

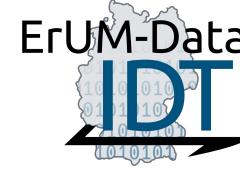
# Generating PXD Background Hitmaps with Generative Adversarial Networks at Belle II

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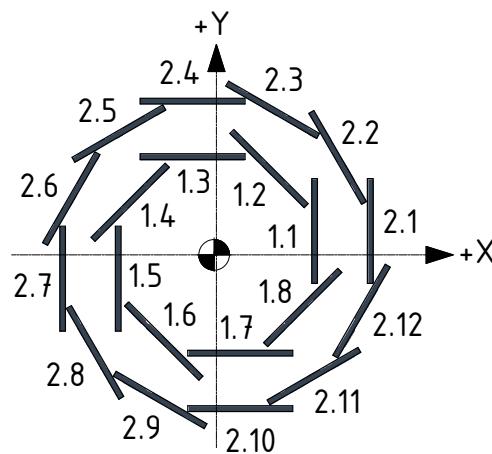
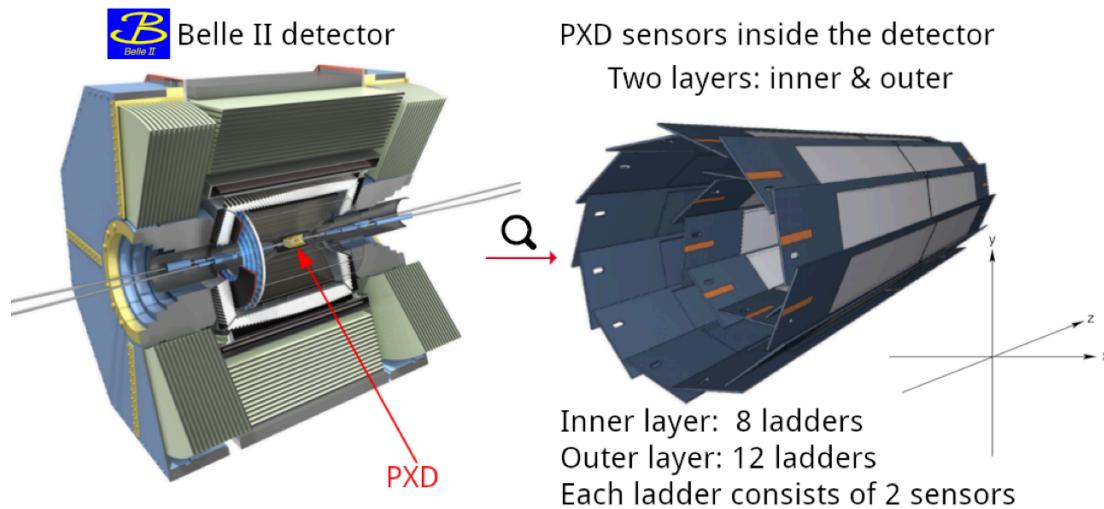


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# Introduction

- ▶ **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  **$250 \times 768$**  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:**

