Modeling of Adaptive Receiver Performance Using Generative Adversarial Networks

Presenter: Priyank Kashyap*

Co-authors: Yongjin Choi†, Sumon Dey†, Dror Baron*, Chau-Wai Wong*, Tianfu Wu*, Chris Cheng†, Paul D. Franzon*

* Electrical and Computer Engineering, North Carolina State University

† Hewlett Packard Enterprise

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Introduction

- Generating IBIS-AMI models requires significant effort
  - Multiple computationally expensive design iterations are required for IBIS-AMI
  - Significant amount of a designer's time used in developing IBIS-AMI models
- Other data-driven approaches are limited
  - Support vector machines can predict only the eye-opening characteristics [1]
  - System identification models can recover the entire eye diagram but require a dedicated model for each configuration of the channel and tap [2,3]
  - Recurrent neural networks are used to recover a pulse response only [4]

[1] R. Trinchero and F. G. Canavero, "Modeling of eye diagram height in high-speed links via support vector machine," in IEEE 22nd Workshop on Signal and Power Integrity (SPI), 2018, pp. 1–4.
[2] T. Lu, J. Sun, K. Wu, and Z. Yang, "High-speed channel modeling with machine learning methods for signal integrity analysis," IEEE Transactions on Electromagnetic Compatibility, vol. 60, no. 6, pp. 1957–1964, 2018.
[3] B. Li, P. Franzen, Y. Choi, and C. Cheng, "Receiver behavior modeling based on system identification," in 2018 IEEE 27th Conference on Electrical Performance of Electronic Packaging and Systems (EPEPS),2018, pp. 299–301.
[4] B. Li, B. Jiao, M. Huang, R. Mayder, and P. Franzon, "Improved system identification modeling for high-speed receiver," in IEEE 28th Conference on Electrical Performance of Electronic Packaging and Systems (EPEPS), 2019, pp. 1–3.

Our Contributions

- We present a data-driven approach that uses a single model to predict a SerDes receiver’s performance through a BER contour plot while handling multiple channels and tap configurations
- We demonstrate that this approach can interpolate between different tap conditions, including previously unseen tap conditions
- We show that the generated BER plots are significant by comparing the bathtub curves of the generated plot to that of the ground truths’

Generative Adversarial Networks (GANs)

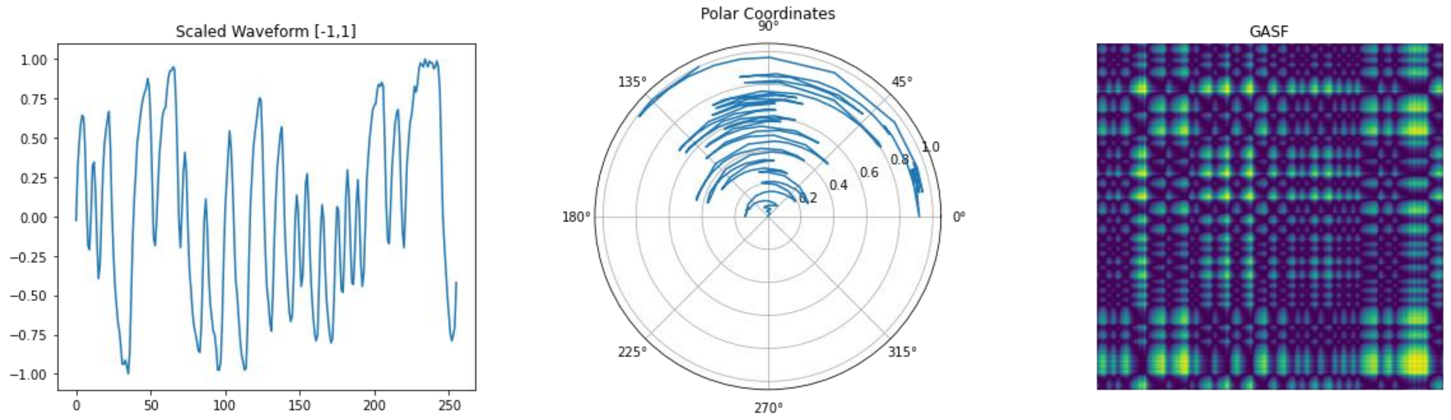
- GANs consist of two modules
  - Generator *(G)*: Creates new examples from a learned latent distribution
  - Discriminator *(D)*: Discerns whether an example provided to it comes from the generator or the dataset
  - Together, they play a zero-sum game and try to outperform each other until they reach equilibrium
- cGANs consist of the same two modules, however,
  - The generator learns to output, *y*, from a given input, *x*, rather than a random vector from a latent space
  - The discriminator discerns whether a sample provided to it comes from the generator or the dataset, given some input
  - The objective function for the cGAN is as follows:

$$L_{cGAN}(G,D) = \mathbf{E}_{x\,y}[\log(D(y|x))] + \mathbf{E}_{x\,z}[\log(1 - D(G(z|x)|x)]$$

where, *z* is randomness introduced by dropout in our implementation

Gramian Angular Sum Field (GASF)

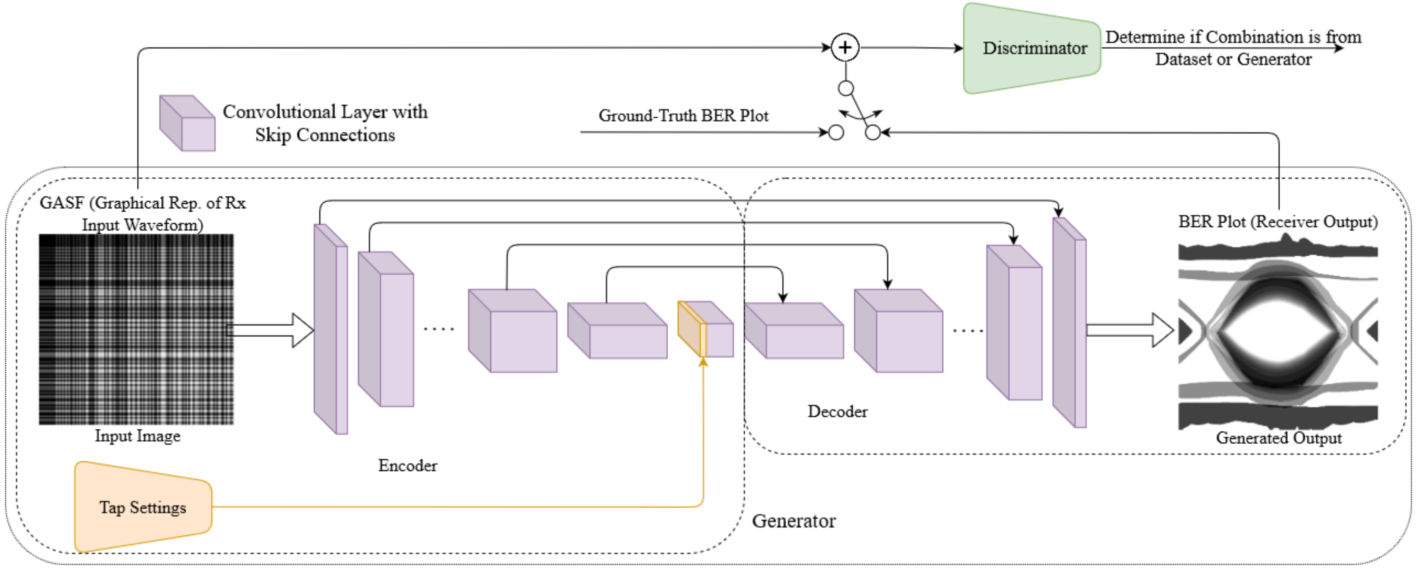
- Encode time-series as an image by transforming to a GASF
  - Rescale the measurements between the interval [-1,1]
  - Convert to the polar coordinate system by taking the *arccosine* of each time step
  - Trigonometric sum between *cosine* of the sum of the i^{th} and the j^{th} angular points to form a GASF
  - Takes < 10ms to finish the GASF generation over the entire dataset
- The temporal dependency between different time steps is captured.
  - Captures the ISI effectively



