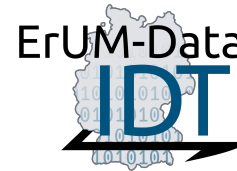


Generating PXD Background Hitmaps with Generative Adversarial Networks at Belle II

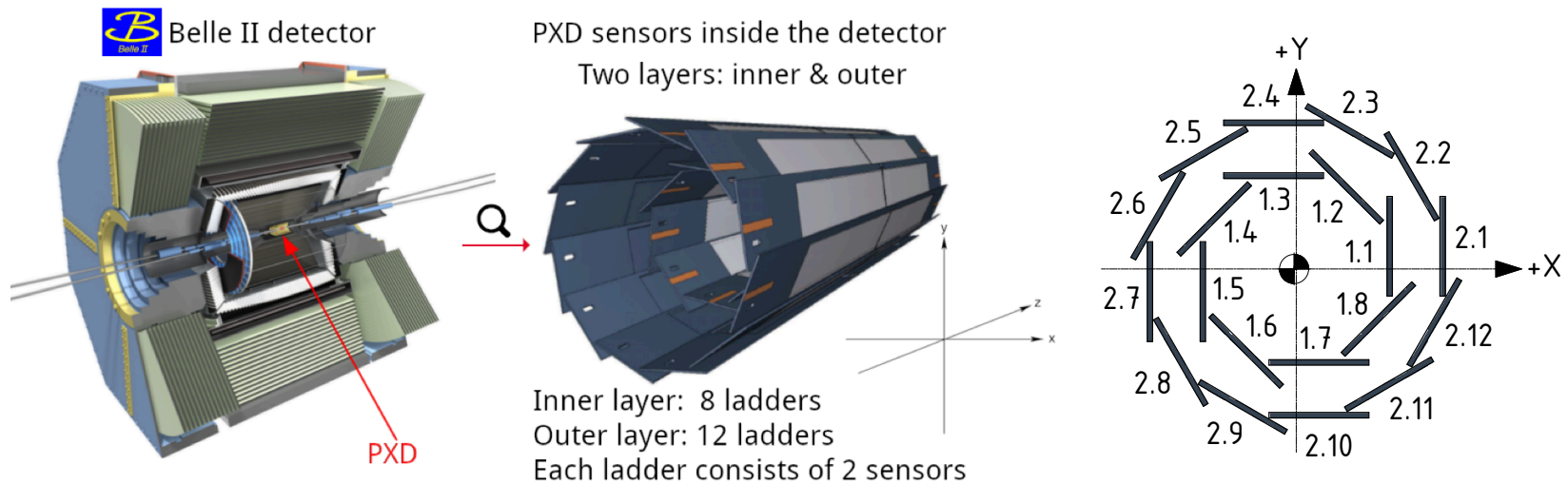
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Thomas Kuhr, Martin Ritter, Matej Srebre*

*Ludwig-Maximilians-Universität München
The ORIGINS Excellence Cluster*



Introduction

- ▶ **The Pixel Vertex Detector (PXD)** is the innermost semi-conductor sub-detector at Belle II.
- ▶ The sensitive area of the PXD is assembled from **40 modules**, where each module consists of a **250 × 768** pixel matrix of the pixel sensors.
- ▶ **The inner layer:** 16 modules implemented into 8 ladders
- ▶ **The outer layer:** 24 modules implemented into 12 ladders



Backgrounds

■ The PXD hits are coming from two sources:

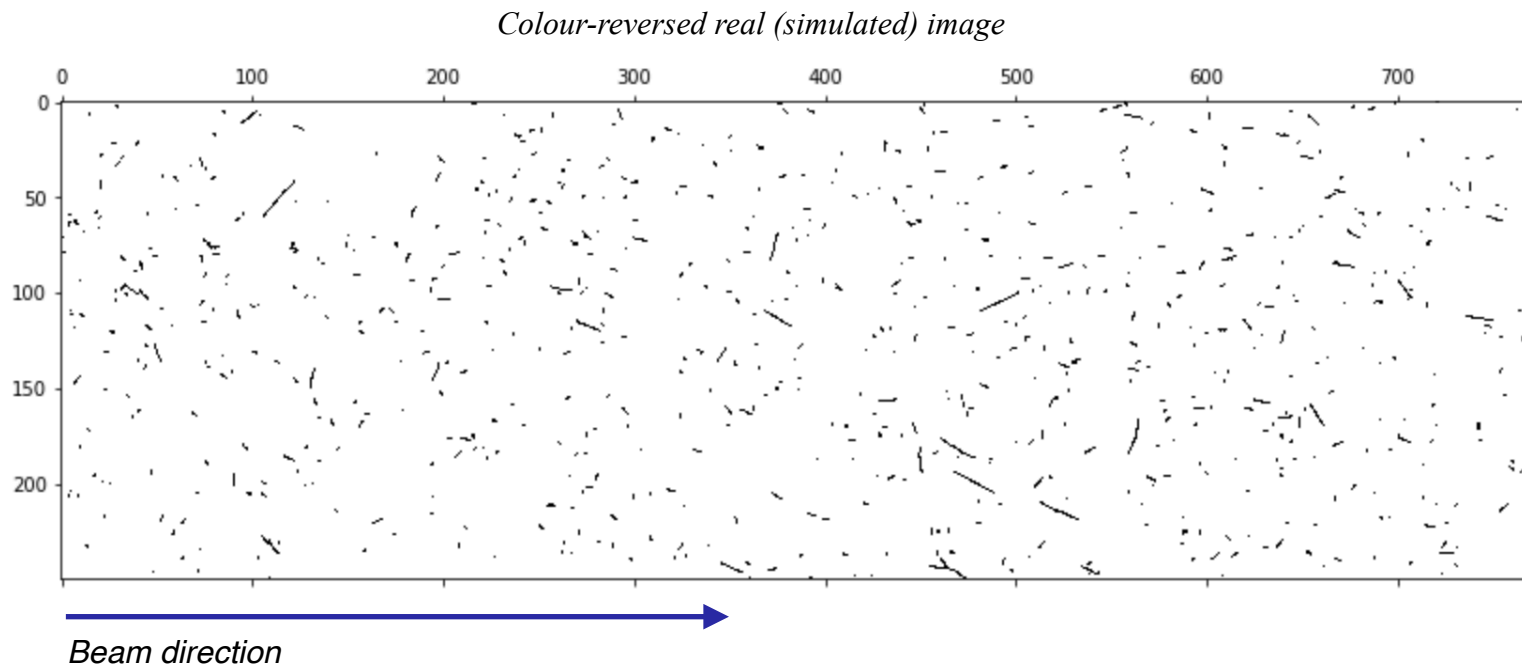
■ Signal Decays:

