High Fidelity Simulation of High Granularity Calorimeters with High Speed

LCWS Workshop

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arxiv:2005.05334











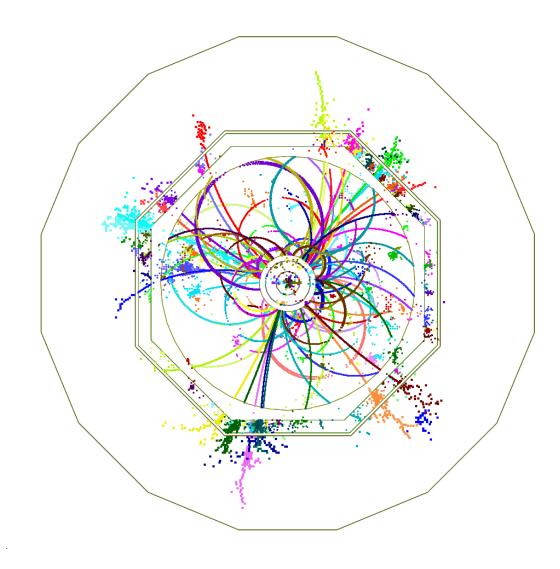
High Granularity Calorimeter

Very fine segmentation of channels

- Reconstruct all individual particle showers
- Optimised for Particle Flow Approach (PFA)
 - ✓ Improve overall precision

Examples:

- ILD detector at ILC (Higgs Factory):
 - * Si-W ECAL (5x5mm) + Scintillator-Steel HCAL (30x30mm)
- CMS High Granularity Calorimeter (HGCAL)



Shower Simulation

- Particle showers in the calorimeter are simulated by Geant4
 First-principle physics based simulation
- Very CPU intensive, due to large number of interacting particles

Goal:

- Reproduce accurate shower simulations with a faster, powerful generator; based on state-of-the-art generative models
- Enormous amounts of CPU time could be potentially saved!

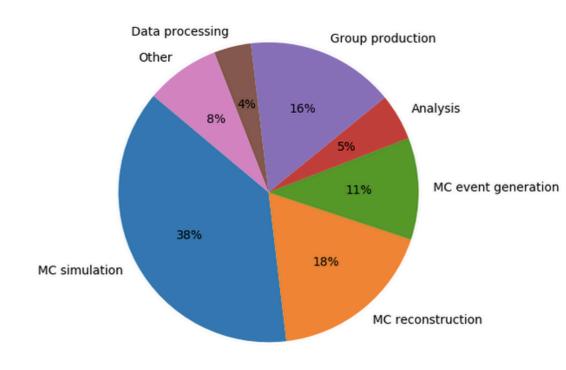
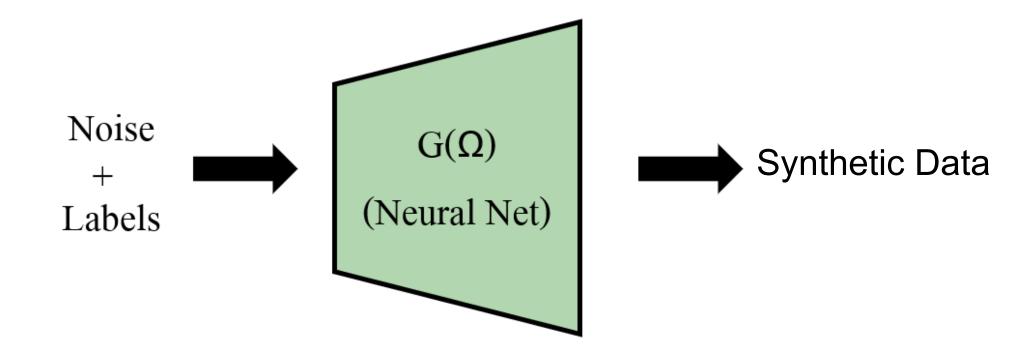


Figure from D.Costanzo, J.Catmore, LHCC meeting

Generative Models

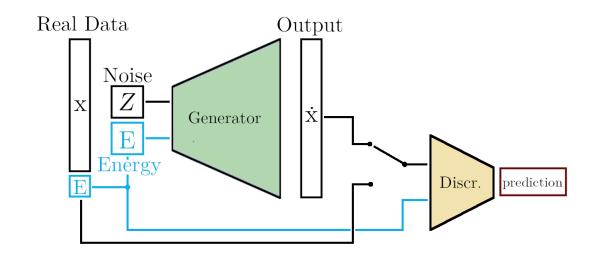
- Promising solution: generative models
 - Generate new samples following the distribution of original data
 - Map random noise to data
 - Conditioning



