

MACHINE LEARNING FOR VBS

Jet 2, pT = 52.5 GeV

Electron 1, pT = 92.7 GeV

Muon 2, pT = 35.0 GeV

Electron 2, pT = 51.1 GeV



Jet 1, pT = 154.0 GeV

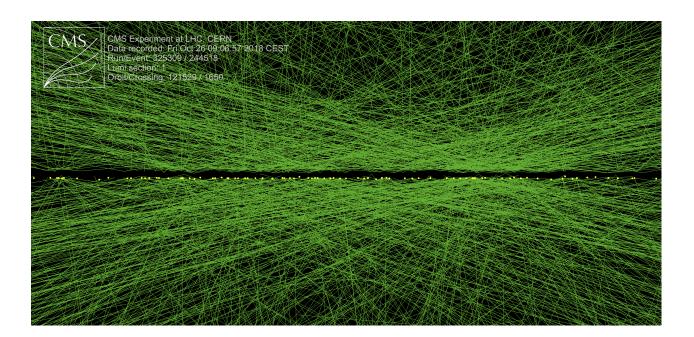
Muon 1, pT = 73.8 GeV

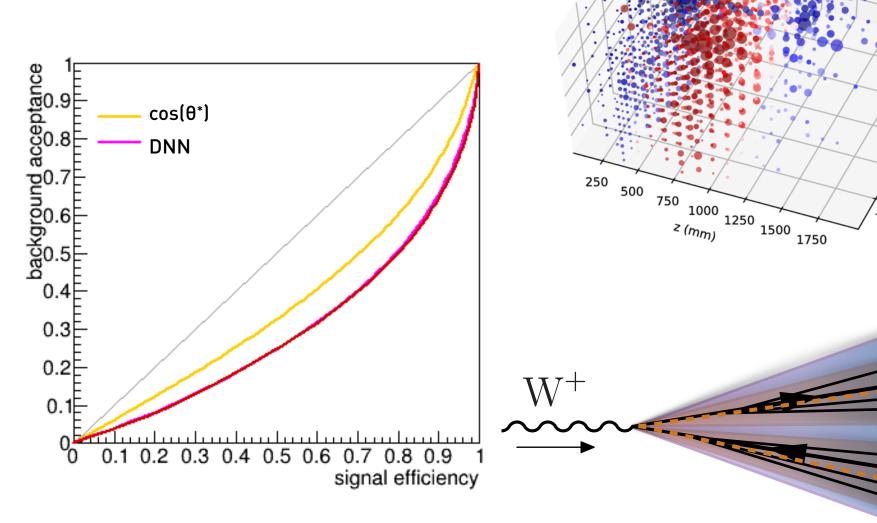
Thea Årrestad (CERN)

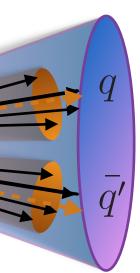
Virtual

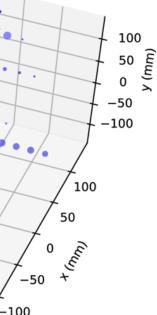
VBS in HL-LHC (and Run3!) extremely exciting

- Luminosity (x2 in Run3, x10 in HL-LHC): More data
- Detectors (e.g CMS High-Granularity Endcap Calorimeter): Better data
- Analysis: Squeeze the most out of bigger and better data!







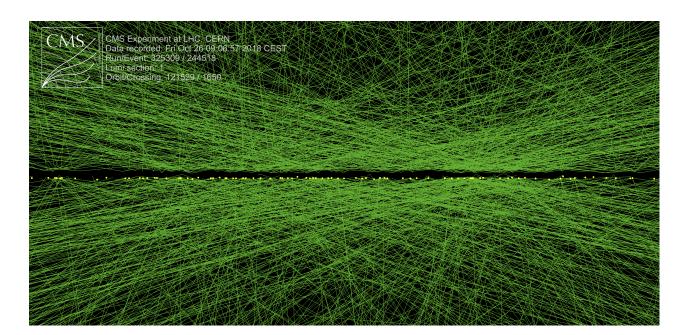


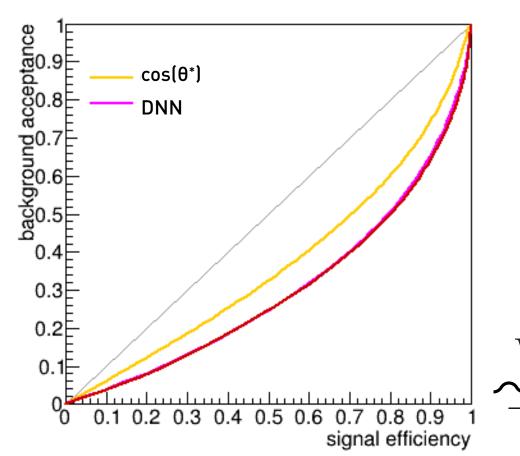
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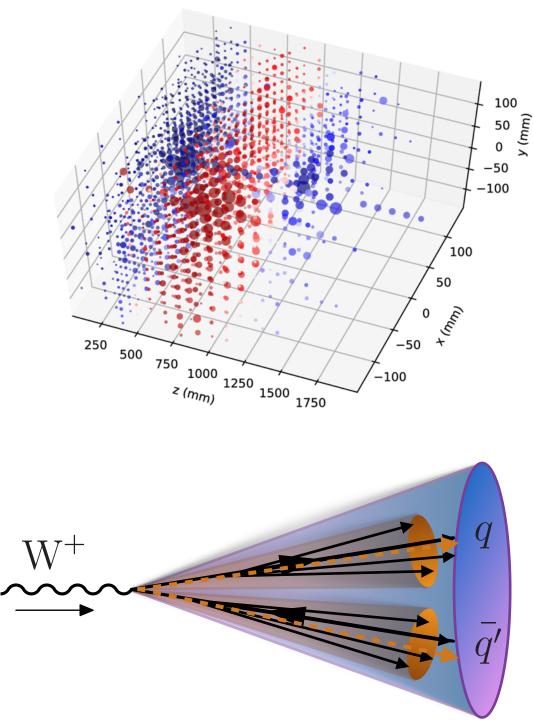
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ML crucial part of all three

- Luminosity: Managing huge data rates
- Detectors: Reconstructing complex patterns in complex new detectors
- Enhancing S/VB to tackle highest-background channels • Analysis:
- Can we dream about all-hadronic VBS? Longitudinal/transverse?







Why VBS is exciting from ML perspective:

Forward (quark) jets

- Quark/gluon separation
- Jet resolution (HGCAL!)
- Pileup mitigation

Vector-bosons

- Hadronic final states(?!)
- Jet substructure
- Longitudinal/transverse

Event

C

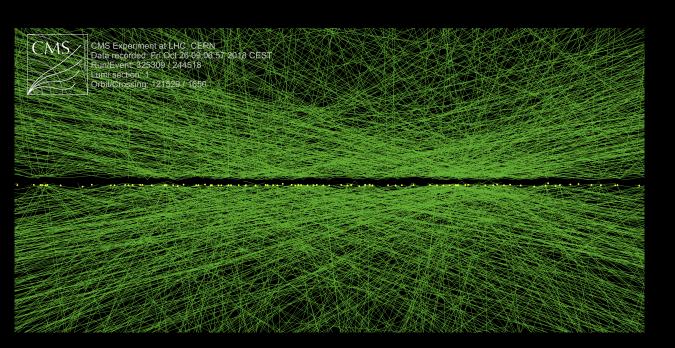
- A lot of event information
- BSM at high E, SM TT as background?

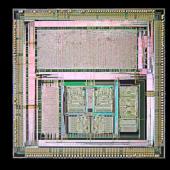
cds.cern.ch/record/2714080



Detector

- Data rate O(100)Tb/s
- O(10) ns latency
- Better endcap calorimetry





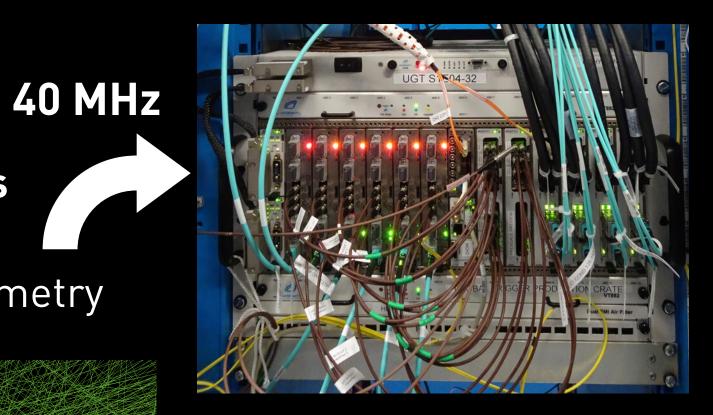
Forward jet resolution

Level-1 hardware trigger

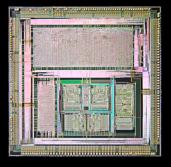
- 12.5 µs latency
- Input bandwidth 54 Tb/s
- Tigger cleanly+reconstruct narrow VBS jets!

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Forward jet resolution

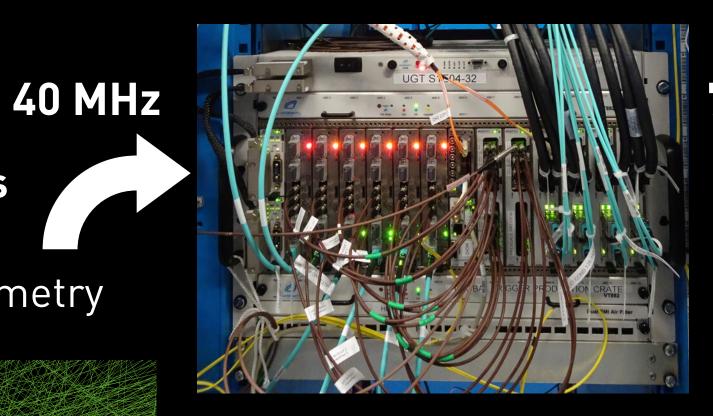
VBS trigger

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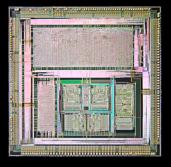
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Detector

- Data rate O(100)Tb/s
- 0(10) ns latency
- Better endcap calorimetry





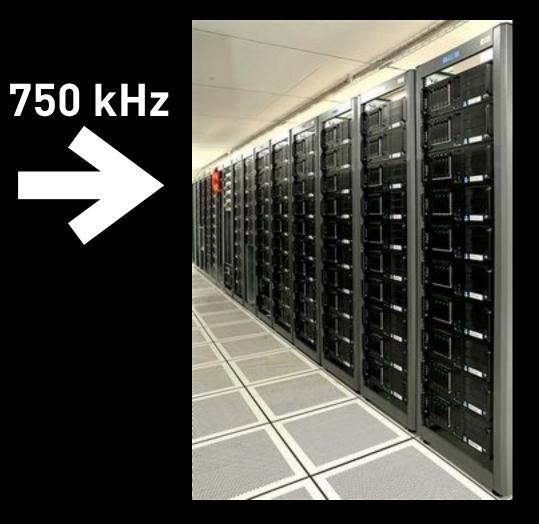


Forward jet resolution

VBS trigger

High Level Trigger

- 0(100) latency
- q/g discrimination!



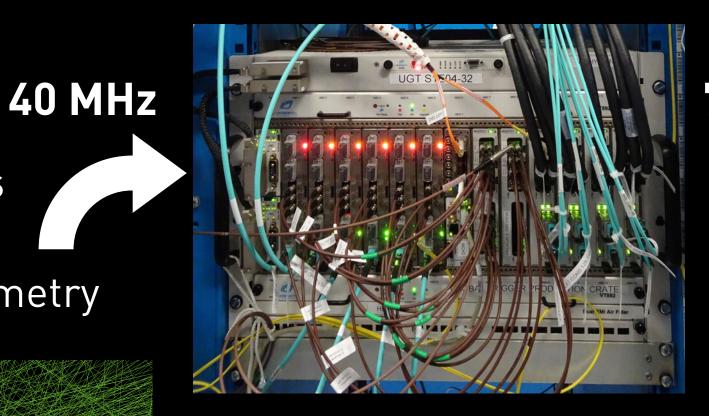
Dedicated ML-based VBS trigger paths

Level-1 hardware trigger

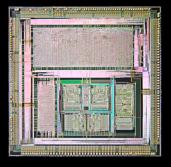
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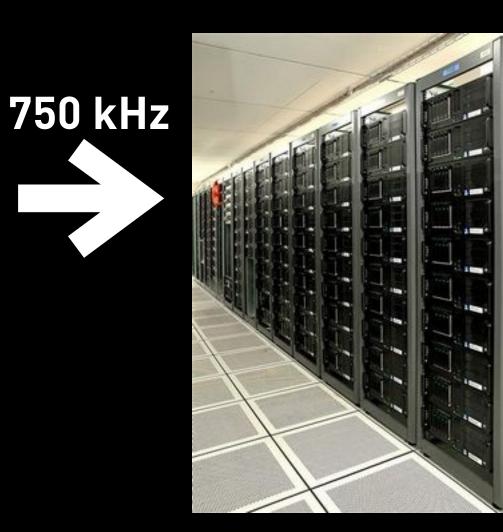


Forward jet resolution

VBS trigger

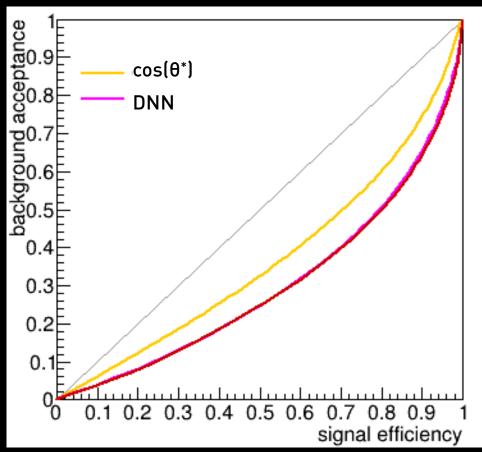
High Level Trigger

- 0(100) latency
- q/g discrimination!