A. particles which originate from the physics processes of interest.

■ Backgrounds:

A. **Beam-induced:** intra-beam scattering, Beam-Gas scattering, synchrotron radiation

B. **Luminosity dependent:** Radiative Bhabha scattering, two-photon process



- **Realistic detector simulation has to take into account effects from background processes**
 - *Simulation requires many PXD hitmaps with statistically independent background.*
 - *Overlay hits from simulated background or random trigger data to hits from signal MC.*
 - *PXD hits have the highest storage consumption, almost 200 kB per event cost.*
 - *Requires distributing over all sites where MC is produced.*

■ Realistic detector simulation has to take into account effects from background processes

- *Simulation requires many PXD hitmaps with statistically independent background.*
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- *PXD hits have high storage consumption, almost 200 kB per event cost.*
- *Realistic simulation requires background MC is produced.*

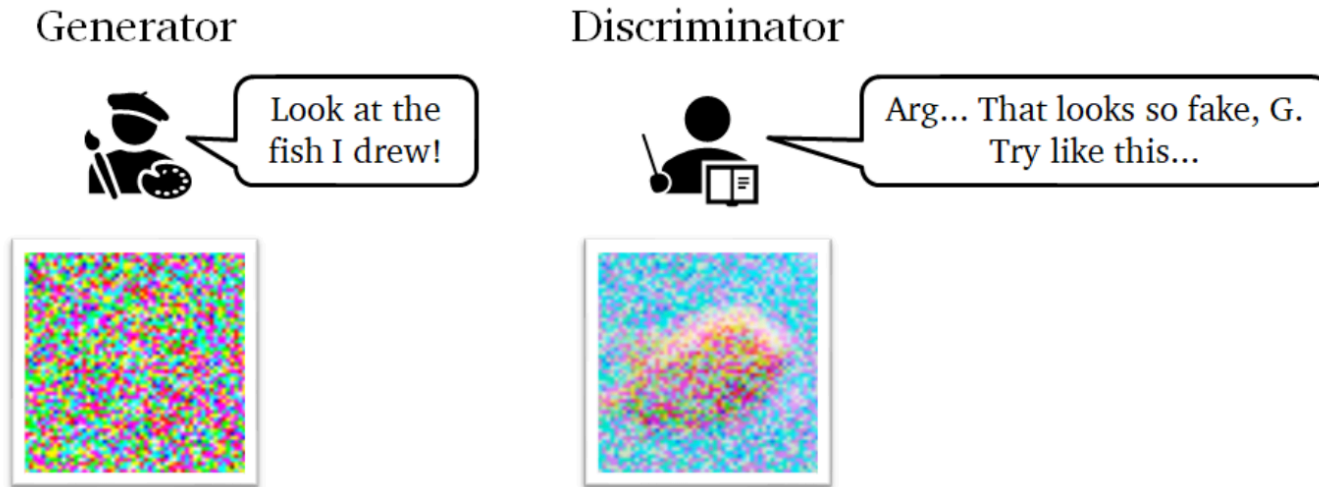
Solution:

Let's generate the bkg on the fly as a by-product of the signal MC production as a way of analysis with Generative Adversarial Networks, instead of storing them.



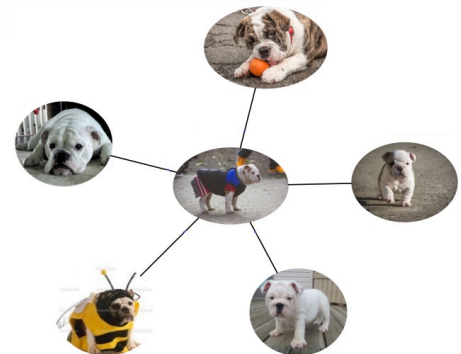
GAN is all you need!

