Making Vanishing Gradients Vanish

Project Proposal for Research in Data Science

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1 Introduction

In 2019 [1] introduced the NeuralODE architecture, which allows us to construct neural networks in a manner where the "depth" of the network is not defined by discrete layers, but rather as a continuum. A follow up paper by [2] built on this model and claimed that by restricting model parameters, they were able to solve the infamous exploding/vanishing gradient problem. However, while the authors did achieve promising empirical results, their claimed proofs are incorrect, as can be shown by simple counter-examples. In this project, we wish to understand whether one can impose similar restrictions to alleviate the problem of exploding/vanishing gradients by other methods, and why the authors of [2] were able to achieve good performance on common reinforcement learning problems, even without their claimed theoretical results.

2 Objectives

In this project, we wish to understand why the authors of [2] were able to achieve good results on common reinforcement learning problems. To this end, we will study

- the NeuralODE architecture, as described in [1],
- the ideas underlying the methods used in [2],
- the behavior of the gradients in [2], and whether the authors were actually able to alleviate the exploding/vanishing gradients problem and
- novel approaches to the exploding/vanishing gradients problem.

3 Methods

In order to work on this project, we will be using `python` and the `JAX` package whenever programming is appropriate. Furthermore, we will be using the website `https://wandb.ai/site` to monitor the training progress of neural networks, in particular when attempting to understand the empirical results in [2].

References

[1] Chen et. al. Neural ordinary differential equations. 2019. doi:https://doi.org/10.48550/arXiv.1806.07366.

[2] Krzysztof Choromanski et. al. An ode to an ode. 2020. doi:https://doi.org/10.48550/arXiv.2006.11421.