LundNet: Robust jet identification using graph neural networks

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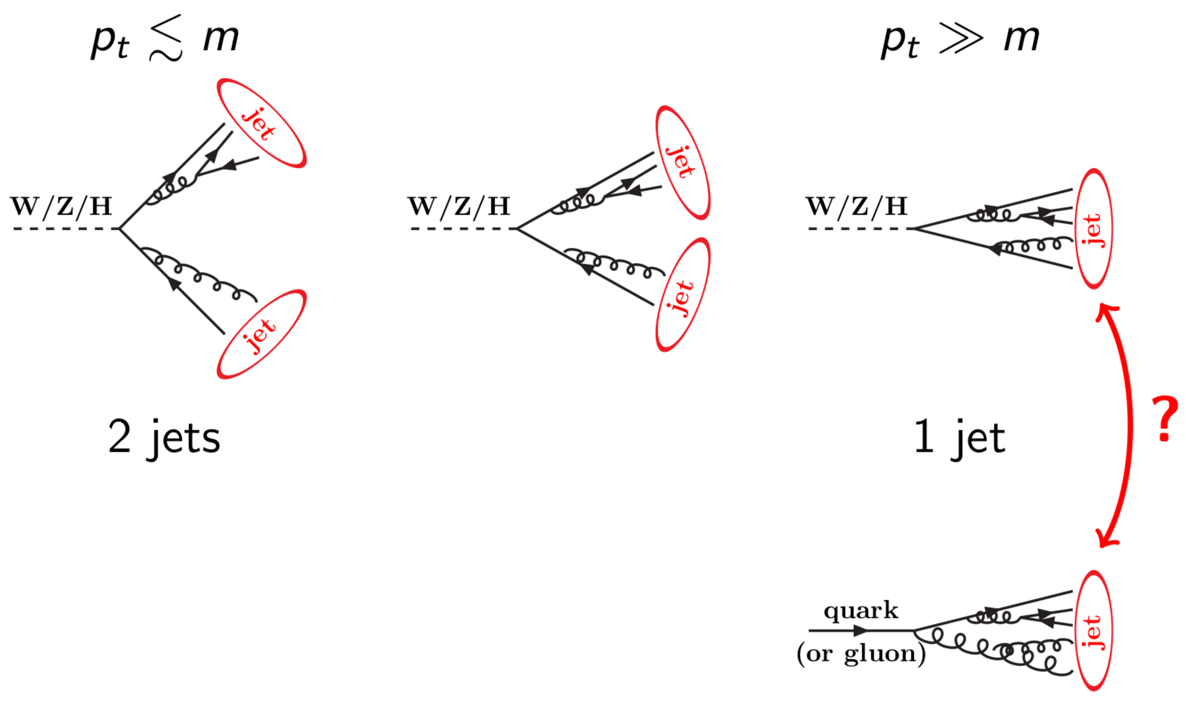
Boosted objects at the LHC

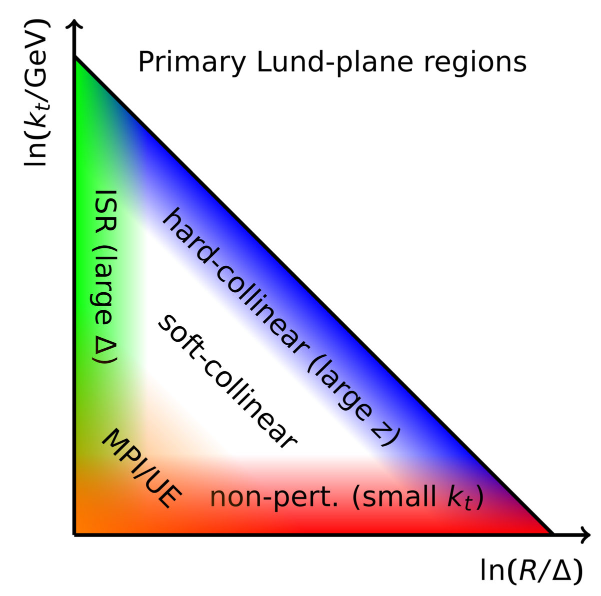
- At LHC energies, EW-scale particles (W/Z/t...) are often produced with $p_t \gg m$, leading to collimated decays.
- Hadronic decay products are thus often reconstructed into single jets.
- Many techniques developed to identify hard structure of a jet based on radiation patterns.



