Loughborough University

A New Channel Coding Scheme with Machine Learning

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Content

1. Introduction

Nowadays, communication engineering field is getting more and more complex and mature, and researchers find it hard to improve the performance by applying expert knowledge. At the same time, deep learning shines in many domains such as computer vision and cyberspace security.

An increasing number of researchers have recognized the potential application of deep learning to the physical layer.

2. Aim and Objectives

➢Aim:

We present and discuss a novel coding and modulation scheme with deep learning.

➢Objectives:

In this thesis, we show how to build an end-to-end learning of communication system based on neural networks, and compare the performance of it with the traditional communication schemes (QPSK and BPSK).
We also present a discussion of some open research challenges in this area and several kinds of future work needed to be done.

3. Background and Theoretical Support

In 2017, T. J. O’Shea and J. Hoydis. in [1] presented 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, [1] also introduces the concept of radio transmitter networks (RTN), a different radio receiver model to improve the performance of autoencoder. Finally, [1] illustrates that deep learning could be useful tools applied to improve current wireless communications. And when channel models are difficult to derive, researchers could turn to deep learning or other machine learning techniques from traditional signal processing algorithms to deduce the channel.

3. Background and Theoretical Support

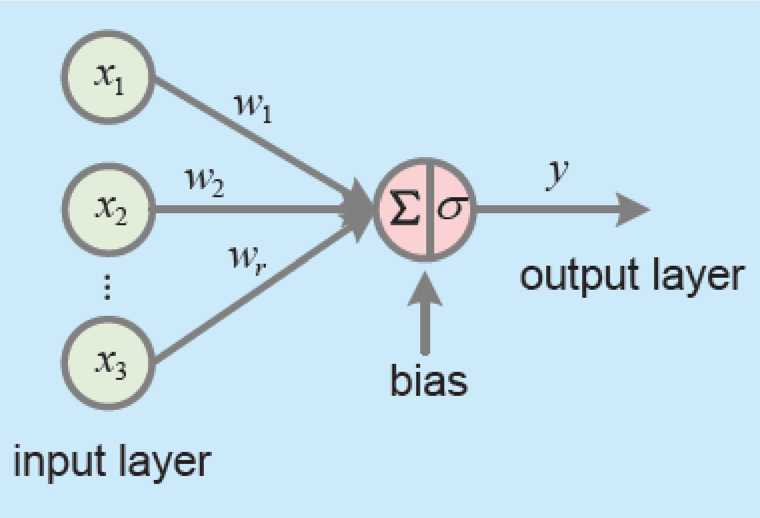


Fig.1. A mathematical model of a neuron.

