**Depth First Learning: Resurrecting the Sigmoid**

**Course outline**

Welcome to Depth First Learning! In this course, we’ll cover the 2017 NIPS paper

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| Pennington, J, Schoenholz, S, and Ganguli, S.[Resurrecting the sigmoid in deep learning through dynamical isometry: theory and practice*.*](http://papers.nips.cc/paper/6857-nonlinear-random-matrix-theory-for-deep-learning.pdf) In *Advances in neural information processing systems,* 2017. |

This paper relies heavily on two main topics, both of which are interesting in their own right:

1. Mean-field theory for neural networks
2. Random matrix theory

**Course goal:** The goal of this 6-week course is for all of us to work through the paper together, using the readings and exercises the instructors have put together as a starting point, and at the end of the course producing a curriculum which will be published on the Depth First Learning website. Ideally, this curriculum will be structured so that a student with minimal background (say, at the level of a final-year undergrad) can use it to learn both the prerequisite knowledge and the contents of the paper itself. For examples of previously-published DFL guides, see:

1. [Wasserstein GAN](https://www.depthfirstlearning.com/2019/WassersteinGAN) by James Allingham
2. [AlphaGoZero](https://www.depthfirstlearning.com/2018/AlphaGoZero) by Cinjon Resnick

The paper we are covering is more theory-heavy than papers that have been covered in the past, and the background required to understand it is not easy, so a solid curriculum which we publish could be a valuable resource for many students.

**Structure of the course:** We will have six online meetings, once per week, tentatively Thursdays at 6 p.m. PST. These will take place via Zoom.

In the first meeting, we will give a lecture-style overview of the paper (covering the background, a brief intro to mean-field analysis, and a brief intro to random matrix theory). We’d like you to complete the prerequisite reading (below) beforehand, but there won’t be a problem set before this week’s lecture.

**Prerequisite reading:** For those of you that aren’t familiar with deep learning, please read the following sections from the book [*Deep Learning* by Ian Goodfellow et al](https://www.deeplearningbook.org/). Feel free to choose whatever subset of sections you feel is necessary, depending on your background.

* 2.7 (Eigendecomposition)
* 2.8 (Singular value decomposition)
* 3.2 (Random variables)
* 3.3 (Probability distributions)
* 3.7 (Independence and conditional independence)
* 3.8 (Expectation, variance, and covariance)
* 5.7 (Supervised learning algorithms)
* 8.2 (Challenges in neural network optimization)
* 8.4 (Parameter initialization strategies)

In addition, if you want some familiarity with some other background to the paper, check out the following optional readings. Since each lecture will be self-contained (apart from the above deep learning prerequisites), **it’s not necessary to read these**, but you might find it helpful.

* [*All you need is a good init*](https://arxiv.org/pdf/1511.06422.pdf) by Mishkin et al. This paper covers the first instance of focusing on weight initialization as a way to improve the training of deep nets, and specifically considers orthogonal weight initialization, which is related to the initialization strategies the paper we’re looking at does.
* [*Understanding the difficulty of training deep feedforward neural networks*](http://proceedings.mlr.press/v9/glorot10a/glorot10a.pdf) by Glorot et al. This paper covers Xavier initialization, which builds on similar ideas as the papers we’re considering does.
* [Random matrix theory and its innovative applications](http://math.mit.edu/~edelman/publications/random_matrix_theory_innovative.pdf) by Alan Edelman and Yuyang Wang. This is a relatively easy-to-read survey of random matrix theory that introduces some clever applications of it in other areas of science.
* Terence Tao’s [lecture notes](https://terrytao.wordpress.com/2010/02/02/254a-notes-4-the-semi-circular-law/) on the Wigner semicircle law. Here, Tao discusses one of the central and most well-known results in random matrix theory, so this can serve as a good introduction to the motivating ideas and methods of random matrix theory.
* [*Exponential expressivity in deep neural networks through transient chaos*](https://papers.nips.cc/paper/6322-exponential-expressivity-in-deep-neural-networks-through-transient-chaos.pdf) by Poole et al. This paper introduces one of the two frameworks that the paper we’re looking at covers: the interpretation of a neural net as a dynamical system.

For most of the other meetings, we’re planning to have them largely be discussion-based, rather than lecture-based. We’ve put together some problem sets which we think will be the best way to learn the material, and we’ll release the problem set a week before the corresponding lecture. So for example, the problem set for lecture 2, on mean-field analysis for neural networks, will be released right after lecture 1. We will also release readings along with the set.

**Lecture contents:**

Lecture 1 - Introduction to neural network initialization

Brief introduction to mean-field analysis

Brief introduction to random matrix theory

Lecture 2 - Mean-field analysis

Lecture 3 - Random matrix theory introduction

Lecture 4 - Random matrix theory, part 2

Lecture 5 - Calculations involved in the Resurrecting Sigmoid paper

Lecture 6 - Results of the Resurrecting Sigmoid paper

Future directions

**Feedback:** Please don’t hesitate to give us feedback on any aspect of the course, from the problem sets to the general structure. The document we create at the end will be a product of all of our efforts, and we’d love to have as much input from you as possible.

**Piazza:** Apart from the lectures, most of the communication will take place through [Piazza](https://piazza.com/class/jy82gn5lwm653x?cid=6).

We’re very excited to get started and as mentioned encourage you to provide any feedback you want and to reach out with any questions you may have!

See you next week!

Riley, Piyush, and Vinay