- ✓ Generate PXD background events with Generative Adversarial Network (GAN)
- ✓ **Whats is GAN?**



The GAN game

- ✓ **Conditional GAN** : *The type of animal is the condition*
- ✓ **Close-Conditional (relational)**

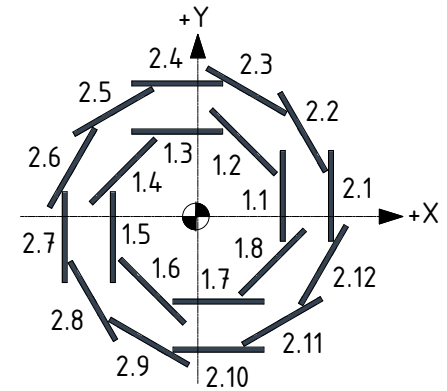
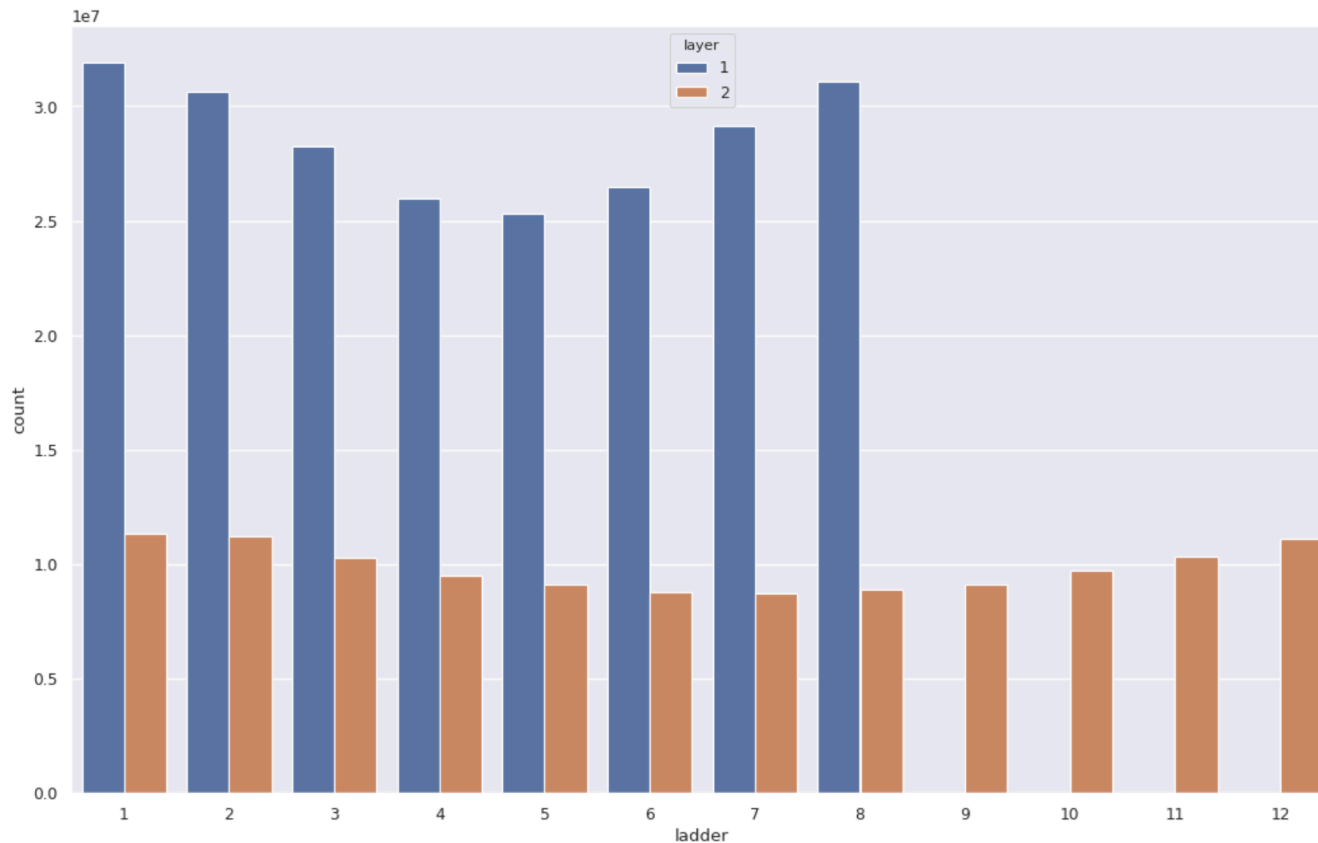


Conditional GAN



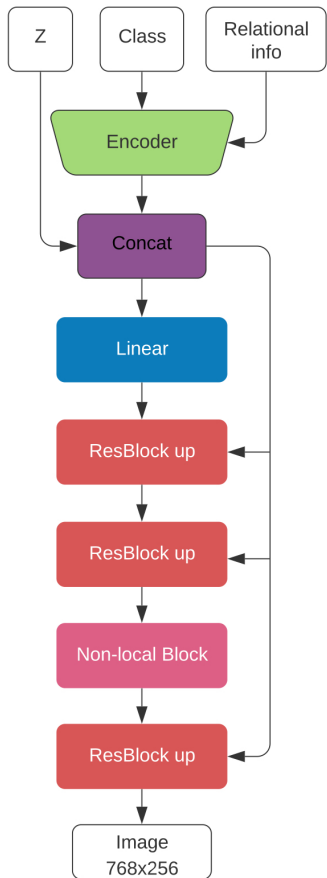
■ Using spatial class-conditions based on the sensor number 1-40:

- ✓ Increase the image fidelity
- ✓ Generation of sensor-dependent images

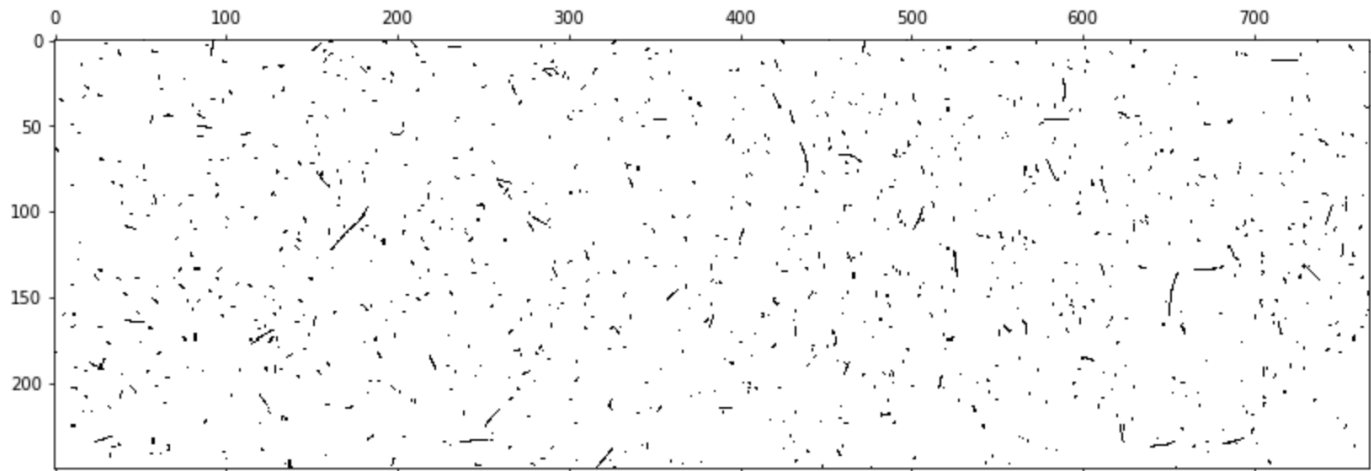


Generated vs Real PXD Images

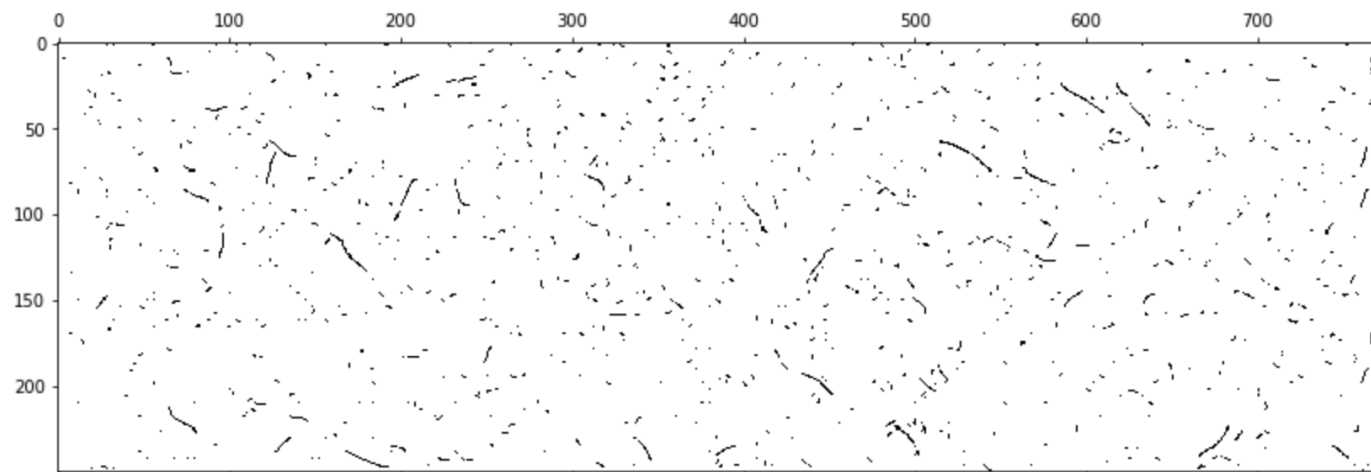
Model: (updated)
Modified BigGAN-deep



Colour-reversed real (simulated) image



Colour-reversed generated image



Validation of generated PXD images

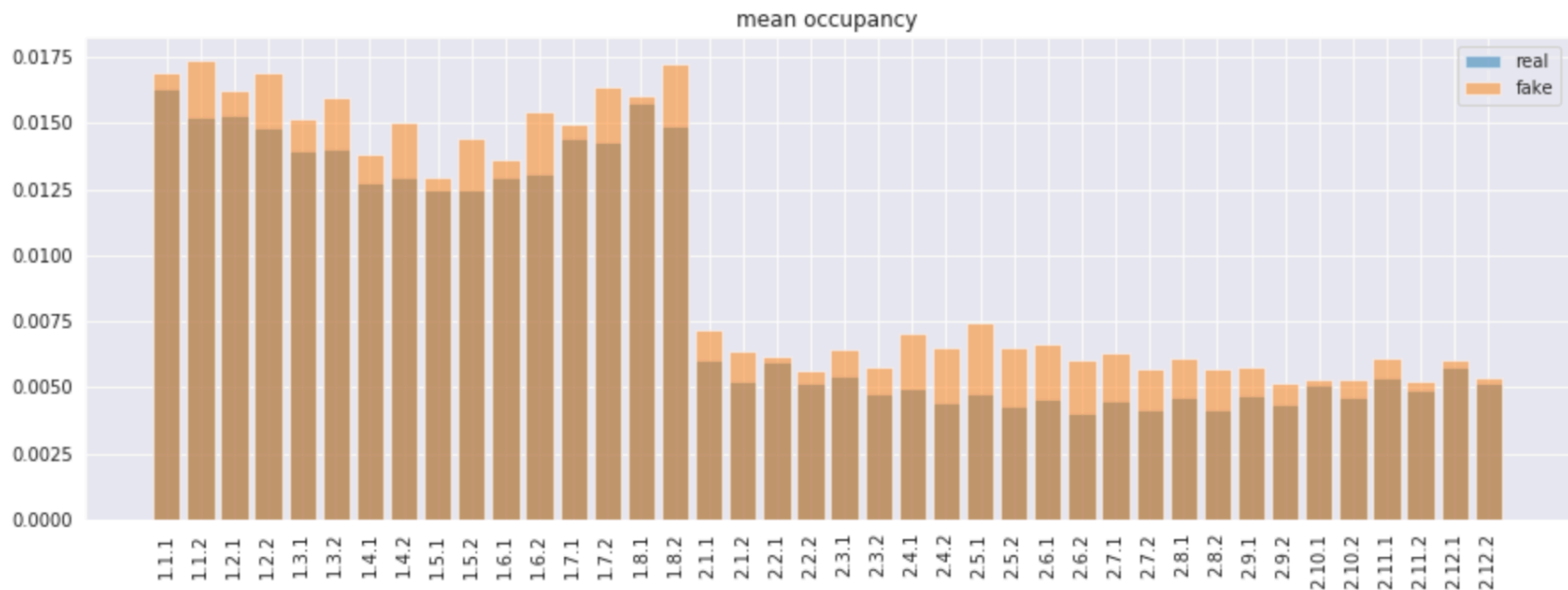


❖ **Problem:**

Finding a metric to say how good the generated images are.

❖ **Solutions:**

- ☑ Compare the occupancy information for PXD (updated)



Summary and Outlook



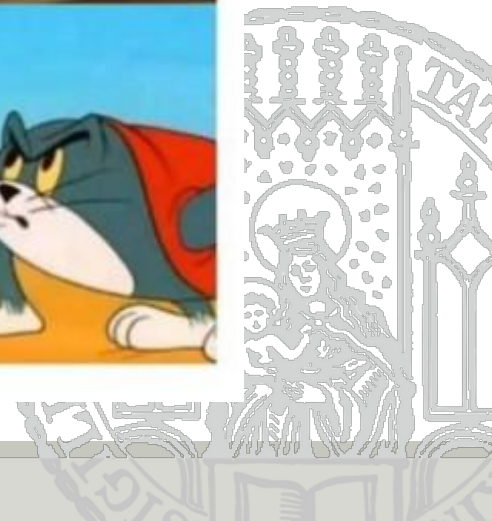
- Successful proof of principle that conditional GANs can be used to generate sensor-dependent PXD background
- Refine the GAN setup in order to capture **correlation** between two layers or each sensor relative to each other for PXD detector.
- Adding bkg types as colour channels to the images.
- Create a custom **Inception Score (IS)**, based on simulated events in order to have a fully automated evaluation metric.
- Doing a comprehensive validation of generated hitmaps by estimating the systematic uncertainty on the tracking efficiency, fake rate and resolution.
- Simulation Software implementation.