7.5 kHz

Offline reconstruction and analysis



Longitudinal vs. transverse? **Enhance BSM?**

Dedicated ML-based VBS trigger paths



Detector

Improve <u>forward jet resolution</u> and reducing <u>pileup</u>
Limited bandwidth and time
High radiation

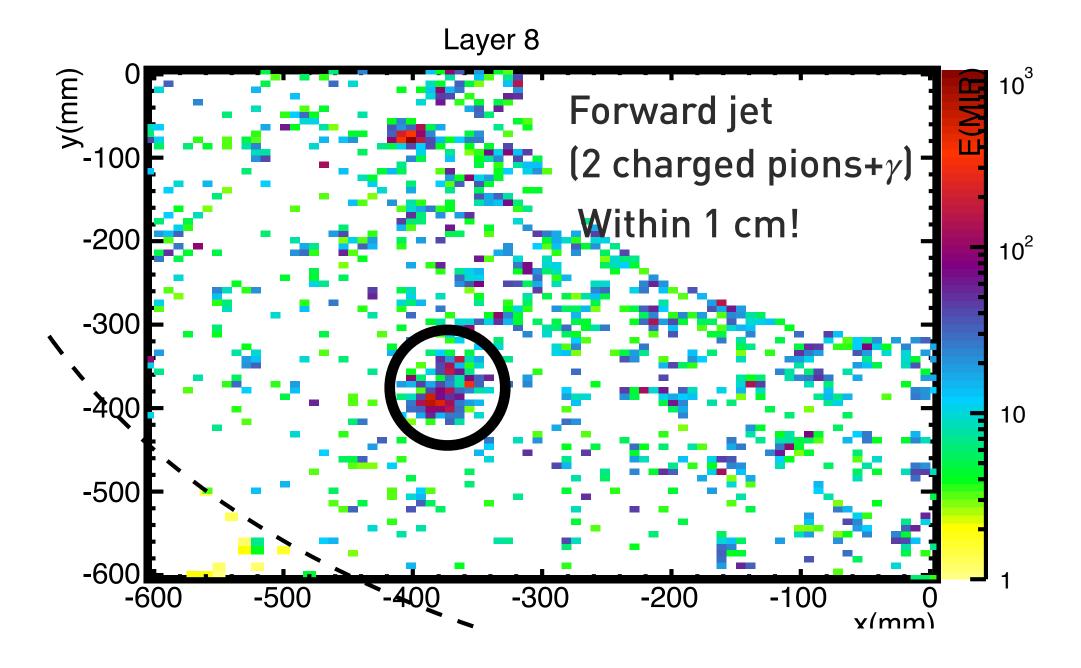
CMS Experiment at LHC, CERN Data recorded, Fri Oct 26 09:06 57 2018 CEST



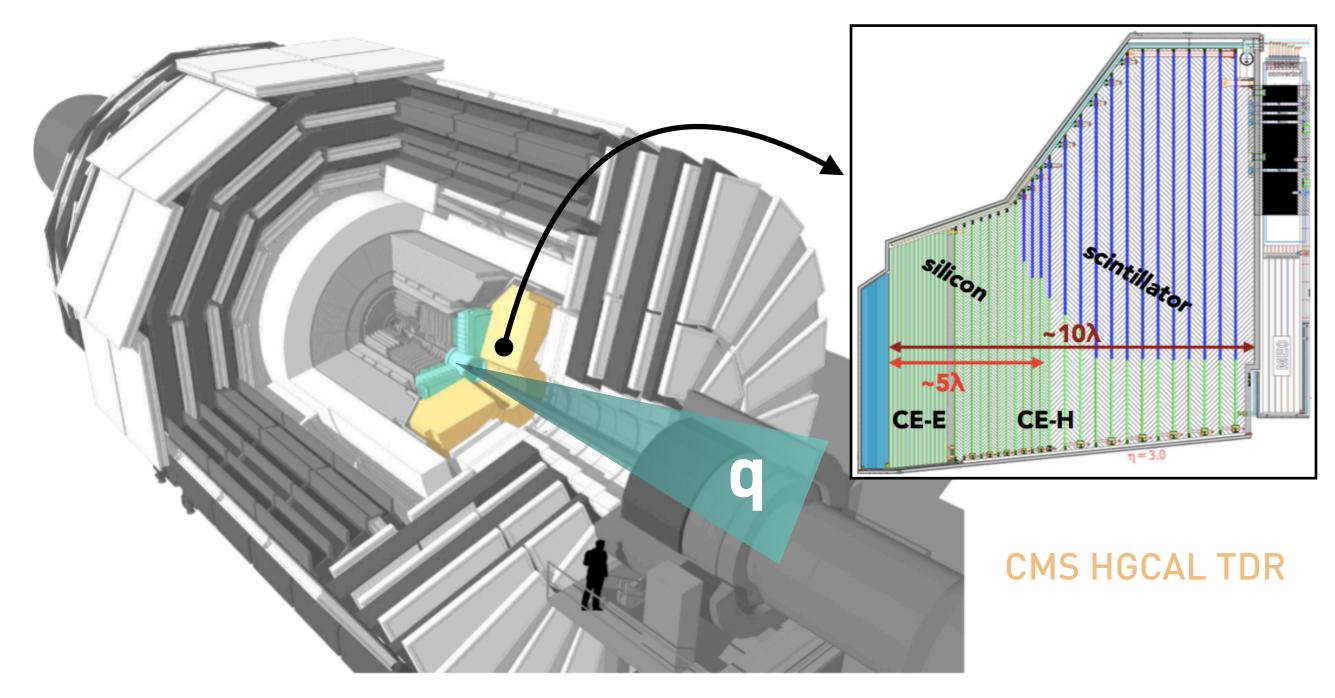
On-detector: HGCAL

CMS Endcap High-Granularity Calorimeter (1.5<η<3)

- Unprecedented transverse/longitudinal segmentation
- Shower development+narrowness of VBS jets



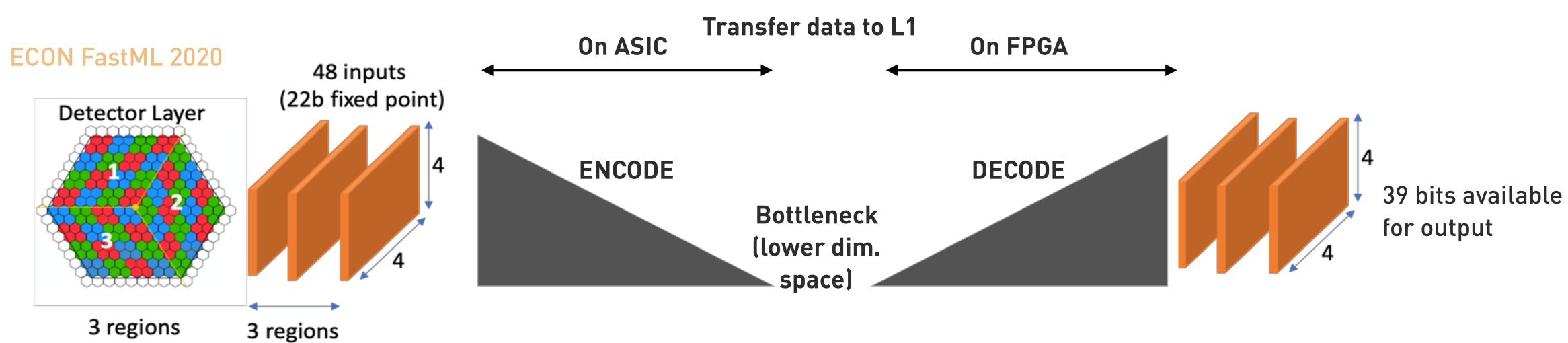
- 52 layers, 6 million silicon channels, limited output bandwidth
- Operate at $-30^{\circ}C \rightarrow$ need low-power on-ASIC preprocessing



andwidth essing

On-detector: HGCAL

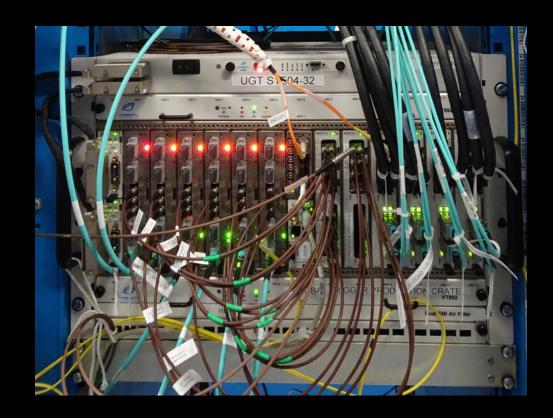
Optimise information output using ML! Maximise resolution on extremely low power.



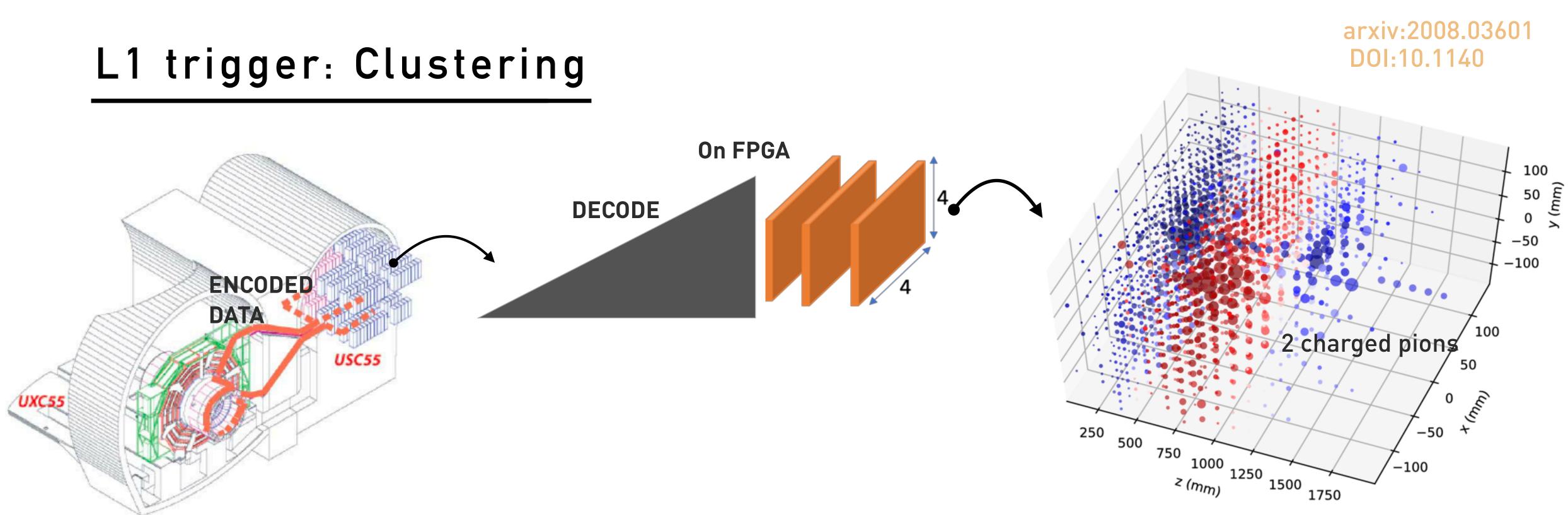


L1 trigger

 Maximise <u>VBS signal acceptance</u> through <u>dedicated triggers</u> High accuracy + low latency



\rightarrow ML on FPGA



After energy deposits are decoded on FPGFA, need to cluster!

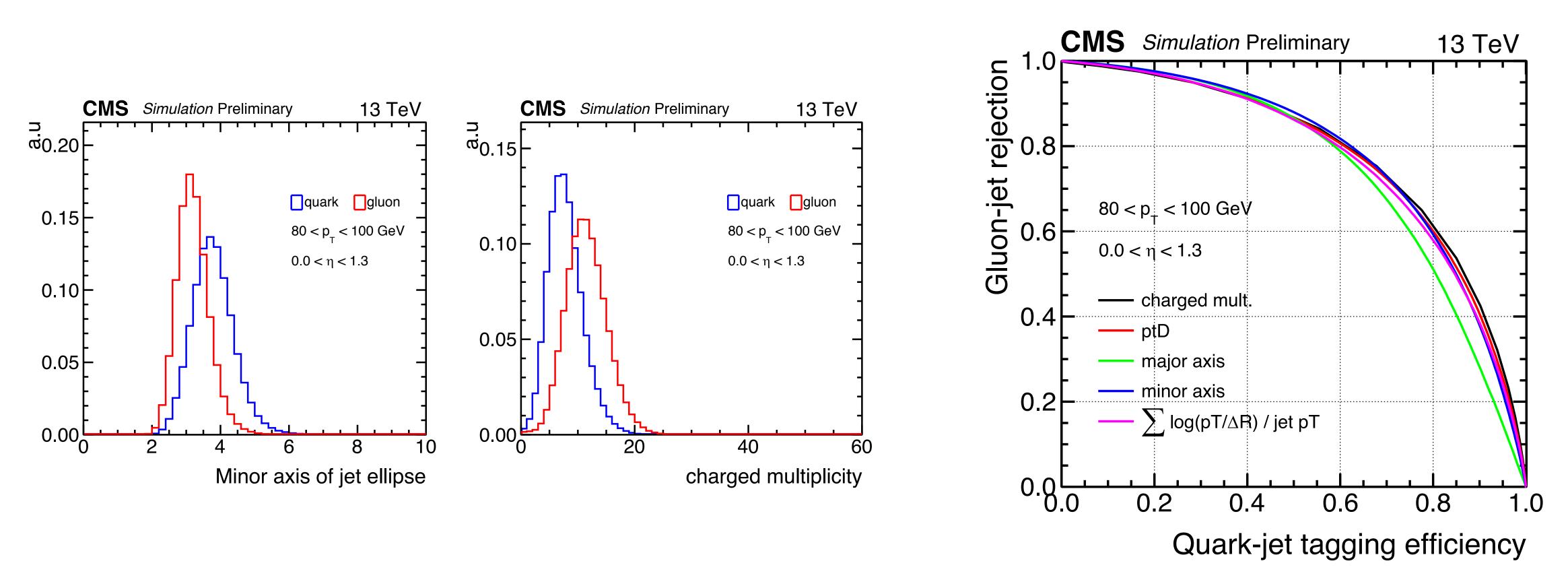
- Exploring Graph Neural Network to cluster energy deposits into disentangled showers from individual particles
- Difficult to achieve desired throughput (huge input!), but has been demonstrated on reduced input sizes

Good energy resolution and clustering important for VBS jets in 200 PU environment!

