Particle Event Generation using Generative Adversarial Networks (GANs)

Samuel Shapley and Anson Poon

Supervisor: Dr. Antonin Vacheret **High Energy Physics Research Group**

The SoLid Experiment

- Sterile neutrinos are a hypothesised neutrino flavour which do not interact via the weak force [1].
- SoLid is a neutrino detector constructed next to a nuclear reactor. It searches for antineutrinos via inverse beta decay [2].
- Comprised of thousands of individual detection cubes.
- Background sources need to be removed from the dataset.
- Atmospheric muons are easily identified within the detector, and this data is cut from the dataset. However, these muons can scatter neutrons which may enter the detector volume.

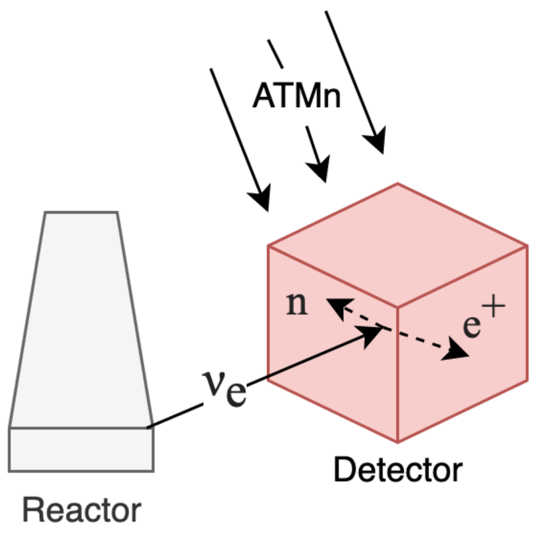

Figure 1: Basic Operation of the SoLid detector.

Research Aims

- Build a Generative Adversarial Network (GAN) for efficient simulation of ATMn events.
- Develop methods to investigate the capabilities of a 2D GAN for the production of 3D data.
- Use data augmentation techniques to improve Signal/Background classification at SoLid.

Atmospheric Neutron Events

- Neutrons scatter electrons along their path which deposit energy in the detector cubes.
- The dataset consists of real events from the detector alongside Monte Carlo simulated events.
- Datasets built from orthogonal projections of each event; produced by summing over each coordinate axis.

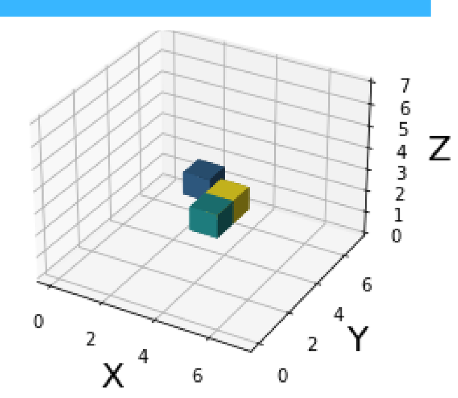

Figure 2: An ATMn event.

Generative Adversarial Networks

- Generative Adversarial Networks (GANs) typically consist of two neural networks: Discriminator and Generator.
- GAN simulation is very computationally inexpensive.
- A Discriminator classifies whether input data is real or generated. The Generator converts an input noise vector into an event.
- They compete with each other in a Zero-sum game [3]:

$$\min_{G}\max_{D} V(D,G) = \mathbb{E}_{\boldsymbol{x}\sim p_{\text{data}}(\boldsymbol{x})}[\log D(\boldsymbol{x})] + \mathbb{E}_{\boldsymbol{z}\sim p_{\boldsymbol{z}}(\boldsymbol{z})}[\log(1 - D(G(\boldsymbol{z})))]$$

- Implemented a 2D DCGAN where the generator uses transposed convolutions and the discriminator is a convolutional neural network (CNN).

