Optimizing Space Communications using Deep Learning

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NASA Glenn Research Center

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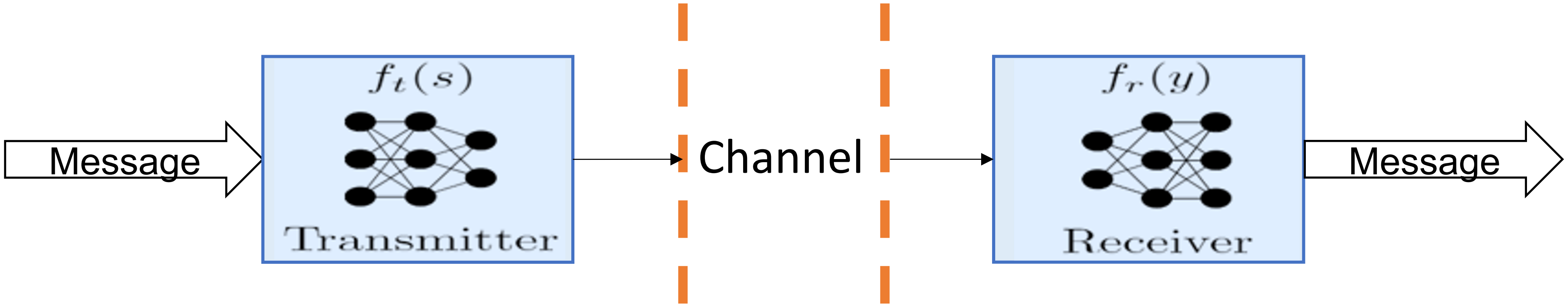
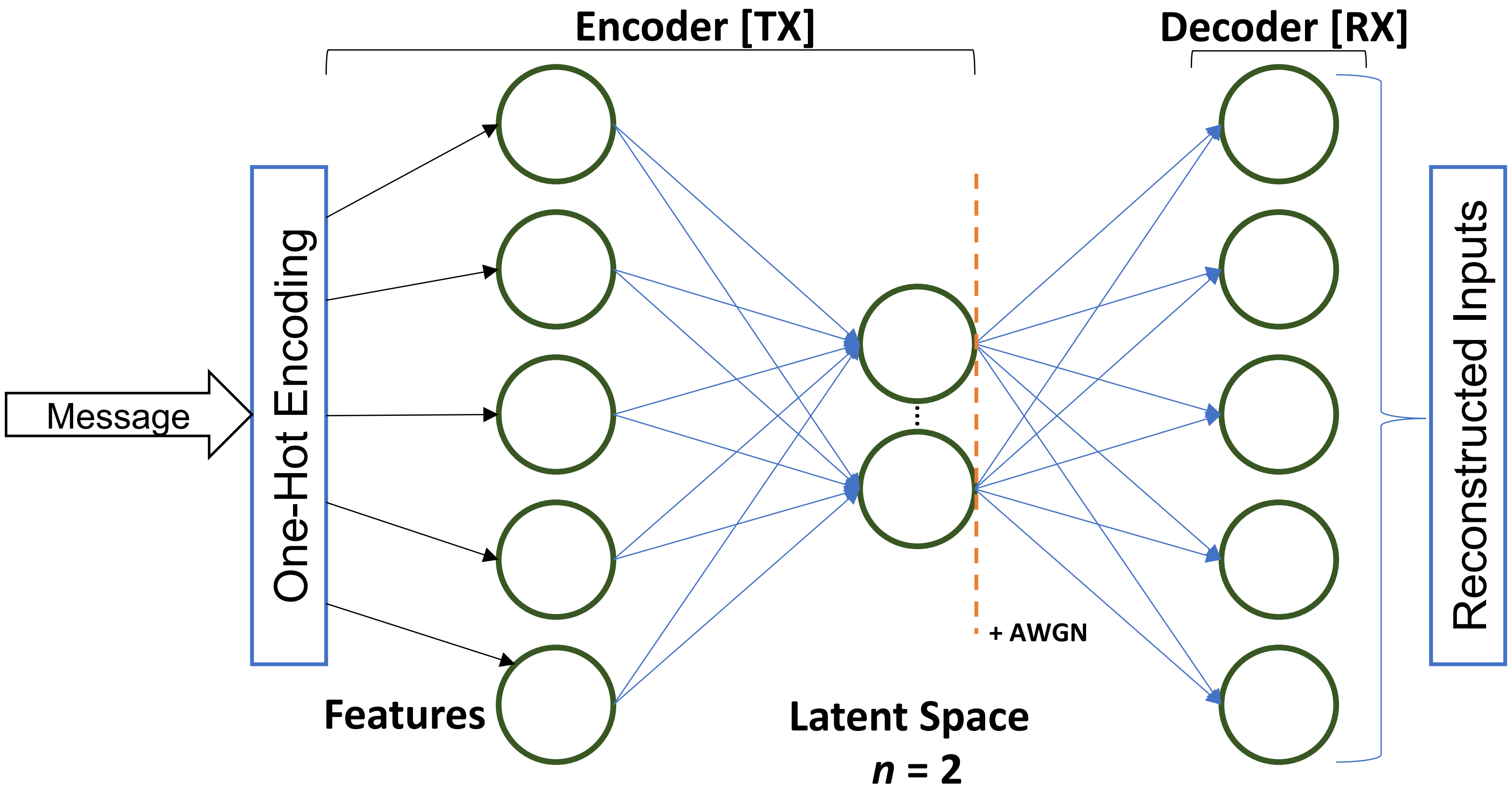
Introduction: End-to-end Communication Systems



