Implementation of QGANs for HEP Analysis at LHC

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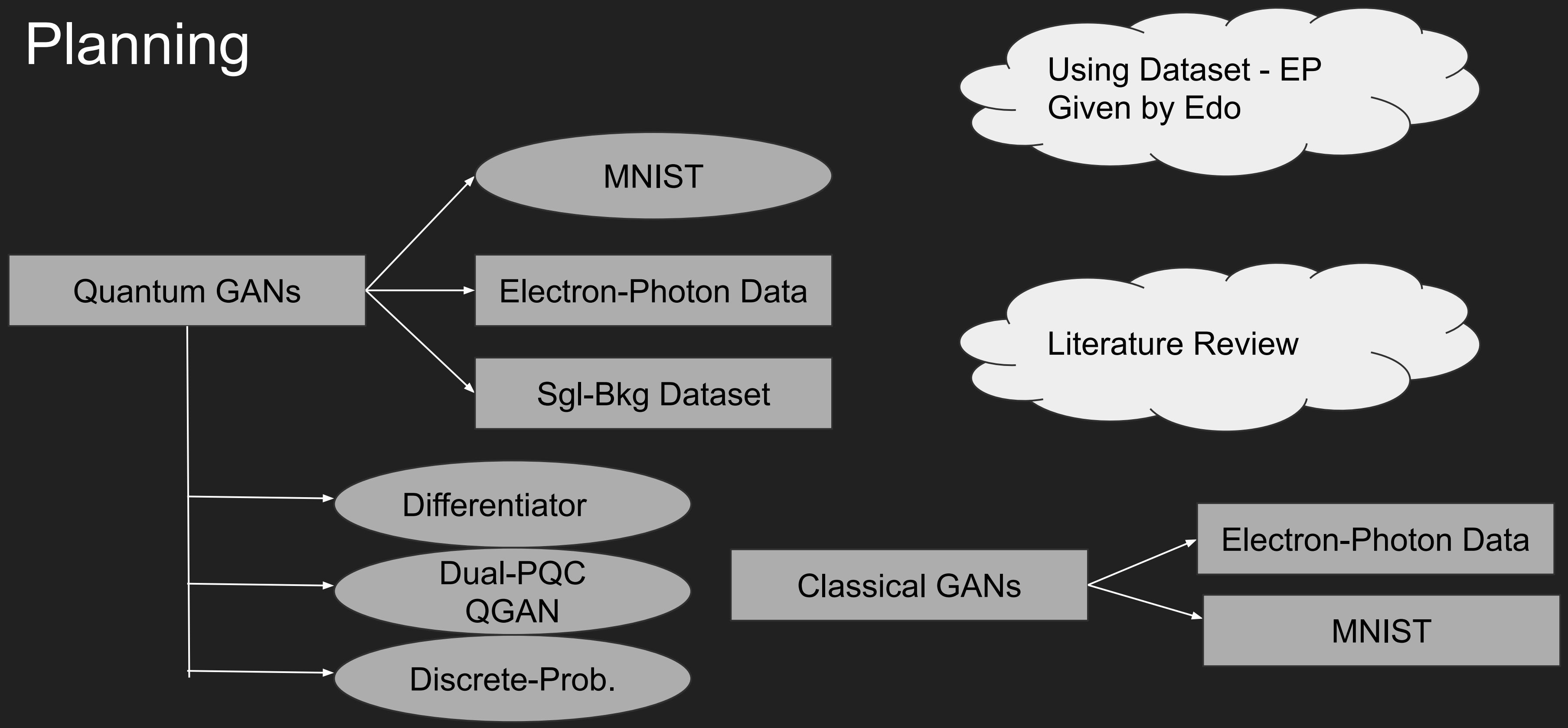
What I'll be discussing:

- Code and results of the QGAN, QWGAN for the dataset - QIS_EXAM_200Events.npz(one given in the tasks)
- Code and results of the Classical GAN for the electron-photon dataset
- Code and results for the QGAN implementation for the Electron-Photon dataset.
- Findings about quple and some of its issues - Discuss
- Literature search findings - Papers,links etc.
- Future Work - Discrete Prob Distribution, Dual-PQC, Differentiator.ParameterShift()

Planning



Using Dataset - EP
Given by Edo
MNIST
Quantum GANs
Electron-Photon Data
Sgl-Bkg Dataset
Literature Review
Differentiator
Dual-PQC
QGAN
Discrete-Prob.
Classical GANs
Electron-Photon Data
MNIST

