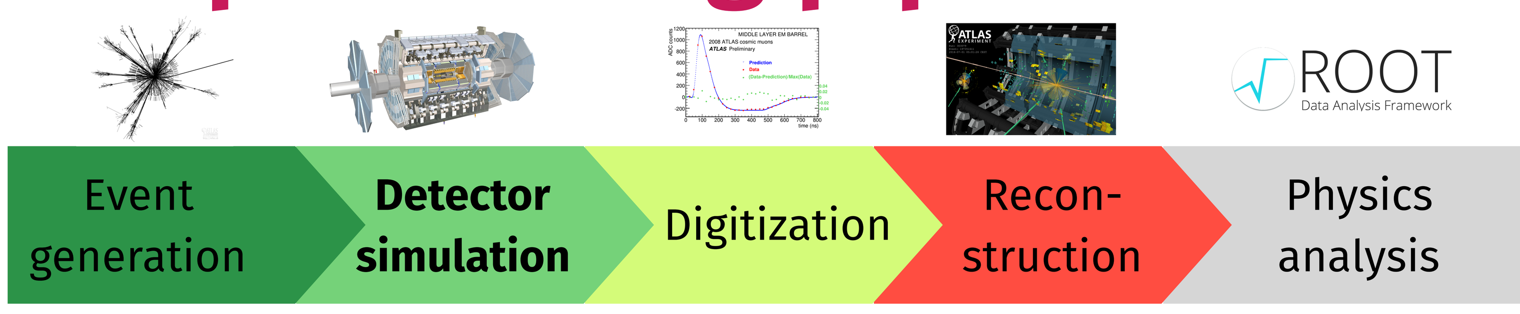
Fast Calorimeter Simulation in ATLAS

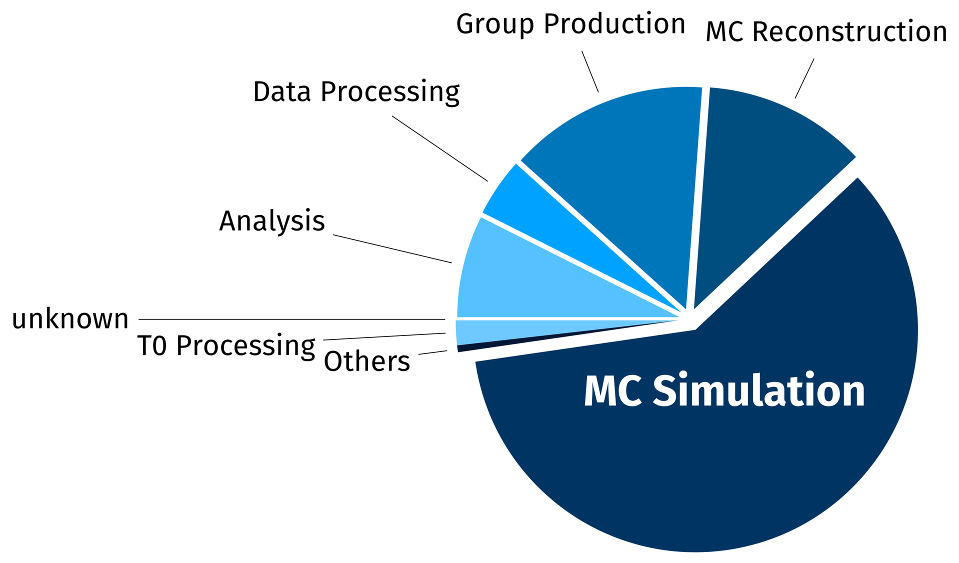
ICHEP 2018 Poster Session, Seoul

Abstract

The need for **large scale and high fidelity simulated samples** for physics analyses at the LHC motivates the development of new simulation techniques. ATLAS already relies strongly on **fast calorimeter simulation** techniques based on thousands of individual parametrizations of the calorimeter response [1], achieving a significant speed-up over the full simulation of the detector response at the cost of accuracy. Current developments [2,3] aim at improving the modelling of the particle shower's substructure. Building on the recent success of deep learning algorithms, the application of **Variational Auto-Encoders** [4,5] and **Generative Adversarial Networks** [6] is investigated, too [7]. The properties of synthesized photon showers in the electromagnetic calorimeter show promising agreement with showers from a full detector simulation using Geant4, opening the possibility to **complement current simulation techniques**.

