

In this feature, we highlight research from across Canada that asks relevant questions and offers insight and solutions to pressing transportation issues. For this edition, we consider social inclusion and automated vehicles.

Start Your Machine Learning Engines and Race to the Edge!

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A friend of mine, Adam, moves about the city in a very unusual and unexpected way. He propels himself backwards in his wheelchair with his feet. His pace is faster than most pedestrians and he cranes his neck to look behind him. His path is not straight and seems to be erratic at times. This is his most efficient and independent means of mobility given his cerebral palsy. Whenever he approaches an intersection he faces the risk that some well-meaning pedestrian will doubt his competency, sobriety and safety, grab his wheelchair, turn it around and push him back on the sidewalk. Clarifying his competency and intent is complicated by the fact that his speech is also affected by his cerebral palsy. He challenges the expectations of most humans not familiar with him personally; it is unlikely that he will be better understood by machines given the trajectory of machine learning. There are many individuals, like Adam, who do not follow expected patterns. If current machine learning strategies used to develop the artificial intelligence that controls automated vehicles do not consider outliers like Adam, they will dangerously amplify the impact of the lack of understanding.

One of the oft-cited promises of automated and connected vehicles is the benefit they can provide to persons with disabilities.¹ This is a compelling motivation, as almost all Canadians will experience a disability in their lifetime.² But **before an intelligent machine can be of help, it must understand us.** There is nothing more frustrating than negotiating with a machine that does not recognize our request, or that misunderstands our command. Automated and connected vehicles must balance a number of goals and priorities when choosing a course of action. This adds additional risk to the prospect of not being recognized because you are excluded from the machine intelligence models.

Machine intelligence is formed by machine learning engines using training data. A variety of learning processes (whether supervised or unsupervised by humans) are employed to use data to create models from which the intelligent machines recognize patterns, formulate inferences, and make decisions. Accuracy is honed through feedback processes that identify and correct mistakes. The emergence of "Big Data" and connected sensors and monitors (e.g.,

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smart phones, health and fitness monitors, security cameras, bio-sensors, connected vehicles, etc.) feed this machine learning, creating intelligence that is more comprehensive and detailed than ever before.

“Big Data” inherits methods from quantitative, statistics-based research. Data is “cleaned” or normed and thereby reduced to find dominant patterns and generalizable findings. This implies eliminating “noise” or outlying data that is assumed to be an anomaly that could muddy the conclusions. For automated vehicles, this data is used to recognize elements in the path and decide the best course of action. It is also used to recognize human commands. **However, people with disabilities are, by definition, different from the norm.** This difference, especially extreme difference, is predominantly treated as outlying data to be eliminated in the process of efficiently finding dominant patterns from which to make inferences.³

The effect of this data handling in machine decisions can already be felt in the failure to recognize impaired speech, process unusual requests, diagnose complicated illnesses, accept unusual applications, or give security access through unexpected biometrics. As machine intelligence permeates our daily lives, this effect will drive a larger wedge of disparity between those that are served and those that are not understood, recognized or served. The most pessimistic scenario is an exponentially amplified vicious cycle of exclusion for individuals already at the margins.³

There is a hopeful thread in this entangled and complex inevitability. As with all wisdom gained and substantiated by supporting precarious values such as accessibility and inclusion, we find that considering the edge benefits everyone. While it is more expedient to move quickly to

dominant patterns, if we learn from edge scenarios and develop our intelligence by exposure and understanding of diversity and difference, we gain in the long run. Intelligence that understands diversity and stretches to encompass the outliers is more noise tolerant, better at predicting risk and opportunity, more capable of processing the unexpected, more adaptable, and more dynamically resilient.⁴

The Inclusive Design Research Centre has challenged machine learning innovators and developers to participate in a “race to the edge.”⁵ Participating universities and colleges will be creating a series of secret tests to see which machine learning engine can effectively and efficiently address scenarios and requests that are not typical or average. The most popular machine learning developers have expressed interest in taking up the challenge. The race will begin this October with the release of the secret tests and the results will be publicly available through the [BIG IDeA website](#). It is hoped that this event will be one of many to enable more diversity supportive artificial intelligence.

As we delegate more and more tasks and decisions to machines, it is important that we attend to what we teach machines. Do our machines understand and serve individuals that are different, or fail to recognize and ignore anyone that does not conform to the model of an average human?



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