Generative ModelsGAN and WGAN

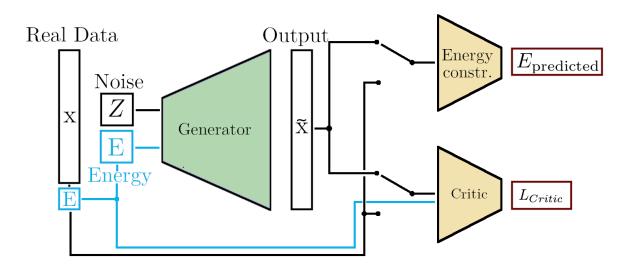
Generative Adversarial Network (GAN)

- Generator generates new fake images from noise
- Discriminator tries to differentiate: Fake or Real?
 - **⇒** Binary classification



Wasserstein GAN (WGAN)

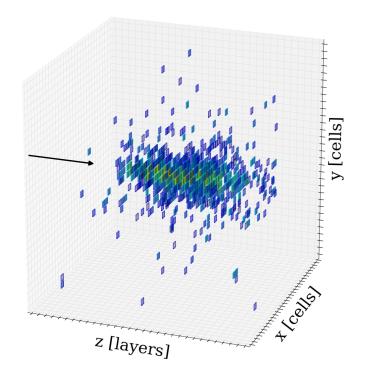
- Alternative to classical GAN training
 - → Helps improve the stability of the training
 - → Use Wasserstein-1 distance as a loss function
 - → Critic network does regression (i.e. gives a score)
- Second network to constrain the energy

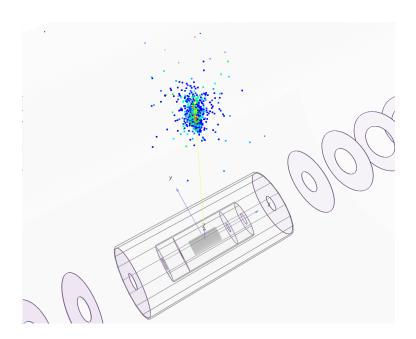


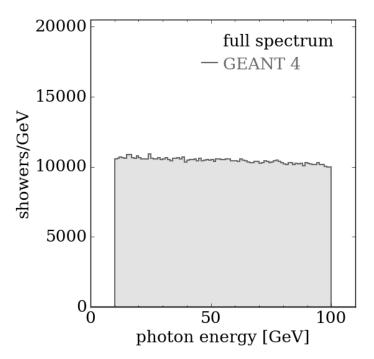
Training Data

Geant4 Simulation

- Shooting photon perpendicular to the ILD-ECAL (Si-W)
 - Constant incident point
 - 950k photon showers
 - Photon energy: 10-100 GeV, continuous!
 - 30x30x30 pixels, centered on beam







Results Intermediate () Output Input Sampling Geant4 Difference Critic $L_{CriticDiff}$ realistic??? Post Processor Network Decoder Encoder y [cells] σ L_{Critic} Critic KLD MSE $L_{CriticL}$ $\mathcal{N}(0,1)$ MMD $L = \mathrm{KLD} + L_{CriticL} + L_{Critic} + L_{CriticDiff}$ $L_{\rm II} = {\rm MMD} + {\rm MSE}$ z [layers] **GAN WGAN** BIB-AE y [cells]

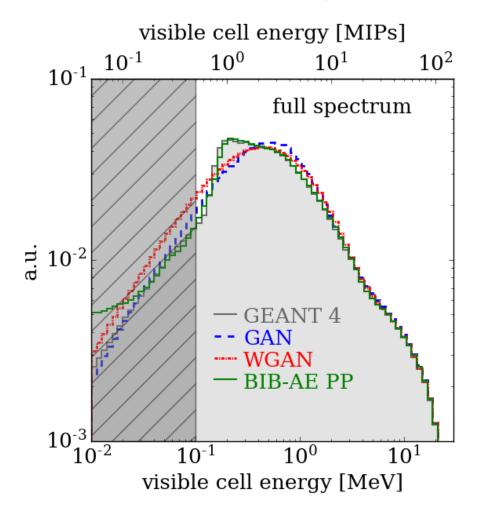
z [layers]

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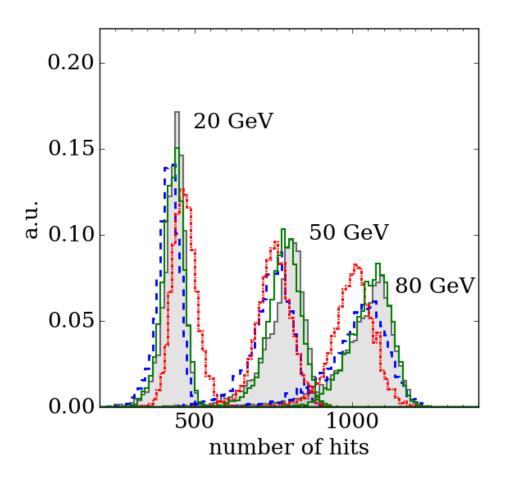
z [layers]

y [cells]

