

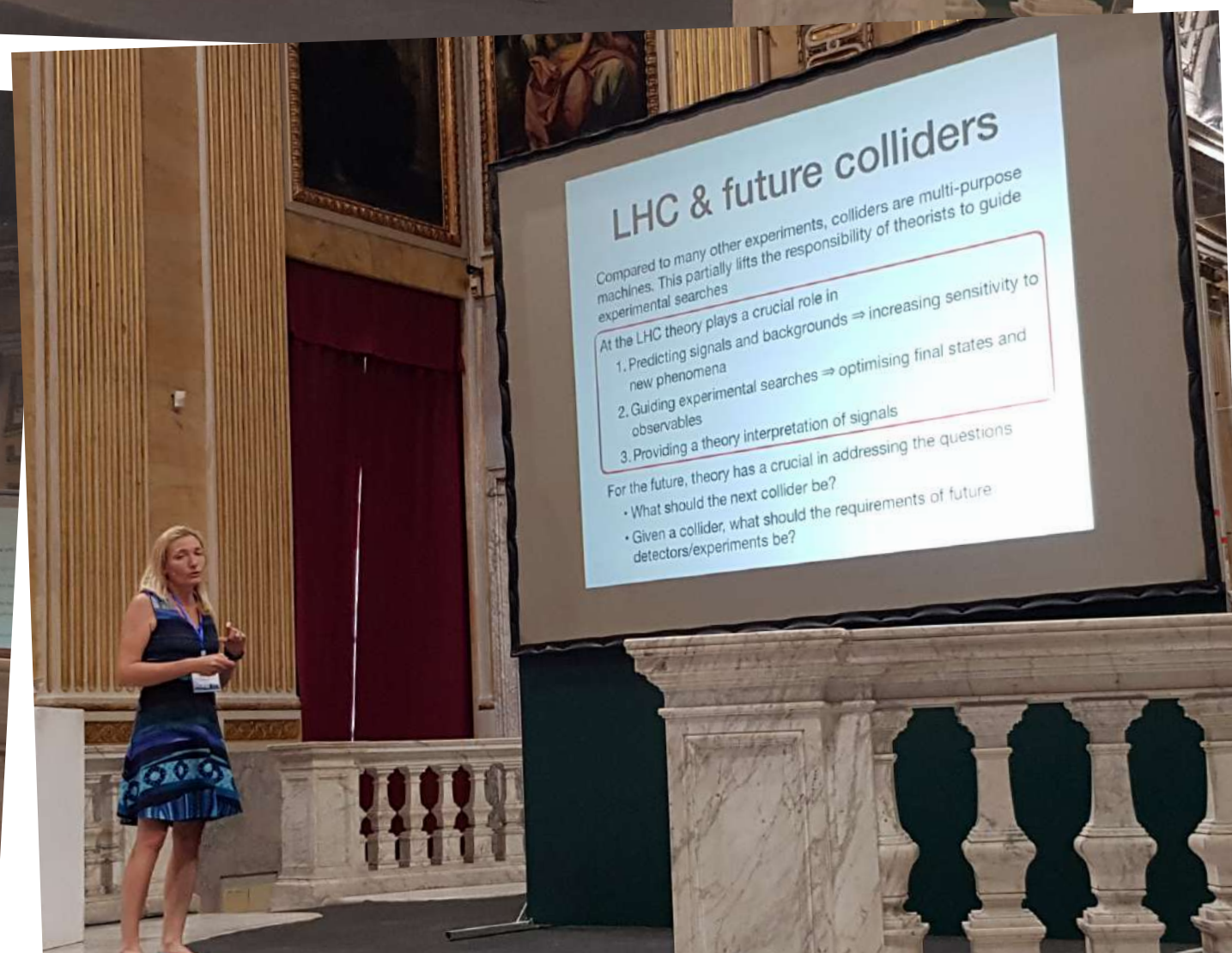
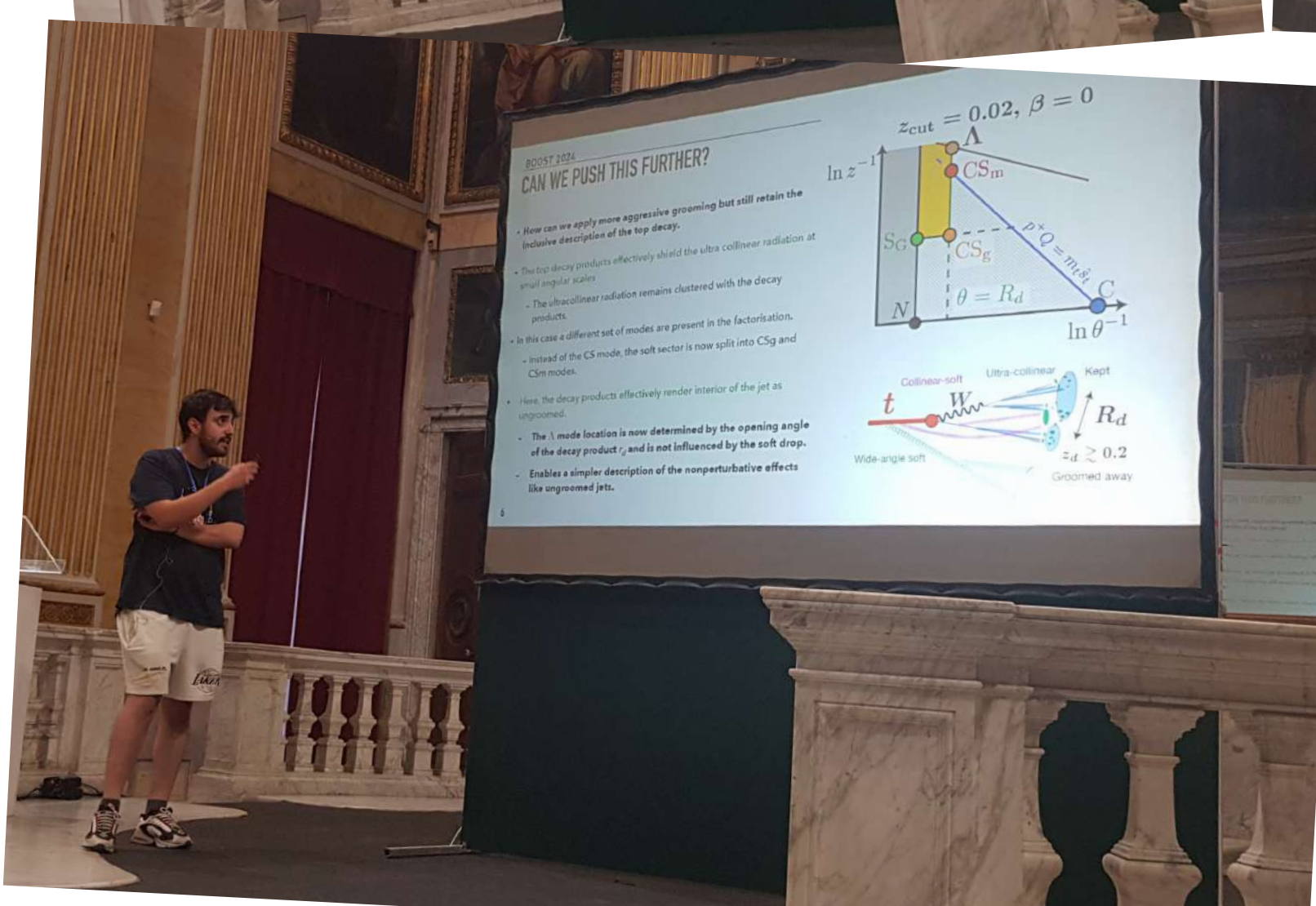
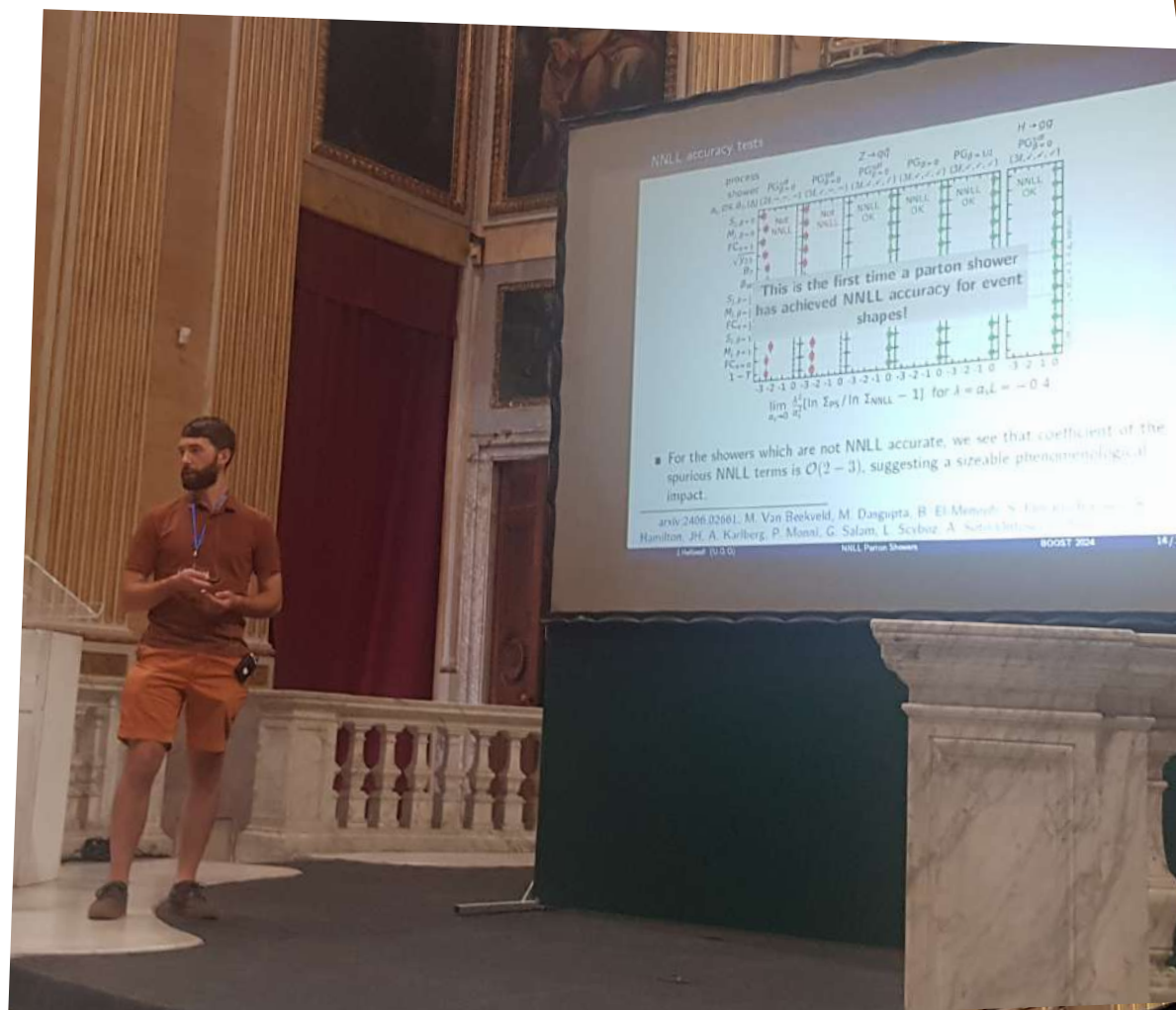
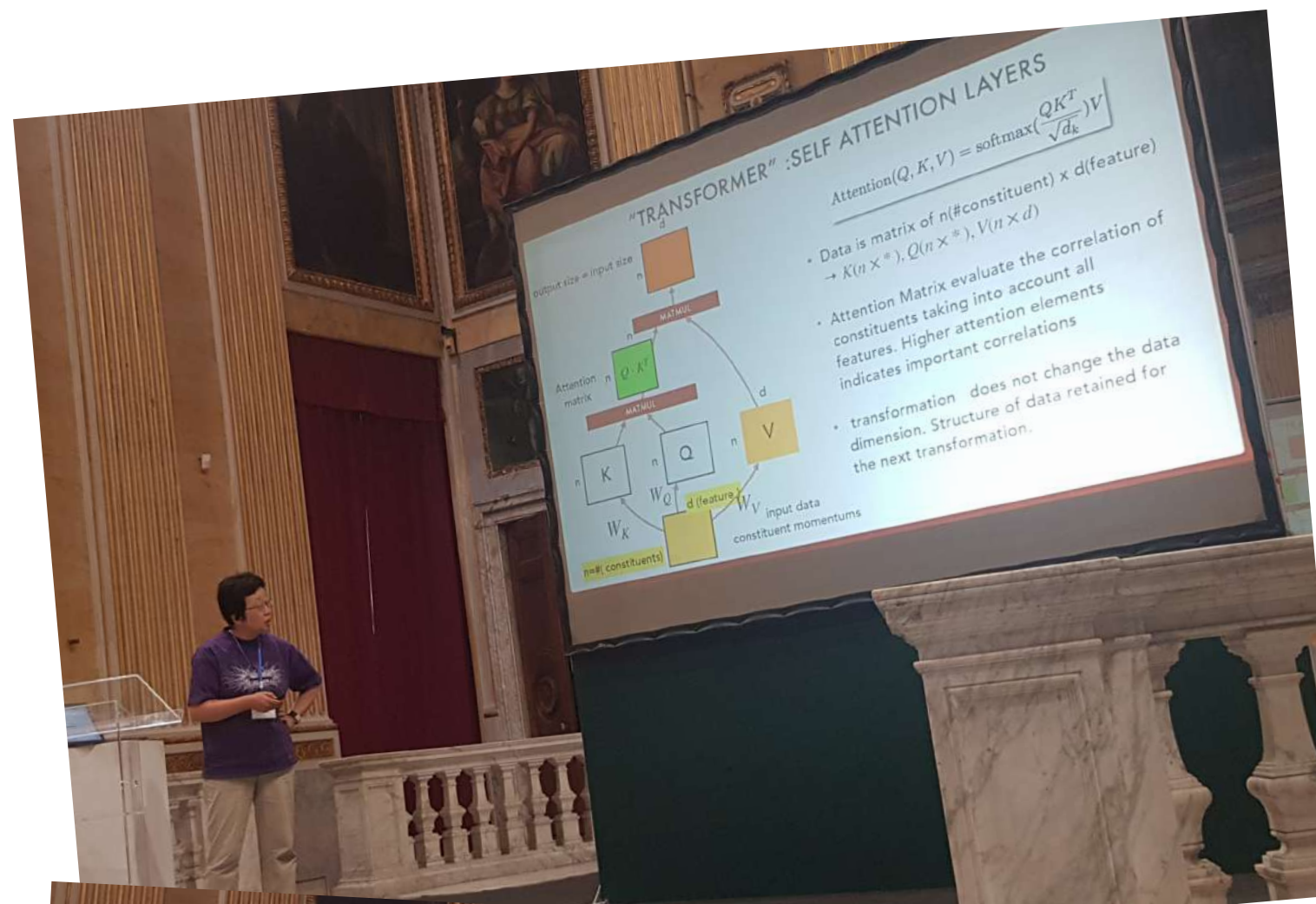
Theory summary boost 2024



Melissa van Beekveld (Nikhef)

Thanks to all the speakers!

You are giving me a difficult job to summarise all of this great work...



All the credits are yours, all misinterpretations mine! Apologies for any omissions or misunderstandings...

History

4th theory summary of a PanScalaBooster

Boost Theory Summary

Gavin Salam

CERN, Princeton University & LPTHE/CNRS (Paris)

Boost 2012

Valencia, Spain, 23–27 July 2012

BOOST 2017 - Theory Summary

Gregory Soyez

July 21 2017

5 years

2 years

Theoretical terms in the word clouds include: quantum, calculation, approach, network, perturbative, measurement, collinear, soft radiation, machine learning, energy, radiation, parameter, event, Higgs boson, detector, method, radiation, parameter, event, energy, machine learning, detector, correlator, representation, effect, logarithm, well, particle, data, model, Monte Carlo, different, gluon discrimination, space, limit, various, problem, production, propose, angle, vis, symmetry, type, consider, impact, object, kinematic, consti, interpretable, trained, range, similar, existing function, strong coupling, Higgs boson, coloured, resonances, deep learning, final state, machine learning, uncertainty, standard, year, fit, wide, vector, decision, computer, feature, tag, shower, based, classification, example, observable, architecture, quark, grooming, next leading, radiate, power, corrections, anomalous, dimension, Python, classification, example, observable, architecture, quark, grooming, next leading, radiate, power, corrections, anomalous, dimension, Python, classification, example, observable, architecture, quark, grooming, next leading, radiate, power, corrections, anomalous, dimension, Python.

Theory Summary
26 July 2019, MIT

Frédéric Dreyer

My prediction:
you'll get
another one for
Boost 2026

5 years

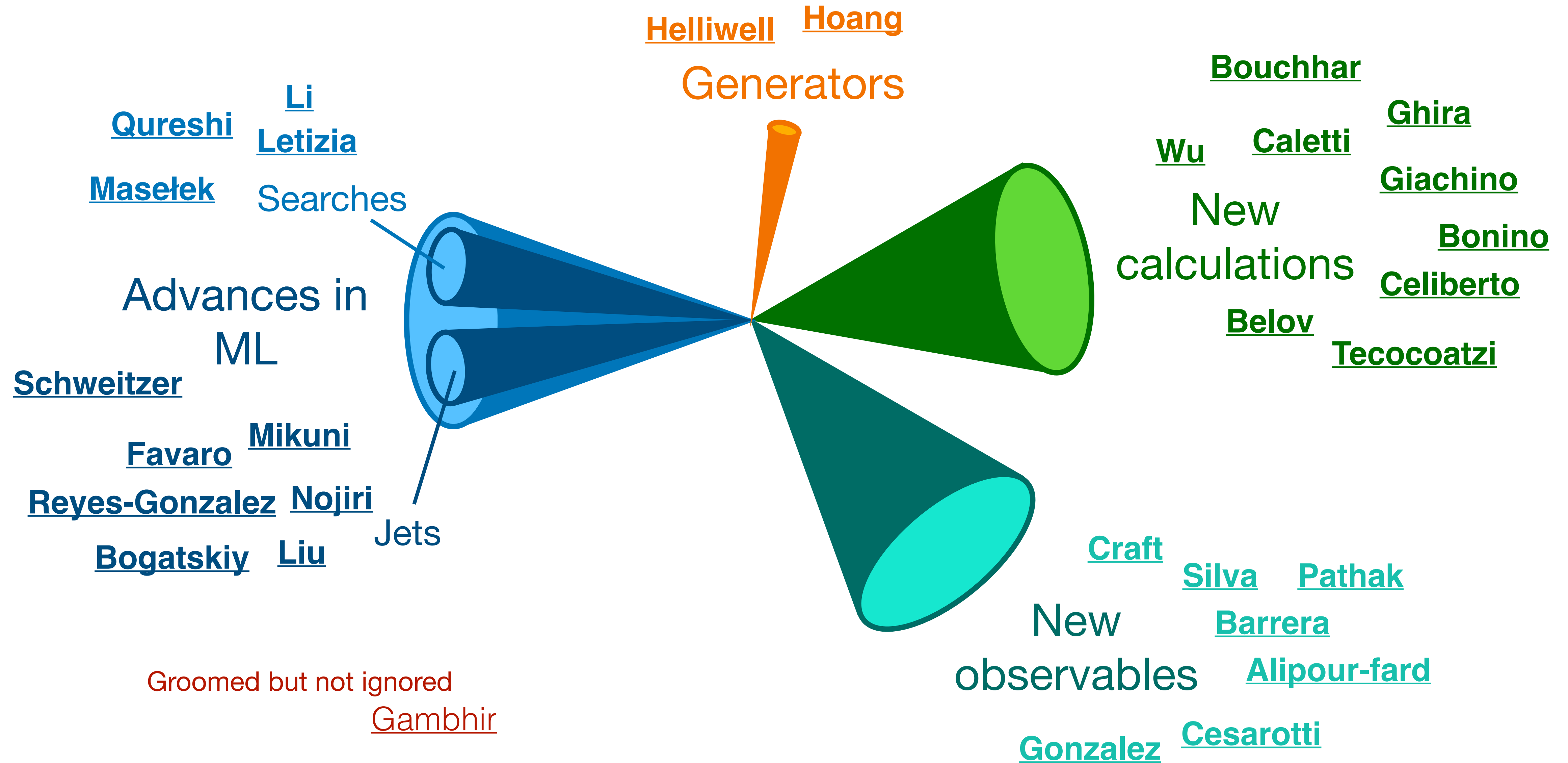
Boost 2024 theory summary

What is a jet?

Jets can be formed out of any 4-vector:

- Simulated particles from monte carlo
- ID tracks in the detector
- Other jets
-
- Boost abstracts!

My classification of boost theory talks

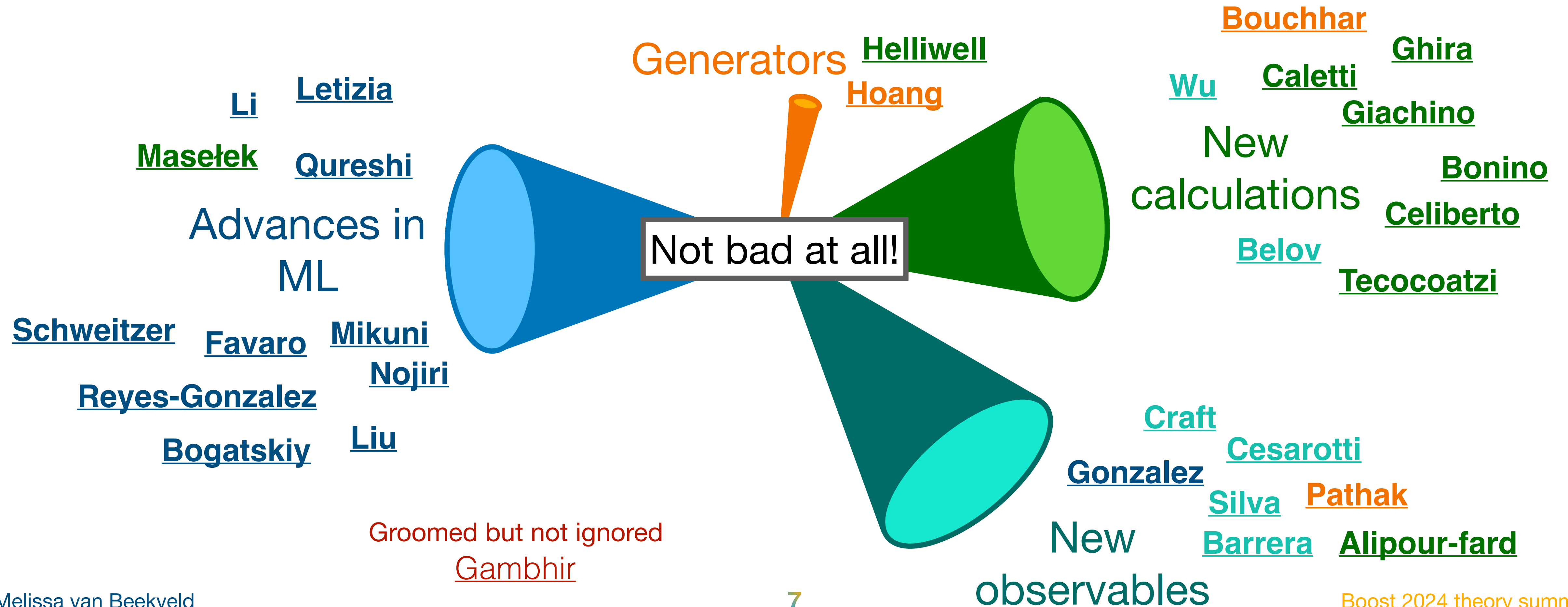


Can we take out the human bias?

1. Map boost abstracts to 3D vectors using NLP
2. Create massless 4-vectors of these
3. Cluster with CA, ask for 4 jets (ignore substructure...)

Can we take out the human bias?

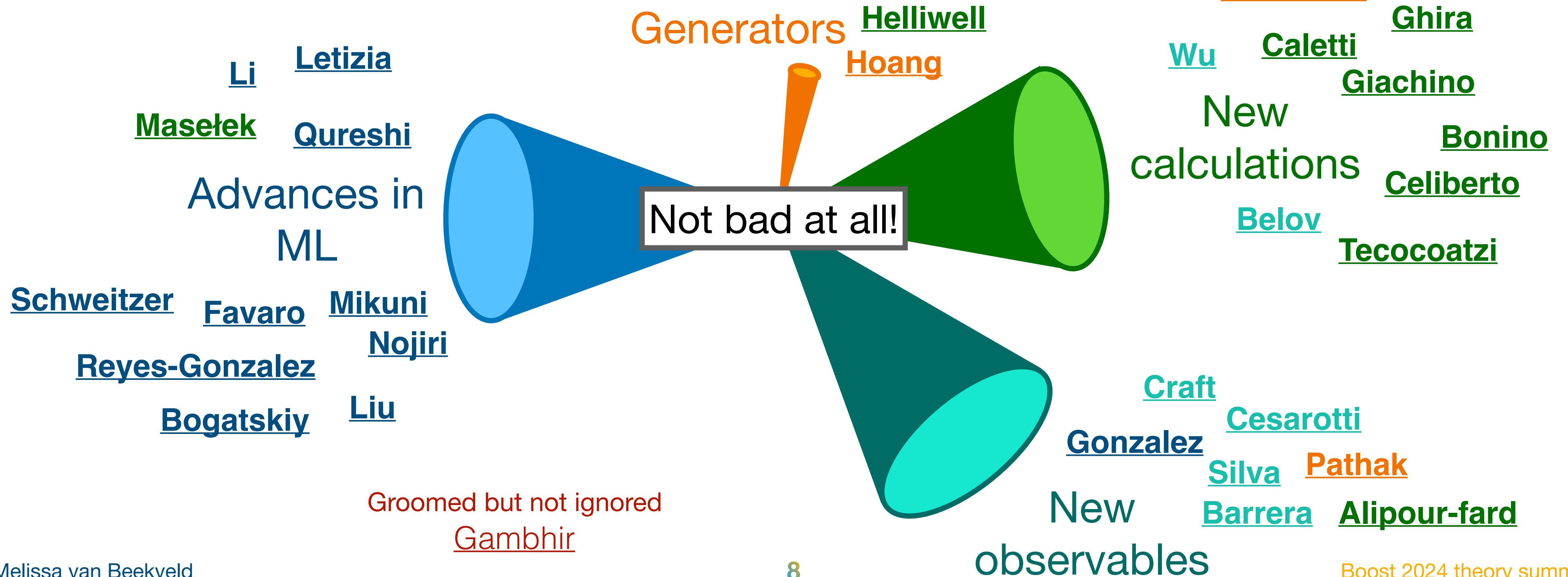
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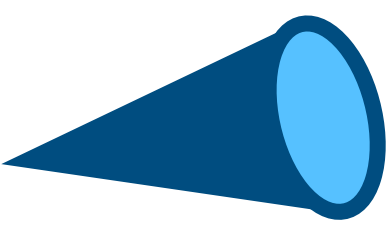
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Bonus points for those who can guess the orange cluster



Using ML for BSM searches

ML



We know there is BSM physics... Can ML **boost** our search?

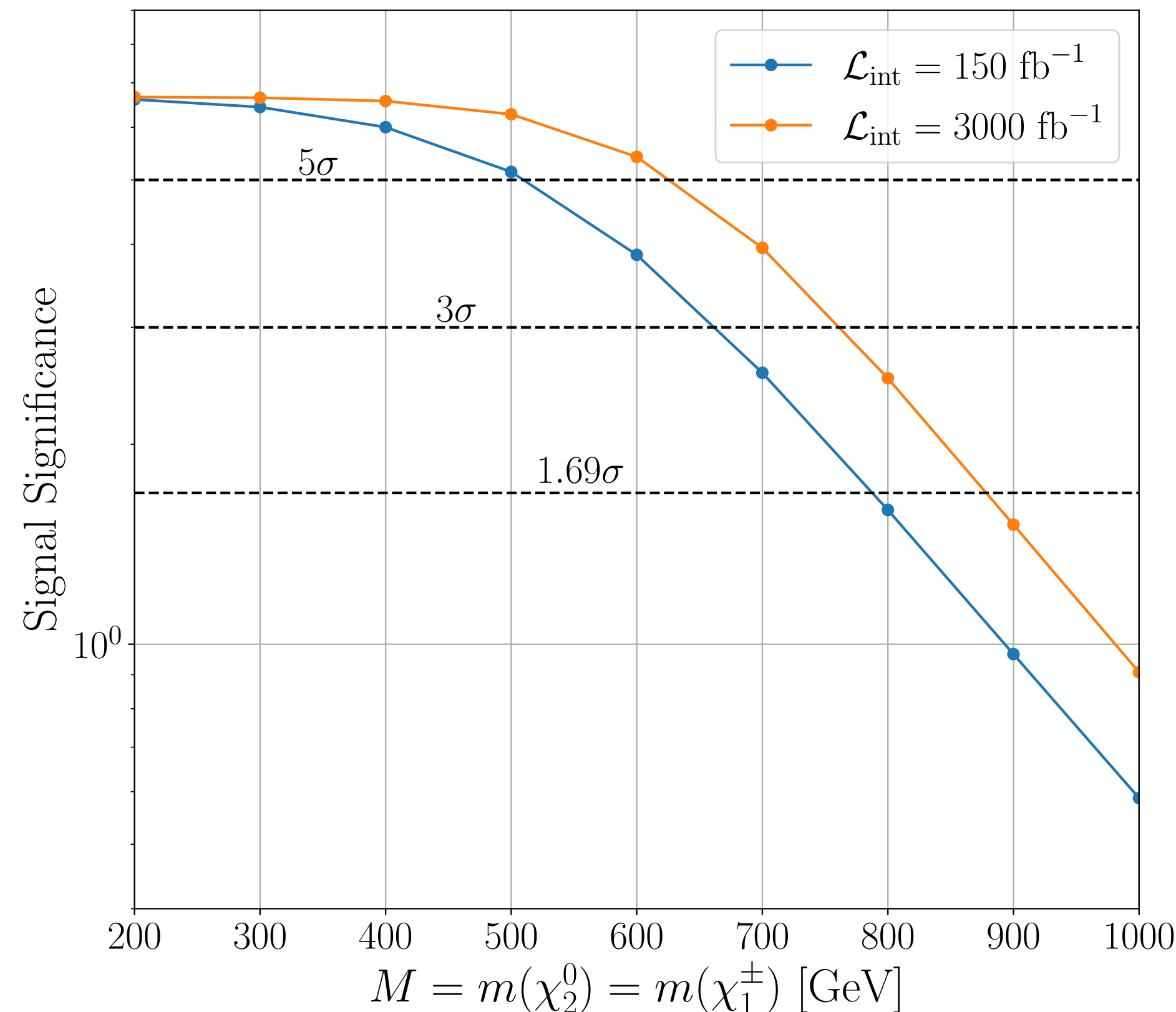
Probing the Supersymmetric Standard Model at the Large Hadron Collider through Vector Boson Fusion Processes and Machine Learning

Umar Qureshi

Can we improve our significance on a well-motivated BSM scenario?

Yes we can!

Using a BDT trained on kinematic variables selected with 'expert knowledge'



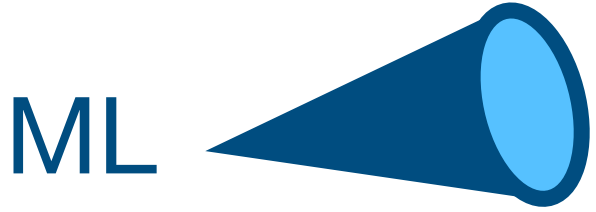
Extending LHC Constrains to SUSY

Constraints to $\tilde{\chi}_2^0$ and $\tilde{\chi}_1^\pm$ masses at a:

- $\geq 5\sigma$ signal significance for masses up to **660 (520) GeV**.
- $\geq 3\sigma$ signal significance for masses up to **770 (620) GeV**.
- $\geq 95\%$ confidence level for masses up to **880 (750) GeV**.

Integrated luminosities of 3000 (150) fb^{-1} .

Using ML for BSM searches



We know there is BSM physics... Can ML **boost** our search?

Enhancing LHC searches for Dark Matter with Graph Neural Networks [Rafal Masełek](#)

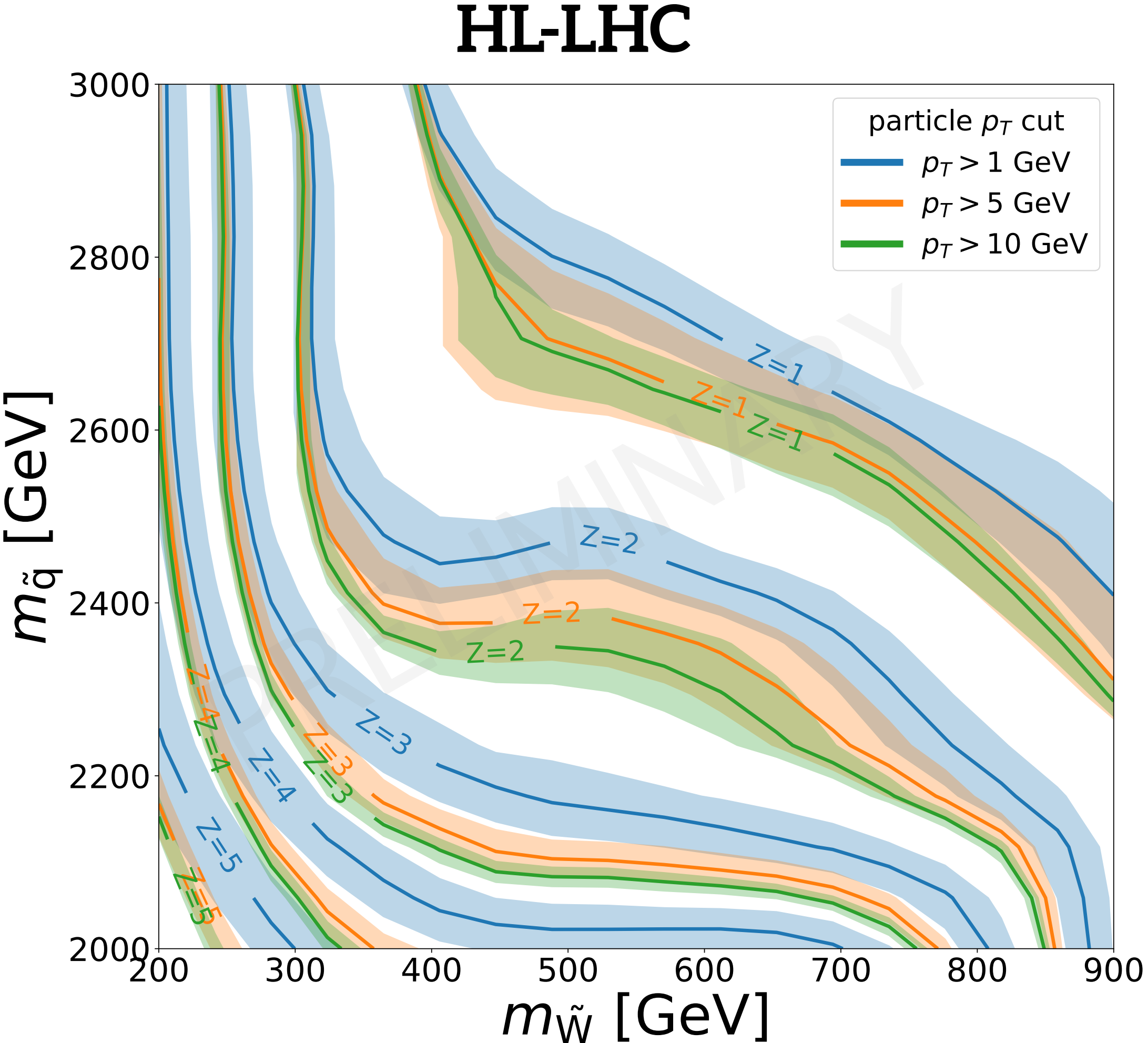
Can we re-analyse traditional BSM signatures?

Yes we can!

Train a GNN with both high level and particle-level input

Study of monojet SUSY search, aim for jet substructure

Depending on softness they find a good coverage of phase-space



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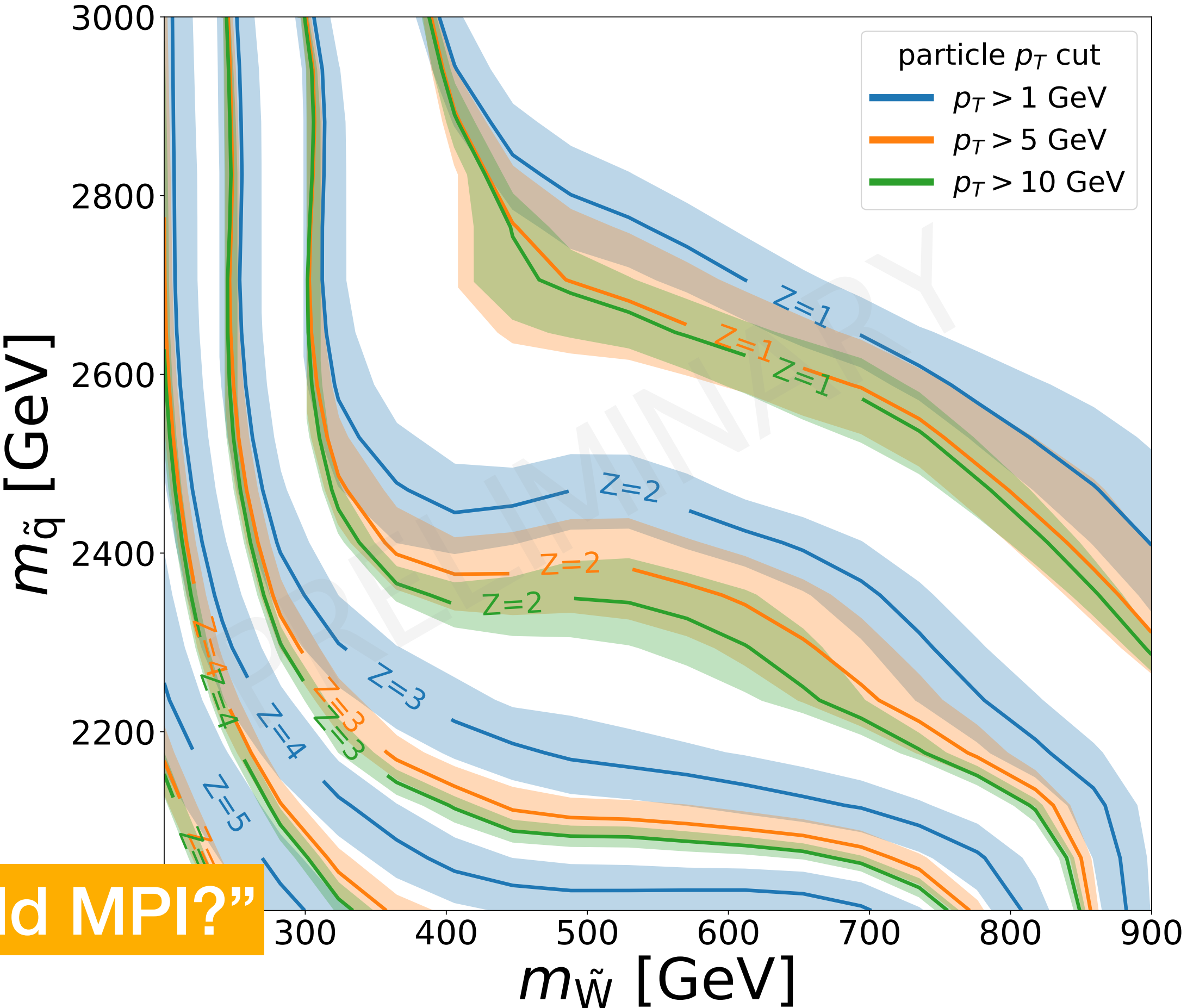
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“What happens if we add MPI?”

HL-LHC



Using ML for BSM searches

We know there is BSM physics... Can ML **boost** our search?

