Blend: A Tapestry of Multi-Disciplinary Narratives

ENGLISH PART - II, MARATHI & HINDI

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17. Economic Impacts of Artificial Intelligence in India

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Introduction

Artificial intelligence questions OECD European Commission (AI) is a term used to describe machines performing human-like cognitive processes such as learning, understanding, reasoning and interacting. It can take many forms, including technical infrastructure (i.e. algorithms), a part of a (production) process, or an end-user product. AI looks increasingly likely to deeply transform the way in which modern societies live and work. Already today, smartphone smart assistants, such as Siri, perform a variety of tasks for users; furthermore, all Tesla cars are connected and things that any one of them learns are shared across the entire fleet. AI also matches prices and cars when one orders an Uber ride, and curates what social media offer to a user based on their past behavior. With the rise of AI come the important of how much it will affect businesses, consumers and the economy in more general terms. Employees are increasingly interested in knowing what AI means for their job and income, while businesses are also keen to find ways in which they can capitalize on the opportunities presented by this powerful phenomenon. There is a global accord that AI technologies have the potential to revolutionize production and contribute to addressing major global challenges, a view shared by organizations such as the and the . Rapidly increasing computing power and connectedness have made it possible to compile and share large volumes of valuable data, which is now more accessible than ever before. This has created momentum for AI technologies. Importantly, AI patents have been on the rise worldwide with a 6 % average yearly growth rate between 2010 and 2015, which is higher than the annual growth rate observed for other patents.

Methodology

The study is explanatory and secondary data sources are considered for understand the Economic impacts of artificial intelligence. The relevant material is collected from various sources like journals, magazines, web pages, Government Gazettes etc.

Objective of the Study

1. To study the machine learning to find behavioural variables.
2. To study the human prediction as imperfect machine learning.
3. To study theEconomic potential of AI.
4. To study theImpact on manufacturing.

Machine Learning to Find Behavioral Variables

Behavioral economics can be defined as the study of natural limits oncomputation, willpower and self-interest, and the implications of those limits formarket equilibrium. A different approach is to define behavioral economics more generally, as simply being open-minded about what variables are likely to influenceeconomic choices.One way to describe this open-mindedness is to list neighboring socialsciences which are likely to be the most fruitful source of explanatory variables-psychology, perhaps sociology (e.g., norms), anthropology (cultural variation incognition), neuroscience, etc. Call this the "behavioral economics borrows from itsneighbors" view.But the open-mindedness could also be characterized even more generally,as an invitation to machine-learn how to predict from the largest possible featureset. In the "behavioral economics borrows from its neighbors" view, features areconstructs and their measures contributed by different sciences. These could beloss-aversion, identity, moral norms, in-group preference, inattention, habit, modelfreereinforcement learning, etc.

Human Prediction as Imperfect Machine Learning

Some Pre-History of Behavioral Economics

Behavioral economics as we know it, and describe it nowadays, began tothrive when challenges to simple rationality principles (then called "anomalies") came to have rugged empirical status and to point to natural improvements intheory (Thaler, Misbehaving; Lewis, Undoing). It was common in those early days todistinguish anomalies about “preferences”, such as mental accounting violations of fungibility and reference-dependence, and anomalies about “judgment” oflikelihoods and quantities.Somewhat hidden from economists, at the time and even now, was the factthat there was active research in many areas of judgment and decision making (JDM) proceeding in parallel and conducted almost entirely in psychologydepartments and some business schools. JDM research was about those judgment“anomalies”. This research flourished because there was a healthy respect forsimple mathematical models and careful testing, which enabled regularities tocumulate and gave reasons to dismiss weak results. So that generalizability of lab results was implicitlyaddressed.An important ongoing debate in JDM was about the cognitive processesinvolved in actual decisions, and the quality of those predictions. There were plentyof careful lab experiments about such phenomena, but also an earlier literature onwhat was then called “clinical versus statistical prediction”. There lies the earliestcomparison between (primitive forms of) AI and (the judgment part of) behavioraleconomics.

