Application of Machine Learning Techniques in Collider Physics Reconstruction & Analysis

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CSI Workshop
BNL
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ATLAS

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Preliminaries

Topics in this talk

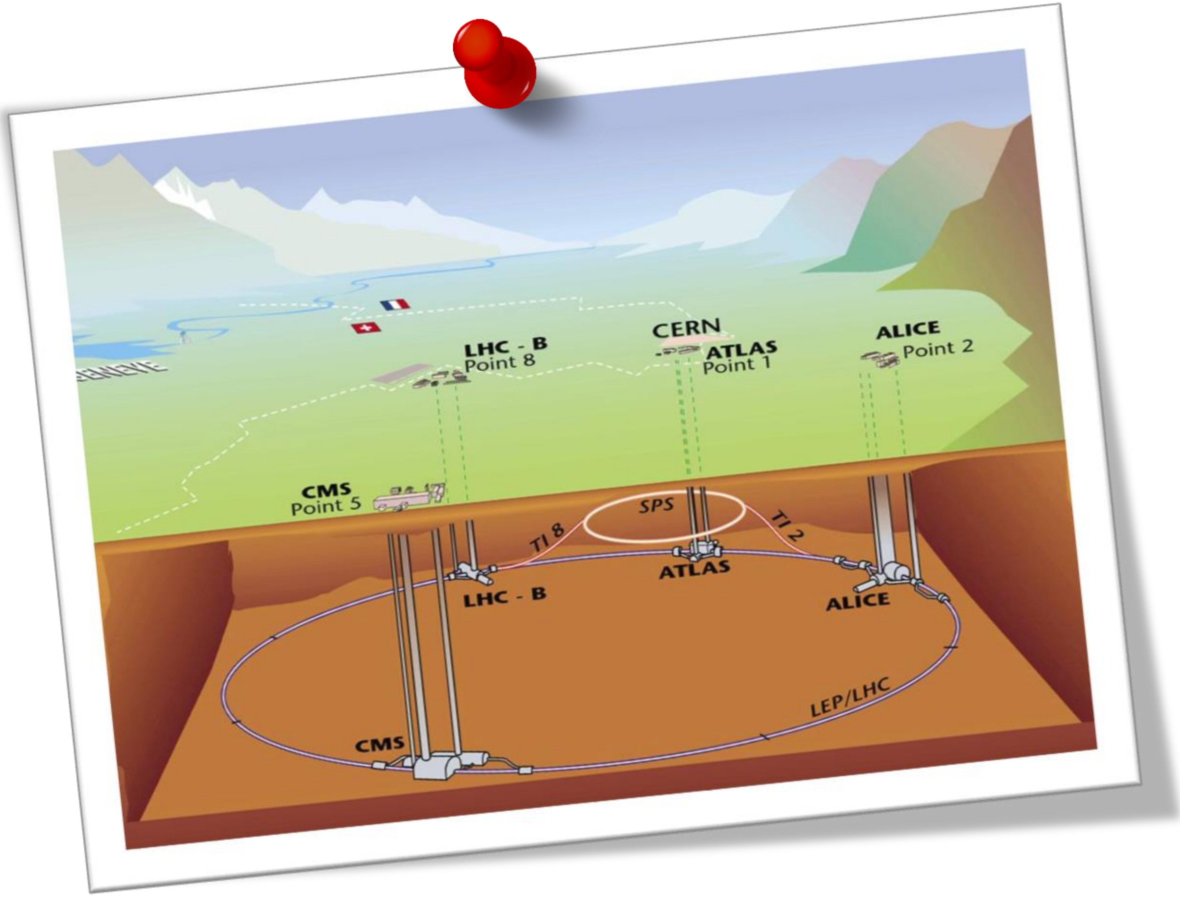
Highly selective & biased choice of topics where machine learning (ML) can be useful in reconstruction of detector signals and physics objects

Calorimeter centric – complex signals especially in the presence of pile-up

Jet focus - composite physics object representing momentum flow generated by partons emitted in a proton–proton collision at LHC

Not at all comprehensive!

Proton–Proton Collisions at the LHC



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Schematic model of a proton–proton collision

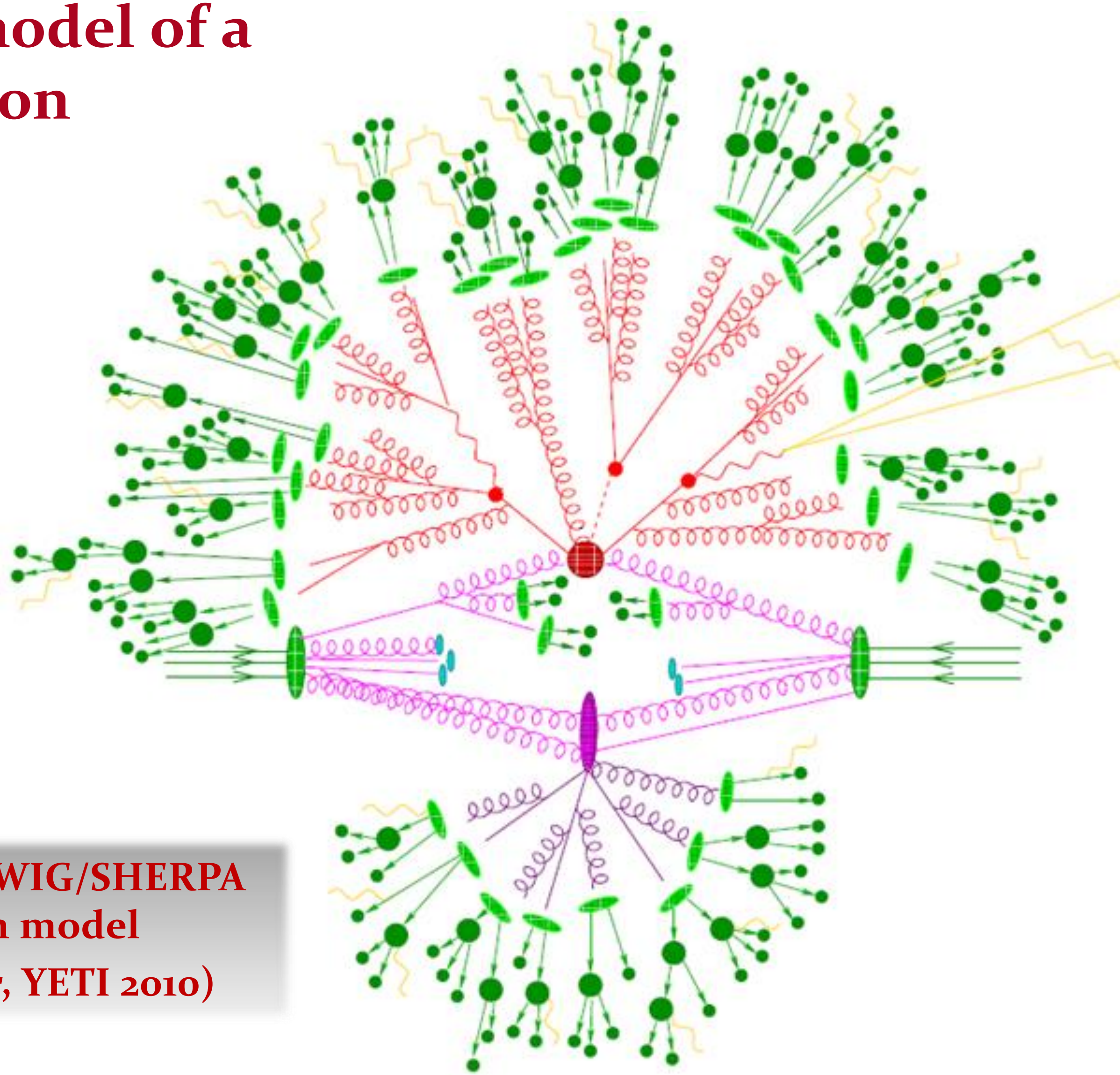
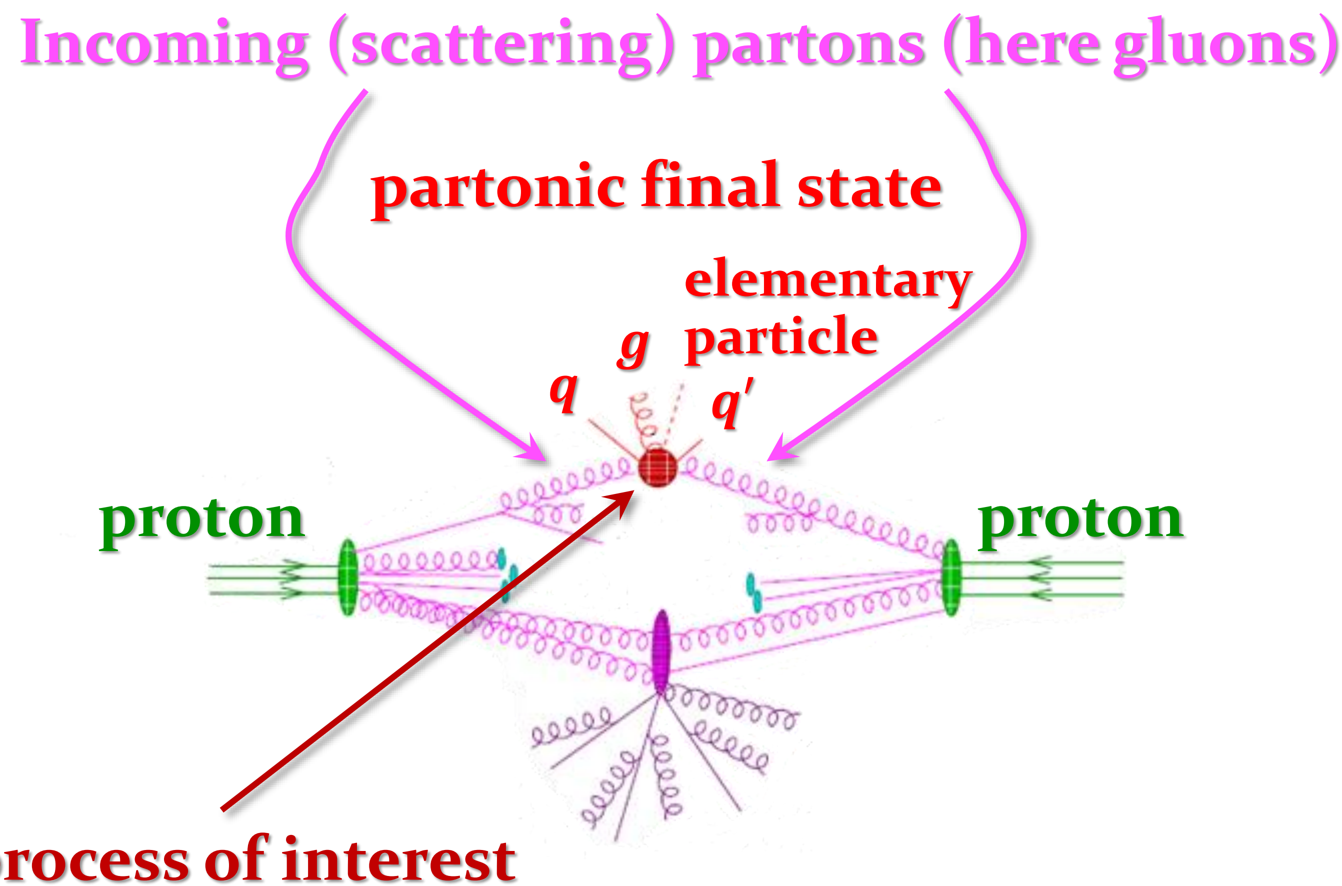


Illustration of HERWIG/SHERPA fragmentation model (Marek Schönherr, YETI 2010)

Schematic model of a proton–proton collision



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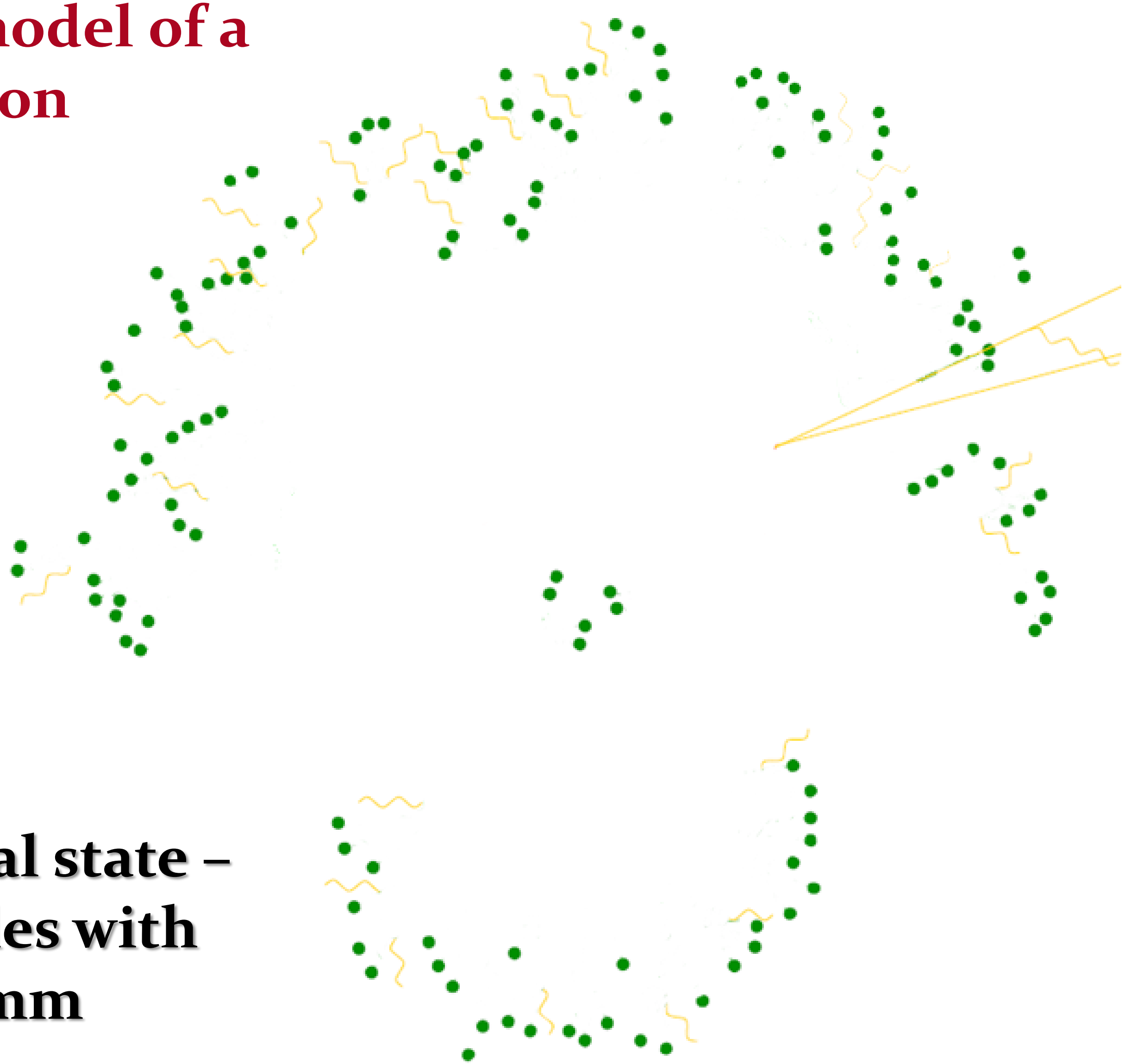
Schematic model of a proton–proton collision

