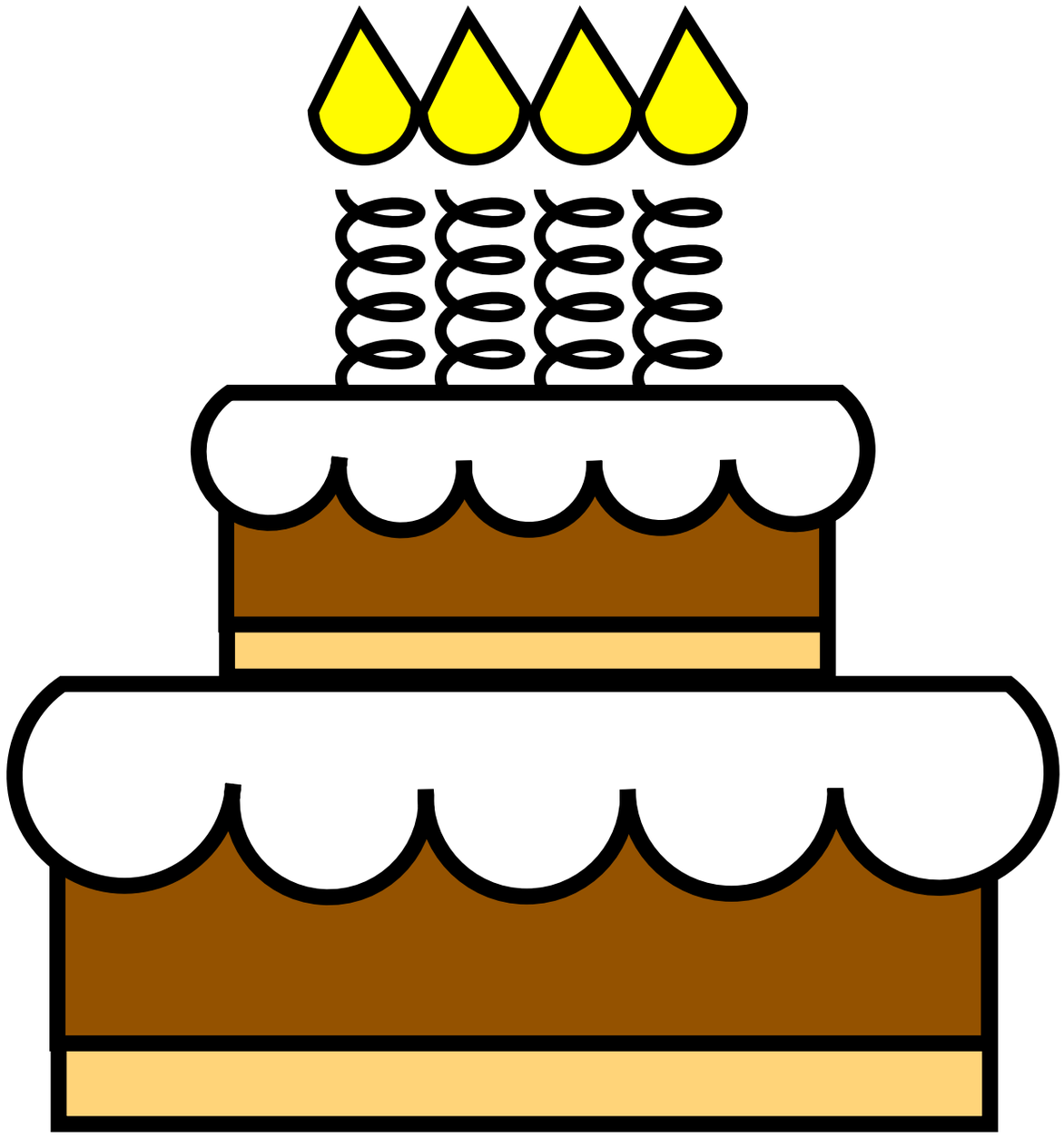
Jet substructure in Run 3/4
an experimental point of view

Benjamin Nachman

Lawrence Berkeley National Laboratory

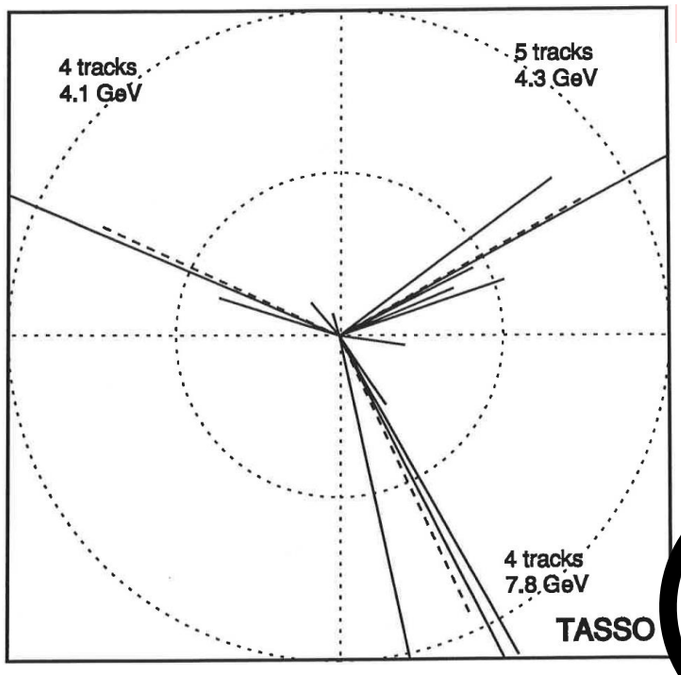
SLAC Workshop, Oct. 2019

2019 is a special year.

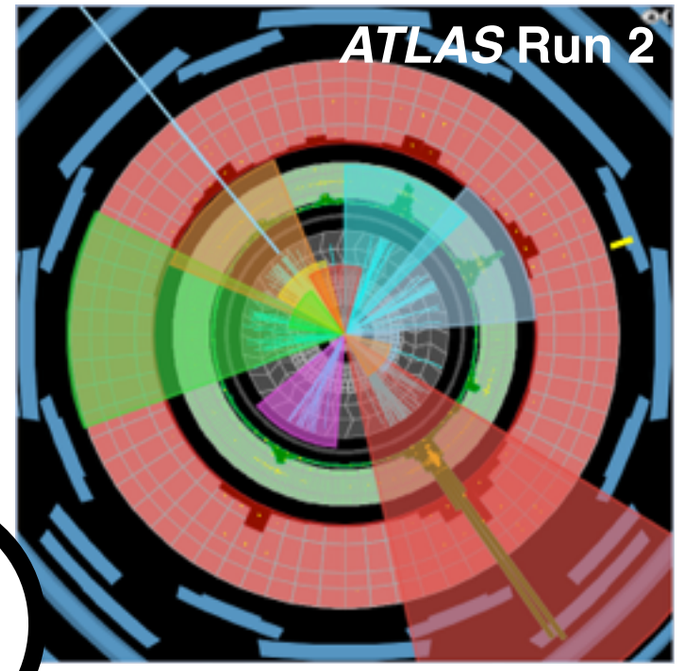


2019 is a special year.

1979

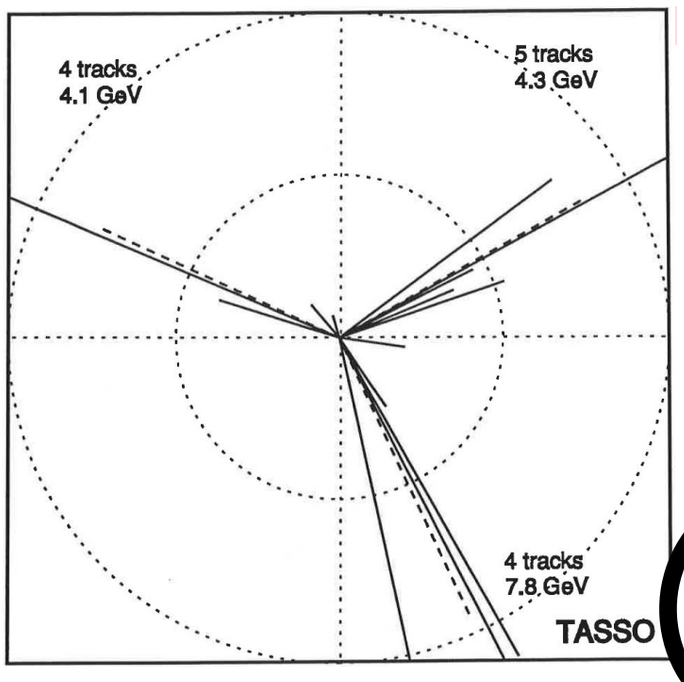


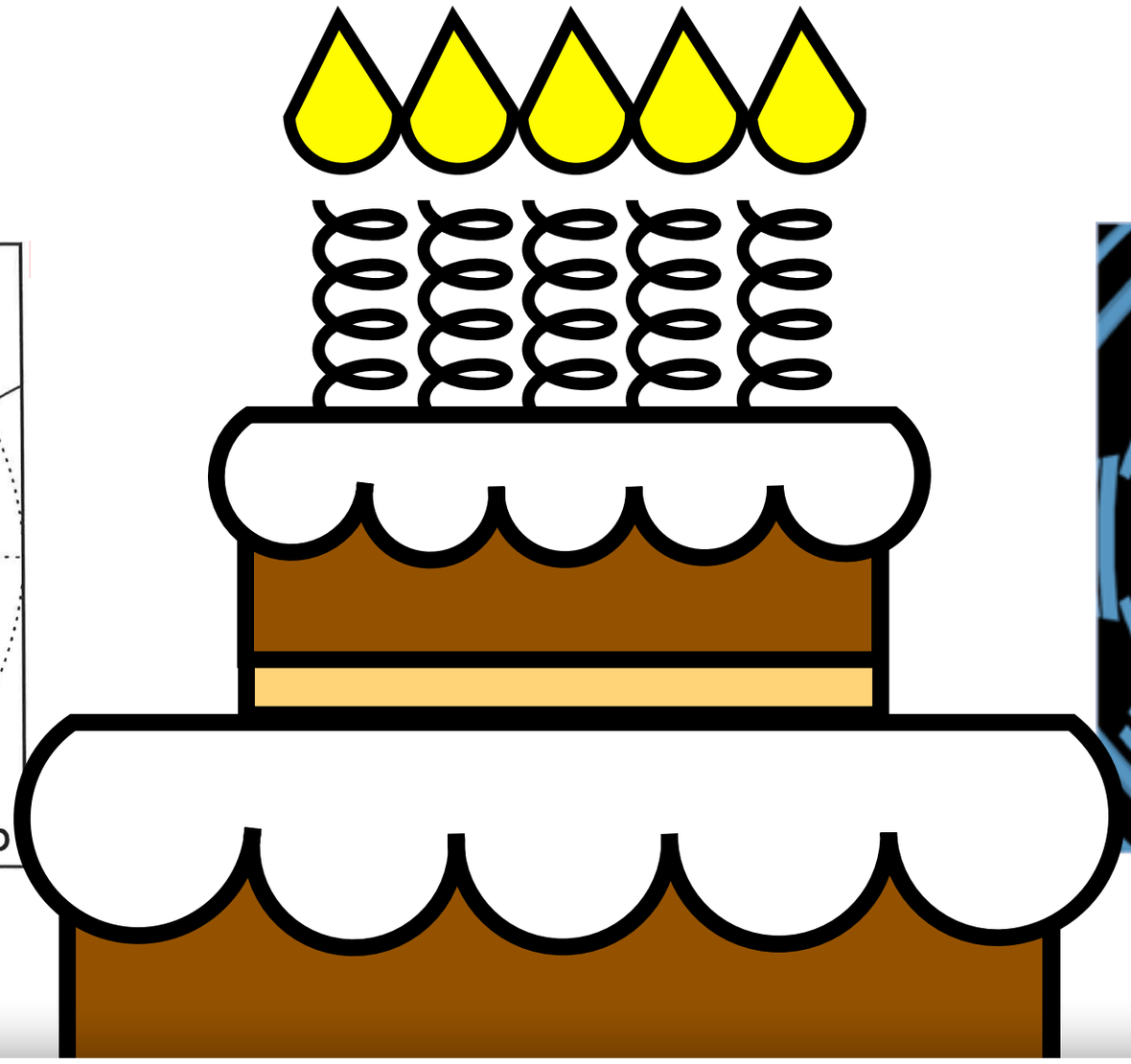
2019



2029 will be even more special!

1979





2029

Where will QCD take us in the next 10 years? Let's discuss!