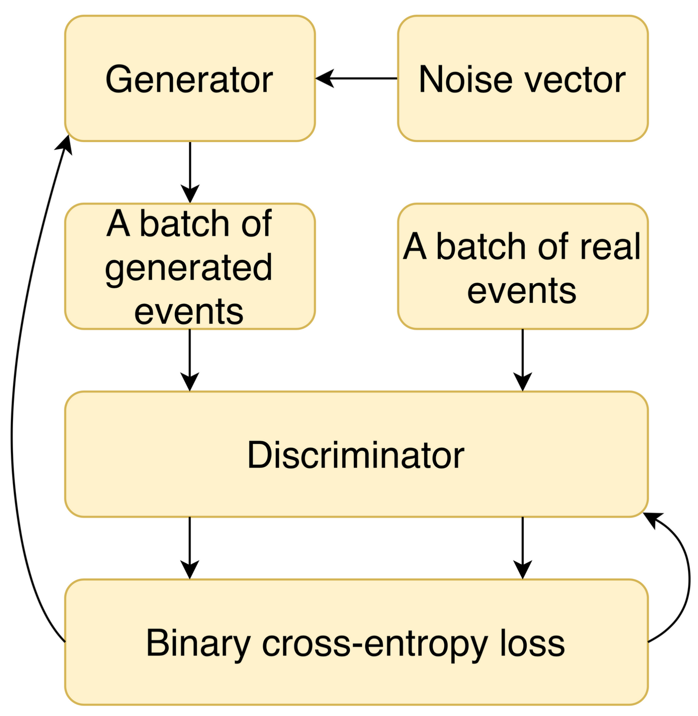

Figure 3: Adapted from [4]. A flow chart of the training process.

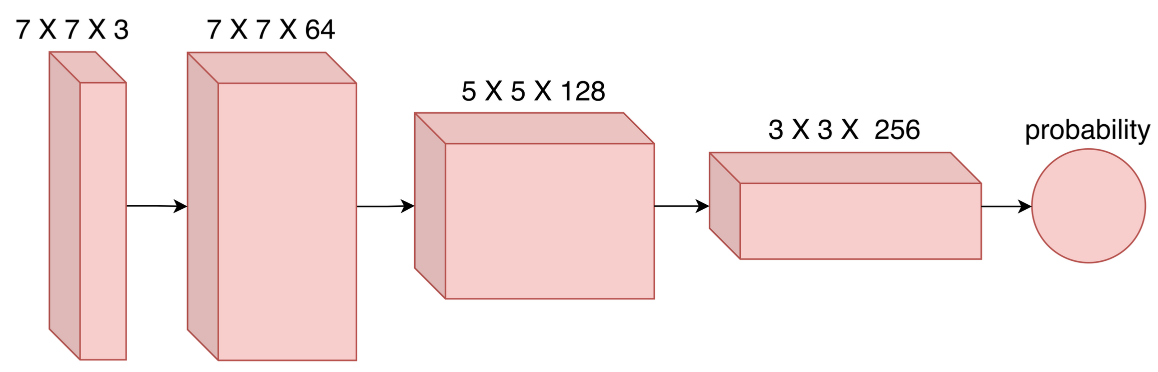

Figure 4: The architecture of the discriminator.

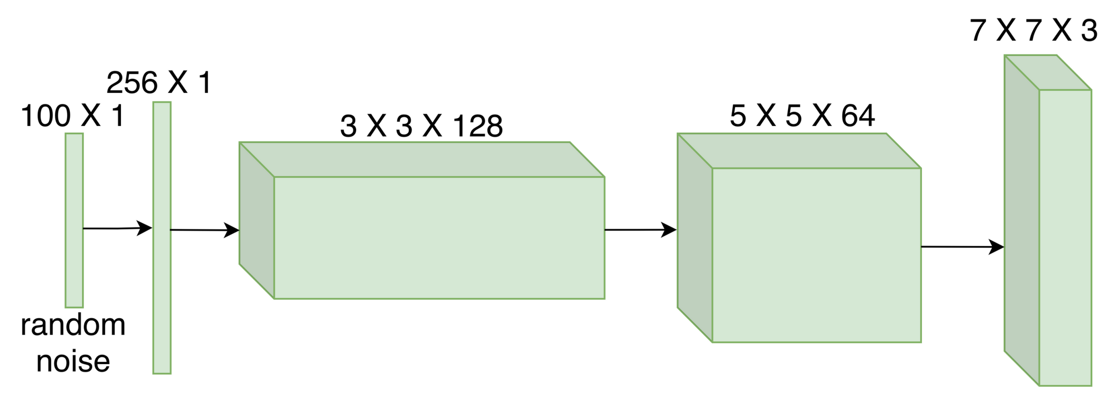

Figure 5: The architecture of the generator.

Results

- Generated events can be compared by eye to real events.