L1 trigger: q/g

With good endcap shower reconstruction:

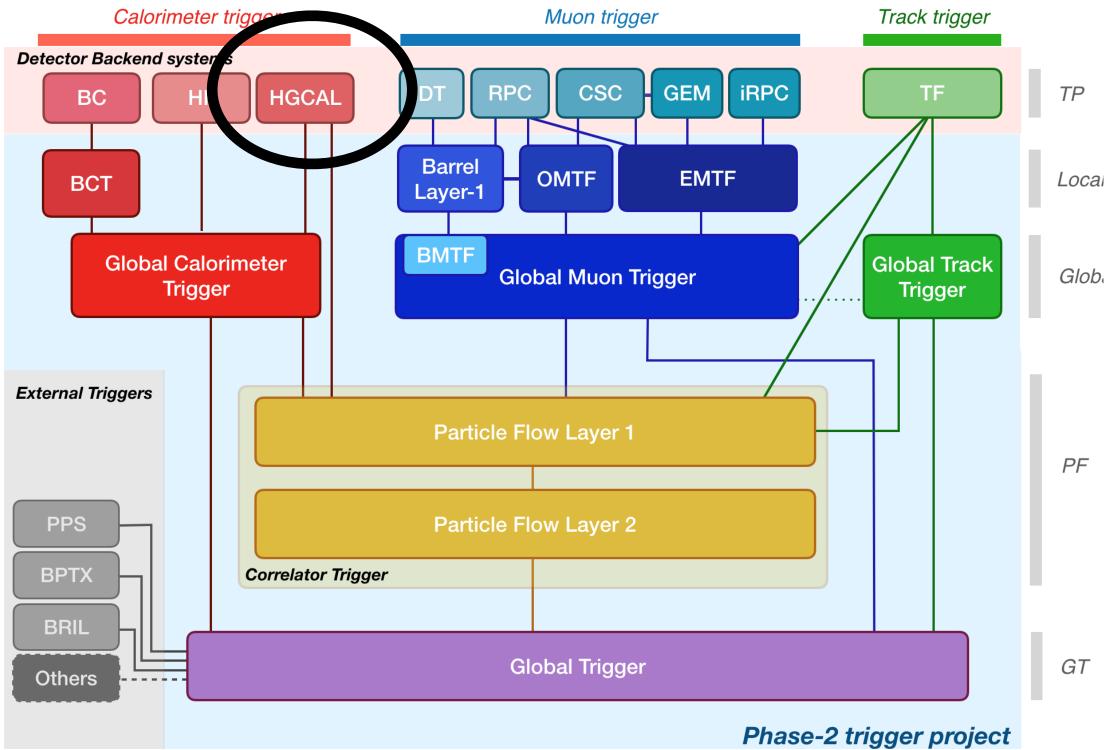
- "Cheap" ways to get q/g separation at L1, eg. simple 5 input BDT (2017)
- High-resolution inputs + better DNN (Kallonen et. al.), q-tag at L1 @ HL-LHC



5 input BDT (2017) , q-tag at L1 @ HL-LHC

CMS Level-1 in HL-LHC has a lot to offer VBS

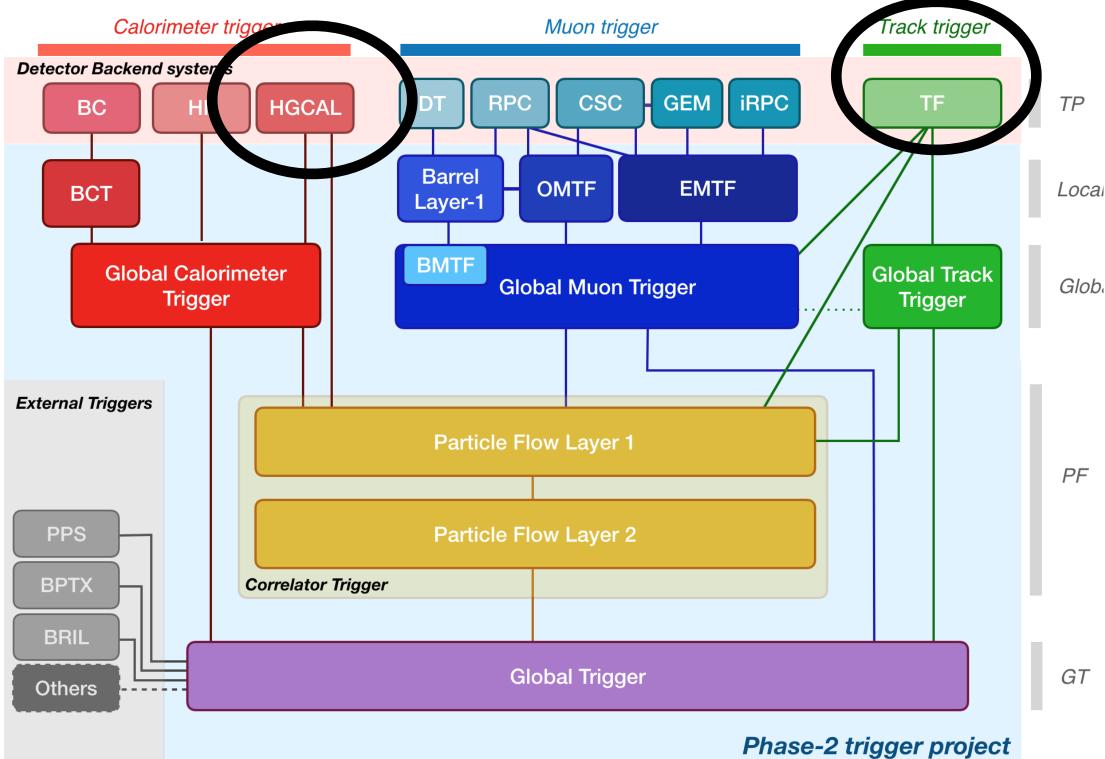
• High resolution forward calorimeter \rightarrow lower m_{qq} thresholds? q/g-tag?



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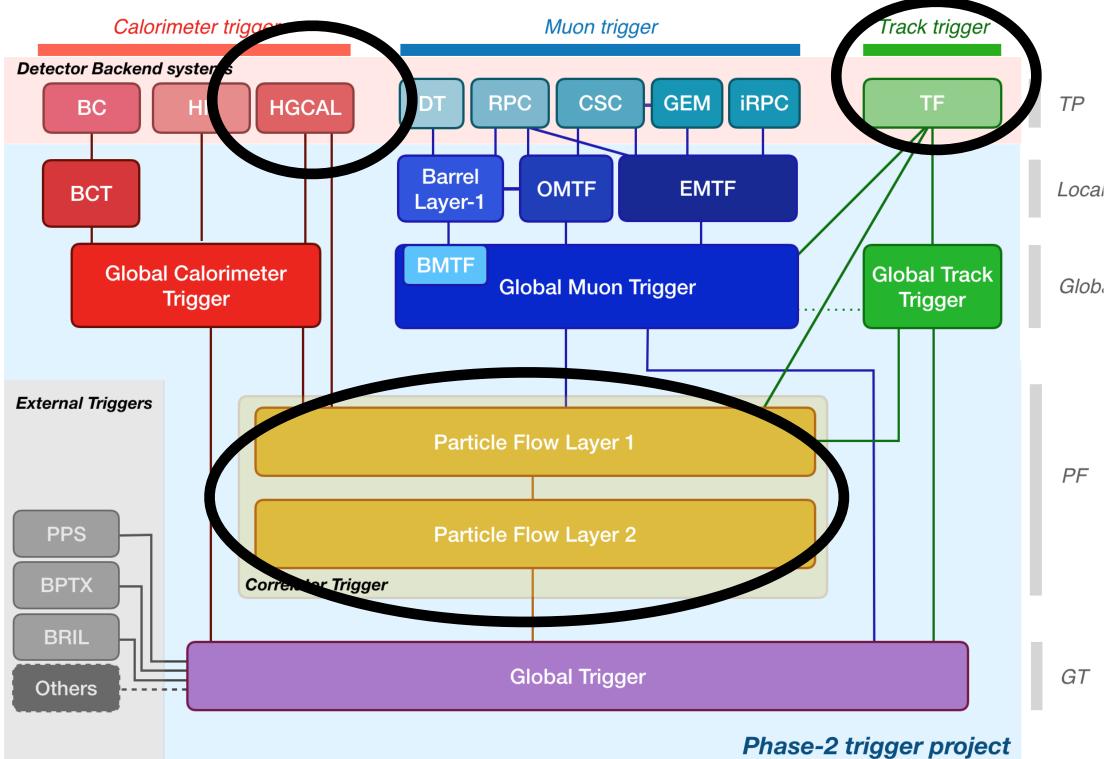
- High resolution forward calorimeter \rightarrow lower $m_{q\overline{q}}$ thresholds? q/g-tag?
- Tracking (η < 2.4)

 \rightarrow charge multiplicity for q/g ++?



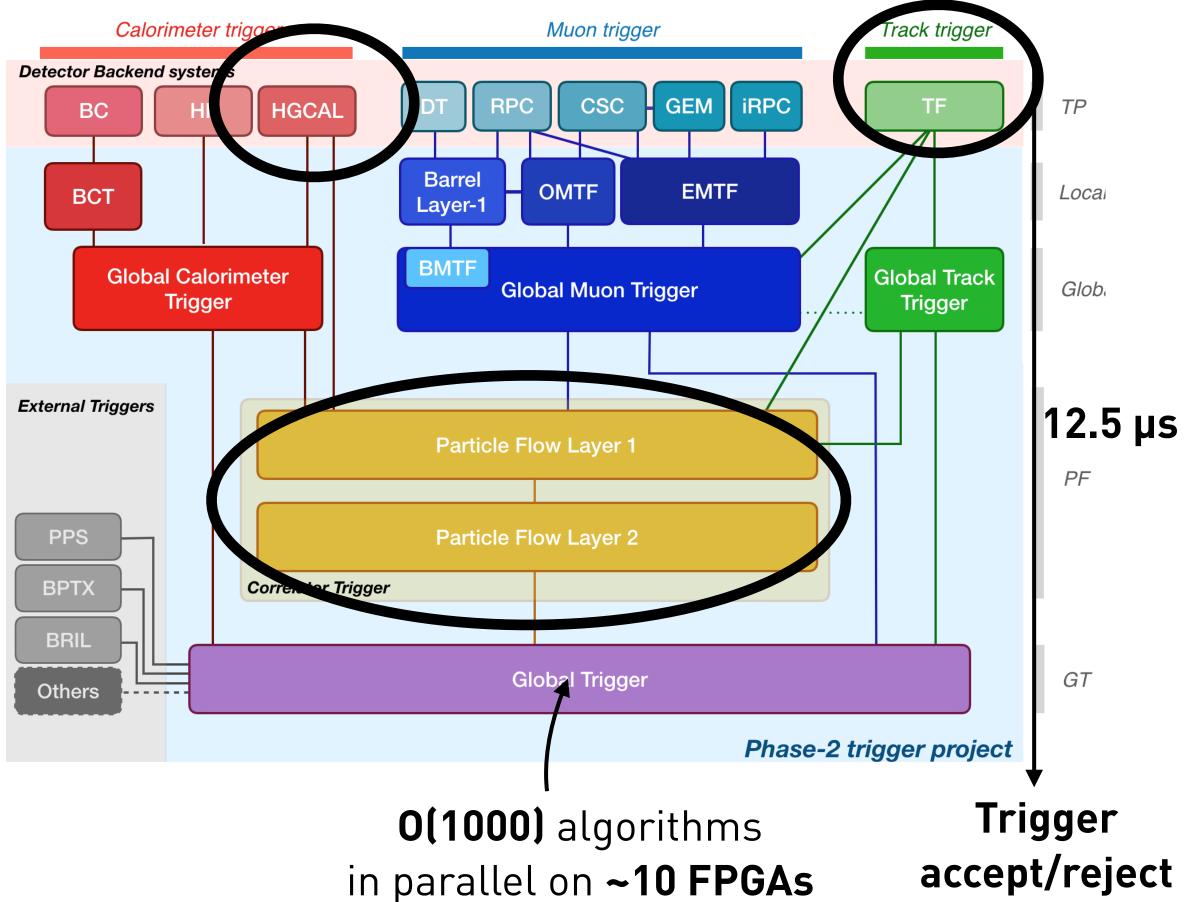
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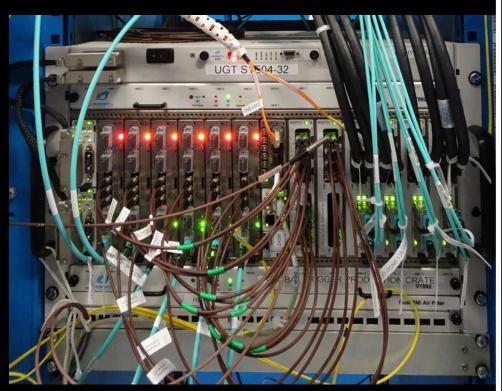
- High resolution forward calorimeter \rightarrow lower m_{qq} thresholds? q/g-tag?
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- ParticleFlow at Level 1
- \rightarrow substructure algorithms for V \rightarrow q \overline{q} and q/g?

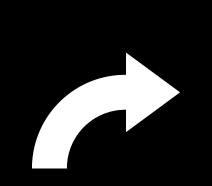


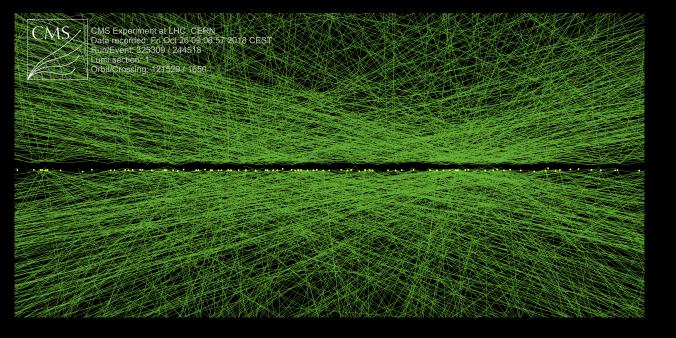
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- ParticleFlow at Level 1 \rightarrow substructure algorithms for V \rightarrow q \overline{q} and q/g?
- Study DNN for jet substructure tagging at L1
- AI can provide highly efficient VBS tags! Boils down to latency, resources and bandwidth









High Level Trigger

 Maximize signal acceptance with all the things we couldn't afford to do at L1 (e.g. jet substructure) More time, limited bandwidth



