Simone Marzani,
Università di Genova & INFN Genova

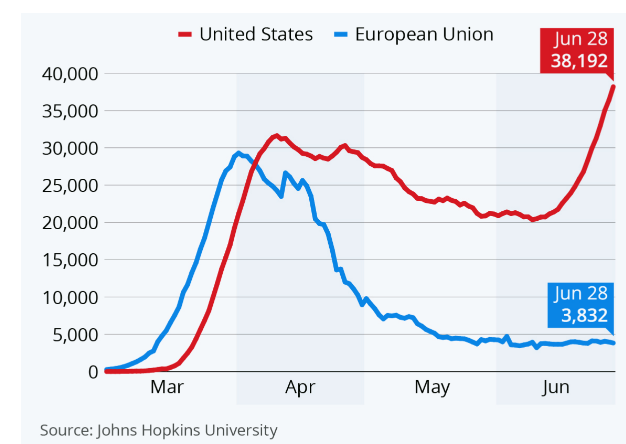
place here nice picture of the conference venue

Theory Advances

Strange times…

What has occupied our minds lately ?

Strange times…

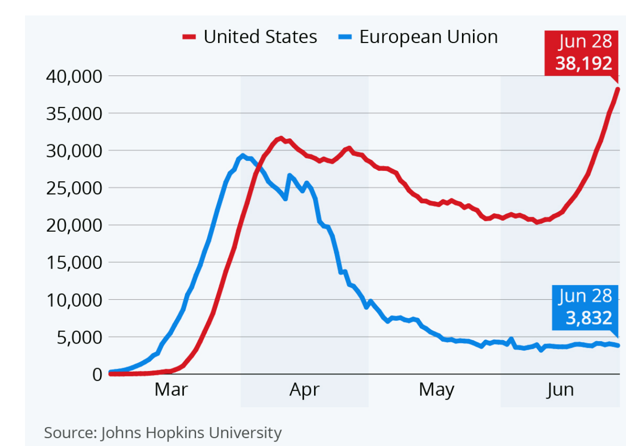


What has occupied our minds lately ?

Strange times…

Epidemiological models

40%



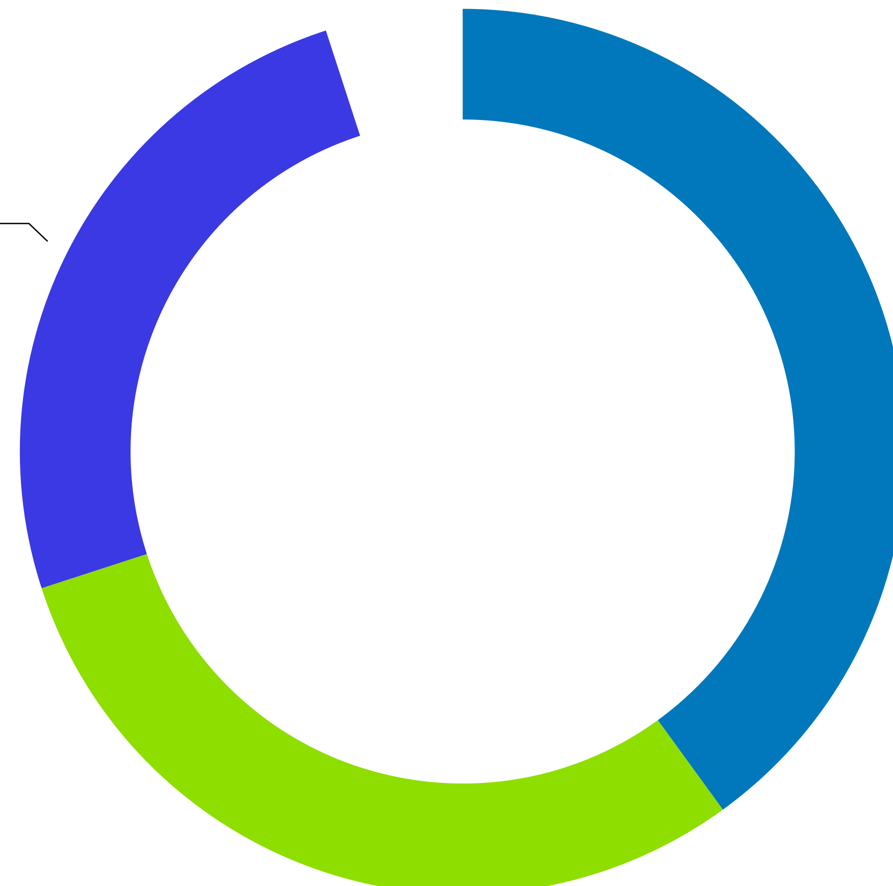
Grocery shortages

30%

vs

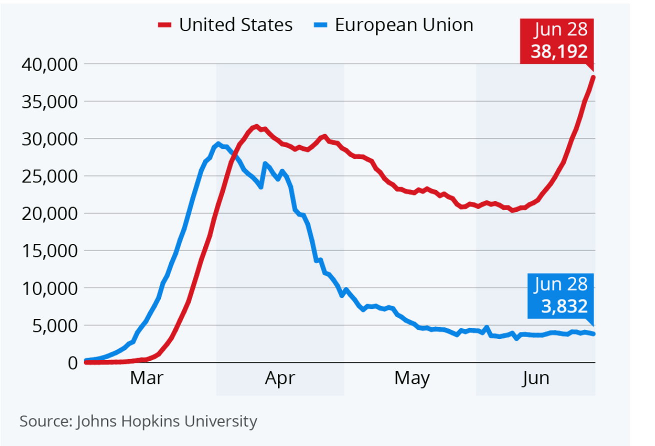
What has occupied our minds lately ?

Strange times...



Epidemiological models

40%



25%

Distance Learning

30%

Grocery shortages

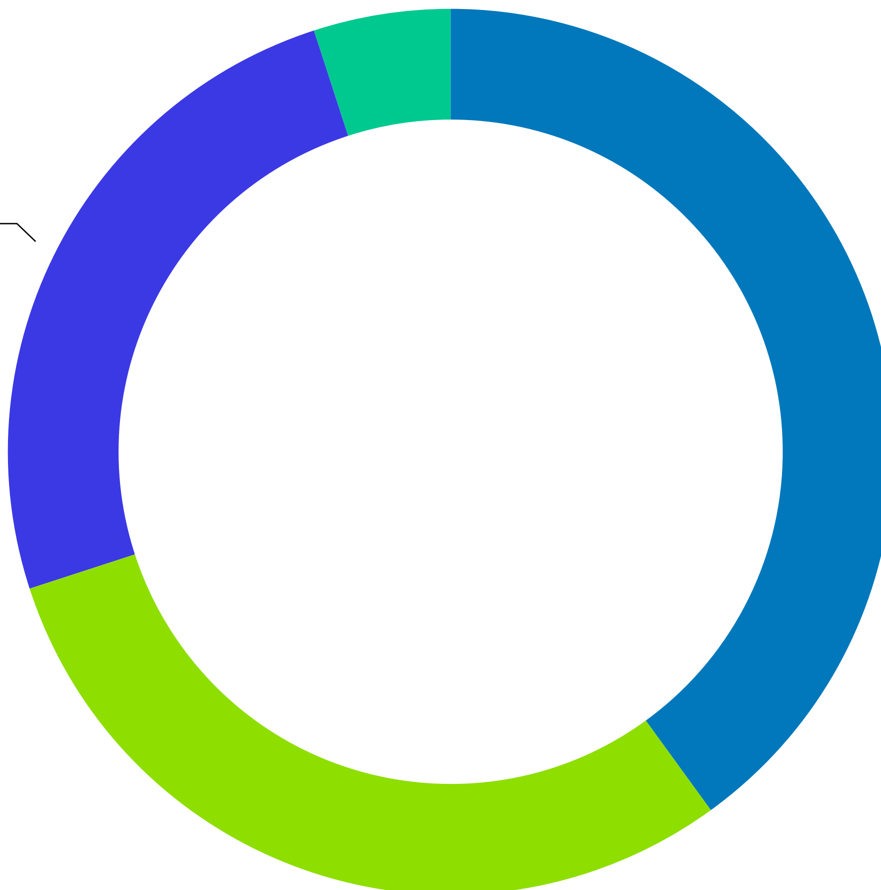
vs

What has occupied our minds lately ?

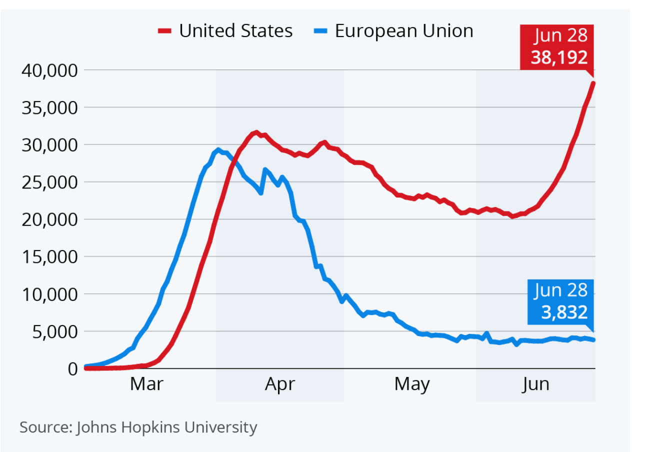
Strange times...

Research! 5%

Distance Learning 25%



Epidemiological models 40%

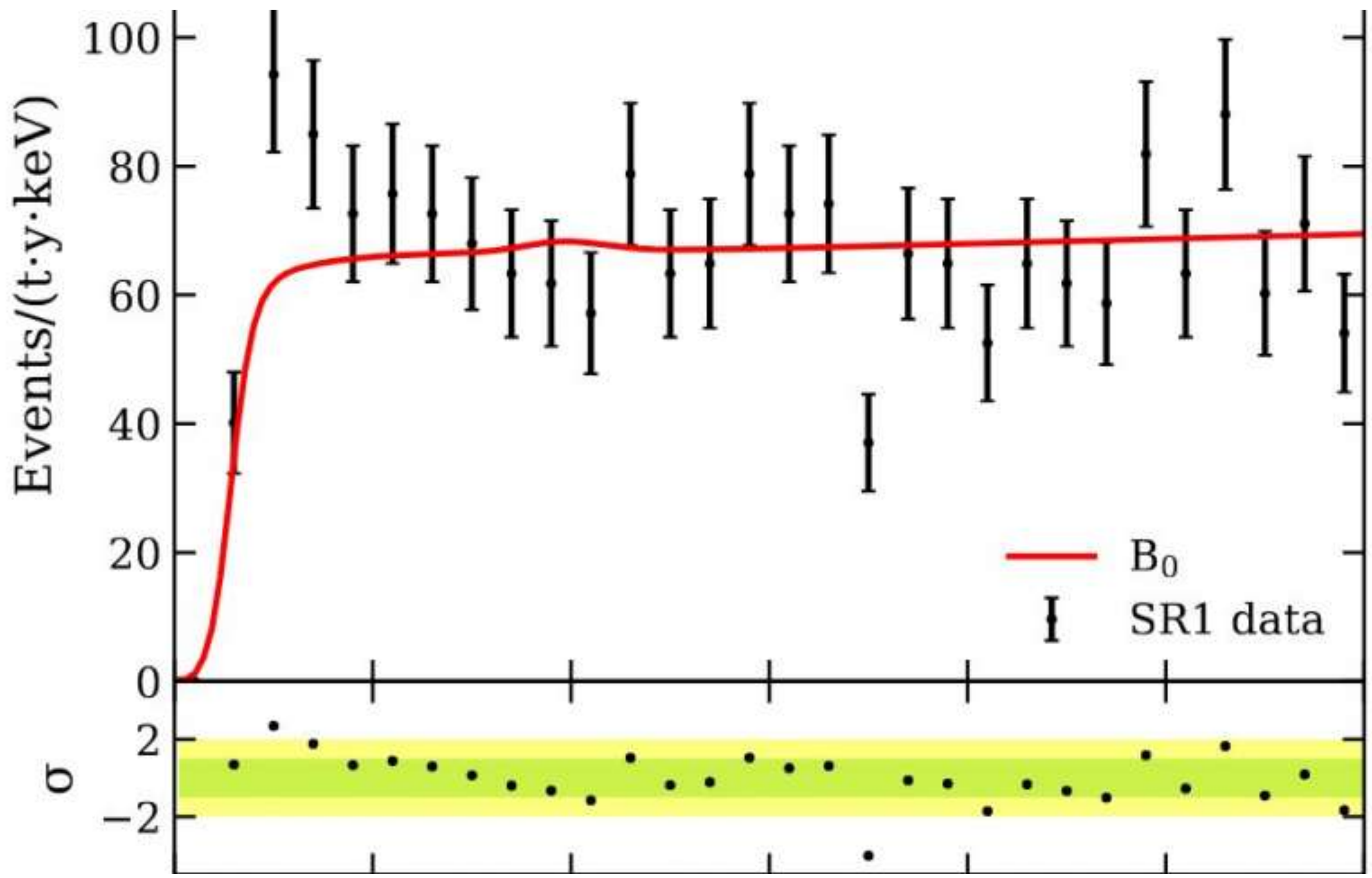


Grocery shortages 30%

vs

What has occupied our minds lately ?

Big news from ~~the LHC~~ XENON1T

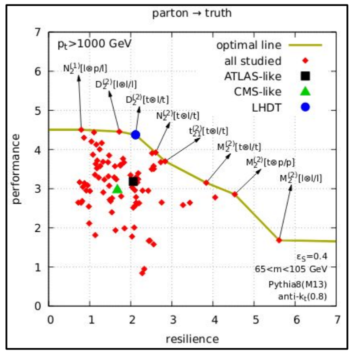


- Despite all of this, it's been (as usual) an incredibly fruitful year for jet physics
- I will do my best to showcase some of the (in my personal opinion) interesting theory results

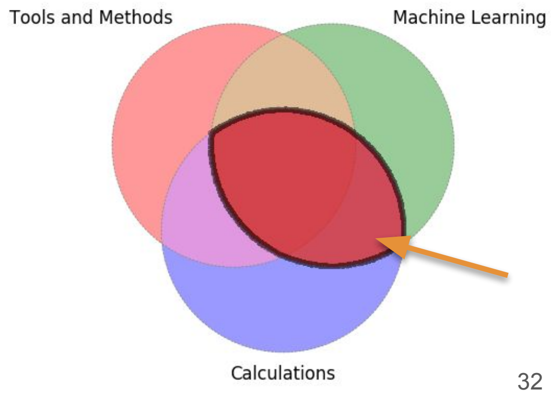
Looking back to 2019

My hopes for 2020

- Can we come up with quantifiable metrics beyond performance for comparisons of different ML algorithms? Different metrics for different applications?
- Is it possible to find ways to leverage performance gains from ML methods in calculable and robust frameworks?
- Can we perform precision calculations for other key jet substructure observables? And compare these calculations with measurements?
- Is it possible to improve non-perturbative modelling, e.g. through improvements of perturbative component of parton showers?