Results: Cell energy and Number of hits

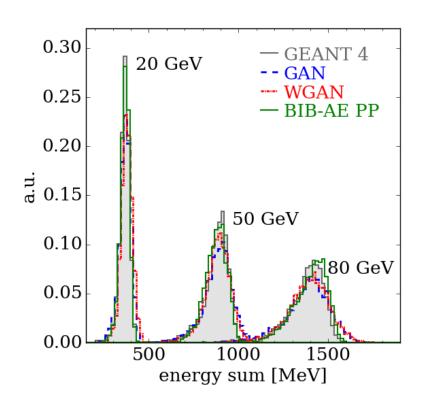


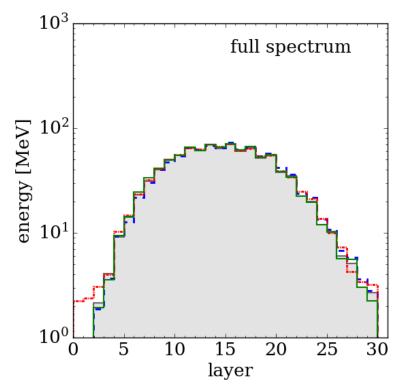
- Both GAN and WGAN <u>fail</u> to capture MIP bump around 0.2 MeV
- ✓ BiB-AE is able to produce this feature thanks
 to Post-Processing network

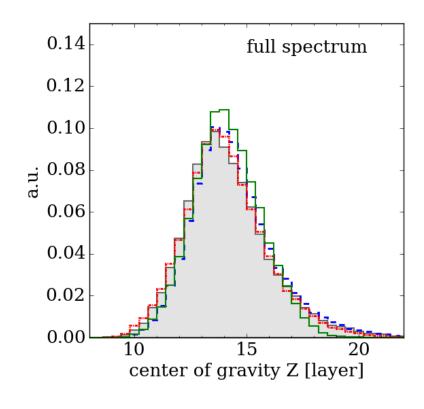


- GAN and WGAN slightly <u>underestimate</u> the total number of hits
- ✓ BiB-AE reproduces the shape and width

Results: Other important distributions







- ✓ the shape, center and width of the peak are well reproduced for all models
- ✓ reproduce the bulk of the distributions very well.
 - slight deviations for the WGAN appear around the edges
- Deviations for BiB-AE:
 - ✓ Explainable via latent space encoding
 - ✓ Recent publication [arxiv: 2102.12491]

Computation Time

| Simulator | Hardware | Batch Size | 15 GeV | Speed-up | 10-100 GeV Flat | Speed-up |
|-----------|----------|------------|--------------------------------|----------|---------------------------------|----------|
| GEANT4 | CPU | N/A | $1445.05 \pm 19.34 \text{ ms}$ | - | $4081.53 \pm 169.92 \text{ ms}$ | - |
| WGAN | CPU | 1 | $64.34 \pm 0.58 \text{ ms}$ | x23 | $63.14 \pm 0.34 \text{ ms}$ | x65 |
| | | 10 | $59.53 \pm 0.45 \text{ ms}$ | x24 | $56.65 \pm 0.33 \text{ ms}$ | x72 |
| | | 100 | $58.31 \pm 0.93 \text{ ms}$ | x25 | $58.11 \pm 0.13 \text{ ms}$ | ×70 |
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| BIB-AE | CPU | 1 | $426.60 \pm 3.27 \text{ ms}$ | х3 | $426.32 \pm 3.62 \text{ ms}$ | x10 |
| | | 10 | $422.60 \pm 0.26 \text{ ms}$ | x3 | $424.71 \pm 3.53 \text{ ms}$ | x10 |
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| | | 10 | $1.56 \pm 0.01 \text{ ms}$ | x1287 | $1.57 \pm 0.01 \text{ ms}$ | x2600 |
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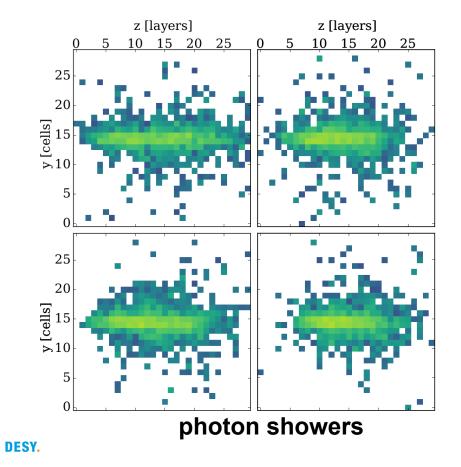
For 10-100 GeV showers, BiB-AE and WGAN

