Jets and Machine Learning for Hard Probes

Raghav Kunnawalkam Elayavalli
Yale/BNL

Summer student lectures @ Prague
26-28 June 2022

raghavke.me

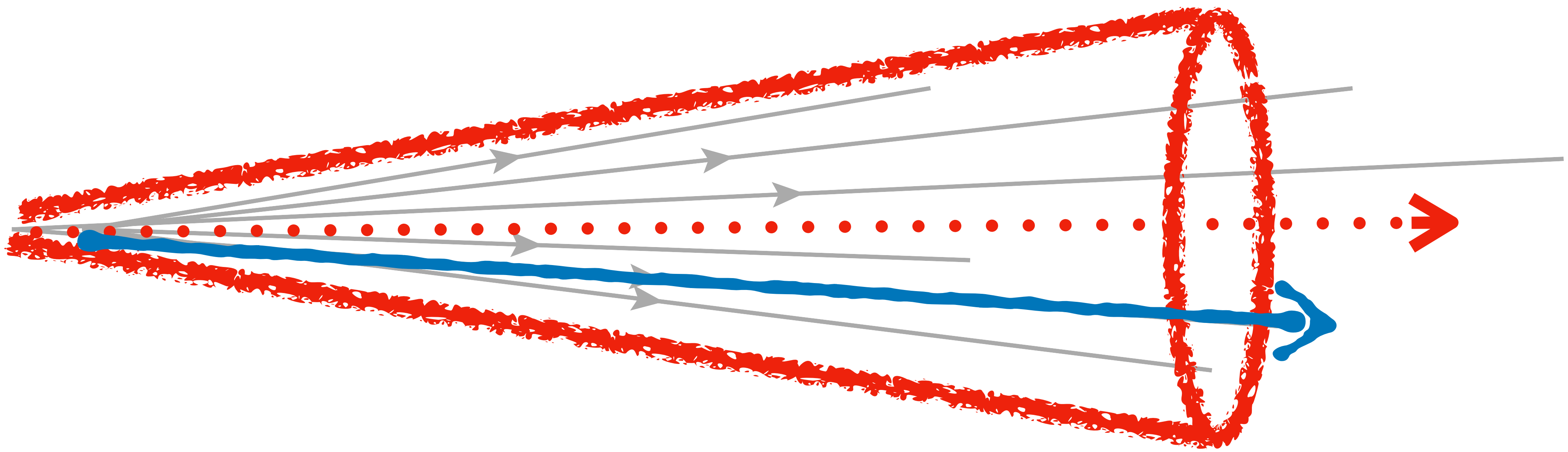
Continuing from yesterday

1st gen - what did we learn?

- Colored probes are opaque whereas QGP appearing transparent to EW probes (γ, Z, W)
  - R_{AA} Nuclear modification factor (comparing yield in AA w.r.t binary collisions scaled pp) for γ/Z ~ 1, hadrons ~ 0.2 and **Jet R_{AA} ~ 0.5** (even at high p_T! With mild momentum dependence)
- **Large momentum asymmetry** in Di-jet, γ/Z+Jet pairs
- Large spread of quenched energy - **Broadening effect**

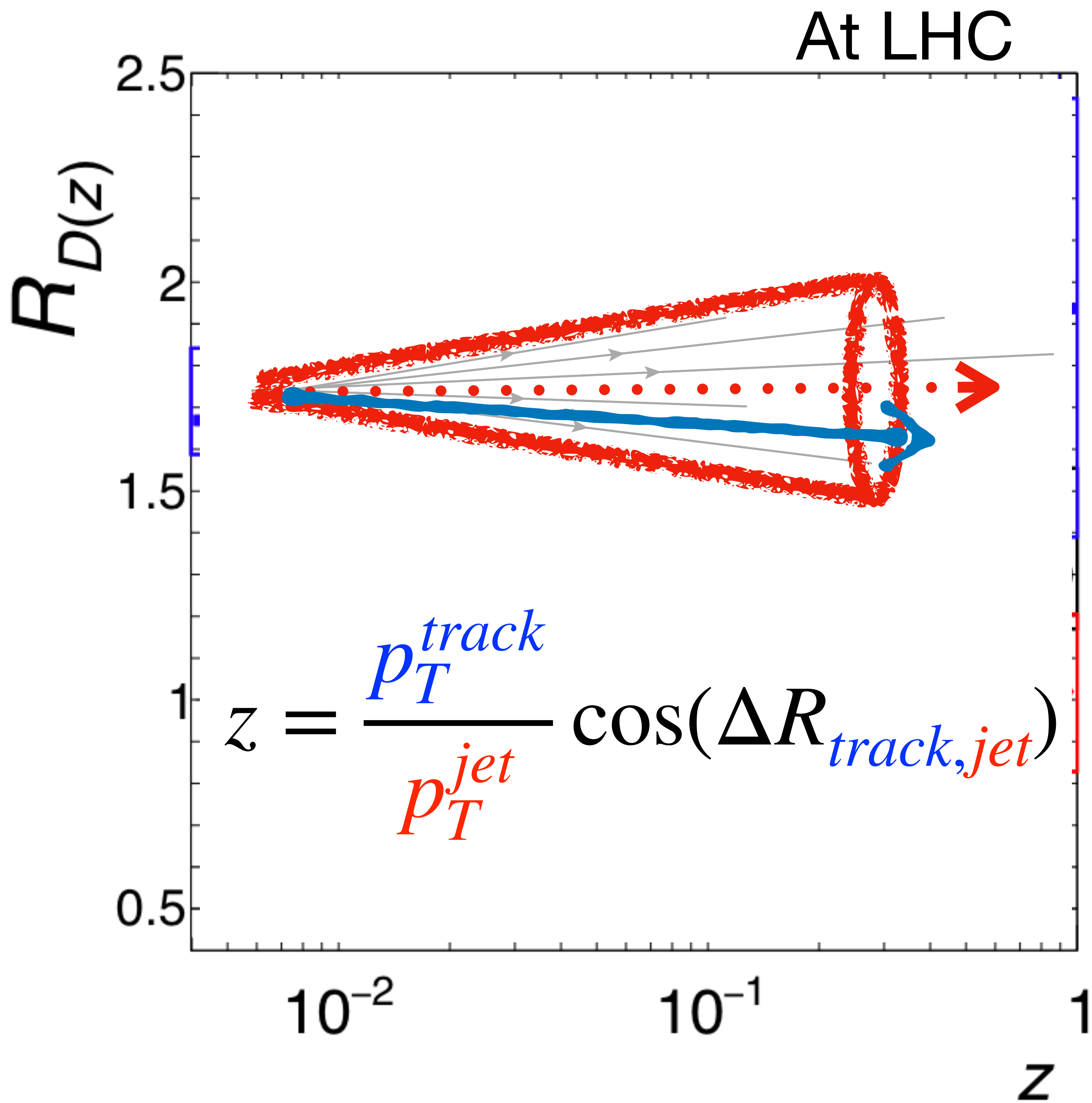
ATLAS Heavy Ion Publications
ALICE Heavy Ion Publications
CMS Heavy Ion Publications
STAR Publications
PHENIX Publications

2nd generation Jet Measurements



Jet structure looks at particle production within the jet

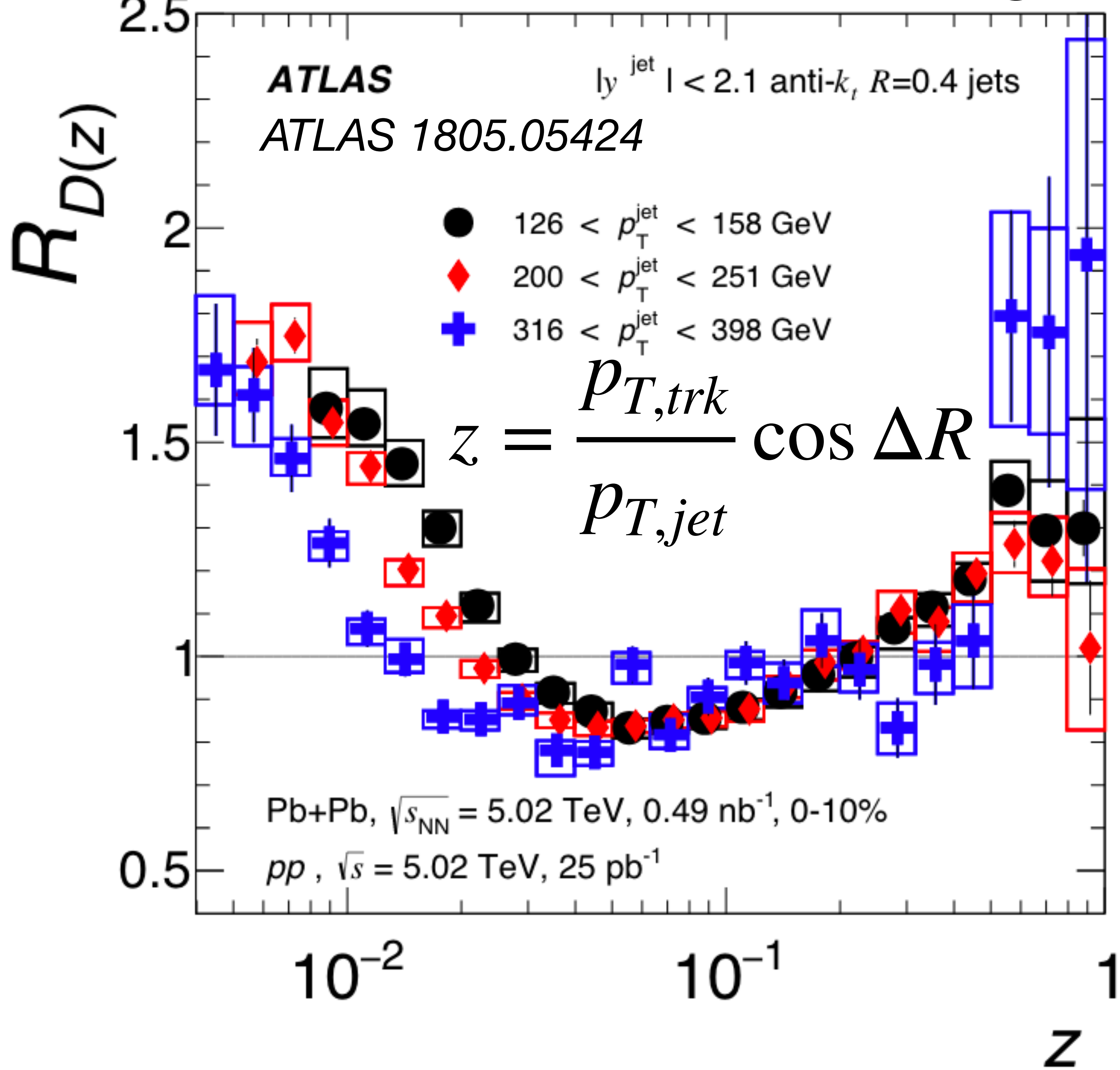
Intra-jet particle production



- Fragmentation Function!
- Whats the momentum fraction carried by a hadron in a jet
- Correction factor for theoretical calculations

Intra-jet particle production

At LHC

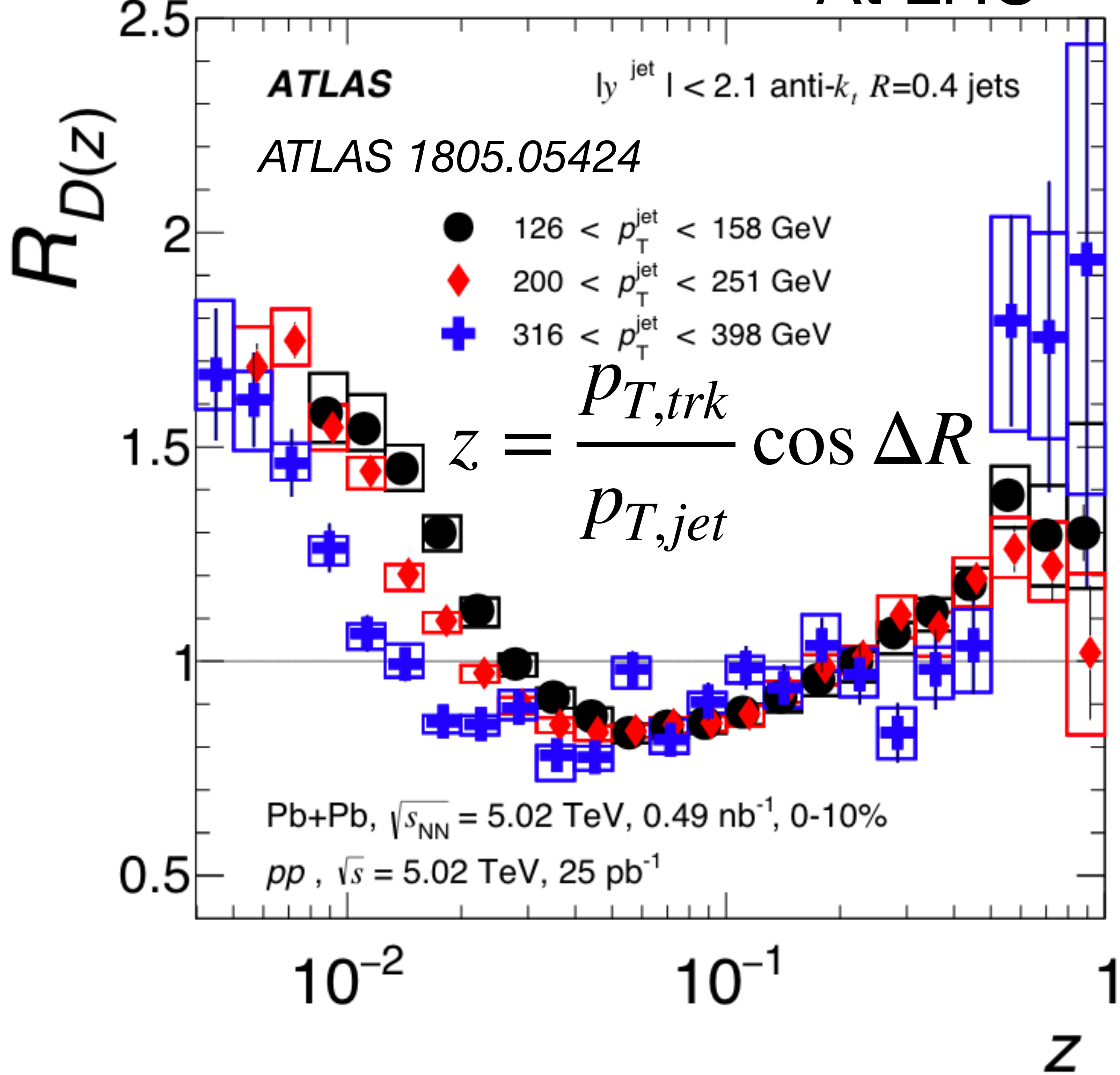


- low z - Enhancement
- Intermediate z - Suppression
- High z - potential enhancement

Is the enhancement at fixed p_T?

Intra-jet particle production

At LHC

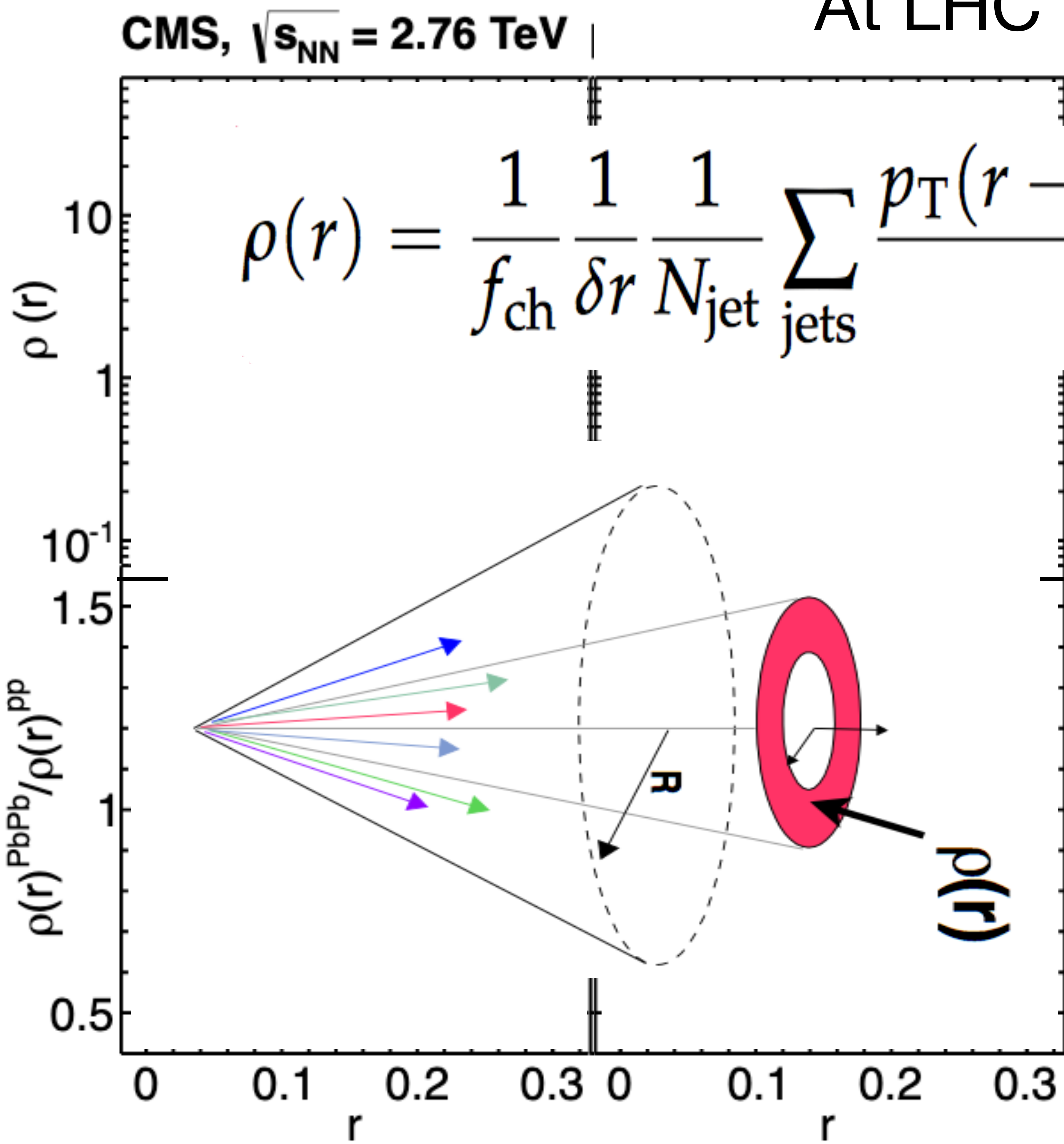


- low z - Enhancement
- Intermediate z - Suppression
- High z - potential enhancement
- low z enhancement occurs at similar p_T (3.5 GeV) - points to a medium scale!

Intra-jet particle production

At LHC

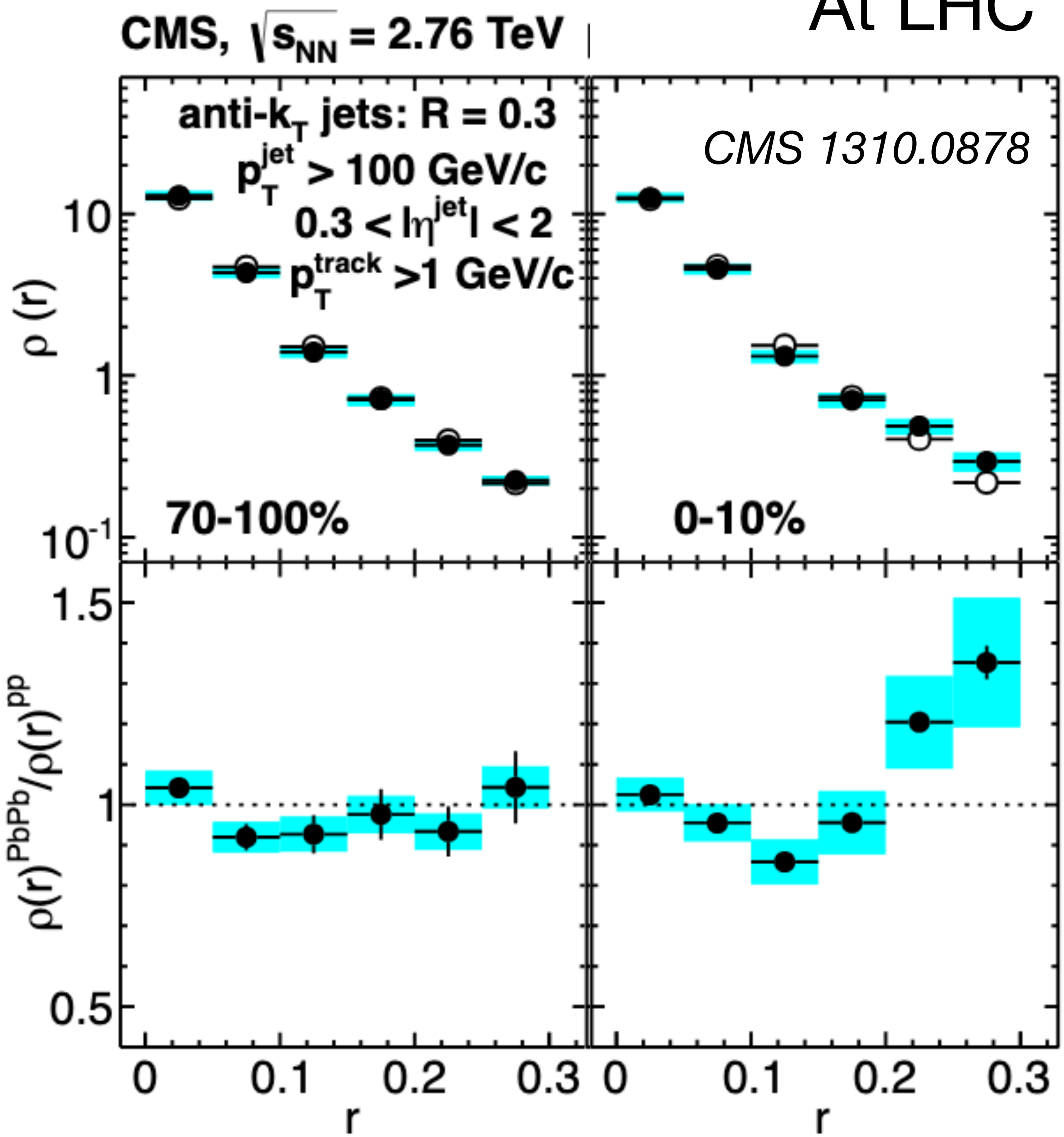
$$\rho(r) = \frac{1}{f_{\mathrm{ch}}} \frac{1}{\delta r} \frac{1}{N_{\mathrm{jet}}} \sum_{\mathrm{jets}} \frac{p_{\mathrm{T}}(r - \delta r/2, r + \delta r/2)}{p_{\mathrm{T}}^{\mathrm{jet}}}$$



- Jet Shapes
- Density particles in an annuli around the jet axis
- Normalized per number of jets

Intra-jet particle production

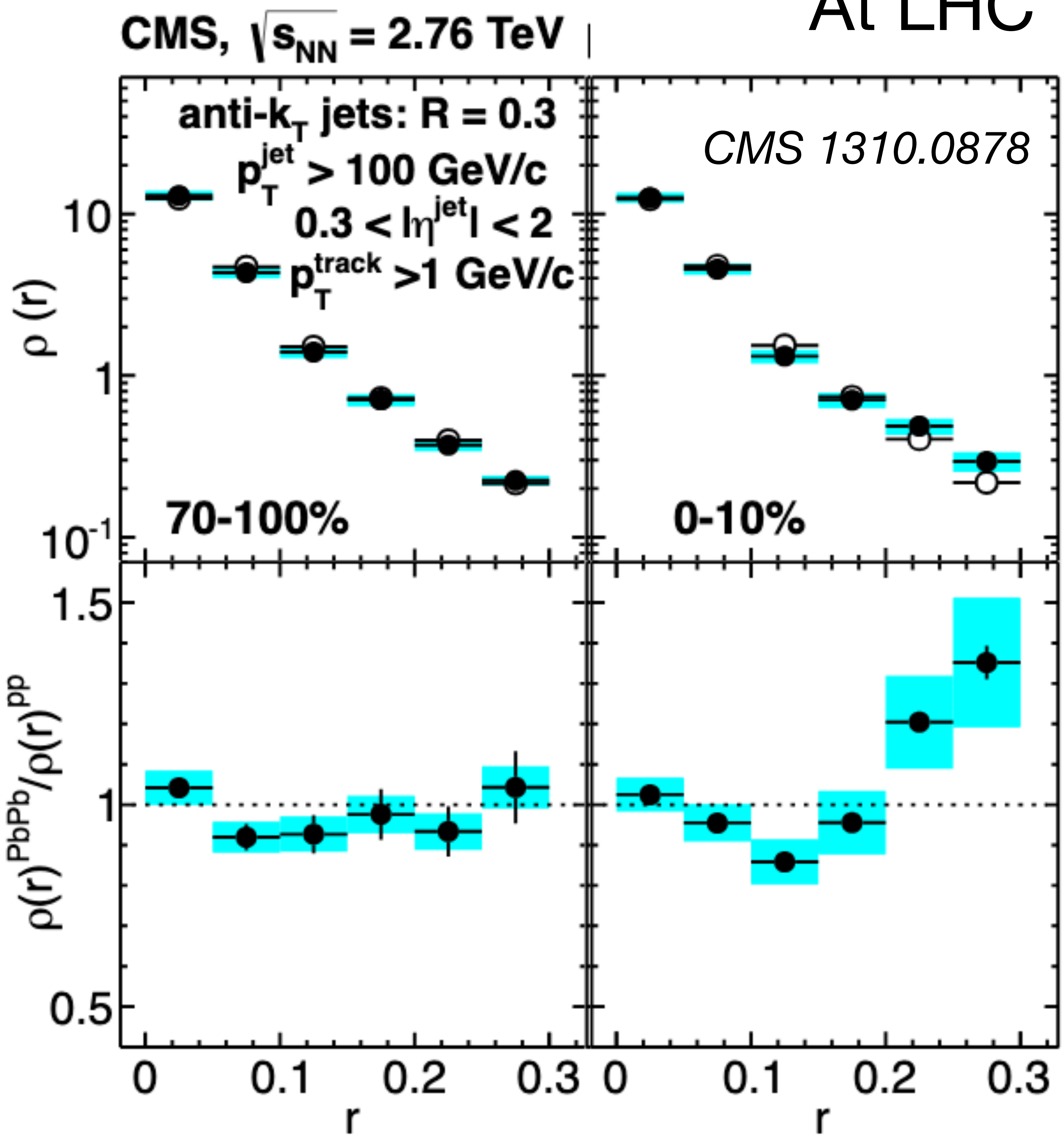
At LHC



- Enhancement of hadrons around the edges of the jet cone (and extending beyond)
- Interesting observation of possible narrowing at the jet core!

Intra-jet particle production

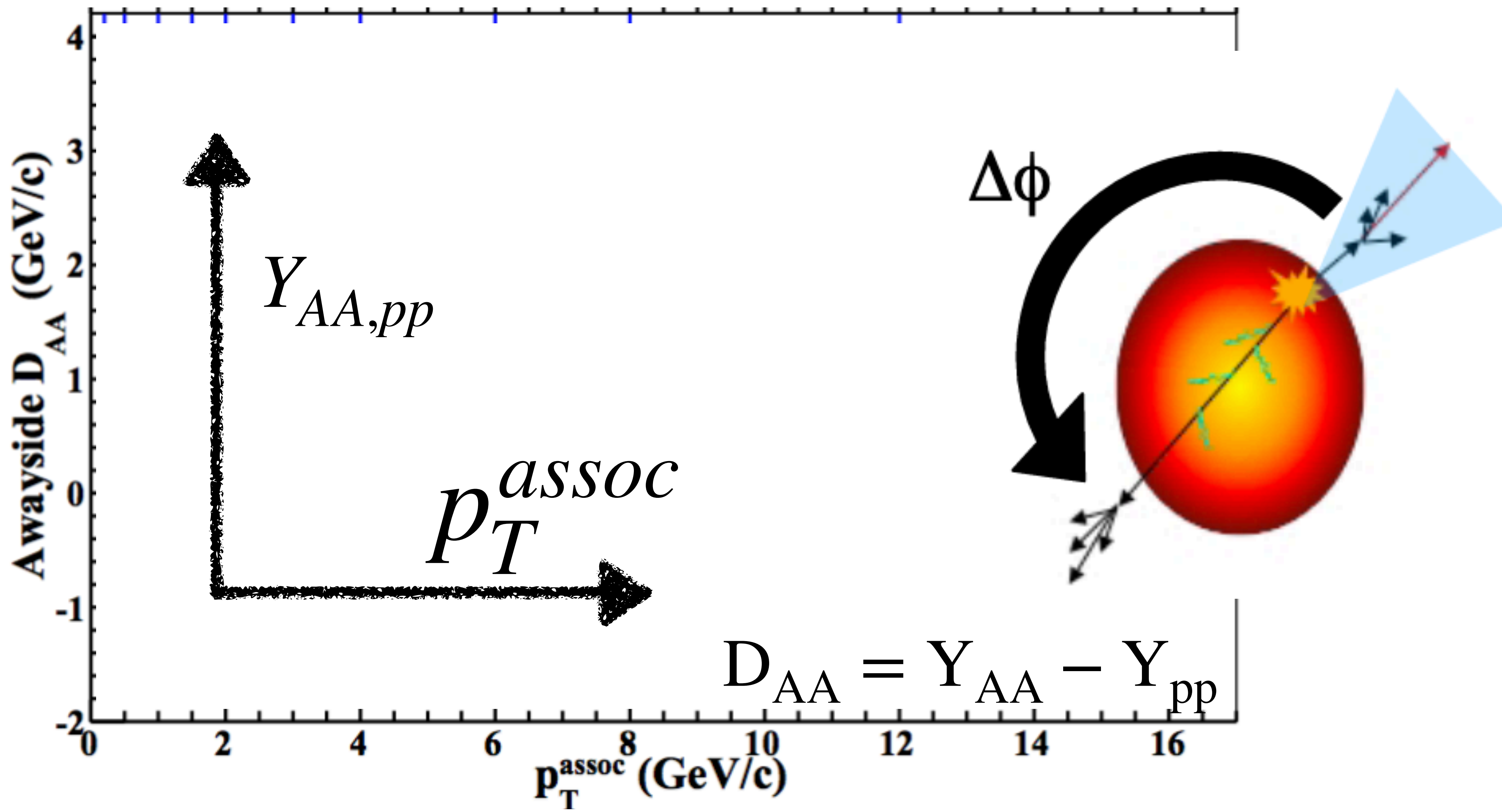
At LHC



- Enhancement of hadrons around the edges of the jet cone (and extending beyond)
- Interesting observation of possible narrowing at the jet core!
- Combining both - enhancement is in soft particles around the jet periphery. Core unaffected potentially narrower!

Jet-Hadron correlations

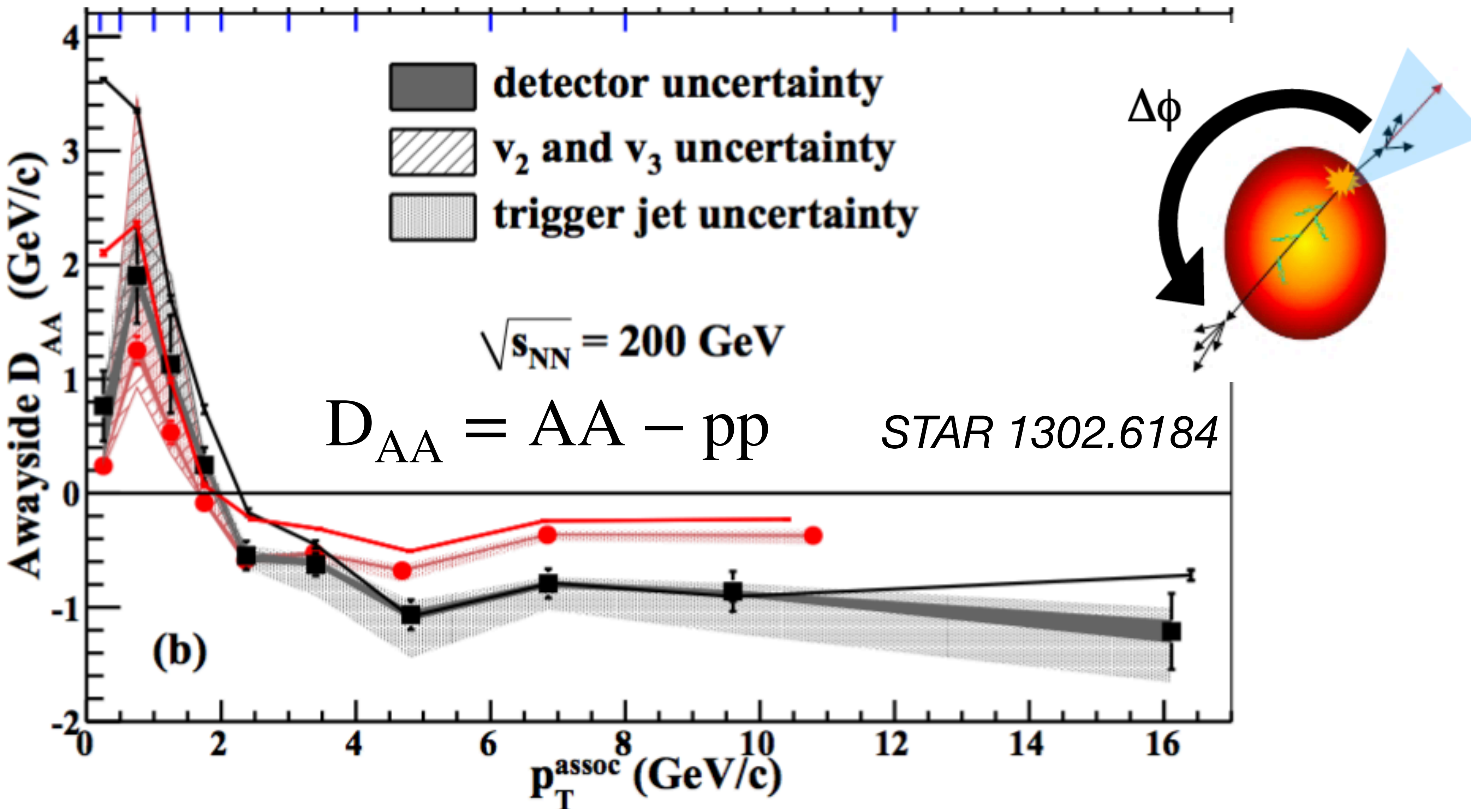
At RHIC



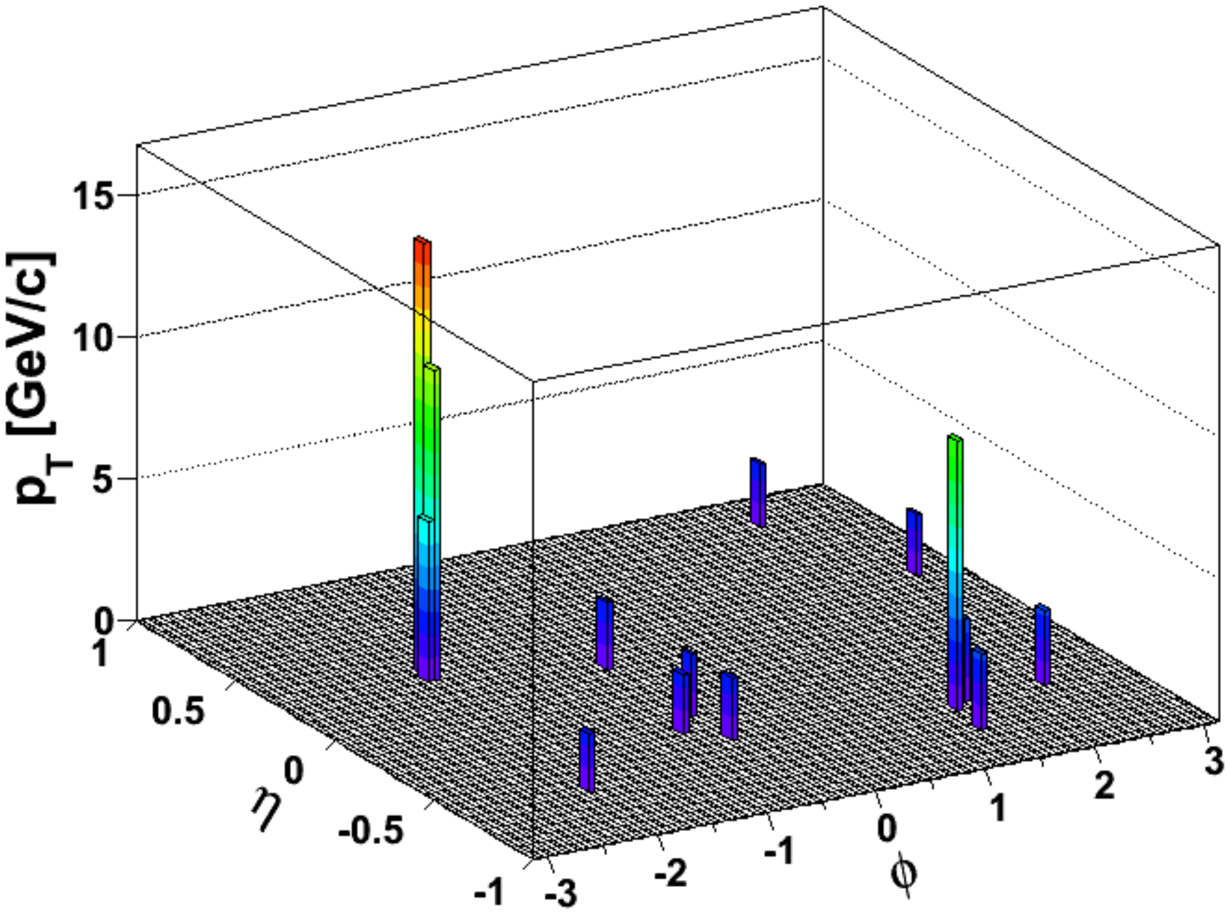
- Energy lost by high p_T (> 2GeV) constituents recovered by low p_T (0.2-2 GeV) excess
- Medium scale (2GeV vs 3.5GeV at LHC) smaller at RHIC as expected

Jet-Hadron correlations

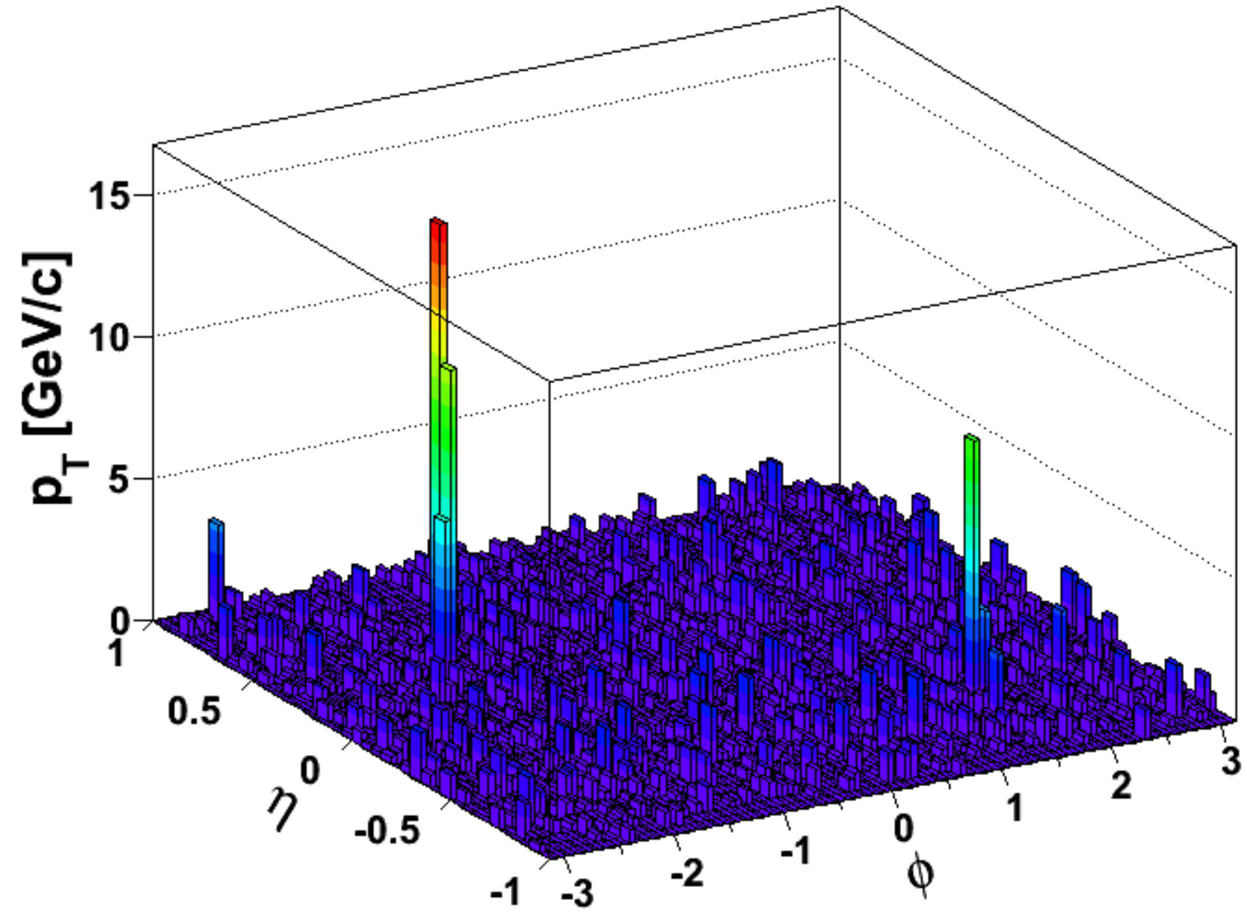
At RHIC



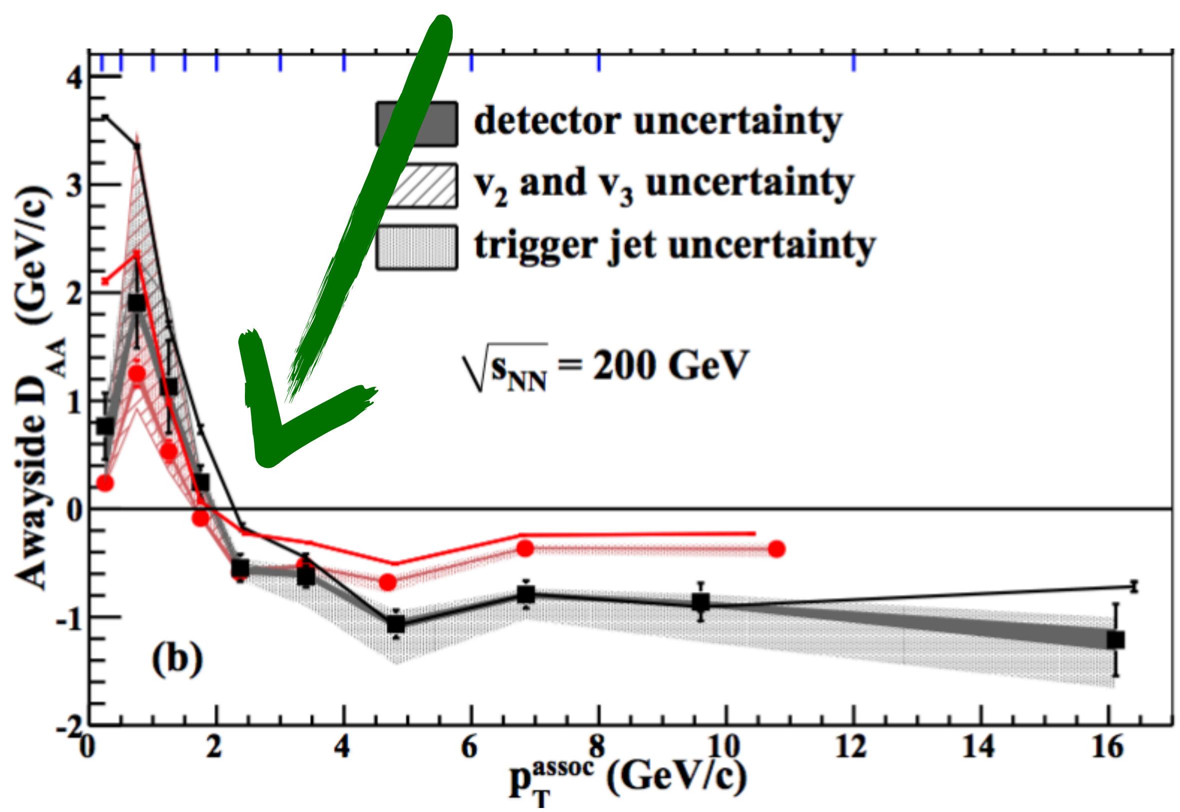
- Energy lost by high p_T (> 2GeV) constituents recovered by low p_T (0.2-2 GeV) excess
- Medium scale (2GeV vs 3.5GeV at LHC) smaller at RHIC as expected