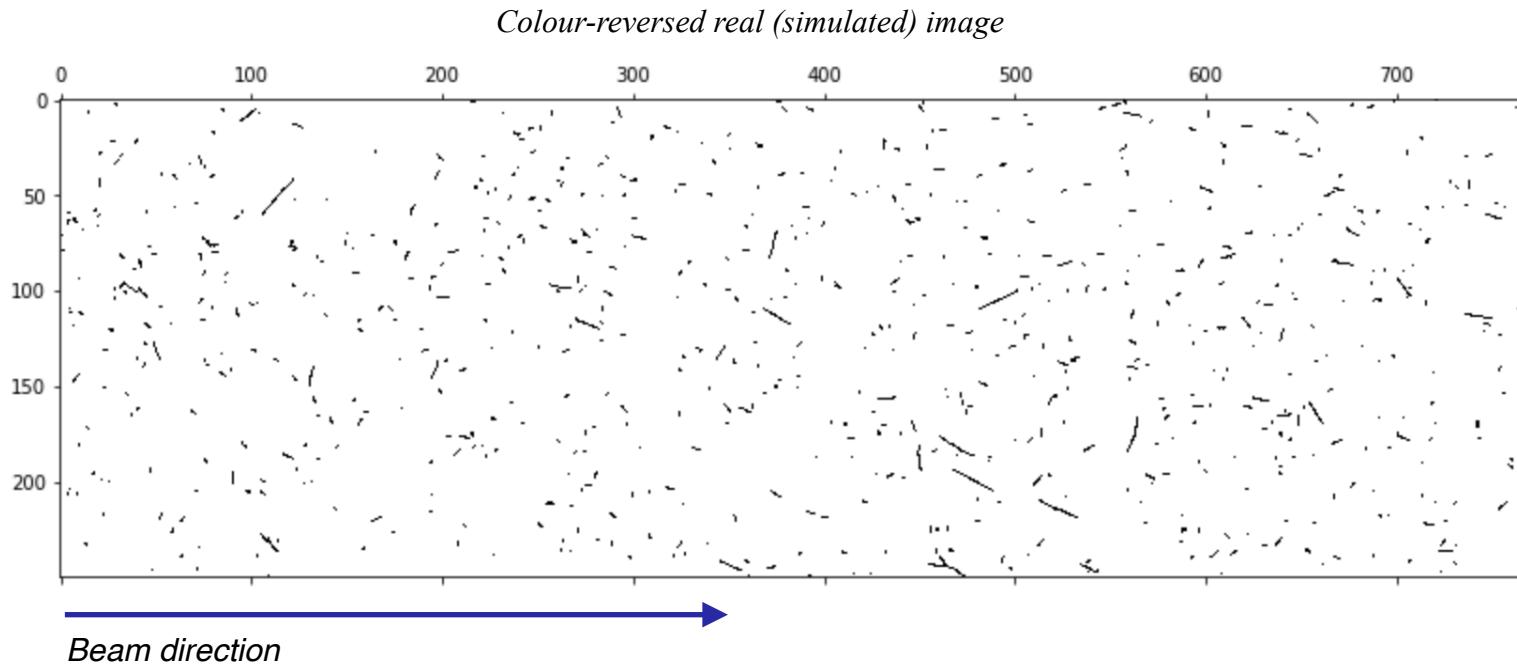
■ **Signal Decays:**

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



# Backgrounds



- **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.*

# Backgrounds

- 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 high memory consumption, almost 200 kB per event cost.*
  - *Re* **Solution:** Let's generate ze bkg on ze way of analysis with Generative Adversarial Networks, instead of storing them.



# Adversarial Learning



## ■ What Is Adversarial?

*Evolve with competition*



Deer-leopard minimax game

$$\min_{\text{leopard}} \max_{\text{deer}} V(\text{deer, leopard}) = \text{distance between deer and leopard}$$

What Doesn't Kill You Makes You Stronger!

# GAN is all you need!

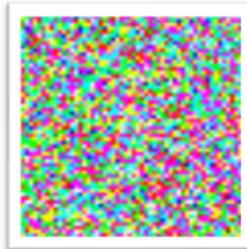
- Generate PXD background events with Generative Adversarial Network (GAN)

## Whats is GAN?

Generator



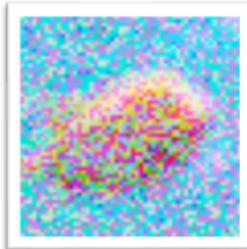
Look at the  
fish I drew!



Discriminator

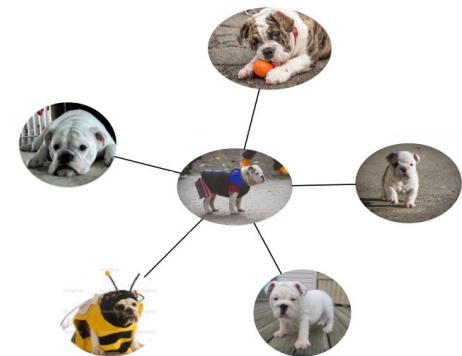


Arg... That looks so fake, G.  
Try like this...