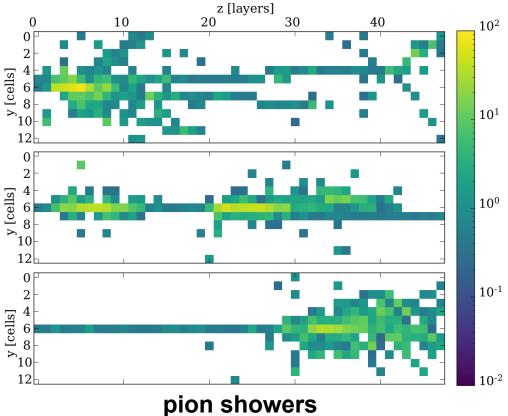
- 3 orders of magnitude speed-up on **GPU**
- 2 orders of magnitude speed-up on **CPU**

Hadron Showers

very preliminary

- After success with GAN based simulation for electromagnetic showers, we started to address hadronic (pion) showers
- Much more complex shower structure
- Currently training with a smaller 3D image containing only the **shower core**
- Started with GAN, WGAN, BIB-AE and alternatives





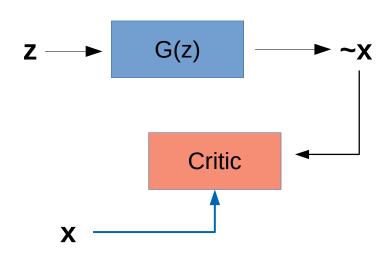
VS.

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A new WGAN

- Trained on pion showers. Approx half a million
- Shower is 48x13x13
- Architectures
 - very similar to WGAN in our "getting high paper"
 - Latent Optimized WGAN, inspired by DeepMind

Our classical WGAN



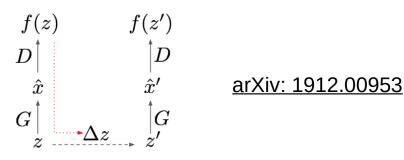
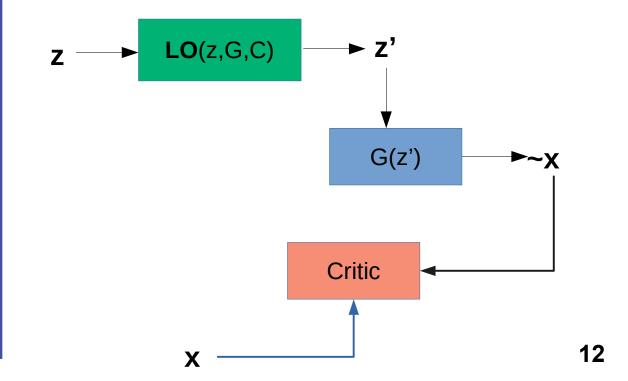
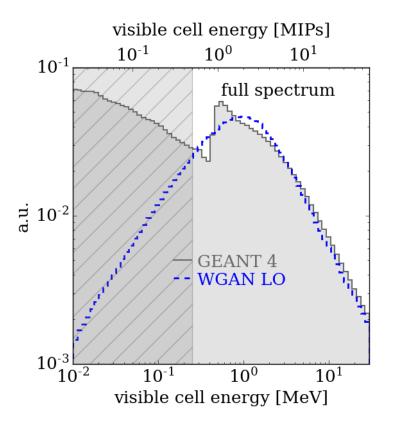


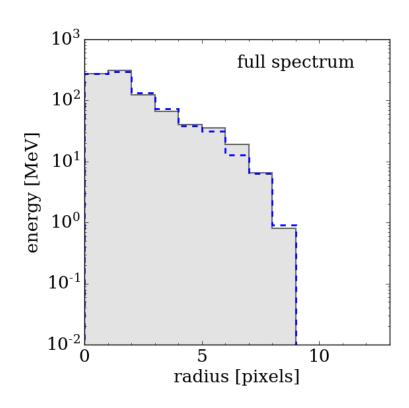
Figure 3: (a) Schematic of LOGAN. We first compute a forward pass through G and D with a sampled latent z. Then, we use gradients from the generator loss (dashed red arrow) to compute an improved latent, z'. After we use this optimised latent code in a second forward pass, we compute gradients of the discriminator back through the latent optimisation into the model parameters θ_D , θ_G . We use these gradients to update the model. (b) Truncation curves illustrate the FID/IS trade-off

