Mind or Matter

The Nature of Artificial Intelligence

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Abstract

Artificial intelligence (AI) has made remarkable progress in completing a wide range of complex tasks. As a result, AI has renewed interest from executives and entrepreneurs, and scrutiny from academics and policy makers. This essay contains summarized excerpts from a series where I review the literature on AI. The first section argues that AI should be framed as a class of artifacts for solving problems that require intelligence. The second section critiques the argument that AI is a centralizing force within the economy. In the final section, I outline how AI's predictive and creative capabilities may restructure economic factors of production.

Artificial Intelligence Is Not Intelligence

To understand artificial intelligence, we must start with understanding intelligence. The *Oxford Universal Dictionary* (1955) leans heavily on the word's Latin root, *intelligere* (to understand), defining intelligence as [1] the faculty of understanding; intellect; and [2] understanding as a quality admitting of degree; *spec.* superior understanding; quickness of mental apprehension; sagacity. While this focus on "understanding" does highlight the capacity to perceive meaning, it is overbroad; we need to look further for more clarity.

Within academic circles, researchers have no universally shared definition of intelligence. Broadly speaking, there are four major viewpoints on intelligence that influence AI. The first group holds that intelligence is a general mental capacity, including, among other things, "the ability to reason, plan, solve problems, think abstractly, comprehend complex ideas, learn quickly and learn from experience" (Gottfredson 1997). The second group believes that there are different types of intelligence. Holding that general intelligence fails to fully explain cognitive ability, researchers point to various modalities of intelligence that emerge in people (Gardner 1983; Sternberg 1985; Goleman 1995). The third group takes a behaviourist view, defining intelligence as the ability to solve problems, focusing on the achievement of outwardly observable results. Finally, the fourth group argues that *all* living things exhibit some sort of intelligent behaviour (Narby 2005). Cianciolo and Sternberg (2004) define intelligence as the ability for organisms to adapt to their environment and learn from experience.

Herbert Simon's dichotomy between the natural and the artificial played an important role in AI's history. Simon (1969) wrote that the natural is produced by nature, while the artificial is produced by art. Although "artificial" carries a pejorative connotation, artificial processes aim to change existing situations into preferred ones. Through the process of design, humans produce material artifacts that exploit the natural world to meet certain assigned ends.

This understanding of the artificial was adopted by early AI pioneers. In the summer of 1956, the field of artificial intelligence was born at Dartmouth College. John McCarthy brought together leading scientists on the "conjecture that every aspect of learning or any other feature of intelligence can in principle be so precisely described that a machine can be made to simulate it. An attempt will be made to find how to make machines use language, form abstractions and concepts, solve kinds of problems now reserved for humans, and improve themselves." This was a highly ambitious undertaking reflecting the early milestones of its attendees: Herbert Simon predicted "machines will be capable, within twenty years, of doing any work a man can do," while Marvin Minsky wrote "within a generation... the problem of creating 'artificial intelligence' will substantially be solved." Put bluntly, this did not happen.

As it did happen, the field prudently converged on more modest definitions of AI oriented around the achievement of goals. Experts put forth less specific definitions like "the ability to solve hard problems" (Marvin Minsky), "the ability to use optimally limited resources—including time—to achieve goals" (Ray Kurzweil), "achieving complex goals in complex environments" (Ben Goertzel), "any system that generates adaptive behaviour to meet goals in a range of environments" (David Fogel), and "combining science and engineering in order to build machines capable of intelligent behaviour" (Joanna Bryson and Jeremy Wyatt). We now think of AI as only being concerned with solving problems that computers aren't *currently* capable of solving. As Minsky (1986) remarked, "the very concept of intelligence is like a stage magician's trick. Like the concept of 'the unexplored regions of Africa,' it disappears as soon as we discover it."

Despite its nebulosity, AI commonly employs algorithms—sets of instructions delivered to generate an output from an input. There are two competing approaches for creating AI: machine learning (ML) and knowledge engineering (KE). ML is the process of teaching a computer to learn. It employs learning algorithms—algorithms that make other algorithms by passing a set of instructions to data (Domingos 2015). By contrast, KE has experts encode their domain knowledge into a machine-parsable language. When faced with problems, these systems reference logic and rules conceived by experts to solve them. ML has become the predominant school of thought following significant advances over the past two decades.

We may mistakenly think artificial intelligence to be like natural intelligence. The field of AI is concerned with using machines to solve problems that require intelligence. Yet, AI is often anthropomorphized because we near automatically think of it in terms of the type of intelligence we know: our own. This is to err. AI employs a range of problem solving techniques inspired by natural intelligence, but bears limited semblance to the operations of a biological brains, which incorporate consciousness, feeling, and volition. Today, a more reflective and useful representation of AI is to frame it a family of artifacts. Framed as artifacts, we focus on the *intent* of designers and users of AI—who use it is a tool to achieve positive or negative ends.

All in all, the "intelligence" in artificial intelligence, if anything, refers to the intelligence of its makers made manifest in machines.

