



Simulation of Z_2 model using Variational Autoregressive Networks (VAN)

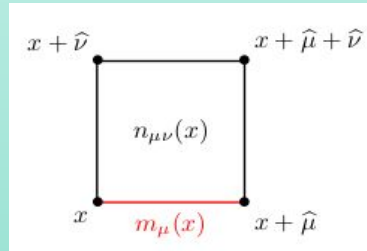
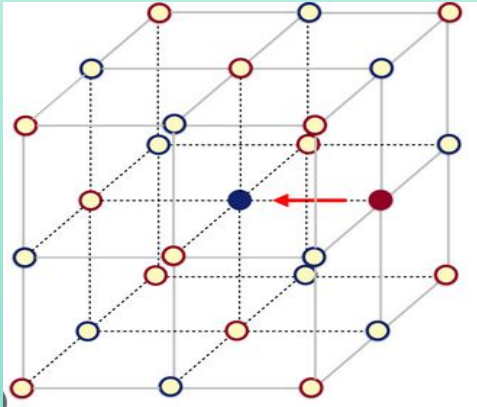
Neural Networks for Local Abelian Gauge Symmetry

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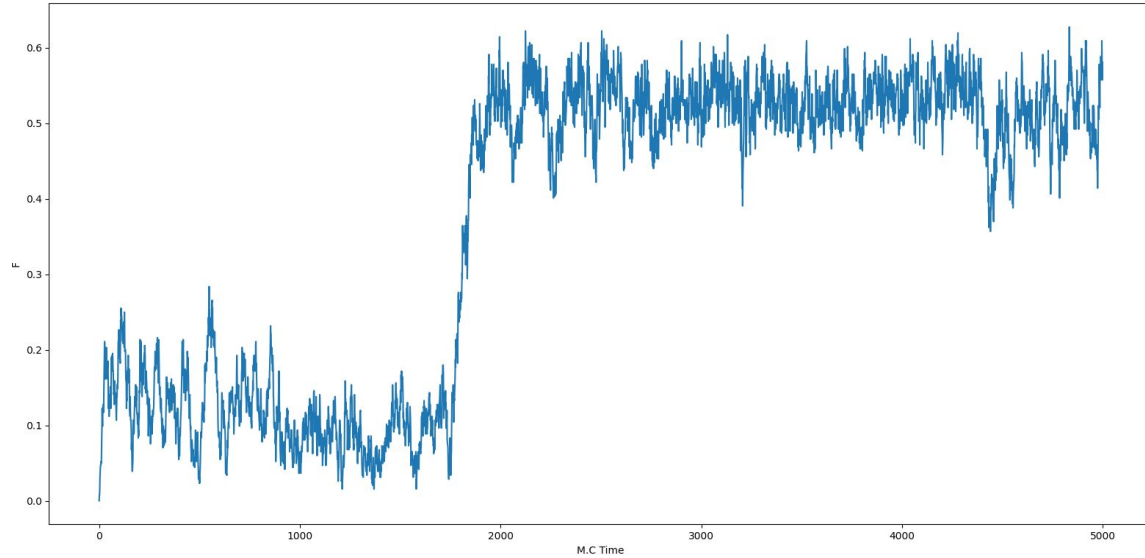
Description of the Model

- The model is a discrete Z_2 Abelian gauge model on a 4D hypercubical lattice.
- Closely related to ising model, shows a phase transition with decreasing temperature.



Hamiltonian:
$$H(\sigma) = \frac{1}{6} \sum_{i,j,k,\ell} P_{ijkl} (1 - \sigma_i \sigma_j \sigma_k \sigma_\ell)$$

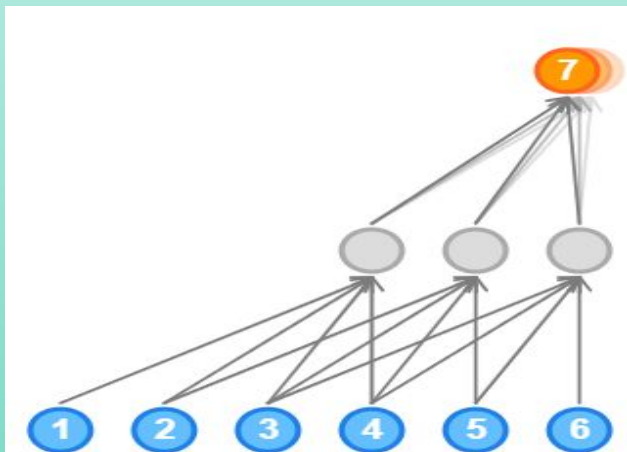
Problems with Monte-Carlo



□

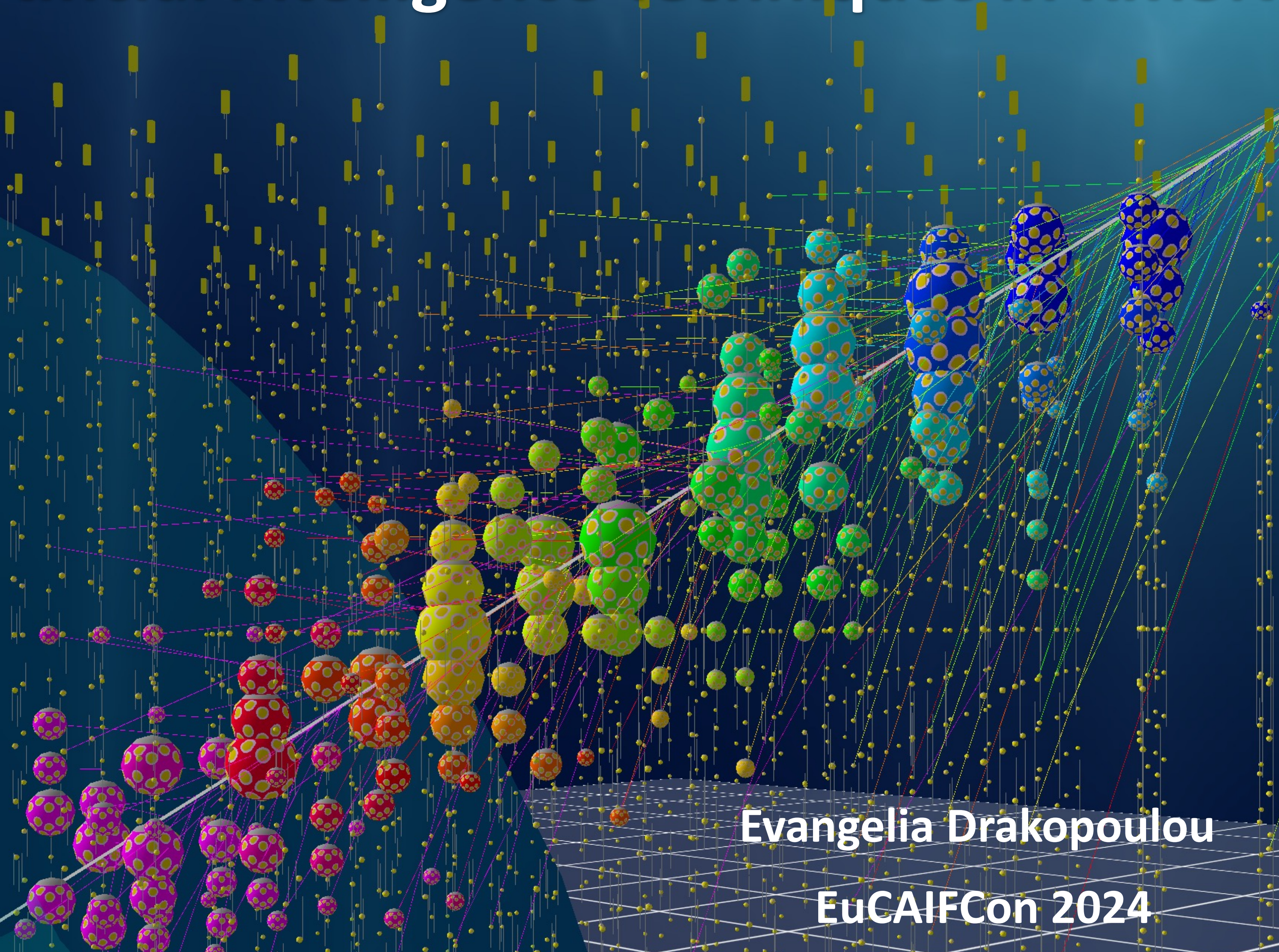
Variational Autoregressive Network (VAN)

