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Generation of PXD background using generative models

Fabio Novissimo, Nikolai Hartmann, Thomas Kuhr

LMU München

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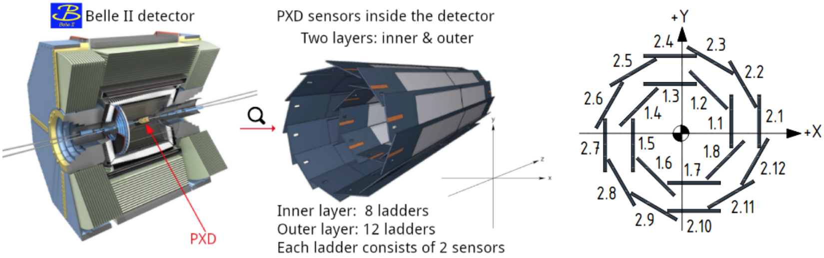
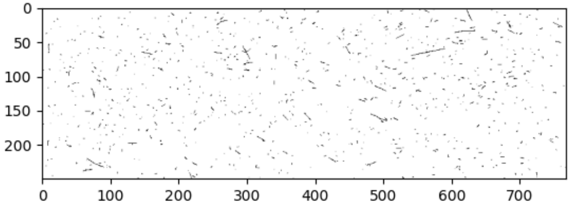
The Pixel Vertex Detector (PXD)

- The **Pixel Vertex Detector (PXD)** is the innermost semi-conductor sub-detector of Belle II, at 1.4 cm from the collision point.
- The sensitive area of the PXD is made up by 40 modules. Each module consists of a 250×758 pixel matrix.
- **Inner layer**: 16 modules implemented into 8 ladders.
- **Outer layer**: 24 modules implemented into 12 ladders.



Background

- PXD hits come mainly from background processes.



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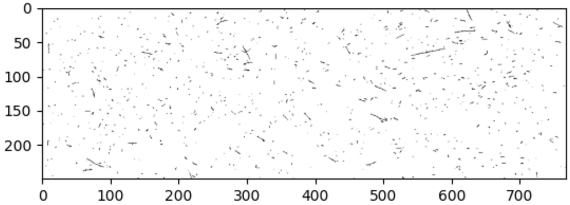
- Two ways to include background processes:
  - Monte Carlo generation $\longrightarrow$ shows sizeable discrepancies with measurements.
  - Taking random trigger events.



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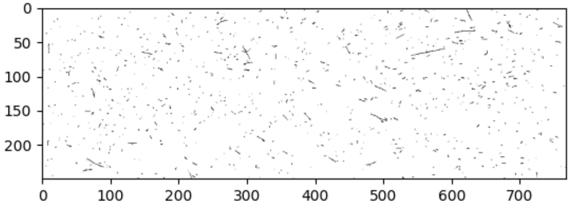
- **Problem: large amount of resources required for storage and distribution of the background data.**



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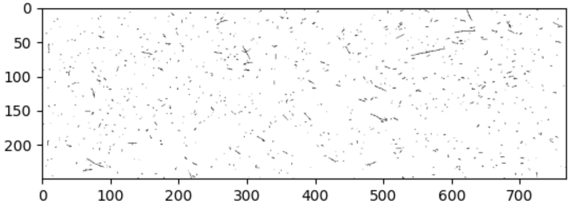
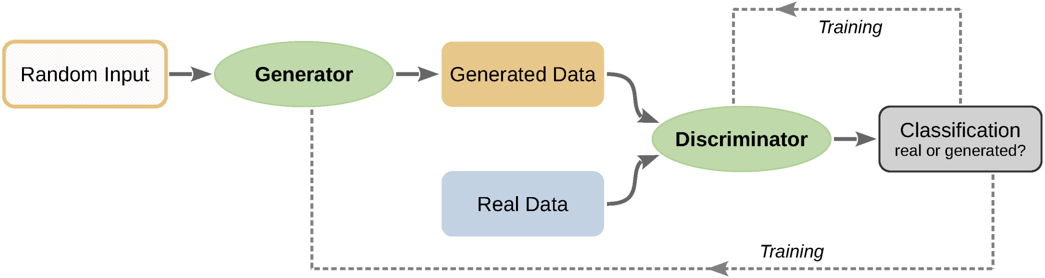
- Solution: generate background hits on the fly for each sensor.



