GRADIENT NORMALIZATION & DEPTH BASED DECAY FOR DEEP LEARNING

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ABSTRACT

In this paper we introduce a novel method of gradient normalization and decay with respect to depth. Our method leverages the simple concept of normalizing all gradients in a deep neural network, and then decaying said gradients with respect to their depth in the network. Our proposed normalization and decay techniques can be used in conjunction with most current state of the art optimizers and are a very simple addition to any network. This method, although simple, showed improvements in convergence time on state of the art networks such as DenseNet and ResNet on image classification tasks, as well as on an LSTM for natural language processing tasks.

1 INTRODUCTION

The problem of vanishing and exploding gradient is one of the most fundamental deep learning optimization problems. This problem has inspired a significant body of work around it, with numerous papers trying many different methods. Many attempts have been made to dynamically modify the learning rate and parameters of deep learning models during training to mitigate this problem. Most of the approaches include simple changes to stochastic gradient descent (SGD) and are reflected in the update rule for back-propagation. In this paper we propose a method similar in spirit to those before but leverages depth information of the layers to decay the gradients. The concept of leveraging depth information is not as well explored as use of other information, yet proves quite useful as true exploding or vanishing gradient problems usually do not occur unless the network is sufficiently deep. By decaying the magnitude of the gradients with respect to depth, our method shows a notable improvement in the convergence speed and can easily be used in conjunction with other optimization methods.

1.1 METHODOLOGY

Our approach builds on prior work to optimize the back propagation step for learning. Traditionally, the back-propagation update rule is formulated as:

\[ w_{dj} = w_{dj} - \eta \delta_{dj} \]

Where \( d \) is the depth of the layer, \( j \) is the element in the later, \( \delta_{ij} \) is the gradient of \( w_{ij} \), and \( \eta \) is the learning rate. Our modification involves adding a decay function such that the learning rate \( \eta \) decays with the depth of the network. The new update rule can be restated as:

\[ w_{dj} = w_{dj} - \eta \frac{N(w)D_\gamma(d)}{\|w_{dj}\|_2} \delta_{dj} \]  

(1)

Where \( D_\gamma(d) \) can be any decay function with respect to depth \( d \) and parameterized by the \( \gamma \) value, which ranges between 0 and 1, and \( N(w) \) denotes some function with respect to all of the weights of the network used to control the gradient size. The two gradient control functions used in this paper are the normalization to 1 and the normalization to the L2 norm of the weights of the final layer.

*Thanks to Hrishikesh Rajeev Vaidya and Jenny Chen
of the network. The two examples of decay functions that we explored in this paper are the linear decay function in equation 2 and the exponential decay function in equation 3.

\[ D_\gamma(d) = (1 - \gamma)^d \quad (2) \]
\[ D_\gamma(d) = e^{-\gamma d} \quad (3) \]

These decay functions, while simple, proved to be powerful enough to produce a meaningful result.

2 RELATED WORK

Our work shares similarities with many commonly used and widely successful optimizers. Many optimization methods work to modify the gradients of a model as it is learning so as to achieve a faster convergence time, or a more robust model. Our method uses techniques similar to many other successful models, in that we modify the gradients as the model learns. There are, however, some important distinctions between our method and other established methods. Though the gradient normalization method described in this paper shares much with some of the more successful optimization methods of the past, it importantly, like batch normalization, can be used in conjunction with many other optimizers.

2.1 RMSProp:

There are many important similarities between our work and the widely used RMSProp [Tieleman & Hinton 2012] method. RMSProp’s method of normalizing the learning rate as a function of the average of recent gradients has been shown to produce meaningful results. Our method similarly divides the learning rate by some function of the gradients, with a key difference being our method leverages depth information so as to approach the exploding and vanishing gradient problem while at the same time helping to speed convergence time.

2.2 Adam:

Adam [Kingma & Ba 2014] was introduced as a method to compute adaptive learning rates for the gradients. One of the main benefits afforded by the Adam paper was that the updates computed by Adam do not depend on any rescaling of the gradient. In this way, our normalization method shares an important similarity with Adam. Neither Adam nor our gradient normalization method depend on the rescaling. However, the most important difference is that Adam uses adaptive learning rates while our method does not. Our method does not modify the learning rate at all, choosing to directly modify the magnitude of the gradients such that all weights are updated a fixed amount per step.

2.3 Batch Normalization

Similar attempts have been made to normalize the parameters of a network, one of the most successful being Batch Normalization [Joffe & Szegedy 2015], which seeks to normalize the inputs of a layer to mean 0 and standard deviation of 1 with learned scale and shift parameters. This normalization allows for a higher learning rate and much faster convergence time as backpropagation is less affected by the scale of the parameter. Our method seeks to achieve the same effect more directly, by normalizing all parameters as opposed to the inputs we ensure that all parameter updates are similarly scaled.