- Variational Autoregressive Network (VAN) used as a mechanism of providing uncorrelated proposals in a Monte Carlo simulation.
- The idea to use self-learning neural network as a sampler for MCMC called Neural Markov Chain Monte Carlo (NMCMC).
- Two models are used: Fully Connected Autoregressive Network and PixelCNN.



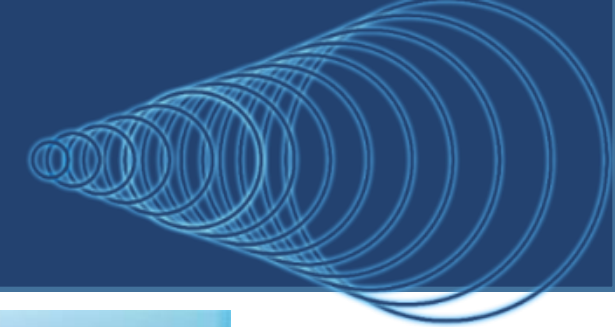


Artificial Intelligence Techniques in KM3NeT

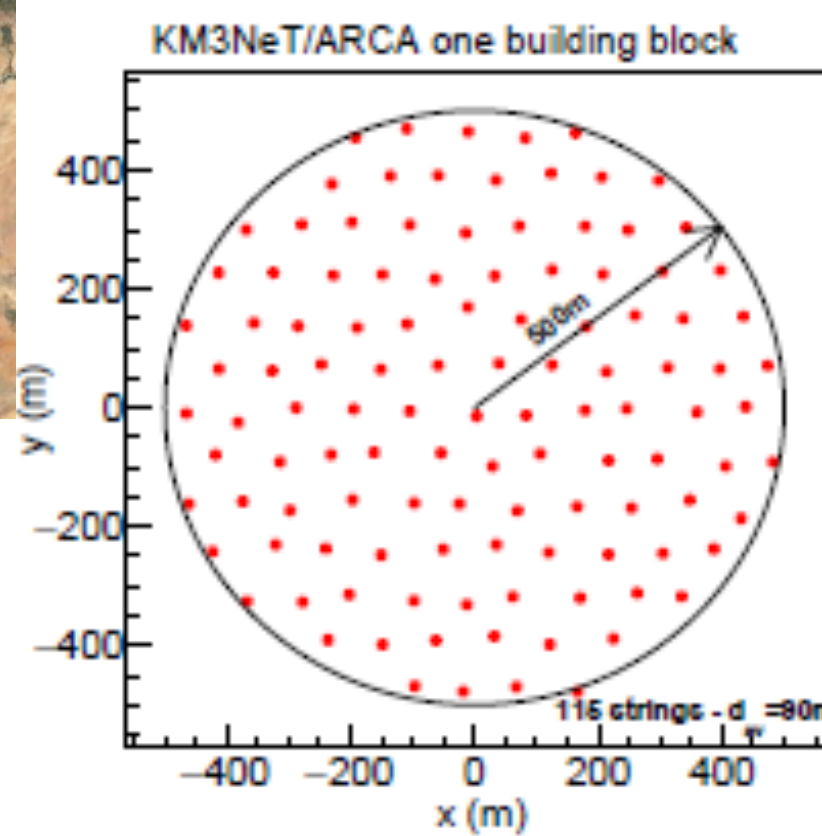


Evangelia Drakopoulou

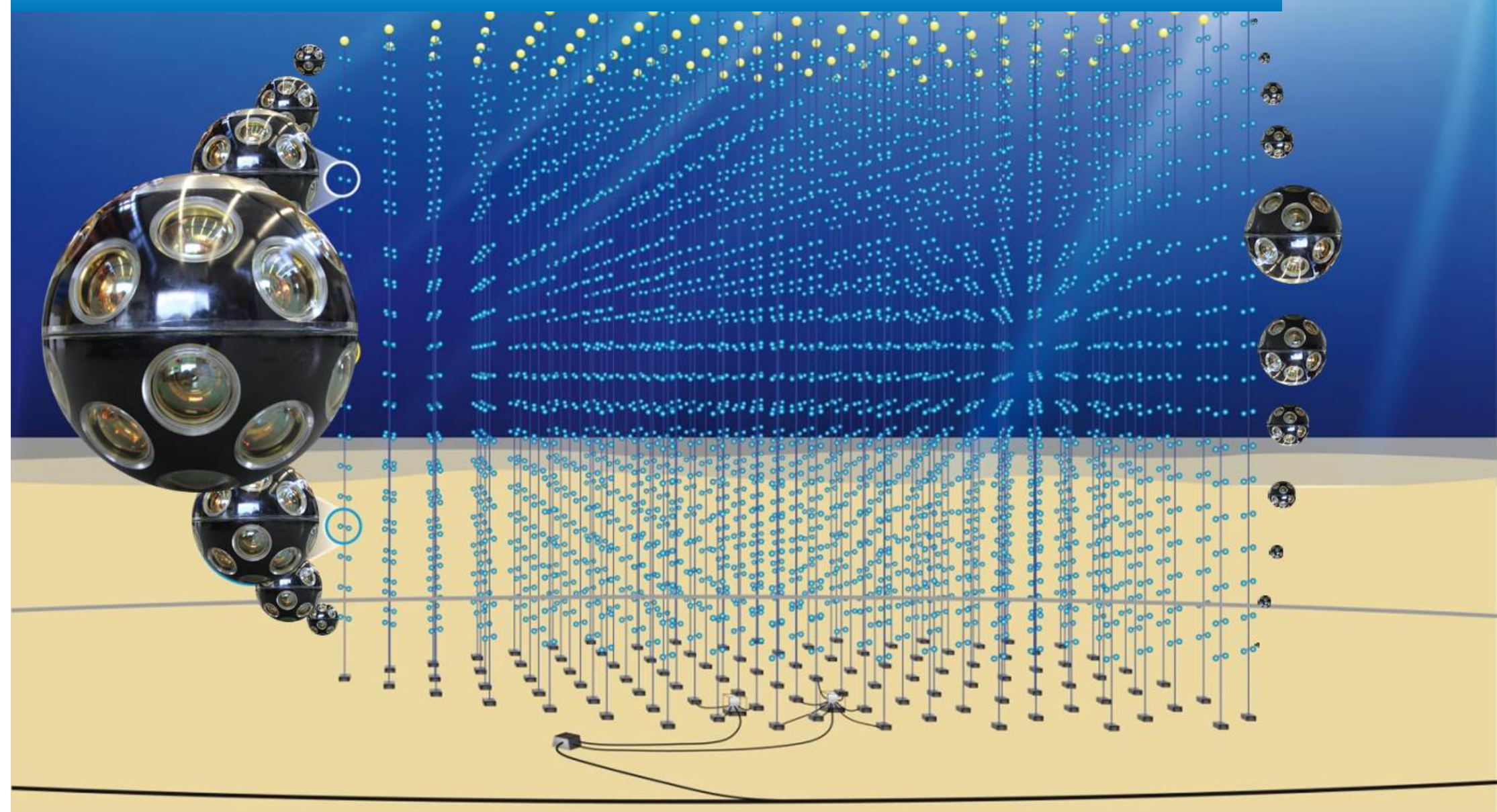
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Identical technology for ARCA and ORCA



KM3NeT: an underwater neutrino telescope



ORCA

Particle Physics
Neutrino Oscillations
Mass Hierarchy

Currently 18 DUs deployed

2x

ARCA

Detection of neutrinos from astrophysical sources

Currently 28 DUs deployed

Detection Unit (DU)

Machine and Deep Learning Projects in KM3NeT (non exhaustive list)

GNNs:

- [Development of detector calibration and graph neural network-based selection and reconstruction algorithms for the measurement of oscillation parameters with KM3NeT/ORCA](#) (D. Guderian, PhD Thesis)
- [Data reconstruction and classification with graph neural networks in KM3NeT/ARCA6-8](#) (F. Filippini et al., PoS(ICRC2023)1194)
- [Cosmic ray composition measurement using Graph Neural Networks for KM3NeT/ORCA](#) (S. Reck, PhD Thesis)
- [Optimisation of energy regression with sample weights for GNNs in KM3NeT/ORCA](#) (B. Setter, MSc Thesis)
- [Tau neutrino identification with Graph Neural Networks in KM3NeT/ORCA](#) (L. Hennig, MSc Thesis)

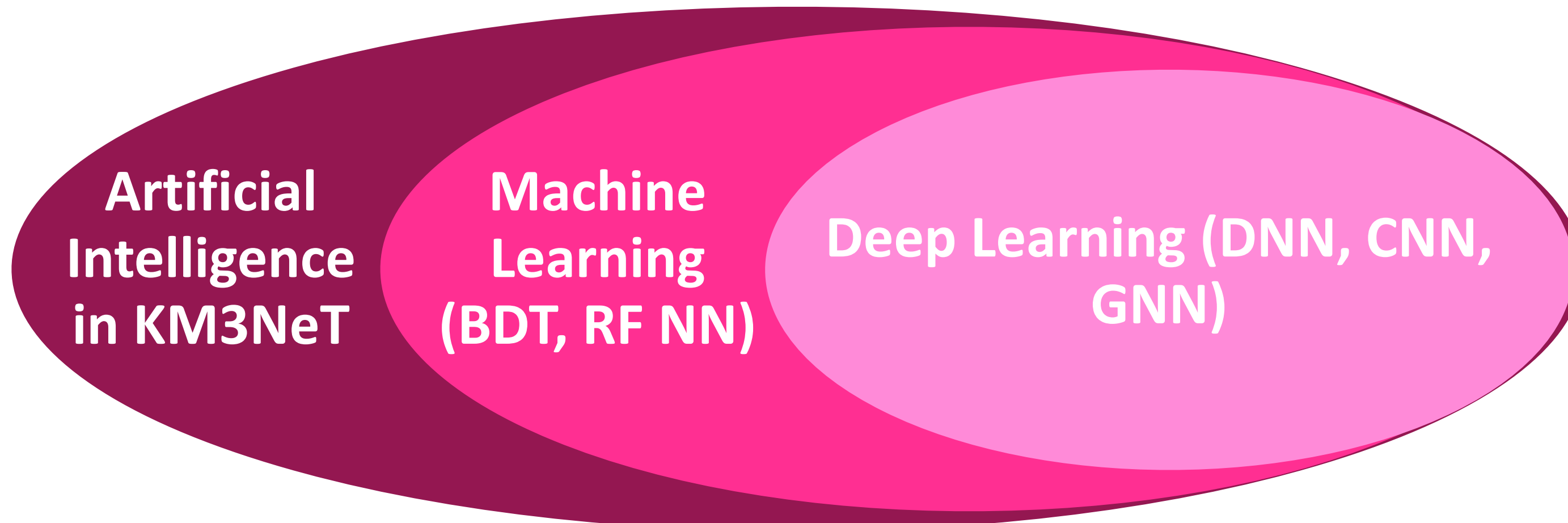
CNNs:

- [Event reconstruction for KM3NeT/ORCA using convolutional neural networks](#) (M. Moser, JINST 15 P10005)

Fully-connected NNs:

- [Deep Neural Networks for combined neutrino energy estimate with KM3NeT/ORCA6](#) (S. Peña Martínez, PoS(ICRC2023)103)

and several Machine Learning-based projects (e.g. BDTs, RFs) as part of online and offline physics analyses ...