[arXiv:1803.07977]



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Conclusions

- Machine learning is here to stay.
- If a problem can be framed in the “right” way, ML can lead to real insights - but it should be primarily viewed as tool!
- Precision calculations of jet substructure observables will be critical for future measurements, notably for α_s extractions
- See you in Hamburg!

Frédéric Dreyer
Boost 2019 Theory Summary

The aim of this talk is to spark a discussion about how much progress we have made on these points

Outline

- New tools (with and without machines): groomers, taggers, observables and new insights
- Opening the black box: machine-learning and expert-knowledge
- Looking ahead: jets for future colliders
- Conclusions

New tools (w/o machines)

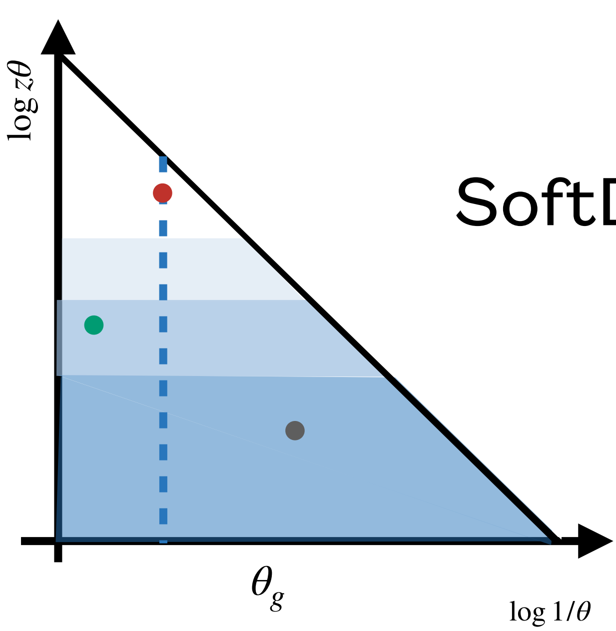
Dynamical grooming

- Find hardest branch in the C/A sequence, i.e.

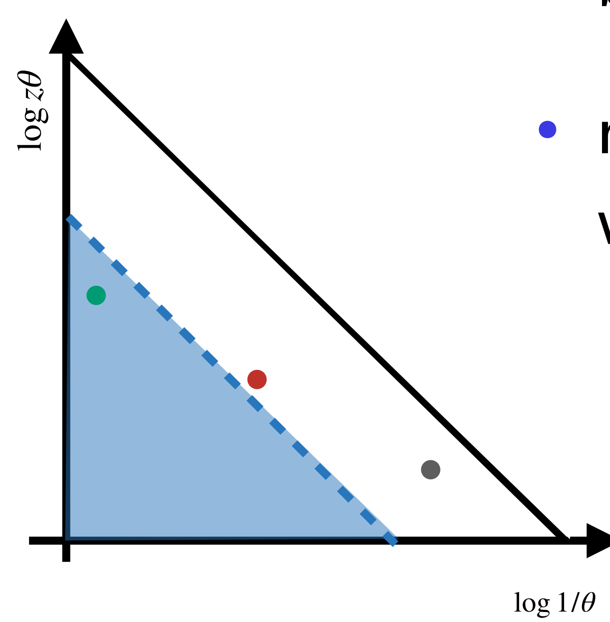
$$\kappa^{(a)} = \frac{1}{p_T} \max_{i \in \mathrm{C/A}} z_i (1 - z_i) p_{T,i} (\theta_i / R)^a$$

- Drop all branches at larger angles

dynamical grooming



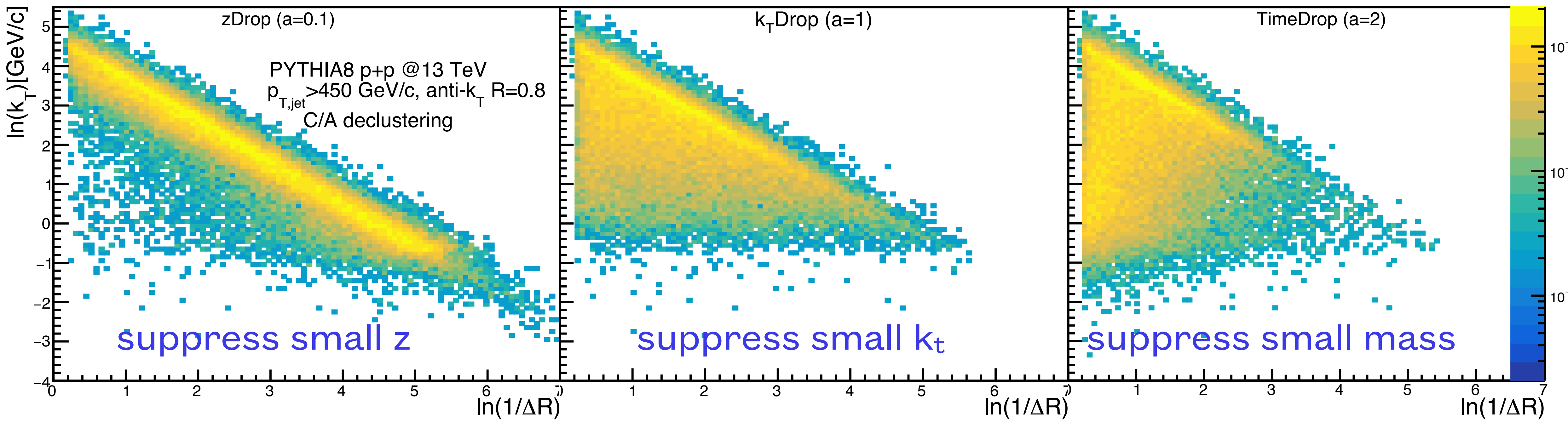
SoftDrop

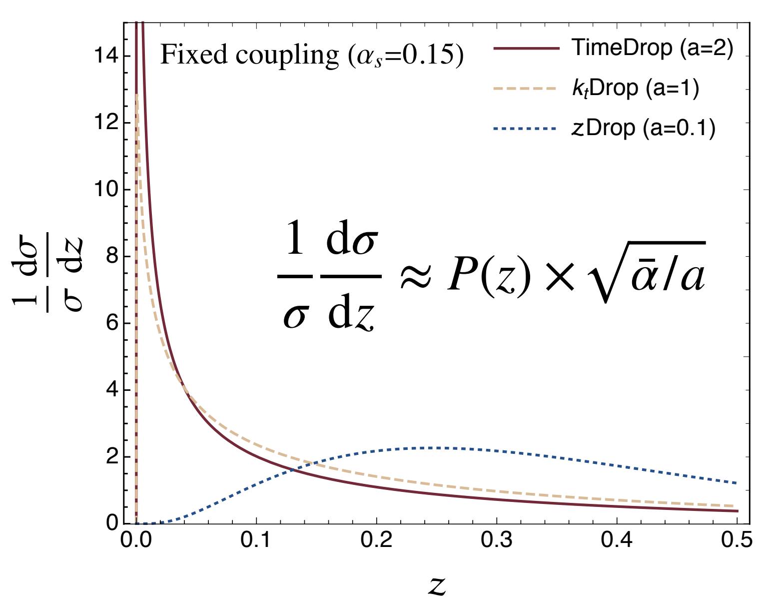


- grooming condition auto-generated on a jet-by-jet basis
- more aggressive grooming with deceasing α

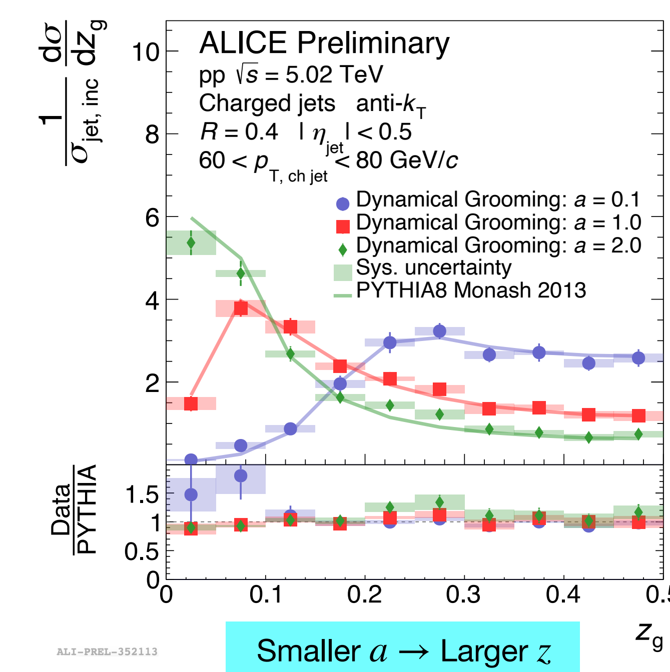
Mehtar-Tani *et al.* arXiv:1911.00375, 2005.07584

Dynamical grooming





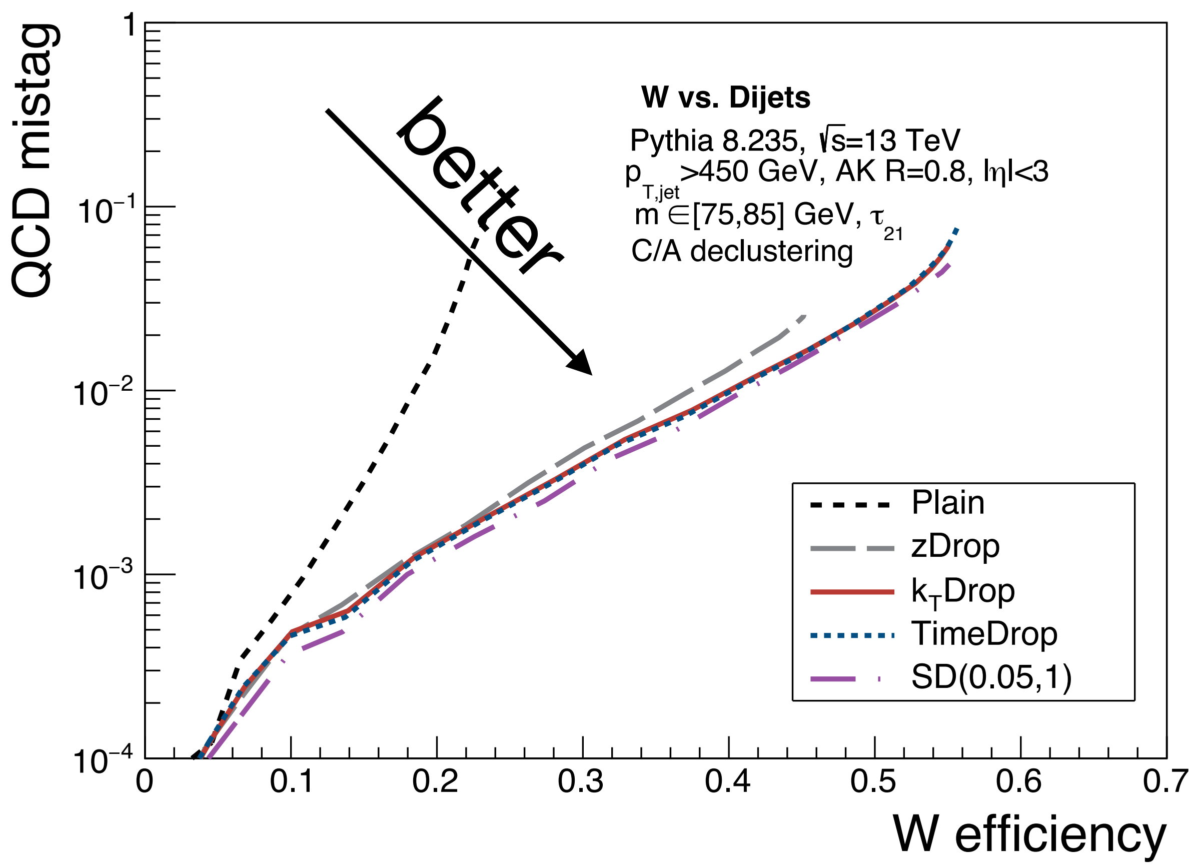
- Modified LL resummation
- Dynamical cut-off
- First comparison to ALICE data

