Using Autoencoders to Optimize Two-Dimensional Signal Constellations for Fiber Optic Communication Systems

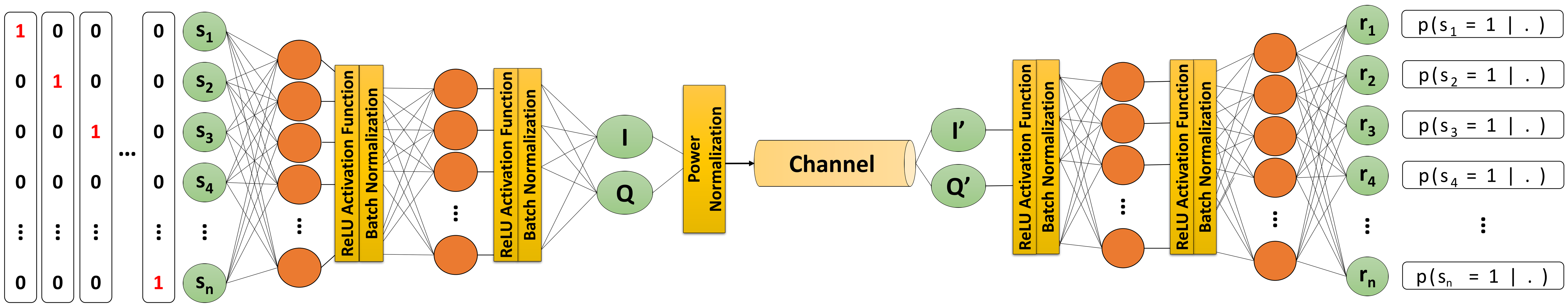
Samaneh Bidabadi, Rémi Cérès, Mattéo Delabre, Liv Nguekap, Amir Omidi

UNIVERSITÉ LAVAL

Abstract

Digital communication is the science of exchanging digital information from a transmitter to a receiver through an analog channel. Both parts agree on a fixed number of transmittable messages and on a signal shape for encoding each message, i.e. a **modulation format.** This encoding must take into account the physical properties of the channel, such as noise introduced in the signal, to **minimize the risk of detection errors** on the receiver side. Coherent detection, a technique of optical communication, enables 2D modulation formats such as *Quadrature Amplitude Modulation* (QAM), where **information is modulated on both the phase and amplitude of the signal.** Each possible message is mapped to a phase/amplitude pair (or **symbol**) which can be plotted on the complex plane, giving a **constellation.** Using QAM, higher efficiency can be achieved by optimizing for the constellation shape. In this project, we tackle the problem of optimizing constellation shapes assuming a *Gaussian Noise* (GN) channel model, for which the best currently known shapes are hexagonal packings [2]. **The aim of this project is to use an autoencoder to solve this problem,** as proposed in [3].

Network Structure



- **Encoder (left):** Models the transmitter. Input is a one-hot-encoded message to be sent through the system. Output is the symbol to which the message is mapped. Uses a sequence of fully connected layers. Each hidden layer is followed by a Rectified Linear Unit (ReLU) that introduces non-linearity and a batch normalization layer that reduces covariate shift. To constrain the constellation's power, the encoder's output is normalized based on its average power (L_2-norm).
  Goal: Optimize the symbols to make the system robust to transmission impairments such as fiber non-linearity.
- **Channel (middle):** Models the communication medium between the transmitter and the receiver. *Additive White Gaussian Noise* (AWGN) dependent on the launch power models the channel interference.
- **Decoder (right):** Models the receiver. Same architecture as the encoder, but reversed. Input is a noisy symbol from the channel. Output is the decision on which original message was sent. Softmax is applied to turn the decoder's output into a probability distribution. For more details, see [3].
  Goal: Learn to classify the impaired symbols.

Training Strategy

- Training using the Adam algorithm.
- Loss is cross-entropy between network input and output.
- Adaptive learning rate: start high to explore more diverse configurations, slowly tune down to improve convergence.

Conclusion

- Autoencoders can be used to shape constellations so as to minimize decoding errors caused by noise.
- Our results are close to state-of-the-art hexagonal constellations.
- GN channel model can be replaced with more complex ones.

References

[1] John R Barry, Edward A Lee, and David G Messerschmitt. *Digital communication*. Springer Science & Business Media, 2012.

[2] Seung Hee Han, John M Cioffi, and Jae Hong Lee. "On the use of hexagonal constellation for peak-to-average power ratio reduction of an ODFM signal". In: *IEEE Transactions on Wireless Communications* 7.3 (2008), pp. 781–786.