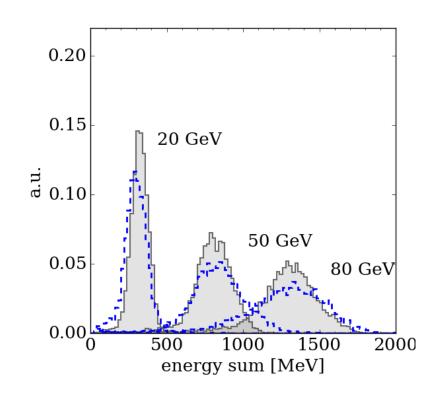


Hadron Showers

very preliminary results



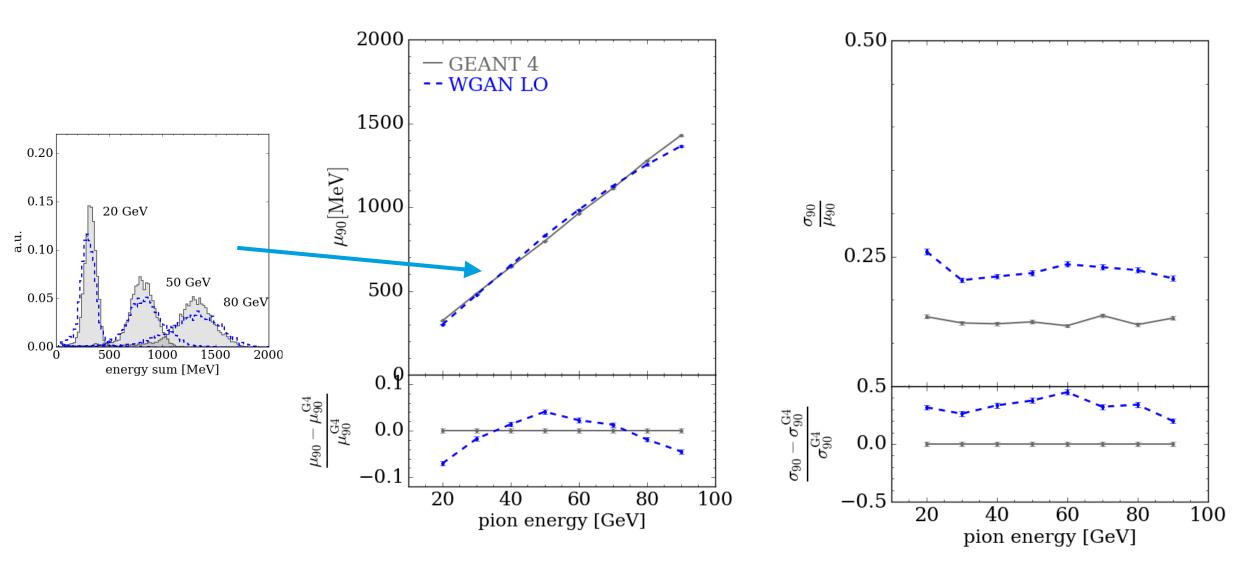




✓ Difficult to model MIP peak, but encouraging results for first attempts!!

Hadron Showers

very preliminary results

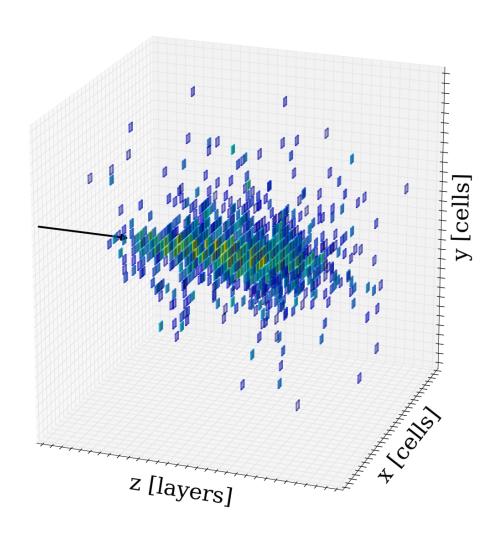


✓ Linearity is overall in a good agreement, room for improvements for the relative width

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Conclusion

- ▶ Application of generative models to high resolution EM shower simulation
 - ✓ Modelling of MIP peak and high fidelity
 - √ Speedup: 3 orders of magnitude
- Architectures:
 - GAN
 - WGAN
 - BIB-AE (New!)
- Future Plans:
 - condition on incident position/angle
 - hadron showers (Promising results!)
 - integrate into existing tools / frameworks



Paper: [arxiv:2005.05334] (submitted to journal, soon to be published)