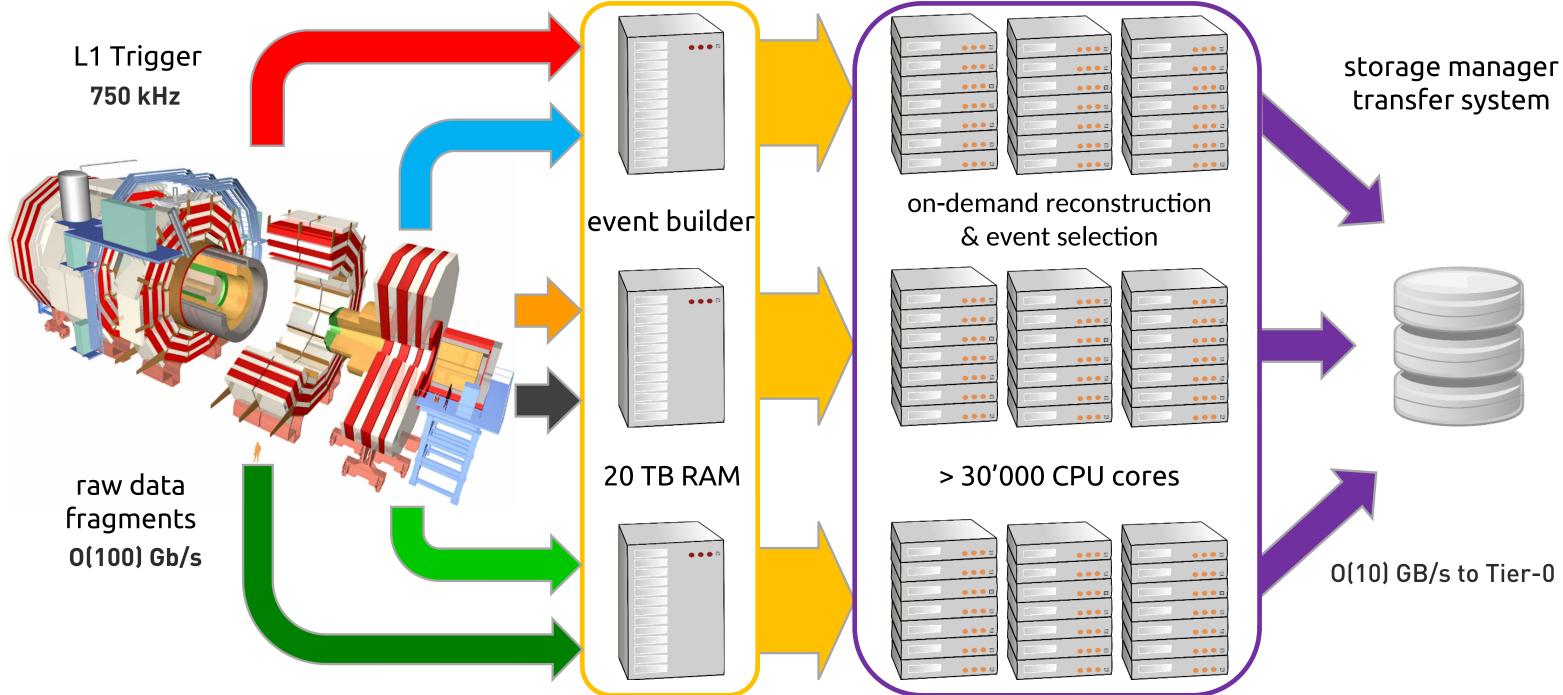
\rightarrow ML on GPU

High Level Trigger

Amount of data we can store for use in analysis limited by bandwidth, O(10) GB/s to Tier-O

- 300 ms to decide keep/reject
- Running thousands of "modules" on many collision events in parallel

750 kHz



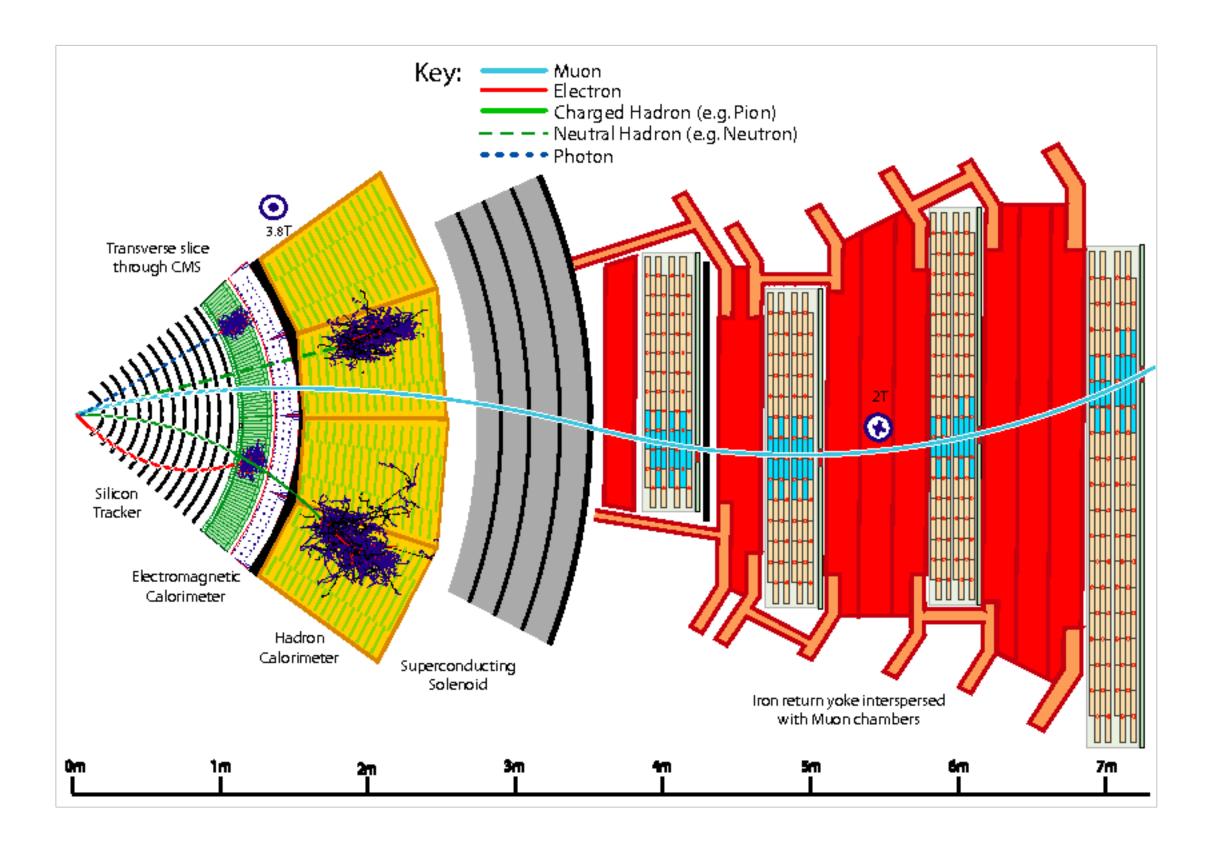
Bandwidth (kB/s) = Event rate (kHz) x Event size (kB)

transfer system



Particle Flow is highest resolution reconstruction at HLT. Slow, can't run on all events! Currently only PF on 17% of total

• High resolution, but small rate

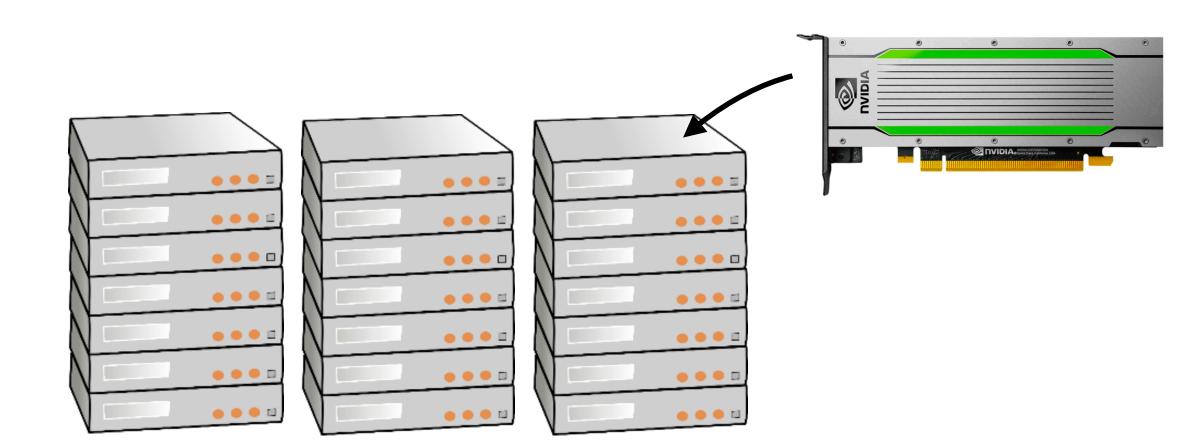


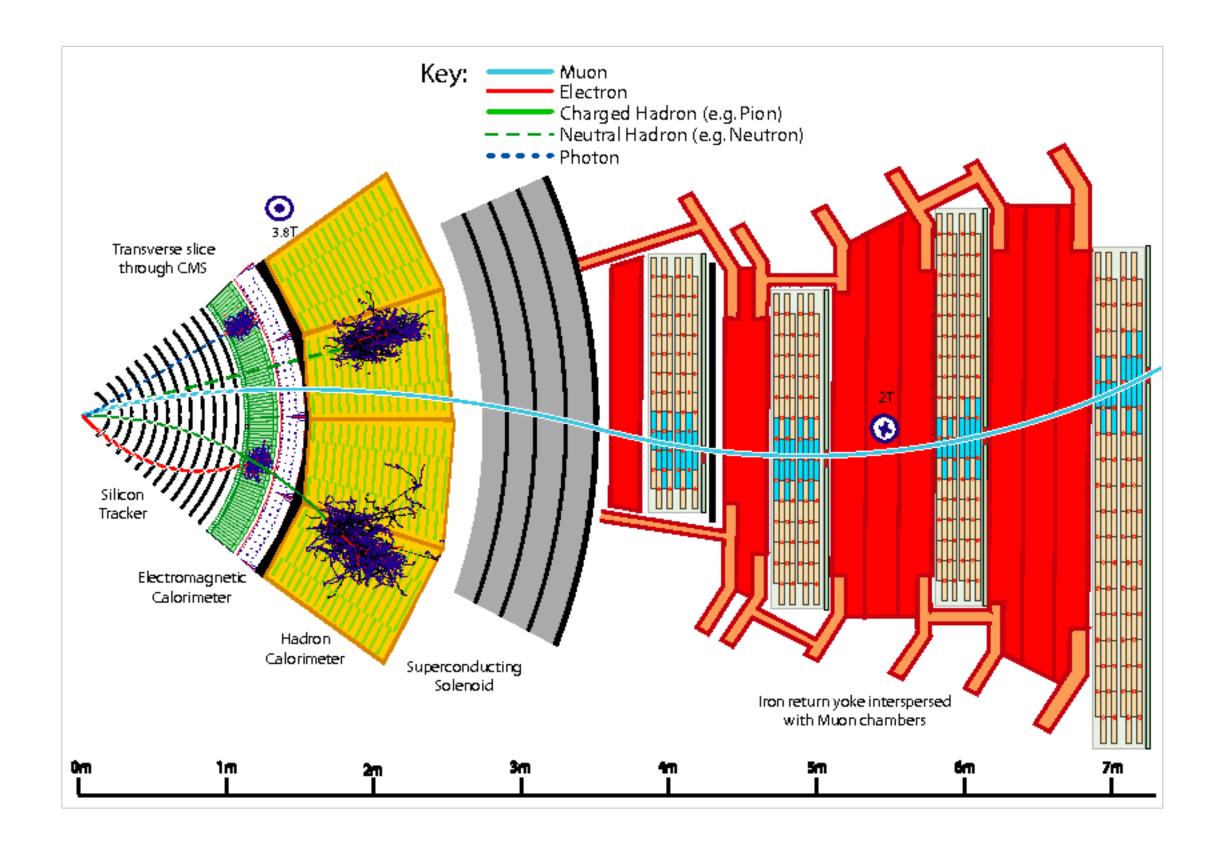
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To handle HL-LHC data rates

- Offload resource-intensive computations to GPU
- Can achieve speed-ups ~x3
- More compute to run PF!



