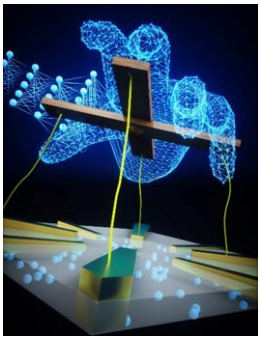
# Seminar: May 17th 2:00 p.m. Seminar Room U5

**For more information: Prof. Marco Fanciulli**

# Materializing Cognition

*Information processing in cognitive matter*



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Throughout history, man has exploited matter to carry out tasks well beyond his biological constraints. Starting from primitive tools with functionality solely derived from shape and structure, we have moved on to responsive matter that can change its properties upon external stimulus and even further to adaptive matter that can change its response depending on the environment. One of the grand scientific and intellectual challenges is to make matter that can actually *learn*. Such matter's behavior would not only depend on the here and now, but also on its past. It would have memory, and ultimately autonomously interact with its environment and self-regulate its action. We may call such matter 'cognitive' or even 'intelligent'[1].

Here we introduce a number of experiments on disordered nanomaterial systems, where we make sure of "material learning" to realize functionality. 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 handwritten digit classification[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]. 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]. Finally, we give examples how simulated multi-DNPU networks can solve more complex tasks than individual DNPUs[7,8].

[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).
[7] H.-C. Ruiz Euler *et al*., Neuromorph. Comput. Eng. **1**, 024002 (2021).
[8] B. van de Ven *et al*., Front. Nanotechnol. **5**, 1055527 (2023).