Recent developments in AI/ML for heavy-ion experiments

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Supported in part by

Outline

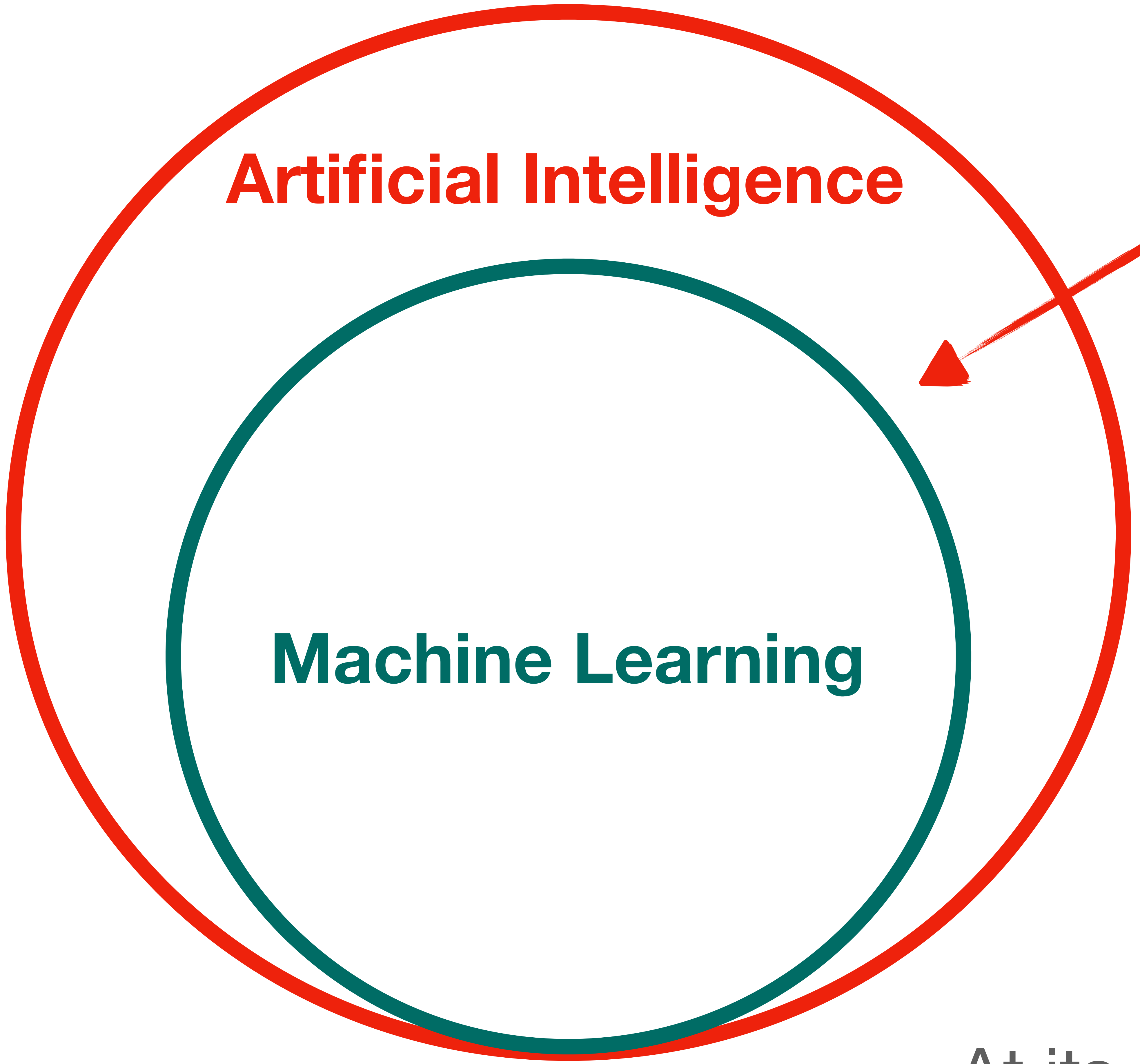
What is AI/ML and why is it useful for heavy-ion physics?

How is AI/ML currently being used by HI experiments?

How will AI/ML be used in the future?

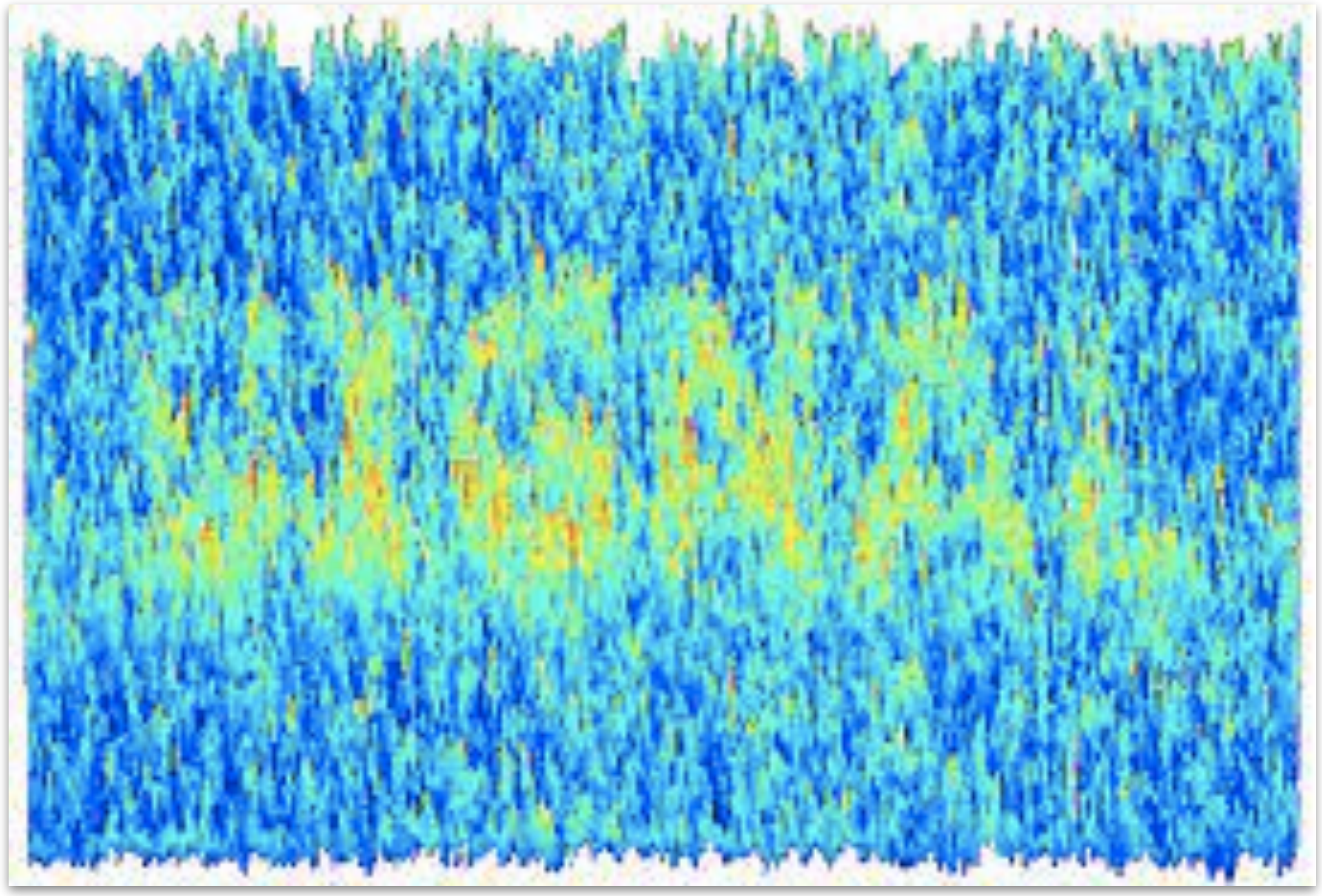
What is machine learning?

Artificial Intelligence: Programs with the ability to acquire and apply knowledge and skills.



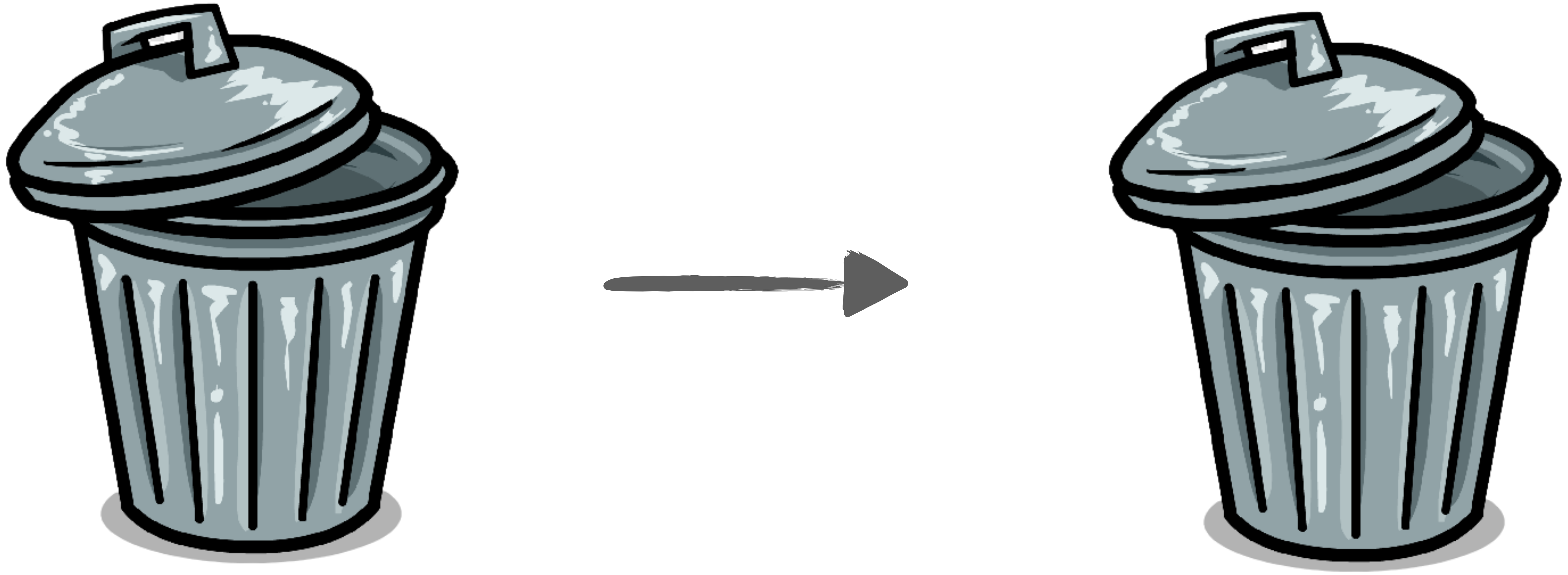
Ex: Chatbots (humans give rules)

Machine Learning: algorithms that imitate human learning, i.e. gradually improving accuracy over time.



At its core, pattern recognition → humans can do this by eye!

What can ML *not* do?



Garbage In *Garbage Out*

- ML cannot replace domain knowledge.
- ML is not a causation tool.

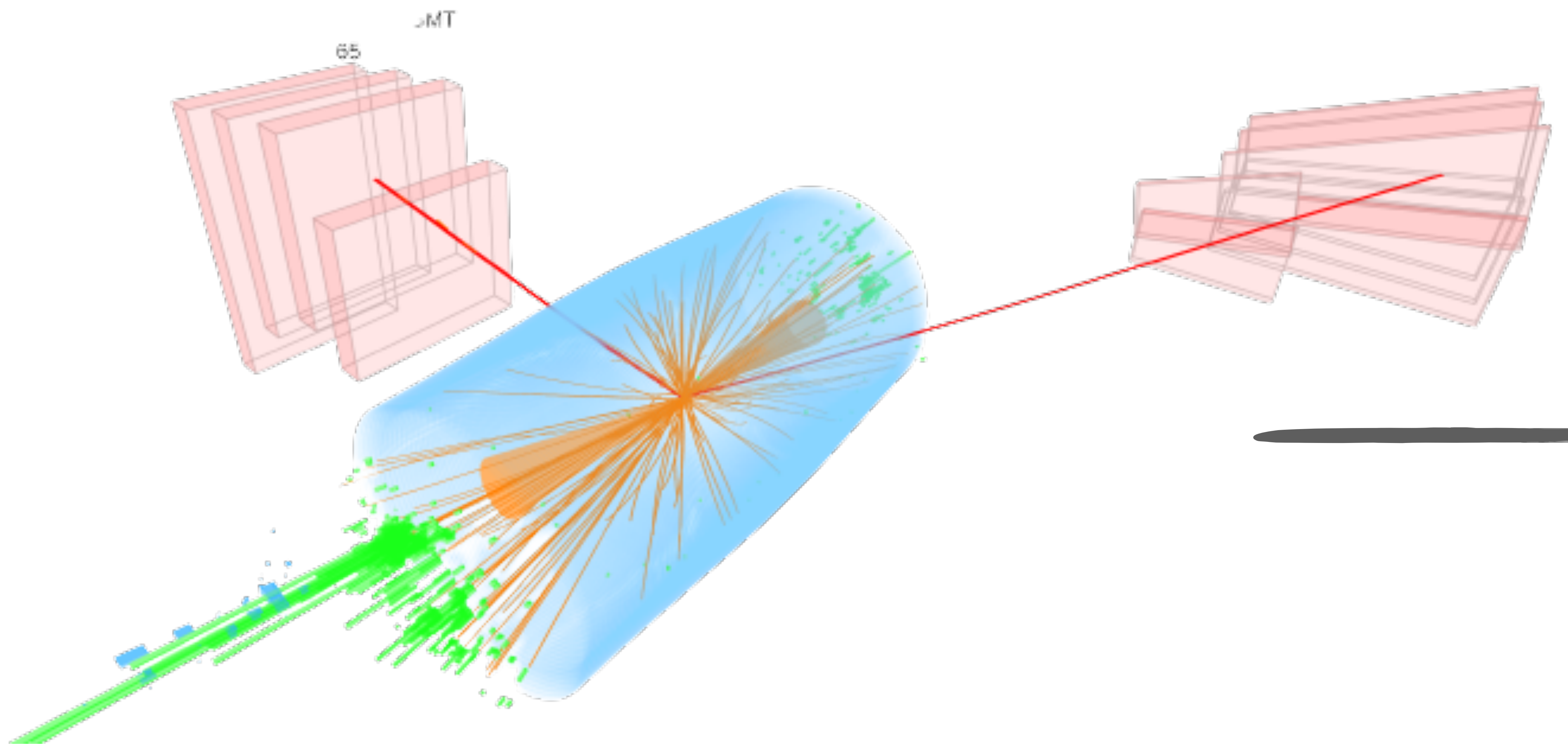
Don't want to be finding cloudy days when you should be finding tanks!

- **ML is not a magic fix!**

Why ML and HEP?

***Goal of HEP measurements:** To extract relevant physics information from available data!*

Conventional approach: (1) make selection using a series of boolean decisions motivated by physics/experimental constraints (2) perform a statistical analysis on selected data.



Optimal decision difficult to derive from expert knowledge alone! Employ algorithms that utilize multiple variables simultaneously → inspired countless ML applications! (Living Review)

ML and HEP

Industry ⇄ Academia

- LHC represents a medium-sized application of ML.

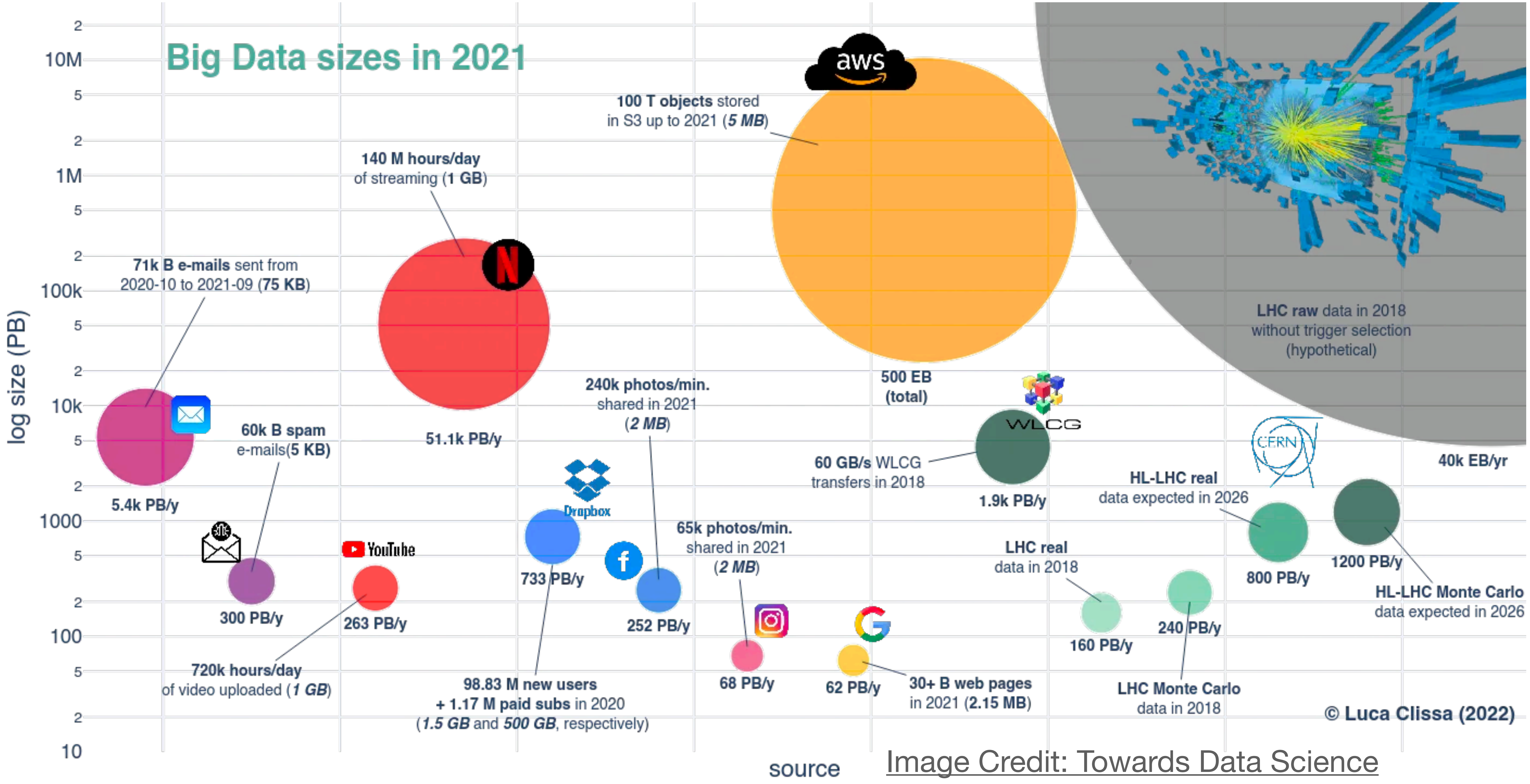
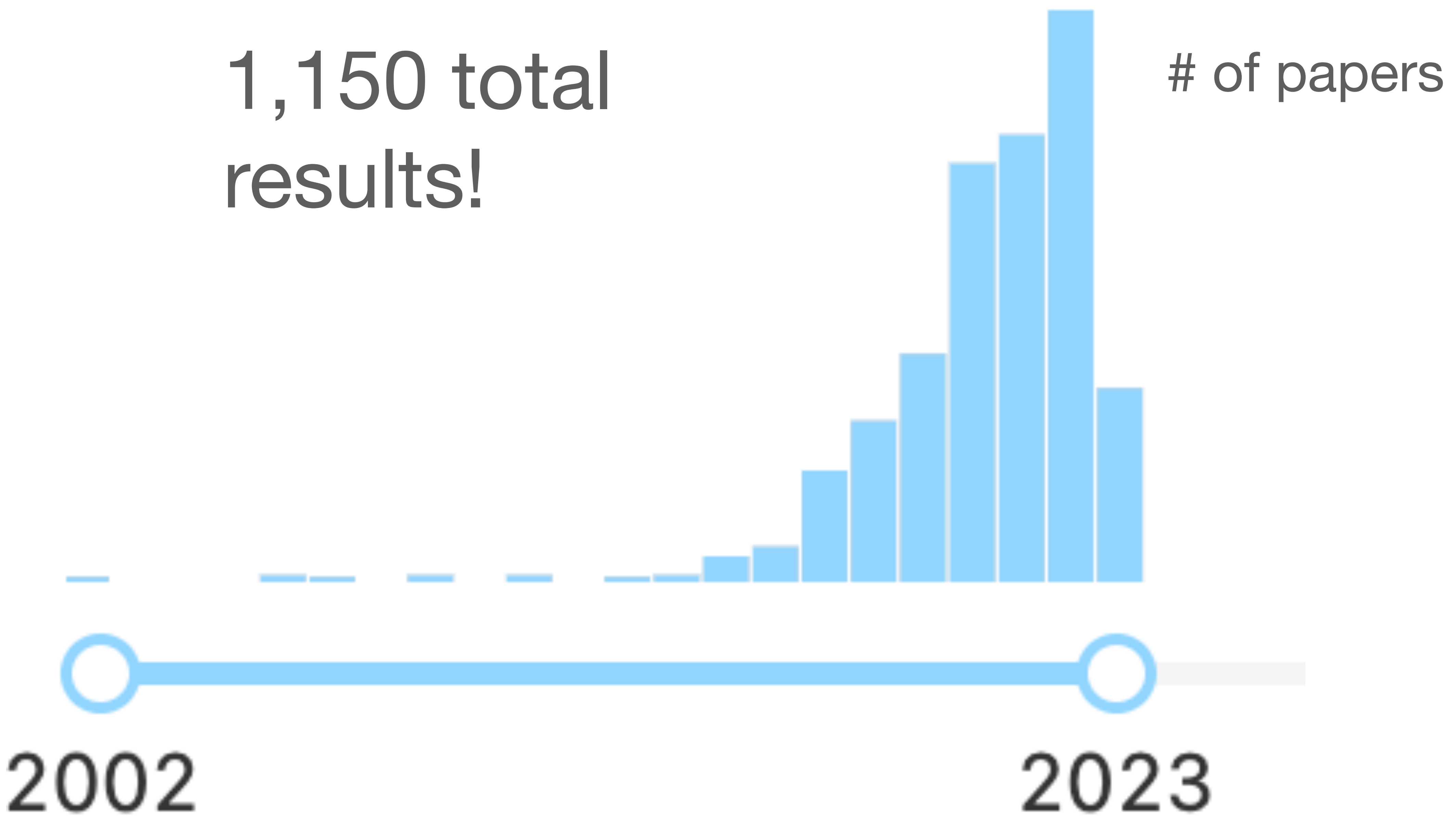


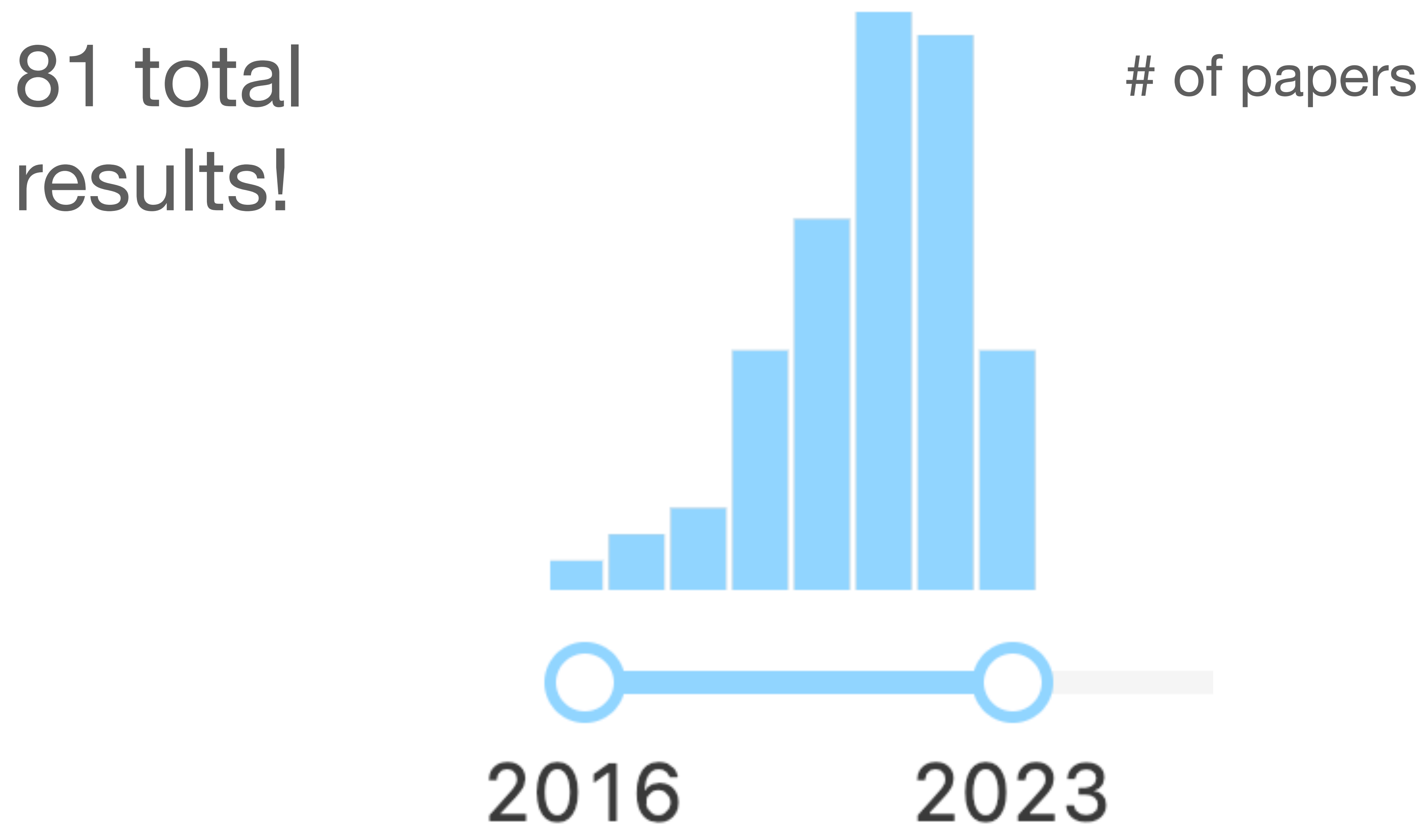
Image Credit: Towards Data Science

ML and heavy-ion physics



Inspire HEP search results for "machine learning HEP"

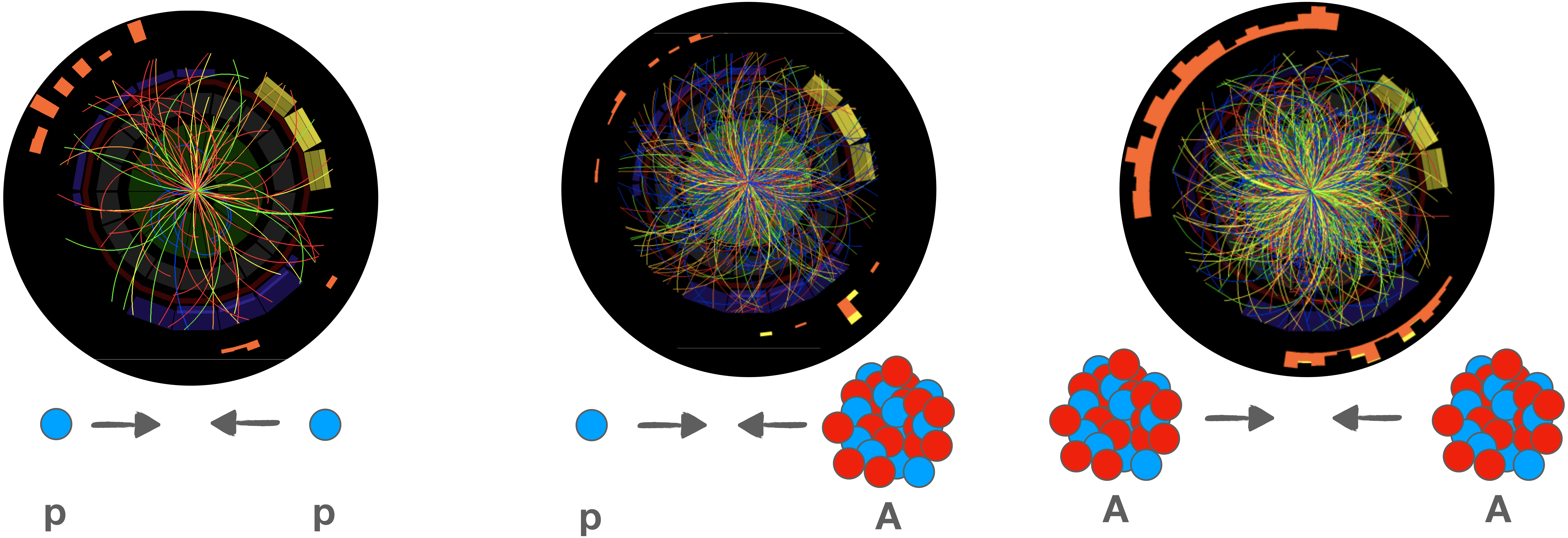
vs.



Inspire HEP search results for "machine learning heavy-ion physics"

ML is a rapidly growing field in HEP and HIs!

ML and heavy-ion physics



HI environment can be challenging for ML.

- Higher particle multiplicities, much more complex system (even by eye)!
- Training difficult due to large sensitivity on simulation used.

Outline

What is AI/ML and why is it useful for heavy-ion physics?

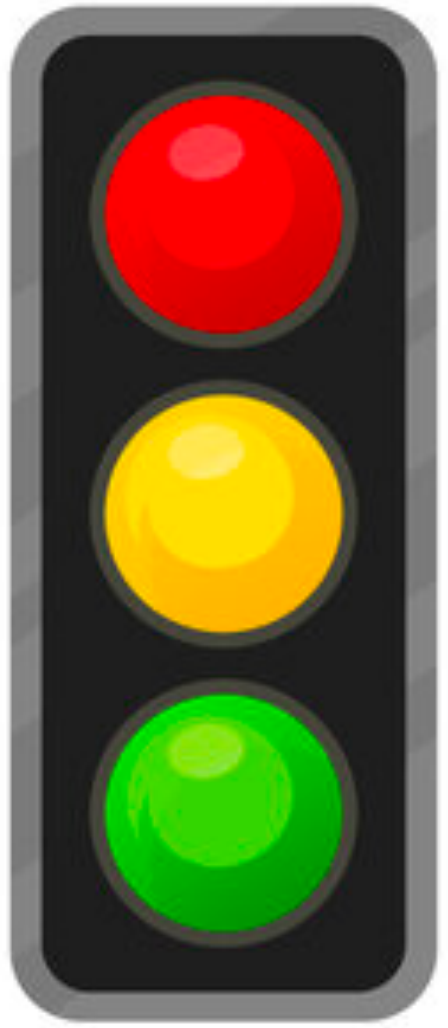
How is AI/ML currently being used by HI experiments?

How will AI/ML be used in the future?

Legend

There will be a lot of ML algorithms, physics applications, and software packages referenced!

Status



Future

Testing

In Use

Jargon

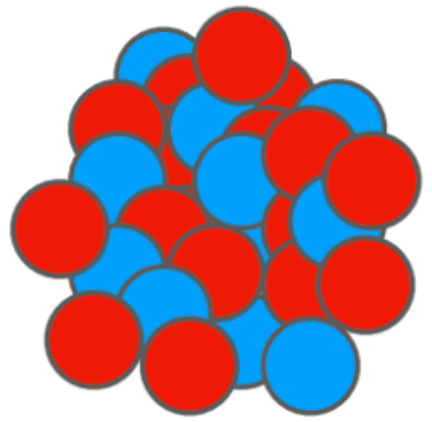
Algorithms

Software

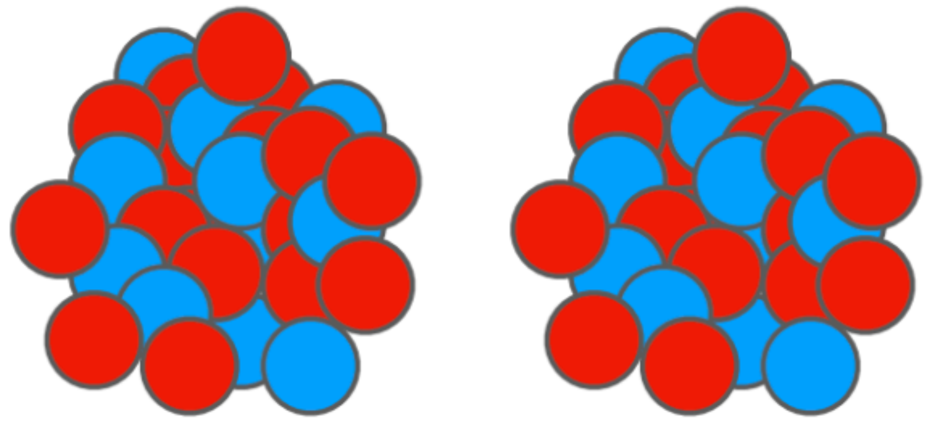
System Size

p—p

p—A



A—A

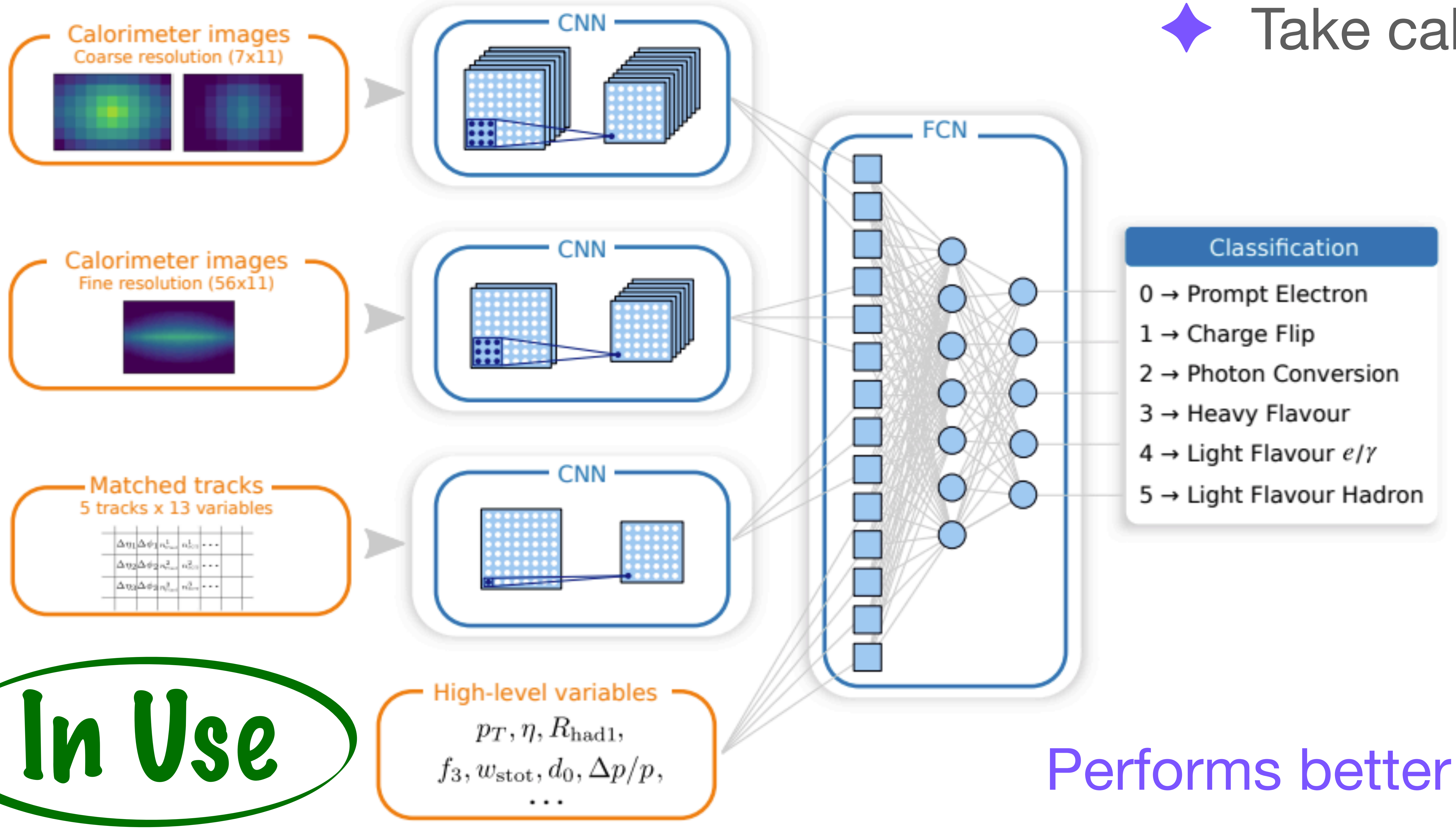


Particle identification

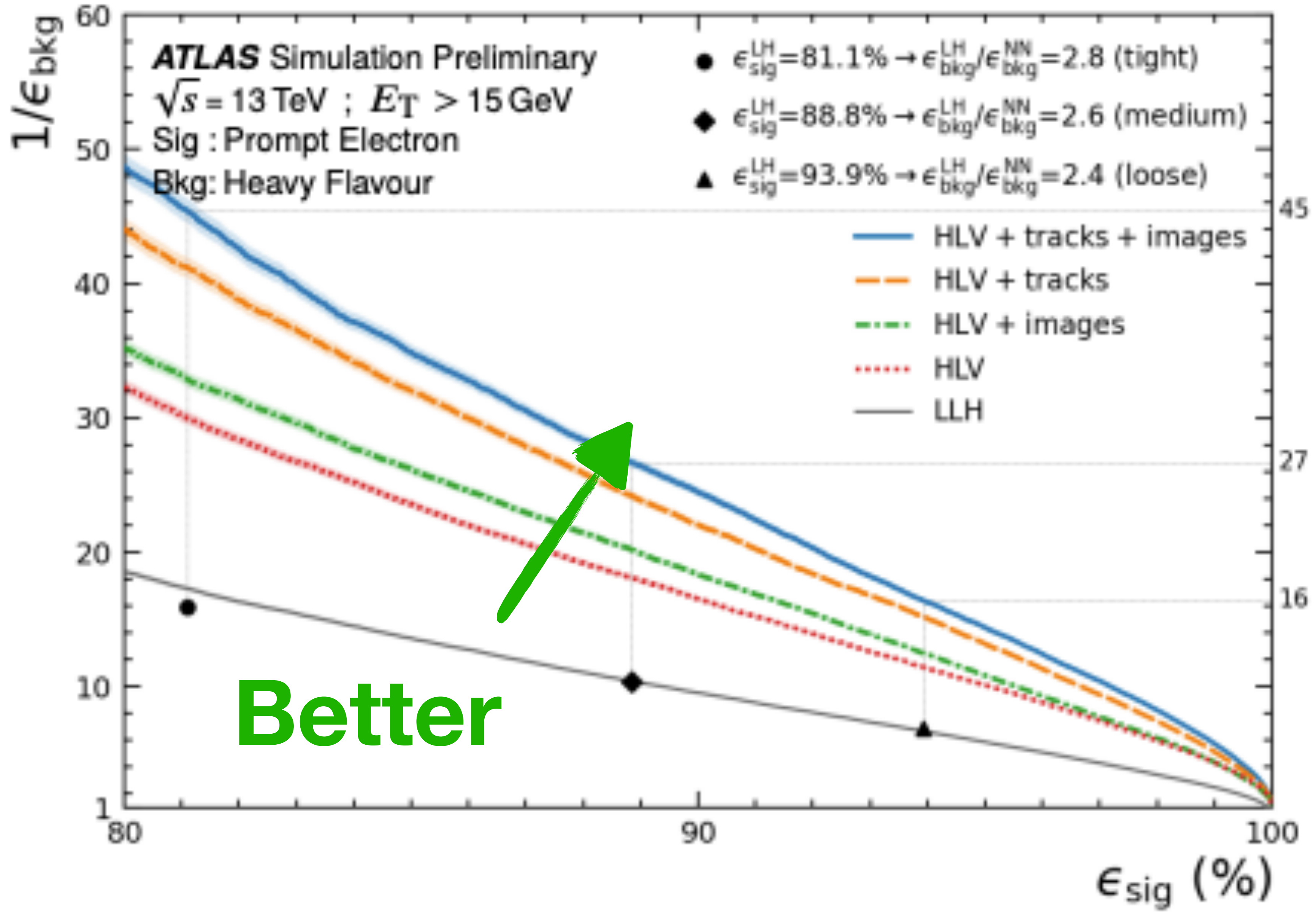
ATL-PHYS-PUB-2023-001

✦ Use convolutional neural network to perform a multi-class electron identification in pp

✦ Take calorimeter images + tracks as input



In Use



Performs better than likelihood methods (LLH)

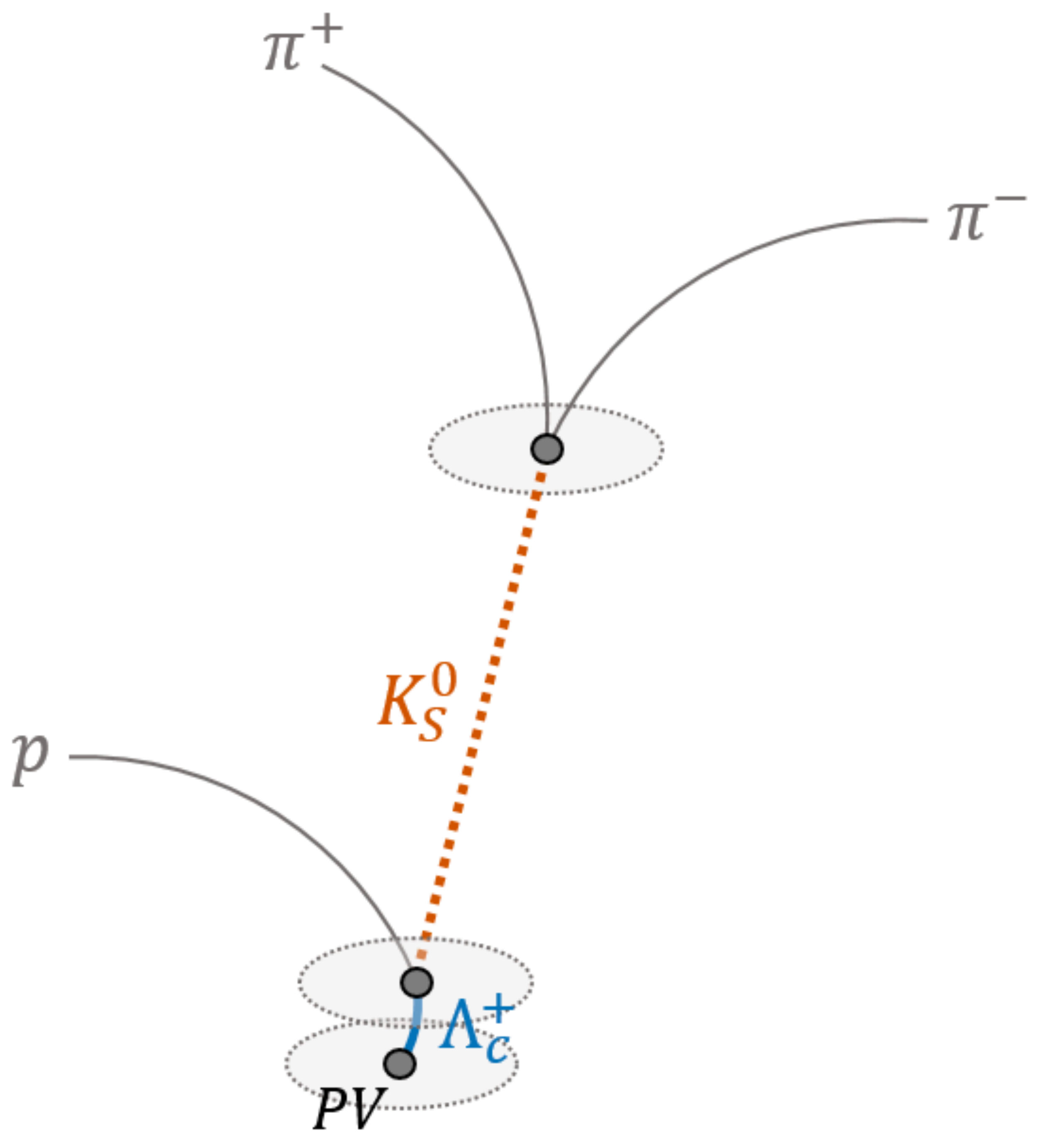
→ Including tracks helps with this!