The GAN game

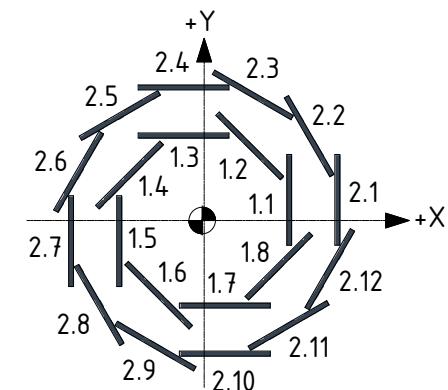
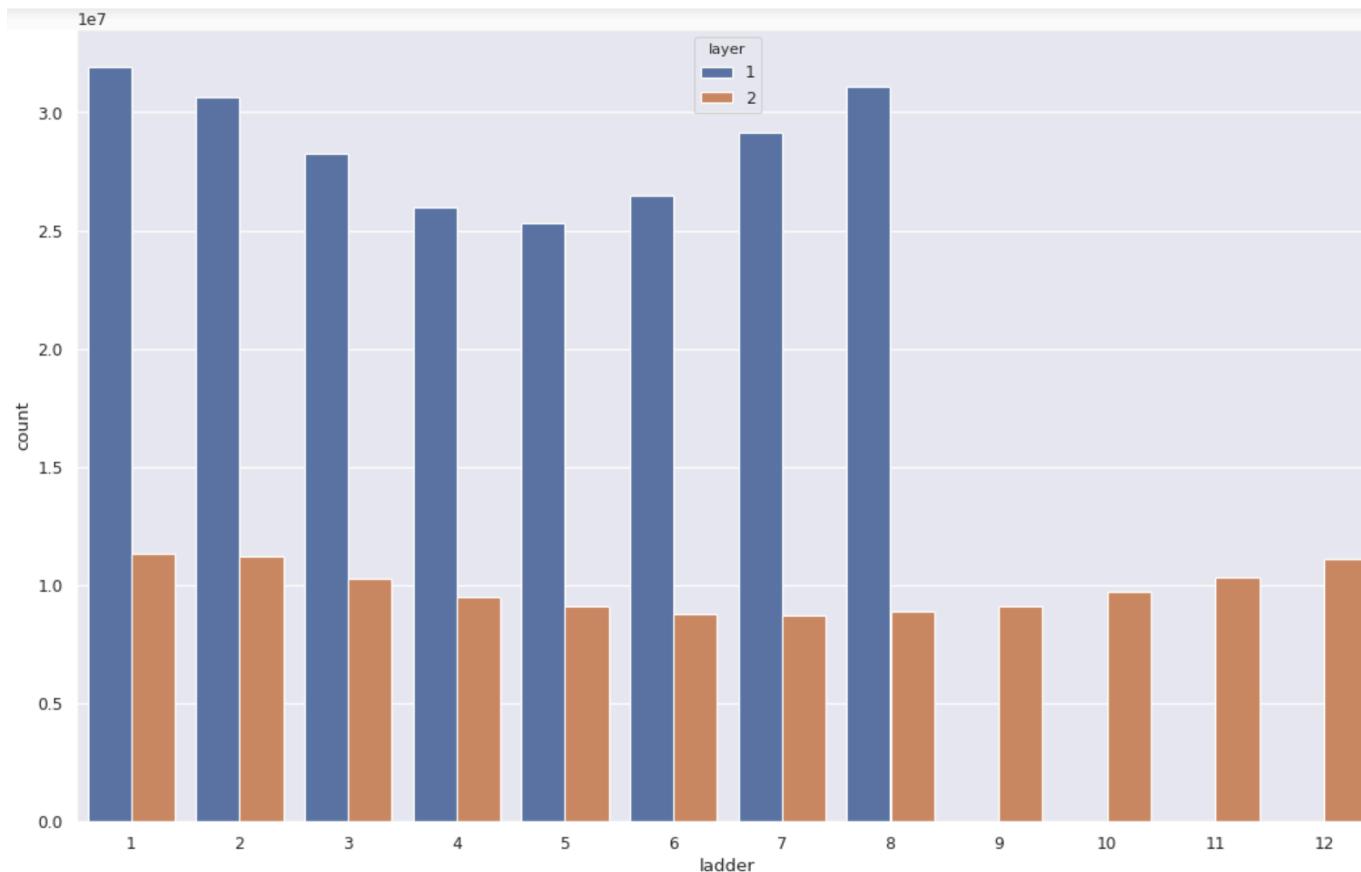
- Conditional GAN** : *The type of animal is the condition*
- Close-Conditional (relational)**



# Conditional GAN

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

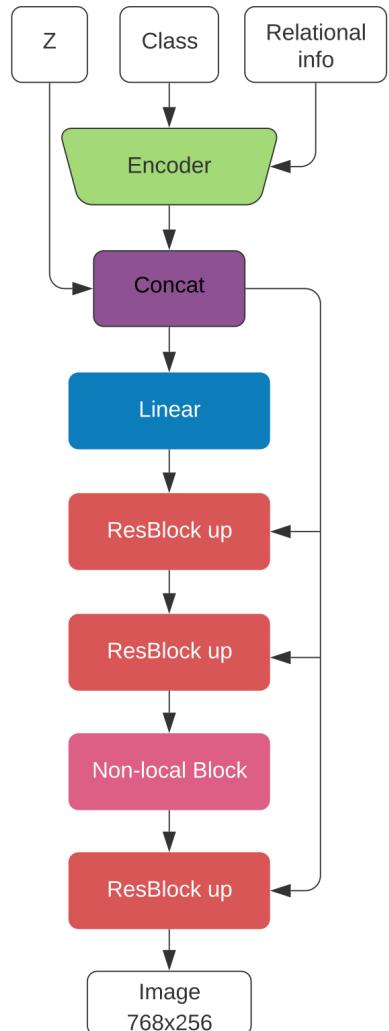
- Increase the image fidelity*
- Generation of sensor-dependent images*



