Adjusting to Autonomous Trucking

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News coverage of automation and machine learning tends to focus on extraordinary events, such as computers winning at Jeopardy and Go, and robotic arms flipping burgers in short-order restaurants. Additional headlines foster a sense of nightmares, conjuring pictures of autonomous cars killing pedestrians and newly automated establishments laying off their workforce. The combination of headlines has unleashed a near-hysteria, as if the near-future Terminator will either kill humans indiscriminately or rob the survivors of employment.

Let’s come into contact with a grounded sense of the future. Some of this sour hype obscures the real technical improvement arising from advances in machine learning, neural networks, sensors, data access and retrieval, and systems engineering. Humans have invented tools for repetitive tasks, and some of those tools are becoming less expensive and more reliable.

This column stresses the basic economic lessons that inform a grounded view. Said simply, where the investments pay off quickly, firms will make use of tools. Experiments are looking for such payoffs right now. However, even with such payoffs, adjustments tend to take time and will slow adoption and change.

Autonomous trucking provides a good example. Considerable economic gains could be had from implementing some basic automation and machine learning in the trucking industry. Such automation will most likely be implemented at scale sometime in the next decade. What will happen to the 3.5 million truck drivers in the US who are focused on keeping their jobs? The basic point of this column is familiar to the experts in the area: Total employment is not at risk in the next decade, but it would not be surprising if a few job titles and assignments change. The hysteria simply gets it wrong.

MARGINS OF ADJUSTMENT

There is plenty of motivation for automating long-haul trucking. Of all trucking jobs, long haul is the most difficult to fill and staff. The work can be uncomfortable. It also creates enormous value in the US, annually carrying freight worth quadrillions—that is not a misprint (quadrillions comes after billions and trillions). Any productivity improvement yields enormous payoff.

Many of the increasingly useful and common forms of machine learning in trucking continue trends seen earlier. New algorithmic loops for error correction take advantage of improving processors. The training sets have become larger, and the maps include more detail, taking advantage of improving memory. Developers now see the potential for placing software on a server in one location, and it is possible to coordinate many users in other locations, taking advantage of improving network infrastructure.
To be sure, trucking has already taken advantage of many advances in electronics. Most trucks contain on-board computers, GPS links, and numerous systems to monitor performance. In many trucks today, the software already moves with the machine. The sensors on mobile vehicles have also improved, and, again, the better software allows for a wider range of situations where the system can operate.

Not all is familiar, however. Many experts forecast that the next wave of sensors and software will address new applications in trucking, as part of a general wave of developments in autonomous vehicles. That forecast comes from borrowing progress in autonomous cars, and in spite of some basic technical issues that constrain progress in autonomous trucking. Trucks are much larger than most vehicles and carry a variety of payloads. Plus, they have their own patterns for accelerating and stopping. They also have rather different utilization records than a taxi or a commuter vehicle. The newest prototypes for autonomous trucking differ so much from those used in smaller cars that autonomous trucks cannot merely borrow the “training” from cars.

Trials in long-haul trucking involve training the vehicles for trips between depots adjacent to highways. At those depots, the trucks are handed off to drivers, who take them into cities for short-haul delivery. Judging from recent prototypes, humans are not disappearing anytime soon. Nobody is talking about installing robots in trucks to do the loading and unloading. The hard work today focuses on other high-value propositions, such as reducing safety issues from things like inattentive driving. A little automation can go a long way for that purpose—it can stop vehicles sooner, issue warnings to drivers, and relay information to dispatchers for use by others in a fleet. The prototypes also continue trends that began with the introduction of electronics into trucking long ago. Partial automation can enable longer continuous vehicle operation, better fuel consumption, and reduced maintenance expenses.

So what limits progress? Like many applications in machine learning, there are too many “edge cases” that the software cannot yet satisfactorily handle—such as road construction, vehicles stopped at the side of the road, detours, pedestrians on the side of the highway, dead animal carcasses in the road, and so on. AI researchers know this problem well. Routine work is not as routine as it seems. Humans are pretty good at handling millions of variants of the little unexpected aspects of road work, police stops, bad weather, poor drivers, and breakdowns.

The statistics of edge cases are quite demanding. Software can be trained to handle much of this, perhaps 99 percent of the issues in a typical drive. But 99 percent is not anywhere near good enough. If, say, 1 percent is still left for humans, that translates into more than half a minute every hour in which a human needs to intervene. It is necessary to do much better than that to justify removing constant human awareness, and much better performance is required to get a sufficient return on the investment in the equipment to make it all work. In the lingo of the industry, partial or conditional automation is the most ambitious goal for the next several years. Full automation is a long way off.

**SCALING**

Any engineer in this area will say the same thing: There are many steps between prototypes and large-scale implementation of a fleet of partially autonomous vehicles. Now I say this: Scaling is exactly the topic in which some economic reasoning provides better guidance than hysterical forecasts.
Scaling requires predictable business processes that can be measured and monitored. The drivers might actively drive less, but they still might help with aspects that affect fueling, safety, liability, and loading and unloading. Take the use of autopilot in commercial airlines today; software-enhanced navigation merely changes what the pilots do and when they apply their expertise.

We should expect that business processes will adjust and adopt new routines. The timing for fueling, maintenance, docking, and inspection will change. New procedures for monitoring daily, weekly, and monthly targets will be put in place. Will that eliminate work? No, but it will shift who does the work, what they do, and how they are trained to do it.

The new timing will require new principles for organizing teams. The new teams will require new principles for responsibility. For example, who pays for the costs of error—the driver or the programmer? Beyond that, economics provides reasons to be cautious. Learning will lead to new services—say, driving in the middle of the night when there’s less traffic. Those new services might also come with new potential logistical limitations, such as inability to drive in certain weather or road conditions.

Will that change work at the organizational level? Yes, sure, and even if we cannot precisely forecast how, it is clear where the type of work will change. The planning department will tackle new issues. So will the legal team, the logistics department, the business partnership liaisons, the sales department, and the billing group. That will feed back into the R&D department, which will be asked to change what patents it applies for. Trucking companies will adjust on many margins to accommodate autonomous trucking at scale.

And here is the kicker. The reduction in cost might generate more demand for services, which might lead to more employment of truckers. It is hard to forecast the totality of all this change.

LESSONS

There was a point to this thought exercise. Let’s review the broad lessons.

There will be adjustments. Tasks will change and so will the regular processes that accompany the execution of these tasks. Team assignments and composition of teams will change, and so too will organizations that manage partnerships with these teams. These changes will be just as difficult to make as the technical inventions that precipitated them.

It is easy to see how the software will improve and bring about costs savings. Most of the consequences are, however, rather unpredictable. When will the biggest technical gains emerge? Will the cost savings be substantial enough to alter productivity and pricing?

And what about employment? Will total employment in trucking go up or down in the next decade as a result of the increasing use of autonomous vehicles? While tasks might change in ways to diminish the need for some work, the costs might lead to an increase in volumes and increase the demand for work. On net, there is no way to predict with certainty. That said, massive layoffs or other employment nightmares are highly unlikely.

CONCLUSION

Gains in neural networks have gone beyond what had been widely appreciated in public conversation. There is much productivity improvement on the near-term horizon. More to the point, there is not much merit to most of the hysteria behind machine learning. There is a lot we have to learn. In the meantime, we all need to keep on trucking, because society is all in for the long haul.

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