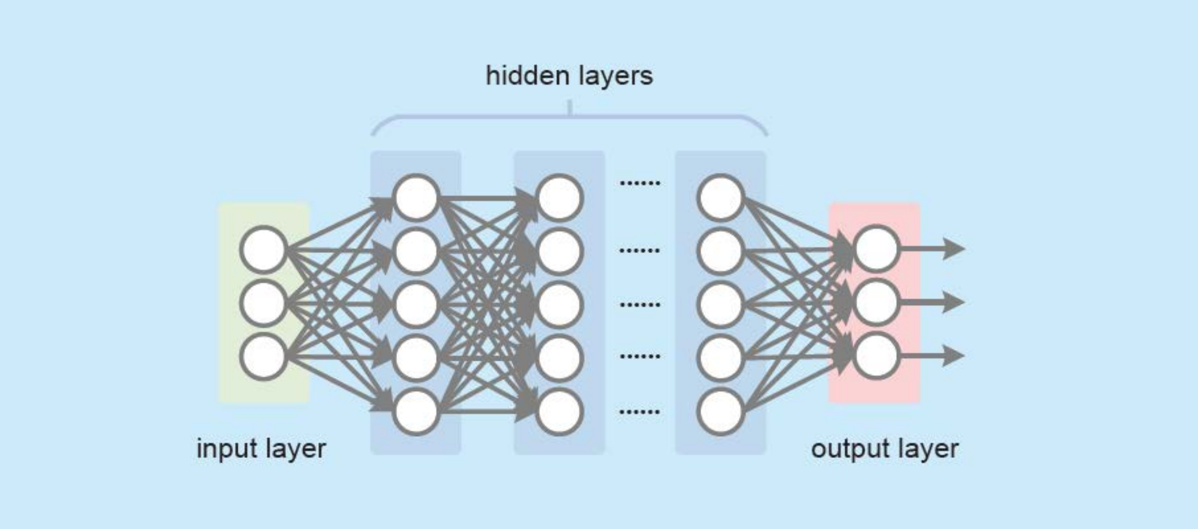


Fig. 2. A fully connected feedforward Neural Network architecture

3. Background and Theoretical Support

Name	$[\sigma(\boldsymbol{u})]_{\mathrm{i}}$	Range
linear	u_i	$(-\infty, \infty)$
ReLU	$\max(0, u_i)$	$[0, \infty)$
tanh	$\tanh(u_i)$	$(-1, 1)$
sigmoid	$\frac{1}{1+e^{-x}}$	$(0, 1)$
softmax	$\frac{e^{u_i}}{\sum_j e^{u_j}}$	$(0, 1)$

Table 1. Activation functions

Name	$l(\boldsymbol{u}, \boldsymbol{v})$
MSE	$\Vert\boldsymbol{u} - \boldsymbol{v}\Vert_2^2$
Categorical cross-entropy	$-\sum_j u_j \log(v_j)$

Table 2. Loss functions

4. End-To-End Learning of Communication System

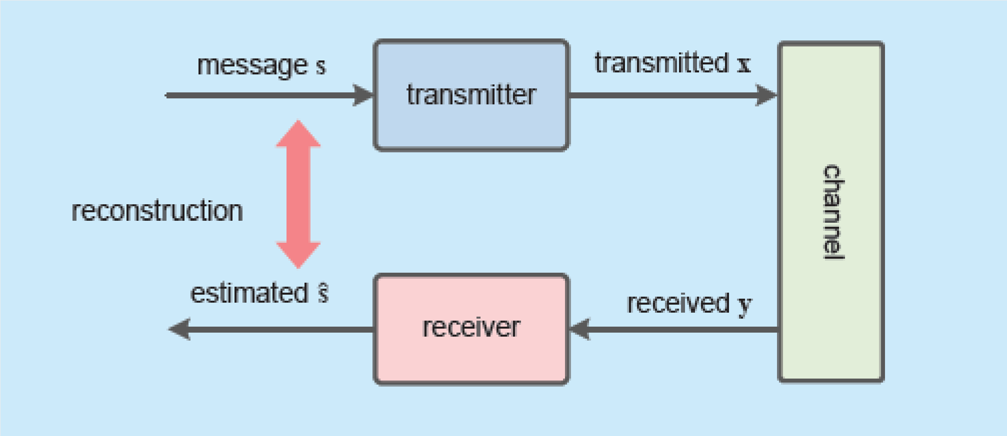


Fig.3. A simple form of communication system

We could consider the communication as a process of end-to-end reconstruction problem. The transmitter sends messages and the receiver reconstructs the messages over a physical channel.