Outline

- **Tagging for BSM searches (and SM measurements)**
  - Uncovered scenarios
  - Trigger and pileup challenges
  - Tracking / calorimeter challenges at high p_T
- **Precision QCD**
  - Physics targets
  - Bottom-up approaches
- **Machine Learning Methods** (come to ML4Jets2020!)
  - Tools
  - Fast inference
  - Anomaly detection
  - Uncertainties

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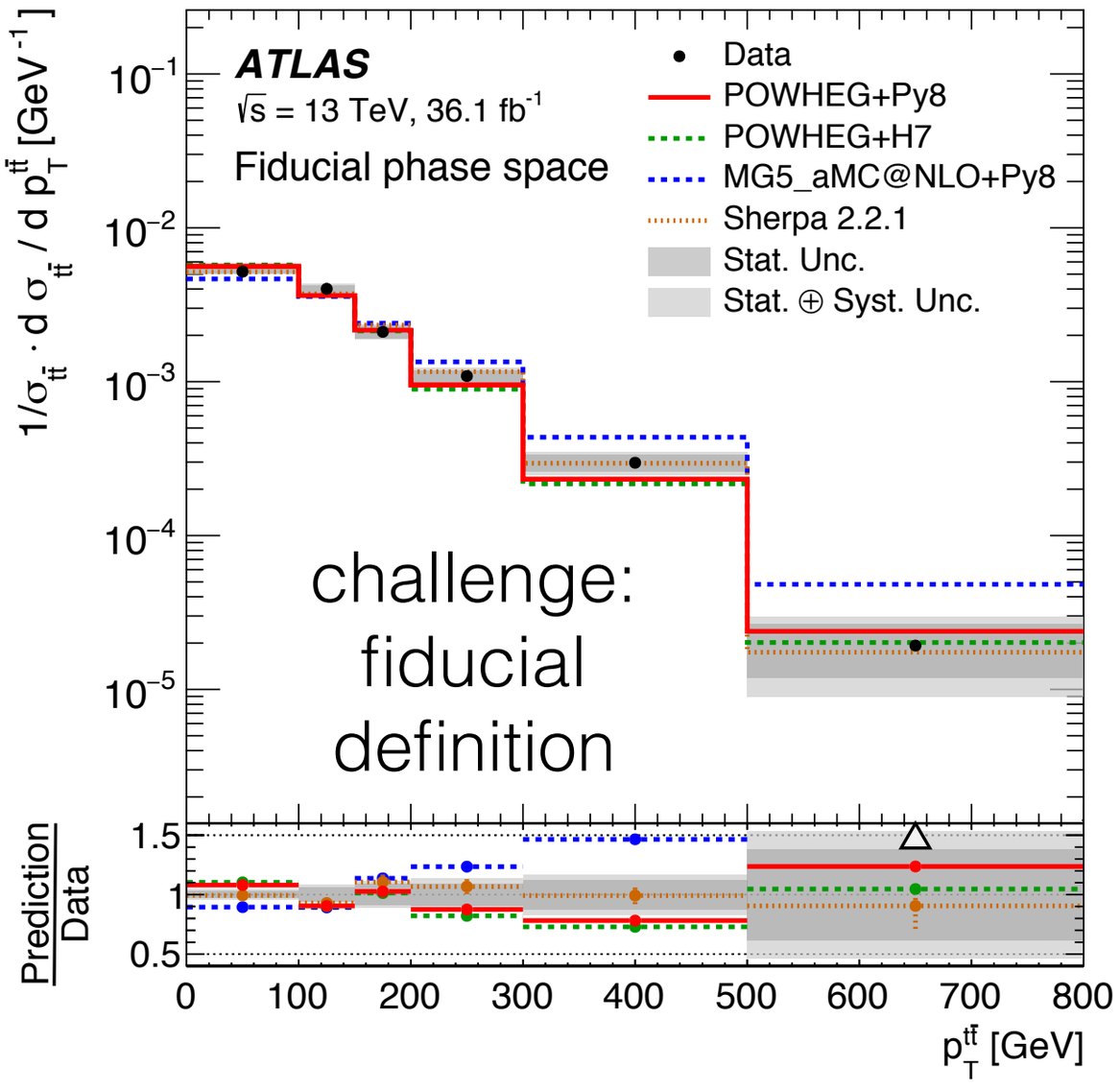
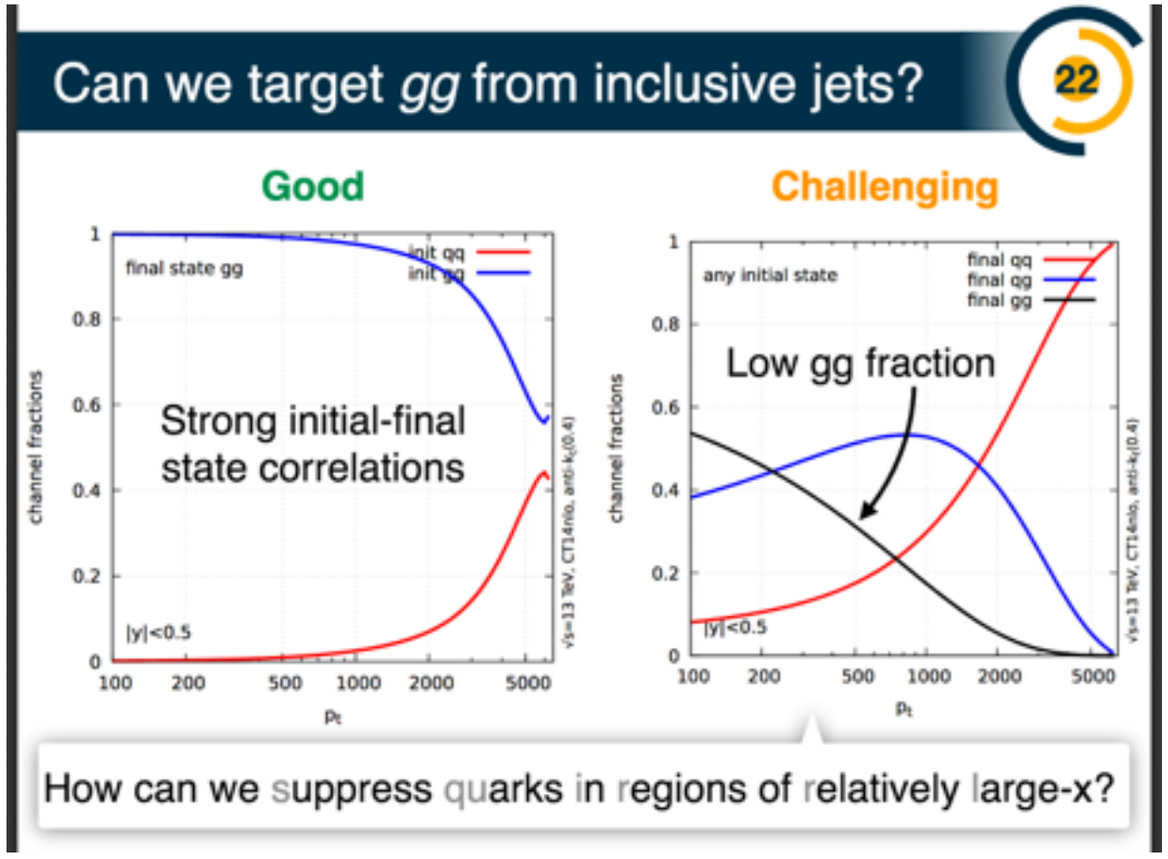
Tagging for SM measurements

A growing number of measurements at high p_T using hadronic channels.