15
10
5
0
p_T [GeV/c]
1
0.5
0
-0.5
-1
η
-3
-2
-1
0
1
2
3
ϕ



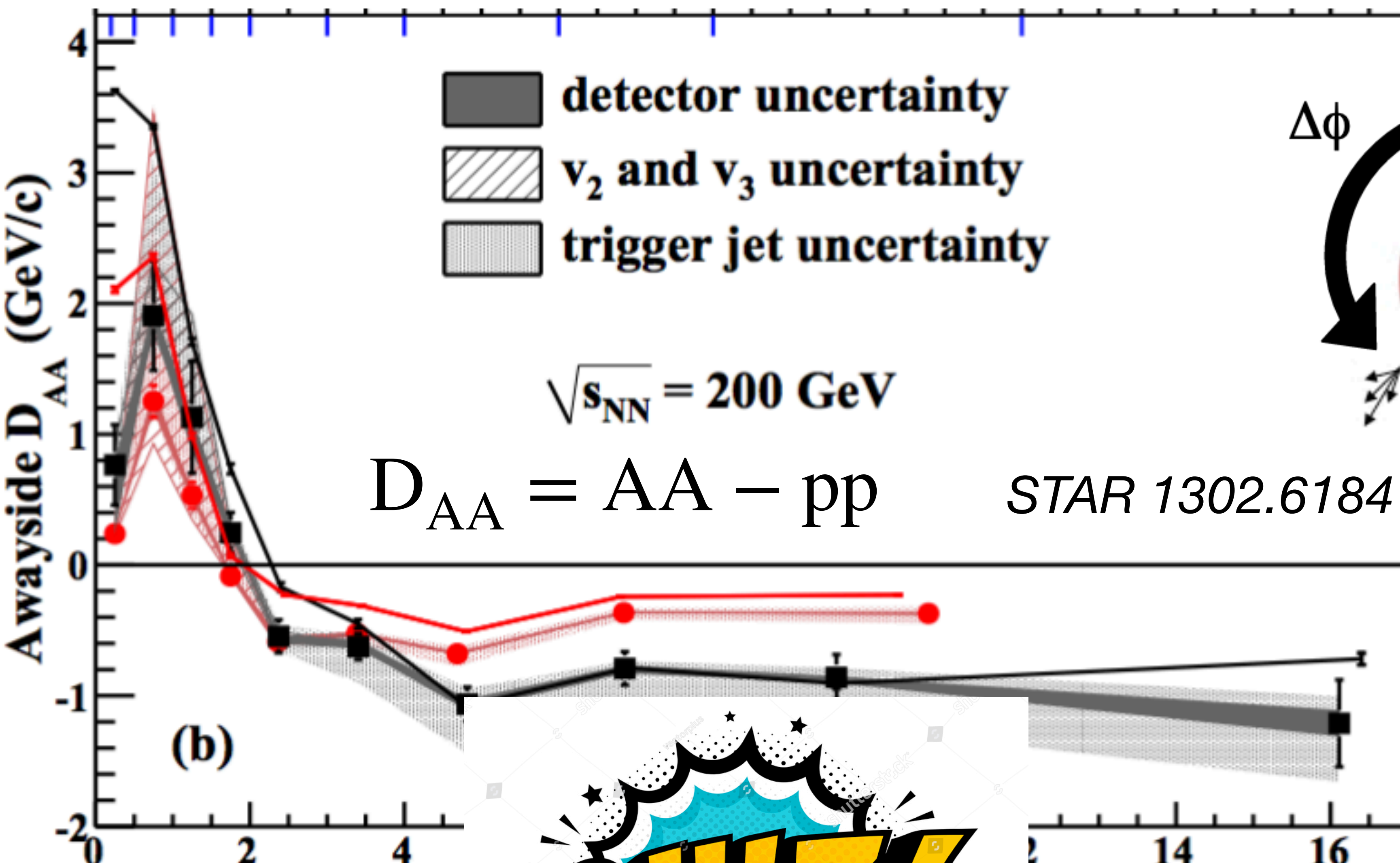
15
10
5
0
p_T [GeV/c]
1
0.5
0
-0.5
-1
η
-3
-2
-1
0
1
2
3
ϕ

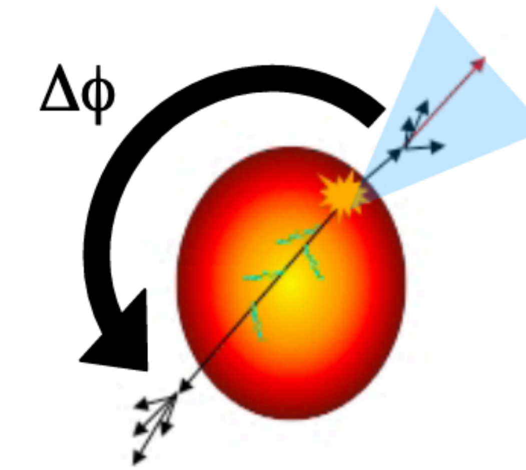


detector uncertainty
v_2 and v_3 uncertainty
trigger jet uncertainty
$\sqrt{s_{NN}} = 200$ GeV
(b)
Awayside D_{AA} (GeV/c)
p_T^{assoc} (GeV/c)

Jet-Hadron correlations

At RHIC





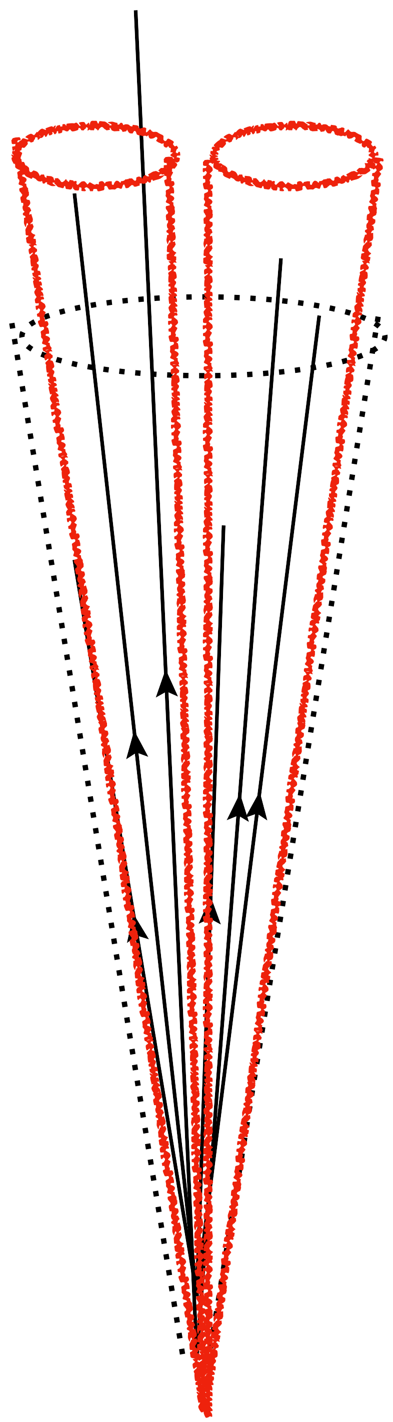
- Energy lost by high p ... uents recovered by low p_T (0.2-2 GeV) excess
- What is this medium scale dependent on?

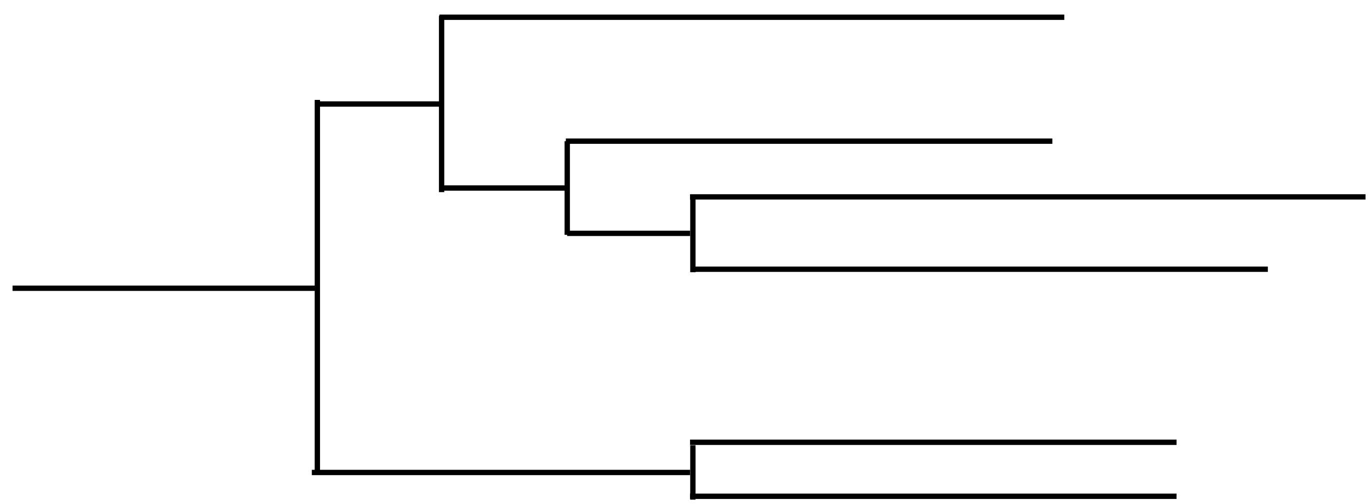
2nd gen - what did we learn?

- Observation of **fragmentation modification at low z and around the jet** - Highlights need for and use of calibrated probes with good reference
- Modification appears to occur at a fixed energy scale
- Large spread of quenched energy - **Broadening effect**
- But we still don't know the 'How' of energy loss

ATLAS Heavy Ion Publications
ALICE Heavy Ion Publications
CMS Heavy Ion Publications
STAR Publications
PHENIX Publications

3rd generation Jet Measurements

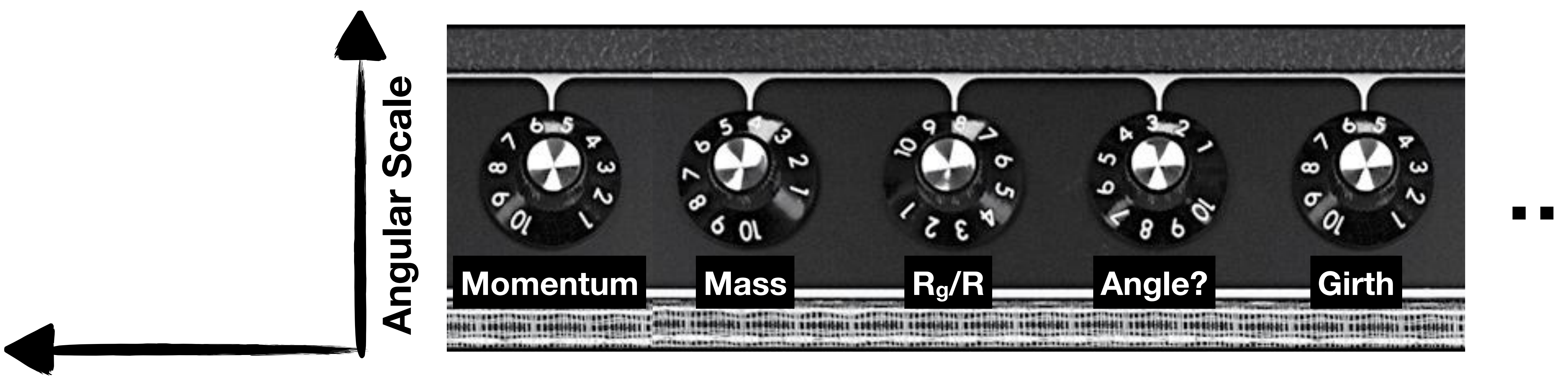




Exploit clustering information to look inside jets and study the evolution

Key Idea
Use jet-substructure as a selection tool

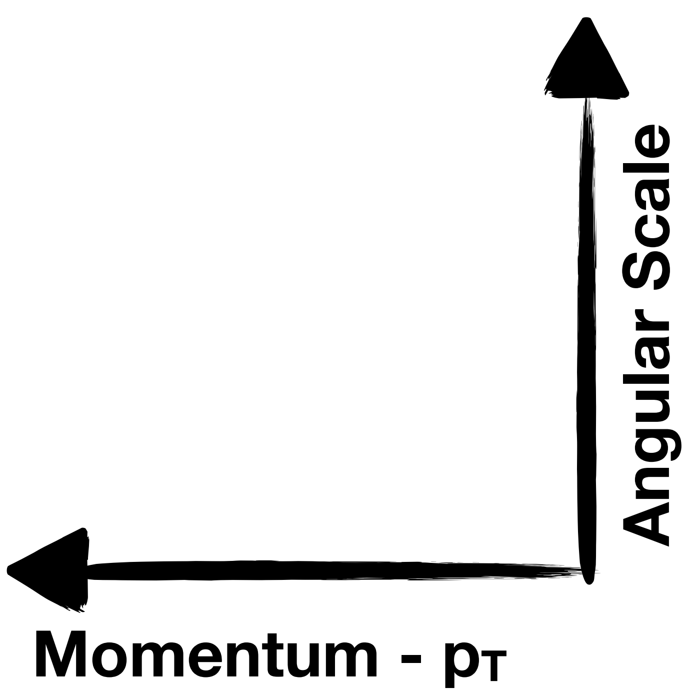
Identify jet observable(s) sensitive to the parton shower kinematics



Partonic energy loss via a differential study in momentum scale and angular scale

Key Idea
Use jet-substructure as a selection tool

Identify jet observable(s) sensitive to the parton shower kinematics



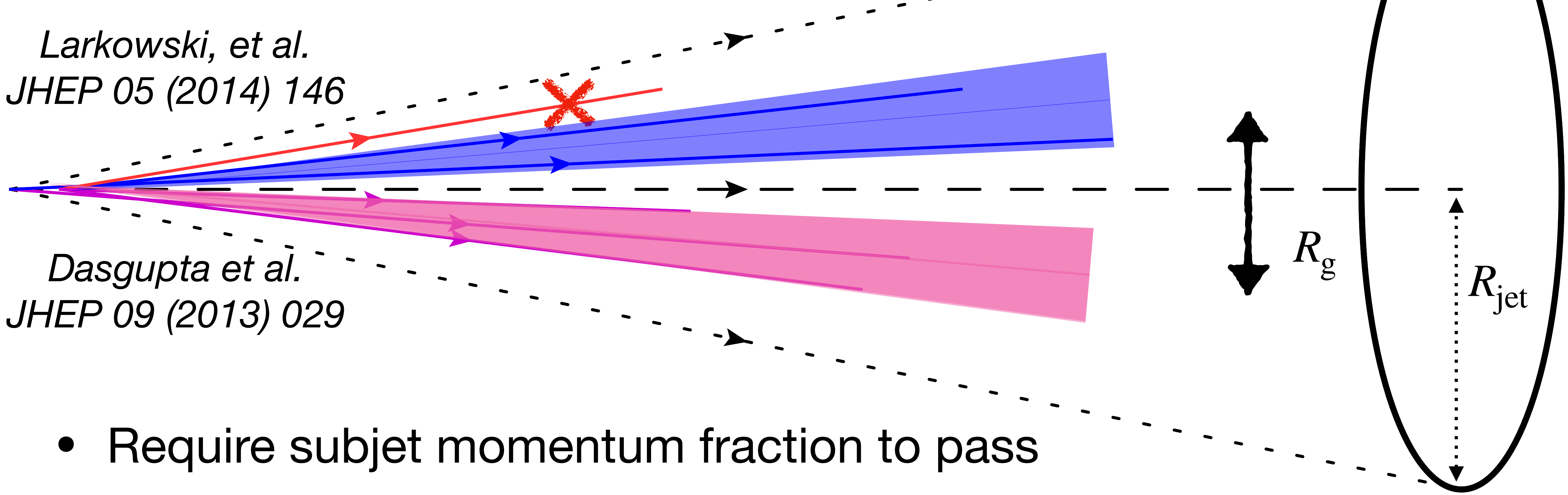
...

Is this cartoon on the left correct?

SoftDrop grooming

Larkowski, et al.
JHEP 05 (2014) 146

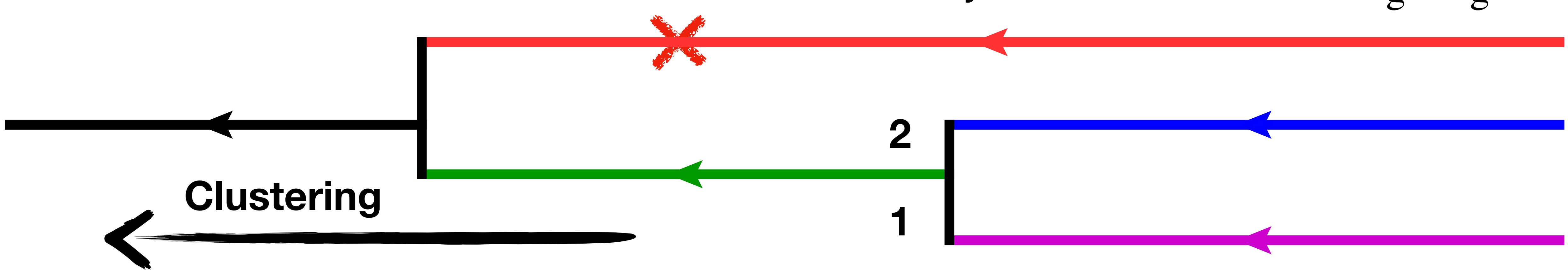
Dasgupta et al.
JHEP 09 (2013) 029



- Require subjet momentum fraction to pass

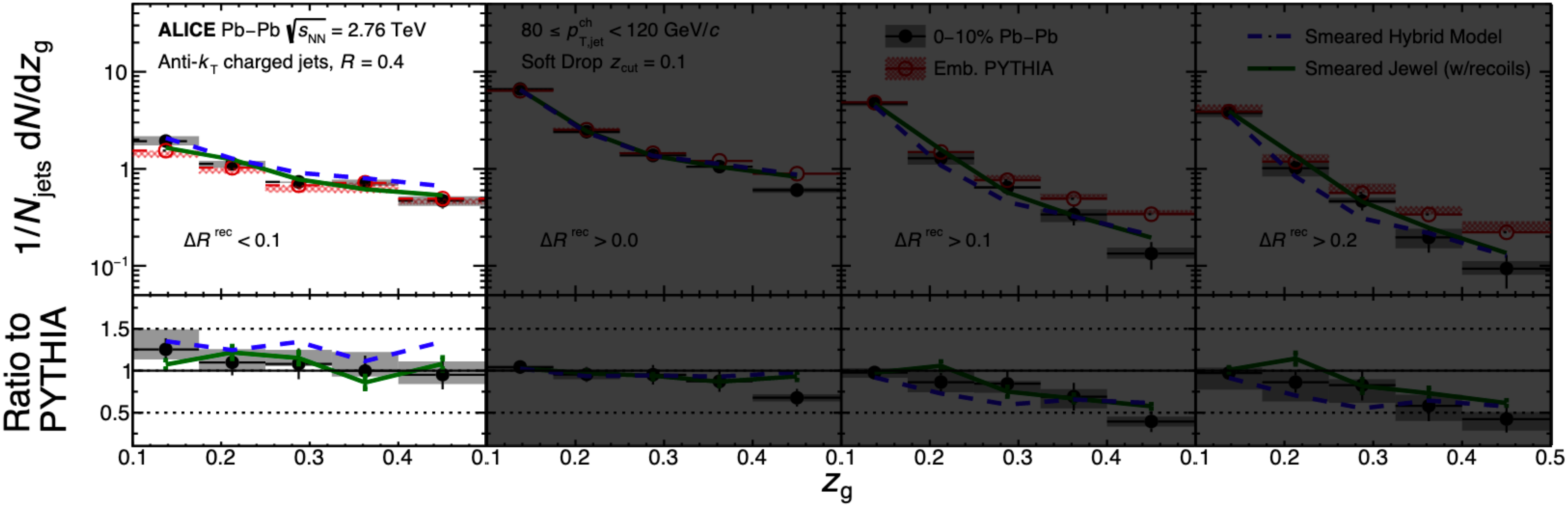
$$z_{\mathrm{g}} = \frac{\min(\mathrm{p}_{\mathrm{T},1}, \mathrm{p}_{\mathrm{T},2})}{p_{\mathrm{T},1} + p_{\mathrm{T},2}} > z_{\mathrm{cut}}(R_{\mathrm{g}}/R_{\mathrm{jet}})^{\beta} \qquad z_{\mathrm{cut}} = 0.1 \quad \beta = 0$$

- With the two surviving branches (first hard split) - we define observables that characterize jet substructure z_{g}, R_{g}



Softdrop splitting at varying opening angles

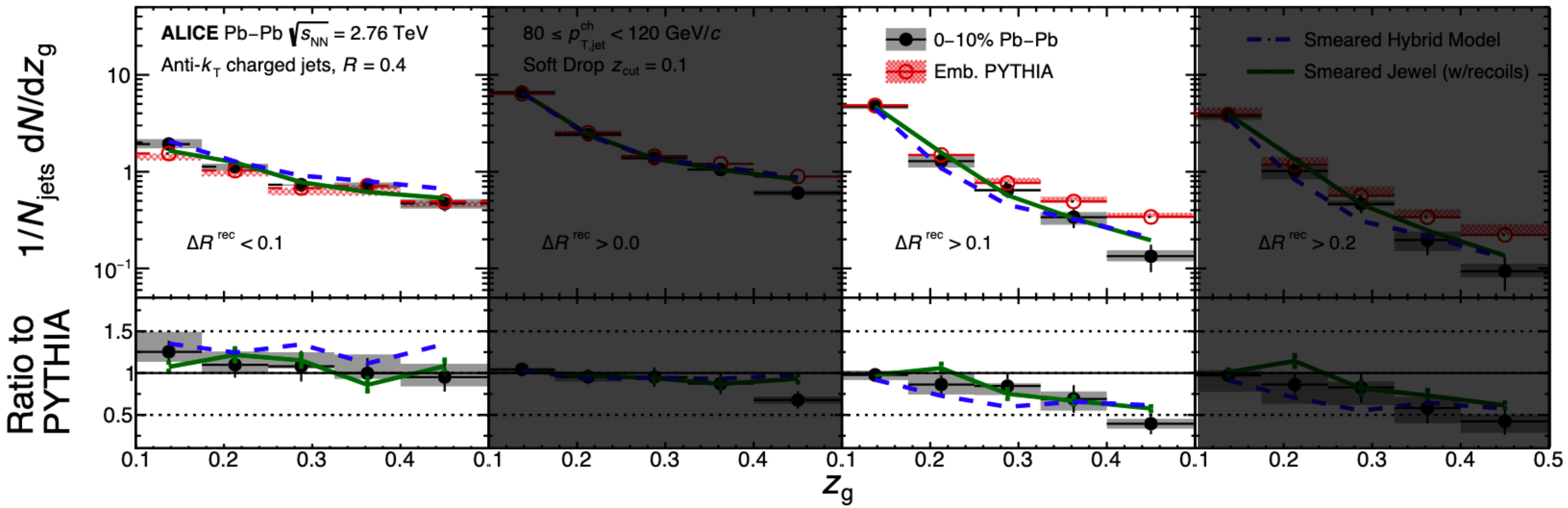
ALICE 1905.02512v1



- Enhancement of narrow angle soft z_g at narrow angle!
- MC models are generally able to reproduce the trend but further systematic studies are needed to discriminate these models

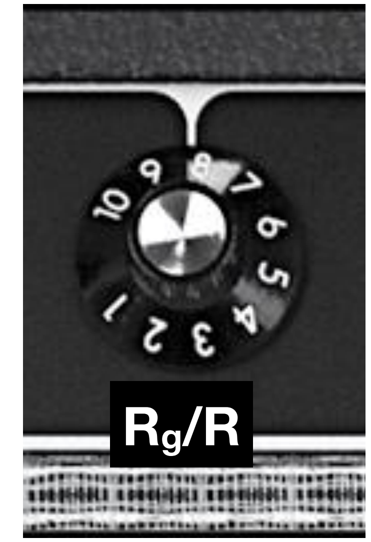
Softdrop splitting at varying opening angles

ALICE 1905.02512v1

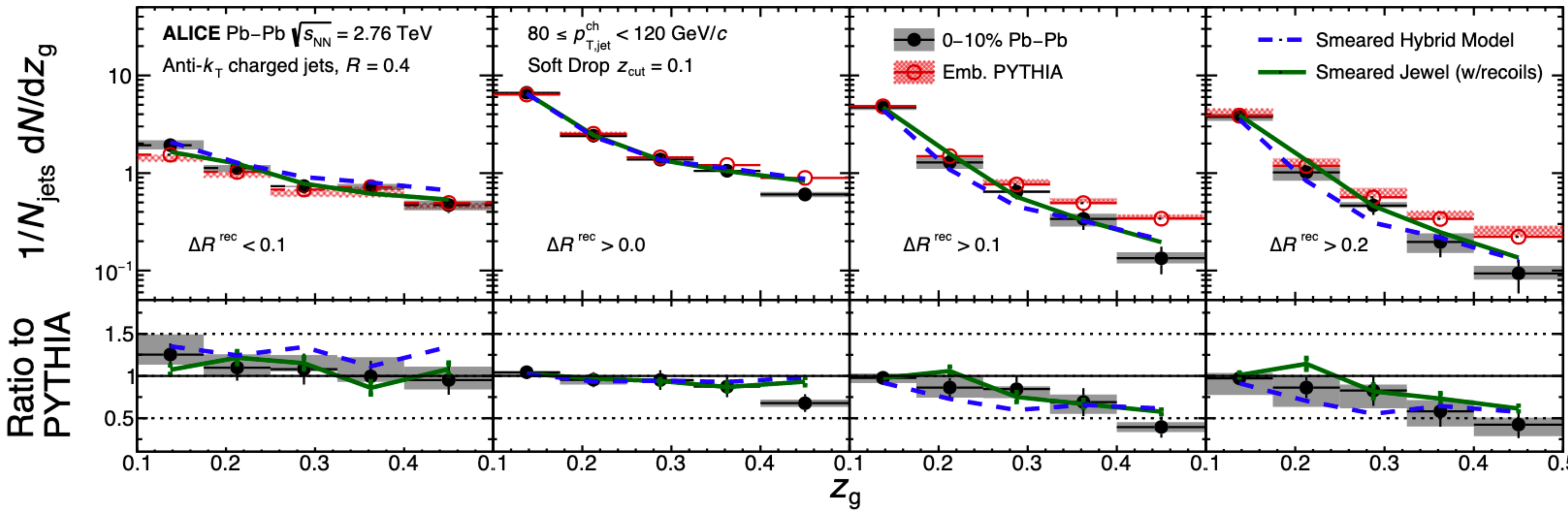


- Suppression of wide angle large z_g splits
- MC models are generally able to reproduce the trend but further systematic studies are needed to discriminate these models

Softdrop splitting at varying opening angles

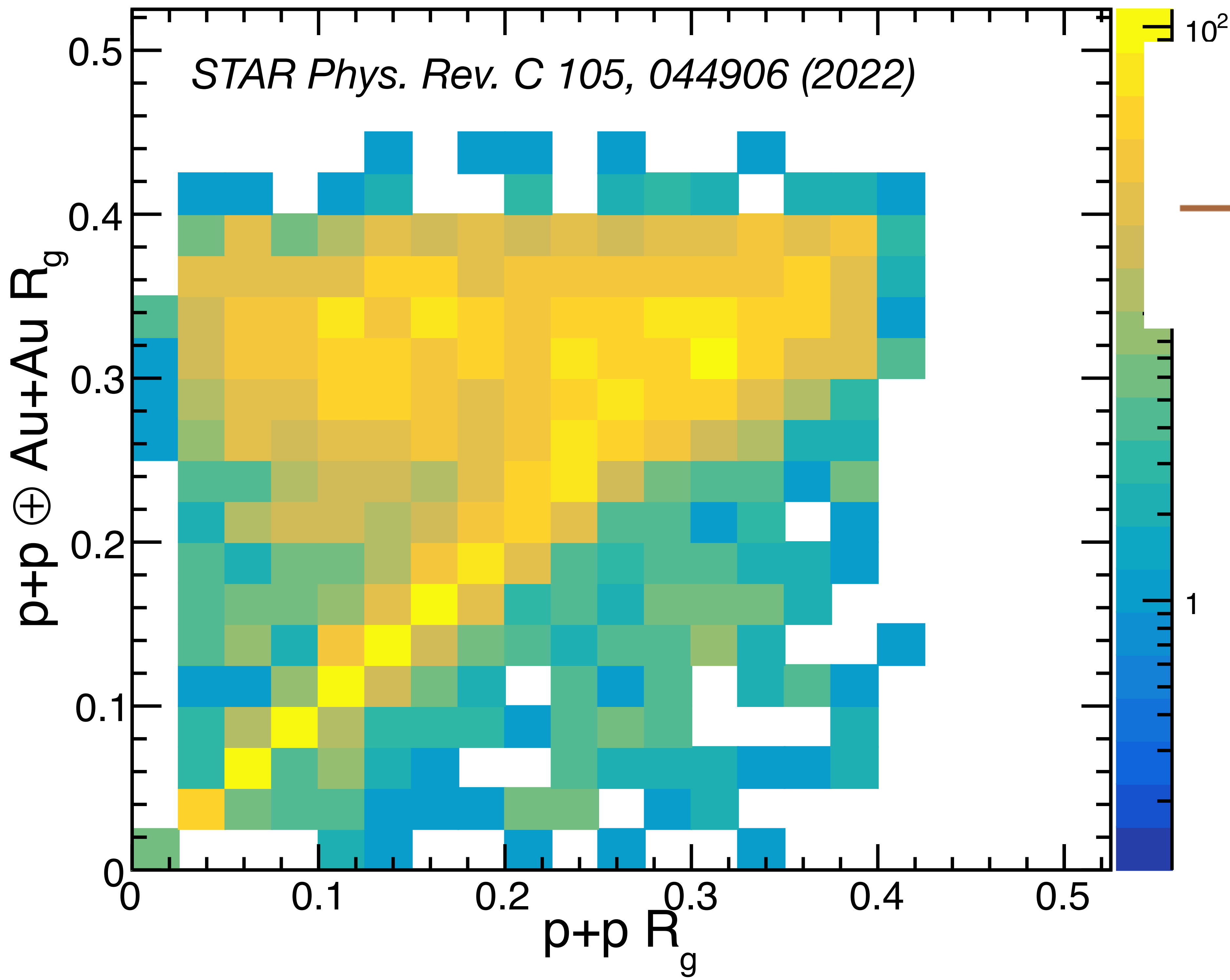


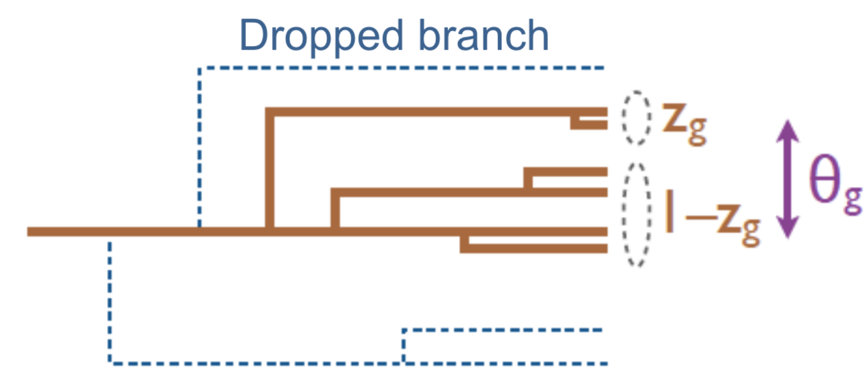
ALICE 1905.02512v1



- Evolution of suppression as you increase the angle
- Data compared to MC at the detector level. How do we trust that we can actually selecting the opening angles we want to select?

Choosing a robust observable



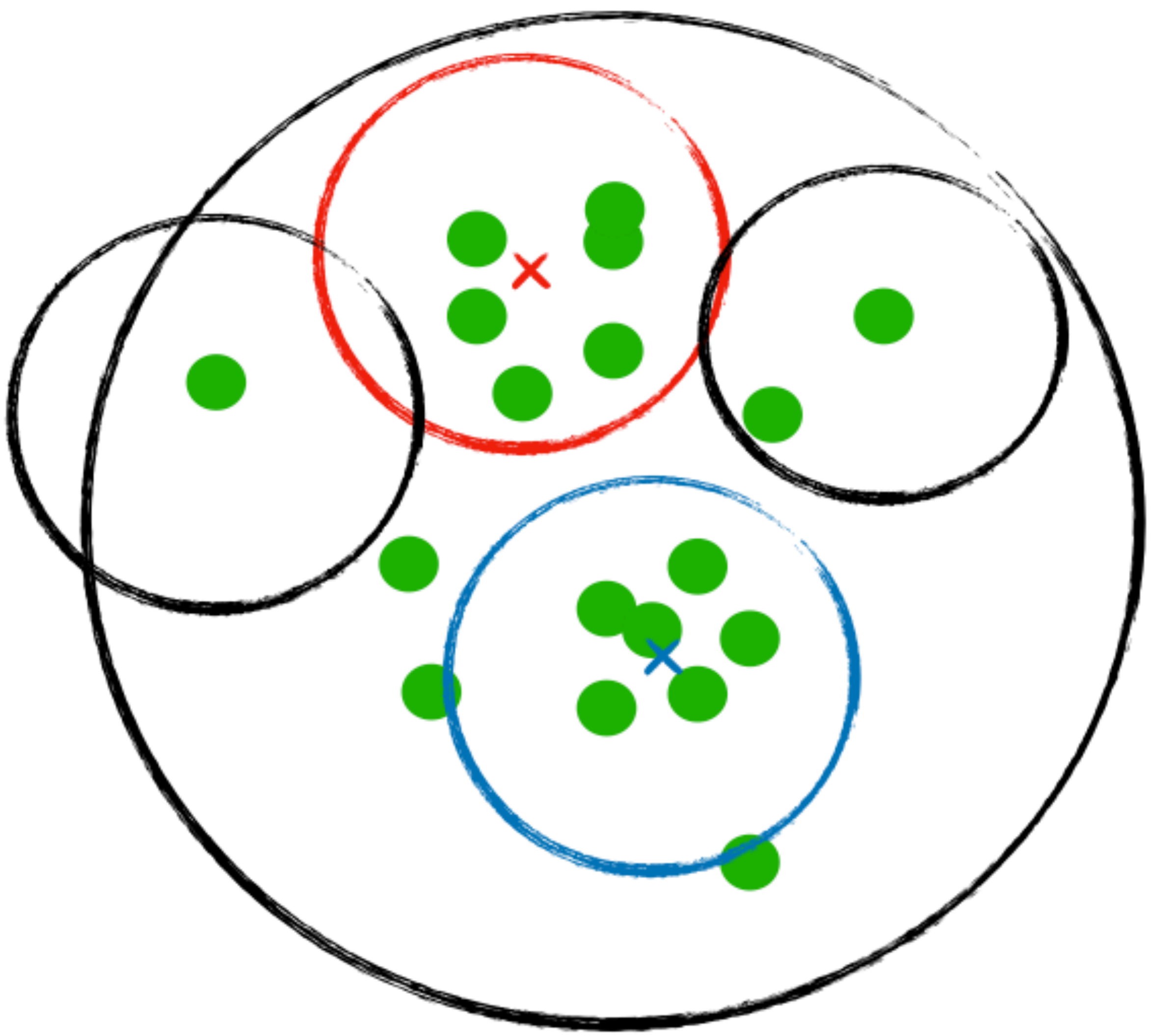


Momentum fraction threshold

Does the medium care about energy or fractional energy?

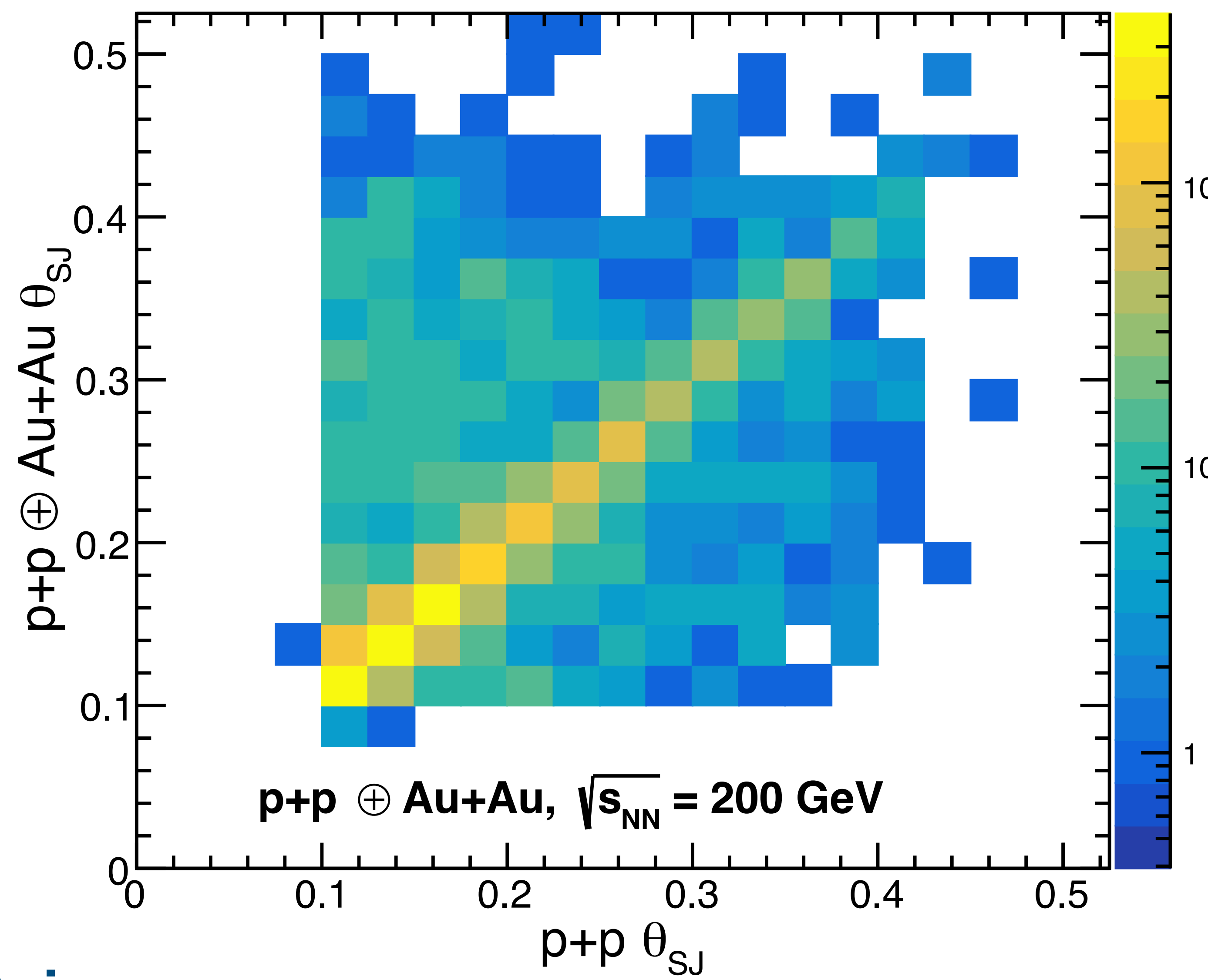
Choosing a robust observable

STAR Phys. Rev. C 105, 044906 (2022)



anti-k$_T$ R=0.1
Leading subjet
Sub-leading subjet

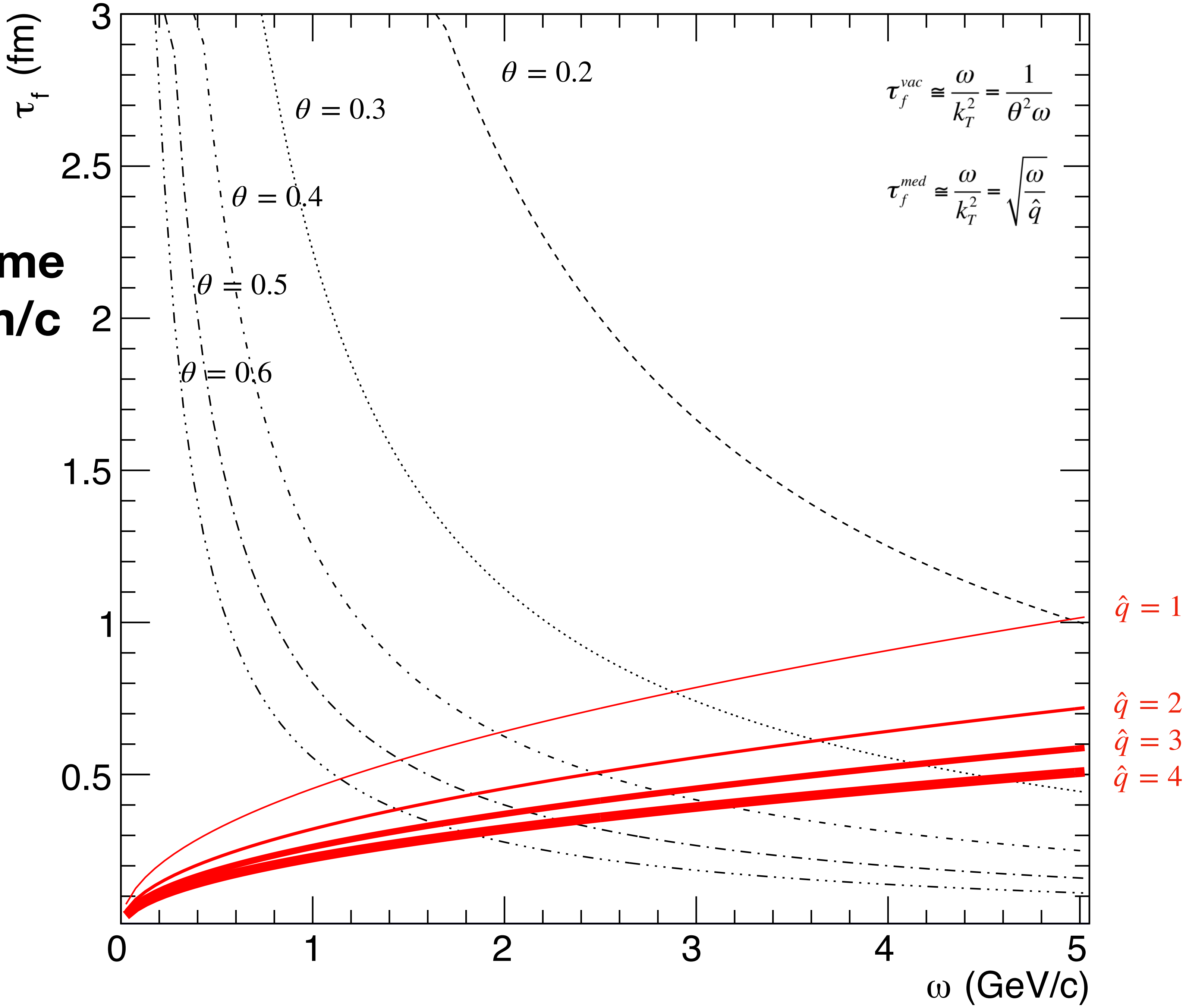
θ_{SJ} = **Δ R (Blue Axis, Red Axis)**



R=0.4 Jets

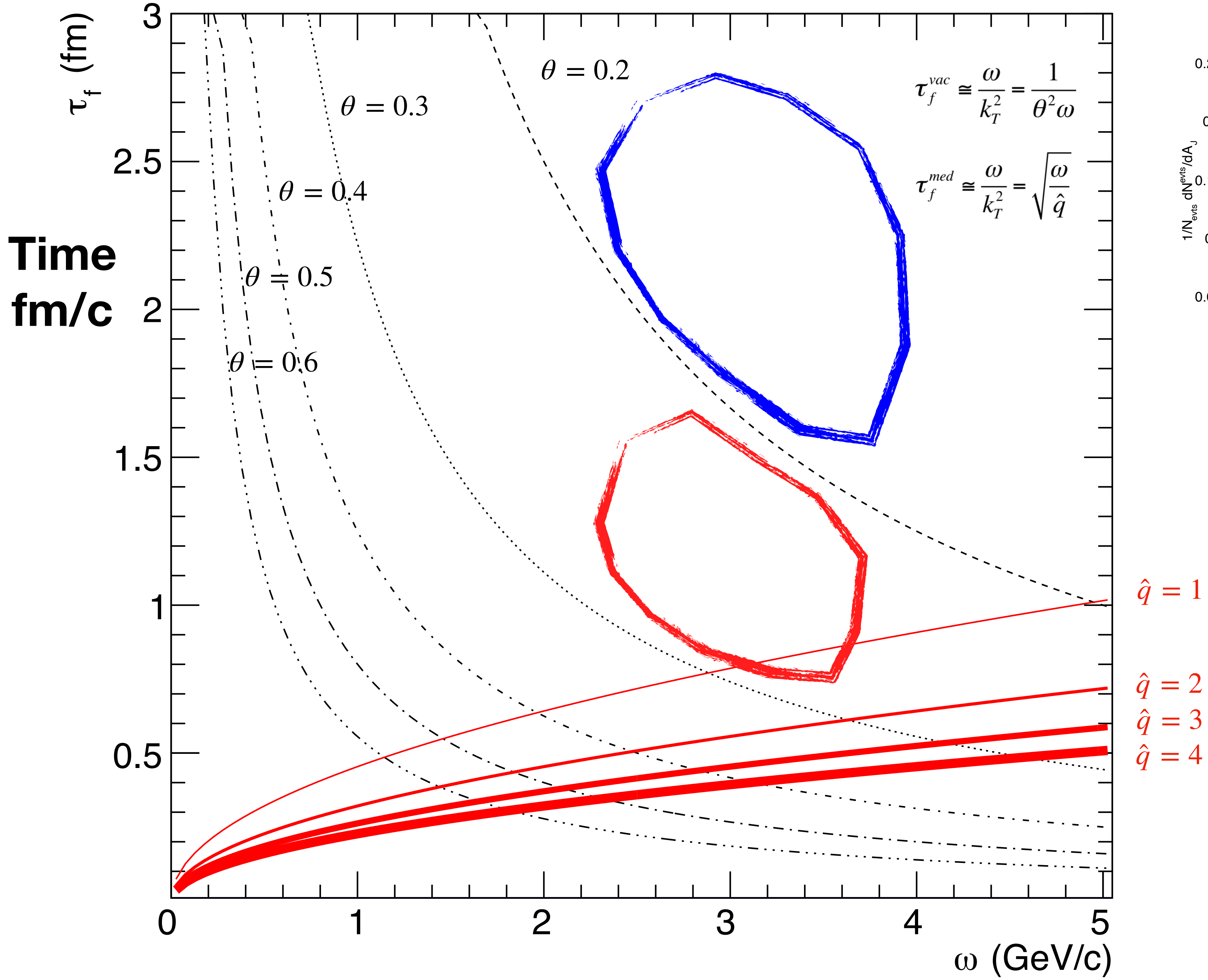
Momentum threshold set at the medium scale!

