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OPTIMISING NEURAL NETWORK USING MORPHNET ARCHITECTURE

Comparing performance difference using vanilla python and tensorflow for neural network performance

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Abstract: Deep Learning is statistical learning made by the means of many-layered artificial neural networks, also called deep neural networks. ANNs essentially are graphs having their basic computational units (nodes or neurons) grouped in sets usually called layers. In order to get a functional neural network, you got to have at least an input layer and an output layer, and one or more intermediate hidden layers. If your ANN does have many of such hidden layers, you got a deep neural network.

Index terms – Machine learning, neural networks, morphnet, tensorflow.

I. INTRODUCTION

Machine learning (ML) is a category of algorithm that allows software applications to become more accurate in predicting outcomes without being explicitly programmed. The basic premise of machine learning is to build algorithms that can achieve input data and use statistical analysis to predict an output while updating outputs as new data becomes available. Machine learning is an evolving branch of computational algorithms that are designed to emulate human intelligence by learning from the surrounding environment. Machine learning systems are used to identify jobs in images, transcribe speech into text, match news items, posts or products with user's interests and select relevant results of search.

II. MACHINE LEARNING

Machine learning methods reach ever deeper into quantum chemistry and materials simulation. Large data sets of molecular properties calculated from quantum chemistry or measured from experiment are equally being used to construct predictive models to explore the vast chemical compound space to find new sustainable catalyst materials, and to design new synthetic pathways. Recent research has explored the potential role of machine learning in constructing approximate quantum chemical methods, as well as predicting MP2 and coupled cluster energies from Hartree–Fock orbitals. There have also been approaches that use neural networks as a basis representation of the wave function [2].

In machine learning, artificial neural networks can be used to perform one or more functions like acquiring, processing, analysing , and understanding various inputs in order to produce an output that includes numerical or symbolic information. A neural network includes one or more algorithms and interconnected nodes that exchange data between one another. The nodes can have numeric weights that can be tuned based on experience, which makes the neural network adaptive and capable of learning [9].

III. NEURAL NETWORKS

Neural networks are machine learning models that afford one or more layers of non linear units to predict an output for a received input. Its possible to detect objects in images using neural network systems. There are one or more hidden layers in addition to the output layer .Each layer produces an output from a received input with respective set of parameters. In some implementations, the system includes one or more regional neural network layers that can process the image. In other implementations, the one or more regional neural network layers include one or more horizontal network layers [1].

Neural networks are indispensable to state-of-the-art artificial intelligence algorithms. However, its high accuracy comes at the cost of high computational complexity which leads to high cost of data centers. An automated algorithm simplifying a pre-trained neural network to reduce its computational complexity has been developed. The algorithm first loosens the constraint on the complexity and then gradually tightens it until the target complexity is met. During this process, a group of simplified neural networks with different accuracy-complexity trade-offs are generated. The algorithm jointly considers the complexity reduction and the accuracy drop, and the hyper-parameters are also more intuitive and easier to tune when compared with other automated algorithms for simplifying neural networks. These features enable designing neural networks with a better accuracy-complexity trade-off, which facilitates the deployment of neural networks on more applications [5].

IV. APPLICATION

Deep Neural Networks have led to tremendous success in various applications, such as image classification, speech recognition, medical applications. Wide deployment of DNNs has raised several major security concerns. For example, in the context of image classification, an example is a carefully modified image that is visually imperceptible to human eyes, but fools the DNN successfully. Recently, there has been a lot of work toward developing new adversarial attack techniques, which have exposed the underlying vulnerability of DNN [8].

The current state of compact architecture search for deep neural networks through both theoretical and empirical analysis of four different compact architecture search algorithms are
i) group lasso regularization
ii) variational dropout.
iii) MorphNet.
iv) Generative Synthesis.

The state of compact architecture search is quite interesting and diverse, and at a stage where real significant gains can be obtained for accelerating the design of deep neural networks.One of the reasons that iterative methods such as MorphNet and Generative Synthesis are able to produce compact deep neural networks with better trade-off between size, speed, and accuracy is the fact that such methods have much greater freedom to explore design search space of different topologies, thus allowing them to better identify optimal neural network architectures [3].

MorphNet, is an approach to automate the design of neural network structures. MorphNet iteratively shrinks and expands a network, shrinking via a resource-weighted sparsifying regularizer on activations and expanding via a uniform multiplicative factor on all layers. In contrast to previous approaches, our method is scalable to large networks, adaptable to specific resource constraints and capable of increasing the network's performance. When applied to standard network architectures on a wide variety of datasets, our approach discovers novel structures in each domain, obtaining higher performance while respectingthe resource constraint [4].

It is said that the deep networks have been successfully applied to unsupervised feature learning for single modalities. Here a series of tasks for multimodal learning and the process for training deep networks to address the tasks are presented. Also the demonstration of a cross modality feature learning where better features of one modality can be learned from multiple modalities are made. A representation between modalities and its evaluation on a unique task, Where the classifier is trained with audio only data and is tested with video only data [6].

The deep artificial neural networks often have far more trainable model parameters than the number of samples they are trained with. Some of these models exhibit remarkably small generalization error like difference between training error and test error. At the same time, it is easy to come up with natural model architectures that generalize other models. Here an answer to what is the reason that is affecting the generalization of neural networks is pointed out [7].

V. MORPHNET IN NEURAL NETWORKS

We presented MorphNet, a technique for learning DNN structures under a constrained resource. In our analysis of model size constraints, we have shown that the form of the trade-off between constraint and accuracy is highly dependent on the specific resource, and that MorphNet can successfully navigate this trade-off when targeting model size [10].

Morphnet's construction and pruning approach to optimise the structure of a feed forward neural network with a single layer that is hidden. The number of hidden nodes or neurons is determined by their contribution ratios, which are calculated using a Fourier decomposition of the variance of the feed forward neural network output. These hidden nodes with a small contribution ratios will be eliminated, while the new nodes will be added when the feed forward neural network is not able to satisfy certain design objectives. The performance of the method stated is evaluated using a number of examples like real life date classification, dynamic system identification etc. The results obtained show that the proposed method effectively optimises the network structure and performs better than some existing steps[11].

The key features of Morhpnet is that it transforms the training problem into a set of quadratic optimization problems which is solved by a number of linear equations. Next feature is that it constructs an appropriate network to meet the training specifications. The third feature is that the resulting network architecture and weights can be refined with standard training algorithms like back propagation that is giving a significant speed-up in the development time of the neural network which is also used to decrease the amount of trial and error usually associated with network development[12].

This paper is about the approaches that are combining genetic algorithms and neural networks which have received a great deal of attention in these years. As a result of this, much work has been reported in two major areas of neural network design which is training and topology optimisation. This paper says about the major issues associated with the problem of pruning a multi layer perceptron with the help of genetic algorithms and simulated annealing. The study presented considers a number of various aspects which is associated with network training which may alter the behaviour of a stochastic topology optimiser[13].

VI. CONCLUSION

We presented MorphNet, a technique for learning DNN structures under a constrained resource. In our analysis of FLOP and model size constraints, we have shown that the form of the trade-off between constraint and accuracy is highly dependent on the specific resource, and that MorphNet can successfully navigate this trade-off when targeting either FLOPs or model size. Furthermore, we have applied MorphNet to large scale problems to achieve improvements over human-designed DNN structures, with little extra training cost compared to training the DNN once. While being highly effective, MorphNet is simple to implement and fast to apply it is definitely a general rule for machine learning practitioners to better automate the task of neural network architecture design[14].

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