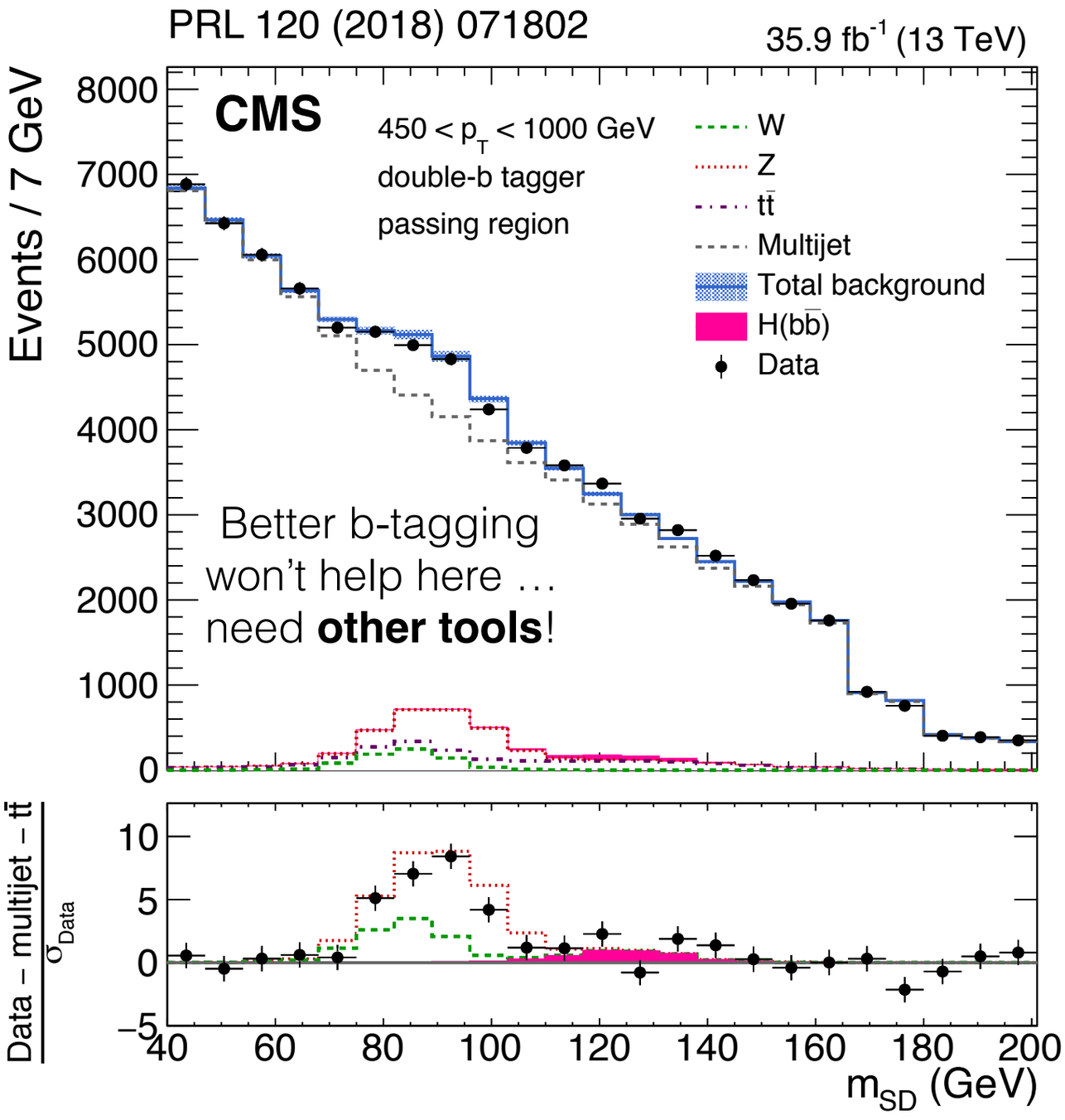


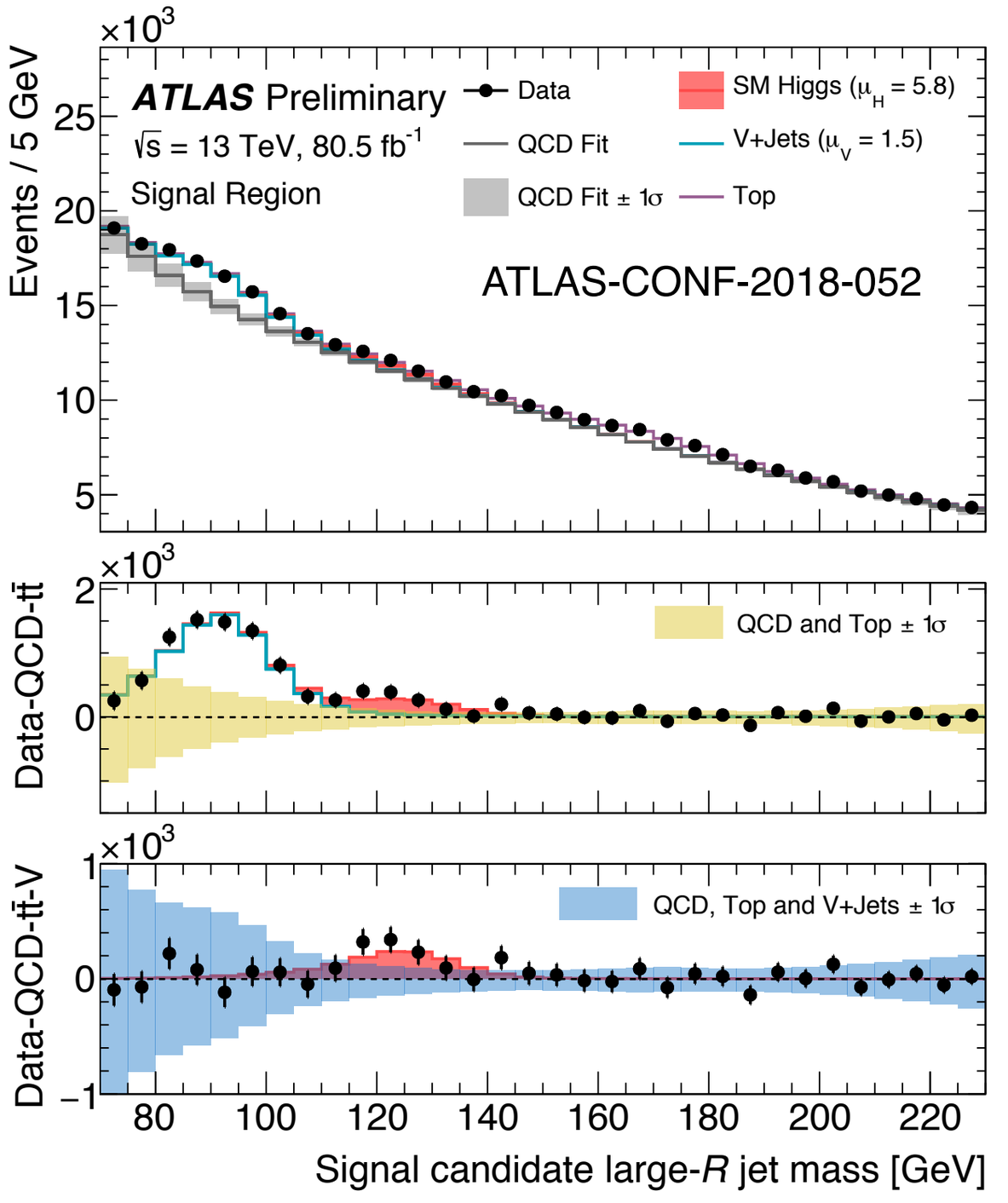


Can we do more? What about a digluon cross section measurement?

Tagging for SM searches

Search for boosted H → bb





See CMS-JME-18-002, 1807.10768, 1710.01305

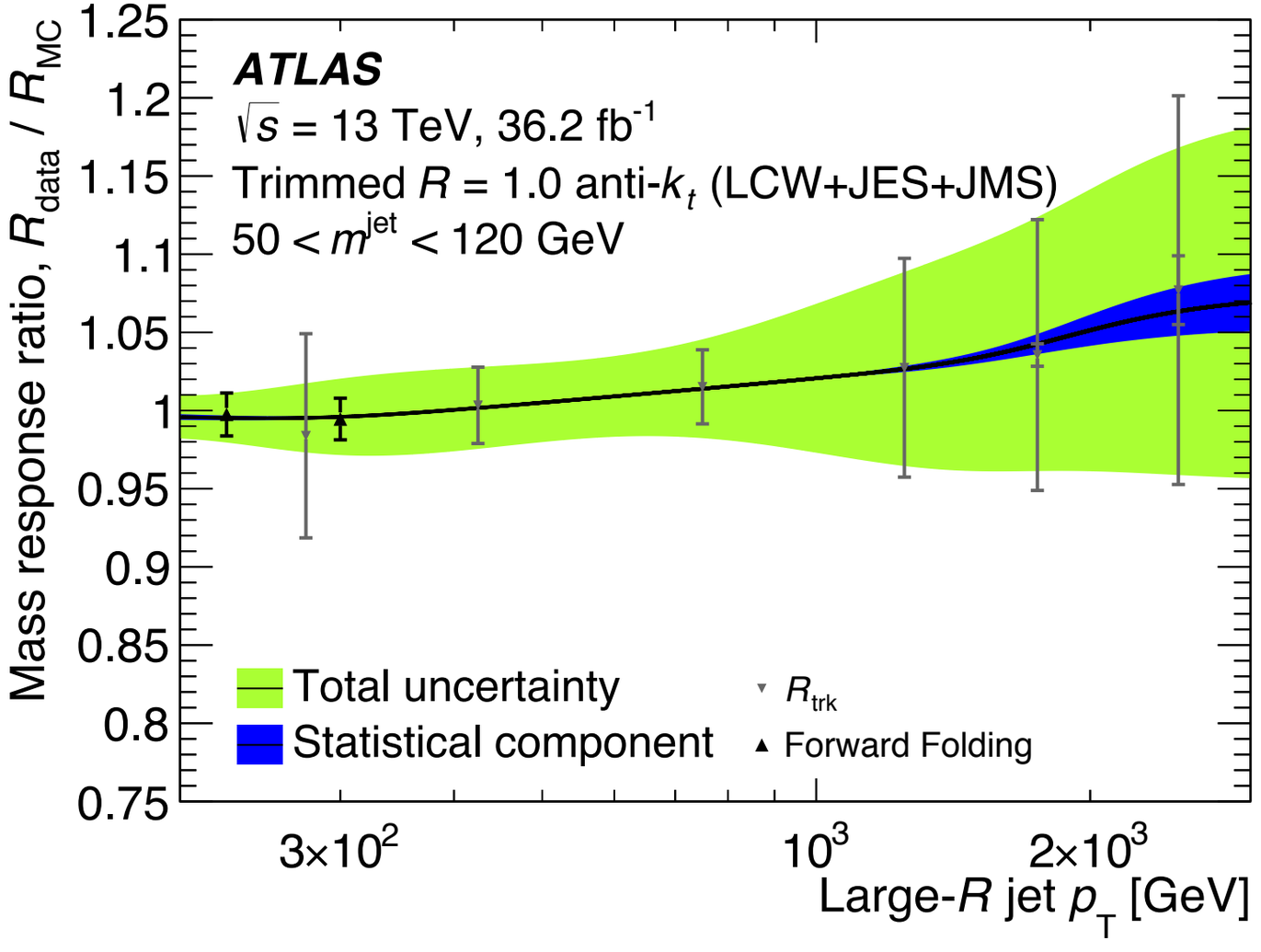
Tagging for BSM searches

Now widespread!

…includes tagging boosted SM particles and boosted BSM particles.

Challenges:

- How to calibrate BSM resonance tagger?
- How to calibrate a tagger beyond were we can calibrate?
- What is the best way to do mass decorrelation?



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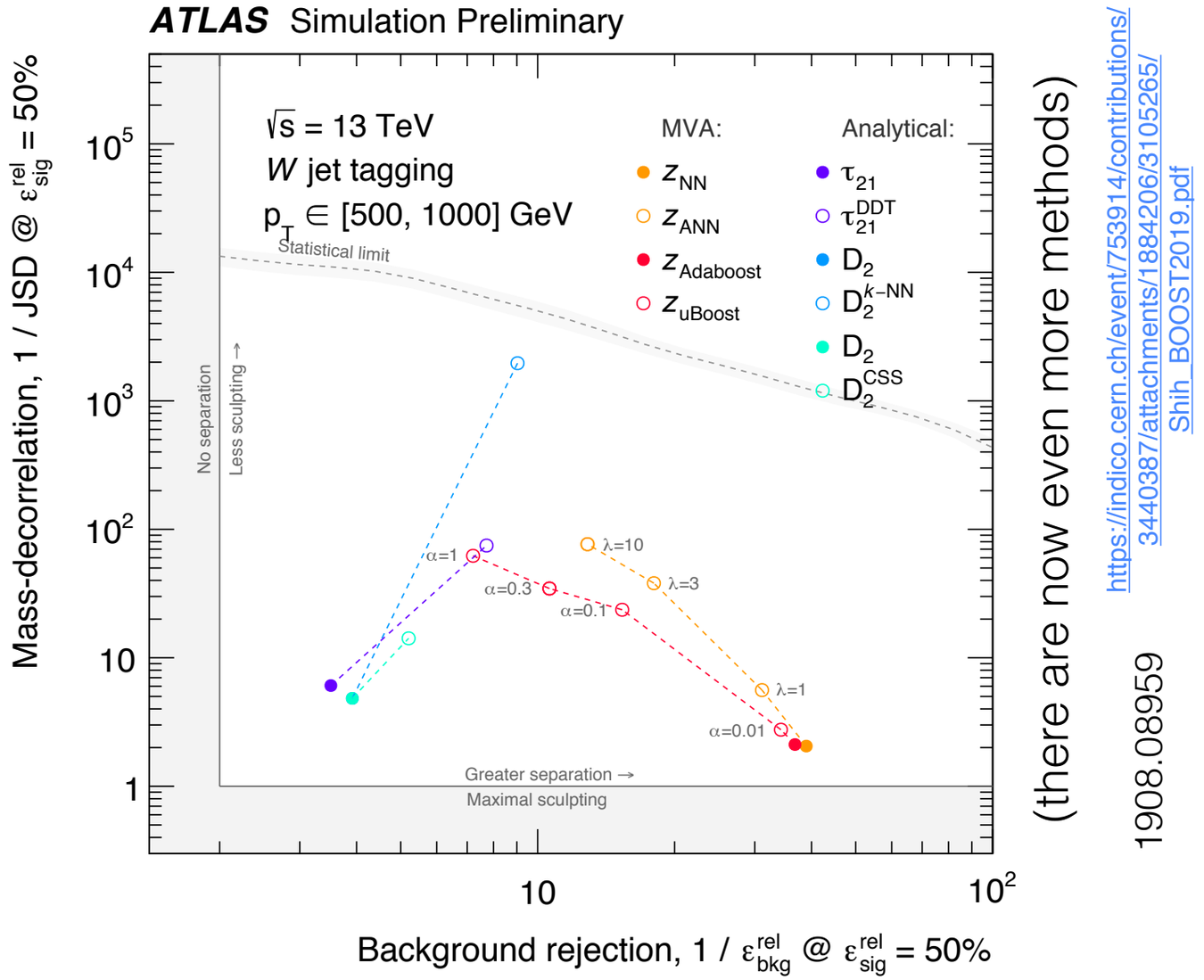
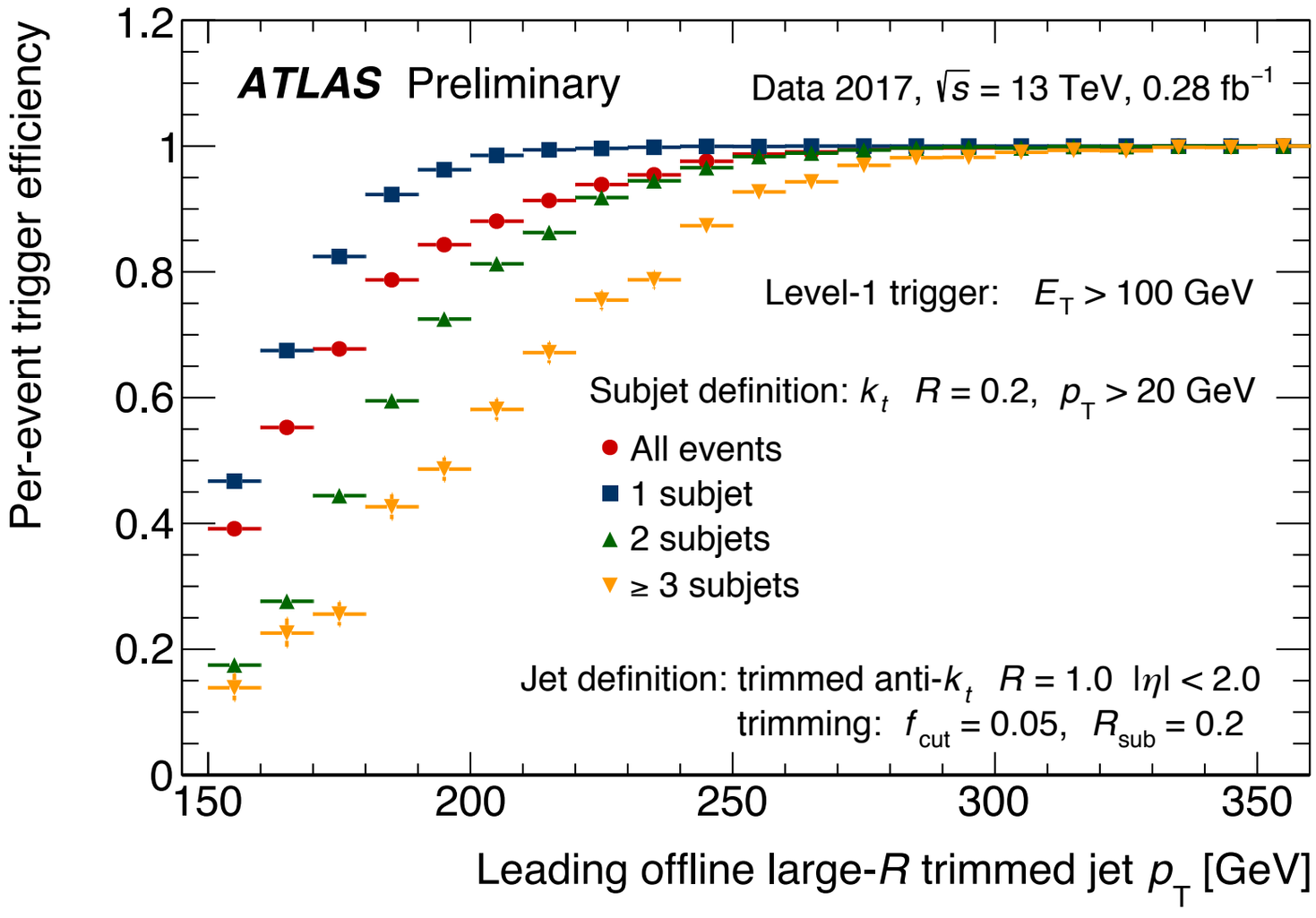