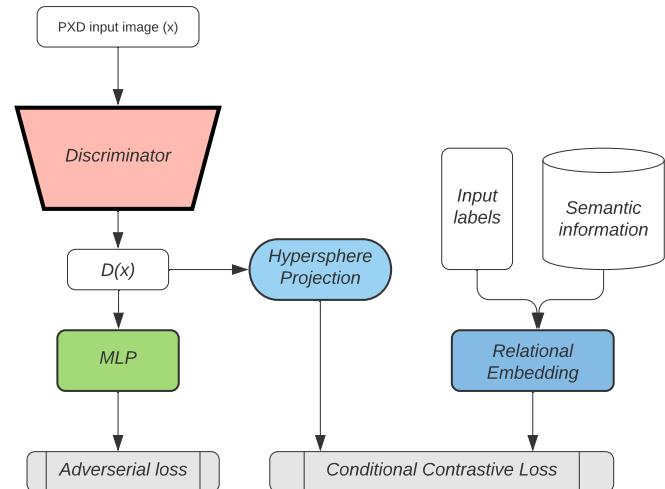
## Modified BigGAN-deep with Contrastive (metric) Learning

### ■ Technologies:

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



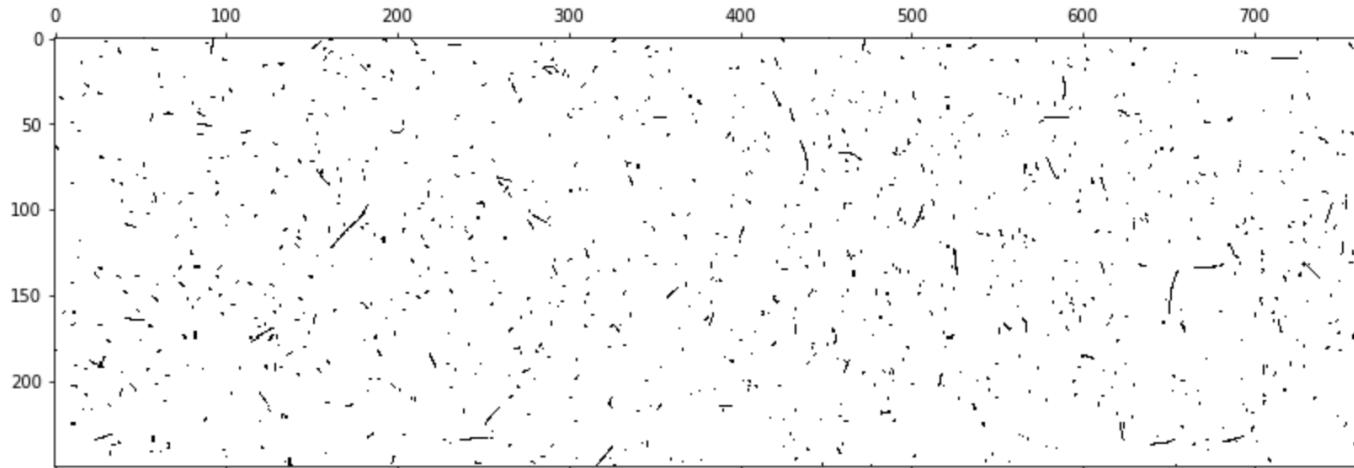
Generator



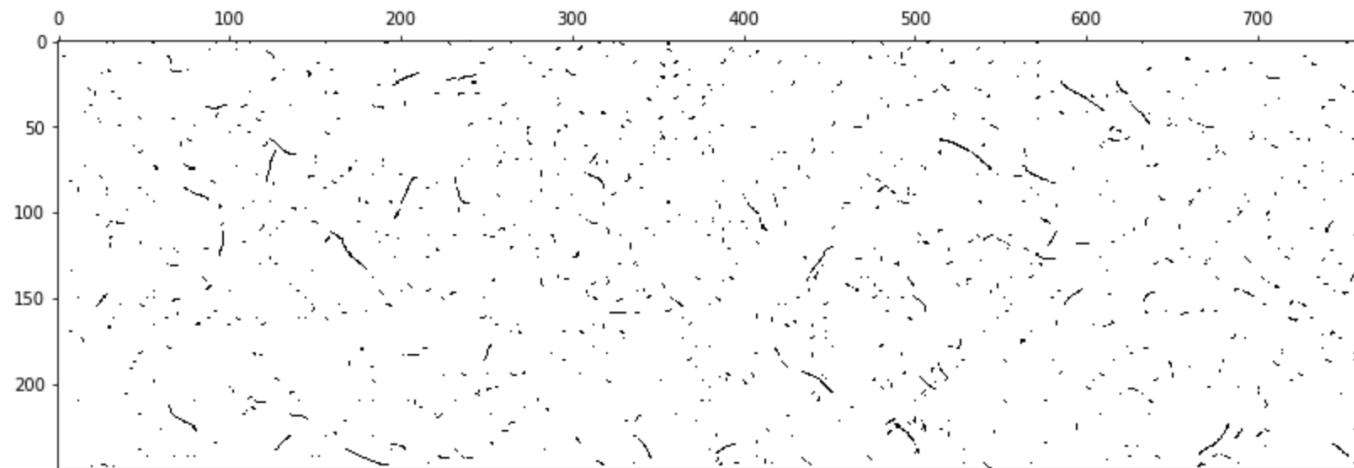
Discriminator

# Generated vs Real PXD Images

Colour-reversed real (simulated) image



Colour-reversed generated image



# Validation of generated PXD images

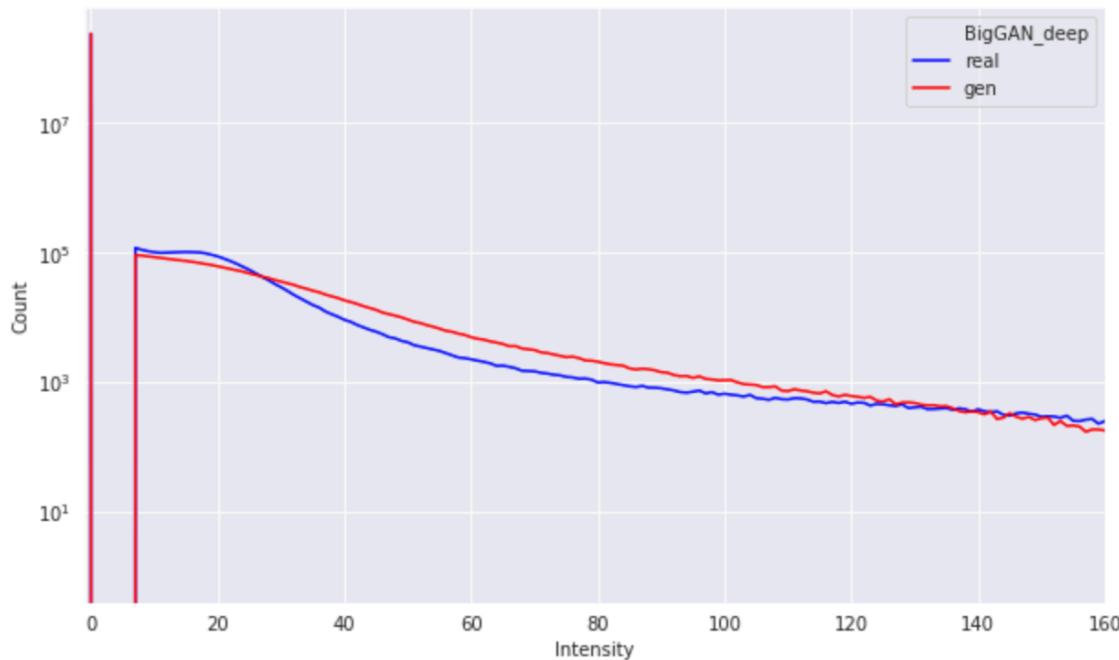
