EUROPEAN AI FOR FUNDAMENTAL PHYSICS CONFERENCE
EuCAIFCon 2024

Simulation of Z_2 model using Variational Autoregressive Networks (VAN)

Neural Networks for Local Abelian Gauge Symmetry

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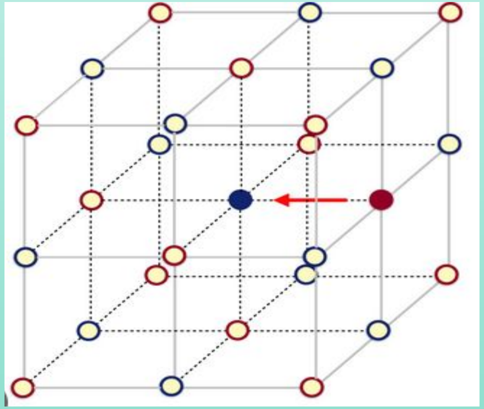
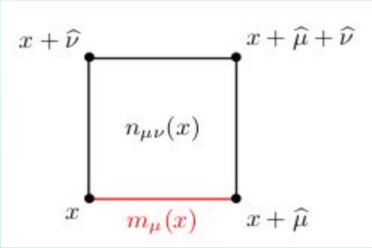
Description of the Model

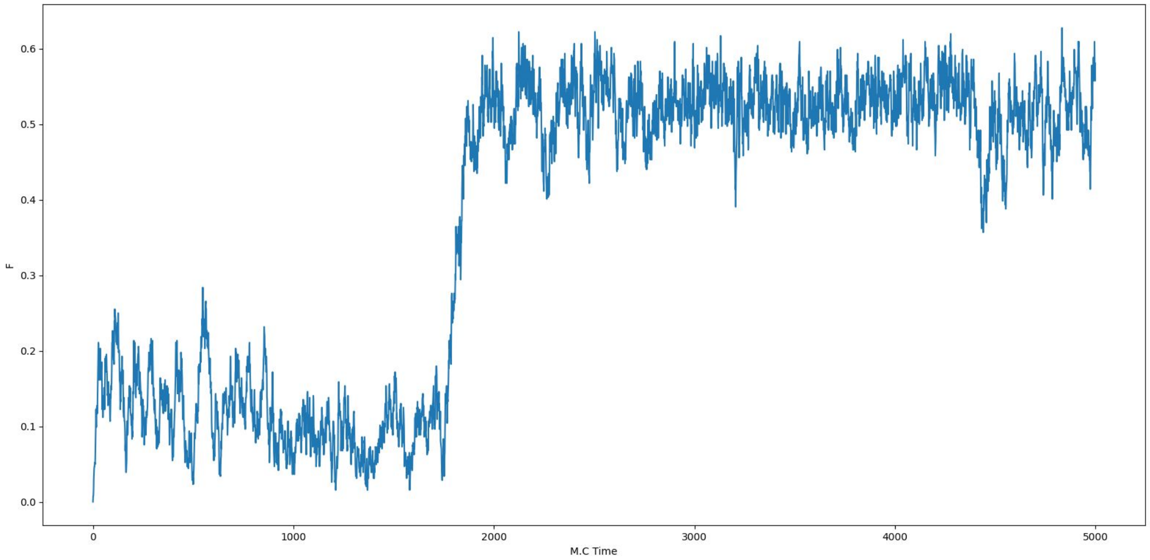
- The model is a discrete Z_2 Abelian gauge model on a 4D hypercubical lattice.
- Closely related to ising model, shows a phase transition with decreasing temperature.





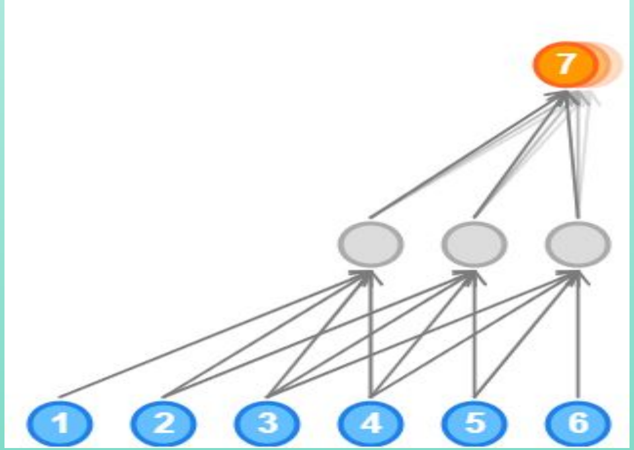
Hamiltonian: $H(\sigma) = \frac{1}{6} \sum_{i,j,k,\ell} P_{ijk\ell} \left(1 - \sigma_i \sigma_j \sigma_k \sigma_\ell\right)$

