**Biologically inspired algorithms for energy efficient machine learning**

Machine learning has experienced an unprecedented development since the emergence some 15 years ago of new hardware, software, and algorithms that allowed researchers to implement deep learning (DL). For example, the adoption of deep convolutional networks halved overnight the error rate in object recognition tasks (Krizhevsky, Sutskever et al. 2017). However, these impressive advances in machine learning came at a cost. During model development and training phase, DL systematically rests on an extraordinarily number of repeated operations such as convolutions that are computationally hungry on big datasets. To gain classification accuracy, deeper and deeper models (with an increasing number of layers) are trained on increasing numbers of examples, leading to an exponential increase in computational load. This computational load has direct consequences in terms of energy demands, and thus on the environment as energy production results in greenhouse gas (GHG) emissions. For example, Strubell et al. showed that designing and training a natural language processing model for translation emits between 0.6 and 260 tonnes of $CO_2$ (Strubell, Ganesh et al. 2019), i.e., the equivalent of $CO_2$ rejection of an average European car driving between 4400 and nearly two million kilometres - 50 times around the world - (Data of CO2 emission from European Environment Agency). Given the dramatic contribution of GHGs to climate change (Crowley 2000), while often unappreciated such a high environmental impact cannot be ignored.

On the other hand, the brain of humans - and other animals – efficiently learns and fine-tunes knowledge during an organism's life. Besides, there is a lot of evidence that the constraint of saving metabolic energy is essential to understand the structure of the brain. For example, the energetic demand of the brain is a strong limitation for its development, and the evolution of a bigger brain in humans has only been possible as a result of a dramatic increase in the calorie yield of the diet (Fonseca-Azevedo and Herculano-Houzel 2012). Moreover, several features of the primate brain are the result of a pressure to minimise metabolic energy while maximising the information extracted by the senses. The best-known example is sparse coding. Sparse coding refers to the constraint for neural systems to balance information coding (a higher rate of information is better) and metabolic expense (a lower expense is better). There is a lot of evidence that the brain processes natural stimuli with a sparse code (Olshausen and Field 1996, Vinje and Gallant 2000, Hyvarinen, Hurri et al. 2009, Haider, Krause et al. 2010). Taken together, the brain seems to be an energy efficient learning machine. It therefore makes sense to explore whether introducing bio-inspired mechanisms in deep neural networks can improve their energy efficiency.

In this project, you will explore this idea. You will use models inspired by the architecture and workings of the brain to assess whether adopting bio-inspired methods is a method of choice to tackle the energetic issues of current machine learning approaches. More precisely, the aims of the project are:

**Aim 1**. To implement the tools to estimate the energy use of machine learning algorithms used in Strubell et al. (Strubell, Ganesh et al. 2019)

**Aim 2**. To compare the energy use of biologically inspired neural networks and of state-of-the-art standard deep neural networks for the same level of accuracy.

In Aim 2, several aspects of biological neural networks can be tested, including, but mot limited to, recurrent networks, modularity, spike code, biologically plausible learning algorithms such as spike timing-dependent plasticity, sparse code etc. A possible dataset for comparing models could be the MNIST dataset.

Experience in Python would be a plus but is not required.

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