Speedup of Extensive Air Shower Simulations with Deep Neural Networks

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CORSIKA Cosmic Ray Simulation Workshop Karlsruhe (2019)

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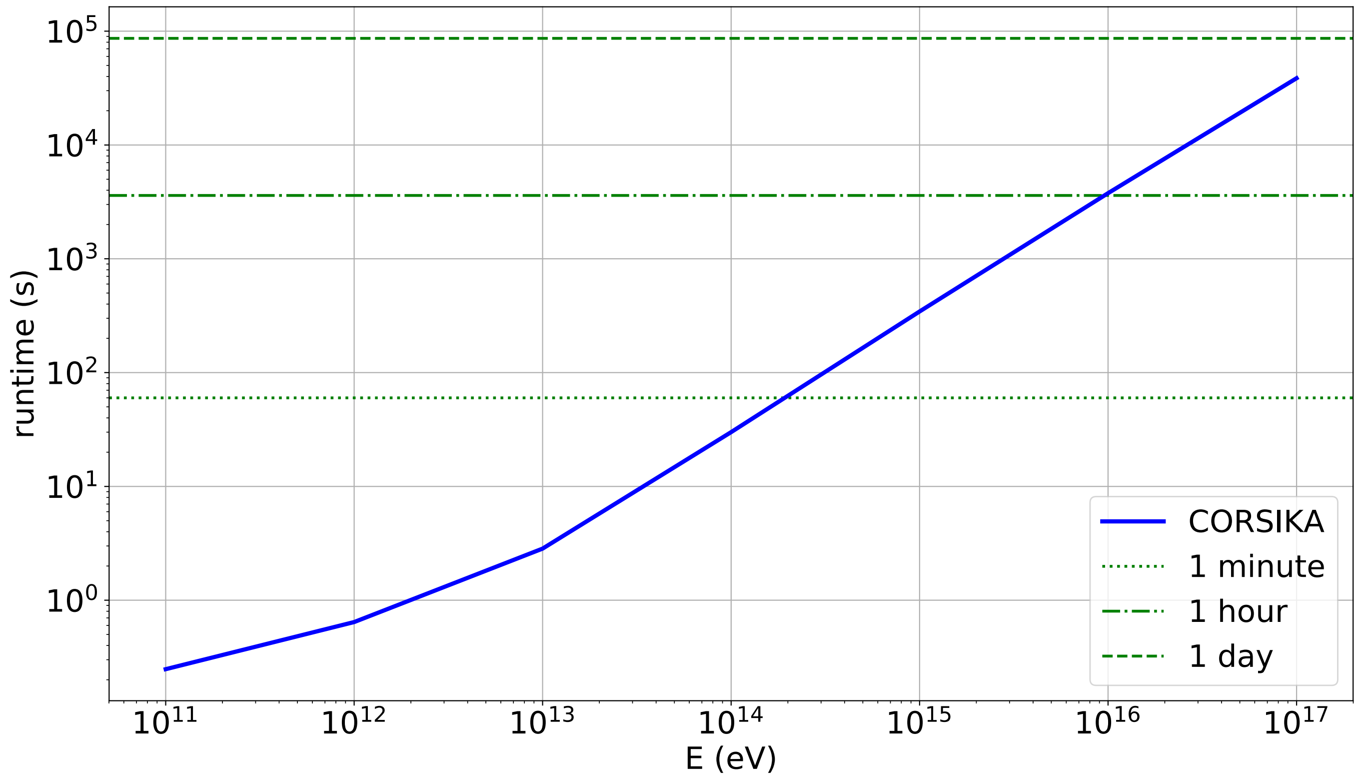
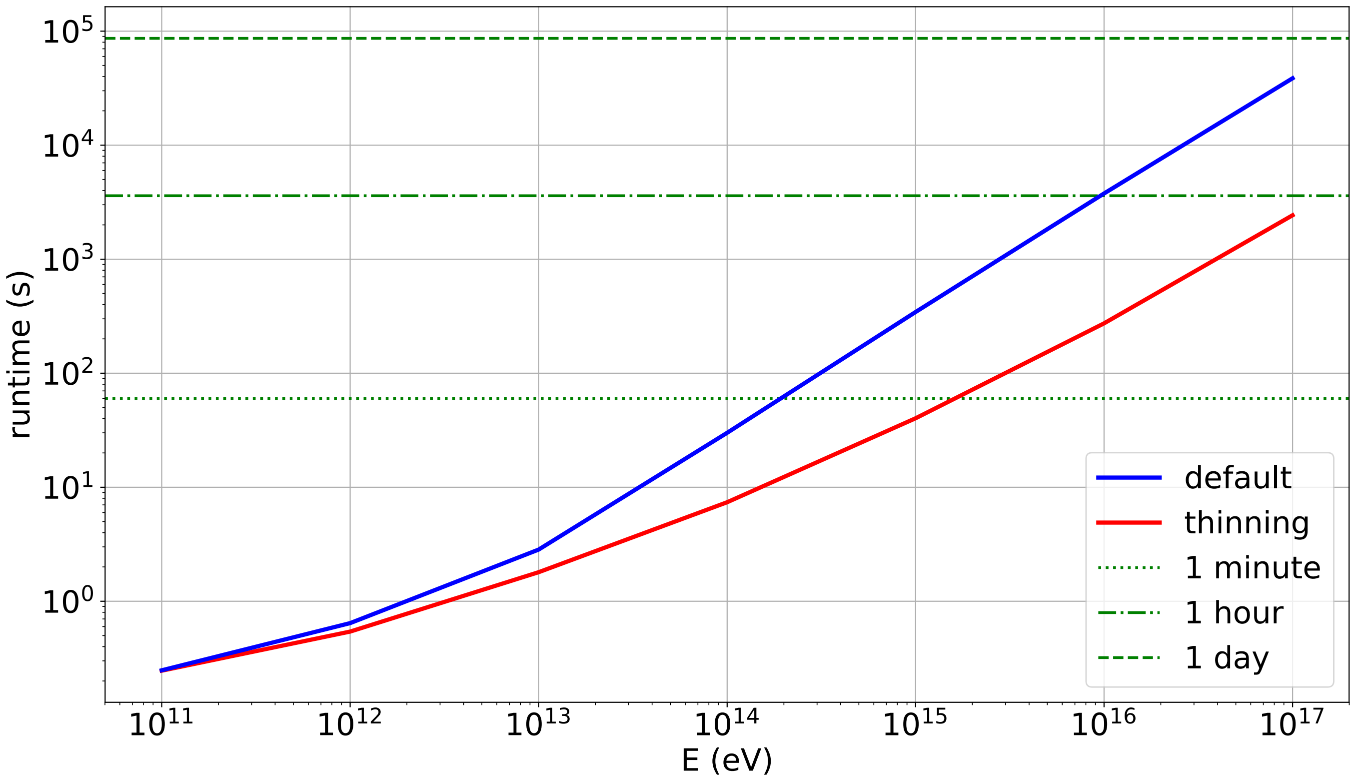
Motivation