4. End-To-End Learning of Communication System

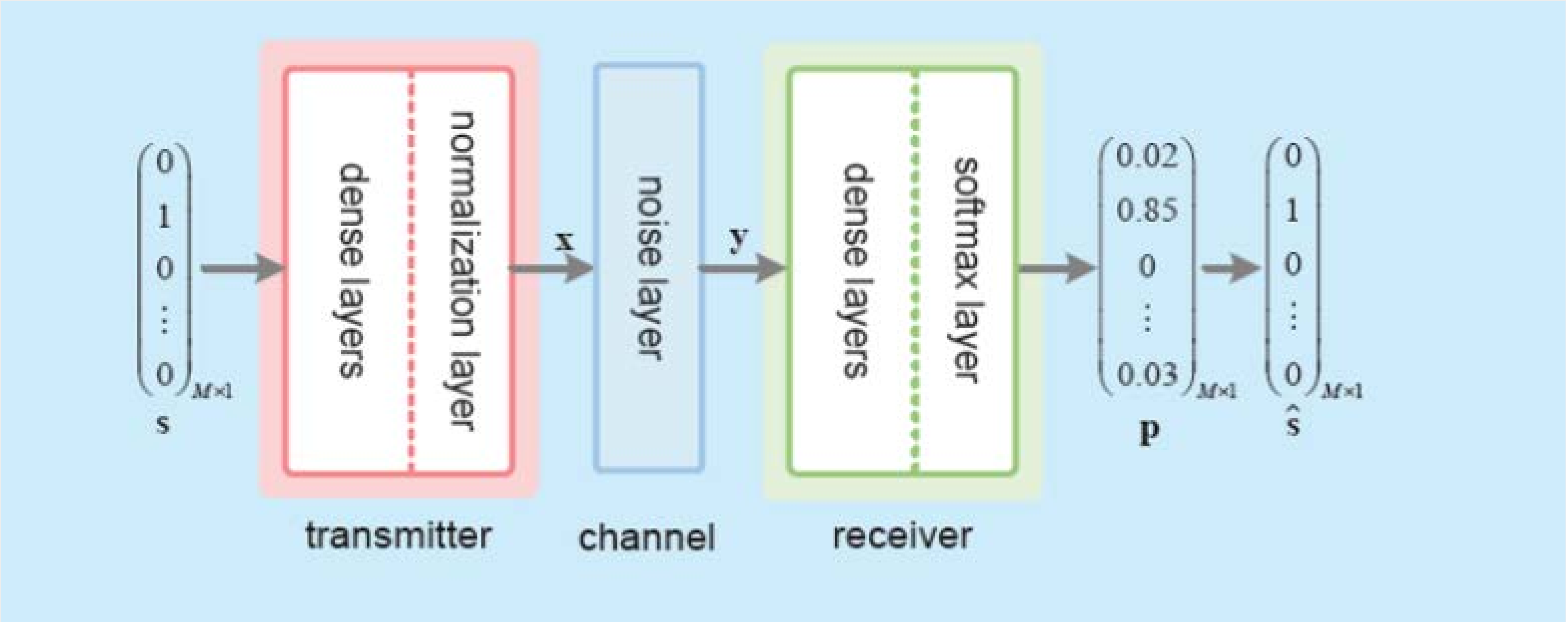


Fig. 4. A simple autoencoder for an end-to-end communication system.

5. Results and Discussion

```
input_signal = Input(shape=(M,))
encoded = Dense(M, activation='relu')(input_signal)
encoded1 = Dense(n_channel, activation='linear')(encoded)
encoded2 = Lambda(lambda x: np.sqrt(n_channel)*tf.nn.l2_normalize(x, dim=1))(encoded1)
EbNo_train = 5.01187 # coverted 7 db of EbNo
encoded3 = GaussianNoise(np.sqrt(1/(2*R*EbNo_train)))(encoded2)
decoded = Dense(M, activation='relu')(encoded3)
decoded1 = Dense(M, activation='softmax')(decoded)
autoencoder = Model(input_signal, decoded1)
adam = Adam(lr=0.01)
autoencoder.compile(optimizer=adam, loss='categorical_crossentropy')
```

To build the neural networks of autoencoders, we use the functions of Keras to generate the dense layers, noise layers, and normalization layers.The code of building neural networks of autoencoder (n; k) is listed in the above.

