders, 2018). Moreover, a 2017 poll finds that roughly twice as many Americans express worry (72%) than enthusiasm (33%) about a future in which robots and computers can substitute for human jobs (Appendix, Figure 1; Pew Research Center, 2017). How will ongoing technological change affect employment, the wider economy and society? Two hundred years of automation and technological progress have not eliminated the demand for human labour. Far from that, employment today is close to an all-time low and the employment-to-population ratio increased alongside the introduction of automation technologies during the past century (Appendix, Figure 3 & 4; Autor, 2015; US Bureau of Labor Statistics, 2019). So should we be concerned that Artificial Intelligence and other automation technologies will eventually replace us entirely?

This paper reviews existing literature to address how increasing workplace automation of due to A.I. may affect employment. I contrast various sources from existing literature. First, I reflect on Economic History to consider how past phases of technological change inform the ongoing debate about technological change. Second, I analyse and compare current economic thinking on the impact of machine automation on labour markets. Third, I outline and explain task-based models of automation. Fourth, I draw lessons for thinking of both large-scale and context-specific impacts of technological change, with a discussion of epistemic limitations and common misconceptions. In conclusion, I consider the consequences and limitations where the range of tasks for which machine substitution is technically possible expands.

Theoretical background

Before we consider the specific potential of artificial intelligence, it will be helpful to situate debates of technological change in the context of economic history. Although some authors such as Brynjolfsson and McAfee (2014) argue that the recent pace of innovation is of impressive scale and scope, others such as Gordon (2016) lament that productivity growth has been insufficient in the face of increasing demographic and economic headwinds. Such concerns are not new and figured prominently in the past, for instance during the an eighty year "Engel's Pause" before the Industrial Revolution's productivity growth was matched by sustained increases in workers' wages in the mid-19th Century (Allen, 2009). Later in the 1930s, Economists John Maynard Keynes and Alvin Harvey Hansen differed in their views of technological progress and its implications for employment and economic growth.

Writing amid the Great Depression, Keynes defends the cause of technological optimism in his essay "Economic Possibilities for our Grandchildren". He attributes the lack of large-scale economic progress before the 18th century to the lack of significant technical improvements and the failure to accumulate capital. Keynes introduces the concept of *technological unemployment* as "unemployment due to our discovery of means of economising the use of labour outrunning the pace at which we can find new uses for labour" and notes that the negative impacts of such innovations are temporary. In perhaps the most famous forecast of economic progress to date, he writes that the resource-scarce past is a poor predictor of future conditions and that assuming no important wars or population growth, the economic problem of meeting absolute needs may be achieved within a hundred years. Nonetheless, Keynes notes that "if the economic problem is solved, mankind will be deprived of its traditional purpose", requiring difficult readjustment to overcome genetic and societal pressures better-suited to a time of resource scarcity. It is then that humans must confront the permanent problem of how to use freedom from economic necessities "to live wisely and agreeably and well." (Keynes, 1930).

In 1939, Hansen, sometimes called "the American Keynes", foreshadowed today's debates on economic progress by proposing a pessimistic interpretation of the times. Noting that the "economic order of the western world" is undergoing a change no less profound than the Industrial Revolution, Hansen argued that rapid declines in population growth and in capital formation would spell alarming stagnation in the absence of state intervention to stimulate aggregate demand through large-scale deficit spending (Hansen, 1939).

Contrasting Keynes and Hansen from today's vantage point suggests that despite recurrent phases of anaemic growth, technological innovation and capital accumulation have enabled long-run economic development and the substantial reduction of the economic problem. Among various innovations, General Purpose Technologies (GPTs) such as the steam engine, electricity and the computer have been instrumental to increasing automation, worker productivity and material living conditions. Such GPTs are pervasive, improve over time and generate complementary innovation (Bresnahan & Trajtenberg, 1995) and it is in its potential to be the most recent GPT that A.I. has generated much of its hype.

Theoretical Framework and Results

In assessing the implications of A.I. for employment, we shall consider a task-based framework where A.I. represents that latest in a series of automation technologies. A prominent approach to modelling automation consists of decomposing a job into its constituent tasks. For instance, the job of a bank teller may include managing deposits, handling customers' requests, explaining bank services, checking accounts and miscellaneous paperwork. The extent to which robots, software or other automation can perform such tasks determines the extent to which capital can *technically* substitute for labour.