- 

- The time complexity of CORSIKA 7 simulations rises approximately linearly with the primary particle energy

Thinning



- Reduces (effective) particle content by particle-aggregation
- Preserves shower properties to leading order
- Reduces shower-to-shower fluctuations

Why Neural Networks?

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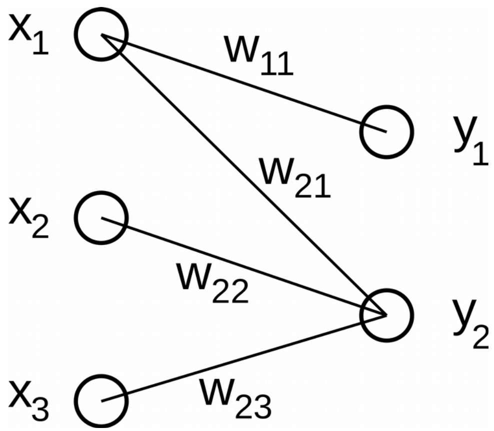
- Can run on specialized **hardware** (GPU / TPU)
- Automatic **parallelization** (TensorFlow)
- Reduction to **essential features**
- Training can **fix meta-parameters**
- **Adjustable accuracy** possible

Neural Networks

- 

$$y_1 = w_{11} \cdot x_1 + w_{12} \cdot x_2 + w_{13} \cdot x_3$$

$$y_2 = w_{21} \cdot x_1 + w_{22} \cdot x_2 + w_{23} \cdot x_3$$

$$\vec{y} = w \cdot \vec{x} \ (+\vec{b})$$

$$\vec{f} = a(\vec{y})$$

- Combination of linear and non-linear functions
- Training via loss function / metric on data pairs $(\vec{x}, \vec{t})$
- $L = L(\vec{f}(\vec{x}), \vec{t}) \quad \Rightarrow \quad w' = w - \alpha \cdot \nabla_w L$

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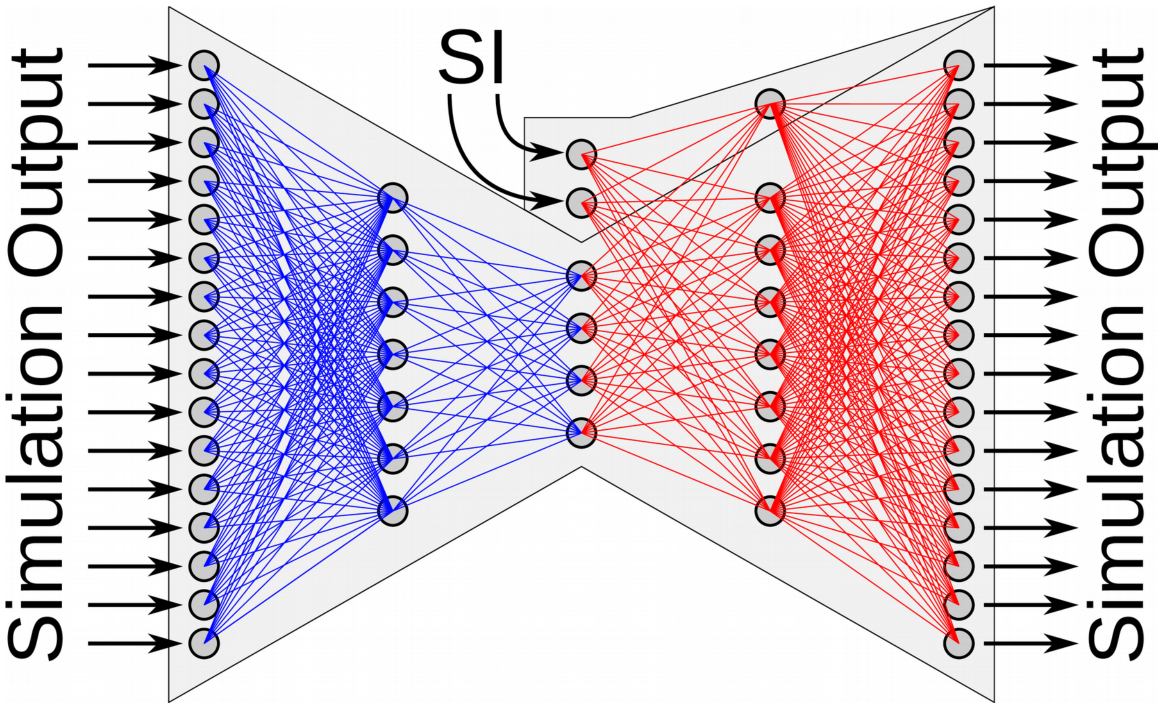
Generative Neural Networks