Many examples of similar tools from other experiments!

Signal/background discrimination

Conventional approach: Apply cuts to tag particle based on decay topology

→ Becomes difficult in HI environment with large background.



ML-Based approach: Use low-level parameters such as constituents, secondary vertices, track impact parameters etc. Learn from simulation in a supervised approach.

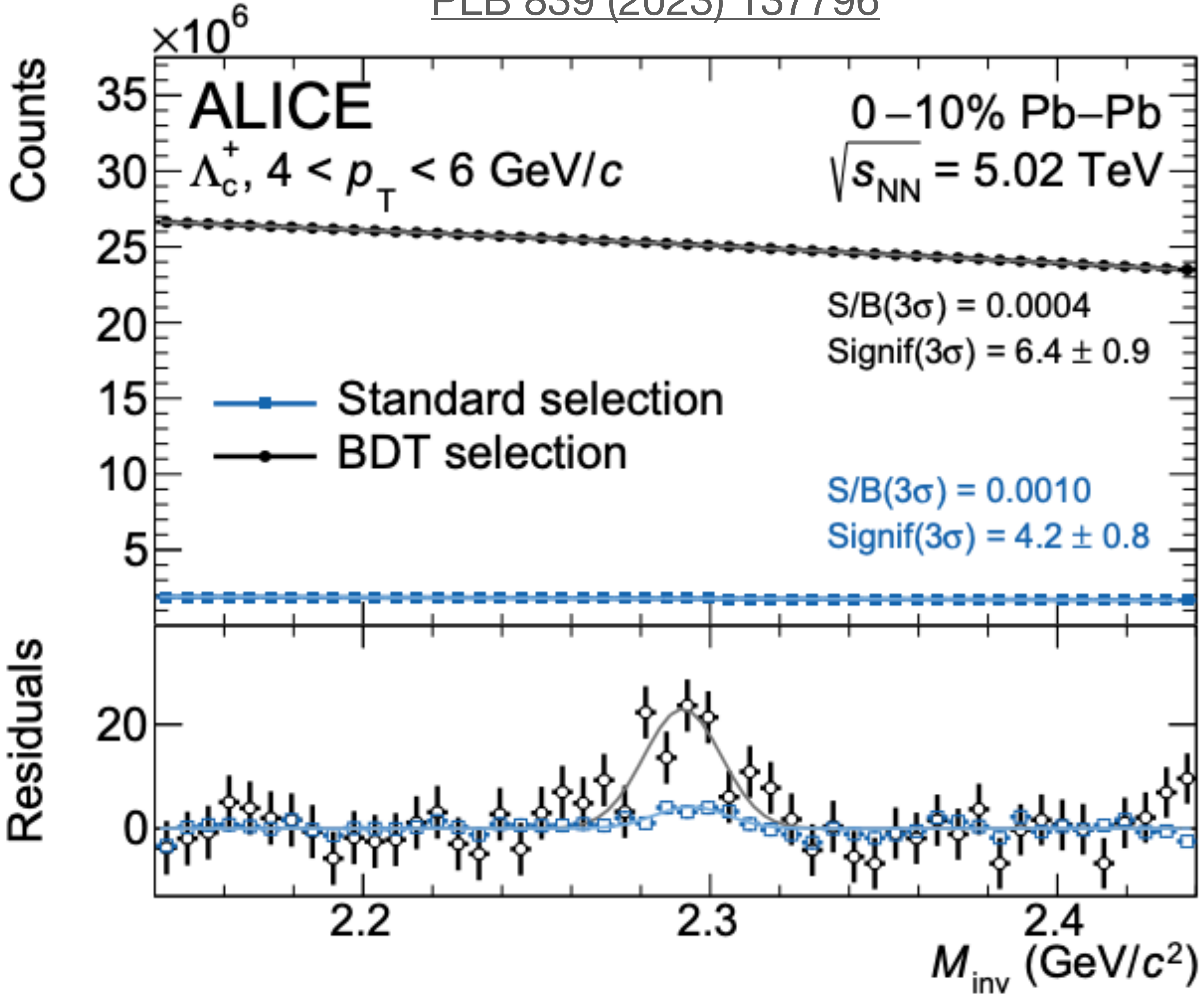
Most experiments implement this! Has made new measurements possible!

Ex: $\Lambda_c^+ \rightarrow K_s^0 + p$

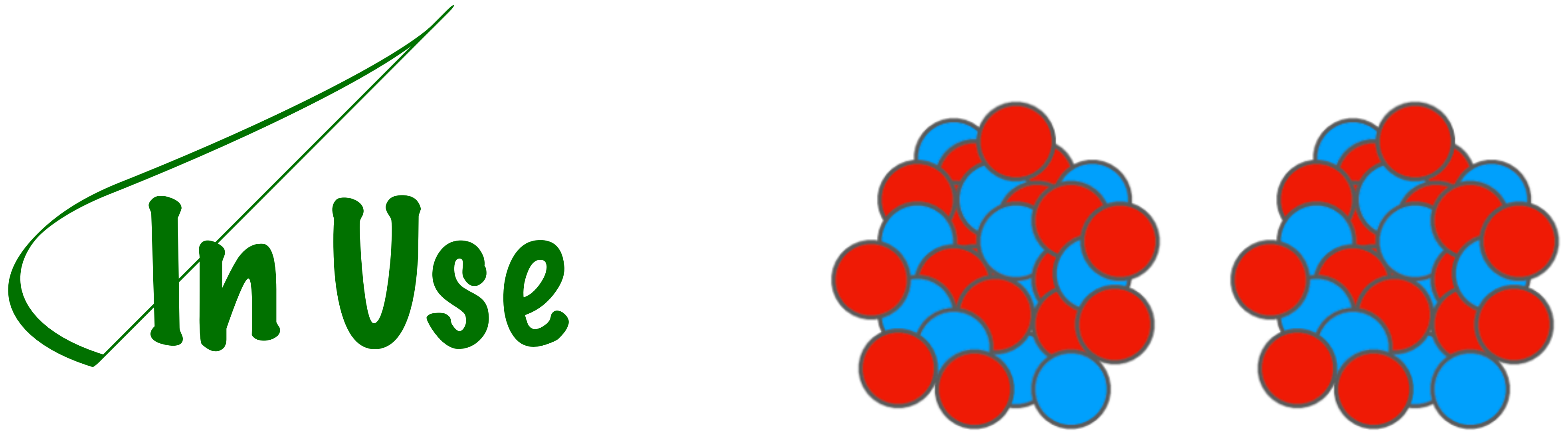
Signal/background discrimination

- ALICE: Boosted Decision Tree implemented in XGBoost using hipe4ML

PLB 839 (2023) 137796



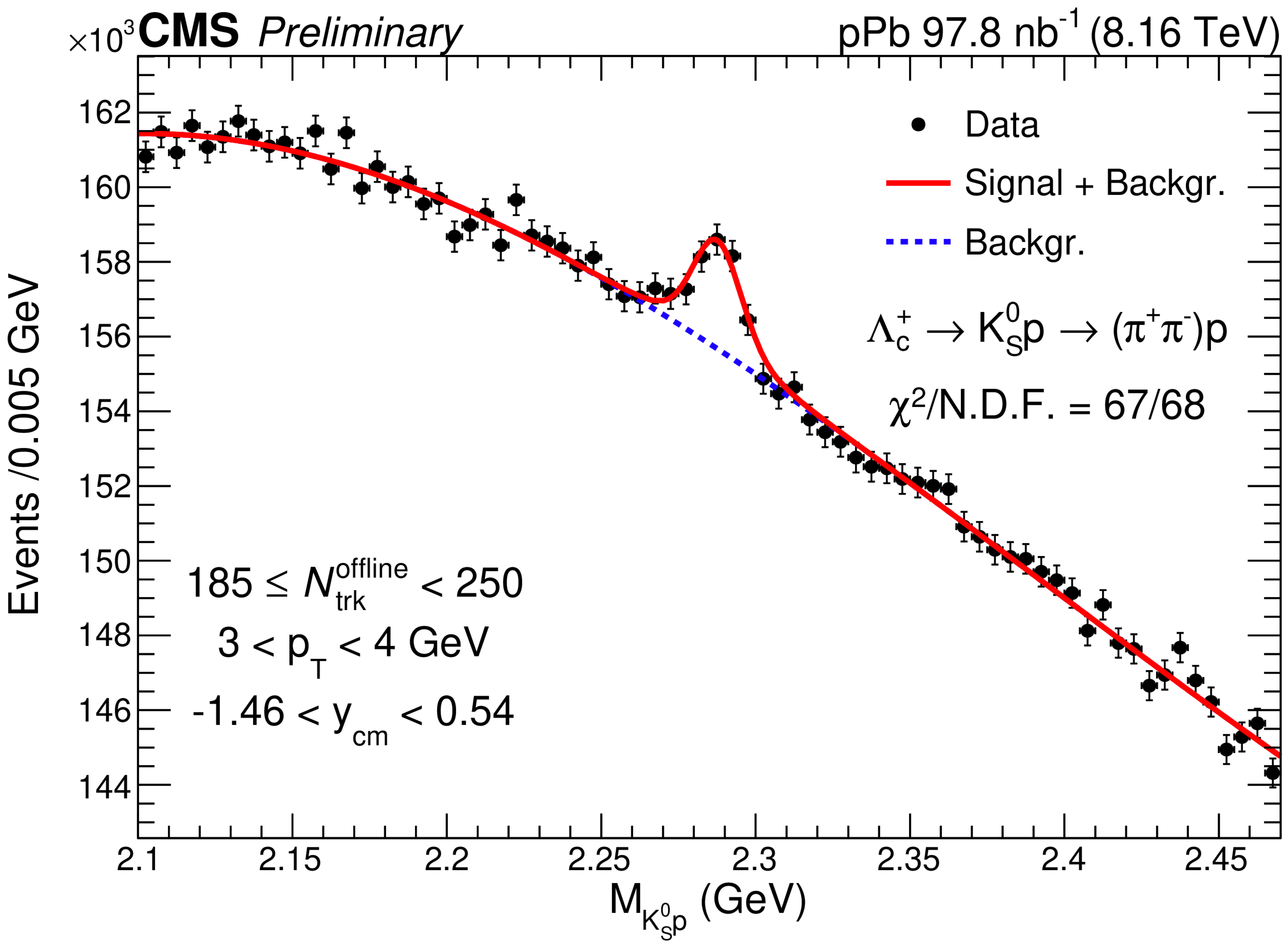
- Supervised learning using MC simulations and topological and PID variables for training.



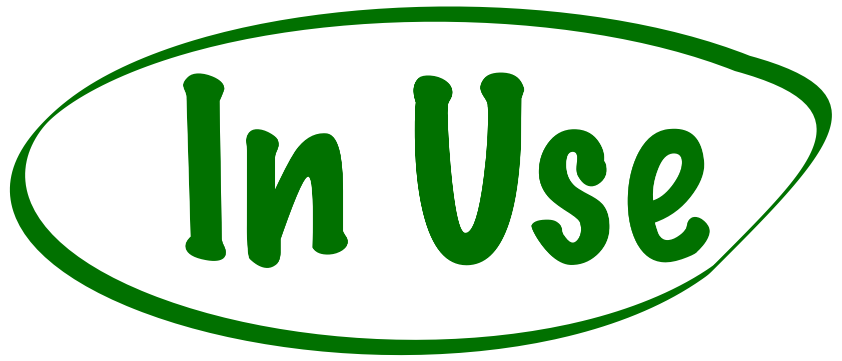
- ML helps increase the statistical significance by ~50% over standard selection!

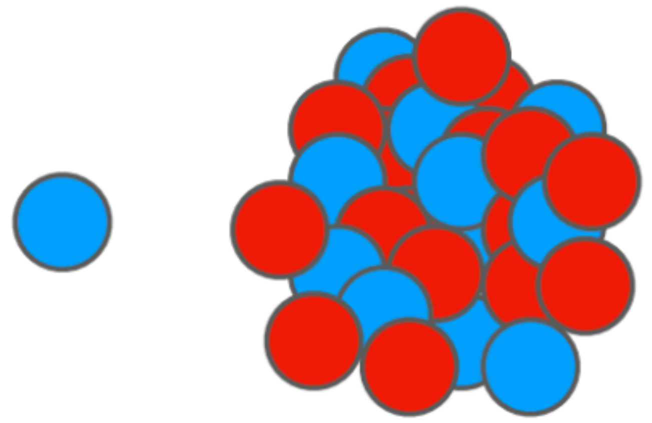
Signal/background discrimination

CMS PAS HIN-21-016



- CMS: Multilayer Perceptron implemented in ROOT TMVA to optimize signal





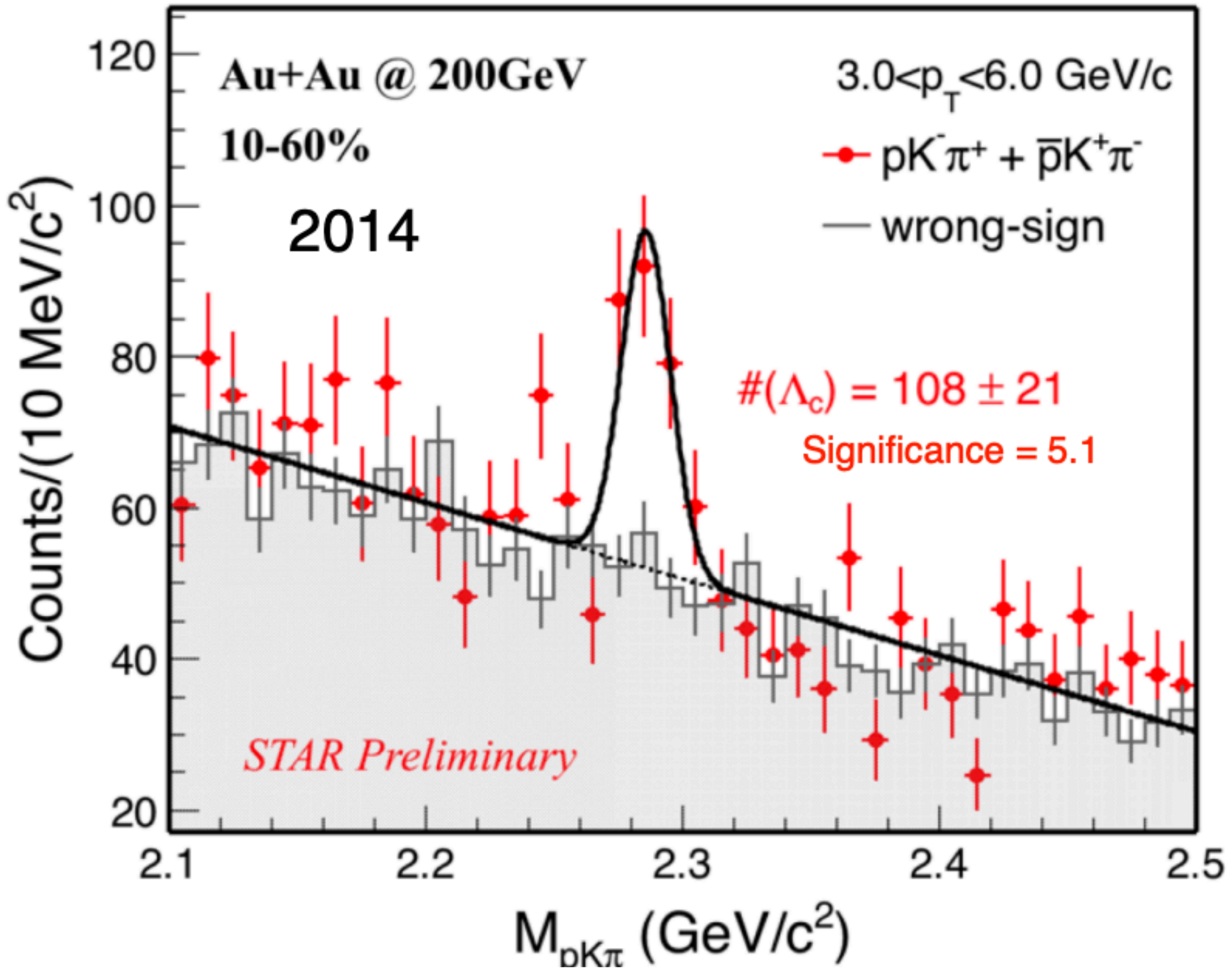
- Supervised learning trained on PYTHIA embedded in EPOS LHC w/ input p and η for the protons, energy loss per length of proton track, cosine of pointing angle

- Boosted decision trees also common in CMS, see $\Upsilon(3s)$ (arXiv:2303.17026), B_c^+ (PRL 128 (2022) 252301), X(3872) (PRL 128 (2022) 032001), and more!

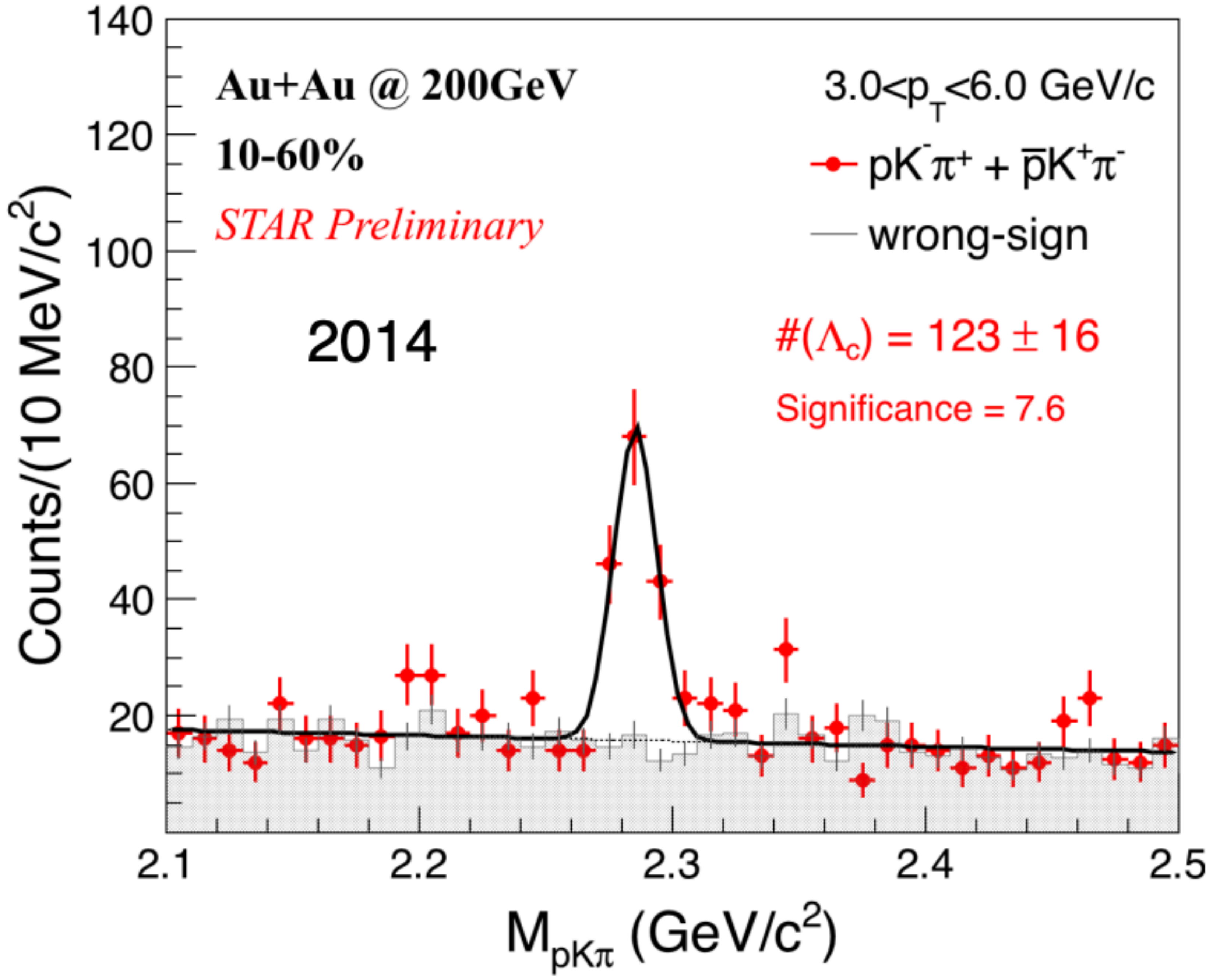
Signal/background discrimination

PRL 124, 172301 (2020)

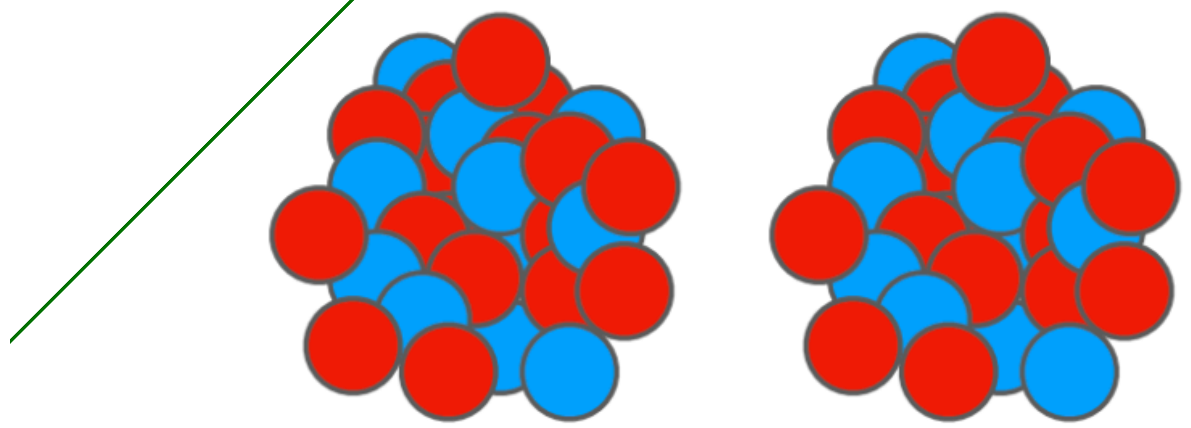
Traditional Techniques



With BDT



STAR



In Use

- STAR: Boosted Decision Tree implemented in ROOT TMVA to optimize signal
- Trained in supervised way with EvtGen.
- 50% increase in signal significance with ML!

Jets as a playground for ML

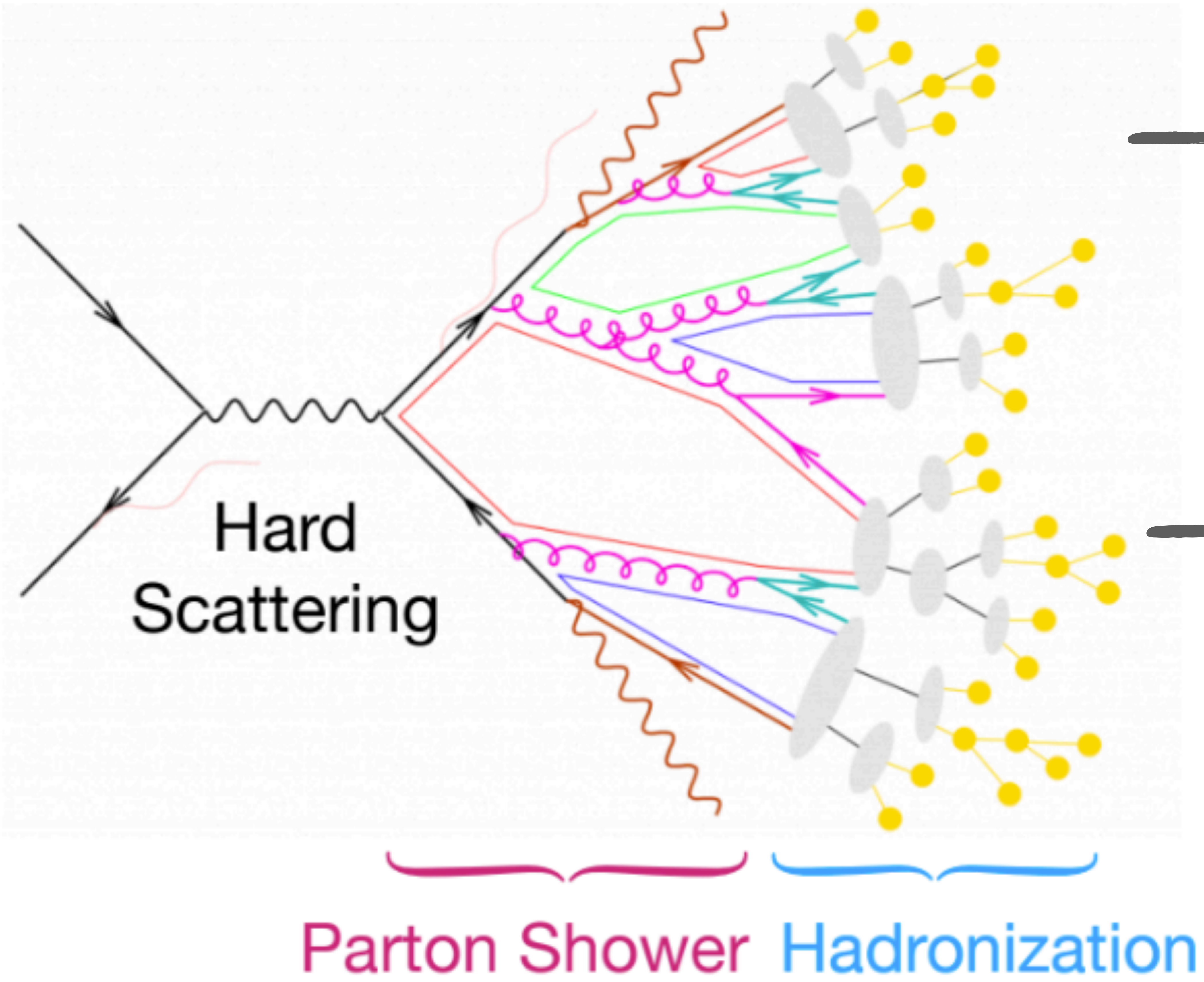


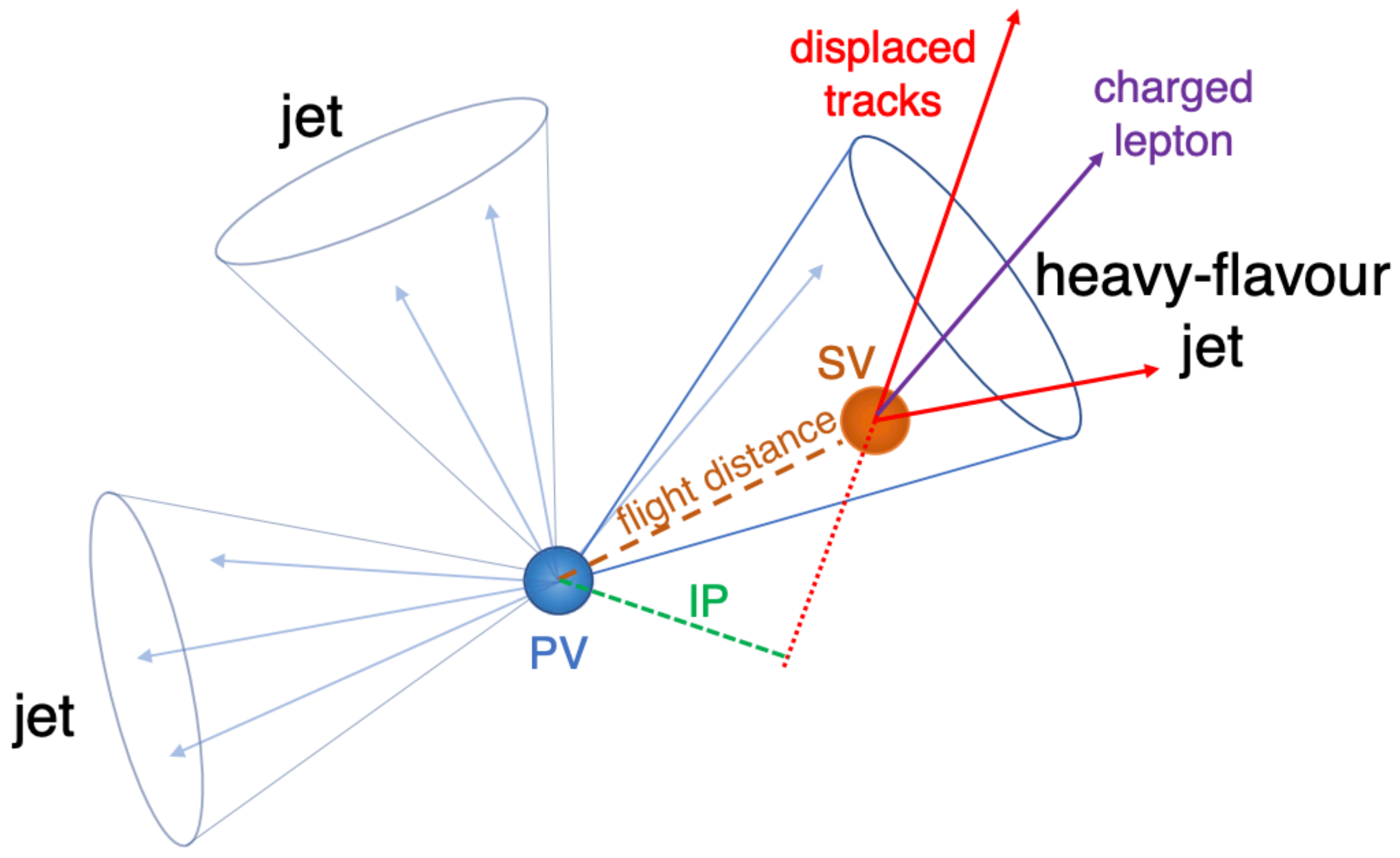
Image Credit: https://arxiv.org/abs/hep-ph/0210294

Jets are the spray of particles that result from the fragmentation and hadronization of a hard-scattered parton

Complex aggregate object sensitive to multiple physics scales (ideal for ML)

Jet physics has been a playground for ML developments! Many associated tasks, possible representations (ex: images, constituents, single object) and information reach.

Heavy flavor jet tagging



JINST 13 (2018) 05, P05011

Goal: identify jets initiated by a heavy-quark (HF jet)

Conventional approach: Apply cuts to select jets with displaced decay vertices and large impact parameter tracks.

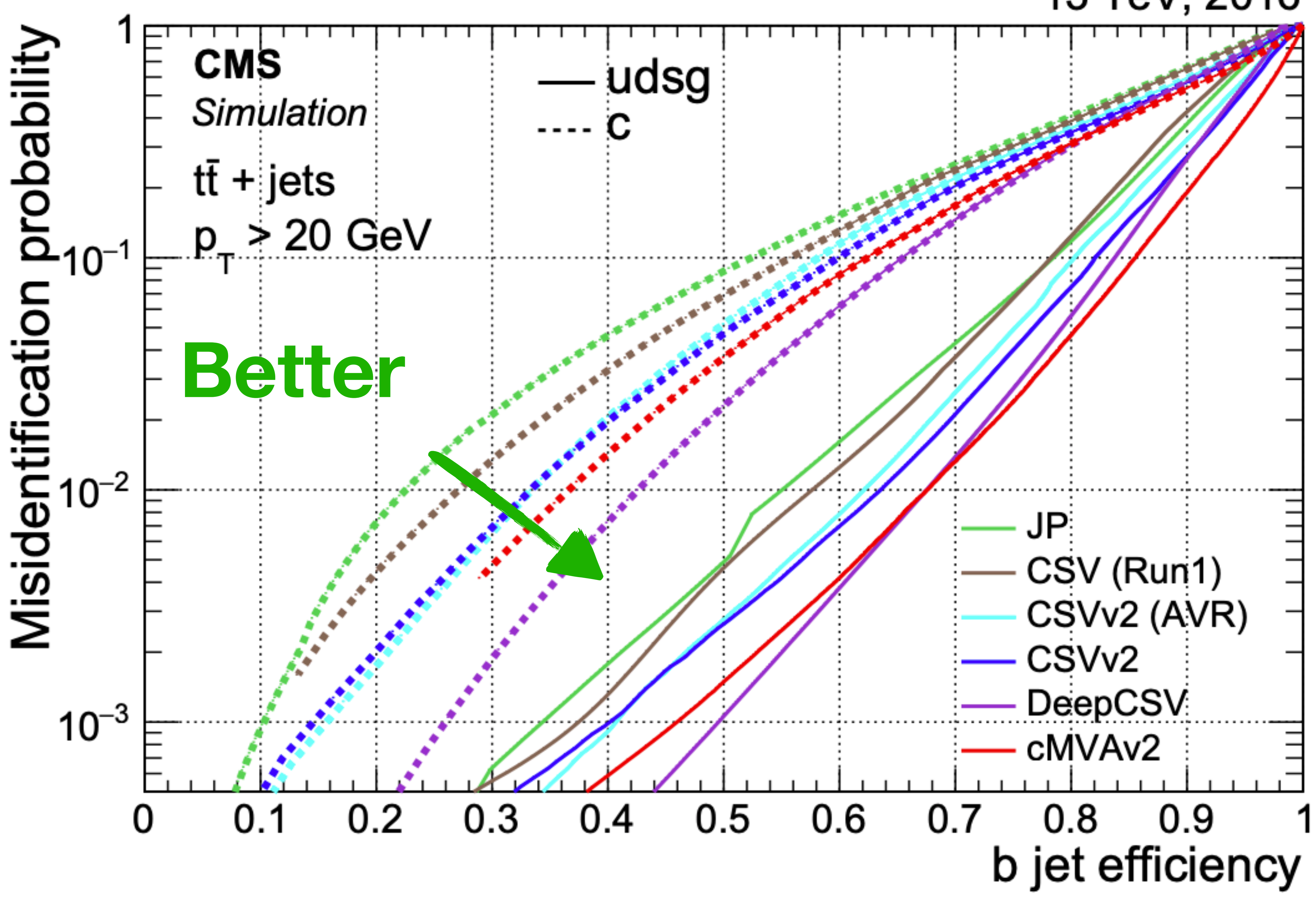
ML approach: Use low-level jet parameters such as constituents, secondary vertices, track impact parameters etc to learn from simulation in a supervised approach.

Some approaches independent of experiments! (see JetVLAD).

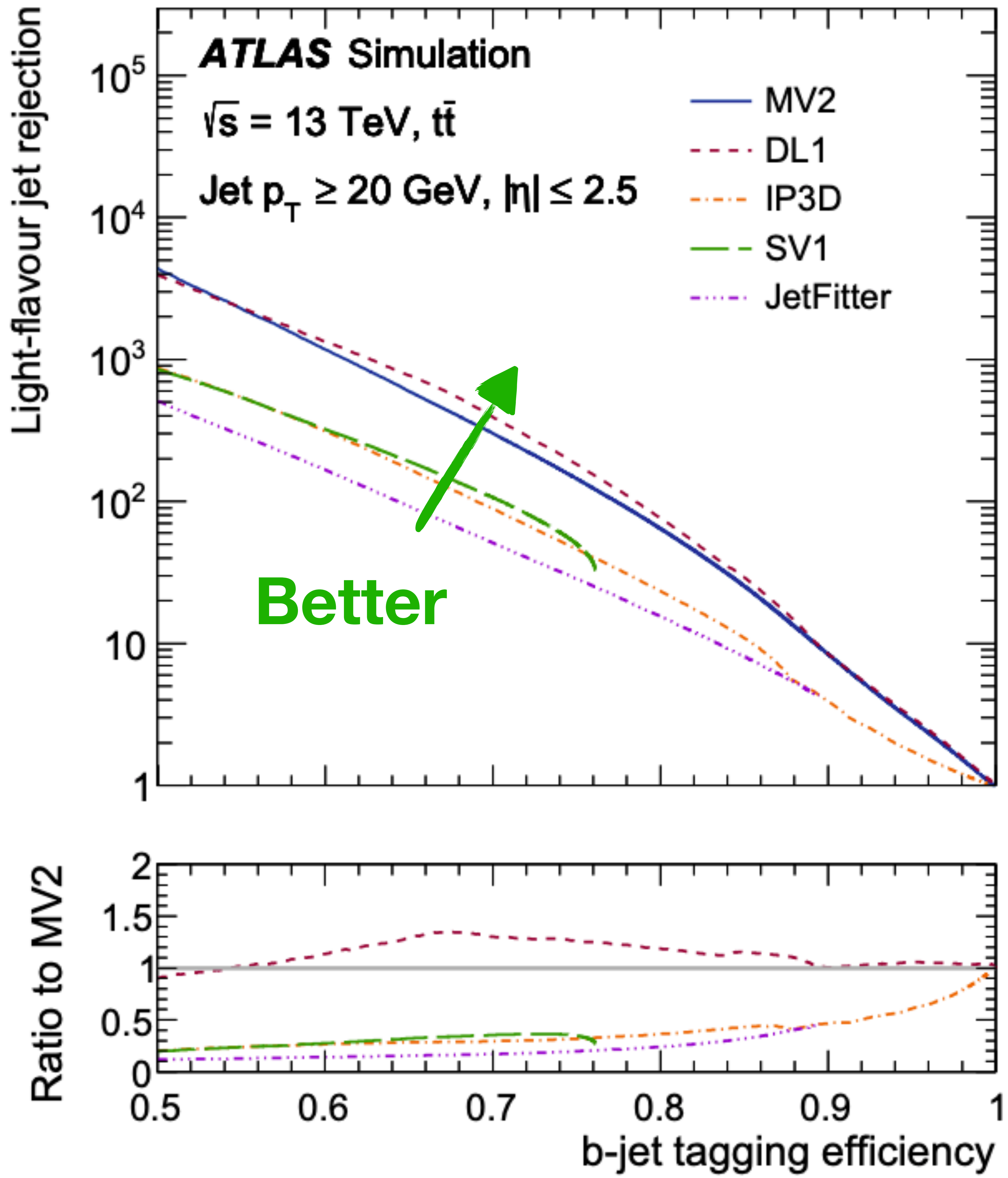
HF-jet tagging

In Use

JINST 13 (2018) 05, P05011



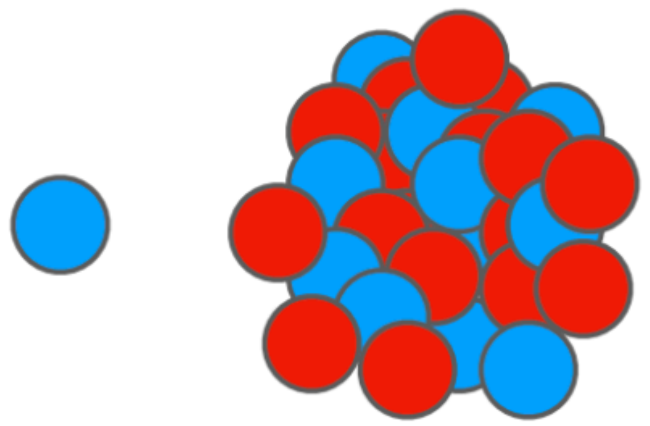
Eur. Phys. J. C 79 (2019) 970



ATLAS and CMS both see that deep learning performs better than traditional techniques!

