

A Communication Channel Density Estimating Generative Adversarial Network

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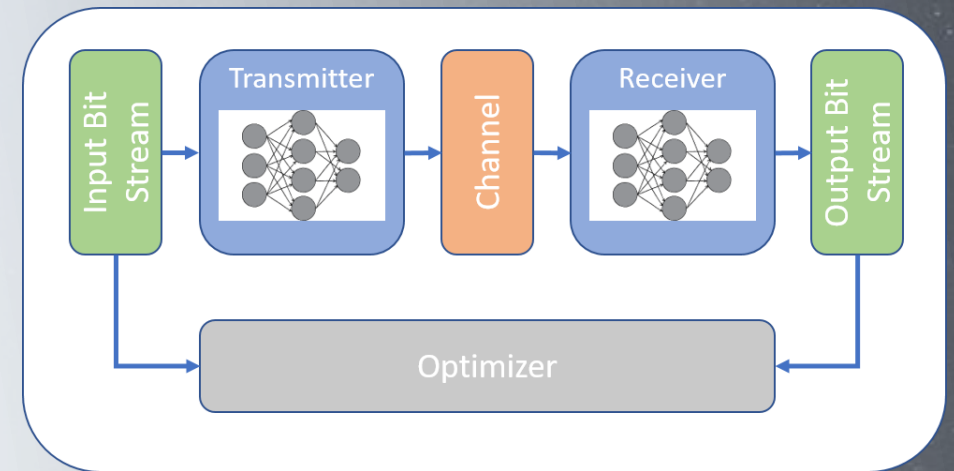
Autoencoder-Based Communications Systems (ABCs)

Background:

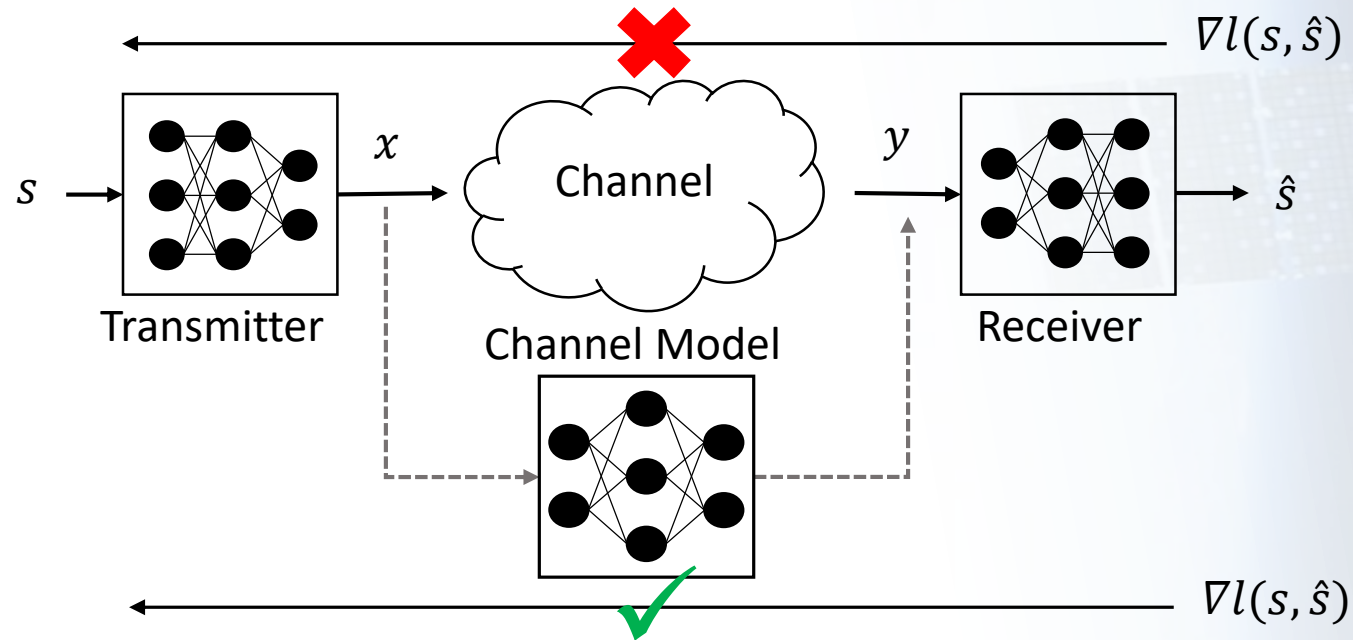
- Recent advances in communication system design have applied deep learning to optimize the physical layer for arbitrary channels
- Promising approach to optimizing performance over channels with difficult analytic solutions