Introduction: Autoencoders



- Best practices in training communications autoencoders are not finalized

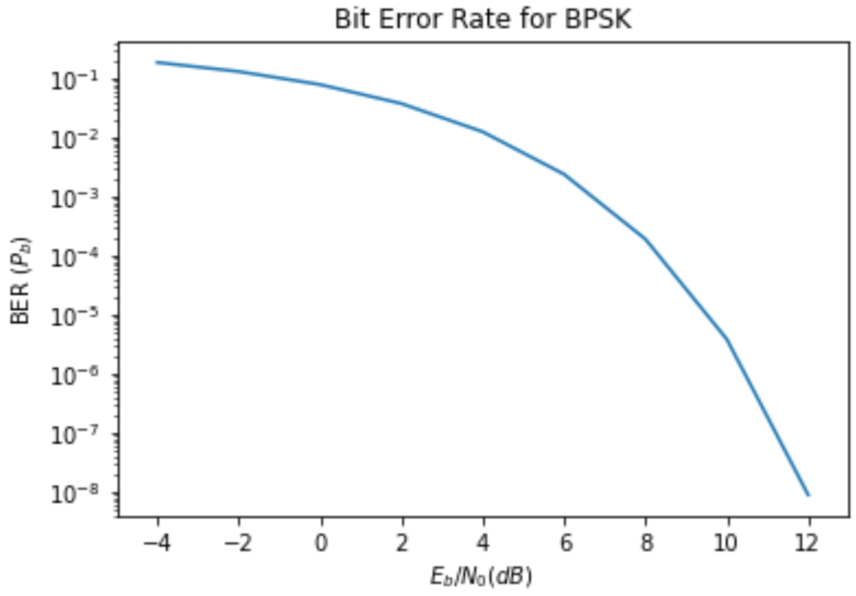
Objective

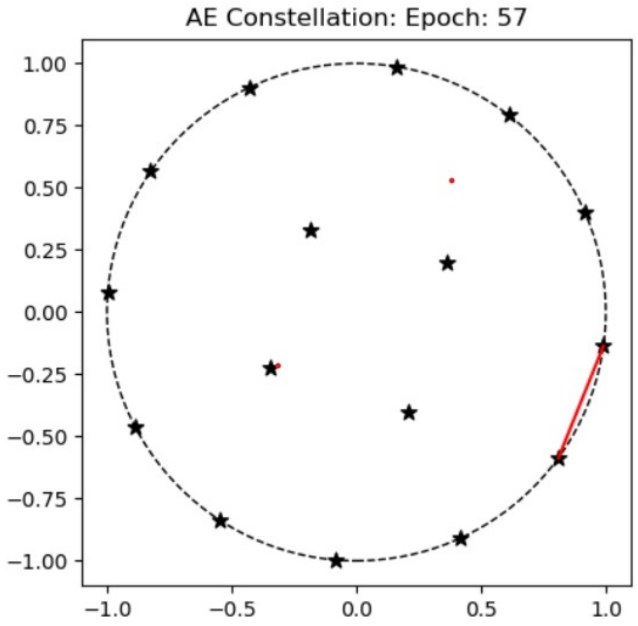
Improve modulation and coding solutions produced by deep neural networks

- Constraining power through normalization
- Enhancing training configurations using non-additive white Gaussian noise solutions
- Implementing gray-coding schemes for optimizing bit-vector placements

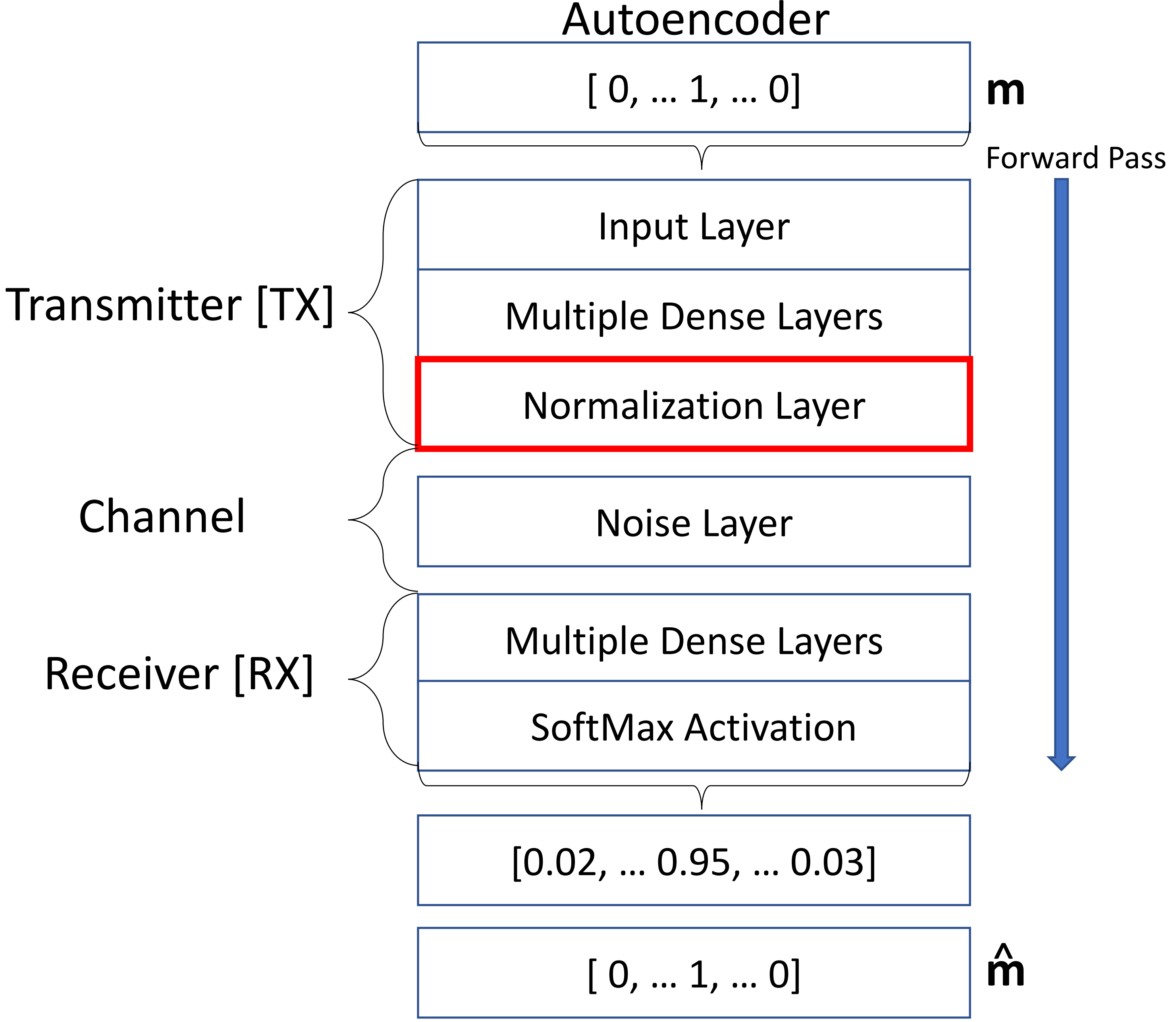
Important Metrics to Consider

- Symbol and Bit Error Rates (SER/BER)
    - Number of symbols/bits misclassified versus total transmitted
- Constellation Figure of Merit (CFM)
    - Euclidean distance between closest symbols