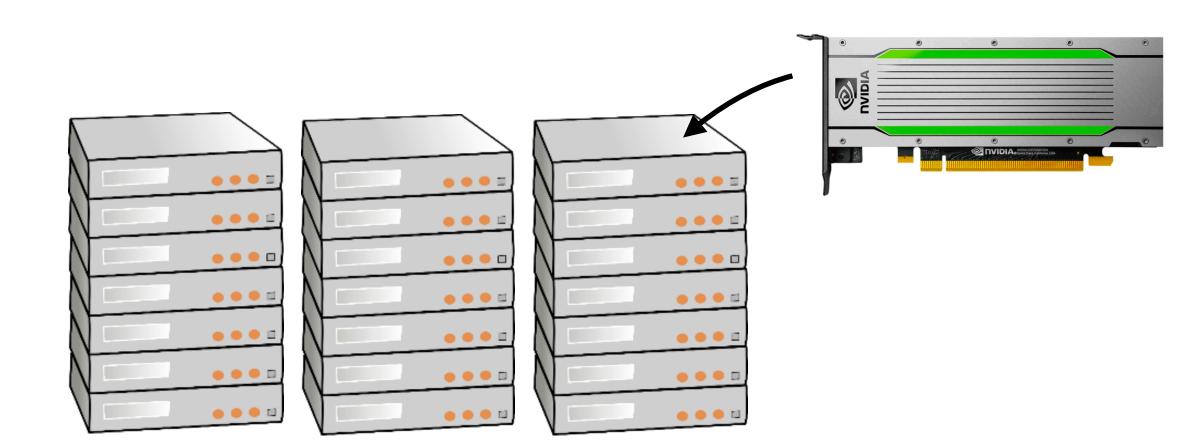


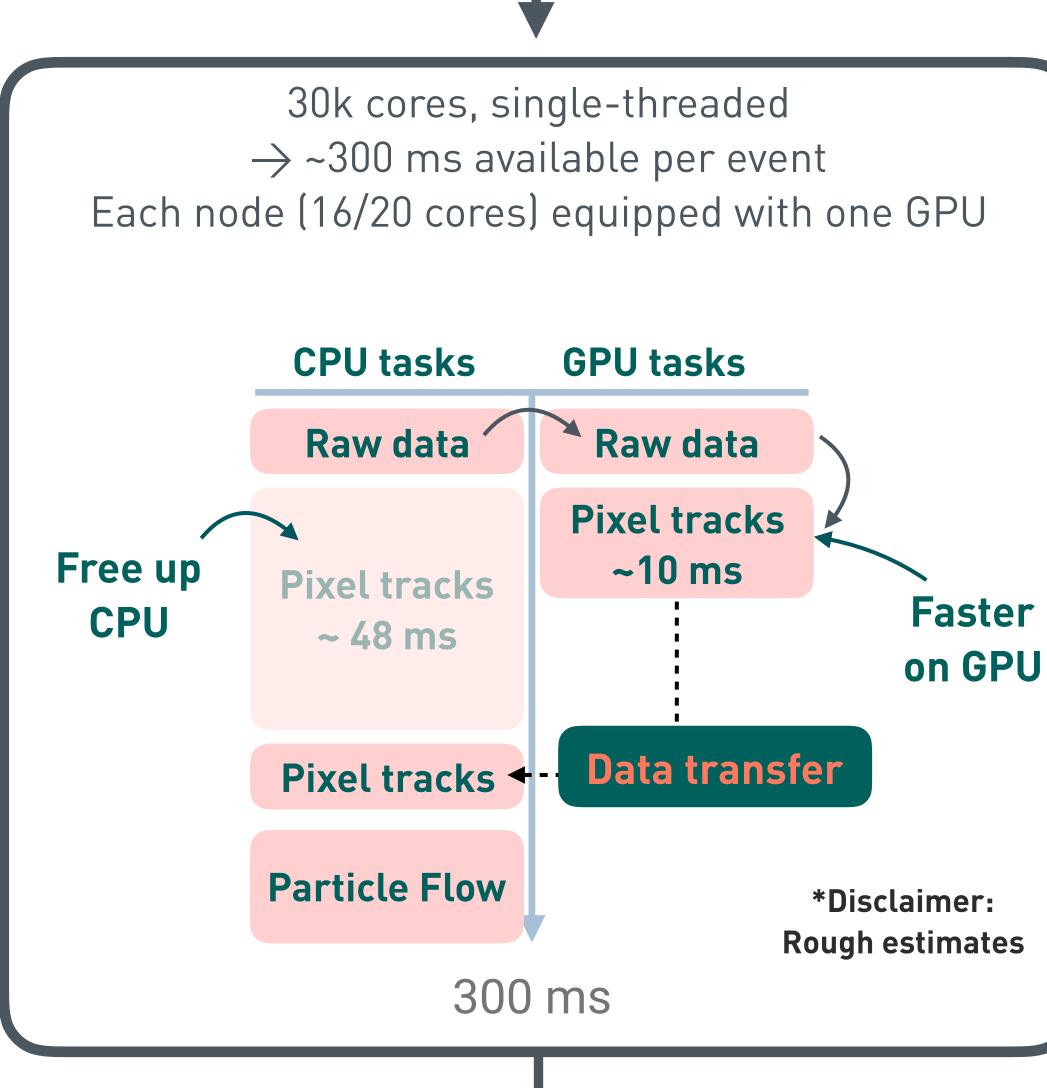
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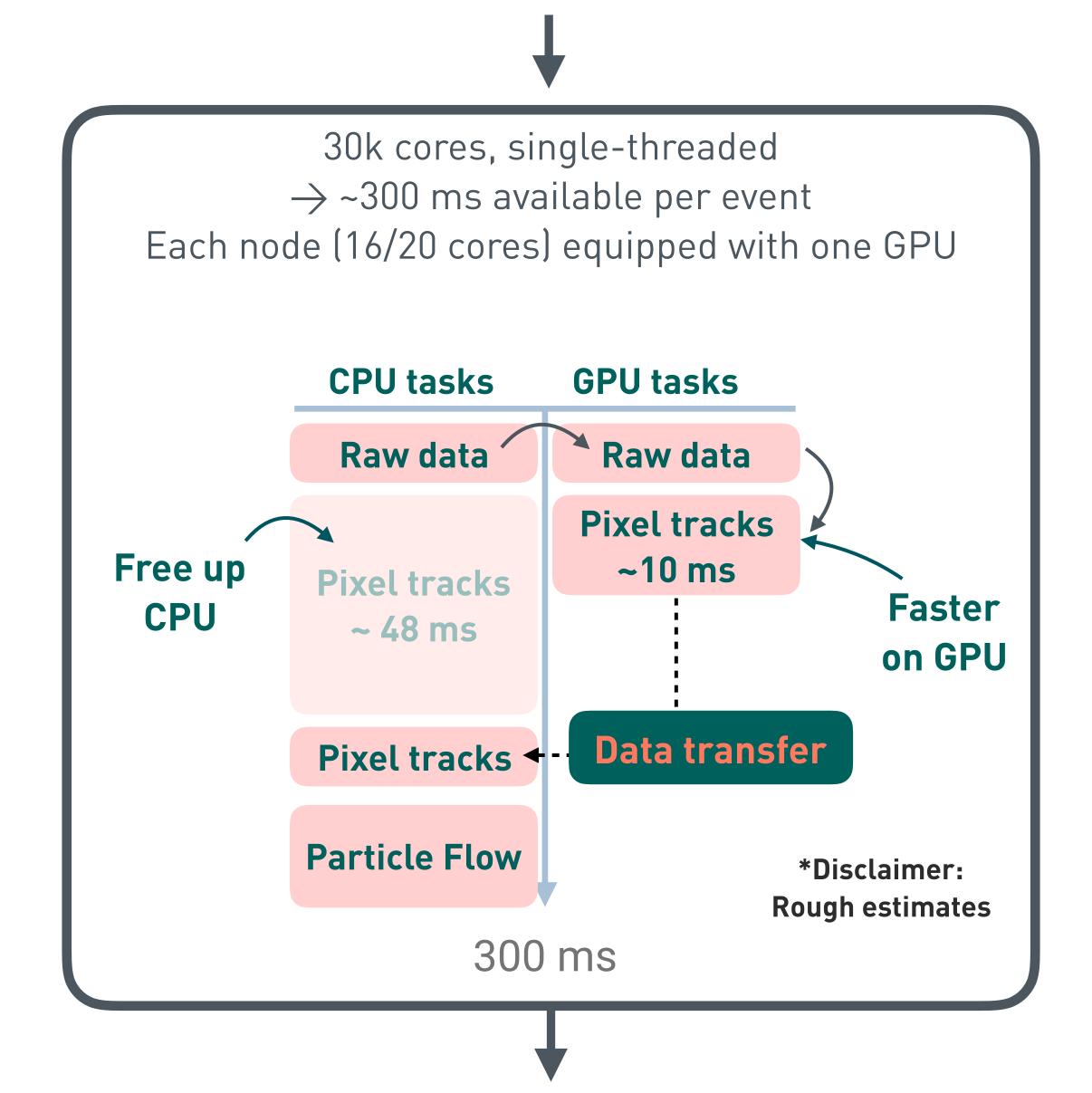
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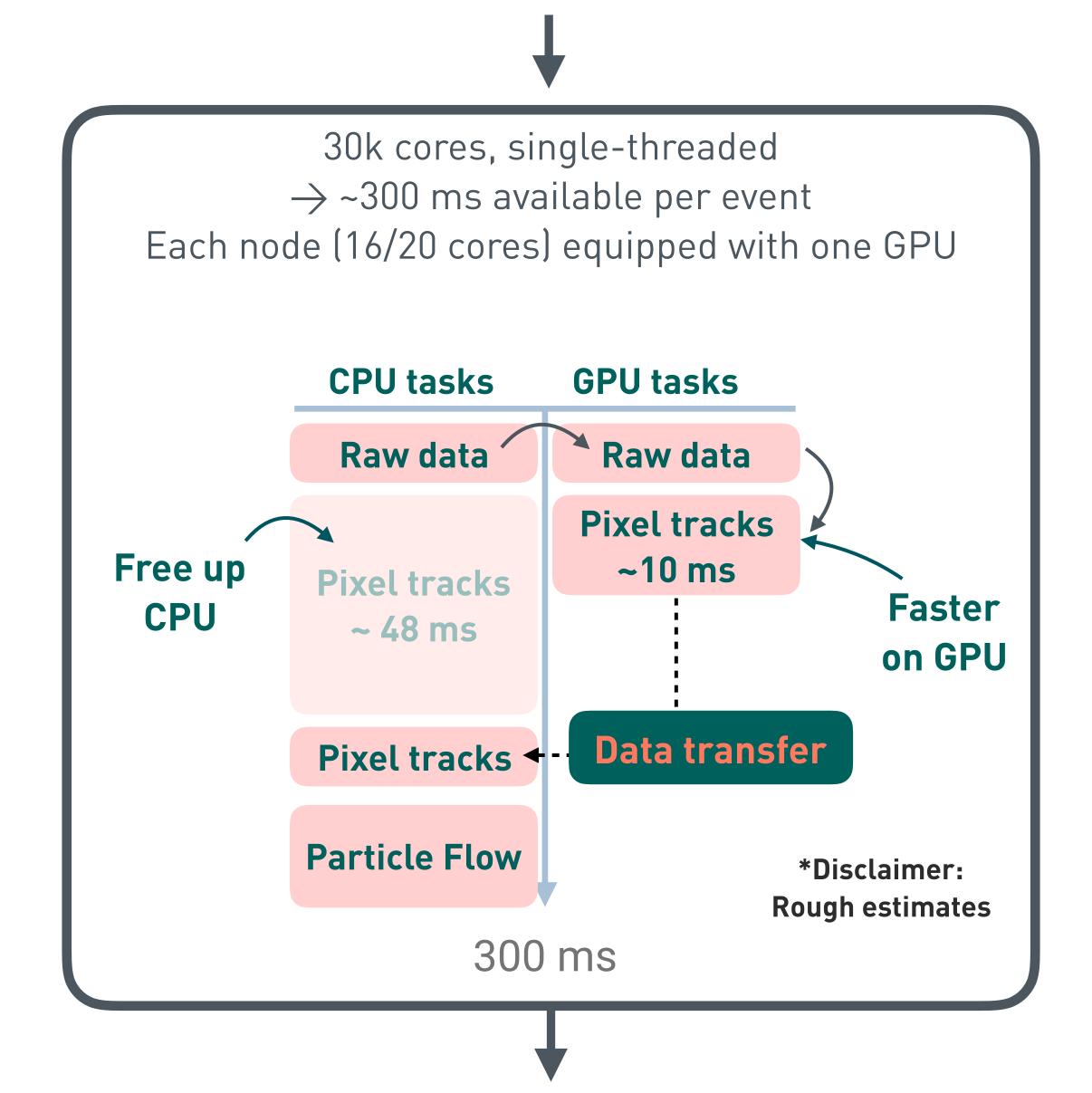




More PF means cleaner VBS triggering!

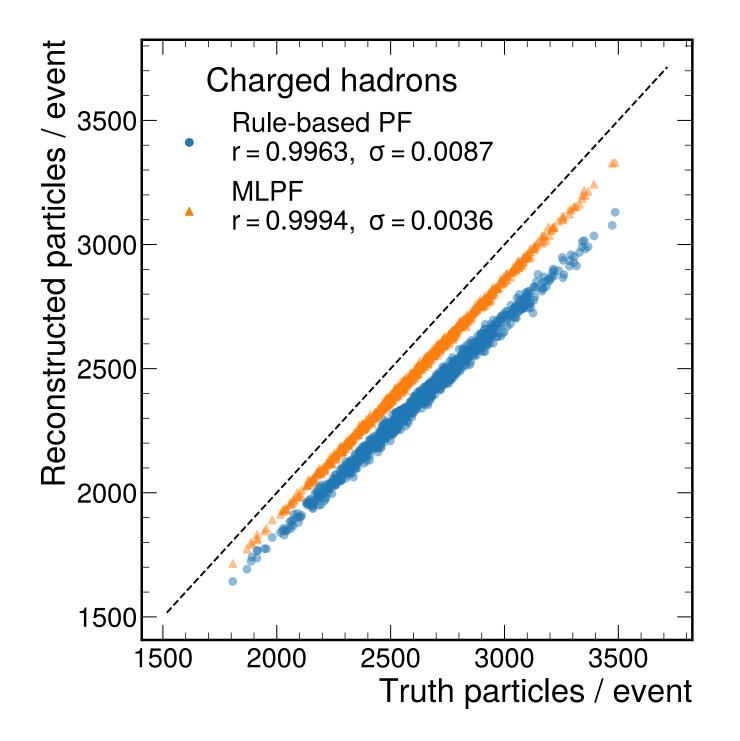
• Especially for all-hadronic VBS, jet substructure at HLT important!

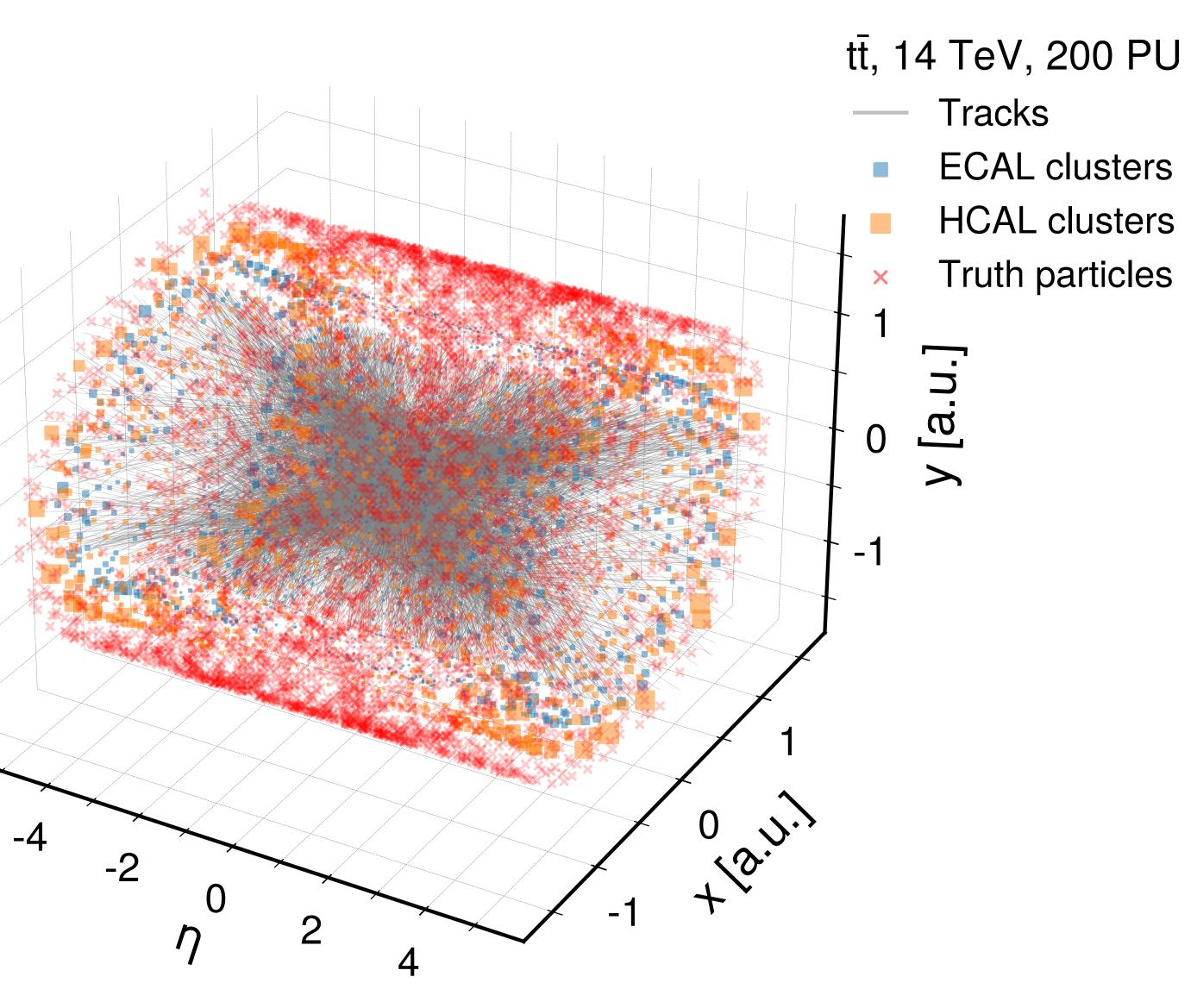
Transfer data GPU \rightarrow CPU expensive, can we avoid it by doing PF on GPU?



