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Singular value Decomposition applied to Associative Memory of Hopfield Neural Network

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Abstract

Content-addressable memories are useful for storage and data retrieval from arrays of sensors. The Hopfield neural network is a model of associative content-addressable memory with a simple flexible structure. Design of this artificial neural network is capable of memorizing large quantity of data and recalling the same from available information. In this work, we have shown that with corrupted input dataset, the correct set of data can be retrieved from approximated or compressed associative memory matrix. The idea has been explained through an experiment using binary datasets. The proposed methodology will increase the storage capacity of associative memory. In the experiment we have shown that it will minimize the number of arithmetic operations involved in recovery process of the Hopfield model but will also ensure correctness of information retrieval from the synaptic matrix from a corrupted dataset as input.

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1. Introduction

After introduction of associative content addressable memory based on neural network by Hopfield [1] three decades have passed. Based on his concept we have seen many development and application in various domains like medical imaging, image analysis, object recognition and detection etc. It has been a major point of interest in the neuroscience community.

The Hopfield neural network is a model of associative content-addressable memory with a simple flexible structure. Designing artificial neural networks capable of memorizing large quantity of data and recalling the same from partially available information had been reviewed by many researchers [1,2,3,4,5,6]. Our work is focused to compress the associative memory and recall the original pattern from partially corrupted input data. This work will increase the capacity of associative memory and minimize the number of arithmetic operation involving recovery process of the Hopfield model. Our goal was to demonstrate that the associative memory can be compressed and in compressed form it can be used to retrieve the information from a corrupted input data.

During this work, we have applied Singular Value Decomposition (SVD) method on Associative memory for approximation. To recall correct information from the erroneous data; instead of using the original Associative memory we have decomposed the components of Associative memory.

In section II, we have briefly discussed the Hopfield model of associative memory. The concept of SVD is explained in Section III. In Section IV we have discussed the effect of SVD on Associative memory of a neural network of \( N \) neurons.

2. The Hopfield Model

Hopfield proposed two basic models of associative memories namely Discrete model & Continuous model [1]. In our work we have considered the discrete format. Hopfield used network energy function to design recurrent network [1][2][6]. Hopfield method popularized the use of recurrent networks for associative memory. Let each neuron has a binary state; let \( V_i \in \{1, -1\} \). Let state of the network with \( N \) neurons is represented by the vector, \( V = [V_1, V_2, ..., V_i, ..., V_N]^T \).

In Hopfield model the network is fully-connected. Let the weight from \( j^{th} \) neuron to \( i^{th} \) neuron is given by, \( w_{ij} \) and weight matrix is represented as W where \( w_{ii}=0 \).

\[
W = \sum_{k=1}^{N} V_k V_k^T - NI_N
\]  

At any time stamp, \( t \), each neuron receives inputs from all other neurons, and updates its own state. The next state of \( i^{th} \) neuron is expressed as a function of current state of the network as follows:

\[
V_i(t+1) = sgn(\sum_{j=1}^{N} W_{ij}V_j(t)) where sgn(a) = \begin{cases} 1, & a \geq 0 \\ -1, & a < 0 \end{cases}
\]  

Eq.2 is iterated with the present input which is the past output of the previous stage. The iteration is continued until the system approaches a minimum energy state using Lyapunov energy function[1][2][6] shown in Eq.3.

\[
E = -\frac{1}{2} \sum_{i=1}^{N} \sum_{j=1}^{N} W_{ij}V_jV_i
\]
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