Motivation:

- Simplify the traditional communication system, reduce dependency on channel models
- Adapt to a changing environment, and optimize over the end-to-end system
- Generalize over hardware, medium, and waveform



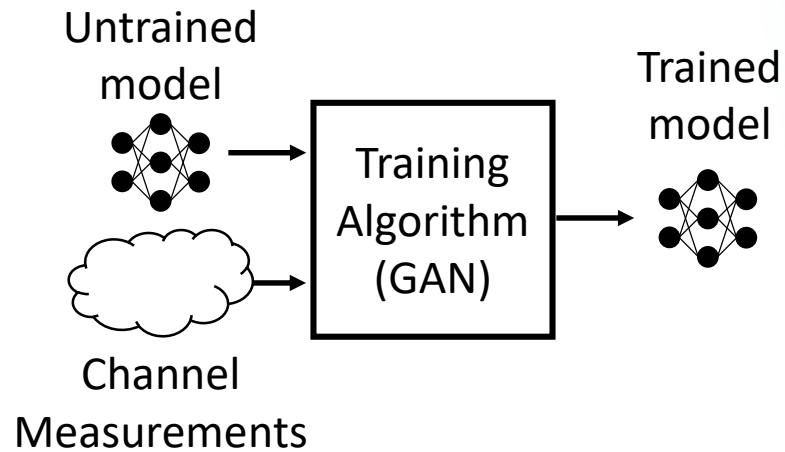
Approximating Channel Gradients



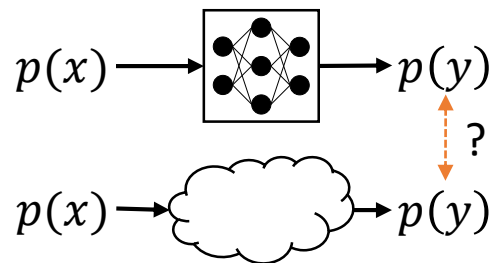
s, \hat{s} – messages (bit sequences)
 x, y – complex baseband symbols

- Backpropagation calculates loss gradients to update weights and biases
- Calculating transmitter updates requires a known channel function
- Ideally, an ABCs would optimize any channel
- NN approximation of a channel provides missing channel gradients

Training and Evaluating a Model



Black-box training



Approximates a distribution



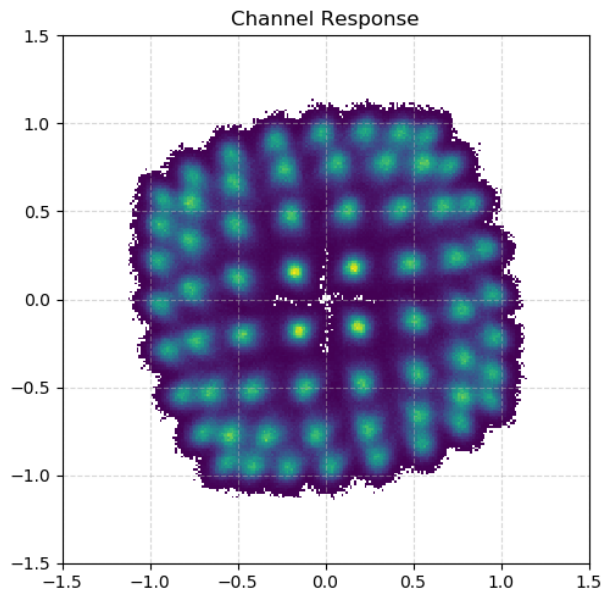
Qualities of a Good Training Algorithm

- **Accurate**
 - > Statistical distance
 - > Qualitative analysis
- **Robust**
 - > Input distribution $p(x)$
 - > 'Difficult' channels
- **Stable**
 - > Converges to a solution
 - > Repeatable results