photons

leptons

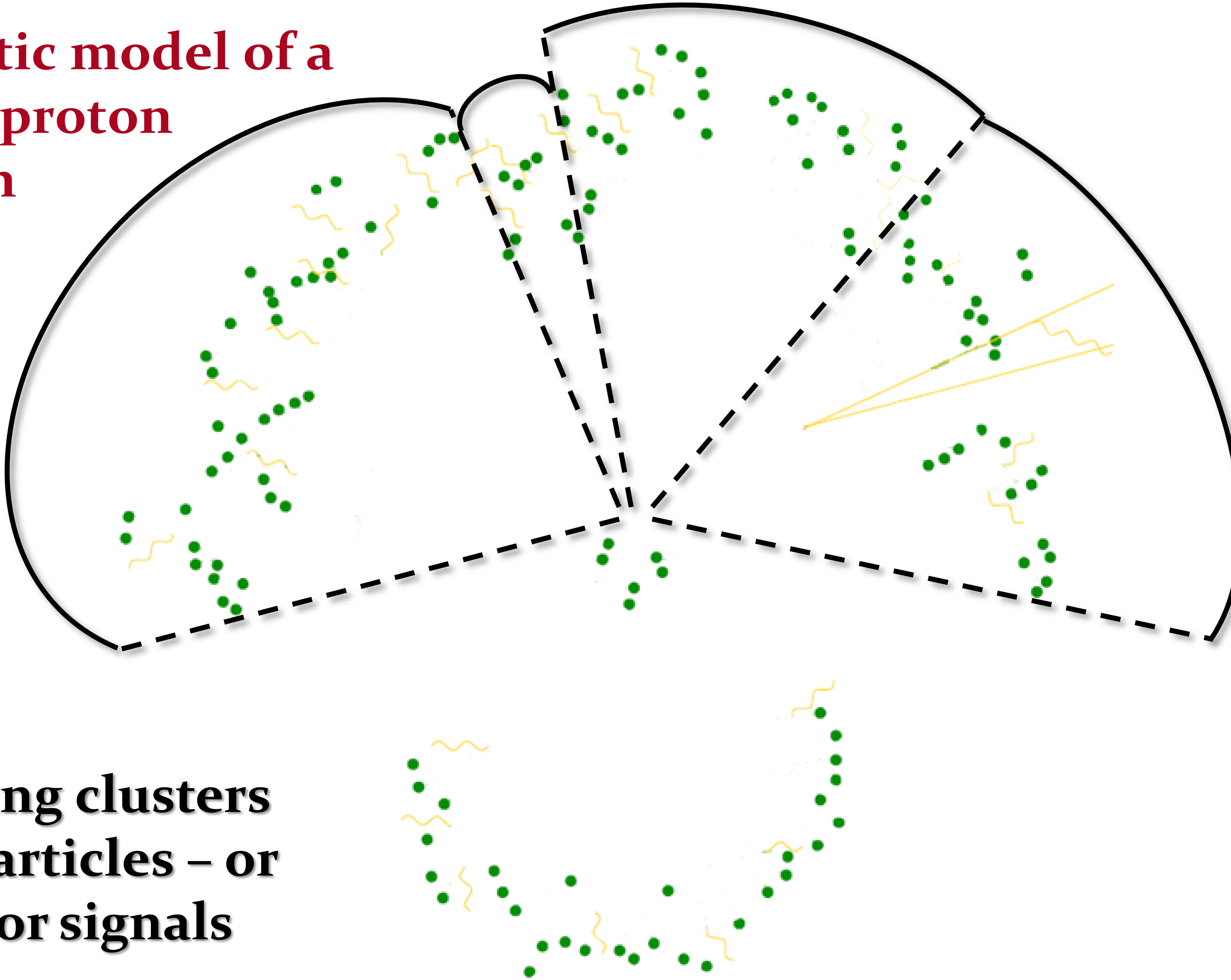
hadrons



detectable final state – stable particles with $c\tau > 10$ mm

Proton-Proton Collisions @ LHC

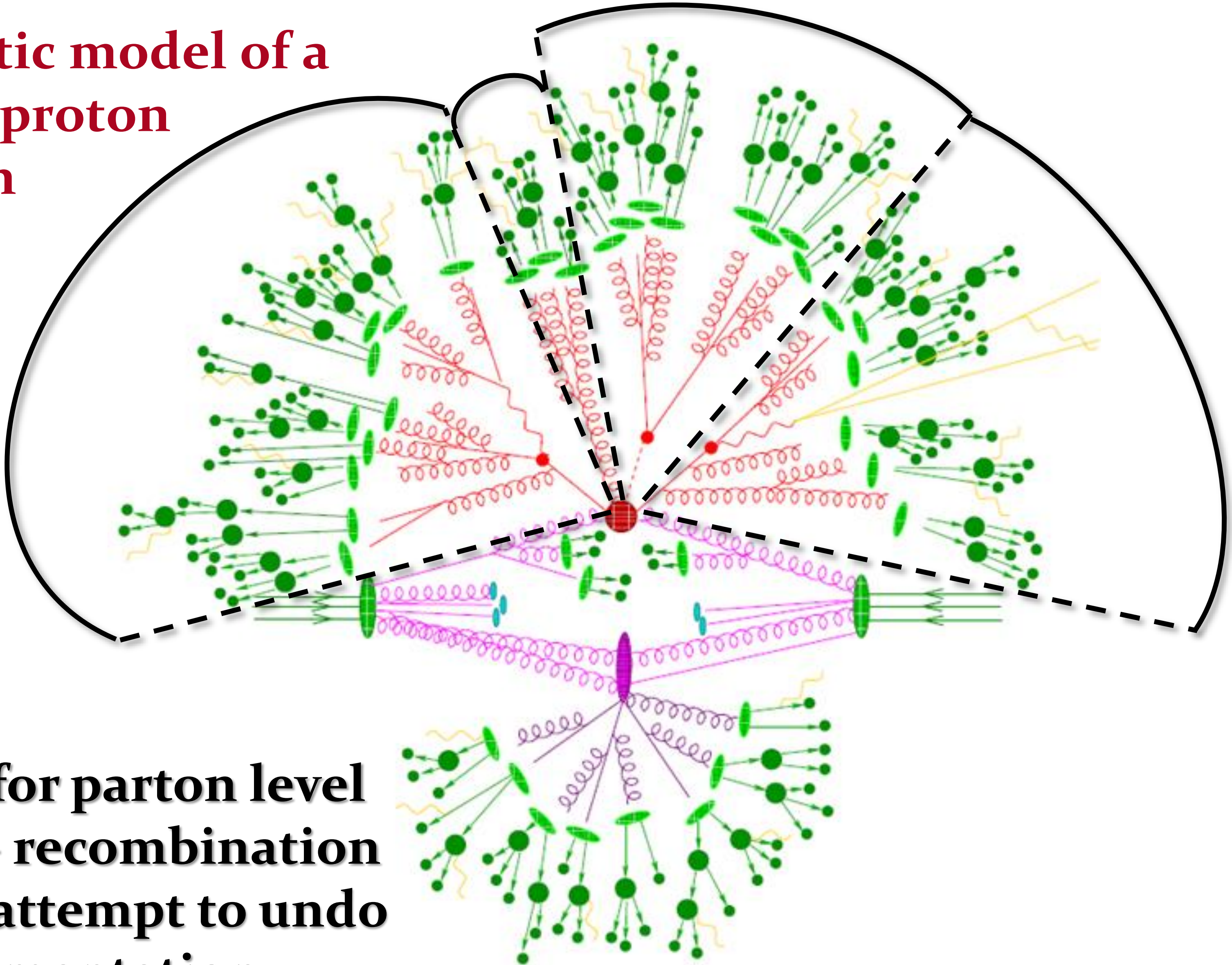
Schematic model of a proton–proton collision



jet finding clusters stable particles – or detector signals

Proton-Proton Collisions @ LHC

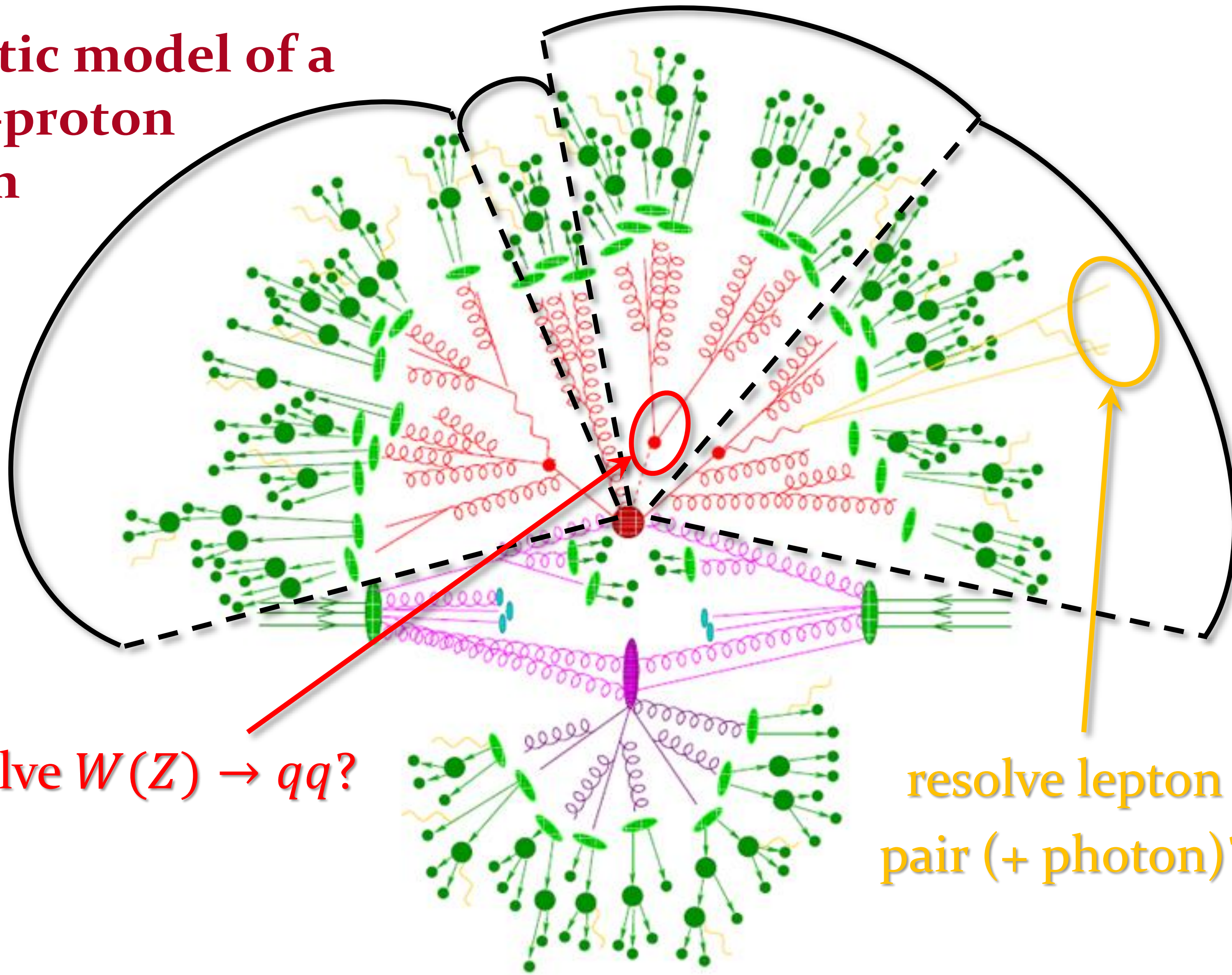
Schematic model of a proton–proton collision



proxies for parton level physics – recombination into jets attempt to undo fragmentation

Proton-Proton Collisions @ LHC

Schematic model of a proton–proton collision



resolve $W(Z) \rightarrow qq$?

resolve lepton pair (+ photon)?

Proton-Proton Collisions @ LHC

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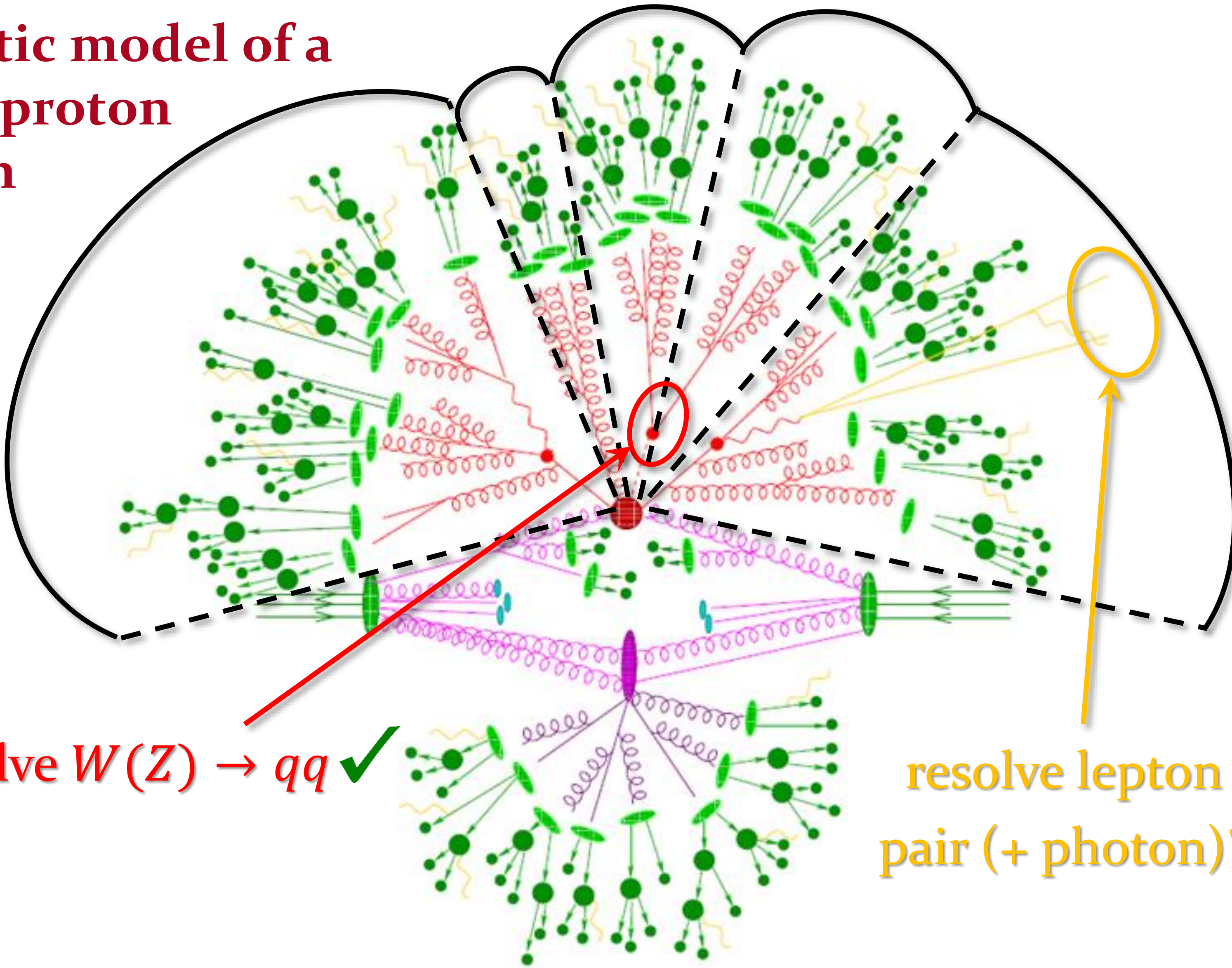
Schematic model of a proton–proton collision



