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The Impact of Artificial Intelligence on Innovation

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Abstract: *The current economy's efficiency may be greatly improved by artificial intelligence. We distinguish between automation-oriented applications like robotics and the potential for recent developments in "deep learning" to serve as a general-purpose method of invention, finding strong evidence of a "shift" in the importance of application-oriented learning research since 2009. However, it may have an even larger impact by serving as a new general-purpose "method of invention" that can reshape the nature of the innovation process and the organization of R&D. We suggest that this will likely result in a significant shift away from routine, labor-intensive research and toward research that makes use of the interaction between improved prediction algorithms and passively generated large datasets. In addition, strong incentives for specific businesses to acquire and control crucial large datasets and application-specific algorithms will likely usher in a period of racing as a result of the potential commercial rewards of mastering this method of research. We suggest that in the future, policies that promote transparency and the sharing of core datasets between public and private actors may be essential for boosting research productivity and encouraging innovation-oriented competition.*

Keywords: Artificial Intelligence

I. INTRODUCTION

The economy and society as a whole are profoundly impacted by the rapid advancements in artificial intelligence. Productivity, employment, and competition will all be significantly impacted by these innovations, which have the potential to directly affect the production as well as the characteristics of a wide variety of goods and services. However, as significant as these effects may be, artificial intelligence also has the potential to alter the innovation process itself, with equally significant repercussions that may eventually outweigh the direct impact.

Take the example of Atom wise, a young company that is developing cutting-edge technology for predicting the bioactivity of candidate molecules using neural networks to identify potential drug candidates (and insecticides).According to the company, its deep convolutional neural networks perform "far better" than conventional "docking" algorithms. The company's Atom Net product is described as being able to "recognize" organic chemistry's fundamental building blocks and generate highly accurate predictions of the outcomes of real-world physical experiments with appropriate training on large amounts of data (Wallach et al.,2015).The productivity of early-stage drug screening may see significant enhancements as a result of such breakthroughs. Obviously, Atom wise's technology and that of other companies using artificial intelligence to improve medical diagnosis or drug discovery is still in its infancy: Despite the fact that their initial results appear to be promising, no new drugs have been released using these new methods. However, regardless of whether Atom wise fulfills all of its promises, its technology exemplifies the ongoing effort to create a new innovation "playbook" that makes use of large datasets and machine learning algorithms to accurately predict biological phenomena and guide the design of effective interventions. Atom wise, for instance, is currently employing this strategy in the process of discovering and developing novel agents and pesticides for the control of crop diseases.

Second, while some applications of artificial intelligence will undoubtedly provide lower-cost or higher-quality inputs to numerous existing production processes, raising concerns about the potential for significant job losses, others, such as deep learning, promise to alter not only the very nature of the innovation process within those domains but also productivity gains across a wide range of sectors. The "invention of a method of invention" has the potential to have a much larger economic impact than the development of any single new product, as famously stated by Griliches (1957). This is because it makes it possible to innovate across a variety of applications.

We argue that recent advancements in machine learning and neural networks are likely to have a particularly significant impact on growth and innovation due to their ability to enhance both the performance of end-use technologies and the innovation process. Understanding the conditions under which various potential innovators are able to gain access to these tools and to use them in a manner that is pro-competitive is a central concern for policy, and as a result, the incentives and obstacles that may shape the development and diffusion of these technologies are an important topic for economic research.

This essay begins by examining the potential impact that advancements in artificial intelligence may have on innovation and the role that institutions and policies may play in providing effective incentives for innovation, diffusion, and competition in this field. In Section II, we begin by focusing on the unique economics of research tools, of which the application of deep learning to R&D issues is such an intriguing example. We focus on the relationship between a new research tool's degree of generalizability and the role of research tools in creating a new "playbook" for innovation as well as improving research efficiency. In Section III, we compare and contrast three important technological trajectories within AI: symbolic systems, deep learning, and robotics. We propose that in the future of innovation and technological change, these often-conflated fields will likely play very different roles. Work on symbolic systems appears to be at a standstill and is unlikely to have much of an impact in the future. In addition, innovation in robotics technologies has a relatively low potential to alter the nature of innovation itself, despite the fact that advancements in robotics have the potential to further displace human labor in the production of numerous goods and services. Deep learning, on the other hand, appears to be a research area with a wide range of applications and the potential to alter the innovation process itself.

