Machine Learning for Collider Event Reconstruction & Analysis

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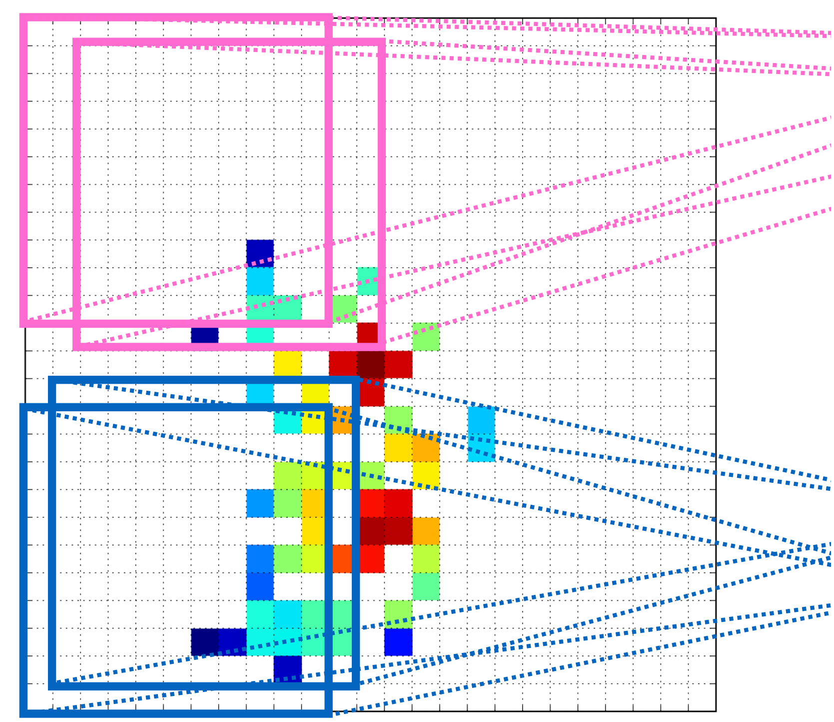

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BERKELEY INSTITUTE FOR DATA SCIENCE

CEPC Workshop

November 11, 2021

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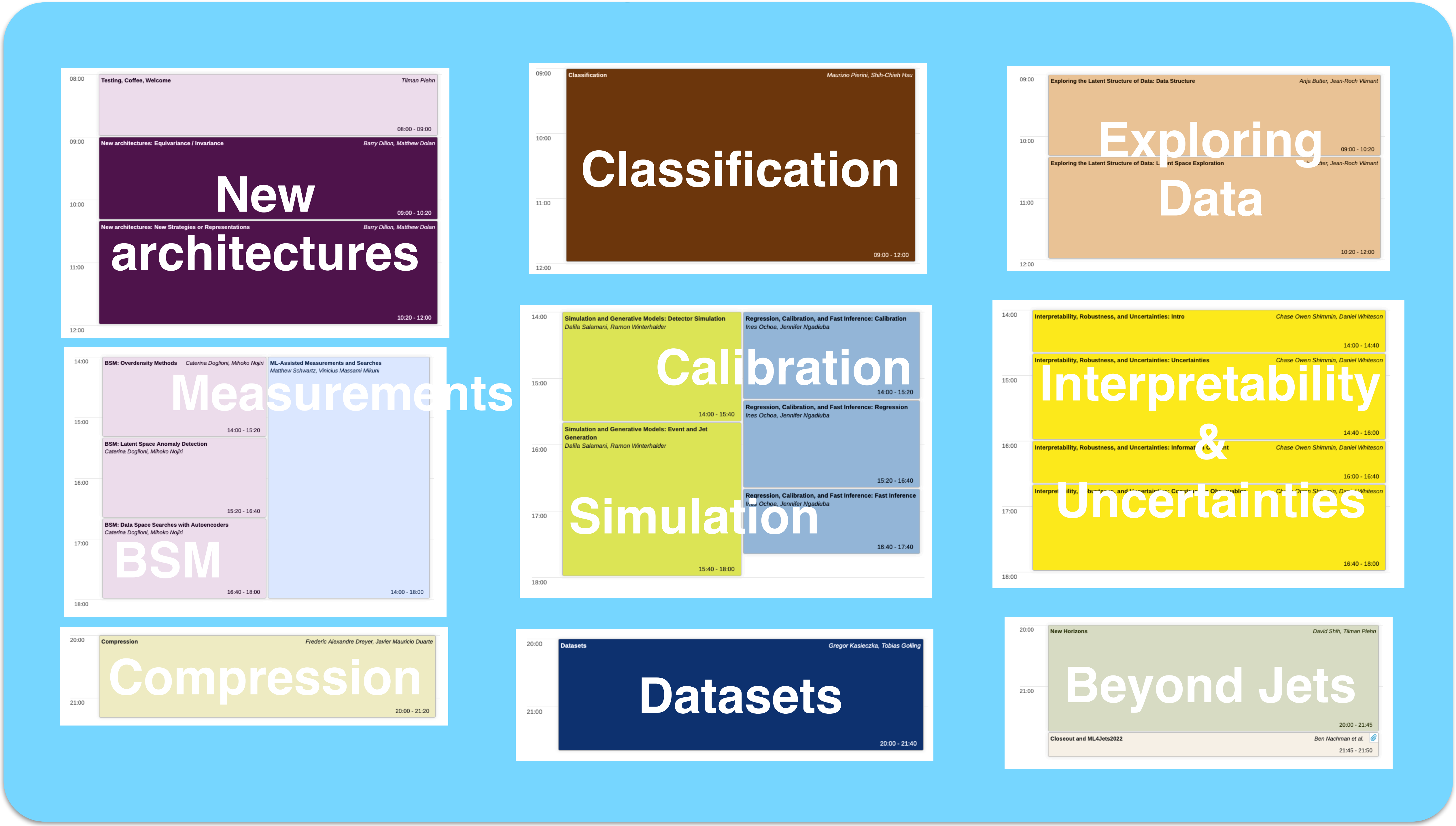
For a comprehensive review (anyone can contribute!) see:
https://iml-wg.github.io/HEPML-LivingReview/

ML4Jets2021

The annual ML4Jets conference a couple of months ago had 100 talks in three days (!)

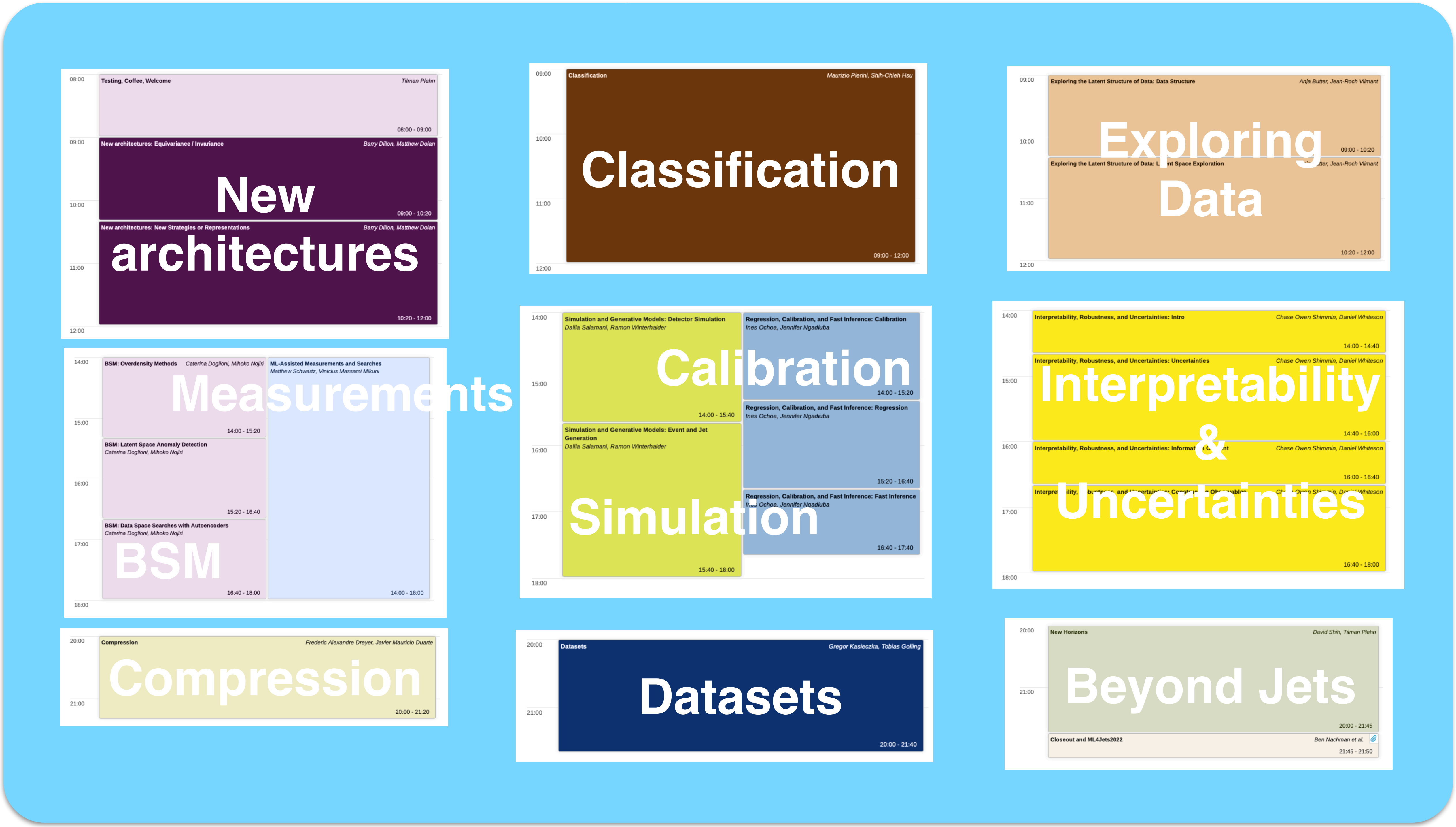
N.B. most plots are links!

