Sparse Autoregressive Models for Scalable Generation of Sparse Images in Particle Physics

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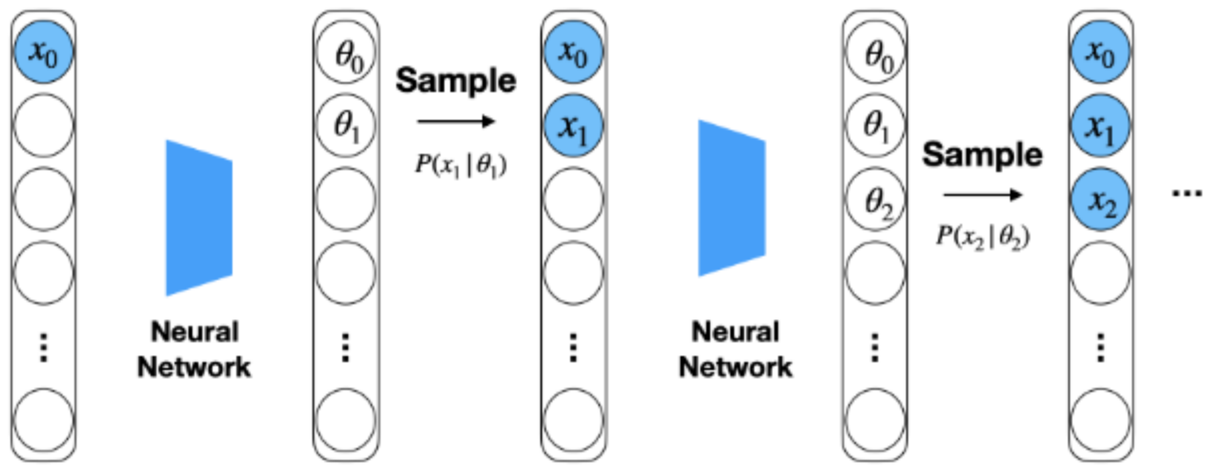
Joint work with Julian Collado, Daniel Whiteson, and Pierre Baldi



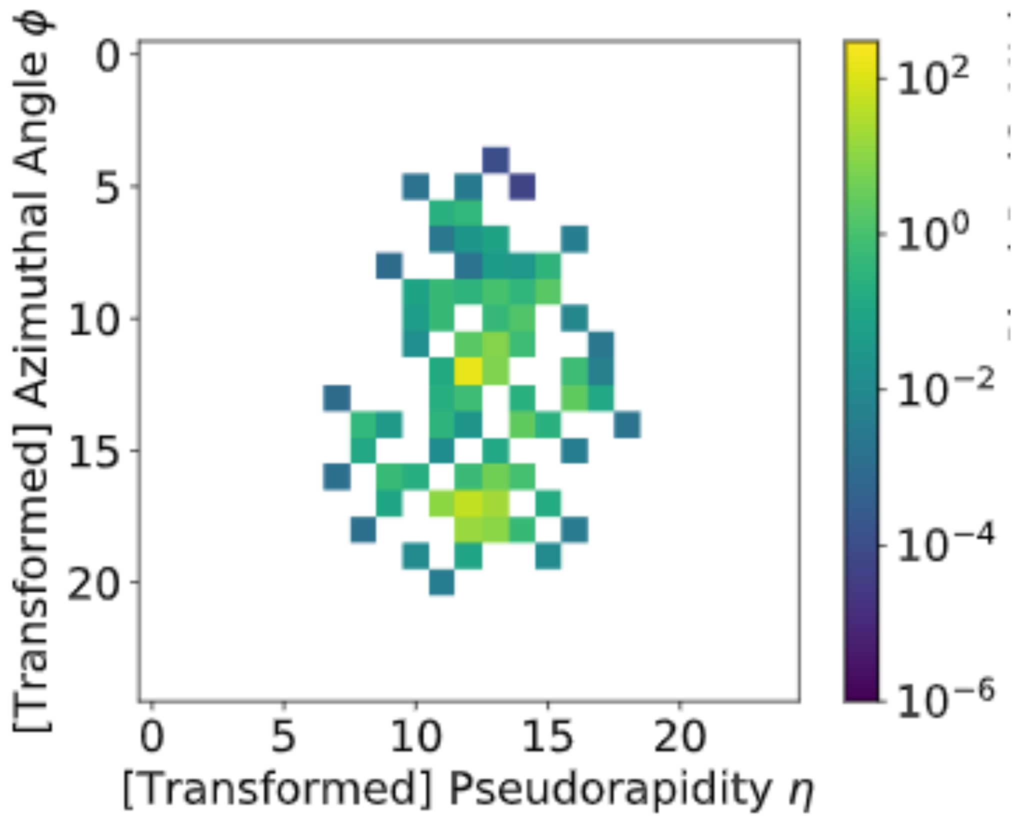
Content

- Background
- Deep Generative Models in Jet Image Simulation
- Sparse Auto-regressive Models
- Experiments

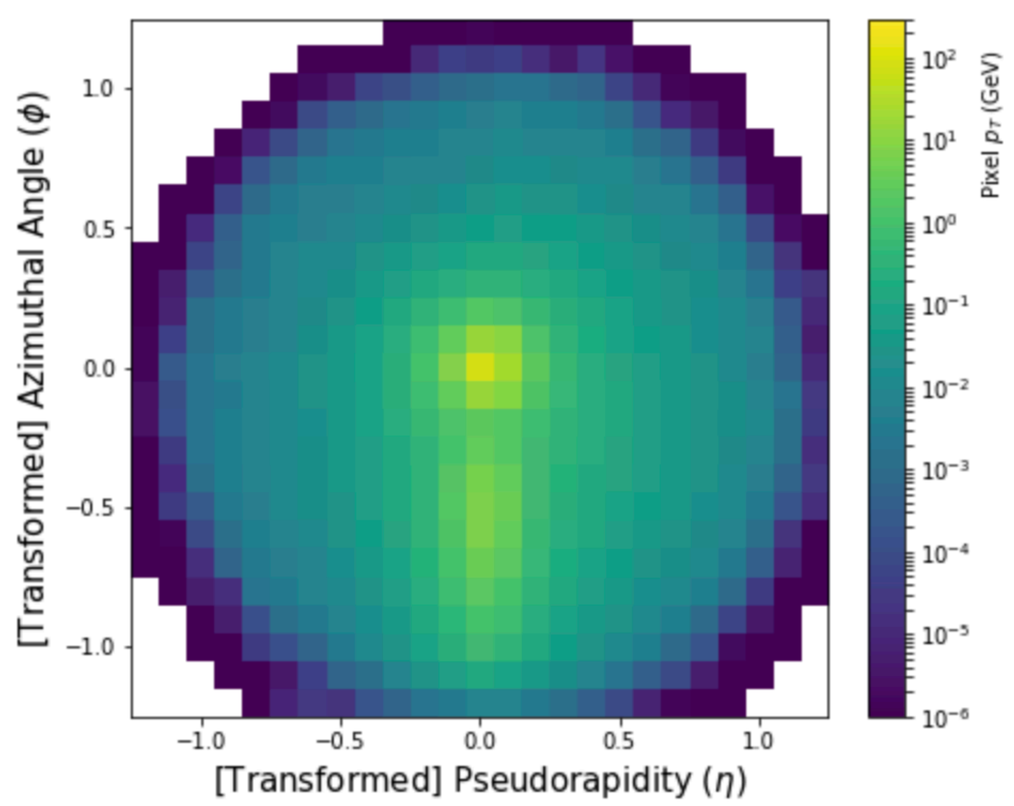
Background: Jet Images

- **Data source**: Calorimeter, particle detector.

