

Fast Calorimeter Simulation With Machine Learning Techniques

MU Days 2022, GSI

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HELMHOLTZ

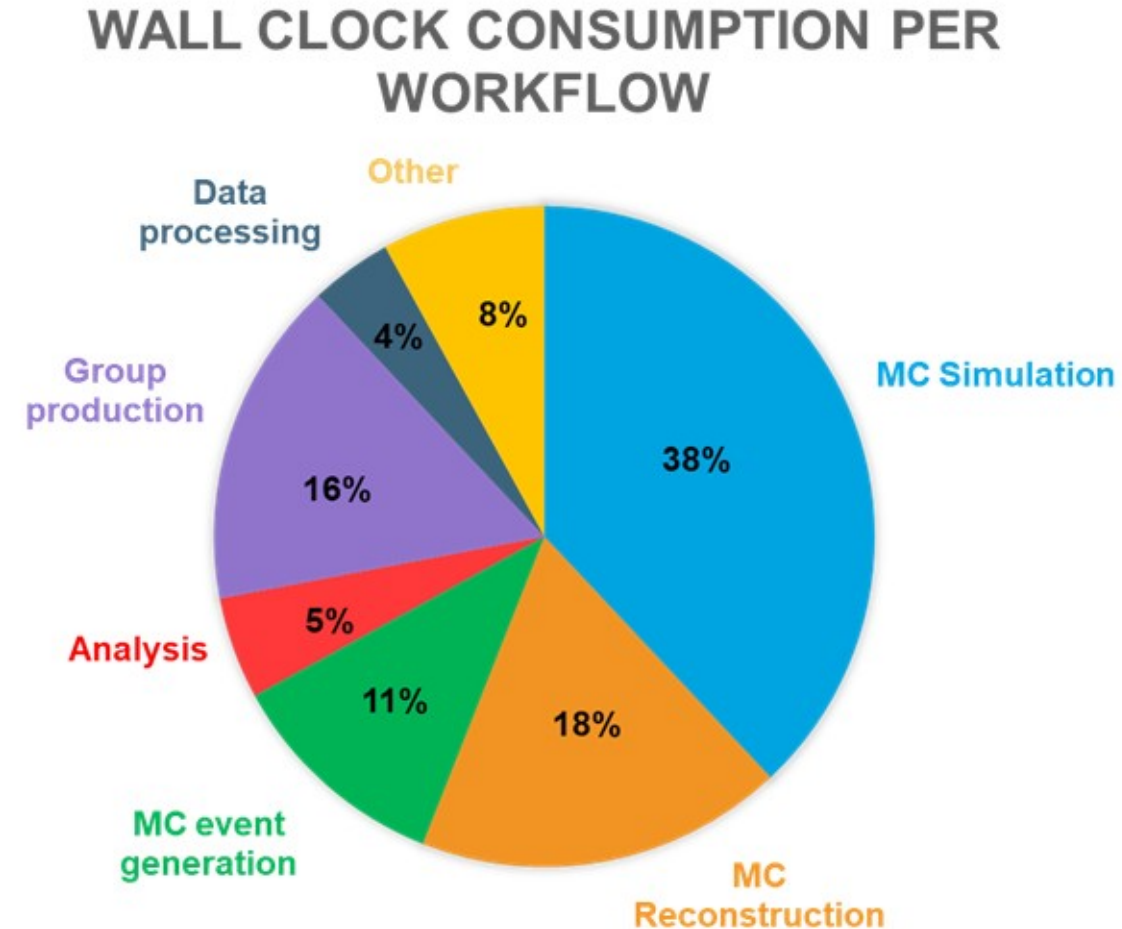


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The Strain on HEP Computing Resources

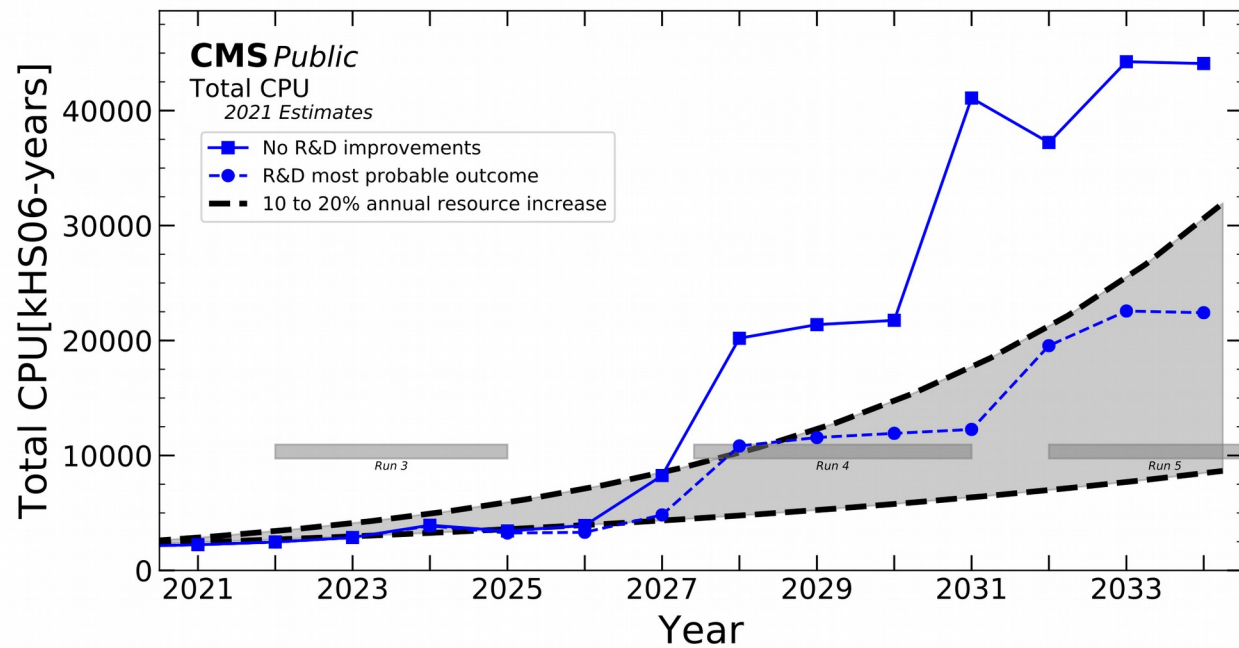
- Ever **increasing demand** for computing resources
 - **MC simulation** largest fraction
 - **Calorimeters** most intensive part of detector simulation
- Projected computing resources required far outstrip what will be available
 - E.g HL-LHC
- **Generative ML models** potentially offer orders of magnitude speed up



