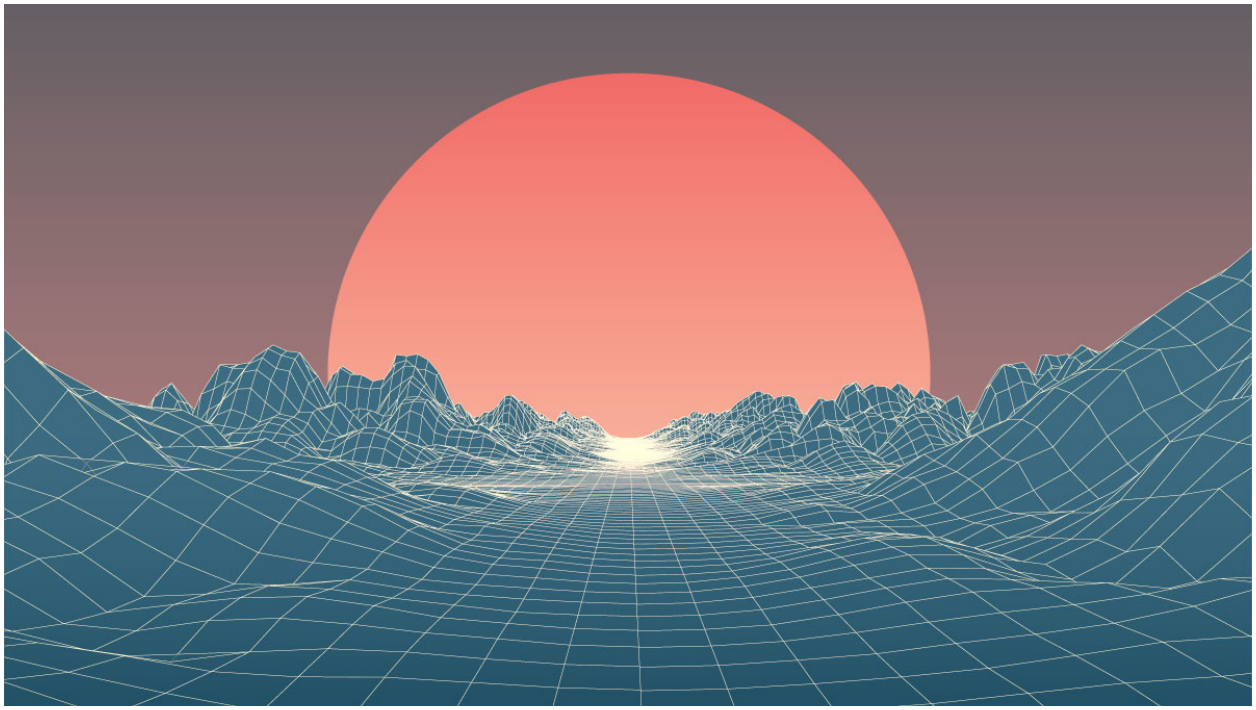
HARVARD BUSINESS REVIEW NOVEMBER 17, 2016
https://hbr.org/2016/11/the-simple-economics-of-machine-intelligence

The Simple Economics of Machine Intelligence

by Ajay Agrawal, Joshua Gans, and Avi Goldfarb



The year 1995 was heralded as the beginning of the "New Economy." Digital communication was set to upend markets and *change everything*. But economists by and large didn't buy into the hype. It wasn't that we didn't recognize that something changed. It was that we recognized that the old economics lens remained useful for looking at the changes taking place. The economics of the "New Economy" could be described at a high level: Digital technology would cause a reduction in the cost of search and communication. This would lead to more search, more communication, and more activities that go together with search and communication. That's essentially what happened.

Today we are seeing similar hype about machine intelligence. But once again, as economists, we believe some simple rules apply. Technological revolutions tend to involve some important activity becoming cheap, like the cost of communication or finding information. Machine intelligence is, in its essence, a prediction technology, so the economic shift will center around a drop in the cost of prediction.

The first effect of machine intelligence will be to lower the cost of goods and services that rely on prediction. This matters because prediction is an input to a host of activities including transportation, agriculture, healthcare, energy manufacturing, and retail.

When the cost of any input falls so precipitously, there are two other well-established economic implications. First, we will start using prediction to perform tasks where we previously didn't. Second, the value of other things that complement prediction will rise.