- **Data format**: *jet images* – 2D representations of energy depositions of the jets interacting with calorimeter.



Typical jet image



Averaged image

Background: Challenges of Simulation in HEP

- Time consuming: few seconds to simulate a single event (where millions or more are needed).
- Space consuming: storing intermediate results in simulation.
- Need a large number of simulations to get events in kinematically unfavorable region.

Deep Generative Models in Jet Image Simulation

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  - Generate according to the learned distribution efficiently.

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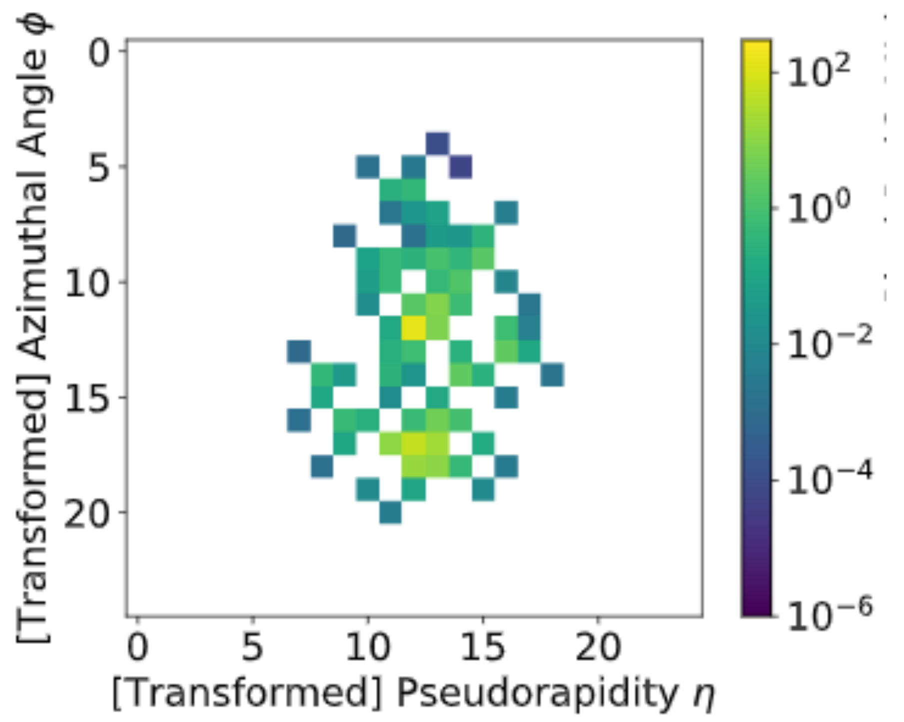
Challenges:

Natural images vs. Jet images.



Deep Generative Models in Jet Image Simulation

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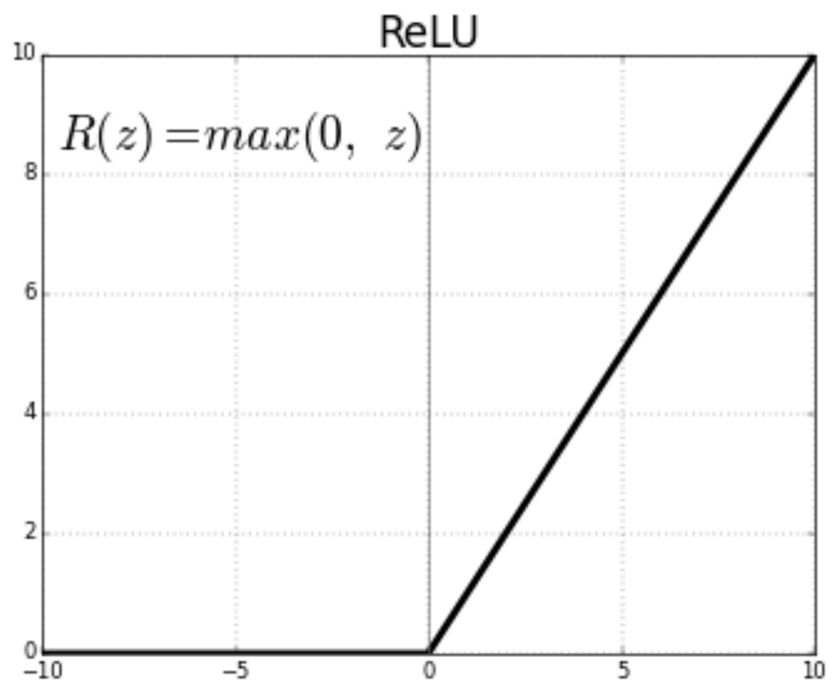
Challenges:

- Sparsity (93% pixels are zeros)
- Faithfully reconstruct distribution of high level observables which can be computed from the jet images, e.g. Mass, pT distributions.

Deep Generative Models in Jet Image Simulation

Challenges with GAN:

- Unstable training and mode collapse (Nagarajan et al., 2017)
- Sparse gradient signal (LAGAN
  Oliveira et al., 2017)
- No likelihood evaluation, less interpretable



Neither GANs nor VAEs produce a tractable marginal likelihood model

Deep Auto-regressive Models

- Directly model the joint distribution of all pixels in an image with auto-regressive conditionals.