II. THE ECONOMICS OF NEW RESEARCH TOOLS: THE INTERPLAY BETWEEN NEW METHODS OF INVENTION AND THE GENERALITY OF INNOVATION

Economists have recognized the potential for significant underinvestment in research, particularly basic research or invention domains with low appropriability for the inventor since Arrow (1962) and Nelson (1959).Both in terms of their overall level and the direction of that research, significant insight has been gained into the conditions under which the incentives for innovation may be more or less distorted. The potential for contracting issues associated with the development of a new broadly applicable research tool and the potential for coordination issues arising from the adoption and diffusion of a new "general purpose technology" seem particularly significant when we consider the potential impact of AI advancements on innovation. We contend that, in contrast to technological advancements in relatively narrow fields like conventional automation and industrial robots, areas of artificial intelligence that are developing at the fastest rates, like deep learning, are likely to present significant difficulties in both dimensions.

First, think about the difficulty of providing the right incentives for innovation when it has the potential to change technology and organizations in many different applications. These kinds of "general purpose technologies "Bresnahan and Trajtenberg, 1995) frequently take the form of fundamental innovations that have the capacity to significantly boost productivity or quality in a wide range of fields or industries. The electric motor's foundational study by David (1990) demonstrated that its invention led to significant technological and organizational shifts in manufacturing, agriculture, retail, and residential construction. Typically, these "GPTs" meet three criteria that set them apart from other innovations: They are utilized extensively in numerous fields; They generate additional innovation in application fields and are rapidly improving themselves.

The economics of research instruments provide a second conceptual framework for considering AI.

Some innovations in the research fields open up new areas of inquiry or simply boost productivity "inside the lab. "Beyond their initial application, some of these advancements appear to have great potential across numerous domains: Some new research tools are inventions that not only create or improve a specific product but also constitute a new method of creating new products with much broader application, as Griliches (1957) highlighted in his classic studies of hybrid corn. Double-cross hybridization's discovery "was the invention of a method of inventing," as Griliches famously put it. "IMI" will be used after.)Hybrid corn was a widely applicable method for breeding numerous new varieties rather than a means of creating a single new corn variety. The development of double-cross hybridization had a significant impact on agricultural productivity when applied to the problem of developing new varieties that are optimized for a wide range of localities, in addition to other crops.

Because of this, one of the important insights that can be gained from thinking about IMIs is that the economic impact of some kinds of research tools is not only limited to their capacity to reduce the costs of particular innovation activities; perhaps even more importantly, they also enable a new approach to innovation by altering the "playbook" for innovation in the domains where the new tool is utilized. This is one of the important insights that can be gained from thinking about IMIs. For instance, before the systematic understanding of the power of "hybrid vigor," improved methods for self-fertilization (i.e., allowing for more and more specialized natural varietals over time) were the primary focus in agriculture. The techniques and conceptual approach for agricultural innovation were shifted once the rules governing hybridization (also known as heterosis) were systematized and the performance benefits of hybrid vigor were demonstrated. This marked the beginning of a lengthy period of systematic innovation that made use of these new tools and knowledge. In the past, technologies with these characteristics—such as digital computing—have had significant and unexpected effects on society as a whole and the economy. Mokyr (2002) highlights the significant impact of IMIs, which are not tools per se but rather innovations in the manner in which research is organized and carried out, such as the establishment of the university. GPTs that are also IMIs (or the other way around) are particularly complicated phenomena whose dynamics are still poorly understood.