Generative Adversarial Network



Generating pixels with GAN

Previous approach:

- GAN conditioned on sensor number with a transformer-based relational reasoning module to reproduce the correlations between sensors(IEA-GAN).

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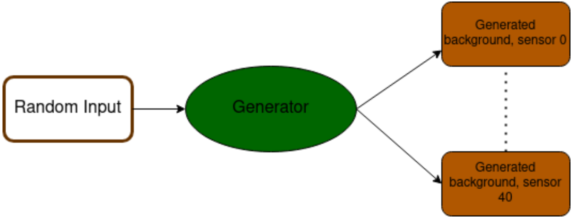
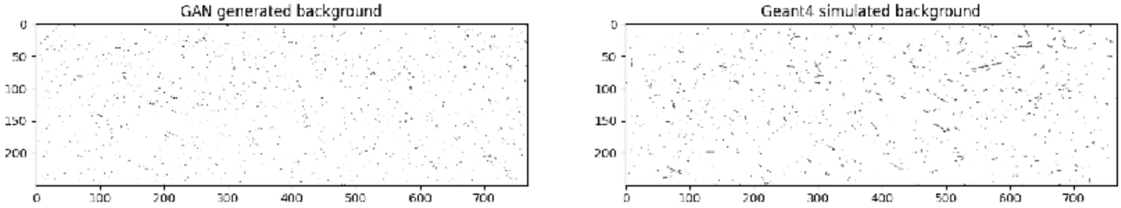
New approach: generate the background using a GAN without conditioning on the sensor number.

- Generate instances of background for all sensors at once.
- Wasserstein GAN with CNN layers used in the Generator and Discriminator.



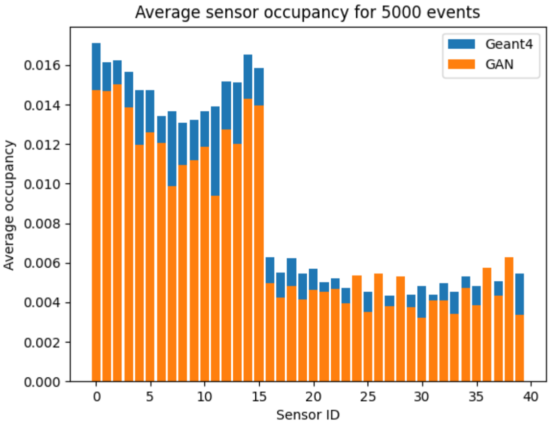
Generated background

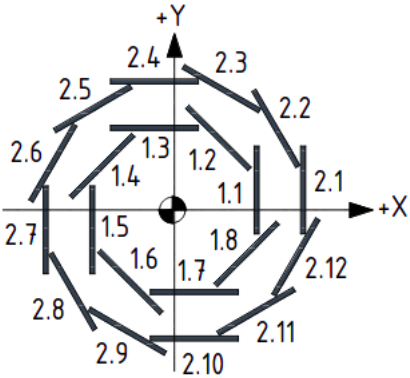
The generated images are visually very similar, but with some subtle differences.



Evaluation - Occupancy per sensor

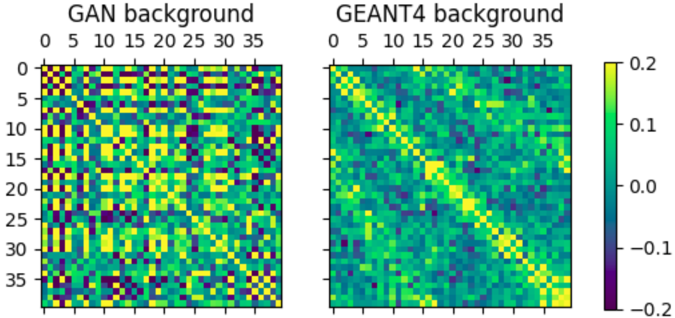
The model seems to reproduce quite well the sensor occupancy, aside from some minor details probably due to some fluctuations in the weights of the model.