Conversion of time series to a polar encoding and then a GASF

Our Approach: 2-Encoder Generator with U-Net Discriminator

- Generator is given the input waveform encoded as a GASF and taps weights to predict the bit error rate (BER) contour plot
  - Uses regular convolution with skip connections (pix2pix)
  - Separate encoder network to learn the tap settings
- Discriminator is a U-Net architecture that predicts both a full pixel map (at decoder output) and a single true/false prediction (at the bottleneck) for a given input
  - Takes the input GASF and either the ground truth BER plot or generated BER plot
  - Predicts whether the concatenated image is from the dataset or generator using two levels of prediction

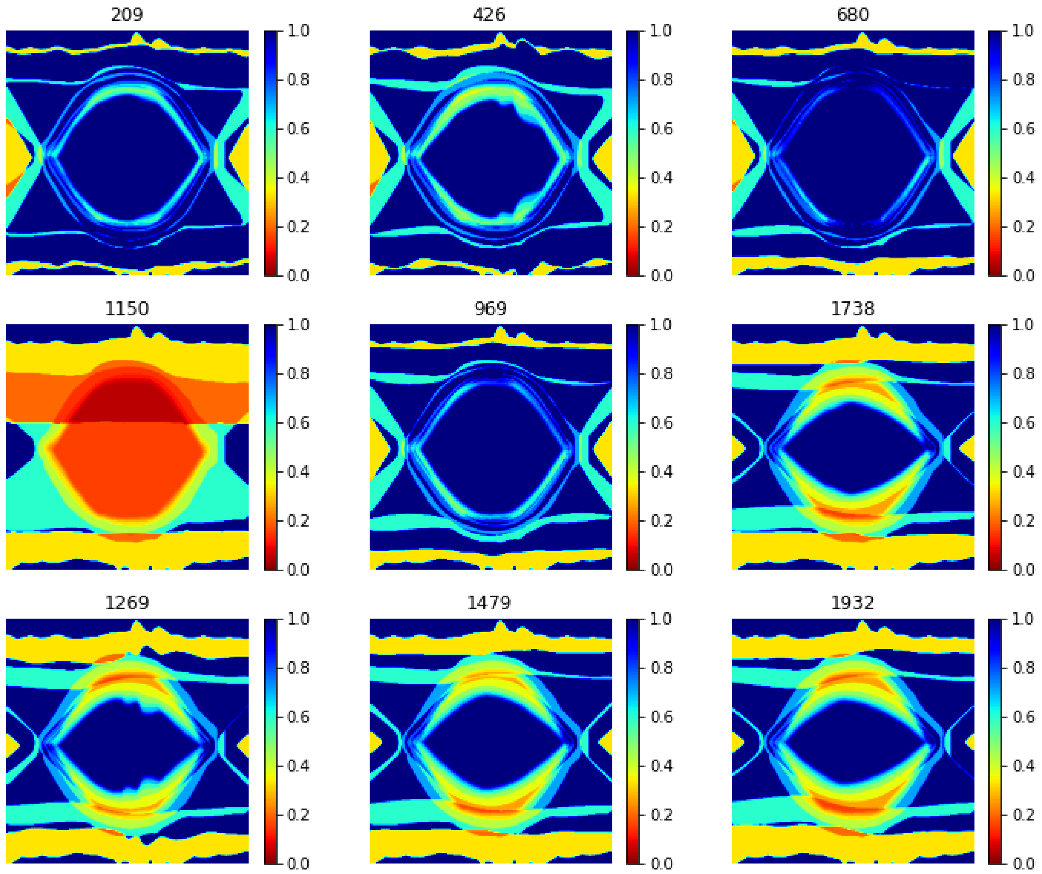


Generator of the cGAN conditioned on the GASF and DFE tap configurations to predict an eye diagram

