Prediction machines the simple economics of artificial intelligence pdf

I'm not robot!

Prediction Machines: The Simple Economics of Artificial Intelligence by Ajay Agrawal, Joshua Gans, and Avi Goldfarb I read this in Fall of 2019 while on vacation. Key Message – The key point of the book is that Artificial Intelligence (AI) technologies will make prediction cheaper and will follow the laws of economics that when the price of something falls, we consume more of it ~ so we will be using a lot more prediction and in areas where it has not been used before. The drop in the cost of prediction will in turn impact and raise the value of substitutes (human prediction). The authors point out that Google made search cheaper; the rise of the internet caused a drop in the cost of distribution and communication and comm flipping on a light switch. Prediction and Decision – Prediction is a key component of any decision but it is not the only component. The other elements of a decision—judgment, data, and action—remain, for now, firmly in the realm of humans. They are complements to prediction meaning they will increase in value as prediction becomes cheaper. Judgment involves determining the relative payoff associated with each possible outcome of a decision, including those associated with mistakes. By lowering the cost of prediction, there will be an increase in the value of understanding the rewards associated with mistakes. By lowering the cost of prediction, there will be an increase in the value of understanding the rewards associated with mistakes. transforming transportation into a prediction problem by minimizing waiting times of riders with available drivers. Prediction of credit card fraud has improved so much that credit card companies detect and address fraud before the users realize it. The enhanced prediction accuracy of ML techniques now enable them to perform tasks, such as translation and navigation, that were previously considered the exclusive domain of human intelligence. Humans vs Machine Predictions and are constantly making predictions regarding what we are about to experience—what we will see, feel, and hear. In contrast to machines, humans are extremely good at prediction with little data; for example managers make decisions on mergers, innovation, and partnerships without data on similar past events for their firms. Humans use analogies and models to make decisions in such unusual situations. Unlike humans, if something has never happened before, a machine cannot predict it. Humans have two types of data that machines don't. First, human senses are powerful. In many ways, human eyes, ears, nose, and skin still surpass machine capabilities. Second, humans are the ultimate arbiters of our own preferences and this is data that humans have that machines do not about individual preferences. Such data has value, and companies currently pay to access it through discounts on using loyalty cards and making searches and e-mails free online. The biggest weakness of prediction machines is that they sometimes provide wrong answers that they are confident are right. How can machines help human decisions – Machine prediction can enhance the productivity of human prediction via three broad pathways. The first is by providing an initial prediction that humans can use to combine with their own assessments. The second opinion after the fact, or a path for monitoring. Third, a major benefit of prediction machines is that they can scale in a way that humans cannot. Future Outlook - In the absence of good prediction, we do a lot of "satisficing," making decisions that are "good enough" given the information available. Always leaving early for the airport and often waiting once you arrive because you're early is an example of satisficing. It is not intuitive for most people to think of airport lounges as a response to a poor prediction but that is a key reason they are there and so airport lounges will be less valuable in an era of powerful prediction machines. More prediction machines most likely to be fully automation will follow; tasks most likely to be fully automated first are the ones for which full automation will follow; tasks most likely to be fully automated first are the ones for which full automation will follow; tasks most likely to be fully automated first are the ones for which full automation will follow; tasks most likely to be fully automated first are the ones for which full automation will follow; tasks most likely to be fully automated first are the ones for which full automation will follow; tasks most likely to be fully automated first are the ones for which full automation will follow; tasks most likely to be fully automated first are the ones for which full automated computer revolution, it will take time to see productivity gains from AI in many mainstream businesses. In deciding how to implement AI, companies will break their work flows down into tasks, estimate the ROI (Return on Investment) for building or buying an AI to perform each task, rank-order the AIs in terms of ROI, and then start from the top of the list and begin working downward. The tasks likely to be automated are those where: (1) the other elements are already automated in coming years); (2) the returns to speed of action in response to prediction are high (e.g., driverless cars); and (3) the returns to reduced waiting time for predictions are high (e.g., space exploration). A