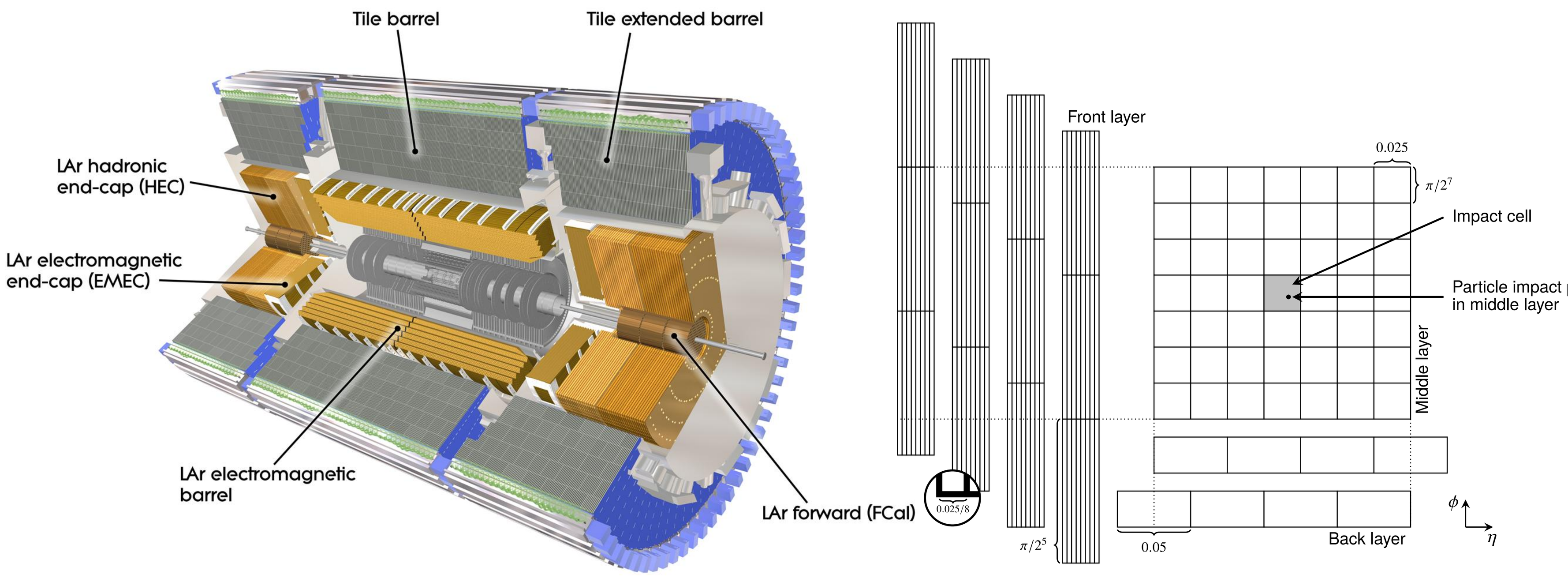
Data processing pipeline





The **grid CPU usage** in 2017 was dominated by MC production, yet many physics analyses are limited by available statistics. A more precise detector simulation leads to higher CPU consumption. With increasing data rates, even more events need to be simulated.