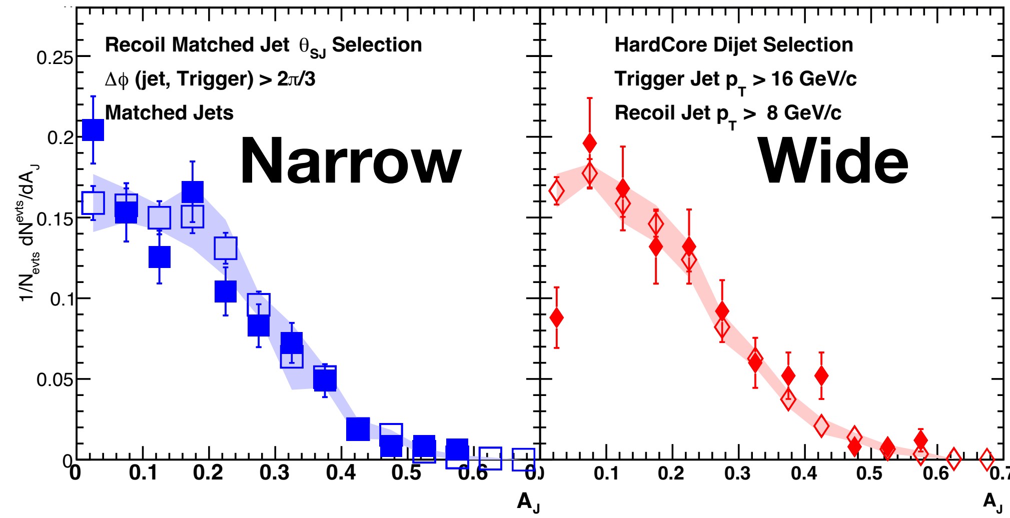
Time fm/c



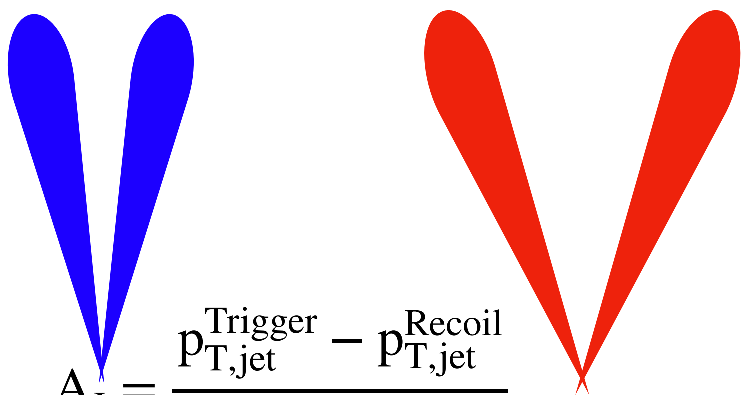
τ_f (fm)
3
2.5
2
1.5
1
0.5
0
1
2
3
4
5
ω (GeV/c)
$\theta = 0.2$
$\theta = 0.3$
$\theta = 0.4$
$\theta = 0.5$
$\theta = 0.6$
$\tau_f^{vac} \cong \frac{\omega}{k_T^2} = \frac{1}{\theta^2 \omega}$
$\tau_f^{med} \cong \frac{\omega}{k_T^2} = \sqrt{\frac{\omega}{\hat{q}}}$
$\hat{q} = 1$
$\hat{q} = 2$
$\hat{q} = 3$
$\hat{q} = 4$

STAR Phys. Rev. C 105, 044906 (2022)



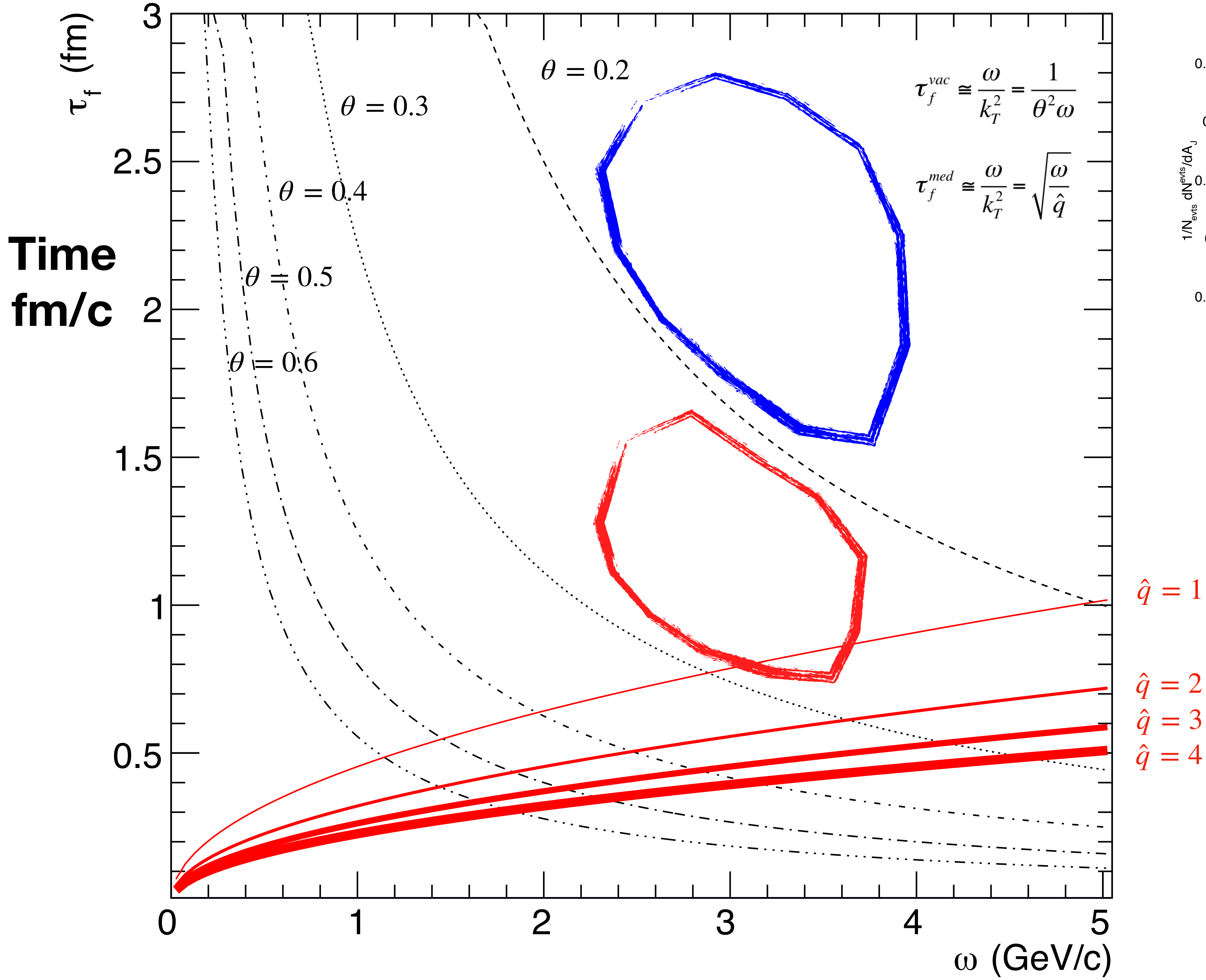


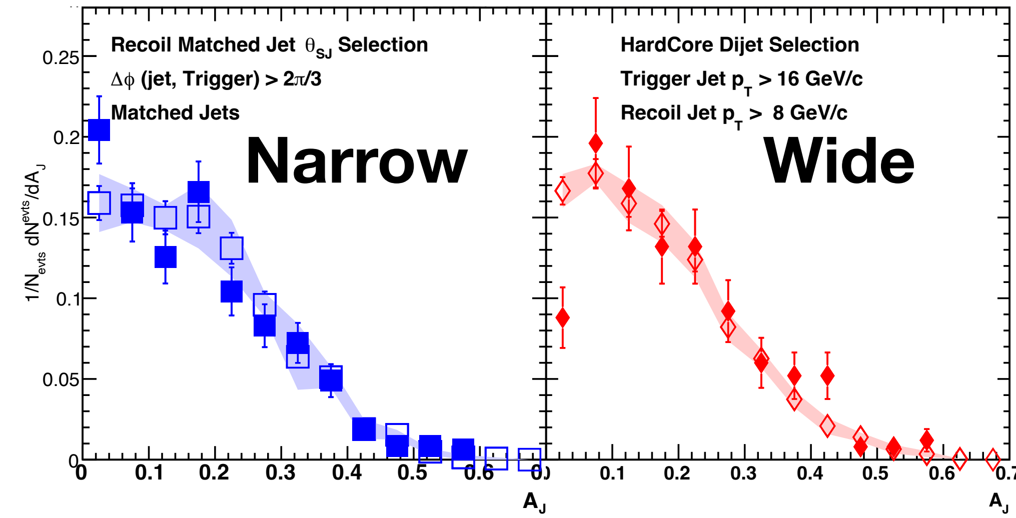
$0.1 < \theta < 0.2$ $\quad 0.2 < \theta < 0.3$

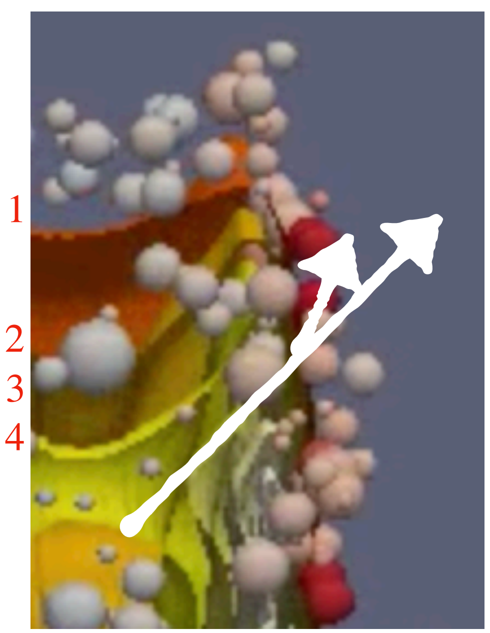


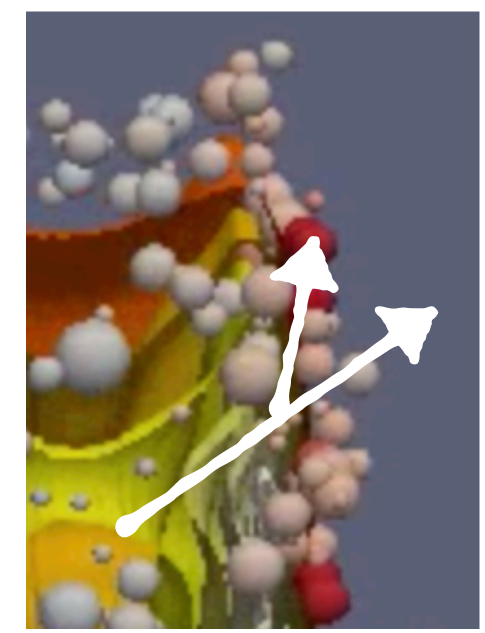
$$A_J = \frac{p_{T,jet}^{Trigger} - p_{T,jet}^{Recoil}}{p_{T,jet}^{Trigger} + p_{T,jet}^{Recoil}}$$

STAR Phys. Rev. C 105, 044906 (2022)









- Energy loss for these dijets is an experimental observation of soft radiation from a single color charge!
- Potential upper limit on the coherence length $\lambda_\perp \sim \frac{1}{\hat{q} t_f} \leq 0.1$

3rd gen jet measurements ongoing!

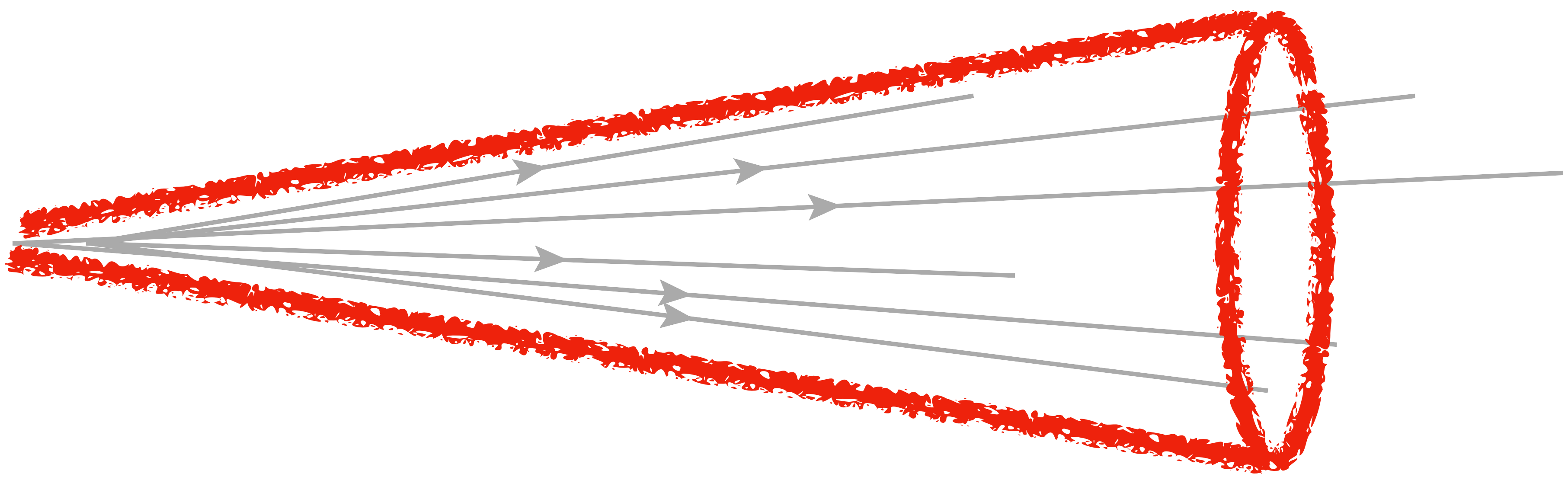
- Jet substructure enables a **systematic exploration of parton-QGP interactions**

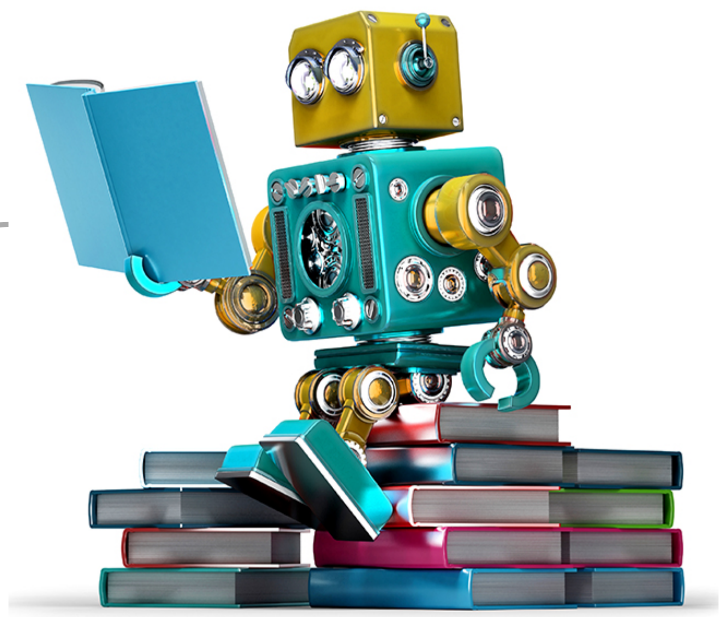
- **Tagging jets** of particular angular scales and studying their **calibrated energy loss** can point us towards quantitative measurements of the QGP's microscopic properties

- Differential measurements further constrain theoretical scenarios and **probe medium at varying resolution scales**

- Consistent picture of energy loss at RHIC for specially selected dijets via **soft gluon emission from a single color charge**

4th generation jet measurements -





Utilizing ML techniques to increase our kinematic phase-space, reduce uncertainties, increase dimensionality etc…

The basics

What is machine learning?

Why are these tools useful in high energy colliders?

How to quantify performance?

Physics with ML

Classifier - Identifying the jet flavor

Regressor - Correcting for detector effects, unfolding

Generator - Learn underlying phenomena

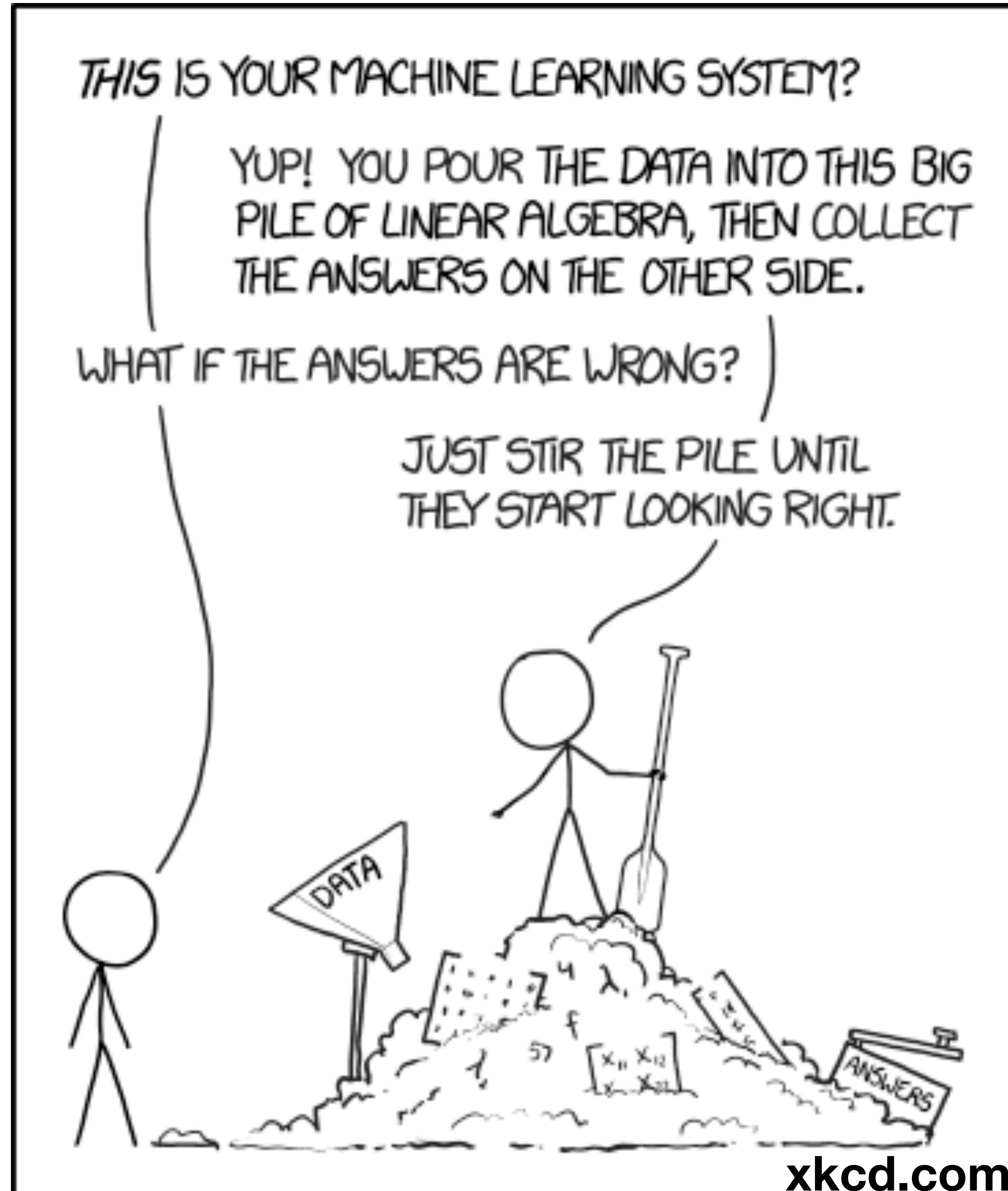
What is Machine Learning

Machine learning is the subfield of computer science that, according to Arthur Samuel, gives "computers the ability to learn without being explicitly programmed."

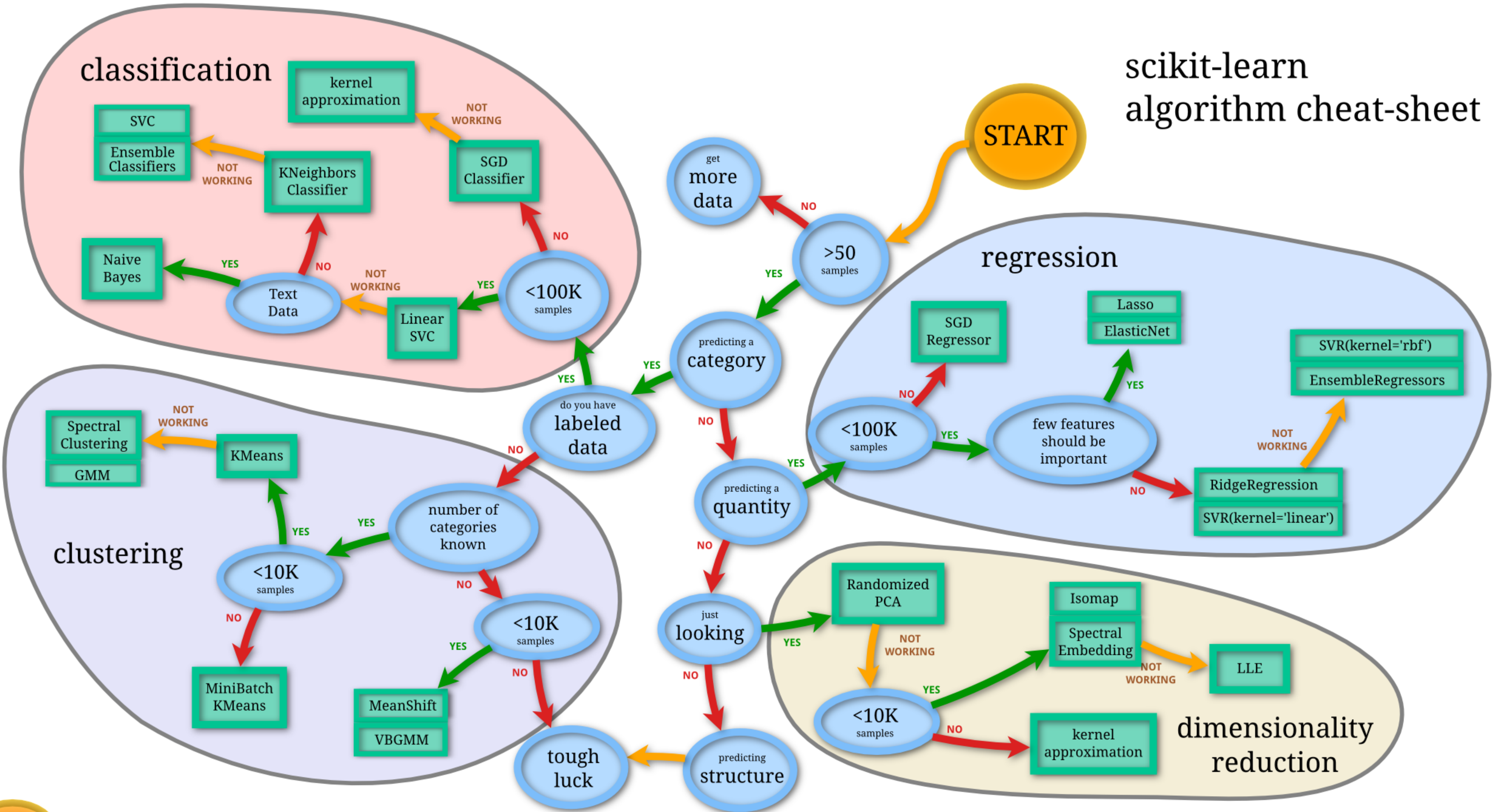
Machine learning - Wikipedia
https://en.wikipedia.org/wiki/Machine_learning

we will want AI to help us debug our thinking by using all data from all experiments optimally and "open our eyes" just as AlphaGo opened the eyes of the professional go players and enhance our intuition and creativity and ability to break paradigms and boxes

Maria Spiropulu (Caltech)

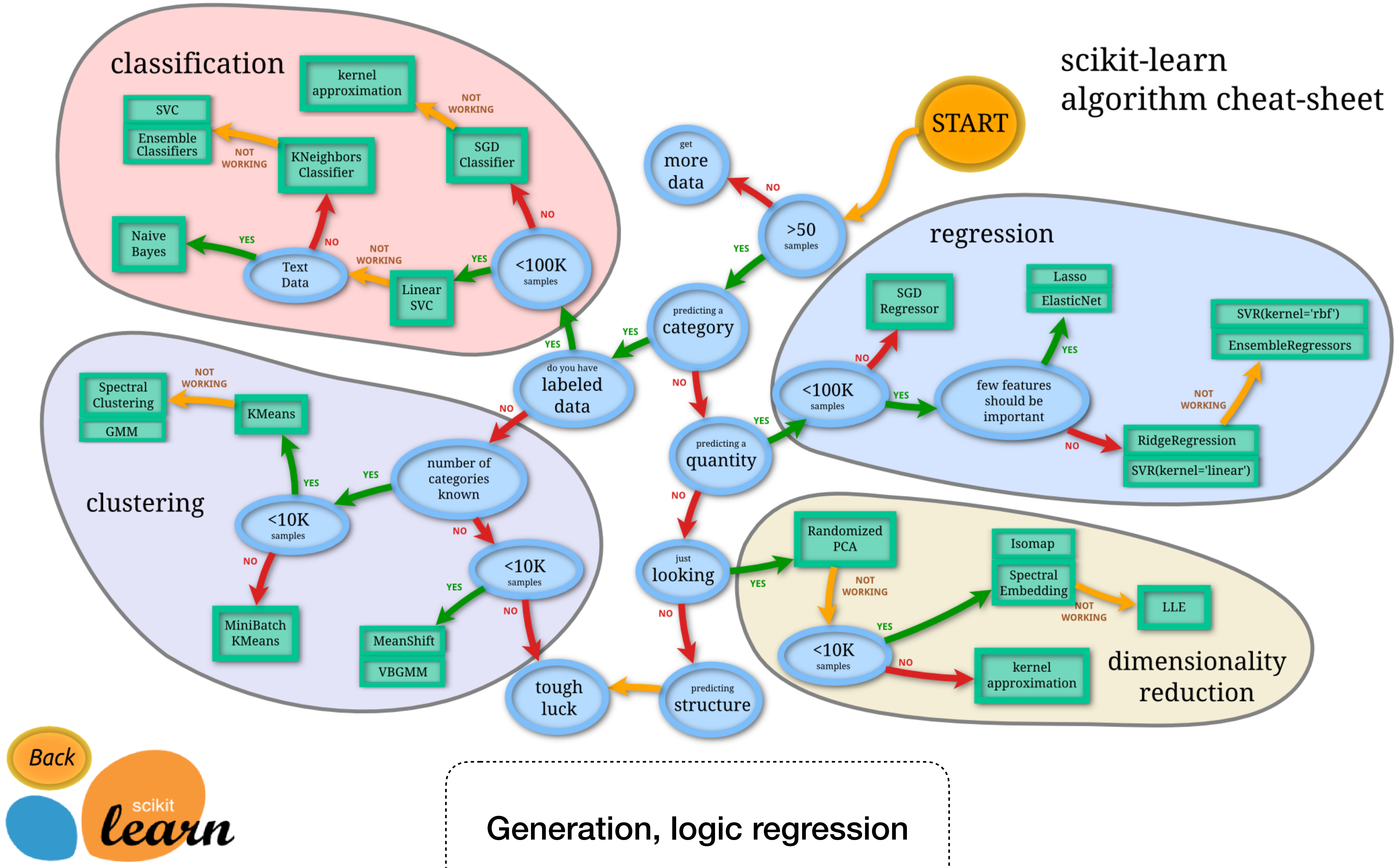


Kind of problems in ML



Back

Kind of problems in ML



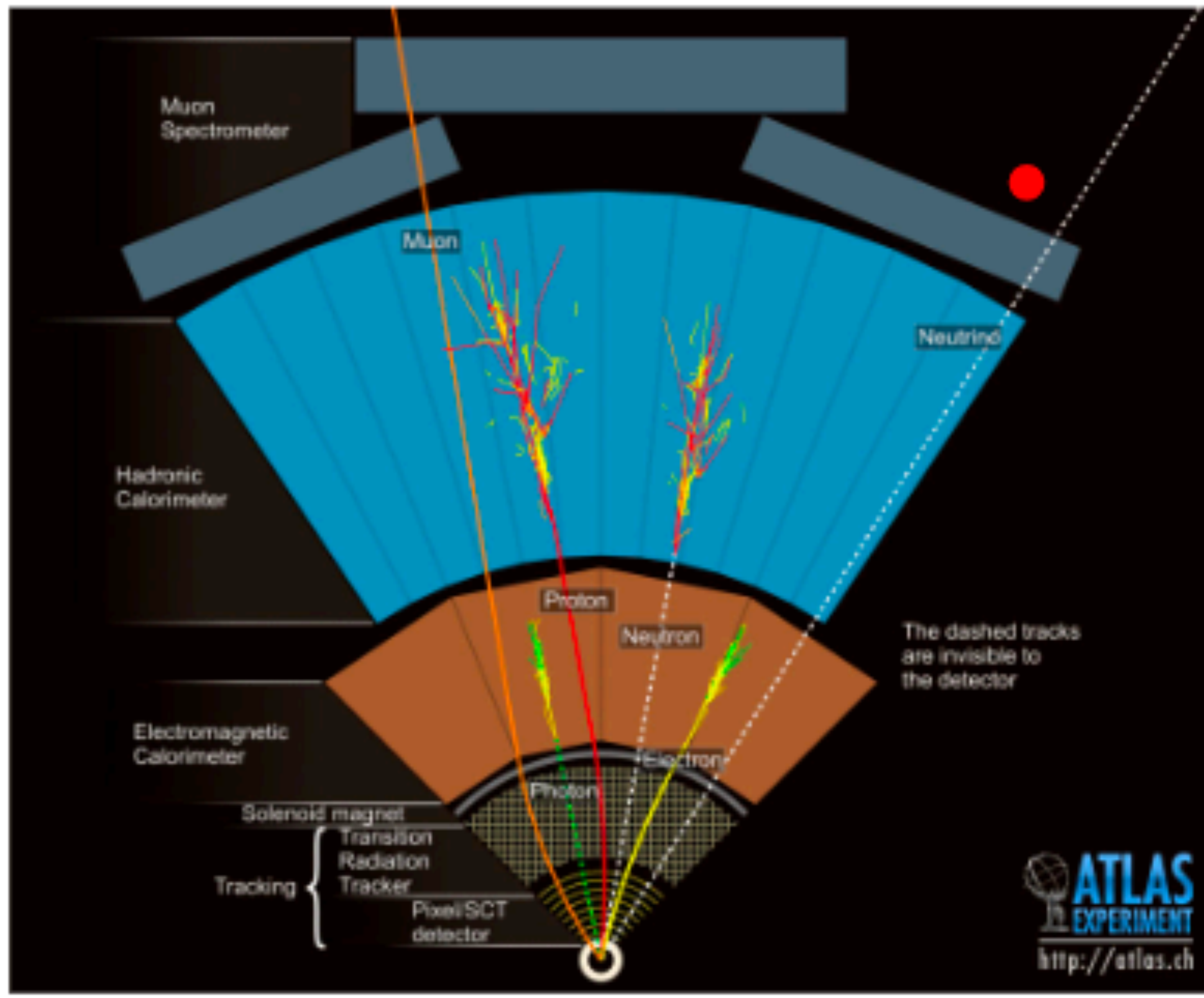
Generation, logic regression

Snapshot of Experimental Workflow - Beam to Physics

Raw

1e7

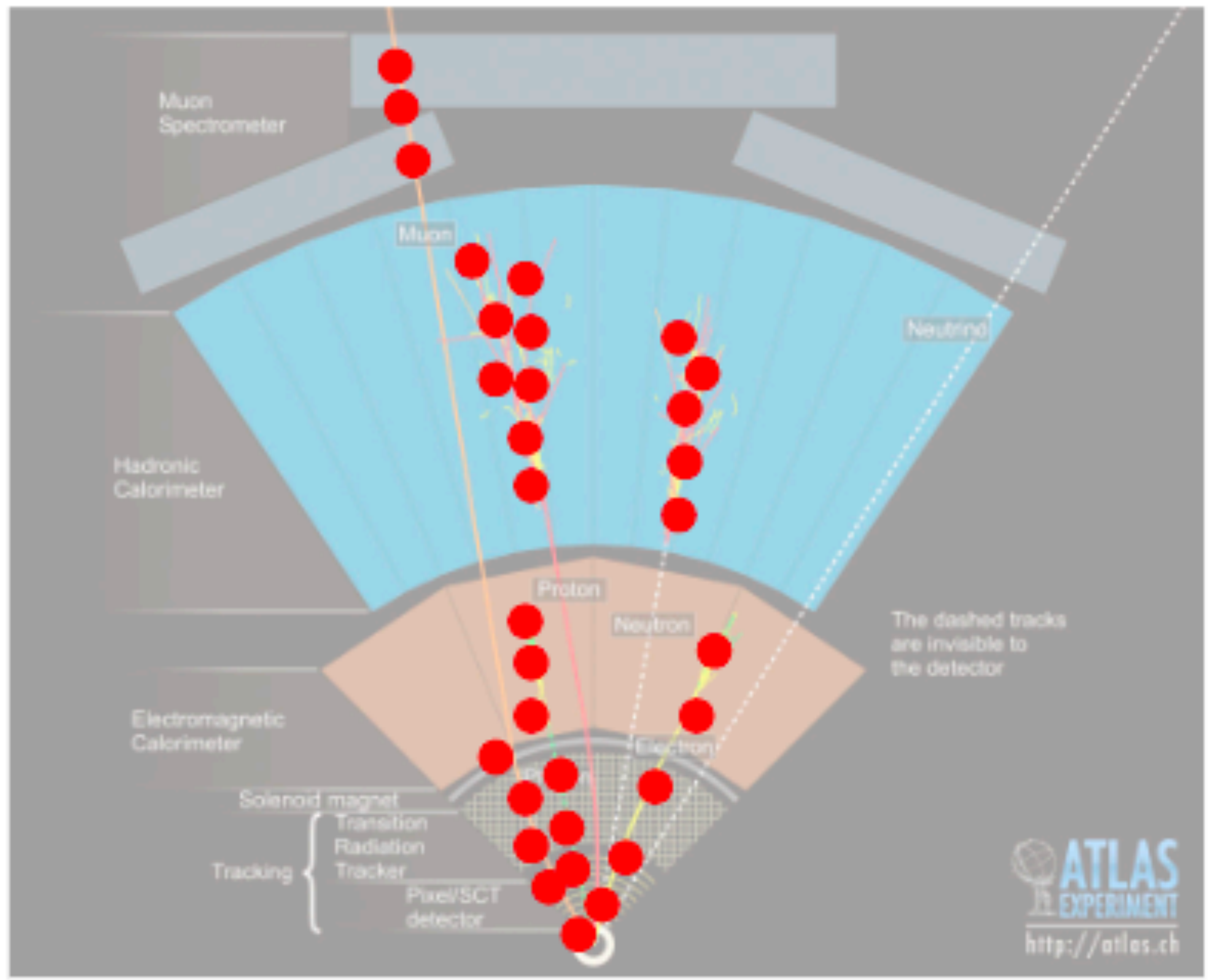
O(inputs)



Snapshot of Experimental Workflow - Beam to Physics

Raw 1e7

Sparsified 1e4



Sparsified

1e4

O(inputs)

Snapshot of Experimental Workflow - Beam to Physics

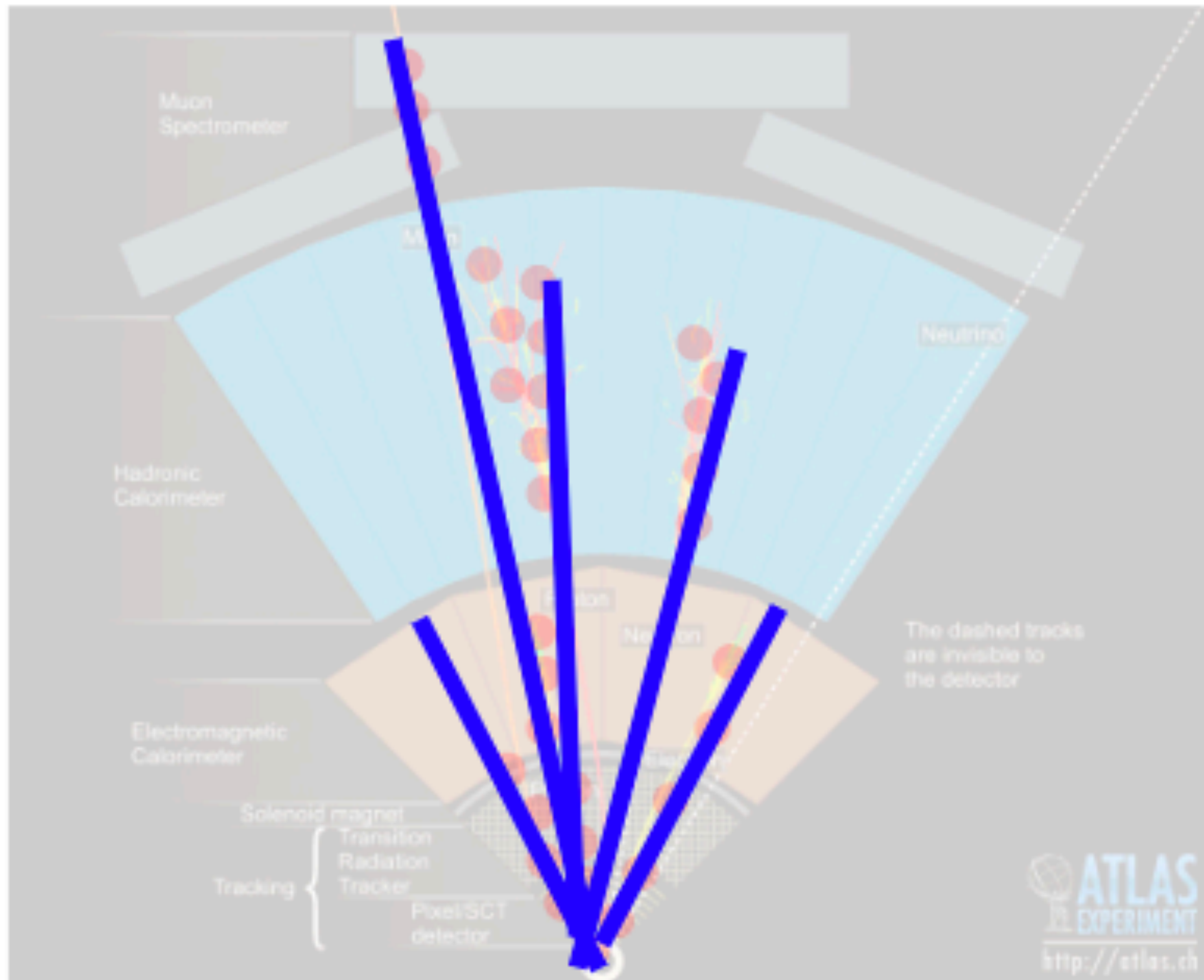
Raw
1e7

Sparsified
1e4

Reco

100-ish*

O(inputs)



Snapshot of Experimental Workflow - Beam to Physics

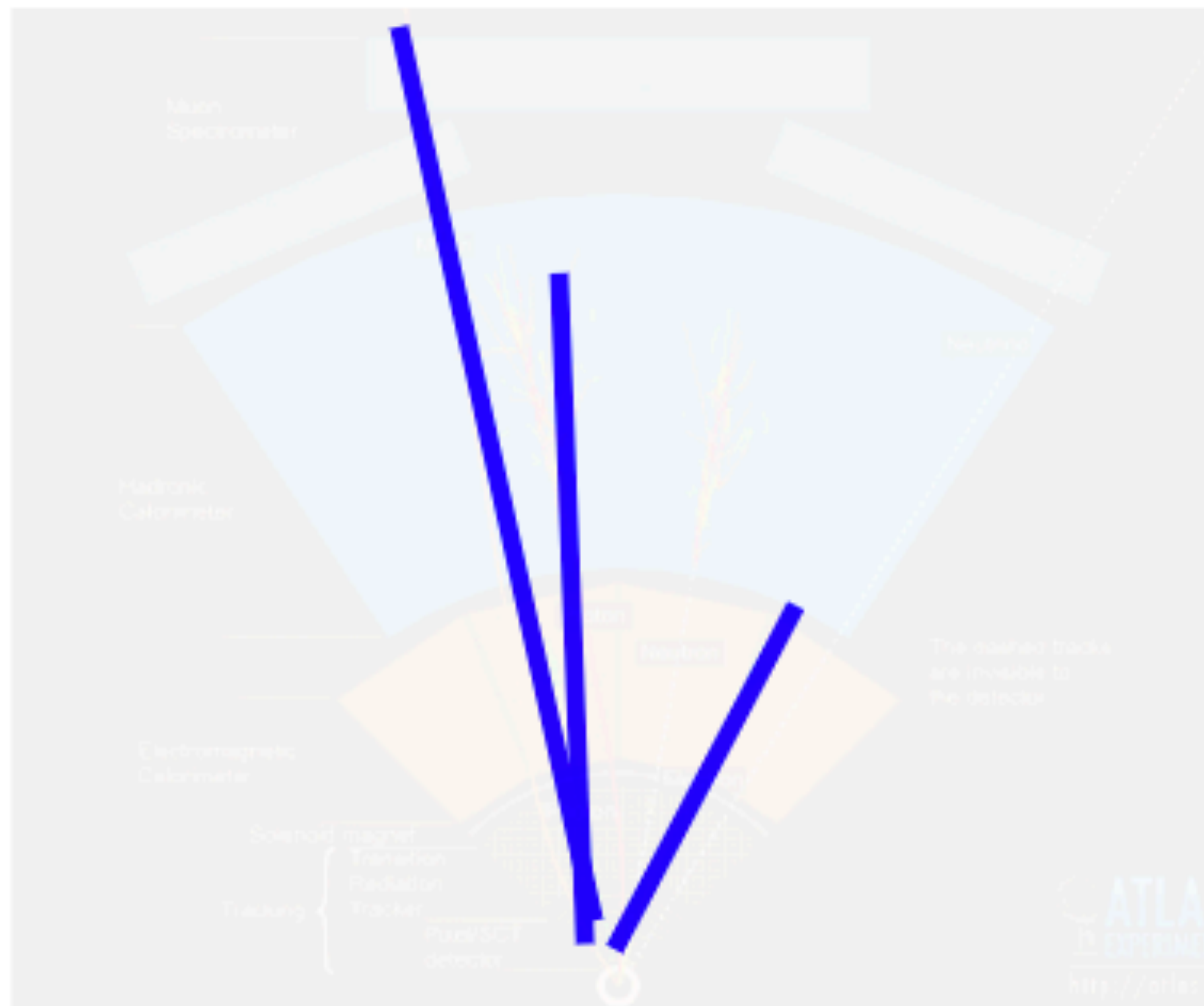
Raw 1e7

Sparsified 1e4

Select

50

O(inputs)