Semi-visible jets, energy-based models, and self-supervision [Luigi Favaro](#)

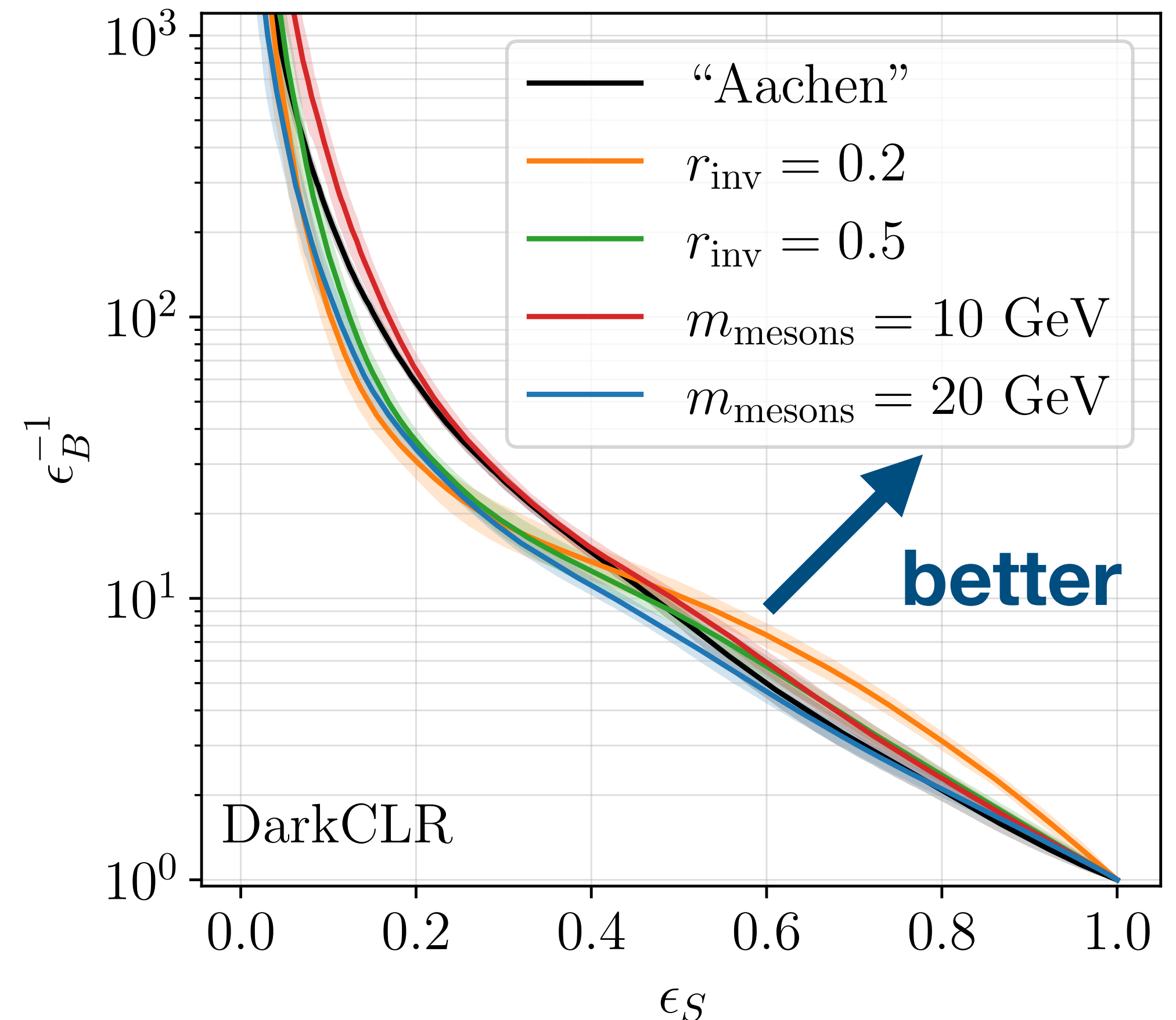
But we don't know what BSM model to look at! Can we be more model agnostic?

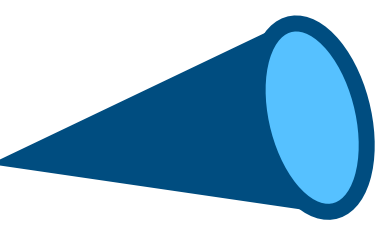
“Still early days, but we can try”

Use density estimation as model-agnostic anomaly scores with a NN

Representation is key → give the NN both real symmetries and BSM-inspired augmentations of the data

Robust method: train on one r_{inv} , predict others





Using ML for BSM searches

We know there is BSM physics... Can ML **boost** our search?

Efficient machine learning for model-independent tests [Marco Letizia](#)

But we don't know what BSM model to look at! Can we be more model agnostic?

Use density estimation as model-agnostic anomaly scores but with a kernel function

Pro's: it is fast and versatile!

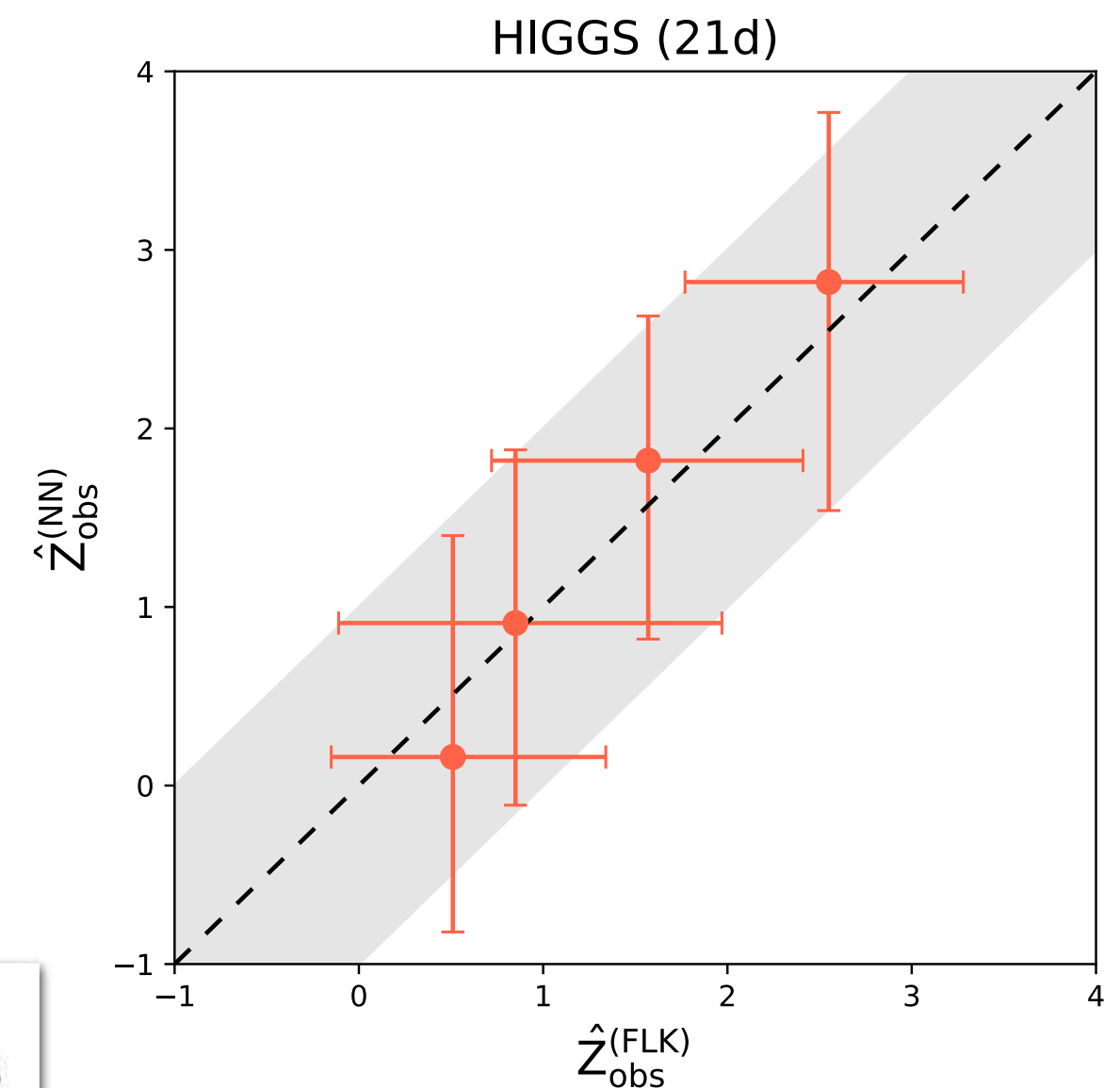
Control data quality

Test generative models

Classification tasks

Table 1 Average training times per single run with standard deviations (low level features and reference toys). Note that time measured in hours (for NN) and seconds (for Falkon)

Model	DIMUON	SUSY	HIGGS
FLK	(44.9 ± 3.4) s	(18.2 ± 1.2) s	(22.7 ± 0.4) s
NN	(4.23 ± 0.73) h	(73.1 ± 10) h	(112 ± 9) h



Also see invited contribution of [Lorenzo Rosasco](#)

The era of foundation models



One model to rule them all

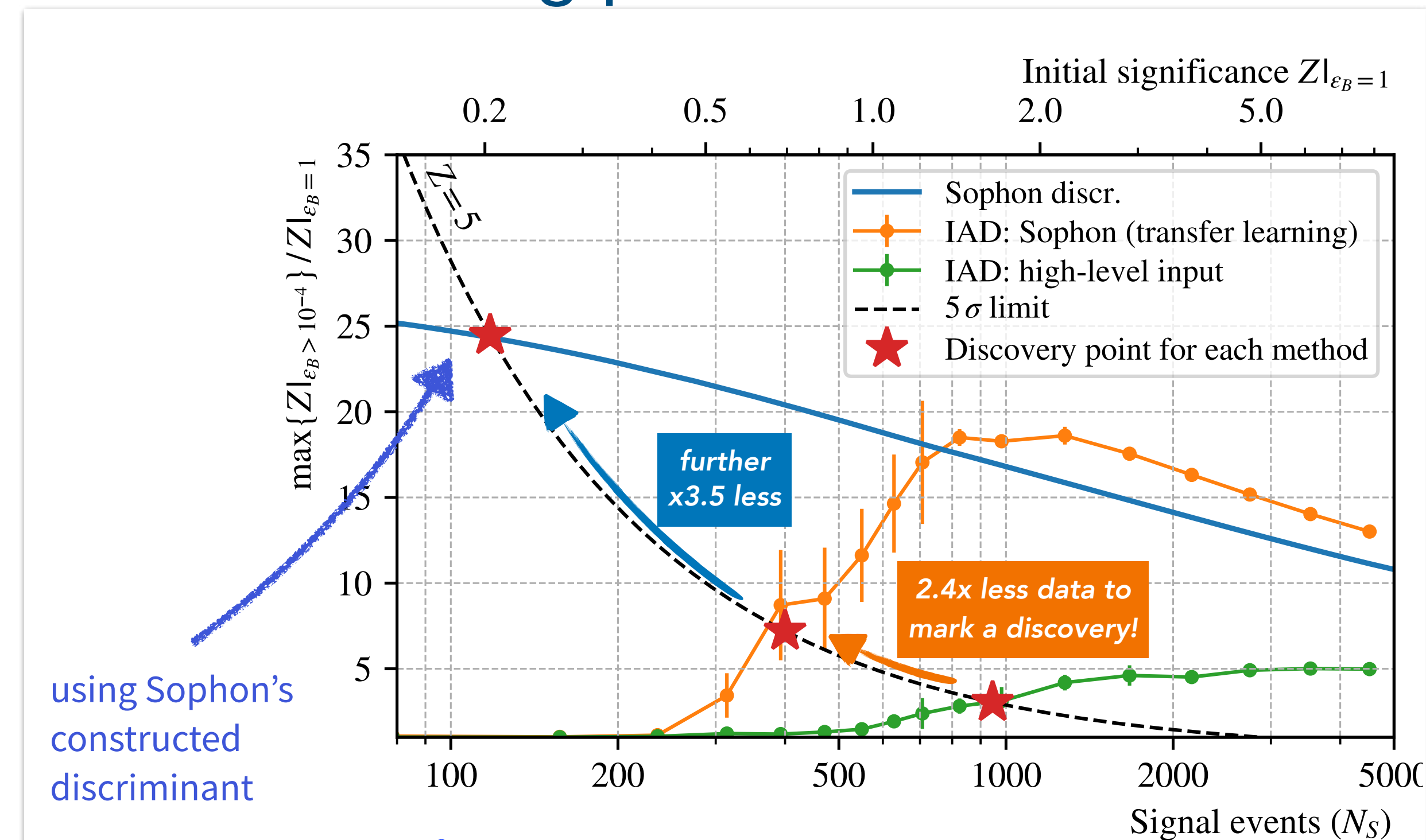
Accelerating resonance searches via signature-oriented pre-training [Congqiao Li](#)

Can we develop a tagger for all types of jets without losing performance?

A ‘foundation classifier’ with a simple task:
connect the jet signature to NP or SM

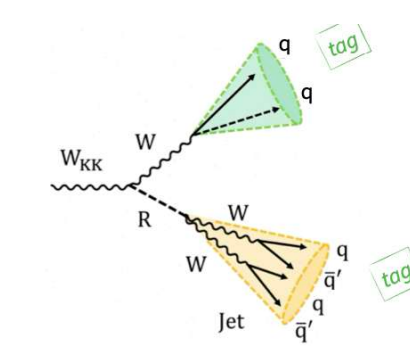
Sophon: model based on particle
transformer architecture

This pre-trained model can be fine-tuned
to specific tasks i.e. classification by
combining with CWoLa



$$\text{discr} = \sum_{\text{jet}=1,2} \frac{g_{A,\text{jet}}}{g_{A,\text{jet}} + \sum_{l=1}^{27} g_{\text{QCD},l,\text{jet}}}$$

$$A = \begin{cases} 0.3 \times \{cs, qq\} \\ + 0.1 \times \{ccss, qqcs, qqqq\} \\ + 0.6 \times \{ccs, ccq, ssc, ssq, qqc, qqs, qqg\} \end{cases}$$



The era of foundation models

One model to rule them all

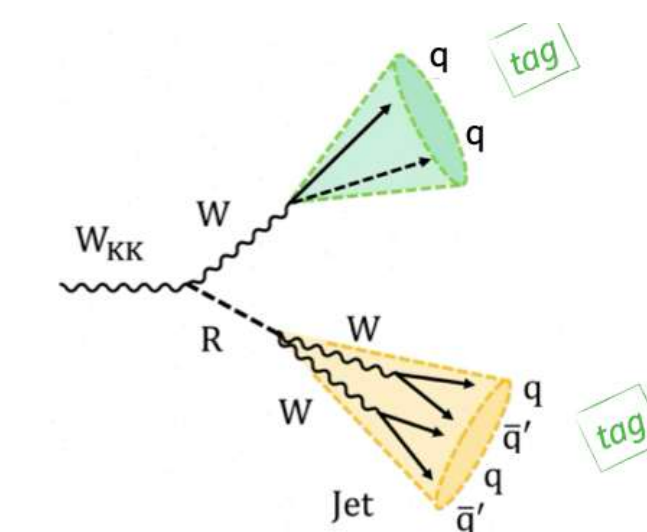
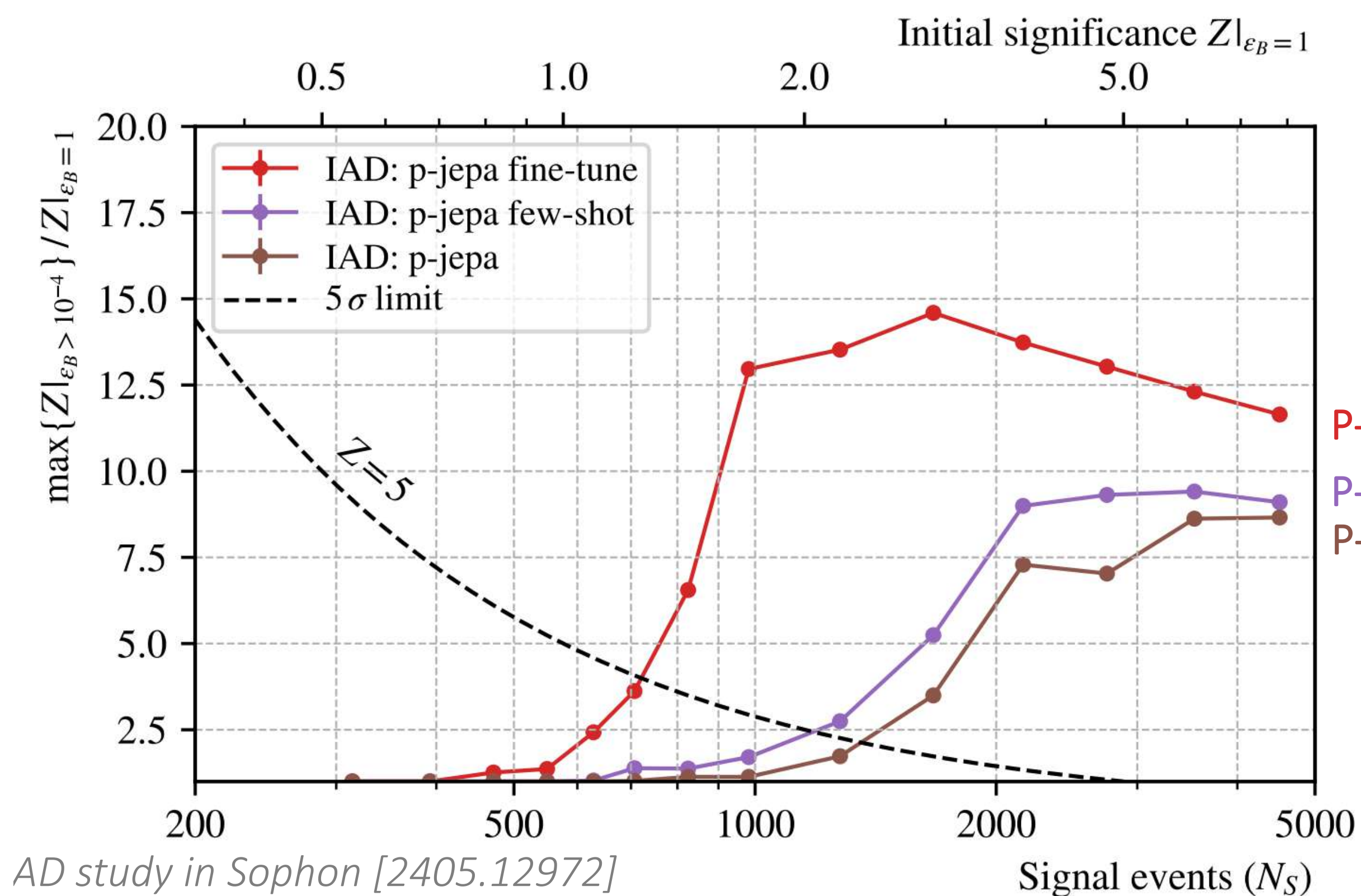
Learning powerful jet representations via self-supervision [Qibin Liu](#)

Can we go without labels, with the ultimate aim to directly learn from data?

P-JEPA: transformer network that needs to learn how to fill in partial jet data in the latent space

Trained on Sophon's JetClass-II

Still underperforms w.r.t. supervised learning



P-jepa + finetune (10M)
P-jepa + few-shot (1k)
P-jepa

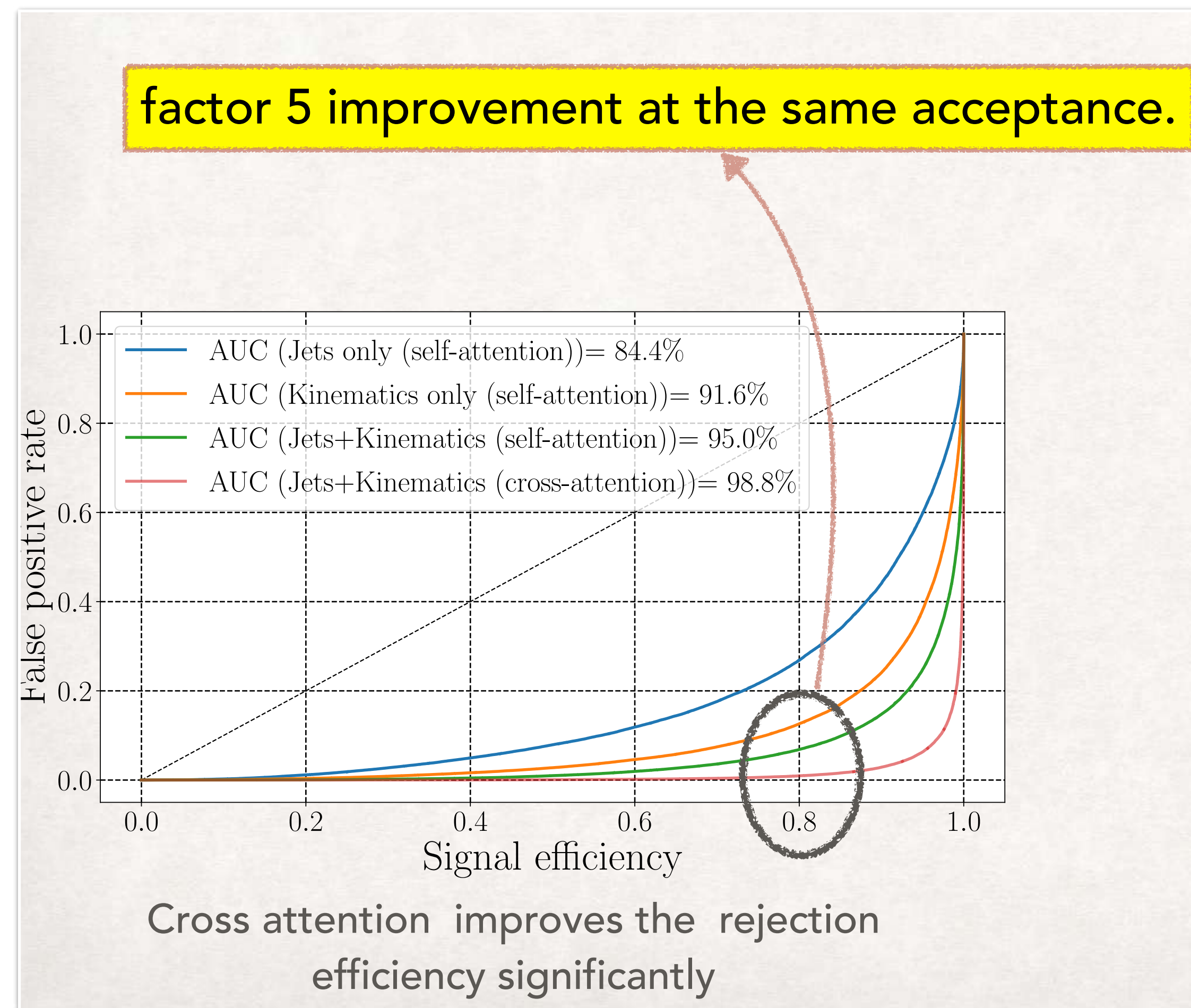
The era of foundation models

One model to rule them all

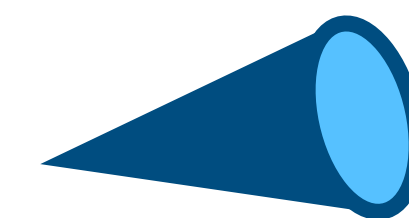
Streamlined jet tagging network assisted by jet prong structure [Mihoko Nojiri](#)

Don't rule out the job of the expert!

Transformer network with a 'cross attention' mechanism: feed in both the subjects and the particles in the jets



The era of foundation models



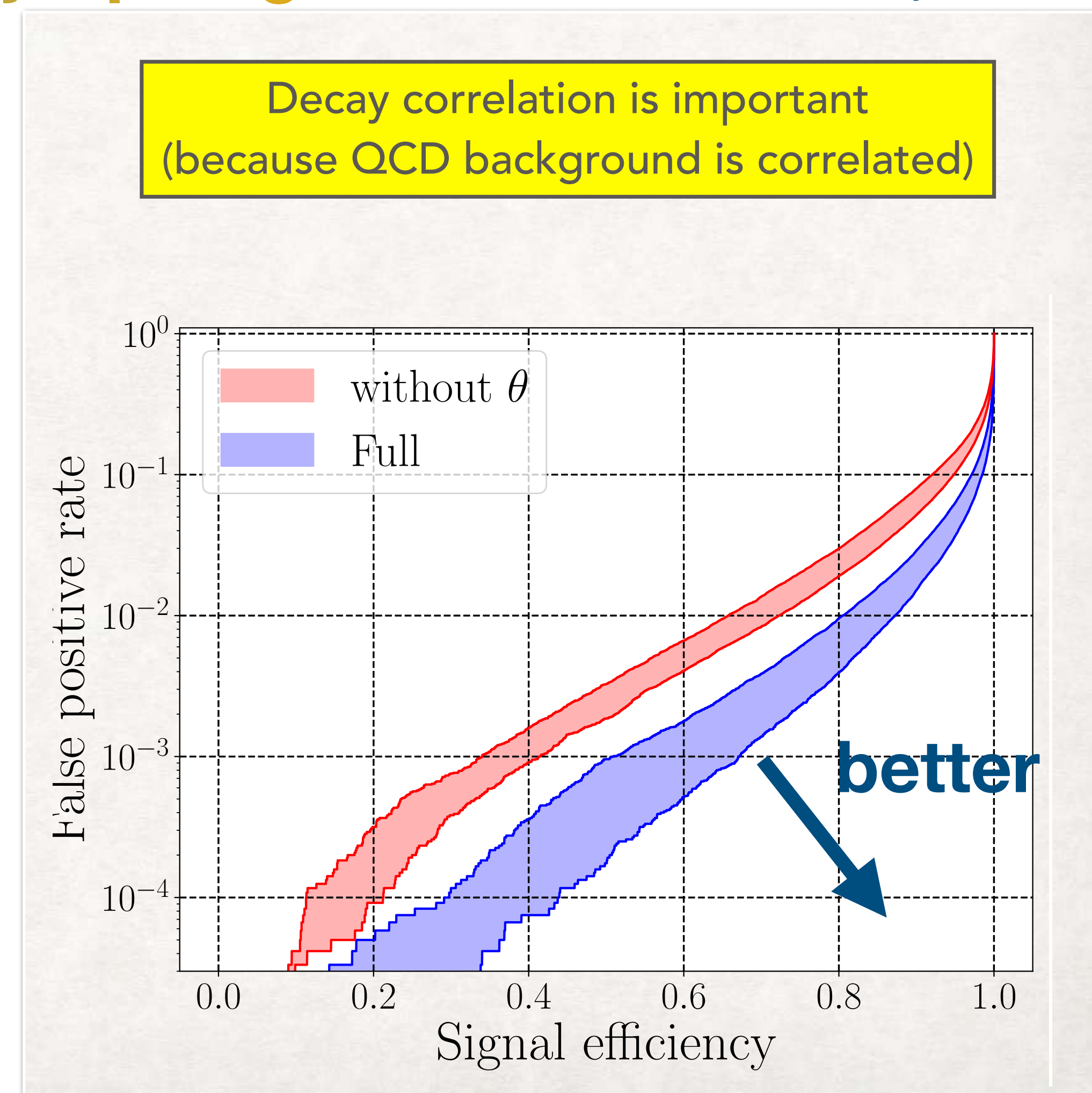
One model to rule them all

Streamlined jet tagging network assisted by jet prong structure [Mihoko Nojiri](#)

Don't rule out the job of the expert!

Transformer network with a 'cross attention' mechanism: feed in both the subjets and the particles in the jets

Another piece of expert knowledge: event orientation matters!



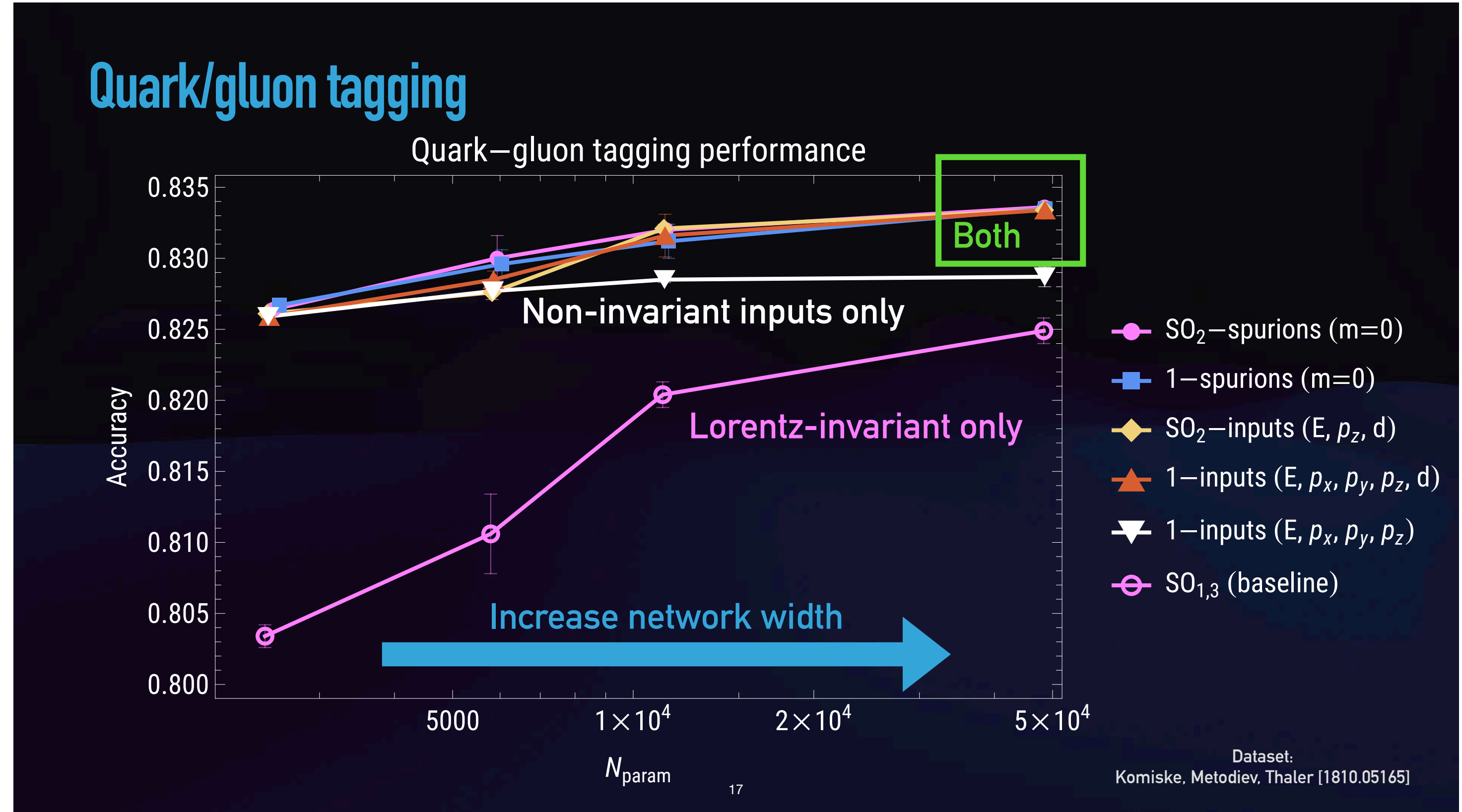
Does equivariance make better models?

What is the ideal information to give to an architecture (PELICAN)?

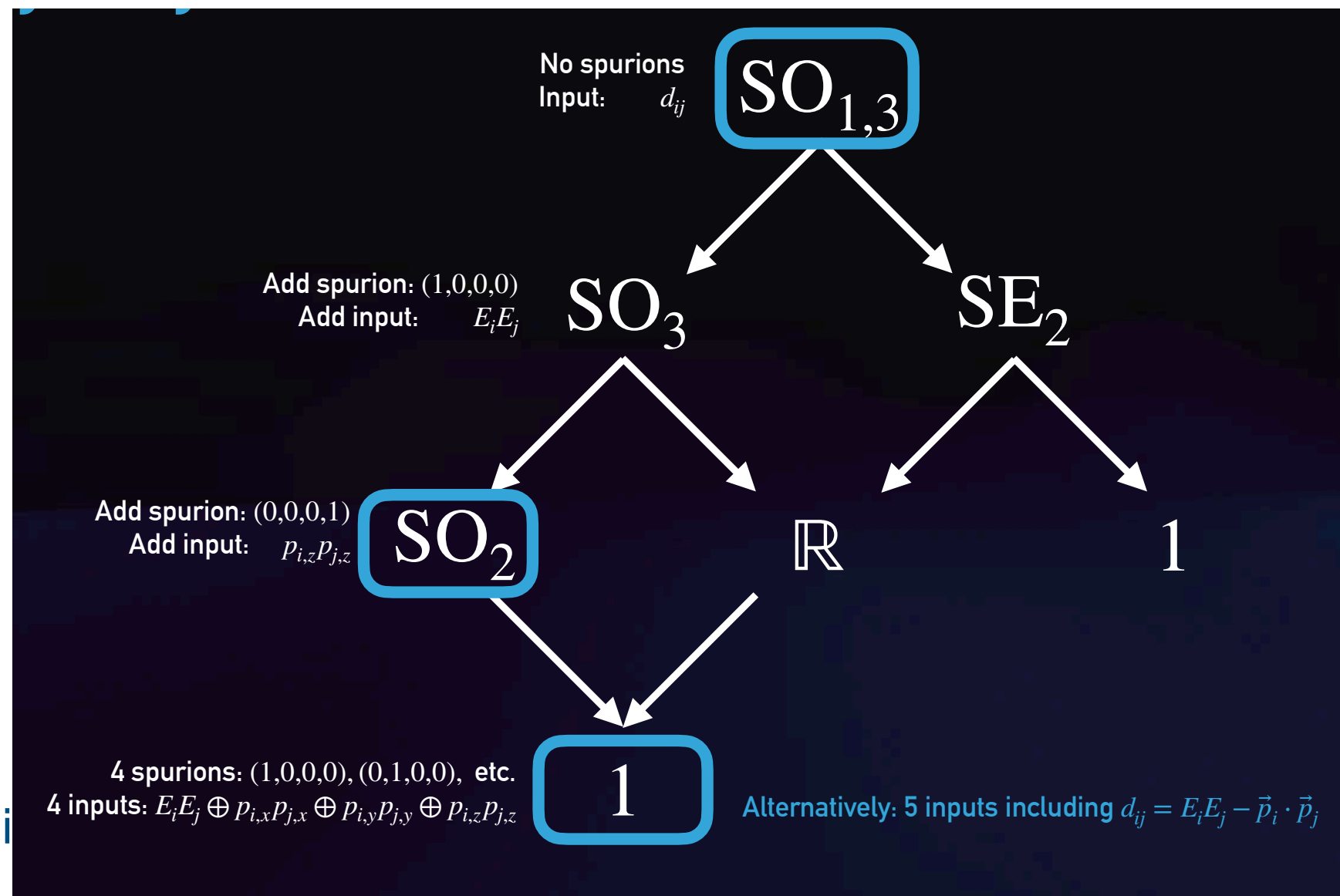
Alexander Bogatskiy

Two methods to break the invariance:

- Spurion: explicitly add vectors that indicate a preferred direction
- Input: add energy/momenta components



Best networks: combination of both methods.



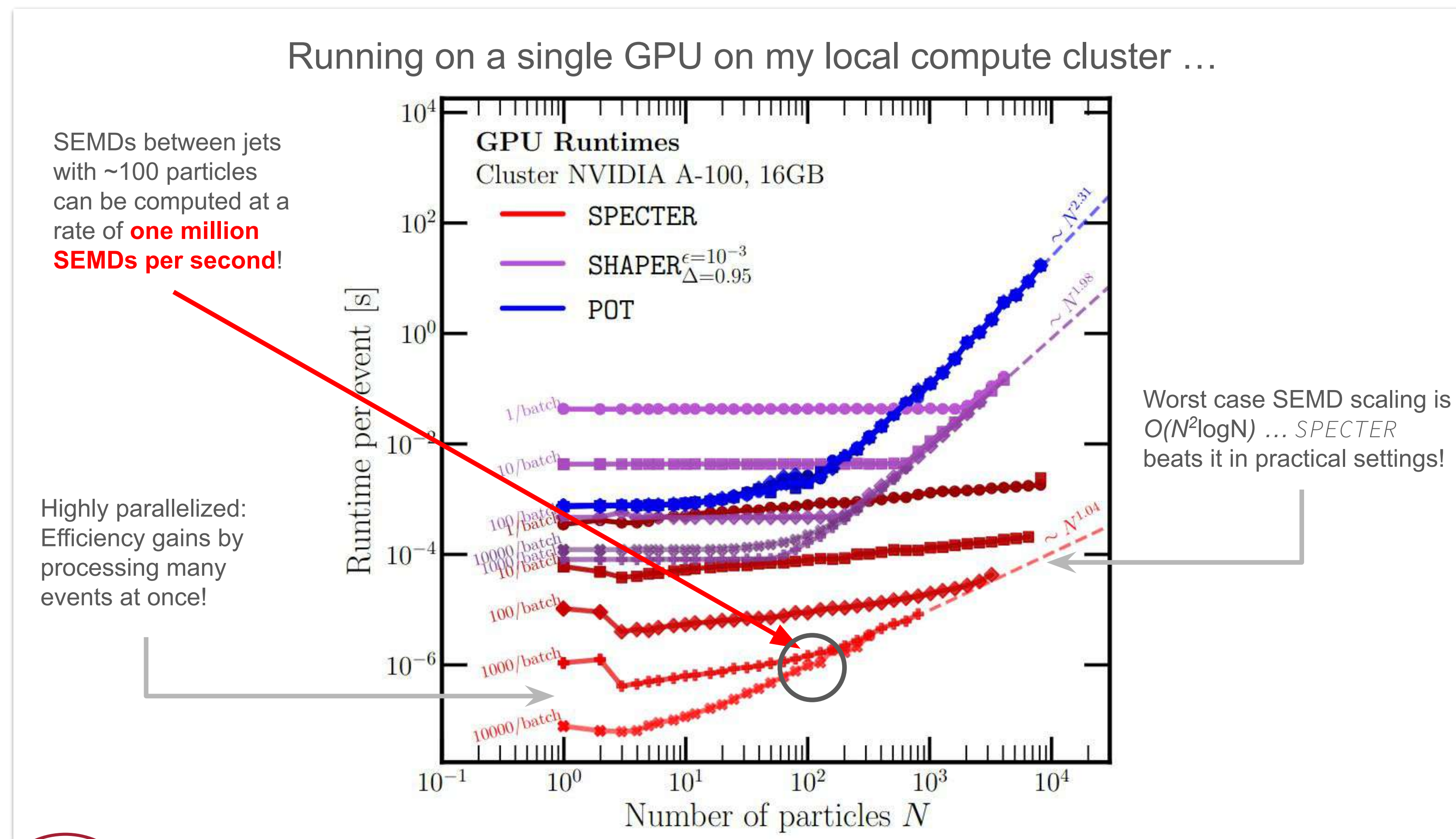
SPECTER: Efficient Evaluation of the Spectral EMD

The EMD provides a way to compare jets but it is hard to calculate

Solution: Spectral EMD

Respects symmetry properties, fast to evaluate

Bonus: some observables have a closed form → amenable to analytic calculations



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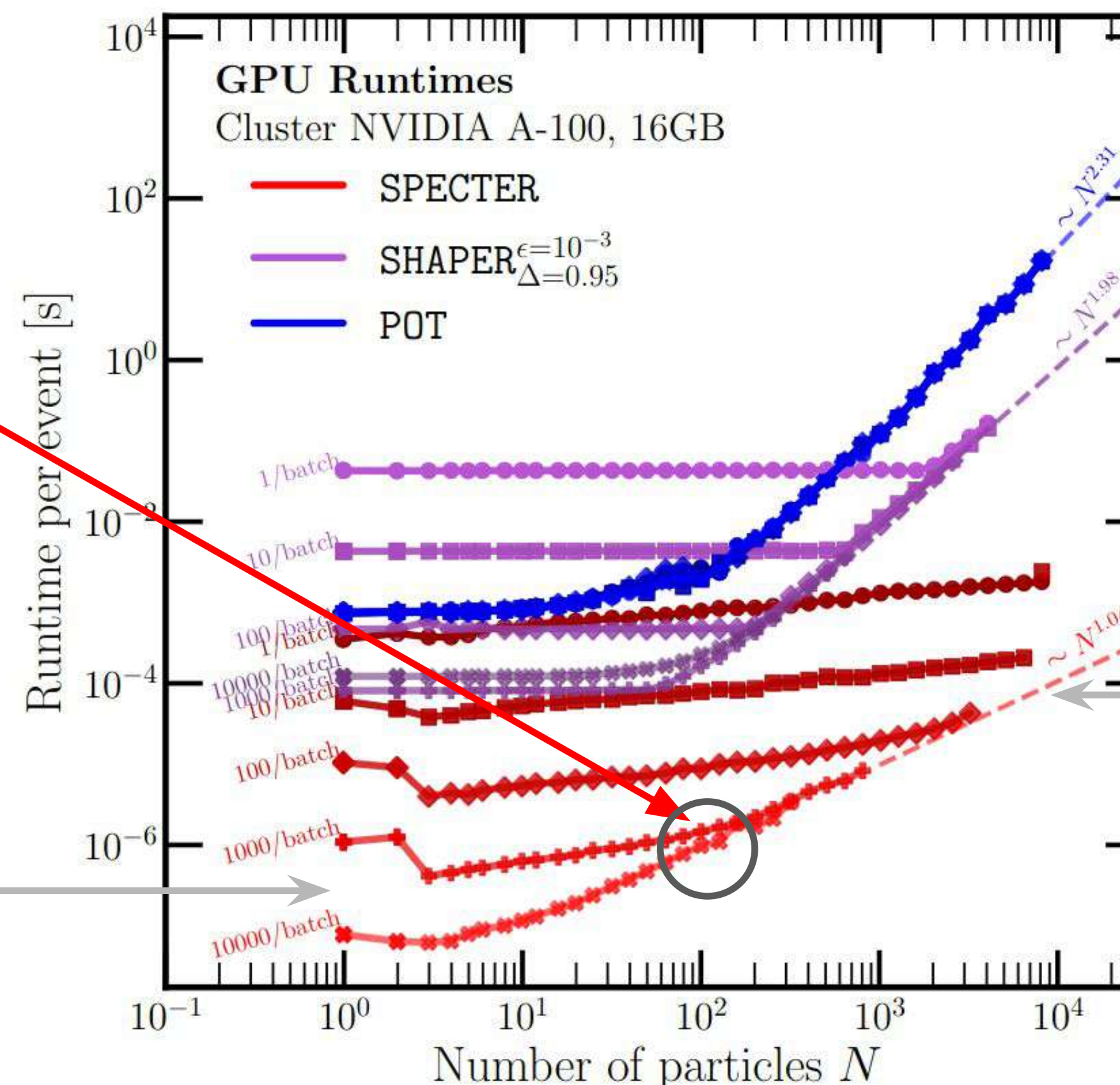
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Aren't we losing too much information? What do typical event-shape observables look like?