Artificial Intelligence techniques in KM3NeT
Evangelia Drakopoulou on behalf of the KM3NeT Collaboration

Abstract: KM3NeT is a research infrastructure housing two underwater Cherenkov telescopes located in the Mediterranean Sea. It consists of two configurations which are currently under construction: ARCA with 230 detection units corresponding to 1 cubic kilometre of instrumented water volume and ORCA with 115 detection units corresponding to a mass of 7 Mton. The ARCA (Astroparticle Research with Cosmics in the Abyss) detector aims at studying neutrinos with energies in the TeV-PeV range coming from distant astrophysical sources, while the ORCA (Oscillation Research with Cosmics in the Abyss) detector is optimised for atmospheric neutrino oscillation studies at energies of a few GeV. Artificial intelligence is increasingly used in KM3NeT for data processing and analysis, aiming to provide a better performance on event reconstruction and significantly faster inference times compared to traditional reconstruction techniques. Classical machine learning algorithms, mainly decision trees for event-type classification, have been in use since the beginning of the project. These have been followed by deep learning algorithms such as Convolutional Neural Networks (CNNs) and recently Graph Neural Networks (GNNs), which have been successfully employed for event classification and neutrino property regression tasks. In this contribution, the artificial intelligence techniques used in KM3NeT, the advances in the various physics analyses as well as the impact on the physics reach of KM3NeT detectors will be presented.

Artificial Intelligence Techniques
Machine and Deep Learning techniques are extensively used in KM3NeT for the discrimination between signal and background events, the distinction between different event topologies (classification) and for the reconstruction of the particle vertex, direction and energy (regression).

Graph Neural Networks (GNNs)
Graph Representation:

- Each hit is one vertex in the graph
- Each vertex has connections to its k nearest neighbours
- Distance between vertices A and B measured by Euclidean distance

KM3NeT uses GNNs based on ParticleNet, the OrcaNet.

Direction Reconstruction for ARCA6 (with 6 DUs)
Muon bundle multiplicity reconstruction

Different GNN architectures (OrcaNet, GraphNet) are currently tested for the energy reconstruction in KM3NeT/ARCA with 21 DUs and seem to result in comparable performances.

Convolutional Neural Networks (CNNs)
CNNs based on TensorFlow were explored first for event classification and neutrino property regression tasks for ORCA.

Boosted Decision Trees (BDTs)
A BDT from the TMVA package is used to discriminate the signal (muon (anti)neutrinos) from background (atmospheric muons) events.

Summary

- KM3NeT/ARCA and KM3NeT/ORCA are currently under construction.
- A plethora of Machine and Deep Learning techniques have been successfully used for event classification and neutrino property regression tasks for both the full geometry of KM3NeT detectors with 115 detection units and the partial geometries with the first detection units deployed.
- Results of the Artificial Intelligence-based algorithms are promising.



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The Landscape of Unfolding with Machine Learning

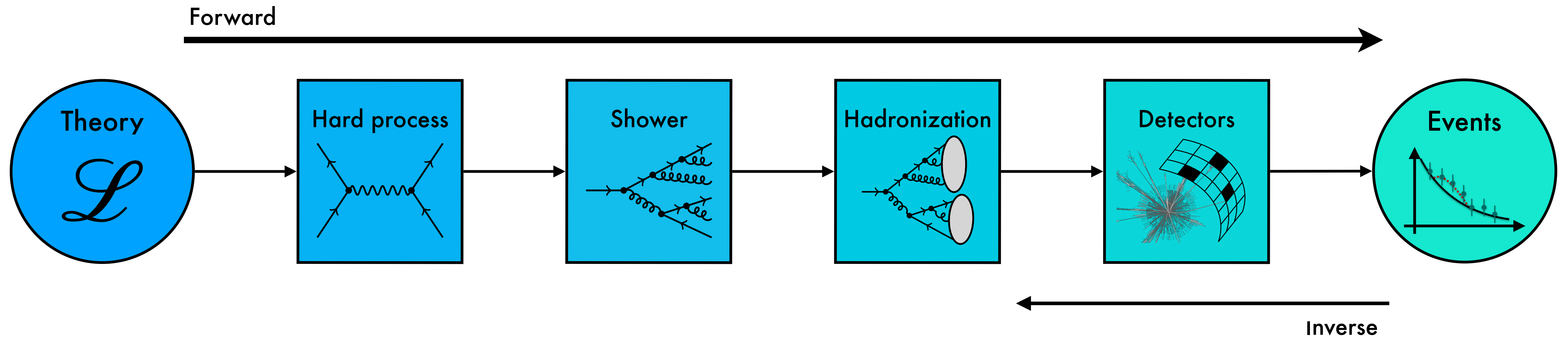
N. Huetsch, J. Mariño Villadamigo, A. Shmakov, S. Diefenbacher,
V. Mikuni, T. Heimel, M. Fenton, K. Greif, B. Nachman, D. Whiteson, A. Butter, T. Plehn
arXiv: 2404.XXXX

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Federal Ministry
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Inverting the LHC Simulation Chain