Lund diagrams

- Lund diagrams in the $(\ln z\theta, \ln\theta)$ plane are a very useful way of representing emissions.
- Different kinematic regimes are clearly separated, used to illustrate branching phase space in parton shower Monte Carlo simulations and in perturbative QCD resummations.
- Soft-collinear emissions are emitted uniformly in the Lund plane

$$dw^2 \propto \alpha_s \frac{dz}{z}\frac{d\theta}{\theta}$$



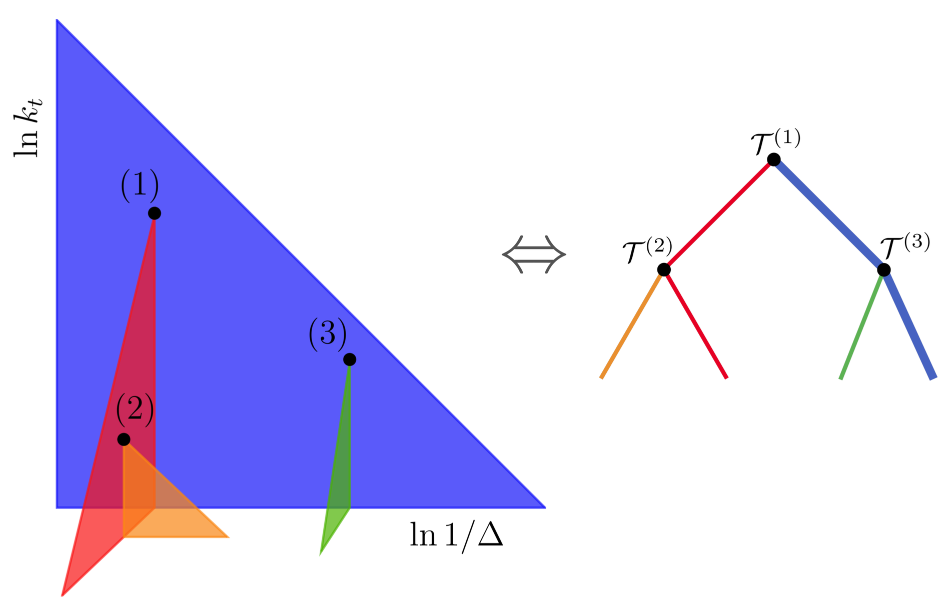
Jets in the Lund plane

The Lund jet plane is obtained by reclustering a jet's constituents with the Cambridge/Aachen algorithm, which sequentially combines the pair of particles i and j closest in rapidity y and azimuthal angle ϕ around the beam axis, minimising $\Delta^2 = (y_i - y_j)^2 + (\phi_i - \phi_j)^2$.

- Cast this clustering as Lund tree where each node d is a tuple $\mathcal{T}^{(d)}$ with kinematic information on splitting