ATLAS calorimeter

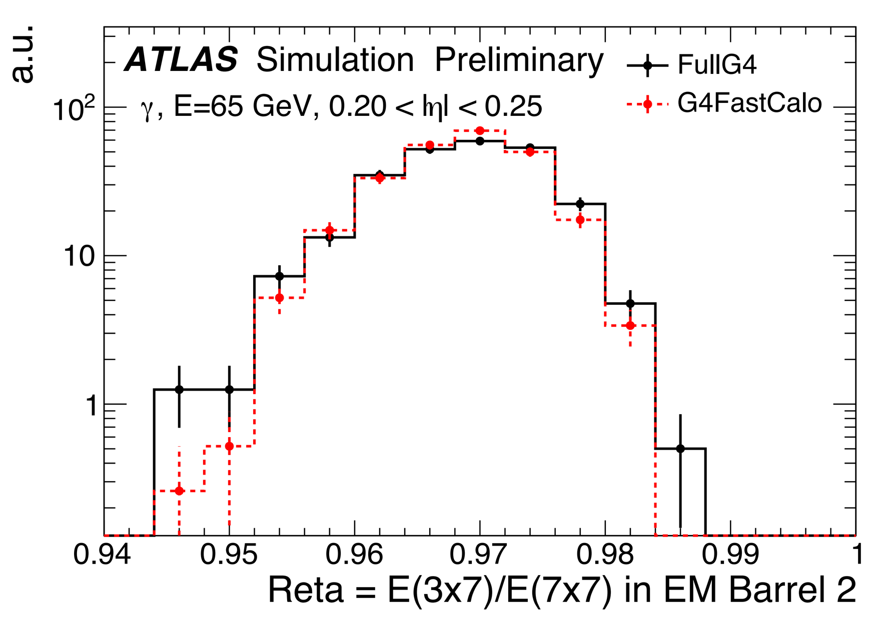


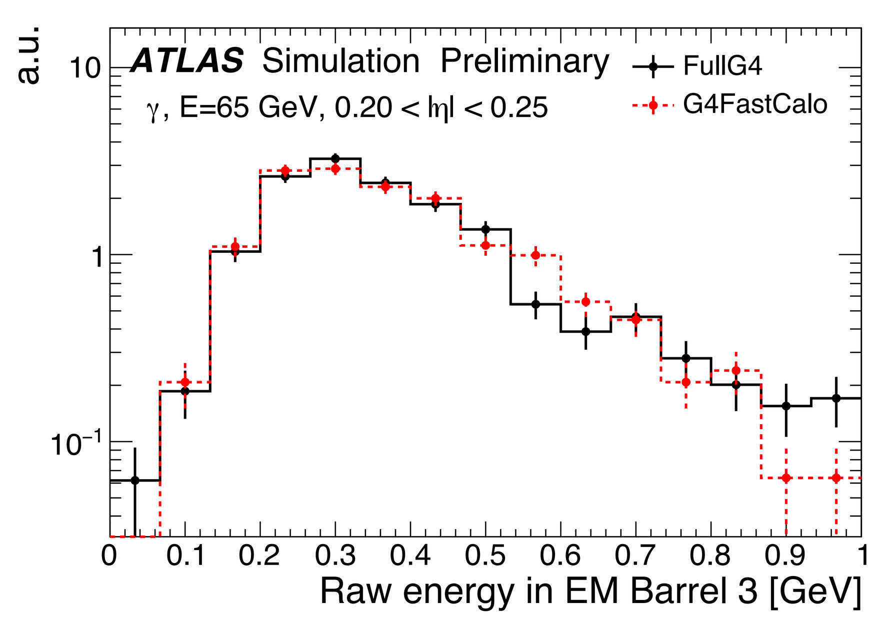
The presented results focus on **photon showers** in the barrel of the electromagnetic (EM) calorimeter, made from liquid argon (active) and lead (absorber). The ATLAS calorimeter has approximately 190.000 readout channels of which approximately 110.000 are in the **EM barrel**. For training generative neural networks rectangular selections containing >99% of the shower energy are applied. FastCaloSim also considers electron and pion showers as well as the hadronic calorimeter and the forward regions.