Agrawal et al. (2018, 2017) argue that GPTs are characterized by widespread substitutability for a ubiquitous task. In a similar manner to the computer revolution which fundamentally reduced the cost of calculation, the long-run economics of A.I. can be understood as a downward shift in the cost of supplying predictions based on data. Since human prediction is an input to a vast range of activities, the decline in the cost and the improvement in the quality of machine prediction is likely to affect a vast range of economic sectors. With the fall in the cost of prediction, complementary tasks such as judgement are likely to be in increased demand, until or unless these tasks can also be effectively substituted by machines.

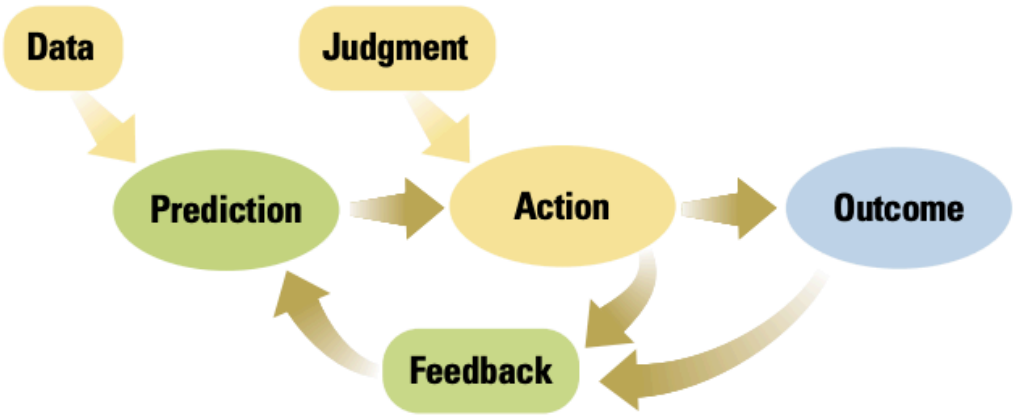

Fig. 2 The Anatomy of a Task (Agrawal, et al., 2017)

There exist many task-based frameworks for modelling automation (Acemoglu & Restrepo, 2018a, 2018b; Aghion et al., 2018; Acemoglu & Autor, 2011; Acemoglu & Zilibotti, 2001; Zeira, 1998). Zeira (1998) develops a straightforward model, where a production function is defined as:

$$Y = AX_1^{\alpha_1}X_2^{\alpha_2} \cdot \ldots \cdot X_n^{\alpha_n} \quad where \quad \sum_{i=1}^{n} \alpha_i = 1.$$

Acemoglu and Autor (2011) adjust this model such that the X_i's correspond to tasks. For any X_i, one unit of labour is required if the task cannot be automated and one unit of capital is required if automation is possible, such that:

$$X_i = \begin{cases} L_i, & \text{if not automated} \\ K_i, & \text{if automated} \end{cases}$$

Under optimal task allocation and ignoring an unimportant constant, the production function becomes

$$Y_t = A_t K_t^{\alpha} L_t^{1-\alpha}$$

where α is the share of automated tasks. In a neoclassical growth model where investment rate is constant and α is the factor income of capital, the long-run growth rate of $y \equiv Y/L$ is given by

$$g_y = \frac{g}{1-\alpha}$$

where g is the growth rate of total factor productivity A. As the range of tasks that can be automated increases, capital share of income α rises. The capital accumulation and its associated multiplier effect lead to an increase in long-run growth rate g_y. This implies that as automation becomes more widespread, both the capital share of income and growth rates increase (Aghion, et al., 2017). This contradicts Kaldor's stylized facts that the capital share of national income and the growth rate of output are relatively constant in the long-run (Kaldor, 1957, 1961). To overcome this issue, Acemoglu and Restrepo (2018) suggest that rate at which new tasks are invented is at least equal to the rate at which old tasks are automated.

In analysing how automation can raise or lower labour demand, Acemoglu and Restrepo (2018) argue that the effects of automation on employment operate through multiple balancing effects. In the short term, automation leads to a *displacement effect* as machines or AI replace workers in tasks that they used to perform. This reduces the demand for labour, wages and employment as the productivity of automation increases. Displaced workers tend to experience a decoupling of wages and labour productivity and this causes the labour share of national income to fall.

