

Loss Landscape Visualization

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Abstract

Neural networks have emerged as powerful function approximators with large parameter sets. These parameters are optimized according to a loss function. Many assumptions have been made about the shape of the resulting loss landscape. However, only recently qualitative and empirical studies have been conducted. Here, we give an overview for recent advances of this field. We will explore different methods in detail and discuss their results and impact.

Introduction

When creating neural networks for a given task, practitioners have to take many decisions. From architecture design, over optimizers, and schedules to hyperparameter choice there are many options that will play a key role in the eventual performance of the model. Anecdotal knowledge, experience and luck often lead to the final configuration and there is little empirical knowledge of what is actually effective. Loss landscape visualization can play a large role in guiding the community towards a more empirically foundation and maybe help build the groundwork for theoretical approaches.

Several recent works have shown that a better knowledge about the loss landscape can help build methods grounded in theory [Mutschler and Zell, 2020, Chaudhari et al., 2019]. Moreover, loss landscape visualization also helped to explain the effectiveness of existing methods such as stochastic gradient descent (SGD) [Robbins and Monro, 1951, Xing et al., 2018] and architectures with residual connections [He et al., 2016, Li et al., 2017].

As the space of parameters is too large to visualize in any meaningful way, methods of loss landscape visualization have to compromise. They might just consider small, visualizable subspace of a model's parameters. Results, thus, should be considered with caution and any conclusions should be drawn only carefully.

The following section will give .. to deep neural network architectures, and explain what a loss landscape is. Then, we will explore different methods of visualizing loss landscapes and see how insights from those methods can be applied. Finally, we discuss the impact of knowing the loss landscape better, see some limitations, and give an outlook on the future of the field.

Background

Methods

Linear Interpolation

Filter Normalization

[Xing et al., 2018]

Results

Conclusions

Literatur

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