$$P(\mathbf{x}) = \prod_{i=1}^{D} P(x_i | x_{j<i})$$

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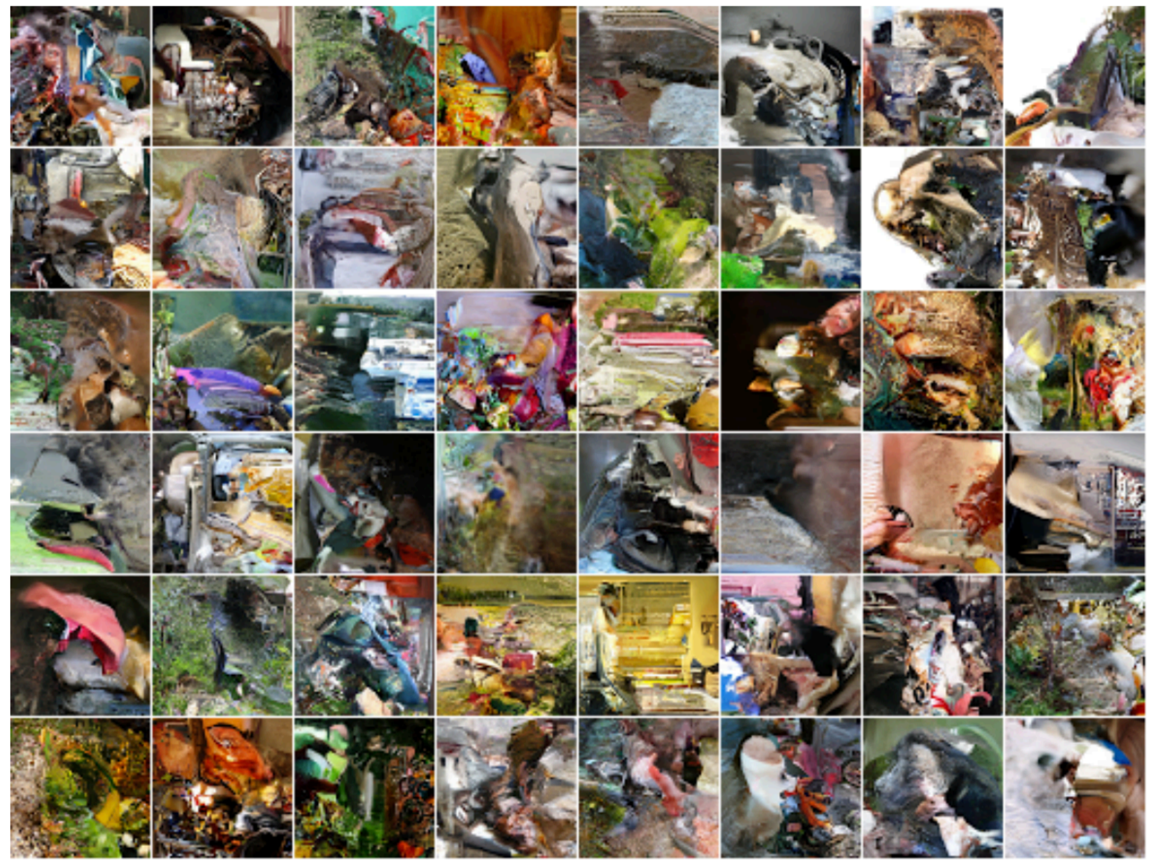
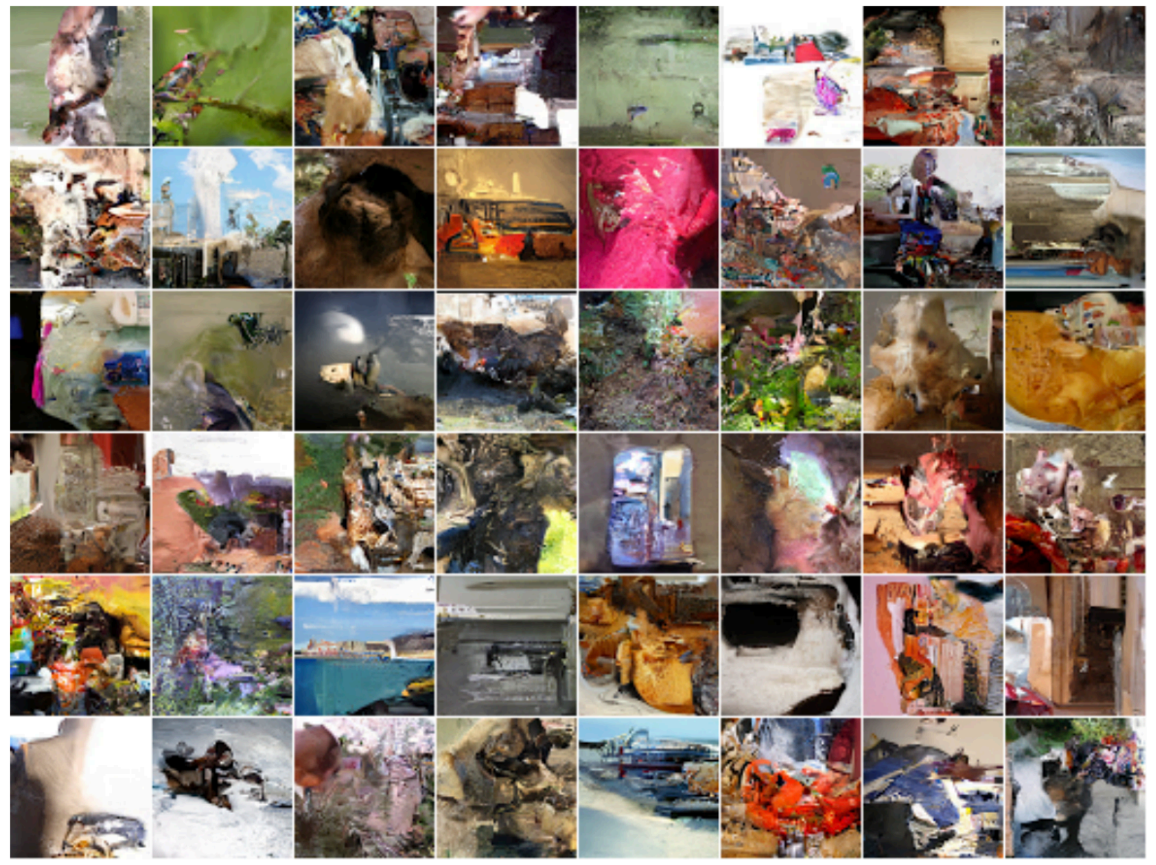
$$P(\mathbf{x}) = \prod_{i=1}^{D} P(x_i \mid x_{j<i})$$

- Achieved state of the art performance in density estimation and image generation





Pixel Recurrent Neural Netowork.
Oord et al., ICML 2016

Sparse Auto-regressive Models (SARM)

Idea: use a mixture model to learn the sparseness and non-zero pixel distribution separately

- **SARM D+C:** Discrete and Continuous Mixture Model

$$p(x_i|\theta_i) = \gamma_i \cdot \delta_{z_i=0} + (1-\gamma_i) \cdot \delta_{z_i \neq 0} \cdot p(\tilde{x}_i|\mu_i, s_i)$$

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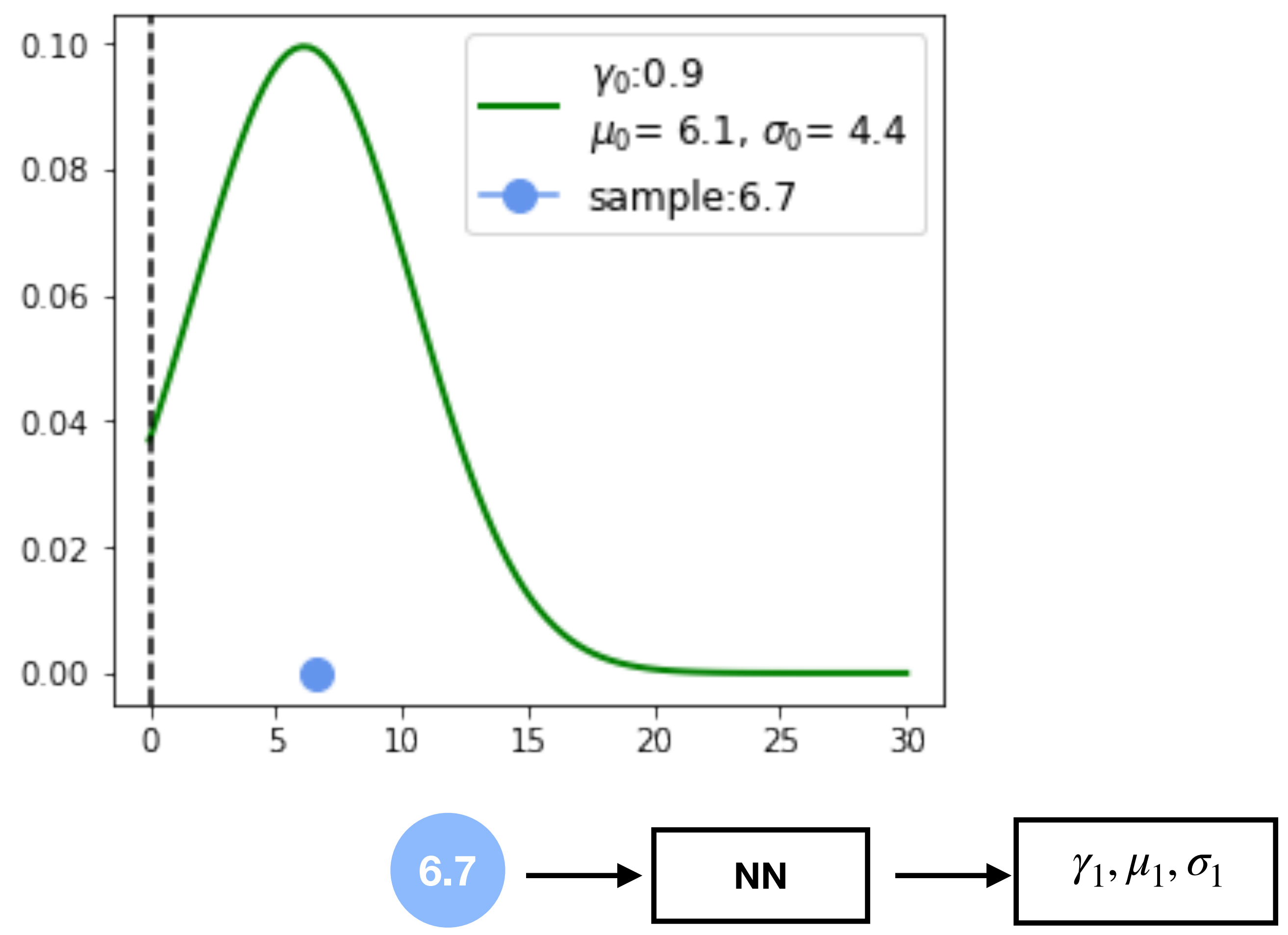