Deep Neural Networks as "fast" approximations of classical ParticleFlow

- In CUDA for free (naturally runs on GPU)
- Inherently parallelizeable, can take advantage of GPU acceleration
- High accuracy in high PU environment



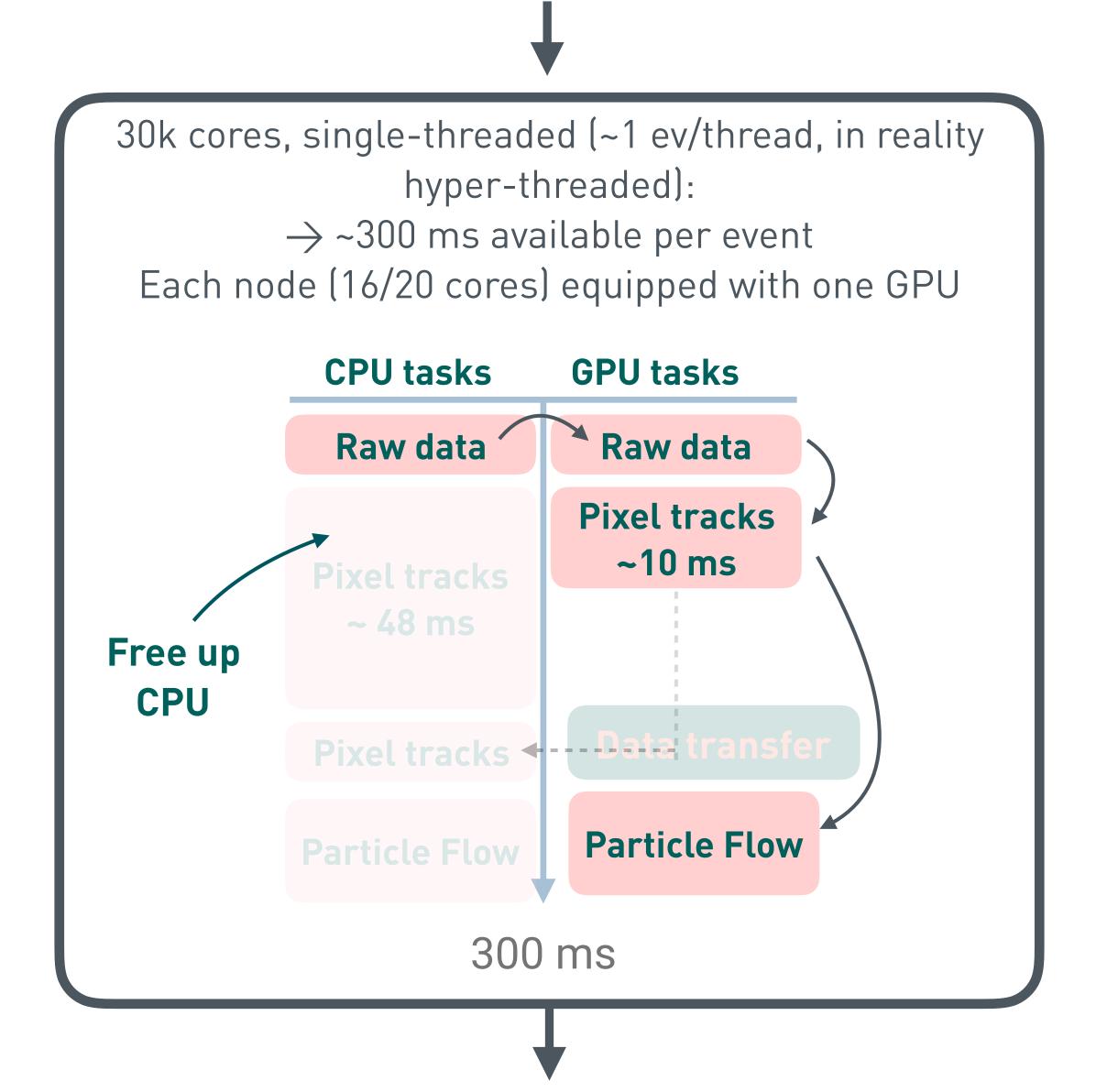


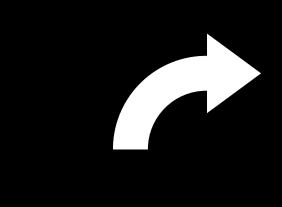
arXiv:2101.08578

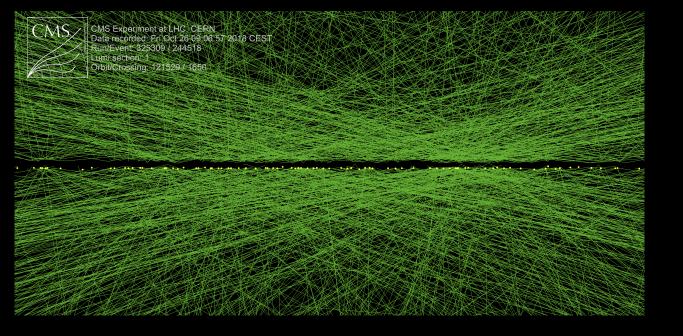


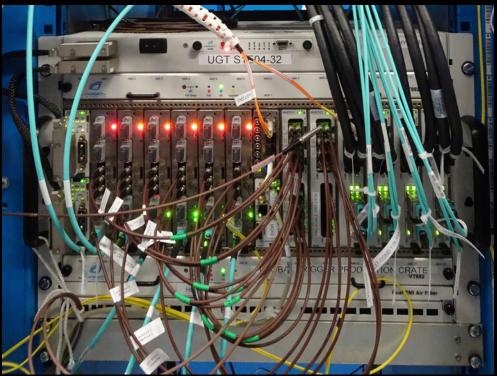
Dedicated VBS PF-based triggers

- q/g is an obvious one
- Jet substructure for $V \rightarrow qq$

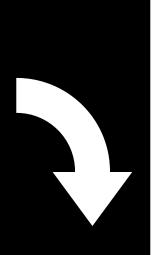






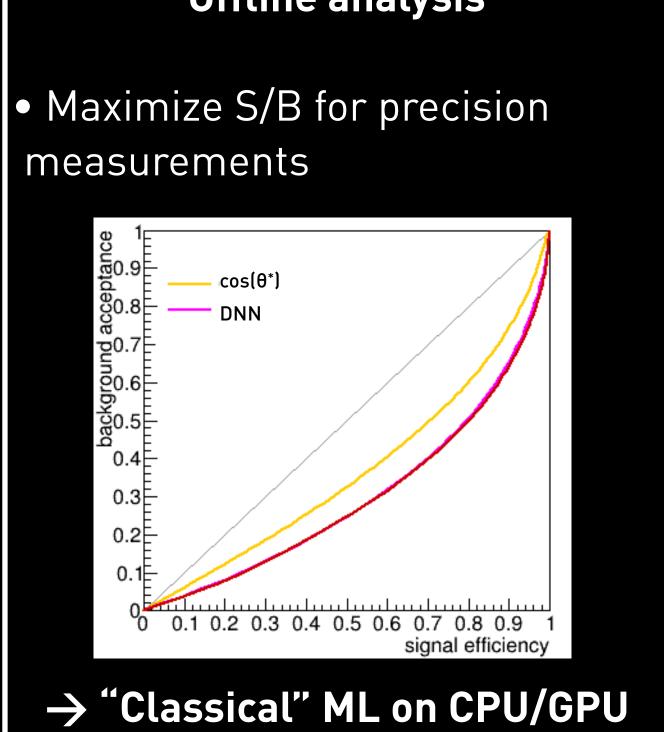






Offline analysis

measurements



$VV \rightarrow V_{L}V_{L}$ scattering

Run 3/HL-LHC: Huge lumi increase, ~same c-o-m energy:

Run 3/HL-LHC: Huge lumi increase at ~same C-O-M energy hunt" for precision

measurements targeting BSM:

BSM bump hunts -> precision measurements targeting BSM.scattering! E.g interference in $2 \rightarrow 2$ scattering

- Quartic coupling
- Higgs without Higgs
- Polarisation fractions (vs E)
- BSM enhancements

At $E >> m_V$, BSM mainly couples to W_L \rightarrow 90% of SM is W_T, irreducible background!

At $E \gg m_V$, BSM mainly couples to W_L

• 90% SM is TT (m_{VV} > 250 GeV), irreducible background!

Can we do W_T vs. W_L ? (See Kenneth's talk)

W W_{I} W

 σ in pb $W_L Z_L \rightarrow W_L Z_L$ without H $W_X Z_X \rightarrow W_X Z_X$ with H 10⁵ $W_X Z_X \rightarrow W_X Z_X$ without 10³ 10 10- 10^{3} 10^{4} 25 $\rm E_{\rm cm}$ in GeV

 $W_L Z_L \rightarrow W_I Z_L$ with H

10[°]

FUTURE IDEAS

$VV \rightarrow V_{L}V_{L}$

All-hadronic VBS as a "golden channel" for polarization (don't laugh)? • $W_{L}W_{L}$ small $\rightarrow BR(V \rightarrow qq)$

- Access to both fermions (caveat: charge) Run 3/HL-LHC: Huge lumi increase,
 Inference grows with energy a boosted jets.
- q-tag on forward jets + two tagged V-jets
- Access polarisation both through storward on jets to vector shows ons

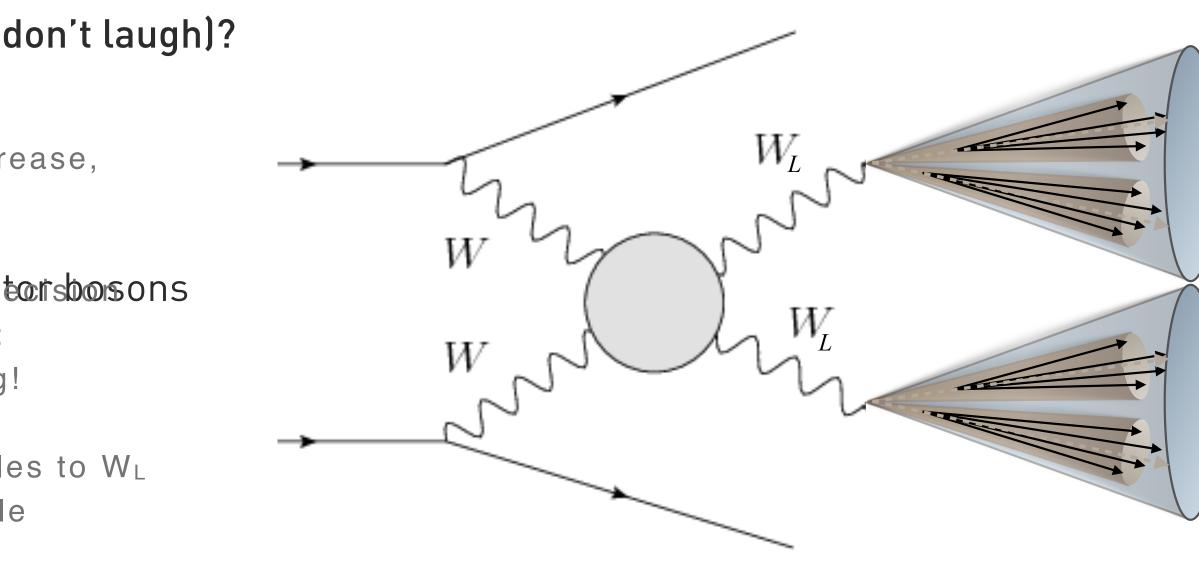
measurements targeting BSM: interference in $2 \rightarrow 2$ scattering!

Two-step problem

- Discriminate VBS from $QCD_{90\%}^{At E} >> m_V$, BSM mainly couples to W_{\perp}
- Discriminate W_T from W_{Lbackground}!

Two powerful tests of SM that can be made feasible by ML

- Crossection measurement in W_L enriched phase space
- Measurement of helicity fractions





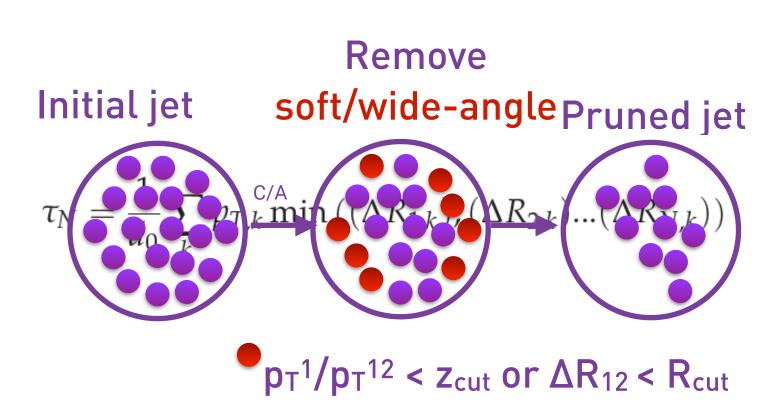
W_T vs. W_L discriminating power observed in jet substructure variables

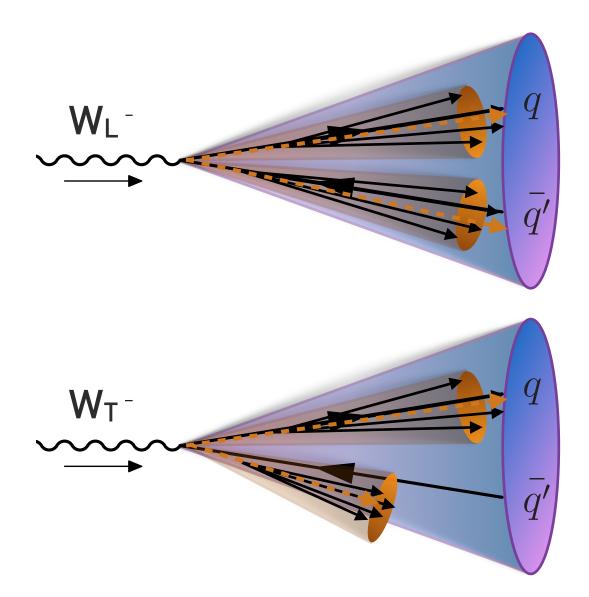
• W_T decay products preferentially (anti-)parallel to W momentum \rightarrow asymmetric p_T between subjects or overlapping partons (lab frame)

Jet substructure techniques

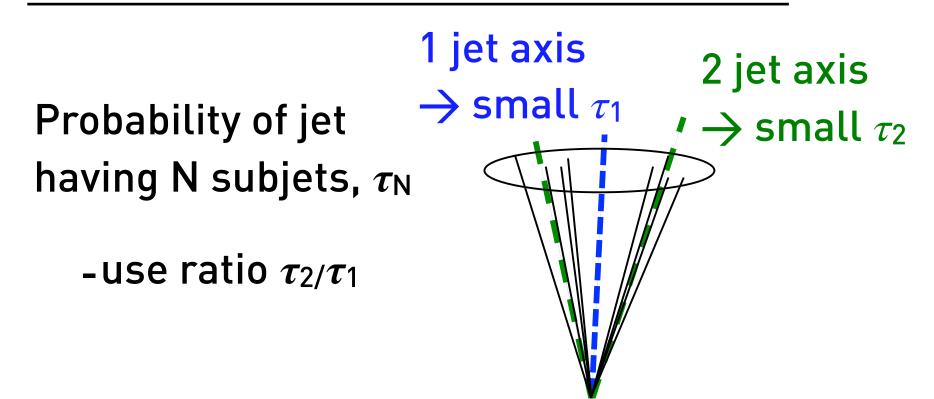
- Grooming: Remove soft+wide angle radiation (bad for asymmetric p_T)
- N-subjettiness: Probability for 2 axes within jet (bad for overlapping partons)