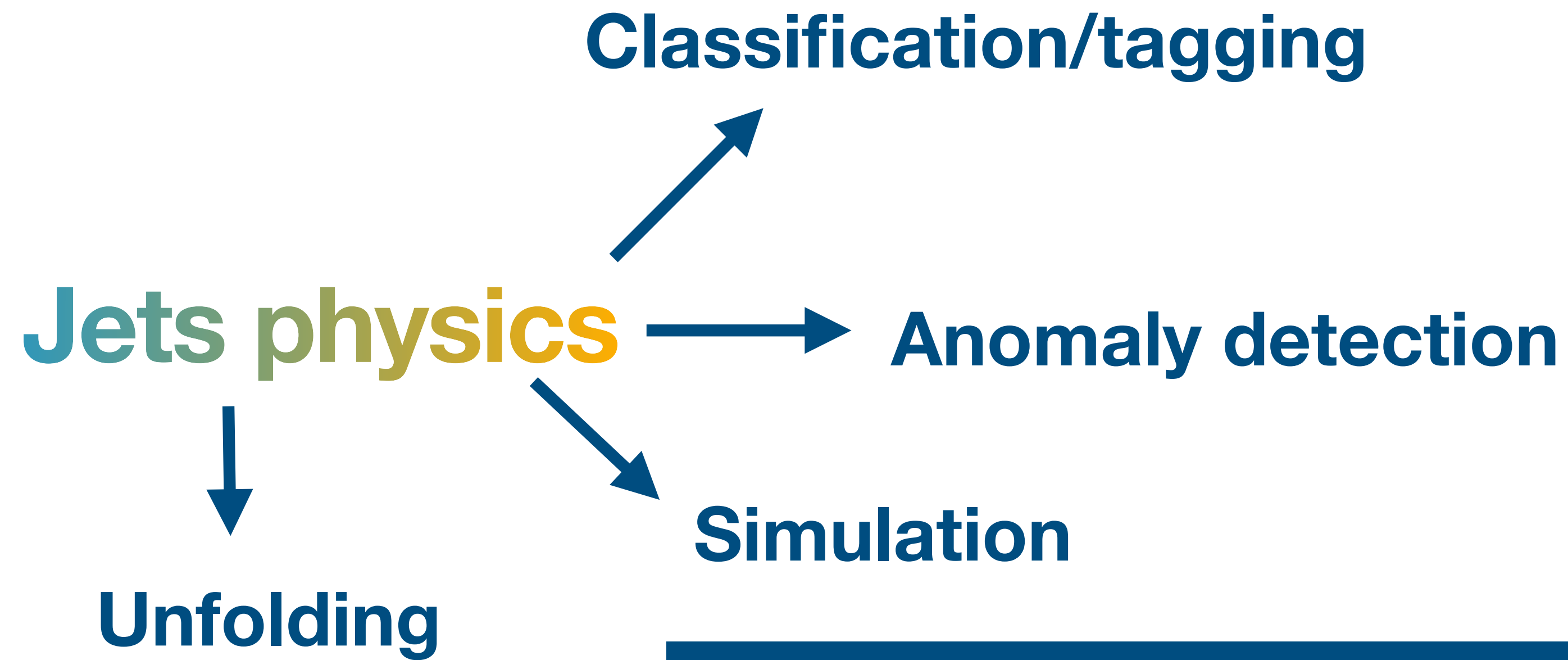
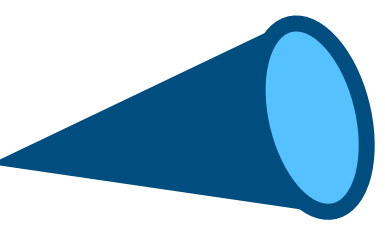
Running on a single GPU on my local compute cluster ...

SEMDs between jets with ~100 particles can be computed at a rate of **one million SEMDs per second!**

Highly parallelized: Efficiency gains by processing many events at once!



Worst case SEMD scaling is $O(N^2 \log N)$... SPECTER beats it in practical settings!



Can we combine all tasks into one tool?

“Can we learn the language of jets?”

[Reyes-Gonzalez](#)

How to teach AI about jets?

[Mikuni](#)

Supervised learning

Omnilearn

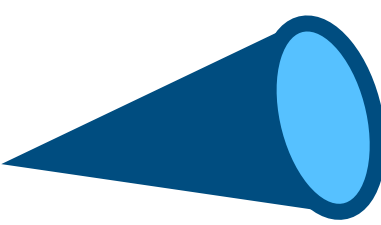
GGN + transformer network

Self-supervised learning

The language of jets

Self-supervised transformer network

ML



Supervised learning Omnilearn

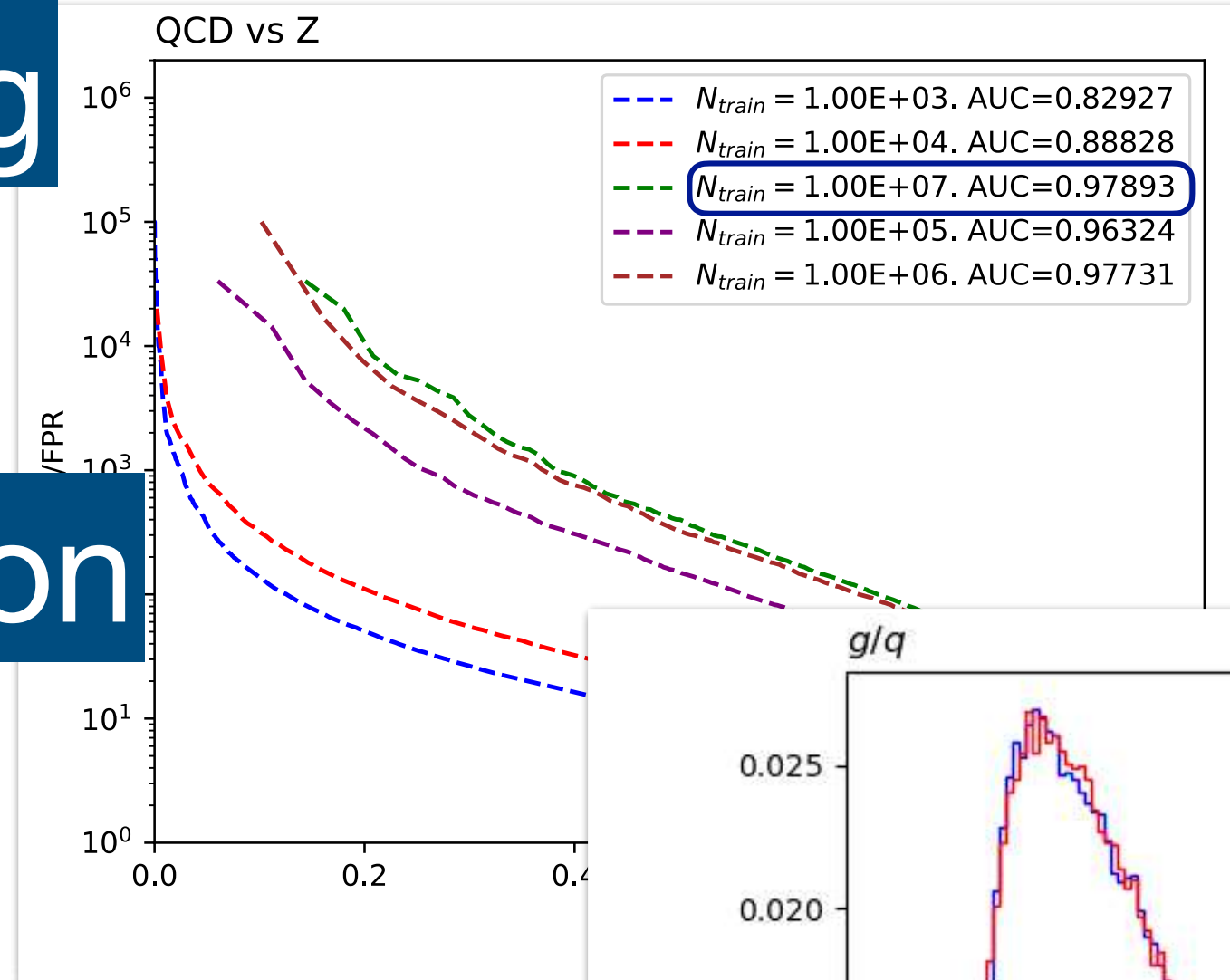
Self-supervised learning The language of jets

2 different jet categories, **AK4 jets** simulated in pp collisions with **Madgraph + Pythia8** with ~~CMS Delphes detector simulation~~

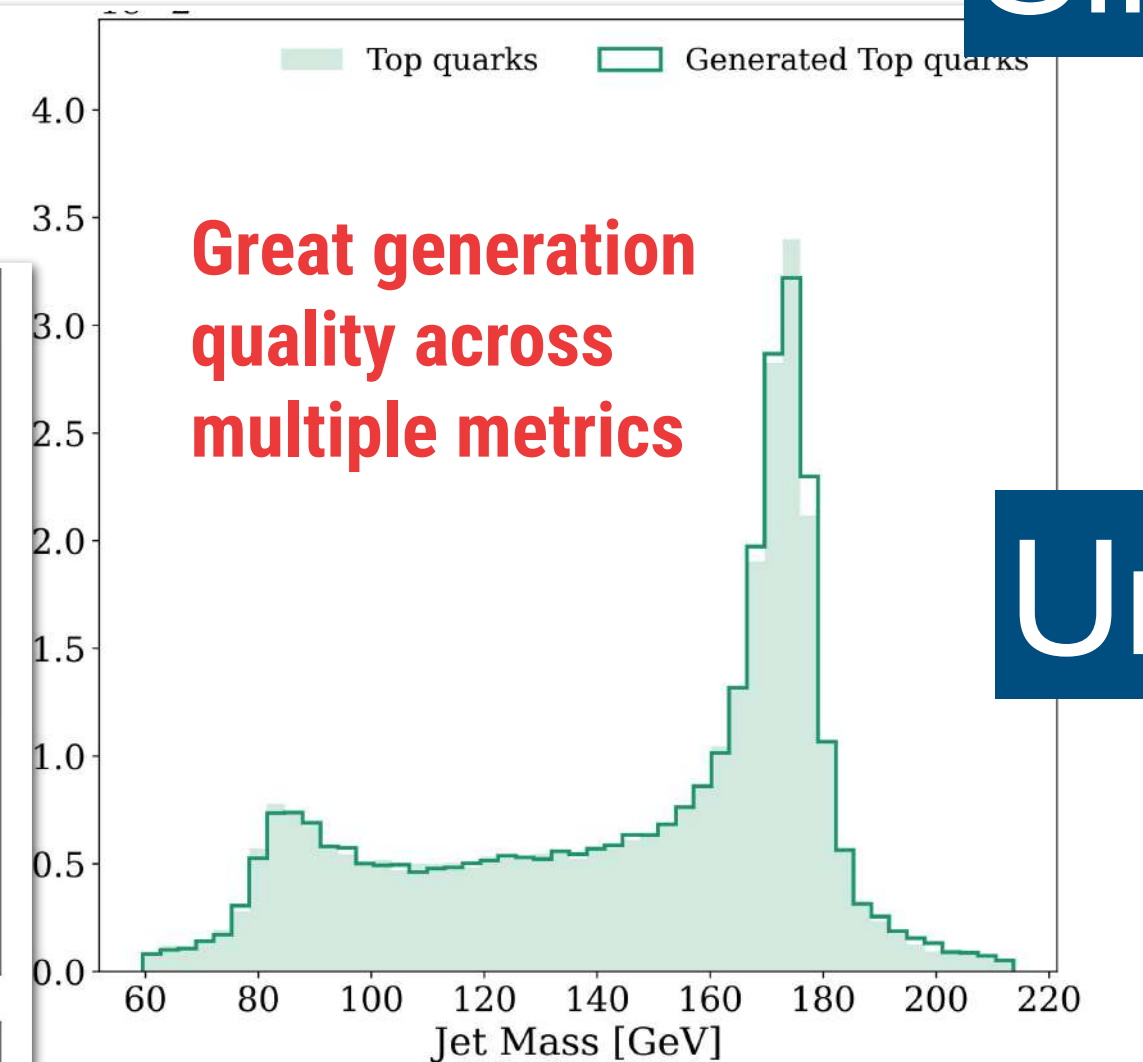
	Acc	AUC	1/ε _B	
			ε _S = 0.5	ε _S = 0.3
P-CNN [38]	0.827	0.9002	34.7	91.0
PFN [35]	-	0.9005	34.7±0.4	-
ParticleNet [38]	0.840	0.9116	39.8±0.2	98.6±1.3
rPCN [39]	-	0.9081	38.6 ± 0.5	-
ParT [42]	0.840	0.9121	41.3 ± 0.3	101.2 ± 1.1
ParT-f.t. [42]	0.843	0.9151	42.4 ± 0.2	107.9 ± 0.5
PET classifier	0.837	0.9110	39.92±0.1	104.9 ± 1.5
OMNILEARN	0.844	0.9159	43.7±0.3	107.7 ± 1.5

Better than all non-fine-tuned models and similar to PartT performance

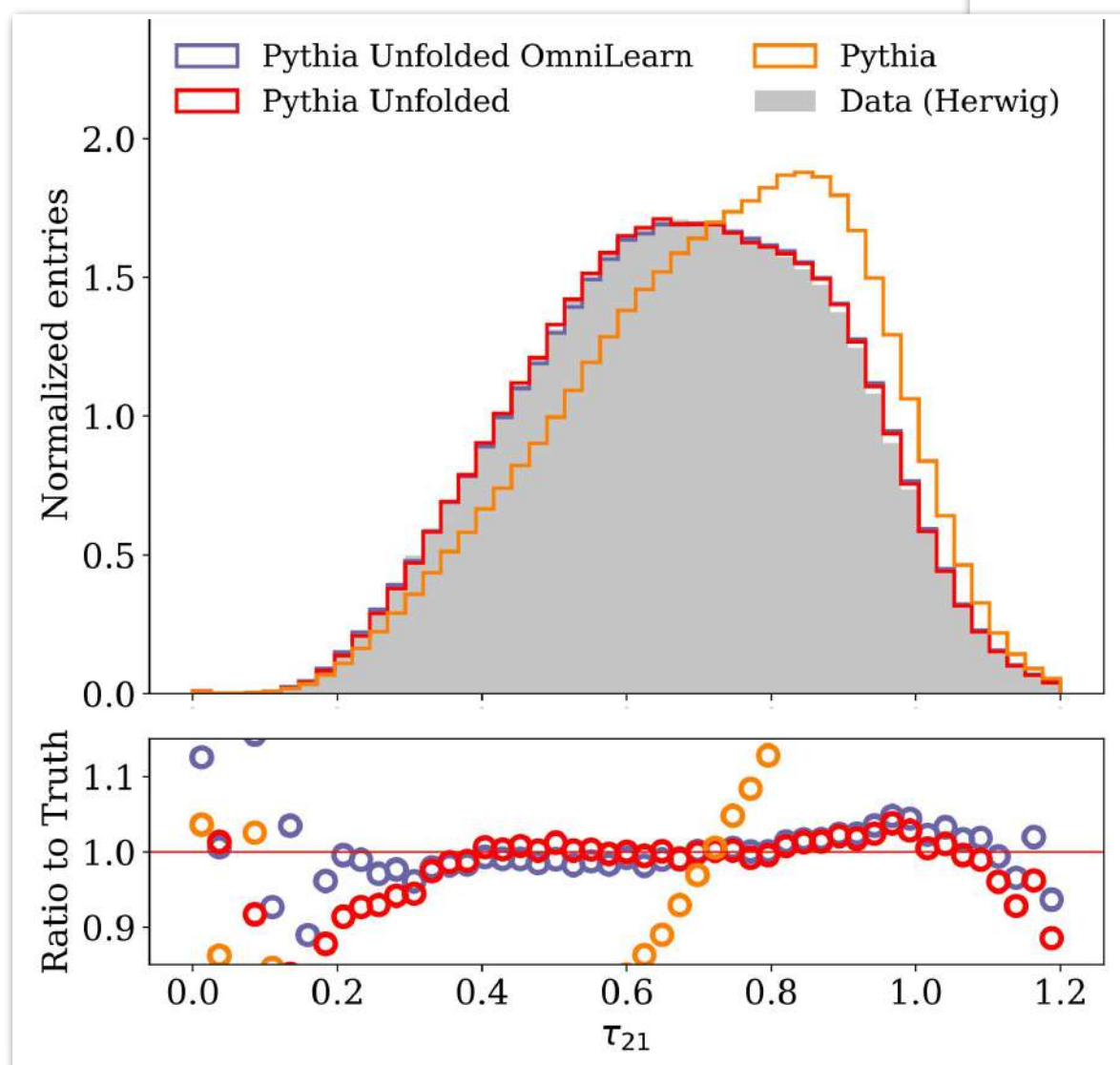
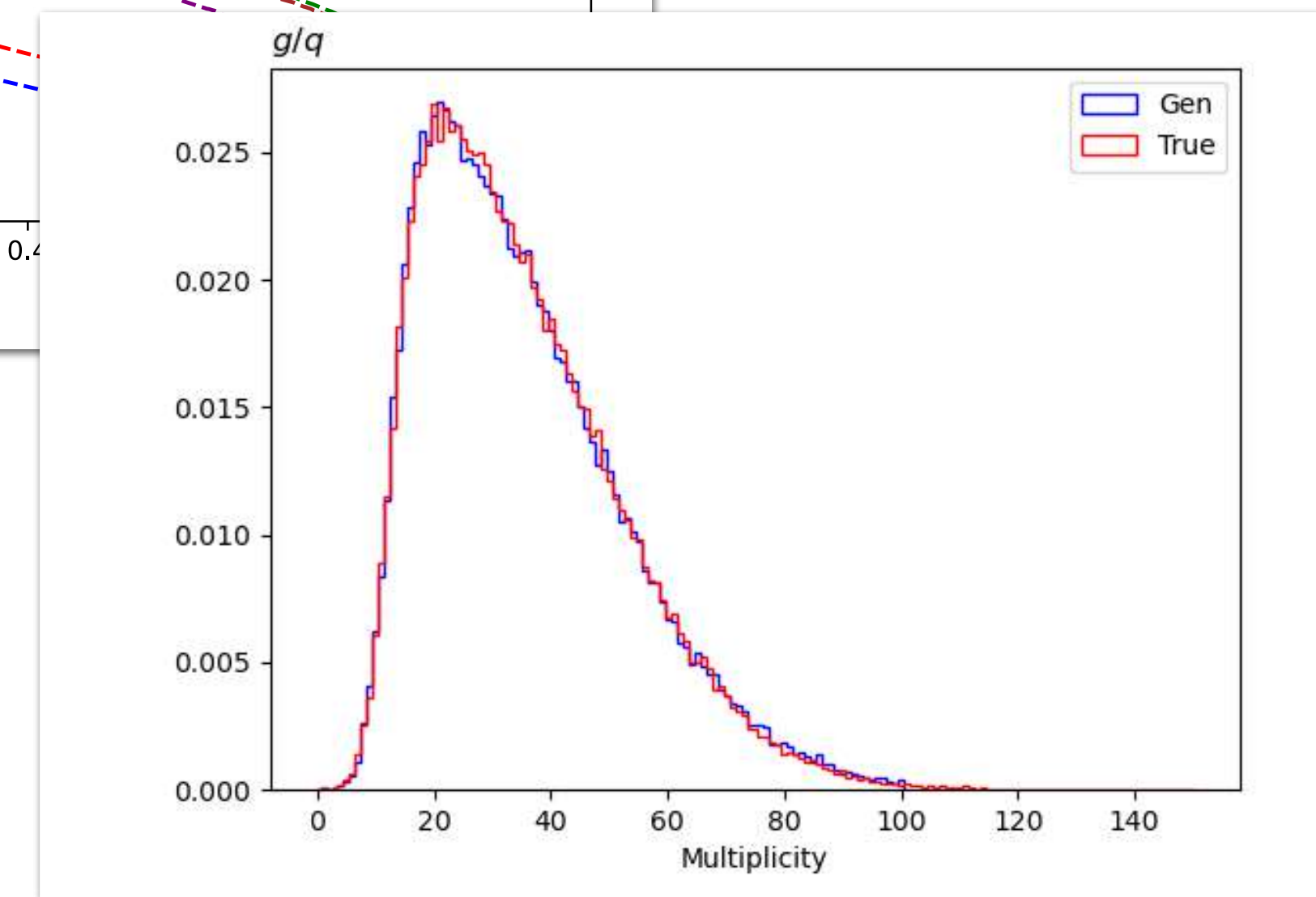
Tagging



Simulation



Unfolding



Supervised learning Omnilearn

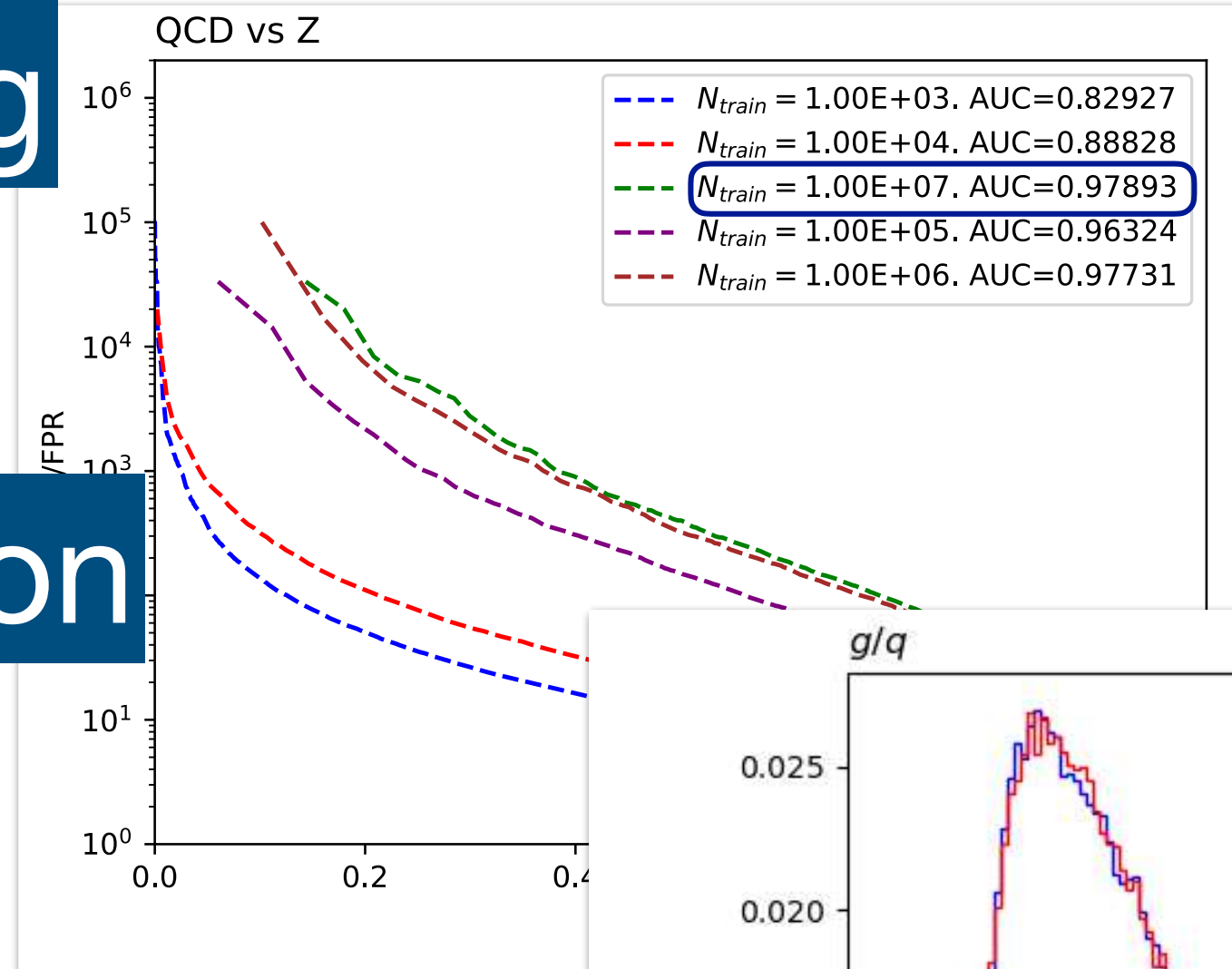
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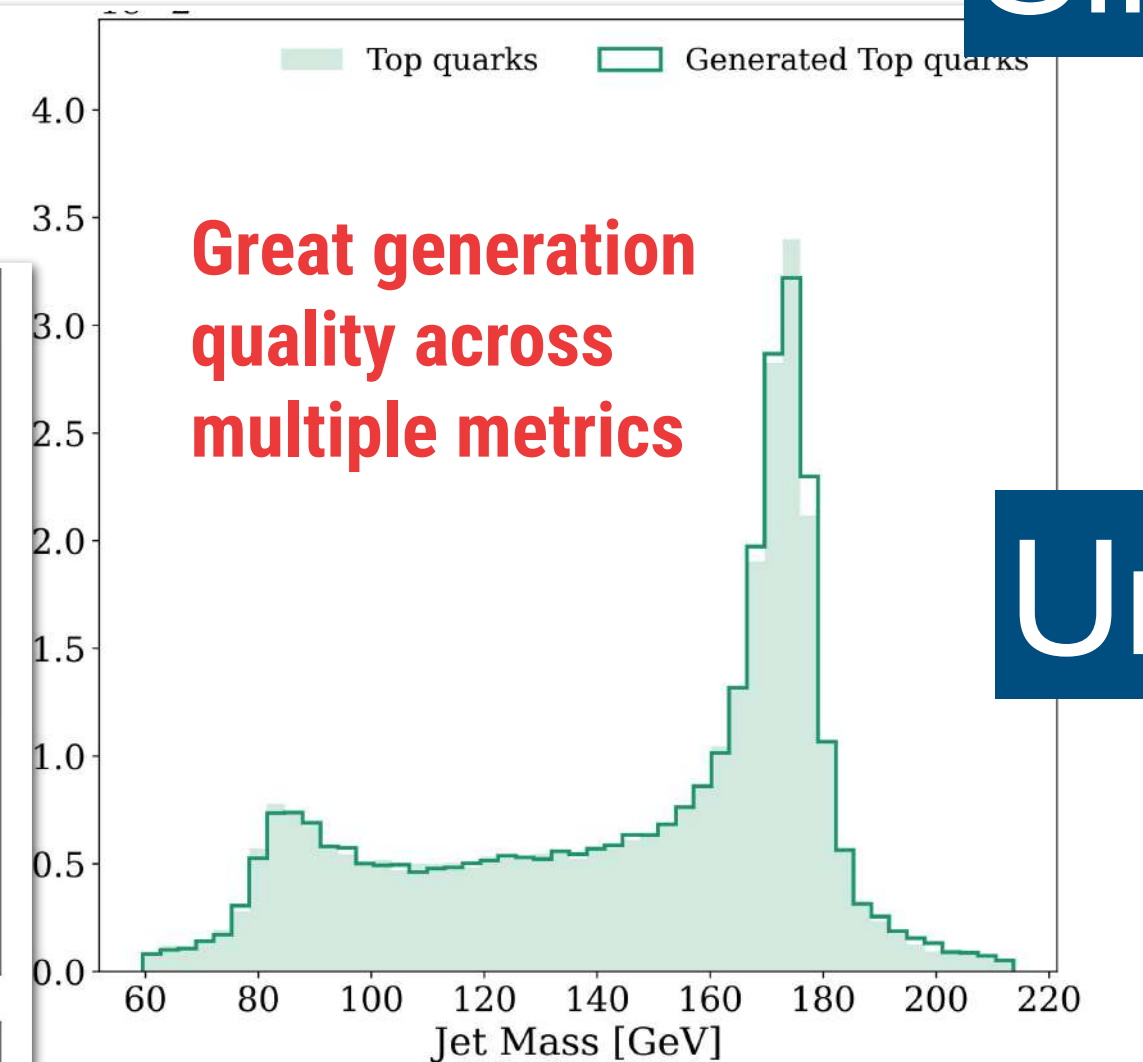
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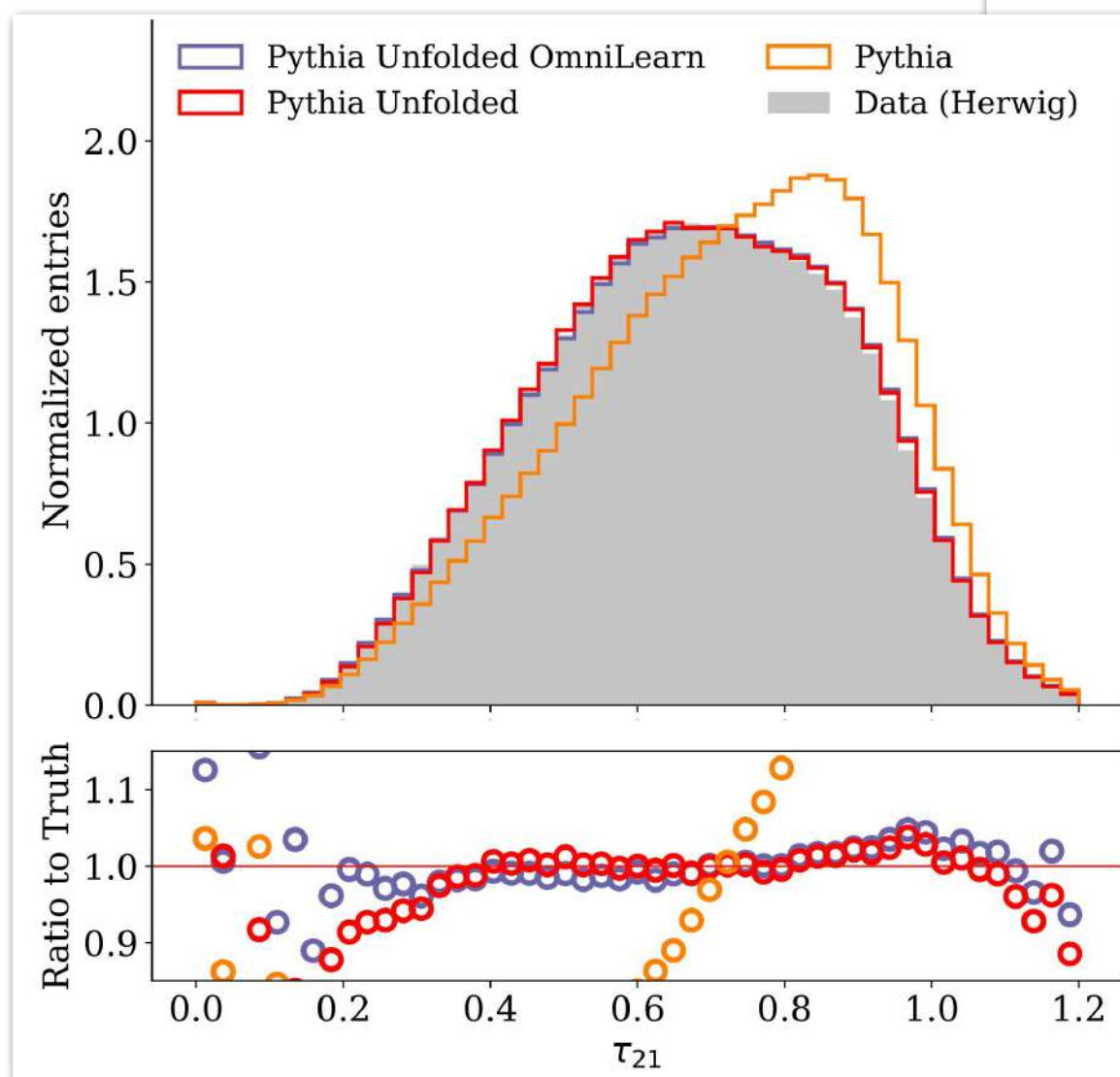
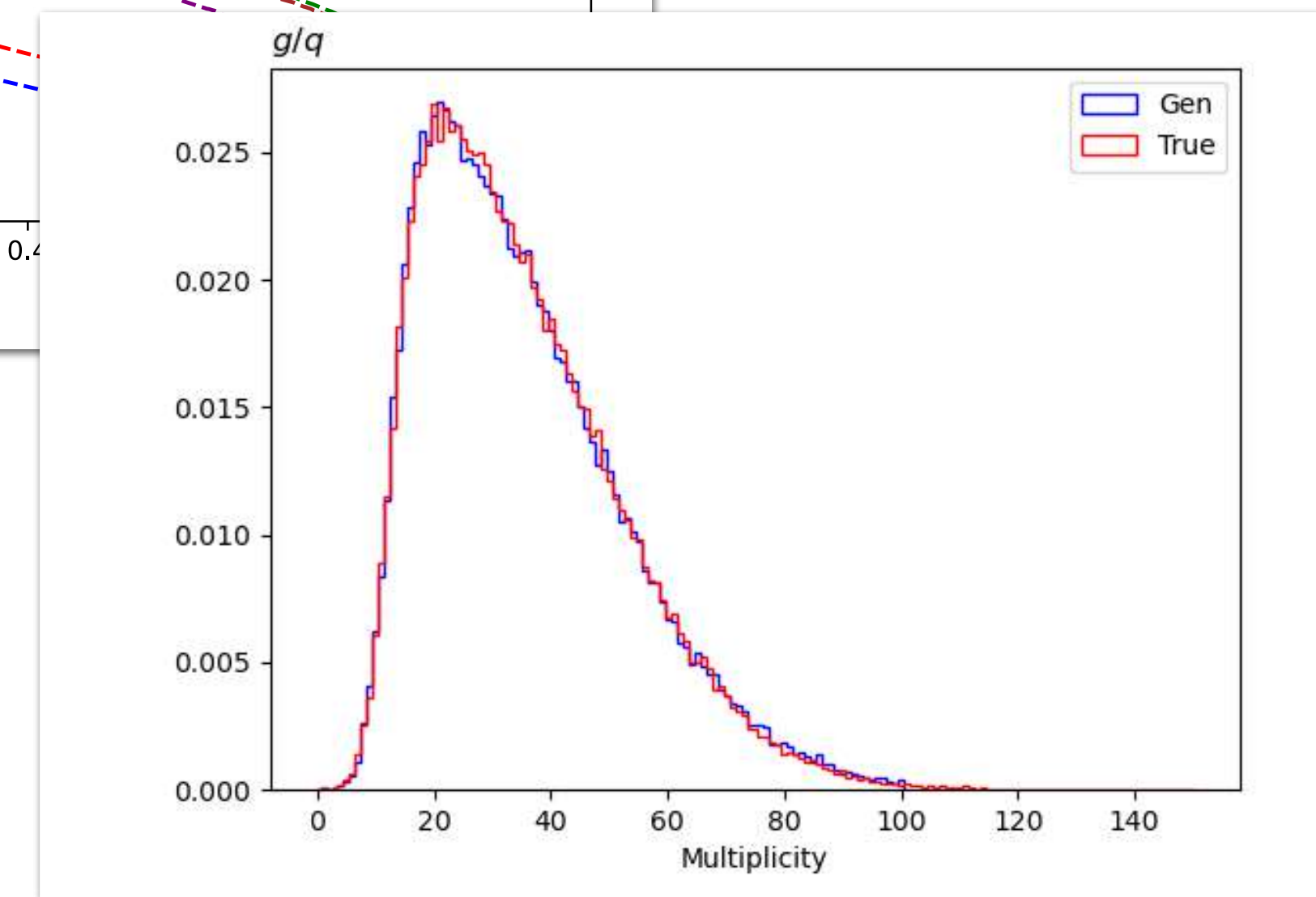
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The fingerprint: are we learning jet physics, or Pythia?

