Hypernetworks methods in Meta-Learning

In recent years, machine learning models have surpassed human-level performance on individual tasks, such as Atari games or object recognition. But still, our Artificial Intelligence models do not imitate human performance to learn.

Current Artificial Intelligence techniques cannot rapidly generalize from a few examples. Most deep neural networks architectures must be trained on large-scale data. In contrast, humans are capable of learning new tasks rapidly by utilizing what they learned in the past. For example, a child who learned how to add can rapidly transfer his knowledge to learn multiplication given a few examples (e.g., $2*3 = 2+2+2$ and $3*1 = 1+1+1$). Another example is that given a few photos of a stranger, a child can easily identify the same person from a large number of photos. **Few-shot learning** tries to fill this gap to learn from a limited number of examples with supervised information, see Fig. 1.

On the other hand, for humans learning from a continuous stream of data is quite normal, as data in the real world come sequentially. Learning new tasks while preserving and leveraging knowledge from previous ones is a crucial requirement for everyday living. Although deep learning models achieved great success in various tasks, they still fail at this essential point exhibiting poor performance on previously learned tasks and a phenomenon called catastrophic forgetting. As a result, deep learning effectively requires data to be i.i.d., which is infeasible in many real-life situations. In **continual learning**, the model learns from a continuous stream of data with supervised information, see Fig. 2.

Figure 1: W present a visualization of a few shot-learning problems. During the training process, we update model parameters based on training tasks. After training, our model has to correctly classify the query set (from the test task) using the element from the support set.

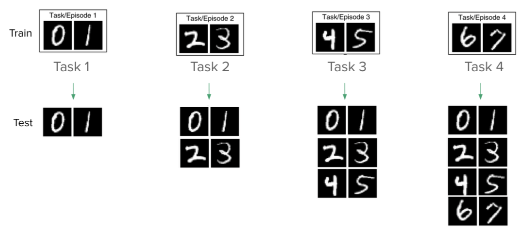

Figure 2: Generally speaking continual learning means the ability of the neural network to effectively learn new tasks while trying to prevent forgetting already learned information (we can not go back in training to previous tasks).

Finally, in most existing learning systems, images, sounds, 3D objects have discrete representations. For example, images are typically viewed as 2D pixel arrays, sounds as time-series, and 3D objects as 3D point clouds (or 3D meshes). On the other hand, humans understand things as a continuous reprehension. In practice, when we look at the image, we extrapolate/hallucinate the unseen part, as it is intuitively done by humans when decomposing a complex scene containing occluded objects. Consequently, we can recognize some objects when we take them from different positions and different resolutions. In machine learning, we can represent objects as a continuous function model by neural networks – **Continuous representing of objects**.

This project plans to reduce the distance between human and artificial intelligence in the above areas. Our main idea relies on controlling the structure of weights in deep neural networks to solve the above problems. First of all, we plan to explore Hypernetworks architecture. Hypernetworks are defined as models that generate weights for a separate target network solving a specific task. Such architecture can condition weights by information from previous/different tasks. In our grant, we will understand the **Hypernetworks paradigm** more broadly as a mechanism that can control the structure of neural network weights.