Economic Potential of AI

The majority of studies emphasize that AI will have a significant economic impact. Research launched by consulting company Accenture covering 12 developed economies, which together generate more than 0.5 % of the world's economic output, forecasts that by 2035, AI could double annual global economic growth rates. AI will drive this growth in three important ways. First, it will lead to a strong increase in labour productivity (by up to 40 %) due to innovative technologies enabling more efficient workforce-related time management. Secondly, AI will create a new virtual workforce – described as 'intelligent automation' in the report – capable of solving problems and self-learning. Third, the economy will also benefit from the diffusion of innovation, which will affect different sectors and create new revenue streams.

It will boost standardization and consequently automation, as well as enhancing the personalization of products and services. PwC sees two main channels through which AI will impact on the global economy. The first involves AI leading to productivity gains in the near term, based on automation of routine tasks, which is likely to affect capital-intensive sectors such as manufacturing and transport. This will include extended use of technologies such as robots and autonomous vehicles. Productivity will also improve due to businesses complementing and assisting their existing workforce with AI technologies. It will require investing in software, systems and machines based on assisted, autonomous and augmented intelligence; this would not only enable the workforce to perform its tasks better and more efficiently but would also free up time allowing it to focus on more stimulating and higher value-added activities. Automation would partially remove the need for labour input, leading to productivity gains overall.

Impact on Manufacturing

AI is one of the cornerstones of the growing digitalization of industry ('Industry 4.0AI solutions OECD mainstream'). Technologies underpinning this process – such as IoT, 5G, cloud computing, big data analytics, smart sensors, augmented reality, 3D printing and robotics – are likely to transform manufacturing into a single cyber-physical system in which digital technology, internet and production are merged in one. In the smart factories of the future, production processes would be connected and would be fundamental in linking the machines, interfaces, and components (using, for example, visual recognition). Large amounts of data would be collected and fed into AI appliances, which would in turn optimize the manufacturing process. The reckons this use of AI can be 'applied to most industrial activities from optimizing multi-machine systems to enhancing industrial research'. Manufacturers would be able to access new markets, since their products would be more customized, varied and of higher quality. Although the building blocks already exist, Industry 4.0 may not be realized before the middle of the next decade, as it demands a combination of various technologies, which, according to some, will take 20-30 years to. The OECD forecasts that in the long-term, AI may lead to scientific breakthroughs that could even create entirely new, unforeseen industries.

Effects on Firms, Industries and Countries

McKinsey argues that AI and automation may on one hand facilitate the rise of massively scaled organizations, and on the other will enable small players and even individuals to undertake project work that is now mostly performed by bigger companies. This could spawn the emergence of very small and very large firms, the end result being a barbell-shaped economy in which mid-sized companies lose out. Other likely effects are increased competition, firms entering new areas outside their previous core business, and a deepening divide between technological leaders and laggards in every sector. 'Early adopters 'winner-takes all superstars OECD ', that is, companies that fully absorb AI tools over the next five to seven years, will most probably benefit disproportionately. At the other end of the spectrum would be the slow adopters or non-adopters, which are likely to experience some economic decline. The market share is likely to shift from the laggards to the front-runners, which would be able to gradually attract more and more of the profit pool of their industry. This would lead to a ' phenomenon, similar to what is currently observed on tech markets. Advances in AI and technology could enable front-runners to make a decisive break from the pack and become " enjoying the highest productivity levels. This can have significant consequences. For example, the has raised the question as to why apparently non-rival technologies are not diffused to all firms. It may well be that the widening productivity gap between firms can be attributed to the highly uneven process of technological diffusion, which favours global frontier firms over laggards.