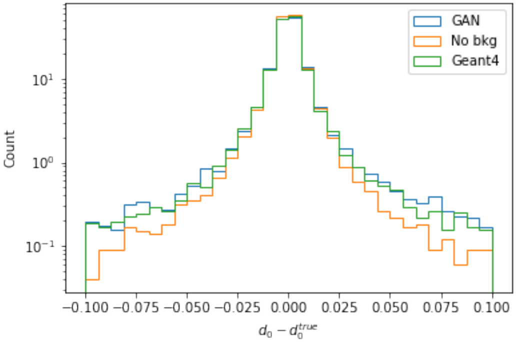
Evaluation - Correlation

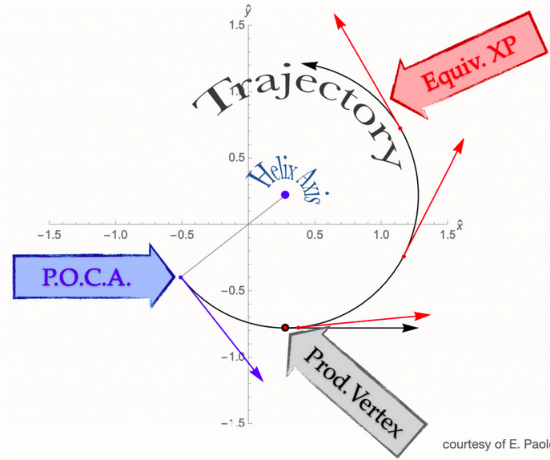
The model does not reproduce correctly the correlation between the sensor occupancy.



Evaluation - helix parameters resolution

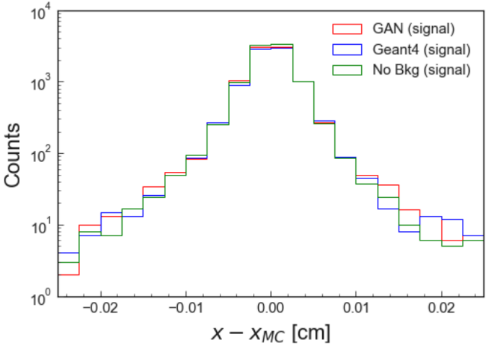
GAN background can be used to reproduce resolution of the helix parameters.

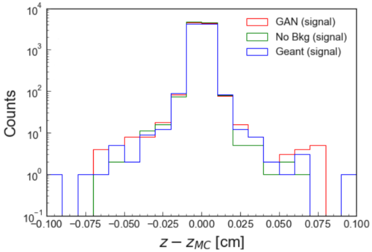


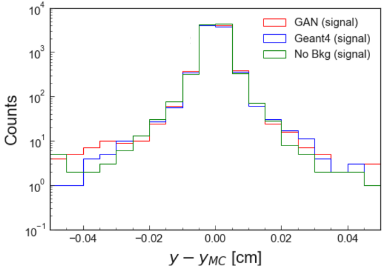


Vertex reconstruction

- Vertex resolution of D^0 in the decay $D^0 \to K^- \pi^+$
- Results suggests that there is no difference when including the background.

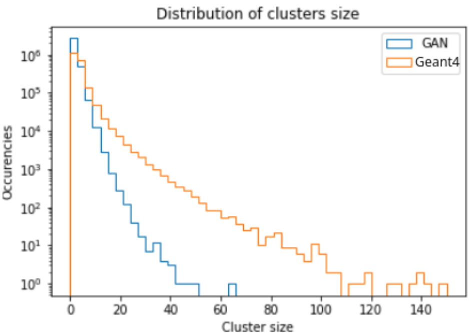


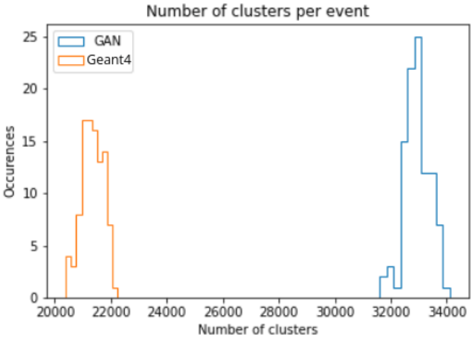




Evaluation: Clusters

The generated background images have different clusters distributions.