Jet mass resolution \rightarrow Pruning





Are there "subjets" \rightarrow n-subjettiness

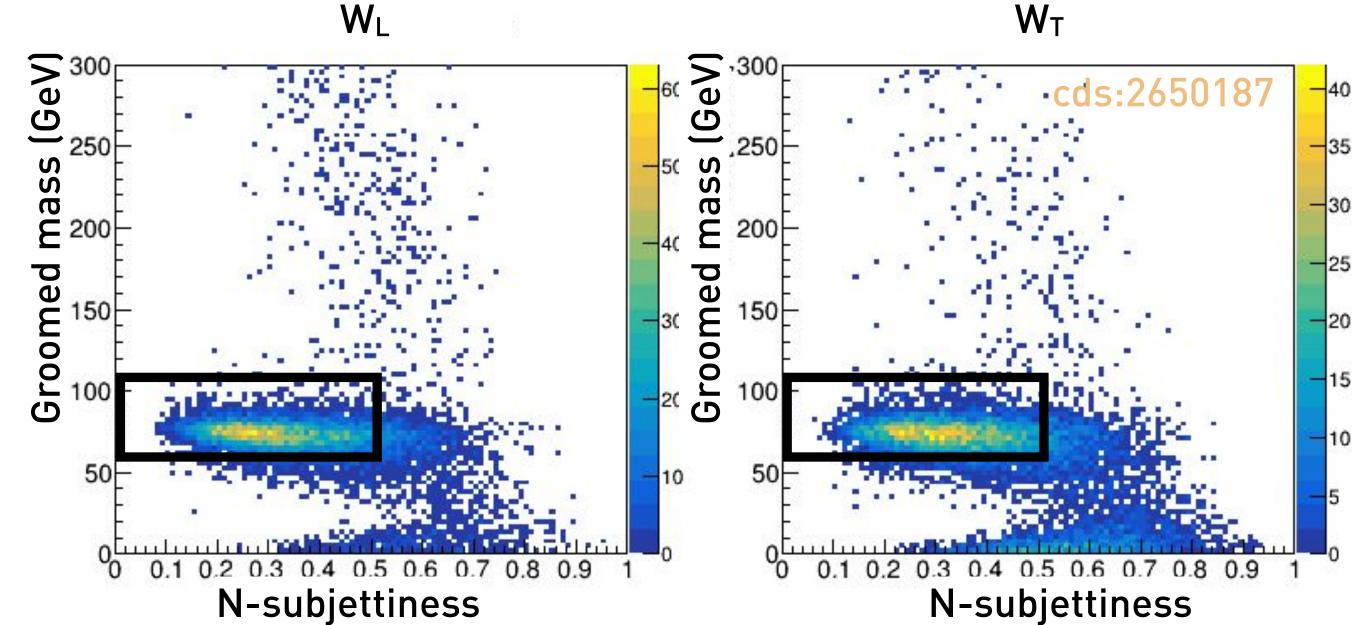


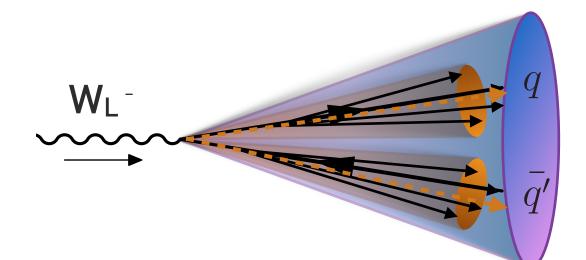
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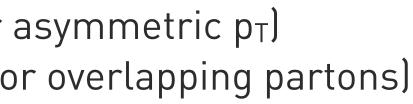
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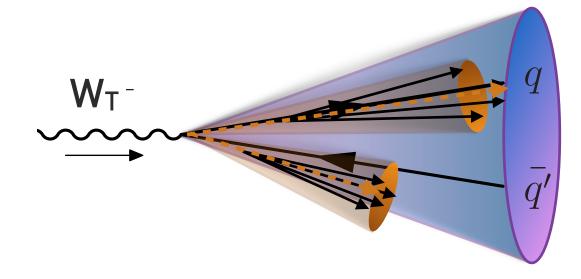
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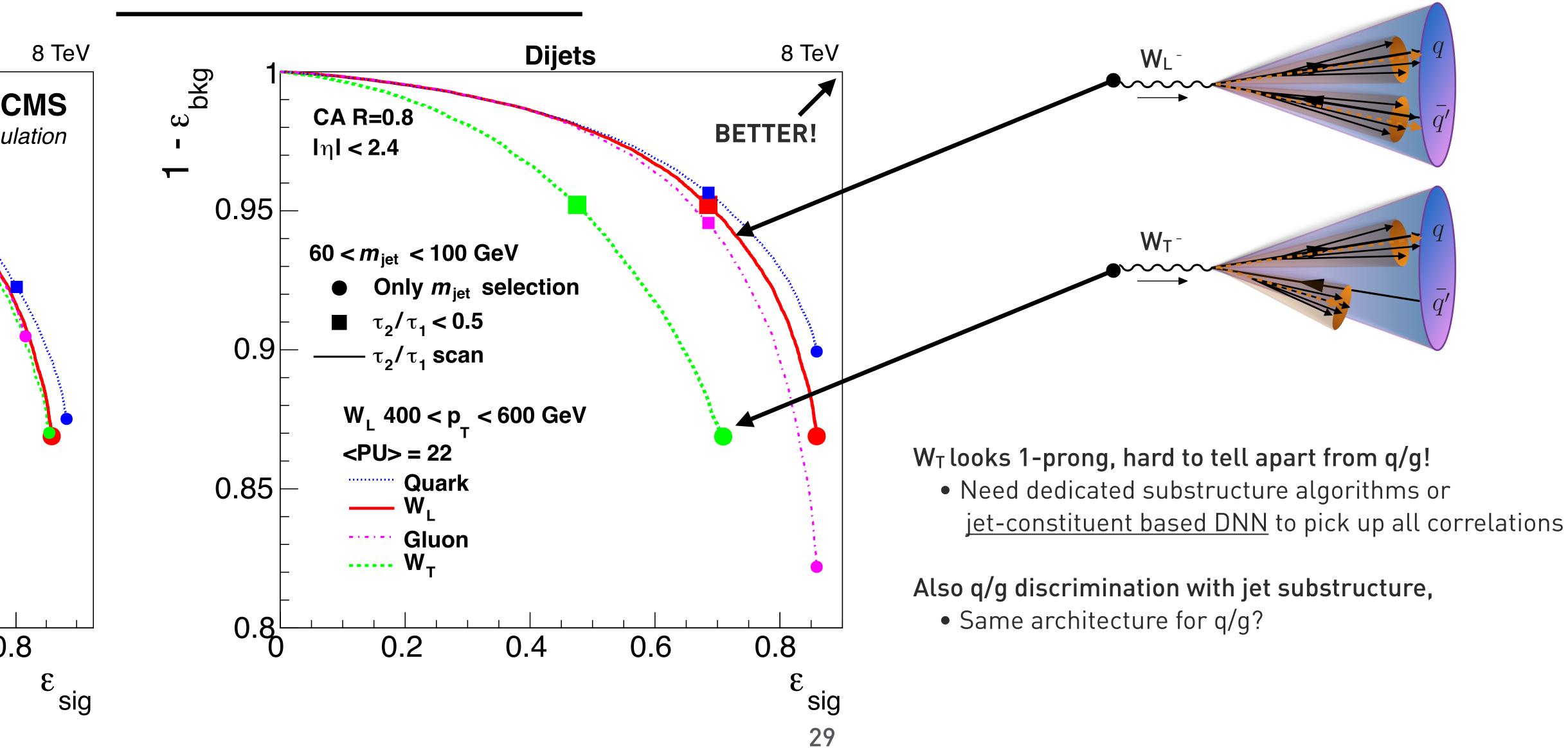








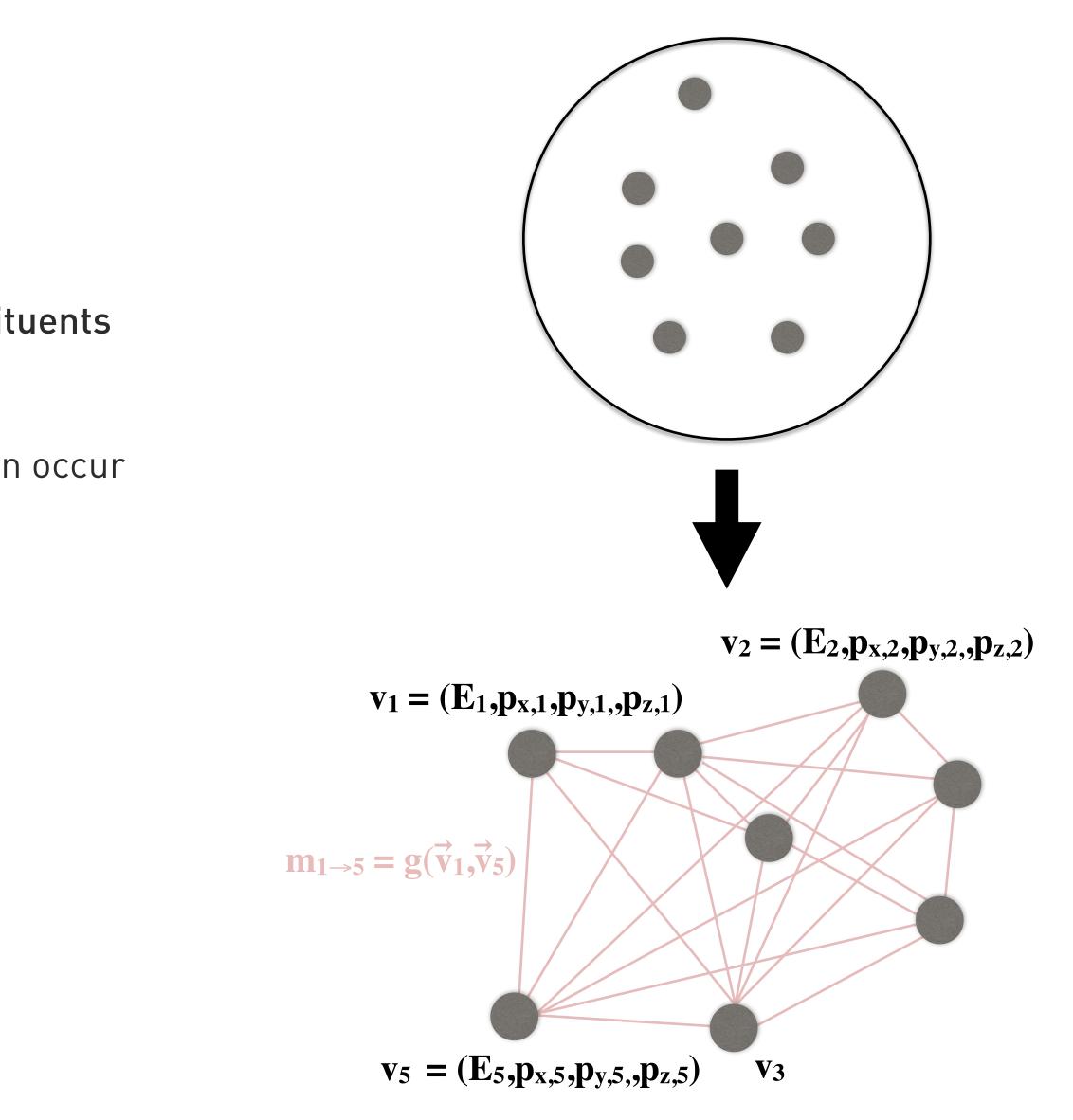
WT



V polarisation: GNNs

Graph Neural Network optimal architecture for jet constituents (sparse, unordered)

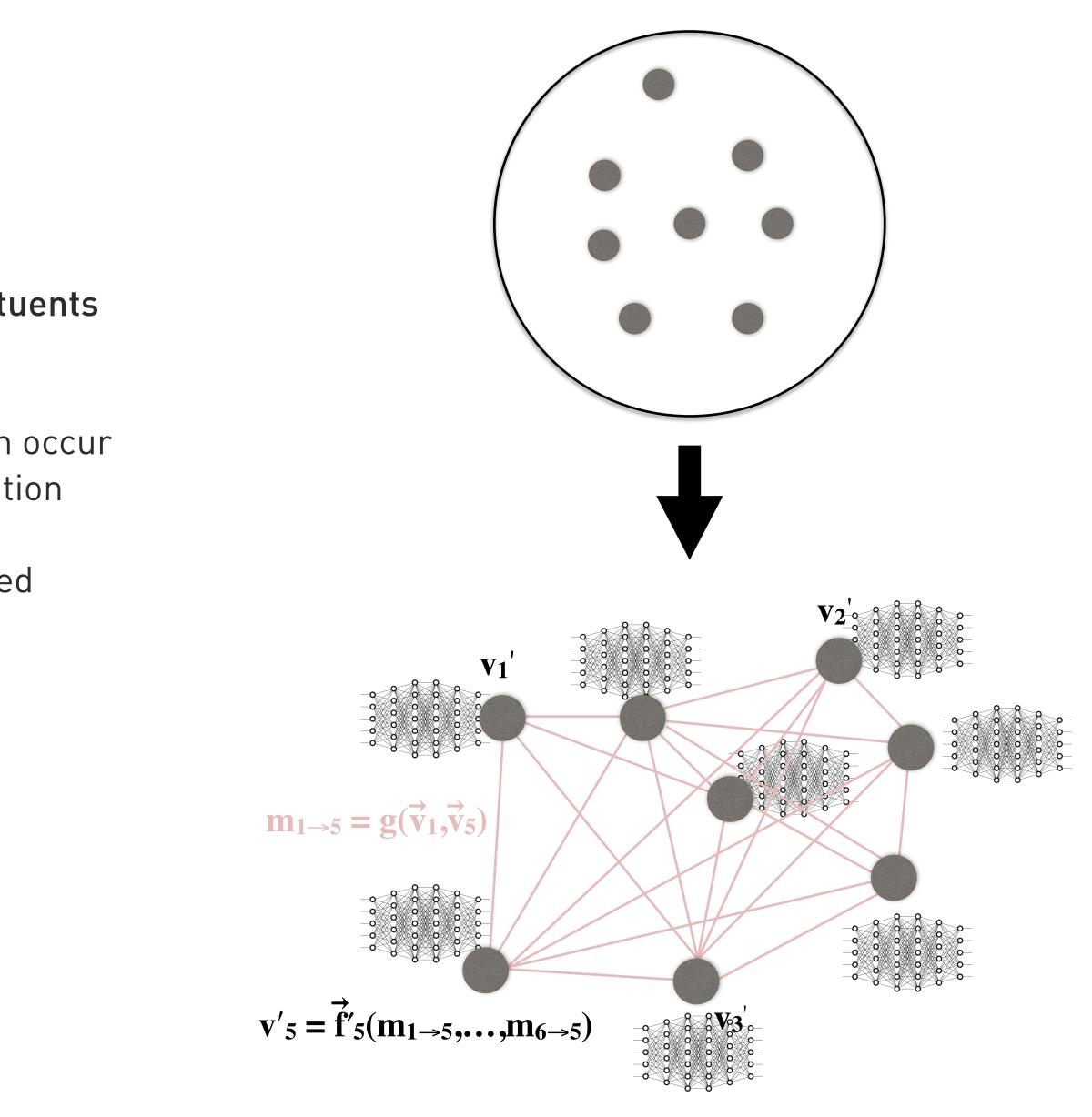
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- Connected through edges where message passing can occur



