量子物理学・ナノサイエンス第 354 回セミナー

Material learning

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日程　：　2 月 1 日（水）11:00-12:00

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概　要

The strong increase in digital computing power in combination with the availability of large amounts of data has led to a revolution in machine learning. Computers now exhibit superhuman performance in activities such as pattern recognition and board games. However, the implementation of machine learning in digital computers is intrinsically wasteful, with energy consumption becoming prohibitively high for many applications. For that reason, people have started looking at natural information processing systems, in particular the brain, that operate much more efficiently. Whereas the brain utilizes wet, soft tissue for information processing, one could in principle exploit nearly any material and its physical properties to solve a problem. Here we give examples of how nanomaterial networks can be trained using the principle of *material learning* to take full advantage of the computational power of matter[1].

We have shown that a 'designless' network of gold nanoparticles can be configured into Boolean logic gates using artificial evolution[2]. We further demonstrated that this principle is generic and can be transferred to other material systems. By exploiting the nonlinearity of a nanoscale network of boron dopants in silicon, referred to as a dopant network processing unit (DNPU), we can significantly facilitate classification. Using a convolutional neural network approach, it becomes possible to use our device for handwritten digit recognition[3]. An alternative material-learning approach is followed by first mapping our DNPU on a deep-neural-network model, which allows for applying standard machine-learning techniques in finding functionality[4]. We also show that the widely applied machine-learning technique of gradient descent can be directly applied *in materia*, opening up the pathway for autonomously learning hardware systems[5]. Finally, we show that kinetic Monte Carlo simulations of electron transport in DNPUs can be used to reproduce the main characteristics and to depict the charge trajectories[6].

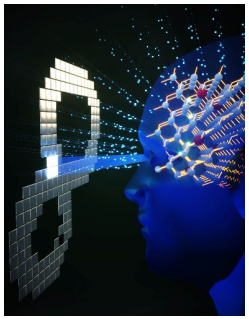

Figure 1: Artist's impression of digit recognition by a dopant network processing unit in silicon[3].

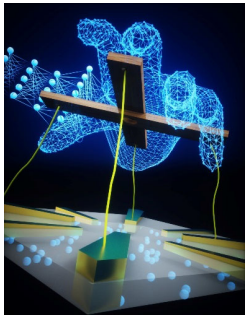

Figure 2: Artist's impression of training a dopant network processing unit by using a deep neural network[4].

References

[1] C. Kaspar *et al*., *Nature* **594**, 345 (2021)
[2] S.K. Bose, C.P. Lawrence *et al*., *Nature Nanotechnol.* **10**, 1048 (2015)
[3] T. Chen *et al*., *Nature* **577**, 341 (2020)
[4] H.-C. Ruiz Euler *et al*., *Nature Nanotechnol.* **15**, 992 (2020)
[5] M.N. Boon *et al*., arxiv.org/abs/2105.11233 (2021)
[6] H. Tertilt, J. Bakker, M. Becker, B. de Wilde *et al*., *Phys. Rev. Appl*. **17**, 064025 (2022)