JET SUBSTRUCTURE

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Standard Model at the LHC 2019

Zurich 23rd-26th April 2019

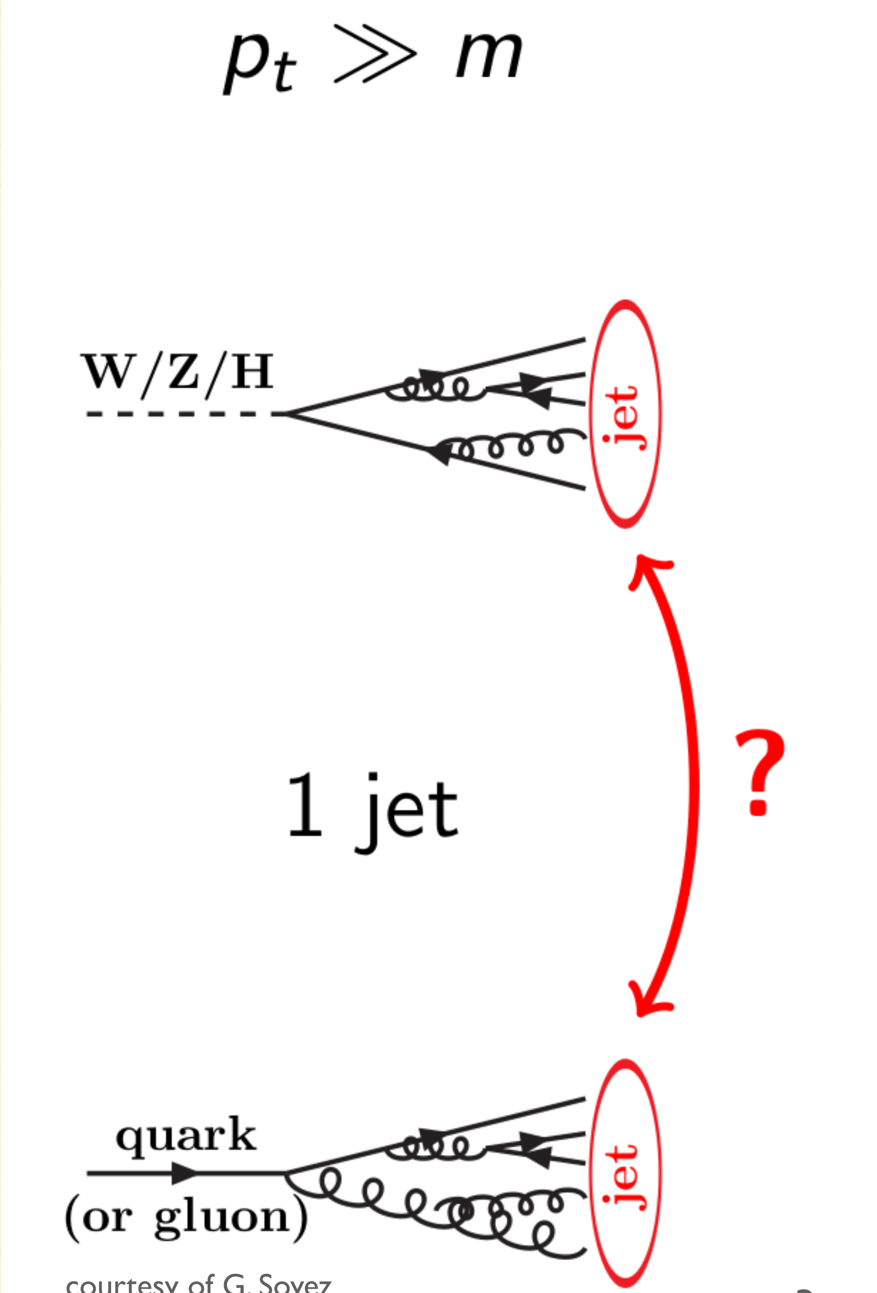
OUTLINE

- Jet substructure: where we are
- Machine-learning for jet physics
- Pen-and-paper learning for jet physics
- Conclusions and Open Questions

from the Organisers: "*The focus of your presentation should be on things we don't understand rather than things we already understand…select subtopics of high interest and discuss them more extensively… instead of trying to be fully comprehensive*"

LOOKING INSIDE JETS

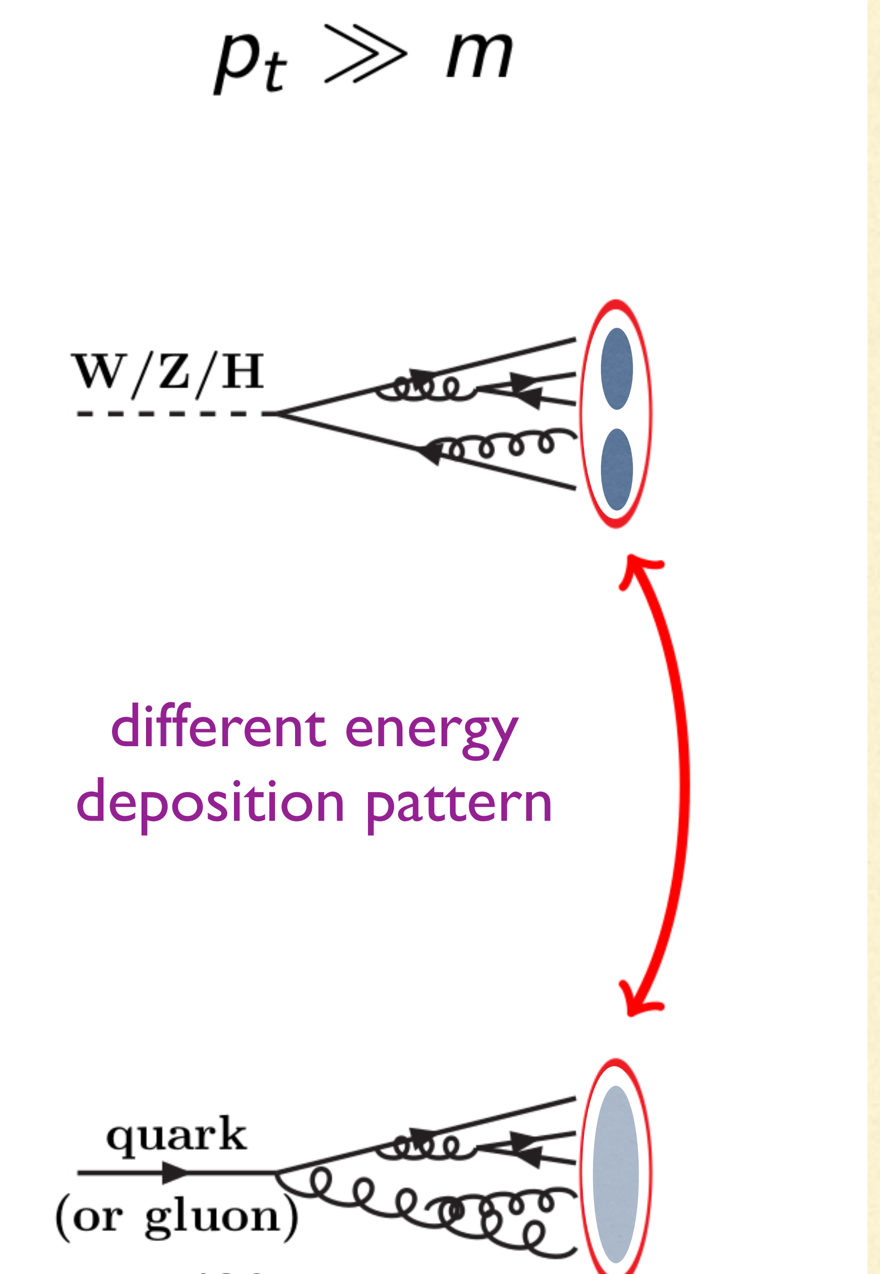
- the two major goals of the LHC
  - search for new particles
  - characterise the particles we know
- jets can be formed by QCD particles but also by the decay of massive particles (if they are sufficiently boosted)
- how can we distinguish signal jets from background ones?



courtesy of G. Soyez

SUBSTRUCTURE IN A NUTSHELL

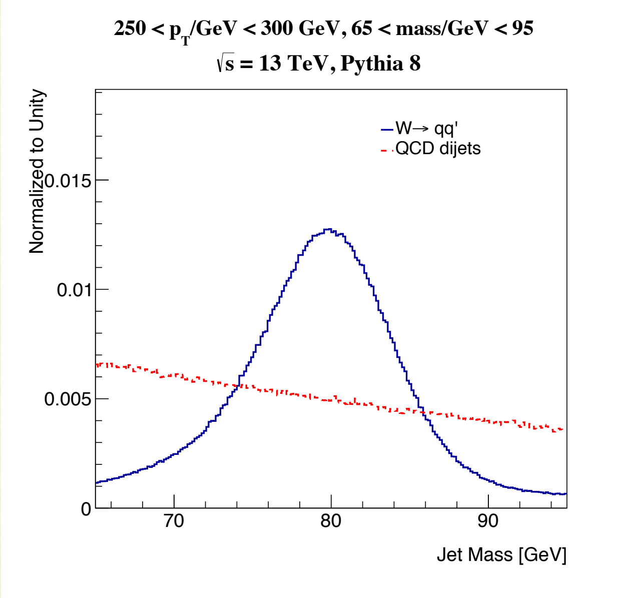
- the final energy deposition pattern is influenced by the originating splitting
- hard vs soft translate into 2-prong vs 1-prong structure
- picture is mudded by many effects (hadronisation, Underlying Event, pileup)
- two-step procedure:
  - *grooming:* clean the jets up by removing soft radiation
  - *tagging:* identify the features of hard decays and cut on them