## ❖ **Problem:**

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

## ❖ **Solutions:**

### 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?



# Validation of generated PXD images

## ❖ **Problem:**

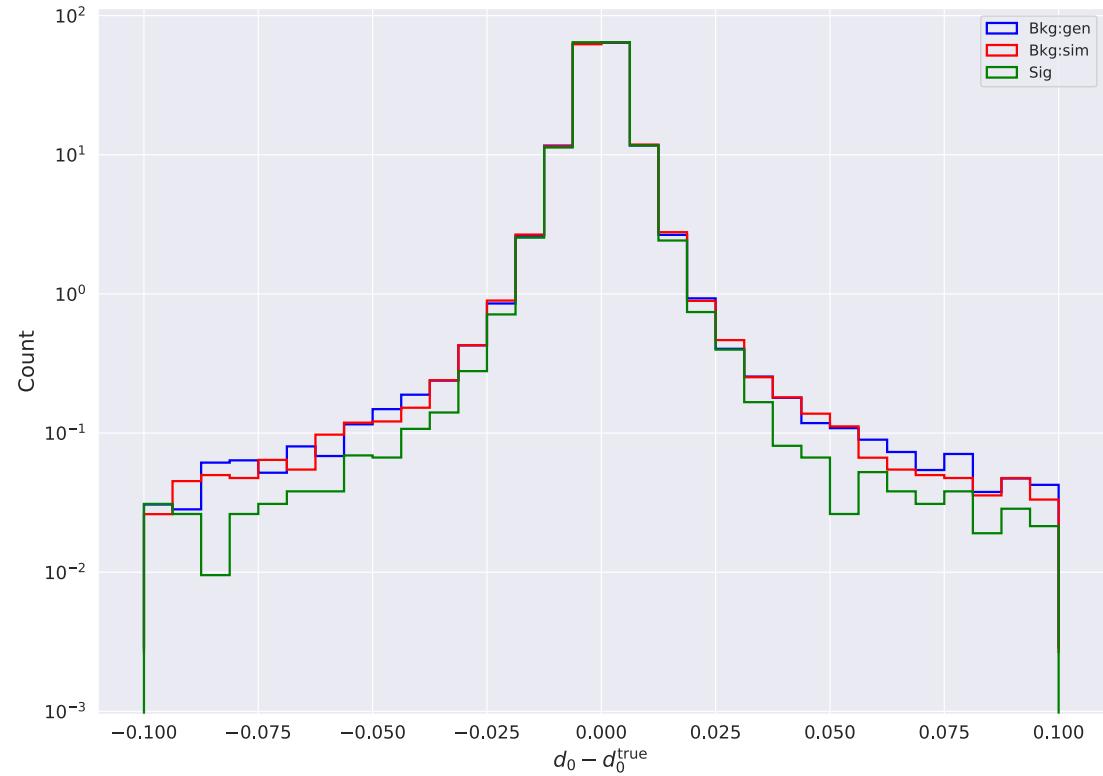
Finding a metric to say how good the generated images are.

## ❖ **Solutions:**

### Evaluate tracking performance

impact parameter residuals:

- Signal + no bkg.
- Signal + simulated bkg.
- Signal + generated bkg.