Problems with Monte-Carlo

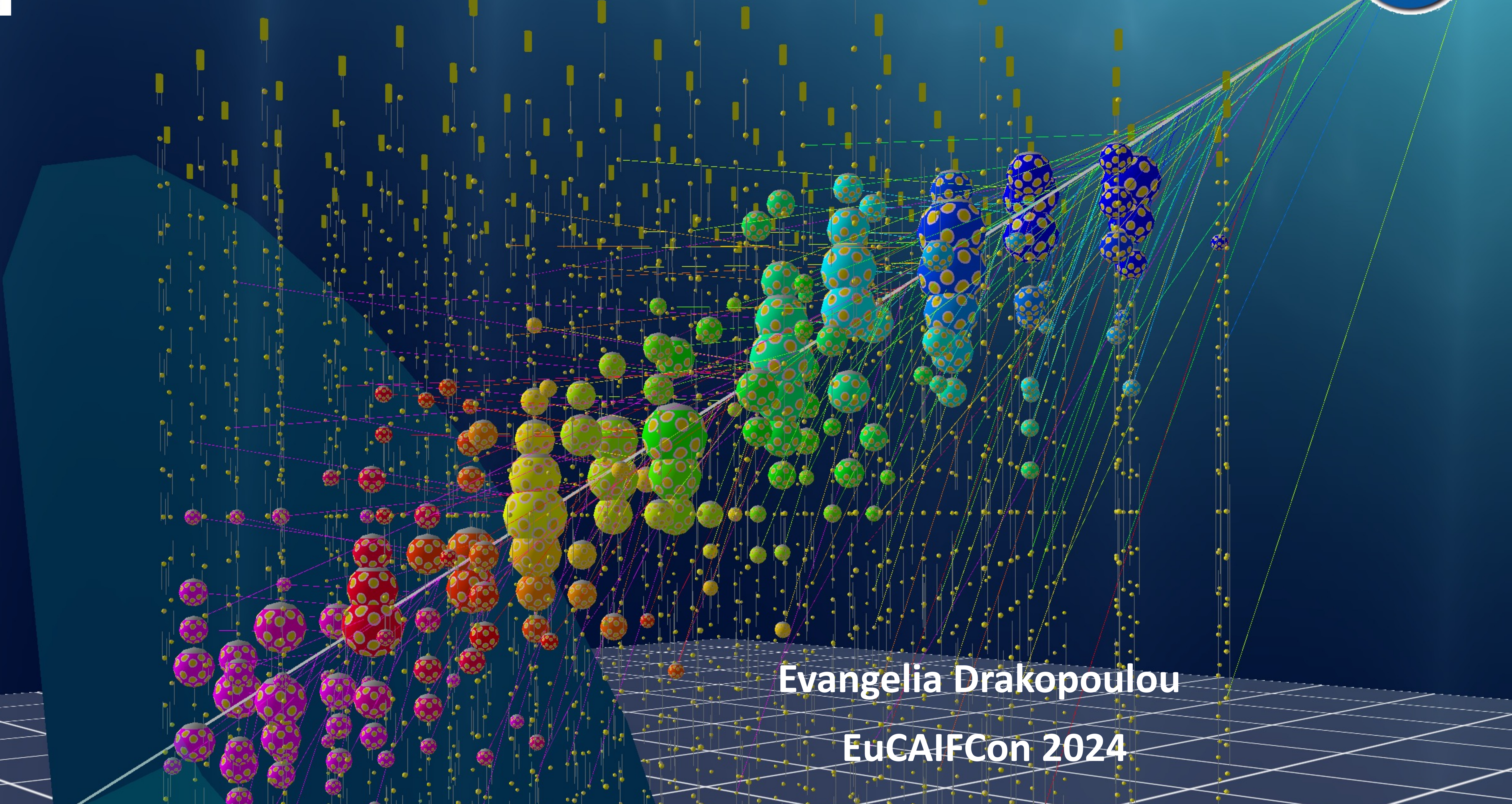


Variational Autoregressive Network (VAN)

