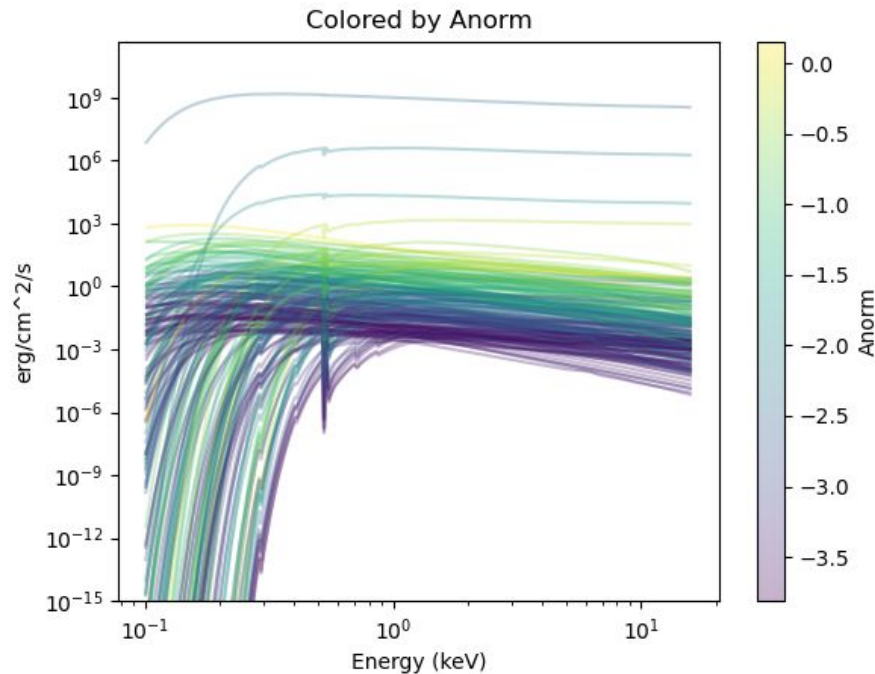
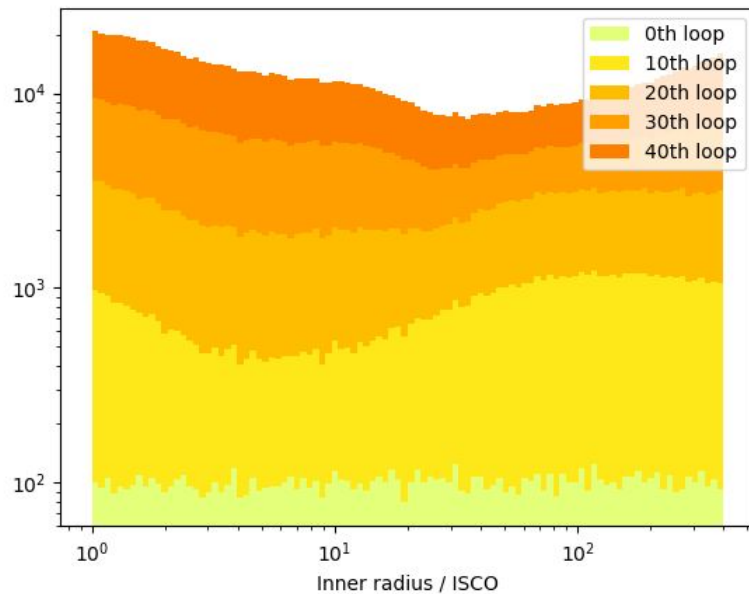
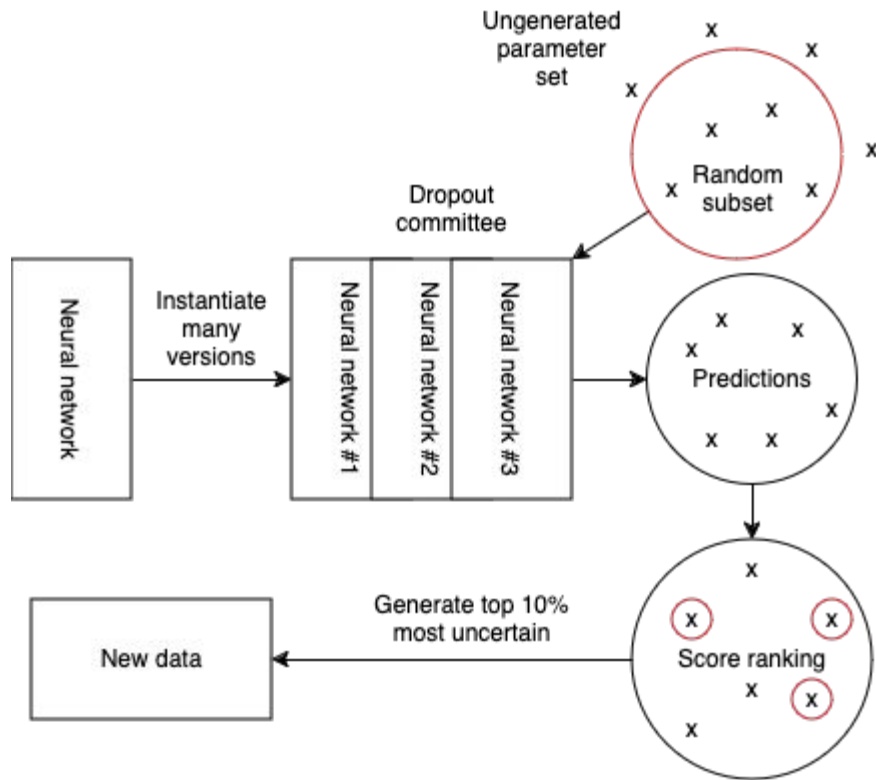


