Extending Deep Learning Techniques to Communication Systems

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***Abstract*—In the era of Big Data, machine learning and deep learning have become ubiquitous and elegant tools for processing data in many forms (images, text, audio, speech, etc.) In particular, deep learning has been transformative in the fields of Computer Vision (CV) and Natural Language Processing (NLP). However, other areas of science may also want to consider the employment of deep learning to handle such large amounts of data. In particular, communications systems have been designed and deployed successfully for transmitting and receiving data, largely without deep learning techniques for many years.**

In this paper, I look to focus on the replacement of the traditional transmitter-channel-receiver model with an end-to-end neural network representation to minimize bit-error-rate (BER). Perhaps by investigating performance through learned experiences, the field of communications can gain a more nuanced perspective. This type of approach is relatively unstudied given its cross-disciplinary nature with expert domain knowledge of communications and data science software tools.

I. Introduction

Wireless communications and Big Data are an interesting pair of companions, since data must originate and be received somewhere. Mobile applications in smartphones, laptops and tablets, as well as the burgeoning Internet-of-Things, all take part in transmitting and receiving massive amounts of data at relatively fast speeds. Consequently, modern communications technologies must be able to handle lots of data. Some methodologies have gained significant traction, such as 5G, massive MIMO and mmWave [2] . However, there may be another approach to tackling the big data challenge.

In general, deep learning has been most recognizably used as tool for applications to process lots of data (images, speech audio, etc.) Thus, it is no coincidence that the emergence of successful deep learning arrived with the rise of Big Data.

When considering the interdisciplinary aspects between signal processing and computer networking, the OSI model may be a valuable reference point. Layer 5 of the OSI model is called the Application Layer. This is where deep learning would provide obvious and immediate results as part of user applications. Nevertheless, by moving down the OSI model, deep learning may also have benefits at Layer 1, the Physical Layer. The actual communication channel of Layer 1 has demands to perform lots of signal processing (lots of data) at real-time speeds without consuming too much energy in the process.

Many times, traditional models assume linear, stationary, Gaussian and deterministic components, which at best, only approximate channel environments [1], [2]. Unfortunately, channels have imperfect realities, so even the best models are limited. Deep learning can be used to rethink this concept to provide end-to-end reliable data transfer between a transmitter and a receiver. Therein lies the potential of applying deep learning techniques to the physical layer. The goals of communications systems may be achieved with deep learning tools.

II. Methodology Outline

Following the work of O'Shea and Hoydis [1], an autoencoder architecture for the neural network may be proposed to model the end-to-end communications process from transmitter to receiver. An autoencoder should be an acceptable architecture because it is used to learn efficient encoding of data, that when uncompressed, is identical or very similar to the original data. For an autoencoder to achieve this type of processing, it has to essentially learn how to perform even in the presence of background noise. This has direct parallels with the goals of conventional transmitter-channel-receiver systems and communications overall.

As part of this project, I will investigate the benefits (if any) that deep learning offers to the broad field of communications. I will be developing my own autoencoder model as a replacement for the traditional transmitter-channel-receiver system. After training my network, I will perform some simulated experiments to visualize BER. I will also detail the challenges and tradeoffs encountered while building and testing the deep learning approach. Finally, I hope to propose some extensions from this work that may be beneficial to the cross-disciplined field of communications and deep learning.

I will use Python libraries such as TensorFlow to build the model. I hope to use a combination of Python and Matlab to perform the simulated experiments after the network has been trained sufficiently. Additionally, I will need access to GPU resources as part of the network training.

References

[1] T.J. OShea and J. Hoydis. (2017) An introduction to deep learning for the physical layer. [Online]. Available: https://arxiv.org/pdf/1702.00832.pdf

[2] T. Wang, C.-K. Wen, H. Wang, F. Gao, T. Jiang, and S. Jin, Deep learning for wireless physical layer: Opportunities and challenges, China Communications, vol. 14, no. 11, pp. 92111, 2017.