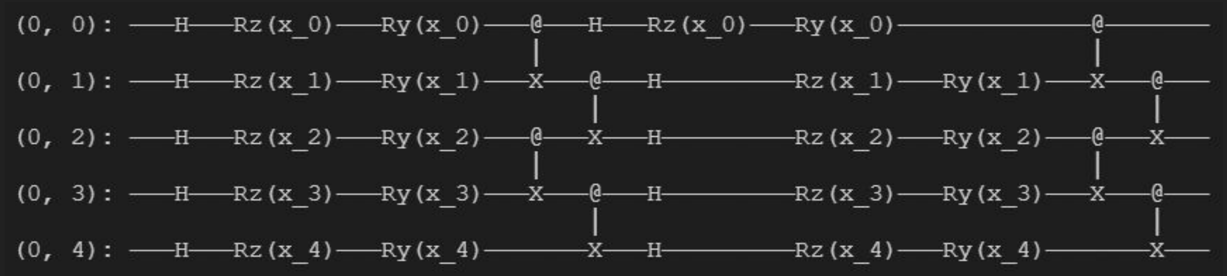
QGAN (dataset = QIS_Exam_200Events.npz)

Two types of QGANs were studied - QGAN and QWGAN

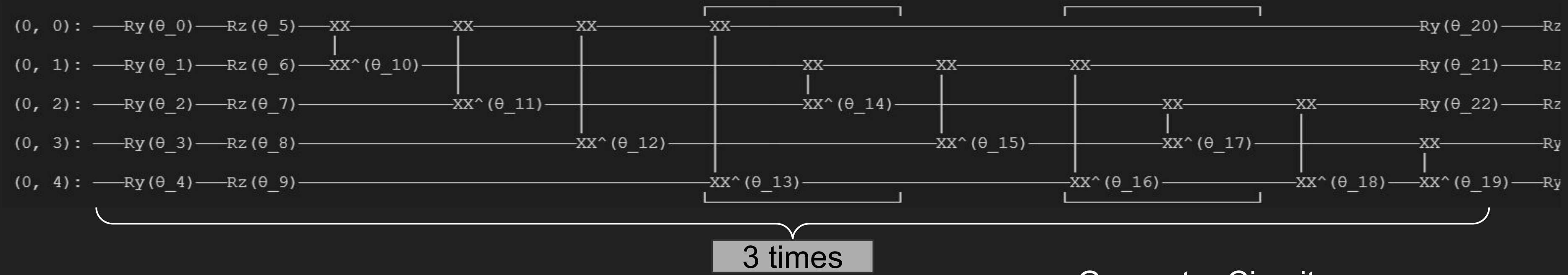
- For QGAN -
  - Generator - IsingCoupling Circuit , Discriminator - ParameterisedCircuit (PauliBlocks)
  - Encoding - ParameterisedCircuit

Then parameter tuning - taking various parameters and checking which gives better results.