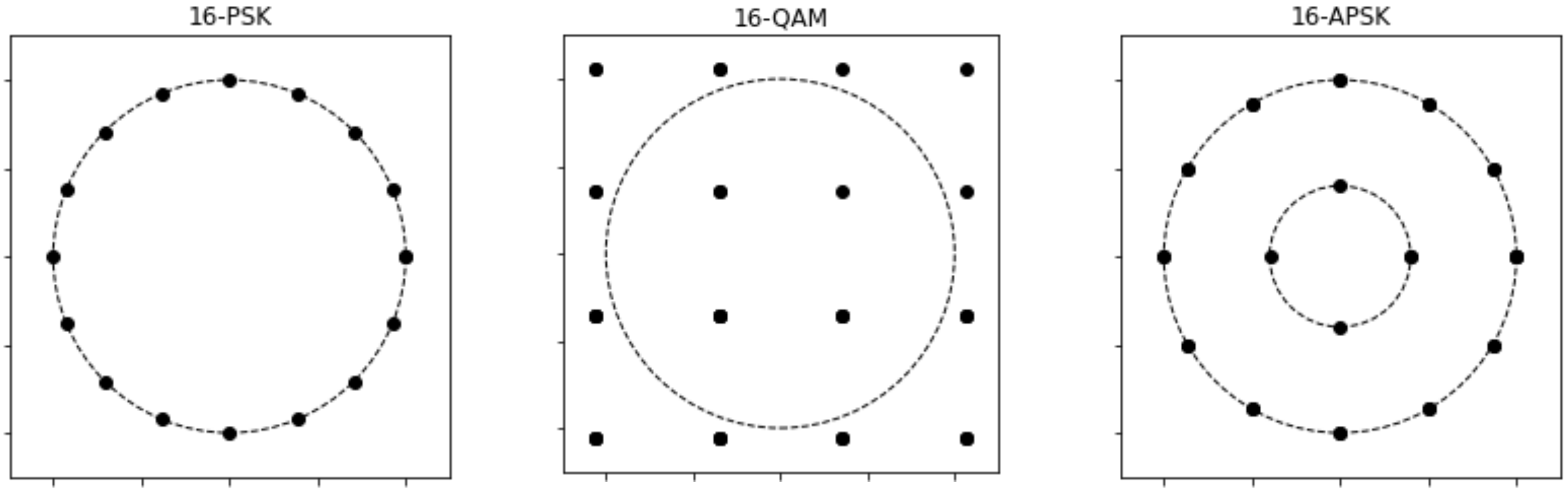
Power Constraint through Normalization



Importance of Normalization Layer

- Normalizing the output of the transmitter
  - Acts as an output energy constraint
- Encourage optimization of the available symbol space

- Two types of constraints:
  - Soft constraints, where the average power of total transmitter symbols must be below a threshold
  - Hard constraints, where all transmitted symbols must be below a threshold