5. Results and Discussion

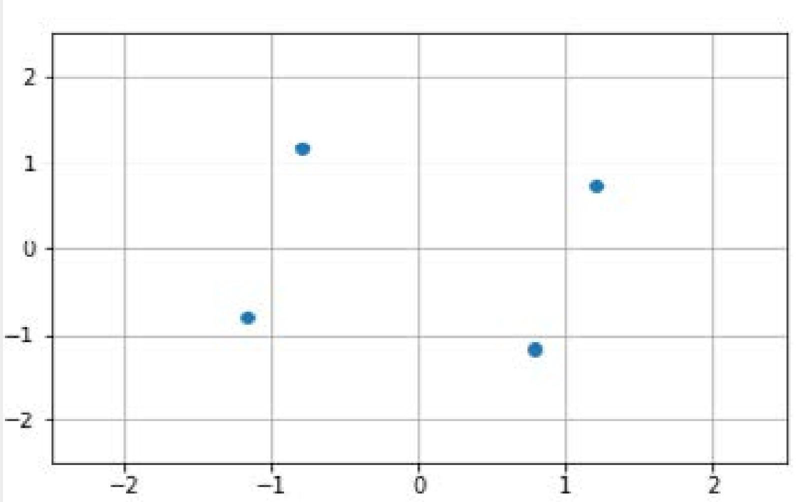


Fig.5. Constellations of Autoencoder (2,2)

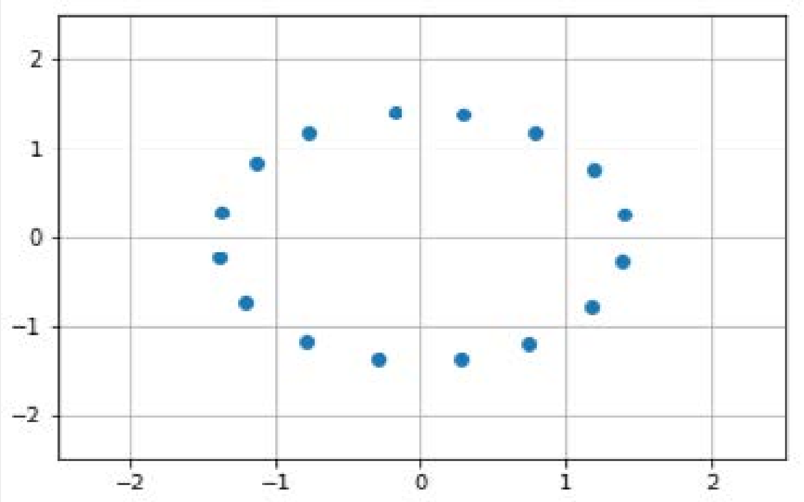


Fig.6. Constellations of Autoencoder (2,4)

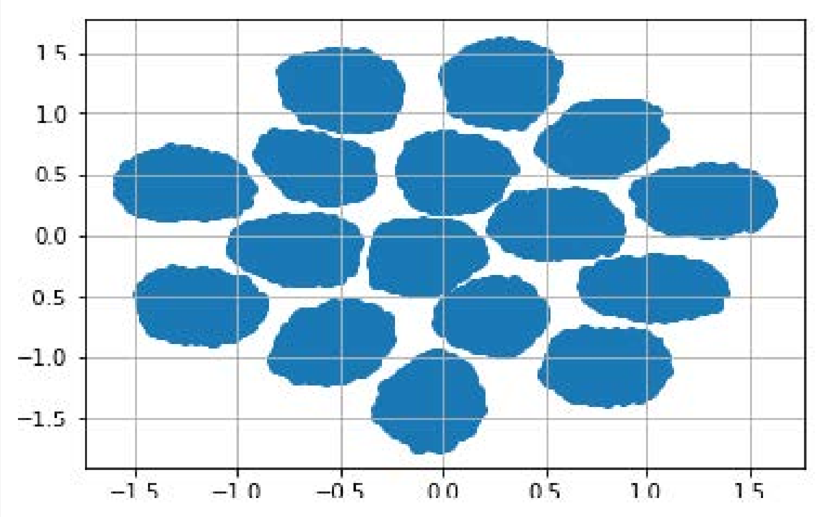


Fig.7. Constellations of Autoencoder (7,4)