Machine learning methods allow for unbinned, high-dimensional unfolding

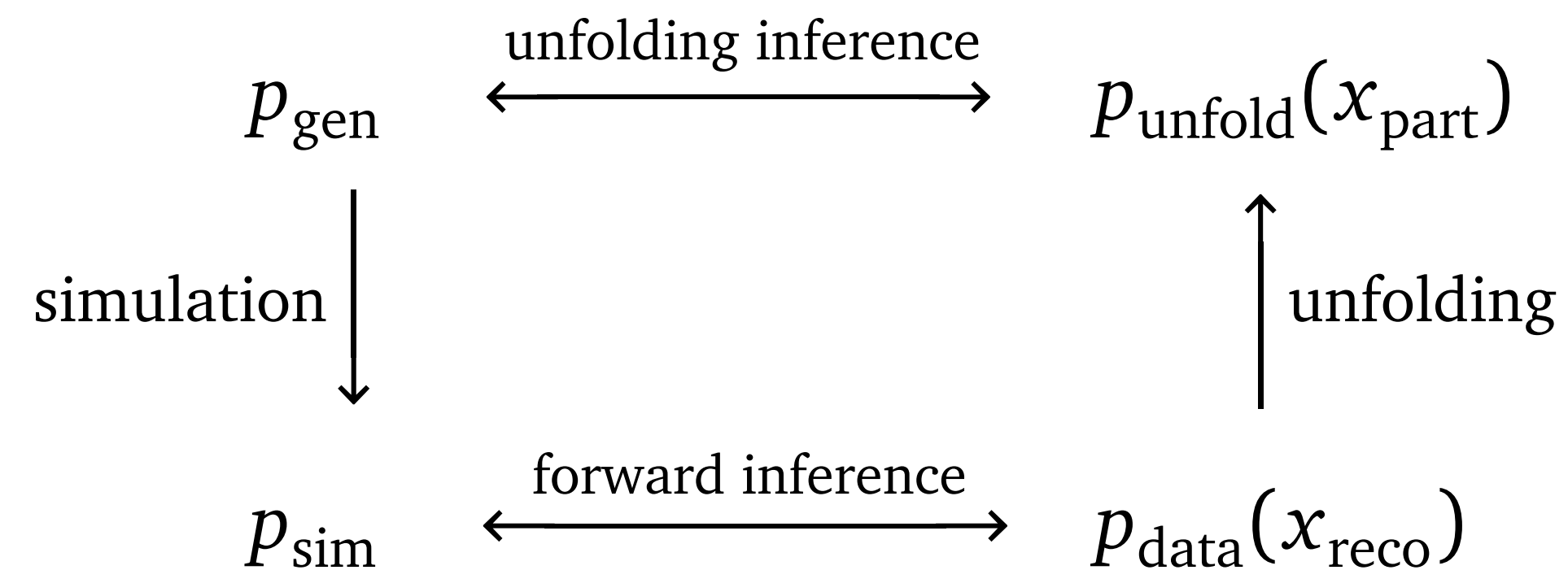
ML-based Unfolding

Reweighting based:
Omnifold

$$P_{gen} \rightarrow P_{unfold}$$

Distribution Mapping

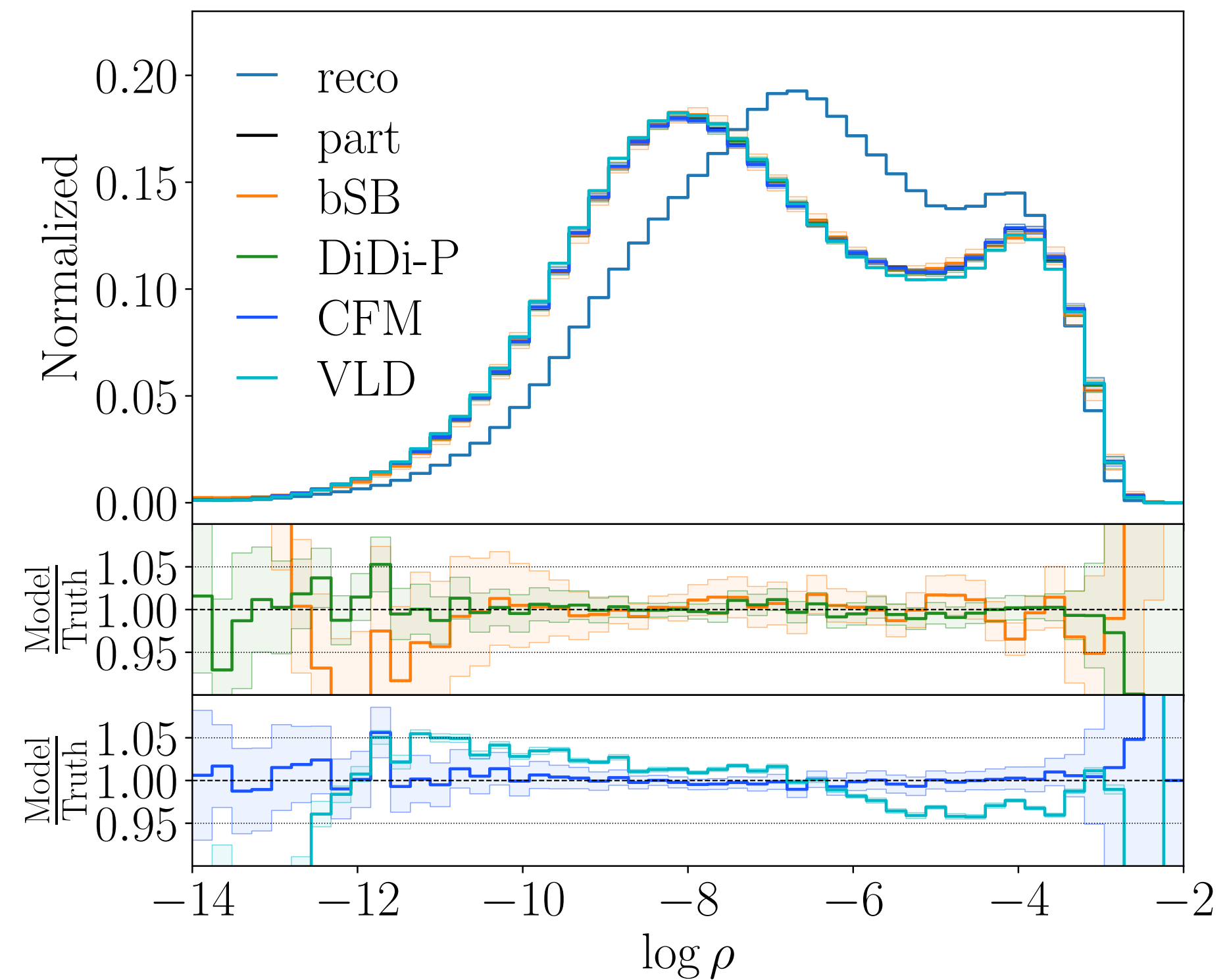
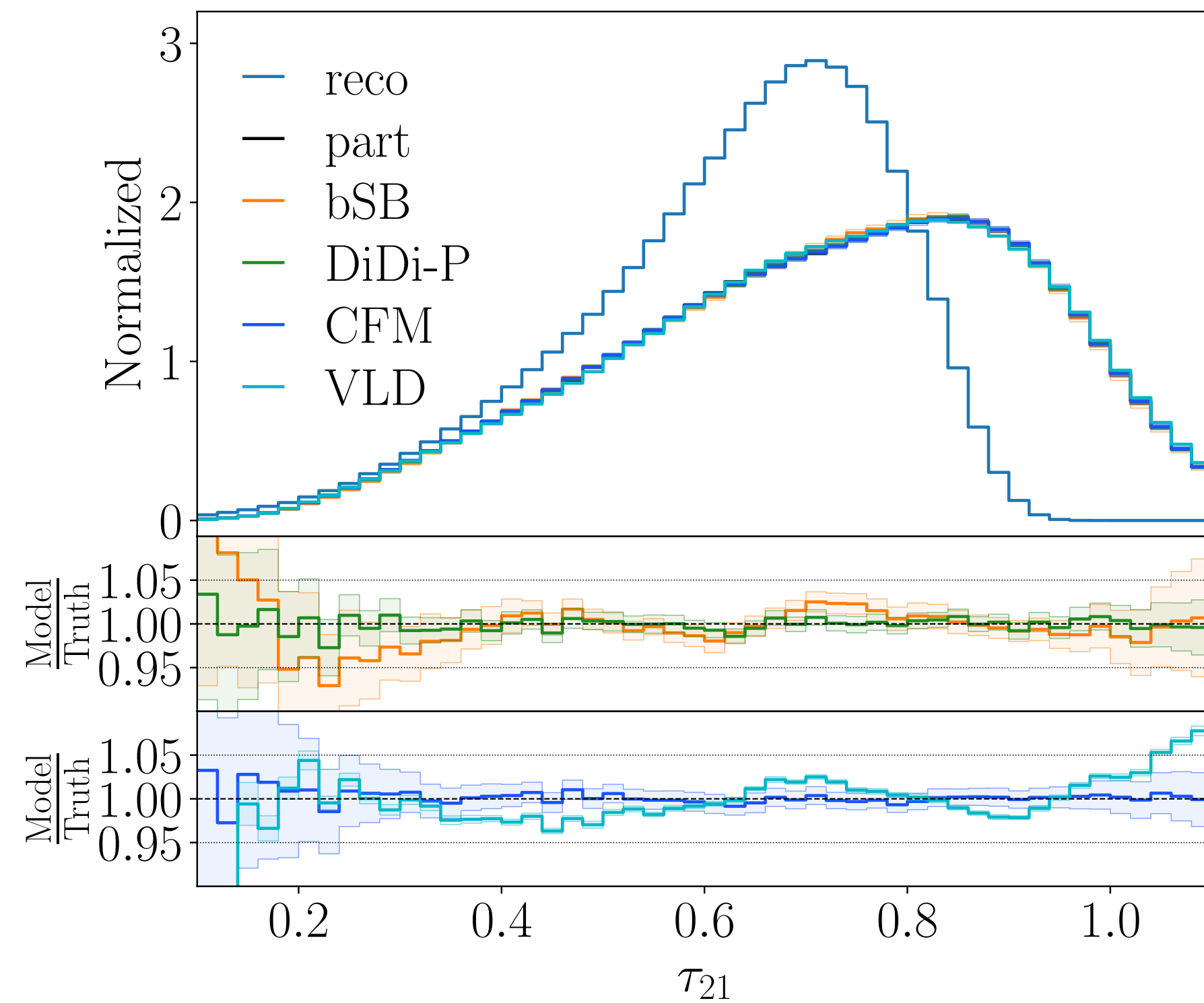
$$P_{data} \rightarrow P_{unfold}$$