ML4Jets2021



ML4Jets2021

I won't cover everything - just giving you a taste!



…my apologies in advance for not covering your / favorite topic.

New architectures

A **hot topic** in this area is **equivariance** / **invariance**

A NN is **equivariant** if it **commutes** with the symmetry group and a NN is **invariant** if the output is **unchanged** under symmetries of the inputs

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Equivariant example

Learn features that transform under rotations in the same way as the inputs - then feed these into further layers

e.g. train a NN that takes as input all constituents inside a jet and outputs the true jet 3-vector.

see e.g. E. Catalina's ML4Jets talk.

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Invariant example

Event/jet constituents are permutation invariant - use Deep Sets, Graph Networks, Transformers, Attention, …

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A NN is **equivariant** if it **commutes** with the symmetry group and a NN is **invariant** if the output is **unchanged** under symmetries of the inputs

e.g. Deep Sets:

$$f(x_1, \ldots, x_n) = F\left(\sum_{i=1}^{N} \Phi(x_i)\right)$$

for permutation invariance

see 1810.05165

Invariant example

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Measurements

Significant interest in ML-based unfolding for high-(or even variable-)dimensional, unbinned measurements

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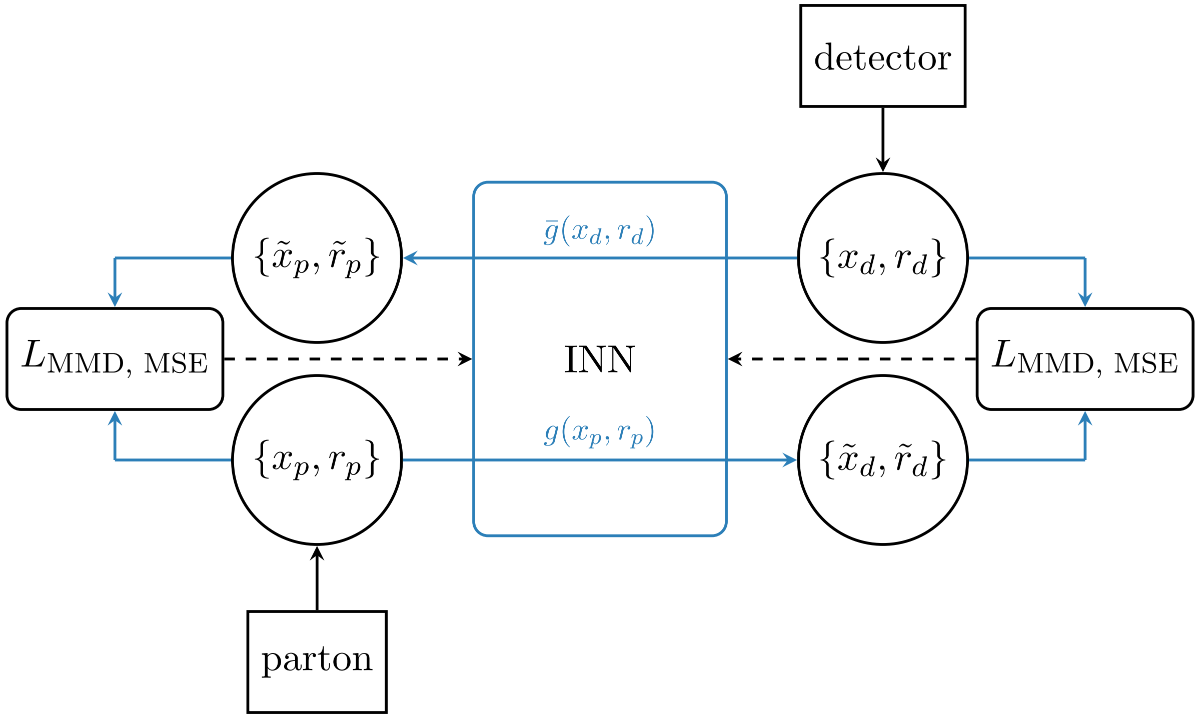
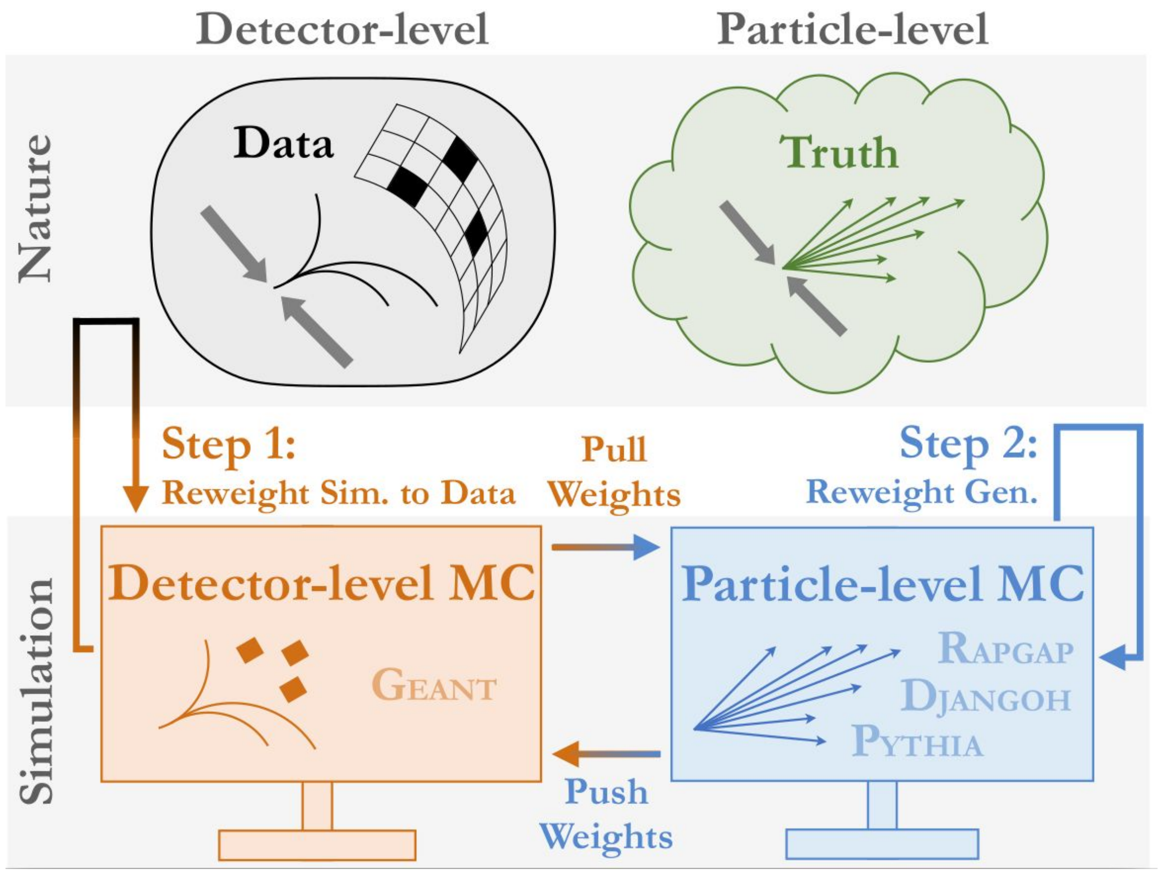




Generative model-based
2006.06685

Classifier-based
1911.09107

Measurements

Significant interest in ML-based unfolding for high-(or even variable-)dimensional, unbinned measurements

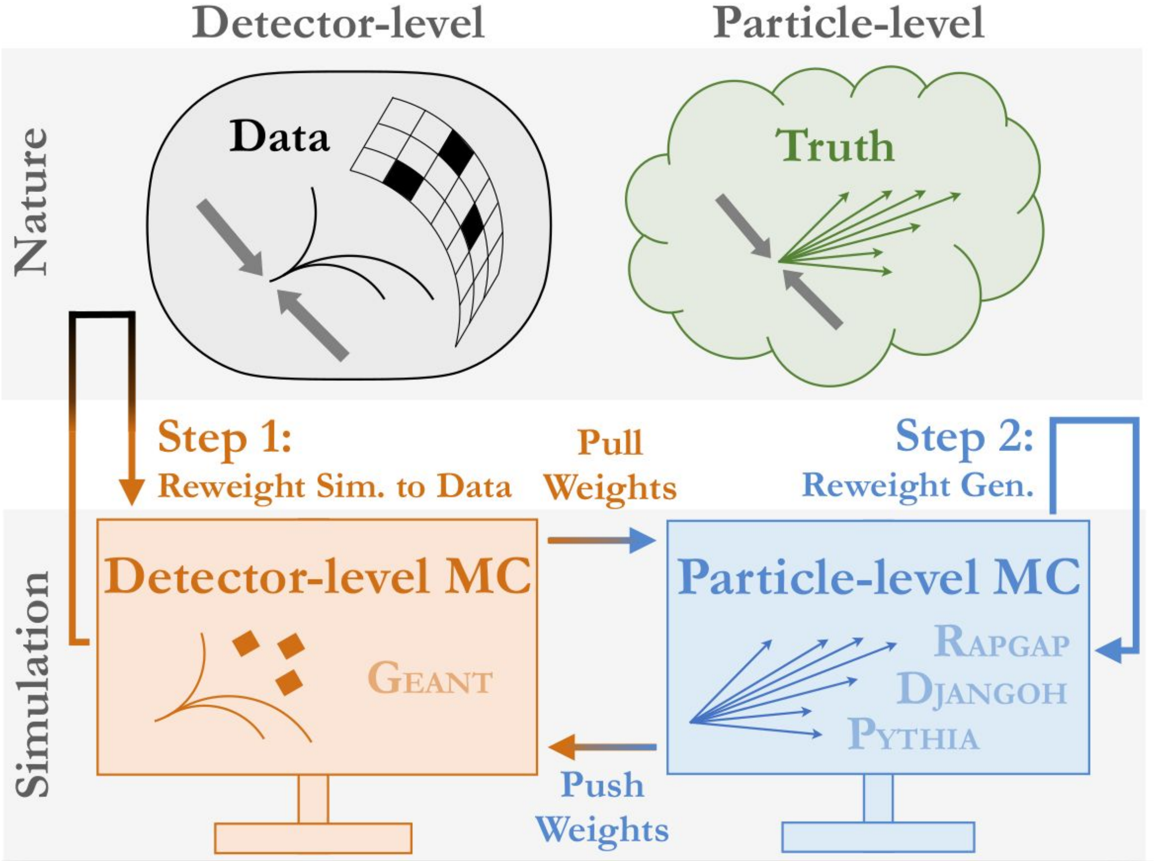
Fact: Neutral networks learn to approximate the likelihood ratio