(there are now even more methods)

https://indico.cern.ch/event/753914/contributions/3440387/attachments/1884206/3105265/Shih_BOOST2019.pdf

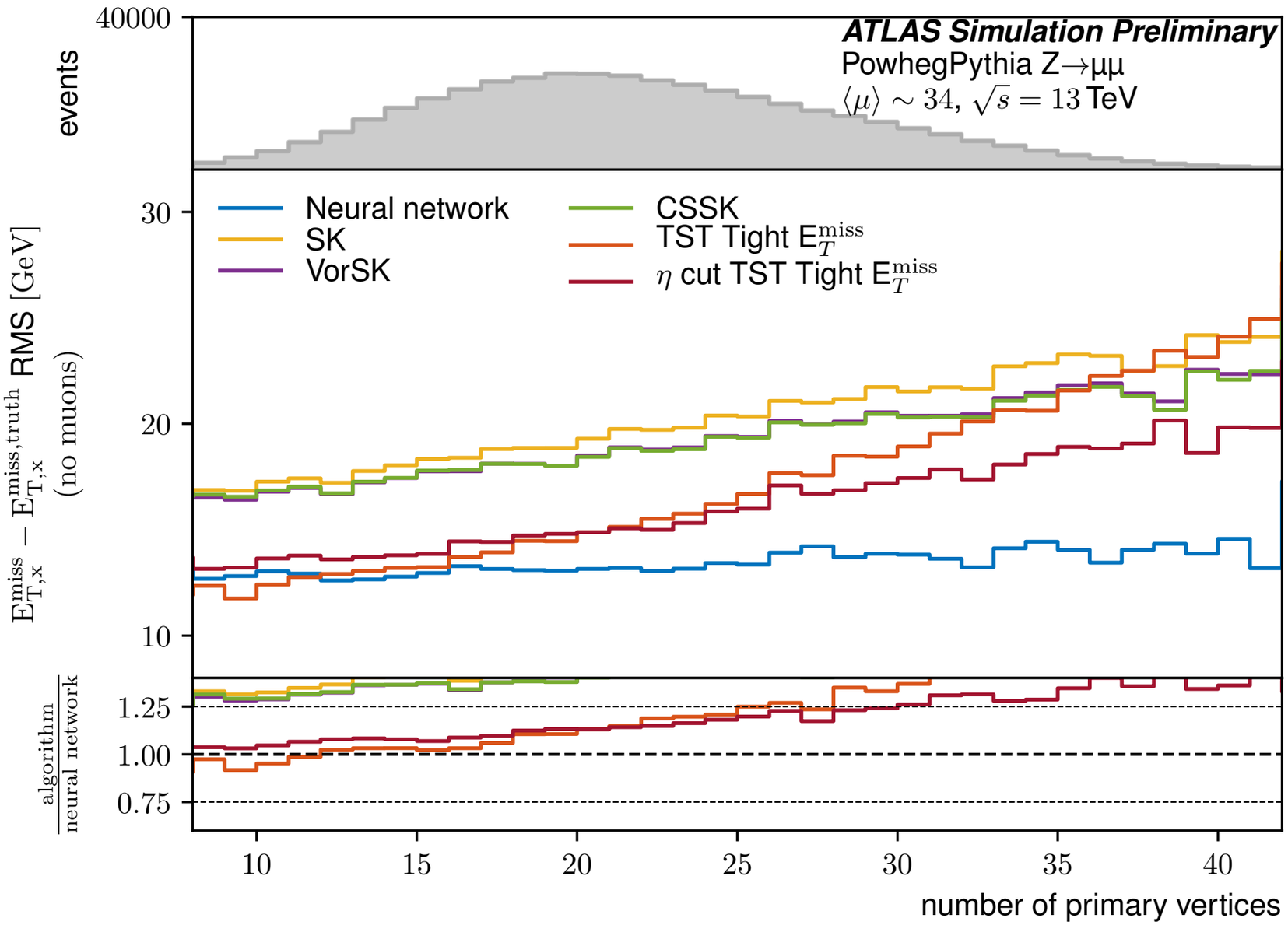
1908.08959

Trigger challenges



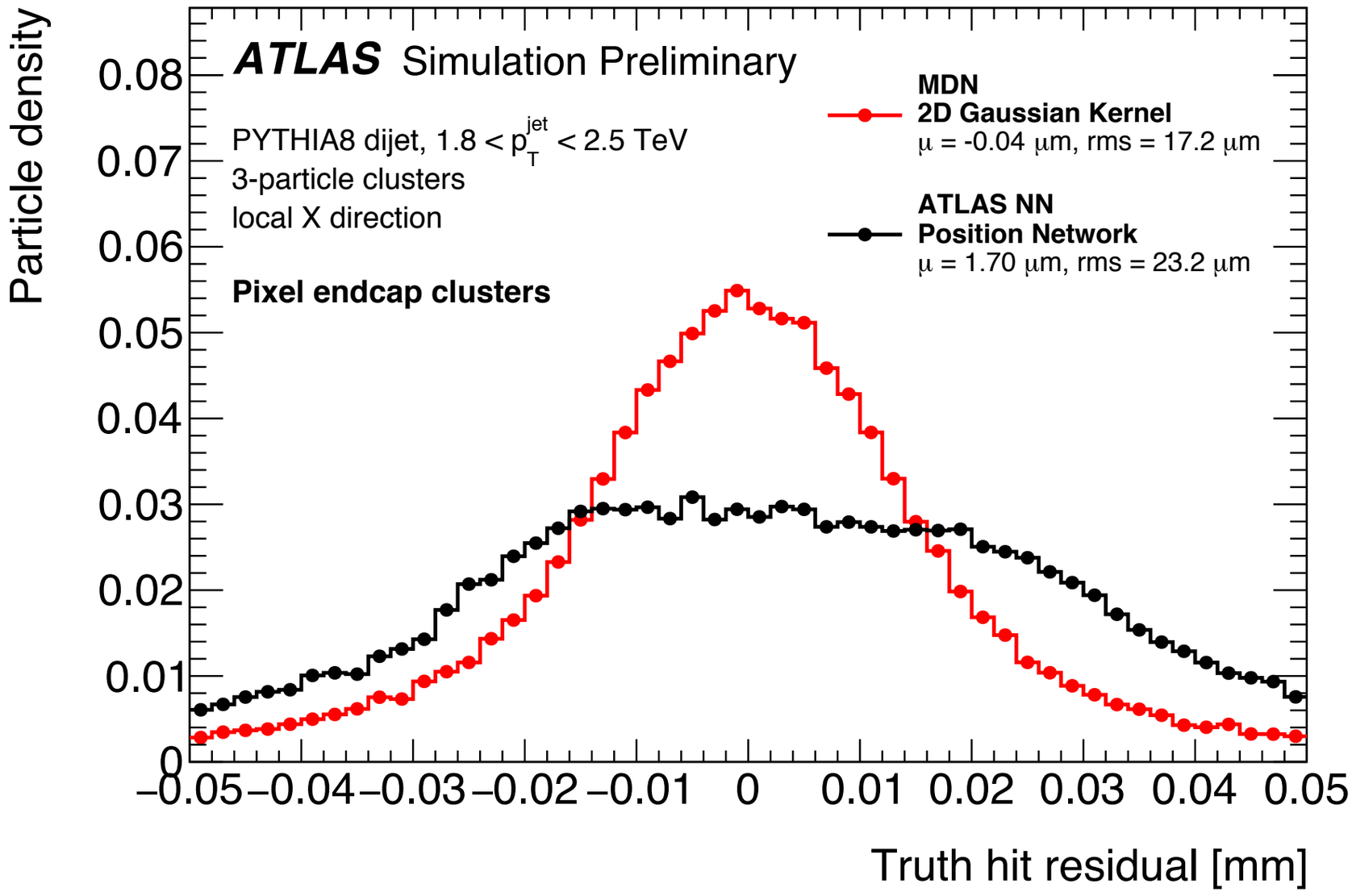
We need to make the online algorithms
as close to offline as possible!
(and maybe even then, that is not good enough)

Pileup



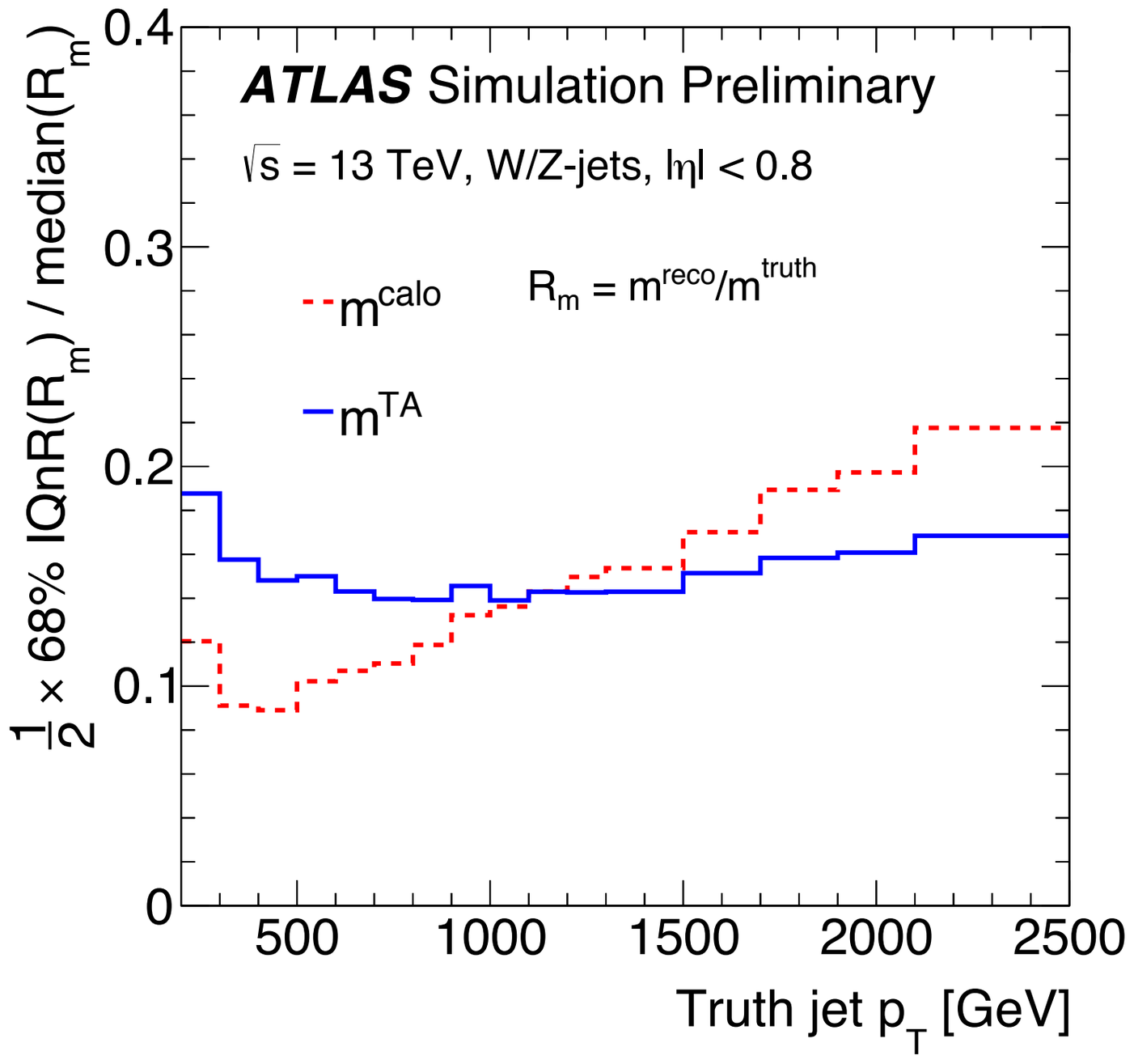
Serious problem for jets, MET, and jet substructure
(ML will help, though clearly work to do!)