Nevertheless, there exists multiple forces that counteract the *displacement effect*. First, as the substitution of cheaper machines for labour engenders cost savings and lowers prices, this *productivity effect* raises labour demand in non-automated tasks. This contributes to economic expansion and a rise in employment. Second, *capital accumulation* leads to an increase in the demand of both capital and labour and raises the rental rate of capital. Third, technological progress also raises the productivity of machines in tasks that have already been automated. This *automation deepening* raises productivity without displacing workers, and thus increases labour demand. However, even when these three countervailing forces are present, automation inherently raises output per worker by more than wages and this reduces labour's share of national income. Instead, it is in the creation of new labour-intensive tasks that displaced labour is reinstated in new activities. The authors emphasize that this last *reinstatement effect* is the most powerful countervailing force and ultimately increases labour share to counterbalance automation's detrimental displacement. The *displacement effect* is immediate whereas the countervailing forces operate by time-lags and are epistemically unpredictable. This and the availability heuristic (Kahneman, 2011) may explain why the labour-displacing effects of automation are more prevalent in discussions of automation than the longer-run effects that eventually raise labour demand and wages.

Conclusion

The impact of automation technologies on employment depends on the effective substitution of capital for tasks previously done by labour. Task-based frameworks and past GPTs suggest that A.I. corresponds to a fall in the cost of prediction tasks. This would increase adoption of machine prediction and raise demand and wages for human skills that complement machine prediction (Agrawal et al. 2018). Although automation raises labour demand, wages and productivity through *productivity*, *capital accumulation* and *automation deepening effects*, it also raises output per worker by more than wages. The *reinstatement* of workers into new tasks where labour still has a comparative advantage is thus crucial and accounts for the strongest countervailing force to workplace automation (Acemoglu & Restrepo, 2018). Nevertheless, the process of worker reallocation to new tasks is costly and the mismatch between skills required and available represents the greatest challenge to reducing the painful readjustment to automation.

Ultimately, the extent to which tasks or jobs will be automated also depends on factors beyond technical feasibility (McKinsey Global Institute, 2017). Besides (a) the task content of a particular job, these include (b) the cost of developing and deploying complementary inventions, (c) the cost of human alternatives to automation, (d) the context-specific output and quality benefits of automation and (e) cultural, legal and political factors, such as regulatory and social acceptance when deployment makes business sense. Collectively, these factors limit the immediate and mass displacement of workers and generate time for us to consider the ongoing technological transition and our shared management of its opportunities and risks.

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Appendix: Figures 1, 3 and 4