FastCaloSim developments

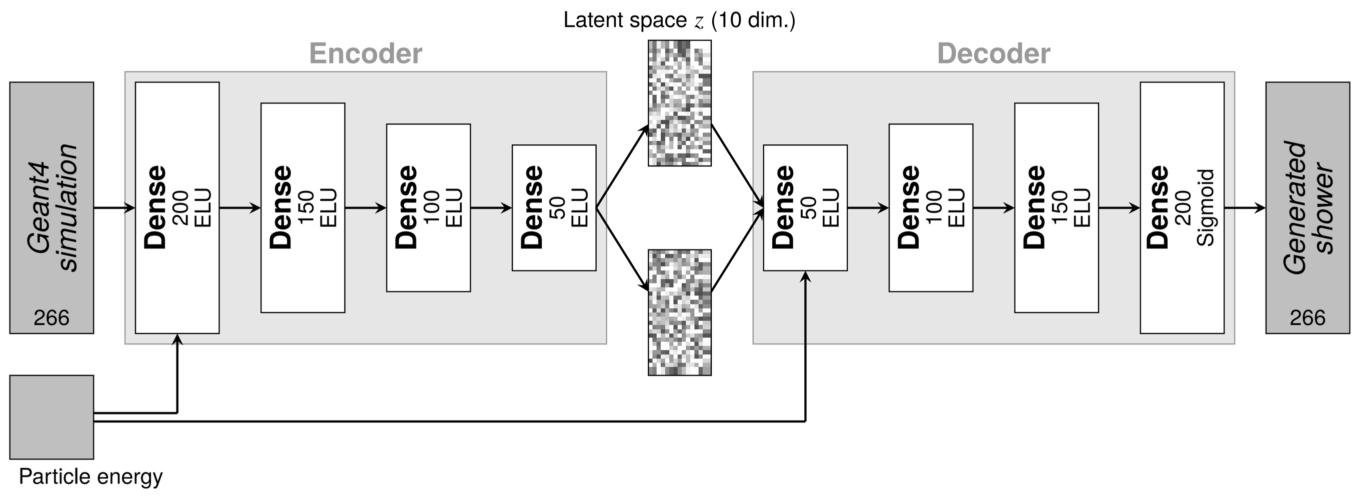
Building on top of a **parametrized calorimeter response** in an E-η grid for the **longitudinal and lateral shower development** derived from Geant4 simulated single particles, several developments are ongoing:

- Improved modelling of the total energy and (correlated) energy deposits per layer through employing a principal component analysis.
- Employ multilayer perceptrons to perform shower regression and reduce memory footprint.
- Incorporate lateral shower fluctuations to describe shower substructure.
- Correct for usage of simplified geometry, and use full forward geometry.