Dataset

Channel + Tap + Bitstream Varied

- 4 low loss channels
  - Open eye regardless of the DFE tap values
- 4 medium loss channels
  - The optimal DFE taps are aggressive to yield a larger eye-opening
- 200 Gaussian samples around the optimal DFE tap settings
  - 1 std deviation- Half of the optimal DFE tap setting

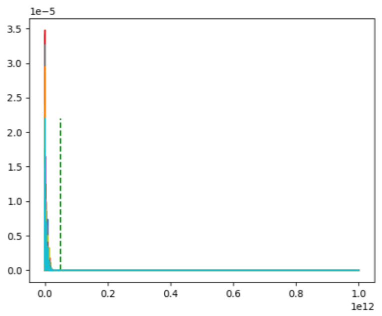


Plot of random designs and their eye diagrams from multiple channels in the dataset

Preprocessing

Time Series Preprocessing

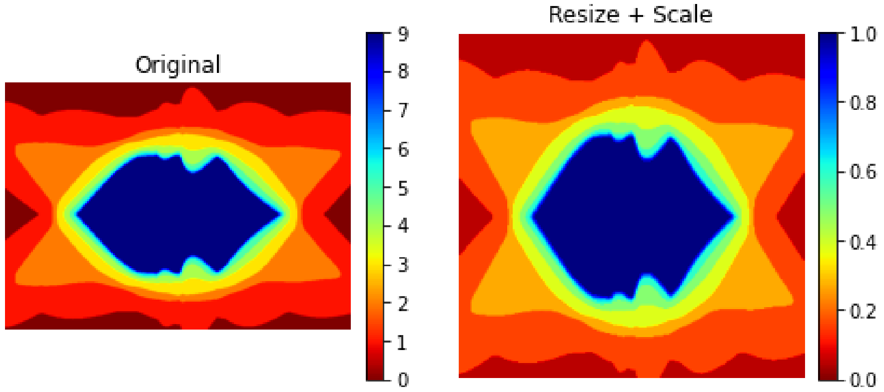
- Original time series is at every 0.5ps for 600 UIs
  - 1 UI = 31.25 ps (32 Gb/s)
  - 10% for the rise and 10% fall time
- Based on the Nyquist rate, determine how much to downsample the input time series
  - Downsample the raw waveform for an efficient generation of a GASF



PSD plot for time series waveforms

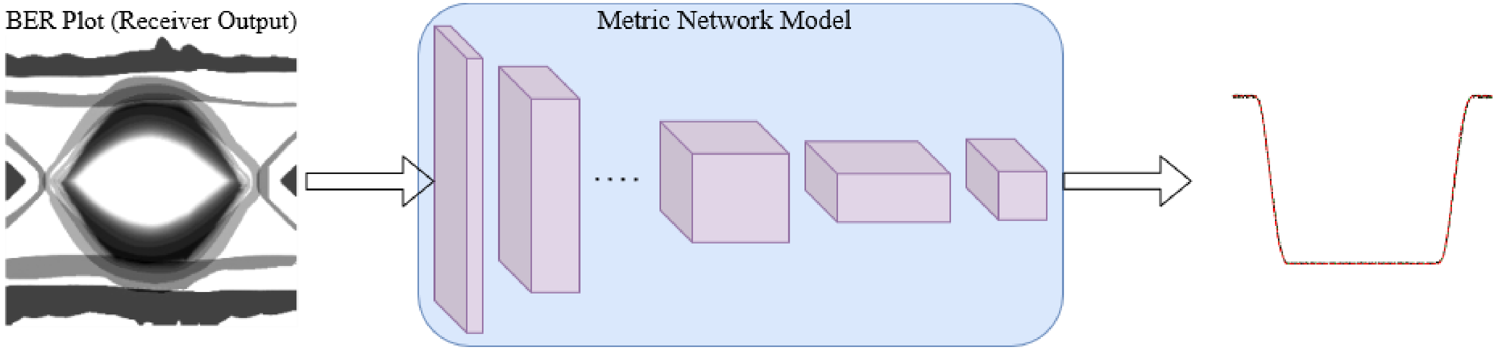
Bit Error Rate (BER) Preprocessing

- It goes up to BER-15 but we limit it to BER-6
  - Actual device measurements are limited to BER-6
- Rescale the BER plot to values between [0,1] for pixel intensities
- The final image is resized to 256x256 to work with the models