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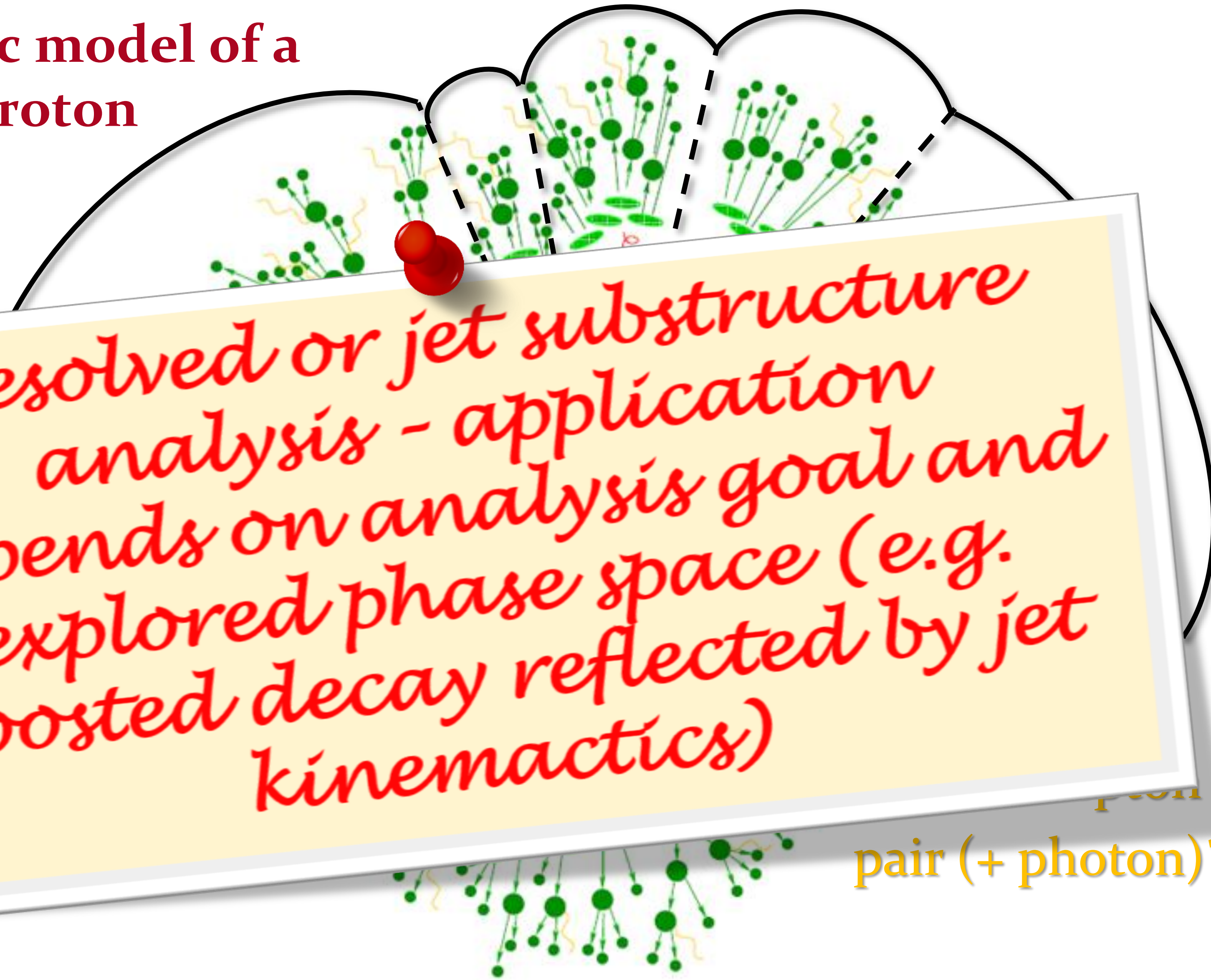
Schematic model of a proton–proton collision



Resolved or jet substructure analysis - application depends on analysis goal and explored phase space (e.g. boosted decay reflected by jet kinemactics)

pair (+ photon)?

Final State (Jet) Reconstruction

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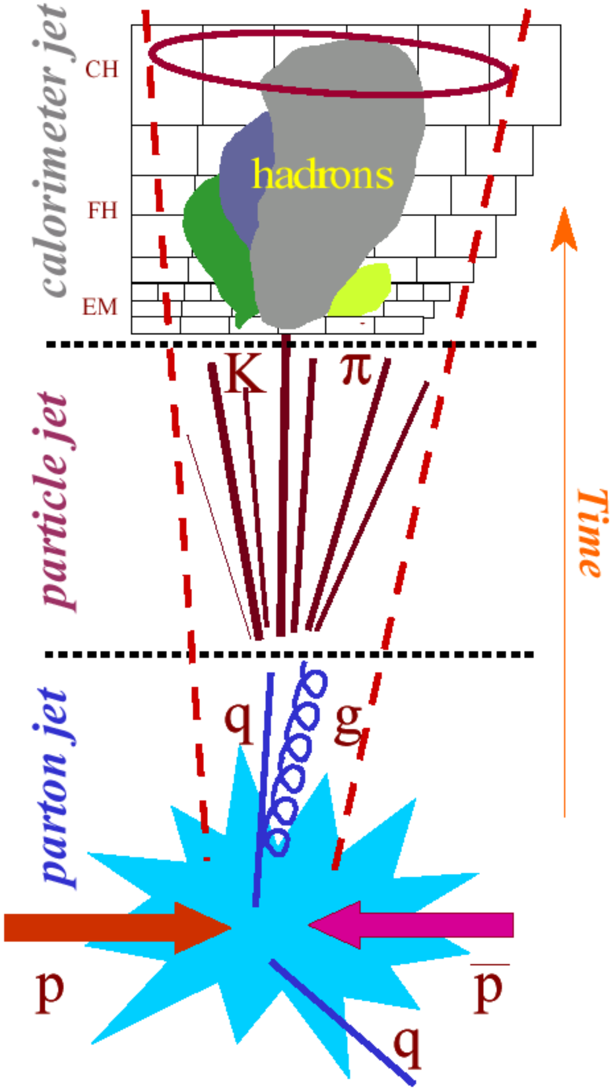
Experiment ("Nature")



Jet Reconstruction Challenges

longitudinal energy leakage
detector signal inefficiencies (dead channels, HV…)
pile-up noise from (off- and in-time) bunch crossings
electronic noise
calo signal definition (clustering, noise suppression…)
dead material losses (front, cracks, transitions…)
detector response characteristics (e/h ≠ 1)
jet reconstruction algorithm efficiency
lost soft tracks due to magnetic field

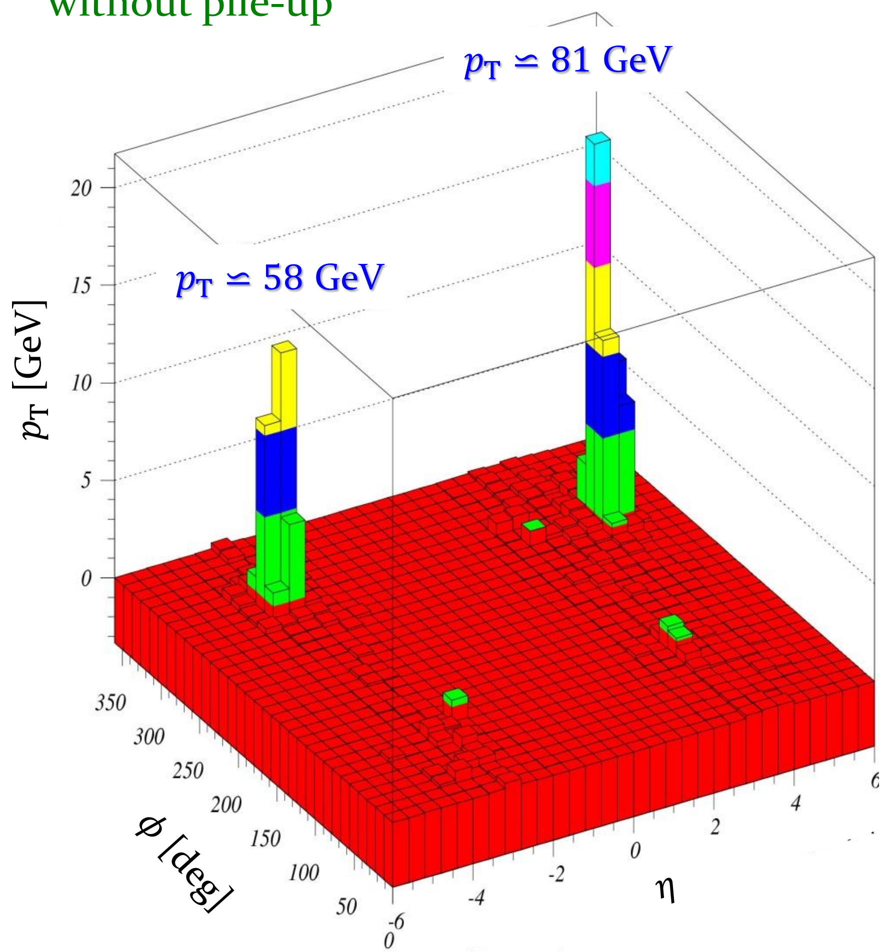
added tracks from underlying event
added tracks from in-time (same trigger) pile-up event
jet reconstruction algorithm efficiency

physics reaction of interest (interaction or parton level)

Pile-up

- Affects jet kinematics and shapes
  - Introduces additional energy/transverse momentum in jets
  - Deteriorates reconstruction of jet mass & internal particle flow features
- Number of pile-up collisions μ
  - $\boldsymbol{\mu = (\mathcal{L}_{\text{inst}} \times \sigma^{pp}_{\text{inel}})/(N_{\text{b}} \times f_{\text{LHC}})}$
  - $\mathcal{L}_{\text{inst}}$ – instantaneous luminosity
  - $\sigma^{pp}_{\text{inel}}$ – inelastic pp cross section
  - N_{b} – number of colliding bunches in LHC
  - f_{LHC} – LHC revolution frequency

without pile-up



$qq \rightarrow qqWW \rightarrow qqH \rightarrow qq\nu\nu\nu\nu$

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Pile-up

Affects jet kinematics and shapes

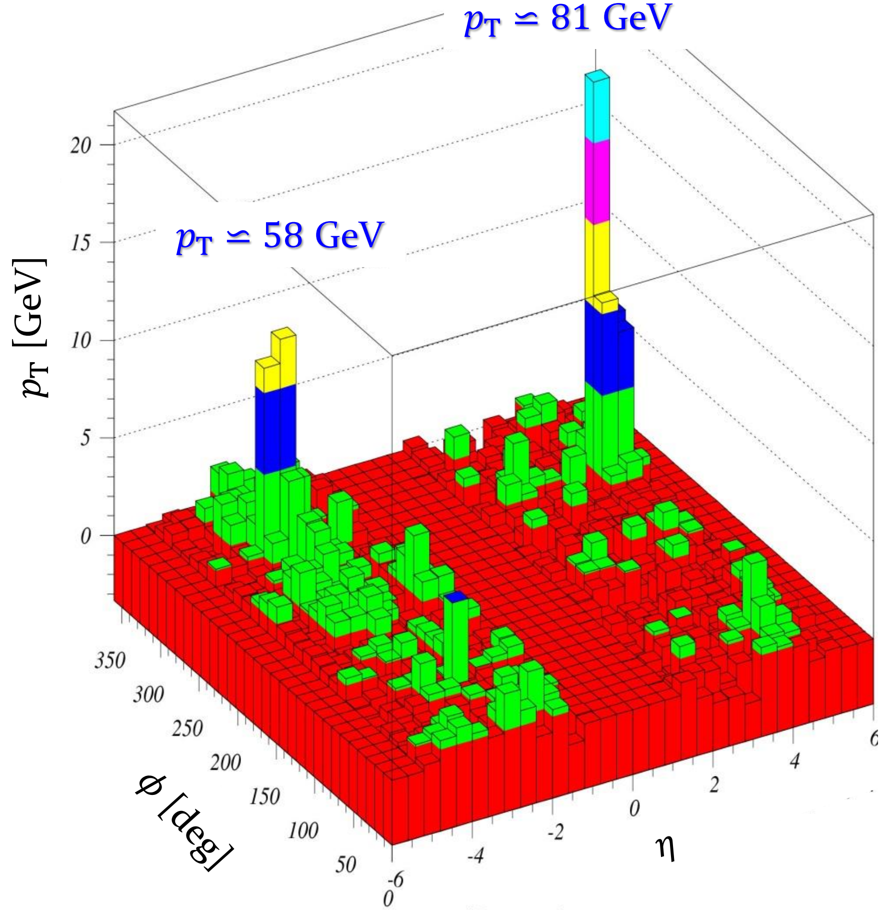
- Introduces additional energy/transverse momentum in jets
- Deteriorates reconstruction of jet mass & internal particle flow features

Number of pile-up collisions μ

$$\boldsymbol{\mu = (\mathcal{L}_{\mathrm{inst}} \times \sigma_{\mathrm{inel}}^{pp})/(N_{\mathrm{b}} \times f_{\mathrm{LHC}})}$$

- $\boldsymbol{\mathcal{L}_{\mathrm{inst}}}$ – instantaneous luminosity
- $\boldsymbol{\sigma_{\mathrm{inel}}^{pp}}$ – inelastic pp cross section
- $\boldsymbol{N_{\mathrm{b}}}$ – number of colliding bunches in LHC
- $\boldsymbol{f_{\mathrm{LHC}}}$ – LHC revolution frequency

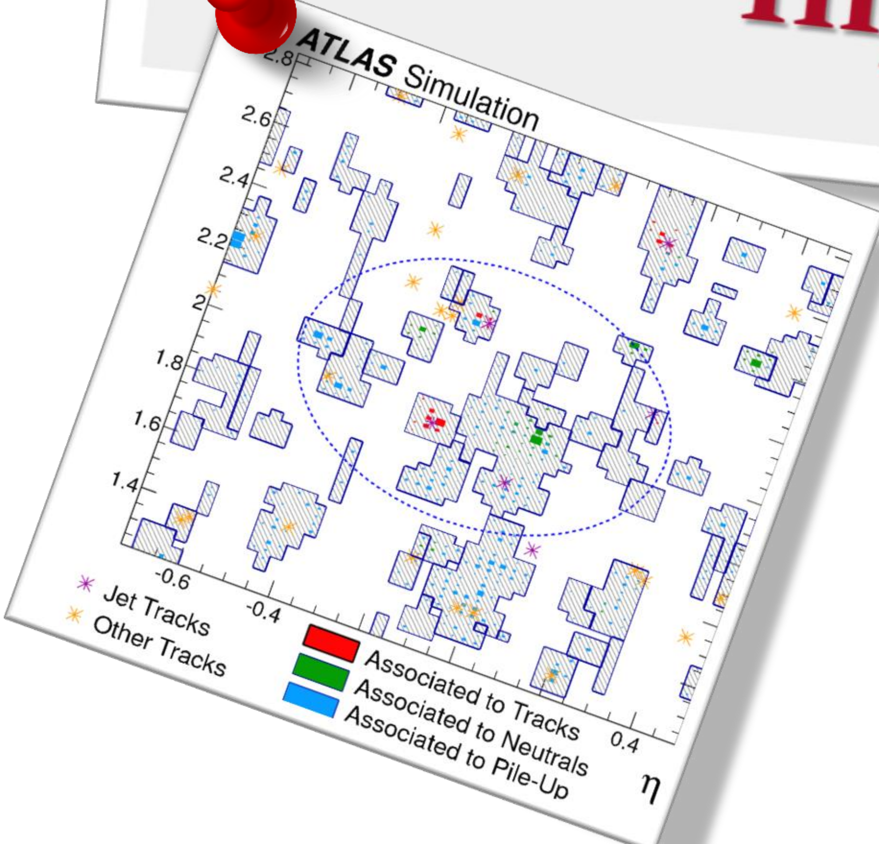
with pile-up @ $\mathcal{L} = 10^{34}\ \mathrm{cm}^{-2}\mathrm{s}^{-1}$

