ETH Zürich - Deep Learning class 2024-2025

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Abstract

This is the project proposal of our group for the Deep Learning class 2024-2025. We choose to work on continuous learning and our goal is to study the influence of model complexity on catastraphic forgetting.

1. Introduction

As the causes of atastrophic forgetting(French, 1999) are not yet fully understood, we want to measure the impact that specific features can have on catastrophic forgetting. We will focus on the impact of model complexity on forgetting. As model complexity can have many definition, see for example the survey(Hu et al., 2021), we first define which measures we will use and then we detail the experimental procedure.

2. Procedure

2.1. Complexity measure

To quantify model complexity, two metrics will be used:

- the number of parameters for the expressive complexity,
- the number of active neurons or the number of linear regions for effective complexity.

The second one is particularly interesting, as according to(Hanin & Rolnick, 2019), it seems to capture different stages during training.

2.2. Benchmark

As a benchmark, we will use a multi-task scenario with commonly used datasets such as splitted MNIST.

2.3. Model selection and experiment

As a baseline, a simple model such as MLP will be used with minimum number of parameters to reach a decent accuracy (greater than 95-98 %).
We will benchmark accuracy loss at each step of the multi-task scenario, varying the number of training epochs, model width and depth and repeating the process multiple times.

2.4. Continuous learning

We will perform experiments on continuous learning algorithms such as "Efficient Lifelong Learning with A-GEM"(Chaudhry et al., 2019) or "Learning Without Forgetting"(Li & Hoiem, 2017).
The continuous learning framework that we selected is the open source framework "mammoth"(Pietro Buzzega, 2024).

References

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