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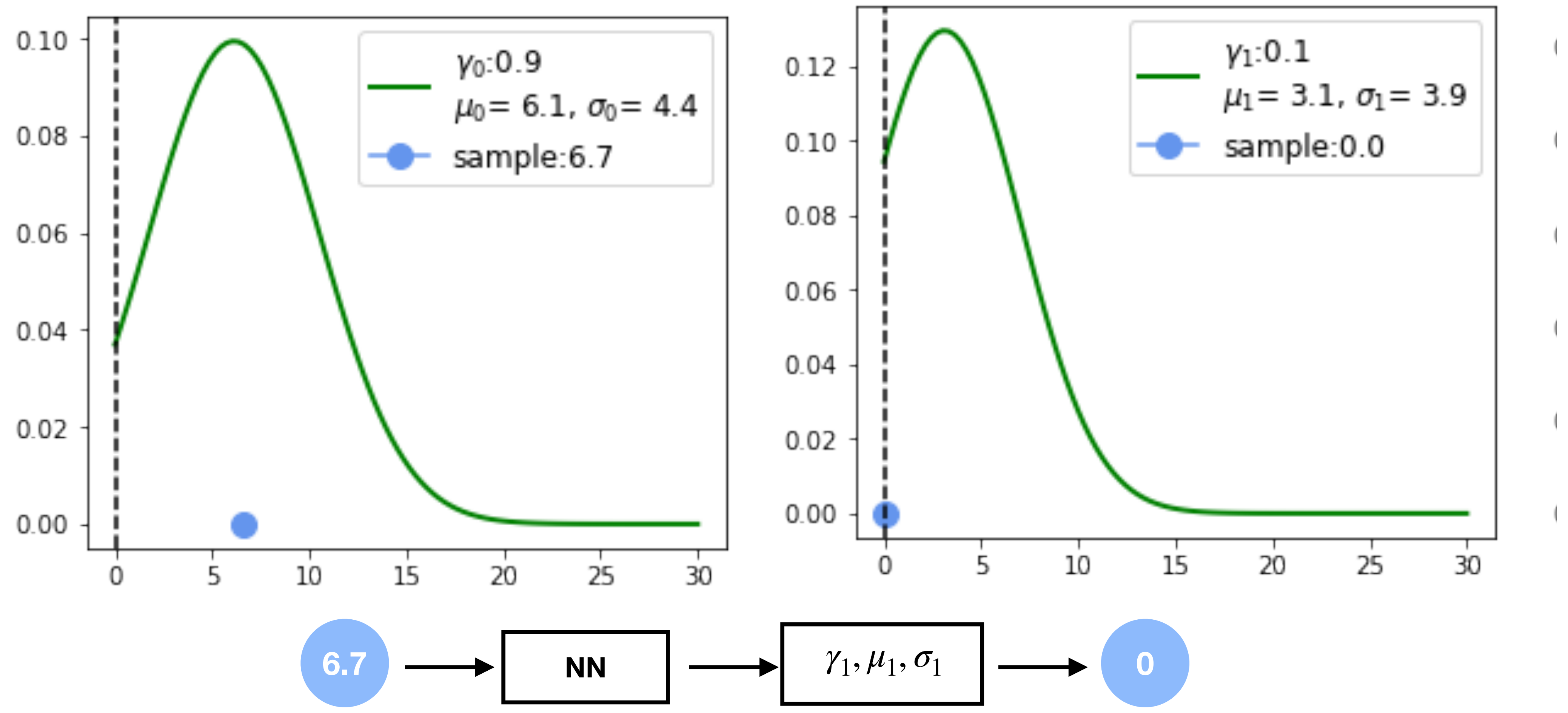

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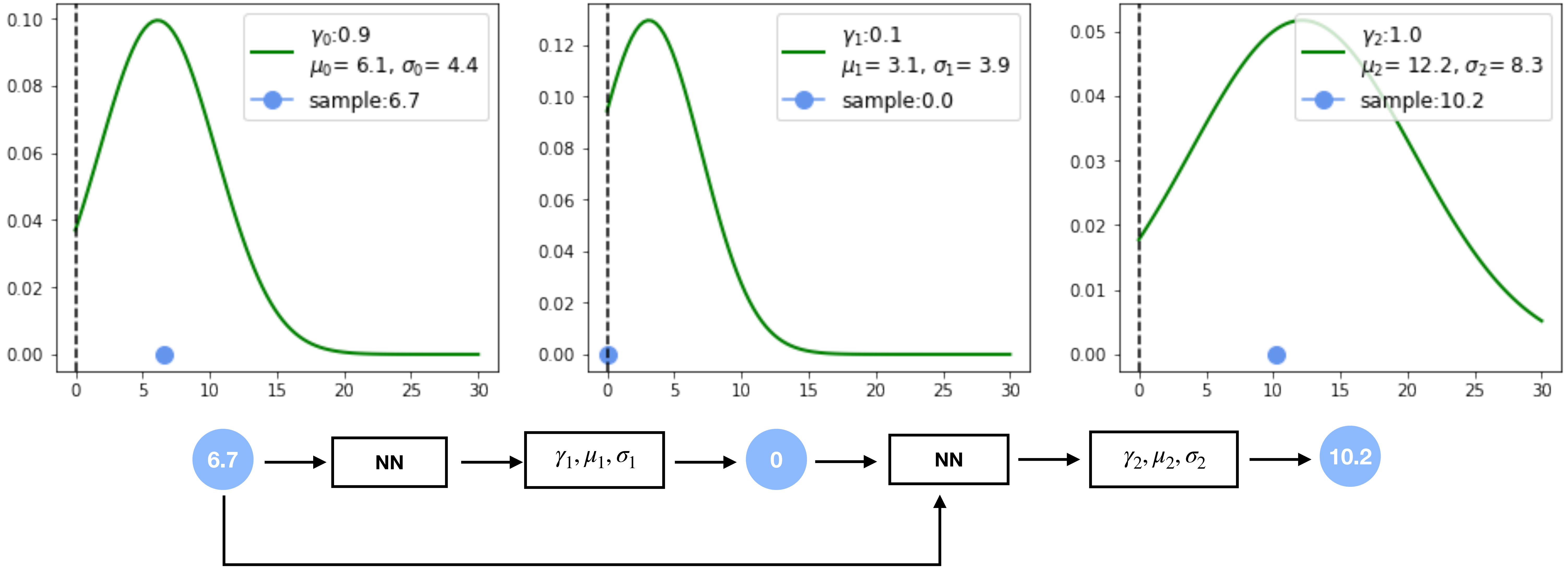