Thank You

GAN output in paper



Your GAN output



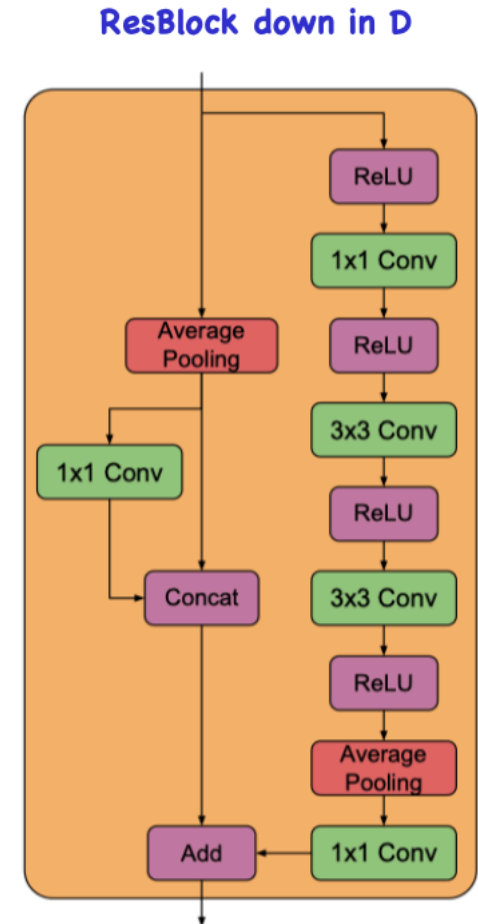
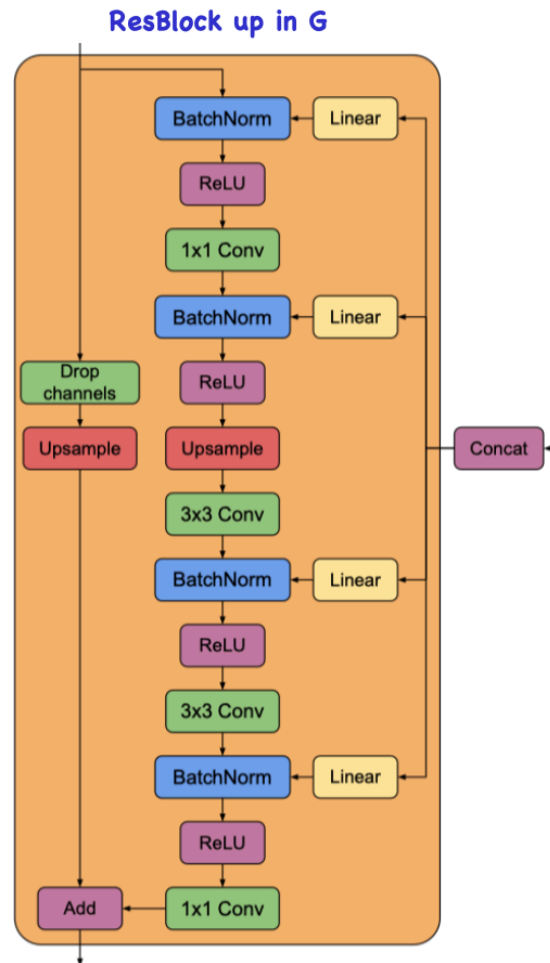
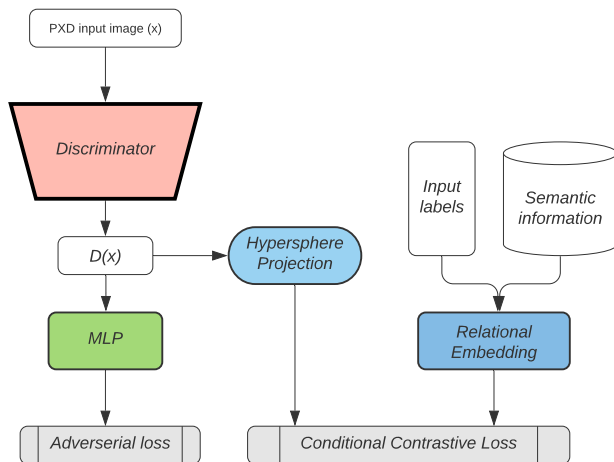
Back up Slides



✓ The Base Model: BigGAN-deep (updated)

■ Technologies:

- ▶ Self-Attention Block
- ▶ Residual blocks
- ▶ Spectral Normalisation
- ▶ Orthogonal Weight init.
- ▶ Orthogonal regularisation
- ▶ Contrastive Learning
- ▶ Hinge Loss
- ▶ Consistency Regularisation



Back up Slides



- The fired pixels are only read out if their value exceeds a threshold, 7 ADU.
- How to capture this prior information about the image?
- Solution: To add this information to the training

Algorithm 1 Pixel-Aware regularization.

Input: generator and discriminator parameters θ_G, θ_D , pixel-aware regularization coefficient λ , Adam hyperparameters α, β_1, β_2 , batch size M , number of discriminator iterations per generator iteration N_D

```
1: for number of training iterations do
2:   for  $t = 1, \dots, N_D$  do
3:     for  $i = 1, \dots, M$  do
4:       sample  $z \sim p(z), x = p_{data}(x)$ 
5:        $L_D^{(i)} \leftarrow D[G(z)] - D(x)$ 
6:     end for
7:      $\theta_D \leftarrow Adam(\frac{1}{M} \sum_{i=1}^M (L_D^{(i)}), \alpha, \beta_1, \beta_2)$ 
8:   end for
9:   sample  $\{z^{(i)}\}_{i=1}^M \sim p(z)$ 
10:   $x_{fake} = G(z)$ 
11:   $F[G(z)] : x_{fake} \mapsto x_{fake}^{cutoff}$  ▷ Threshold wrt. the pixel constraints.
12:   $L_{pr}^{(i)} \leftarrow \|G(z) - F[G(z)]\|^2$ 
13:   $L_G^{(i)} \leftarrow -D[G(z)]$ 
14:   $\theta_G \leftarrow Adam(\frac{1}{M} \sum_{i=1}^M (L_G^{(i)} + L_{pr}), \alpha, \beta_1, \beta_2)$ 
15: end for
```