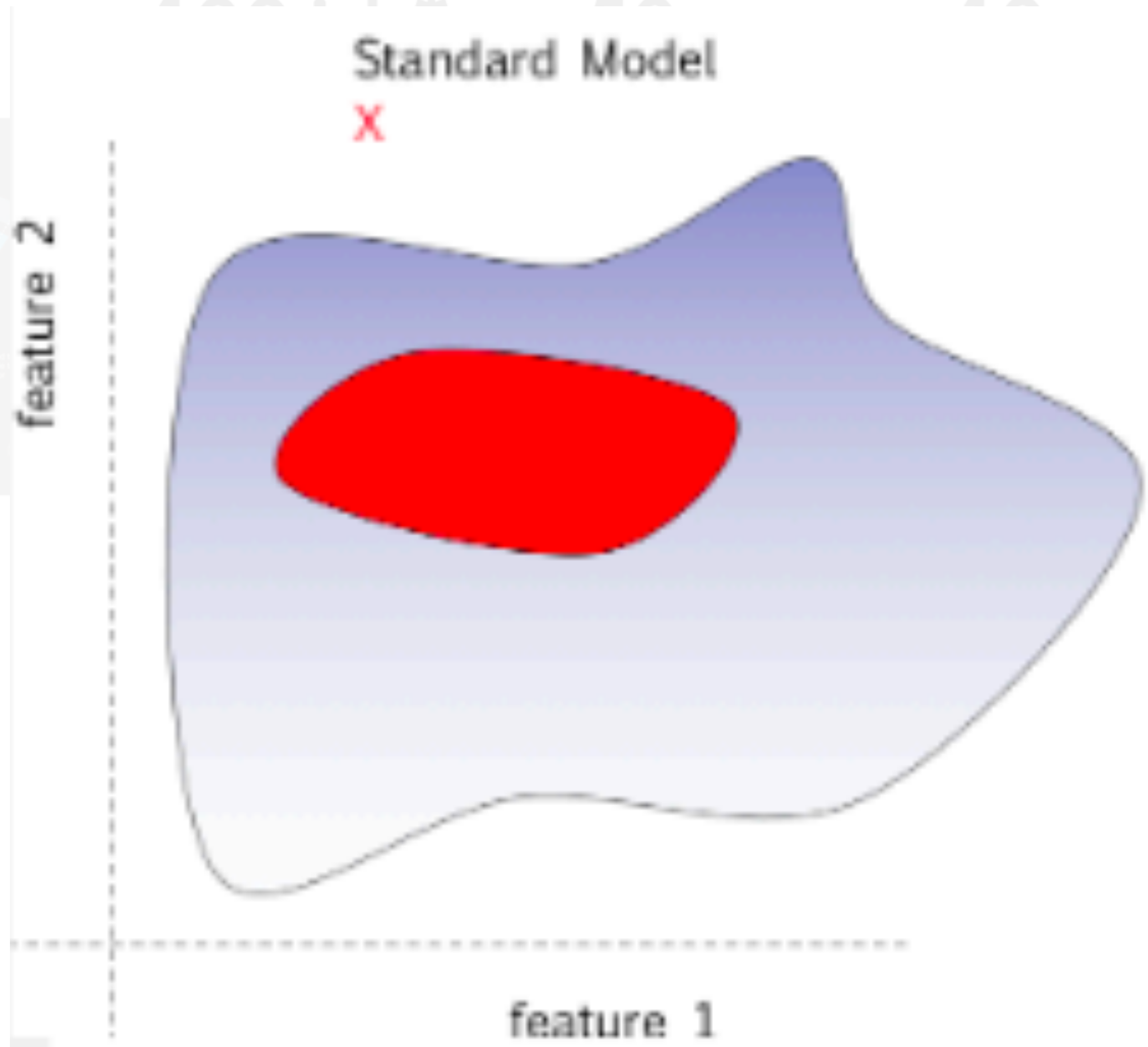
Snapshot of Experimental Workflow - Beam to Physics

Raw	Sparsified	Reco	Select	Physics	Ana
1e7	1e4				1

Physics

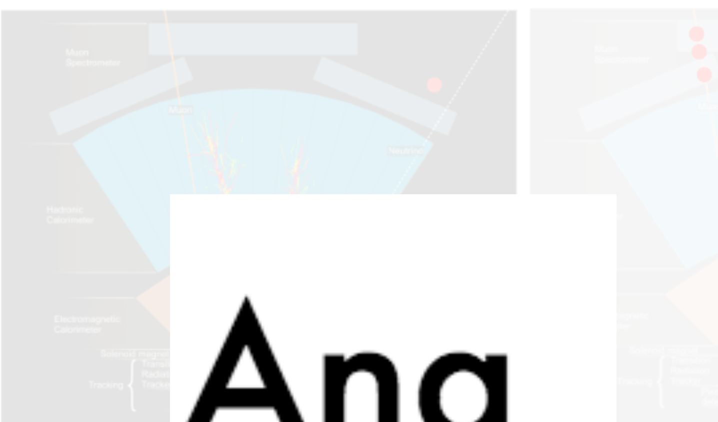
10

O(inputs)



Snapshot of Experimental Workflow - Beam to Physics

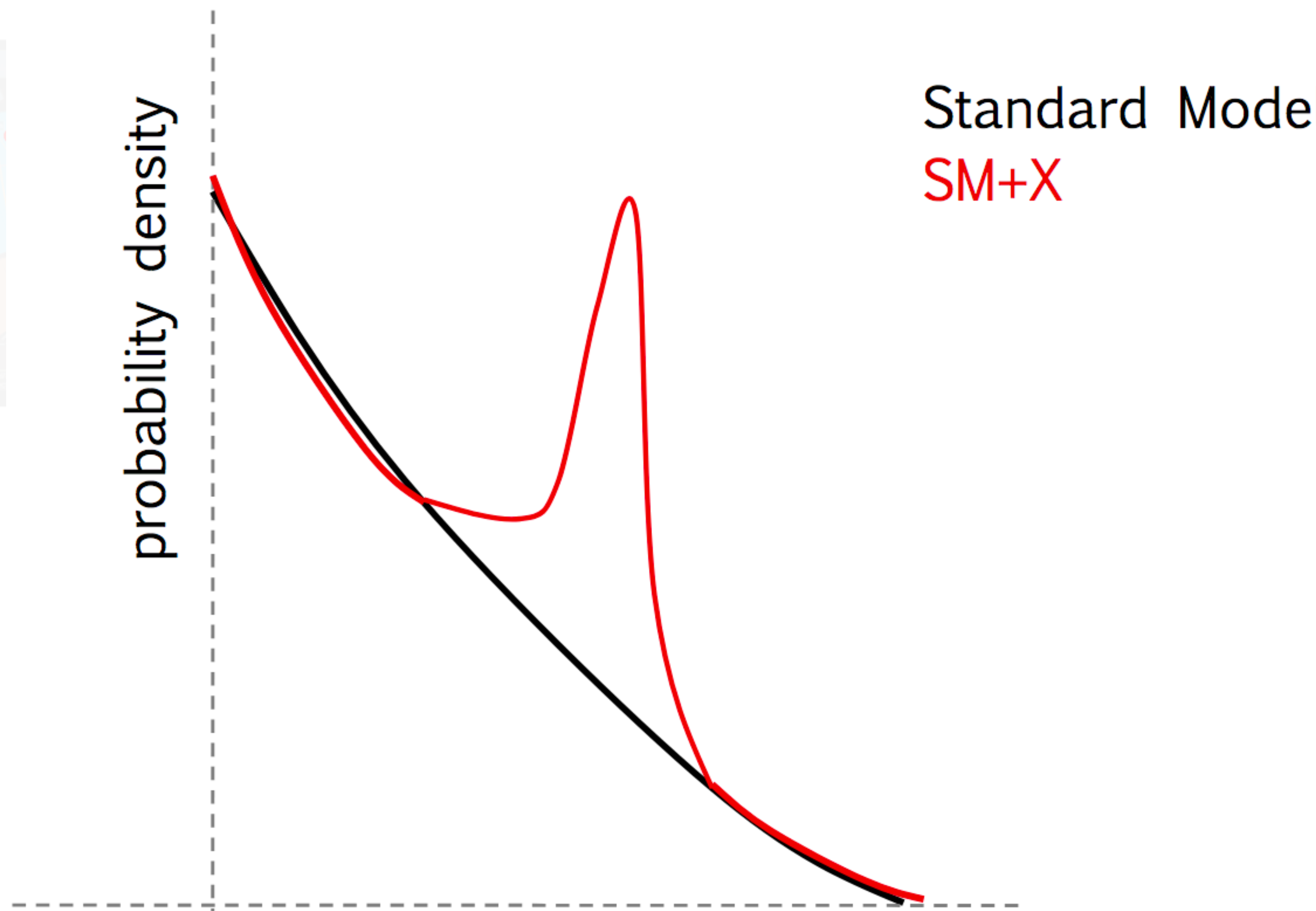
Raw	Sparsified	Reco	Select	Physics	Ana
1e7	1e4	100 ish*	50	10	1



Ana

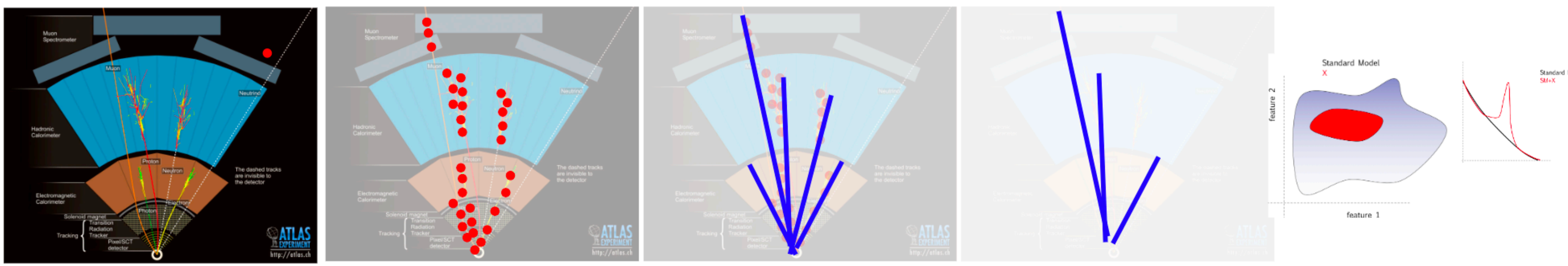
1

O(inputs)



Snapshot of Experimental Workflow - Beam to Physics

Raw	Sparsified	Reco	Select	Physics	Ana
1e7	1e4	100-ish*	50	10	1

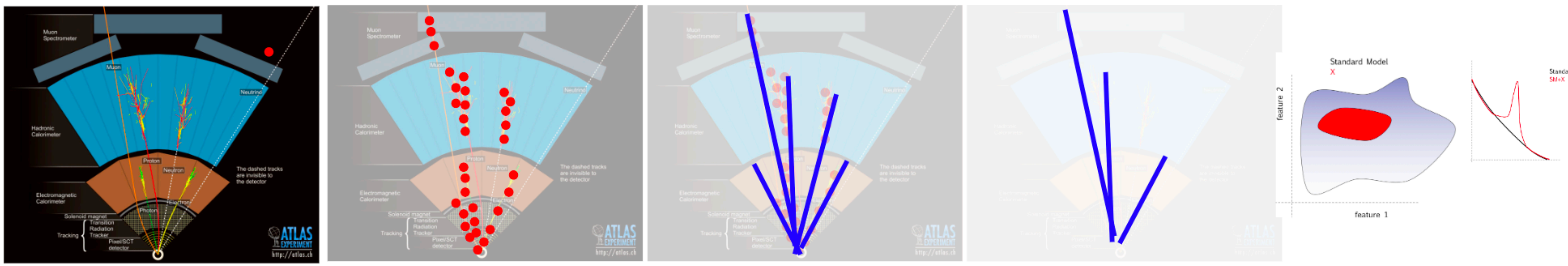


Particle Physics	Zero suppression	Reconstruction	Quality Selection	Observables
Machine Learning	Down-Sampling	Dimensionality Reduction	Low Level Features	High Level Features

- Who does this work?

Snapshot of Experimental Workflow - Beam to Physics

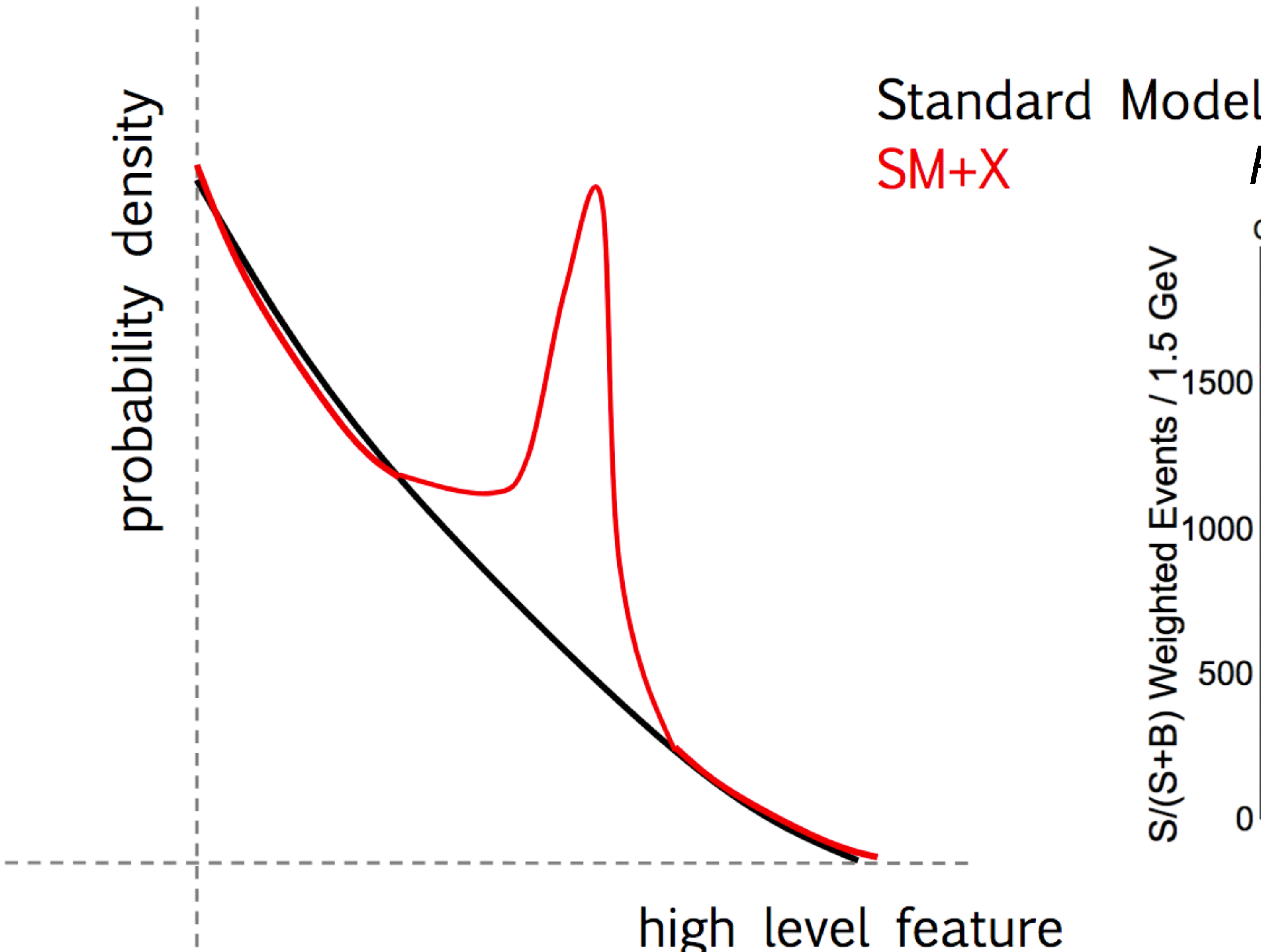
Raw	Sparsified	Reco	Select	Physics	Ana
1e7	1e4	100-ish*	50	10	1



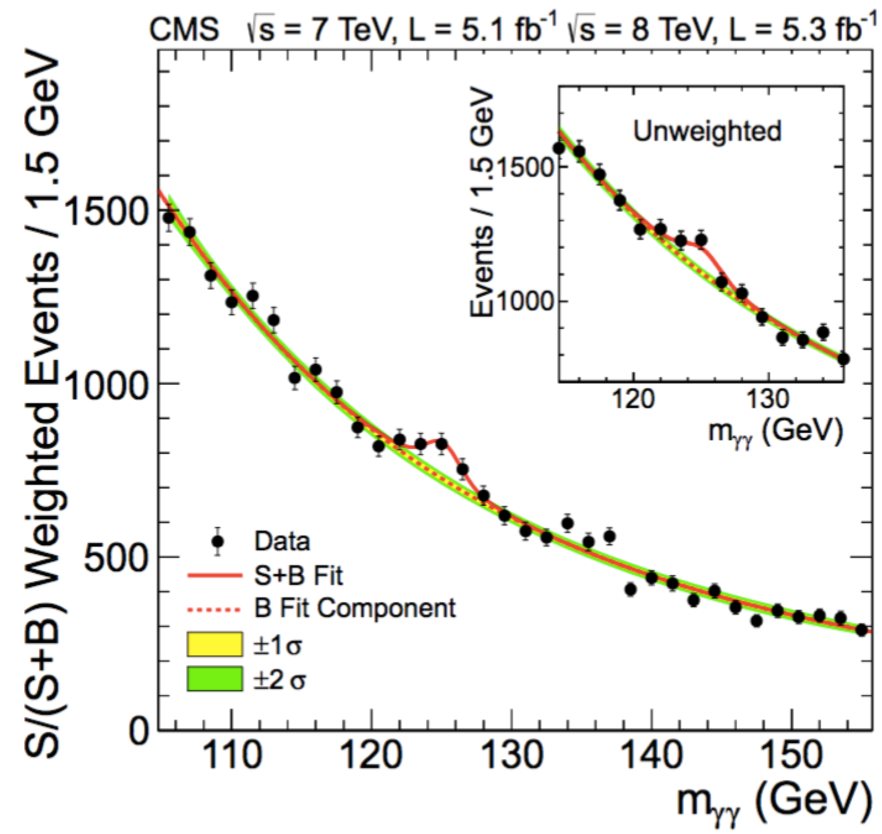
Particle Physics	Zero suppression	Reconstruction	Quality Selection	Observables
Machine Learning	Down-Sampling	Dimensionality Reduction	Low Level Features	High Level Features

- Active human input in going from ‘Raw’ to ‘High Level’ feature(s)
- Algorithms run (extremely quickly) to select events with useful features for further human analysis

Successful analysis!

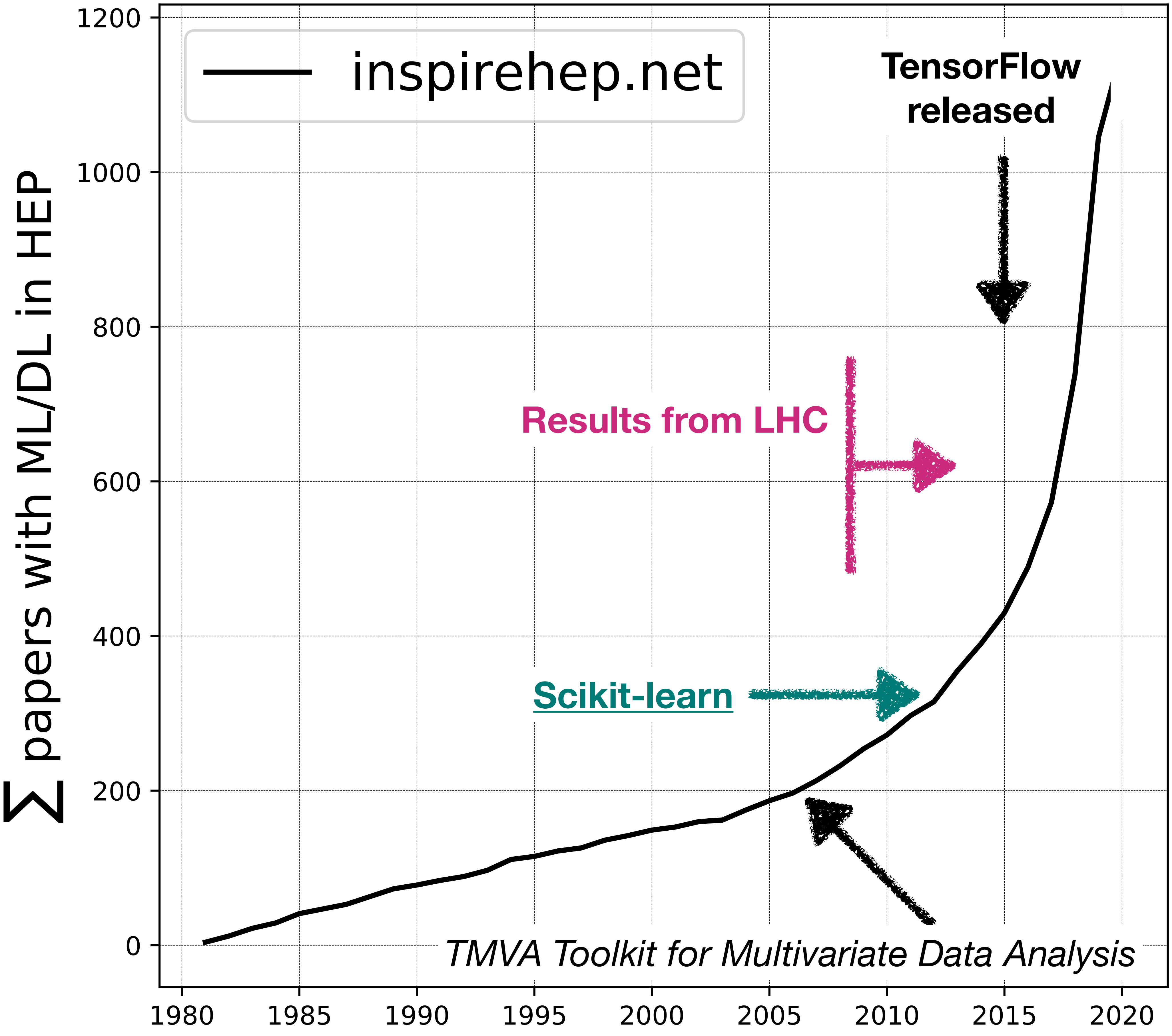


Phys. Lett. B 716 (2012) 30

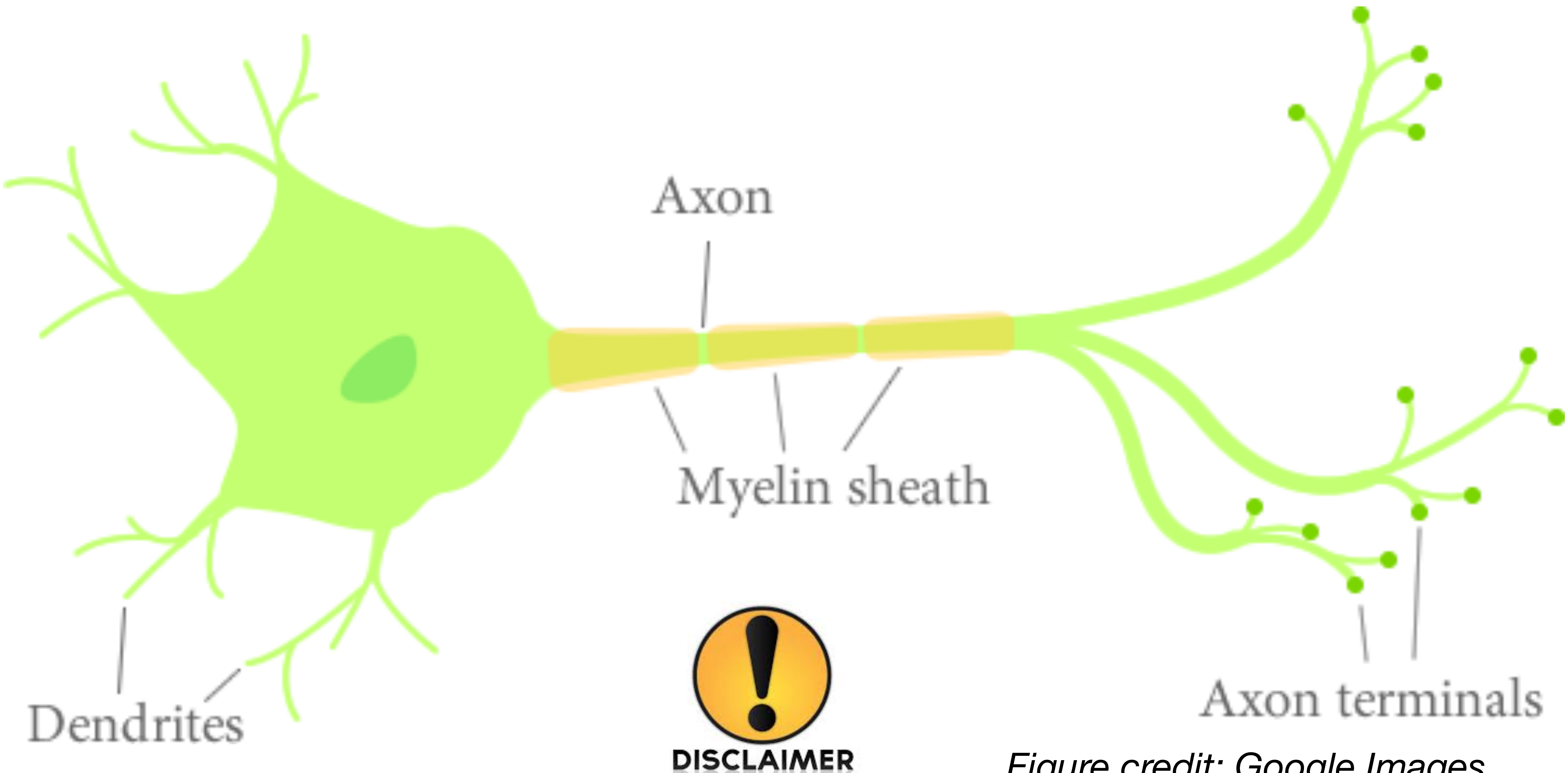


The Nobel Prize in Physics 2013
François Englert, Peter Higgs

We look for a region in feature space where the two hypotheses have large differences in their predictions.


inspirehep.net
TensorFlow released
Results from LHC
Scikit-learn
TMVA Toolkit for Multivariate Data Analysis
$\sum$ papers with ML/DL in HEP
0
200
400
600
800
1000
1200
1980
1985
1990
1995
2000
2005
2010
2015
2020

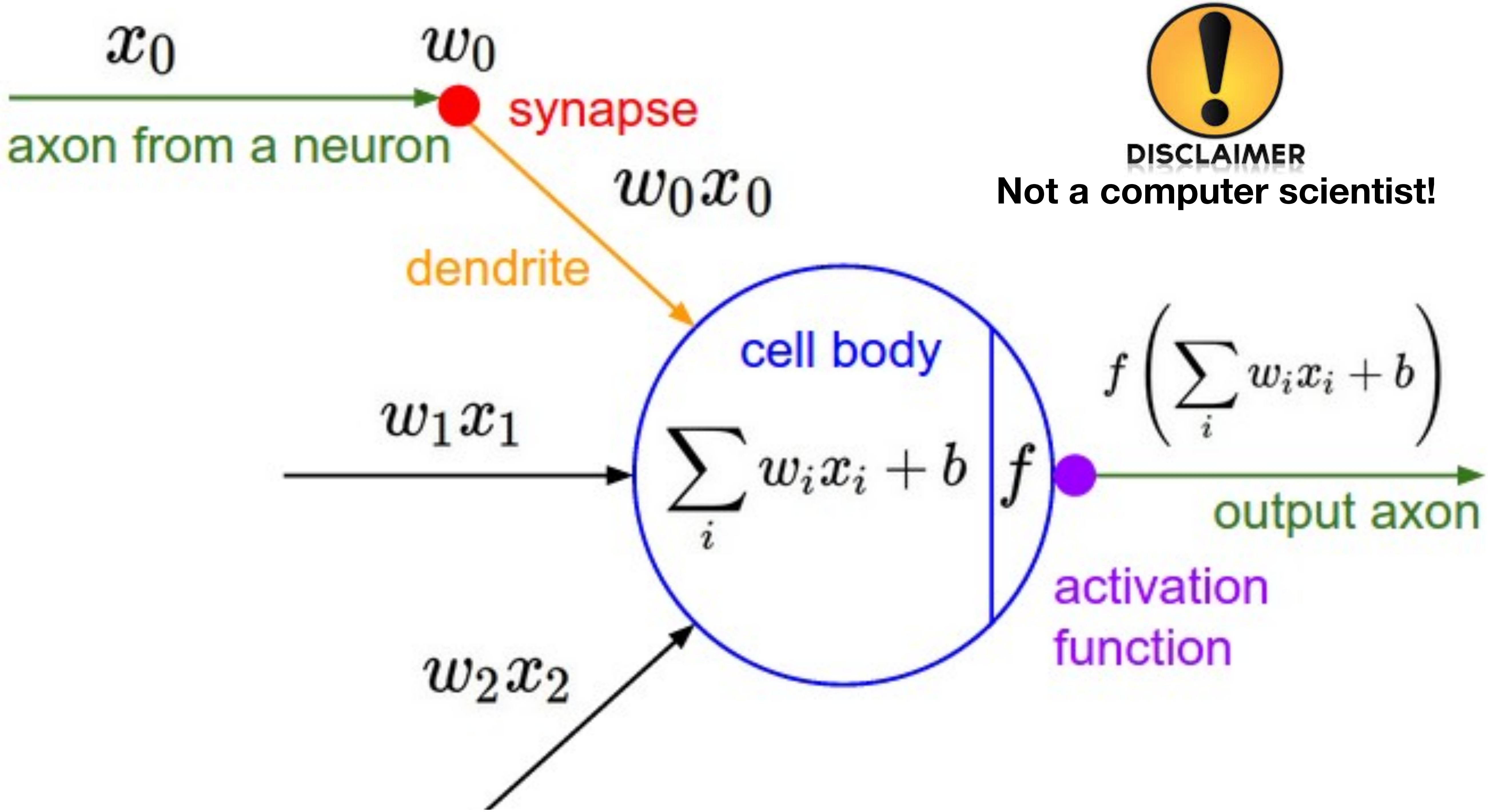
Real Neuron



Not a biologist!

Figure credit: Google Images

Artificial Neuron

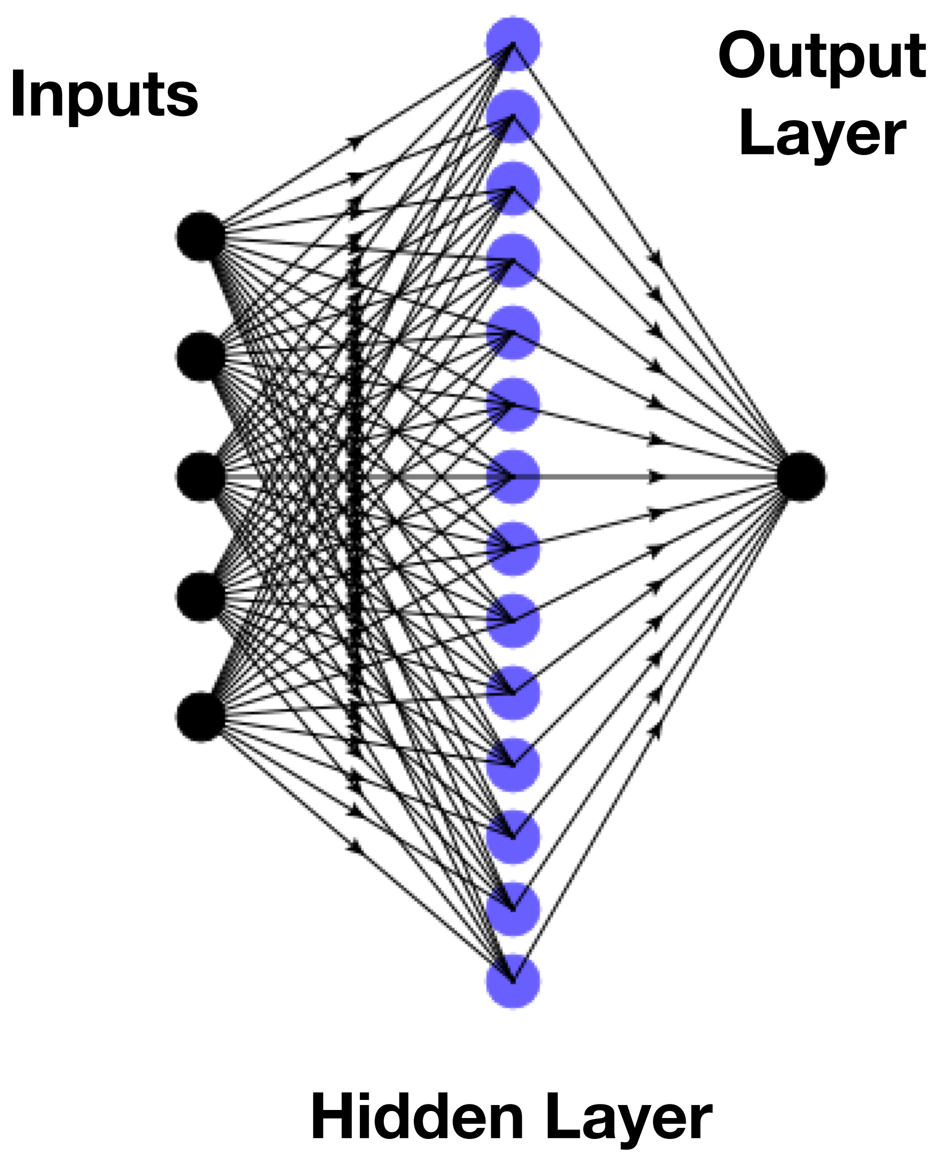


DISCLAIMER

Not a computer scientist!

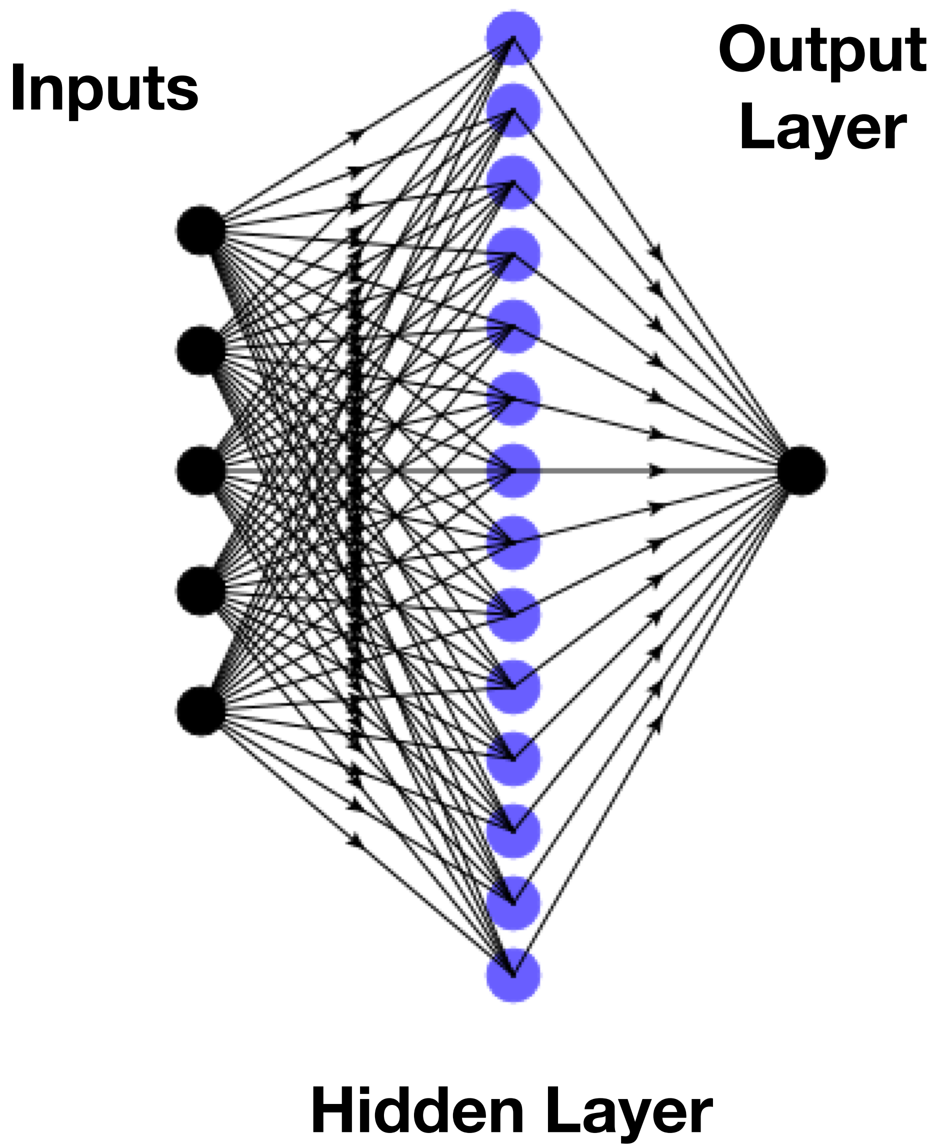
https://leonardoaraujosantos.gitbooks.io/artificial-inteligence/content/neural_networks.html

MultiLayer Perceptron (MLP)



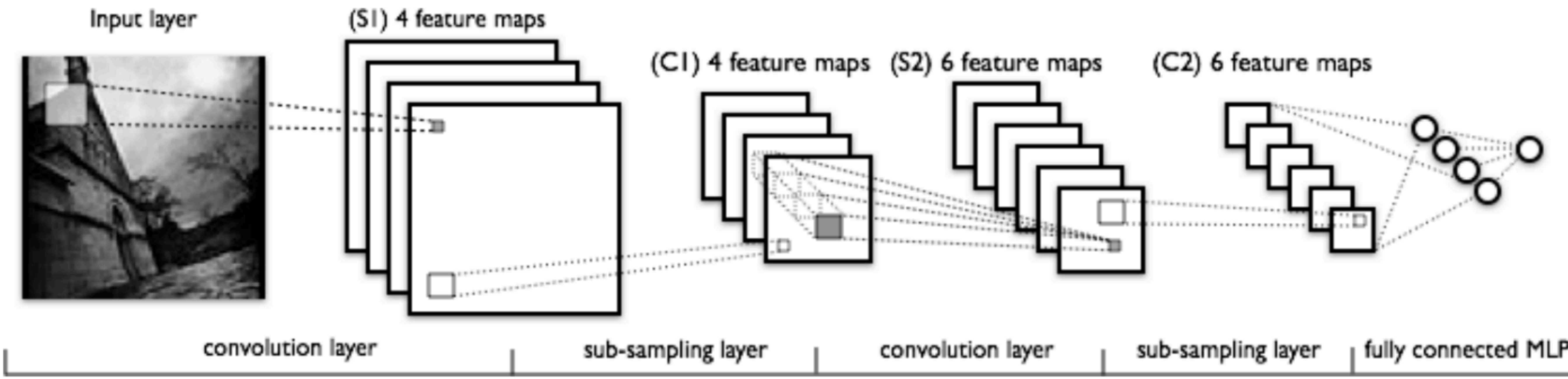
- Hidden node ● = h_i + AF(Sum w_i ●)
- AF : Activation Functions (non-Linear)
- Output Layer -> For binary classification problems [0,1]
- For non-linear behavior?