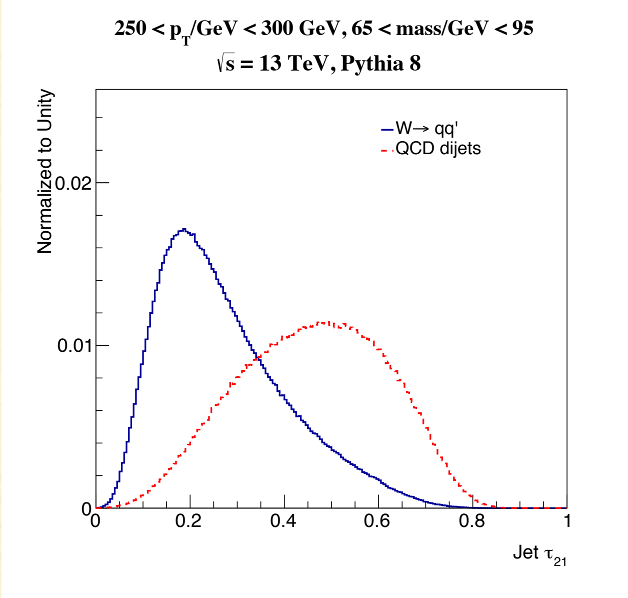


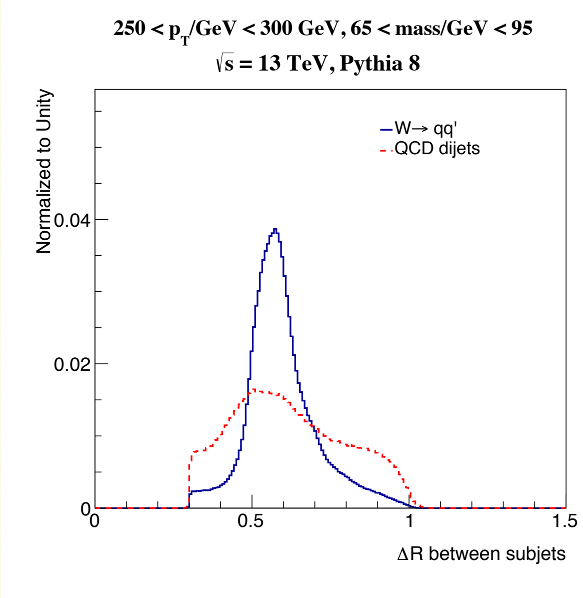
courtesy of G. Soyez

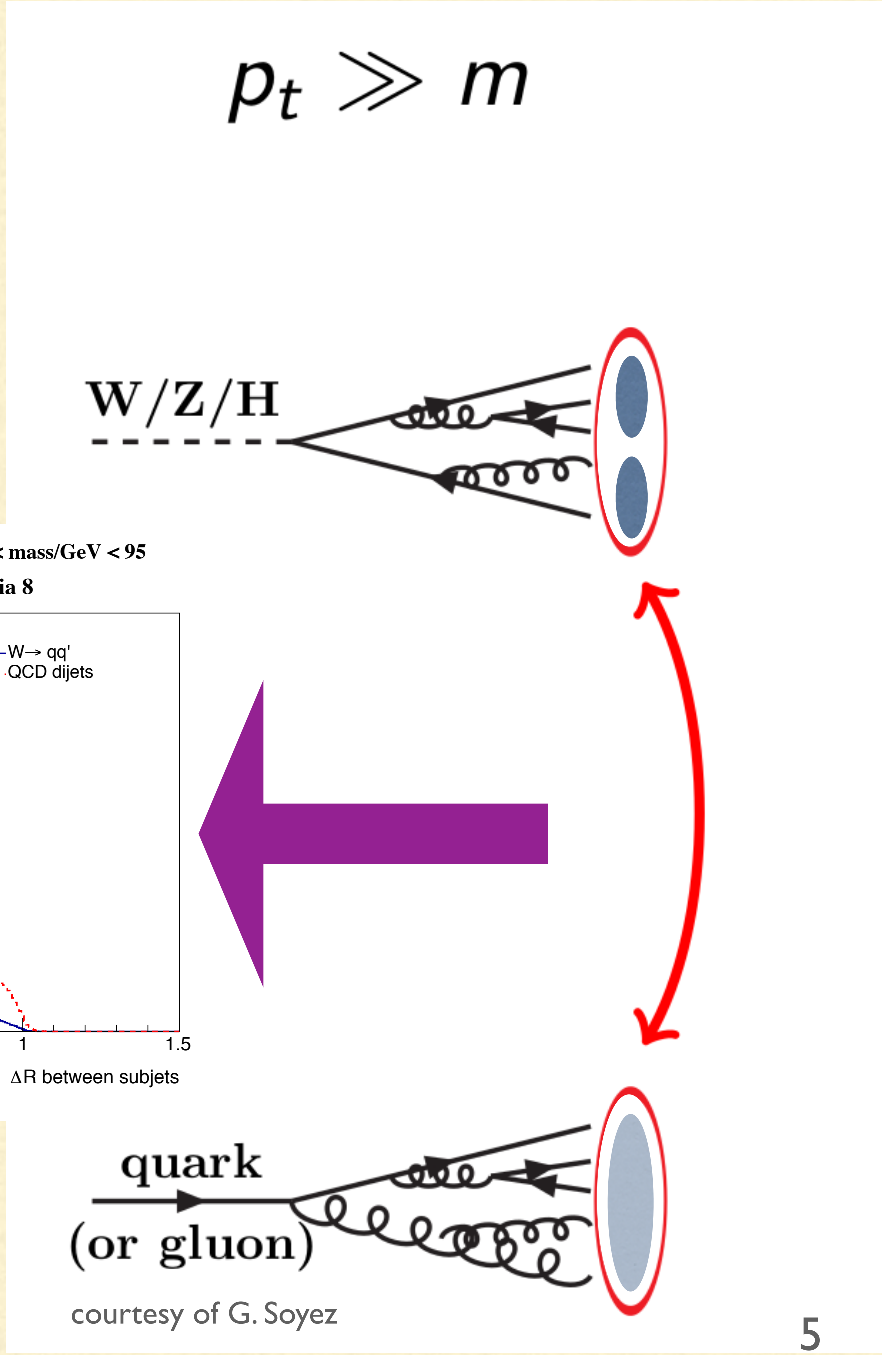
A THEORIST'S JOB

- devise clever ways to project the multi-dimensional parameter space of final-state momenta into suitable lower dimensional (typically 1-D) distributions









for an introduction see SM, Soyez, Spannowsky

PERFORMANCE & RESILIENCE

- first-principle understanding of groomers' and taggers' perturbative properties has reached remarkable levels

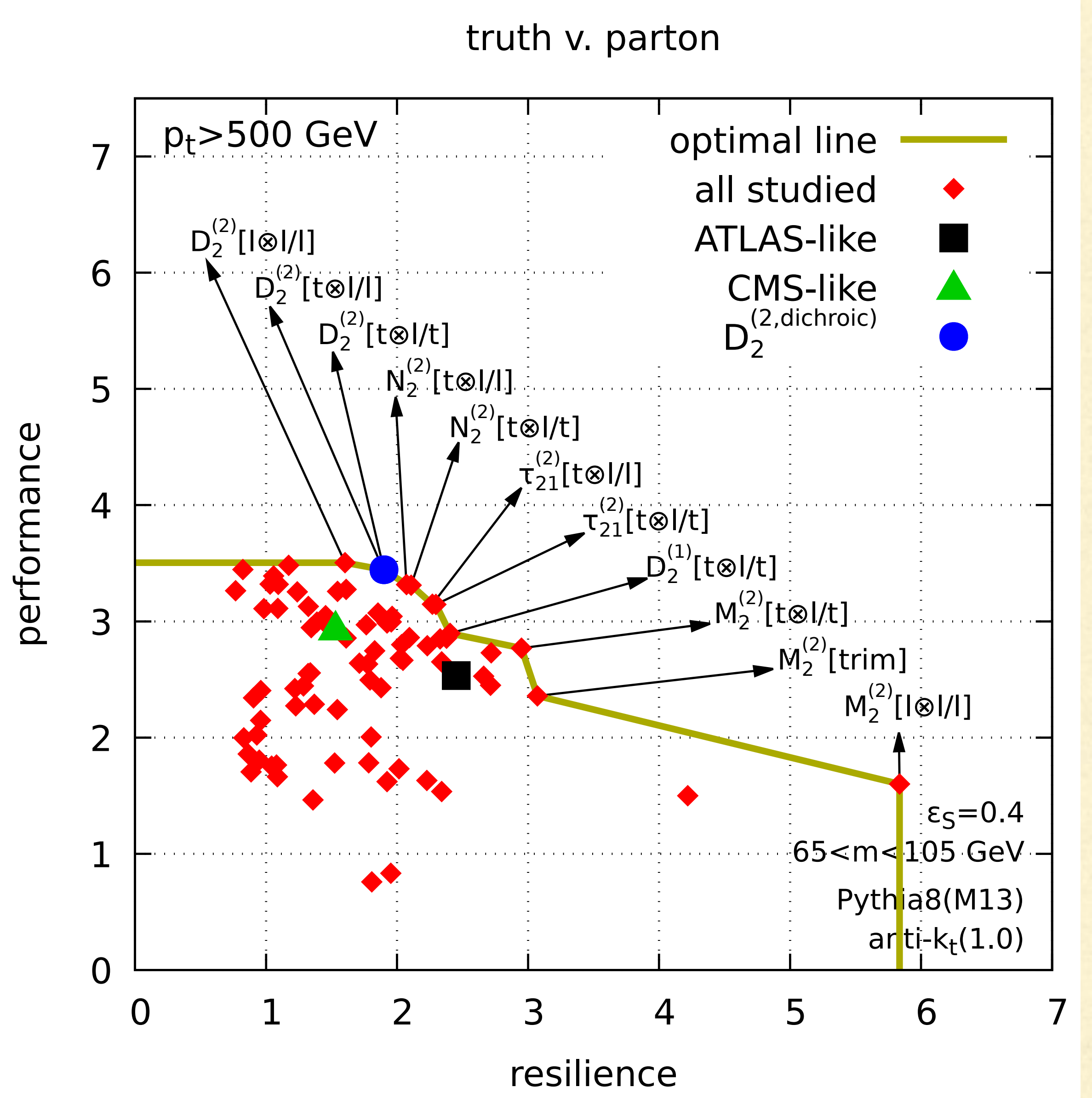
- resilience measures a tagger's robustness against non-perturbative effects (hadronisation and UE)

- it is defined in terms of signal/background efficiencies with/without non-pert. contributions Looking inside jets

$$\zeta = \left(\frac{\Delta\epsilon_S^2}{\langle\epsilon\rangle_S^2} + \frac{\Delta\epsilon_B^2}{\langle\epsilon\rangle_B^2} \right)^{-1/2}$$

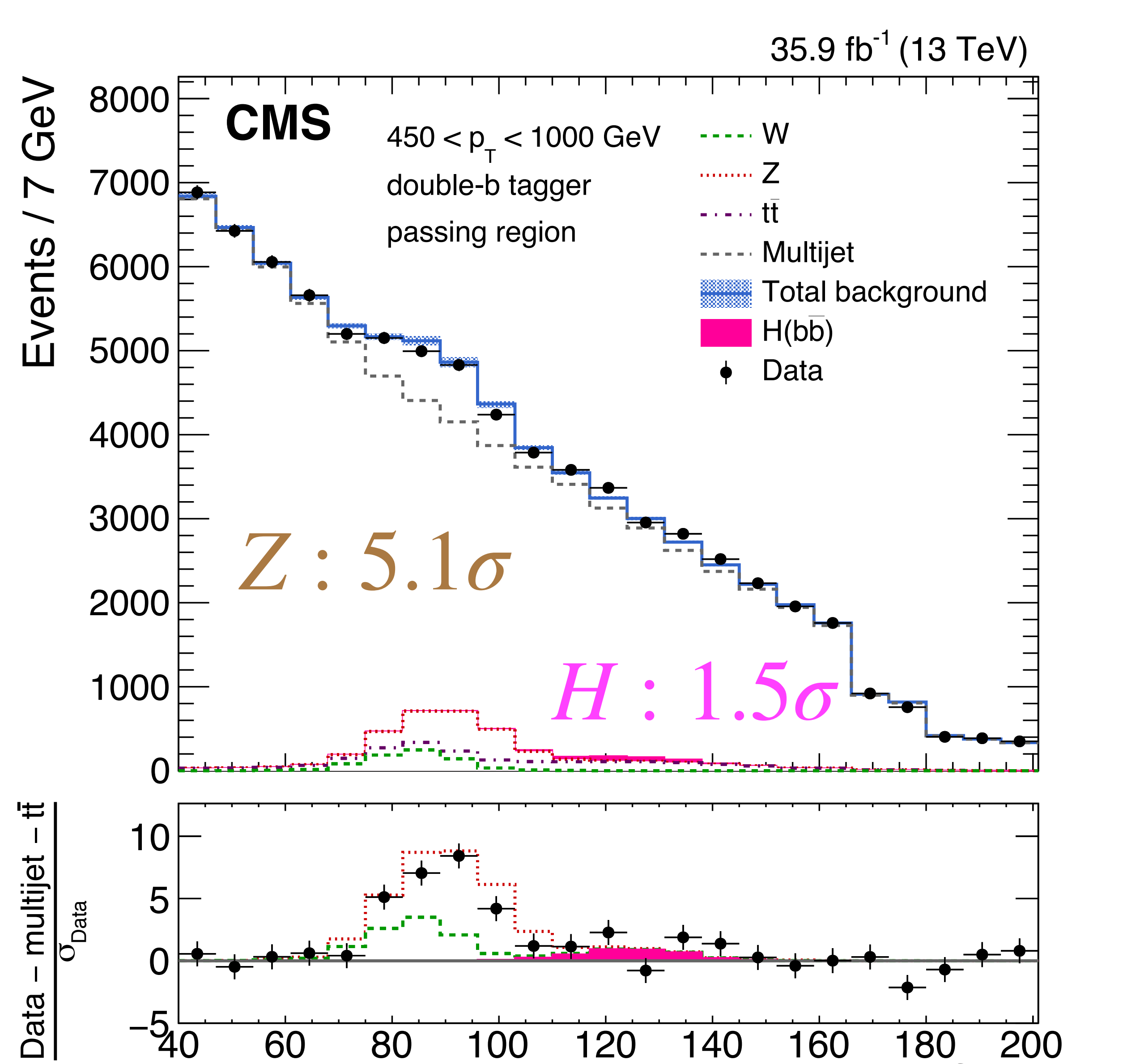
$$\Delta\epsilon_{S,B} = \epsilon_{S,B} - \epsilon'_{S,B},$$

$$\langle\epsilon\rangle_{S,B} = \frac{1}{2}\left(\epsilon_{S,B} + \epsilon'_{S,B}\right)$$



HARD WORK DOES PAY OFF

- QCD and EW corrections to obtain Z+jets and W+jets
- Higgs p_T spectrum corrected for finite top mass effects
- inclusion of N^{3}LO normalisation
- matching NLO-PS
- state-of-the arts PDFs



Phys.Rev.Lett. 120 (2018) no.7, 071802

- state-of-the art jet reconstruction (anti-k_t & particle-flow)
- b-tagging
- soft-drop grooming
- 2-prong jets identified with energy correlation function N^1_2
- decorrelation: $N^1_2 \rightarrow N^{1,DDT}_2$