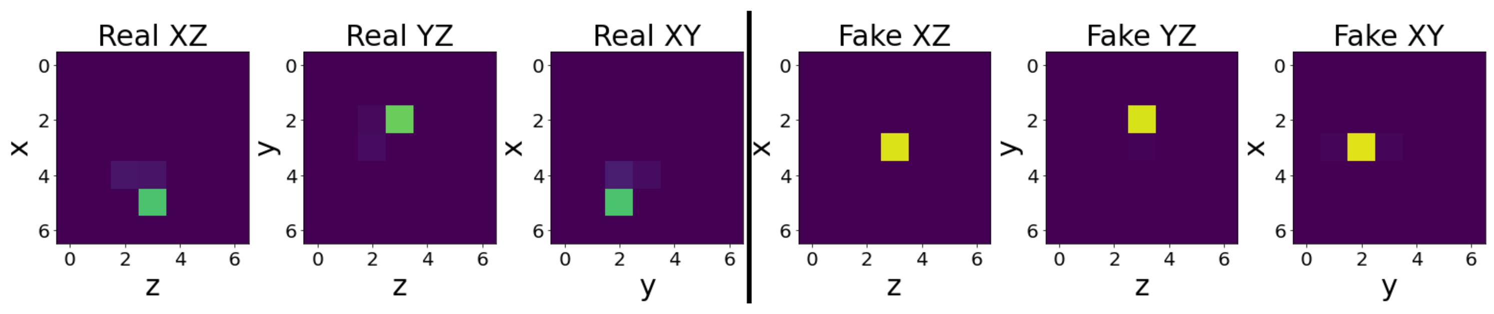

Figure 6: A real event and a fake event displayed for visual comparison. Brighter pixels represent higher energy.

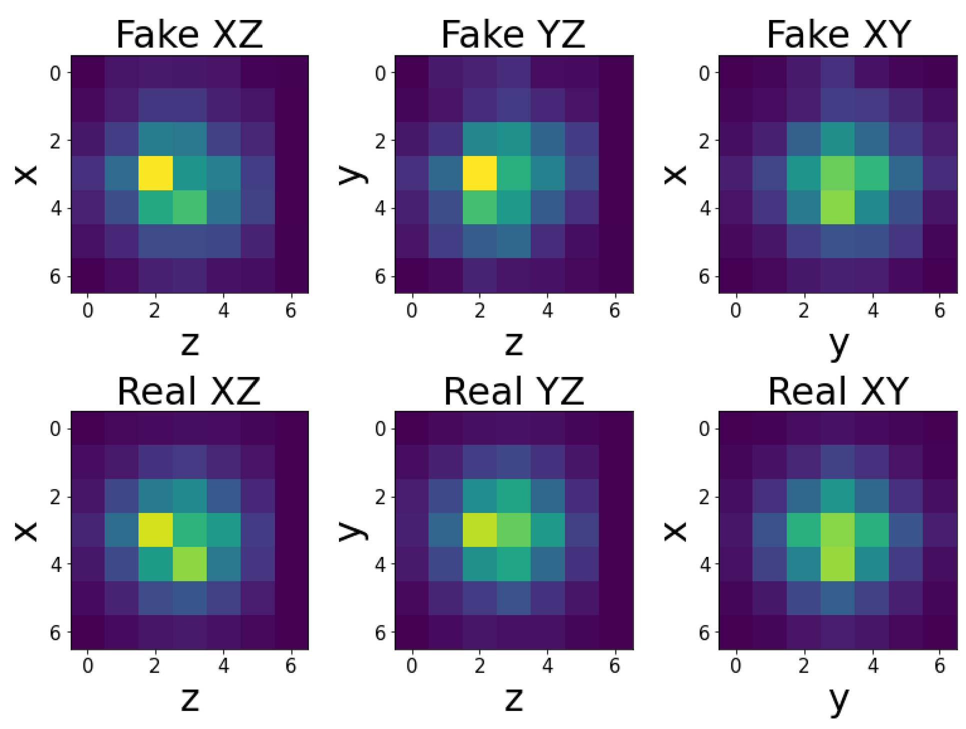

Figure 7: Average images produced from the fake and real dataset.

- The average of the dataset for each plane can be compared.
- These scores are a general measure, a GAN should be able to learn specific features within events.
- A key feature is the energy distribution of the maximum pixels.