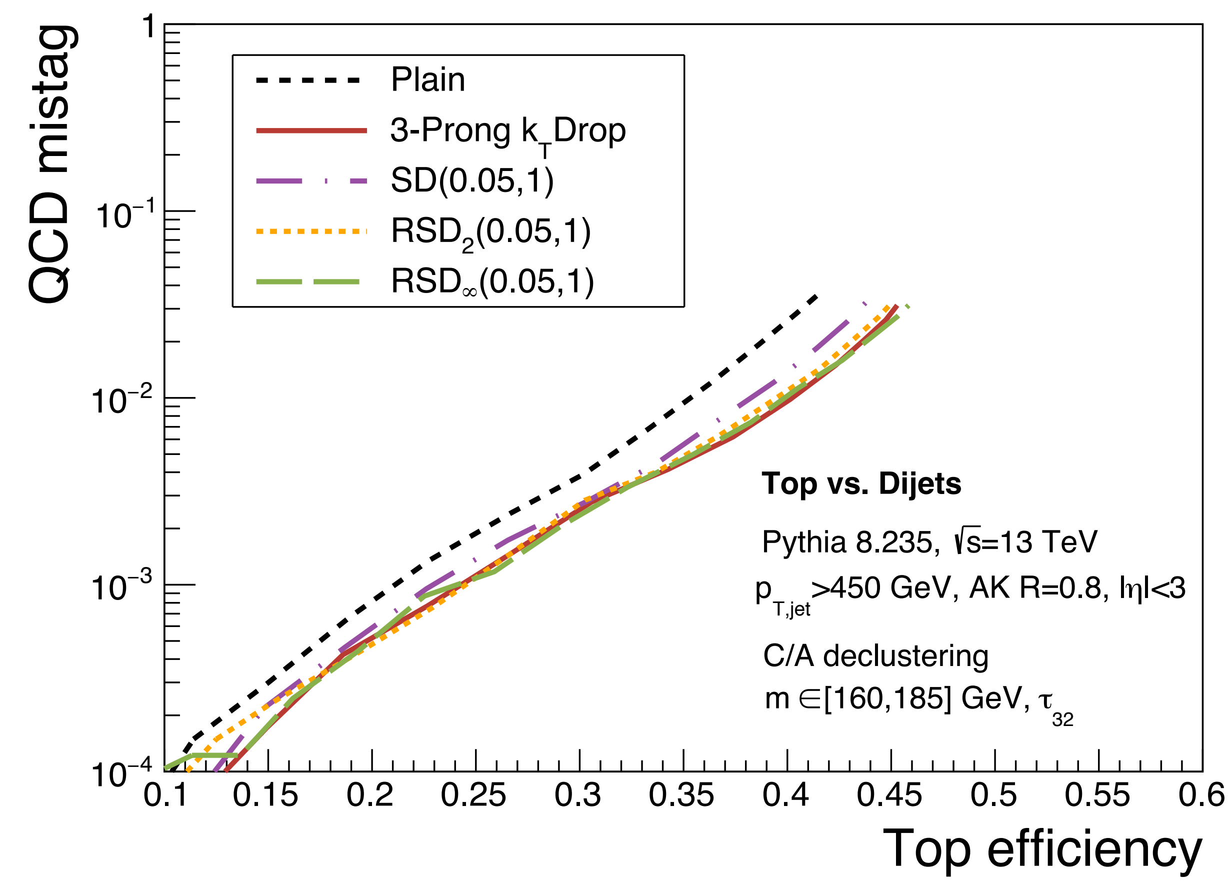


Mehtar-Tani *et al.* arXiv:1911.00375, 2005.07584

Dynamical grooming

- Recently applied to W and top tagging
- Good performance is found, comparable to recursive SoftDrop but with less fine-tuning





Mehtar-Tani *et al.* arXiv:1911.00375, 2005.07584

Color ring

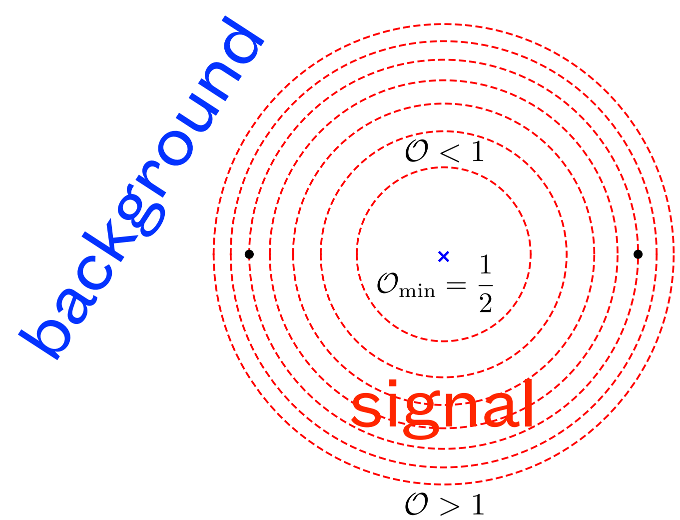
- Design a simple and versatile colour-singlet tagger looking at the behaviour of matrix elements in the soft and limit
- Signal (colour singlet) and background are typically characterised by different colour correlations (we look at the boosted limit of the dipole)

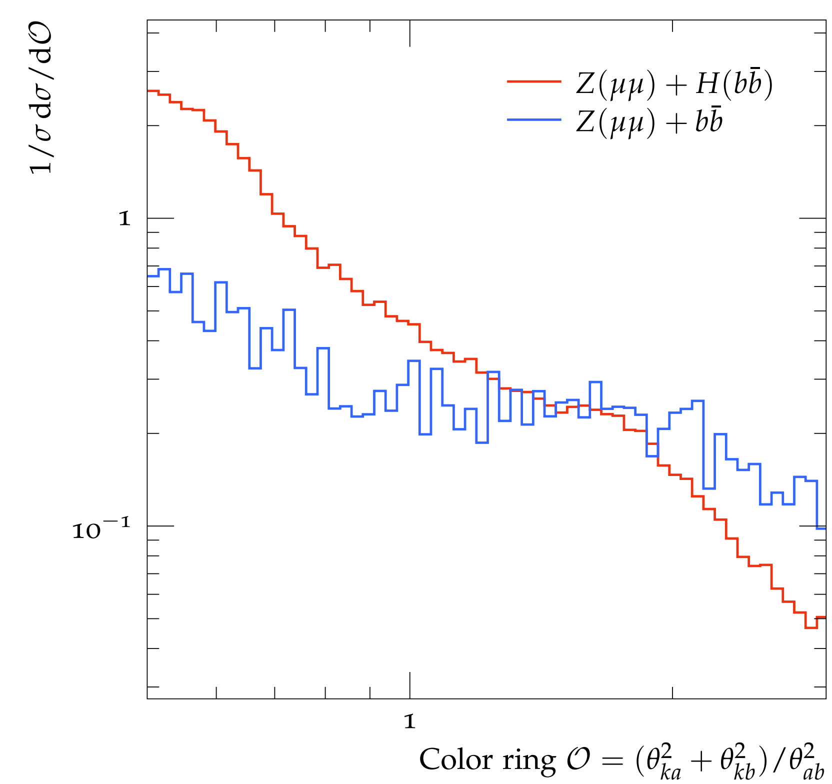
$$\frac{|\mathcal{M}_{\mathcal{B}}|^2}{|\mathcal{M}_{\mathcal{S}}|^2} = \frac{C_{\mathcal{B}}}{C_{\mathcal{S}}} + \frac{\widetilde{C}_{\mathcal{B}}}{C_{\mathcal{S}}}\left(\frac{(n_a\cdot\bar{n})(n_b\cdot k)}{(n_a\cdot n_b)(\bar{n}\cdot k)} + \frac{(n_b\cdot\bar{n})(n_a\cdot k)}{(n_a\cdot n_b)(\bar{n}\cdot k)}\right)$$

[up to monotonic functions]

$$\simeq \frac{1-\cos\theta_{ak}+1-\cos\theta_{bk}}{1-\cos\theta_{ab}}$$

$$\mathcal{O} = \frac{\theta_{ak}^2+\theta_{bk}^2}{\theta_{ab}^2}$$

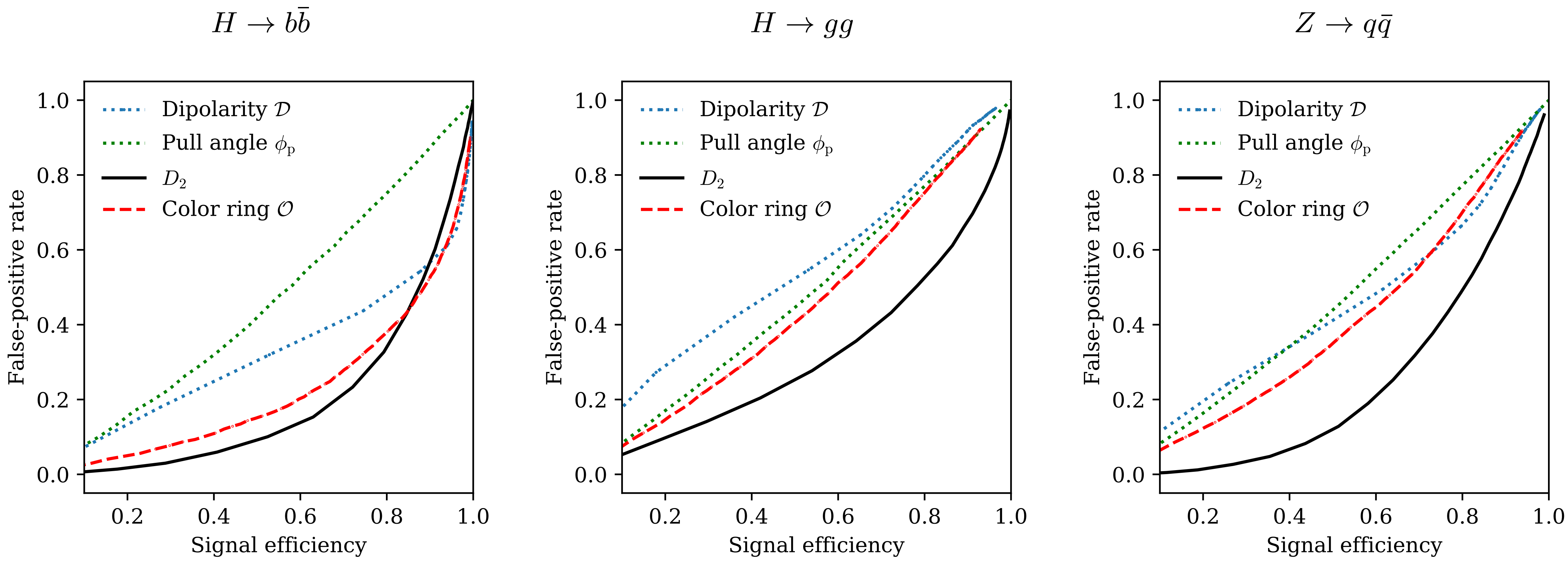




Buckely *et al.* arXiv:2006.10480

Color ring

- Good performance in distinguishing singlet vs octet but performs worse with more complicated (QCD) backgrounds



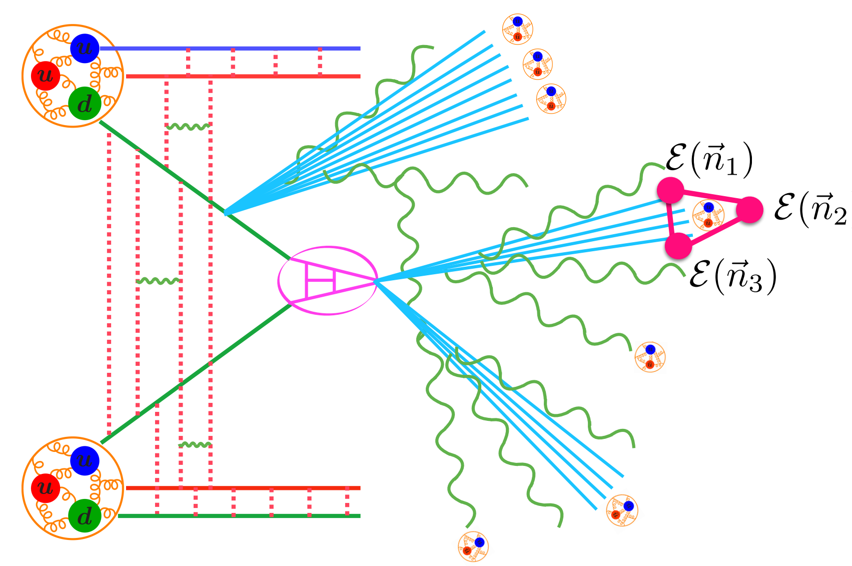
- Limitation probably due to modelling the extra (sub)jet with one soft gluon
- Interesting interplay with standard observable D_2

Buckely *et al.* arXiv:2006.10480

Jets with Energy Correlators

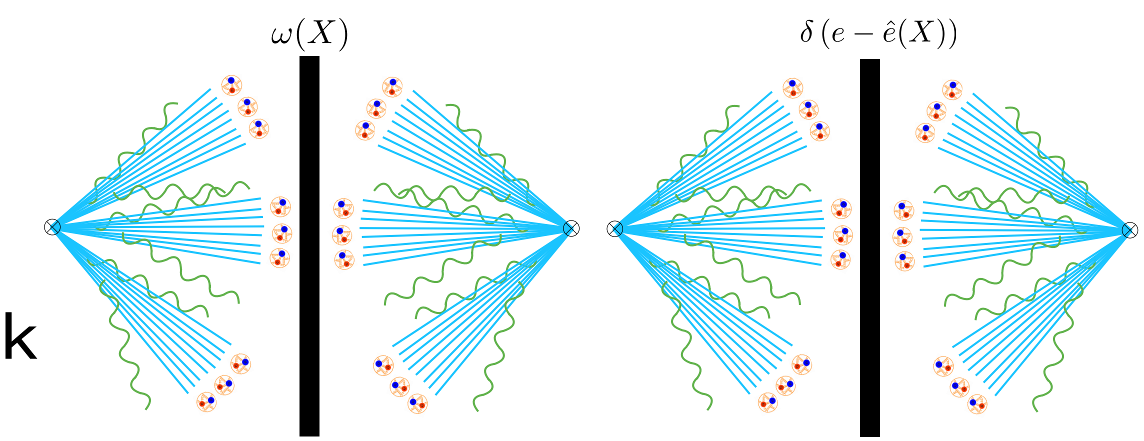
- Energy Flow Operators are natural objects in field theory

$$\mathcal{E}(\vec{n}) = \int_0^\infty dt \lim_{r\to\infty} r^2 n^i T_{0i}(t, r\vec{n})$$



- However, standard observables are not directly related to these operators (although moments are)

- Ian Moult will give more details in this talk
  Here I will only mention a few highlights