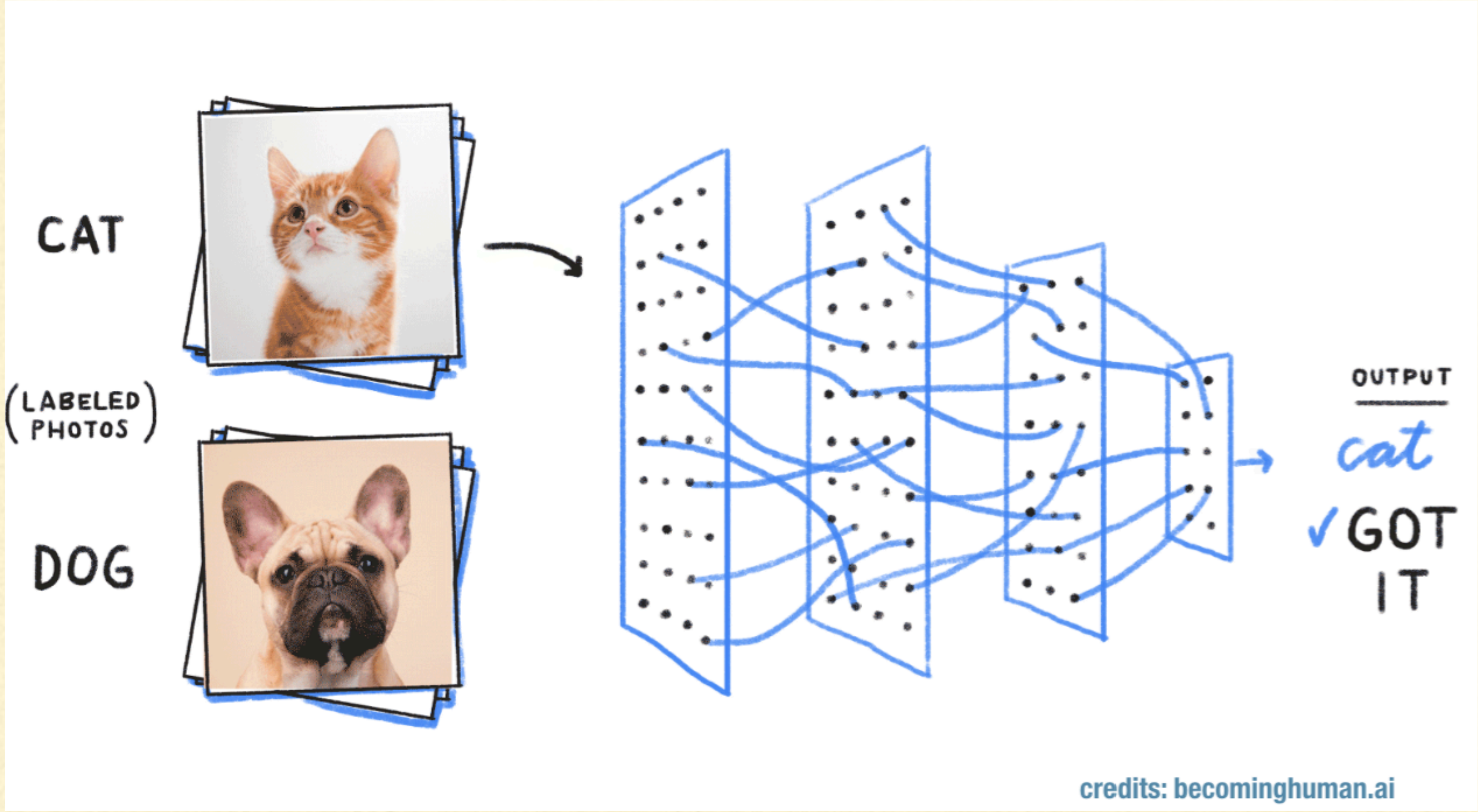
see also Fabrizo Caola's talk

WHAT'S LEFT TO DO?

- $H \to bb$ is the holy grail of jet substructure, where it all started … embarrassingly it's not been observed yet!
- Need more efficient tools?
  - enter machine-learning
- Tremendous work went into understanding groomers and taggers, what's the best use of these methods?
  - deep thinking meets deep learning
  - precision measurements using jet substructure

DEEP LEARNING

- a wave of machine learning algorithms has hit jet physics in the past 3/4 years
- ML algorithms are powerful tools for classification, can we then apply them to our task?

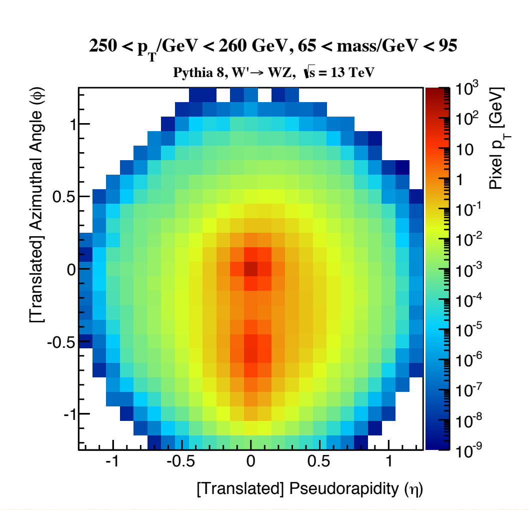


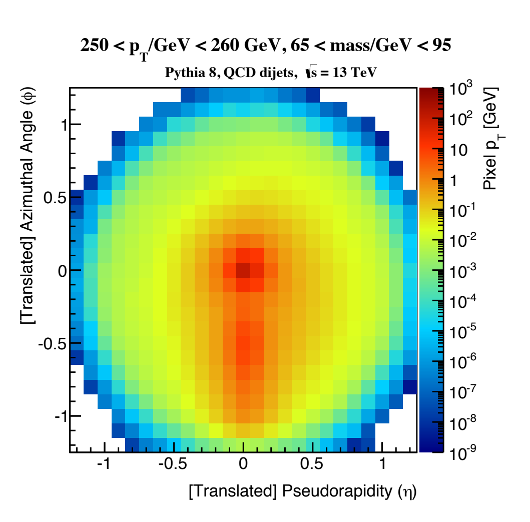
- if an algorithm can distinguish pictures of cats and dogs, can it also distinguish QCD jets from boosted-objects?
- number of papers trying to answer this question has recently exploded!
- very active and fast-developing field

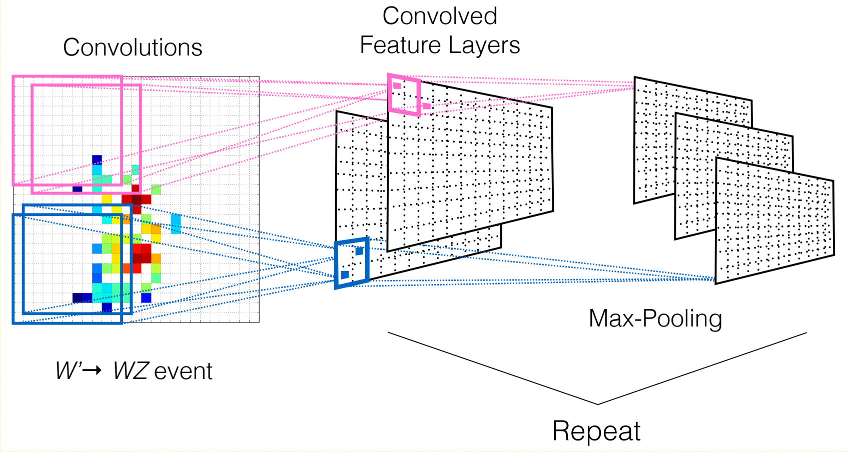
JETS AS IMAGES

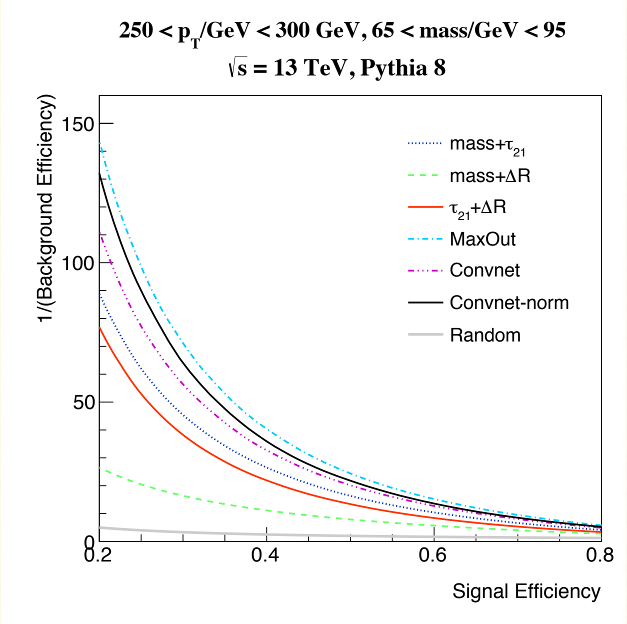
- jet images do what they say: project the jet into a *nxn* pixel image, where intensity is given by energy deposition
- use convolutional neural network (CNN) to classify
- right pre-processing is crucial for many reasons: we average over many events and Lorentz symmetry would wash away any pattern

Cogan, Kagan, Strauss, Schwartzman (2015)
de Olivera, Kagan, Mackey, Nachman, Schwartzman (2016)



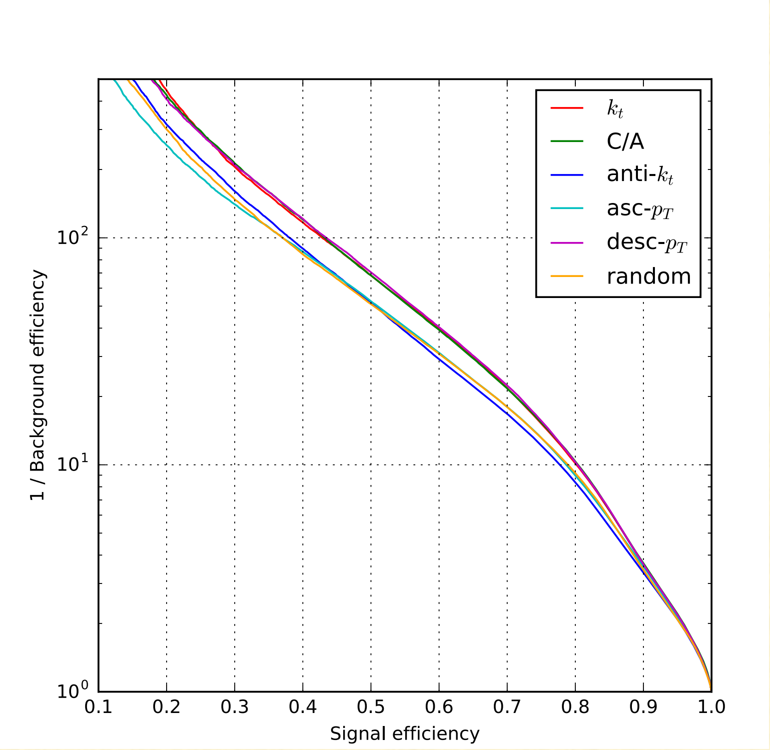


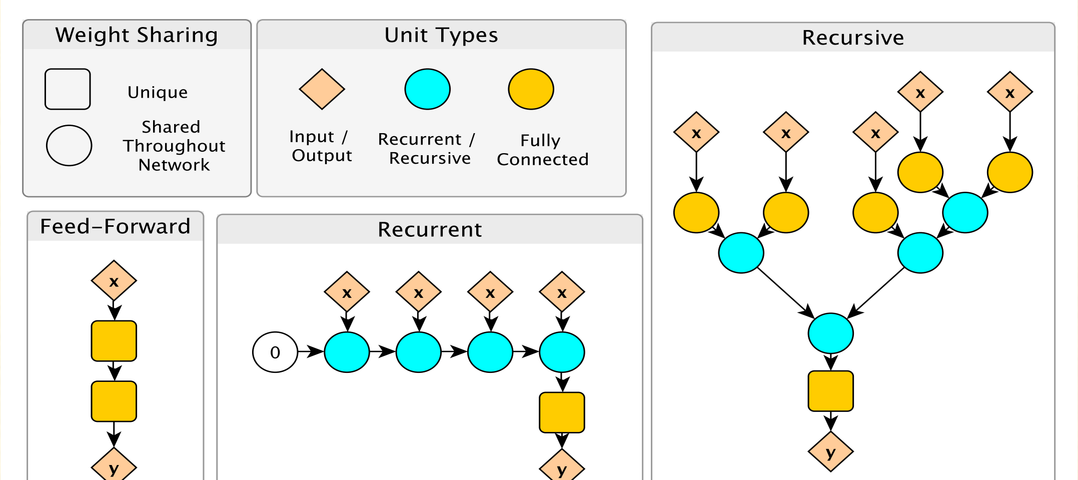




BEYOND IMAGES: 4-MOMENTA

- analyses typically have access to more information than energy deposit in the calorimeter: e.g. particle id, tracks, clustering history in a jet, etc.
- build network that take 4-momenta as inputs:
  - clever N-body phase-space parametrisation to maximise information Datta, Larkoski (2017)
  - recurrent / recursive neural networks to model jet clustering history (using techniques borrowed from language recognition) Louppe, Cho, Cranmer (2017)