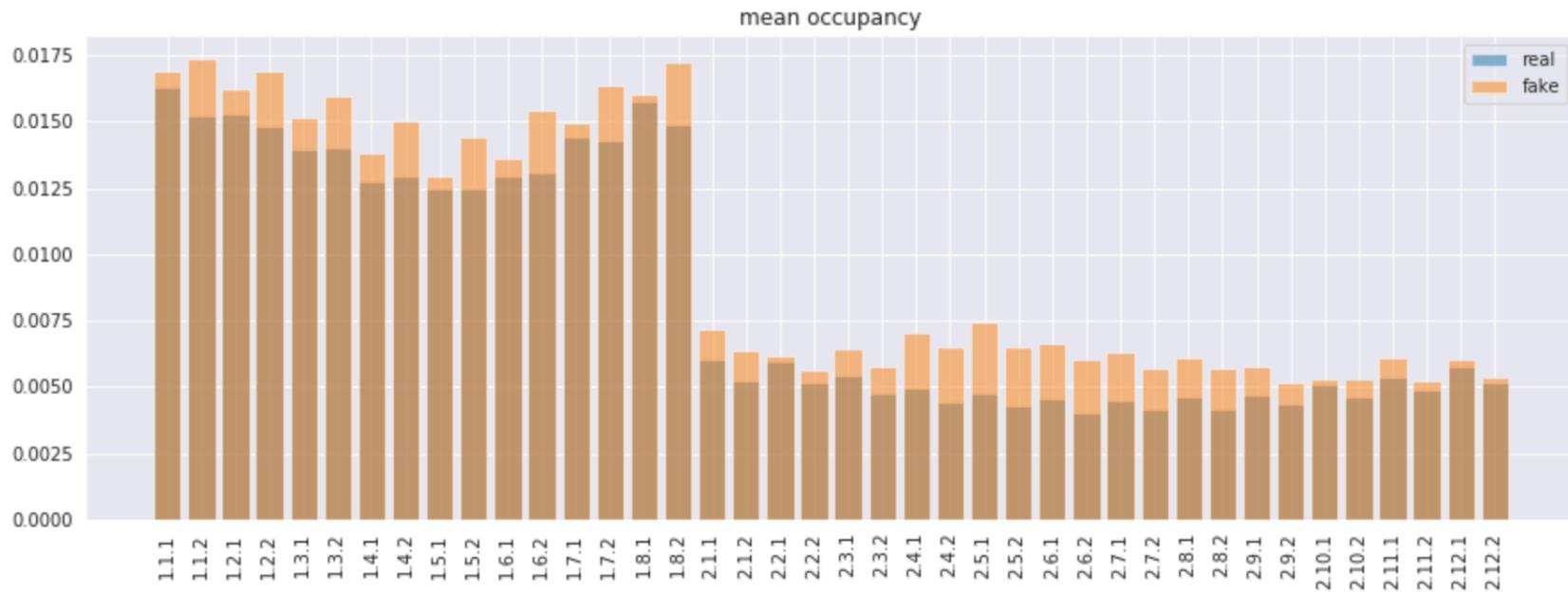
# Validation of generated PXD images

## ❖ **Problem:**

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

## ❖ **Solutions:**

- Compare the occupancy information for PXD



# 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 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

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## Algorithm 1 Pixel-Aware regularization.