HF-jet tagging

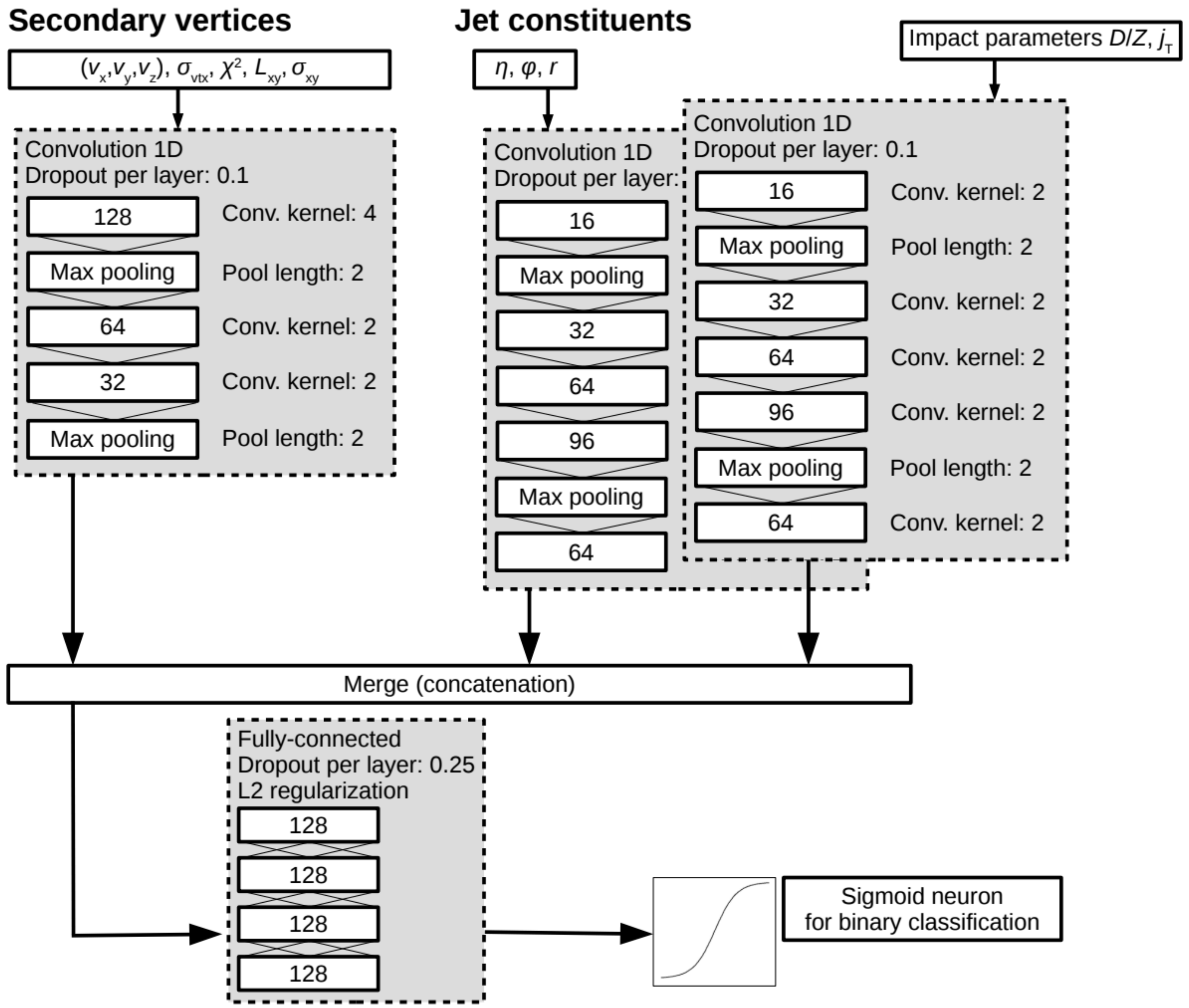
Testing

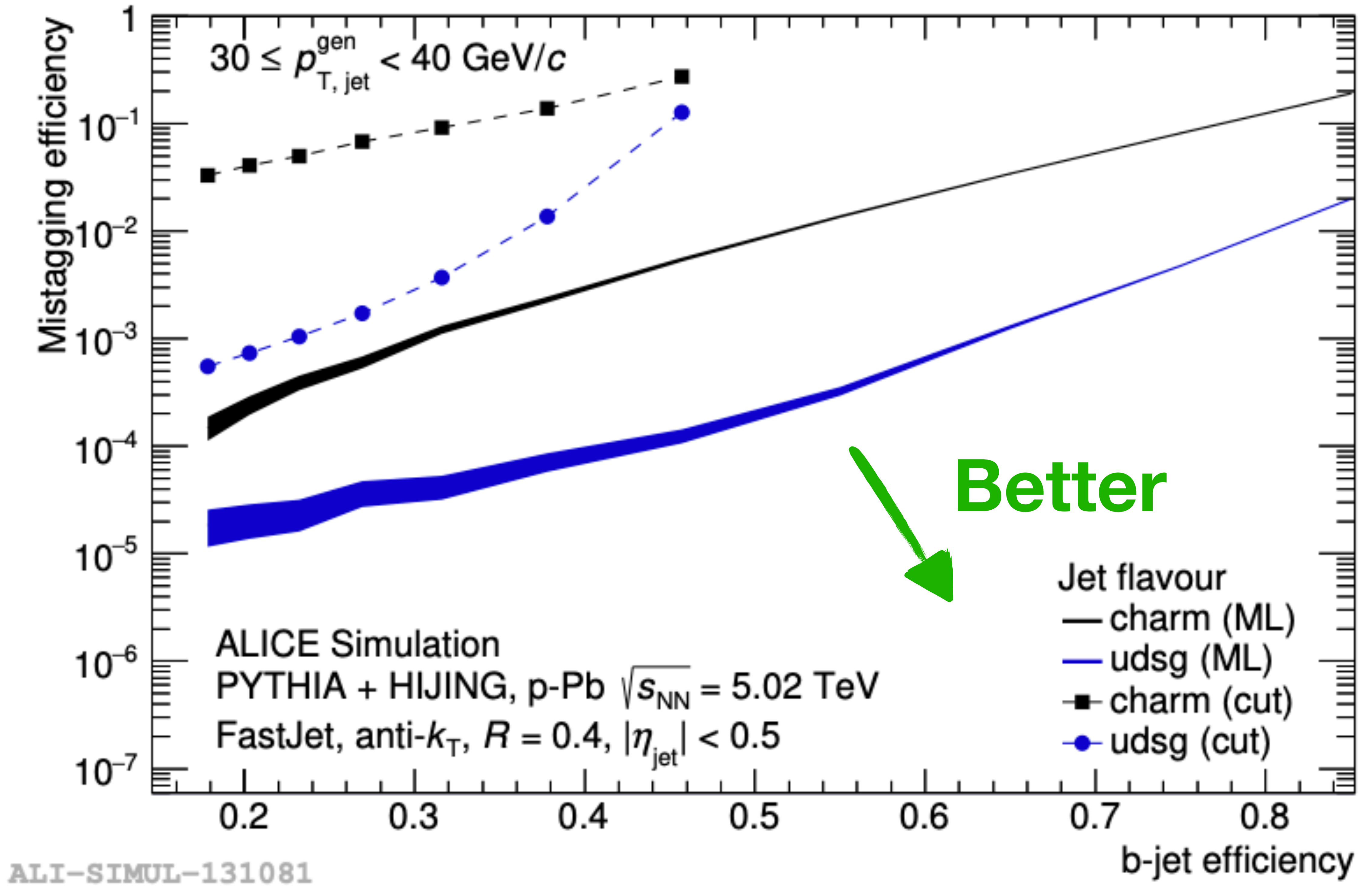


ALICE

ALICE: Use multi-layer Convolutional Neural Network.

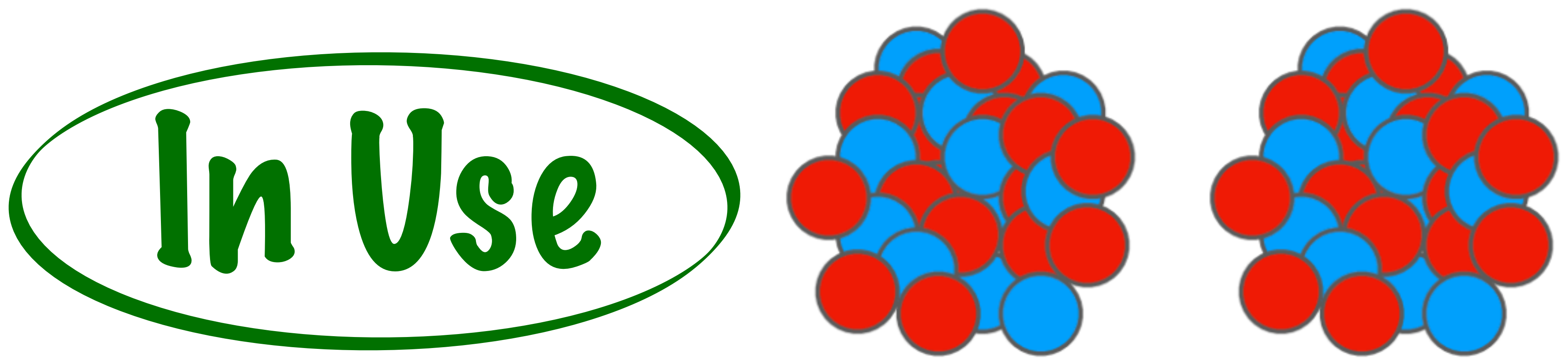
arXiv:1709.08497



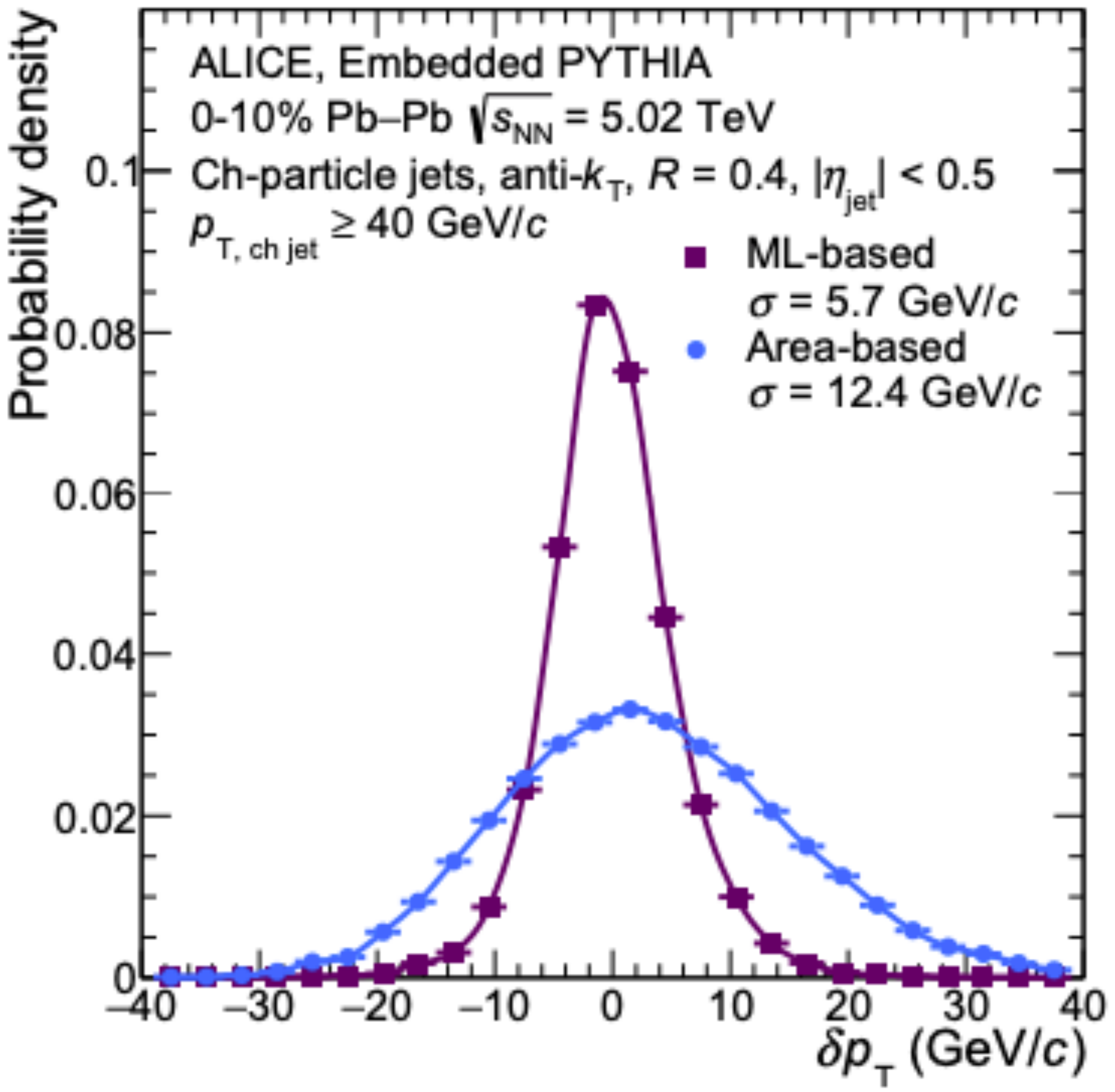


Mistagging efficiency lower for all b-jet efficiencies with ML!

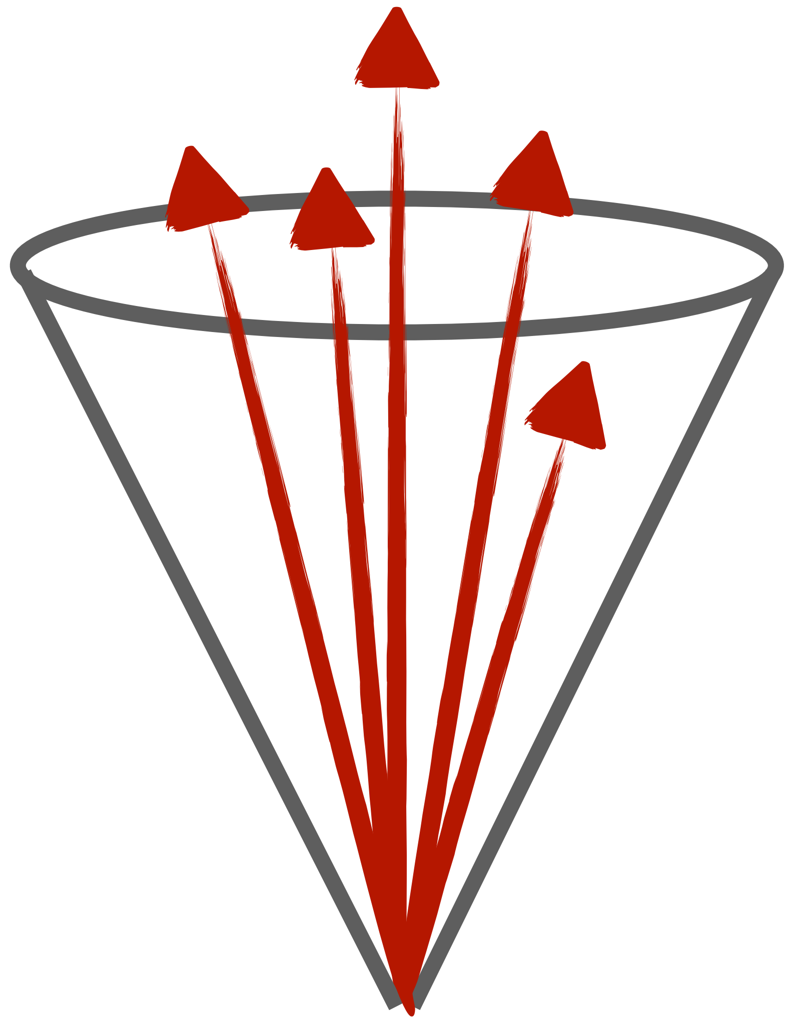
Correction to the jet p_T



arXiv:2303.00592, submitted to PLB



$$\delta p_T = p_{T,\text{rec}} - p_{T,\text{true}}$$



→ Supervised regression task: Use properties of the jet and its constituent to determine the background-corrected jet p_T

→ Shallow Neural Network in scikit-learn (simple tools) trained on PYTHIA embedded into HI background

R.Haake, C. Loizides Phys. Rev. C 99, 064904 (2019)

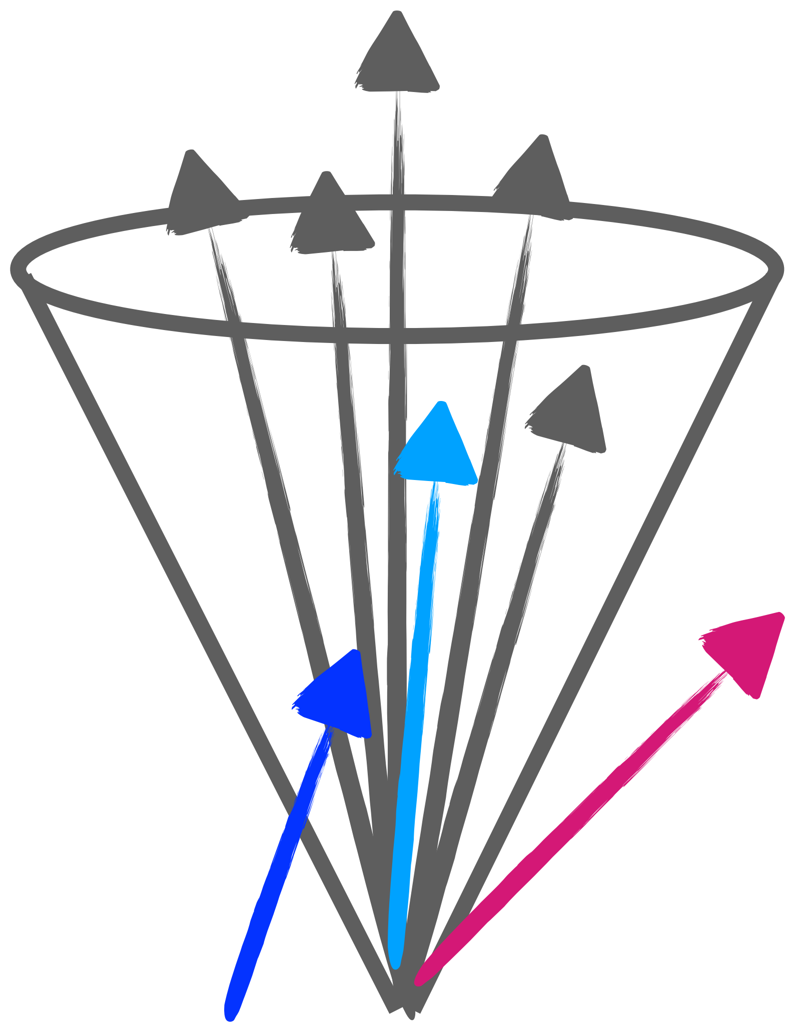
Shows improved performance over standard techniques →allows measurement to lower in jet p_T and larger in R.

Study of fragmentation bias

arXiv:2303.00592, submitted to PLB

- Address dependency on fragmentation in simulation introduced by including constituent information

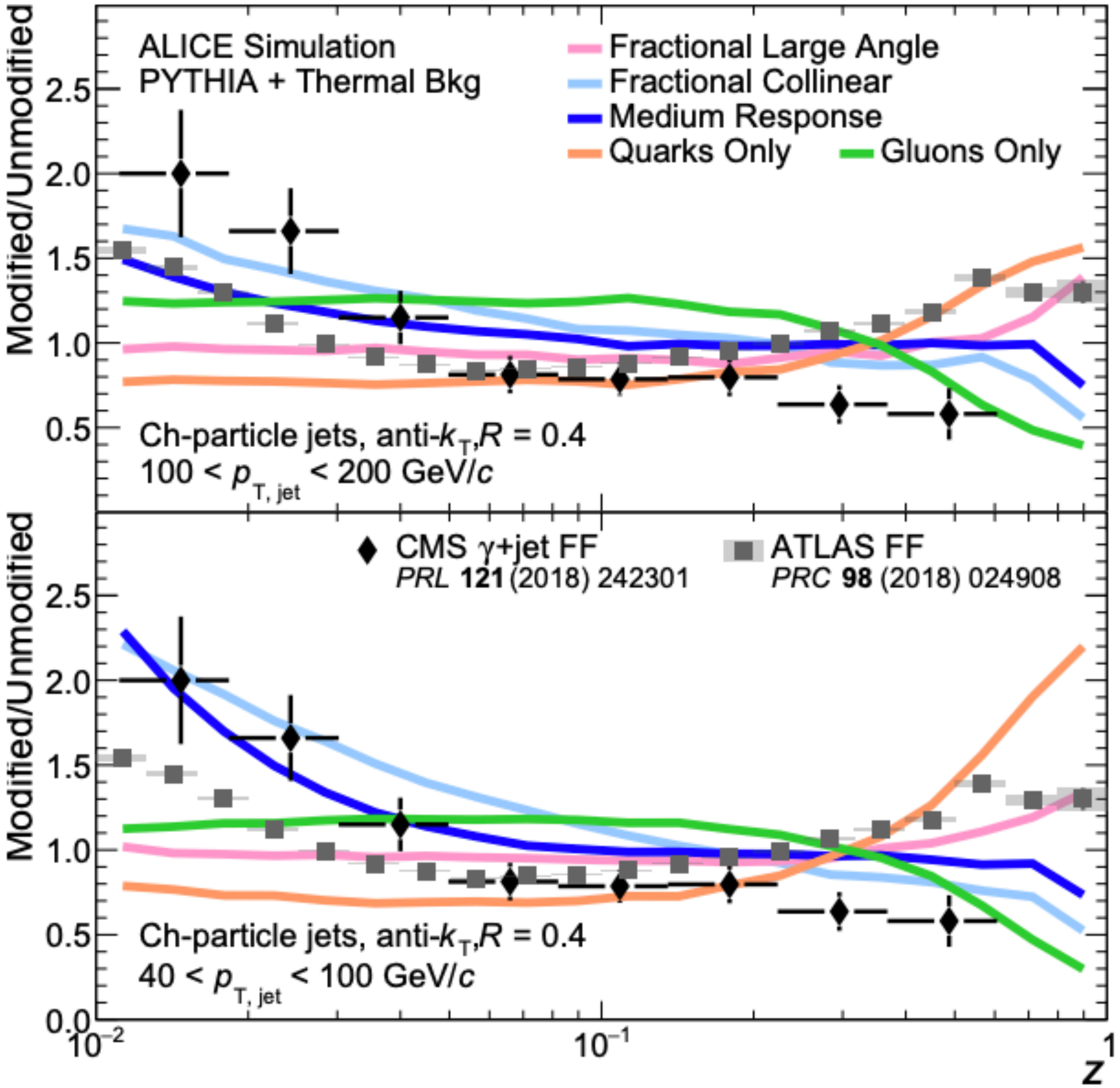
- Temporary solution: use toy modifications to demonstrate sensitivity to the training.



Fractional large angle

Fractional collinear

Medium Response

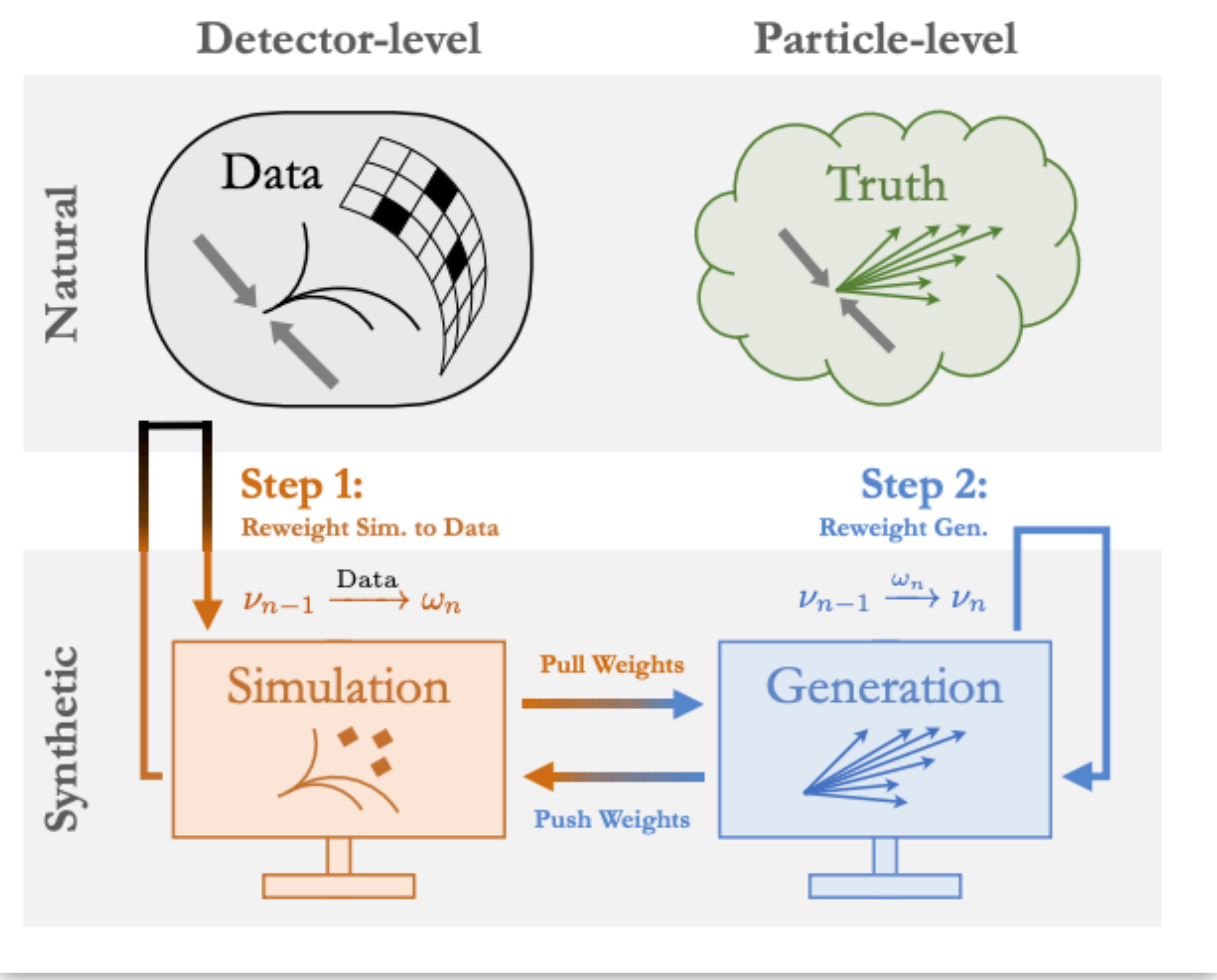


Apply difference in result as systematic uncertainty.

Unfolding with ML

Goal: Correct for detector effects and background fluctuations

Phys. Rev. Lett. 124, 182001 (2020)



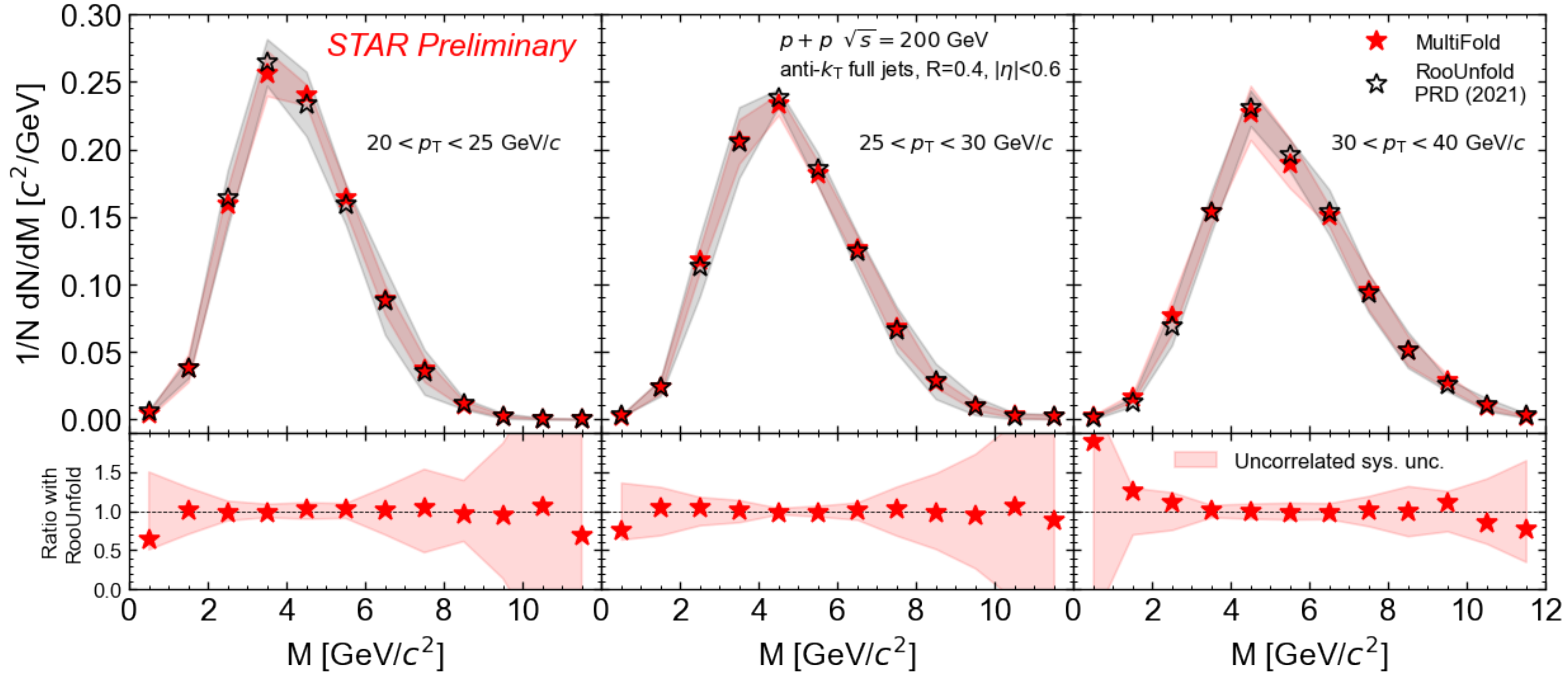
Conventional Approach: Apply unfolding procedure on a binned distribution and repeat for each observable.

ML-based Approach: Use ML to calculate weighting factors and unfold the phase space all at once, before the choice of binning or observable!

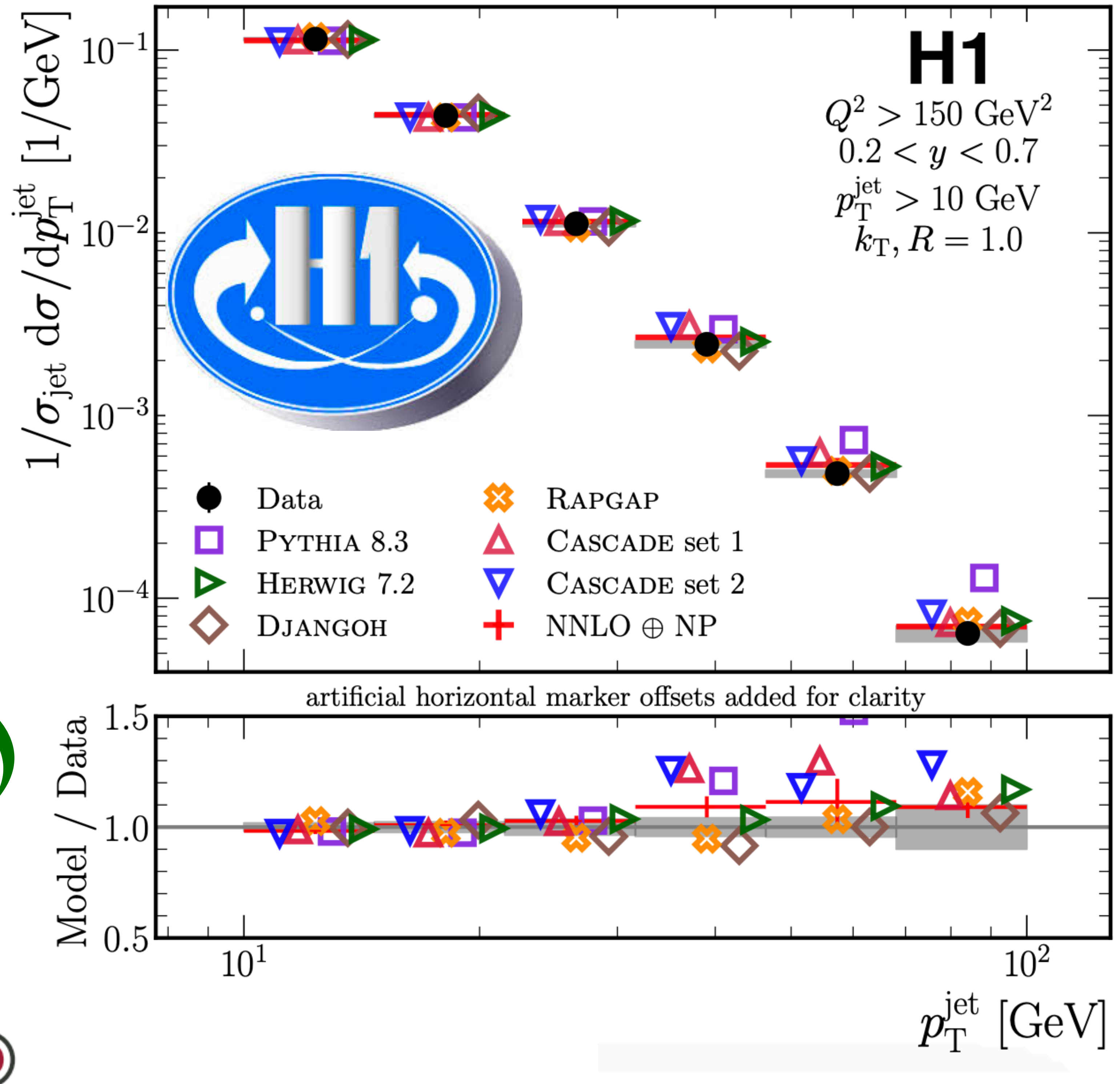
Main-benefit is multi-dimensional unbinned measurements! Can measure correlations between variables.

Experimental applications

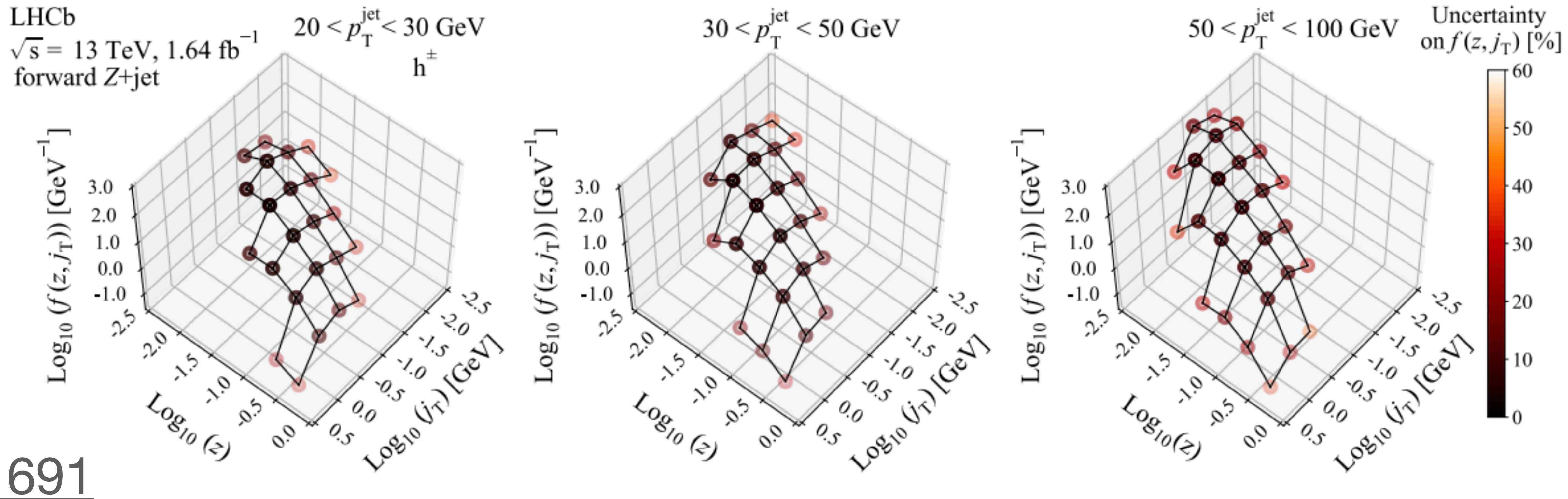
STAR ☆ See Dave Stewart's talk tomorrow @ 3:00pm!



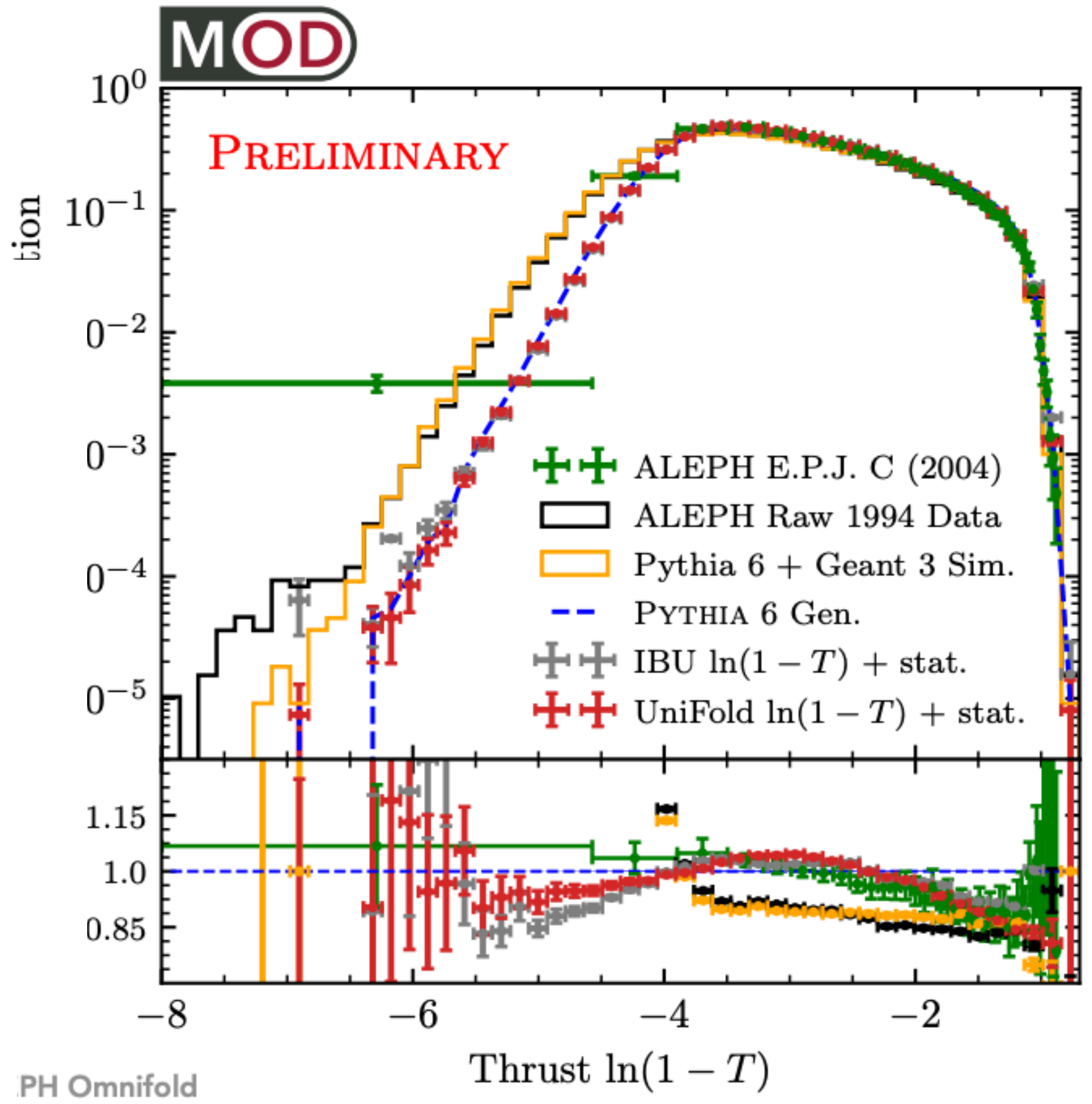
PRL 128 (2022) 13, 132002



In Use



arXiv:2208.11691



ALEPH archived data, see ICHEP 2020 talk by Anthony Badea

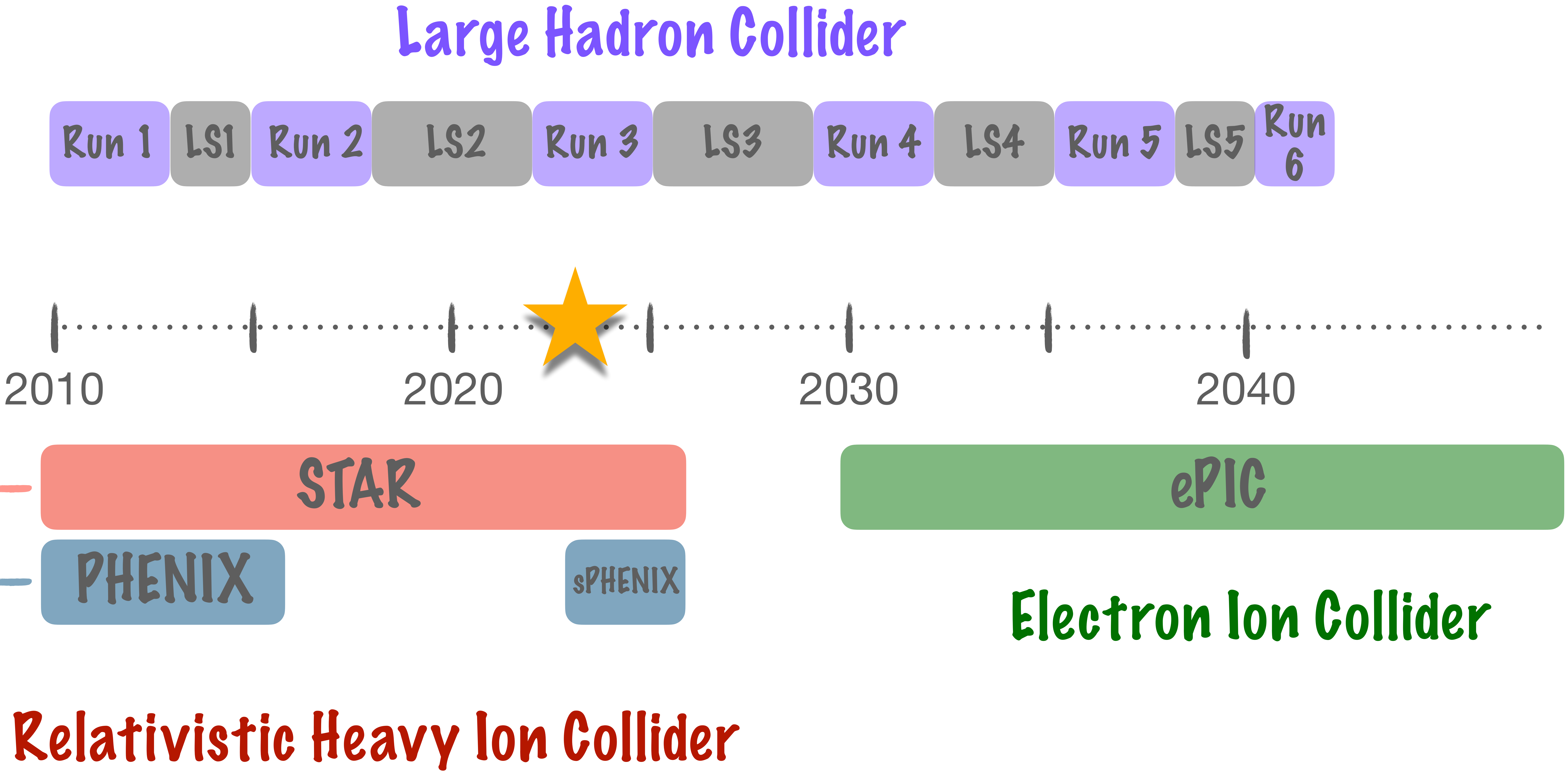
Outline

What is AI/ML and why is it useful for heavy-ion physics?

How is AI/ML currently being used by HI experiments?

How will AI/ML be used in the future?

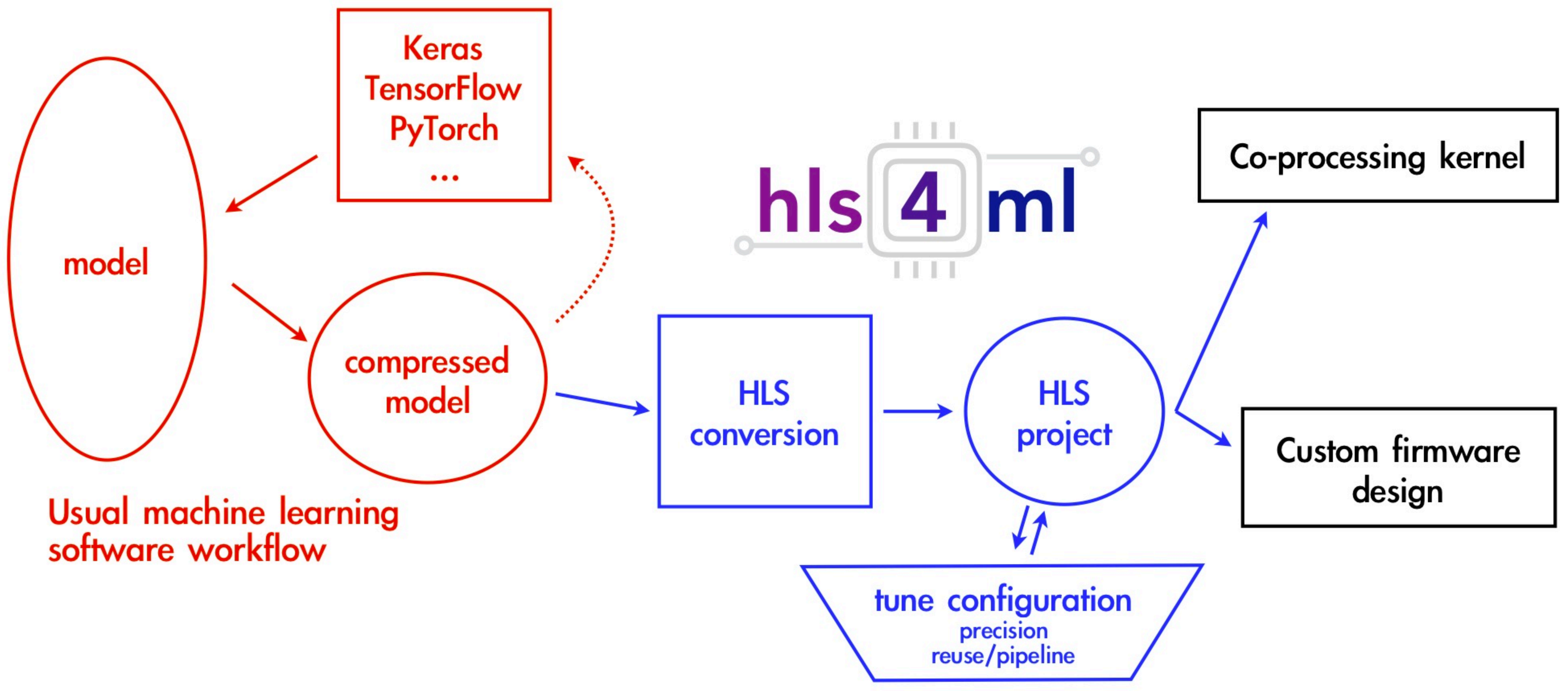
Where are we going?