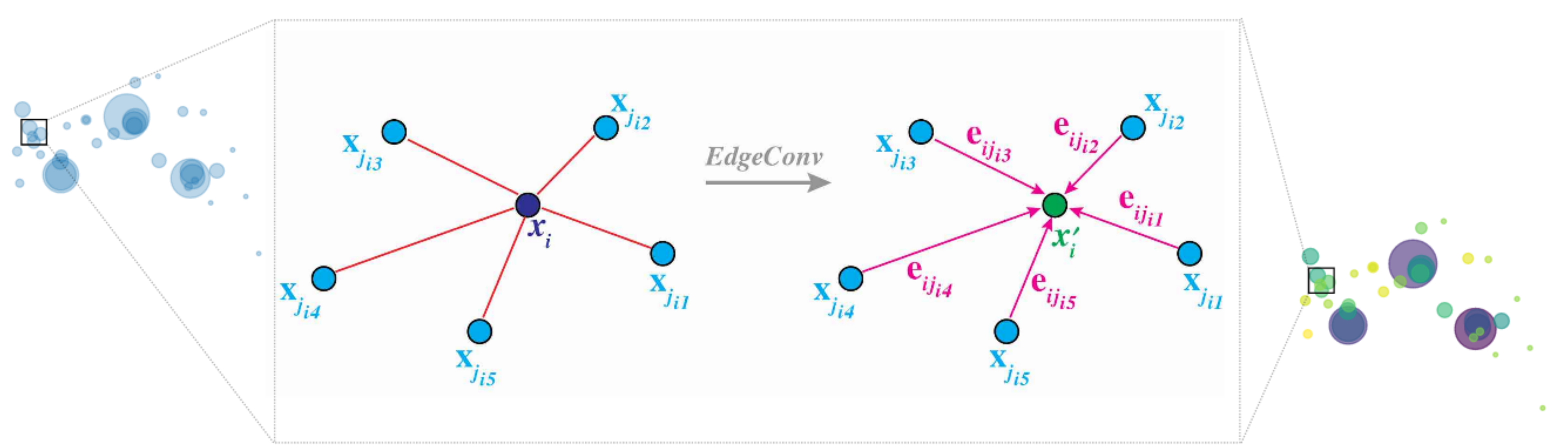
$$\mathcal{T}^{(d)} = \{z, \Delta_{ab}, \psi, m, k_t\}$$

- A subset of this tree of particular significance is the primary list of tuples $\mathcal{L}_{\text{primary}}$ containing the kinematic variables of each splitting along the primary hard branch of the tree (shown in blue).



Jet tagging using the full jet information

- Log-likelihood and LSTM network applied on primary Lund sequence can provide substantial improvement over best-performing substructure observables.
- Performance can be improved further by taking secondary Lund planes into account, particularly relevant for top tagging.
- Dynamic Graph CNN based methods perform particularly well, treating the full Lund diagram as a vertices on a graph.



LundNet models

We study two separate models, one which optimises performance and one designed to reduce the complexity of the model and improve its robustness.

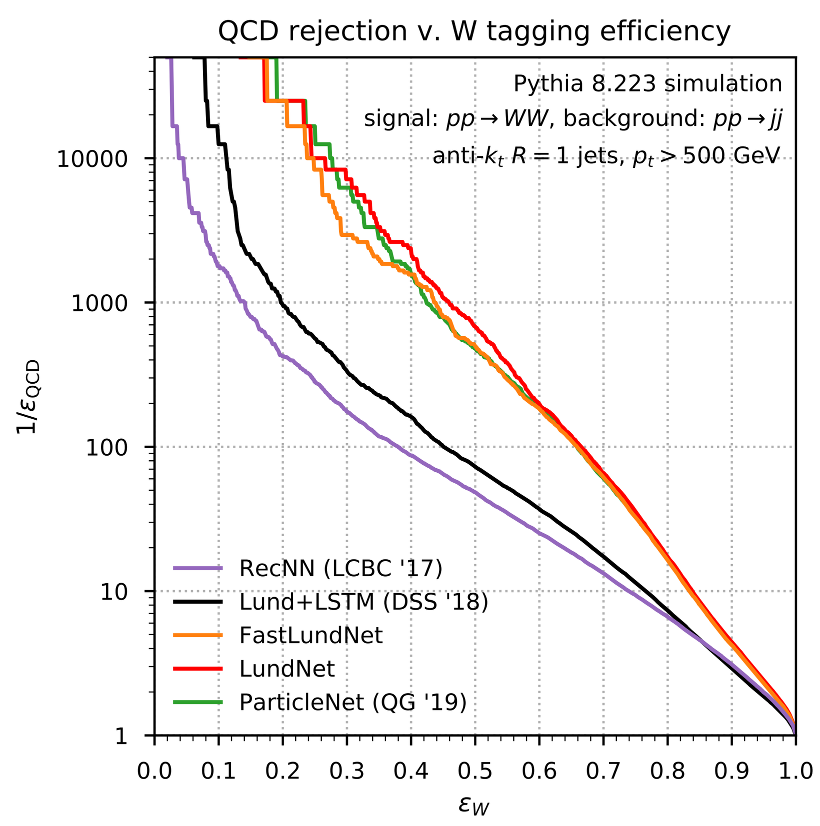
In both cases, the graph network starts by constructing a graph for a jet, with each node corresponding to a Lund declustering.