Towards NNLL accurate parton showers

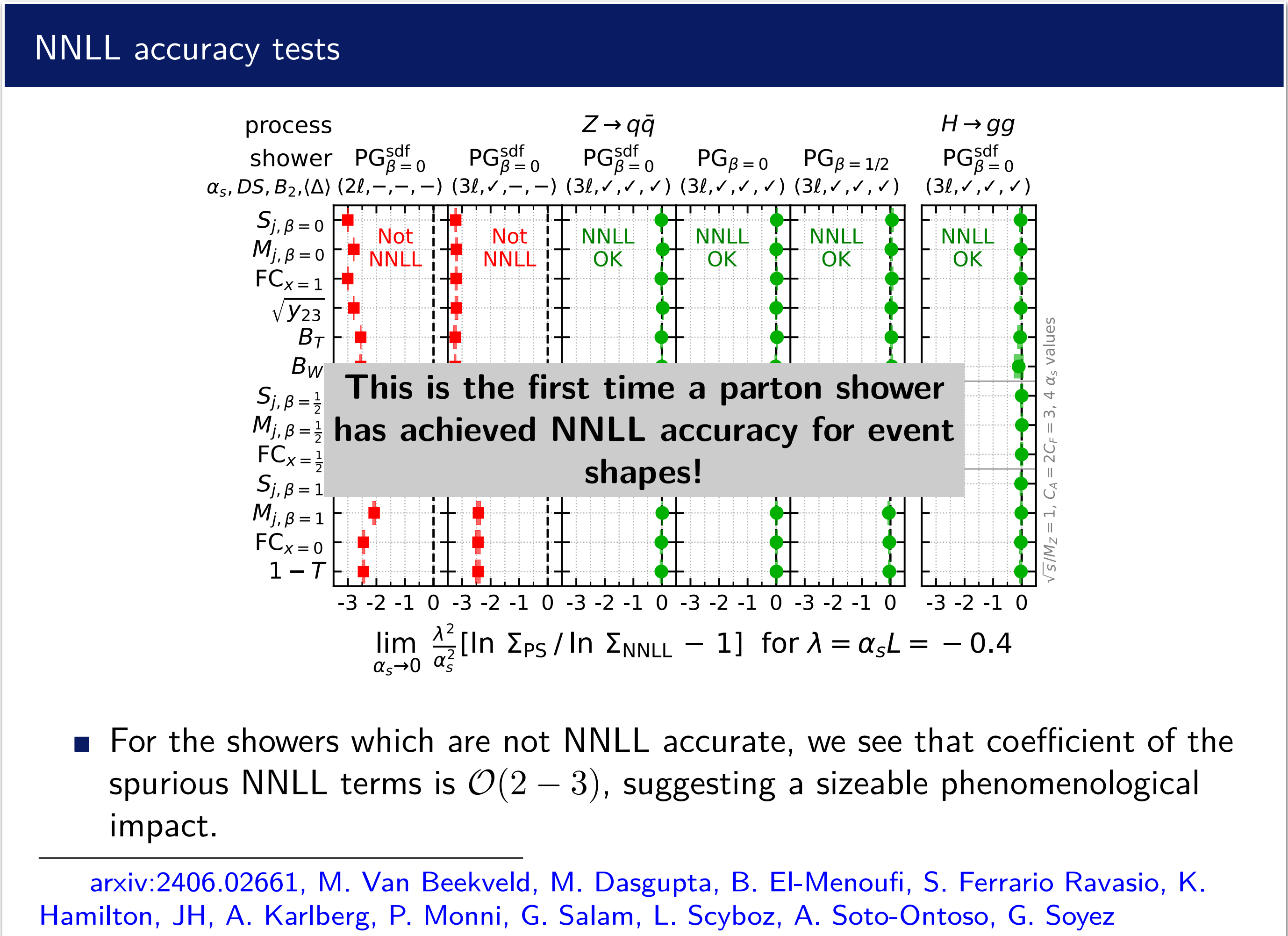
We saw:

1. Many ML models trained on MC data

2. Many data-MC discrepancies

We want AI to learn nature, not MC

The era of parton showers that achieve a higher formal accuracy

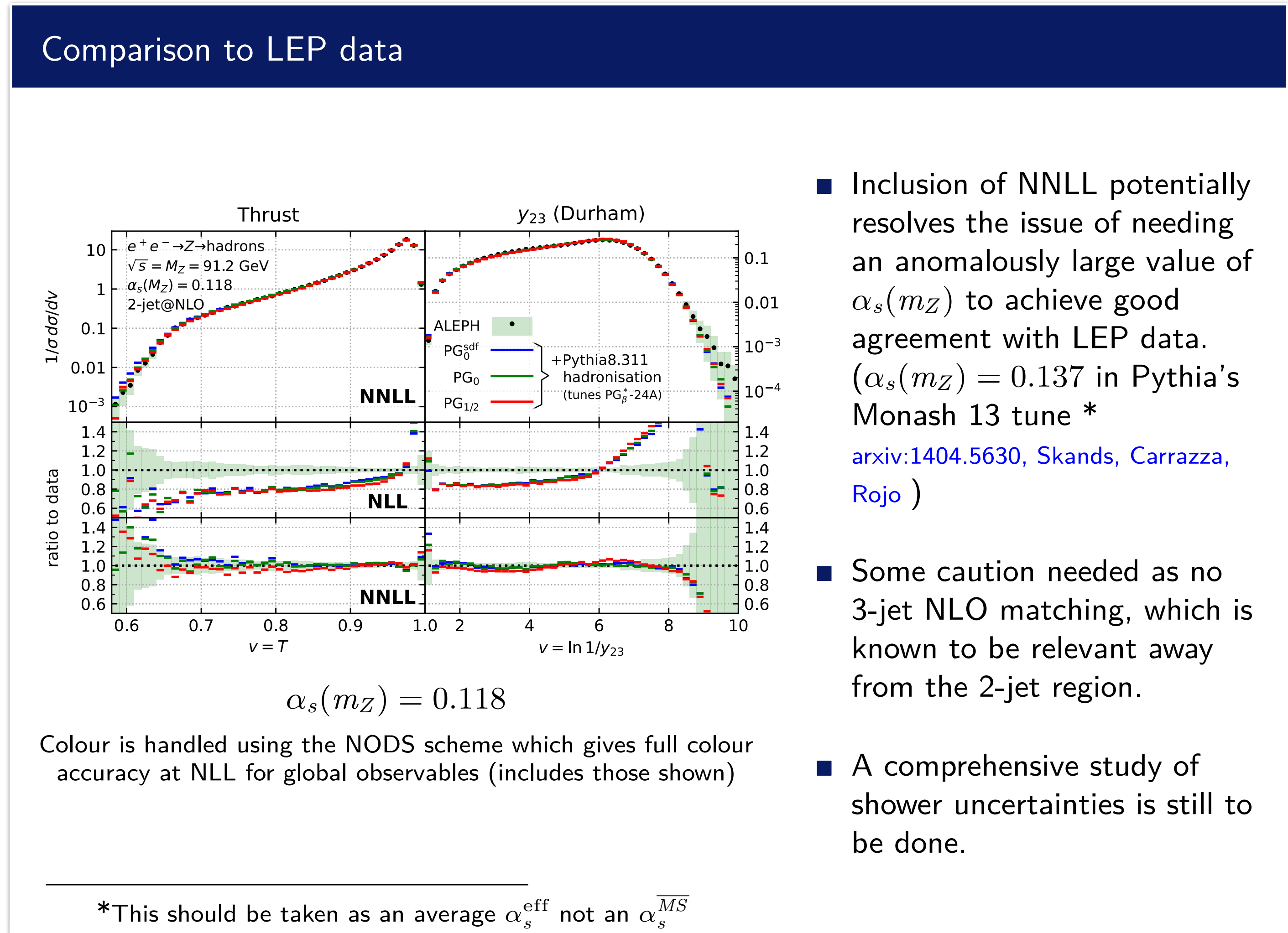


Towards NNLL accurate parton showers

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 2. Many data-MC discrepancies
- We want AI to learn nature, not MC

The era of parton showers that achieve a higher formal accuracy



- Inclusion of NNLL potentially resolves the issue of needing an anomalously large value of $\alpha_s(m_Z)$ to achieve good agreement with LEP data. ($\alpha_s(m_Z) = 0.137$ in Pythia's Monash 13 tune *)
[arxiv:1404.5630](https://arxiv.org/abs/1404.5630), Skands, Carrazza, Rojo)
- Some caution needed as no 3-jet NLO matching, which is known to be relevant away from the 2-jet region.
- A comprehensive study of shower uncertainties is still to be done.

Work towards pp is ongoing

High-purity gluon jet showers using secondary Lund jet planes

New observables 

Can we constrain the gluon shower better?

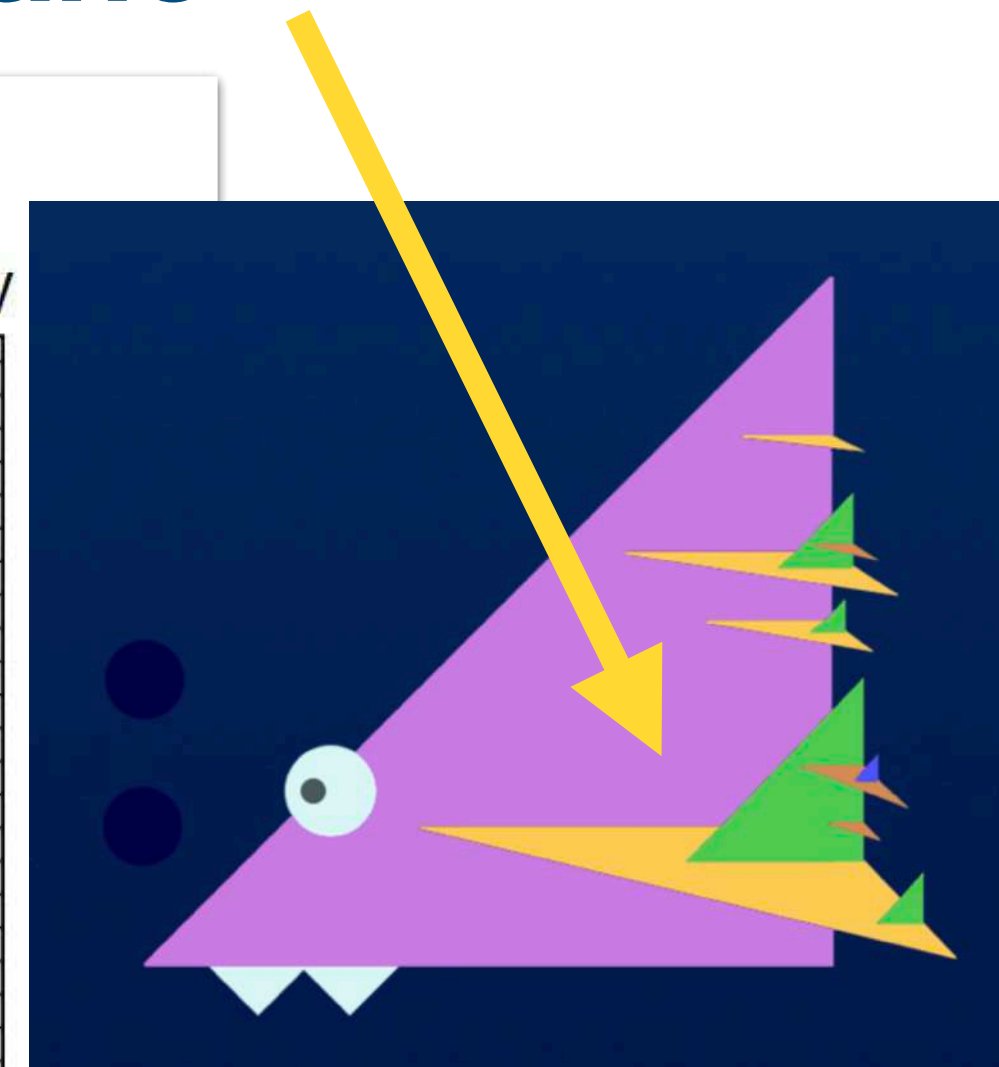
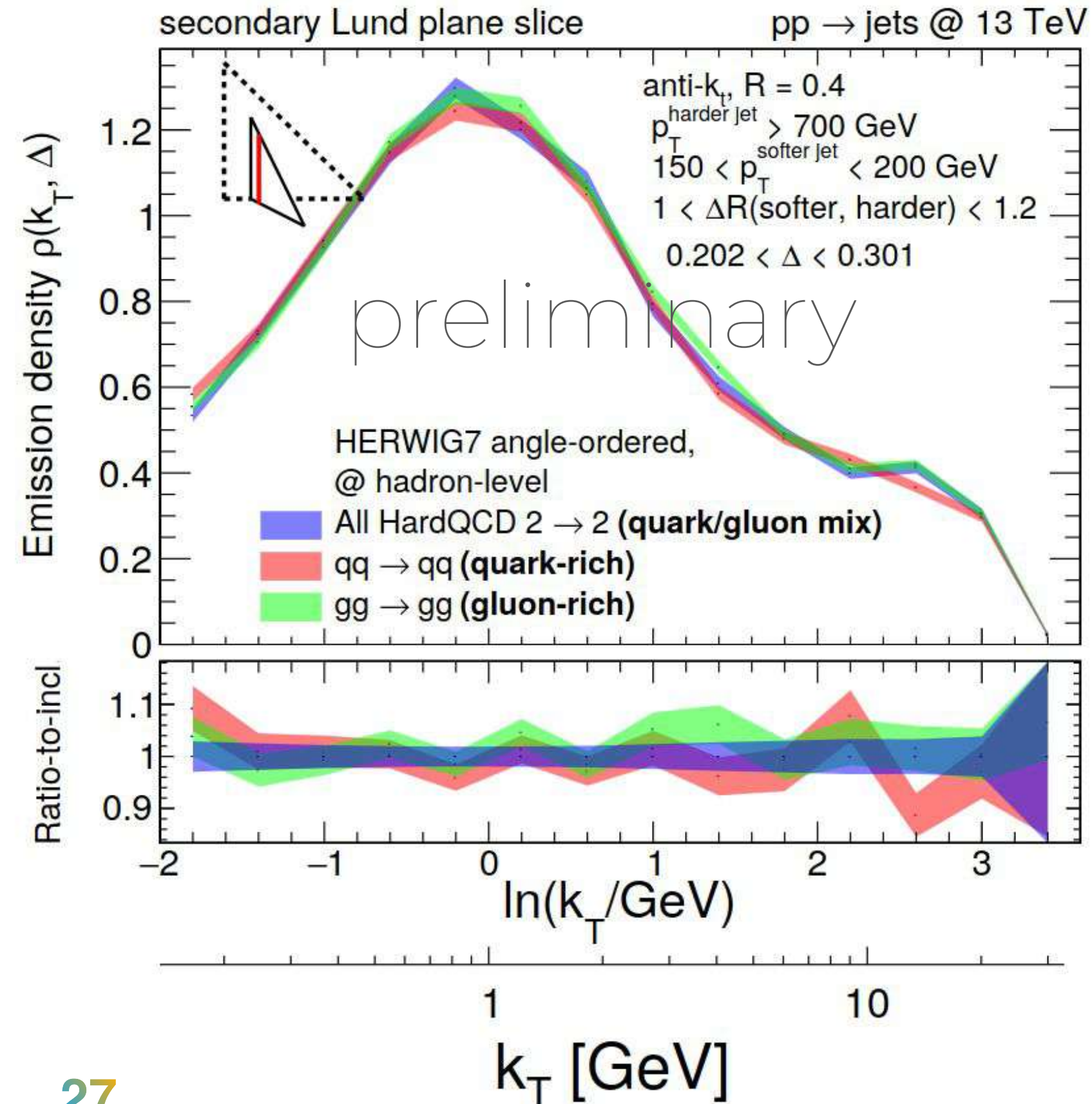
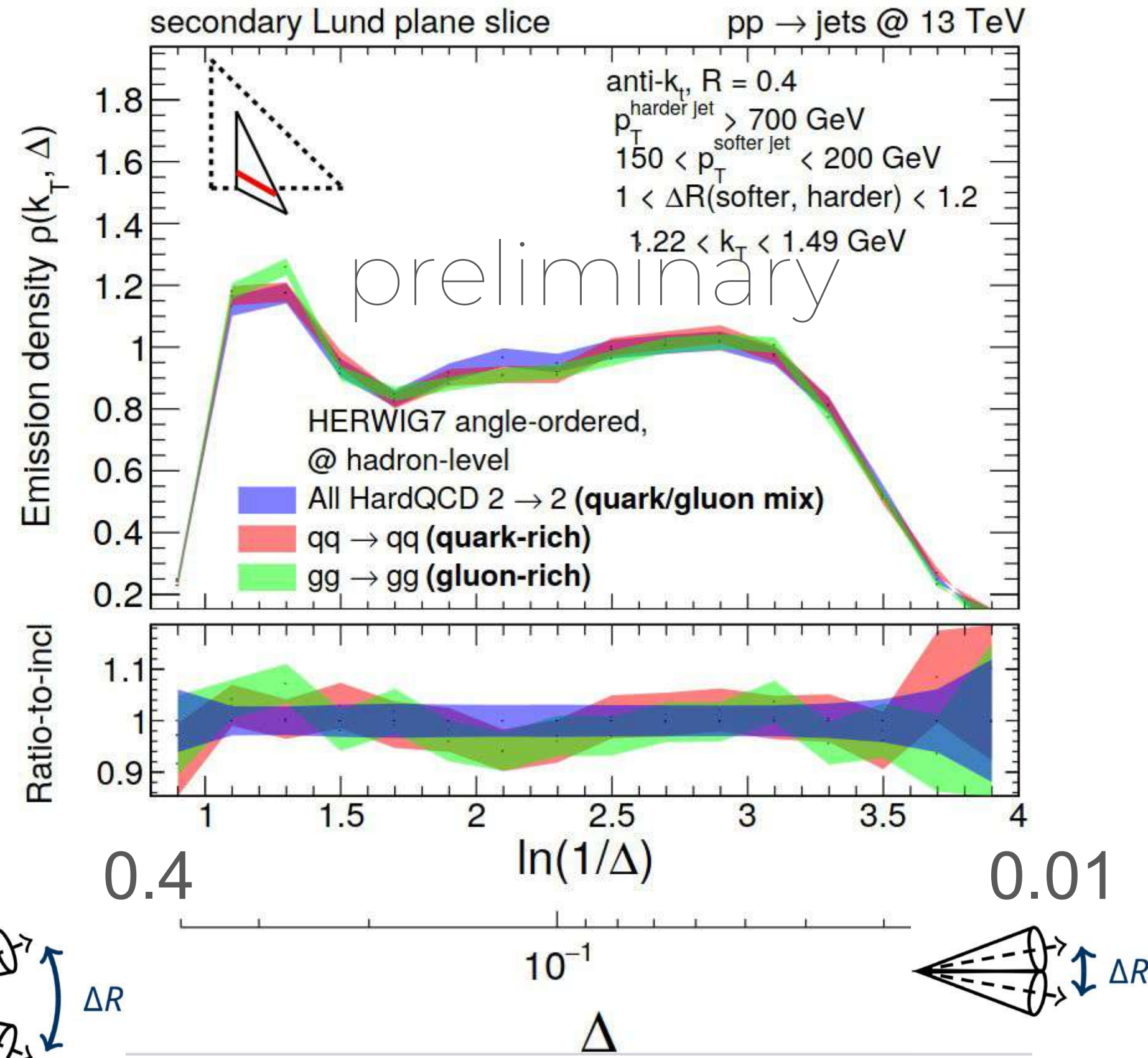
Input for e.g. heavy-ion studies and jet calibration



Use the secondary Lund jet plane

[Cristian Barrera](#)

Process-independence, PDF-independence



High-purity gluon jet showers using secondary Lund jet planes

New observables 

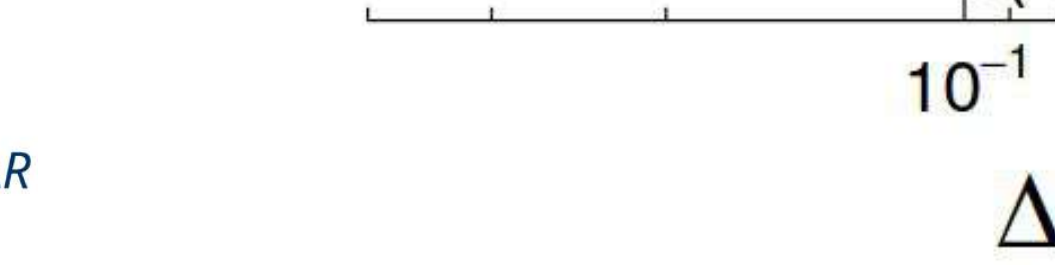
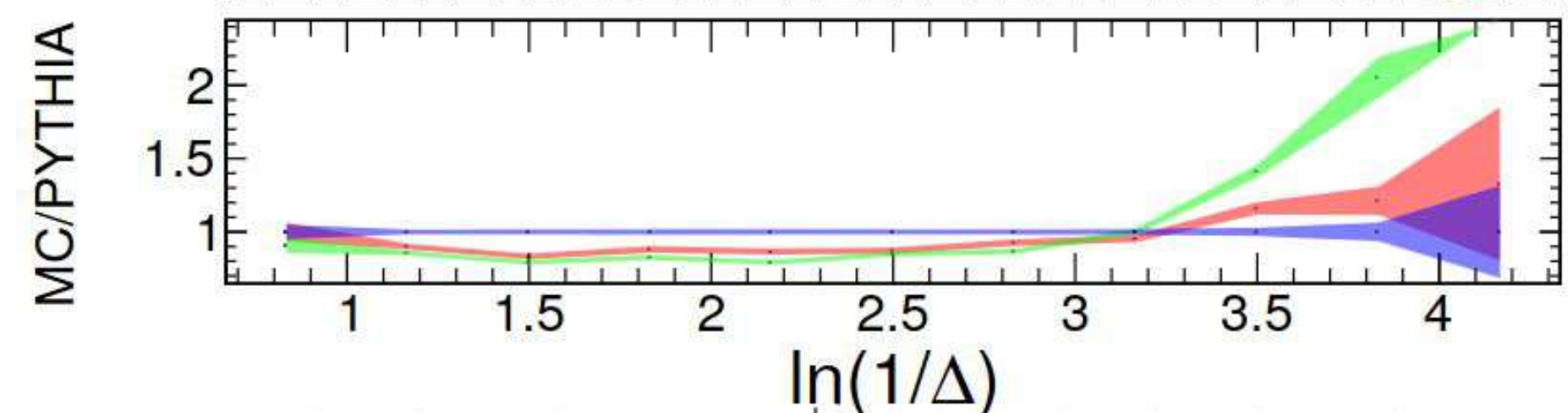
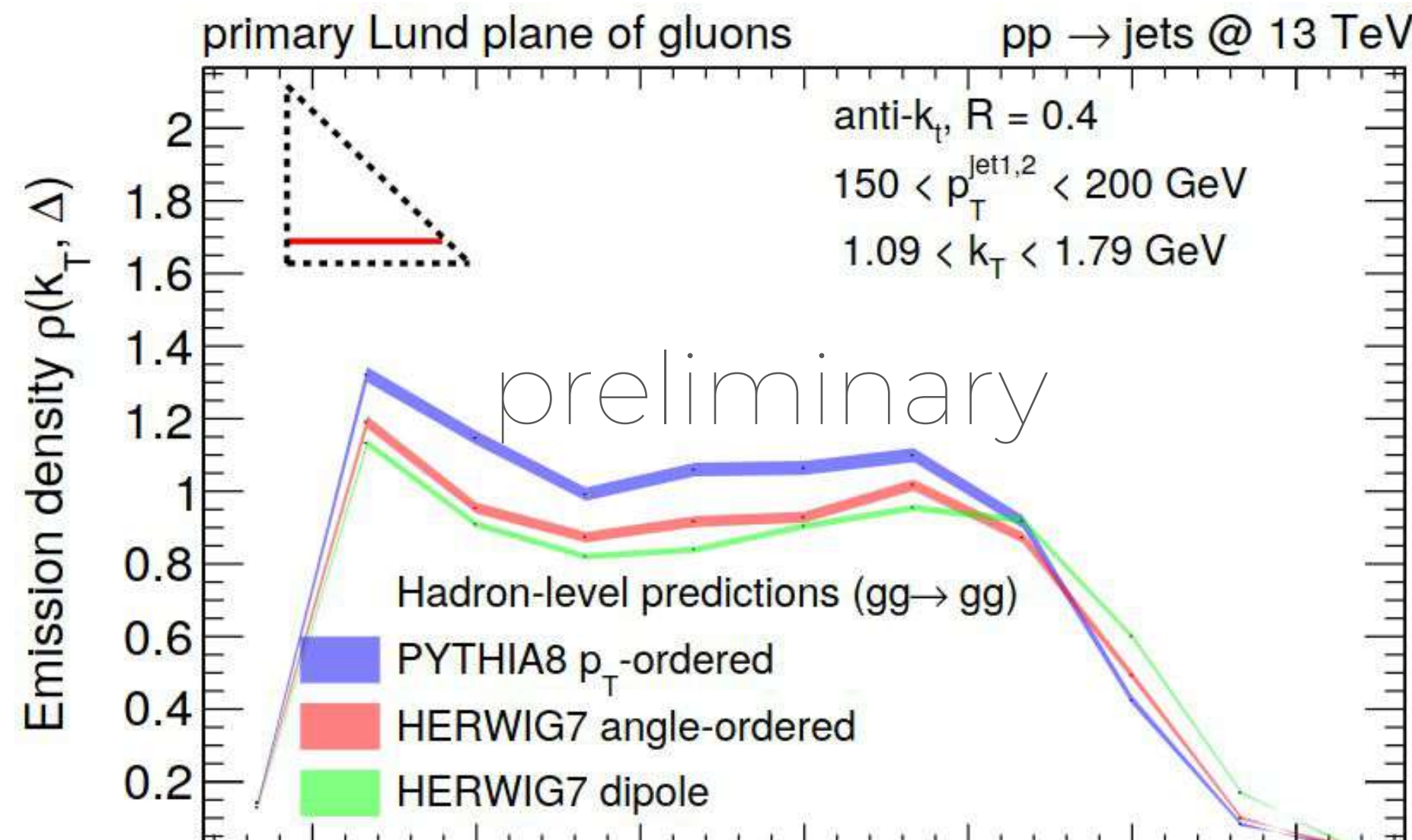
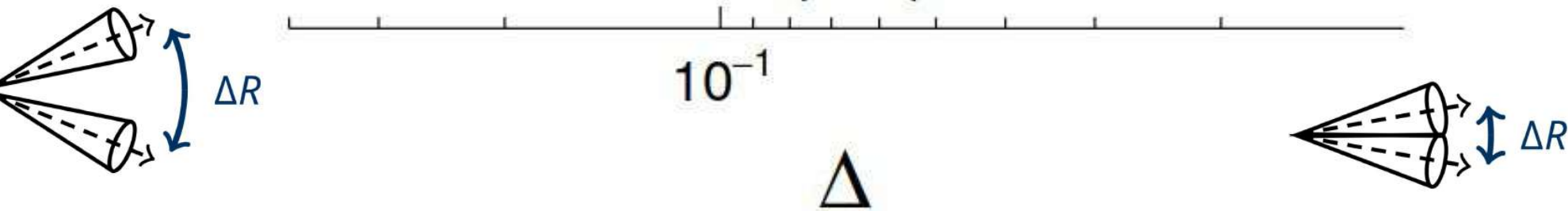
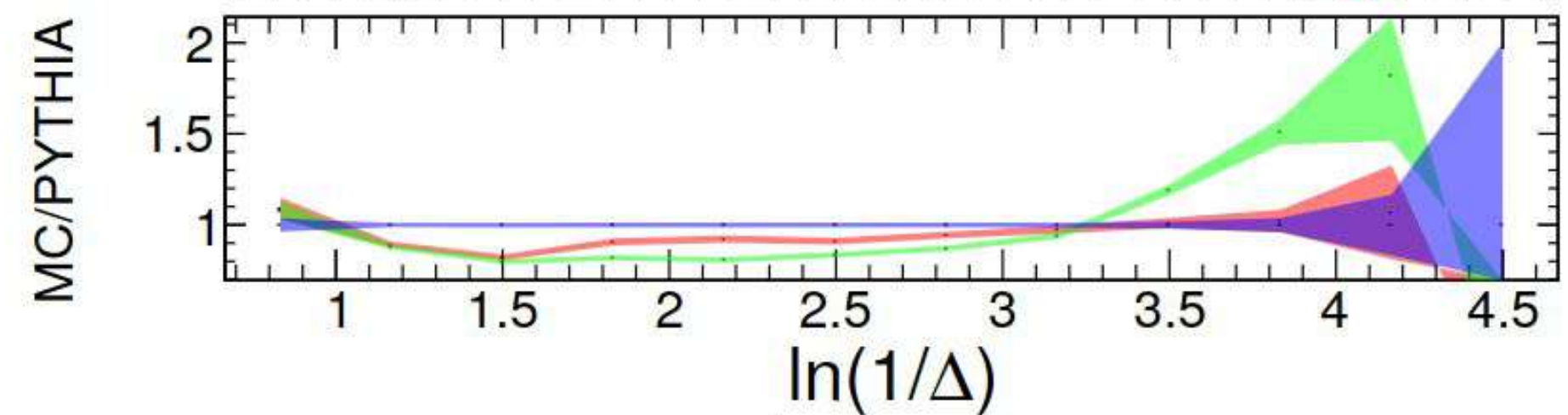
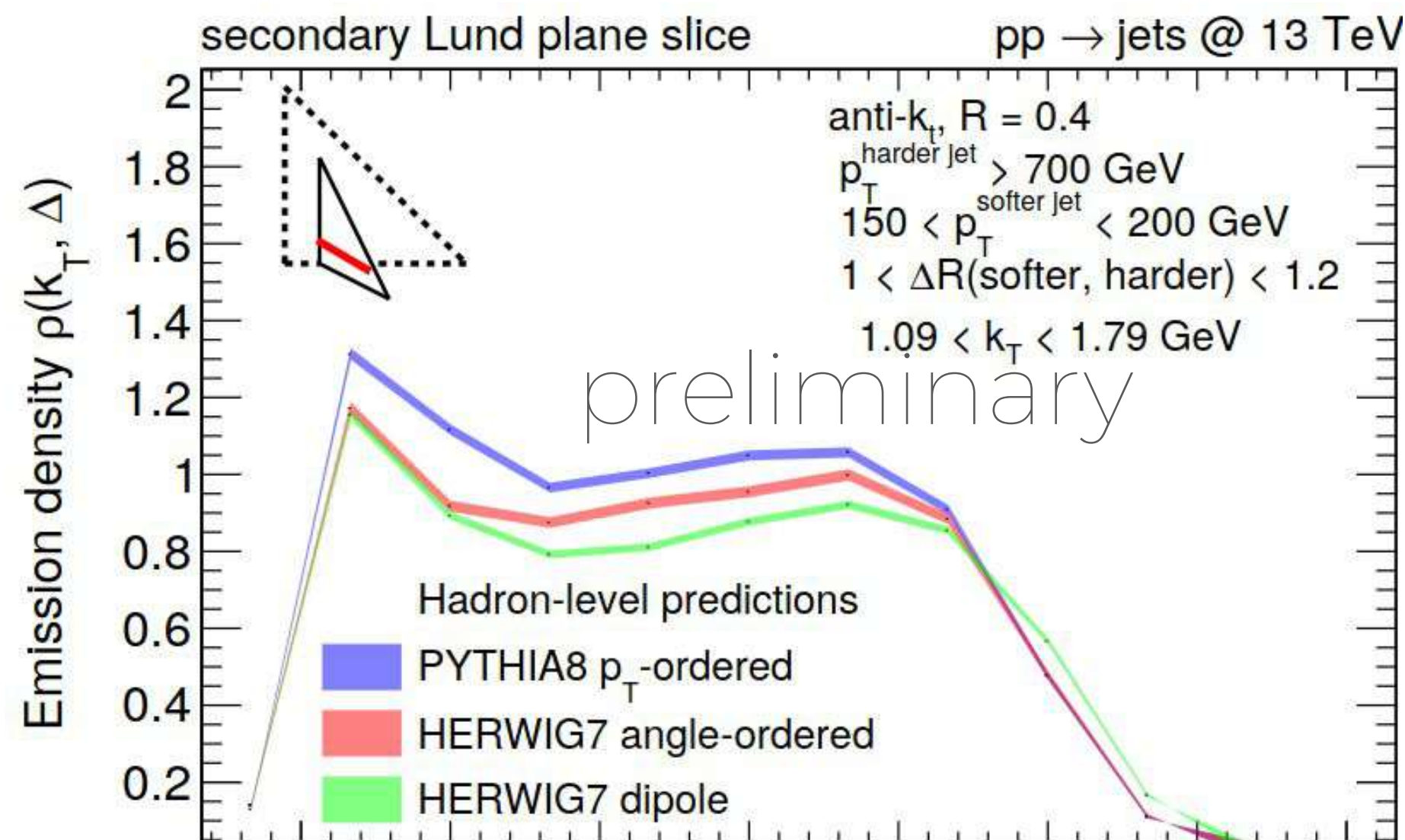
Can we constrain the gluon shower better?

Input for e.g. heavy-ion studies and jet calibration



Use the secondary Lund jet plane

[Cristian Barrera](#)




Can we understand this generator-dependence? Is any of them correct?

How do heavy quarks fragment into hadrons (w one heavy quark)?

$$\bullet \frac{1}{\sigma_Q^{tot}} \sigma_Q(Q, m) = \frac{1}{\sigma_Q^{tot}} \sigma^{(0)} \sum_{i,j} C_i(Q, \mu, \mu_F) E_{ij}(\mu_F, \mu_{0F}) D_{j \rightarrow Q}(\mu_{0F}, m)$$

2 factorisation scales:
 μ_F and μ_{0F}

- Initial conditions $D_{j \rightarrow Q}$ @ NNLO [Melnikov, Mitov '04] [Mitov '04] [Maltoni et al. '22]
- DGLAP Evolution (ZM-VFNS @ NLO) E_{ij} with MELA [Bertone et al. '15] [Ridolfi et al. '19] 
- Coefficient functions C_i @ NNLO [Rijken, van Neerven '97] [Blümlein, Ravindran '06] [Mitov, Moch '06]
- Poor behaviour in large- N ($x \rightarrow 1$) region (Sudakov region)
 - Need resummation @ NNLL in initial conditions and coefficient functions [Cacciari, Catani '01] [Aglietti et. al '06] [Maltoni et al. '22] [Czakon et al. '22]

Heavy Quark Fragmentation in e+e- Collisions to NNLO+NNLL Accuracy in Perturbative QCD

New calculations 

Leonardo Bonino

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et. al '06] [Maltoni et al. '22] [Czakon et al. '22]

When will NNLO be relevant

- we want $2 \rightarrow 3$ e.g. W/Z +jet or dijets (so as to have at least 2 particles in the jet!)
- $2 \rightarrow 2$ is available
- rule of thumb adding one loop or one leg takes $\mathcal{O}(10)$ years

\Rightarrow NNLO meets BOOST around 2025

Only one year off!

- Note 1: large community effort so we may hope for better
- Note 2: Boost=small angles \Rightarrow delicate corner of phase space



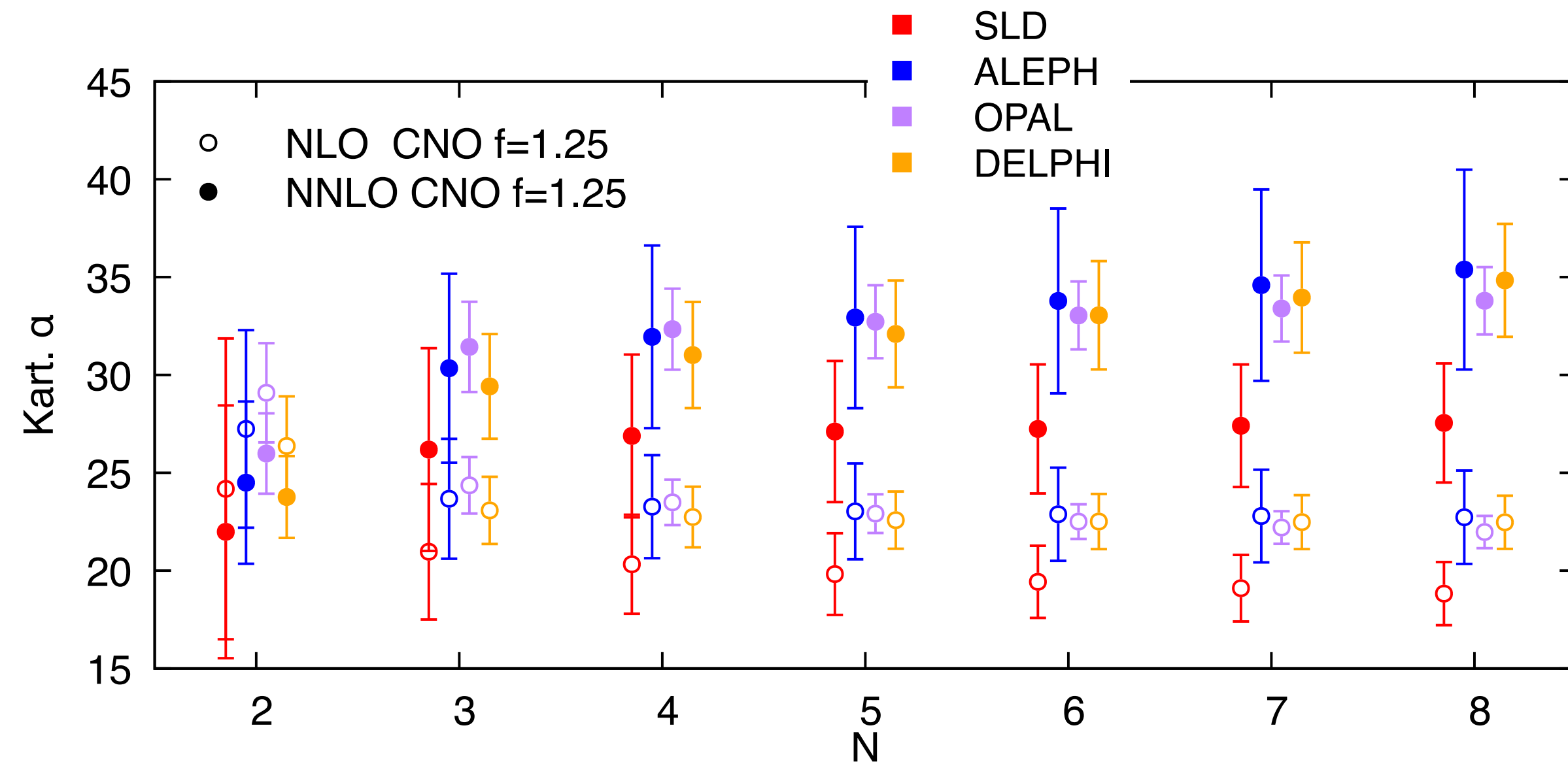
Heavy Quark Fragmentation in e+e- Collisions to NNLO+NNLL Accuracy in Perturbative QCD

New calculations 

[Leonardo Bonino](#)

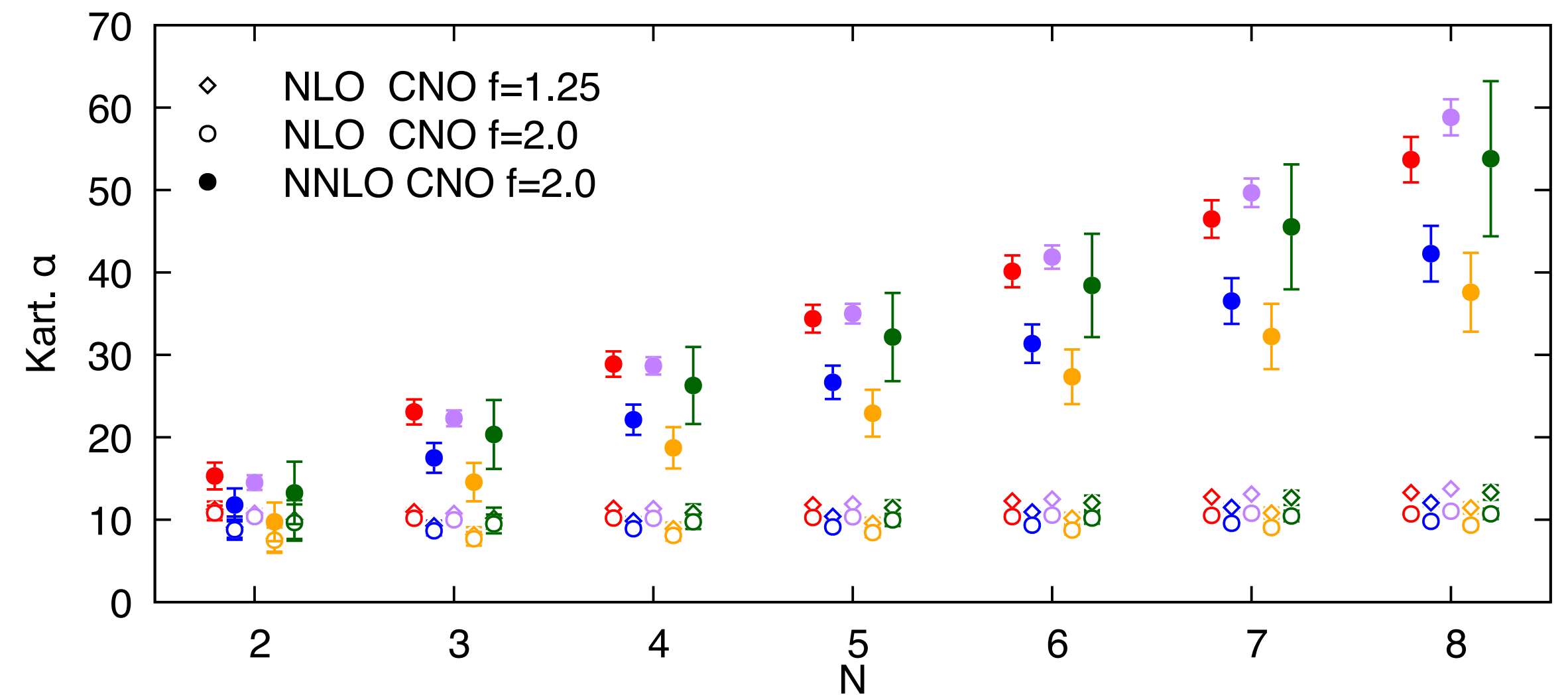
How do heavy quarks fragment into hadrons (w one heavy quark)?

Extraction of FF is OK for bottom...



- Single parameter non-perturbative function

$$D_K^{np}(x) = (\alpha + 1)(\alpha + 2)x^\alpha(1 - x) \text{ [Kartvelishvili et al. '78]}$$



Which regularisation scheme is more sensible? Do we need to come up with something new?

... but not so much for charm

Towards Quarkonium Fragmentation from Heavy-Flavor Non- Relativistic Evolution

New 
calculations

Francesco Celiberto

How do heavy quarks fragment into hadrons (w ~~one~~ heavy quark)?

HADRONIC STRUCTURE
QUARKONIUM THEORY

PRECISION QCD
COLLINEAR FACTORIZATION

Guiding principle \Rightarrow ; Use the best of the Two Worlds as much as we can !