Chen *et al.* arXiv:2004.11381

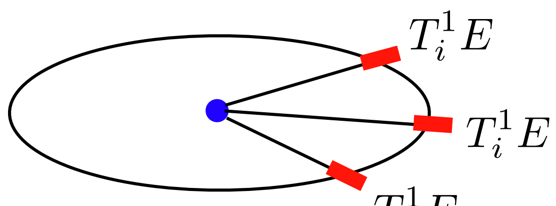
Jets with Energy Correlators

- To make contact with experiment, we would like to define observables that are distributions of one variable
- Starting from the two-point correlator, one can define consider higher points, integrating out the extra directions with some constraints
- This projected *N*-point correlators are an infinite family of jet observables
- We can go further and analytically continue in the complex plane *N*→ν
- Incorporating track information for these observables is much simpler than in the traditional case

$$\frac{d\sigma}{d\bar{e}} = \sum_N \int d\Pi_N \frac{d\bar{\sigma}_N}{d\Pi_N} \int \prod_{i=1}^{N} dx_i\, T_i(x_i)\delta\left[e - \hat{e}(\{x_i p_i^\mu\})\right]$$

vs

$$E_i \to \int dx_i\, x_i T_i(x_i) E_i = T_i^{(1)} E_i$$



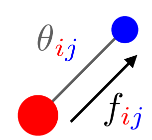
Chen *et al.* arXiv:2004.11381

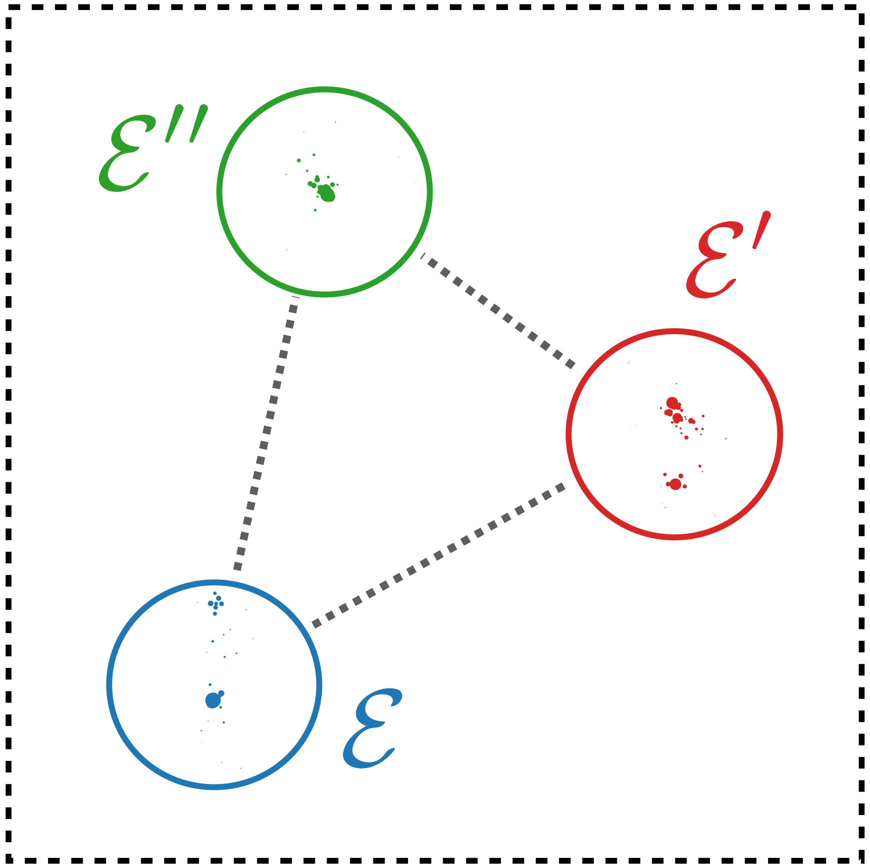
Geometry of events

- When are two collider events similar?
- Define a metric (~~Earth~~ Energy Moving Distance) that tells us how much work is required to move one event to another one

$$\mathrm{EMD}_{\beta,R}(\mathcal{E},\mathcal{E}') = \underbrace{\min_{\{f_{ij}\geq 0\}} \sum_i \sum_j f_{ij} \left(\frac{\theta_{ij}}{R}\right)^{\beta}}_{\text{Cost of optimal transport}} + \underbrace{\left|\sum_i E_i - \sum_j E'_j\right|}_{\text{Cost of energy creation}}$$

$$\underbrace{\sum_j f_{ij} \leq E_i, \quad \sum_i f_{ij} \leq E'_j, \quad \sum_{ij} f_{ij} = \min\left(\sum_i E_i, \sum_j E'_j\right)}_{\text{Capacity constraints to ensure proper transport}}$$





- Theorists are alway happy when we can phrase a problem using geometry

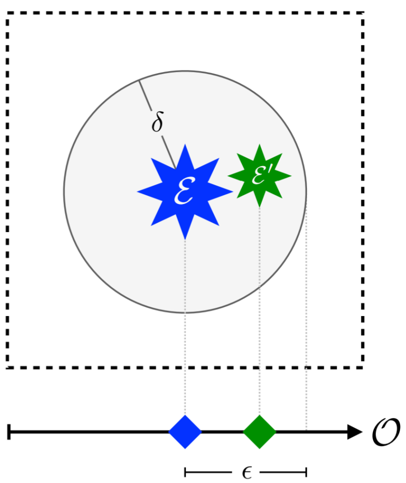
Komiske, Metodiev, Thaler, arXiv:2004.04159

Geometry of events

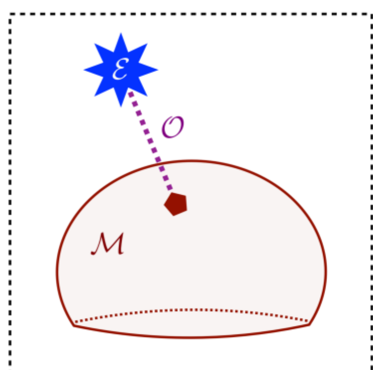
Six Decades of Collider Techniques as Geometry!

beautiful slide by Eric Metodiev

IRC Safety is smoothness in the space of events

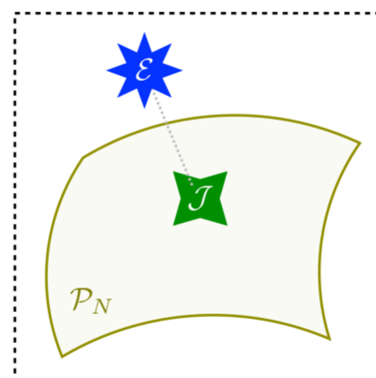


Event shapes are distances from events to manifolds.



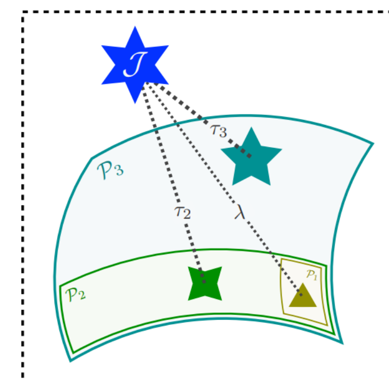
$\mathcal{O}(\mathcal{E}) = \min_{\mathcal{E}'\in\mathcal{M}} \mathrm{EMD}_{\beta,R}(\mathcal{E},\mathcal{E}')$

Jets are projections to few-particle manifolds.

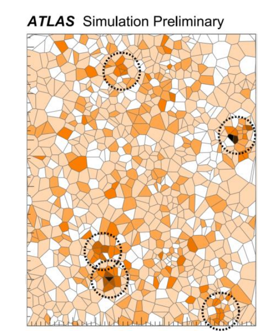


$\mathcal{J} = \operatorname{argmin}_{\mathcal{E}'\in\mathcal{P}_N} \mathrm{EMD}_{\beta,R}(\mathcal{E},\mathcal{E}')$

Substructure resolves emissions within the jet.



$\tau(\mathcal{J}) = \min_{\mathcal{E}'\in\mathcal{P}_N} \mathrm{EMD}_{\beta}(\mathcal{J},\mathcal{E}').$



Taming infinities — Event Shapes — Jet Algorithms — Jet Substructure — Pileup

1960 — 2020

1962-1964
Infrared Safety
[Kinoshita, JMP 1962]
[Lee, Nauenberg, PR 1964]

1977
Thrust, Sphericity
[Farhi, PRL 1977]
[Georgi, Machacek, PRL 1977]

1993
k_T jet clustering
[Ellis, Soper, PRD 1993]
[Catani, Dokshitzer, Seymour, Webber, NPB 1993]

1997-1998
C/A jet clustering
[Wobisch, Wengler, 1998]
[Doskhitzer, Leder, Moretti,Webber, JHEP 1997]

2010-2015
N-(sub)jettiness, XCone
[Stewart, Tackmann, Waalewijn, PRL 2010]
[Thaler, Van Tilburg, JHEP 2011]
[Stewart, Tackmann, Thaler, Vermilion, Wilkason, JHEP 2015]

2014-2019
Constituent Subtraction
[Berta, Spousta, Miller, Leitner, JHEP 2014]
[Berta, Masetti, Miller, Spousta, JHEP 2019]

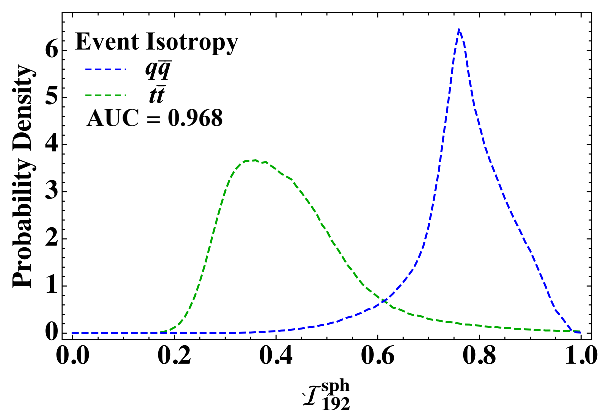
And many more!

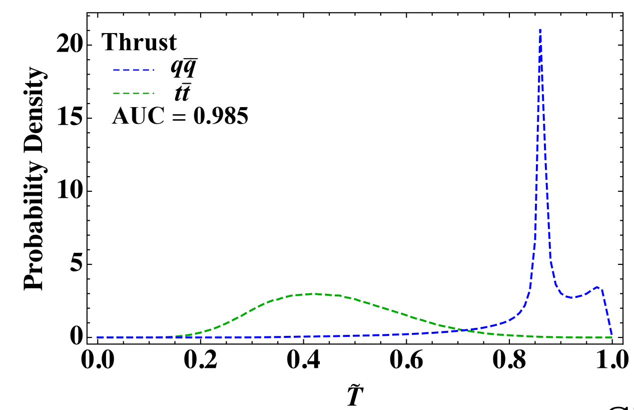
SIMONE MARZANI, UNIVERISITÀ DI GENOVA & INFN GENOVA

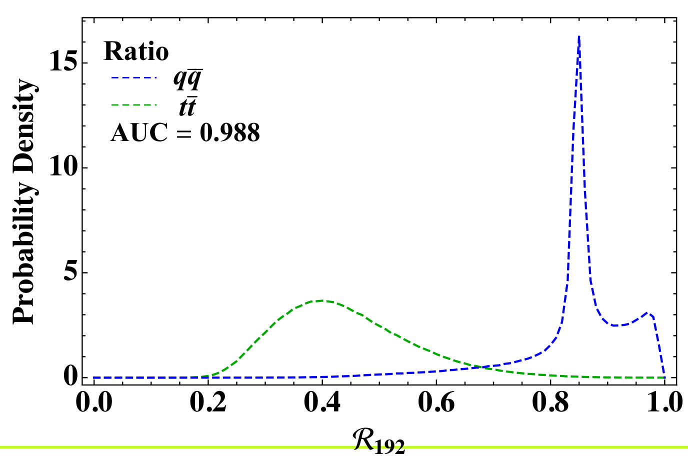
Komiske, Metodiev, Thaler, arXiv:2004.04159

Event Isotropy

- Geometrical interpretation of collider events is in its infancy but has already produced some fruits
- New observable called event isotropy directly based on the Energy Mover's Distance of an event from a uniform energy distribution







$$\mathcal{R}_n \equiv \frac{\mathcal{I}_n^{\text{sph}}}{\mathcal{I}_n^{\text{sph}} + (1 - \widetilde{T})}$$

see Cari Cesarotti video poster for details

Cesarotti and Thaler, arXiv:2004.06125

Opening the black box

Jet tagging made easy

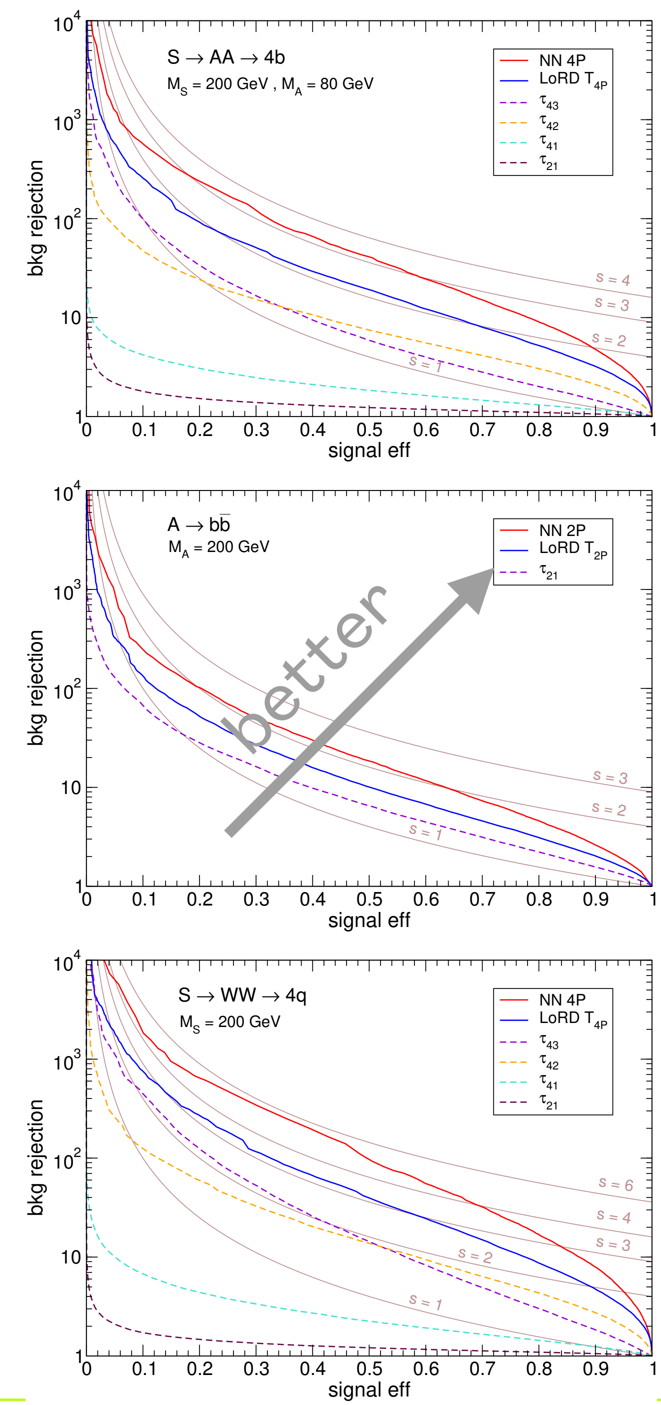
- Developing a set of multi-prong taggers exploiting N-subjettiness variables (see talks by A. Larkoski on q/g discrimination last year)