Sparse Auto-regressive Models (SARM)

- **SARM D+D**: Discrete Mixture Model:

$$p(x_i|\theta_i) = \gamma_{i,0} \cdot \delta_{x_i=0} + \sum_{j=1}^{N} \gamma_{i,j} \cdot \delta_{x_i=g_j}$$

Where $x_i \in \{0,1,\ldots,N\}$ with probability $\gamma_i = (\gamma_{i,0}, \ldots, \gamma_{i,N})$, which is a function of $x_1, \ldots, x_{i-1}$

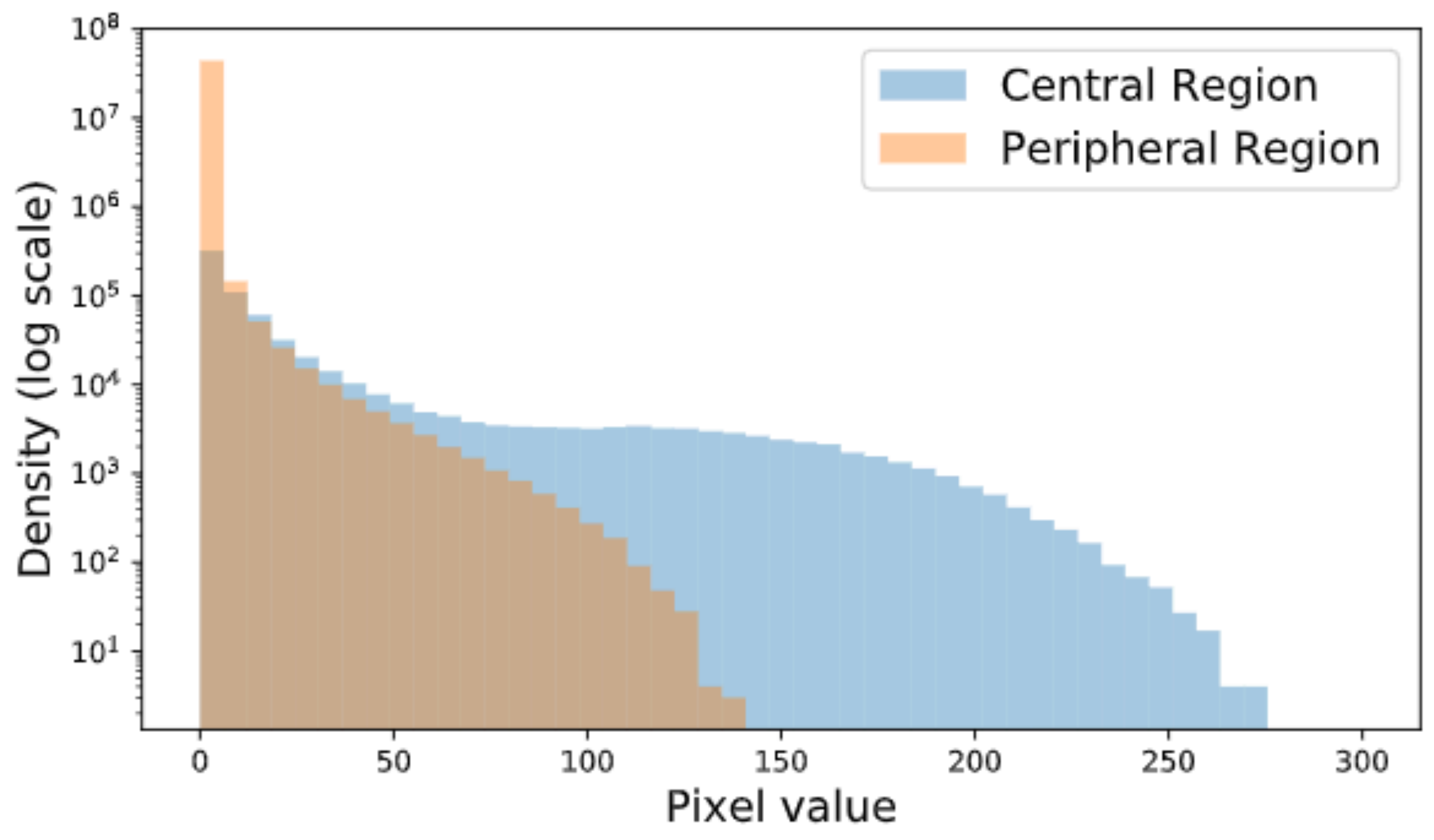
- Drawbacks: more computationally intensive

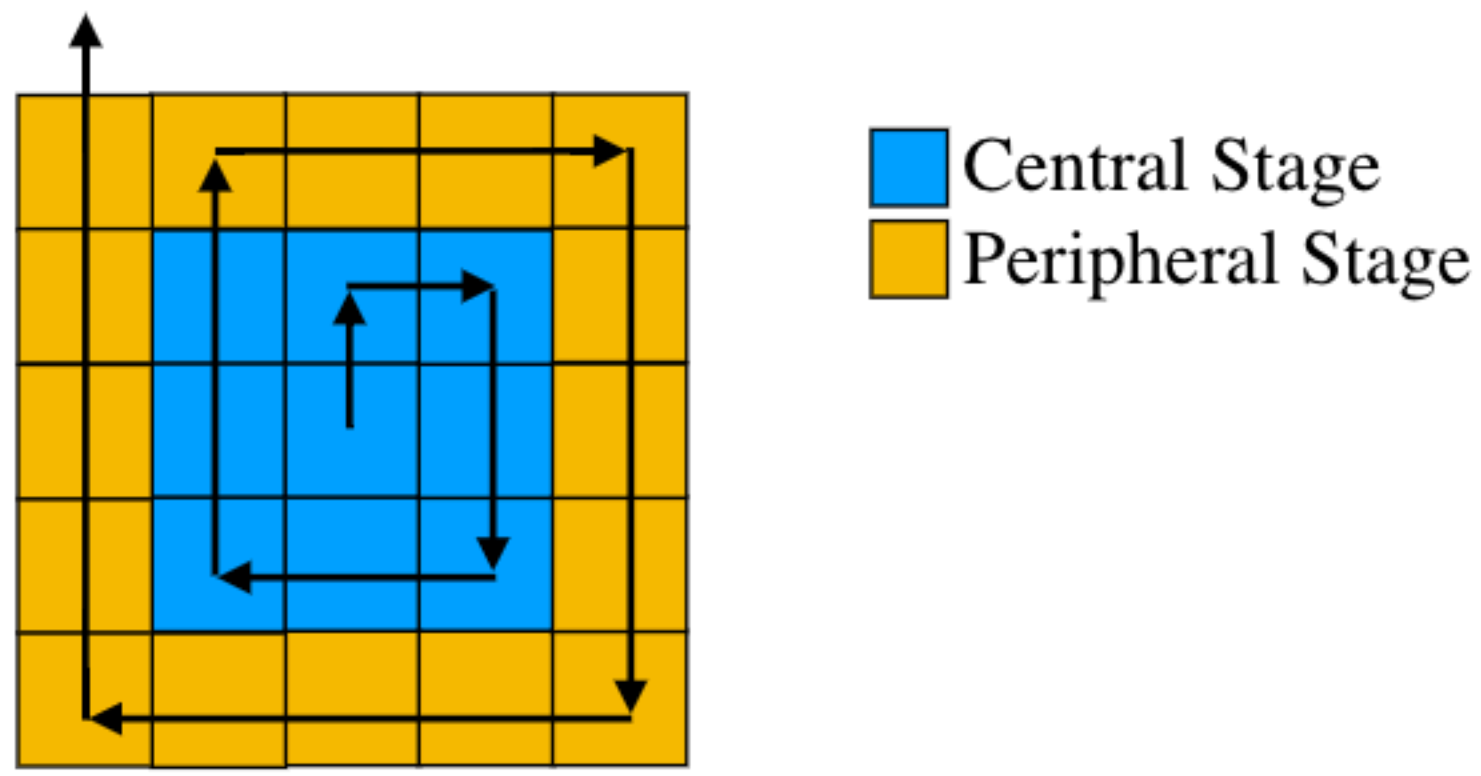
- Advantage: easier to learn multimodal distribution in practice.