Backup

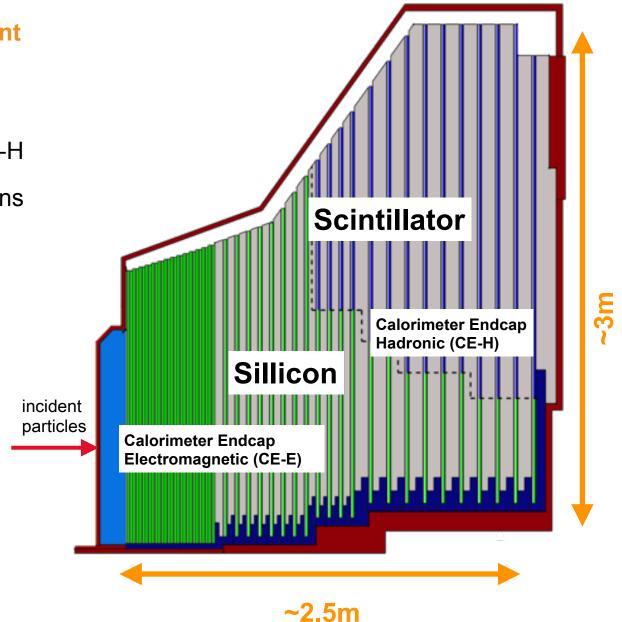
New Challenge: CMS HGCal

Planned High Granular Calorimeter for CMS Experiment

- HGCAL is a sampling calorimeter
- Silicon sensors in CE-E and high radiation regions of CE-H
- Scintillating tiles with SiPM readout in low-radiation regions of CE-H
- 3D imaging calorimeter with timing capabilities

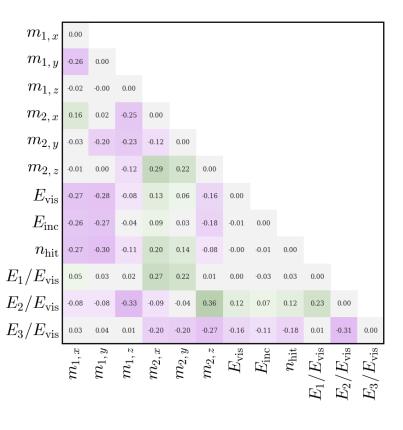
Application of generative networks to CMS HGCal has started in our group with close collaboration with experts in the field

Stay tuned for our preliminary results!!

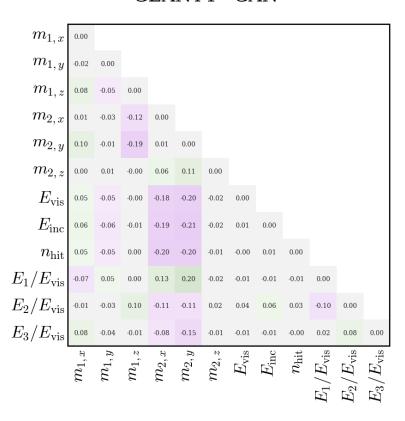


Correlations

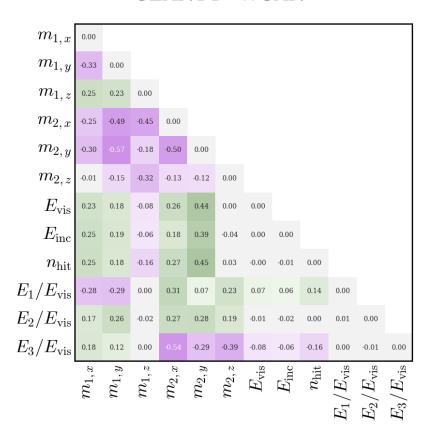
GEANT4 - BIB-AE PP



GEANT4 - GAN



GEANT4 - WGAN



✓ Correlations between individual shower properties present in GEANT4 are correctly reproduced by our generative models

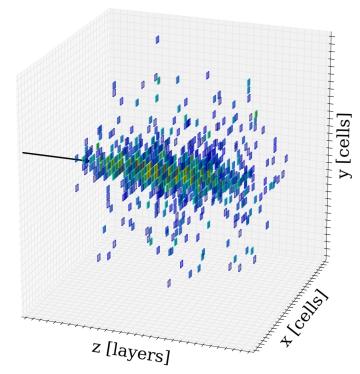
Challenges

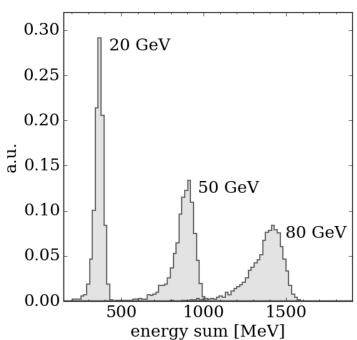
Quality measures:

- Reproduce Geant4 showers
- <u>Shower shape variables</u> have to be examined, especially:
 - Number of hits
 - Radial & longitudinal profile
- Differential energy distributions: shape & accuracy