D. Costanzo, J. Catmore, ATLAS Computing update, LHCC meeting , 2019

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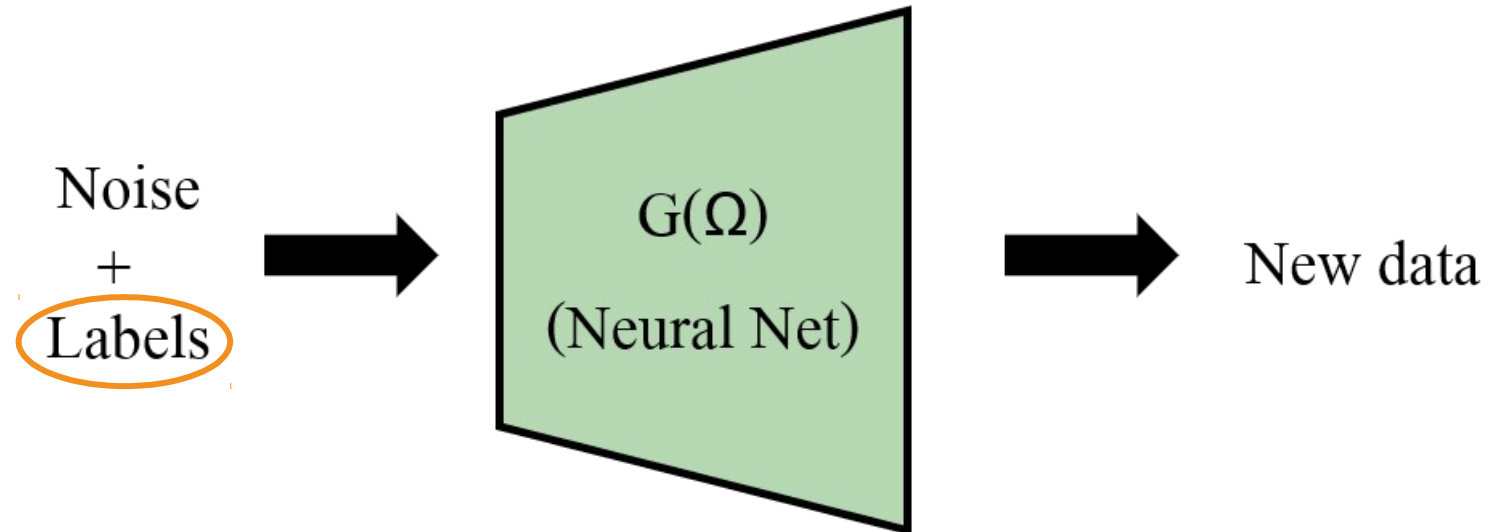


CMS Collaboration, Offline and Computing Public Results (2021),
<https://twiki.cern.ch/twiki/bin/view/CMSPublic/CMSOfflineComputingResults>

Generative Models

- Approach to fast simulation- **amplify statistics**
- Aim: **augment** full physics-based **GEANT4** simulation by learning a **transfer function**
- Promising solution: **generative models**
 - Generate **new samples** following the distribution of original data
 - Map random noise to data
 - Highly **parallelizable**
 - **Conditioning (E.g., E , θ , ϕ)**

Butter et. al, GANplifying event samples, SciPost Phys. 10, 139 (2021)

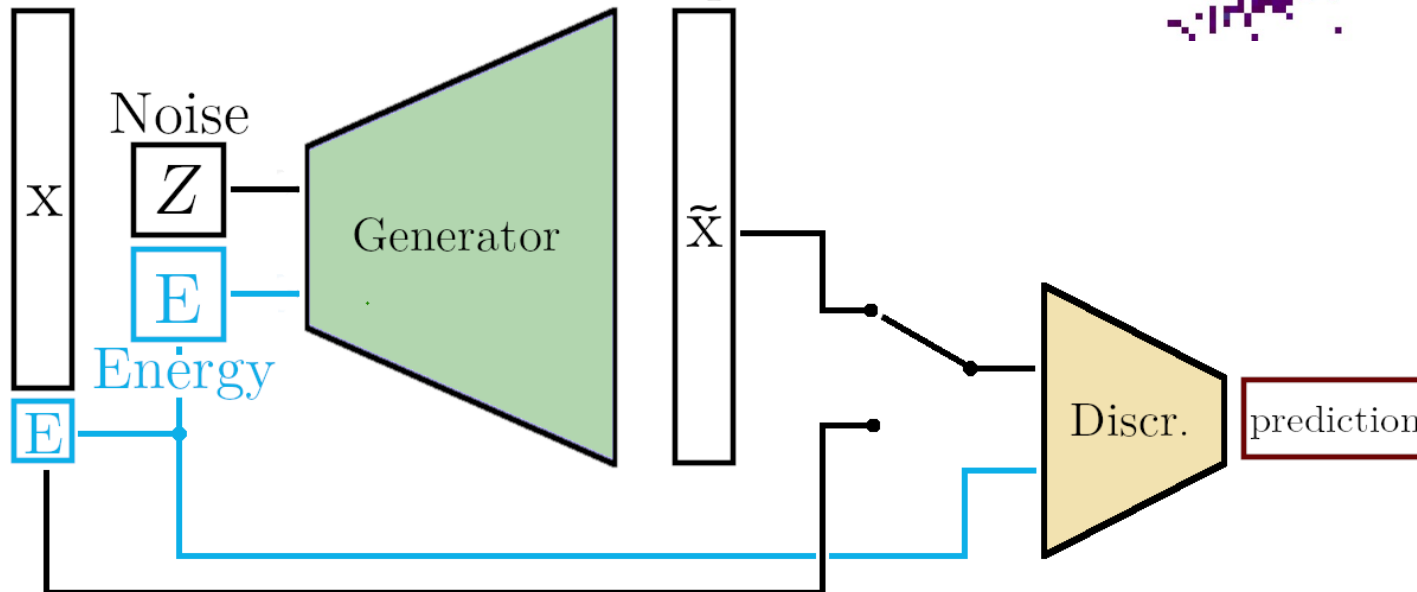


Common Generative Models

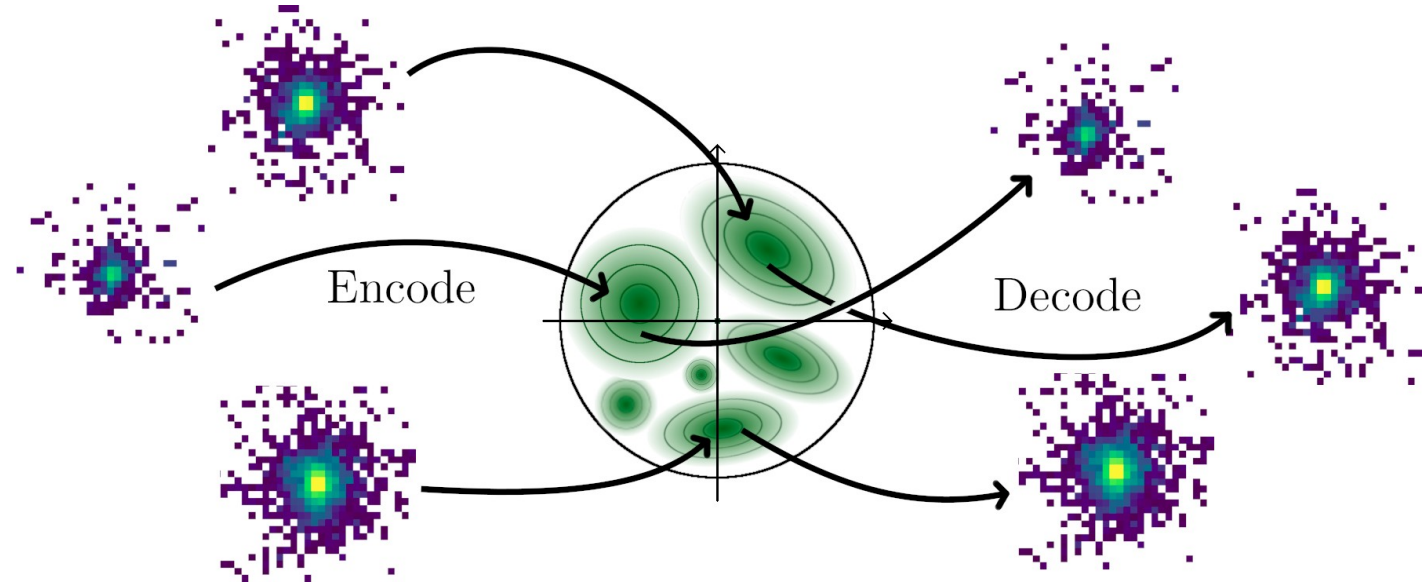
Generative Adversarial Network (GAN)