Sparse Auto-regressive Models (SARM)

Multi-stage generation:

- Different models for central region and peripheral region to account for heterogeneous pixel distribution





Experiments

Two Case Studies:

- Jet substructure study
- Muon Isolation study

Training data for jet substructure study: Public dataset (Oliveira et al., 2017) simulated from *Pythia 8.219* with energy 14 TEV, and jet transverse momentum pt between 250GeV to 300 GeV,

- 400k signal images: jets originating from high energy W bosons,
- 400k background images: jets originating from generic quark and gluons.
- Each image has size 28 by 28.

Experiments

Baselines:

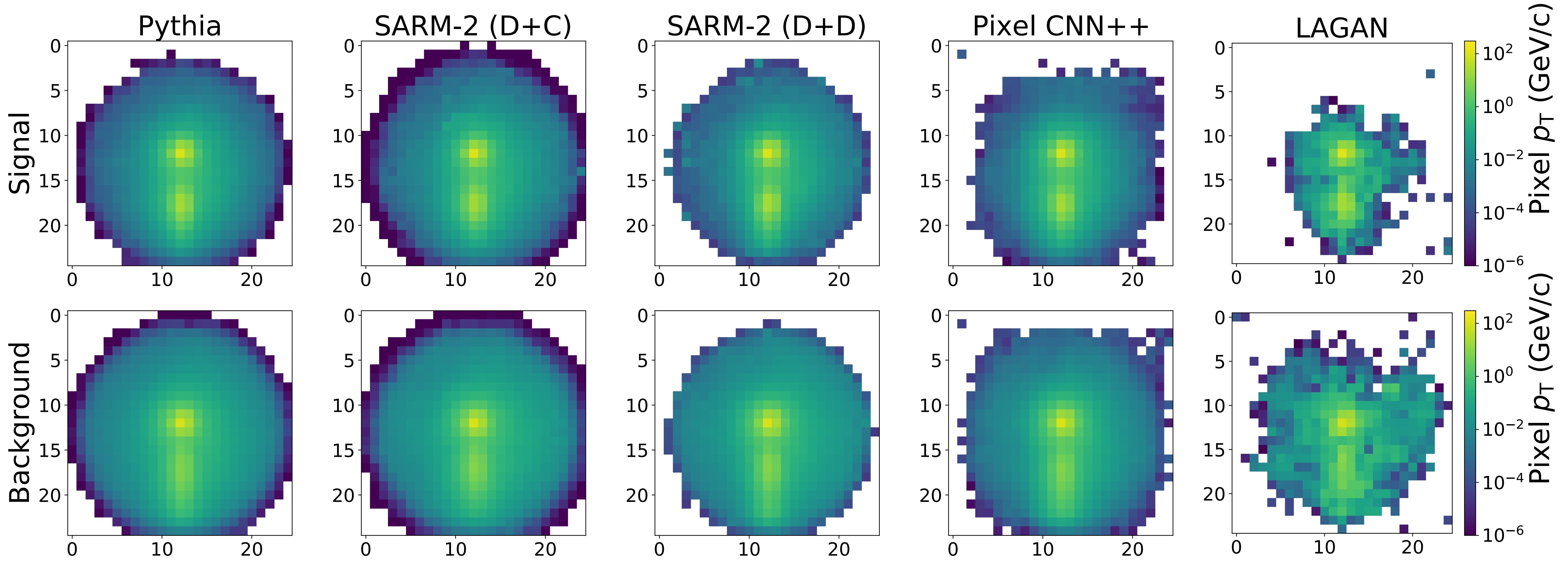
- Monte Carlo Simulator (PYTHIA 8.219)
- LAGAN (Oliveira et al., 2017)
- Pixel CNN++ (Salimans et al., 2017)

Qualitative Analysis: Generated Images

Comparison of images produced by: SARM, LAGAN, and Monte Carlo Simulation (Pythia)

- Both SARM D+C and SARM D+D produce high fidelity mean images.

- Smoother transition from center to outer comparing images produced by LAGAN.