- The Authors develop here a phenomenological LoRD of Taggers which is build using and it's decorrelated from the mass

$$T = \bar{T} - b\rho - a\,,$$

$$\bar{T} = \sum_{n,\beta} c_n^{\beta} \log \tau_n^{(\beta)}$$

- the coefficients c^{β}_{n} are determined via logistic regression on simulated training samples



Aguilar-Saavedra and Zaldívar, arXiv:2002.12320

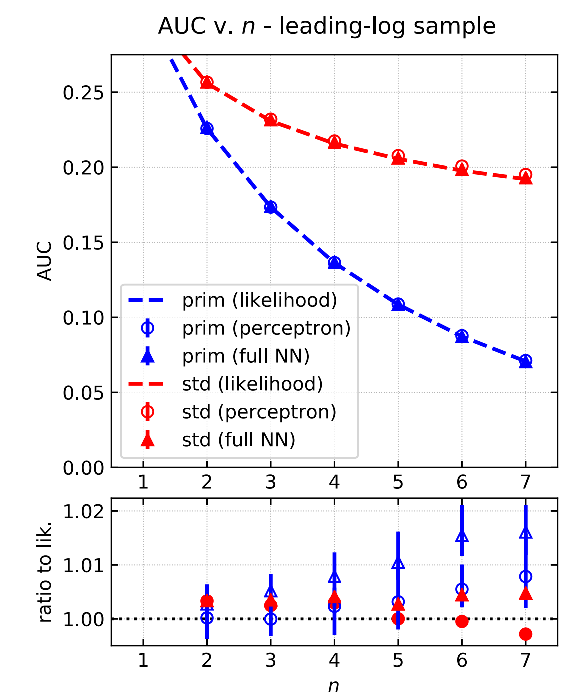
Towards analytics for NN

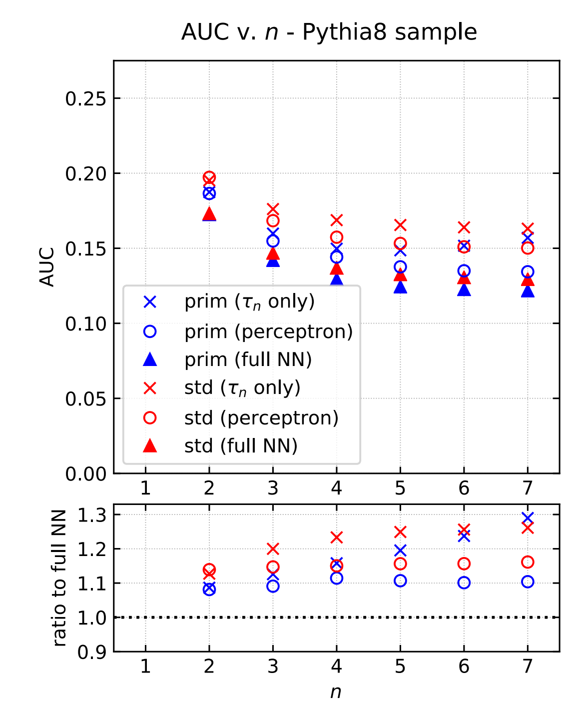
- Exploit expert-knowledge of the underlying theory (QCD) to study the behaviour of a simple network
- Focussing on the question of quark/gluon discrimination, a novel version of *N-subjettiness*, which at leading-log is only sensitive to primary splittings

$$\mathcal{T}_N = \sum_{i=N}^{m} z_i \left(\frac{\Delta_i}{R_0}\right)^{\beta}$$

- If one measure n such variables, the optimal discriminant at leading log is just a cut on the last one

$$\mathcal{L}^{\rm LL} = \left(\frac{C_A}{C_F}\right)^{n} \exp\left[-(C_A - C_F)\mathcal{R}(\mathcal{T}_n)\right]$$



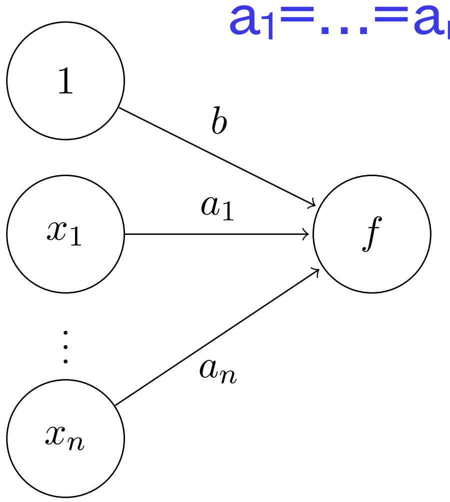


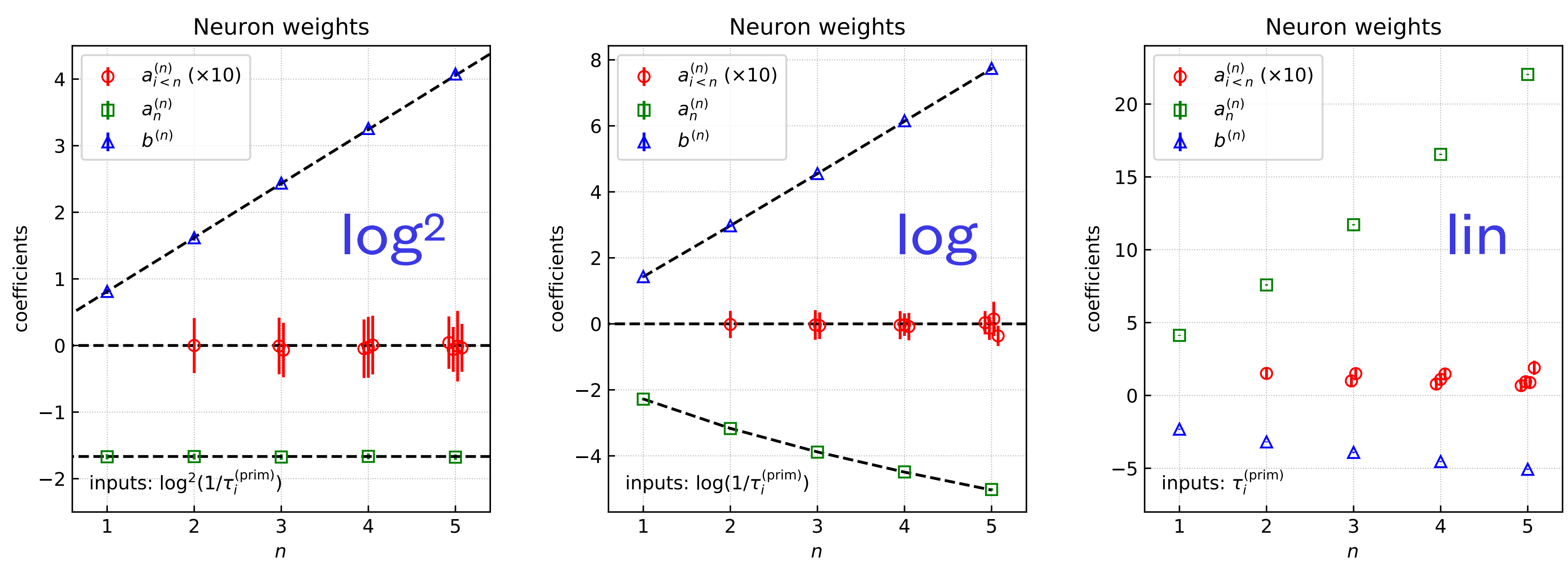
Kasieczka *et al.* arXiv:2007.04319

Towards analytics for NN

- The behaviour of the system and the optimal discriminant are so simple that we can ask ourselves whether a one-neuron network can achieve it
- We can determine (semi) analytically whether such simple network reaches optimal performance by looking for the cost function minima
- Remarkably, it depends on the functional form of the inputs!

leading-log optimal is $a_1=\ldots=a_{n-1}=0$

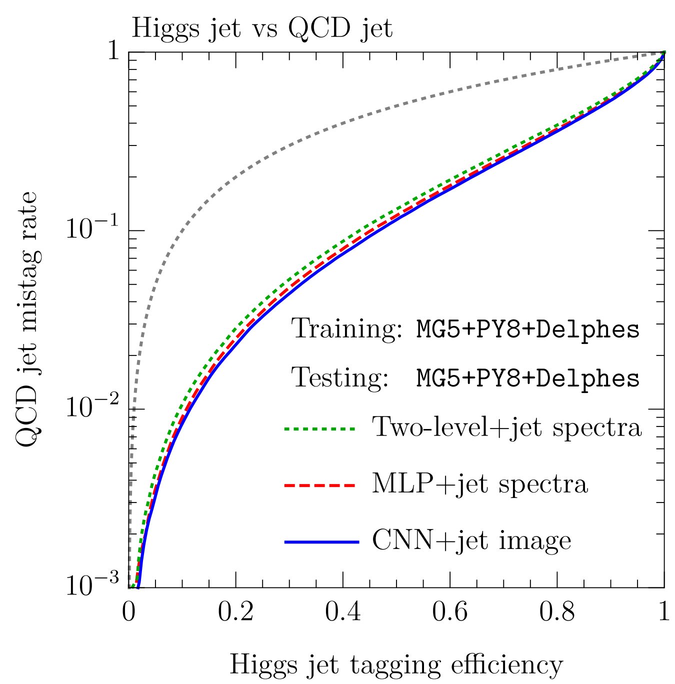




see Giovanni Stagnitto video poster for details

Jet morphology

- Classifiers exploiting convolutional NN and jet images typically outperform standard top taggers (a detailed comparison can be found here)
- What is a CNN-based top tagger learning?
- It has been argued that most of information that these classifiers exploit come from IRC safe observables
- For Higgs tagging against QCD a NN classifier fed with IRC safe two-point EC performs similarly to more complex CNN
- This is not the case for top tagging



Chakraborty *et al.* arXiv:2003.11787

Jet morphology

- What is the role of IRC unsafe (counting) observables?
- Beyond counting: Minkowski functionals (well-developed integral geometry)

Chakraborty *et al.* arXiv:2003.11787

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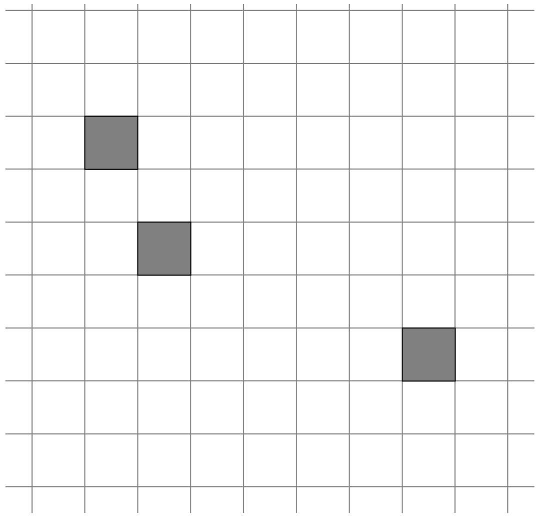

$N^{(0)}$

1. Start with pixels with finite energy deposition $N^{(0)}$

Chakraborty *et al.* arXiv:2003.11787

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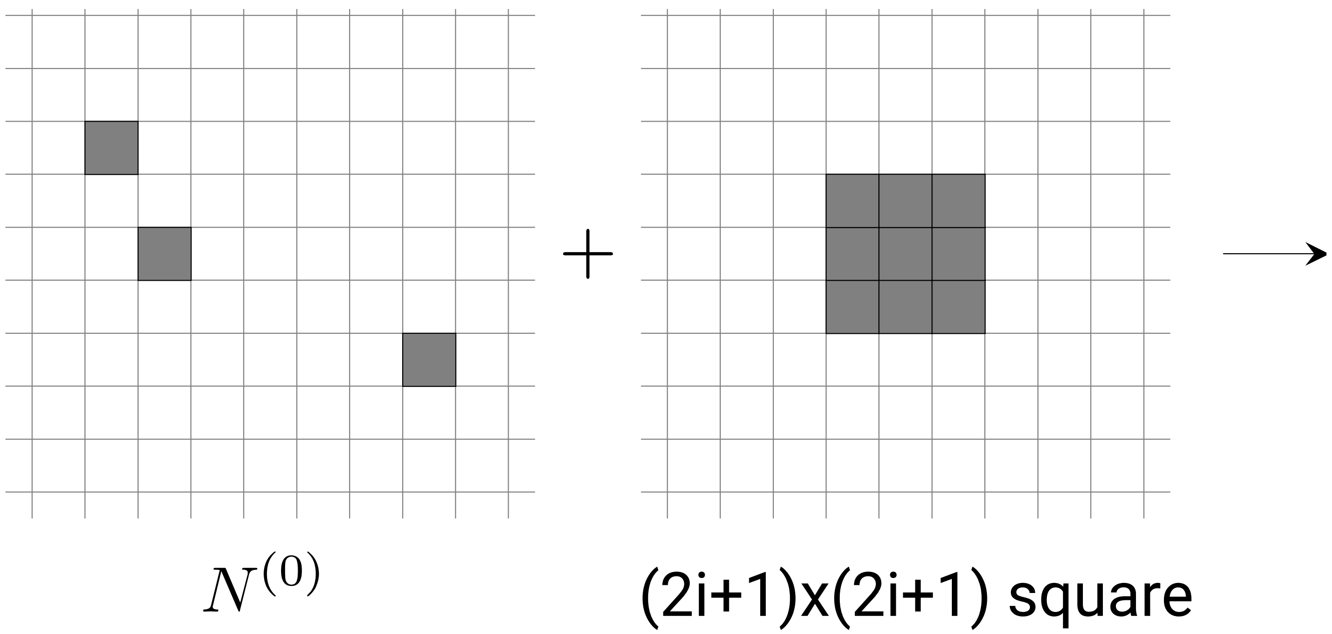

1. Start with pixels with finite energy deposition $N^{(0)}$
2. Count the number of pixels $N^{(0)}$ in a (2 i+1)x(2i+1) squares around each original pixel