Tracking inside jets



Highly boosted resonances lead to efficiency losses inside jets - many of these are recoverable!

Calorimeter reconstruction inside jets



Angular resolution is a serious challenge at high p_T. Can we improve on both the calo side and the use of tracks?

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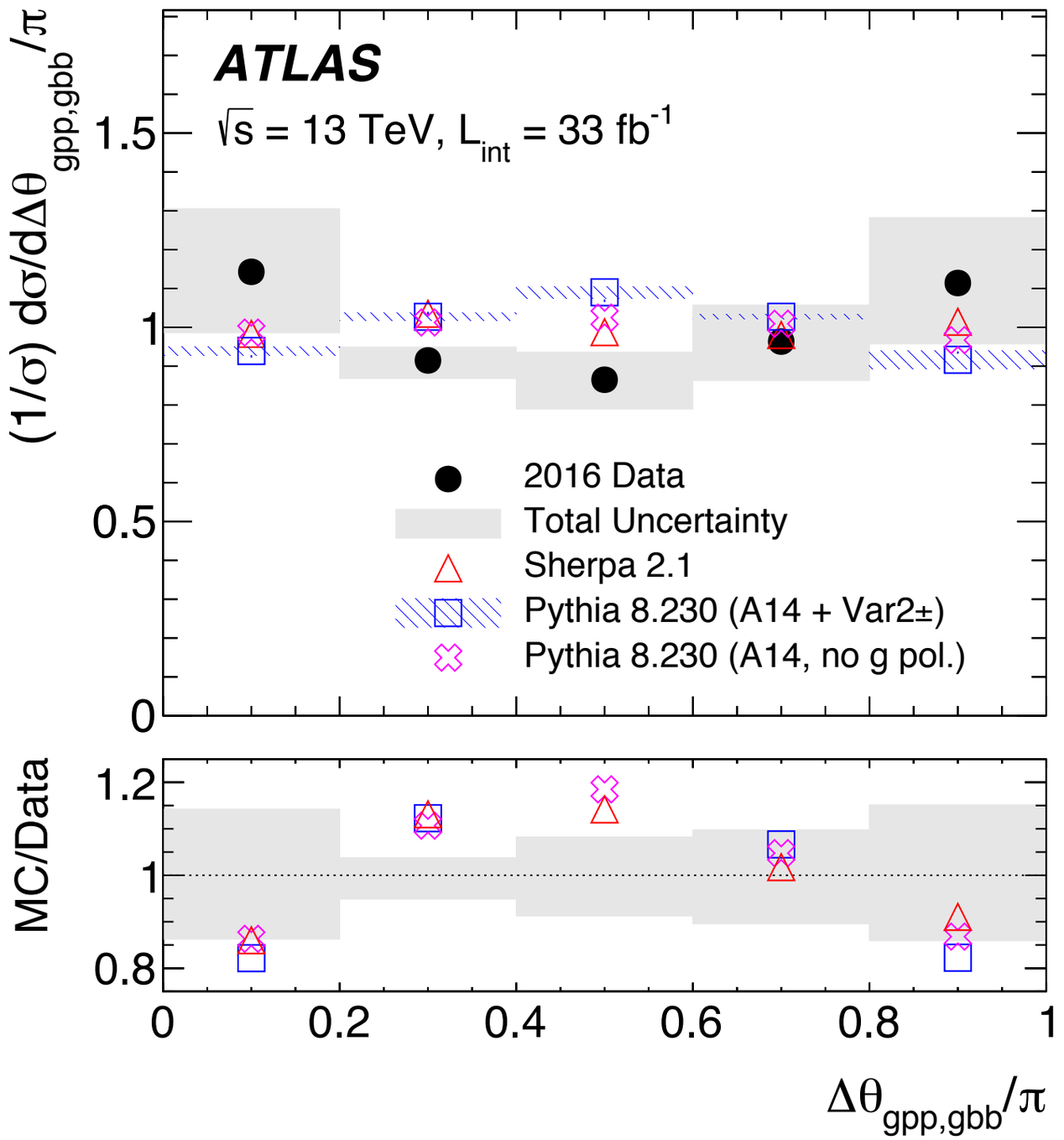
Physics targets

Standard Model parameters (see Ian's talk)

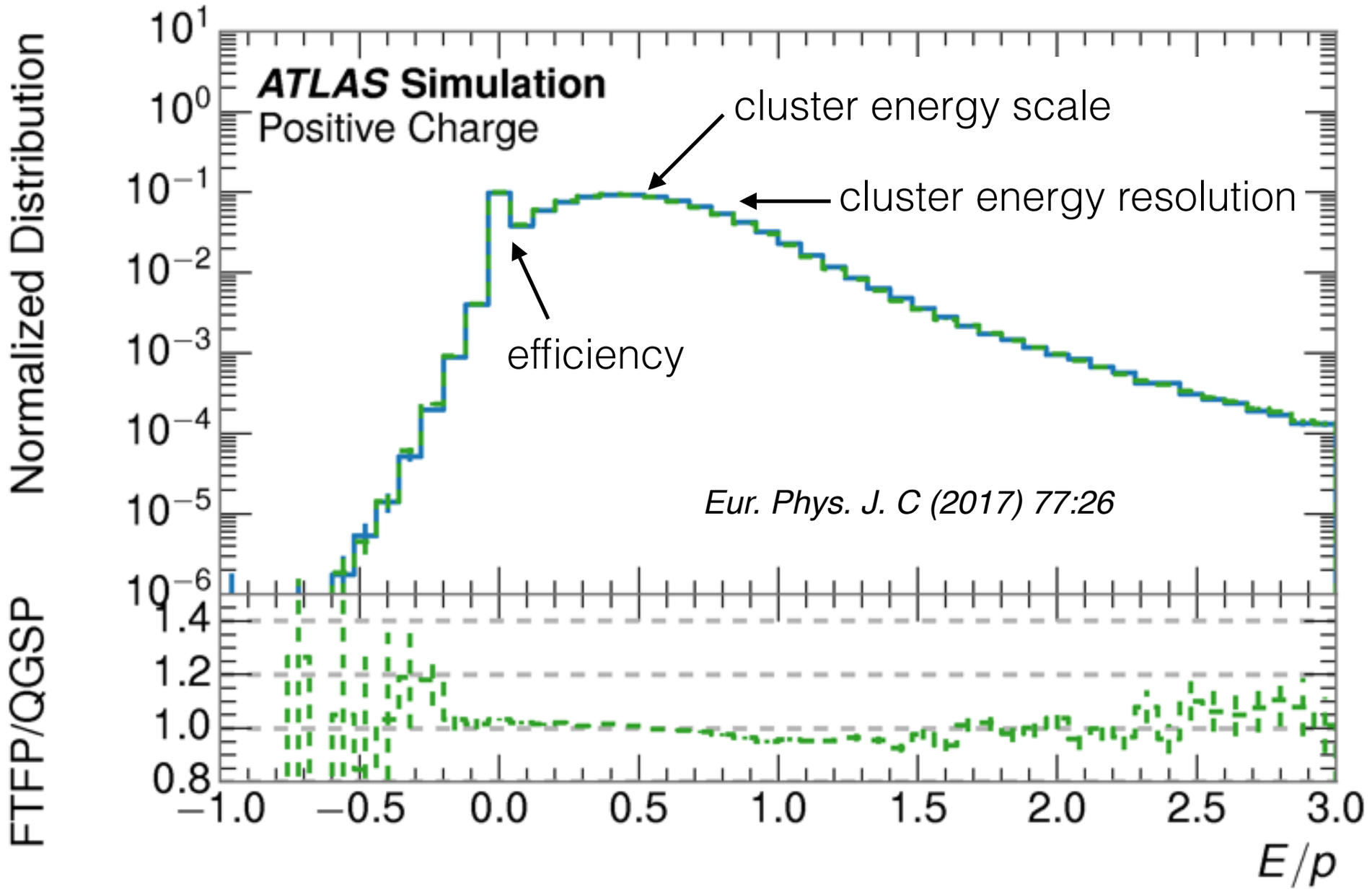
Tuning (critical for other measurements and searches)

Other higher order, emergent, quantum, EW, …. effects

(quite a broad and exciting program that is still in its infancy!)



Bottom up calibrations / uncertainties



Calibrations from resonances not directly applicable to QCD jets - perhaps we can calibrate from the bottom up?

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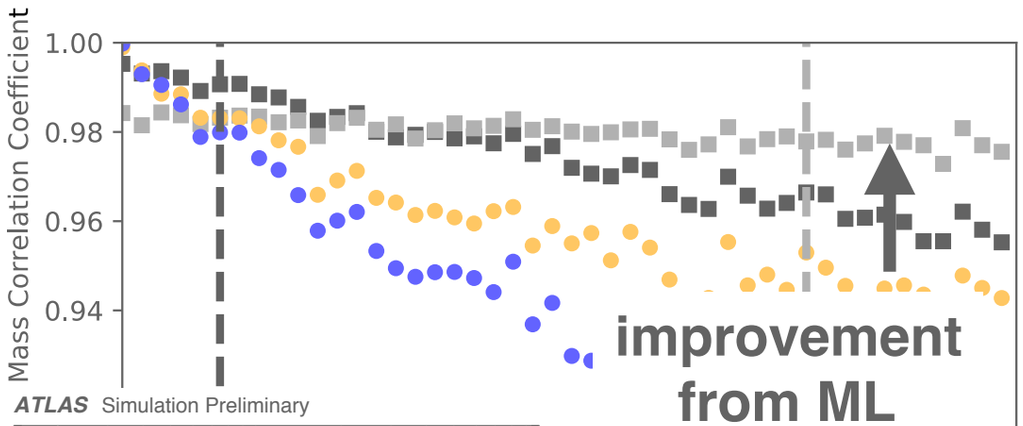
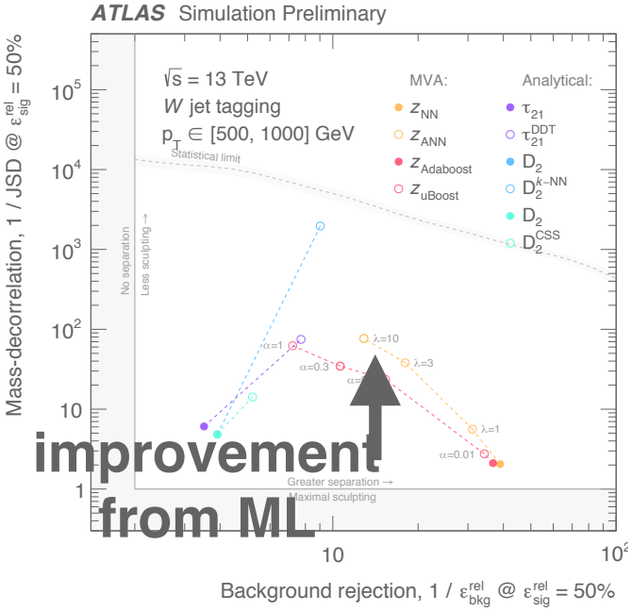
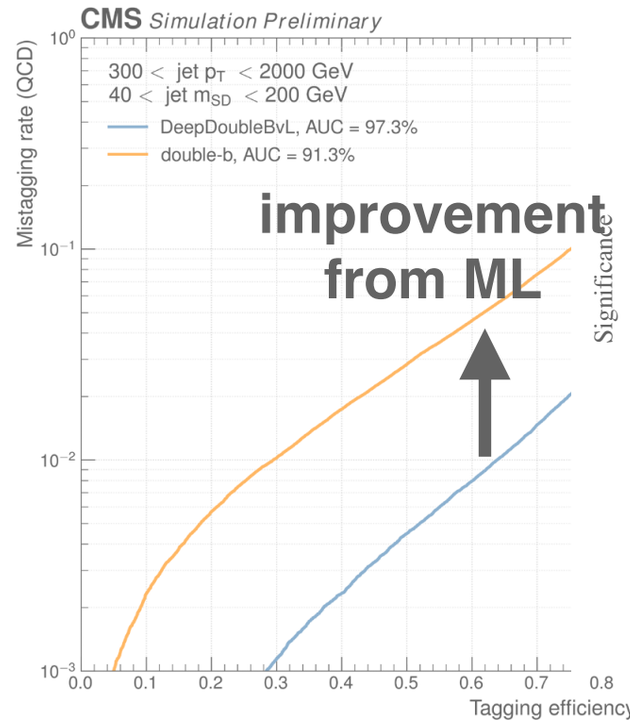
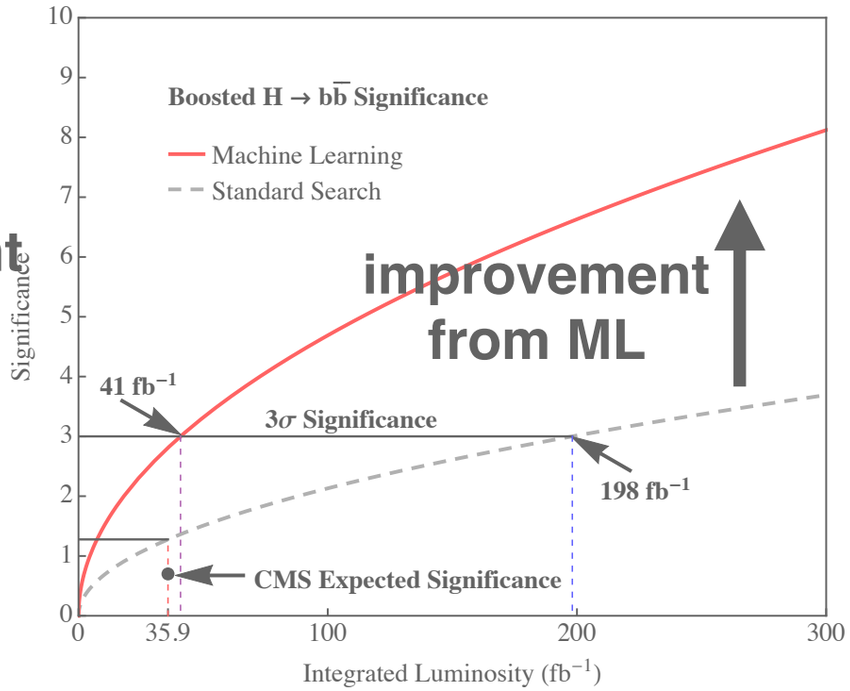
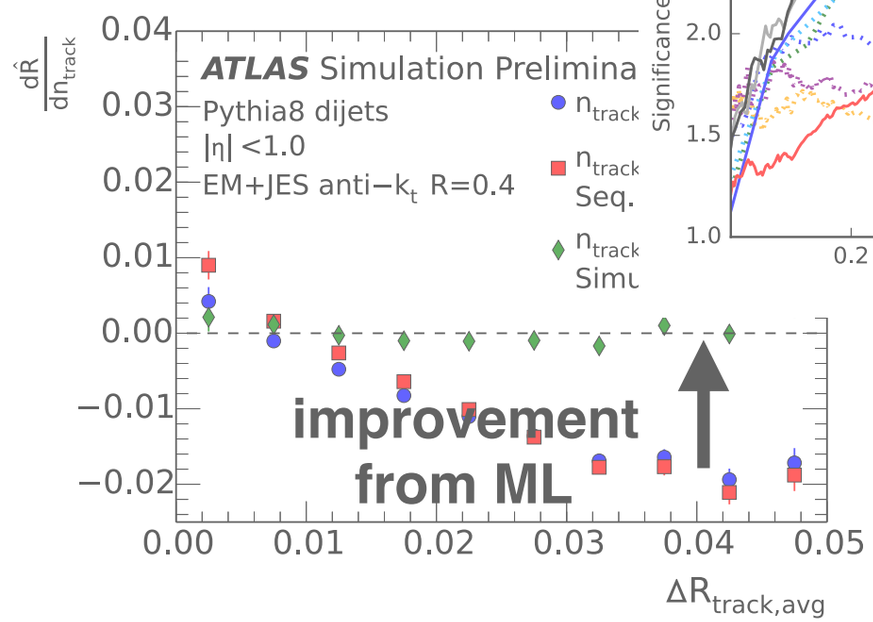
Tools

