Jonathan Lee
Dr. Nelson
Neural Networks
7 May 2015

Applications of Artificial Neural Networks

INTRODUCTION

Artificial neural networks have demonstrated tremendous potential for applications in a wide variety of fields. Because of the ability of neural networks to deal with large amounts of data and adapt to certain data sets, they can be used for almost any type of classification, prediction and recognition task. The primary advantage of the neural network is that it can maintain the same pattern of propagation and structure but can still adapt to different contexts. The structure of a network is in no way specific to the task, only the weights are. This paper examines some of the histories, advantages and limitations of neural networks in the contexts of two tasks: data compression and computer vision.

DATA COMPRESSION

The tasks of neural networks usually reside in the domains of classification. However, the long-standing problem of data compression presents a new opportunity for networks. One of the main purposes of data compression is to minimize data while also minimizing the loss of information during the process of compression. It should be noted however that there are *lossy* data compression techniques where some of the quality of the information is expected to be lost in exchange for more data reduction. Lossy compression may be appropriate for certain situations.

There are two components to every compression algorithm: encoding and decoding. For a network compression, the encoding and decoding processes occur during propagation. The structure of a compression network has an equally sized input and output layers with smaller sized intermediate layers. The data are encoded as the they propagate to an intermediate layer. This intermediate layer thus represents the compressed data which can be decoded by propagating through the remaining layers to the output layer.

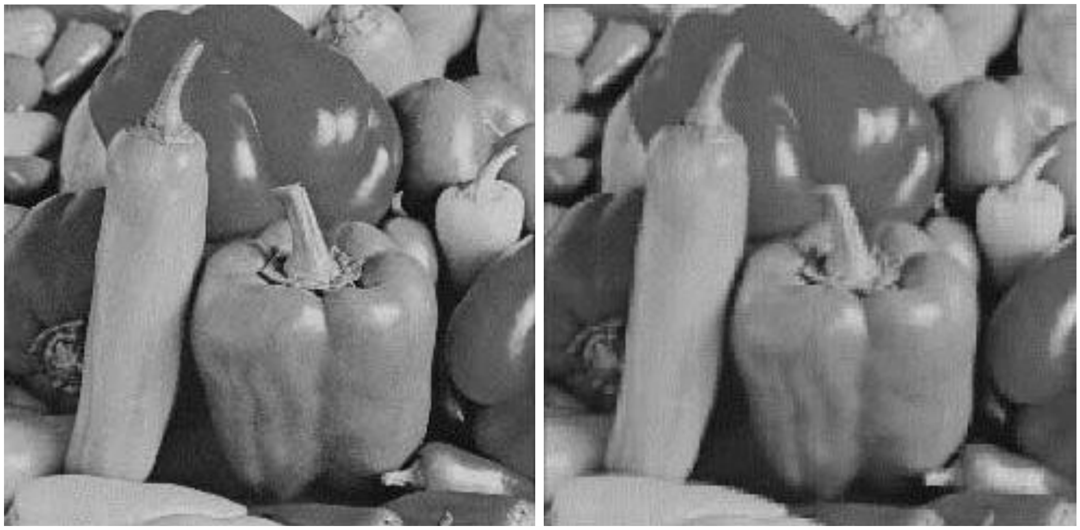

Figure 1: This figure shows two images from cs.stanford.edu. The left is the original image and the right is the same image after propagation through the compression network. The right image clearly has lost some quality.

The limitation that becomes apparent is that the intermediate layer values are represented as decimal values usually between zero and one or negative one and one depending on the activation function of the network. Large numbers of bits would be needed to represent every possible decimal value. The solution is to create binary codes that represent ranges of intermediate decimal values. However, this solution causes the network compression to be lossy. Since decimal values are grouped into ranges, different values can end up in the same range and then encoded by the same binary codes. Thus they are not decoded into unique outputs. *Figure 1* demonstrates the quality of an image before and after compression.