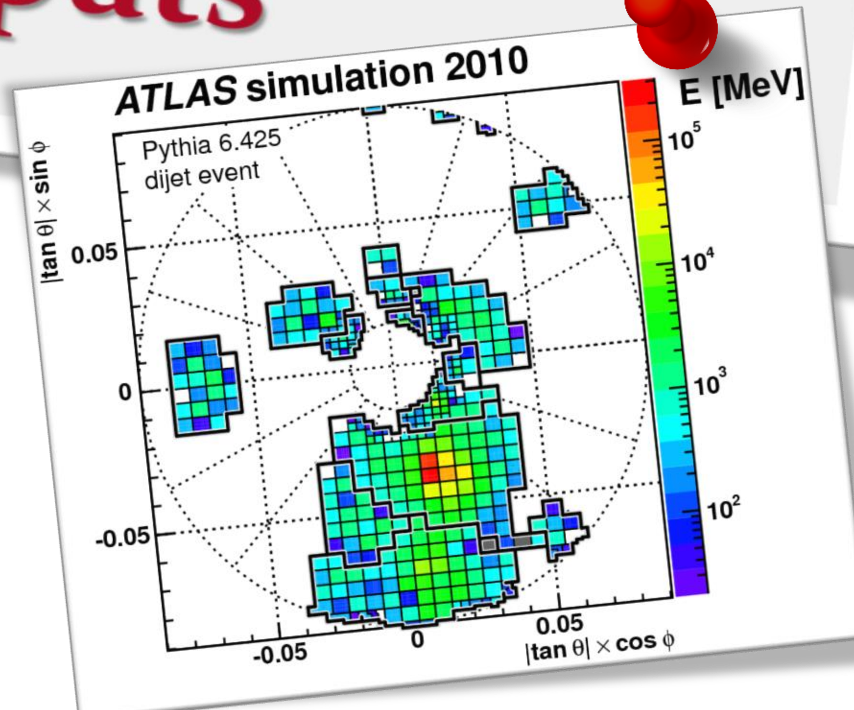


$qq \to qqWW \to qqH \to qq\nu\nu\nu\nu$

Prog.Part.Nucl.Phys.60:484-551,2008

Jet Reconstruction Inputs





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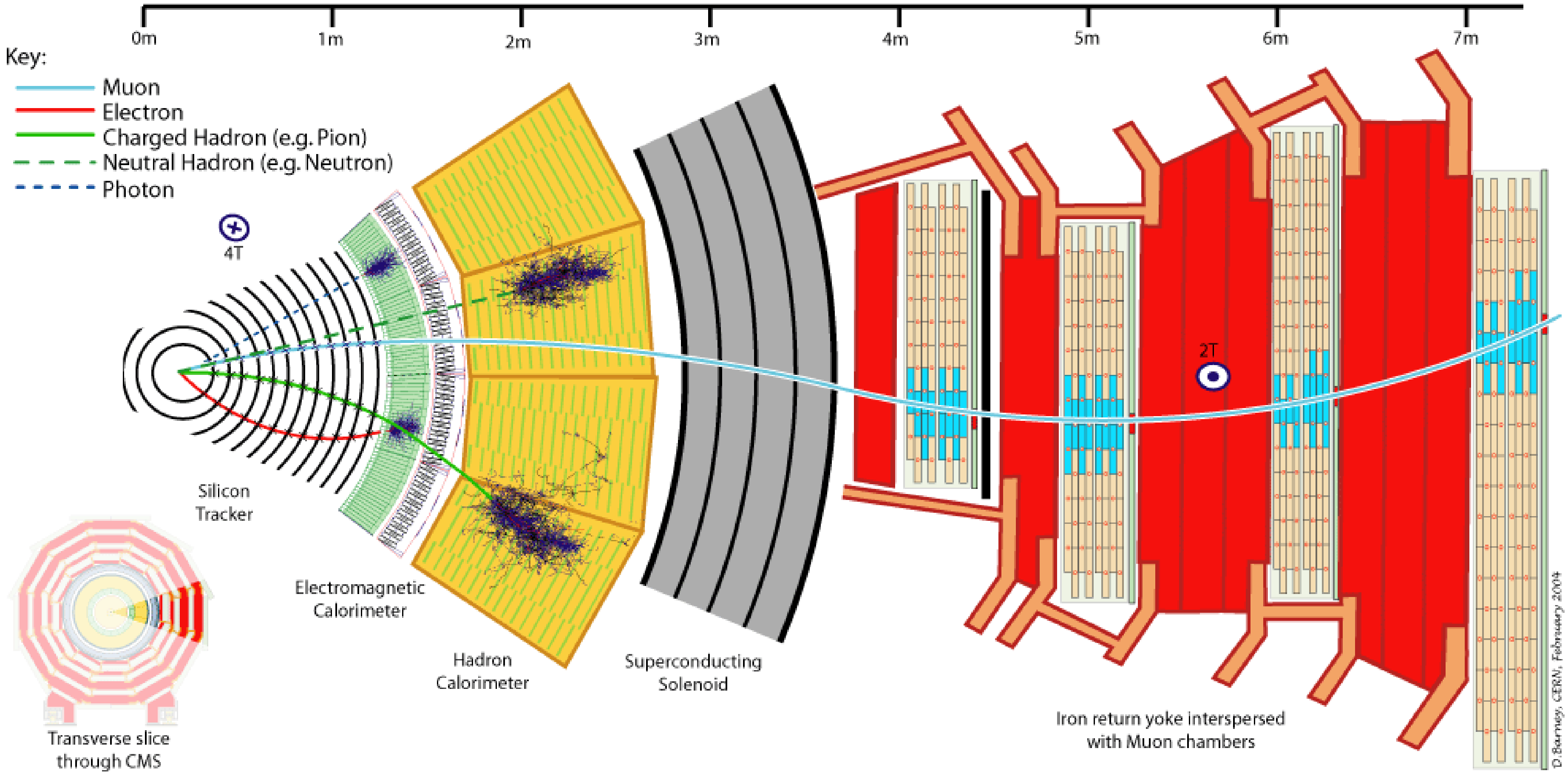
Basic Detector Design



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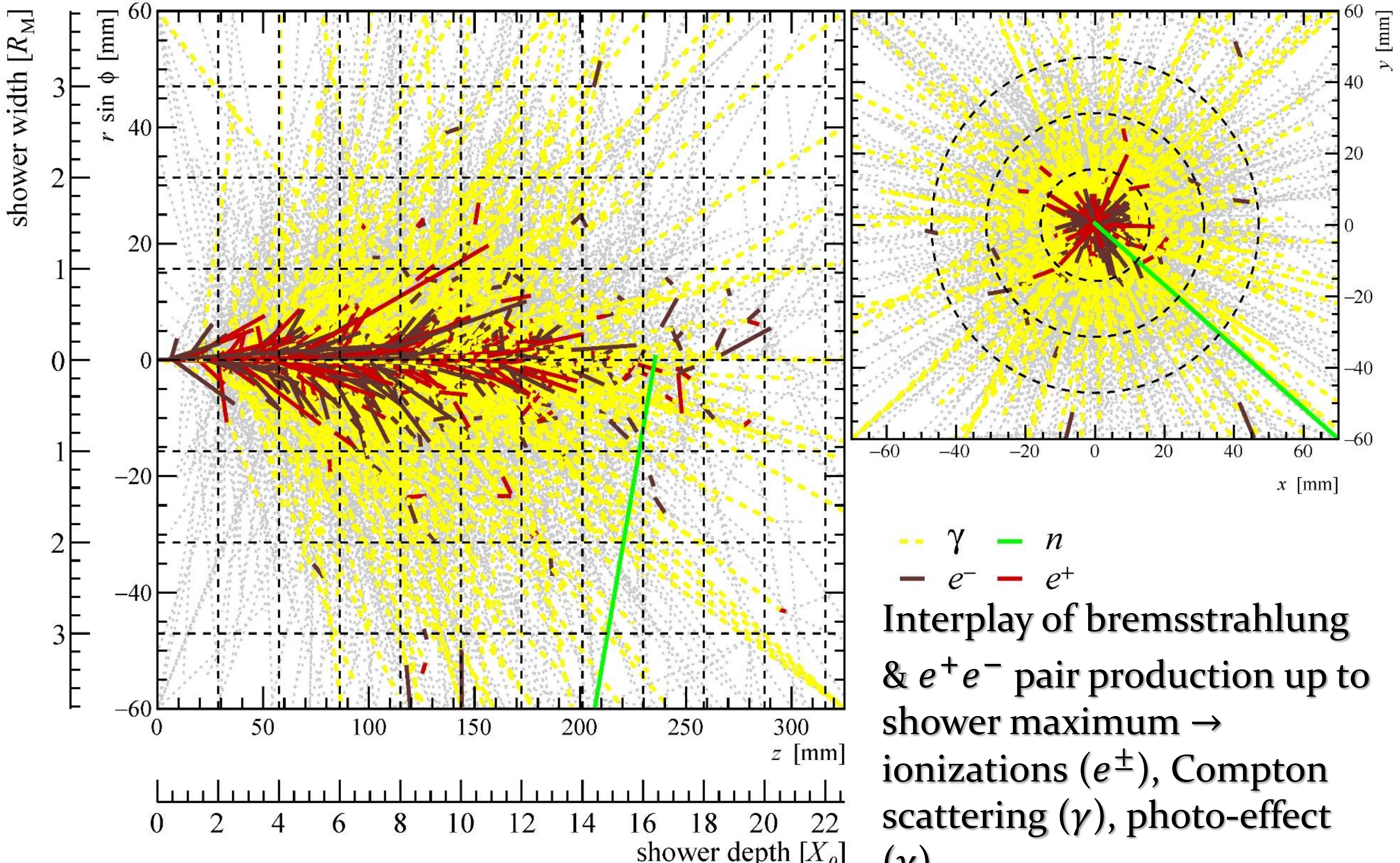
Electromagnetic Showers

GEANT4 Simulation: 10 GeV e^- in copper



Interplay of bremsstrahlung & e^+e^- pair production up to shower maximum → ionizations ($e^\pm$), Compton scattering (γ), photo-effect (γ)

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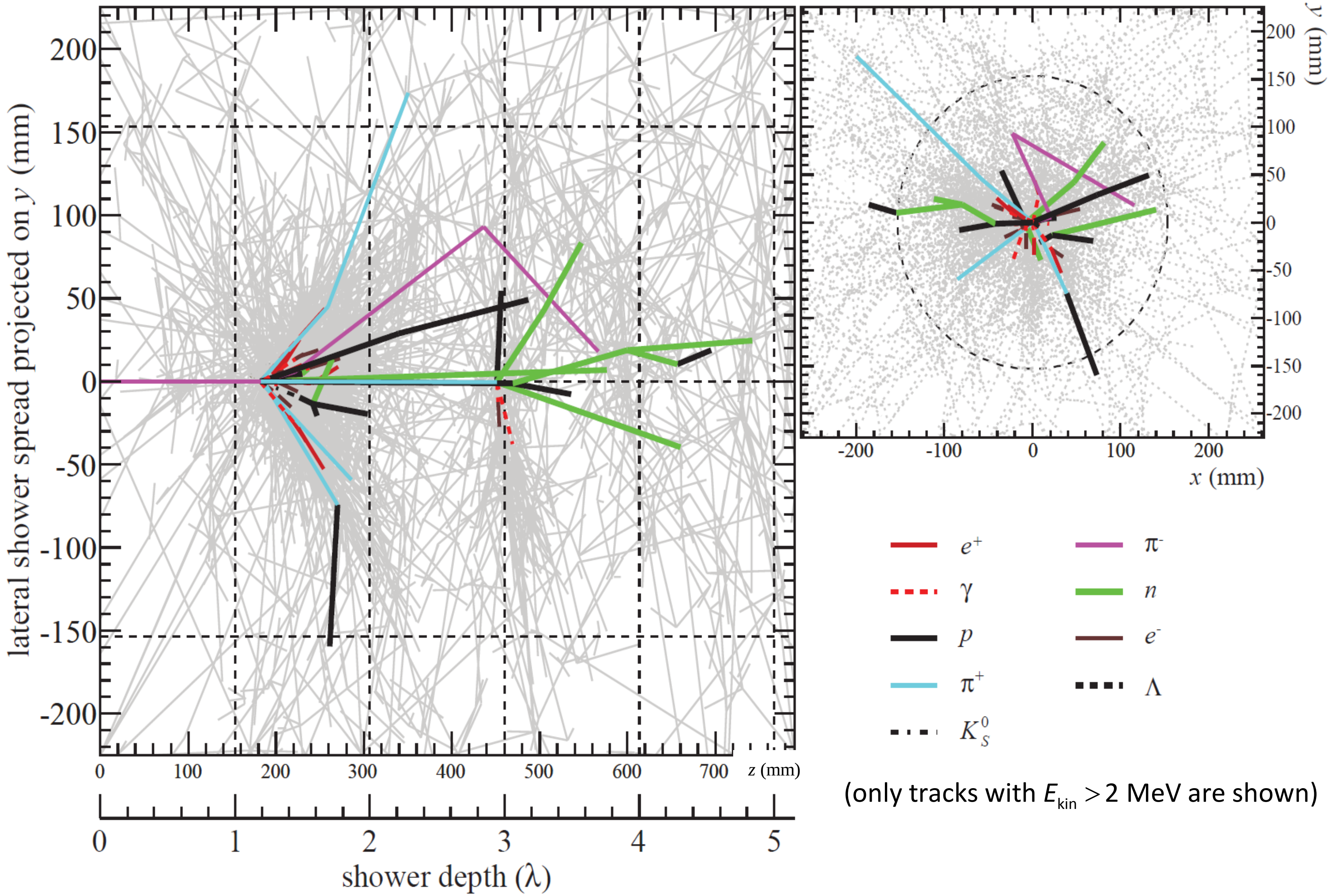
Hadronic Showers