MultiLayer Perceptron (MLP)



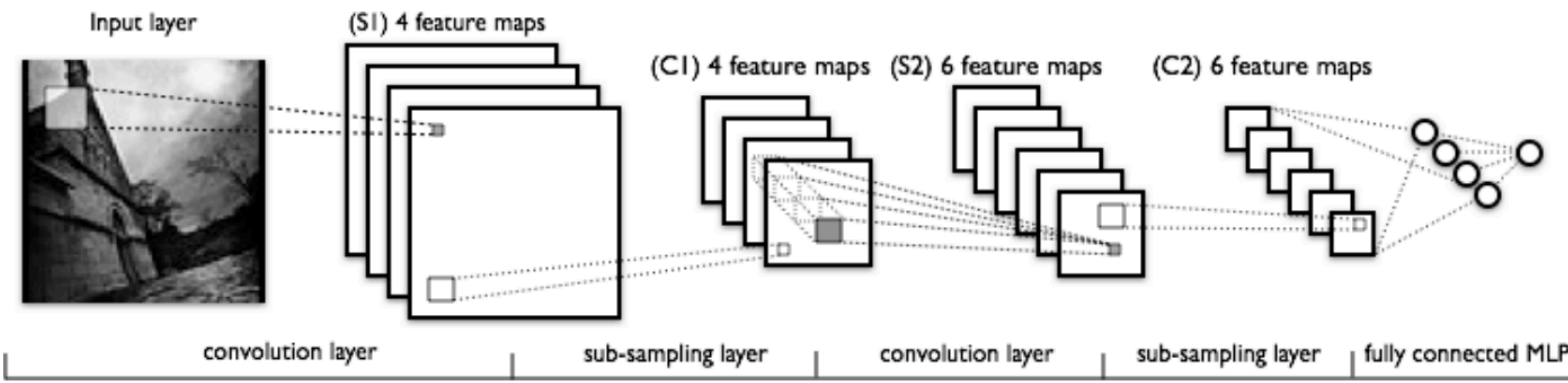
- Hidden node ● = h_i + AF(Sum w_i ●)
- AF : Activation Functions (non-Linear)
- Output Layer -> For binary classification problems [0,1]
- For non-linear behavior - increase number of hidden layers and vary activation functions
- This is a fully connected network

Convolutional Neural Networks



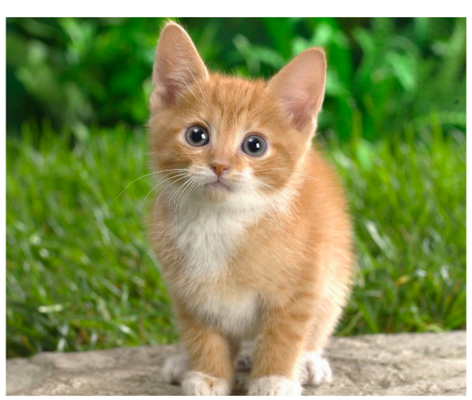
https://skymind.ai/wiki/convolutional-network

Convolutional Neural Networks

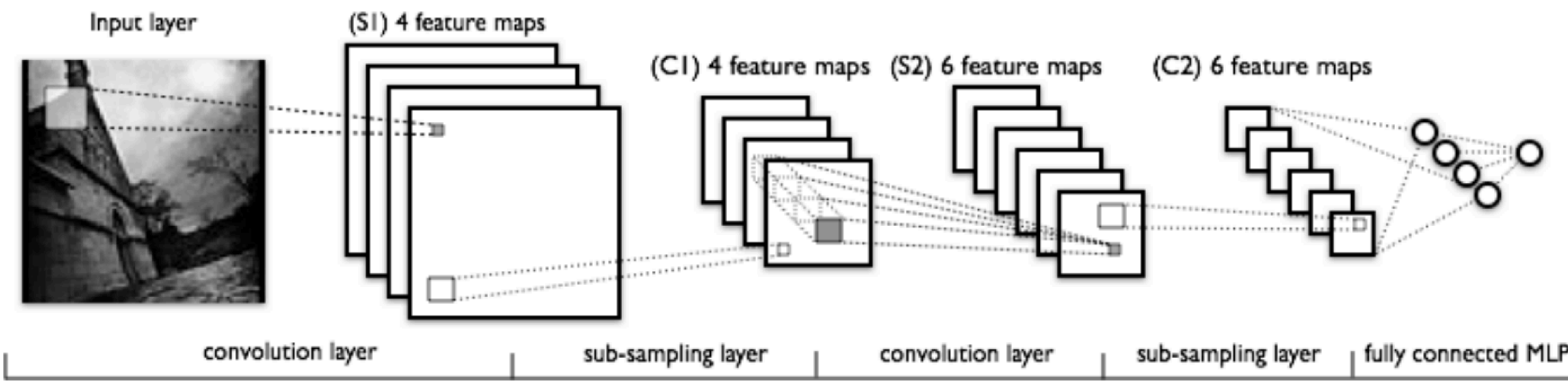


https://skymind.ai/wiki/convolutional-network

Classification

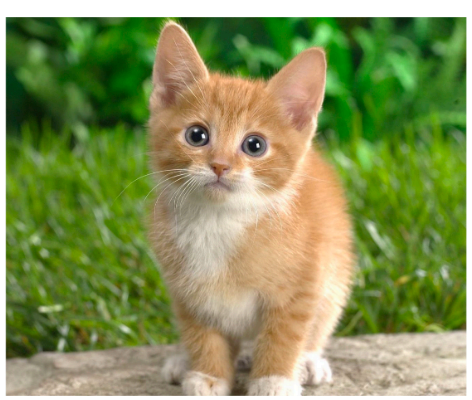


Convolutional Neural Networks

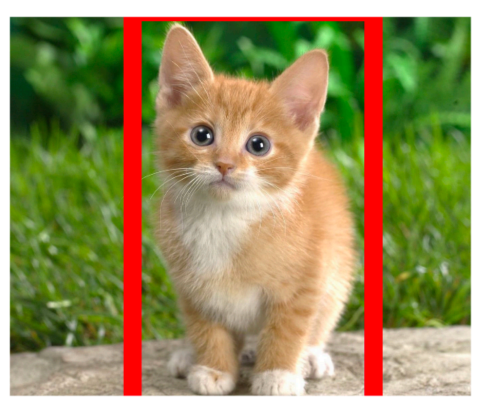


https://skymind.ai/wiki/convolutional-network

Classification

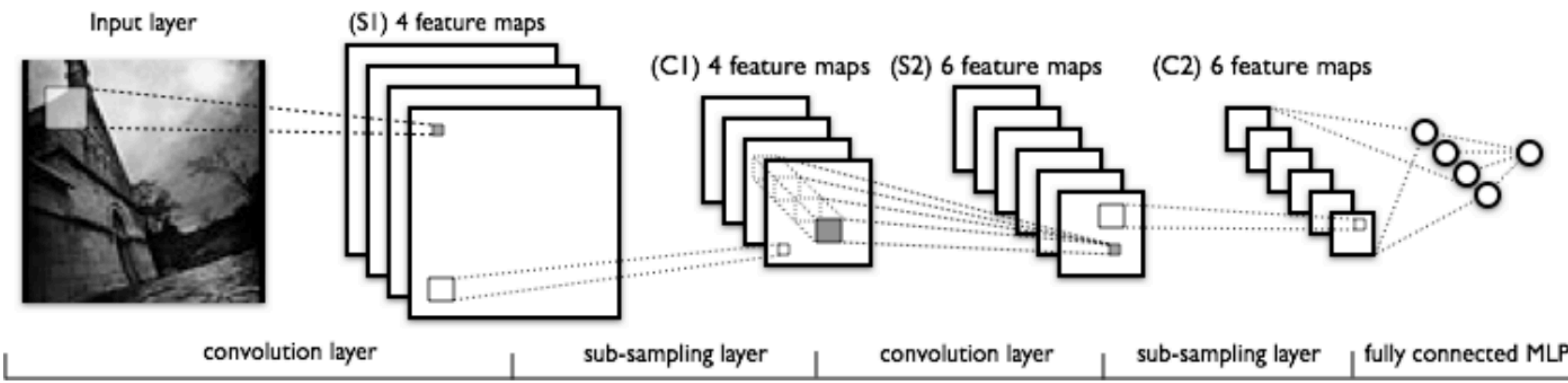


Classification + Localization



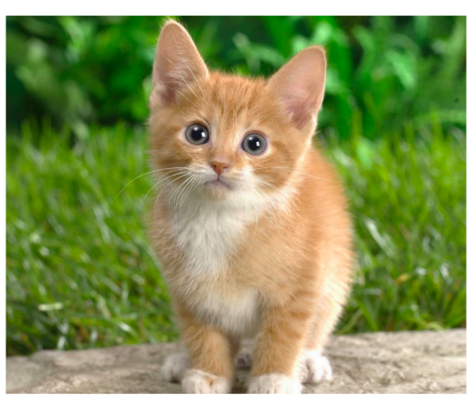
Cat

Convolutional Neural Networks

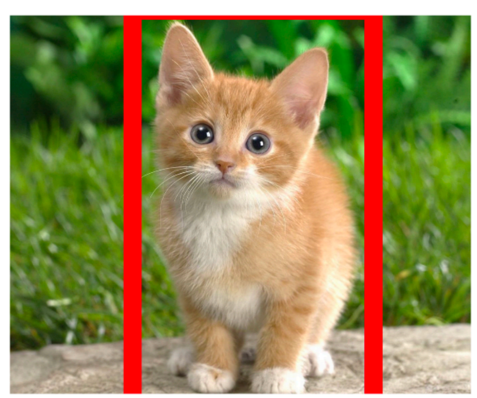


https://skymind.ai/wiki/convolutional-network

Classification

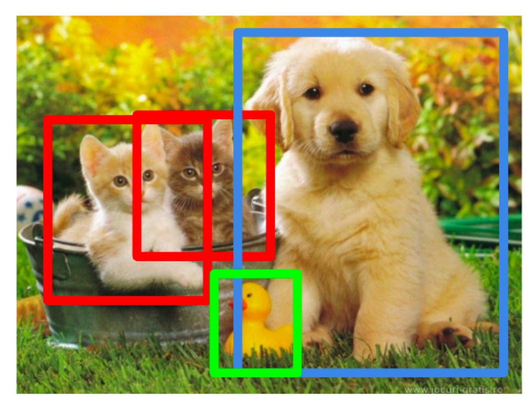


Classification + Localization



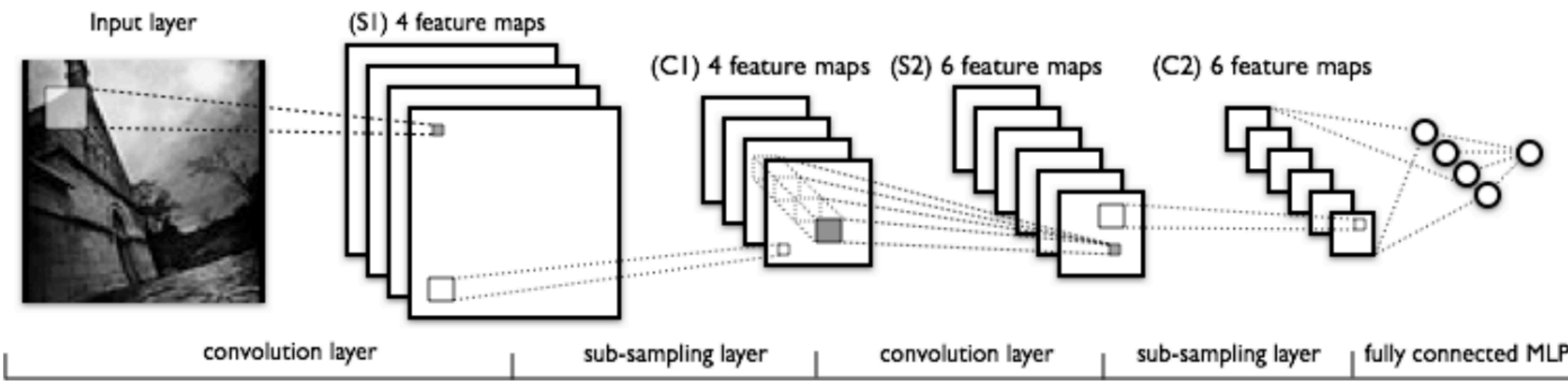
Cat

Object detection



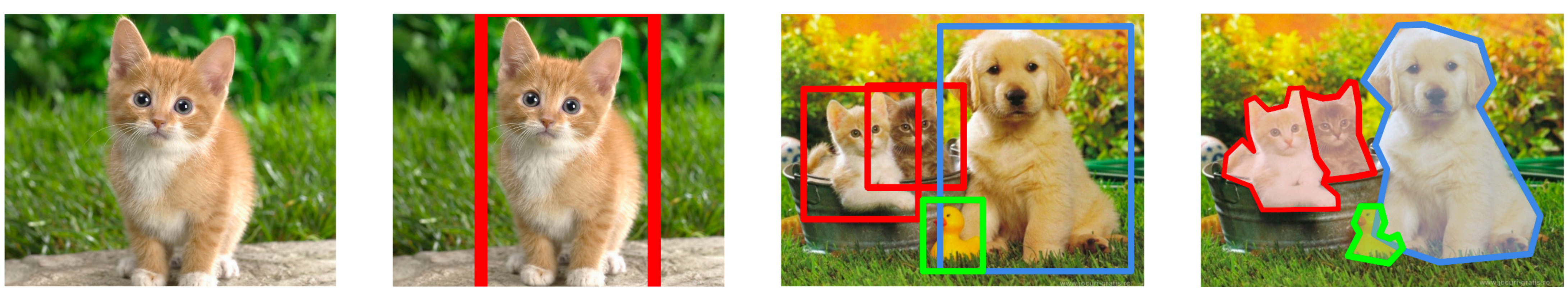
Cat, Dog, Duck

Convolutional Neural Networks



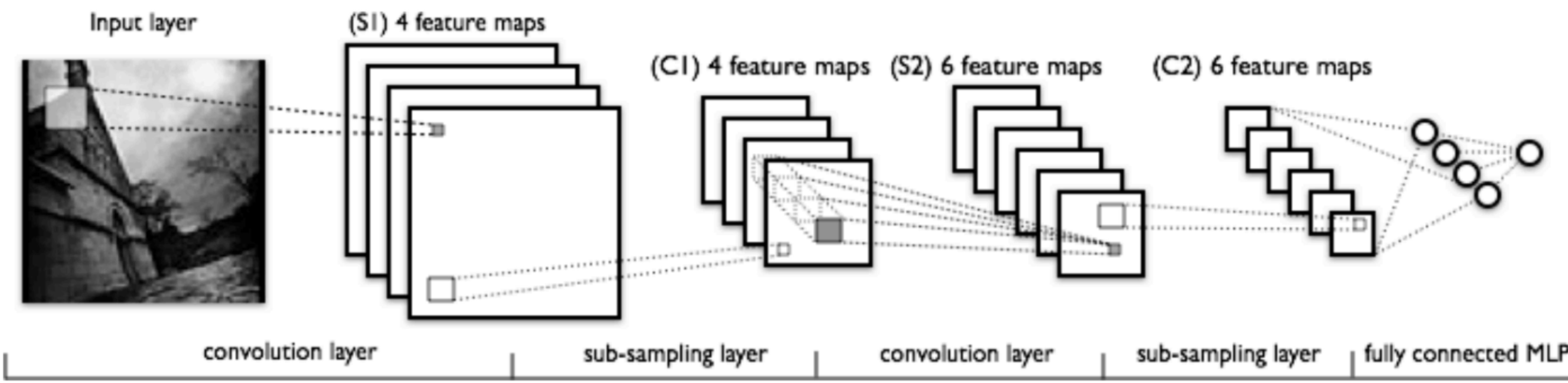
https://skymind.ai/wiki/convolutional-network

Classification | Classification + Localization | Object detection | Instance segmentation



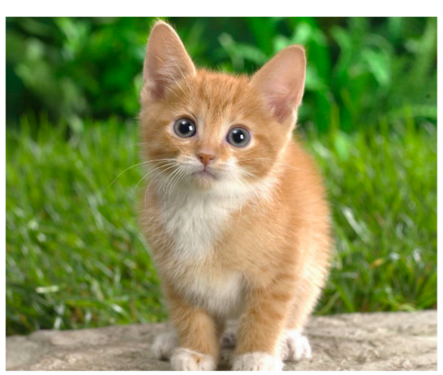
Cat | Cat, Dog, Duck | Cat, Dog, Duck

Convolutional Neural Networks

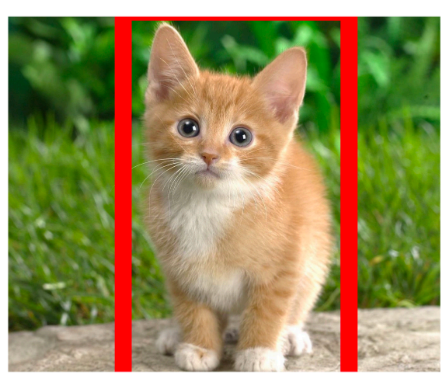


https://skymind.ai/wiki/convolutional-network

Classification

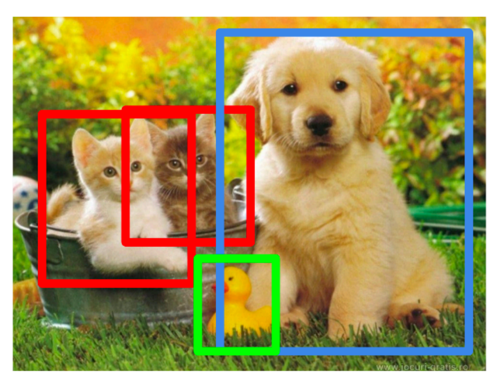


Classification + Localization



Cat

Object detection

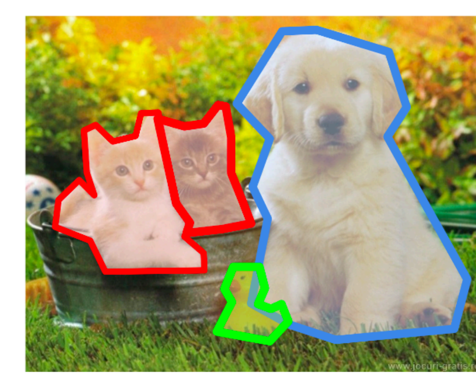


Cat, Dog, Duck

Instance segmentation

Cat, Dog, Duck

Image read-out



“There is a dog and two cats sitting down”

Tools of the trade

https://www.tensorflow.org/ *https://keras.io/* *http://pytorch.org/*

- TensorFLow - Google developed backend for multi-dimensional vectors and their manipulations
- Keras - External Package good for beginners
- PyTorch - more state of the art with potential for multiple variations

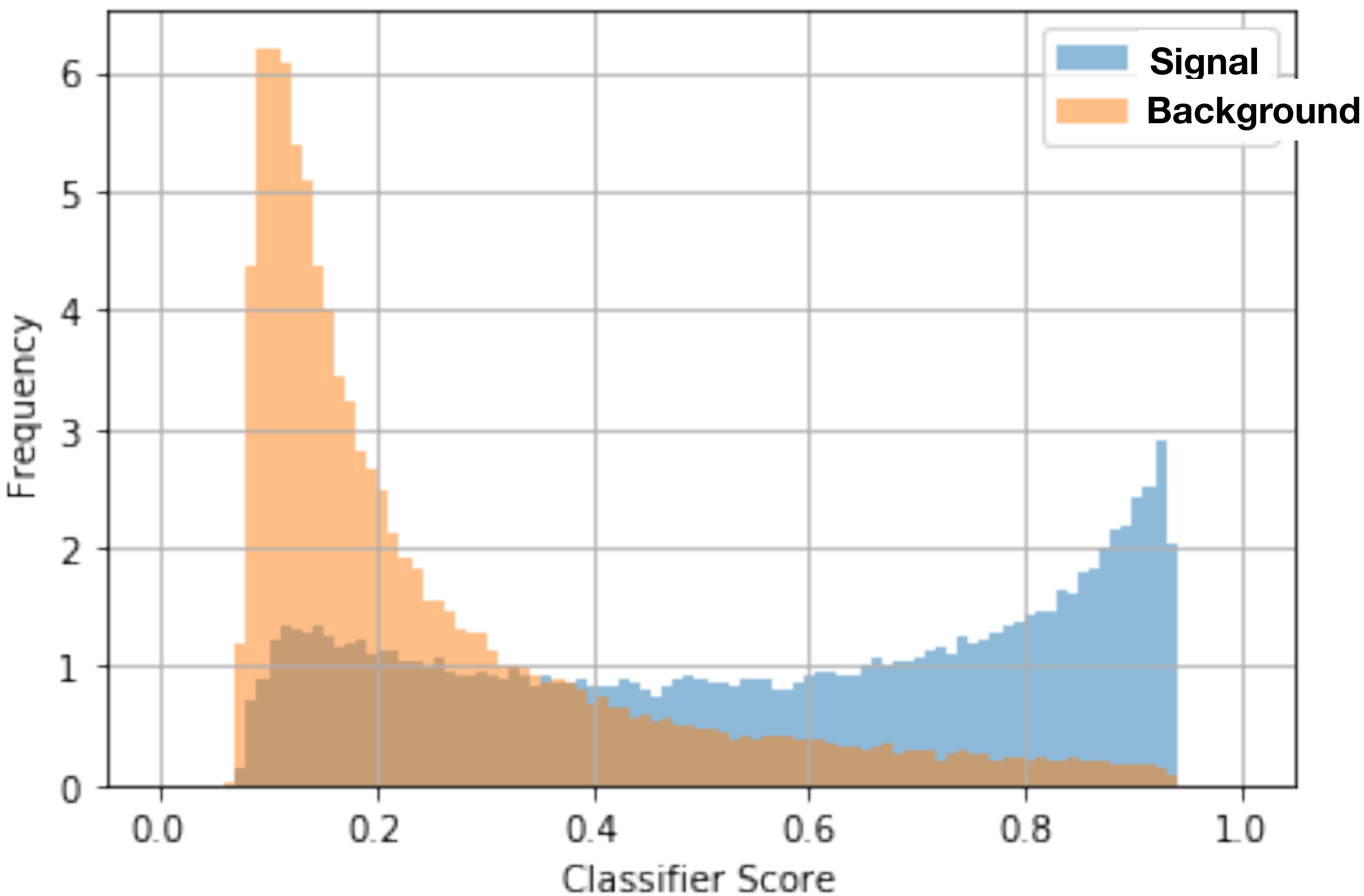
How to quantify or grade a model at classification

Name in Physics	Name in ML/CV	Definition
Efficiency	True Positive Rate/Recall	$TPR = \frac{TP}{P} = \frac{TP}{TP + FN}$
Misid. Probability	False Positive Rate	$FPR = \frac{FP}{N} = \frac{FP}{FP + TN}$
Rejection	----------------------------	$Rej = \frac{1}{FPR}$
Purity	Precision	$PREC = \frac{TP}{TP + FP}$

- T: True, F: False, P: Positive, N: Negative

ROC Curves

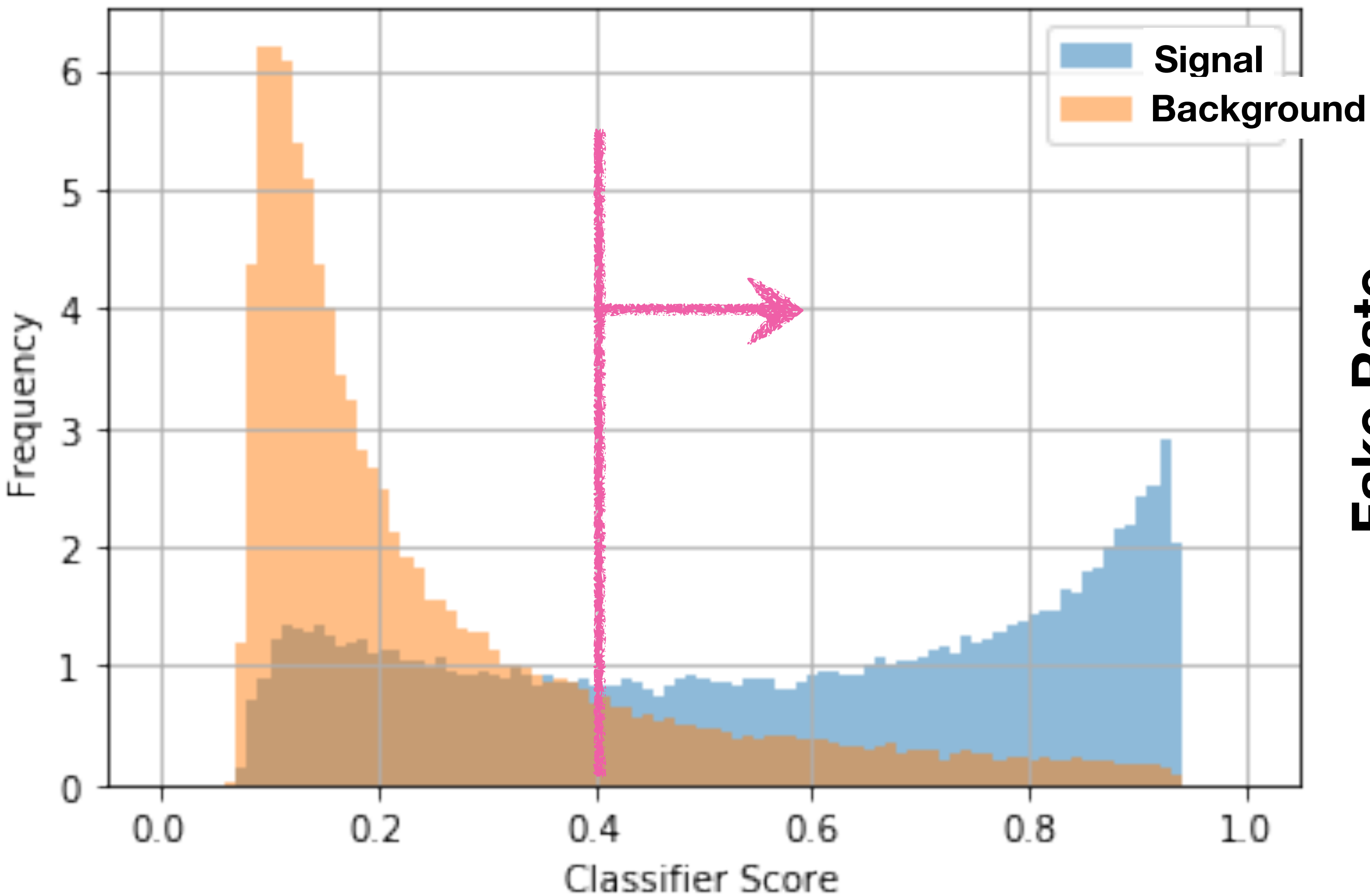
Receiver Operator Characteristic

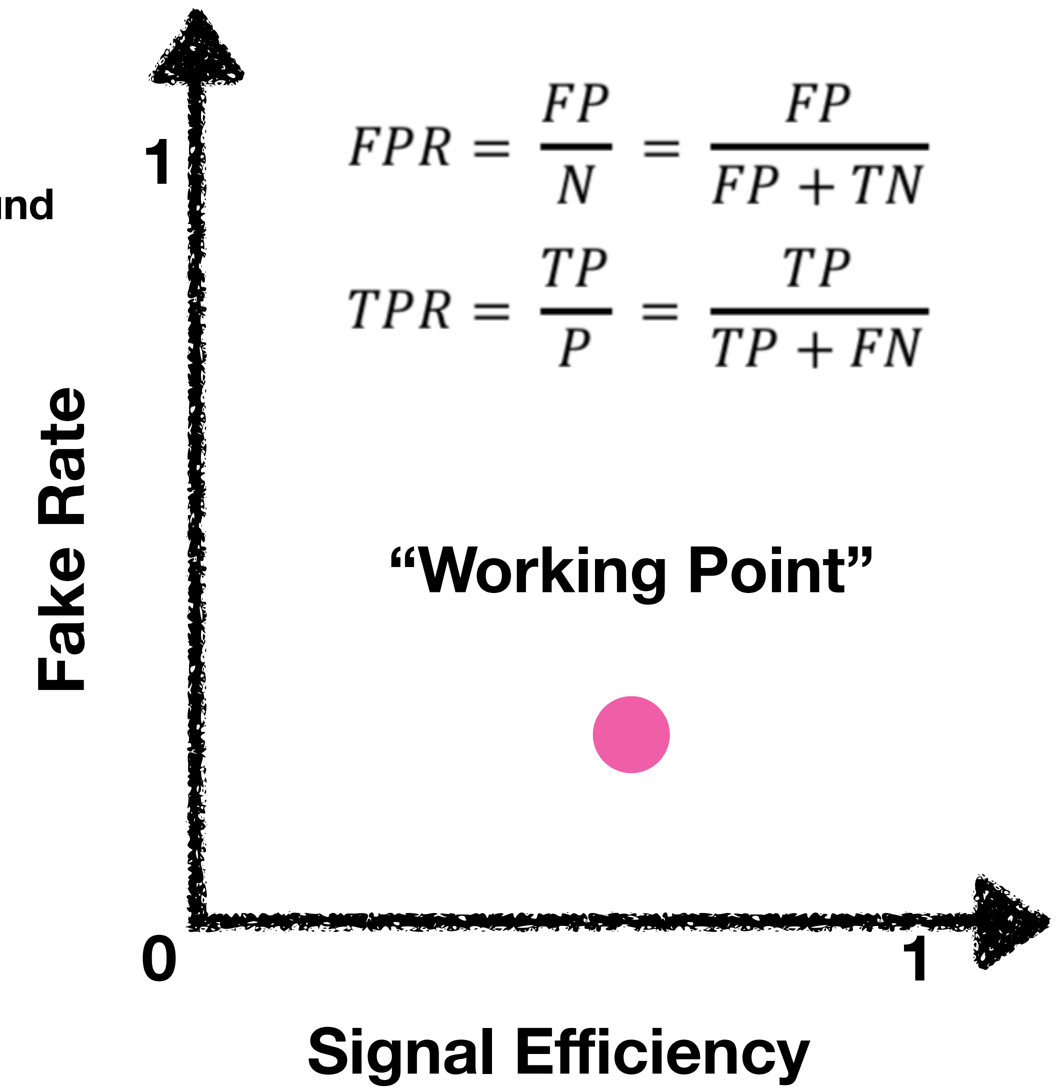


- Classifier score - Values from the output layer

ROC Curves

Receiver Operator Characteristic

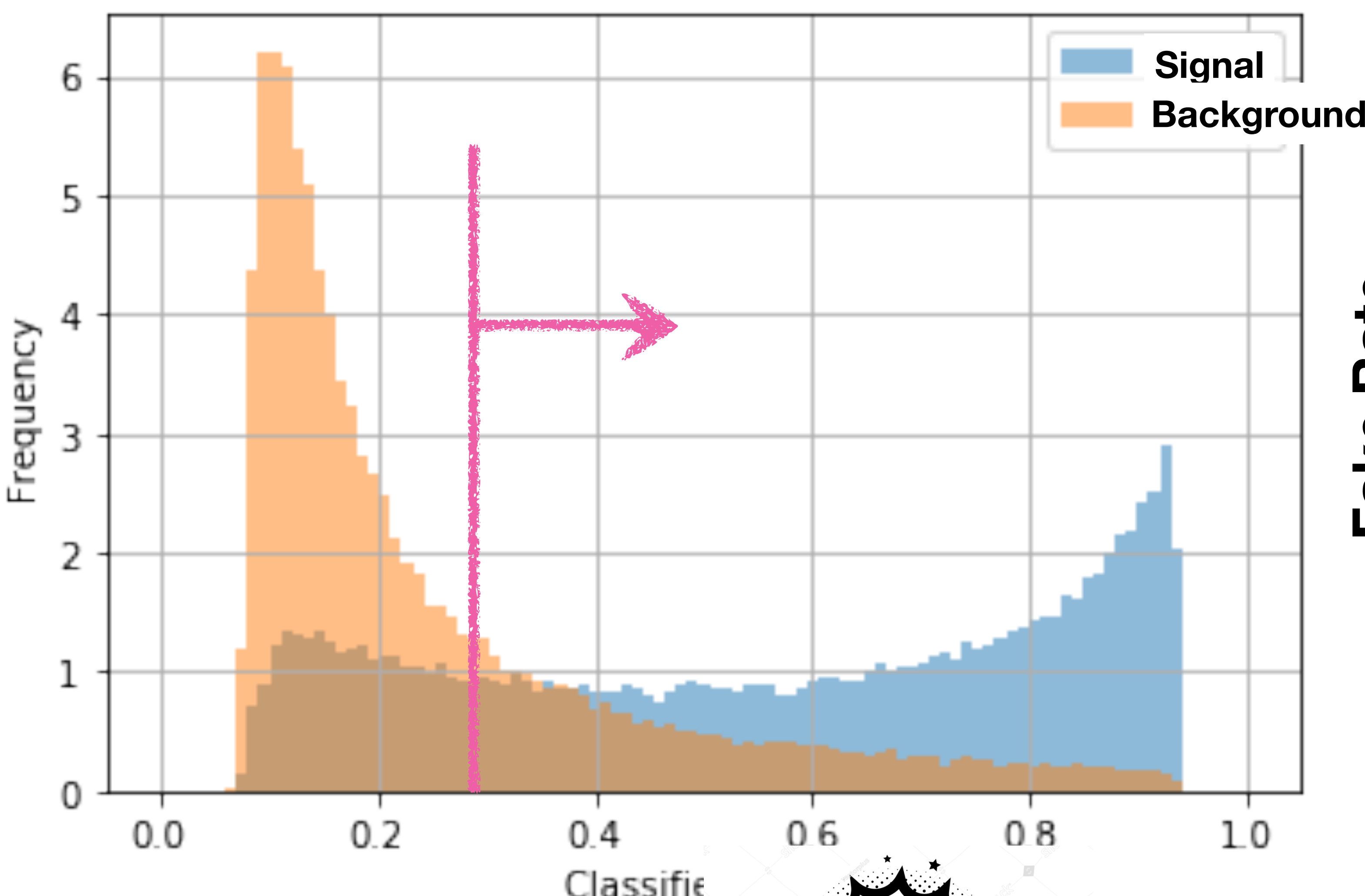


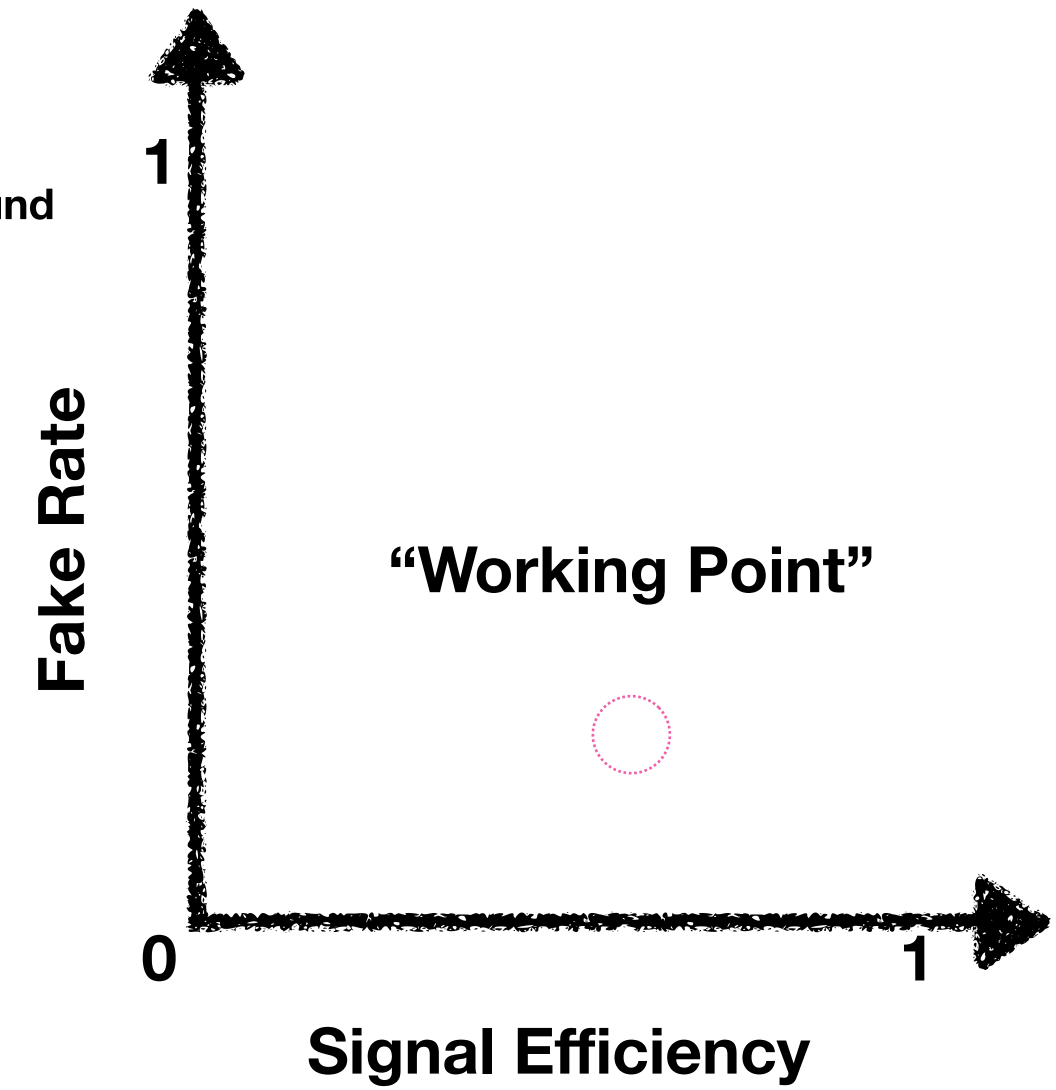


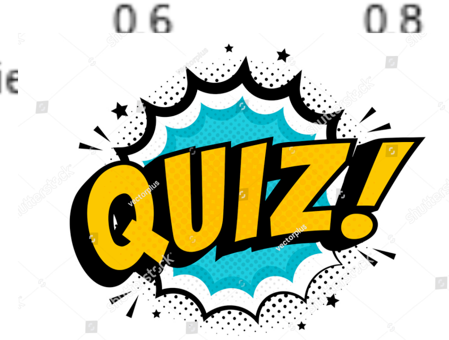
- Choose a particular value and estimate Efficiency/Fake-Rate
- Efficiency = Selected Blue / Total Blue
- Fake Rate = Selected Yellow / Total Selected

ROC Curves

Receiver Operator Characteristic



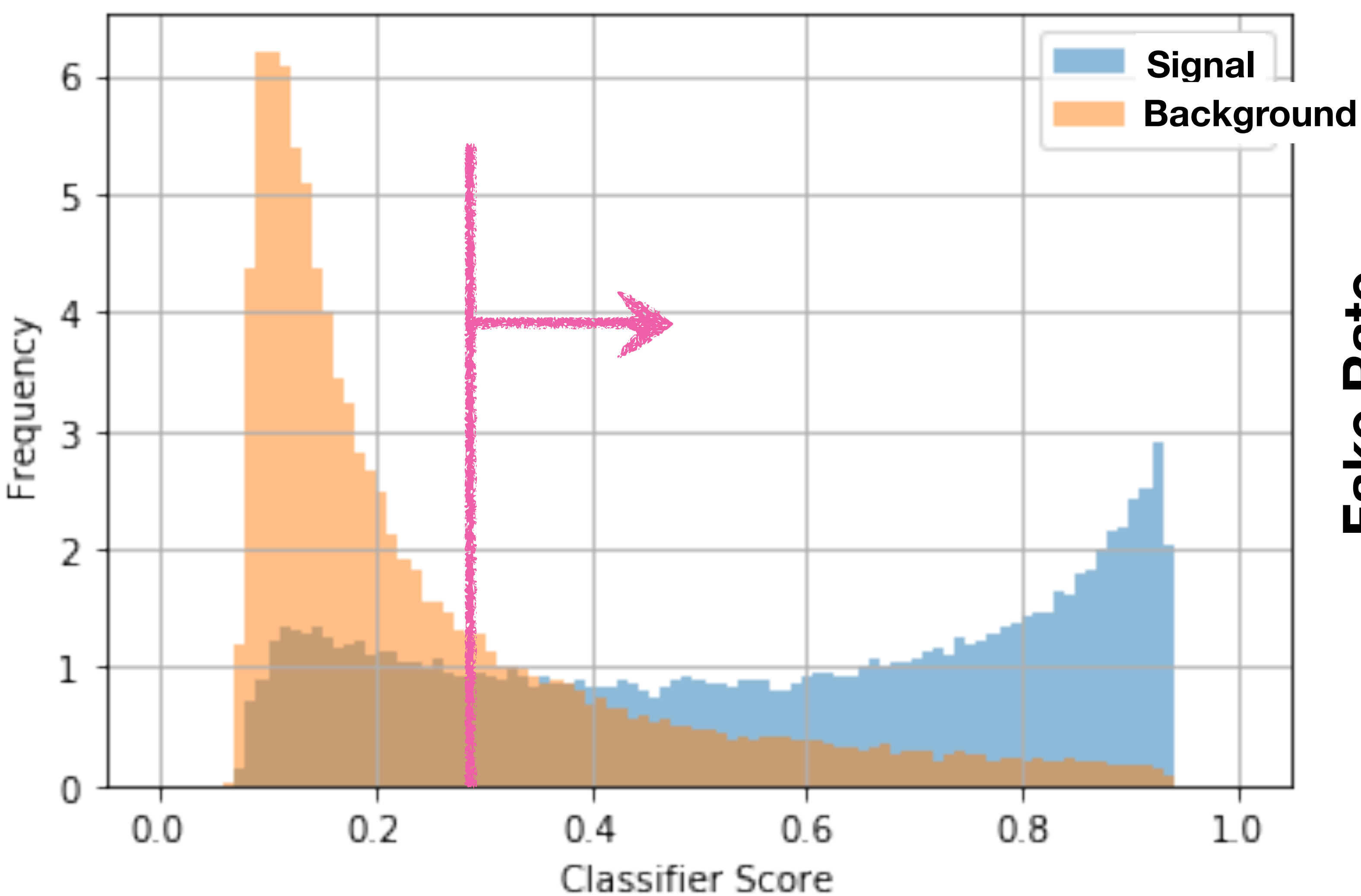


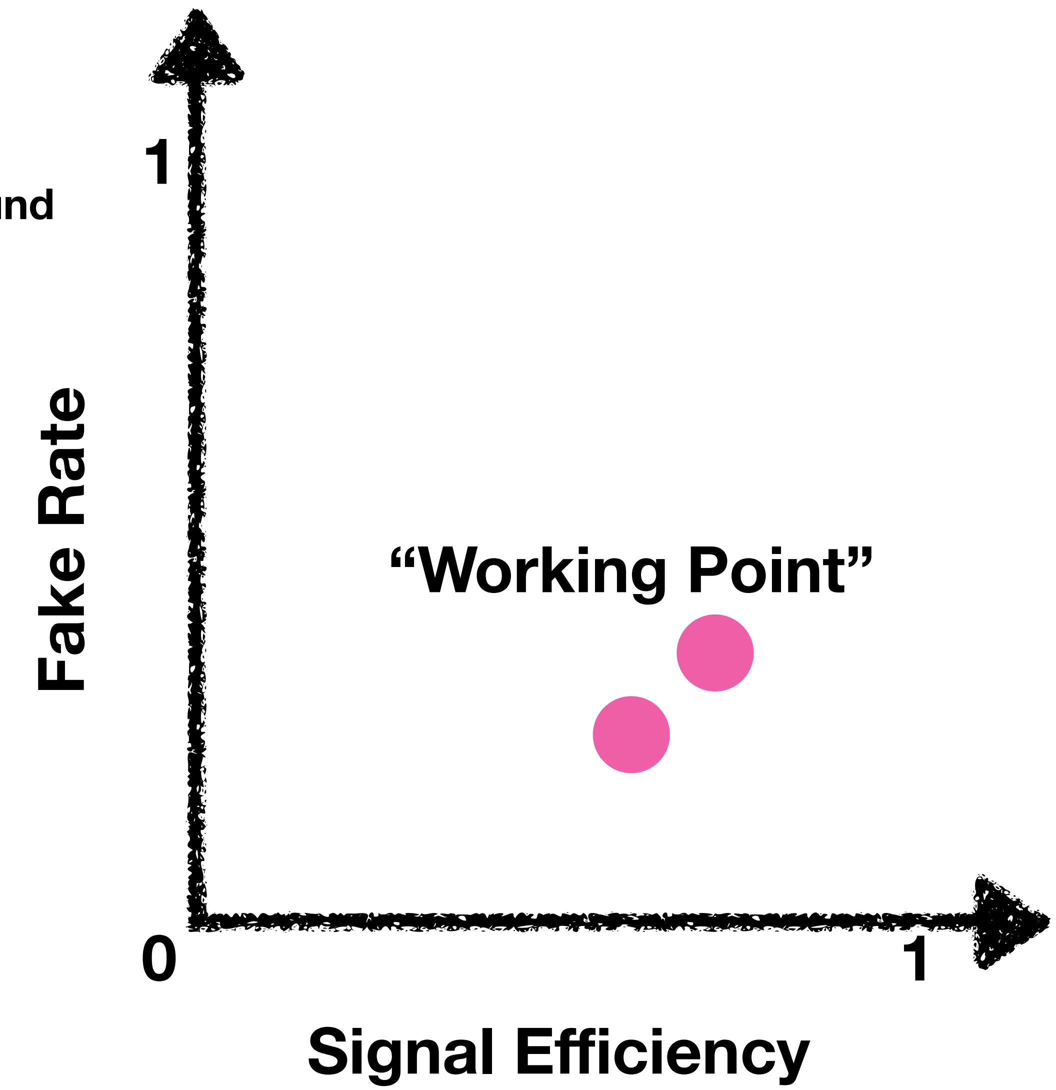


Where is the new working point?