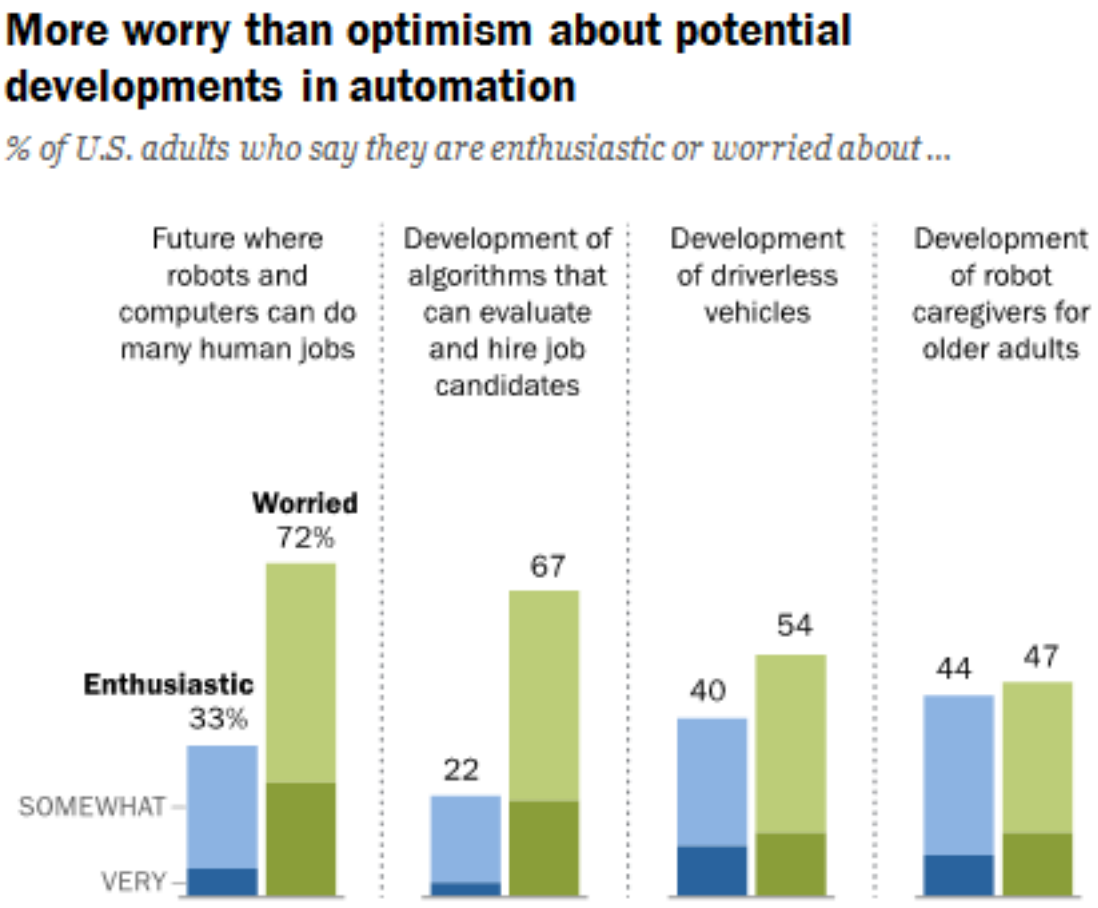

Figure 1: U.S. Survey Respondents on Automation in Everyday Life (Pew Research Center, 2018)

Figure 3: U.S. Seasonally Adjusted Unemployment Rate (US Bureau of Labor Statistics, February 2019)

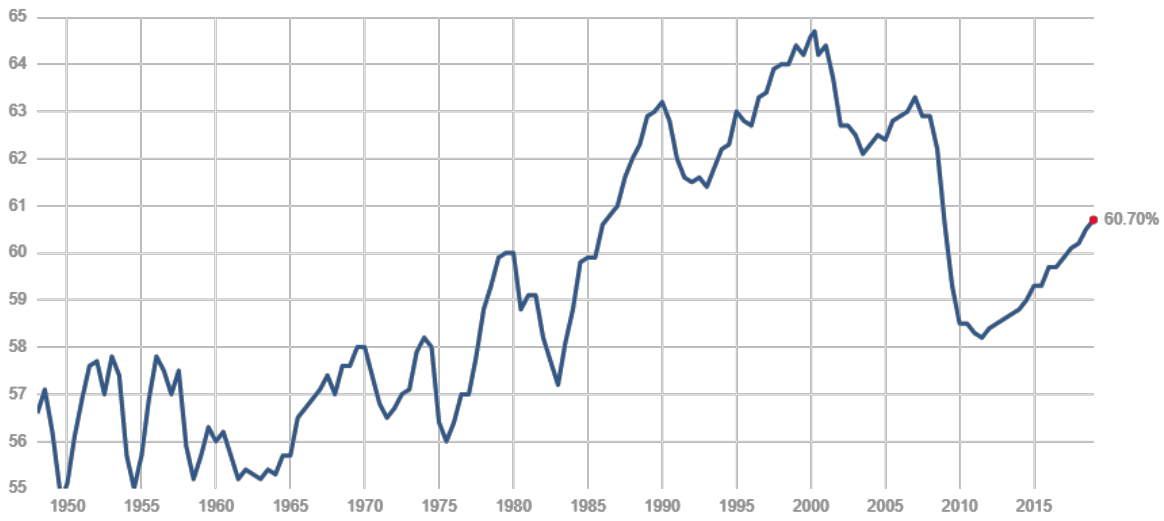

Figure 4: U.S. Employment-to-population ratio. This shows the percentage of US working-age population (age 16+) that are employed. Unlike the US Unemployment Rate, this accounts for individuals who have left the labour force. (US Bureau of Labor Statistics, February 2019)