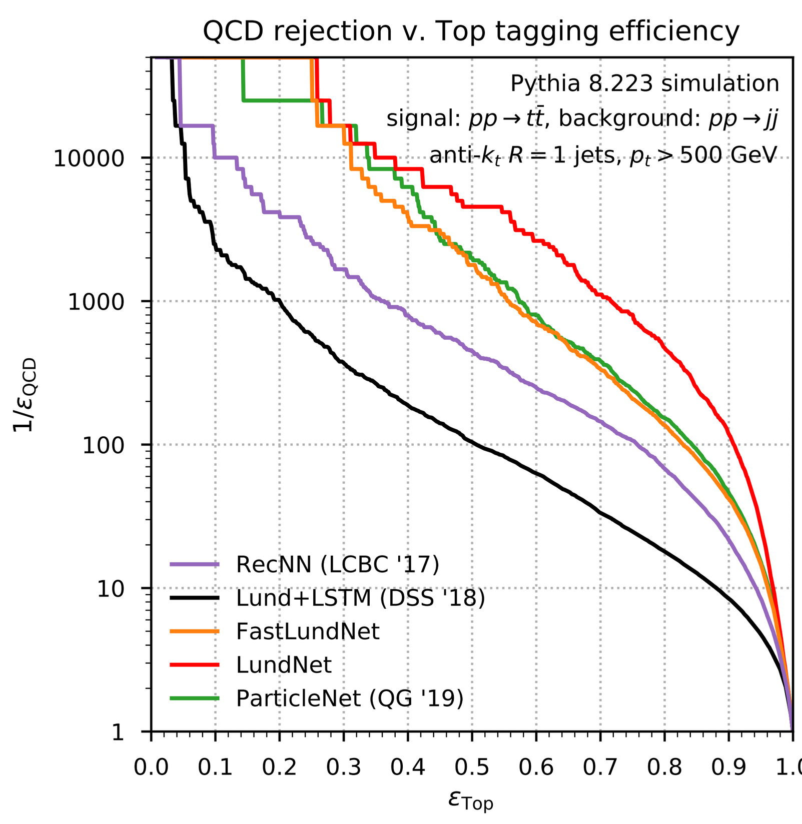
LundNet:
The kinematic input for each node is $(\ln z, \ln\Delta, \psi, \ln m, \ln k_t)$.
Three EdgeConv layers using $k = 16$ nearest neighbors in the pseudorapidity-azimuth plane

FastLundNet:
The kinematic input for each node is $(\ln z, \ln\Delta, \ln k_t)$.
Six EdgeConv layers using the immediate neighbours on the jet clustering tree for the graph convolutions.

