Machine Learning for Simulations in Collider Physics

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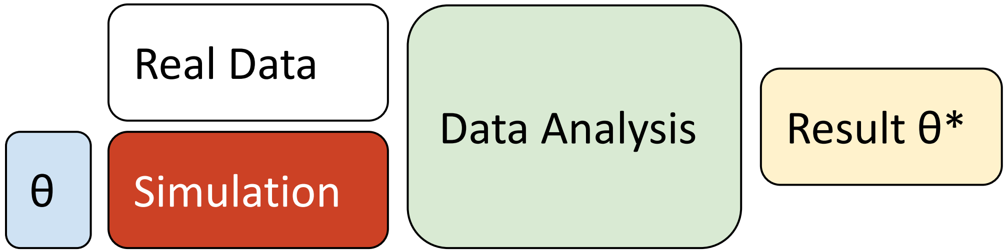
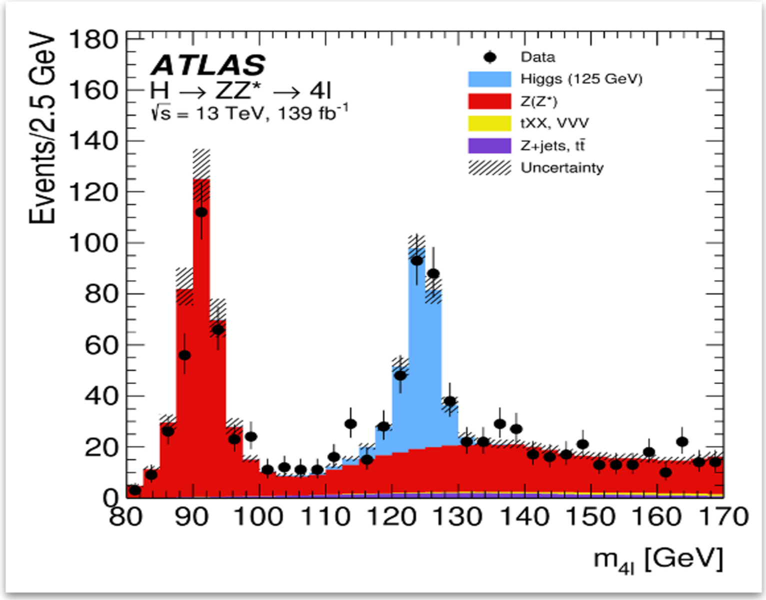
Simulation at Colliders

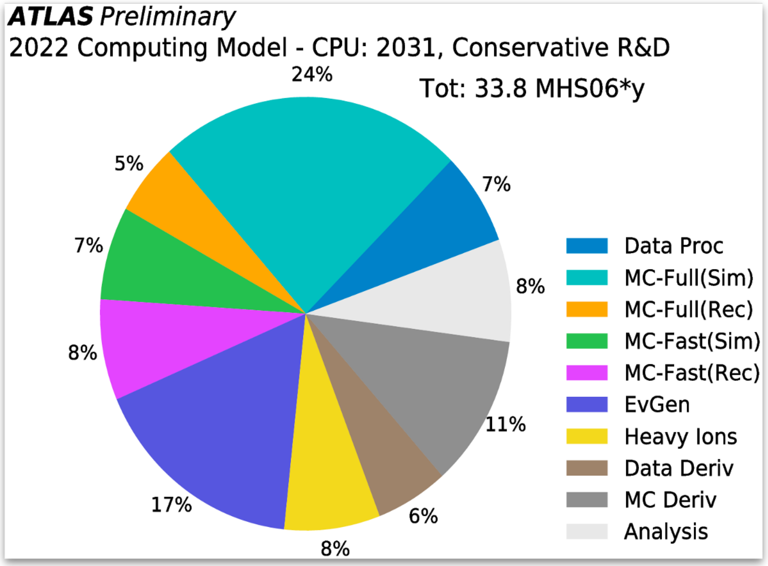


Collider Physics relies heavily on simulation for data analysis, design, etc.