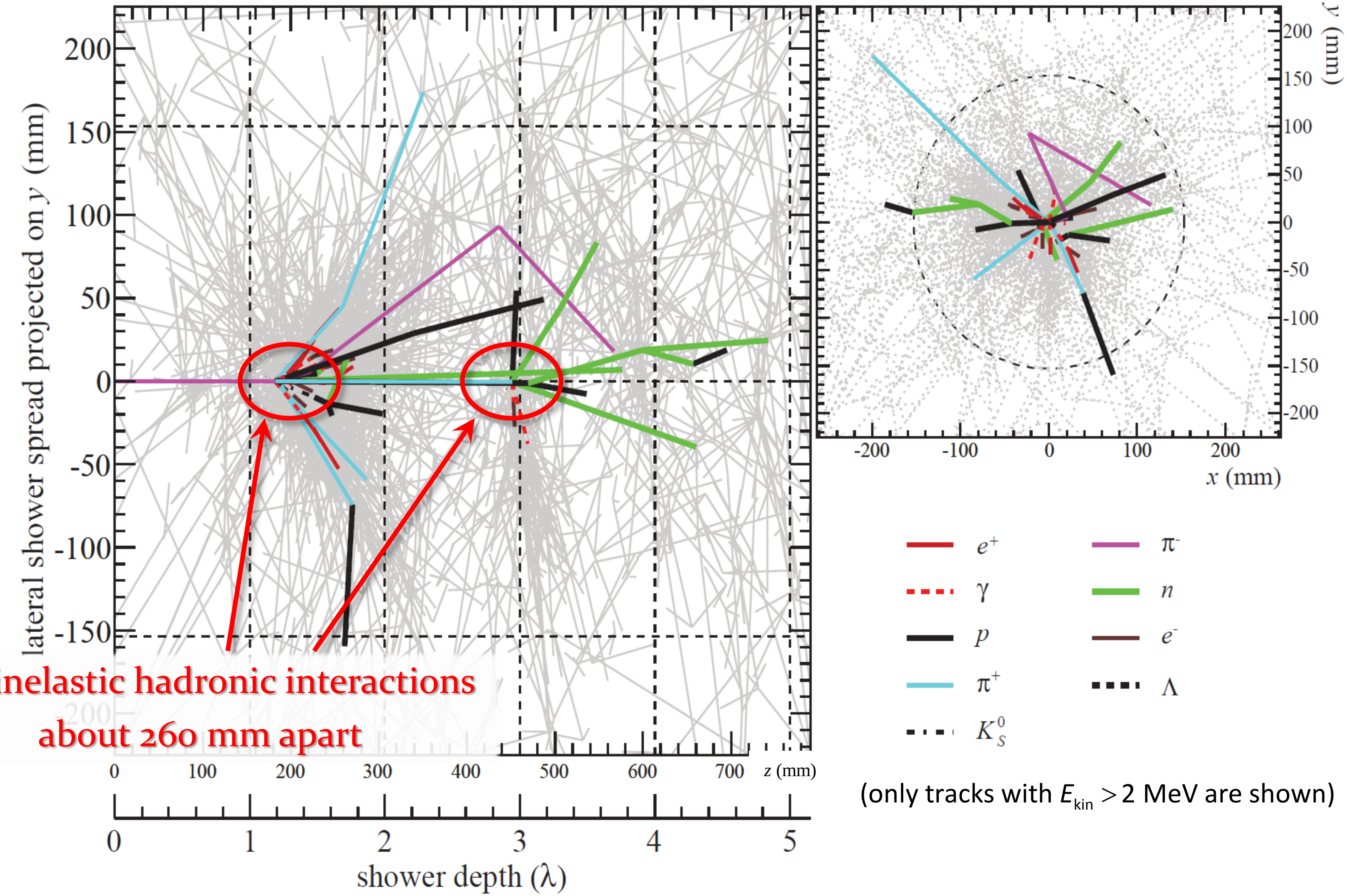
GEANT4 Simulation: 10 GeV π^+ in copper



(only tracks with $E_{\mathrm{kin}} > 2$ MeV are shown)

Hadronic Showers

GEANT4 Simulation: 10 GeV π^+ in copper



two inelastic hadronic interactions
about 260 mm apart

(only tracks with $E_{\text{kin}} > 2$ MeV are shown)

Hadronic Showers

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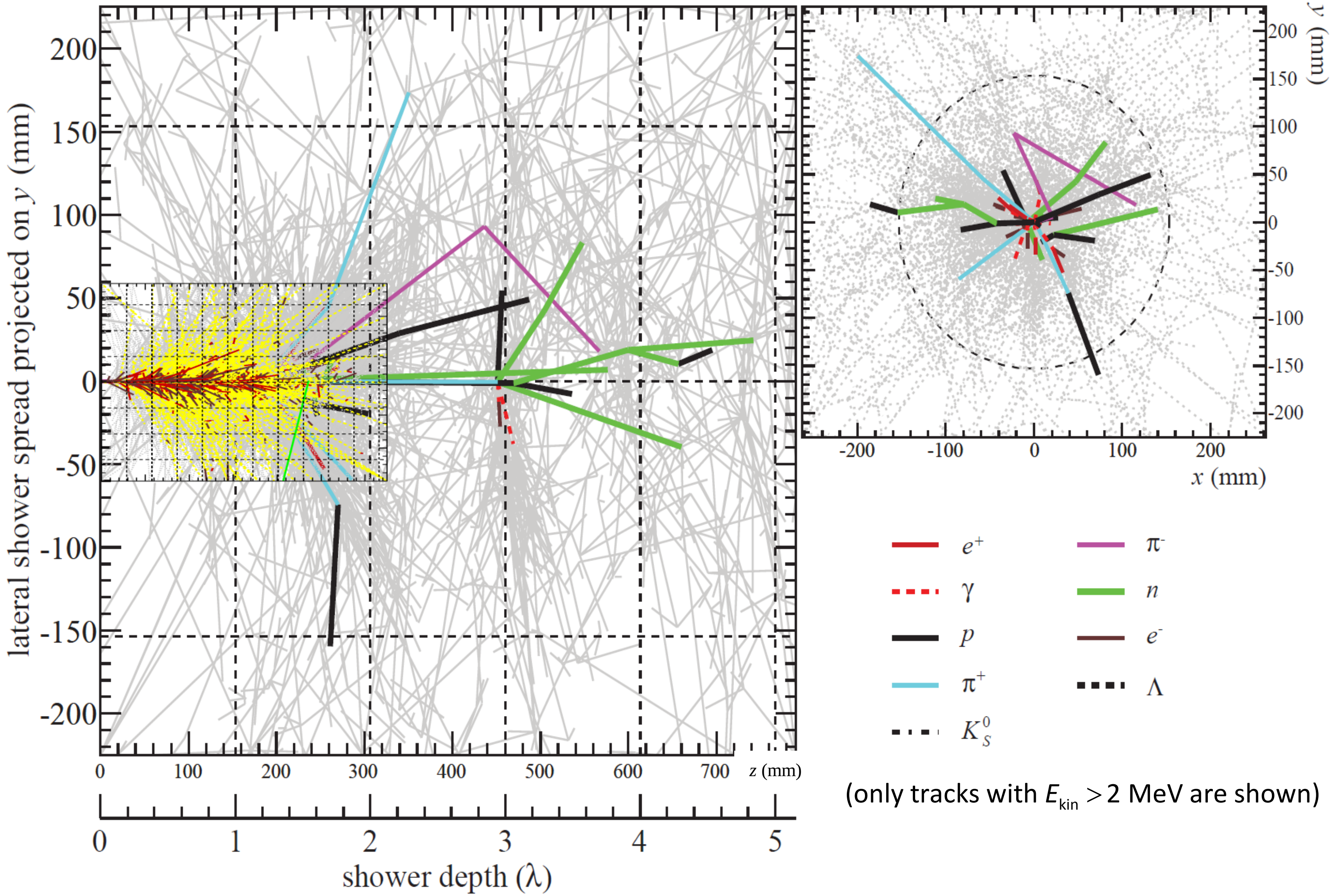
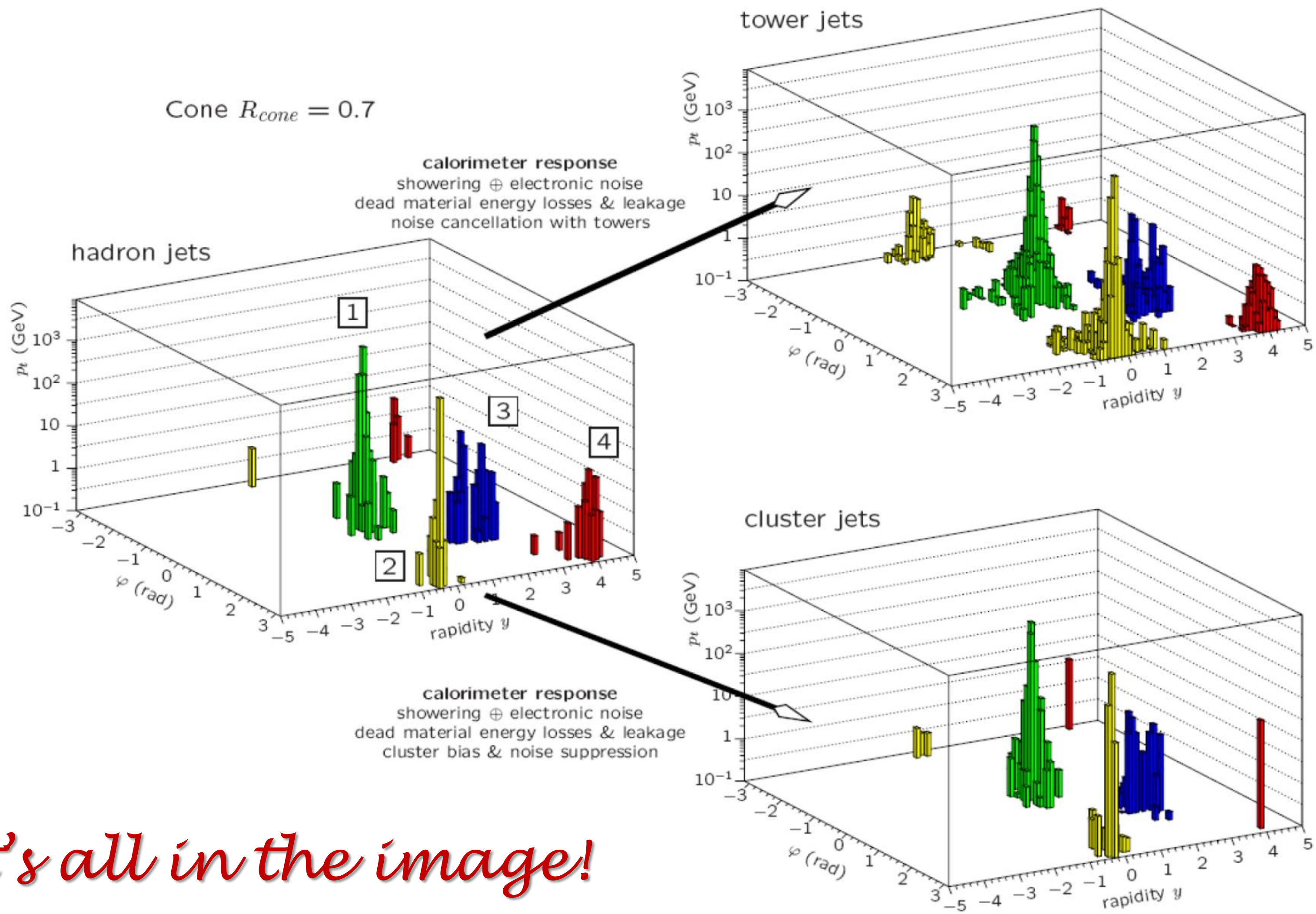
GEANT4 Simulation: 10 GeV π^+ in copper



(only tracks with $E_{\mathrm{kin}} > 2$ MeV are shown)

Calorimeter Jets



It's all in the image!

S.D. Ellis, J. Huston, K. Hatakeyama, P. Loch, M. Toennesmann, **Prog.Part.Nucl.Phys.60:484-551,2008**

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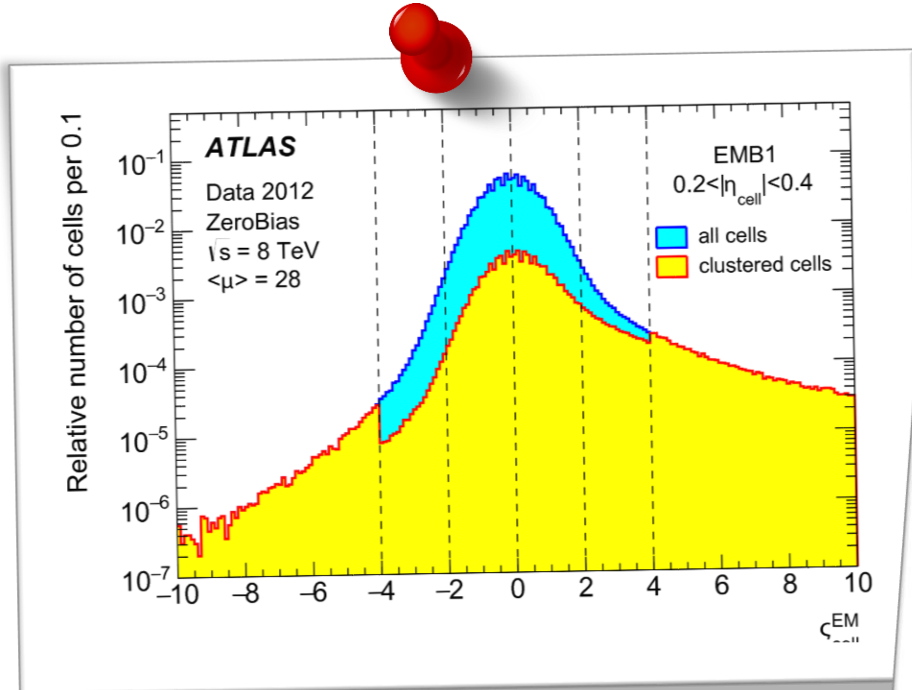
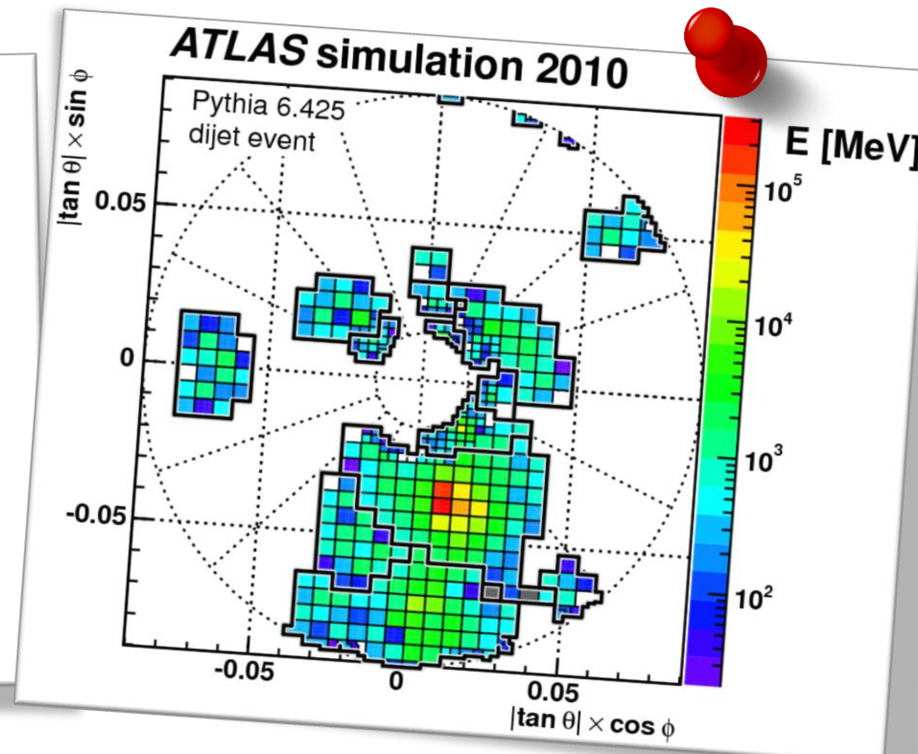
Follow signal significance patterns

Extract calorimeter cells with significant signals or topologically connected to significant signals (high signal-over-noise)