III. THE EVOLUTION OF ARTIFICIAL INTELLIGENCE: ROBOTICS, SYMBOLIC SYSTEMS, AND NEURAL NETWORKS

Nilsson (2010) defines AI as "that activity devoted to making machines intelligent, and intelligence is that quality that enables an entity to function appropriately and with foresight in its environment" in his comprehensive historical account of AI research. His account explains how biology, linguistics, psychology and the cognitive sciences, neuroscience, mathematics, philosophy and logic, engineering, and computer science all played a role in AI's successes. Naturally, artificial intelligence research has always been unified by its engagement with Turing (1950) and his discussion of the possibility of mechanizing intelligence, regardless of their distinct approaches.

The field of robotics has largely been the focus of a second influential AI trajectory. While the concept of "robots" as machines that can perform human tasks dates at least to the 1940s, the field of robotics began to meaningfully grow from the 1980s onward through the development of more adaptive but still rules-based robotics that rely on active sensing of a known environment and advances in numerically controlled machine tools. With the widespread deployment of "industrial robots" in manufacturing applications, this is perhaps the most economically impactful AI application to date.

In a highly controlled environment, these machines are precisely programmed to perform a specific function. These purpose-built tools, which are frequently situated in "cages" within highly specialized industrial processes (most notably automobile manufacturing), are perhaps more appropriately referred to as highly sophisticated numerically controlled machines rather than as robots containing a significant amount of AI. Innovations in robotics have had a significant impact on manufacturing and automation over the past two decades, most notably through the introduction of robots that are more responsive and rely on programmed response algorithms that are able to respond to a variety of stimuli. Rod Brooks' (1990) famously pioneered this strategy, which shifted AI's focus from modeling human-like intelligence toward providing feedback mechanisms that would make robotics practical and effective for specific applications. The Roomba and other adaptable industrial robots that could interact with humans, such as the Baxter from Rethink Robotics, were a result of this insight, among other applications. The ability of robotic devices to sense and interact with their environment, in particular, and the continued innovation in robotics technologies may lead to a wider range of applications and adoption outside of industrial automation.

These advancements are significant, and when the term AI is mentioned, the most advanced robots continue to captivate the public's imagination. However, robotics innovations generally are not IMIs. Although advances in robotics aren't directly linked to the underlying ways in which researchers themselves might develop approaches to undertake innovation themselves across multiple domains, increasing automation of laboratory equipment certainly increases research productivity. Naturally, there are examples to the contrary of this assertion: The ability of automated remote sensing devices to collect data on a very large scale or in challenging environments may transform some fields of research. Robotic space probes have been a very important research tool in planetary science. However, robots are still primarily utilized in niche, end-use "production" applications.

Finally, a third line of research known as a "learning" approach is one that has been at the heart of AI research since its inception. The learning approach aims to develop reliable and accurate methods for the prediction of specific physical or logical events in the presence of specific inputs rather than focusing on symbolic logic or precise sense-and-react systems. In this field, the idea of a neural network has been particularly significant. A neural network is a program that converts a set of inputs into a set of outputs using a combination of weights and thresholds, then adjusts the weights it uses to bring the outputs closer to reality by measuring their "closeness" to reality. Neural networks are able to learn as they receive more inputs in this manner (Rosenblatt, 1958;1963).Through the creation of "back-propagating multi-layer" methods that further enhance their potential for supervised learning, Hinton and his co-authors further advanced the conceptual framework on which neural networks are based during the 1980s.

The field of neural networks has fluctuated in popularity, particularly in the United States, despite being initially hailed as having significant promise. From the 1980s to the middle of the 2000s, their problem seemed to be that the technology had a lot of limitations that couldn't be easily fixed by using larger training datasets or adding more layers of "neurons. "However, in the middle of the 2000s, a small number of new algorithmic approaches demonstrated that back propagation through multiple layers could improve prediction. As these neural networks were applied to increasingly large datasets, their predictive power increased, and they were able to scale to any level (Hinton and Salakhutdinov, among others, is an important reference here).In the context of the ImageNet visual recognition project competition, which was started by Fei-Fei Li at Stanford, these advancements demonstrated a "surprising" level of performance improvement (Krizhevsky, Sutskever, and Hinton, 2012).