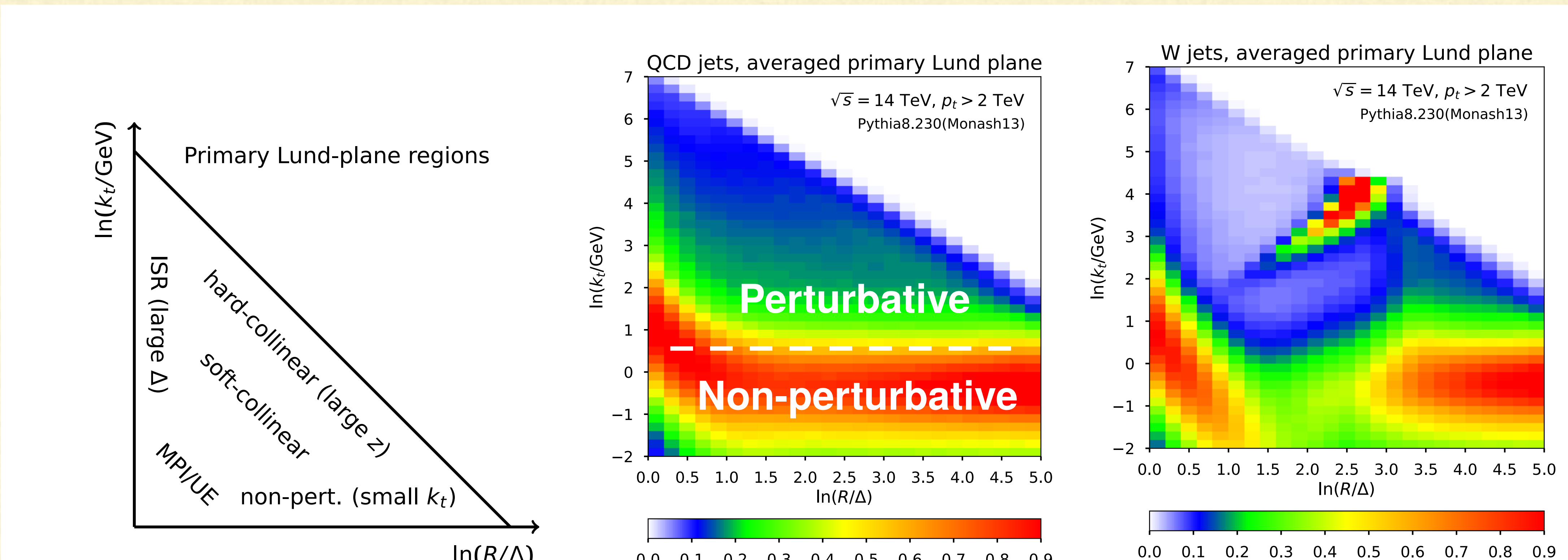




Guest, Cranmer, Whiteson (2018)

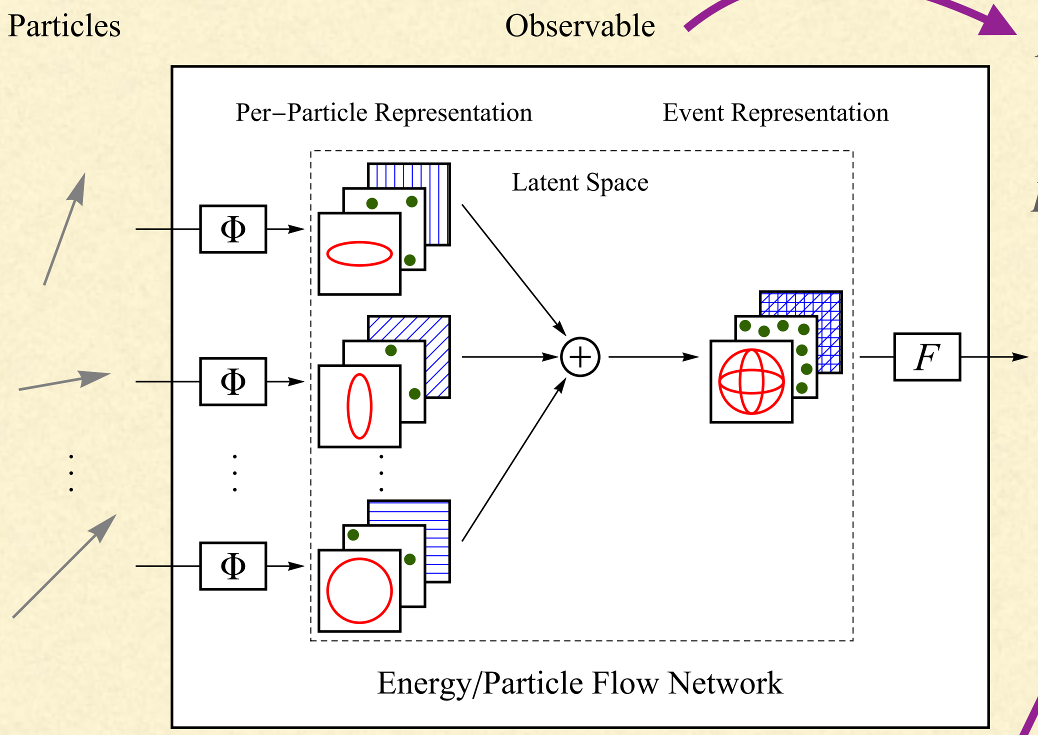
DEEP LEARNING MEETS DEEP THINKING: LUND JET PLANE

- inputs of ML algorithms can be low-level (calorimeter cells/particle 4-momenta) but also higher-level variables
- physics intuition can lead us to construct better representations of a jet: the Lund jet plane
  - de-cluster the jet following the hard branch and record (kt, Δ) at each step
  - feed this representation to a log-likelihood or a ML algorithm



Dryer, Salam, Soyez (2018)

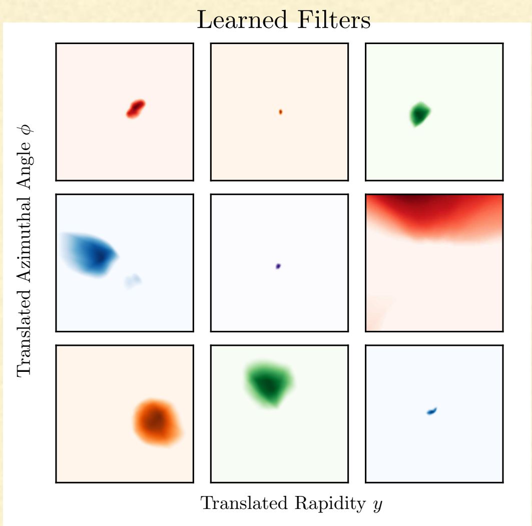
DEEP LEARNING MEETS DEEP THINKING: ENERGY FLOW NET



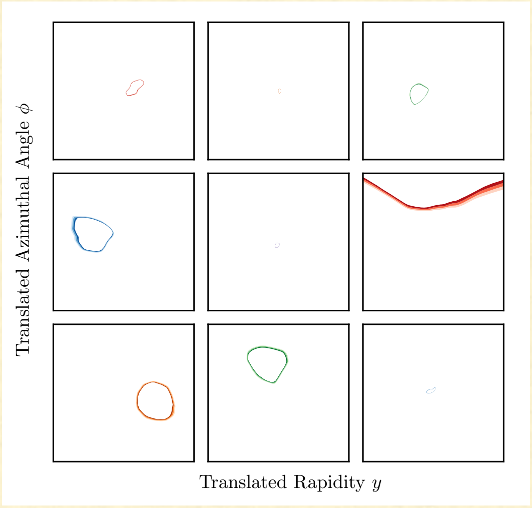
$$EFN : F\left(\sum_{i=1}^{M} z_i \Phi(\theta_i, \phi_i)\right)$$

$$PFN : F\left(\sum_{i=1}^{M} \Phi(p_i)\right)$$

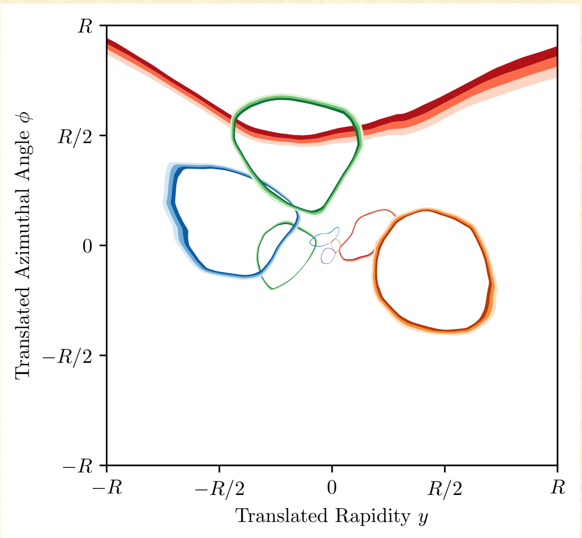
Observable $\mathcal{O}$		Map Φ	Function F
Mass	m	p^μ	$F(x^\mu) = \sqrt{x^\mu x_\mu}$
Multiplicity	M	1	$F(x) = x$
Track Mass	m_{track}	$p^\mu \mathbb{I}_{\text{track}}$	$F(x^\mu) = \sqrt{x^\mu x_\mu}$
Track Multiplicity	M_{track}	$\mathbb{I}_{\text{track}}$	$F(x) = x$
Jet Charge [72]	$\mathcal{Q}_\kappa$	$(p_T, Q\, p_T^\kappa)$	$F(x, y) = y/x^\kappa$
Eventropy [74]	$z \ln z$	$(p_T, p_T \ln p_T)$	$F(x, y) = y/x - \ln x$
Momentum Dispersion [93]	p_T^D	(p_T, p_T^2)	$F(x, y) = \sqrt{y/x^2}$
C parameter [94]	C	$(\lvert\vec{p}\rvert, \vec{p} \otimes \vec{p}/\lvert\vec{p}\rvert)$	$F(x, Y) = \frac{3}{2x^2}[(\mathrm{Tr}\, Y)^2 - \mathrm{Tr}\, Y^2]$



contour

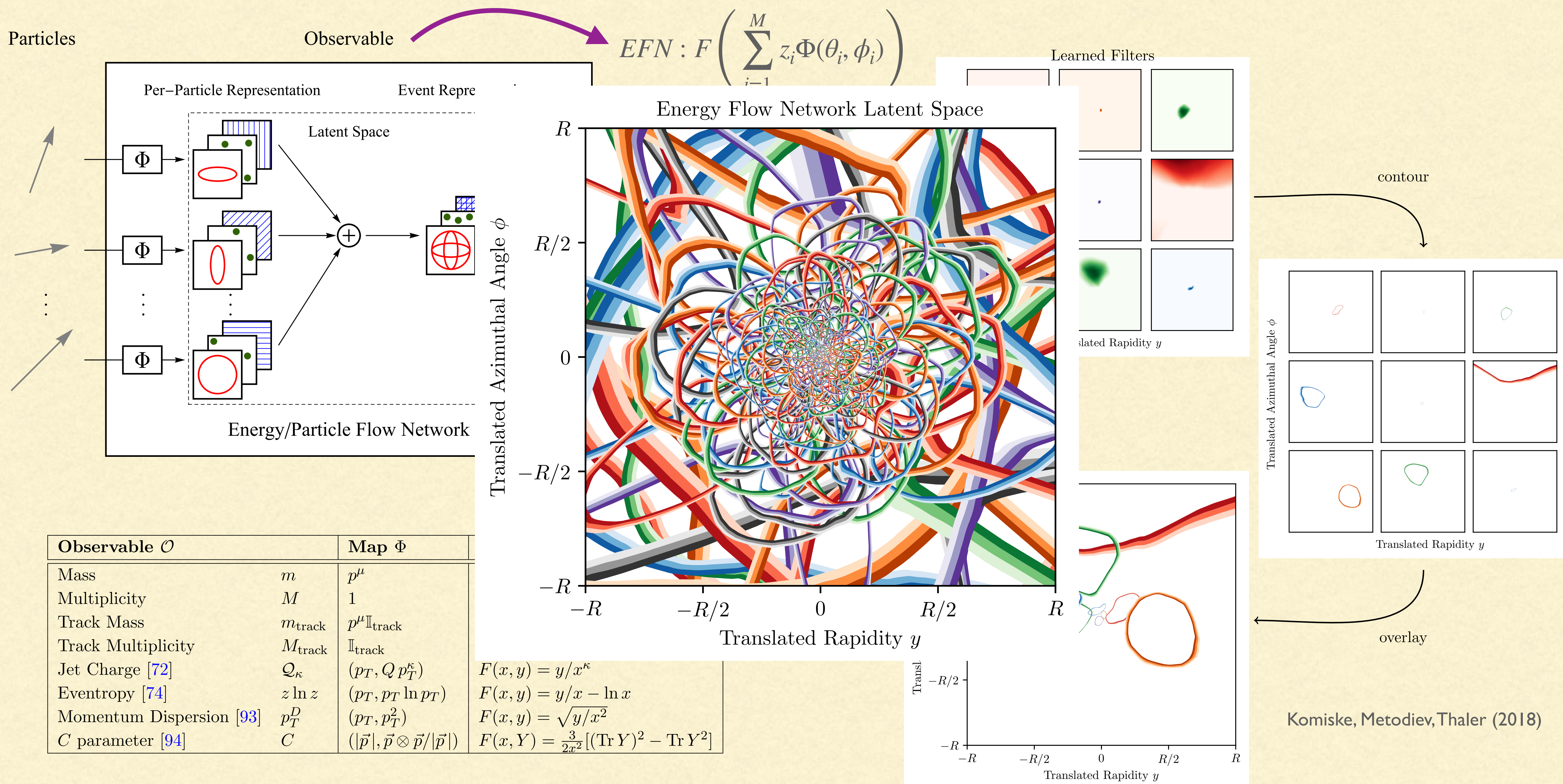


overlay



Komiske, Metodiev, Thaler (2018)