Real Data

Output

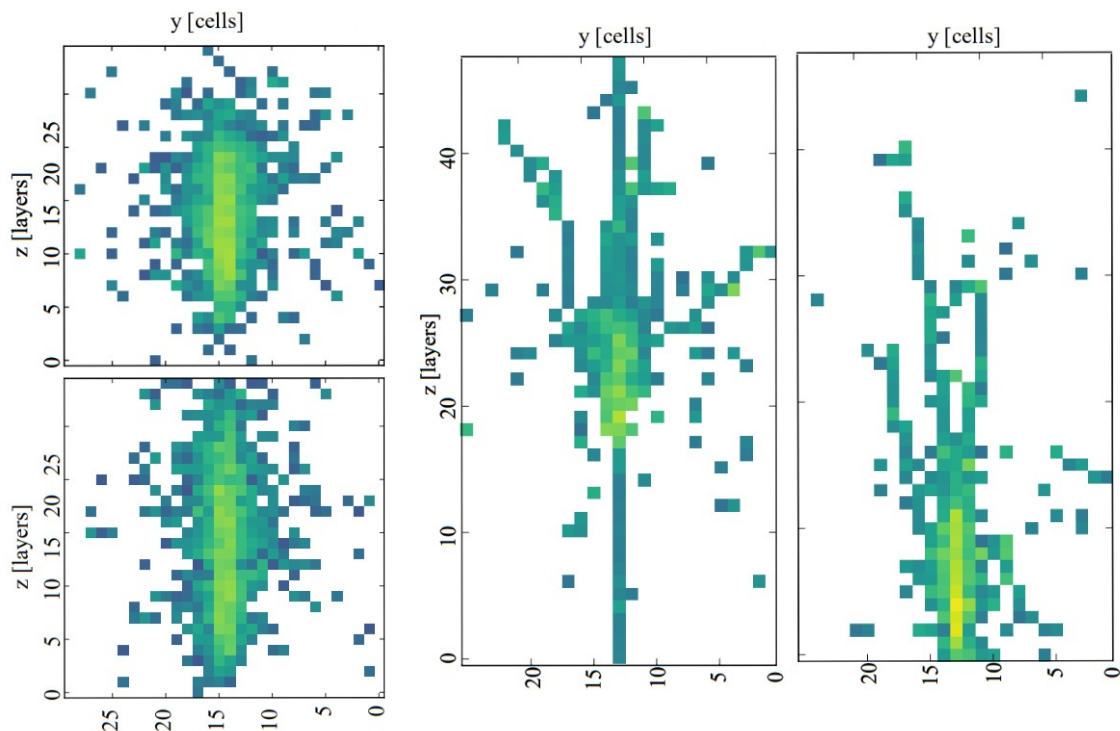


Variational Autoencoder (VAE)



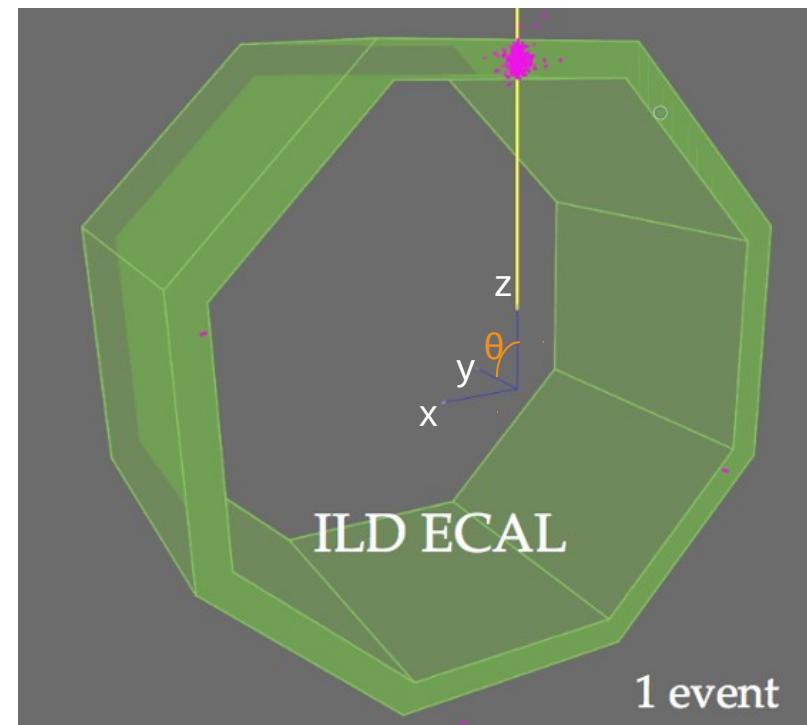
- Models studied:
 - Wasserstein GAN (**WGAN**)
 - Bounded Information Bottleneck Autoencoder (**BIB-AE**)

Challenges for Generative ML Calorimeter Simulations



From Photons to Pions

- **Hadronic** showers significantly harder to learn than electromagnetic showers
 - **Complex** topologies
 - Large event-to-event **fluctuations**



Multi-Parameter Conditioning

- **Simultaneous conditioning** on multiple parameters crucial for a general simulation tool
 - Start with **photons**
 - Vary incident **energy and angle**

Latest Progress

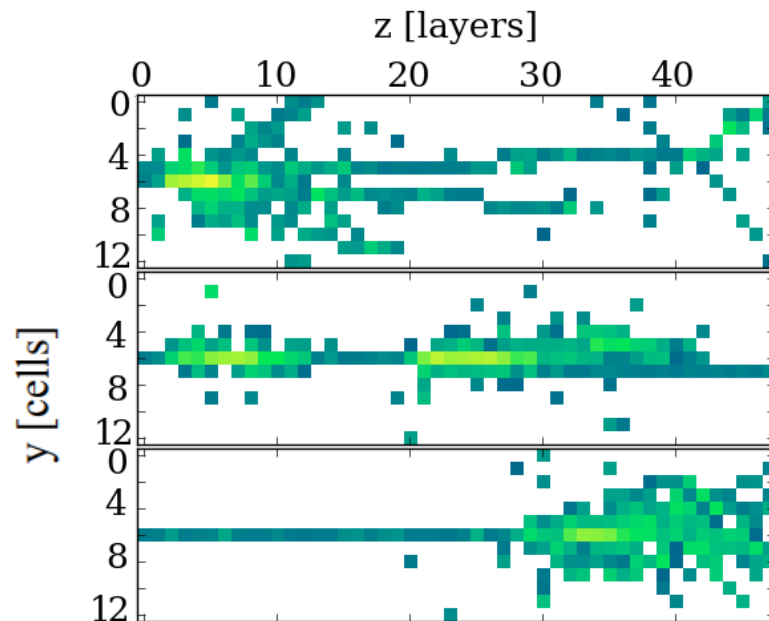
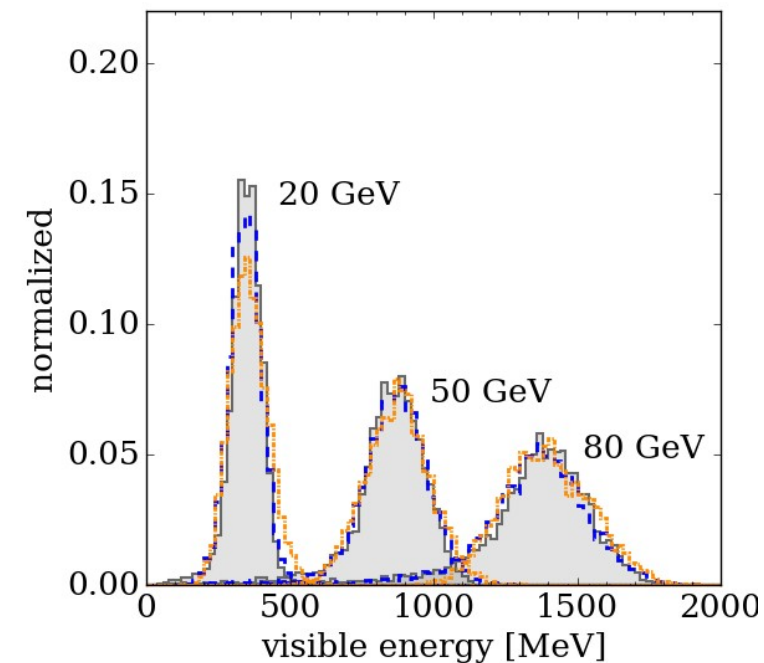
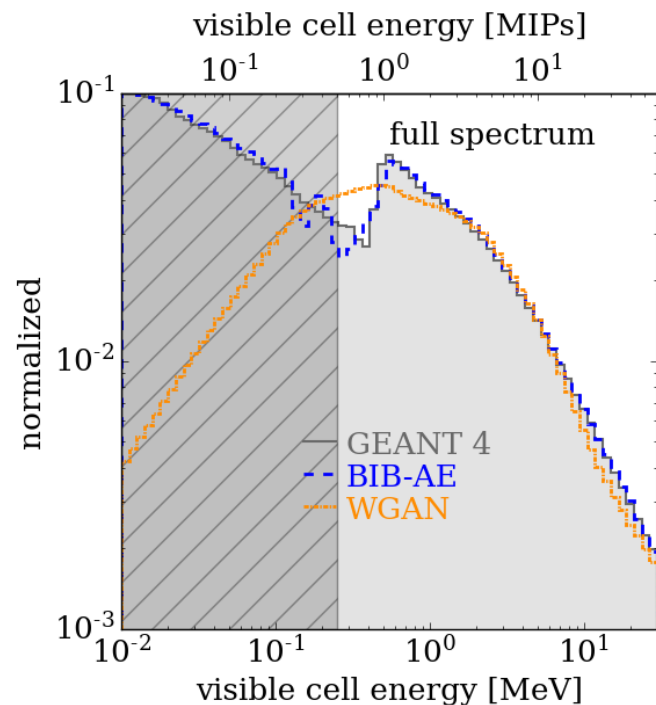
Hadronic Calorimeter Showers