Conditional Generative Unfolding

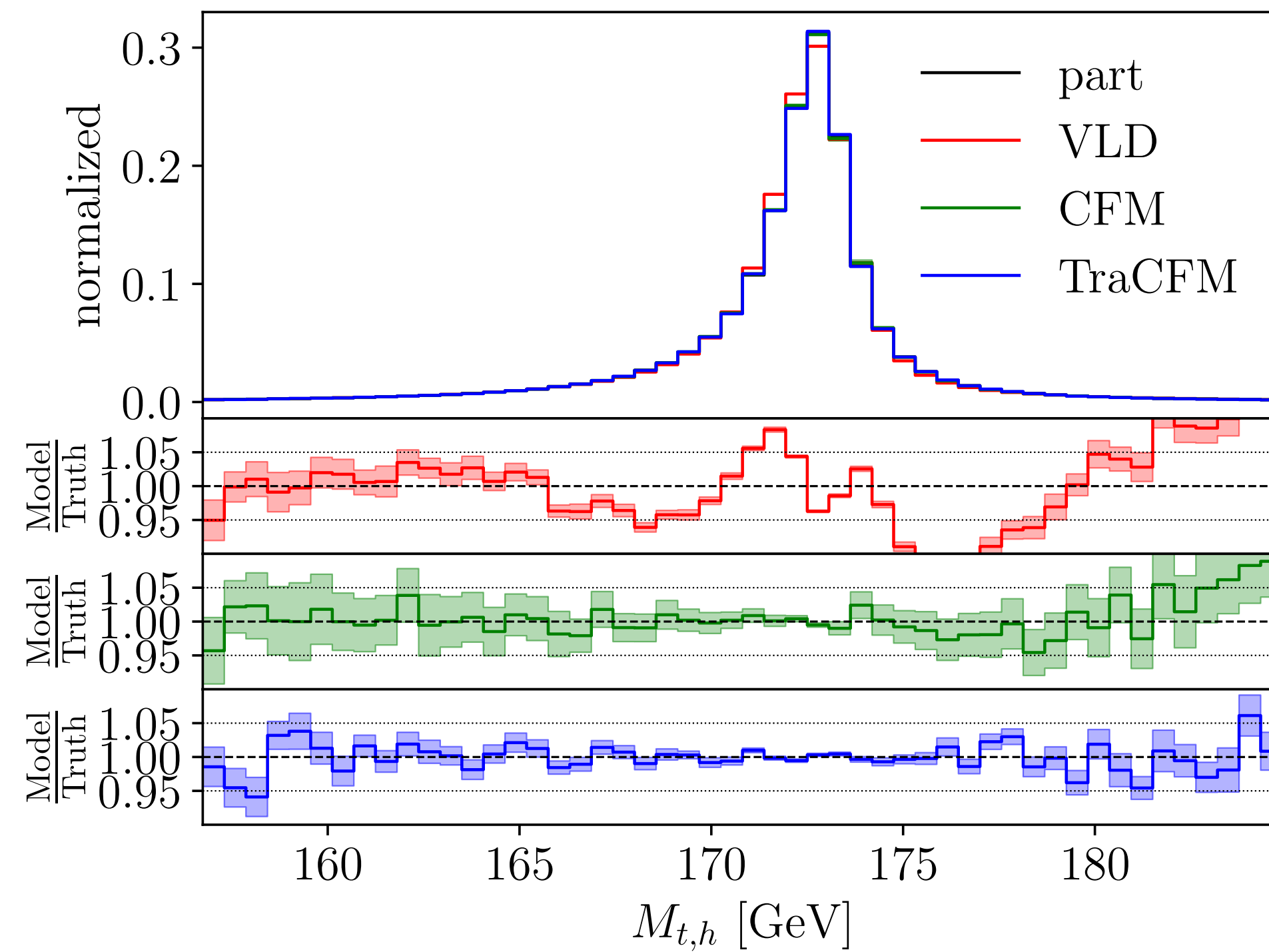
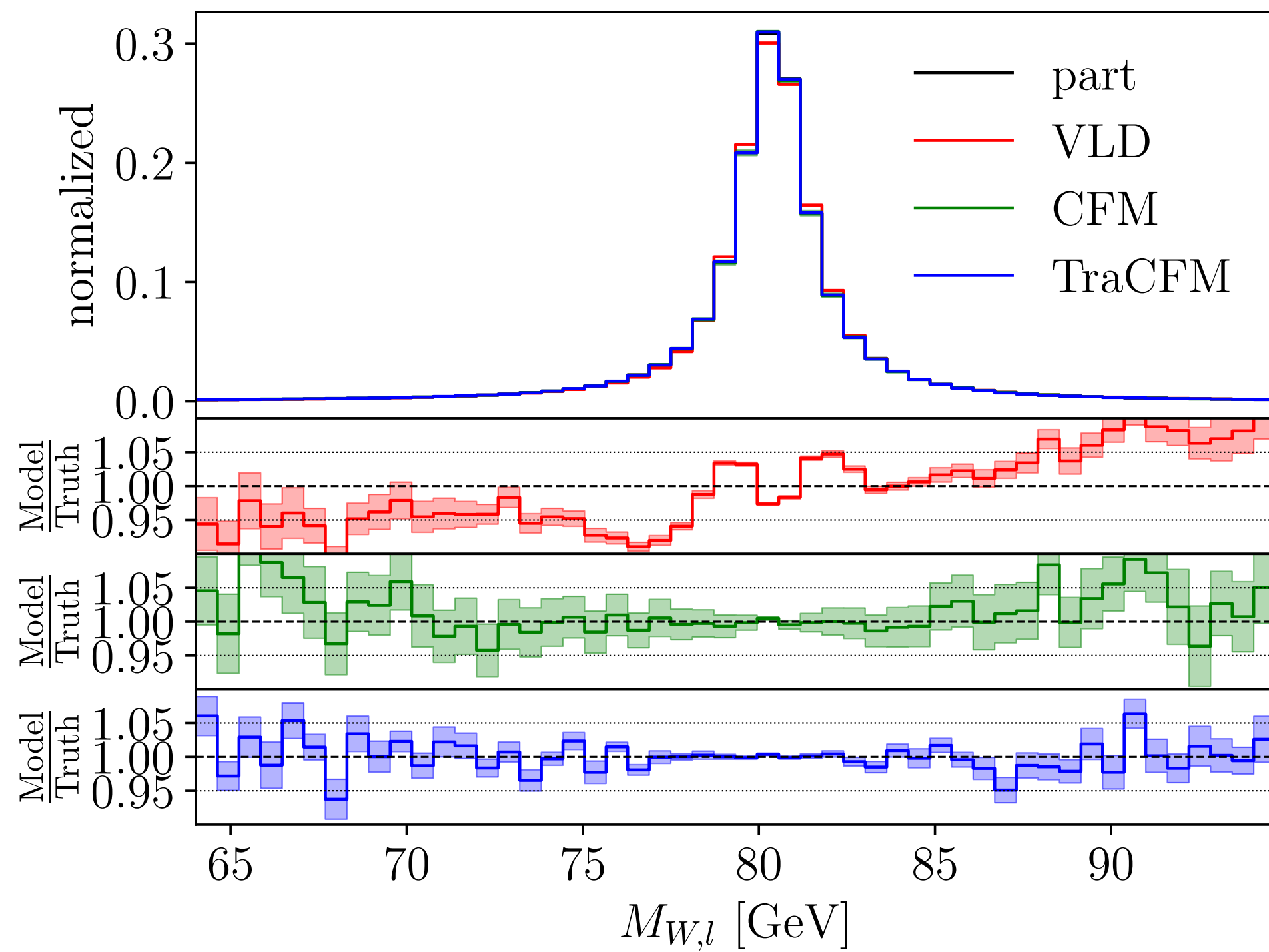
$$p(x_{part} | x_{reco})$$