3 EXPERIMENTS

The experiments in this paper involved the use of the publicly available Pytorch implementations of DenseNet [Huang et al. 2017] and ResNet [He et al. 2015], and a LSTM called LM LSTM CRF [Liu et al. 2018]. All of the experiments in this section were baselined first without any additional gradient normalization and run again with only exponential and linear decay functions added for 50 epochs. For each of the following graphs, the red line denotes the best results achieved by the baseline model.
3.1 ResNet

Gradient normalization with linear decay of $\gamma = 0.5$ and exponential decay of $\gamma = 0.01$ showed significant improvement in the convergence of the standard ResNet network when run for 50 epochs, as seen in Figure 1. The accuracy achieved by ResNet at the final epoch was achieved at epoch 19 under linear decay and epoch 22 under exponential decay. This experimental result is particularly notable as one of the intentions of a ResNet is to control the growth of the gradients through the passing of the residuals. It is a notable result that the decay of the gradients provided by our method showed a significant improvement despite these residuals. This result speaks to the effectiveness of our method for improving on results that were created specifically to tackle the exploding gradient problem. The clear improvement shown in these results suggests that for less complex networks, such as traditional convolutional neural networks and multi layer perceptrons we would expect to see a very large improvement in the convergence time.

3.2 DenseNet

Gradient normalization when applied to DenseNet also showed a quicker convergence rate, with a linear decay function with $\gamma = 0.5$ reaching the same precision at epoch 28 as the baseline DenseNet did at epoch 48. This result can be seen in Figure 2. In tests over most decay $\gamma$ the exponential
decay function showed the fastest convergence, although in the highest performing experiments shown in the graph above, the linear decay function has a slightly improved final accuracy to that of an exponential decay function with $\gamma = 0.01$. While results on DenseNet are not as significant as those on ResNet, our method of gradient normalization shows improvement over DenseNet for every epoch after epoch 5. These results on the state of the art method suggest that our method has potential to improve the state of the art convergence time in a variety of other domains, with less complex models.

3.3 LM LSTM CRF

The LM LSTM CRF paper showed some of the highest results in Named Entity Recognition to date [Liu et al. (2018)]. Gradient Normalization on this case showed a split result, but in the exponential decay case, with $\gamma = 0.001$ and normalized to the norm of the last weight matrix, Gradient Normalization continued to show improved convergence time and an improved final result. The exploding and vanishing gradient problem is very prevalent in recurrent neural networks, so in the general case, one would expect to see gradient normalization show improvements in the ease of training RNNs. However, for LSTMs, which already have a built in method for mitigating exploding and vanishing gradients [Hochreiter & Schmidhuber (1997)], it is understandable why gradient normalization would not perform as well as on other deep neural networks. However the fact that, despite the LSTM showing profound success in reducing the exploding gradient problem, the exponential decay function used in our method showed a reduced network loss at every epoch over the baseline, while achieving the same final loss achieved by the baseline at epoch 33, only two thirds of the training time, further speaks to the general application of our model.

4 Future Work

Although many different optimization techniques have been emerging recently in the space of deep learning, there is not a great body of work on any theory as to why these methods work. As such, a future direction for work on this topic to take would be to explore theoretical reasons as to why this method shows notable the improvements it does. There has been some recent work done by Balduzzi et al. [2017] which suggests a framework for analyzing the changes in gradients and how correlations between gradients results in improved results. Additionally, there has been work on using Mutual Information [Schwartz-Ziv & Tishby (2017)] which suggests a similar framework instead utilizing Mutual Information between activations as a method of analyzing neural networks. Our work explored a fairly limited subset of possible decay functions and gradient normalization techniques. Some more application focused directions for future work would include investigating more complicated methods of decaying the gradients. Although our simplistic methods proved themselves successful they act mostly as a proof of concept of the potential power of this new
normalization method. Another potentially more complicated direction of future work would be to include the decay function and normalization as learned parameters in the network. There is no reason to believe that the decay function could not be learned in a meta optimization fashion and may yield interesting results.

5 CONCLUSION

Our contribution in this paper is a novel method to solve the vanishing and exploding gradient problem. Although much work has been done in this field, little of it focuses on modifying parameters with one of the main culprits of the vanishing gradient problem: layer depth. Our approach involves the use of a separate decay function and normalization technique, which together normalizes and decays the gradients with respect to depth. We explore the use of linear and exponential decay functions, although there is potential for future work in evaluating a full battery of other decay functions, potentially as a learned function. Similarly, our normalization techniques were very simple, normalizing to 1 or to the norm of the gradient of the final layer, and this is also an area where future work may potentially have success.

Our results suggest that, with proper parameter tuning, this method can show improved convergence on a variety of deep and recurrent networks. Our result is exciting not only because of our positive results, but also due to the fact that this method can be applied in conjunction with many other optimization techniques. As a result, our method should be able to improve convergence speeds in a wide variety of deep neural networks.

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