Analyzing Artificial Intelligence and Machine Learning’s Impact on the U.S. Economy and Jobs

Robert B. Cohen, PhD, Senior Fellow, Economic Strategy Institute, March 15, 2018

Changes in the Macro Economy and the Rise of Big Data

Previous analysis¹ predicted that nearly half of U.S. jobs would be at risk of being displaced due to the automation of more routine skills. A shortcoming of this work was its inability to estimate how the introduction of digital processes and operations built upon innovative computing and software might have more complementary impacts on key parts of the economy. This analysis addresses this gap.

As firms’ operations rely in a much greater way on data analytics and data-insights and Big Data, more intelligent analytics and improvements in software development processes are becoming more central to the success of operations and a key determinant of competitiveness. Once there is wider use of machine learning (ML), artificial intelligence (AI), visualization and other tools for sophisticated analytics, the performance improvements achieved by this new focus on data are likely to be more apparent:

1. Firms will need to analyze how new processes impact their operations. This will put a premium on their ability to capture and interpret data in “real time”.
2. Big Data will become indispensable. Firms’ now focus on sharpening their perception of what data are critical to business decisions, but this will reinforce it. They also will amass crucial data sets and to hire those with skills to manage and oversee them. Data and how it is harnessed will help determine a firm’s competitiveness.
3. To strengthen the benefits of data analysis, firms will redesign how they develop software to assess data and interpret the performance of processes. This will accelerate the deployment of more streamlined tools.

Our approach to discern the impact of AI and ML is to focus on the scale and growth of intelligent functions. This perspective places analytics in a central economic role; analytics implement new efficiencies throughout the economy. If we add intelligence² to our analysis of the roll-out or growing scale in which AI and ML are employed, we can define several levels of scaling or optimization that characterize how these technologies are applied in business processes:

1. Asset optimization – based upon the Internet of Things, networks of sensors and data analytics. This reflects an increase in the management of individual pieces of equipment or services. Here, optimization relies upon data analysis and data science.
2. Facilities optimization – based on Application Performance Management (APM)³ as well as the initial stages during which machines will learn to make decisions about operations in concert with

human operators and managers. “Brilliant” or intelligent factories define when firms reach this stage.

3. Fleet optimization - where fleets of planes or other means of transportation, groups of factories or large facilities such as hospitals employ analytics such as APM to manage operations in addition to ML. This stage represents a linking together of intelligent factories to create interactive and interconnected systems.

4. Network or Ecosystem optimization – where intelligent systems of operations – factories and service delivery facilities -- automatically decide how to adjust ecosystems of factories, planes, power systems, or hospitals. This will rely upon interactive, sophisticated, digital modeling.

Several related “gating factors”⁴ or facilitators are likely to determine how rapidly AI and ML scale up in different industries. These include⁵:

1. The speed of core computing technology. This encompasses improvements in areas such as Natural Language Processing that are moving twice as rapidly as the pace of Moore’s law’s historic pace for semiconductors. Intel’s Nirvana roadmap and NVIDIA’s roadmap demonstrate the rapid increase in flops per second, although the rapid increase in speed is creating a power challenge. The NVIDIA TensorRT3 programmable inference processor and the Tesla 100 HGX-1 accelerator dedicated to AI applications⁶ are good examples of changes in computing power that are likely to influence the adoption of AI. An influential innovation in this area is the ability to capture and analyze data in real time. This is the aim of Amazon’s Kinesis Firehose⁷, Amazon Kinesis Data Analytics⁸, Amazon Aurora and Amazon Aurora Serverless⁹ tools. The Aurora serverless tool permits developers to focus on application development because it automates the provisioning of computing and storage resources.

2. The use of Open Source platforms to define common solutions that can be adopted across industries. This also shifts innovation to the application level.

3. Advances in algorithms or programming languages that support software development. This includes how efficiently Big Data can be analyzed.

4. Changes in software architecture, such as the increasing adoption of microservices architecture.¹⁰

---

⁴ We use this term to indicate that these factors can accelerate or retard, i.e., turn on or turn off the adoption of AI and ML. This parallels its use in electrophysiology, where gating signifies the activation or deactivation of ion channels.