Original and resized BER

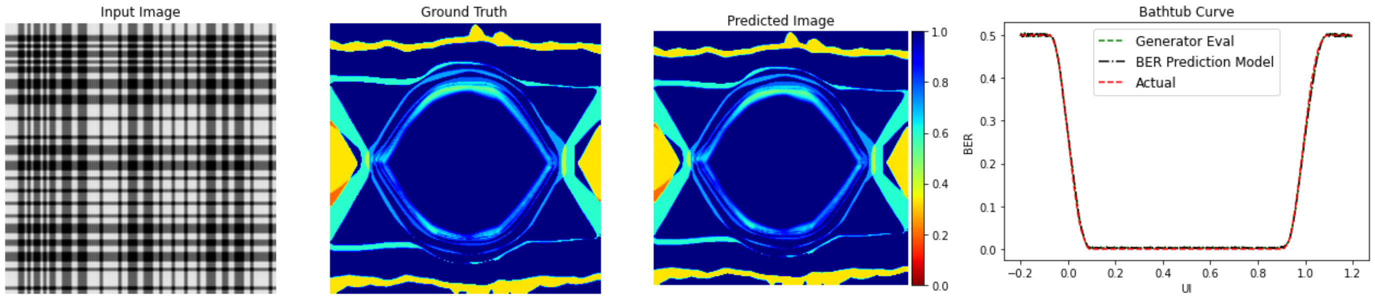
Metric Network



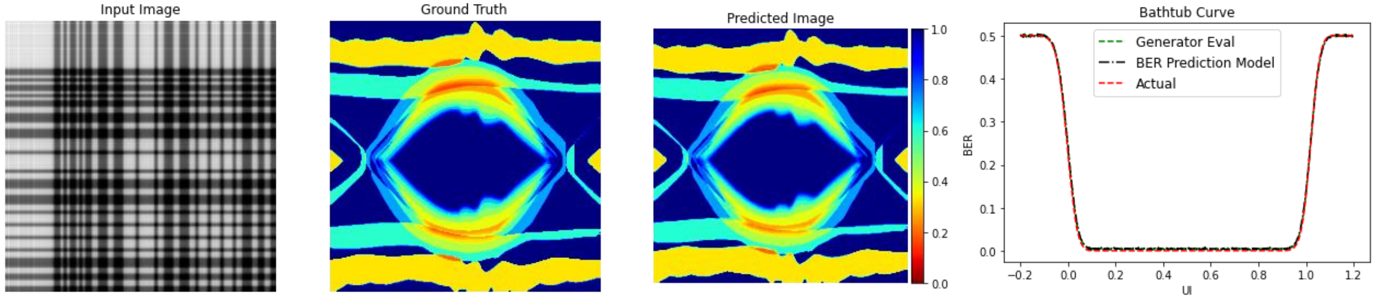
Neural network used to predict the bathtub curves from the ground truth model

- To evaluate the quality of images generated we use a deep neural network (DNN) trained on the ground truths eye diagram and their corresponding characteristics
  - Uses encoder model architecture from the GAN generator/discriminator
  - Consists of successive Convolution and Batch Normalization layers to reduce the dimension of the input image
- Output neurons correspond to the number of points in the bathtub curve that are being used to evaluate the generated BER plots
  - In our case, there are 700 points in the bathtub curve
  - We calculate the Pearson Correlation Coefficient as well as the root mean squared error of the generated bathtub curve to the ground-truth bathtub curve to evaluate the generated BER plot