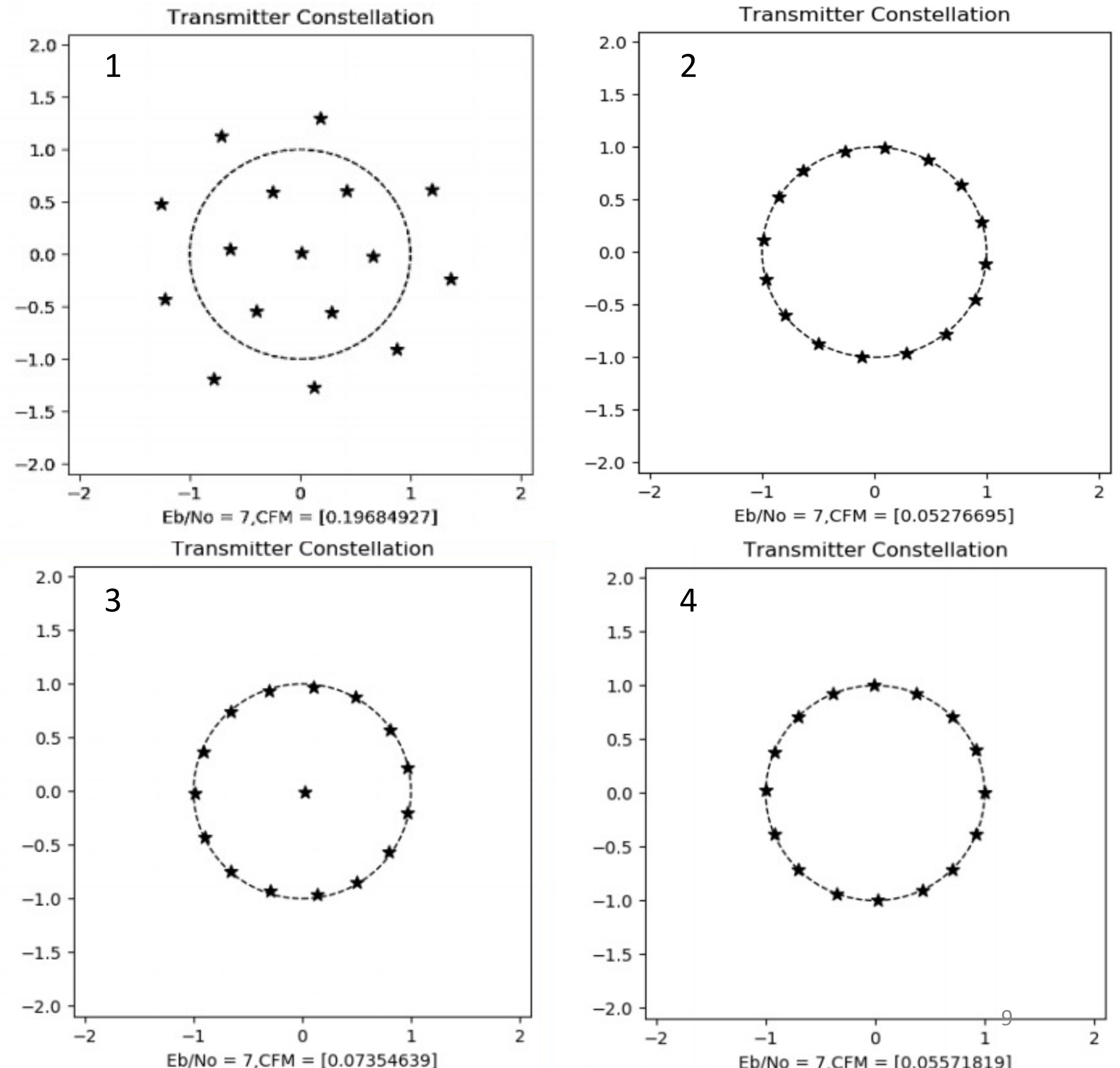


Types of Normalization Layers

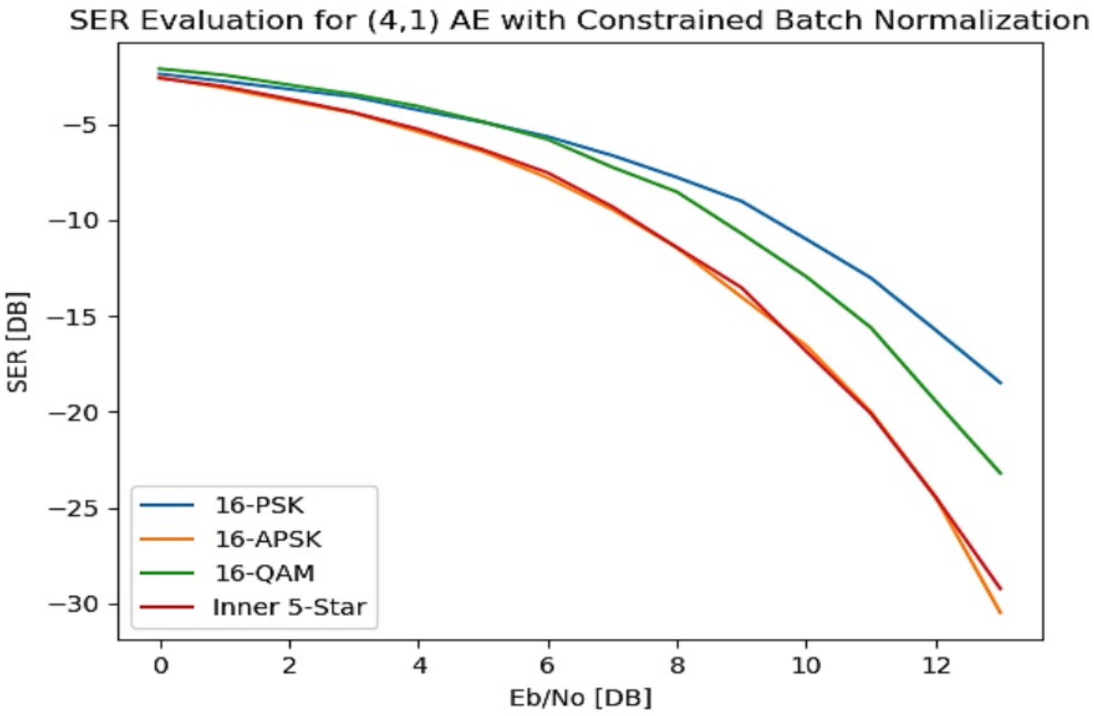
Name	Constraint
Average Power	$\mathbb{E}[\lvert x_i \rvert] \leq 1 \forall i$
Max	$\lvert x_i \rvert \leq 1 \ \forall i$
Linear	$\frac{\lvert x_i \rvert}{argmax(\lvert x_i \rvert)} \forall i$
Saleh	$\alpha = 1, \beta = 2$ $w = \frac{\alpha}{1 + \beta * \lvert x_i \rvert^2} \Rightarrow w * x_i$
Constrained Batch (CBN)	$\gamma, \beta \in Batch\ Normalization\ (BN)$ $x_{i,BN} = BN(x_i) \mid \beta = 0\ \&\ \max\lvert\gamma\rvert \leq 0.9$ $\lvert x_{i,BN} \rvert \leq 1$

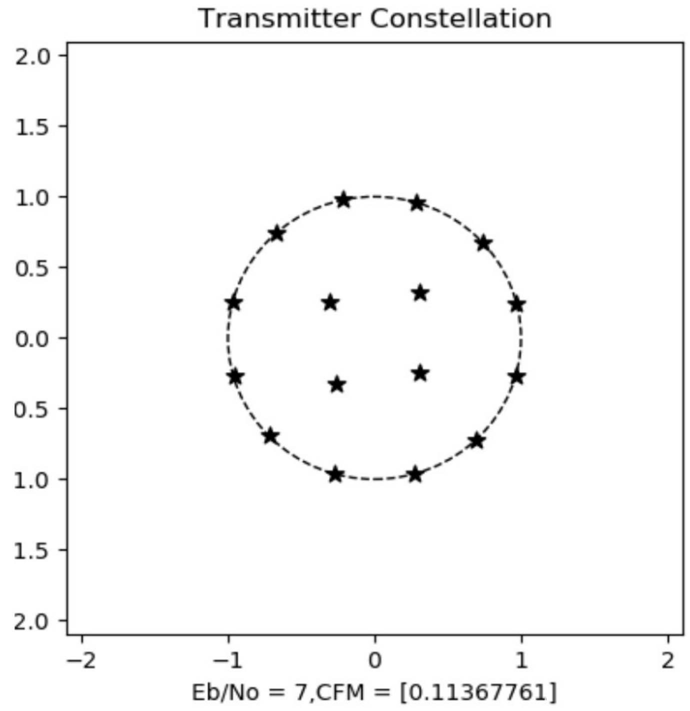
Normalization Results

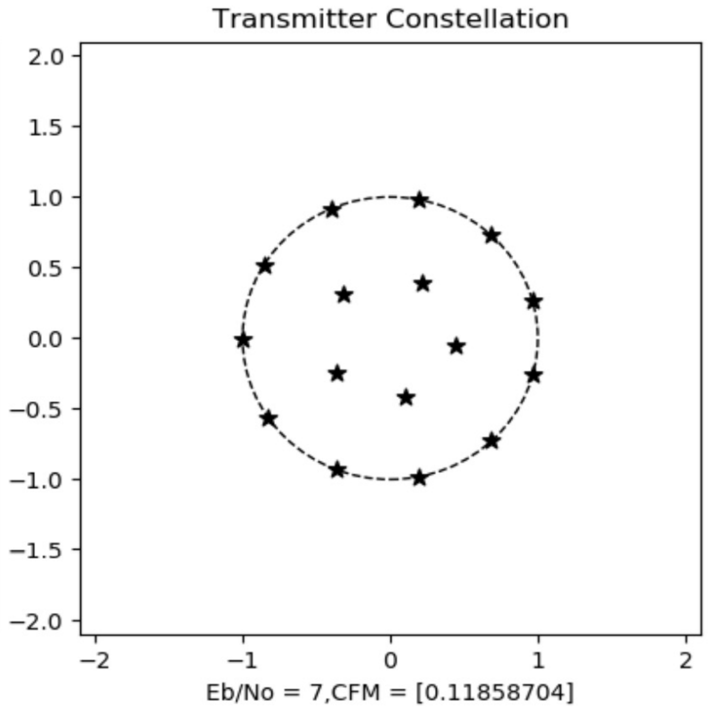
1. Average Norm
   $$\mathbb{E}[|x_i|] \le 1 \forall i$$
2. Max Norm
   $$|x_i| \le 1 \ \forall i$$
3. Linear Norm
   $$\frac{|x_i|}{argmax(|x_i|)} \forall i$$
4. Saleh Norm
   $$w = \frac{\alpha}{1 + \beta * |x_i|^2} \Rightarrow w * x_i$$