Heavy flavor non relativistic evolution

Towards Quarkonium Fragmentation from Heavy-Flavor Non-Relativistic Evolution

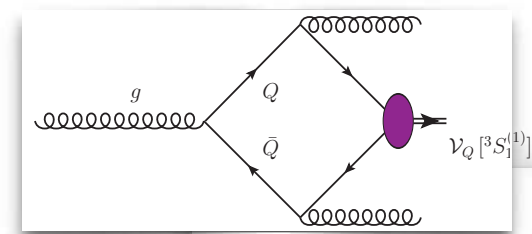
New calculations 

Francesco Celiberto

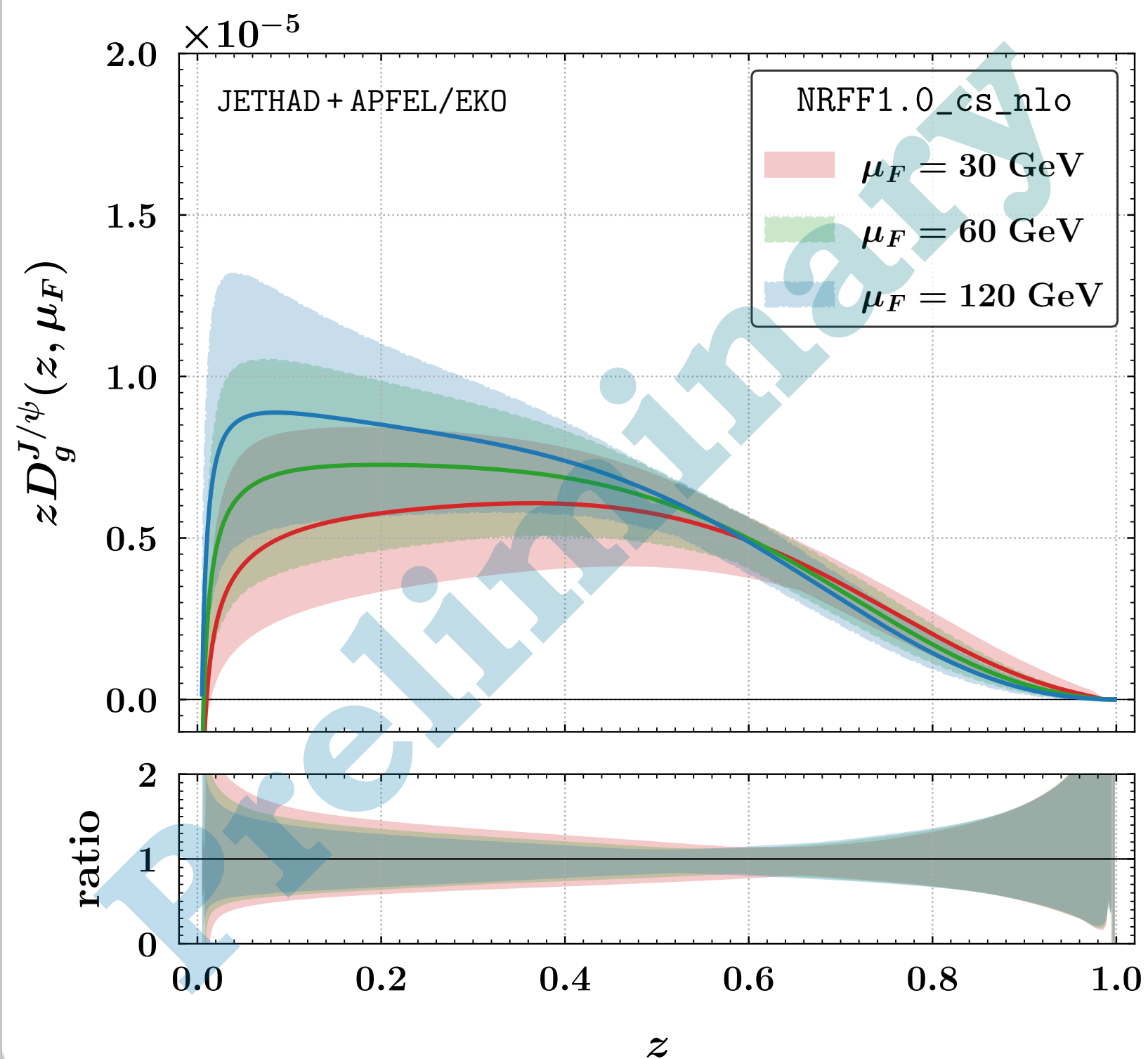
How do heavy quarks fragment into hadrons (w ~~one~~ heavy quark)?

NRFF1.0: Gluon fragmentation to charmonia

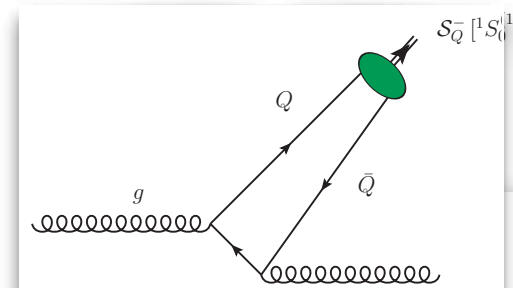
Vector J/ψ



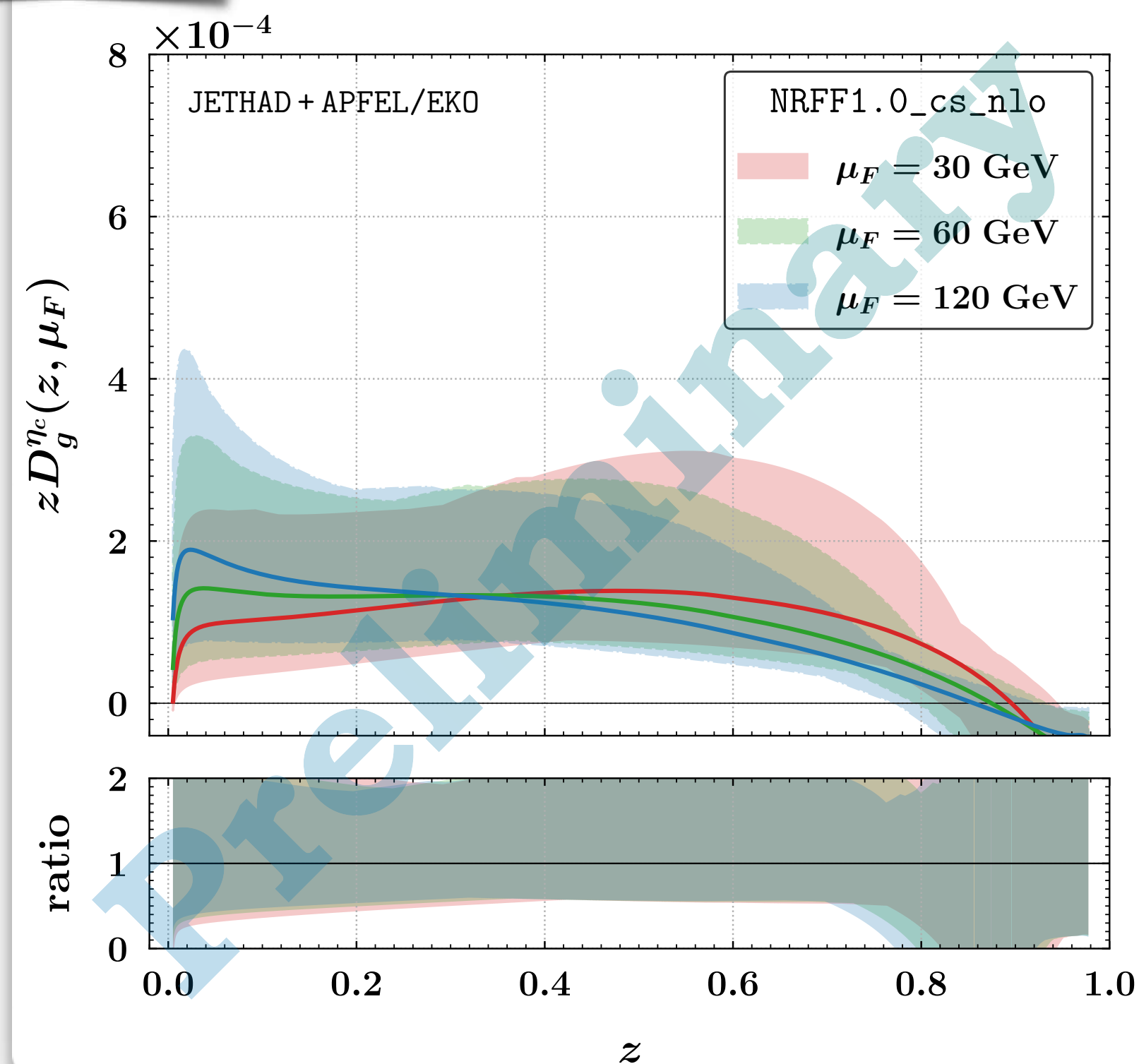
$(g \rightarrow J/\psi)$ fragmentation channel



Scalar η_c



$(g \rightarrow \eta_c)$ fragmentation channel



One-loop gauge invariant amplitudes with a spacelike gluon in hybrid kT-factorization

New calculations 

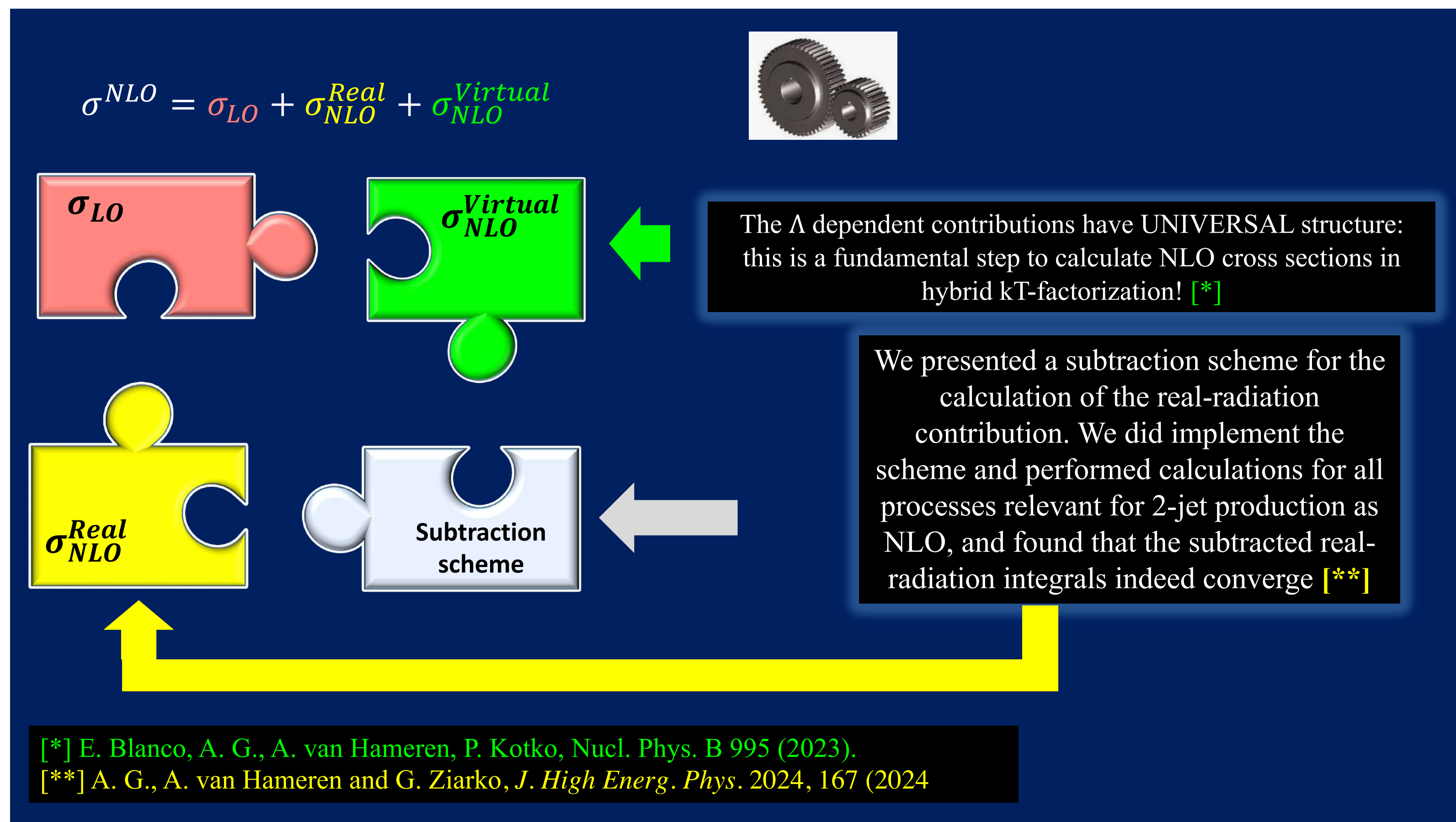
[Alessandro Giachino](#)

k_T factorisation naturally describes small-x / forward physics better

Issue: difficult to formulate beyond LO



Let's start with a hybrid approach first!



“Stay tuned for automated NLO calculations”

Heavy flavour jet substructure

New
calculations 



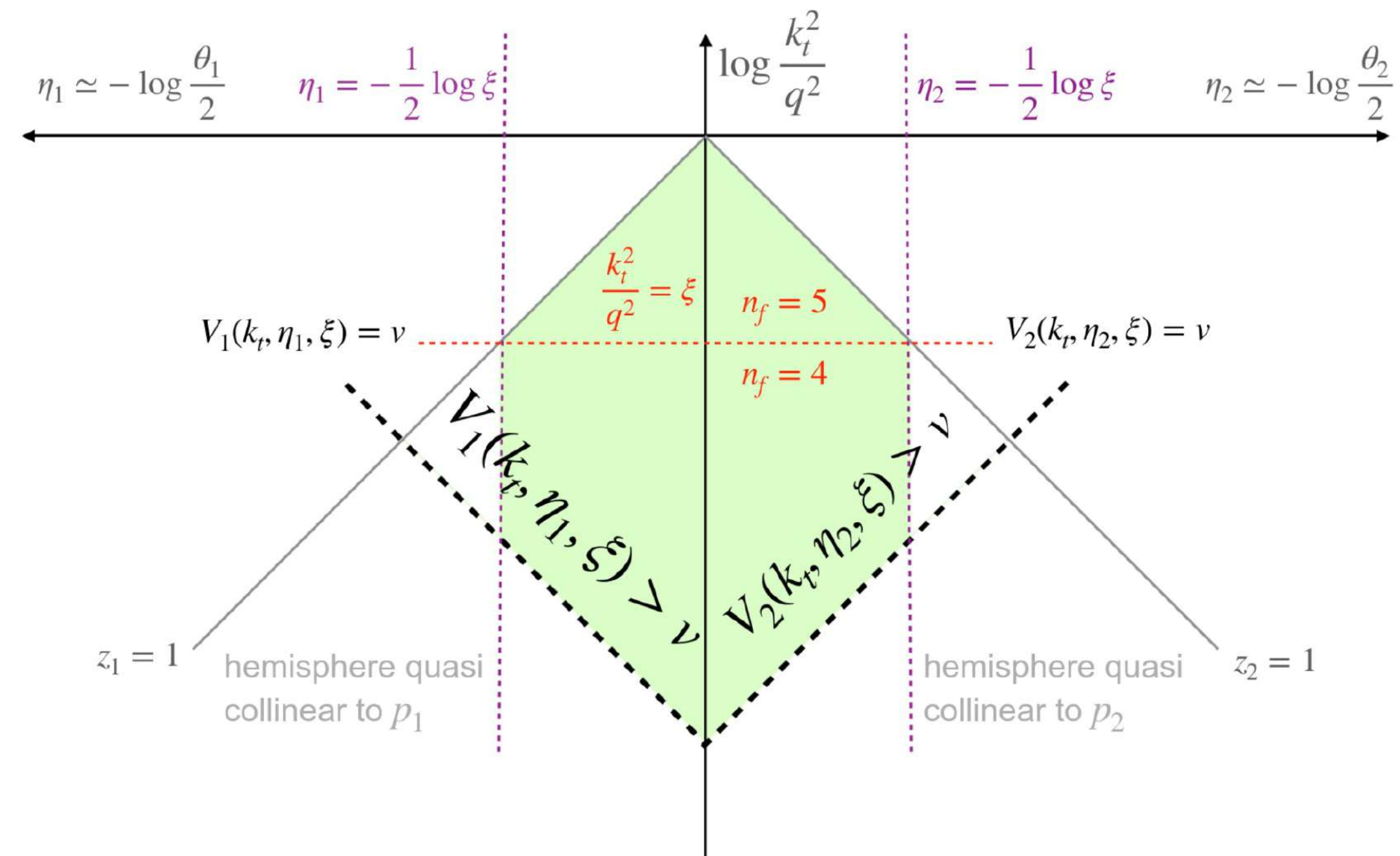
Reuse the massless resummation techniques for the massive case

Lund Plane for massive particles

[Ghira, Marzani, Ridolfi (2309.06139)]

In the massive case the following we have

- to consider the quasi-collinear splitting function $P_{Qg \leftarrow Q}$
- to modify the PS (aka the Lund Plane) introducing a new boundary (dead cone effect)
 → new vertical lines
- to introduce boundaries corresponding to 4 and 5 active flavour threshold (or 3 and 4)
 → new horizontal lines
- to take into account that the observable might explicitly depends on the HQ mass
 → dashed lines are deformed



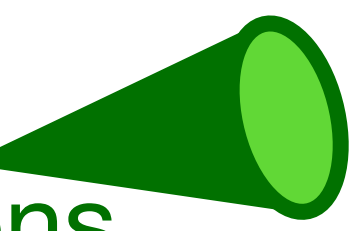
Observables studied (or under investigation) exploiting this framework:

Andrea Ghira

θ_g Simone Caletti z_g
this talk

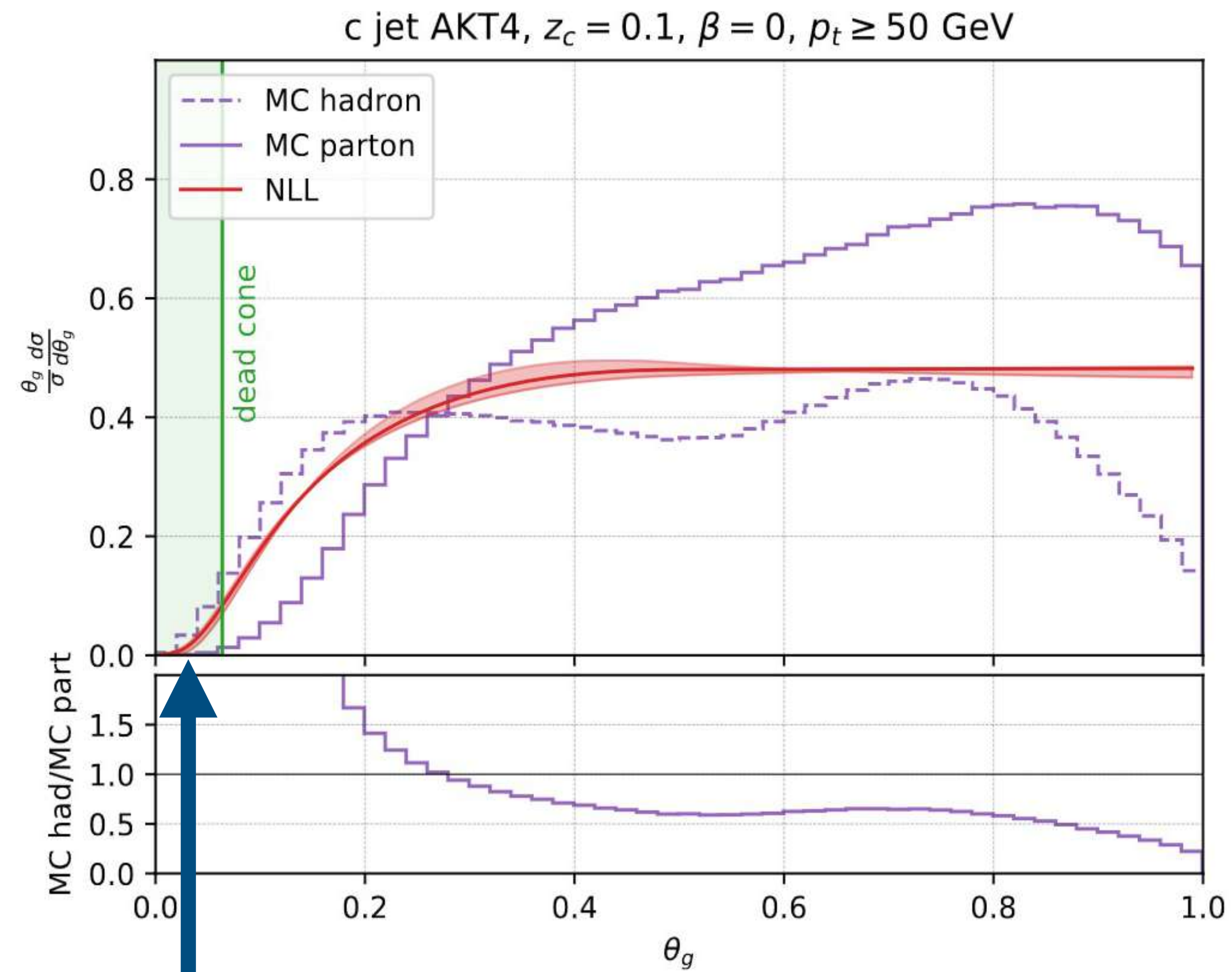
λ_α
see Andrea's talk

ECF



Soft-drop z_g and θ_g

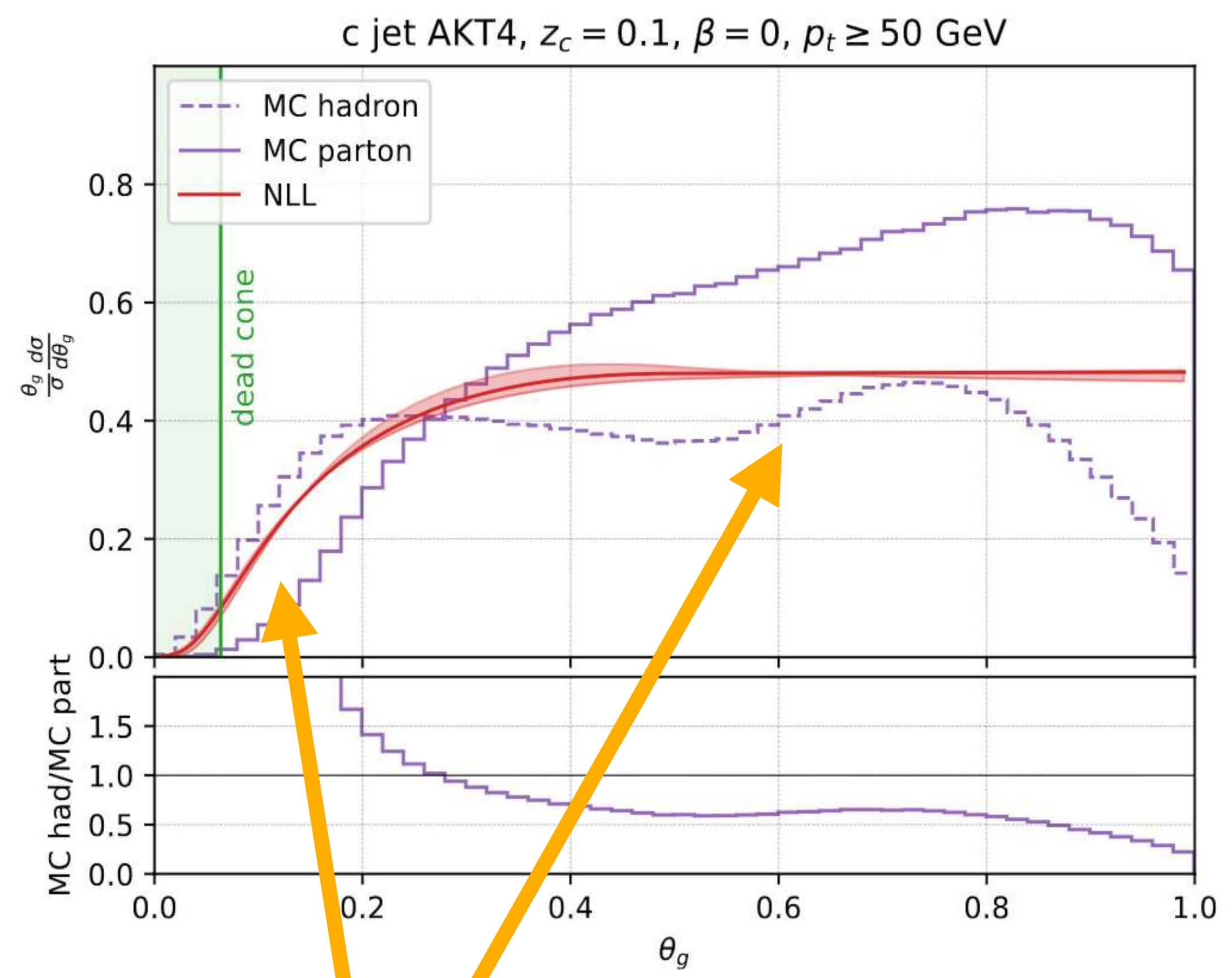
Jet angularities



Deadcone suppression

Soft-drop z_g and θ_g

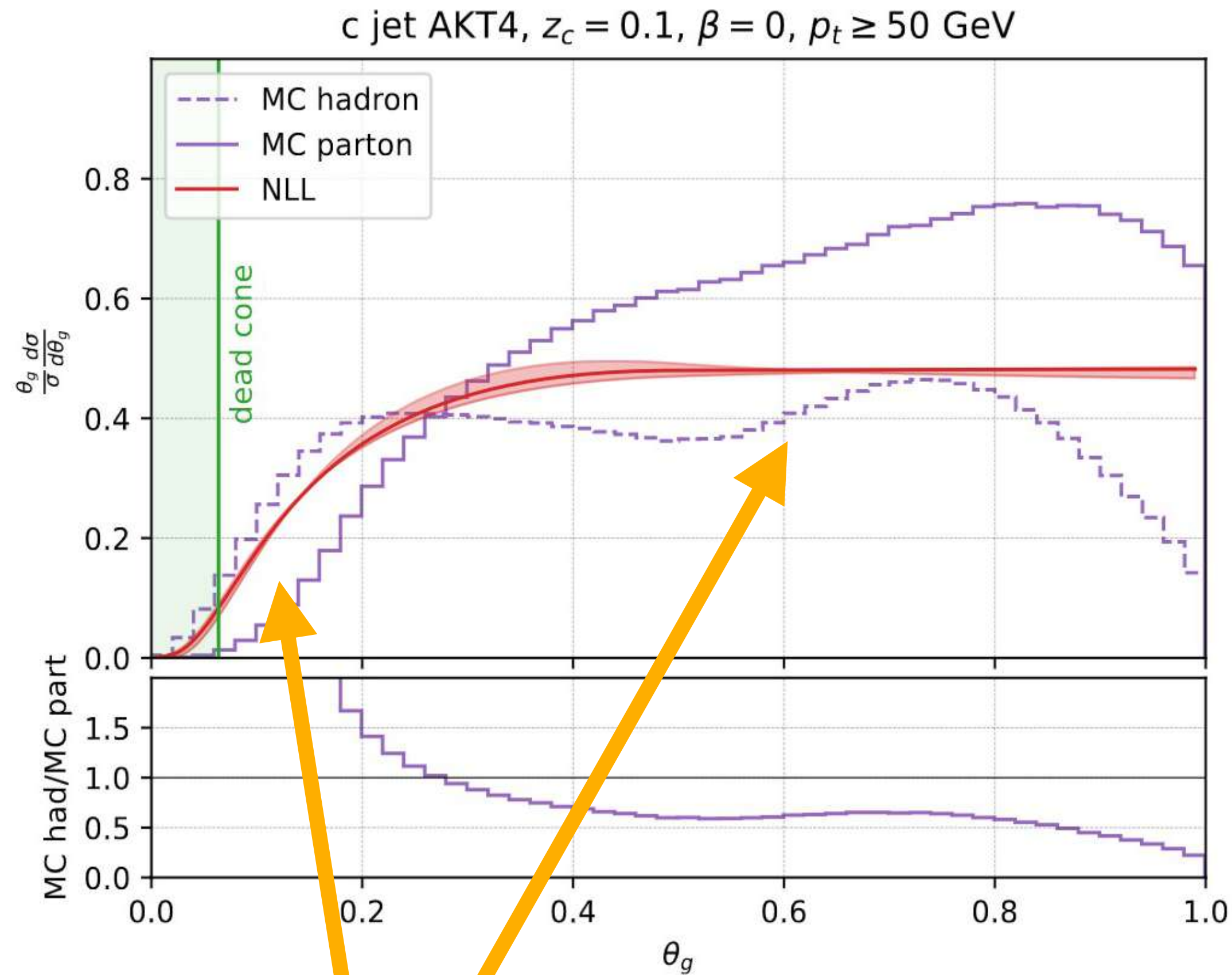
Jet angularities



Large non-perturbative effects,
no agreement with NLL

Soft-drop z_g and θ_g

Jet angularities



Large non-perturbative effects, no agreement with NLL

What definition to take?

WTA axis (massless)

WTA axis (massive)

$$\dot{\lambda}_0^\alpha = \sum_i \frac{p_{t_i}}{p_t} \left(\frac{2p_i \cdot \bar{n}}{p_{t_i} R_0^2} \right)^{\frac{\alpha}{2}}, \quad \dot{\lambda}^\alpha = \sum_i \frac{p_{t_i}}{p_t} \left(\frac{2p_i \cdot n}{p_{t_i} R_0^2} \right)^{\frac{\alpha}{2}}$$

$$\lambda^\alpha = \sum_i \frac{p_{t_i}}{p_t} \left(\frac{\Delta R_i}{R_0} \right)^\alpha, \quad \dot{\lambda}_0^\alpha = \sum_{i \neq n} \frac{p_{t_i}}{p_t} \left(\frac{2p_i \cdot \bar{n}}{p_{t_i} R_0^2} \right)^{\frac{\alpha}{2}}, \quad \dot{\lambda}^\alpha = \sum_{i \neq n} \frac{p_{t_i}}{p_t} \left(\frac{2p_i \cdot n}{p_{t_i} R_0^2} \right)^{\frac{\alpha}{2}}$$

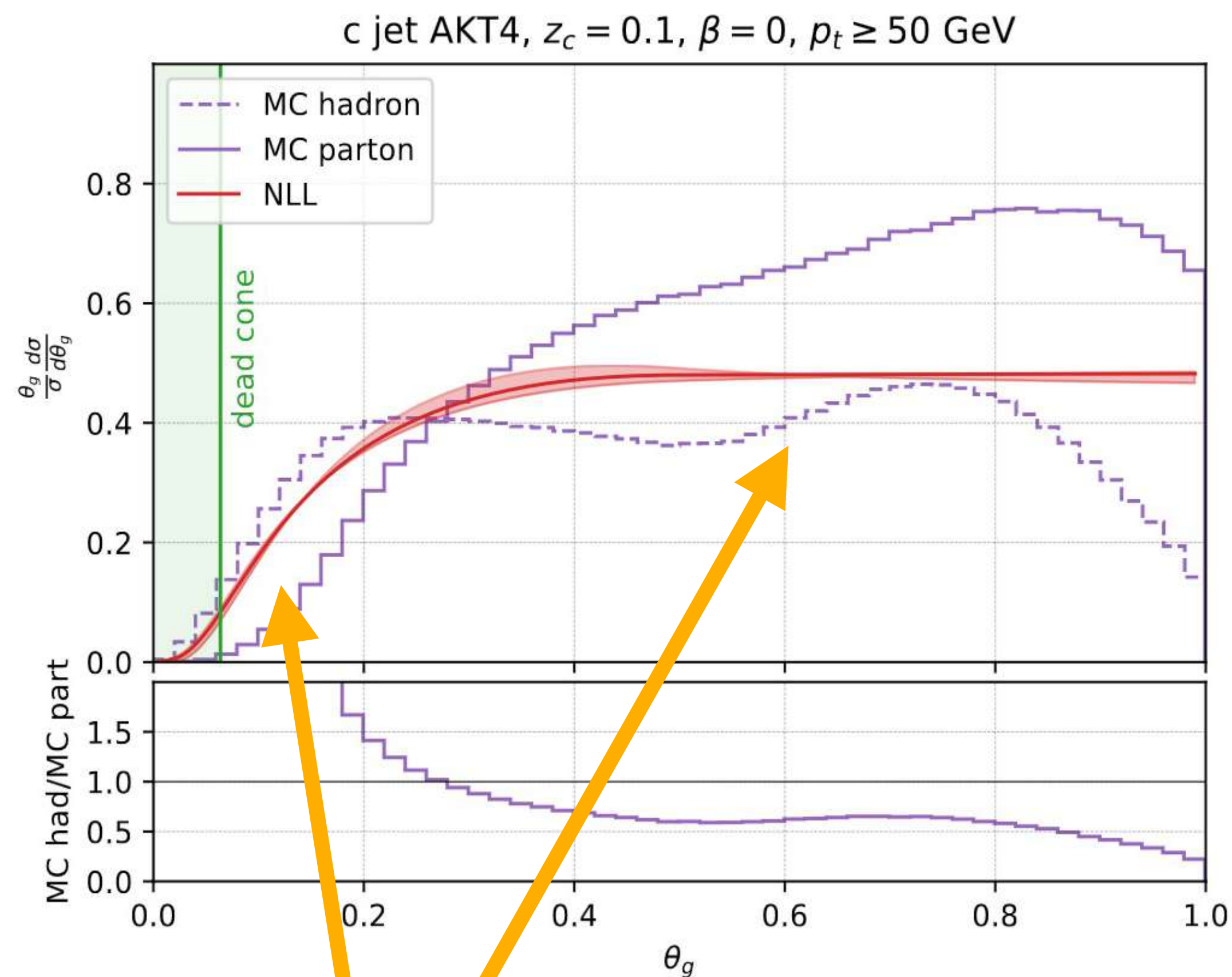
Goal: highest sensitivity to deadcone effect



Soft-drop z_g and θ_g

Jet angularities

calculations



Large non-perturbative effects,
no agreement with NLL

What definition to take?

Don't resum well

~~$$\dot{\lambda}_0^\alpha = \sum_i \frac{p_{t_i}}{p_t} \left(\frac{2p_i \cdot \bar{n}}{p_{t_i} R_0^2} \right)^{\frac{\alpha}{2}} \quad \dot{\lambda}^\alpha = \sum_i \frac{p_{t_i}}{p_t} \left(\frac{2p_i \cdot n}{p_{t_i} R_0^2} \right)^{\frac{\alpha}{2}}$$~~

$$\lambda^\alpha = \sum_i \frac{p_{t_i}}{p_t} \left(\frac{\Delta R_i}{R_0} \right)^\alpha, \quad \dot{\lambda}_0^\alpha = \sum_{i \neq n} \frac{p_{t_i}}{p_t} \left(\frac{2p_i \cdot \bar{n}}{p_{t_i} R_0^2} \right)^{\frac{\alpha}{2}}, \quad \dot{\lambda}^\alpha = \sum_{i \neq n} \frac{p_{t_i}}{p_t} \left(\frac{2p_i \cdot n}{p_{t_i} R_0^2} \right)^{\frac{\alpha}{2}}$$

Have larger NP corrections

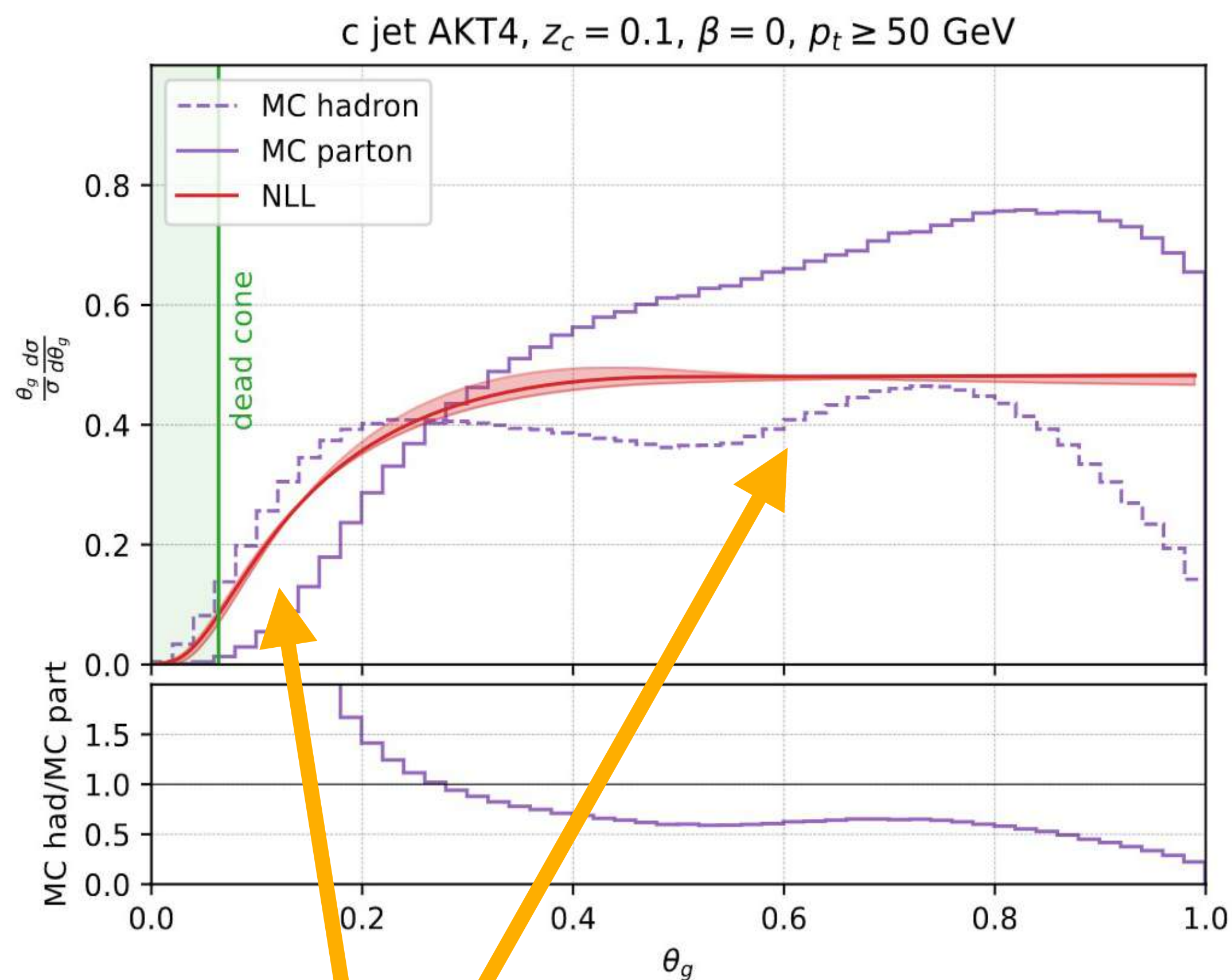
Take $\alpha = 1$

Soft-drop z_g and θ_g

Simone Caletti

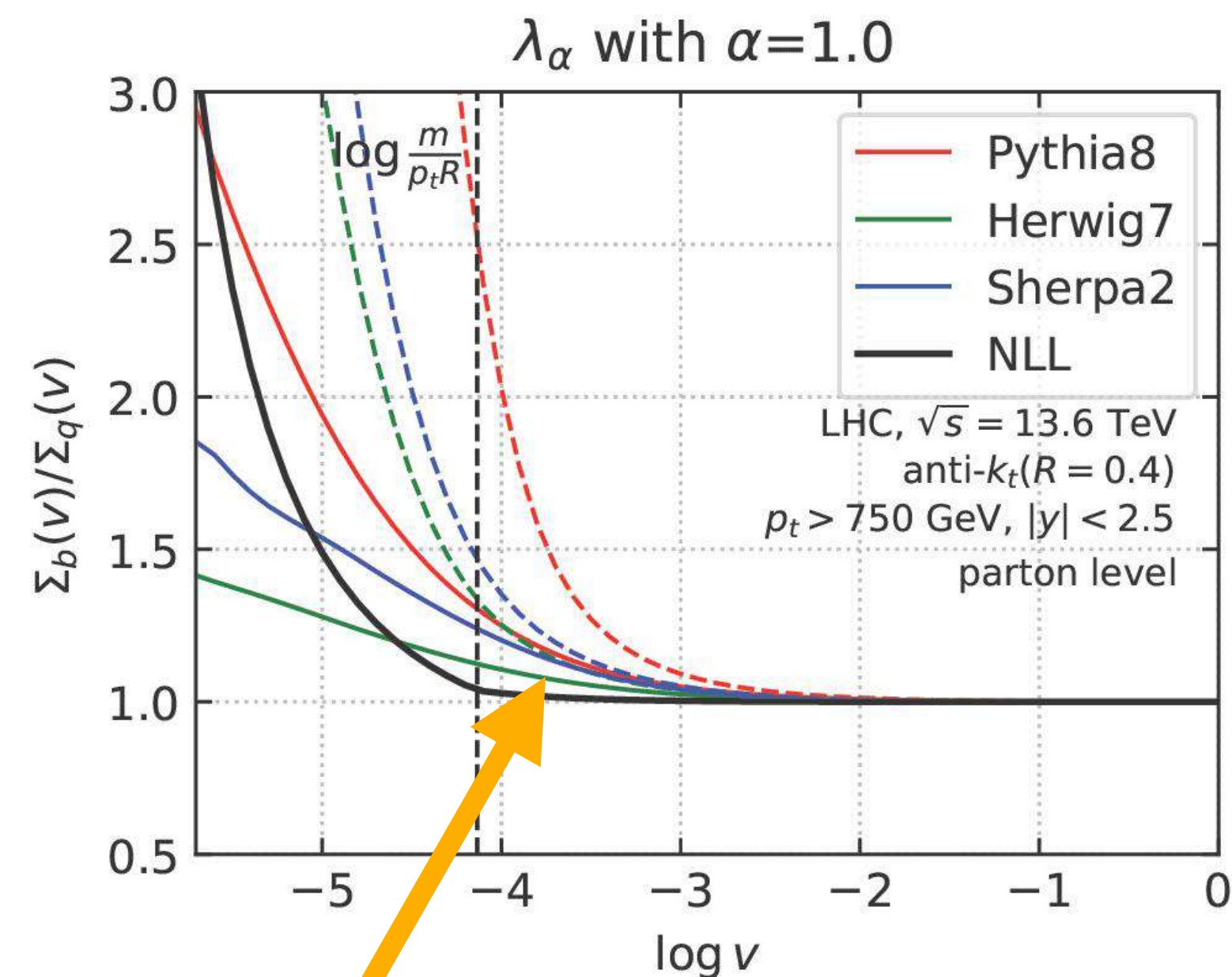
Andrea Ghira

New calculations 



Large non-perturbative effects, no agreement with NLL

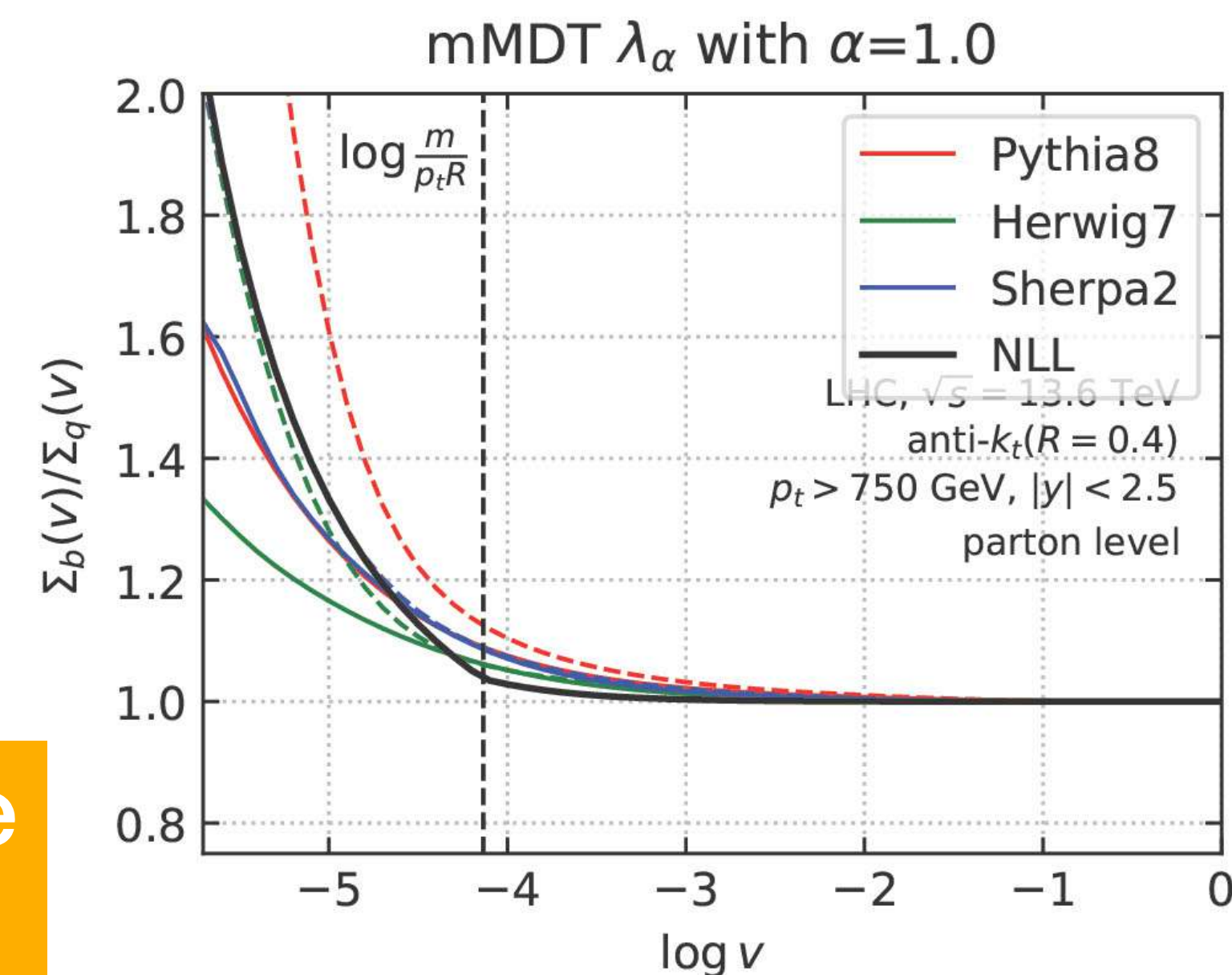
Jet angularities



Too early onset of the deadcone effect?