Applies splitting algorithm to resolve spatial energy flow

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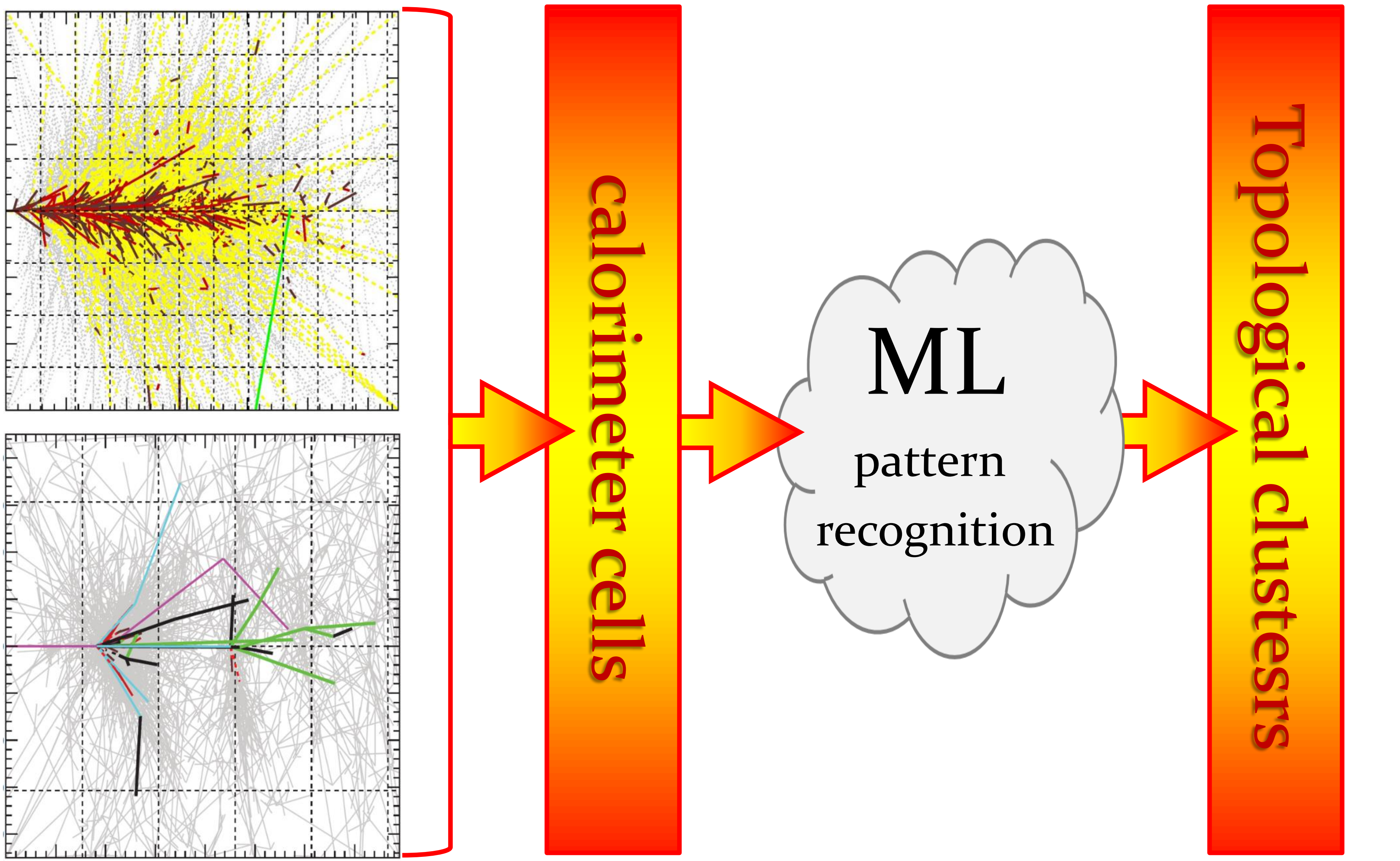
ML for Topo-Cluster Formation



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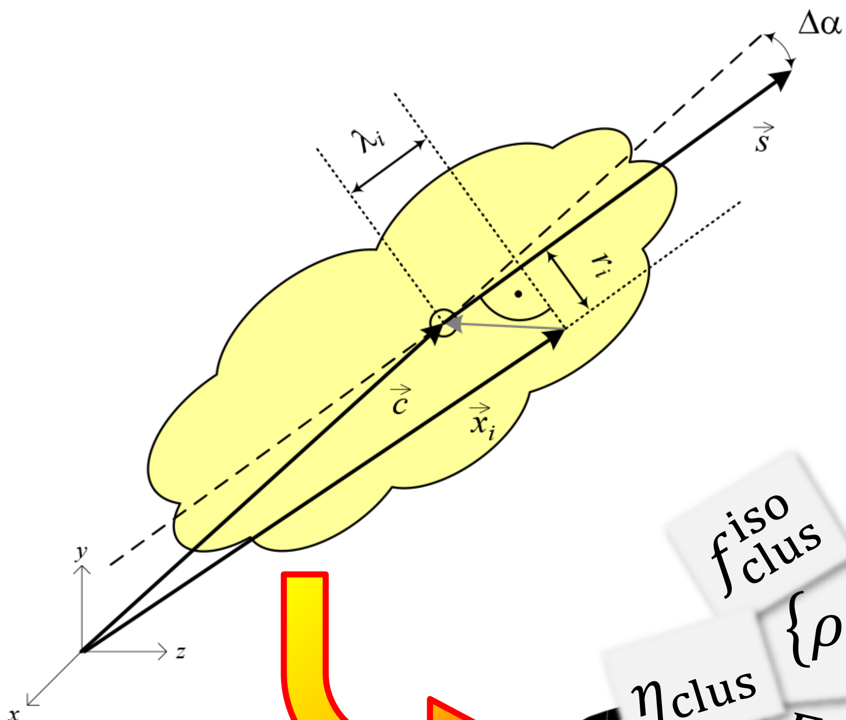

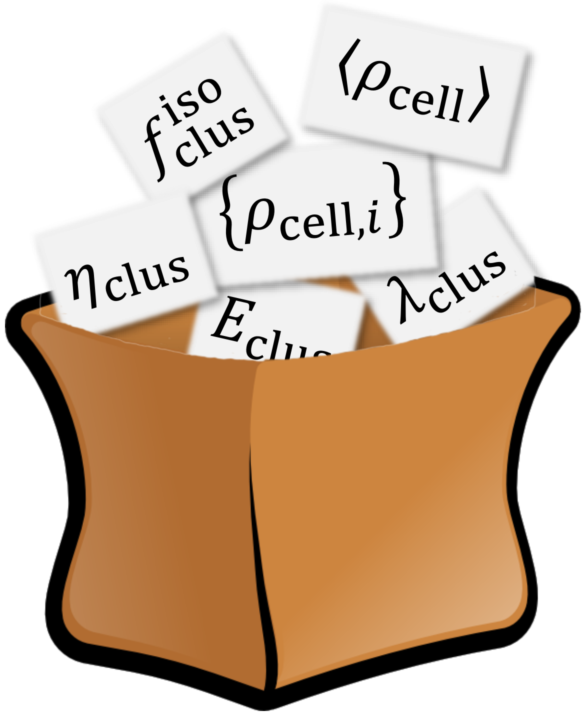

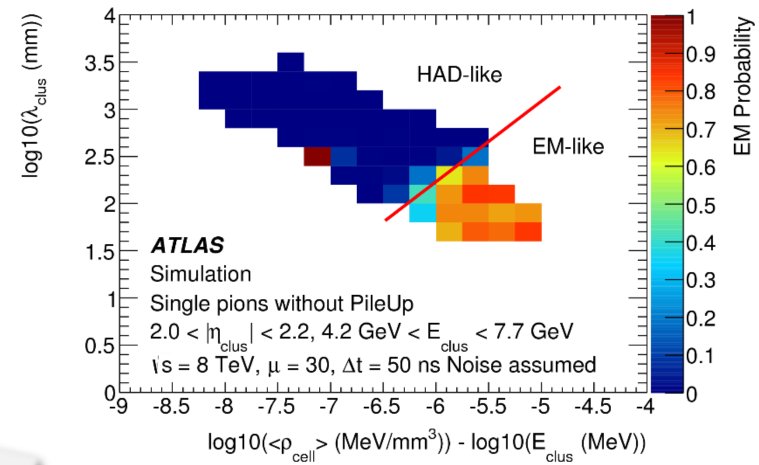

$$(E,\eta,\varphi)_{\mathrm{clus}} \mapsto (E,\eta,\varphi)_{\mathrm{true}}$$

Topo-Cluster Calibration Parameter Choices

Physics & detector

- Sensitive to differences in electromagnetic and hadronic cascades – different response (≡ signal from electrons/photons larger than signal from hadrons at the same deposited energy)
- Reflecting local response characteristics in calorimeter regions and boundaries

Finding observables

- Checked if simulation and experimental data agree – chose best described parameters also in pile-up signal environment
- Ran multi-variate tests (Fischer discriminant) to verify choices – seem to have found the best ones right away

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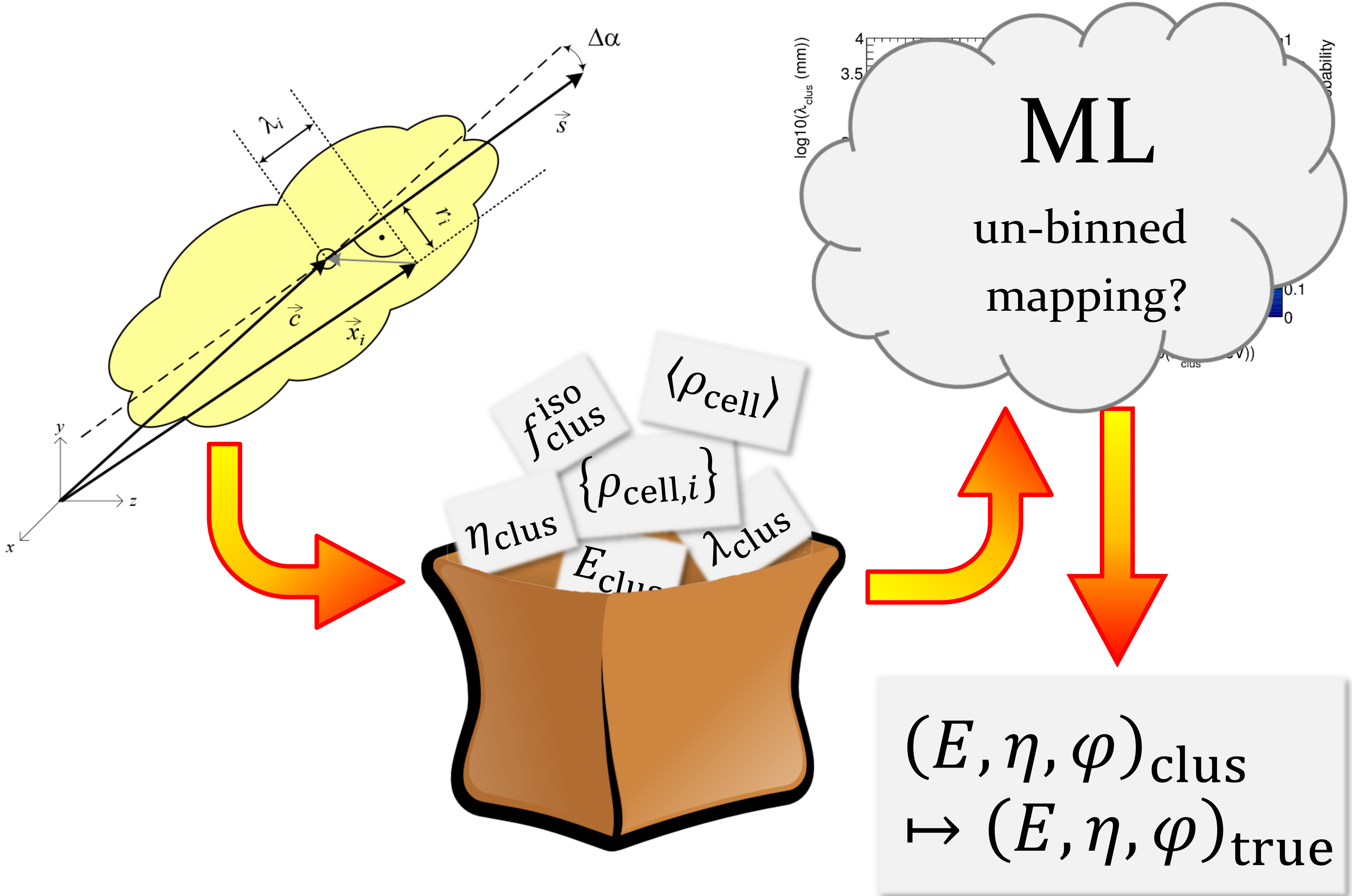
Topo-Cluster Calibration With ML



Jet Substructure

Why Looking Inside Jets at LHC?

Kinematic reach at LHC allows production of (highly) boosted particles

- All decay products of hadronically decaying Standard Model particles can be collected into single jet
  - $W \to qq$, Higgs bosons $H \to bb$, top quarks $t \to Wb \to qqb$
- Searches for new heavy particles with boosted (SM) decay products
  - Single jet mass indicative observable for new particle production

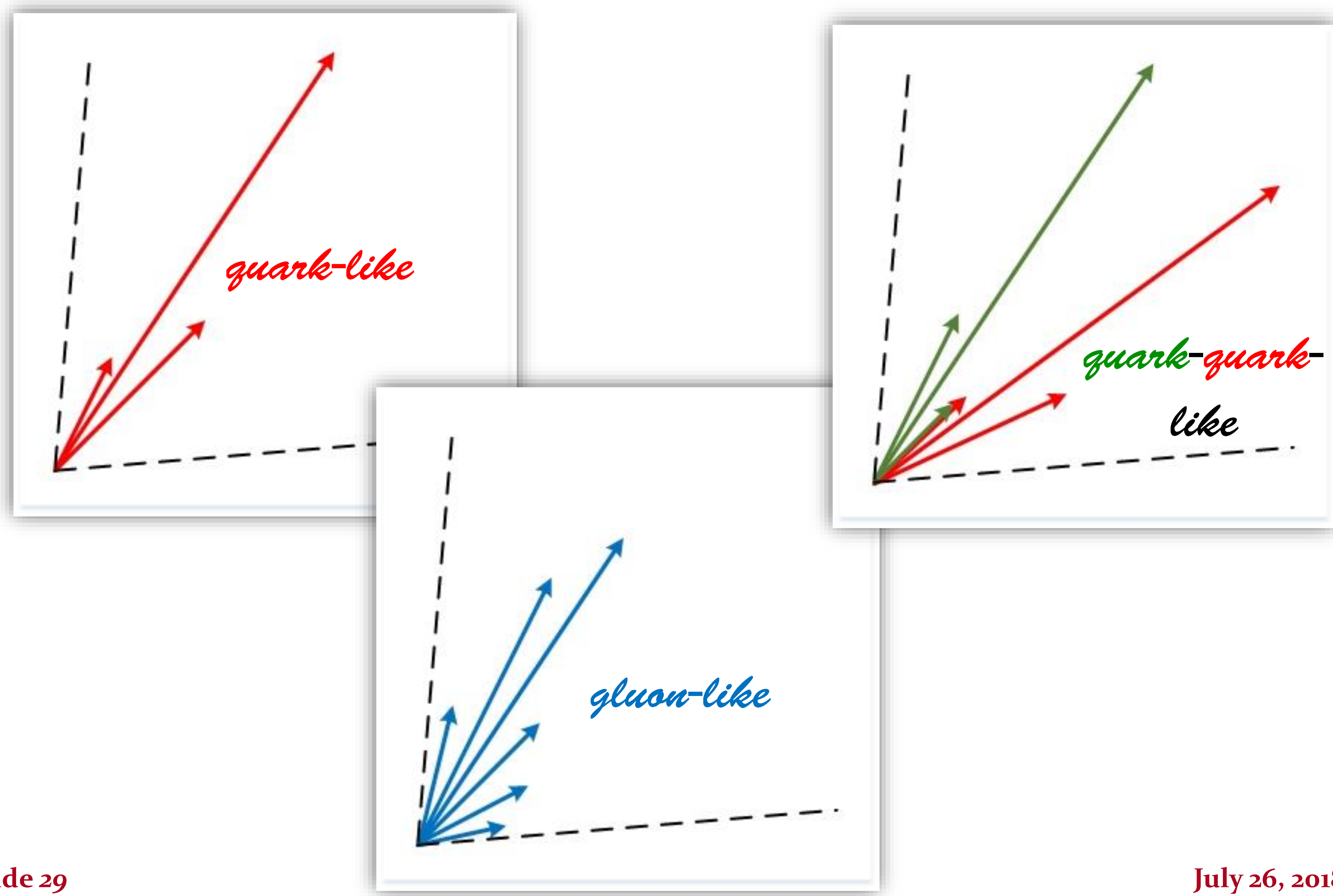
Experimental challenges – detector granularity & pile-up