- 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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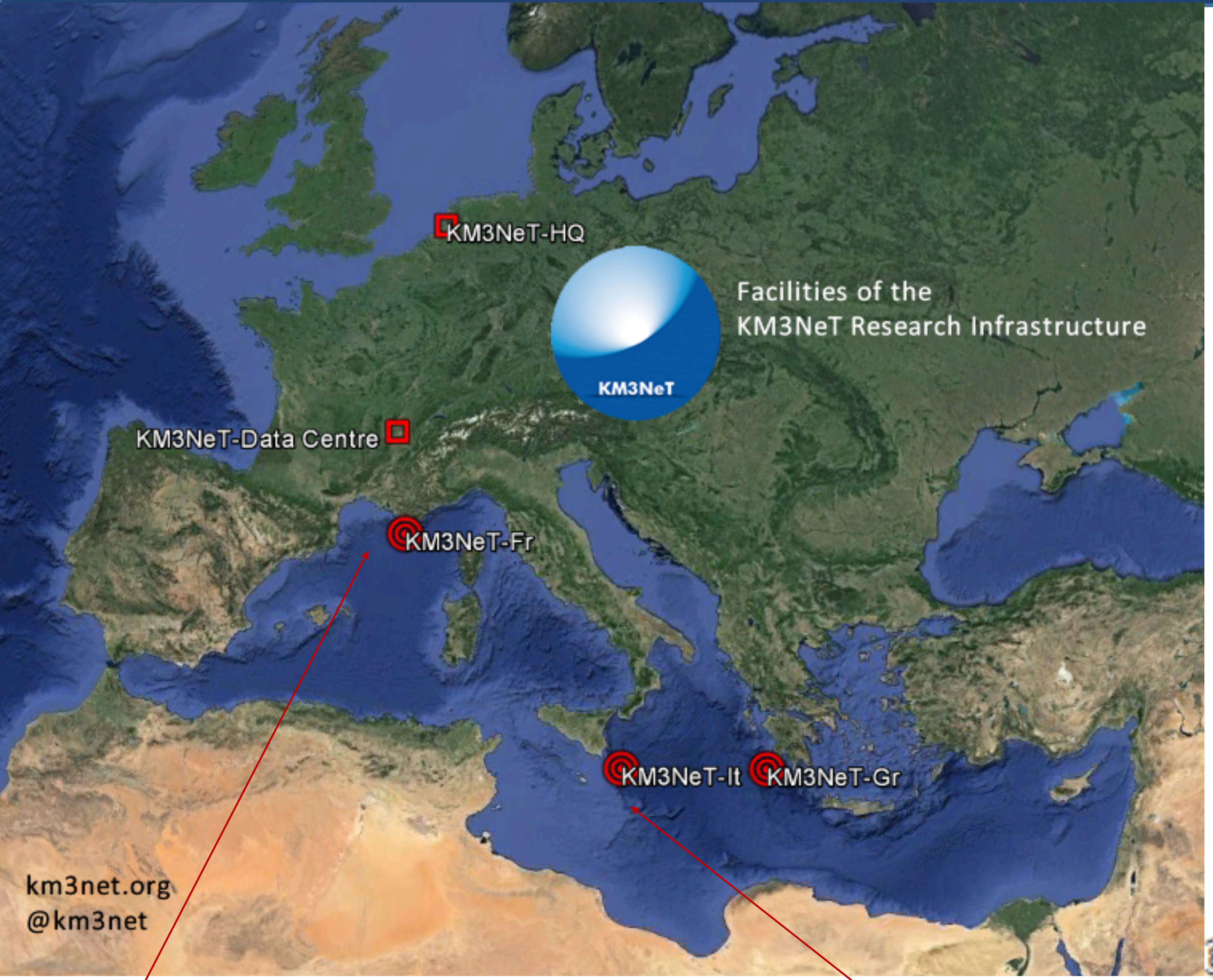
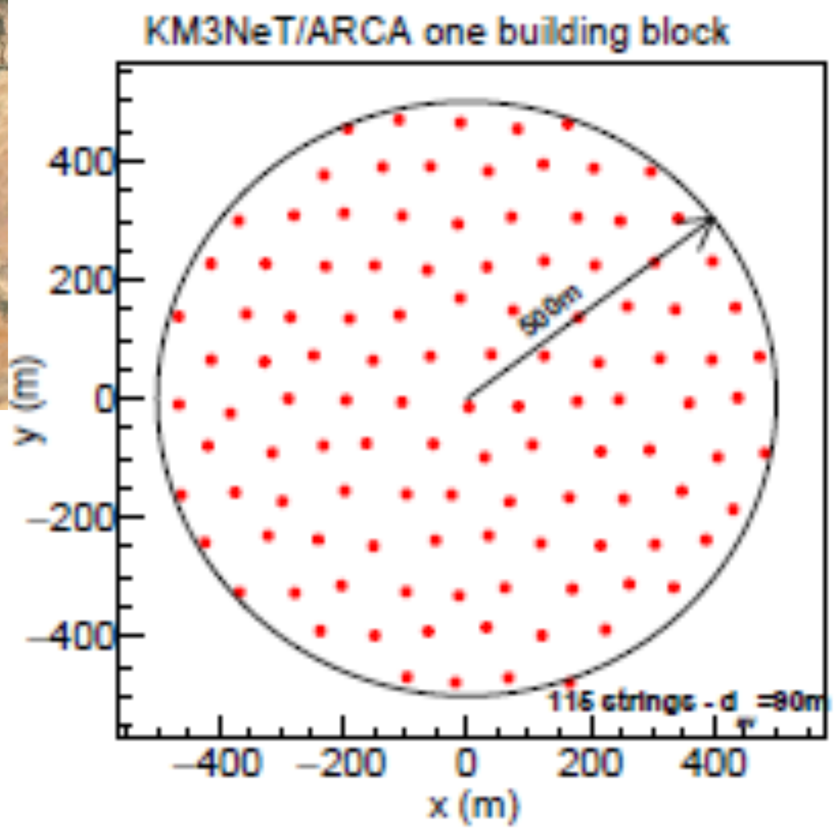
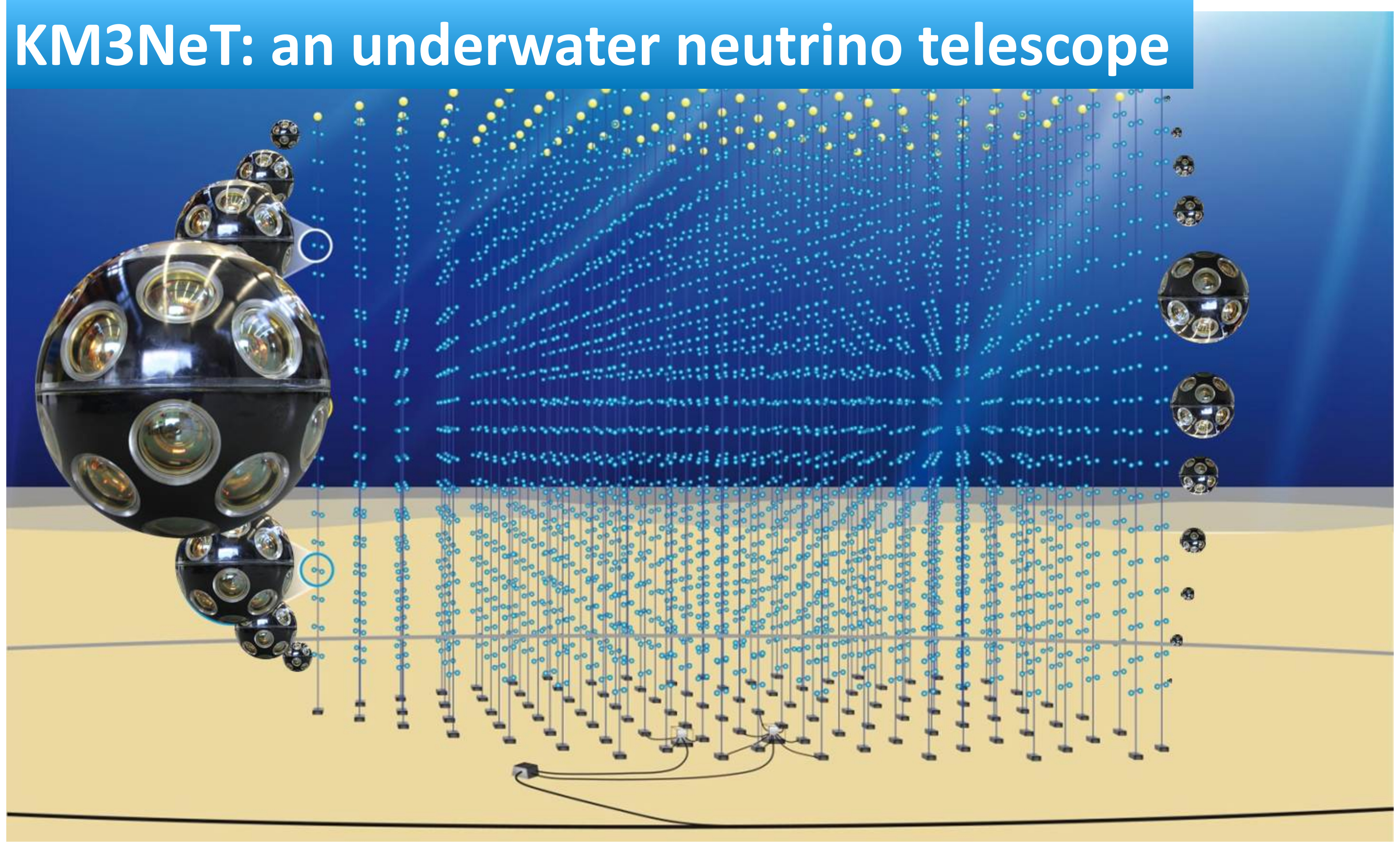
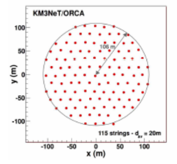
KM3NeT: A Distributed Research Infrastructure