Dashed:

$$\frac{\Sigma_b^{hadron}}{\Sigma_q^{hadron}}$$



Can we understand these differences better?

Heavy flavour jet substructure for heavy ion collisions

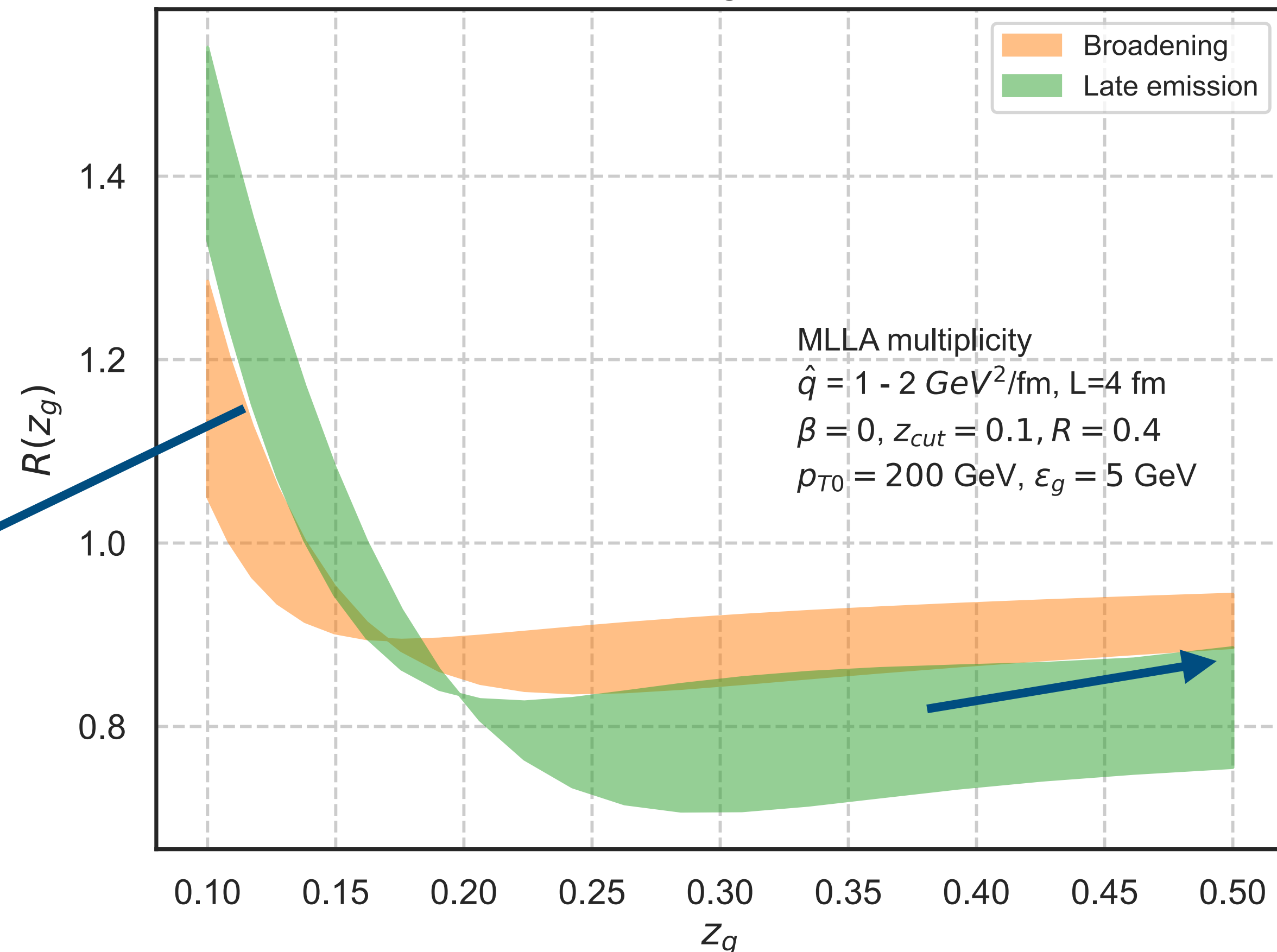
Can we get a pure measurement of emissions originating from medium?

Medium-induced emissions appear at angles $<$ deadcone \rightarrow isolate this region!

Caucal, Iancu, Soyez

Vacuum emissions happen fast, medium dynamics happen later \rightarrow extend this picture to account for quark masses

Ratio medium over vacuum z_g distribution



medium-induced emissions

vacuum-induced emissions

Unbiased quantification of jet energy loss

Can we estimate jet energy loss when they travel through a medium?

We want to compare vacuum and medium predictions, but hard because of pT migration → we need to calculate this migration (or have a hard probe)

Energy loss dependence on color charge

(Pseudo-)Quantiles, introduced by J. Brewer, J. Milhano, J. Thaler can do this for you

$$q \text{ --- } \sim C_F$$

$$g \text{ --- } \sim C_A$$

$$\delta + \text{jet} \sim q \text{ mit. jets}$$

$$R_{AA}^{\delta j} > R_{AA}^{j j}$$

See ATLAS

dijet \sim mixture of q and g mit. jets

=
Casimir scaling
in jets ?

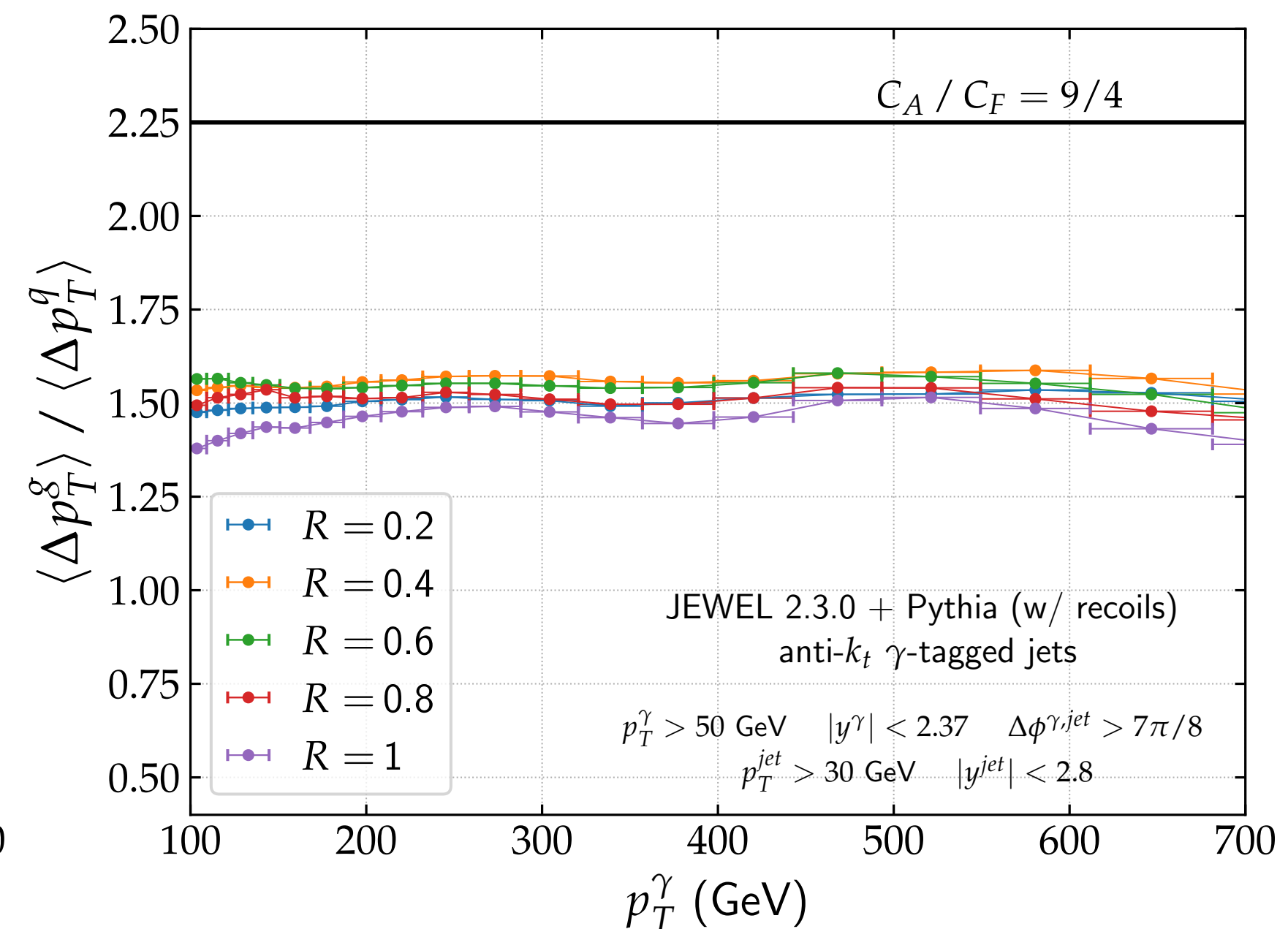
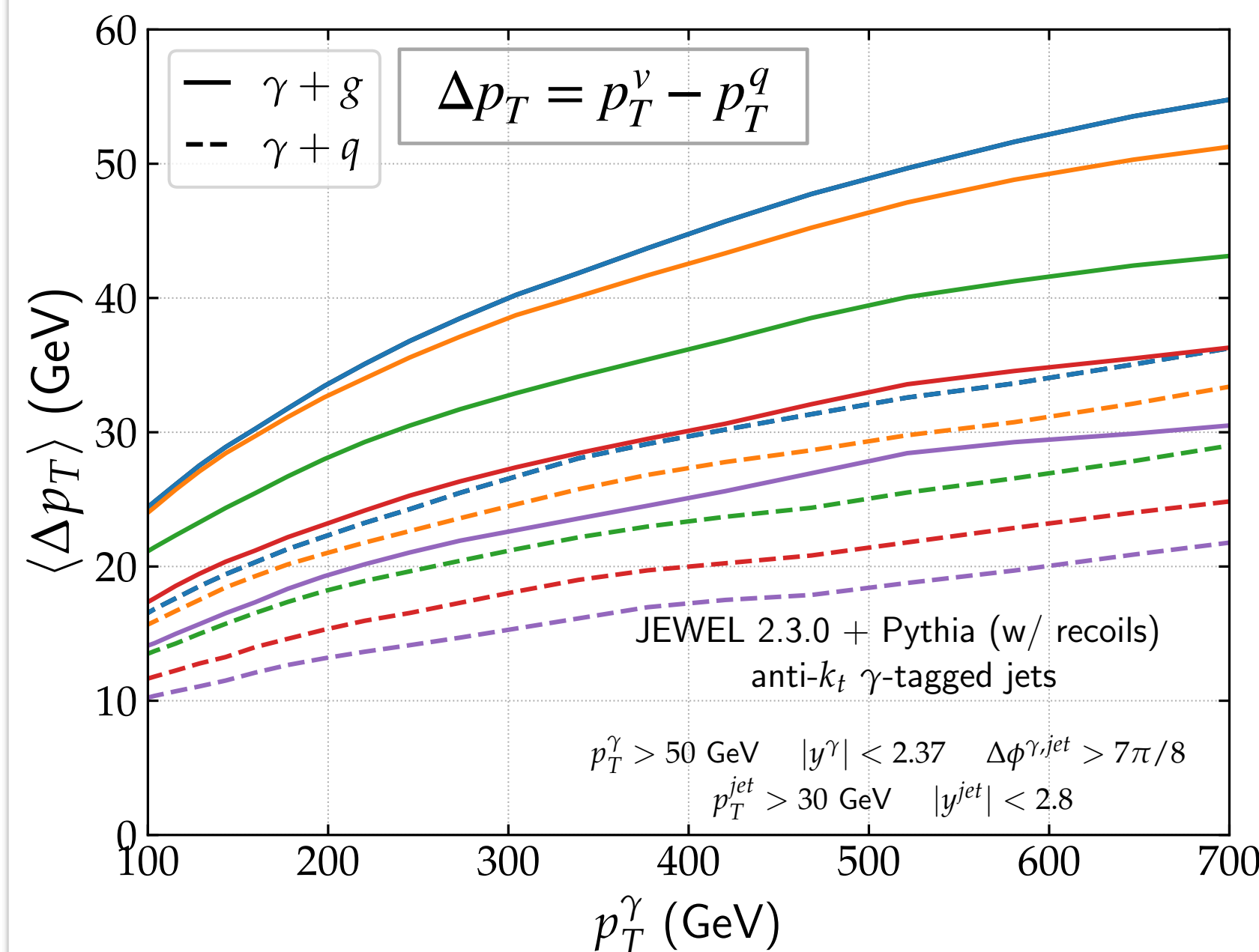
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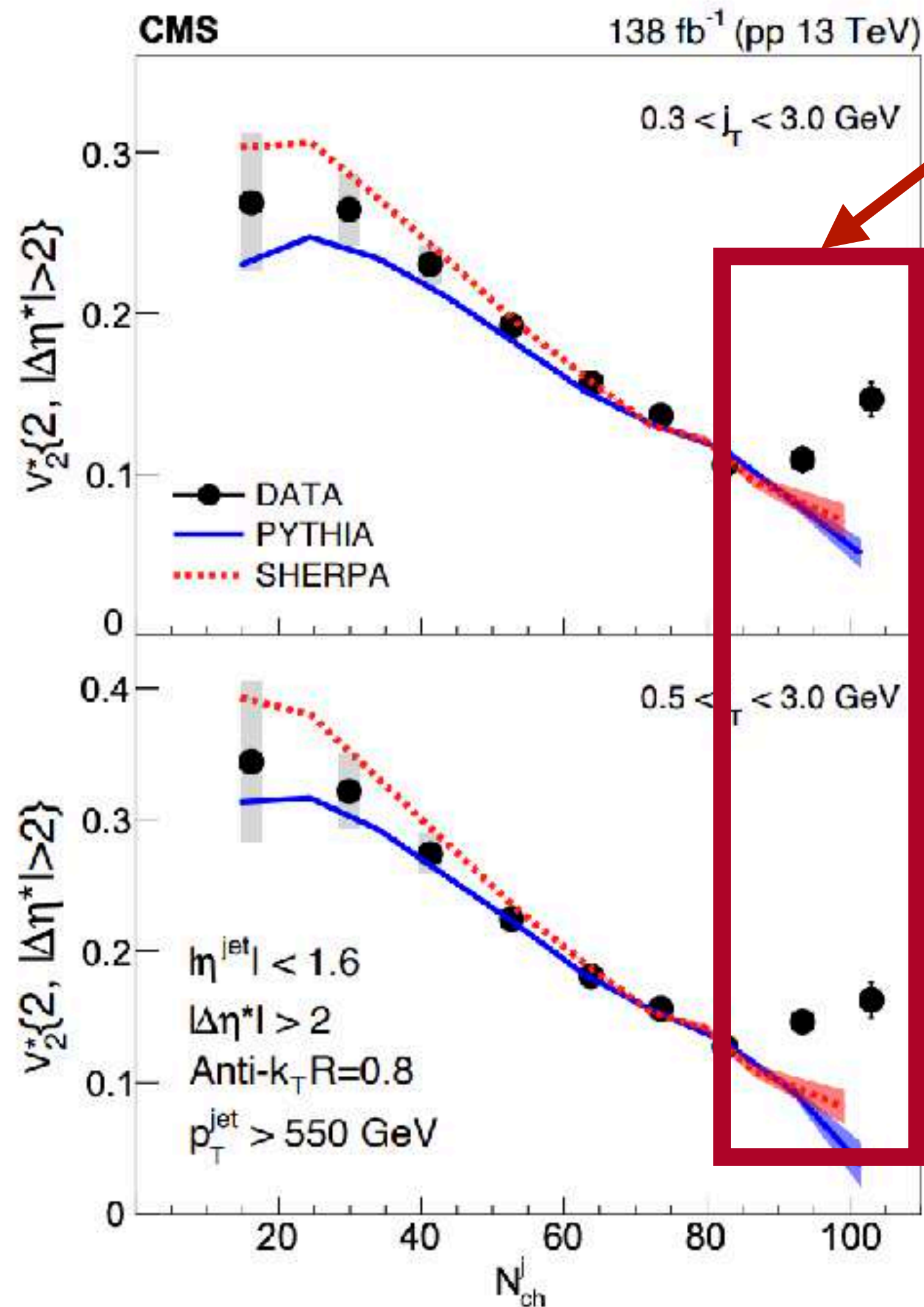


Casimir scaling is significantly reduced with respect to naive single parton scaling

Event shapes of High Multiplicity Jets

Intrigued by an experimental observation...

Elliptic anisotropy coefficient for large η separation

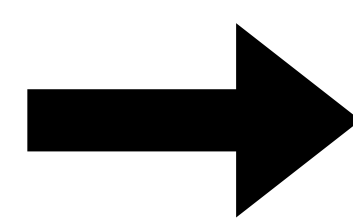


Are we seeing new QCD dynamics?

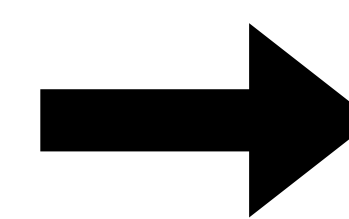
Can we build a MC chain that predicts this?

*Pipeline for studying hydrodynamics in jets
(Work in progress)*

Pythia 8
*Simulate CMS
jet samples*



Trajectum
*Apply
hydrodynamics to jet
constituents*



Compute
Event Shapes
*See if with hydro we
can better match
data
Compare v_2 to ring EMD?
(See ATLAS 2305.16930)*

*Could reveal more about the
nature of QCD!*

Single heavy baryon study via spectra and decay width

Where do we need to look to find new hadrons and their excitations?

To get full info: calculate their mass spectrum AND their decay widths

- The masses of the heavy singly baryon states are calculated as the eigenvalues of the Hamiltonian, E. Santopinto, A. Giachino, J. Ferretti, H. Garcia-Tecocoatzi, M.A. Bedolla, R. Bijker, E. Ortiz-Pacheco, EPJC 79(12), 1012 (2019), which is modeled as:

$$H = H_{\text{h.o.}} + P_s \mathbf{S}^2 + P_{sl} \mathbf{S} \cdot \mathbf{L} + P_l \mathbf{L}^2 + P_f \mathbf{C}_2(\text{SU}(3)_f), \quad (1)$$

- The two-body strong decay widths are calculated with the predicted masses and their predicted quantum numbers
- The 3P_0 model is used for calculating the strong-decay widths of a singly heavy baryon A into a singly heavy baryon B plus a meson C , or a singly heavy baryon A into a light baryon B plus a heavy meson C , $A \rightarrow BC$

$$\Gamma = \frac{2\pi\gamma_0^2}{2J_A + 1} \Phi_{A \rightarrow BC}(q_0) \sum_{M_{J_A}, M_{J_B}} |\mathcal{M}^{M_{J_A}, M_{J_B}}|^2 \quad (4)$$

Single heavy baryon study via spectra and decay width

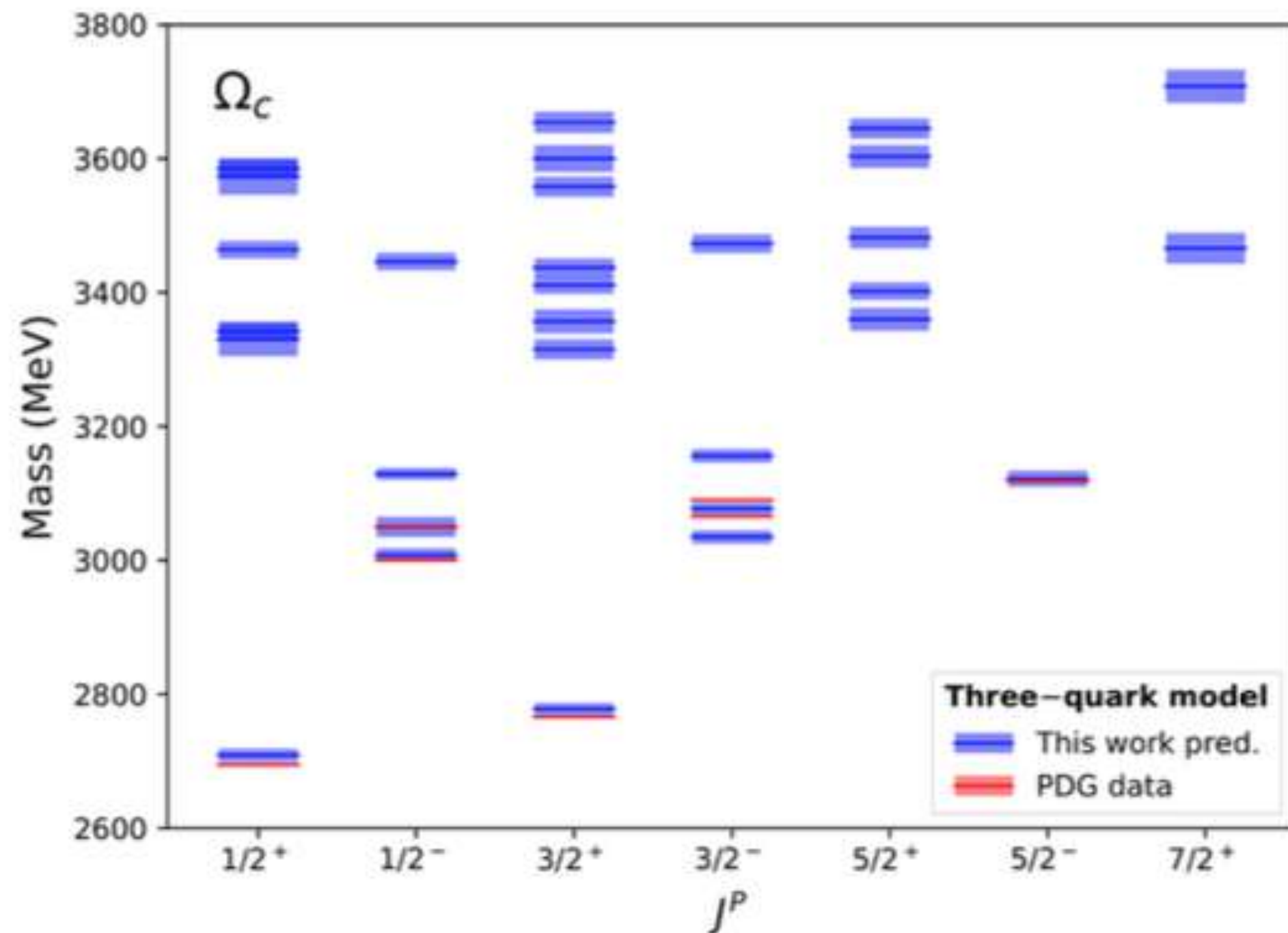
New calculations

 Hugo Tecocoatzi

Where do we need to look to find new hadrons and their excitations?

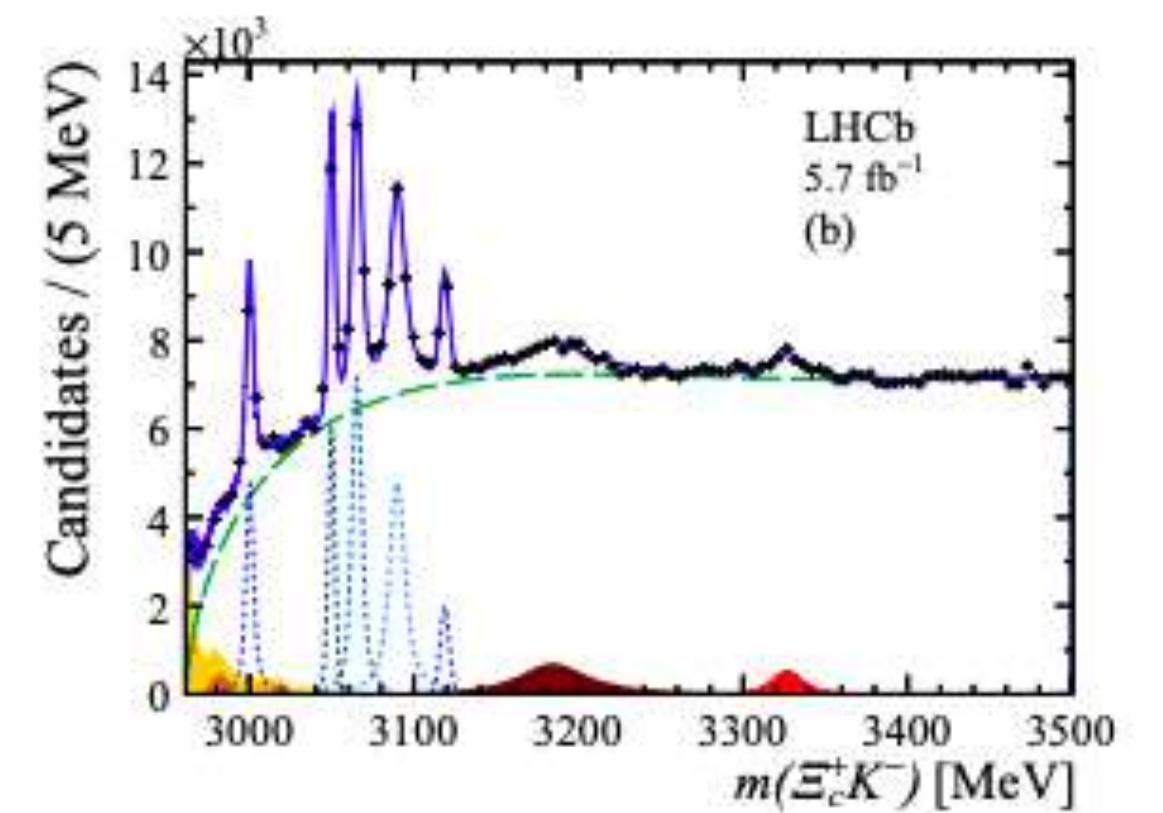
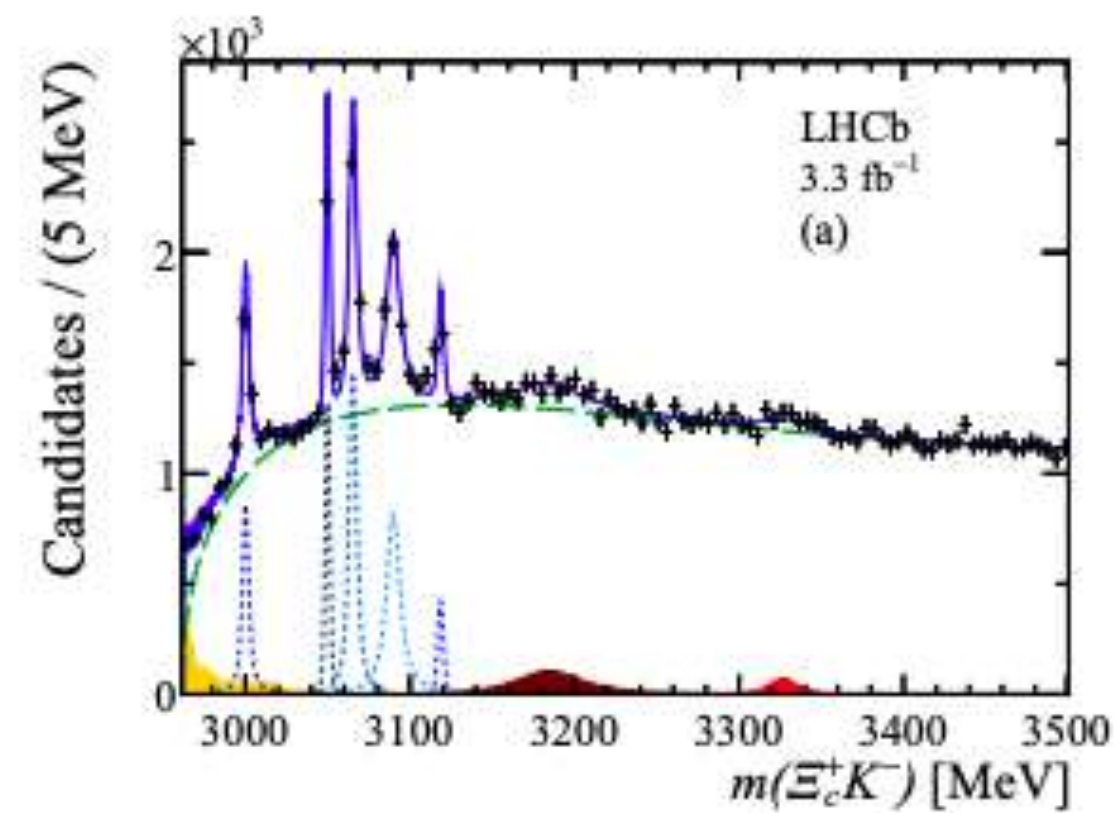
To get full info: calculate their mass spectrum AND their decay widths

Predicted spectrum for Ω_c



LHCb new observed state agrees

New state $\Omega_c(3327)$ with mass= 3327.1 ± 1.2 MeV and $\Gamma = 20 \pm 5$ MeV



$ l_\lambda = 2, l_\rho = 0, k_\lambda = 0, k_\rho = 0\rangle$	${}^2D_{3/2}$	3315^{+15}_{-14}	3306^{+14}_{-14}	†	11^{+5}_{-5}
$ l_\lambda = 2, l_\rho = 0, k_\lambda = 0, k_\rho = 0\rangle$	${}^2D_{5/2}$	3360^{+17}_{-16}	3348^{+17}_{-17}	†	24^{+12}_{-12}
$ l_\lambda = 2, l_\rho = 0, k_\lambda = 0, k_\rho = 0\rangle$	${}^4D_{1/2}$	3330^{+25}_{-25}	3328^{+24}_{-23}	†	16^{+8}_{-8}
$ l_\lambda = 2, l_\rho = 0, k_\lambda = 0, k_\rho = 0\rangle$	${}^4D_{3/2}$	3357^{+18}_{-18}	3354^{+17}_{-17}	†	20^{+15}_{-15}

Single heavy baryon study via spectra and decay width

New calculations
Hugo Tecocoatzi

Where do we need to look to find new hadrons and their excitations?

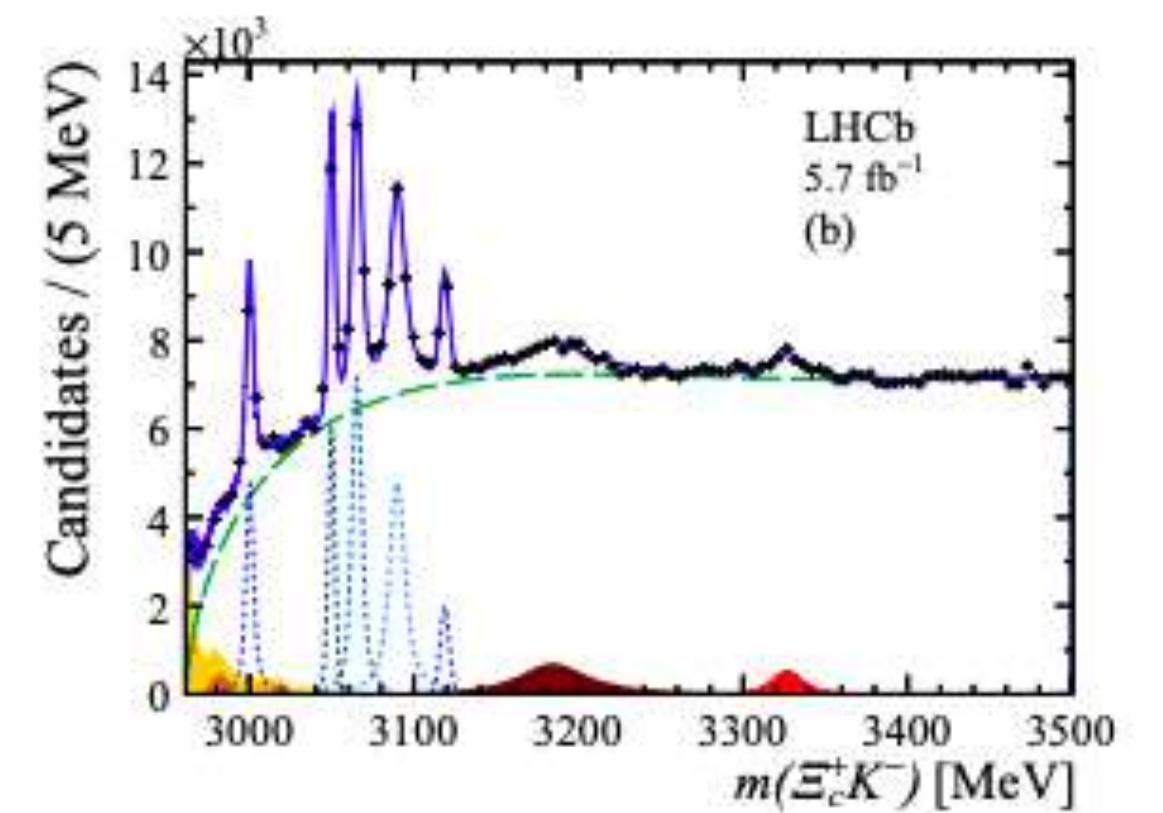
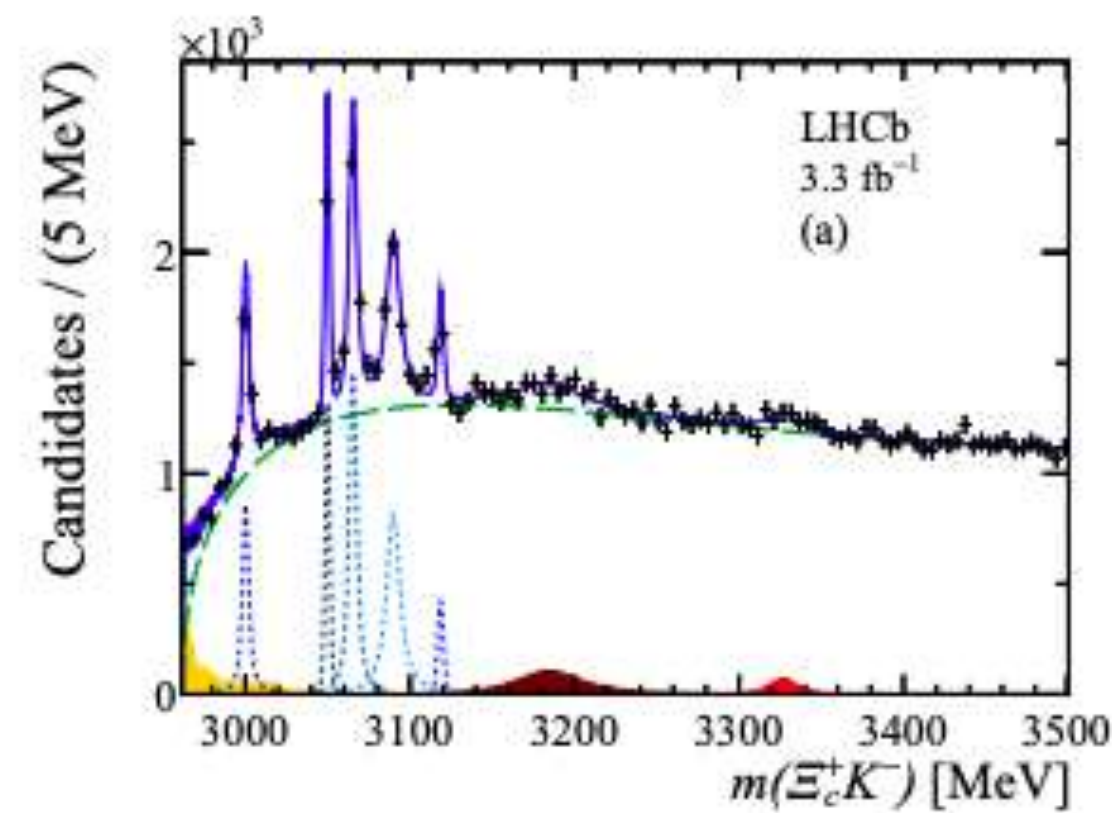
To get full info: calculate their mass spectrum AND their decay widths