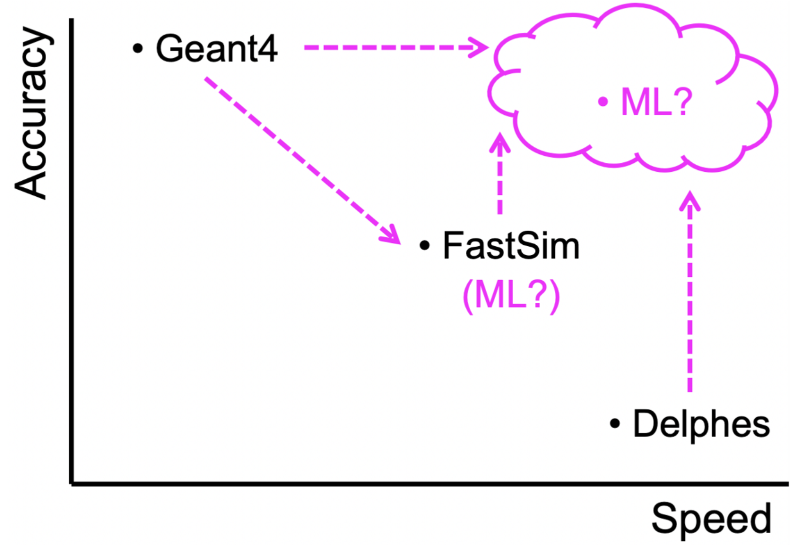
High fidelity simulations are expensive

- Especially detector simulations!

