Properties of Manifold Induced Neural Network Architecture

Kiran Bist (Undergraduate Research Student), QEP

Department of Mathematics, William Carey University

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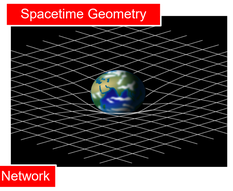
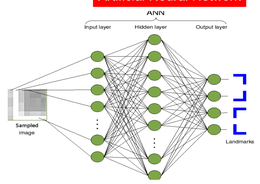
Introduction

Machine Learning

Spacetime Geometry



Artificial Neural Network



- Machine Learning is a method where a computers learn through training of datasets.
- Artificial Neural Network are the biology-inspired network architectures which are based on the structure of neurons and synapses.
- Spacetime is the physical idea originated by Einstein/Minkowski and others in which space and time are described by a single entity. It is most often modelled as manifold in Einstein's theory of relativity.

Conventional model in artificial neural network (a specific branch of machine learning) are based on Euclidean geometry (i.e. Newtonian physics). However, the universe performs in the form of Lorentzian/Minkowski geometry (i.e. Relativity). This project will show how spacetime based neural networks perform better for some machine learning tasks.

Outline of the Project

We build a neural network architecture based on spacetime model. After the desired network is obtained, we train it with breast cancer dataset to see the performance. The construction is shown below (Euclidean Case):

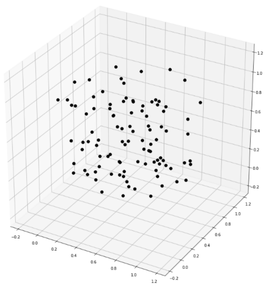


Fig 1.0

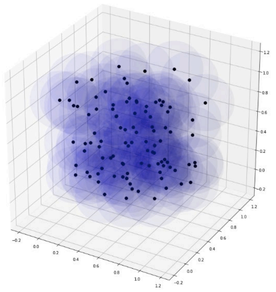


Fig 1.1

- First, we scatter random nodes in n-dimensional space (in this case n=3). (see Fig 1.0)
- We use distance function ($s = \sqrt{x^2 + y^2 + z^2}$) to construct the connection for information flow. The halo around each node represent all the possible points around the node. The overlap of halo signifies connection. (see Fig 1.1)

- We will restrict the direction of information flow as "up the page" analogous to the direction of time in spacetime model. The edges connecting the nodes will signify an information flow.(see Fig 1.2)
- It is difficult to see the structure of our network even with the "up the page" convention. So, we need to decompose our network structure into layers. We use layer decomposition via "sequential past-to-future greedy algorithm". (see Fig 1.3)

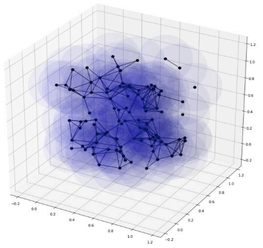


Fig 1.2

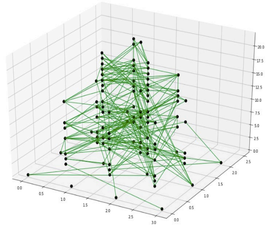
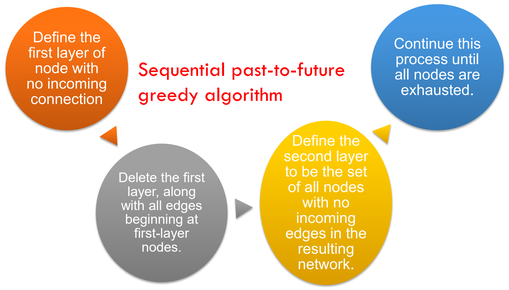


Fig 1.3: Same figure as Fig 1.2 but rearranged to show layer structure.



Lorentzian Network

difficult to limit the number of layers without creating a very sparse structure where a lot of nodes were disconnected. This means there will be fewer input data which isn't beneficial. Now, we introduce a network based on Lorentzian/Minkowski geometry.