$\Omega_c(ssc)$	$\mathcal{F} = 6_f$	$\Xi_c K$	$\Xi'_c K$	$\Xi_c^* K$
$\Omega_c(2709)^2S_{1/2}$	0	0	0	0
$\Omega_c(2778)^4S_{3/2}$	0	0	0	0
$\Omega_c(3008)^2P_{1/2}$	4.1	0	0	0
$\Omega_c(3050)^4P_{1/2}$	7.5	0.1	0	0
$\Omega_c(3035)^2P_{3/2}$	26.3	0	0	0
$\Omega_c(3077)^4P_{3/2}$	6.3	0.4	0	0
$\Omega_c(3122)^4P_{3/2}$	40.9	8.9	0.3	0
$\Omega_c(3129)^2P_{1/2}$	—	8.9	5.5	—
$\Omega_c(3156)^2P_{3/2}$	—	61.1	10.5	—
$\Omega_c(3315)^2D_{3/2}$	1.9	1.8	2.3	—
$\Omega_c(3360)^2D_{5/2}$	5.4	5.1	0.5	—
$\Omega_c(3330)^4D_{1/2}$	0.2	0.2	3.3	—
$\Omega_c(3357)^4D_{3/2}$	2.0	0.5	5.2	—
$\Omega_c(3402)^4D_{5/2}$	5.0	1.2	5.0	—
$\Omega_c(3466)^4D_{7/2}$	7.8	2.0	5.0	—
$\Omega_c(3342)^2S_{1/2}$	0.2	0.3	0.1	—
$\Omega_c(3411)^4S_{3/2}$	0.2	0.1	0.4	—
$\Omega_c(3585)^2S_{1/2}$	0.3	1.0	0.7	—
$\Omega_c(3654)^4S_{3/2}$	0.1	0.1	1.2	—
$\Omega_c(3437)^2D_{3/2}$	—	6.5	107.0	—

We need to look in different channels to find all excitations

LHCb new observed state agrees

New state $\Omega_c(3327)$ with mass= 3327.1 ± 1.2 MeV and $\Gamma = 20 \pm 5$ MeV

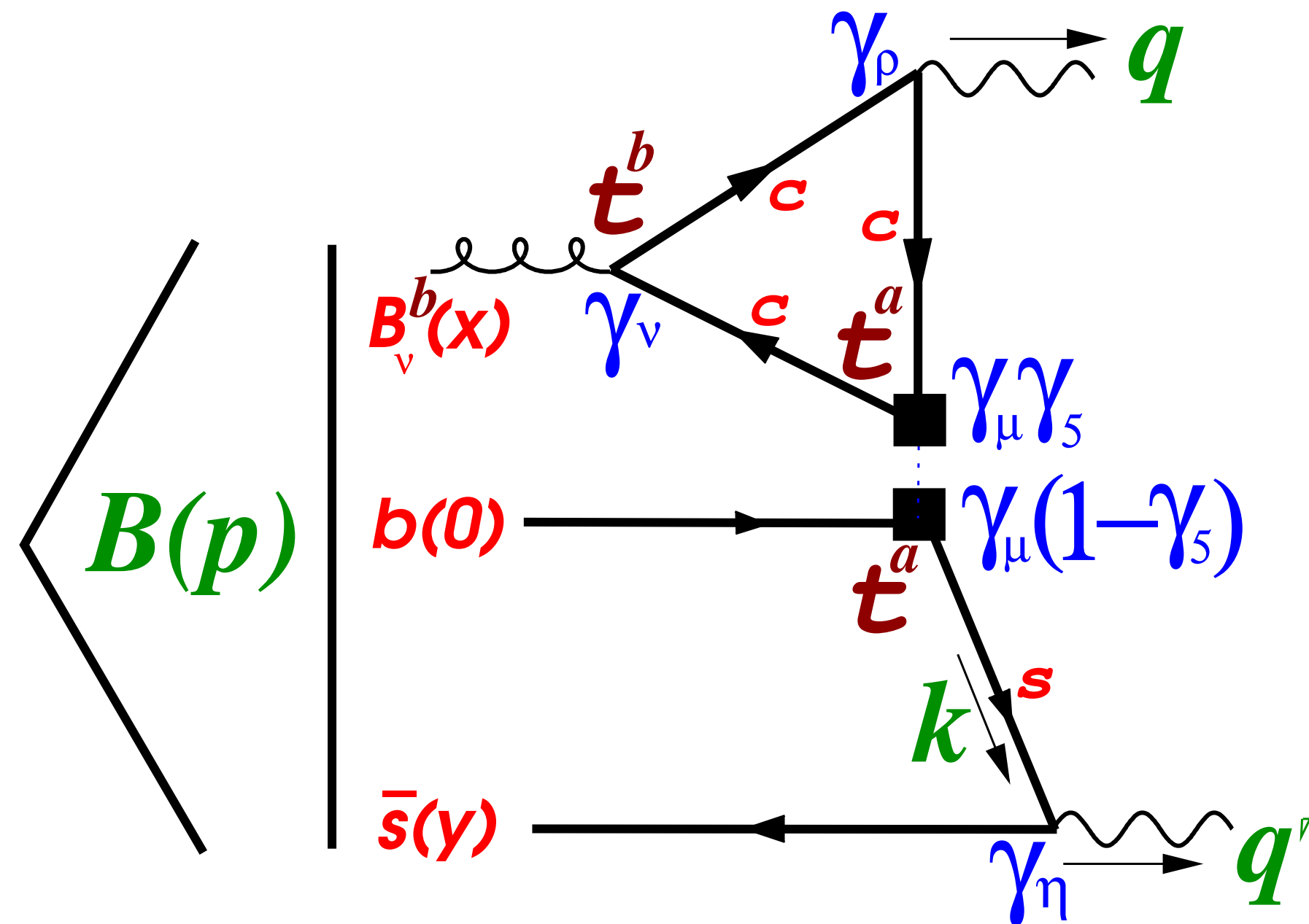


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Nonfactorizable charm loop in rare $B_s \rightarrow \gamma l+l-$ decay

Flavour-changing neutral currents are suppressed in the SM

We don't want to falsely claim new physics \rightarrow
we need to have an accurate SM prediction



**Non-factorizable
charm loops have
not been taken into
account to far**

Nonfactorizable charm loop in rare $B_s \rightarrow \gamma l^+ l^-$ decay

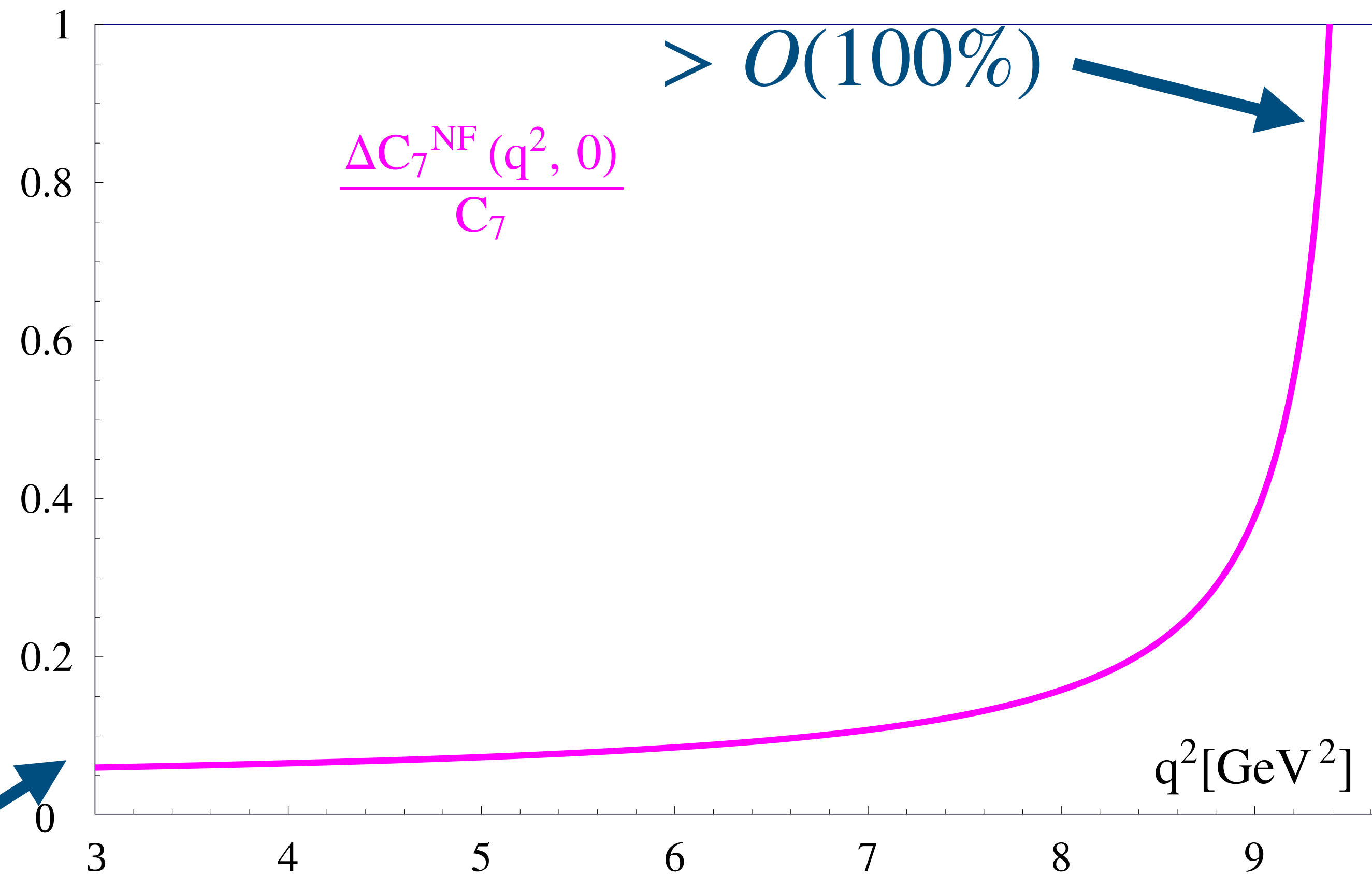
New calculations 

[Ilia Belov](#)

Flavour-changing neutral currents are suppressed in the SM

We don't want to falsely claim new physics \rightarrow
we need to have an accurate SM prediction

**Results show
sizable correction
for $B_s \rightarrow \gamma l^+ l^-$
that has same sign
as the factorisable
contributions**



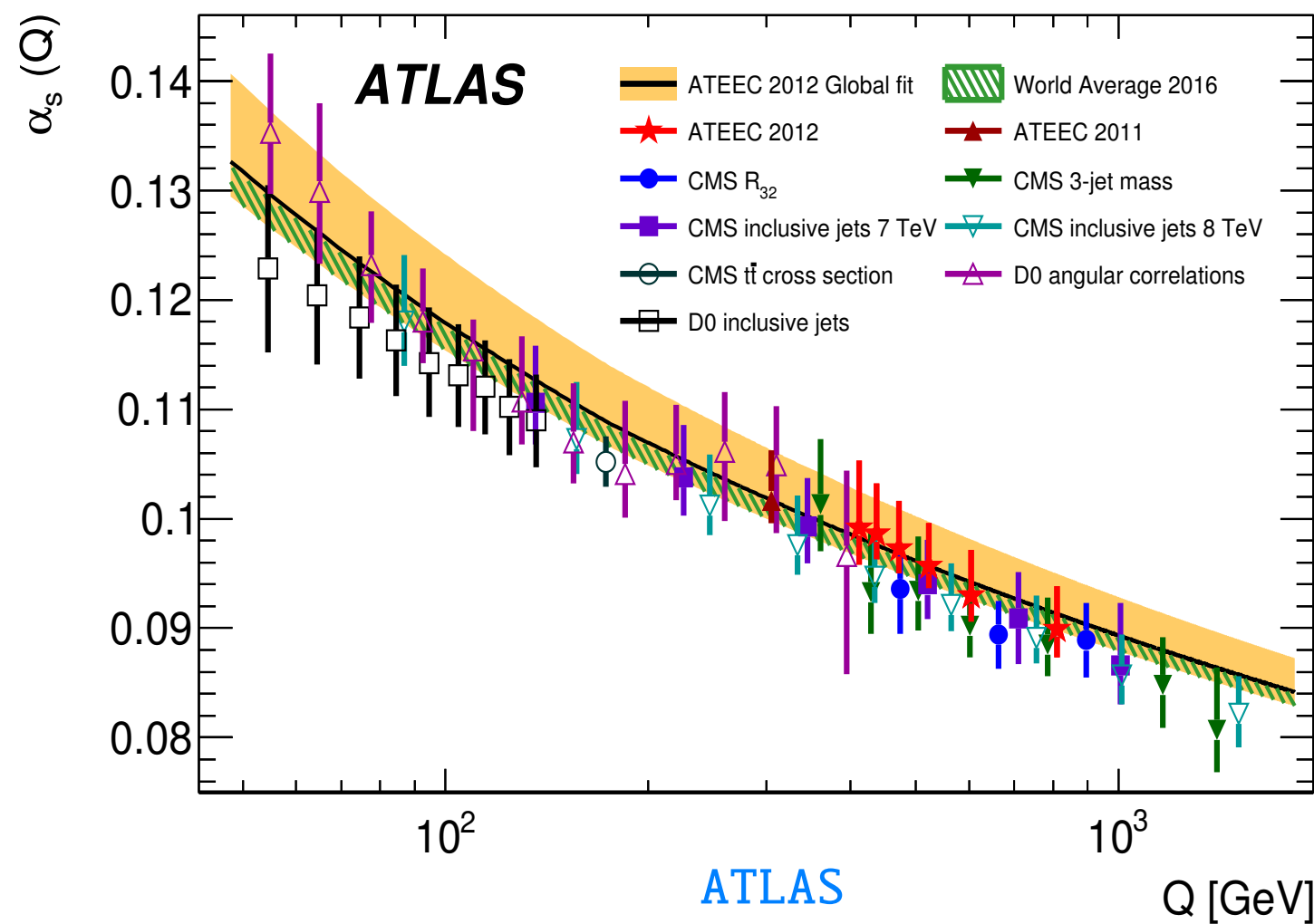
EEC: success story

The EEC: What makes it special?

The **EEC** addresses several important goals of QCD phenomenology, including:

$$\left\langle \sum_{\text{pairs } (i,j): \theta_{ij}=\theta} E_i E_j \right\rangle$$

Measurements of α_s



ATLAS: [1508.01579]
[1707.02562]

[CMS PAS SMP-22-015]

HERA: [2008.00271]

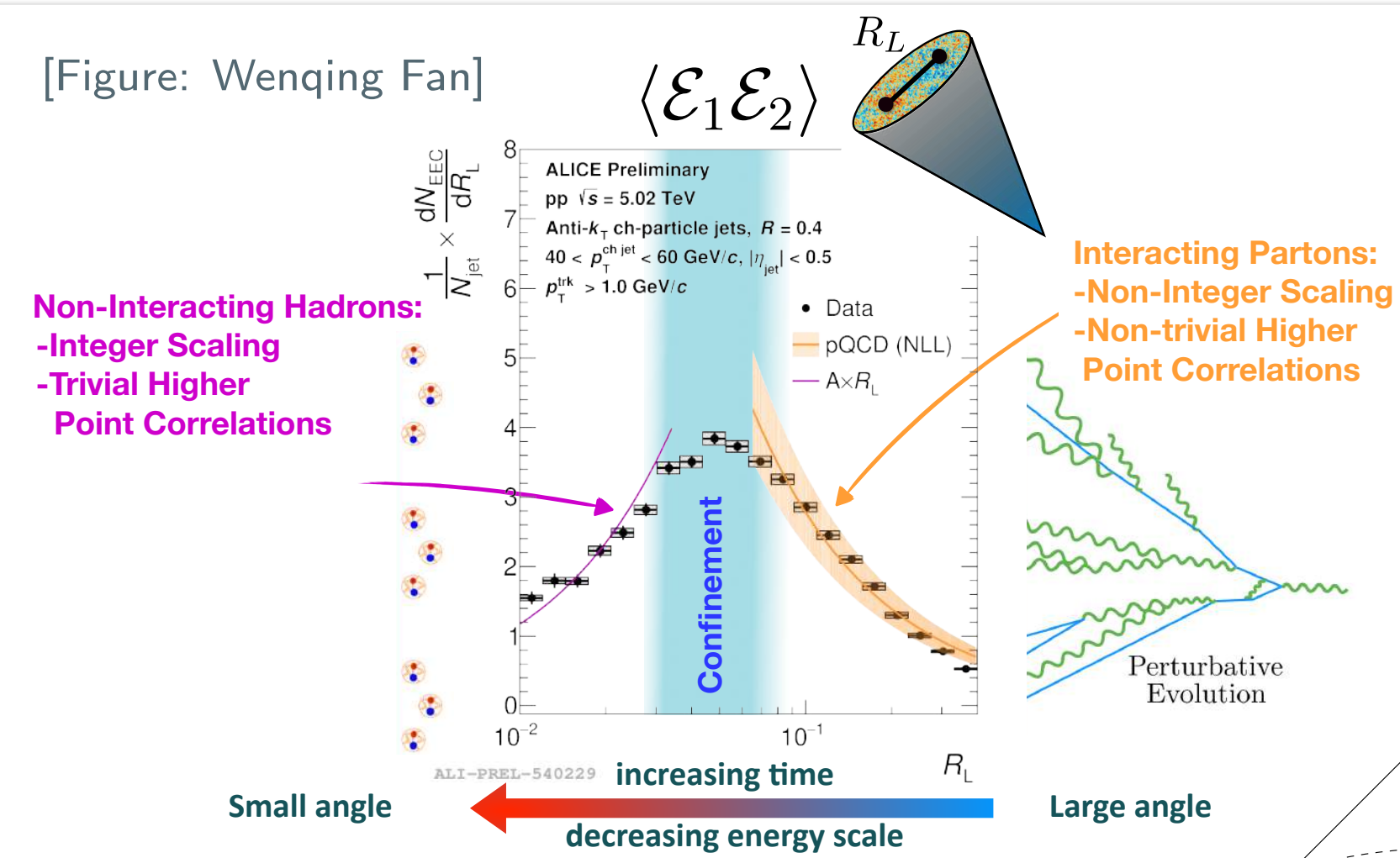
LEP+: [1804.09146]

Samuel Alipour-fard

Correlation function of detectors \Rightarrow jet substructure observable

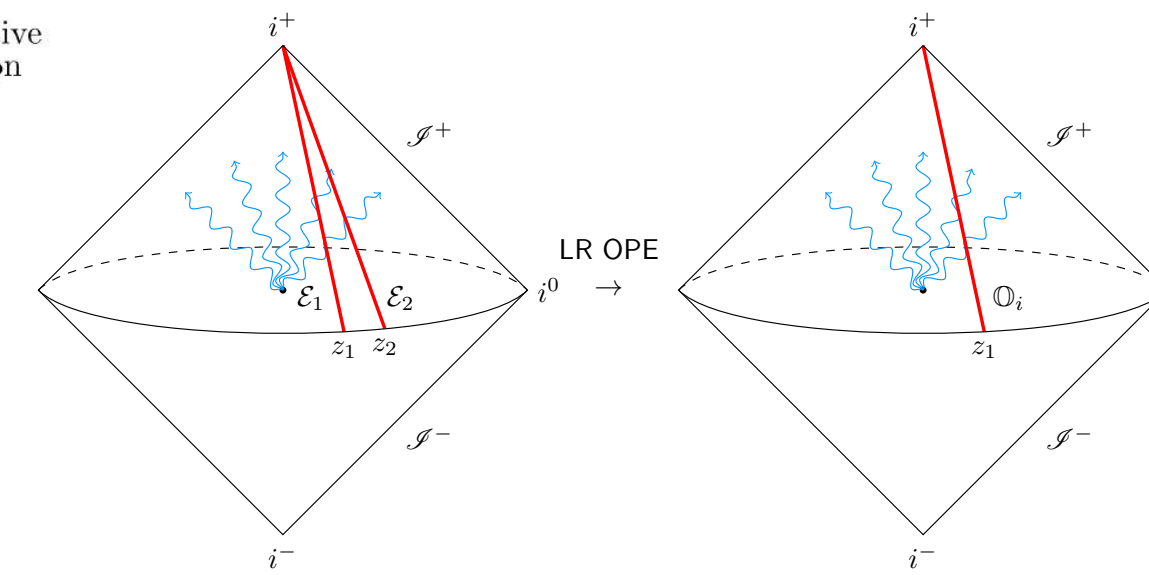
A clear link between theory and experiment!

[Figure: Wenqing Fan]



- Evolution of the jet goes from right to left

- Distinct scaling regimes corresponding to partonic and hadronic physics
- Transitions image the physical scales of QCD



Perturbative scaling predicted by the light-ray OPE

\Rightarrow Universal scaling behavior!

$$\mathcal{E}(\hat{n}_1)\mathcal{E}_2(\hat{n}_2) \sim \sum_i \theta^{\tau_i - 4} \mathcal{O}_i^+(\hat{n}_1)$$

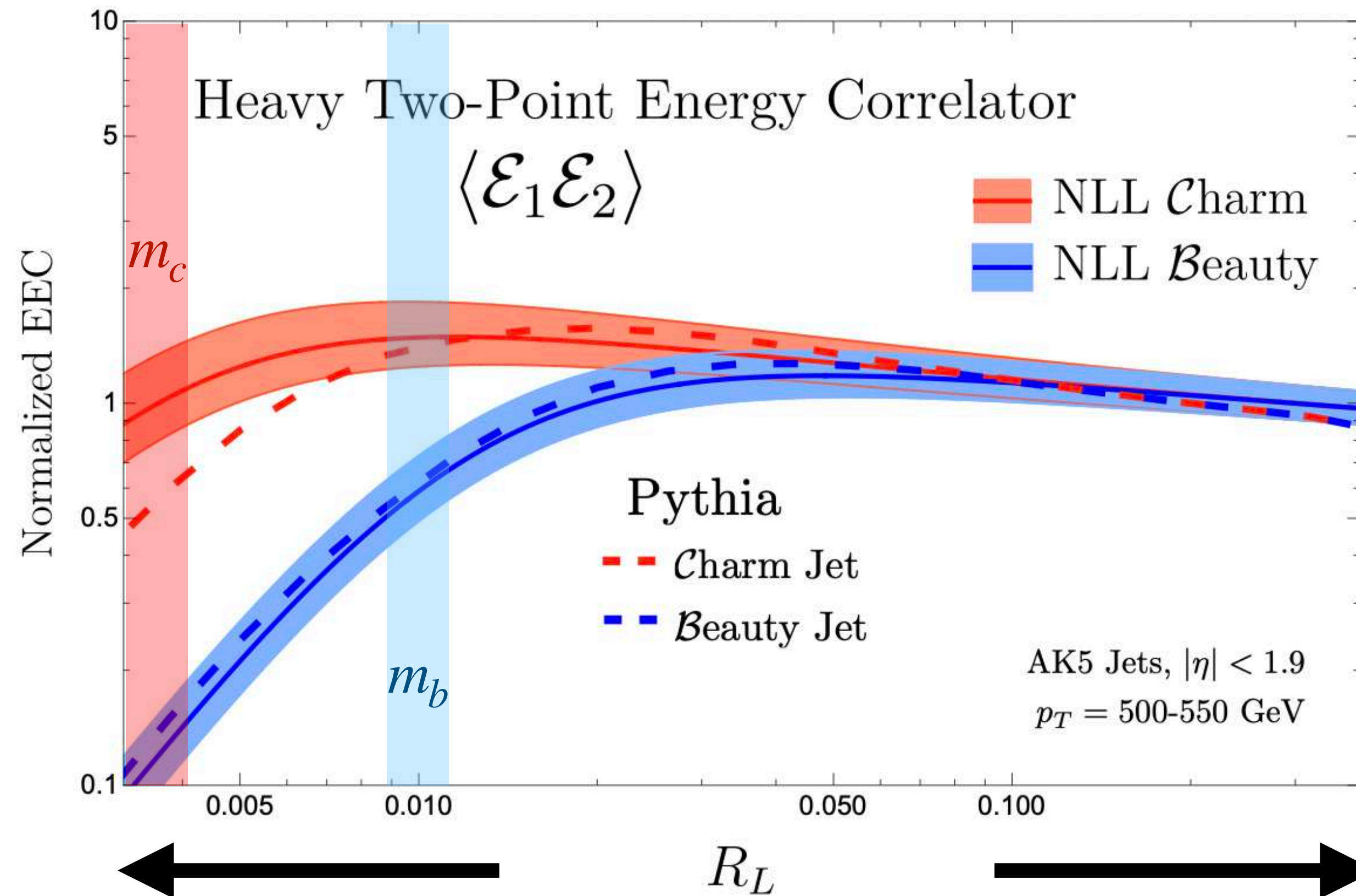
Boosters

EEC

Soft drop

What else can we do?

Can we use a 2-point EEC to measure the deadcone?



Next boost: a measurement of the deadcone using EECs?

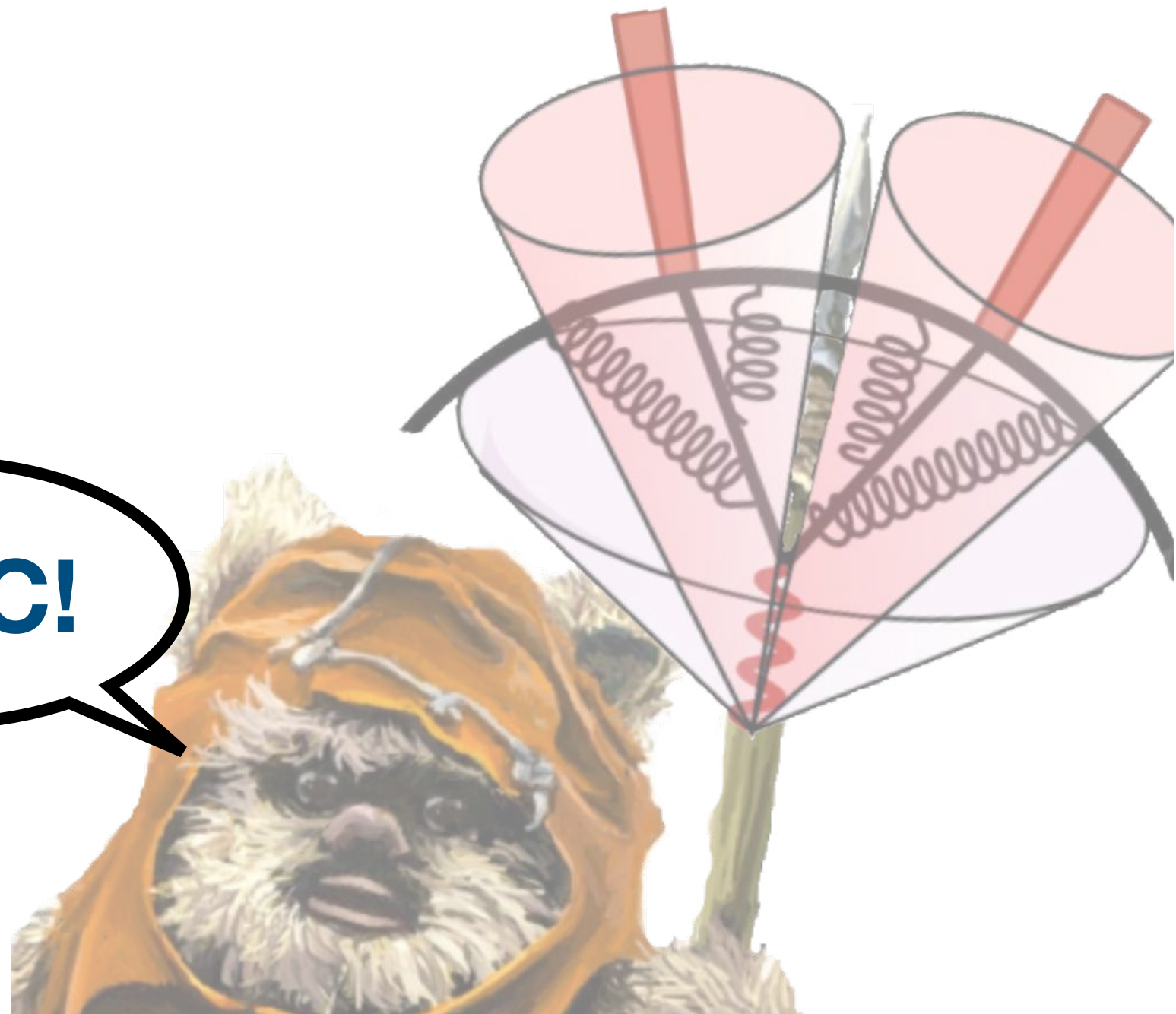
Sensitivity to the quark mass scale at $R_L \sim m_Q/p_T$

Scaling identical to that of massless quarks

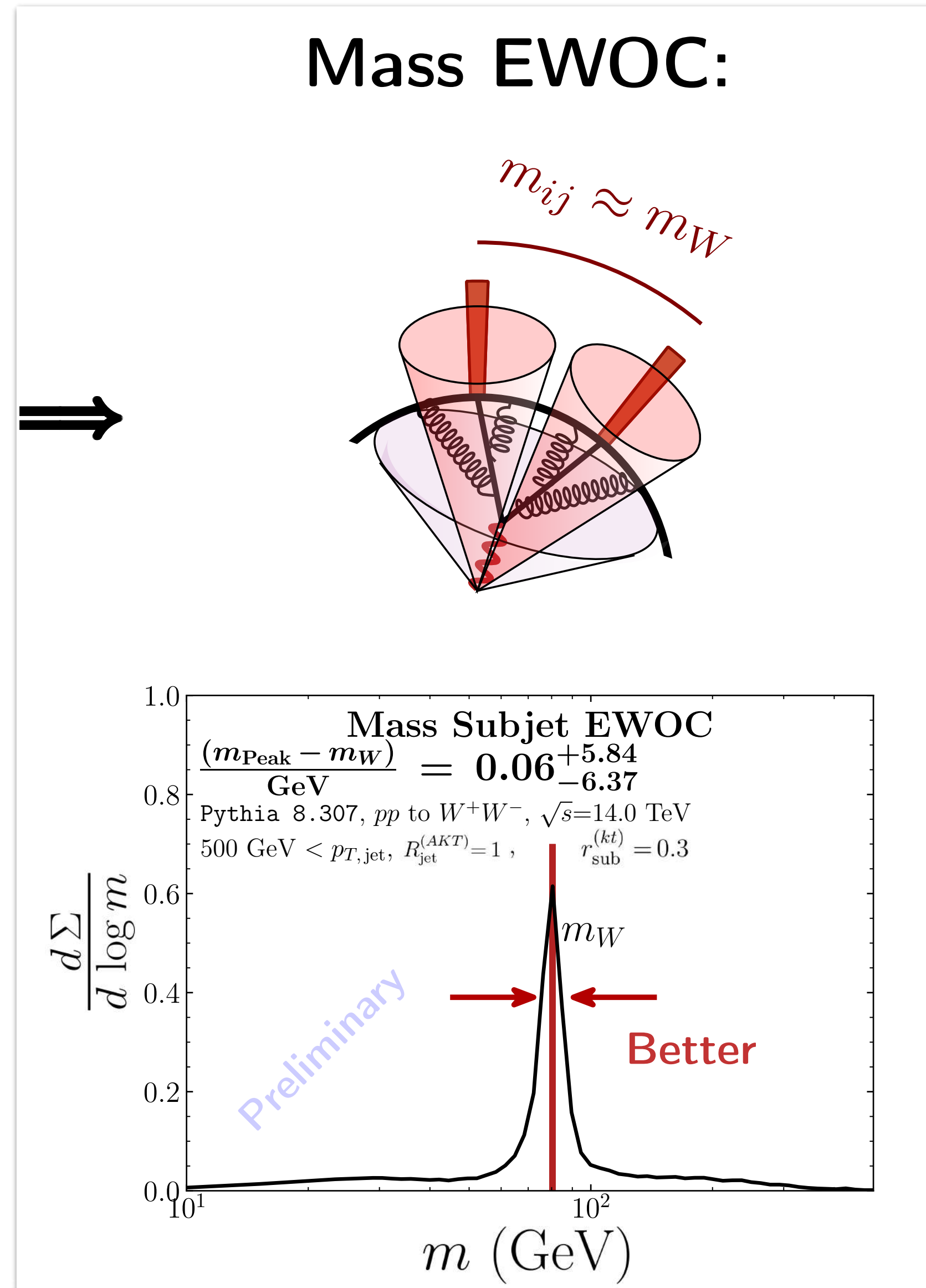
Energy Correlators Beyond Angles

Can we use a 2-point EEC to measure m_W ?

EWOC!



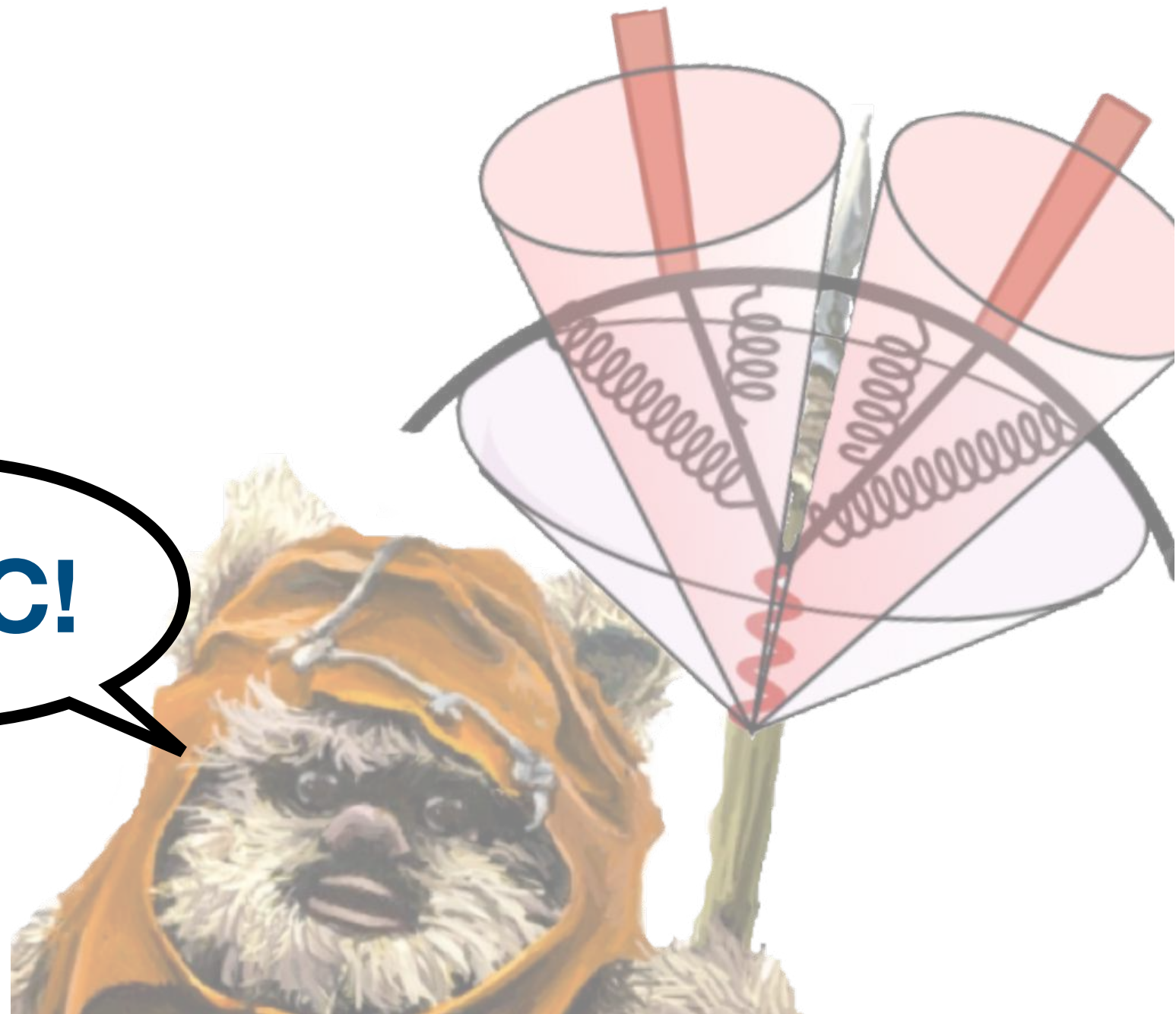
1. Take subjets instead of points
2. Measure mass instead of angle



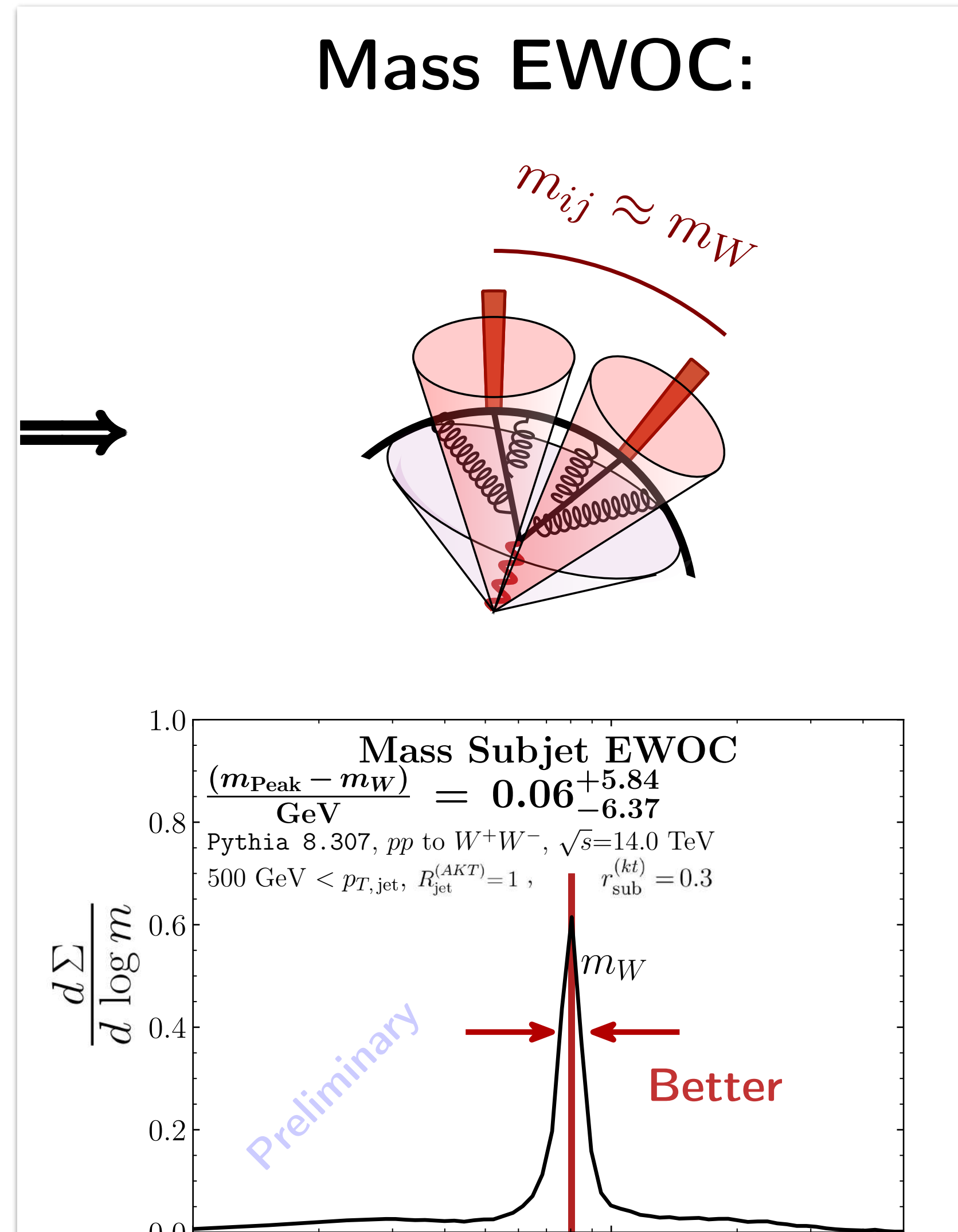
Energy Correlators Beyond Angles

Can we use a 2-point EEC to measure m_W ?

EWOC!



1. Take subjects instead of points
2. Measure mass instead of angle



Using the W as a Standard Candle to Reach the top

New observables 

Can we use m_W to measure m_t directly without modeling bias?