ROC Curves

Receiver Operator Characteristic

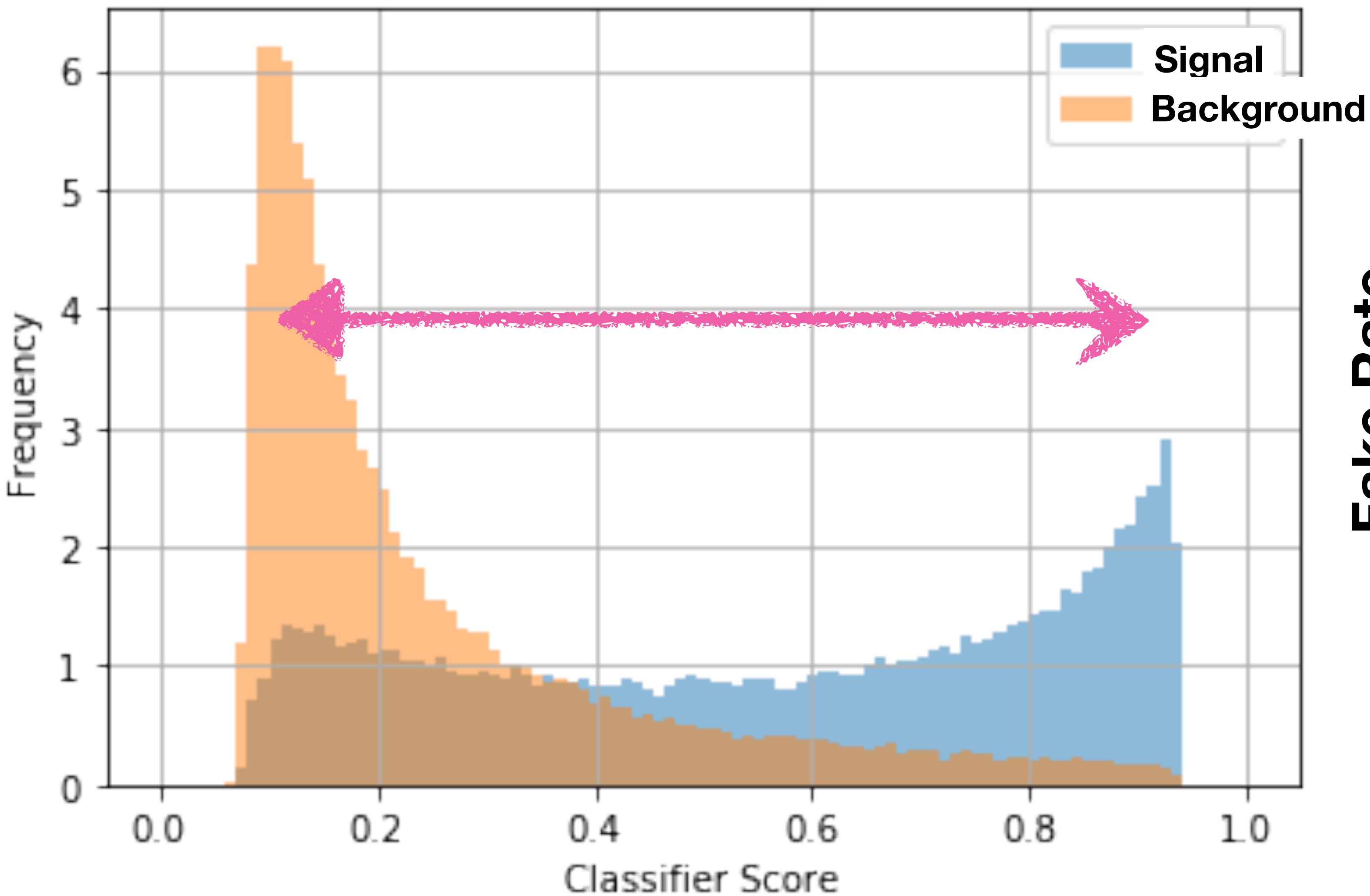


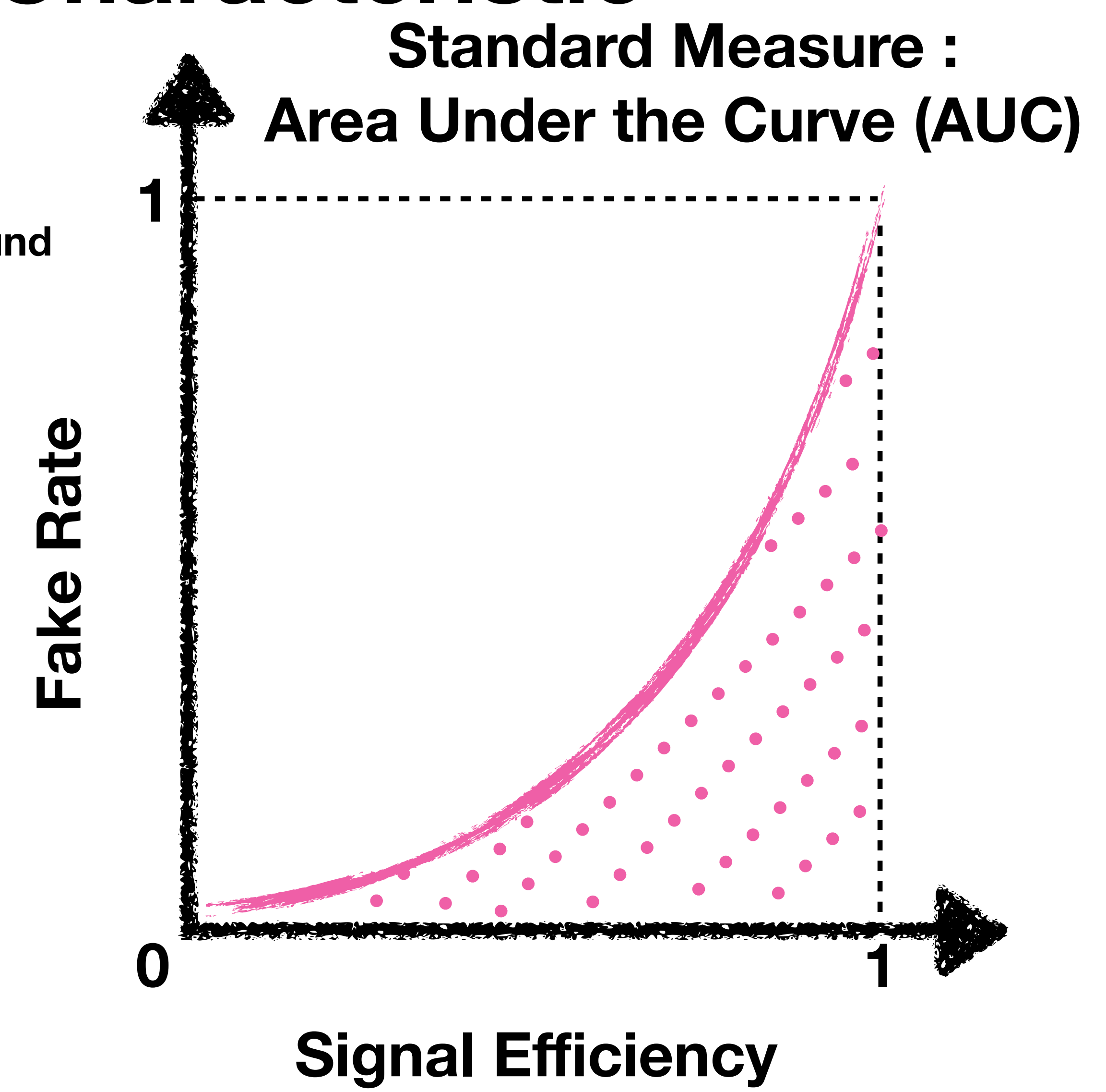


- Scanning across the classifier score, builds up a ROC

ROC Curves

Receiver Operator Characteristic

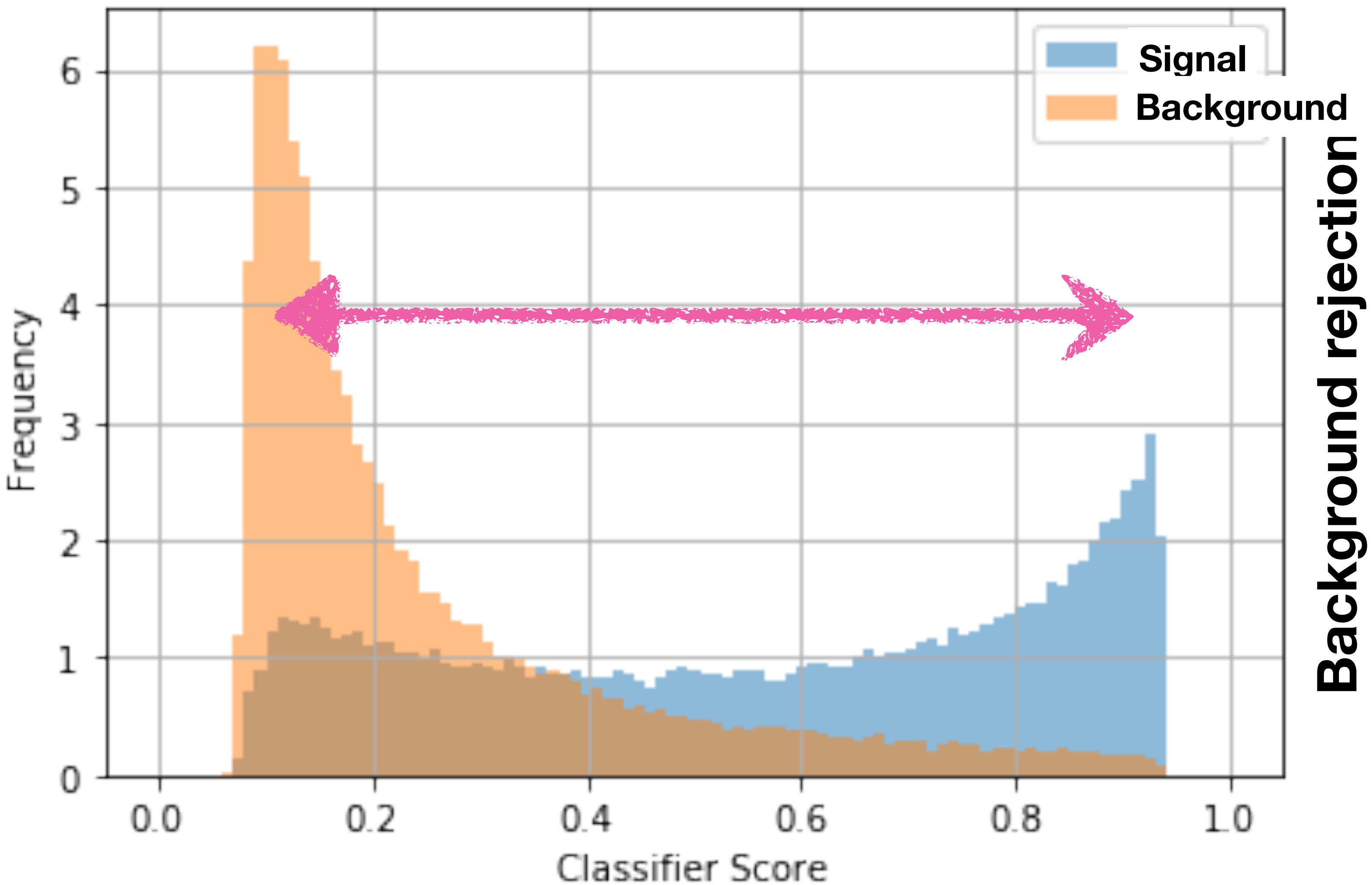


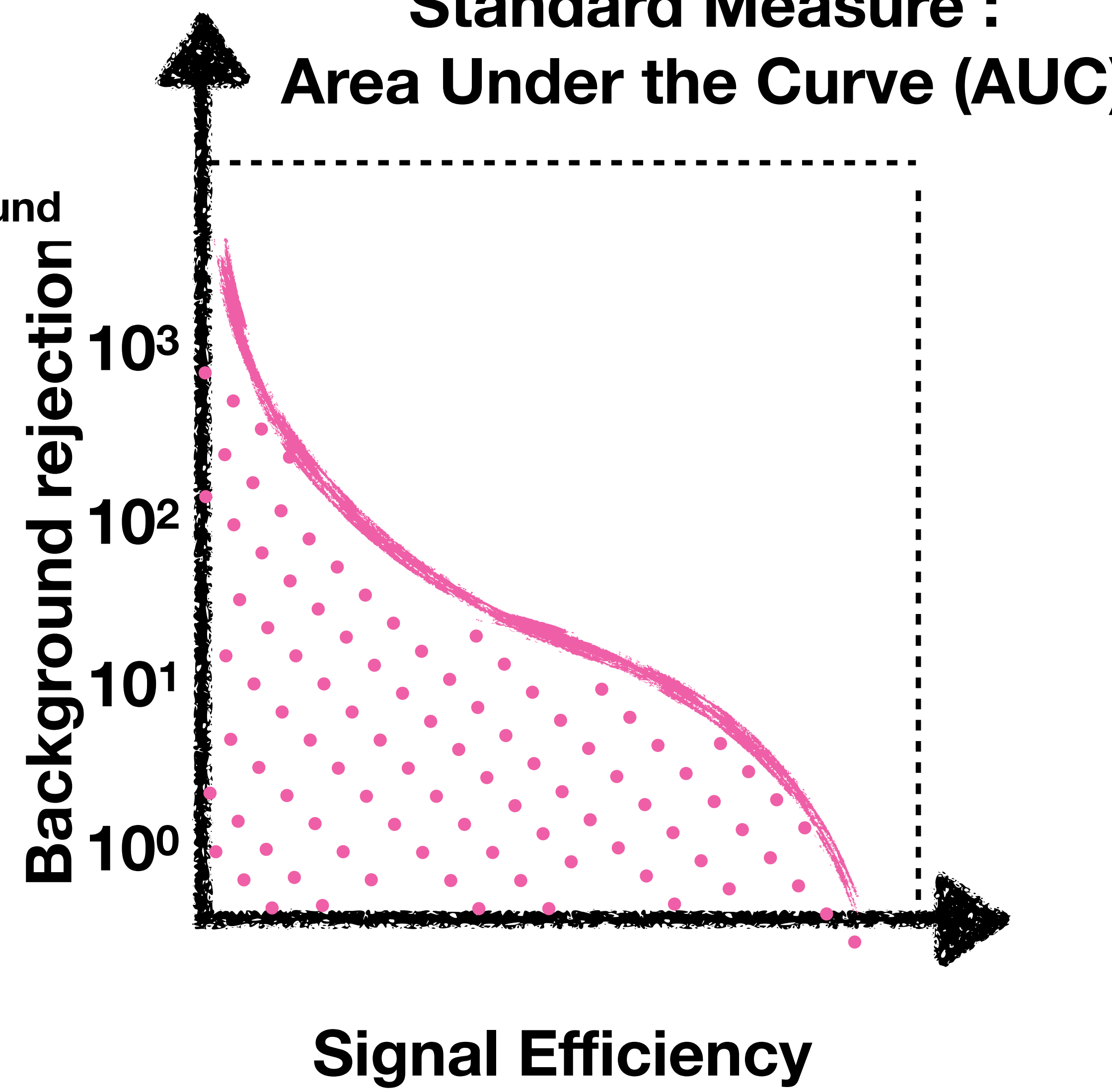


- AUC useful measure for comparing models
  - NOTE: not an ultimate measure

ROC Curves

Receiver Operator Characteristic





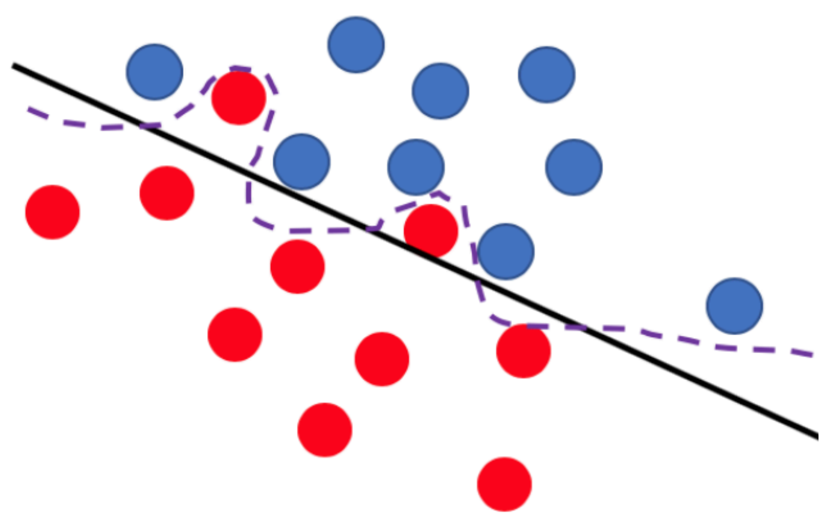
- Sometimes, the ROC curve is represented as efficiency vs background rejection (in log scale highlights differences between similar curves)

Model validation

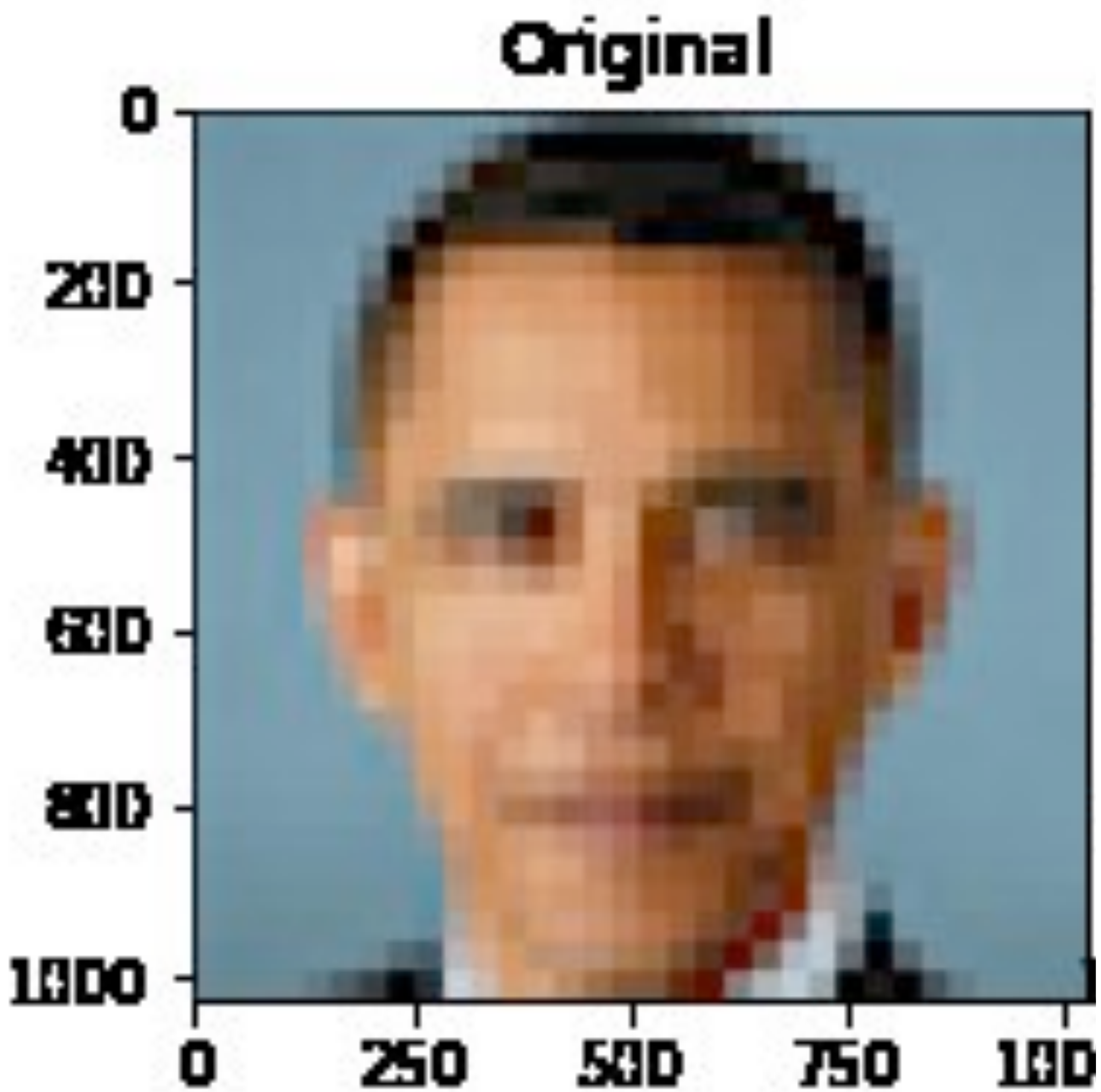
ML is not a magic fix!

- *Put garbage in, get garbage out!*
- ML cannot replace domain knowledge.
- ML is not a causation tool.
- Model should be generalizable (i.e. should perform well on unseen data).

Hannah Bossi (Yale) RHIC/AUM 2021

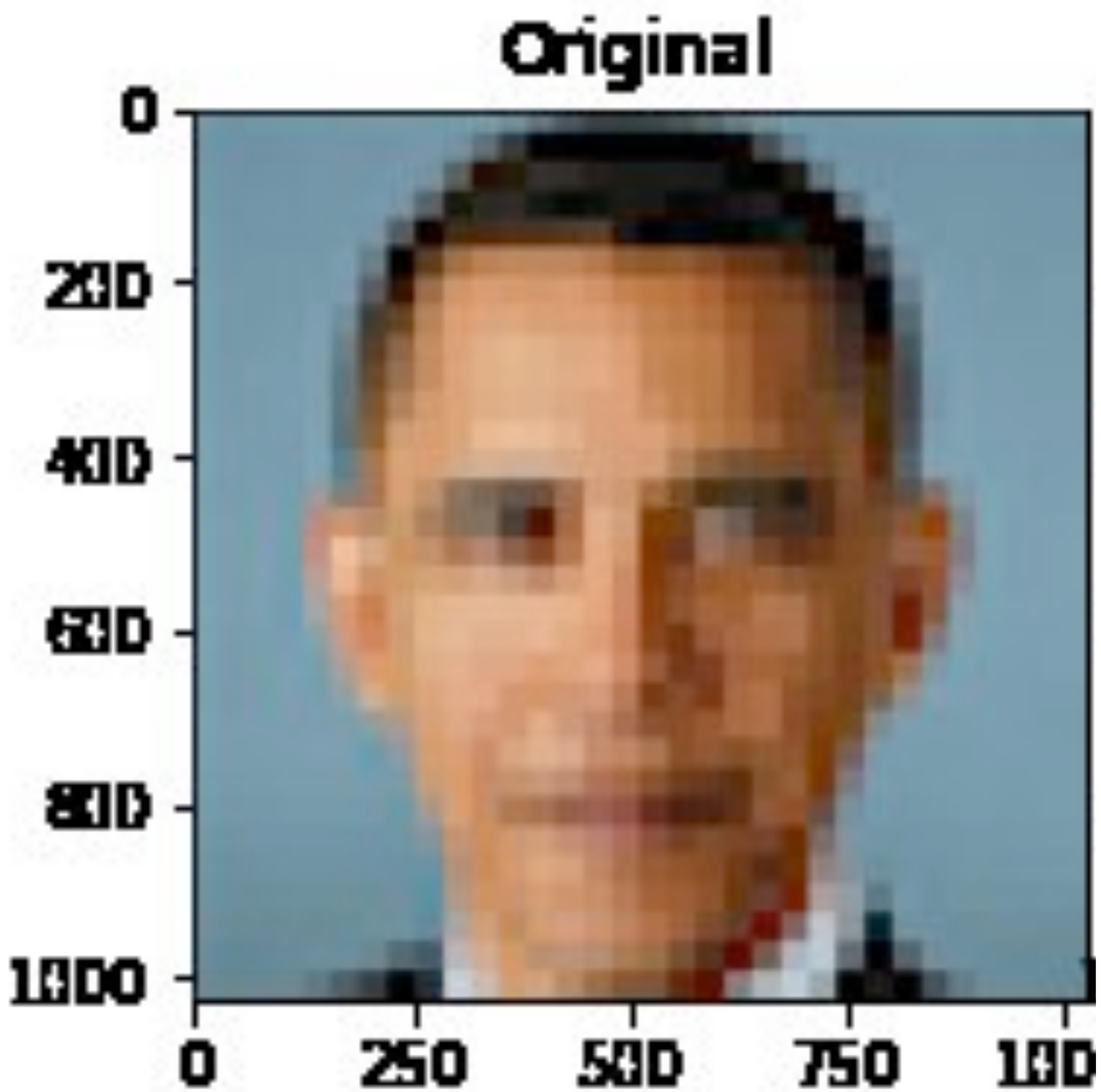


Quick example



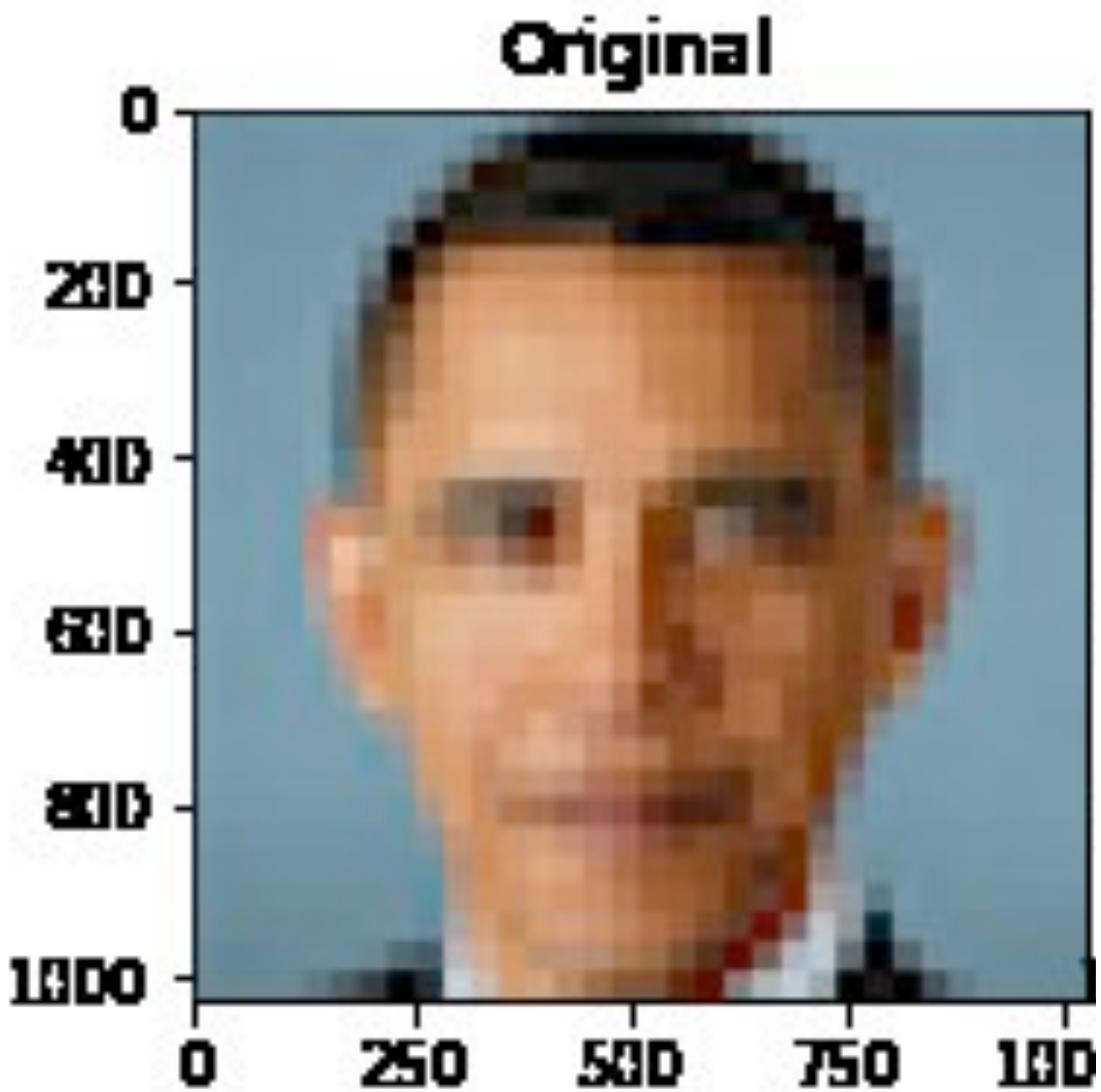
https://colab.research.google.com/github/tg-bomze/Face-Depixelizer/blob/master/Face_Depixelizer_Eng.ipynb

Quick example



https://colab.research.google.com/github/tg-bomze/Face-Depixelizer/blob/master/Face_Depixelizer_Eng.ipynb

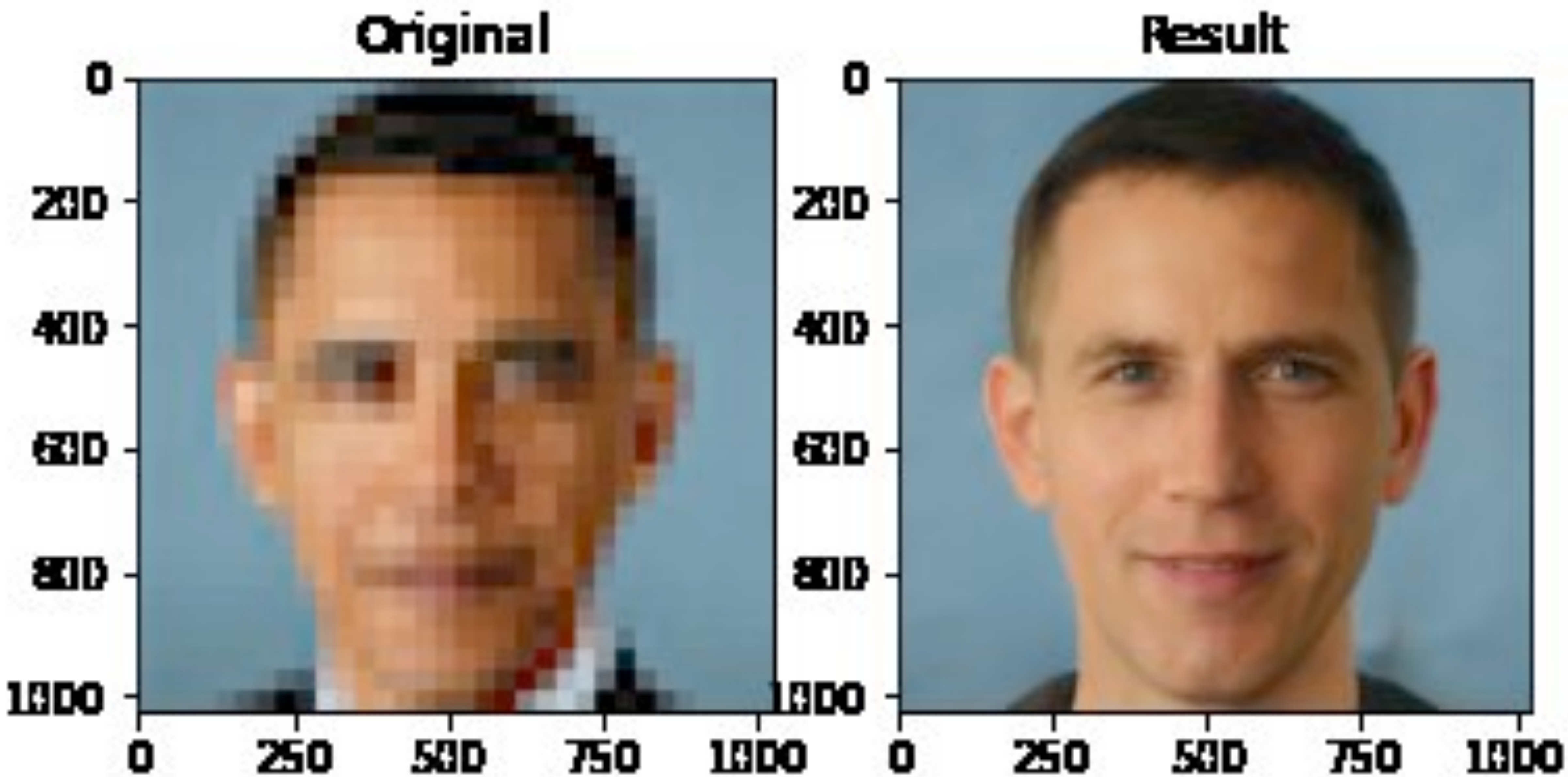
Quick example



What do you think is going to happen?

https://colab.research.google.com/github/tg-bomze/Face-Depixelizer/blob/master/Face_Depixelizer_Eng.ipynb

Quick example



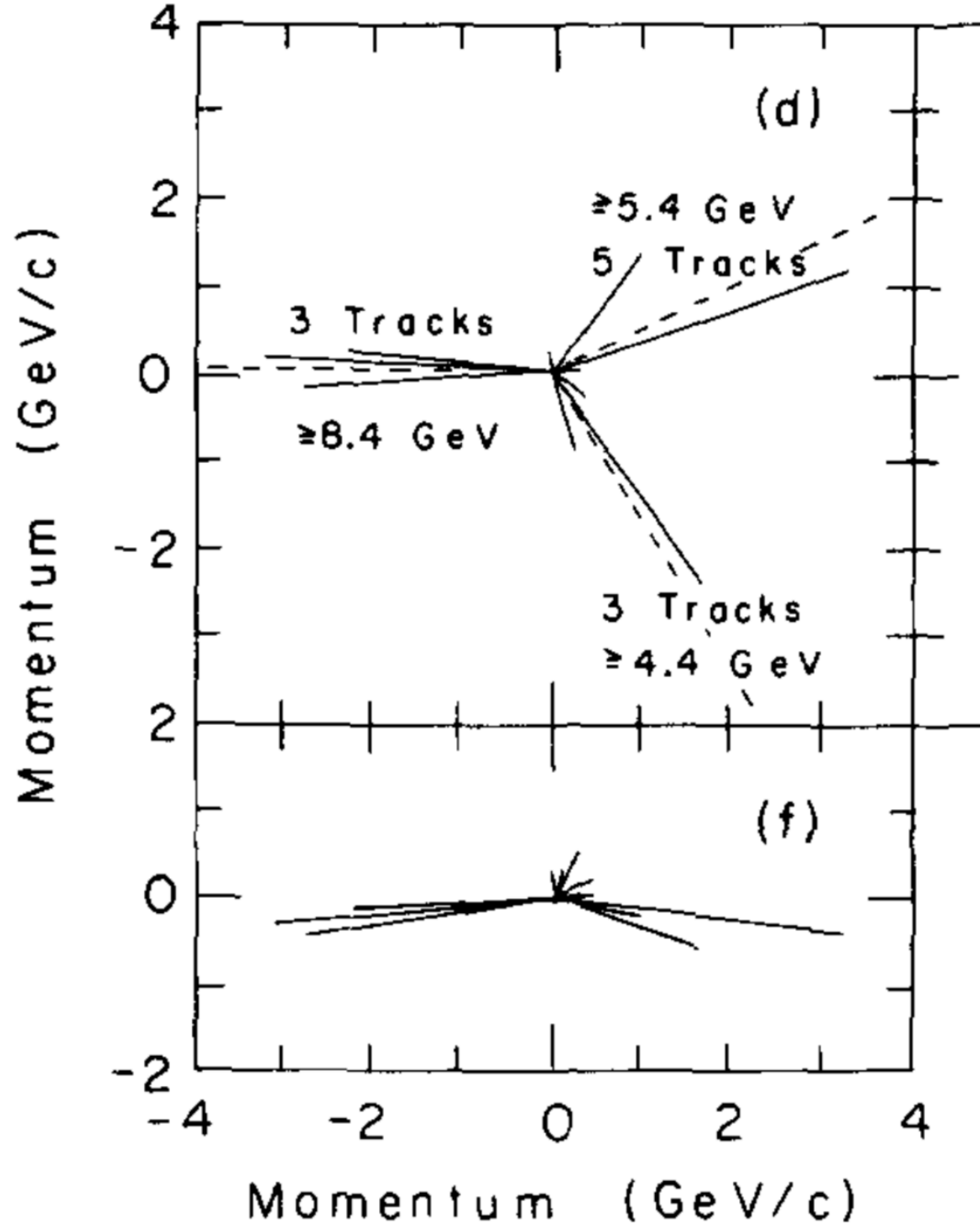
https://colab.research.google.com/github/tg-bomze/Face-Depixelizer/blob/master/Face_Depixelizer_Eng.ipynb

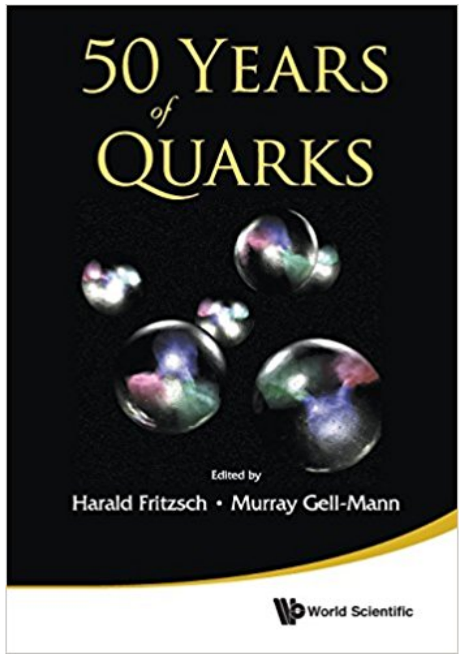
Recap - 1

- Direct connection between analysis tools in physics and modern ML techniques
- The ML community has advanced and well calibrated classification (and regression, as we shall see) tools for us to exploit and adapt to our purposes
- Garbage in… Garbage out. Biased data will result in unreliable biased learning

Onto some classification!

Phys.Lett. B 86 (1979) 243-249





The Discovery of the Gluon

https://arxiv.org/abs/1409.4232

John Ellis

Theoretical Particle Physics and Cosmology Group, Department of Physics, King's College London, London WC2R 2LS, United Kingdom & Theory Division, CERN, CH-1211 Geneva 23, Switzerland, John.Ellis@cern.ch

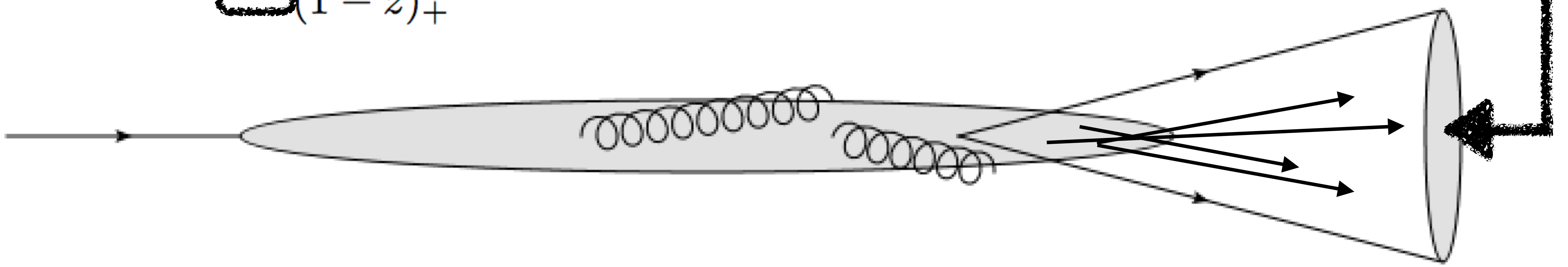
The public announcement of the gluon discovery came at the Lepton/Photon Symposium held at Fermilab in August 1979. All four PETRA experiments showed evidence: JADE and PLUTO followed TASSO in presenting evidence for jet broadening and three-jet events as suggested in our 1976 paper, while the Mark J collaboration led by Sam Ting presented an analysis of antenna patterns along the lines of our 1978 paper. There was a press conference at which one of the three-jet events was presented, and a journalist asked which jet was the gluon. He was told that the smart money was on the jet on the left (or was it the right?). Refereed publications by TASSO [37] and the other PETRA collaborations [38] soon appeared, and the gluon finally joined the Pantheon of established particles as the second gauge boson to be discovered, joining the photon.

Quark vs Gluon Jets

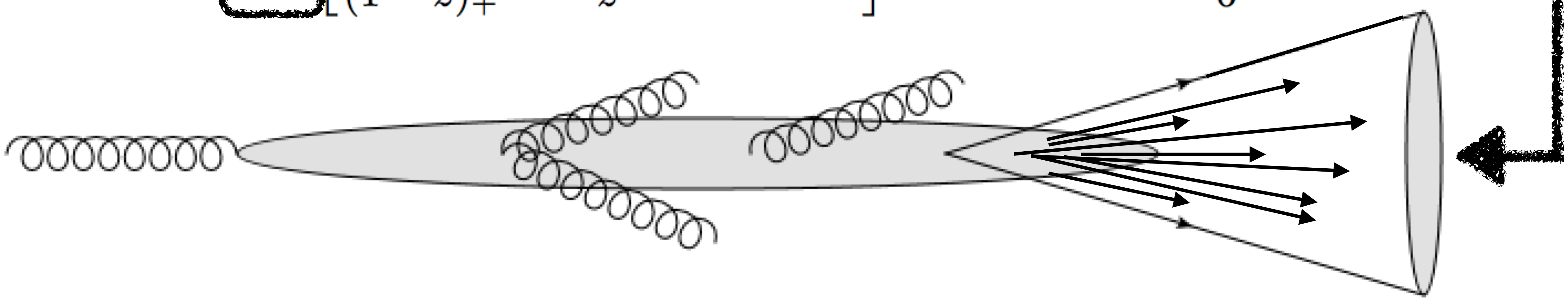
Jet Algorithm

$$P_{q\to qg}(z) = \boxed{C_F}\frac{1+z^2}{(1-z)_+}$$

DGLAP Splitting Functions



$$P_{g\to gg}(z) = \boxed{2C_A}\left[\frac{z}{(1-z)_+} + \frac{1-z}{z} + z(1-z)\right] + \delta(1-z)\frac{11C_A - 4n_f T_R}{6}$$

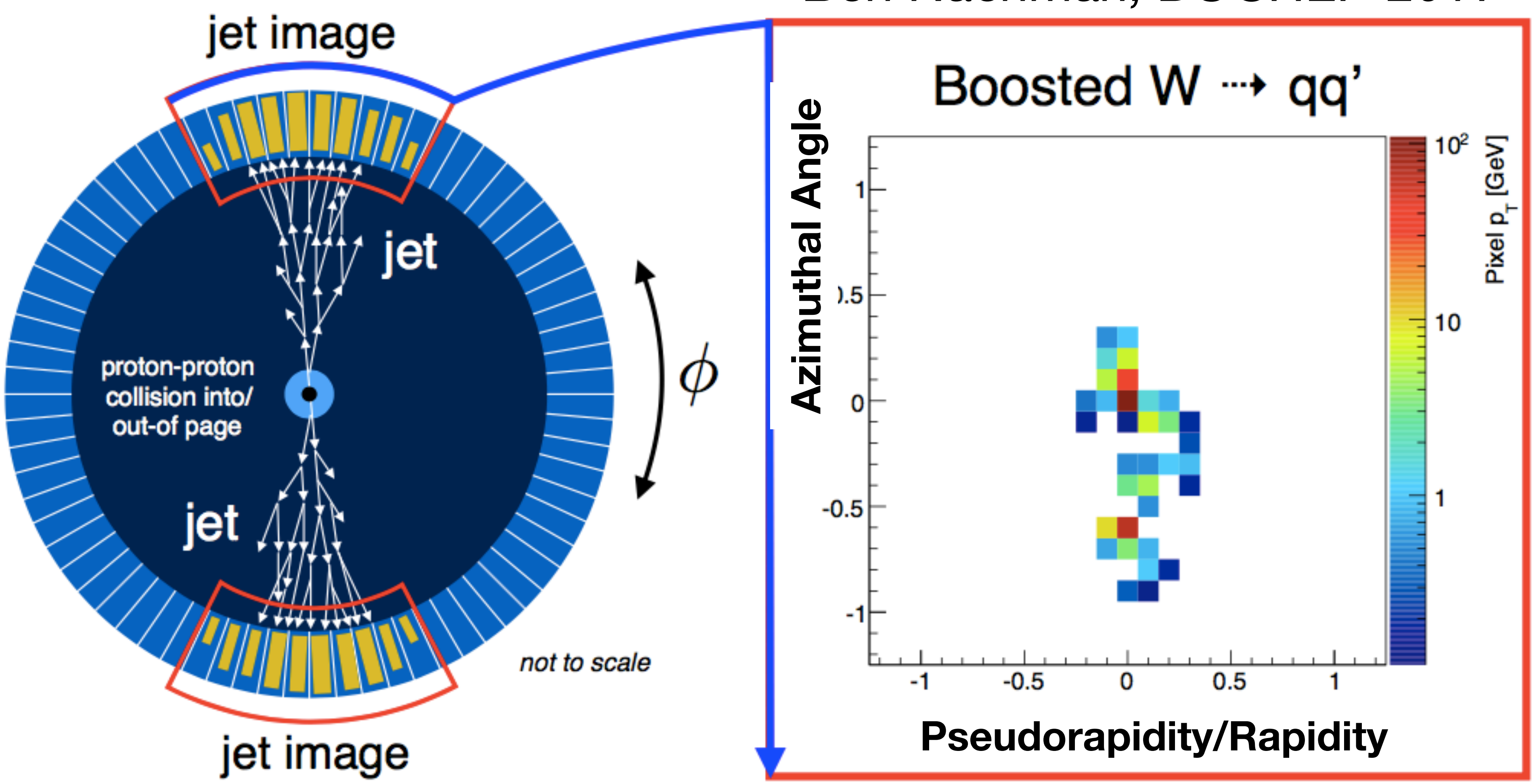


C_A vs C_F primary difference could potentially lead to larger multiplicity and overall width for gluon jets

What is a Jet Image?