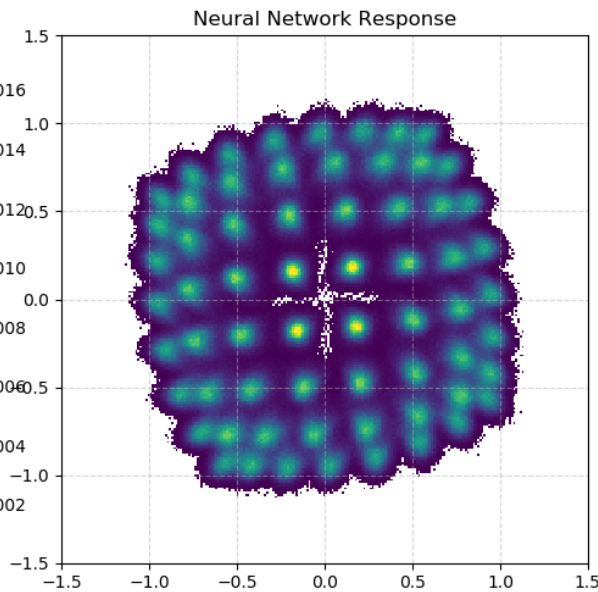
Training Demonstration

5M symbols / Random 64-QAM Input

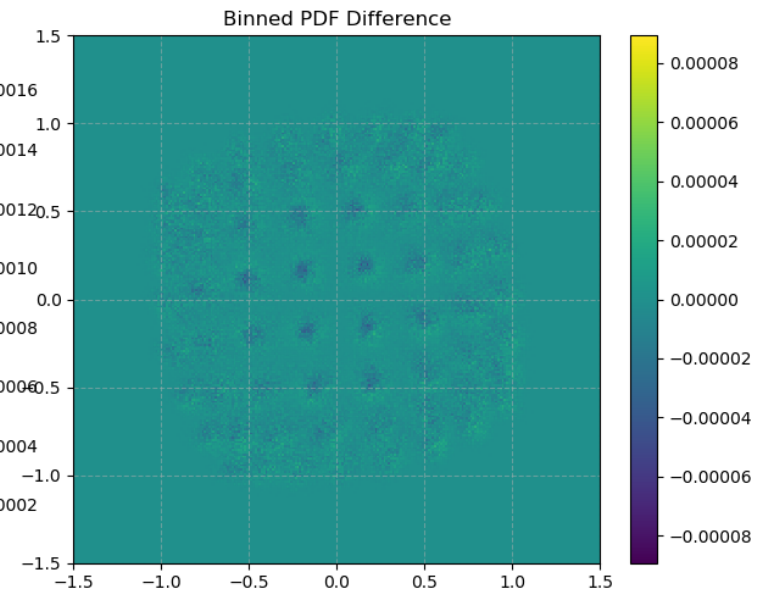
Channel Response



Neural Network Response

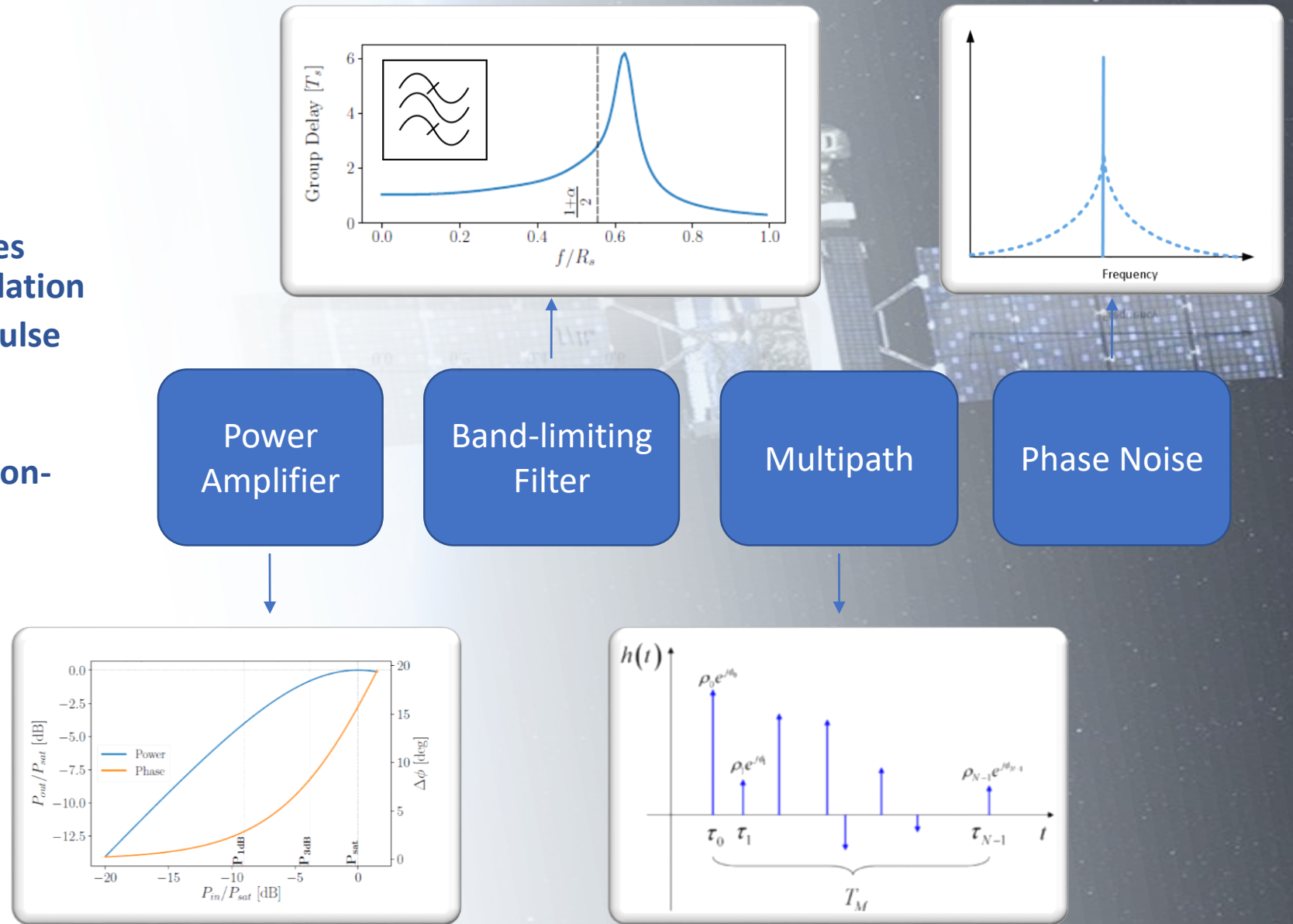


Binned Difference



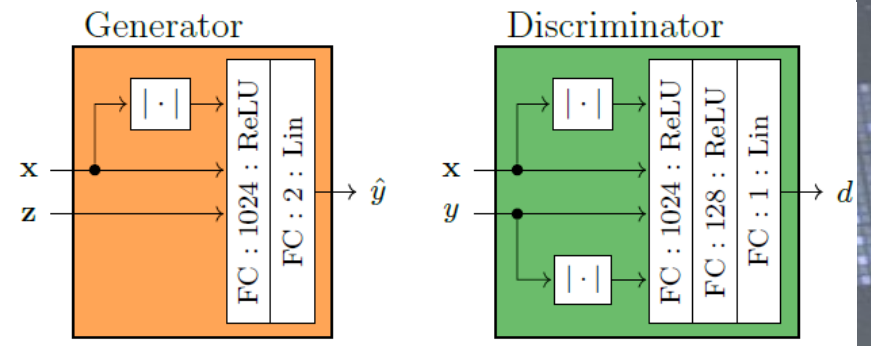
Channel Simulations

- “Channels” include all processes between modulation/demodulation
- Non-linear amplification and pulse shaping cause ISI
- Dispersive channels cause ISI
- Equalization more difficult in non-linear channels
- Non-Gaussian noise

