Training a Neural Network via All-Optical Coupling Control in Polariton Condensate Lattices

Eryk R. Imos[1], Luciano S. Ricco[2], and Helgi Sigurðsson[1,2]

[1] *Institute of Experimental Physics, Faculty of Physics, University of Warsaw, ul. Pasteura 5, PL-02-093 Warsaw, Poland*

[2] *Science Institute, University of Iceland, Dunhagi-3, IS-107 Reykjavik, Iceland*

Exciton-polariton condensates have recently been explored theoretically and experimentally as ultrafast nonlinear optical elements for both digital and analog computing [1]. This growing interest comes from their all-optical tunability and measuring their response *in situ*, as well as the possibility of building distinct lattice configurations using structured excitation light (e.g. spatial light modulators) [2]. In this scenario, we explore the possibility of employing a network of coupled polariton condensates as a oscillatory neural network (ONN), see Fig. 1(a). Distinct from previous works that mostly focus on reservoir computing [3] and binarized networks [4], here we propose a deep-learning device whose interactions between polariton condensates from distinct lattice sites are trainable by all-optical means [5]. We start our preliminary analysis by describing the condensate NN using the discretized driven-dissipative Gross-Pitaevskii equation (dGPE) [5]. In the limit of fast active reservoir relaxation, the dGPE particularly corresponds to the paradigmatic Stuart-Landau model (Hopf model) of phase and amplitude coupled oscillators [Fig. 1(b)]. Condensate networks undergo ultrafast synchronization into solutions that enable training i.e. nondirect information encoding. The system yields a variational energy function that depends on the condensate eigenstate, driving force and couplings. Given this variational feature, we propose equilibrium propagation [6] for ONN training, leveraging system dynamics for most required calculations in training and inference. We expect that through proper training of the synaptic weights, (inter-condensate interactions) and neuronal biases, (driving forces), the number of required neurons (condensates) will dramatically decrease, making a practical device design much more feasible. We further expect that our optical-based training strategies will enhance the overall energy efficiency of the proposed polariton ONN architecture while maintaining high accuracy.

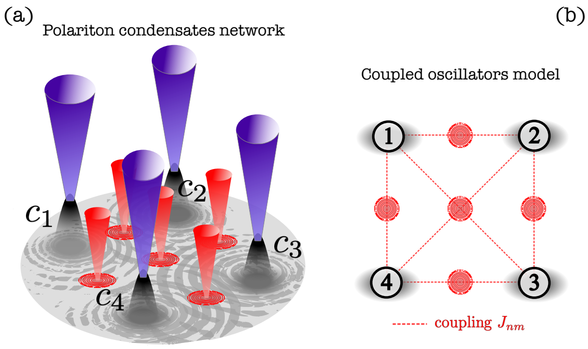

Figure 1: (a) Sketch of a representative NN of polariton condensates in a square lattice, with c_n describing each condensate ($n = 1, \ldots, 4$). Non-resonant pump beams (bigger cones) with power above the condensation threshold excite each condensate, while pumps below the condensation threshold (smaller cones) modulate the interaction between condensates from distinct sites and resonant driving beams (included in bigger cones) apply driving force to condensates. (b) Mapped NN from panel (a) into a four-coupled oscillator model.

[1] A. Opala and M. Matuszewski, *Opt. Mater. Express* **13**, 2674-2689 (2023).
[2] J. D. Töpfer, I. Chatzopoulos, H. Sigurðsson, et al., *Optica* **8**, 106–113 (2021).
[3] D. Ballarini, A. Gianfrate, R., A. Opala, et al., *Nano Letters* **20** (5), 3506-3512 (2020).
[4] R. Mirek, A. Opala, P. Comaron, et al., *Nano Letters* **21** (9), 3715-3720 (2021).
[5] S. Alyatkin, J.D. Töpfer, A. Askitopoulos, et al., *Phys. Rev. Lett.* **124**, 207402 (2020).
[6] B. Scellier Y. and Bengio, *Front. Comput. Neurosci.* **11**, 24 (2017).