In parallel, the introduction of this new research paradigm is likely to necessitate a significant shift in innovation management. For instance, it is possible that the democratization of innovation will also be accompanied by a decrease in the theoretical or technical depth of the workforce due to a lack of investment by individual researchers in specialized research skills and expertise in any given area. Long-term incentives for breakthrough research that can only be carried out by people who are at the frontier of research may be undermined by this shift away from career-oriented research trajectories toward the capacity to derive new findings based on deep learning.AI may also "break science" in some fields by disrupting the career ladders and labor markets that support the relatively long periods of training and education required in many scientific and technical occupations if it replaces skilled technical labor on a large scale in the research sector.

Last but not least, it's possible that deep learning will alter the very nature of technological and scientific advancement itself. A mode of inquiry that is based on an underlying theory and focuses on identifying a relatively small number of causal drivers of underlying phenomena drives many science and engineering fields (Einstein's parsimony principle states that theory should be “as simple as possible but no simpler”).Deep learning, on the other hand, offers a new paradigm based on the ability to predict complex multi-cause phenomena using a "black box" method that abstracts away from the underlying causes but allows for a single prediction index that can provide sharp insight. There may be costs associated with ignoring causal mechanisms and abstract relationships: The capacity to utilize a comprehension of the theoretical structure of the "big picture" in order to make sense of and recognize the implications of smaller discoveries is necessary for many significant advancements in science. For instance, it is simple to imagine a deep learning system that has been trained on a large amount of x-ray diffraction data "discovering" the double helix structure of DNA in a very short amount of time and at very low marginal cost. On the other hand, it is likely that human judgment and insight into a much broader biological context would be required in order to realize that the proposed structure suggests a direct mechanism for heredity.

Beyond the organization of individual research projects and the nature of what constitutes "science" in a particular field, a second area of impact will be the appropriate design and governance of innovation process-governing institutions. There are three clear repercussions.

First, as previously mentioned, research conducted over the course of the previous two decades has emphasized the significant role that institutions play in encouraging the production of cumulative knowledge by providing independent, low-cost access to research tools, materials, and data (Furman and Stern, 2012;2015 (Murray et al. However, the issues of replicability and transparency have received little attention within the deep learning community up to this point. Online communities and hubs that organize grassroots efforts to promote openness are to be commended. Even among academic researchers or private sector research communities, there is likely to be a significant gap between the private and social incentives to share and aggregate data. This divergence may suggest that it will be crucial to develop mechanisms for replicating the results and rules of credit and attribution whenever a single research result relies on the collection of data from multiple sources.

IV. CONCLUDING THOUGHTS

This exploratory essay has not attempted to provide clear policy or innovation management guidance or a systematic account or prediction of the likely impact of AI on innovation. Instead, our objective has been to raise a specific possibility—that deep learning is a new general-purpose invention of a method of invention—and to identify some preliminary implications for management, institutions, and policy based on that hypothesis.

A few key ideas that have not yet been at the center of the economics and policy debate are the focus of our preliminary analysis. First, it is useful, at least from the point of view of innovation, to distinguish between the potential for a general-purpose method of invention based on the application of multi-layered neural networks to large amounts of digital data to be an "invention in the method of invention" and significant advancements in fields like robotics. A striking shift toward deep learning-based application-oriented research since 2009 is documented by both the existing qualitative evidence and our preliminary empirical analysis, which is consistent with this possibility. Second, and this is related, the possibility of a change in the innovation process raises important questions for a number of policy and management areas. These questions include how to evaluate this new type of science and whether prediction methods can create new barriers to entry in a variety of industries. A very promising area for future research seems to be proactive analysis of the appropriate private and public policy responses to these breakthroughs.

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