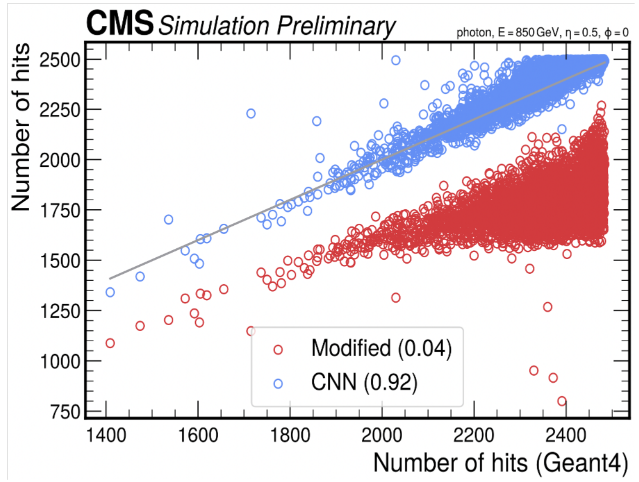




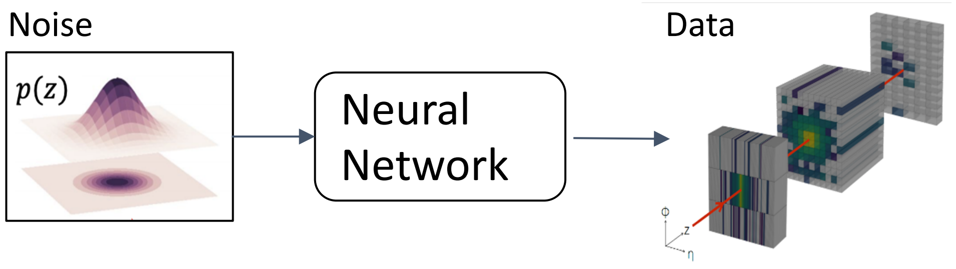
Machine Learning in Simulations

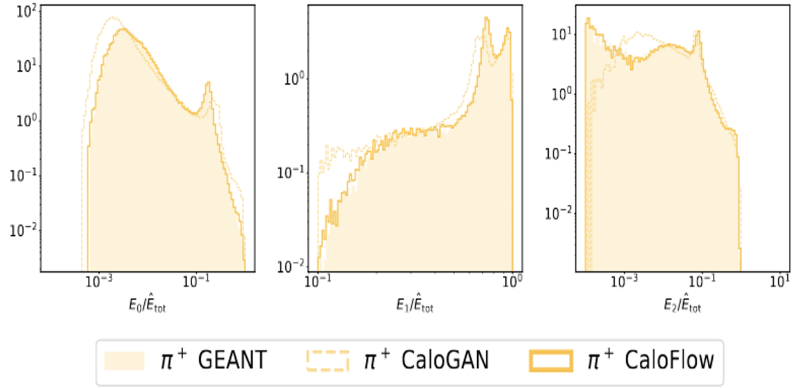


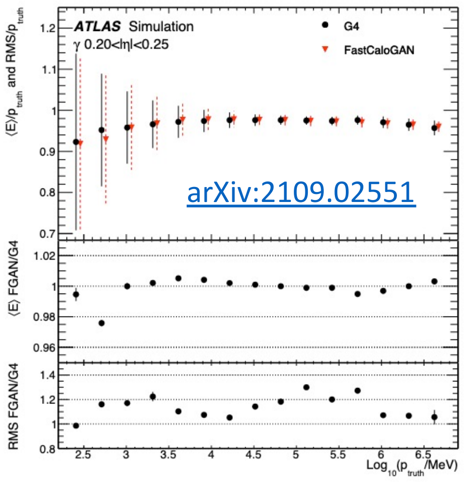
Correct Low Fidelity Simulations



Replace with *Generative Models*



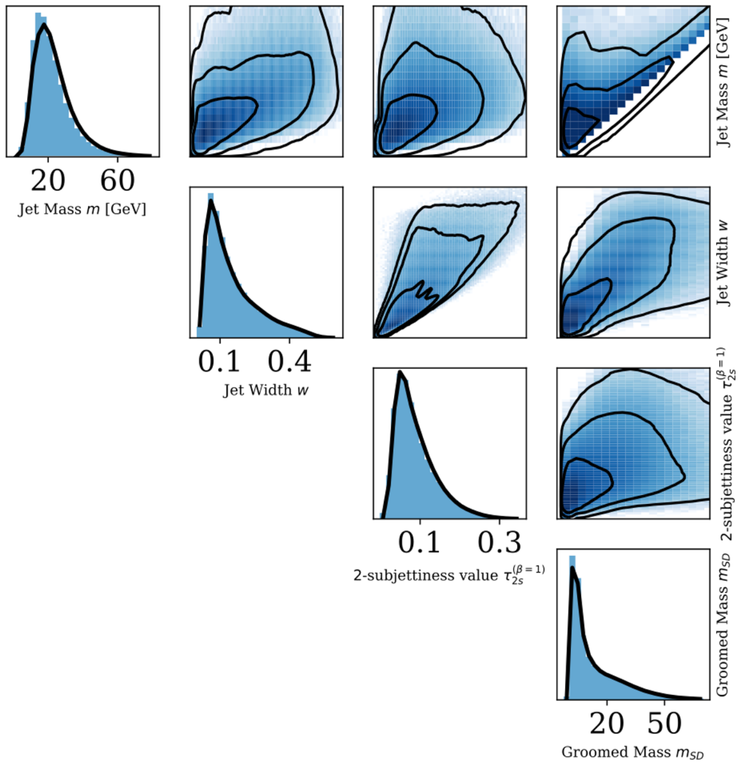




arXiv:2109.02551

Using Surrogates Beyond Data Generation

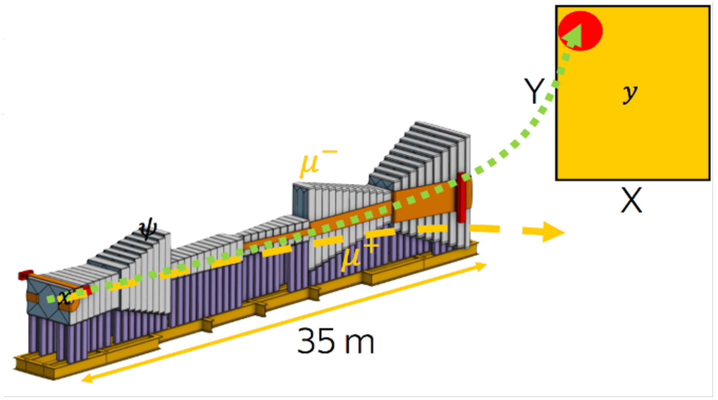
Multi-Dimensional Unfolding



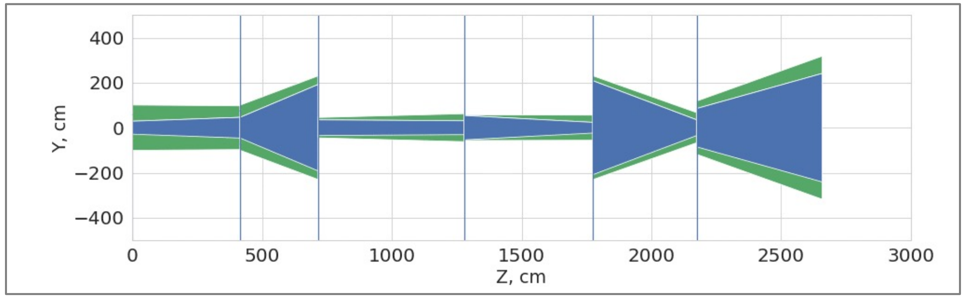
Vandegar, Kagan, et. al,
AISTATS 2021, arXiv:2011.05836