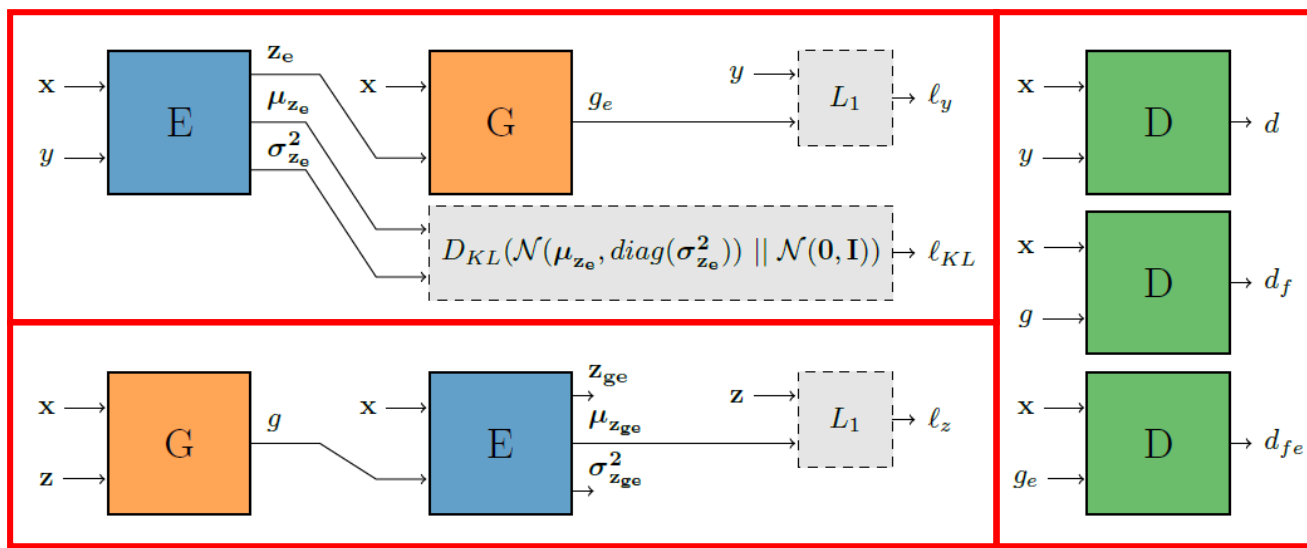


GAN Architecture

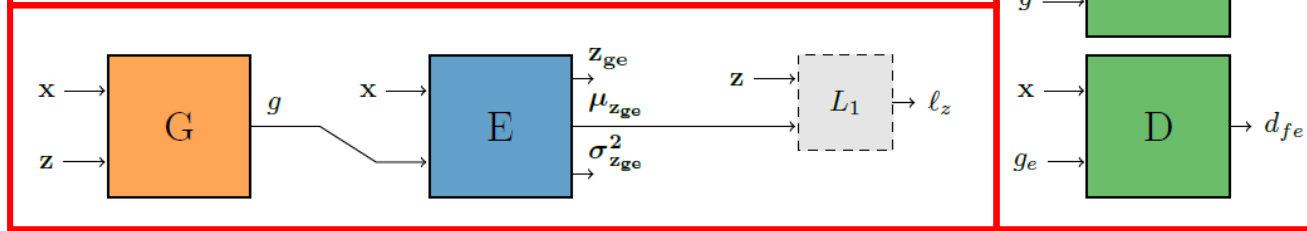
1. Discriminator learns to classify real/fake channel responses
2. Stabilize training with VAE cycle (y-z-y)
3. Discourage mode collapse with latent regression (z-y-z)