or something monotonically related to it in a known way

Solution: train a neural network to distinguish the two datasets!

This turns the problem of **density estimation** (**hard**) into a problem of **classification** (**easy**)

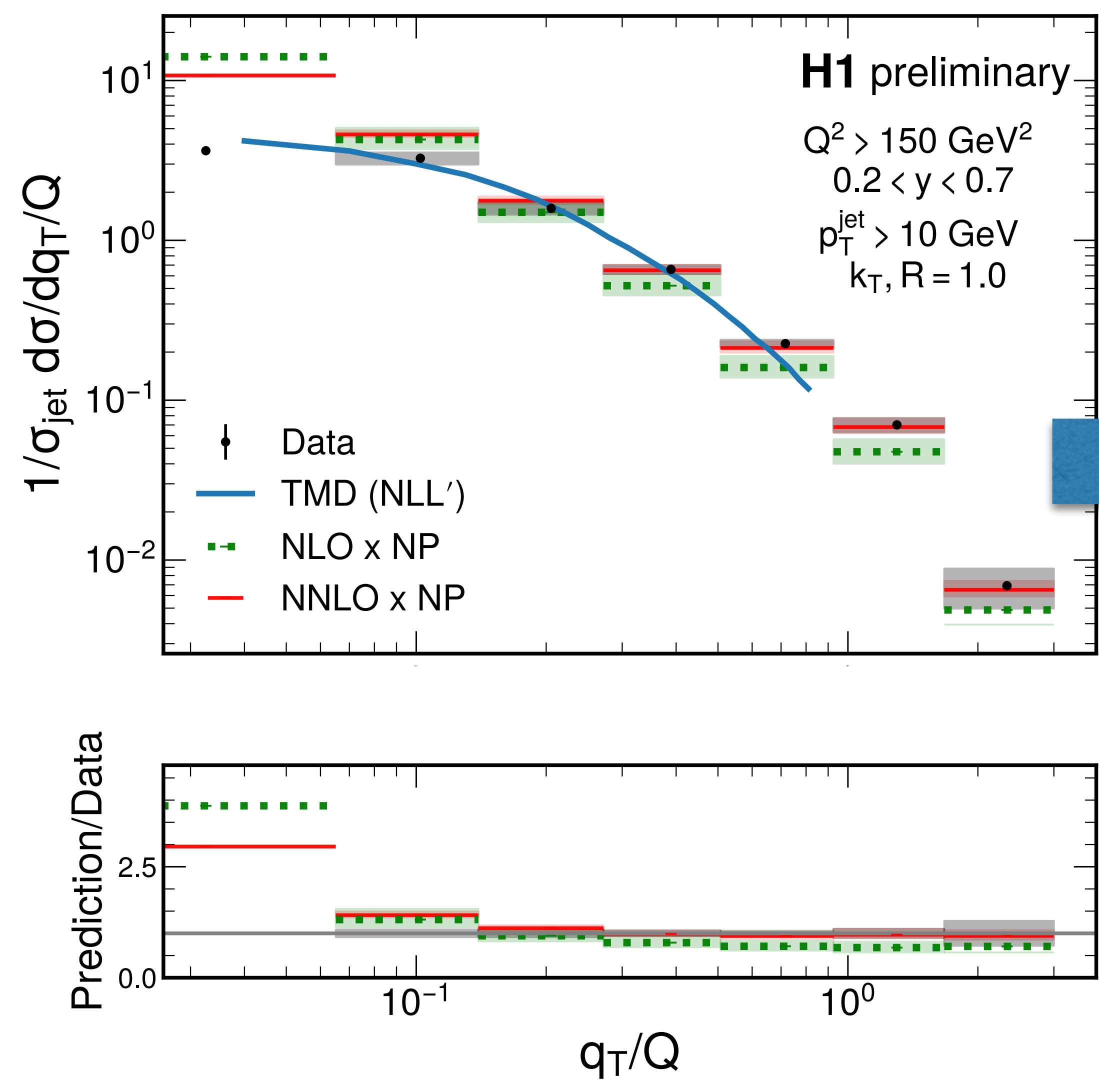
(this is a form of **likelihood-free inference**)



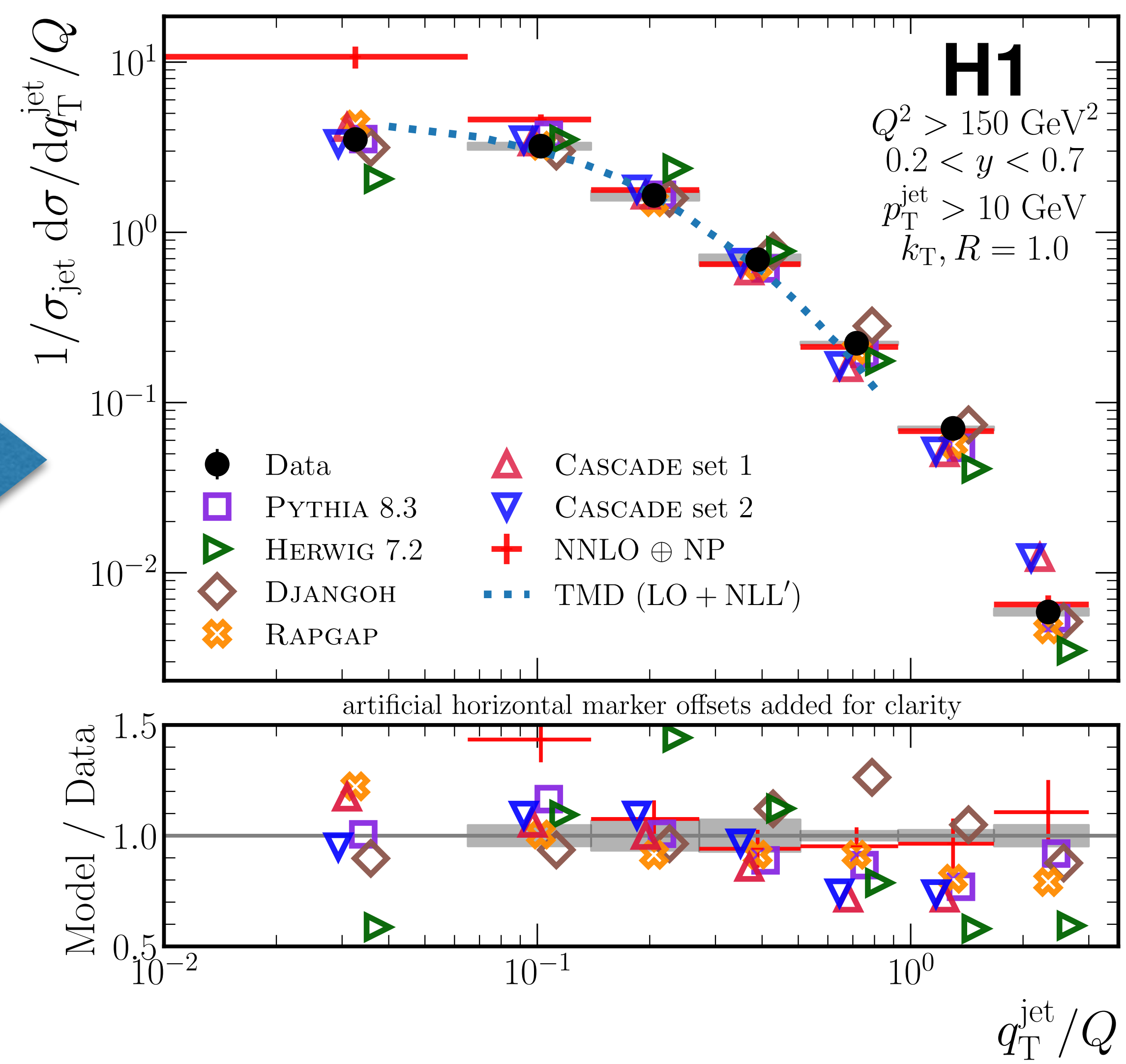
Classifier-based
1911.09107

Measurements

First application to collider data!



H1prelim-21-031



2108.12376
(very recent!)

