



## Satellite Workshop Neuroscience and Artificial Intelligence

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Tuesday, May 18, 2021 from 8:55 h to 16:30 h

### Program

08:55	<i>welcome</i>
09:00	<b>Xiao-Jing Wang</b> Center for Neural Science, NYU, USA <b>Artificial intelligence needs the prefrontal cortex</b>  <b>Abstract</b> Today's remarkably successful AI systems roughly correspond to the biological systems of perception, but have not yet benefitted from neurobiological understanding of the brain regions (such as the prefrontal cortex, often called the "CEO of the brain") of crucial importance for higher cognition. Here I will present our work, inspired by the PFC, on a recurrent network model that learns to carry out many cognitive tasks depending on decision-making, categorization and control of behavioral responses. This line of research motivated us to investigate how the brain utilizes previously acquired knowledge to accelerate learning in solving a new problem (learning-to-learn). Both rule-based multi-tasking and learning-to-learn are frontier topics in the field of machine learning, therefore bridging the brain and the AI.
09:45	<b>Klaus-Robert Müller</b> Machine Learning Group, TU Berlin, Germany <b>Decoding and analysing brain data using machine learning</b>  <b>Abstract</b> In this talk I will discuss recent directions of our research where nonlinear learning methods such as deep learning are employed for analysing multimodal brain data, both in the context of BCI and beyond – essentially summarizing some steps taken by the BBCI team and co-workers. If time permitting, I will also touch upon novel explanation techniques that allow to gain neuroscientific understanding despite the nonlinearities of the learning method.
10:30	<i>coffee break</i>

10:45	<p><b>Viktor Jirsa</b>  Institut de Neurosciences des Systèmes, Aix-Marseille Université, France  <b>Virtual Brain modeling in clinical applications for personalised medicine</b></p> <p><b>Abstract</b>  Over the past decade we have demonstrated that the fusion of subject-specific structural information of the human brain with mathematical dynamic models allows building biologically realistic brain network models, which have a predictive value, beyond the explanatory power of each approach independently. The network nodes hold neural population models, which are derived using mean field techniques from statistical physics expressing ensemble activity via collective variables. Our hybrid approach fuses data-driven with forward-modeling-based techniques and has been successfully applied to explain healthy brain function and clinical translation including stroke and epilepsy.</p> <p>Here we illustrate the workflow along the example of epilepsy: we reconstruct personalized connectivity matrices of human epileptic patients using Diffusion Tensor weighted Imaging (DTI). Subsets of brain regions generating seizures in patients with refractory partial epilepsy are referred to as the epileptogenic zone (EZ). During a seizure, paroxysmal activity is not restricted to the EZ, but may recruit other healthy brain regions and propagate activity through large brain networks. The identification of the EZ is crucial for the success of neurosurgery and presents one of the historically difficult questions in clinical neuroscience. The application of latest techniques in Bayesian inference and model inversion, in particular Hamiltonian Monte Carlo, allows the estimation of the EZ, including estimates of confidence and diagnostics of performance of the inference. The example of epilepsy nicely underwrites the predictive value of personalized large-scale brain network models. The workflow of end-to-end modeling is an integral part of the European neuroinformatics platform EBRAINS and enables neuroscientists worldwide to build and estimate personalized virtual brains.</p>
11:30	<p><b>Srdjan Ostojic</b>  Laboratoire de Neurosciences Cognitives &amp; Computationnelles, ENS, Paris, France  <b>Using Recurrent Neural Networks to reveal mechanisms of neural computations</b></p> <p><b>Abstract</b>  In the recent years, artificial neural networks trained on neuroscience tasks have emerged as popular model systems for exploring how large ensembles of neuron-like units implement computations that underlie behavior. In contrast to biological brains, artificial networks offer unhindered access to the activity of all neurons and the full connectivity among them, while their function is explicitly predefined. Trained neural networks therefore hold the promise of revealing the structure-to-function mapping, yet understanding the relation between connectivity, activity and computations remains highly challenging. In this presentation, I will review some recent approaches for interpreting how connectivity determines the computational mechanisms in recurrent neural networks performing classical systems neuroscience tasks.</p>
12:15	<i>lunch break</i>
13:30	<p><b>Julian Göltz, Walter Senn</b>  Petrovici Lab, Physics, U Heidelberg, Germany   Senn Lab, Physiology, U Bern, Switzerland  <b>Fast and deep: energy-efficient neuromorphic learning with first-spike times</b></p> <p><b>Abstract</b>  For a biological agent operating under environmental pressure, energy consumption and reaction times are of critical importance. Similarly, engineered systems also strive for short time-to-solution and low energy-to-solution characteristics. At the level of neuronal implementation, this implies achieving the desired results with as few and as early spikes as possible. In the time-to-first-spike-coding framework, both of these goals are inherently emerging features of learning. Here, we describe a rigorous derivation of learning such first-spike times in networks of leaky integrate-and-fire neurons, relying</p>