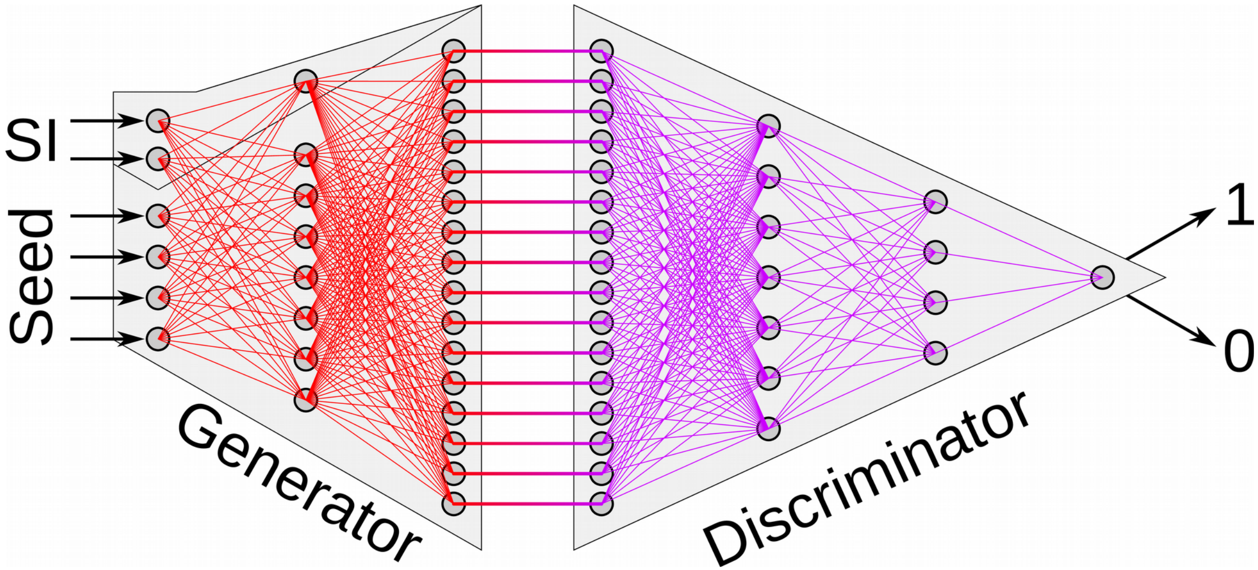
- Autoencoder



- Problem: Explicit definition of metric

Generative Neural Networks

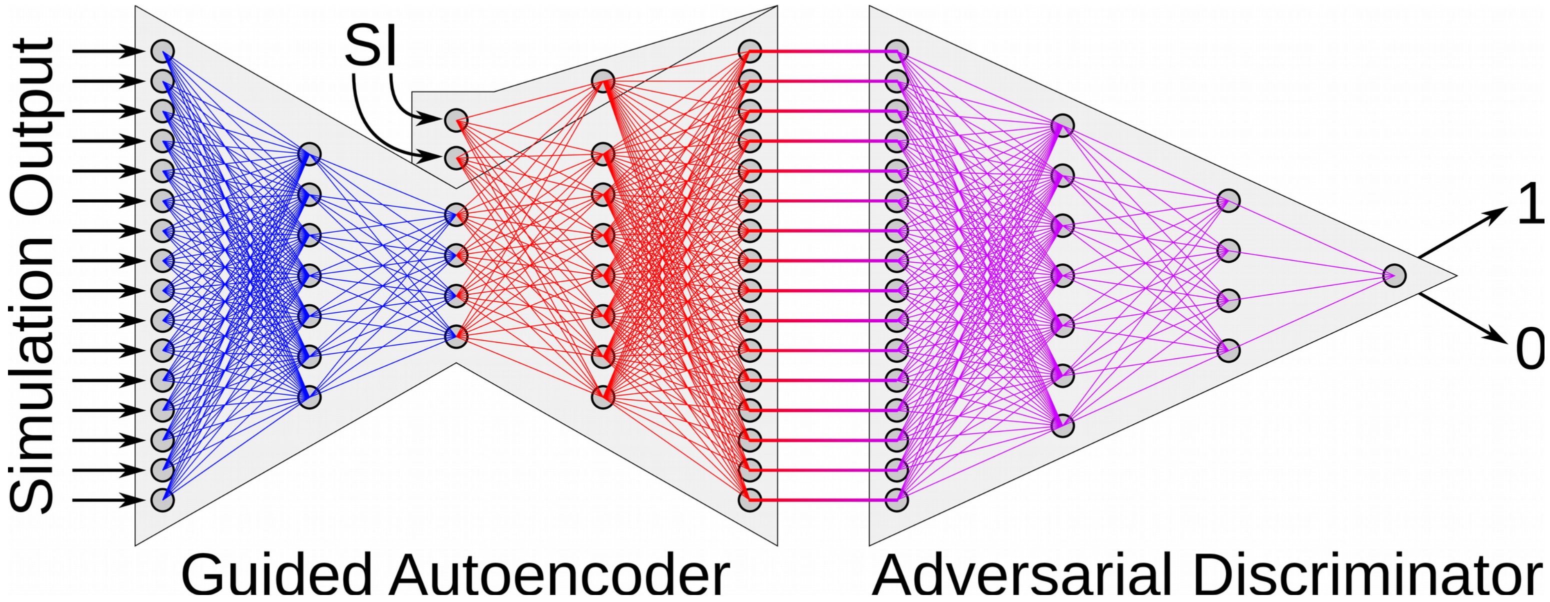
- Adversarial Neural Network



- Train discriminator on real (1) and generated (0) data
- Train generator to outsmart the discriminator

Fast Implicit Simulation Heuristic

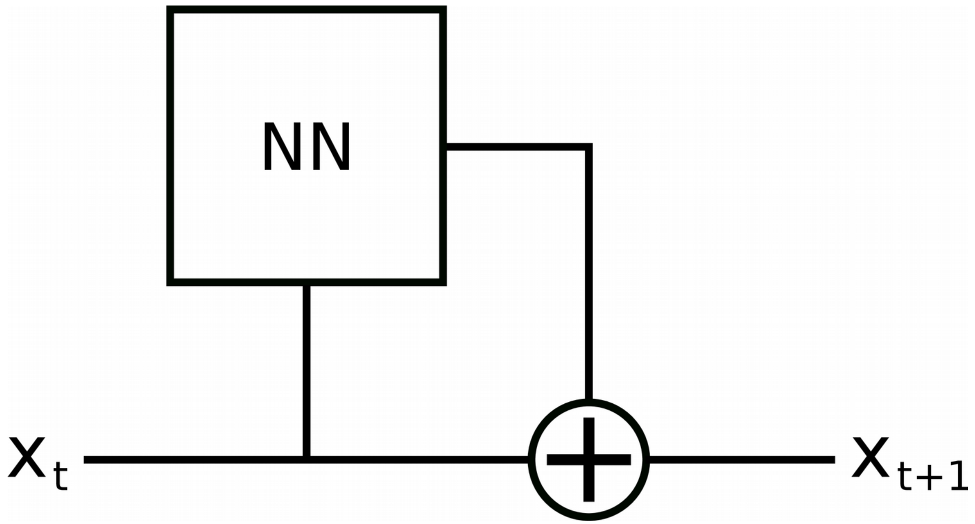
- Autoencoder with Adversarial Metric



- Simulation Input (SI) can be extended with meta-parameters
- Discriminator can be refined with real measurements

Adjustable Accuracy [1]

- ResNet



- Translate to ordinary differential equation (ODE)

$$x_{t+1} = x_t + f(x_t, \theta_t) \quad \Rightarrow \quad \frac{dx(t)}{dt} = f(x(t), t, \theta)$$

- Solve with standard ODE solver

- Adapt solver accuracy on the fly (training: high, inference: low)

Working Example [2]