- We introduce a different manifold geometry known as Minkowski space. It is a Lorentzian manifold with distance function $s = \sqrt{-(ct)^2 + x^2 + y^2}$. (see Fig 2.1)

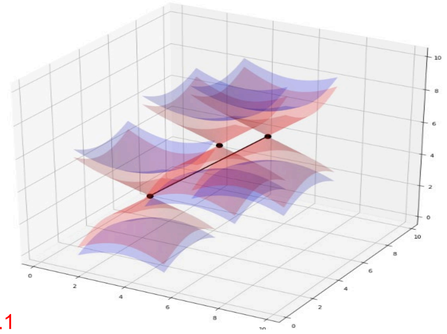


Fig 2.1

- In Fig 2.1, the accessible points within a certain distance of a given node are those *between* a particular cone and a particular hyperboloid of two sheets centered at the node. The nodes connected through a line are closer together in a Lorentzian sense, because each is between the cone and hyperboloid of the other.
- Each cone is called a null cone of its apex node because it consists of each points at distance zero from the node. Physically , the null cone is the familiar light cone from relativity.
- Here, for the purpose of comparison to the Euclidian model, we look at the Lorentzian network with the Lorentzian halo. (see Fig 2.2)

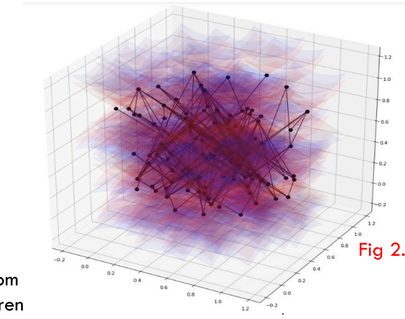


Fig 2.2

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Performance of Spacetime Architecture with Breast Cancer Dataset

We will apply the spacetime inspired network to a medical dataset for diagnoses of Breast cancer from University of Wisconsin. We approach the training and testing of data in a following order:

- We preprocess data before feeding it to the Lorentzian network we design. Fig 3.1 shows a Lorentzian network with 4 layers (2 deep layers) and with 31 input nodes and 5 output nodes .
- We prune network to achieve a desired input layer of 30 input nodes and 2 output nodes. Fig 3.2 shows the pruned network.

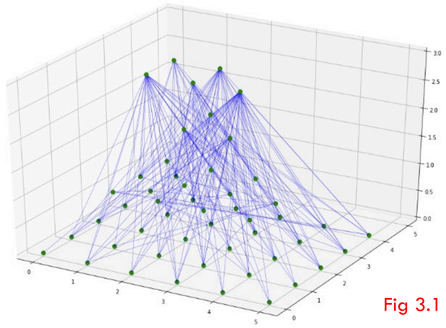

Fig 3.1

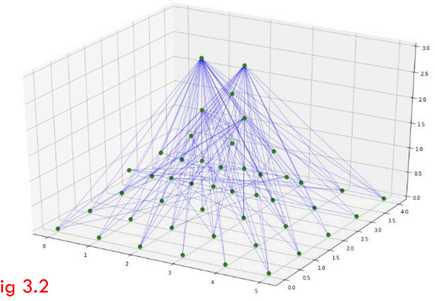

Fig 3.2

- Now, we the convert the resulting compressed edge template into a list and initialize a neural network using this template. Then we set the weight as independent and train the network.

Confirmation

We receive an accuracy of 98% with the medical problem of Breast cancer diagnoses. Spacetime inspired network performed exceptionally well. With further experiment it is expected to perform better. Fig 3.3 shows the error--loss plot.

Fig 3.3

References

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Contact Information

Kiran Bist
Undergraduate Research Student (WCU)
Email:
kbist349963@student.wmcarey.edu
Cell phone: (+01)601-310-9478