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**Input:** generator and discriminator parameters  $\theta_G, \theta_D$ , pixel-aware regularization coefficient  $\lambda$ , Adam hyperparameters  $\alpha, \beta_1, \beta_2$ , 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
```

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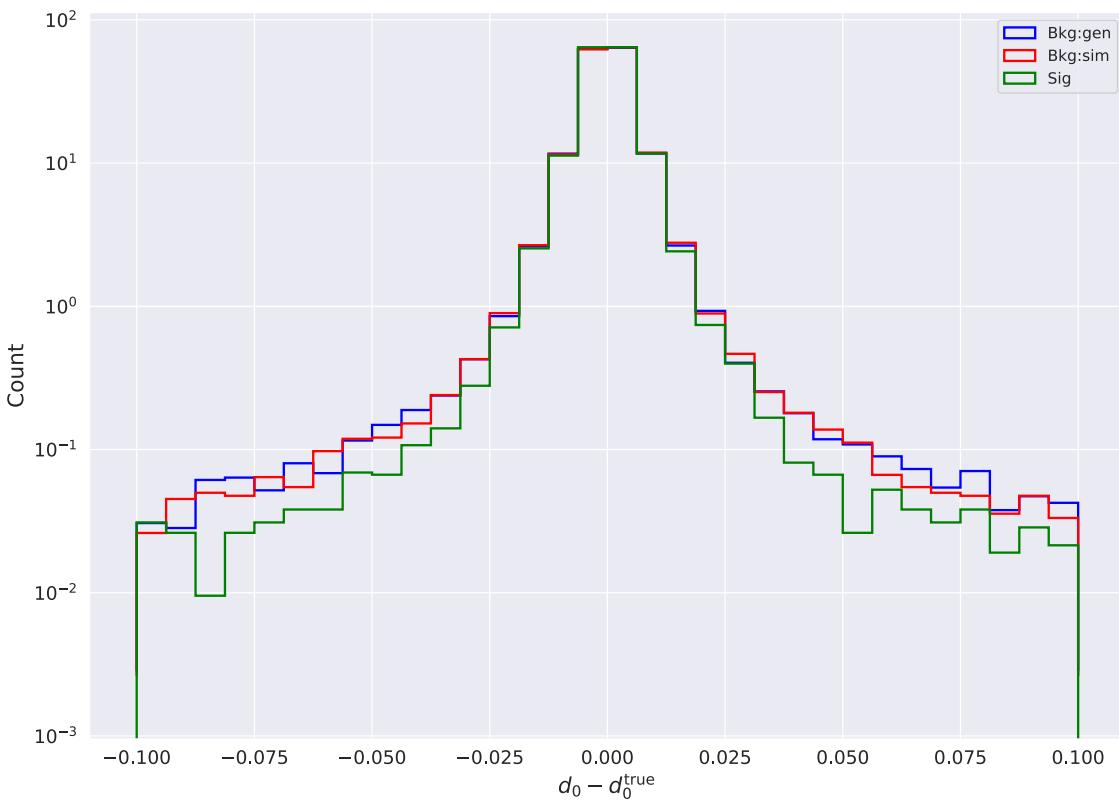