	<p>solely on input and output spike times, and show how it can implement error backpropagation in hierarchical spiking networks. Furthermore, we emulate our framework on the BrainScaleS-2 neuromorphic system and demonstrate its capability of harnessing the chip's speed and energy characteristics. Finally, we examine how our approach generalizes to other neuromorphic platforms by studying how its performance is affected by typical distortive effects induced by neuromorphic substrates.</p>
14:15	<p><b>Claudia Clopath</b> Imperial College London, UK <b>Neural manifold under plasticity in a goal driven learning behavior</b></p> <p><b>Abstract</b> Neural activity is often low dimensional and dominated by only a few prominent neural covariation patterns. It has been hypothesised that these covariation patterns could form the building blocks used for fast and flexible motor control. Supporting this idea, recent experiments have shown that monkeys can learn to adapt their neural activity in motor cortex on a timescale of minutes, given that the change lies within the original low-dimensional subspace, also called neural manifold. However, the neural mechanism underlying this within-manifold adaptation remains unknown. Here, we show in a computational model that modification of recurrent weights, driven by a learned feedback signal, can account for the observed behavioural difference between within- and outside-manifold learning. Our findings give a new perspective, showing that recurrent weight changes do not necessarily lead to change in the neural manifold. On the contrary, successful learning is naturally constrained to a common subspace.</p>
15:00	<i>coffee break</i>
15:15	<p><b>Joschka Bödecker</b> Neurorobotics, U Freiburg, Germany <b>Reinforcement learning for optimizing and understanding neuronal systems</b></p> <p><b>Abstract</b> While we are able to record from and stimulate neuronal systems like cell cultures, brain slices, or even brain areas in freely moving animals with increasing precision, we still only have a partial understanding of how to best control the dynamics of complex neuronal networks, or how to relate complex neural firing patterns in the brain to the behavior of an animal. Machine Learning, and in particular Reinforcement Learning techniques, offer a way to learn approximately optimal stimulation strategies and to recover an internal reward function of an animal to explain its behavior in a data-driven way, without the need for pre-existing mechanistic system models. I will present the challenges and results from our investigation of applying Deep Q-Learning to optimize the dynamics of spontaneously active neuronal cell cultures towards desired goals, and from our recent advances in Inverse Reinforcement Learning. I will highlight the potential of these methods to advance our understanding of the external and internal factors driving animal behaviour, and will present first results in rodents.</p>
16:00	<p><b>Matthias Bethge</b> Computational Neuroscience &amp; Machine Learning, U Tübingen, Germany <b>Learning to see like humans</b></p> <p><b>Abstract</b> How can we teach machines to see the world like humans? Taking inspiration from the ventral pathway in the visual brain, convolutional neural networks (CNNs) have become a key tool for solving computer vision problems—often reaching human-level performance on benchmark tasks like object recognition or detection. Despite these successes perceptual decision making and generalization in machines is still very different from humans. In this talk, I will present ongoing work of my lab to better understand</p>

these differences between human vision and CNNs studying constrained architectures, adversarial testing, and out-of-domain generalization.

16:45

*end of workshop*

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