Very large volumes of data being taken - new tools will be *increasingly important*!

Hardware triggers with ML

Future



https://github.com/fastmachinelearning/hls4ml

→ Due to limited computing resources, will require rejecting most (~99%) of data in real time!

Solution: perform selection with ML integrated into firmware using Field Programable Gating Arrays (FPGAs).

✦ Use hls4ml to translate models into FPGA bitstreams!

sPHENIX → ePIC

Potential test in pp data-taking

Use from day 1!

ML at the EIC

→ Futuristic detector being designed with futuristic techniques in mind!

Ongoing Activities w/ AI

- ✦ Detector design (see backup)
- ✦ Simulation
- ✦ Reconstruction
- ✦ PID
- ✦ Analysis

In Use

Testing

Future

See AI4EIC workshop for more!

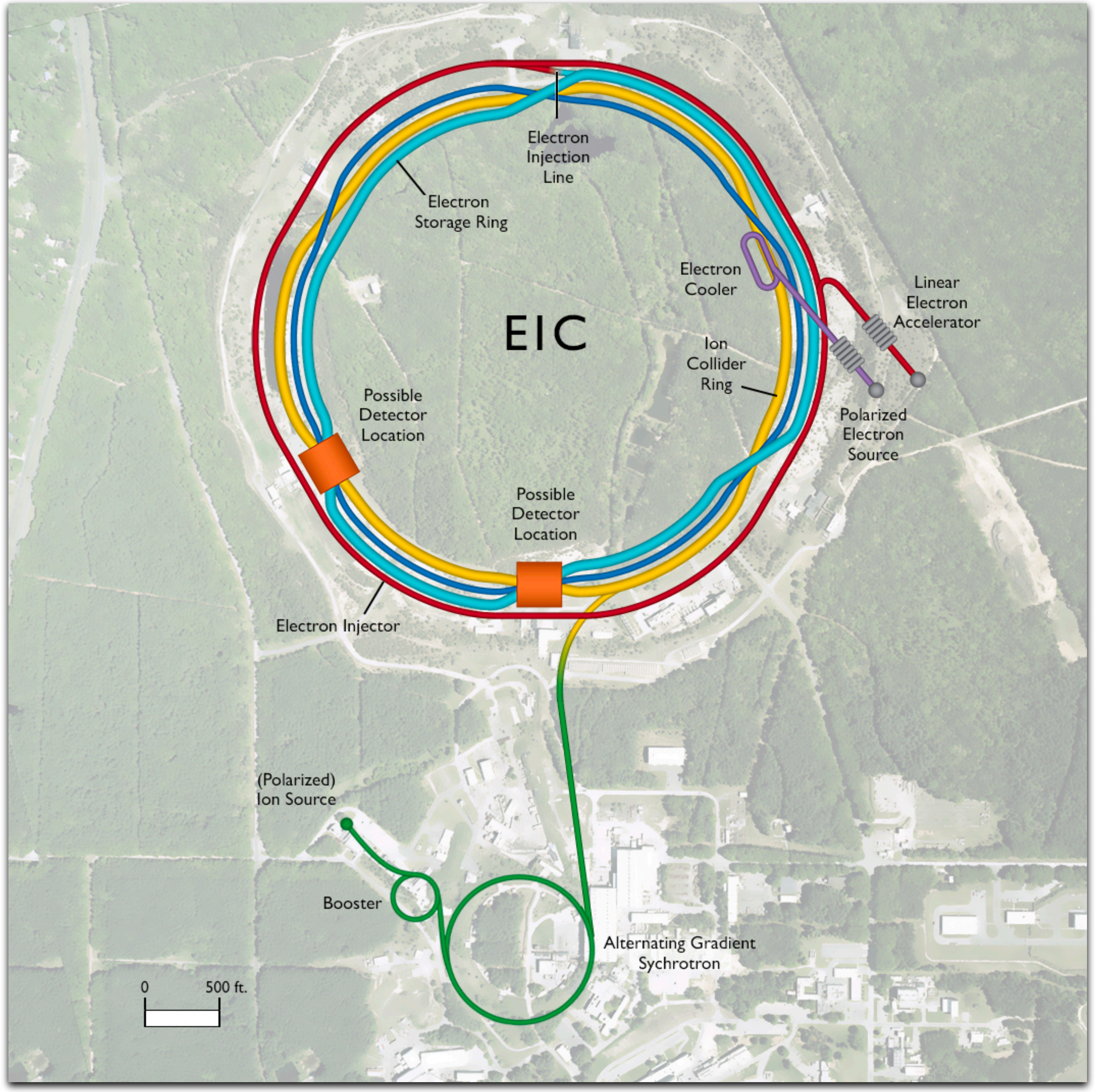


Image Credit: Brookhaven National Lab

Future Activities: Streaming readout/control

Track reconstruction at the HL LHC

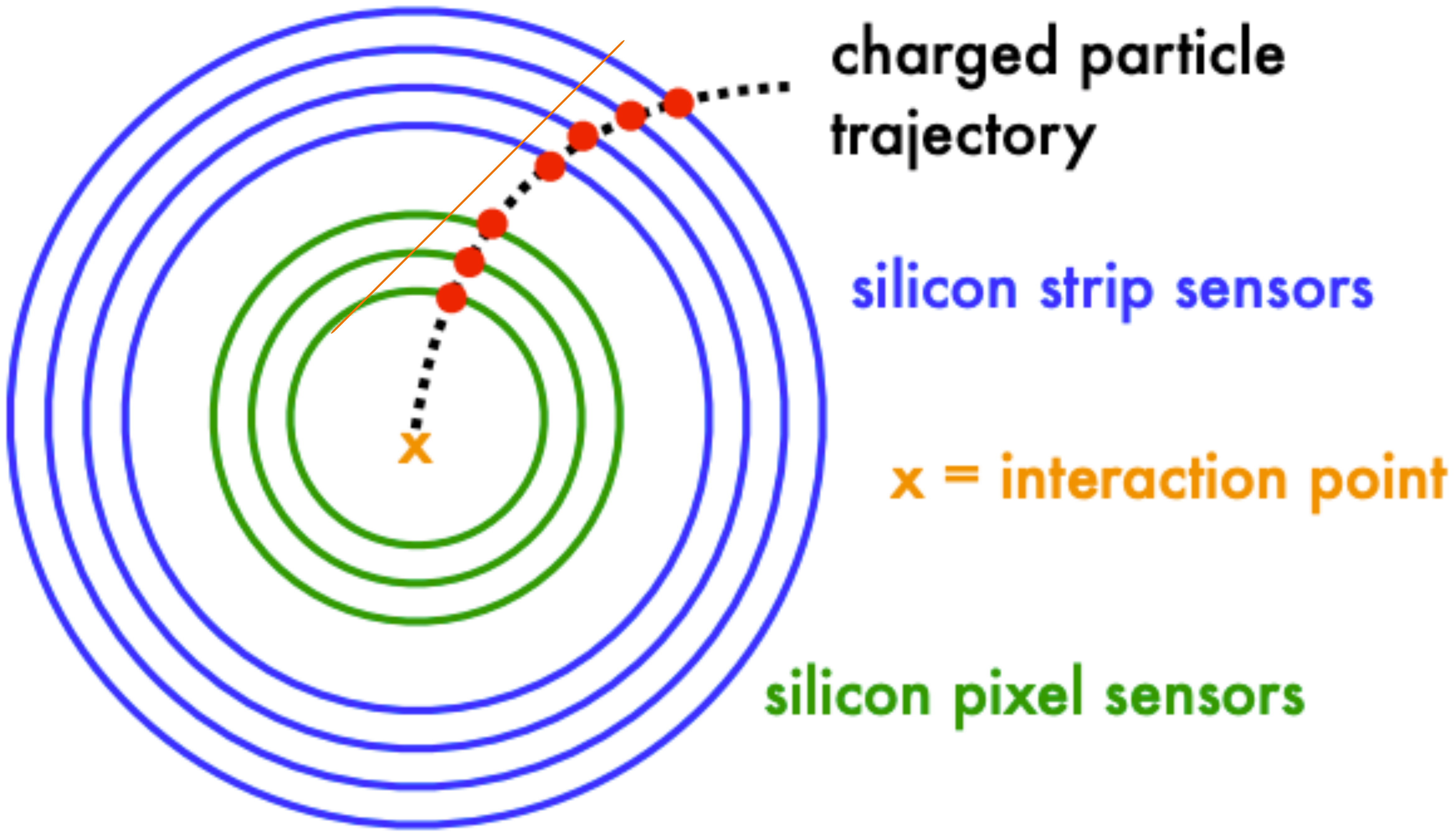
→ Data volume and reconstruction will also be a problem for the HL-LHC

→ Reconstructing charged particle trajectory is computationally expensive - scales with detector occupancy.

Standard approach: Kalman Filter used to locate hits in charged particle trajectory

ML-based approach: Use ML tools to speed this up such as…

- ✦ Recurrent Neural Network: arXiv:2212.02348
- ✦ Convolutional Neural Network: See Here



Testing

ML for underlying physics

Could we use ML to directly access underlying physics mechanisms?

"Data"-based learning complements simulation-based inference.

~ Given an answer
~ "White Box" ML
~ Underlying physics

~ Domain knowledge
~ "Black Box" ML
~ Answer

This is a long term effort!

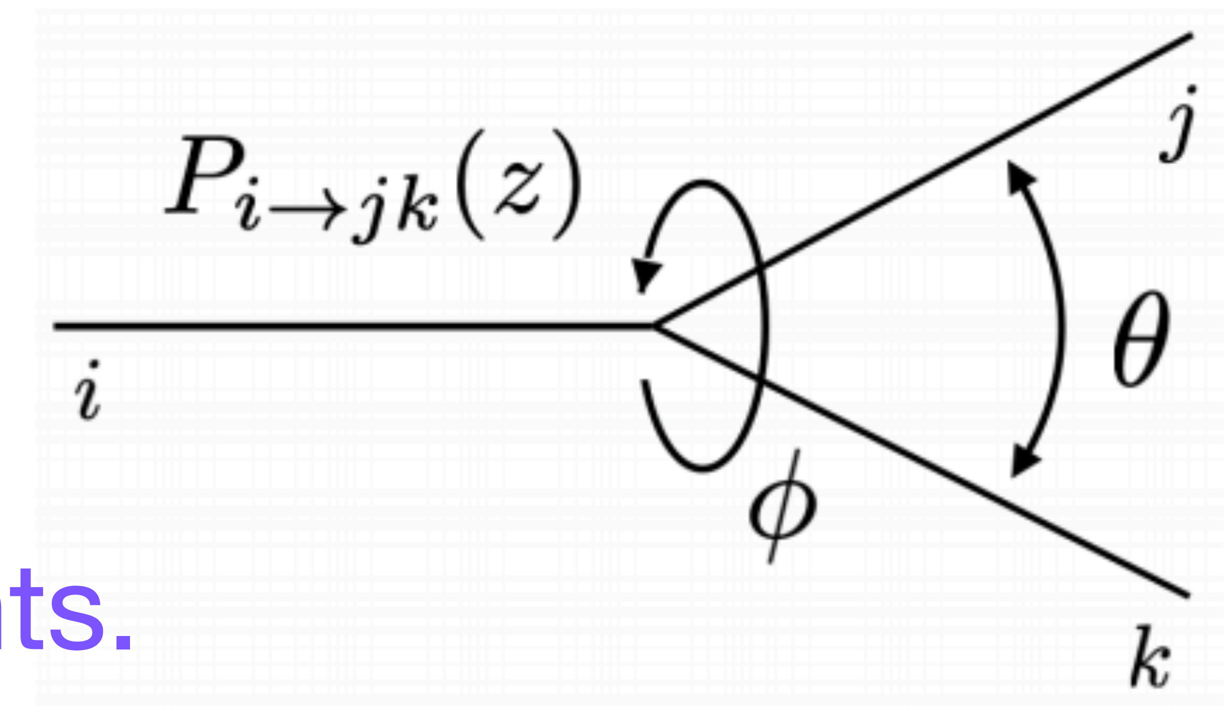
Learning from data is difficult due to systematic experimental biases.

Future

Helpful in understanding uncertainties or shortcomings of models!

Proof of concept

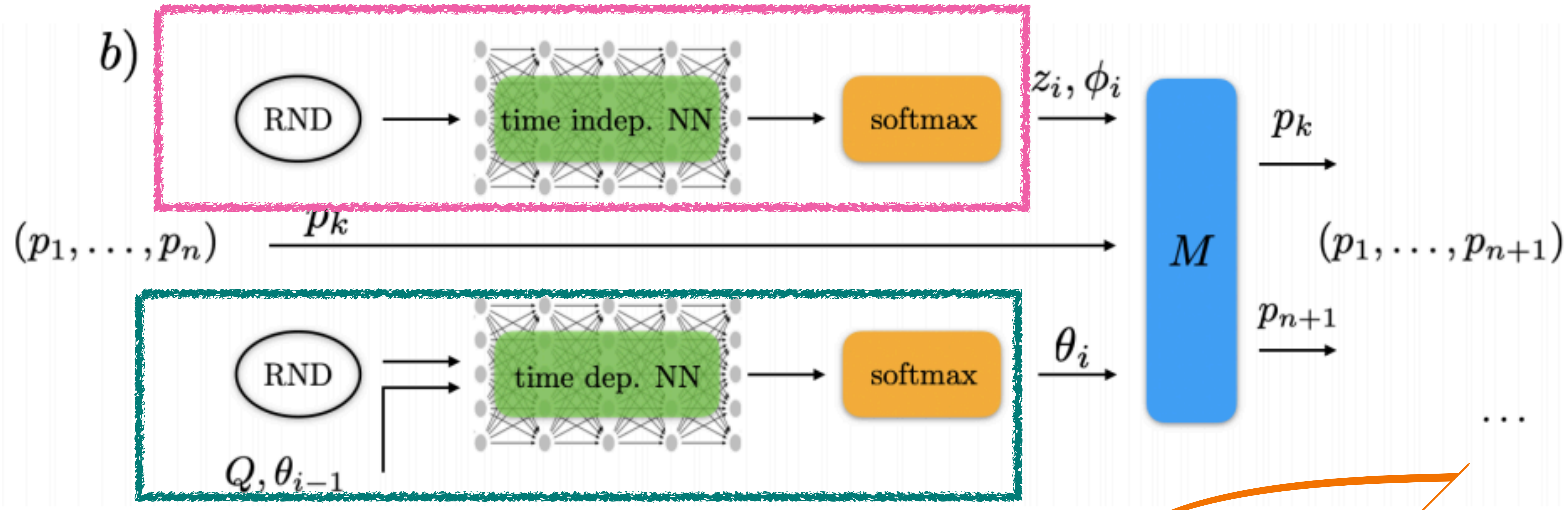
PLB 829 (2022) 137055



→ Extract splitting function from the network in white-box ML.

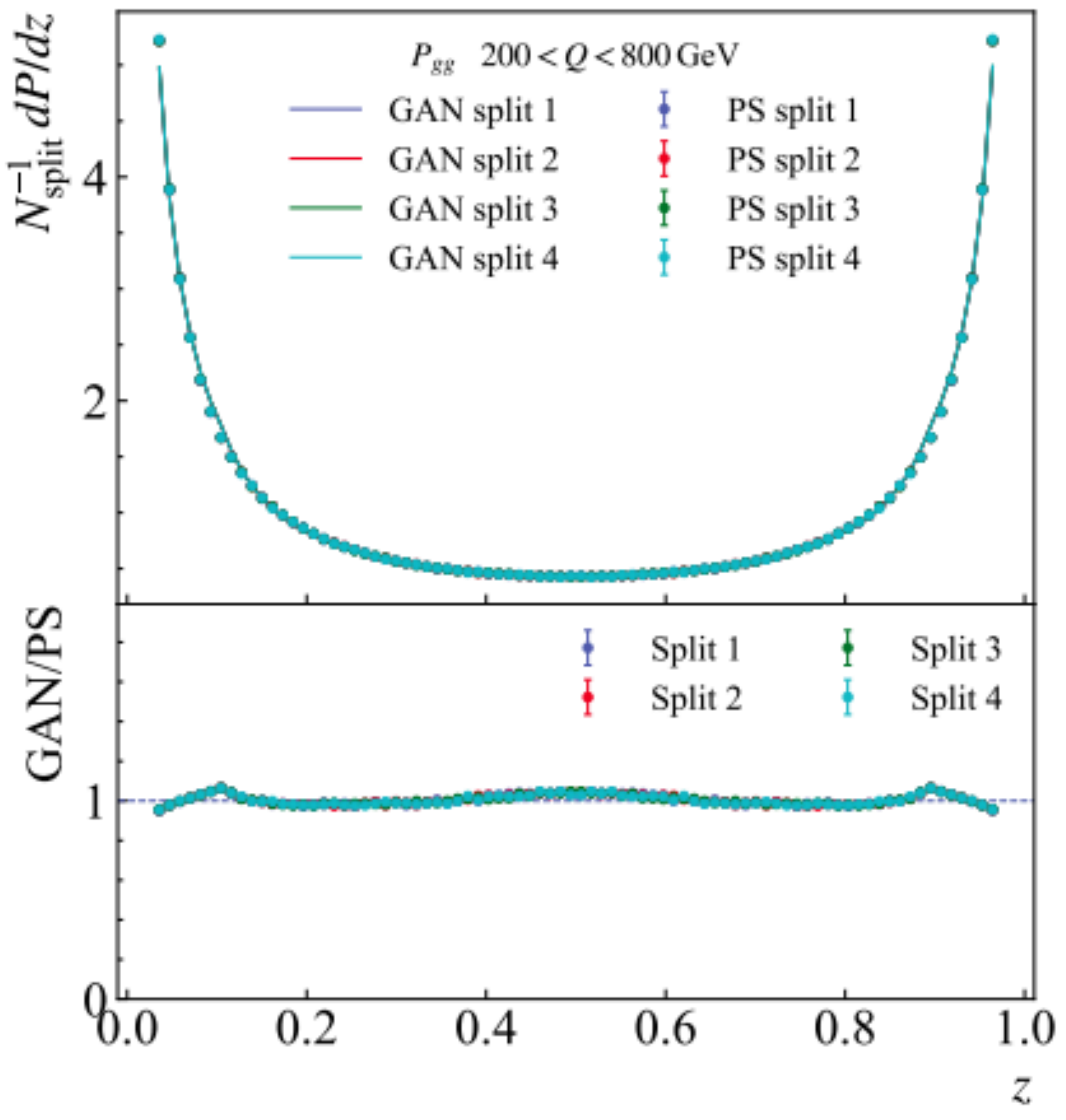
Done with a Generative Adversarial Network split into two components.

1. Time independent learns the z, ϕ



2. Time dependent learns the θ

Testing



→ Was able to reproduce AP splitting function.

Focus for next 5ish years

How do we quantify uncertainty?

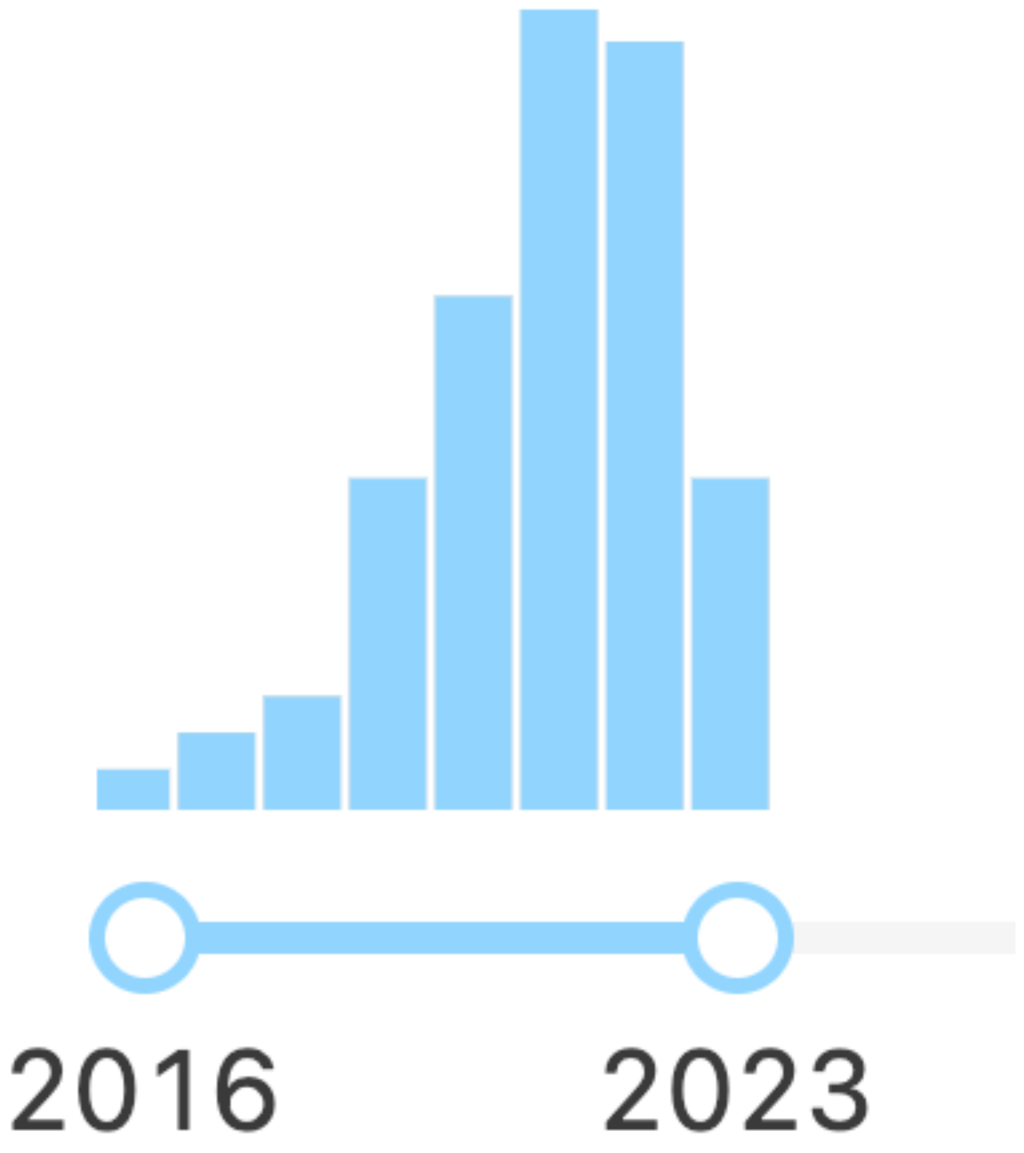
How can we construct more interpretable models?

Do we need to standardize ML applications across experiments?

Continue to develop deep/advanced techniques tested on simulations!

Conclusions

- We are taking more data and making more complex measurements than ever before!
- Machine learning and its use in heavy-ion experiments is becoming increasingly important!
- Lots of great experimental progress through the whole data analysis pipeline!



Future is very bright!

Resources & Future Workshops

This was a brief and biased overview! Many great conferences/workshops!

- For more ML at this conference, see also Kai Zhou's talk on Thursday at 16:30 and Henry Hirvonen's talk tomorrow at 17:30! (More theoretical)

ML4Jets2023

6–10 Nov 2023
DESY
Europe/Zurich timezone

Universität Hamburg
DER FORSCHUNG | DER LEHRE | DER BILDUNG

CLUSTER OF EXCELLENCE
QUANTUM UNIVERSE

DESY.

ML4jets 2023 was just announced!
Abstracts due September 10th!

Resources Hub For Machine Learning

Here is a collection of resources that I've found helpful in order to learn about machine learning and explore its applications for jet measurements! Feel free to distribute this guide to anyone who may be able to benefit from it! If there are any resources that you would like to see included in this list, email me at **hannah.bossi@yale.edu** and I will happily add them! Enjoy! ~ Hannah

- Resources to Learn About ML in General
  - Overview Websites
  - Conferences/Meetings
- Resources to Learn About ML Applications in Jet Physics
  - Overview Websites
  - Papers
  - Conferences/Meetings

→ To learn about ML see resource guide!

Thank you!!

Backup

Types of learning

Supervised Learning

Algorithm learns from a labeled set of "true values".

Driven by the Task

Analogy: Taking a test

Unsupervised Learning

Algorithm finds structure in the data without knowing the desired outcome.

Driven by the Data

Analogy: Discovering allergies

Reinforcement Learning

Algorithm learns in a reward based system to determine a series of actions.

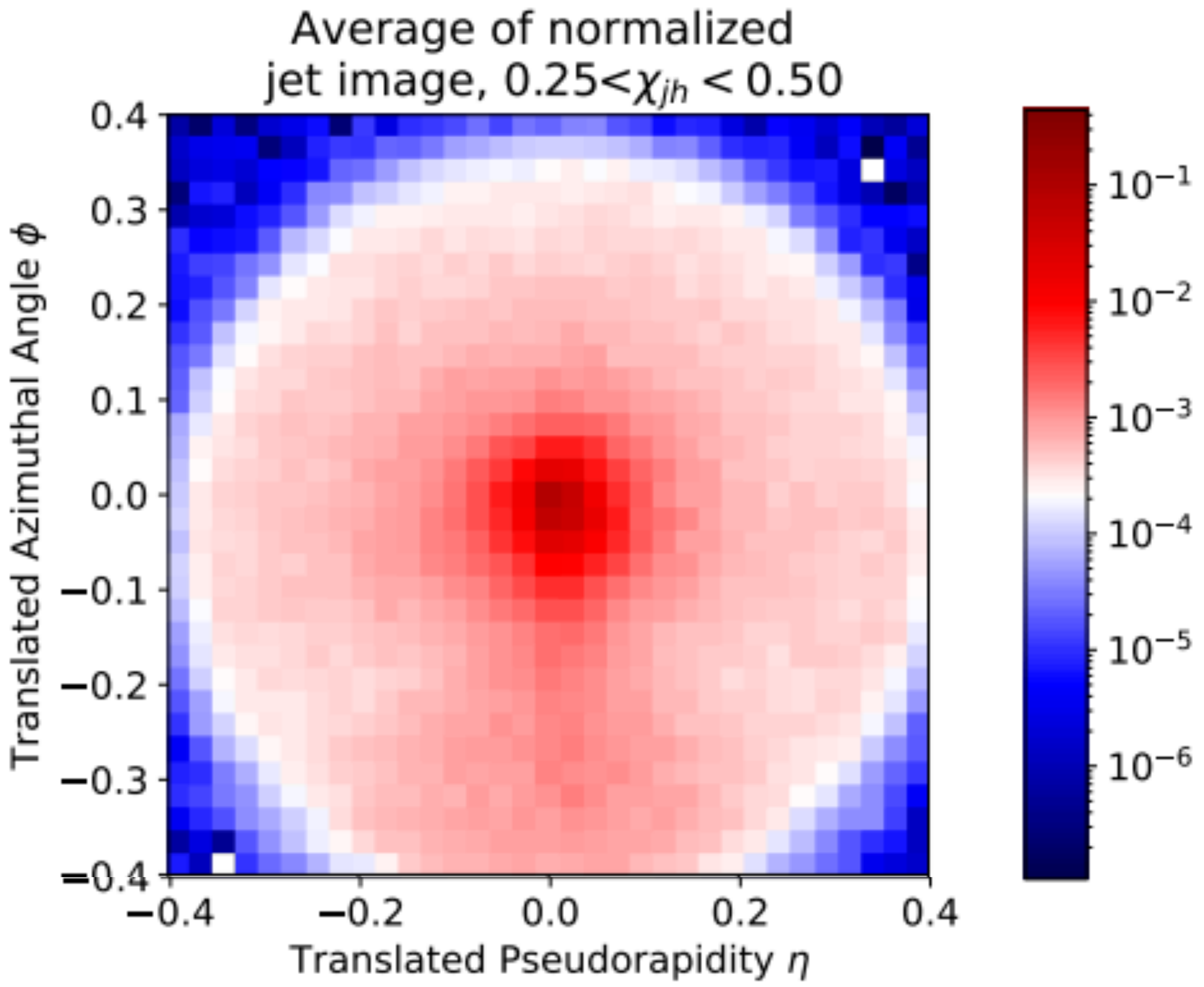
Driven by the Reward

Analogy: Dog training

Jet representations

Jets as images

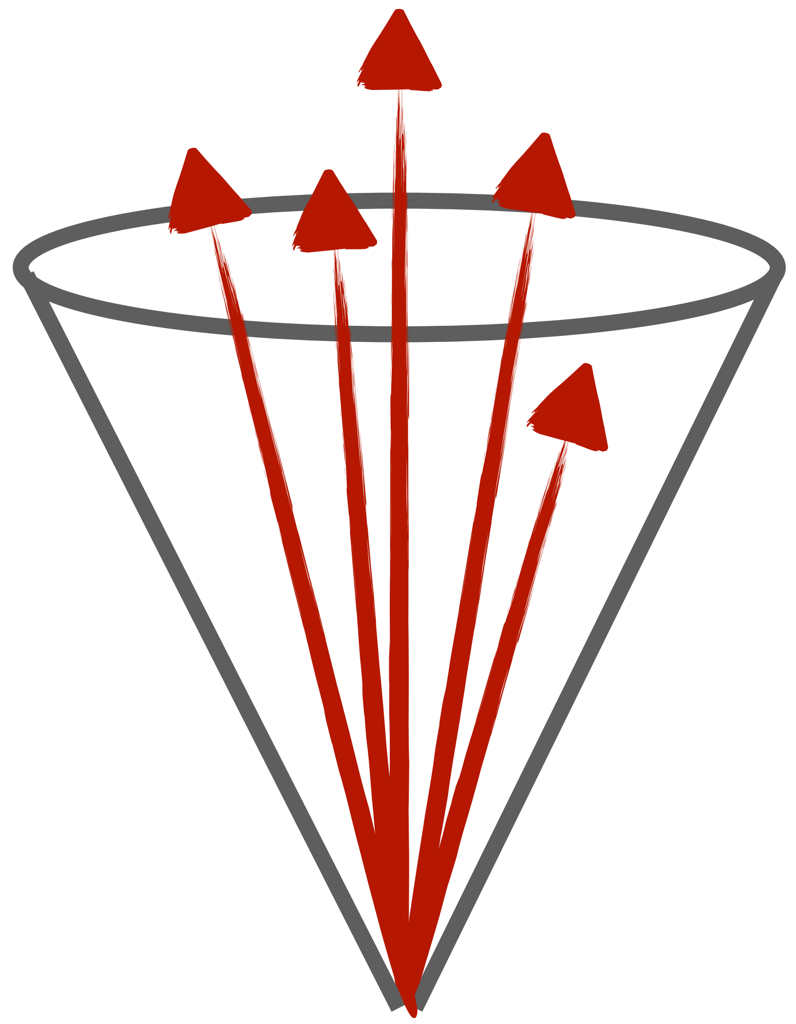
Input: jet image



JHEP 2021, 206 (2021)

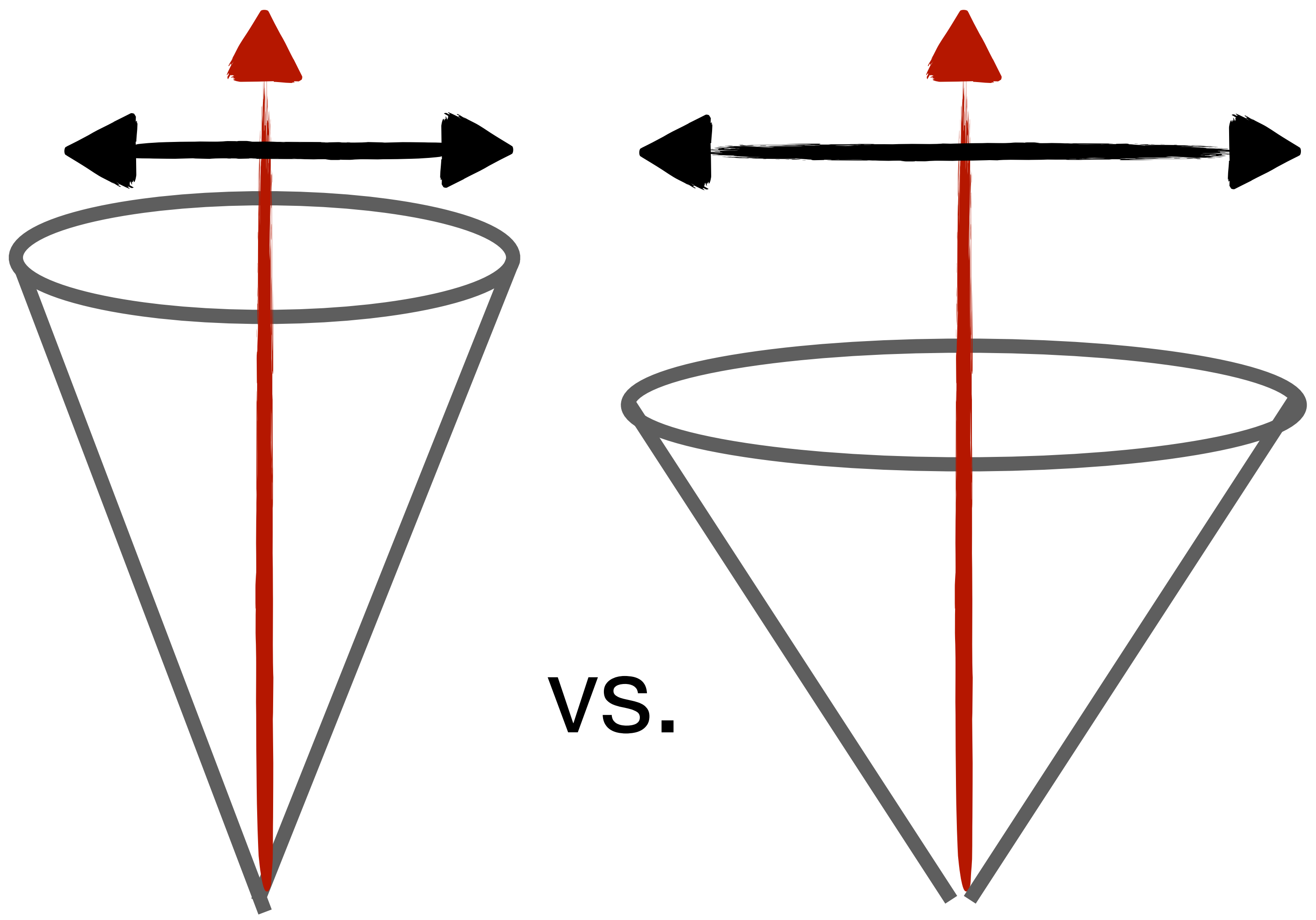
Jets as a collection of objects

Input: declustering history, order of constituent p_T



Jets as a single object

Input: jet mass, radial moments, other jet properties…



Different representations suitable for different problems → also different ML algorithms!

AI for detector design

“AI techniques that can optimize the design of complex, larger scale experiments could completely revolutionize the way experimental nuclear physics is done” - *DOE Town Hall AI for Science 2019 Report*

In Use

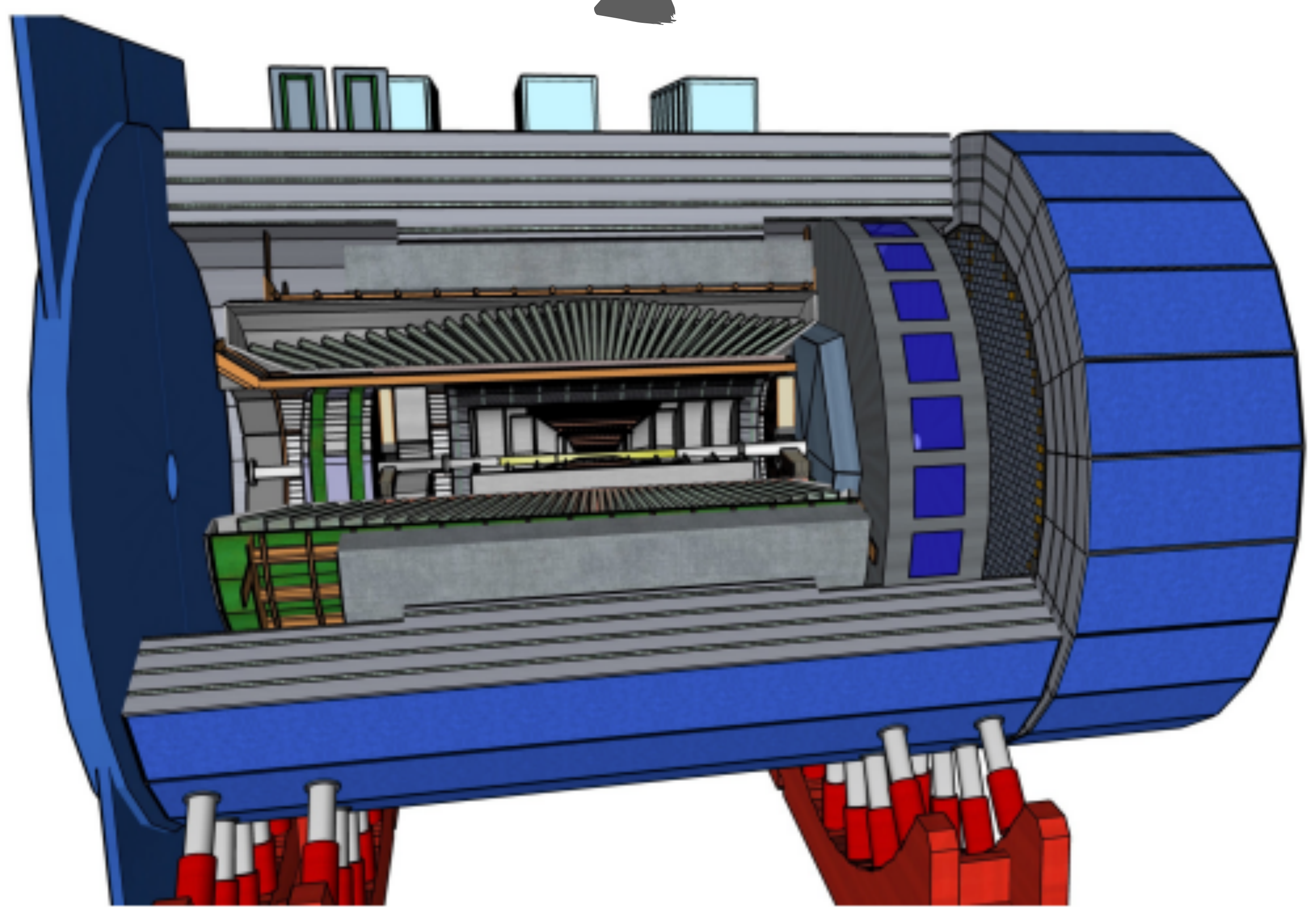
ECCE

AI Model

Design parameters

Physics Objectives

Injection of Physics Events

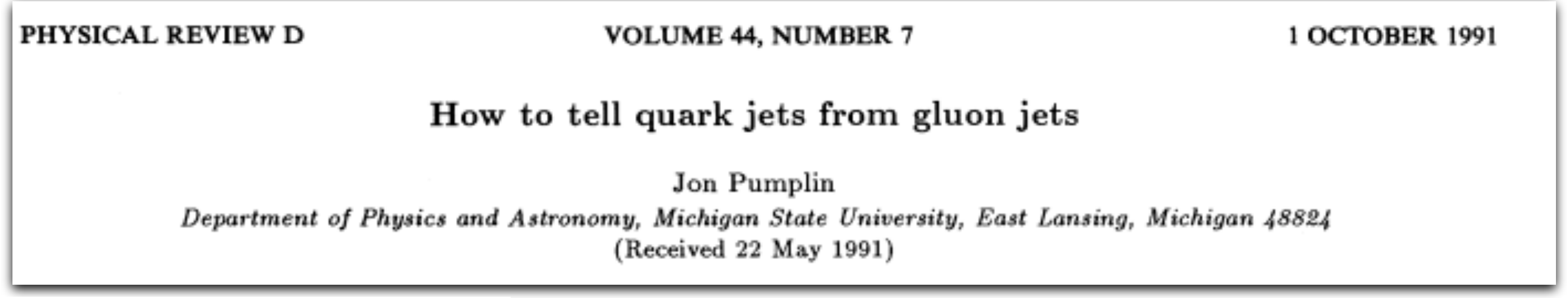


Detector Simulation

Analysis of reconstructed of events

C. Fanelli, JINST 17 (2022) 04, C04038

Quark vs. gluon jet tagging


PHYSICAL REVIEW D VOLUME 44, NUMBER 7 1 OCTOBER 1991

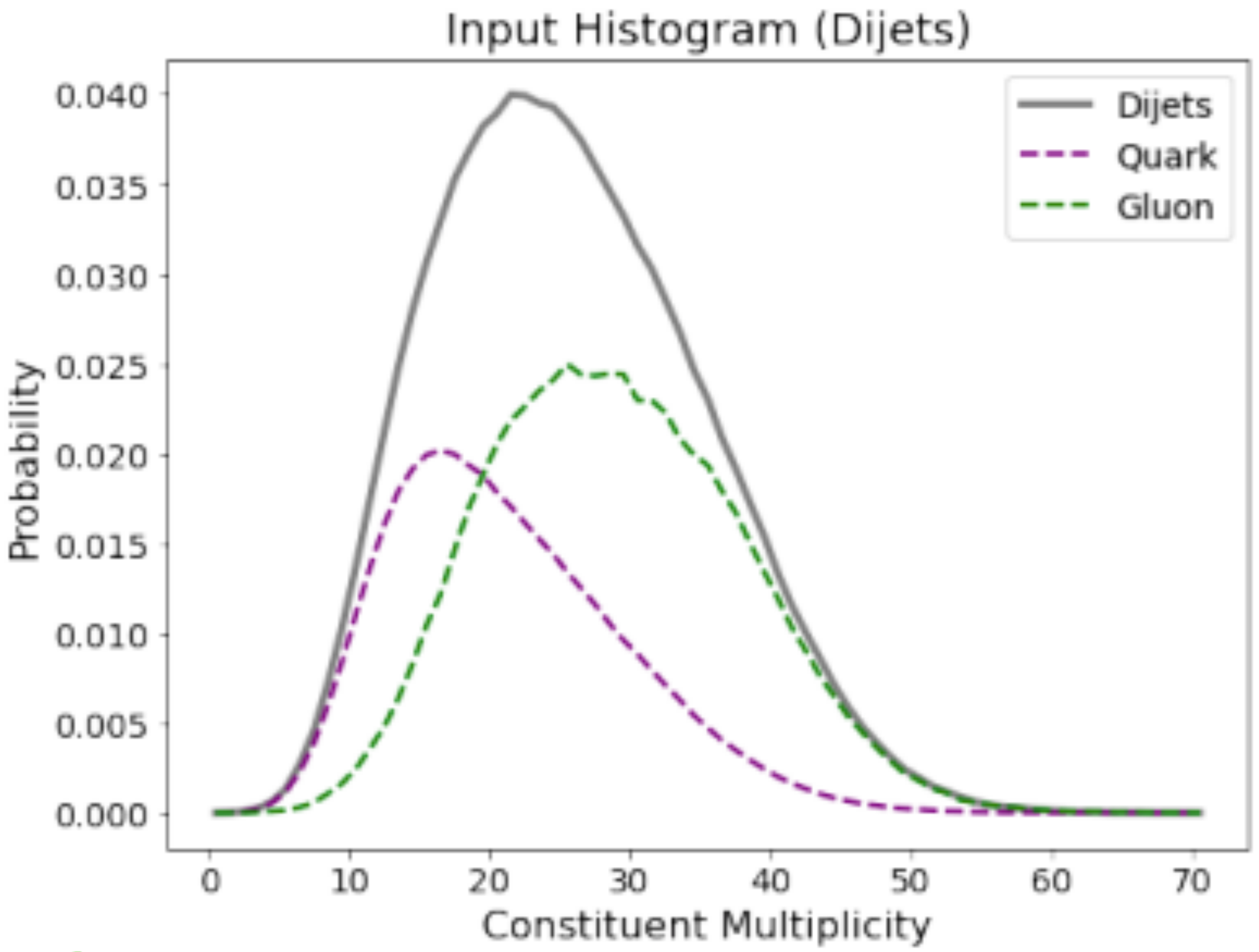
How to tell quark jets from gluon jets

Jon Pumplin

Department of Physics and Astronomy, Michigan State University, East Lansing, Michigan 48824

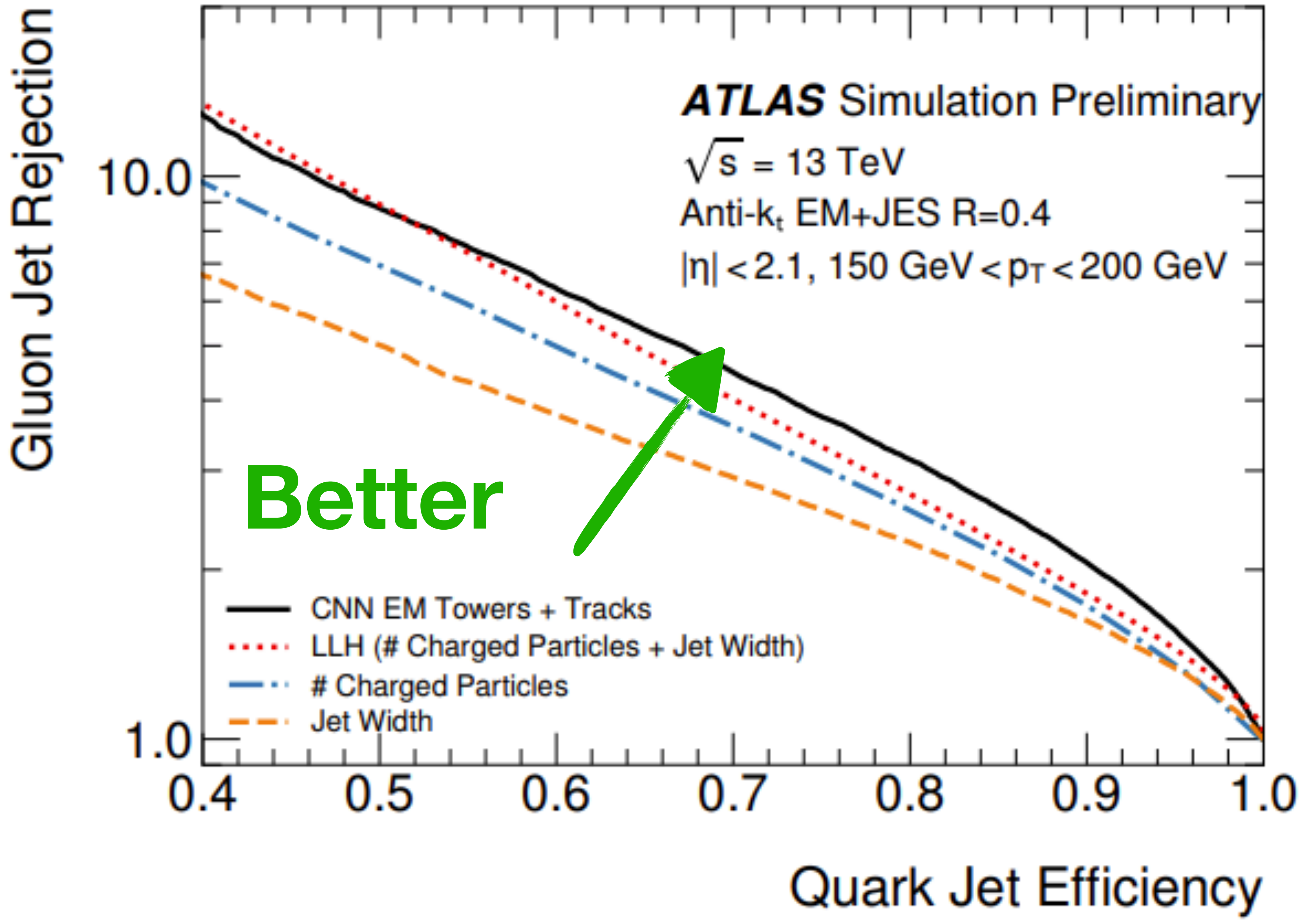
(Received 22 May 1991)

→ Longstanding effort (since 1991)!