5. The amount of data that is being created, particularly through the Internet of Things, or real world digital data.
6. The creation of broad standard platforms\textsuperscript{11} for AI and ML that simplify their adoption in a range of different industries. One complement to this may be Ceph, the free-software storage platform.\textsuperscript{12}
7. The amount of venture capital.

Research Approach

The characteristics we use to describe the impact of AI and ML suggest several approaches could be productive:

1. Develop a forecast for key industries that adopt AI and ML, often with IoT, and explore how this adoption would happen; i.e., what “gating” factors might affect the ramp-up. Peter Evans and Marco Annunziata\textsuperscript{13} suggest this approach for capturing the importance of scale and intelligence.
   a. To get a better idea of gating factors and their importance, we could perform a factor or cluster analysis to get a better idea of which “gating” factors are more closely related to the scaling out of AI and ML.
   b. It might also be possible to compare many industries that deploy AI and ML with a group that does not. This approach would make it possible to do a “difference in the differences” analysis, with the “non-adopters” serving as a control group. This analysis might be repeated using other statistical techniques.
2. A factor analysis with data on industries that are early adopters of AI and ML. We would hypothesize that this would result in a series of driving variables that combine several “gating” factors with traditional variables such as the scale and intelligence levels in AI and ML deployments.
3. A regression analysis that explains the scale of the growth of AI and ML or the combined scale and intelligence represented in AI and ML. This analysis could be developed to incorporate the importance of the “gating factors” and facilitators mentioned above.

We believe the measurement challenge is a multidimensional one. We plan to proceed in the following way:

1. Develop case studies of the benefits that early enterprise adopters of smart or “brilliant” factories obtain as they move beyond early data analysis of the Internet of Things. Among the early adopters are Intel, NVIDIA, Microsoft, GE, Goldman Sachs, Bank of America, Proctor & Gamble, Nordstrom, the National Institutes of Health, and Pitney Bowes.

\textsuperscript{11} This idea is proposed in Chris Thomas, “How A.I. is Different in China,” as posted in Jeffrey Towson, “What Everyone is Getting Wrong about Artificial Intelligence in China,” January 28, 2019.
\textsuperscript{12} “Ceph (software), Wikipedia. https://en.wikipedia.org/wiki/Ceph\_\_software"
\textsuperscript{13} Peter C. Evans and Marco Annunziata, pp. 9, 19-30.
2. Develop measures of the economic benefits of AI and ML based upon these case studies. In a previous study, we identified four groups of industries\(^4\) based upon the speed of their deployment of software-defined cloud computing. We will evaluate whether this early estimation is valid for the analysis of the deployment of AI and ML in addition to The Internet of Things.

3. Develop estimates of the economic gains due to AI and ML by groups of industries and develop a forecast for the impacts of these gains that focuses on the scale and intelligence in the deployment of AI and ML as well as the “gating factors” that could accelerate or retard their adoption.

4. Complement this analysis by examining the demand for jobs that require AI and ML. We will employ the Burning Glass job posting information to do this analysis (see below). This analysis may also help identify industries where the pace of adoption is moving faster or slower than the industry analysis may indicate. This would permit us to adjust the forecasts we prepare.

The results of this analysis should include:

1. Estimates of the benefits of AI and ML at an industry level assuming a certain pace for the deployment of the Internet of Things and software-defined cloud infrastructure.

2. A forecast of how substantial these gains could be to 2030, employing a multidimensional analysis of key driving factors, such as scaling, intelligence and “gating factors”.

3. Using the forecast of gains by industry to estimate the job gains that would be created in the economy. We’d estimate probable job displacement from AI and ML and use this estimate of displacement to forecast a “net” new jobs estimate for a range of industries and the economy.

4. Using the estimate new investment tied to AI and ML to model the macroeconomic impacts such as GDP gains. This would most likely require an input/output analysis to support a forecast based upon changes in investment and new consumption patterns. It would let us estimate productivity gains and price changes for the U.S. economy as well as for industries.

Analyzing the Job Impacts of AI and ML using emerging digital occupations focused on “intelligence” for analytics, computing and networking

We have developed a classification of three groups of emerging digital occupations:

1. Data analytics – data scientists and jobs in data governance, predictive analytics, process management, and data center functions.