5. Constrained Batch Normalization



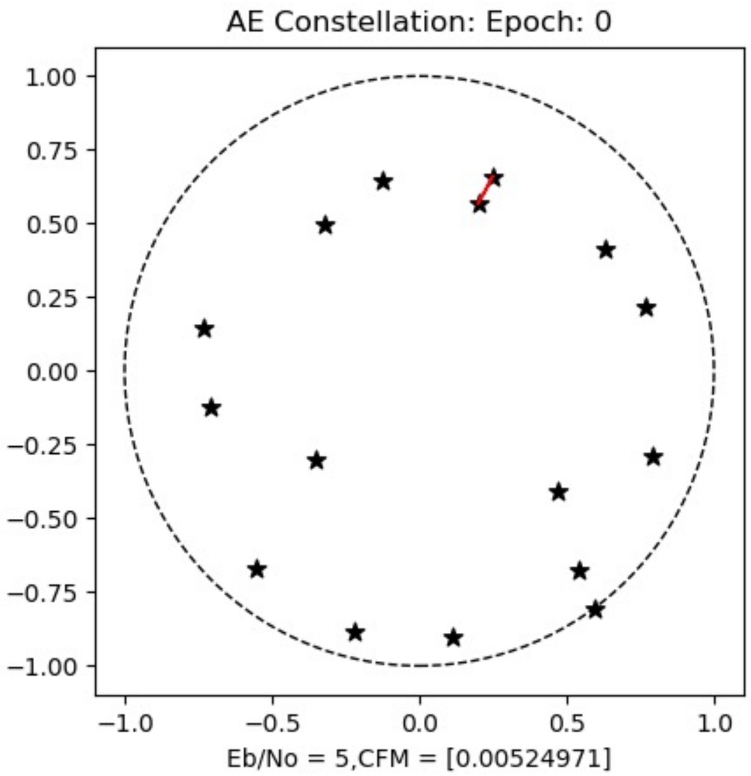


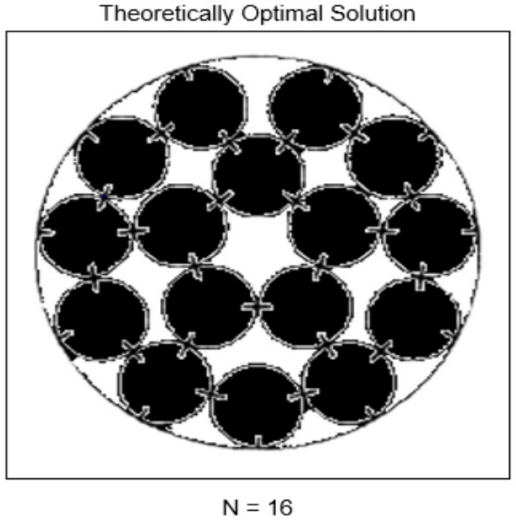


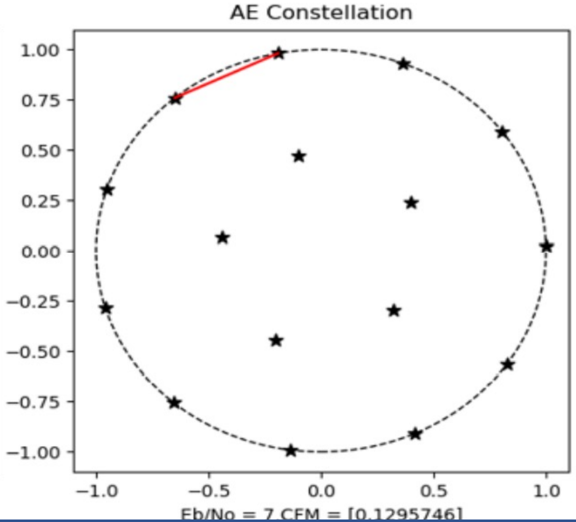
- 16-APSK-like SER performance as a function of Eb/No formation, with four and five inner points formations

Constrained Batch Normalization

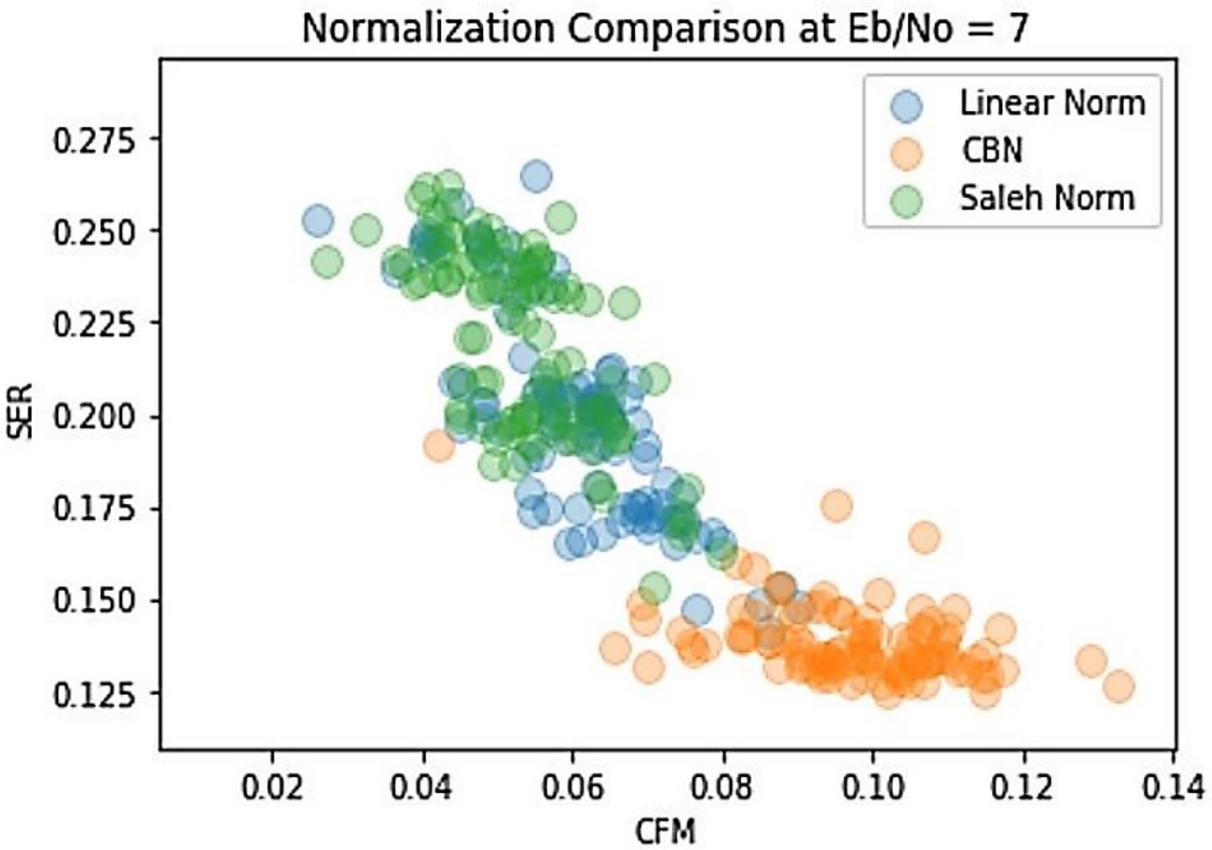
- Optimizes the use of internal unit circle space to achieve higher CFM values
- Solutions resemble circle-packing theory