Boosted W and top tagging

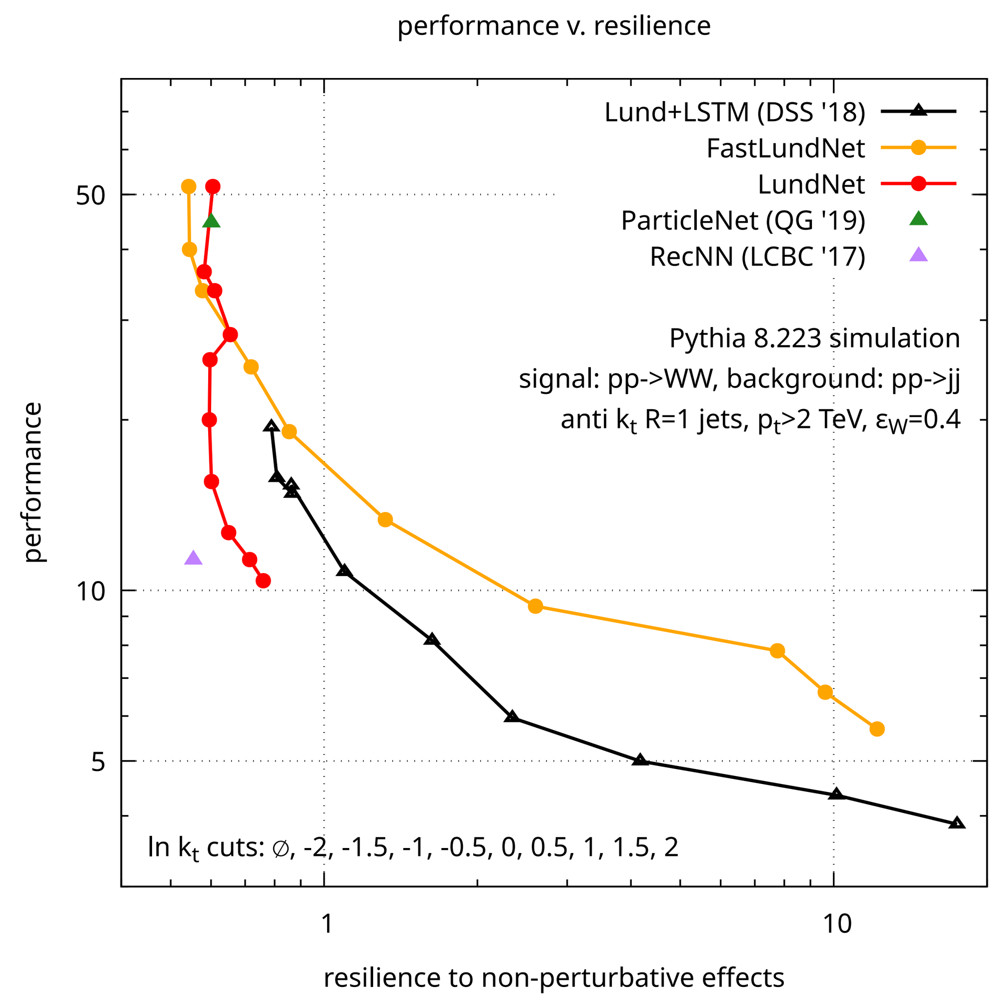
- Graph-based methods outperform our previous benchmark significantly.
- The LundNet model provides substantial improvement over ParticleNet for top tagging.
- FastLundNet achieves almost the same performance with a lightweight and robust model.





Robustness to non-perturbative effects

- Performance compared to resilience to MPI and hadronisation corrections.
- Vary cut on k_t, which reduces sensitivity to the non-perturbative region.



$$\Delta\epsilon = \epsilon - \epsilon'$$

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

$$\langle\epsilon\rangle = \frac{1}{2}(\epsilon + \epsilon')$$

- LundNet & ParticleNet reach high performance, but are not particularly resilient to NP effects.
- FastLundNet model achieves high resilience while retaining most of the performance.

Conclusions

- Jet substructure provides a unique practical playground for recent developments in machine learning.
- We describe a new way to study and exploit **radiation patterns in a jet** using the Lund plane.
- Introduced two models, **LundNet** and **FastLundNet**, which can achieve state-of-the-art performance on jet tagging benchmarks.
- Combination of physical insight and machine learning allows for models that combine performance and robustness.