2006.06685

1911.09107

BSM

A **hot topic** in this area is **anomaly detection**

i.e. using unsupervised/weakly-supervised/semi-supervised learning to reduce signal/background model dependence

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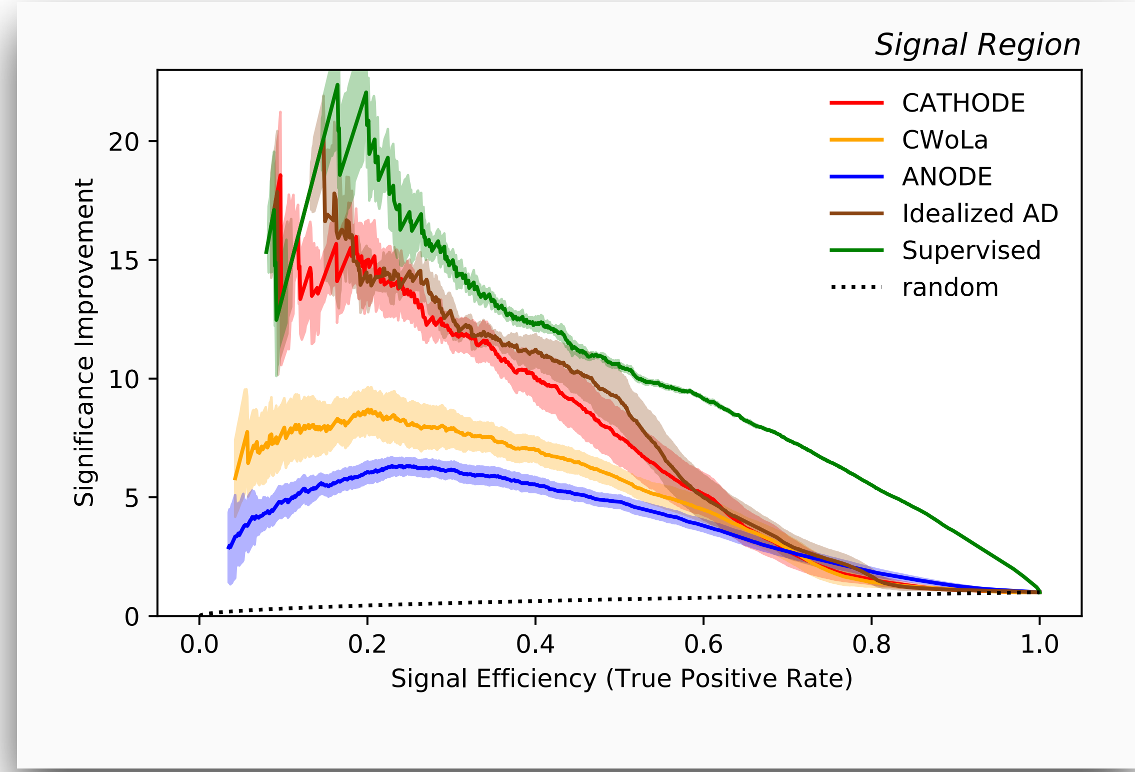

New methods are saturating **bounds** in some regimes

Context: LHC Olympics

Features: jet substructure

Methods:

CATHODE: density + classifier

CWoLa: classifier

ANODE: density + density

(sideband model + signal region model)

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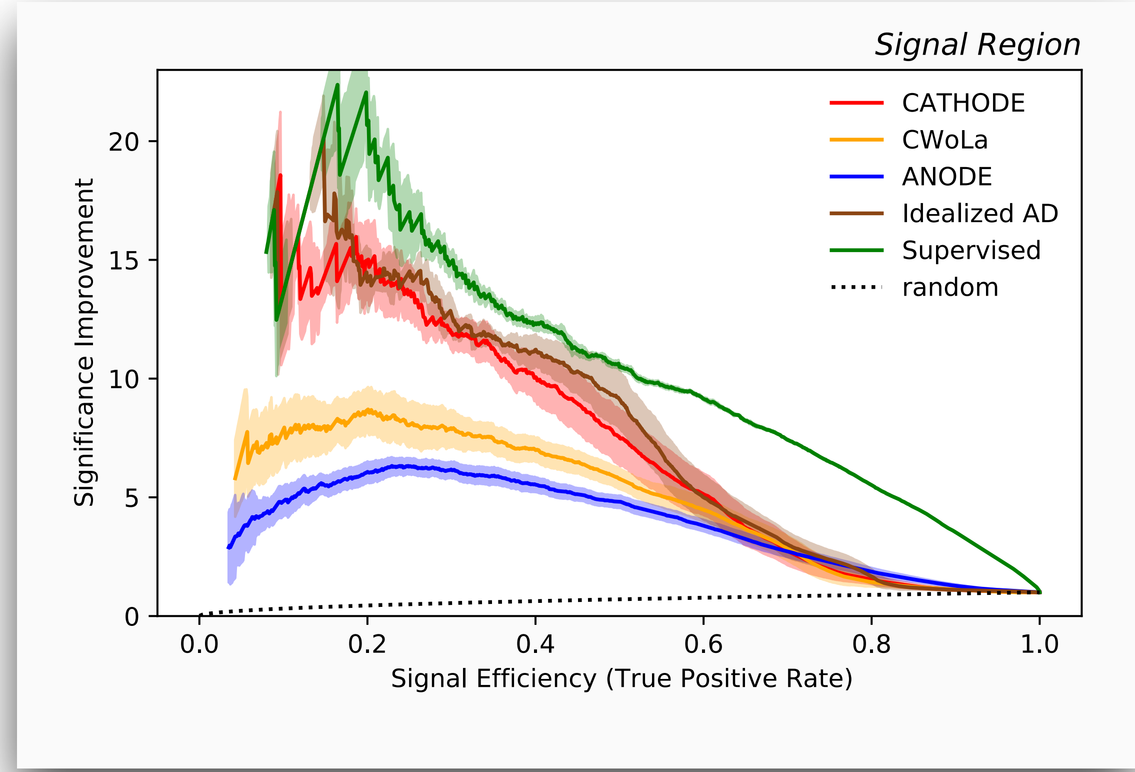
i.e. using unsupervised/weakly-supervised/semi-supervised learning to reduce signal/background model dependence



Key questions remain: *how to do model selection for unsupervised methods? How to best estimate the background? What about the non-resonant case?*

New methods are saturating **bounds** in some regimes

Classification

1902.09914 + H. Qu

Top tagging landscape

	AUC	Acc	$1/\epsilon_B$ ($\epsilon_S = 0.3$) single	mean	median	#Param
CNN [16]	0.981	0.930	914±14	995±15	975±18	610k
ResNeXt [30]	0.984	0.936	1122±47	1270±28	1286±31	1.46M
TopoDNN [18]	0.972	0.916	295±5	382± 5	378 ± 8	59k
Multi-body N-subjettiness 6 [24]	0.979	0.922	792±18	798±12	808±13	57k
Multi-body N-subjettiness 8 [24]	0.981	0.929	867±15	918±20	926±18	58k
TreeNiN [43]	0.982	0.933	1025±11	1202±23	1188±24	34k
P-CNN	0.980	0.930	732±24	845±13	834±14	348k
ParticleNet [47]	0.985	0.938	1298±46	1412±45	1393±41	498k
LBN [19]	0.981	0.931	836±17	859±67	966±20	705k
LoLa [22]	0.980	0.929	722±17	768±11	765±11	127k
Energy Flow Polynomials [21]	0.980	0.932	384			1k
Energy Flow Network [23]	0.979	0.927	633±31	729±13	726±11	82k
Particle Flow Network [23]	0.982	0.932	891±18	1063±21	1052±29	82k
GoaT	0.985	0.939	1368±140		1549±208	35k
ParticleNet-Lite	0.984	0.937	1262±49			26k
ParticleNet	0.986	0.940	1615±93			366k
ParticleNeXt	0.987	0.942	1923±48			560k

See Huilin's talk @ this workshop!

Graph-based

State-of-the-art classification performance continues to improve! New tricks like self-attention, etc.

Calibration

This is often set up as a regression task.

Innovation on many fronts, including the combination of various sources of information, mitigation of pileup, …

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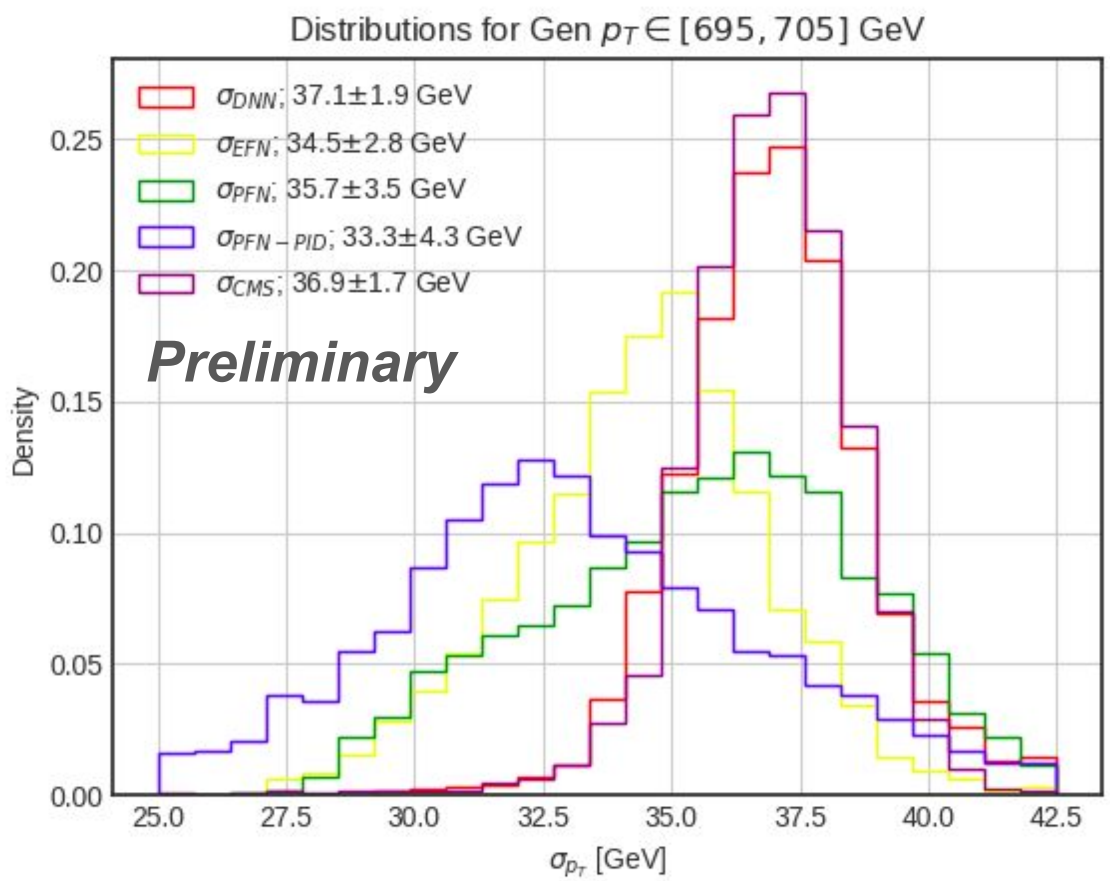

