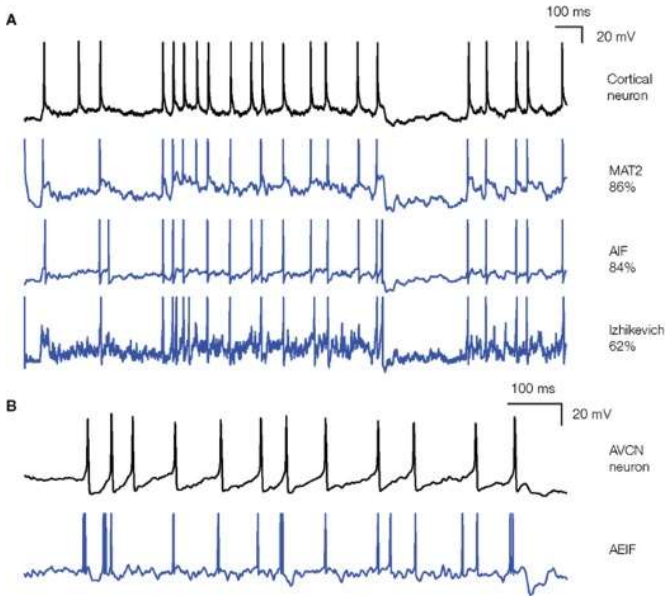
Bio-inspired networks for AI and ML

Deep Neural Networks (DNN) have made a significant number of progresses possible over the last decade and allowed several tasks in AI and ML to be solved with unsurpassed accuracy. In spite of their advantages, DNN also pose some problems. One of them is that DNN need a huge amount of training data to reach a good accuracy level. By contrast, real biological systems (e.g., the **human brain**) do not need this huge number of examples in order to learn a "concept", but can instead learn with very few examples. In addition, biological systems can easily extrapolate a learned concept to other examples or concepts when DNNs have behave poorly when examples with properties that differ from those present in the training data are presented. This may be due to the fact that DNNs do not learn from example in the same way that biological systems do. For example, backpropagation mechanisms, which are at the core of the performance of DNNs, are not present in biological systems. On the other hand, mechanisms that are fundamental for learning in biological systems, such as spike timing-dependent plasticity (STDP), are not present in DNNs because the units in DNNs are not defined by spikes, unlike biological neurons.



Example of electrophysiological measurements of the activity of a neuron (black curves) and computational simulations (blue curves) using different computational models.

Using a completely novel approach, some works in c**omputational neuroscience** have started to implement the Spiking Neural Networks (SNNs) architectures (e.g., Tavanei et al, 2019). These architectures reproduce the individual activity of every neuron, including its temporal activity (the exact timing of individual spikes), as well as the general dynamics of the network (synchronicity, oscillations, etc). In addition, these architectures implement a learning mechanism observed in the synapses of biological neurons: STDP. This is a Hebbian-learning based mechanism that allows neurons to automatically learn patterns without supervision. Importantly, these recent works on SNNs show that these biologically inspired models perform tasks such as object classification (with small databases such as MNIST and CIFAR, Illing et al., 2019) with much smaller training data sets and the same accuracy as conventional DNN.

These works suggest that the future of AI and ML is in the use of biological information from the neural mechanisms present in the human brain. The incorporation of biological mechanisms and

architectures into AI has the potential of overcoming some of the main issues and limits of AI as, for example, the huge amount of data needed to train systems, or the difficulty for AI algorithm to implement continuous learning.

In this project, the **objectives** are:

O1) Implement a small SNN architecture using NEST (https://www.nest-simulator.org/).

O2) Use STDP mechanism to perform object classification on small datasets such as MNIST.

In O1) the student will reproduce the Illing et al (2019) paper, and optionally introduce biological properties not considered in the original work such as ON-OFF segregation and, inhibitory inter-neurons.

Experience in Python is desired.

Bibliography

- Illing et al, Neural Networks, 118 (2019) 90-101

- Tavanei et al, Neural Networks 111 (2019) 47-63

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