limiting factor will be regulations; governments regulate activities that generate externalities. As noted in book, Goldman Sachs's CFO R. Martin Chavez recently remarked that many of the 146 distinct tasks in the initial public offering process were "begging to be automated" however since there is lot of regulation in an IPO there is minimal automation there now. A side effect of the increase in the number of lower-paid Uber drivers, we expect to see the same phenomenon in other areas and even medicine and finance. As noted, AI and people have one important difference: software scales, but people don't. This means that once an AI is better than humans at a particular task, job losses will happen quickly. Workers' income will fall, while that accruing to the owners of the AI will rise. AI might exacerbate the income inequality problem for two reasons. First, by taking over certain tasks and secondly AIs might increase competition among humans for the remaining tasks. Strategic Change – AI can lead to strategic change if all of these three factors are present: (1) there is a core trade-off in the business model (e.g., shop-thenship versus ship-then-shop); (2) the trade-off is influenced by uncertainty (e.g., higher costs from returned items due to uncertainty about what customers will buy); and (3) an AI tool that reduces uncertainty tips the scales of the trade-off so that the optimal strategy changes from one side of the trade to the other (e.g., an AI that reduces uncertainty by predicting what a customer will buy tips the scale such that the returns from a ship-then-shop model outweigh those from the traditional model). Use of AI has four implications for future jobs; AI tools may augment jobs, as in the example of spreadsheets and bookkeepers. AI tools may contract jobs, as in fulfillment centers. AI tools may lead to the reconstitution of jobs, with some tasks added and others taken away, as with radiologists. AI tools may shift the emphasis on the specific skills required for a particular job, as with radiologists. AI tools may lead to the reconstitution of jobs, with some tasks added and others taken away, as with radiologists. AI tools may shift the emphasis on the specific skills required for a particular job, as with school bus drivers. Future Job Skills and Performance Assessment – With the use of more AI based predictions, job responsibilities will have to become less explicit and more relational. Managers will evaluate and reward employees based on subjective processes and with performance reviews that take into account the complexity of the tasks. AI will shift HR management toward the relational and away from the transactional. The reason is twofold. First, human judgment, where it is valuable will be utilized more because it is difficult to program such judgment into a machine predictive means and criteria. Humans are critical to decision making where the goals are subjective. For that reason, the management of such people will likely be more relational. The employees' main role will be to exercise judgment in decision making and which by definition, cannot be well specified in a contract. Experience is a scarce resource, some of which will need to be allocated to humans to avoid deskilling. Importance of Data and Prediction – With AI, data plays three roles; like oil, data has different grades —training, input, and feedback data. First is input data, which is used to produce a prediction. Second is training data, which is used to generate the algorithm in the first place. Training data is used to train the AI to become good enough to predict in the wild. Finally, there is feedback data. Data has decreasing returns to scale: as you get more data, each additional piece is less valuable. From a business viewpoint, data might be most valuable if you have more and better data than your competitor. Increasing data brings disproportionate rewards in the market. Thus, from an economic point of view, in such cases data may have increasing returns to scale. Risks – AI carries many types of risk and six of the most salient types are these. Prediction machines and are more broadly vulnerable to attack by hackers. The diversity of prediction machines involves a trade-off between individual- and system-level outcomes. Less diversity may benefit individual-level performance, but increase the risk of massive failure. Prediction machines can be interrogated, exposing you to intellectual property theft and to attackers who can identify weaknesses. Feedback can be manipulated so that prediction machines learn destructive behavior. Background: What is Prediction is the process of filling in missing information you have (called "data") and uses it to generate information you don't have. What is regression? Prediction is done most commonly through regression which finds a prediction based on the average by maximizing what is called "goodness of fit." Machine Learning is now increasingly being used for prediction and an important difference between machine learning and regression is the way in which new models/techniques are developed. Traditional statistical methods like regression require the development of a hypotheses or a human intuition for model specification. However, machine learning has less need to specify in advance what goes into the model and can accommodate the equivalent of much more complex models with many more interactions between variables. via Books I read