DEEP LEARNING MEETS DEEP THINKING: ENERGY FLOW NET



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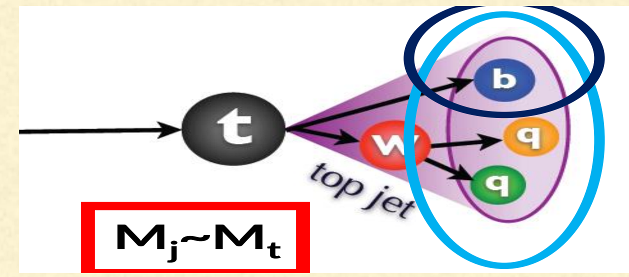
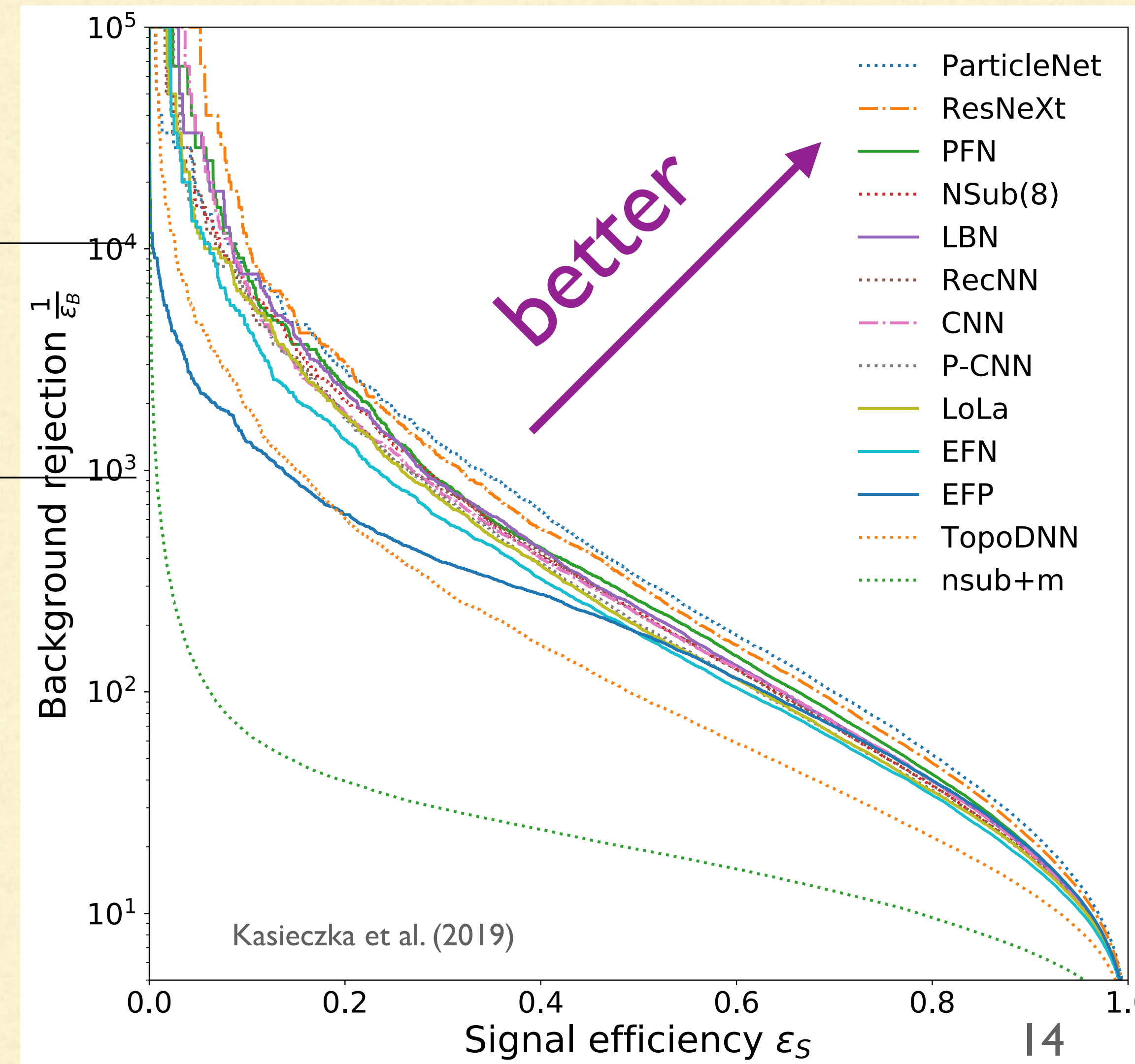
Komiske, Metodiev, Thaler (2018)

ML FOR TOP TAGGING

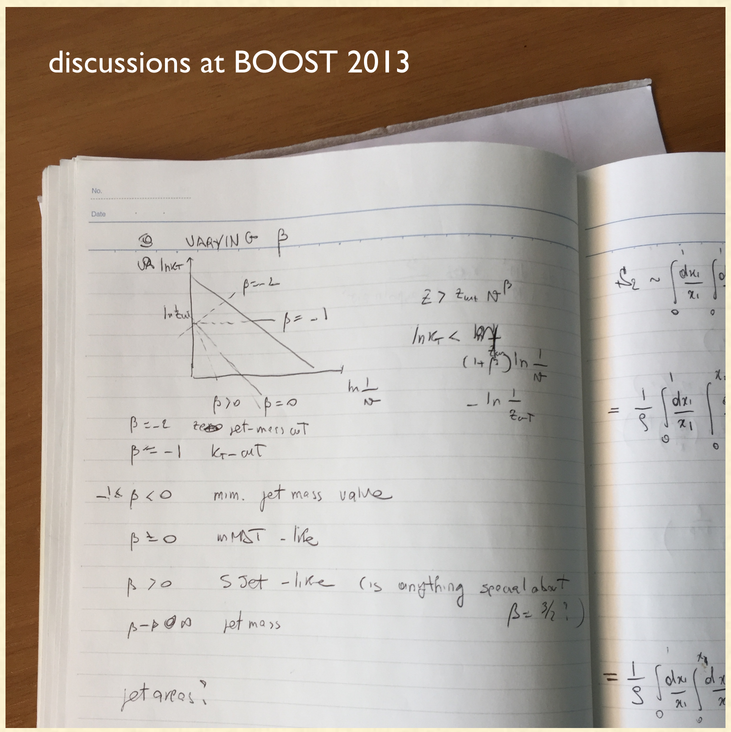
		AUC	Accuracy	$1/\epsilon_B$ ($\epsilon_S = 0.3$)	#Parameters
images	CNN [16]	0.981	0.930	780	610k
	ResNeXt [32]	0.984	0.936	1140	1.46M
four-momenta	TopoDNN [18]	0.972	0.916	290	59k
	Multi-body N-subjettiness 6 [24]	0.979	0.922	856	57k
	Multi-body N-subjettiness 8 [24]	0.981	0.929	860	58k
	RecNN	0.981	0.929	810	13k
	P-CNN	0.980	0.930	760	348k
	ParticleNet [45]	0.985	0.938	1280	498k
theory-inspired	LBN [19]	0.981	0.931	860	705k
	LoLa [22]	0.980	0.929	730	127k
	Energy Flow Polynomials [21]	0.980	0.932	380	1k
	Energy Flow Network [23]	0.979	0.927	600	82k
	Particle Flow Network [23]	0.982	0.932	880	82k

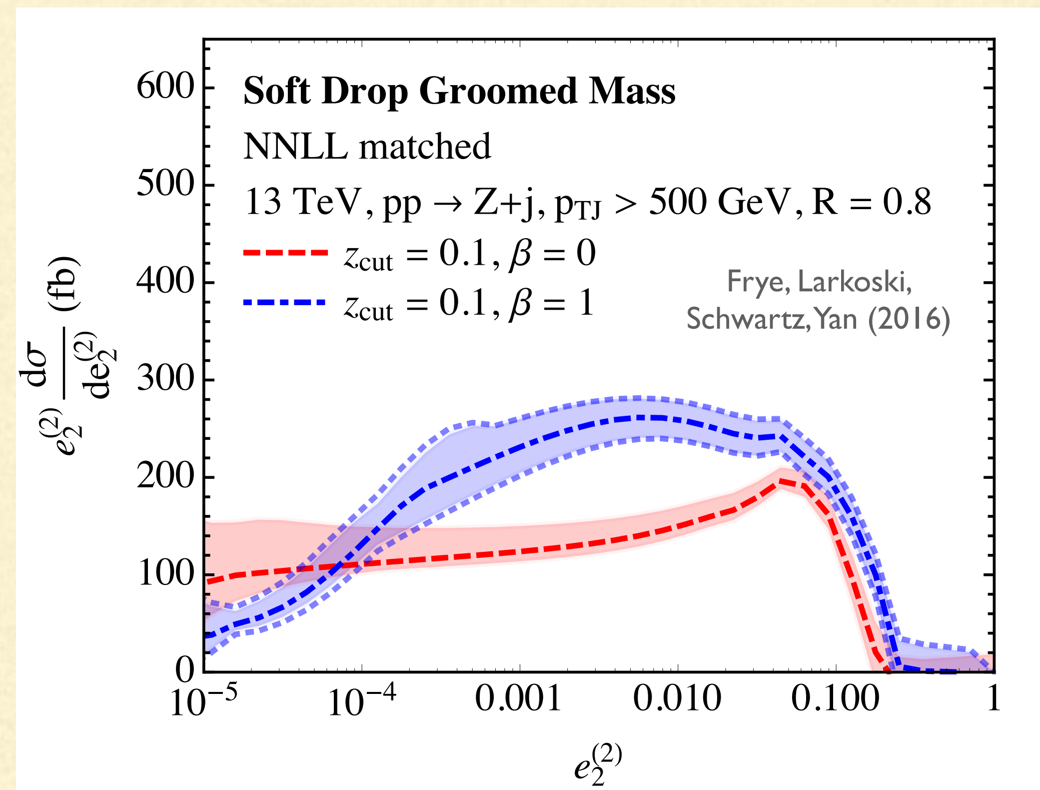




- all solutions offer big improvement over standard analysis (nsub+m)
- similar performances
- physics intuition useful to match performance of highly-sophisticated architectures

FROM IDEAS TO PRECISION

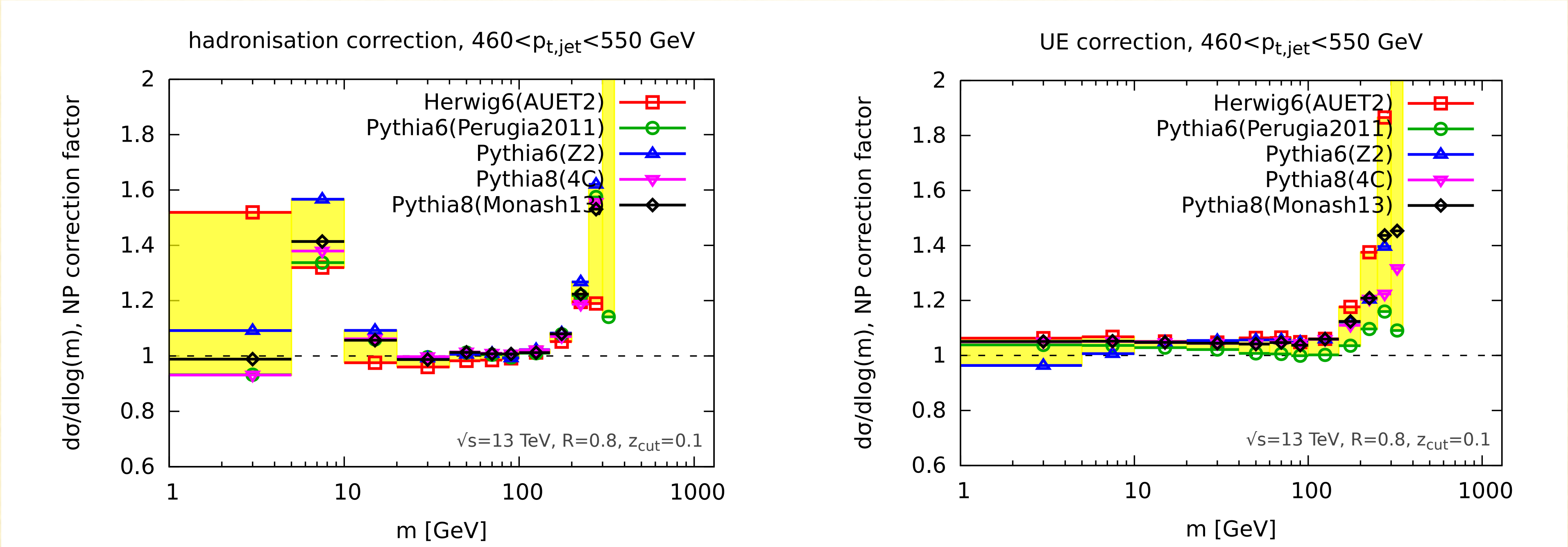




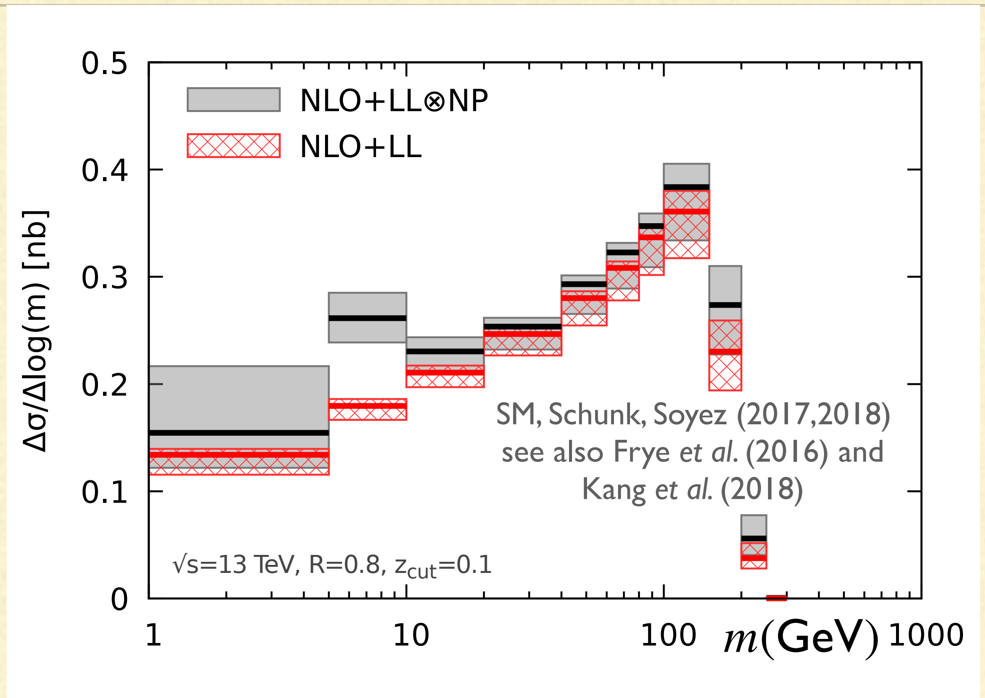
- understanding of groomers and taggers led to the definition of theory-friendly efficient tools, e.g. soft drop:
  - good perturbative properties (convergence, absence of soft effects such as non-global logs)
  - small non-perturbative corrections