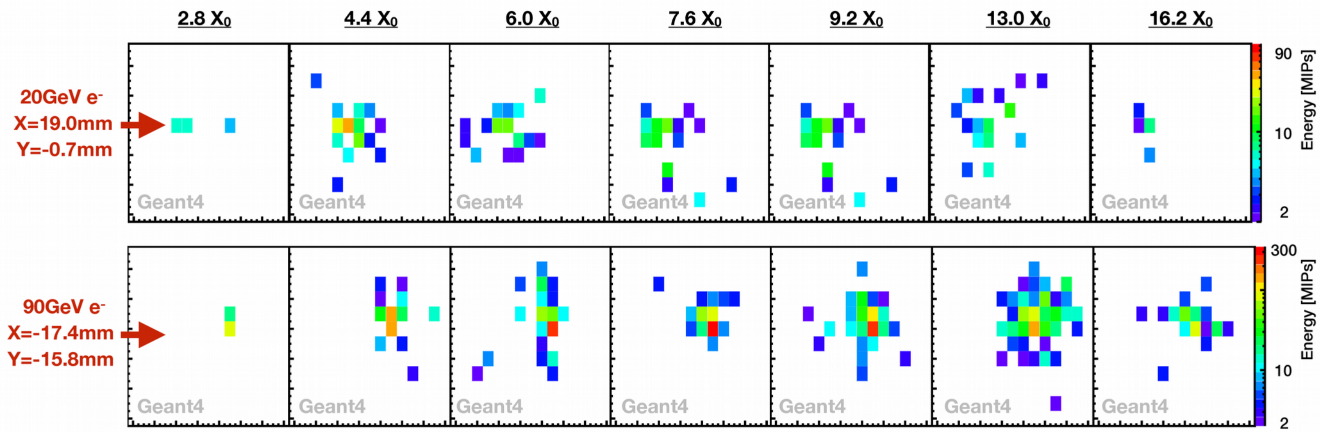
- „Precise simulation of electromagnetic calorimeter showers using a Wasserstein Generative Adversarial Network“ - Martin Erdmann, Jonas Glombitza, Thorben Quast – arXiv: 1807.01954

  Some Highlights:

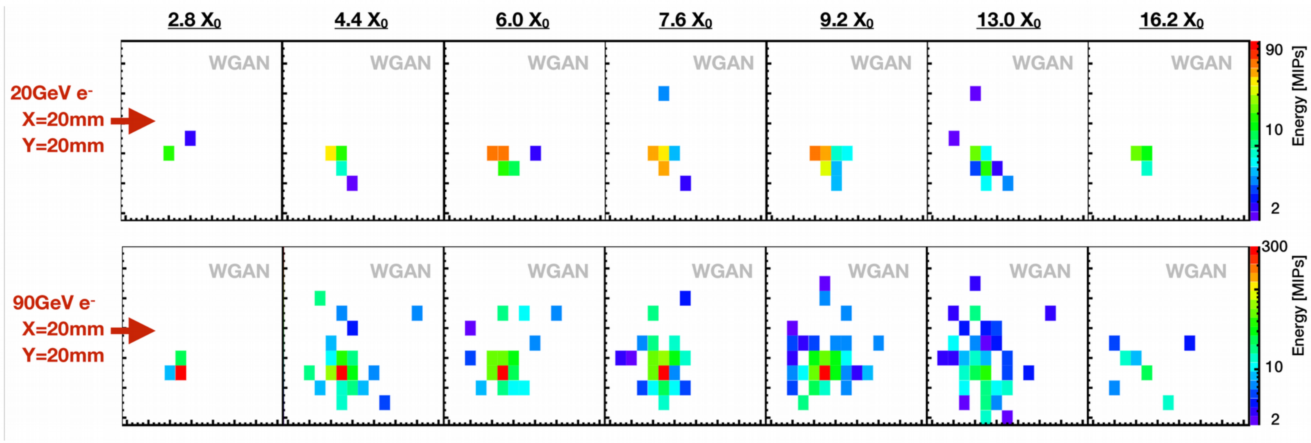
- **Wasserstein GAN** for HEP Geant4 simulations
- **Interpolation** between training energies
- Up to **x6660 faster** than Geant4
- Runtime is **independent of particle energy**

Geant4 vs. Wasserstein GAN [2]