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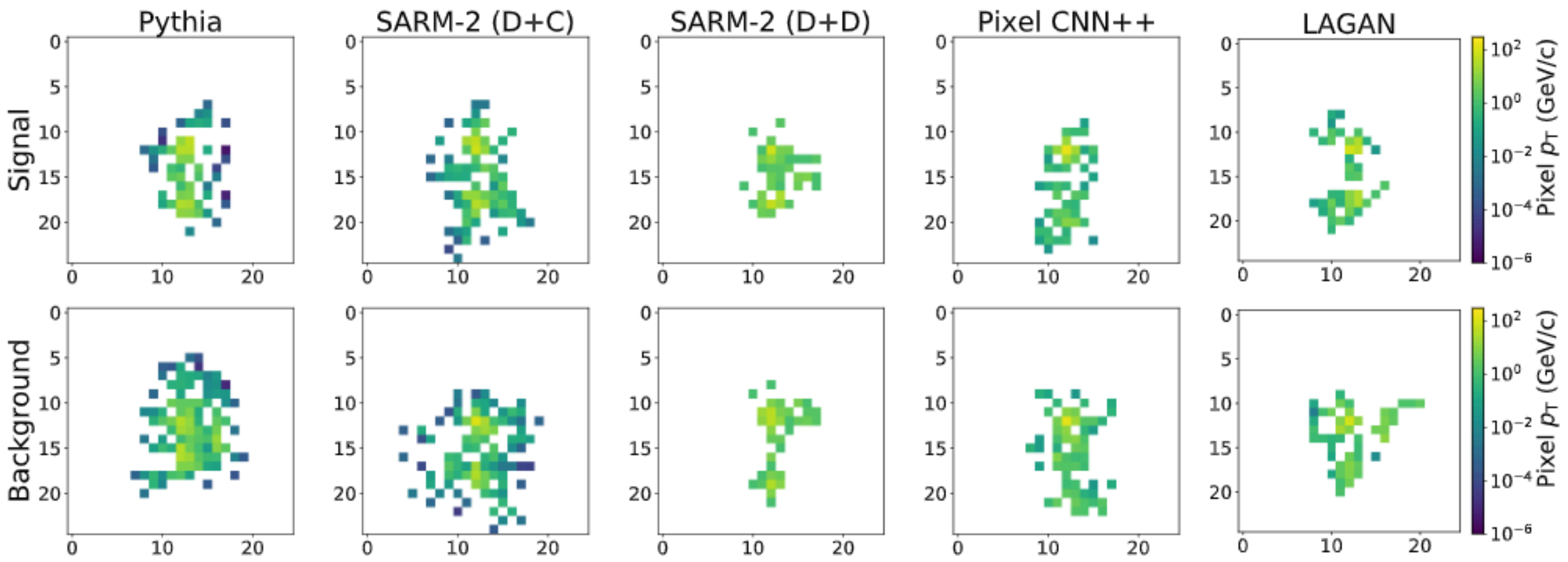
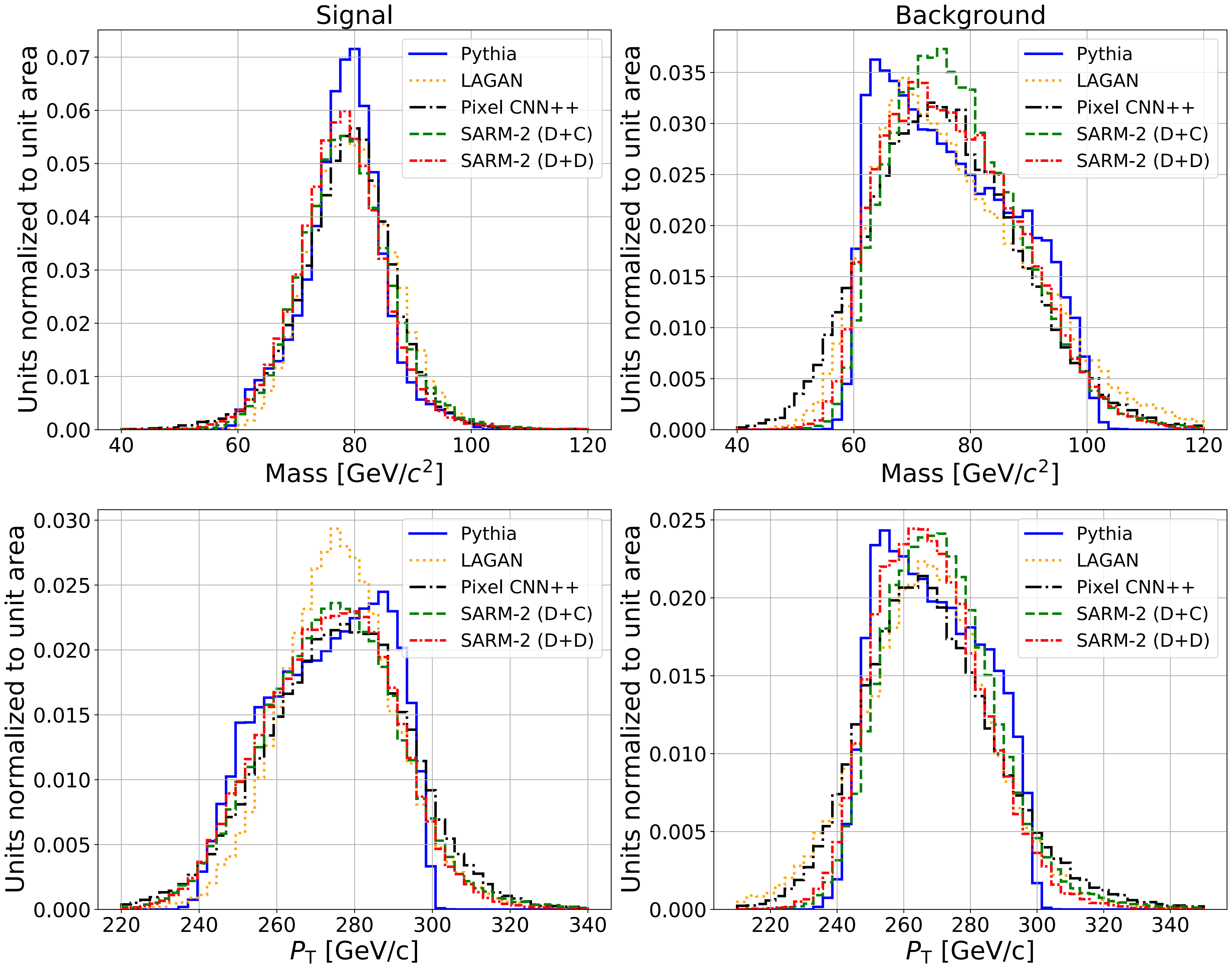


Quantitive Analysis: High Level Observables



Earth mover's distance between distributions of Pythia images and generated images

Model	P_T Signal	P_T Background	Mass Signal	Mass Background
LAGAN	3.15	3.29	1.45	1.39
Pixel CNN++	3.46	3.59	1.09	1.56
SARM-1 (D+C)	2.33	2.46	1.07	1.54
SARM-2 (D+C)	2.32	2.71	1.06	1.39
SARM-1 (D+D)	1.95	2.52	1.34	2.45
SARM-2 (D+D)	**1.44**	**1.66**	**0.94**	**0.92**

Quantitive Analysis: Classification on Generated Images

High-level test of the image quality:

- Training data: images generated by different models (200k signal + 200k background)
- Evaluation data: Pythia images (20k signal + 20k background)

Better quality of generated images leads to better performance in the classification