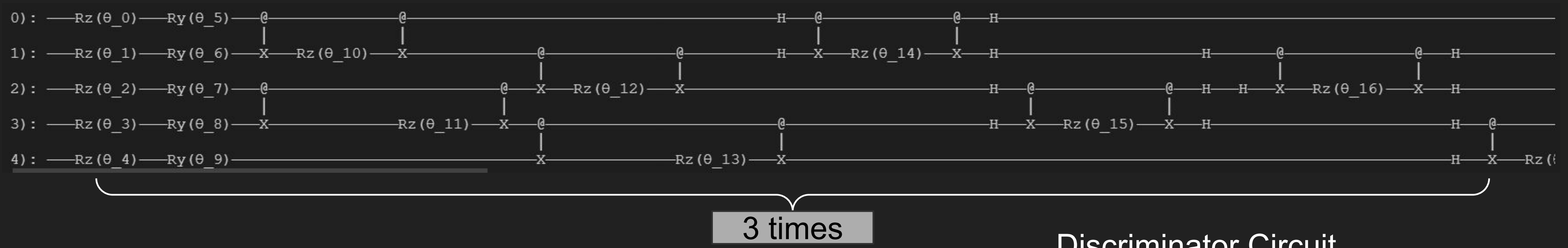
- For QWGAN -
  -



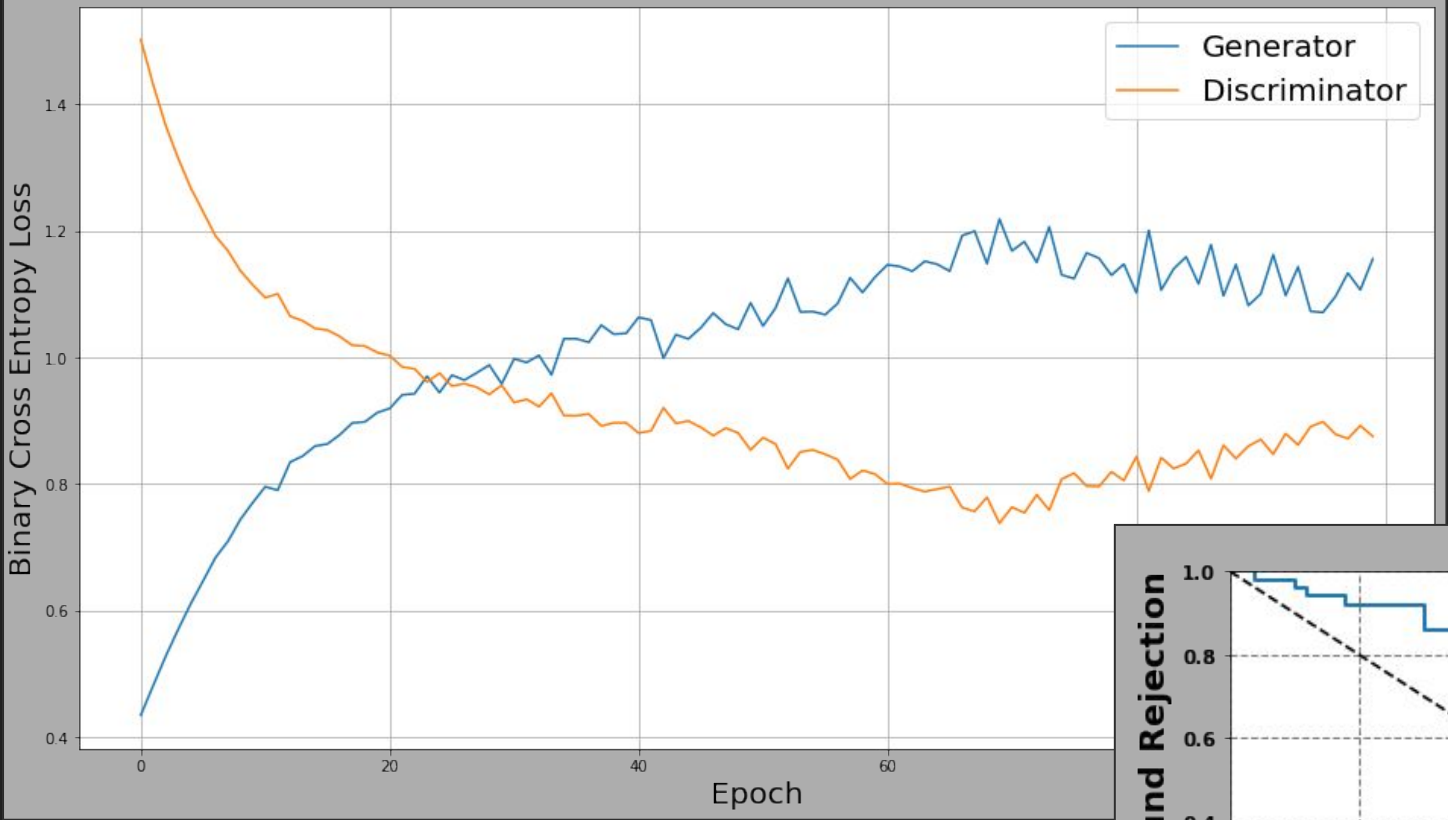
Encoding Circuit

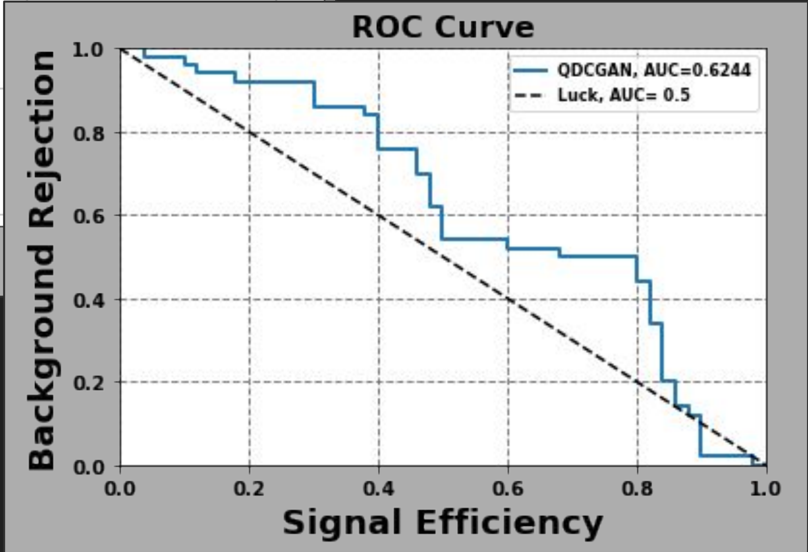


Generator Circuit