- Limited granularity introduces limits in resolving sub-structure in a jet
  - E.g., signals from near-by particles can easily overlap in calorimeters
- Presence of pile-up can disturb single jet mass reconstruction from internal flow measurements
  - Needs to extract relevant internal jet energy flow structures for mass reconstruction etc. from diffuse pile-up contributions

Jet substructure analysis

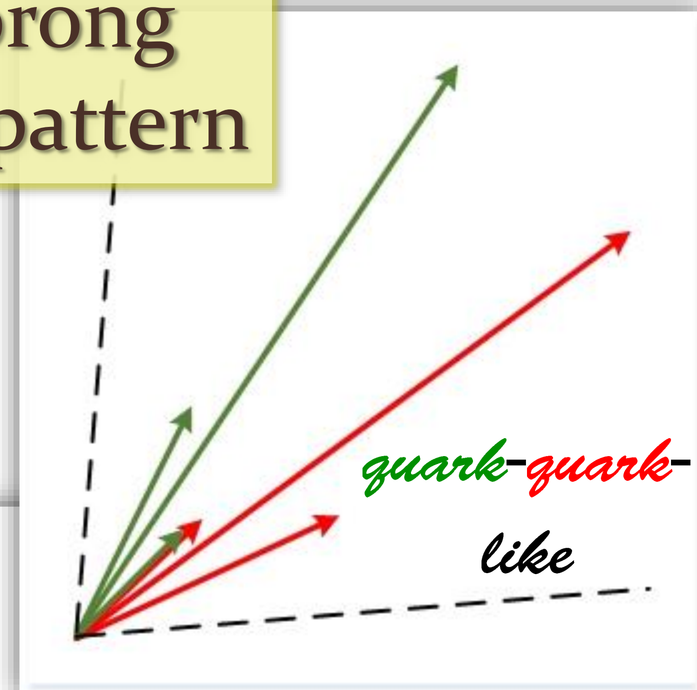
- Collection of techniques aiming at enhancing two- or three-particle (“prongs”) decay patterns in single jets
  - Typically leads to suppression of QCD-like backgrounds from quark- and gluon jets with their typical parton shower and fragmentation driven internal flow structure

Separation of Flow Patterns

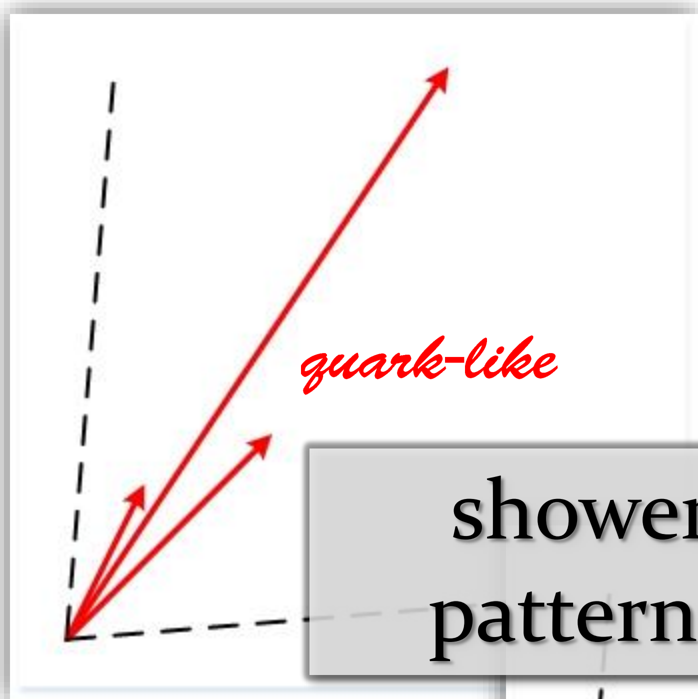


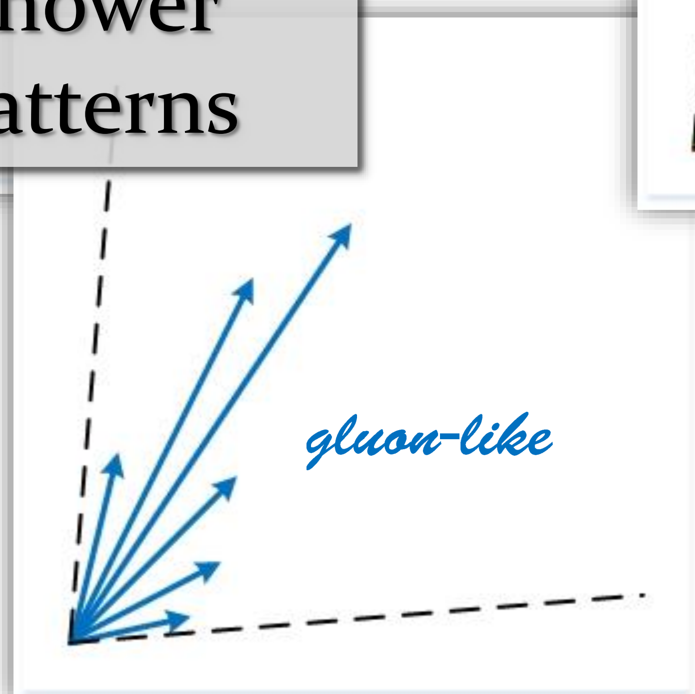
Separation of Flow Patterns

N*-prong decay pattern



shower patterns





*staged fast decays like $t \to Wb \to qqb$, boosted system of > 1 decaying particle, like in $HH \to bbbb$ etc.

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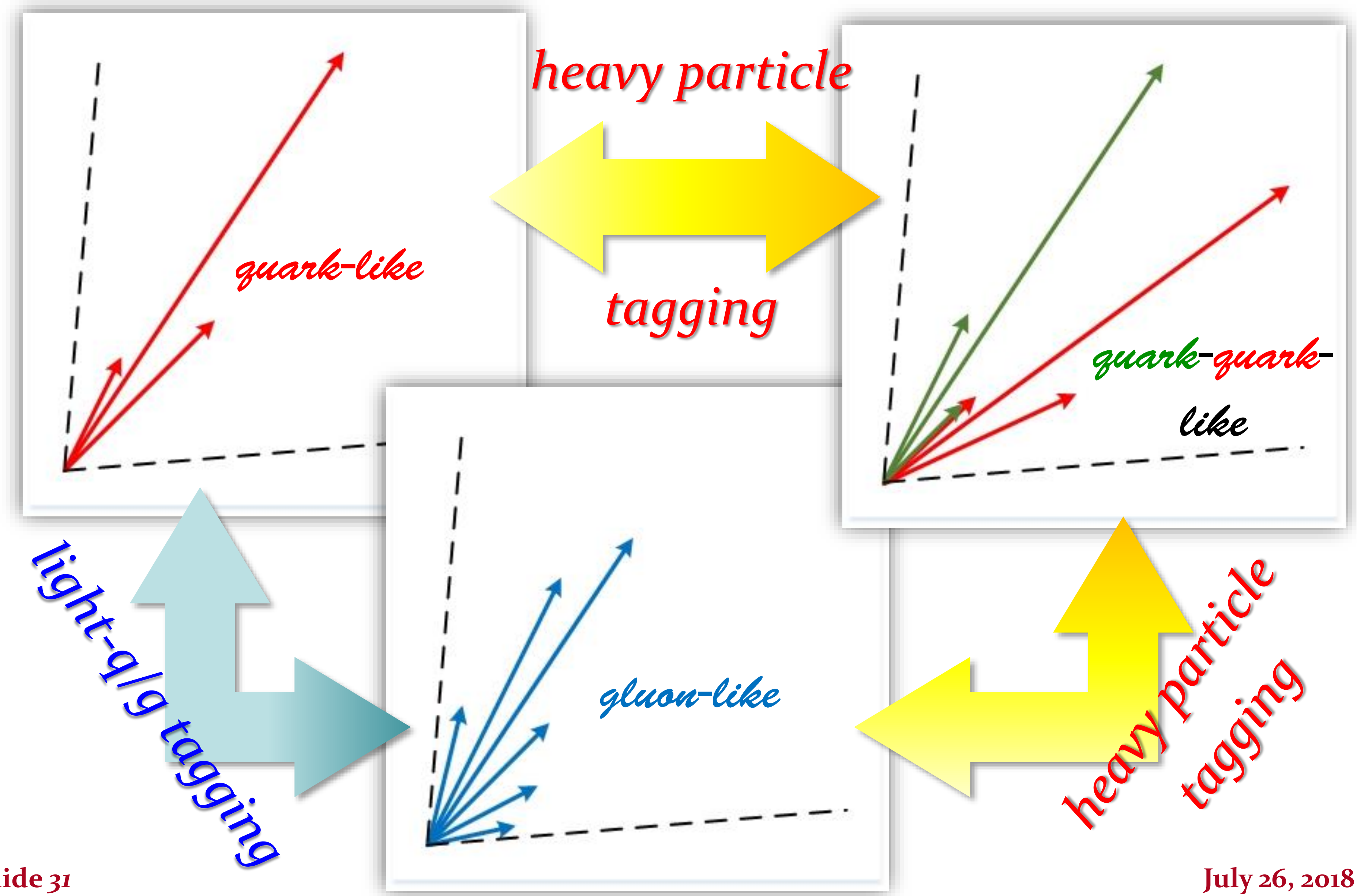
Separation of Flow Patterns



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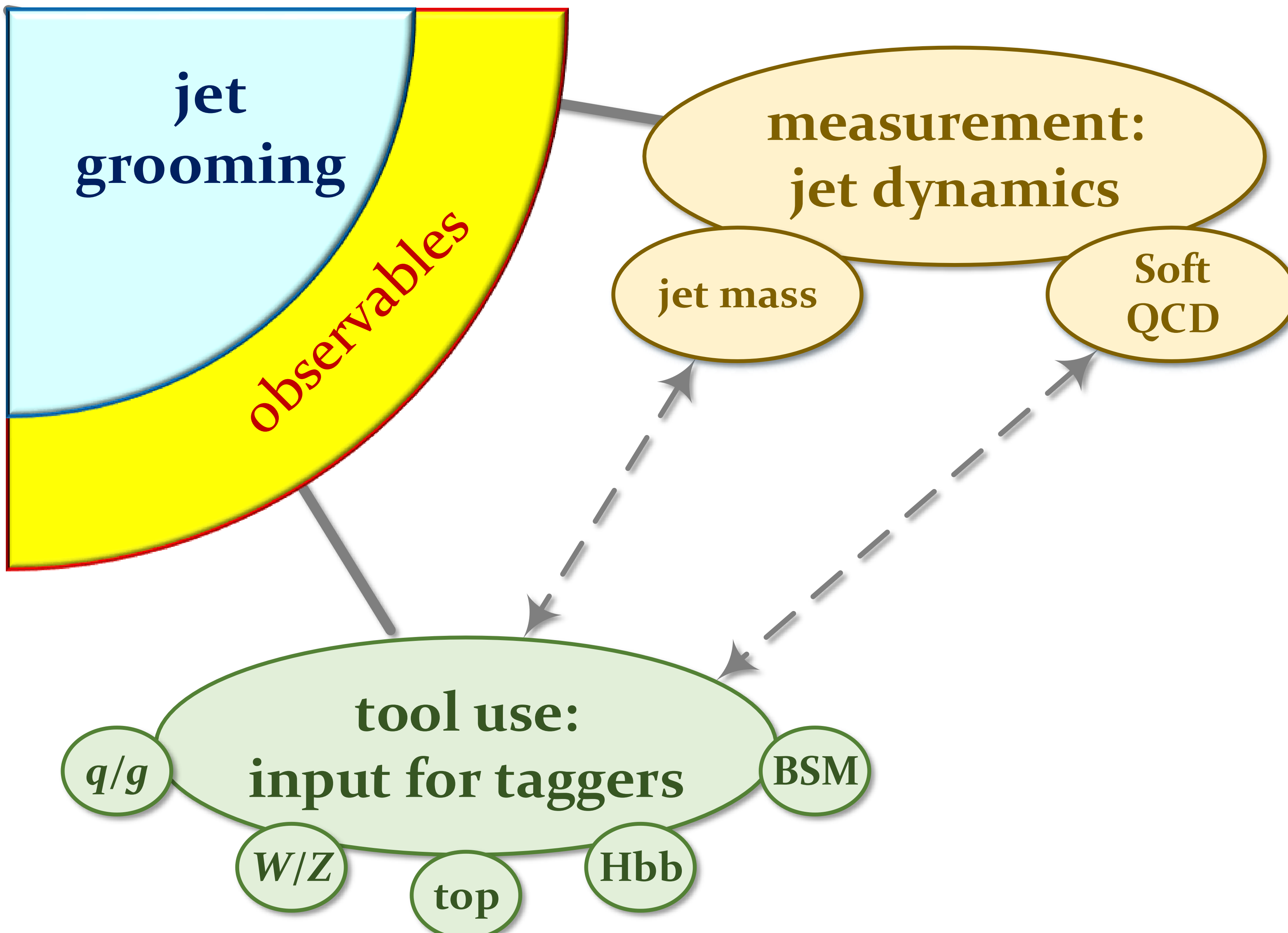
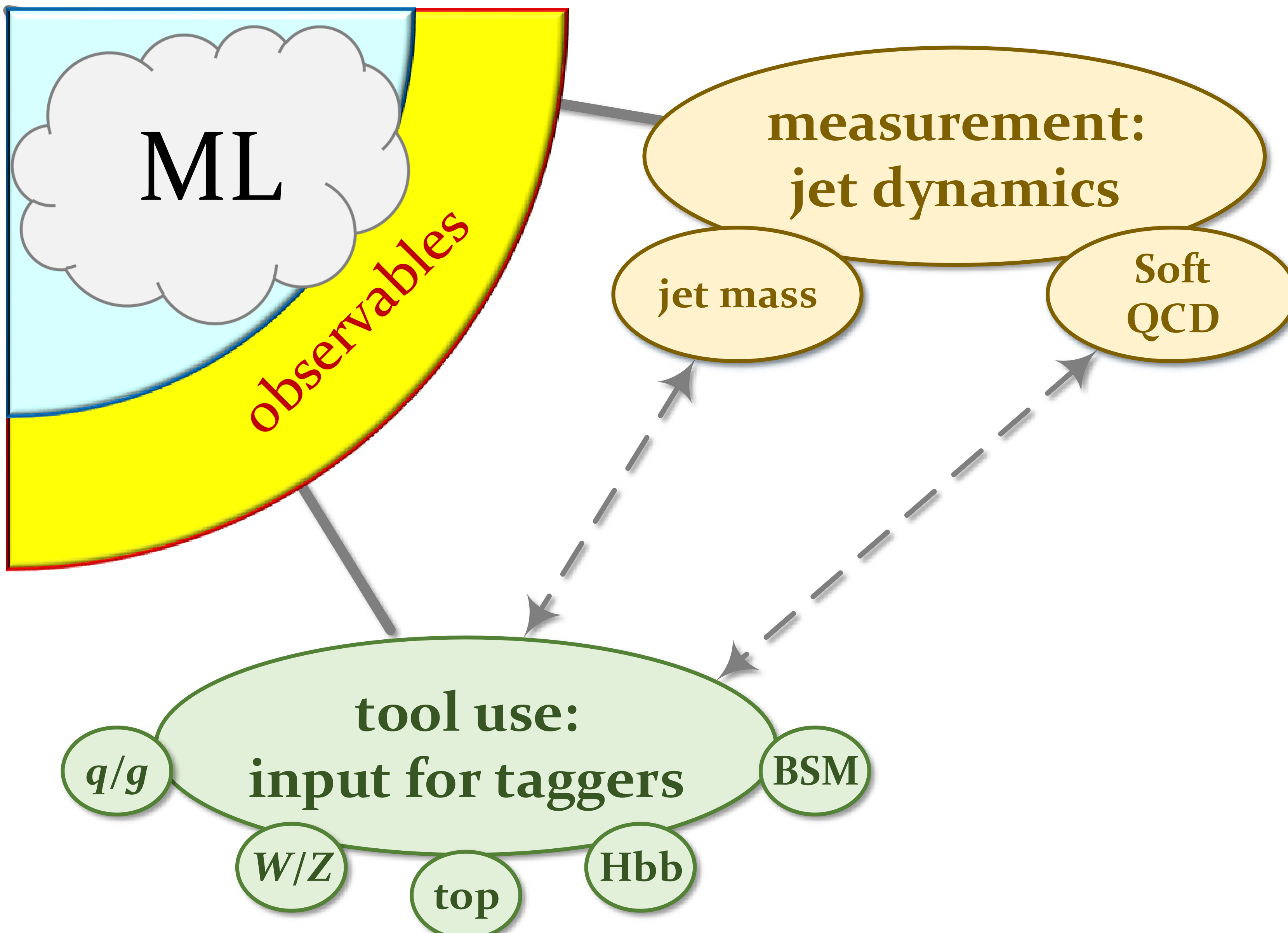