Normalization Summary

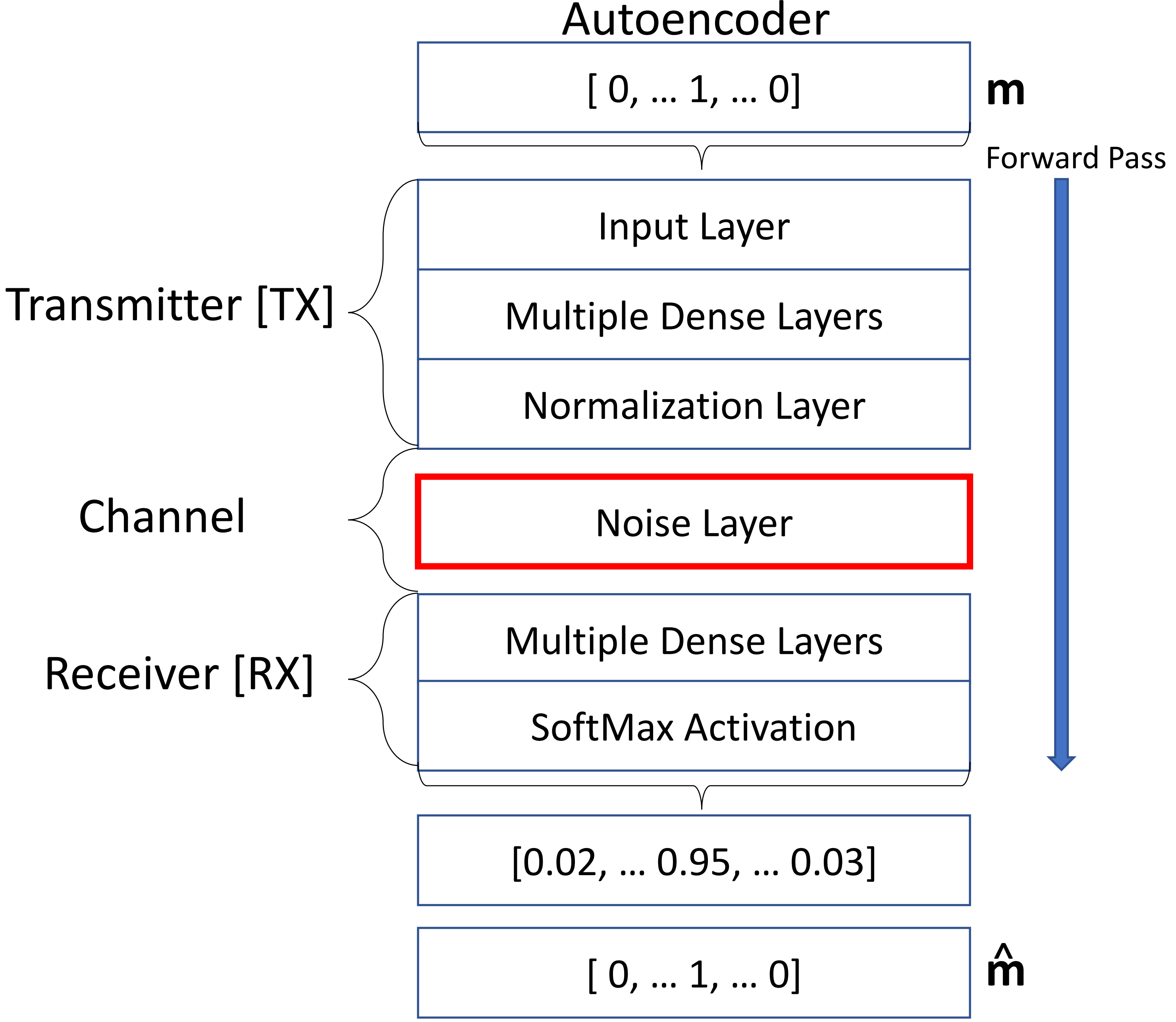


Average CFM and SER values over 100 autoencoder trainings

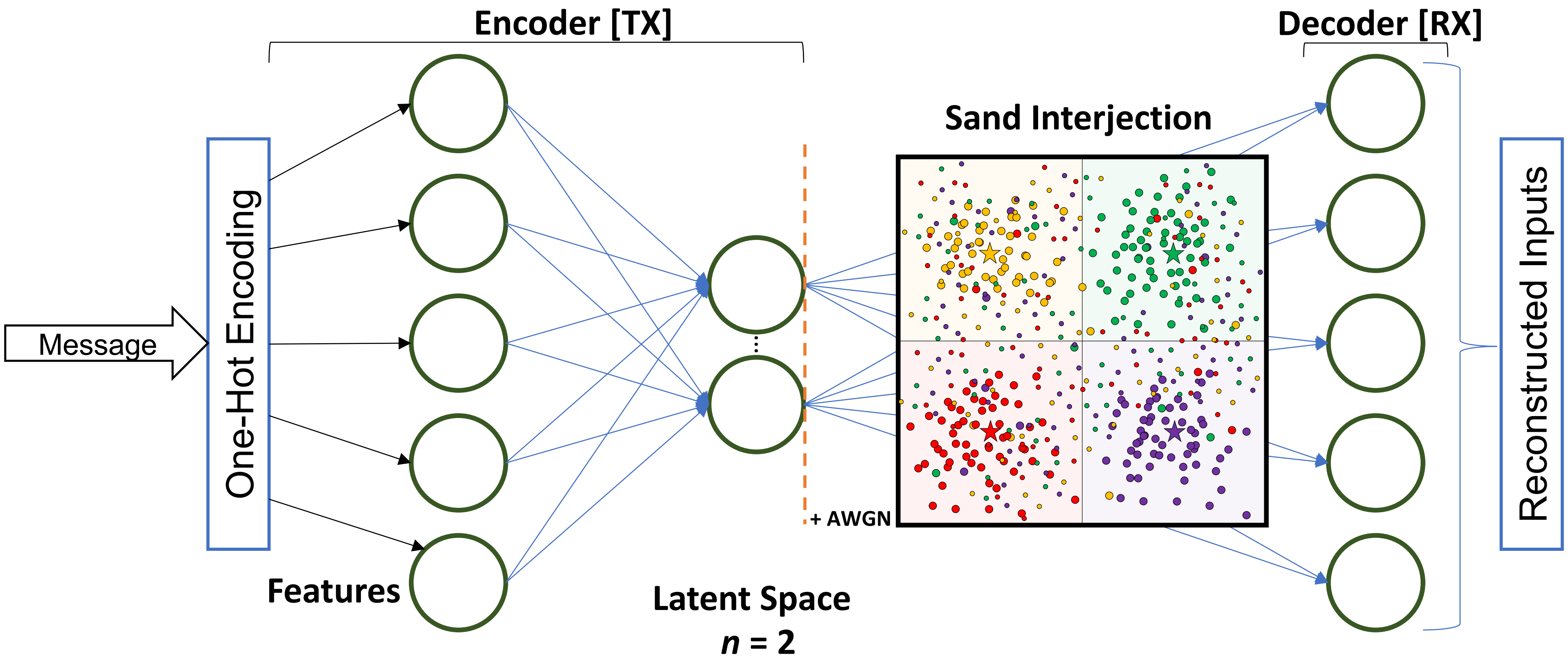
Eb/No	CFM	SER [dB]
Max	0.039	-6.99
Saleh	0.053	-6.55
Linear	0.060	-6.57
CBN	0.097	-8.59

- CBN outperforms the other hard constraint layers, navigating to lower SER and higher CFM values