5. Results and Discussion

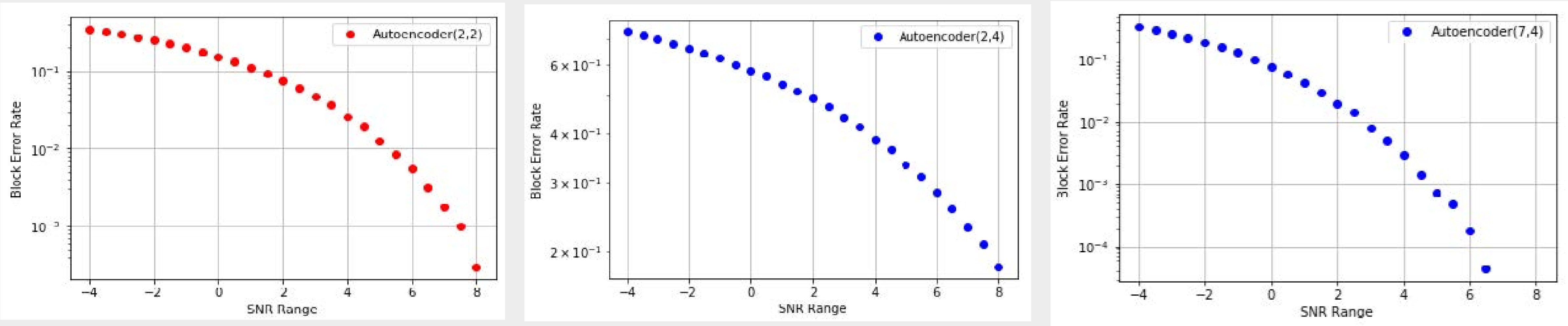


Fig.8. BLER versus Eb/N0 of Autoencoder for different parameters (2,2), (2,4), (7,4)

