Applying Back-propagation in Convolutional Neuron Network for Image Classification Learning

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Abstract. Image classification is a basic subject in the research of machine learning area. Many different structures have been used to improve the accuracy of image classification, in which the Convolutional Neural Network gives a high accuracy according to the previous work. The most frequently used algorithm in modern neuron network should be the back-propagation. In this research, I have tried to apply back-propagation into convolutional neuron network task in image classification. And tried to find out a way to improve the accuracy in image classification by applying back-propagation in different layers in the CNN network.

Keywords: back-propagation, convolution neural network, MNIST dataset

1 Introduction

Machine learning encompasses algorithms that learn a task from a series of examples. There are various subfields of machine learning. It's an easy task for human to recognize objects from cluttered scenes saw by the eyes and learn the meaning of different objects. However, it may be a big challenge for the artificial system to learn from the view and tell the objects in it. To help to make the artificial system recognize object like human, hierarchical neural models often used in emulating human visual system. CNNs are hierarchical neural networks whose convolutional layers alternate with sub sampling layers, reminiscent of simple and complex cells in the primary visual cortex [13]. In the aspect of image classification in machine learning, CNN have given a good performance.

Despite the drawback of taking long time or may stuck into the locality minimum, the back-propagation algorithm has excellent accurate and easy to compile. In the paper, I tried to apply back-propagation algorithm into CNN structure to improve the accuracy of image classification on the handwritten digit benchmark MNIST dataset [14].

2 Method

Neural network is a classic machine learning model, like the regression problem, the neural network model is actually creating a multi-dimensional input and output function based on training samples. And uses this function to predict. The network training process is the process of adjusting the parameters of the function to improve the prediction accuracy.

At present, most neural network models belong to feed-forward neural network, in which the data flows from input to output in one direction, and there is no loop or return channel. The back-propagation algorithm is an abbreviation for error back propagation. As a supervised learning algorithm, the training process of the back-propagation neural network is based on the comparison between the predicted value obtained by feed-forward and the reference value, then adjust the connection weight according to the error. Thus, the training process is called back-propagation, and the data flow is the opposite of the feed-forward process.

In the single label image classification tasks, the Convolutional Neural Network has shown promising performance. As the increasing in the number of connections in CNN, applying back-propagation algorithm is different from that in the simple deep neural network.

2.1 Back-propagation Algorithm

Back-propagation algorithm is an algorithm works on the units in a neuron network. The algorithm working by adjusting the weights of the links in the network over and over, to calculate a minimum measurement of the difference between the desired output vector and the actual output given by the neuron network.

In MLP, for the output layer neuron, its input is calculated as follows (ignoring offset): [5]

$$xj=\sum iyiwji \tag{1}$$

It can be seen that its input is equal to the weighted sum of the output of all neurons in the previous layer and the corresponding connection, as shown above. And the output is calculated as follows:

$$yj=11+e-xj \tag{2}$$

Then is a nonlinear transformation sigmoid.

2.2 Convolutional Neural Network

With the use of Deep Neural Network in computer vision, researchers have found a way in the object classification task to achieve the human-level recognition performance [19]. However, important differences on processing and architecture still exist between the human visual system and the state of are DNNs. Then the Convolutional Neural Network had been developed and applied to the object classification task.

Convolutional Neural Networks(CNN) are hierarchical neural networks whose convolutional layers alternate with sub sampling layers, reminiscent of simple and complex cells in the primary visual cortex [13]. The deep CNN has shown a great success in the field of image classification.

In the classification of image, CNN focuses not only on the global features, but also makes uses of local features which are important in the image recognition. CNN takes the advantages of the algorithm to extract local features into neural network. And the extract of the connection between local features and image itself is difficult for other algorithms. The comprehensive understand on the local and global features is very important in the deep learning in image classification [16].

Back-propagation algorithm is an efficient algorithm for gradient decent. In CNN, the basic process to apply back-propagation algorithm is the same. However, due to the fully connection between multiple layers, there are more calculate need to be done according to different features in different layers. In the paper Notes on Convolutional Neural Networks (Jake Bouvrie), the details of the calculation in the convolutional layer and sub-sampling layer were explained properly, which inspires me a lot.

2.3 MNIST Dataset

The handwritten digit benchmark MNIST dataset is about the classification on handwritten digit image created by LeCun. It contains 60,000 handwritten digit images for the classifier training and 10,000 handwritten digit images for the classifier testing [17]. The dataset can be download from its official website, which contains four parts for the training and testing part on images and labels. The dataset is also included in the inbuild database of Python, which can be imported directly and makes the use much easier.

The MNIST dataset is a classic dataset for the image classification task. It’s a simple label classification contains labels only from zero to nine, which makes it easy to determine the performance of image classification algorithm. And the size of the dataset also suitable for the algorithm testing, which can get a fairly accurate result without too much training and experiment time.

3 Results and Discussion

In the previous research, I have tried to apply the back-propagation algorithm to linear classification on statistical votes dataset.

the Congressional Voting Records Data Set from the Irvine database (Murphy &Aha, 1991), which basically record the investigation of questions about the preference on 16 national fundamental policies of 435 people, as well as their votes for the U.S. House of Representatives Congressmen. The dataset has a proportion of 45.2% and 54.8% for the 2 classes.

When using the linear algorithm for the classification of the votes dataset, it ends to show an accuracy of 80%. After applying the back-propagation algorithm, the result turns out to be an accuracy of 86%, which is better than the linear algorithm, but still not so good as the 93% from the Smyth et al.'s (1990) report, 1984 United States Congress.

The back-propagation algorithm improved the performance of the machine learning result on the linear model. Then I adapted the algorithm to the Convolutional Neural Network, and tested on the MNIST dataset. Before the applying of back-propagation algorithm, the CNN can already have a good performance on the classification with an accuracy of 97%. However, after applying the algorithm, the accuracy of classification still have an improvement to 99%, which is a better result compared to the previous one.

But the applying of back-propagation algorithm also have its drawback. Using back-propagation algorithm actually need to take longer time and may stuck into the locality minimum. The increasing in training time is acceptable on the MNIST dataset because of the small size of the dataset. But may be a significant problem when applying to a bigger dataset.

4 Conclusion and Future Work

We can get the conclusion that the back-propagation algorithm is a better algorithm to some extent. It works good on both the normal deep neural network and convolutional neural network. On the classification on image, a good result has been drawn from the test on the MNIST dataset that the combination on back-propagation algorithm and CNN makes improvement to the image classification. And it does not take too much time in learning, which is a good aspect.

However, the MNIST dataset is a simple dataset in the image classification. The next step that needed to do is test the structure on different dataset in the image classification, like the place recognition task and the training set from ImageNet. Also, the increasing of training time due to back-propagation algorithm may be a problem. Although it's acceptable on the MNIST dataset, it may cause significant cost on a large-scale dataset. Thus, a solution to minimum the increasing of training time is needed.

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