FROM THEORY TO DATA

- time is mature for theory / data comparison
- reduced sensitivity to non-pert physics (hadronisation and UE) should make the comparison more meaningful
- what is the value of unfolded measurements / theory comparisons for "discovery" tools?
    - understanding systematics (e.g. kinks and bumps)
    - where non-pert. corrections are small, test perturbative showers in MCs
    - at low mass, hadronisation is large but UE is small: TUNE!

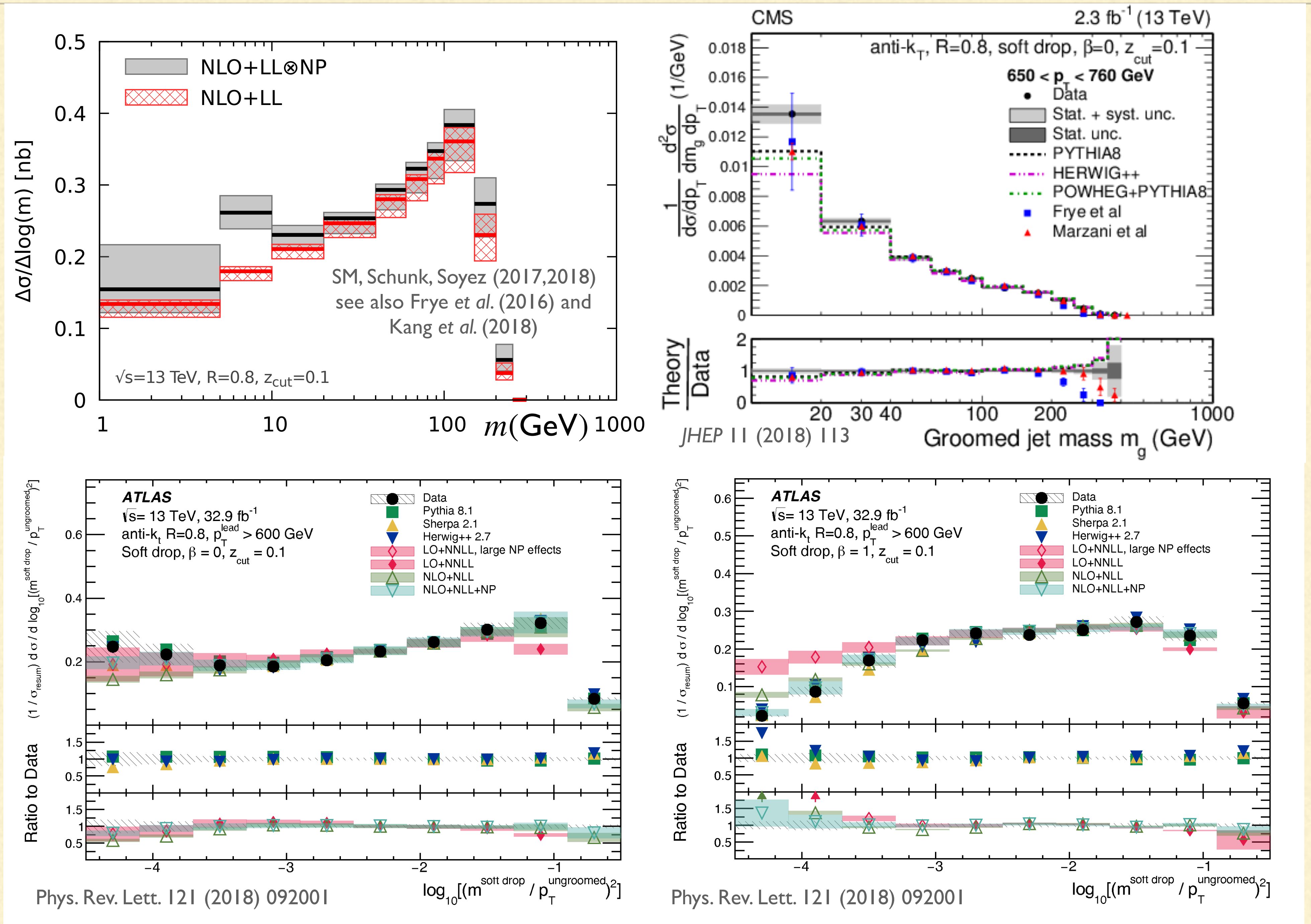


THEORY PREDICTIONS…



- large range of masses where non-pert. corrections are small and we can trust resummation
- they can be included through MC or analytical modelling

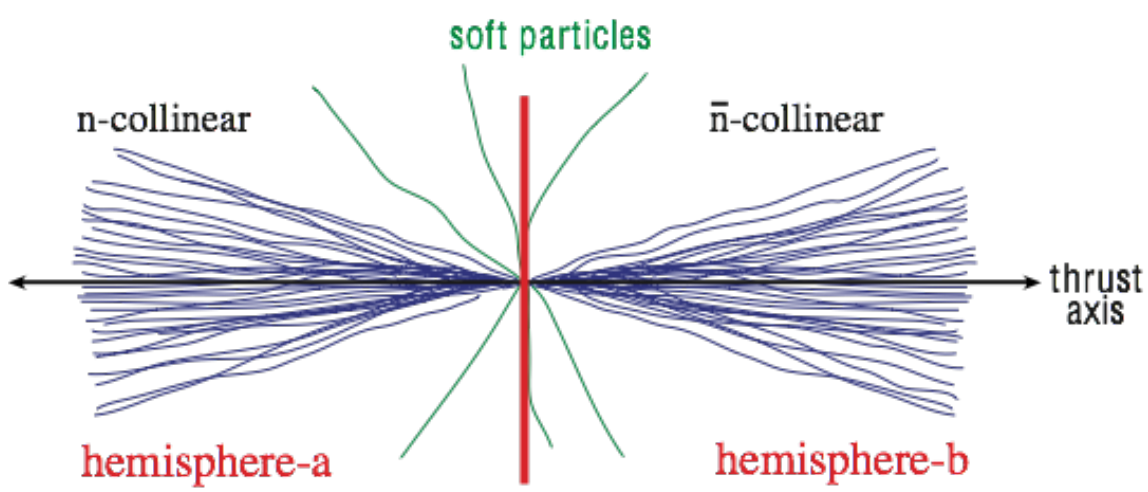
...AND THE DATA

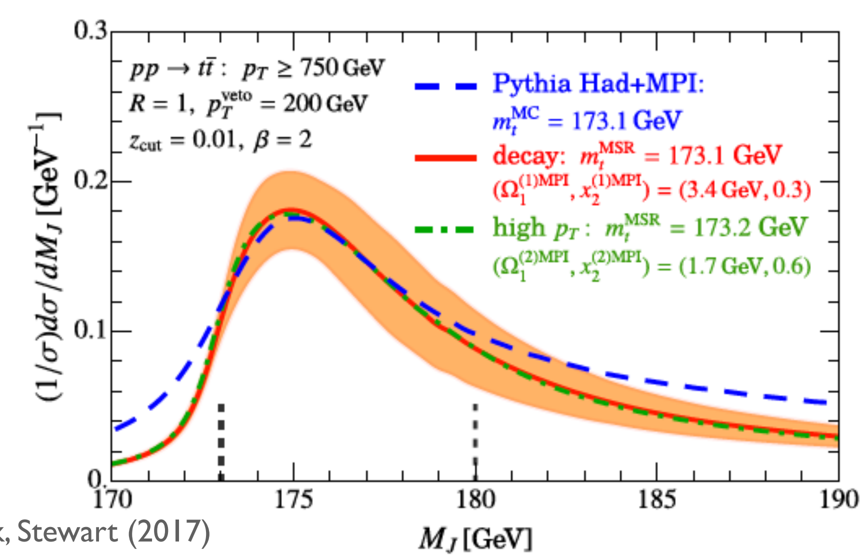


NLO+LL⊗NP
NLO+LL
Δσ/Δlog(m) [nb]
SM, Schunk, Soyez (2017,2018)
see also Frye et al. (2016) and
Kang et al. (2018)
√s=13 TeV, R=0.8, z_cut=0.1
m(GeV)
CMS
2.3 fb^-1 (13 TeV)
anti-k_T, R=0.8, soft drop, β=0, z_cut=0.1
650 < p_T < 760 GeV
Data
Stat. + syst. unc.
Stat. unc.
PYTHIA8
HERWIG++
POWHEG+PYTHIA8
Frye et al
Marzani et al
Theory / Data
Groomed jet mass m_g (GeV)
JHEP 11 (2018) 113
ATLAS
√s= 13 TeV, 32.9 fb^-1
anti-k_t R=0.8, p_T^lead > 600 GeV
Soft drop, β = 0, z_cut = 0.1
Soft drop, β = 1, z_cut = 0.1
Data
Pythia 8.1
Sherpa 2.1
Herwig++ 2.7
LO+NNLL, large NP effects
LO+NNLL
NLO+NLL
NLO+NLL+NP
Ratio to Data
Phys. Rev. Lett. 121 (2018) 092001
Phys. Rev. Lett. 121 (2018) 092001

TOP MASS WITH SOFT-DROP JETS

- determination of other fundamental parameters may benefit from grooming, e.g. the top quark mass
- in the context of e^+e^- collisions SCET factorisation theorems allow for a precision-determination of the top-jet mass
- the picture at *pp* collisions is polluted by wide-angle soft radiation
- grooming “turns” *pp* observables into e^+e^- ones

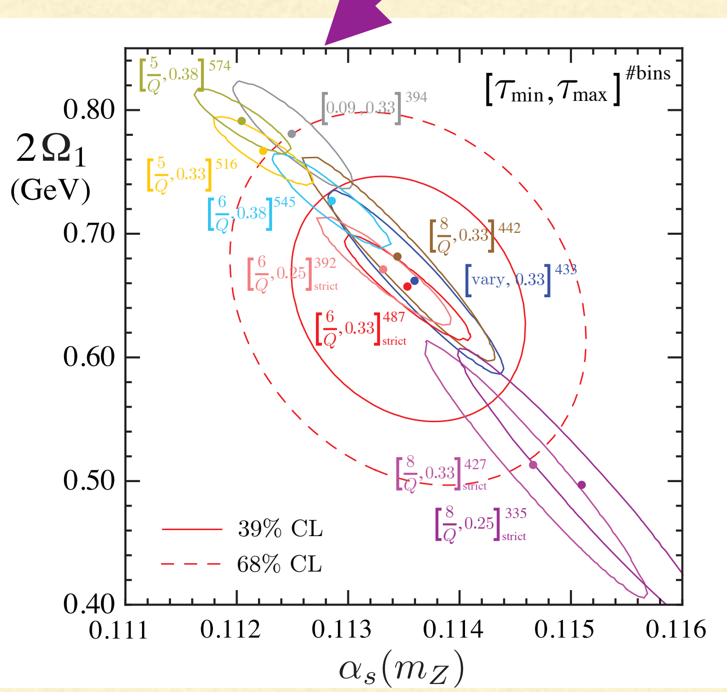


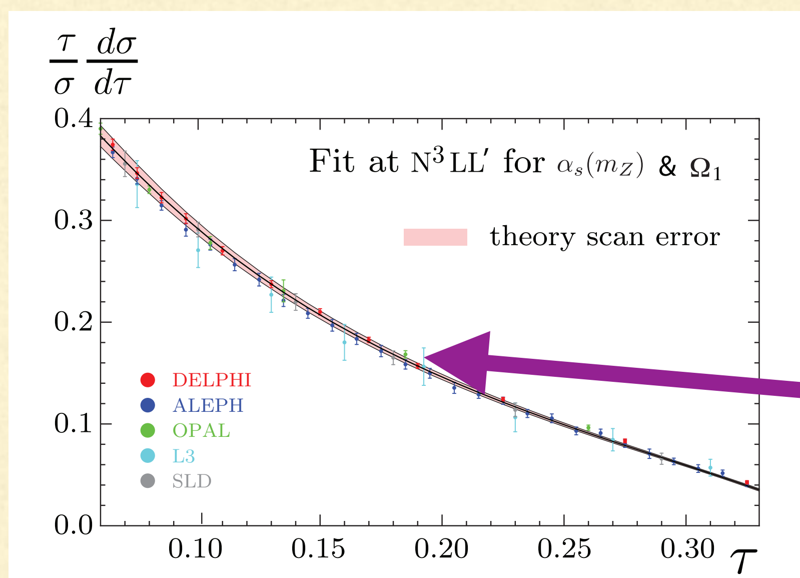


Hoang, Mantry, Pathak, Stewart (2017)