# Back up Slides

- 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  $\mu_2 = N(m_2, C_2)$ .

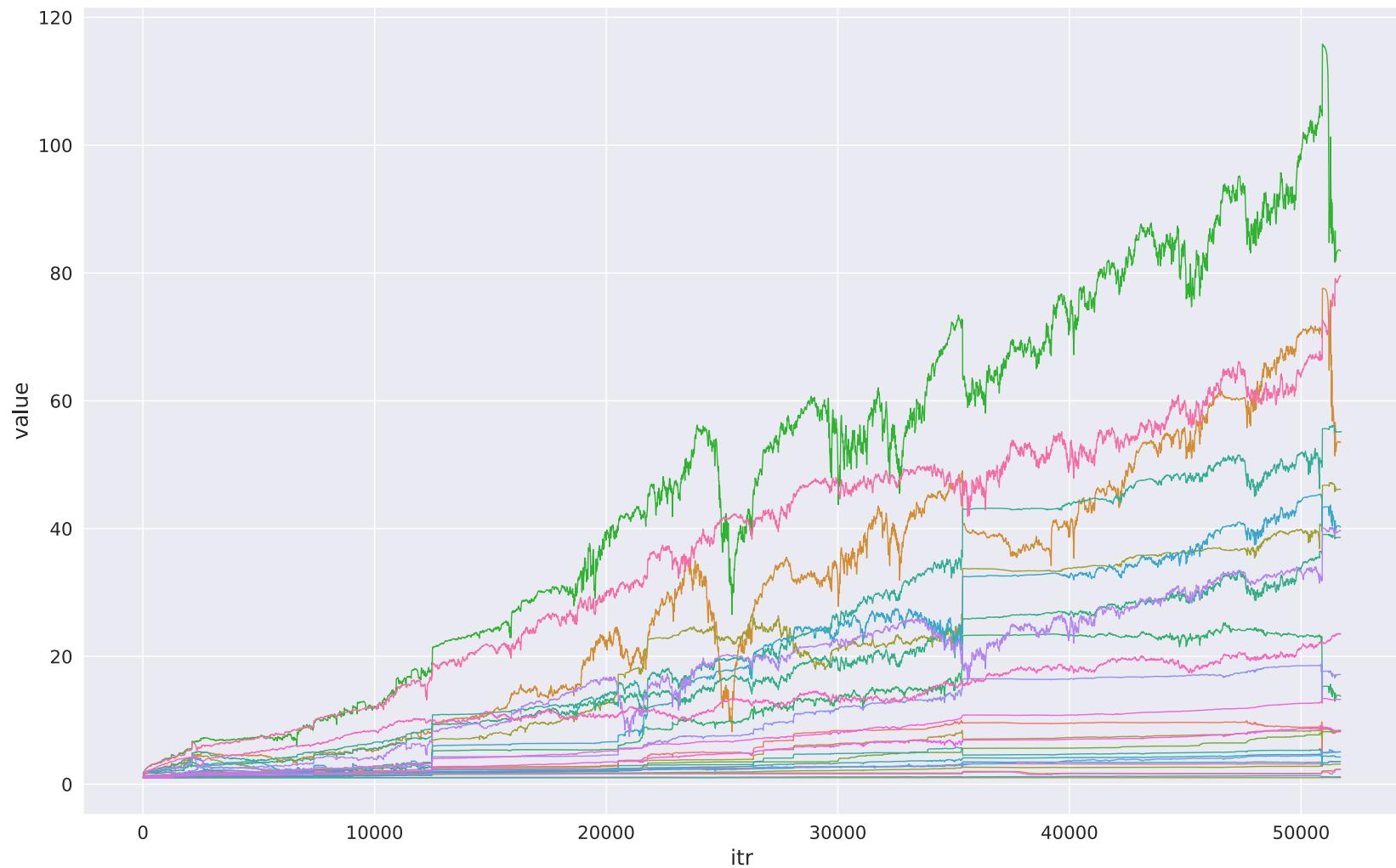
The Lower the FD score, the better the image quality and diversity from the physics point of view.



**FD scores of between:**

- sim-sig : 5.42e-4
- gen-sim : 7.41e-4
- gen-sig : 1.64e-5

# An Example of Collapse



# A Healthy Model

