Editorial

Photonics for computing and computing for photonics

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The liaison between photonics and computing is a pillar of modern optics and subject of cutting-edge research for more than half a century. As in many scientific disciplines, high-performance computational methods have become essential for describing, designing, interpreting and ultimately predicting an optical system's behaviour, and today the wide availability of high-performance photonic components is testimony of how computing has boosted the field of photonics. At the same time, photonic architectures offer fascinating possibilities for carrying out computations scaling beyond today's computing hardware. This establishes an almost uniquely reciprocal relationship between photonics and computing.

The interest in *photonics for computing and computing for photonics* is currently exploding despite decades of research activities. As the performance of standard digital computers is levelling out, new concepts such as neural networks (NNs) or combinatorial optimization in the form of Ising and XY machines lead the way to new frontiers in information processing and are already being explored with profound commercial relevance. These evolving concepts differ significantly from conventional computing paradigms, and the quest for new, better suited types of computing hardware is accelerating with photonics offering outstanding opportunities. Simultaneously, high-performance off-the-shelf computers can now model and design increasingly complex photonic devices and systems in great detail and accuracy. These developments have created unique conditions: photonics is a promising technology for the next generation of computing hardware, and at the same time, the recent progress of digital computers has enabled design, modelling and development of a new class of photonic devices and systems with unprecedented complexities.

Many demonstrations of computing schemes based on photonic systems have by now achieved seminal status within the optics community: this includes computational Fourier optics [1], the optical Hopfield network [2], NNs [3], digital photonic computing architectures [4], as well as the emulation and minimization of Ising and XY Hamiltonians [5]. For the most part, powerful computational concepts require nonlinearities, and the inverse design of such systems [6, 7] has significantly advanced thanks to adjoint methods [8]. This special issue on "*photonics for computing and computing for photonics*" provides a snapshot of the growing reciprocal relationship between photonics and computing through review and research articles.

Abdollahramezani et al. [9] review the potential of meta-optics for analogue optical computing, while Stark et al. [10] and Ferreira de Lima et al. [11] provide overviews of the field of NNs by, respectively, focussing on potential opportunities for integrating photonic NNs and a primer on silicon neuromorphic processors. Mengu et al. [12] report misalignment resilient diffractive optical networks, Dinc et al. [13] demonstrate computer generated optical volume elements fabricated by additive manufacturing, while Ahmed et al. [14] discuss integrated photonic Fourier transformations for optical convolutions towards efficient and high-speed NNs. Romeira et al. [15] investigate nano light-emitting diodes (nano-LEDs) for energy-efficient and gigahertz-speed spike-based subwavelength neuromorphic photonic computing, Estébanez et al. [16] accelerate photonic computing by bandwidth enhancement of a time-delay reservoir, while Andreoli et al. [17] report their findings for Boolean learning under noise perturbations in hardware NNs. Gershenzon et al. [18] establish an exact mapping between a laser network's loss rate and the classical XY Hamiltonian by laser loss control, Miri et al. [19] extend the field by optical Potts machines using networks of three-photon down-conversion oscillators, while Kalinin et al. [20] introduce new concepts for polaritonic XY-Ising Machines enabling long range coupling. Parto et al. [21] discuss nanolaser-based optical spin emulators, while Pierangeli et al. [22] introduce noise-enhanced spatial-photonic Ising machines. Finally, Christensen et al. [23] use predictive and generative machine learning models for photonic crystals.

In conclusion, this special issue provides introductions, reviews and current research articles covering the diverse interactions between photonics and computing with a focus on photonic NNs, photonic XY and Ising machines and the utilization of NNs for the design of photonic components. We hope that this collection of articles serves as inspiration for students and young as well as established researchers. We would like to thank the Nanophotonics Publishing editor