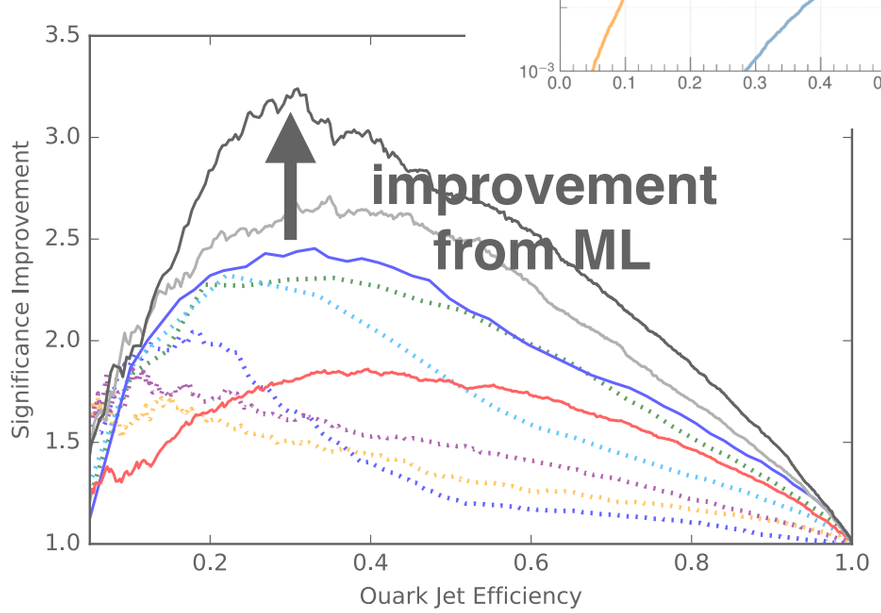

Mass Correlation Coefficient
1.00
0.98
0.96
0.94
improvement
from ML
ATLAS Simulation Preliminary
on NPU=20
on NPU=140
100
125
150
175
NPU

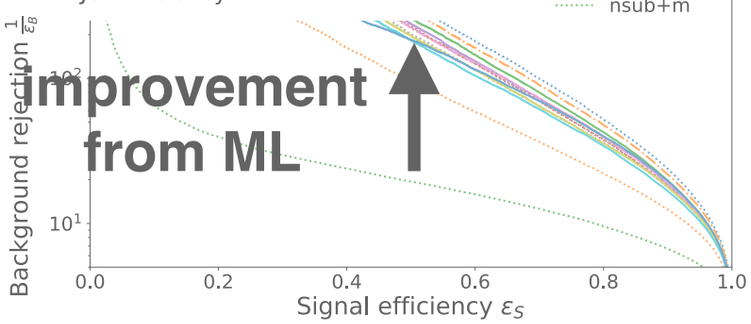

Mass-decorrelation, 1 / JSD @ ε_{sig}^{rel} = 50%
$\sqrt{s}$ = 13 TeV
W jet tagging
$p_T \in$ [500, 1000] GeV
MVA:
Analytical:
z_{NN}
z_{ANN}
$z_{Adaboost}$
z_{uBoost}
τ_{21}
τ_{21}^{DDT}
D_2
$D_2^{\kappa-NN}$
D_2
D_2^{CSS}
Statistical limit
No separation
Less sculpting →
Greater separation →
Maximal sculpting
improvement
from ML
Background rejection, 1 / ε_{bkg}^{rel} @ ε_{sig}^{rel} = 50%


CMS Simulation Preliminary
300 < jet p_T < 2000 GeV
40 < jet m_{SD} < 200 GeV
DeepDoubleBvL, AUC = 97.3%
double-b, AUC = 91.3%
Mistagging rate (QCD)
improvement
from ML
Tagging efficiency (H → bb̄)

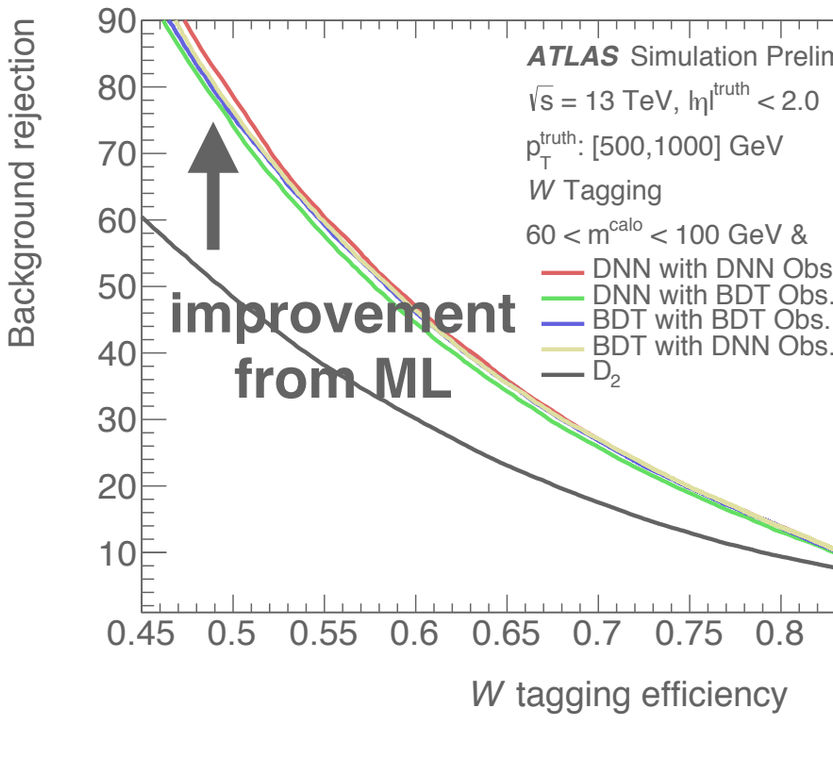

Boosted H → bb̄ Significance
Machine Learning
Standard Search
improvement
from ML
Significance
41 fb^{-1}
3σ Significance
198 fb^{-1}
CMS Expected Significance
35.9
Integrated Luminosity (fb^{-1})


$\frac{d\hat{R}}{dn_{track}}$
ATLAS Simulation Prelimina
Pythia8 dijets
|η| <1.0
EM+JES anti−k_t R=0.4
n_{track}
n_{track} Seq.
n_{track} Simu
improvement
from ML
$\Delta R_{track,avg}$

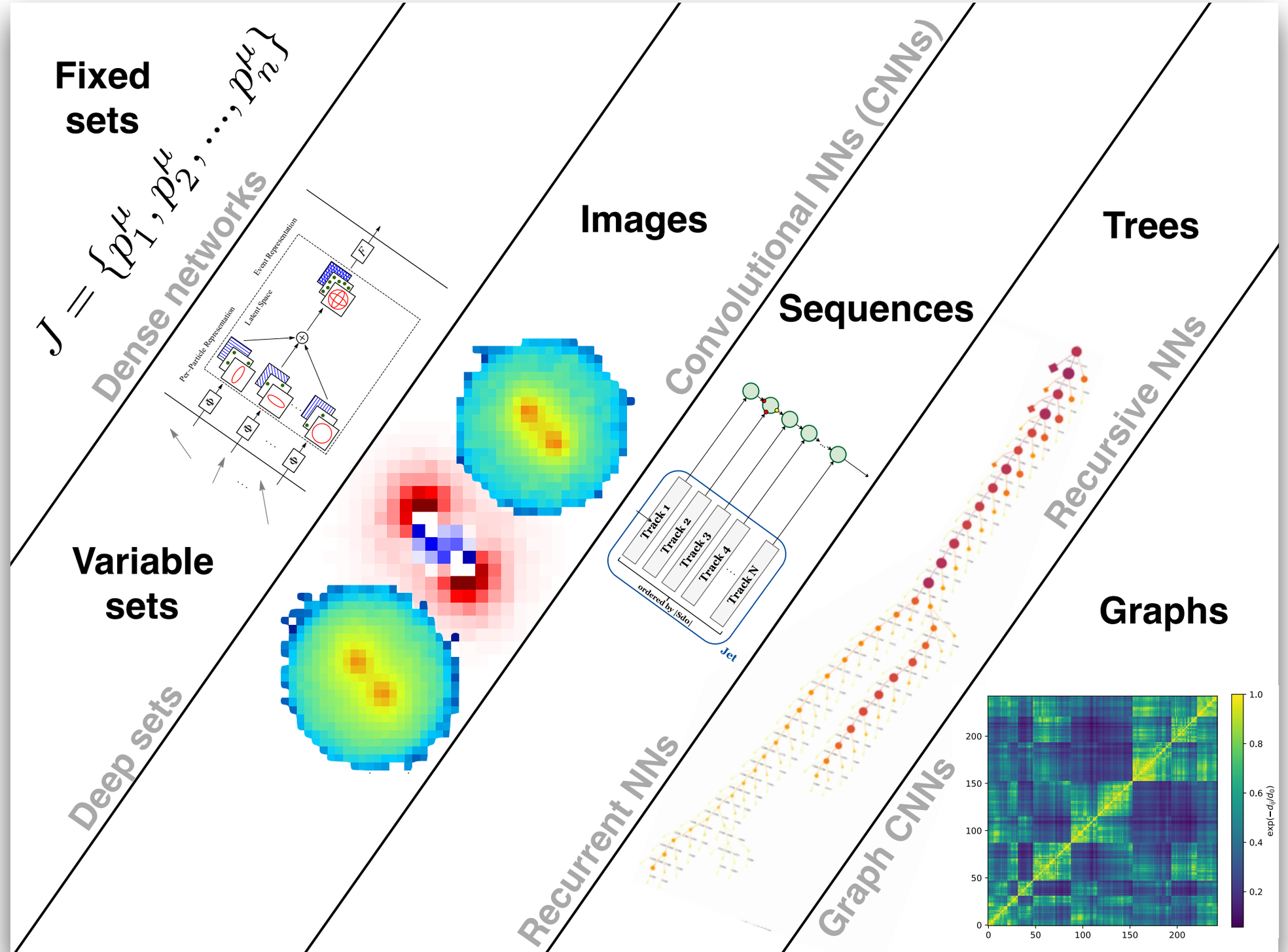

Significance Improvement
improvement
from ML
Ouark Jet Efficiency


Background rejection $\frac{1}{\varepsilon_B}$
improvement
from ML
Signal efficiency ε_S