- Achieve **significant speedups** (CPU/GPU)
- Achieve **high degree of fidelity**

Hadrons, Better, Faster, Stronger,

E. Buhmann, et al.

[MLST 3 025014 \(2022\)](#)

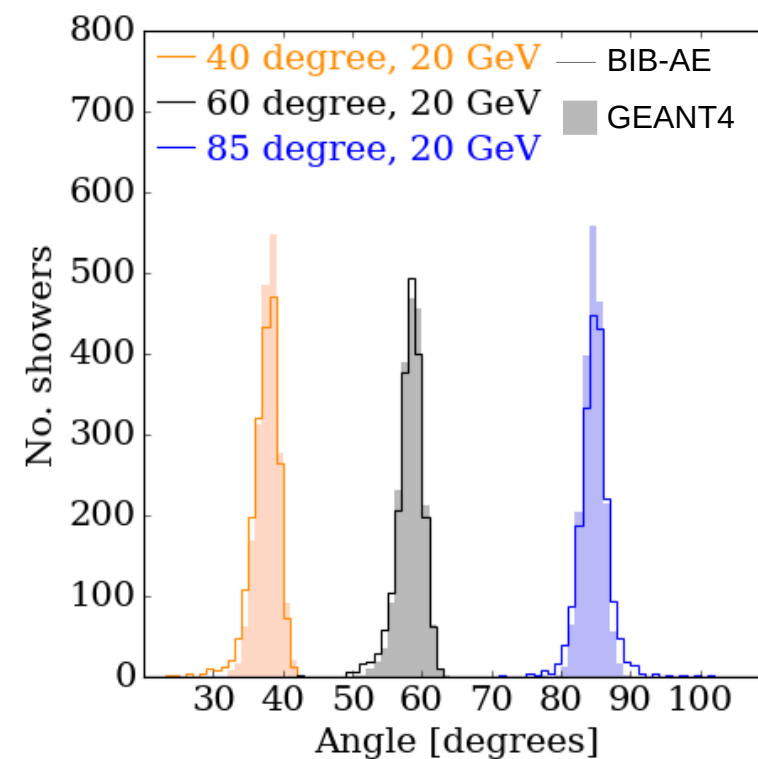
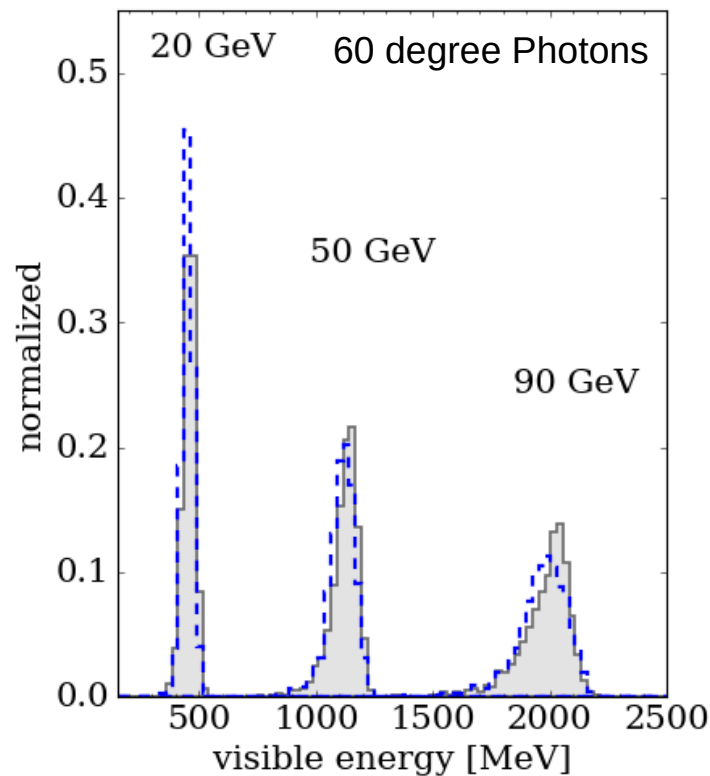
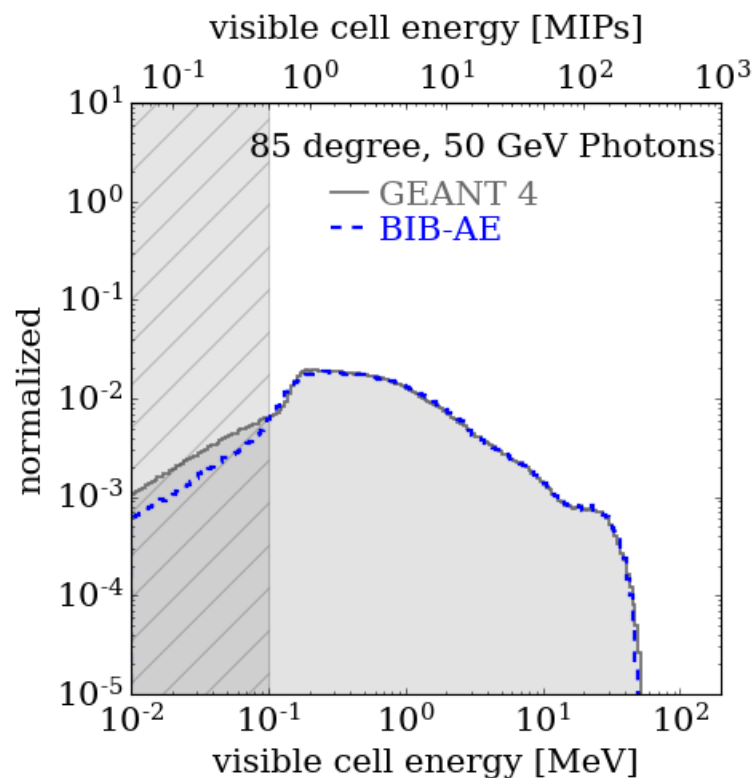
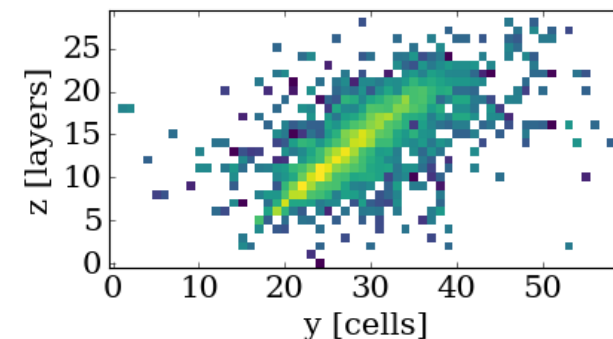
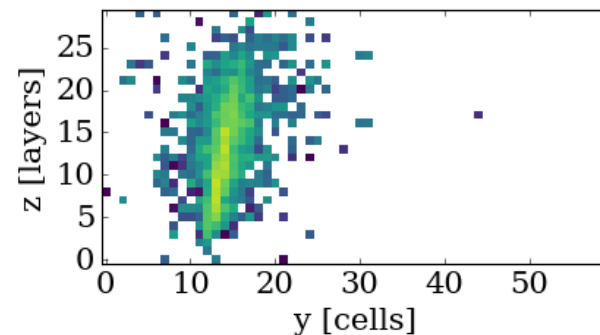