Validation of generated PXD images



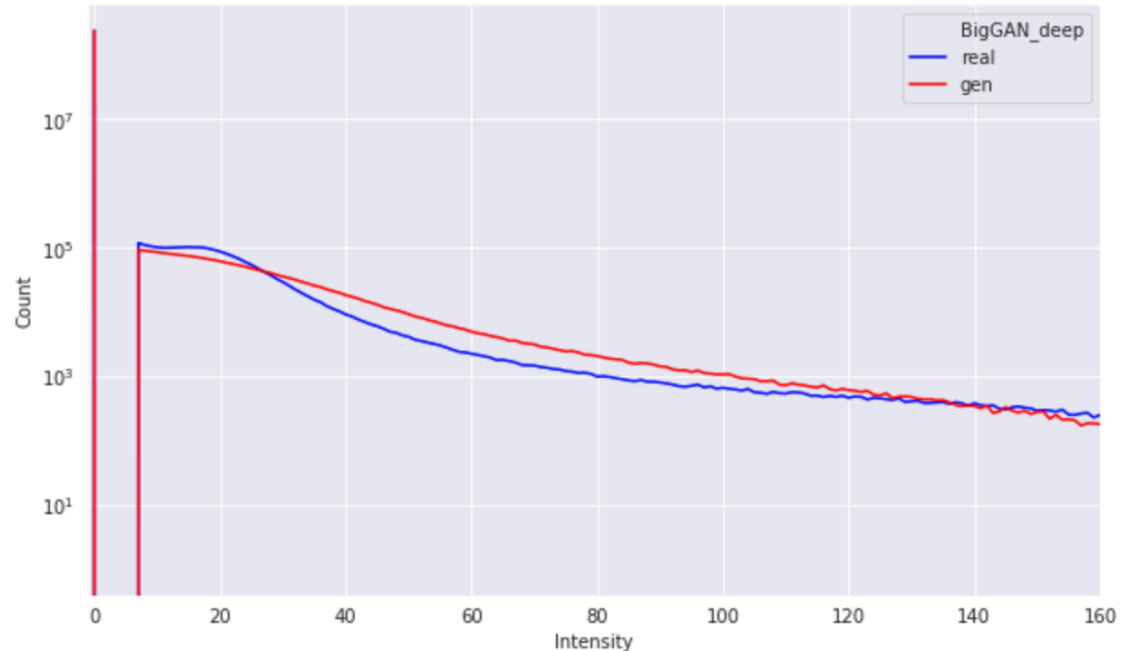
❖ **Problem:**

Finding a metric to say how good the generated images are.

❖ **Solutions:**

☑ Image pixel intensity analysis:

- Pixel value 0 means complete blackness
- The fired pixels are only read out if their value exceeds a threshold, 7 ADU.
- How to capture this prior information about the image?



Back up Slides



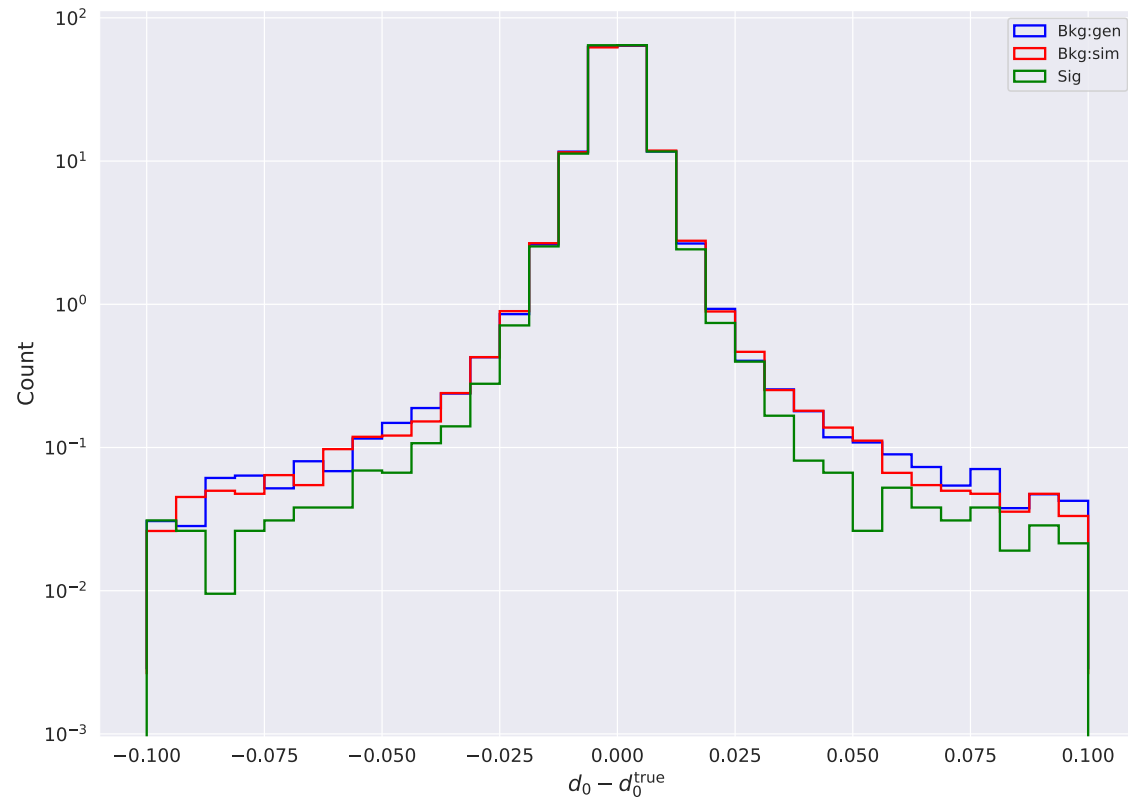
- Evaluate tracking performance for
 - Signal + no bkg.
 - Signal + nominal bkg.
 - Signal + generated bkg.