Sand Noise as a Training Enhancement



Sand Noise as a Training Enhancement

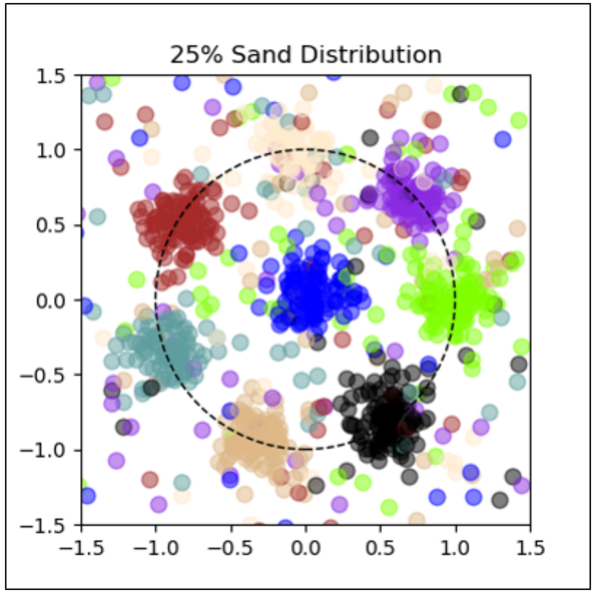


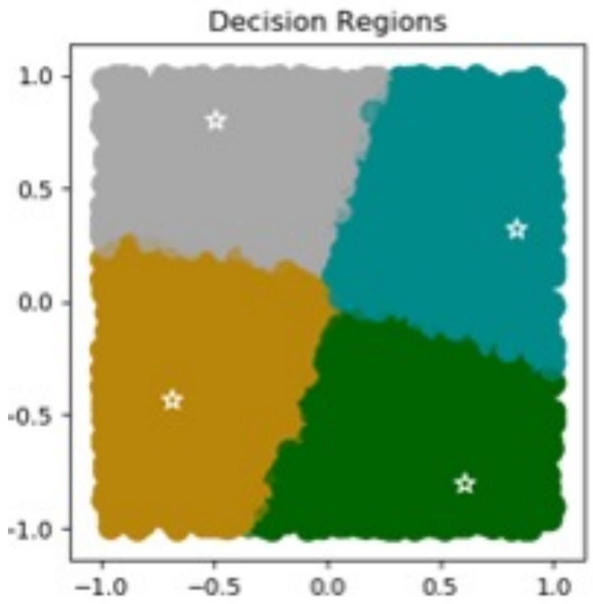
- Suggested by researchers at MIT for decision boundaries to “train harder”
- Sampled transmitter output with a sample drawn from a random 2-D distribution

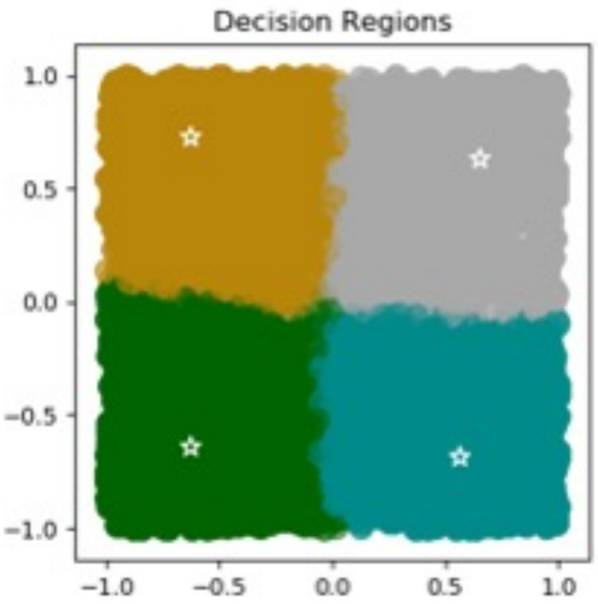
Zheng, L., “Using Neural Networks in Communications Problems – Theory and Examples,” Globecom Keynote, December 10, 2019. (unpublished)

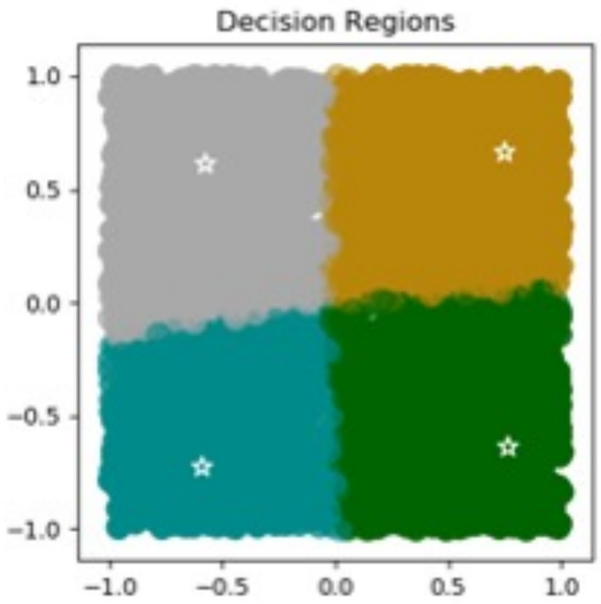
Results/Conclusions

- As a standalone layer
- As a noise enhancer
  - A 60% reduction in average SER value across 10 trials for both 5% and 10% sand cases was observed, with a better preforming constellation