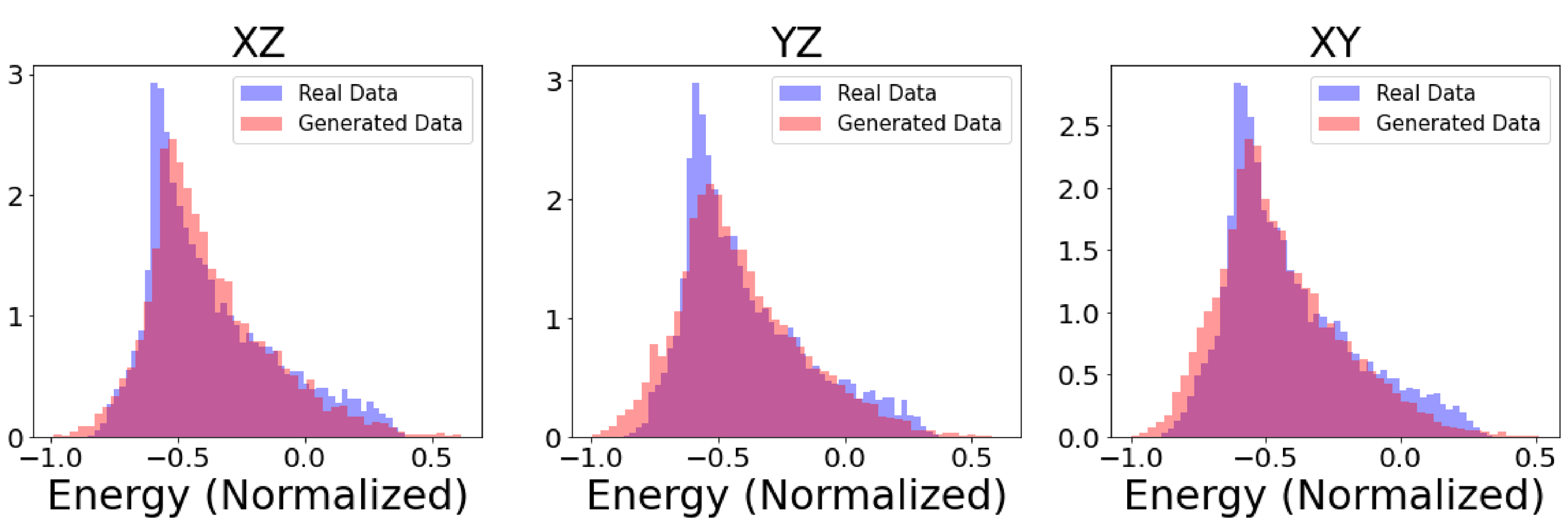

Figure 8: Distributions of maximum energy in each plane.

Can a 2D GAN learn 3D Space?

- Similar averages of cross-plane correlations suggest 3D space has been learnt.
- A CNN was trained to establish the probability of a generated event existing in real space.
- The training data is real correlation planes, shuffling to create fake data.

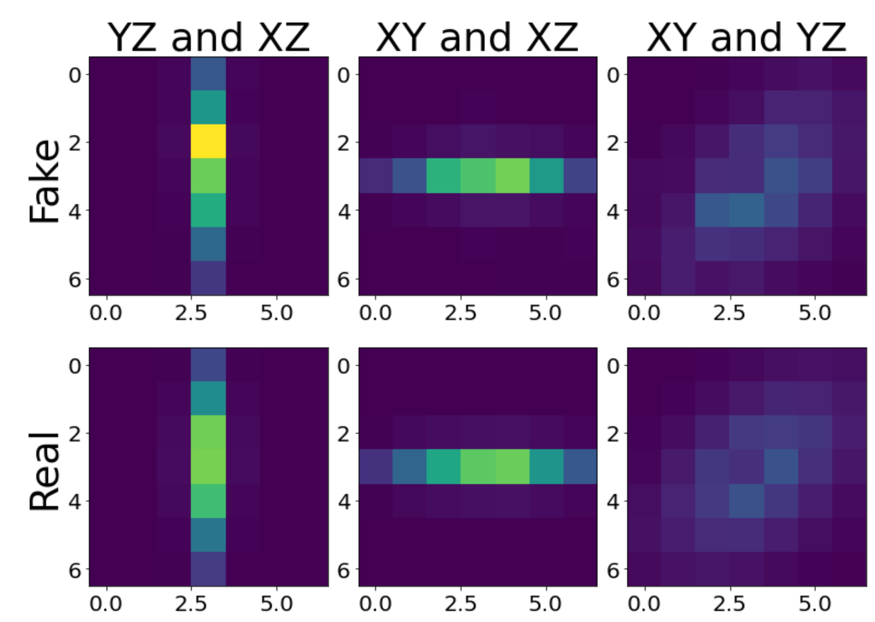

Figure 9: Average 2D correlations of the planes.

