# Rise of the learning machines

Artificial intelligence deployment in photonics has spawned much research activity during 2020, but optimism must be balanced by realism. This month we celebrate the advances in the field with a focus issue.

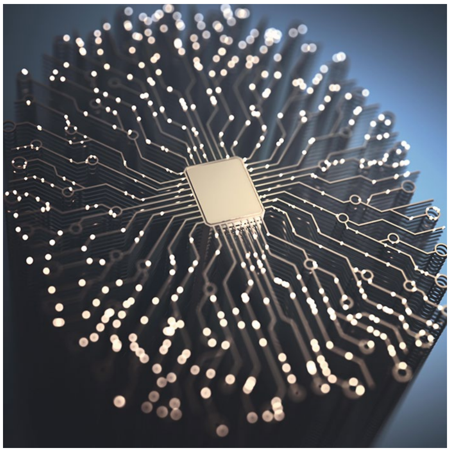
The refinement of data analysis techniques, stemming from well-known processes such as linear regression, has led to efficient 'machine learning' algorithms. The outcomes of these systems can improve and give the appearance of learning. In actuality there is no sentience; the 'learning' and output is predetermined by the human written code and data input. Nonetheless, such systems are adept at efficiently solving certain types of problems, such as image pattern recognition.

If machine learning algorithms are sufficiently complex and 'deep' in terms of the 'layers', then machine learning can become what is known as deep learning, neural networking, or deep-neural networking. All of these terms loosely fit under the umbrella of machine learning and 'artificial intelligence' algorithms; no matter the name, machine learning appears to be nearly unbounded in applications.

There appears to be particular synergy with photonics, especially in terms of power efficiency and parallelism. There are now two major thrusts to apply machine learning in photonics, as discussed in a Q&A by David Pile with Aydogan Ozcan.

One of the two main directions is using artificial intelligence algorithms, implemented on conventional computers, to design optical structures and devices with improved, task specific, performance. Although the approach does draw comparison with (non-machine learning) inverse-design algorithm approaches, the results are no doubt impressive and frequently surpass what can be achieved by human-controlled design. This does sometimes lead to a bit of a 'black-box' feeling, in which intuition and understanding can be lacking, but this situation may improve as researchers endeavour to interpret findings.

For a general overview and introduction to deep learning for the design of photonic structures see the Review by Wei Ma, Zhaocheng Liu, Zhaxylyk Kudyshev, Alexandra Boltasseva, Wenshan Cai and Yongmin Liu. They give a historical background, outline the algorithm fundamentals and then show how the models can be used to design photonic devices for specific tasks.



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The other, perhaps more ambitious, direction, is the attempt to implement artificial intelligence computation using optical systems, rather than electronic ones. Yet, this goal has been somewhat plagued, along with fields including optical logic devices and non-machine learning optical computation, by similar misunderstandings and false claims.

Logic gates, computation and neural networks, for example, are all necessarily active (nonlinear) phenomena that can't be realized with passive (linear) systems. The output of a linear system, for example conventional optical interference through slits, gratings or other passive structures, no matter how complex, may appear to provide logic (a dim 'zero' or a bright 'one', for example depending on where you observe, or by varying input) but the system does not, and cannot, actively vary the outcome. Researchers will often show that you can 'actively' change the outcome, achieving logic or computation, by varying the input or modifying the setup/structure, but in this case the 'active' component here is the experimentalist (for example adjusting a laser, or changing a structure), not the device itself. Similar arguments apply to artificial intelligence. For example, in the case of neural networks, an activation function is required and its purpose is to provide the required nonlinearity. There is a good reason that transistors (active/nonlinear devices) form the core or electronic processing units, rather than resistors, capacitors and inductors (typically passive linear components). All that said, the genuine progress being made is truly astounding.

The efforts to mimic neurobiological architectures of the nervous system in photonic systems and conduct neuromorphic computing are discussed by Bhavin Shastri, Alexander Taitc, Thomas Ferreira de Limab, Wolfram Perniced, Harish Bhaskarane, C. David Wright and Paul Prucnal in a Review. Photonic neuromorphic computation appears set to offer huge opportunities, such as sub-nanosecond latencies, but as outlined in the Review there are some real challenges needed to be overcome.

Speaking of rapid phenomena, an area in which machine learning may be particularly impactful is in its application to ultrafast photonics. In another Review, Goëry Genty, Lauri Salmela, John Dudley, Daniel Brunner, Alexey Kokhanovskiy, Sergei Kobtsev and Sergei Turitsyn discuss what has already been achieved, including the design and operation of pulsed lasers, and the characterization and control of ultrafast propagation dynamics, and outline future challenges.

The potential of machine learning reaches far beyond the conventional fodder of photonics researchers, as Sean Rodrigues, Ziqi Yu, Paul Schmalenberg, Jae Lee, Hideo Iizuka and Ercan Dede, from the Toyota Research Institute of North America, explain in their Correspondence. It's in applications such as autonomous vehicles, requiring limited numeric precision, high inference speed, and parallelism, that optical neural network processing may find the niche market it needs to find commercial success. ❐

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