Identical technology for ARCA and ORCA







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)

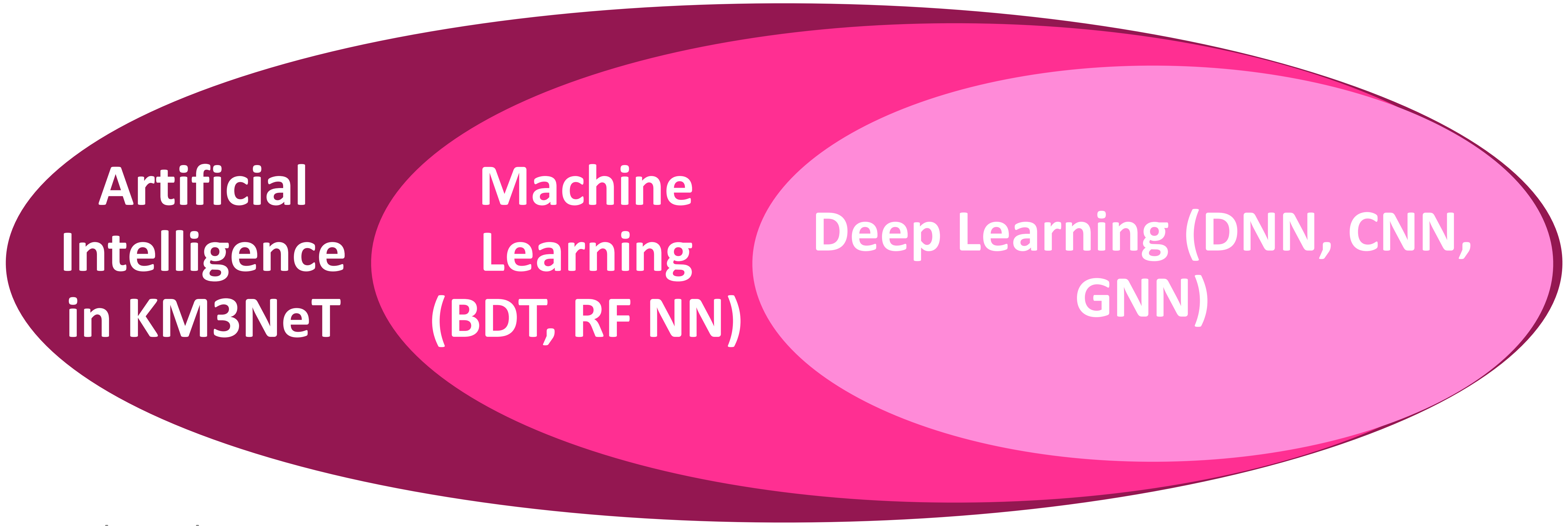
CNNs:

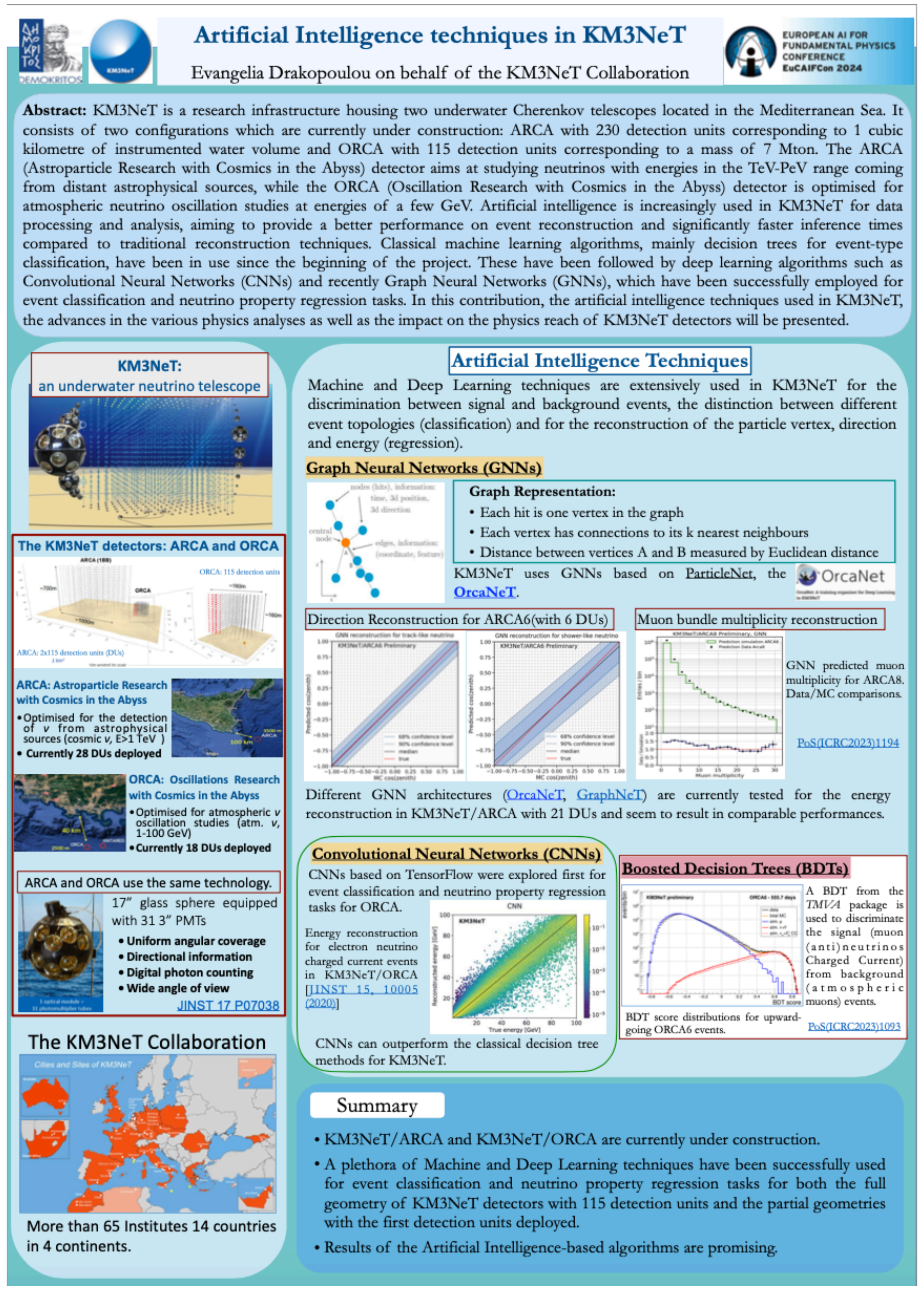
- Event reconstruction for KM3NeT/ORCA using convolutional neural networks (M. Moser, *JINST* 15 P10005)