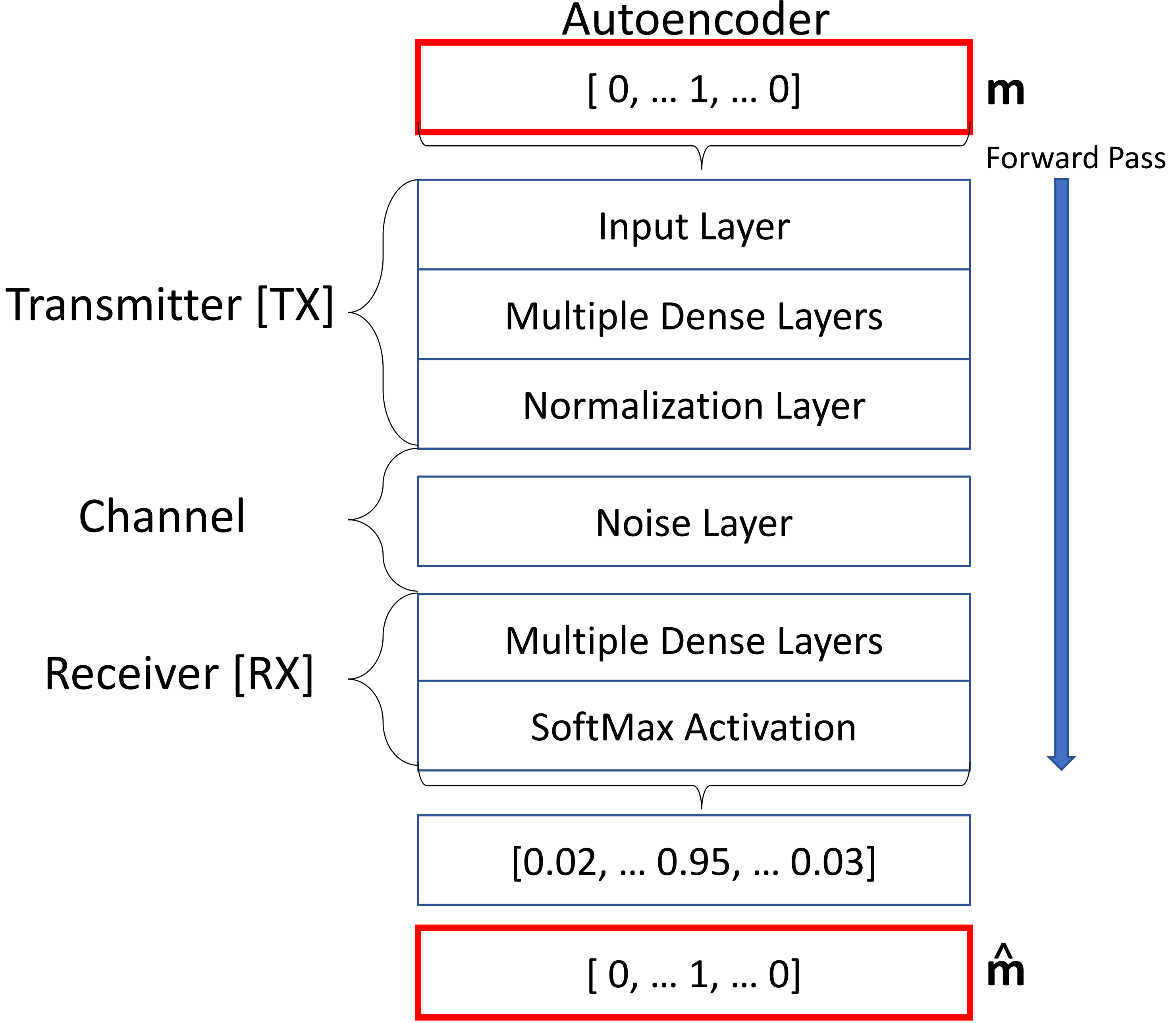






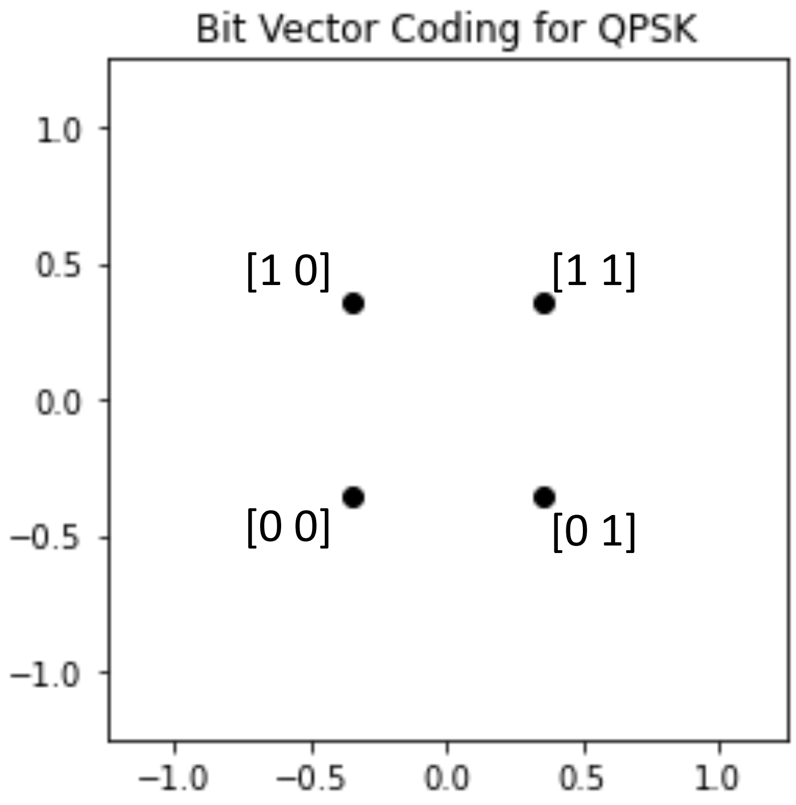


One-Hot versus Bit-Vector Encoding

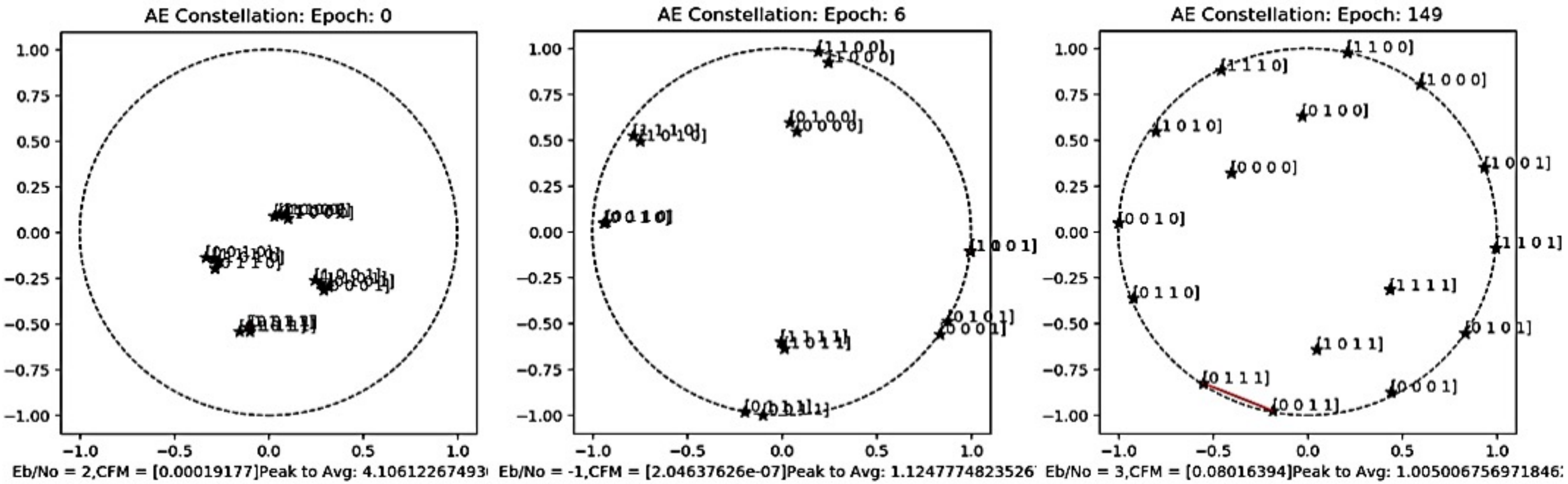


One-Hot versus Bit-Vector Encoding

- Introduced a custom loss function
  - Exponentially increase loss per bit flip
- Encourage autoencoder to strategically place bit vectors to minimize bit error



Results



- A “Splitting Effect” was achieved over the course of training
- Moves towards the idea of gray-coding solutions

Conclusions

- Constrained batch normalization outperformed other hard constraining methods through optimization of the latent space
- Sand interjection did not improve constellation formation for greater modulation orders
- A splitting effect indicated error-reducing bit vector placements in latent space

Acknowledgments

- Cognitive Signal Processing Branch at Glenn Research Center
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