Ex: Prior-independent jet calibrations

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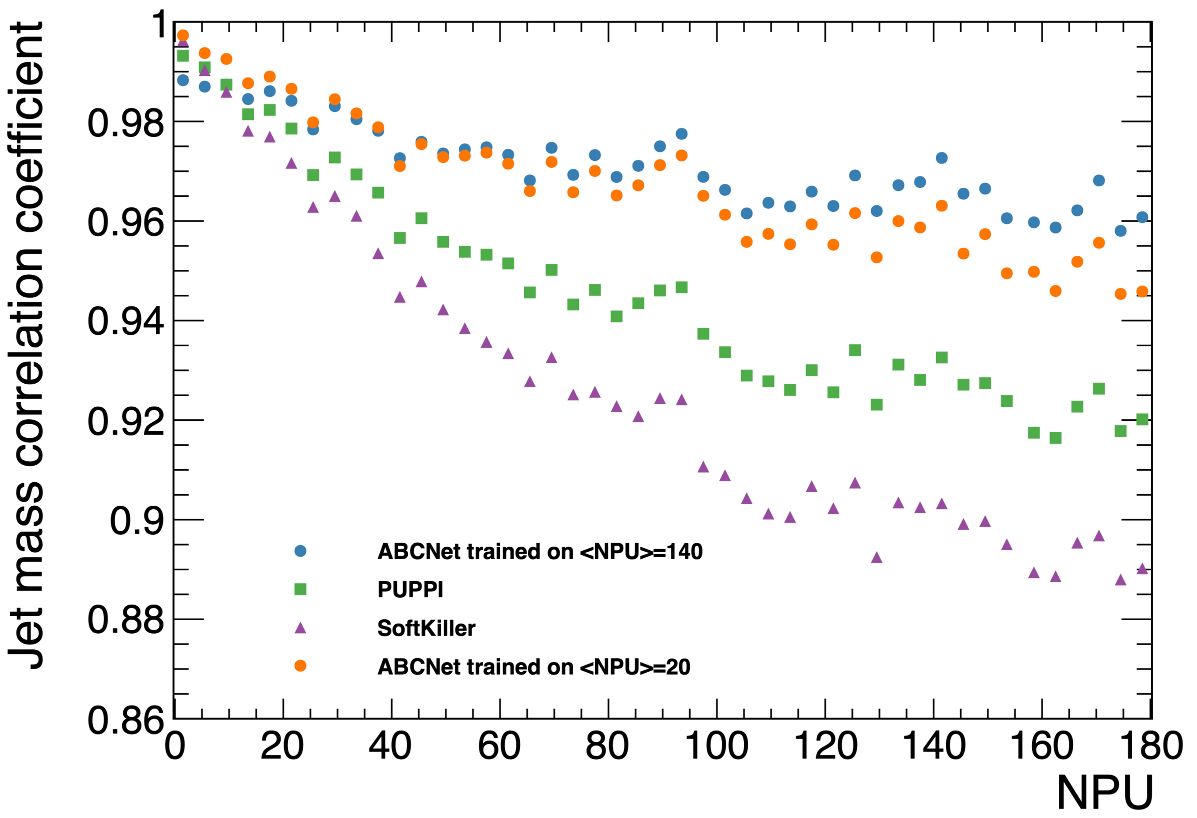

Ex: Graph-based Pileup Mitigation

Simulation

A **hot topic** in this area is **fast calorimeter simulation**

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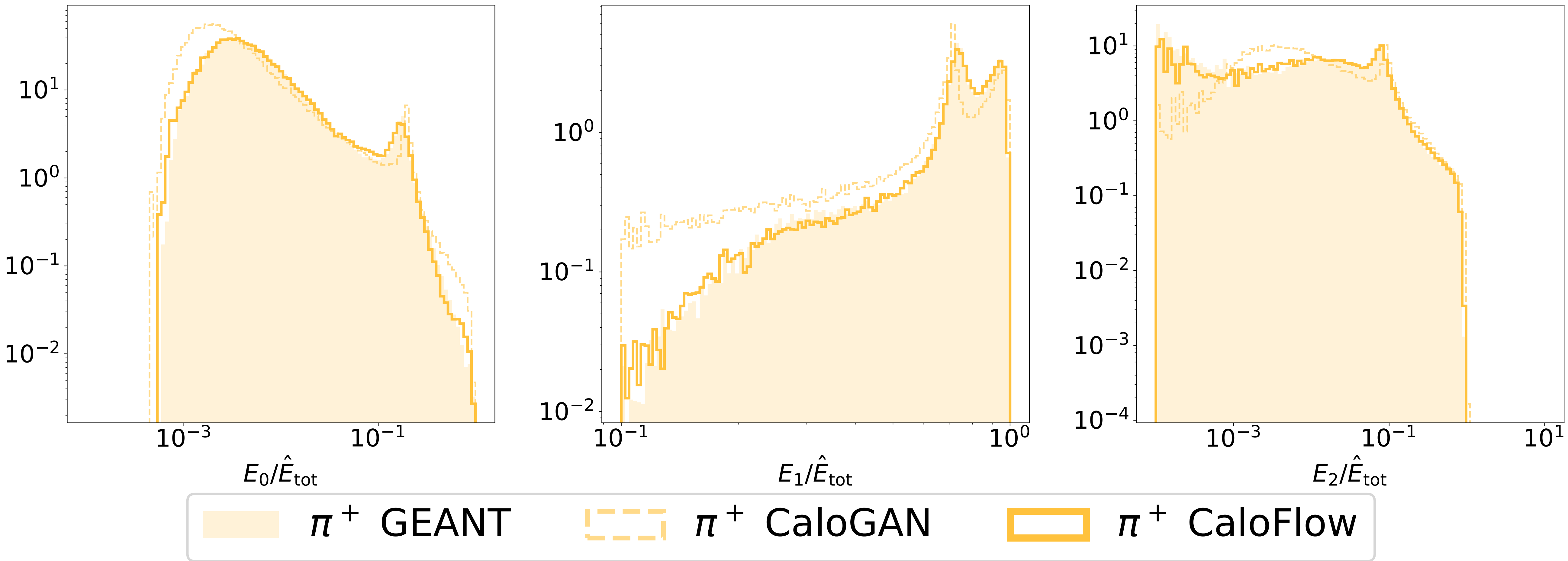
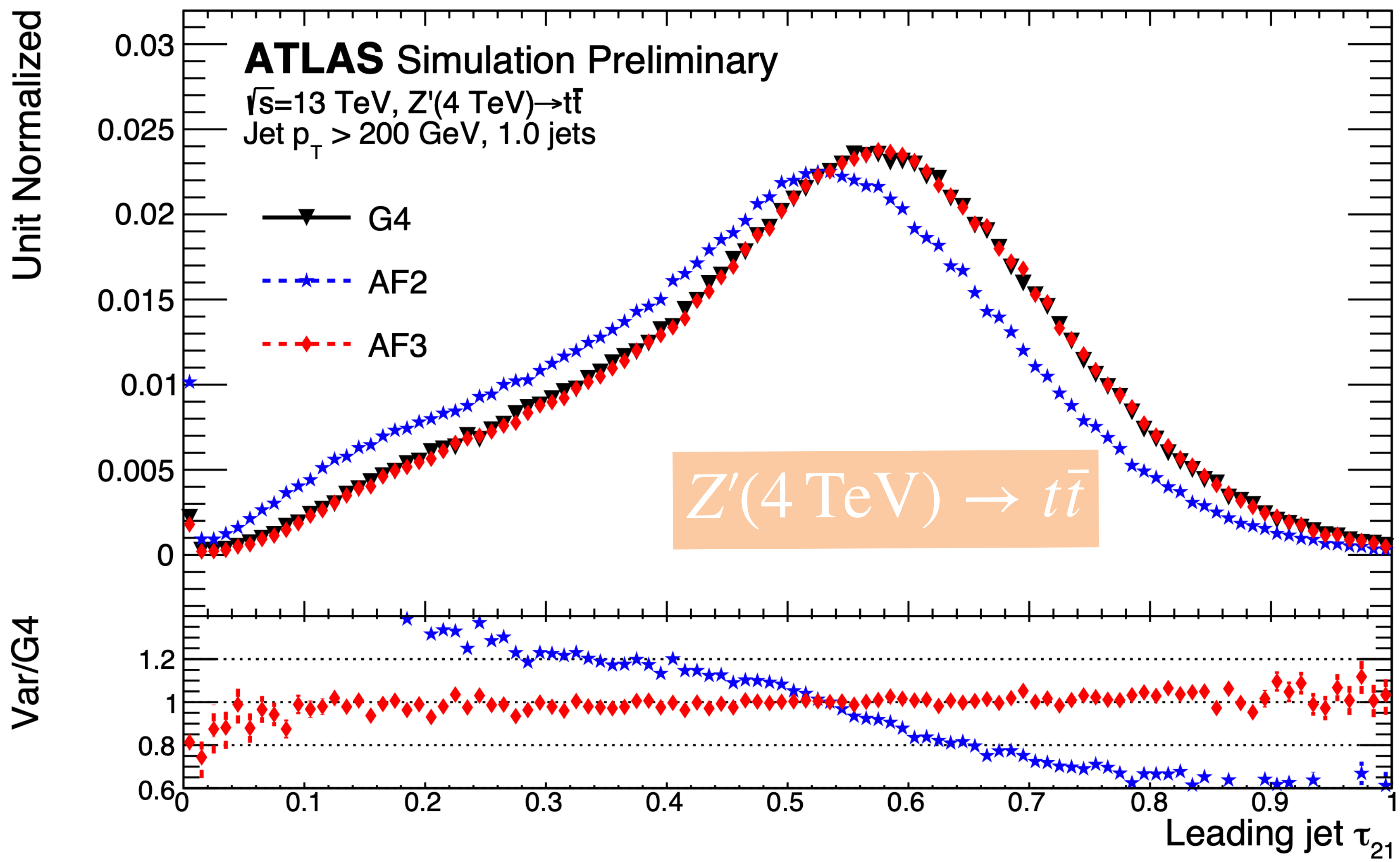
2106.05285