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 …





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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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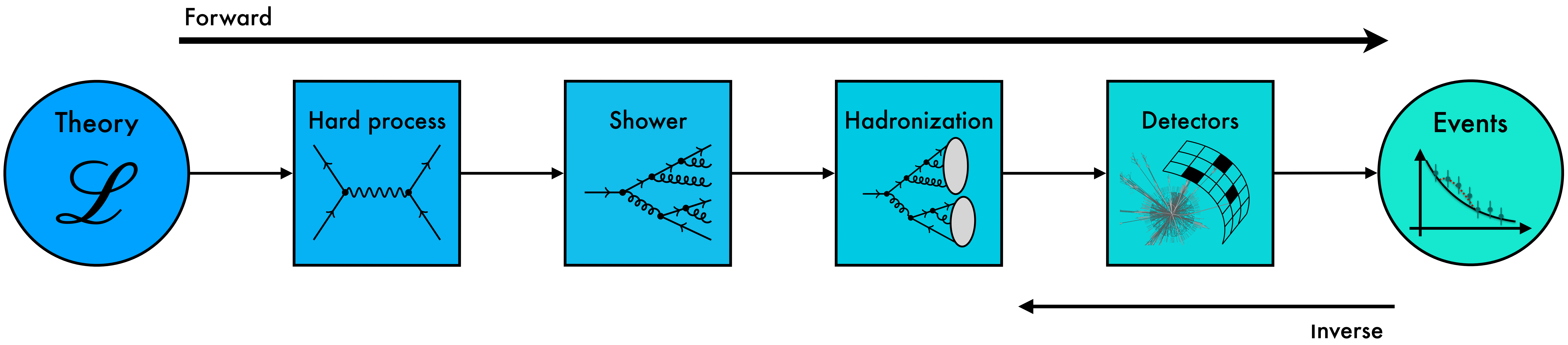
Inverting the LHC Simulation Chain