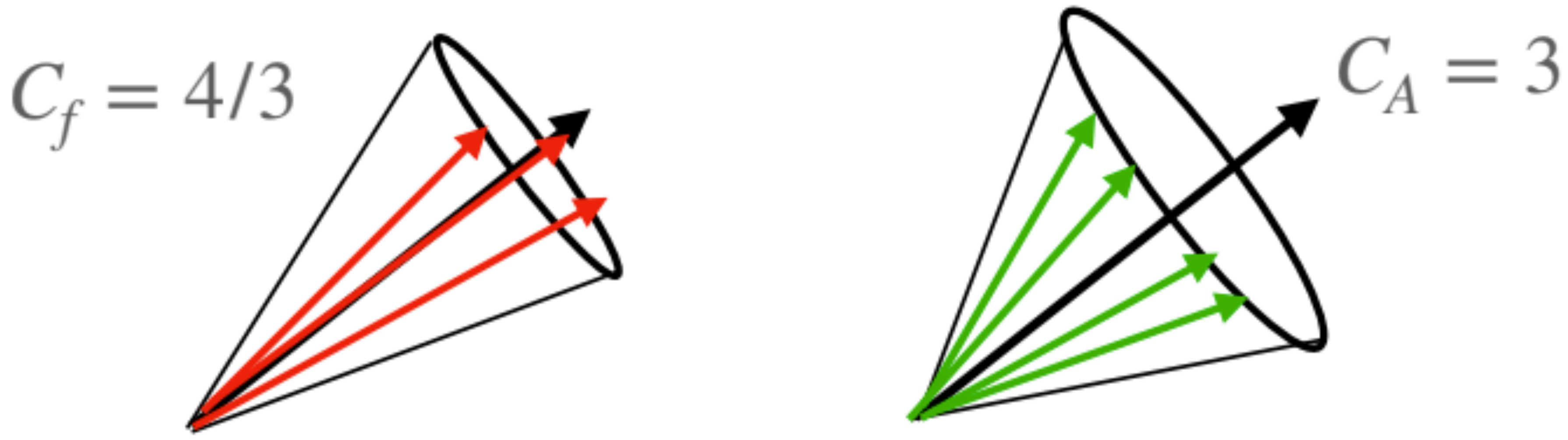
arXiv:2204.00641

ATL-PHYS-PUB-2017-017



Quark Jets

Gluon Jets



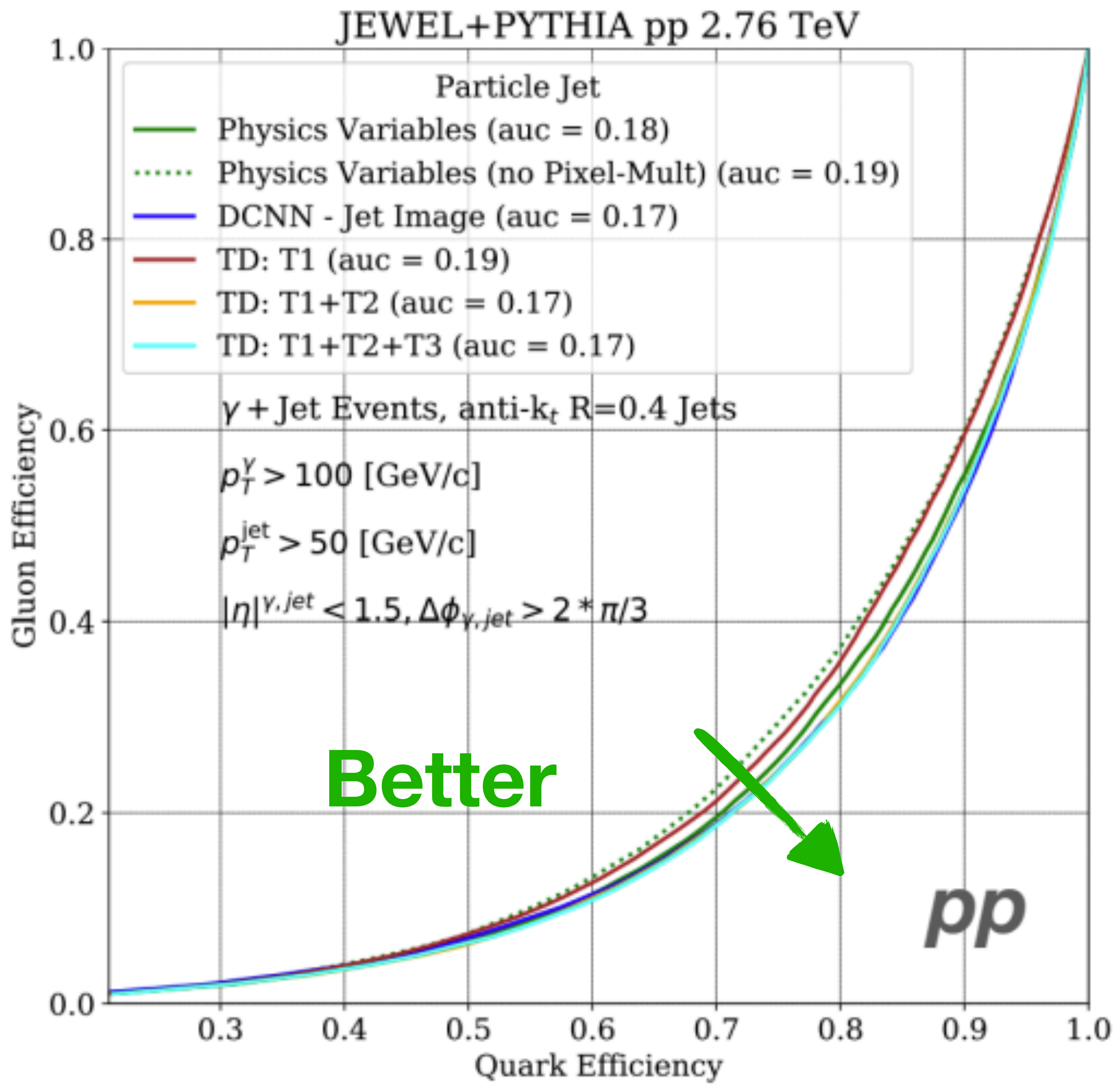
→ Difficult to do (even in pp)

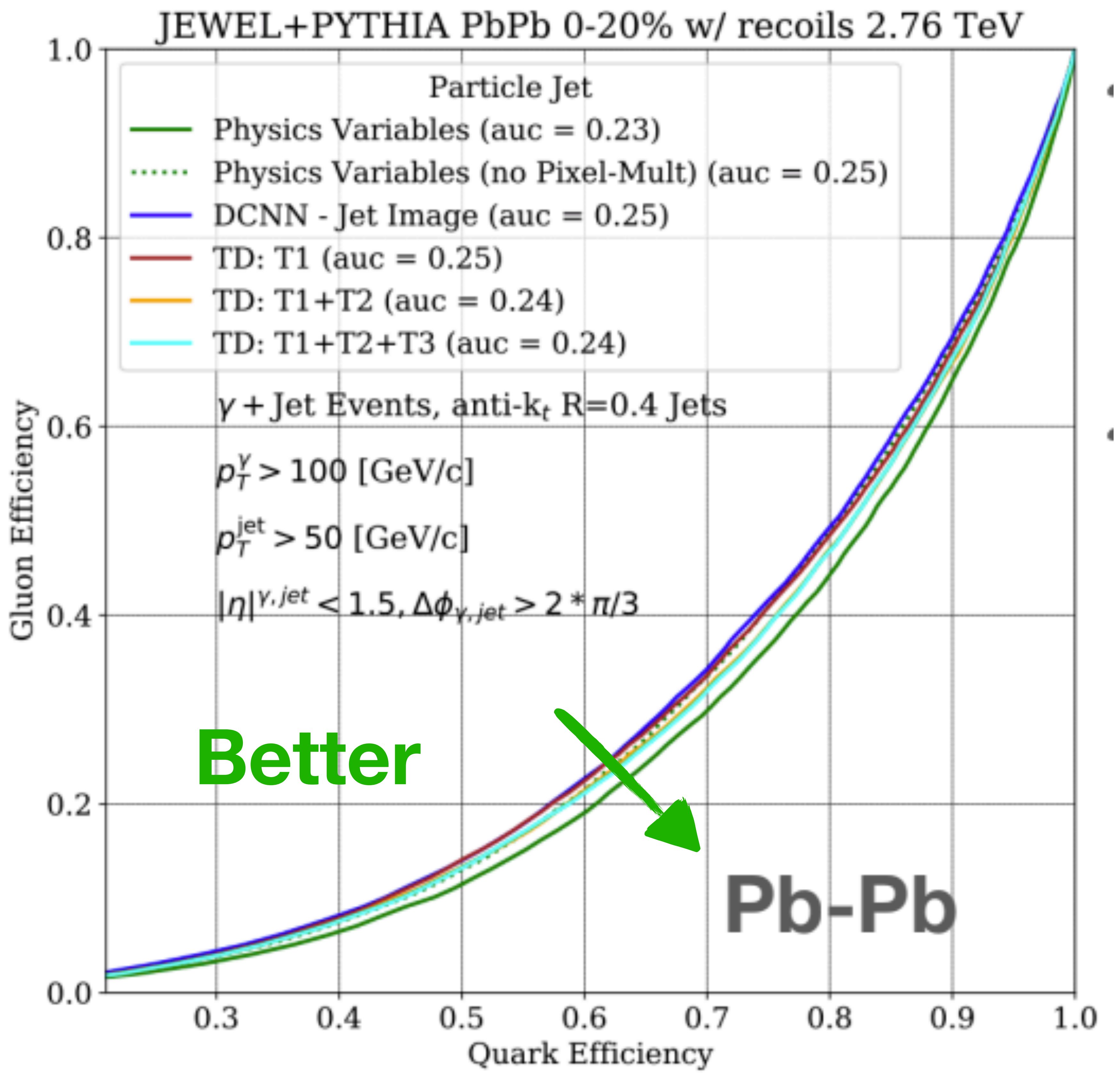
→ Large overlap between samples

ATLAS uses CNNs, improvement over traditional techniques in pp

Quark vs. gluon jet tagging in HIs

Y.Chien, R.Elayavalli, arXiv:1803.03589





→ Early indications in JEWEL simulations that this will be much more difficult in HI collisions!

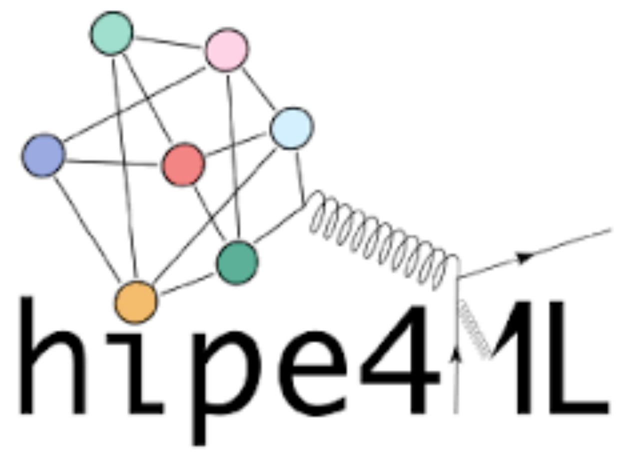
In HIs - this is an ongoing effort!

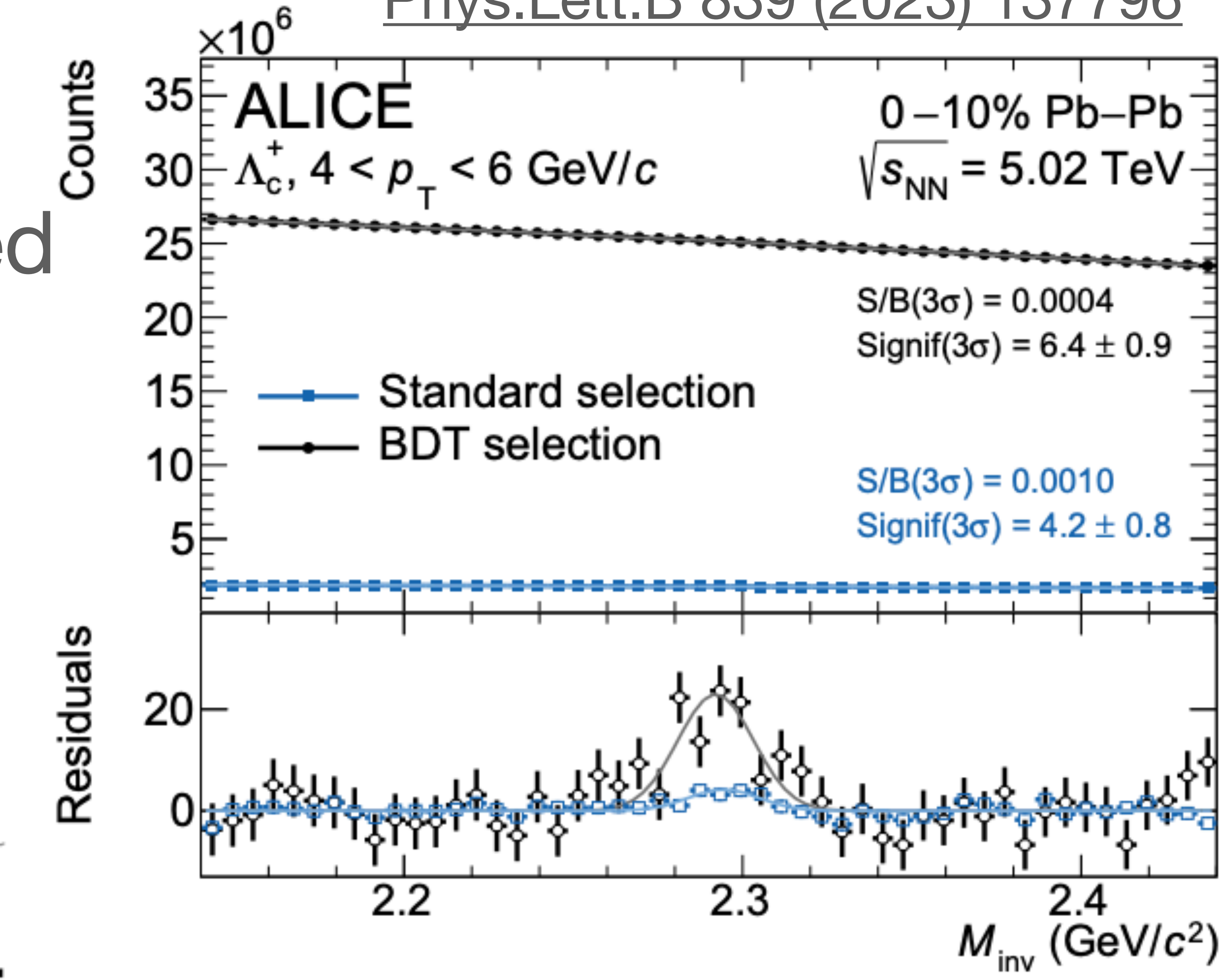
Signal/background discrimination

Select HF hadron w/ ML Ex: $\Lambda_c^+ \rightarrow pK_s^0$

Phys.Lett.B 839 (2023) 137796

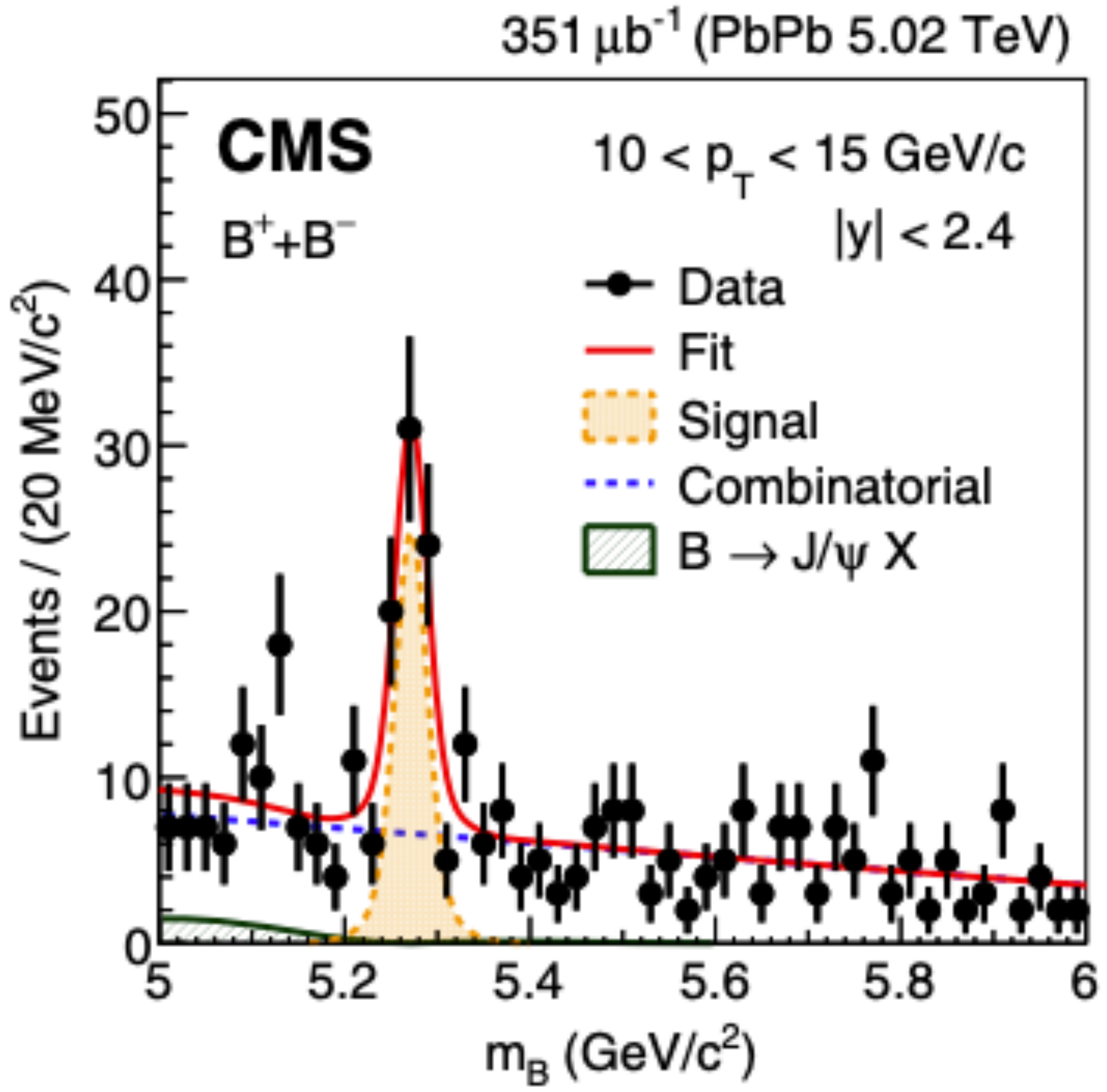
- BDT implemented in XGBoost using hipe4ML





ML gives 4x better signal/background ratio!

PRL 119 (2017) 152301



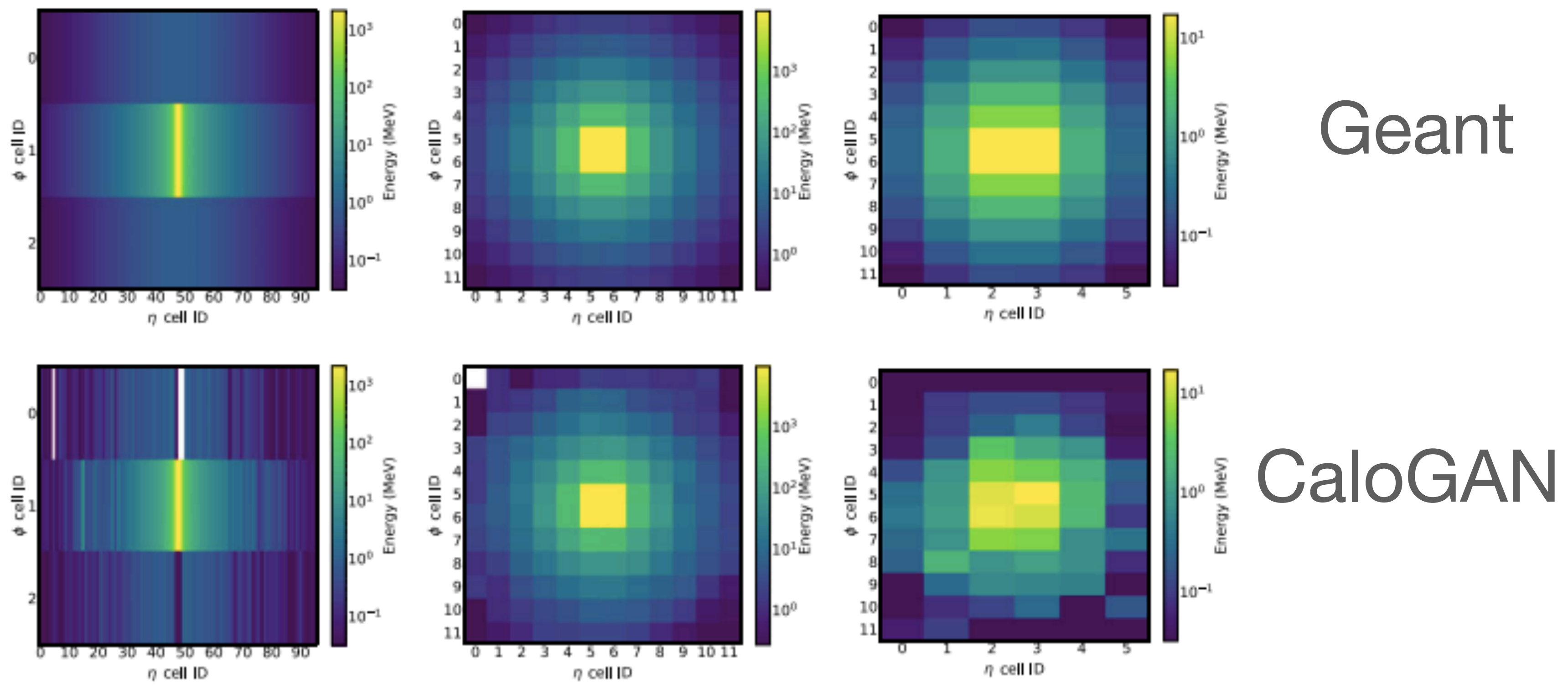
Cut optimization for open beauty done with ROOT TMVA.

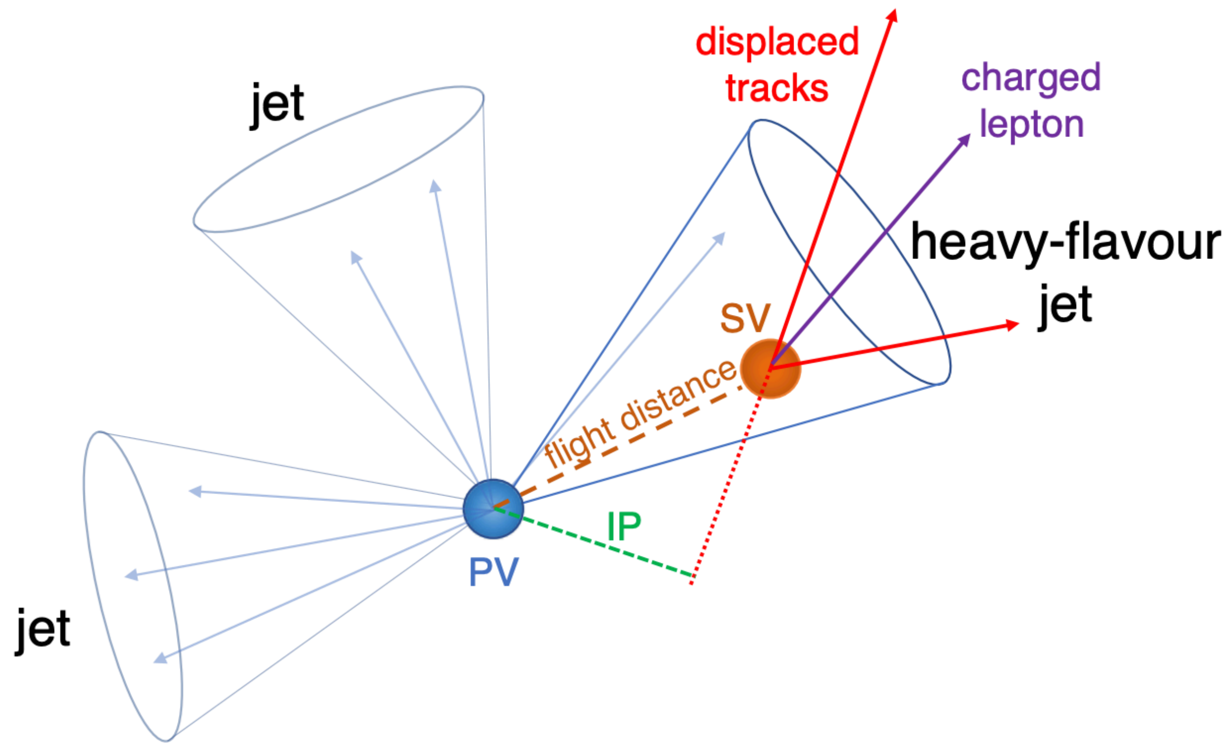
Uses of ML for High Energy Physics

Many broad categories of applications!

Triggering Systematic Uncertainty Reduction
Anomaly Detection Object Classification
Data Quality Assessment Detector Simulation
New Physics Searches

Anomaly detection (LHC Olympics, arXiv:2101.08320)





What about heavy-ion physics specifically?

Detector Simulation
(CaloGAN, PRL 120, 042003 (2018))

Object Classification arXiv: 1712.07158

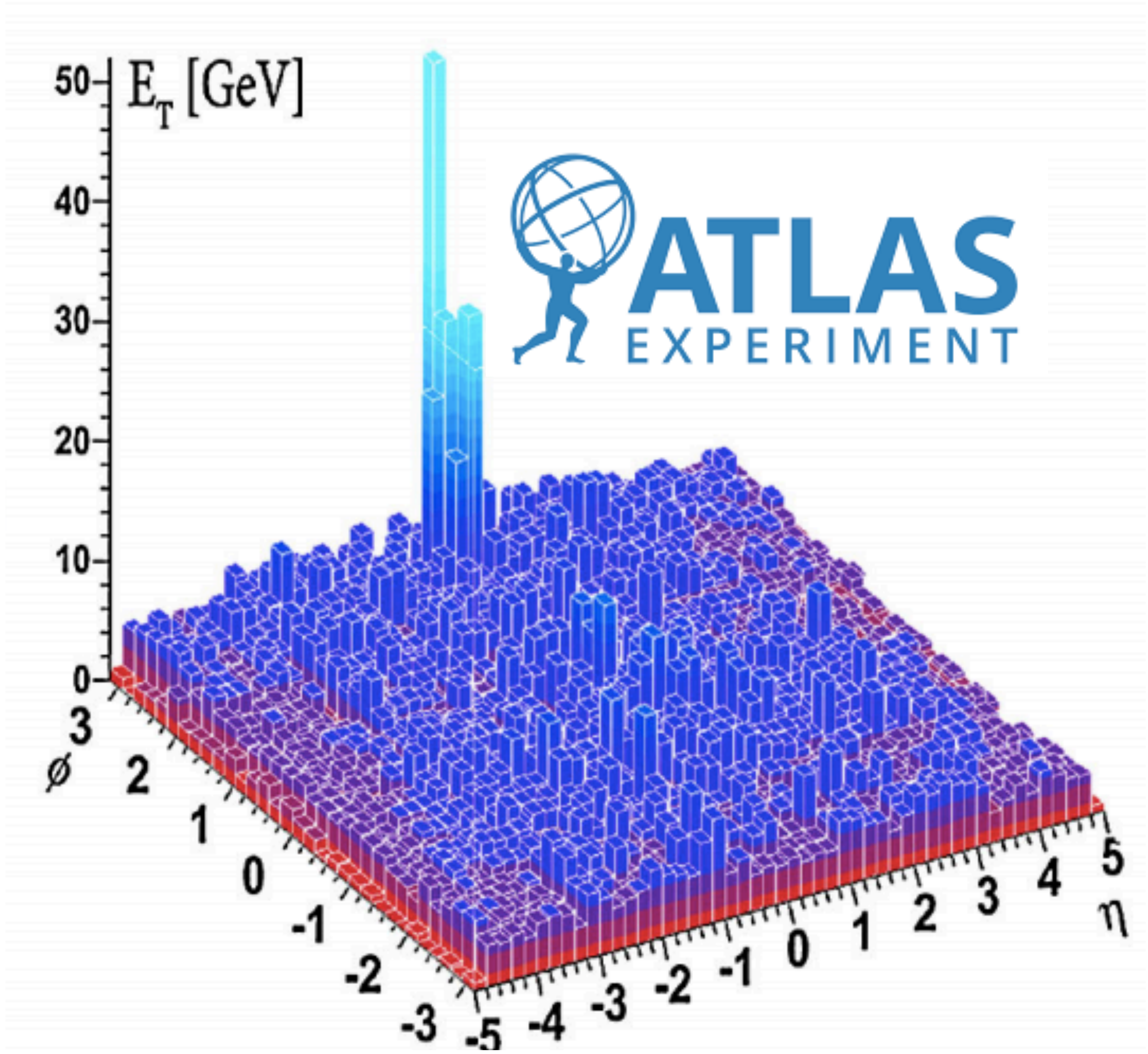
The conventional approach

- Typically (in ALICE) perform a pedestal subtraction of the background.

$$p_{\mathrm{T,rec}} = p_{\mathrm{T,raw}} - \rho A_{\mathrm{jet}}$$

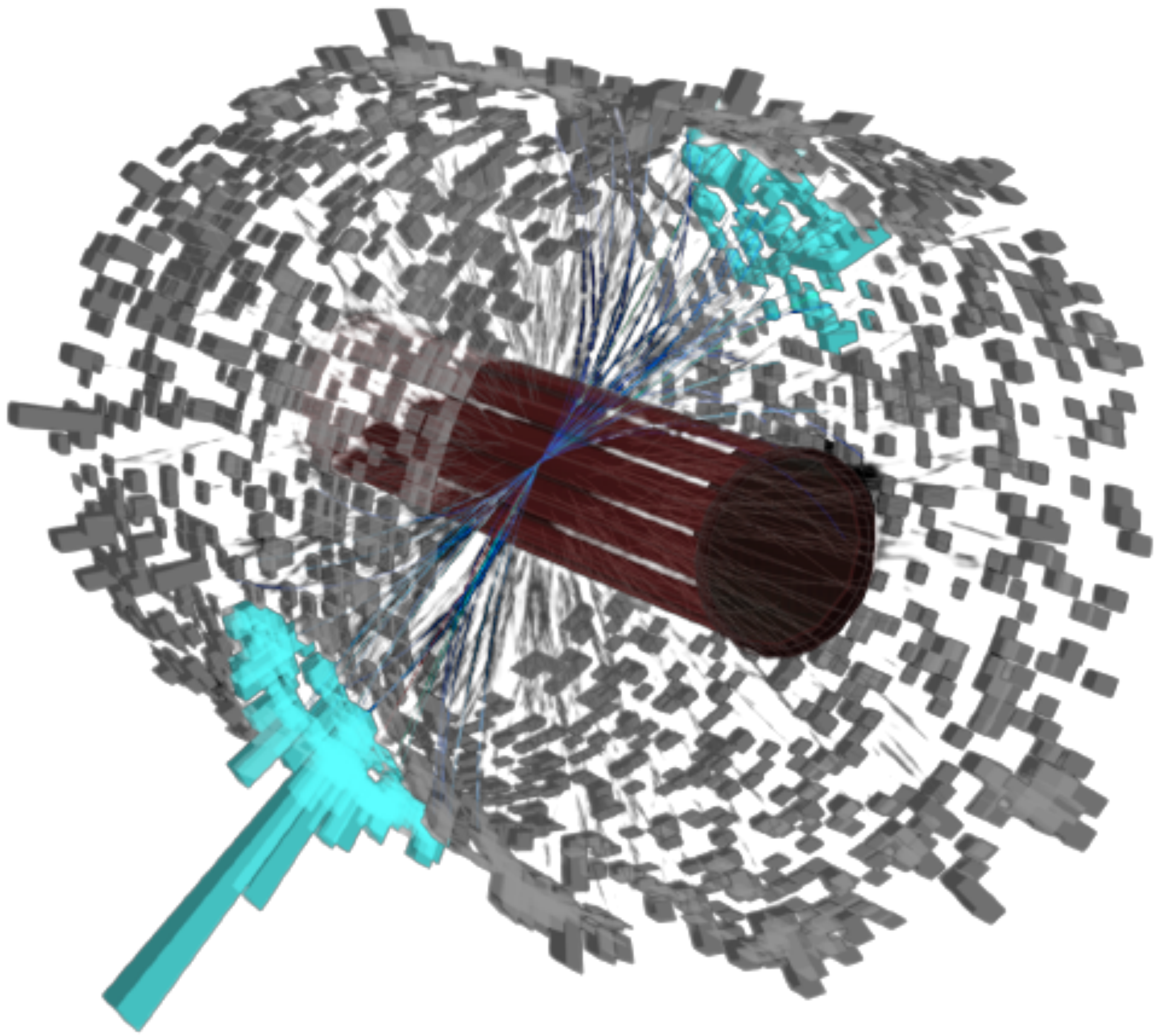
- Corrects for the background in the average case, but neglects residual fluctuations.

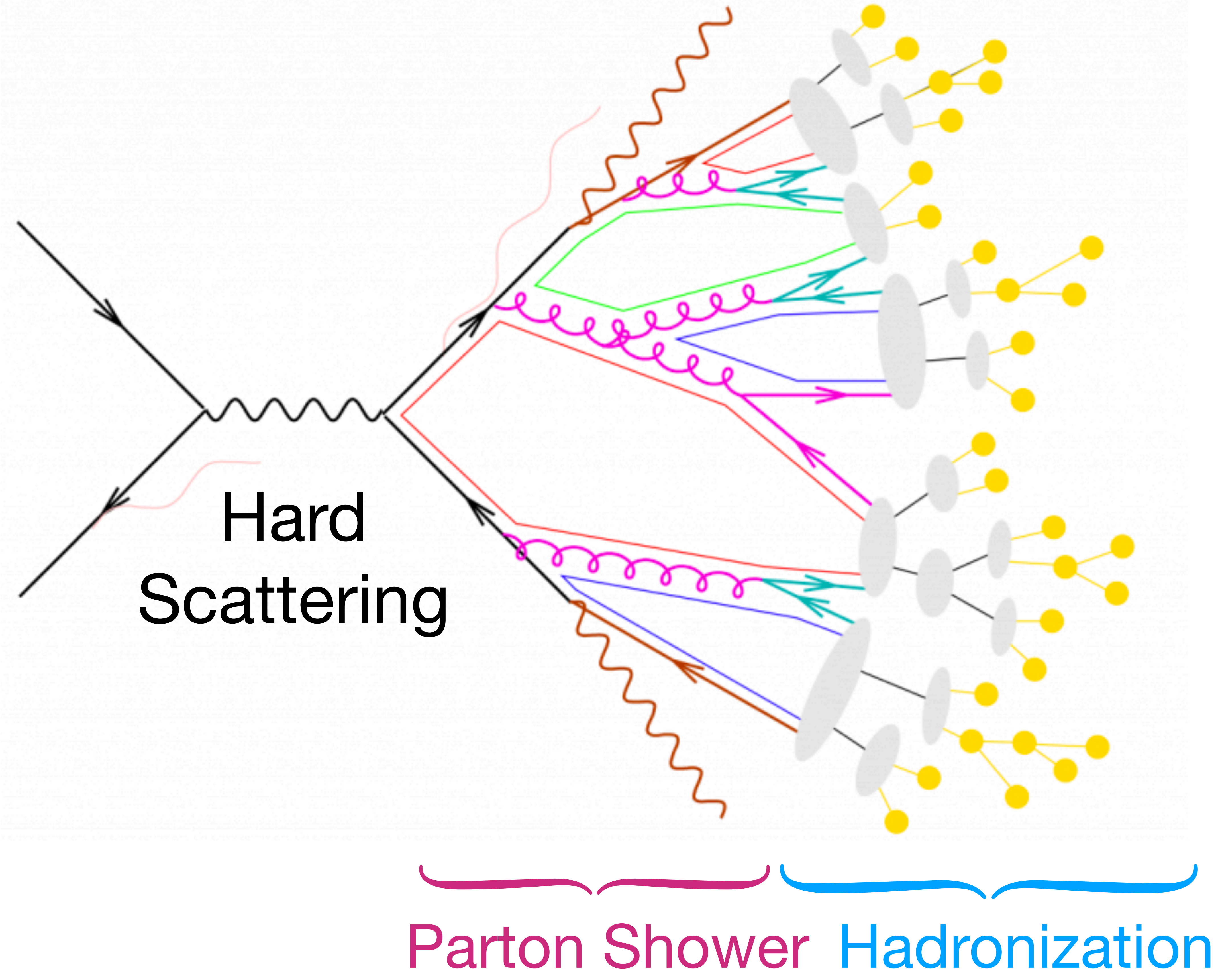
- A cut on the leading track of the jet is commonly also applied to remove fake jets, but biases the jet population.



ML and jet signals

- ML allows for a multi-variate treatment of signal and background discrimination.