V polarisation: GNNs

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- New representation of node created based on information gathered across graph
- Inference at each node using input features and learned representation



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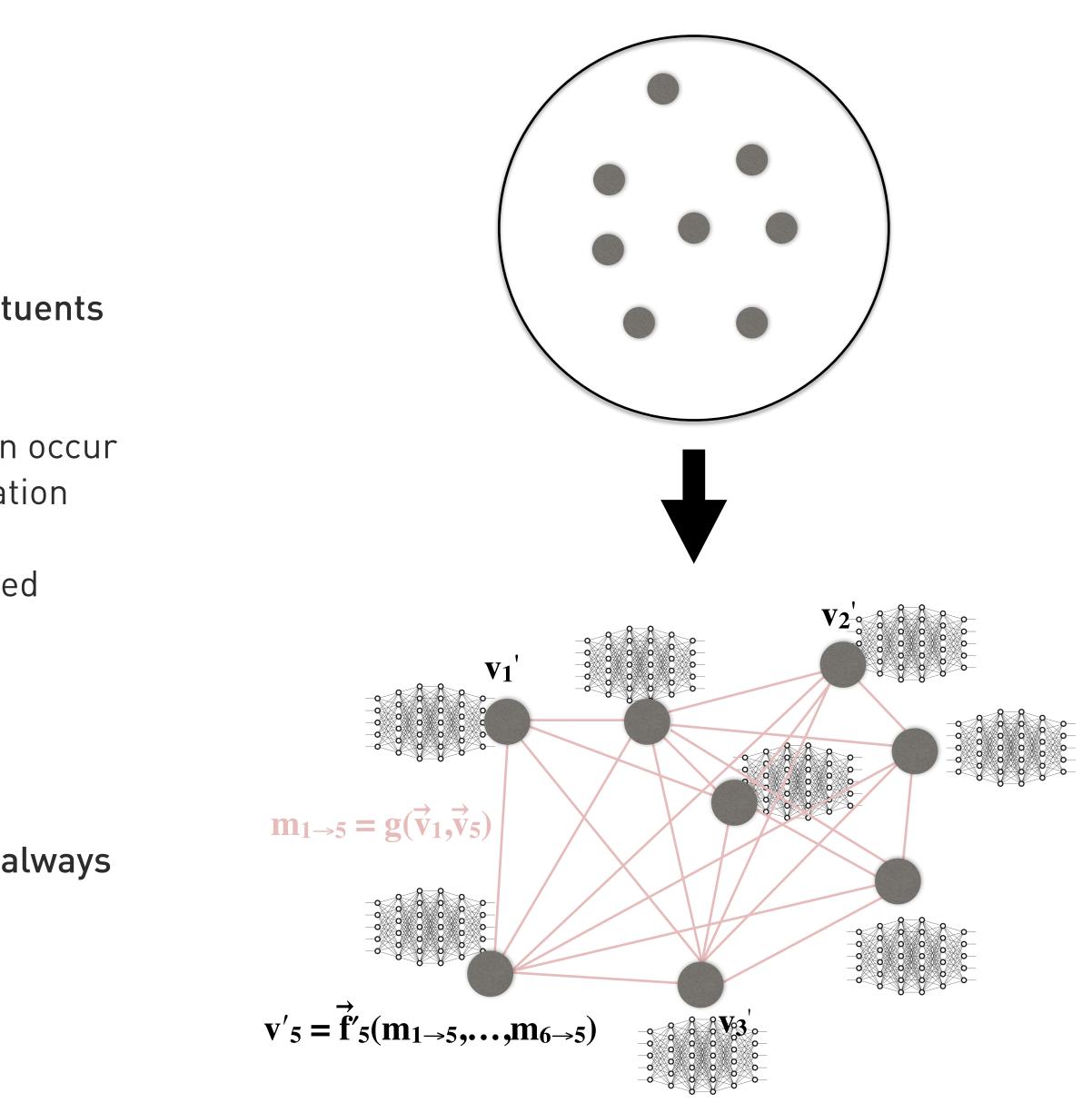
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Can be defined as N-output multi-classifier

• W_T, W_L, q, g...

Jet constituents good to pick up correlations, but almost always good to extend base by adding high-level features

• Energy correlation functions, au_N , groomed masses



Proof-of-principle, simple DNN 80% $W_{\rm L}\,$ signal efficiency at ~40% $W_{\rm T}$ mistag rate

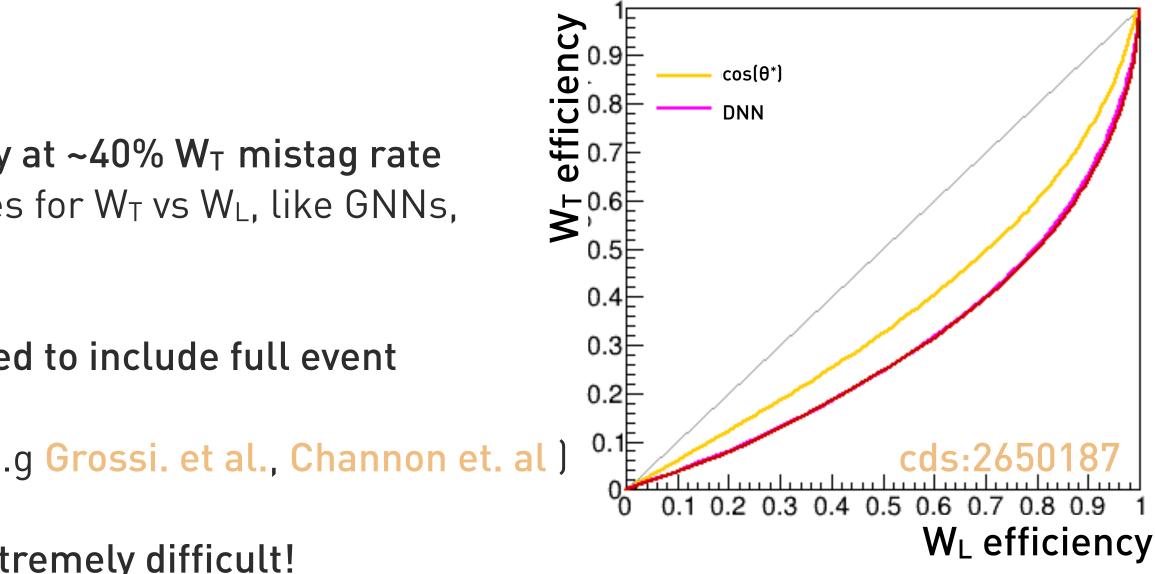
 Can we do better? Using more advanced architectures for W_T vs W_L, like GNNs, under study (H. Kirschenmann et. al.)

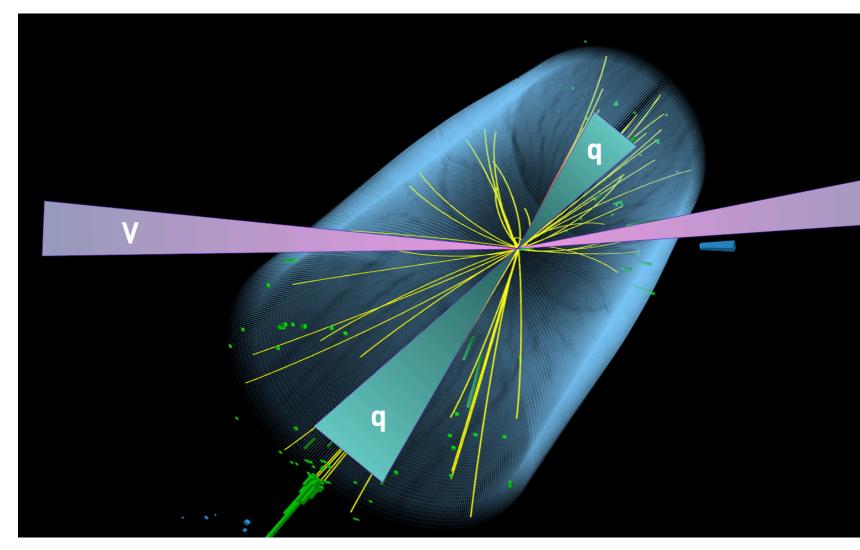
Single-object tag might not reach desired sensitivity, need to include full event information

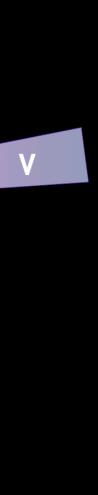
• Di-fat jet correlations, forward jet correlations etc. (e.g Grossi. et al., Channon et. al)

Systematic uncertainties and data corrections will be extremely difficult!

• Calibration objects? Standard candles? Energy-dependence?







Ultimately want to extract components of polarisation density matrix

- Differential measurement of polarization fraction vs. E
- Simultaneous fit to extract amplitudes
- Look for deviations from SM in tail 10⁻⁵ ⊨

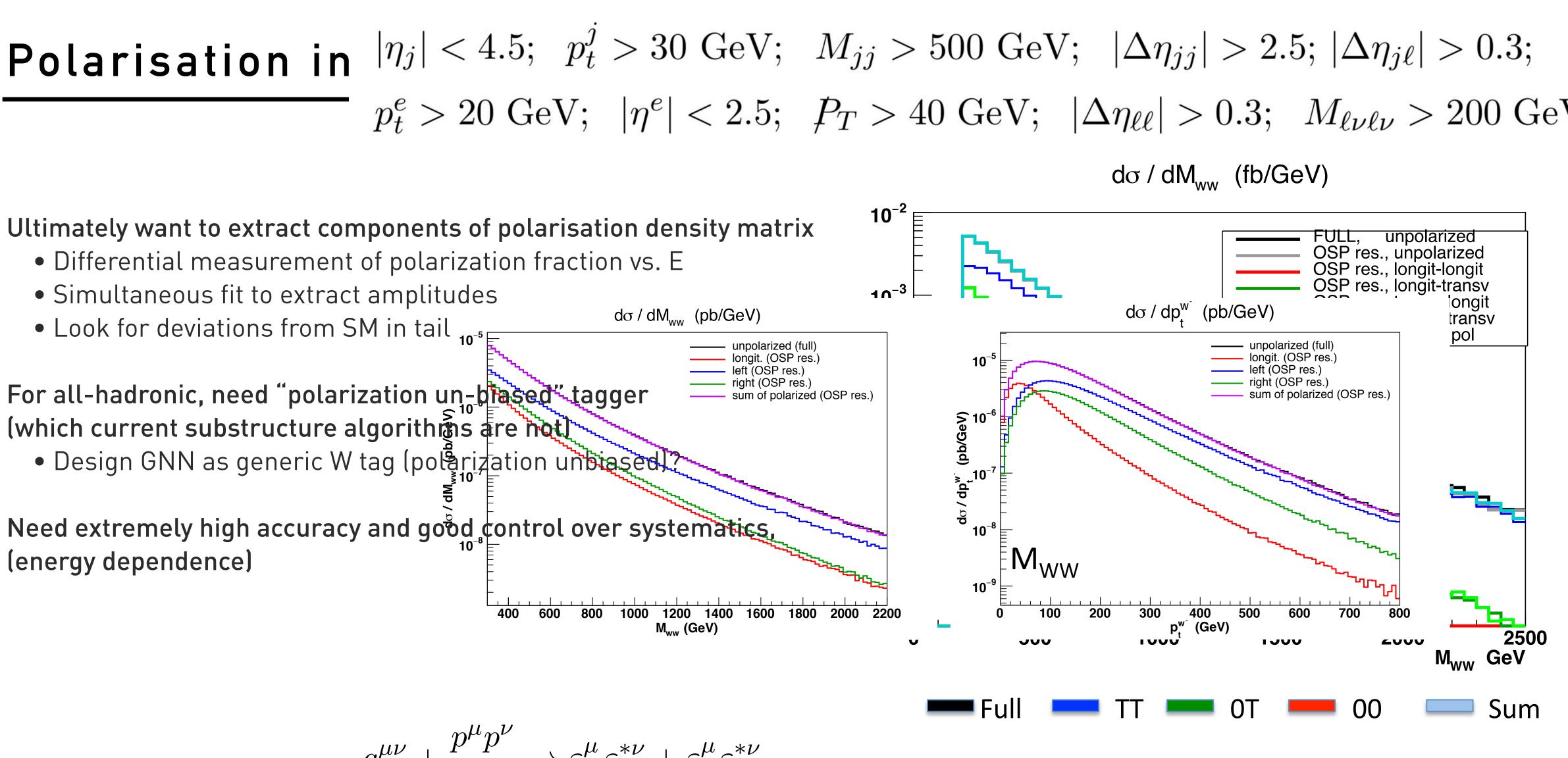
For all-hadronic, need "polarization un-blased" tagger (which current substructure algorithms are not)

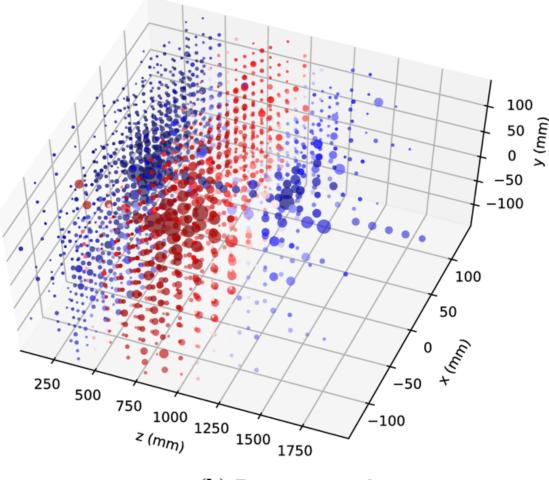
Design GNN as generic W tag (polarization unbigged)

Need extremely high accuracy and good control over systematics (energy dependence)

> 800 600

 $-g^{\mu\nu} + \frac{p^{\mu}p^{\nu}}{M^2} \to \varepsilon_R^{\mu}\varepsilon_R^{*\nu} + \varepsilon_L^{\mu}\varepsilon_L^{*\nu}$





(b) Reconstructed