[3] Rasmus T Jones et al. "Geometric Constellation Shaping for Fiber Optic Communication Systems via End-to-end Learning". In: *arXiv preprint* (2018).

Experimental Results

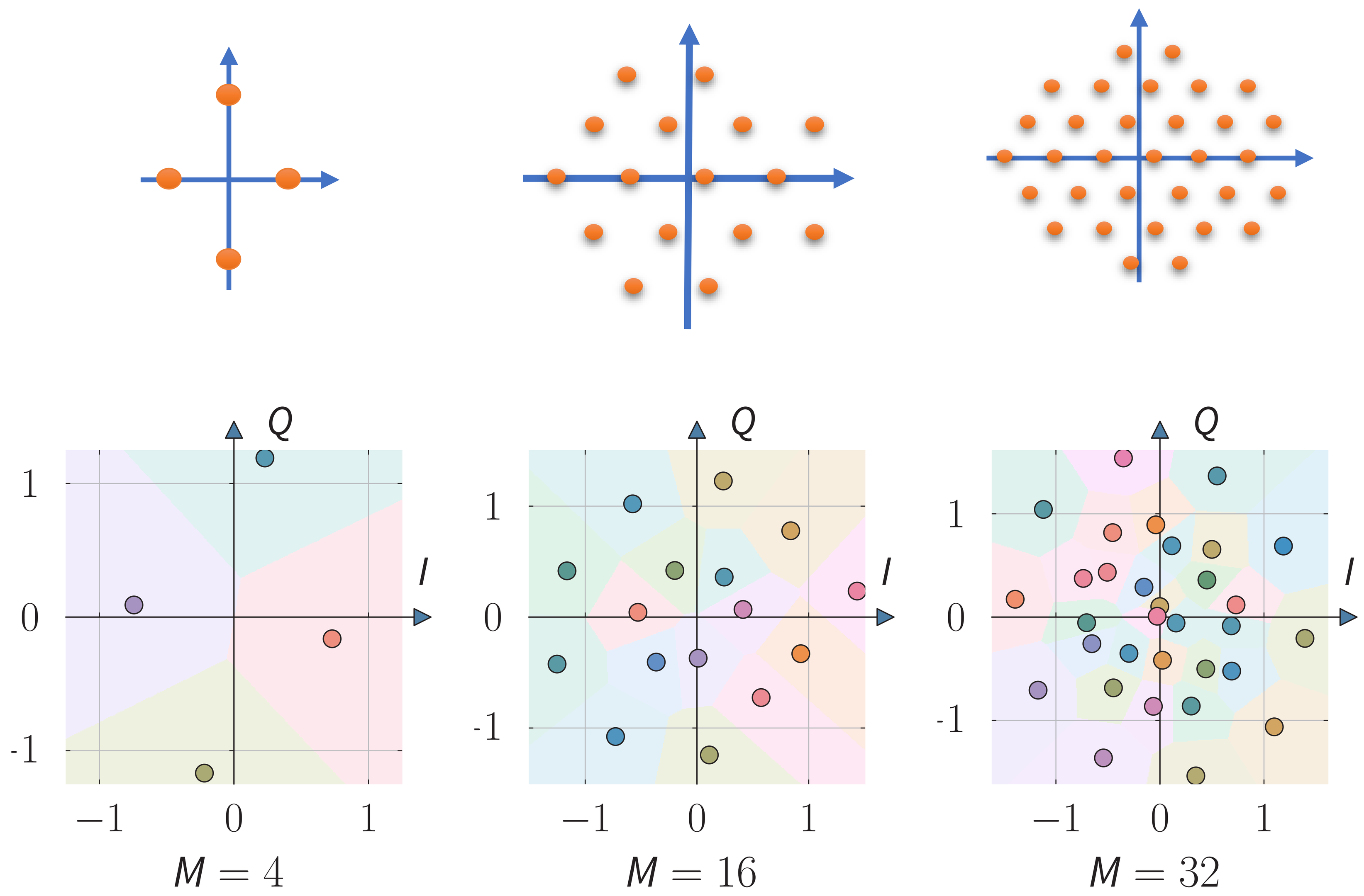


Figure: Optimal Hexagonal packings (top) and simulation results of autoencoder training (bottom) for various constellation orders.

Order	Batch size	Learning rate	Hidden layers	**Loss**
4	2048	0.01	(4)	0.0397
16	2048	0.1	(8, 4)	0.9118
32	2048	0.1	(24, 20)	1.5598

Table: Best training configurations by constellation order.