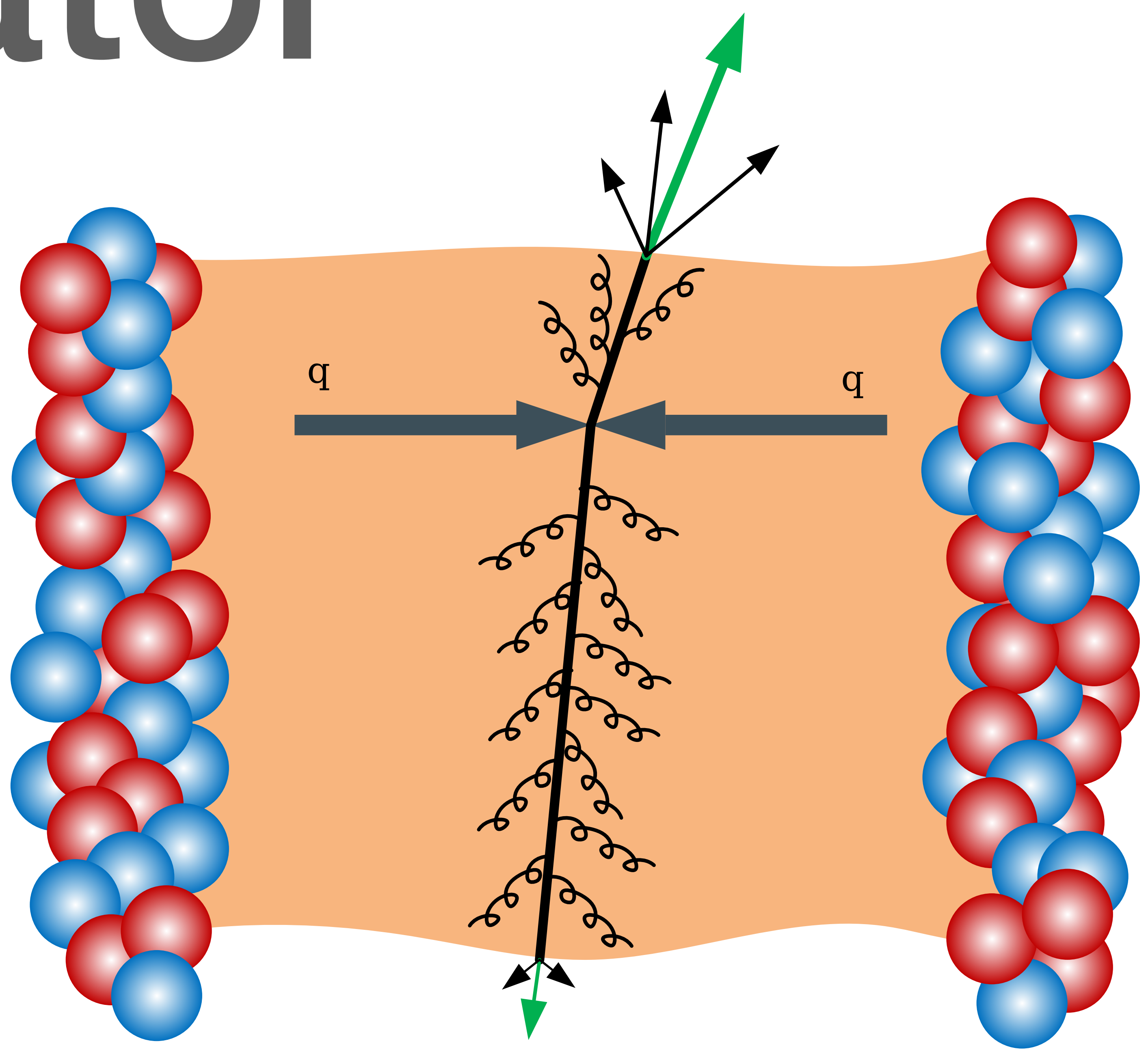


- Generalized and optimized version of the conventional approach!

ML background estimator

ML approach: Use ML to construct the mapping between measured and corrected jet without a leading track bias.

Aim: To extend measurements to regions where the background has a large impact (lower p_{T} and large R).



Jet Properties

(Including constituent properties)

ML →

Corrected Jet p_{T}

→

Unfold for fluctuations and detector effects

R.Haake, C. Loizides Phys. Rev. C 99, 064904 (2019)

Process

Training (PYTHIA fragmentation)

Train on “hybrid event” created by embedding PYTHIA jets into Pb-Pb Background

Shallow neural network

Testing

Apply ML estimator to hybrid events not used in training.

Key is that this background is *realistic.*

Do we get back the signal we put in?

We intentionally utilize “simple” ML techniques! This leads to greater interpretability!

Features for training

Ask ourselves two questions

How important is the feature to the model? → Feature Scores

Higher the feature score, more often variable is used in training.

How correlated is the feature with other features?

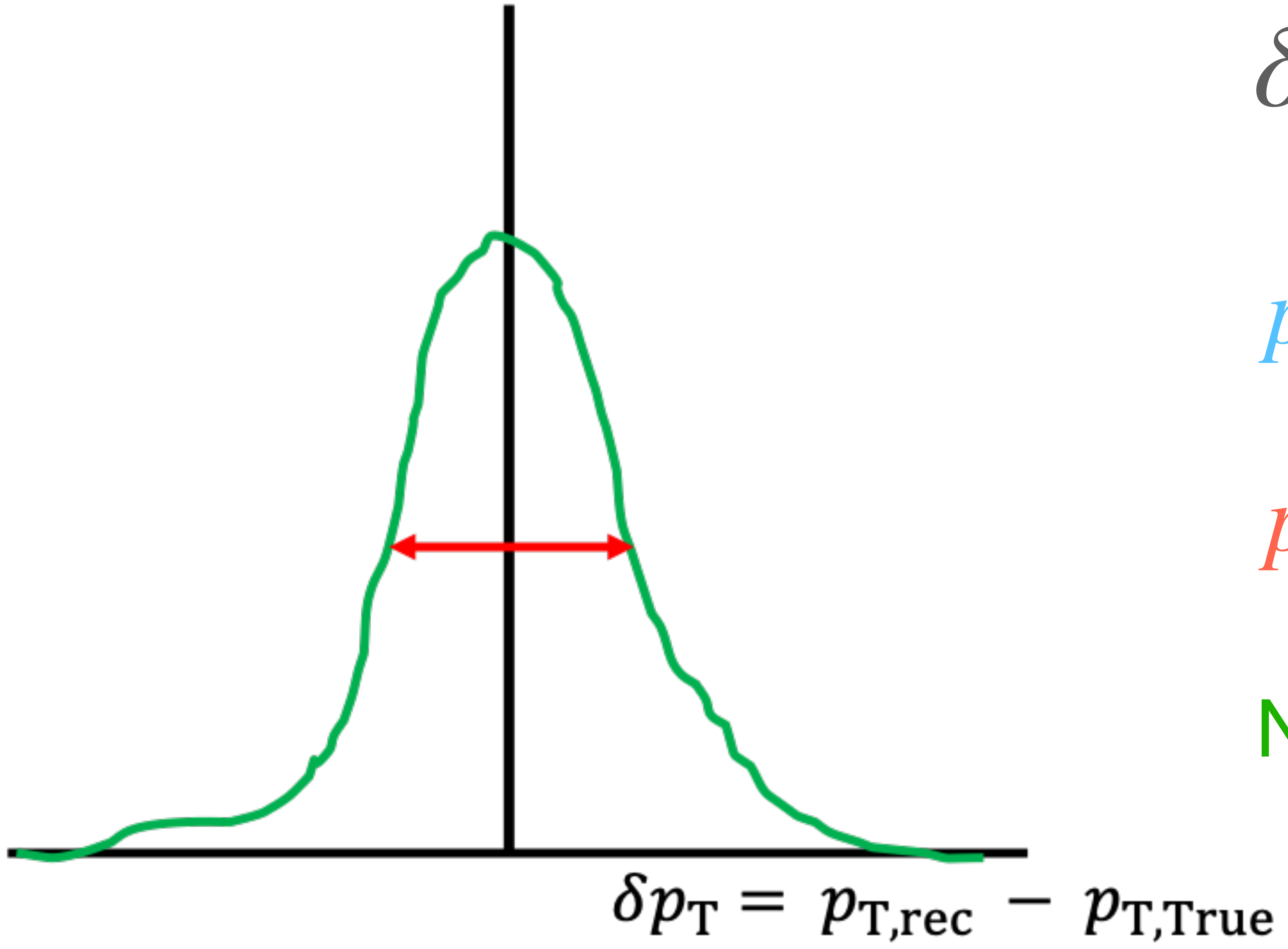
Feature Score = Mean Decreased Impurity

Feature	Score	Feature	Score
Jet p_T (no corr.)	**0.1355**	$p^1_{T,const}$	0.0012
Jet mass	0.0007	$p^2_{T,const}$	**0.0039**
Jet Area	0.0005	$p^3_{T,const}$	0.0015
Jet p_T (area based corr.)	**0.7876**	$p^4_{T,const}$	0.0011
LeSub	0.0004	$p^5_{T,const}$	0.0009
Radial moment	0.0005	$p^6_{T,const}$	0.0009
Momentum dispersion	0.0007	$p^7_{T,const}$	0.0008
Number of constituents	0.0008	$p^8_{T,const}$	0.0007
Mean of constituent p_Ts	**0.0585**	$p^9_{T,const}$	0.0006
Median of Constituent p_Ts	0.0023	$p^{10}_{T,const}$	0.0007

Iteratively remove unimportant or highly correlated features!

R.Haake, C. Loizides Phys. Rev. C 99, 064904 (2019)

Evaluating the performance



$$\delta p_T = p_{T,rec} - p_{T,true}$$

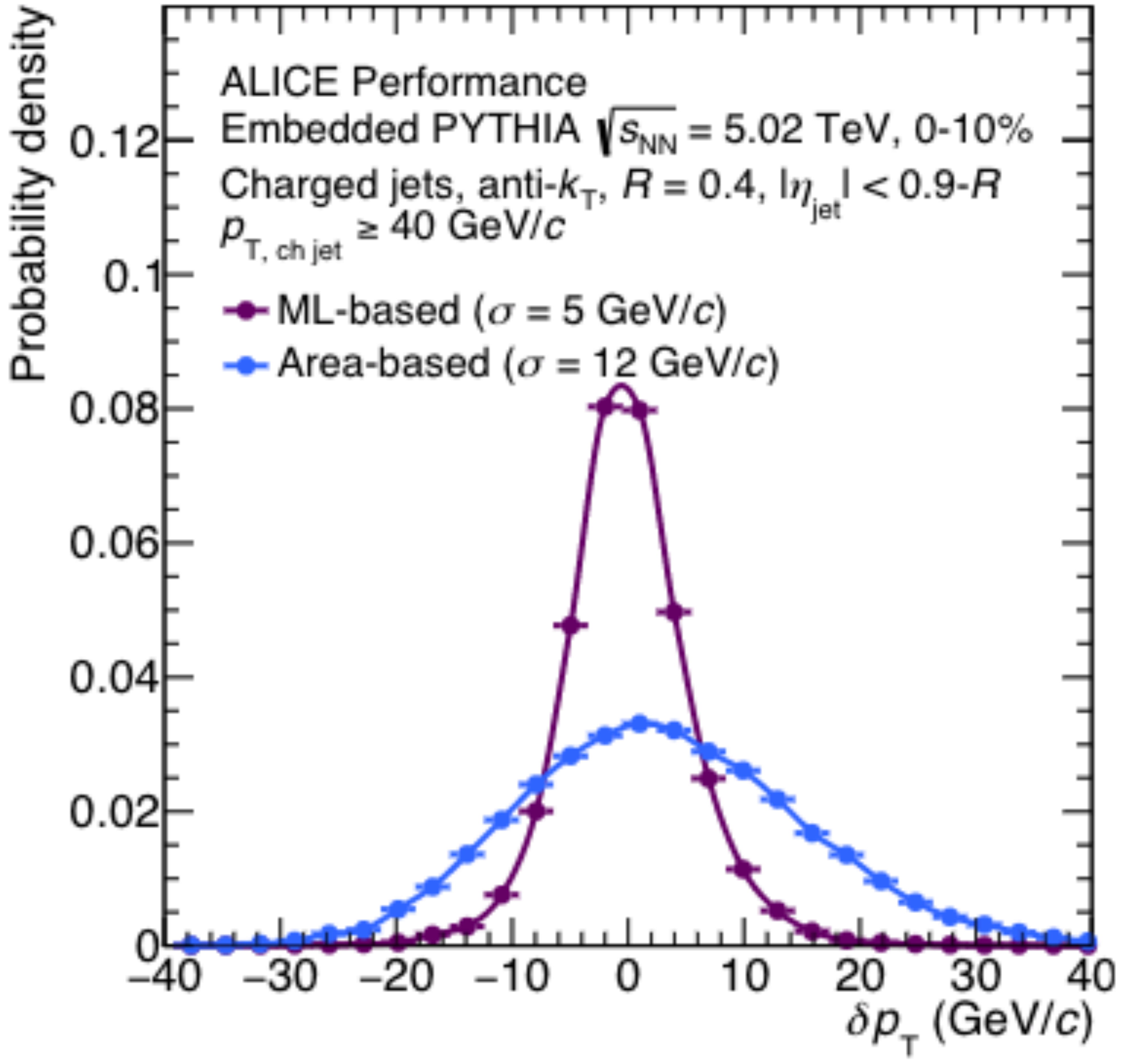
$p_{T,rec}$ = prediction from ML for target

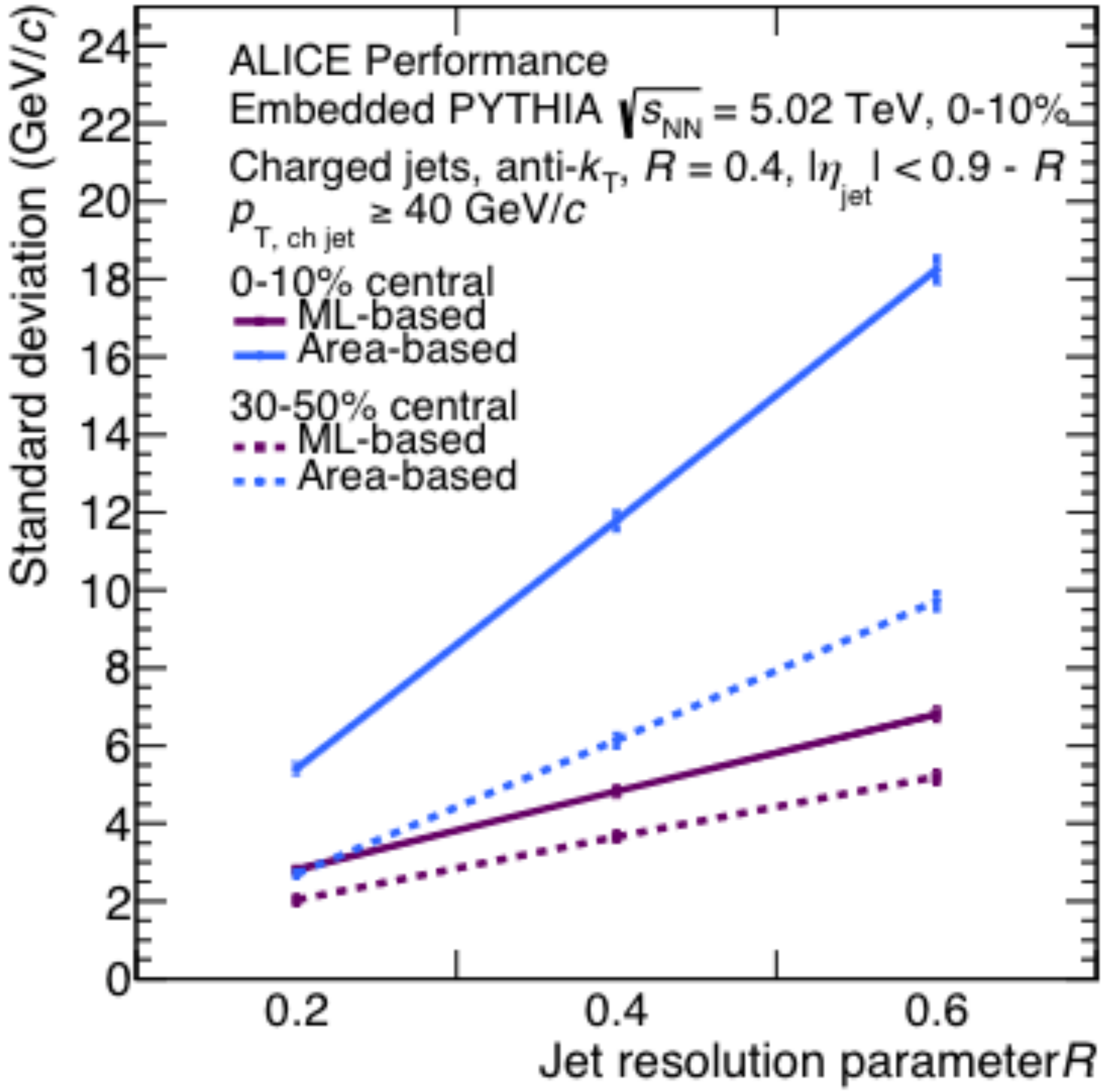
$p_{T,true}$ = *target* (matched PYTHIA detector level jet)

Narrow $\delta p_T \rightarrow$ Reduced residual fluctuations

Are we getting back to the *target?* Is the ML working?

Evaluating the performance



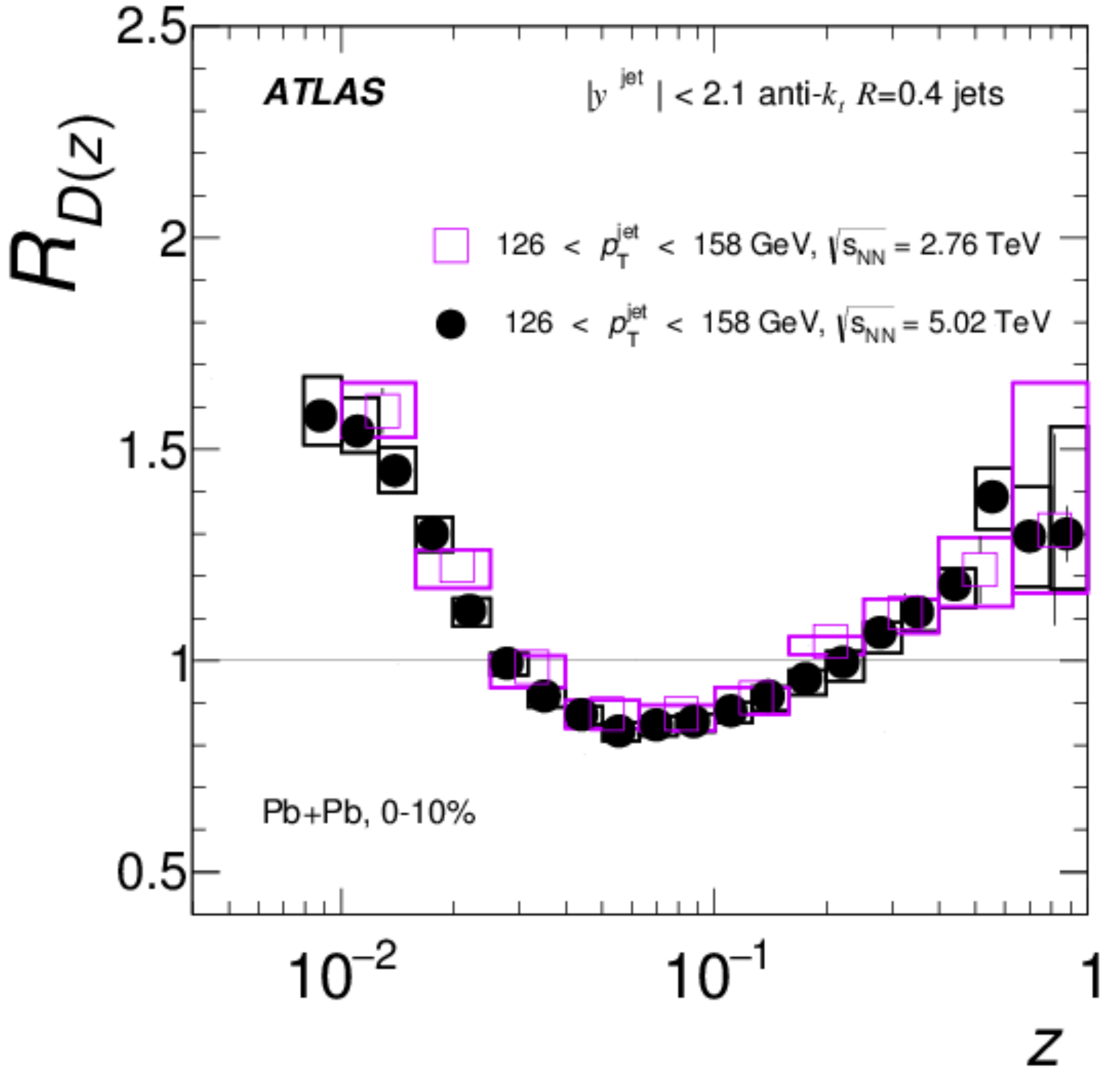


Residual fluctuations significantly reduced!

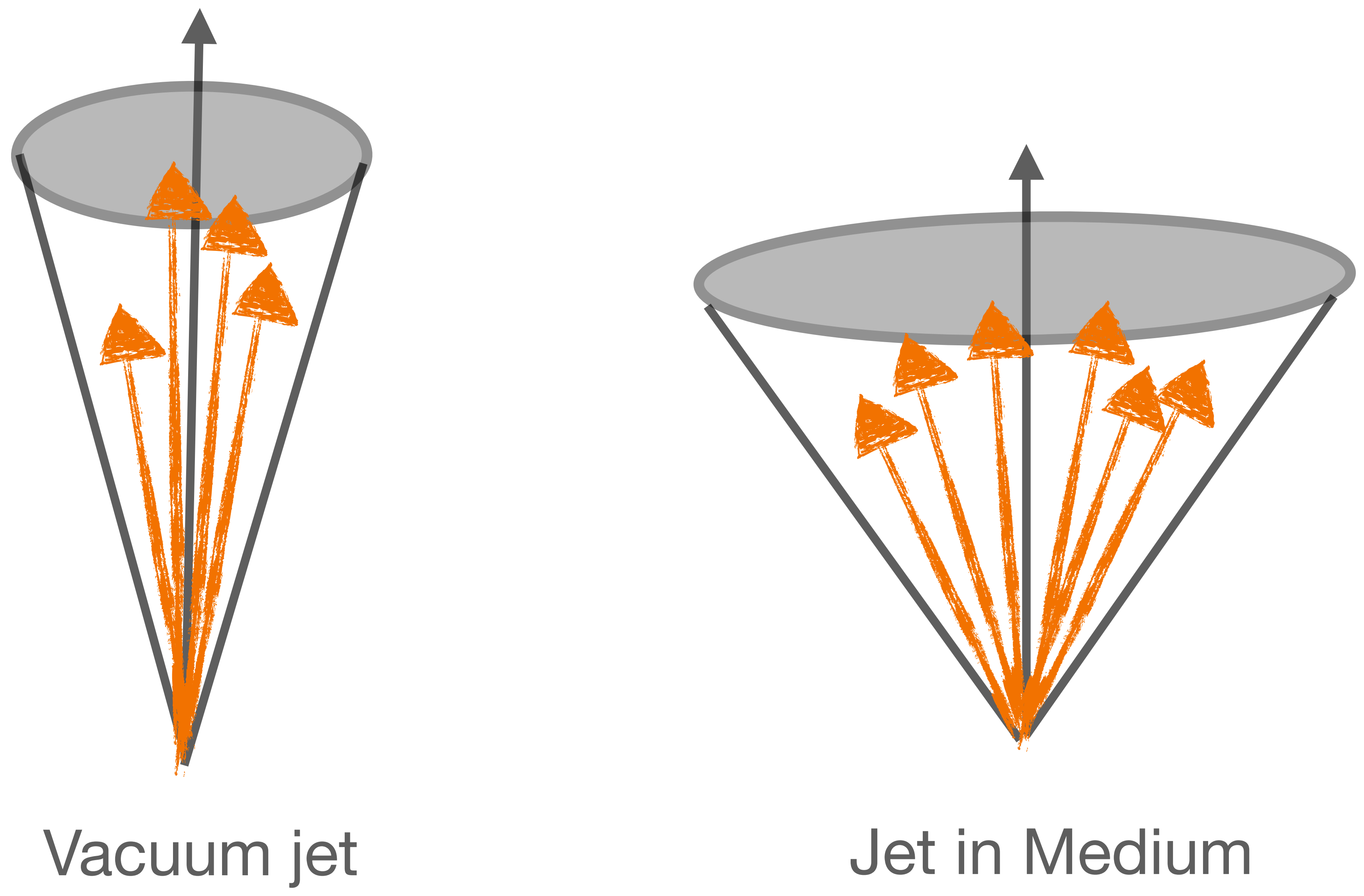
$$\delta p_T = p_{T,\text{rec}} - p_{T,\text{true}}$$

Fragmentation bias

Learning on constituents introduces a fragmentation bias because our training sample is PYTHIA.



Phys. Rev. C 98, 024908 (2018)



We know that fragmentation in heavy-ion collisions is modified by the presence of the medium.

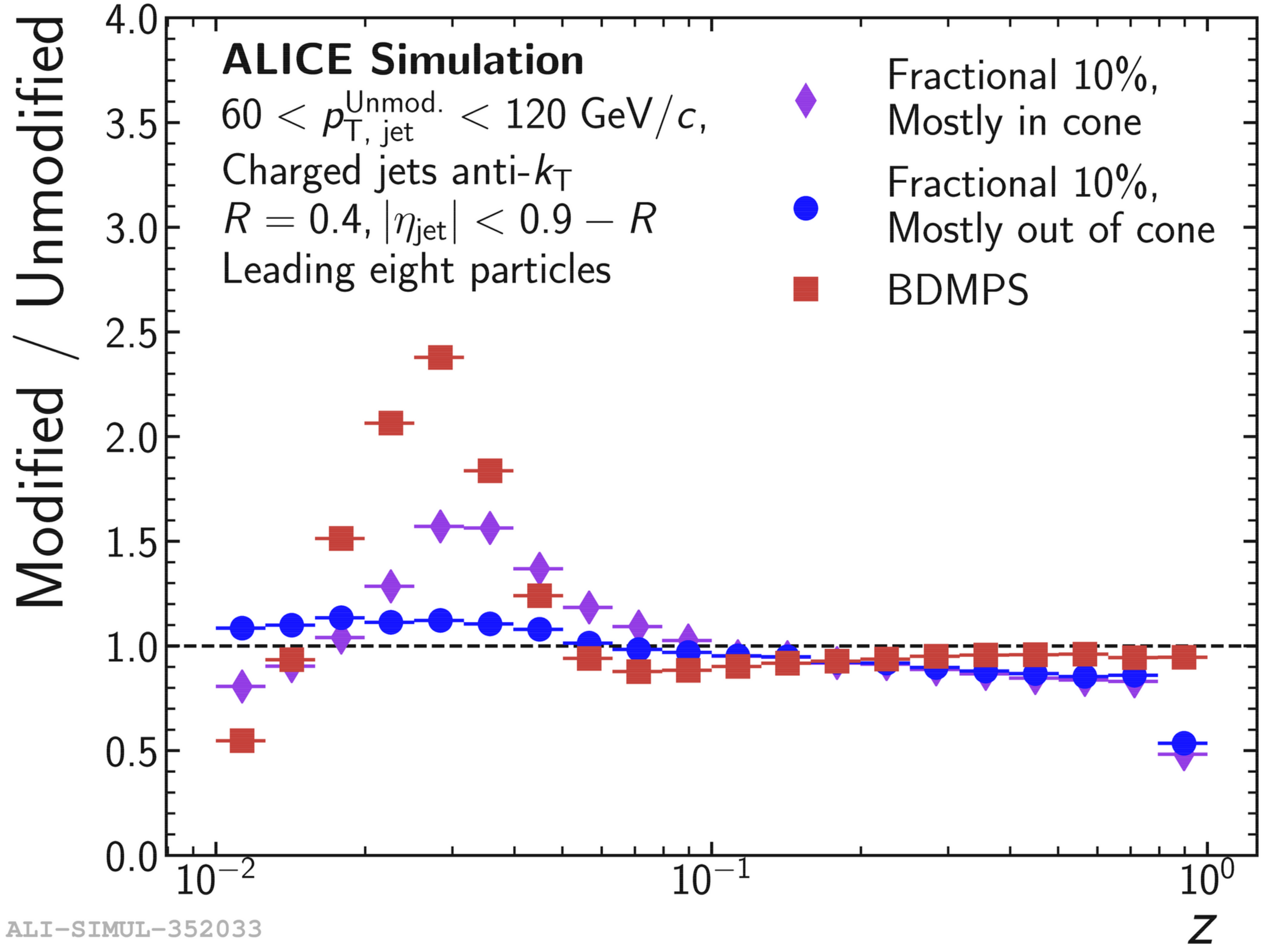
We want to investigate how this impacts the final result we get with ML!

Toy model studies

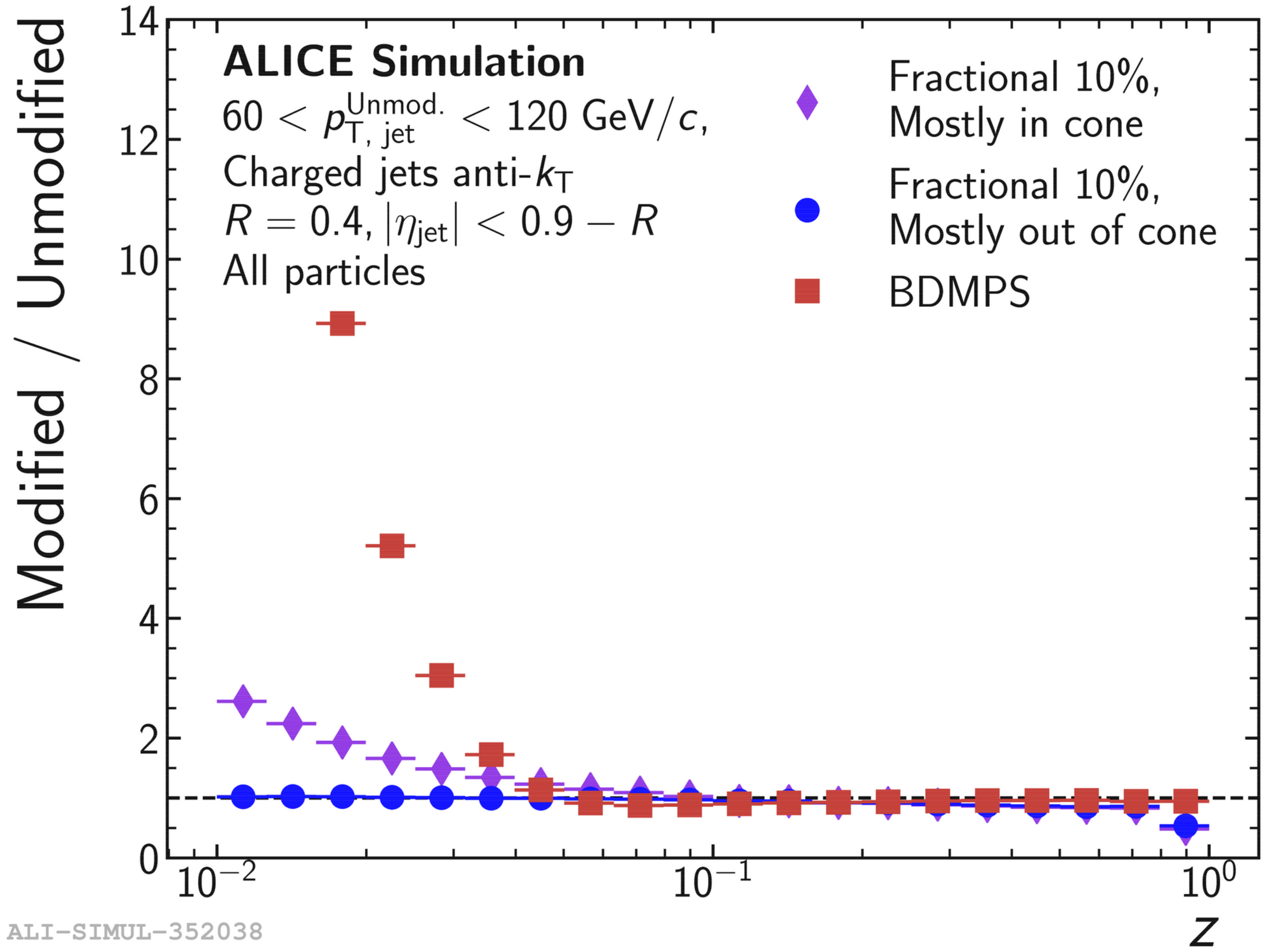
We also study a toy model with three different ways to alter constituents of the jet, changing the fragmentation to generate a different training set

Modification to the fragmentation function

Leading 8 particles



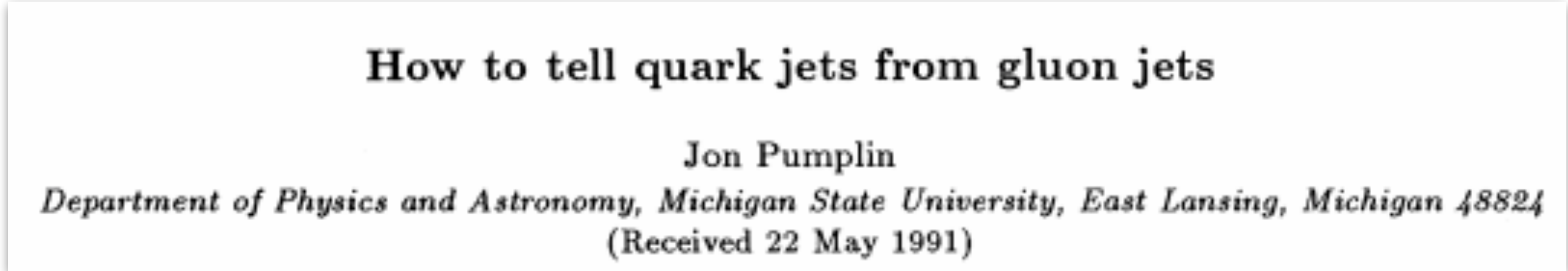
Inclusive particles



Toy model modifications indeed modify the fragmentation, some modifications are more extreme than others.

8 leading particles are what we chose to train on.

Quark vs. Gluon Jets with ML


How to tell quark jets from gluon jets

Jon Pumplin

Department of Physics and Astronomy, Michigan State University, East Lansing, Michigan 48824

(Received 22 May 1991)

Long-standing effort starting around 1991!

Quark and gluon jets have different color factors and substructure!

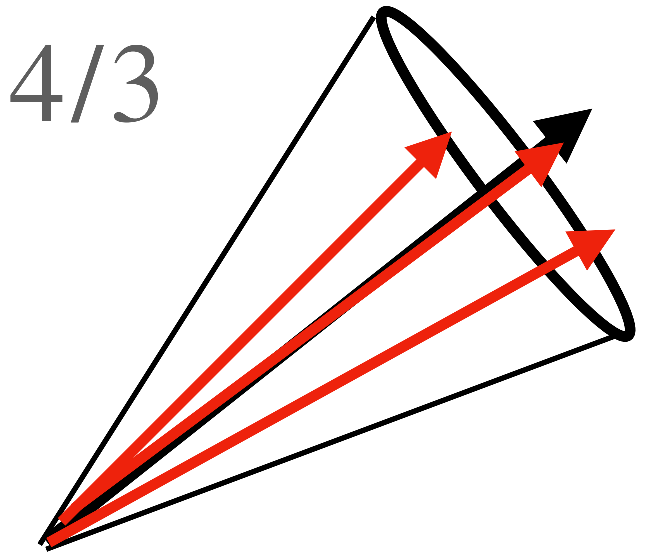
We will focus on an effort in HI collisions!