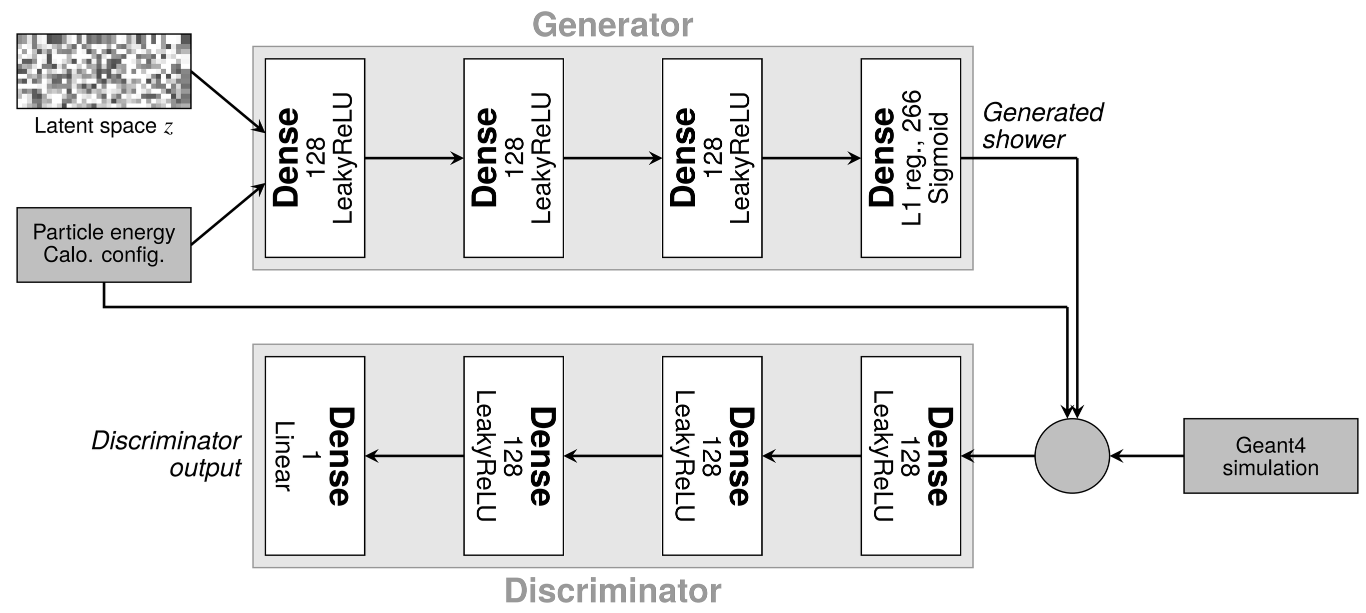


Variational Auto-Encoder



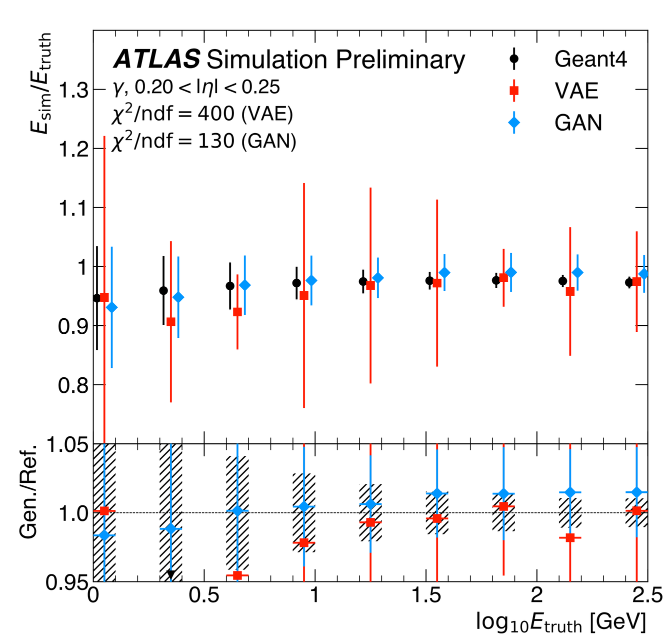
Variational Auto-Encoders (VAEs) are a class of unsupervised learning algorithms combining **deep learning** with **variational Bayesian methods**. Two stacked neural networks act as **encoder** and **decoder** respectively. VAEs are **latent variable models** that introduce a set of random variables that are not directly observed but used to explain and reveal underlying structures in the data. The encoder compresses the shower into the latent space, while the decoder reconstructs it. By sampling from the latent representation, new showers can be generated. The training of the model maximises the **variational lower bound on the marginal log-likelihood** for the data and **penalises deviations in the total shower energy and the shower development**.