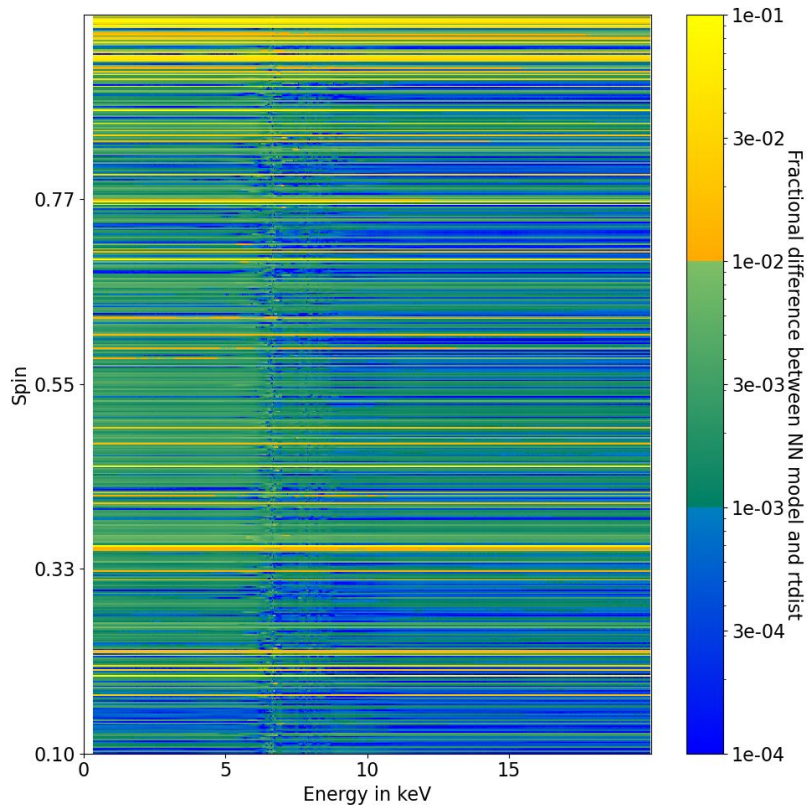
Emulation by committee: faster AGN fitting



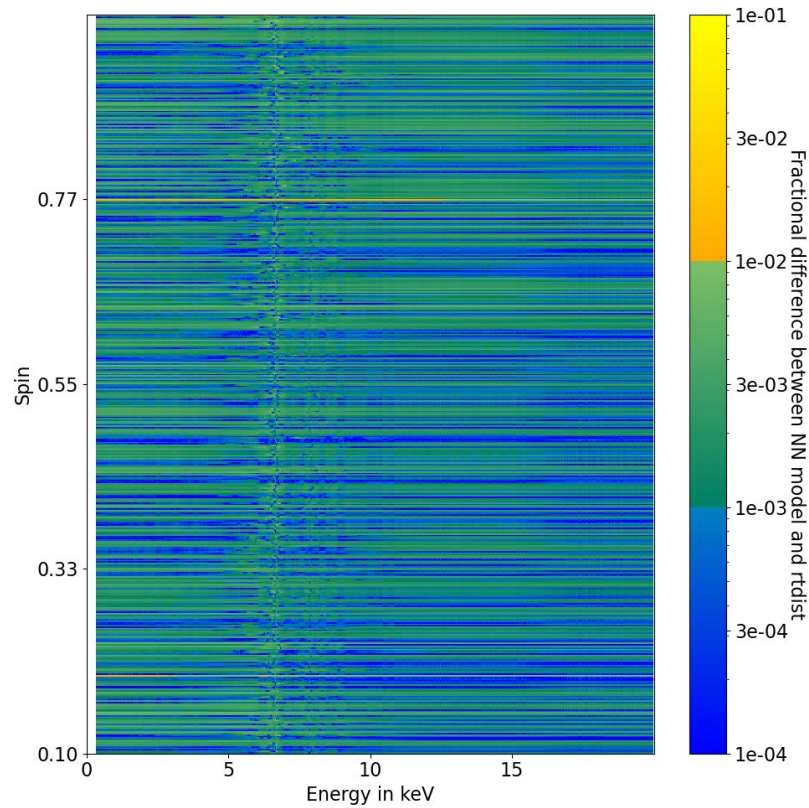
Query by dropout committee



Grid learning



Active learning



Estimating classical mutual information for spin systems and scalar field theories using generative neural networks

