Notes on Deep Neural Networks

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1 Neural Network Basics

1.1 Weight Initializations

1.1.1 Lecun's Distribution

Presented in [1, Sec 4.6], Lecun's distribution assumes a linear model and is based on the following argument: suppose we have a neural network activation layer that uses $tanh(X)$ as a nonlinear squashing function. In order for convergence to occur quickly, the weights should be initialized so that (1) the weights are not too small, causing the gradient function to be small and (2) the $tanh$ is not saturated (the weights are not too large), also causing the gradient function to be small. Assuming that the data is properly normalized, all we need to do is initialize the weights to have $\mu = 0$ and $\sigma = 1$.

$$X \sim N\left[-\frac{1}{\sqrt{n_j}}, \frac{1}{\sqrt{n_j}} \right] \tag{1}$$

$$X \sim U\left[-\frac{3}{\sqrt{n_j}}, \frac{3}{\sqrt{n_j}} \right] \tag{2}$$

1.1.2 Glorot Distribution

Presented in [2, 4.2].

$$X \sim N\left[-\frac{\sqrt{2}}{\sqrt{n_j + n_{j+1}}}, \frac{\sqrt{2}}{\sqrt{n_j + n_{j+1}}} \right] \tag{3}$$

$$X \sim U \left[-\frac{\sqrt{6}}{\sqrt{n_j + n_{j+1}}}, \frac{\sqrt{6}}{\sqrt{n_j + n_{j+1}}} \right] \tag{4}$$

1.1.3 He Distribution

Previous assumes linear activation function, which is not suitable for ReLU or its derivatives. Thus, the authors of [3][pg. 4] derive a theoretically sound initialization for networks utilizing the ReLU activation family.

$$X \sim N \left[-\sqrt{\frac{2}{n_j}}, \sqrt{\frac{2}{n_j}} \right] \tag{5}$$

$$X \sim U \left[-\sqrt{\frac{6}{n_j}}, \sqrt{\frac{6}{n_j}} \right] \tag{6}$$

References

[1] Y. A. LeCun, L. Bottou, G. B. Orr, and K.-R. Müller, "Efficient backprop," in *Neural networks: Tricks of the trade*, pp. 9–48, Springer, 2012.

[2] X. Glorot and Y. Bengio, "Understanding the difficulty of training deep feedforward neural networks," in *International conference on artificial intelligence and statistics*, pp. 249–256, 2010.

[3] K. He, X. Zhang, S. Ren, and J. Sun, "Delving deep into rectifiers: Surpassing human-level performance on imagenet classification," *CoRR*, vol. abs/1502.01852, 2015.