State-of-the-art with GANs and Normalizing Flows are reaching precision!

Simulation

Now with a full integration into a collider simulation!

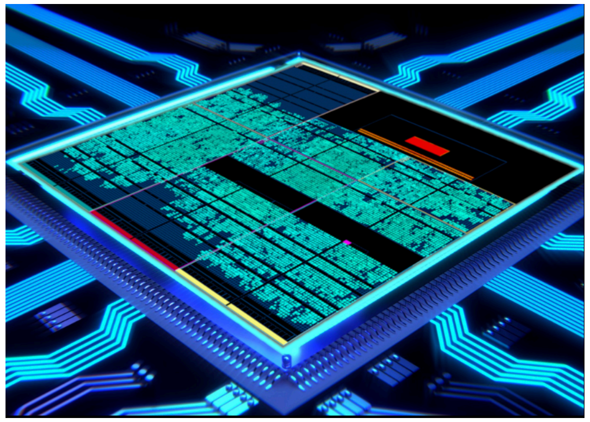


(AF3 uses a GAN for intermediate energies)

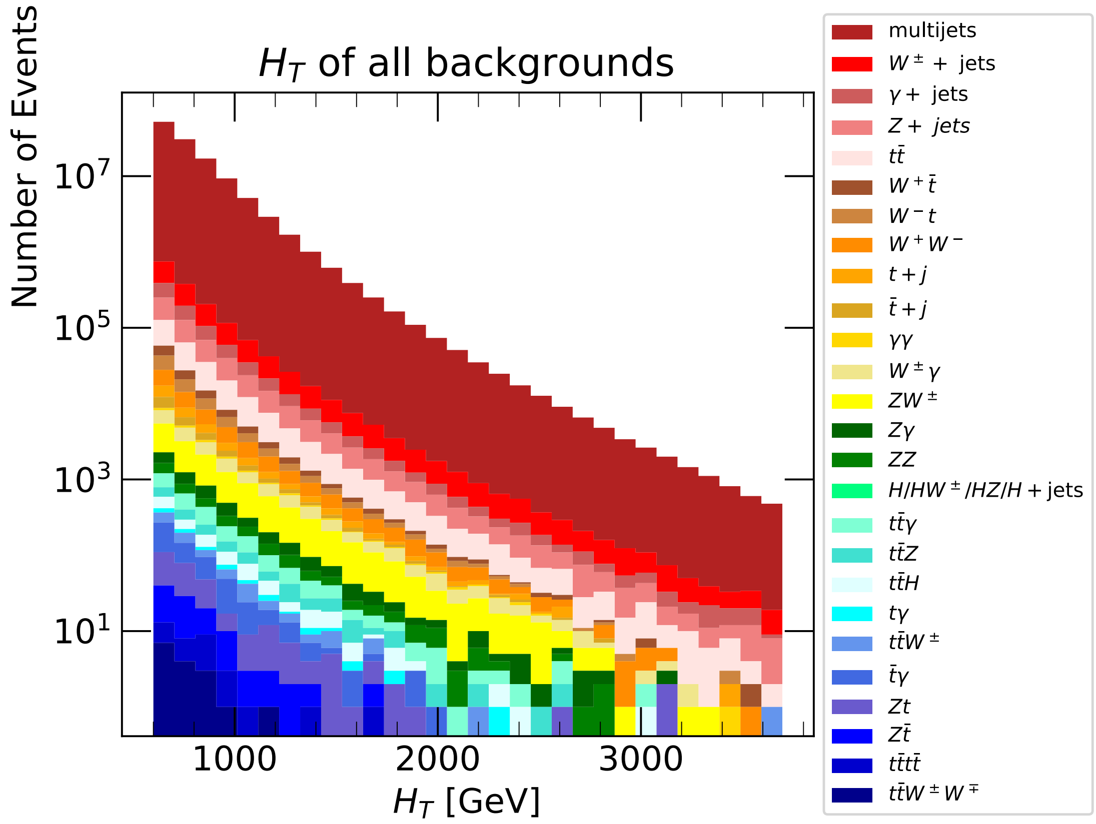
see yesterday's simulation session for more…

Datasets

LHC Olympics



Real-time Anomaly Detection



Dark Machines

+ more presented at ML4Jets and beyond!

see also https://iml.web.cern.ch/public-datasets

Exploring Data

Discovering / categorizing **latent** structure in data

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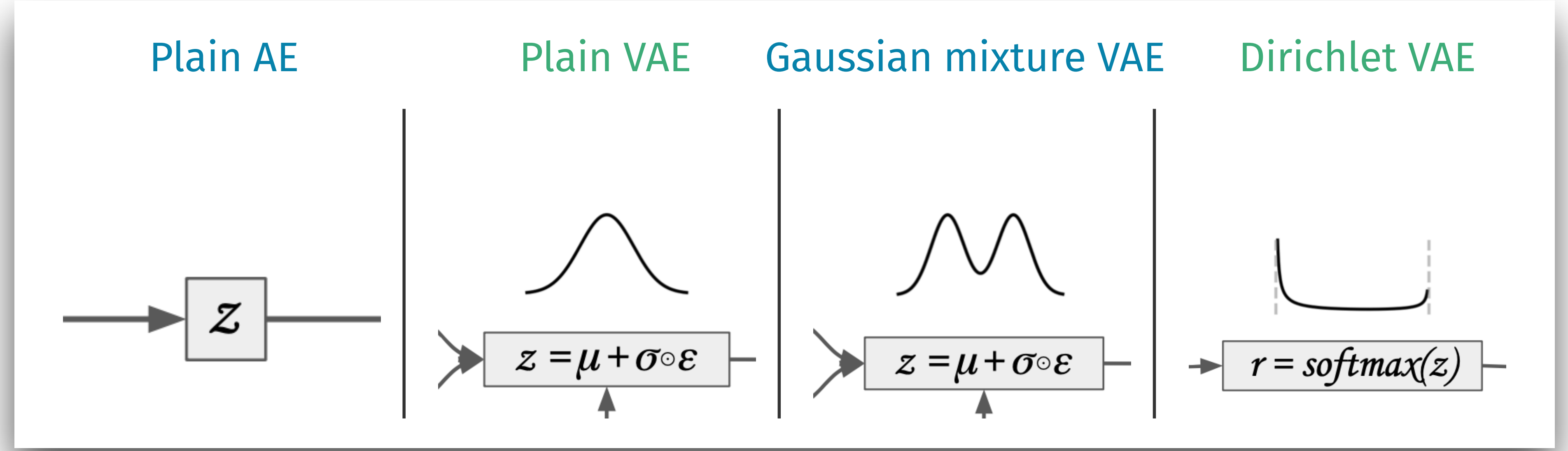
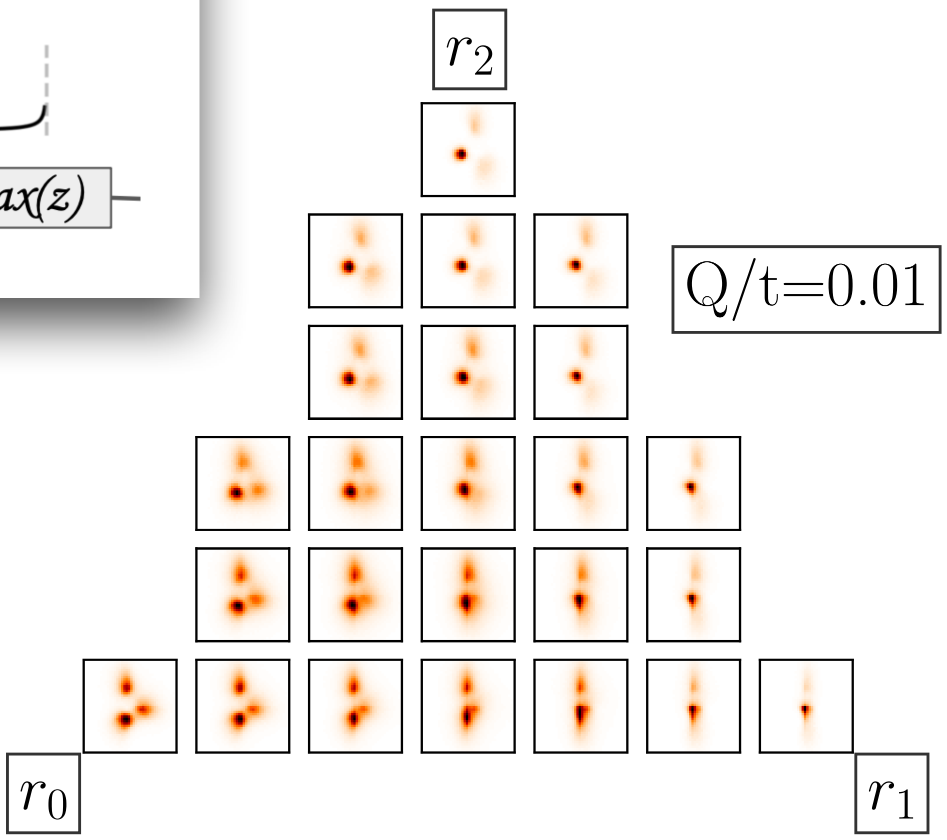