Piotr Białaś, Piotr Korcyl, Tomasz Stebel



Location: 44

2.2 Generative models & Simulation of physical systems

ML enhanced Monte Carlo simulations

Mutual information

Mutual information quantifies the "amount of information" obtained about one random variable by observing the other random variable. The bipartite partitioning into A, B allows defining the Shannon mutual information as

$$I = \sum_{a,b} p(a,b) \log \frac{p(a,b)}{p(a)p(b)}$$

Ancestral sampling using autoregressive neural networks

We factorize the probability into a product of conditional probabilities

$$p(s) = p(s^1) \prod_{i=2}^N p(s^i | s^1, \dots, s^{i-1}) \approx q_{\theta}(s^1) \prod_{i=2}^N q_{\theta}(s^i | s^1, \dots, s^{i-1}).$$

Using reweighting from p to q_{θ} provides us with access to the full partition function $Z(\beta)$ as well as $Z(a, \beta)$ and $Z(b, \beta)$ and write MI as

$$I(\beta) = \log \langle \hat{w}(a,b) \rangle_{q_{\theta}} - \beta \langle w(a,b) E(a,b) \rangle_{q_{\theta}} \\ - \langle w(a,b) \log Z(a) \rangle_{q_{\theta}} - \langle w(a,b) \log Z(b) \rangle_{q_{\theta}}.$$

Applications

Our group has applied this approach to various models:

- quantum entanglement in the Ising chain
⇒ Dawid Zapolski *Calculating entanglement entropy with generative neural networks*, [Location 41](#)
- hierarchical algorithm for the three-dimensional Ising model
⇒ Mateusz Winiarski *Applying hierarchical autoregressive neural networks for three-dimensional Ising model*, [Location 74](#)
- higher-dimensional Ising model and Z_2 gauge model
⇒ Vaibhav Chahar *Simulation of Z_2 model using Variational Autoregressive Network (VAN)*, [Location 1](#)
- Potts model

Flow-based generative models for particle calorimeter simulation

— EuCAIFCon, Amsterdam, NL —

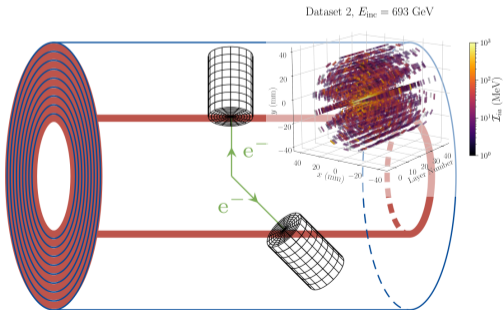
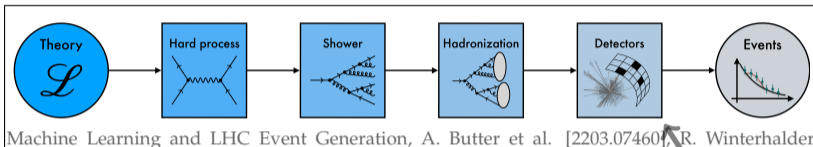
Claudius Krause

Institute of High Energy Physics (HEPHY), Austrian Academy of Sciences (OeAW)

April 30, 2024

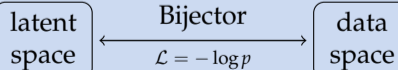


Our computational resources are limited!



We need fast and faithful surrogates.

⇒ Normalizing Flows are both.



Flow-based generative models for particle calorimeter simulation

- 1 Learn how total energy is distributed across layers: $p_1(E_1, E_2, \dots, E_n | E_{\text{inc}})$
- 2 Learn normalized shower:
 - ▶ direct: learn $p_2(\hat{\mathcal{I}}_{1:n} | E_{1:n}, E_{\text{inc}})$
 - ▶ autoregressive: learn first layer $p_2(\hat{\mathcal{I}}_1 | E_1, E_{\text{inc}})$ and step from $(n-1)$ to n : $p_3(\hat{\mathcal{I}}_n | \hat{\mathcal{I}}_{n-1}, n, E_n, E_{n-1}, E_{\text{inc}})$

CaloChallenge datasets

Dataset		Method	generation time per shower [ms] ↓	AUC on voxels ↓
1: γ 368-dim		GEANT4	$\mathcal{O}(10^4)$	0.499(2)
	d	CALOFLOW IAF	0.79 ± 0.01	0.761(2)
	d	CALOINN	0.51 ± 0.03	0.626(4)
1: π^+ 533-dim		GEANT4	$\mathcal{O}(10^4)$	0.609(4)
	d	CALOFLOW IAF	1.00 ± 0.02	0.884(2)
	d	CALOINN	0.44 ± 0.01	0.784(2)
2: e^- 6480-dim		GEANT4	$\mathcal{O}(10^5)$	0.500(2)
	a	iCALOFLOW IAF	13.2 ± 0.5	0.819(4)
	d	CALOINN	1.18 ± 0.03	0.743(2)
3: e^- 40500-dim		GEANT4	$\mathcal{O}(10^5)$	0.498(2)
	a	iCALOFLOW IAF	16.7 ± 0.5	0.891(3)

Classify Showers vs. GEANT4 as metric.