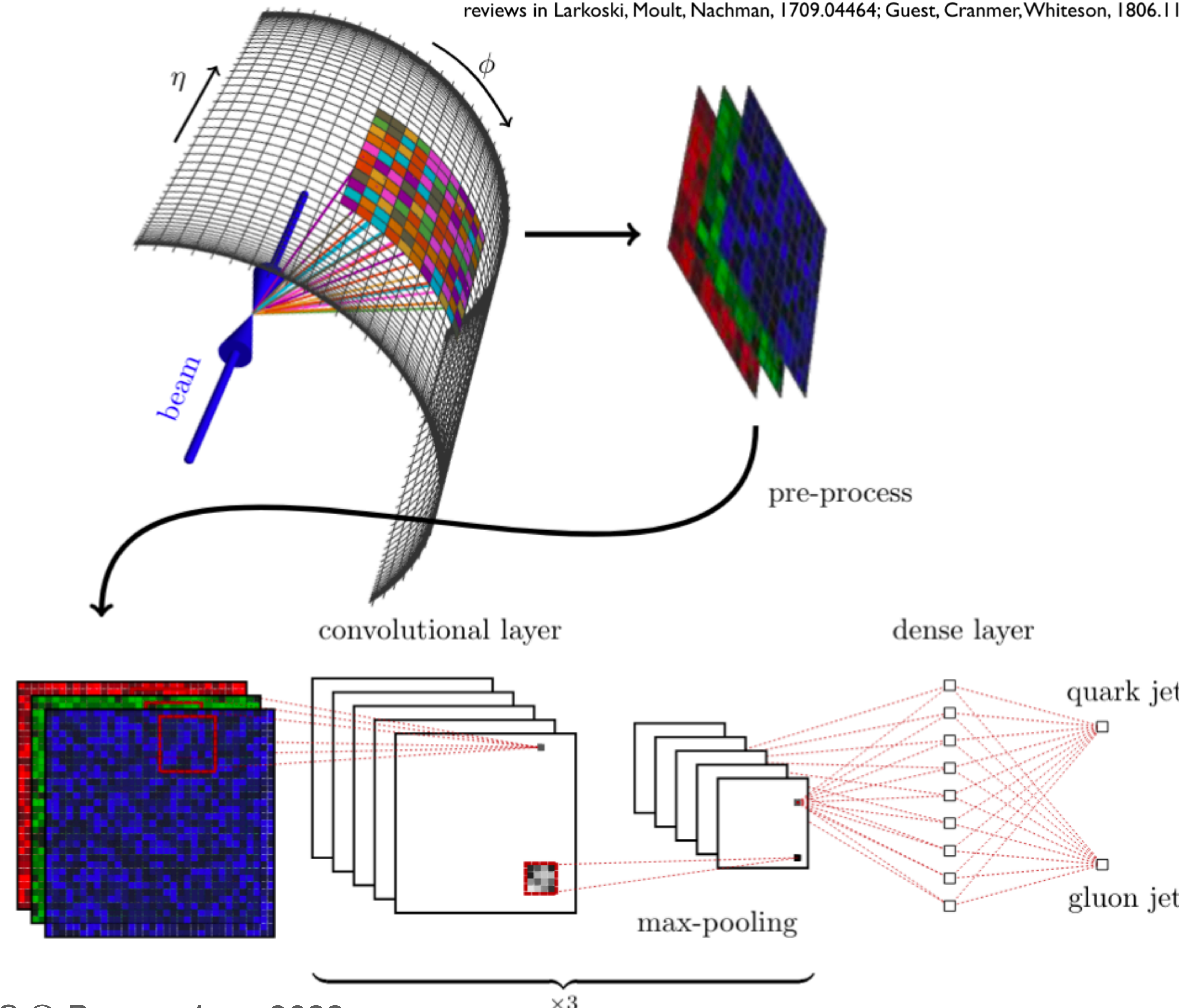
- Jet Image: A two-dimensional fixed representation of radiation pattern inside a jet

Ben Nachman, DS@HEP 2017

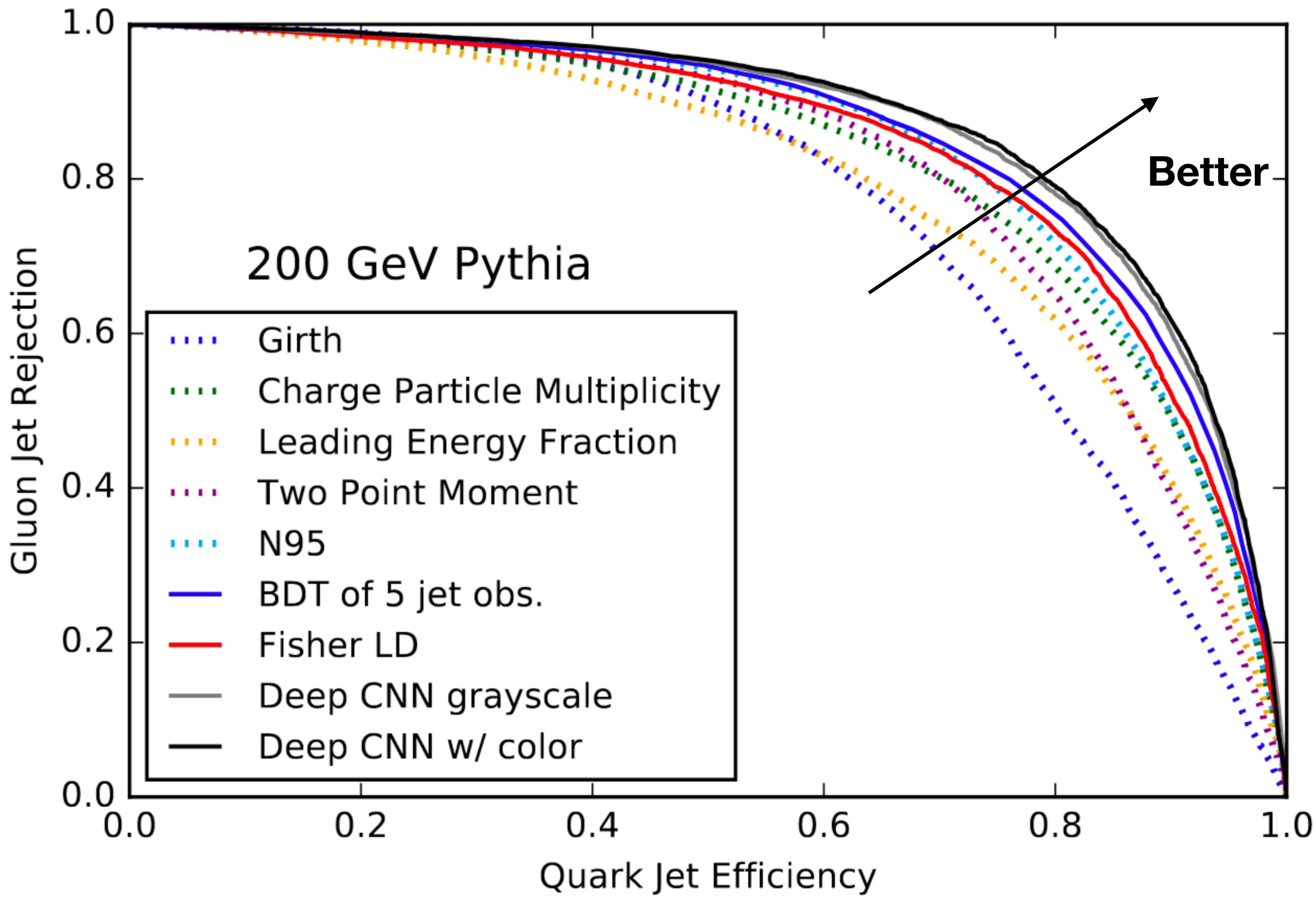


- Including pre-processing to fix center at (0,0), rotating image (Δη-Δφ) so that secondary peak lies along 6-o clock direction

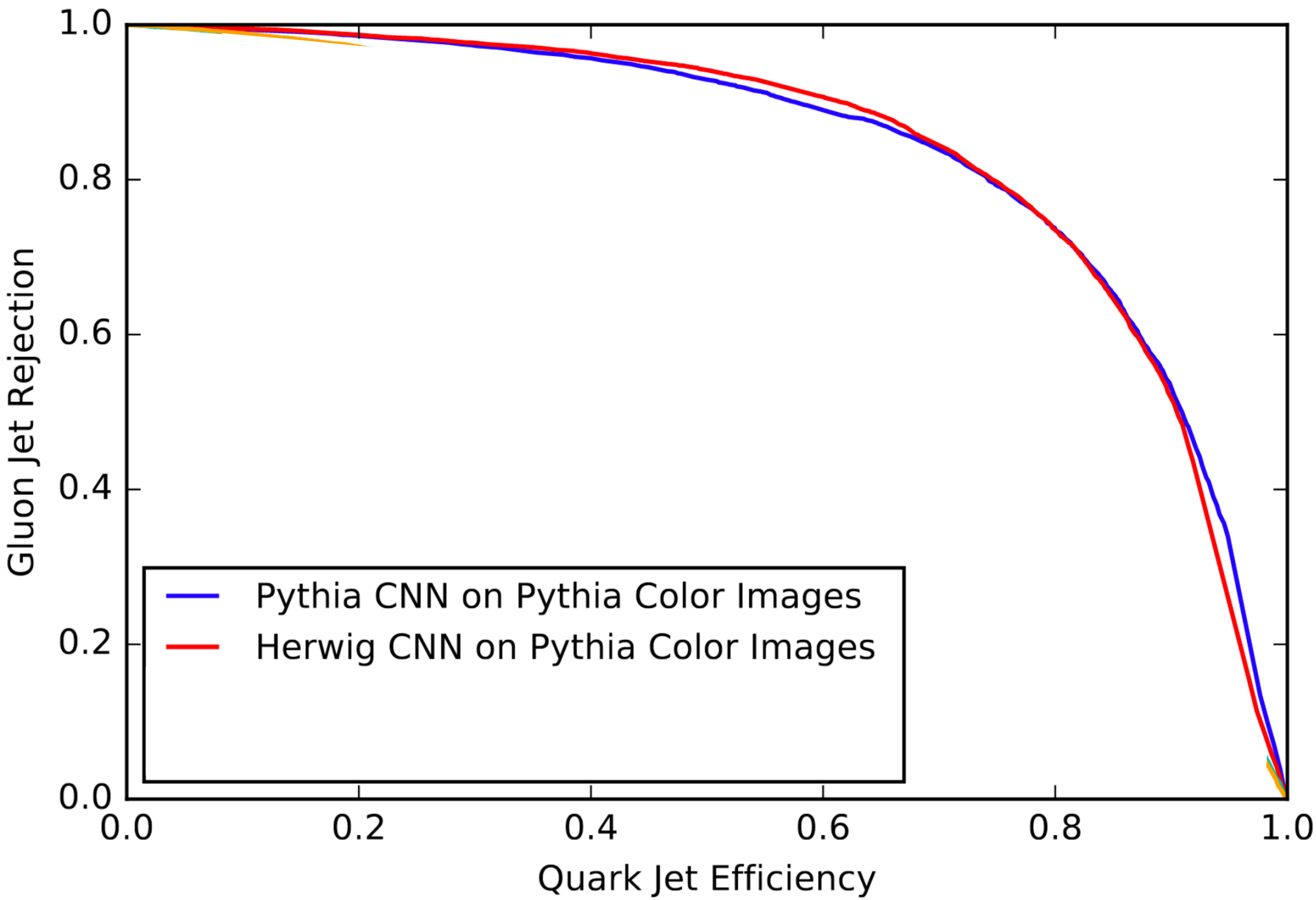
[e.g. Komiske, Metodiev, Schwartz, 1612.01551; Nachman, Boost 2018 Talk, July 20, 2018; reviews in Larkoski, Moult, Nachman, 1709.04464; Guest, Cranmer, Whiteson, 1806.11484]



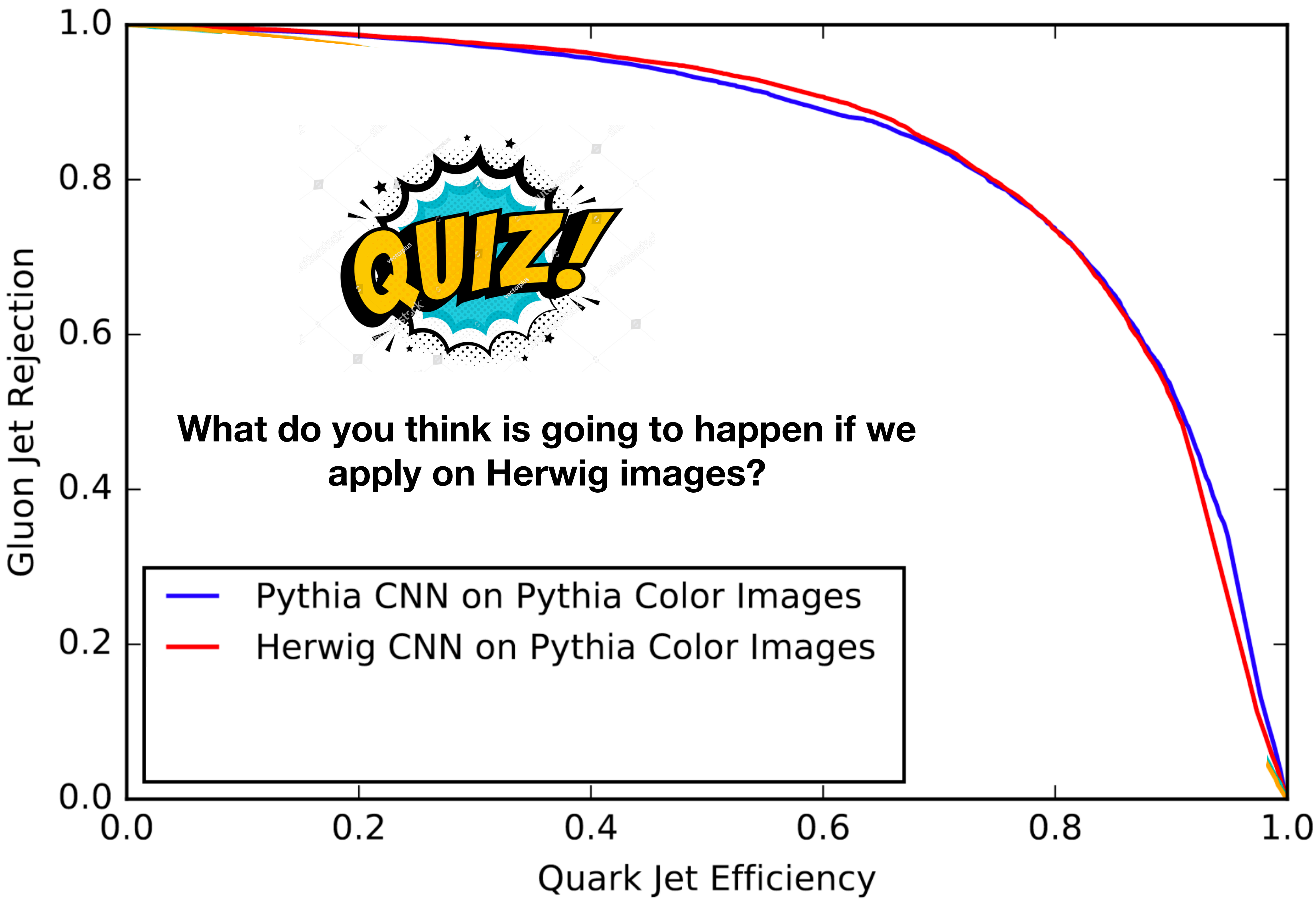
Comparing a variety of methods



Effect of the MC training bias

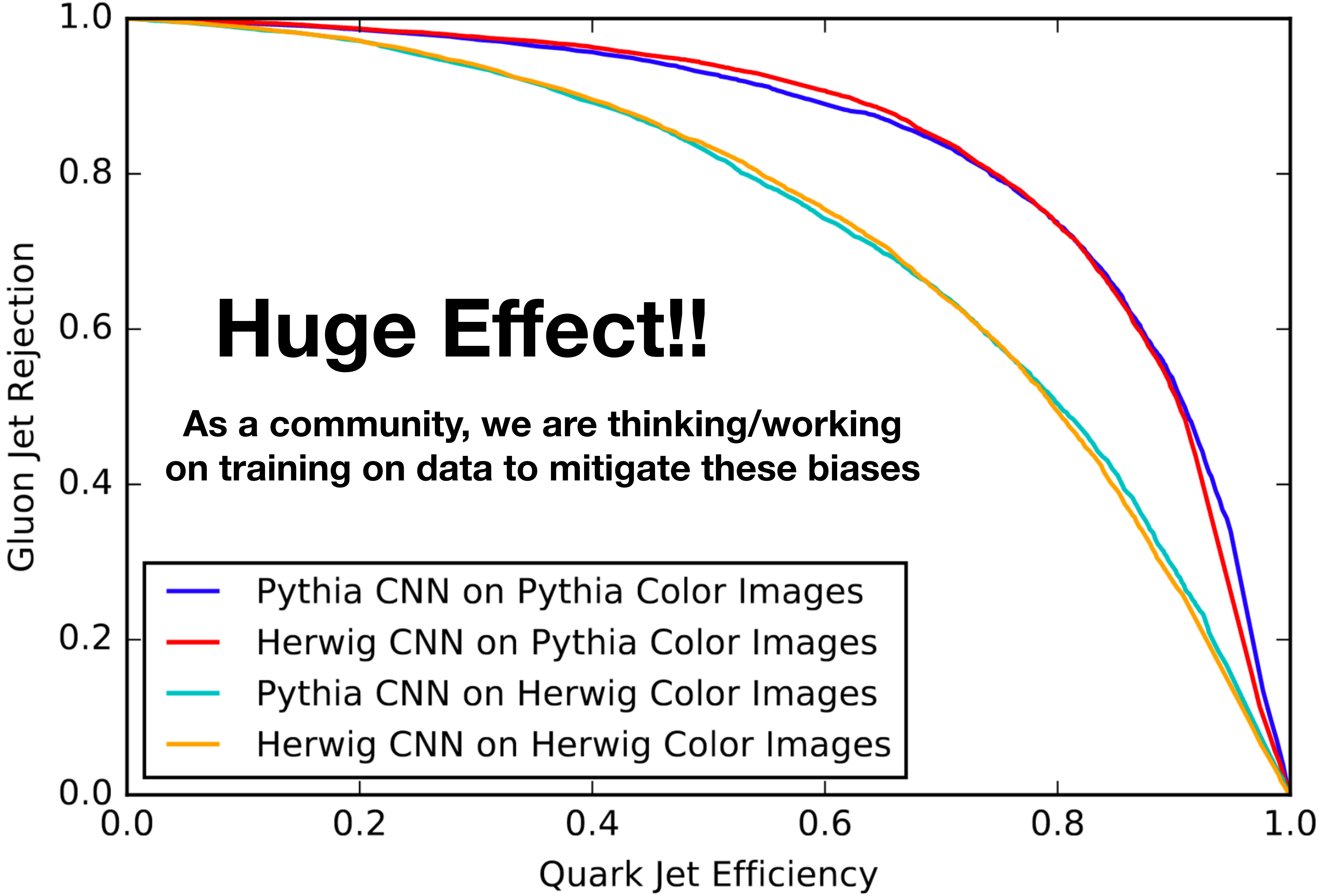


Effect of the MC training bias



What do you think is going to happen if we apply on Herwig images?

Effect of the MC training bias



Recap - 2

- Classifiers in our field are mostly supervised - with a potential built-in bias (utilize it!)
- There are many different ways to represent jets - information content is available to be exploited
- They are deployed in pp, but how about it in heavy ions?

Lets regress the truth!

Regression in HEP

- Correction procedures for energy scales and resolutions
- Multi-dimensional unfolding techniques

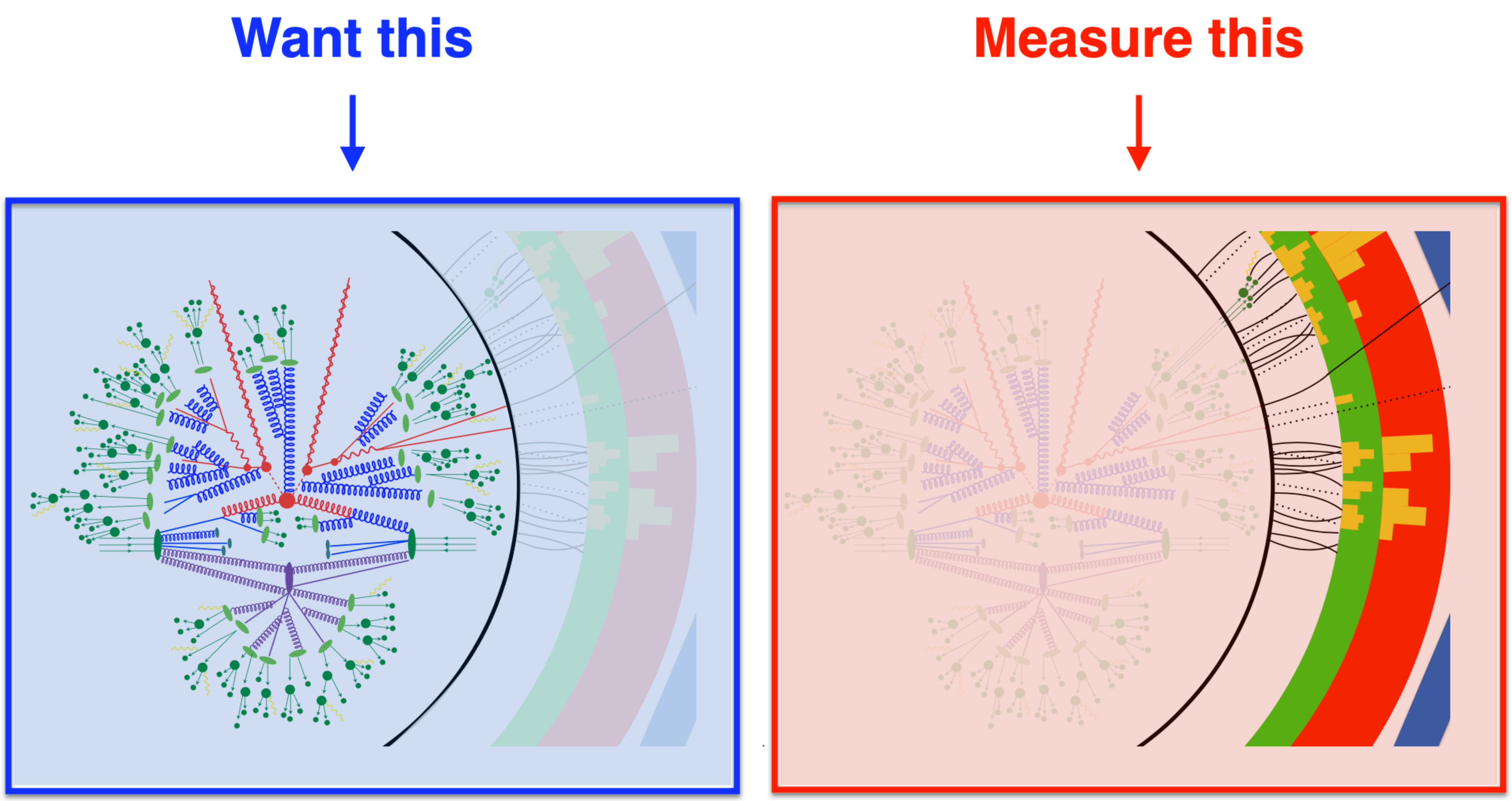
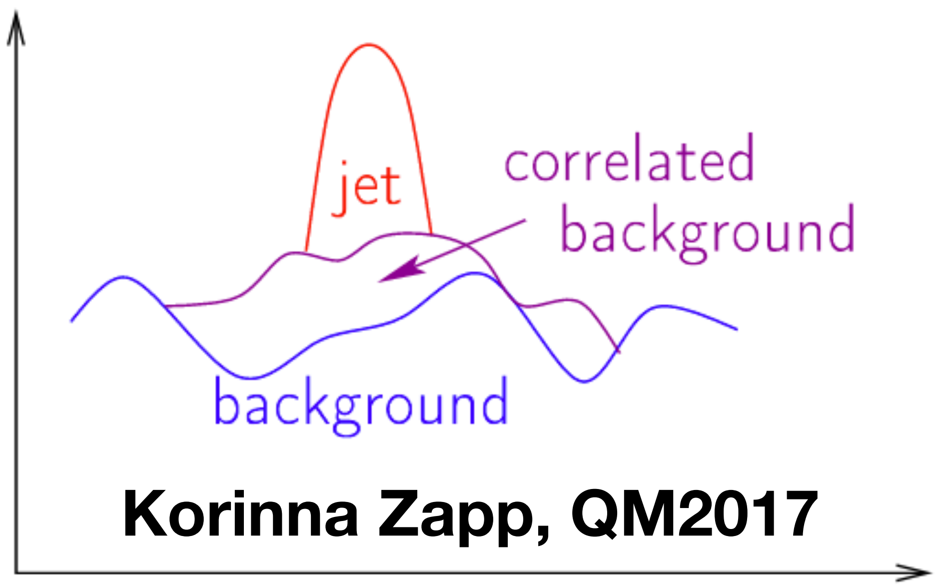
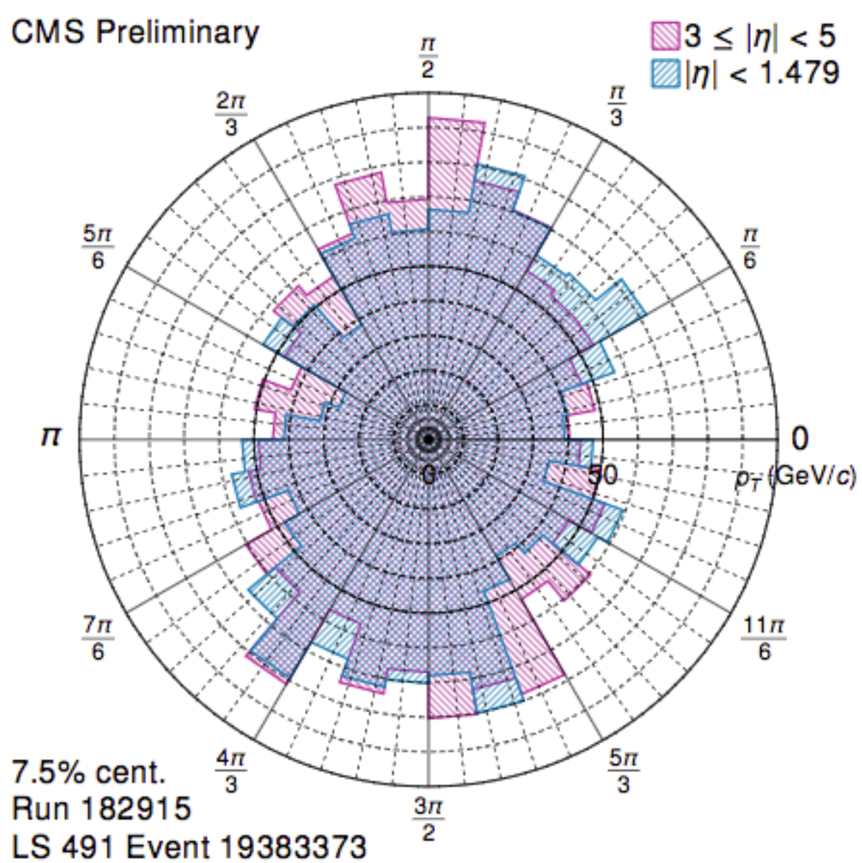


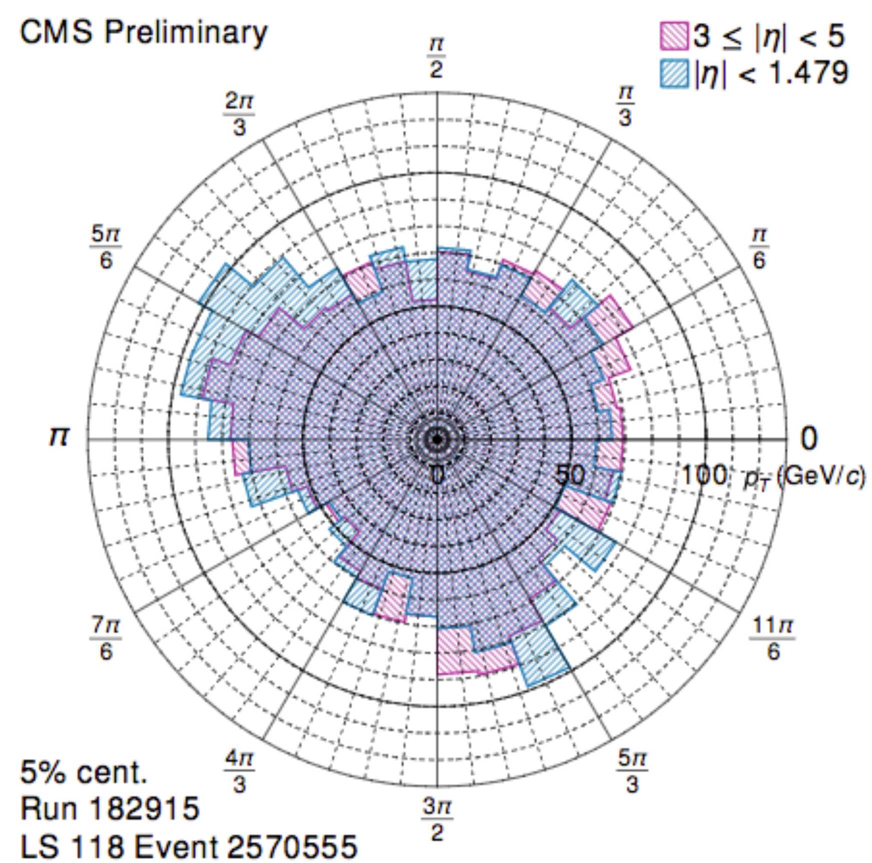
Image credit: Ben Nachman

Impact of the heavy ion background



Underlying event has flow, fluctuations and is correlated with the jet (like a wake)





ALICE method of ML based subtraction

Hannah Bossi (Yale) RHIC/AUM 2021

Training (PYTHIA fragmentation)

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

Shallow neural network

Testing

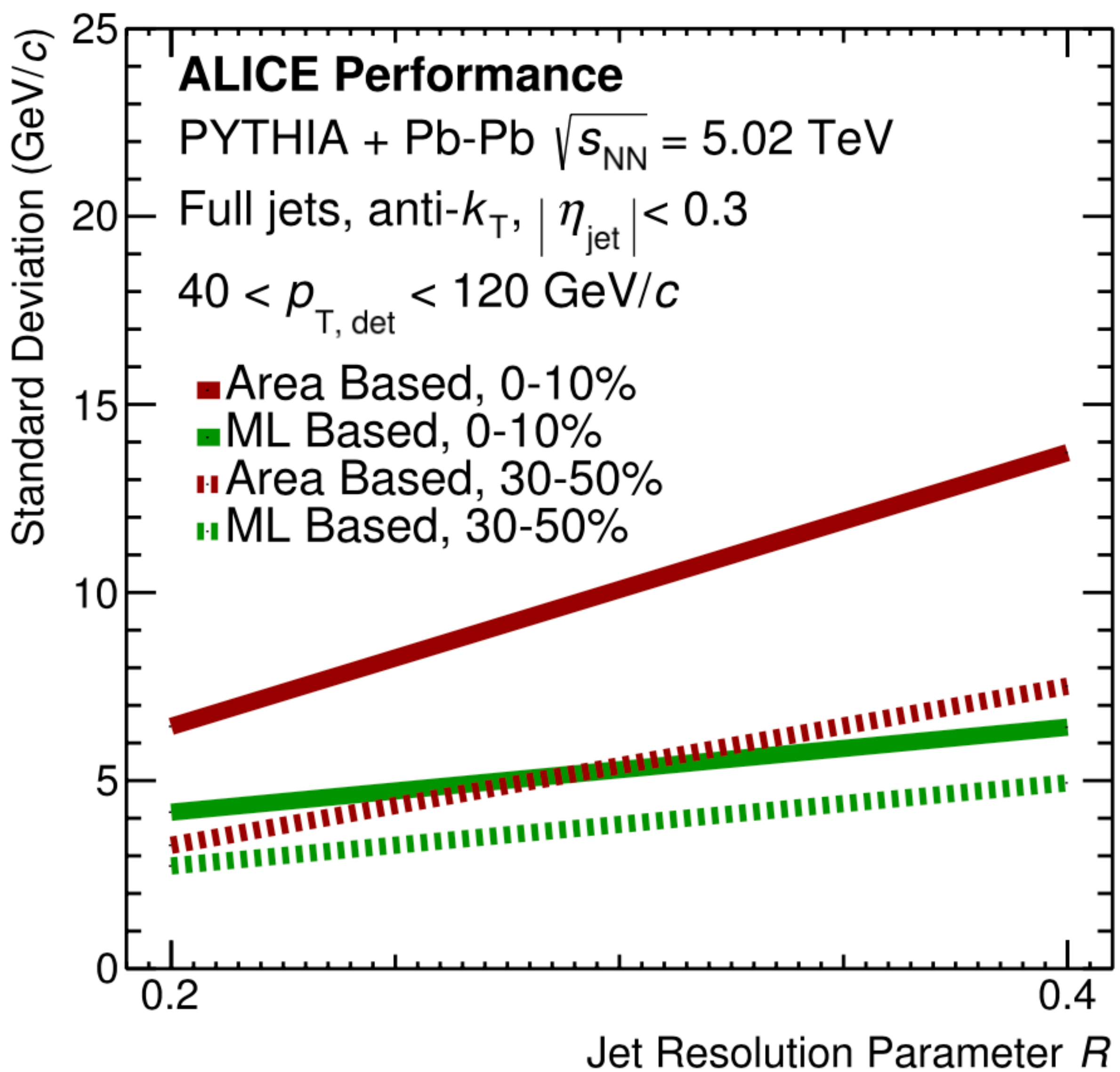
Apply ML estimator to hybrid events not used in training.

Key is that this background is *realistic.*

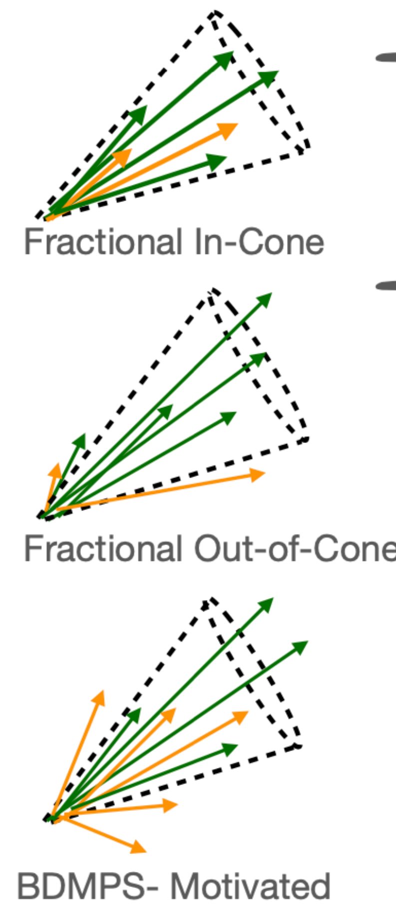
Simple question,
relatively simple network
can get a short clear answer!

Do we get back the signal we put in?

ML corrector in action

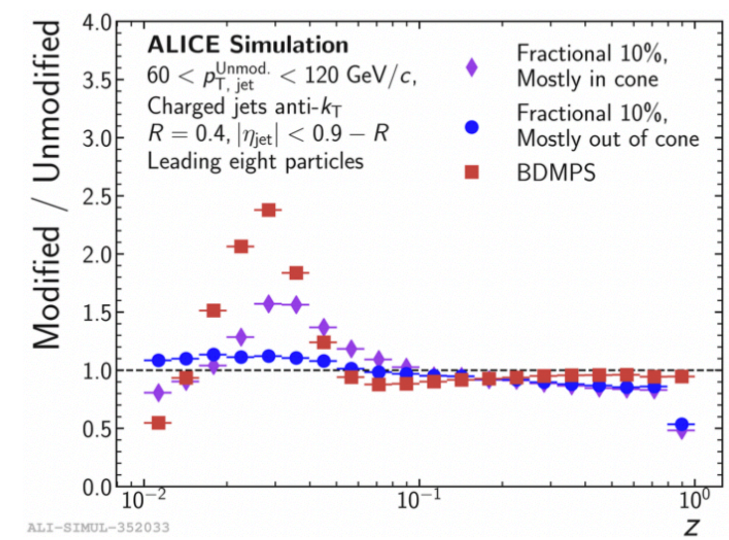


Hannah Bossi (Yale) RHIC/AUM 2021



Learning on constituents introduces a bias towards PYTHIA fragmentation!

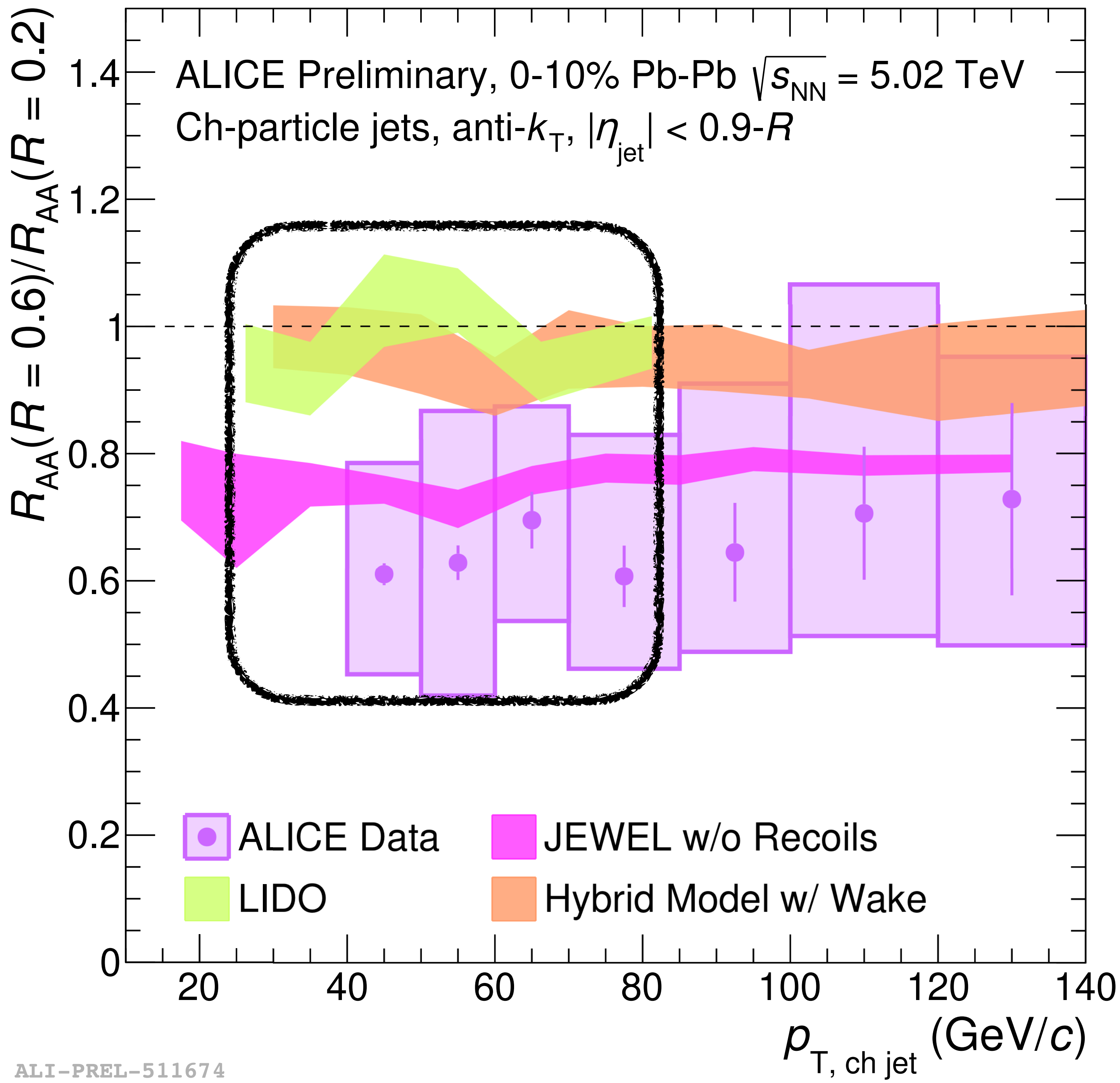
Modify PYTHIA jets to change the fragmentation.



Train on the modified toy model and apply to data; measure bias.

- Significantly less jet energy resolution with the ML based method along with first ever estimate of impact of truth shape 'bias' in correction

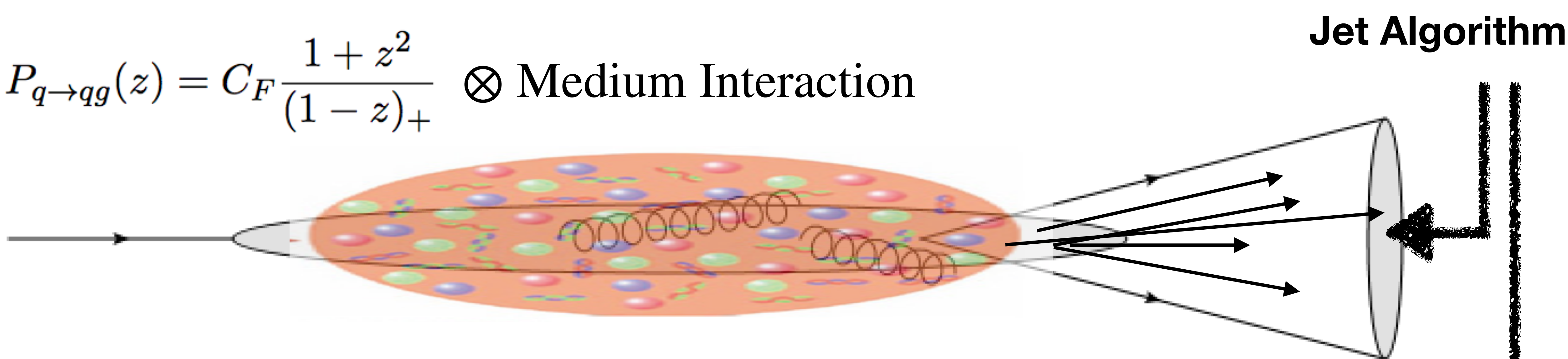
What did it enable us to do?



- Extend our measurements to lower momentum range where the impact of the background is large
- Reduced uncertainties key to making a potentially tantalizing statement about radial dependence of energy loss

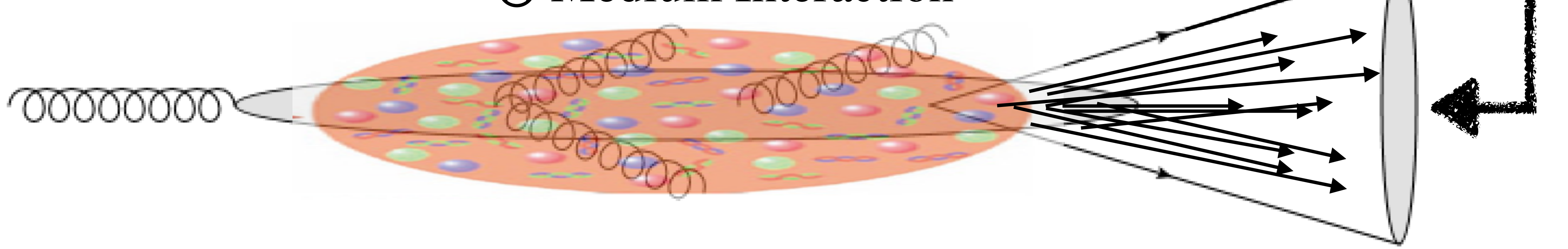
Quark and Gluon Jets

$$P_{q\to qg}(z) = C_F \frac{1+z^2}{(1-z)_+} \otimes \text{Medium Interaction}$$



$$P_{g\to gg}(z) = 2C_A\left[\frac{z}{(1-z)_+} + \frac{1-z}{z} + z(1-z)\right] + \delta(1-z)\frac{11C_A - 4n_f T_R}{6}$$

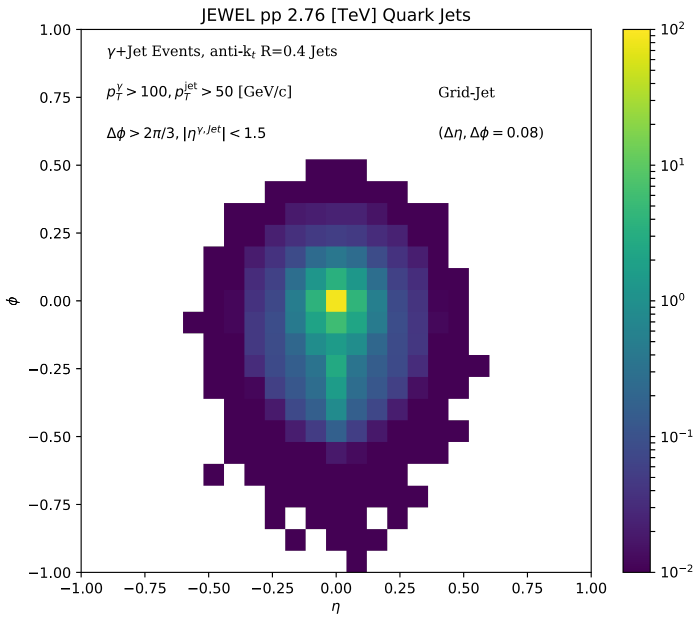
$$\otimes \text{Medium Interaction}$$



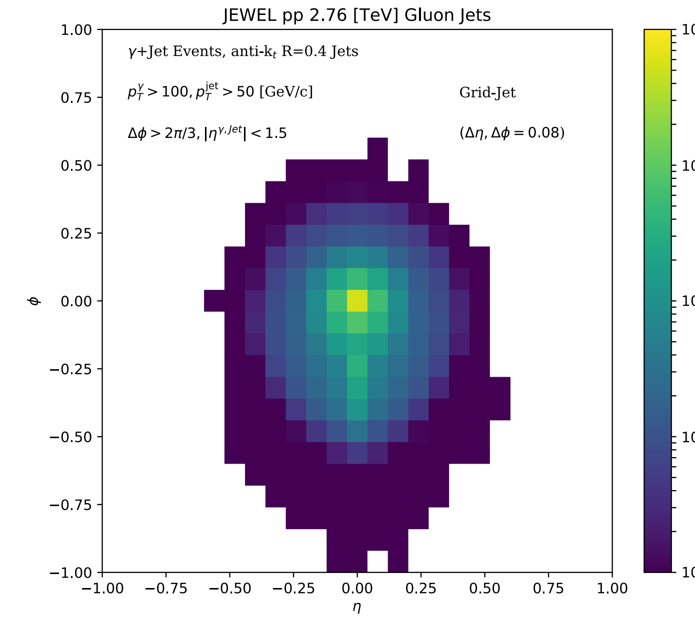
Effects of the QGP on jet propagation manifests via modifications to jet energy and jet sub-structure

Jet Images

PP Q-Jet



PP G-Jet



QCD Color factor
G-Jets are broader

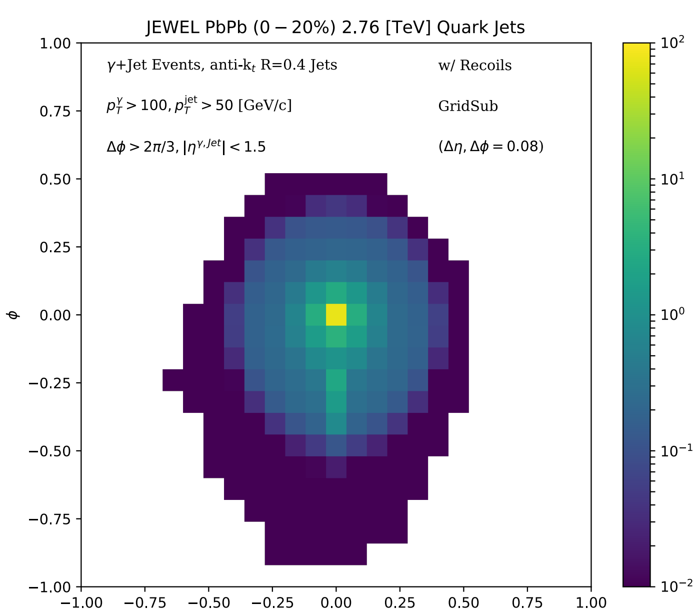
JEWEL

Pros
- Image representation should contain all info.
- Current State of the art - easy to implement

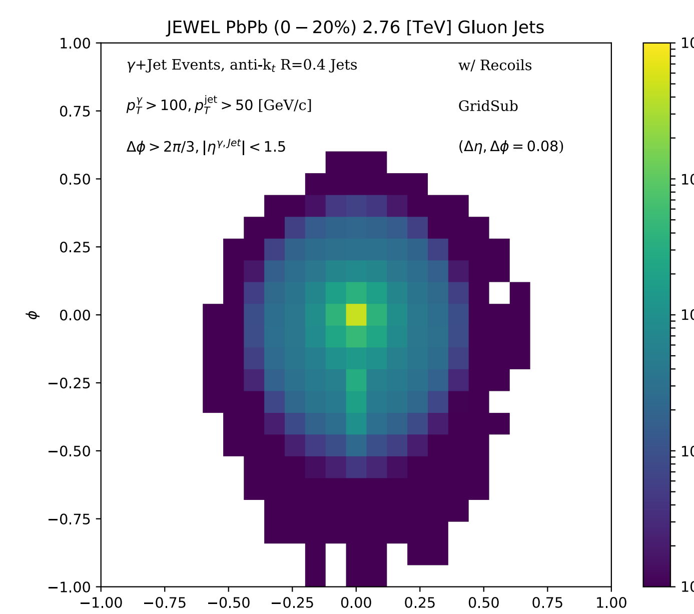
Cons
- classification in non-physics basis
- Best case scenario - no fluctuating background!

