

Artificial Neural Networks: Tricks of the Trade and Neural Smithing

Alexander G. Ororbia II Introduction to Machine Learning CSCI-635 11/27/2023

So now we can train ANNs with backprop, so we are done, right? Machine learning is solved, class finally dismissed?





The Vanishing Gradient Problem

- Solving credit assignment problem with backpropagation (backprop) too difficult
 - Difficult to know how much importance to accord to remote inputs (Bengio et al., 1994)
 - Information passed through chain of multiplications back through network – *vanishing gradients*
 - Any value slightly less than 1 in Hadamard product, derivative signal quickly shrinks to useless values (near zero)
 - Learning long-term dependencies in temporal sequences becomes near impossible
- Complementary problem: *exploding gradients*
 - Any value greater than 1 in Hadamard product, derivative signal increases dramatically (numerical overflow)



The Logistic Sigmoid and Its Derivative:

THE IMPORTANCE OF STARTING OUT RIGHT: INITIALIZATION

How to make those gradients work for you!

Why do we care how parameters are initialized?

- Initialization affects final performance
 - Will put closer to some spots in function space and farther from others



- Where we end up in function space will often correlate w/ our error performance
- Figure 5: 2D visualizations with tSNE of the functions represented by 50 networks with and 50 networks without pre-training, as supervised training proceeds over MNIST. See Section 6.3 for an explanation. Color from dark blue to cyan and red indicates a progression in training iterations (training is longer without pre-training). The plot shows models with 2 hidden layers but results are similar with other depths.

"Why Does Unsupervised Pre-training Help Deep Learning?", Erhan et al. 2010 http://jmlr.org/papers/volume11/erhan10a/erhan10a.pdf

Pre-Training: Learning Your Initialization

RBM

 h_3

h2

- General idea:
 - Train another model,
 e.g., *deep belief network* →
 - Dump its parameters into the one you care about
 - Fine-tune final model



Pretraining: Stacked (Neural) Models

Iterative pre-training construction of Deep Belief
 Network (DBN) (Hinton et al., 2006)



from: Larochelle et al. (2007). An Empirical Evaluation of Deep Architectures on Problems with Many Factors of Variation.

White Board Time!

A Simple (Denoising) Autoencoder



Research Efforts in Pre-Training

Pre-training works! (Erhan et al., 2010), but...

- 2-stage learning (Bengio et al., 2007)
 - Step 1: (Greedy) unsupervised pre-training
 - Deep Belief Networks: Contrastive Divergence (CD-k) or SML/PCD
 - Stacked Denoising Autoencoders: Back-propagation w/ cross-entropy loss
 - Step 2: Supervised fine-tuning
 - 1) Toss old model, dump parameters into MLP
 - 2) (Gentle) back-propagation fine-tuning

So...

- Hybrid, single-stage training (Larochelle et al., 2012; Ororbia et al., 2015)
 - Why not learn a generative & discriminative model at same time?

OR...Smarter Random Initializations

- Classical approaches
 - Sample from ~U(-a, a), where is a small scalar
 - Sample from $\sim N(0, a)$, where is a small standard deviation
- Fan-in-Fan-out (number inputs, number output)
 - Calibrate by variances of neuronal activities
- Simple distributional schemes
 - Fan-in/Fan-out Uniform
 - Fan-in/Fan-out Gaussian (good for ReLU activations)
- Orthogonal Initialization
 - Use Singular Value Decomposition (SVD) to find initial weights
- Identity Initialization / Constraint (for RNNs)
 - Does not always work unless constraint is enforced

QUESTIONS?