Results I: Unfolding to pre-detector



Unfolding Delphes 

Results II: Unfolding to partons



Unfolding Pythia 



More with less: *sparse* kernel methods with dictionary learning

Expressive, regularized and *interpretable* models for statistical anomaly detection



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²School of Engineering and Applied Sciences, Harvard University, Cambridge, MA ³MIT Laboratory for Nuclear Science, Cambridge, MA

GOAL

Signal-agnostic statistical detection of new physical processes

Maximum-likelihood-ratio goodness-of-fit test:

$$t(\mathcal{D}) = 2 \max_{\theta} \log \frac{\mathcal{L}(\mathcal{D}|\mathbf{H}_{\theta})}{\mathcal{L}(\mathcal{D}|\mathbf{H}_0)}$$

$$= -2 \min_{\theta} L_{\text{LR}}[f_{\theta}]$$

Loss function:

$$L_{\text{LR}}[f_{\theta}] = \sum_{x \in \mathcal{R}} w_0(x) (\exp[f_{\theta}(x)] - 1) - \sum_{x \in \mathcal{D}} f_{\theta}(x)$$

$$n(x|\mathbf{H}_{\theta}) = n(x|\mathbf{H}_0) \exp[f_{\theta}(x)]$$

PROBLEM

How to design $f_{\theta}(x)$ to capture *rare* and *unexpected* subtle perturbations on top of the known physics?



More with less: *sparse* kernel methods with dictionary learning

Expressive, regularized and *interpretable* models for statistical anomaly detection



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SOLUTION

Sparse linear combination of Gaussian Kernels (SGK)

$$f_{\mu,w}(x) = \sum_{i=1}^M w_i k(x; \mu_i, \sigma_i)$$

Local interpretability

Active kernels highlight anomalous regions

$$k(x; \mu_i, \sigma_i) = A \exp \left[-\frac{\|x - \mu_i\|^2}{2\sigma_i^2} \right]$$

Sparse model ($M \ll N$)

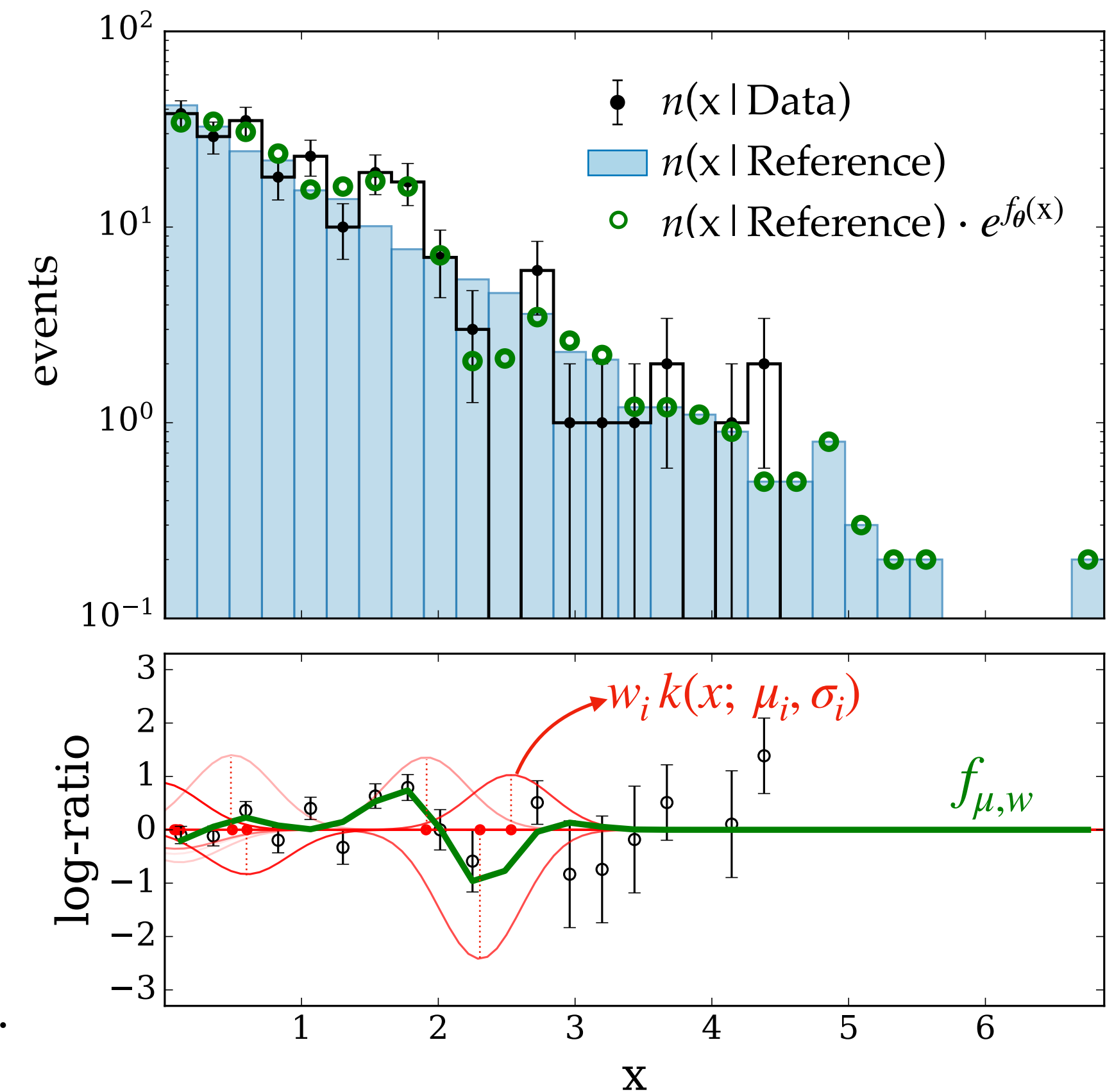
competition between data points to attract the kernels