Cluster generation with GAN

- Train GAN to directly generate clusters instead of full sensor pixels.
- Trained using clusters of sizes from 1 to 30.
- Training dataset uniform in cluster size.

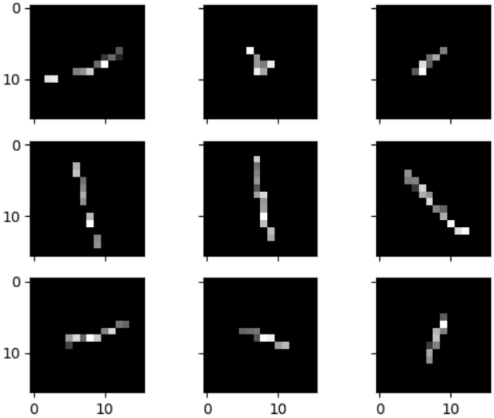
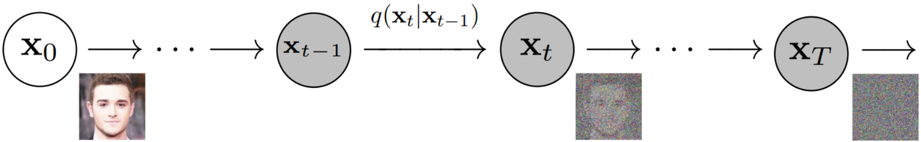


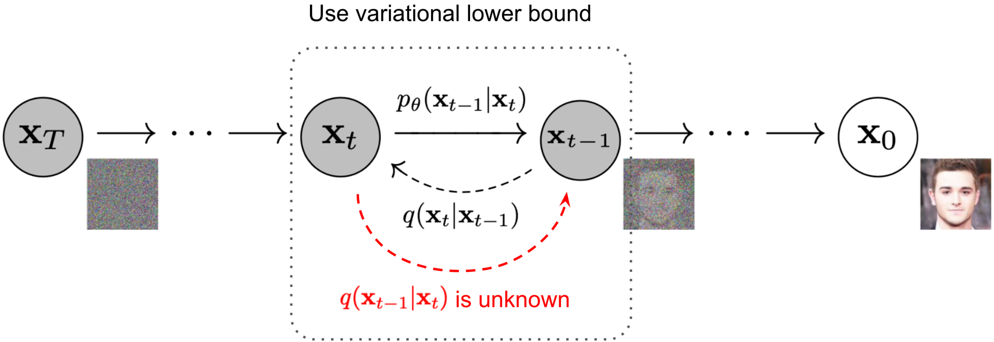
Figure: Example of generated clusters

Diffusion model: forward process



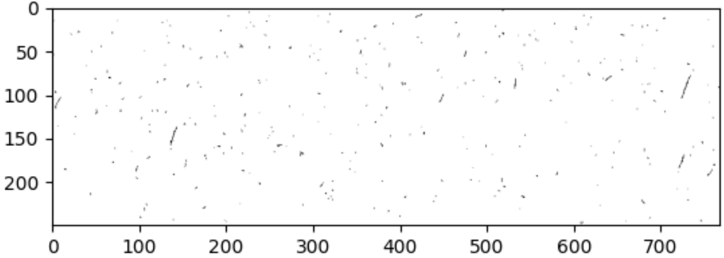
$$q(\mathbf{x}_t|\mathbf{x}_{t-1}) = \mathcal{N}(\mathbf{x}_t; \sqrt{1-\beta_t}\mathbf{x}_{t-1}, \beta_t\mathbb{I}) \qquad \{\beta_t \in (0,1)\}_{t=1}^{T}$$