Jet Substructure in Physics Analysis



Jet Substructure in Physics Analysis

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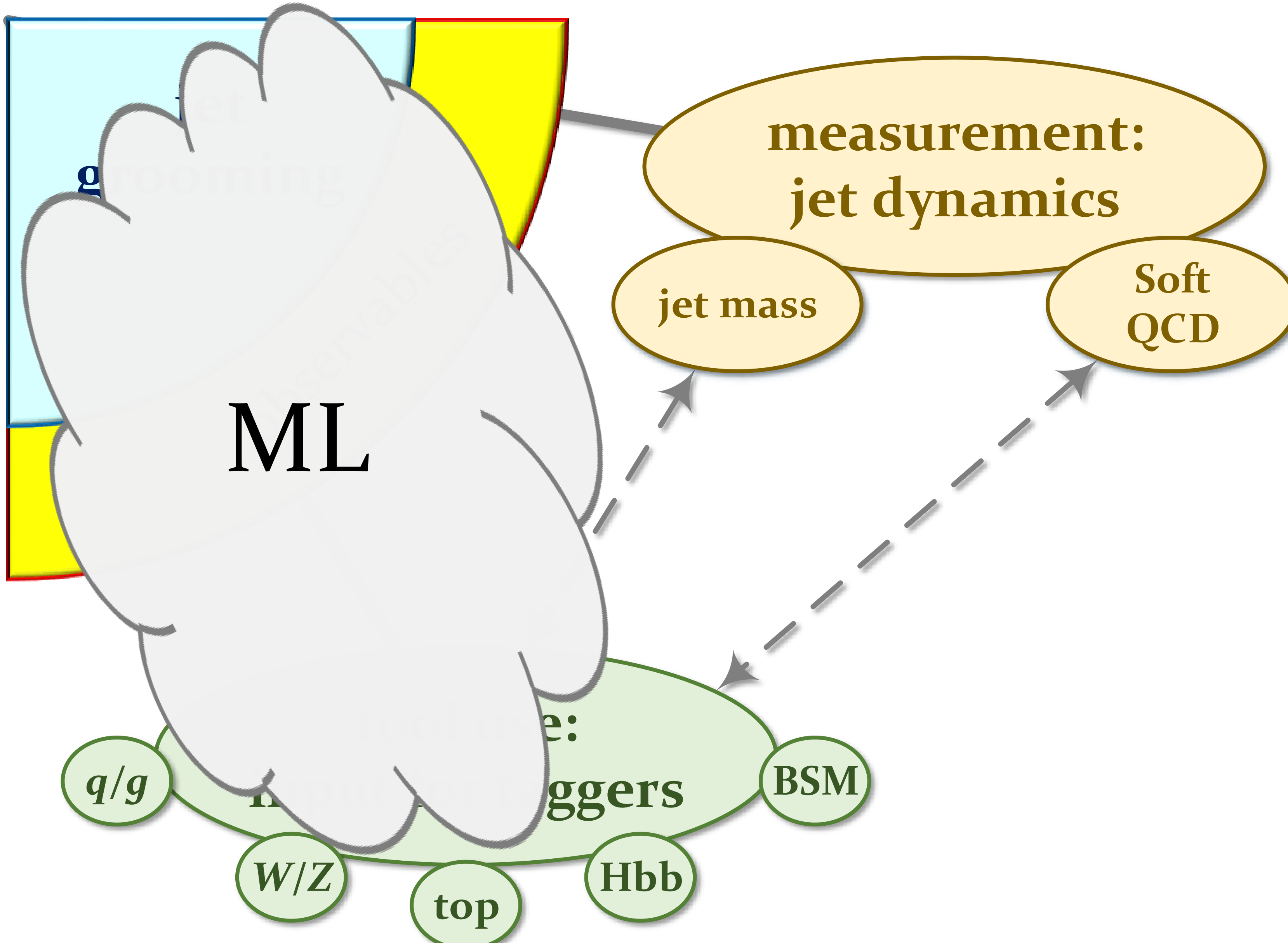

ML in Jet Substructure Analysis

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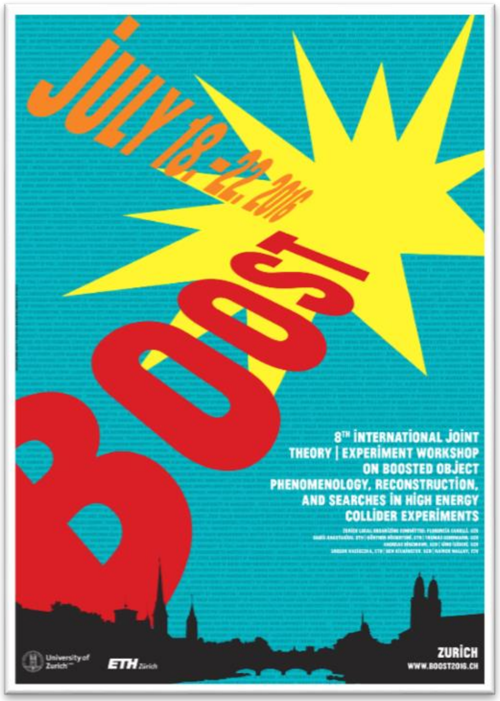
Already widely explored – mostly by theorists

Can clearly help to characterize jets beyond simple cuts – better exploration of residual uncorrelated features in relevant observables leads to improved measurements of structure

BOOST	#talks	#ML talks
2016	48	3 (6.3%)
2017	46	3 (6.5%)
2018	46	7 (15.2%)



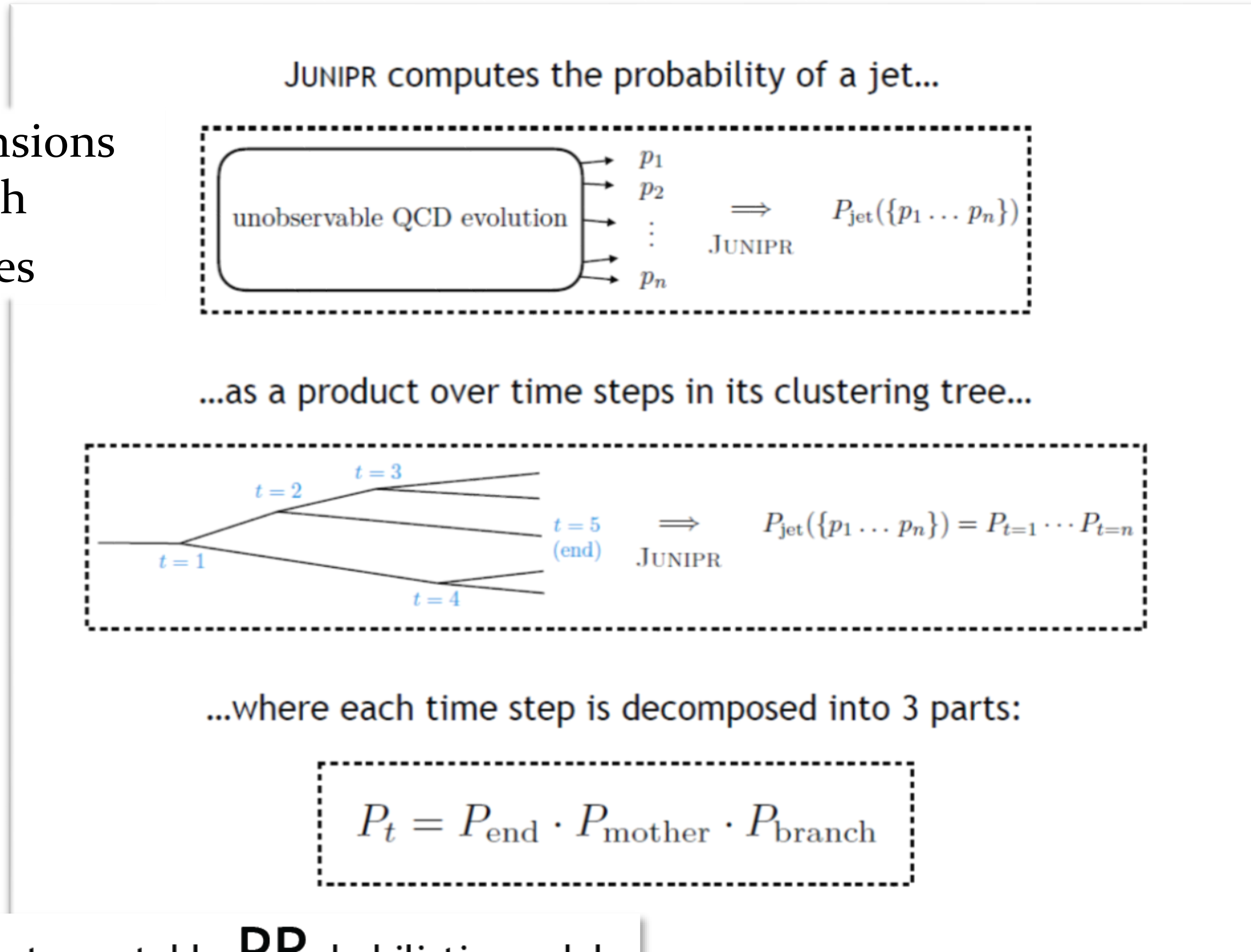
https://indico.cern.ch/event/649482/

Example: JUNIPR

ML analysis of jet branching by investing QCD

$\mathcal{O}(100)$ dimensions for jet with 30 particles

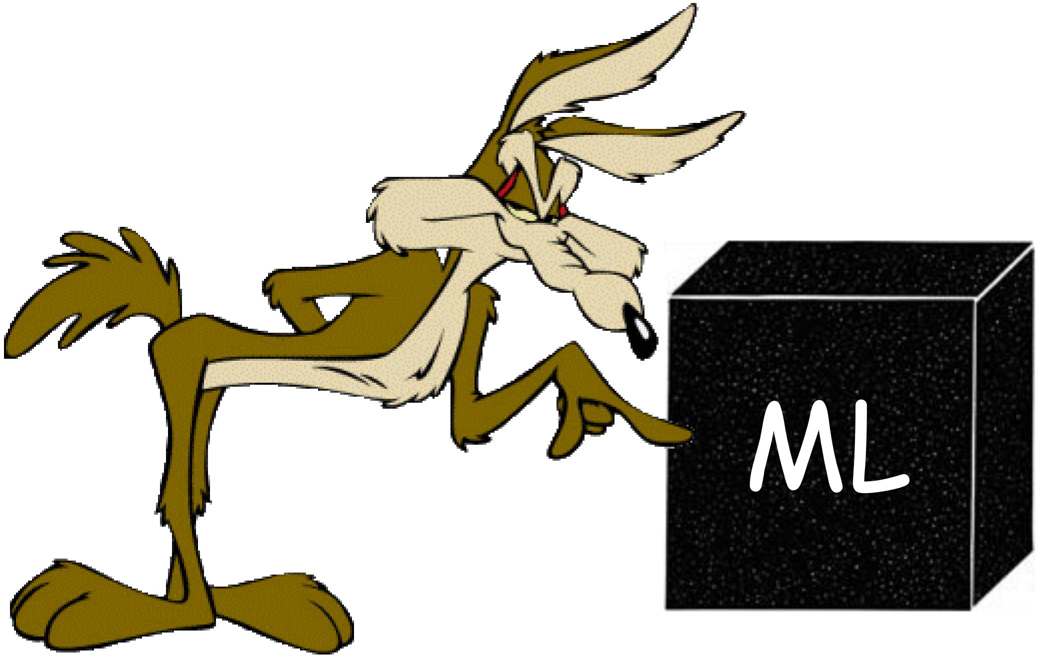
Andreassen, Feige, Fry, Schwartz
[arXiv:1804:09720]



Jets using UNsupervised Interpretable PRobabilistic models

https://indico.cern.ch/event/649482/contributions/3009032/attachments/1689533/2718078/frye-boost-2018.pdf

Experimental Issues (?)



Systematic uncertainties

- Pattern recognition – tagging efficiencies
  - Characterization of individual jets, full event, …
  - Bottoms-up approach starts with uncertainties for input observables – possibly non-trivial (unknown?) propagation through ML kernel?
  - Non-trivial due to correlations through common nuisances – not always possible to determine
  - Often can only test assumptions no (0%) or full (100%) correlations
  - Impractical for large number of inputs – just heard 650 (!) at BOOST2018
  - Hidden biases – how to detect/avoid?
- Signal extraction & measurements
  - Pile-up often overlapping signal features in simple phase spaces – suppression using ML? Jet-by-jet? Full event?
  - Precision measurement of e.g. jet features – how to test/avoid observation biases, control of systematics, …

No fast track here

- But clearly promising first impressions
  - Most obvious application for pattern recognition/image-based analysis

ML in Signal Reconstruction

Calorimeter signal extraction & calibration

Topological cluster formation

- Subject to large fluctuations in number of clusters, cluster shapes, and cluster response in ATLAS calorimeter for hadrons of the same energy – mostly due to fluctuations in shower development (process) and (weak) shape correlations
- More obvious for electromagnetic response – fairly regular and well correlated shapes with small process fluctuations

Cluster calibration

- Can help to reduce bin effects in lookup tables – presently addressed by interpolations (limited to 2-dim)
- Systematic uncertainties can probably be determined similar to present strategies comparing response expectations with calibrated signals

Similar issues with calorimeter jets …

Computing Resources

ML may have to run on large test samples

- Scanning large data samples for signal (and background) features
  - Extract events with a given likelihood to contain e.g. boosted decays, certain jet pattern, etc.
  - May include signal ambiguity resolution – same detector signals contributing to different physics objects in the same event
- Presently using derived data for event characterization
  - Minimal information content to include signal and background in a given phase space
  - Often more than one "view" of the same event in the same data set – derived data production may apply ML for object and event classification and/or filtering