Adaptive model (learnable μ)

directing *attention* to anomalous features

Smooth model ($\sigma^2 = \sigma_{\text{exp}}^2 + \sigma_X^2$)

Physics constraints (e.g. experimental resolution).
What is the scale of New Physics?





More with less: *sparse* kernel methods with dictionary learning

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RESULTS

Model	#par	time	Ref
■ NN	96		
✕ GK*	10k (M=10k, random)		
○ SGK*	600 (M=100, learned)		

* $\sigma = q_{50\%}$: median of pair-wise dist

more with l

Same or improved sensitivity t

IMPLICATIONS

Resource efficient represent

→ Interpretability

→ Data compression?

Want to know more?

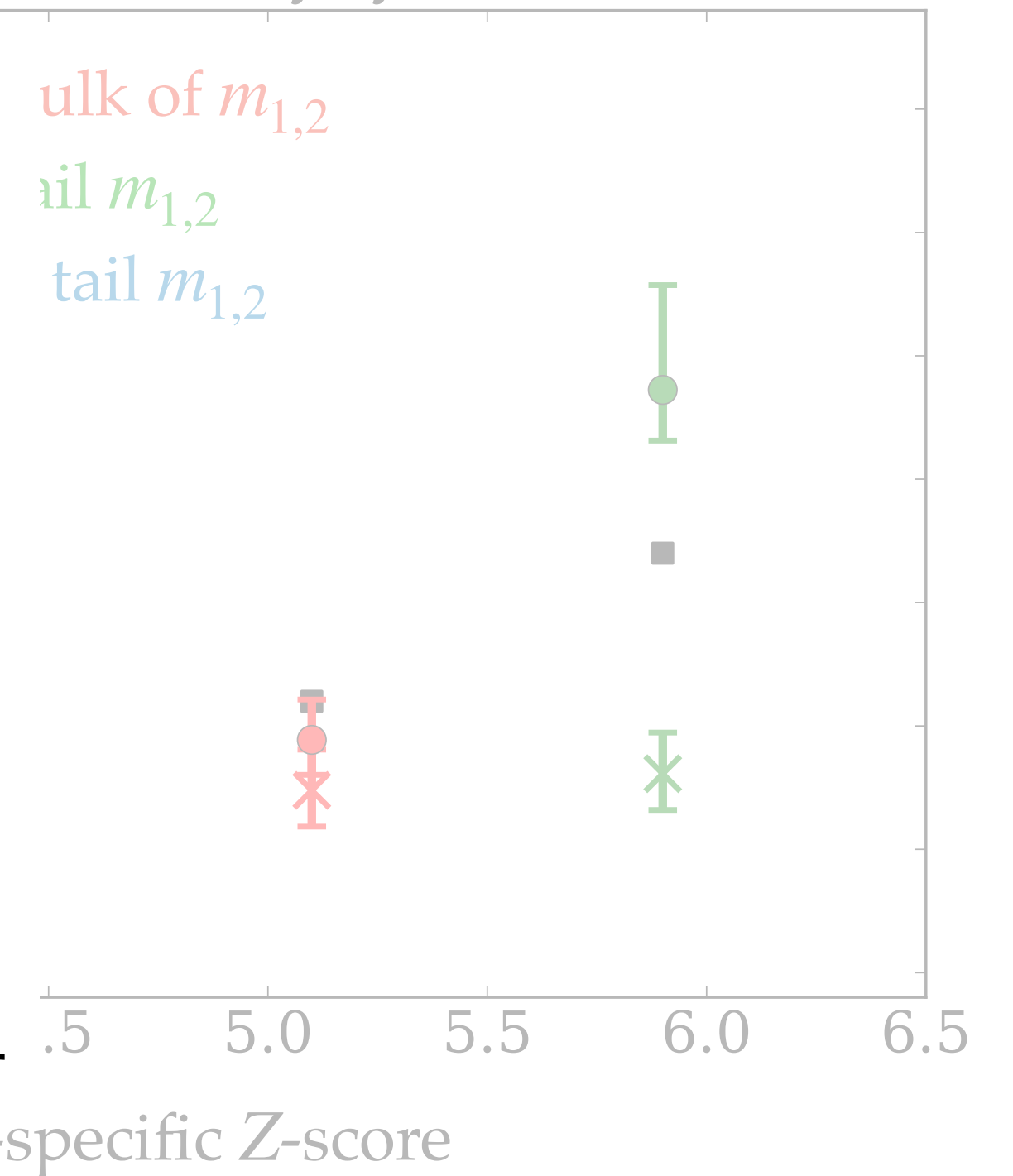
Drop by LOC 8

on Wednesday

for the poster session

5D two-body system

bulk of $m_{1,2}$
tail $m_{1,2}$



[1] "Learning multivariate new physics" *Eur. Phys. J. C* 81, 89 (2021)

[2] "Learning new physics efficiently with nonparametric methods" *Eur. Phys. J. C*, 82(10)