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References

[1] C. S. Weaver and J. W. Goodman, "A technique for optically convolving two functions," *Appl. Opt.*, vol. 5, no. 7, pp. 1248–1249, Jul. 1966.
[2] N. H. Farhat, D. Psaltis, A. Prata, and E. Paek, "Optical implementation of the Hopfield model," *Appl. Opt.*, vol. 24, no. 10, p. 1469, May 1985.
[3] Y. Shen, N. C. Harris, S. Skirlo et al., "Deep learning with coherent nanophotonic circuits," *Nat. Photon.*, vol. 11, pp. 441–446, June 2017.
[4] A. Szöke, V. Daneu, J. Goldhar, and N. A. Kurnit, "Bistable optical element and its applications," *Appl. Phys. Lett.*, vol. 15, no. 11, pp. 376–379, Dec. 1969.
[5] A. Marandi, Z. Wang, K. Takata, R. L. Byer, and Y. Yamamoto, "Network of time-multiplexed optical parametric oscillators as a coherent Ising machine," *Nat. Photon.*, vol. 8, pp. 1–6, Oct. 2014.
[6] T. W. Hughes, M. Minkov, Y. Shi, and S. Fan, "Training of photonic neural networks through in situ backpropagation and gradient measurement," *Optica*, vol. 5, no. 7, p. 864, Jul. 2018.
[7] E. Khoram, A. Chen, D. Liu, et al., "Nanophotonic media for artificial neural inference," *Photon. Res.*, vol. 7, no. 8, p. 823, Aug. 2019.
[8] T. W. Hughes, M. Minkov, I. A. D. Williamson, and S. Fan, "Adjoint method and inverse design for nonlinear nanophotonic devices," *ACS Photon.*, vol. 5, no. 12, pp. 4781–4787, Dec. 2018.
[9] S. Abdollahramezani, O. Hemmatyar, and A. Adibi, "Meta-optics enabled optical analog computing," *Nanophotonics*, vol. 9, no. 13, pp. 4075–4095, 2020.
[10] P. Stark, F. Horst, R. Dangel, J. Weiss, and B. J. Offrein, "Opportunities for integrated photonic neural networks," *Nanophotonics*, vol. 9, no. 13, pp. 4221–4232, 2020.
[11] T. Ferreira de Lima, A. N. Tait, A. Mehrabian et al., "Primer on silicon neuromorphic photonic processors: architecture and compiler," *Nanophotonics*, vol. 9, no. 13, pp. 4055–4073, 2020.
[12] D. Mengu, Y. Zhao, N. Yardimci, Y. Rivenson, M. Jarrahi, and A. Ozcan, "Misalignment resilient diffractive optical networks," *Nanophotonics*, vol. 9, no. 13, pp. 4207–4219, 2020.
[13] N. U. Dinc, J. Lim, E. Kakkava, C. Moser, and D. Psaltis, "Computer generated optical volume elements by additive manufacturing," *Nanophotonics*, vol. 9, no. 13, pp. 4173–4181, 2020.
[14] M. Ahmed, Y. Al-Hadeethi, A. Bakry, H. Dalir, and V. J. Sorger, "Integrated photonic FFT for optical convolutions towards efficient and high-speed neural networks," *Nanophotonics*, vol. 9, no. 13, pp. 4097–4108, 2020.
[15] B. Romeira, J. M. L. Figueiredo, and J. Javaloyes, "NanoLEDs for energy-efficient and gigahertz-speed spike-based sub-wavelength neuromorphic photonic computing," *Nanophotonics*, vol. 9, no. 13, pp. 4149–4162, 2020.
[16] I. Estébanez, I. Fischer, and A. Argyris, "Accelerating photonic computing by bandwidth enhancement of a time- delay reservoir," *Nanophotonics*, vol. 9, no. 13, pp. 4163–4171, 2020.
[17] L. Andreoli, X. Porte, S. Chrétien, M. Jacquot, L. Larger, and D. Brunner, "Boolean learning under noise-perturbations in hardware neural networks," *Nanophotonics*, vol. 9, no. 13, pp. 4139–4147, 2020.
[18] I. Gershenzon, G. Arwas, S. Gadasi et al., "Exact mapping between a laser network loss rate and the classical XY Hamiltonian by laser loss control," *Nanophotonics*, vol. 9, no. 13, pp. 4117–4126, 2020.
[19] M. Honari-Latifpour and M.-A. Miri, "Optical Potts machine through networks of three-photon down-conversion oscillators," *Nanophotonics*, vol. 9, no. 13, pp. 4199–4205, 2020.
[20] K. P. Kalinin, A. Amo, J. Bloch, and N. G. Berloff, "Polaritonic XY-ising machine," *Nanophotonics*, vol. 9, no. 13, pp. 4127–4138, 2020.
[21] M. Parto, W. E. Hayenga, A. Marandi, D. N. Christodoulides, and M. Khajavikhan, "Nanolaser-based optical spin emulators," *Nanophotonics*, vol. 9, no. 13, pp. 4193–4198, 2020.
[22] D. Pierangeli, G. Marcucci, D. Brunner, and C. Conti, "Noise-enhanced spatial-photonic Ising machine," *Nanophotonics*, vol. 9, no. 13, pp. 4109–4116, 2020.
[23] T. Christensen, C. Loh, S. Picek et al., "Predictive and generative machine learning models for photonic crystals," *Nanophotonics*, vol. 9, no. 13, pp. 4183–4192, 2020.

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