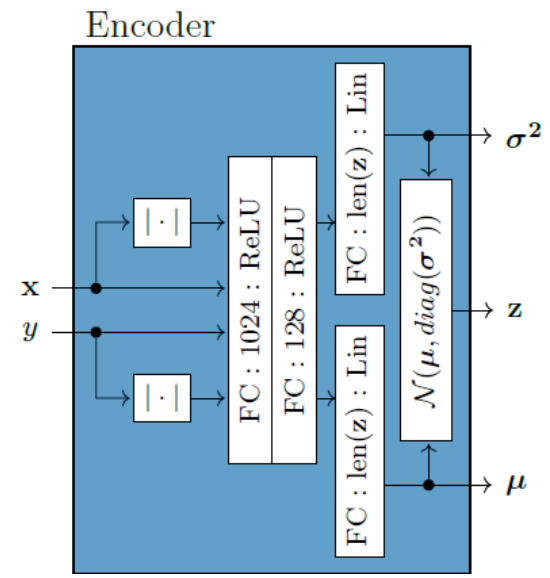
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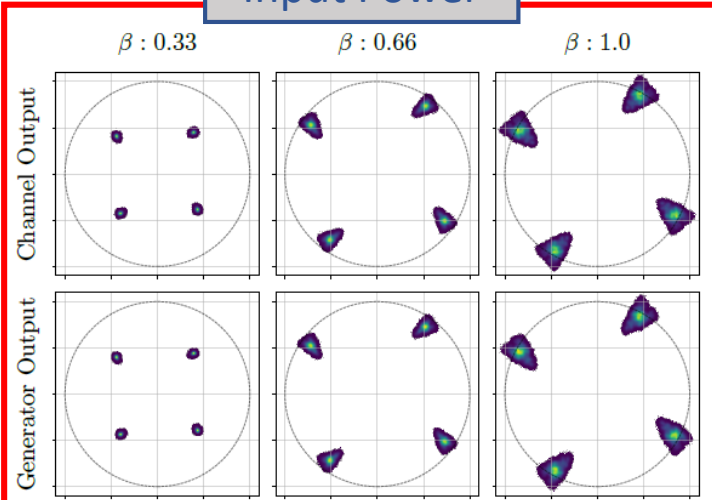


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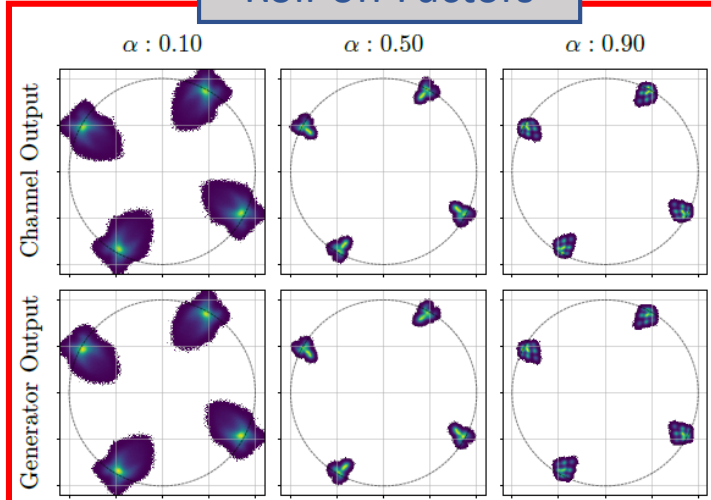