Chakraborty *et al.* arXiv:2003.11787

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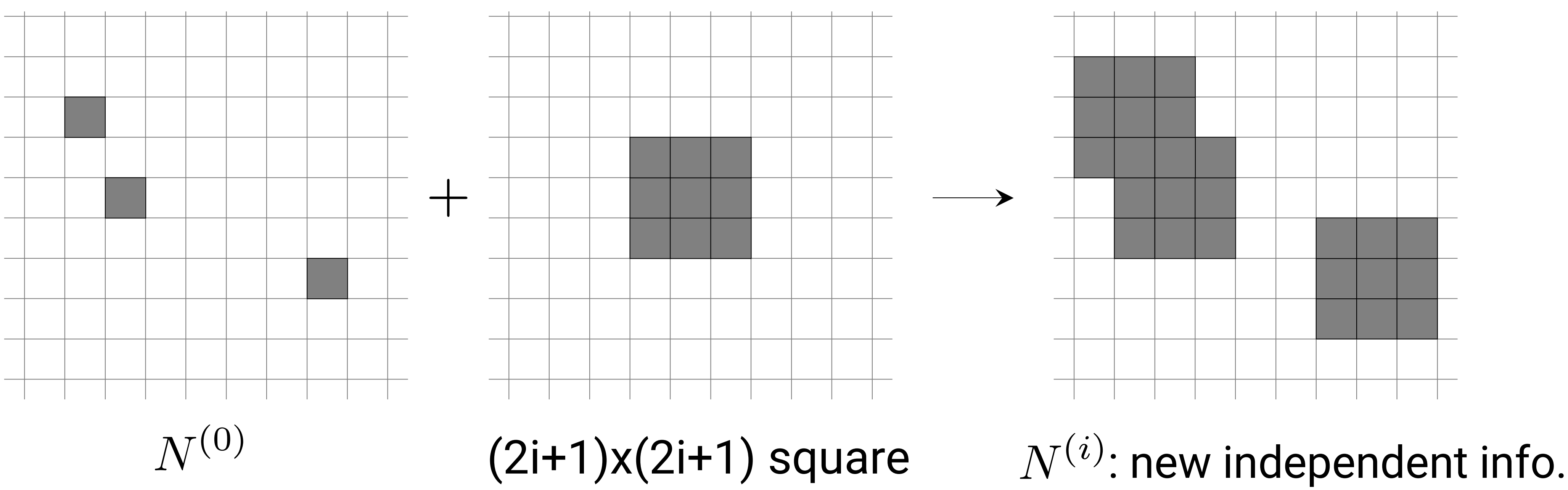
- Beyond counting: Minkowski functionals (well-developed integral geometry)

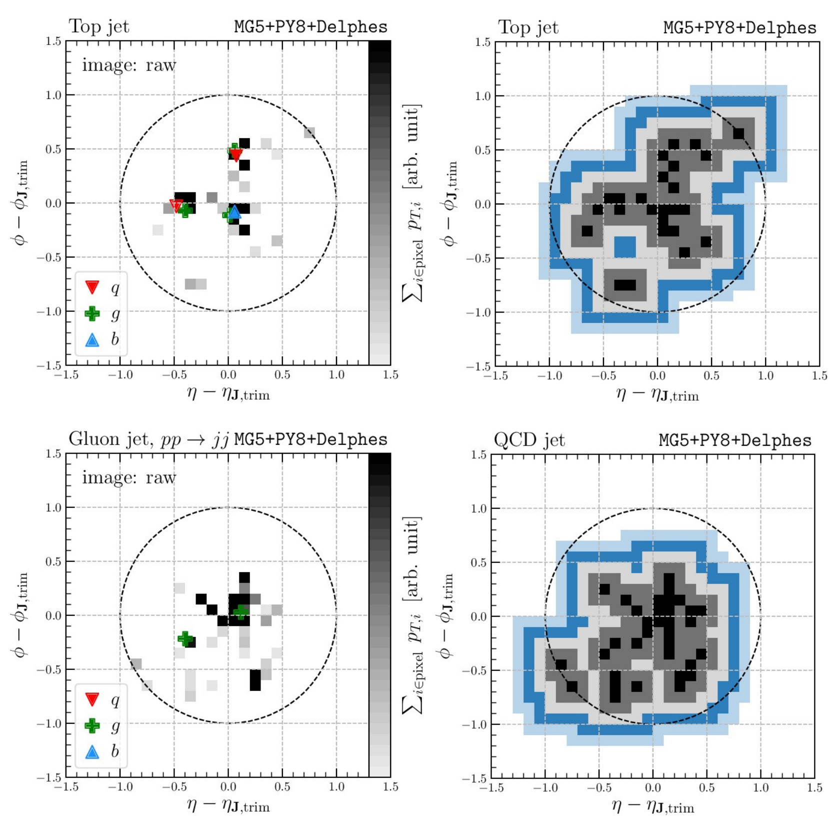


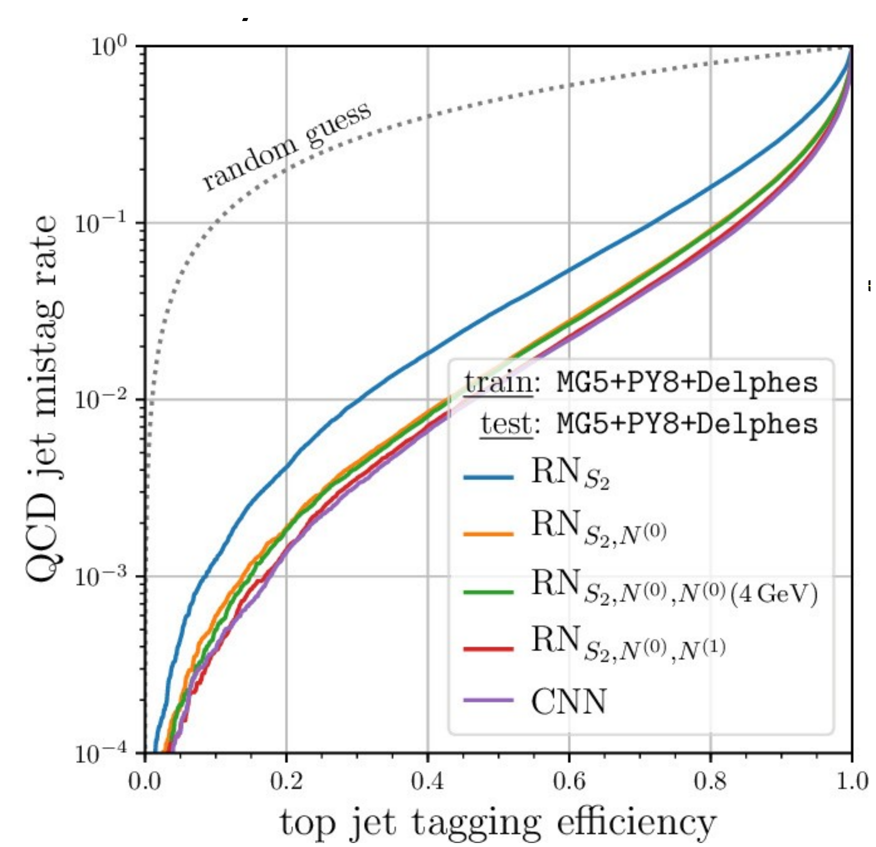
1. Start with pixels with finite energy deposition $N^{(0)}$
2. Count the number of pixels $N^{(0)}$ in a (2 i+1)x(2i+1) squares around each original pixel
3. The sequence of $N^{(i)}$ gives a quantitative description of the spatial distribution of pixels in the jet

Chakraborty *et al.* arXiv:2003.11787

Jet morphology

- A top tagger is build using IRC safe (two-point EC) and IRC unsafe (Minkowski sequence) inputs to a NN





- The use of Minkowski sequence nicely fills the gap between the performance of the NN purely based on two-point EC and the CNN

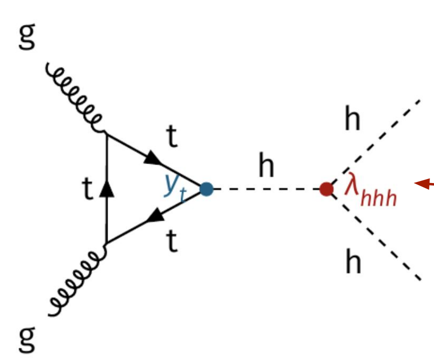
Chakraborty *et al.* arXiv:2003.11787

Looking ahead

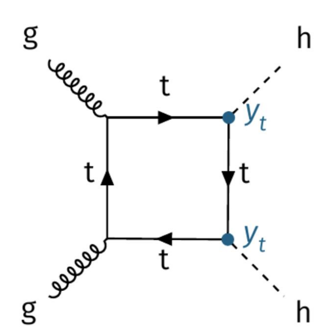
Higgs tagging @ HL-LHC

- Exposing the Higgs trilinear coupling is one of the main goal of the High-Luminosity LHC

- Incredibly challenging, it's even worse in the SM than you could have imagined because of destructive interference at Born level (calculating higher-order corrections is a fascinating topic… a story for another time)



Higgs self-coupling only in triangle



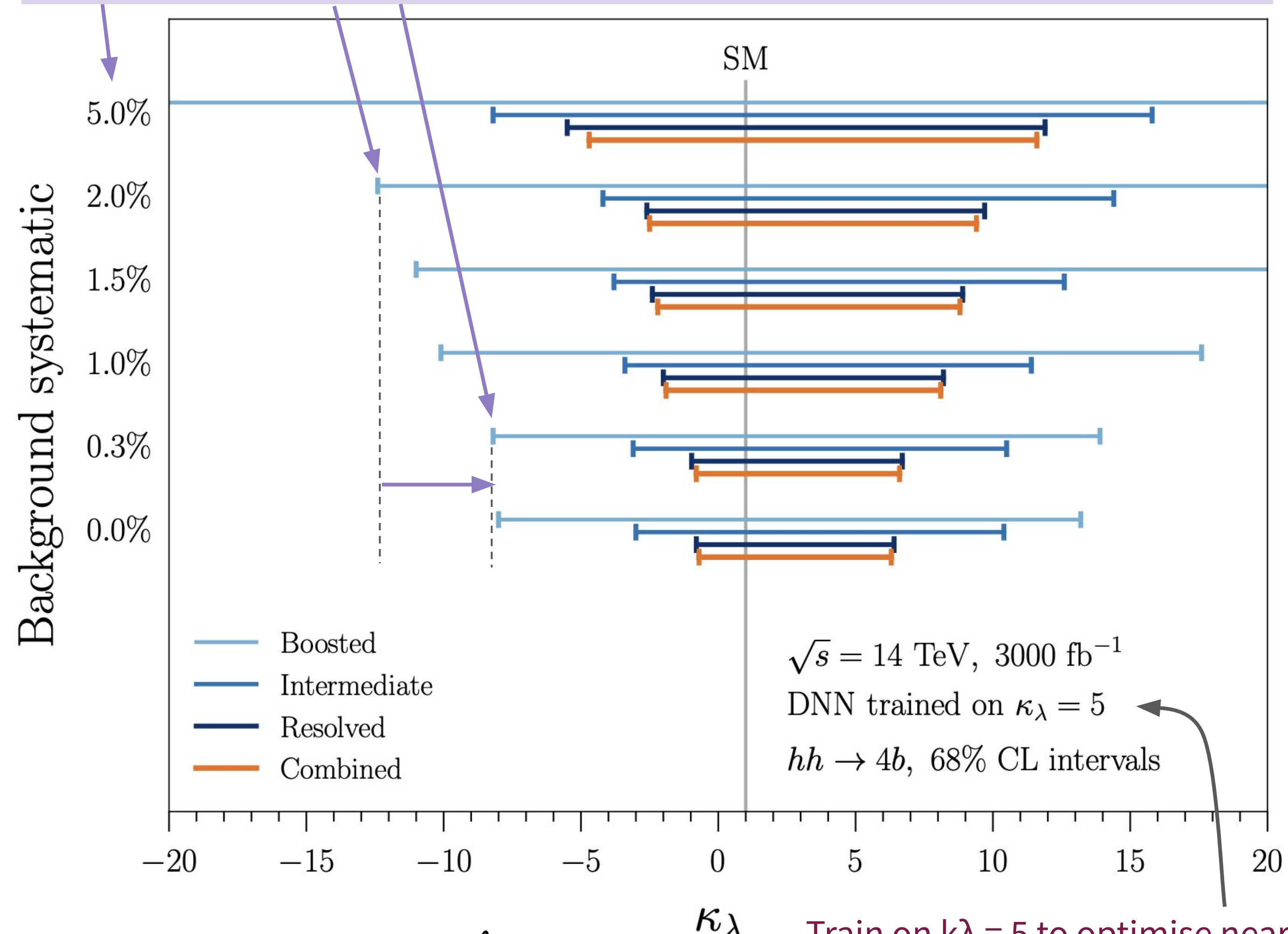
But experimentally can only see | triangle + box |^2

- Higgs pair production cross-section 40fb, which implies 10^5 di-Higgs events at HL-LHC but we have to fight a formidable multi jet background