Machine learning methods allow for unbinned, high-dimensional unfolding

ML-based Unfolding

Reweighting based: Omnifold

$$p_{gen} \rightarrow p_{unfold}$$

Distribution Mapping

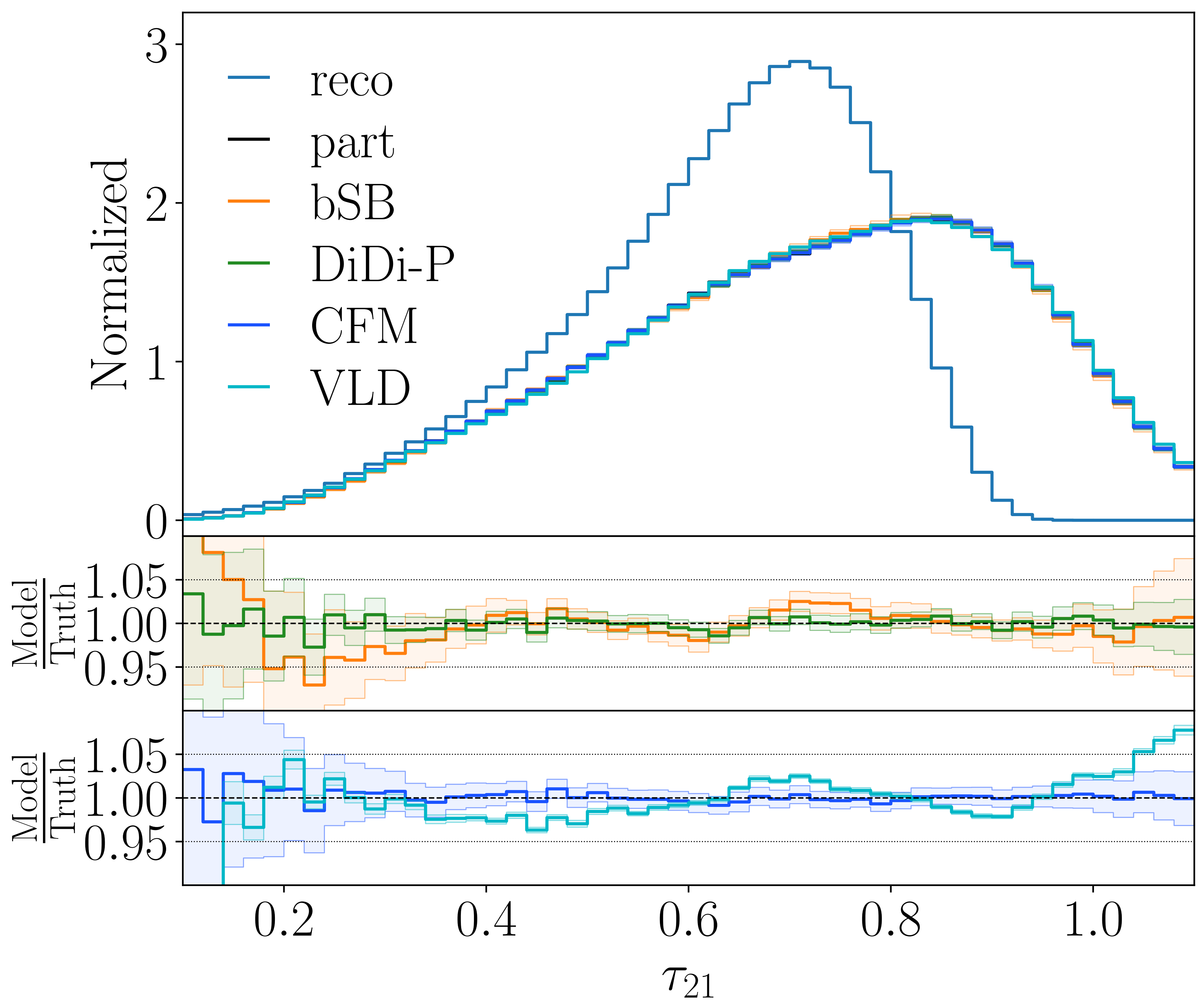
$$p_{data} \rightarrow p_{unfold}$$

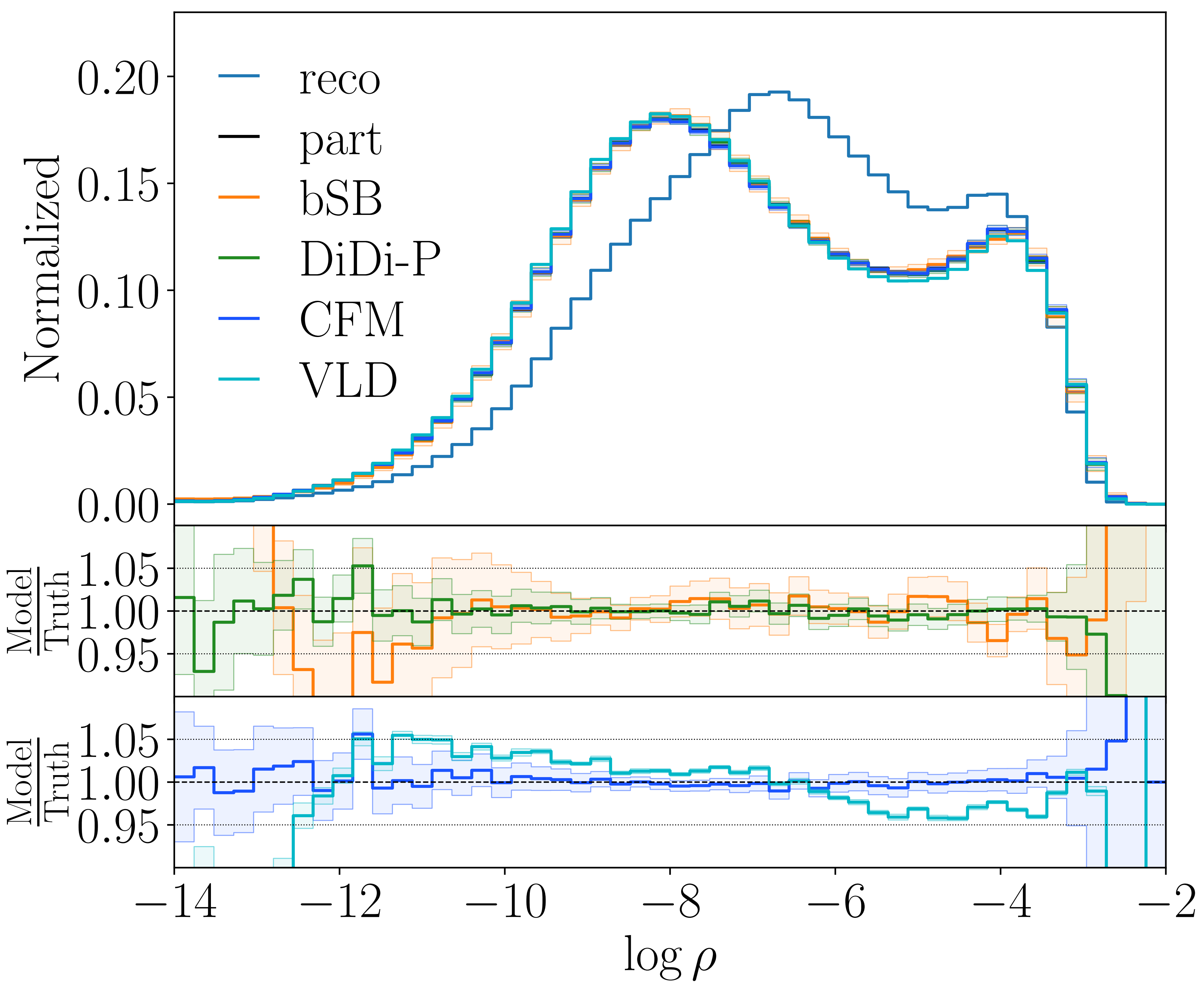
$$\begin{tikzcd}
p_{\mathrm{gen}} \arrow[rr, leftrightarrow, "\text{unfolding inference}"] \arrow[d, "\text{simulation}"'] & & p_{\mathrm{unfold}}(x_{\mathrm{part}}) \\
p_{\mathrm{sim}} \arrow[rr, leftrightarrow, "\text{forward inference}"] & & p_{\mathrm{data}}(x_{\mathrm{reco}}) \arrow[u, "\text{unfolding}"']
\end{tikzcd}$$

