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Opinion

Too many AI researchers think real-world problems are not relevant

The community's hyperfocus on novel methods ignores what's really important.

by **Hannah Kerner** August 18, 2020

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Any researcher who's focused on applying machine learning to real-world problems has likely

These words are straight from a review I received for a paper I submitted to the NeurIPS (Neural Information Processing Systems) conference, a top venue for machine-learning research. I've seen the refrain time and again in reviews of papers where my coauthors and I presented a method motivated by an application, and I've heard similar stories from countless others.

This makes me wonder: If the community feels that aiming to solve high-impact real-world problems with machine learning is of limited significance, then what are we trying to achieve?

The goal of artificial intelligence (pdf) is to push forward the frontier of machine intelligence. In the field of machine learning, a novel development usually means a new algorithm or procedure, or—in the case of deep learning—a new network architecture. As others have pointed out, this hyperfocus on novel methods leads to a scourge of papers that report marginal or incremental improvements on benchmark data sets and exhibit flawed scholarship (pdf) as researchers race to top the leaderboard.

Meanwhile, many papers that describe new applications present both novel concepts and high-impact results. But even a hint of the word "application" seems to spoil the paper for reviewers. As a result, such research is marginalized at major conferences. Their authors' only real hope is to have their papers accepted in workshops, which rarely get the same attention from the community.

This is a problem because machine learning holds great promise for advancing health, agriculture, scientific discovery, and more. The first image of a black hole was produced using machine learning. The most accurate predictions of protein structures, an important step for drug discovery, are made using machine learning. If others in the field had prioritized real-world applications, what other groundbreaking discoveries would we have made by now?

This is not a new revelation. To quote a classic paper titled "Machine Learning that Matters" (pdf), by NASA computer scientist Kiri Wagstaff: "Much of current machine learning research has lost its connection to problems of import to the larger world of science and society." The same year that Wagstaff published her paper, a convolutional neural network called AlexNet won a high-profile competition for image recognition centered on the popular ImageNet data set, leading to an explosion of interest in deep learning. Unfortunately, the disconnect she described appears to have grown even worse since then.

The wrong questions

More than half of the images in ImageNet (pdf) come from the US and Great Britain, for example. That imbalance leads systems to inaccurately classify images in categories that differ by geography (pdf). Popular face data sets, such as the AT&T Database of Faces, contain primarily light-skinned male subjects, which leads to systems that struggle to recognize dark-skinned and female faces.

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When studies on real-world applications of machine learning are excluded from the mainstream, it's difficult for researchers to see the impact of their biased models, making it far less likely that they will work to solve these problems.

One reason applications research is minimized might be that others in machine learning think this work consists of simply applying methods that already exist. In reality, though, adapting machine-learning tools to specific real-world problems takes significant algorithmic and engineering work. Machine-learning researchers who fail to realize this and expect tools to work "off the shelf" often wind up creating ineffective models. Either they evaluate a model's performance using metrics that don't translate to real-world impact, or they choose the wrong target altogether.

For example, most studies applying deep learning to echocardiogram analysis try to surpass a physician's ability to predict disease. But predicting normal heart function (pdf) would actually save cardiologists more time by identifying patients who do not need their expertise. Many studies applying machine learning to viticulture aim to optimize grape yields (pdf), but winemakers "want the right levels of sugar and acid, not just lots of big watery berries," says Drake Whitcraft of Whitcraft Winery in California.

More harm than good

Another reason applications research should matter to mainstream machine learning is that the field's benchmark data sets are woefully out of touch with reality.

New machine-learning models are measured against large, curated data sets that lack noise and have well-defined, explicitly labeled categories (cat, dog, bird). Deep learning does well for these problems because it assumes a largely stable world (pdf).

But in the real world, these categories are constantly changing over time or according to likely to be no better than existing versions at representing real-world scenarios. The results could do more harm than good. People who might have been helped by these researchers' work will become disillusioned by technologies that perform poorly when it matters most.

Because of the field's misguided priorities, people who are trying to solve the world's biggest challenges are not benefiting as much as they could from AI's very real promise. While researchers try to outdo one another on contrived benchmarks, one in every nine people in the world is starving. Earth is warming and sea level is rising at an alarming rate.

As neuroscientist and AI thought leader Gary Marcus once wrote (pdf): "AI's greatest contributions to society … could and should ultimately come in domains like automated scientific discovery, leading among other things towards vastly more sophisticated versions of medicine than are currently possible. But to get there we need to make sure that the field as whole doesn't first get stuck in a local minimum."

For the world to benefit from machine learning, the community must again ask itself, as Wagstaff once put it: "What is the field's objective function?" If the answer is to have a positive impact in the world, we must change the way we think about applications.

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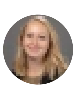
Author  Hannah Kerner