Discriminator Circuit

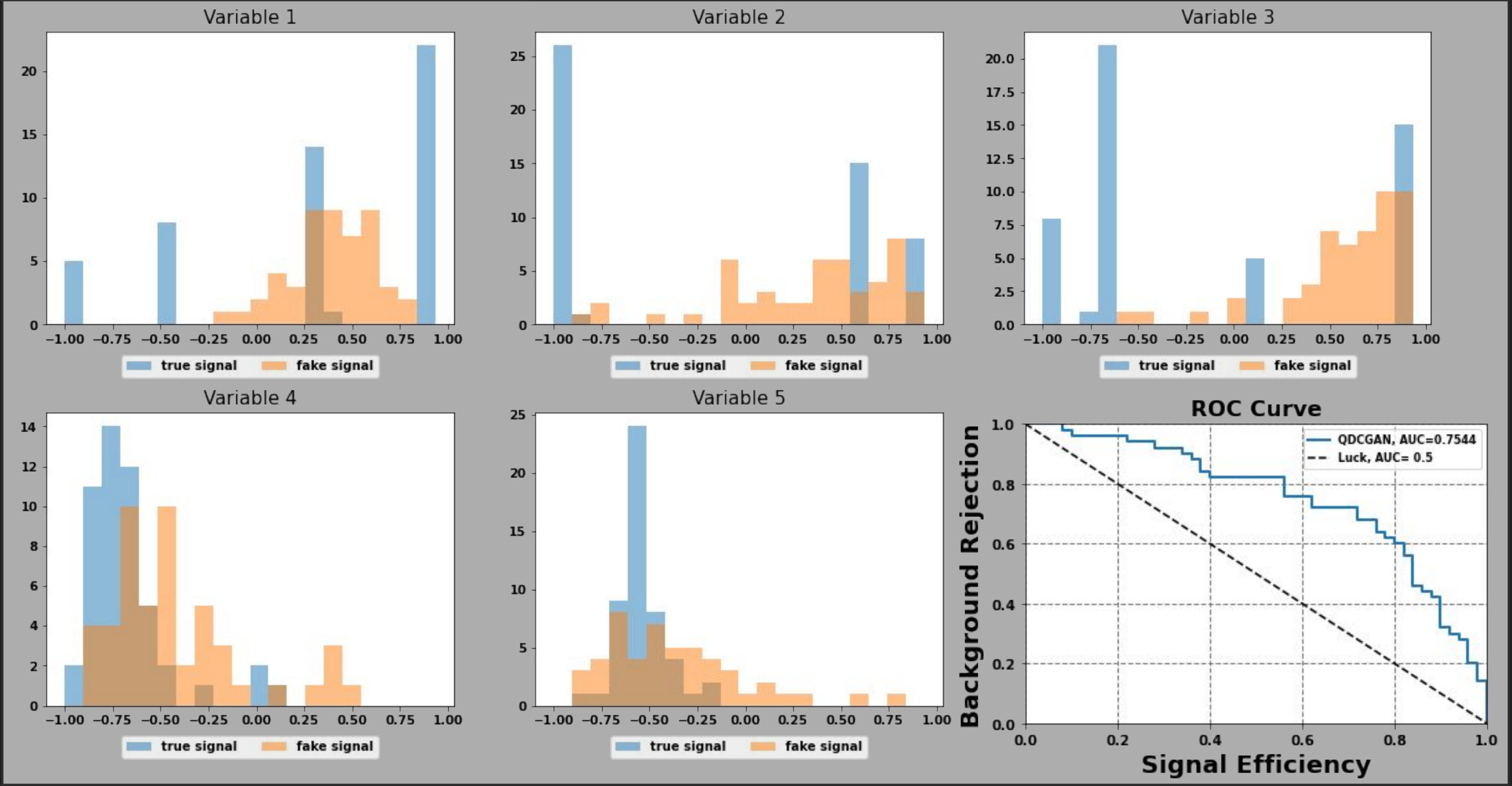




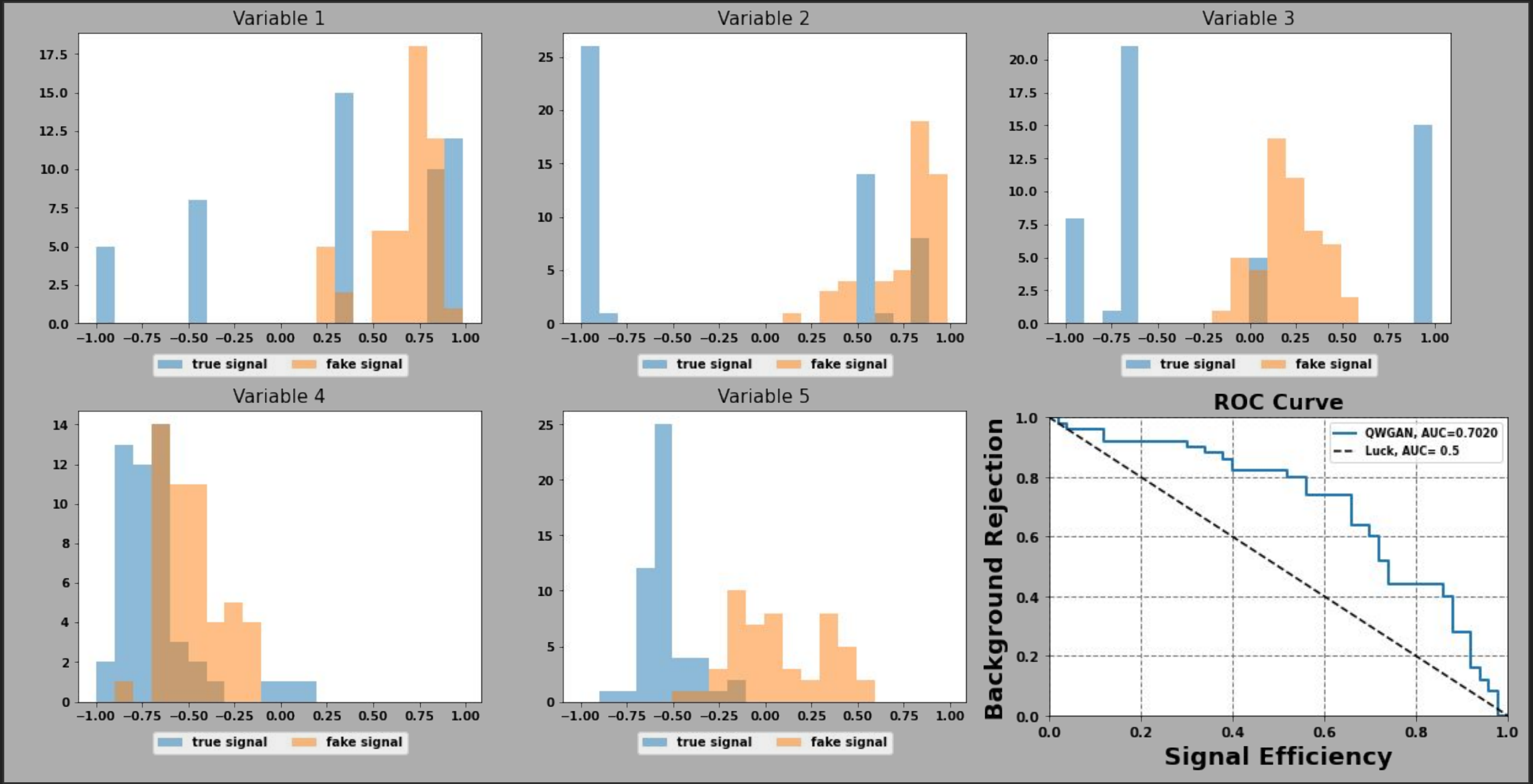
Initial without hyperparameter tuning

```
The best lr combination so far is:
{'g_lr': 0.01, 'd_lr': 0.001}
With test auc = 0.7544000000000001
```

Took very less values, would increase the number of values and give update about it on slack!!