Conditional Generative Unfolding

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

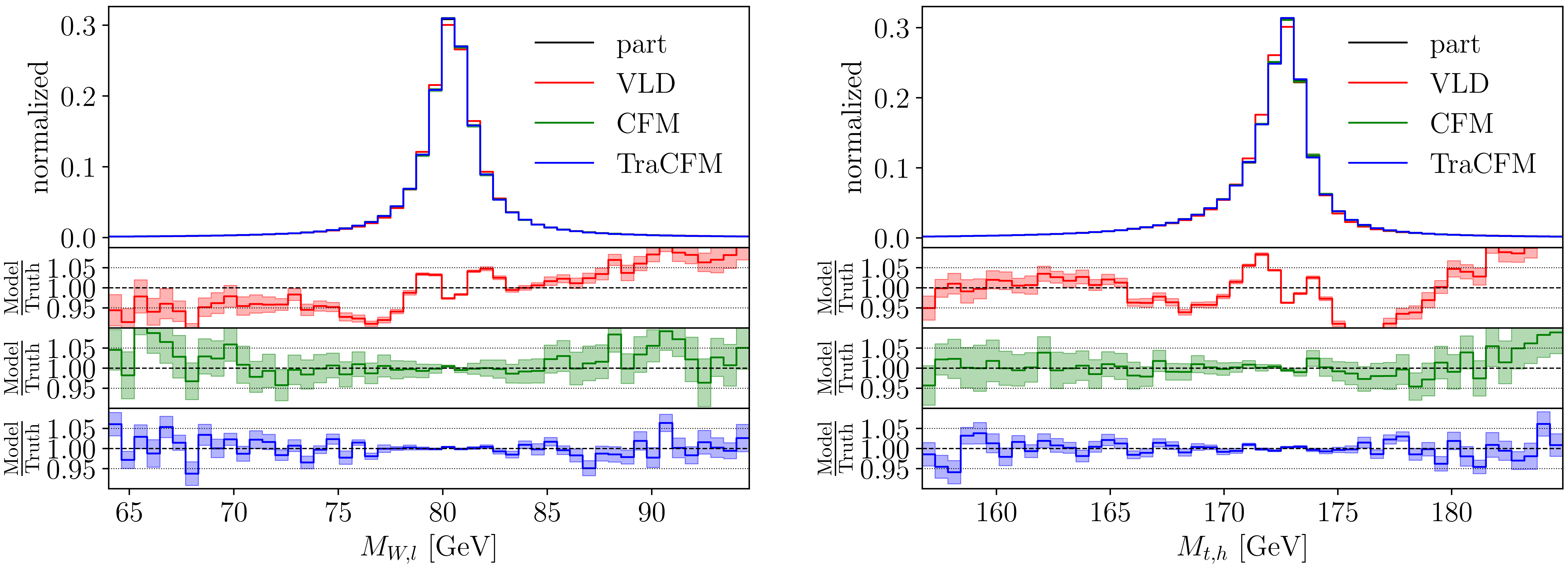
Results I: Unfolding to pre-detector





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**

Gaia Grosso[1,2,3], Demba Ba[1,2], Phil Harris[1,3]

[1]NSF Institute for Artificial Intelligence and Fundamental Interaction (IAIFI)

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

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GOAL

Signal-agnostic statistical detection of new physical processes

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

$$t(\mathcal{D}) = 2\max_{\boldsymbol{\theta}} \log \frac{\mathcal{L}(\mathcal{D}|\mathrm{H}_{\boldsymbol{\theta}})}{\mathcal{L}(\mathcal{D}|\mathrm{H}_{\mathbf{0}})}$$

$$\boxed{n(x|\mathrm{H}_{\boldsymbol{\theta}}) = n(x|\mathrm{H}_{\mathbf{0}})\ \exp[f_{\boldsymbol{\theta}}(x)]}$$

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

Loss function:

$$\boxed{L_{\mathrm{LR}}[f_{\boldsymbol{\theta}}] = \sum_{x\in\mathcal{R}} w_{\mathbf{0}}(x)\left(\exp[f_{\boldsymbol{\theta}}(x)] - 1\right) - \sum_{x\in\mathcal{D}} f_{\boldsymbol{\theta}}(x)}$$

PROBLEM

How to design $f_{\boldsymbol{\theta}}(x)$ 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

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

Sparse model (M ≪ N)

competition between data points to attract the kernels

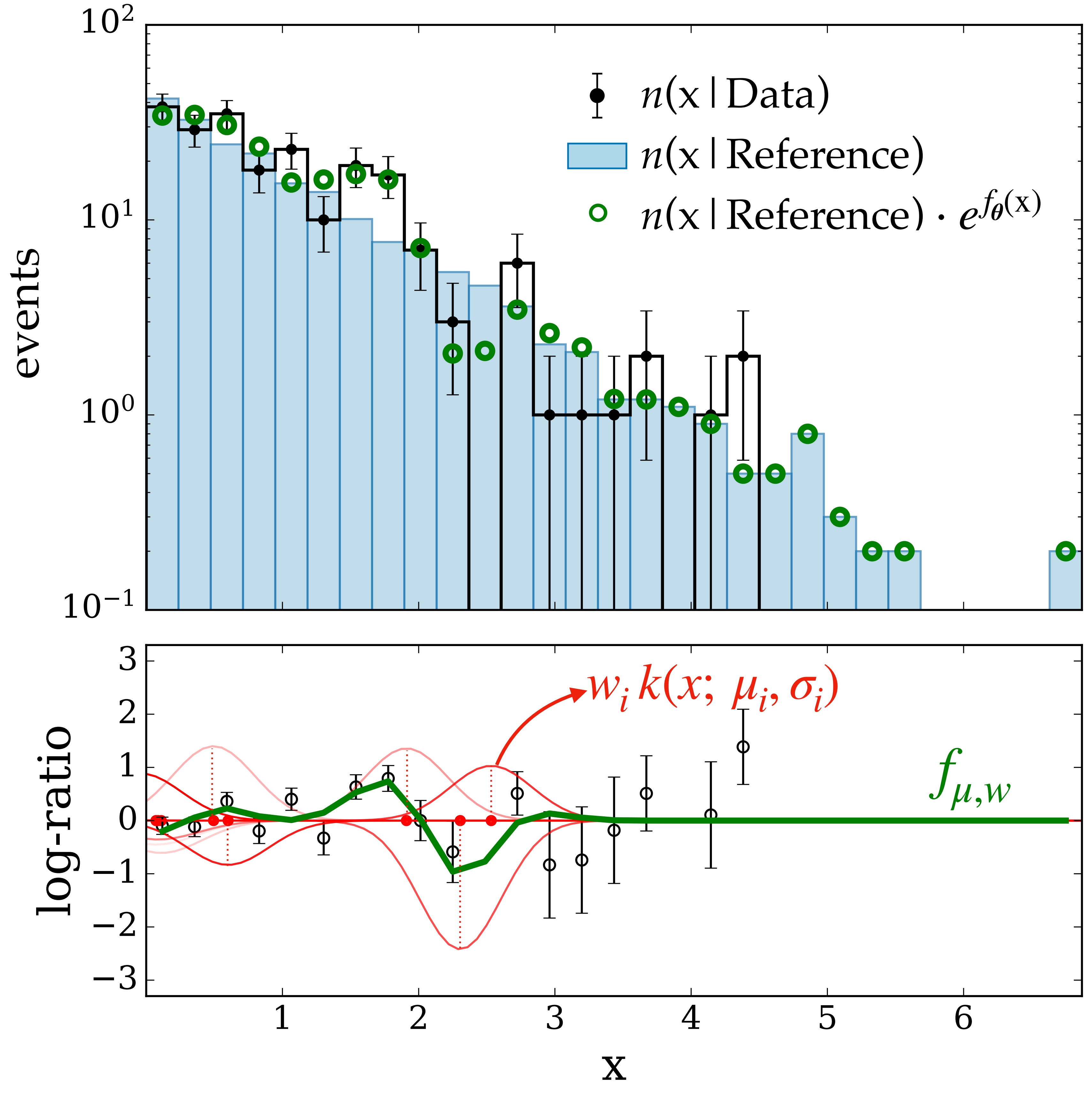
Adaptive model (learnable μ)