2. Software development and deployment – jobs with skills in software engineering, DevOps, Docker/Containers, microservices and serverless computing.

3. “Intelligence” for analytics, computing and networking – jobs in artificial intelligence and machine learning, business intelligence, cybersecurity, and network virtualization.

Firms’ perceived greater value for the data they collect from their web-based and internal operations is likely to transform the **skills** needed for these jobs. It is now more critical to capture and analyze this data

in “real-time”. This insures that unwanted intrusions do not persist and cause operational problems. Firms also want to know that new software programs are functioning properly.

As firms become more dependent on data, they need to refine how they oversee and monitor complex systems for manufacturing, service delivery and analytics. These jobs will demand human judgement and new skills to support “data-related” functions in the modern firm.

Important **new skills** are likely to be needed to manage and oversee Big Data, more intelligent analytics and software development processes that will be central to businesses operations. Some of these changes will be encouraged by wider use of ML, AI, visualization and other tools for sophisticated analytics.

While firms are just beginning to adopt more intelligent analytics and the impact on the workforce is difficult to forecast, we expect many new jobs will require high school and less-than-college-level degrees. Here are a few examples of these jobs:

1. “Domain Experts” In machine learning, there will be a need for people who are domain experts. They learn what data are crucial to evaluate a specific industry. This will support the development of machine learning software. These support jobs would offer middle-level salaries and seek high school or junior college graduates.
2. “Data Interpreters” -- Artificial intelligence can analyze project performance and provide insights that improve sales and marketing or predict staffing requirements. This will open middle-level positions for sales and marketing staff who can analyze the results and explain them to managers as well as employees involved in service delivery. There should also be opportunities for human resources employees who need to understand recommendations from analytic systems.
3. “Marketing Trend Evaluators” -- Software providers are building artificial intelligence into their products. For instance, Salesforce has developed “Einstein Discovery”\(^\text{15}\) -- using data on customer relationships, such as sales and profitability – to give firms more insights about marketing, operations management and data development efforts. By including these tools within a packaged service, employees with without university degrees can understand the analytic insights that “Einstein Discovery” provides. These employees can interpret trends that affect sales and marketing. Many of the employees interpreting these findings are likely to be high school or junior college graduates, not Ph.D. data scientists.
4. “Data Governance and Data Management Professionals” -- As “intelligent” analysis provides firms with more insights into their operations, the size of the data that they need will expand. This will require more people to collect and manage data bases as well as employees to support the hardware and software systems that companies have built. This should expand demand for jobs with middle-level salaries that understand data collection and data storage. This demand is likely to grow as firms expand their data resources. The same phenomenon may characterize professional services firms that support data analytics and services providers that maintain data centers and process information.

5. “On-Demand Support Staff” – As firms develop more service-oriented areas of their business, such as GM’s new on-demand, Zip Car-like, Maven startup\(^\text{16}\) they need employees to manage and support the vehicles that they provide. This will be more like a garage management function and will not require high levels of education.

Research Approach

Our approach is to explore job posting data to analyze the skills required for jobs that request AI and ML skills. We would estimate the number of these requests by industry, evaluate how they are changing over time, examine the salaries that are common to the postings, and evaluate which firms are the main ones requesting these jobs.

Results of this analysis

1. What are the skill characteristics of new digital jobs that include “intelligence” – jobs in artificial intelligence and machine learning, business intelligence, cybersecurity, and network virtualization?
2. How rapidly have postings, i.e., advertisements, for these jobs been growing?
3. What industries have been the key ones hiring different types of “intelligent” digital jobs?
4. How do these jobs compare to other digital jobs such as data analysts, data scientists and DevOps professionals?
5. What related jobs for “Domain Experts,” “Data Interpreters,” “Marketing Trend Evaluators,” “Data Governance and Data Management Professionals,” and “On-Demand Support Staff” are likely to develop in concert with the growth of ‘intelligent’ digital occupations?
6. What jobs that support or service “intelligent” digital occupations are also beginning to emerge as these occupations expand?