Energy conditioning

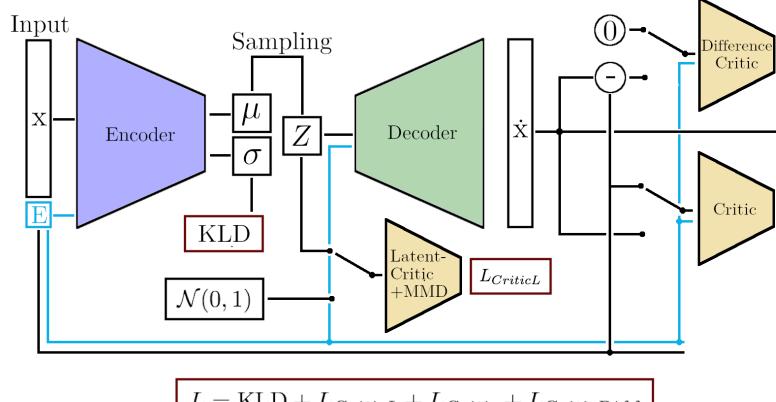
- Condition generator / decoder on incoming particle's energy
 - Not same as visible (or reconstructed) energy!





BiB-AE

arXiv:1912.00830

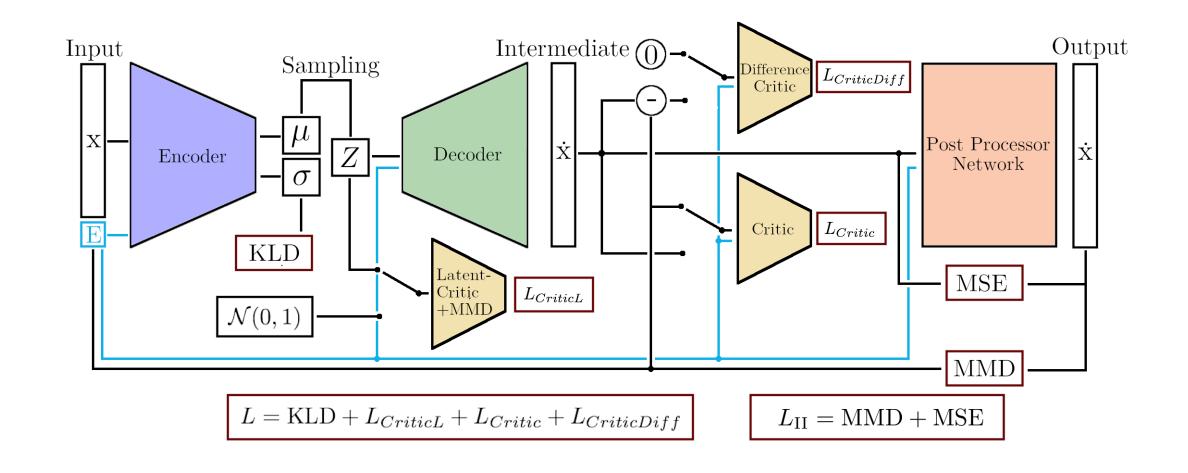


$$L = KLD + L_{CriticL} + L_{Critic} + L_{CriticDiff}$$

Bounded Information Bottleneck AutoEncoder (BiB-AE)

- It expands VAE structure
- Additional critics for
 - ▶ Latent space regularisation
 - Reconstruction
- Inspired by CS paper