Hardware	Simulator	Time / Shower [ms]		Speed-up
CPU	GEANT4	2684	± 125	$\times 1$
	WGAN	47.923	± 0.089	$\times 56$
	BIB-AE	350.824	± 0.574	$\times 8$
GPU	WGAN	0.264	± 0.002	$\times 10167$
	BIB-AE	2.051	± 0.005	$\times 1309$

Latest Progress

Angular Photon Showers

- Simultaneous **Energy and Angular conditioning** demonstrated with high physics performance
 - Publication in preparation



Summary

Achieved

- Generative models hold promise for **fast** simulation of calorimeter showers with **high fidelity**
- Demonstrated high fidelity simulation of **hadronic** showers with generative models
- Demonstrated high fidelity simulation of **photon** showers with **angular and energy conditioning**

Next Steps

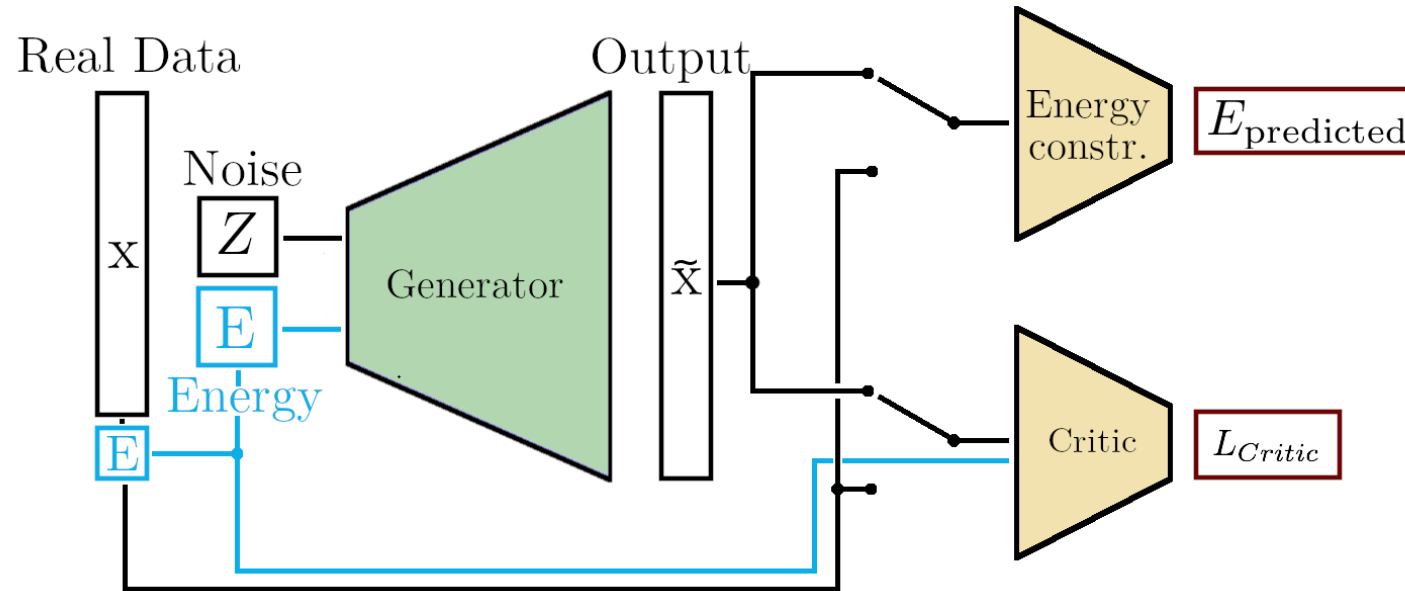
- Strategies for dealing with **complex** and **irregular geometries**
- **Integration** into the existing tools (Geant4)
- Full benchmark of **physics performance** after **reconstruction**

Backup

Architectures: WGAN

WGAN

- Alternative to classical GAN training; Generator and Critic Networks
- Wasserstein-1 distance as loss with gradient penalty: **improve stability**
- **Addition of auxiliary constrainer network for improved conditioning performance**