Design Optimization

Optimization of SHiP Magnetic Shield Design



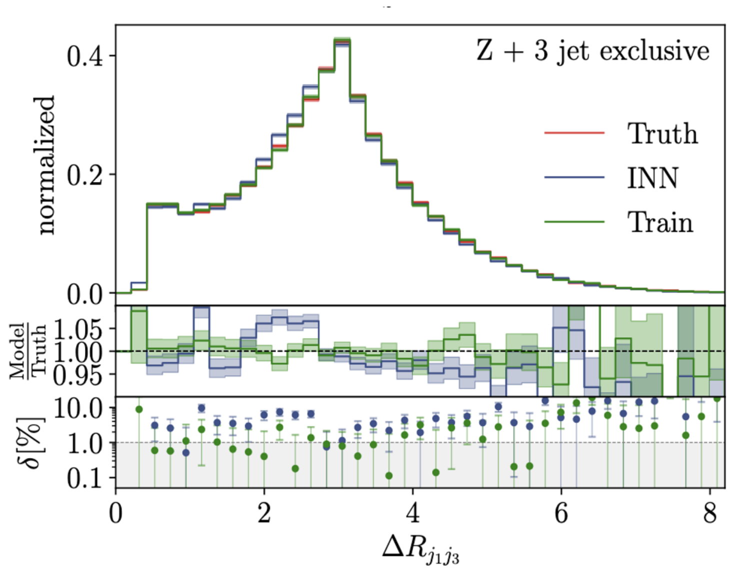
Method	Loss	Length (m)	Weight (kt)
Ours	~ 2200	33.39	1.05
Bayesian opt.	~ 3000	35.44	1.27



Kagan, et. al,
NeurIPS 2020, arXiv:2002.04632

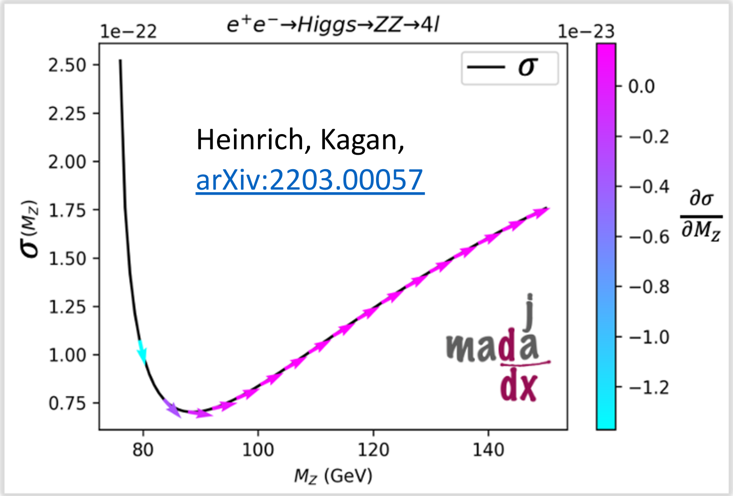
Machine Learning and LHC Event Generation

Surrogate methods can also be used to improve sampling / integration of Matrix Elements



At SLAC, we are pioneering a new direction in *Differentiable Programming for HEP*

- Make HEP codes “differentiable” and integrate into optimization or ML pipelines
- Get more from each simulated event
- Example: MadJax differentiable matrix elements



The Future

- How to we best design, train, and validate the models?
- How do we integrate these models with experiments and simulation code-bases?
- What can we use these models for, beyond just generating data?
- How can we mix scientific software with ML to build more accurate, robust, and interpretable scientific ML methods?

Machine Learning and LHC Event Generation

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Abstract

First-principle simulations are at the heart of the high-energy physics research program. They link the vast data output of multi-purpose detectors with fundamental theory predictions and interpretation. This review illustrates a wide range of applications of modern machine learning to event generation and simulation-based inference, including conceptional developments driven by the specific requirements of particle physics. New ideas and tools developed at the interface of particle physics and machine learning will improve the speed and precision of forward simulations, handle the complexity of collision data, and enhance inference as an inverse simulation problem.

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New directions for surrogate models and differentiable programming for High Energy Physics detector simulation

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Abstract

The computational cost for high energy physics detector simulation in future experimental facilities is going to exceed the current available resources. To overcome this challenge, new ideas on surrogate models using machine learning methods are being explored to replace computationally expensive components. Additionally, differentiable programming has been proposed as a complementary approach, providing controllable and scalable simulation routines. In this document, new and ongoing efforts for surrogate models and differential programming applied to detector simulation are discussed in the context of the 2021 Particle Physics Community Planning Exercise ('Snowmass').

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