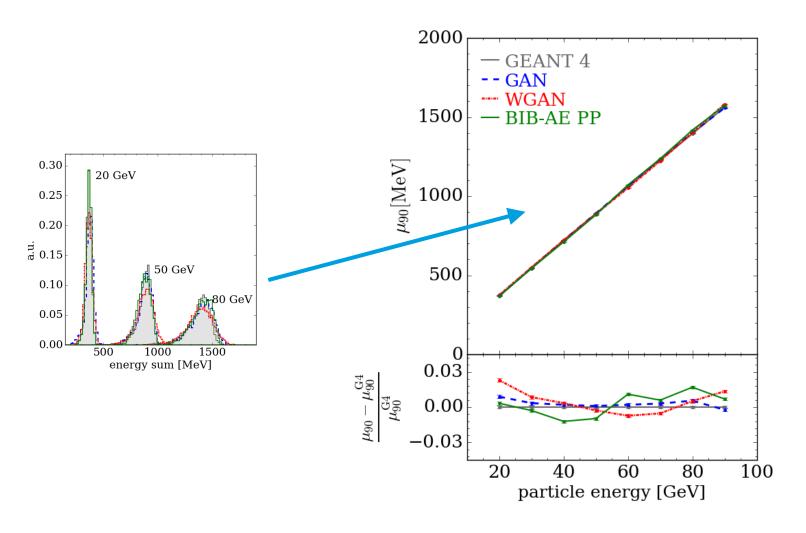
BiB-AE

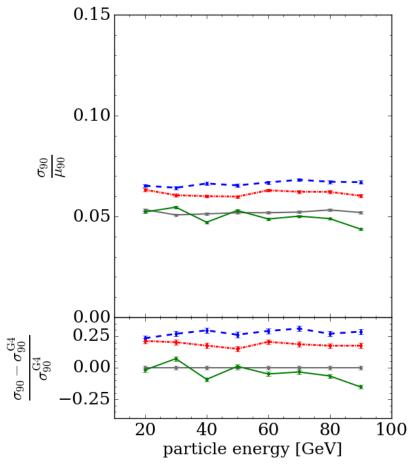


Post Processor Network for final cell-energy tuning!!

DESY. 21:

Results: Linearity and Width

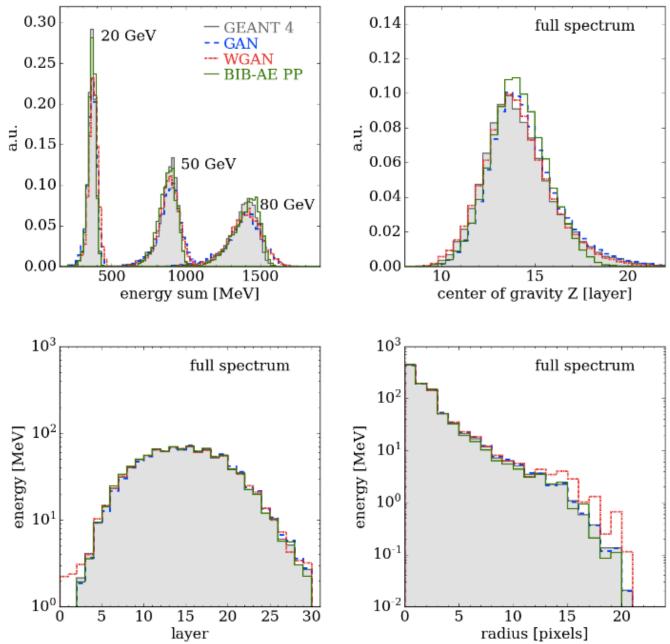




✓ Overall good modelled by all generative models. Deviations up to few percent

Overestimated by GAN and WGAN

Distributions...



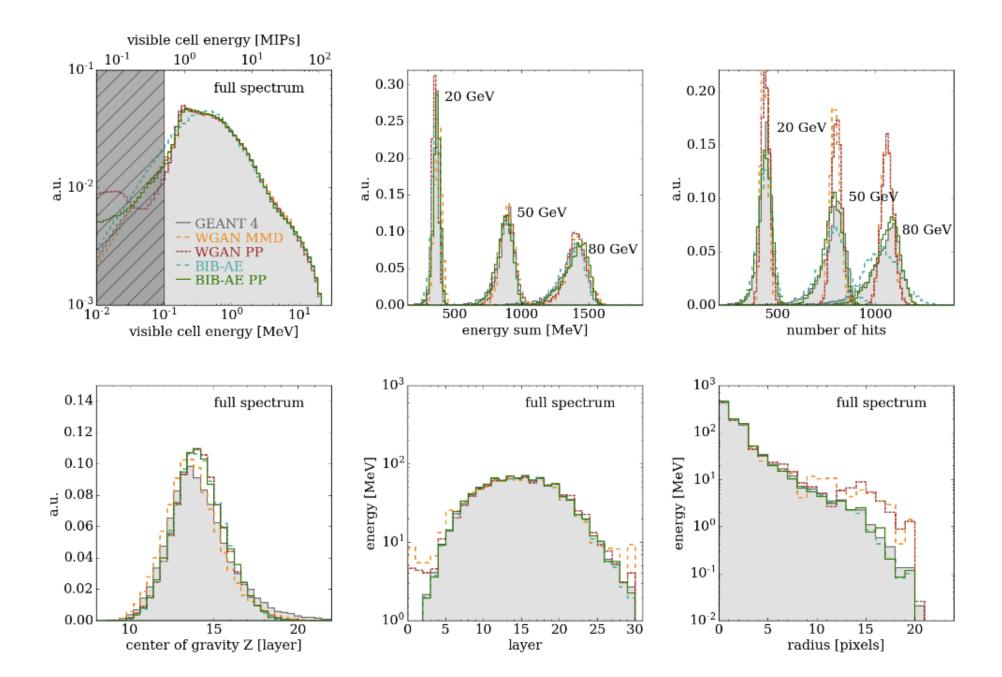
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For 10-100 GeV showers, Bib-AE and WGAN

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WGAN + PP



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