Distinction between features extracted using Deep Belief Networks

Mohammad Pezeshki  
Department of Computer Eng. and IT  
Amirkabir University of Technology  
Tehran, Iran  
m.pezeshki@aut.ac.ir

Sajjad Gholami  
Department of Computer Eng. and IT  
Amirkabir University of Technology  
Tehran, Iran  
s.gholami@aut.ac.ir

Ahmad Nickabadi  
Department of Computer Eng. and IT  
Amirkabir University of Technology  
Tehran, Iran  
nickabadi@aut.ac.ir

Abstract

Data representation is an important pre-processing step in many machine learning algorithms. There are a number of methods used for this task such as Deep Belief Networks (DBNs) and Discrete Fourier Transforms (DFTs). Since some of the features extracted using automated feature extraction methods may not always be related to a specific machine learning task, in this paper we propose two methods in order to make a distinction between extracted features based on their relevancy to the task. We applied these two methods to a Deep Belief Network trained for a face recognition task.

1 Introduction

Efficiency of many machine learning algorithms depends on the quality of features used for training [1]. There are some automated feature extraction methods such as Principle Component Analysis and Deep Belief Networks. The result of these methods is potentially useful, but there is one issue with these features. It is not always transparent which features will be relevant for a given machine learning task. As a result, it would be a great job to separate extracted features based on their relevant to the task.

One of the state-of-the-art tools for feature extraction is Deep Belief Network (DBN). It would be useful if we were able to distinguish between nodes which present different features. For example, in a face recognition task, the main subject of the task is objects of face and side information such are considered as noise. If we use a DBN for feature extraction, it is expected that some nodes in the last layer of the DBN present the face and others present side information. Therefore, if we find nodes presenting face singly, obviously the efficiency of the face recognition task would be increased significantly. In this paper, we propose two methods in order to make a distinction between last layer nodes of a DBN and in particular, examine the ability of a DBN to separate different features and represent them in distinct groups of nodes.

2 Deep Belief Networks

Deep Belief Networks (DBNs) are probabilistic graphical models which have multiple hidden layers. DBN is a mixed directed-undirected model such that all layer are connected with directed
links except the top layer which forms an undirected bipartite graph. [Figure 1 (a)]. Hinton et al. introduced a fast greedy layer-wise algorithm which can be used for learning DBNs. [2]

DBNs can be constructed by staking multiple bipartite undirected graphical models called Restricted Boltzmann Machines (RBMs). RBM is a Boltzmann Machine which is restricted to have only one hidden layer and one visible layer and also have no visible-visible and hidden-hidden connections [3]. A graphical depiction of an RBM is shown in Figure 2 (b).

Figure 1: (a) Restricted Boltzmann Machine. (b) A stack of RBMs. (c) The corresponding DBN. [4]

3 Proposed Methods

In this section, we will discuss proposed methods to make a distinction between last layer nodes in a DBN.

3.1 Method of Variances

This method based upon the fact that inputs with different aspects (set of features) activate different nodes. Trying this process on some same-aspect inputs should force some nodes to have a significant variation against others. If we feed the network with a group of inputs consisting of just one aspect, the values of some particular nodes in the last layer would change significantly. Consequently, these nodes would have higher variations. Hence, a statistical criterion such as Variance could be a good tool to distinguish between different kinds of nodes.

3.2 Method of Relative Activities

The second method relies on the concept of relative activity. Relative activity is an indicator for revealing the dependency of last layer nodes of a network to the features of the given input. In this technique, relative activity of nodes can be computed by subtracting the values of top layer nodes for two kinds of inputs. First input consists of only one feature, and second input consists of previous feature alongside another feature.

4 Experimental results

To evaluate the above-mentioned methods, we train a DBN with 4 hidden layers: 2000-1000-500-100. Training and testing done using the following dataset which consisted three parts:

1. Face images from CMU PIE face database [5], size: 10,000
2. Handwritten digits from MNIST dataset [6], size: 5000
3. Face images corrupted by digit images, size: 5000
Some sample inputs are shown in Figure 2.

![Sample inputs](image)

Figure 2: Sample inputs.

To discover the nodes presenting the face images we applied our two proposed methods in the following ways:

### 4.1 Using method of Variance

According to method 1, a group of inputs consisting of faces images singly are fed to the network. Now the Variance of nodes is computed and nodes with a Variance higher than 0.1 are considered as nodes which present the face images. Again the DBN is fed with another input consisting of digit images. In the same way, nodes with a Variance upper than 0.1 have a higher activity in comparison with other nodes as shown in Figure 2-a.

### 4.2 Using method of Relative activities

According to method 2, each mixed image and its corresponding clear digit image are given to the network respectively. Node-from-node difference between last layer nodes for these two images show the relative activity. Finally, the average relative activity for all images are computed and nodes with an average relative activity higher than 0.7 are considered as nodes presenting the face features. This process is illustrated in Figure 2-b.

![Relative activity](image)

Figure 3: (a) Different images activates different nodes. (Method of Variances) (b) Relative activity can be computed by subtracting the values of nodes. (Method of Relative activities)

By applying methods mentioned in the preceding paragraphs, we discovered face nodes (the nodes which present faces images). Now when a mixed image is fed to the DBN, all nodes are active. To reconstruct the whole face image which was previously corrupted by a digit, it is necessary to make digit nodes (the nodes which present digit images) inactive. Digit nodes would be inactive, when a neutral value is put instead of their current value. These neutral values can be computed by averaging on the values of these nodes when only face images are fed to the network. Now only the face nodes are used in reconstruction process in practice. The Figure 3 shows how the results of reconstruction process is improved when digit nodes are inactivated.

### 5 Conclusion

In this paper we focused on the properties of the features extracted using Deep Belief Networks. Obviously, it would be quite useful if we are able to make a distinction between the features extracted
using a DBN. We proposed two novel methods in order to understand which nodes are presenting which features. In our methods Variance and Relative activity are two criteria to make a distinction between nodes. We evaluated these methods on a data set consisting of MNIST handwritten digits and CMU PIE faces databases.

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