Aditya Pathak

3-pronged decay \rightarrow use EEEEC

Production mechanism:

- PDF uncertainty
- Hard scattering corrections

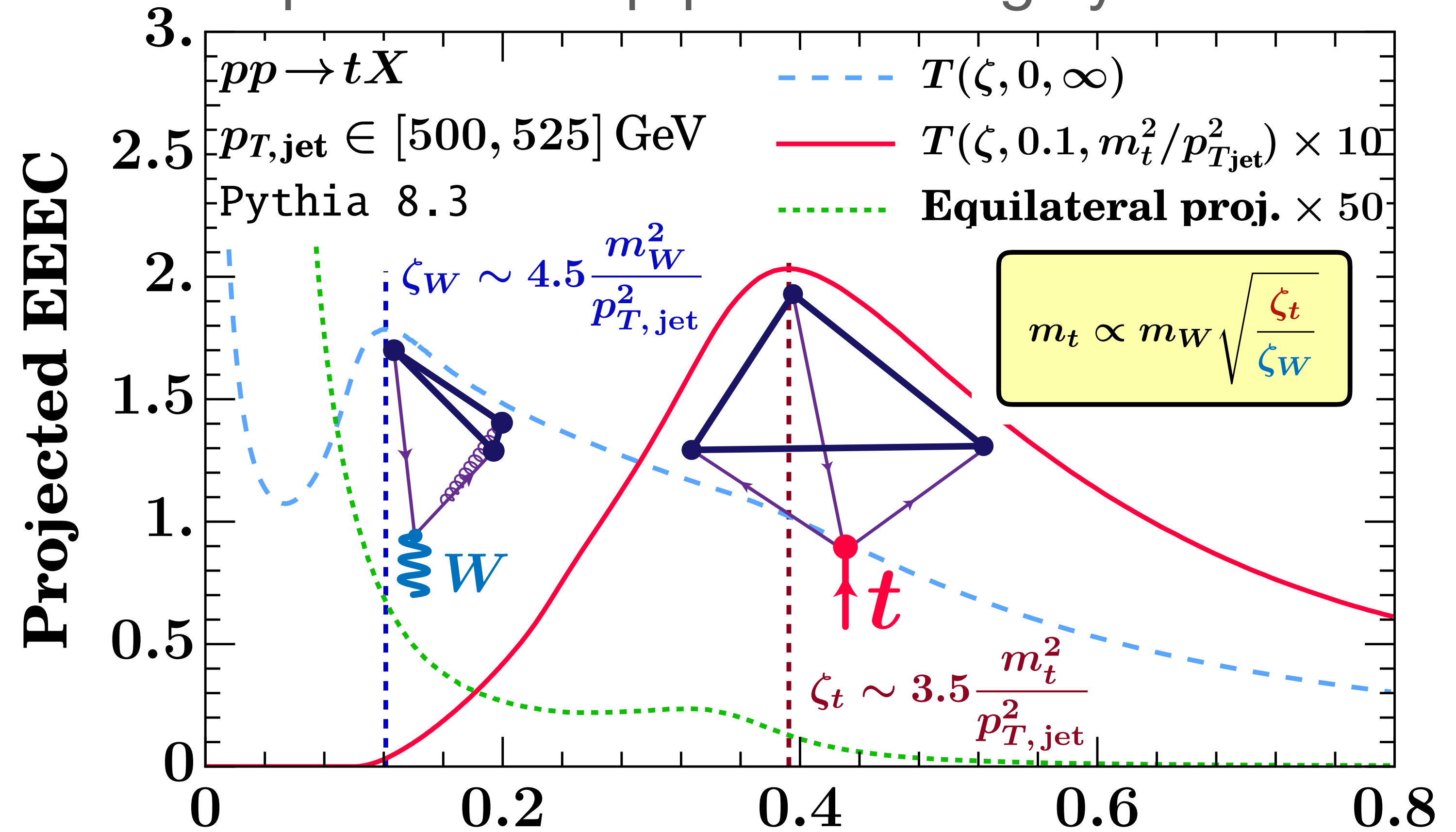
Jet substructure:

- Jet radius dependence
- Hadronization effects
- Impact of underlying event
- Wide angle soft physics
- Perturbative uncertainty

Experimental feasibility:

- Statistical sensitivity
- Jet energy scale
- Constituent energy scale
- Track efficiency
- Heavy flavor dependence

W peak and top peak are highly correlated



Prospects of **better than 500 MeV (0.3%)** ζ
 precise M_{top} at the HL-LHC!

Next boost: new m_t measurement?

Interpretation of the MC top mass parameter with the soft-dropped groomed jet mass

Back to soft drop, not all is forgotten

Can we understand the m_t^{MC} ?

Resurrect an 'old' idea but with more aggressive grooming → reduces impact MPI

- Model uses three parameters, m_t^{Pole} , Ω_1^{had} , and x_2 associated with **first-** and **second-moment non-perturbative corrections.**
- Idea is to obtain **value of parameters in NNLL theory** calculation that **best describe MC prediction.**

Mass relation (pp):

$$\Delta^{Pole} = m_t^{MC} - m_t^{Pole} = 590_{-320}^{+375} \text{ MeV}$$

Mass relation (e^+e^-):

$$\Delta^{Pole} = m_t^{MC} - m_t^{Pole} = 600_{-215}^{+275} \text{ MeV}$$

Suggests universality between the e^+e^- and pp processes.

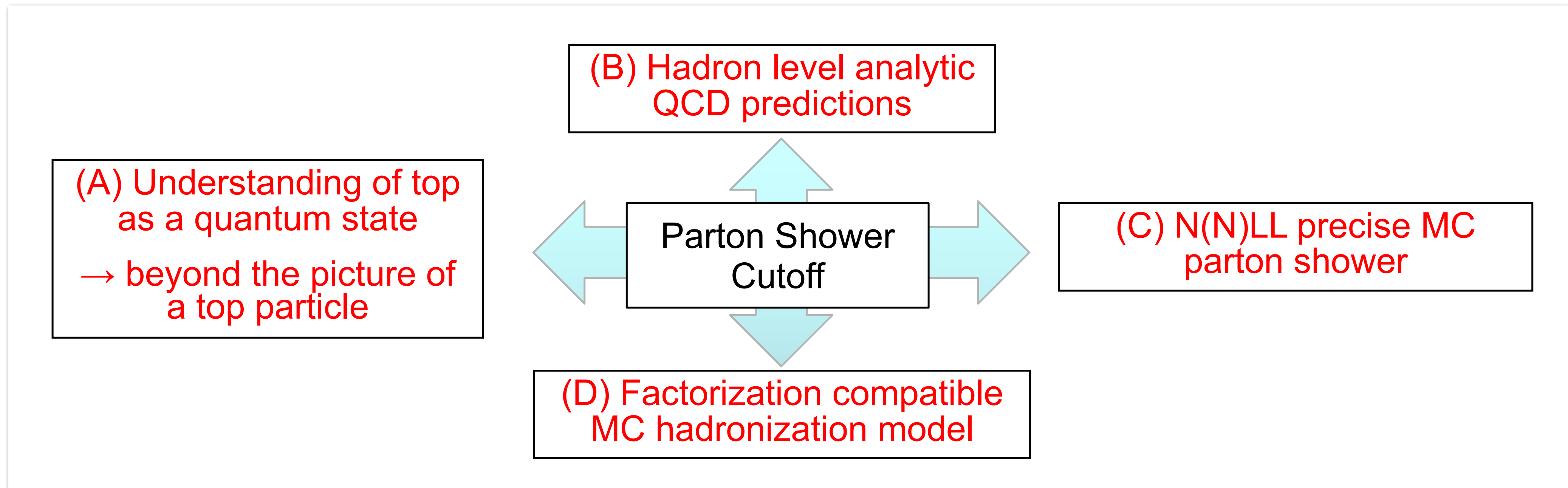
What happens with a different shower model?

An approach to pin down the top quark mass parameter in MC event generators

Can we make m_t^{MC} more physical?

Can we promote m_t^{MC} to a renormalisation scheme (such that it can be translated to other schemes)?

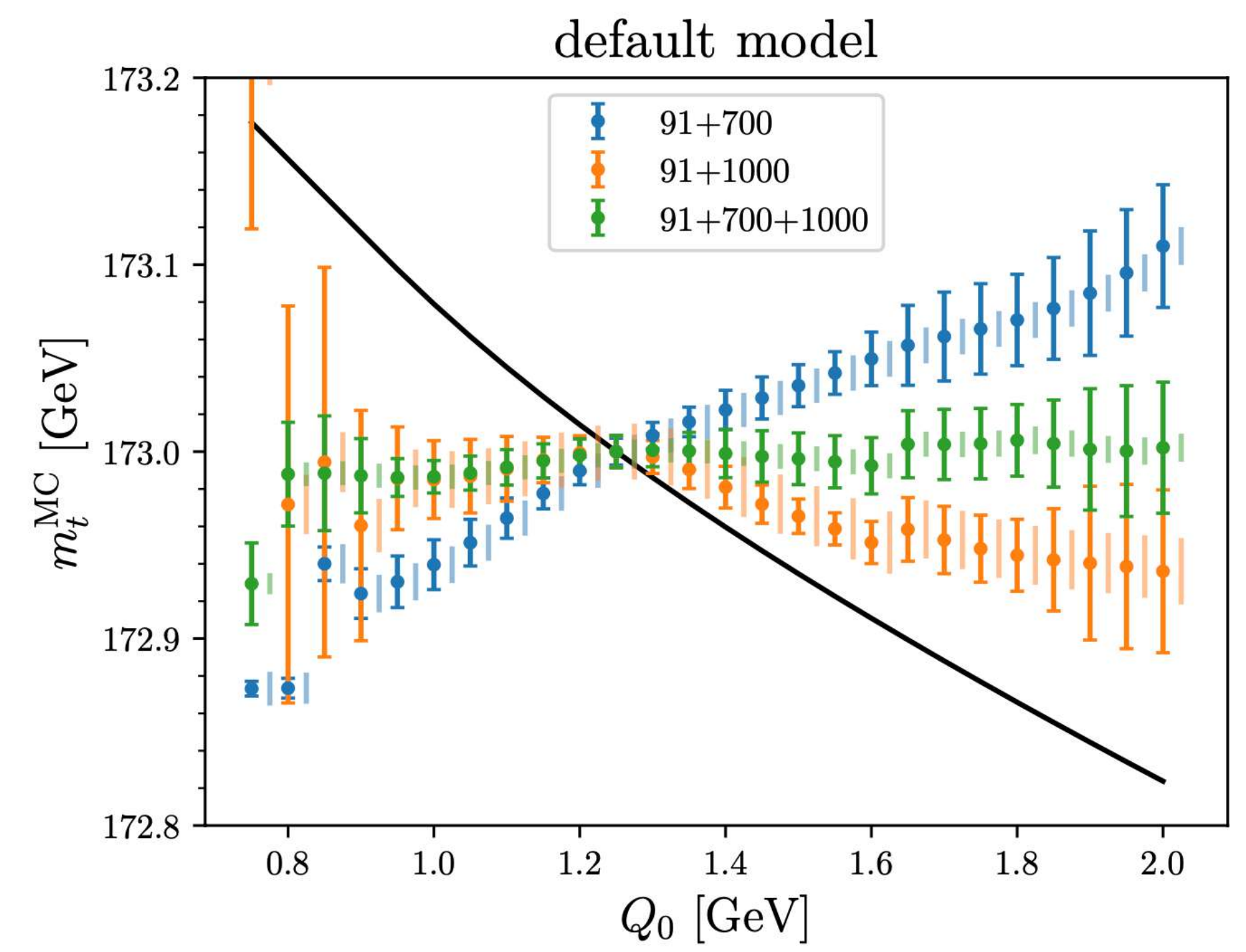
Yes, but you need quite a list of ingredients



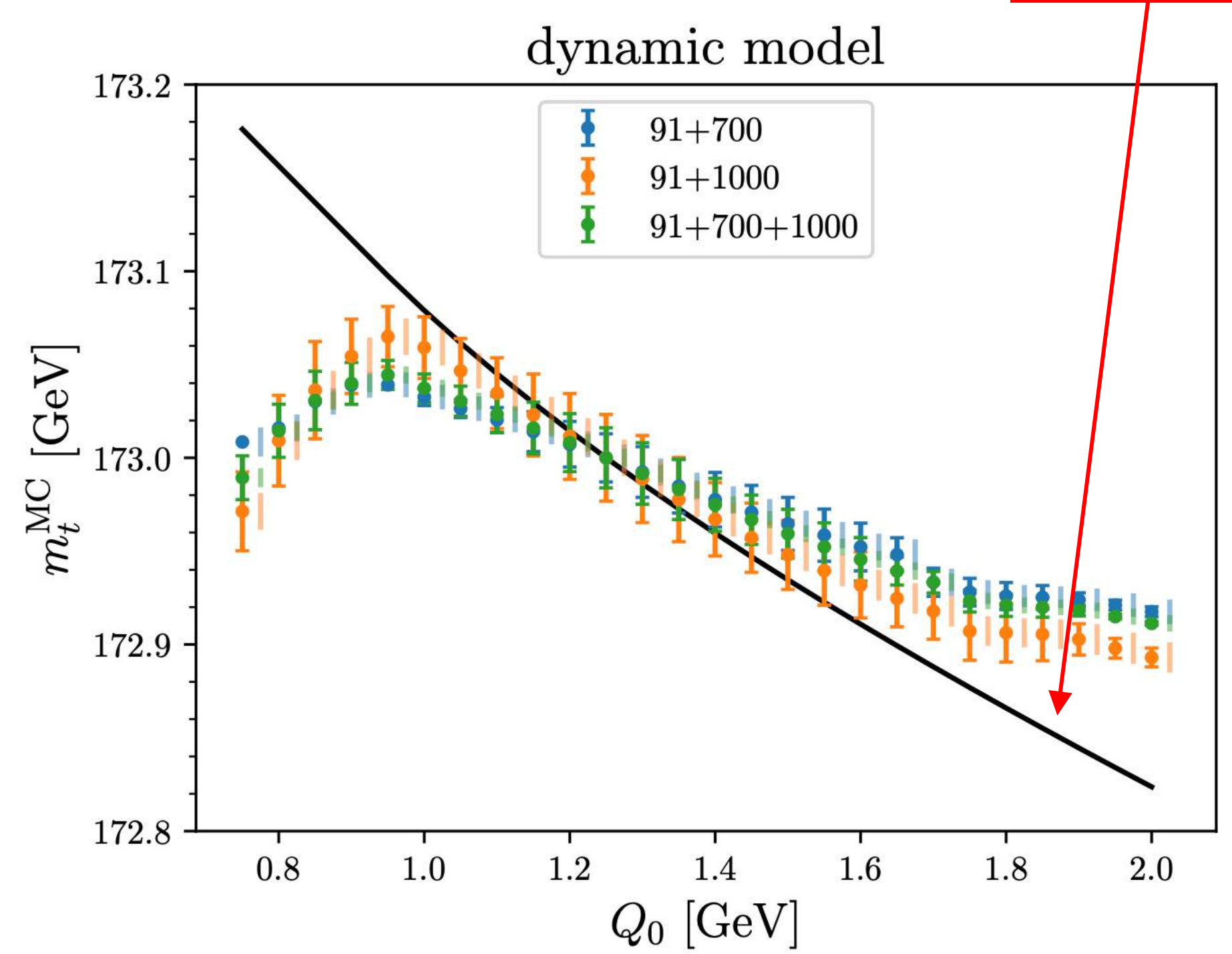
An approach to pin down the top quark mass parameter in MC event generators

Can we make m_t^{MC} more physical?

Tune m_t^{MC} for different values of Q_0 to ref. data for $Q_0 = 1.25$ GeV



Default Herwig hadronization model modifies m_t^{MC} in an unphysical way incompatible with QCD factorization: uncertainty ~ 0.5 GeV



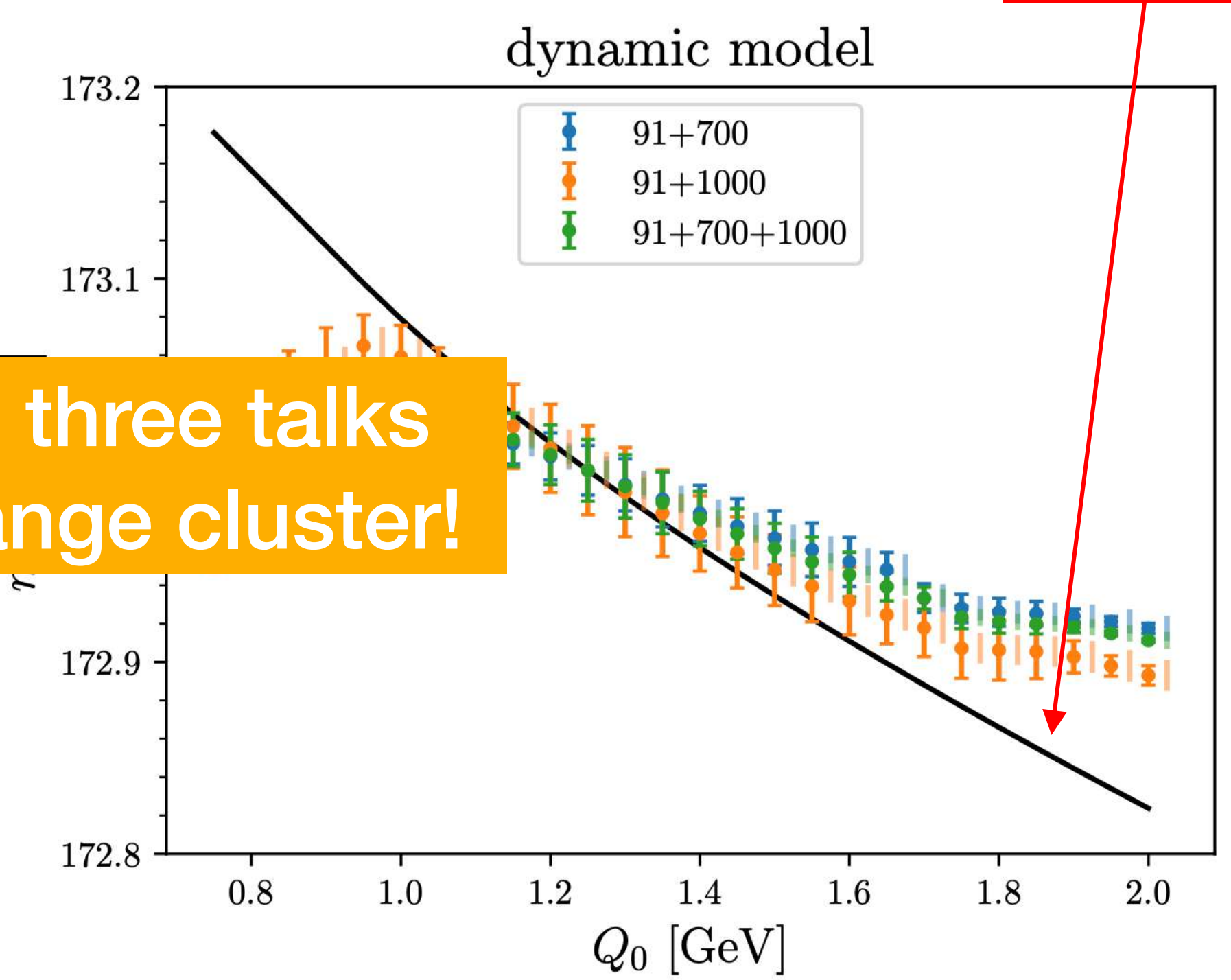
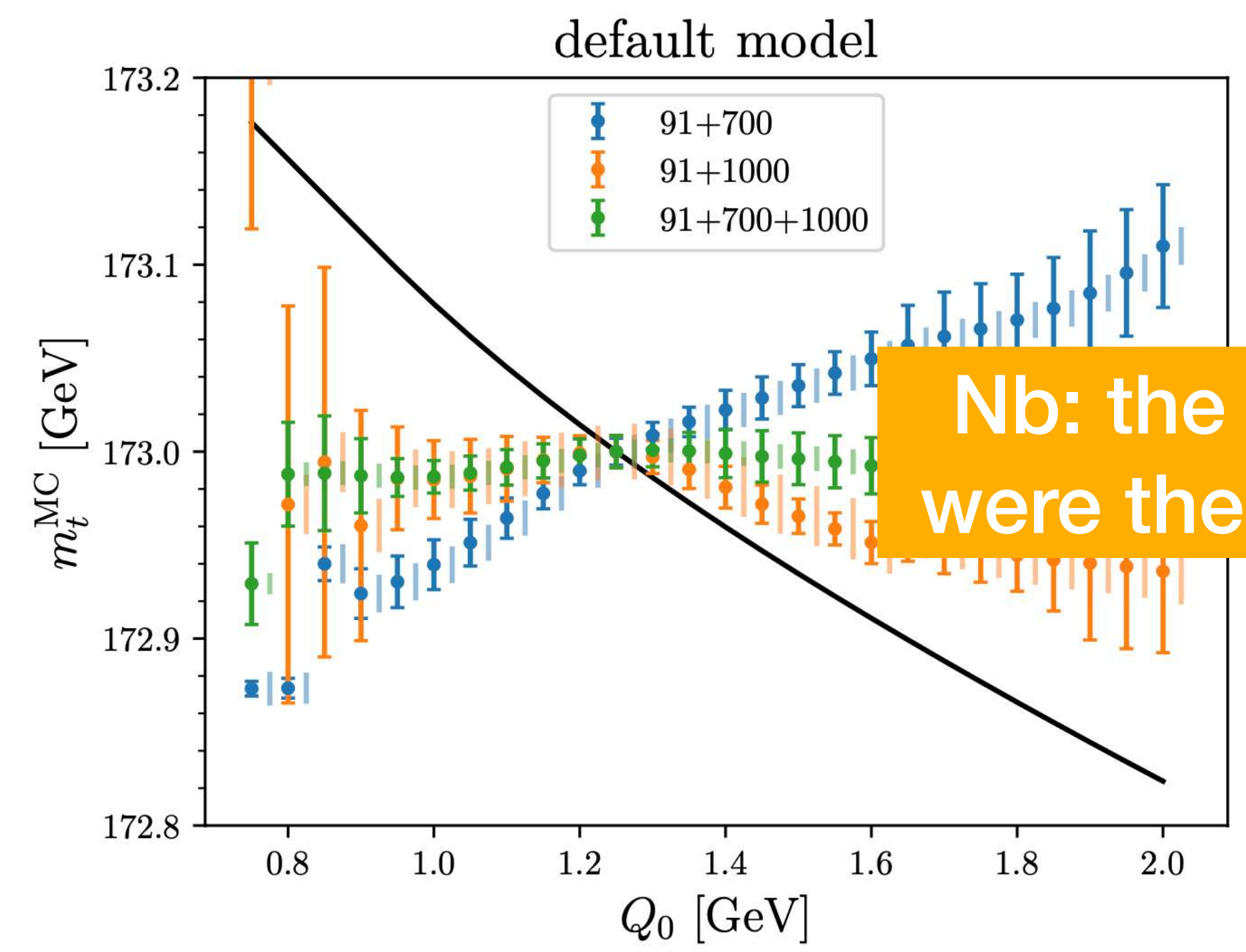
Agreement of m_t^{MC} with $m_t^{CB}(Q_0)$ within 50 MeV !

Q_0 dependence expected from $m_t^{CB}(Q_0)$

An approach to pin down the top quark mass parameter in MC event generators

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Nb: the last three talks were the orange cluster!

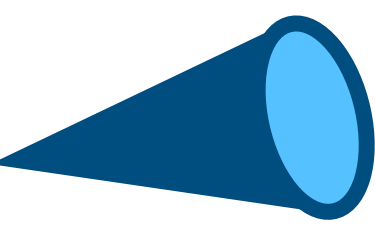
Q_0 dependence expected from $m_t^{CB}(Q_0)$

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Agreement of m_t^{MC} with $m_t^{CB}(Q_0)$ within 50 MeV !

How to unfold top decays

ML



Sofia Schweitzer

Can we learn how to unfold top decay products?

Goal: learn transformation latent \rightarrow gen phase space conditioned on reco event

During training, use paired events of forward simulation

After training, repeated sampling from latent space with constant condition allows probabilistic single event unfolding

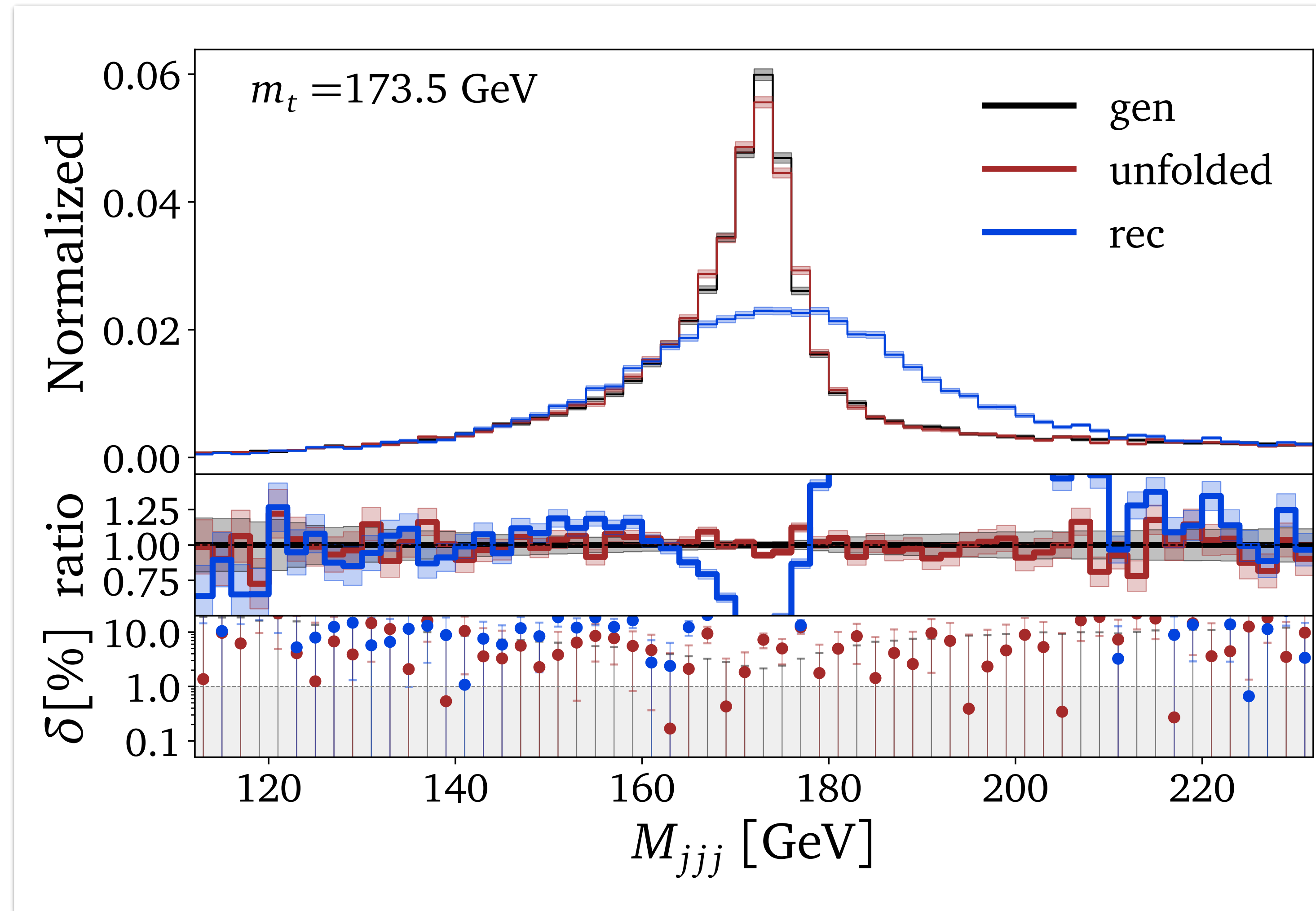
Sofia's prediction: "I'm not gonna tell you about the generative model, this will change anyway in two years or so"

How to unfold top decays

Can we learn how to unfold top decay products?

Be careful with:

1. Mapping the resonances
→ pick the right input
2. Dependence on the model
→ train on different masses



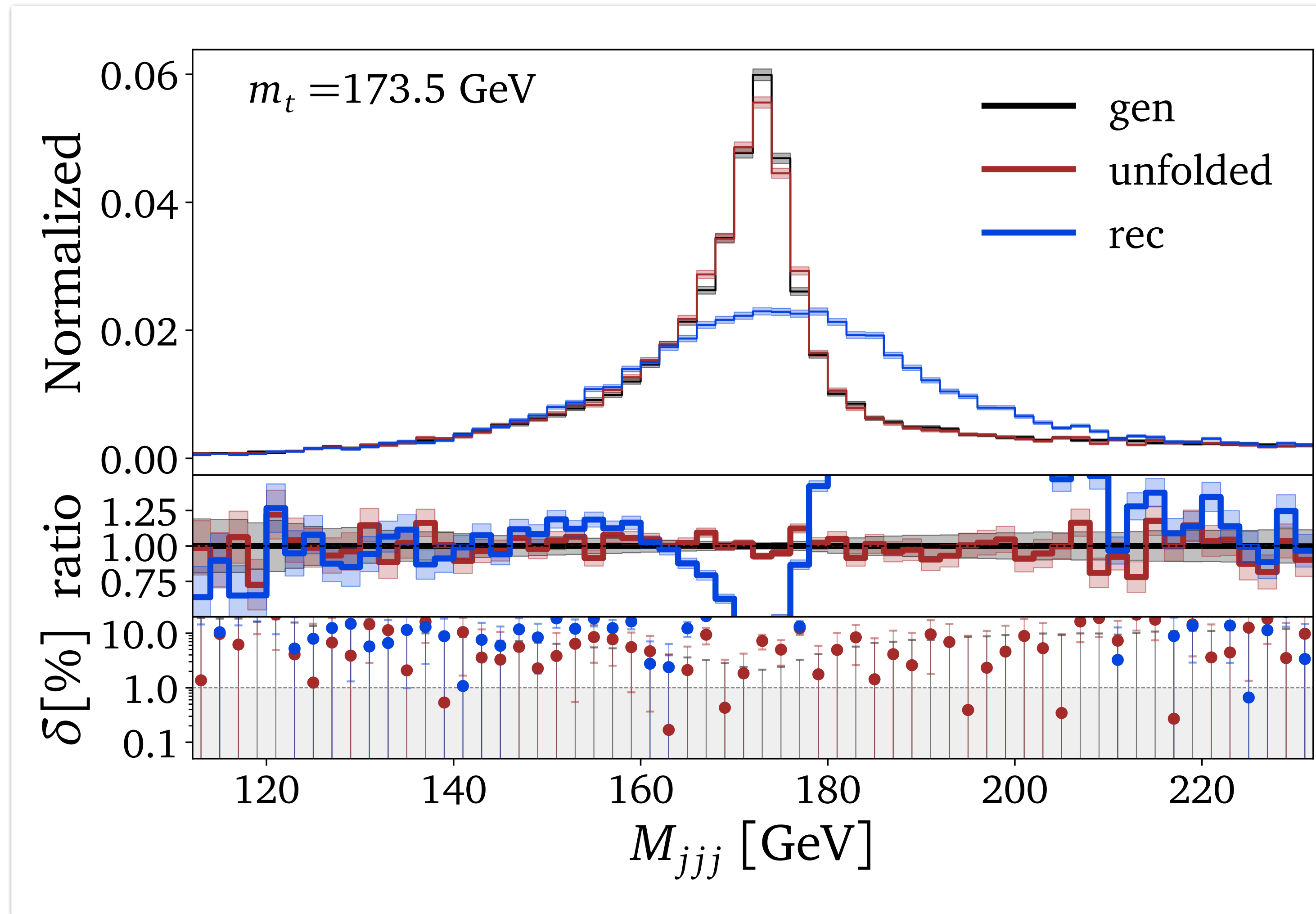
How to unfold top decays

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→ pick the right input
2. Dependence on the model
→ train on different masses

What happens with
different tunes/
hadronisation/shower?



Detectorology and its Phenomenological Applications

New observables 

Mark Gonzalez

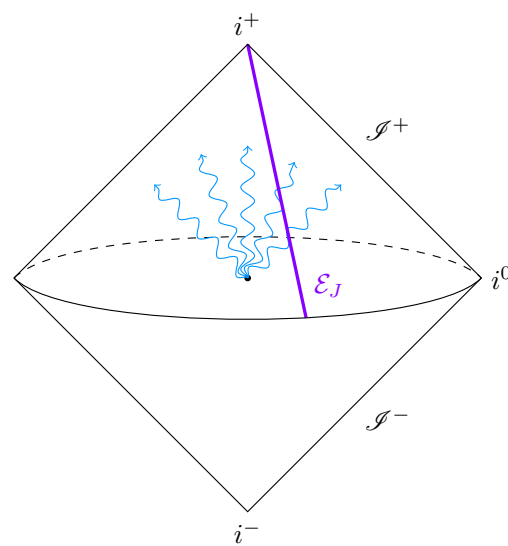
Back to the EEC.. Can we generalise it?

\mathcal{E}_J Detectors

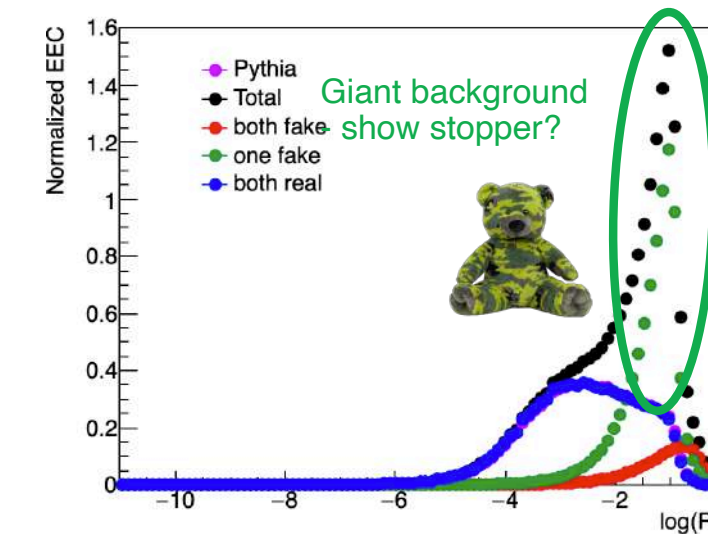
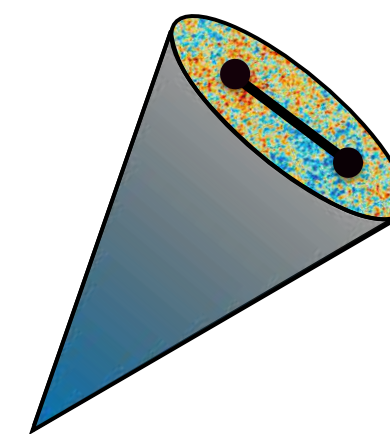
A new camera which measures the energy flux to an arbitrary power, E^{J-1} with $J \in \mathbb{C}$

$$\mathcal{E}_J(\hat{n})|X\rangle = \sum_i E_{k_i}^{J-1} \delta^{d-2}(\Omega_{\hat{n}} - \Omega_{\hat{k}_i})|X\rangle$$

- Formally: $\mathcal{E}_J(z) \sim \mathbb{O}_J^+(\infty, z)$
 - Analytically continued twist-2, spin- J light-ray operator
 - Energy weighting is related to spin

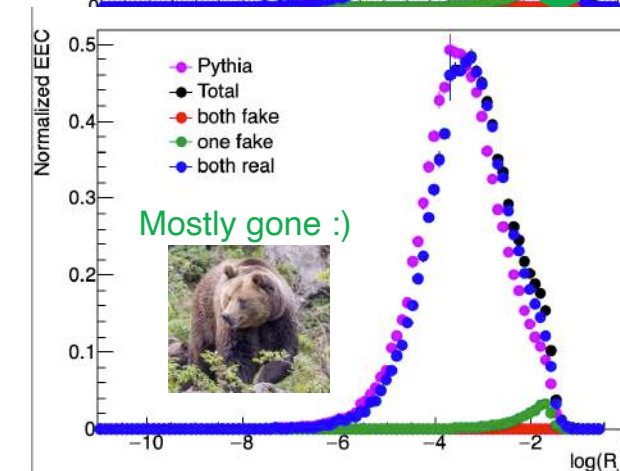
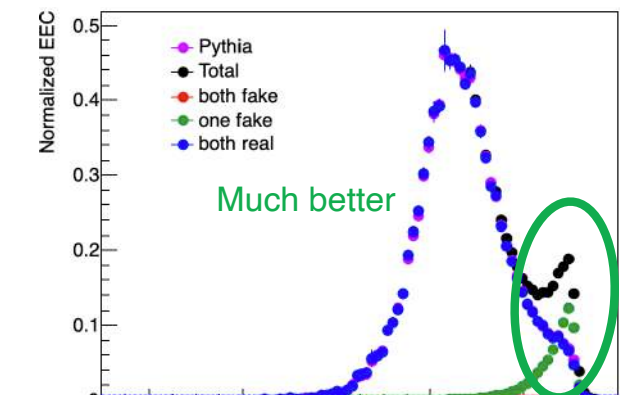


Detector Applications



$n=2, R=0.4$
 $n=2, R=0.2$

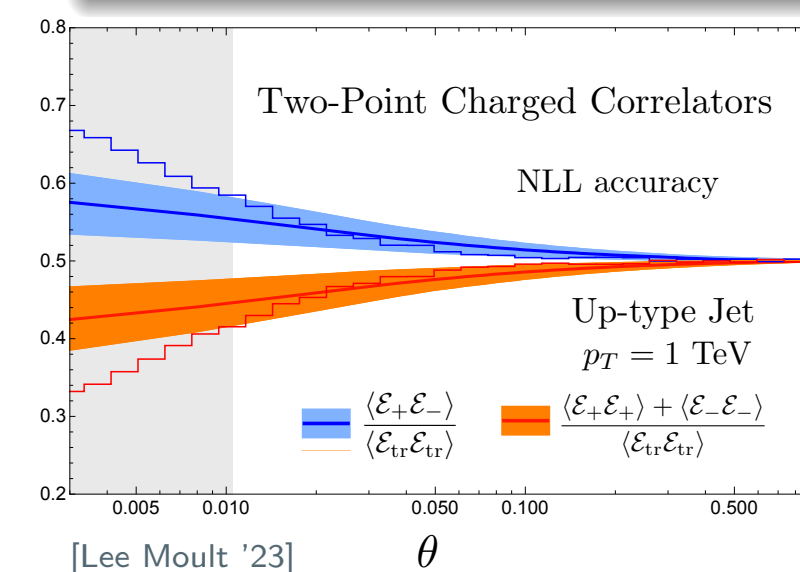
[Figure: L Havener, A Rai]



\mathcal{E}_J Detectors

Large (small) powers of energy suppress (enhance) soft physics:

Applications in hot and cold QCD



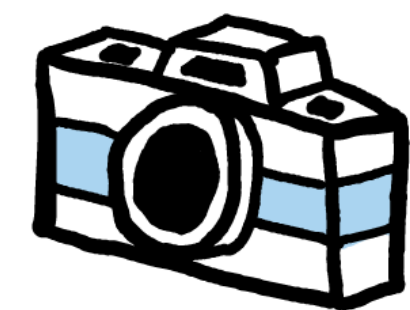
\mathcal{E}_Q Detectors

- Great resolution on charged tracks
- More hadronization/ non-perturbative information

As an operator in a perturbative scalar field theory

$$\mathcal{D}_{J_L}^+(z) = \frac{1}{C_{J_L}} \int d\alpha_1 d\alpha_2 : \bar{\varphi}(\alpha_1, z) \varphi(\alpha_2, z) : \times [(\alpha_1 - \alpha_2 + i\epsilon)^{2(\Delta_\varphi - 1) + J_L} + (\alpha_2 - \alpha_1 + i\epsilon)^{2(\Delta_\varphi - 1) + J_L}]$$

- Twist-2, spin- J_L , and "charge/spin even"
- Observables are no longer collinear safe due to energy weighting
 - Access to universal non-perturbative physics through multi-hadron fragmentation functions



[Kravchuk Simmons-Duffin '18]

[Caron-Huot, Koloğlu, Kravchuk, Meltzer '18]

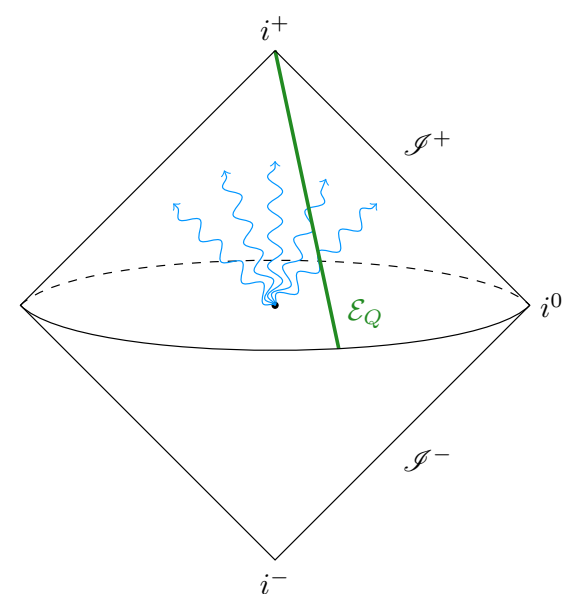
M

\mathcal{E}_Q Detectors

We can also build cameras that probe different quantum numbers!

Sensitivity to a charge Q (times the energy)

$$\mathcal{E}_Q(\hat{n})|X\rangle = \sum_i E_{k_i}^{J-1} Q_{k_i} \delta^{d-2}(\Omega_{\hat{n}} - \Omega_{\hat{k}_i})|X\rangle$$



Plus these operators are 'renormalisable' in conformal theories
→ we can do calculations

My (biased) hopes/predictions for 2025

- Can we understand better what ML tools are learning: is it physics or generators?
- We will see the first full NNLO-meets-boost calculation
- A better representation of the Monte Carlo community (I want a fat MC jet)
Jing: “showers are everywhere”
- Can we understand better differences between showers that we are seeing all across different measurements?
- And of course new cool calculations, measurements, novel techniques, and all the enthusiasm I saw this week!

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BOOS-TI-AMO!!!