Another characteristic of network compression is that the network should be trained in a way that it generalizes the interpretation of inputs. This characteristic suggests that instead of training the network for the entire dataset, small subsets can be trained in order for the network to encode and decode frequent subsets that occur in many datasets.

According to Matthew Mahoney at the Florida Institute of Technology, neural networks have typically been avoided as a compression technique because they are slow compared to those compression techniques devised by Burrows and Wheeler in 1994. However the primary reason for continued research in network compression is that networks are capable of recognizing complex patterns that other compressions techniques are not capable of recognizing. In his 2000 paper “Fast Text Compression with Neural Networks,” Mahoney describes methods of increasing the speeds of neural networks to make them competitive with other compression techniques. Mahoney has done a significant amount of research into data compression with other techniques aside from neural networks as well. Other than Mahoney’s work in 2000, there is relatively little available information about recent advancements or research in compression with neural networks.

OBJECT RECOGNITION AND COMPUTER VISION

Computer and machine vision is one of the earliest topics of study in artificial intelligence. The goal of the field is to essentially process and understand large amounts of data in the form of images in a similar fashion as human vision. Research in computer vision dates back to the1960s (Harvey, DiCaprio, Heinemann, 1991). However in the 1990s, researchers such as Harvey *et al.* (1991) began to incorporate neural networks into the field. The primary objective was to find a method of computer vision that would recognize many different images adaptively. Eventually, neural networks were used to accurately classify objects such as military vehicles and human cells. Harvey *et al.* noted that the same essential structure of neural networks can be used for many different tasks aside from vehicle and cell recognition.

Within the last decade, neural networks for computer vision have maintained popularity. For example large technology companies such as Google have taken a strong interest in the field. Just within the last year it was reported that Google and Stanford developed neural networks that could describe the events in various pictures. Google has employed neural networks for computer vision in all kinds of other situations as well. Some examples include recognizing signs in Street View.

CONCLUSIONS

With advancements in computer hardware and new techniques for improving speed and efficiency of algorithms, neural networks have made a comeback in popularity in recent years. Due to their ability to recognize complex patterns, neural networks have become increasingly promising. Even beyond academia, major technology companies have been improving and researching the effectiveness of neural networks in certain contexts. For example Facebook AI researchers Weston, Chopra and Bordes recently published a paper on “Memory Networks” that incorporate a “long-term memory component” into typical learning algorithms such as neural networks. The applications of neural networks continue to grow as advancements such as “Memory Networks” are made.

Works Cited

Blelloch, Guy E. "Introduction to Data Compression." 31 Jan. 2013. PDF file.

Harris, Derrick. "Google Stanford Build Hybrid Neural Networks That Can Explain Photos." *Gigaom*. N.p., n.d. Web. 9 May 2015. <https://gigaom.com/2014/11/18/google-stanford-build-hybrid-neural-networks-that-can-explain-photos/>.

Harvey, Robert L., Paul N. DiCaprio, and Karl G. Heinemann. *A Neural Network Architecture for General Image Recognition*. N.p.: Lincoln Laboratory Journal, 1991. Print.

Mahoney, Matthew V. *Fast Text Compression with Neural Networks*. N.p.: American Association for Artificial Intelligence, 2000. Print.

"Neural Networks and Image Compression." *Stanford Computer Science*. N.p., n.d. Web. 9 May 2015. <http://cs.stanford.edu/people/eroberts/courses/soco/projects/2000-01/neural-networks/Applications/imagecompression.html>.

Shiffman, Daniel. "Neural Networks." *The Nature of Code*. N.p., n.d. Web. 9 May 2015. <http://natureofcode.com/book/chapter-10-neural-networks/>.

Weston, Jason, Sumit Chopra, and Antoine Bordes. "Memory Networks." International Conference on Learning Representations. 2015. Print.

Whitwam, Ryan. "Google's Street View Neural Network Can Now Decrypt Captchas Better than a Human." *Extreme Tech*. N.p., n.d. Web. 9 May 2015.