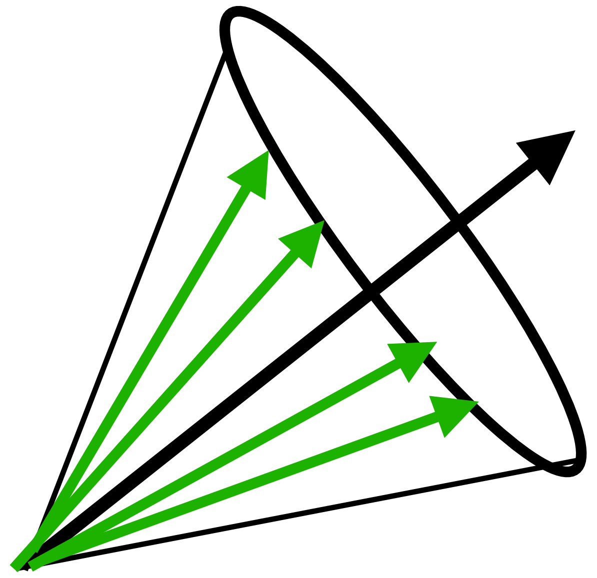
Y. Chien, R. Elayavalli: 1803.3589

Quark Jets

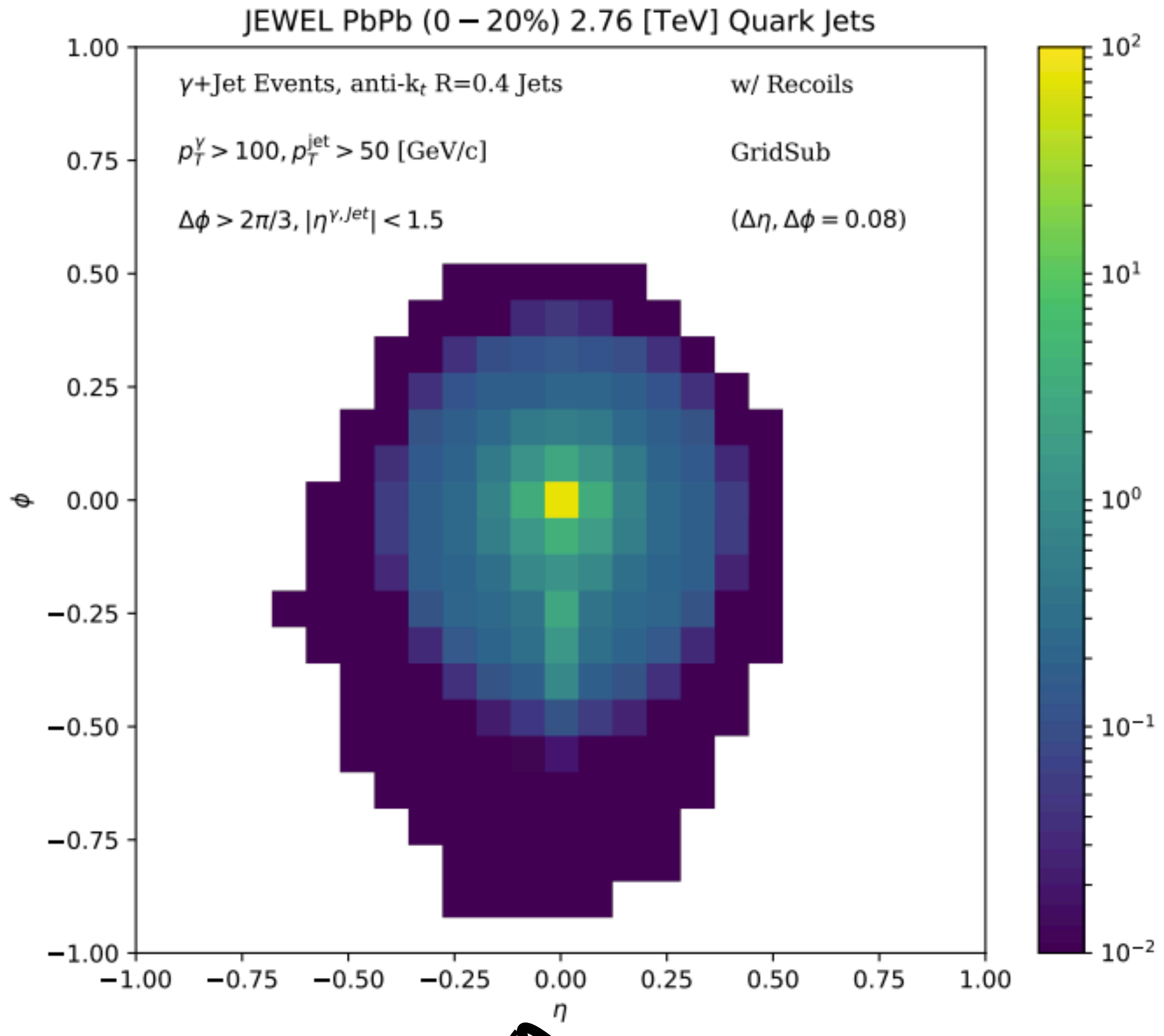
Gluon Jets

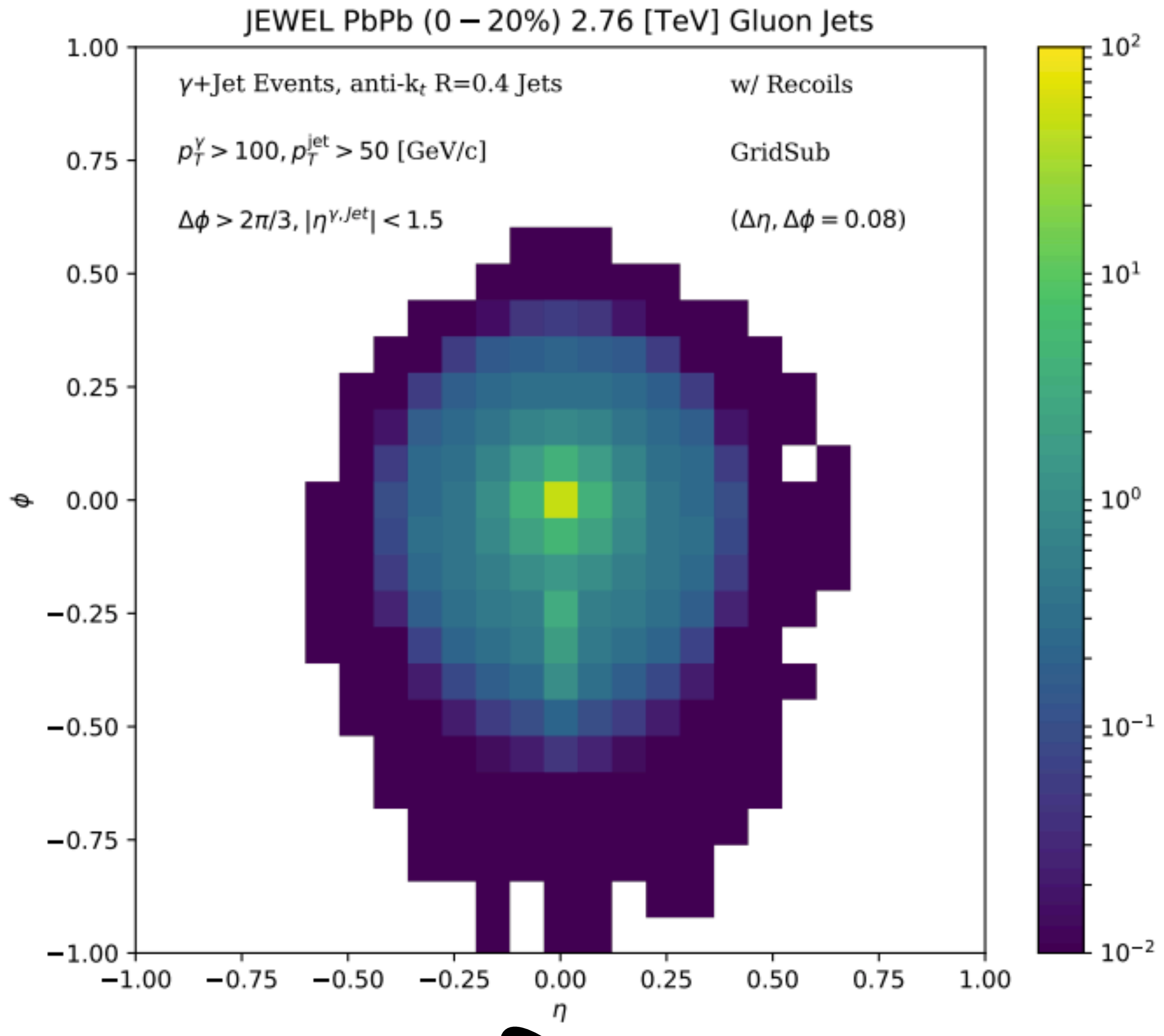
$C_f = 4/3$

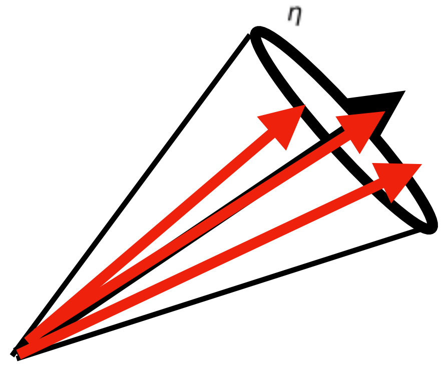


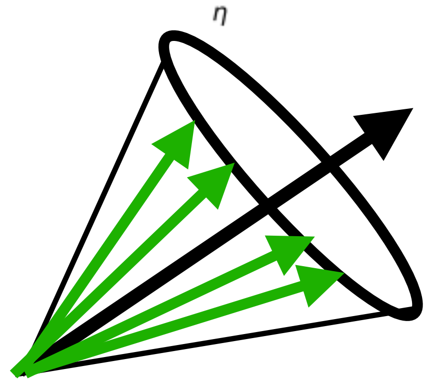


$C_A = 3$







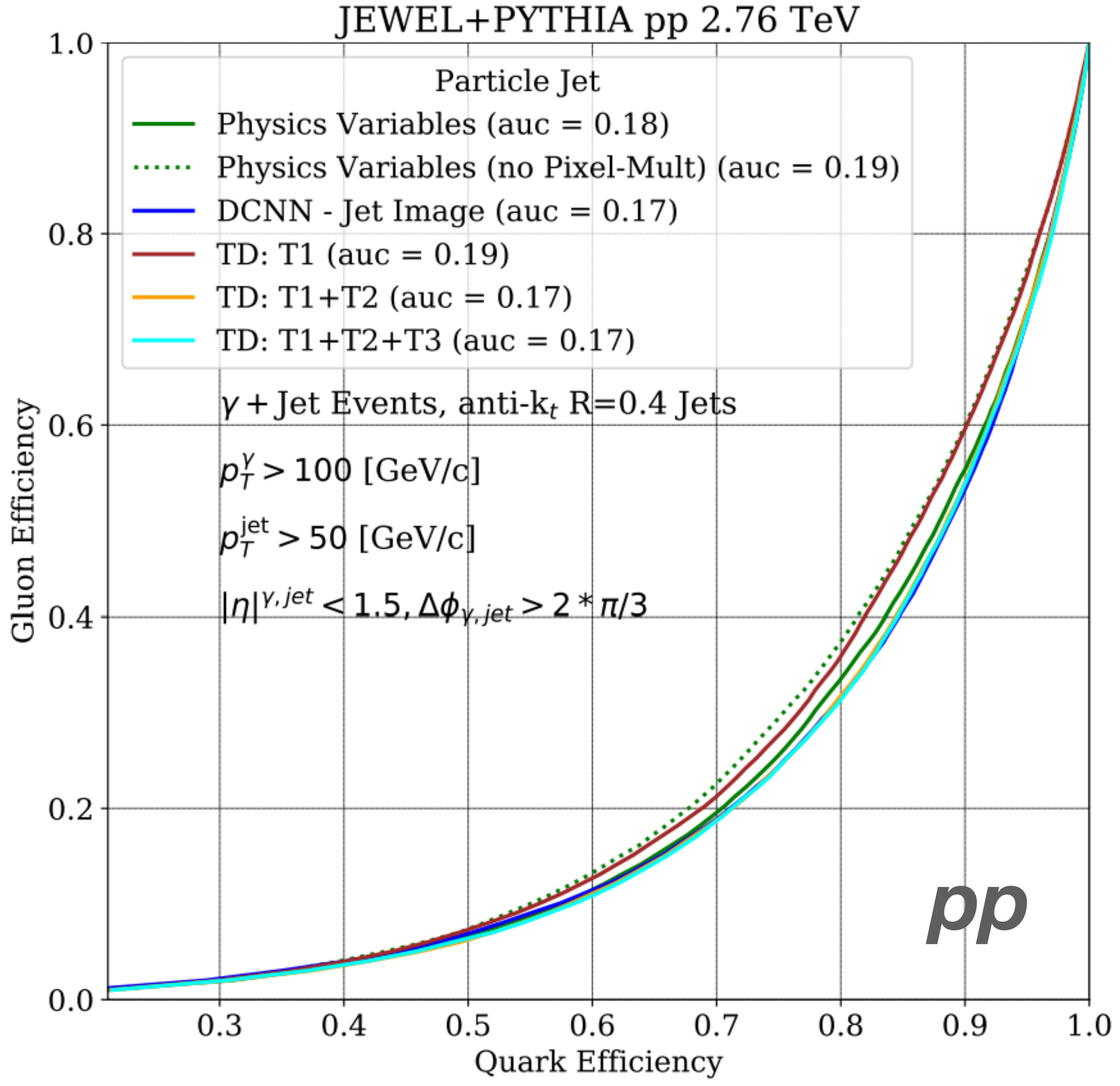


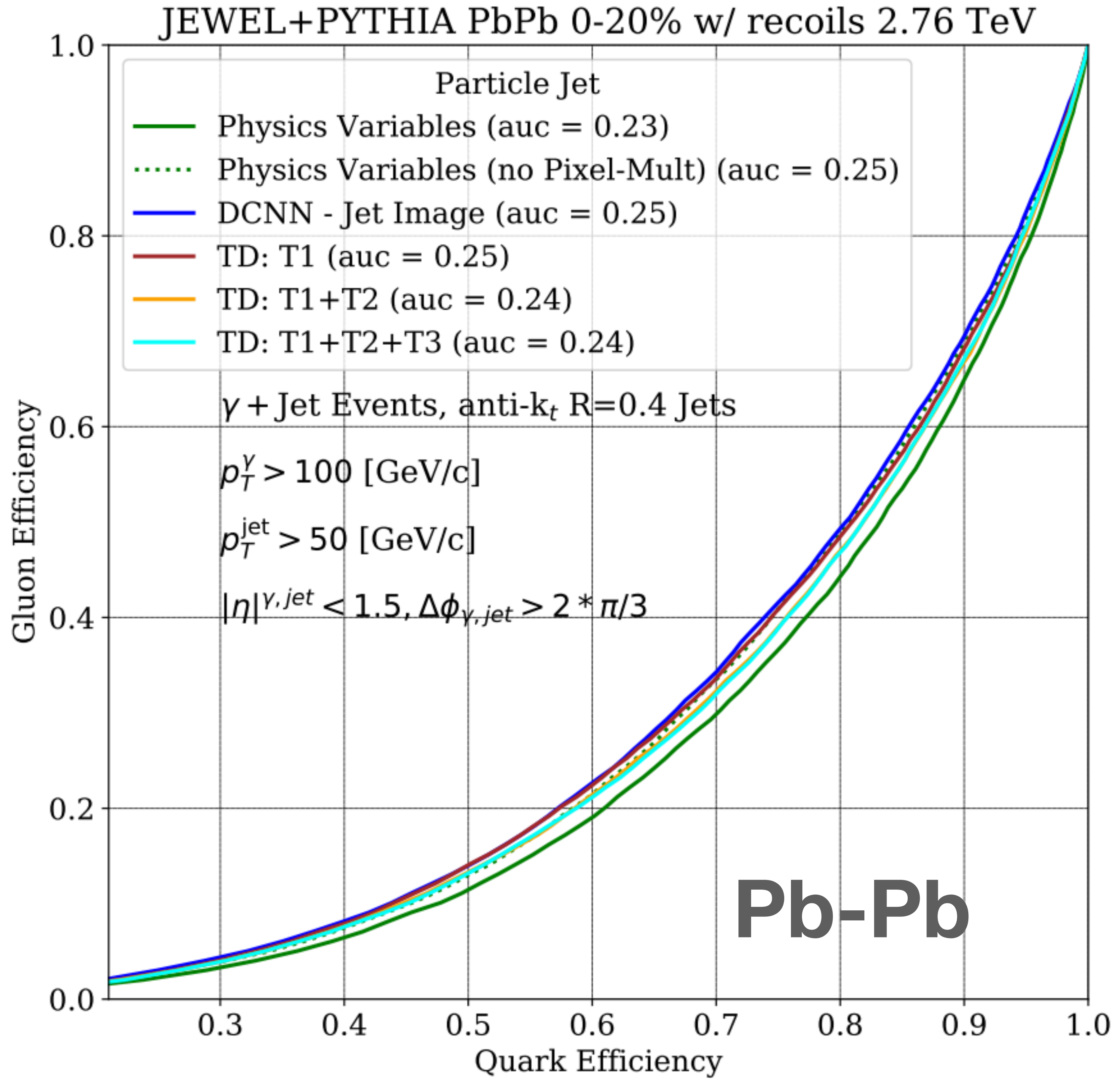
Use jet images with deep CNNs (DCNNs) to discriminate q/g.

Train using jet images in JEWEL! (Supervised Learning)

Quark vs. Gluon Jets with ML

Y. Chien, R. Elayavalli: 1803.3589





- *Lower the curve, the better the performance.*
- All methods explored tend to perform consistently, indicating that they may be picking up on similar features.
- The performance worsens for Pb—Pb, due to the large UE.

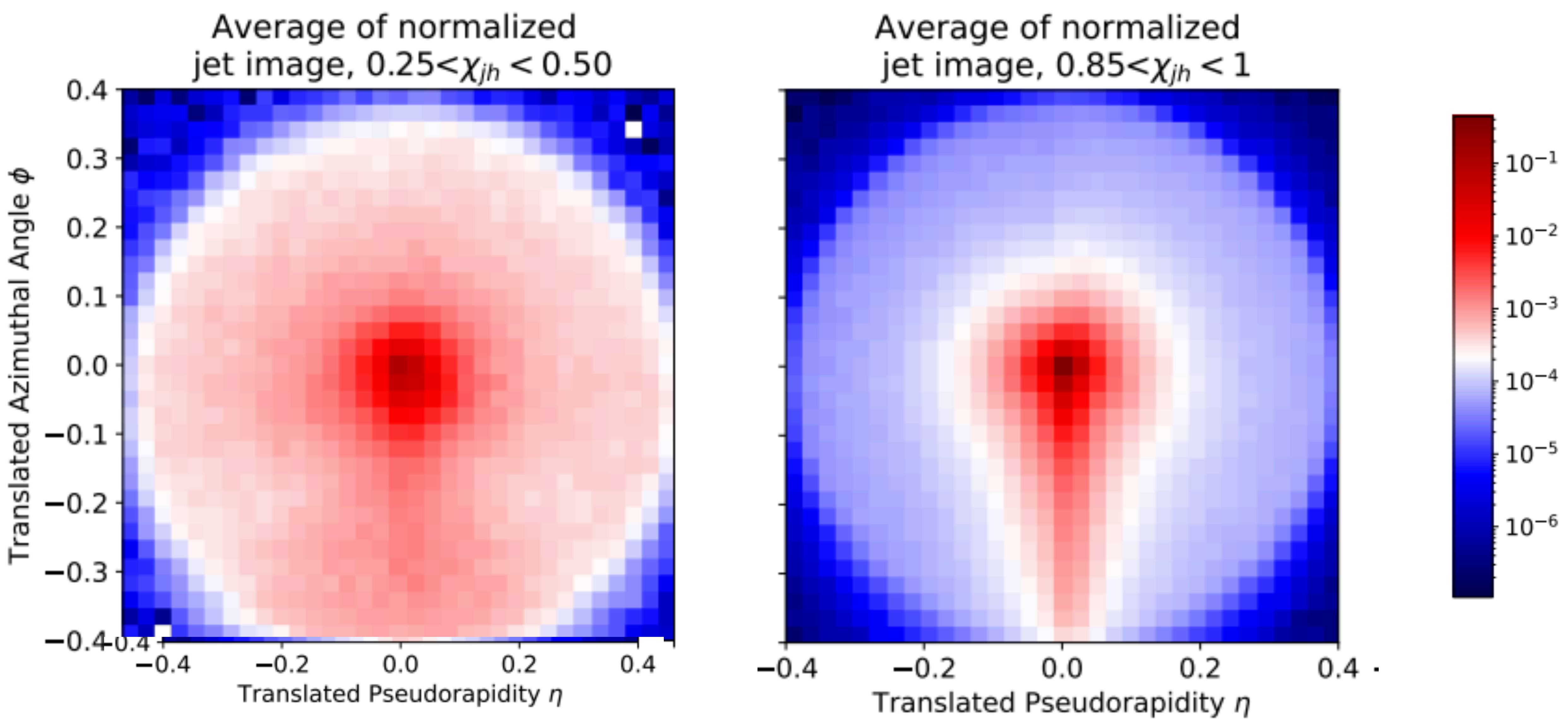
Quark and gluon discrimination is a difficult and ongoing effort in HIs!

Future: Apply these methods to data in pp and Pb—Pb!

Deep Learning Jet Modifications

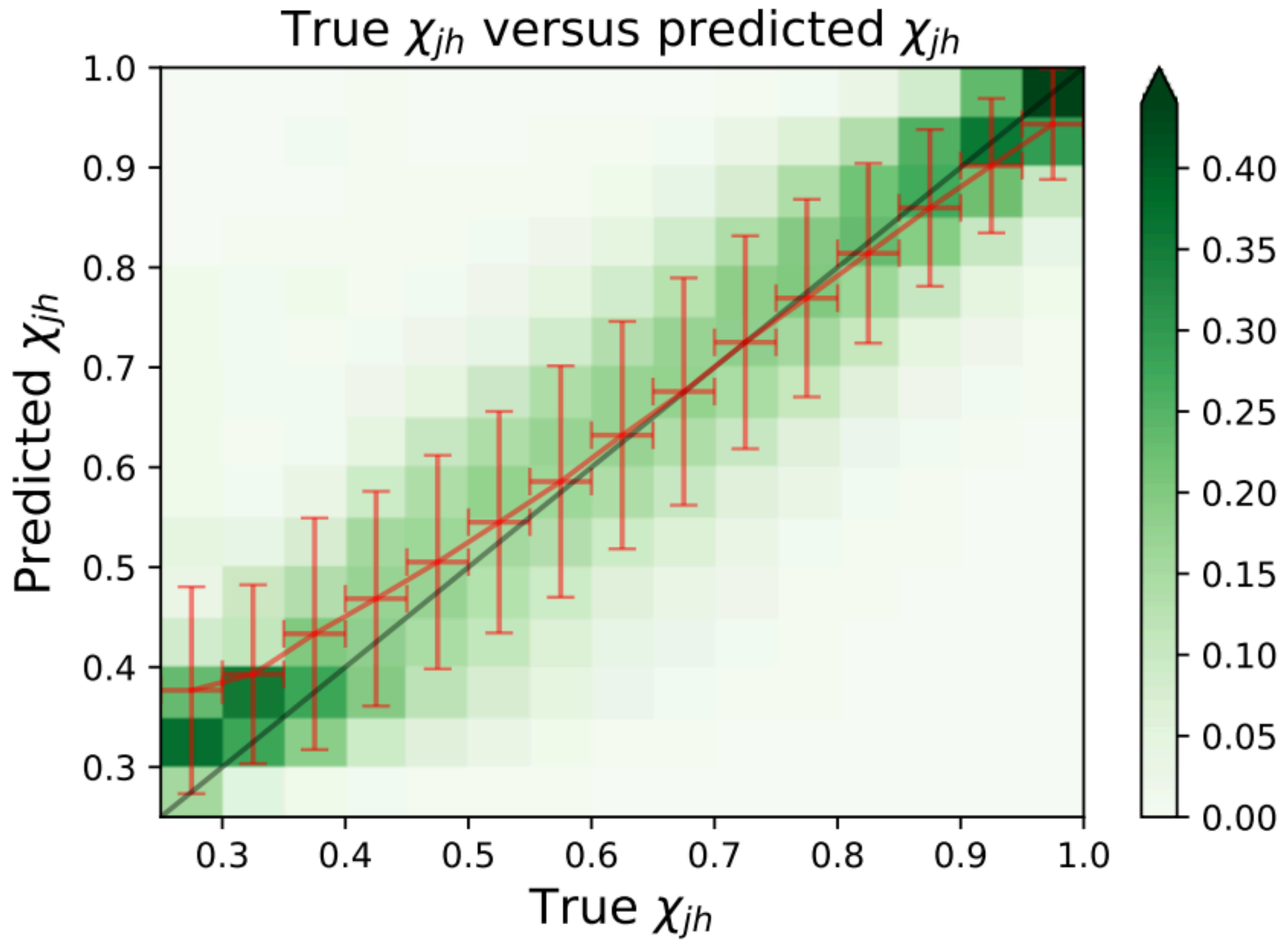
Use supervised learning on jet images with a CNN to perform the regression task of predicting the energy loss ratio in HI collisions (hybrid model).

Y. Du, D. Pablos, K. Tywoniuk: 2101.07797



quenched **unquenched**

$$\chi_{jh} = \frac{E_f^h}{E_i^h}$$



Shows good performance!

Very useful to separate and study quenched vs. unquenched jets as well as extracting the initial energy of the jet.

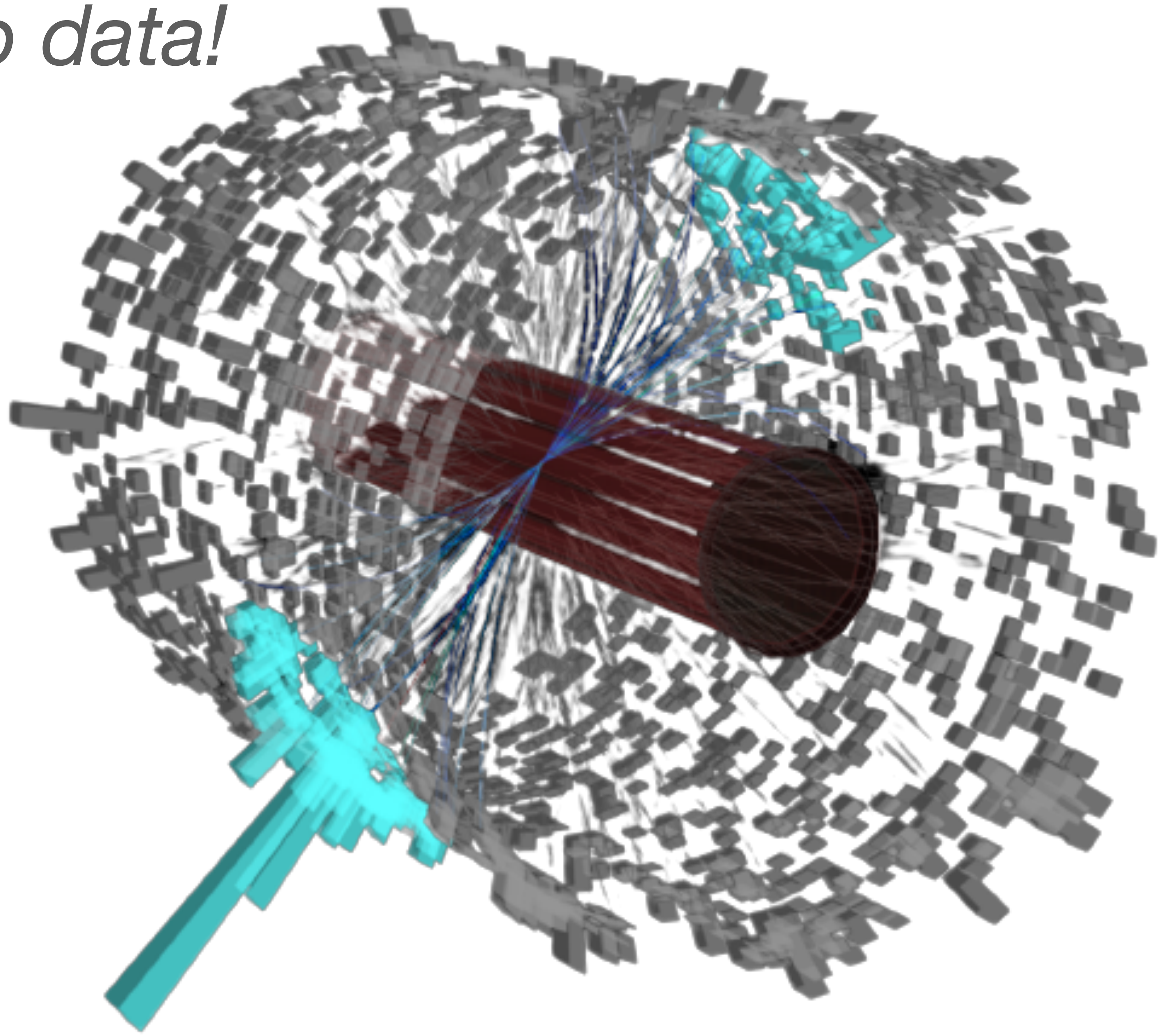
Future: Apply these methods to different models & variables, improve performance.

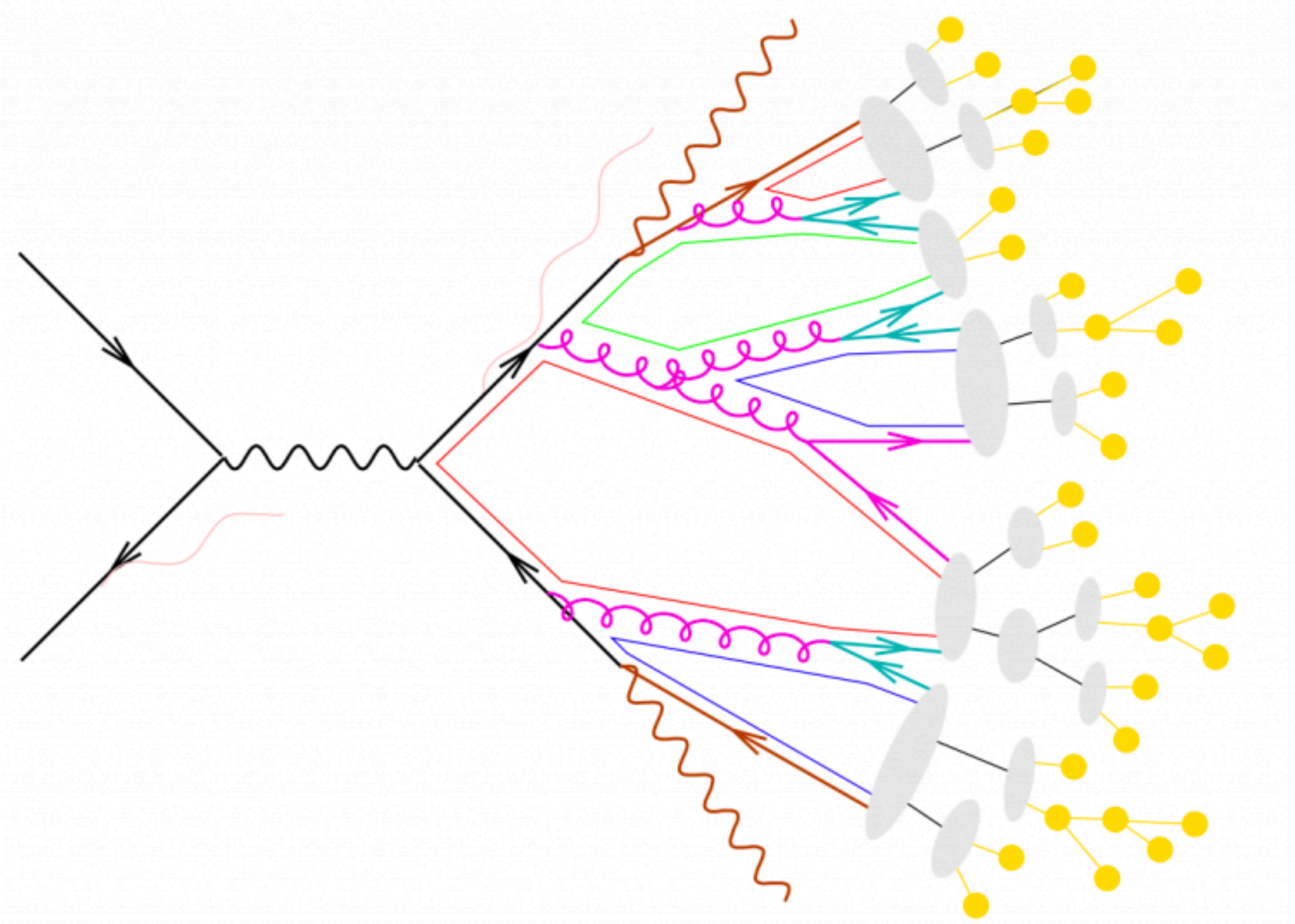
Far future: Apply these methods to data!

Summary and Conclusions

Machine learning is a great tool for both understanding heavy-ion physics and making measurements, especially with jets! (Jets are also a great playground for ML!)

Despite many great developments, still ongoing challenges → especially for applying ML to data!





Coming years are an exciting time for ML + heavy-ions → lots of uncharted phase space and opportunities to get involved!

ML is everywhere!

Recommendation Software

ML automated Go player

Voice assistants

Autonomously driving cars

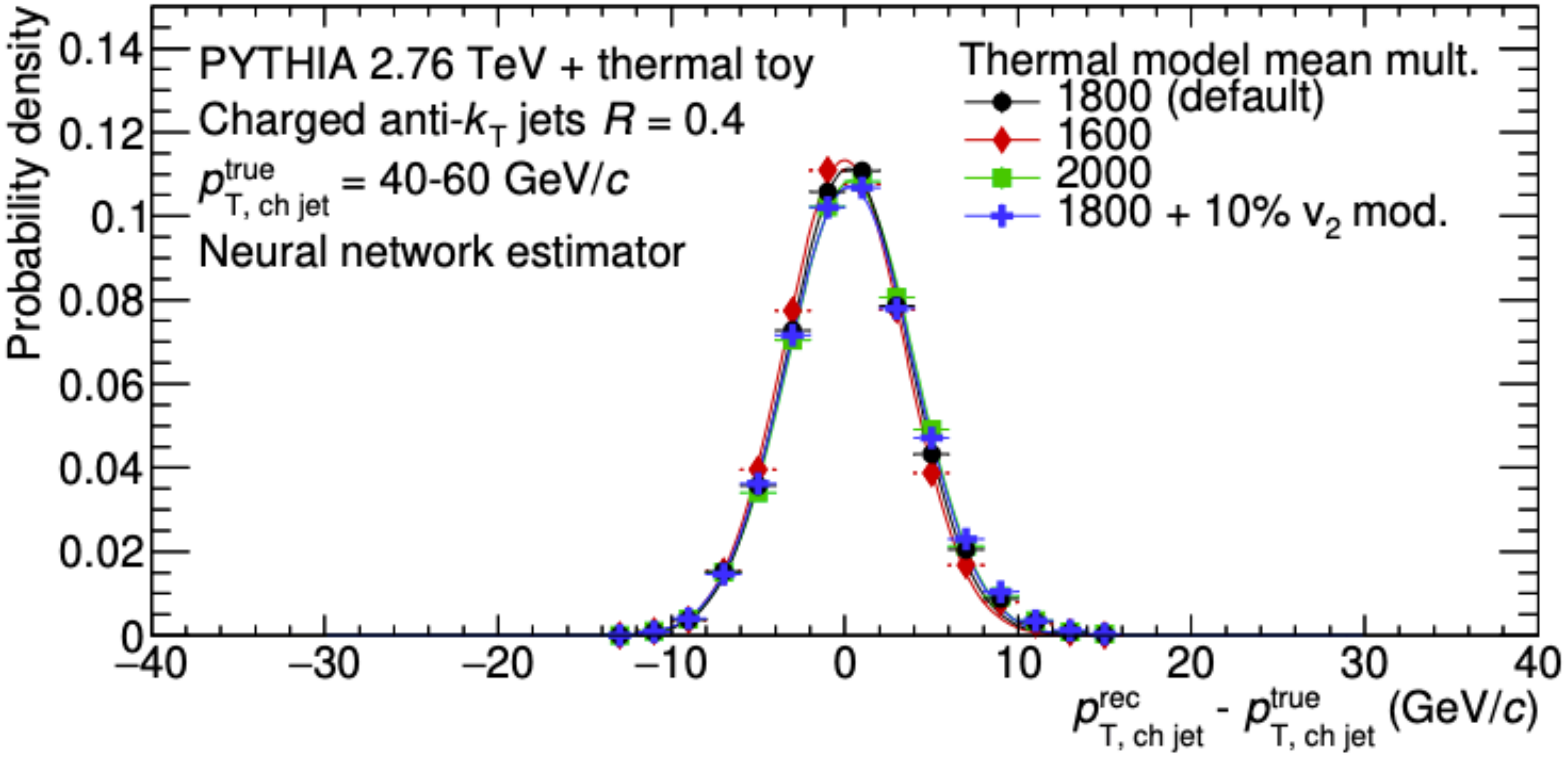
Quantitative hedge funds

→ **ML is a fundamental part of countless technologies we use every day!**

→ Where does HEP fit in here?

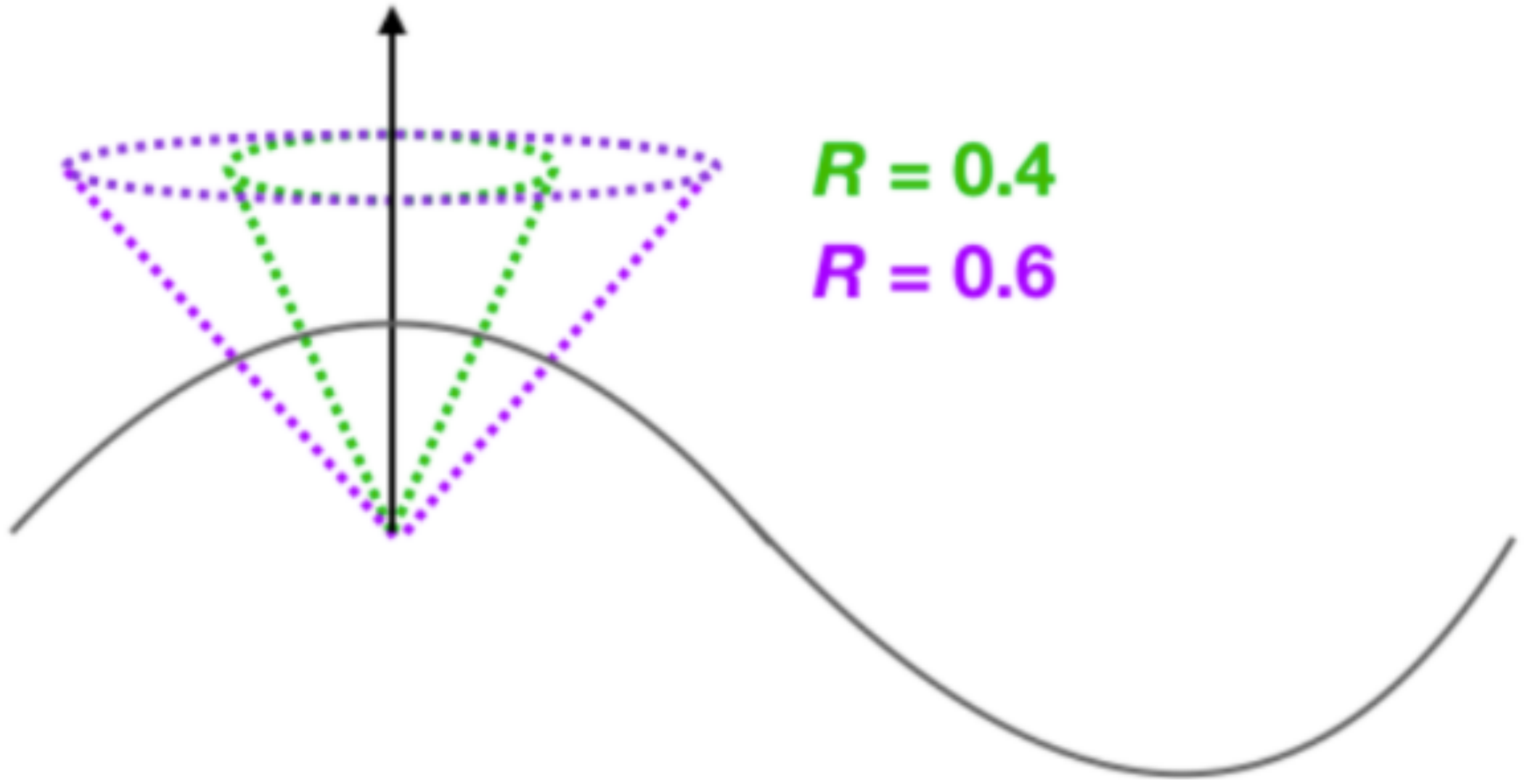
ML Addressing Flow

arXiv: 1810.06324



- The area based method does not account for the fact that the background fluctuates.
- When we add in a v2, we see that the ML still performs well! → Is still correcting for this flow!

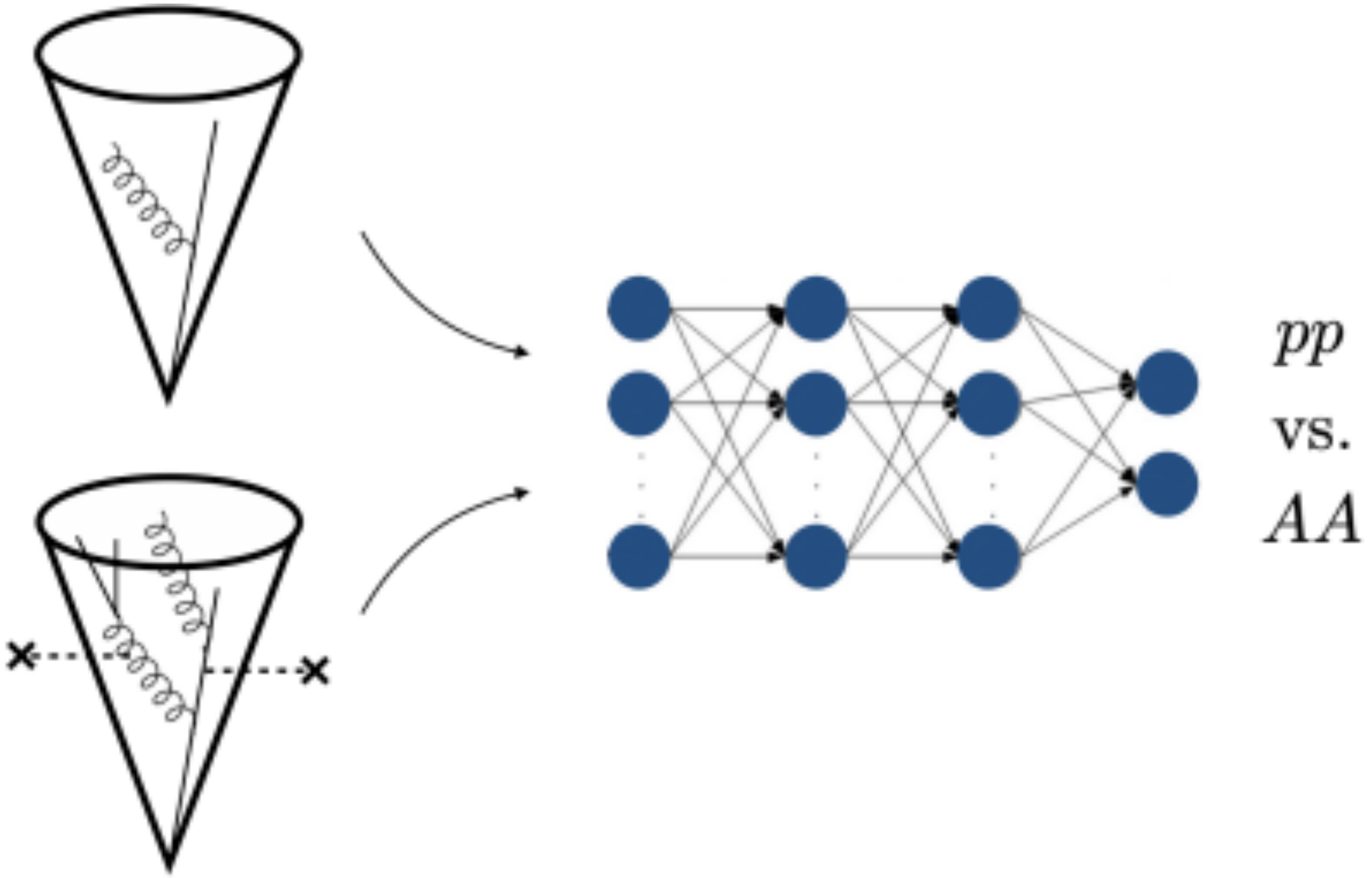
- When applying to data, the ML performs similarly across all event planes →ML is performing a flow correction.
- This is important especially for larger R jets.

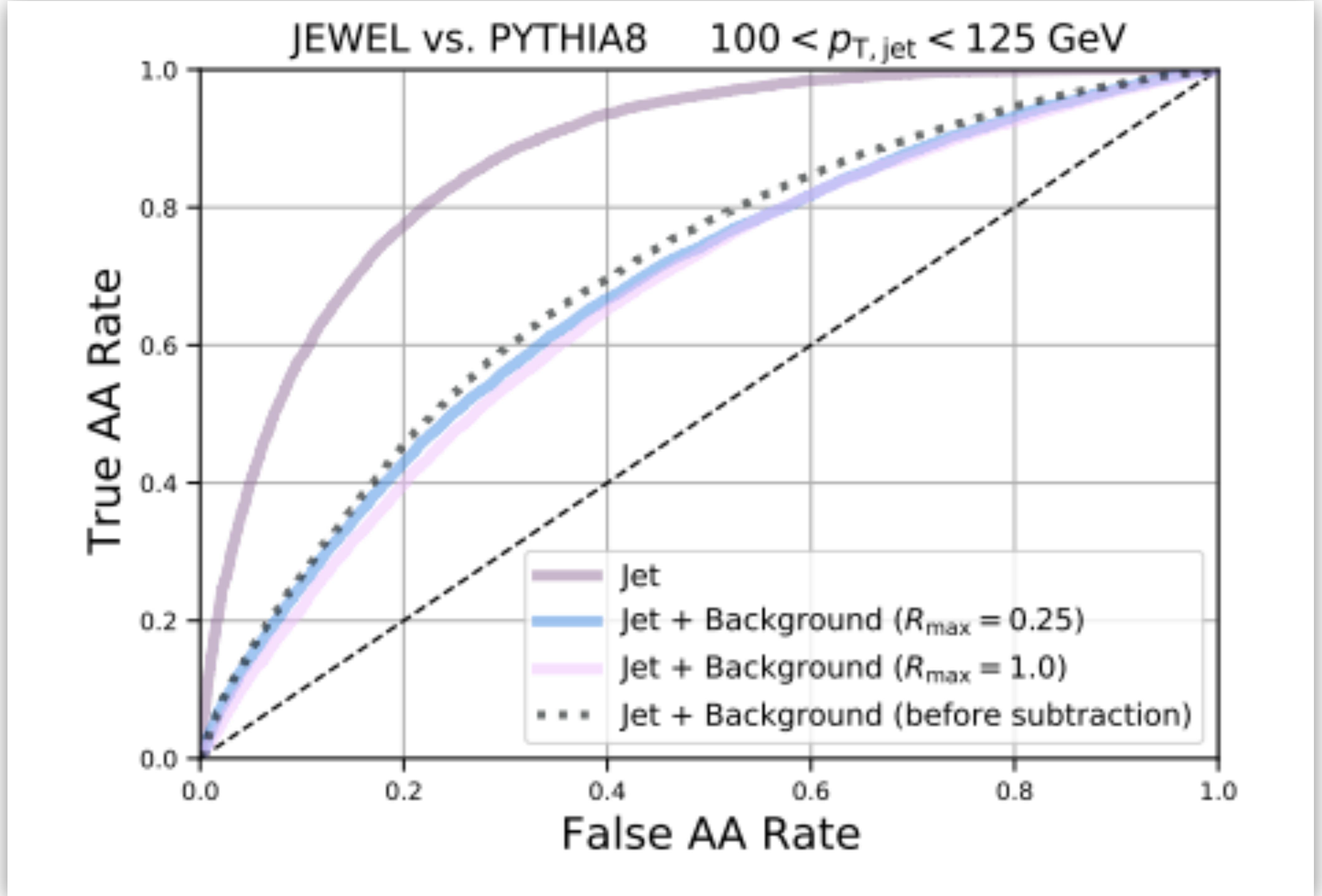


ML for Observable Design

Could we use ML to construct a maximally discriminative observable to characterize a jet signal?

→ Step 1: Set up a binary classification between PbPb and pp jets.





Y. Lai, J. Mulligan, M. Ploskon, F. Ringer: 2111.14589

ML for Observable Design

Could we use ML to construct a maximally discriminative observable?

→ Step 2: Once we have the classifier, create an observable which approximates the classifier.

Benefits

- No model dependence.
- Observable will be theoretically calculable.

Challenges

- Variation in detector response across data taking period.
- Observable can be difficult to interpret, complex.