JEWEL

Quenched Q-Jet



Quenched G-Jet



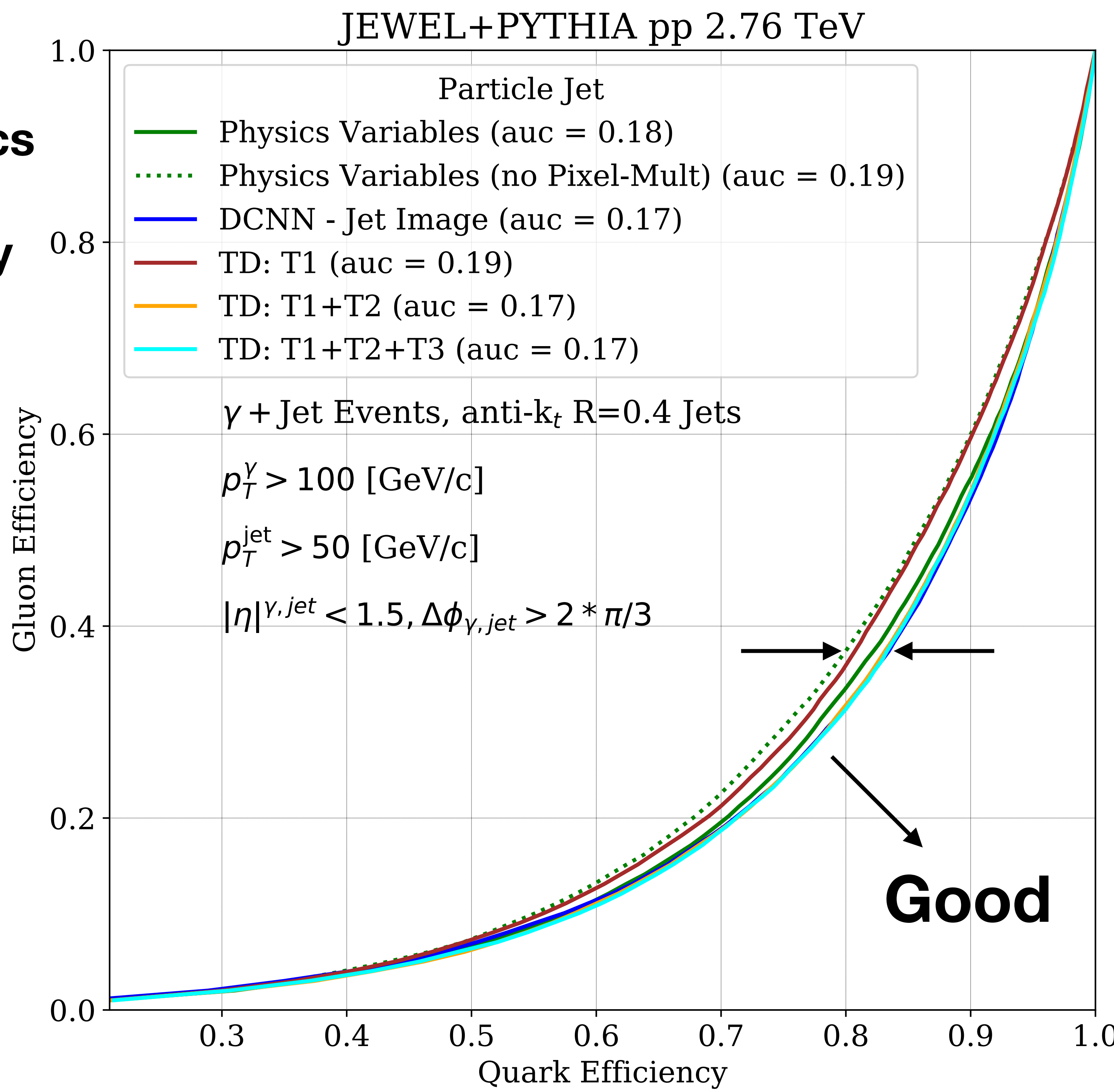
Quenched Q-Jet looks similar to G-Jet

G-Jet Still broader

ROC curve for pp Particle Jets

Traditional Physics variables are also consistently good

TD: 3rd order and DCNN gives the best performance!



All methods are relatively close to each other

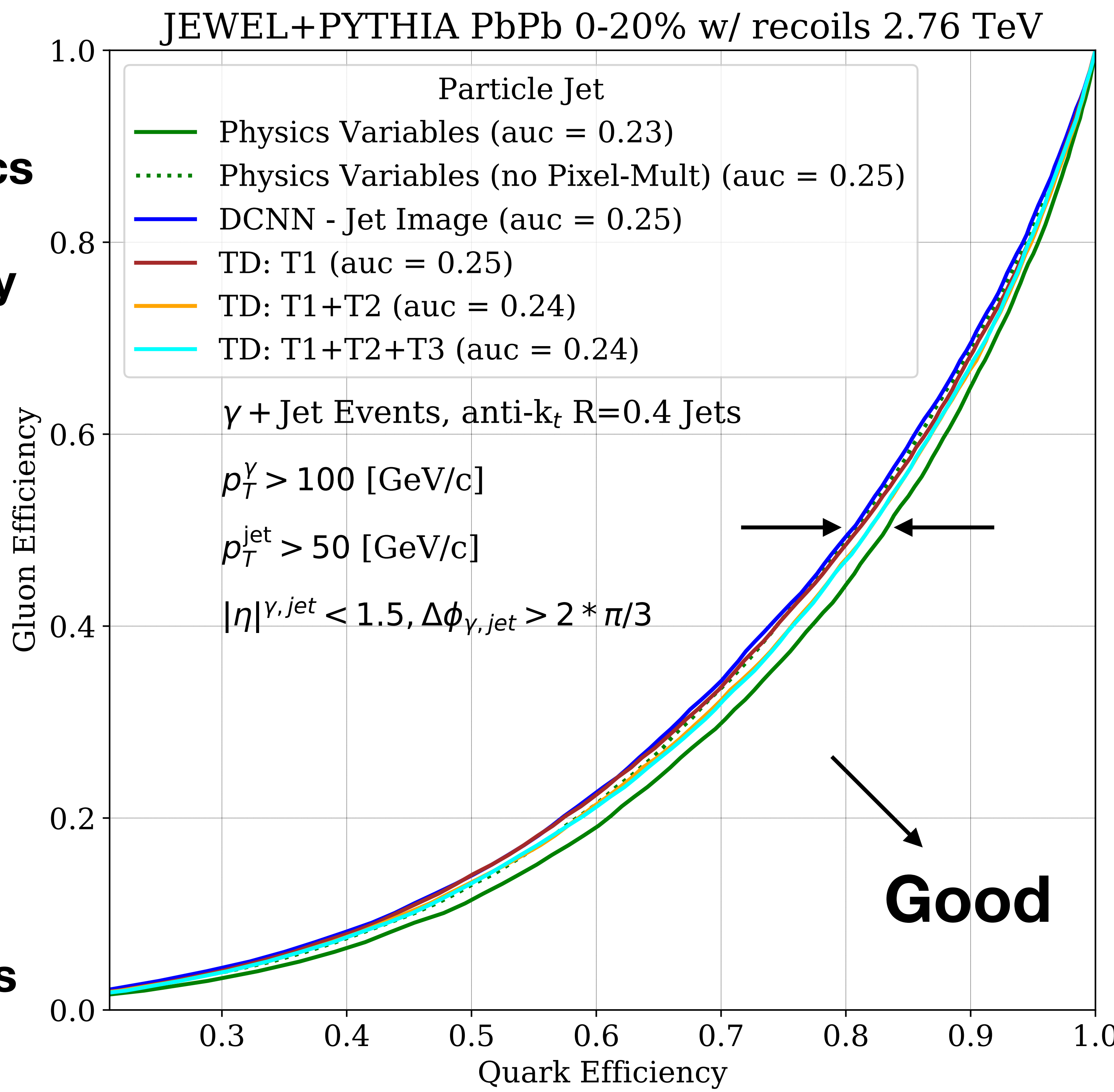
How about Quenched jets?

ROC curve for Quenched PbPb Particle Jets

Traditional physics variables relies on jet multiplicity

TD: Increasing order saturates performance

DCNN seems to be worst! On par with physics variables w/o multiplicity



All methods are relatively close to each other

Performance reduces!

The basics

What is machine learning?

Why are these tools useful in high energy colliders?

How to quantify performance?

Physics with ML

Classifier - Can select Heavy-Flavor or Quark vs Gluons

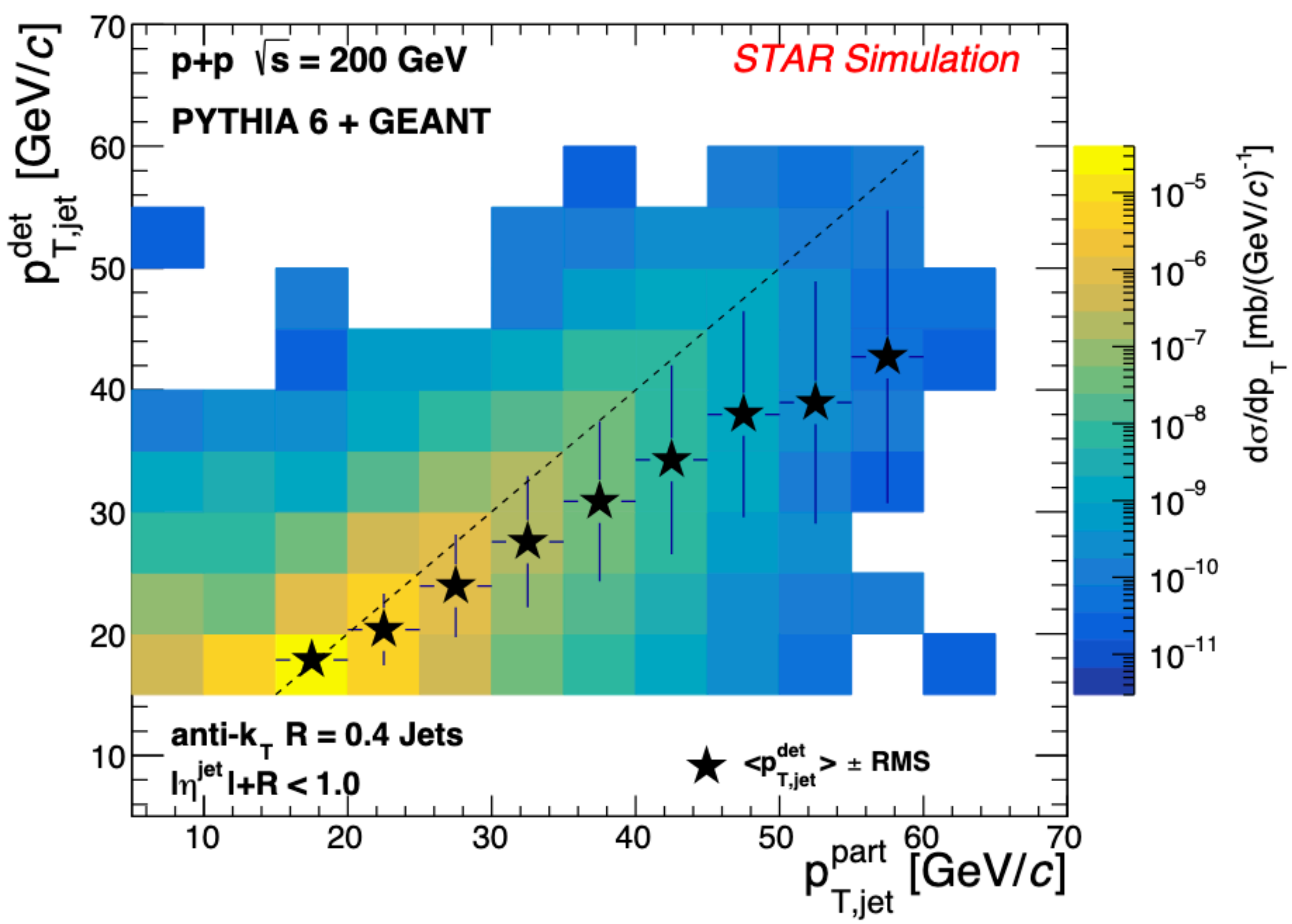
Regressor - multi-dimensional correction and unfolding

Generator - learn underlying physics of MC generators

Unfolding - a quick primer

Corrections for Detector Resolution

Response Matrix



For a given generator jet p_T - the probability get reconstructed at a certain p_T

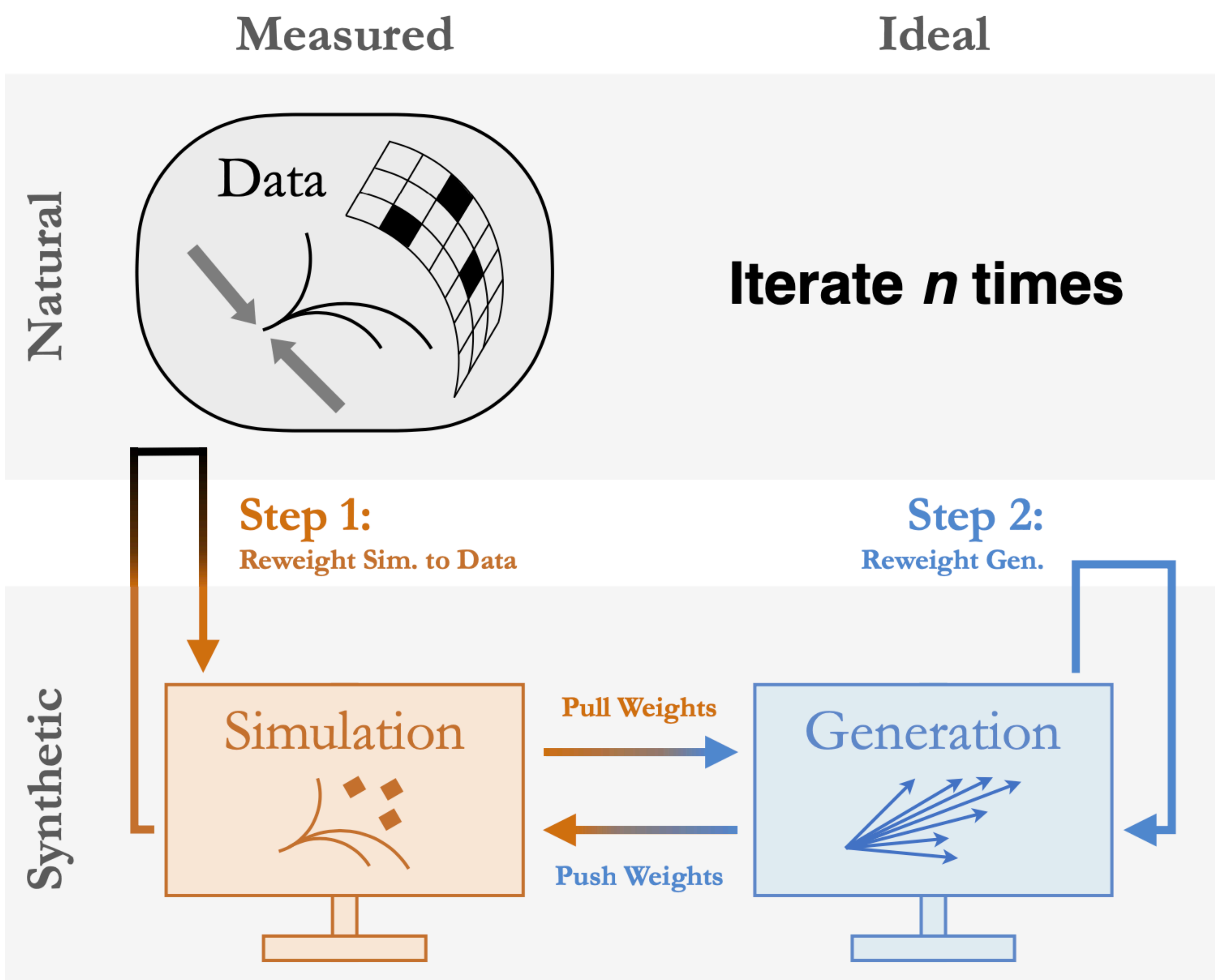
Two separate methods

- Bayesian
- Single Value Decomposition

Based on RooUnfold Package

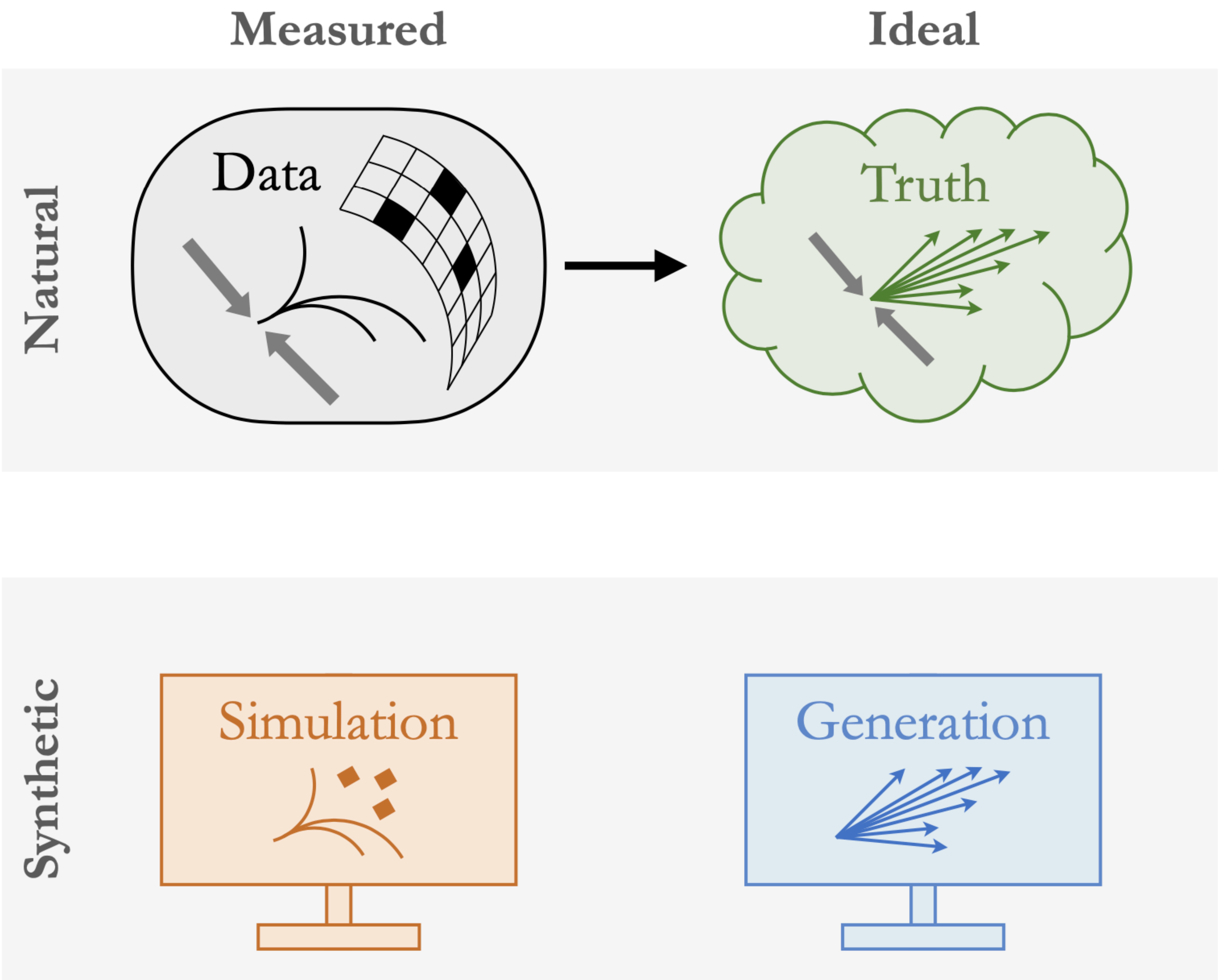
After unfolding - can directly compare with theory calculations

MultiFold (Omnifold)



Ben Nachman (LBL)

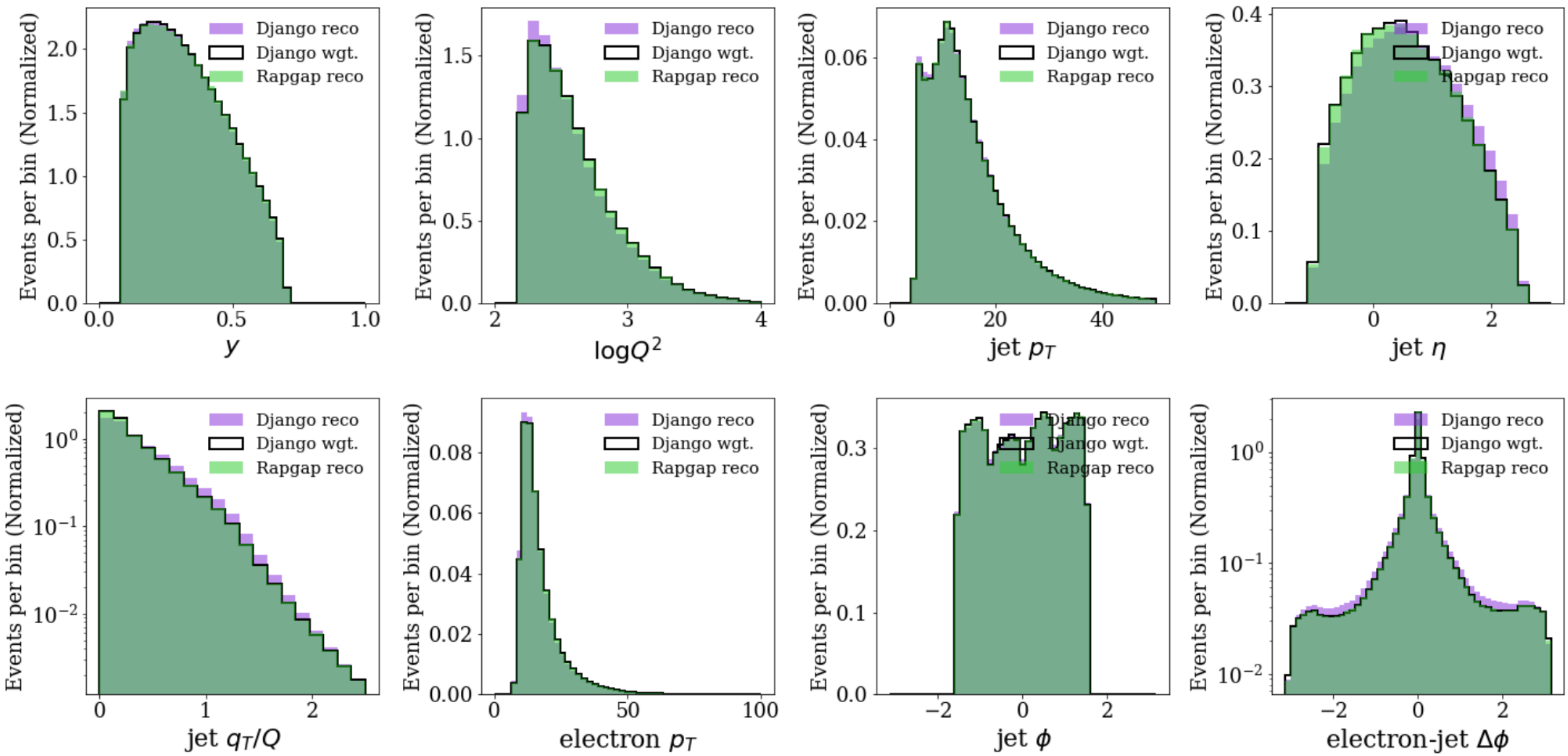
MultiFold (Omnifold)



Ben Nachman (LBL)

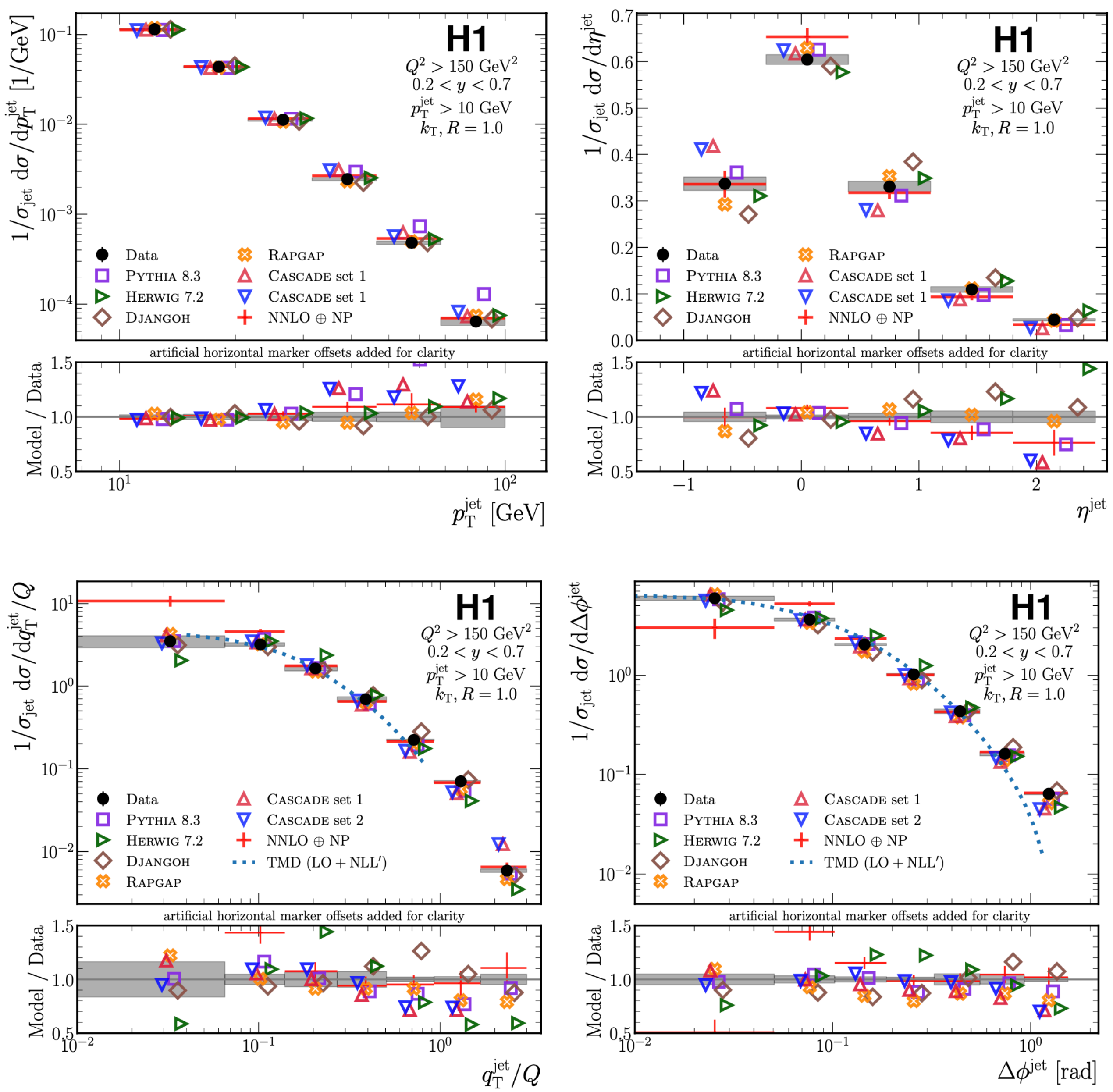
Unfolding closure tests using two different MC samples

All of these distributions are simultaneously reweighted!

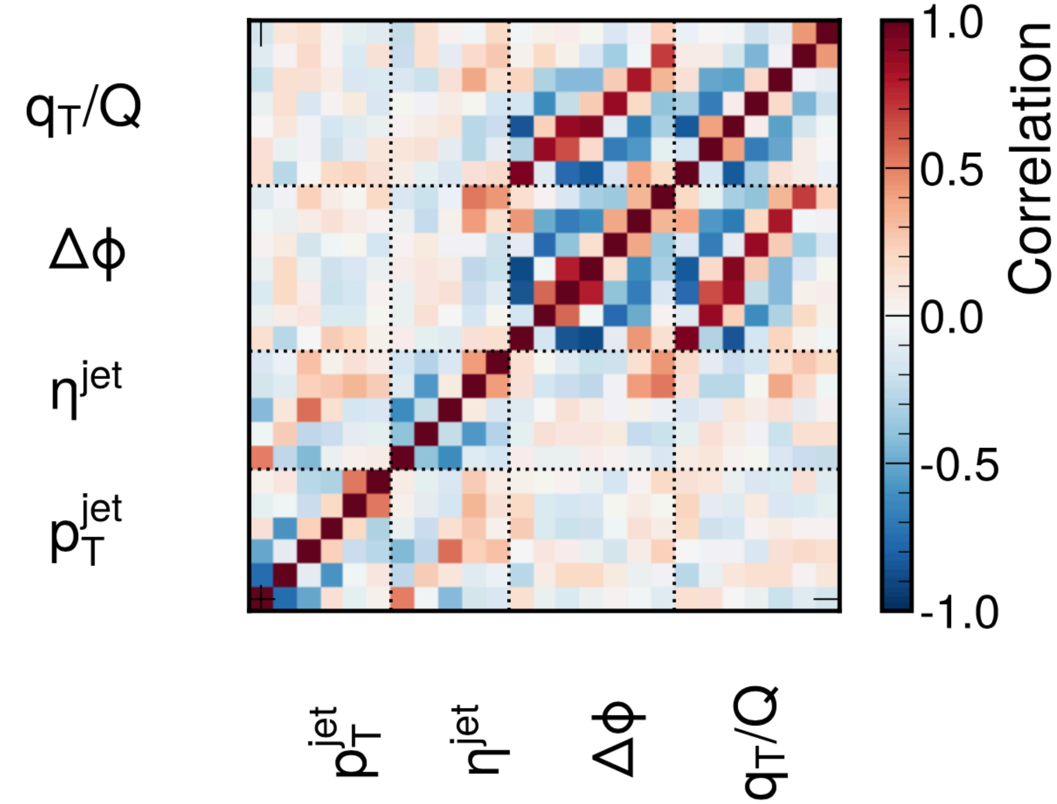


Ben Nachman (LBL)

What you get at the end?



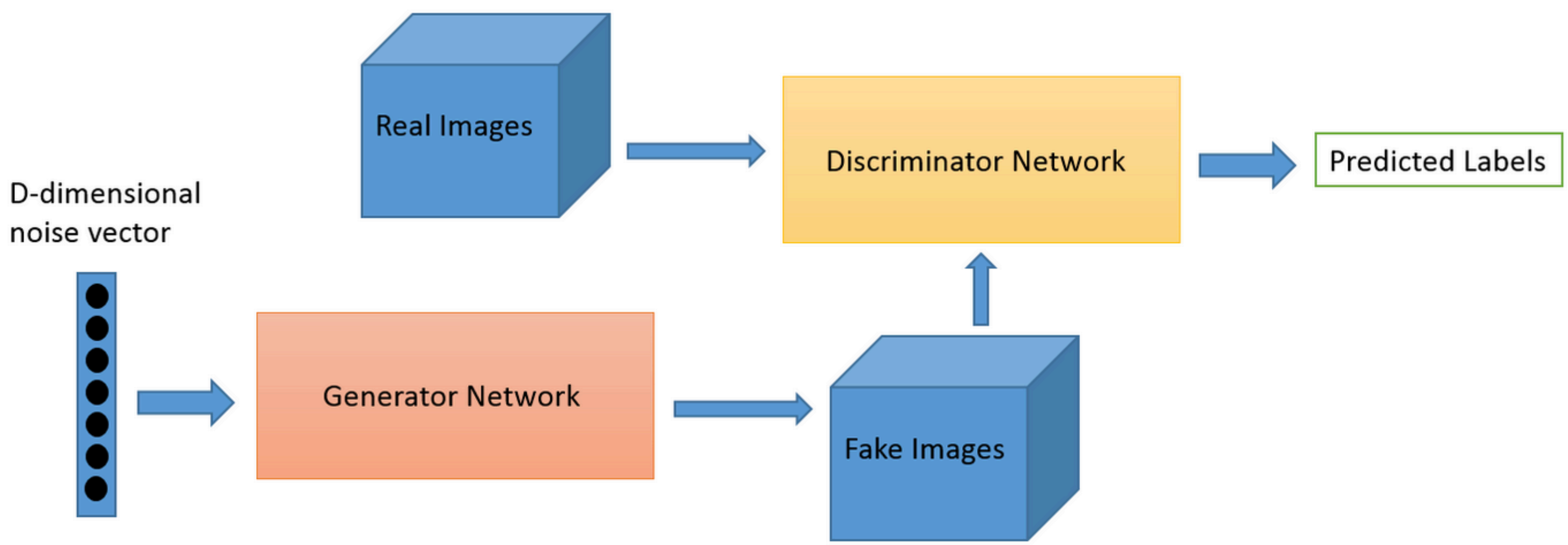
Ben Nachman (LBL)



- Multi-dimensional measurements ‘un-binned’
- You get the correlations for ‘free’

Lets ask the AI to learn physics (or something..?)

- Given a particle-by-particle, event-by-event distribution of quantities - can a model early the intricacies of the generation?
- Enter Generative-Adversarial-Networks (GAN) - playing one network vs another



Credit: O'Reilly

https://skymind.ai/wiki/generative-adversarial-network-gan

A few things GANs can do!

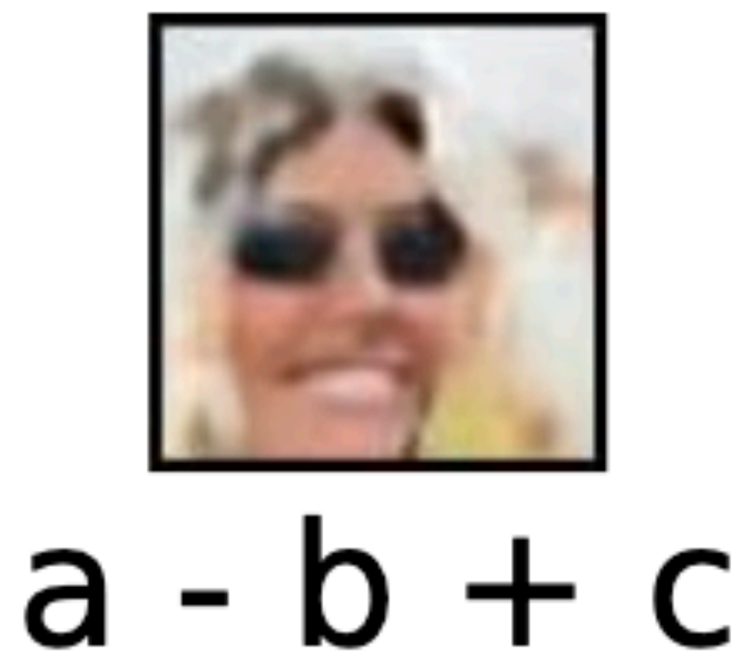
Generate Faces!

Nearest training set

Ian Goodfellow et. al, 1406.2661

A few things GANs can do!

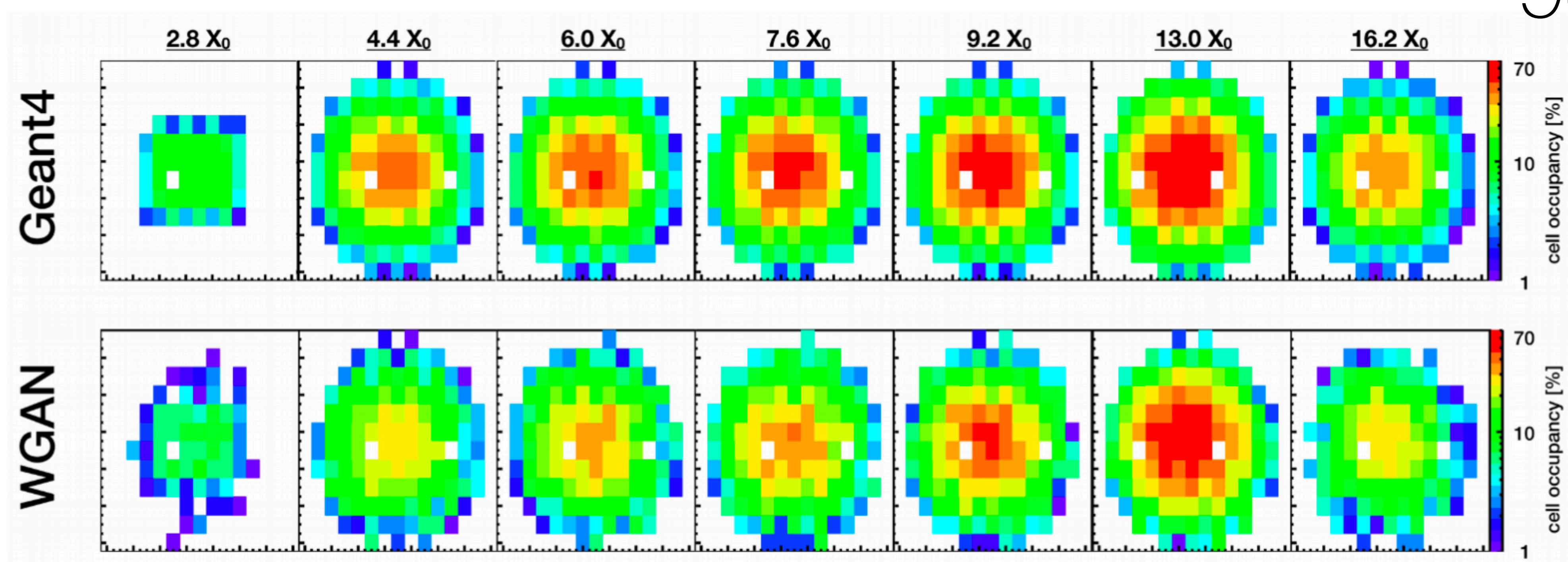
latent space arithmetic : Reduce images to its inherent hidden representation (same-dimensions) so we can perform mathematical operations!



Piotr Bojanowski et. al, 1707.05776

Facebook AI

CMS
High-Granularity HF



Yannik Rath (Aachen), ML4Jets18

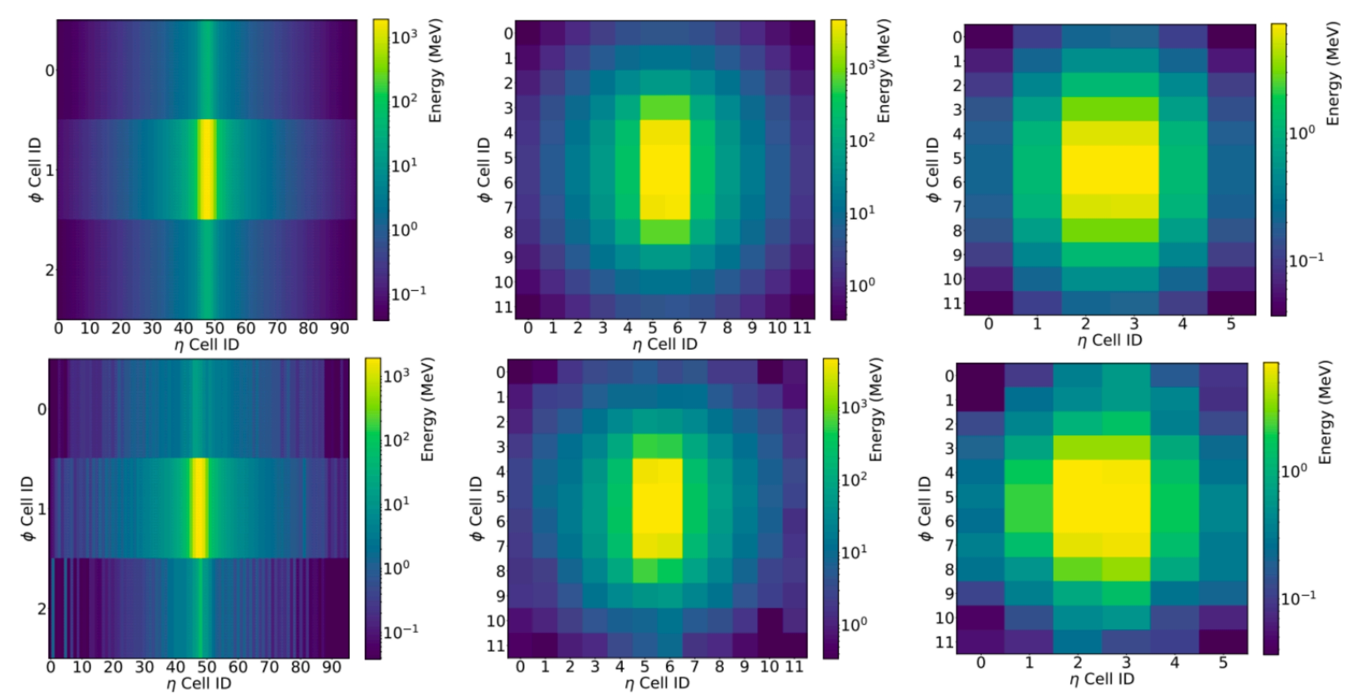
Average positron shower in each calorimeter layer

ATLAS
Longitudinally
segmented Calorimeter

Pagnini M, Nachman B, Olivera L
Phys. Rev. D 97, 014021 (2018)

GEANT

CaloGAN



Michela Pagnini (Yale, LBNL), ML4Jets17

Individual positron showers and generated nearest neighbors

GEANT 1st layer deposition

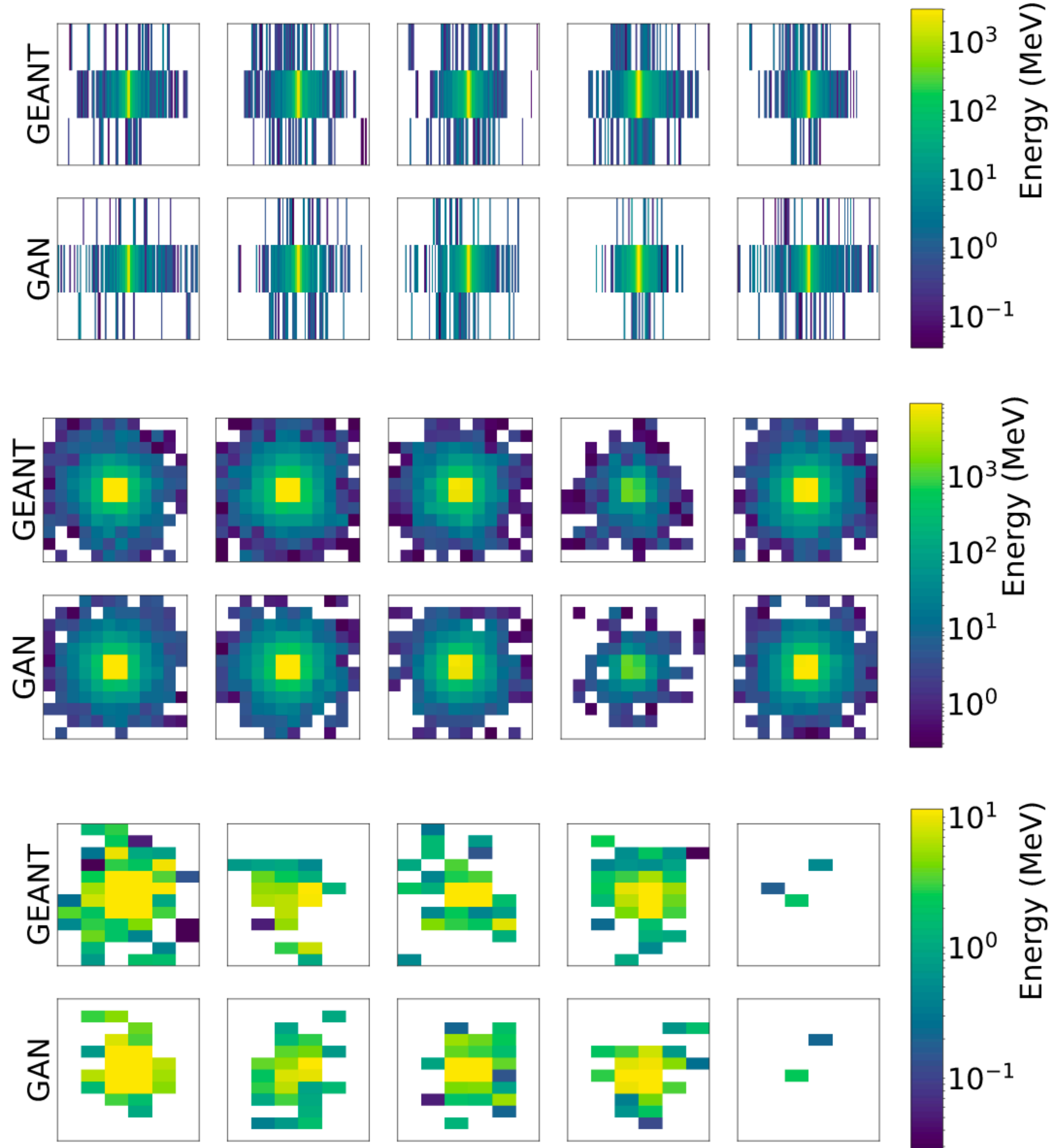
CaloGAN 1st layer deposition

GEANT 2nd layer deposition

CaloGAN 2nd layer deposition

GEANT 3rd layer deposition

CaloGAN 3rd layer deposition



Michela Pagnini (Yale, LBNL), ML4Jets17