Results-I: Baseline Models



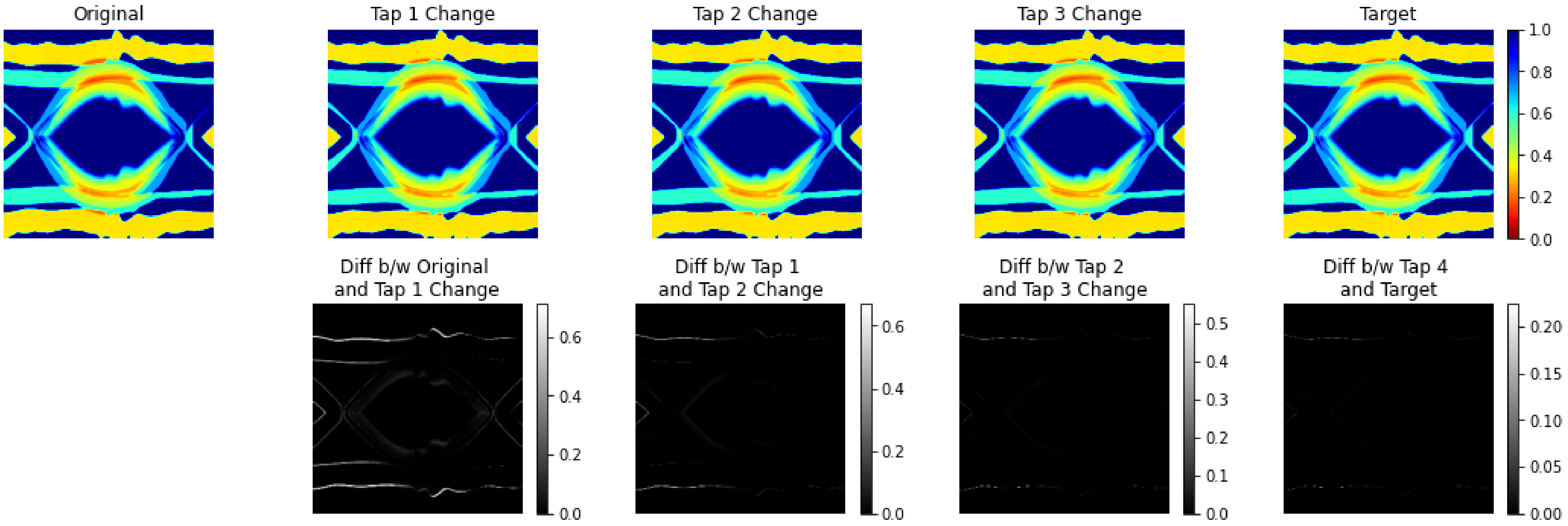
GASF representation of the time series, the corresponding ground-truth BER plot, the generator's predicted BER, comparison of the underlying bathtub curves



GASF representation of the time series, the corresponding ground-truth BER plot, the generator's predicted BER, comparison of the underlying bathtub curves

- Training and inference times of the model are comparable to prior work
  - 18 seconds per training iteration
  - 192 ms for inference
- Bathtub curves of the generate images and ground truth are correlated and have a RMSE 0.014

Results-II: Tap Interpolation



The BER plots being varied on configurations in the test set (original and target) by changing one tap at a time and differences it yields in the BER plot (bottom row)

Conclusion

- We present a data-driven approach that uses a single GAN which can handle a receiver with
    - Varying bitstreams
    - Multiple channel conditions
    - Varying DFE tap configurations
- GASF is an excellent intermediate representation to learn from
    - Preprocessing the waveforms and GASF have overhead associated with them
- The dataset we use to train is smaller in comparison to other GAN models, which require thousands of samples, and training takes as long as other data-driven methods
- We demonstrate that this approach can interpolate between different tap conditions, including previously unseen tap conditions
- We evaluate the generated BER plots on their corresponding bathtub curves and show that they are a good fit