

VICTORIA UNIVERSITY OF WELLINGTON
Te Whare Wānanga o te Ūpoko o te Ika a Māui



School of Engineering and Computer Science
Te Kura Mātai Pūkaha, Pūrorohiko

PO Box 600
Wellington
New Zealand

Tel: +64 4 463 5341
Fax: +64 4 463 5045
Internet: office@ecs.vuw.ac.nz

**Richer, Restricted Boltzmann
Machines**

Max Godfrey

Supervisor: Marcus Frean

Submitted in partial fulfilment of the requirements for
Bachelor of Engineering with Honours.

Abstract

In machine learning encoding prior knowledge about a task can be essential to the techniques ability to perform well on said task.(Big mental leap here....) This report explores and evaluates a novel approach to modelling data that is caused by two, independent sources. The theory has been proposed by Frean, Marcus and Marsland, Stephen, leveraging the popular Restricted Boltzmann Machine as a model for a source and a Sigmoid Belief Network as the way for these complex causes to combine. A new algorithm is presented under the dynamics of this model that allow independent representations of multi-cause data to be represented given a multi-cause input.

Contents

1	Introduction	1
1.1	Problem	1
1.1.1	Deep Belief Networks can achieve state of the art performance	1
1.1.2	DBNs have no mechanism for separating sources	1
1.1.3	Restricted Boltzmann Machines cannot separate sources either	1
1.1.4	Sigmoid Belief Networks; Intractably rich in practice	1
1.2	Solution	2
1.2.1	Trading tractibility for Source Separation	2

Chapter 1

Introduction

1.1 Problem

1.1.1 Deep Belief Networks can achieve state of the art performance

Deep Belief networks are powerful models that have proven to achieve state of the art performance in many domains. For instance a non-exhaustive list is image classification, dimensionality reduction, natural language recognition, Document classification, Semantic Analysis and .

DBNs capture non-linear interactions between low level features, in the context of image classification the lower layers should capture image filters.

1.1.2 DBNs have no mechanism for separating sources

Despite a DBNs expressiveness, there is no way to extract these interactions. If an input has multiple sources then the complex combination is instead learnt, the network has no mechanism for extracting multiple causes. This is the motivation for this project, to be able to separate the sources of data in a new model.

1.1.3 Restricted Boltzmann Machines cannot separate sources either

Restricted Boltzmann Machines are two layer, fully connected, unsupervised neural networks. DBNs are constructed by stacking RBMs. Being the building block of the powerful DBN, RBMs are a natural starting point for representing multiple sources. RBMs make the assumption that the features of the input data are dependant in the prior, as they are independant in the posterior. The latter makes them tractable to use in practice, but also means they model/encode a single representation. Again using the example of images, an input image will map to a single representation, again there is a lack of mechanism for modelling sources that are acting independantly.

1.1.4 Sigmoid Belief Networks; Intractably rich in practice

The Sigmoid Belief Network, the parameterized version of a Bayesian/Belief network appears as a natural choice for modelling independant sources in that it makes a polar assumption to the RBM; – Warning Semicolon Use – Every feature has an independant cause. The sigmoid belief networks assumption could capture data that has multiple sources, but this is intractable in practice.

1.2 Solution

1.2.1 Trading tractability for Source Separation

Frean and Marsland propose a generative model that aims to trade a small amount of the RBMs performance for richness, finding a middle ground between the sigmoid belief network and the restricted boltzmann machine. Frean and Marsland also propose an algorithm to invert this model, separating the sources of an input.

The new generative model, referred to onwards as an ORBM, uses an RBM to model each source and a sigmoid belief network to capture their combination to form data. This project explores the ORBM use for separating two causes.

Figure 1.1: The proposed generative model for capturing two causes, the ORBM.

Given the proposed model and algorithm, this project answers the following questions:

- Can this model encode data comprised of more than one cause as it's constituted causes? That is, can the model and new algorithm for inverting it, perform source separation.
- Is the ORBMs two cause structure too rich to be tractable in practice?

Bibliography