ParticleNet
ResNeXt
PFN
NSub(8)
LBN
RecNN
CNN
P-CNN
LoLa
EFN
EFP
TopoDNN
nsub+m


Background rejection
ATLAS Simulation Prelim
$\sqrt{s}$ = 13 TeV, $|\eta|^{truth}$ < 2.0
p_T^{truth}: [500,1000] GeV
W Tagging
60 < m^{calo} < 100 GeV &
DNN with DNN Obs
DNN with BDT Obs.
BDT with BDT Obs.
BDT with DNN Obs.
D_2
improvement
from ML
W tagging efficiency

Tools

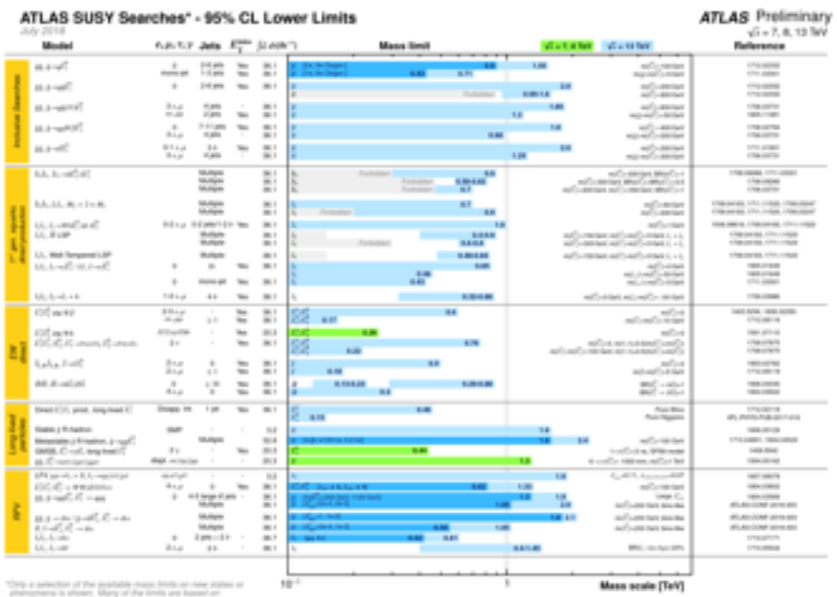

Fixed sets
$J = \{p_1^\mu, p_2^\mu, \ldots, p_n^\mu\}$
Dense networks
Images
Convolutional NNs (CNNs)
Sequences
Trees
Recursive NNs
Variable sets
Deep sets
Recurrent NNs
Graph CNNs
Graphs
Track 1
Track 2
Track 3
Track 4
Track N
ordered by |Sdo|
Jet

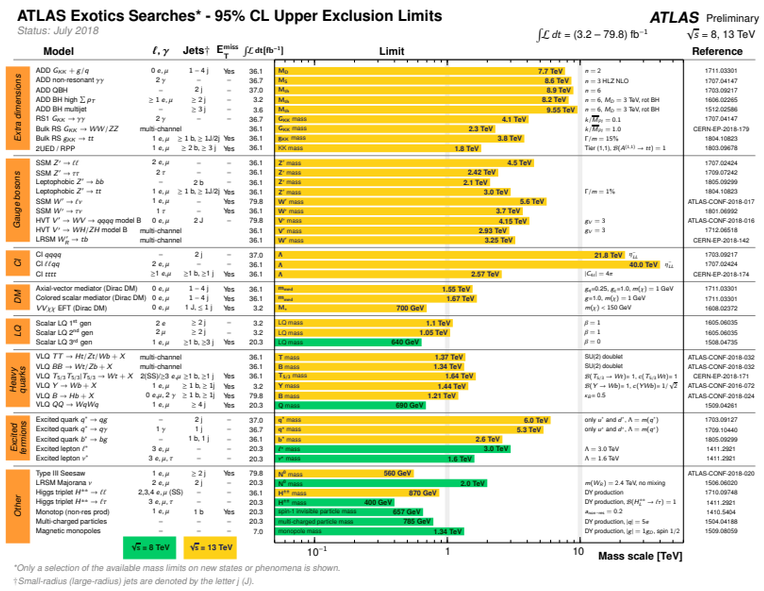
Practical matters

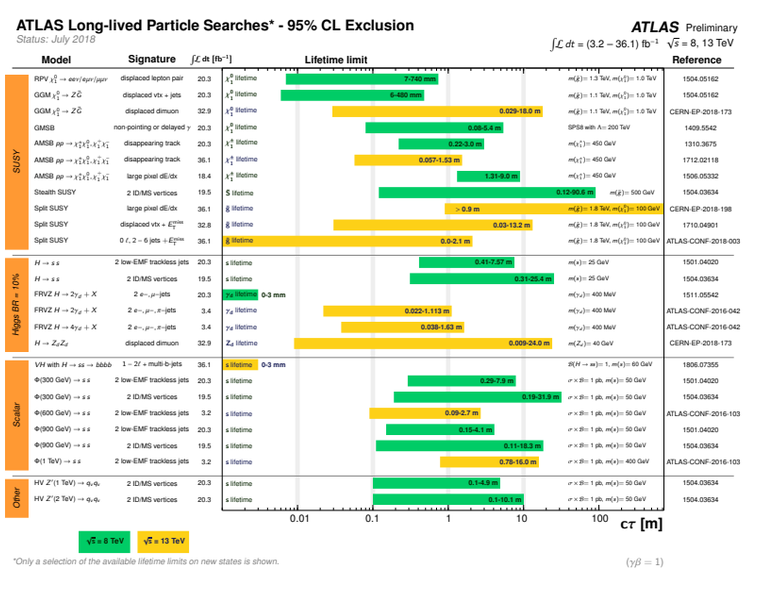
- Fast inference (see recent FNAL workshop)
- Specialized hardware (GPUs, …)
- Integration into ATLAS/CMS software
- Publishing NNs (for recasting, etc.)
- Sufficient training stats. / transfer learning

Anomaly detection

We have performed hundreds of hypothesis tests and have never rejected the null (the Standard Model)