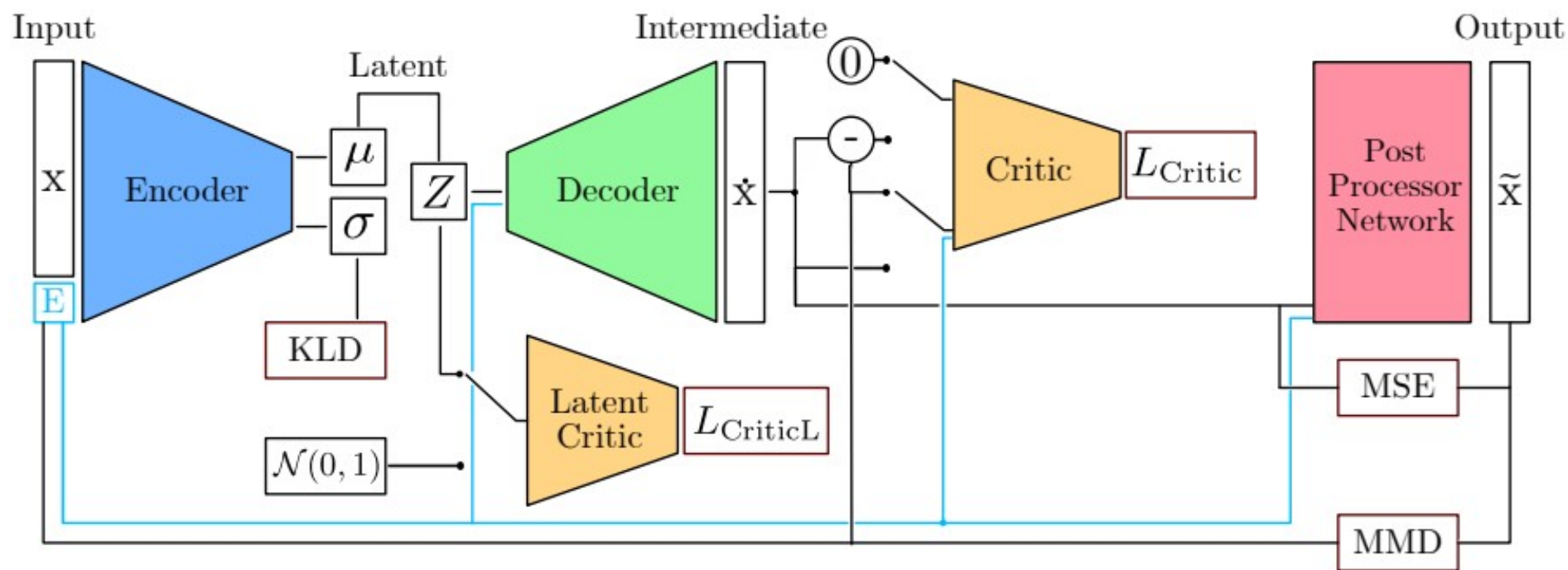
Architectures: BIB-AE

Bounded-Information Bottleneck Autoencoder (BIB-AE)

- **Unifies** features of both **GANs** and **VAEs**
- **Post-Processor** network: Improve per-pixel energies; second training
- Multi-dimensional KDE sampling: better modeling of latent space

Voloshynovskiy et. al: Information bottleneck through variational glasses, [arXiv:1912.00830](https://arxiv.org/abs/1912.00830) (2019)

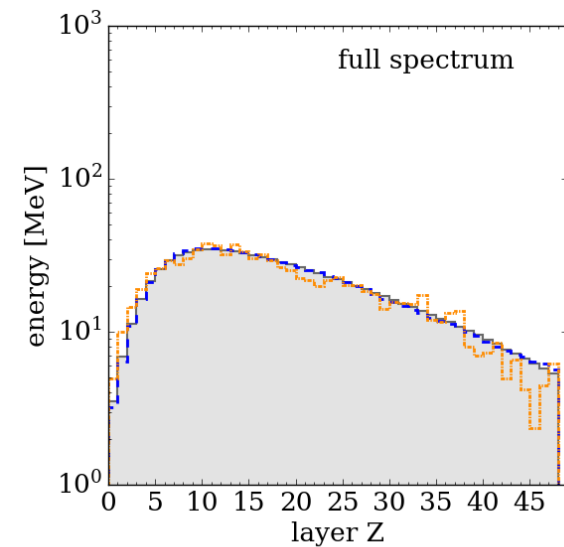
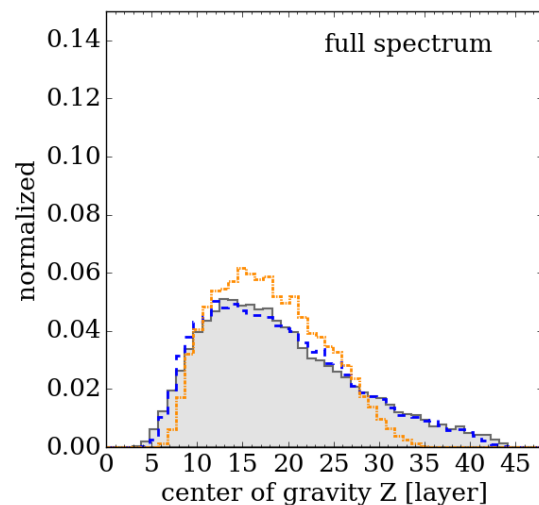
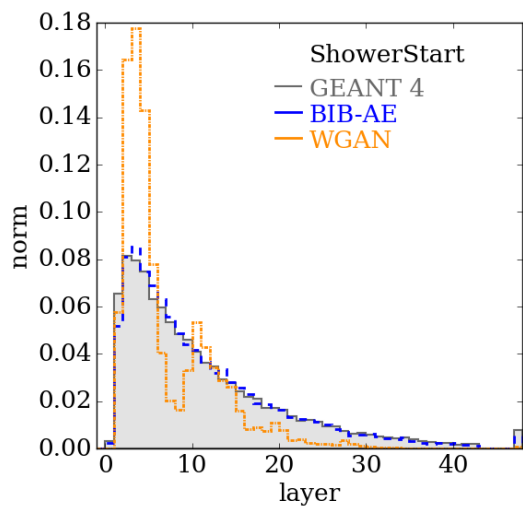
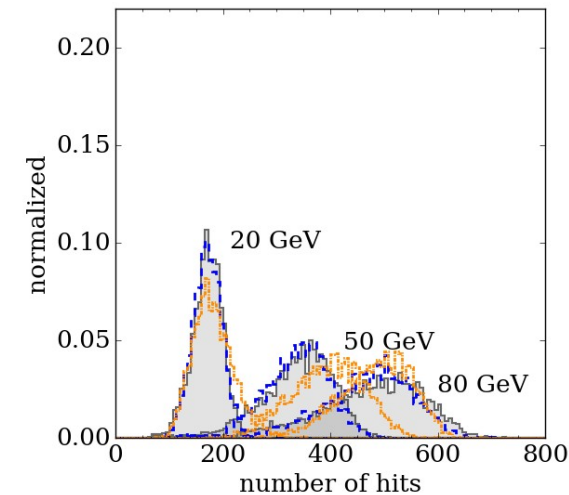
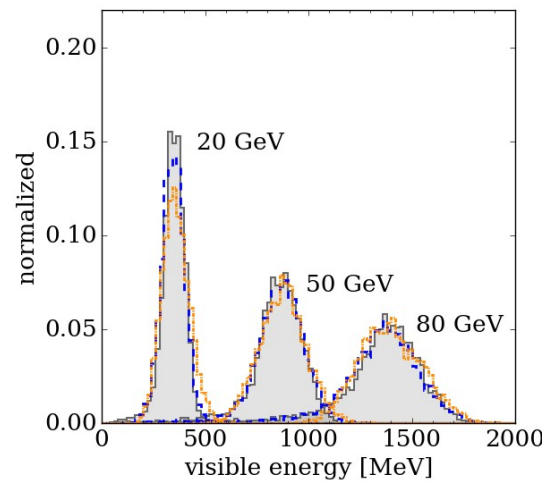
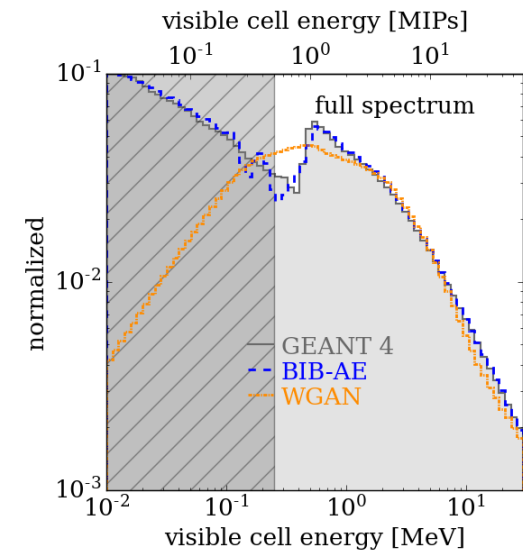
Buhmann et. al: **Getting High: High Fidelity Simulation of High Granularity Calorimeters with High Speed**, [CSBS 5, 13](https://arxiv.org/abs/2105.01313) (2021)