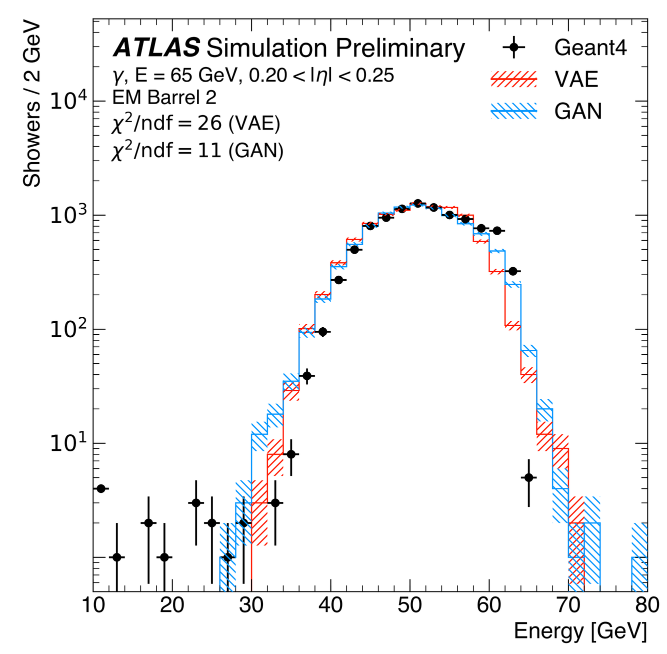
Generative Adversarial Network

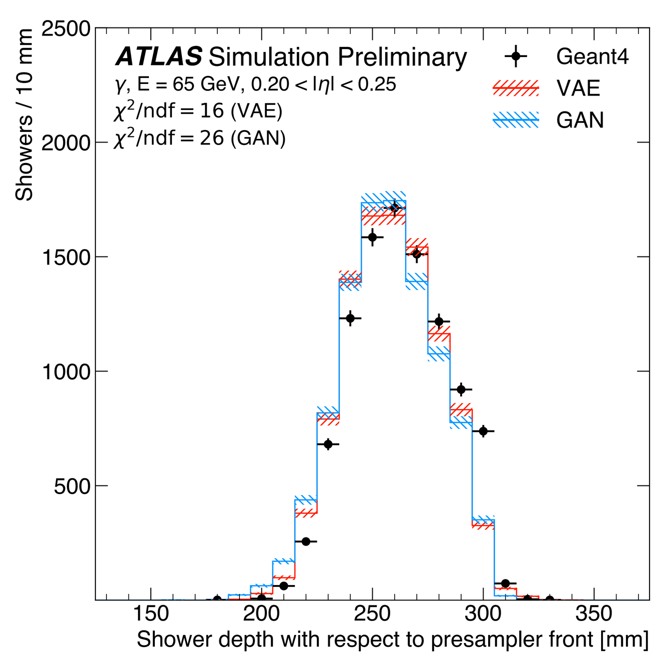


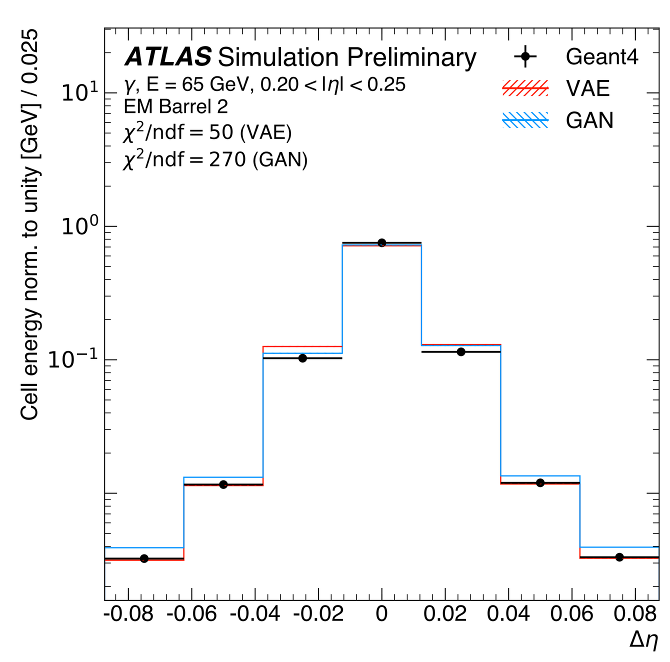
Generative Adversarial Networks (GANs) are a class of unsupervised learning algorithms implemented as a deep **generative** neural network taking feedback from an additional **discriminative** neural network. The generator network learns generating calorimeter showers from a **latent space** distribution. These shower candidates are compared to the full simulation by the discriminator whose training objective it is to **identify the synthesised instances**. The generator is trained to increase the discriminator's misclassification rate and thus generate gradually more realistic distributions. The robustness of the training and the quality of the generated showers is improved through employing a **Wasserstein loss** and a two-sided **gradient penalty** [8] for gradients greater than one.

Validation results









References

[1] The ATLAS Collaboration, ATL-PHYS-PUB-2010-013 (2010).
[2] F. Dias, PoS **ICHEP2016** (2016) 184.
[3] J. Schaarschmidt, J. Phys. Conf. Ser. **898** (2017) 042006.
[4] D. P. Kingma and M. Welling, arXiv: 1312.6114 [stat.ML].
[5] D. Jimenez Rezende, S. Mohamed and D. Wierstra, arXiv: 1401.4082 [stat.ML].
[6] I. J. Goodfellow et al., arXiv: 1406.2661 [stat.ML].
[7] The ATLAS Collaboration, to be published (2018).
[8] I. Gulrajani et al., arXiv: 1704.00028 [stat.ML].

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