5. Results and Discussion

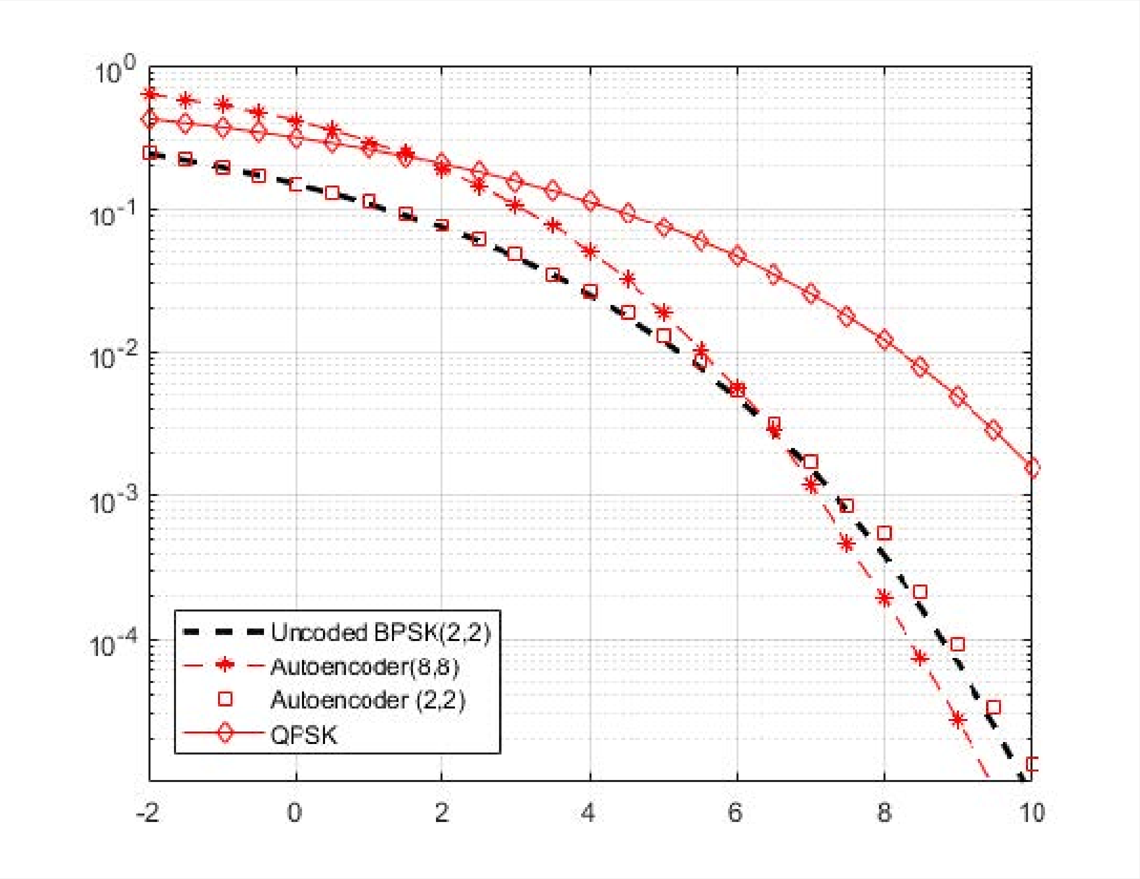
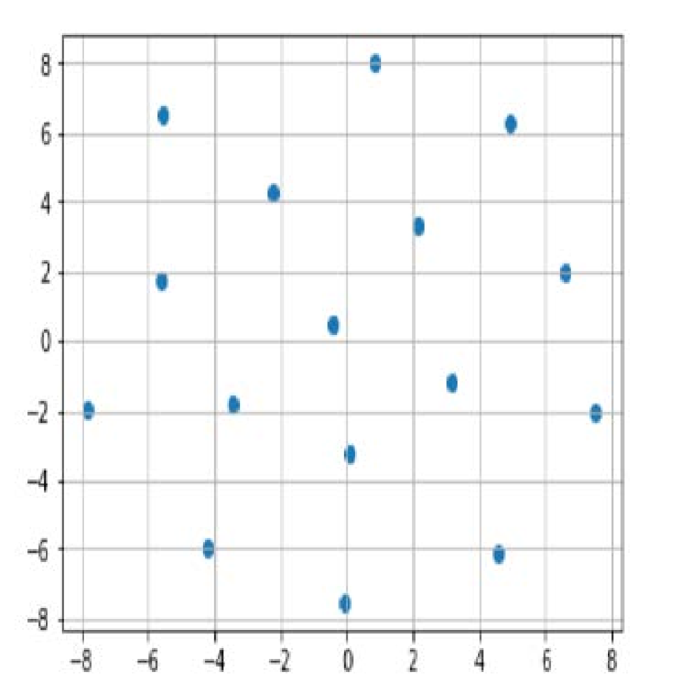


Fig.9. BLER versus Eb/N0 for different autoencoders and traditional systems

6. Conclusion and Future Work



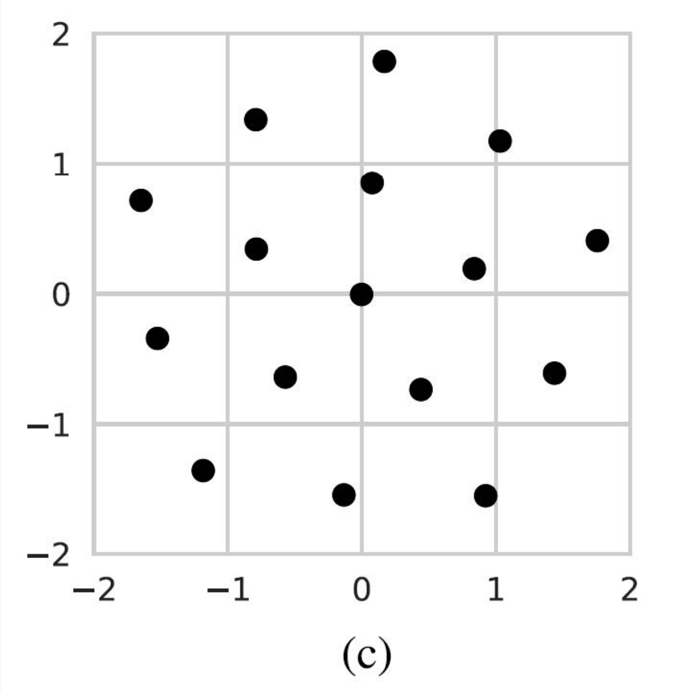


Fig.10. The constellation diagram of the failed simulation of autoencoder (2,4) with power constraint