$$L_{BIB-AE} = KLD + L_{CriticL} + L_{Critic}$$

$$L_{Post} = MMD + MSE$$

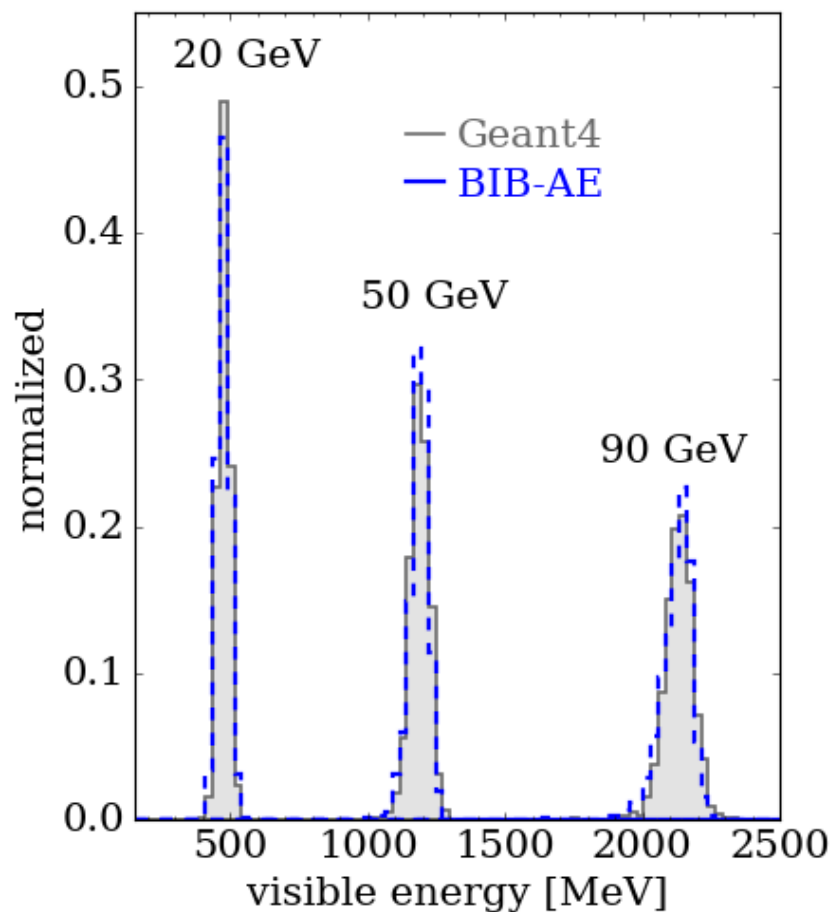
Pion Showers: Sim Level Results



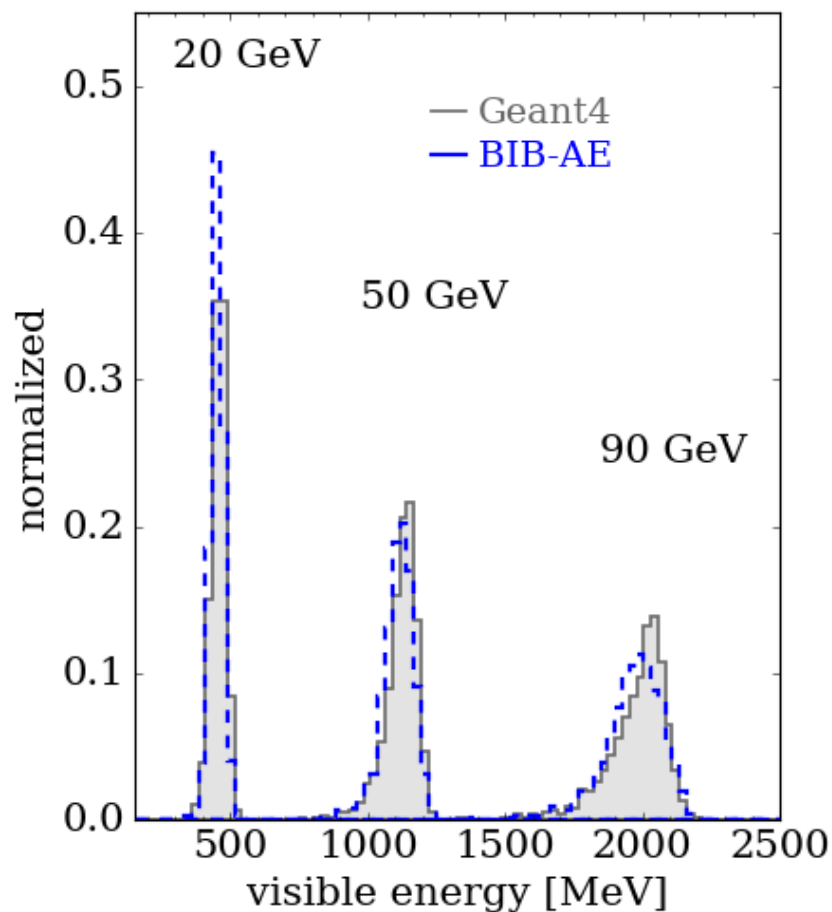
Results: Visible Energy Sum

- Visible energy is nicely described for different incident angles and energies

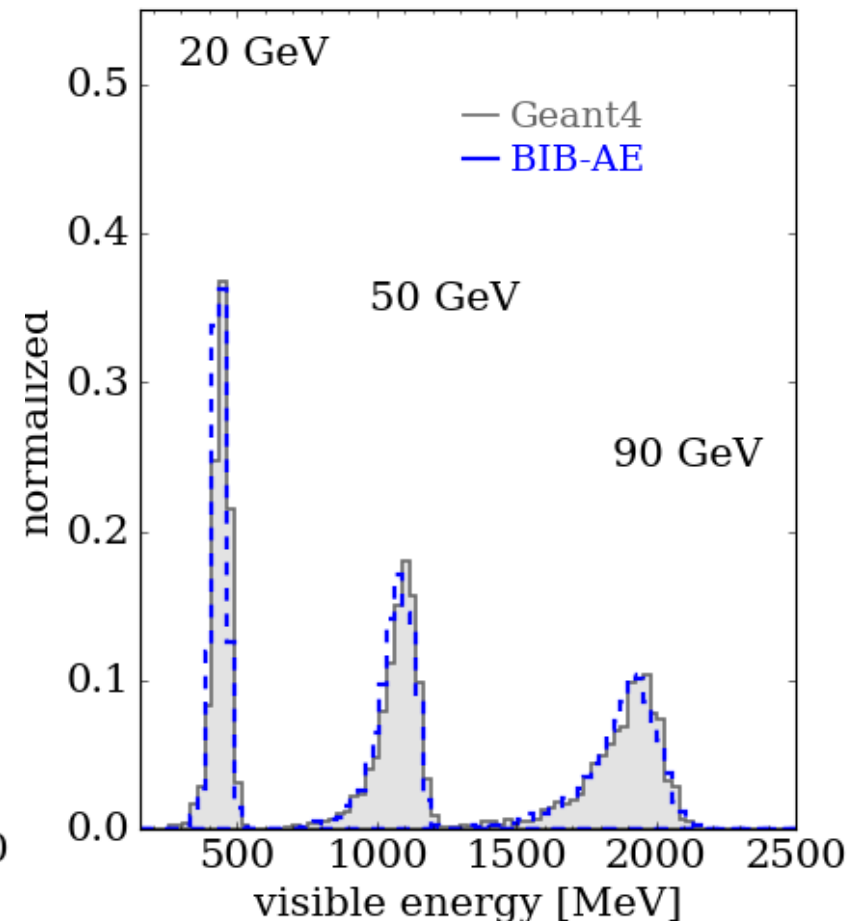
40 degree Photons



60 degree Photons

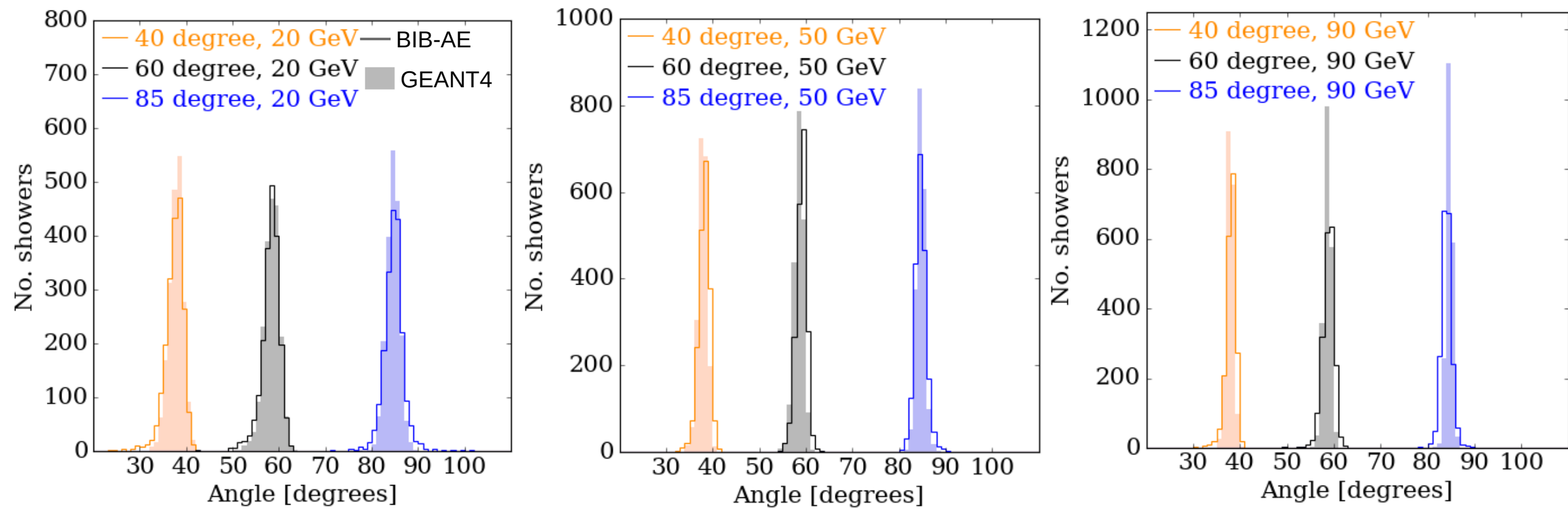


85 degree Photons



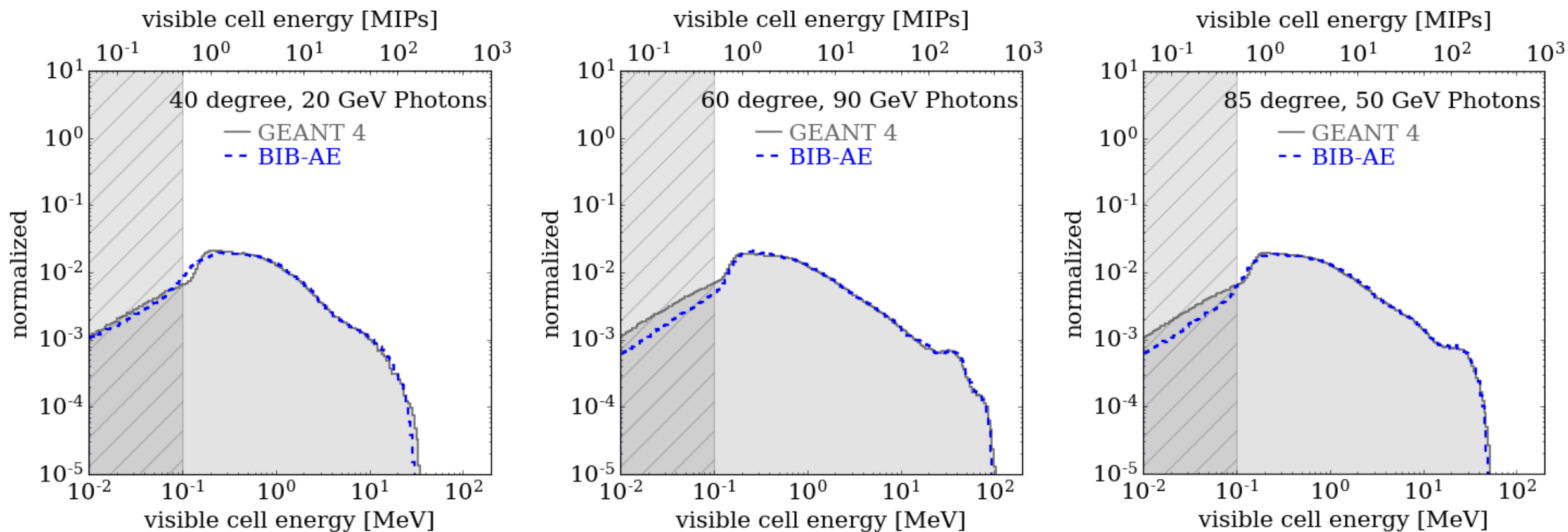