directing *attention* to anomalous features

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

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, rando		
○	**SGK***	**600**	**(M=100, learn**		

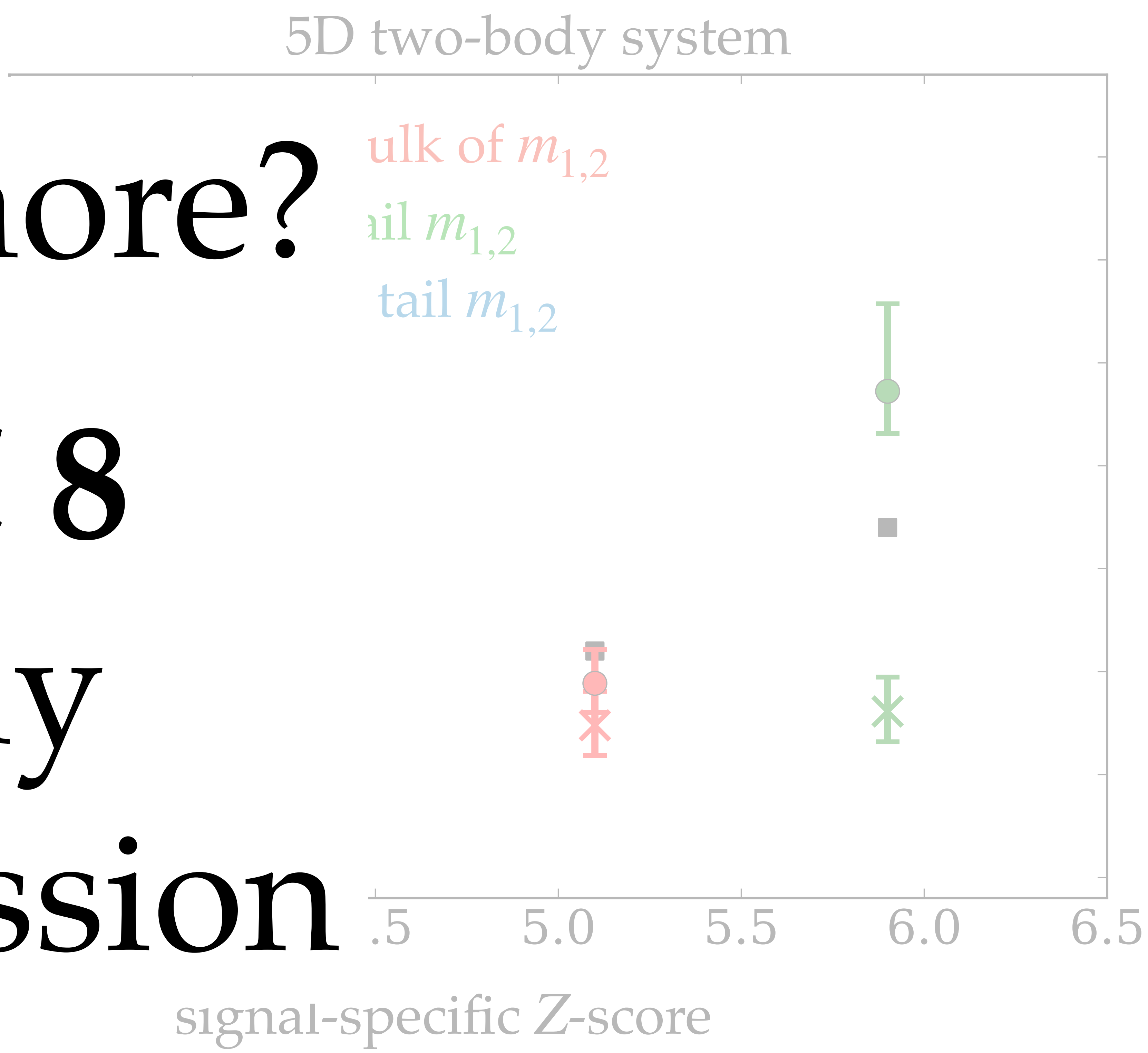
$^*\sigma = q_{50\%}$ **: median of pair-wise dist**

more with l

Same or improved sensitivity t

Want to know more?

Drop by **LOC 8**
on Wednesday
for the poster session



IMPLICATIONS

Resource efficient represent

→ Interpretability

→ Data compression?

[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)