Diffusion model: inverse process

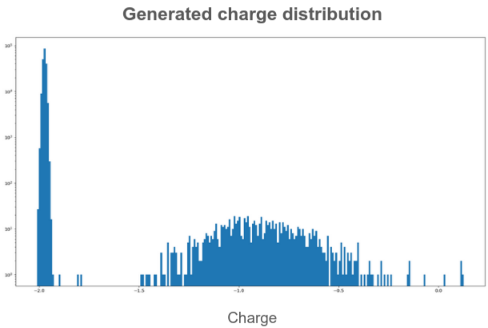


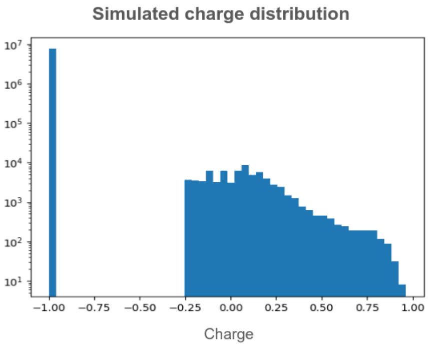
$$p_\theta(\mathbf{x}_{t-1}|\mathbf{x}_t) = \mathcal{N}(\mathbf{x}_{t-1}; \mu_\theta(\mathbf{x}_t, t), \Sigma_\theta(\mathbf{x}_t, t))$$

Preliminary results: background



Preliminary results: charge distribution





Summary and outlook

- Successfully trained a GAN to generate PXD hitmaps.
- Differences between simulated and generated images, especially regarding sensor occupancy correlation and clusters.
- Generated background reproduces helix parameters resolution well and does not have any effect on the vertex resolution for the decay $D^0 \to K^-\pi^+$.
- Successfully trained a GAN to generate clusters.
- Trained a diffusion model to generate background images.

Further steps:

- Investigate the reason behind the mismodeling of the generated charge distribution.
- Look at memory and CPU resources needed for inference with the aim to get something that can run in production.
- Condition on the background level.

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Thanks for your attention!

Backup - Generator

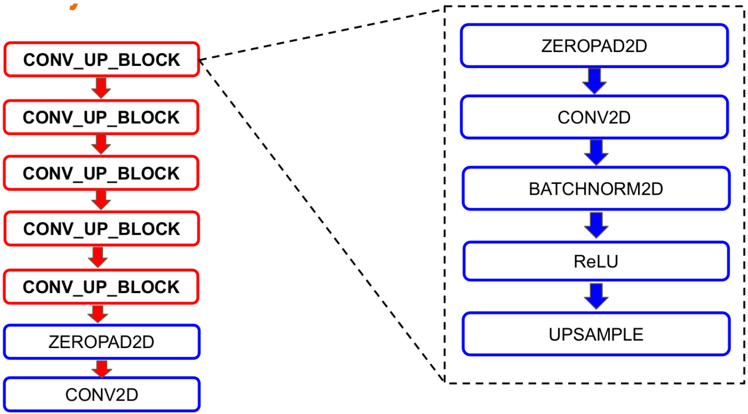

Figure: Generator architecture

Backup - Discriminator

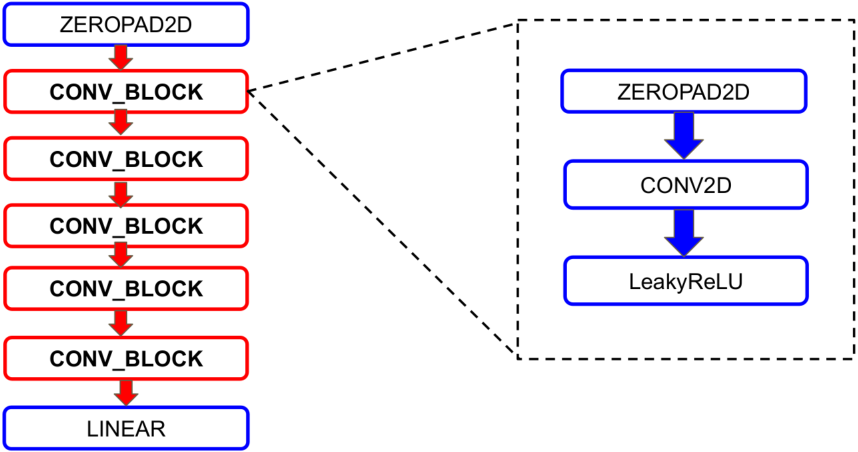

Figure: Discriminator architecture

Evaluation: cluster size