Results: Angular Reconstruction Distributions

- Angular distributions agree well for given incident energies after reconstruction with a PCA



Results: Cell Energy Spectrum

- Post Processor Network retains its ability to correctly describe the cell energy distribution

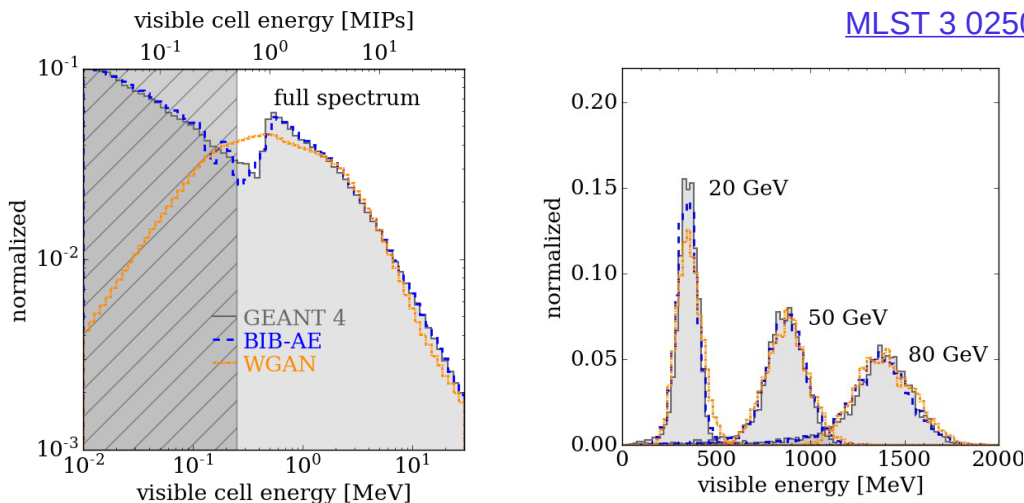


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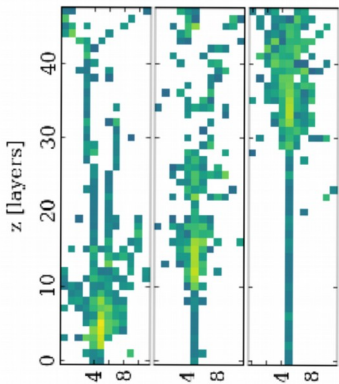
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