

## Course Description

### Theory of Neural Dynamics and Applications to Machine Learning based on Reservoir Computing

This course is about the dynamics of spiking neuron models and how to implement them in the bio-inspired machine learning algorithm called reservoir computing. Neural dynamics allow for the possibility of nonlinear and interaction effects in neural computation and determine how biological neurons in our brain make firing decisions that enable them to learn. The course lays the foundations for a neurally grounded understanding of the fundamental processes in spiking neurons that enable information encoding. Neural grounding will be provided at the level of single neurons and populations of spiking neurons that form recurrent neural networks driven by biological learning algorithms such as spike-timing-dependent plasticity.

The theoretical concepts on which the course is based come from introductory dynamical systems theory and probability theory. Tutorials on the relevant mathematical concepts will be provided as the course evolves so that basic training in differential equations and probability is useful but not a prerequisite for the course. These mathematical concepts are used to characterize spiking processes in recurrent neural networks as dynamic neural systems in which stable activation states emerge from the connectivity patterns within neural populations. This leads to dynamic neural activation fields as the building blocks of neural cognitive architectures, where instabilities can induce a change of attractor states from which cognitive functions such as working memory, classification, and prediction emerge.

A key challenge for neural modeling is to explain how stereotypical recurrent neural circuits of neurons can process a stream of input from a rapidly changing environment in real time. Thus, in the second part of the course, we will use the spiking neuron models, and their dynamics studied in the first part to implement reservoir computing (RC) algorithms – a type of machine learning algorithm inspired by the dynamic behavior of biological neural networks. RC does not require a task-dependent construction of neural circuits. Instead, it is based on principles of high-dimensional dynamical systems in combination with statistical learning theory. It uses the concept of a “reservoir” of spiking neurons, whose states are transformed and then used as input to a simple linear readout layer. This allows the system to learn and process temporal sequences, making it well-suited for tasks like speech recognition, chaotic signal processing, and time-series prediction. In essence, reservoir computing combines the temporal dynamics of spiking neurons with the simplicity of linear regression, providing a powerful tool for bio-inspired machine learning.

$$\begin{cases} \frac{dv_i}{dt} = F_1(v_i, w_i) - \frac{1}{k_i} \sum_{j=1}^N \ell_{ij}(t) g_{ij}(t) s_j(t - \tau) [v_i(t) - v_r] + I_{stochastic} \\ \frac{dw_i}{dt} = \varepsilon F_2(v_i, w_i) \end{cases}$$