The Economics of Artificial Intelligence

In 2018, the venture capitalist Peter Thiel described AI as a centralizing force, where large institutions are empowered by massive volumes of data they have collected. For instance, industry incumbents with years of accumulated data can leverage AI to perpetually refine offerings that outperform competitors, while public institutions consolidate citizen and economic data to centrally plan services. While this argument has merit, a review of the economics of AI—with our focus on ML—suggests more nuanced effects: AI is a source of market power that has an entropic rather than centralizing effect.

We focus on the fundamentals of ML systems, which include infrastructure, software, and data, along with requisite labour of each element. The value of an ML system is contingent on having *all* three elements.

The physical infrastructure to process data and train algorithms is oligopolistic due to economies of scale. Infrastructure is capital-intensive, requiring components such as memory to store data, chips to process algorithms operating on data, and servers to process requests. A few major players offer infrastructure as a service, spreading its cost among many customers. Yet, despite this industry consolidation, costs of deploying AI services have dramatically fallen. While anticompetitive in that companies are locked into a provider's ecosystem, it has enabled new companies to challenge incumbents in other sectors by democratizing access to hardware.

Software for ML is abundant. Companies that bore the cost of developing algorithms are paradoxically behaving like universities in open-sourcing software. For instance, Alphabet published TensorFlow, the learning algorithm powering Google's search engine. Firms made the calculation that the spillover effects offered benefits that outweighed threats to their businesses. The code of the final program, trained from data, remains a secret, but the starting point (learning algorithm) can be shared. Yet, if there is a centralizing force, it is in the labour market for software. In order for ML to be useful, it requires labour to prepare data for analysis, train the model, and productionize it for real-world use. Technology incumbents are aggressively hiring sparse global talent, limiting the ability for the rest of the economy to access top talent. In late 2017, Tencent published a report stating that there are roughly 300,000 AI researchers and practitioners globally—far short of market demand in the millions.

Data to train learning algorithms are paradoxically ubiquitous and sparse, and do not yet provide a clear indicator on market structure. Data are costly to collect, cheap to store, and equivocal in value. High costs reflect capital-intensive investments to capture data, which is somewhat reconciled by an often-low marginal cost of acquiring data once the foundation is set. Of an amassed volume of data, only a small fraction can be valuable—suggesting that while incumbents lead in *quantity* of data, a *high-quality* dataset can be obtained by firms of any size to build certain competitive ML systems. It remains to be seen whether advances in AI like transfer learning and reinforcement learning will increase or decrease the importance of data.

Overall, the market structure of ML suggests that it equips firms in other industries to challenge their respective incumbents. Outside of universities, its development is predominantly influenced by a handful of firms. AI is centralized within its own sector, but is an entropic force to other sectors of the economy.

The Restructuring Ahead

AI is an omni-use, general-purpose technology (GPT) that is at the early stages of restructuring global factors of production. Just as the computer's core functionality of arithmetic changed the nature of how the global economy operates, AI's ability to make inferences—perhaps addressing Hume's problem of epistemology—is poised to affect virtually all industries. What follows is a cursory exploration of how two capabilities of AI could impact labour and capital.

AI’s predictive capabilities may influence the composition of labour markets. One way to simplify AI is to think of it as a technology for prediction—which is the process of filling in missing information (Agrawal, Gans, and Goldfarb 2018). While this definition of prediction may be overbroad, it enables economic analysis on how AI impacts decision making, which lies at the core of many tasks people perform. Decision making involves applying *judgement* to a *prediction* in order to make an *action* that leads to an outcome. If AI lowers the cost of prediction, there are three implications: the value of human prediction will decrease; cheaper AI will increase the volume of predictions; and the value of human judgement will increase (humans are highly capable at expressing the relative rewards from taking different actions). This suggest that existing jobs will face either contraction, augmentation, or skill reconstitution, and new jobs may be created from savings on labour expenditures being spent or invested elsewhere in the economy.

Yet, the effects of AI are not apparent in productivity statistics (Brynjolfsson, Rock, Syverson 2017). One explanation is that while AI is being used in concentrated pockets, there is a time lag between its development and its complete impact. This restructuring lag is a result of the time to build AI into systems, and the dependency on complementary innovations to realize its full benefit. We cannot see productivity improvements now, but we can expect them in the future.

Meanwhile, the world’s capital stock—machines, tools, and other artifacts which are used in the production of goods—may be restructured from AI’s creative capabilities. Carpo (2018) contrasts the design-to-production workflow of industrial-age tools to AI-powered tools. Industrial production is based on mass production and economies of scale. Because costly, specialized machinery to make products was required, it made sense to use it to make as many goods as possible, amortize their cost, and employ marketing to boost demand. In contrast, AI-era production shares similarities with the pre-industrial artisan economy. AI alters the way products are designed using generative algorithms that generate many possibilities. As these designs are passed to additive and subtractive digital fabrication—which forgo mechanical matrixes, casts, and molds—a flat marginal cost model emerges where economies of scale for products does not apply; every product can be different for the same cost (save differences in material costs). Yet, this model is not advantageous for products that benefit from standardization. AI is often used to improve industrial workflows but—depending on evolving consumer preferences, material costs, and adjacent innovations—could enable an expansion of the domains where it fundamentally changes how goods are produced.

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