Results

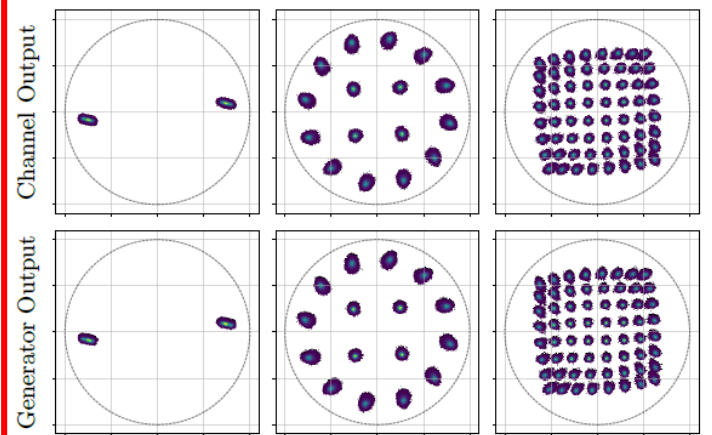
Input Power



Roll-off Factors

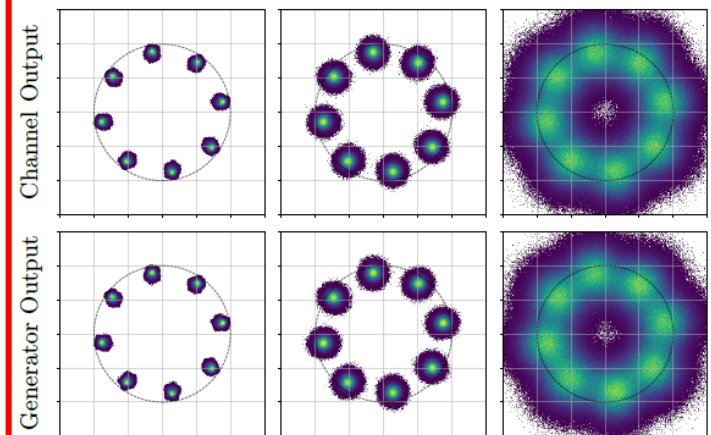


BPSK 16-APSK 64-QAM

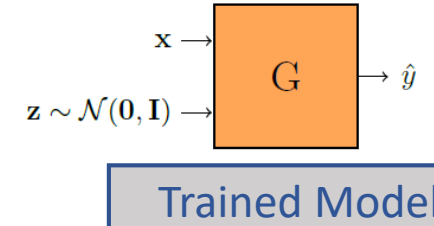


Input Constellation

$P_n/P_{sat} : -35$ dB $P_n/P_{sat} : -22.5$ dB $P_n/P_{sat} : -10$ dB



AWGN Power



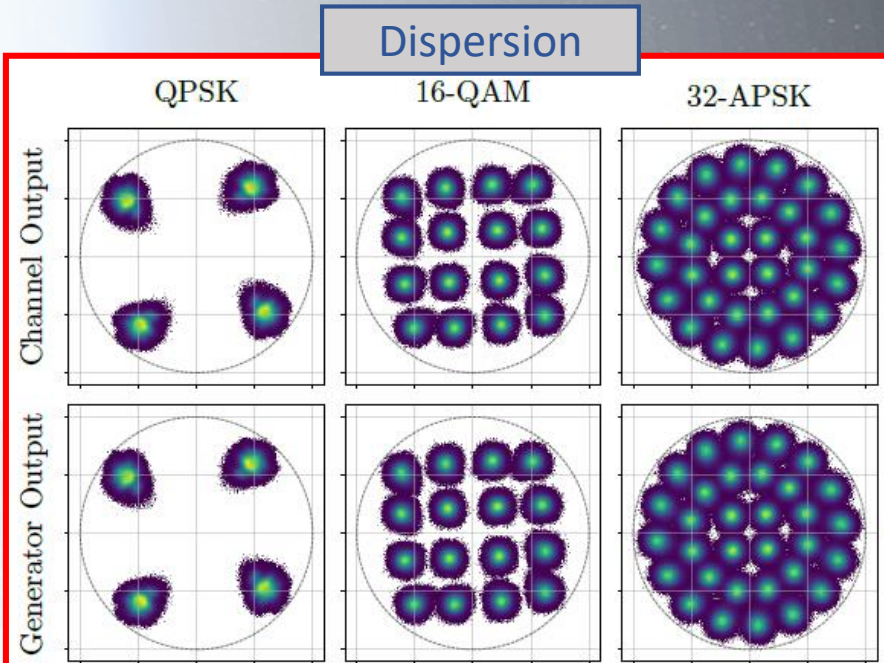
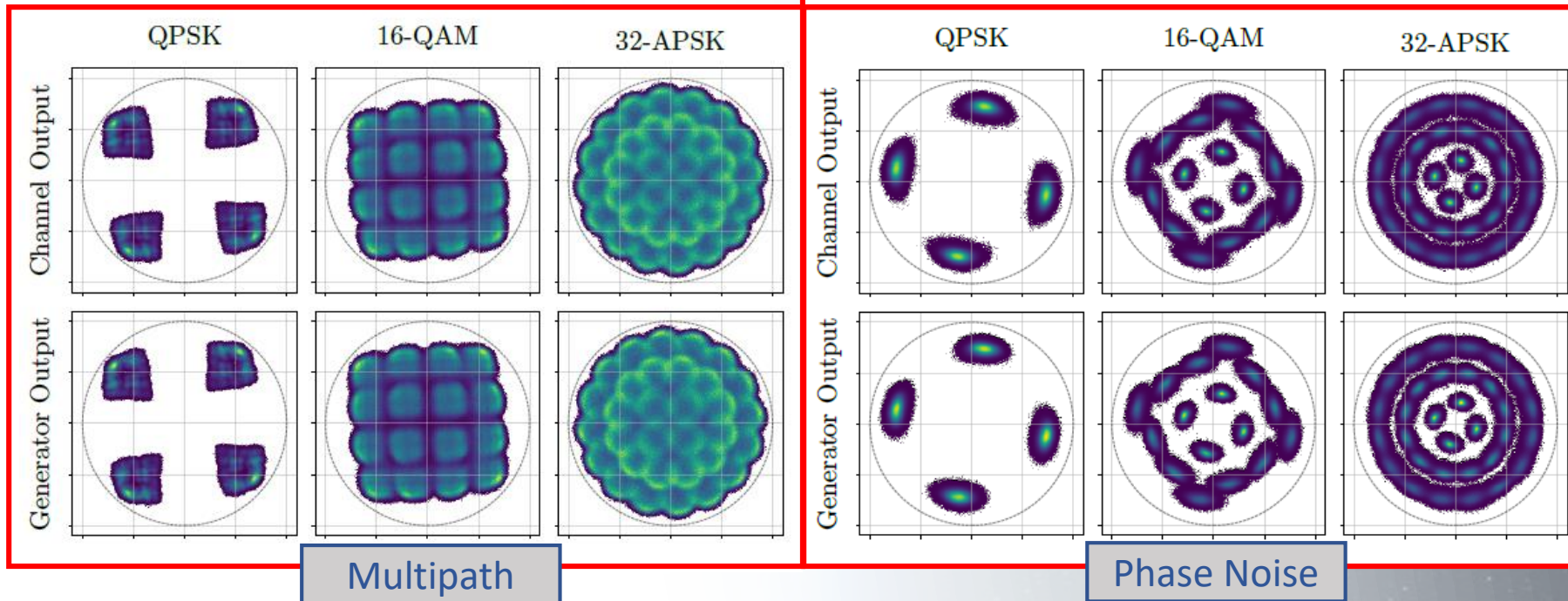
The GAN learned

- **Arbitrary Inputs**
 - > Amplifier amplitude/phase characteristics
 - > ISI distortions for high energy symbols
 - > Distortions specific to constellation
- **Channel Parameters**
 - > Distortions specific to the RRC roll-off factor
 - > Both high/low AWGN powers

Results Cont.

The GAN learned

- ISI due to group delay variation
- ISI from multipath model
- Non-Gaussian noise process



Conclusions

ABCs provide an end-to-end optimization, but gradients cannot be calculated by the transmitter. This can be circumvented by approximating the channel with a neural network. We provide a new GAN architecture for this purpose. We demonstrate the utility of our architecture by evaluating the GAN on channels that contain non-linearities, intersymbol interference, and non-Gaussian statistics.

Next steps include

- **ABCs utilization of GAN architecture**
- **Lab demonstration**