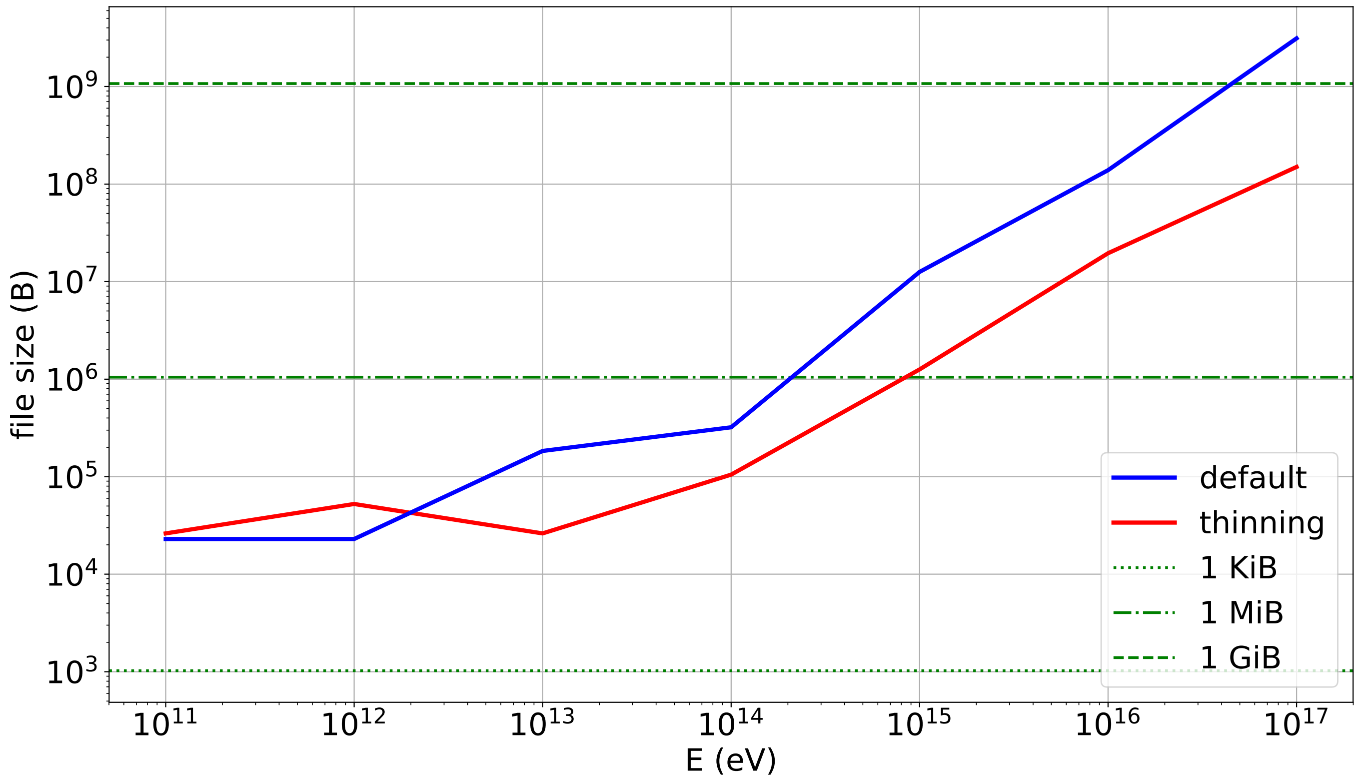
- Geant4:



- Wasserstein GAN:



Integration into CORSIKA 8



- Shower library needed for analyses and model training
- Trained model = effective compression of shower library
- Integrate training into CORSIKA 8? $\Rightarrow$ Transmit model updates?

Summary

- Deep Neural Networks can serve as an effective simulation heuristic
- Can improve runtime and (effective) data compression
- Can employ specialized hardware
- Trained models can be conditioned on meta-parameters
- Adjustable accuracy is possible
- ErUM: Innovative Digitale Technologien zur Erforschung von Universum und Materie

References

- Title picture:
  Karlsruhe Castle - Meph666 [CC BY-SA 3.0]
  https://commons.wikimedia.org/wiki/File:Karlsruhe-Schloss-meph666-2005-Apr-22.jpg

- [1] „Neural Ordinary Differential Equations“ - Ricky T. Q. Chen, Yulia Rubanova, Jesse Bettencourt, David Duvenaud – arXiv: 1806.07366

- [2] „Precise simulation of electromagnetic calorimeter showers using a Wasserstein Generative Adversarial Network“ - Martin Erdmann, Jonas Glombitza, Thorben Quast – arXiv: 1807.01954