Your Awesome Research: ML@B Poster Template

William Guss
Machine Learning at Berkeley

Abstract

In this project, we generalize ANNs to infinite dimensional Banach spaces by developing a practical analog to the feedforward propagation algorithm. Using this new class of algorithms, GANN, we prove a new universal approximation theorem for bounded linear operators and show that representation of weights by samples from a multivariate weight polynomial can drastically reduce the dimensionality of a learning problem. Lastly, we give a practical implementation of the error back-propagation algorithm in this space for the classification of continuous data.

Introduction

Although neural networks have proven an extremely effective mechanism of machine learning [1], theoretically they remain a black-box model. In answer to this problem [2] examined the notion of infinite hidden nodes with a network proving that such a construction becomes a Gaussian kernel. Then, [2] described a model for affine neural networks with continuous hidden layers in alignment with [1]. These authors showed effectively the viability of a "continuous" neural network, but left many similar constructions unexplored.
[1].

Artificial Neural Networks

Definition 1. *We say $\mathcal{N}: \mathbb{R}^n \to \mathbb{R}^m$ is a feed-forward neural network if for an input vector $\boldsymbol{x}$,*

$$\begin{aligned}\mathcal{N}: \sigma_j^{(l+1)} &= g\left(\sum_{i\in Z^{(l)}} w_{ij}^{(l)}\sigma_i^{(l)} + \beta^{(l)}\right)\\ \sigma_j^{(1)} &= g\left(\sum_{i\in Z^{(0)}} w_{ij}^{(0)} x_i + \beta^{(0)}\right),\end{aligned} \tag{1}$$

where $1 \le l \le L-1$. Furthermore we say $\{\mathcal{N}\}$ is the set of all neural networks.

Functional Neural Networks

Suppose that we wish to map one functional space to another with a neural network. Consider the standard model of an ANN as the number of neural nodes for every layer becomes uncountable. The index for each node then becomes real-valued, along with the weight and input vectors.

Definition 2. *We call $\mathcal{F}: L^1(X) \to L^1(Y)$ a functional neural network if,*

$$\begin{aligned}\mathcal{F}: \sigma^{(l+1)}(j) &= g\left(\int_{R^{(l)}} \sigma^{(l)}(i) w^{(l)}(i,j)\, di\right)\\ \sigma^{(0)}(j) &= \xi(j).\end{aligned} \tag{2}$$

Furthermore let $\{\mathcal{F}\}$ denote the set of all functional neural networks.

Methods

Lorem ipsum dolor **sit amet**, consectetur adipiscing elit. Sed laoreet accumsan mattis. Integer sapien tellus, auctor ac blandit eget, sollicitudin vitae lorem. Praesent dictum tempor pulvinar. Suspendisse potenti. Sed tincidunt varius ipsum, et porta nulla suscipit et. Etiam congue bibendum felis, ac dictum augue cursus a. **Donec** magna eros, iaculis sit amet placerat quis, laoreet id est. In ut orci purus, interdum ornare nibh. Pellentesque pulvinar, nibh ac malesuada accumsan, urna nunc convallis tortor, ac vehicula nulla tellus eget nulla. Nullam lectus tortor, *consequat tempor hendrerit* quis, vestibulum in diam. Maecenas sed diam augue.

Important Result

Theorem. *Given a functional neural network $\mathcal{F}$ then some layer $l \in \mathcal{F}$, the let $K: C(R^{(l)}) \to C(R^{(l)})$ be a bounded linear operator. If we denote the operation of layer l on layer $l-1$ as $\sigma^{(l+1)} = g\left(\Sigma_{l+1}\sigma^{(l)}\right)$, then for every $\epsilon > 0$, there exists a weight polynomial $w^{(l)}(i,j)$ such that the supremum norm over $R^{(l)}$*

$$\left\|K\sigma^{(l)} - \Sigma_{l+1}\sigma^{(l)}\right\|_\infty < \epsilon \tag{3}$$

Mathematical Section

Nam quis odio enim, in molestie libero. Vivamus cursus mi at nulla elementum sollicitudin. Nam quis odio enim, in molestie libero. Vivamus cursus mi at nulla elementum sollicitudin.

$$E = mc^2 \tag{4}$$

Nam quis odio enim, in molestie libero. Vivamus cursus mi at nulla elementum sollicitudin. Nam quis odio enim, in molestie libero. Vivamus cursus mi at nulla elementum sollicitudin.

$$\cos^3\theta = \frac{1}{4}\cos\theta + \frac{3}{4}\cos 3\theta \tag{5}$$

Results

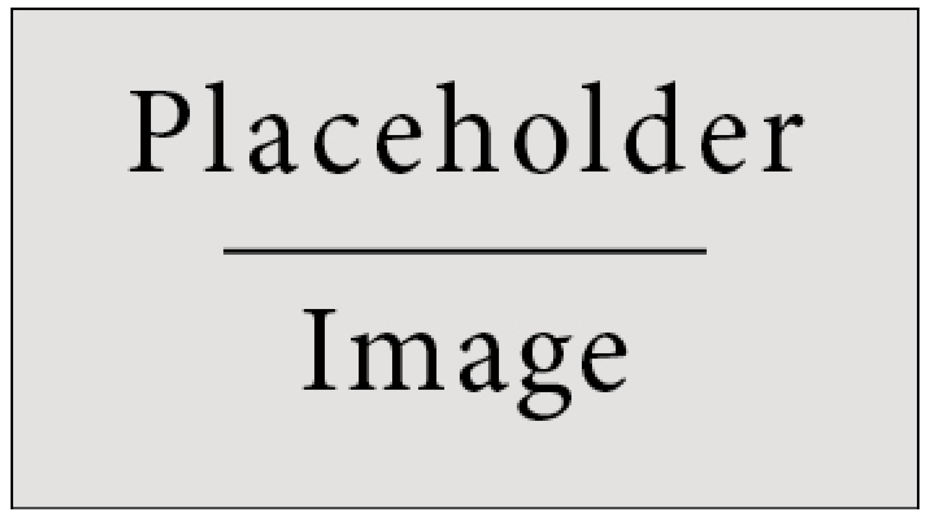

Figure 1: Figure caption

Nunc tempus venenatis facilisis. Curabitur suscipit consequat eros non porttitor. Sed a massa dolor, id ornare enim:

Conclusion

Nunc tempus venenatis facilisis. **Curabitur suscipit** consequat eros non porttitor. Sed a massa dolor, id ornare enim. Fusce quis massa dictum tortor **tincidunt mattis**. Donec quam est, lobortis quis pretium at, laoreet scelerisque lacus. Nam quis odio enim, in molestie libero. Vivamus cursus mi at *nulla elementum sollicitudin*.

Additional Information

Maecenas ultricies feugiat velit non mattis. Fusce tempus arcu id ligula varius dictum.

- Curabitur pellentesque dignissim
- Eu facilisis est tempus quis
- Duis porta consequat lorem

References

[1] J. M. Smith and A. B. Jones.
Book Title.
Publisher, 7th edition, 2012.

[2] A. B. Jones and J. M. Smith.
Article Title.
Journal title, 13(52):123–456, March 2013.

Acknowledgements

Nam mollis tristique neque eu luctus. Suspendisse rutrum congue nisi sed convallis. Aenean id neque dolor. Pellentesque habitant morbi tristique senectus et netus et malesuada fames ac turpis egestas.

Contact Information

- Web: http://www.university.edu/smithlab
- Email: john@smith.com
- Phone: +1 (000) 111 1111