Gaussian Discrete Restricted Boltzmann Machine: Theory and Its Applications

Subha Manoharan

A thesis presented in partial fulfilment of the requirements of the degree of

Master of Engineering

in

Electronics and Computer Engineering

at Massey University, Albany,

New Zealand

2015

Abstract

Restricted Boltzmann Machine (RBM) is a two-layer neural network, popular for its efficient training methodology in many applications involving data recall, classification, and recognition. Traditionally RBM is designed with binary neurons in both layers. RBMs with Gaussian (continuous-valued) neurons in visible layer have been introduced for ease of integration with real data. However, the hidden layer still consists of binary neurons. Recently, theoretical studies in discrete RBM with discrete visible and hidden nodes have shown that increasing the number of hidden states improves reconstruction error. Motivated by this finding, the research in this thesis aims to develop an RBM with a Gaussian visible layer and a discrete multi-state hidden layer, called the Gaussian Discrete RBM (GDRBM). The equations governing this new model have been worked out and a contrastive divergence training algorithm has been developed based on these equations. Performance results using the MNIST and CBCL benchmark datasets show that the performance of a GDRBM with 4-state hidden neurons is approximately the same as that of other Gaussian RBMs with binary hidden neurons when the size of the hidden layer is doubled. This GDRBM has also been used to form one layer of a deep autoencoder. This is the first time an autoencoder has been designed with a multi-state discrete layer. Initial experimental results show that a GDRBM-based deep autoencoder is able to reconstruct the inputs reasonably well. However the pretraining is not very effective and the amount of initial reconstruction error need to be reduced to make it perform at the same level of a traditional deep autoencoder. Further research will be needed to understand how GDRBM could be used in a deep autoencoder.

Acknowledgements

I would like to express my heartfelt thanks to my supervisor Assoc. Prof. Edmund Lai for his guidance and great efforts throughout the duration of this degree. I am grateful to him for his unbelievable support to complete this thesis. His guidance not only teaches me research skills but also many life skills which help in my entire life.

I would like to extend my gratitude to Graduate Research School, Professors, PhD students and International office in Massey University for their support and assistance for this course.

I wish to express my special thanks to Chathurani Silvia and her family, Vaitheki Sanjeeharan, Ibtisam Abbas, Sadia Alam and Annaniah Sundarajan for their encouragement and moral support during the initial stage of my studies. I would also like to thank Mr. Raj Narayanan for his financial support during my stay in New Zealand. Thank you all for your personal support to complete this degree.

Lastly, I thank my entire family for their co-operation to complete this study.

This thesis would not be completed without the support from all the above mentioned people. Once again, I appreciate all friends, family and Massey University for their precious resources and encouragement.

I dedicate this thesis to my supervisor Dr. Edmund Lai to express my thankful towards his support.

Table of Contents

List of Figures

List of Tables

List of Algorithms

List of Acronyms

AI	Artificial Intelligence
ANN	Artificial Neural Network
BM	Boltzmann Machine
CD	Contrastive Divergence
CBCL	Center for Biological and Computational Learning
DBN	Deep Belief Network
DBM	Deep Boltzmann Machine
FPCD	Fast Persistent Contrastive Divergence
GRBM	Gaussian RBM
GBRBM	Gaussian Bernoulli RBM
GDRBM	Gaussian Discrete RBM
IGRBM	Improved Gaussian Bernoulli RBM
IBGRBM	Improved Bernoulli Gaussian RBM
MSE	Mean Square Error
PCD	Persistent Contrastive Divergence
PT	Parallel Tempering
RNN	Recurrent Neural Network
RBM	Restricted Boltzmann Machine