Amacker, *et al.* arXiv:2004.04240

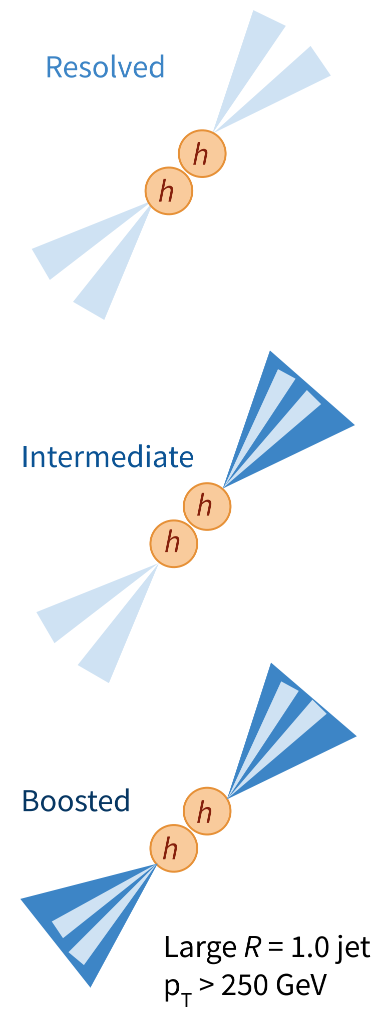
Higgs tagging @ HL-LHC

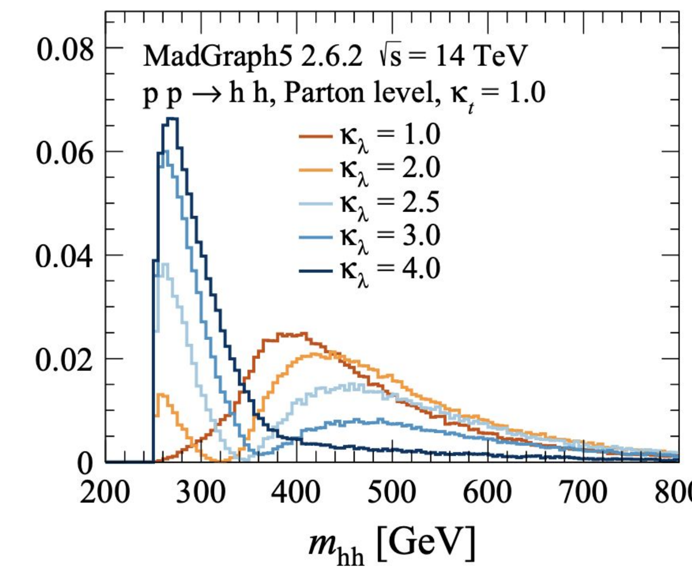
How we can control multijet background systematics
with boosted Higgs tagging is challenging but important open question

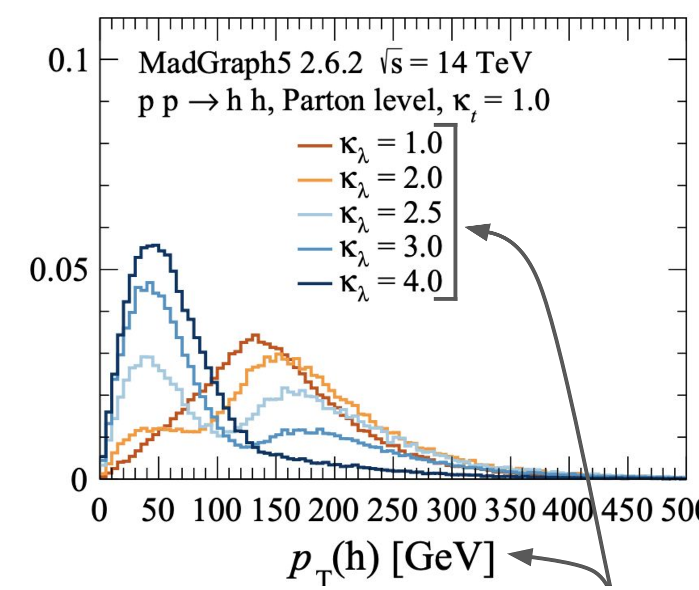


Train on kλ = 5 to optimise near sensitivity boundary

$$\kappa_\lambda = \frac{\lambda_{\mathrm{BSM}}}{\lambda_{\mathrm{SM}}}$$







interference removed
in BSM scenarios

Amacker, *et al.* arXiv:2004.04240

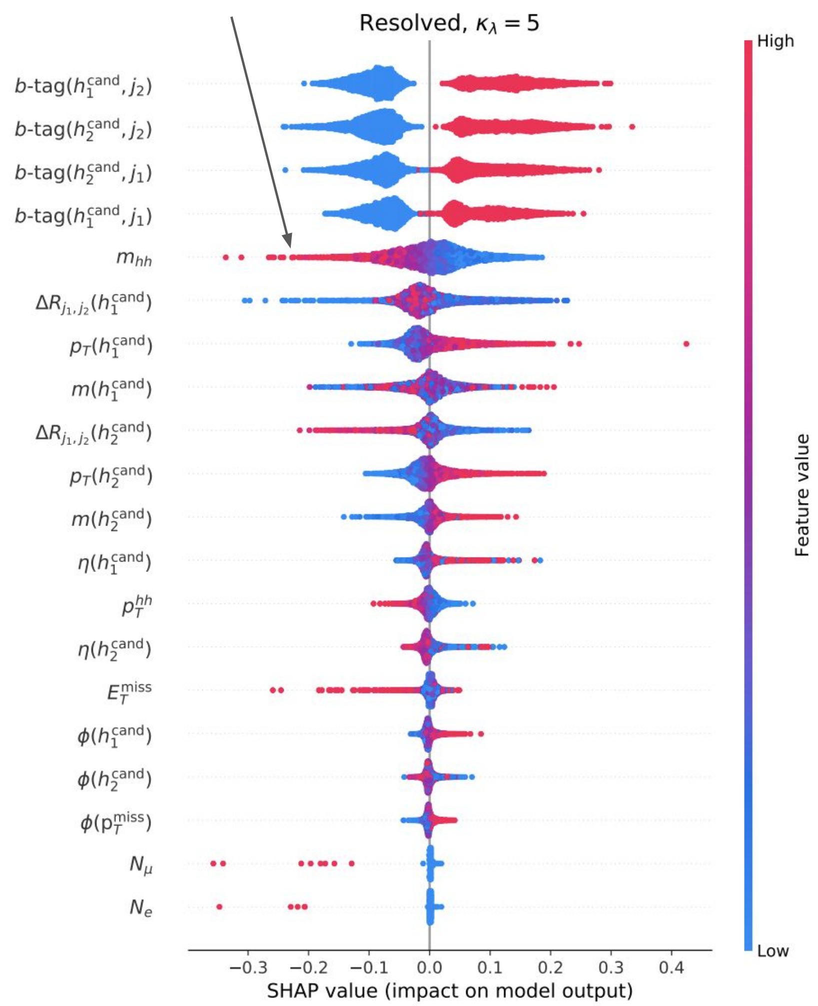
Higgs tagging @ HL-LHC

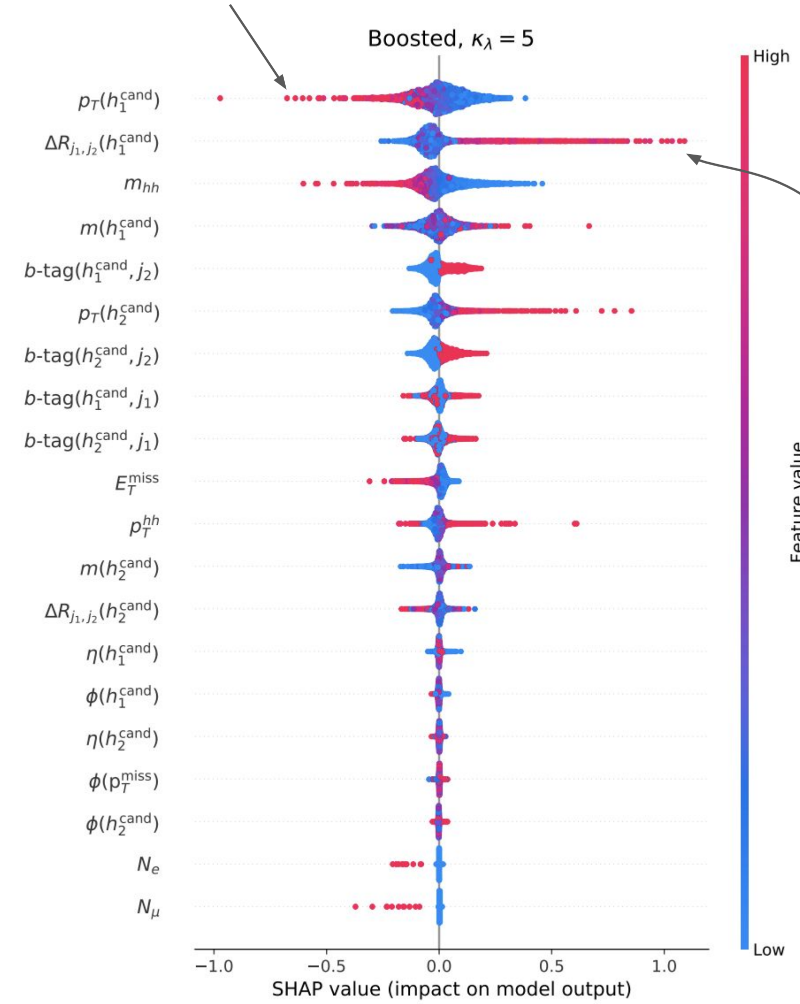
- What is the machine learning? Using the SHapley Additive exPlanations framework

Lower m(hh) leads to higher signal score

Higgs boost important in high boost regimes

Variables fed in to DNN ranked in decreasing order of impact





More positive impact on DNN signal score

Angular separation of sub-jets powerful

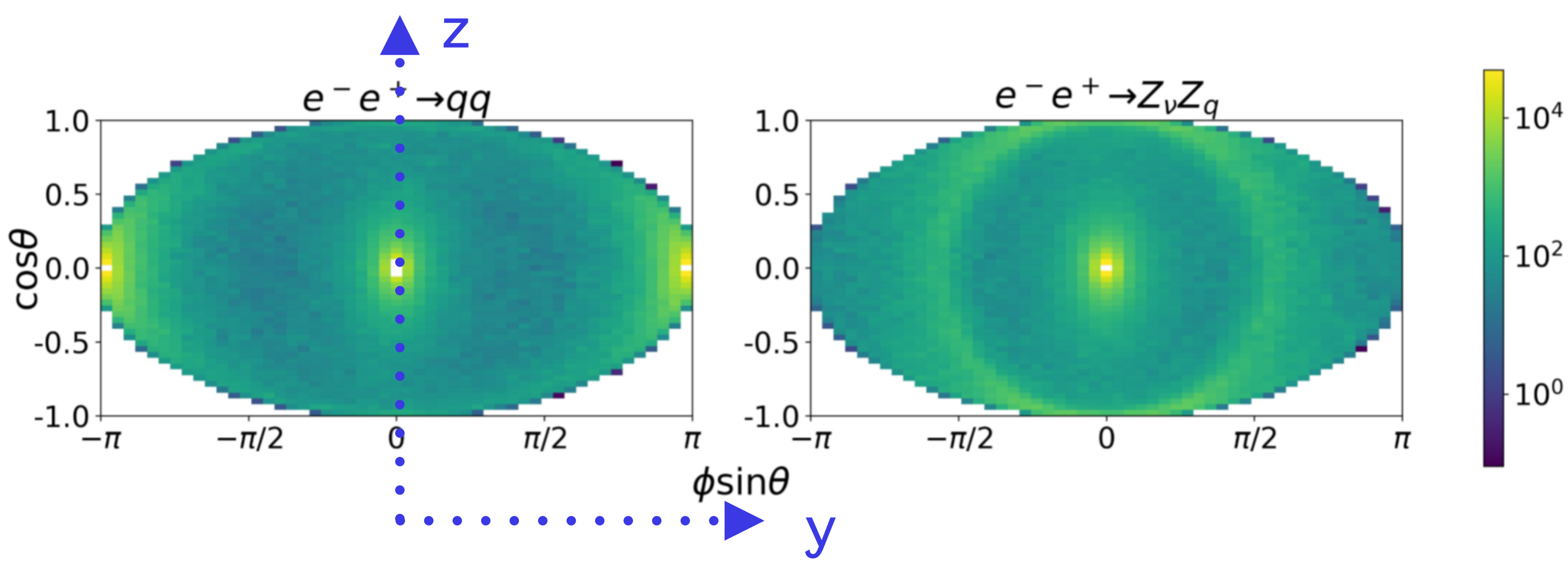
Amacker, *et al.* arXiv:2004.04240

Future e^+e^- colliders

- Issues with jet clustering:
  - information distortion: hadrons from different Z clustered in the same jet
  - information loss: jet algorithms map particles momenta into a lower-dimensional space
- at lepton colliders we can successfully use event shapes that avoid jet clustering

cumulative Mollweide projection (10^4 events):

- z axis along the beams
- x axis in the direction of the most energetic particles