- **Scoring:** Using Frechet Distance (2-Wasserstein distance):

$$W_2(\mu_1, \mu_2)^2 = \|m_1 - m_2\|_2^2 + \text{trace}(C_1 + C_2 - 2(C_2^{1/2} C_1 C_2^{1/2})^{1/2}).$$

for $\mu_1 = N(m_1, C_1)$ and $\mu_2 = N(m_2, C_2)$.

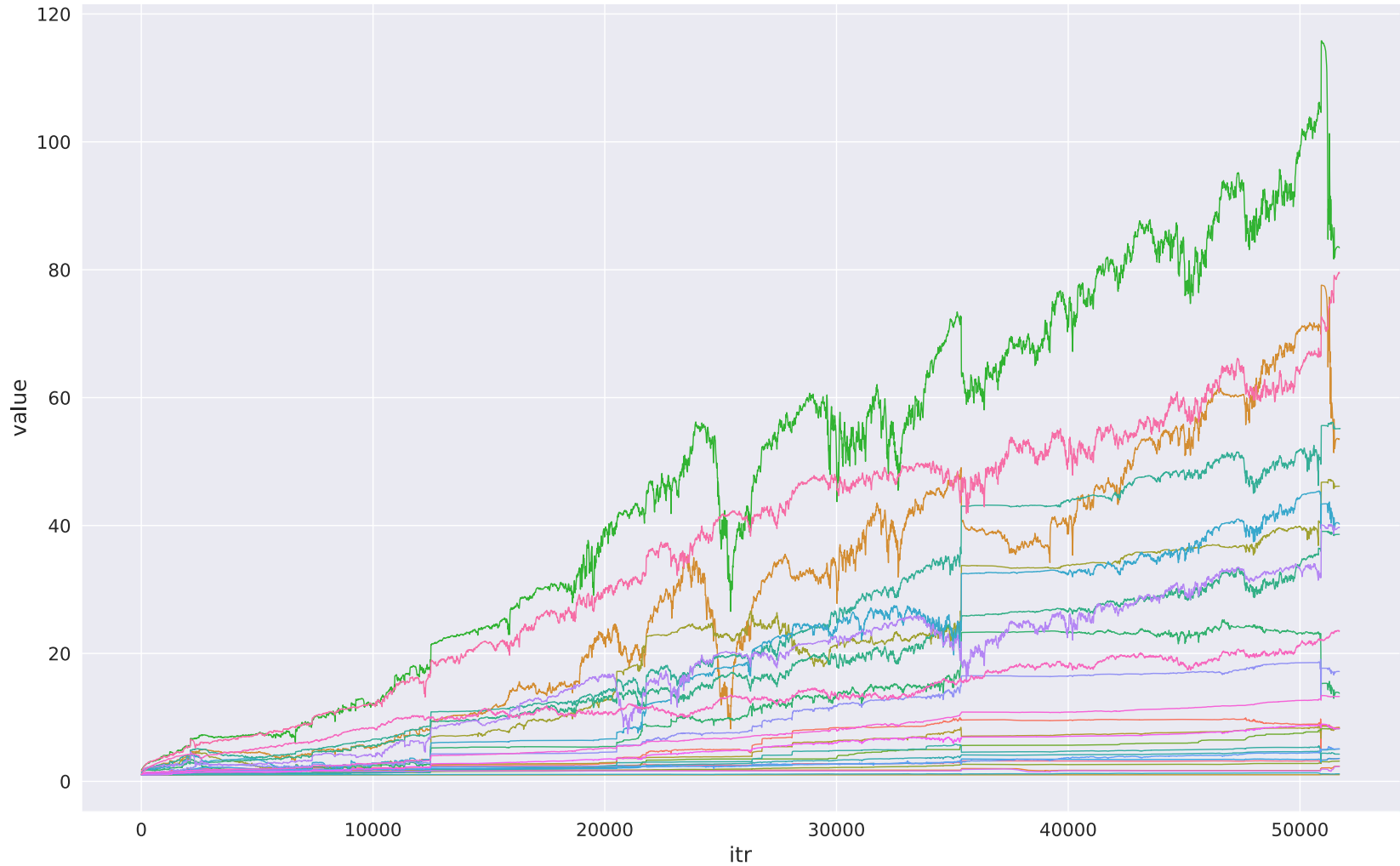
The Lower the FD score, the better the image quality and diversity from the physics point of view.



FD scores of between:

- A. sim-sig : 5.42e-4
- B. gen-sig : 7.41e-4
- C. gen-sig : 1.64e-5

An Example of Collapse



A Healthy Model