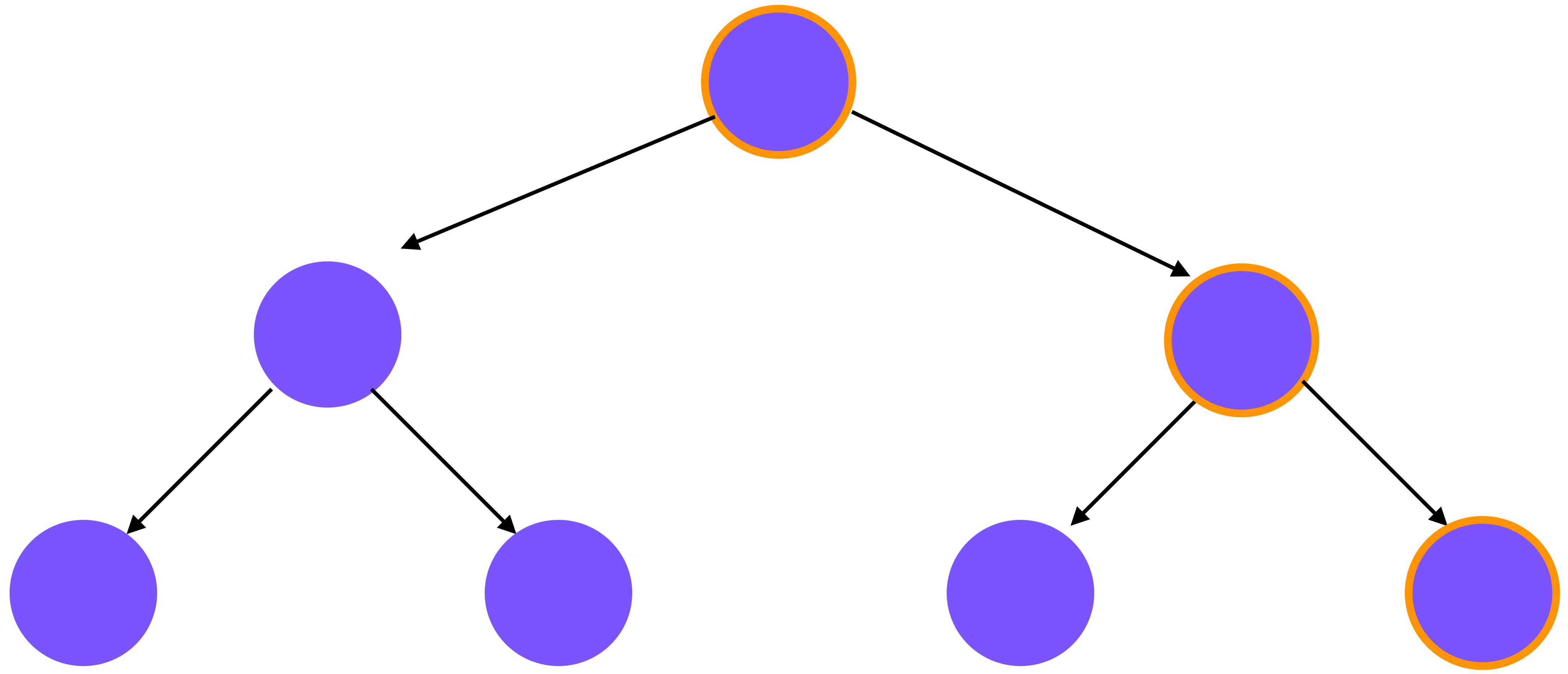
Y. Lai, J. Mulligan, M. Ploskon, F. Ringer: 2111.14589

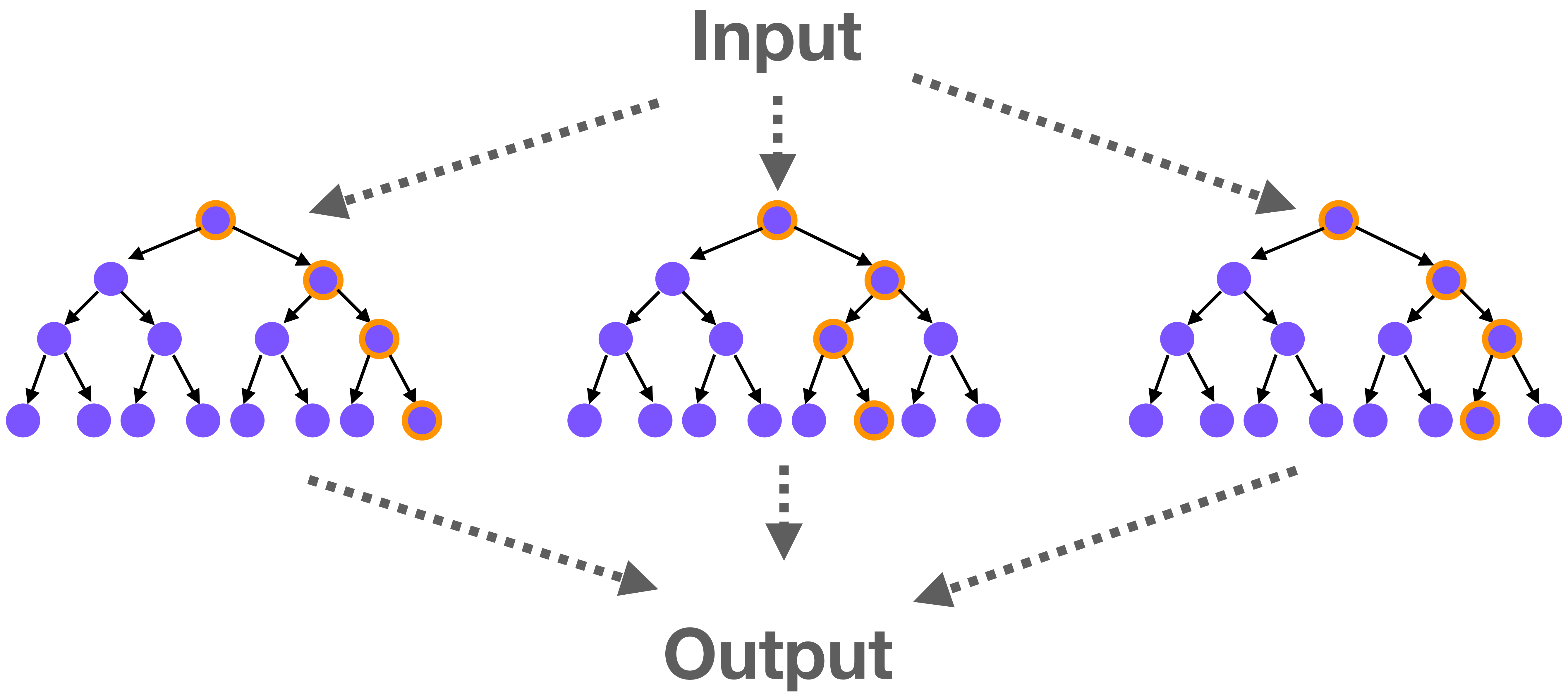
Intro to Random Forest

Random forests are composed of decision trees.

Decision trees are a set of rules organized in a tree structure.

Each node is a rule which subdivides the dataset into two or more parts (think 20 questions).





Output of the random forest is a combination of the output of each of the decision trees.

In training, the algorithm sets up the rules of each decision tree.

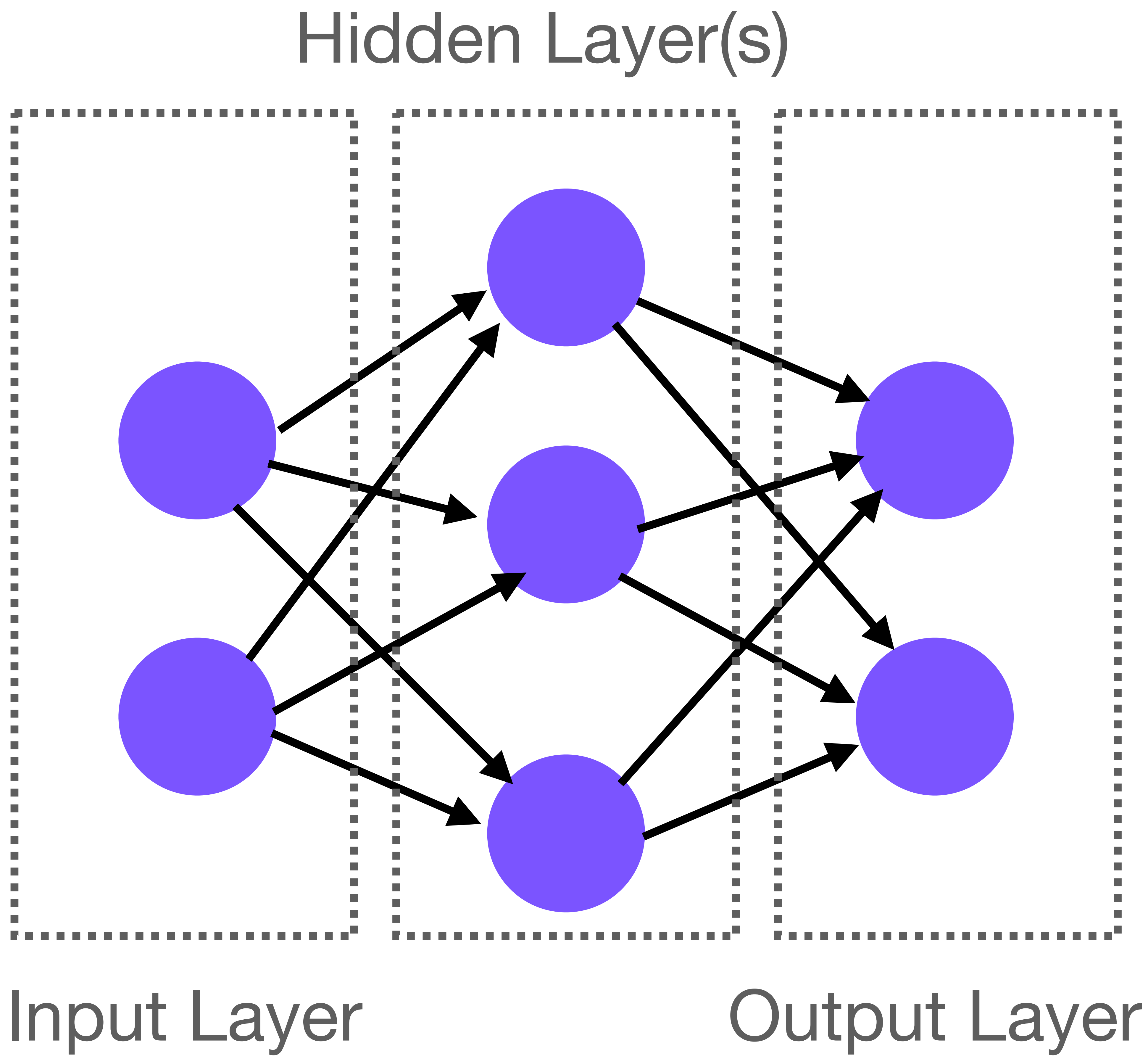
Neural Networks

Flow of information happens between nodes.

A weight is associated with each input to a given node.

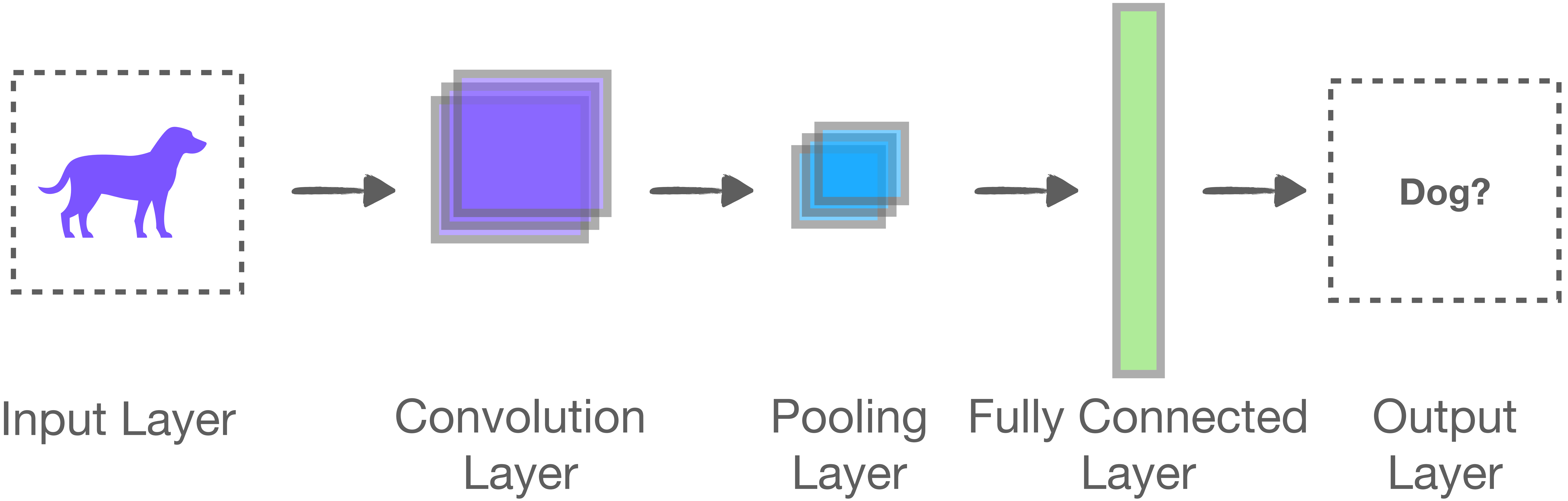
The output of each node is a function of the weighted inputs. The output of a node j, is generally written something like

$$O_j = \sum_{i=0}^{N-1} w_{ij} O_i$$

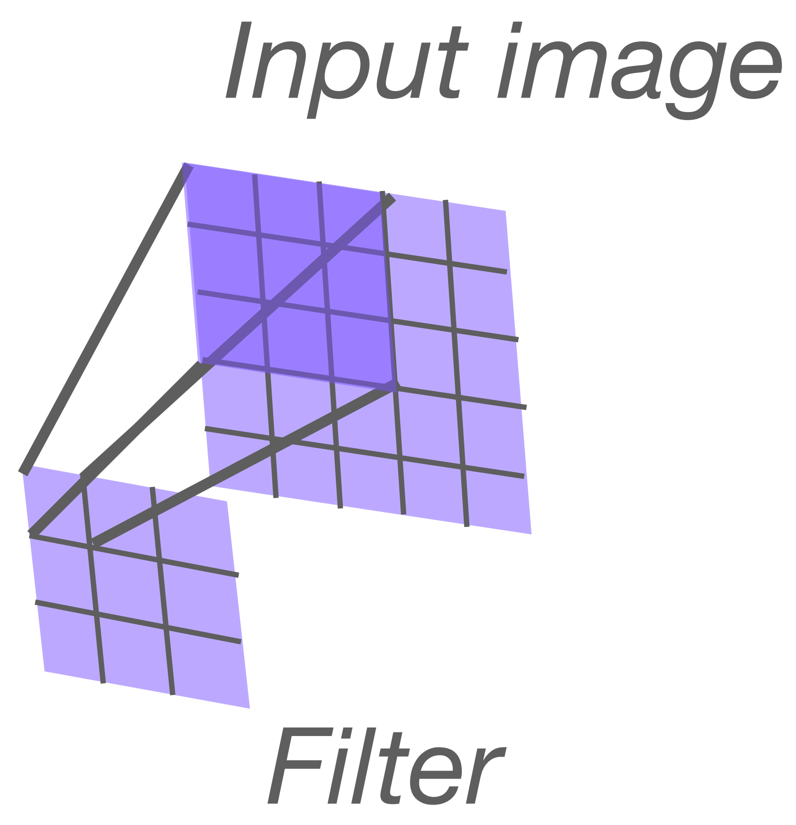


In training we seek to learn the set of weights which minimize the total error of the network.

Convolutional Neural Networks (CNNs)



Key component of a CNN is the **convolution layer**, which (with the help of a filter) will determine if a feature/pattern is present.



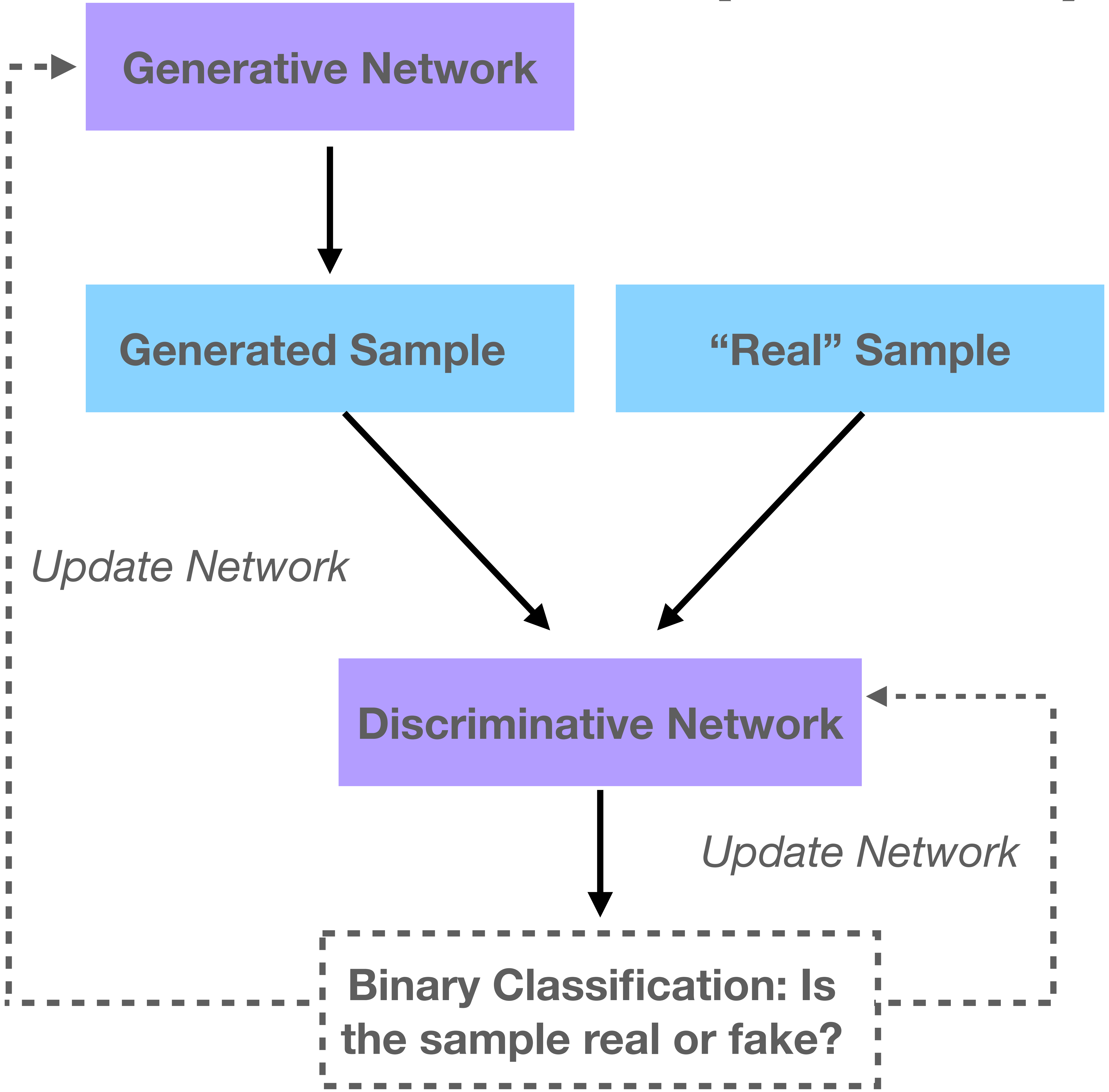
Generative Adversarial Networks (GANs)

Two networks compete with one another in a game.

The generative network seeks to fool the discriminative network.

The discriminative network seeks to find the real sample from the generated samples.

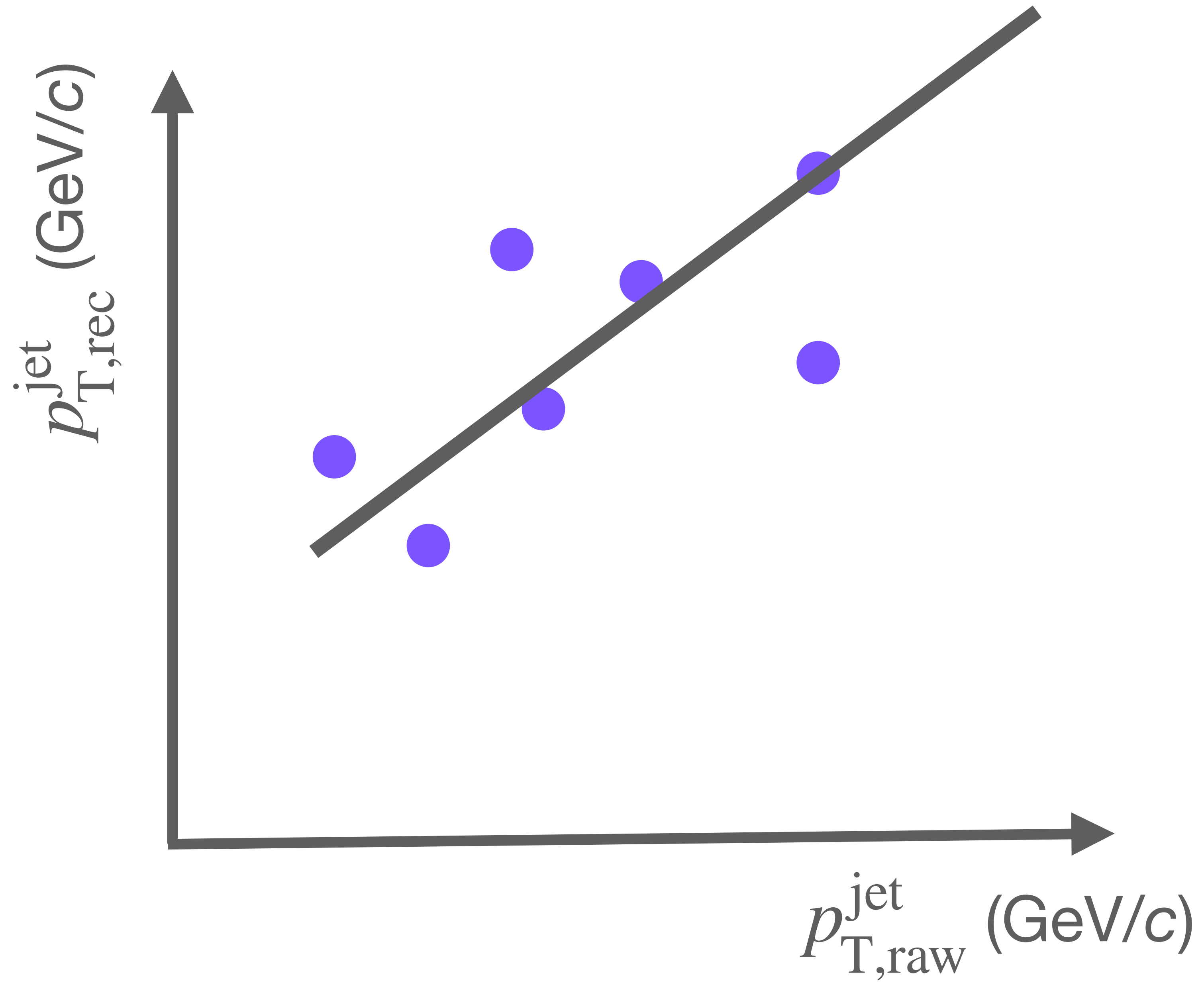
Indirect training → generative network never sees the true distribution!



Intro to Linear Regression

Linear regression predicts the value of a **dependent variable** based on a given **independent variable** (feature x1 with a given weight w1).

$$y = b + w_1 x_1$$

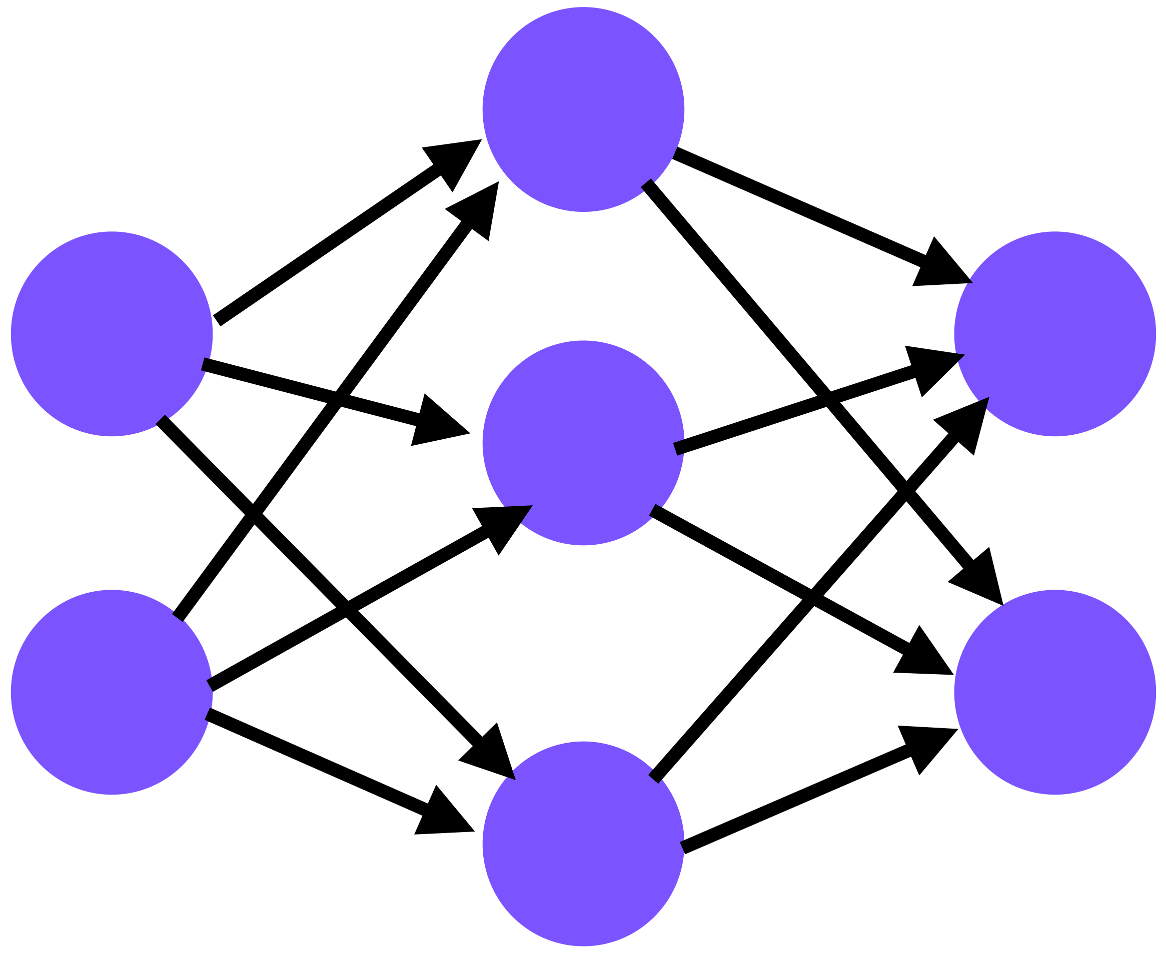


The example at the right is a simplified view in reality we have multiple features each having a separate weight.

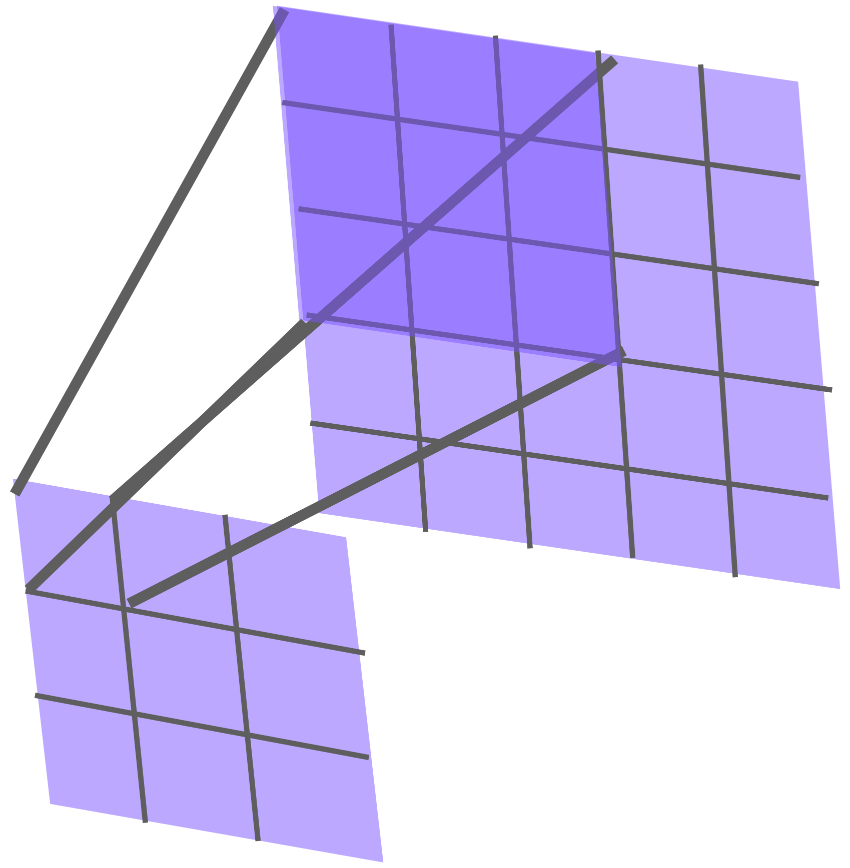
$$y = b + w_1 x_1 + w_2 x_2 + w_3 x_3 \ldots\ldots$$

Training determines the optimal weight for each feature.

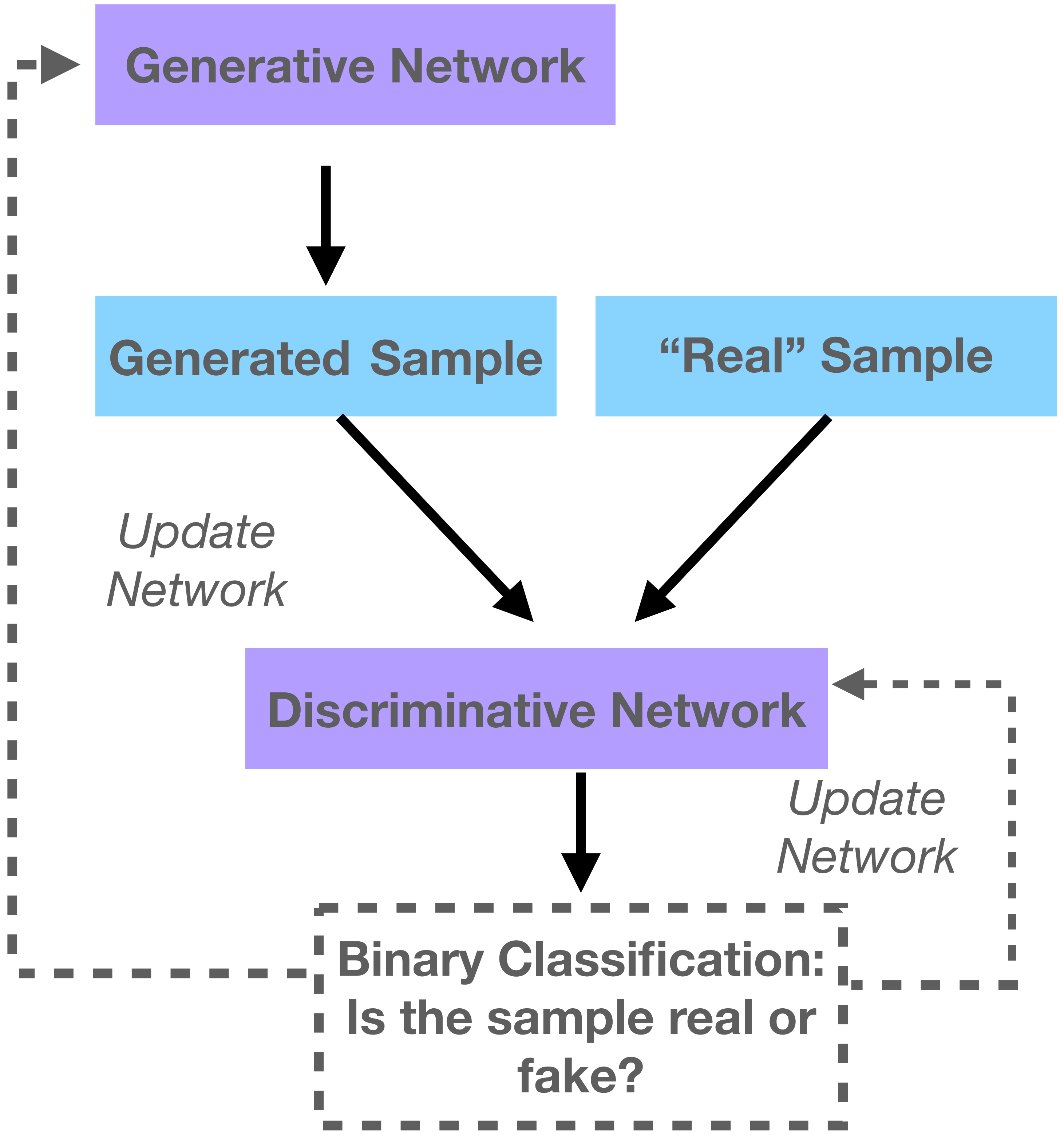
Different algorithms for different problems!



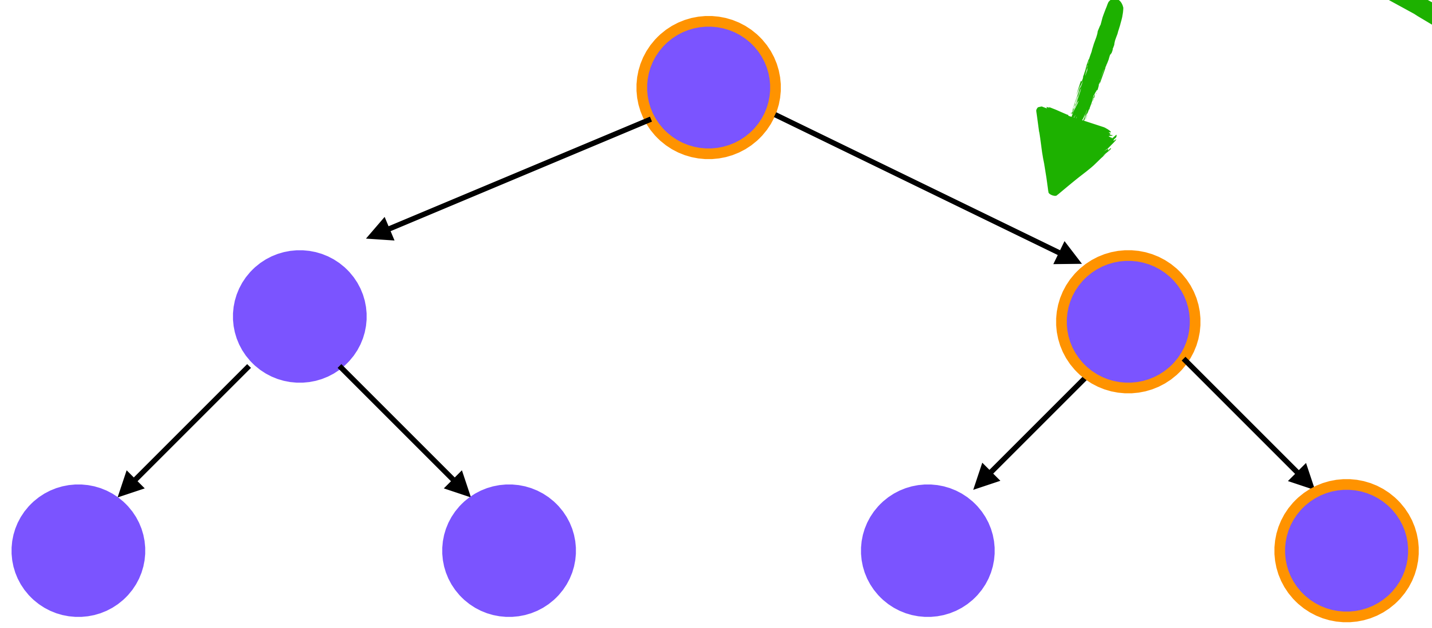
(Shallow or Deep) Neural Networks → *Great for making predictions!*



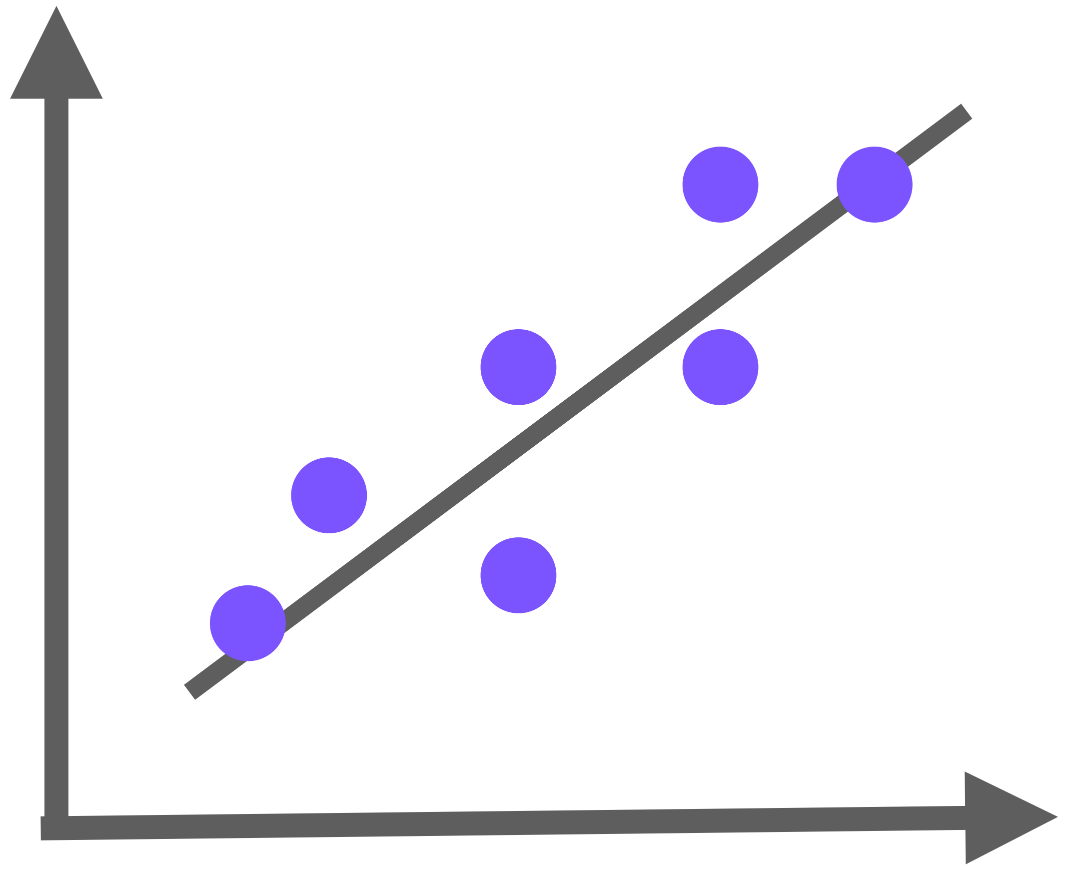
Convolutional Neural Networks (CNNs)→ *Great for image processing!*



Generative Adversarial Networks (GANs) → *Powerful tool for generating samples!*



Random Forest (Decision Trees)



Linear Regression

Technical Details of the ML

Regression task where the regression target is the detector level jet p_{T}.

Here we are prioritizing a simple model!

Training sample 10%, testing sample 90%.

Implemented in *scikit-learn*. Default parameters used unless otherwise specified.

Shallow Neural Network

Shallow, 3 layers with [100, 100, 50] nodes

ADAM optimizer, stochastic gradient descent algorithm.

Nodes/neurons activated by a ReLU activation function.

Linear Regression

Normalization set to true by default.

Random Forest

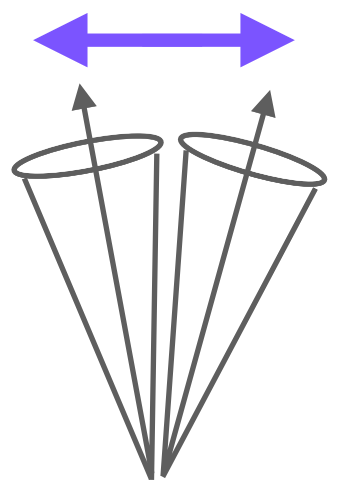
Ensemble of 30 decision trees.

Maximum number of features set to 15.

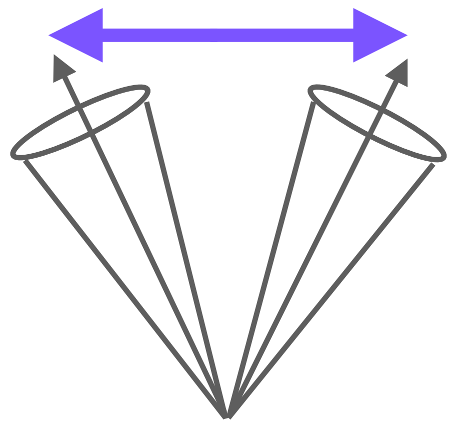
Deep Learning Jet Modifications

Ex: Groomed jet radius

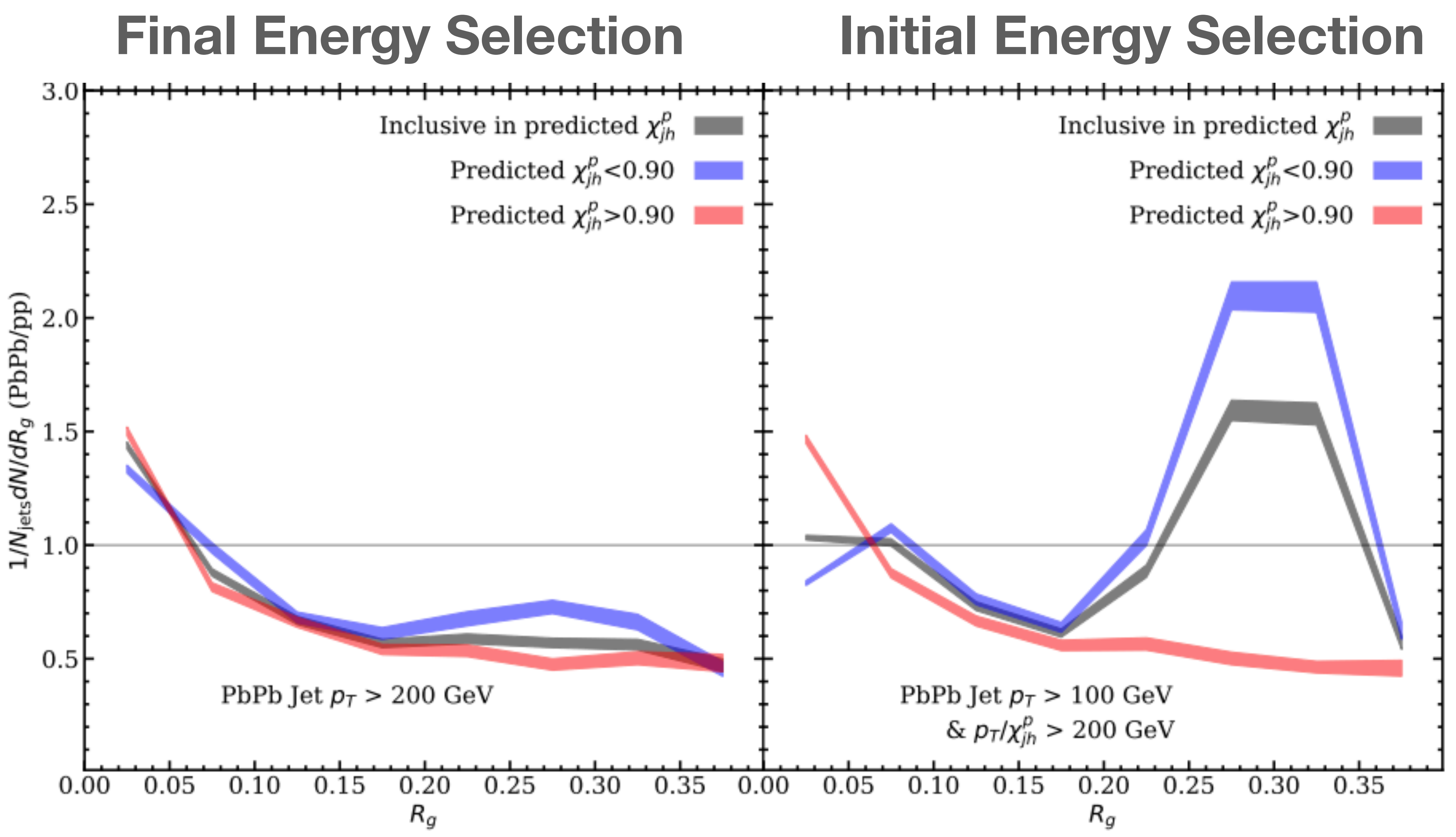
arXiv:2101.07797



Small R_g (Collimated)



Large R_g (wide)



Unquenched jets != jets in vacuum
→ selection bias!

Jets that fall into the "unquenched class" tend to be narrower than average jet population in vacuum.

ML is a cool tool to begin to think about selection biases and its impact on how we see quenching!

Future: Apply these methods to different models & variables, improve performance.