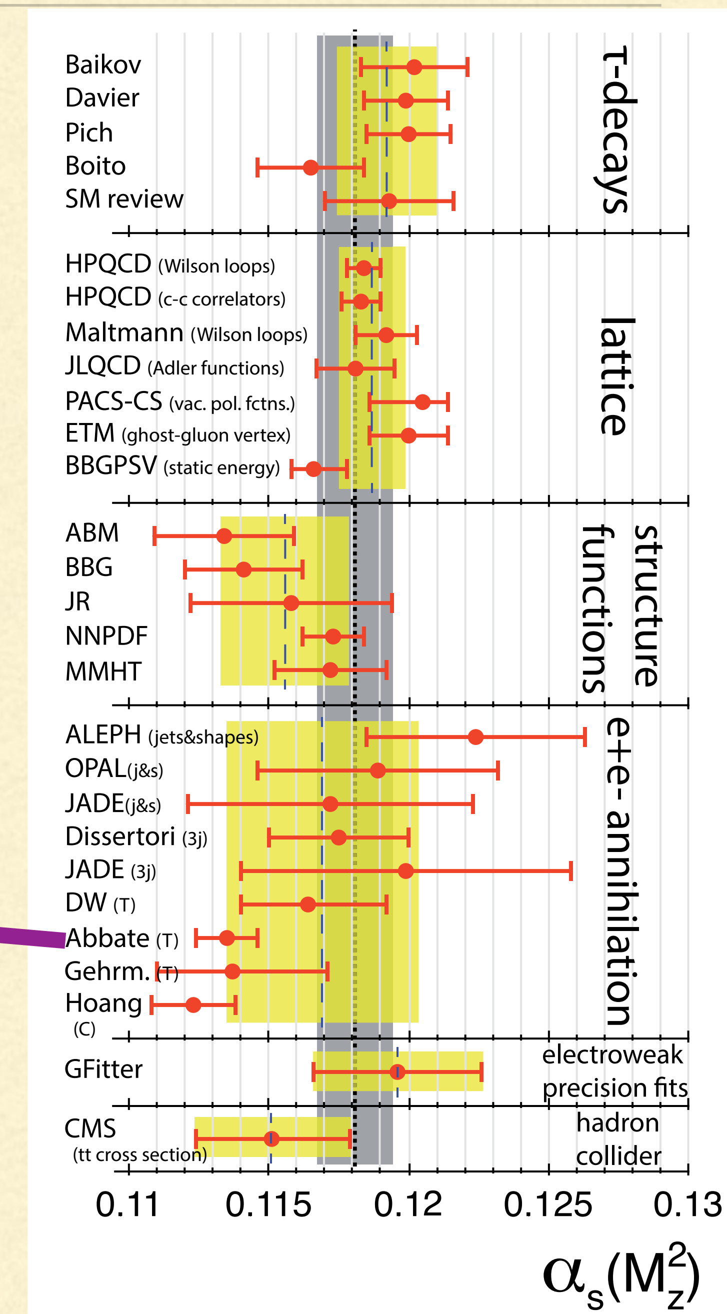
MEASURING THE STRONG COUPLING

- current precision below 1%, dominated by lattice extractions
- LEP event shapes also very precise (5%)
- however they are in tension with the world average
- thrust (and C parameter) known with outstanding accuracy

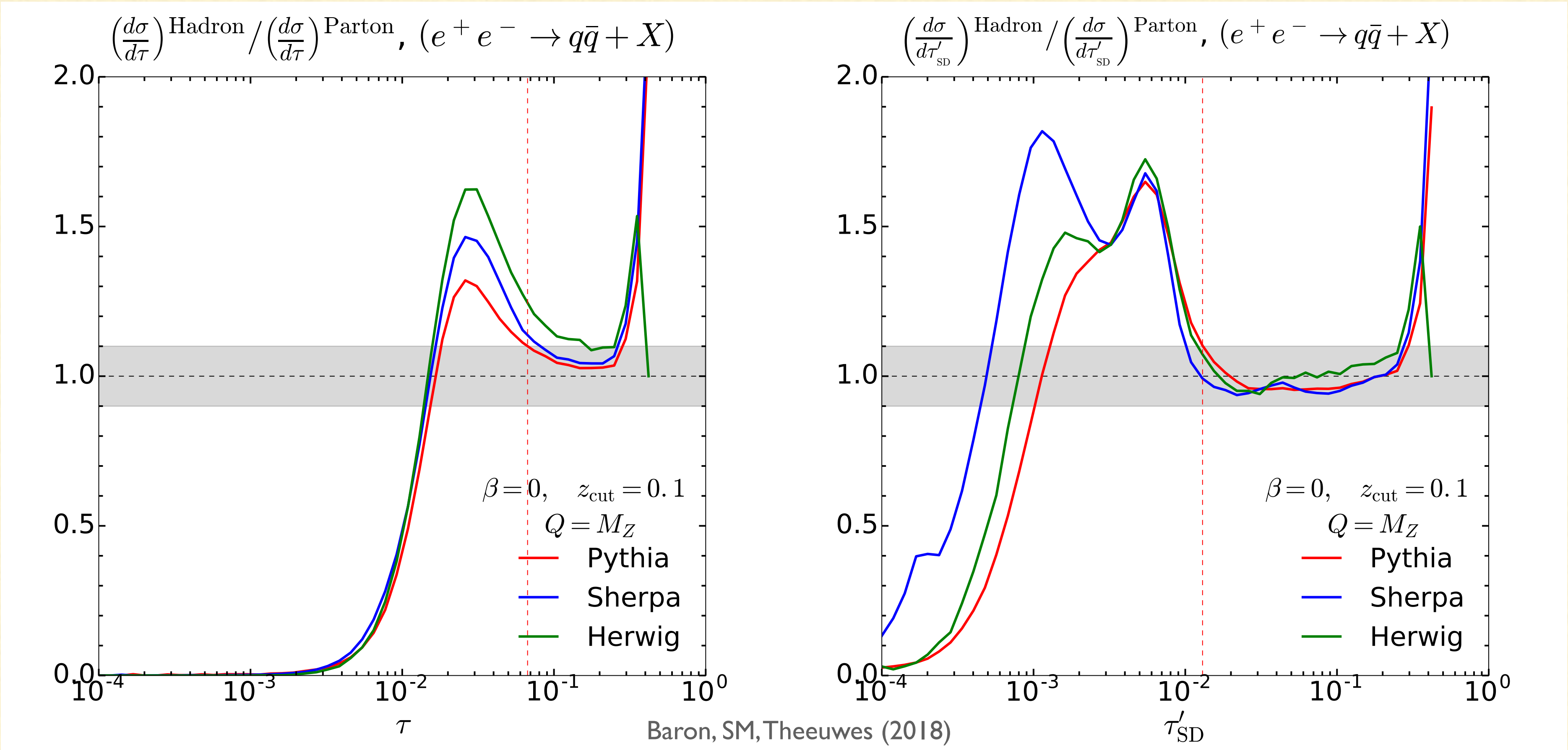




strong correlation with non-perturbative parameter



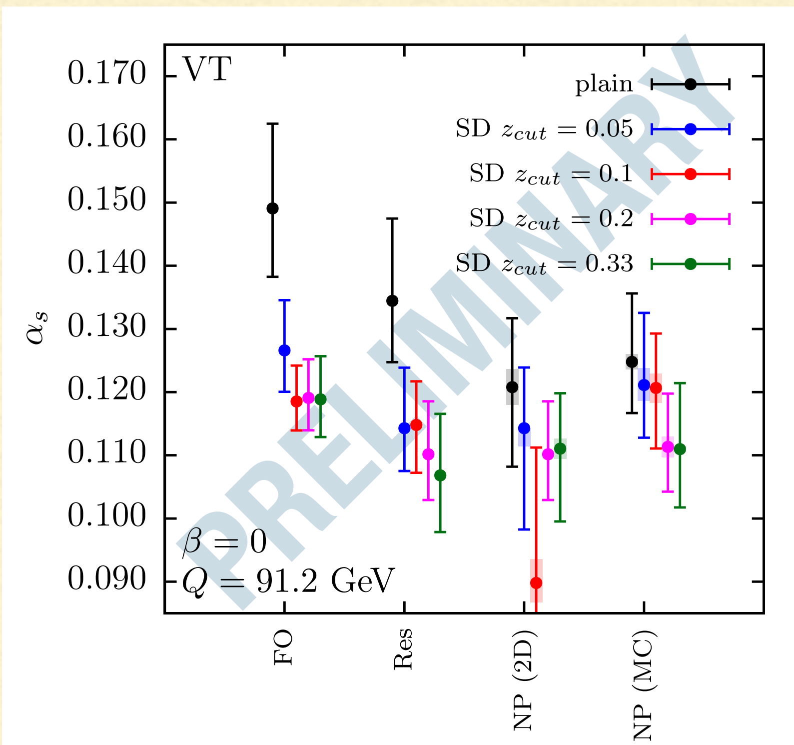
SOFT-DROP EVENT SHAPES



Baron, SM, Theeuwes (2018)

- noticeable reduction of non-pert. corrections may allow to disentangle the degeneracy
- can we compute it at the same accuracy as standard event shapes?
- NNLO calculations recently performed Kardos, Somogyi, Trocsanyi (2018)

α_S WITH SOFT-DROP THRUST

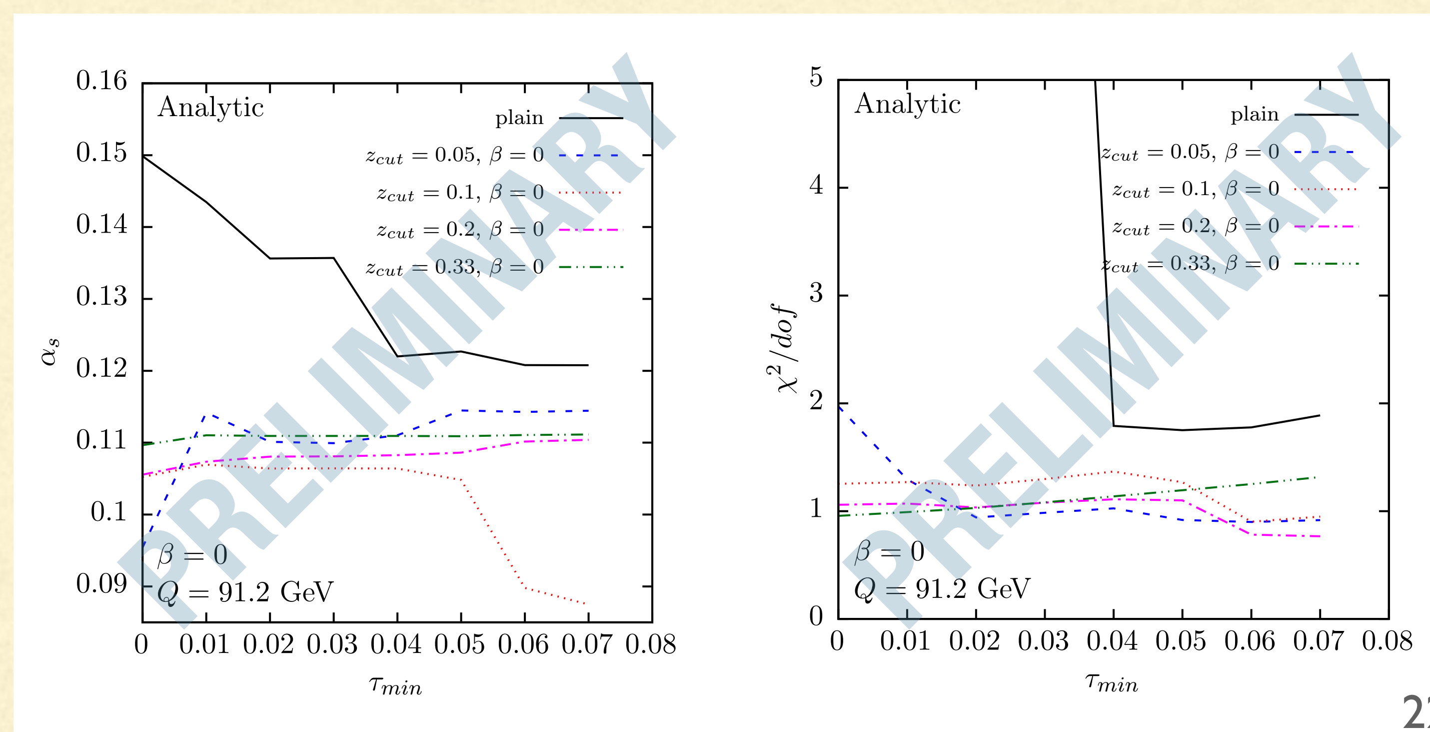


- fits to pseudo-data generated by SHERPA
- preliminary results shows reduced dependence on non-pert. corrections
- subleading effects are under investigation

