RELATED WORK

Since very recently, open-source DL software libraries (e.g., Caffe [38], MXNet [39], TensorFlow [40], Theano [41], Torch [42], Keras [43]), and powerful specialized hardware, such as field programmable gate arrays (FPGAs) and processing units (GPUs) are cheaply and readily available. Thanks to these rapid developments, the applications of DL are applied to almost every research domain [6-7] 和[5-7]. Especially, DL shines in domains such as computer vision (CV) and natural language processing (NLP), which are difficult to characterize practical tasks with rigid mathematical models.

[38] Y. Jia *et al.*, “Caffe: Convolutional architecture for fast feature embedding,”

in *Proc. 22nd ACM Int. Conf. Multimedia*, Orlando, FL, USA,

2014, pp. 675–678.

[39] T. Chen *et al.*, “MXNet: A flexible and efficient machine learning

library for heterogeneous distributed systems,” *arXiv preprint*

*arXiv:1512.01274*, 2015.

[40] M. Abadi *et al.* (2015). *TensorFlow: Large-Scale Machine Learning on*

*Heterogeneous Systems*. [Online]. Available: http://tensorflow.org/

[41] R. Al-Rfou *et al.*, “Theano: A Python framework for fast computation

of mathematical expressions,” *arXiv preprint arXiv:1605.02688*, 2016.

[42] R. Collobert, K. Kavukcuoglu, and C. Farabet, “Torch7: A MATLABlike

environment for machine learning,” in *Proc. BigLearn NIPS*

*Workshop*, 2011, pp. 1–6.

[43] F. Chollet. (2015). *Keras*. [Online]. Available:

https://github.com/fchollet/keras

[6] Y. LeCun, “Generalization and network design strategies,” in

*Connectionism in Perspective*. Amsterdam, The Netherlands:

North-Holland, 1989, pp. 143–155.

[7] K. He, X. Zhang, S. Ren, and J. Sun, “Delving deep into rectifiers:

Surpassing human-level performance on imagenet classification,”

in *Proc. IEEE Int. Conf. Comput. Vis.*, Santiago, Chile, 2015,

pp. 1026–1034.

[5] D. Wang, A. Khosla, R. Gargeya, H. Irshad, and A. H. Beck,

“Deep learning for identifying metastatic breast cancer,” arXiv preprint

arXiv:1606.05718, 2016.

[6] D. George and E. A. Huerta, “Deep neural networks to enable real-time

multimessenger astrophysics,” arXiv preprint arXiv:1701.00008, 2016.

[7] D. Silver, A. Huang, C. J. Maddison, A. Guez, L. Sifre, G. Van

Den Driessche, J. Schrittwieser, I. Antonoglou, V. Panneershelvam,

M. Lanctot et al., “Mastering the game of go with deep neural networks

and tree search,” Nature, vol. 529, no. 7587, pp. 484–489, 2016.

In communications, researchers have tried to extend machine learning (ML) towards communications in the past, but they mainly focus on cyberspace security [2-4].

[2] Buczak A L, Guven E. A survey of data mining and machine learning methods for cyber security intrusion detection. IEEE Communications Surveys & Tutorials, 2016, 18(2): 1153-1176

[3] Sommer R, Paxson V. Outside the closed world: on using machine learning for network intrusion detection// Proceedings of the 2010 IEEE Symposium on Security and Privacy. Washington, USA, 2010: 305-316

[4] Cannady J. Artificial neural networks for misuse detection//Proceedings of the 1998 National Information Systems Security Conference. Arlington, USA, 1998: 443-456 (引用的格式不统一)

Although several researchers have also addressed problems related to physical layer with ML such as channel modelling and prediction, equalization, quantization [19-20], etc., ML did not cause any fundamental impact on the physical layer. The main reason for this is that the way we design and implement communications systems is generally depended on the complex and mature expert knowledge. Based on information theory, statistics, and signal processing, as long as the system model sufficiently characterize real effects, we could design extremely accurate communication systems that enable robust algorithms for symbol detection.

[19] M. Ibnkahla, “Applications of neural networks to digital

communications—A survey,” *Elsevier Signal Process.*, vol. 80,

no. 7, pp. 1185–1215, 2000.

[20] M. Bkassiny, Y. Li, and S. K. Jayaweera, “A survey on machine-learning

techniques in cognitive radios,” *IEEE Commun. Surveys Tuts.*, vol. 15,

no. 3, pp. 1136–1159, 3rd Quart., 2013.