Three possibilities

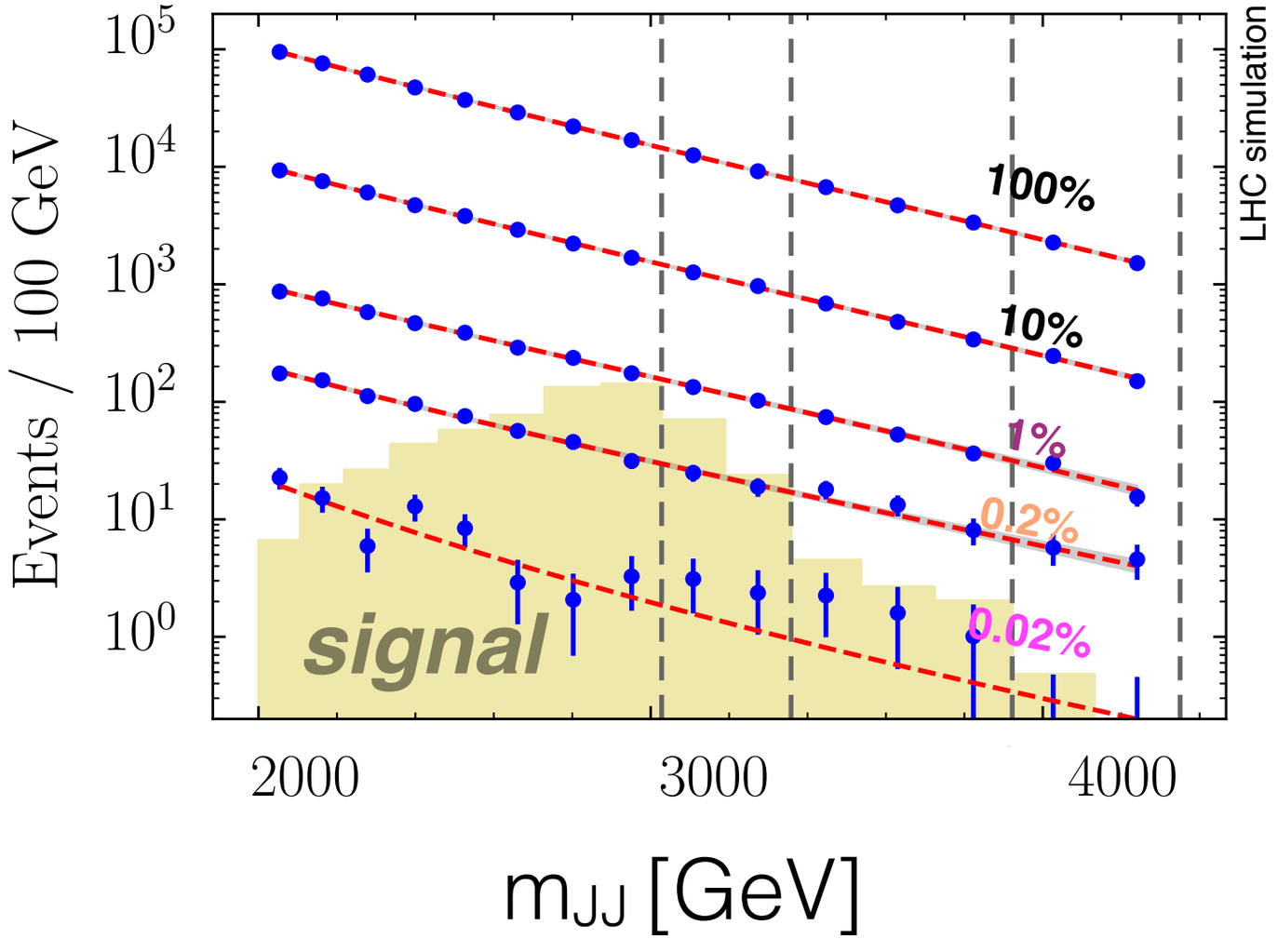
(1) There is nothing new

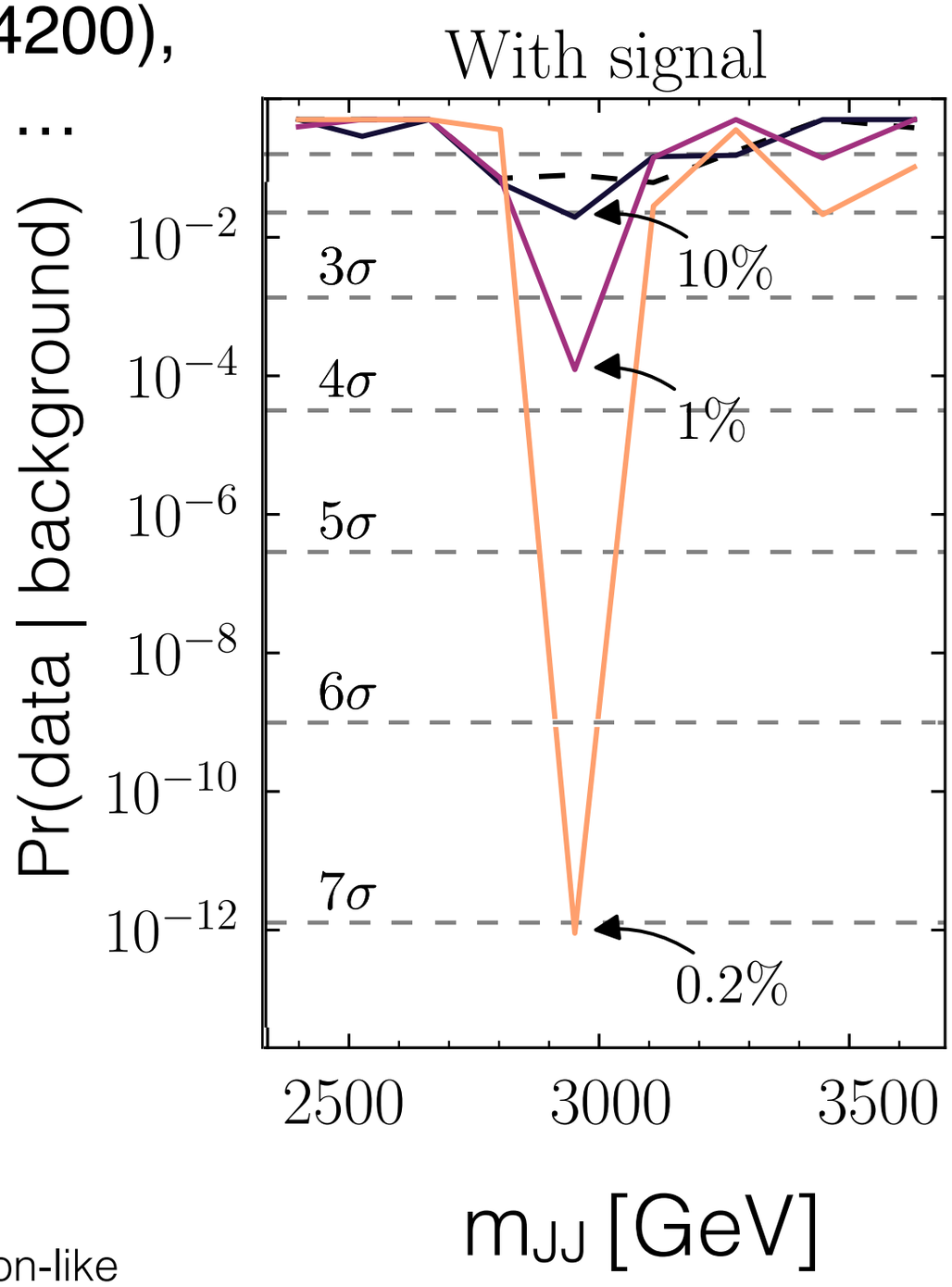
(2) Patience! (new stuff is just rare)

(3) We are just not looking in the right place

Anomaly detection

CWoLa Hunting (1805.02664), auto encoders (1808.08992, 1808.08979, …), LDA (1904.04200), + methods that depend strongly on MC + …





no cut on NN

most 10% signal-region-like

most 1% signal-region-like

most 0.2% signal-region-like

Uncertainties

“But what are the uncertainties on the NN”?

- question asked by every review board

Uncertainties

Precision / Optimality: $\mathrm{NN(x)} \neq \frac{p_{\mathrm{true}}(x|\mathrm{S+B})}{p_{\mathrm{true}}(x|\mathrm{B})}$

limited training statistics

$p_{\mathrm{train}}(x) \neq p_{\mathrm{true}}(x)$

inaccurate training data

$\mathrm{NN(x)}|_{p_{\mathrm{true}}=p_{\mathrm{train}}} \neq \frac{p_{\mathrm{true}}(x|\mathrm{S+B})}{p_{\mathrm{true}}(x|\mathrm{B})}$

model/optimization flexibility

Statistical uncertainty | **Systematic uncertainty**

limited prediction statistics

$p_{\mathrm{prediction}}(x) \neq p_{\mathrm{true}}(x)$

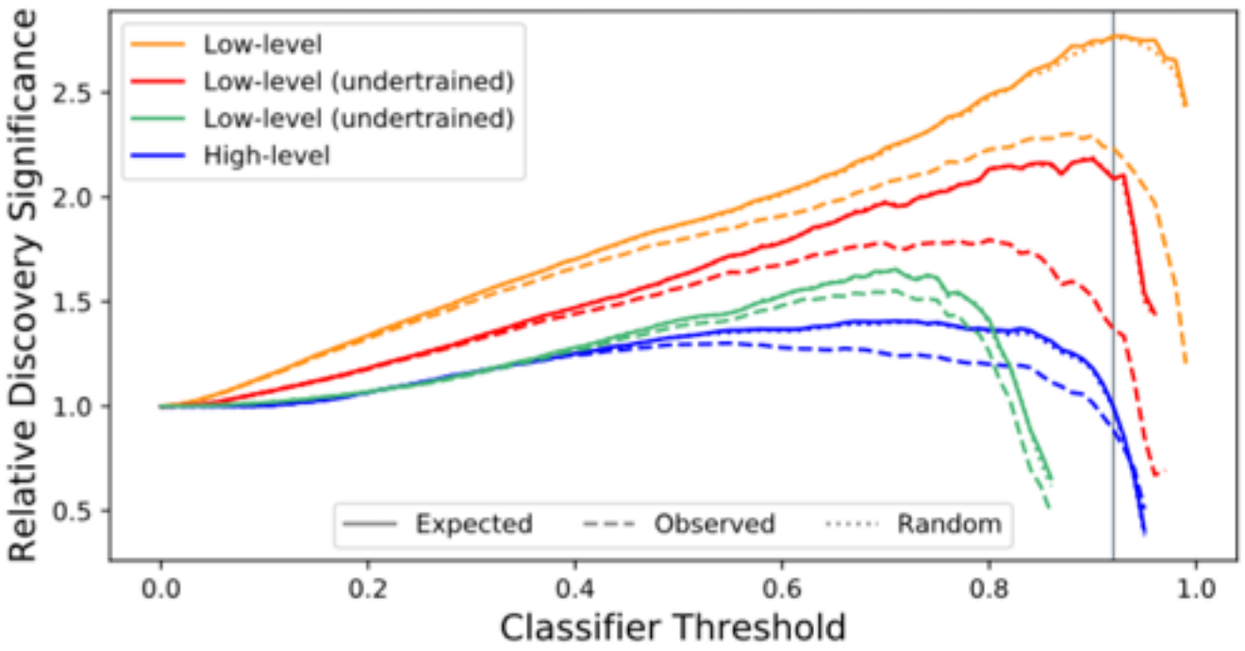
inaccurate prediction data

Accuracy / Bias: $p_{\mathrm{prediction}}(\mathrm{NN}) \neq p_{\mathrm{true}}(\mathrm{NN})$

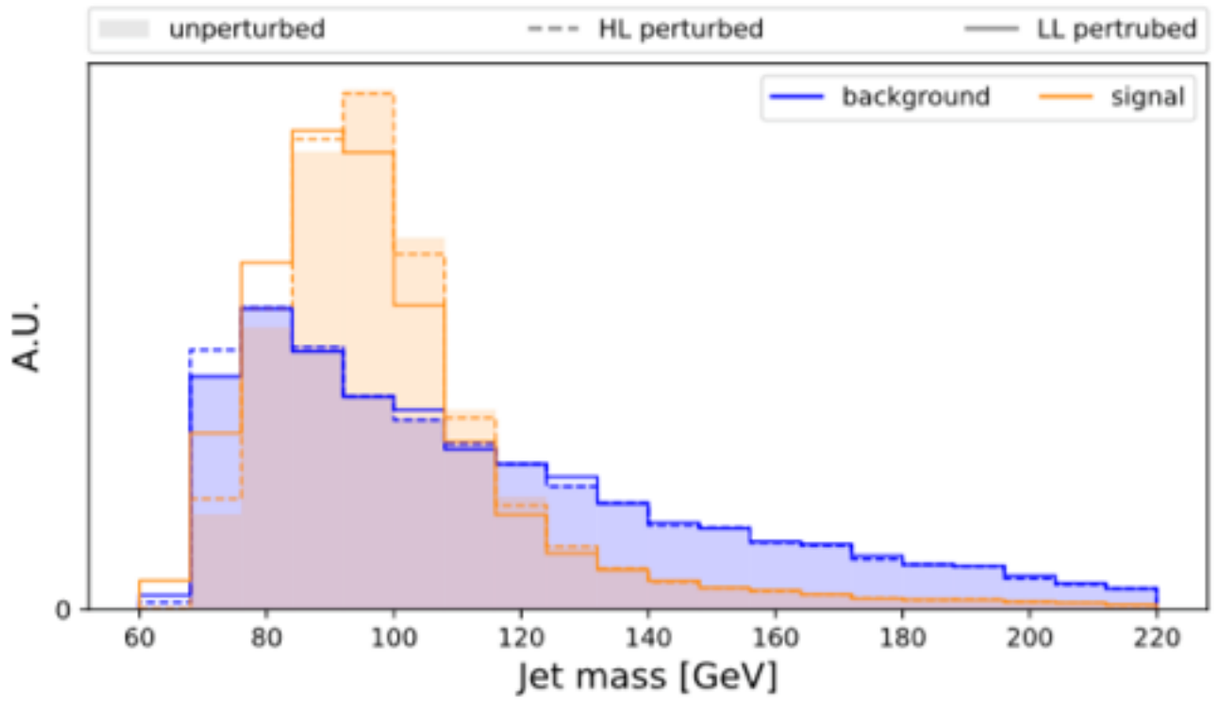
1909.03081

Uncertainties II

What if you are using a NN to extrapolate into a SR?



…we need to do better than Pythia versus Herwig!



1910.08606

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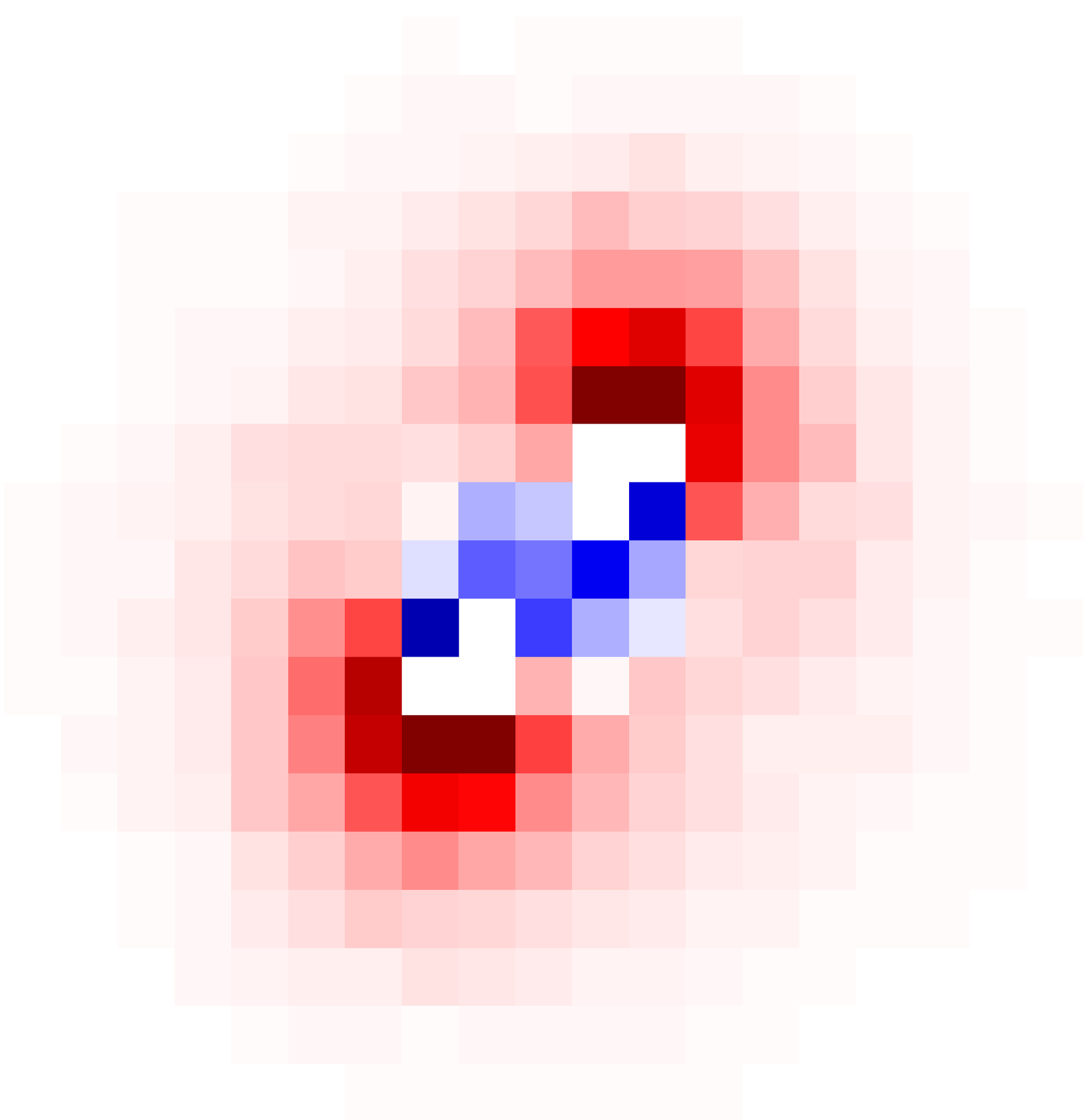

Fin.