QWGAN Results



Classical GAN for Electron-Photon Dataset (EPD)

- Tried classical GAN implementation
  - The outputs were somewhat accurate but they also had noise
- Tried normalising - Normalised after and before the scaling and cropping part
  - Before cropping - Gave a very distributed image of the dataset which would increase noise
  - After cropping and resizing - Just look at the major contributing part of the distribution
  - Gave okayish results
- Further work
  - Improving the output of the GAN so that we can compare the best classical GAN with the quantum GAN

Layer (type)	Output Shape	Param #
dense_19 (Dense)	(None, 256)	25600
batch_normalization_30 (BatchNormalization)	(None, 256)	1024
leaky_re_lu_48 (LeakyReLU)	(None, 256)	0
reshape_10 (Reshape)	(None, 2, 2, 64)	0
conv2d_transpose_30 (Conv2DTranspose)	(None, 2, 2, 32)	51200
batch_normalization_31 (BatchNormalization)	(None, 2, 2, 32)	128
leaky_re_lu_49 (LeakyReLU)	(None, 2, 2, 32)	0
conv2d_transpose_31 (Conv2DTranspose)	(None, 4, 4, 16)	2048
batch_normalization_32 (BatchNormalization)	(None, 4, 4, 16)	64
leaky_re_lu_50 (LeakyReLU)	(None, 4, 4, 16)	0
conv2d_transpose_32 (Conv2DTranspose)	(None, 8, 8, 1)	144

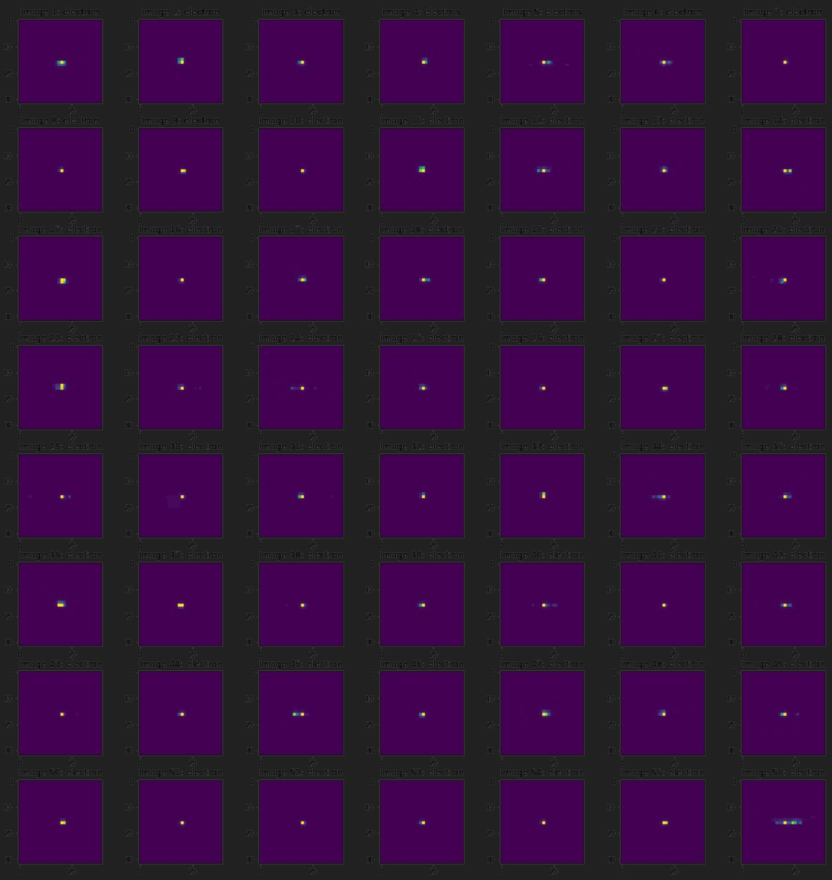
Total params: 80,208
Trainable params: 79,600
Non-trainable params: 608

Layer (type)	Output Shape	Param #
conv2d_18 (Conv2D)	(None, 4, 4, 64)	640
leaky_re_lu_51 (LeakyReLU)	(None, 4, 4, 64)	0
dropout_18 (Dropout)	(None, 4, 4, 64)	0
conv2d_19 (Conv2D)	(None, 2, 2, 128)	32896
leaky_re_lu_52 (LeakyReLU)	(None, 2, 2, 128)	0
dropout_19 (Dropout)	(None, 2, 2, 128)	0
flatten_9 (Flatten)	(None, 512)	0
dense_20 (Dense)	(None, 1)	513