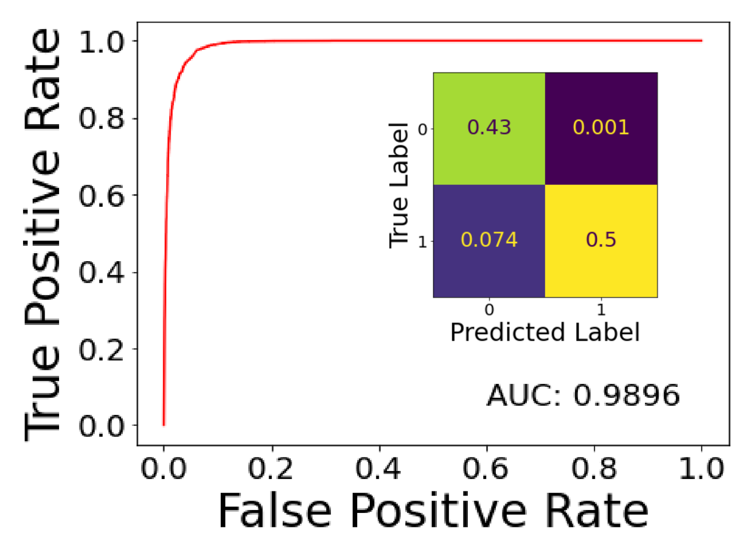

Figure 10: Confusion matrix (inset) and ROC curve for the trained CNN.

- An ideal classifier performance yields a diagonal matrix.
- The area under a ROC curve (AUC) is 1 for an ideal classifier [5].
- Other types of background are classified as real with high probability; CNN identifies 3D features which are irrespective of the background type.
- High, convergent output of CNN as GAN trains gives confidence that images are 3D events.
- Initial output is 1; Random noise looks correlated to the CNN.
- Standard deviation of CNN predictions falls over time.

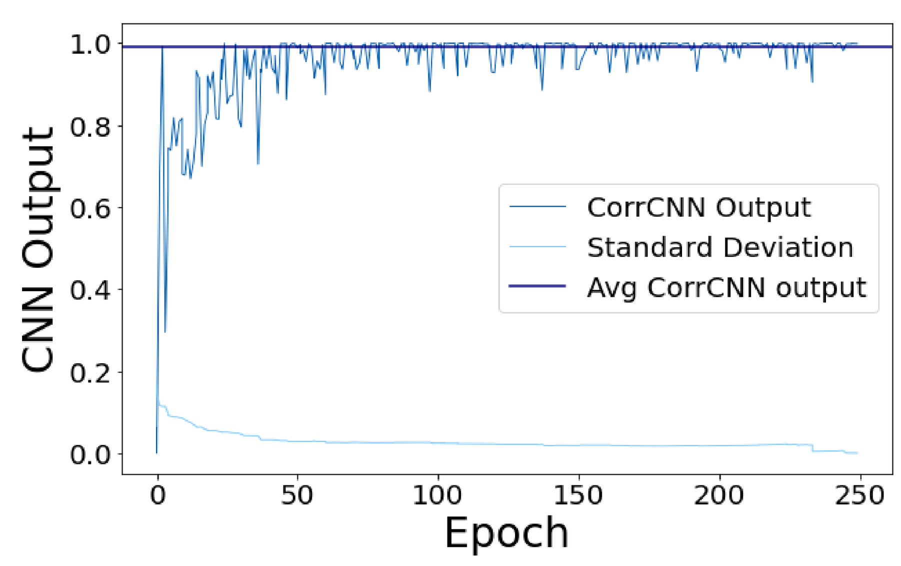

Figure 11: CNN output during GAN training.

Conclusions

- The GAN's performance can be evaluated by visual metrics, such as comparing events, average planes and energy distribution.
- An additional CNN is able to explicitly demonstrate that the 2D GAN is capable of learning 3D space events.

Future Investigations

- The CNN outputs can be used within the GAN training to constrain the training; this may help it to learn the 3D correlations quicker.
- A HybridGAN could be implemented to produce additional variables alongside the image planes.

References:

[1] B. Pontecorvo, Neutrino experiments and the problem of conservation of leptonic charge, J. Exptl. Theoret. Phys. 53 (1967) 1717–1725.

[2] SoLid Collaboration, 2021. SoLid: a short baseline reactor neutrino, Journal of Instrumentation experiment. 16(02), pp.P02025-P02025.

[3] Isaksson, M., 2020. Towards Data Science. Towards Data Science. Available at: https://towardsdatascience.com/exploring-generative-adversarial-networks-gans-488e1d901d4a

[4] Goodfellow, I., Pouget-Abadie, J., Mirza, M., Xu, B., Warde-Farley, D., Ozair, S., Courville, A. and Bengio, Y., 2020. Generative adversarial networks. Communications of the ACM, 63(11), pp.139-144.

[5] G. James et al, An Introduction to Statistical Learning with Applications in R. (1st ed.) 2013. DOI: 10.1007/978-1-4614-7138-7.