Lots of tasks will be reframed as prediction problems

As machine intelligence lowers the cost of prediction, we will begin to use it as an input for things for which we never previously did. As a historical example, consider semiconductors, an area of technological advance that caused a significant drop in the cost of a different input: arithmetic. With semiconductors we could calculate cheaply, so activities for which arithmetic was a key input, such as data analysis and accounting, became much cheaper. However, we also started using the newly cheap arithmetic to solve problems that were not historically arithmetic problems. An example is photography. We shifted from a film-oriented, chemistry-based approach to a digital-oriented, arithmetic-based approach. Other new applications for cheap arithmetic include communications, music, and drug discovery.

The same goes for machine intelligence and prediction. As the cost of prediction falls, not only will activities that were historically prediction-oriented become cheaper — like inventory management and demand forecasting — but we will also use prediction to tackle other problems for which prediction was not historically an input.

Consider navigation. Until recently, autonomous driving was limited to highly controlled environments such as warehouses and factories where programmers could anticipate the range of scenarios a vehicle may encounter, and could program if-then-else-type decision algorithms accordingly (e.g., "If an object approaches the vehicle, then slowdown"). It was inconceivable to put an autonomous vehicle on a city street because the number of possible scenarios in such an uncontrolled environment would require programming an almost infinite number of if-then-else statements.

Inconceivable, that is, until recently. Once prediction became cheap, innovators reframed driving as a prediction problem. Rather than programing endless if-then-else statements, they instead simply asked the AI to predict: "What would a human driver do?" They outfitted vehicles with a variety of sensors – cameras, lidar, radar, etc. – and then collected millions of miles of human driving data. By linking the incoming environmental data from sensors on the outside of the car to the driving decisions made by the human inside the car (steering, braking, accelerating), the AI learned to predict how humans would react to each second of incoming data about their environment. Thus, prediction is now a major component of the solution to a problem that was previously not considered a prediction problem.

Judgment will become more valuable

When the cost of a foundational input plummets, it often affects the value of other inputs. The value goes up for complements and down for substitutes. In the case of photography, the value of the hardware and software components associated with digital cameras went up as the cost of arithmetic dropped because demand increased – we wanted more of them. These components were complements to arithmetic; they were used together. In contrast, the value of film-related chemicals fell – we wanted less of them.

All human activities can be described by five high-level components: data, prediction, judgment, action, and outcomes. For example, a visit to the doctor in response to pain leads to: 1) x-rays, blood tests, monitoring (data), 2) diagnosis of the problem, such as "if we administer treatment A, then we predict outcome X, but if we administer treatment B, then we predict outcome Y" (prediction), 3) weighing options: "given your age, lifestyle, and family status, I think you might be best with treatment A; let's discuss how you feel about the risks and side effects" (judgment); 4) administering treatment A (action), and 5) full recovery with minor side effects (outcome).

As machine intelligence improves, the value of human prediction skills will decrease because machine prediction will provide a cheaper and better substitute for human prediction, just as machines did for arithmetic. However, this does not spell doom for human jobs, as many experts suggest. That's because the value of human judgment skills will increase. Using the language of economics, judgment is a complement to prediction and therefore when the cost of prediction falls demand for judgment rises. We'll want more human judgment.

For example, when prediction is cheap, diagnosis will be more frequent and convenient, and thus we'll detect many more early-stage, treatable conditions. This will mean more decisions will be made about medical treatment, which means greater demand for the application of ethics, and for emotional support, which are provided by humans. The line between judgment and prediction isn't clear cut – some judgment tasks will even be reframed as a series of predictions. Yet, overall the value of prediction-related human skills will fall, and the value of judgment-related skills will rise.

Interpreting the rise of machine intelligence as a drop in the cost of prediction doesn't offer an answer to every specific question of how the technology will play out. But it yields two key implications: 1) an expanded role of prediction as an input to more goods and services, and 2) a change in the value of other inputs, driven by the extent to which they are complements to or substitutes for prediction. These changes are coming. The speed and extent to which managers should invest in judgment-related capabilities will depend on the how fast the changes arrive.

Ajay Agrawal is the Peter Munk Professor of Entrepreneurship at the Rotman School of Management, University of Toronto. He is also a Research Associate at the National Bureau of Economic Research in Cambridge, MA, co-founder of The Next 36, founder of Creative Destruction Lab, and Academic Director of the Centre for Innovation and Entrepreneurship.

Joshua Gans is professor of strategic management at the Rotman School of Management. His latest book, *The Disruption Dilemma,* is published by MIT Press.

Avi Goldfarb is Professor of Marketing at the Rotman School of Management, University of Toronto.