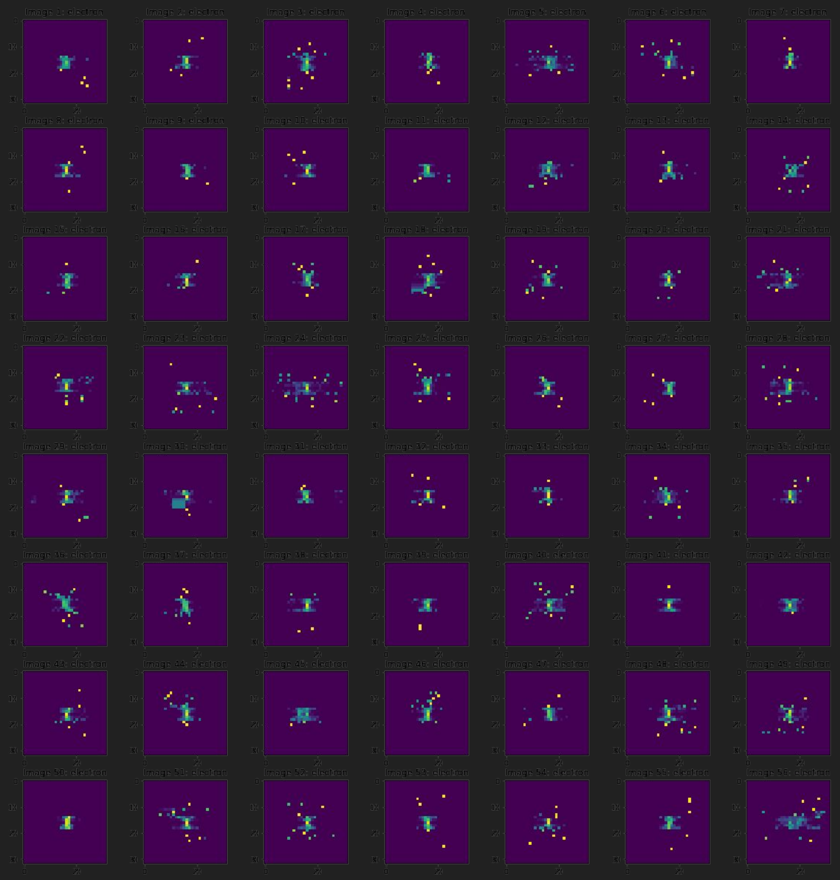
Total params: 34,049
Trainable params: 34,049
Non-trainable params: 0

Generator and Discriminator Layers of Classical GAN

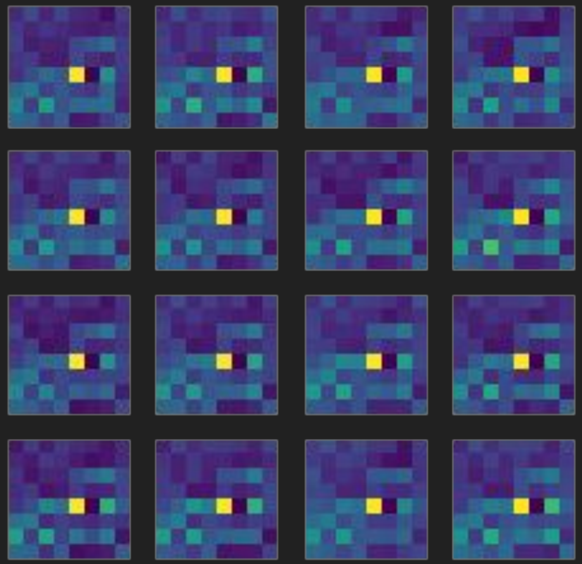
The effect of Normalisation before the cropping/rescaling

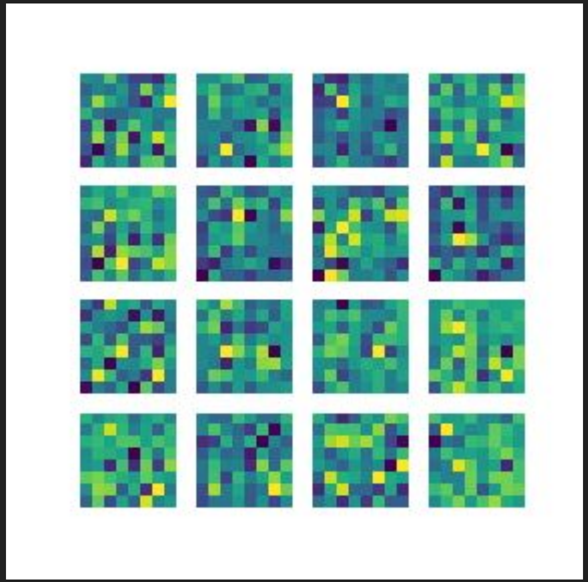


Original Dataset



Normalised(before) Dataset





The center spot is being rightly placed which means that the GAN is learning data almost correctly but need to reduce the amount of noise and false results arising