However, [8] presents a completely new way to think about communications systems design by representing a communication system as an autoencoder, which is a deep neural network (NN) typically used to learn how to reconstruct the input at the output. In order to incorporate (也可用integrate) expert knowledge in the deep learning, [8] also introduces the concept of radio transmitter networks (RTN), a different radio receiver model to improve the performance of autoencoder. Finally, [8] illustrates that DL could be useful tools applied to improve current wireless communications. And when channel models are difficult to derive, researchers could turn to DL from traditional signal processing algorithms to deduce the channel.

Based on these ideas from [8], [9] implements a communication system using only deep neural networks by software-define-radios (SDRs). The results from [9] demonstrate that the autoencoder idea could be implemented in the reality. To implement this fascinating novel antoencoder concept using SDRs, [9] extends the existing concepts toward continuous signal transmission, which entails the receiver synchronization issue. [9] overcomes this problem by introducing another neural network layer for frame synchronization.

[8] Timothy J. O’Shea and Jakob Hoydis. An introduction to machine

learning communications systems. CoRR, abs/1702.00832, 2017.

[9] S. D¨orner, S. Cammerer, J. Hoydis, and S. ten Brink. Deep Learning-

Based Communication Over the Air. ArXiv e-prints, July 2017.

Some other examples of deep learning tools applied to address problems in physical layer include detection of data sequences [10], modulation recognition [31], compressed sensing [19], [20], learning of encryption/decryption schemes for an eavesdropper channel [24]. There are two main different viewpoints of applying DL to the communication systems in these papers. The goal is to either completely replace existing communication algorithms with DL, or to apply DL only for improving/augmenting them.

*Notations:*

[10] Nariman Farsad and Andrea J. Goldsmith. Neural network detection of data sequences in communication systems. 2018

[31] T. J. O’Shea, J. Corgan, and T. C. Clancy, “Convolutional radio modulation

recognition networks,” in *Proc. Int. Conf. Eng. Appl. Neural Netw.*,

Aberdeen, U.K., 2016, pp. 213–226.

[19] M. Borgerding and P. Schniter, “Onsager-corrected deep learning for

sparse linear inverse problems,” arXiv preprint arXiv:1607.05966, 2016.

[20] A. Mousavi and R. G. Baraniuk, “Learning to invert: Signal recovery via

deep convolutional networks,” arXiv preprint arXiv:1701.03891, 2017.

[24] M. Abadi and D. G. Andersen, “Learning to protect communications

with adversarial neural cryptography,” arXiv preprint arXiv:1610.06918,

2016.

Since very recently, open-source DL software libraries (e.g., Caffe [38], MXNet [39], TensorFlow [40], Theano [41], Torch [42], Keras [43]), and powerful specialized hardware, such as field programmable gate arrays (FPGAs) and processing units (GPUs) are cheaply and readily available. Thanks to these rapid developments, the applications of DL are applied to almost every research domain [6-7] 和[5-7]. Especially, DL shines in domains such as computer vision (CV) and natural language processing (NLP), which are difficult to characterize practical tasks with rigid mathematical models.

In communications, researchers have tried to extend machine learning (ML) towards communications in the past, but they mainly focus on cyberspace security [2-4]. Although several researchers have also addressed problems related to physical layer with ML such as channel modelling and prediction, equalization, quantization [19-20], etc., ML did not cause any fundamental impact on the physical layer. The main reason for this is that the way we design and implement communications systems is generally depended on the complex and mature expert knowledge. Based on information theory, statistics, and signal processing, as long as the system model sufficiently characterize real effects, we could design extremely accurate communication systems that enable robust algorithms for symbol detection.

However, [8] presents a completely new way to think about communications systems design by representing a communication system as an autoencoder, which is a deep neural network (NN) typically used to learn how to reconstruct the input at the output. In order to incorporate expert knowledge in the deep learning, [8] also introduces the concept of radio transmitter networks (RTN), a different radio receiver model to improve the performance of autoencoder. Finally, [8] illustrates that DL could be useful tools applied to improve current wireless communications. And when channel models are difficult to derive, researchers could turn to DL from traditional signal processing algorithms to deduce the channel.

Based on these ideas from [8], [9] implements a communication system using only deep neural networks by software-define-radios (SDRs). The results from [9] demonstrate that the autoencoder idea could be implemented in the reality. To implement this fascinating novel antoencoder concept using SDRs, [9] extends the existing concepts toward continuous signal transmission, which entails the receiver synchronization issue. [9] overcomes this problem by introducing another neural network layer for frame synchronization.

Some other examples of deep learning tools applied to address problems in physical layer include detection of data sequences [10], modulation recognition [31], compressed sensing [19], [20], learning of encryption/decryption schemes for an eavesdropper channel [24]. There are two main different viewpoints of applying DL to the communication systems in these papers. The goal is to either completely replace existing communication algorithms with DL, or to apply DL only for improving/augmenting them.

*Notations:*