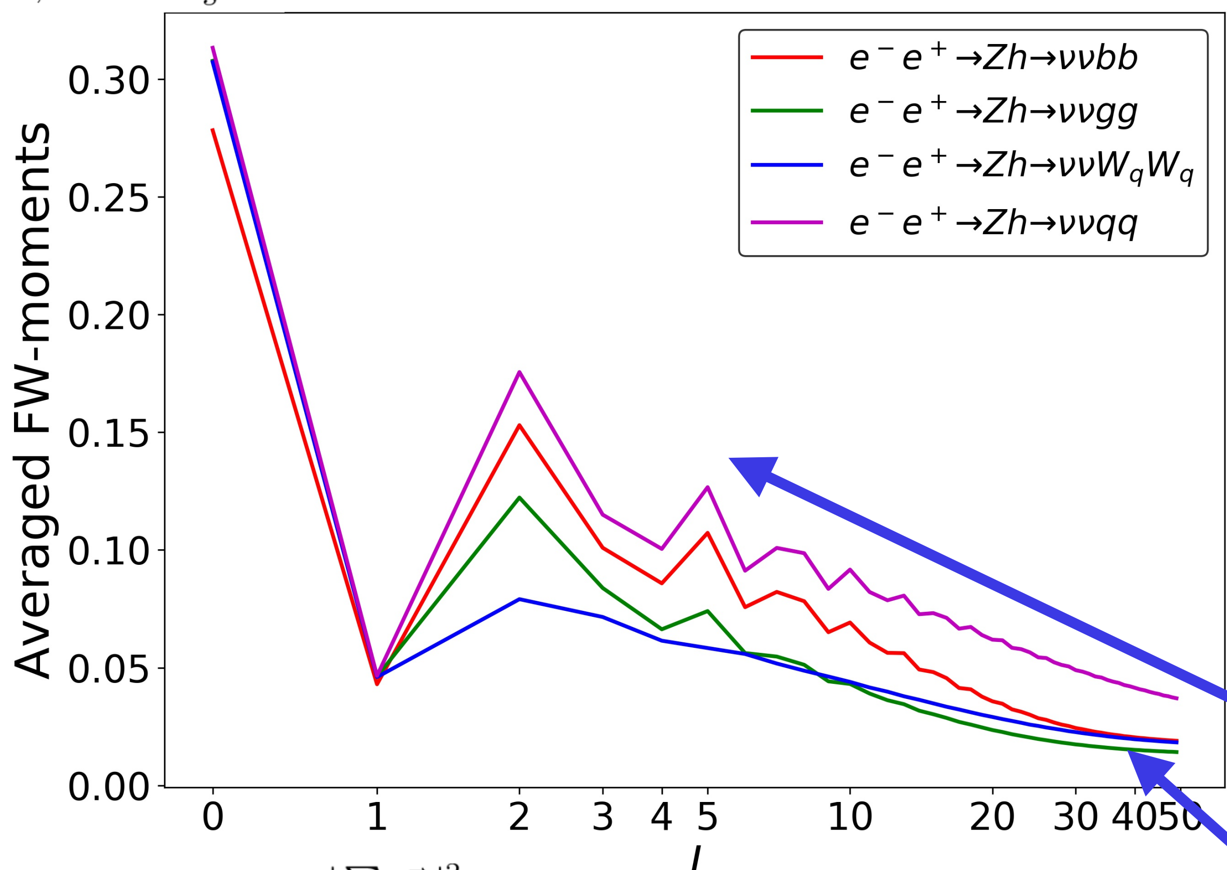


Li, *et al.* arXiv:2004.15013

Future e⁺e⁻ colliders

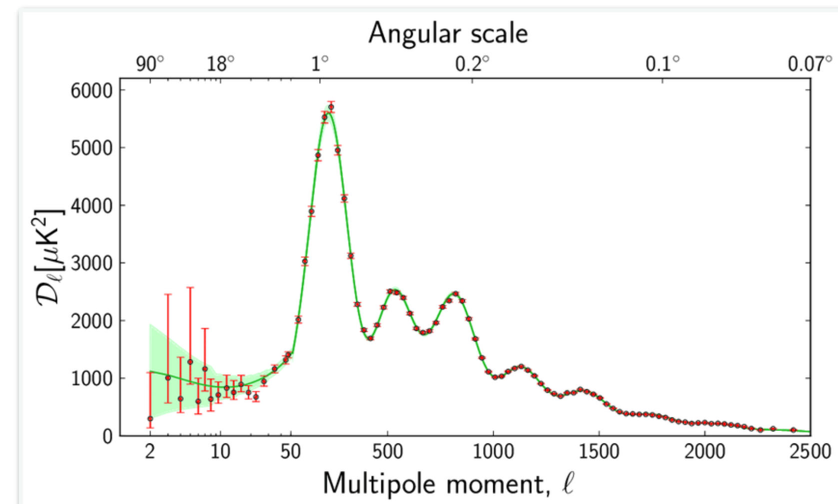
- Fox-Wolfram moments of the energy distribution are considered
- evident analogies with CMB power spectrum

$$H_{EE;0} = \frac{(\sum_i E_i)^2}{s}$$



$$H_{EE;1} = \frac{|\sum_i \vec{p}_i|^2}{s}$$

$$H_{EE;l} = \sum_{ij} \frac{E_i E_j}{s} P_l(\cos \Omega_{ij})$$



- physics at characteristic scales shows up as “acoustic peaks”
- partonic channels
- tail sensitive to hadronisation

Li, *et al.* arXiv:2004.15013

Future e+e- colliders

- Train a Deep Neural Network with different strategies, involving jets, track or images
- study on the achievable precision for the Higgs width for collisions at 240 GeV and $5ab^{-1}$

	Jet	Jet+FW	Jet+FW+track	Image	Image+track
Precision (%)	J1	J2	J3	E1	E2
$\sigma(Z_\nu h_{W_{lq}})$	1.7 (1.6)	1.4 (1.6)	1.5 (1.6)	1.5 (1.4)	1.5 (1.4)
$\sigma(Z_\nu h_{W_{qq}})$	1.6 (1.6)	1.2 (1.2)	1.1 (1.1)	1.1 (1.1)	1.1 (1.1)
$\sigma(\nu\nu h_h)$	2.8 (2.7)	1.8 (1.7)	1.9 (1.8)	1.4 (1.4)	1.3 (1.3)
Γ_h	$3.2^{+0.9}_{-0.3}$ (3.1)	$2.3^{+0.7}_{-0.2}$ (2.2)	$2.3^{+0.7}_{-0.2}$ (2.3)	$1.9^{+0.5}_{-0.1}$ (1.9)	$1.9^{+0.4}_{-0.1}$ (1.9)

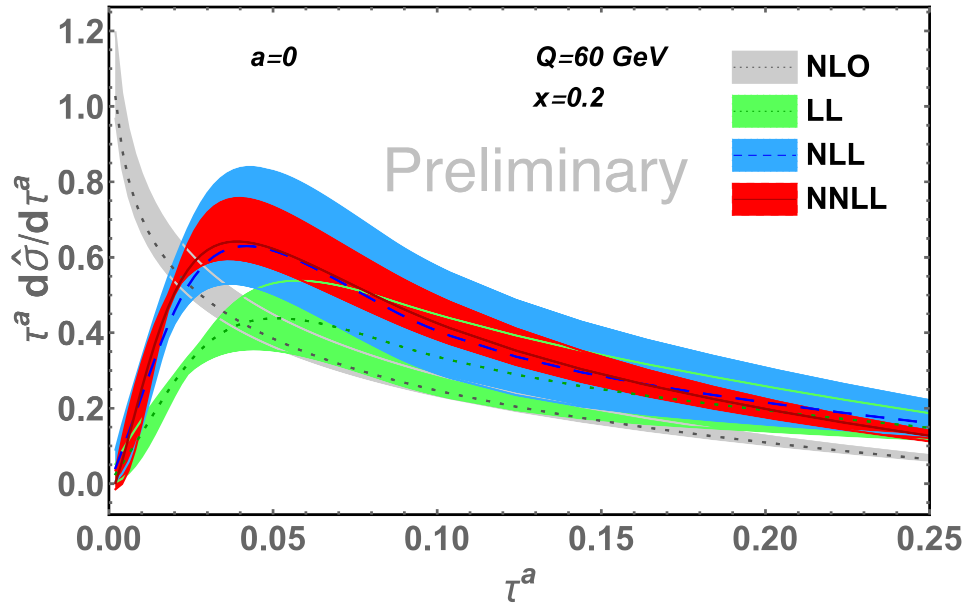
- the precision achieved is robust against the rescaling of detector resolutions and different detector templates

Li, *et al.* arXiv:2004.15013

Future ep colliders

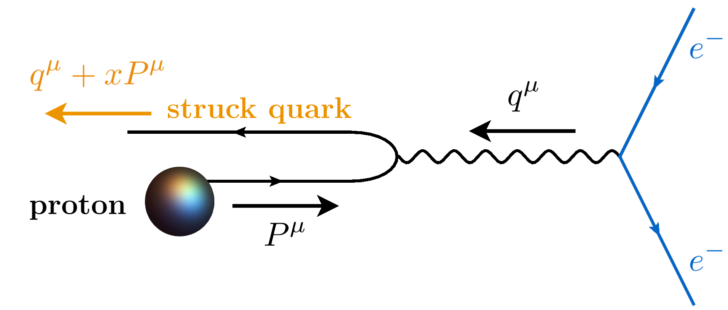
- Our understanding our QCD is founded on deep-inelastic scattering experiments
- HERA ceased operations in 2007, the year before what we think as the jet substructure revolution
- We must apply (or rethink) what we have learned about jets in pp collisions to be ready for the Electron Ion Collider (EIC)
- For instance, jet angularities in DIS

$$\tau_a = \frac{2}{Q^2} \sum_{i \varepsilon \mathscr{X}} min\left\{ (q_B.p_i) \left(\frac{q_B.p_i}{q_J.p_i} \right)^{-a/2}, (q_J.p_i) \left(\frac{q_J.p_i}{q_B.p_i} \right)^{-a/2} \right\}$$

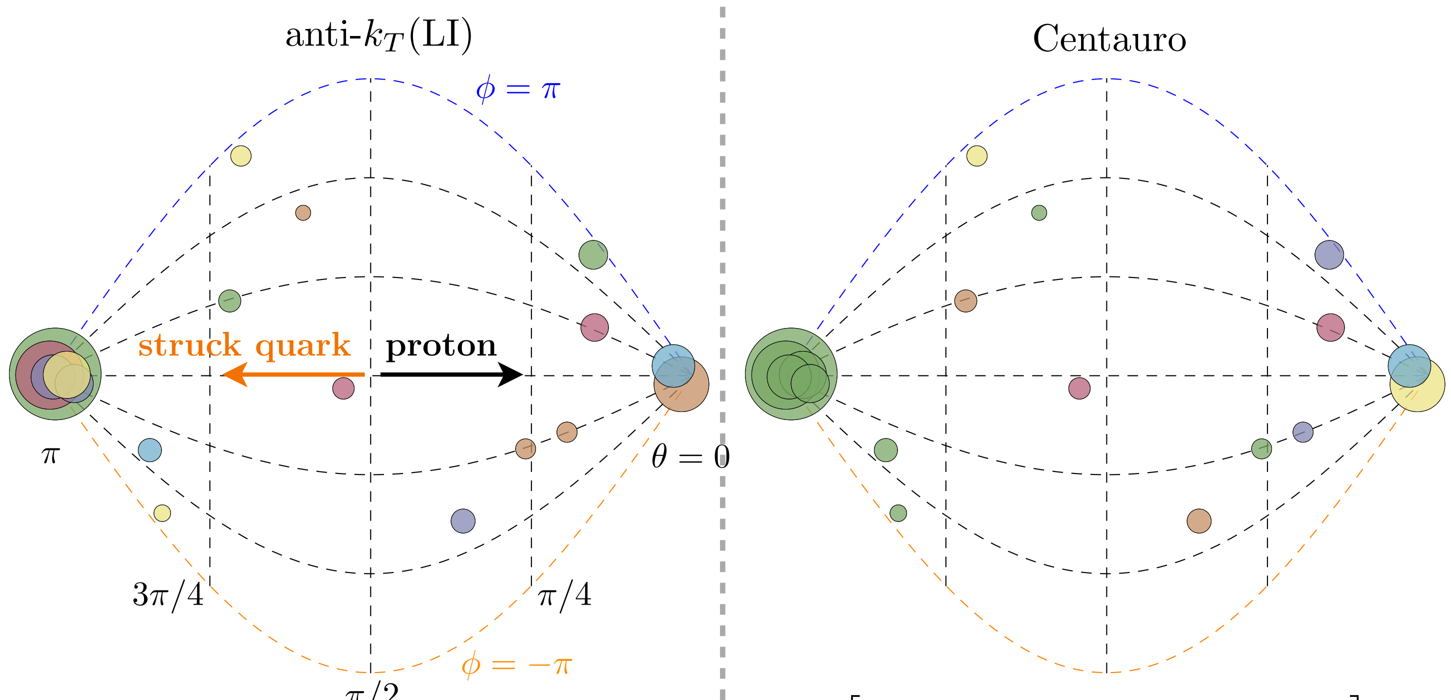


Kang and Maji arXiv:1912.10656

Future ep colliders



- The Breit frame plays a central role in DIS studies
- Standard pp clustering algorithms not suited for objects at infinity rapidities
- New Centauro algorithm



$$d_{ij} = \min(p_{Ti}^{2p}, p_{Tj}^{2p})\Delta R_{ij}^2/R^2$$
$$d_{iB} = p_{Ti}^{2p}$$

$$d_{ij} = \left[(\Delta f_{ij})^2 + 2 f_i f_j (1 - \cos\Delta\phi_{ij})\right]/R^2$$
$$d_{iB} = 1$$

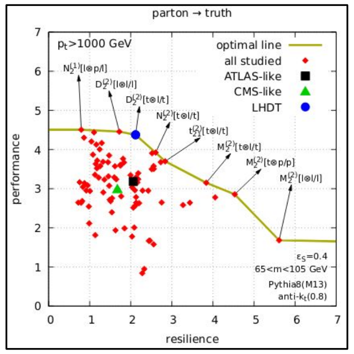
$$d_{ij} = \min(E_i^{2p}, E_j^{2p})\frac{1 - c_{ij}}{1 - c_R}$$
$$d_{iB} = E_i^{2p}$$

Arratia *et al.* arXiv:2006.10751

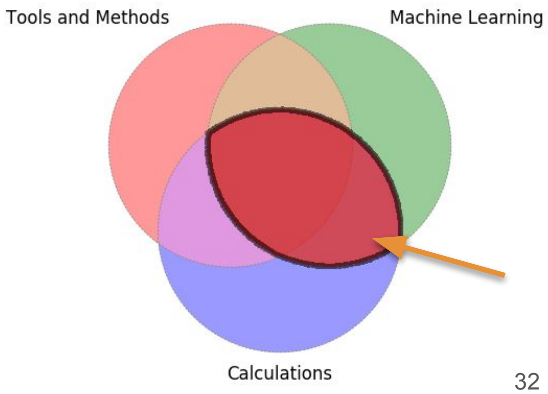
Conclusions

My hopes for 2020

- Can we come up with quantifiable metrics beyond performance for comparisons of different ML algorithms? Different metrics for different applications?
- Is it possible to find ways to leverage performance gains from ML methods in calculable and robust frameworks?
- Can we perform precision calculations for other key jet substructure observables? And compare these calculations with measurements?
- Is it possible to improve non-perturbative modelling, e.g. through improvements of perturbative component of parton showers?



[arXiv:1803.07977]



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- If a problem can be framed in the “right” way, ML can lead to real insights - but it should be primarily viewed as tool!
- Precision calculations of jet substructure observables will be critical for future measurements, notably for α_s extractions
- See you in Hamburg!

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- “Robustness”: how much a ML tool performance depends on physics we do (not) control, e.g. leading-log, PS at parton level, PS at hadron level
- New taggers, groomers and observables are often inspired by theory, i.e. they are derived having both robustness and performance in mind

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Points for discussion

- Should we do what we know we are good at?
  - calculable observables have tremendous value on their own
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- Should we try new ways of thinking about jets?
  - it seems to me that a recurrent theme in the past year has been *geometry* (not new for jets, but it's seen a resurgence)
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Special thanks to: Jesse Liu, Lingfeng Li, Sung Hak Lim, Eric Metodiev, Alba Soto Ontoso for providing inputs and materials for this talk.

I hope I was able to represent their work in a decent way and I'm sure ***they*** will be happy to answer any question you might have

Thank you very much!