Literature Review - Papers

- Quantum Generative Adversarial Networks for learning and loading random distributions; Christa Zoufal 1,2*, Aurélien Lucchi2 and Stefan Woerner
- TOWARDS PRINCIPLED METHODS FOR TRAINING GENERATIVE ADVERSARIAL NETWORKS; Martin Arjovsky Leon Bottou
- Quantum Machine Learning Beyond Kernel Methods; Sofiene Jerbi,1 Lukas J. Fiderer
- Quantum semi-supervised generative adversarial network for enhanced data classifcation; Kouhei Nakaji* & NaokiYamamoto
- Generative Quantum Learning of Joint Probability Distribution Functions;Elton Yechao Zhua , Sonika Johri
- Impact of quantum noise on the training of quantum Generative Adversarial Networks; Kerstin Borras1,2 , Su Yeon Chang
- Simulation of quantum neural network with evaluation of its performance; Rafał Potempa
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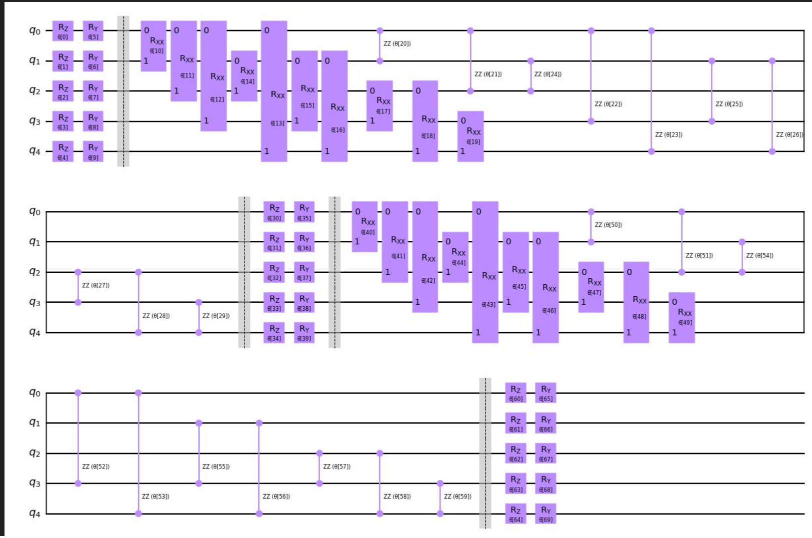
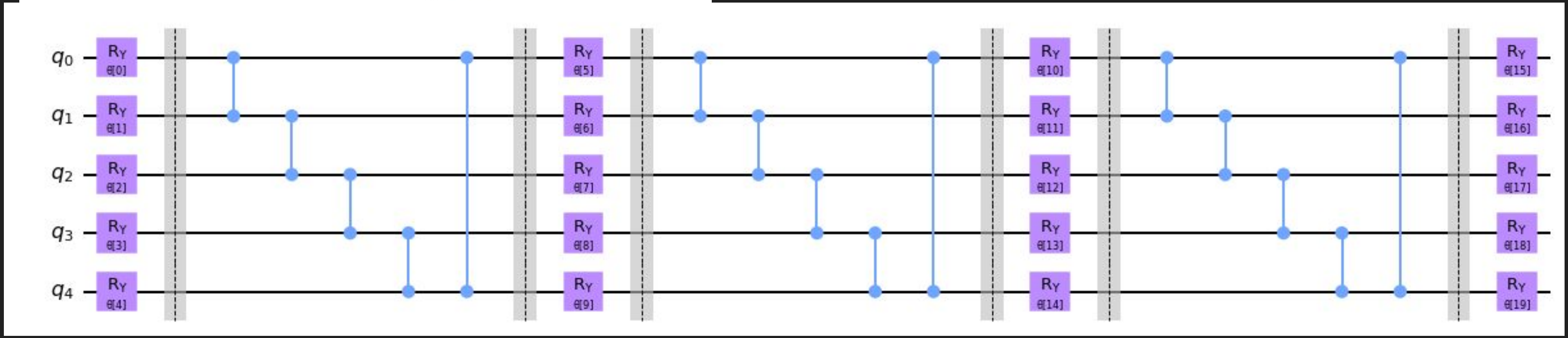
Some more encoding attempts





The various generator and discriminator circuits need to be tested !!

Thank You