Fig.11. The constellation diagram of autoencoder (2,4) with power constraint

6. Conclusion and Future Work

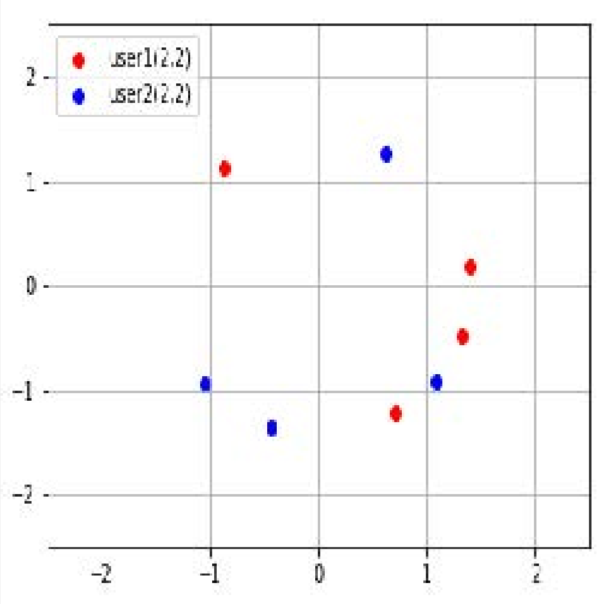


Fig.12. The simulation result of constellation diagram for two-user with parameters (2; 2) (not expected)

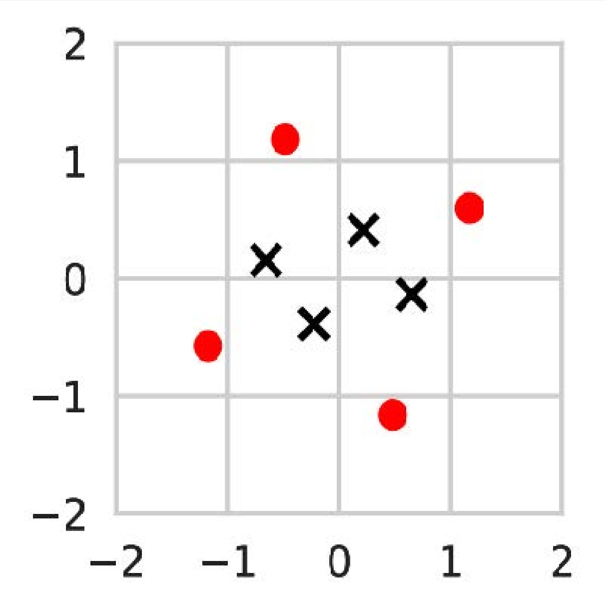


Fig.11. The constellation diagram [1] for two-user with parameters (2; 2)

6. Conclusion and Future Work

➢Conclusion

1. One advantage of DL-based communication system is the autoencoder could learn how to communicate even if the optimal schemes are unknown.

2. The autoencoders for communication systems have excellent expressive capacity and convenient optimization.

3. In the future work, if we use deep learning instead of neural networks (deep learning training method is greedy layer-wise training), and add more layers in the transmitter and receiver, we might achieve better performance.

4. We still need to find out how to represent the output vectors of the transmitter and figure out the effective analysis methodology.

5. For now, it is a promising research area and far from maturity. A wide range of studies into DL for physical layer is needed to be done.

References

[1] T. J. O'Shea and J. Hoydis. (2017) An introduction to deep learning for the physical layer. [Online]. Available: https://arxiv.org/abs/1702.00832, preprint.
[2] Y. Wang and K. Xu, "source code and simulation results," https://github.com/asueeer/Source-code-and-simulation-results, 2018

Thank You!

Any Questions?