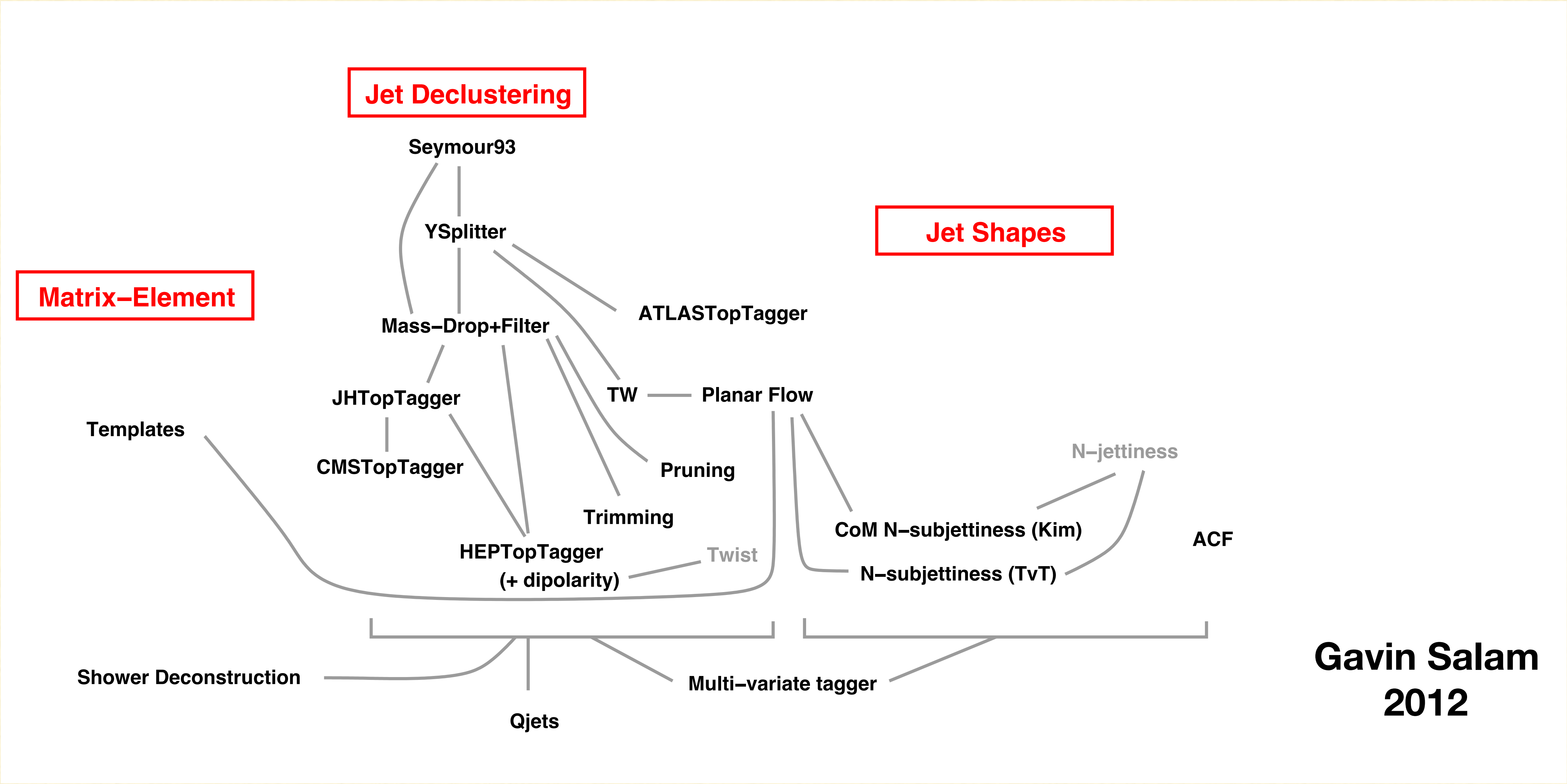
SM, Reichelt, Schumann, Soyez, and Theeuwes (soon to appear)

- soft-drop allows us to extend the fit range
- Generale question: is there a natural way to define soft-drop event shapes? e.g. bottom-up soft-drop

Dreyer, Necib, Soyez, Thaler (2018)
Baron (in preparation)



CONCLUSIONS



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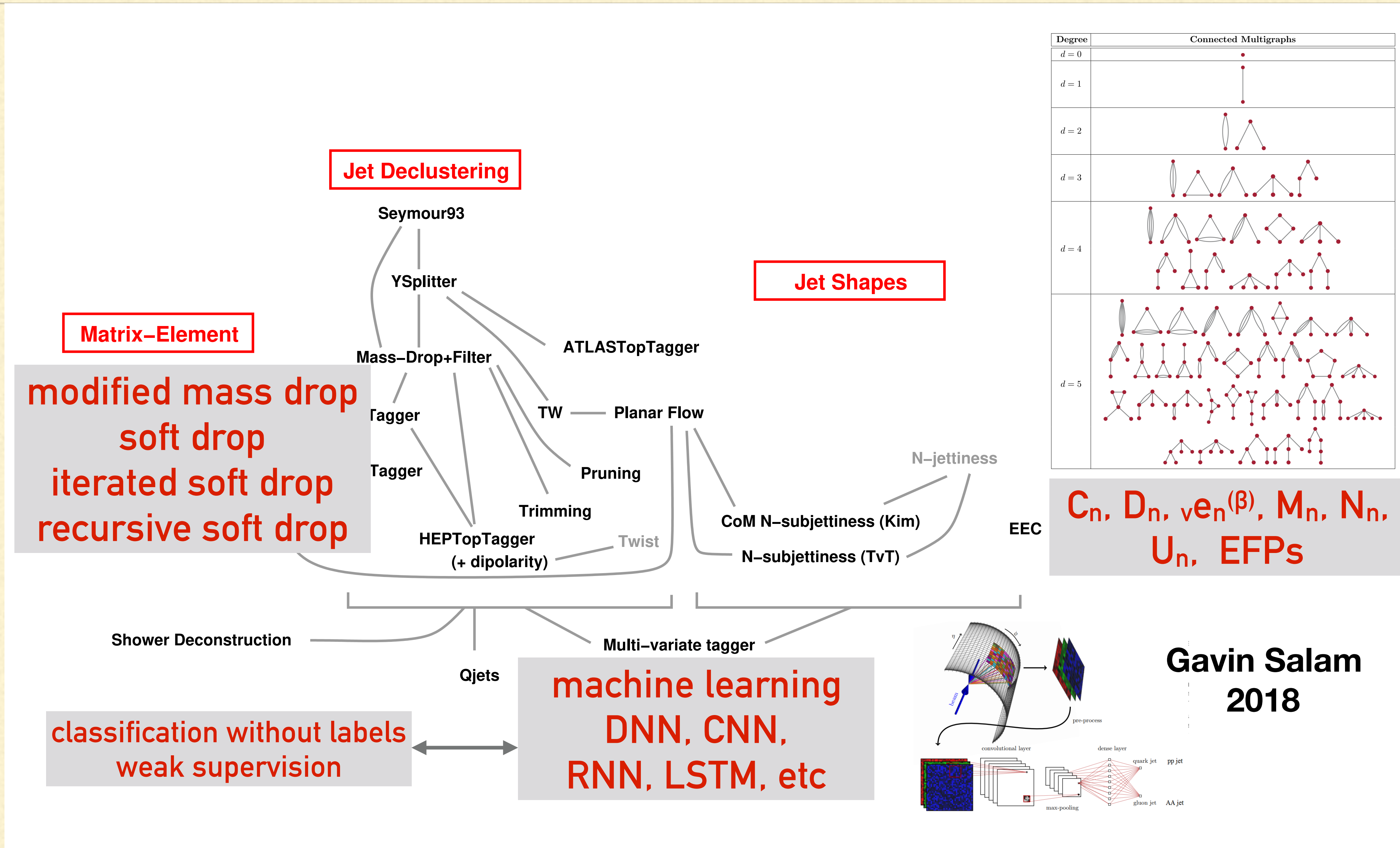

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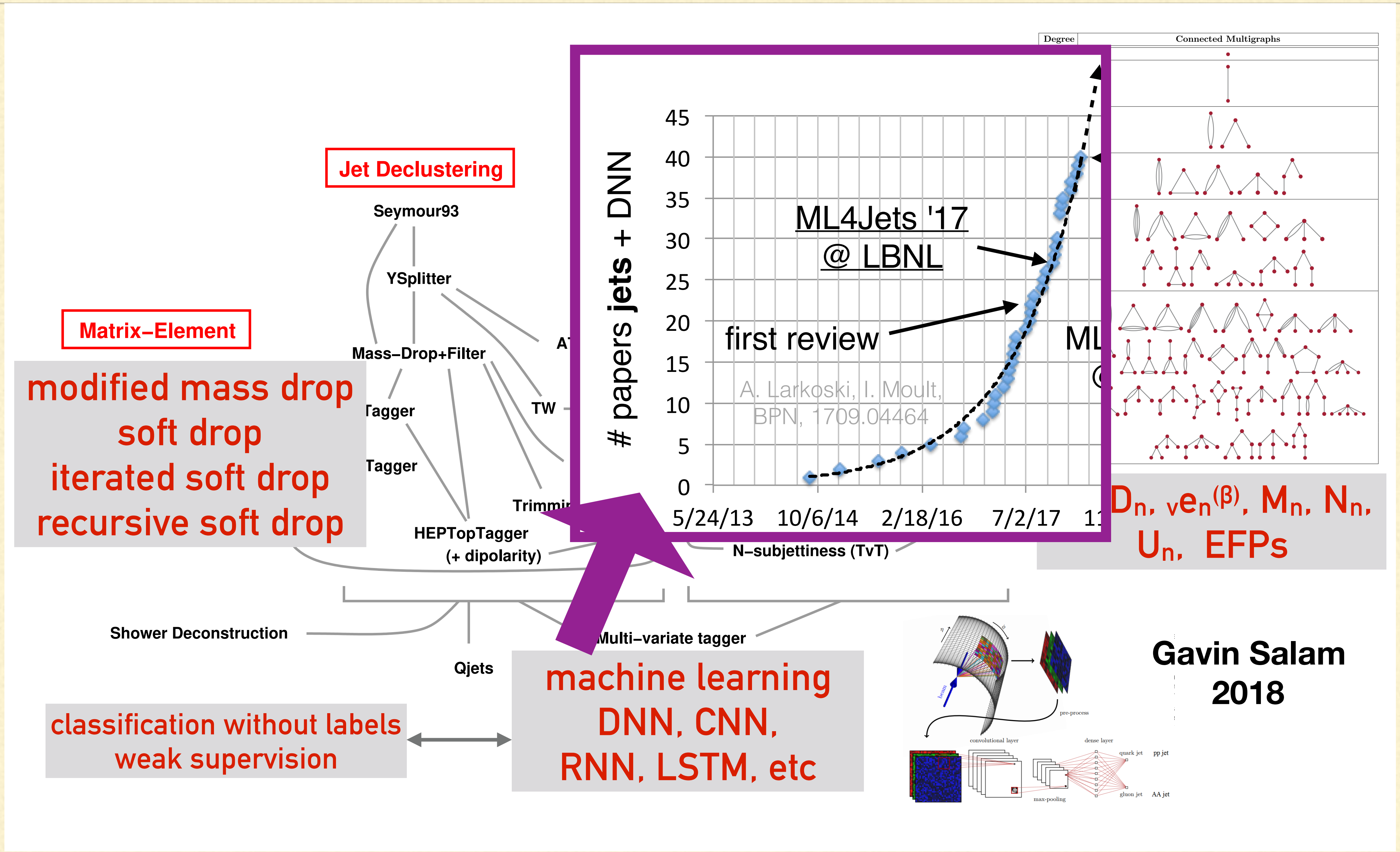

OPEN QUESTIONS

- Are we suspicious of black-boxes? Should we?
  - can we move from machine-learning to learning-from-machines? Interpretable neural networks? Prescriptive analytics?
  - can we devise ML learning algorithms that preserve calculability? (jet topics, grooming through reinforcement learning …)
- What's the best use of first-principle knowledge in jet physics?
  - extraction of SM parameters? PDFs with q/g tagging?
  - jet substructure probes of quark-gluon plasma in heavy ion collisions

(there are links to things I hadn't time to discuss)

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THANK YOU !