Imposing structure can lead to more interpretable latent spaces



2104.0829

Interpretability and Uncertainties

Key questions: *what are uncertainties associated with neural networks? How to make networks use uncertainty information (uncertainty-aware)? How to make networks optimal with respect to downstream analysis (Inference-aware)?*

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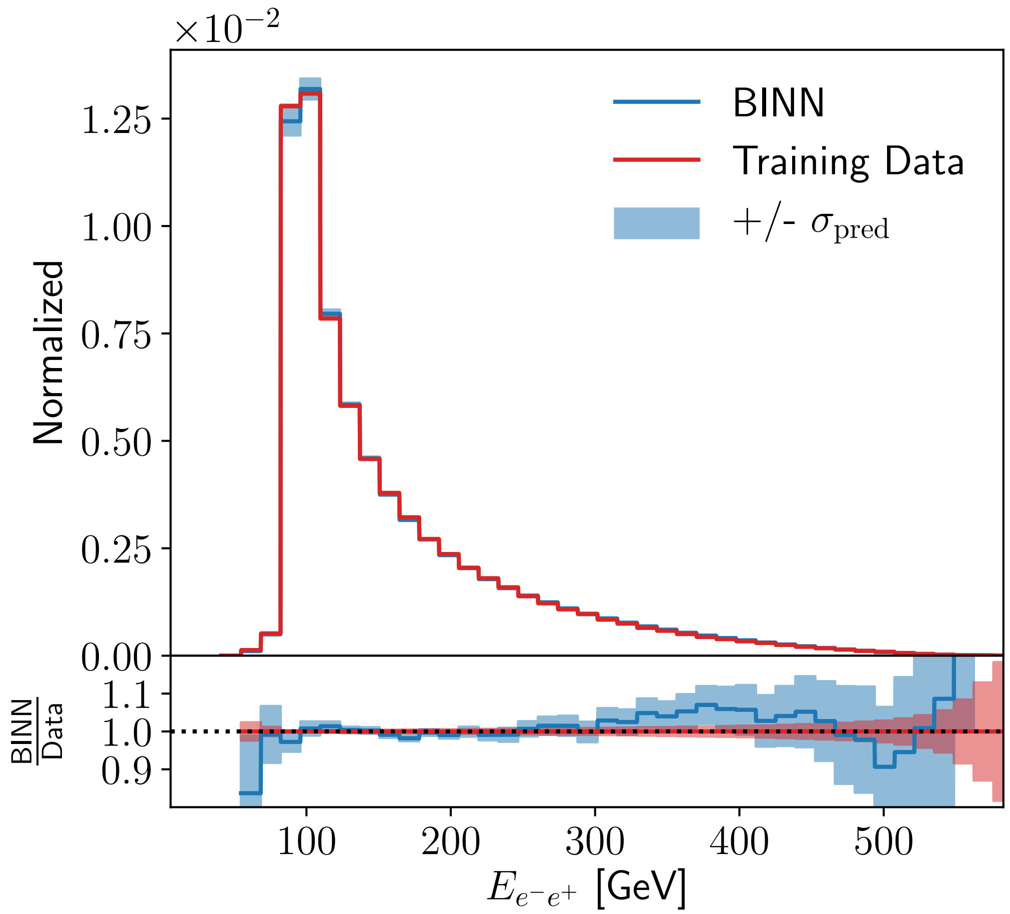

Bayesian generative models, parameterized uncertainty networks, …

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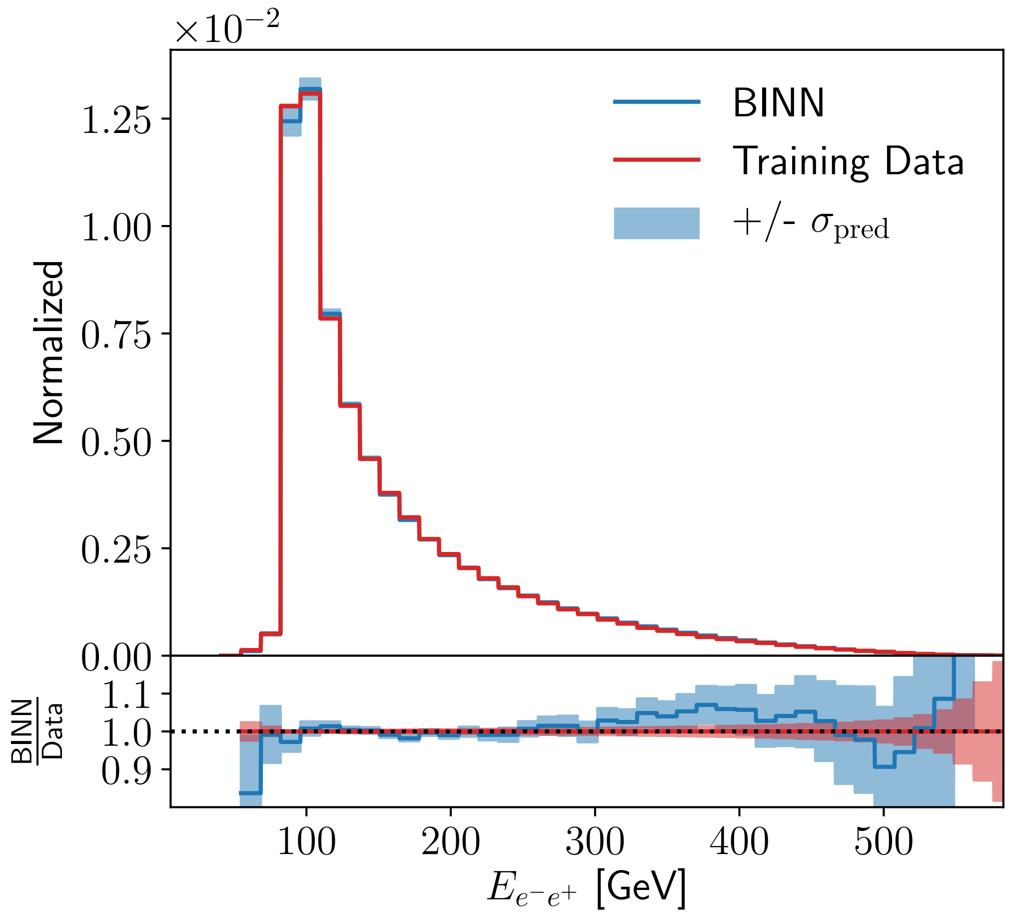
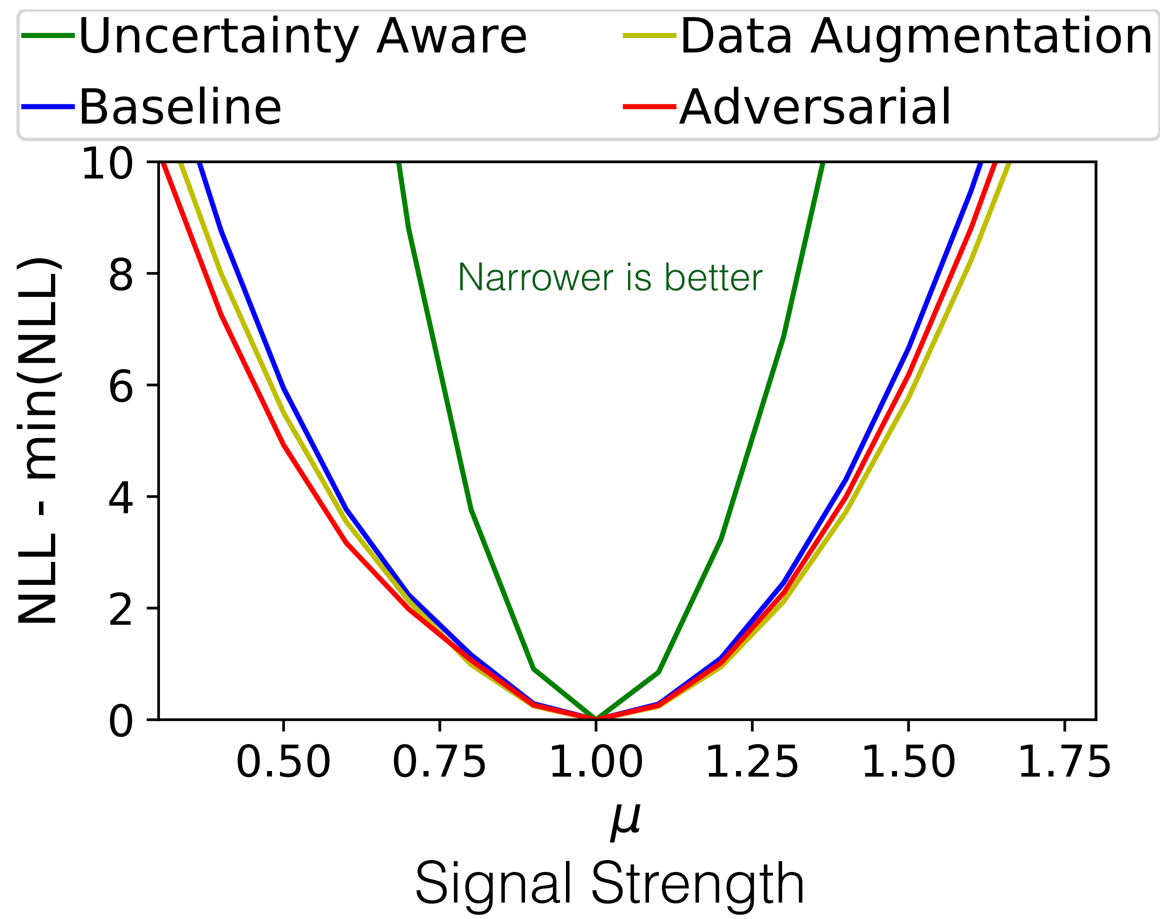