AI impact on labour markets and redistributive effects of AI

If indeed technologies, such as AI, robotics and automation, are widely deployed across the economy, there will be job creation (as a result of demand in sectors that arise or flourish due to this deployment), as well as job destruction (replacement of humans by technology). As a 2018 meta-study Bruegel jobs job polarization patterns job creation of results shows, there is no consensus among experts, with predictions ranging 'from optimistic to devastating, differing by tens of millions of jobs even when comparing similar time frames'.Furthermore, is probable: lower-paid jobs that typically require routine manual and cognitive skills stand the highest risk of being replaced by AI and automation, while well-paid skilled jobs that typically require non-routine cognitive skills will be in higher demand. Studying the of previous industrial revolutions indicates that job destruction will be stronger in the short and possibly medium term, while will prevail in the longer term.

Selected Policy Implications

AI has significant potential to boost economic growth and productivity, but at the same time it creates equally serious risks of job market polarization, rising inequality, structural unemployment and emergence of new undesirable industrial structures. EU policy needs to create the conditions necessary for nurturing the potential of AI, while considering carefully how to address the risks it involves. A recent economic paper shows that if labour income distributing the gains does not benefit from the economic gains generated by AI, consumption may stagnate and restrict growth, thereby having an adverse effect on the economy. Questions about from AI are therefore fundamental in managing its outcomes. Tax policies could help to rebalance the shift from labour to capital, and shelter vulnerable groups from socio-economic exclusion. The European Political Strategy Centre describes the internal and external challenges the EU is facing.

The former include low investment and a slow uptake of AI technologies by companies and the public sector, and the necessity to establish a regulatory framework that does not stifle technological progress, while at the same time adhering to key fundamental EU principles. The centre suggests that the EU should address these by developing an investment-conducive framework and becoming a leader in setting global AI quality standards. A precondition to successfully harness the potential of AI is to develop relevant skills in education and work as well as funding research and pooling resources to deliver true EU added value. Importantly, the EU has the necessary tools, such as a powerful competition policy, to address market distortions and power asymmetries. Issues, such as responsibility and liability, security and safety of AI-driven decision-making, raise many questions that need to be addressed in the near future.

AI Technology as a Bionic Patch, or Malware, for Human Limits

We spend a lot of time in behavioral economics thinking about how politicaland economic systems either exploit bad choices or help people make good choices.What behavioral economics has to offer to this general discussion is to specify amore psychologically accurate model of human choice and human nature than thecaricature of constrained utility-maximization (as useful as it has been).AI enters by creating better tools for both making inferences about what aperson wants or will do. Sometimes these tools will hurt and sometimes they willhelp.

AI Helps

A clear example is recommender systems. Good systems are a kindof behavioral prosthetic to remedy human limits on attention and the resultingincompleteness of preferences.Consider Netflix movie recommendations. Netflix uses a person’s viewingand ratings history, as well as opinions of others and movie properties, as inputs toa variety of algorithms to suggest what content to watch. As their data scientistsexplained (Gomez-Uribe and Hunt, 2015):a typical Netflix member loses interest after perhaps 60 to 90 seconds ofchoosing, having reviewed 10 to 20 titles (perhaps 3 in detail) on one or two screens.

Conclusion

This chapter discussed three ways in which AI, particularly machine learning,connect with behavioral economics. One way is that ML can be usedto mine the large set of features that behavioral economists think *could*improve prediction of choice. I gave examples of simple kinds of ML (withmuch smaller data sets than often used) in predicting bargaining outcomes,risky choice, and behavior in games.The second way is by construing typical patterns in human judgment asthe output of implicit machine- learning methods that are inappropriatelyapplied. For example, if there is no correction for over fitting, then the gap between training set accuracy and test- set accuracy will grow and grow ifmore features are used. This could be a model of human over confidence. The third way is that AI methods can help people "assemble" preferencepredictions about unfamiliar products (e.g., through recommender systems)and can also harm consumers by extracting more surplus than ever before (through better types of price discrimination).

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