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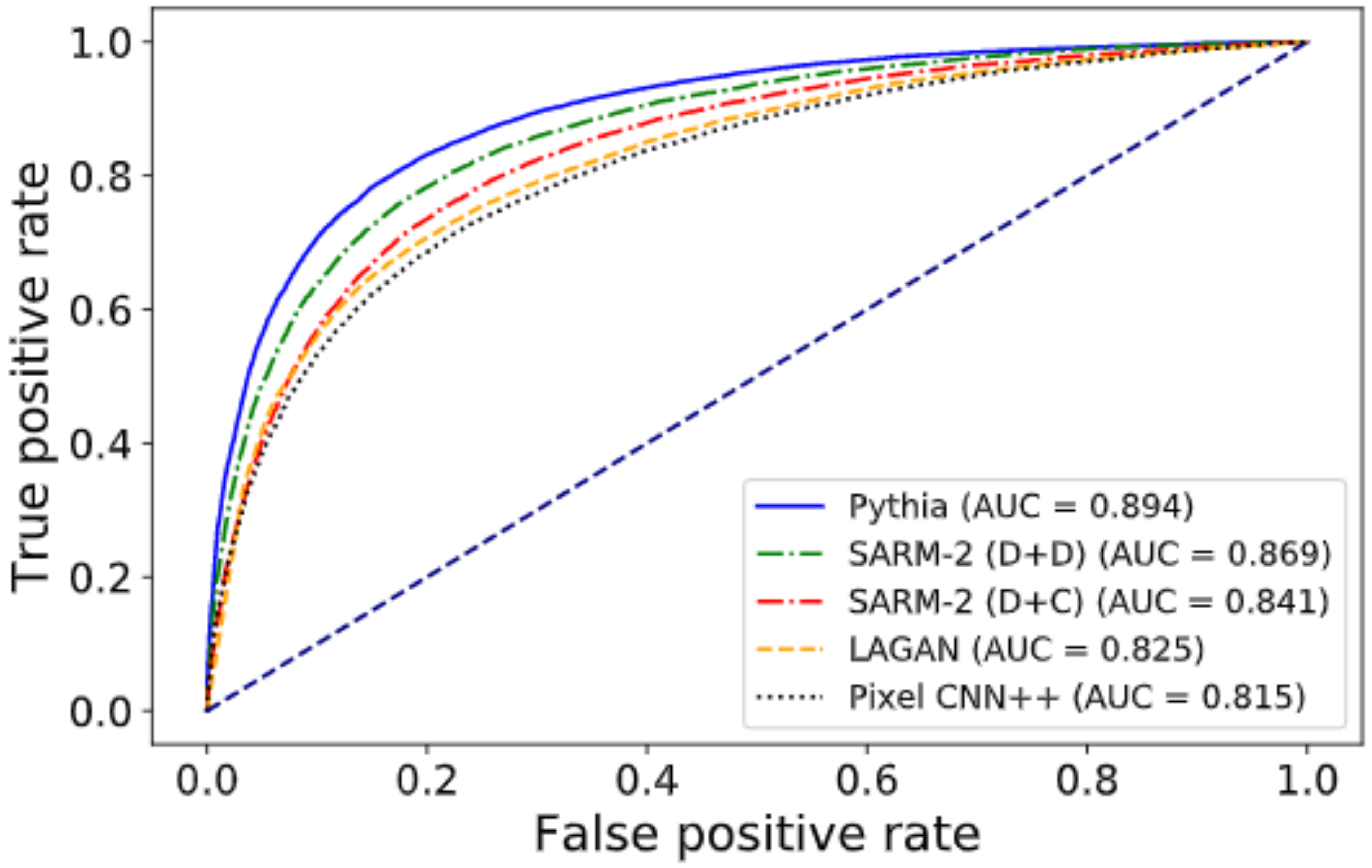
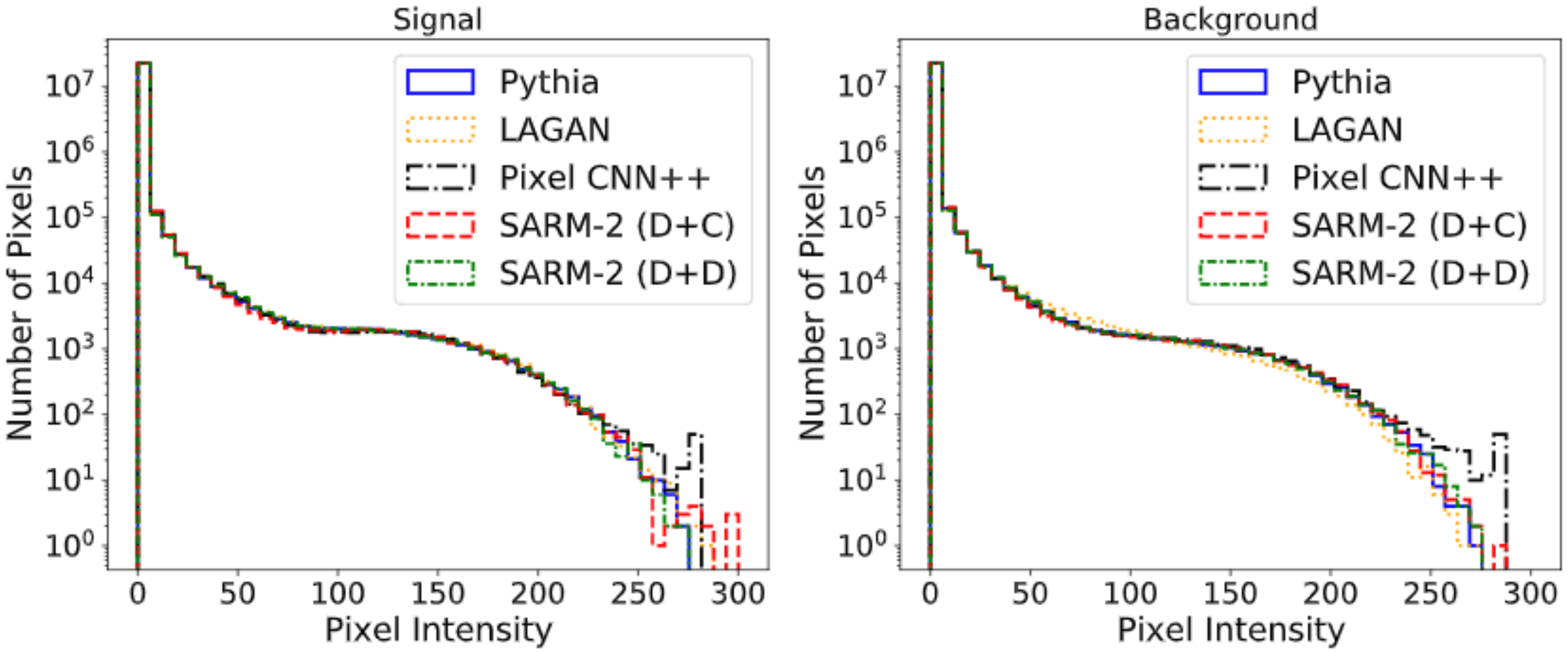


Quantitive Analysis: Aggregated Pixel Intensity

All of the models are able to capture the pixel distribution in both signal and background datasets.



NN models are evaluated on 4 TITANX GPU each with 12G memory

Generation Speed:

Model	Speed (images/sec)
Pythia [6]	34
Pixel CNN++	50
SARM-2 (D+D)	1612
SARM-2 (D+C)	2480
LAGAN	10176

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Conclusion:

- SARM outperforms the state-of-the-art generative models by 24-52% in terms of Wassertein distance, in jet substructure study
- SARM is two orders of magnitude faster than Monte Carlo simulation, while being slower than GAN based generator.
- Easy to expand to other studies involving sparse image generation, e.g. super resolution.

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Yadong Lu, Julian Collado, Daniel Whiteson, and Pierre Baldi. Sparse autoregressive models for scalable generation of sparse images in particle physics. *Phys. Rev. D 103, 036012, 2021*

Yadong Lu, Julian Collado, Kevin Bauer, Daniel Whiteson, Pierre Baldi. Sparse Image Generation with Decoupled Generative Models. *MLPS Workshop, NeurIPS 2019*

Thank you and questions

Appendix

Effect of Generation Orders:

	P_{T} (std)	Mass (std)
Spiral-out CCW	1.94 (0.09)	1.38 (0.10)
Spiral-out CW	2.47 (0.23)	1.53 (0.22)
Spiral-in CCW	3.64 (0.32)	1.62 (0.14)
Spiral-in CW	3.20 (0.22)	1.45 (0.16)
Row-wise	3.06 (0.30)	2.01 (0.11)
Column-wise	3.38 (0.39)	1.90 (0.08)
Random I	4.05 (0.51)	1.74 (0.53)
Random II	3.41 (0.33)	1.25 (0.26)

Non-random, systematic generation orders that have good continuity and congruence properties perform well (and outperform random orders)

Appendix

Difference in the average images (generated - Pythia)