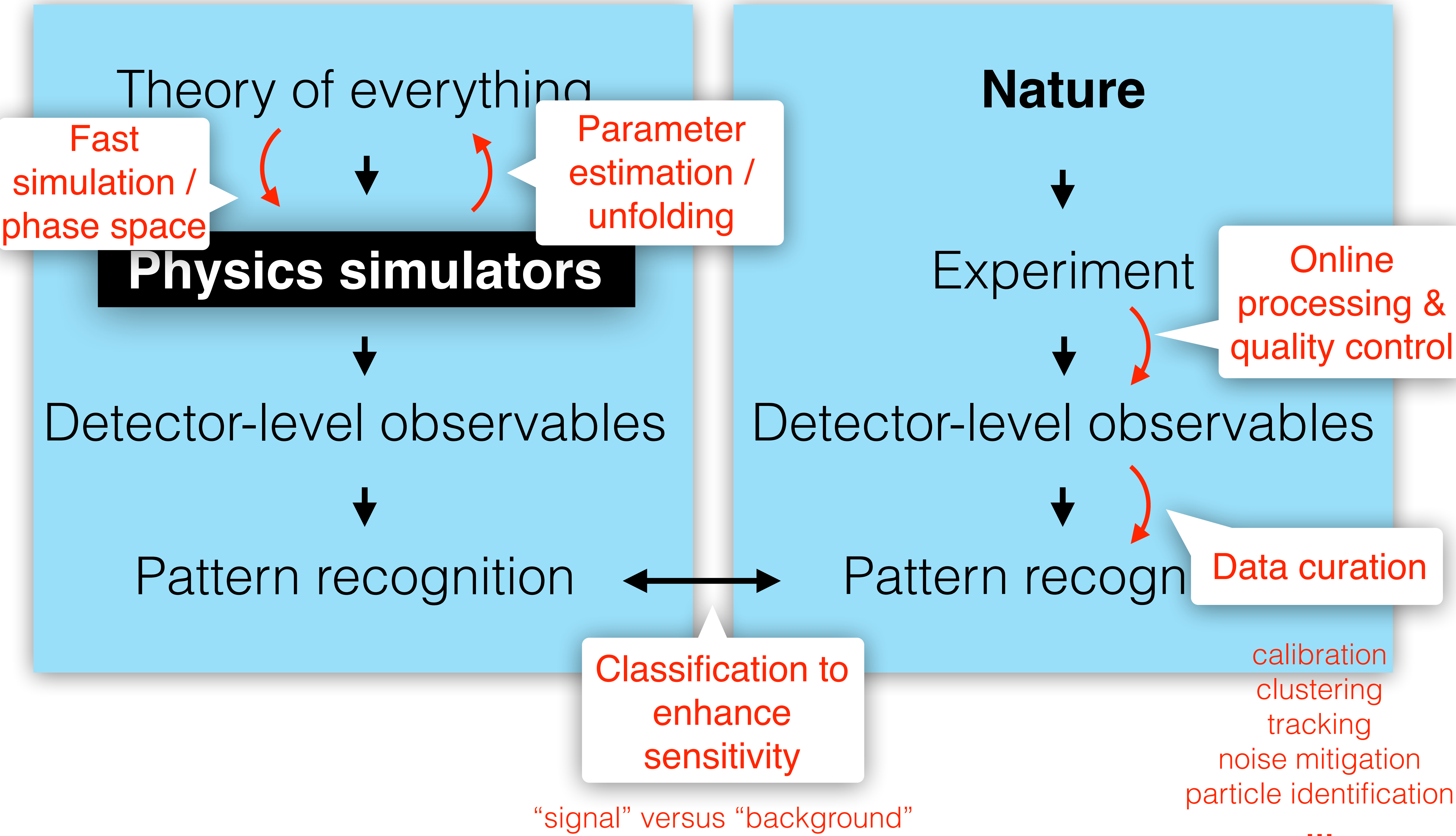


Bayesian generative models, **parameterized uncertainty networks**, …

Data analysis in NP/HEP

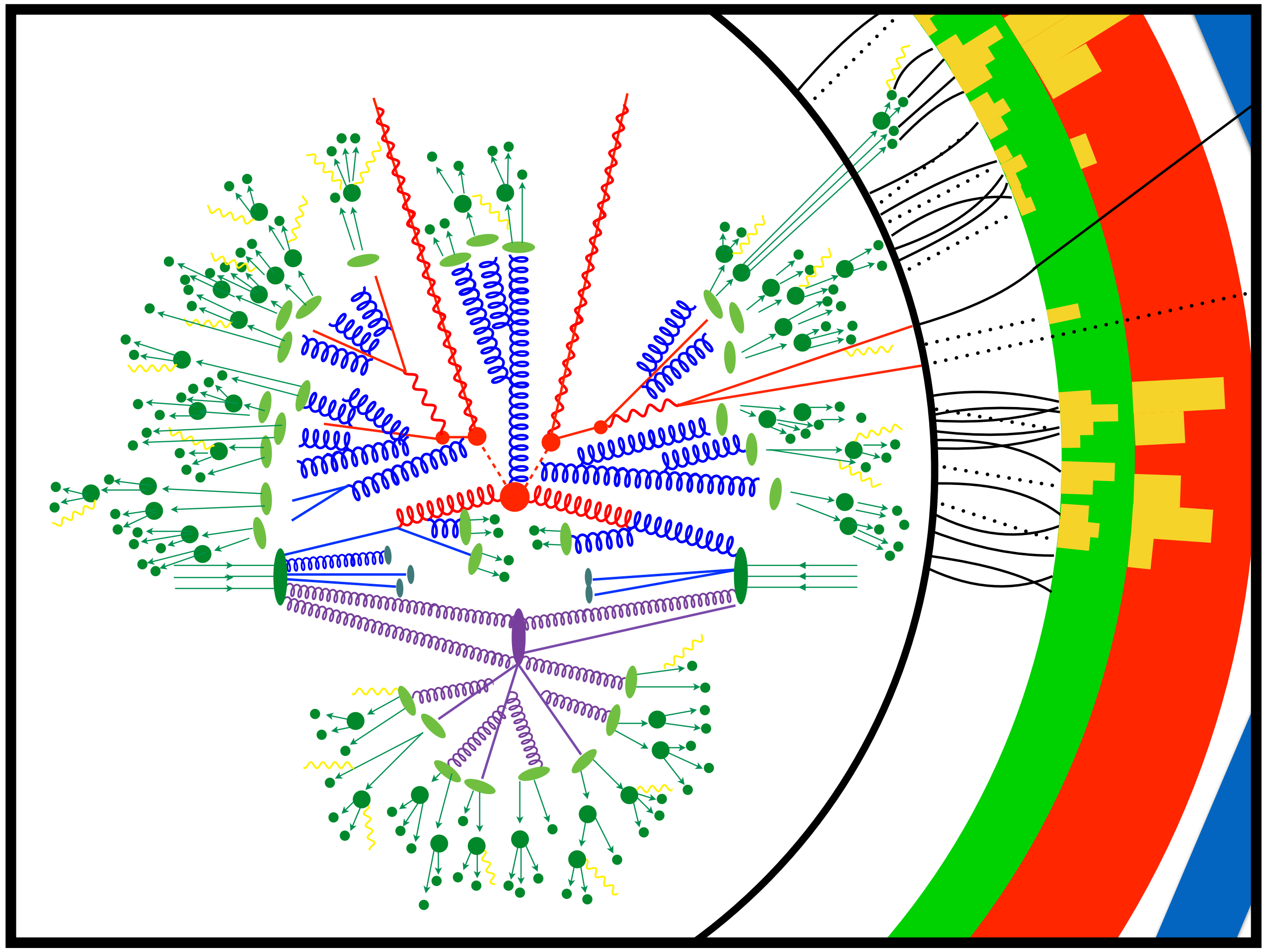
Theory of everything	**Nature**
↓	↓
Physics simulators	Experiment
↓	↓
Detector-level observables	Detector-level observables
↓	↓
Pattern recognition ⟷	Pattern recognition

Data analysis in NP/HEP + ML



Conclusions and outlook

Deep learning has a great potential to **enhance**, **accelerate**, and **empower** analyses with jets



Due to the limited time, I was only able to cover a small selection of new ideas and results

Backup